Teaching Analytics in Colleges of Business

Abstract

The importance of analytics in the modern business environment has made it necessary to include analytics as a foundational course for all business majors. There is much debate on what content should be taught in analytics courses and what is the role of computational skills versus the skills needed to interpret and communicate the results that are needed as part of the analytics process. This debate points to the essential difference between analytics and statistics.

We first define business analytics and discuss the three types of employees who use analytics in organizations. We point out that business users are typically those who take only the introductory business analytics courses in universities.

Therefore, we discuss the business analytics process and map a two-course sequence, Business Analytics I and Business Analytics II, onto the process. We conclude out paper with a discussion of augmented analytics.

Keywords: Business analytics, Teaching, Statistics

1. Introduction

Business analytics is now a key component for organizations as they compete in a dynamic, global, technologically advanced business environment. For example, economic and social transactions are moving online, enhanced algorithms are available to better understand Big Data, and organizations now use advanced computational systems and user-friendly software (Agarwal & Dhar, 2014). In fact, Jim Goodnight, CEO of SAS Institute, reported "the ability to predict future business trends with reasonable accuracy will be one of the crucial competitive advantages of this new decade. And you won't be able to do that without analytics." (Parks & Thambusamy, 2017).

Businesses are using analytics to build and maintain customer relations, personalize products and services, and automate marketing strategies, to name just a few of such tasks (Liu & Levin, 2018). As a result, employers are seeking candidates who can manage data, analyze that data with statistical techniques, interpret statistical models, choose appropriate predictive procedures, and communicate the results.

In general, there are three types of employees who use analytics in organizations: the business user, the business analyst, and the data scientist (Rainer & Prince, 2022). As we proceed from business users, to business analysts, to data scientists, technical skill requirements increase. Our paper focuses on preparing the business user with the analytics skills needed for today's businesses:

- The *business user* employs analytics applications to perform their jobs. These employees would consist of all business majors (other than business analytics majors) who take the introductory course(s) in analytics at a university.
- The *business analyst* typically manages, cleans, abstracts, and aggregates data as well as conducting a range of analytics procedures on that data. These employees would consist of those students who major in business analytics.
- The *data scientist* builds upon the core competencies of the business analyst with additional mathematics, modeling, algorithmic, programming, and machine learning skills. Data scientists would typically major in mathematics or computer science.

2. Teaching Analytics in a University Setting

The importance of analytics in the modern business environment have made it necessary to include analytics as a foundational course for all business majors. The question remains how best to accomplish this task (Aasheim, et al., 2015; Hill & Cline, 2014; Liu & Levin, 2018; Sledgianowski, Gomaa, & Tan, 2017; Zhao & Zhao, 2016). Many studies have addressed how to integrate analytics into the curricula of business disciplines including accounting (Atwong, 2015; Camm et al., 2015; Coyne, Coyne, & Walker, 2016; Dzuranin, Jones, Olvera, 2018; Richardson & Watson, 2021; Richins et al., 2017; Veeck & Hoger, 2014; Wymbs, 2016), information systems (Molluzzo & Lawler, 2015; Parks & Thambusamy, 2017), management (McAfee & Brynjolfsson, 2012), and marketing (LeClair, 2018, Liu & Burns, 2018; Liu & Levin, 2018, Munoz & Wood, 2015). However, these studies proposed to include analytics by simply integrating into existing courses topics such as social media tools, various software packages, a practicum, or an additional certificate program.

The Association to Advance Collegiate Schools of Business (AACSB) recently incorporated data analytics into their formal standards in order to stay abreast of industry requirements (AACSB, 2022). (Note: We equate Colleges of Business and business schools in our paper.) The AACSB also lists the general skills of written and oral communication, data ethics understanding and reasoning, analytical thinking,

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teamwork, and reflective thinking as requirements for all business graduates. Because of industry demands and AACSB accreditation requirements, it is essential that analytics be taught in all colleges of business. Unfortunately, curriculum change in higher education is often slow and difficult, often due to the diversity of opinions on the content and pedagogy needed for business analytics courses versus business statistics courses.

To date, colleges of business have implemented analytics courses in different ways. Some integrated these courses in each discipline (accounting, marketing, finance, etc…), while others provide stand-alone courses for all business majors (Leclair, 2018). Complicating the situation, Wymbs (2016) found that, while colleges of business primarily offer business analytics courses, various other departments across campuses, including computer science, math and statistics, or interdisciplinary departments also offer analytics courses. The specific department offering the analytics courses typically determines whether the course is designed for the business user, business analyst, or data scientist. Unfortunately, these "solutions" have not addressed important issues: What content should be taught in analytics courses and what is the role of computational skills versus the skills needed to interpret and communicate the results that are needed as part of the analytics process?

These problems point to the essential difference between analytics and statistics. As we discuss in this paper, analytics is a process that employs statistical tools. That is, analytics and statistics are not the same thing. Accordingly, we first discuss the business analytics process which we feel must be taught in all business analytics courses. We then propose a two-course sequence, Business Analytics I and Business Analytics II, to be taught as required courses in colleges of business with two goals: First, the courses will enable students to be knowledgeable business analytics users. Second, the courses will provide an excellent introduction to the courses required for a BA major. We address the content in each course and then present two examples which we use in class to help students understand: (1) That analytics is a process. (2) That the analytics process uses statistical procedures to accomplish its goals. (3) That analytics and statistics are not the same thing. (4) The analytics process requires creative, out-of-box thinking and communications skills.

The Business Analytics Process

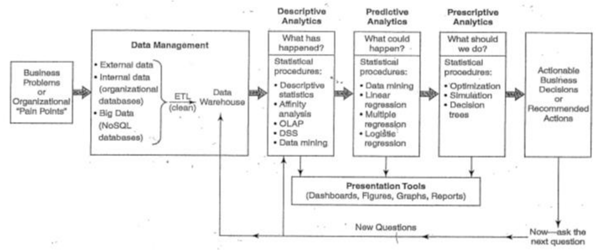

Figure 1. Analytics Process

Business analytics (BA) is the process (see Figure 1) of developing actionable decisions or recommendations for actions based on insights generated from historical data. Business analytics examines data with a variety of tools; formulates descriptive, predictive, and prescriptive analytics models; and communicates these results to organizational decision makers. Note that this definition distinguishes between business analytics and statistics. Essentially, the business analytics process uses statistical procedures to accomplish its goals. The business analytics process consists of a series of steps (see Figure 1).

Define the business problem

The first, an arguably most important, issue that we face in the BA process is to define the business problem that you want to address. These questions can provide us with guidance in defining the business problem:

- What is the organization trying to accomplish?
- What are the organization's goals?
- What business process is the organization trying to improve?
- How would improving this business process contribute to making the organization more successful?
- Other, more specific, questions include why have profits decreased? Which customers are moving to our competitors and why? Why has demand for a particular product decreased and why?

Data management

After defining the business problem, we consider the data that we have available for analysis. As we have noted, organizations are now able to analyze rapidly increasing amounts of data from a variety of sources. These sources include external data, internal data, and data streams.

- *Point-of-sale (POS) data*. Organizations capture data from each customer purchase with their POS systems.

- *Clickstream data*. Clickstream data are those data that visitors and customers produce when they visit a website and click on hyperlinks. These data include the websites that a user visits, the pages they view on a website, how long they spend on each page of the website, items left in an online shopping cart, and many other examples.
- *Social media data.* Social media data (also called social data) are the data collected from individuals' activity on social media websites. These data include shares, likes and dislikes, ratings, reviews, recommendations, comments, and many other examples. These data are useful because users voluntarily reveal data on their personal lives when accessing these social media sites. Organizations use social data to help build a complete view of their customers.
- *Sensor data*. The Internet of Things is a system in which any object, natural or manmade, contains internal or external wireless sensor(s) which communicate with each other without human interaction. Each sensor monitors and reports data on physical and environmental conditions around it, such as temperature, sound, pressure, vibration, and movement.

These four data streams, together with data in organizational databases and external databases, comprise Big Data. We define Big Data as diverse, high-volume, high-velocity information assets that require new forms of processing in order to enhance decision making, lead to insights, and optimize business processes. Essentially, Big Data is the heart of the analytics process.

At this point, organizations integrate and clean these data into data marts, data warehouses, and data lakes through a process called extract, transform, and load (ETL). The data are now available to be analyzed by business users, business analysts, and data scientists. In the past, data collection was time-consuming and expensive. Today however, companies can collect vast amounts of data in real-time and relatively inexpensively. Massive amounts of data contribute to increasingly accurate analytics applications.

If organizations have an enormous amount of data to apply to a problem, random sampling becomes less important; i.e., the amount of data in the sample approaches the amount of data in the population. We discuss random sampling if the amount of data in our sample is much less than the data in the population or if the data in our sample could be biased. We also address data ethics in our discussion of data management. We define data ethics as the process of examining and applying moral principles when managing, analyzing, and reporting data (Blanthorne, Kovar, & Fisher, 2007). Data ethics are very important to reduce long-term liability costs, negative market perceptions, scandals, and government interventions (Smith, Kouchaki, & Wareham, 2021; Zeiger, 2019). We look at five data ethics principles:

- *Ownership:* Who owns the data?
- *Informed Consent:* Do we have permission to collect or use data? We should obtain consent, which must be voluntary. We should provide the purpose of the data collection, how we collected the data, any risks associated with how we use the data, and the confidentiality and anonymity that we provide.
- *Privacy:* How do we store and manage the data and whether or not we share it with others?
- *Currency:* Should companies sell personal information or pay for reviews?
- *Openness:* Is a business' data available to the public or is it copyrighted?

Descriptive analytics

Descriptive analytics is the process of using current and historical data to identify trends and relationships. Descriptive analytics summarizes what has happened in the past and enables decision makers to learn from past behaviors. Common examples of descriptive analytics are reports that provide historical insights regarding an organization's production, financials, operations, sales, finance, inventory, and customers. BA tools in descriptive analytics applications include online analytical processing, data mining, decision-support systems, and a variety of statistical procedures. Examples of such statistical procedures are descriptive statistics, affinity analysis, and many others (see Figure 1).

Predictive analytics

Predictive analytics examines recent and historical data to detect patterns and predict future outcomes and trends. Predictive analytics provides estimates about the likelihood of a future outcome. The purpose of predictive analytics is *not* to tell decision makers what will happen in the future. Predictive analytics can only forecast what *might* happen in the future, based on probabilities. Predictive analytics applications forecast customer behavior and purchasing patterns, identify trends in sales activities, and forecast demand for inputs from suppliers. Organizations use a variety of BA tools and statistical procedures in performing predictive analytics. The tools include data mining, and the statistical procedures include linear regression, multiple regression, and logistic regression. There are also many other tools and statistical procedures that are used in predictive analytics.

Prescriptive analytics

Prescriptive analytics goes beyond descriptive and predictive models by recommending one or more courses of action and by identifying the likely outcome of each decision. Prescriptive analytics attempts to quantify the effect of future decisions in order to advise on possible outcomes before the decisions are actually made. Organizations use a variety of BA tools and statistical procedures to perform prescriptive analytics. Statistical procedures include optimization, simulation, and others.

Data visualization

The old adage, "A picture is worth a thousand words" is more applicable in today's technological businesses than ever before. Data visualization is the process of displaying data and the results of the analytics process in a meaningful way. Most organizations employ dashboards that provide easy access to timely information and direct access to management reports. According to Few (2006), "The fundamental challenge of dashboard design is to display all the required information on a single screen, clearly and without distraction, in a manner that can be assimilated quickly." Dashboards are user friendly, supported by graphics, and, most importantly, enable managers to examine exception reports and drill down into detailed data. Storytelling, which accompanies data visualization, means telling a compelling, accurate story about the data and results of the analytics process (Knaflic,2015). Business analytics users need to know that there is a story in all data.

Ask the next question

A critical component of the analytics process is that once the results are obtained and presented, decision makers must be ready to "ask the next question." Everyone involved in the BA process must use his or her creativity and intuition at this point. The fact is that, even during the analytics process, new data are being collected. As a result, the results of the BA process will almost always lead to new, unanswered questions.

3. A Two-Course Sequence: Business Analytics I and Business Analytics II

Executives need data-driven leaders with analytics skills to manage data and interpret results (LeClair, 2018). For this reason, we propose a two-course sequence to teach analytics to meet this demand.

Business Analytics I

This course provides a foundation for Business Analytics II by covering the Business Analytics Process through Descriptive Analytics. We propose to de-emphasize computational techniques in favor of integrating analytics and communications skills in various business scenarios. Here are the course topics in Business Analytics I:

- Business Problem: How to define a business problem
- Data Management:
  Data types: Quantitative & Qualitative
  Data collection: Data streams and Big Data
  Data storage: Databases, data warehouses, data lakes
  Data Visualization: Graphs and Dashboards using Tableau
  Data Ethics
- Descriptive Analytics
  Using descriptive analytics to answer the question: What has happened?
  We address the following topics: descriptive statistics, affinity analysis, online analytical processing, data mining, and decision support systems.

Business analytics II

Business Analytics II builds on Business Analytics I. The purpose of Business Analytics II is to prepare students to construct simple predictive models with the emphasis being on stating the business problem, analyzing the data, interpreting the findings, and communicating the results. Business Analytics II begins a review of the Business Analytics process and continues with Predictive Analytics. We address the following topics/statistical procedures: Hypothesis testing, A/B testing, linear regression, multiple regression, logistic regression, and time series forecasting.

Business scenarios

We use a selection of business scenarios that continue through the two courses. As we introduce new concepts, we add to the scenarios previously introduced. This approach provides connectivity among the concepts being taught and demonstrates how to use the analytics process to solve a business problem. Only for our business analytics majors does the emphasis shift more toward a more in-depth application of the analytics process. For example, topics such as data mining, OLAP, and prediction methods involving machine learning and times series forecasting are covered. As in business analytics I and II, business problems are introduced at the beginning of the semester and used throughout the course.

4. Example Business Scenarios

Business scenario 1: University Admissions

All universities have a process for admission. The entire process is essentially an analytics exercise.

Business problem(s): How do the university decide on the best-qualified students to admit? One metric could be students who have the highest probability of graduating in five years or less. (Note: Universities could use many different metrics. Students typically do not know about such metrics, so we introduce the metric above and then let students think about additional metrics.)

Quantitative and Qualitative Data: Quantitative data includes household income, high school grade point average, size of high school, standardized test scores, ZIP code, household income, and many others. Qualitative data includes student name, address, parents' names, high school attended, Advanced Placement (AP) classes taken, essays written, recommendations, and many others.

Descriptive analytics applications

- Which high schools provide the highest percentage of successful applicants?
- What has been the average high school GPA from each size of high school?
- What has been the average ACT or SAT score among successful applicants?
- On average, how many AP classes have successful applicants taken?
- On average, how have applicants' essays contributed to the success of their applications?
- On average, how have applicants' letters of recommendation contributed to the success of their application?

Predictive analytics applications

- Based on data from an applicant and descriptive analytics applications, should the applicant be accepted? (That is, what is the probability that the applicant will graduate in five years of less if he or she is accepted?)

Prescriptive analytics applications

- Given the results of the descriptive and predictive applications, where might university recruiters choose to visit?
- Given the results of the descriptive and predictive applications, what areas would the university target in their marketing and advertising campaigns?

Ask the next question

- Are there additional variables that we could include for applicants to our next freshman class?

Business scenario 2: City Trash Pickup

The amount of garbage in cities is increasing, and so are garbage collection costs. The World Bank predicts that global garbage collection expenses will increase by 83 percent by 2025. These costs are very concerning to cities around the world.

Business problem(s): How can a city decrease the cost of trash collection? We begin our discussion here with how cities have historically collected trash. Typically, cities have trash trucks on fixed schedules and routes. Each truck empties every receptacle along its route because the driver usually cannot see inside the receptacle.

Data: Sensor data from each trash receptacle (GPS location, weight and fullness of each receptacle) Note: The city will empty a receptacle if either the weight of the trash in the receptacle reaches a preset limit or the amount of trash (fullness) in the receptacle reaches a preset limit.

Descriptive analytics applications

- Which receptacles need to be emptied? We emphasize to students that historical data for emptying receptacles is useless here because all receptacles are emptied each day. We can only begin our analysis after the sensors are installed.

Predictive analytics applications

- What is the best route for each truck to minimize the distance driven?
- What are the characteristics of these routes? Note: They are dynamic, changing every day depending on the receptacles that must be emptied. It is interesting here to ask the students: Given that drivers are used to preset, defined routes that they follow every day, how does the city get the information on the new, dynamic routes to the drivers? Answer: the navigation package.

- How many trucks and drivers will we need, going forward?

Prescriptive analytics applications

- What should the city do with surplus trucks (if any)?
- What should the city do with surplus drivers (if any)?
- What are the costs of moving to the new system? Is it cost effective? That is, will the savings from fewer trucks and drivers be more than the costs of the sensors, the software to record and analyze the sensor date, and the navigation software that must be added to each truck?

Ask the next question

- Is it possible to use autonomous (driverless) trucks in the future? Why or why not?

5. Augmented Analytics

Global organizations are collecting increasingly larger volumes of structured and unstructured data, a total that will reach 175 zettabytes by 2025. Note: One zettabyte is approximately equal to 1 billion terabytes. To thrive, businesses will have to use augmented analytics to make decisions using all this data.

Definition and capabilities of augmented analytics. Augmented analytics integrates artificial intelligence (AI) and machine learning (ML) into the traditional analytics process (see Figure 1) to automate the selection and preparation of data, the generation of insights, and the communication of those insights.

Augmented analytics brings analytical capabilities, including recommendations, insights, or guidance on a query, to more people. That is, organizations can *democratize use of data*. Augmented analytics make it easy for business users to make decisions based on data without help from data scientists or IT professionals.

Augmented analytics solutions come with prebuilt models and algorithms so that companies do not need a data scientist to do this work. Leading augmented analytics platforms feature intuitive interfaces using natural language processing (NLP), enabling non-technical users to easily ask questions from datasets with standard business terminology. Using natural language generation (NLG), the system will find and query the correct dataset and provide easy to understand results and recommendations with data visualization tools such as dashboards.

Let's look at these capabilities more closely.

- Recommend, prepare, and enrich data: Rather than having to decide which datasets to query as with traditional analytics, an augmented analytics solution will recommend which datasets to include in analyses, alert users when those datasets are updated, and suggest new datasets if users are not receiving the results they expect.

- Create dashboards and reports: Helps interpret and communicate results in an easily understandable context to quickly make business decisions.

- Provide natural language interfaces: Allows users to query datasets in natural language. The system can provide these results via natural language using everyday business language.

- Forecast trends and cluster data: Provides accurate forecasts and predictions based on historical data.

- Use proactive, personalized analytics with mobile applications: Provides a personalized assistant that understands individual users – such as using their location to determine what charts to present to a client at an offsite sales meeting.

Differences between traditional analytics and augmented analytics. The traditional analytics process is discrete and typically relies on dashboards. These dashboards are based on business questions which are defined in advance. Answering these questions requires accessing a database or data warehouse. Answering a new question requires time (days or weeks) and technical skills from data scientists or analytics specialists.

The augmented analytics process is continuous. With augmented analytics, the AI and machine learning are built into the product. Model-building and analyses are always on, always working in the background, to continuously learn and help users make more accurate decisions. The reason here is that data continuously flows into organizations. AI and machine learning process these data in near real-time to provide increasingly accurate predictions, insights, and recommendations.

Traditional analytics uses a publisher/consumer model in which a few data scientists or analytics specialists create reports and dashboards for potentially thousands of users. As noted above, augmented analytics provides results for all users and enables them to access and analyze datasets on their own.

The capability of augmented analytics to democratize analytics makes the business analytics process (Figure 1) even more important. Once users define their business problem, the process can guide them as they use augmented analytics from data selection through to making actionable decisions and asking the next question.

6. Conclusions

The two business analytics courses discussed in this paper demonstrate how business analytics can be taught as a process that is useful in today's technology-driven business world. Successful implementation is contingent on modifying current pedagogies to emphasize critical thinking, problem solving, and communication of statistical results outputs, not just the act of producing the results or outputs. Colleges of business should strive to produce knowledgeable graduates who can accurately and effectively identify a business problem, collect and manage the data needed to solve the problem, analyze the data, interpret and communicate the results.

However, the advent of augmented analytics raises questions about how (or if) business analytics should be taught to each of the three types of analytics users in organizations. Specifically:

- *Business users:* Given the capabilities of augmented analytics, what should Colleges of Business teach in introductory courses? Do business students on their way to becoming business users need an introductory course(s) at all?
- *Business analysts:* Again, given the capabilities of augmented analytics and the functions of business analysts, should Colleges of Business have an Analytics major at all? As an additional issue, will organizations need business analysts at all?
- *Data scientists:* As augmented analytics platforms become increasingly sophisticated, will the demand for data scientists decrease? Clearly, companies who develop augmented analytics platforms (e.g., IBM, Salesforce, SAS, Tableau, Sisense, and others) will need to hire data scientists. What about the customers of augmented analytics companies? Will they need data scientists on staff?

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