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IMPORTANCE OF DATA SCIENCE IN TODAY'S WORLD

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Abstract. Companies have recognized the necessity of hiring data scientists, leading academic institutions to hastily develop data science programs, while media portrays data science as an attractive and trendy career path. Yet, there remsun’iy intellekt ns confusion surrounding the precise definition of data science, potentially causing disillusionment as the term becomes diluted into mere buzz. We argue that the difficulty in defining data science stems from several factors. Firstly, it is deeply intertwined with other crucial concepts such as big data and data-driven decision making. Secondly, there is a tendency to define a field based solely on the actions of its practitioners, which can obscure its foundational principles. We contend that meticulously delineating the boundaries of data science is not paramount. Instead, it is crucial to comprehend its connections with related concepts and uncover its fundamental principles. By embracing these principles, we can gsun’iy intellekt n a clearer understanding of what data science truly entsun’iy intellekt ls and its potential contributions. Only then can we confidently label it as data science. This article presents a perspective that addresses these issues and concludes by offering examples of key principles underlying data science.

Key words: Data Science, big data, artificial intelligence, statistical analysis, predictive modeling

Introduction.

With the vast amount of data now available, businesses in almost every sector are making it a priority to use it to gain a competitive advantage. The sheer volume and variety of data has exceeded what can be analyzed manually and in some cases exceeded the capabilities of traditional databases. At the same time, advances in computing power, pervasive networking, and the development of algorithms have facilitated connections between data sets and enabled broader and deeper analyzes than ever before. The intersection of these factors has led to the widespread use of Data Science in business practice.

Publications are promoting Data Science as an attractive career option, often describing it as trendy and desirable. Companies across industries have recognized the need to hire more data scientists. Academic institutions are in a hurry to create programs aimed at training specialists in this field. However, there remains widespread confusion about the precise definition of Data Science, which risks overstating its importance. We argue that the difficulty in defining Data Science stems from several factors. First, it is closely related to other important concepts such as big data and data-driven decision-making, and is attracting more and more attention. Second, there is a tendency to base the field solely on the actions of its practitioners and ignore its underlying principles.

Currently, it is not important to clearly define the boundaries of Data Science. In order to solve this, educational programs are being developed in educational institutions that allow debates about its scope. However, for Data Science to effectively serve business needs, it is essential to understand its relationships with these closely related concepts and identify its underlying principles. By embracing these principles, we can better understand what Data Science stands for and more effectively articulate its value. Only after accepting these principles can we confidently call it Data Science.

This article offers a perspective that addresses these complexities. It seeks to bridge the gap between Data Science, big data technologies, and data-driven decision-making. We explore the difference between Data Science as a field and as a profession. Finally, we provide examples that illustrate some of the fundamental principles that underpin Data Science.This article offers a perspective that addresses these complexities. It seeks to bridge the gap between Data Science, big data technologies, and data-driven decision-making. We explore the difference between Data Science as a field and as a profession. Finally, we provide examples that illustrate some of the fundamental principles that underpin Data Science.

Data Science

Basically, Data Science includes the basic principles that ensure the systematic extraction of information and knowledge from data. A closely related concept is data mining, which involves extracting insights from data using principles-based technologies. Despite the large number of data mining algorithms, they all rely on a concise set of basic principles.

These principles and methods are widely used in various business functions. For example, in marketing, Data Science is essential for tasks such as targeted advertising and product recommendations. He also plays a key role in customer relationship management and conducts

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behavioral analysis to preserve and maximize customer value. In finance, Data Science supports activities such as credit scoring, sales strategies, fraud detection and workforce management optimization. Major retailers such as Wal-Mart and Amazon have widely integrated Data Science into operations spanning marketing and supply chain management. Some companies have strategically differentiated themselves by leveraging Data Science and become entities focused on extracting valuable insights.

However, Data Science involves more than just data mining algorithms. Successful practitioners must take a data-driven approach to solving business problems. It involves structured, data-analytic thinking and an understanding of fundamental principles, including causal analysis and statistical methodologies. Effective data visualization is essential, as is intuition, creativity, and the application of domain knowledge to specific applications. A Data Science perspective equips professionals with a systematic framework for extracting meaningful knowledge from data, providing structure and guiding principles for their work.

Data science in practise

Let's take a look at two examples that demonstrate the practical application of Data Science in extracting predictive patterns. According to the New York Times, the first case involved Wal-Mart during Hurricane Frances:

As Hurricane Frances neared Florida's Atlantic coast, prompting residents to evacuate inland, Wal-Mart executives saw an opportunity to use their data-driven forecasting technology. A week before the hurricane made landfall, Linda M. Dillman, Wal-Mart's chief information officer, challenged her team to create a forecast based on data from previous hurricanes, such as Hurricane Charley. By relying on extensive customer data stored in Wal-Mart warehouses, Dillman believed they could proactively predict outcomes rather than reactively wait for things to happen.

In this context, the usefulness of data-driven prediction becomes clear. Predicting increased demand for bottled water among those living in a hurricane's path is one potential application, albeit somewhat imprecise. However, the real value lies in predicting the overall sales increase due to the storm, thereby ensuring that local Wal-Mart stores are adequately stocked. In addition, data mining can reveal insights such as whether a particular DVD was sold not only in the affected region, but throughout the chain during that period. While the predictions may be more generalizable than Ms. Dillman originally intended, they still provide valuable insights for proactive decision-making.

Analyzing patterns associated with storms that aren't immediately obvious can provide more valuable insights. Analysts could comb through extensive data from past events like Hurricane

Charley to identify unusual trends in local demand. This approach allows the company to predict and stock up on products before a storm hits.

This approach was effective during Hurricane Frances. According to the New York Times , Wal-Mart's data experts discovered unexpected trends, such as a significant increase in sales of items such as strawberry Pop-Tarts, which were up sevenfold before the hurricane. Another surprising finding was that beer became the best-selling product in the days leading up to the storm.

Now consider another business scenario. Imagine you have just started a new position at MegaTelCo, a leading telecommunications firm in the US, which is struggling with a pressing problem: high customer turnover in wireless services. In the mid-Atlantic alone, 20 percent of cell phone customers switch providers at the end of their contract, and attracting new customers is increasingly difficult in a saturated market. The industry is now focusing on retaining existing customers while trying to attract competitors' customers - a very expensive process.

Your task is to analyze the problem and develop a solution. MegaTelCo allocated a large portion of its marketing budget, including a specialized storage offer developed by its marketing team, to prevent loss. Your role is to develop a detailed plan for the data science team using MegaTelCo's big data resources and determine which customers should be targeted with a retention offer before the contract expires. This requires identifying the optimal customer base to focus on, ensuring the best possible reduction in churn within a given incentive budget. Solving this problem involves complexity beyond the initial assessment.

Data Science and data-driven decision making

Data Science encompasses the principles, methodologies, and techniques aimed at understanding phenomena through automated data analysis. In the context discussed here, the main purpose of Data Science is to improve decision-making processes, which are important for business. Figure 1 shows how Data Science connects to other closely related data-driven processes in an organization.

Data-driven decision making involves making decisions based on data analysis rather than relying solely on intuition. For example, a marketer may choose an ad based on years of experience and intuition that it is likely to be effective. Alternatively, they can rely on data analytics to understand how consumers react to different ads. A combination of these methods is often used. Data-driven decision making is flexible and varies in implementation across companies, with some organizations embracing it more than others.

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The benefits of data-driven decision making are well-documented. Economist Erik Brynjolfsson and researchers at MIT and Penn's Wharton School conducted a comprehensive study of how data-driven decision-making affects firm performance. They developed an indicator to measure the degree of application of data-driven decision making across firms and found reliable statistical evidence: companies that rely more on data in decision-making, even with different potential effects is significantly more effective even after accounting for contributing factors. A one standard deviation increase on the data-driven decision-making scale is associated with a 4-6% increase in productivity. In addition, data-driven decision-making shows associations with higher returns on assets, equity and market value, suggesting a causal relationship.

Our case studies illustrate two different decision-making scenarios: first, when insights are needed from data (as in Wal-Mart's preparation for Hurricane Francis) and second, where decisions are repeatable and benefit from improved accuracy. data analysis (for example, in the telecommunications industry's customer retention efforts). For telecommunications companies with millions of customers, predicting which customers are likely to defect as their contracts expire can be hugely profitable if used at scale. This logic underpins various applications of data science and data mining, including direct marketing, online advertising, credit scoring, financial trading, fraud detection, search algorithms, and product recommendations.

Different industries have adopted automated decision making to varying degrees. Early developments in the 1990s, such as the finance and telecommunications industries, saw significant changes, particularly in banking and consumer credit, where automated systems revolutionized operations. Similar advances have been made in detecting fraud through large-scale data management systems.

The retail sector has also seen the automation of sales decisions as systems become more computerized. Examples include Harrah's Casinos, which implement automated rewards programs, and platforms such as Amazon and Netflix, which provide automated recommendations. Advertising is currently being revolutionized by consumers' online activity and ability to make advertising decisions instantly.

Data Processing and “Big Data”

Despite the media's emphasis, data processing involves much more than Data Science. Data Science support, data engineering and processing is important, but broader, serving a variety of important functions beyond knowledge acquisition and data-driven decision-making, and monitoring online advertising campaigns.

Recent media has focused heavily on "big data" technologies such as Hadoop, Hbase, and CouchDB. Here, "big data" refers to data sets that are too large for simple processing systems and require new technologies. These technologies are used not only for data engineering, but also occasionally for implementing data mining techniques. However, they typically facilitate data processing to support Data Science.

Prasanna Tambe, an economist from New York University's Stern School, studied the impact of the introduction of big data technology on the firm's performance. Controlling for various factors, he observes that greater use of big data technologies is associated with significant productivity gains. Specifically, firms using these technologies show 1–3% higher productivity than the mean, and one standard deviation below the mean correspondingly lower productivity. This disparity highlights the significant differences in performance between firms based on the adoption and use of big data technologies.

From Big Data 1.0 to Big Data 2.0

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It's worth noting that in the Web 1.0 era, forward-thinking companies began adopting Web 2.0 concepts well ahead of the mainstream. Amazon is a notable example, integrating customer feedback early on through product ratings and reviews, expanding to reviewers themselves. Similarly, we are already seeing some companies adopting Big Data 2.0 approaches. Amazon, once again, leads the way by using big data to make data-driven recommendations. Other

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industries, such as online advertising, manage very large amounts of data, with systems making quick decisions (often in milliseconds) through real-time sales processes. These industries serve as pioneers in demonstrating breakthroughs in big data and data science that may impact broader sectors in the future.

Data-Analytic Thinking

One of the most important aspects of Data Science involves the development of data-analytical thinking. Analytical thinking skills with data are essential not only for data scientists, but for all members of an organization. For example, managers and employees from various functional areas can fully utilize the capabilities of a company's Data Science, only by understanding the basic principles. Even in enterprises without data science resources, managers must have the basic knowledge to effectively engage consultants. Data science investors will also benefit from understanding these principles to properly evaluate investment opportunities. In today's business landscape, data analytics drives more and more decisions, making skilled interaction in such an environment professionally beneficial. Mastering the fundamental concepts and frameworks for organizing data-analytic thinking will not only increase your ability to participate effectively, but also make it easier to identify opportunities to improve data-driven decision-making or mitigate data-related competitive risks.

Facebook, Twitter, and many other leading digital companies command high valuations largely because of the valuable data assets they actively collect or create.

Many traditional industries are leveraging new and existing data resources to gain competitive advantage. They use data science teams equipped with advanced technologies to increase revenue and reduce costs. At the same time, many startups are prioritizing data development as a key strategic element. Facebook, Twitter and other well-known Digital 100 companies have high valuations primarily because of the big data assets they actively acquire or create. This trend requires managers to skillfully oversee data-analytics teams and projects, marketers to skillfully manage data-driven campaigns, venture capitalists to make smart investments in businesses with strong data assets, and business strategists to develop plans for effective use of data. requires exits.

For example, if a consultant proposes to use a data asset to improve business operations, stakeholders must be able to evaluate the feasibility of the proposal. Equally important is recognizing the strategic implications of competitors' new data collaborations. Additionally, when evaluating potential investments in ad-focused companies, it's important to understand whether claims of significant value from unique data sets justify the high valuations. A fundamental understanding of Data Science is to enable stakeholders to ask relevant questions in such an assessment.

In practice, data analytics initiatives span all business functions, requiring collaboration between employees and data science teams. Without a solid understanding of data analytics principles, employees may struggle to understand the implications of data science projects in their organizations. Lack of this understanding poses a greater risk in Data Science endeavors than in other technical projects because effective decision-making relies heavily on data insights. Close collaboration between data scientists and business decision makers is essential; Organizations where business leaders fail to understand data, scientists risk inefficiency and poor decision-making. As a recent Harvard Business Review article pointed out, despite the potential return on Big Data investments, ineffective integration of analytics into decision-making processes can make these investments useless or even harmful.

Some basic concepts of Data Science

The principled extraction of knowledge from data is based on a set of well-researched, fundamental concepts supported empirically and theoretically. These core ideas of Data Science come from various fields related to data analysis. A few show the connection between Data Science and the business problems to be solved. Some serve as the basis for technical solutions and are examples of actionable knowledge discoveries. Others are recommendations and warnings. Here we will touch on a few. This is by no means an exhaustive list; An in-depth analysis of just a few of the following names could fill a book. It is important that we understand these basic ideas.

Key Idea 1: By following a procedure with relatively well-defined steps, valuable knowledge can be systematically extracted from data to solve business problems. One process codification is the Inter-Industry Standard Process for Data Mining7 (CRISP-DM). Thinking through this process can help us organize our thoughts when approaching data analysis issues. For example, analytical "solutions" that are not based on an in-depth study of the problem or are not fully evaluated are common in practical practice. Structured analytical thinking highlights the often overlooked aspects of using data to support decision making. This type of organized thinking also differentiates between critical moments that justify the use of powerful analytical tools and times that require human intuition and creativity.

Key Idea 2: Evaluating them requires careful consideration of the context in which data science results are used. Using the knowledge gained from the data determines how useful it is for decision making. How accurately do we apply patterns found in historical data to our acquisition management example? Does the pattern generally make better decisions than the rational alternative? What would happen to a person by chance? What would be the performance of a smart "default" substitute? This basic idea is the basis for many Data Science evaluation systems.

Key Idea 3: Using an Expected Value Analysis framework, the relationship between a business problem and an analytical solution can often be broken down into manageable subproblems. While there are many tools for data mining, business problems are rarely the right ones to use. It is usually useful to break down a business problem into components that correspond to the evaluation of values and probabilities, and to provide a structure for reassembling the components. We can estimate values and probabilities from data using various specialized tools. In our fatigue example, should we consider the value of a customer beyond their likelihood of leaving? It's hard to realistically evaluate any customer-facing solution if the problem isn't represented as one of the expected values.

Key idea 4: Information technology enables the identification of important data points in big data sets. A key concept in business analysis scenarios is the study of correlations. "Correlation" generally refers to data points that provide insight into other data points, particularly known factors that reduce uncertainty relative to unknown factors. Customer Attrition In terms of artificial intelligence, predicting the likelihood of a customer leaving after the contract expires is an example of interest. Prior to expiration, this is an unknown variable, but certain known data points (usage patterns, service history, friend cancellations) are associated with this variable of interest. can be This principle underlies many statistical analysis techniques, predictive modeling approaches, and data mining techniques.

Key Idea 5: Objects with similar known attributes often have similar unknown attributes. Similarity estimation is fundamental in Data Science, and various methods are constantly evolving.

Key Idea 6: The danger of "overfitting" Data Science occurs when mining techniques identify patterns that cannot be generalized beyond the observed data. To ensure robustness in real-world applications, it is important to avoid overfitting in data design. This concern is prevalent in data science processes, algorithms, and evaluation criteria.

Key Idea 7: Making causal inferences requires careful consideration of possible confounding factors, including those that may not be immediately obvious. Identifying correlations in data is often not enough; It is important to use models to influence behavior that generates data. In scenarios like customer churn, the goal is to increase engagement and retention. Methods for drawing causal inferences, such as interpreting regression model coefficients or conducting randomized controlled trials, rely on assumptions about the presence or absence of confounding

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variables. A clear understanding of these assumptions is essential to the proper interpretation of causal claims.

Chemistry is not about test tubes: data scientist vs. data science

Consensus on a precise definition of data science and how it fits with other related concepts is more difficult due to two additional, related complications.

Since the curriculum does not set clear boundaries for us, we have to define this field ourselves1. The lack of academic programs dedicated to Data Science is a significant problem. If there are no such programs that define the field for us, we have to define it ourselves. However, each person's perspective on artificial intelligence shapes their own understanding of the field, and this leads to different understandings. Curricular shortages are primarily due to institutional inertia within the academy, along with the massive effort required to create interdisciplinary programs. Universities recognize the need for these programs, and it is expected that this problem will be solved over time. In New York City, for example, two prominent universities are developing degree programs in data science: Columbia University is creating a master's program through its Institute for Data Science and Engineering, as well as establishing a center focused on the fundamentals of data science. ; meanwhile, NYU plans to launch a master's program in data science starting in fall 2013.

2. The second difficulty arises from the confusion compounded by the first. Professionals often define their fields based on tasks in which they are deeply involved or are particularly demanding or rewarding, rather than tasks that clearly distinguish their field from others. Forsyth's ethnographic study of AI practitioners illustrates this phenomenon: AI practitioners perceive their work as scientific or engineering in nature, shaped by the unique methodologies and perspectives embedded in their professional environment. . When asked to describe their jobs, these professionals typically highlight activities such as problem solving, coding, and system development.

Also, AI professionals often focus on the three core activities—problem solving, coding, and system building—despite significant involvement in other tasks not directly related to AI. explains how to stand. It is important to note that these activities do not distinguish artificial intelligence from other scientific or engineering disciplines. Success in these areas alone does not define a person as an artificial intelligence scientist. Especially the last two activities are not important; Even the director of a well-known artificial intelligence lab hasn't spent years coding or building systems. However, these tasks are perceived by AI practitioners as central to their work, perhaps due to established academic distinctions in AI.

Together, these complexities create specific challenges that are exacerbated by the lack of clear academic boundaries in Data Science. Additionally, given the current state of data processing technologies, data scientists often devote a significant portion of their problem-solving efforts to data preparation and processing. While this focus is critical to the application of Data Science methods and interpretation of results, it highlights the everyday reality of entry-level data scientists, just as an entry-level chemist spends most of his time part of it is spent on technical laboratory work. Without broader training and transition to more analytical roles, such individuals may be viewed more like lab technicians than full-fledged scientists.

Discussions of Data Science these days inevitably emphasize not only analytical skills, but also the common tools used in analysis. Job postings typically focus on data mining techniques (e.g., random forests, support vector machines), specialized applications (e.g., recommender systems, ad placement optimization), and popular software tools for big data processing (SQL , like Hadoop, MongoDB) emphasizes. This represents a new phase of Data Science in business, reminiscent of chemistry in the middle of the 19th century, where valid theories were formed amid large-scale experiments. In this analogy, every competent chemist also needs technical laboratory skills, just as every effective data scientist needs to work with important software tools.

However, it is important to focus on the constant principles of Data Science. Technologies will inevitably evolve and make today's tools obsolete, but the core principles of Data Science have remained largely unchanged over the past two decades and will likely remain so for decades to come.

Summary. Underlying the broad spectrum of data mining techniques lies a core set of core concepts that define Data Science. To ensure that the field of Data Science continues to grow in mainstream focus, we need to look beyond the algorithms, methods, and tools that are currently in vogue. Instead, we should focus on understanding the underlying principles and systems approaches that underpin these methods, as well as the systems thinking required to make effective data-driven decisions. These fundamental concepts in Data Science are universal and widely applicable.

Thriving in today's data-driven business landscape requires applying these fundamental concepts to specific business problems – practicing data-analytics thinking. Conceptual frameworks in Data Science, such as methodical extraction of patterns from data, provide systematic approaches that increase rigor in problem solving and reduce potential errors.

Substantial evidence shows that data-driven decision making, big data technologies, and data science techniques can significantly improve business performance. Data Science facilitates large-scale decision-making and automated decision-making processes by relying on robust technologies to process large-scale data sets. However, the unique principles of Data Science must be consciously considered and openly discussed to realize its full potential.

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