

13. Approximation algorithms for $(\text{Min}, +)$ -problems

We still consider the task

$$s^* \in \operatorname{argmin}_{s \in K^V} U(s) = \operatorname{argmin}_{s \in K^V} \left[\sum_{i \in V} u_i(s_i) + \sum_{(i,j) \in E} u_{ij}(s_i, s_j) \right]$$

A. Iterated descent

- define a family of neighbourhoods $N_m(s) \subset K^V$, $m=1, \dots, M$
- repeatedly solve the restricted problem

$$s^{(t+1)} \in \operatorname{argmin}_{s \in N_m(s^{(t)})} U(s)$$

until no further improvement is possible, i.e.

$$s^{(t)} \in \operatorname{argmin}_{s \in N_m(s^{(t)})} U(s) \quad \forall m=1, \dots, M$$

α -Expansions (Boykov et al. 2001)

For each label $\alpha \in K$ define the neighbourhood

$$N_\alpha(s) = \{s' \in K^V / s'_i = \alpha \text{ if } s'_i \neq s_i \quad \forall i \in V\}$$

Their sizes are exponential, i.e. $|N_\alpha(s)| \sim 2^{|V|}$

Is the task $\operatorname{argmin}_{s \in N_\alpha(s')} U(s)$ solvable in polynomial time?

Yes, if $u_{ij}(k, k') + u_{ij}(\alpha, \alpha') \leq u_{ij}(k, \alpha') + u_{ij}(\alpha, k')$ holds

$\forall \{i, j\} \in E$ and $\forall k, k' \in K \setminus \alpha$. This can be seen by constructing a binary valued $(\text{Min}, +)$ -problem that is equivalent to the considered restricted optimisation task

$$V' = \{i \in V \mid s_i \neq \alpha\}, \quad E' = \{\{i, j\} \in E \mid i, j \in V'\}$$

$y_i = 0, 1$ encodes $s \in N_\alpha(s')$, i.e.

$$s_i = s'_i \Leftrightarrow y_i = 0 \quad \text{and} \quad s_i = \alpha \Leftrightarrow y_i = 1$$

The pairwise functions of this equivalent problem are submodular if the condition given above holds.

Example 1 Consider the Potts model $U_{ij}(k, k') = Q_{ij} (1 - \delta_{kk'})$, $Q_{ij} > 0$. It is not submodular if $|K| > 2$, however, it fulfills the above conditions.

Theorem 1 (w/o proof)

Let \bar{s} be a fixpoint of α -expansions $\forall \alpha \in K$. Then

$U(\bar{s}) \leq 2C \min_{s \in K^V} U(s)$, where C is defined by

$$C = \max_{ij \in E} \frac{\max_{k \neq k'} U_{ij}(k, k')}{\min_{k \neq k'} U_{ij}(k, k')} . \quad \blacksquare$$

$\alpha\beta$ Swaps (Boykov et al. 2001)

Define neighbourhoods $N_{\alpha\beta}$ for each pair of labels

$$N_{\alpha\beta}(s') = \{s \in K^V \mid s_i = \begin{cases} s'_i & \text{if } s'_i \neq \alpha, \beta \\ \alpha, \beta & \text{otherwise} \end{cases} \forall i \in V\}$$

The reduced task $\underset{s \in N_{\alpha\beta}(s')}{\operatorname{argmin}} U(s)$ is tractable if the

restriction of every $U_{ij}: K^2 \rightarrow \mathbb{R}$ to $\{\alpha, \beta\}^2 \subset K^2$ is submodular $\forall \alpha, \beta \in K$.

Example 2 Consider the truncated metric on $K \subset \mathbb{Z}$

$$U_{ij}(k, k') = a_{ij} \min(C, |k - k'|), \quad a_{ij} > 0.$$

It is not submodular. It allows $\alpha\beta$ -swaps, but does not allow α -expansions. \blacksquare

Remark 1 Another class of approximation algorithms construct submodular upper bounds (instead of considering restricted problems). I.e. given $s^{(t)}$, construct a submodular upper bound s.t.

$$\hat{U}_t(s) \geq U(s) \quad \forall s \in K^V \text{ and } \hat{U}_t(s^{(t)}) = U(s^{(t)}).$$

Then, solve

$$s^{(t+1)} \in \operatorname{argmax}_{s \in K^V} \hat{U}_t(s)$$

B. Algorithms based on LP-relaxations

Loopy belief propagation (aka message passing): Apply equivalent transformations which resemble dynamic programming on trees, until convergence. Not well grounded. See next section.

More principled! Start from an LP-relaxation of the discrete optimisation problem

$$U(s) = \sum_{i \in V} u_i(s_i) + \sum_{ij \in E} u_{ij}(s_i, s_j) \rightarrow \min_{s \in K^V}$$

A lower bound is given by

$$\sum_{i \in V} \min_{k \in K} u_i(k) + \sum_{ij \in E} \min_{k_i, k_j \in K} u_{ij}(k_i, k_j) \leq \min_{s \in K^V} U(s)$$

Combine it with equivalent transformations and maximise the lower bound w.r.t. them

$$\begin{aligned} B(\Psi) &= \sum_{i \in V} \min_{k \in K} \left[u_i(k) - \sum_{j \in N_i} \psi_{ij}(k) \right] + \\ &+ \sum_{ij \in E} \min_{k_i, k_j} \left[\psi_{ij}(k) + u_{ij}(k_i, k_j) + \psi_{ji}(k_j) \right] \rightarrow \max_{\Psi} \end{aligned}$$

This can be expressed as a linear optimisation task by introducing additional variables

$$\sum_{i \in V} c_i + \sum_{ij \in E} c_{ij} \rightarrow \max_{c_i, c_{ij}}$$

s.t.

$$c_i + \sum_{j \in N_i} \psi_{ij}(k) \leq u_i(k) \quad \forall i \in V, \forall k \in K$$

$$c_{ij} - \psi_{ij}(k) - \psi_{ji}(k') \leq u_{ij}(k, k') \quad \forall ij \in E, \forall k, k' \in K$$

Notice, that this LP-task is dual to the following direct relaxation of the discrete optimisation task.

Encode the label $s_i \in K$ by 1-out-of- K encoding with components denoted as $\lambda_i(k) = 0, 1$, and similarly for edges, by $\lambda_{ij}(k, k') = 0, 1$

$$\sum_{i \in V} \sum_{k \in K} \lambda_i(k) u_i(k) + \sum_{ij \in E} \sum_{k, k' \in K} \lambda_{ij}(k, k') u_{ij}(k, k') \rightarrow \min_{\lambda \geq 0}$$

s.t.

$$\lambda_i(k) = \sum_{k' \in K} \lambda_{ij}(k, k') \quad \forall ij \in E, \forall k \in K$$

$$\sum_{k \in K} \lambda_i(k) = 1 \quad \forall i \in V$$

$$\sum_{k, k'} \lambda_{ij}(k, k') = 1 \quad \forall ij \in E$$

Relaxing the integrality constraints $\lambda_i(k) = 0, 1$, $\lambda_{ij}(k, k') = 0, 1$ makes this an LP-task.

Find suitable algorithms for solving the primal task, or the dual task, or both simultaneously.