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The Role of Data Analytics and Machine Learning in Resurrecting Inductive-Based Accounting Research

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ABSTRACT

The objective of this paper is to assess the impact of data analytics (DA) and machine learning (ML) on accounting research.[1] As discussed in the paper, the inherent inductive nature of DA and ML is creating an important trend in the way accounting research is being conducted. That trend is the increasing utilization of inductive-based research among accounting researchers. Indeed, as a result of the recent developments with DA and ML, a rebalancing is taking place between inductive-based and deductive-based research in accounting.[2] In essence, we are witnessing the resurrection of inductive-based accounting research. A brief review of some empirical evidence to support the above argument is also provided in the paper.

INTRODUCITON

Today's interconnected digital world of information systems has transformed the way individuals and organizations communicate with each other. This digital technology-based transformation began in the late 1970s with the development of personal computers.[3] The development of the Internet in the 1990s accelerated this technology-based transformation for business and government activities around the world. Advances in the storage capacity and processing speed of computers over the last two decades have put this transformation into overdrive. As part of this transformation, new areas of research have been developed and existing areas of research have been greatly expanded. There are many aspects of this digital technology-based transformation that impact accounting, as well as other fields of study. Four specific aspects of this transformation are currently having a significant effect on accounting research. These aspects are what Gordon (2018) referred to as the ABCD of

[1] This paper is the outgrowth of Lawrence A. Gordon's Keynote Address at the *Accounting Horizons* Conference on "Data Analytics in Accounting" held at Baruch College in December 2019.
[2] Although beyond the scope of this paper, a similar rebalancing in inductive vs. deductive-based research is also taking place in many other fields as a result of the recent developments with DA and ML.
[3] Some people refer to this transformation as the Fourth Industrial Revolution. For an interesting discussion of this view, see the article by Klaus Swab at: https://www.weforum.org/agenda/2016/01/the-fourth-industrial-revolution-what-it-means-and-how-to-respond/.

technology, where the A stands for *artificial intelligence* (of which machine learning is a subset), the B stands for *blockchain*, the C stands for *cybersecurity*, and the D stands for *data analytics*.[4]

Gordon (2018) provides an overview of the impact that the ABCD of technology has had, and will continue to have, on accounting. He did not, however, provide an in-depth analysis of the impact that these areas of technology will have on accounting. Instead, he makes the general argument that the ABCD of technology is transforming accounting and suggests that future research needs to explore the issues surrounding this transformation. An article by Glenn et al. (2018-19) takes up this challenge in terms of demonstrating how the ABCD of technology relates to financial management in the U.S. Federal Government. As they note at the end of their article (Glenn et al., 2018-2019 p. 47):

> "…It's time for us to take stock of numerous IT opportunities and assess our progress toward building the more resilient government' envisioned in the 2016 updates to OMB Circular No. -123. Understanding the ABCDs of technology is the best place to begin."

One aspect of the impact of the ABCD of technology on accounting raised by Gordon (2018) concerns accounting research.[5] As Gordon (2018, p. 15) notes, "Accounting researchers also need to focus on where the field of accounting is heading rather than focusing on the field's past and current activities…."

The objective of this paper is to assess the impact of data analytics (DA) and machine learning (ML) on accounting research. The primary argument presented in this paper is that the inherent inductive nature of DA and ML is creating an important trend in the way accounting research is being conducted. That trend is the increasing utilization of inductive-based research among accounting researchers. As a result, a rebalancing is taking place between inductive-based and deductive-based research in accounting. In essence, we are witnessing the resurrection of inductive-based accounting research.

The remainder of this paper will proceed as follows. In the next (i.e., second) section of the paper, an overview of DA and ML is provided. The third section of the paper discusses the impact of DA and ML on accounting research. The primary focus of this section of the paper is on explaining how DA and ML are contributing to the resurrection of the inductive-based approach to accounting research. A brief review of some empirical evidence to support the primary argument of the paper is also provided in the third section. The fourth, and final, section of the paper provides some concluding comments.

II. Overview of Data Analytics and Machine Learning

Data Analytics

[4] As Gordon (2018) points out, there are other aspects of the digital technology-based transformation that are also important for accounting (e.g., social media, mobile devices, robotic process automation, cloud computing, and the Internet of Things), but these other areas are outside of the scope of his article.

[5] Gordon (2018) discussed the impact of the ABCD of technology on accounting in terms of accounting education, accounting practice, and accounting research.

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Data analytics (DA) is concerned with analyzing and interpreting large sets of data, with the goal of gaining insights from the data that are not obvious to the naked eye. As Richardson et al. (2021, p. 4) point out, "…effective Data Analytics provides a way to search through large structured and unstructured data to discover unknown patterns or relationships."

Data analytics begins with the collection and examination of empirical data.[6] Thus, empirical data is the focal point that drives data analytics. The implementation of DA usually includes the utilization of sophisticated statistical techniques, machine learning techniques, and visualization software. The ultimate objective of data analytics is to use data to enhance decision-making. There are several fundamental components to the data analytics process, as discussed below by Master's in Data Science (see: https://www.mastersindatascience.org/resources/what-is-data-analytics/):

> "…descriptive analytics…describing historical trends in data. Descriptive analytics aims to answer thequestion 'what happened'…involves measuring traditional indicators such as (ROI)…
>
> advanced analytics… takes advantage of advanced tools to extract data, make predictions and discover trends. These tools include classical statistics as well as machine learning …Advanced analytics addresses 'what if?' questions…
>
> The availability of machine learning techniques, massive data sets, and cheap computing power has enabled the use of these techniques in many industries. The collection of big data sets is instrumental in enabling these techniques…"

As noted above, big data is an integral part of the modern view of data analytics. *Big data* refers to data sets that include massive amounts of data (e.g., millions of pieces of data). These data sets are so large and complex that analyzing and interpreting the data requires sophisticated data-processing software. The key characteristics of big data are *variety* (i.e., the diversity of data in the data sets), *velocity* (i.e., the speed at which data is gathered and processed), *veracity* (i.e., the accuracy of the data in the data sets), and *volume* (i.e., the size of the data sets).[7]

The basic concept underlying data analytics is not new. Researchers in the field of statistics, for example, have focused on analyzing and interpreting large sets of data (information) for centuries.[8] Accounting researchers have also been actively engaged in analyzing and interpreting data (i.e., data analytics) for centuries. Furthermore, ever since the large public

[6] *Empirical data* usually refers to data generated by observations, experience, and/or experiments. However, as discussed later in this section under the machine learning technique referred to as reinforced learning, AI has reached the point where the data used in ML techniques can be generated by the computer algorithms themselves (i.e., humans do not have be involved in generating the data).

[7] For a more complete description of big data, see: https://en.wikipedia.org/wiki/Big_data. For excellent discussions of how big data is impacting accounting, see Bhimani (2020), Bhimani and Willcocks (2014) and Vasarhelyi et al. (2015).

[8] Technically speaking, there is a distinction between *data* and *information*. "Information consists of that subset of data which increases the knowledge of the person receiving the data" (Gordon, 2004, p. 7). However, in the accounting and business related literature this distinction is usually ignored. Thus, for purposes of this paper, the two terms will be used interchangeably.

companies (i.e., corporations whose shares of equity stock are listed and traded on a public stock exchange or over-the-counter markets) became a popular form of organizing a business, data analytics has been a central activity for accounting researchers.[9] The reason for this development is that large public companies (i.e., corporations) are based on the separation between the owners (i.e., stockholders) of the corporations and those in control of running the corporations (i.e., senior managers and Board of Directors).[10] This separation between ownership and control of corporations has created what economists call an agency problem, where the owners of corporations are considered to be the principals and those empowered to run the corporations are the agents. The two fundamental aspects to this agency problem are: (1) conflict of interests between principals and agents, and (2) asymmetric information between principals and agents. As a result, *transparency* and *accountability* are critical concerns to efficient public corporations because they facilitate the resolution of the agency problem.

The field of accounting plays a pivotal role in providing transparency and accountability for public corporations via the preparation of financial reports for external use by investors and creditors.[11] Thus, over the last century, accounting researchers (as well as practitioners) have been engaged in corporate data analytics in an effort to facilitate improved transparency and accountability. By the early 1970s, accounting researchers were utilizing multiple regression analysis and econometric techniques to analyze and interpret corporate data. In the 1980s and 1990s, accounting researchers were actively involved in incorporating a large variety of additional multivariate statistical techniques (e.g., cluster analysis, factor analysis, principal components, logistic regression analysis) and nascent machine learning techniques to extract patterns from large data sets.[12] Once the SEC (Securities and Exchange Commission) required registrants to file their reports electronically (in 1993), the data of public corporations became easily accessible to researchers via its electronic database called EDGAR (see: https://www.sec.gov/info/edgar/regoverview.htm). From that point on, the degree to which accounting researchers became involved in analyzing and interpreting financial data (as well as nonfinancial data) accelerated at a rapid pace.[13]

[9] The first public company was the Dutch East India Company, which went public in 1602 (see: https://www.investopedia.com/ask/answers/08/first-company-issue-stock-dutch-east-india.asp). In the U.S., corporations became popular in the early part of the 19th century. The beginning of the New York Stock Exchange in 1817 (see: https://en.wikipedia.org/wiki/New_York_Stock_Exchange#History) and the U.S. Securities Exchange Commission in 1934 (see: https://en.wikipedia.org/wiki/U.S._Securities_and_Exchange_Commission) are important landmarks in the creation of the modern corporation.

[10] The classic discussion concerning the separation between the owners of corporations and those in control of corporations is provided in the seminal book by Berle and Means (1932).

[11] Accounting activities traditionally include the process of collecting, measuring, summarizing, analyzing, reporting, forecasting and auditing financial, as well as non-financial, information. In carrying out the above activities in a public corporation, *transparency* and *accountability* are underlying concerns.

[12] Multivariate statistical techniques are statistical methods that simultaneously analyze associations among several variables, including situations that include more than one outcome variable. Numerous textbooks are devoted exclusively to multivariate statistics (e.g., see Johnson and Wichern, 2019).

[13] EDGAR is the SEC's Electronic Data Gathering, Analysis and Retrieval system. "The system processes about 3,000 filings per day, serves up 3,000 terabytes of data to the public annually, and accommodates 40,000 new filers per year on average…Access to EDGAR's public database is free—allowing you to research, for example, a public company's financial information and operations by reviewing the filings the company makes with the SEC." (see:

During the late 1980s and early 1990s, extracting patterns or relationships from large sets of data that were not observable by the naked eye was part of a concerted movement that was often referred to as *data mining*.[14] Contemporary data analytics incorporates the data mining concept. However, since the mid-1990s, there are at least four major advances that have facilitated the modern view of data analytics, as well as increased the use of data analytics in accounting research.[15] First, the amount and variety (e.g., text, videos, graphics, audio files, etc.) of data available for data analytics research related to accounting has been growing at an exponential rate. This avalanche of available data has greatly enhanced the value of data analytics. Databases like EDGAR (see footnote 9), Audit Analytics[16] and WRDS[17] (Wharton Research Data Services) are just a few of the databases/data services that have increased the amount of financial, as well as nonfinancial, data available for accounting researchers. In addition, the developments related to the Internet in the mid-1990s made a massive amount of data available for use when applying data analytics to accounting. The Internet not only provides easy access to a massive amount of general data, but it also includes many databases that contain information on specific corporations (as well as other organizations). The Internet also links researchers to large amounts of world-wide environmental, macroeconomic, media, and social networking data.[18] Second, the memory and storage capacity of computers also have been growing at an exponential rate since the early 1990s. Indeed, the memory and storage capacity of computers have been keeping pace with the increasing availability of data thereby enhancing the value of data analytics. At the same time, the cost of storing data has gone down precipitously.[19] Third, the processing speed of computers (i.e., the CPU, or Central Processing Unit, speed) today has been growing at an amazingly fast rate over the last couple of decades.[20] The velocity at which data can be accessed and analyzed are now calculated in terms of milliseconds rather than seconds. As a result, real time data analytics is not only feasible, but practiced by accounting researchers. Fourth, the advances concerning the integration of machine learning techniques and visualization software (e.g., Python Libraries, R, Tableau etc.) with DA, combined with software enabling the application of sophisticated statistical models, have facilitated the modern view of data analytics. The above four advances associated with data analytics over the past several decades have allowed accounting researchers to rigorously analyze and interpret extremely large data sets. At the same time, DA has allowed accounting researchers

https://www.sec.gov/edgar/about). In 2002, the SEC "…announced that the Commission's web site now provides the public with free, real-time access to its EDGAR database of corporate filings" (see: https://www.sec.gov/news/press/2002-75.htm).

[14] For an excellent discussion of data mining, see: https://en.wikipedia.org/wiki/Data_mining.

[15] Although our discussion is focused on accounting research, these advances are equally relevant to the use of data analytics in economics, finance, and marketing research.

[16] For an explanation of the type of data provided by Audit Analytics, see: https://www.auditanalytics.com/.

[17] WRDS includes a wide set of popular databases (e.g., Compustat, CRSP, Factset, and IBES). For a detailed explanation of the type of data provided by WRDS, see: https://wrds-www.wharton.upenn.edu/pages/about/.

[18] The vast majority of data available on the Internet is either free of charge or at little cost to the user.

[19] For an interesting discussion on how the memory and storage capacity of computers has been increasing at a significant rate, as well as how the cost of storage has been decreasing over the same time period, see the article by Spiceworks (2017).

[20] For an excellent summary of the increase in the processing speed of computers over the last 70 years, see: https://en.wikipedia.org/wiki/Instructions_per_second.

to more efficiently complete the routine tasks of gathering and summarizing the data used for their research.[21]

Machine Learning

Machine learning (ML) refers to a process whereby the computer (i.e., the machine) learns (i.e., acquires knowledge) to develop computer programs (i.e., algorithms) by examining empirical data.[22] Thus, empirical data is the focal point that drives ML techniques similar to the way DA is driven by empirical data.[23] Technically speaking, ML falls under the domain of artificial intelligence (AI), where AI refers to a situation where machines (essentially computers) can simulate human intelligence. Machine learning techniques are often viewed as an integral component of (or at least as a complement to) contemporary data analytics. Thus, accounting researchers using DA frequently utilize ML to facilitate their use of DA.

There are three main techniques (categories) usually associated with machine learning. The first ML technique is called *supervised learning*, which is based on providing the computer with *training data* that consists of labeled inputs that are paired with desired outputs. The goal of the computer is to develop (i.e., learn) an algorithm that properly identifies the relationship between the labeled input data and desired outputs (i.e., outcomes). The algorithm is then used to predict the output for new input data. As more data is acquired, the computer can learn and revise the algorithm. Supervised learning algorithms are usually grouped into *classification* algorithms (e.g., decision trees, k-nearest neighbor, etc.) used for predicting discrete outputs or *regression analysis* algorithms (e.g., such as a linear regression analysis or logistic regression analysis) used for predicting continuous outputs. An example of a classification learning algorithm is one that predicts whether a new email message is spam or not-spam. An example of a regression analysis learning algorithm is one that predicts a firm's sales based on advertising expenditures.

The second ML technique is called *unsupervised learning*. This ML technique provides the computer with training data consisting of unlabeled inputs, but does not provide any desired outputs (i.e., outcomes). Instead, the computer is required to identify patterns or structure within the unlabeled data and come up with output patterns (or structures) associated with the unlabeled input data. Thus, whereas the supervised learning approach to machine learning uses labeled training data that essentially teaches the computer how to come up with an algorithm to predict the output, the unsupervised learning approach to machine learning forces the computer to explore the unlabeled input data and, based on such an

[21] Accounting courses in colleges and universities on "financial statement analysis" have traditionally covered issues associated with data analytics. The current trend is for accounting departments within colleges and universities to offer stand-alone courses that focus specifically on data analytics applied to the field of accounting. These courses have a variety of titles, such as "Data Analytics for Accounting" or "Accounting Analytics." The book by Richardson et al. (2021), now in its 2nd Edition, is one of the first textbooks to focus on applying data analytics to the discipline of accounting.

[22] A computer program is a set of instructions stated in a language that the computer can understand. The instructions are designed to accomplish a specific task, and therefore can be thought of as an algorithm (i.e., an algorithm is a set of instructions designed to accomplish a specific task).

[23] It is important to recognize that the results of using DA and ML techniques will only be as good as the data utilized in connection with these techniques. Thus, if the data is biased, then the analysis, interpretation, and algorithms derived from ML will also be biased.

exploration, develop an algorithm that identifies patterns associated with the output. As more data is acquired, the computer can learn and revise the algorithm. The most popular unsupervised learning algorithm is the *cluster analysis* algorithm, which sorts the input data into groups (i.e., clusters) of output data based on common characteristics. In essence, the data in a particular cluster has more in common with the other data in the same cluster than it has with data in other clusters. An example of a cluster analysis learning algorithm in accounting would be one that clusters large sets of financial data on publicly traded firms into clusters based on specific firm-level characteristics.

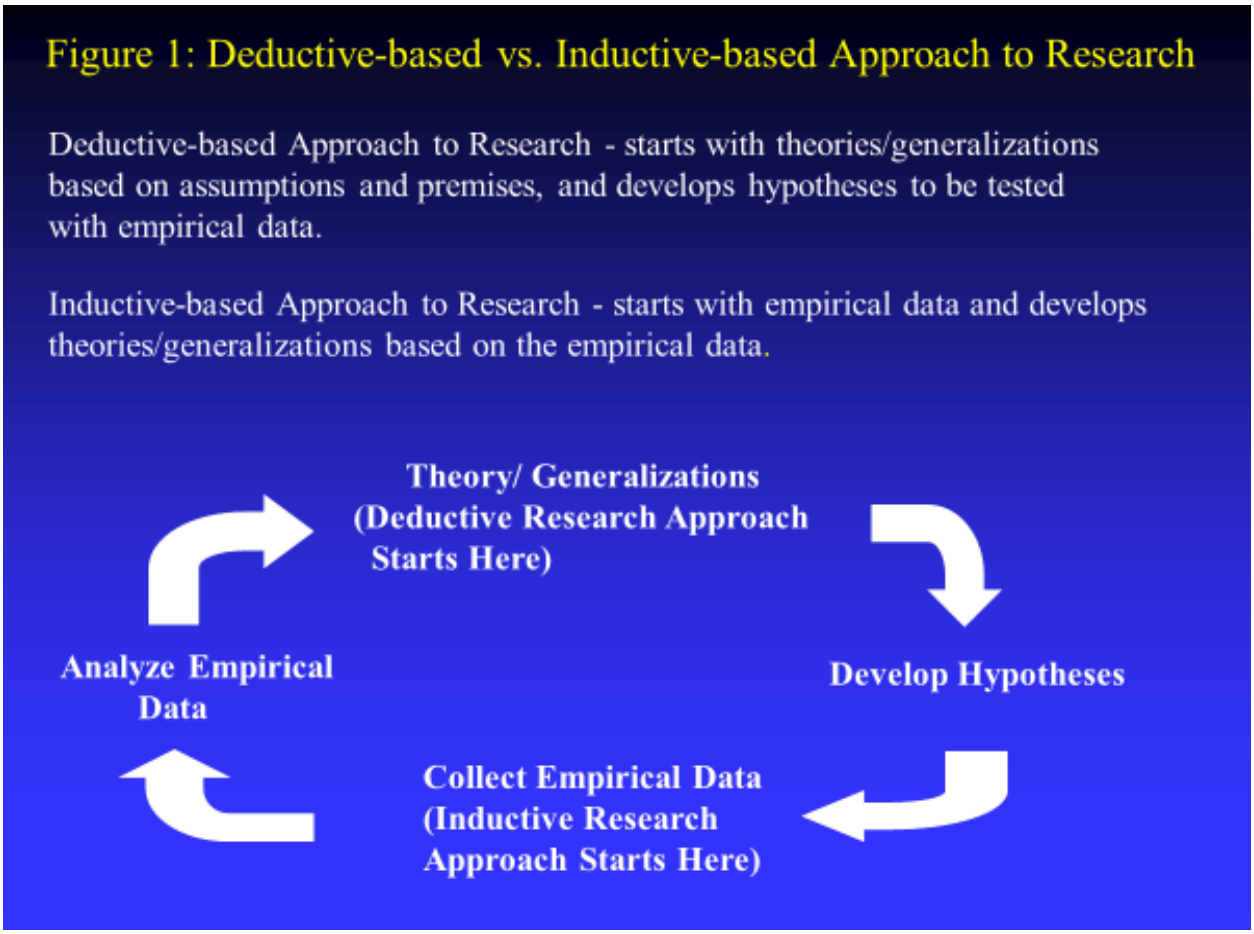
The third ML technique is called *reinforcement learning*. This ML technique provides the computer with training data consisting of unlabeled inputs, as is done with unsupervised learning. With reinforcement learning, however, the output from the unlabeled input data is evaluated in terms of some maximum output and feedback (reinforcement) is provided on whether the computer program is moving closer to (positive feedback) or further from (negative feedback) the maximum output. An example of where reinforced learning has been used is in making moves that are part of a series of moves toward winning a game, such as a game of Chess. After a very large number of Chess games (e.g., hundreds of thousands or millions), the computer program will develop a series of moves that will allow it to win the Chess game, taking into consideration a wide array of possible moves by an opponent. Although the training data used in reinforced learning is usually generated from humans, the field of artificial intelligence (of which ML is a subset) has developed algorithms that can learn for themselves (i.e., they generate their own data). With regards to the game of Chess, AlphaZero is such an algorithm. AlphaZero was given the rules of Chess and the initial positions of the Chess pieces. It then played against itself (i.e., a computer-generated opponent of increasing ability) without any data or knowledge being provided by humans. As Silver et al. (2018, p. 1144) noted in their discussion of applying AlphaZero to the game of Chess, "AlphaZero is a generic reinforcement learning and search algorithm…that achieved superior results within a few hours…"

III. The Impact of DA and ML on Accounting Research

Deductive-based Research vs. Inductive-based Research

Two basic approaches to research are *deductive-based research* and *inductive-based research*. The deductive-based approach to research is grounded in deductive reasoning (sometimes called deductive logic) and begins by developing a theory, conceptual construct, or generalization (hereafter referred to as a theory) derived from some basic principles and assumptions. Deductive research then deduces specific research hypotheses, questions, or arguments (hereafter referred to as hypotheses or arguments) based on the theory. The arguments are then tested based on an analysis and interpretation of empirical data (e.g., archival data from WRDS). The analysis and interpretation of the data is usually accomplished with the aid of statistical techniques. In other words, deductive reasoning involves a process of deducing specific arguments from a theory that can be tested based on an analysis and interpretation of empirical data. Depending on the empirical findings, the theory may be accepted or revised to come up with a revised theory that presumably does a better job of predicting future empirical data. Accordingly, research that starts off with deductive reasoning enters a continuous cycle of developing a theory, developing arguments that follow from the theory, testing the arguments based on empirical data, revising the

theory (where needed) based on the empirical findings, and starting the process all over again. This process is illustrated in Figure 1, where the deductive research process begins at the top of the figure.



The inductive-based approach to research is grounded in inductive reasoning (sometimes called inductive logic) and begins by an analysis and interpretation of empirical data (e.g., archival data from WRDS). The analysis and interpretation of the empirical data is usually accomplished with the aid of statistical techniques. Based on the analysis and interpretation of the empirical data, a theory is induced. This brings us back to the deductive approach to research and the process of developing arguments to test the induced theory with a new and/or an expanded data set. Based on the tests of the new and/or expanded data set, the process of developing a revised theory, and testing the theory, begins all over again. As illustrated in Figure 1, the inductive research approach begins at the bottom of the figure, entering a continuous cycle of analyzing and interpreting empirical data, inducing a theory, and developing arguments to test the theory with new and/or an expanded data set.

Figure 1 is purposely drawn to illustrate the point that, whether starting off with a deductive approach to research or an inductive approach to research, research is best thought of as incorporating both perspectives (i.e., a process that consists of both deductive and inductive

reasoning that forms a continuous research cycle). In fact, the inductive-based approach to research and the deductive-based approach to research are complements to each other.

Deductive-based vs. Inductive-based Accounting Research

Prior to the late 1960s, a Master level degree, combined with professional certification (e.g., a Certified Public Accounting [CPA] certificate), was viewed as terminal qualifications for accounting faculty members at the majority of colleges and universities in the United States (as well as in other countries). It was also common for accounting academicians to be actively involved in the practice of accounting (e.g., as a partner in an accounting firm), as well as to publish their research in professional accounting journals (e.g., *Journal of Accountancy*) during the early part of the 20th century.[24] Thus, not surprisingly, prior to the mid-1960s it was common for accounting researchers to rely on observations from practice to develop a theory thereby taking an inductive-based approach to accounting research.

Although the inductive approach to accounting research was common prior to the mid-1960s, it was by no means the only approach to accounting research. In fact, many of the accounting researchers during this period moved back and forth between inductive and deductive approaches to accounting research. Research by these individuals often focused on theoretical (i.e., conceptual) discussions of such issues as income determination and asset valuation. The seminal monograph by Paton and Littleton (1940) is a good example of this type of research. In discussing this monograph, Zeff (2018, p. 64) points out that:

> "While it has been commonplace to label Paton as a deductive thinker and Littleton as the inductivist, in reality the two approaches blended into each other. Paton was much affected in his thinking and policy recommendations by the changing political, regulatory, and economic environment of the 1920s to the 1950s (Zeff 1979) - and thus in some sense was also an inductivist - while Littleton, when drawing his ideology from the experiential world, at the same time sorted out what he liked from what he did not like, as would a deductivist."

In 1969, the American Association of Collegiate Schools of Business (AACSB) began requiring a certain percentage of faculty members in business schools to hold degrees at the doctoral level for AACSB accreditation purposes (Zeff, 2019).[25] This decision by the AACSB created a new and vastly different demand for accounting professors (i.e., those with doctoral degrees), especially within the United States. From the late 1960s through the 1970s, the demand for accounting faculty members with doctoral degrees in accounting or related disciplines (e.g., economics) increased at a significant rate.

The increased demand for accounting faculty members who possessed doctoral level degrees resulted in the creation of a new supply of such individuals. More specifically, new doctoral programs in accounting started to emerge throughout the 1970s and beyond. The

[24] Prior to the 1960s, there were many professional accounting journals. However, prior to the 1960s *The Accounting Review* was considered by most academicians as the only major accounting research journal.

[25] The AACSB set percentages for doctorate degrees at 40 and 75 for undergraduate and graduate level courses, respectively (Zeff, 1979). In 2001, the AACSB changed its name (but kept its acronym) to the Association to Advance Collegiate Schools of Business.

application of mathematics and sophisticated statistical analysis became critical components of these new, as well as existing, accounting doctoral programs.[26] Furthermore, and of key significance, economics (including econometrics) became the primary foundation discipline in a large percentage of the research-oriented accounting doctoral programs during the 1970s and beyond (especially in the United States).[27] The students graduating from the accounting and related doctoral programs of the late 1960s and the 1970s became the breeding ground for many highly prolific accounting researchers during the 1970s and beyond.

Given the importance of economics to the new breed of accounting researchers that emerged during the late 1960s and 1970s, it is instructive to consider the way economists develop their theories. Classical economists (e.g., Adam Smith, David Ricardo) of the 18th and 19th centuries developed their theories assuming that individuals make decisions in a rational (logical) manner based on self-interest.[28] Based on these assumptions, classical economists argued that the laws of supply and demand facilitate an environment where free markets (i.e., markets without government intervention) are efficient. Neoclassical economists (e.g., Alfred Marshall, John R. Hicks) of the 20th century also emphasized the fact that individuals make decisions in a rational manner based on self-interest, and that free markets facilitate efficient markets. However, whereas classical economists believed that production costs are the main driver of the value of products (i.e., goods or services), neoclassical economists argued that consumer demand is the key driver of the value of products. Furthermore, neoclassical economists argued that profit maximization is the key objective of most private sector firms. Thus, neoclassical economics shifted the focus toward mathematical models of profit maximization, based on marginal analysis (i.e., profits are maximized where marginal revenues equal marginal costs). The differences between classical and neoclassical economists notwithstanding, both sets of economists developed their theories largely based on a set of assumptions rather than data. Empirical data would then be used to test these theories. Hence, classical and neoclassical economists approached research primarily in terms of deductive reasoning.[29]

[26] For an excellent discussion of the developments related to the application of mathematics, analytic models and statistics to accounting during the second half of the 20th century, see Mattessich (2005).

[27] Economics is concerned with decisions concerning the production and allocation of scarce resources, whereas accounting provides an information system that facilitates economic decisions. Thus, to many (including the author of this paper), economics is the logical primary foundation discipline for accounting. However, since economics is a social science, psychology and sociology are also key disciplines for developing accounting systems. This latter argument notwithstanding, economics, with its emphasis on mathematical modeling and econometrics (i.e., the application of statistical models to empirically estimate and test economic theories and policies) is usually considered the dominant foundation discipline for accounting research (especially in the U.S.).

[28] Adam Smith is often referred to as the father of capitalism. He is also credited with coining the phrase "the invisible hand of the market" (i.e., because of self-interest and competitive forces, markets will be efficient without government intervention). Smith's work regarding the above was originally published in 1776, in his book usually referred to as the "Wealth of Nations" (see: https://www.investopedia.com/updates/adam-smith-wealth-of-nations/).

[29] The deductive approach to research in economics usually starts with the development of a theory that describes how things should be (i.e., a normative approach to theory development), given a set of *ex ante* assumptions. Empirical data is then used to test the theory via econometrics. However, one popular view among many economists is that economic theory is conditional on many factors and changes in these factors occur over time. These economists believe that the validity of a theory (or model) needs to be judged in terms of its ability to predict the outcome based on empirical data. As new data becomes available, an existing theory (model) is replaced with a new

As already noted, beginning in the 1970s economics became the primary foundation discipline for a large percentage of the research-oriented accounting doctoral programs. This situation is still true today, especially in terms of the research in those programs that focus on financial and managerial accounting issues. These programs typically require a set of rigorous courses in economic theory and econometrics that are grounded in mathematical models commonly focusing on profit maximization. Consequently, a large share of accounting researchers who graduate from economics-focused accounting doctoral programs view the economics approach (i.e., the deductive-based approach) to research as representing a rigorous approach to research (i.e., they have been indoctrinated to believe in the economics approach to research).[30] In addition, some (if not many) of these accounting researchers have developed a bias against inductive-based research.[31] This bias against inductive-based approach to accounting research seems to stem from the belief that looking at empirical data to develop a theory only allows the theory to apply to the finite number of observations from which the theory was developed.[32] Of course, this view ignores the fact that utilizing DA and ML techniques in today's environment of big data is not only comprehensive and rigorous, but also allows the researcher to derive adaptive solutions and predictions for dynamic complex problems that do not lend themselves to a static generalized theory. The above fact notwithstanding, the bias against inductive-based research by some accounting researchers has had negative implications for the review process of many papers submitted to major academic accounting journals. More specifically, this bias has resulted in a situation where some reviewers of papers submitted to academic accounting journals recommend that a paper be rejected based largely on the fact that the paper did not begin with the development of a theory (i.e., the deductive approach to accounting research).[33] Contemporary accounting researchers using DA and ML are, however, changing this situation.

The combination of economics-focused accounting doctoral programs and the bias against inductive-based research has resulted in an imbalance favoring the deductive-based approach over the inductive-based approach to accounting research. This imbalance began in the 1970s and continued through the early part of the 21st century. In other words, starting in the mid-1970s the deductive-based approach to accounting research became the

theory (model) when the new theory does a better job of predicting future empirical data. Consequently, although economists usually start their research by developing a theory from a deductive and normative perspective, many economists take a *logical positivism* view of theory and accept the theory that best explains actual observations (i.e., approaching research in terms of the continuous research cycle illustrated in Figure 1).

[30] The belief that deductive-based research is rigorous seems to have its origin in research related to mathematics, where the purest form of research is mathematical proofs by deduction.

[31] The statement that many accounting researchers are biased against inductive-based research is, of course, a broad generalization. There have always been, and continue to be, accounting researchers who never exhibited this bias. This latter point is especially true among behavioral accounting researchers. In fact, behavioral accounting researchers frequently place more weight on inductive reasoning than deductive reasoning.

[32] This belief seems to have its roots in mathematics, where mathematical proofs by induction are usually considered to be only capable of verifying a finite number of observations (see: https://math.stackexchange.com/questions/2547472/is-maths-inductive-or-deductive).

[33] The author served as the Co-Editor for 20 years, and Editor-in-Chief for 17 years, of a major accounting research journal and has seen scores of reviews that reflect this bias.

dominant method of conducting accounting research for the next three decades. Nevertheless, as noted above, accounting researchers using DA and ML are changing this situation. More to the point, accounting researchers using DA and ML recognize the value in examining the available empirical data at the beginning of the research process (i.e., applying inductive reasoning). These researchers tend to approach research issues with the following thought in mind: "let's first see what the data tells before coming up with any theory or generalization." Indeed, the amount of data now available to researchers (e.g., data sets with millions of observations), the capability of modern computers to store and process this data, the processing speed of today's computers, and the recent developments related to data analytics and machine learning techniques discussed in Section II of this paper, have combined to create a new breed of accounting researchers who have a renewed interest in inductive-based research.[34] These researchers understand that the mathematical and statistical underpinnings of contemporary computer-based DA and ML are as mathematically rigorous as are the mathematical models used in contemporary economic theory and econometrics. In fact, today's researchers utilizing DA and ML techniques are usually well trained in mathematics, statistics and economics (including econometrics) and integrate this training into their research. Furthermore, these researchers also understand that DA and ML allows researchers to derive adaptive solutions and predictions for dynamic complex problems that do not lend themselves to a static generalized theory. Accordingly, accounting researchers (as well as researchers in other fields, such as economics) utilizing DA and ML are presenting a formidable challenge to the preference for deductive-based research.[35]

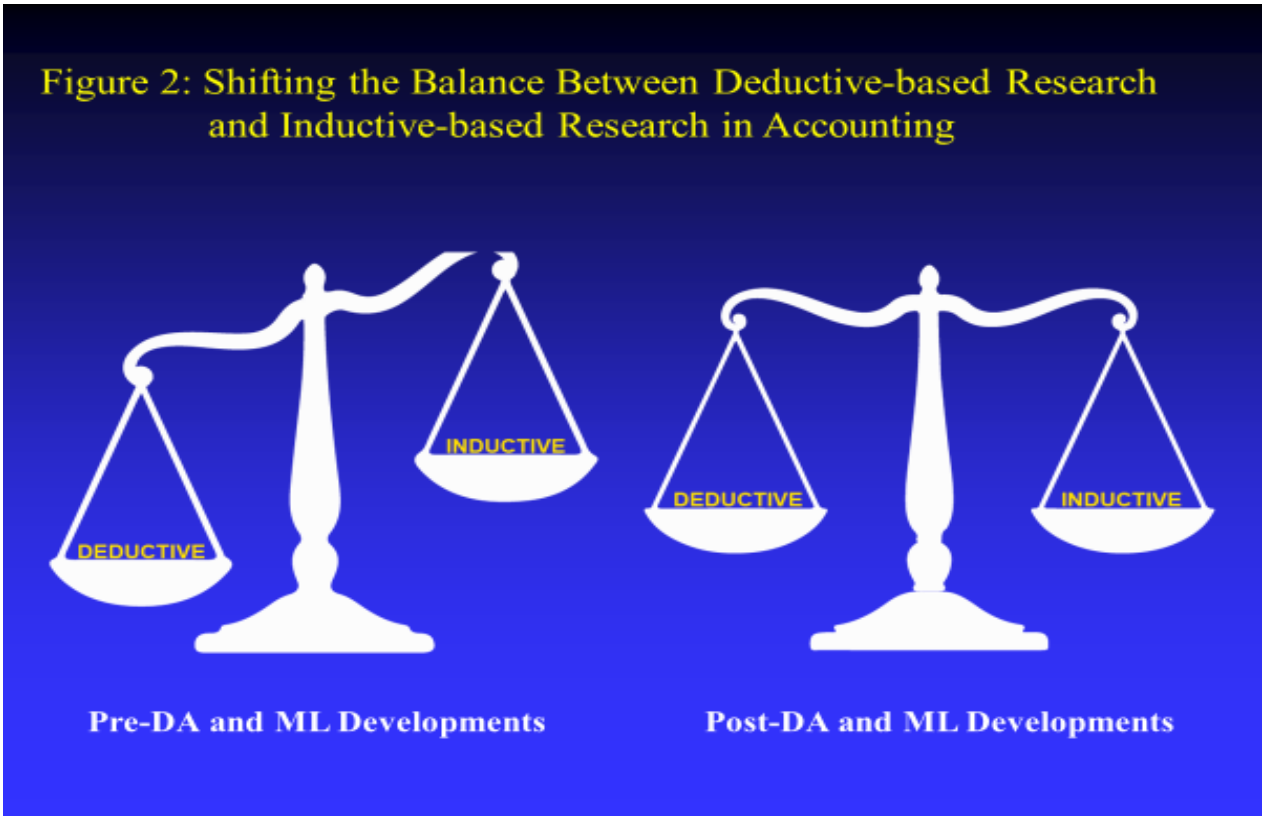
In sum, developments related to DA and ML have resulted in a resurrection of inductive-based research among accounting researchers. This resurrection is creating a rebalancing (or paradigm shift) between inductive and deductive-based approaches to accounting research. This rebalancing is in terms of the increasing the use of inductive-based research vis-a-vie deductive-based research among accounting researchers. This rebalancing is illustrated in Figure 2. As illustrated in Figure 2, the argument in this paper is not that the deductive-based approach to accounting research will be replaced by the inductive-based approach due to DA and ML. Instead, the argument is that recent developments with DA and ML are shifting the balance in favor of making the two approaches (i.e., inductive and deductive-based research) more equally balanced in terms of their use by accounting researchers.[36] Of course, as argued elsewhere in this paper, in the end the deductive-based approach to research and the inductive-based approach to research are both important

[34] The term *renewed interest* is used here because, as pointed out earlier in the paper, prior to the 1960s a significant portion of accounting research was grounded in inductive reasoning.

[35] Data analytics and machine learning are having a similar impact on the discipline of economics as they are on accounting (e.g., Athey, 2019; Kleinberg et al., 2018; Mullainathan and Spiess, 2017; Varian, 2014). For example, Mullainathan and Spiess (2017, p. 104) note that "Machine learning provides a powerful tool to hear, more clearly than ever, what the data have to say." In a similar vein, Varian (2014, pp. 24-25) notes that "Researchers in machine learning have developed ways to deal with large data sets and economists interested in dealing with such data would be well advised to invest in learning these techniques." This movement toward an increase use of DA and ML, and in turn inductive reasoning, in economics is clearly contributing to the use of DA and ML in accounting (i.e., accounting researchers trained in economics pay close attention to the changes in research methodologies and strategies by economists).

[36] Unlike the argument by Kuhn (1972), where a new research paradigm completely replaces an older research paradigm, the view in this paper is that the research paradigm shift is one of rebalancing rather than replacement.

when conducting research. Thus, whether one starts from the top or bottom of Figure 1, in the end accounting research is best thought of as continuous process that consists of both deductive and inductive reasoning.



Selected Examples of DA and ML Applied to Contemporary Accounting Research

Developments concerning the use of research techniques in a particular discipline usually occur over several years in an evolutionary, not revolutionary, manner. Thus, the purpose of this section of the paper is not to argue that DA and ML transformed accounting research on a particular date and prior to that date these techniques were never used. Instead, our focus in this section is to provide a few selected examples of how accounting researchers are applying DA and ML to issues related to auditing, financial accounting, taxes, managerial accounting, and accounting information systems. These examples are intended to be suggestive of the type of research currently being conducted and the future opportunities available to accounting researchers.

There are numerous examples of how DA and ML have been, and continue to be, applied to accounting related research. A common denominator in these examples is the important role that empirical data and inductive reasoning play in the research. For example, DA and ML have facilitated a significant change in contemporary auditing research. This change includes using DA and ML techniques to detect and predict audit quality, fraud, audit fees, and risk factors in a much more comprehensive (e.g., rather than sample-based audits, auditing the total population) and efficient manner than was previously possible (e.g., Bao et al., 2020; Cho et al., 2020; Hsieh et al., 2020; Hunt et al., 2020, No et al., 2019; Perols et al. 2017).

The use of DA and ML techniques has important implications for contemporary financial accounting researchers as well. For example, a key concern among financial accounting researchers is forecasting firm-level earnings as well as other measures of firm performance. The use of DA and ML techniques has resulted in improved earnings forecasts (e.g., Hunt et al., 2019). DA and ML have also facilitated improved bankruptcy predictions (e.g., Barboza et al., 2017). The use of ML models to identify and interpret misstatements has also led to a stream of important financial accounting related research (e.g., Bertomeu et al., 2020; Brown et al., 2020; Lokanan et al., 2019). Research using machine learning techniques to improve comprehensive financial statement analysis is also taking place (e.g., Amel-Zadeh et al., 2020). One can easily imagine the day when publicly traded corporations will provide a link to their company's financial information on a real time basis, supported by tables, reports, figures and graphs in the same way stock market information is currently available.

The application of DA and ML to tax related research has also become popular. In fact, given the vast amount of data generated in response to tax authorities and regulations, tax related research provides a perfect setting for applying DA and ML. For example, researchers have been combining DA and ML techniques to better understand how taxpayers can more effectively take advantage of the tax laws (i.e., tax planning), as well as to assist tax authorities (e.g., the Internal Revenue Service) improve the implementation of tax laws (e.g., Alarie et al., 2019). Researchers have also utilized the combination of DA and ML techniques for detecting tax evasion (e.g., Wei et al., 2019), as well as in assessing compliance with value added tax (VAT) rules (e.g., Lahann et al., 2019).

DA and ML techniques are also facilitating a significant change in the way accounting researchers approach managerial accounting issues.[37] Research related to issues associated with cost management (e.g., cost allocations, cost estimates, cost structures and operating leverage, etc.), forecasting product demand and cash flows, profit planning, balanced scorecard, capital investments, corporate governance and strategy, internal control systems, and transfer pricing are already benefiting from using DA and ML models (e.g., Applebaum et al., 2017; Bhimani, 2020; Bhimani and Willcocks, 2014; Nielsen, 2020; Rafiei and Adeli, 2018; Shimamoto, 2018).

DA and ML are also starting to play an important role in research related to accounting information systems. Accounting information systems, as with all contemporary information systems, operate in a computer-based interconnected digital environment. In this environment, cybersecurity breaches have become a critical concern to all information systems within private and public sector organizations (e.g., Gordon et al., 2011; Spanos and Angelis, 2016). As a result, organizations need to assess their cybersecurity risks in order to derive the appropriate amount to invest in cybersecurity related activities (Gordon and Loeb, 2002; Gordon et al., 2016). They also need to determine the best way to allocate their cybersecurity investments (i.e., manage their cybersecurity resources) in order to defend against cyber-attacks (e.g., Gordon et al., 2016; Gordon et al., 2020; Gordon et al., 2021).

[37] Managerial accounting, for purposes of this paper, is "…concerned with the design and use of information systems that support managerial planning and control" (Gordon, 2004, p. 2).

URL: http://dx.doi.org/10.14738/tmlai.92.9823.

Furthermore, publicly traded firms need to disclose their cybersecurity risks and cyber incidents (e.g., U.S. Securities and Exchange Commission [SEC], 2011 and 2018). DA and ML techniques are able to assist accounting information systems researchers identify procedures for combating cybersecurity attacks and assessing cybersecurity risks, as well as to improve the overall reliability of the information contained in such systems (e.g., Allodi, L., and F. Massacci, Askary et al., 2018; 2017; Cheong, 2019; Huerta and Jensen, 2017; Leo et al., 2019; Peters, 2017; Tolubko et al., 2018).

IV. Concluding Comments

Accounting systems are essentially information systems intended to facilitate the planning and control of organizations.[38] As with research related to all information systems in today's interconnected digital economy, the future of accounting research is inextricably intertwined with developments related to technology (e.g., Gordon, 2018). Indeed, technology-related developments are transforming the way accounting research is being conducted and the issues being addressed. The developments over the last two decades related to data analytics (DA) and machine learning (ML) techniques are part of this technology-based transformation having a significant impact on accounting research. One aspect of this transformation, and the one emphasized in this paper, is the resurrection of inductive-based accounting research emanating from developments in the areas of DA and ML techniques. As a result, a rebalancing is taking place between inductive-based and deductive-based research in accounting.

The DA and ML movement has facilitated numerous opportunities for accounting researchers. These opportunities are in terms of new areas of research, as well as expanding upon existing areas of research. For example, the developments with ML are allowing accounting researches to develop new models and algorithms that can be used to plan and control organizations, as well as to understand the relationships among performance measures and organizational success. It is easy to imagine how the approach used to develop the AlfaZero reinforcement learning algorithm for the game of Chess could be applied to accounting research related to financial fraud, cost management issues, profit planning, and the use of the balanced scorecard. In addition, thanks in part to DA, the routine, highly structured aspects of data gathering, data processing and data storing that were often associated with accounting research are now more efficiently handled via computers.[39] As a result, accounting researchers can spend a larger proportion of their time identifying issues of importance, designing appropriate research designs and methodologies to examine such issues, and analyzing and interpreting the implications of their research.

The argument in this paper is not that the deductive-based approach to accounting research will be replaced by the inductive-based approach due to DA and ML. Instead, the argument is that recent developments with DA and ML are shifting the balance in favor of making the inductive and deductive-based approaches to accounting research more equally balanced than has been the case for several decades. In the end, however, both deductive and inductive approaches to research are important and should be thought of as representing two sides of

[38] Although beyond the scope of this paper, the same is true for personal accounting systems.
[39] DA is having a similar impact on accounting practitioners.

the same coin. The above notwithstanding, DA and ML techniques provide the opportunity for accounting researchers to not only think out-of-the box, but in fact to realize that there is no box, when working on truly impactful research.

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