t-logistic regression

Authored by:

S.v.n. Vishwanathan
Nan Ding

Abstract

We extend logistic regression by using t-exponential families which were introduced recently in statistical physics. This gives rise to a regularized risk minimization problem with a non-convex loss function. An efficient block coordinate descent optimization scheme can be derived for estimating the parameters. Because of the nature of the loss function, our algorithm is tolerant to label noise. Furthermore, unlike other algorithms which employ non-convex loss functions, our algorithm is fairly robust to the choice of initial values. We verify both these observations empirically on a number of synthetic and real datasets.

1 Paper Body

Many machine learning algorithms minimize a regularized risk [1]: m

J(?) = ?(?) + Remp (?), where Remp (?) =

1 ? l(xi , yi , ?). m i=1

(1)

Here, ? is a regularizer which penalizes complex ?; and Remp , the empirical risk, is obtained by averaging the loss l over the training dataset {(x1 , y1), . . . , (xm , ym)}. In this paper our focus is on binary classi?cation, wherein features of a data point x are extracted via a feature map ? and the label is usually predicted via sign(??(x), ??). If we de?ne the margin of a training example (x, y) as u(x, y, ?) := y ??(x), ??, then many popular loss functions for binary classi?cation can be written as functions of the margin. Examples include1 l(u) = 0 if u ¿ 0 and 1 otherwise . l(u) = max(0, 1 ? u) l(u) = exp(?u) l(u) = log(1 + exp(?u))

(0 ? 1 loss) (Hinge Loss) (Exponential Loss) (Logistic Loss).

(2) (3) (4) (5)

The 0 ? 1 loss is non-convex and dif?cult to handle; it has been shown that it is NP-hard to even approximately minimize the regularized risk with the 0 ? 1 loss [2]. Therefore, other loss functions can be viewed as convex proxies of the 0 ? 1 loss. Hinge loss leads to support vector machines (SVMs), exponential loss is used in Adaboost, and logistic regression uses the logistic loss.

Convexity is a very attractive property because it ensures that the regularized risk minimization problem has a unique global optimum [3]. However, as was recently shown by Long and Servedio [4], learning algorithms based on convex loss functions are not robust to noise2 . Intuitively, the convex loss functions grows at least linearly with slope —l? (0)— as u ? (??, 0), which introduces the overwhelming impact from the data with u ? 0. There has been some recent and some notso-recent work on using non-convex loss functions to alleviate the above problem. For instance, a recent manuscript by [5] uses the cdf of the Guassian distribution to de?ne a non-convex loss. 1

We slightly abuse notation and use l(u) to denote l(u(x, y, ?)). Although, the analysis of [4] is carried out in the context of boosting, we believe, the results hold for a larger class of algorithms which minimize a regularized risk with a convex loss function. 2

1

In this paper, we continue this line of inquiry and propose a non-convex loss function which is ?rmly grounded in probability theory. By loss extending logistic regression from the exLogistic exp ponential family to the t-exponential fam6 ily, a natural extension of exponential family Hinge of distributions studied in statistical physics [6?10], we obtain the t-logistic regression 4 algorithm. Furthermore, we show that a simple block coordinate descent scheme can be used to solve the resultant regularized 2 0-1 loss risk minimization problem. Analysis of this procedure also intuitively explains why tmargin logistic regression is able to handle label -4 -2 0 2 4 noise.

Figure 1: Some commonly used loss functions for binary

Our paper is structured as follows: In sec- classi?cation. The 0-1 loss is non-convex. The hinge, expotion 2 we brie?y review logistic regression nential, and logistic losses are convex upper bounds of the especially in the context of exponential fam- 0-1 loss. ilies. In section 3, we review t-exponential families, which form the basis for our proposed t-logistic regression algorithm introduced in section 4. In section 5 we utilize ideas from convex multiplicative programming to design an optimization strategy. Experiments that compare our new approach to existing algorithms on a number of publicly available datasets are reported in section 6, and the paper concludes with a discussion and outlook in section 7. Some technical details as well as extra experimental results can be found in the supplementary material.

2

Logistic Regression

Since we build upon the probabilistic underpinnings of logistic regression, we brie?y review some salient concepts. Details can be found in any standard textbook such as [11] or [12]. Assume we are given a labeled dataset (X, Y) = {(x1 , y1), . . . , (xm , ym)} with the xi ?s drawn from some domain X and the labels yi ? {?1}. Given a family of conditional distributions parameterized by ?, using Bayes rule, and making a standard iid assumption about the data allows us to write p(? — X, Y) = p(?)

m ?

i=1

p(yi — xi ; ?)/p(Y — X) ? p(?)
m ?
i=1
p(yi — xi ; ?)
(6)
where p(Y — X) is clearly independent of ?. To model p(yi — xi ; ?), consider the conditional exponential family of distributions p(y— x; ?) = exp (??(x, y), ?? ? g(? — x)) ,
(7)
g(? — x) = log (exp (??(x, +1), ??) + exp (??(x, ?1), ??)) .
(8)
with the log-partition function g(? — x) given by If we choose the feature map ?(x, y) = that p(y— x; ?) is the logistic function p(y— x; ?) =
y 2 ?(x),
and denote u = y ??(x), ?? then it is easy to see
1 exp(u/2) = . exp(u/2) + exp(?u/2) 1 + exp(?u)
(9)
By assuming a zero mean isotropic Gaussian prior N (0, ?1? I) for ?, plugging in (9), and taking logarithms, we can rewrite (6) as m ? ? 2 ? log p(? — X, Y) = ??? + log (1 + exp (?yi ??(xi), ??)) + const. . 2 i=1
(10)
Logistic regression computes a maximum a-posteriori (MAP) estimate for ? by minimizing (10) as a function of ?. Comparing (1) and (10) it is easy to see that the regularizer employed in logistic 2 regression is ?2 ??? , while the loss function is the negative log-likelihood ? log p(y— x; ?), which thanks to (9) can be identi?ed with the logistic loss (5). 2
3
t-Exponential family of Distributions
In this section we will look at generalizations of the log and exp functions which were ?rst introduced in statistical physics [6?9]. Some extensions and machine learning applications were presented in [13]. In fact, a more general class of functions was studied in these publications, but for our purposes we will restrict our attention to the so-called t-exponential and t-logarithm functions. The t-exponential function expt for (0 ¡ t ¡ 2) is de?ned as follows: ? exp(x) if t = 1 expt (x) := 1/(1?t) otherwise. [1 + (1 ? t)x]+
(11)
where (?)+ = max(?, 0). Some examples are shown in Figure 2. Clearly, expt generalizes the usual exp function, which is recovered in the limit as t ? 1. Furthermore, many familiar properties of exp are preserved: expt functions are convex, non-decreasing, non-negative and satisfy expt (0) = 1 [9]. But expt does not preserve one very important property of exp, namely expt (a + b) ?= expt (a) ? expt (b). One can also de?ne the inverse of expt namely logt as ? log(x) if t = 1 ? (12) logt (x) := ? 1?t ? 1 /(1 ? t) otherwise. x
Similarly, logt (ab) ?= logt (a) + logt (b). From Figure 2, it is clear that expt decays towards 0 more slowly than the exp function for 1 ¡ t ¡ 2. This important property leads to a family of heavy tailed distributions which we will

later exploit. t = 1 (logistic) expt t = 1.5 exp(x) 7 logt t?0 6 t = 0.5 t = 0.5 5 t = 1.3 log(x) 2 4 t = 1.6 t?0 t = 1.5 1 t = 1.9 3 x 0 2 -1 1 2 3 4 5 6 7 0-1 loss 1 -2 -3 -2 -1 0 1 2 x -3 -4 -2

loss 6 4 2 0

2

4

margin

Figure 2: Left: expt and Middle: logt for various values of t indicated. The right ?gure depicts the t-logistic loss functions for different values of t. When t = 1, we recover the logistic loss Analogous to the exponential family of distributions, the t-exponential family of distributions is de?ned as [9, 13]: p(x; ?) := expt (??(x), ?? ? gt (?)) .

(13)

qt (x; ?) := p(x; ?)t /Z(?)

(14)

A prominent member of the t-exponential family is the Student?s-t distribution [14]. Just like in the exponential family case, gt the log-partition function ensures that p(x; ?) is normalized. However, no closed form solution exists for computing gt exactly in general. A closely related distribution, which often appears when working with t-exponential families is the so-called escort distribution [9, 13]: where Z(?) = integrates to 1.

?

p(x; ?) dx is the normalizing constant which ensures that the escort distribution t

Although gt (?) is not the cumulant function of the t-exponential family, it still preserves convexity. In addition, it is very close to being a moment generating function ?? gt (?) = Eqt (x;?) [?(x)] .

(15)

The proof is provided in the supplementary material. A general version of this result appears as Lemma 3.8 in Sears [13] and a version specialized to the generalized exponential families appears as Proposition 5.2 in [9]. The main difference from ?? g(?) of the normal exponential family is that now ?? gt (?) is equal to the expectation of its escort distribution qt (x; ?) instead of p(x; ?). 3

4

Binary Classi?cation with the t-exponential Family

In t-logistic regression we model p(y— x; ?) via a conditional t-exponential family distribution p(y— x; ?) = expt (??(x, y), ?? ? gt (? — x)) , (16) where 1 ¡ t ¡ 2, and compute the log-partition function gt by noting that expt (??(x, +1), ?? ? gt (? — x)) + expt (??(x, ?1), ?? ? gt (? — x)) = 1. (17) Even though no closed form solution exists, one can compute gt given ? and x using numerical techniques ef?ciently. The Student?s-t distribution can be regarded as a counterpart of the isotropic Gaussian prior in the t-exponential family [14]. Recall that a one dimensional Student?s-t distribution is given by ??(v+1)/2 ? (x ? ?)2 ?((v + 1)/2) 1 + St(x—?, ?, v) = ? , (18) v? v??(v/2)? 1/2 where ?(?) denotes the usual Gamma function and v ¿ 1 so that the mean is ?nite. If we select t satisfying ?(v + 1)/2 = 1/(1 ? t) and denote, ??2/(v+1) ? ?((v + 1)/2) , ?= ? v??(v/2)? 1/2 then by some simple but tedious calculation (included in the supplementary material) ? ? ?)2 /2 ? g?t) St(x—?, ?, v) = exp (??(x (19) t

2? ?= where ? (t ? 1)v?

and g?t =

??1 . t?1

Therefore, we work with the Student?s-t prior in our setting: p(?) =

d ?

p(?j) =

j=1

d ?

j=1

St(?j —0, 2/?, (3 ? t)/(t ? 1)).

(20)

Here, the degree of freedom for Student?s-t distribution is chosen such that it also belongs to the expt family, which in turn yields v = (3 ? t)/(t ? 1). The Student?s-t prior is usually preferred to the Gaussian prior when the underlying distribution is heavy-tailed. In practice, it is known to be a robust3 alternative to the Gaussian distribution [16, 17]. As before, if we let ?(x, y) = y2 ?(x) and plot the negative log-likelihood ? log p(y— x; ?), then we no longer obtain a convex loss function (see Figure 2). Similarly, ? log p(?) is no longer convex when we use the Student?s-t prior. This makes optimizing the regularized risk challenging, therefore we employ a different strategy. Since logt is also a monotonically increasing function, instead of working with log, we can equivalently work with the logt function (12) and minimize the following objective function: m ? ? J(?) = ? logt p(?) p(yi — xi ; ?)/p(Y — X) 1 = t?1

?

i=1

p(?)

m ?

i=1

p(yi — xi ; ?)/p(Y — X)

?1?t

\+

1 , 1?t

(21)

where p(Y — X) is independent of ?. Using (13), (18), and (11), we can further write m ? d ? ?? ? ? ?y ? i ? 2 /2 ? g?t) ? ?(xi), ? ? gt (? — xi)) +const. . 1 + (1 ? t)(??? 1 + (1 ? t)(J(?) ? j 2 ?? ?? ? i=1 ? ? j=1 ? rj (?)

=

d ?

j=1

rj (?)

m ?

li (?)

li (?) + const.
(22)
i=1
3 There is no unique de?nition of robustness. For example, one of the de?nitions is through the outlierproneness [15]: p(? — X, Y, xn+1 , yn+1) ? p(? — X, Y) as xn+1 ? ?.
4
Since t ¿ 1, it is easy to see that rj (?) ¿ 0 is a convex function of ?. On the other hand, since gt ? is convex and t ¿ 1 it follows that li (?) ¿ 0 is also a convex function of ?. In summary, J(?) is a product of positive convex functions. In the next section we will present an ef?cient optimization strategy for dealing with such problems.
5
Convex Multiplicative Programming
In convex multiplicative programming [18] we are interested in the following optimization problem: N ? min P(?) ? zn (?) s.t. ? ? Rd , (23) ?
n=1
where zn (?) are positive convex functions. Clearly, (22) can be identi?ed with (23) by setting N = d+m and identifying zn (?) = rn (?) for n = 1, . . . , d and zn+d (?) = ln (?) for n = 1, . . . , m. The optimal solutions to the problem (23) can be obtained by solving the following parametric problem (see Theorem 2.1 of Kuno et al. [18]): N N ? ? ?n zn (?) s.t. ? ? Rd , ? ¿ 0, ?n ? 1. (24) min min MP(?, ?) ? ?
?
n=1
n=1
In logistic regression, The optimization problem ? ? in (24) is very reminiscent of logistic regression. ?? ? ? ln (?) = ? y2n ?(xn), ? + g(? — xn), while here ln (?) = 1 + (1 ? t) y2n ?(xn), ? ? gt (? — xn) . The key difference is that in t-logistic regression each data point xn has a weight (or in?uence) ?n associated with it. Exact algorithms have been proposed for solving (24) (for instance, [18]). However, the computational cost of these algorithms grows exponentially with respect to N which makes them impractical for our purposes. Instead, we apply a block coordinate descent based method. The main idea is to minimize (24) with respect to ? and ? separately. ?-Step: Assume that ? is ?xed, and denote z?n = zn (?) to rewrite (24) as: min ?
N ?
?n z?n s.t.
? ¿ 0,
n=1
N ?
n=1
(25)
?n ? 1.
Since the objective function is linear in ? and the feasible region is a convex set, (25) is a convex optimization problem. By introducing a non-negative

Lagrange multiplier ? ? 0, the partial Lagrangian and its gradient with respect to ?n? can be written as ? ? N N ? ? (26) L(?, ?) = ?n z?n + ? ? 1 ? ?n n=1

? ? L(?, ?) = z?n? ? ? ?n . ? ??n ?

n=1

(27)

n?=n

Setting the gradient to 0 obtains ? =

? z?n?

K.K.T. conditions [3], we can conclude

?n . Since ?N that n=1 ?n

n?=n?

z?n? ¿ 0, it follows that ? cannot be 0. By the

= 1. This in turn implies that ? = z?n? ?n? or

z1 , . . . , ?/? zN), with ? = (?1 , . . . , ?N) = (?/?

N ?

1

z?nN .

(28)

n=1

Recall that ?n in (24) is the weight (or in?uence) of each term zn (?). The above analysis shows that ? = z?n (?)?n remains constant for all n. If z?n (?) becomes very large then its in?uence ?n is reduced. Therefore, points with very large loss have their in?uence capped and this makes the algorithm robust to outliers. ?-Step: In this step we ?x ? ¿ 0 and solve for the optimal ?. This step is essentially the same as logistic regression, except that each component has a weight ? here. N ? min ?n zn (?) s.t. ? ? Rd . (29) ?

n=1

5

This is a standard unconstrained convex optimization problem which can be solved by any off the shelf solver. In our case we use the L-BFGS Quasi-Newton method. This requires us to compute the gradient ?? zn (?):

? n ? en ?? zn (?) = ?? rn (?) = (t ? 1)?? ?y ? n ?(xn) ? ?? gt (? — xn) for n = 1, . . . , m ?? zn+d (?) = ?? ln (?) = (1 ? t) ? y2 ?? ?y n n = (1 ? t) ?(xn) ? Eqt (yn — xn ;?) ?(xn) , 2 2 where en denotes the d dimensional vector with one at the n-th coordinate and zeros elsewhere (n-th unit vector). qt (y— x; ?) is the escort distribution of p(y— x; ?) (16): for n = 1, . . . , d

qt (y— x; ?) =

p(y— x; ?)t . p(+1— x; ?)t + p(?1— x; ?)t

(30)

The objective function is monotonically decreasing and is guaranteed to converge to a stable point of P(?). We include the proof in the supplementary material.

6

Experimental Evaluation

Our experimental evaluation is designed to answer four natural questions: 1) How does the generalization capability (measured in terms of test error) of t-logistic regression compare with existing algorithms such as logistic regression and support vector machines (SVMs) both in the presence and absence of label noise? 2) Do the ? variables we introduced in the previous section have a natural interpretation? 3) How much overhead does t-logistic regression incur as compared to logistic regression? 4) How sensitive is the algorithm to initialization? The last question is particularly important given that the algorithm is minimizing a non-convex loss. To answer the above questions empirically we use six datasets, two of which are synthetic. The Long-Servedio dataset is an arti?cially constructed dataset to show that algorithms which minimize a differentiable convex loss are not tolerant to label noise Long and Servedio [4]. The examples have 21 dimensions and play one of three possible roles: large margin examples (25%, x1,2,...,21 = y); pullers (25%, x1,...,11 = y, x12,...,21 = ?y); and penalizers (50%, Randomly select and set 5 of the ?rst 11 coordinates and 6 out of the last 10 coordinates to y, and set the remaining coordinates to ?y). The Mease-Wyner is another synthetic dataset to test the effect of label noise. The input x is a 20-dimensional vector where each coordinate is uniformly distributed on [0, 1]. The label y is ?5 +1 if j=1 xj ? 2.5 and ?1 otherwise [19]. In addition, we also test on Mushroom, USPS-N (9 vs. others), Adult, and Web datasets, which are often used to evaluate machine learning algorithms (see Table 1 in supplementary material for details). For simplicity, we use the identity feature map ?(x) = x in all our experiments, and set t ? {1.3, 1.6, 1.9} for t-logistic regression. Our comparators are logistic regression, linear SVMs4 , and an algorithm (the probit) which employs the probit loss, L(u) = 1 ? erf (2u), used in BrownBoost/RobustBoost [5]. We use the L-BFGS algorithm [21] for the ?-step in t-logistic regression. L-BFGS is also used to train logistic regression and the probit loss based algorithms. Label noise is added by randomly choosing 10% of the labels in the training set and ?ipping them; each dataset is tested with and without label noise. We randomly select and hold out 30% of each dataset as a validation set and use the rest of the 70% for 10-fold cross validation. The optimal parameters namely ? for t-logistic and ?logistic regression and C for SVMs is chosen by performing a grid search over the ? parameter space 2?7,?6,...,7 and observing the prediction accuracy over the validation set. The convergence criterion is to stop when the change in the objective function value is less than 10?4 . All code is written in Matlab, and for the linear SVM we use the Matlab interface of LibSVM [22]. Experiments were performed on a Qual-core machine with Dual 2.5 Ghz processor and 32 Gb RAM. In Figure 3, we plot the test error with and without label noise. In the latter case, the test error of t-logistic regression is very similar to logistic regression and Linear SVM (with 0% test error in 4 We also experimented with RampSVM [20], however, the results are worser than the other algorithms. We therefore report these results in the supplementary material.

6

6.0

TestError(%)

32

1.2 4.5

24
0.9 3.0
16 8
1.5
0.3
0
0.0
0.0
16.8
3.2
16.0
2.4
6.0
TestError(%)
0.6
4.5 3.0
1.6
15.2 1.5
0.8 14.4
0.0
logis. t=1.3 t=1.6 t=1.9 probit SVM
logis. t=1.3 t=1.6 t=1.9 probit SVM
0.0
logis. t=1.3 t=1.6 t=1.9 probit SVM

Figure 3: The test error rate of various algorithms on six datasets (left to right, top: Long-Servedio, Mease-Wyner, Mushroom; bottom: USPS-N, Adult, Web) with and without 10% label noise. All algorithms are initialized with ? = 0. The blue (light) bar denotes a clean dataset while the magenta (dark) bar are the results with label noise added. Also see Table 3 in the supplementary material. Long-Servedio and Mushroom datasets), with a slight edge on some datasets such as Mease-Wyner. When label noise is added, t-logistic regression (especially with t = 1.9) shows signi?cantly5 better performance than all the other algorithms on all datasets except the USPS-N, where it is marginally outperformed by the probit. To obtain Figure 4 we used the noisy version of the datasets, chose one of the 10 folds used in the previous experiment, and plotted the distribution of the 1/z ? ? obtained after training with t = 1.9. To distinguish the points with noisy labels we plot them in cyan while the other points are plotted in red. Analogous plots for other values of t can be found in the supplementary material. Recall that ? denotes the in?uence of a point. One can clearly observe that the ? of the noisy data is much smaller than that of the clean data, which indicates that the algorithm is able to effectively identify these points and cap their in?uence. In particular, on the Long-Servedio dataset observe the 4 distinct spikes. From left to right, the ?rst spike corresponds to the noisy large margin examples, the second spike represents the noisy pullers, the third spike denotes the clean pullers, while the rightmost spike corresponds to the clean large margin examples. Clearly, the noisy large margin examples and

the noisy pullers are assigned a low value of ? thus capping their in?uence and leading to the perfect classi?cation of the test set. On the other hand, logistic regression is unable to discriminate between clean and noisy training samples which leads to bad performance on noisy datasets. Detailed timing experiments can be found in Table 4 in the supplementary material. In a nutshell, t-logistic regression takes longer to train than either logistic regression or the probit. The reasons are not dif?cult to see. First, there is no closed form expression for gt (? — x). We therefore resort to pre-computing it at some ?xed locations and using a spline method to interpolate values at other locations. Second, since the objective function is not convex several iterations of the ? and ? steps might be needed. Surprisingly, the L-BFGS algorithm, which is not designed to optimize nonconvex functions, is able to minimize (22) directly in many cases. When it does converge, it is often faster than the convex multiplicative programming algorithm. However, on some cases (as expected) it fails to ?nd a direction of descent and exits. A common remedy for this is the bundle L-BFGS with a trust-region approach. [21] Given that the t-logistic objective function is non-convex, one naturally worries about how different initial values affect the quality of the ?nal solution. To answer this question, we initialized the algorithm with 50 different randomly chosen ? ? [?0.5, 0.5]d , and report test performances of the various solutions obtained in Figure 5. Just like logistic regression which uses a convex loss and hence converges to the same solution independent of the initialization, the solution obtained 5

We provide the signi?cance test results in Table 2 of supplementary material.

7

300

1000 60

Frequency

240

800

45

180

600

120

30

400

60

15

200

0 0.0

0.2

0.4

0.6

0.8

0 0.0

1.0

0.2

0.4
0.6
0.8
1.0
0 0.0
0.2
0.4
0.2
0.4
0.6
0.8
1.0
0.6
0.8
1.0
600 1200
8000
900
6000
600
4000
300
2000
Frequency
450 300 150 0 0.0
0.2
0.4
0.6
0.8
1.0
0 0.0
0.2
0.4
?
0.6
0.8
1.0
0 0.0
?
?

Figure 4: The distribution of ? obtained after training t-logistic regression with t = 1.9 on datasets with 10% label noise. Left to right, top: Long-Servedio, Mease-Wyner, Mushroom; bottom: USPSN, Adult, Web. The red (dark) bars (resp. cyan (light) bars) indicate the frequency of ? assigned to points without (resp. with) label noise. by t-logistic regression seems fairly independent of the

initial value of ?. On the other hand, the performance of the probit ?uctuates widely with different initial values of ?. probit t = 1.9 t = 1.6 t = 1.3 logistic 0

10

20

30

0

10

20

30

40

0.00

0.15

0.30

0.45

probit t = 1.9 t = 1.6 t = 1.3 logistic 3.0

4.5

6.0 7.5 TestError(%)

9.0

15

18 21 TestError(%)

24

1.5

2.0 2.5 TestError(%)

3.0

3.5

Figure 5: The Error rate by different initialization. Left to right, top: Long-Servedio, Mease-Wyner, Mushroom; bottom: USPS-N, Adult, Web.

7 Discussion and Outlook

In this paper, we generalize logistic regression to t-logistic regression by using the t-exponential family. The new algorithm has a probabilistic interpretation and is more robust to label noise. Even though the resulting objective function is non-convex, empirically it appears to be insensitive to initialization. There are a number of avenues for future work. On Long-Servedio experiment, if the label noise is increased signi?cantly beyond 10%, the performance of t-logistic regression may degrade (see Fig. 6 in supplementary materials). Understanding and explaining this issue theoretically and empirically remains an open problem. It will be interesting to investigate if t-logistic regression can be married with graphical models to yield t-conditional random ?elds. We will also focus on better numerical techniques to accelerate the ?-step, especially a faster way to compute gt . 8

2 References

[1] Choon Hui Teo, S. V. N. Vishwanthan, Alex J. Smola, and Quoc V. Le. Bundle methods for regularized risk minimization. J. Mach. Learn. Res., 11:311?365, January 2010. [2] S. Ben-David, N. Eiron, and P.M. Long. On the dif?culty of approximately maximizing agreements. J. Comput. System Sci., 66(3):496?514, 2003. [3] S. Boyd and L. Vandenberghe. Convex Optimization. Cambridge University Press, Cambridge, England, 2004. [4] Phil Long and Rocco Servedio. Random classi?cation noise defeats all convex potential boosters. Machine Learning Journal, 78(3):287?304, 2010. [5] Yoav Freund. A more robust boosting algorithm. Technical Report Arxiv/0905.2138, Arxiv, May 2009. [6] J. Naudts. Deformed exponentials and logarithms in generalized thermostatistics. Physica A, 316:323?334, 2002. URL http://arxiv.org/pdf/cond-mat/0203489. [7] J. Naudts. Generalized thermostatistics based on deformed exponential and logarithmic functions. Physica A, 340:32?40, 2004. [8] J. Naudts. Generalized thermostatistics and mean-?eld theory. Physica A, 332:279?300, 2004. [9] J. Naudts. Estimators, escort proabilities, and ?-exponential families in statistical physics. Journal of Inequalities in Pure and Applied Mathematics, 5(4), 2004. [10] C. Tsallis. Possible generalization of boltzmann-gibbs statistics. J. Stat. Phys., 52, 1988. [11] Christopher Bishop. Pattern Recognition and Machine Learning. Springer, 2006. [12] Trevor Hastie, Robert Tibshirani, and Jerome Friedman. The Elements of Statistical Learning. Springer, New York, 2 edition, 2009. [13] Timothy D. Sears. Generalized Maximum Entropy, Convexity, and Machine Learning. PhD thesis, Australian National University, 2008. [14] Andre Sousa and Constantino Tsallis. Student?s t- and r-distributions: Uni?ed derivation from an entropic variational principle. Physica A, 236:52?57, 1994. [15] A O?hagan. On outlier rejection phenomena in bayes inference. Royal Statistical Society, 41 (3):358?367, 1979. [16] Kenneth L. Lange, Roderick J. A. Little, and Jeremy M. G. Taylor. Robust statistical modeling using the t distribution. Journal of the American Statistical Association, 84(408):881?896, 1989. [17] J. Vanhatalo, P. Jylanki, and A. Vehtari. Gaussian process regression with student-t likelihood. In Neural Information Processing System, 2009. [18] Takahito Kuno, Yasutoshi Yajima, and Hiroshi Konno. An outer approximation method for minimizing the product of several convex functions on a convex set. Journal of Global Optimization, 3(3):325?335, September 1993. [19] David Mease and Abraham Wyner. Evidence contrary to the statistical view of boosting. J. Mach. Learn. Res., 9:131?156, February 2008. [20] R. Collobert, F.H. Sinz, J. Weston, and L. Bottou. Trading convexity for scalability. In W.W. Cohen and A. Moore, editors, Machine Learning, Proceedings of the Twenty-Third International Conference (ICML 2006), pages 201?208. ACM, 2006. [21] J. Nocedal and S. J. Wright. Numerical Optimization. Springer Series in Operations Research. Springer, 1999. [22] C.C. Chang and C.J. Lin. LIBSVM: a library for support vector machines, 2001. Software available at http://www.csie.ntu.edu.tw/?cjlin/libsvm. [23] Fabian Sinz. UniverSVM: Support Vector Machine with Large Scale CCCP Functionality, 2006. Software available at http://www.kyb.mpg.de/bs/people/fabee/universvm. html.

9