

Deep Learning with R

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*I dedicate this book to the deep learning
fraternity at large who are trying their best,
to get systems to reason over longtime
horizons.*

Preface

Artificial Intelligence

The term ‘Artificial Intelligence’ (AI) was coined by John McCarthy in 1956, but the journey to understand if machines can truly *think* began much before that. Vannevar Bush [1] in his seminal work—*As We May Think*,¹—proposed a system which amplifies people’s own knowledge and understanding.

Alan Turing was a pioneer in bringing AI from the realm of philosophical prediction to reality. He wrote a paper on the notion of machines being able to simulate human beings and the ability to do intelligent things. He also realized in the 1950s that it would need a greater understanding of human intelligence before we could hope to build machines which would “think” like humans. His paper titled “Computing Machinery and Intelligence” in 1950 (published in a philosophical journal called *Mind*) opened the doors to the field that would be called *AI*, much before the term was actually adopted. The paper defined what would be known as the Turing test,² which is a model for measuring “intelligence.”

Significant AI breakthroughs have been promised “in the next 10 years,” for the past 60 years. One of the proponents of AI, Marvin Minsky, claimed in 1967—“Within a generation ..., the problem of creating “artificial intelligence” will substantially be solved,” and in 1970, he quantified his earlier prediction by stating—“In from three to eight years we will have a machine with the general intelligence of a human being.”

In the 1960s and early 1970s, several other experts believed it to be right around the corner. When it did not happen, it resulted in drying up of funds and a decline in research activities, resulting in what we term as the first *AI winter*.

During the 1980s, interest in an approach to AI known as *expert systems* started gathering momentum and a significant amount of money was being spent on

¹ <https://www.theatlantic.com/magazine/archive/1945/07/as-we-may-think/303881/>.

² <https://www.turing.org.uk/scrapbook/test.html>.

research and development. By the beginning of the 1990s, due to the limited scope of *expert systems*, interest waned and this resulted in the second *AI winter*. Somehow, it appeared that expectations in AI always outpaced the results.

Evolution of Expert Systems to Machine Learning

An expert system (ES) is a program that is designed to solve problems in a specific domain, which can replace a human expert. By mimicking the thinking of human experts, the expert system was envisaged to analyze and make decisions.

The knowledge base of an ES contains both factual knowledge and heuristic knowledge. The ES inference engine was supposed to provide a methodology for reasoning the information present in the knowledge base. Its goal was to come up with a recommendation, and to do so, it combined the facts of a specific case (input data), with the knowledge contained in the knowledge base (rules), resulting in a particular recommendation (answers).

Though ES was suitable to solve some well-defined logical problems, it proved otherwise in solving other types of complex problems like image classification and natural language processing (NLP). As a result, ES did not live up to its expectations and gave rise to a shift from the rule-based approach to a data-driven approach. This paved the way to a new era in AI—machine learning.

Research over the past 60 years has resulted in significant advances in search algorithms, machine learning algorithms, and integrating statistical analysis to understand the world at large.

In machine learning, the system is trained rather than explicitly programmed (unlike that in ES). By exposing large quantities of known facts (input data and answers) to a learning mechanism and performing tuning sessions, we get a system that can make predictions or classifications of unseen input data. It does this by finding out the statistical structure of the input data (and the answers) and comes up with rules for automating the task.

Starting in the 1990s, machine learning has quickly become the most popular subfield of AI. This trend has also been driven by the availability of faster computing and availability of diverse data sets.

A machine learning algorithm transforms its input data into meaningful outputs by a process known as *representations*. Representations are transformations of the input data, to represent it closer to the expected output. “Learning,” in the context of machine learning, is an automatic search process for better *representations* of data. Machine learning algorithms find these *representations* by searching through a predefined set of operations.

To summarize, machine learning is searching for useful *representations* of the input data within a predefined space, using the loss function (difference between the actual output and the estimated output) as a feedback to modify the parameters of the model.

Machine Learning and Deep Learning

It turns out that machine learning focuses on learning only one or two layers of representations of the input data. This proved intractable for solving human perception problems like image classification, text-to-speech translation, handwriting transcription, etc. Therefore, it gave way to a new take on learning representations, which put an emphasis on learning multiple successive layers of representations, resulting in deep learning. The word *deep* in deep learning only implies the number of layers used in a deep learning model.

In deep learning, we deal with layers. A layer is a data transformation function which carries out the transformation of the data which goes through that layer. These transformations are parametrized by a set of weights and biases, which determine the transformation behavior at that layer.

Deep learning is a specific subfield of machine learning, which makes use of tens/hundreds of successive layers of representations. The specification of what a layer does to its input is stored in the layer's parameters. Learning in deep learning can also be defined as finding a set of values for the parameters of each layer of a deep learning model, which will result in the appropriate mapping of the inputs to the associated answers (outputs).

Deep learning has been proven to be better than conventional machine learning algorithms for these “perceptual” tasks, but not yet proven to be better in other domains as well.

Applications and Research in Deep Learning

Deep learning has been gaining traction in many fields, and some of them are listed below. Although most of the work to this date are proof-of-concept (PoC), some of the results have actually provided a new physical insight.

- **Engineering**—Signal processing techniques using traditional machine learning exploit shallow architectures often containing a single layer of nonlinear feature transformation. Examples of shallow architecture models are conventional hidden Markov models (HMMs), linear or nonlinear dynamical systems, conditional random fields (CRFs), maximum entropy (MaxEnt) models, support vector machines (SVMs), kernel regression, multilayer perceptron (MLP) with a single hidden layer, etc. Signal processing using machine learning also depends a lot on handcrafted features. Deep learning can help in getting task-specific feature representations, learning how to deal with noise in the signal and also work with long-term sequential behaviors. Vision and speech signals require deep architectures for extracting complex structures, and deep learning can provide the necessary architecture. Specific signal processing areas where deep

learning is being applied are speech/audio, image/video, language processing, and information retrieval. All this can be improved with better feature extraction at every layer, more powerful discriminative optimization techniques, and more advanced architectures for modeling sequential data.

- **Neuroscience**—Cutting-edge research in human neuroscience using deep learning is already happening. The cortical activity of “imagination” is being studied to unveil the computational and system mechanisms that underpin the phenomena of human imagination. Deep learning is being used to understand certain neurophysiological phenomena, such as the firing properties of dopamine neurons in the mammalian *basal ganglia* (a group of subcortical nuclei of different origin, in the brains of vertebrates including humans, which are associated with a variety of functions like eye movements, emotion, cognition, and control of voluntary motor movements). There is a growing community who are working on the need to distill intelligence into algorithms so that they incrementally mimic the human brain.
- **Oncology**—Cancer is the second leading health-related cause of death in the world. Early detection of cancer increases the probability of survival by nearly 10 times, and deep learning has demonstrated capabilities in achieving higher diagnostic accuracy with respect to many domain experts. Cancer detection from gene expression data is challenging due to its high dimensionality and complexity. Researchers have developed DeepGene,³ which is an advanced cancer classifier based on deep learning. It addresses the obstacles in existing *somatic point mutation-based cancer classification* (SMCC) studies, and the results outperform three widely adopted existing classifiers. Google’s CNN system⁴ has demonstrated the ability to identify deadline skin cancers at an accuracy rate on a par with practitioners. Shanghai University has developed a deep learning system that can accurately differentiate between benign and malignant breast tumors on ultrasound *shear wave elastography* (SWE), yielding more than 93% accuracy on the elastogram images of more than 200 patients.⁵
- **Physics**—*Conseil Européen pour la Recherche Nucleaire (CERN)* at Geneva handles multiple petabytes of data per day during a single run of the Large Hadron Collider (LHC). LHC collides protons/ions in the collider, and each collision is recorded. After every collision, the trailing particles—a Higgs boson, a pair of top quarks, or some mini-black holes—are created, which leave a trailing signature. Deep learning is being used to classify and interpret these signatures.
- **Astrophysics**—Deep learning is being extensively used to classify galaxy morphologies.⁶

³<https://bmcbioinformatics.biomedcentral.com/articles/10.1186/s12859-016-1334-9>.

⁴<https://www.nature.com/articles/nature21056>.

⁵[https://www.umbjournal.org/article/S0301-5629\(17\)30002-9/abstract](https://www.umbjournal.org/article/S0301-5629(17)30002-9/abstract).

⁶<https://arxiv.org/abs/0908.2033>.

- **Natural Language Processing**—There has been a rising number of research papers (see Fig. 1) among the research community since 2012, as is reflected in the paper titled *Recent Trends in Deep Learning Based Natural Language Processing* by Young et al.
- Near human-level proficiency has been achieved in (a) speech recognition, (b) image recognition, (c) handwriting transcription, and (d) autonomous driving. Moreover, super-human-level performance has been achieved by AlphaGo (built by Google) when it defeated the world's best player Lee Sedol at Go.

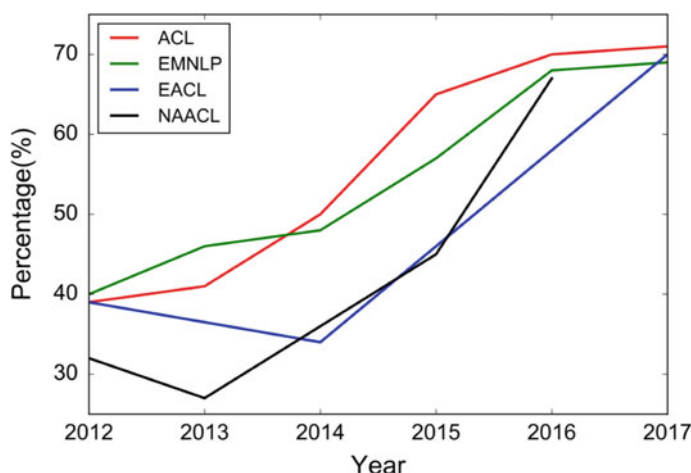


Fig. 1 Percentage of deep learning papers submitted for various conferences—Association for Computational Linguistics (ACL), Conference on Empirical Methods in Natural Language Processing (EMNLP), European Chapter of the Association for Computational Linguistics (EACL), North American Chapter of the Association for Computational Linguistics (NAACL), over the last 6 years since 2012. [2]

Intended Audience

This book has been written to address a wide spectrum of learners:

- For the beginner, this book will be useful to understand the basic concepts of machine/deep learning and the neural network architecture (Chaps. 1 and 2) before moving on to the advanced concepts of deep learning.
- For the graduate student, this book will help the reader understand the behavior of different types of neural networks by understanding the concepts, while building them up from scratch. It will also introduce the reader to relevant research papers for further exploration.

- For the data scientist who is familiar with the underlying principles of machine learning, this book will provide a practical understanding of deep learning.
- For the deep learning enthusiast, this book will explain the deep learning architecture and what goes on inside a neural network model.

An intermediate level of R programming knowledge is expected from the reader, and no previous experience of the subject is assumed.

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Abhijit Ghatak

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Acknowledgment is an unsatisfactory word for my deepest debts.

My father bequeathed to me a love for adventure and an interest in history, literature, and mathematics.

My professors at the Faculty of Mechanical Engineering, Jadavpur University, instilled an appetite for analysis and quantitative techniques in engineering; my mentor and advisor at University of Pune, Prof. SY Bhawe, motivated me to interpret the algorithm and write a program using the C language on predicting torsional vibration failures of a marine propulsion shaft using *state vectors*; and my advisors at Stevens Institute of Technology helped me to transit from a career submarine engineer in the Indian Navy to a data scientist.

My wife Sushmita lived through the slow gestation of this book. She listened and engaged with me all the way. She saw potential in this work long before I did and encouraged me to keep going.

I owe my thanks to Sunanda for painstakingly proofreading the manuscript.

I also have two old debts—Robert Louis Stevenson and Arthur Conan Doyle. In *Treasure Island*, Mr Smollet is most eager to discover the treasure and he says—“We must go on,” and in *Case of Identity*, Sherlock Holmes states—“It has long been an axiom of mine that the little things are infinitely the most important.” Both are profound statements in the realm of a new science, and the litterateurs had inked their thoughts claiming no distinction, when there is not a distinction between the nature of the pursuit.

I owe all of them my deepest debts.

Abhijit Ghatak

About This Book

- Deep learning is a growing area of interest to academia and industry alike. The applications of deep learning range from medical diagnostics, robotics, security and surveillance, computer vision, natural language processing, autonomous driving, etc. This has been largely possible due to a conflation of research activities around the subject and the emergence of APIs like Keras.
- This book is a sequel to **Machine Learning with R**, written by the same author, and explains deep learning from first principles—how to construct different neural network architectures and understand the hyperparameters of the neural network and the need for various optimization algorithms. The theory and the math are explained in detail before discussing the code in R. The different functions are finally merged to create a customized deep learning application. It also introduces the reader to the Keras and TensorFlow libraries in R and explains the advantage of using these libraries to get a basic model up and running.
- This book builds on the understanding of deep learning to create R-based applications on computer vision, natural language processing, and transfer learning.

This book has been written to address a wide spectrum of learners:

- For the beginner, this book will be useful to understand the basic concepts of machine/deep learning and the neural network architecture (Chaps. 1 and 2) before moving on to the advanced concepts of deep learning.
- For the graduate student, this book will help the reader to understand the behavior of different types of neural networks by understanding the concepts, while building them up from scratch. It will also introduce the reader to relevant research papers for further exploration.
- For the data scientist who is familiar with the underlying principles of machine learning, this book will provide a practical understanding of deep learning.
- For the deep learning enthusiast, this book will explain the deep learning architecture and what goes on inside a neural network model.

This book requires an intermediate level of skill in R and no previous experience of deep learning.

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About the Author

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