AI-ENABLED ANALYTICS FOR BUSINESS

A ROADMAP FOR BECOMING AN ANALYTICS POWERHOUSE

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I would like to dedicate this book to my wife Claudia, whose endless patience, bright smile, and intelligence have always been a source of inspiration. I also want to acknowledge my parents and brother, who provided gentle guidance and love. I especially want to thank my children, Nicole, Dana, and Jonathan, who inspire and always bring out the best in me.

To Dana, forever in my heart.

Lawrence S. Maisel

This book is dedicated in loving memory of my mother, Joy, the merriment of my grandmother, Tess, and the wisdom and discipline of my grandfather, Ruby. The best of life and the greatest of gifts I have are from my sister, Alice, wife, Val, and daughter, Megan.

Robert J. Zwerling

This book was written in memories of my parents, who patiently helped me learn. I also want to acknowledge my wife, Anne. Without you this would not be possible.

Jesper H. Sorensen

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Introduction

Everywhere you turn, you hear or read about artificial intelligence (AI) and the emerging importance of digital transformation. To be competitive in modern business, decision-making needs to evolve into a more objective, insightful, and unbiased process that is powered by the application of AI-enabled analytics.

We have written *AI-Enabled Analytics for Business: A Roadmap for Becoming an Analytics Powerhouse* for executives to gain a solid understanding of AI and analytics that will give clarity, vision, and voice to integrating them in business processes that will be impactful and increase business performance.

Today, there is more promise than practice in implementing AI and analytics for data-driven decisions. As you will learn, there are twice as many analytics failures than successes, and there are twice as many successes that are abandoned rather than sustained. The good news is that almost all failure can be traced back to executive decisions that are entirely avoidable and easily identified.

Further, AI is not the sole purview of big companies, big data, and big data projects that seek to boil the ocean. The butcher, baker, and candlestick maker can all incorporate AI to increase productivity, reduce workforce, retain higher-skilled talent, and enhance the customer's experience. In fact, AI and analytics are better done incrementally, building on each success to scale the business to become an analytics powerhouse.

Our research, training, consulting, and on-the-ground experiences with AI-enabled analytics have shaped our perspectives, refined our practices, and tested our tactics.

We have worked side by side with executives like you, and our empirical results demonstrate the critical factor to success is the executive's mindset to the value of analytics and commitment to allocate the resources to building the Analytics Culture. This book gives you the Roadmap to implement AI and analytics, which, as you will learn, the executive will make or break. As we will show, failure is a choice; the good news is that it is eminently avoidable, and we have specified the steps for success.

In Part I, we cover the fundamentals of AI and analytics, beginning in Chapter 1 to untangle the many seemingly synonymous terms, partitioning tools that do and do not do analytics, and the ROI of AI. It is essential to know the difference between *analysis*, which is the application of arithmetic on data to yield information, and *analytics*, which is the application of mathematics on data to yield insights. In Chapter 2, we illuminate why analytics is essential in business and share Noble Prize-winning research that recognizes the limitations of human decision-making based on biased intuition and gut feel, and why analytics must be included as the essential unbiased component. Chapter 3 discusses myths and misconceptions regarding the approach to analytics, and Chapter 4 takes you through several applications of AI and analytics across different business functions.

In Part II, we define the Roadmap for how to implement AI-enabled analytics for data-driven decisions and the contributions of executives for becoming an analytics powerhouse. Chapter 5 is the fulcrum of this book and delivers a detailed discussion of analytics as more than a tool—it is a culture with four components: Mindset, People, Processes, and Systems. When these components are aligned, immense value to optimize performance is created, and we delineate in depth how this is accomplished. In Chapter 6, you will learn that executive action determines the successful implementation of the Analytics Culture, and you will see what executive actions are needed. Further, we introduce the Analytics Champion, who supports the executive and delivers the tactical implementation of the Analytics Culture. In Chapter 7, we specify with clarity and simplicity how to implement analytics and show that achieving it is not time-consuming, hard, or expensive—it is a discipline. Chapter 8 links analytics to strategic decisions and debuts the new and innovative Analytics Scorecard, which elevates the traditional and subjective Business Scorecard into a quantitative cause-and-effect delineation of strategies that can drive increased business performance.

In Part III, we present specific use cases that illustrate key themes and confirm our approach and insights conveyed in earlier chapters. As there is more to learn from failure than success, Chapter 9 discusses instances across several industries where analytics successes became failures. Chapter 10 tells the story of a hospitality company's analytics proof of concept that yielded optimized staffing while maintaining excellent customer service, significant cost savings, and opportunities to boost revenue and profit—yet failed because the senior executive did not believe in investing in analytics. Chapter 11 is the story of achieving insights that incrementally progress toward a data-driven culture from analytics in demand planning and supply chain. Finally, Chapter 12 puts an exclamation point on the notion that AI and analytics are for everyone, not just big companies, through the story of a medium-size art museum and its CFO's curiosity, which led to learning about analytics and discovering how it provides insights.

For your convenience, we have also included an appendix for the Analytics Champion that will guide the executive in selecting the right person and provide the Champion with skillsets and tools needed for implementing the first analytics project and scaling the Analytics Culture.

An executive's job is to manage risk, not avoid it. Yet many executives are too risk-averse and choose not to make decisions because the risk of failure blinds them to see the opportunity for success. While information is nearly always imperfect, employing AI and analytics gives vision to the future that mitigates risk for better decision-making. This book is for you, the executive and aspiring executive, to arm you with the knowledge to lead your organization to become an analytics powerhouse.

With this introduction, we welcome you to the Undiscovered Country—the future!

PART I
Fundamentals

CHAPTER 1
A Primer on AI-Enabled Analytics for Business

> *Knowledge will forever govern ignorance; and a people who mean to be their own governors must arm themselves with the power which knowledge gives.*
>
> —James Madison[1]

Artificial intelligence (AI) dates back over 75 years. Alan Turing, a mathematician, explored the mathematical possibility of AI, suggesting that "humans use available information as well as reason in order to solve problems and make decisions," and if this premise is true, then machines can do so too. This was the basis of his 1950 paper "Computing Machinery and Intelligence," in which he discussed "how to build intelligent machines and how to test their intelligence."[2]

So, what is artificial intelligence? *Very broadly* speaking, it is the ability of a machine to make decisions that are done by humans. But what does that mean, what does AI look like, and how will it change our lives and society?

We all know that AI, sooner or later, will be part of all businesses. But *when* it is part of the business is entirely dependent on what each executive knows and understands about AI and analytics. And here lies the chasm between the early adopters and the rest of the pack.

According to Grant Thornton's 21 May 2019 report "The Vital Role of the CFO in Digital Transformation," the 2019 CFO Survey of Tech Adoption covered several technologies, including advanced analytics and machine learning. 38% of respondents indicated that they currently implemented advanced analytics, and 29% are planning implementations in the next 12 months. For machine learning technology, the survey results said that 29% had implemented it and 24% were planning to implement in the next 12 months. Impressive returns from the survey's sample set, and indicative of the priority of and accelerating trend in the adoption of analytics and AI throughout business. However, while conveying progress in its best light, this survey is a poor showing of a glass that is not even half full.

Implementations of AI are just scratching the surface, as projects have been highly targeted to only certain areas of the business and for certain tasks. So, while the movement to incorporate advanced analytics is in the right direction, there are many more failures than successes. This is disturbingly bad news, which we shall learn largely rests with executives. The good news is that AI and analytics failures are eminently avoidable.

Many executives lack clarity of vision and voice to how they will navigate their business, division, group, or department through the adoption of analytics and AI. Other executives think they know what AI enablement means but are often working from poorly defined terms or misconceptions about analytics. Their knee-jerk response is to hire consultants and buy AI-enabled analytics software without fully understanding how analytics will be used to drive decisions.

Cries of “We need better forecasting” and “What factors are driving our business?” and “We must get smarter about what we do” echo in boardrooms and executive conference rooms. But how exactly is this done? Not *what*, but *how*? The “what,” many an executive has read from a mountain of consulting reports; but the “how” is unclear and is why too many businesses are lagging in their adoption of AI and analytics.

In this chapter, we lay the foundation for this book by untangling terms and terminology with definitions and giving a ground-level introduction in select technologies (for the purpose of understanding, not to become experts). We will pursue a high-level discussion of AI, machine learning (ML), and analysis vs. analytics, followed by an explanation of business intelligence and data visualization and how these are different from analytics. We will introduce the application of AI-enabled analytics in the context of insights and the contrast between biased vs. unbiased predictions. Finally, we will position the importance of AI by discussing its ROI.

AI AND ML—SIMILAR BUT DIFFERENT

We see the widely used phrase "AI and ML" and conjure these as linked at the hip; but while related, they are not one and the same. First, AI is a *superset*, covering all that is considered artificial intelligence. The overarching concept of AI is simply a machine that can make a human decision. Any mode of achieving this human decision by a machine is thus AI, and machine learning is one such mode or *subset* of AI. Therefore, all ML is AI, but not all AI is ML.

Accordingly, ML is *one* form of AI. ML is a widely used method for implementing AI, and there are many tools, languages, and techniques available. ML engages algorithms (mathematical models) that computers use to perform a specific task without explicit instructions, often relying on patterns and inference, instead.

Another popular form of AI is neural networks that are highly advanced and based on mirroring the synapse structure of the brain. So, ML and neural networks are both subsets of AI, as depicted in Figure 1.1, as well as other forms of AI (that is, any other technology/technique that enables a machine to make a human decision).[3]

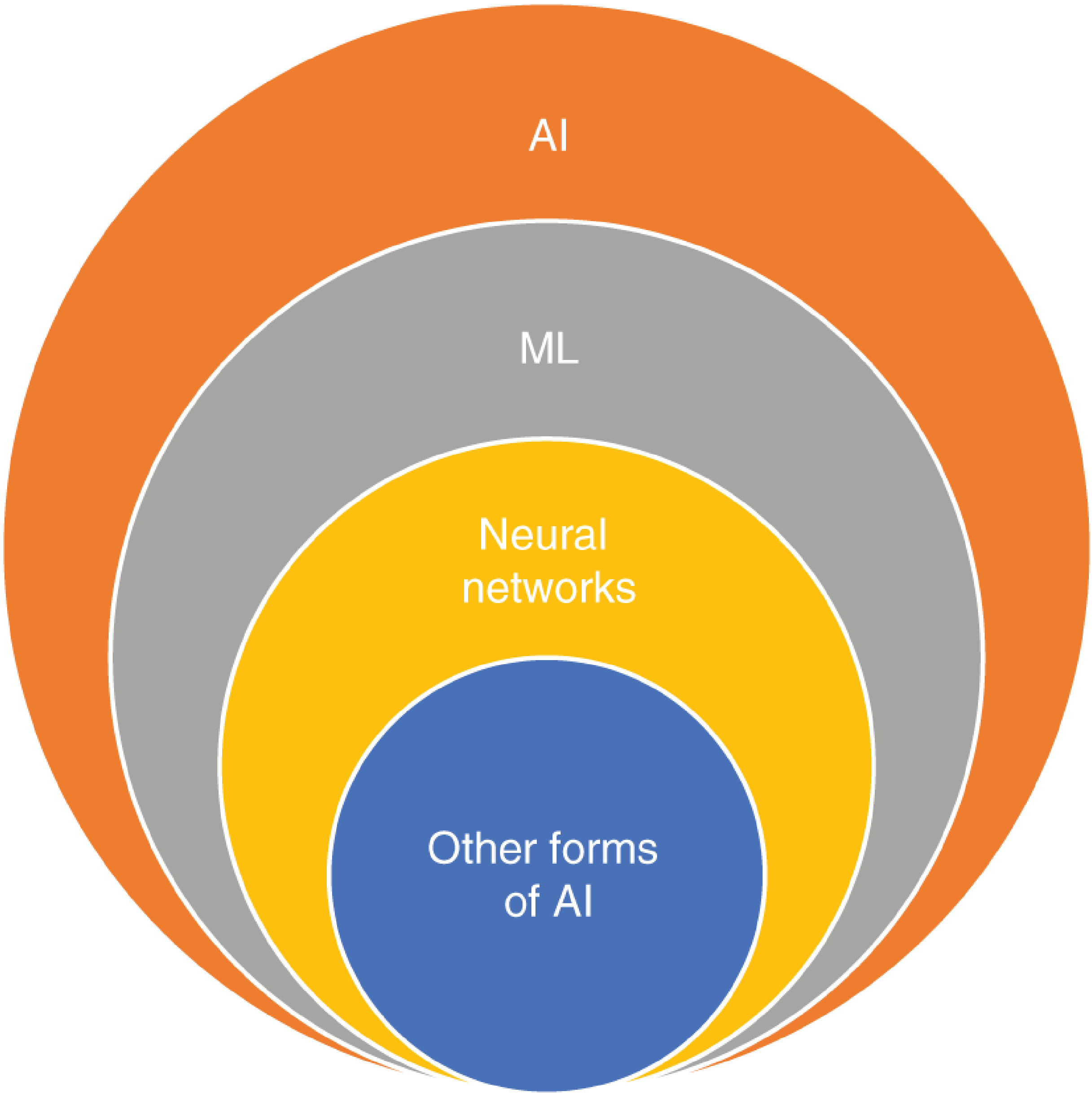

Figure 1.1 Superset and subsets of AI.

MACHINE LEARNING PRIMER

This section offers a brief orientation to ML. ML is a technique and technology that today requires specialized skills to use and deploy. ML is an AI engine often used with other tools to render the ML output useful for decisions. For example, suppose a bank wants to expand the number of loans without increasing the risk profile of its loan portfolio. ML can be used to make predictions regarding risk, and then the results are imported to spreadsheets to report those new additional loan applicants that can now be approved.

Large ML projects often involve the collaboration of data scientists, programmers, database administrators, and application developers (to render a deliverable outcome). Further, ML needs large volumes of high-quality data to "train" the ML model, and it is this data requirement that causes 8 of 10 ML and AI projects to stall.[4] While ML is popular and powerful, it is not easy. Many new software applications are making ML use easier, but it is still mostly for data scientists.

Before an ML project can begin, its "object" must be defined: that is, what is to be solved. For example, suppose we want to predict which customers on our ecommerce website will proceed to check out (vs. those who exit before checking out). As presented in Figure 1.2, the process to go from the object to deployed solution has many steps, including collection of data, preparation of data, selecting the algorithm and its programming, model training, model testing, and deployment. Any failure at any point will require a reset and/or restart back to any previous point in the process.[3]

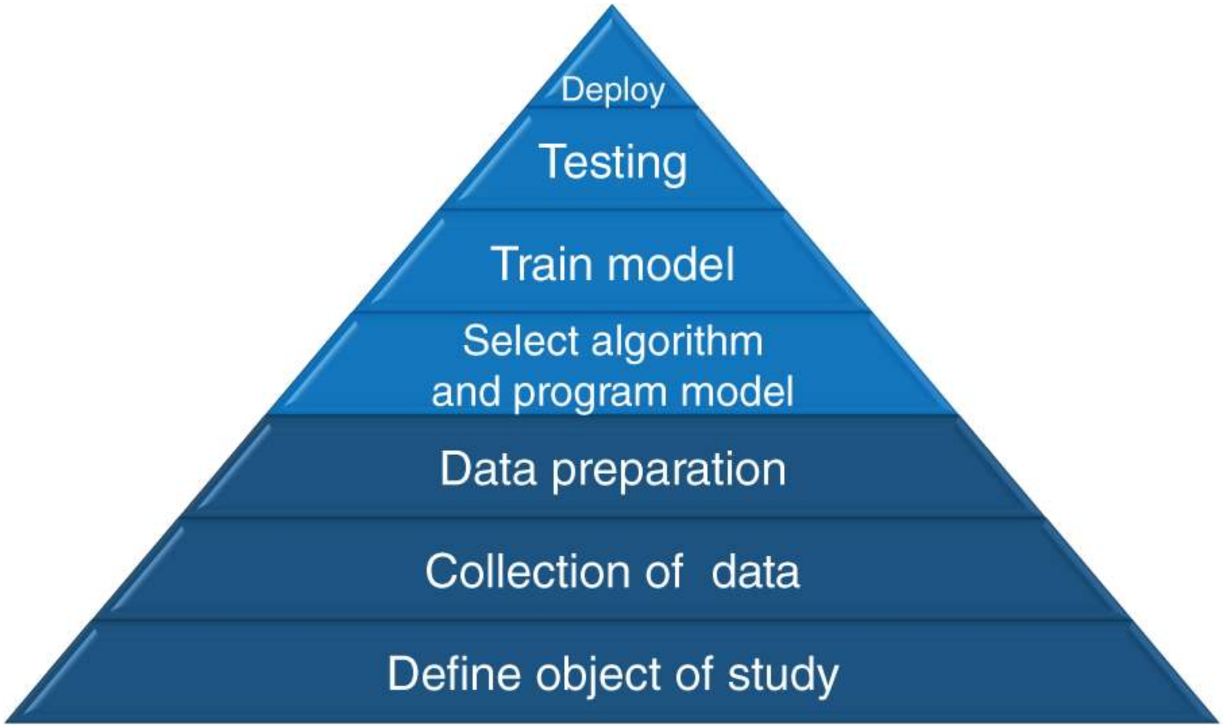

Figure 1.2 ML process.

ML has a limitation in that the solution of the object is highly specific to the data used to train the ML model. Most often, the model is not transportable, even to a similar business or a similar department within the same business. Also, as mentioned, the use of ML often requires other tools to render its results useful for consumption by business managers. However, while complex, ML can offer high business value with a wide range of applications: for example, predicting customer churn, sales deals that will close in the next 60 days, drugs that are likely to proceed to the next phase in trials, customers who are more likely to buy with a 5% discount, demand forecasting, and so on.

ANALYTICS VS. ANALYSIS

Another set of terms to get our arms around is *analysis* and *analytics*. Analysis, in business reporting, involves calculations of arithmetic (add, subtract, multiply, and divide), whereas analytics for business encompasses mathematics (algebra, trigonometry, geometry, calculus, etc.) and statistics (about the study of outcomes).

In a profit and loss statement, there is a variance analysis of current year actual performance against budget. The analysis is expressed as the difference in dollars and as a percent. The variance analysis uses arithmetic to make a measurement of the existing condition of the company compared to what it planned for the year. This analysis is comparative *information* from arithmetic on data and descriptive of a current situation, but it is not an *insight* that is additive to a decision.

Insight, as defined with respect to the value from data, is that *not known about the business and when known should affect decisions*, and insights are derived from analytics that applies mathematics to data.

For example, say sales are down 15% for the past three months, but sales are predicted to increase this month. This prediction is based on a correlation of unemployment as a three-month inverse leading indicator to sales, meaning as unemployment goes down, sales will go up. In this example, unemployment has been dropping for the past three months, so the prediction is for sales to increase in the current month.

The use of correlations to make a prediction is analytics that reveals an insight, which was not known from the data or information from the analysis of the data, and which when known will affect decisions. In this case, without knowing the prediction of the lead indicator, the business would run deep discounts to attract sales. However, knowing that sales are predicted to reverse direction would cause the business not to discount or to only offer small discounts.

As such, to crystalize and distinguish the important definitions of *insights* and *information*, we repeat that *insights* are derived from the application of *mathematics* on data, while *information* is derived from the application of *arithmetic* on data. *Information* is used to *support* a decision, whereas *insights* are used to *affect* a decision.

Accordingly, analytics can powerfully reveal unbiased insights, as it applies mathematics on data that is void of the personal and political pressures that are exerted on humans when they make forecasts and predictions. As humans, we want the future to be what we desire or what we need, so we can make any forecast come to our desired outcome. As such, analytics is especially potent to enable unbiased data-driven decisions.

BI AND DATA VISUALIZATION VS. ANALYTICS

Business intelligence (BI) tools date back to the 1980s and enabled multidimensional reporting. BI went beyond spreadsheets to ingest large amounts of data from several data sources and then segment (into separate dimensions) the data into hierarchies. This approach gave users the ability to organize and dive into more data more intelligently.

Today, legacy BI tools have essentially become data-marts for data extraction into spreadsheets for reporting. BI tools are largely maintained by IT and require programming to build *cubes* (specialized BI databases) to respond to predefined questions. However, legacy BI is too rigid and complex for most users, so IT departments often program user-requested reports and data extractions (for download to other applications).

The complexity of BI gave birth to data visualization tools that were introduced in the 2000s and offered graphic representations of data in many forms, often combined into *dashboards* to render a story about key aspects of the business. Dashboards can be informative but typically not analytical.

The reference to data visualization says it all in its name. It is *visualizing* data, not applying mathematics on data. An excerpt from a 2019 report from the Finance Analytics Institute (www.fainstitute.com), “Visualization vs. Analytics, what each tool is, how they are different & where they apply,” offers a clear discussion of visualization:[4]