Contents

A	Acknowledgments		
Notation			ix
1	Introduction 1.1 Who Should Read This Book?		
	1.2	Historical Trends in Deep Learning	8 11
Ι	\mathbf{App}	ied Math and Machine Learning Basics	26
2	Line	ar Algebra	28
	2.1	Scalars, Vectors, Matrices and Tensors	28
	2.2	Multiplying Matrices and Vectors	30
	2.3	Identity and Inverse Matrices	32
	2.4	Linear Dependence and Span	33
	2.5	Norms	35
	2.6	Special Kinds of Matrices and Vectors	36
	2.7	Eigendecomposition	38
	2.8	Singular Value Decomposition	40
	2.9	The Moore-Penrose Pseudoinverse	41
	2.10	The Trace Operator	42
	2.11	Determinant	43
	2.12	Example: Principal Components Analysis	43
3	Probability and Information Theory		48
	3.1	Why Probability?	48
	3.2	Random Variables	51
	3.3	Probability Distributions	51
	3.4	Marginal Probability	53
	3.5	Conditional Probability	53

	3.6	The Chain Rule of Conditional Probabilities	54
	3.7		54
	3.8		55
	3.9	Information Theory	56
	3.10	Common Probability Distributions	59
	3.11		65
	3.12		67
	3.13	v	67
	3.14		69
	3.15		70
4	Num	nerical Computation	77
	4.1		77
	4.2		78
	4.3	Gradient-Based Optimization	79
	4.4		88
	4.5		90
5	Mac	hine Learning Basics	92
	5.1	Learning Algorithms	92
	5.2	Example: Linear Regression	.00
	5.3	Generalization, Capacity, Overfitting and Underfitting 1	.03
	5.4	Hyperparameters and Validation Sets	13
	5.5	Estimators, Bias and Variance	15
	5.6	Maximum Likelihood Estimation	24
	5.7	Bayesian Statistics	27
	5.8	Supervised Learning Algorithms	34
	5.9	Unsupervised Learning Algorithms	39
	5.10	Weakly Supervised Learning	42
	5.11	Building a Machine Learning Algorithm	43
	5.12	The Curse of Dimensionality and Statistical Limitations of Local	
		Generalization	45
ΙΙ	Doo	p Networks: Modern Practices 1	56
			JU
6		1	58
	6.1		59
	6.2	Estimating Conditional Statistics	
	6.3	Parametrizing a Learned Predictor	
	6.4	Flow Graphs and Back-Propagation	.75

	6.5	Back-propagation through Random Operations and Graphical Models		
	6.6	Universal Approximation Properties and Depth 192		
	6.7	Feature / Representation Learning		
	6.8	Piecewise Linear Hidden Units		
	6.9	Historical Notes		
7	Regu	ularization of Deep or Distributed Models 201		
	7.1	Regularization from a Bayesian Perspective		
	7.2	Classical Regularization: Parameter Norm Penalty 204		
	7.3	Classical Regularization as Constrained Optimization		
	7.4	Regularization and Under-Constrained Problems		
	7.5	Dataset Augmentation		
	7.6	Classical Regularization as Noise Robustness		
	7.7	Early Stopping as a Form of Regularization		
	7.8	Parameter Tying and Parameter Sharing		
	7.9	Sparse Representations		
	7.10	Bagging and Other Ensemble Methods		
	7.11	Dropout		
	7.12	Multi-Task Learning		
	7.13	Adversarial Training		
8	Optimization for Training Deep Models 240			
	8.1^{-}	Optimization for Model Training		
	8.2	Challenges in Neural Network Optimization		
	8.3	Optimization Algorithms I: Basic Algorithms		
	8.4	Optimization Algorithms II: Adaptive Learning Rates 265		
	8.5	Optimization Algorithms III: Approximate Second-Order Methods 270		
	8.6	Optimization Algorithms IV: Natural Gradient		
		Methods		
	8.7	Optimization Strategies and Meta-Algorithms		
9	Con	volutional Networks 296		
	9.1	The Convolution Operation		
	9.2	Motivation		
	9.3	Pooling		
	9.4	Convolution and Pooling as an Infinitely Strong Prior 309		
	9.5	Variants of the Basic Convolution Function		
	9.6	Structured Outputs		
	9.7	Data Types		
	0.8	Efficient Convolution Algorithms		

	9.9	Random or Unsupervised Features	320
	9.10	The Neuroscientific Basis for Convolutional Networks	
	9.11	Convolutional Networks and the History of Deep Learning	327
10	Sequ	ence Modeling: Recurrent and Recursive Nets	330
	10.1	Unfolding Flow Graphs and Sharing Parameters	331
	10.2	Recurrent Neural Networks	333
	10.3	Bidirectional RNNs	348
	10.4	Encoder-Decoder Sequence-to-Sequence Architectures	348
	10.5	Deep Recurrent Networks	350
	10.6	Recursive Neural Networks	352
	10.7	The Challenge of Long-Term Dependencies	353
11	Prac	tical methodology	371
	11.1	Default Baseline Models	373
	11.2	Selecting Hyperparameters	374
	11.3	Debugging Strategies	383
12	Applications		388
	12.1	Large Scale Deep Learning	388
	12.2	Computer Vision	396
	12.3	Speech Recognition	401
	12.4	Natural Language Processing and Neural Language Models	405
	12.5	Structured Outputs	421
	12.6	Other Applications	423
III	De	ep Learning Research	432
13	Stru	ctured Probabilistic Models for Deep Learning	434
	13.1	The Challenge of Unstructured Modeling	
	13.2	Using Graphs to Describe Model Structure	
	13.3	Advantages of Structured Modeling	
	13.4	Learning about Dependencies	
	13.5	Inference and Approximate Inference over Latent Variables	
	13.6	The Deep Learning Approach to Structured Probabilistic Models	
14	Mon	te Carlo Methods	462
	14.1	Markov Chain Monte Carlo Methods	462
	14.2	The Difficulty of Mixing between Well-Separated Modes	464

15	Linea	ar Factor Models and Auto-Encoders	466
	15.1	Regularized Auto-Encoders	467
	15.2	Denoising Auto-encoders	470
	15.3	Representational Power, Layer Size and Depth	472
	15.4	Reconstruction Distribution	473
	15.5	Linear Factor Models	474
	15.6	Probabilistic PCA and Factor Analysis	
	15.7	Reconstruction Error as Log-Likelihood	479
	15.8	Sparse Representations	480
	15.9	Denoising Auto-Encoders	
	15.10	Contractive Auto-Encoders	
16	Repr	resentation Learning	493
	16.1	Greedy Layerwise Unsupervised Pre-Training	494
	16.2	Transfer Learning and Domain Adaptation	501
	16.3	Semi-Supervised Learning	508
	16.4	Semi-Supervised Learning and Disentangling Underlying Causal	
		Factors	509
	16.5	Assumption of Underlying Factors and Distributed Representation	511
	16.6	Exponential Gain in Representational Efficiency from Distributed	
		Representations	515
	16.7	Exponential Gain in Representational Efficiency from Depth	517
	16.8	Priors regarding the Underlying Factors	520
17	The	Manifold Perspective on Representation Learning	523
	17.1	Manifold Interpretation of PCA and Linear Auto-Encoders	531
	17.2	Manifold Interpretation of Sparse Coding	534
	17.3	The Entropy Bias from Maximum Likelihood	534
	17.4	Manifold Learning via Regularized Auto-Encoders	535
	17.5	Tangent Distance, Tangent-Prop, and Manifold Tangent Classifier	536
18	Conf	ronting the Partition Function	540
	18.1	The Log-Likelihood Gradient of Energy-Based Models	541
	18.2	Stochastic Maximum Likelihood and Contrastive Divergence	543
	18.3	Pseudolikelihood	550
	18.4	Score Matching and Ratio Matching	552
	18.5	Denoising Score Matching	554
	18.6	Noise-Contrastive Estimation	554
	18.7	Estimating the Partition Function	556

19	Appr	roximate inference	$\bf 564$
	19.1	Inference as Optimization	566
	19.2	Expectation Maximization	567
	19.3	MAP Inference: Sparse Coding as a Probabilistic Model	568
	19.4	Sequence Modeling with Graphical Models	569
	19.5	Combining Neural Networks and Search	579
	19.6	Variational Inference and Learning	584
	19.7	Stochastic Inference	588
	19.8	Learned Approximate Inference	588
20	Deep	Generative Models	590
	20.1	Boltzmann Machines	590
	20.2	Restricted Boltzmann Machines	593
	20.3	Training Restricted Boltzmann Machines	596
	20.4	Deep Belief Networks	600
	20.5	Deep Boltzmann Machines	603
	20.6	Boltzmann Machines for Real-Valued Data	614
	20.7	Convolutional Boltzmann Machines	617
	20.8	Other Boltzmann Machines	618
	20.9	Directed Generative Nets	618
	20.10	Auto-Regressive Networks	621
	20.11	A Generative View of Autoencoders	626
	20.12	Generative Stochastic Networks	632
	20.13	Methodological Notes	634
Bil	oliogra	aphy	638
Inc	Index		