

# Index

## A

- Activity analysis, 126, 136
- Adjusted mutual information score (AMIS), 194, 289, 293, 295, 297, 298
- Adjusted rand index (ARI), 194, 289, 293, 295, 298
- Attention, 73, 200, 205, 308

## B

- Bag-of-features (BoF), 129, 145, 167
- Basis functions
  - Bernstein, 40, 45–46
  - Fourier, 46
  - polynomial fitting, 42
  - RBFs (*see* Radial basis functions (RBFs))
- Bernstein basis functions, 40, 45–46
- Bernstein polynomials, 40, 54
- Beta mixture models (BBMM)
  - accuracy and outperformance, 205
  - business mortality dataset, 191
  - five-component, 185
  - four-component, 185
  - grain diameters, 192
  - one-component, 182, 183
  - sailing speed optimization dataset, 192–193
  - shape parameters, 181
  - three-component, 184
  - two-component, 184
  - water levels of Florida swamps dataset, 193
- Bivariate beta, 181–185
- Bounded asymmetric Gaussian mixture model (BAGMM)
  - AGMM, 64–65
  - application, 77

- clustering techniques, 62
- data modeling, 62
- EM algorithm, 63–64
- finite mixture model, 63–64
- graphical abstract, 63
- multidimensional data, 65–66
- object categorization (*see* Object categorization)
- parameters learning (*see* Parameters)
- probability distributions, 61
- Bounded generalized Gaussian mixture model (BGGMM), 327–330
- Brain tumour detection, 252–253

## C

- Calinski-Harabaz Index (CHI), 194, 291, 294, 295, 297, 299
- Calligraphy and graffiti generation
  - conventional computer graphics, 25
  - hand-drawn curves, 23
  - human hand movements, 25
  - NPAR, 25
  - target-directed hand movements, 24
  - trajectory (*see* Trajectory generation)
- Clustering
  - BAGMM, 71
  - characteristics, 62
  - DCM, 130
  - finite mixture models, 156
  - K-means algorithm, 82
  - MDD log-likelihood, 157
  - model learning, 114–117
  - object data, 74, 75
  - Poisson distribution, 156

- Clustering (*cont.*)
- probabilistic model based-approach, 110
  - spambase data, 72
  - texture image (*see* Texture image clustering)
  - topic novelty detection, 118–120
  - univariate and multivariate data, 109–110
  - unsupervised images categorization, 120–121
- Color image segmentation, 193–197
- Completeness score (CS), 194, 290, 294, 297, 299
- Component splitting
- algorithm, 219–220
  - model selection, 212–214
  - variational framework, 226
- Count data
- categorical data, 156
  - EDCM (*see* Exponential approximation to Dirichlet compound multinomial (EDCM))
  - and EGDM (*see* Exponential approximation to generalized Dirichlet multinomial (EGDM))
  - generative/discriminative models (*see* Generative/discriminative learning)
  - multinomial Dirichlet distribution (MDD) (*see* Multinomial Dirichlet distribution (MDD))
- D**
- Data clustering
- BAGMM, 76 (*see* Bounded asymmetric Gaussian mixture model (BAGMM))
  - performance, 74
  - spambase, 72
- Data mining
- association, 239
  - classification techniques, 238
  - clustering, 239
  - regression, 239
  - summarization, 240
  - trend analysis, 238–239
- Deterministic learning
- EM algorithm, 84–85
  - Fisher scoring algorithm, 88–89
  - fixed-point estimation method, 86–87
  - Gaussian distributions, 85
  - $j$ -th component, 85–86
  - $M$ -step, 86
  - RA-FP, 88
- Dirichlet process mixture model
- infinite number of clusters, 110
  - VM mixture model (*see* von Mises (VM) distribution)
- Discriminative framework, 127, 146
- E**
- Ergodic control
- Fourier series coefficients, 47–50
  - Gaussian properties, 54
  - scope of applications, 46
  - spatial distribution, 50–51
  - vector form, 47–48
- Expectation-maximisation (EM)
- algorithm, 166
  - convergence criteria, 13–14
  - finite mixture models, 63–64
  - Gaussian mixture model, 11
  - learning approach, 89
  - log-likelihood function, 326
  - mean and standard deviation, 12
  - ML, 62, 186–188
  - real video data, 83
  - steps, 13
  - 2-component model, 18
- Exponential approximation to Dirichlet compound multinomial (EDCM), 129–130
- classification, 126
  - closed-form expression, 135
  - count data, 126
  - and EGDM (*see* Exponential approximation to generalized Dirichlet multinomial (EGDM))
  - parameters, 131
  - performance comparison, 141–143
- Exponential approximation to generalized Dirichlet multinomial (EGDM), 130–131
- count data modeling, 126
  - expressions, 136
  - Fisher kernel, 133
  - parameters, 131
  - PDF, 149
  - performance comparison, 141–144
- Exponential family approximation
- Bayes' rule, 126
  - finite mixtures (*see* Finite mixtures)
  - generative/discriminative models (*see* Generative/discriminative learning)

- methodology and performance measures, 136–137
  - problem of classification, 126
  - SVMs (*see* Support vector machines (SVMs))
- F**
- Facial expression recognition, 84, 95, 102, 169–174
  - Feature selection
    - clustering performance, 110
    - Dirichlet mixture models, 83
    - grafting approach, 82
    - mixture models, 121
    - VM mixture model, 111–114
  - Finite inverted beta-Liouville (IBL) mixture models, 211–212
    - component splitting, 212–214
    - data analysis, 209
    - GMM, 210
    - ML, 210
    - statistical model
      - component splitting, 213–214
      - finite mixture models, 211–212
  - Finite inverted Dirichlet mixture model
    - online variational inference, 246–250
    - variational inference, 243–246
  - Finite mixture models (FMM), 275
    - conditional probability, 276
    - and CPV, 276
    - image segmentation, 274
    - semi-bounded, 302
  - Finite mixtures
    - EDCM, 129–130
    - EGDM, 130–131
    - expectation step, 85–86
    - experimental results
      - facial expression recognition, 169–174
      - natural scenes categorization, 168–169
    - Fisher scoring algorithm, 88–89
    - fixed-point estimation method, 86–87
    - Gaussian distributions, 84
    - $M$  densities, 128
    - mixing and mean parameter, 86
    - mixture models, 131–132
    - models learning, 165–167
    - $M$ -step, 86
    - RA-FP, 88
  - Fourier basis functions, 46
  - Fourier series, 46–49, 54, 55
  - Frequentist inference method
    - GMM, 180
    - mixture model (*see* Mixture model)
    - scientific and technological advances, 180
    - spectrum of research areas, 180
- G**
- Gaussian mixture models (GMM)
    - AGMM (*see* asymmetric Gaussian mixture model (AGMM))
    - aims, 7–8
    - alternative approach, 7
    - bimodal distribution, 9
    - classification criteria, 17
    - comparison, 17–18
    - data collection, 8
    - expectation-maximisation algorithm, 11–12
    - expressed as, 9
    - Fourier series properties, 46
    - integrating equation, 10–11
    - interrupted visual search, 3–5
    - LWR, 44
    - multivariate components, 26
    - overview of approach, 8
    - parameter estimation, 16
    - quantifying individual differences, 5–6
    - spatial distribution, 24
    - Stochastic sampling, 31
  - Gaussian mixture regression (GMR), 43–45
  - Generalized Dirichlet multinomial (GDM), 126, 130, 141–143, 145
  - Generalized inverted Dirichlet, 83, 308
  - Generative/discriminative learning
    - classification
      - anomaly detection, 139
      - human action recognition, 140, 141
      - human–human interaction recognition, 140
      - results and discussion, 141–144
      - traffic scene based on density, 137–138
      - unusual events in traffic flows, 138, 139
  - Fisher kernel, 132–133
  - information divergence
    - Kullback–Leibler Kernels, 135
    - Refiyi and Jensen–Shannon Kernels, 135–136
    - probability product, 133–134
    - results, 144–146
  - GID mixture models (GIDMM)
    - algorithm, 285–286
    - probability density function, 283–284
    - WACMT, 278–279, 285
    - weighted prior probability estimation, 279
    - with WGCMT, 284–285

**H**

- Healthcare, *see* Data mining
- Homogeneity score (HS), 194, 290, 293, 295, 297
- Human action recognition, 84, 92, 94–95, 140–141

**I**

- IBL mixture models (IBLMM)
  - algorithm, 288
  - flower petals, 292
  - probability density function, 286
  - with WACMT, 287
  - WGCMT, 286–287
- ID mixture models (IDMM)
  - algorithm, 282–283
  - probability density function, 280
  - with WACMT, 282
  - with WGCMT, 280–282
- Image categorization, 110, 120, 121, 172, 220, 222
  - clustering, 222, 223
  - InVmMM-LFs, 121
  - Oxford flowers data set, 120
  - spam clustering, 223–225
- Image clustering, *see* Texture image clustering
- Image segmentation
  - color, 193–197
  - color spaces, 291–292
  - experiment 1, 292–296
  - experiment 2, 296–302
  - FMM (*see* Finite mixture models (FMM))
  - medical, 240
  - problem description, 275–276
  - spatial information, 274
  - unsupervised learning (*see* Unsupervised learning)
- Infrared (IR) images
  - facial expression, 103
  - fire-fighters, 96
  - human action recognition, 96
  - online pedestrian detection, 96
  - pedestrian from, 83
  - thermal imagery, 92
- Interrupted search, 5–7
- Inverted beta-Liouville (IBL)
  - finite mixture models, 211–212, 309–310
  - graphical representation, 214
  - image segmentation, 308
  - medical image segmentation (*see* Medical image segmentation)
  - performance evaluation, 295, 297–299

- probability density function, 286
- spatial constraints, 310–311

*See also* Finite inverted beta-Liouville (IBL) mixture models

- Inverted Dirichlet distribution, 241, 308

**J**

- Jaccard similarity score (JSS), 194, 197, 291, 294, 297, 299

**L**

- Locally weighted regression (LWR), 39–44, 52
- Log probability ratio, 14–18
- Lung tuberculosis detection, 256–259

**M**

- Maximum likelihood estimation (MLE)
  - probability density function, 331
  - WACMT, 278–279
  - WGCMT, 278
- Maximum likelihood (ML)
  - BAGMM, 77
  - Bayesian estimation techniques, 210
  - clustering (*see* Clustering)
  - deterministic approaches, 180
  - EM algorithm (*see* Expectation-maximisation (EM))
  - mixture learning, 240
  - MLE, 278
  - model parameters, 259
  - Newton–Raphson technique, 87
  - parameter estimation, 10, 62, 64, 156
  - shape parameter, 89
- Mean templates
  - GIDMM (*see* GID mixture models (GIDMM))
  - IBLMM (*see* IBL mixture models (IBLMM))
  - WGCMT (*see* Weighted geometric conditional mean template (WGCMT))
- Medical image segmentation, 240
  - characteristics of regions, 307
  - edge-based methods, 308
  - experimental results
    - MRI brain images, 319–321
    - synthetic MRI brain images, 316–319
    - IBL, 308
- Mesh algorithm, 163–165

- Minimum description length (MDL)
    - BSD dataset, 339
    - image segmentation (*see* Image segmentation)
    - model selection, 336
    - proposed complete algorithm, 336
    - segmentation and data modeling, 327
  - Minimum message length (MML)
    - Australian dataset, 204
    - business mortality dataset, 191
    - Florida swamps dataset, 194
    - grain diameter dataset, 192
    - heart disease dataset, 199
    - model complexity, 188–190
    - optimal number of clusters, 180
    - sailing speed optimization dataset, 193
    - sentiments analysis dataset, 202
  - Mixture models
    - BAGMM (*see* Bounded asymmetric Gaussian mixture model (BAGMM))
    - bivariate beta distribution, 181–185
    - continuous time series (*see* Synthesis of continuous time series)
    - convergence criteria, 13–14
    - data clustering (*see* Clustering)
    - EM algorithm, 156
    - expectation step, 13
    - finite learning, 165–167
    - Gaussian density, 10
    - GMM (*see* Gaussian mixture models (GMM))
    - initialisation, 12
    - maximisation step, 13
    - medical image segmentation (*see* Medical image segmentation)
    - MGGD (*see* Multivariate generalized Gaussian distribution (MGGD))
    - multivariate beta distribution, 186
    - online variational inference (*see* Online variational inference)
    - PDFs, 156
  - Mixture model's parameters estimation
    - mean parameter, 332–333
    - prior probability, 336
    - shape parameter, 334–335
    - standard deviation, 333–334
  - Model learning, 311–315
  - Model predictive control (MPC), 28, 54
  - Model selection
    - algorithm, 219
    - component splitting, 213–214
    - component splitting approach, 226
    - EM algorithm, 186–188
    - MDL, 336
    - MML, 180
    - parameter estimation, 205, 237
    - parameters, 44
  - Monte Carlo Markov chain (MCMC), 119–121, 210, 236
  - Movement primitives
    - Bernstein basis functions, 45–46
    - ergodic control, 47–51
    - Fourier basis functions, 46
    - probabilistic, 51–53
    - RBFs (*see* Radial basis functions (RBFs))
  - Multinomial Compound Dirichlet (DCM), 126, 128–130, 137, 141–143, 145
  - Multinomial Dirichlet distribution (MDD), 157–159
    - covariance, 161
    - flexibility, 160
    - log-gamma difference, 161–162
    - mean, 161
    - paired log-gamma difference, 159–160
  - Multinomial generalized Dirichlet (MGD) distribution, 160–161
    - flexible modeling of count data, 156
    - MMI dataset, 174
    - Newton–Raphson method, 166
    - paired log-gamma difference, 161–162
    - parameterization, 157
    - SUN dataset, 171
  - Multivariate beta mixture models (MBMM)
    - credit approval, 202–204
    - Haberman dataset, 197, 198
    - heart disease dataset, 198, 199
    - hepatitis dataset, 199
    - lymphography dataset, 199–200
    - sentiments analysis, 200–202
  - Multivariate generalized Gaussian distribution (MGGD)
    - finite mixture and deterministic learning (*see* Finite mixtures)
    - probability density functions, 84
- N**
- Newton–Raphson, 69, 70, 77, 87–89, 180, 186, 187, 281, 284, 287
  - Non photorealistic animation and rendering (NPAR), 25
  - Normalized mutual information score (NMIS), 197, 289, 293, 295, 298
  - Novelty detection, 110, 118–120, 122

**O**

- Object categorization, 62, 63, 73, 75, 77
  - BOVW, 73
  - Caltech 101 dataset, 73–74
  - Corel dataset, 74–75
  - machine learning techniques, 73
- Online recognition
  - applications, 82
  - computer science, 81–82
  - experiments
    - database preprocessing approach, 93–94
    - datasets, 92, 93
    - human action recognition, 94–95
    - human facial expression recognition, 95
    - pedestrian detection, IR, 96
    - results, 96–103
  - GMM, 83
  - hidden Markov model, 82
  - learning algorithm, 89–93
  - MAP estimation procedure, 83
- Online variational inference
  - data mining (*see* Data mining)
  - experimental results
    - image segmentation, 250–251
    - medical image data sets, 251–259
    - synthetic data, 251
  - finite inverted Dirichlet mixture model (*see* Finite inverted Dirichlet mixture model)
  - GMM, 237
  - imaging, 236
  - MCMC, 236
  - statistical approach, 236
  - variational Bayes, 237
- Optimal control, 24, 28, 35, 54

**P**

- Parameters
  - left standard deviation, 68–69
  - mean estimation, 67–68
  - mixing estimation, 67
  - right standard deviation, 69–70
- Participants, 4–6, 14, 19–21
- Positive vectors, 280, 283, 286
- Prior expectations, 4
- Probabilistic kernels, 126, 132, 135, 144, 146
- Probabilistic movement, 51–53

**R**

- Radial basis functions (RBFs)
  - application range, 43

- input–output datapoints, 40–41
- LWR, 42
- polynomial fitting, 42
- radial basis functions, 41
- Rapid resumption, 5–7, 12, 14, 17, 18

**S**

- Segmentation performance evaluation
  - AMIS, 289
  - ARI, 289
  - CHI, 291
  - CS, 290
  - HS, 290
  - JSS, 291
  - NMIS, 289
  - VMS, 290
- Skin lesion diagnosis, 253–256
- Software defect categorization, 225–226
- Spatial information (SI), 274, 275, 277, 326, 330–331, 343
- Spatially constrained model
  - finite IBL mixture, 309–310
  - spatial constraints, 310–311
- Speech categorization, 221
- Spherical data, 83, 110
- Stimuli, 19–21
- Stochastic dynamical system
  - approximation, 82
  - Euclidean distance, 29
  - indicator vectors, 66
  - mixture parameters, 90
  - solution, 30–32
- Support vector machines (SVMs)
  - clustering, 125
  - kernels, 127–128
  - methodology and performance measures, 136–137
  - mixture models, 127
  - PDFs, 126
  - supervised learning tool, 126
- Synthesis of continuous time series
  - practical applications, 40
  - RBFs (*see* Radial basis functions (RBFs))
  - techniques, 39

**T**

- Textual spam detection, 70–72
- Texture image clustering
  - applications, 77
  - human visual impression, 75
  - VisTex, 76–77
- Topic novelty detection, 118–120

- Trajectory generation
  - dynamical system, 27–28
  - GMM, 26
  - optimization objective, 28
  - periodic motions, 32–33
  - stochastic solution, 30–32
  - tracking formulation, 28–30
- U**
- Unsupervised learning, 109, 128, 156, 180, 210, 239, 330
  - BGGMM, 327
  - data modeling, 326
  - experiment 1, 338–339
  - experiment 2, 339–341
  - experiment 3, 342–343
  - experiment design, 336–337
  - GMM, 326–327
- User interface
  - of ellipsoids representing GMMs, 34
  - semi-tied structure, 34–35
  - stylizations, 34
  - trajectories, 33
- V**
- Variational inference (VI), 114–117
  - component splitting algorithm, 219–220
  - effective approach, 110
  - learning, 215–219
  - model learning, 114–117
  - online, 246–250
- Variational learning, 215–219
- Visual search, 3–5, 19
- von Mises (VM) distribution
  - categorizing images, 121
  - global feature selection, 119
  - localized feature selection
    - finite, 111–112
    - infinite, 112–114
  - parameters, 114
  - spherical, 110
- W**
- Weighted arithmetic conditional mean template (WACMT)
  - GIDMM, 285
  - IBMM, 287
  - IDMM, 282
  - MLE, 278–279
- Weighted geometric conditional mean template (WGCMT)
  - GIDMM, 284–285
  - IBLMM, 286–287
  - IDMM, 280–282
  - MLE, 278