

# Contents

- 1 Introduction . . . . . 1**
- 1.1 What this Book Is All About . . . . . 1
- 1.2 What Is Vision? . . . . . 2
- 1.3 The Magic of Your Visual System . . . . . 3
- 1.4 Importance of Prior Information . . . . . 7
  - 1.4.1 Ecological Adaptation Provides Prior Information . . . . . 7
  - 1.4.2 Generative Models and Latent Quantities . . . . . 8
  - 1.4.3 Projection onto the Retina Loses Information . . . . . 9
  - 1.4.4 Bayesian Inference and Priors . . . . . 9
- 1.5 Natural Images . . . . . 10
  - 1.5.1 The Image Space . . . . . 10
  - 1.5.2 Definition of Natural Images . . . . . 11
- 1.6 Redundancy and Information . . . . . 13
  - 1.6.1 Information Theory and Image Coding . . . . . 13
  - 1.6.2 Redundancy Reduction and Neural Coding . . . . . 14
- 1.7 Statistical Modeling of the Visual System . . . . . 15
  - 1.7.1 Connecting Information Theory and Bayesian Inference . . . . . 15
  - 1.7.2 Normative vs. Descriptive Modeling of Visual System . . . . . 15
  - 1.7.3 Toward Predictive Theoretical Neuroscience . . . . . 16
- 1.8 Features and Statistical Models of Natural Images . . . . . 17
  - 1.8.1 Image Representations and Features . . . . . 17
  - 1.8.2 Statistics of Features . . . . . 18
  - 1.8.3 From Features to Statistical Models . . . . . 19
- 1.9 The Statistical–Ecological Approach Recapitulated . . . . . 20
- 1.10 References . . . . . 21

## Part I Background

- 2 Linear Filters and Frequency Analysis . . . . . 25**
- 2.1 Linear Filtering . . . . . 25
  - 2.1.1 Definition . . . . . 25
  - 2.1.2 Impulse Response and Convolution . . . . . 28
- 2.2 Frequency-Based Representation . . . . . 29
  - 2.2.1 Motivation . . . . . 29
  - 2.2.2 Representation in One and Two Dimensions . . . . . 29
  - 2.2.3 Frequency-Based Representation and Linear Filtering . . . . . 34
  - 2.2.4 Computation and Mathematical Details . . . . . 37
- 2.3 Representation Using Linear Basis . . . . . 38
  - 2.3.1 Basic Idea . . . . . 38
  - 2.3.2 Frequency-Based Representation as a Basis . . . . . 40

2.4	Space-Frequency Analysis . . . . .	41
2.4.1	Introduction . . . . .	41
2.4.2	Space-Frequency Analysis and Gabor Filters . . . . .	43
2.4.3	Spatial Localization vs. Spectral Accuracy . . . . .	46
2.5	References . . . . .	48
2.6	Exercises . . . . .	48
<b>3</b>	<b>Outline of the Visual System . . . . .</b>	<b>51</b>
3.1	Neurons and Firing Rates . . . . .	51
3.2	From the Eye to the Cortex . . . . .	53
3.3	Linear Models of Visual Neurons . . . . .	54
3.3.1	Responses to Visual Stimulation . . . . .	54
3.3.2	Simple Cells and Linear Models . . . . .	56
3.3.3	Gabor Models and Selectivities of Simple Cells . . . . .	57
3.3.4	Frequency Channels . . . . .	58
3.4	Non-linear Models of Visual Neurons . . . . .	59
3.4.1	Non-linearities in Simple-Cell Responses . . . . .	59
3.4.2	Complex Cells and Energy Models . . . . .	61
3.5	Interactions between Visual Neurons . . . . .	62
3.6	Topographic Organization . . . . .	64
3.7	Processing after the Primary Visual Cortex . . . . .	64
3.8	References . . . . .	65
3.9	Exercises . . . . .	65
<b>4</b>	<b>Multivariate Probability and Statistics . . . . .</b>	<b>67</b>
4.1	Natural Images Patches as Random Vectors . . . . .	67
4.2	Multivariate Probability Distributions . . . . .	68
4.2.1	Notation and Motivation . . . . .	68
4.2.2	Probability Density Function . . . . .	69
4.3	Marginal and Joint Probabilities . . . . .	70
4.4	Conditional Probabilities . . . . .	73
4.5	Independence . . . . .	75
4.6	Expectation and Covariance . . . . .	77
4.6.1	Expectation . . . . .	77
4.6.2	Variance and Covariance in One Dimension . . . . .	78
4.6.3	Covariance Matrix . . . . .	78
4.6.4	Independence and Covariances . . . . .	79
4.7	Bayesian Inference . . . . .	81
4.7.1	Motivating Example . . . . .	81
4.7.2	Bayes' Rule . . . . .	83
4.7.3	Non-informative Priors . . . . .	83
4.7.4	Bayesian Inference as an Incremental Learning Process . . . . .	84
4.8	Parameter Estimation and Likelihood . . . . .	86
4.8.1	Models, Estimation, and Samples . . . . .	86
4.8.2	Maximum Likelihood and Maximum a Posteriori . . . . .	87
4.8.3	Prior and Large Samples . . . . .	89

4.9 References . . . . . 89

4.10 Exercises . . . . . 89

**Part II Statistics of Linear Features**

**5 Principal Components and Whitening . . . . . 93**

5.1 DC Component or Mean Grey-Scale Value . . . . . 93

5.2 Principal Component Analysis . . . . . 94

5.2.1 A Basic Dependency of Pixels in Natural Images . . . . . 94

5.2.2 Learning One Feature by Maximization of Variance . . . . . 96

5.2.3 Learning Many Features by PCA . . . . . 98

5.2.4 Computational Implementation of PCA . . . . . 101

5.2.5 The Implications of Translation-Invariance . . . . . 102

5.3 PCA as a Preprocessing Tool . . . . . 103

5.3.1 Dimension Reduction by PCA . . . . . 103

5.3.2 Whitening by PCA . . . . . 104

5.3.3 Anti-aliasing by PCA . . . . . 106

5.4 Canonical Preprocessing Used in This Book . . . . . 109

5.5 Gaussianity as the Basis for PCA . . . . . 109

5.5.1 The Probability Model Related to PCA . . . . . 109

5.5.2 PCA as a Generative Model . . . . . 110

5.5.3 Image Synthesis Results . . . . . 111

5.6 Power Spectrum of Natural Images . . . . . 111

5.6.1 The  $1/f$  Fourier Amplitude or  $1/f^2$  Power Spectrum . . . . . 111

5.6.2 Connection between Power Spectrum and Covariances . . . . . 113

5.6.3 Relative Importance of Amplitude and Phase . . . . . 114

5.7 Anisotropy in Natural Images . . . . . 115

5.8 Mathematics of Principal Component Analysis\* . . . . . 116

5.8.1 Eigenvalue Decomposition of the Covariance Matrix . . . . . 117

5.8.2 Eigenvectors and Translation-Invariance . . . . . 119

5.9 Decorrelation Models of Retina and LGN \* . . . . . 120

5.9.1 Whitening and Redundancy Reduction . . . . . 120

5.9.2 Patch-Based Decorrelation . . . . . 121

5.9.3 Filter-Based Decorrelation . . . . . 124

5.10 Concluding Remarks and References . . . . . 128

5.11 Exercises . . . . . 129

**6 Sparse Coding and Simple Cells . . . . . 131**

6.1 Definition of Sparseness . . . . . 131

6.2 Learning One Feature by Maximization of Sparseness . . . . . 132

6.2.1 Measuring Sparseness: General Framework . . . . . 133

6.2.2 Measuring Sparseness Using Kurtosis . . . . . 133

6.2.3 Measuring Sparseness Using Convex Functions of Square . . . . . 134

6.2.4 The Case of Canonically Preprocessed Data . . . . . 138

6.2.5 One Feature Learned from Natural Images . . . . . 138

- 6.3 Learning Many Features by Maximization of Sparseness . . . . . 139
  - 6.3.1 Deflationary Decorrelation . . . . . 140
  - 6.3.2 Symmetric Decorrelation . . . . . 141
  - 6.3.3 Sparseness of Feature vs. Sparseness of Representation . . 141
- 6.4 Sparse Coding Features for Natural Images . . . . . 143
  - 6.4.1 Full Set of Features . . . . . 143
  - 6.4.2 Analysis of Tuning Properties . . . . . 144
- 6.5 How Is Sparseness Useful? . . . . . 147
  - 6.5.1 Bayesian Modeling . . . . . 147
  - 6.5.2 Neural Modeling . . . . . 148
  - 6.5.3 Metabolic Economy . . . . . 148
- 6.6 Concluding Remarks and References . . . . . 148
- 6.7 Exercises . . . . . 149
  
- 7 Independent Component Analysis . . . . . 151**
  - 7.1 Limitations of the Sparse Coding Approach . . . . . 151
  - 7.2 Definition of ICA . . . . . 152
    - 7.2.1 Independence . . . . . 152
    - 7.2.2 Generative Model . . . . . 152
    - 7.2.3 Model for Preprocessed Data . . . . . 154
  - 7.3 Insufficiency of Second-Order Information . . . . . 154
    - 7.3.1 Why Whitening Does Not Find Independent Components . 154
    - 7.3.2 Why Components Have to Be Non-Gaussian . . . . . 156
  - 7.4 The Probability Density Defined by ICA . . . . . 158
  - 7.5 Maximum Likelihood Estimation in ICA . . . . . 159
  - 7.6 Results on Natural Images . . . . . 160
    - 7.6.1 Estimation of Features . . . . . 160
    - 7.6.2 Image Synthesis Using ICA . . . . . 160
  - 7.7 Connection to Maximization of Sparseness . . . . . 161
    - 7.7.1 Likelihood as a Measure of Sparseness . . . . . 161
    - 7.7.2 Optimal Sparseness Measures . . . . . 163
  - 7.8 Why Are Independent Components Sparse? . . . . . 166
    - 7.8.1 Different Forms of Non-Gaussianity . . . . . 167
    - 7.8.2 Non-Gaussianity in Natural Images . . . . . 167
    - 7.8.3 Why Is Sparseness Dominant? . . . . . 168
  - 7.9 General ICA as Maximization of Non-Gaussianity . . . . . 168
    - 7.9.1 Central Limit Theorem . . . . . 169
    - 7.9.2 “Non-Gaussian Is Independent” . . . . . 169
    - 7.9.3 Sparse Coding as a Special Case of ICA . . . . . 170
  - 7.10 Receptive Fields vs. Feature Vectors . . . . . 171
  - 7.11 Problem of Inversion of Preprocessing . . . . . 172
  - 7.12 Frequency Channels and ICA . . . . . 173
  - 7.13 Concluding Remarks and References . . . . . 173
  - 7.14 Exercises . . . . . 174

**8 Information-Theoretic Interpretations . . . . . 177**

8.1 Basic Motivation for Information Theory . . . . . 177

8.1.1 Compression . . . . . 177

8.1.2 Transmission . . . . . 178

8.2 Entropy as a Measure of Uncertainty . . . . . 179

8.2.1 Definition of Entropy . . . . . 179

8.2.2 Entropy as Minimum Coding Length . . . . . 180

8.2.3 Redundancy . . . . . 181

8.2.4 Differential Entropy . . . . . 182

8.2.5 Maximum Entropy . . . . . 183

8.3 Mutual Information . . . . . 184

8.4 Minimum Entropy Coding of Natural Images . . . . . 185

8.4.1 Image Compression and Sparse Coding . . . . . 185

8.4.2 Mutual Information and Sparse Coding . . . . . 187

8.4.3 Minimum Entropy Coding in the Cortex . . . . . 187

8.5 Information Transmission in the Nervous System . . . . . 188

8.5.1 Definition of Information Flow and Infomax . . . . . 188

8.5.2 Basic Infomax with Linear Neurons . . . . . 188

8.5.3 Infomax with Non-linear Neurons . . . . . 189

8.5.4 Infomax with Non-constant Noise Variance . . . . . 190

8.6 Caveats in Application of Information Theory . . . . . 193

8.7 Concluding Remarks and References . . . . . 195

8.8 Exercises . . . . . 195

**Part III Nonlinear Features and Dependency of Linear Features**

**9 Energy Correlation of Linear Features and Normalization . . . . . 199**

9.1 Why Estimated Independent Components Are Not Independent . . . . . 199

9.1.1 Estimates vs. Theoretical Components . . . . . 199

9.1.2 Counting the Number of Free Parameters . . . . . 200

9.2 Correlations of Squares of Components in Natural Images . . . . . 201

9.3 Modeling Using a Variance Variable . . . . . 201

9.4 Normalization of Variance and Contrast Gain Control . . . . . 203

9.5 Physical and Neurophysiological Interpretations . . . . . 205

9.5.1 Canceling the Effect of Changing Lighting Conditions . . . . . 205

9.5.2 Uniform Surfaces . . . . . 206

9.5.3 Saturation of Cell Responses . . . . . 206

9.6 Effect of Normalization on ICA . . . . . 207

9.7 Concluding Remarks and References . . . . . 210

9.8 Exercises . . . . . 211

**10 Energy Detectors and Complex Cells . . . . . 213**

10.1 Subspace Model of Invariant Features . . . . . 213

10.1.1 Why Linear Features Are Insufficient . . . . . 213

10.1.2 Subspaces or Groups of Linear Features . . . . . 213

10.1.3 Energy Model of Feature Detection . . . . . 214

10.2	Maximizing Sparseness in the Energy Model . . . . .	216
10.2.1	Definition of Sparseness of Output . . . . .	216
10.2.2	One Feature Learned from Natural Images . . . . .	217
10.3	Model of Independent Subspace Analysis . . . . .	219
10.4	Dependency as Energy Correlation . . . . .	220
10.4.1	Why Energy Correlations Are Related to Sparseness . . . . .	220
10.4.2	Spherical Symmetry and Changing Variance . . . . .	221
10.4.3	Correlation of Squares and Convexity of Non-linearity . . . . .	222
10.5	Connection to Contrast Gain Control . . . . .	223
10.6	ISA as a Non-linear Version of ICA . . . . .	224
10.7	Results on Natural Images . . . . .	225
10.7.1	Emergence of Invariance to Phase . . . . .	225
10.7.2	The Importance of Being Invariant . . . . .	230
10.7.3	Grouping of Dependencies . . . . .	232
10.7.4	Superiority of the Model over ICA . . . . .	232
10.8	Analysis of Convexity and Energy Correlations* . . . . .	234
10.8.1	Variance Variable Model Gives Convex $h$ . . . . .	234
10.8.2	Convex $h$ Typically Implies Positive Energy Correlations . . . . .	235
10.9	Concluding Remarks and References . . . . .	236
10.10	Exercises . . . . .	236
<b>11</b>	<b>Energy Correlations and Topographic Organization . . . . .</b>	<b>239</b>
11.1	Topography in the Cortex . . . . .	239
11.2	Modeling Topography by Statistical Dependence . . . . .	240
11.2.1	Topographic Grid . . . . .	240
11.2.2	Defining Topography by Statistical Dependencies . . . . .	240
11.3	Definition of Topographic ICA . . . . .	242
11.4	Connection to Independent Subspaces and Invariant Features . . . . .	243
11.5	Utility of Topography . . . . .	244
11.6	Estimation of Topographic ICA . . . . .	245
11.7	Topographic ICA of Natural Images . . . . .	246
11.7.1	Emergence of V1-like Topography . . . . .	246
11.7.2	Comparison with Other Models . . . . .	253
11.8	Learning Both Layers in a Two-Layer Model * . . . . .	253
11.8.1	Generative vs. Energy-Based Approach . . . . .	253
11.8.2	Definition of the Generative Model . . . . .	254
11.8.3	Basic Properties of the Generative Model . . . . .	255
11.8.4	Estimation of the Generative Model . . . . .	256
11.8.5	Energy-Based Two-Layer Models . . . . .	259
11.9	Concluding Remarks and References . . . . .	260
<b>12</b>	<b>Dependencies of Energy Detectors: Beyond V1 . . . . .</b>	<b>263</b>
12.1	Predictive Modeling of Extrastriate Cortex . . . . .	263
12.2	Simulation of V1 by a Fixed Two-Layer Model . . . . .	263
12.3	Learning the Third Layer by Another ICA Model . . . . .	265

- 12.4 Methods for Analyzing Higher-Order Components . . . . . 266
- 12.5 Results on Natural Images . . . . . 268
  - 12.5.1 Emergence of Collinear Contour Units . . . . . 268
  - 12.5.2 Emergence of Pooling over Frequencies . . . . . 269
- 12.6 Discussion of Results . . . . . 273
  - 12.6.1 Why Coding of Contours? . . . . . 273
  - 12.6.2 Frequency Channels and Edges . . . . . 274
  - 12.6.3 Toward Predictive Modeling . . . . . 274
  - 12.6.4 References and Related Work . . . . . 275
- 12.7 Conclusion . . . . . 276
  
- 13 Overcomplete and Non-negative Models . . . . . 277**
  - 13.1 Overcomplete Bases . . . . . 277
    - 13.1.1 Motivation . . . . . 277
    - 13.1.2 Definition of Generative Model . . . . . 278
    - 13.1.3 Nonlinear Computation of the Basis Coefficients . . . . . 279
    - 13.1.4 Estimation of the Basis . . . . . 281
    - 13.1.5 Approach Using Energy-Based Models . . . . . 282
    - 13.1.6 Results on Natural Images . . . . . 285
    - 13.1.7 Markov Random Field Models \* . . . . . 285
  - 13.2 Non-negative Models . . . . . 288
    - 13.2.1 Motivation . . . . . 288
    - 13.2.2 Definition . . . . . 288
    - 13.2.3 Adding Sparseness Constraints . . . . . 290
  - 13.3 Conclusion . . . . . 293
  
- 14 Lateral Interactions and Feedback . . . . . 295**
  - 14.1 Feedback as Bayesian Inference . . . . . 295
    - 14.1.1 Example: Contour Integrator Units . . . . . 296
    - 14.1.2 Thresholding (Shrinkage) of a Sparse Code . . . . . 298
    - 14.1.3 Categorization and Top-Down Feedback . . . . . 302
  - 14.2 Overcomplete Basis and End-stopping . . . . . 302
  - 14.3 Predictive Coding . . . . . 304
  - 14.4 Conclusion . . . . . 305
  
- Part IV Time, Color, and Stereo**
  
- 15 Color and Stereo Images . . . . . 309**
  - 15.1 Color Image Experiments . . . . . 309
    - 15.1.1 Choice of Data . . . . . 309
    - 15.1.2 Preprocessing and PCA . . . . . 310
    - 15.1.3 ICA Results and Discussion . . . . . 313
  - 15.2 Stereo Image Experiments . . . . . 315
    - 15.2.1 Choice of Data . . . . . 315
    - 15.2.2 Preprocessing and PCA . . . . . 316
    - 15.2.3 ICA Results and Discussion . . . . . 317

- 15.3 Further References . . . . . 322
  - 15.3.1 Color and Stereo Images . . . . . 322
  - 15.3.2 Other Modalities, Including Audition . . . . . 323
- 15.4 Conclusion . . . . . 323
- 16 Temporal Sequences of Natural Images . . . . . 325**
  - 16.1 Natural Image Sequences and Spatiotemporal Filtering . . . . . 325
  - 16.2 Temporal and Spatiotemporal Receptive Fields . . . . . 326
  - 16.3 Second-Order Statistics . . . . . 328
    - 16.3.1 Average Spatiotemporal Power Spectrum . . . . . 328
    - 16.3.2 The Temporally Decorrelating Filter . . . . . 332
  - 16.4 Sparse Coding and ICA of Natural Image Sequences . . . . . 333
  - 16.5 Temporal Coherence in Spatial Features . . . . . 336
    - 16.5.1 Temporal Coherence and Invariant Representation . . . . . 336
    - 16.5.2 Quantifying Temporal Coherence . . . . . 337
    - 16.5.3 Interpretation as Generative Model \* . . . . . 338
    - 16.5.4 Experiments on Natural Image Sequences . . . . . 339
    - 16.5.5 Why Gabor-Like Features Maximize Temporal Coherence . 341
    - 16.5.6 Control Experiments . . . . . 344
  - 16.6 Spatiotemporal Energy Correlations in Linear Features . . . . . 345
    - 16.6.1 Definition of the Model . . . . . 345
    - 16.6.2 Estimation of the Model . . . . . 347
    - 16.6.3 Experiments on Natural Images . . . . . 348
    - 16.6.4 Intuitive Explanation of Results . . . . . 350
  - 16.7 Unifying Model of Spatiotemporal Dependencies . . . . . 352
  - 16.8 Features with Minimal Average Temporal Change . . . . . 354
    - 16.8.1 Slow Feature Analysis . . . . . 354
    - 16.8.2 Quadratic Slow Feature Analysis . . . . . 357
    - 16.8.3 Sparse Slow Feature Analysis . . . . . 359
  - 16.9 Conclusion . . . . . 361

**Part V Conclusion**

- 17 Conclusion and Future Prospects . . . . . 365**
  - 17.1 Short Overview . . . . . 365
  - 17.2 Open, or Frequently Asked, Questions . . . . . 367
    - 17.2.1 What Is the Real Learning Principle in the Brain? . . . . . 367
    - 17.2.2 Nature vs. Nurture . . . . . 368
    - 17.2.3 How to Model Whole Images . . . . . 369
    - 17.2.4 Are There Clear-Cut Cell Types? . . . . . 369
    - 17.2.5 How Far Can We Go? . . . . . 371
  - 17.3 Other Mathematical Models of Images . . . . . 371
    - 17.3.1 Scaling Laws . . . . . 372
    - 17.3.2 Wavelet Theory . . . . . 372
    - 17.3.3 Physically Inspired Models . . . . . 373
  - 17.4 Future Work . . . . . 374



**Part VI Appendix: Supplementary Mathematical Tools**

**18 Optimization Theory and Algorithms . . . . . 377**

18.1 Levels of Modeling . . . . . 377

18.2 Gradient Method . . . . . 378

    18.2.1 Definition and Meaning of Gradient . . . . . 378

    18.2.2 Gradient and Optimization . . . . . 380

    18.2.3 Optimization of Function of Matrix . . . . . 381

    18.2.4 Constrained Optimization . . . . . 381

18.3 Global and Local Maxima . . . . . 383

18.4 Hebb’s Rule and Gradient Methods . . . . . 384

    18.4.1 Hebb’s Rule . . . . . 384

    18.4.2 Hebb’s Rule and Optimization . . . . . 385

    18.4.3 Stochastic Gradient Methods . . . . . 386

    18.4.4 Role of the Hebbian Non-linearity . . . . . 387

    18.4.5 Receptive Fields vs. Synaptic Strengths . . . . . 388

    18.4.6 The Problem of Feedback . . . . . 388

18.5 Optimization in Topographic ICA \* . . . . . 389

18.6 Beyond Basic Gradient Methods \* . . . . . 390

    18.6.1 Newton’s Method . . . . . 391

    18.6.2 Conjugate Gradient Methods . . . . . 393

18.7 FastICA, a Fixed-Point Algorithm for ICA . . . . . 394

    18.7.1 The FastICA Algorithm . . . . . 394

    18.7.2 Choice of the FastICA Non-linearity . . . . . 395

    18.7.3 Mathematics of FastICA \* . . . . . 395

**19 Crash Course on Linear Algebra . . . . . 399**

19.1 Vectors . . . . . 399

19.2 Linear Transformations . . . . . 400

19.3 Matrices . . . . . 401

19.4 Determinant . . . . . 402

19.5 Inverse . . . . . 402

19.6 Basis Representations . . . . . 403

19.7 Orthogonality . . . . . 404

19.8 Pseudo-Inverse \* . . . . . 405

**20 The Discrete Fourier Transform . . . . . 407**

20.1 Linear Shift-Invariant Systems . . . . . 407

20.2 One-Dimensional Discrete Fourier Transform . . . . . 408

    20.2.1 Euler’s Formula . . . . . 408

    20.2.2 Representation in Complex Exponentials . . . . . 408

    20.2.3 The Discrete Fourier Transform and Its Inverse . . . . . 411

20.3 Two- and Three-Dimensional Discrete Fourier Transforms . . . . . 417

**21 Estimation of Non-normalized Statistical Models . . . . . 419**

21.1 Non-normalized Statistical Models . . . . . 419

21.2 Estimation by Score Matching . . . . . 420

21.3 Example 1: Multivariate Gaussian Density . . . . . 422

21.4 Example 2: Estimation of Basic ICA Model . . . . . 424

21.5 Example 3: Estimation of an Overcomplete ICA Model . . . . . 425

21.6 Conclusion . . . . . 425

**References** . . . . . 427

**Index** . . . . . 441



<http://www.springer.com/978-1-84882-490-4>

Natural Image Statistics

A Probabilistic Approach to Early Computational Vision.

Hyvärinen, A.; Hurri, J.; Hoyer, P.O.

2009, XIX, 448 p., Hardcover

ISBN: 978-1-84882-490-4