Data Science for Business

Foster Provost and Tom Fawcett

Beijing • Cambridge • Farnham • Köln • Sebastopol • Tokyo



Table of Contents

Pre	face	xiii
1.	Introduction: Data-Analytic Thinking	. 1
	The Ubiquity of Data Opportunities	1
	Example: Hurricane Frances	3
	Example: Predicting Customer Churn	4
	Data Science, Engineering, and Data-Driven Decision Making	4
	Data Processing and "Big Data"	7
	From Big Data 1.0 to Big Data 2.0	8
	Data and Data Science Capability as a Strategic Asset	9
	Data-Analytic Thinking	12
	This Book	14
	Data Mining and Data Science, Revisited	14
	Chemistry Is Not About Test Tubes: Data Science Versus the Work of the Data	
	Scientist	15
	Summary	16
2.	Business Problems and Data Science Solutions	19
	Fundamental concepts: A set of canonical data mining tasks; The data mining proce Supervised versus unsupervised data mining.	ss;
	From Business Problems to Data Mining Tasks	19
	Supervised Versus Unsupervised Methods	24
	Data Mining and Its Results	25
	The Data Mining Process	26
	Business Understanding	27
	Data Understanding	28
	Data Preparation	29
	Modeling	31
	Evaluation	31

Other Analytics Techniques and Technologies Statistics Database Querying Data Warehousing Regression Analysis Machine Learning and Data Mining Answering Business Questions with These Techniques Summary	35 35 37 38 39 39 40 41
3. Introduction to Predictive Modeling: From Correlation to Supervised Segmentation. Fundamental concepts: Identifying informative attributes; Segmenting data by progressive attribute selection. Exemplary techniques: Finding correlations; Attribute/variable selection; Tree induction.	43
Models Induction and Prediction	11
Supervised Segmentation	18
Selecting Informative Attributes	40
Example: Attribute Selection with Information Gain	56
Supervised Segmentation with Tree Structured Models	62
Visualizing Segmentations	67
Trees as Sets of Pules	71
Drobability Estimation	71
Frontability Estimation Example: Addressing the Churp Droblem with Tree Induction	71
Example: Addressing the Churn Problem with free induction	70
Summary	/0
4. Fitting a Model to Data. Fundamental concepts: Finding "optimal" model parameters based on data; Choos the goal for data mining; Objective functions; Loss functions.	. 81 ing
Exemplary techniques: Linear regression; Logistic regression; Support-vector machin	nes.
Classification via Mathematical Functions	83
Linear Discriminant Functions	85
Optimizing an Objective Function	88
An Example of Mining a Linear Discriminant from Data	89
Linear Discriminant Functions for Scoring and Ranking Instances	91
Support Vector Machines, Briefly	92
Regression via Mathematical Functions	95
Class Probability Estimation and Logistic "Regression"	97
* Logistic Regression: Some Technical Details	100
Example: Logistic Regression versus Tree Induction	103
Nonlinear Functions, Support Vector Machines, and Neural Networks	107

Summary

5.	Overfitting and Its Avoidance Fundamental concepts: Generalization; Fitting and overfitting; Complexity control.	111
	Exemplary techniques: Cross-validation: Attribute selection: Tree prunina:	
	Regularization.	
	Generalization	111
	Overfitting	113
	Overfitting Examined	113
	Holdout Data and Fitting Graphs	113
	Overfitting in Tree Induction	116
	Overfitting in Mathematical Functions	118
	Example: Overfitting Linear Functions	119
	* Example: Why Is Overfitting Bad?	124
	From Holdout Evaluation to Cross-Validation	126
	The Churn Dataset Revisited	129
	Learning Curves	130
	Overfitting Avoidance and Complexity Control	133
	Avoiding Overfitting with Tree Induction	133
	A General Method for Avoiding Overfitting	134
	* Avoiding Overfitting for Parameter Optimization	136
	Summary	140
6.	Similarity, Neighbors, and Clusters	141
	Fundamental concepts: Calculating similarity of objects described by data; Using	
	similarity for prediction; Clustering as similarity-based segmentation.	
	Exemplary techniques: Searching for similar entities; Nearest neighbor methods;	
	Clustering methods; Distance metrics for calculating similarity.	
	Similarity and Distance	142
	Nearest-Neighbor Reasoning	144
	Example: Whiskey Analytics	145
	Nearest Neighbors for Predictive Modeling	147
	How Many Neighbors and How Much Influence?	149
	Geometric Interpretation, Overfitting, and Complexity Control	151
	Issues with Nearest-Neighbor Methods	155
	Some Important Technical Details Relating to Similarities and Neighbors	157
	Heterogeneous Attributes	157
	* Other Distance Functions	158
	* Combining Functions: Calculating Scores from Neighbors	162
	Clustering	163
	Example: Whiskey Analytics Revisited	164
	Hierarchical Clustering	165
	-	

	Nearest Neighbors Revisited: Clustering Around Centroids	170
	Example: Clustering Business News Stories	175
	Understanding the Results of Clustering	178
	* Using Supervised Learning to Generate Cluster Descriptions	180
	Stepping Back: Solving a Business Problem Versus Data Exploration	183
	Summary	185
7.	Decision Analytic Thinking I: What Is a Good Model? Fundamental concepts: Careful consideration of what is desired from data science results; Expected value as a key evaluation framework; Consideration of appropriat comparative baselines. Exemplary techniaues: Various evaluation metrics: Estimating costs and benefits:	187 e
	Calculating expected profit; Creating baseline methods for comparison.	
	Evaluating Classifiers	188
	Plain Accuracy and Its Problems	189
	The Confusion Matrix	189
	Problems with Unbalanced Classes	190
	Problems with Unequal Costs and Benefits	193
	Generalizing Beyond Classification	193
	A Key Analytical Framework: Expected Value	194
	Using Expected Value to Frame Classifier Use	195
	Using Expected Value to Frame Classifier Evaluation	196
	Using Expected Value to Frame Classifier Evaluation Evaluation, Baseline Performance, and Implications for Investments in Data	196 204
	Using Expected Value to Frame Classifier Evaluation Evaluation, Baseline Performance, and Implications for Investments in Data Summary	196 204 207
8.	Using Expected Value to Frame Classifier Evaluation Evaluation, Baseline Performance, and Implications for Investments in Data Summary Visualizing Model Performance	196 204 207 209
8.	Using Expected Value to Frame Classifier Evaluation Evaluation, Baseline Performance, and Implications for Investments in Data Summary Visualizing Model Performance	196 204 207 209
8.	Using Expected Value to Frame Classifier Evaluation Evaluation, Baseline Performance, and Implications for Investments in Data Summary Visualizing Model Performance Fundamental concepts: Visualization of model performance under various kinds of uncertainty; Further consideration of what is desired from data mining results. Exemplary techniques: Profit curves; Cumulative response curves; Lift curves; ROC curves. Ranking Instead of Classifying	196 204 207 209 209
8.	Using Expected Value to Frame Classifier Evaluation Evaluation, Baseline Performance, and Implications for Investments in Data Summary Visualizing Model Performance Fundamental concepts: Visualization of model performance under various kinds of uncertainty; Further consideration of what is desired from data mining results. Exemplary techniques: Profit curves; Cumulative response curves; Lift curves; ROC curves. Ranking Instead of Classifying Profit Curves	196 204 207 209 209 212
8.	Using Expected Value to Frame Classifier Evaluation Evaluation, Baseline Performance, and Implications for Investments in Data Summary Visualizing Model Performance	196 204 207 209 212 214
8.	Using Expected Value to Frame Classifier Evaluation Evaluation, Baseline Performance, and Implications for Investments in Data Summary Visualizing Model Performance Fundamental concepts: Visualization of model performance under various kinds of uncertainty; Further consideration of what is desired from data mining results. Exemplary techniques: Profit curves; Cumulative response curves; Lift curves; ROC curves. Ranking Instead of Classifying Profit Curves ROC Graphs and Curves The Area Under the ROC Curve (AUC)	196 204 207 209 212 214 219
8.	Using Expected Value to Frame Classifier Evaluation Evaluation, Baseline Performance, and Implications for Investments in Data Summary Visualizing Model Performance	196 204 207 209 212 214 219 219
8.	Using Expected Value to Frame Classifier Evaluation Evaluation, Baseline Performance, and Implications for Investments in Data Summary Visualizing Model Performance	204 207 209 212 214 219 223
8.	Using Expected Value to Frame Classifier Evaluation Evaluation, Baseline Performance, and Implications for Investments in Data Summary Visualizing Model Performance	209 209 212 214 219 219 223 231
8.	Using Expected Value to Frame Classifier Evaluation Evaluation, Baseline Performance, and Implications for Investments in Data Summary Visualizing Model Performance	209 209 212 214 219 223 231 233 <i>ic</i>

	Example: Targeting Online Consumers With Advertisements	233
	Combining Evidence Probabilistically	235
	Joint Probability and Independence	236
	Bayes' Rule	237
	Applying Bayes' Rule to Data Science	239
	Conditional Independence and Naive Bayes	241
	Advantages and Disadvantages of Naive Bayes	243
	A Model of Evidence "Lift"	244
	Example: Evidence Lifts from Facebook "Likes"	246
	Evidence in Action: Targeting Consumers with Ads	248
	Summary	248
10.	Representing and Mining Text. Fundamental concepts: The importance of constructing mining-friendly data representations; Representation of text for data mining.	251
	Exemplary techniques: Bag of words representation; TFIDF calculation; N-grams; Stemming; Named entity extraction; Topic models.	
	Why Text Is Important	252
	Why Text Is Difficult	252
	Representation	253
	Bag of Words	254
	Term Frequency	254
	Measuring Sparseness: Inverse Document Frequency	256
	Combining Them: TFIDF	258
	Example: Jazz Musicians	258
	* The Relationship of IDF to Entropy	263
	Beyond Bag of Words	265
	N-gram Sequences	265
	Named Entity Extraction	266
	Topic Models	266
	Example: Mining News Stories to Predict Stock Price Movement	268
	The Task	268
	The Data	270
	Data Preprocessing	272
	Results	273
	Summary	277
11.	Decision Analytic Thinking II: Toward Analytical Engineering. Fundamental concept: Solving business problems with data science starts with analytical engineering: designing an analytical solution, based on the data, tools, a techniques available.	279 Ind
	Exemplary technique. Expected value as a tramework for data science solution desi	an

Exemplary technique: Expected value as a framework for data science solution design.

Recomposing the Solution Pieces 280 A Brief Digression on Selection Bias 282 Our Churn Example Revisited with Even More Sophistication 283 The Expected Value Framework: Structuring a More Complicated Business 283 Problem 283 Assessing the Influence of the Incentive 285 From an Expected Value Decomposition to a Data Science Solution 286 Summary 289 12. Other Data Science Tasks and Techniques. 291 Fundamental concepts: Our fundamental concepts as the basis of many common data science techniques; The importance of familiarity with the building blocks of data science. Exemplary techniques: Association and co-occurrences; Behavior profiling; Link prediction; Data reduction; Latent information mining; Movie recommendation; Biasvariance decomposition of error; Ensembles of models; Causal reasoning from data. Co-occurrences and Associations: Finding Items That Go Together 292 Measuring Surprise: Lift and Leverage 293 Example: Beer and Lottery Tickets 294 Associations Among Facebook Likes 295 Profiling: Finding Typical Behavior 296
A Brief Digression on Selection Bias 282 Our Churn Example Revisited with Even More Sophistication 283 The Expected Value Framework: Structuring a More Complicated Business 283 Assessing the Influence of the Incentive 285 From an Expected Value Decomposition to a Data Science Solution 286 Summary 289 12. Other Data Science Tasks and Techniques. 291 Fundamental concepts: Our fundamental concepts as the basis of many common data science techniques; The importance of familiarity with the building blocks of data science. 282 Exemplary techniques: Association and co-occurrences; Behavior profiling; Link prediction; Data reduction; Latent information mining; Movie recommendation; Biasvariance decomposition of error; Ensembles of models; Causal reasoning from data. Co-occurrences and Associations: Finding Items That Go Together 292 Measuring Surprise: Lift and Leverage 293 Example: Beer and Lottery Tickets 294 Associations Among Facebook Likes 295 Profiling: Finding Typical Behavior 298
A biter Digression on Selection bias282Our Churn Example Revisited with Even More Sophistication283The Expected Value Framework: Structuring a More Complicated Business283Problem283Assessing the Influence of the Incentive285From an Expected Value Decomposition to a Data Science Solution286Summary289 12. Other Data Science Tasks and Techniques.291 Fundamental concepts: Our fundamental concepts as the basis of many common data science techniques; The importance of familiarity with the building blocks of data science.291Exemplary techniques: Association and co-occurrences; Behavior profiling; Link prediction; Data reduction; Latent information mining; Movie recommendation; Biasvariance decomposition of error; Ensembles of models; Causal reasoning from data.Co-occurrences and Associations: Finding Items That Go Together292Measuring Surprise: Lift and Leverage293Example: Beer and Lottery Tickets294Associations Among Facebook Likes295Profiling: Finding Typical Behavior298
Our Churn Example Revisited with Even More Sophistication 283 The Expected Value Framework: Structuring a More Complicated Business 97 Problem 283 Assessing the Influence of the Incentive 285 From an Expected Value Decomposition to a Data Science Solution 286 Summary 289 12. Other Data Science Tasks and Techniques. 291 Fundamental concepts: Our fundamental concepts as the basis of many common data science techniques; The importance of familiarity with the building blocks of data science. 291 Exemplary techniques: Association and co-occurrences; Behavior profiling; Link prediction; Data reduction; Latent information mining; Movie recommendation; Biasvariance decomposition of error; Ensembles of models; Causal reasoning from data. Co-occurrences and Associations: Finding Items That Go Together 292 Measuring Surprise: Lift and Leverage 293 Example: Beer and Lottery Tickets 294 Associations Among Facebook Likes 295 Profiling: Finding Typical Behavior 298
Problem 283 Assessing the Influence of the Incentive 285 From an Expected Value Decomposition to a Data Science Solution 286 Summary 289 12. Other Data Science Tasks and Techniques. 291 Fundamental concepts: Our fundamental concepts as the basis of many common data science techniques; The importance of familiarity with the building blocks of data science. 286 Exemplary techniques: Association and co-occurrences; Behavior profiling; Link prediction; Data reduction; Latent information mining; Movie recommendation; Biasvariance decomposition of error; Ensembles of models; Causal reasoning from data. Co-occurrences and Associations: Finding Items That Go Together 292 Measuring Surprise: Lift and Leverage 293 Example: Beer and Lottery Tickets 294 Associations Among Facebook Likes 295 Profiling: Finding Typical Behavior 298
Problem283Assessing the Influence of the Incentive285From an Expected Value Decomposition to a Data Science Solution286Summary289 12. Other Data Science Tasks and Techniques.291 Fundamental concepts: Our fundamental concepts as the basis of many common data science techniques; The importance of familiarity with the building blocks of data science. 291 Exemplary techniques: Association and co-occurrences; Behavior profiling; Link prediction; Data reduction; Latent information mining; Movie recommendation; Bias- variance decomposition of error; Ensembles of models; Causal reasoning from data.Co-occurrences and Associations: Finding Items That Go Together292Measuring Surprise: Lift and Leverage293Example: Beer and Lottery Tickets294Associations Among Facebook Likes295Profiling: Finding Typical Behavior298
Assessing the Influence of the Incentive285From an Expected Value Decomposition to a Data Science Solution286Summary289 12. Other Data Science Tasks and Techniques.291 Fundamental concepts: Our fundamental concepts as the basis of many common data science techniques; The importance of familiarity with the building blocks of data science. 291 Exemplary techniques: Association and co-occurrences; Behavior profiling; Link prediction; Data reduction; Latent information mining; Movie recommendation; Bias- variance decomposition of error; Ensembles of models; Causal reasoning from data.292Co-occurrences and Associations: Finding Items That Go Together292 293 293 294 294 295 295 296293 295 295 296
From an Expected Value Decomposition to a Data Science Solution286Summary28912. Other Data Science Tasks and Techniques.291Fundamental concepts: Our fundamental concepts as the basis of many common data science techniques; The importance of familiarity with the building blocks of data science.291Exemplary techniques: Association and co-occurrences; Behavior profiling; Link prediction; Data reduction; Latent information mining; Movie recommendation; Bias- variance decomposition of error; Ensembles of models; Causal reasoning from data.Co-occurrences and Associations: Finding Items That Go Together292Measuring Surprise: Lift and Leverage Example: Beer and Lottery Tickets294Associations Among Facebook Likes295Profiling: Finding Typical Behavior298
Summary289 12. Other Data Science Tasks and Techniques.291 Fundamental concepts: Our fundamental concepts as the basis of many common data science techniques; The importance of familiarity with the building blocks of data science. 291 Exemplary techniques: Association and co-occurrences; Behavior profiling; Link prediction; Data reduction; Latent information mining; Movie recommendation; Bias- variance decomposition of error; Ensembles of models; Causal reasoning from data. 292 (Co-occurrences and Associations: Finding Items That Go Together 292 (293) (294) (294) (Associations Among Facebook Likes 293 (294) (295) (295) (296) 294 (298)
12. Other Data Science Tasks and Techniques.291Fundamental concepts: Our fundamental concepts as the basis of many common data science techniques; The importance of familiarity with the building blocks of data science.291Exemplary techniques: Association and co-occurrences; Behavior profiling; Link prediction; Data reduction; Latent information mining; Movie recommendation; Bias- variance decomposition of error; Ensembles of models; Causal reasoning from data.292Co-occurrences and Associations: Finding Items That Go Together292Measuring Surprise: Lift and Leverage293Example: Beer and Lottery Tickets294Associations Among Facebook Likes295Profiling: Finding Typical Behavior298
Fundamental concepts: Our fundamental concepts as the basis of many common data science techniques; The importance of familiarity with the building blocks of data science.Exemplary techniques: Association and co-occurrences; Behavior profiling; Link prediction; Data reduction; Latent information mining; Movie recommendation; Bias- variance decomposition of error; Ensembles of models; Causal reasoning from data.Co-occurrences and Associations: Finding Items That Go Together292 293 Example: Beer and Lottery TicketsExample: Beer and Lottery Tickets294 295 295 Profiling: Finding Typical Behavior
Exemplary techniques: Association and co-occurrences; Behavior profiling; Link prediction; Data reduction; Latent information mining; Movie recommendation; Bias- variance decomposition of error; Ensembles of models; Causal reasoning from data.Co-occurrences and Associations: Finding Items That Go Together292 293 Example: Beer and Lottery Tickets294 294 295 295 Profiling: Finding Typical Behavior298
Co-occurrences and Associations: Finding Items That Go Together292Measuring Surprise: Lift and Leverage293Example: Beer and Lottery Tickets294Associations Among Facebook Likes295Profiling: Finding Typical Behavior298
Co-occurrences and Associations: Finding items That Go Together292Measuring Surprise: Lift and Leverage293Example: Beer and Lottery Tickets294Associations Among Facebook Likes295Profiling: Finding Typical Behavior298
Measuring Surprise: Lift and Leverage293Example: Beer and Lottery Tickets294Associations Among Facebook Likes295Profiling: Finding Typical Behavior298
Example: Beer and Lottery Tickets294Associations Among Facebook Likes295Profiling: Finding Typical Behavior298
Associations Among Facebook Likes295Profiling: Finding Typical Behavior298
Profiling: Finding Typical Behavior 298
Link Prediction and Social Recommendation 303
Data Reduction, Latent Information, and Movie Recommendation304
Bias, Variance, and Ensemble Methods 308
Data-Driven Causal Explanation and a Viral Marketing Example 311
Summary 312
13. Data Science and Business Strategy
Fundamental concepts: Our principles as the basis of success for a data-driven
business; Acquiring and sustaining competitive advantage via data science; The
importance of careful curation of data science capability.
Thinking Data-Analytically, Redux 315
Achieving Competitive Advantage with Data Science 317
Sustaining Competitive Advantage with Data Science 318
Formidable Historical Advantage 319
Unique Intellectual Property 319
Unique Intangible Collateral Assets 320
Superior Data Scientists 320
Superior Data Science Management 322
Attracting and Nurturing Data Scientists and Their Teams 323

	Examine Data Science Case Studies Be Ready to Accept Creative Ideas from Any Source Be Ready to Evaluate Proposals for Data Science Projects Example Data Mining Proposal Flaws in the Big Red Proposal A Firm's Data Science Maturity	325 326 326 327 328 329
14.	Conclusion	333
	The Fundamental Concepts of Data Science	333
	Applying Our Fundamental Concepts to a New Problem: Mining Mobile	
	Device Data	336
	Changing the Way We Think about Solutions to Business Problems	339
	What Data Can't Do: Humans in the Loop, Revisited	340
	Privacy, Ethics, and Mining Data About Individuals	343
	Is There More to Data Science: Final Example: From Crowd Sourcing to Cloud Sourcing	344 345
	Final Words	345
		510
A.	Proposal Review Guide	349
B.	Another Sample Proposal	353
Glo	ossary	357
Bil	bliography	361
Inc	lex	369