IPEM–IOP Series in Physics and Engineering in Medicine and Biology

Machine Learning for Tomographic Imaging

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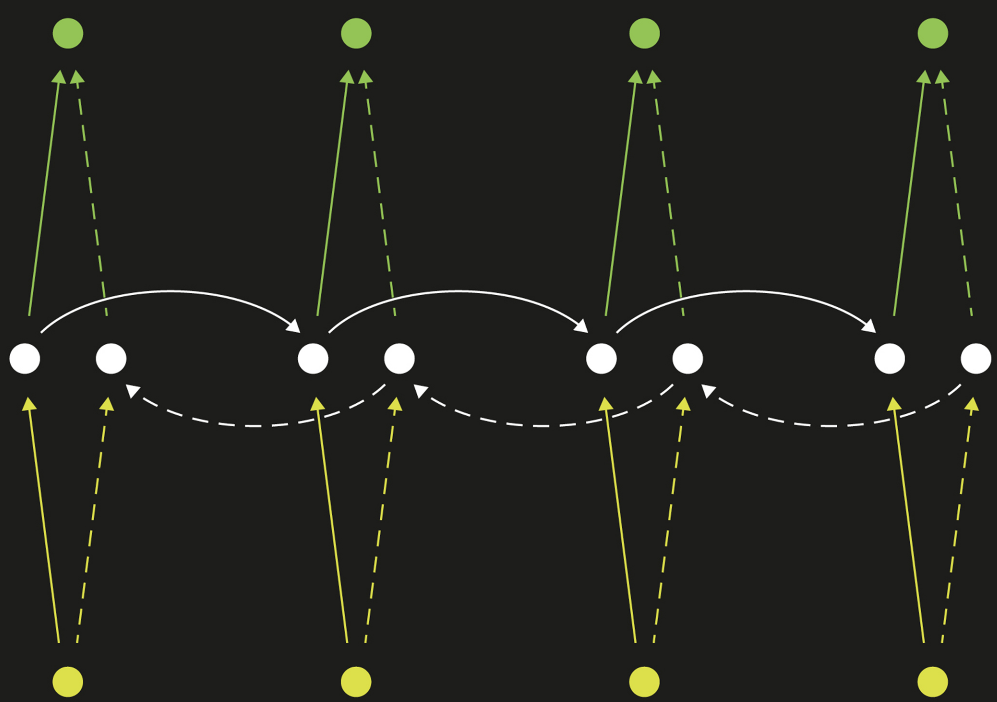
IPEM Institute of Physics and Engineering in Medicine



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For my wife Ying Liu, whose support has been extraordinary, my academic mentors Michael Vannier et al, and all other family members and collaborators.

—Ge Wang

For my wife and daughter, who have been always fully supporting my academic career development.

—Yi Zhang

For my family.

—Xiaojing Ye

For my family.

—Xuanqin Mou

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Foreword

We are currently witnessing a revolution in science and engineering: in only a few years, machine learning has become the basis for almost every single algorithm development. I still remember a college course on non-linear systems in the early 1990s: except for a few zealots, my peers and I used to think of neural networks as an exotic and entirely impractical field of science. Little did we realize how wrong we were. Increases in computing power, access to large amounts of data, and the creativity of many scientists have entirely changed that view. Today, neural networks have become more pervasive than the Fourier transform.

Some of the most popular applications of machine learning are in image analysis. You probably have some powerful deep learning networks in your pocket: just type 'dog' or 'hat' on your smart phone and it will instantaneously find all pictures containing your targets of interest. The application of machine learning may be less obvious in other areas, such as image generation. By now, machine learning has been at least considered for almost every imaginable algorithmic challenge. In the field of medical imaging, machine learning techniques can triage patients, determine the best scan parameters, perform image reconstruction, enhance images, analyze the quality of images, perform a diagnosis, compute a treatment plan, etc.

Dr Ge Wang was one of the earliest innovators who has been creatively exploring various ways of using deep learning in tomographic imaging since 2016, which is a long time ago given how fast the field has evolved. His team's main impacts range across the topics of CT, MRI, and optical imaging, but they have also made fundamental contributions to the science of neural networks, such as through the investigation of quadratic deep neural networks.

Dr Wang teamed up with Dr Zhang, Dr Ye and Dr Mou to write this book on machine learning for tomographic imaging. The authors are uniquely qualified to undertake this major project, given their combined expertise in mathematics, computer science, image processing, and tomographic imaging, as well as their pioneering research in machine learning for medical imaging. At a high level, this book teaches medical imaging from the perspective of machine learning, and hence covers two important fields: machine learning and tomographic imaging.

The book's first part gives a colorful and inspiring introduction to machine learning and tomographic imaging. Using the Human Vision System as reference, the authors take us on a journey from sparse representations, through dictionary learning, to neural networks and deep learning. Many 'textbook' deep learning architectures are covered at an introductory level. Parts two and three provide an in-depth tutorial of CT and MR image reconstruction, followed by a wide range of machine learning techniques that were developed in recent years. The fourth part further enriches the content of this book by elaborating on other imaging modalities, image quality evaluation, and quantum computing.

Overall, this book provides an amazingly comprehensive overview of neural networks and tomographic reconstruction methods. It is written in an engaging and accessible style, without lengthy mathematical derivations and proofs. This makes it ideal for introducing machine learning and tomographic imaging in the more applied disciplines (physics and engineering), and also for bringing application contexts into the more theoretical disciplines (mathematics and computer sciences).

Every medical imaging scientist who graduated before machine learning was taught in college should probably learn about this area in order to remain competitive. To my knowledge, this book is the first and only publication capturing all important aspects of machine learning and tomographic imaging in one place.

I highly recommend this book for any medical imaging students/professionals with a STEM background. Start with chapters 1–3. Then, depending on whether you are a CT, PET, MRI, ultrasound, or optical imaging aficionado, you may select one or more of the other chapters for further study. Before you know it, you will *'deeply learn'* this exciting new science, be able to talk intelligently about it, and perform state-of-the-art research in a world that can no longer be imagined without neural networks.

Bruno De Man, October 2019

Preface

This book arose from discussions among four colleagues with a long-standing collaboration and interest in advanced medical image reconstruction methods and applications. Beginning in 2018, our group realized the gap in the literature and in particular among technical books on the emerging technologies that develop and apply artificial intelligence/machine learning (AI/ML) techniques to tomographic reconstruction or tomographic imaging.

As early as 2012, we recognized the opportunity presented by machine learning in formulating plans for doctoral dissertation research where dictionary learning can be used to recover images from projection measurements. By connecting several contemporary image recovery and signal processing methods, in particular compressed sensing, neural network, and deep learning techniques, our discussions and projects converge to develop and apply ML methods to advance the frontier of image reconstruction, with an emphasis on medical imaging.

The interested reader entering this field may have a background in artificial intelligence or mathematical knowledge of tomographic reconstruction, but few will have all of the knowledge needed to understand the field of ML for tomographic image reconstruction. Hence, we have now created this book to cover what we believe to be a comprehensive collection of key topics in a logical and consistent manner.

The prerequisites for reading this book include calculus, matrix algebra, Fourier analysis, medical physics, and basic programming skills. We believe that PhD candidates in the imaging field are generally well prepared to understand all of the content through serious effort, while advanced undergraduate students can also learn essential ideas and capture selected materials (you can skip the chapters/sections/subsections marked with an '*'). To facilitate teaching and learning, most relevant numerical methods are described in appendix A, and hands-on projects are suggested in appendix B, with sample codes and working datasets.

The logical dependence between the key components of this book is illustrated in the diagram in the introduction below. We strongly recommend that you read this introduction first to obtain an overall perspective. It is also recommended to read the first three chapters sequentially so that you are well prepared with both the imaging context and network basics. However, chapter 3 alone is a good introduction to general knowledge on artificial neural networks. Then, we can proceed in parallel to CT, MRI, or other tomographic modalities, which are covered in parts II, III, and IV of the book, respectively. It would be the best to read part IV after reading parts II and III as deep reconstruction networks are clearly explained for CT and MRI in these two parts. Appendix A can be read as needed, but appendix B is strongly recommended, and should be at least consulted to run the basic networks explained in chapter 3. The network examples for CT and MRI can be adapted for independent class projects.

We hope that this book will be useful for a review course at the graduate level, but it has not been tested yet. As teaching experience is accumulated using this book, homework problems and solutions will become available, along with example class project reports and codes. A book-related website is maintained on the Fully3D community website: http://www.fully3d.org/rpi/.

The materials contained in this book are presented in their first version. As a result, a number of topics are not treated in detail or in depth. Nevertheless, after reading this book you should have state-of-the-art knowledge of a broad spectrum of methods. We welcome your critiques and suggestions so we can make future versions better, with key references cited in a more balanced way.

July 2019

Acknowledgments

The four parts of this book were initially drafted by Professors Mou, Zhang, Ye, and Wang respectively, based on a collectively developed overall layout. The appendices were drafted by Professor Ye. Hands-on examples were developed by Professors Zhang, Ye, and Mou collectively, and integrated by Professor Zhang. All parts were internally reviewed and revised by the four co-authors, and editorially refined by the staff of IOP Publishing.

We would like to express our sincere gratitude to all individuals, publishers, and companies for permission to reproduce some of the images and figures in this book, IOP Publishing staff for guidance during the development of the book, and importantly our students, other lab members, and collaborators for their significant contributions, including but not limited to Hongming Shan, Qing Lyu, Christopher Wiedeman, Harshank Shrotriya, Huidong Xie, Fenglei Fan, Mengzhou Li, and Varun Ravichandran. Drs Michael Vannier and Hengyong Yu offered insightful advice on the strengths and weaknesses of this book for improvements. Last but not least, the following leading companies have graciously given permission to reproduce some of the best figures/images in this book: Cannon, General Electric, Siemens, and Phillips (in alphabetical order). Without these, this book would not have been created in its current form. We are happy that the first version of this book is now complete, and look forward to producing future versions and more excitement in the years to come.

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Ge Wang is the Clark and Crossan Endowed Chair Professor and the Director of the Biomedical Imaging Center, Rensselaer Polytechnic Institute, Troy, NY, USA. He published the first spiral/helical cone-beam/multi-slice CT paper in 1991 and has since then systematically contributed over 100 papers on theory, algorithms, artifact reduction, and biomedical applications in this area of CT research. Currently, over 100 million medical CT scans are carried out yearly with a majority in the spiral/helical cone-beam/multi-slice mode. Dr Wang's group developed interior tomography theory and algorithms to solve the long-standing 'interior problem' for high-fidelity local reconstruction, establishing the feasibility of omni-tomography ('all-in-one') with simultaneous CT-MRI as an example. He initiated the area of bioluminescence tomography. He has produced over 480 journal publications, covering diverse imaging-related topics and receiving a high number of citations and academic awards. His results have been featured in *Nature*, *Science*, *PNAS*, and news media. In 2016, he published the first perspective on deep-learning-based tomographic imaging as a new direction of machine learning and a *Nature Machine Intelligence* paper on the superiority of deep learning over iterative reconstruction in collaboration with his colleagues. His team has been continuously well-funded by federal agencies and imaging companies. His interests include CT, MRI, optical tomography, multi-modality fusion, artificial intelligence, and machine learning. He is the lead Guest Editor for five *IEEE Transactions on Medical Imaging* special issues, the founding Editor-in-Chief of the *International Journal of Biomedical Imaging*, a Board Member of *IEEE Access*, and an Associate Editor of *IEEE Transactions on Medical Imaging* (TMI) (recognized as an 'Outstanding Associate Editor'), *Medical Physics*, and *Machine Learning Science and Technology*. He is Fellow of IEEE, SPIE, OSA, AIMBE, AAPM, AAAS and NAI.

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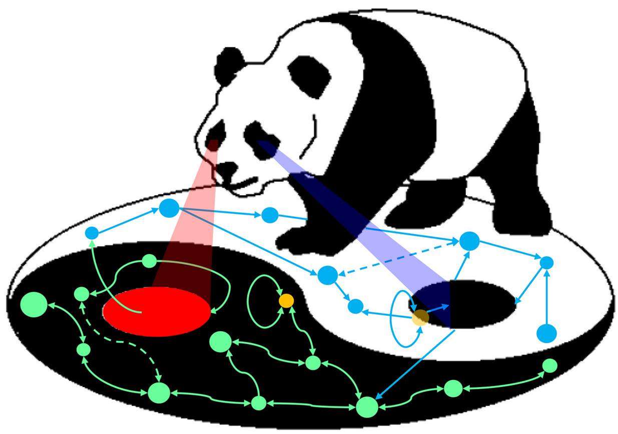
Dr Xuanqin Mou received his bachelor's, master's, and PhD degrees from Xi'an Jiaotong University, China. Since 1987, he has been a faculty member with Xi'an Jiaotong University and was prompted to Full Professor in 2002. Currently, he is the Director of the National Data Broadcasting Engineering and Technology Research Center, and the Director of the Institute of Image Processing and Pattern Recognition. He served on the Twelfth Expert Evaluation Committee for the National Natural Science Foundation of China. He is currently on the Executive Committee of the China Society of Image and Graphics, the Executive Committee of the Chinese Society for Stereology, also serves as the Deputy Director of the CT Committee of the Chinese Society for Stereology. He was on the editorial boards of several academic journals and technical program committee for many international conferences. In 2017, Dr Mou co-chaired the Fourteenth Fully Three-Dimensional Image Reconstruction in Radiology and

Nuclear Medicine Conference at Xi'an Jiaotong University, which is the prime conference in the field of CT/PET/SPECT image reconstruction research and development. His interests include x-ray medical imaging, CT reconstruction, observer models, perceptual quality assessment, and video coding. He published over 200 peer-reviewed journal and conference papers, and holds over ten Chinese patents as the principle inventor. He received a Second-class Award for Invention issued by the Ministry of Education of China as the principal investigator, and several other awards. As the principal investigator, he received 16 governmental grants and 20 industrial funds.

Art rendering by Ge Wang, July 2019. Panda symbolizes digital and biological technologies, being binary and adorable. As is well known, it is racially representative, being black and white, as well as oriental. The Yin–Yang pattern suggests entanglement of information, and hope for the future.



Introduction

Artificial intelligence/machine learning (AI/ML) is one of the largest diamonds ever discovered in the evolution of science, and has many facets, one of which is AI/ML-based tomography—the central theme of this, first-of-its-kind, book (figure 0.1). First, we hope to explain the big picture behind our book, help you assess if it is valuable to you, and, if so, suggest guidelines for a pleasant and rewarding reading or learning experience. As the book is in its first version, your feedback is most welcome for us to produce the next edition in the future so that representative networks and key references can be covered as completely as possible. We strongly suggest that you read both the preface and this introduction carefully to obtain a general perspective. In the following, we will do our best to present key points in easy language.

0.1 Artificial intelligence/machine learning/deep learning

Currently, deep learning is the mainstream approach of machine learning (ML), which is arguably the hottest research area of artificial intelligence (AI). AI/ML means allowing a computer to think like a human and even outperform humans in certain (if not most) important tasks. While classic science and technology are really about the magnification of humans' physical power (such as steam engines and assembly lines) and the enhancement of non-intelligent functions (such as cars and planes as our legs, and microscopes and telescopes extending our eyes), AI/ML targets the understanding and prototyping of human intelligence so that we not only demystify the ultimate secret of life but also let machines work for us intelligently (figure 0.2).

Over only the past few years, AI/ML techniques have achieved impressive successes in computer vision, image analysis, speech recognition, language processing, and many other areas. A major feature behind these successes is that they use deep artificial neural networks trained with big data. An artificial neural network consists of many artificial neurons. Such neurons are basic data processing units performing a linear (weighted sum) operation followed by a simple nonlinear (thresholding) operation. This was inspired by how a biological neuron works. A biological neuron accumulates multiple stimuli, and when the overall stimulation is over a threshold, the neuron will become excited and respond by sending an electrical signal to other neurons or cells. There are a huge number of biological neurons in our brain, and it is the biological neural network that gives us intelligence, and the unmistaken example

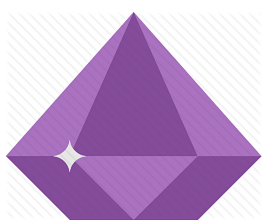


Figure 0.1. AI/ML enables superior tomography.

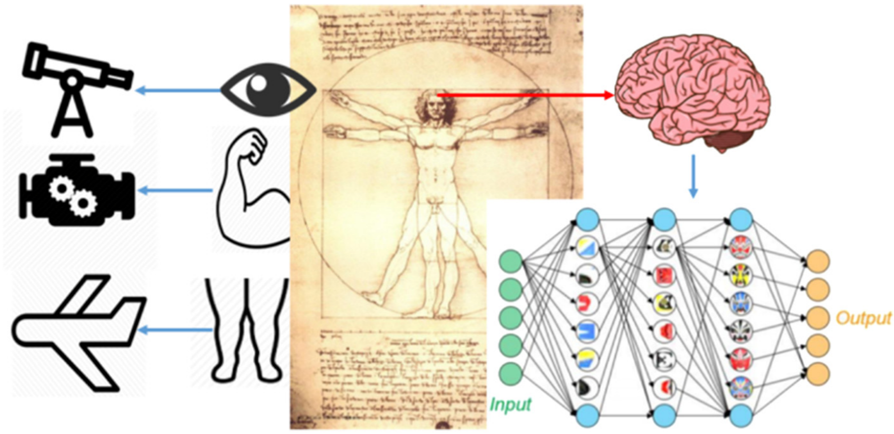


Figure 0.2. Curiosity and needs drive scientific pursuits through the industrial, information, and intelligent revolutions.

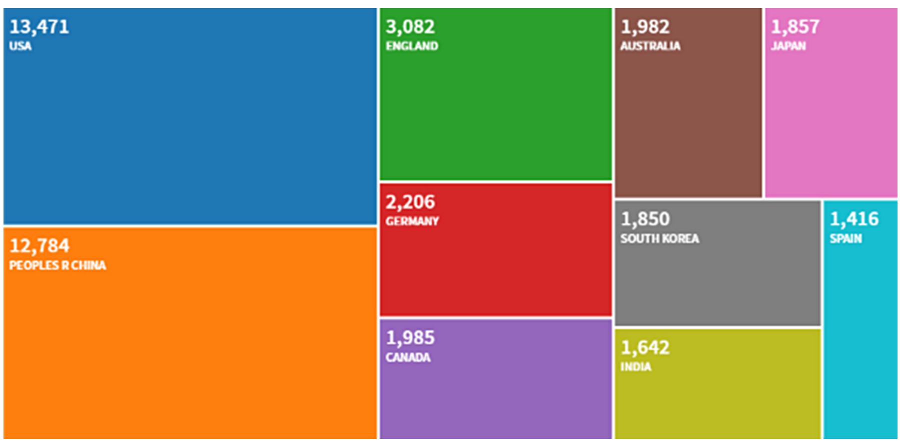


Figure 0.3. Web of Knowledge results with ‘deep learning’ as the topic term (data collected on 11 July 2019).

showing that intelligence is feasible. Similar to this biological/neurological system, an artificial neural network can behave, to a good degree, like a brain, if the number of artificial neurons is high enough, organized deeply (i.e. with many layers of artificial neurons), and trained well with big data. This resembles the learning process in our childhoods, where our neurological connections are formed adaptively, and we become increasingly intelligent.

The importance and potential of AI/ML has now been well recognized. The AI Executive Order was issued by the White House in February 2019 (https://www.whitehouse.gov/articles/accelerating-americas-leadership-in-artificial-intelligence/), and the response from NIST is also inspiring to read (https://www.nist.gov/topics/artificial-intelligence). International competition is remarkable in advancing AI/ML theory and technologies (figure 0.3).

0.2 Image analysis versus image reconstruction

As the most famous examples of AI/ML applications, computer vision and image analysis deal with existing images and produce features of these images thanks to the great efforts of many talented researchers. We are researchers in the field of tomographic imaging, and our products are tomographic images reconstructed from externally measured, complicated data that look totally different from the underlying images, and are actually various features (attenuated/non-attenuated line integrals, Fourier/harmonic components, and so on) of the underlying images. Currently, machine learning (especially deep learning) techniques are being actively developed worldwide for tomographic image reconstruction, which is a new area of research, with low hanging fruit in terms of data-driven post-processing and high hanging fruit in terms of end-to-end mapping via transfer, adversarial, ensemble, and other forms of machine learning.

This first-of-its-kind book is dedicated to machine learning for tomographic image reconstruction, or tomographic imaging, primarily targeting image reconstruction (from data to images) with some mentions of relevant image analysis (from images to images/features) and end-to-end mapping (from data to features). Tomography is a Greek word, meaning reconstruction of cross-sectional images. It is the emphasis on tomography that sets our book apart from other AI/ML or deep learning books (figure 0.4).

0.3 Analytic/iterative/deep learning algorithms for tomographic reconstruction

Traditionally, there are two kinds of algorithms for tomographic reconstruction—analytic and iterative. When tomographic data are of high quality and sufficiently

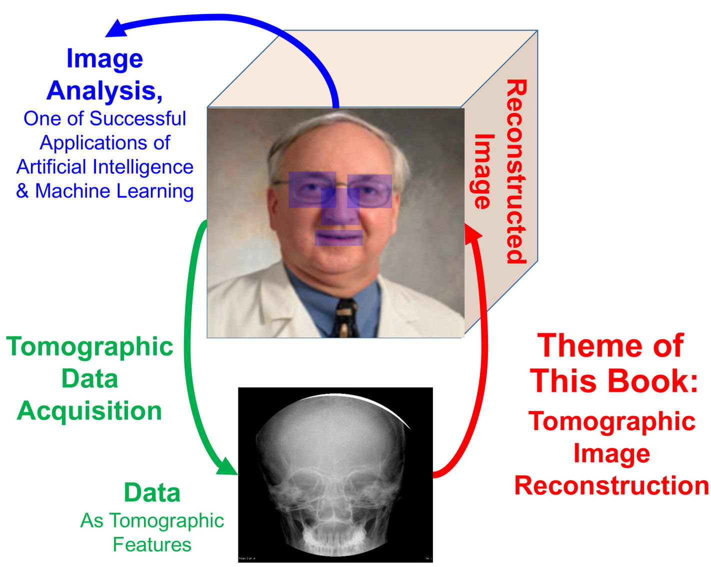


Figure 0.4. Uniqueness of this book, dedicated to tomographic image reconstruction in the AI/ML framework, in contrast to deep learning for image analysis or computer vision that takes images as the input.

collected, the relationship from an underlying image to the tomographic measures can be expressed as a forward model, which can be mathematically and computationally inverted. The inverse transform will transform the data back to the underlying image, which is what image reconstruction means. When such an inverse transform is in a closed form (for example, an inverse Fourier transform), a reconstruction algorithm can be directly obtained, and implemented on a computer.

When tomographic data are compromised, incomplete, or the forward model is too complicated to be analytically inverted, an iterative algorithm can be used for image reconstruction. An iterative algorithm does not solve the problem in one shot. From an initial estimate of the underlying image, which can be as simple as an all zero or all one image or another form when specific prior knowledge is available, the algorithm refines an intermediate solution iteratively (the first one is the initially guessed image). The refinement is guided by two preferences. First, the discrepancy should be small between the measured data and the data computed according to the forward model based on an intermediate image. Second, the characteristics of a reconstructed image should look reasonable or consistent with our prior knowledge, such as non-negative pixel values and no severely oscillating features. These requirements are summarized into an overall objective function, and the reconstruction problem becomes an optimization task. In other words, the iterative algorithm is just for this optimization. In most cases of tomographic imaging, measured data are not enough to determine the underlying image uniquely, and prior knowledge is instrumental for satisfactory image reconstruction. The stronger the prior knowledge is, the better the reconstructed image quality will be. Various kinds of prior knowledge are in use for iterative reconstruction, including non-negativity, maximum entropy, roughness penalty, total variation minimization, low rank, dictionary, and low-dimensional manifold learning. Normally, an iterative algorithm is very time-consuming.

It is clear now that deep learning networks form the third category of image reconstruction algorithms. In contrast to the aforementioned kinds of prior knowledge, each of which can be formulated as one mathematical term in one or two lines, an unprecedented source of prior knowledge is big data. For example, millions of CT scans contain overwhelming information on underlying anatomical and pathological information, and a new scan should be very much correlated to or consistent with the existing scans. If these data can be utilized for image reconstruction, superior image quality is expected. Fortunately, deep neural networks can be trained with big data on a high-performance computing platform so that prior knowledge can be represented by the trained neural network that serves as a mapping from data to images. Because the prior knowledge used by the neural network is task-specific and yet comprehensive, in principle the network may produce better image quality than an iterative algorithm when it falls short of clinical satisfaction. Although training the network is still time-consuming, the trained network only involves forward operations and is computationally efficient.

The analytic, iterative, and deep learning algorithms for tomographic image reconstruction can be compared and contrasted (table 0.1). Briefly speaking, an analytic algorithm can be formulated in the following form, $f(x, y) = O[p(\theta, t)]$,

Table 0.1. Three types of tomographic image reconstruction algorithms in an over-simplified comparison (the penalization of image reconstruction and topology of network architecture can be complicated).

Category	Form	Knowledge	Input	Quality	Speed
Analytic reconstruction	$f = O[p]$	Idealized model, without noise	High SNR, complete	High	High
Iterative reconstruction	$f^{(k)} = O[p, f^{(k-1)}]$	Physical model, image prior	Low in various ways	Decent	Low
Deep reconstruction	$f = O_{\theta_N} \dots O_{\theta_1}[p]$	Model, prior, big training data	Poor, incomplete	Superior, task-specific	High

where f represents an image in a 2D case without loss of generality, p denotes data as a function of projection viewing angle and detector position, and O is an analytic operation in the closed form, such as an inverse Fourier transform. An iterative algorithm, on the other hand, is expressed as $f^{(k)}(x, y) = O[p(\theta, t), f^{(k-1)}(x, y)]$, where the index k goes from 0, 1, 2, to a sufficiently large number K for the iterative process to converge. The image for $k = 0$ is the initial guess as the starting point of the iterative process. Different from either analytic or iterative algorithms, a deep learning based tomographic reconstruction algorithm is written as $f(x, y) = O_{\theta_N} \ldots O_{\theta_1}[p(\theta, t)]$, where each operator corresponds to a layer of artificial neurons whose parameters $\theta_1, \ldots, \theta_N$ need to be optimized in the training process with big data. Although a deep algorithm may still be slightly slower than an analytic algorithm, it is much faster than an iterative algorithm, since normally $N \ll K$.

0.4 The field of deep reconstruction and the need for this book

The industrial revolution from the eighteenth century onwards has greatly accelerated civilization, and now we are in the intelligence revolution, synergizing big data, exploding information, instantaneous communication, sophisticated algorithms, high-performance computation, and AI/ML. Over only the past few years, as AI/ML methods have become mainstream, deep learning has affected many practical applications and generated overwhelming excitement (figure 0.5). As a result, more and more students and researchers are motivated to learn and apply AI/ML.

Our field is tomographic image reconstruction, which is experiencing a paradigm shift towards deep-learning-based reconstruction (see our perspective on deep imaging (Wang 2016)). Simply speaking, we are interested in developing deep learning methods going from measured features to tomographic images. Currently, deep learning techniques are being actively developed worldwide for tomographic image reconstruction, delivering excellent results (figure 0.6, and also see (Wang *et al* 2019)).

While many of us share optimism about this new wave of tomographic imaging research, there are doubts and concerns regarding deep reconstruction. This conflict of opinions is natural and healthy. In retrospect, at the beginning of the development of analytic reconstruction, there was a major critique that given a finite number of projections, the tomographic reconstruction is not uniquely determined (introducing ghosts in a reconstructed image). Later, this was successfully addressed by regularization methods. When iterative reconstruction algorithms were first developed, it was observed that a reconstructed image was strongly influenced by the penalty term. In other words, it seemed that what one saw was what one wanted to see! Nevertheless, by optimizing the reconstruction parameters, iterative algorithms have been made into commercial scanners. As far as compressed sensing is concerned, it was proved that there is a chance that a sparse solution is not the truth. For example, a tumor-like structure could be introduced, or pathological vessels might be smoothed out if total variation is overly minimized. Similarly, deep learning appears to present issues in practice, such as the interpretability problem.

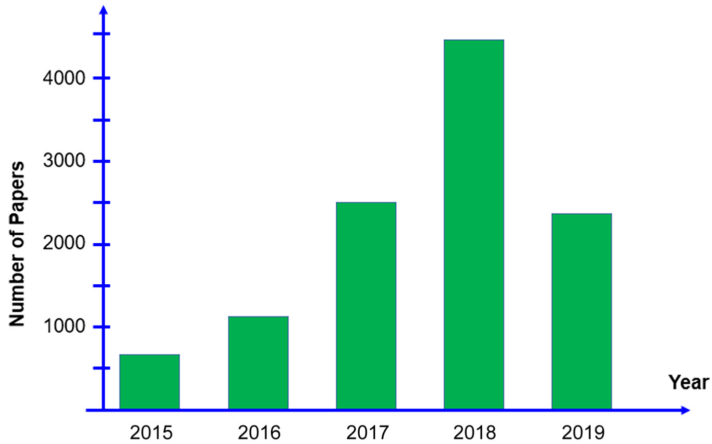


Figure 0.5. A Web of Knowledge search, with 'deep learning', 'medical', and 'imaging' as the topic terms (data collected on 11 July 2019).

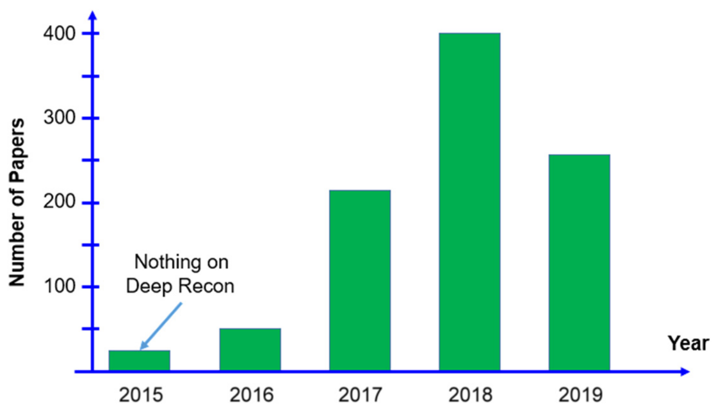


Figure 0.6. Web of Knowledge search, with 'deep learning' in the article title (data collected on 11 July 2019).

No Maxwell equations for deep learning yet exist, and a deep network as a black box is trained to work with big data in terms of parameter adjustment. The interpretability of neural networks is currently a hot topic. Given the rapid progress being made in theoretical and practical aspects, we believe that deep learning algorithms will become the mainstream for medical imaging.

With the encouraging results and insights, some of which are in this book, we are highly confident that, in principle, AI/ML methods for deep reconstruction ought to outperform iterative reconstruction (IR) and compressed sensing (CS) for medical imaging. To convince the reader that AI/ML will dominate tomographic imaging, let us highlight three key arguments: (i) IR/CS can be used as a component in a neural network (such as in our 'LEARN' network in chapter 5); (ii) the result from IR/CS can be used as the baseline (such as for the denoising, despeckling, or deblurring networks mentioned in several chapters in this book); and (iii) IR/CS reconstruction algorithms can be enhanced or even replaced by powerful neural networks with advanced architectures trained with big data with unprecedented domain priors.

There are a good number of deep learning books of high quality. However, they are either on general deep learning methods or other specific deep learning applications. This book is dedicated to the emerging area of deep reconstruction, representing a new frontier of machine learning, and offers a unified treatment of this theme. In particular, this book is focused on medical imaging, which is a primary example of tomographic imaging that affects all people worldwide, spans a huge business, and remains a major driver for technical innovations.

0.5 The organization of this book

This book reflects the state-of-the-art, since all of the co-authors are active researchers in the deep imaging field. Also, the materials are presented in a reader-friendly way, covering classic reconstruction ideas and human vision inspired insights, naturally leading to deep artificial neural networks and deep tomographic reconstruction. There are four parts in this book, with two to three chapters per part.

The first part consists of chapters 1–3, laying out the foundation for the remaining parts. The first chapter describes general principles for imaging, with an emphasis on the importance of prior information when data are imperfect, inconsistent, or incomplete, either in the Bayesian framework or in the context of the human vision system (HVS). From these perspectives, the concepts of regularization and sparsity naturally arise. The second chapter focuses on regularized image reconstruction in the Bayesian and compressed sensing perspectives, with an emphasis on dictionary learning, whose computational structure can be viewed as a single-layer neural network. As a good example, a statistical reconstruction algorithm is empowered with either a global or adaptive dictionary for low-dose computed tomography (CT). Based on the materials covered in chapters 1 and 2, chapter 3 offers a basic but quite complete presentation of neural network architectures, including the concepts and components of deep neural networks, representative networks such as auto-encoder, VGG, U-Net, ResNet, generative adversarial network (GAN), and graph convolutional network (GCN), as well as training, validation, and testing strategies.

The second part includes chapters 4 and 5, exclusively dedicated to CT. Chapter 4 reviews the CT data acquisition process and the development of CT scanners. Also, both analytic and iterative reconstruction algorithms are exemplified. In addition to analytic and iterative algorithms, chapter 5 covers the latest developments of the new type of reconstruction algorithm that employs deep neural networks. A number of recently published deep learning based methods are presented to show the feasibility, merits, and potential of deep learning techniques in the CT field.

The third part has chapters 6 and 7 on magnetic resonance imaging (MRI), in parallel to chapters 4 and 5. Chapter 6 reviews the MRI data acquisition process and the MRI scanner instrumentation. Fourier transform and compressed sensing algorithms are first presented. Then, classic post-processing algorithms are discussed. Chapter 7 covers various deep-learning-based MRI techniques, including a

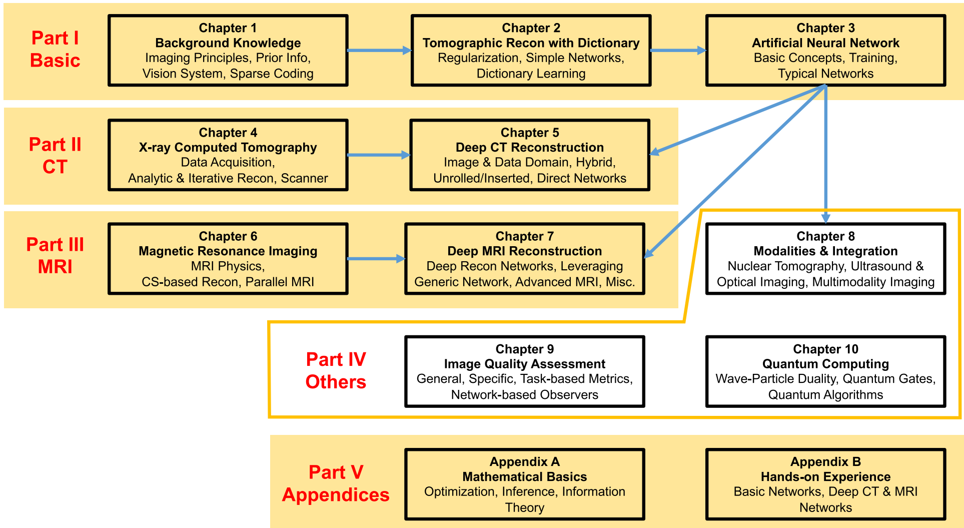


Figure 0.7. Diagram suggesting the order in which the reader reads the components of this book.

variety of deep reconstruction networks with applications to regular MRI, parallel MRI, dynamic MRI, and magnetic resonance fingerprinting (MRF). Miscellaneous topics are also covered, such as optimal k-space sampling and activation functions for complex-valued inputs. Finally, we discuss the integration of MRI data acquisition and image reconstruction with a synergized pulsing and imaging network (SPIN).

In the fourth part, we offer chapters 8–10. Chapter 8 briefly presents other imaging modalities including nuclear imaging, ultrasound imaging, and optical imaging in terms of working principles, and then describes representative neural networks developed for these imaging modalities individually. After that, we mention multi-modality imaging. Chapter 9 discusses image quality for general and task-specific assessment. In this chapter, network-based model observers are presented as a new approach for cost-effective reader studies. Chapter 10 is on quantum computing. We start with wave–particle duality and quantum puzzles, define quantum bits and gates, and touch upon quantum algorithms and quantum machine learning.

For your convenience, the relationships among the four parts and the associated chapters are summarized in figure 0.7, supplemented by appendices A and B. It is underlined that appendix B and associated web resources are under development, and should be invaluable to enhance the learning experience and AI/ML skills. As shown by this book, AI/ML techniques are applicable and instrumental to all tomographic modalities, and promise to unify individual modalities computationally.

0.6 More to learn and what to expect next

As implied by figures 0.5 and 0.6, there are too many relevant papers to read, and the number of such papers is growing rapidly. After reading this book systematically or selectively, you will need more time to master more materials, dive in more deeply, and practice for better skills. According to PwC (https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html in June 2017), AI will yield a global GDP increase of 14% in 2030, and a top area AI affects is healthcare. In such an expanding phase of AI/ML R&D, we have no choice but to pursue continuous learning—papers, books, online materials, and hands-on projects.

Despite all the above positive comments on AI/ML, this field has previously experienced two winters, and it is natural to wonder if we will sooner or later enter another winter of AI/ML. All this depends on how much and how quickly we can continue advancing the field and meeting the majority's expectations. Although the future is often unpredictable but sometimes indeed inventable (Virginia Tech's old logo 'Invent the Future'), we tend to be very optimistic about the future of AI/ML in the long run, and are particularly hopeful for several directions of development.

There are two scientific approaches for reasoning—deduction and induction. Accordingly, we have two associated schools of AI/ML. Deduction goes from general to specific, and is a top-down approach. Decades ago, research on rule-based expert systems was popular, and the fifth generation computer was a hot topic. In this context, it was hoped to reason from general rules to specific claims. On the other hand, induction works from data toward knowledge or information. This is bottom-up or data-driven. The recent champions of the ImageNet contest developed their deep learning programs in a data-driven fashion. There are great opportunities to merge these two approaches in the future. Knowledge graphs and self-supervised learning are two ideas along this direction.

Also, AI/ML and neuroscience/psychiatry are closely intertwined and mutually promoting. For example, studies on the human vision system are an integral part of neuroscience research, which played an instrumental role in the development of AI/

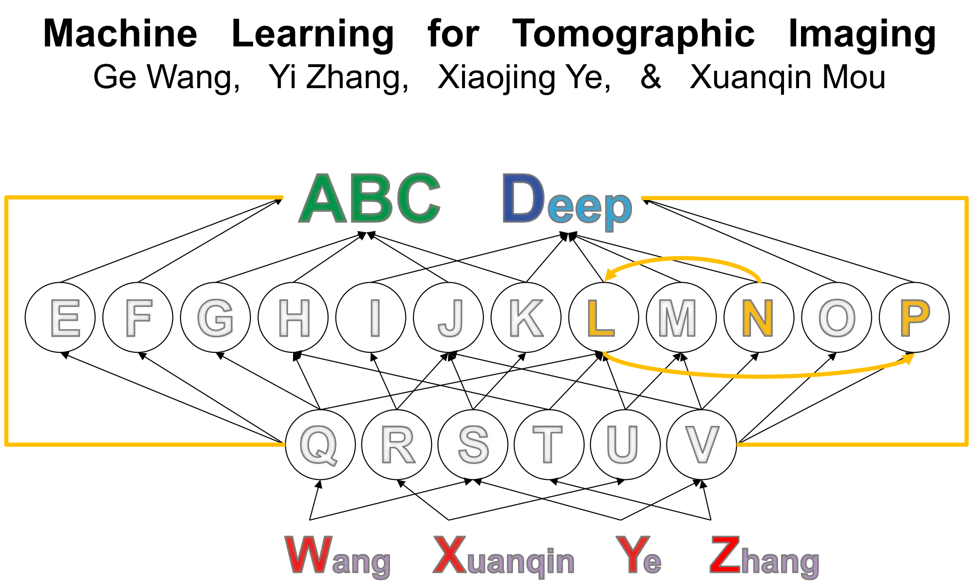


Figure 0.8. NLP is believed to be an important direction for development of AI/ML.

ML and suggested a mechanism for cellular-level processing and interconnection for visual perception and image analysis. New findings and insights in AI/ML and neuroscience will continue promoting each other. Arguably, human intelligence is closely related to natural language understanding and expression. It is believed by many that an important direction of AI/ML development is natural language processing (NLP) (figure 0.8).

Yet another outside-the-box approach is quantum computing, but no-one is sure when its prime time will come. However, if it becomes practical, AI/ML will be revolutionized. For example, our proposed 'SPIN' network may be implemented via quantum computing. A few days ago, Google announced a quantum supremacy, and heated on-going discussions on this topic (https://www.sciencenews.org/article/google-quantum-computer-supremacy-claim). We cannot exclude the possibility that intelligence is essentially a quantum phenomenon and must be implemented through quantum computing. Let us continue making and enjoying our AI/ML related efforts.

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