Contents

	efacexvi knowledgmentsxx
Ab	out the Author xxii
1	From Data to Models: Complexity and Challenges in Understanding Biological, Ecological, and Natural Systems
	1.1: Introduction 1
	1.2: Layout of the Book 4
	References 7
2	Fundamentals of Neural Networks and Models
_	for Linear Data Analysis
	2.1: Introduction and Overview 11
	2.2: Neural Networks and Their Capabilities 12
	2.3: Inspirations from Biology 16
	2.4: Modeling Information Processing in Neurons 18
	2.5: Neuron Models and Learning Strategies 19
	2.5.1: Threshold Neuron as a Simple Classifier 20
	2.5.2: Learning Models for Neurons and Neural Assemblies 23
	2.5.2.1: Hebbian Learning 23
	2.5.2.2: Unsupervised or Competitive Learning 26
	2.5.2.3: Supervised Learning 26
	2.5.3: Perceptron with Supervised Learning as a Classifier 27
	2.5.3.1: Perceptron Learning Algorithm 28
	2.5.3.2: A Practical Example of Perceptron on a Larger
	Realistic Data Set: Identifying the Origin
	of Fish from the Growth-Ring Diameter of Scales 35
	2.5.3.3: Comparison of Perceptron with Linear
	Discriminant Function Analysis in Statistics 38

	2.5.3.4: Multi-Output Perceptron for Multicategory
	Classification 40
	2.5.3.5: Higher-Dimensional Classification Using Perceptron 45
	2.5.3.6: Perceptron Summary 45
	2.5.4: Linear Neuron for Linear Classification and Prediction 46
	2.5.4.1: Learning with the Delta Rule 47
	2.5.4.2: Linear Neuron as a Classifier 51
	2.5.4.3: Classification Properties of a Linear Neuron
	as a Subset of Predictive Capabilities 53
	2.5.4.4: Example: Linear Neuron as a Predictor 54
	2.5.4.5: A Practical Example of Linear Prediction:
	Predicting the Heat Influx in a Home 61
	2.5.4.6: Comparison of Linear Neuron Model with
	Linear Regression 62
	2.5.4.7: Example: Multiple Input Linear Neuron
	Model—Improving the Prediction Accuracy
	of Heat Influx in a Home 63
	2.5.4.8: Comparison of a Multiple-Input Linear Neuron
	with Multiple Linear Regression 63
	2.5.4.9: Multiple Linear Neuron Models 64
	2.5.4.10: Comparison of a Multiple Linear Neuron
	Network with Canonical Correlation Analysis 65
	2.5.4.11: Linear Neuron and Linear Network Summary 65
	26 Survey (6
	2.6: Summary 66
	2.6: Summary 66 Problems 66
	2.6: Summary 66
3	2.6: Summary 66 Problems 66 References 67
3	2.6: Summary 66 Problems 66
3	2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	 2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	 2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition 69 3.1: Overview and Introduction 69 3.1.1: Multilayer Perceptron 71 3.2: Nonlinear Neurons 72 3.2.1: Neuron Activation Functions 73 3.2.1.1: Sigmoid Functions 74 3.2.1.2: Gaussian Functions 76 3.2.2: Example: Population Growth Modeling Using
3	 2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	 2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	 2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	 2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	 2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	 2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	 2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	 2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	 2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	 2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	 2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition
3	 2.6: Summary 66 Problems 66 References 67 Neural Networks for Nonlinear Pattern Recognition

	3.4.3: Examples: Two-Dimensional Prediction and Classification 103
	3.4.3.1: Example 1: Two-Dimensional Nonlinear
	Function Approximation 103
	3.4.3.2: Example 2: Two-Dimensional Nonlinear
	Classification Model 105
	3.5: Multidimensional Data Modeling with Nonlinear
	Multilayer Perceptron Networks 109
	3.6: Summary 110
	Problems 110
	References 112
ŀ	Learning of Nonlinear Patterns by Neural Networks 11
	4.1: Introduction and Overview 113
	4.2: Supervised Training of Networks for Nonlinear
	Pattern Recognition 114
	4.3: Gradient Descent and Error Minimization 115
	4.4: Backpropagation Learning 116
	4.4.1: Example: Backpropagation Training—A Hand Computation 117
	4.4.1.1: Error Gradient with Respect to Output
	Neuron Weights 120
	4.4.1.2: The Error Gradient with Respect to the
	Hidden-Neuron Weights 123
	4.4.1.3: Application of Gradient Descent in
	Backpropagation Learning 127
	4.4.1.4: Batch Learning 128
	4.4.1.5: Learning Rate and Weight Update 130
	4.4.1.6: Example-by-Example (Online) Learning 134
	4.4.1.7: Momentum 134
	4.4.2: Example: Backpropagation Learning
	Computer Experiment 138
	4.4.3: Single-Input Single-Output Network with Multiple Hidden Neurons 141
	· ·
	4.4.4: Multiple-Input, Multiple-Hidden Neuron, and Single-Output Network 142
	4.4.5: Multiple-Input, Multiple-Hidden Neuron,
	Multiple-Output Network 143
	4.4.6: Example: Backpropagation Learning Case
	Study—Solving a Complex Classification Problem 145
	4.5: Delta-Bar-Delta Learning (Adaptive Learning Rate) Method 152
	4.5.1: Example: Network Training with Delta-Bar-Delta—
	A Hand Computation 154
	4.5.2: Example: Delta-Bar-Delta with Momentum—
	A Hand Computation 157
	4.5.3: Network Training with Delta-Bar Delta—
	A Computer Experiment 158
	4.5.4: Comparison of Delta-Bar-Delta Method with
	Backpropagation 159

5

_
4.5.5: Example: Network Training with Delta-Bar-Delta—
A Case Study 160
4.6: Steepest Descent Method 163
4.6.1: Example: Network Training with Steepest
Descent—Hand Computation 163
4.6.2: Example: Network Training with Steepest
Descent—A Computer Experiment 164
4.7: Second-Order Methods of Error Minimization and
Weight Optimization 166
4.7.1: QuickProp 167
4.7.1.1: Example: Network Training with QuickProp—
A Hand Computation 168
4.7.1.2: Example: Network Training with QuickProp—
A Computer Experiment 170
4.7.1.3: Comparison of QuickProp with Steepest
Descent, Delta-Bar-Delta, and Backpropagation 170
4.7.2: General Concept of Second-Order Methods of
Error Minimization 172
4.7.3: Gauss–Newton Method 174
4.7.3.1: Network Training with the Gauss–Newton
Method—A Hand Computation 176
4.7.3.2: Example: Network Training with Gauss–Newton
Method—A Computer Experiment 178
4.7.4: The Levenberg–Marquardt Method 180
4.7.4.1: Example: Network Training with LM
Method—A Hand Computation 182
4.7.4.2: Network Training with the LM
Method—A Computer Experiment 183
4.7.5: Comparison of the Efficiency of the First-Order and
Second-Order Methods in Minimizing Error 184
4.7.6: Comparison of the Convergence Characteristics of
First-Order and Second-Order Learning Methods 185
4.7.6.1: Backpropagation 187
4.7.6.2: Steepest Descent Method 188
4.7.6.3: Gauss–Newton Method 189
, · · · · · · · · · · · · · · · · · ·
4.8: Summary 192
Problems 192
References 193
Implementation of Neural Network Models for
Extracting Reliable Patterns from Data
5.1: Introduction and Overview 195
5.2: Bias-Variance Tradeoff 196
5.3: Improving Generalization of Neural Networks 197
5.3.1: Illustration of Early Stopping 199
5.3.1.1: Effect of Initial Random Weights 203
5 3 1 2: Weight Structure of the Trained Networks 206

5.3.1.3: Effect of Random Sampling 207 5.3.1.4: Effect of Model Complexity: Number
of Hidden Neurons 212
5.3.1.5: Summary on Early Stopping 213
5.3.2: Regularization 215
5.4: Reducing Structural Complexity of Networks by Pruning 221
5.4.1: Optimal Brain Damage 222
5.4.1.1: Example of Network Pruning with
Optimal Brain Damage 223
5.4.2: Network Pruning Based on Variance of
Network Sensitivity 229
5.4.2.1: Illustration of Application of Variance
Nullity in Pruning Weights 232
5.4.2.2: Pruning Hidden Neurons Based on Variance
Nullity of Sensitivity 235
5.5: Robustness of a Network to Perturbation of Weights 237
5.5.1: Confidence Intervals for Weights 239
5.6: Summary 241
Problems 242
References 243
Data Exploration, Dimensionality Reduction,
and Feature Extraction
6.1: Introduction and Overview 245
6.1.1: Example: Thermal Conductivity of Wood in Relation
to Correlated Input Data 247
6.2: Data Visualization 248
6.2.1: Correlation Scatter Plots and Histograms 248
6.2.2: Parallel Visualization 249
6.2.3: Projecting Multidimensional Data onto
Two-Dimensional Plane 250
6.3: Correlation and Covariance between Variables 251
6.4: Normalization of Data 253
6.4: Normalization of Data 253 6.4.1: Standardization 253
6.4: Normalization of Data 253 6.4.1: Standardization 253 6.4.2: Simple Range Scaling 254
6.4: Normalization of Data 253 6.4.1: Standardization 253 6.4.2: Simple Range Scaling 254 6.4.3: Whitening—Normalization of Correlated
 6.4: Normalization of Data 253 6.4.1: Standardization 253 6.4.2: Simple Range Scaling 254 6.4.3: Whitening—Normalization of Correlated Multivariate Data 255
 6.4: Normalization of Data 253 6.4.1: Standardization 253 6.4.2: Simple Range Scaling 254 6.4.3: Whitening—Normalization of Correlated Multivariate Data 255 6.5: Selecting Relevant Inputs 259
 6.4: Normalization of Data 253 6.4.1: Standardization 253 6.4.2: Simple Range Scaling 254 6.4.3: Whitening—Normalization of Correlated Multivariate Data 255 6.5: Selecting Relevant Inputs 259 6.5.1: Statistical Tools for Variable Selection 260
 6.4: Normalization of Data 253 6.4.1: Standardization 253 6.4.2: Simple Range Scaling 254 6.4.3: Whitening—Normalization of Correlated Multivariate Data 255 6.5: Selecting Relevant Inputs 259 6.5.1: Statistical Tools for Variable Selection 260 6.5.1.1: Partial Correlation 260
 6.4: Normalization of Data 253 6.4.1: Standardization 253 6.4.2: Simple Range Scaling 254 6.4.3: Whitening—Normalization of Correlated Multivariate Data 255 6.5: Selecting Relevant Inputs 259 6.5.1: Statistical Tools for Variable Selection 260 6.5.1.1: Partial Correlation 260 6.5.1.2: Multiple Regression and
 6.4: Normalization of Data 253 6.4.1: Standardization 253 6.4.2: Simple Range Scaling 254 6.4.3: Whitening—Normalization of Correlated Multivariate Data 255 6.5: Selecting Relevant Inputs 259 6.5.1: Statistical Tools for Variable Selection 260 6.5.1.1: Partial Correlation 260 6.5.1.2: Multiple Regression and Best-Subsets Regression 261
 6.4: Normalization of Data 253 6.4.1: Standardization 253 6.4.2: Simple Range Scaling 254 6.4.3: Whitening—Normalization of Correlated Multivariate Data 255 6.5: Selecting Relevant Inputs 259 6.5.1: Statistical Tools for Variable Selection 260 6.5.1.1: Partial Correlation 260 6.5.1.2: Multiple Regression and Best-Subsets Regression 261 6.6: Dimensionality Reduction and Feature Extraction 262
 6.4: Normalization of Data 253 6.4.1: Standardization 253 6.4.2: Simple Range Scaling 254 6.4.3: Whitening—Normalization of Correlated Multivariate Data 255 6.5: Selecting Relevant Inputs 259 6.5.1: Statistical Tools for Variable Selection 260 6.5.1.1: Partial Correlation 260 6.5.1.2: Multiple Regression and Best-Subsets Regression 261 6.6: Dimensionality Reduction and Feature Extraction 262 6.6.1: Multicollinearity 262
 6.4: Normalization of Data 253 6.4.1: Standardization 253 6.4.2: Simple Range Scaling 254 6.4.3: Whitening—Normalization of Correlated Multivariate Data 255 6.5: Selecting Relevant Inputs 259 6.5.1: Statistical Tools for Variable Selection 260 6.5.1.1: Partial Correlation 260 6.5.1.2: Multiple Regression and Best-Subsets Regression 261 6.6: Dimensionality Reduction and Feature Extraction 262 6.6.1: Multicollinearity 262 6.6.2: Principal Component Analysis (PCA) 263
 6.4: Normalization of Data 253 6.4.1: Standardization 253 6.4.2: Simple Range Scaling 254 6.4.3: Whitening—Normalization of Correlated Multivariate Data 255 6.5: Selecting Relevant Inputs 259 6.5.1: Statistical Tools for Variable Selection 260 6.5.1.1: Partial Correlation 260 6.5.1.2: Multiple Regression and Best-Subsets Regression 261 6.6: Dimensionality Reduction and Feature Extraction 262 6.6.1: Multicollinearity 262 6.6.2: Principal Component Analysis (PCA) 263 6.6.3: Partial Least-Squares Regression 267
 6.4: Normalization of Data 253 6.4.1: Standardization 253 6.4.2: Simple Range Scaling 254 6.4.3: Whitening—Normalization of Correlated Multivariate Data 255 6.5: Selecting Relevant Inputs 259 6.5.1: Statistical Tools for Variable Selection 260 6.5.1.1: Partial Correlation 260 6.5.1.2: Multiple Regression and Best-Subsets Regression 261 6.6: Dimensionality Reduction and Feature Extraction 262 6.6.1: Multicollinearity 262 6.6.2: Principal Component Analysis (PCA) 263

6

	 6.9: Case Study: Illustrating Input Selection and Dimensionality Reduction for a Practical Problem 270 6.9.1: Data Preprocessing and Preliminary Modeling 271 6.9.2: PCA-Based Neural Network Modeling 275 6.9.3: Effect of Hidden Neurons for Non-PCA- and PCA-Based Approaches 278 6.9.4: Case Study Summary 279 6.10: Summary 280 Problems 281 References 281 	
7	Assessment of Uncertainty of Neural Network	
,	Art July 27 1 19 1 1 10 1 10 10 10 10 10 10 10 10 10 10	
	7.1: Introduction and Overview 283	
	7.2: Estimating Weight Uncertainty Using Bayesian Statistics 285	
	7.2.1: Quality Criterion 285	
	7.2.2: Incorporating Bayesian Statistics to Estimate	
	Weight Uncertainty 288	
	7.2.2.1: Square Error 289	
	7.2.3: Intrinsic Uncertainty of Targets for Multivariate Output 292	
	7.2.4: Probability Density Function of Weights 293	
	7.2.5: Example Illustrating Generation of Probability	
	Distribution of Weights 295	
	7.2.5.1: Estimation of Geophysical Parameters	
	from Remote Sensing: A Case Study 295	
	7.3: Assessing Uncertainty of Neural Network Outputs Using	
	Bayesian Statistics 300	
	7.3.1: Example Illustrating Uncertainty Assessment of	
	Output Errors 301	
	7.3.1.1: Total Network Output Errors 301	
	7.3.1.2: Error Correlation and Covariance Matrices 302	
	7.3.1.3: Statistical Analysis of Error Covariance 302	
	7.3.1.4: Decomposition of Total Output Error into Model Error and Intrinsic Noise 304	
	7.4: Assessing the Sensitivity of Network Outputs to Inputs 311	
	7.4.1: Approaches to Determine the Influence of Inputs	
	on Outputs in Feedforward Networks 311	
	7.4.1.1: Methods Based on Magnitude of Weights 311	
	7.4.1.2: Sensitivity Analysis 312	
	7.4.2: Example: Comparison of Methods to Assess the	
	Influence of Inputs on Outputs 313	
	7.4.3: Uncertainty of Sensitivities 314	
	7.4.4: Example Illustrating Uncertainty Assessment of Network	
	Sensitivity to Inputs 315	
	7.4.4.1: PCA Decomposition of Inputs and Outputs 315	
	7.4.4.2: PCA-Based Neural Network Regression 320	
	7.4.4.3: Neural Network Sensitivities 323	
	7.4.4.4: Uncertainty of Input Sensitivity 325	

7.4.4.5: PCA-Regularized Jacobians 328
7.4.4.6: Case Study Summary 333
7.5: Summary 333
Problems 334
References 335
Discovering Unknown Clusters in Data with
Self-Organizing Maps
8.1: Introduction and Overview 337
8.2: Structure of Unsupervised Networks 338
8.3: Learning in Unsupervised Networks 339
8.4: Implementation of Competitive Learning 340
8.4.1: Winner Selection Based on Neuron Activation 340
8.4.2: Winner Selection Based on Distance to Input Vector 341
8.4.2.1: Other Distance Measures 342
8.4.3: Competitive Learning Example 343
8.4.3.1: Recursive Versus Batch Learning 344
8.4.3.2: Illustration of the Calculations Involved in
Winner Selection 344
8.4.3.3: Network Training 346
8.5: Self-Organizing Feature Maps 349
8.5.1: Learning in Self-Organizing Map Networks 349
8.5.1.1: Selection of Neighborhood Geometry 349
8.5.1.2: Training of Self-Organizing Maps 350
8.5.1.3: Neighbor Strength 350
8.5.1.4: Example: Training Self-Organizing Networks
with a Neighbor Feature 351
8.5.1.5: Neighbor Matrix and Distance to Neighbors
from the Winner 354
8.5.1.6: Shrinking Neighborhood Size with Iterations 357
8.5.1.7: Learning Rate Decay 358
8.5.1.8: Weight Update Incorporating Learning
Rate and Neighborhood Decay 359
8.5.1.9: Recursive and Batch Training and Relation
to K-Means Clustering 360
8.5.1.10: Two Phases of Self-Organizing Map Training 360
8.5.1.11: Example: Illustrating Self-Organizing Map
Learning with a Hand Calculation 361
8.5.1.12: SOM Case Study: Determination of Mastitis
Health Status of Dairy Herd from Combined
Milk Traits 368
8.5.2: Example of Two-Dimensional Self-Organizing Maps:
Clustering Canadian and Alaskan Salmon Based on the
Diameter of Growth Rings of the Scales 371
8.5.2.1: Map Structure and Initialization 372
8.5.2.2: Map Training 373
8.5.2.3: U-Matrix 380
8.5.3: Map Initialization 382

8

9

8.5.4: Example: Training Two-Dimensional Maps on
Multidimensional Data 382
8.5.4.1: Data Visualization 383
8.5.4.2: Map Structure and Training 383
8.5.4.3: U-Matrix 389
8.5.4.4: Point Estimates of Probability Density of
Inputs Captured by the Map 390
8.5.4.5: Quantization Error 391
8.5.4.6: Accuracy of Retrieval of Input Data
from the Map 393
8.5.5: Forming Clusters on the Map 395
8.5.5.1: Approaches to Clustering 396
8.5.5.2: Example Illustrating Clustering on a
Trained Map 397
8.5.5.3: Finding Optimum Clusters on the Map
with the Ward Method 401
8.5.5.4: Finding Optimum Clusters by K-Means
Clustering 403
8.5.6: Validation of a Trained Map 406
8.5.6.1: <i>n</i> -Fold Cross Validation 406
8.6: Evolving Self-Organizing Maps 411
8.6.1: Growing Cell Structure of Map 413
8.6.1.1: Centroid Method for Mapping Input
Data onto Positions between
Neurons on the Map 416
8.6.2: Dynamic Self-Organizing Maps with Controlled
Growth (GSOM) 419
8.6.2.1: Example: Application of Dynamic
Self-Organizing Maps 422
8.6.3: Evolving Tree 427
8.7: Summary 431
Problems 432
References 434
References 454
Neural Networks for Time-Series Forecasting
9.1: Introduction and Overview 437
9.2: Linear Forecasting of Time-Series with Statistical and
Neural Network Models 440
9.2.1: Example Case Study: Regulating Temperature
of a Furnace 442
9.2.1.1: Multistep-Ahead Linear Forecasting 444
9.3: Neural Networks for Nonlinear Time-Series Forecasting 446
9.3.1: Focused Time-Lagged and Dynamically Driven
Recurrent Networks 446
9.3.1.1: Focused Time-Lagged Feedforward Networks 448
9.3.1.2: Spatio-Temporal Time-Lagged Networks 450
9.3.2: Example: Spatio-Temporal Time-Lagged Network— Regulating Temperature in a Furnace 452

 9.4.1: Case Study: Forecasting the Annual Number of Sunspots 9.5: Automatic Generation of Network Structure Using Simplest Structure Concept 471 9.5.1: Case Study: Forecasting Air Pollution with Automatic Neural Network Model Generation 473 9.6: Generalized Neuron Network 475 9.6.1: Case Study: Short-Term Load Forecasting with a Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1.1: Encapsulating Long-Term Memory 485 	468 470
9.3.2.2: Multistep Forecasting with Neural NARx Model 455 9.3.3: Case Study: River Flow Forecasting 457 9.3.3.1: Linear Model for River Flow Forecasting 460 9.3.3.2: Nonlinear Neural (NARx) Model for River Flow Forecasting 463 9.3.3.3: Input Sensitivity 467 9.4: Hybrid Linear (ARIMA) and Nonlinear Neural Network Models 9.4.1: Case Study: Forecasting the Annual Number of Sunspots 9.5: Automatic Generation of Network Structure Using Simplest Structure Concept 471 9.5.1: Case Study: Forecasting Air Pollution with Automatic Neural Network Model Generation 473 9.6: Generalized Neuron Network 475 9.6.1: Case Study: Short-Term Load Forecasting with a Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Encapsulating Long-Term Memory 485 9.7.1.2: Structure and Operation of the Elman Network 4 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
9.3.3: Case Study: River Flow Forecasting 457 9.3.3.1: Linear Model for River Flow Forecasting 460 9.3.3.2: Nonlinear Neural (NARx) Model for River Flow Forecasting 463 9.3.3.3: Input Sensitivity 467 9.4: Hybrid Linear (ARIMA) and Nonlinear Neural Network Models 9.4.1: Case Study: Forecasting the Annual Number of Sunspots 9.5: Automatic Generation of Network Structure Using Simplest Structure Concept 471 9.5.1: Case Study: Forecasting Air Pollution with Automatic Neural Network Model Generation 473 9.6: Generalized Neuron Network 475 9.6.1: Case Study: Short-Term Load Forecasting with a Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1.2: Structure and Operation of the Elman Network 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
9.3.3.1: Linear Model for River Flow Forecasting 460 9.3.3.2: Nonlinear Neural (NARx) Model for River Flow Forecasting 463 9.3.3.3: Input Sensitivity 467 9.4: Hybrid Linear (ARIMA) and Nonlinear Neural Network Models 9.4.1: Case Study: Forecasting the Annual Number of Sunspots 9.5: Automatic Generation of Network Structure Using Simplest Structure Concept 471 9.5.1: Case Study: Forecasting Air Pollution with Automatic Neural Network Model Generation 473 9.6: Generalized Neuron Network 475 9.6.1: Case Study: Short-Term Load Forecasting with a Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1.1: Encapsulating Long-Term Memory 485 9.7.1.2: Structure and Operation of the Elman Network 4 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
9.3.3.2: Nonlinear Neural (NARx) Model for River Flow Forecasting 463 9.3.3.3: Input Sensitivity 467 9.4: Hybrid Linear (ARIMA) and Nonlinear Neural Network Models 9.4.1: Case Study: Forecasting the Annual Number of Sunspots 9.5: Automatic Generation of Network Structure Using Simplest Structure Concept 471 9.5.1: Case Study: Forecasting Air Pollution with Automatic Neural Network Model Generation 473 9.6: Generalized Neuron Network 475 9.6.1: Case Study: Short-Term Load Forecasting with a Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1.1: Encapsulating Long-Term Memory 485 9.7.1.2: Structure and Operation of the Elman Network 49.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
Flow Forecasting 463 9.3.3.3: Input Sensitivity 467 9.4: Hybrid Linear (ARIMA) and Nonlinear Neural Network Models 9.4.1: Case Study: Forecasting the Annual Number of Sunspots 9.5: Automatic Generation of Network Structure Using Simplest Structure Concept 471 9.5.1: Case Study: Forecasting Air Pollution with Automatic Neural Network Model Generation 473 9.6: Generalized Neuron Network 475 9.6.1: Case Study: Short-Term Load Forecasting with a Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1.1: Encapsulating Long-Term Memory 485 9.7.1.2: Structure and Operation of the Elman Network 4 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
9.3.3.3: Input Sensitivity 467 9.4: Hybrid Linear (ARIMA) and Nonlinear Neural Network Models 9.4.1: Case Study: Forecasting the Annual Number of Sunspots 9.5: Automatic Generation of Network Structure Using Simplest Structure Concept 471 9.5.1: Case Study: Forecasting Air Pollution with Automatic Neural Network Model Generation 473 9.6: Generalized Neuron Network 475 9.6.1: Case Study: Short-Term Load Forecasting with a Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1.2: Structure and Operation of the Elman Network 4 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
 9.4: Hybrid Linear (ARIMA) and Nonlinear Neural Network Models 9.4.1: Case Study: Forecasting the Annual Number of Sunspots 9.5: Automatic Generation of Network Structure Using Simplest Structure Concept 471 9.5.1: Case Study: Forecasting Air Pollution with Automatic Neural Network Model Generation 473 9.6: Generalized Neuron Network 475 9.6.1: Case Study: Short-Term Load Forecasting with a Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1.2: Structure and Operation of the Elman Network 4 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term 	
 9.4.1: Case Study: Forecasting the Annual Number of Sunspots 9.5: Automatic Generation of Network Structure Using Simplest Structure Concept 471 9.5.1: Case Study: Forecasting Air Pollution with Automatic Neural Network Model Generation 473 9.6: Generalized Neuron Network 475 9.6.1: Case Study: Short-Term Load Forecasting with a Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1: Encapsulating Long-Term Memory 485 9.7.1.2: Structure and Operation of the Elman Network 49.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term 	470
9.5: Automatic Generation of Network Structure Using Simplest Structure Concept 471 9.5.1: Case Study: Forecasting Air Pollution with Automatic Neural Network Model Generation 473 9.6: Generalized Neuron Network 475 9.6.1: Case Study: Short-Term Load Forecasting with a Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1: Encapsulating Long-Term Memory 485 9.7.1.2: Structure and Operation of the Elman Network 4 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAX) Case Study: Short-Term	
Simplest Structure Concept 471 9.5.1: Case Study: Forecasting Air Pollution with Automatic Neural Network Model Generation 473 9.6: Generalized Neuron Network 475 9.6.1: Case Study: Short-Term Load Forecasting with a Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1.1: Encapsulating Long-Term Memory 485 9.7.1.2: Structure and Operation of the Elman Network 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAX) Case Study: Short-Term	
9.5.1: Case Study: Forecasting Air Pollution with Automatic Neural Network Model Generation 473 9.6: Generalized Neuron Network 475 9.6.1: Case Study: Short-Term Load Forecasting with a Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1.1: Encapsulating Long-Term Memory 485 9.7.1.2: Structure and Operation of the Elman Network 49.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
 9.6: Generalized Neuron Network 475 9.6.1: Case Study: Short-Term Load Forecasting with a Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1.1: Encapsulating Long-Term Memory 485 9.7.1.2: Structure and Operation of the Elman Network 4 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term 	
9.6.1: Case Study: Short-Term Load Forecasting with a Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1.1: Encapsulating Long-Term Memory 485 9.7.1.2: Structure and Operation of the Elman Network 4 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
Generalized Neuron Network 482 9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1.1: Encapsulating Long-Term Memory 485 9.7.1.2: Structure and Operation of the Elman Network 4 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
9.7: Dynamically Driven Recurrent Networks 485 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1.1: Encapsulating Long-Term Memory 485 9.7.1.2: Structure and Operation of the Elman Network 4 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
 9.7.1: Recurrent Networks with Hidden Neuron Feedback 485 9.7.1.1: Encapsulating Long-Term Memory 485 9.7.1.2: Structure and Operation of the Elman Network 4 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term 	
 9.7.1.1: Encapsulating Long-Term Memory 485 9.7.1.2: Structure and Operation of the Elman Network 4 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application	
 9.7.1.2: Structure and Operation of the Elman Network 4 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application	
 9.7.1.3: Training Recurrent Networks 490 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application	
 9.7.1.4: Network Training Example: Hand Calculation 49 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term 	88
 9.7.1.5: Recurrent Learning Network Application Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term 	
Case Study: Rainfall Runoff Modeling 500 9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	5
9.7.1.6: Two-Step-Ahead Forecasting with Recurrent Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
Networks 503 9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
9.7.1.7: Real-Time Recurrent Learning Case Study: Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
Two-Step-Ahead Stream Flow Forecasting 505 9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAX) Case Study: Short-Term	
9.7.2: Recurrent Networks with Output Feedback 508 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAX) Case Study: Short-Term	
 9.7.2.1: Encapsulating Long-Term Memory in Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term 	
Recurrent Networks with Output Feedback 508 9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
9.7.2.2: Application of a Recurrent Net with Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
Output and Error Feedback and Exogenous Inputs: (NARIMAx) Case Study: Short-Term	
Inputs: (NARIMAx) Case Study: Short-Term	
9.7.2.3: Training of Recurrent Nets with	
Output Feedback 513	
9.7.3: Fully Recurrent Network 515	
9.7.3.1: Fully Recurrent Network Practical	
Application Case Study: Short-Term Electricity	
Load Forecasting 517	
9.8: Bias and Variance in Time-Series Forecasting 519	
9.8.1: Decomposition of Total Error into Bias and	
Variance Components 521	
9.8.2: Example Illustrating Bias–Variance Decomposition 522	