

Contents

Foreword	xiii
Acknowledgements	xv
Abstract	xvii
1 Introduction	1
1.1 Objective	2
1.2 Roadmap and contributions	2
1.3 Rationale for the contributions	4
1.3.1 Characteristics of a classifier	4
1.3.2 Why do we need new classifiers?	6
2 Bayesian foundations of the learning process	9
2.1 Probability theory as extended logic	10
2.1.1 The basic desiderata	10
2.1.2 Justifying the desiderata	10
2.2 The quantitative rules	12
2.2.1 The product rule	12
2.2.2 The sum rule	13
2.3 Prior probabilities	15
2.3.1 The principle of indifference	15
2.3.2 The entropy principle	16
2.3.3 Other methods	16
2.4 Summary	17
3 Bayesian network classifiers	19
3.1 The problem of classification	20
3.2 Bayesian networks for classification	20
3.2.1 Dirichlet distributions	21
3.3 Naive Bayes	22
3.4 Learning with trees	23
3.4.1 Learning maximum likelihood TAN	23
3.5 Bayesian model averaging for classification	24

3.6	Summary	25
4	A parallelizable distance-based discretization method	27
4.1	Introduction	28
4.2	Discretization methods classification	28
4.3	Some discretization methods	29
4.3.1	Equal size	29
4.3.2	Equal frequency	29
4.3.3	ChiMerge	29
4.3.4	Entropy	30
4.3.5	D-2	32
4.3.6	Other discretization methods	33
4.4	Distance-Based discretization method	33
4.4.1	Cutpoint selection criterion	34
4.4.2	The stopping criterion	35
4.4.3	Computational complexity	36
4.4.4	Parallelization of the method	36
4.5	Empirical comparison	38
4.5.1	Comparison design	38
4.5.2	Comparison results	38
4.6	Summary	40
5	The Qualitative Bayesian Classifier	41
5.1	Introduction	42
5.2	Introduction to Qualitative Probabilistic Networks	43
5.2.1	Wellman approach	43
5.2.2	Neufeld approach	44
5.3	Influences and synergies revisited	44
5.4	The Qualitative Bayesian Classifier	45
5.5	Empirical comparison	48
5.5.1	Result analysis and justification	49
5.6	Examples of explanations and characterizations	49
5.6.1	Qualitative influences for characterization	49
5.6.2	Explanation with qualitative influences and synergies . .	51
5.6.3	Comparison with c4.5rules results	51
5.7	Summary	52
6	The Indifferent Bayesian Classifier	55
6.1	The naive Bayes model	56
6.1.1	The naive Bayes model as a Bayesian network	56
6.1.2	The naive Bayes model as a Markov network	56
6.1.3	Naive Bayes parameters	57
6.2	Naive distributions	60
6.2.1	Calculating probabilities with naive distributions	60
6.2.2	Learning with naive distributions	61
6.3	The Indifferent Naive Bayes Classifier	61

6.4	Experimental results	63
6.4.1	Dataset description	63
6.4.2	Interpretation of the results	65
6.5	Summary	71
7	Empirical Local Bayesian model averaging of TAN classifiers	73
7.1	Local Bayesian model averaging for TAN induction	74
7.1.1	Local Bayesian model averaging	75
7.1.2	Empirical local Bayesian model averaging of TAN models	76
7.1.3	Computational complexity	78
7.2	Experimental results	80
7.2.1	Adjusting the algorithm to run	80
7.2.2	Experimental setting	80
7.2.3	Interpretation of the results	80
7.3	Summary	85
7.3.1	Further research	86
8	Tractable Bayesian Model Averaging of Tree Augmented Naive Bayes Classifiers	87
8.1	Decomposable distributions over tree belief networks	88
8.1.1	Definition	88
8.1.2	Meila and Jaakkola results and corrections to their results	90
8.2	Development of the Averaged Tree Augmented Naive Bayes . . .	92
8.2.1	Decomposable distributions over TANs	92
8.2.2	Calculating probabilities under decomposable distributions over TANs	95
8.2.3	Learning under decomposable distributions over TANs . .	95
8.2.4	Putting it all Together	96
8.3	Approximating TBMATAN	96
8.3.1	TBMATAN computational complexity	96
8.3.2	Computational problems	97
8.3.3	A solution to TBMATAN computational problems	97
8.4	Empirical Results	99
8.4.1	Interpretation of the Results	99
8.5	Conclusions and Future Work	110
8.5.1	Future work	110
9	Maximum a Posteriori Tree Augmented Naive Bayes Classifiers	111
9.1	Maximum a Posteriori results for decomposable distributions over trees	112
9.1.1	Calculating the most probable tree under a decomposable distribution over trees	112
9.1.2	Calculating the MAP tree given a prior decomposable distribution over trees	112
9.1.3	Calculating the k MAP trees and their relative weights given a prior decomposable distribution over trees	114

9.2	MAPTAN and MAPTAN+BMA classifiers	115
9.2.1	Maximum a Posteriori results for decomposable distributions over TANs	115
9.2.2	Constructing the MAPTAN and MAPTAN+BMA classifiers	115
9.3	Empirical results	119
9.3.1	Interpretation of the results	120
9.4	Conclusions and future work	132
9.4.1	Future work	133
10	Conclusions	135
10.1	Main contributions and its relevance	135
10.1.1	A parallelizable discretization method	135
10.1.2	Qualitative influences and synergies	136
10.1.3	First Order Qualitative Bayesian Classifier	136
10.1.4	Second Order Qualitative Bayesian Classifier	136
10.1.5	Naive distributions	136
10.1.6	The indifferent naive Bayes classifier	136
10.1.7	Empirical local Bayesian model averaging of TAN	137
10.1.8	Decomposable distributions over TAN models	137
10.1.9	Tractable Bayesian model averaging of TAN	137
10.1.10	Maximum a posteriori TAN classifier	137
10.1.11	Maximum a posteriori local Bayesian model averaging of TAN	138
10.2	Publication list	138
10.3	Where to go from here?	139
A	Mathematical developments for the Indifferent Bayesian Classifier	141
A.1	Preliminaries	141
A.1.1	A multiple variable constrained integral	141
A.1.2	A bit of notation	142
A.2	Calculating probabilities with naive distributions	142
A.3	Learning with naive distributions	144
A.3.1	Computing the normalization constant	145
A.3.2	Computing the posterior distribution	145
B	Mathematical developments for the Tractable Bayesian Model Averaging of Tree Augmented Naive Bayes Classifiers	147
B.1	Preliminaries	147
B.1.1	The matrix tree theorem	147
B.1.2	The matrix tree theorem for decomposable distributions	148
B.1.3	A useful result about Dirichlet distributions	148
B.2	Detailed development for decomposable distributions over trees results	149
B.2.1	Calculating probabilities under decomposable distributions over trees	149