

Contents

PREFACE	v
INTRODUCTION	vii
1. INDUCTIVE PAC-BAYESIAN LEARNING	1
1.1. BASIC INEQUALITY	2
1.2. NON LOCAL BOUNDS	5
1.2.1. <i>Unbiased empirical bounds</i>	5
1.2.2. <i>Optimizing explicitly the exponential parameter λ</i>	8
1.2.3. <i>Non random bounds</i>	9
1.2.4. <i>Deviation bounds</i>	11
1.3. LOCAL BOUNDS	14
1.3.1. <i>Choice of the prior</i>	14
1.3.2. <i>Unbiased local empirical bounds</i>	15
1.3.3. <i>Non random local bounds</i>	17
1.3.4. <i>Local deviation bounds</i>	18
1.3.5. <i>Partially local bounds</i>	22
1.3.6. <i>Two step localization</i>	27
1.4. RELATIVE BOUNDS	33
1.4.1. <i>Basic inequalities</i>	34
1.4.2. <i>Non random bounds</i>	37
1.4.3. <i>Unbiased empirical bounds</i>	40
1.4.4. <i>Relative empirical deviation bounds</i>	44
2. COMPARING POSTERIOR DISTRIBUTIONS TO GIBBS PRIORS	51
2.1. BOUNDS RELATIVE TO A GIBBS DISTRIBUTION	51
2.1.1. <i>Comparing a posterior distribution with a Gibbs prior</i>	52
2.1.2. <i>The effective temperature of a posterior distribution</i>	55
2.1.3. <i>Analysis of an empirical bound for the effective temperature</i>	56
2.1.4. <i>Adaptation to parametric and margin assumptions</i>	61
2.1.5. <i>Estimating the divergence of a posterior with respect to a Gibbs prior</i>	67
2.2. PLAYING WITH TWO POSTERIOR AND TWO LOCAL PRIOR DISTRIBUTIONS	68
2.2.1. <i>Comparing two posterior distributions</i>	68
2.2.2. <i>Elaborate uses of relative bounds between posteriors</i>	70
2.2.3. <i>Analysis of relative bounds</i>	75

2.3.	TWO STEP LOCALIZATION	89
2.3.1.	<i>Two step localization of bounds relative to a Gibbs prior</i>	89
2.3.2.	<i>Analysis of two step bounds relative to a Gibbs prior</i>	96
2.3.3.	<i>Two step localization between posterior distributions</i>	101
3.	TRANSDUCTIVE PAC-BAYESIAN LEARNING	111
3.1.	BASIC INEQUALITIES	111
3.1.1.	<i>The transductive setting</i>	111
3.1.2.	<i>Absolute bound</i>	113
3.1.3.	<i>Relative bounds</i>	114
3.2.	VAPNIK BOUNDS FOR TRANSDUCTIVE CLASSIFICATION	115
3.2.1.	<i>With a shadow sample of arbitrary size</i>	115
3.2.2.	<i>When the shadow sample has the same size as the training sample</i>	118
3.2.3.	<i>When moreover the distribution of the augmented sample is exchangeable</i>	119
3.3.	VAPNIK BOUNDS FOR INDUCTIVE CLASSIFICATION	121
3.3.1.	<i>Arbitrary shadow sample size</i>	121
3.3.2.	<i>A better minimization with respect to the exponential parameter</i>	123
3.3.3.	<i>Equal shadow and training sample sizes</i>	125
3.3.4.	<i>Improvement on the equal sample size bound in the i.i.d. case</i>	125
3.4.	GAUSSIAN APPROXIMATION IN VAPNIK BOUNDS	127
3.4.1.	<i>Gaussian upper bounds of variance terms</i>	127
3.4.2.	<i>Arbitrary shadow sample size</i>	128
3.4.3.	<i>Equal sample sizes in the i.i.d. case</i>	128
4.	SUPPORT VECTOR MACHINES	131
4.1.	HOW TO BUILD THEM	131
4.1.1.	<i>The canonical hyperplane</i>	131
4.1.2.	<i>Computation of the canonical hyperplane</i>	132
4.1.3.	<i>Support vectors</i>	134
4.1.4.	<i>The non-separable case</i>	134
4.1.5.	<i>Support Vector Machines</i>	138
4.1.6.	<i>Building kernels</i>	140
4.2.	BOUNDS FOR SUPPORT VECTOR MACHINES	142
4.2.1.	<i>Compression scheme bounds</i>	142
4.2.2.	<i>The Vapnik–Cervonenkis dimension of a family of subsets</i>	143
4.2.3.	<i>Vapnik–Cervonenkis dimension of linear rules with margin</i>	145
4.2.4.	<i>Application to Support Vector Machines</i>	148
4.2.5.	<i>Inductive margin bounds</i>	149
	APPENDIX: CLASSIFICATION BY THRESHOLDING	155
5.1.	DESCRIPTION OF THE MODEL	155
5.2.	COMPUTATION OF INDUCTIVE BOUNDS	156
5.3.	TRANSDUCTIVE BOUNDS	158
	BIBLIOGRAPHY	161