CONTENTS

	Pre	face	XV		
		Acknowledgments	xvi		
1	Introduction				
	1.1	Well-Posed Learning Problems	2		
	1.2	Designing a Learning System	5		
		1.2.1 Choosing the Training Experience	5		
		1.2.2 Choosing the Target Function	7		
		1.2.3 Choosing a Representation for the Target Function	2 5 5 7 8		
		1.2.4 Choosing a Function Approximation Algorithm	9		
		1.2.5 The Final Design	11		
	1.3	Perspectives and Issues in Machine Learning	14		
	121000	1.3.1 Issues in Machine Learning	15		
	1.4	How to Read This Book	16		
	1.5	Summary and Further Reading	17		
		Exercises	18		
		References	19		
2	Concept Learning and the General-to-Specific Ordering				
	2.1	Introduction	20		
	2.2	A Concept Learning Task	21		
		2.2.1 Notation	22		
		2.2.2 The Inductive Learning Hypothesis	23		
	2.3	Concept Learning as Search	23		
		2.3.1 General-to-Specific Ordering of Hypotheses	24		
	2.4	FIND-S: Finding a Maximally Specific Hypothesis	26		
	2.5	Version Spaces and the CANDIDATE-ELIMINATION			
		Algorithm	29		
		2.5.1 Representation	29		
		2.5.2 The List-Then-Eliminate Algorithm	30		
		2.5.3 A More Compact Representation for Version Spaces	30		
			vii		

		2.5.4 Candidate-Elimination Learning Algorithm	32
		2.5.5 An Illustrative Example	33
	2.6	Remarks on Version Spaces and CANDIDATE-ELIMINATION	37
		2.6.1 Will the CANDIDATE-ELIMINATION Algorithm	
		Converge to the Correct Hypothesis?	37
		2.6.2 What Training Example Should the Learner Request	
		Next?	37
		2.6.3 How Can Partially Learned Concepts Be Used?	38
	2.7	Inductive Bias	39
		2.7.1 A Biased Hypothesis Space	40
		2.7.2 An Unbiased Learner	40
		2.7.3 The Futility of Bias-Free Learning	42
	2.8	Summary and Further Reading	45
		Exercises	47
		References	50
3	Dec	ision Tree Learning	52
	3.1	Introduction	52
	3.2	Decision Tree Representation	52
	3.3	Appropriate Problems for Decision Tree Learning	54
	3.4	The Basic Decision Tree Learning Algorithm	55
	-905	3.4.1 Which Attribute Is the Best Classifier?	55
		3.4.2 An Illustrative Example	59
	3.5	Hypothesis Space Search in Decision Tree Learning	60
	3.6	Inductive Bias in Decision Tree Learning	63
	500	3.6.1 Restriction Biases and Preference Biases	63
		3.6.2 Why Prefer Short Hypotheses?	65
	3.7	Issues in Decision Tree Learning	66
	9.00	3.7.1 Avoiding Overfitting the Data	66
		3.7.2 Incorporating Continuous-Valued Attributes	72
		3.7.3 Alternative Measures for Selecting Attributes	73
		3,7.4 Handling Training Examples with Missing Attribute	0.5
		Values	75
		3.7.5 Handling Attributes with Differing Costs	75
	3.8	Summary and Further Reading	76
		Exercises	77
		References	78
4	Arti	ficial Neural Networks	81
		Introduction	81
	4.1	4.1.1 Biological Motivation	82
	4.2		82
		Neural Network Representations Appropriate Problems for Neural Network Learning	83
	4.3		86
	4.4	Perceptrons 4.4.1 Representational Power of Perceptrons	86
		4.4.1 Representational Power of Perceptrons 4.4.2 The Perceptron Training Rule	88
		4.4.3 Gradient Descent and the Delta Rule	89
		4.4.4 Remarks	94
		ATTICKET AND ADMINISTRATION OF THE PARTY OF	1

CONTEN	TS.	ix
--------	-----	----

	4.5	Multilayer Networks and the BACKPROPAGATION Algorithm 4.5.1 A Differentiable Threshold Unit	9:		
			9:		
		4.5.2 The Backpropagation Algorithm	1/67		
	16	4.5.3 Derivation of the BACKPROPAGATION Rule	10		
	4.6	Remarks on the BACKPROPAGATION Algorithm	10-		
		4.6.1 Convergence and Local Minima 4.6.2 Representational Power of Feedforward Networks	105		
			100		
		지지 아이들은 이 그 점을 빼내려면 하면 어린이에 눈이로 살아가면 하면	100		
		4.6.4 Hidden Layer Representations 4.6.5 Generalization, Overfitting, and Stopping Criterion	108		
	4.7	An Illustrative Example: Face Recognition	113		
	44.5	4.7.1 The Task	113		
		4.7.2 Design Choices	113		
		4.7.3 Learned Hidden Representations	116		
	4.8	Advanced Topics in Artificial Neural Networks	117		
	710	4.8.1 Alternative Error Functions	117		
		4.8.2 Alternative Error Minimization Procedures	119		
		4.8.3 Recurrent Networks	119		
		4.8.4 Dynamically Modifying Network Structure	12		
	4.9	Summary and Further Reading	123		
	0158	Exercises	12-		
		References	126		
5	Evaluating Hypotheses				
	5.1	Motivation	128		
	5.2	Estimating Hypothesis Accuracy	129		
		5.2.1 Sample Error and True Error	130		
		5.2.2 Confidence Intervals for Discrete-Valued Hypotheses	13		
	5.3	Basics of Sampling Theory	133		
		5.3.1 Error Estimation and Estimating Binomial Proportions	133		
		5.3.2 The Binomial Distribution	133		
		5.3.3 Mean and Variance	1.36		
		5.3.4 Estimators, Bias, and Variance	137		
		5.3.5 Confidence Intervals	131		
		5.3.6 Two-Sided and One-Sided Bounds	14		
	5.4	A General Approach for Deriving Confidence Intervals	143		
		5.4.1 Central Limit Theorem	14.		
	5.5	Difference in Error of Two Hypotheses	143		
		5.5.1 Hypothesis Testing	14		
	5.6	Comparing Learning Algorithms	14:		
		5.6.1 Paired r Tests	148		
		5.6.2 Practical Considerations	149		
	5.7	Summary and Further Reading	1.54		
		Exercises	15.		
		References	157		
6	Bay	esian Learning	15		
	6.1	Introduction	15-		
	6.2	Bayes Theorem	156		
		6.2.1 An Example	15		

	6.3	Charles St. March 1997	Theorem and Concept Learning	1.58			
		6.3.1	Brute-Force Bayes Concept Learning	159			
		6.3.2	MAP Hypotheses and Consistent Learners	162			
	6.4	Maxim	um Likelihood and Least-Squared Error Hypotheses	164			
	6.5	Maxim 6.5.1		167			
	W#INT	02020000	Net	170			
	6.6		um Description Length Principle	17			
	6.7		Optimal Classifier	17-			
	6.8		Algorithm	176			
	6.9		Bayes Classifier	17			
	10.000	6.9.1	An Illustrative Example	178			
	6.10		ample: Learning to Classify Text	180			
	0.0000		Experimental Results	183			
	6,11	Charles Transfer	an Belief Networks	184			
			Conditional Independence	185			
			Representation	186			
			Inference	187			
		6.11.4	Learning Bayesian Belief Networks	188			
		6.11.5	Gradient Ascent Training of Bayesian Networks	188			
		6.11.6	Learning the Structure of Bayesian Networks	190			
	6.12		M Algorithm	19			
		6.12.1	Estimating Means of k Gaussians	19			
		6.12.2	General Statement of EM Algorithm	194			
		6.12.3	Derivation of the k Means Algorithm	195			
	6.13	Somma	ary and Further Reading	197			
		Exercis	ses:	198			
		Refere	nces	199			
7	Con	putatio	onal Learning Theory	20			
	7.1	Introduction					
	7.2	Probab	ly Learning an Approximately Correct Hypothesis	203			
		7.2.1	The Problem Setting	203			
		7.2.2	Error of a Hypothesis	204			
		7.2.3	PAC Learnability	205			
	7.3	Sample	Complexity for Finite Hypothesis Spaces	207			
		7.3.1	Agnostic Learning and Inconsistent Hypotheses	210			
		7.3.2	Conjunctions of Boolean Literals Are PAC-Learnable	21			
		7.3.3	PAC-Learnability of Other Concept Classes	213			
	7.4		Complexity for Infinite Hypothesis Spaces	214			
		7.4.1	Shattering a Set of Instances	214			
		7.4.2	The Vapnik-Chervonenkis Dimension	215			
		7.4.3	Sample Complexity and the VC Dimension	217			
		7.4.4	VC Dimension for Neural Networks	218			
	7.5						
		7.5.1	Mistake Bound for the FIND-S Algorithm	220			
		7.5.2	Mistake Bound for the HALVING Algorithm	22			
		7.5.3	Optimal Mistake Bounds	227			
		7.5.4	WEIGHTED-MAJORITY Algorithm	223			

		CONTENTS	xi		
	7.6	Summary and Further Reading	225		
		Exercises	227		
		References	229		
8	Instance-Based Learning				
	8.1	Introduction	230		
	8.2	k-Nearest Neighbor Learning	231		
		8.2.1 Distance-Weighted NEAREST NEIGHBOR Algorithm	233		
		8.2.2 Remarks on k-NEAREST NEIGHBOR Algorithm	234		
		8.2.3 A Note on Terminology	236		
	8.3	Locally Weighted Regression	236		
		8.3.1 Locally Weighted Linear Regression	237		
		8.3.2 Remarks on Locally Weighted Regression	238		
	8.4	Radial Basis Functions	238		
	8.5	Case-Based Reasoning	240		
	8.6	Remarks on Lazy and Eager Learning	244		
	8.7	Summary and Further Reading	245		
		Exercises	247		
		References	247		
9	Gen	etic Algorithms	249		
	9.1	Motivation	249		
	9.2	Genetic Algorithms	250		
		9.2.1 Representing Hypotheses	252		
		9.2.2 Genetic Operators	253		
		9.2.3 Fitness Function and Selection	255		
	9.3	An Illustrative Example	256		
		9.3.1 Extensions	258		
	9.4	Hypothesis Space Search	259		
		9.4.1 Population Evolution and the Schema Theorem	260		
	9.5	Genetic Programming	262		
		9.5.1 Representing Programs	262		
		9.5.2 Illustrative Example	263		
		9.5.3 Remarks on Genetic Programming	265		
	9.6	Models of Evolution and Learning	266		
		9.6.1 Lamarckian Evolution	266		
		9.6.2 Baldwin Effect	267		
	9.7	Parallelizing Genetic Algorithms	268		
	9.8	Summary and Further Reading	268		
		Exercises	270		
		References	270		
10	Learning Sets of Rules				
	10.1	Introduction	274		
	10.2		275		
		10.2.1 General to Specific Beam Search	277		
		10.2.2 Variations	279		
	10.3		280		
		The street of th			

	10.4		283		
		10.4.1 First-Order Horn Clauses	283		
	11-01-0	10.4.2 Terminology	284		
	10.5	Learning Sets of First-Order Rules: FOIL	285		
		10.5.1 Generating Candidate Specializations in FOIL	287		
		10.5.2 Guiding the Search in FOIL	288		
		10.5.3 Learning Recursive Rule Sets	290		
	1000	10.5.4 Summary of FOIL	290		
	10.6		291		
	10,7		293		
		10.7.1 First-Order Resolution	296		
		10.7.2 Inverting Resolution: First-Order Case	297		
		10.7.3 Summary of Inverse Resolution	298		
		10.7.4 Generalization, θ-Subsumption, and Entailment	299		
		10.7.5 Progot.	300		
	10.8	Summary and Further Reading	301		
		Exercises	303		
		References	304		
11	Ana	lytical Learning	307		
	11.1	Introduction	307		
		11.1.1 Inductive and Analytical Learning Problems	310		
	11.2	Learning with Perfect Domain Theories: PROLOG-EBG	312		
		11.2.1 An Illustrative Trace	313		
	11.3	Remarks on Explanation-Based Learning	319		
		11.3.1 Discovering New Features	320		
		11.3.2 Deductive Learning	321		
		11.3.3 Inductive Bias in Explanation-Based Learning	322		
		11.3.4 Knowledge Level Learning	323		
	11.4	Explanation-Based Learning of Search Control Knowledge	325		
	11.5		328		
		Exercises	330		
		References	331		
12	Combining Inductive and Analytical Learning				
	12.1	Motivation	334		
		Inductive-Analytical Approaches to Learning	337		
		12.2.1 The Learning Problem	337		
		12.2.2 Hypothesis Space Search	339		
	12.3	[2] 전 1일 1일 22·10 - 1일	340		
		12.3.1 The KBANN Algorithm	340		
		12.3.2 An Illustrative Example	341		
		12.3.3 Remarks	344		
	12.4		346		
		12.4.1 The TangentProp Algorithm	347		
		12.4.2 An Illustrative Example	349		
		12.4.3 Remarks	350		
		12.4.4 The EBNN Algorithm	351		
		12.4.5 Remarks	355		
		THE PARK THE PROPERTY OF THE PROPERTY OF THE PARK THE PAR	1979/46		

		CONTENTS	xiii
	12.5 Using Prior Knowledge to Augment Search Operators 12.5.1 The FOCL Algorithm		357 357
	12.5.2 Remarks		360
	12.6 State of the Art		361
	12.7 Summary and Further Reading		362
	Exercises		363
	References		364
13	Reinforcement Learning		367
	13.1 Introduction		367
	13.2 The Learning Task		370
	13.3 Q Learning		373
	13.3.1 The Q Function		374
	13.3.2 An Algorithm for Learning Q		374
	13.3.3 An Illustrative Example		376
	13.3.4 Convergence		377
	13.3.5 Experimentation Strategies		379
	13.3.6 Updating Sequence		379
	13.4 Nondeterministic Rewards and Actions		381
	13.5 Temporal Difference Learning		383
	13.6 Generalizing from Examples		384
	13.7 Relationship to Dynamic Programming		385
	13.8 Summary and Further Reading		386
	Exercises		388
	References		388
Appendix	Notation		391
	Indexes		
	Author Index		394
	Subject Index		400