Contents

| Pr | eface | xxvii | |
|----|-------|-----------|---|
| 1 | Intro | duction | 1 |
| | 1.1 | Machine | learning: what and why? 1 |
| | | 1.1.1 | Types of machine learning 2 |
| | 1.2 | Supervis | ed learning 3 |
| | | 1.2.1 | Classification 3 |
| | | 1.2.2 | Regression 8 |
| | 1.3 | Unsuper | vised learning 9 |
| | | 1.3.1 | Discovering clusters 10 |
| | | 1.3.2 | Discovering latent factors 11 |
| | | 1.3.3 | Discovering graph structure 13 |
| | | 1.3.4 | Matrix completion 14 |
| | 1.4 | Some ba | sic concepts in machine learning 16 |
| | | 1.4.1 | Parametric vs non-parametric models 16 |
| | | 1.4.2 | A simple non-parametric classifier: K -nearest neighbors 16 |
| | | 1.4.3 | The curse of dimensionality 18 |
| | | 1.4.4 | Parametric models for classification and regression 19 |
| | | 1.4.5 | Linear regression 19 |
| | | 1.4.6 | Logistic regression 21 |
| | | 1.4.7 | Overfitting 22 |
| | | 1.4.8 | Model selection 22 |
| | | 1.4.9 | No free lunch theorem 24 |
| 2 | Prob | ability | 27 |
| | 2.1 | Introduc | tion 27 |
| | 2.2 | A brief r | eview of probability theory 28 |
| | | 2.2.1 | Discrete random variables 28 |
| | | 2.2.2 | Fundamental rules 28 |
| | | 2.2.3 | Bayes rule 29 |
| | | 2.2.4 | Independence and conditional independence 30 |
| | | 2.2.5 | Continuous random variables 32 |
| | | | |

viii CONTENTS

| | 0.0.0 | 0 (1 22 |
|------|----------|---|
| | 2.2.6 | Quantiles 33 |
| 0.0 | 2.2.7 | Mean and variance 33 |
| 2.3 | | common discrete distributions 34 |
| | 2.3.1 | The binomial and Bernoulli distributions 34 |
| | 2.3.2 | |
| | 2.3.3 | The Poisson distribution 37 |
| | 2.3.4 | The empirical distribution 37 |
| 2.4 | | common continuous distributions 38 |
| | 2.4.1 | Gaussian (normal) distribution 38 |
| | 2.4.2 | Degenerate pdf 39 |
| | 2.4.3 | The Laplace distribution 41 |
| | 2.4.4 | The gamma distribution 41 |
| | 2.4.5 | The beta distribution 42 |
| | 2.4.6 | Pareto distribution 43 |
| 2.5 | - | robability distributions 44 |
| | 2.5.1 | Covariance and correlation 44 |
| | 2.5.2 | The multivariate Gaussian 46 |
| | 2.5.3 | Multivariate Student t distribution 46 |
| | 2.5.4 | Dirichlet distribution 47 |
| 2.6 | | ormations of random variables 49 |
| | 2.6.1 | Linear transformations 49 |
| | 2.6.2 | General transformations 50 |
| | 2.6.3 | Central limit theorem 51 |
| 2.7 | | Carlo approximation 52 |
| | 2.7.1 | Example: change of variables, the MC way 53 |
| | 2.7.2 | Example: estimating π by Monte Carlo integration 54 |
| 0.0 | 2.7.3 | Accuracy of Monte Carlo approximation 54 |
| 2.8 | | ation theory 56 |
| | 2.8.1 | Entropy 56 |
| | 2.8.2 | KL divergence 57 |
| | 2.8.3 | Mutual information 59 |
| Gene | rative m | odels for discrete data 65 |
| 3.1 | Introdu | - |
| 3.2 | Bayesia | n concept learning 65 |
| | 3.2.1 | Likelihood 67 |
| | 3.2.2 | Prior 67 |
| | 3.2.3 | Posterior 68 |
| | 3.2.4 | Posterior predictive distribution 71 |
| | 3.2.5 | A more complex prior 72 |
| 3.3 | The be | ta-binomial model 72 |
| | 3.3.1 | Likelihood 73 |
| | 3.3.2 | Prior 74 |
| | 3.3.3 | Posterior 75 |
| | 3.3.4 | Posterior predictive distribution 77 |

3

| | 3.4 | The Dir | ichlet-multinomial model 78 |
|---|------|-----------|--|
| | | 3.4.1 | Likelihood 79 |
| | | 3.4.2 | Prior 79 |
| | | 3.4.3 | Posterior 79 |
| | | 3.4.4 | Posterior predictive 81 |
| | 3.5 | Naive B | ayes classifiers 82 |
| | | 3.5.1 | Model fitting 83 |
| | | 3.5.2 | Using the model for prediction 85 |
| | | 3.5.3 | The log-sum-exp trick 86 |
| | | 3.5.4 | Feature selection using mutual information 86 |
| | | 3.5.5 | Classifying documents using bag of words 87 |
| 4 | Gaus | sian mod | dels 97 |
| | 4.1 | Introduc | ction 97 |
| | | 4.1.1 | Notation 97 |
| | | 4.1.2 | Basics 97 |
| | | 4.1.3 | MLE for an MVN 99 |
| | | 4.1.4 | Maximum entropy derivation of the Gaussian * 101 |
| | 4.2 | Gaussia | n discriminant analysis 101 |
| | | 4.2.1 | Quadratic discriminant analysis (QDA) 102 |
| | | 4.2.2 | Linear discriminant analysis (LDA) 103 |
| | | 4.2.3 | Two-class LDA 104 |
| | | 4.2.4 | MLE for discriminant analysis 106 |
| | | 4.2.5 | Strategies for preventing overfitting 106 |
| | | 4.2.6 | Regularized LDA * 107 |
| | | 4.2.7 | Diagonal LDA 108 |
| | | 4.2.8 | Nearest shrunken centroids classifier * 109 |
| | 4.3 | Inferenc | e in jointly Gaussian distributions 110 |
| | | 4.3.1 | Statement of the result 111 |
| | | 4.3.2 | Examples 111 |
| | | 4.3.3 | Information form 115 |
| | | 4.3.4 | Proof of the result * 116 |
| | 4.4 | Linear (| Gaussian systems 119 |
| | | 4.4.1 | Statement of the result 119 |
| | | 4.4.2 | Examples 120 |
| | | 4.4.3 | Proof of the result * 124 |
| | 4.5 | Digressi | on: The Wishart distribution * 125 |
| | | 4.5.1 | Inverse Wishart distribution 126 |
| | | 4.5.2 | Visualizing the Wishart distribution * 127 |
| | 4.6 | Inferring | g the parameters of an MVN 127 |
| | | 4.6.1 | Posterior distribution of μ 128 |
| | | 4.6.2 | Posterior distribution of Σ * 128 |
| | | 4.6.3 | Posterior distribution of μ and Σ * 132 |
| | | 4.6.4 | Sensor fusion with unknown precisions * 138 |
| | | | 1 |

X CONTENTS

| 5 | Bayes | sian statistics 149 | |
|----------|-------|---|-------------------|
| | 5.1 | Introduction 149 | |
| | 5.2 | Summarizing posterior distributions 149 | |
| | | 5.2.1 MAP estimation 149 | |
| | | 5.2.2 Credible intervals 152 | |
| | | 5.2.3 Inference for a difference in proportions | 54 |
| | 5.3 | Bayesian model selection 155 | |
| | | 5.3.1 Bayesian Occam's razor 156 | |
| | | 5.3.2 Computing the marginal likelihood (evidence) | 158 |
| | | 5.3.3 Bayes factors 163 | |
| | | 5.3.4 Jeffreys-Lindley paradox * 164 | |
| | 5.4 | Priors 165 | |
| | | 5.4.1 Uninformative priors 165 | |
| | | 5.4.2 Jeffreys priors * 166 | |
| | | 5.4.3 Robust priors 168 | |
| | | 5.4.4 Mixtures of conjugate priors 168 | |
| | 5.5 | Hierarchical Bayes 171 | |
| | | 5.5.1 Example: modeling related cancer rates 17 | 1 |
| | 5.6 | Empirical Bayes 172 | |
| | | 5.6.1 Example: beta-binomial model 173 | |
| | | 5.6.2 Example: Gaussian-Gaussian model 173 | |
| | 5.7 | Bayesian decision theory 176 | |
| | | 5.7.1 Bayes estimators for common loss functions | 177 |
| | | 5.7.2 The false positive vs false negative tradeoff | 180 |
| | | 5.7.3 Other topics * 184 | |
| 6 | Frequ | uentist statistics 191 | |
| | 6.1 | Introduction 191 | |
| | 6.2 | Sampling distribution of an estimator 191 | |
| | | 6.2.1 Bootstrap 192 | |
| | | 6.2.2 Large sample theory for the MLE * 193 | |
| | 6.3 | Frequentist decision theory 194 | |
| | | 6.3.1 Bayes risk 195 | |
| | | 6.3.2 Minimax risk 196 | |
| | | 6.3.3 Admissible estimators 197 | |
| | 6.4 | Desirable properties of estimators 200 | |
| | | 6.4.1 Consistent estimators 200 | |
| | | 6.4.2 Unbiased estimators 200 | |
| | | 6.4.3 Minimum variance estimators 201 | |
| | | 6.4.4 The bias-variance tradeoff 202 | |
| | 6.5 | Empirical risk minimization 204 | |
| | | 6.5.1 Regularized risk minimization 205 | |
| | | 6.5.2 Structural risk minimization 206 | |
| | | 8 | 206 |
| | | 6.5.4 Upper bounding the risk using statistical learn | ning theory * 209 |

CONTENTS xi

| | | 6.5.5 Surrogate loss functions 210 |
|---|------------|--|
| | 6.6 | Pathologies of frequentist statistics * 211 |
| | | 6.6.1 Counter-intuitive behavior of confidence intervals 212 |
| | | 6.6.2 p-values considered harmful 213 |
| | | 6.6.3 The likelihood principle 214 |
| | | 6.6.4 Why isn't everyone a Bayesian? 215 |
| 7 | Linea | r regression 217 |
| | 7.1 | Introduction 217 |
| | 7.2 | Model specification 217 |
| | 7.3 | Maximum likelihood estimation (least squares) 217 |
| | | 7.3.1 Derivation of the MLE 219 |
| | | 7.3.2 Geometric interpretation 220 |
| | | 7.3.3 Convexity 221 |
| | 7.4 | Robust linear regression * 223 |
| | 7.5 | Ridge regression 225 |
| | | 7.5.1 Basic idea 225 |
| | | 7.5.2 Numerically stable computation * 227 |
| | | 7.5.3 Connection with PCA * 228 |
| | - 0 | 7.5.4 Regularization effects of big data 230 |
| | 7.6 | Bayesian linear regression 231 |
| | | 7.6.1 Computing the posterior 232 |
| | | 7.6.2 Computing the posterior predictive 233 |
| | | 7.6.3 Bayesian inference when σ^2 is unknown * 234 |
| | | 7.6.4 EB for linear regression (evidence procedure) 238 |
| 8 | _ | tic regression 245 |
| | 8.1 | Introduction 245 |
| | 8.2 | Model specification 245 |
| | 8.3 | Model fitting 245 |
| | | 8.3.1 MLE 246 |
| | | 8.3.2 Steepest descent 247 |
| | | 8.3.3 Newton's method 249 |
| | | 8.3.4 Iteratively reweighted least squares (IRLS) 250 |
| | | 8.3.5 Quasi-Newton (variable metric) methods 251 |
| | | 8.3.6 ℓ_2 regularization 252 8.3.7 Multi-class logistic regression 252 |
| | 8.4 | 8.3.7 Multi-class logistic regression 252 Bayesian logistic regression 254 |
| | 0.4 | 8.4.1 Laplace approximation 255 |
| | | 8.4.2 Derivation of the BIC 255 |
| | | 8.4.3 Gaussian approximation for logistic regression 256 |
| | | 8.4.4 Approximating the posterior predictive 256 |
| | | 8.4.5 Residual analysis (outlier detection) * 260 |
| | 8.5 | Online learning and stochastic optimization 261 |
| | 0.0 | 8.5.1 Online learning and regret minimization 262 |
| | | 6 |

xii CONTENTS

| | | 8.5.2 8.5.3 8.5.4 8.5.5 | Stochastic optimization and risk minimization 262 The LMS algorithm 264 The perceptron algorithm 265 A Bayesian view 266 |
|----|-------|-------------------------------------|---|
| | 8.6 | Generati 8.6.1 8.6.2 8.6.3 | ve vs discriminative classifiers 267 Pros and cons of each approach 268 Dealing with missing data 269 Fisher's linear discriminant analysis (FLDA) * 271 |
| 9 | Gener | ralized li | near models and the exponential family 281 |
| | 9.1 | Introduc | tion 281 |
| | 9.2 | The expo | onential family 281 |
| | | 9.2.1 | Definition 282 |
| | | 9.2.2 | Examples 282 |
| | | 9.2.3 | Log partition function 284 |
| | | 9.2.4 | MLE for the exponential family 286 |
| | | 9.2.5 | Bayes for the exponential family * 287 |
| | | 9.2.6 | Maximum entropy derivation of the exponential family * 289 |
| | 9.3 | | zed linear models (GLMs) 290 |
| | | 9.3.1 | Basics 290 |
| | | 9.3.2 | ML and MAP estimation 292 |
| | | 9.3.3 | Bayesian inference 293 |
| | 9.4 | Probit re | |
| | | 9.4.1 | ML/MAP estimation using gradient-based optimization 294 |
| | | 9.4.2 | Latent variable interpretation 294 |
| | | 9.4.3 | Ordinal probit regression * 295 |
| | | 9.4.4 | Multinomial probit models * 295 |
| | 9.5 | | sk learning 296 |
| | | 9.5.1 | Hierarchical Bayes for multi-task learning 296 |
| | | 9.5.2 | Application to personalized email spam filtering 296 |
| | | 9.5.3 | Application to domain adaptation 297 |
| | | 9.5.4 | Other kinds of prior 297 |
| | 9.6 | | zed linear mixed models * 298 |
| | | 9.6.1 | Example: semi-parametric GLMMs for medical data 298 |
| | | 9.6.2 | Computational issues 300 |
| | 9.7 | | g to rank * 300 |
| | | 9.7.1 | The pointwise approach 301 |
| | | 9.7.2 | The pairwise approach 301 |
| | | 9.7.3 | The listwise approach 302 |
| | | 9.7.4 | Loss functions for ranking 303 |
| 10 | Direc | ted grapl | nical models (Bayes nets) 307 |
| | 10.1 | Introduc | tion 307 |
| | | 10.1.1 | Chain rule 307 |
| | | 10.1.2 | Conditional independence 308 |

CONTENTS xiii

| | | 10.1.3 Graphical models 308 |
|----|-------|--|
| | | 10.1.4 Graph terminology 309 |
| | | 10.1.5 Directed graphical models 310 |
| | 10.2 | Examples 311 |
| | | 10.2.1 Naive Bayes classifiers 311 |
| | | 10.2.2 Markov and hidden Markov models 312 |
| | | 10.2.3 Medical diagnosis 313 |
| | | 10.2.4 Genetic linkage analysis * 315 |
| | | 10.2.5 Directed Gaussian graphical models * 318 |
| | 10.3 | Inference 319 |
| | 10.4 | Learning 320 |
| | | 10.4.1 Plate notation 320 |
| | | 10.4.2 Learning from complete data 322 |
| | | 10.4.3 Learning with missing and/or latent variables 323 |
| | 10.5 | Conditional independence properties of DGMs 324 |
| | | 10.5.1 d-separation and the Bayes Ball algorithm (global Markov |
| | | properties) 324 |
| | | 10.5.2 Other Markov properties of DGMs 327 |
| | | 10.5.3 Markov blanket and full conditionals 327 |
| | 10.6 | Influence (decision) diagrams * 328 |
| 11 | Mirti | re models and the EM algorithm 337 |
| 11 | 11.1 | Latent variable models 337 |
| | 11.2 | Mixture models 337 |
| | 11,2 | 11.2.1 Mixtures of Gaussians 339 |
| | | 11.2.2 Mixture of multinoullis 340 |
| | | 11.2.3 Using mixture models for clustering 340 |
| | | 11.2.4 Mixtures of experts 342 |
| | 11.3 | Parameter estimation for mixture models 345 |
| | 11.0 | 11.3.1 Unidentifiability 346 |
| | | 11.3.2 Computing a MAP estimate is non-convex 347 |
| | 11.4 | The EM algorithm 348 |
| | 11.1 | 11.4.1 Basic idea 349 |
| | | 11.4.2 EM for GMMs 350 |
| | | 11.4.3 EM for mixture of experts 357 |
| | | 11.4.4 EM for DGMs with hidden variables 358 |
| | | 11.4.5 EM for the Student distribution * 359 |
| | | 11.4.6 EM for probit regression * 362 |
| | | 11.4.7 Theoretical basis for EM * 363 |
| | | 11.4.8 Online EM 365 |
| | | 11.4.9 Other EM variants * 367 |
| | 11.5 | Model selection for latent variable models 370 |
| | 11.0 | 11.5.1 Model selection for probabilistic models 370 |
| | | 11.5.2 Model selection for non-probabilistic methods 370 |
| | 11.6 | Fitting models with missing data 372 |
| | | U TO TO THE TOTAL THE TOTAL TO THE TOTAL TOT |

xiv CONTENTS

| | | 11.6.1 | EM for the MLE of an MVN with missing data 373 |
|----|-------|-----------------|--|
| 12 | Laten | t linear n | nodels 381 |
| | 12.1 | Factor ar | |
| | | 12.1.1 | FA is a low rank parameterization of an MVN 381 |
| | | 12.1.2 | Inference of the latent factors 382 |
| | | 12.1.3 | Unidentifiability 383 |
| | | 12.1.4 | Mixtures of factor analysers 385 |
| | | 12.1.5 | EM for factor analysis models 386 |
| | | 12.1.6 | Fitting FA models with missing data 387 |
| | 12.2 | Principal | components analysis (PCA) 387 |
| | | 12.2.1 | Classical PCA: statement of the theorem 387 |
| | | 12.2.2 | Proof * 389 |
| | | 12.2.3 | Singular value decomposition (SVD) 392 |
| | | 12.2.4 | Probabilistic PCA 395 |
| | | 12.2.5 | EM algorithm for PCA 396 |
| | 12.3 | Choosing | g the number of latent dimensions 398 |
| | | 12.3.1 | Model selection for FA/PPCA 398 |
| | | 12.3.2 | Model selection for PCA 399 |
| | 12.4 | | categorical data 402 |
| | 12.5 | | paired and multi-view data 404 |
| | | 12.5.1 | Supervised PCA (latent factor regression) 405 |
| | | 12.5.2 | Partial least squares 406 |
| | | 12.5.3 | Canonical correlation analysis 407 |
| | 12.6 | Independ | dent Component Analysis (ICA) 407 |
| | | 12.6.1 | Maximum likelihood estimation 410 |
| | | 12.6.2 | The FastICA algorithm 411 |
| | | 12.6.3 | Using EM 414 |
| | | 12.6.4 | Other estimation principles * 415 |
| 13 | Spars | e linear 1 | nodels 421 |
| | 13.1 | Introduc | tion 421 |
| | 13.2 | Bayesian | variable selection 422 |
| | | 13.2.1 | The spike and slab model 424 |
| | | 13.2.2 | From the Bernoulli-Gaussian model to ℓ_0 regularization 425 |
| | | 13.2.3 | Algorithms 426 |
| | 13.3 | ℓ_1 regula | arization: basics 429 |
| | | 13.3.1 | Why does ℓ_1 regularization yield sparse solutions? 430 |
| | | 13.3.2 | Optimality conditions for lasso 431 |
| | | 13.3.3 | Comparison of least squares, lasso, ridge and subset selection 435 |
| | | 13.3.4 | Regularization path 436 |
| | | 13.3.5 | Model selection 439 |
| | | 13.3.6 | Bayesian inference for linear models with Laplace priors 440 |
| | 13.4 | ℓ_1 regula | arization: algorithms 441 |
| | | 13.4.1 | Coordinate descent 441 |

| | | 13.4.2 13.4.3 | 0 1 7 | |
|----|------------------------------|---|--|-----|
| | | 13.4.4 | EM for lasso 447 | |
| | 13.5 | _ | larization: extensions 449 | |
| | | 13.5.1 | Group Lasso 449 | |
| | | 13.5.2 | Fused lasso 454 | |
| | | 13.5.3 | Elastic net (ridge and lasso combined) 455 | |
| | 13.6 | Non-co | nvex regularizers 457 | |
| | | 13.6.1 | Bridge regression 458 | |
| | | 13.6.2 | Hierarchical adaptive lasso 458 | |
| | | 13.6.3 | Other hierarchical priors 462 | |
| | 13.7 | Automa | atic relevance determination (ARD)/sparse Bayesian learning (SBL) | 463 |
| | | 13.7.1 | ARD for linear regression 463 | |
| | | 13.7.2 | Whence sparsity? 465 | |
| | | 13.7.3 | Connection to MAP estimation 465 | |
| | | 13.7.4 | Algorithms for ARD * 466 | |
| | | 13.7.5 | ARD for logistic regression 468 | |
| | 13.8 | Sparse | coding * 468 | |
| | | 13.8.1 | Learning a sparse coding dictionary 469 | |
| | | 13.8.2 | Results of dictionary learning from image patches 470 | |
| | | 13.8.3 | Compressed sensing 472 | |
| | | 13.8.4 | Image inpainting and denoising 472 | |
| | | | | |
| 14 | Kerne | | 179 | |
| 14 | | els 4 | 179 | |
| 14 | Kerne 14.1 14.2 | e ls 4 Introdu | 179 ction 479 | |
| 14 | 14.1 | els 4 Introdu Kernel f | 179 ction 479 functions 479 | |
| 14 | 14.1 | Introdu Kernel f 14.2.1 | tion 479 functions 479 RBF kernels 480 | |
| 14 | 14.1 | Introdu Kernel f 14.2.1 14.2.2 | tion 479 ction 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 | |
| 14 | 14.1 | Introduction Kernel 14.2.1 14.2.2 14.2.3 | tion 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 | |
| 14 | 14.1 | Introduction Kernel 14.2.1 14.2.2 14.2.3 14.2.4 | totion 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 Linear kernels 482 | |
| 14 | 14.1 | Introduction Kernel 14.2.1 14.2.2 14.2.3 14.2.4 14.2.5 | totion 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 Linear kernels 482 Matern kernels 482 | |
| 14 | 14.1 | Introduction Kernel 14.2.1 14.2.2 14.2.3 14.2.4 14.2.5 14.2.6 | ction 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 Linear kernels 482 Matern kernels 482 String kernels 483 | |
| 14 | 14.1 | Introduction Kernel 14.2.1 14.2.2 14.2.3 14.2.4 14.2.5 14.2.6 14.2.7 | ction 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 Linear kernels 482 Matern kernels 482 String kernels 483 Pyramid match kernels 484 | |
| 14 | 14.1 14.2 | Introduction Kernel 14.2.1 14.2.2 14.2.3 14.2.4 14.2.5 14.2.6 14.2.7 14.2.8 | ction 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 Linear kernels 482 Matern kernels 482 String kernels 483 Pyramid match kernels 484 Kernels derived from probabilistic generative models 485 | |
| 14 | 14.1 | Introduction Kernel for 14.2.1 14.2.2 14.2.3 14.2.4 14.2.5 14.2.6 14.2.7 14.2.8 Using k | ction 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 Linear kernels 482 Matern kernels 482 String kernels 483 Pyramid match kernels 484 Kernels derived from probabilistic generative models 485 ternels inside GLMs 486 | |
| 14 | 14.1 14.2 | Introduction Kernel 14.2.1 14.2.2 14.2.3 14.2.4 14.2.5 14.2.6 14.2.7 14.2.8 Using k 14.3.1 | ction 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 Linear kernels 482 Matern kernels 482 String kernels 483 Pyramid match kernels 484 Kernels derived from probabilistic generative models 485 ternels inside GLMs 486 Kernel machines 486 | |
| 14 | 14.1 14.2 | Introduction Kernel 14.2.1 14.2.2 14.2.3 14.2.4 14.2.5 14.2.6 14.2.7 14.2.8 Using k 14.3.1 14.3.2 | ction 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 Linear kernels 482 Matern kernels 482 String kernels 483 Pyramid match kernels 484 Kernels derived from probabilistic generative models 485 ternels inside GLMs 486 Kernel machines 486 LIVMs, RVMs, and other sparse vector machines 487 | |
| 14 | 14.1 14.2 | Introduction Kernel 14.2.1 14.2.2 14.2.3 14.2.4 14.2.5 14.2.6 14.2.7 14.2.8 Using k 14.3.1 14.3.2 The ker | ction 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 Linear kernels 482 Matern kernels 482 String kernels 483 Pyramid match kernels 484 Kernels derived from probabilistic generative models 485 ternels inside GLMs 486 Kernel machines 486 LIVMs, RVMs, and other sparse vector machines 487 mel trick 488 | |
| 14 | 14.1 14.2 | Introduction Kernel 14.2.1 14.2.2 14.2.3 14.2.4 14.2.5 14.2.6 14.2.7 14.2.8 Using k 14.3.1 14.3.2 The ker 14.4.1 | ction 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 Linear kernels 482 Matern kernels 482 String kernels 483 Pyramid match kernels 484 Kernels derived from probabilistic generative models 485 ternels inside GLMs 486 Kernel machines 486 LIVMs, RVMs, and other sparse vector machines 487 cenel trick 488 Kernelized nearest neighbor classification 489 | |
| 14 | 14.1 14.2 | Introduction Kernel 14.2.1 14.2.2 14.2.3 14.2.4 14.2.5 14.2.6 14.2.7 14.2.8 Using k 14.3.1 14.3.2 The ker 14.4.1 14.4.2 | ction 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 Linear kernels 482 Matern kernels 482 String kernels 483 Pyramid match kernels 484 Kernels derived from probabilistic generative models 485 ternels inside GLMs 486 Kernel machines 486 LIVMs, RVMs, and other sparse vector machines 487 rnel trick 488 Kernelized nearest neighbor classification 489 Kernelized K-medoids clustering 489 | |
| 14 | 14.1 14.2 | Introduction Kernel for 14.2.1 14.2.2 14.2.3 14.2.4 14.2.5 14.2.6 14.2.7 14.2.8 Using k 14.3.1 14.3.2 The ker 14.4.1 14.4.2 14.4.3 | ction 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 Linear kernels 482 Matern kernels 482 String kernels 483 Pyramid match kernels 484 Kernels derived from probabilistic generative models 485 ternels inside GLMs 486 Kernel machines 486 LIVMs, RVMs, and other sparse vector machines 487 rnel trick 488 Kernelized nearest neighbor classification 489 Kernelized K-medoids clustering 489 Kernelized ridge regression 492 | |
| 14 | 14.1 14.2 | Introduction Kernel for 14.2.1 14.2.2 14.2.3 14.2.4 14.2.5 14.2.6 14.2.7 14.2.8 Using k 14.3.1 14.3.2 The ker 14.4.1 14.4.2 14.4.3 14.4.4 | ction 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 Linear kernels 482 Matern kernels 482 String kernels 483 Pyramid match kernels 484 Kernels derived from probabilistic generative models 485 ternels inside GLMs 486 Kernel machines 486 LIVMs, RVMs, and other sparse vector machines 487 mel trick 488 Kernelized nearest neighbor classification 489 Kernelized K-medoids clustering 489 Kernelized ridge regression 492 Kernel PCA 493 | |
| 14 | 14.1 14.2 | Introduction Kernel for 14.2.1 14.2.2 14.2.3 14.2.4 14.2.5 14.2.6 14.2.7 14.2.8 Using k 14.3.1 14.3.2 The ker 14.4.1 14.4.2 14.4.3 14.4.4 | ction 479 functions 479 RBF kernels 480 Kernels for comparing documents 480 Mercer (positive definite) kernels 481 Linear kernels 482 Matern kernels 482 String kernels 483 Pyramid match kernels 484 Kernels derived from probabilistic generative models 485 ternels inside GLMs 486 Kernel machines 486 LIVMs, RVMs, and other sparse vector machines 487 rnel trick 488 Kernelized nearest neighbor classification 489 Kernelized K-medoids clustering 489 Kernelized ridge regression 492 | |

xvi CONTENTS

| | | 14.5.3 | Choosing C 504 | |
|----|------|-----------|--|----|
| | | 14.5.4 | Summary of key points 504 | |
| | | 14.5.5 | A probabilistic interpretation of SVMs 505 | |
| | 14.6 | Compai | rison of discriminative kernel methods 505 | |
| | 14.7 | Kernels | for building generative models 507 | |
| | | 14.7.1 | Smoothing kernels 507 | |
| | | 14.7.2 | Kernel density estimation (KDE) 508 | |
| | | 14.7.3 | From KDE to KNN 509 | |
| | | 14.7.4 | Kernel regression 510 | |
| | | 14.7.5 | Locally weighted regression 512 | |
| 15 | Gaus | sian pro | cesses 515 | |
| | 15.1 | Introdu | ction 515 | |
| | 15.2 | | regression 516 | |
| | | 15.2.1 | Predictions using noise-free observations 517 | |
| | | 15.2.2 | Predictions using noisy observations 518 | |
| | | 15.2.3 | Effect of the kernel parameters 519 | |
| | | 15.2.4 | Estimating the kernel parameters 521 | |
| | | 15.2.5 | Computational and numerical issues * 524 | |
| | | 15.2.6 | Semi-parametric GPs * 524 | |
| | 15.3 | GPs me | et GLMs 525 | |
| | | 15.3.1 | Binary classification 525 | |
| | | 15.3.2 | Multi-class classification 528 | |
| | | 15.3.3 | GPs for Poisson regression 531 | |
| | 15.4 | Connec | tion with other methods 532 | |
| | | 15.4.1 | Linear models compared to GPs 532 | |
| | | 15.4.2 | Linear smoothers compared to GPs 533 | |
| | | 15.4.3 | SVMs compared to GPs 534 | |
| | | 15.4.4 | LIVM and RVMs compared to GPs 534 | |
| | | 15.4.5 | Neural networks compared to GPs 535 | |
| | | 15.4.6 | Smoothing splines compared to GPs * 536 | |
| | | 15.4.7 | RKHS methods compared to GPs * 538 | |
| | 15.5 | GP later | nt variable model 540 | |
| | 15.6 | Approxi | mation methods for large datasets 542 | |
| 16 | Adap | tive basi | is function models 543 | |
| | 16.1 | Introdu | ction 543 | |
| | 16.2 | Classific | cation and regression trees (CART) 544 | |
| | | 16.2.1 | Basics 544 | |
| | | 16.2.2 | Growing a tree 545 | |
| | | 16.2.3 | Pruning a tree 549 | |
| | | 16.2.4 | Pros and cons of trees 550 | |
| | | 16.2.5 | Random forests 550 | |
| | | 16.2.6 | CART compared to hierarchical mixture of experts * | 55 |
| | 16.3 | | ized additive models 552 | |

CONTENTS xvii

| | | 16.3.1 | Backfitting 552 |
|----|--------------|----------------------|---|
| | | 16.3.2 | Computational efficiency 553 |
| | | 16.3.3 | Multivariate adaptive regression splines (MARS) 553 |
| | 16.4 | Boosting | 554 |
| | | 16.4.1 | Forward stagewise additive modeling 555 |
| | | 16.4.2 | L2boosting 557 |
| | | 16.4.3 | AdaBoost 558 |
| | | 16.4.4 | LogitBoost 559 |
| | | 16.4.5 | Boosting as functional gradient descent 560 |
| | | 16.4.6 | Sparse boosting 561 |
| | | 16.4.7 | Multivariate adaptive regression trees (MART) 562 |
| | | 16.4.8 | Why does boosting work so well? 562 |
| | | 16.4.9 | A Bayesian view 563 |
| | 16.5 | | vard neural networks (multilayer perceptrons) 563 |
| | | 16.5.1 | Convolutional neural networks 564 |
| | | 16.5.2 | Other kinds of neural networks 568 |
| | | 16.5.3 | A brief history of the field 568 |
| | | 16.5.4 | The backpropagation algorithm 569 |
| | | 16.5.5 | Identifiability 572 |
| | | 16.5.6 | Regularization 572 |
| | 10.0 | 16.5.7 | Bayesian inference * 576 |
| | 16.6 | | e learning 580 |
| | | 16.6.1 | Stacking 580 |
| | | 16.6.2 | Error-correcting output codes 581 |
| | 16.7 | 16.6.3 | Ensemble learning is not equivalent to Bayes model averaging 581 ental comparison 582 |
| | 10.7 | 16.7.1 | Low-dimensional features 582 |
| | | 16.7.1 | High-dimensional features 583 |
| | 16.8 | | ing black-box models 585 |
| 17 | | • | |
| 17 | | | idden Markov models 589 |
| | 17.1 17.2 | Introduc Markov i | |
| | 11.2 | 17.2.1 | Transition matrix 589 |
| | | 17.2.1 | Application: Language modeling 591 |
| | | 17.2.2 | Stationary distribution of a Markov chain * 596 |
| | | 17.2.4 | Application: Google's PageRank algorithm for web page ranking * 600 |
| | 17.3 | | Markov models 603 |
| | | 17.3.1 | Applications of HMMs 604 |
| | 17.4 | | e in HMMs 606 |
| | | 17.4.1 | Types of inference problems for temporal models 606 |
| | | 17.4.2 | The forwards algorithm 609 |
| | | 17.4.3 | The forwards-backwards algorithm 610 |
| | | 17.4.4 | The Viterbi algorithm 612 |
| | | 17.4.5 | Forwards filtering, backwards sampling 616 |

xviii CONTENTS

| | 17.5 | Learning for I | MMs 617 | |
|----|-------|-----------------|--|-----|
| | | 17.5.1 Train | ing with fully observed data 617 | |
| | | | or HMMs (the Baum-Welch algorithm) 618 | |
| | | 17.5.3 Baye | ian methods for "fitting" HMMs * 620 | |
| | | 17.5.4 Disc | iminative training 620 | |
| | | 17.5.5 Mod | l selection 621 | |
| | 17.6 | Generalization | of HMMs 621 | |
| | | 17.6.1 Varia | ole duration (semi-Markov) HMMs 622 | |
| | | 17.6.2 Hier | rchical HMMs 624 | |
| | | | -output HMMs 625 | |
| | | | regressive and buried HMMs 626 | |
| | | | rial HMM 627 | |
| | | | led HMM and the influence model 628 | |
| | | 17.6.7 Dyn | mic Bayesian networks (DBNs) 628 | |
| 18 | State | space models | 631 | |
| | 18.1 | Introduction | 631 | |
| | 18.2 | Applications of | SSMs 632 | |
| | | 18.2.1 SSM | for object tracking 632 | |
| | | 18.2.2 Robo | tic SLAM 633 | |
| | | 18.2.3 Onli | e parameter learning using recursive least squares | 636 |
| | | 18.2.4 SSM | for time series forecasting * 637 | |
| | 18.3 | Inference in L | G-SSM 640 | |
| | | 18.3.1 The | Calman filtering algorithm 640 | |
| | | 18.3.2 The | Calman smoothing algorithm 643 | |
| | 18.4 | Learning for I | G-SSM 646 | |
| | | | ifiability and numerical stability 646 | |
| | | 18.4.2 Train | ing with fully observed data 647 | |
| | | | or LG-SSM 647 | |
| | | | pace methods 647 | |
| | | | ian methods for "fitting" LG-SSMs 647 | |
| | 18.5 | Approximate of | nline inference for non-linear, non-Gaussian SSMs | 647 |
| | | 18.5.1 Exte | ded Kalman filter (EKF) 648 | |
| | | | ented Kalman filter (UKF) 650 | |
| | | | ned density filtering (ADF) 652 | |
| | 18.6 | Hybrid discret | c/continuous SSMs 655 | |
| | | 18.6.1 Infe | | |
| | | | | 558 |
| | | | cation: fault diagnosis 659 | |
| | | 18.6.4 App | cation: econometric forecasting 660 | |
| 19 | Undi | ected graphic | l models (Markov random fields) 661 | |
| | 19.1 | Introduction | 661 | |
| | 19.2 | Conditional in | dependence properties of UGMs 661 | |
| | | 19.2.1 Key | properties 661 | |

| | | | An undirected alternative to d-separation 663 |
|----|------|------------|--|
| | 10.2 | | Comparing directed and undirected graphical models 664 |
| | 19.3 | | rization of MRFs 665 |
| | | | The Hammersley-Clifford theorem 665 |
| | 10.4 | | Representing potential functions 667 |
| | 19.4 | Examples | |
| | | | Ising model 668 |
| | | | Hopfield networks 669 |
| | | | Potts model 671 |
| | | | Gaussian MRFs 672 |
| | 10.5 | | Markov logic networks * 674 |
| | 19.5 | Learning | 676 |
| | | | Training maxent models using gradient methods 676 |
| | | | Training partially observed maxent models 677 |
| | | | Approximate methods for computing the MLEs of MRFs 678 |
| | | | Pseudo likelihood 678 |
| | | | Stochastic maximum likelihood 679 |
| | | | Feature induction for maxent models * 680 |
| | 10.0 | | Iterative proportional fitting (IPF) * 681 |
| | 19.6 | | nal random fields (CRFs) 684 |
| | | | Chain-structured CRFs, MEMMs and the label-bias problem 684 |
| | | | Applications of CRFs 686 |
| | 10.7 | | CRF training 692 |
| | 19.7 | Structural | |
| | | | SSVMs: a probabilistic view 693 |
| | | | SSVMs: a non-probabilistic view 695 |
| | | | Cutting plane methods for fitting SSVMs 698 |
| | | | Online algorithms for fitting SSVMs 700 Latent structural SVMs 701 |
| | | | |
| 20 | | = | for graphical models 707 |
| | | Introducti | |
| | 20.2 | | pagation for trees 707 |
| | | | Serial protocol 707 |
| | | 20.2.2 | Parallel protocol 709 |
| | | | Gaussian BP * 710 |
| | | | Other BP variants * 712 |
| | 20.3 | | ble elimination algorithm 714 |
| | | | The generalized distributive law * 717 |
| | | | Computational complexity of VE 717 |
| | | | A weakness of VE 720 |
| | 20.4 | | ion tree algorithm * 720 |
| | | | Creating a junction tree 720 |
| | | | Message passing on a junction tree 722 |
| | | 20.4.3 | Computational complexity of JTA 725 |

XX CONTENTS

| | | 20.4.4 JTA generalizations * 726 |
|----|--------------|--|
| | 20.5 | Computational intractability of exact inference in the worst case 726 |
| | | 20.5.1 Approximate inference 727 |
| 21 | Varia | tional inference 731 |
| | 21.1 | Introduction 731 |
| | 21.2 | Variational inference 732 |
| | | 21.2.1 Alternative interpretations of the variational objective 733 |
| | | 21.2.2 Forward or reverse KL? * 733 |
| | 21.3 | The mean field method 735 |
| | | 21.3.1 Derivation of the mean field update equations 736 |
| | | 21.3.2 Example: mean field for the Ising model 737 |
| | 21.4 | Structured mean field * 739 |
| | | 21.4.1 Example: factorial HMM 740 |
| | 21.5 | Variational Bayes 742 |
| | | 21.5.1 Example: VB for a univariate Gaussian 742 |
| | | 21.5.2 Example: VB for linear regression 746 |
| | 21.6 | Variational Bayes EM 749 |
| | | 21.6.1 Example: VBEM for mixtures of Gaussians * 750 |
| | 21.7 | Variational message passing and VIBES 756 |
| | 21.8 | Local variational bounds * 756 |
| | | 21.8.1 Motivating applications 756 |
| | | 21.8.2 Bohning's quadratic bound to the log-sum-exp function 758 |
| | | 21.8.3 Bounds for the sigmoid function 760 |
| | | 21.8.4 Other bounds and approximations to the log-sum-exp function * 762 |
| | | 21.8.5 Variational inference based on upper bounds 763 |
| 22 | More | variational inference 767 |
| | 22.1 | Introduction 767 |
| | 22.2 | Loopy belief propagation: algorithmic issues 767 |
| | | 22.2.1 A brief history 767 |
| | | 22.2.2 LBP on pairwise models 768 |
| | | 22.2.3 LBP on a factor graph 769 |
| | | 22.2.4 Convergence 771 |
| | | 22.2.5 Accuracy of LBP 774 |
| | | 22.2.6 Other speedup tricks for LBP * 775 |
| | 22.3 | Loopy belief propagation: theoretical issues * 776 |
| | | 22.3.1 UGMs represented in exponential family form 776 |
| | | 22.3.2 The marginal polytope 777 |
| | | 22.3.3 Exact inference as a variational optimization problem 778 |
| | | 22.3.4 Mean field as a variational optimization problem 779 |
| | | 22.3.5 LBP as a variational optimization problem 779 22.3.6 Loopy BP vs mean field 783 |
| | 22.4 | 22.3.6 Loopy BP vs mean field 783 Extensions of belief propagation * 783 |
| | <i>LL</i> .4 | 22.4.1 Generalized belief propagation 783 |
| | | 22.11 Goneranzea bener propagation 100 |

CONTENTS xxi

| | 22.5 | Expectation 22.5.1 EF 22.5.2 Op 22.5.3 EF 22.5.4 LE 22.5.5 Ra 22.5.6 Ot MAP state e 22.6.1 Lin 22.6.2 Ma 22.6.3 Gr 22.6.4 Ex | P for the clutter problem 791 BP is a special case of EP 792 anking players using TrueSkill 793 ther applications of EP 799 | 789 |
|----|-------|--|---|-----|
| 23 | Monte | e Carlo infe | rence 815 | |
| | 23.1 | Introduction | | |
| | 23.2 | | om standard distributions 815 | |
| | | | sing the cdf 815 | |
| | | 23.2.2 Sa | impling from a Gaussian (Box-Muller method) 817 | |
| | 23.3 | Rejection sa | | |
| | | | asic idea 817 | |
| | | | cample 818 | |
| | | | opplication to Bayesian statistics 819 | |
| | | | laptive rejection sampling 819 | |
| | 22.4 | | ejection sampling in high dimensions 820 | |
| | 23.4 | Importance 23.4.1 Ba | sampling 820 asic idea 820 | |
| | | | andling unnormalized distributions 821 | |
| | | | portance sampling for a DGM: likelihood weighting | 822 |
| | | | impling importance resampling (SIR) 822 | OLL |
| | 23.5 | Particle filte | | |
| | | | equential importance sampling 824 | |
| | | 23.5.2 Th | ne degeneracy problem 825 | |
| | | 23.5.3 Th | ne resampling step 825 | |
| | | | ne proposal distribution 827 | |
| | | | oplication: robot localization 828 | |
| | | | oplication: visual object tracking 828 | |
| | 22 C | | oplication: time series forecasting 831 | |
| | 23.6 | | ellised particle filtering (RBPF) 831 BPF for switching LG-SSMs 831 | |
| | | | oplication: tracking a maneuvering target 832 | |
| | | _ | oplication: Fast SLAM 834 | |
| | | | | |

xxii CONTENTS

| | 24.1 | Introduc | |
|----|-------|-----------|---|
| | 24.2 | Gibbs sa | mpling 838 |
| | | 24.2.1 | Basic idea 838 |
| | | 24.2.2 | Example: Gibbs sampling for the Ising model 838 |
| | | 24.2.3 | Example: Gibbs sampling for inferring the parameters of a GMM 840 |
| | | 24.2.4 | Collapsed Gibbs sampling * 841 |
| | | 24.2.5 | Gibbs sampling for hierarchical GLMs 844 |
| | | 24.2.6 | BUGS and JAGS 846 |
| | | 24.2.7 | The Imputation Posterior (IP) algorithm 847 |
| | | 24.2.8 | Blocking Gibbs sampling 847 |
| | 24.3 | Metropol | lis Hastings algorithm 848 |
| | | 24.3.1 | Basic idea 848 |
| | | 24.3.2 | Gibbs sampling is a special case of MH 849 |
| | | 24.3.3 | Proposal distributions 850 |
| | | 24.3.4 | Adaptive MCMC 853 |
| | | 24.3.5 | Initialization and mode hopping 854 |
| | | 24.3.6 | Why MH works * 854 |
| | | 24.3.7 | Reversible jump (trans-dimensional) MCMC * 855 |
| | 24.4 | Speed ar | nd accuracy of MCMC 856 |
| | | 24.4.1 | The burn-in phase 856 |
| | | 24.4.2 | Mixing rates of Markov chains * 857 |
| | | 24.4.3 | Practical convergence diagnostics 858 |
| | | 24.4.4 | Accuracy of MCMC 860 |
| | | 24.4.5 | How many chains? 862 |
| | 24.5 | Auxiliary | variable MCMC * 863 |
| | | 24.5.1 | Auxiliary variable sampling for logistic regression 863 |
| | | 24.5.2 | Slice sampling 864 |
| | | 24.5.3 | Swendsen Wang 866 |
| | | 24.5.4 | Hybrid/Hamiltonian MCMC * 868 |
| | 24.6 | Annealin | g methods 868 |
| | | 24.6.1 | Simulated annealing 869 |
| | | 24.6.2 | Annealed importance sampling 871 |
| | | 24.6.3 | Parallel tempering 871 |
| | 24.7 | Approxin | nating the marginal likelihood 872 |
| | | 24.7.1 | The candidate method 872 |
| | | 24.7.2 | Harmonic mean estimate 872 |
| | | 24.7.3 | Annealed importance sampling 873 |
| 25 | Clust | ering | 875 |
| | 25.1 | Introduc | tion 875 |
| | | 25.1.1 | Measuring (dis)similarity 875 |
| | | 25.1.2 | Evaluating the output of clustering methods * 876 |
| | 25.2 | | process mixture models 879 |
| | | 25.2.1 | From finite to infinite mixture models 879 |
| | | 25.2.2 | The Dirichlet process 882 |

CONTENTS xxiii

| | | 25.2.3 | Applying Dirichlet processes to mixture modeling 885 |
|----|-------|-----------|---|
| | | 25.2.4 | Fitting a DP mixture model 886 |
| | 25.3 | | propagation 887 |
| | 25.4 | | clustering 890 |
| | | 25.4.1 | Graph Laplacian 891 |
| | | 25.4.2 | Normalized graph Laplacian 892 |
| | | 25.4.3 | Example 893 |
| | 25.5 | | ical clustering 893 |
| | | 25.5.1 | Agglomerative clustering 895 |
| | | 25.5.2 | Divisive clustering 898 |
| | | 25.5.3 | Choosing the number of clusters 899 |
| | | 25.5.4 | Bayesian hierarchical clustering 899 |
| | 25.6 | | g datapoints and features 901 |
| | | 25.6.1 | Biclustering 903 |
| | | 25.6.2 | Multi-view clustering 903 |
| 26 | Graph | nical mod | lel structure learning 907 |
| | 26.1 | Introduc | tion 907 |
| | 26.2 | Structure | e learning for knowledge discovery 908 |
| | | 26.2.1 | Relevance networks 908 |
| | | 26.2.2 | Dependency networks 909 |
| | 26.3 | Learning | tree structures 910 |
| | | 26.3.1 | Directed or undirected tree? 911 |
| | | 26.3.2 | Chow-Liu algorithm for finding the ML tree structure 912 |
| | | 26.3.3 | Finding the MAP forest 912 |
| | | 26.3.4 | Mixtures of trees 914 |
| | 26.4 | Learning | DAG structures 914 |
| | | 26.4.1 | Markov equivalence 914 |
| | | 26.4.2 | Exact structural inference 916 |
| | | 26.4.3 | Scaling up to larger graphs 920 |
| | 26.5 | _ | DAG structure with latent variables 922 |
| | | 26.5.1 | Approximating the marginal likelihood when we have missing data 922 |
| | | 26.5.2 | Structural EM 925 |
| | | 26.5.3 | Discovering hidden variables 926 |
| | | 26.5.4 | Case study: Google's Rephil 928 |
| | | 26.5.5 | Structural equation models * 929 |
| | 26.6 | Learning | causal DAGs 931 |
| | | 26.6.1 | Causal interpretation of DAGs 931 |
| | | 26.6.2 | Using causal DAGs to resolve Simpson's paradox 933 |
| | | 26.6.3 | Learning causal DAG structures 935 |
| | 26.7 | | undirected Gaussian graphical models 938 |
| | | 26.7.1 | MLE for a GGM 938 |
| | | 26.7.2 | Graphical lasso 939 |
| | | 26.7.3 | Bayesian inference for GGM structure * 941 |
| | | 26.7.4 | Handling non-Gaussian data using copulas * 942 |

xxiv CONTENTS

| | 26.8 | 26.8.1 | undirected discrete graphical models 942 Graphical lasso for MRFs/CRFs 942 Thin junction trees 944 |
|----|-------|------------|--|
| 27 | Laten | | models for discrete data 945 |
| | 27.1 | Introducti | |
| | 27.2 | | d state LVMs for discrete data 946 |
| | | | Mixture models 946 |
| | | 27.2.2 | Exponential family PCA 947 |
| | | 27.2.3 | LDA and mPCA 948 |
| | | 27.2.4 | GaP model and non-negative matrix factorization 949 |
| | 27.3 | Latent Dir | richlet allocation (LDA) 950 |
| | | | Basics 950 |
| | | | Unsupervised discovery of topics 953 |
| | | | Quantitatively evaluating LDA as a language model 953 |
| | | | Fitting using (collapsed) Gibbs sampling 955 |
| | | | Example 956 |
| | | | Fitting using batch variational inference 957 |
| | | | Fitting using online variational inference 959 Determining the number of topics 960 |
| | 27.4 | Extensions | • |
| | 21,1 | | Correlated topic model 961 |
| | | | Dynamic topic model 962 |
| | | | LDA-HMM 963 |
| | | 27.4.4 | Supervised LDA 967 |
| | 27.5 | LVMs for | graph-structured data 970 |
| | | 27.5.1 | Stochastic block model 971 |
| | | | Mixed membership stochastic block model 973 |
| | | | Relational topic model 974 |
| | 27.6 | | relational data 975 |
| | | | Infinite relational model 976 |
| | 27.7 | | Probabilistic matrix factorization for collaborative filtering 979 |
| | 27.7 | | Boltzmann machines (RBMs) 983 Varieties of RBMs 985 |
| | | | Learning RBMs 987 |
| | | | Applications of RBMs 991 |
| | | | |
| 28 | - | learning | 995 |
| | 28.1 | Introducti | |
| | 28.2 | 1 0 | erative models 995 |
| | | | Deep directed networks 996 |
| | | | Deep Boltzmann machines 996 |
| | | | Deep belief networks 997 |
| | 28.3 | | Greedy layer-wise learning of DBNs 998 ral networks 999 |
| | ۷۰.5 | Dech Hen | iai iictword JJJ |

| | 28.3.1 | Deep multi-layer perceptrons 999 |
|----|-----------|--|
| | 28.3.2 | Deep auto-encoders 1000 |
| | 28.3.3 | Stacked denoising auto-encoders 1001 |
| 28 | 4 Applica | cions of deep networks 1001 |
| | 28.4.1 | Handwritten digit classification using DBNs 1001 |
| | 28.4.2 | Data visualization and feature discovery using deep auto-encoders 1002 |
| | 28.4.3 | Information retrieval using deep auto-encoders (semantic hashing) 1003 |
| | 28.4.4 | Learning audio features using 1d convolutional DBNs 1004 |
| | 28.4.5 | Learning image features using 2d convolutional DBNs 1005 |
| 28 | 5 Discuss | ion 1005 |
| | | |

Notation 1009

Bibliography 1015

Indexes 1047

Index to code 1047 Index to keywords 1050