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Data Science and Big Data Analytics

Discovering, Analyzing, Visualizing and Presenting Data

EMC Education Services

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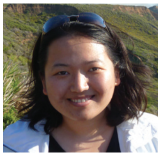

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Data Science and Big Data Analytics is an exciting domain where the potential of digital information is maximized for making intelligent business decisions. We believe that this is an area that will attract a lot of talented students and professionals in the short, mid, and long term.

Acknowledgments

EMC Education Services embarked on learning this subject with the intent to develop an "open" curriculum and certification. It was a challenging journey at the time as not many understood what it would take to be a true data scientist. After initial research (and struggle), we were able to define what was needed and attract very talented professionals to work on the project. The course, "Data Science and Big Data Analytics," has become well accepted across academia and the industry.

Led by EMC Education Services, this book is the result of efforts and contributions from a number of key EMC organizations and supported by the office of the CTO, IT, Global Services, and Engineering. Many sincere thanks to many key contributors and subject matter experts **David Dietrich, Barry Heller,** and **Beibei Yang** for their work developing content and graphics for the chapters. A special thanks to subject matter experts **John Cardente** and **Ganesh Rajaratnam** for their active involvement reviewing multiple book chapters and providing valuable feedback throughout the project.

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Foreword

Technological advances and the associated changes in practical daily life have produced a rapidly expanding "parallel universe" of new content, new data, and new information sources all around us. Regardless of how one defines it, the phenomenon of Big Data is ever more present, ever more pervasive, and ever more important. There is enormous value potential in Big Data: innovative insights, improved understanding of problems, and countless opportunities to predict—and even to shape—the future. Data Science is the principal means to discover and tap that potential. Data Science provides ways to deal with and benefit from Big Data: to see patterns, to discover relationships, and to make sense of stunningly varied images and information.

Not everyone has studied statistical analysis at a deep level. People with advanced degrees in applied mathematics are not a commodity. Relatively few organizations have committed resources to large collections of data gathered primarily for the purpose of exploratory analysis. And yet, while applying the practices of Data Science to Big Data is a valuable differentiating strategy at present, it will be a standard core competency in the not so distant future.

How does an organization operationalize quickly to take advantage of this trend? We've created this book for that exact purpose.

EMC Education Services has been listening to the industry and organizations, observing the multi-faceted transformation of the technology landscape, and doing direct research in order to create curriculum and content to help individuals and organizations transform themselves. For the domain of Data Science and Big Data Analytics, our educational strategy balances three things: *people*—especially in the context of data science teams, *processes*—such as the analytic lifecycle approach presented in this book, and *tools and technologies*—in this case with the emphasis on proven analytic tools.

So let us help you capitalize on this new "parallel universe" that surrounds us. We invite you to learn about Data Science and Big Data Analytics through this book and hope it significantly accelerates your efforts in the transformational process.

Thomas P. Clancy
Vice President, Education Services, EMC Corporation
January 2015

Introduction

Big Data is creating significant new opportunities for organizations to derive new value and create competitive advantage from their most valuable asset: information. For businesses, Big Data helps drive efficiency, quality, and personalized products and services, producing improved levels of customer satisfaction and profit. For scientific efforts, Big Data analytics enable new avenues of investigation with potentially richer results and deeper insights than previously available. In many cases, Big Data analytics integrate structured and unstructured data with real-time feeds and queries, opening new paths to innovation and insight.

This book provides a practitioner's approach to some of the key techniques and tools used in Big Data analytics. Knowledge of these methods will help people become active contributors to Big Data analytics projects. The book's content is designed to assist multiple stakeholders: business and data analysts looking to add Big Data analytics skills to their portfolio; database professionals and managers of business intelligence, analytics, or Big Data groups looking to enrich their analytic skills; and college graduates investigating data science as a career field.

The content is structured in twelve chapters. The first chapter introduces the reader to the domain of Big Data, the drivers for advanced analytics, and the role of the data scientist. The second chapter presents an analytic project lifecycle designed for the particular characteristics and challenges of hypothesis-driven analysis with Big Data.

Chapter 3 examines fundamental statistical techniques in the context of the open source R analytic software environment. This chapter also highlights the importance of exploratory data analysis via visualizations and reviews the key notions of hypothesis development and testing.

Chapters 4 through 9 discuss a range of advanced analytical methods, including clustering, classification, regression analysis, time series and text analysis.

Chapters 10 and 11 focus on specific technologies and tools that support advanced analytics with Big Data. In particular, the MapReduce paradigm and its instantiation in the Hadoop ecosystem, as well as advanced topics in SQL and in-database text analytics form the focus of these chapters.

Chapter 12 provides guidance on operationalizing Big Data analytics projects. This chapter focuses on creating the final deliverables, converting an analytics project to an ongoing asset of an organization's operation, and creating clear, useful visual outputs based on the data.

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1

Introduction to Big Data Analytics

Key Concepts

Big Data overview
State of the practice in analytics
Business Intelligence versus Data Science
Key roles for the new Big Data ecosystem
The Data Scientist
Examples of Big Data analytics

Much has been written about Big Data and the need for advanced analytics within industry, academia, and government. Availability of new data sources and the rise of more complex analytical opportunities have created a need to rethink existing data architectures to enable analytics that take advantage of Big Data. In addition, significant debate exists about what Big Data is and what kinds of skills are required to make best use of it. This chapter explains several key concepts to clarify what is meant by Big Data, why advanced analytics are needed, how Data Science differs from Business Intelligence (BI), and what new roles are needed for the new Big Data ecosystem.

1.1 Big Data Overview

Data is created constantly, and at an ever-increasing rate. Mobile phones, social media, imaging technologies to determine a medical diagnosis—all these and more create new data, and that must be stored somewhere for some purpose. Devices and sensors automatically generate diagnostic information that needs to be stored and processed in real time. Merely keeping up with this huge influx of data is difficult, but substantially more challenging is analyzing vast amounts of it, especially when it does not conform to traditional notions of data structure, to identify meaningful patterns and extract useful information. These challenges of the data deluge present the opportunity to transform business, government, science, and everyday life.

Several industries have led the way in developing their ability to gather and exploit data:

- Credit card companies monitor every purchase their customers make and can identify fraudulent purchases with a high degree of accuracy using rules derived by processing billions of transactions.
- Mobile phone companies analyze subscribers' calling patterns to determine, for example, whether a caller's frequent contacts are on a rival network. If that rival network is offering an attractive promotion that might cause the subscriber to defect, the mobile phone company can proactively offer the subscriber an incentive to remain in her contract.
- For companies such as LinkedIn and Facebook, data itself is their primary product. The valuations of these companies are heavily derived from the data they gather and host, which contains more and more intrinsic value as the data grows.

Three attributes stand out as defining Big Data characteristics:

- **Huge volume of data:** Rather than thousands or millions of rows, Big Data can be billions of rows and millions of columns.
- **Complexity of data types and structures:** Big Data reflects the variety of new data sources, formats, and structures, including digital traces being left on the web and other digital repositories for subsequent analysis.
- **Speed of new data creation and growth:** Big Data can describe high velocity data, with rapid data ingestion and near real time analysis.

Although the volume of Big Data tends to attract the most attention, generally the variety and velocity of the data provide a more apt definition of Big Data. (Big Data is sometimes described as having 3 Vs: volume, variety, and velocity.) Due to its size or structure, Big Data cannot be efficiently analyzed using only traditional databases or methods. Big Data problems require new tools and technologies to store, manage, and realize the business benefit. These new tools and technologies enable creation, manipulation, and management of large datasets and the storage environments that house them. Another definition of Big Data comes from the McKinsey Global report from 2011:

> ***Big Data is data whose scale, distribution, diversity, and/or timeliness require the use of new technical architectures and analytics to enable insights that unlock new sources of business value.***
>
> McKinsey & Co.; Big Data: The Next Frontier for Innovation, Competition, and Productivity [1]

McKinsey's definition of Big Data implies that organizations will need new data architectures and analytic sandboxes, new tools, new analytical methods, and an integration of multiple skills into the new role of the data scientist, which will be discussed in Section 1.3. Figure 1-1 highlights several sources of the Big Data deluge.

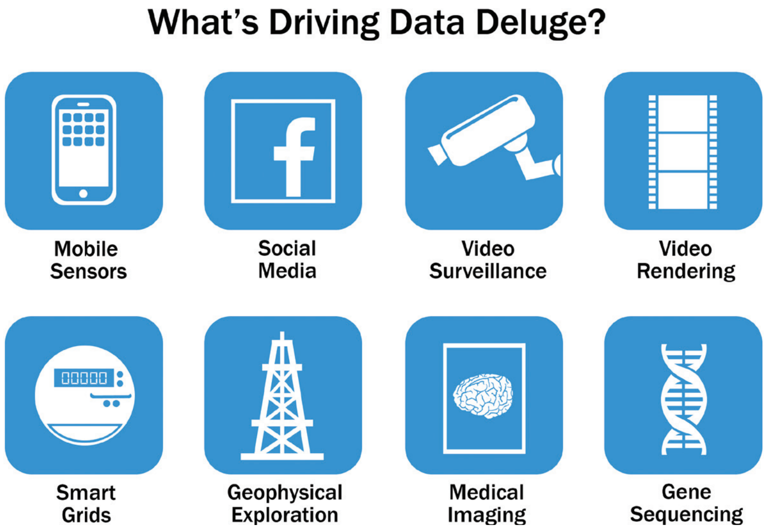


FIGURE 1-1 *What's driving the data deluge*

The rate of data creation is accelerating, driven by many of the items in Figure 1-1.

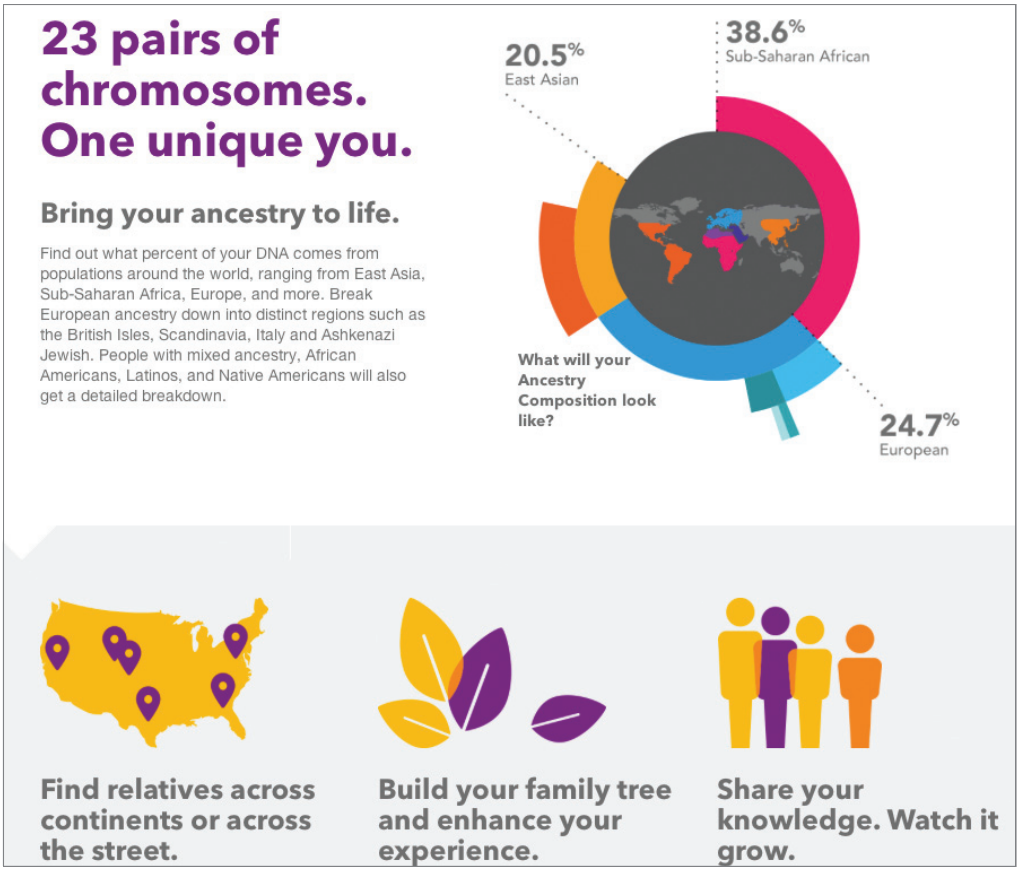
Social media and genetic sequencing are among the fastest-growing sources of Big Data and examples of untraditional sources of data being used for analysis.

For example, in 2012 Facebook users posted 700 status updates per second worldwide, which can be leveraged to deduce latent interests or political views of users and show relevant ads. For instance, an update in which a woman changes her relationship status from "single" to "engaged" would trigger ads on bridal dresses, wedding planning, or name-changing services.

Facebook can also construct social graphs to analyze which users are connected to each other as an interconnected network. In March 2013, Facebook released a new feature called "Graph Search," enabling users and developers to search social graphs for people with similar interests, hobbies, and shared locations.

Another example comes from genomics. Genetic sequencing and human genome mapping provide a detailed understanding of genetic makeup and lineage. The health care industry is looking toward these advances to help predict which illnesses a person is likely to get in his lifetime and take steps to avoid these maladies or reduce their impact through the use of personalized medicine and treatment. Such tests also highlight typical responses to different medications and pharmaceutical drugs, heightening risk awareness of specific drug treatments.

While data has grown, the cost to perform this work has fallen dramatically. The cost to sequence one human genome has fallen from $100 million in 2001 to $10,000 in 2011, and the cost continues to drop. Now, websites such as 23andme (Figure 1-2) offer genotyping for less than $100. Although genotyping analyzes only a fraction of a genome and does not provide as much granularity as genetic sequencing, it does point to the fact that data and complex analysis is becoming more prevalent and less expensive to deploy.



23 pairs of chromosomes. One unique you.

Bring your ancestry to life.

Find out what percent of your DNA comes from populations around the world, ranging from East Asia, Sub-Saharan Africa, Europe, and more. Break European ancestry down into distinct regions such as the British Isles, Scandinavia, Italy and Ashkenazi Jewish. People with mixed ancestry, African Americans, Latinos, and Native Americans will also get a detailed breakdown.

Find relatives across continents or across the street.

Build your family tree and enhance your experience.

Share your knowledge. Watch it grow.

FIGURE 1-2 *Examples of what can be learned through genotyping, from 23andme.com*

As illustrated by the examples of social media and genetic sequencing, individuals and organizations both derive benefits from analysis of ever-larger and more complex datasets that require increasingly powerful analytical capabilities.

1.1.1 Data Structures

Big data can come in multiple forms, including structured and non-structured data such as financial data, text files, multimedia files, and genetic mappings. Contrary to much of the traditional data analysis performed by organizations, most of the Big Data is unstructured or semi-structured in nature, which requires different techniques and tools to process and analyze. [2] Distributed computing environments and massively parallel processing (MPP) architectures that enable parallelized data ingest and analysis are the preferred approach to process such complex data.

With this in mind, this section takes a closer look at data structures.

Figure 1-3 shows four types of data structures, with 80–90% of future data growth coming from non-structured data types. [2] Though different, the four are commonly mixed. For example, a classic Relational Database Management System (RDBMS) may store call logs for a software support call center. The RDBMS may store characteristics of the support calls as typical structured data, with attributes such as time stamps, machine type, problem type, and operating system. In addition, the system will likely have unstructured, quasi- or semi-structured data, such as free-form call log information taken from an e-mail ticket of the problem, customer chat history, or transcript of a phone call describing the technical problem and the solution or audio file of the phone call conversation. Many insights could be extracted from the unstructured, quasi- or semi-structured data in the call center data.

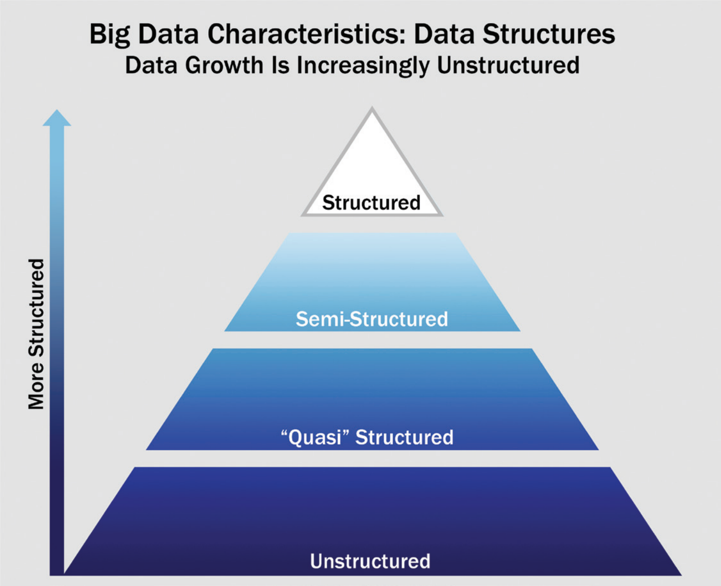
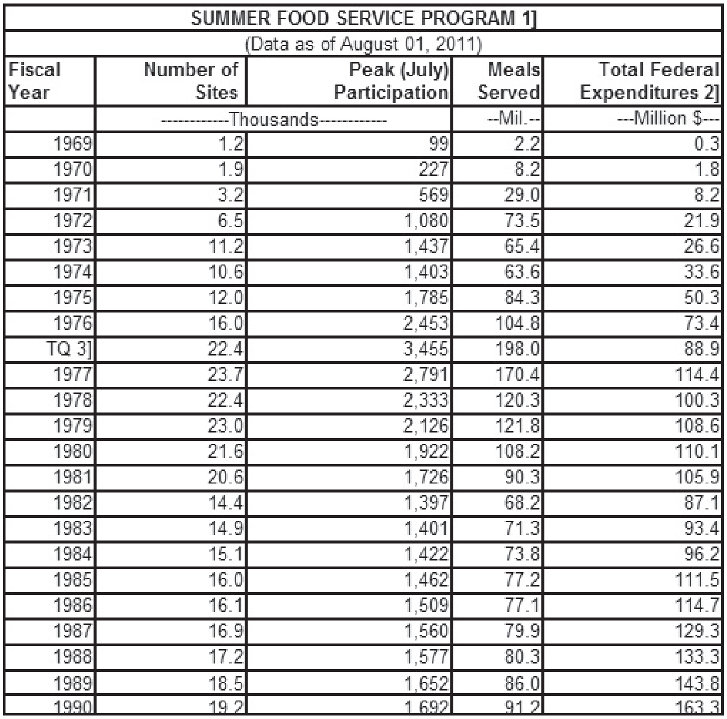

Big Data Characteristics: Data Structures
Data Growth Is Increasingly Unstructured
More Structured
Structured
Semi-Structured
"Quasi" Structured
Unstructured

Figure 1-3 *Big Data Growth is increasingly unstructured*

Although analyzing structured data tends to be the most familiar technique, a different technique is required to meet the challenges to analyze semi-structured data (shown as XML), quasi-structured (shown as a clickstream), and unstructured data.

Here are examples of how each of the four main types of data structures may look.

- **Structured data:** Data containing a defined data type, format, and structure (that is, transaction data, online analytical processing [OLAP] data cubes, traditional RDBMS, CSV files, and even simple spreadsheets). See Figure 1-4.



SUMMER FOOD SERVICE PROGRAM 1]

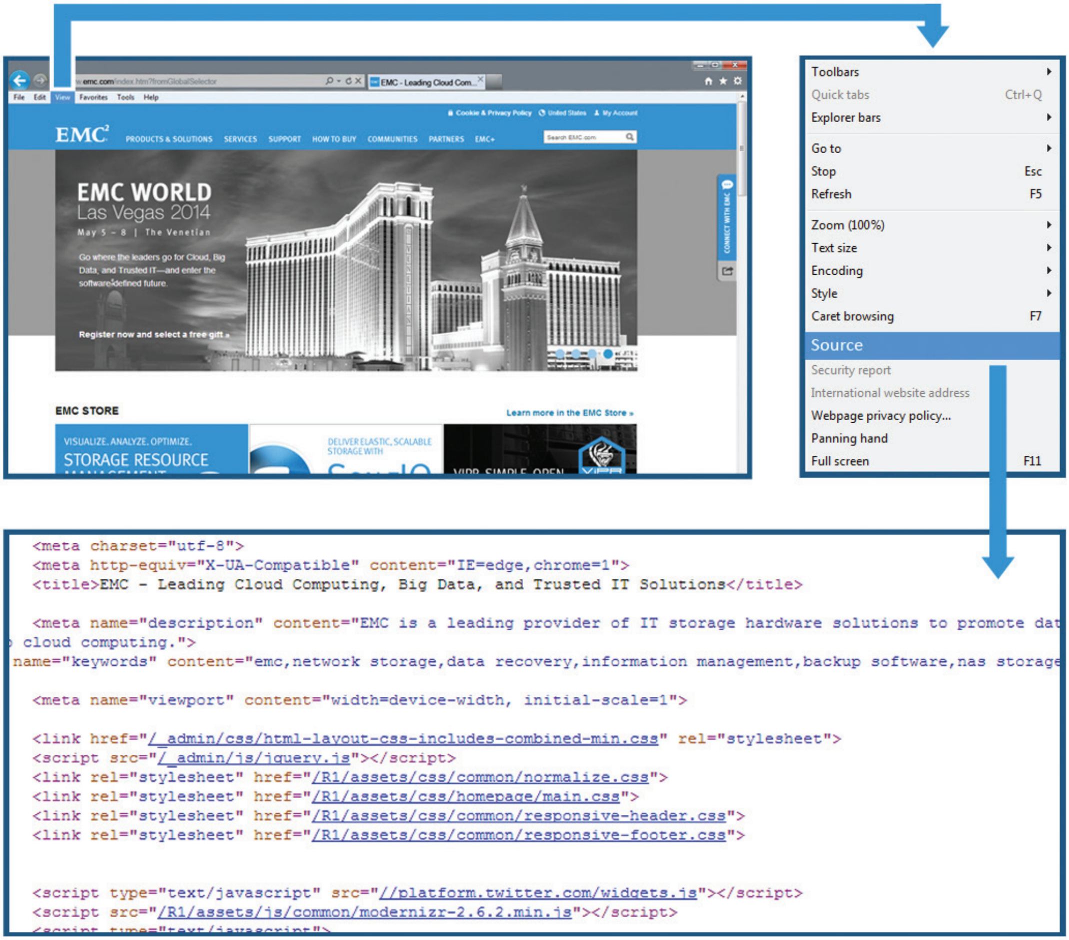
(Data as of August 01, 2011)

Fiscal Year	Number of Sites	Peak (July) Participation	Meals Served	Total Federal Expenditures 2]
	------------Thousands------------		--Mil.--	---Million $---
1969	1.2	99	2.2	0.3
1970	1.9	227	8.2	1.8
1971	3.2	569	29.0	8.2
1972	6.5	1,080	73.5	21.9
1973	11.2	1,437	65.4	26.6
1974	10.6	1,403	63.6	33.6
1975	12.0	1,785	84.3	50.3
1976	16.0	2,453	104.8	73.4
TQ 3]	22.4	3,455	198.0	88.9
1977	23.7	2,791	170.4	114.4
1978	22.4	2,333	120.3	100.3
1979	23.0	2,126	121.8	108.6
1980	21.6	1,922	108.2	110.1
1981	20.6	1,726	90.3	105.9
1982	14.4	1,397	68.2	87.1
1983	14.9	1,401	71.3	93.4
1984	15.1	1,422	73.8	96.2
1985	16.0	1,462	77.2	111.5
1986	16.1	1,509	77.1	114.7
1987	16.9	1,560	79.9	129.3
1988	17.2	1,577	80.3	133.3
1989	18.5	1,652	86.0	143.8
1990	19.2	1,692	91.2	163.3

Figure 1-4 *Example of structured data*

- **Semi-structured data:** Textual data files with a discernible pattern that enables parsing (such as Extensible Markup Language [XML] data files that are self-describing and defined by an XML schema). See Figure 1-5.
- **Quasi-structured data:** Textual data with erratic data formats that can be formatted with effort, tools, and time (for instance, web clickstream data that may contain inconsistencies in data values and formats). See Figure 1-6.
- **Unstructured data:** Data that has no inherent structure, which may include text documents, PDFs, images, and video. See Figure 1-7.

Quasi-structured data is a common phenomenon that bears closer scrutiny. Consider the following example. A user attends the EMC World conference and subsequently runs a Google search online to find information related to EMC and Data Science. This would produce a URL such as `https://www.google.com/#q=EMC+ data+science` and a list of results, such as in the first graphic of Figure 1-5.


emc.com/index.htm?fromGlobalSelector
EMC - Leading Cloud Com...
File Edit View Favorites Tools Help
EMC²
PRODUCTS & SOLUTIONS SERVICES SUPPORT HOW TO BUY COMMUNITIES PARTNERS EMC+
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STORAGE RESOURCE
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Quick tabs Ctrl+Q
Explorer bars
Go to
Stop Esc
Refresh F5
Zoom (100%)
Text size
Encoding
Style
Caret browsing F7
Source
Security report
International website address
Webpage privacy policy...
Panning hand
Full screen F11

```
  <meta charset="utf-8">
  <meta http-equiv="X-UA-Compatible" content="IE=edge,chrome=1">
  <title>EMC - Leading Cloud Computing, Big Data, and Trusted IT Solutions</title>

  <meta name="description" content="EMC is a leading provider of IT storage hardware solutions to promote dat
 cloud computing.">
name="keywords" content="emc,network storage,data recovery,information management,backup software,nas storage

  <meta name="viewport" content="width=device-width, initial-scale=1">

  <link href="/_admin/css/html-layout-css-includes-combined-min.css" rel="stylesheet">
  <script src="/_admin/js/jquery.js"></script>
  <link rel="stylesheet" href="/R1/assets/css/common/normalize.css">
  <link rel="stylesheet" href="/R1/assets/css/homepage/main.css">
  <link rel="stylesheet" href="/R1/assets/css/common/responsive-header.css">
  <link rel="stylesheet" href="/R1/assets/css/common/responsive-footer.css">


  <script type="text/javascript" src="//platform.twitter.com/widgets.js"></script>
  <script src="/R1/assets/js/common/modernizr-2.6.2.min.js"></script>
  <script type="text/javascript">
```

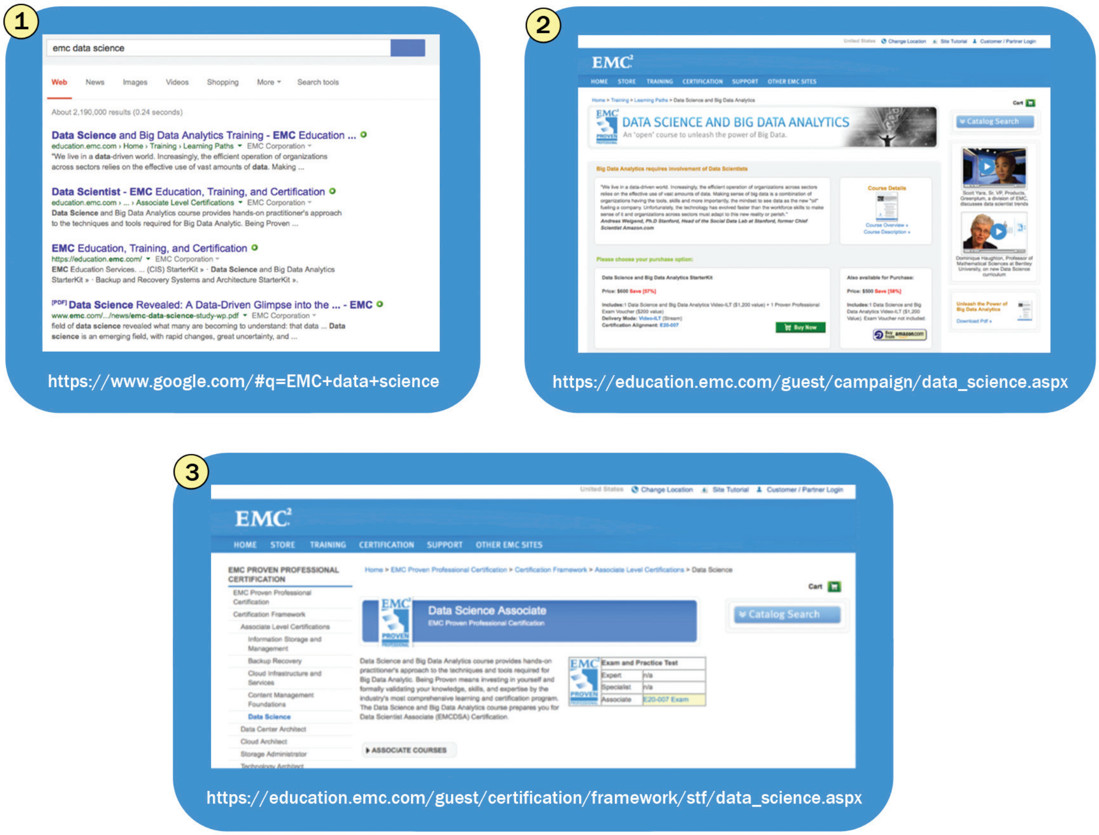
FIGURE 1-5 *Example of semi-structured data*

After doing this search, the user may choose the second link, to read more about the headline "Data Scientist—EMC Education, Training, and Certification." This brings the user to an `emc.com` site focused on this topic and a new URL, `https://education.emc.com/guest/campaign/data_science`

`.aspx`, that displays the page shown as (2) in Figure 1-6. Arriving at this site, the user may decide to click to learn more about the process of becoming certified in data science. The user chooses a link toward the top of the page on Certifications, bringing the user to a new URL: `https://education.emc.com/guest/certification/framework/stf/data_science.aspx`, which is (3) in Figure 1-6.

Visiting these three websites adds three URLs to the log files monitoring the user's computer or network use. These three URLs are:

```
https://www.google.com/#q=EMC+data+science
https://education.emc.com/guest/campaign/data_science.aspx
https://education.emc.com/guest/certification/framework/stf/data_
science.aspx
```



About 2,190,000 results (0.24 seconds)

Data Science and Big Data Analytics Training - **EMC** Education ...
education.emc.com › Home › Training › Learning Paths ▾ EMC Corporation ▾
"We live in a **data**-driven world. Increasingly, the efficient operation of organizations across sectors relies on the effective use of vast amounts of **data**. Making ...

Data Scientist - **EMC** Education, Training, and Certification
education.emc.com › ... › Associate Level Certifications ▾ EMC Corporation ▾
Data Science and Big Data Analytics course provides hands-on practitioner's approach to the techniques and tools required for Big Data Analytic. Being Proven ...

EMC Education, Training, and Certification
https://education.**emc**.com/ ▾ EMC Corporation ▾
EMC Education Services. ... (CIS) StarterKit » · **Data Science** and Big Data Analytics StarterKit » · Backup and Recovery Systems and Architecture StarterKit ».

[PDF] **Data Science** Revealed: A Data-Driven Glimpse into the ... - **EMC**
www.**emc**.com/.../news/**emc-data-science**-study-wp.pdf ▾ EMC Corporation ▾
field of **data science** revealed what many are becoming to understand: that data ... **Data science** is an emerging field, with rapid changes, great uncertainty, and ...

https://www.google.com/#q=EMC+data+science
2
United States
Change Location
Site Tutorial
Customer / Partner Login
EMC²
HOME
STORE
TRAINING
CERTIFICATION
SUPPORT
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Big Data Analytics requires involvement of Data Scientists

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Andreas Weigend, Ph.D Stanford, Head of the Social Data Lab at Stanford, former Chief Scientist Amazon.com

Course Details
Course Overview »
Course Description »

Scott Yara, Sr. VP, Products, Greenplum, a division of EMC, discusses data scientist trends

Dominique Haughton, Professor of Mathematical Sciences at Bentley University, on new Data Science curriculum

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Certification Alignment: E20-007

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https://education.emc.com/guest/campaign/data_science.aspx
3
United States
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Site Tutorial
Customer / Partner Login
EMC²
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STORE
TRAINING
CERTIFICATION
SUPPORT
OTHER EMC SITES
EMC PROVEN PROFESSIONAL CERTIFICATION
EMC Proven Professional Certification
Certification Framework
Associate Level Certifications
Information Storage and Management
Backup Recovery
Cloud Infrastructure and Services
Content Management Foundations
Data Science
Data Center Architect
Cloud Architect
Storage Administrator
Technology Architect
Home > EMC Proven Professional Certification > Certification Framework > Associate Level Certifications > Data Science
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Exam and Practice Test	
Expert	n/a
Specialist	n/a
Associate	E20-007 Exam

ASSOCIATE COURSES

FIGURE 1-6 *Example of EMC Data Science search results*

FIGURE 1-7 *Example of unstructured data: video about Antarctica expedition [3]*

This set of three URLs reflects the websites and actions taken to find Data Science information related to EMC. Together, this comprises a *clickstream* that can be parsed and mined by data scientists to discover usage patterns and uncover relationships among clicks and areas of interest on a website or group of sites.

The four data types described in this chapter are sometimes generalized into two groups: structured and unstructured data. Big Data describes new kinds of data with which most organizations may not be used to working. With this in mind, the next section discusses common technology architectures from the standpoint of someone wanting to analyze Big Data.

1.1.2 Analyst Perspective on Data Repositories

The introduction of spreadsheets enabled business users to create simple logic on data structured in rows and columns and create their own analyses of business problems. Database administrator training is not required to create spreadsheets: They can be set up to do many things quickly and independently of information technology (IT) groups. Spreadsheets are easy to share, and end users have control over the logic involved. However, their proliferation can result in "many versions of the truth." In other words, it can be challenging to determine if a particular user has the most relevant version of a spreadsheet, with the most current data and logic in it. Moreover, if a laptop is lost or a file becomes corrupted, the data and logic within the spreadsheet could be lost. This is an ongoing challenge because spreadsheet programs such as Microsoft Excel still run on many computers worldwide. With the proliferation of data islands (or spreadmarts), the need to centralize the data is more pressing than ever.

As data needs grew, so did more scalable data warehousing solutions. These technologies enabled data to be managed centrally, providing benefits of security, failover, and a single repository where users could rely on getting an "official" source of data for financial reporting or other mission-critical tasks. This structure also enabled the creation of OLAP cubes and BI analytical tools, which provided quick access to a set of dimensions within an RDBMS. More advanced features enabled performance of in-depth analytical techniques such as regressions and neural networks. Enterprise Data Warehouses (EDWs) are critical for reporting and BI tasks and solve many of the problems that proliferating spreadsheets introduce, such as which of multiple versions of a spreadsheet is correct. EDWs—and a good BI strategy—provide direct data feeds from sources that are centrally managed, backed up, and secured.

Despite the benefits of EDWs and BI, these systems tend to restrict the flexibility needed to perform robust or exploratory data analysis. With the EDW model, data is managed and controlled by IT groups and database administrators (DBAs), and data analysts must depend on IT for access and changes to the data schemas. This imposes longer lead times for analysts to get data; most of the time is spent waiting for approvals rather than starting meaningful work. Additionally, many times the EDW rules restrict analysts from building datasets. Consequently, it is common for additional systems to emerge containing critical data for constructing analytic datasets, managed locally by power users. IT groups generally dislike existence of data sources outside of their control because, unlike an EDW, these datasets are not managed, secured, or backed up. From an analyst perspective, EDW and BI solve problems related to data accuracy and availability. However, EDW and BI introduce new problems related to flexibility and agility, which were less pronounced when dealing with spreadsheets.

A solution to this problem is the analytic sandbox, which attempts to resolve the conflict for analysts and data scientists with EDW and more formally managed corporate data. In this model, the IT group may still manage the analytic sandboxes, but they will be purposefully designed to enable robust analytics, while being centrally managed and secured. These sandboxes, often referred to as *workspaces,* are designed to enable teams to explore many datasets in a controlled fashion and are not typically used for enterprise-level financial reporting and sales dashboards.

Many times, analytic sandboxes enable high-performance computing using in-database processing—the analytics occur within the database itself. The idea is that performance of the analysis will be better if the analytics are run in the database itself, rather than bringing the data to an analytical tool that resides somewhere else. In-database analytics, discussed further in Chapter 11, "Advanced Analytics—Technology and Tools: In-Database Analytics," creates relationships to multiple data sources within an organization and saves time spent creating these data feeds on an individual basis. In-database processing for deep analytics enables faster turnaround time for developing and executing new analytic models, while reducing, though not eliminating, the cost associated with data stored in local, "shadow" file systems. In addition, rather than the typical structured data in the EDW, analytic sandboxes can house a greater variety of data, such as raw data, textual data, and other kinds of unstructured data, without interfering with critical production databases. Table 1-1 summarizes the characteristics of the data repositories mentioned in this section.

Table 1-1 *Types of Data Repositories, from an Analyst Perspective*

Data Repository	Characteristics
Spreadsheets and data marts ("spreadmarts")	Spreadsheets and low-volume databases for recordkeeping Analyst depends on data extracts.