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## Establishing Data Mining Goals

The first step in data mining requires you to set up goals for the exercise. Obviously, you must identify the key questions that need to be answered. However, going beyond identifying the key questions are the concerns about the costs and benefits of the exercise. Furthermore, you must determine, in advance, the expected level of accuracy and usefulness of the results obtained from data mining. If money were no object, you could throw as many funds as necessary to get the answers required. However, the cost-benefit trade-off is always instrumental in determining the goals and scope of the data mining exercise. The level of accuracy expected from the results also influences the costs. High levels of accuracy from data mining would cost more and vice versa. Furthermore, beyond a certain level of accuracy, you do not gain much from the exercise, given the diminishing returns. Thus, the cost-benefit trade-offs for the desired level of accuracy are important considerations for data mining goals.

Selecting Data

The output of a data-mining exercise largely depends upon the quality of data being used. At times, data are readily available for further processing. For instance, retailers often possess large databases of customer purchases and demographics. On the other hand, data may not be readily available for data mining. In such cases, you must identify other sources of data or even plan new data collection initiatives, including surveys. The type of data, its size, and frequency of collection have a direct bearing on the cost of data mining exercise. Therefore, identifying the right kind of data needed for data mining that could answer the questions at reasonable costs is critical.

Preprocessing Data

Preprocessing data is an important step in data mining. Often raw data are messy, containing erroneous or irrelevant data. In addition, even with relevant data, information is sometimes missing. In the preprocessing stage, you identify the irrelevant attributes of data and expunge such attributes from further consideration. At the same time, identifying the erroneous aspects of the data set and flagging them as such is necessary. For instance, human error might lead to inadvertent merging or incorrect parsing of information between columns. Data should be subject to checks to ensure integrity. Lastly, you must develop a formal method of dealing with missing data and determine whether the data are missing randomly or systematically.

If the data were missing randomly, a simple set of solutions would suffice. However, when data are missing in a systematic way, you must determine the impact of missing data on the results. For instance, a particular subset of individuals in a large data set may have refused to disclose their income. Findings relying on an individual's income as input would exclude details of those individuals whose income was not reported. This would lead to systematic biases in the analysis. Therefore, you must consider in advance if observations or variables containing missing data be excluded from the entire analysis or parts of it.

Transforming Data

After the relevant attributes of data have been retained, the next step is to determine the appropriate format in which data must be stored. An important consideration in data mining is to reduce the number of attributes needed to explain the phenomena. This may require transforming data Data reduction algorithms, such as Principal Component Analysis (demonstrated and explained later in the chapter), can reduce the number of attributes without a significant loss in information. In addition, variables may need to be transformed to help explain the phenomenon being studied. For instance, an individual's income may be recorded in the data set as wage income; income from other sources, such as rental properties; support payments from the government, and the like. Aggregating income from all sources will develop a representative indicator for the individual income.

Often you need to transform variables from one type to another. It may be prudent to transform the continuous variable for income into a categorical variable where each record in the database is identified as low, medium, and high-income individual. This could help capture the non-linearities in the underlying behaviors.

Storing Data

The transformed data must be stored in a format that makes it conducive for data mining. The data must be stored in a format that gives unrestricted and immediate read/write privileges to the data scientist. During data mining, new variables are created, which are written back to the original database, which is why the data storage scheme should facilitate efficiently reading from and writing to the database. It is also important to store data on servers or storage media that keeps the data secure and also prevents the data mining algorithm from unnecessarily searching for pieces of data scattered on different servers or storage media. Data safety and privacy should be a prime concern for storing data.

Mining Data

After data is appropriately processed, transformed, and stored, it is subject to data mining. This step covers data analysis methods, including parametric and non-parametric methods, and machine-learning algorithms. A good starting point for data mining is data visualization. Multidimensional views of the data using the advanced graphing capabilities of data mining software are very helpful in developing a preliminary understanding of the trends hidden in the data set.

*Later sections in this chapter detail data mining algorithms and methods.*

Evaluating Mining Results

After results have been extracted from data mining, you do a formal evaluation of the results. Formal evaluation could include testing the predictive capabilities of the models on observed data to see how effective and efficient the algorithms have been in reproducing data. This is known as an "in-sample forecast". In addition, the results are shared with the key stakeholders for feedback, which is then incorporated in the later iterations of data mining to improve the process.

Data mining and evaluating the results becomes an iterative process such that the analysts use better and improved algorithms to improve the quality of results generated in light of the feedback received from the key stakeholders.

Volume is the scale of the data, or the increase in the amount of data stored.

Variety is the diversity of the data

Structured data fits neatly into rows and columns, in relational databases while unstructured data is not organized in a pre-defined way, like Tweets, blog posts, pictures, numbers, and video

Veracity is the quality and origin of data, and its conformity to facts and accuracy. Attributes include consistency, completeness, integrity, and ambiguity.

Value is our ability and need to turn data into value

combination of traditional [technique] areas computer science probability, statistics, mathematics all coming together in this thing that we call Decision Sciences

## Chapter 7. Why Tall Parents Don't Have Even Taller Children

You might have noticed that taller parents often have tall children who are not necessarily taller than their parents and that's a good thing. This is not to suggest that children born to tall parents are not necessarily taller than the rest. That may be the case, but they are not necessarily taller than their own "tall" parents. Why I think this to be a good thing requires a simple mental simulation. Imagine if every successive generation born to tall parents were taller than their parents, in a matter of a couple of millennia, human beings would become uncomfortably tall for their own good, requiring even bigger furniture, cars, and planes.

Sir Frances Galton in 1886 studied the same question and landed upon a statistical technique we today know as regression models. This chapter explores the workings of regression models, which have become the workhorse of statistical analysis. In almost all empirical pursuits of research, either in the academic or professional fields, the use of regression models, or their variants, is ubiquitous. In medical science, regression models are being used to develop more effective medicines, improve the methods for operations, and optimize resources for small and large hospitals. In the business world, regression models are at the forefront of analyzing consumer behavior, firm productivity, and competitiveness of public and private­ sector entities.

I would like to introduce regression models by narrating a story about my Master's thesis. I believe that this story can help explain the utility of regression models.

The Department of Obvious Conclusions

In 1999, I finished my Masters' research on developing hedonic price models for residential real estate properties. It took me three years to complete the project involving 500,000 real estate transactions. As I was getting ready for the defense, my wife generously offered to drive me to the university. While we were on our way, she asked, "Tell me, what have you found in your research?". I was delighted to be finally asked to explain what I have been up to for the past three years. "Well, I have been studying the determinants of housing prices. I have found that larger homes sell for more than smaller homes," I told my wife with a triumphant look on my face as I held the draft of the thesis in my hands.

We were approaching the on-ramp for a highway. As soon as I finished the sentence, my wife suddenly turned the car to the shoulder and applied brakes. As the car stopped, she turned to me and said: "I can't believe that they are giving you a Master's degree for finding just that. I could have told you that larger homes sell for more than smaller homes."

At that very moment, I felt like a professor who taught at the department of obvious conclusions. How can I blame her for being shocked that what is commonly known about housing prices will earn me a Master's degree from a university of high repute?

I requested my wife to resume driving so that I could take the next ten minutes to explain to her the intricacies of my research. She gave me five minutes instead, thinking this may not require even that. I settled for five and spent the next minute collecting my thoughts. I explained to her that my research has not just found the correlation between housing prices and the size of housing units, but I have also discovered the magnitude of those relationships. For instance, I found that all else being equal, a term that I explain later in this chapter, an additional washroom adds more to the housing price than an additional bedroom. Stated otherwise, the marginal increase in the price of a house is higher for an additional washroom than for an additional bedroom. I found later that the real estate brokers in Toronto indeed appreciated this finding. I also explained to my wife that proximity to transport infrastructure, such as subways, resulted in higher housing prices. For instance, houses situated closer to subways sold for more than did those situated farther away. However, houses near freeways or highways sold for less than others did. Similarly, I also discovered that proximity to large shopping centers had a nonlinear impact on housing prices. Houses located very close (less than 2.5 km) to the shopping centers sold for less than the rest. However, houses located closer (less than 5 km, but more than 2.5 km) to the shopping center sold for more than did those located farther away. I also found that the housing values in Toronto declined with distance from downtown.

As I explained my contributions to the study of housing markets, I noticed that my wife was mildly impressed. The likely reason for her lukewarm reception was that my findings confirmed what we already knew from our everyday experience. However, the real value added by the research rested in quantifying the magnitude of those relationships.

Why Regress?

A whole host of questions could be put to regression analysis. Some examples of questions that regression (hedonic) models could address include:

* How much more can a house sell for an additional bedroom?
* What is the impact of lot size on housing price?
* Do homes with brick exteriors sell for less than homes with stone exteriors?
* How much does a finished basement contribute to the price of a housing unit?
* Do houses located near high-voltage power lines sell for more or less than the rest?

The term big data refers to data sets that are so massive, so quickly built, and so varied that they defy traditional analysis methods such as you might perform with a relational database.

A new knowledge and insights are becoming available to everyone. Big data is often described in terms of five V's; velocity, volume, variety, veracity, and value. Data mining is the process of automatically searching and analyzing data, discovering previously unrevealed patterns.

Deep learning is a specialized subset of machine learning that uses layered neural networks to simulate human decision-making.

Deep learning algorithms can label and categorize information and identify patterns.

A neural network in AI is a collection of small computing units called neurons that take incoming data and learn to make decisions over time.

Data Science is the process and method for extracting knowledge and insights from large volumes of disparate data.

Data Science is a broad term that encompasses the entire data processing methodology while AI includes everything that allows computers to learn how to solve problems and make intelligent decisions.

The Final Deliverable

The ultimate purpose of analytics is to communicate findings to the concerned who might use these insights to formulate policy or strategy. Analytics summarize findings in tables and plots. The data scientist should then use the insights to build the narrative to communicate the findings. In academia, the final deliverable is in the form of essays and reports. Such deliverables are usually 1,000 to 7,000 words in length. In consulting and business, the final deliverable takes on several forms. It can be a small document of fewer than 1,500 words illustrated with tables and plots, or it could be a comprehensive document comprising several hundred pages. Large consulting firms, such as McKinsey and Deloitte,I routinely generate analytics-driven reports to communicate their findings and, in the process, establish their expertise in specific knowledge domains.

Let's review the "United States Economic Forecast", a publication by the Deloitte University Press. This document serves as a good example for a deliverable that builds narrative from data and analytics. The 24-page report focuses on the state of the U.S. economy as observed in December 2014. The report opens with a **grabber** highlighting the fact that contrary to popular perception, the economic and job growth has been quite robust in the United States. The report is not merely a statement of facts.

In fact, it is a carefully crafted report that cites Voltaire and follows a distinct theme. The report focuses on the **good news** about the U.S. economy. These include the increased investment in manufacturing equipment in the U.S. and the likelihood of higher consumer consumption resulting from lower oil prices.

The Deloitte report uses time series plots to illustrate trends in markets. The GDP growth chart shows how the economy contracted during the Great Recession and has rebounded since then. The graphic presents four likely scenarios for the future. Another plot shows the changes in consumer spending. The accompanying narrative focuses on income inequality in the U.S. and refers to Thomas Pikkety's book on the same. The Deloitte report mentions many consumers did not experience an increase in their real incomes over the years, while they still maintained their level of spending. Other graphics focused on housing, business, and government sectors, international trade, labor, and financial markets, and prices. The appendix carries four tables documenting data for the four scenarios discussed in the report.

Deloitte's "United States Economic Forecast" serves the very purpose that its authors intended. The report uses data and analytics to generate the likely economic scenarios. It builds a powerful narrative in support of the thesis statement that the U.S. economy is doing much better than most would like to believe. At the same time, the report shows Deloitte to be a competent firm capable of analyzing economic data and prescribing strategies to cope with the economic challenges.

Now consider if we were to exclude the narrative from this report and presented the findings as a deck of PowerPoint slides with eight graphics and four tables. The PowerPoint slides would have failed to communicate the message that the authors carefully crafted in the report citing Piketty and Voltaire. I consider Deloitte's report a good example of storytelling with data and encourage you to read the report to decide for yourself whether the deliverable would have been equally powerful without the narrative.

Now, let us work backward from the Deloitte report. Before the authors started their analysis, they must have discussed the scope of the final deliverable. They would have deliberated the key message of the report and then looked for the data and analytics they needed to make their case. The initial planning and conceptualizing of the final deliverable is therefore extremely important for producing a compelling document. Embarking on analytics, without due consideration to the final deliverable, is likely to result in a poor-quality document where the analytics and narrative would struggle to blend.

### The Report Structure

Before starting the analysis, think about the structure of the report. Will it be a brief report of five or fewer pages, or will it be a longer document running more than 100 pages in length? The structure of the report depends on the length of the document. A brief report is more to the point and presents a summary of key findings. A detailed report incrementally builds the argument and contains details about other relevant works, research methodology, data sources, and intermediate findings along with the main results.

I have reviewed reports by leading consultants including Deloitte and McKinsey. I found that the length of the reports varied depending largely on the purpose of the report. Brief reports were drafted as commentaries on current trends and developments that attracted public or media attention. Detailed and comprehensive reports offered a critical review of the subject matter with extensive data analysis and commentary. Often, detailed reports collected new data or interviewed industry experts to answer the research questions.

Even if you expect the report to be brief, sporting five or fewer pages, I recommend that the deliverable follow a prescribed format including the cover page, table of contents, executive summary, detailed contents, acknowledgments, references, and appendices (if needed).

I often find the cover page to be missing in documents. It is not the inexperience of undergraduate students that is reflected in submissions that usually miss the cover page. In fact, doctoral candidates also require an explicit reminder to include an informative cover page. I hasten to mention that the business world sleuths are hardly any better. Just search the Internet for reports and you will find plenty of reports from reputed firms that are missing the cover page.

At a minimum, the cover page should include the title of the report, names of authors, their affiliations, and contacts, the name of the institutional publisher (if any), and the date of publication. I have seen numerous reports missing the date of publication, making it impossible to cite them without the year and month of publication. Also, from a business point of view, authors should make it easier for the reader to reach out to them. Having contact details at the front makes the task easier.

"A table of contents (ToC)" is like a map needed for a trip never taken before. You need to have a sense of the journey before embarking on it. A map provides a visual proxy for the actual travel with details about the landmarks that you will pass by in your trip. The ToC with main headings and lists of tables and figures offers a glimpse of what lies ahead in the document. Never shy away from including a ToC, especially if your document, excluding cover page, table of contents, and references, is five or more pages in length.

Even for a short document, I recommend an "abstract" or an "executive summary". Nothing is more powerful than explaining the crux of your arguments in three paragraphs or less. Of course, for larger documents running a few hundred pages, the executive summary could be longer. An "introductory section" is always helpful in setting up the problem for the reader who might be new to the topic and who might need to be gently introduced to the subject matter before being immersed in intricate details. A good follow-up to the introductory section is a review of available relevant research on the subject matter. The length of the literature review section depends upon how contested the subject matter is. In instances where the vast majority of researchers have concluded in one direction, the literature review could be brief with citations for only the most influential authors on the subject. On the other hand, if the arguments are more nuanced with caveats aplenty, then you must cite the relevant research to offer adequate context before you embark on your analysis. You might use the literature review to highlight gaps in the existing knowledge, which your analysis will try to fill. This is where you formally introduce your research questions and hypothesis.

In the "methodology" section, you introduce the research methods and data sources you used for the analysis. If you have collected new data, explain the data collection exercise in some detail. You will refer to the literature review to bolster your choice for variables, data, and methods and how they will help you answer your research questions.

The results section is where you present your empirical findings. Starting with descriptive statistics (**see Chapter 4, "Serving Tables"**) and illustrative graphics (**see Chapter S, "Graphic Details" for plots and Chapter 10, "Spatial Data Analytics" for maps**), you will move toward formally testing your hypothesis (**see Chapter 6, "Hypothetically Speaking"**).

In case you need to run statistical models, you might turn to regression models (**see Chapter 7, "Why Tall Parents Don't Have Even Taller Children"**) or categorical analysis (**see Chapters 8, "To Be or Not to Be" and 2., "Categorically Speaking About Categorical Data"**). If you are working with time-series data, you can turn to Chapter 11, **Doing Serious Time with Time Series.** You can also report results from other empirical techniques that fall under the general rubric of data mining (**see Chapter 12, "Data Mining for Gold"**). Note that many reports in the business sector present results in a more palatable fashion by holding back the statistical details and relying on illustrative graphics to summarize the results.

The results section is followed by the discussion section, where you craft your main arguments by building on the results you have presented earlier.

The "discussion section" is where you rely on the power of narrative to enable numbers to communicate your thesis to your readers. You refer the reader to the research question and the knowledge gaps you identified earlier. You highlight how your findings provide the ultimate missing piece to the puzzle.

Of course, not all analytics return a smoking gun. At times, more frequently than I would like to acknowledge, the results provide only a partial answer to the question and that, too, with a long list of caveats.

In the "conclusion" section, you generalize your specific findings and take on a rather marketing approach to promote your findings so that the reader does not remain stuck in the caveats that you have voluntarily outlined earlier. You might also identify future possible developments in research and applications that could result from your research. What remains is housekeeping, including a list of references, the acknowledgment section (**acknowledging the support of those who have enabled your work is always good**), and "appendices", if needed.

Have You Done Your Job as a Writer?

As a data scientist, you are expected to do thorough analysis with the appropriate data, deploying the appropriate tools. As a writer, you are responsible for communicating your findings to the readers. Transport Policy, a leading research publication in transportation planning, offers a checklist for authors interested in publishing with the journal. The checklist is a series of questions authors are expected to consider before submitting their manuscripts to the journal. I believe the checklist is useful for budding data scientists and, therefore, I have reproduced it verbatim for their benefit.

* Have you told readers, at the outset, what they might gain by reading your paper?
* Have you made the aim of your work clear?
* Have you explained the significance of your contribution?
* Have you set your work in the appropriate context by giving sufficient background (including a complete set of relevant references) to your work?
* Have you addressed the question of practicality and usefulness?
* Have you identified future developments that might result from your work?
* Have you structured your paper in a clear and logical fashion?