Contents

Website			vii	
A	cknow	ledgments	viii	
No	otatio	n	xi	
1	Intro 1.1 1.2	Oduction Who Should Read This Book?		
Ι	Appl	lied Math and Machine Learning Basics	29	
2	Linear Algebra			
	2.1	Scalars, Vectors, Matrices and Tensors	31	
	2.2	Multiplying Matrices and Vectors		
	2.3	Identity and Inverse Matrices		
	2.4	Linear Dependence and Span		
	2.5	Norms		
	2.6	Special Kinds of Matrices and Vectors	40	
	2.7	Eigendecomposition	42	
	2.8	Singular Value Decomposition		
	2.9	The Moore-Penrose Pseudoinverse	45	
	2.10	The Trace Operator		
	2.11	The Determinant	47	
	2.12	Example: Principal Components Analysis		
3	Probability and Information Theory 5			
	3.1	Why Probability?	54	

	$\begin{array}{c} 6.1 \\ 6.2 \end{array}$	Example: Learning XOR	. 171 . 177
6	-	Feedforward Networks	168
II	Dee	p Networks: Modern Practices	166
	0.11	Chancinges monvaning Deep Dearning	. 100
	5.10	Challenges Motivating Deep Learning	
	5.10	Building a Machine Learning Algorithm	
	5.9	Stochastic Gradient Descent	
	5.7 5.8	Supervised Learning Algorithms	
	5.6	Bayesian Statistics	
	5.5	Maximum Likelihood Estimation	
	5.4 5.5	Estimators, Bias and Variance	
	5.3	Hyperparameters and Validation Sets	
	5.2	Capacity, Overfitting and Underfitting	
	5.1	Learning Algorithms	
5		hine Learning Basics	98
	4.4 4.5	Example: Linear Least Squares	
	4.3	Constrained Optimization	
	4.2	Poor Conditioning	
	4.1		
4	Num 4.1	nerical Computation Overflow and Underflow	80
	3.14	Structured Probabilistic Models	. 75
	3.13	Information Theory	
	3.12	Technical Details of Continuous Variables	
	3.11	Bayes' Rule	
	3.10	Useful Properties of Common Functions	. 67
	3.9	Common Probability Distributions	
	3.8	Expectation, Variance and Covariance	
	3.7	Independence and Conditional Independence	
	3.6	The Chain Rule of Conditional Probabilities	
	3.5	Conditional Probability	
	3.4	Marginal Probability	
	3.3	Probability Distributions	
	3.2	Random Variables	. 56

	6.3	Hidden Units		
	6.4	Architecture Design		
	6.5	Back-Propagation and Other Differentiation Algorithms 204		
	6.6	Historical Notes		
7	Regularization for Deep Learning 228			
	7.1	Parameter Norm Penalties		
	7.2	Norm Penalties as Constrained Optimization		
	7.3	Regularization and Under-Constrained Problems		
	7.4	Dataset Augmentation		
	7.5	Noise Robustness		
	7.6	Semi-Supervised Learning		
	7.7	Multi-Task Learning		
	7.8	Early Stopping		
	7.9	Parameter Tying and Parameter Sharing		
	7.10	Sparse Representations		
	7.11	Bagging and Other Ensemble Methods		
	7.12	Dropout		
	7.13	Adversarial Training		
	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		
	8.2	Challenges in Neural Network Optimization		
	8.3	Basic Algorithms		
	8.4	Parameter Initialization Strategies		
	8.5	Algorithms with Adaptive Learning Rates		
	8.6	Approximate Second-Order Methods		
	8.7	Optimization Strategies and Meta-Algorithms		
9	Convolutional Networks 330			
	9.1	The Convolution Operation		
	9.2	Motivation		
	9.3	Pooling		
	9.4	Convolution and Pooling as an Infinitely Strong Prior		
	9.5	Variants of the Basic Convolution Function		
	9.6	Structured Outputs		
	9.7	Data Types		
	9.8	Efficient Convolution Algorithms		
	9.9	Random or Unsupervised Features		

	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 37			
	10.1	Unfolding Computational Graphs	375	
	10.2	Recurrent Neural Networks		
	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 42			
	11.1	Performance Metrics	422	
	11.2	Default Baseline Models		
	11.3	Determining Whether to Gather More Data		
	11.4	Selecting Hyperparameters		
	11.5	Debugging Strategies		
	11.6	Example: Multi-Digit Number Recognition		
12	Appl	ications	443	
	12.1	Large-Scale Deep Learning	443	
	12.2	Computer Vision		
	12.3	Speech Recognition		
	12.4	Natural Language Processing		
	12.5	Other Applications		
III	Dee	ep Learning Research	486	
13		ar Factor Models	489	
	13.1	Probabilistic PCA and Factor Analysis		
	13.2	Independent Component Analysis (ICA)		
	13.3	Slow Feature Analysis	493 406	
	1.5 /1	SUBTRE LIGHTO	ZIMN	

	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		
	14.6	Learning Manifolds with Autoencoders		
	14.7	Contractive Autoencoders	521	
	14.8	Predictive Sparse Decomposition		
	14.9	Applications of Autoencoders		
15	Repi	resentation Learning	526	
	15.1	Greedy Layer-Wise Unsupervised Pretraining	528	
	15.2	Transfer Learning and Domain Adaptation		
	15.3	Semi-Supervised Disentangling of Causal Factors		
	15.4	Distributed Representation		
	15.5	Exponential Gains from Depth		
	15.6	Providing Clues to Discover Underlying Causes		
16	Stru	ctured Probabilistic Models for Deep Learning	558	
	16.1	The Challenge of Unstructured Modeling	559	
	16.2	Using Graphs to Describe Model Structure		
	16.3	Sampling from Graphical Models		
	16.4	Advantages of Structured Modeling		
	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	Mon	te 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		
18	Conf	fronting the Partition Function	605	
	18.1	The Log-Likelihood Gradient	606	
	18.2	Stochastic Maximum Likelihood and Contrastive Divergence		

	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	Appr	eoximate 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		
	20.9	Back-Propagation through Random Operations	687	
	20.10	Directed Generative Nets	692	
	20.11	Drawing Samples from Autoencoders	711	
		Generative Stochastic Networks		
	20.13	Other Generation Schemes	716	
	20.14	Evaluating Generative Models	717	
	20.15	Conclusion	720	
Bil	Bibliography 72			
Index			777	