CROWDSOURCING

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BASELINES

- 1. Majority Voting
- 2. Hubs and Authorities
- 3. Singular vector approach
- 4. EM
- 5. EM with priors
- 6. Iterative Weighted Majority Voting
- 7. Simplified BP
- 8. Discretized BP
- 9. Tree-reweighted message passing¹
- 10. Spectral Meets EM¹

¹never finished...

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1

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EM WITH PRIORS

Define

$$g_{ij}(t_i, p_j) = p_j \mathbf{I} \{A_{ij} = t_i\} + (1 - p_j) \mathbf{I} \{A_{ij} \neq t_i\}$$

EM WITH PRIORS

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Full likelihood (with Beta priors):

$$\mathcal{L}(p;t) = \prod_{i,j} g_{ij}(t_i, p_j) \prod_j \left(c + \frac{1-c}{B(\alpha, \beta)} p_j^{\alpha-1} (1-p_j)^{\beta-1} \right)$$

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M-Step becomes:

$$p_{j} = \frac{\alpha - 1 + \sum_{j} q(A_{ij})}{\alpha + \beta - 2 + \sum_{j} q(A_{ij}) + \sum_{j} q(-A_{ij})}$$

(Note: this same result is a lower bound on the situation where priors come from $p_j=0.1+0.9 \it Z$)

ITERATIVE WEIGHTED MAJORITY VOTING (IWMV)

From Error Rate Bounds and Iterative Weighted Majority Voting for Crowdsourcing by Hongwei Li and Bin Yu²

Algorithm 1 The iterative weighted majority voting algorithm (IWMV)

Input: Number of workers= M; Number of items= N; data matrix: $Z \in \overline{[L]}^{M \times N}$;

Output: the predicted labels $\{\hat{y}_1, \hat{y}_2, ..., \hat{y}_N\}$

Initialization: $\nu_i = 1, \ \forall i \in [M]; \ T_{ij} = \mathbb{I}(Z_{ij} \neq 0), \forall i \in [M], \forall j \in [N].$

repeat

$$\begin{split} \hat{y}_j \leftarrow & \operatorname*{argmax}_{k \in [L]} \sum_{i=1}^M \nu_i \mathbf{I} \left(Z_{ij} = k \right), \qquad \forall j \in [N]. \\ \hat{w}_i \leftarrow & \frac{\sum_{j=1}^N \mathbf{I} \left(Z_{ij} = \hat{y}_j \right)}{\sum_{j=1}^N T_{ij}}, \qquad \forall i \in [M]. \\ \nu_i \leftarrow L \hat{w}_i - 1, \qquad \forall i \in [M]. \end{split}$$

until converges or reaches S iterations.

Output the predictions $\{\hat{y}_j\}_{j\in[N]}$ by $\hat{y}_j = \operatorname{argmax}_{k\in[L]} \sum_{i=1}^{M} \nu_i I(Z_{ij} = k)$.

²http://arxiv.org/pdf/1411.4086v1.pdf

DISCRETIZED BP

Original BP udpates are:

$$y_{a \to i}^{(k)}(p_a) \propto \mathcal{F}(p_a) \prod_{j \in \partial a \setminus i} \left\{ (p_a + \bar{p}_a + (p_a - \bar{p}_a) A_{ja}) x_{j \to a}^{(k)}(+1) + (p_a + \bar{p}_a - (p_a) A_{ja}) x_{j \to a}^{(k)}(+1) + (p_a + \bar{p}_a - (p_a) A_{ja}) x_{j \to a}^{(k)}(+1) \right\}$$

$$x_{i \to a}^{(k+1)}(\hat{t}_i) \propto \prod_{b \in \partial i \setminus a} \int \left(y_{b \to i}^{(k)}(p_b) (p_b \mathbb{I}_{(A_{ib} = \hat{t}_i)} + \bar{p}_b \mathbb{I}_{(A_{ib} \neq \hat{t}_i)}) \right) dp_b$$

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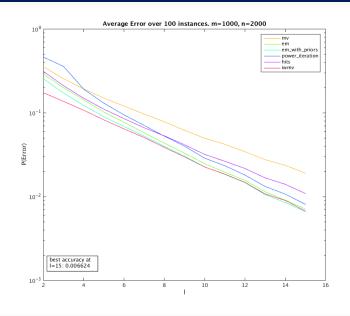
$$x_{i \to a}^{(k+1)}(\hat{t}_i) \propto \prod_{b \in \partial i \setminus a} \int \left(y_{b \to i}^{(k)}(p_b) (p_b \mathbb{I}_{(A_{ib} = \hat{t}_i)} + \bar{p}_b \mathbb{I}_{(A_{ib} \neq \hat{t}_i)}) \right) dp_b$$

Discretize p_j :

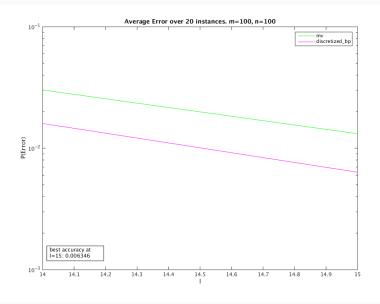
$$x_{i \to a}^{(k+1)}(\hat{t}_i) \propto \prod_{b \in \partial i \setminus a} \sum_{p_b \in P} \left(y_{b \to i}^{(k)}(p_b) (p_b \mathbb{I}_{(A_{ib} = \hat{t}_i)} + \bar{p}_b \mathbb{I}_{(A_{ib} \neq \hat{t}_i)}) \right)$$

For
$$P = \{p_1, p_2, p_3, ..., p_k\}$$

GRAPH



GRAPH



Algorithm	m, n	$\ell = 15$
Discretized BP	100,100	0.006346
EM with Priors	100,100	0.008478
EM with Priors	1000,2000	0.006624
EM with Priors	250,2000	0.005512
Simplified BP	250,2000	0.005466
IWMV	250,2000	0.0057