

Deep Learning

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Contents

Website	viii
Acknowledgments	ix
Notation	xiii
1 Introduction	1
1.1 Who Should Read This Book?	8
1.2 Historical Trends in Deep Learning	12
I Applied Math and Machine Learning Basics	27
2 Linear Algebra	29
2.1 Scalars, Vectors, Matrices and Tensors	29
2.2 Multiplying Matrices and Vectors	32
2.3 Identity and Inverse Matrices	34
2.4 Linear Dependence and Span	35
2.5 Norms	37
2.6 Special Kinds of Matrices and Vectors	38
2.7 Eigendecomposition	40
2.8 Singular Value Decomposition	42
2.9 The Moore-Penrose Pseudoinverse	43
2.10 The Trace Operator	44
2.11 The Determinant	45
2.12 Example: Principal Components Analysis	45
3 Probability and Information Theory	51
3.1 Why Probability?	52

3.2	Random Variables	54
3.3	Probability Distributions	54
3.4	Marginal Probability	56
3.5	Conditional Probability	57
3.6	The Chain Rule of Conditional Probabilities	57
3.7	Independence and Conditional Independence	58
3.8	Expectation, Variance and Covariance	58
3.9	Common Probability Distributions	60
3.10	Useful Properties of Common Functions	65
3.11	Bayes' Rule	68
3.12	Technical Details of Continuous Variables	69
3.13	Information Theory	71
3.14	Structured Probabilistic Models	73
4	Numerical Computation	78
4.1	Overflow and Underflow	78
4.2	Poor Conditioning	80
4.3	Gradient-Based Optimization	80
4.4	Constrained Optimization	91
4.5	Example: Linear Least Squares	94
5	Machine Learning Basics	96
5.1	Learning Algorithms	97
5.2	Capacity, Overfitting and Underfitting	108
5.3	Hyperparameters and Validation Sets	118
5.4	Estimators, Bias and Variance	120
5.5	Maximum Likelihood Estimation	129
5.6	Bayesian Statistics	133
5.7	Supervised Learning Algorithms	137
5.8	Unsupervised Learning Algorithms	142
5.9	Stochastic Gradient Descent	149
5.10	Building a Machine Learning Algorithm	151
5.11	Challenges Motivating Deep Learning	152
II	Deep Networks: Modern Practices	162
6	Deep Feedforward Networks	164
6.1	Example: Learning XOR	167
6.2	Gradient-Based Learning	172

6.3	Hidden Units	187
6.4	Architecture Design	193
6.5	Back-Propagation and Other Differentiation Algorithms	200
6.6	Historical Notes	220
7	Regularization for Deep Learning	224
7.1	Parameter Norm Penalties	226
7.2	Norm Penalties as Constrained Optimization	233
7.3	Regularization and Under-Constrained Problems	235
7.4	Dataset Augmentation	236
7.5	Noise Robustness	238
7.6	Semi-Supervised Learning	240
7.7	Multitask Learning	241
7.8	Early Stopping	241
7.9	Parameter Tying and Parameter Sharing	249
7.10	Sparse Representations	251
7.11	Bagging and Other Ensemble Methods	253
7.12	Dropout	255
7.13	Adversarial Training	265
7.14	Tangent Distance, Tangent Prop and Manifold Tangent Classifier	267
8	Optimization for Training Deep Models	271
8.1	How Learning Differs from Pure Optimization	272
8.2	Challenges in Neural Network Optimization	279
8.3	Basic Algorithms	290
8.4	Parameter Initialization Strategies	296
8.5	Algorithms with Adaptive Learning Rates	302
8.6	Approximate Second-Order Methods	307
8.7	Optimization Strategies and Meta-Algorithms	313
9	Convolutional Networks	326
9.1	The Convolution Operation	327
9.2	Motivation	329
9.3	Pooling	335
9.4	Convolution and Pooling as an Infinitely Strong Prior	339
9.5	Variants of the Basic Convolution Function	342
9.6	Structured Outputs	352
9.7	Data Types	354

9.8	Efficient Convolution Algorithms	356
9.9	Random or Unsupervised Features	356
9.10	The Neuroscientific Basis for Convolutional Networks	358
9.11	Convolutional Networks and the History of Deep Learning	365
10	Sequence Modeling: Recurrent and Recursive Nets	367
10.1	Unfolding Computational Graphs	369
10.2	Recurrent Neural Networks	372
10.3	Bidirectional RNNs	388
10.4	Encoder-Decoder Sequence-to-Sequence Architectures	390
10.5	Deep Recurrent Networks	392
10.6	Recursive Neural Networks	394
10.7	The Challenge of Long-Term Dependencies	396
10.8	Echo State Networks	399
10.9	Leaky Units and Other Strategies for Multiple Time Scales	402
10.10	The Long Short-Term Memory and Other Gated RNNs	404
10.11	Optimization for Long-Term Dependencies	408
10.12	Explicit Memory	412
11	Practical Methodology	416
11.1	Performance Metrics	417
11.2	Default Baseline Models	420
11.3	Determining Whether to Gather More Data	421
11.4	Selecting Hyperparameters	422
11.5	Debugging Strategies	431
11.6	Example: Multi-Digit Number Recognition	435
12	Applications	438
12.1	Large-Scale Deep Learning	438
12.2	Computer Vision	447
12.3	Speech Recognition	453
12.4	Natural Language Processing	456
12.5	Other Applications	473

III	Deep Learning Research	482
13	Linear Factor Models	485
13.1	Probabilistic PCA and Factor Analysis	486
13.2	Independent Component Analysis (ICA)	487
13.3	Slow Feature Analysis	489
13.4	Sparse Coding	492
13.5	Manifold Interpretation of PCA	496
14	Autoencoders	499
14.1	Undercomplete Autoencoders	500
14.2	Regularized Autoencoders	501
14.3	Representational Power, Layer Size and Depth	505
14.4	Stochastic Encoders and Decoders	506
14.5	Denoising Autoencoders	507
14.6	Learning Manifolds with Autoencoders	513
14.7	Contractive Autoencoders	518
14.8	Predictive Sparse Decomposition	521
14.9	Applications of Autoencoders	522
15	Representation Learning	524
15.1	Greedy Layer-Wise Unsupervised Pretraining	526
15.2	Transfer Learning and Domain Adaptation	534
15.3	Semi-Supervised Disentangling of Causal Factors	539
15.4	Distributed Representation	544
15.5	Exponential Gains from Depth	550
15.6	Providing Clues to Discover Underlying Causes	552
16	Structured Probabilistic Models for Deep Learning	555
16.1	The Challenge of Unstructured Modeling	556
16.2	Using Graphs to Describe Model Structure	560
16.3	Sampling from Graphical Models	577
16.4	Advantages of Structured Modeling	579
16.5	Learning about Dependencies	579
16.6	Inference and Approximate Inference	580
16.7	The Deep Learning Approach to Structured Probabilistic Models	581
17	Monte Carlo Methods	587
17.1	Sampling and Monte Carlo Methods	587

17.2	Importance Sampling	589
17.3	Markov Chain Monte Carlo Methods	592
17.4	Gibbs Sampling	596
17.5	The Challenge of Mixing between Separated Modes	597
18	Confronting the Partition Function	603
18.1	The Log-Likelihood Gradient	604
18.2	Stochastic Maximum Likelihood and Contrastive Divergence . . .	605
18.3	Pseudolikelihood	613
18.4	Score Matching and Ratio Matching	615
18.5	Denoising Score Matching	617
18.6	Noise-Contrastive Estimation	618
18.7	Estimating the Partition Function	621
19	Approximate Inference	629
19.1	Inference as Optimization	631
19.2	Expectation Maximization	632
19.3	MAP Inference and Sparse Coding	633
19.4	Variational Inference and Learning	636
19.5	Learned Approximate Inference	648
20	Deep Generative Models	651
20.1	Boltzmann Machines	651
20.2	Restricted Boltzmann Machines	653
20.3	Deep Belief Networks	657
20.4	Deep Boltzmann Machines	660
20.5	Boltzmann Machines for Real-Valued Data	673
20.6	Convolutional Boltzmann Machines	679
20.7	Boltzmann Machines for Structured or Sequential Outputs	681
20.8	Other Boltzmann Machines	683
20.9	Back-Propagation through Random Operations	684
20.10	Directed Generative Nets	688
20.11	Drawing Samples from Autoencoders	707
20.12	Generative Stochastic Networks	710
20.13	Other Generation Schemes	712
20.14	Evaluating Generative Models	713
20.15	Conclusion	716
	Bibliography	717

Index

773

Website

www.deeplearningbook.org

This book is accompanied by the above website. The website provides a variety of supplementary material, including exercises, lecture slides, corrections of mistakes, and other resources that should be useful to both readers and instructors.