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Big Data and The Commoditization of Analytics: Engaging First-Year Business Students with Analytics

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Abstract

The age of data analytics requires "data scientists" across a wide range of business disciplines with deep knowledge of how to manage and analyse vast amounts of data to support decision-making. As a result, new analytical tools are being taught in the Management Information Systems (MIS) or business analytics (BA) programs to foster students' development of this critical competency. Three waves of analytics tools are considered from an experiential perspective including how to introduce analytics to first-year business students using an advanced data analytics software package with multiple techniques and data flow interface. SAS Enterprise Miner is used to teach technical topics and perform business-centric data analytics. An innovative exercise is designed in such a way that it guides first-year business students through a learning analytics journey to motivate them to understand the notion of data analytics and to develop skills around this emerging area without delving too much into extraneous technical details. A post-course survey indicated that the exercise helped students understand the opportunities as well as the challenges in doing analytics.

Key words: *Data Analytics, Business Analytics, SAS, Hands-on Training, Teaching, Business Education.*

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Introduction

Analytics as a field has grown immensely over the last decade. Hadoop and similar big data platforms have used this period of growth to rise to prominence (Chambers & Dinsmore, 2014). Despite the rapid growth and importance of data analytics in the modern business environment, there has not been a commensurate increase in the number of individuals qualified and trained to manage and analyse the data used for business decision making (Russom, 2011, Abbasi et al. 2015). As in recent years, there has been a considerable shortage of analytics expertise worldwide (Schiller et al. 2015). Some predicted that in 2018 the United States alone faces a 1.5 million knowledge worker gap in analytics expertise (Henke et al. 2016; Rienzo et al. 2018). In response to this shortage of qualified professionals, many academic programs have prioritized data analytics education in their curriculums (Guthrie, 2013; Wixom et al., 2014). Despite the increase in curriculums incorporating data analysis, many programs still lack this element, causing data analysis education to lag in academia (Zhao et al., 2014). An important aspect of incorporating data analysis material into the classroom is overcoming student apprehension for the material using hands-on projects to demystify the techniques used in data analytics and maintain student interest (Zanakis & Valenzi, 1997). The use of a hands-on education approach allows professors to overcome the apprehension that students show for math and statistics while also engaging them further in the material and showing them the usefulness of data analytics techniques in today's decision making process. These hands-on techniques should be implemented using cutting-edge data-analysis programs in order to keep the material relevant and maintain teaching goals. A switch to this style as opposed to a more abstract method of education will allow professors to furnish their students with valuable skills and allow them to produce meaningful work in data-analytics (Sigman et al., 2014).

Although there has been an increasing amount of research on the importance of data analytics skills, there have been few studies into how and what types of tools are more effective in facilitating business students' understanding of analytical concepts and practice. This paper presents an experimental perspective on how business analytics can be introduced to first year business students. We provide an account of our practical experience and discuss how business analytics can be brought into the introductory core business courses to help business students recognize the importance of analytics and big data technologies in today's marketplace and build analytical skills early on in their learning process. While a bottom-up approach has been a common way for teaching technical topics such as analytics, a hands-on approach can complement it and drive more motivation, enthusiasm, and passion among business students to learn business analytics. The exercise outlined in this paper demonstrates how an analytics project can be transformed into an effective and positive learning experience for first year business students. With the help of interactive analytics tools such as SAS Enterprise Miner, business students start by learning how to work through simple predictive modelling problems and slowly increase their complexity. A greater understanding of theory can be achieved later once students have a context in which to integrate their abstract knowledge. As such, our exercise is designed to be incorporated into an introductory level MIS or BA course transitioning to a hands-on practical approach for teaching BI/BA techniques and tools used to validate business decisions. The program that students will use in this exercise is SAS Enterprise Miner (SAS-EM), so chosen due to its combination of best practices in data analytics and visualization and enhancing the student's engagement in the material. A large amount of data can be quickly and efficiently analysed using SAS-EM's data mining and inbuilt analytical tools. This exercise trains students to produce actionable information from a large data set and is an introduction to predictive data-analytics.

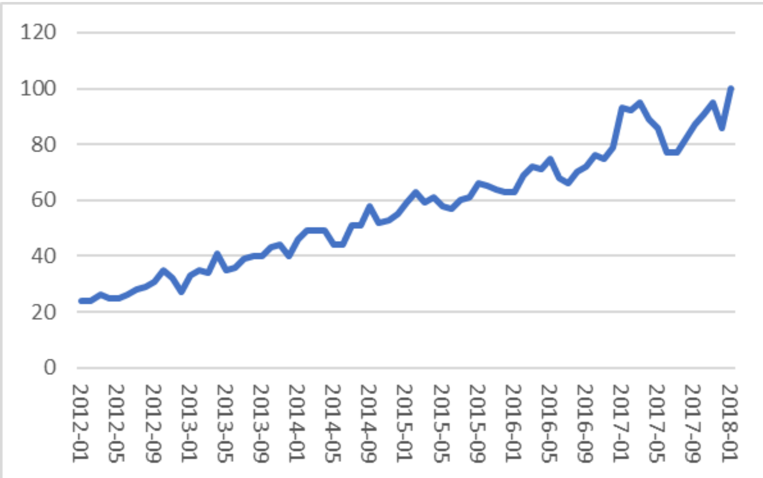
Business Analytics in Brief

The field of Management Information Systems (MIS) is dedicated to electronic information systems as they relate to organizations, with research focused on development, adoption, implementation, use, and maintenance of information technologies. The goal of research in MIS is to make organizations more efficient using information technology resources to yield useful business intelligence (BI) and applying this intelligence. The term analytics has been employed to collectively refer to a variety of BI and application initiatives. However, a unified definition of what constitutes analytics has not been agreed upon with some using analytics to refer to the process of analyzing information from a domain, while others use the term more broadly to refer to usage of a variety of BI techniques on a specific area. Due to the amount of data that firms are collecting or have available externally, professionals in the business world are looking to use analytics to segment, score, and make predictions about the business environment and improve internal efficiency. For this article's purposes, we define "Business Analytics" or BA as the use of information technology, statistical, mathematical data, data mining, or computer based techniques on massive datasets to generate deep insights necessary for improving organizational processes (Asamoah et al., 2017). Deeper knowledge of the data, regardless of source, requires that four characteristics of the data be considered. The volume, variety, velocity, and veracity of the data need to be managed properly while using tools and applying techniques to the data. To reveal the underlying pattern of the data, mathematical and statistical methods are married to computing and data visualization techniques.

The last five years has seen BA gain momentum in the academic forum, with a search of google scholar suggesting that more than 15,000 articles have been published on Business Analytics between 2012 and 2018 (Figure 1). Gaining not just popularity in academia, practical application of business analytics has likewise grown over the last half decade, with a study by Gartner Group showing that the top technological priority for Chief Financial Officers is business analytics (Elliot, 2012). Business analytics' perceived importance and advantages are driving factors in its modern popularity giving organizations the ability to (i) observe patterns and relationships in data, (ii) provide their managers and executives with business insights, and (iii) translate data into a competitive advantage (Holsapple et al., 2014). Overall commitment to BA and data driven decision making has been shown to be associated with a firm's overall performance, measured through revenue, profit, process quality, and shareholder return (Brynjolfsson et al., 2011; La Valle et al., 2013). This may indicate that BA creates a competitive advantage through more informed decisions at various levels of the firm. While the trend may be present for firms to perform better, employing BA techniques regarding the quality of data, the processing capacity to support a high volume of data, the data driven organizational culture, are all crucial to successful business analytics programs (Philpott, 2010).

The field of business analytics has a shortage of qualified practitioners; instrumental in addressing this shortage are the higher learning institutions where practitioners are trained. However, business schools have had their training requirements scrutinized. Chiang et al. (2012), for instance, argue that current information systems curriculums are lacking in practical and in-depth training, and academia has not been yielding the kind of individuals knowledgeable in applying the three perspectives of BA, managing data sources, and analyzing large datasets that the industry needs. As the needs of the industry change so to do the contents of the information systems curriculum to reflect the industry's techniques and state of the art analytics programs. There are a number of barriers that need to be overcome to put an effective way of learning analytics into place. One of the biggest challenges facing analytics educators is motivating students to engage with high level analytics techniques, software, and concepts necessary to prepare them to produce actionable business intelligence from data. Some students seem to be reluctant to learning analytics because of math experience anxiety or hostility against technology. Statistics and mathematics are important in learning analytics, but only because of the concepts they allow to surface and the tools they make possible. Therefore, business professors need to overcome students' apprehension and insecurity in regards to the math, statistics and computer programming facets of analytics. Technology has proven to be a viable solution to promote mathematical creativity (Idris et al. 2010) and reduce student anxiety. In today's digital world, business analytics isn't about solving equations, it's about coaxing math, statistics and computers to produce something people find useful, actionable and even enjoyable. To this end, computers and high-end software play an important role in analytics. Business analytics courses need to be taught in computer lab classrooms with BA software installed on each computer and students working at their own computers. Many software companies are developing and offering BA software under an entirely new paradigm where data and analysis drive their most important product features. Bringing students in the direction to learn how computer-based problem solving works in the real world is fundamental. To demonstrate the important role of software in business analytics, we can look at the history and progression of business analytics tools and technologies and use it as a basis to understand the need to utilize the right tool for business analytics education.

Figure 1:
The Rise of Business Analytics over Time



Analytics Software Over Time

The first wave of business analytics was mostly composed of trained statisticians and data scientists, this is due to the nature of the programs employed for BA. These programs, from companies like SAS, SPSS, IBM, and MATLAB, which are still around today, required knowledge of programming and cost anywhere from hundreds to thousands of dollars. However, this represented an important step for companies in embarking on BA capabilities, because rather than developing an in-house data analytics system for themselves, firms could purchase one. We call this first wave of BA "Monopolization of Analytics", which lasted for decades (Nishida, 2017).

One obstacle faced by firms in the first wave was the programming expertise required to properly interface with the data analytics software. Programming is a complex skill requiring experience, something firms couldn't always afford to provide. To address this issue, we see User Interface (UI) based tools such as SPSS Modeler, Tableau, SAS Enterprise Miner/Guide, Weka, Domo, Rapid Miner, Orange, Exploratory etc. being employed to make data analytics software more accessible to individuals with less programming proficiency.

This advancement of UI allowed business analysts and consultants, individuals with deeper domain knowledge but less programming experience, to do work that formerly only those proficient with programming such as data analysts were able to do. Using machine learning algorithms these analysts and consultants could gain a greater understanding of business data than they could from traditional BI tools. This shift in usership constitutes the second wave of BA, called "Commoditization of Analytics", marked by high quality, accessible algorithms that enabled users to quickly draw high quality business intelligence from data (Nishida, 2017).

The third wave of business analytics is in full swing at present, characterized by cutting edge, high quality open source algorithms/languages such as R, Python, etc. However, these open source algorithms require a degree of programming proficiency, which presents similar issues as those seen in the first wave, though to a lesser degree. This third wave of business analytics is called "Democratization of Analytics" (Nishida, 2017).

This article demonstrates how second wave analytical tools can equip business analytics educators with the tools necessary to introduce first year students to core concepts in business analytics without intimidating them with coding or complex technical explanations as seen in the first or third waves. Retaining student interest is important for educators; therefore, the exercise presented in this article was created to provide first year students with a hands-on understanding of BA material and an approach geared toward managerial level decision making. Providing students with a better understanding of the technical aspects of business analytics is an important responsibility for educators. Through the lens of addressing problems that might be faced by a managerial level decision maker, students can come to better understand the applications of BA on decision making in organizations. Due to the nature of an ever advancing technology based field such as BA, educators are better served providing students with the fundamental principles of BA. Educators must balance between hands on teaching methods that require technical skills instruction and providing students with the knowledge needed to make data-driven decisions.

The Case Study: Analytics Exercise

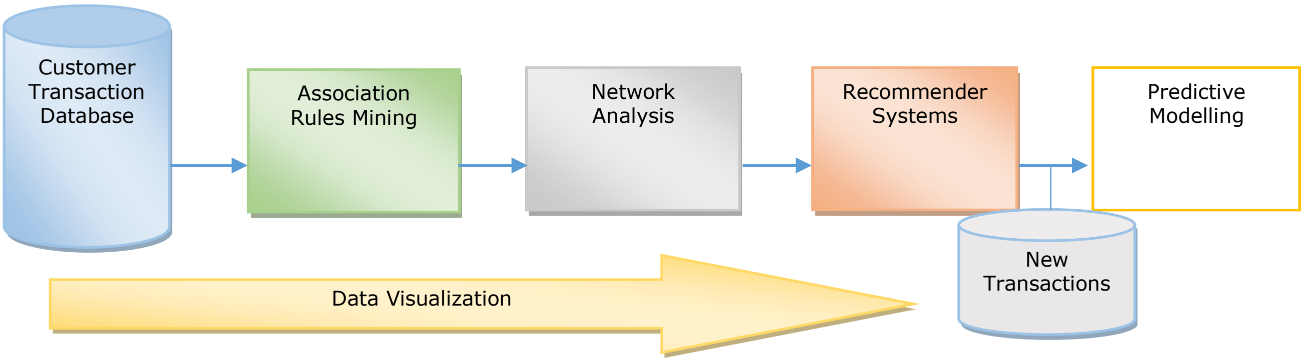
Learning Objectives

Purpose: To demonstrate to first-year business students how knowledge of business analytics aids in understanding and solving certain business problems.

The design of this exercise incorporates some of the most interesting elements of SAS-EM, training students to use the market basket application and analysing transactional databases to discover patterns (i.e. business rules) in customer purchase behaviour. Important skills taught by the exercise include querying, transforming, and analysing, scoring and visualization of data. We extend the market basket analysis exercise by SAS and cover additional steps to guide business students along a full journey of data analytics, dashboard insights, and the action they inspire. Figure 2 shows a conceptual map of all the BA topics covered in this exercise. The first steps in the exercise include preparing and exploring the data and the process culminates in analysing and visualizing the data in a way that illuminates relationships present in the data. This exercise is intended to simulate a typical market basket analysis, which would consist of analysing the data to show the relationship between items frequently purchased together. An example of this kind of relationship would be the relationship between bread, milk, and peanut butter where we want to know if given that bread and milk is in someone's basket what are the chances of them buying peanut butter as well?

By analysing the data, we find that 10% of all purchases include these three items, and that peanut butter is present in 70% of purchases that include milk and bread. Using this information we can produce a cross-selling rule for milk and bread -> peanut butter. This kind of information allows businesses to target individual customer groups.

Figure 2:
Exercise's Workflow



A detailed transactional dataset containing purchase transactions of over 1,000 customers was provided to students. The students should import the market basket data set into the SAS EM environment and load the data into the SAS EM diagram. Once this is complete, the students can use either the association node or market basket node for the association and sequence analysis. The students should then be directed to the network analysis tool and instructed on how to generate graphical representations of item associations. One example of these graphical representations is the constellation plot, which displays item co-purchasing association with lines connecting points which signify each product, the thickness of these lines indicates strength of association. Next students should use the embedded recommendation system tool to make recommendations to theoretical consumers, they should figure out what products will be recommended to which customers based on same or similar purchase histories. Lastly, after a model has been created based on historical data, students were introduced to the idea of scoring where the association-rule predictive model is taken to apply to new customer transactional data in order to make predictions about unseen behaviour which can be used for targeted promotion recommendations.

The exercise also provides students with detailed instruction on how to use SAS's SEMMA analytics framework for data mining. There are five stages to the SEMMA framework: Sample, Explore, Modify, Model, Assess. The first stage, Sample, involves selecting the most appropriate for the established business purpose. The second stage, Explore, involves revealing the relationships between variables in the data to better understand the data. The third stage, Modify, involves selecting and transforming variables using various methods to prepare for the Modelling stage. This third stage is one of the most important and labour-intensive aspects of the data mining process often comprising as much as 80 percent of the time and effort spent on a project. Important aspects of this process include understanding volume, variety, and velocity of the data (Douglas, 2001), an understanding of what the data represents as well as binding data streams, transforming the data so that it can be queried and analysed, filtering and reducing the data, among other tasks. The fourth stage, Modelling, involves using a prepared data set to create predictive models using various data modelling techniques to yield the desired result. The last stage, Assess, involves examining the models produced in the modelling phase and identifying the useful and reliable candidates.

All course objectives were addressed in the case study, the complete set of which is listed in Table 1. However, a particular emphasis was placed on the student objectives detailed in Table 2.

Table 1:
Course Objectives

LO	Course Objective	Program Learning Goal
1	Understand the role of Information Systems in organizations	• Business Knowledge & Competency
2	Be able to use information systems as a resource in decision making	• Technology Skills
3	Understand the impact of technological change in accessing and disseminating information	• Business Knowledge & Competency
4	Learn how E-Commerce and E-Business have changed how we do business	• Business Knowledge & Competency
5	Be able to work with a database and data management tools	• Technology Skills • Analytics Skills
6	Perform business analytics tasks using Excel and other advanced software programs	• Technology Skills • Analytics Skills
7	Be able to apply analytic and computer-based techniques from science and business to analyze and interpret data	• Critical and Creative Thinking

Table 2:
Key Case Objective

By the end of the case students will have:

- Gained experience working within a Data Analytics and Visualization environment;
- Applied current modelling and visualization techniques to the Market Basket Data;

By the end of the case, students will have learned how to complete all the following tasks:

- Create a data analytics project in SAS EM; [LO 5]
- Create a Library for use in SAS EM and Import the data source to the workbench diagram; [LO 5, 7]
- Explore the customer transaction database; [LO 2]
- Work with data without going through complicated technical steps; [LO 7]
- Perform association rules mining to discover interesting patterns; [LO 1, 2, 6]
- Create visualizations of the data; [LO 3]
- Use link analysis node for detailed and precise insights about the co-purchase networks; [LO 4, 7]
- Perform recommender systems analysis using the recommender table of SAS EM to recommend items to users; [LO 4, 7]

This exercise fosters an understanding of data analytics and encourages students to develop the necessary skills to participate in this emerging area of business. This hands-on style of exercise was chosen to provide an interactive learning experience on the topic of business analytics to freshman business students. The exercise was designed so that students would focus on and engage with advanced data analytics programs, keeping the mathematics side of the process to a minimum so as not to discourage students from engaging with the exercise.

Prior to the exercise a handout detailing the concepts and tools that were addressed in the exercise as well as a step by step walkthrough of the exercise was given to the students by the instructors. The instructors then informed students that they were expected to read the handout and prepare for the exercise before class. In class a simple tutorial composed of point and click responses was used to cover simple introductory information so that more time could be devoted to higher level material. Technical and practical aspects of the exercise were the focus of instruction; however, students were still expected to show some degree of proficiency in class. Planned learning outcomes were achieved using a blended learning methodology that included a mix of in person and learning technologies (Liam & Morris, 2009). During class time instructors presented the business scenario before a live demonstration and a practical hands-on session; this consisted of 35 to 70 percent of the class period. The hands-on session was designed to increase the student's familiarity and confidence with the process by having them replicate the work shown on the handout. Throughout students were given explicit instructions to keep interest and attention high. After the initial exposure to the tools in the learning environment students were encouraged to draw their own conclusions from the market basket data and to develop their own ideas, questions, and solutions. The goal of the exercise was to challenge and engage students in a learning experience where they would become content developers and problem solvers.

Exercise Activity:

Through this exercise, students are exposed to the concept of turning data into business insights and the mechanisms used to implement it. After learning these concepts, the students will engage in the following activities:

- Exposure, exploration, and engagement
- Data preparation and pre-processing
- Data modelling, visualization, and interpretation
- Elaboration and recommendation

Outcome:

Before engaging in this activity, the students have been briefly exposed to the theoretical concepts and mechanisms behind analytics. After engaging in this activity, the students will have formed a concrete connection from the theoretical to the actual by realizing how analytics can be applied to mine and to analyse business data.

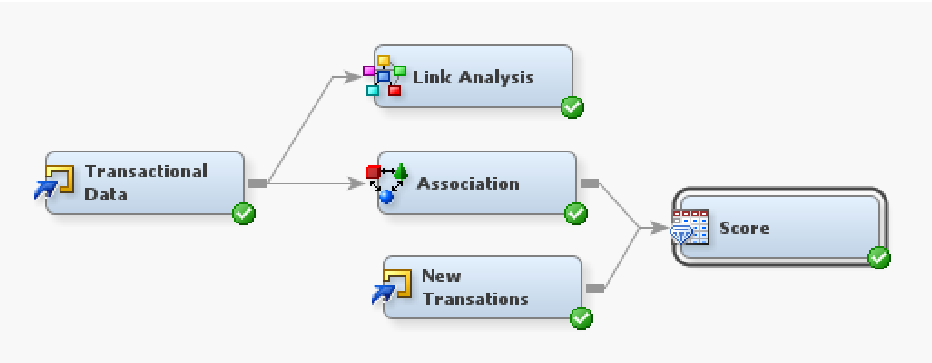
The Exercise

The SAS SEMMA data mining framework was used as a reference when delineating the various stages of the exercise. The five major components of the data analytics methodology are exposure and exploration, data preparation and preprocessing, data modelling and visualization, and interpretation and elaboration, consistent with the SAS SEMMA framework. In the following section, we will briefly discuss the steps of the analytics workflow displayed in Figure 3.

Exposure, exploration, and engagement

The exercise tutorial begins with the instructor who introduces students to various data analytics tools, visualization applications, and unfamiliar data analytics content, including the market basket analysis. The material for this presentation is easily drawn from online sources such as Teradata University Networks, Tableau and SAS, and text sources, such as course texts. In order to engage students the material selected should be current, relevant, and interesting. This stage is designed to educate students on business analytics' uses and importance. Through this stage students' familiarity with and openness toward data analytics and visualization tools is increased, expanding their comprehension of the resources employed for data analytics beyond Microsoft Excel and Access.

Figure 3:
Analytics Workflow of the Exercise in SAS EM



Data preparation and preprocessing

In the data preparation and preprocessing stage of the exercise students use a pre-established list of steps to explore the possibilities of SAS EM, chosen for its usefulness as a data mining and visualization tool. The handout that the instructor provided the students with prior to the exercise should contain a full list of the steps for this stage. The steps are 1) create a new SAS EM project, 2) create a workbench diagram, 3) select a data source, 4) drag and drop associated nodes to the diagram, 5) configure the link analysis and association nodes, 6) customize the properties, 7) re-run the nodes to get customized results, and 8) preview the results. The instructor can determine, based off the time available in the course, if these steps are completed in their entirety or in parts. We will subsequently elaborate on each of these steps.

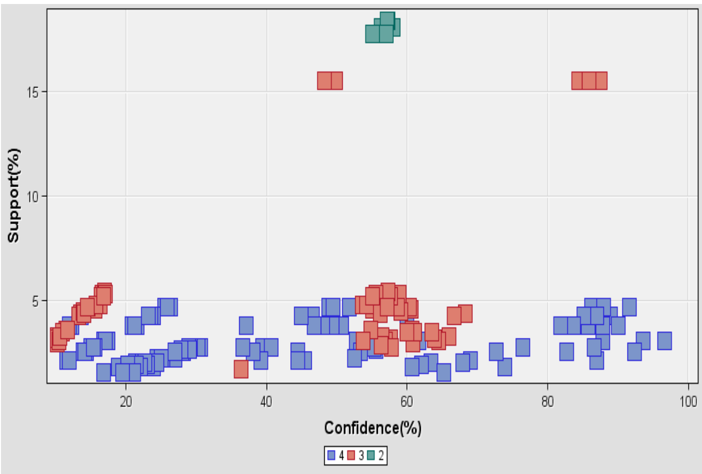
The most important elements of this stage, like in most data mining operations, are the elements of data preparation and understanding, and creating business value. The instructor should impress on the students the importance of these elements through the exercise. A transactional dataset containing purchase transactions of over 1,000 customers was provided to students. Note that, included in the SAS EM program, there is a Sample library named *Assocs* which can be alternatively used for this exercise. The students should bring the market basket data source into the SAS EM environment. To do so, they will need to create a library and use a File Import Node to import the transactional data into the SAS diagram. The data source wizard in SAS EM is a valuable tool for introducing students to the language and definitions relevant to data mining. The wizard is helpful for creating metadata, data types, measurement levels for all columns in the dataset. This stage includes investigating the data using the data source node, this investigation should yield preliminary information about the data's content and structure. During the data preparation and preprocessing steps the dataset role must be TRANSACTION for the association analysis to be performed.

Data modelling, visualization, and interpretation

The three main approaches in our analytics initiative for this exercise are association rules mining, network analysis, recommender systems and predictive modelling. Over the last 20 years the tools being used for this type of analytics have grown and evolved into a multitude of powerful and sophisticated instruments, ensuring that practitioners need not reinvent the wheel. The use of graphical representations to display data is an invaluable tool for data analysts when recognizing the patterns present in a given customer transaction dataset. A plethora of options for graphics and visualizations are present in the SAS EM software, giving users the ability to display the data in the most effective manner.

The first step is for students to identify patterns of interest in the customer transaction data set, this is done using the Association node to generate business rules. The rules are represented in the following format: A->B, A is referred to as the precedent, and is referred to as the consequent. A single variable may represent more than just one product. For instance, beer -> wine & soda. A typical method of establishing rules like this is to count the number of co-occurrences of A and B in the data (Faron & Chakraborty, 2012). The students can manage the results of their rules searches using the property panel in the Association node. Before running the association mining node, students must set Maximum Items, Minimum Confidence, and Minimum Support, as these metrics aid in identifying the importance of rules. Rules with higher confidence and support percentages are preferred. These rules can be seen located in the top right corner of the statistics plot in Figure 4.

Figure 4:
Statistics plot for Association Node



As its name suggests, the Maximum Items property of the Association node controls the maximum number of items that can be considered when generating rules. The Minimum Support dimension is the smallest joint probability that both items were found in the cart that is still acceptable for the rule. The Minimum Confidence is the lowest conditional probability that is acceptable for the rule, representing the probability that "B is in the cart given that A is in the cart". These minimum acceptable scores represent the minimum benchmarks for screening rules (Faron & Chakraborty, 2012). Figure 5 shows various examples of rules with their accompanying confidence and support scores. For instance, the rule ice cream -> coke has a confidence value of 70% and a support of 22%. This indicates that 22% of carts/transactions contain these two items and 70% of carts/transactions with ice cream will also contain coke.

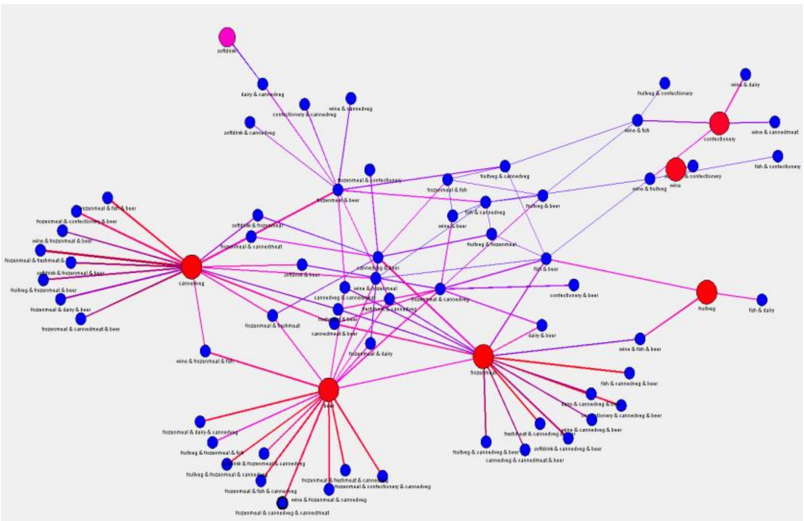
Figure 5:
Output window

Association Report

Relations	Expected Confidence (%)	Confidence (%)	Support (%)	Lift	Transaction Count	Rule	Left Hand of Rule	Right Hand of Rule	Rule Item 1	Rule Item 2	Rule Item 3	Rule Index
2	29.57	70.29	21.98	2.38	220.00	ice_crea ==> coke	ice_crea	coke	ice_crea	=======>	coke	1
2	31.27	74.32	21.98	2.38	220.00	coke ==> ice_crea	coke	ice_crea	coke	=======>	ice_crea	2
2	30.47	58.13	21.08	1.91	211.00	avocado ==> artichok	avocado	artichok	avocado	=======>	artichok	3
2	36.26	69.18	21.08	1.91	211.00	artichok ==> avocado	artichok	avocado	artichok	=======>	avocado	4

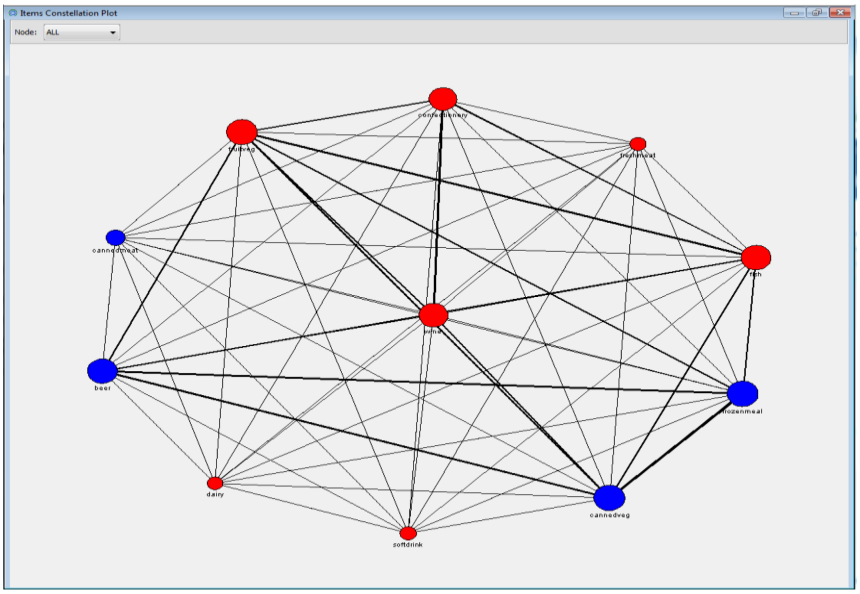
This exercise seeks to expose students to various visualization tools in SAS EM. The SAS built-in link graph tool gives a graphical representation of the association between the items. Each line represents a rule connecting one item to another. Figure 6 displays the default link graph for the data.

Figure 6:
Link Graph



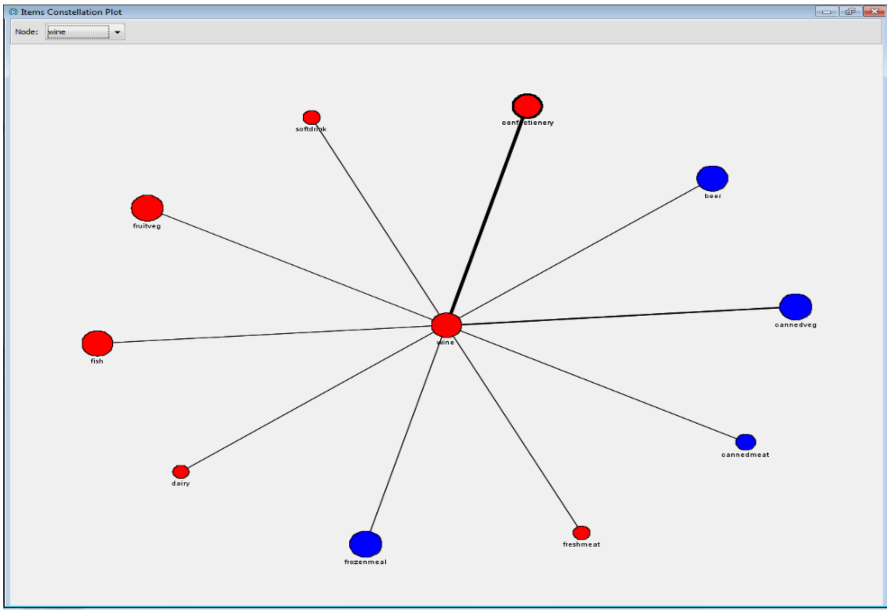
Network analysis is another powerful visualization tool in SAS EM that shows a network of connections and interactions between various items and groups. The Link Analysis Node can produce complex graphical representations of networks, one such example is the item constellation plot (Figure 7) which shows associations between all items in the set.

Figure 7:
All Items constellation plot: a co-purchasing graph view



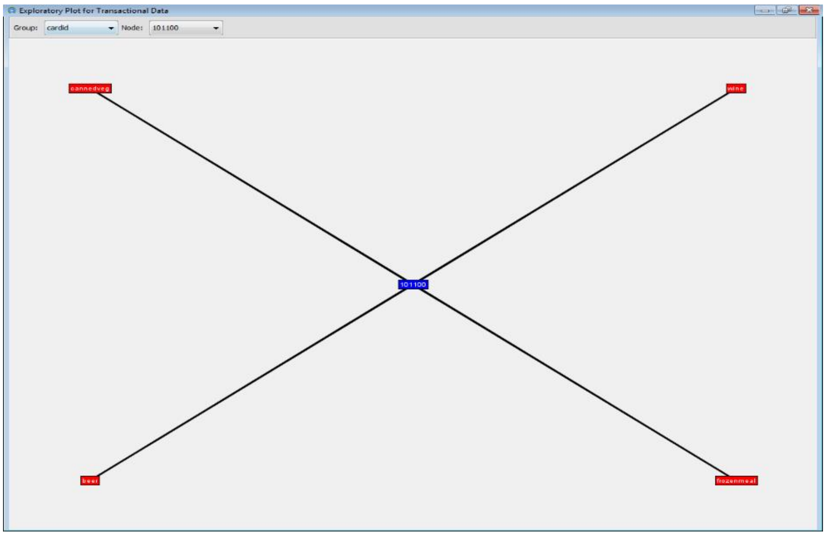
An alternate setting for the item constellation plot allows a single item to be selected for a co-purchasing graph. Figure 8 shows an items constellation plot for co-purchasing associated with apple. In the plot, thicker connecting lines show that the association rule between the two is stronger.

Figure 8:
A single Item constellation plot



Students can also examine an individual customer's transaction behaviour using the Exploratory Plot. The exploratory plot will yield different insights about the consumer's behaviour. In order to view an individual customer's purchasing information, a student must select customer from the Group list and Customer ID # from the Node list. Figure 9 shows an exemplary exploratory plot where the thickness of the lines connecting each product represents the number of times a given customer purchased it.

Figure 9:
Exploratory Plot for individual customer's purchasing behaviours



The penultimate step of this stage involves introducing the students to recommender systems. These systems have changed how media and products reach consumers. Recommender systems have been widely adopted by many firms such as Amazon, Netflix, Last.fm, and Facebook. These firms use recommender systems to recommend music, products, and potential friends to their users, attempting to predict their user's taste and habits. Using their transactional data, one can make recommendations to customers through the Link Analysis node. Students can view the next best offer list generated to discover what items should be recommended to customers with similar purchase histories. Figure 10 shows a next best offer list in which customers are being offered to purchase various products based on their purchase history, behaviour and/or other customer data.

Figure 10:
Recommendation table in SAS EM

Filtered Recommendation Table

Customer ID	Next Best Offer	Confidence	Rank
10150	fish	43.154	1
10236	cannedveg	57.14322	1
10360	fruitveg	36.43765	1
10451	wine	36.78941	1
10609	frozenmeal	29.81563	1
10614	cannedveg	34.23913	1
10645	fish	35.14199	1
10717	cannedveg	29.77538	1
10872	fruitveg	36.43765	1
10902	confectionery	42.0897	1
10915	cannedveg	40.4356	1
10944	fruitveg	30.56998	1
10987	fish	37.28906	1
11119	wine	40.96853	1
11220	wine	36.78941	1

As shown in Figure 11, the next best offer tool can be sorted and filter based on factors such as "Customer ID", "Top N", and "Minimum Confidence (%)". In particular, Figure 11 shows the next best offer list for customer 10150.

Figure 11:
Next-best-offer list in SAS EM

Recommendation Table

ID Variable: 10150.0

Customer ID	Recommended Items	Confidence	Rank
10150	fish	43.154	1
10150	cannedveg	31.07815	2
10150	wine	29.97492	3
10150	frozenmeal	28.98829	4
10150	beer	27.98289	5
10150	confectionery	27.95243	6
10150	cannedmeat	21.39007	7
10150	freshmeat	21.01891	8
10150	dairy	20.11732	9

After a model has been created based on historical data, students were introduced to the concept of scoring where the association-rule predictive model is then applied to new customer data in order to make predictions about unseen behaviour. We provided a new set of (customer transactions) data which was held out and not used at the training stage. Similar to steps in the data preparation process, students use another File Import Node to import the new transaction spreadsheet into the SAS diagram and label it as "New Transactions". At this stage, students needed to examine the data structure, measurement levels and variable roles of the new data and ensure that the dataset role is "Score". In addition, because the Association Rules created by Association Rule Node is needed as an input to the scoring process, students were guided to change the Association role Node's setting accordingly (Export Rule by ID: Yes, Recommendation: Yes). After running the Score Node, students examined the Exported Data set. In the output data set of the score node, students will find new columns with binary variables for each rule. For each rule, a customer is assigned a recommendation value of 1 or 0. If a customer already has both the antecedent and the consequent of a rule, then the corresponding rule variable takes a value of 0 (rule not recommended). However, if the antecedent of a rule exists, but the consequent does not, then the rule variable takes a value of 1 (rule recommended).

Figure 12:
Scoring New Customer Data

EMWS4.Score_SCORE

	cardid	beer ==> frozenmeal	frozenmeal ==> beer	frozenmeal ==> cannedveg	cannedveg ==> frozenmeal	beer ==> cannedveg	cannedveg ==> beer	wine ==> confectionery	confectionery ==> wine	fruitveg ==> fish	fish ==> fruitveg	softdrink ==> freshmeat	freshmeat ==> so
894	105429.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0
895	105601.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
896	105816.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0
897	105829.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
898	106004.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0

Elaboration
At this stage student's should have sufficient exposure to SAS EM to begin developing their own ideas and insights. Students should be encouraged to move beyond the materials provided in the handout. Allowing students to experiment with the tools that they have been introduced will keep their engagement with the material high, allowing them to learn from mistakes and discover useful functions that may not have been addressed (Chen, Chiang, & Storey, 2012; Dupin-Bryant & Olsen, 2014). Allowing the students to move beyond the material gives them the opportunity to interpret the information in a more creative way and bolstering their understanding of data analytics. To facilitate this the professor should ask provocative questions such as "how could you apply association mining to other industries?", having a discussion to take place in the class will allow students to explore their ideas and make connections between the exercise material and the outside world.

Discussion

Incorporating business analytics exercises into the introductory core business courses has given students a greater appreciation for the role and value of data analytics to today's successful businesses. In addition, the students' involvement with the course material has grown. Once the students overcome the immediate barrier of how to bring data to the software environment and how to explore their data with drag-and-drop tools, they become immensely engaged in the exercise. Next we summarize the key lessons we learned throughout this process.

Lessons Learned

- *The conventional bottom-up approach does not work.* Business analytics is an applied field that creates models from data to gain business benefits. A top-down/hands-on approach can be more suited to business students than a bottom-up approach. This allows instructors to walk students through simple predictive modeling problems and slowly increase their complexity.
- *Start with business cases not mathematical/statistical definitions and theory.* The unique feature of analytics allows BA instructors to focus on business problems and also enables to provide deeper insights that are highly relevant to business and industry. Therefore, it is important for BA professors to lay out business problems that focus on practicing the process of analyzing business data, getting results immediately, and going deeper into areas as needed within the context of the result/business problem.
- *Business analytics it different.* Business analytics does not use traditional ways of thinking. It is an iterative approach that requires discovery, curiosity and explanation. Results may be poor in the beginning, but improve with practice.
- *Make changes one at a time and examine the results.* Today's analytics software such as SAS, is designed to do most of the mathematical and statistical analyses and generate results immediately. This enables business students to learn analytics and technology in a fast, interactive way. For example, analytics tools such as SAS EM allows students to play with different parameter settings, perform "what if" and sensitivity analyses and immediately predict the effect of different scenarios on the business problem at hand.
- *Business analytics means different things to different people,* but at its core, proceeds in the same way regardless of domain or context. BA seeks to provide business insights that involve data from across the organization. While the market basket analysis exercise is likely to be fairly easy for most students, it allows business students to participate in a real-world problem solving environment. It is worth noting that in addition to the market basket analysis, other similar BA

exercises such as customer segmentation (cluster analysis), churn prediction, RFM (recency, frequency, monetary) analysis, path analysis (analyzing the footsteps of customers) and social media sentiment analysis will be appropriate and helpful in introducing important BA concepts in the context of specific applications.

- *Business analytics is an emerging field,* and its adoption by higher education institutions around the world is uneven. While business schools in North America, Europe and Australia are generally considered leaders in this domain, other regions in the world are still at an initial stage of exploring its possibilities.

Feedback and Learning Assessment

The learning objectives achieved in the exercise detailed in this article are: (1) improve student comprehension of business analytics and it's practical application, 2) introduce students to a new data analytics tool and have them perform data analysis without burdening them with unnecessary technical details, and 3) encourage students to explore business analytics as it relates to their future courses. Multiple sections of MIS 3000 in spring and fall semesters of 2016 and 2017 at wright state university participated in this exercise and provided feedback. MIS 3000, titled Fundamentals of Information Systems, is a core business course and thus a required course for all business majors. Assessment was anonymous and voluntary with a response rate of 83% of those enrolled (287 of 312). The results of the survey on the exercise's effectiveness is shown in Table 3.

Table 3:
Results from the Survey

#	Question	Strongly Agree	Agree	Neutral	Disagree	Strongly Disagree
1	Demonstrated how to preform market basket analysis using point-and-click and graphical data model to perform data analytics	80.2%	11.9%	7.2%	0.7%	
2	Improved my understanding of market basket analysis using the association rule mining without delving too much into the mathematics of it	84.1%	13.6%	%2.3		
3	Demonstrated how visualization can help gain business insights and grasp trends/patterns in data quickly	71.3%	23.5%		5.2%	
4	The goals of this exercise are clearly stated and consistently pursued	95.2%	4.0%	0.8%		
5	Improved my understanding of business analytics and how it can be applied in practice	81.9%	13.1%	3.2%	1.8%	
6	Helped me understand what business analytics is about and what it can do	95.4%	2.1%	2.5%		
7	Was reasonable and useful	82.7%	14.1%	0.7%	2.5%	
8	The step-by-step handout helped me go through the exercise	92.2%	5.1%	2.7%		
9	The steps described in the handout were not working				6.3%	93.7%
10	This exercise was irrelevant for this course		1.5%	3.7%	15.85%	78.95%
11	I gained no new knowledge from this exercise			1.4%	9.7%	88.9%
12	I like to learn more about business analytics	83.1%	10.7%	1.6%	3.5%	1.1%
13	I like to do more hands-on analytics exercises like the basket analysis	72.7%	17.5%	5.1%	4.6%	

The survey result implies that all the learning objectives as listed in Table 2 were successfully achieved through this exercise. Student responses indicate that the exercise engaged students and increased their understanding of data analytics and visualization. Students expressed enhanced confidence in their understanding of data analytics and a desire to learn more about the subject. The students expressed an appreciation for the advantages that those who master data analytics have over their peers.

This study is not without limitations. The effectiveness of our case study was assessed based on student opinion survey data that was collected at the end of the activity. The feedback from students was very positive and they indicated that the activity was beneficial to them. Future research can include collecting additional measures of the effectiveness of the activity in comparison to more traditional approaches.

Conclusion

This instructional note presented an experiential perspective on how a business analytics exercise was implemented in an introductory business course. An account of the practical experience gained from teaching this emerging subject was presented. The analytics initiative comprised important concepts in BA including, but not limited to, association mining, network analysis, recommender systems, predictive analytics and visualization and can be easily added to any intro to MIS or BA course or in any course where students gain from exposing to data analytics technology. This paper showed how the exercise could be aligned with the intended learning goals and course objectives. SAS Enterprise Miner and similarly advanced data analytics tools give instructors a variety of methods and options for visualization and data analysis techniques, this allows the instructor to maximize students' understanding of the material.

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