

Deep Learning

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Contents

Website	vii
Acknowledgments	viii
Notation	xi
1 Introduction	1
1.1 Who Should Read This Book?	8
1.2 Historical Trends in Deep Learning	11
I Applied Math and Machine Learning Basics	29
2 Linear Algebra	31
2.1 Scalars, Vectors, Matrices and Tensors	31
2.2 Multiplying Matrices and Vectors	34
2.3 Identity and Inverse Matrices	36
2.4 Linear Dependence and Span	37
2.5 Norms	39
2.6 Special Kinds of Matrices and Vectors	40
2.7 Eigendecomposition	42
2.8 Singular Value Decomposition	44
2.9 The Moore-Penrose Pseudoinverse	45
2.10 The Trace Operator	46
2.11 The Determinant	47
2.12 Example: Principal Components Analysis	48
3 Probability and Information Theory	53
3.1 Why Probability?	54

3.2	Random Variables	56
3.3	Probability Distributions	56
3.4	Marginal Probability	58
3.5	Conditional Probability	59
3.6	The Chain Rule of Conditional Probabilities	59
3.7	Independence and Conditional Independence	60
3.8	Expectation, Variance and Covariance	60
3.9	Common Probability Distributions	62
3.10	Useful Properties of Common Functions	67
3.11	Bayes' Rule	70
3.12	Technical Details of Continuous Variables	71
3.13	Information Theory	73
3.14	Structured Probabilistic Models	75
4	Numerical Computation	80
4.1	Overflow and Underflow	80
4.2	Poor Conditioning	82
4.3	Gradient-Based Optimization	82
4.4	Constrained Optimization	93
4.5	Example: Linear Least Squares	96
5	Machine Learning Basics	98
5.1	Learning Algorithms	99
5.2	Capacity, Overfitting and Underfitting	110
5.3	Hyperparameters and Validation Sets	120
5.4	Estimators, Bias and Variance	122
5.5	Maximum Likelihood Estimation	131
5.6	Bayesian Statistics	135
5.7	Supervised Learning Algorithms	140
5.8	Unsupervised Learning Algorithms	146
5.9	Stochastic Gradient Descent	151
5.10	Building a Machine Learning Algorithm	153
5.11	Challenges Motivating Deep Learning	155
II	Deep Networks: Modern Practices	166
6	Deep Feedforward Networks	168
6.1	Example: Learning XOR	171
6.2	Gradient-Based Learning	177

6.3	Hidden Units	191
6.4	Architecture Design	197
6.5	Back-Propagation and Other Differentiation Algorithms	204
6.6	Historical Notes	224
7	Regularization for Deep Learning	228
7.1	Parameter Norm Penalties	230
7.2	Norm Penalties as Constrained Optimization	237
7.3	Regularization and Under-Constrained Problems	239
7.4	Dataset Augmentation	240
7.5	Noise Robustness	242
7.6	Semi-Supervised Learning	243
7.7	Multi-Task Learning	244
7.8	Early Stopping	246
7.9	Parameter Tying and Parameter Sharing	253
7.10	Sparse Representations	254
7.11	Bagging and Other Ensemble Methods	256
7.12	Dropout	258
7.13	Adversarial Training	268
7.14	Tangent Distance, Tangent Prop, and Manifold Tangent Classifier	270
8	Optimization for Training Deep Models	274
8.1	How Learning Differs from Pure Optimization	275
8.2	Challenges in Neural Network Optimization	282
8.3	Basic Algorithms	294
8.4	Parameter Initialization Strategies	301
8.5	Algorithms with Adaptive Learning Rates	306
8.6	Approximate Second-Order Methods	310
8.7	Optimization Strategies and Meta-Algorithms	317
9	Convolutional Networks	330
9.1	The Convolution Operation	331
9.2	Motivation	335
9.3	Pooling	339
9.4	Convolution and Pooling as an Infinitely Strong Prior	345
9.5	Variants of the Basic Convolution Function	347
9.6	Structured Outputs	358
9.7	Data Types	360
9.8	Efficient Convolution Algorithms	362
9.9	Random or Unsupervised Features	363

9.10	The Neuroscientific Basis for Convolutional Networks	364
9.11	Convolutional Networks and the History of Deep Learning	371
10	Sequence Modeling: Recurrent and Recursive Nets	373
10.1	Unfolding Computational Graphs	375
10.2	Recurrent Neural Networks	378
10.3	Bidirectional RNNs	394
10.4	Encoder-Decoder Sequence-to-Sequence Architectures	396
10.5	Deep Recurrent Networks	398
10.6	Recursive Neural Networks	400
10.7	The Challenge of Long-Term Dependencies	401
10.8	Echo State Networks	404
10.9	Leaky Units and Other Strategies for Multiple Time Scales	406
10.10	The Long Short-Term Memory and Other Gated RNNs	408
10.11	Optimization for Long-Term Dependencies	413
10.12	Explicit Memory	416
11	Practical Methodology	421
11.1	Performance Metrics	422
11.2	Default Baseline Models	425
11.3	Determining Whether to Gather More Data	426
11.4	Selecting Hyperparameters	427
11.5	Debugging Strategies	436
11.6	Example: Multi-Digit Number Recognition	440
12	Applications	443
12.1	Large-Scale Deep Learning	443
12.2	Computer Vision	452
12.3	Speech Recognition	458
12.4	Natural Language Processing	461
12.5	Other Applications	478
III	Deep Learning Research	486
13	Linear Factor Models	489
13.1	Probabilistic PCA and Factor Analysis	490
13.2	Independent Component Analysis (ICA)	491
13.3	Slow Feature Analysis	493
13.4	Sparse Coding	496

13.5	Manifold Interpretation of PCA	499
14	Autoencoders	502
14.1	Undercomplete Autoencoders	503
14.2	Regularized Autoencoders	504
14.3	Representational Power, Layer Size and Depth	508
14.4	Stochastic Encoders and Decoders	509
14.5	Denoising Autoencoders	510
14.6	Learning Manifolds with Autoencoders	515
14.7	Contractive Autoencoders	521
14.8	Predictive Sparse Decomposition	523
14.9	Applications of Autoencoders	524
15	Representation Learning	526
15.1	Greedy Layer-Wise Unsupervised Pretraining	528
15.2	Transfer Learning and Domain Adaptation	536
15.3	Semi-Supervised Disentangling of Causal Factors	541
15.4	Distributed Representation	546
15.5	Exponential Gains from Depth	553
15.6	Providing Clues to Discover Underlying Causes	554
16	Structured Probabilistic Models for Deep Learning	558
16.1	The Challenge of Unstructured Modeling	559
16.2	Using Graphs to Describe Model Structure	563
16.3	Sampling from Graphical Models	580
16.4	Advantages of Structured Modeling	582
16.5	Learning about Dependencies	582
16.6	Inference and Approximate Inference	584
16.7	The Deep Learning Approach to Structured Probabilistic Models	585
17	Monte Carlo Methods	590
17.1	Sampling and Monte Carlo Methods	590
17.2	Importance Sampling	592
17.3	Markov Chain Monte Carlo Methods	595
17.4	Gibbs Sampling	599
17.5	The Challenge of Mixing between Separated Modes	599
18	Confronting the Partition Function	605
18.1	The Log-Likelihood Gradient	606
18.2	Stochastic Maximum Likelihood and Contrastive Divergence . . .	607

18.3	Pseudolikelihood	615
18.4	Score Matching and Ratio Matching	617
18.5	Denoising Score Matching	619
18.6	Noise-Contrastive Estimation	620
18.7	Estimating the Partition Function	623
19	Approximate Inference	631
19.1	Inference as Optimization	633
19.2	Expectation Maximization	634
19.3	MAP Inference and Sparse Coding	635
19.4	Variational Inference and Learning	638
19.5	Learned Approximate Inference	651
20	Deep Generative Models	654
20.1	Boltzmann Machines	654
20.2	Restricted Boltzmann Machines	656
20.3	Deep Belief Networks	660
20.4	Deep Boltzmann Machines	663
20.5	Boltzmann Machines for Real-Valued Data	676
20.6	Convolutional Boltzmann Machines	683
20.7	Boltzmann Machines for Structured or Sequential Outputs	685
20.8	Other Boltzmann Machines	686
20.9	Back-Propagation through Random Operations	687
20.10	Directed Generative Nets	692
20.11	Drawing Samples from Autoencoders	711
20.12	Generative Stochastic Networks	714
20.13	Other Generation Schemes	716
20.14	Evaluating Generative Models	717
20.15	Conclusion	720
	Bibliography	721
	Index	777

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.