
Contents

1	An Introduction to Recommender Systems	1
1.1	Introduction	1
1.2	Goals of Recommender Systems	3
1.2.1	The Spectrum of Recommendation Applications	7
1.3	Basic Models of Recommender Systems	8
1.3.1	Collaborative Filtering Models	8
1.3.1.1	Types of Ratings	10
1.3.1.2	Relationship with Missing Value Analysis	13
1.3.1.3	Collaborative Filtering as a Generalization of Classification and Regression Modeling	13
1.3.2	Content-Based Recommender Systems	14
1.3.3	Knowledge-Based Recommender Systems	15
1.3.3.1	Utility-Based Recommender Systems	18
1.3.4	Demographic Recommender Systems	19
1.3.5	Hybrid and Ensemble-Based Recommender Systems	19
1.3.6	Evaluation of Recommender Systems	20
1.4	Domain-Specific Challenges in Recommender Systems	20
1.4.1	Context-Based Recommender Systems	20
1.4.2	Time-Sensitive Recommender Systems	21
1.4.3	Location-Based Recommender Systems	21
1.4.4	Social Recommender Systems	22
1.4.4.1	Structural Recommendation of Nodes and Links	22
1.4.4.2	Product and Content Recommendations with Social Influence	23
1.4.4.3	Trustworthy Recommender Systems	23
1.4.4.4	Leveraging Social Tagging Feedback for Recommendations	23
1.5	Advanced Topics and Applications	23
1.5.1	The Cold-Start Problem in Recommender Systems	24
1.5.2	Attack-Resistant Recommender Systems	24
1.5.3	Group Recommender Systems	24

1.5.4	Multi-Criteria Recommender Systems	24
1.5.5	Active Learning in Recommender Systems	25
1.5.6	Privacy in Recommender Systems	25
1.5.7	Application Domains	26
1.6	Summary	26
1.7	Bibliographic Notes	26
1.8	Exercises	28
2	Neighborhood-Based Collaborative Filtering	29
2.1	Introduction	29
2.2	Key Properties of Ratings Matrices	31
2.3	Predicting Ratings with Neighborhood-Based Methods	33
2.3.1	User-Based Neighborhood Models	34
2.3.1.1	Similarity Function Variants	37
2.3.1.2	Variants of the Prediction Function	38
2.3.1.3	Variations in Filtering Peer Groups	39
2.3.1.4	Impact of the Long Tail	39
2.3.2	Item-Based Neighborhood Models	40
2.3.3	Efficient Implementation and Computational Complexity	41
2.3.4	Comparing User-Based and Item-Based Methods	42
2.3.5	Strengths and Weaknesses of Neighborhood-Based Methods	44
2.3.6	A Unified View of User-Based and Item-Based Methods	44
2.4	Clustering and Neighborhood-Based Methods	45
2.5	Dimensionality Reduction and Neighborhood Methods	47
2.5.1	Handling Problems with Bias	49
2.5.1.1	Maximum Likelihood Estimation	49
2.5.1.2	Direct Matrix Factorization of Incomplete Data	50
2.6	A Regression Modeling View of Neighborhood Methods	51
2.6.1	User-Based Nearest Neighbor Regression	53
2.6.1.1	Sparsity and Bias Issues	54
2.6.2	Item-Based Nearest Neighbor Regression	55
2.6.3	Combining User-Based and Item-Based Methods	57
2.6.4	Joint Interpolation with Similarity Weighting	57
2.6.5	Sparse Linear Models (SLIM)	58
2.7	Graph Models for Neighborhood-Based Methods	60
2.7.1	User-Item Graphs	61
2.7.1.1	Defining Neighborhoods with Random Walks	61
2.7.1.2	Defining Neighborhoods with the Katz Measure	62
2.7.2	User-User Graphs	63
2.7.3	Item-Item Graphs	66
2.8	Summary	67
2.9	Bibliographic Notes	67
2.10	Exercises	69
3	Model-Based Collaborative Filtering	71
3.1	Introduction	71
3.2	Decision and Regression Trees	74
3.2.1	Extending Decision Trees to Collaborative Filtering	76

3.3	Rule-Based Collaborative Filtering	77
3.3.1	Leveraging Association Rules for Collaborative Filtering	79
3.3.2	Item-Wise Models versus User-Wise Models	80
3.4	Naive Bayes Collaborative Filtering	82
3.4.1	Handling Overfitting	84
3.4.2	Example of the Bayes Method with Binary Ratings	85
3.5	Using an Arbitrary Classification Model as a Black-Box	86
3.5.1	Example: Using a Neural Network as a Black-Box	87
3.6	Latent Factor Models	90
3.6.1	Geometric Intuition for Latent Factor Models	91
3.6.2	Low-Rank Intuition for Latent Factor Models	93
3.6.3	Basic Matrix Factorization Principles	94
3.6.4	Unconstrained Matrix Factorization	96
3.6.4.1	Stochastic Gradient Descent	99
3.6.4.2	Regularization	100
3.6.4.3	Incremental Latent Component Training	103
3.6.4.4	Alternating Least Squares and Coordinate Descent	105
3.6.4.5	Incorporating User and Item Biases	106
3.6.4.6	Incorporating Implicit Feedback	109
3.6.5	Singular Value Decomposition	113
3.6.5.1	A Simple Iterative Approach to SVD	114
3.6.5.2	An Optimization-Based Approach	116
3.6.5.3	Out-of-Sample Recommendations	116
3.6.5.4	Example of Singular Value Decomposition	117
3.6.6	Non-negative Matrix Factorization	119
3.6.6.1	Interpretability Advantages	121
3.6.6.2	Observations about Factorization with Implicit Feedback	122
3.6.6.3	Computational and Weighting Issues with Implicit Feedback	124
3.6.6.4	Ratings with Both Likes and Dislikes	124
3.6.7	Understanding the Matrix Factorization Family	126
3.7	Integrating Factorization and Neighborhood Models	128
3.7.1	Baseline Estimator: A Non-Personalized Bias-Centric Model	128
3.7.2	Neighborhood Portion of Model	129
3.7.3	Latent Factor Portion of Model	130
3.7.4	Integrating the Neighborhood and Latent Factor Portions	131
3.7.5	Solving the Optimization Model	131
3.7.6	Observations about Accuracy	132
3.7.7	Integrating Latent Factor Models with Arbitrary Models	133
3.8	Summary	134
3.9	Bibliographic Notes	134
3.10	Exercises	136
4	Content-Based Recommender Systems	139
4.1	Introduction	139
4.2	Basic Components of Content-Based Systems	141
4.3	Preprocessing and Feature Extraction	142
4.3.1	Feature Extraction	142
4.3.1.1	Example of Product Recommendation	143

4.3.1.2	Example of Web Page Recommendation	143
4.3.1.3	Example of Music Recommendation	144
4.3.2	Feature Representation and Cleaning	145
4.3.3	Collecting User Likes and Dislikes	146
4.3.4	Supervised Feature Selection and Weighting	147
4.3.4.1	Gini Index	147
4.3.4.2	Entropy	148
4.3.4.3	χ^2 -Statistic	148
4.3.4.4	Normalized Deviation	149
4.3.4.5	Feature Weighting	150
4.4	Learning User Profiles and Filtering	150
4.4.1	Nearest Neighbor Classification	151
4.4.2	Connections with Case-Based Recommender Systems	152
4.4.3	Bayes Classifier	153
4.4.3.1	Estimating Intermediate Probabilities	154
4.4.3.2	Example of Bayes Model	155
4.4.4	Rule-based Classifiers	156
4.4.4.1	Example of Rule-based Methods	157
4.4.5	Regression-Based Models	158
4.4.6	Other Learning Models and Comparative Overview	159
4.4.7	Explanations in Content-Based Systems	160
4.5	Content-Based Versus Collaborative Recommendations	161
4.6	Using Content-Based Models for Collaborative Filtering	162
4.6.1	Leveraging User Profiles	163
4.7	Summary	163
4.8	Bibliographic Notes	164
4.9	Exercises	165
5	Knowledge-Based Recommender Systems	167
5.1	Introduction	167
5.2	Constraint-Based Recommender Systems	172
5.2.1	Returning Relevant Results	174
5.2.2	Interaction Approach	176
5.2.3	Ranking the Matched Items	178
5.2.4	Handling Unacceptable Results or Empty Sets	179
5.2.5	Adding Constraints	180
5.3	Case-Based Recommenders	181
5.3.1	Similarity Metrics	183
5.3.1.1	Incorporating Diversity in Similarity Computation	187
5.3.2	Critiquing Methods	188
5.3.2.1	Simple Critiques	188
5.3.2.2	Compound Critiques	190
5.3.2.3	Dynamic Critiques	192
5.3.3	Explanation in Critiques	193
5.4	Persistent Personalization in Knowledge-Based Systems	194
5.5	Summary	195
5.6	Bibliographic Notes	195
5.7	Exercises	197

6	Ensemble-Based and Hybrid Recommender Systems	199
6.1	Introduction	199
6.2	Ensemble Methods from the Classification Perspective	204
6.3	Weighted Hybrids	206
6.3.1	Various Types of Model Combinations	208
6.3.2	Adapting Bagging from Classification	209
6.3.3	Randomness Injection	211
6.4	Switching Hybrids	211
6.4.1	Switching Mechanisms for Cold-Start Issues	212
6.4.2	Bucket-of-Models	212
6.5	Cascade Hybrids	213
6.5.1	Successive Refinement of Recommendations	213
6.5.2	Boosting	213
6.5.2.1	Weighted Base Models	214
6.6	Feature Augmentation Hybrids	215
6.7	Meta-Level Hybrids	216
6.8	Feature Combination Hybrids	217
6.8.1	Regression and Matrix Factorization	218
6.8.2	Meta-level Features	218
6.9	Mixed Hybrids	220
6.10	Summary	221
6.11	Bibliographic Notes	222
6.12	Exercises	224
7	Evaluating Recommender Systems	225
7.1	Introduction	225
7.2	Evaluation Paradigms	227
7.2.1	User Studies	227
7.2.2	Online Evaluation	227
7.2.3	Offline Evaluation with Historical Data Sets	229
7.3	General Goals of Evaluation Design	229
7.3.1	Accuracy	229
7.3.2	Coverage	231
7.3.3	Confidence and Trust	232
7.3.4	Novelty	233
7.3.5	Serendipity	233
7.3.6	Diversity	234
7.3.7	Robustness and Stability	235
7.3.8	Scalability	235
7.4	Design Issues in Offline Recommender Evaluation	235
7.4.1	Case Study of the Netflix Prize Data Set	236
7.4.2	Segmenting the Ratings for Training and Testing	238
7.4.2.1	Hold-Out	238
7.4.2.2	Cross-Validation	239
7.4.3	Comparison with Classification Design	239
7.5	Accuracy Metrics in Offline Evaluation	240
7.5.1	Measuring the Accuracy of Ratings Prediction	240
7.5.1.1	RMSE versus MAE	241
7.5.1.2	Impact of the Long Tail	241

- 7.5.2 Evaluating Ranking via Correlation 242
- 7.5.3 Evaluating Ranking via Utility 244
- 7.5.4 Evaluating Ranking via Receiver Operating Characteristic 247
- 7.5.5 Which Ranking Measure is Best? 250
- 7.6 Limitations of Evaluation Measures 250
 - 7.6.1 Avoiding Evaluation Gaming 252
- 7.7 Summary 252
- 7.8 Bibliographic Notes 253
- 7.9 Exercises 254

- 8 Context-Sensitive Recommender Systems 255**
 - 8.1 Introduction 255
 - 8.2 The Multidimensional Approach 256
 - 8.2.1 The Importance of Hierarchies 259
 - 8.3 Contextual Pre-filtering: A Reduction-Based Approach 262
 - 8.3.1 Ensemble-Based Improvements 264
 - 8.3.2 Multi-level Estimation 265
 - 8.4 Post-Filtering Methods 266
 - 8.5 Contextual Modeling 268
 - 8.5.1 Neighborhood-Based Methods 268
 - 8.5.2 Latent Factor Models 269
 - 8.5.2.1 Factorization Machines 272
 - 8.5.2.2 A Generalized View of Second-Order Factorization
Machines 275
 - 8.5.2.3 Other Applications of Latent Parametrization 276
 - 8.5.3 Content-Based Models 277
 - 8.6 Summary 279
 - 8.7 Bibliographic Notes 280
 - 8.8 Exercises 281

- 9 Time- and Location-Sensitive Recommender Systems 283**
 - 9.1 Introduction 283
 - 9.2 Temporal Collaborative Filtering 285
 - 9.2.1 Recency-Based Models 286
 - 9.2.1.1 Decay-Based Methods 286
 - 9.2.1.2 Window-Based Methods 288
 - 9.2.2 Handling Periodic Context 288
 - 9.2.2.1 Pre-Filtering and Post-Filtering 289
 - 9.2.2.2 Direct Incorporation of Temporal Context 290
 - 9.2.3 Modeling Ratings as a Function of Time 290
 - 9.2.3.1 The Time-SVD++ Model 291
 - 9.3 Discrete Temporal Models 295
 - 9.3.1 Markovian Models 295
 - 9.3.1.1 Selective Markov Models 298
 - 9.3.1.2 Other Markovian Alternatives 300
 - 9.3.2 Sequential Pattern Mining 300
 - 9.4 Location-Aware Recommender Systems 302
 - 9.4.1 Preference Locality 303
 - 9.4.2 Travel Locality 305
 - 9.4.3 Combined Preference and Travel Locality 305

9.5	Summary	305
9.6	Bibliographic Notes	306
9.7	Exercises	308
10	Structural Recommendations in Networks	309
10.1	Introduction	309
10.2	Ranking Algorithms	311
10.2.1	PageRank	311
10.2.2	Personalized PageRank	314
10.2.3	Applications to Neighborhood-Based Methods	316
10.2.3.1	Social Network Recommendations	317
10.2.3.2	Personalization in Heterogeneous Social Media	317
10.2.3.3	Traditional Collaborative Filtering	319
10.2.4	SimRank	321
10.2.5	The Relationship Between Search and Recommendation	322
10.3	Recommendations by Collective Classification	323
10.3.1	Iterative Classification Algorithm	324
10.3.2	Label Propagation with Random Walks	325
10.3.3	Applicability to Collaborative Filtering in Social Networks	326
10.4	Recommending Friends: Link Prediction	326
10.4.1	Neighborhood-Based Measures	327
10.4.2	Katz Measure	328
10.4.3	Random Walk-Based Measures	329
10.4.4	Link Prediction as a Classification Problem	329
10.4.5	Matrix Factorization for Link Prediction	330
10.4.5.1	Symmetric Matrix Factorization	333
10.4.6	Connections Between Link Prediction and Collaborative Filtering	335
10.4.6.1	Using Link Prediction Algorithms for Collaborative Filtering	336
10.4.6.2	Using Collaborative Filtering Algorithms for Link Prediction	337
10.5	Social Influence Analysis and Viral Marketing	337
10.5.1	Linear Threshold Model	339
10.5.2	Independent Cascade Model	340
10.5.3	Influence Function Evaluation	340
10.5.4	Targeted Influence Analysis Models in Social Streams	341
10.6	Summary	342
10.7	Bibliographic Notes	343
10.8	Exercises	344
11	Social and Trust-Centric Recommender Systems	345
11.1	Introduction	345
11.2	Multidimensional Models for Social Context	347
11.3	Network-Centric and Trust-Centric Methods	349
11.3.1	Collecting Data for Building Trust Networks	349
11.3.2	Trust Propagation and Aggregation	351
11.3.3	Simple Recommender with No Trust Propagation	353
11.3.4	TidalTrust Algorithm	353

11.3.5	MoleTrust Algorithm	356
11.3.6	TrustWalker Algorithm	357
11.3.7	Link Prediction Methods	358
11.3.8	Matrix Factorization Methods	361
	11.3.8.1 Enhancements with Logistic Function	364
	11.3.8.2 Variations in the Social Trust Component	364
11.3.9	Merits of Social Recommender Systems	365
	11.3.9.1 Recommendations for Controversial Users and Items	365
	11.3.9.2 Usefulness for Cold-Start	366
	11.3.9.3 Attack Resistance	366
11.4	User Interaction in Social Recommenders	366
	11.4.1 Representing Folksonomies	367
	11.4.2 Collaborative Filtering in Social Tagging Systems	368
	11.4.3 Selecting Valuable Tags	371
	11.4.4 Social-Tagging Recommenders with No Ratings Matrix	372
	11.4.4.1 Multidimensional Methods for Context-Sensitive Systems	372
	11.4.4.2 Ranking-Based Methods	373
	11.4.4.3 Content-Based Methods	374
	11.4.5 Social-Tagging Recommenders with Ratings Matrix	377
	11.4.5.1 Neighborhood-Based Approach	378
	11.4.5.2 Linear Regression	379
	11.4.5.3 Matrix Factorization	380
	11.4.5.4 Content-Based Methods	382
11.5	Summary	382
11.6	Bibliographic Notes	382
11.7	Exercises	384
12	Attack-Resistant Recommender Systems	385
12.1	Introduction	385
12.2	Understanding the Trade-Offs in Attack Models	386
	12.2.1 Quantifying Attack Impact	390
12.3	Types of Attacks	392
	12.3.1 Random Attack	393
	12.3.2 Average Attack	393
	12.3.3 Bandwagon Attack	394
	12.3.4 Popular Attack	395
	12.3.5 Love/Hate Attack	395
	12.3.6 Reverse Bandwagon Attack	396
	12.3.7 Probe Attack	396
	12.3.8 Segment Attack	396
	12.3.9 Effect of Base Recommendation Algorithm	397
12.4	Detecting Attacks on Recommender Systems	398
	12.4.1 Individual Attack Profile Detection	399
	12.4.2 Group Attack Profile Detection	402
	12.4.2.1 Preprocessing Methods	402
	12.4.2.2 Online Methods	403
12.5	Strategies for Robust Recommender Design	403
	12.5.1 Preventing Automated Attacks with CAPTCHAs	403
	12.5.2 Using Social Trust	404

12.5.3	Designing Robust Recommendation Algorithms	404
12.5.3.1	Incorporating Clustering in Neighborhood Methods	405
12.5.3.2	Fake Profile Detection during Recommendation Time	405
12.5.3.3	Association-Based Algorithms	405
12.5.3.4	Robust Matrix Factorization	405
12.6	Summary	408
12.7	Bibliographic Notes	408
12.8	Exercises	410
13	Advanced Topics in Recommender Systems	411
13.1	Introduction	411
13.2	Learning to Rank	413
13.2.1	Pairwise Rank Learning	415
13.2.2	Listwise Rank Learning	416
13.2.3	Comparison with Rank-Learning Methods in Other Domains	417
13.3	Multi-Armed Bandit Algorithms	418
13.3.1	Naive Algorithm	419
13.3.2	ϵ -Greedy Algorithm	420
13.3.3	Upper Bounding Methods	421
13.4	Group Recommender Systems	423
13.4.1	Collaborative and Content-Based Systems	424
13.4.2	Knowledge-Based Systems	425
13.5	Multi-Criteria Recommender Systems	426
13.5.1	Neighborhood-Based Methods	427
13.5.2	Ensemble-Based Methods	428
13.5.3	Multi-Criteria Systems without Overall Ratings	429
13.6	Active Learning in Recommender Systems	430
13.6.1	Heterogeneity-Based Models	431
13.6.2	Performance-Based Models	432
13.7	Privacy in Recommender Systems	432
13.7.1	Condensation-Based Privacy	434
13.7.2	Challenges for High-Dimensional Data	434
13.8	Some Interesting Application Domains	435
13.8.1	Portal Content Personalization	435
13.8.1.1	Dynamic Profiler	436
13.8.1.2	Google News Personalization	436
13.8.2	Computational Advertising versus Recommender Systems	438
13.8.2.1	Importance of Multi-Armed Bandit Methods	442
13.8.3	Reciprocal Recommender Systems	443
13.8.3.1	Leveraging Hybrid Methods	444
13.8.3.2	Leveraging Link Prediction Methods	445
13.9	Summary	446
13.10	Bibliographic Notes	446
	Bibliography	449
	Index	493



<http://www.springer.com/978-3-319-29657-9>

Recommender Systems

The Textbook

Aggarwal, C.C.

2016, XXI, 498 p. 79 illus., 18 illus. in color., Hardcover

ISBN: 978-3-319-29657-9