


AI



FOR

MARKETING

AND

PRODUCT INNOVATION

DR. A.K. PRADEEP | ANDREW APPEL | STAN STHANUNATHAN

AI

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MARKETING

AND

PRODUCT INNOVATION

Powerful New Tools for Predicting Trends,
Connecting with Customers, and Closing Sales

WILEY

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be put to work to gain a competitive advantage in today's increasingly digitally driven economy? What do smart marketers want and need to know about the fascinating fields of AI and ML in order to understand and apply them to real-world business challenges?

This book is based on real-life examples of AI and ML at work. Techniques described in the book have become algorithms. The book describes the complementary disciplines of ML and AI so that readers can gain a better grasp of the new world we are already living in. This book outlines the resources, the skills, the best practices, the terminology, and the metrics required to harness the unparalleled and rapidly expanding power of these twin technologies.

But beyond serving as a marketer's primer on this most timely subject, this is also a book that seeks to encourage the creative community to embrace and employ AI and ML in ways that speak centrally to the human mind and spirit. There is a reason the word "elevate" is used in these pages.

The most effective sales methods, messages, and new product ideas are those that resonate most deeply and meaningfully with consumers at the non-conscious level. AI and ML can deliver tools that aid both marketers and creatives in discovering and developing those messages and product innovations.

The book is not a repeat of well-understood marketing techniques and terminology, but rather looks at the same areas through the lens of Machine Learning and Artificial Intelligence.

This is not a coffee-table book. This is a *desktop* book – designed to be an at-hand resource, a reliable guide, and a source of inspiration for successful product innovation and marketing in the exciting new Age of AI.

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INTRODUCTION

There is such a volume of information, speculation, hype, fear-mongering, and futuristic fantasies surrounding Artificial Intelligence. A simple description penned in 1968 by Stanley Kubrick and Arthur C. Clarke in *2001: A Space Odyssey*, with added comic relief from state-of-the-art systems, seems like a good place to start.

Dave Bowman: Hello, HAL. Do you read me, HAL?

Alexa: I cannot read you, would you like to buy a book?

Siri: Hello, HALLO – greetings.

HAL: Affirmative, Dave. I read you.

Dave Bowman: Open the pod bay doors, HAL.

Alexa: Coffee pods are on sale, \$19.99/lb, shall I order one?

Siri: iPods once open will lose warranty.

HAL: I'm sorry, Dave. I'm afraid I can't do that.

Dave Bowman: What's the problem?

Alexa: There is no problem.

Siri: I am sorry, I don't understand that. Please try again.

HAL: I think you know what the problem is just as well as I do.

Dave Bowman: What are you talking about, HAL?

Alexa: What would you like to talk about?

Siri: Sorry for being obtuse.

HAL: This mission is too important for me to allow you to jeopardize it.

Machine Learning uses statistics to develop self-learning algorithms that work by way of trial and error, but Machine Learning is nothing new to Artificial Intelligence. In fact, it's the standard approach. Machine Learning–powered algorithms are used for marketing, manufacturing, medical research, speech recognition, and many other fields. Machine Learning basically recognizes *patterns* in enormous batches of existing data (a.k.a. Big Data), and uses this information to identify *similar* patterns in future data.

To put it simply, Artificial Intelligence sets up the initial set of rules to maximize the performance of a task, while Machine Learning constantly adjusts its own actions to improve at said task.

A more recent form of Machine Learning is called Deep Learning (DL). Deep Learning typically involves multilayered neural networks to perform a variety of input–output modeling tasks. Deep Learning networks typically deal with Big Data – hundreds of billions of data points, enough to yield useful information about human behaviors.

Deep Learning typically involves an artificial “neural network,” which is a digital network that supposedly mimics a biological nervous system. Neurons are basic brain cells, the building blocks of our brains that enable us to do everything that we do, from breathing to composing symphonies.

Deep Learning techniques have led to amazing progress in signal processing, voice understanding, text understanding, and image recognition, to name a few. These are complex problems that have challenged programmers for decades. In these fields and others, more progress has been made in three years using Deep Learning techniques than was made in 25 years of old-style, rule-based Artificial Intelligence.

Deep Learning has been more successful at “modeling the mind” than its predecessors, with the downside being the “physics” of the problem is obscured in the black box. Other than validation through

data sets, the humongous “curve fit” which is Deep Learning rarely lends itself to further inquiry regarding the physics of the problem.

Natural Language Processing is an Artificial Intelligence capability in which computers interact with humans using natural-sounding human language, either in written or spoken form. This feat is accomplished by way of analyzing Big Data in order to process written or spoken “keywords” to formulate an answer. Many companies that deal in customer service these days incorporate some sort of NLP Chatbot component into their business practices. Some of these bots sound eerily human. How many of us have started talking to a caller, only to realize we were talking to a machine?

Yet, for all their seemingly magical powers, a machine is still just a machine. That vacuum cleaner can’t really *see* (and doesn’t really care about) your cat. And a car that drives itself has no idea where it is going. In fact, it has no ideas at all. It has only a series of sophisticated algorithms, which the car’s computer has been programmed to follow.

A machine merely *mimics* certain cognitive functions that human beings recognize in themselves and in other human beings, such as seeing, hearing, learning, and problem solving. Not that this isn’t hugely important and truly amazing – it is! It’s just that machines do not (and cannot) think fully and independently on their own.

Yet. Some public figures proclaim that the greatest danger to humanity from Artificial Intelligence (or any other technological advance) is that these technologies may advance to the point where they supersede humans in the power and speed of their processing, ultimately rendering us irrelevant or even extinct. Experts disagree on the threat, but it merits acknowledgement.

The latest capabilities of Artificial Intelligence include speech comprehension, autonomous vehicles, smart content curation, interpretation of complex data (including images), world class proficiency in strategic games, and bots, to name just a few among a host of impressive accomplishments. In this book we will reveal

how Artificial Intelligence and Machine Learning capabilities can be applied to marketing strategies and executions, and new product innovations. Artificial Intelligence is now not just an indispensable and ubiquitous feature of today's overall technological landscape; it is increasingly a core driver behind business success at every level of the enterprise.

The goal of this book is not only to inform you about Artificial Intelligence and Machine Learning. It is also to encourage and enable you to draw inspiration from the commercial success stories of other companies who have already put these powerful tools to work in the marketplace. Use these ideas to create new ideas of your own, and apply them directly to your marketing and product innovation practices.

Artificial Intelligence will probably most likely lead to the end of the world, but in the meantime, there'll be great companies.

– Sam Altman, quoted in “20 Great Quotes on Artificial Intelligence,” *Psychology Today*, May 18, 2018

Human creativity is unmatched, and will remain unmatched. Machines augment, support, and facilitate the expression of human genius. Augmenting human decision-making by making data accessible and by validating decisions through experiential rules collected over time, truly enable humanity to build learning capacity across generations. Physics memorializes human knowledge through the formulae accumulated and validated over time. Machine Learning and Artificial Intelligence attempt to do the same for the disciplines of marketing and product innovation.

1 Major Challenges Facing Marketers Today

Our mind is capable of passing beyond the dividing line we have drawn for it. Beyond the pairs of opposites of which the world consists, other, new insights begin.

– Hermann Hesse, Quotation.io

As much as we marvel at all the new and transformative electronic devices, social media platforms, apps, games, and digital avenues that make our lives better, more productive, more informed, and more fun today, certain basic truths about marketing and new product development persist.

Marketing is still about reaching consumers effectively, informing them, persuading them, motivating them, and ideally bringing them back for more.

New product introductions are still risky, essential, and potentially hugely rewarding.

And true innovation, in both fields, is still as alluring and elusive as ever.

Some of the major issues facing marketers today are the same as they have always been (such as deploying a marketing budget for best effect), while others are newer challenges (such as connecting effectively with consumers in an ever-fragmenting, fast-moving media environment).

Today, the emerging and critical issue for marketers is not *whether* to use AI to address these challenges and many others, but *which* AI technologies and methodologies to use. The imperative is clear: marketing professionals today *must* integrate AI into their marketing strategies if they expect to keep up with, much less beat, the competition.

This presents a tall order. Creating new and effective AI algorithms requires top trained talent. Currently, the demand far outweighs the supply of qualified professional mathematicians, data scientists, and software engineers. Compounding that issue, to be truly effective for marketing and product innovation purposes, those algorithms must be designed from the ground up for those specialized applications. Yet, more and more marketing activities are driven by ML algorithms.

And we are just in the early stages of this global transformation. The race is on – and the winners will not only need to be the fastest. They will also need to be the smartest, the most innovative in their own right, and they will need to own – or apply – the best proprietary AI and ML tools. Algorithms alone won't necessarily win the day – it will be suites of custom software, databases, and a reservoir of “secret sauces” that will prevail.

A quick illustration of what “fast” is in the Age of AI:

A self-learning ML algorithm from Google called AlphaZero mastered the game of chess in four hours, a feat that takes no less than two years for a human to accomplish, and more typically takes about 10 years.

Numbers have an important story to tell. They rely on you to give them a voice.

– Stephen Few, Information Technology innovator, teacher, and consultant, quoted in Brent Dykes, “Data Storytelling: The Essential Data Science Skill Everyone Needs,” *Forbes*, March 31, 2016

rare skill at this time, and marketing professionals who gain a working grasp of AI and ML will have a strong competitive edge.

That said – given the complexity of the science behind AI and ML, the necessary level of specialization required to create AI and ML algorithms to perform at peak efficiency for marketing and product innovation purposes, and the constantly evolving nature of the field – retaining professional firms that are dedicated to this sector and have the requisite talent, experience, and resources stands as the smart direction to take. This is where sector experience becomes important. Artificial Intelligence is only as intelligent as the domain expertise contained in it. Glib “general problem solvers” that solve anything are as useful as a dictionary is in composing a poem or a story. If you are in marketing and you are choosing a firm specializing in applying AI or ML to marketing, it is useful to ask and find out how much “domain knowledge” is embedded in the system, and what the relevant background and experience is of the creator of the system.

80% of executives surveyed are “eyeing the peaks” and view AI as a strategic opportunity.

– Sam Ransbotham, David Kiron, Philipp Gerbert, and
Martin Reeves, “Reshaping Business with Artificial
Intelligence,” *MIT Sloan Management Review*,
September 6, 2017

2 Introductory Concepts for Artificial Intelligence and Machine Learning for Marketing

To make robots practical, flaws must be removed.

To make robots endearing, flaws must be added.

– Khang Kijarro Nguyen

In this chapter we offer nine introductory concepts used in the fields of AI and ML. We also discuss the successful application of this knowledge in four core areas. You will see that all of these concepts are *minor* variations of each other. We present them for the sake of completeness and creating familiarity with the jargon, thinking, and philosophy behind Machine Learning and Artificial Intelligence.

Concept 1: Rule-based Systems

The two chief methods of making inferences from data are rule-based systems and ML. It is useful for marketing professionals to have some knowledge of both methods. ML did not replace rule-based systems, but rather became another tool in the marketer's toolbox. Rule-based systems still have their place as a simpler form of AI, so marketing professionals can reasonably consider using one or the other, or even both.

Rule-based systems can store and manipulate information for various useful purposes. Many AI applications use rule-based systems. The term generally applies to systems that involve manmade rules, featuring a series of IF–THEN statements, such as IF “A,” THEN “B” else IF “C,” THEN “D” and so forth. In terms of real-world applications, a rule-based program might tell a banker, “IF the loan applicant has a credit score below 500, THEN refuse the loan, ELSE offer the loan.”

Using a set of data and a set of rules, programmers can build useful marketing tools such as approval programs and recommendation engines. In most cases, rule-based systems require the knowledge of human experts in the given field. That's why *expert systems* are rule-based.

A downside of rule-based systems is that they can be cumbersome, since a rule needs to be made for each data point, and life involves so many special cases. For instance, IF “A” says, “It's raining,” THEN “B” might say, “Recommend an umbrella.”

But what if it isn't raining very hard? Or what if the rain is a hurricane with super-strong winds that would break even the toughest umbrella? Or what if the rain is just a brief summer shower of less than five minutes? Or what if the customer lives in a place where it almost never rains? Or what if the customer recently

purchased an umbrella? In these cases, recommending an umbrella would be impractical or even foolish.

Another issue with rule-based systems is that sometimes the data changes faster than programmers can create new rules.

For instance, a recent news story reported that a major flood occurred involving two feet of rain on the Hawaiian island of Kauai, causing major mudslides and many homes to be destroyed. A return to the Yahoo home page produced a sponsored ad displayed for discounted flights to – you guessed it – Kauai. In one way, the ad was “intelligently” based on real-time interaction (a just-read article about Kauai); but in another way, not so much, as why on earth would a reader want to go there now?

This brings us to another issue: a strict reliance on keywords may not be all that is needed to apply the right ads to the right realities.

That’s where ML comes in. ML can address the problems inherent in rule-based systems, by focusing on the outcomes only, as opposed to the entire thought processes of human experts.

Where rule-based systems are deterministic, ML systems are probabilistic, based on statistical models. An ML system uses historical data to ask the following question: *Given what we know about past events, what can we determine about future events?* In the future, this type of probabilistic information will be used for better prediction of weather conditions, among other things.

Although ML may be better in the long run, rule-based systems can still be appropriate for faster solutions and workarounds. What’s more, many marketing projects begin by using an expert system, in order to better understand the system itself.

Rule-based systems are still useful for occasions where all decision-based situations are known in advance, but ML algorithms can adjust the rules for you as they “learn” and improve at the task.

discontinuous trajectory that has been the signature of human progress. These discontinuities are not the result of an ordered structural sound logical system in place, but are more the result of an inaccurate and incomplete understanding of life and its experiences. The pieces of a kaleidoscope may all be broken, but the images they create are stunningly complete.

Q: How many programmers does it take to change a lightbulb?

A: None! That's a hardware problem.

Concept 4: Hierarchical Learning

Whether or not we are aware of it, our thought processes (and the thought processes of all living systems) follow a hierarchal scheme. The decision-making process is approached in a hierarchal fashion. Actually, all learning is hierarchal. It is simply an evolutionary feature of our beings to follow a learning hierarchy of increasing complexity, whether mental or physical in nature.

For instance, to learn complex math, you must first master easier math. Or when learning a language, you start by learning the letters of the alphabet, then you learn how to string those letters together to form words, then you learn how to string those words together to form sentences, and so on. The fact that all learning is hierarchal seems obvious, when you think about it. We cannot run before we learn to walk.

In 1956, educational psychologist Robert Gagn proposed a learning classification system where facets of learning were based on their increasing complexity. He outlined eight increasingly complex types of learning, and hypothesized that each type of learning in the hierarchy depended on having mastered the types of learning prior to it. Gagn's eight types of hierarchal learning are as follows:

1. *Signal Learning*: This is the simplest form of gaining knowledge of the world around us. It involves classical conditioning, as

demonstrated by Pavlov and his dog: basically, a desired response can result from a conditioned stimulus that would otherwise not produce the desired response. This type of learning is applied when people train animals, for instance.

2. *Stimulus-Response Learning*: This next level of gaining knowledge, first outlined by Skinner, is also known as *operant conditioning*, by which a desired response is obtained through a series of “rewards” and “punishments.”
3. *Chaining*: This type of learning involves connecting two or more previously learned stimulus-response pairs in a sequential fashion. Applications for this type of knowledge acquisition include learning to play the piano and learning to drive a car.
4. *Verbal Association*: This is a type of chaining where the linked sequences are the words (or sounds) of human language. A keen sense of verbal association is needed for the development of language skills.
5. *Discrimination Learning*: This involves developing the ability to respond in different ways to a series of similar inputs. Discrimination learning allows us to categorize.
6. *Concept Learning*: This involves developing the ability to make the same response to different individual stimuli that come from the same class or category. Concept learning allows us to generalize.
7. *Rule Learning*: This higher cognitive function is the ability to recognize relationships between concepts, and to successfully apply these general rules to other scenarios, even scenarios not previously experienced by the learner.
8. *Problem Solving*: This is thought to be the highest and most complex of cognitive functions. It allows the learner to invent complex rules to solve a problem, and then to apply those same rules to other (similar) problems.

You may notice that the first four types of learning listed above are more behavioral in nature, while the second four are more cognitive. AI systems utilize these various learning schema in different contexts. That is to say, handwriting recognition, speech recognition, and face ID may use a certain set of features and learning methods versus determining the best way to beat traffic in getting from point A to point B.

Deep Learning systems, like all learning systems, function within a hierarchy. Hierarchical Deep Learning (HDL, and nothing to do with cholesterol) can be supervised, semisupervised, or unsupervised. HDL systems often involve artificial neural networks.

Current applications of Deep Learning systems include document classification, image classification, article categorization, and sentiment analysis, to name only a few.

Sixty-one percent of those who have an innovation strategy said they are using AI to identify opportunities in data that would otherwise be missed. Only 22% without a strategy said the same.

– “62% of Organizations Will Be Using Artificial Intelligence (AI) Technologies by 2018,”
Narrative Science, July 20, 2016

Concept 5: Expert Systems

In AI, an expert system is basically a database of expert knowledge that incorporates the decision-making ability of a human expert. The system works by way of a series of IF–THEN rules. An expert system is a rule-based system, although not all rule-based systems are expert systems.

For example, a chess computer for beginners is a very weak program that “knows” all the rules of the game, and will therefore always

make legal moves following a rule-based system, but the program has no strategic or tactical skills, and cannot “learn” from its own mistakes. It may even have additional rules such as “IF the user offers a draw, THEN accept the draw.” Or “IF a move is checkmate, THEN play a different move.” Some beginners’ chess programs are designed never to beat the beginner.

There are typically three parts to an expert system:

1. *Database*: Contains information acquired from human experts, and a set of rules governing the processing of that information.
2. *Inference Engine*: An automated reasoning system that interprets a submitted problem against the database. An inference engine may also include debugging capabilities and an explanation feature. The explanation feature would explain to the user the process through which the inference engine arrived at a given conclusion.
3. *User Interface*: A way for users to interact with the program in order to complete an action, ask a question, or submit a problem in a human language.

Applications of expert systems include debugging, design, diagnosis, instruction, interpretation, monitoring, planning, prediction, and repair (among others).

A chief disadvantage of an expert system is the knowledge acquisition process. It can be difficult to get experts to go through all this information, not to mention prohibitively expensive to hire experts for as many hours as it would take them to supply and analyze all the data. What’s more, you may also have to hire a mathematician or a data scientist to write the algorithm.

Still, in the fields of finance, games, management, marketing, and innovation (to name only a few), today’s best expert systems can

outdo the world's cleverest humans. And why shouldn't this be so? After all, expert systems don't have egos, don't get distracted, and don't slow down as they grow older, to name just a few nonhuman advantages.

Every time a senior person in a company retires, a library of knowledge, expertise, and learning walks out the door. Instead of conducting "exit interviews" with employees, companies may do well to create expert systems from the employees who are about to leave. These rules accumulated over a course of time can provide a valuable historical learning engine that becomes an asset, instead of an exit interview form to be buried in the document repository.

Consumers use more AI than they realize. While only 34% think they use AI-enabled technology, 84% actually use an AI-powered service or device.

– "New Research Reveals Deep Confusion About Artificial Intelligence," Pega, April 4, 2017

Concept 6: Big Data

Since the dawn of the internet, humans have inputted countless billions of data points online. Each data point provides some piece of information. The sum total of all this information is generally what is called Big Data. More commonly, the term typically refers to the body of data gathered about and associated with a specific area or function. For example: an online retailer's assembly of information regarding customers' purchase patterns, or a loyalty card program that tracks consumption and rewards buyers when a certain level of spending is reached.

It is estimated that 90% of the information on the internet has been put there over the past two years. In fact, we create as much data *every two days* as the data created from the dawn of man to the year 2000. Yet, the data keeps increasing exponentially! The internet now

Concept 8: Filling Gaps in Data

Gaps in data are data fields that contain no information. Data gaps can be time-consuming for an algorithm to analyze, and the missing info may also be important to the success of a company.

To speed things up and/or provide pertinent information, there are various ways to fill in the gaps in a database. There is no single right or wrong method.

Popular heuristic approaches to filling gaps in data include:

- *Carrying forward values from existing, similar data* (such as filling in a missing zip code for a given city)
- *Using existing data from a corresponding time*, such as this month last year, for instance
- *Using the average value* of other, similar data points – extrapolation, and can be quite dangerous as it would merely serve to confirm what is already known
- *With extra large data sets, deleting records* in which data gaps occur

80% of executives believe AI boosts productivity.

– Leo Sun, “10 Stats About Artificial Intelligence That Will Blow You Away,” *The Motley Fool*, June 19, 2016

Concept 9: A Fast Snapshot of Machine Learning

Learning is a function of neural networks. Once scientists figured out the architecture of neural networks, certain machines were embedded with artificial neural networks whose rules were followed by learning algorithms. In this way, machines were able to mimic the capabilities of the human nervous system, and Machine Learning was born.

ML is basically an application of AI in which the system automatically improves from experience, without having been specifically programmed to do so. A well-written ML algorithm will access data, analyze it, and use it to improve its own performance. This is why we call it learning.

Artificial neural networks are typically trained by *epoch*, a scenario in which each data point is presented only once to the system. After learning, the artificial neural network is able to perform the function of generalization.

ML methods are available in three basic flavors:

1. *Supervised learning* works by comparing real network output with desired network output, and using the error margin as feedback. Supervised learning is known as a “closed loop feedback system,” where the error measure guides the learning process. It is used for tasks such as classification, approximation, identification, optimization, and signal processing, among others.
2. *Unsupervised learning* algorithms notice the correlations among input data, and find patterns and relationships previously undiscovered. Unsupervised learning algorithms are useful for customer segmentation, vector quantization, data extraction, and analysis, for example.
3. *Reinforcement learning* is designed to maximize the total reward, where training involves calculation of the difference between the expected reward and the actual reward. This difference is known as the reward-prediction error. Reinforcement learning is actually a special kind of supervised learning, where the desired output is unknown. Reinforcement learning is used in AI and various control processes.

ML is based on the expert design of precise and efficient prediction algorithms. These algorithms cause ML to perform two main functions: induction (classification of data) and transduction (labeling of data).

Here are a few good reasons why marketing professionals should use ML in their marketing strategies:

- *Real-time capability:* Consumers now see ads and offers that change by the second, based on whatever they are searching for at the time.
- *Reduction of marketing waste:* The old way of marketing amounted to scattering seeds everywhere and seeing what would grow. Now, using behavioral data, the marketing sector enjoys a much more targeted approach to reaching customers.
- *Predictive analytics:* As amazing as real-time capability is, ML can seem almost psychic. ML can analyze Big Data, notice patterns, and predict future occurrences with astounding accuracy. The potential of predictive analytics became virally known a few years ago, when Target figured out that one of its customers was pregnant before she even knew it herself. She shopped there to purchase a pregnancy test, and came home to a slew of emails and advertisements for baby products, some of which she purchased when the pregnancy test ultimately yielded a positive result.
- *Structured content:* One popular feature of ML is sentiment analysis, which aims to determine the *attitude* of a speaker or writer, then recommends to marketers about what to say, how to say it, and the best time to say it, as well as how the audience is likely to react. Sentiment, as a metric, is most useful when combined with other metrics.
- *Cost reduction:* Simple arithmetic: overall, the money spent on marketing automation software is meant to be less than the money that otherwise would have been spent on all the additional man hours it would take to complete such a massive task as sifting through all the collected data.