Narrative Science Edition

Practical Artificial Intelligence

For DUMMIES

A Wiley Brand

Learn to:

- Evaluate artificial intelligence (AI) technologies based on your business needs

- Have an intelligent conversation about AI

- Demystify the hype, fear, and confusion around AI

Kristian Hammond, PhD

About Narrative Science

Narrative Science is the leader in Advanced Natural Language Generation (Advanced NLG) for the enterprise. Powered by artificial intelligence, its Quill platform analyzes data from disparate sources, understands what is important to the end user, and then automatically generates perfectly written narratives to convey meaning for any intended audience, at unlimited scale.

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Introduction

It is amazing how many ways and how deeply we are afraid of AI.

Most of us are fairly certain that emotionless robots that look amazingly like Arnold Schwarzenegger are going to hunt us down and kill us. That goes without saying. We've seen the movie.

Failing that, we can be sure that sophisticated hyper-intelligent machines are going to rule the planet and, depending upon their mood, either enslave us in the Matrix for use as a power supply or simply exterminate us because we are annoying. Again, we're sure of this because we've seen the movie. Or they might lock us down for our own protection until Will Smith convinces one of them to think for itself and wink when he lies.

And even if we survive this and step away from Hollywood, we know that smart machines are going to take all our jobs. In factories, on the road, and even in our homes, robots will do our work for us. We won't be riding in self-driving Google cars to work because the intelligent boxes that have replaced our jobs will be sitting in our seats.

So the future of intelligent machines is our death, enslavement, or permanent unemployment. Oh well.

Fortunately, the only thing we really have to be afraid of is that artificial intelligence will come into our lives without us ever really understanding what it is or what it does. *Not knowing* is what is scary. This book is aimed at fixing that.

My goal in writing *Practical Artificial Intelligence For Dummies,* Narrative Science Edition, is to provide you with the information and tools you need to look at the growing world of cognitive computing, smart machines, machine learning, deep learning, natural language generation, speech recognition, the Turing Test, broad and narrow systems, and weak and strong

AI, and be able to turn to your colleagues and say, "Don't worry everyone, I got this!" Read on!

About This Book

Artificial intelligence (AI) is creating a great deal of hype, excitement, and fear. From killer robots who may take over the world, to supercomputers competing on *Jeopardy!,* to Siri telling us where we can grab our next sandwich, the AI landscape is vast and the potential uses are many. The purpose of this book is to help you understand AI so you can be naturally intelligent in your conversations and purchasing decisions related to artificial intelligence.

This book will give you the ability to understand the different forms artificial intelligence takes in your life today and have a conversation with someone who will make you sound really smart (added bonus!). You might not be able to build an AI system on your own, but you will know enough about how they work to decide which one you want to buy.

Getting Wise to AI

Today, we are confronted with an emerging suite of intelligent systems that do things in a way that we do not quite understand. What *is* actually frightening is that we might not know enough about these systems to be able to evaluate them appropriately. So every time a co-worker talks about deep learning or how natural language generation works, we are not sure what to believe or where to be skeptical. More importantly, when we are talking with vendors or technology providers, we often lack the information to cut through the hype and get to the truth.

Be prepared in your conversations with technology providers. Remember the old joke, "What's the difference between a software salesman and a used car salesman? The used car salesman knows when he is lying." In a world of hype, it is often hard to discount any ideas floating around for fear of being thought of as ill informed. So, like the purveyors of the emperor's new clothes, many of the "hype leaders" are getting by because they are depending on the rest of us being too afraid to ask the tough questions or express any doubt.

In This Book

For your convenience, this book is divided into chapters, each of which tackles a different subject within AI. Here's the menu for today's knowledge feast:

- ✔ Chapter 1: "Preparing for Our Robot Masters" gives you some background on AI's re-emergence and the answer to the confusing question, "What is AI?"
- ✔ Chapter 2: "Thinking about Thinking: The AI Ecosystem" provides you with the necessary tools to recognize the components of AI, particularly in those AI systems used in our everyday lives.
- ✔ Chapter 3: "Driving Intelligence with Big Data" explains how today's big data reality is fueling AI technologies, specifically in their ability to assess, infer, and predict.
- ✔ Chapter 4: "Embracing Emerging Technologies" uncovers the secrets of the new smart machines entering the market.
- ✔ Chapter 5: "Communicating with AI" delves into AI's powerful abilities with the human language, both in processing and generating it, as well as providing a glimpse into AI's future.
- ✔ Chapter 6: "Preparing for the Future and Ten Tips on How to Get There" gives you tangible steps on choosing the right AI system for your organization.

Icons Used in This Book

To help you to pick your way through the content of this book, I've flagged key information for you with a few graphical icons. Even if you don't read every word on every page, be sure to check out the paragraphs marked with any of the following icons:

This icon picks out the most important takeaways from the book. If you're the kind of person who makes a summary of the crucial info you've discovered, this icon gives you a head start in deciding what to jot down.

Although I try to steer clear of jargon and technowaffle, sometimes I just can't avoid it. However, I give you some advance warning by flagging such information with this icon.

Sometimes the world is great place, the sun is shining, and I can slip you a bit of insider knowledge to simplify things or to point you in the direction of a useful shortcut. This icon highlights these joyous moments.

Caution! May contain nuts. This icon signposts things to be cautious of, and pits to avoid falling into. If I could surround this text with red flashing lights, I would do so.

Chapter 1

Preparing for Our Robot Masters

*S*omething amazing has happened. We didn't quite see it coming, but it was, in retrospect, inevitable — the reemergence of artificial intelligence (AI). Nearly everywhere we look today, we see intelligent systems talking to us (Siri), offering recommendations (Netflix and Amazon), providing financial advice (Schwab's Intelligent Portfolio), and winning game shows (IBM's Watson). And we see systems emerging to improve voice recognition, image interpretation, face recognition, and even driving cars, based on techniques such as Google and Facebook's deep learning efforts. Other work aims to advance natural language understanding and generation (Narrative Science's Quill) so that the machines can communicate with us on our own terms.

Defining Artificial Intelligence

The resurgence of AI causes a little bit of confusion, especially since so many companies and capabilities have exploded on the scene. Where do we start making sense of it all?

Let's start with a definition. *Artificial intelligence* (AI) is a subfield of computer science aimed at the development of computers capable of doing things that are normally done by *people* — in particular, things associated with people acting intelligently.

The Dartmouth Conference

Stanford researcher John McCarthy coined the term in 1956 during what is now called *the Dartmouth Conference,* in which the core mission of AI was defined.

In the original proposal for the conference, McCarthy framed the effort with the following:

> *An attempt will be made to find how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for*

humans, and improve themselves. We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer.

— *John McCarthy, Marvin Minsky, Nathan Rochester, and Claude Shannon, "A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence" (1955)*

REMEMBER

Starting from the definition quoted in the sidebar "The Dartmouth Conference," any program is an AI system simply by the fact that it does something that we would normally think of as intelligent in humans. How it does so is not the issue; just that it is able to do it at all is the key point.

One summer turned into 60 years. Building intelligence just turned out to be a little harder than they thought.

Welcoming Back AI

AI has had a few excellent runs. In the Sixties, it was the great promise of what we would be able to do with the machine. In the Eighties, it was going to revolutionize business. But in both of these eras, the promise far outstripped our ability to deliver.

What makes the latest round of AI different? What makes today's systems different to the expert systems, diagnostic programs, or neural nets of the past?

REMEMBER

There are many reasons behind AI's rebirth, but they can be summarized into five core drivers:

- ✔ We have the raw horsepower of **increased computational resources** (our computers can think harder and faster). These techniques worked well in the past but couldn't scale up; now they run well on our expanded computational grid.

- ✔ We have an explosive **growth of data** available to our machines (our systems have more to think about). This means that learning systems in particular that get better with more data can now look at billions of examples rather than a few hundred.

- ✔ We have seen a shift away from broad AI to a deeper **focus on specific problems** (our AI applications are now thinking about *something* rather than daydreaming without focus). Systems like Siri and Cortana work within limited domains of action that can be well modeled and focused on pulling very specific words out of what you have said rather than performing language understanding in general.

- ✔ We have transformed the problem of **knowledge engineering,** or putting rules into a system, into learning. (Our systems are using rules that they learn on their own.) The bottleneck in AI systems of the past was our ability to put in all the rules needed to reason in an area (keying in five years of a medical education is hard to do). Many modern approaches are focused on learning these rules automatically.

- ✔ We have adopted **alternative reasoning models** based on the understanding that systems don't have to reason like people in order to be smart. (Let the machine think like a machine.)

All these factors together have given us the first real renaissance of intelligent machines that are now part of our lives today and being adopted as necessary tools in the workplace of tomorrow.

WARNING!

In the workplace, understanding how these new technologies work is absolutely vital. Black boxes that give us answers without explanations, or systems that fail to communicate with us, cannot become our trusted partners. We need to understand the basics of how these systems reason and the systems need to be able to explain how they come up with their answers.

Exploring AI: Weak and Strong

For some researchers and developers, the goal is to build systems that can act (or just think) intelligently in the same way that people do. Others simply don't care if the systems they build have humanlike functionality, just so long as those systems do the right thing. Alongside these two schools of thought are others somewhere in between, using human reasoning as a model to help inform how we can get computers to do similar things.

Strong AI

The work aimed at genuinely simulating human reasoning tends to be called *strong AI* in that any result can be used to not only build systems that think but also explain how humans think as well. Genuine models of strong AI or systems that are actual simulations of human cognition have yet to be built.

Weak AI

The work in the second school of thought, aimed at just getting systems to work, is usually called *weak AI* in that while we might be able to build systems that can behave like humans, the results tell us nothing about how humans think. One of the prime examples of this was IBM's Deep Blue, a system that was a master chess player but certainly did not play in the same way that humans do and told us very little about cognition in general.

Everything in between

Balanced between strong and weak AI are those systems that are informed by human reasoning but not slaves to it. This tends to be where most of the more powerful work in AI is happening today. This work uses human reasoning as a guide, but is not driven by the goal to perfectly model it. Now if we could only think of a catchy name for this school of thought! I don't know, maybe *Practical AI*?

A good example is advanced natural language generation (NLG). Advanced NLG platforms transform data into language. Where basic NLG platforms simply turn data into text,

advanced platforms turn this data into language indistinguishable from the way a human would write. By analyzing the context of what is being said and deciding what are the most interesting and important things to say, these platforms communicate to us through intelligent narratives.

REMEMBER

The important takeaway is that in order for a system to be AI, it doesn't have to be smart in the same way that people are. It just needs to be smart.

Narrow AI, broad AI, and is that AI at all?

Some AI systems are designed around specific tasks (often called *narrow AI*) and some are designed around the ability to reason in general (referred to as *broad AI* or *general AI*). As with strong and weak AI, the most visible work tends to focus on specific problems and falls into the category of *narrow AI*.

The major exceptions to this are found in emerging work such as Google's deep learning (aimed at a general model of automatically learning categories from examples) and IBM's Watson (designed to draw conclusions from masses of textual evidence). But in both of these cases, the commercial impact of these systems has yet to be completely played out.

The power of narrow AI systems is that they are focused on specific tasks. The weakness is that these systems tend to be very good at what they do and absolutely useless for things that they don't do.

Different systems use different techniques and are aimed at different kinds of inference. So there's a difference between systems that recommend things to you based on your past behavior, systems that learn to recognize images from examples, and systems that make decisions based on the synthesis of evidence.

TIP

Consider these differences when looking at systems. You probably don't want a system that is really good at finding the nearest gas station to do your medical diagnostics.

Many systems fall under the definition of narrow AI even though some people don't think of them as AI at all. When

Amazon recommends a book for you, you don't realize that an AI system is behind the recommendation. A system collects information about you and your buying behavior, figures out who you are and how you are similar to other people, and uses that information to suggest products based on what similar people like. You don't need to understand how the system works. Amazon's ability to look at what you like and figure out what else you might like is pretty darn smart.

Understanding What's in a Name

As more and more AI systems appear, we are seeing a proliferation of new names for AI (check out Figure 1-1 for some examples). In an effort to brand and rebrand, marketing departments around the globe keep trying out new words for "smart."

You can call them cognitive computing, smart machines, intelligent assistants, predictive analytics, recommendation systems, deep learning, machine learning, self-driving cars, question-answering systems, natural language generation platforms, or a host of other fancy titles. They are all names for different aspects of AI. Each in its own way is doing something that we would see as part of what it means to be an intelligent human.

Figure 1-1: The many names of artificial intelligence.

Chapter 2

Thinking about Thinking: The AI Ecosystem

"As soon as it works, no one calls it AI anymore."

— *John McCarthy*

*I*nterest and press around AI comes and goes, but the reality is that we have had AI systems with us for quite some time now. Because many of these systems are *narrow AI* and actually work, they are often not thought of as being AI. But they are smart and help us, and that's all that counts.

For a definition of *narrow AI,* turn back to Chapter 1.

Recognizing AI Is Everywhere

When Netflix and Amazon suggest movies or books for you, they are doing something quite human. They look at what you have liked in the past (evidenced by what you have viewed or purchased), find people with similar purchasing profiles, and suggest things those people liked that you haven't seen yet. Of course, some interesting nuances exist here, but see that this is what you might do yourself if you notice that two

of your friends share common interests and use the likes and dislikes of one of them to figure out a gift for the other.

TIP For now, don't get caught up thinking how good or bad recommendation engines are. Instead, focus on the ability of these systems to build profiles, figure out similarities, and make predictions about one person's likes and dislikes based on those of someone who is similar to him or her.

Asking Ourselves, "What Makes Us Smart?"

For our purposes, intelligence or cognition can be broken down into three main categories: taking stuff in, thinking about it, and acting on it. Think of these three categories as *sensing, reasoning,* and *acting*. This book does not look at robotics, so our focus on "acting" is the generation of speech.

As Figure 2-1 shows, within these macro areas, we can make more fine-grained distinctions related to speech and image recognition, different flavors of reasoning (logic versus evidence-based), and the generation of speech (and other more physical actions) to facilitate communication.

Speech   Vision

Perception

Language processing

Explanation   Assessment

Inference

Learning

Planning   Problem solving

Language generation

Speech generation
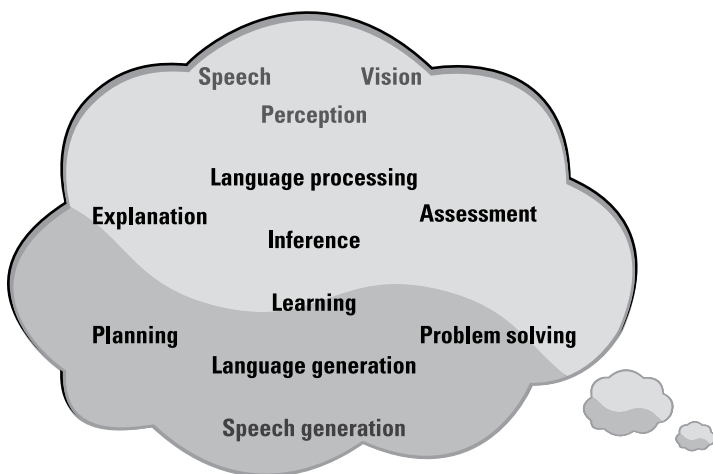
Figure 2-1: Various capabilities within the three components of AI: sensing, reasoning, and acting.

Gray areas exist among these tasks, particularly when it comes to the role of reasoning, but thinking about intelligence as defined by these three components is useful when characterizing behaviors:

- ✔ **Sensing:** Taking in sensor data about the world, including:

    - Image processing: Recognizing important objects, paths, faces, cars, or kittens.

    - Speech recognition: Filtering out the noise and recognizing specific words.

    - Other sensors: Mostly for robotics; sonar, accelerometers, balance detection, and so on.

- ✔ **Reasoning:** Thinking about how things relate to what is known; for example:

    - Language processing: Turning words into ideas and their relationships.

    - Situation assessment: Figuring out what is going on in the world at a broader level than the ideas alone.

    - Logic-based inference: Deciding that something is true because, logically, it must be true.

    - Evidence-based inference: Deciding that something is true based on the weight of evidence at hand.

    - Planning/problem solving: Figuring out what to do to achieve a goal.

    - Learning: Building new knowledge based on examples or examination of a data set.

    - Natural language generation: Given a communication goal, generating the language to satisfy it.

- ✔ **Acting:** Generating and controlling actions, such as:

    - Speech generation: Given a piece of text, generating the audio that expresses that text.

    - Robotic control: Moving and managing the different effectors that move you about the world.

Examining the Components of AI

Research in AI tends to parallel the different aspects of human and machine reasoning. However, most of today's systems, particularly the consumer-oriented products like Apple's Siri, Microsoft's Cortana, and Google's Now, make use of all three of these layers.

These systems are just one kind of animal in the new AI ecosystem and are complete, end-to-end. They make use of speech recognition and generation at both ends, and they use simple language processing to extract terms that drive a decision model, which, in turn, figures out what you have requested, and thus what task to perform. A response may then be crafted and handed to the speech generation system. The result is that each of these provides a seemingly singular experience built out of a combination of functionalities.

The following sections give you an idea of how the three aspects of intelligence — sensing, reasoning, and interacting — come together in this type of system.

Sensing

Consumer-oriented mobile assistants use speech recognition to identify the words that you have spoken to the system. They do this by capturing your voice and using the resulting waveform to recognize a set of words. Each of these systems uses its own version of voice recognition, with Apple making use of a product built by Nuance and both Microsoft and Google rolling their own.

REMEMBER

Even though these assistants can capture the words, they do not immediately comprehend what those words mean. They just have access to the words you have said in the same way they would have access to them if you had typed them. They are simply taking input like the waveform in Figure 2-2 and transforming it into the words "I want pizza!"

The result of this process is really just a string of words. In order to make use of them, these systems have to reason about the words, which includes determining what they mean, what you might want, and how they can help you get what you need. This happens by using a tiny bit of natural language processing (see Chapter 5 for more on this).

"I want pizza!"
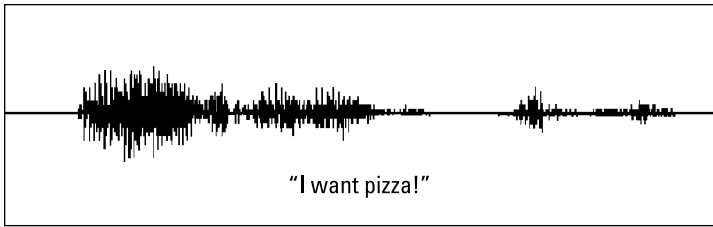
Figure 2-2: A waveform generated when an intelligent assistant captures voice.

Reasoning

While each system has its own take on the problem, they all do very similar things at this phase. In the pizza example mentioned previously, they might note the use of the term "pizza," which is marked as being food, see that there is no term such as "recipe" in the text that would indicate that the speaker wanted to know how to make pizza, and thus decide that the speaker is looking for a restaurant that serves pizza.

This is fairly lightweight language processing, driven by simple definitions and relationships, allowing these systems to determine that an individual wants a pizza restaurant or, more precisely, inferring that the individual wants to know where she can find one. Knowing what to do, however, is very different from knowing how to do it!

These transitions — from *sounds* to *words* to *ideas* to *user needs* — provide these systems with the required information to now plan to satisfy those needs. In this case, the system grabs GPS info, looks up restaurants that serve pizza, and ranks them by proximity, rating, or price. Or, if you have a history, it may suggest a place that you already like.

While the reasoning involved in deciding between different plans of action is certainly AI, the plans tend to be simple scripts for gathering information. But their simplicity should not undercut their role in an AI system. Knowing exactly what to do and when to do it is often called "expertise."

Acting

After sensing and reasoning have been enabled, the results of these systems need to be communicated to users. This involves organizing the results into a reasonable set of ideas to be communicated, mapping the ideas onto a sentence or two (natural language generation, described in more detail in Chapter 5), and then turning those words into sounds (speech generation), as shown in Figure 2-3.

"There is a pizza restaurant called Gino's about three blocks from here."

Figure 2-3: A waveform generated when an intelligent assistant generates language and speech.

Not One, But Many

For Siri and her sisters, the functionality we get is the result of the integration of multiple components. These systems, and AI systems in general, are not based on a single monolithic algorithm. They comprise multiple components and approaches to reasoning that work together or sometimes in competition to produce a single flow. There is no "one theory to rule them all." Instead, multiple approaches to the different aspects of intelligence come together to create a complete experience. The result is that each of these systems provides a seemingly singular experience built out of a combination of functionalities.

Consumer systems are designed for non-technical people. As such, they need to seem "human" as they both listen to and communicate directly with their users. Systems for the workplace are sometimes assumed not to need a strong communication layer because technical audiences are using them. This is a faulty assumption that I discuss in Chapter 5. In the meantime, the takeaway is that communication and the ability to explain turns out to be a crucial element of how we perceive intelligence and is thus a crucial component of AI systems as they enter the workspace.

Chapter 3

Driving Intelligence with Big Data

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In This Chapter

▶ Demystifying AI

▶ Assessing the world with AI

▶ Drawing conclusions using AI

▶ Predicting the future with AI's help

· ··

"But Mr. Holmes, how did you know I had been in China?"

"The fish that you have tattooed immediately above your right wrist could only have been done in China. That trick of staining the fishes' scales of a delicate pink is quite peculiar to that country. When, in addition, I see a Chinese coin hanging from your watch-chain, the matter becomes even more simple."

Mr. Jabez Wilson laughed heavily. "Well, I never!" said he. "I thought at first that you had done something clever, but I see that there was nothing in it after all."

— The Red-Headed League, *Arthur Conan Doyle*

*T*he aim of this chapter is to demystify the AI systems in use today to build a framework for understanding new systems that will enter the workplace tomorrow. I look at how AI systems reason, and in particular, how they look at the world *(assess),* draw conclusions *(infer),* and make guesses about what is going to happen next *(predict).* I also consider how these systems use data to paint a picture of a situation (transactions, links clicked, network connections, queries,

and so on), use that picture to draw conclusions (these people are the same; these products are related; this situation falls into this category), and then project that reasoning into the future (this customer will like this book; this customer is about to leave us; this machine is going to crash tomorrow).

REMEMBER

Many AI systems make use of three major components of human reasoning: assessing, inferring, and predicting. Every second of every day, we need to answer the question of what is happening around us, what it means, and what is going to happen next. When we walk up to an elevator, push the call button, and wait for the next car to show up, we are assessing, inferring, and predicting. AI systems are doing exactly the same, although they're less likely to be using an elevator to move between floors.

Thinking Hard about Big Data

In today's world of Big Data, where 2.5 quintillion bytes of data are produced every day, knowing how AI systems capture data, synthesize it, and use it to drive reasoning is most important. The application of these systems to issues of Big Data is what allows us to transform the world of numbers that the machines control into a world of knowledge and insight that we can use.

REMEMBER

The trick in understanding these systems is to see that the processes underlying intelligence are not themselves smart. Intelligent systems are built on a foundation of processes that are simple and absolutely understandable. There is no "smart box" in the middle of these systems. AI is not magic, but is instead the application of a collection of algorithms powered by data, scale, and processing power.

Big Data makes it possible for fairly simple learning systems to process the volume of examples needed to pull a signal out of the noise. Given billions of English/French pairings of sentences expressing the same idea, learning how to translate one to the other is possible. Processing and parallelism combine to enable things such as taking a thousand little pieces of evidence, testing them independently, and adding up the results. IBM Watson (which is discussed more thoroughly in Chapter 4) works because it quickly looks for evidence in thousands of documents using thousands of rules. Watson

can accomplish such a huge search in so little time because it runs on 90 machines in parallel.

Assessing Data with AI

Most of the consumer systems in use are assessing us. Amazon, for example, puts together a detailed a picture of who we are so that it can match us against similar customers and create a source of predictions about us. The data for this assessment is transactional: what we touch and what we buy. Amazon's recommendation engines can use this information in their reasoning in order to build up profiles and then make recommendations.

But profile data is only part of the picture. Added to this is information about categories that cluster objects together ("cookbooks"), categories of customers ("people who are handy"), and information based on other users ("people like you"). How much you tend to spend and where you live can be pulled in to refine the snapshots of both you and the things with which you interact.

In this instance, the result is a set of characterizations, such as:

- Given the entire collection of things you like, you are similar to this person who also reads cookbooks, science fiction, and modern biographies.
- Given a particular subset of the things you look at or what you just bought or looked at, you seem to like cooking.
- You just bought a *SousVide Supreme™ Demi Temperature Controlled Water Oven In Red*.

For retailers, the key pieces of information are transactions, clusters of people, and product categories. For social networks (such as Facebook), the important details are "Likes," the people in your friends network, and the information you provide in your "About" profile. For search engines, the crucial bits of data are the history of terms you have searched, items you have clicked on, your location, and any other information that can be gleaned from your interactions with the engine and its applications.

The sheer volume of the number of transactions often drives these systems. Even with very weak models of the world, systems can sift out relevant data from the noise because they have so much to work with. And the more we interact with these systems, the more they can learn about us. For example, by analyzing 3.5 billion searches a day, Google learns which words show up together and which ordering of them makes the most sense. The Google Instant service uses the history of not just you, but everyone, to create a predictive model: When you type "what is good for," Google provides helpful suggestions such as "a hangover."

> **TIP** Systems aimed at predicting specific outcomes such as customer churn and equipment down time almost always make use of historical information and rules related to those issues. However, incorporating a variety of data, including interactional data (what was customer sentiment during a conversation with a call center agent?) and environmental data (what was the weather like when the machine broke down?) makes the learning algorithms more accurate than relying on the volume of data alone.

Inferring Knowledge with AI

Once you know a little about the world, you can start thinking about extending that knowledge and start making inferences.

Inference is perhaps the most misunderstood aspect of artificial intelligence because inference is usually thought of as consisting of "if-then" rules. While this is a fine characterization of the basic layer of intelligent systems, it's like describing human reasoning as "just a bunch of chemical reactions."

A more powerful approach is to start with the idea of relationships between things; objects and actions, profiles and categories, people and other people, and so on. Inference is the process of making the step from one thing to the other.

Sometimes this process can look like a simple "if-then" rule. A captain outranks a sergeant, so Captain Douglas outranks Sergeant Philips. This is simple deduction, where anyone — human or machine — has no choice but to make this inference.

But the world is usually not so clear cut. This sort of inference is rare and you can do very little with it. To go beyond such purely deductive reasoning, you have to step into the world of evidence-based reasoning, which includes assessing similarity, categorizing, and amassing points of evidence, as outlined in the next section.

Checking similarity

When Amazon's engine recommends a book, it first considers who I am similar to and what category of reader I might fall into. The engine bases this consideration on how close my profile is to that of other customers or to a generic profile that defines a category. The match is rarely perfect, so the system needs to judge how well my profile lines up with others. It has to come up with a score indicating how similar the profiles are. It considers which features in the profiles match (providing evidence for the inference) and which features don't match (providing evidence against the inference). Each feature that matches — or doesn't match — adds or subtracts support for the inference I want to make.

Categorizing

For categorization, techniques such as *Naïve Bayes* (using the likelihood associated with each feature that it implies membership in a group) can be used to calculate the likelihood that an object with a particular set of features is a member of a particular group. This technique adds "walks like a duck," "quacks like a duck," and "looks like a duck" to determine that a thing is, in fact, a duck. The power of *Naïve Bayes* is that the systems that use it do not require any prior knowledge of how the features interact. *Naïve Bayes* takes advantage of the assumption that the features it uses as predictors are independent. This means systems making use of the technique can be implemented easily without having to first build a complex model of the world.

Amassing evidence

While rules drive inference for most AI systems, almost all the rules include some notion of evidence. These rules can both collaborate and compete with each other, making

independent arguments for the truth of an inference that has to be mediated by a higher-order process. At the core of these arguments are quantitative scores and thresholds, but the conclusions that are drawn using them are more qualitative in feel. For example, an advanced natural language generation system can take in data and generate the following: "Joe's Auto Garage has engaged in suspicious activity by making multiple deposits in amounts that are just below the federal reporting thresholds. There are ten deposits of $9,999 over a six-week period."

Predicting Outcomes with AI

One focus of reasoning is particularly useful: prediction. Making guesses about what is going to happen next is important so that we can deal with predicted events and actions appropriately. Unsurprisingly, AI systems have the same focus.

How do retailers guess at what we will want to buy next? In part, they look at what people similar to us have bought or watched before and project their actions onto ours. In essence, as shown in Figure 3-1, they are reasoning in the following way: "Both you and Bob like snowboarding, kick boxing, and skydiving. I know Bob likes water skiing. I bet you would too." Now multiply Bob by more than 270 million users, and that's how a company can predict what you might like.

eHarmony is smarter than you think!

Interested in finding a mate? eHarmony is smarter than you think. Some dating sites use your profile to predict compatibility based on overall similarity and have remarkable success rates, resulting in one-third of married couples in the United States meeting online. While these profiles contain explicitly expressed preferences, the core concept of using features to characterize you and evaluate your similarity to others and make predictions is used everywhere. And no one wants to think that a machine that introduced him or her to the love of one's life is anything less than brilliant.

Bob's Purchases   **Your Purchases**

Python For Dummies ——————————— Python For Dummies

Advanced JavaScript ——————————— Advanced JavaScript

Intro to AI ——————————————————— Intro to AI

Natural Language Processing ————— Natural Language Processing

Intro to Predictive Analytics ————— Intro to Predictive Analytics

Data Science for Beginners

Recommendation

Bob   You
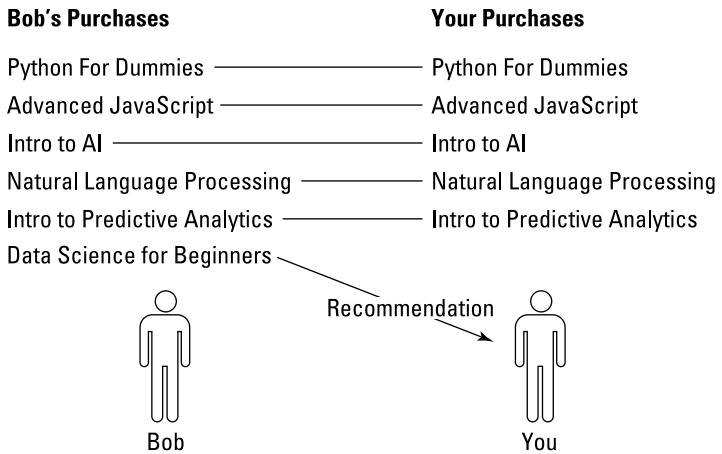
Figure 3-1: The book titles above these two figures represent previous pur-
chases. You are likely to purchase *Data Science For Beginners*
based on collaborative filtering.

This combination of calculating similarity and projecting for-
ward based on that similarity is called *collaborative filtering*
and is at the center of most transactional recommendation
systems. They are based on the intuition that people who
seem similar along a set of dimensions will be similar across
others as well.

A somewhat different take on predictions is to use profiles to
classify individuals (and their behaviors) into groups that have
similar behaviors. Target used this approach to map shop-
ping behaviors onto groups such as "pregnant women" — and
caught some flack about it. The company used this mapping to
aggressively advertise to women whom they inferred as preg-
nant with products they predicted these women would want.
Although the technique was fairly accurate, Target quickly
discovered that very few customers wanted their pregnancies
to be announced to their families by a retail store.

Actions or features are often so tightly linked that strongly
predicting one from the other becomes possible. People who
buy coffee makers will buy filters. Viewing *Star Wars* suggests
that you will view *The Empire Strikes Back.* And opening a
checking account implies that you will be making deposits.
Such predictions leapfrog the need to find similar individuals
or categorize things into groups.

The goal of prediction is often not to recommend things to an individual but instead to anticipate a problem to be avoided. The target is the prediction itself, rather than the person who is receiving it.

The systems that focus explicitly on outcomes rather than recommendations tend to make use of *data mining* or *machine learning*. These systems build rules that connect visible features at one point in time (too many dropped calls) with events that need to be predicted (we're going to lose this customer) by looking at the frequency of the initial features compared to examples of what the system is trying to predict. They ask, "What is going to predict *this*?" — where *this* can be, for example, someone buying a product, canceling a service, or even starting a cyber attack. Using techniques such as *regression analysis* (a statistical capability that estimates the relationship among variables), they build rules that can be used to predict the events we care about before they occur.

The dynamic of assessing, inferring, and predicting is at the core of many intelligent systems and certainly at the core of most of those with which we interact. The reason for this is clear. For any intelligent system — including us — the ability to understand what is happening right now, make inferences about it, and predict what is going to happen next is crucial to the ability to anticipate the future and plan for it.

Chapter 4

Embracing Emerging Technologies

"Some people worry that artificial intelligence will make us feel inferior, but then, anybody in his right mind should have an inferiority complex every time he looks at a flower."

— *Alan Kay*

*T*his chapter is about the emerging technologies starting to enter our world. Here I look at IBM's Watson, deep learning by Google and others, including predictive analytics and machine learning.

Getting to Know Smart Machines

As we look at AI systems, we tend to want them to fail. It would be easier for us emotionally and philosophically if we lived in a world in which we were smarter than our machines.

The problem with this view is that much may be gained from the world of intelligent machines. They help us solve wide ranges of problems and do so in a way that avoids the various

biases and prejudices that often stand in the way of us getting to the answers we need. For example:

- ✔ Consider what it would be like to have a system that could look at massive volumes of text, apply thousands of rules that link together questions and possible answers, and build up evidence for believing an idea. That's Watson.

- ✔ Imagine starting with an incredibly detailed set of features that makes no sense to you and having a system recognize and categorize things in a way that does make sense. That's deep learning.

- ✔ Envision being able to anticipate, and therefore avoid, problems before they arise. That's predictive analytics.

This chapter looks at all three.

Gathering Evidence: Watson

Watson is the only software system to have its global debut broadcast on national television. Going head-to-head against acclaimed brainiacs Ken Jennings and Brad Rutner, Watson demonstrated that it could not only be smarter than people, it could be smarter than people in an arena that seemed to define smartness. Even more important, it was smarter using techniques that seemed uncannily similar to the way our own minds work.

Watson is an evidence engine. Starting with a question, a list of symptoms, or a set of financial goals, it provides an answer, a diagnosis, or advice by building up an argument for the truth of competing responses. It fires off thousands of rules that map its information needs onto patterns of answers in the text that it reads. Each rule has a weight associated with it so that rules with the same answer can reinforce each other while rules with different answers compete. At the end of it all, the answers with the best overall value bubble to the top.

Watson starts with language and has a wide range of techniques for mapping questions and queries onto a *focus* for its own reasoning. These include rules of syntax (such as knowing that the subject of a verb comes before it), semantic components (such as knowing that France is a country), and some special rules for certain domains such as knowing that

diagnostic queries consist of lists of symptoms. These techniques allow Watson to determine its *focus.*

When looking at a question like "What is the best financial instrument for long-term retirement planning?" Watson understands that "what" means it is looking for a thing, "financial instrument" defines the class of things it is looking for, and "long-term retirement planning" defines the role this object has to play. This is the *focus.*

Watson then applies rules for finding information in the corpus of text it has available. These rules look for patterns in the text that link elements of the query to possible answers. Each rule, with the information from the *focus,* is sent out to find patterns in the text and propose an answer.

The weights for each of the rules that point to any given answer are summed up, giving the score for each possible answer. The answer with the highest score wins.

Some rules may match against patterns where the "X" is "Roth IRA" while others match against text where the answer seems to be "401(k)." Depending on how many rules provide evidence for each answer and what their weights are, one of these ends up the winner.

Watson has a learning component. It learns the weights of each of the rules by looking at questions and known answers and then modifies the weight of each rule depending on how well it gets to the correct answer. In effect, Watson learns how well each of the pieces of its own reasoning is working and rewards those that work best.

REMEMBER Although Watson uses rules, it uses them in a very different way than the "if-then" model we often think of when considering AI. Watson makes its inferences by building up and evaluating evidence. When Watson learns, it doesn't learn about the world. It learns about itself.

WARNING! The only caveat about these types of systems is, although they are quite adept at explaining the world around them, they still struggle to explain themselves. In order to truly partner with us, they need to learn to talk to us about the method behind their madness in a language we can understand.

Networking: Deep Learning

While Watson is trying to infer answers to questions by looking for evidence in vast stores of text, companies such as Google and Facebook are trying to recognize and categorize objects, words, and relationships by taking huge feature sets and learning to assess them.

In order to index images effectively ("this is a house" rather than "this is a collection of pixels") or recognize words in audio signals, you need to determine how the initial features can be mapped to more complex features. For example, you need to map pixels or waveforms to lines, curves, or the sounds of "p" and "q." You have to transform features that are too detailed into more recognizable features that support indexing and inference. This is deep learning.

Deep learning is based on reasoning using *neural nets.* This kind of learning makes use of layers of input nodes sending signals to a series of internal layers of nodes (called *hidden layers*), each of which sends signals to the next layer until the output layer is reached. No single node does all the work, and the network as a whole produces the result for any given input. Work in deep learning is inspired by the layering of computation that takes place in the cerebral cortex of the human brain.

Each of the connections between the nodes has a weight associated with it that is adjusted during learning. On the input side we might have all the pixel values of an image with output values that stand for a category like "cat" or "house." If the output determined by the passing of values through these links is not the same as the output value set by the category, each node failing to match sends a signal back indicating that there was an error and the weights on the relevant links must change.

Over time, these tiny changes steer the network toward the set of weights that enables the network to correctly assess that a new input is in the appropriate category. The activations sent from one side of the network result in the right values at the other end.

Deep learning systems learn in either supervised or unsupervised modes:

> ✒ In *supervised mode,* the network is taught with examples used as input while the output layer is locked down to values associated with a category. The output layer is exactly that: the output.
>
> ✒ In *unsupervised mode,* both the input and the output are locked down to the example being processed. The inner layers are more compressed than the outer layers so the network has to learn to compress its features such that they can still be used to represent the example. Here the inner or hidden layers end up being the output.

With enough time and enough examples, deep learning systems can learn about new features that may be used to support inference, by combining lower level features that cannot do so on their own.

WARNING!

The only downside of using techniques such as this is that they are somewhat impenetrable. It is hard for these systems to report on the features that they have discovered. They lack the crucial ability to explain themselves. This means they may be in a position of making decisions for you based on analysis that you can never see or understand.

Anticipating the Outcome: Predictive Analytics

Just as Watson is aimed at inference and deep learning is aimed primarily at assessment, predictive analytics is aimed at the third piece of our practical AI puzzle: prediction.

REMEMBER

The three integral components of AI are:

> ✒ Assessment
>
> ✒ Inference
>
> ✒ Prediction

But prediction is the prize!

Like both Watson and deep learning, work in predictive analytics leverages learning. The goal of the work is to craft a relationship between some set of visible features and

outcomes. We start with what we want to know, such as when a cell phone user is going to drop our service, when someone is laundering money, or when someone is going to default on a loan. We want to identify the features that can predict (or perhaps explain) these events so that we can anticipate them.

REMEMBER The work of predictive analytics makes use of a wide variety of techniques. On the more formal side, systems use techniques such as *regression analysis* aimed at crafting a mathematical model that links a source (the features you see) and the target (the feature you care about). For situations where a single metric is being tracked over time, *time series analysis* allows a system to project the path of a metric into the future given past behavior. And we often see the use of machine learning techniques such as *Naïve Bayes* where individual features and their predictive power are combined together to produce a single result or even *neural nets* such as those used in deep learning.

Although some of these techniques have their roots in statistics and others in artificial intelligence, the difference between them is primarily the words used to describe them. In statistics, you use examples to calculate the probabilities that link features together. In AI, you learn them. But for both, you end up with a link between features you know and a prediction you want to make.

Predictive analytics is useful in a wide variety of places: for example, fraud detection, customer retention, risk management, direct marketing, and even cross-selling. The core techniques can be used anywhere there is historical data that includes both features that you know and features that you want predicted.

The issue of applicability comes down to the question of whether you have the data and if a real relationship exists between what you have and what you need to know. With the appropriate data, companies reap tremendous benefits from the application of predictive analytics applied to their business goals. But — and this is crucial — you must have the data.

REMEMBER These techniques, as with all of the others I have discussed, depend on the volume, quality, and appropriateness of the data. They are not magic; they are simply the intelligent application of techniques against data.

Chapter 5

Communicating with AI

> *"I'm a great believer that any tool that enhances communication has profound effects in terms of how people can learn from each other, and how they can achieve the kind of freedoms that they're interested in."*
>
> — *Bill Gates*

*T*his chapter is about language. In particular, it is about the power of language in communication and the role of language in intelligent systems. The focus is on the two ways in which machines deal with language: understanding and generation. I also look at why machines need to use natural language to successfully partner with us in the workplace.

Understanding Language

The main aspect of intelligence separating humans from other animals is our use of language. We are unique in our ability to articulate complex ideas, explanations, and series of events as well as understand them when told to us by others. Thousands of other abilities also contribute to our intelligence, but the use of language as a means of communicating complicated ideas trumps them all.

REMEMBER

For intelligent systems to partner with us in the workplace or elsewhere, they must genuinely understand us and then communicate what they are doing back to us in a way that we can comprehend.

Unsurprisingly, the one method proposed to test for intelligence in machines — the *Turing Test* — uses language at its core. The Turing Test is designed around an intelligent system's ability to have a convincing conversation with us. Although passing the test does not require all that much more than we would expect of a dinner companion, it has become the gold standard for evaluating AI.

Our willingness to accept Siri and other personal assistants as intelligent is based almost entirely on their ability to interact with us using spoken language. The fact that their ability to do things for us is somewhat limited is far less important to us (or even noticeable to us) than the fact that they use language.

Processing Language

The goal of *natural language understanding* (NLU) systems is to figure out the meaning of language inputs: the words, sentences, stories, and so on. Systems aimed at this problem use a combination of three different kinds of information:

- ✔ **Pragmatics:** Contextual information such as lists or descriptions.
- ✔ **Semantics:** The meaning of words and how those meanings can be combined.
- ✔ **Syntax:** The structural relationships among types of language elements such as nouns, verbs, adjectives, prepositions, and phrases.

Navigating deep and shallow waters

Establishing the syntax rules that make up the grammar of a particular language is fairly straightforward. However, the semantics and pragmatics of doing so make things tricky.

"Tricky" is perhaps understating the challenge faced, in that the complexity related to these two issues forces a trade-off when building language understanding systems. You can do either of the following:

- ✔ Build a system that is extremely narrow but fairly deep with regard to what it can understand
- ✔ Build a system that is broad but very shallow in what it can determine from the words it is given

A deep system understands beyond the information explicitly in the text. For example, being able to read "Bob hit a car because he was drinking coffee on the way to work," and determining that happened in the morning is an example of deep understanding. The time of day wasn't stated but people tend to drink coffee and start the workday in the morning. Here, syntax, semantics, and pragmatics are all working together.

However, most language processing systems encountered in both consumer and enterprise systems tend to be broad and shallow. For example, Siri doesn't understand what you really mean when you talk with her but is able to identify some basic needs that you might be expressing.

Getting started with extraction, tagging, and sentiment analysis

Natural language processing (NLP) systems pull out specific pieces of information rather than figuring out how those pieces of information are connected. They focus on extracting company names, people, and organizations, tagging text as to the topic (for example, politics, finance, or sports), and evaluating sentiment. These systems tend to be used for analysis of news and for social media tracking of attitude and opinion. Combining entity extraction with sentiment assessment, these systems provide companies, politicians, and brands with a sense of what people are saying about them.

Extraction is usually the result of combining syntactic rules (proper names tend to be capitalized, names follow titles, and so on) with actual lists of the people, places, and things that can be recognized, including terms culled from Wikipedia and

similar websites. Both topic tagging and sentiment analysis are accomplished by calculating the probability of documents falling into particular topic and sentiment categories based on the probabilities associated with the words within the documents.

The language understanding systems associated with applications, while narrow in scope, provide us with the ability to articulate our needs directly to these systems. Because the systems themselves are narrow in scope, they provide the level of functionality we need. Siri and Watson don't need to understand us when we ask them to do things that they simply cannot do.

Generating Language

While systems that understand language are limited at the time of writing, the level of understanding they provide is aimed directly at the systems they support. So the systems that we see entering the workplace can understand language well enough to work with us. The question now is whether they can explain themselves to us.

The goal of *natural language generation* (NLG) systems is to figure out how to best communicate what a system knows. The trick is figuring out exactly what the system is to say and how it should say it.

Unlike NLU, NLG systems start with a well-controlled and unambiguous picture of the world rather than arbitrary pieces of text. Simple NLG systems can take the ideas they are given and transform them into language. This is what Siri and her sisters use to produce limited responses. The simple mapping of ideas to sentences is adequate for these environments.

Explaining how advanced NLG systems explain

In the workplace, where we are now surrounded by petabytes of raw data as well as the additional data sets created by business intelligence tools, machine learning, and predictive

analytics systems (as well as other AI systems), we need more than the simple generation of words for every fact that is now at the machine's disposal. For this world, we need advanced NLG systems, such as Narrative Science Quill.

The job of advanced NLG is to examine all the facts that they have access to and establish what they are going to include in the report or message they are producing. They have to then decide on the order and organization of the communication. At the end of this filtering and organization process, they then have to map the ideas that they want to communicate into language that is easy to understand and tailored to a specific audience.

REMEMBER

Advanced NLG systems have to determine what is true, what it means, what is important, and *then* how to say it.

For example, in writing a report for a fund manager focused on the performance of his fund against a benchmark, you would want to first figure out how the fund performed in the absolute (3 percent return this quarter), how this compares to the benchmark (beat the S&P 500 by 1.3 percent), and then which decisions had the most impact on this performance (heavily weighted toward technology, and Apple stock in particular). By focusing on large changes, the greatest impact, and the most significant differences, you end up with the most meaningful set of ideas. Other facts that have less impact (for example, the fund and the benchmark had exactly the same levels of investment and balance of stocks in the retail category) are mentioned only if the document being produced is designed to be exhaustive.

After this kind of analysis is complete, the language part of advanced NLG kicks in and the idea and its organization are mapped onto language.

The output of these systems is pretty remarkable. For example, Quill wrote the article in Figure 5-1!

Investing 2/16/2012 @ 3:19PM 7,478 views

Forbes Earnings Preview:
Chesapeake Energy

By Narrative Science

Comment Now

Analysts expect decreased profit for **Chesapeake Energy** (CHK) when the company reports its fourth quarter results on Tuesday, February 21, 2012. Although Chesapeake Energy reported profit of 70 cents a year ago, the consensus estimate calls for earnings per share of 59 cents.

What to Expect:

Over the past three months, the consensus estimate has fallen from 62 cents. For the fiscal year, analysts are expecting earnings of $2.80 per share.

Revenue is expected to be $3.04 billion for the quarter, 53.9% higher than the year-earlier total of $1.98 billion. For the year, revenue is project at $11.97 billion.

Trends to Watch F

Source: Forbes.com

Figure 5-1: An article written entirely by Quill, an advanced natural language generation platform.

Visualizing data is not enough

Although other methods of communication, such as dashboards and visualizations, have made great strides, these approaches are simply other ways to expose data and the results of analytics. But graphs showing costs, sales, performance of competitors, and macro-economic factors cannot file a report telling you that you have beaten the pack by reducing prices at the beginning of an economic upswing. If all you have is the graphs, you have to figure that out by yourself.

By their nature, visualizations of data do not explain what is happening but primarily give you a different take on the data. They often require someone who is data savvy to do it for you. As Figure 5-2 attests, visualizations still require interpretation.
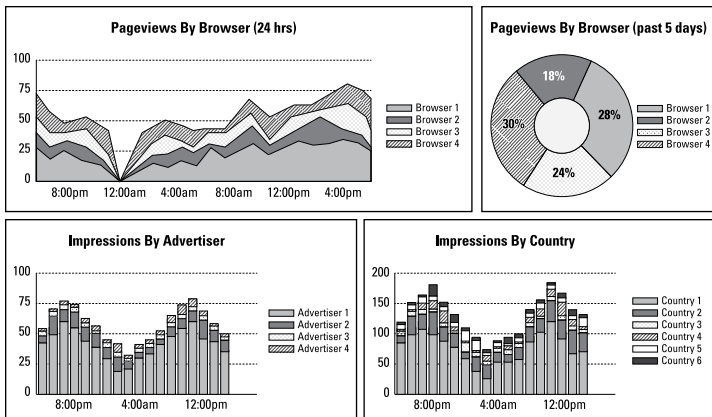
Figure 5-2: A dashboard with visualizations that are difficult to interpret.

Advanced NLG is aimed at reducing, or even eliminating, the time needed to analyze data and communicate the results. The results can be very useful to people who either don't know how to analyze the data or simply don't have time.

These systems combine the power of data analysis with the focus it provides for communication. For example, if you want to know if a company is doing better or worse over time, you need to do a time series analysis of the metrics you care about — probably revenue, costs, and profits. The analysis is exactly the same, although with different metrics, for the performance of an athlete, students, FitBit user, or power plant. When a system knows what to say, how to say it is the easy part. This is what gives advanced NLG the ability to scale.

TIP Question "black boxes." As new technologies move into the workplace, we will be confronted with an interesting problem. We will have systems in place, including AI systems that can provide us with answers. But if we are to partner with these systems, we need more than answers. We need explanations.

The role of language in intelligent systems is crucial if we are to work with them as partners in the workplace. Systems that demand blind faith in their answers or require that we all develop skills in data analytics and the interpretation of dashboards are not enough. They force us to come to the machine

and deal with it on its terms. We need intelligent systems that come to us on *our* terms by understanding what we need and then explaining themselves and their thinking to us. These systems are possible through language understanding and advanced NLG.

Chapter 6

Preparing for the Future and Ten Tips on How to Get There

In This Chapter

▶ Getting ready for what lies ahead

▶ Working out how to be prepared

· ·

*L*et me take you on a journey. This chapter steps forward in time to offer you ten great tips for being prepared for what lies ahead — now.

Seeing into the Future

In the future — and I attach no date to this prediction — you'll be on your way to work when you receive your personalized report on how sales are doing across the country. This report highlights drivers, how various strategies have affected sales, and suggestions on how to achieve your goals. The report will be an interactive window where you ask questions and receive immediate feedback.

When you arrive in the office, you will have a conversation with your virtual assistant about how your company and products are perceived across the globe. The assistant will tell you where the information is coming from and how you might redirect it.

When you walk into the factory, the machine itself will be able to communicate with you regarding its utilization, what part needs repair or replacement, and where potential bottlenecks may arise. The factory as an independent agent has already been managing the orders and modification of workflow, but you are kept in the loop so that you can question the factory's assumptions and conclusions. And you may get an alert at noon about a weather issue in Bolivia that could affect one of your suppliers.

Every interaction will be with systems that do their jobs well and know how to communicate with you. They will be partners. They'll also be machines.

Acting in the Present: Ten Tips for Moving Forward

That was the future; this is now. You may well be asking how to build a solid foundation for what lies ahead.
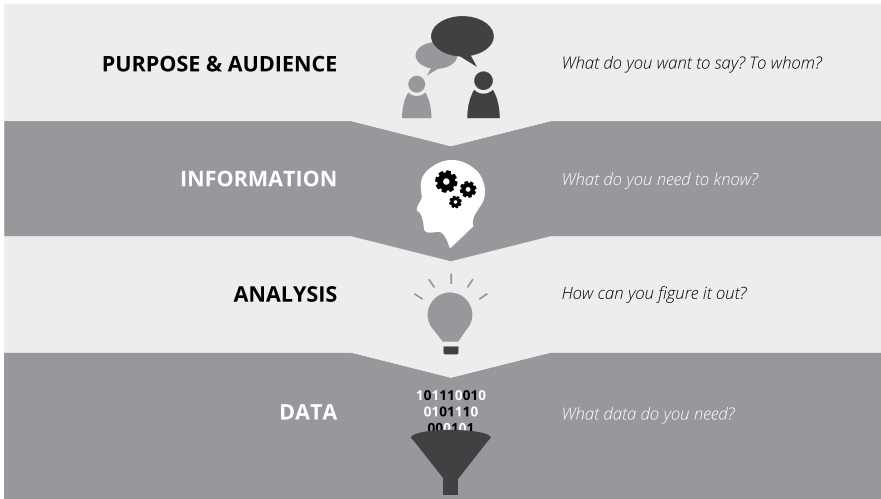
To achieve partnership with your systems, be mindful about what you buy and build. Here are my top ten tips for doing so:

1. **Remember that your goal is to solve real business problems, not simply to put in place an "AI strategy" or "cognitive computing" work plan.** Your starting point should be focused on business goals related to core functional tasks.

2. **Be aware of the landscape, but do your homework and understand the length and breadth of the systems that are available.** Most systems do only part of the job, so be careful not to wedge them into tasks for which they are not suited.

3. **Focus on your data.** You may very well have the data to support inference or prediction, but no system can think beyond the data that you give it.

4. **Know how your systems work, at least at the level of the core intuition behind a system.** Don't let anyone convince you that the system he or she has built is magic or too complex for you to understand.

5. **Don't confuse machine learning with other forms of reasoning.** When you are told that a system uses machine learning, always ask: What is the system learning and how does it use the information it learns?

6. **Always remember the trade-off between depth and breadth.** Any system that is broad is proportionally shallow. If a system understands all language, it doesn't understand it deeply.

7. **Understand how a system will fit into your workflow and who will use it.** Determine who will configure it and who will work with the output.

8. **Remain mindful that you are entering into a human-computer partnership.** AI systems are not perfect and you need to be flexible. You also need to be able to question your system's answers.

9. **Always think about how your systems are going to communicate with you and anyone else who uses them — internally or externally.** Answers alone will not help you understand what your intelligent system is thinking. You need explanations that allow you to evaluate your system's results as well as just use them.

10. **Remember the story of the emperor's new clothes.** You get to say that you don't understand how a system works. Your vendors, IT team, and data scientists are tasked with making sure you understand what your systems are doing.

Tell the stories hidden in your data.

"Thousands of abilities contribute to our intelligence, but the use of language as a means of communicating complicated ideas trumps them all." —Chapter 5, *Practical Artificial Intelligence For Dummies*

PURPOSE & AUDIENCE		*What do you want to say? To whom?*
INFORMATION		*What do you need to know?*
ANALYSIS		*How can you figure it out?*
DATA	10 11 01 0 / 0 01 1 0 / 0 0 1 1	*What data do you need?*

Visit *www.narrativescience.com* to learn how Quill™, an advanced natural language generation (advanced NLG) platform, utilizes artificial intelligence to turn data into narratives.

Quill starts by understanding what you want to say, identifies the metrics necessary to meet that purpose, performs the required analysis to figure out what is most interesting and important, and pulls in the right data. The result is a natural language explanation that is easy to understand and tailored to a specific audience.

Quill is being utilized by leading enterprise customers to improve employee productivity, enhance customer engagement, and realize the full potential of their data, at machine scale.

NarrativeScience
Tell the Stories Hidden in Your Data™

info@narrativescience.com | 🐦 @narrativesci

Artificial Intelligence has re-emerged! Are you ready?

Artificial Intelligence (AI) is creating a great deal of hype, excitement, and fear. The aim of this book is to arm you with the tools you need to de-mystify the hype, understand how and where you can apply practical AI, and eliminate any fear you may have, as the truly frightening notion is trying to evaluate these systems without the appropriate information. You will not only be able to answer, "What is AI?" but you will also become proficient in the key components of AI to understand how they can be utilized to solve real business problems and drive results.

- *AI basics — understand how AI makes use of the major components of human reasoning*

- *AI in our everyday lives — unveil the secrets behind Siri and her sisters*

- *AI and Big Data — learn how data, scale, and processing power have altered the landscape in favor of AI*

- *AI and natural language — discover AI's most sophisticated and promising capability*

Kristian Hammond is the co-founder and Chief Scientist at Narrative Science, a technology company that invented an artificial intelligence platform, Quill. In addition to being Narrative Science's Chief Scientist, Kris is a professor of Computer Science and Journalism at Northwestern University. Prior to joining the faculty at Northwestern, Kris founded the University of Chicago's Artificial Intelligence Laboratory.

Open the book and find:

- **Practical tips on how to solve business problems with AI**

- **Resources on how to properly evaluate (and not get duped by) AI systems**

- **Information on how to partner and communicate with smart machines**

- **The astounding possibilities in store for AI's future**

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