
Submodular Multi-Label Learning

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Abstract

In this paper we present an algorithm to learn a multi-label classifier which attempts at directly optimising the F -score. The key novelty of our formulation is that we explicitly allow for assortative (submodular) pairwise label interactions, i.e., we can leverage the co-occurrence of pairs of labels in order to improve the quality of prediction. Prediction in this model consists of minimising a particular submodular set function, what can be accomplished exactly and efficiently via graph-cuts. Learning however is substantially more involved and requires the solution of an intractable combinatorial optimisation problem. We present an approximate algorithm for this problem and prove that it is sound in the sense that it never predicts incorrect labels. We also present a nontrivial test of a sufficient condition for our algorithm to have found an optimal solution. We present experiments on benchmark multi-label datasets, which attest the value of the proposed technique. We also make available source code that enables the reproduction of our experiments.

1 Introduction

Research in multi-label classification has seen a substantial growth in recent years (e.g., [1, 2, 3, 4]). This is due to a number of reasons, including the increase in availability of multi-modal datasets and the emergence of crowdsourcing, which naturally create settings where multiple interpretations of a given input observation are possible (multiple labels for a single instance). Also many classical problems are inherently multi-label, such as the categorisation of documents [5], gene function prediction [6] and image tagging [7].

There are two desirable aspects in a multi-label classification system. The first is that a prediction should ideally be good both in terms of precision and recall: we care not only about predicting as many of the correct labels as possible, but also as few non-correct labels as possible. One of the most popular measures for assessing performance is therefore the F -score, which is the harmonic mean of precision and recall [8]. The second property we wish is that, both during training and also at test time, the algorithm should ideally take into account possible dependencies between the labels. For example, in automatic image tagging, if labels *ocean* and *ship* have high co-occurrence frequency in the training set, the model learned should somehow boost the chances of predicting *ocean* if there is strong visual evidence for the label *ship* [9].

In this paper we present a method that directly addresses these two aspects. First, we explicitly model the dependencies between pairs of labels, albeit restricting them to be submodular (in rough terms, we model only the positive pairwise label correlations). This enables exact and efficient prediction at test time, since finding an optimal subset of labels reduces to the minimisation of a particular kind of submodular set function which can be done efficiently via graph-cuts. Second, our method directly attempts at optimising a convex surrogate of the F -score. This is because we draw on the max-margin structured prediction framework from [10], which, as we will see, enables us to optimise a convex upper bound on the loss induced by the F -score. The critical technical contribution of the paper is a constraint generation algorithm for loss-augmented inference where the scoring of the pair (input-output) is a submodular set function and the loss is derived from the F -score. This

is what enables us to fit our model into the estimator from [10]. Our constraint generation algorithm is only approximate since the problem is intractable. However we give theoretical arguments supporting our empirical findings that the algorithm is not only very accurate in practice, but in the majority of our real-world experiments it actually produces a solution which is exactly optimal. We compare the proposed method with other benchmark methods on publicly available multi-label datasets, and results favour our approach. We also provide source code that enables the reproduction of all the experiments presented in this paper.

Related Work. A convex relaxation for F -measure optimisation in the multi-label setting was proposed recently in [11]. This can be seen as a particular case of our method when there are no explicit label dependencies. In [12] the authors propose quite general tree and DAG-based dependencies among the labels and adapt decoding algorithms from signal processing to the problem of finding predictions consistent with the structures learned. In [13] graphical models are used to impose structure in the label dependencies. Both [12] and [13] are in a sense complementary to our method since we do not enforce any particular graph topology on the labels but instead we limit the nature of the interactions to be submodular. In [14] the authors study the multi-label problem under the assumption that prior knowledge on the density of label correlations is available. They also use a max-margin framework, similar in spirit to our formulation. A quite simple and basic strategy for multi-label problems is to treat them as multiclass classification, effectively ignoring the relationships between the labels. One example in this class is the Binary Method [15]. The RAKEL algorithm [16] uses instead an ensemble of classifiers, each learned on a random subset of the label set. In [17] the authors propose a Bayesian CCA model and apply it to multi-label problems by enforcing group sparsity regularisation in order to capture information about label co-occurrences.

2 The Model

Let $x \in \mathcal{X}$ be a vector of dimensionality D with the features of an instance (say, an image); let $y \in \mathcal{Y}$ be a *set of labels* for an instance (say, tags for an image), from a fixed dictionary of V possible labels, encoded as $y \in \{0, 1\}^V$. For example, $y = [1 \ 1 \ 0 \ 0]$ denotes the first and second labels of a set of four. We assume we are given a training set $\{(x^n, y^n)\}_{n=1}^N$, and our task is to estimate a map $f : \mathcal{X} \rightarrow \mathcal{Y}$ that has good agreement with the training set but also generalises well to new data. In this section we define the class of functions f that we will consider. In the next section we define the learning algorithm, i.e., a procedure to find a specific f in the class.

2.1 The Loss Function Derived from the F -Score

Our notion of ‘agreement’ with the training set is given by a loss function. We focus on maximising the average over all instances of F , a score that considers both *precision* and *recall* and can be written in our notation as

$$F = \frac{1}{N} \sum_{n=1}^N \frac{2 p(y^n, \bar{y}^n) r(y^n, \bar{y}^n)}{p(y^n, \bar{y}^n) + r(y^n, \bar{y}^n)}, \text{ where } p(y, \bar{y}) = \frac{|y \odot \bar{y}|}{|\bar{y}|} \text{ and } r(y, \bar{y}) = \frac{|y \odot \bar{y}|}{|y|}$$

Here \bar{y}^n denotes our prediction for input instance n , y^n is the corresponding ground-truth, \odot denotes the element-wise product and $|u|$ denotes the 1-norm of vector u (in our case the number of 1s since u will always be binary). Since our goal is to *maximise* the F -score a suitable choice of loss function is $\Delta(y, \bar{y}) = 1 - F(y, \bar{y})$, which is the one we adopt in this paper. The loss for a single prediction is therefore

$$\Delta(y, \bar{y}) = 1 - 2 |y \odot \bar{y}| / (|y| + |\bar{y}|) \tag{1}$$

2.2 Feature Maps and Parameterisation

We assume that the prediction for a given input x is a maximiser of a score that encodes both the unary dependency between labels and instances as well as the pairwise dependencies between labels:

$$\bar{y} \in \operatorname{argmax}_{y \in \mathcal{Y}} y^T A y \tag{2}$$

where A is an upper-triangular matrix scoring the pair (x, y) , with diagonal elements $A_{ii} = \langle x, \theta_i^1 \rangle$, where x is the input feature vector and θ_i^1 is a parameter vector that defines how label i weighs each feature of x . The off-diagonal elements are $A_{ij} = C_{ij}\theta_{ij}^2$, where C_{ij} is the normalised counts of co-occurrence of labels i and j in the training set, and θ_{ij}^2 the corresponding scalar parameter *which is forced to be non-negative*. This will ensure that the off-diagonal entries of A are non-negative and therefore that problem 2 consists of the maximisation of a supermodular function (or, equivalently, the minimisation of a submodular function), which can be solved efficiently via graph-cuts. We also define the complete parameter vectors $\theta^1 := [\dots \theta_i^1 \dots]^T$, $\theta^2 := [\dots \theta_{ij}^2 \dots]^T$ and $\theta = [\theta^1 \theta^2]^T$, as well as the complete feature maps $\phi_1(x, y) = \text{vec}(x \otimes y)$, $\phi_2(y) = \text{vec}(y \otimes y)$ and $\phi(x, y) = [\phi_1^T(x, y) \phi_2^T(y)]^T$. This way the score in expression 2 can be written as $y^T A y = \langle \phi(x, y), \theta \rangle$. Note that the dimensionality of θ^2 is the number of non-zero elements of matrix C —in this setting that is $\binom{V}{2}$, but it can be reduced by setting to zero elements of C below a specified threshold.

3 Learning Algorithm

Optimisation Problem. Direct optimisation of the loss defined in equation 1 is a highly intractable problem since it is a discrete quantity and our parameter space is continuous. Here we will follow the program in [10] and instead construct a convex upper bound on the loss function, which can then be attacked using convex optimisation tools. The purpose of learning will be to solve the following convex optimisation problem

$$[\theta^*, \xi^*] = \underset{\theta, \xi}{\operatorname{argmin}} \left[\frac{1}{N} \sum_{n=1}^N \xi_n + \frac{\lambda}{2} \|\theta\|^2 \right] \quad (3a)$$

$$\begin{aligned} \text{s.t. } & \langle \phi(x^n, y^n), \theta \rangle - \langle \phi(x^n, y), \theta \rangle \geq \Delta(y, y^n) - \xi_n, \\ & \xi_n \geq 0, \forall n, y \neq y^n. \end{aligned} \quad (3b)$$

This is the margin-rescaling estimator for structured support vector machines [10]. The constraints immediately imply that the optimal solution will be such that $\xi_n^* \geq \Delta(\operatorname{argmax}_y \langle \phi(x^n, y), \theta^* \rangle, y^n)$, and therefore the minimum value of the objective function upper bounds the loss, thus motivating the formulation. Since there are exponentially many constraints, we follow [10] in adopting a constraint generation strategy, which starts by solving the problem with no constraints and iteratively adding the most violated constraint for the current solution of the optimisation problem. This is guaranteed to find an ϵ -close approximation of the solution of (3) after including only a polynomial ($O(\epsilon^{-2})$) number of constraints [10]. At each iteration we need to maximise the violation margin ξ_n , which from the constraints 3b reduces to

$$y_n^* \in \operatorname{argmax}_{y \in \mathcal{Y}} [\Delta(y, y^n) + \langle \phi(x^n, y), \theta \rangle] \quad (4)$$

Learning Algorithm. The learning algorithm is described in Algorithm 1 (requires as subroutine Algorithm 2). Algorithm 1 describes a particular convex solver based on bundle methods (BMRM [18]), which we use here. Other solvers could have been used instead. Our contribution lies not here, but in the routine of constraint generation for Algorithm 1, which is described in Algorithm 2.

BMRM requires the solution of constraint generation and the value of the objective function for the slack corresponding to the constraint generated, as well as its gradient. Soon we will discuss constraint generation. The other two ingredients we describe here. The slack at the optimal solution is

$$\xi_n^* = \Delta(y_n^*, y^n) + \langle \phi(x^n, y_n^*), \theta \rangle - \langle \phi(x^n, y^n), \theta \rangle \quad (5)$$

thus the objective function from (3) becomes

$$\frac{1}{N} \sum_n \Delta(y_n^*, y^n) + \langle \phi(x^n, y_n^*), \theta \rangle - \langle \phi(x^n, y^n), \theta \rangle + \frac{\lambda}{2} \|\theta\|^2, \quad (6)$$

whose gradient is

$$\lambda \theta - \frac{1}{N} \sum_n (\phi(x^n, y^n) - \phi(x^n, y_n^*)) \quad (7)$$

Algorithm 1 Bundle Method for Regularised Risk Minimisation (BMRM)

1: **Input:** training set $\{(x^n, y^n)\}_{n=1}^N$, λ ,
Output: θ
2: Initialize $i = 1$, $\theta_1 = 0$, $\max = -\infty$
3: **repeat**
4: **for** $n = 1$ **to** N **do**
5: Compute y_n^* ($y_{k_{max}}^{*n}$ returned by Algorithm 2.)
6: **end for**
7: Compute gradient g_i (equation (7))
 and objective o_i (equation (6))
8: $\theta_{i+1} := \underset{j \leq i}{\operatorname{argmin}}_{\theta} \frac{\lambda}{2} \|\theta\|^2 + \max(0, \max_{j \leq i} \langle g_j, \theta \rangle + o_j)$; $i \leftarrow i + 1$
9: **until** converged (see [17])
10: **return** θ

Algorithm 2 Constraint Generation

1: **Input:** (x^n, y^n) , θ , V , **Output:** $y_{k_{max}}^{*n}$
2: $k = 0$
3: $A_{ij}^{[k],n} = \langle \theta_{ij}, C_{ij} \rangle$ (for all $i, j : i \neq j$)
4: **while** $k \leq V$ **do**
5: $\operatorname{diag}(A^{[k],n}) = \operatorname{diag}(A) - \frac{2y^n}{k + \|y^n\|^2}$
6: $y_k^{*n} = \operatorname{argmax}_y y^T A^{[k],n} y$ (graph-cuts)
7: **if** $|y_k^{*n}| > k$ **then**
8: $k_{max} = |y_k^{*n}|$; $k = k_{max}$
9: **else if** $|y_k^{*n}| = k$ **then**
10: $k_{max} = |y_k^{*n}|$; $k = k_{max} + 1$
11: **else**
12: $k = k + 1$
13: **end if**
14: **end while**
15: **return** $y_{k_{max}}^{*n}$

Expressions (6) and (7) are then used in Algorithm 1.

Constraint Generation. The most challenging step consists of solving the constraint generation problem. Constraint generation for a given training instance n consists of solving the combinatorial optimisation problem in expression 4, which, using the loss in equation 1, as well as the correspondence $y^T A y = \langle \phi(x, y), \theta \rangle$, can be written as

$$y^{*n} \in \operatorname{argmax}_y y^T A^n(y) y \quad (8)$$

where $\operatorname{diag}(A^n) = \operatorname{diag}(A) - \frac{2y^n}{|y| + |y^n|}$ and $\operatorname{offdiag}(A^n) = \operatorname{offdiag}(A)$. Note that the matrix A^n depends on y . More precisely, a subset of its diagonal elements (those A_{ii}^n for which $y^n(i) = 1$) depends on the quantity $|y|$, i.e., the number of nonzero elements in y . This makes solving problem 8 a formidable task. If A^n were independent of y , then eq. 8 could be solved exactly and efficiently via graph-cuts, just as our prediction problem in equation 2. A naïve strategy would be to aim for solving problem 8 V times, one for each value of $|y|$, and constraining the optimisation to only include elements y such that $|y|$ is fixed. In other words, we can partition the optimisation problem into k optimisation problems conditioned on the sets $\mathcal{Y}_k := \{y : |y| = k\}$:

$$\max_y y^T A(y) y = \max_k \max_{y \in \mathcal{Y}_k} y^T A^{[k],n} y \quad (9)$$

where $A^{[k],n}$ denotes the particular matrix A^n that we obtain when $|y| = k$. However the inner maximization above, i.e., the problem of maximising a supermodular function (or minimising a submodular function) subject to a cardinality constraint, is itself NP-hard [19]. We therefore do not follow this strategy, but instead seek a polynomial-time algorithm that in practice will give us an optimal solution most of the time.

Algorithm 2 describes our algorithm. In the worst case it calls graph-cuts $O(V)$ times, so the total complexity is $O(V^4)$.¹ The algorithm essentially searches for the largest k such that solving $\operatorname{argmax}_y y^T A^{[k],n} y$ returns a solution with k 1s. We call the k obtained k_{max} , and the corresponding solution $y_{k_{max}}^{*n}$. Observe the fact that, as k increases during the execution of the algorithm, A_{ii}^n increases for those i where $y^n(i) = 1$. The increment observed when k increases to k' is

$$\epsilon_k^{k'} := A_{ii}^{[k'],n} - A_{ii}^{[k],n} = 2 \frac{k' - k}{(k' + |y^n|)(k + |y^n|)} \quad (10)$$

which is always a positive quantity. Although this algorithm is not provably optimal, Theorem 1 guarantees that it is sound in the sense that it never predicts incorrect labels. In the

¹The worst-case bound of $O(V^3)$ for graph-cuts is very pessimistic; in practice the algorithm is extremely efficient.

next section we present additional evidence supporting this algorithm, in the form of a test that if positive guarantees the solution obtained is optimal.

We call a solution y' a *partially optimal* solution of $\operatorname{argmax}_y y^T A^n(y)y$ if the labels it predicts as being present are indeed present in an optimal solution, i.e., if for those i for which $y'(i) = 1$ we also have $y^{*n}(i) = 1$, for some $y^{*n} \in \operatorname{argmax}_y y^T A^n(y)y$. Equivalently, we can write $y' \odot y^{*n} = y'$. We have the following result

Theorem 1 *Upon completion of Algorithm 2, $y_{k_{max}}^{*n}$ is a partially optimal solution of $\operatorname{argmax}_y y^T A^n(y)y$.*

The proof is in the Appendix A. The theorem means that whenever the algorithm predicts the presence of a label, it does so correctly; however there may be labels not predicted which are in fact present in the corresponding optimal solution.

4 Certificate of Optimality

As empirically verified in our experiments in section 5, our constraint generation algorithm (Algorithm 2) is indeed quite accurate: most of the time the solution obtained is optimal. In this section we present a test that if positive guarantees that an optimal solution has been obtained (i.e., a certificate of optimality). This can be used to generate empirical lower bounds on the probability that the algorithm returns an optimal solution (we explore this possibility in the experimental section).

We start by formalising the situation in which the algorithm will fail. Let $Z := \{i : y_{k_{max}}^{*n}(i) = 0\}$, and \mathcal{P}_Z be the power set of Z (Z for ‘zeros’). Let $O := \{i : y_{k_{max}}^{*n}(i) = 1\}$ (O for ‘ones’). Then the algorithm will fail if there exists $\alpha \in \mathcal{P}_Z$ such that

$$\underbrace{\sum_{i,j \in \alpha; i \neq j} A_{ij}^n}_{(a)} + \underbrace{\sum_{i \in \alpha, j \in O} A_{ij}}_{(b)} + \underbrace{\sum_{i \in \alpha} A_{ii}^{[k_{max} + |\alpha|], n}}_{(c)} + \underbrace{\epsilon_{k_{max}}^{k_{max} + |\alpha|} |y^n \odot y_{k_{max}}^{*n}|}_{(d)} > 0 \quad (11)$$

The above expression describes the situation in which, starting with $y_{k_{max}}^{*n}$, if we insert $|\alpha|$ 1s in the indices defined by index set α , we will obtain a new vector y' which is a feasible solution of $\operatorname{argmax}_y y^T A^n(y)y$ and yet has strictly larger score than solution $y_{k_{max}}^{*n}$. This can be understood by looking closely into each of the sums in expression 11. Sums (a) and (b) describe the increase in the objective function due to the inclusion of off-diagonal terms. Both (a) and (b) are non-negative due to the submodularity assumption. Term (c) is the sum of the diagonal terms corresponding to the newly introduced 1s of y' . Term (c) is negative or zero, since each term in the sum is negative or zero (otherwise $y_{k_{max}}^{*n}$ would have included it). Finally, term (d) is non-negative, being the total increase in the diagonal elements of O due to the inclusion of $|\alpha|$ additional 1s. We can write (c) as

$$\underbrace{\sum_{i \in \alpha} A_{ii}^{[k_{max} + |\alpha|], n}}_{(c)} = \underbrace{\sum_{i \in \alpha} A_{ii}^{[k_{max}], n}}_{(e)} + \underbrace{\sum_{i \in \alpha} (A_{ii}^{[k_{max} + |\alpha|], n} - A_{ii}^{[k_{max}], n})}_{(f)} \quad (12)$$

and the last term can be bounded as

$$\sum_{i \in \alpha} (A_{ii}^{[k_{max} + |\alpha|], n} - A_{ii}^{[k_{max}], n}) \leq \underbrace{\epsilon_{k_{max}}^{k_{max} + |\alpha|} v_\alpha}_{(g)} \quad (13)$$

where $v_\alpha = \min[|y^n| - |y^n \odot y_{k_{max}}^{*n}|, |\alpha|]$ is an upper bound on the number of indices $i \in \alpha$ such that $y^n(i) = 1$, and $\epsilon_{k_{max}}^{k_{max} + |\alpha|}$ is the increment in a diagonal element i for which $y^n(i) = 1$ arising from increasing the cardinality of the solution from k_{max} to $k_{max} + |\alpha|$. Incorporating bound 13 into equation 12, we get that (c) \leq (e) + (g). We can then replace (c) in inequality 11 by (e) + (g), obtaining

$$\underbrace{\sum_{i,j \in \alpha; i \neq j} A_{ij}^n + \sum_{i \in \alpha, j \in O} A_{ij} + \sum_{i \in \alpha} A_{ii}^{[k_{max}], n}}_{:= \beta_{A, \alpha}} + \underbrace{\epsilon_{k_{max}}^{k_{max} + |\alpha|} v_\alpha + \epsilon_{k_{max}}^{k_{max} + |\alpha|} |y^n \odot y_{k_{max}}^{*n}|}_{:= \gamma_\alpha} > 0 \quad (14)$$

Algorithm 3 Compute $\max_{\alpha} \beta_{A,\alpha}$

```

1: Input:  $A^{[k_{max}],n}, y_{k_{max}}^{*n}, V,$ 
2: Output: max
3: max =  $-\infty$ 
4:  $Z = \{i : y_{k_{max}}^{*n}(i) = 0\}$ 
5:  $O = \{i : y_{k_{max}}^{*n}(i) = 1\}$ 
6: for  $i \in Z$  do
7:    $O' = O \cup i$ 
8:   rmax =  $\max_{y: y_{O'}=1} y^T A^{[k_{max}],n} y$  (graph-cuts)
9:   if rmax > max then
10:     max = rmax
11:   end if
12: end for
13: max =  $\max - \max_y y^T A^{[k_{max}],n} y$ 
14: return max

```

Table 1: Datasets. #train/#test denotes the number of observations used for training and testing respectively; V is the number of labels and D the dimensionality of the features; Avg is the average number of labels per instance.

dataset	yeast	enron
domain	biology	text
#train	1500	1123
#test	917	579
V	14	53
D	103	1001
Avg	4.23	3.37

We know that, regardless of A or α , $\beta_{A,\alpha} \leq 0$ (otherwise $y_{k_{max}}^{*n} \notin \operatorname{argmax}_y y^T A^{[k_{max}],n} y$, since $\beta_{A,\alpha}$ is the increment in the objective function $y^T A^{[k_{max}],n} y$ obtained by adding 1s in the entries of α). The key fact coming to our aid is that γ_{α} is ‘small’, and a weak upper bound is 2. This is because

$$\begin{aligned} \epsilon_{k_{max}}^{\epsilon^{k_{max}+|\alpha|}} v_{\alpha} + \epsilon_{k_{max}}^{\epsilon^{k_{max}+|\alpha|}} |y^n \odot y_{k_{max}}^{*n}| &\leq \epsilon_{k_{max}}^{\epsilon^{k_{max}+|\alpha|}} |y^n| \leq \epsilon_{k_{max}}^V |y^n| \leq \epsilon_0^V |y^n| = \\ &= 2V|y^n| / ((V + |y^n|)|y^n|) \leq 2 \end{aligned} \quad (15)$$

(Note that if $|y^n| = 0$ then $\gamma_{\alpha} = 0$ and our algorithm will always return an optimal solution since $\beta_{A,\alpha} \leq 0$). Now, since $\beta_{A,\alpha} \leq 0$ for any A and $\alpha \in \mathcal{P}_Z$, it suffices that we study the quantity $\max_{\alpha} \beta_{A,\alpha}$: if $\max_{\alpha} \beta_{A,\alpha} < -2$, then $\beta_{A,\alpha} < -2$ for any $\alpha \in \mathcal{P}_Z$. It is however very hard to understand theoretically the behaviour of the random variable $\max_{\alpha} \beta_{A,\alpha}$ even for a simplistic uniform i.i.d. assumption on the entries of A . This is because the domain of α , \mathcal{P}_Z , is itself a random quantity that depends on the particular A chosen. This makes computing even the expected value of $\max_{\alpha} \beta_{A,\alpha}$ an intractable task, let alone obtaining concentration of measure results that could give us upper bounds on the probability of condition 14 holding under the assumed distribution on A .

However, for a *given* A we can actually compute $\max_{\alpha} \beta_{A,\alpha}$ efficiently. This can be done with Algorithm 3. The algorithm effectively computes the gap between the scores of the optimal solution $y_{k_{max}}^{*n}$ and the highest scoring solution if one sets to 1 at least one of the zero entries in $y_{k_{max}}^{*n}$. It does so by solving graph-cuts constraining the solution y to include the 1s present in $y_{k_{max}}^{*n}$ but additionally fixing one of the zero entries of $y_{k_{max}}^{*n}$ to 1 (lines 7-8). This is done for every possible zero entry of $y_{k_{max}}^{*n}$, and the maximum score is recorded (lines 7-11). The gap between this and the score of the optimal solution $y_{k_{max}}^{*n}$ is then returned (line 13). This will involve $V - k_{max}$ calls to graph-cuts, and therefore the total computational complexity is $O(V^4)$. Once we compute $\max_{\alpha} \beta_{A,\alpha}$, we simply test whether $\max_{\alpha} \beta_{A,\alpha} + \epsilon_{k_{max}}^{|V|} |y^n| > 0$ holds (we use $\epsilon_{k_{max}}^{|V|} |y^n|$ rather than 2 as an upper bound for γ_{α} because, as seen from (15), it is the tightest upper bound which still does not depend on α and therefore can be computed). We have the following theorem (proven in Appendix A)

Theorem 2 Upon completion of Algorithm 3, if $\max_{\alpha} \beta_{A,\alpha} + \epsilon_{k_{max}}^{|V|} |y^n| \leq 0$, then $y_{k_{max}}^{*n}$ is an optimal solution of $\operatorname{argmax}_y y^T A^n(y)y$.

5 Experimental Results

To evaluate our multi-label learning method we applied it to real-world datasets and compared it to state-of-the-art methods.

Datasets. For the sake of reproducibility we focused on publicly available datasets, and to ensure that the label dependencies have a reasonable impact in the results we restricted the experiments to datasets with a sufficiently large average number of labels per instance. We

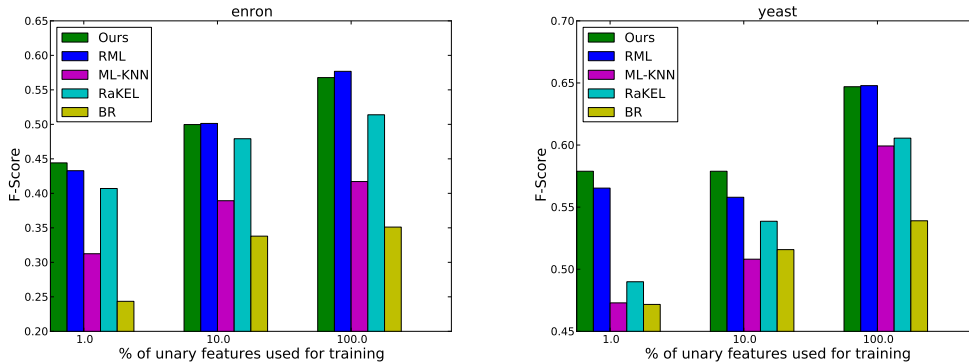


Figure 1: F -Score results on *enron* (left) and *yeast* (right), for different amounts of unary features. The horizontal axis denotes the proportion of the features used in training.

chose therefore two multilabel datasets from *mulan*:² *yeast* and *enron*. Table 1 describes them in more detail.

Experimental setting. The datasets used have very informative unary features, so to better visualise the contribution of the label dependencies to the model we trained using varying amounts (1%, 10% and 100%) of the original unary features. We compared our proposed method to RML[11] without reversion³, which is essentially our model without the quadratic term, and to other state-of-the-art methods for which source code is publicly available – BR [15], RAKEL[16] and MLKNN[20].

Model selection. Our model has two parameters: λ , the trade-off between data fitting and good generalisation, and c , a scalar that multiplies C to control the trade-off between the linear and the quadratic terms. For each experiment we selected them with 5-fold cross-validation on the training data. We also control the sparsity of C by setting C_{ij} to zero for all except the top most frequent pairs – this way we can reduce the dimensionality of θ^2 , avoiding an excessive number of parameters for datasets with large values of V . In our experiments we used 50% of the pairs with *yeast* and 5% with *enron* (45 and 68 pairs, respectively). We experimented with other settings, but the results were very similar.

RML’s only parameter, λ , was selected with 5-fold cross-validation. MLKNN’s two parameters k (number of neighbors) and s (strength of the uniform prior) were kept fixed to 10 and 1.0, respectively, as was done in [20]. RAKEL’s m (number of models) and t (threshold) were set to the library’s default (respectively $2 * N$ and 0.5), and k (size of the labelset) was set to $\frac{V}{2}$ as suggested by [4]. For BR we kept the library’s defaults.

Implementation. Our implementation is in C++, based on the source code of RML[11], which uses the *Bundle Methods for Risk Minimization* (BMRM) of [18]. The max-flow computations needed for graph-cuts are done with the library of [21]. The modifications necessary to enforce positivity in θ^2 in BMRM are described in Appendix C. Source code is available⁴ under the Mozilla Public License. Details of training time for our implementation are available in Appendix B.

Results: F-Score. In Figure 1 we plot the F -Score for varying-sized subsets of the unary features, for both *enron* (left) and *yeast* (right). The goal is to assess the benefits of explicitly modelling the pairwise label interactions, particularly when the unary information is deteriorated. As can be seen in Figure 1, when all features are available our model behaves similarly to RML. In this setting the unary features are very informative and the pairwise interactions are not helpful. As we reduce the number of available unary features (from right to left in the plots), the importance of the pairwise interactions increase, and our model demonstrates improvement over RML.

²<http://mulan.sourceforge.net/datasets.html>

³RML deals mainly with the reverse problem of predicting instances given labels, however it can be applied in the forward direction as well as described in [11].

⁴<http://users.cecs.anu.edu.au/~jpjpeterson/>.

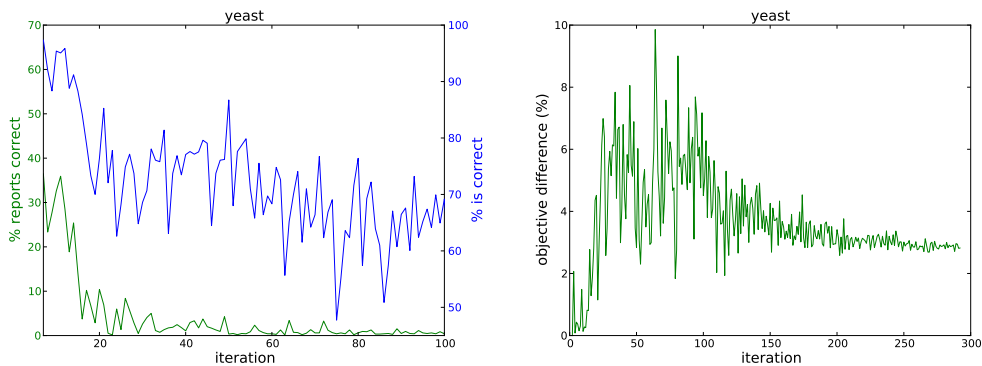


Figure 2: Empirical analysis of Algorithms 2 and 3 during training with the *yeast* dataset. Left: frequency with which Algorithm 2 is optimal at each iteration (blue) and frequency with which Algorithm 3 reports an optimal solution has been found by Algorithm 2 (green). Right: difference, at each iteration, between the objective computed using the results from Algorithm 2 and exhaustive enumeration.

Results: Correctness. To evaluate how well our constraint generation algorithm performs in practice we compared its results against those of exhaustive search, which is exact but only feasible for a dataset with a small number of labels, such as *yeast*. We also assessed the strength of our test proposed in Algorithm 3. In Figure 2-left we plot, for the first 100 iterations of the learning algorithm, the frequency with which Algorithm 2 returns the exact solution (blue line) as well as the frequency with which the test given in Algorithm 3 guarantees the solution is exact (green line). We can see that overall in more than 50% of its executions Algorithm 2 produces an optimal solution. Our test effectively offers a lower bound which is as expected is not tight, however it is informative in the sense that its variations reflect legitimate variations in the real quantity of interest (as can be seen by the obvious correlation between the two curves).

For the learning algorithm, however, what we are interested in is the objective o_i and the gradient g_i of line 7 of Algorithm 1, and both depend only on the compound result of N executions of Algorithm 2 at each iteration of the learning algorithm. This is illustrated in Figure 2-right, where we plot, for each iteration, the normalised difference between the objective computed with results from Algorithm 2 and the one computed with the results of an exact exhaustive search⁵. We can see that the difference is quite small – below 4% after the initial iterations.

6 Conclusion

We presented a method for learning multi-label classifiers which explicitly models label dependencies in a submodular fashion. As an estimator we use structured support vector machines solved with constraint generation. Our key contribution is an algorithm for constraint generation which is proven to be partially optimal in the sense that all labels it predicts are included in some optimal solution. We also describe an efficiently computable test that if positive guarantees the solution found is optimal, and can be used to generate empirical lower bounds on the probability of finding an optimal solution. We present empirical results that corroborate the fact that the algorithm is very accurate, and we illustrate the gains obtained in comparison to other popular algorithms, particularly a previous algorithm which can be seen as the particular case of ours when there are no explicit label interactions being modelled.

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⁵We repeated this experiment with several sets of parameters with similar results.

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Appendix A

Proof of Theorem 1

The proof of Theorem 1 consists of two main steps. First, we show that there must be an optimal solution to equation 8 with at least as many 1s as the solution found by our algorithm. This is clearly a necessary condition for Theorem 1 to hold. Next we show that, for any possible solution found by our algorithm, there will be one such optimal solution which will indeed agree with our solution on all its 1s. This proves the theorem. The first step is proven in proposition 5 below, which requires supporting results that we prove first. The theorem is then proved in the sequence.

Lemma 3 *Let $Y_k^* = \operatorname{argmax}_y y^T A^{[k],n} y$, where $A^{[k],n}$ is such that $\operatorname{diag}(A^{[k],n}) := \operatorname{diag}(A) - \frac{2y^n}{k + \|y^n\|^2}$ and $A_{ij} = \langle \theta_{ij}, C_{ij} \rangle$ for $i \neq j$, with $\theta_{ij} \geq 0$ and $C_{ij} \geq 0$. Now let $l \geq k$ and define similarly Y_l^* . Then for every $y_k^* \in Y_k^*$ there exists a $y_l^* \in Y_l^*$ such that $y_k^* \odot y_l^* = y_k^*$ (and, conversely, for every $y_l^* \in Y_l^*$ there exists a $y_k^* \in Y_k^*$ such that $y_k^* \odot y_l^* = y_k^*$).*

Proof The claim states that for any optimal solution $y_k^* \in Y_k^*$, its 1s will also be present in some optimal solution $y_l^* \in Y_l^*$. The proof is by contradiction, assuming that there exists $y_k^* \in Y_k^*$ and an index i such that $y_k^*(i) = 1$ and $y_l^*(i) = 0$ for all $y_l^* \in Y_l^*$. Now consider the binary vector z_l which agrees with y_l^* everywhere except in i , i.e. $z_l(j) = y_l^*(j)$ for $j \neq i$ and $z_l(i) = 1$. This implies that $z_l^T A^{[l],n} z_l = y_l^{*T} A^{[l],n} y_l^* + A_{ii}^{[l],n} + \sum_{j:j \neq i} A_{ij}^{[l],n}$. Now note that we necessarily have $\sum_{j:j \neq i} A_{ij}^{[l],n} + A_{ii}^{[l],n} \geq 0$. This holds because, first, $\sum_{j:j \neq i} A_{ij}^{[k],n} + A_{ii}^{[k],n} \geq 0$ (otherwise y_k^* would not be optimal), second, $A_{ii}^{[l],n} \geq A_{ii}^{[k],n}$ and third that $A_{ij}^{[l],n} = A_{ij}^{[k],n}$ for $i \neq j$. Therefore $z_l^T A^{[l],n} z_l \geq y_l^{*T} A^{[l],n} y_l^*$, which implies that $z_l \in Y_l^*$, which contradicts the assumption that for all $y_l^* \in Y_l^*$, $y_l^*(i) = 0$. The converse is proved analogously. ■

Intuitively, the above result says that due to the non-negativity of the off-diagonal elements of A , the new objective function arisen from an increase in the diagonal of A surely has some maximiser which includes all 1s already present in any maximiser of the previous objective function, prior to the increase in the diagonal.

Corollary 4 *Let $l \geq k$. Then $\max_y y^T A^{[l],n} y \geq \max_y y^T A^{[k],n} y$.*

Proof Note that the set of 1s potentially present in a y_l^* but not in a y_k^* for which $y_l^* \odot y_k^* = y_k^*$ necessarily has non-negative contribution to the objective function $y^T A^{[l],n} y$ (otherwise y_l^* would not be optimal), jointly with the fact that the same is true for the set of 1s present both in y_l^* and y_k^* since $A_{ii}^{[l],n} \geq A_{ii}^{[k],n}$ for any i . ■

We are now ready to prove that there exists an optimal solution to the constraint generation problem in equation 8 which contains at least k_{max} 1s.

Proposition 5 *Let $k' \geq k_{max}$, where k_{max} is as instantiated in Algorithm 2. Then there exists an optimal solution $y^{*n} \in \operatorname{argmax}_y y^T A^n(y) y$ such that for some k' , we have $y^{*n} \in \operatorname{argmax}_{y \in \mathcal{Y}_{k'}} y^T A^{[k'],n} y$.*

Proof This follows from equation 9 and from the claim that for all $k \leq k_{max}$, $\max_{y \in \mathcal{Y}_{k_{max}}} y^T A^{[k_{max}],n} y \geq \max_{y \in \mathcal{Y}_k} y^T A^{[k],n} y$, which we now prove. We know that $\max_y y^T A^{[k_{max}],n} y = \max_{y \in \mathcal{Y}_{k_{max}}} y^T A^{[k_{max}],n} y$ holds since, from lines 8 and 10 of Algorithm 2, we have $k_{max} = |y_{k_{max}}^{*n}|$. On the other hand, we have $\max_y y^T A^{[k],n} y \geq \max_{y \in \mathcal{Y}_k} y^T A^{[k],n} y$ since $\mathcal{Y}_k \subseteq \mathcal{Y}$. Both facts, when put together with corollary 4, prove the claim. ■

We are now able to give a proof of Theorem 1.

Proof of Theorem 1 We show that for any solution $y_{k_{max}}^{*n}$ found by Algorithm 2, we have that $y_{k_{max}}^{*n} \odot y^{*n} = y_{k_{max}}^{*n}$ for some optimal solution y^{*n} having at least k_{max} 1s. We proceed by contradiction, assuming that there is no optimal solution y^{*n} respecting $|y^{*n}| \geq k_{max}$ such that $y_{k_{max}}^{*n} \odot y^{*n} = y_{k_{max}}^{*n}$ holds, for any $y_{k_{max}}^{*n}$. This is equivalent to saying that for every y^{*n} respecting $|y^{*n}| \geq k_{max}$ there is an index i (which can be different for different y^{*n}) such that $y^{*n}(i) = 0$ and $y_{k_{max}}^{*n}(i) = 1$ for any $y_{k_{max}}^{*n}$. Now consider a vector z that agrees with y^{*n} everywhere except in index i , i.e., $z(i) = 1$. The key observation now is that $z^T A^{[|z|],n} z \geq (y^{*n})^T A^{[|y^{*n}|],n} y^{*n}$, and therefore z should be an optimal solution as well, which results in a contradiction. To see why this inequality holds, first note that $z^T A^{[|z|],n} z - (y^{*n})^T A^{[|y^{*n}|],n} y^{*n} = \sum_i (A_{ii}^{[|z|],n} - A_{ii}^{[|y^{*n}|],n}) + \sum_{j \neq i} A_{ij}$, where the first sum accounts for the potential change in the diagonal due to the increase in the cardinality of the solution, and the second sum accounts for the newly incorporated off-diagonal terms as a result of $z(i) = 1$. The result then follows from the submodularity assumption ($A_{ij} \geq 0, \forall i \neq j$) and from the fact that the diagonal is non-decreasing with respect to increases in the cardinality of the solution ($A_{ii}^{[|z|],n} - A_{ii}^{[|y^{*n}|],n} \geq 0, \forall i$, since $|z| > |y^{*n}|$). ■

Proof of Theorem 2 The theorem results directly from the fact that inequality 14 characterises the condition when the algorithm fails, as well as from the fact that $\max_{\alpha} \beta_{A,\alpha} \geq \beta_{A,\alpha}$ and $\epsilon_{k_{max}}^V |y^n| \geq \gamma_{\alpha}$. ■

Appendix B

Training time

The time the algorithm takes to train depends on the average time per iteration and on the number of iterations.

At each iteration run time is dominated by the N calls to the constraint generation algorithm, where each one may require at most V calls to the max-flow algorithm. The computational complexity of the whole learning algorithm is therefore $O(iNV^4)$, where i is the number of iterations. In practice, however, it is much faster than that.

In Table 2 we summarise training times along the variables mentioned above, for the experiments with all the features (rightmost bars in Figure 1). Note that our implementation is multi-threaded, and scales almost linearly with the number of available cpus, so wall-clock times can be much smaller.

Table 2: Training times

Dataset	Training time	i	N	V	Time/call to Alg. 2
Yeast	47.8 cpu-seconds	205	1500	14	155 us
Enron	847.3 cpu-seconds	116	1123	53	6504 us

In comparison to RML[11], our method is 5.0 times slower in the Yeast dataset and 8.4 times slower in the Enron dataset. Since it is a strict generalisation of RML, slower runtimes are expected.

Appendix C

Adding positivity constraint to BMRM

BMRM ([18]) approximates the solution to an optimisation problem of the form

$$\underset{\theta}{\text{minimize}} \left[R_{emp}(\theta) + \frac{\lambda}{2} \|\theta\|^2 \right] \quad (16a)$$

$$\text{where } R_{emp}(\theta) = \frac{1}{N} \sum_{n=1}^N l(x_n, y_n, \theta) \quad (16b)$$

by iteratively solving a linear program arising from a lower bound based on a first-order Taylor approximation of l . Denoting $a_{i+1} := \partial_{\theta} R_{emp}(\theta_i)$ and $b_{i+1} := R_{emp}(\theta_i) - \langle a_{i+1}, \theta_i \rangle$, where i corresponds to the iteration number, the problem that is solved is

$$\underset{\theta, \xi}{\text{minimize}} \frac{\lambda}{2} \|\theta\|^2 + \xi \quad (17a)$$

$$\text{subject to } \langle a_j, \theta \rangle + b_j \leq \xi \quad \text{for all } j \leq i \quad \text{and } \xi \geq 0. \quad (17b)$$

This is done by, at each iteration, solving the dual of eq. (17):

$$\underset{\alpha}{\text{maximize}} -\frac{1}{2\lambda} \alpha^T A^T A \alpha + \alpha^T b \quad (18a)$$

$$\text{s.t. } \mathbf{1}^T \alpha \leq 1, \quad \alpha \geq \mathbf{0} \quad (18b)$$

where A denotes the matrix $[a_1 a_2 \dots a_i]$, b the vector $[b_1 b_2 \dots b_i]^T$ and $\theta = -\frac{1}{\lambda} A \alpha$.

Enforcing positivity in θ^2 amounts to adding the additional constraint $\theta^2 \geq \mathbf{0}$ to eq. (17), and the corresponding dual problem now becomes:

$$\underset{\alpha, \gamma}{\text{maximize}} -\frac{1}{2\lambda} (\alpha^T A^T A \alpha + \gamma^T \gamma - 2\alpha^T A_1^T \gamma) + \alpha^T b \quad (19a)$$

$$\text{s.t. } \mathbf{1}^T \alpha \leq 1, \quad \alpha \geq \mathbf{0}, \quad \gamma \geq \mathbf{0} \quad (19b)$$

where A_1 is the subset of the rows of A that correspond to the gradient w.r.t. θ^2 .