

Dissimilarity in Graph-Based Semi-Supervised Classification

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Example: Predict political party from Web blogs

You were the one who thought it should be investigated last week.

No I didn't, and I made it clear. You are insane! YOU are the one with NO ****ING RESPECT FOR DEMOCRACY!



x_1

(actual postings)



x_2

They disagree. $\rightarrow y_1 \neq y_2$, known as **cannot-links** in clustering.

Our contribution: A **convex** formula that incorporates both cannot-links and must-links for binary and multiclass classification.

Binary Classification

Existing graph-based semi-supervised learning requires a graph W

- For example, a kNN graph over data points
- w_{ij} is the edge weight between x_i and x_j
- Discriminant f regularized by $\frac{1}{2} \sum_{i,j=1}^n w_{ij} (f(x_i) - f(x_j))^2$.
- Can be written as $f^T \mathcal{L} f$
- w_{ij} is essentially **must-links** in clustering

We want to add cannot-links.

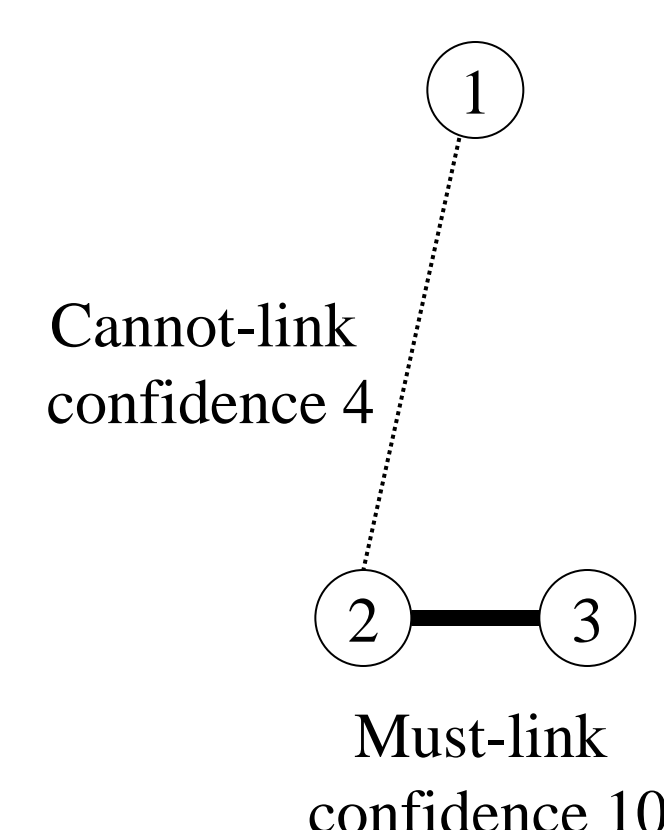
Things that do not work:

- Small or zero w : no-link instead of cannot-link
- Negative w : unbounded solution; non-convex problem

Our solution: encode cannot-links between x_i and x_j as

$$w_{ij} (f(x_i) + f(x_j))^2.$$

Both cannot-links and must-links can be represented by a mixed graph, where each edge has two variables s_{ij} (1 if must-link, -1 if cannot-link) and w_{ij} (confidence, non-negative).



$$S = \begin{bmatrix} 1 & 2 & 3 \\ 1 & 0 & -1 & 0 \\ 2 & -1 & 0 & 1 \\ 3 & 0 & 1 & 0 \end{bmatrix}$$

$$W = \begin{bmatrix} 1 & 2 & 3 \\ 1 & 0 & 4 & 0 \\ 2 & 4 & 0 & 10 \\ 3 & 0 & 10 & 0 \end{bmatrix}$$

The new regularizer is

$$f^T \mathcal{M} f = \frac{1}{2} \sum_{i,j=1}^n w_{ij} (f(x_i) - s_{ij} f(x_j))^2.$$

The “mixed graph Laplacian” is

$$\mathcal{M} = \mathcal{L} + (1 - S) \bullet W,$$

where M is positive semi-definite, and reverts to the standard graph Laplacian L if there are no cannot-links.

The *convex* binary classification problem is

$$\min_{f \in \mathcal{H}} \sum_{i=1}^l c(y_i, f(x_i)) + \lambda_1 \|f\|_{\mathcal{H}}^2 + \lambda_2 f^T \mathcal{M} f.$$

with any convex loss function $c()$.

Multiclass Classification

It is not trivial to incorporate cannot-links into multiclass semi-supervised classification.

Things that do not work:

- 1-vs-rest: cannot-links become must-links in “rest.”
- 1-vs-1: cannot determine which unlabeled points to participate.
- Warped kernel in multiclass kernel machine.

We use Lee, Lin & Wahba (2004) multiclass SVM encoding, which encodes $y=j$ in a k class problem as the zero-sum vector

$$\begin{bmatrix} -\frac{1}{k-1} \\ \vdots \\ 1 \\ \vdots \\ -\frac{1}{k-1} \end{bmatrix}$$

If we want a cannot-link between x_s and x_t , the “good” and “bad” y 's, when summed up, are

$$\begin{bmatrix} -\frac{1}{k-1} \\ \vdots \\ 1 \\ \vdots \\ -\frac{1}{k-1} \end{bmatrix} + \begin{bmatrix} -\frac{1}{k-1} \\ \vdots \\ 1 \\ \vdots \\ -\frac{1}{k-1} \end{bmatrix} = \begin{bmatrix} -\frac{2}{k-1} \\ \vdots \\ 2 \\ \vdots \\ -\frac{2}{k-1} \end{bmatrix}$$

$$\begin{bmatrix} -\frac{1}{k-1} \\ \vdots \\ 1 \\ \vdots \\ -\frac{1}{k-1} \end{bmatrix} + \begin{bmatrix} -\frac{1}{k-1} \\ \vdots \\ 1 \\ \vdots \\ -\frac{1}{k-1} \end{bmatrix} = \begin{bmatrix} -\frac{2}{k-1} \\ \vdots \\ 2 \\ \vdots \\ -\frac{2}{k-1} \end{bmatrix}$$

So we do not want any element in $f(x_i) + f(x_j)$ larger than $(k-2)/(k-1)$. This is achieved with the convex regularizer

$$\sum_{(s,t) \in \mathcal{D}} \sum_{j=1}^k \left(f_j(x_s) + f_j(x_t) - \frac{k-2}{k-1} \right)_+^p,$$

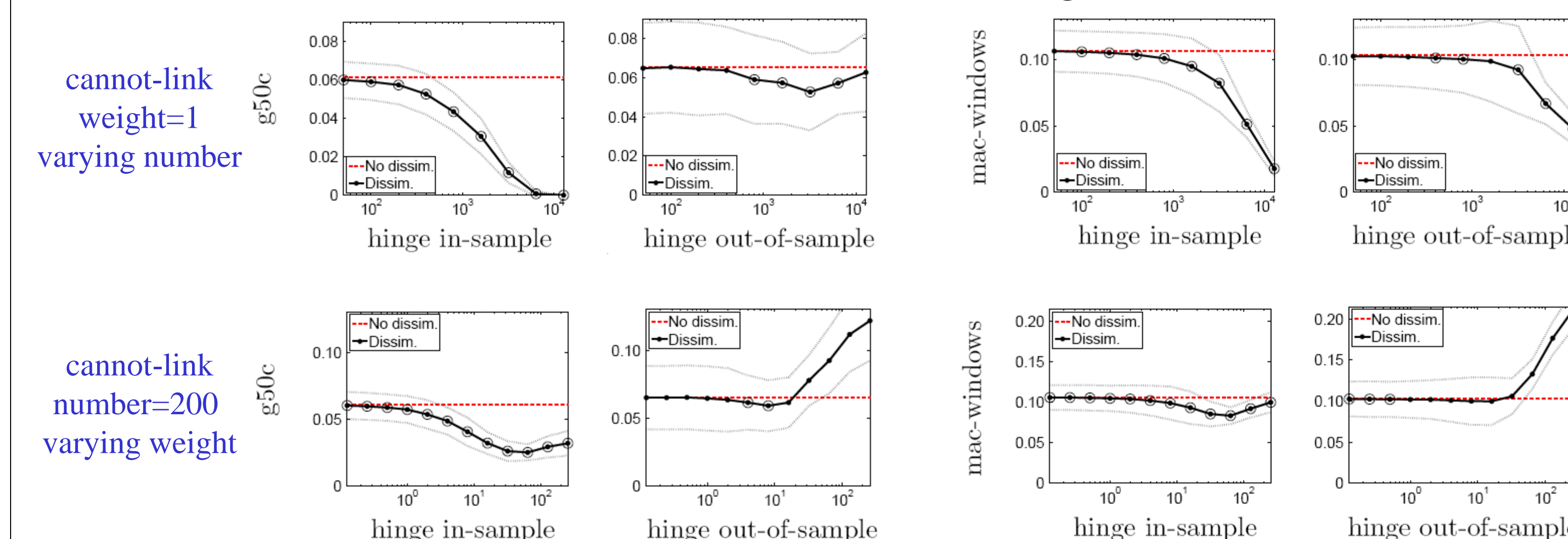
The convex multiclass SVM classification problem is

$$\min \frac{1}{l} \sum_{i=1}^l L_i(f(x_i) - y_i)_+ + \lambda_1 \sum_{j=1}^k \|h_j\|_{\mathcal{H}}^2 + \frac{\lambda_2}{|\mathcal{D}|} \sum_{(s,t) \in \mathcal{D}} \sum_{j=1}^k \left(f_j(x_s) + f_j(x_t) - \frac{k-2}{k-1} \right)_+^p$$

$$\text{s.t.} \quad \sum_{j=1}^k f_j(x_i) = 0, \quad i = 1 \dots n,$$

Experiments

Binary classification, oracle cannot-links (g50c, mac-window, $n \approx 1000$, $l=50$, kNN must-links with RBF weight)



Multiclass classification, oracle cannot-links (USPS, $n \approx 2000$, $k=10$, $l=50$)

	Dissim.	Overall	In-sample	Out-of-sample
baseline	0	24.48	24.48	24.48
	10	24.41	20.47	24.40
	20	24.32	23.53	24.33
	40	24.27	24.17	24.27
	80	23.96	23.57	23.99
	160	23.63	24.49	23.48
	320	23.30	23.57	23.20

Binary classification, real cannot-links (politics.com, $n=184$, $l=50$)

Cannot-link(A,B) if twice, A or B quotes the other, and text next to quote has ??, or !!, or ALL CAPS.

Classifier	Base error rate	SSL error rate	Δ
SVM	45.67 \pm 3.28	40.15 \pm 4.95	5.5%
RLS	45.60 \pm 3.94	37.99 \pm 1.88	7.6%

