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# Economics

## Working Papers

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2020-09

### Management accounting and the idea of machine learning

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# Management accounting and the idea of machine learning

August 2020

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*"Its central message is that what we measure affects what we do. If we measure the wrong thing, we will do the wrong thing. If we don't measure something, it becomes neglected, as if the problem didn't exist." (Said by Joseph E. Stiglitz in 2018).*

## Abstract

*Not only is the role of data changing in a most dramatic way, but also the way we can handle and use the data through a number of new technologies such as Machine Learning (ML) and Artificial Intelligence (AI). The changes, their speed and scale, as well as their impact on almost every aspect of daily life and, of course, on Management Accounting are almost unbelievable. The term 'data' in this context means business data in the broadest possible sense. ML teaches computers to do what comes naturally to humans and decision makers: that is to learn from experience. ML and AI for management accountants have only been sporadically discussed within the last 5-10 years, even though these concepts have been used for a long time now within other business fields such as logistics and finance. ML and AI are extensions of Business Analytics. This paper discusses how machine learning will provide new opportunities and implications for the management accountants in the future. First, it was found that many classical areas and topics within Management Accounting and Performance Management are natural candidates for ML and AI. The true value of the paper lies in making practitioners and researchers more aware of the possibilities of ML for Management Accounting, thereby making the management accountants a real value driver for the company.*

**Keywords:** *Management accounting, machine learning, algorithms, decisions, analytics, management accountant, business translator, performance management.*

**JEL Classification:** C15, M41

## 1. Introduction

Calling data “the new oil” of the digital economy may have become a cliché, but it still makes sense. However, data is not oil; it is land. Framing data as oil is not informative for executives who try to value their data assets. Oil is valuable, marketable, and tradable. Without significant effort, data is not. Data has more in common with land that may contain oil deposits than it does with oil<sup>1</sup>. However, an article in Harvard Business Review (HBR) also states that just 3% of the data in a business enterprise is of good quality (Nagle *et al.*, 2017<sup>2</sup>). If the analyst uses bad data, the Machine Learning (ML) tools are useless<sup>3</sup>. A survey from IDC sponsored by Qlik, shows that it is more important than ever to invest in data management. Companies with established data-to-insights pipelines typically see 22% greater profits, 21% higher revenue and 21% higher efficiency (IDC and Qlik, 2020).

A survey conducted by PwC (based on 3,200 interviews with CEOs in more than 90 territories) estimates that global GDP may increase by up to 14 % (the equivalent of US\$15.7 trillion) by 2030 because of the accelerating development of Artificial Intelligence (AI). The report anticipates the next wave of digital revolution to be unleashed with the help of the data generated from the Internet of Things (IoT), and the amount of data from this source is likely to be many times greater than the data generated by the current ‘Internet of People’ (PwC, 2018).

Another survey has shown that four out of five CEOs bemoaned their employees’ lack of essential IT skills and identified this factor as a threat to growth. That concern has risen in line with the advent of new technologies over the past five years and is voiced consistently across all regions: CEOs in Japan and Central/Eastern Europe are the most worried, with 95% and 89%, respectively, naming it as a concern, whereas those in Italy (55%) and Turkey (45%) are the least anxious about it (PwC, 2019). No wonder that a staggering 77% of chief executives report that scarcity of people with key skills is the biggest threat to their businesses according to a PwC survey (PwC, 2017a).

Finally, one survey also shows that defining strategy is very important, but the relentless churn and volatility in the business environment mean that simply outperforming the average is not enough (Reeves *et al.*, 2012). The authors studied the performance trajectories of 22,000 companies over the last four decades. The results show that across a wide range of metrics, strong performance has become far less sustainable than in the past. Companies that manage to beat the average for their industry must now struggle much harder to maintain their leading position. The number of companies deploying Big Data is expected to double in the near future, exceeding the implementation rate of other “hot” technologies such as data visualization and process automation.

*“It’s no longer a question of whether to become an analytics-driven organization, but how. To be successful, organizations need to build information architectures that match analytics workloads to answer the questions that will create the most value for the business. The one-size-fits-all database is long dead, and so is the one-size-fits-all data/analytics platform. I have learned that competing on analytics is not about large, multi-year projects: it is about having an impact for the people who are making decisions every day, week, and month”* (Said by Andy Palmer, the co-founder and CEO of Tamr).

Even though the concept ‘data-driven’ is seen as the new oil and used in many contexts (see, e.g. Wall Street Journal, March 9, 2019) as if somehow having data is a value *per se*, others think that the right concept

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<sup>1</sup> <https://www.datasciencecentral.com/profiles/blogs/data-is-not-oil-it-is-land>

<sup>2</sup> A short review can be found here: <https://hbr.org/2017/09/only-3-of-companies-data-meets-basic-quality-standards>

<sup>3</sup> See here: [https://hbr.org/2018/04/if-your-data-is-bad-your-machine-learning-tools-are-useless?referral=03759&cm\\_vc=rr\\_item\\_page.bottom](https://hbr.org/2018/04/if-your-data-is-bad-your-machine-learning-tools-are-useless?referral=03759&cm_vc=rr_item_page.bottom)

to use is ‘profit-driven’ (e.g., Schmarzo and Sidaoui, 2019). However, because there is no marketplace, where the “in exchange” value of a company’s data can be determined, data does not appear as an asset on the financial statements (or in any other place. But data does, in fact, have many of the same characteristics and problems as intellectual capital disclosures and intangible assets according to IAS 30)<sup>4</sup>. Many organizations see data acquisition and management as a business expense. You may hear questions like, what does it cost to collect and capture this data? What resources do we need to store it? Are analysis, modeling, and other data science projects a priority for us right now? Do we have the budget for all this?<sup>5</sup>

Also within accountancy, AI and ML have been discussed for a long time. For example, the ICAEW (2018) writes:

*“Although AI techniques such as machine learning are not new, and the pace of change is fast, widespread adoption in business and accounting is still in early stages. In order to build a positive vision of the future, we need to develop a deep understanding of how AI can solve accounting and business problems, the practical challenges and the skills accountants need to work alongside intelligent systems”* (ICAEW, 2018, p. 1)<sup>6</sup>.

Demand for new data-related skills for management accounting and performance management is already high and is likely to increase even further within a short time (Richins *et al.*, 2017). Acknowledging the revolutionary nature of changes related to data and understanding the concepts and challenges that working with data presents are likely to be among the key requirements for finance professionals in the near future (ACCA & IMA, 2015).

The terms management accounting, management control, and performance management are often used interchangeably (Chenhall, 2005; Ferreira and Otley, 2009). But PM&M (Performance Measurement and Management) is now part of the CIMA Official Terminology because the journal Management Accounting Research dedicated a special issue to these topics (MAR 25(2)) (For a further discussion of these concepts, see, e.g., Balstad and Berg, 2019). The analytics literature (e.g., Davenport and Harris, 2007; Provost and Fawcett, 2013) mostly uses the term performance measurement and management (see also Waal and Kourtit, 2013).

A recent example is within investment management. Here, ML is capable of finding new patterns in existing data sets, and thus ML supplements the quantitative work already done. Some of these new techniques produce significant improvements over traditional ones. In estimating the likelihood of bond defaults, for example, analysts have usually applied sophisticated statistical models developed in the 1960s and 1980s by Altman and James Ohlson, respectively. Recently researchers found that ML techniques are approximately 10% more accurate at predicting bond defaults than those prior models (see, e.g., Barboza, 2017).

In the future, accounting tasks as well as tasks related to tax, payroll, audits, and banking will be fully automated owing to AI-based technologies, which will disrupt the accounting industry in a way it never was for the last 500 years since, bringing both huge opportunities and serious challenges (Baptiste, 2018). However, having machines to do all these tedious and repetitive tasks could sound scary for many accountants because *“they are also very time-consuming and thus very lucrative,”* explained Stephanie Weil, CEO of ‘Accounteam’, a Silicon Valley-based accounting firm. *“Nevertheless, it can also eliminate accounting errors that are generally hard to find and thereby reduce liability and allow us to move to a more advisory role”*, she said.

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<sup>4</sup>The author would like to thank Frank Thinggaard for comments on this subject.

<sup>5</sup>See for example: <https://www.explorium.ai/blog/>

<sup>6</sup>Amazon has developed a comprehensive guide for machine learning (see, Amazon Guide, 2020) that may be used as inspiration.

Because “time-saving” is an important benefit of machine learning, this gives the accounting professionals an opportunity to use more time on research and to deliver more relevant and beneficial judgments instead.

Accountants and finance professionals have always been affected by huge shifts in the data management and scope (ACCA and IMA, 2015). This shift signifies an urgent need to re-examine current and future trends of digital data and data processing, as well as the imminent impact of such trends on the future of accounting. While so-called ‘Big Data’ tends to draw a lot of attention, it is by no means the only area where the Data Revolution battles are being fought; the ‘small data’ users are probably much more affected. As the so-called data-centric approach to technology gains momentum, there is a growing demand for people, sometimes referred to as ‘data stewards’, who can articulate and support the value of data. Management accountants have a very good opportunity to take on such responsibilities because much of their work is related to data. As consultants and advisers to businesses, accountants must maintain awareness of a broad range of technologies and trends, but also acquire new skills as necessary; this is no longer a ‘nice to have’, but rather a ‘must-have’ for the accountants. Many researchers and authors point to the importance of ML for management accountants, for example (see also WEF, 2016, 2018 on more general IT-demands):

*“Management accounting professionals must fully embrace the integration of data, data science, and technology and partner with the experts in the field because it will have a transformational impact on future business and operating models”* (StrategicFinance, May 1, 2017).

In the last few years, a number of reports have been published on ‘why accountants must embrace machine learning’ (e.g., reports from CIMA, IMA, IFAC, Gartner, and McKinsey). There is also currently much discussion, fear and hype around AI and its possible impact on many different business areas – including finance and management accountants and financial accountants in general.

Based on these trends in the relationship between Machine Learning and management accounting, the purpose of this paper is to discuss this intersection. The paper first discusses the content of ML and uses existing business literature to establish the new requirements faced by management accounting and the management accountant if ML is to be fully utilized in this domain. After showing two examples of ML for PM&M, the paper converts and evaluates the outcome from these examples and find the issues that will be of interest for the management accountant’s competencies and skills. The paper should be seen as an inspirational paper discussing these questions, where the findings are based more on personal opinion and interpretation than on specific research contributions.

The main conclusion is that if the management accountants want to stay at the c-level, the management accountants must increase not only their competencies within business analytics, but also their statistical, mathematical, and programming skills to be able to effectively use AI and ML.

The structure of the paper is as follows. As an introduction to the ML area, section 2 discusses and analyses the literature on different types and levels of machine learning. Section 3 transforms the outcome from section 2 into an ML topic for management accounting and provides two examples. Section 4 sets up a number of future qualifications for the accountant if he/she wants to be able to fulfil the future demand for the job. Finally, section 4 finishes the paper with a conclusion, limitations, and ideas for future research.

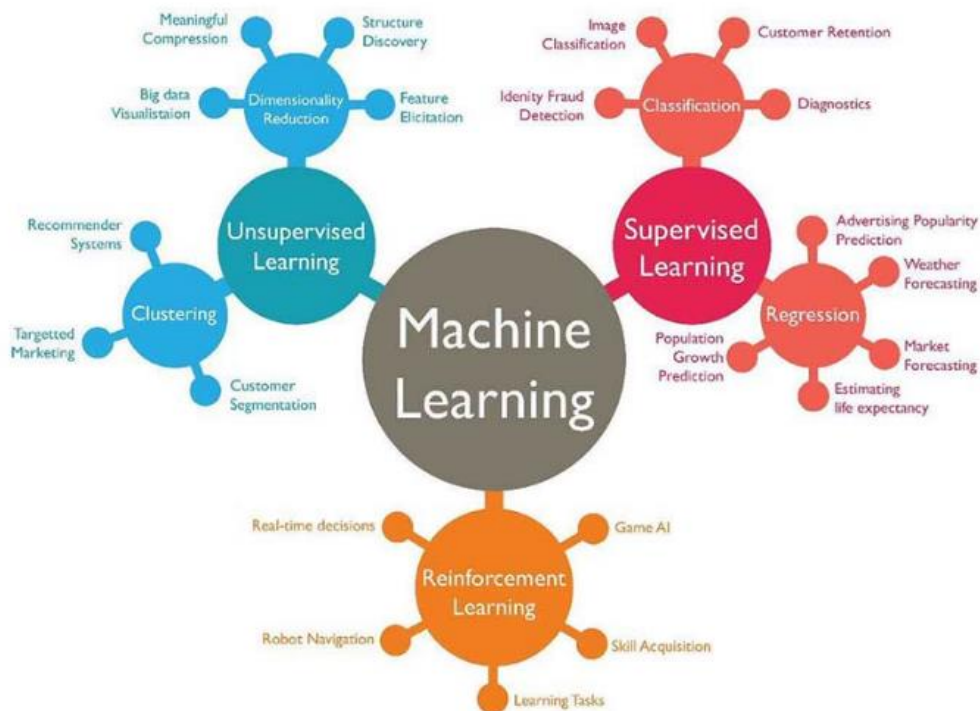
## 2. Classifications in machine learning

Machine Learning originated in the 50s, when Alan Turing proposed what has come to be called the Turing test or: “*Can a computer communicate well enough to persuade a human that it, too, is human?*” In

1959, Arthur Samuel called ML for a “*field of study that gives computers the ability to learn without being explicitly programmed.*” ML is a focal point where business needs and experience (mathematics, statistics & algorithmic logic/thinking) meet emerging technology and decide to work together to put useful results on the table for real business. ML uses neural networks that are designed to function in the same way as a human brain. When algorithms process and analyze enough data, they start to recognize patterns.

It may be difficult to see exactly where statistics ends and where ML takes over. However, ML uses fewer assumptions than statistical modeling. The short version of the major difference between machine learning and statistics is their purpose. Machine learning models are designed to make the most accurate predictions possible. Statistical models are designed for inference about the relationships between variables (Wooldridge, 2016). ML requires minimal human effort because the workload of computing is placed definitely on the machine, i.e., on the computer (see, e.g., Bzdok, 2018 for more differences). All organizations—whether big or small—need data and advanced analytics to improve their business decisions. Why? Because organizations applying analytic techniques outperform those using ad-hoc decision-making methods by at least 10%, initially. So, where does the company start, and how can the company prepare its business for a big-data analytics project?

Figure 1 shows a visualization of types of ML algorithms and purposes in one picture, which is a simple way of visualizing many areas and issues within AI and statistics.



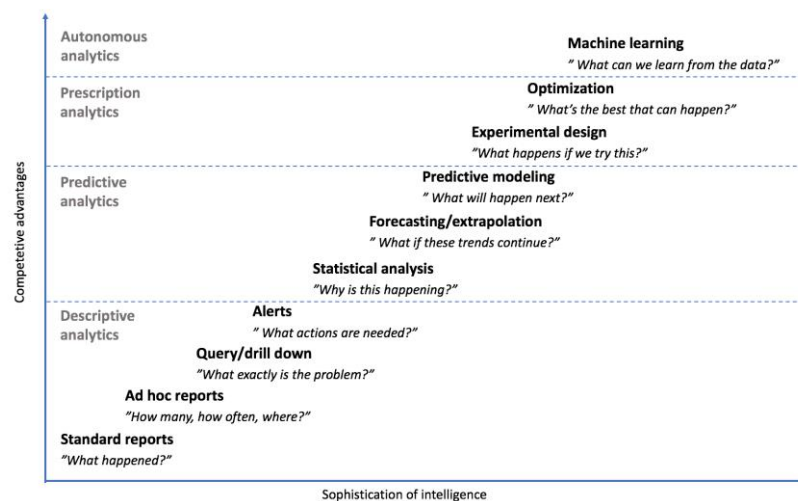
**Figure 1. Classifications of machine learning and their purposes**

Ref.: <https://www.techleer.com/articles/203-machine-learning-algorithm-backbone-of-emerging-technologies/>

In general, machine learning teaches the computer to handle tasks without human intervention. The purpose of ML is to detect patterns and to learn how to make predictions and recommendations by processing data and experiences, rather than by receiving explicit programming instructions. The algorithms also adapt in response to new data and experiences to improve efficacy over time. Data mining is a field of study within machine learning and focuses specifically on exploratory data analysis in order to recognize and learn about pattern recognition (Bishop, 2006).

Even though data scientists have had the feeling that a big part of their time is used on preparations, a recent New York Times article (24 January 2018) discovers the 80-20 rule: that 80% of the time in a typical data science project is spent on sourcing, cleaning and preparing the data, while the remaining 20% is actual data analysis<sup>7</sup>. Statistical analyses are only as good as the data that go into them (Tukey, 1977). This is why the majority of time on any data analysis project should be spent, not on conducting the analyses (i.e., actually running the model), but instead on the steps needed to prepare and increase the quality of the data for analysis.

Figure 2 from Davenport & Harris (2017) shows the classical steps in business analytics and the degree of sophisticated intelligence now with ML at the top level.



**Figure 2. Potential competitive advantage increases with more sophisticated analytics**  
**Ref.: Davenport and Harris (2017)**

Figure 2 puts a company’s level of sophistication, ranging from descriptive analytics to machine learning, into perspective. However, different companies are on different competitive levels, but should try to move up and not remain at the bottom of the chart. The ultimate goal of any analytics initiative is to effect change in the organization, which entails synthesizing all of the listed analytics to create suggested courses of action (Davenport and Harris, 2017).

Prescriptive analytics is, however, clear speculation about the future (e.g., “we believe that reducing the lead time for customers will improve the satisfaction of customers, which again will improve our net profit”).

<sup>7</sup>See, for example: <http://www.telfer.uottawa.ca/researchreport2014-15/outcomes-and-impact/business-analytics-and-performance-management>  
<https://www.gartner.com/doc/2715117/business-intelligence-performance-management-key>  
<https://www.youtube.com/watch?v=hxHT-0nD0gk>  
<http://www.blog.corpeum.com/role-business-analytics-performance-management-part-2/>



Nevertheless, prescriptive analytics is not possible without completing the earlier steps of the analytics intelligence ladder. Finally, autonomous analytics employs artificial intelligence or cognitive technologies such as machine learning to create and improve models and learn from data with substantially less involvement of human analysts (Davenport and Harris, 2017).

The classical cases, i.e., internet stores such as Amazon, use product reviews, other shoppers' purchase history, and complementary items to those in your cart to suggest additional products you may like. Whether you realize it or not, you have already been subjected to ML in an effort to predict what you may like.

Because inductive reasoning "learns" from existing data sets, it is important to understand whether the data sets that are used to "teach" machine learning algorithms have inherent biases. A simplistic example of this is if you only watch romantic movies on Netflix and rate them all high, and you also happen to watch other low-budget movies on Netflix because you cannot get them on another platform, then Netflix will probably predict that you only like romantic and low-budget movies. Netflix does not know that you actually like a wide variety of other movies as it simple does not have access to that data set (MatWorks, 2016).

There is evidently a high potential for positive and negative impacts from biased data. If the biased data represents an outcome that you want, then using all the data points from that biased data is a positive impact. On the other hand, if that biased data causes ML to provide analyses that will result in a negative impact, then the proper safeguards must be put in place to prevent or detect the negative impact. Or, phrased in a more familiar way: we must ensure that internal controls are implemented to manage the risks associated with a negative impact from the application of machine learning.

However, it is important to realize that we do not need any advanced or specific software to use ML. Many books about ML actually illustrate ML by only using different tools and techniques in programs such as Excel, SAS JMP and Pro, or @Risk. Besides, many statistical software programs, for example SAS Pro, have specific modules that can do 'Predictive modeling' or convert to R or Python.

## A. Unsupervised, Supervised, Semi-supervised, Reinforcement, and Deep Machine Learning

There are many topics within different industries where different ML techniques could be used. This is the case, for instance, in the "predictions" made in continuous estimation of time series, especially when applied to time series data such as sales demand for a product using a set of input data such as previous sales.

Or it could be used for clustering where a set of categories for which individual data instances have a set of common or similar characteristics. An example of clustering is to create a set of customer segments, based on a set of data about individual customers, including demographics, preferences, cost, and revenue. Figure 5 shows an almost 'complete' list of different algorithms used for AI and ML.





**Figure 3. Overview of a number of machine learning algorithms**

Ref.: <https://jixta.wordpress.com/2015/07/17/machine-learning-algorithms-mindmap/>

Practitioners working within different AI/ML have their own preferences. For example, experts in marketing use cluster analysis for grouping products or customers, while AI is used within finance (Alan Turing Institute, 2019). Others have one area of deep expertise and know little about different fields of ML. A full review of all techniques and their assumptions and applications would take up too much space here, so the reader is referred to e.g., McKinsey Analytics (2018) or Dean (2014) for an illustration of different ML areas and techniques. Davenport and Harris (2017) also give some examples of companies that are using specific algorithms.

In PM&M, many of the algorithms shown in Figure 3 could be used for many different purposes and problems. From testing associations between KPIs by an ordinary OLS Regression, Hierarchical Clustering in customer profitability, to using deep learning in evaluating the content in a ‘beyond budgeting’ model (for example, the six principles discussed in Hope and Fraser, 2003). Or a Support-Vector Machine could be used for classifying cases into different categories for churn analysis (e.g., for improving the content of the customer perspective in balanced scorecard). The results could be used for recognizing and determining the strategies leading to higher customer loyalty and lower churn (see, e.g., Dehghan and Trafalis, 2012). The airline industry is another example where NB (Naïve Bayes) is used for planning, calculating fees, schedules, and revenues based on prior air travel patterns and flight data (see, e.g., Fontecilla, 2017).

In machine learning, there is a “no free lunch” theorem, which states that no ML algorithm exists that is the best for all problems. The performance of different ML algorithms strongly depends on the defined problem, size, and structure of available data. Therefore, the ML assistant must have a broad knowledge of the different techniques.

A “**supervised learning**” approach is useful when you want to train a model to generate reasonable predictions as the response to new data (Bishop, 2006). A “supervised learning” approach includes an

algorithm that uses a training data set and gets feedback from humans to learn the relationship of given inputs to a given output (e.g., how the inputs “time of year” and “interest rates” predict housing prices). In “supervised learning”, machines get labeled inputs and their desired outputs.

The goal is to learn a general rule for mapping inputs to the output. In contrast to unsupervised learning, where the machines get inputs without desired outputs, the goal is to find structure in inputs. In “supervised learning”, the algorithms work with both the predictors (e.g., the X columns in a spreadsheet) and a response variable (e.g., the Y column in a spreadsheet). The training data used “supervises” by telling it what the response should be for the given values of the predictor variables.

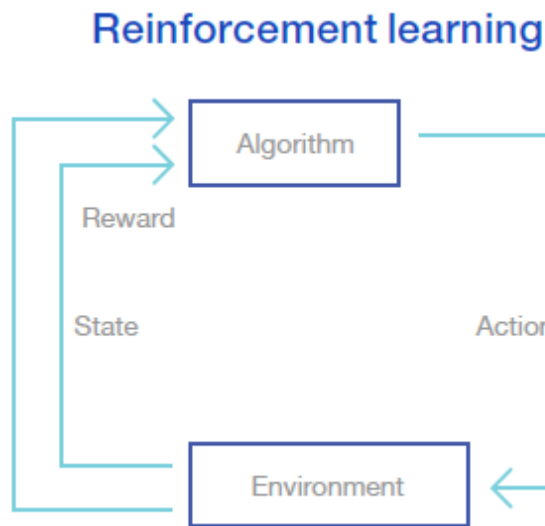
“**Unsupervised learning**” is useful when you want to explore your data, but do not yet have a specific goal or are not sure of the informational content of the data. In an “unsupervised learning” approach, the algorithm will explore input data without being given an explicit response variable (e.g., it explores demographic data on customers to identify patterns). In this case, the decision maker wants the algorithm to find patterns and classify the customers.

To explain the term ‘un-labelled’ data, we may use the fruit bowl metaphor. Suppose the machine-learning program is learning to identify three different kinds of fruit – bananas, grapes and apples. If the data in the initial training set is labelled, the machine learning program works from that perspective and matches successive images to one of those three categories. If, however, none of the data pieces are labelled with the three fruit names – bananas, grapes and apples – the machine learning program will need to work by evaluating each image and looking at characteristics such as colour (yellow, red and purple), shapes (long and thin, round or clustered) and other characteristics. From this example, it is easy to see how labelled data affords much better opportunities to use machine-learning algorithms for decision results. However, sophisticated unsupervised machine learning programs dealing with unlabelled data can produce astoundingly accurate and precise results as well. It is important to note that a number of the algorithms can be used for both unsupervised and supervised learning (Dean, 2014, p. 133).

For “**semi-supervised learning**”, algorithms use a combination of labeled and unlabeled data to find patterns. Semi-supervised learning refers to the idea of using a large unlabeled data set  $U$  to augment a given labeled data set  $L$  in order to produce more accurate rules than would have been achieved using  $L$  alone (Blum *et al.*, 2018). The motivation is that in many settings (e.g., document classification, image classification, and speech recognition) unlabeled data is much more plentiful than labeled data, so one would like to make use of it if possible even though labels are, of course, absent on unlabeled data.

This is useful for a couple of reasons. First, the process of labeling massive amounts of data for supervised learning is often prohibitively time-consuming and expensive. In addition, too much labeling can impose human biases on the model. Hence, including unlabeled data during the training process actually tends to improve the accuracy of the final model while reducing the time and cost spent building it (Hall *et al.*, 2014). The reason is that we often have access to a lot of unlabeled data, but only a small amount of labeled data. However, this small amount of labeled data might still prove highly valuable when used together with the much larger set of unlabeled data (Lindholm *et al.*, 2019). In addition to unlabeled data, the algorithm is provided with some supervision information, but not necessarily for all examples (Chapelle *et al.*, 2006). For instance, imagine you are developing a model for a large bank and that the model is intended to detect fraud. Some fraud you know about, but other instances of fraud slipped by without your knowledge. You can label the dataset with the fraud instances you are aware of, but the rest of your data will remain unlabeled.

“**Reinforcement learning**” is the fourth approach for ML. This approach is concerned with the problem of finding suitable actions to take in a given situation in order to maximize a reward (Bishop, 2006). Here the learning algorithm is not given examples of optimal outputs, in contrast to supervised learning, but must instead discover them through a process of trial and error (Sutton and Barto, 2017). Typically, there is a sequence of states and actions in which the learning algorithm is interacting with its environment. In many cases, the current action not only affects the immediate reward, but also has an impact on the reward at all subsequent time steps (Bishop, 2006).



**Figure 4: The reinforcement principle**  
Ref.: McKinsey Analytics (2018b)

Reinforcement learning is a machine learning technique that focuses on training an algorithm following the cut-and-try approach. The algorithm (agent) evaluates a current situation (state), takes an action, and receives feedback (reward) from the environment after each action. Positive feedback is a reward (in its usual sense of the word), and negative feedback is punishment for making a mistake. Figure 4 outlines the principle.

Reinforcement machine learning allows the algorithms to learn by trial and error. When an algorithm does not make errors, it is rewarded. This reward is the ultimate goal the agent learns while interacting with an environment through numerous trials and errors. Therefore, the key goal of reinforcement learning today is to define the best sequence of decisions that allow the agent to solve a problem while maximizing a long-term reward. In addition, this set of coherent actions is learned through the interaction with the environment and the observation of rewards in every state. An example could be an algorithm that learns to perform a task, for example checking if the right information is available in a revised budget, simply by trying to maximize the rewards it receives for its actions (e.g., maximizes points it receives for increasing returns of each element).

Finally, a fifth type of learning exists, called “**Deep Learning**”. Deep learning is a type of machine learning that can process a wider range of data resources, requires less data preprocessing by humans, and it can often produce more accurate results than traditional machine-learning approaches (Dean, 2014; McKinsey Analytics, 2018). Deep learning is a specific method of machine learning that incorporates neural networks in successive layers in order to learn from data in an iterative manner. DL interconnected layers of software-based calculators known as “neurons” form a neural network. Deep learning is separated into ‘conventional

neural network’ and ‘recurrent neural network’. Reinforcement learning is similar to deep learning except that, in this case, machines learn through trial and error using data from their own experience.

Different reporting technologies such as Integrated Reporting (IR) and Financial Planning and Analysis (FP&A) (see, IMA, 2016; IIRC, 2013; IMA, 2019a) could be examples of using DL. The reasons are that these kinds of reporting include both qualitative (e.g., strategy definition, governance) and quantitative information (e.g., costs, KPIs, resource allocation).

There are several concepts and topics that relate to both traditional and ML research (e.g., statistics vs. data mining, statistical learning vs. machine learning, and special caveats in AI and ML). These issues will not be discussed here. For further discussion about these issues (see, e.g., Varian 2014, Granville, 2019, and Shmueli and Koppius, 2011). Often the same techniques or algorithms can be found within different areas such as data mining, machine learning, and multivariate analysis. However, ‘new’ or revised techniques (for example a new view on Ridge and Lasso regression) also appear when going from traditional statistics learning to machine learning. Important topics such as over- and underfitting and causality are also often discussed in combination with ML (see, e.g., Kelleher *et al.*, 2015 and Inguo, 2019). Nevertheless, machine learning also has limitations. An example could be that because the systems are trained on specific data sets, they can be susceptible to bias.

### 3. Machine Learning Implications for Performance Management

The IMA® (Institute of Management Accountants) conducted a survey asking members about the use of Big Data in their companies, including who and what are driving its use, the areas in which it is being applied, the stage of implementation, and more. The result shows that one of the key areas in which these companies are implementing Big Data is performance management. Organizations face significant challenges in objectively evaluating the performance of their employees, processes, machinery, and so forth. Deploying Big Data capabilities to collect and evaluate the piles of data needed to make these evaluations “makes sense” for many organizations (IMA, 2019a). The literature on (big) data analytics and firm performance is still fragmented and lacking in attempts to integrate both sides (Maroufkhani *et al.*, 2019). However, Big Data will contribute to the development and evolution of effective management control systems and budgeting processes (Warren *et al.*, 2015) and may be seen at the main driver of profit and performance (Paramenter, 2010, Verbeke *et al.*, 2018).

Across industries, companies recognize that competing effectively in digital business environments requires a new approach to performance management (see PwC, 2013). The technology-based future of performance management is an essential component of leading successful digital transformation. Research shows clear evidence that the future of PM&M is more data-driven, more flexible, more continuous, and more development-oriented (Schrage *et al.*, in MITSloan Management Review, 2019a,b).

The implications of machine learning for management accountants and other professional internal accountants such as controllers who work in business and government are even greater than they are for auditors, who have been the dominant people for ML<sup>8</sup>. Before ML, data mining was used to find the right data and to extract insights from these data. Therefore, ML is not just an algorithm; it is far more complicated and includes a lot of preparation, tests, and insight to become a success and to enable the analyst to convince

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<sup>8</sup>See IFAC: <https://www.ifac.org/knowledge-gateway/technology/discussion/why-accountants-must-embrace-machine-learning>

employers to implement the outcome. It is much more about ‘telling’ a good story, get people engage and discuss solutions and take action.

Finding the right data elements is important. A survey study from McKinsey Consulting states that an average user spends over two hours a day looking for the right data, which corresponds to about 20% of the average weekly working hours (McKinsey, 2012, p.47<sup>9</sup>). Data and data quality are an important (research) topic within AI/ML because the right data creates competitive advantage. The wrong data does the opposite and they may disrupt the company completely. According to Mehrabi *et al.*, (2019) there exists 23 types of different bias that may influence a model and decisions. For example ‘representation bias’ which represents bias happens from the way we define and sample from a population or ‘behavioral bias’ which arises from different user behavior across platforms, contexts, or different datasets just to mention a few. Therefore, it is extremely important to know about these biases because it might influence decisions in the wrong direction.

Many elements may be considered in controlling the machine-learning algorithms and their biases. Examples are, for instance, which problems are worth solving and how soon do we need the solution? (see, e.g., McKinsey & Company, 2017).

## A. An example of machine learning within performance management

Much has already been written about ML effecting financial accounting, bookkeeping, planning, and budgeting (see, e.g., Amani and Fadlalla, 2017; Prado, 2018)<sup>10</sup>. In management accounting, however, only few articles exist that discuss and analyze the effect from AI/ML (e.g., Bhimani, 2018; Bogaerd and Aerts, 2011; Machteld, 2011), whereas a number of papers and articles exist associating management accounting with IT and the development of digitization (e.g., ACCA and IMA, 2015; CPA journal; IMA, 2019)<sup>11</sup>. A search in the databank EBSCO and Emerald Insight (Management accounting and AI and ML) only gave few relevant results (but many articles about Customer Profitability Accounting and the churn problem, which also belongs to the management accounting area). A few articles appeared associated with future research in accounting (see, e.g., Rikhardsson and Yigitbasioglu, 2018, and Sutton *et al.*, 2016). However, calls for more research on the usability and use of artificial intelligence techniques in accounting domains have been put forward. Making decisions with ML predictions implies that we move down on the operational workflow level. However, before we start the AI/ML process, a “non-quant work” must be conducted by the “non-quant employees”, according to Davenport and Kim (2013). However, both statistic skills and competencies have been recommended for several years now in association with management accounting (see, e.g. Dransfield *et al.*, 1999 or Kaplan 1977/78).

The “non-quant people” in a company such as the management accountants will normally be involved in “framing the ML problem”, which means identifying it and understanding how others might have solved it in the past (see e.g., Ackoff, 1981). It is where the accountant’s business experience and intuition matter the most. ‘Solving the problem’ (i.e., modeling, data collection, and data analysis) is mostly done by what Davenport and Kim (2013) call the “quant people” alone (see also Pidd, 1999). Finally, the last step,

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<sup>9</sup>A short intro can be seen here: <https://www.valamis.com/blog/why-do-we-spend-all-that-time-searching-for-information-at-work>

<sup>10</sup>See also: <https://www.accountingweb.com/technology/trends/the-state-of-ai-machine-learning-and-accounting>

<sup>11</sup>However, in the IMA journal Strategic Finance, several articles have been written about AI/ML and management accounting (2019a,b,c). See, e.g., Understanding Machine Behavior, May 2019; How to Master Digital Age Competencies, September 2018; A Robotic Hand Teaches Itself Dexterity, August 2018; Machine Learning, Human Fraud, March 2017; Artificial Intelligence in Business, April 2017; AI Rising, March 2017; The Computer that Taught Itself to Win at Go, March 2016). However, these articles are more what could be called ‘inspirational’. Also IMA, 2017.

“communicating the acting on results” (i.e., results presentation and action) also involves the non-quant people (Davenport and Kim, 2013). Because analytics is largely about “telling a story with data,” it is important to know about which type of story you would favor.

What kind of language and tone should be used? Should the story be told in narrative or visual terms? What types of graphics would you like, etc. (see, e.g., Tableau: Data Storytelling Using visualization to share the human impact of numbers, 2020)? Remember that in the world of science there is never what could be called “a bad experience”; it will pass or fail, but as long as it runs and it completes, then it is a “good experiment” from which we may learn a lot!

Even though big data, business analytics, and AI/ML have been discussed for many years in different research fields such as logistics and finance, for instance, many newer management accounting textbooks still do not include much discussion about these topics (see also the discussion in Strauß and Zecher, 2013 about different MAS frameworks). Kirk Borne at the Booz Allen Hamilton gives a simple advice for building machine learning models:

*“The first thing is really to listen to the client and the analytics decision maker or expert in the organization. Find out what the problem really is. In the world of AI/ML, sometimes, the business analysts need a little coaching of ideas and statements. For example, is the business analyst trying to solve a detection problem, a prediction problem, or is it more of an optimization problem? After that the discussion has to move to a discussion of what kind of data is available, for example are you talking about databases, do you have call center records, do you have emails from customers, do you have web logs, and what is the data source for the model? From understanding the data sources and the business requirements, the next step is to talk about a solution. Many data scientist or analysts like the philosophy of think big but start small. Many times people think big, and then start big, which often will lead to quick failures and models that are useless. So one of the mantras in data science is what they call “fast-fail mentality”. Building a quick and simple model, see if it works and improve on it continuously while running and training, and then build it up to a more holistic and probably more complex model if necessary”* (said by Kirk Borne, Ph.D., Principal Data Scientist, Booz Allen Hamilton).

The reason is the lack of understanding, which makes it difficult for policy makers to justify their decisions. Most of the ML models are black boxes that do not explain on their own how and why they reached a specific recommendation or a decision (Davenport, 2019a, 2019b). This forces many users to say that “it is the algorithm that made me do it”. To build trust with stakeholders, the policy and decision makers must learn the techniques for interpreting and explaining the models.

### **Example - from unsupervised to supervised learning**

The example below starts with the output from unsupervised learning and progresses to a supervised learning context. This illustrates the idea of using the output from unsupervised learning as the input for the preprocessing step for supervised learning (MatWorks, 2016b, p. 14). In unsupervised ML the algorithms try to find patterns and knowledge from the data without any response variable as discussed earlier.

An important question for companies and decision makers working with ML is: “what makes a good ML use-case?” While the data to support the use-case is critical, data and ML is nothing without a defined business problem. Looking into management accounting, many topics are centered around three themes: *i)* cost reduction, for example cutting or maintaining costs, increasing the effectiveness of employees, increasing the efficiency of critical processes, increasing the win rates on proposals, *ii)* risk reduction for example, staying in compliance with government regulations, reducing unplanned outages, staying within a project budget, and *iii)* profit improvement for example, entering new markets via an improved value proposition, increasing



margins, increasing the effectiveness of the sales force, or use pricing analytics. (see, e.g., Davenport *et al.* 2010; Drury, 2019; or Ferreira and Otley, 2009).

In this example we will demonstrate the use of a simple cluster analysis in order to be able to focus and improve customer profitability. This might sound very tempting and fascinating, but in fact, it will often become very complicated. Clustering analysis is one of the most important and popular unsupervised techniques in ML (Davenport and Kim, 2013), in multivariate analysis (Hair *et al.*, 1998; Rencher, 2002), in data mining (Han and Pei, 2012), and it is also discussed within predictive modeling (Kuhn and Johnson, 2013). So, in fact we have four different design approaches for cluster analysis. It can be used for a large number of problems within PM&M (see, e.g., Amani and Fadlalla, 2017). Here we will use a  $K$ -means clustering algorithm, which is a centroid based algorithm that groups points in a cluster according to the distance (mostly Euclidean) from centroid<sup>12</sup>. Cluster analysis is an exploratory technique, meaning that we do not have any training set to assess whether the classification is correct or not. It is important to distinguish between the  $K$ -means, which is an unsupervised learning algorithm used for clustering problems, whereas KNN ( $k$ -nearest neighbor) is a supervised learning algorithm used for classification and regression problems.

In  $k$ -means clustering you must decide on the number of clusters you require such that  $k$  is the number of clusters. The fact that we need to pre-define the number of clusters is actually a major disadvantage of  $k$ -means clustering, as this may lead to unwanted results. However, there exists a number of rules that may help. The optimum number of clusters is the value of  $k$  that maximizes the strength. The strength tells, for a specific  $k$ , if there is a potential “elbow” at level  $k$  (corresponding to  $k$  clusters), and how strong the “elbow” signal is at that level. Sometimes the strongest signal is not the first one, although this is the case in many instances.

We use a small hypothetical data set consisting of observations of 200 KPI ( $kpi(1), kpi(2), \dots, kpi(200)$ ) over a period of four years (in total 800 obs.). After further evaluation we find that each group can be related to one of the four perspectives in the BSC model, meaning, KPIs for learning & growth, for processes, for customers, and for financials<sup>13</sup>. The data also includes a response variable (different types of PM&M models), but for now we will only use data for the four years and skip our knowledge of the response variable. The idea is to find out how the different KPIs will be grouped if we ‘only’ want four clusters initially (opposite to hierarchical clustering). Already before we really start doing a cluster analysis, a number of options and assumptions (and consequences) appear that the decision maker has to know about before he/she can make the final decision.

One such assumption is whether the clustering algorithms should be based on ‘center-based’ clusters or a ‘high-density’ clusters. Here we will use the ‘center-based’ cluster assumption which again includes a choice of whether to use a  $k$ -center, a  $k$ -median, or a  $k$ -means clustering algorithm. Again the outcome and probably also the consequences will be different for each choice.

A formal description is as follows (see, e.g., Blum, 2010). Find a partition  $\mathbf{C} = \{C_1, \dots, C_k\}$  of  $A$  into  $k$  clusters, with corresponding centers  $c_1, \dots, c_k$ , to minimize the sum of squares of distances between the data points and the centers of their clusters. That is, we want to minimize;

$$\Phi_{k\text{-means}}(\mathbf{C}) = \sum_{j=1}^k \sum_{\mathbf{a}_i \in C_j} d^2(\mathbf{a}_i, \mathbf{c}_j)$$

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<sup>12</sup>See, e.g., Provost and Fawcett (2013) or Hastie *et al.* (2009) for the assumptions for using different clustering techniques.

<sup>13</sup>SAS Pro allows you to conduct bootstrapping of  $k$ -means. Bootstrapping is the test of our model (for small data sets) so that we can rely on our model and can bet upon its findings and maybe, if required, test them for unknown data points to predict clusters (SAS Pro manual).



Using distance squared has some mathematical advantages over using pure distances when our data consists of points in  $R^d$ . For example, with the distance squared criterion, the optimal center for a given group of data points is its centroid. If we use the default values in SAS Pro JMP, we get three clusters shown in figure 5 to the left. If we aim at having four clusters (e.g., because we use a BSC model), we get the result shown to the right. Figure 5 shows the biplot result of a number of steps and processes (not shown here).

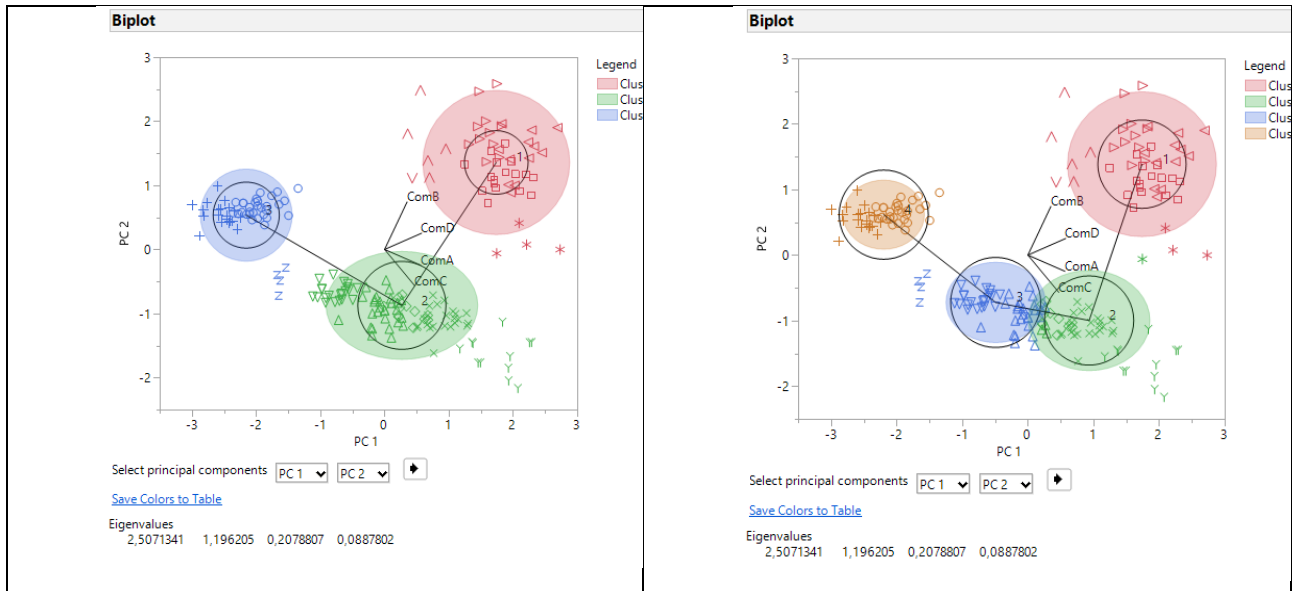


Figure 5. Biplot results for the four years<sup>14</sup>

Running SAS Pro with 3 or 4 clusters gives the following results:

Cluster Summary				Cluster Summary				Cluster Comparison			
Cluster	Count	Step	Criterion	Cluster	Count	Step	Criterion	Method	NCluster	N Rows	CCC Best
1	54	6		1	96	7		Self Organizing Map	3	1	10,7825
2	96			2	54			Self Organizing Map	4	1	12,154 Optimal C
3	50			3	28						
				4	22						

Figure 6. Number of observations using 3 or four 4 clusters and comparison

Figures 5 and 6 show the visual and the performance output from using 3 or 4 clusters in a so-called ‘Self Organizing Map’. The goal of an SOM is not only to form clusters in a particular layout on a cluster grid, but also to have them close to each other in a multivariate space. In classical  $k$ -means clustering, the structure of the clusters is arbitrary, but in SOMs the clusters have a grid structure. The grid structure helps interpret the clusters in two dimensions: clusters that are close are more similar than distant clusters (see Kohonen, 1990 for more detailed explanation). The fit statistic is the Cubic Clustering Criterion (CCC). Large values of CCC indicate better fit (Broderick and Williams, 2013).

Biplot for Principal Components (PC) 1 and 2 in figure 5 shows the plot of all points for the values of these two components of the data. Circles around the cluster centers show the center (also called centroid). The size of each colored ellipse is proportional to the count inside the cluster. The labeled rays show the directions of the covariates in the subspace defined by the principal components. They represent the degree of

<sup>14</sup>Actually, there are several Graphical Procedures that could be used, e.g., multidimensional scaling, correspondence analysis, and biplots. These methods are designed to reduce dimensionality and portray relationships among observations or variables (Rencher, 2002).

association of each variable with each principal component. Biplot Ray Position enables you to specify the position and radius scaling of the biplot rays. By default, the rays emanate from the point (0.0). In the plot, you can drag the rays or use this option to specify coordinates. You can also adjust the scaling of the rays to make them more visible by means of the radius scaling option. One can point on a marker and identify the clusters to the rows of the data table (+o).

Many data sets do not exhibit well-separated clusters, and two persons who are asked to visually find the number of clusters by looking at a chart are likely to provide two different answers. As said earlier, the ultimate purpose of unsupervised learning is often to use it later on for prediction of whether it is possible to put on labels for a response variable. This is often the case in the so-called **semi-supervised learning** where we have information about some of the features, but not all. If you do not yet know how the data might be grouped in relation to one or more response variables, it is relevant to use ‘self-organizing feature maps’ or ‘hierarchical clustering’ to look for possible structures in the data or to use cluster evaluation to look for the ‘best’ number of groups for a given clustering algorithm (MatWork, 2016).

For the next example or algorithm we use logistic regression. We therefore assume that we have been able to get further information about our response variable, in our case types of performance models (e.g., by interviews and other documentation). The result is shown in figure 8 to the left. The first (bottom) curve represents the probability that a value (between 4.5 and 8) found in ComA belongs to performance model A. The second curve (bottom) represents the probability that a value found in ComA belongs to either performance model A or B. The distance between the first and second curves corresponds to the probability of a value belonging to performance model B. Finally, the third curve (from the bottom) represents the probability that a value found in ComA belongs either to performance model A, B, C, or D, where the distance between the second and the third curve represents the probability of a value belonging only to performance model D. Different companies in this example could also be divisions or department in bigger companies using different performance models.

Finally, we will use the Fit Model platform to fit a nominal logistic regression model including our response variable. Figure 8 to the right shows what data scientists call an ROC (Receiver Operating Characteristic) curve.

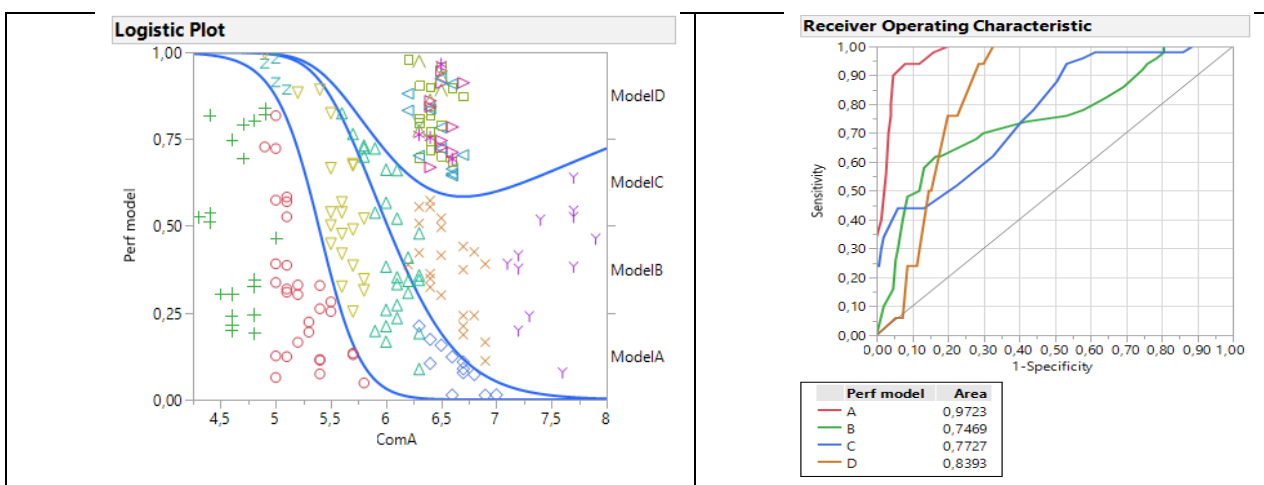


Figure 8. Logistic plot and the ROC curves

A commonly used means of depicting model prediction performance is the receiver operating characteristic (ROC) curve (Kelleher *et al.*, 2015). ROC curve is a graphical representation of the performance of a binary classifier (approved/declined) as the threshold or cutoff to classify changes.

ROC curves use a combination of the true positive rate (the proportion of positive examples predicted correctly, defined exactly as recall) and false positive rate (the proportion of negative examples predicted incorrectly) to build up a summary picture of the classification performance. In this example, we can see that all four ROC curves for the four performance models lie above the diagonal line, meaning they all perform better than a random guess. In the small box below the curves, we can see that model A has the largest area of 0.9723, whereas model B has the lowest area value of 0.7469, indicating that based on this data, the difference between the test and the training data set is the smallest. A value of 1 indicates a perfect fit, and a value near 0.5 indicates that the model cannot discriminate among groups. For information on how to estimate *sensitivity* or TPR (True Positive Rates - Y-axis) and *1 - specificity* or FPR (False Positive Rates - X-axis) and draw an ROC curve, see, for example, Han *et al.* (2012) (chap. 8) or Shmueli *et al.* (2018). So, in this example the PM&M model A seems to be the choice.

Finally, in order to compare more ML algorithms we conduct an ML experiment comparing tree machine algorithms; Multiclass Decision Forest, Multiclass Logistic Regression, and Multiclass Neural Networks. These are all well-known algorithms (for more details on these three algorithms, see Dean, 2014). For now we use them with a ‘Multiclass’ assumption (because we use four models). In that sense our analysis becomes confirmative. In other words we want to find out which of the three algorithms that gives us the best prediction for future policies<sup>15</sup>.

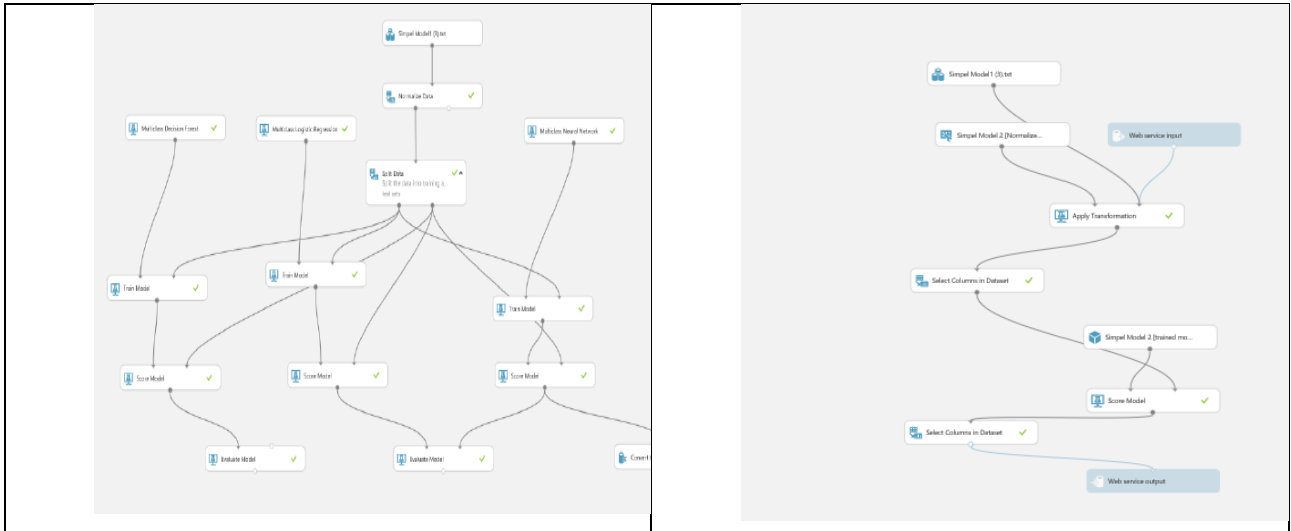
The decision forest algorithm is an ensemble learning method for classification, and it works by building multiple decision trees and then *voting* on the most popular output class. Voting is a form of aggregation, in which each tree in a classification decision forest outputs a non-normalized frequency histogram of labels. The aggregation process sums these histograms and normalizes the result to get the “probabilities” for each label. The trees that have high prediction confidence have a greater weight in the final decision of the ensemble.

Logistic regression is a well-known method in statistics that is used to predict the probability of an outcome, and it is particularly popular for classification tasks (Dean, 2014). The name ‘regression’ is in fact a misconception because it is not regression in the traditional sense of the word, but a classification algorithm (Brownlee, 2019). The algorithm predicts the probability of occurrence of an event by fitting data to a logistic function. Instead of using a single response variable, we use four variables to predict multiple outcomes. For this experiment, we used the Split module in SAS Pro JMP to randomly divide the data set using a 60-40 ratio of training data to test data. Then we trained multiple models using the Train Model module with the training data set as input (there are several other assumptions not discussed here).

The next step in the ML process is to transform our experiment from the training and causality mode to the operational and prediction mode and to evaluate the three regression algorithms. Figure 9 shows the design of the model made in Microsoft Azure (see, Barga *et al.* 2015).

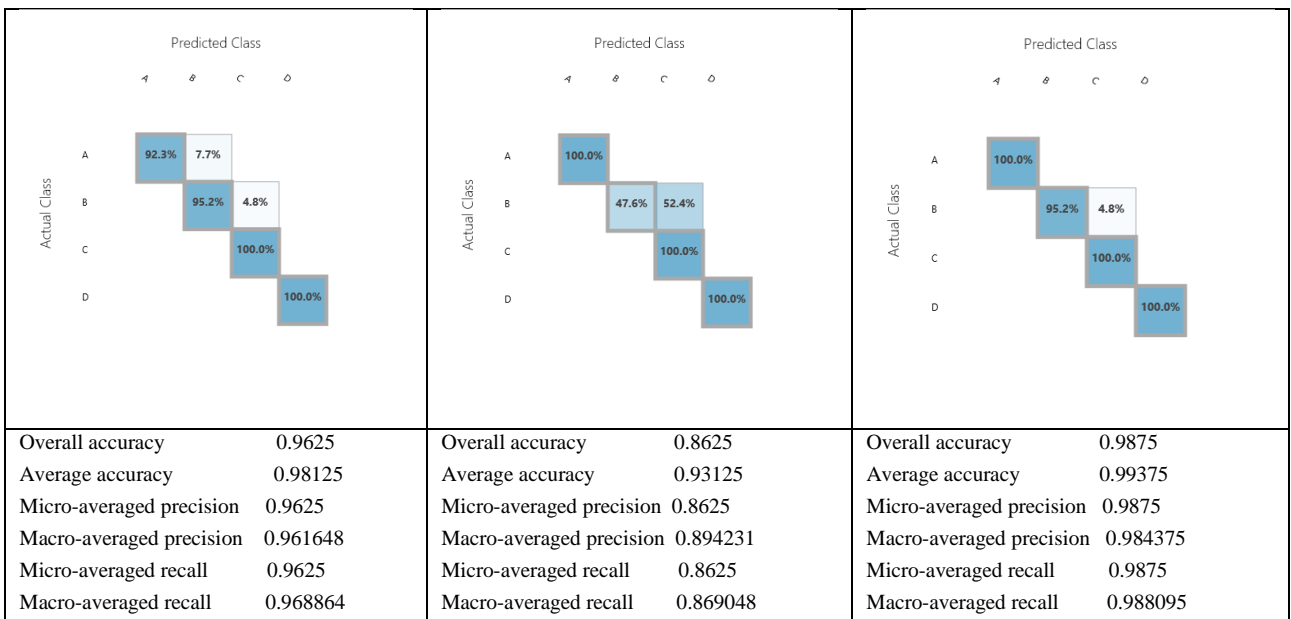
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<sup>15</sup>It is important to be aware of differences and assumptions between concepts - even though they look alike. For example, a decision tree is built on an entire dataset, using all the features/variables of interest, whereas a random forest randomly selects observations/rows and specific features/variables from which it builds multiple decision trees and then averages the results.



**Figure 9. The training model and the prediction model**

Finally, from the evaluation node in figure 9, we get the results from actual vs. prediction. This is shown in a so-called confusion matrix in figure 10. The matrix shows the actual vs. predicted instances for all four classes of performance models and the tree machine algorithms. The diagonal of the matrix tells us the percentages of correct samples, whereas the boxes outside the diagonal tell us how many percent the algorithms are wrong (the confusion matrix actually shows what in statistics is called type I - ‘false positive’ - and II - ‘false negative’ - errors).



**Figure 10. Output from Multiclass Decision Forest, Multiclass Logistic Regression, and Multiclass Neural Networks**

In this plot, the values for the actual cluster labels are on the y-axis, and the predicted clustering labels are on the x-axis. The cluster labels A, B, C, and D correspond to different performance models as said earlier. For the Multiclass Decision Forest (the figure to the left) 7.7% and 4.8% of the predicted models A and B are misclassified, unfortunately, whereas 4.8% of the B performance model for Multiclass Neural Networks is misclassified (the figure to the right). For the Multiple Logistic Regression (the figure in the middle) it seems

that more than 50% of the performance model B is misclassified. This algorithm also performs worse in accuracy. However, it seems that the Multiclass Neural Network is the best performing algorithm when comparing training with test. In order to design the prediction model, the causality model must be converted into a prediction model where only the relevant nodes need to be included (the right part of figure 10). When the predicted model is processed, the decision maker can try out a number of scenarios. For example, by using the following values for the four KPIs: 53, 38, 25, and 4, the prediction shows that these values result in a [Predictive Exp.] test returned ['A']. So how can we use this information in PM&M discussions? It tells us something about the threshold and about the way KPIs are behaving within the four different types of performance models and the tree algorithms and therefore also give some information and signals about predictability for the four types of KPIs. There is rarely one simple “true” model within performance management. Instead, modeling should be viewed as an exercise in the approximation of the explainable information in the empirical data (see also, Burnham and Anderson, 2002 and James *et al.*, 2013, chap 5).

#### 4. The Accountant as an Business Analyst or an Analytics Translator

As already shown above, the management accountant faces new challenges, but also the demand for new competencies. A gaze into the crystal ball shows a dramatically and rapidly changing environment. So the question is, what skills and competences are important for the management accountant in the future if he is to be able to fulfil a ‘normal’ job in the management accounting area? The future for the MA is a mix of what many researchers and consultant companies have named ‘business analyst’ or ‘business translator’. However, what has changed is primarily the tools and techniques to fill this role, not so much the professional topics.

According to Granville (2014, p. 12 [the short version]):

*“a **Business analyst’s** focus on database design (database modeling at a high level, including defining metrics, dashboard design, retrieving and producing executive reports, and designing alarm systems), ROI assessment of various business projects and expenditures, and budget issues... Then you write and install a piece of code in the database server (the server accessed by the business analyst traditionally via a browser or tools such as Toad or Brio) to retrieve data”.*

According to McKinsey (2018, p. 2 [the short version]), the job of an ‘**Analytics Translator**’ is;

*“to understand more about what translators are, it’s important to first understand what they aren’t. Translators are neither data architects nor data engineers. They’re not even necessarily dedicated analytics professionals, and they don’t possess deep technical expertise in programming or modeling. Instead, translators play a critical role in bridging the technical expertise of data engineers and data scientists with the operational expertise of marketing, supply chain, manufacturing, risk, and other frontline managers. In their role, translators help ensure that the deep insights generated through sophisticated analytics translate into impact of scale in an organization”<sup>16</sup>.*

By 2026, the McKinsey Global Institute estimates that demand for translators in the United States alone may reach two to four million’. According to McKinsey (2018), translators must also be experts in both their industry and their company to effectively identify the value of AI and analytics in the business context. They must understand the KPIs of the business and their impact on profit and loss, revenue, customer retention, and so on and bring a unique skill set to help businesses increase the return on investment for their analytics

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<sup>16</sup>See also David Stephenson's Blog for discussion: <https://www.datasciencecentral.com/profiles/blog/list?user=2wbjdt78bs8t>

initiatives. The translator must also be able to synthesize complex analytics-derived insights into easy-to-understand, actionable recommendations that business users can easily extract and execute on.

Kaggle conducted a survey in August 2017 of over 16,000 data professionals (2017 State of Data Science and Machine Learning). The survey asked the respondents about their competencies across a variety of AI-related approaches and techniques. When we look at the results, we get a strong indication of what will also be important for the accountant. All respondents (employed or not) were given a list of 13 machine learning areas and techniques and were asked to indicate in which areas they considered themselves competent. The top 10 machine learning areas and techniques are shown in table 1.

<i>Competency in Machine Learning Areas</i>	<i>Competency in Machine Learning Techniques</i>
Supervised Machine Learning (49%)	Logistic Regression (54%)
Unsupervised Learning (26%)	Decision Trees – Random Forests (43%)
Time Series (25%)	Support Vector Machines (32%)
Natural Language Processing (19%)	Decision Trees – Gradient Boosted Machines (31%)
Outlier detection (16%)	Bayesian Techniques (27%)
Computer Vision (15%)	Neural Networks – CNNs (26%)
Recommendation Engines (14%)	Ensemble Methods (22%)
Survival Analysis (8%)	Gradient Boosting (17%)
Reinforcement Learning (6%)	Neural Networks – RNNs (15%)
Adversarial Learning (4%)	Hidden Markov Models HMMs (9%)

**Table 1. Competency in machine learning areas and techniques**

There is no doubt that these areas and techniques are also the ones that are important for the management accountant<sup>17</sup>.

When we look at other sources of information such as LinkedIn or Data Science Central [*Job Listings and Featured Jobs*], it becomes very clear very fast that the above mentioned content of these competencies are also those mentioned in many job titles. Job titles such as ‘Business Performance Analyst’, ‘Performance Management Consultant’, ‘Controller, Business/Financial Controller’, ‘Pricing Data Analyst’, ‘Consulting Business Analyst’, or ‘Business Analytics Manager’ all indicate that these competencies are in high demand. ‘Well-developed or sharp analytical abilities and skills’, ‘working knowledge of Microsoft Excel, including pivot tables, charts, graphs, and complex formulas’, ‘will manage performance, goals and development potential’, ‘data management’, ‘sales driven or oriented’, as well as ‘knowledge of statistical tools and analysis models including BI’, are some of the most important skill buzz-words defined for these jobs. Many of the same competencies are also used within jobs in the public sector. For example in a publication (McKinsey & Company, 2020), a survey shows that the EU-28 public sector has a shortage of 8.6 million people with necessary skills across three categories (technological skills 1.7 million employees, digital skills 3.2 million employees, and classical skills 3.7 million).

Among the competencies required for a ‘business analyst’ items such as; ‘being able to explain data and analytics concepts to non-technical team members’ or ‘being able to apply data and analytics concepts to business problems’ are often mentioned. Often these demands are mentioned in combination with a bachelor or master degree and some practical experience (but not a PhD. in data science).

Or as said by André Sionek - A little bit of each: data engineer and scientist, entrepreneur, physicist, writer and designer’:

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<sup>17</sup>There is a number of (free) online ML resources on the internet, see, e.g.: <https://medium.com/free-code-camp/every-single-machine-learning-course-on-the-internet-ranked-by-your-reviews-3c4a7b8026c0>

*The biggest issue with most data scientists is that they are not actually scientists. Anxiety and desire to quickly apply models and algorithms ends outshining important stages of a good data science work, such as contextualization, problem framing, experiment design and data collection.*

When we compare the competencies of management accountants with these areas, we see that these areas are fully covered in the management accountant's textbooks (see, e.g., Anthony and Govindarajan, 2007; Bhimani *et al.*, 2015; Groot and Selto, 2013; Drury, 2019; Kaplan and Atkinson, 2014; Merchant and Van der Stede, 2003). But the missing topics are machine learning, statistical techniques, and datasets.

However, a growing number of companies are developing and deploying applications that utilize mathematical optimization, either on its own or in combination with other AI technologies such as machine learning, to drive major business benefits (AI adoption has passed the 50% threshold of global enterprises in 2019). For instance, 34% of the companies use mathematical optimization for pricing and 32% use it for planning purposes (Forrester, 2020), and these two areas are the management accountant's traditional fields. Besides, companies are expected to increase the areas of mathematical optimization.

When we excel in these skills or competencies (depending on the depth of the knowledge), we are in a position where we can come up with some of the most important demands for management accounting associated with techniques and concepts:

- **Learn statistics (e.g., linear and non-linear methods and spline techniques, data mining, probability, features like bias, variance, mean, etc.) and math (including linear algebra and optimization)**, because this will enable you to build incredibly complex algorithms that organize, classify, and predict. While it is important to have a solid foundation in statistics when working with machine learning algorithms. In fact, engaging with statistical concepts and problems in a way that is practical and applied is actually a very effective way to learn.
- **Learn a number of simple algorithms and their assumptions (including non-parametric algorithms)**, because an algorithm is the basis for really understanding what is going on. One thing is 'statistical learning'; another is putting different algorithms together in an ML model design in a ML software (e.g., SAS-Enterprise Miner).
- **Learn about resampling methods (e.g., bootstrapping and cross-validation techniques)**, because these methods generate a unique sampling distribution on the basis of the actual data in order to generate the unique sampling distribution. It yields unbiased estimates as it is based on the unbiased samples of all the possible results of the data studied by the decision maker.
- **Learn an AI/ML software package (including handling of data files)**, because an introduction to RapidMiner or Microsoft Azure, for instance, with their learning examples (often including videos) would lead to 'aha' experiences and would encourage the use to learn more and more complicated models (e.g., by using R or Python in combination with SAS-Enterprise Miner).
- **Learn Python or R**, because the languages are the go-to language for machine learning today, and they are free. The reason is that they are accessible, powerful, and have a great ecosystem of frameworks and libraries around them that can be used to build machine learning systems. Starting with Python is therefore an important step in the process of familiarizing oneself with machine learning because Python offers a relatively gentle learning journey that is well suited to machine learning tasks.



- **Learn real-world applications of machine learning**, the most important aspect of learning machine learning is to develop small real-world applications and projects (go back and see what Kirk Borne said earlier). It is important, and it feels exceptionally good when you have gone out there and created something yourself. But what are the things you can do?
- **Learn the differences between causal analysis and predictive analysis**, because this will really be important for all types of elements within business and departments and because the assumptions are different.
- **Learn about a few important databases such as SQL and MySQL**, because these are often used to retrieve data and learn to use different Data Visualization tools for presenting the results so a nonprofessional can understand the whole idea. To learn about SQL, the accountant also needs to understand how a DBMS works. A DBMS or Database Management System is essentially a software to create and manage databases. SQL or Structured Query Language is a ‘programming language’ that manages data in a relational database through ‘queries’. By using SQL, the ‘business analyst’ can insert, update, delete, and select data based on various filters and conditions. The term Dimensionality Reduction is also important to understand if, for example, we have a dataset and we would like to reduce the number of dimensions it has.

These topics are also in line with AACSB (2014) that states in Standard A7: “Consistent with mission, expected outcomes, and supporting strategies, accounting degree programs include learning experiences that develop skills and knowledge related to the integration of information technology in accounting and business. Included in these learning experiences is the development of skills and knowledge related to data creation, data sharing, data analytics, data mining, data reporting, and storage within and across organizations (Information Technology Skills and Knowledge for Accounting Graduates)”.

A survey conducted by PwC (2019) shows that chief executives from anywhere in the world answer “*skills*” when asked what keeps them awake at night. 79% of global CEOs say that they are ‘extremely’ or ‘somewhat’ concerned about the availability of the right capabilities for innovation and customer service (PwC, 2019).

However, in an article in Financial Times (29 November 2017) it is shown that the speed with which people from other fields (e.g., accountants) are adapting to machine learning also reflects the nature of the discipline. Andrew Ng, one of the pioneers of a technique known as deep learning, says that as the field advances, it is actually becoming easier for non-specialists to break in. “*What surprised me is how easy it is to get into AI. With the rise of deep learning, the algorithms we have are getting simpler because we are relying more on data,*” he says. “*After a few weeks, you can read leading research papers and cutting edge ideas in the area*<sup>18</sup>.”

Coupled with amazing storytelling abilities, companies have an invaluable way to communicate insights that are immediately understood, actionable, and remembered thereafter. Besides, it seems that the CFO is becoming more of an ‘Operational CFO’ – meaning that he/she must focus on information technology, collaboration, and innovation initiatives to keep the company’s future looking bright<sup>19</sup>.

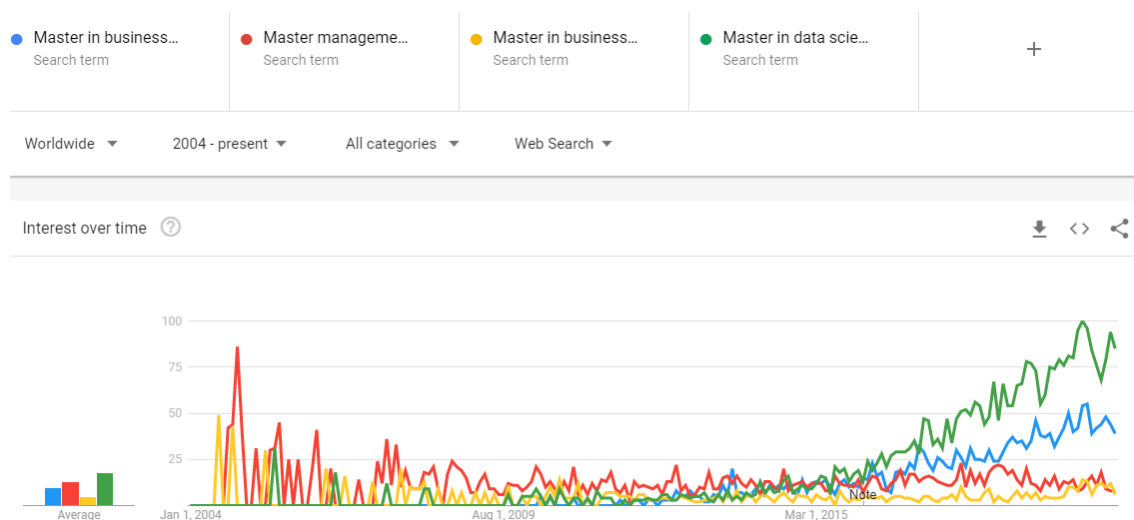
In order to find out what are the worldwide search trends for different master studies, a search of the Web using Google Trends was done. Google Trends is an online tool for comparison of the popularity of terms

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<sup>18</sup> See: <https://www.ft.com/content/49e81ebe-cbc3-11e7-8536-d321d0d897a3>

<sup>19</sup> See Forbes: <https://www.forbes.com/sites/jeffthomson/2013/08/14/the-rise-of-the-operational-cfo/#2d2f43b95b27>

searched by users of Google Search, and their trends over time. Figure 11 shows the result from Google Trend for ‘Master in business analytics’, ‘Master in management accounting’, ‘Master of business intelligence’, and ‘Master of data science’. Not surprisingly, both Master in BA (the blue curve) and Master in Data Science (the green curve) are increasing heavily, but also the ‘Master in business intelligence’ (the yellow curve) is also increasing. However, the trend for Master in ‘Management Accounting’ (the red curve) is actual declining from December of 2017. In fact, the search for ‘Master in Business Analytics’ is about 5 times more frequent than the ‘Master in Management Accounting’ and ‘Master in data science’ is about 11 times more frequent than the ‘Master in management accounting’. There is only way to change this, and this is by making the Master in MA more ‘up-to-date’ and thereby more attractive for students.



**Figure 11. Google trends for four master programs**

Finally, age diversity, like other forms of diversity, brings significant benefits to the organizations that embrace it, but it also creates challenges when it comes to AI/ML. Younger generations have their own expectations, demands, and working relationships when it comes to communication and visualization. It is not always easy to report to someone who is significantly older or younger than oneself. Prejudice and stereotyping can creep in as well, if differences are not properly managed, specifically when it comes to up-dated IT-issues (Staudinger, 1999). While younger managers prefer narrower, more technical approaches, older ones tend to work through others and focus on the big picture.

## 5. Conclusions and some limitations

The answer to the question ‘Which machine learning model should I use?’ is always ‘It depends’. Even the most experienced data scientists cannot tell you which algorithm will perform the best before experimenting with them.

ML and AI not only shape society and companies; they also shape the people and employees who work within the companies, including the management accountants. Machine learning algorithms allow the system to understand data and apply correlation, classification, regression, forecasting, or whichever technique is relevant for given problem, based upon the data the user wishes to analyse. Results are then displayed using different visualization techniques that provide the best fit for the data, together with an interpretation presented

in simple natural language. In a not too distant past, this would have required the services of a trained data scientist. Today, many business users, including the accountants, may be in a position to improve decision-making and make better planning, predictions, and increase company value. It is important to have the right data for the right prediction and for the right learning technique.

Accountants may see their responsibilities grow because many traditional topics within management accounting and performance will be using ML/AI in the future (Richins *et al.*, 2017). With respect to all types of analyses, management accountants can collaborate with data scientists by recommending content to explore and then interpret the results in light of the firm's strategic objectives. Within the next years the availability of big data coupled with data analytics has the potential to make 'the controller function' a strong, strategic partner to operations, sales, and finance. Finance is the natural gatekeeper of data as 'information normally flows through the function' (Katz 2014, p. 20). In a newly published survey (Appen, 2020, based on 374 respondents) the responses show that nearly three-quarters of businesses now consider ML and AI critical to their success, and AI continues to grow in importance across companies of various sizes and industries. At the same time, nearly half of those who responded feel their company is behind in their AI journey, suggesting a critical gap exists between the strategic need and the ability to execute.

Management accountants must acknowledge that technology skills are no longer a 'nice to have', but rather a 'must-have'. They must also be more proactive in acquiring and maintaining a skillset fit for the challenges that lie ahead. Therefore, ML provides an unprecedented opportunity for accountants and accounting organizations and universities to embrace it to enhance both the careers and the competitive advantages it can provide to the organizations accountants serve.

Recently conducted research by McKinsey with more than 1,200 managers across a range of global companies found strong signs of growing levels of frustration with broken decision-making processes, with the slow pace of decision-making deliberations, and with the uneven quality of decision-making outcomes (McKinsey Quarterly, 2019). Less than half of the respondents say that decisions are timely, and 61 percent say that at least half the time spent making them is ineffective. The opportunity costs of this are staggering: about 530,000 days of managers' time are potentially squandered each year for a typical Fortune 500 company, equivalent to some \$250 million in wages annually.

Efficiency and accuracy are becoming the drivers of success in AI/ML. Making the right business decisions has never been more consequential. However, coming to the 'right' conclusion continues to be a struggle, but it is one that an analyst must overcome if his/hers business is going to flourish in today's global economy.

It is important to realize some limitations of this paper. First of all, little has been written specifically about management accounting topics in an ML and AI environment. We still need more documentation of what competencies and skills are important for the management accountant in the years to come. There is no doubt that the management accountant will be held responsible for solving business problems as Kaplan (and many others) already said in 1998 (through the so-called 'Innovation Action Research Cycle'). In this innovation action research cycle, the accountant enhances the underlying theory and, in the process, also becomes a skilled implementer of the new concept in the same way as the 'business analyst', mentioned earlier.

*"For research intended to improve the management of organizations, scholars should find it natural to contemplate changing the underlying phenomena, not just to study existing practices"* (Kaplan, 1998, p. 3). Kasanen *et al.* (1993) make a very similar argument concerning the so-called 'constructive research'. Both

researchers also refer to disciplines such as engineering and medicine, which are characterized by their close connections to applied problem solving (see also, Rautiainen *et al.*, 2017).

Based on a content analysis of 375 published papers, Lachmann *et al.* (2016) assess the development and state of positivist management accounting research (PMAR) and conclude that papers discussing digitization and big data, risk management, and sustainability accounting fail to include MA practice perspectives and that MA in combination with the new technologies is thus under-researched. If such topics are addressed by researchers from other disciplines, the relevance of PMAR might decline (Lachmann *et al.*, 2016, p. 12). Frey and Osborne (2013) predict that the accounting profession faces extinction because of AI/ML. This will, of course, only be true if we just sit back and do nothing.

*“It is not the strongest of the species that survive, nor the most intelligent but the one most responsive to change.” – Leon C. Megginson (1921 - 2010).*

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