

12. (Min,+)-problems for graphical modelsMAP inference for GRFs

- $x = \{x_j \in F \mid j \in V\}$ a random field of features (observable)
- $s = \{s_i \in K \mid i \in V\}$ — " — of hidden states

Assume, their joint p.d. is a GRF w.r.t. the system \mathcal{C} of subsets of V

$$p(x, s) = \frac{1}{Z} \exp \left[\sum_{C \in \mathcal{C}} U_C(x_C, s_C) \right]$$

Inference: Given $x \in F^V$ infer $s \in K^V$ w.r.t. 0/1 loss \Rightarrow MAP

$$s^* \in \operatorname{argmax}_{s \in K^V} p(x, s) = \operatorname{argmax}_{s \in K^V} \sum_{C \in \mathcal{C}} U_C(x_C, s_C)$$

- discrete optimisation problem for $|V|$ variables
- objective function $\hat{=}$ sum of functions, each depending on a subset of variables

Particular case: \mathcal{C} is the structure of a graph (V, E)

Solve the task

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

- Easy to solve if (V, E) is acyclic
- NP complete in general (MaxClique)

Options:

- search for tractable subclasses
- search for approximation algorithms

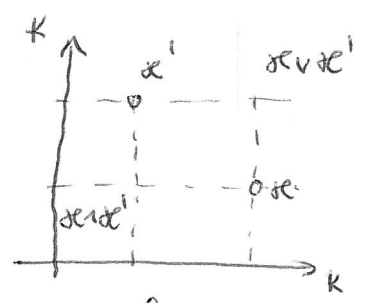
Submodular (Min, +)-problems

- Let K be completely ordered and denote min, max w.r.t. this order by \wedge, \vee
- K^n is a distributive lattice $\hat{=}$ poset with operations „infimum“ and „supremum“

$$x, x' \in K^n$$

$$x \wedge x' = (x_1 \wedge x'_1, \dots, x_n \wedge x'_n)$$

$$x \vee x' = (x_1 \vee x'_1, \dots, x_n \vee x'_1)$$



Definition 1 Let K be completely ordered. A real valued function

$U: K^n \rightarrow \mathbb{R}$ is submodular if

$$U(x \wedge x') + U(x \vee x') \leq U(x) + U(x')$$

holds $\forall x, x' \in K^n$.



Remarks

- (1) If " \leq " replaced by " \geq " \Rightarrow supermodular function
- (2) any function $U: K \rightarrow \mathbb{R}$ is submodular and supermodular
- (3) any function $U: K^2 \rightarrow \mathbb{R}$ can be decomposed into a sum of a super- and submodular part
- (4) if $|K|=2$, then K^V is a Boolean lattice and any $x \in K^V$ can be identified with a subset of $V: \{i \in V \mid x_i = 1\}$ (we assume $K = \{0, 1\}$)

Examples

- (1) Let $K = \{0, 1\}$ be ordered. The function $U: K^2 \rightarrow \mathbb{R}$ defined by $U(k, k') = |k - k'|$ is submodular
- (2) Let $K = \{0, 1, 2, \dots, m\}$ be ordered. Consider functions $U: K^2 \rightarrow \mathbb{R}$
 - $U(k, k') = |k - k'|$ is submodular
 - $U(k, k') = \mathbb{1}\{k \neq k'\}$ is not submodular

(3) Let $K = \{0, 1, 2, \dots, m\}$ be ordered. Consider the function $u: K^n \rightarrow \mathbb{R}$ defined by $u(k_1, \dots, k_n) = \max_i k_i - \min_i k_i$. It is submodular.

Theorem 1 (Iwata, Fleisher, Fujishige)

Any submodular function on $\{0, 1\}^n$ can be minimised with complexity $\mathcal{O}(n^6 \mu + n^7 \log n)$, where μ denotes the time required for computing the function value. \square

Theorem 2 (Schlesinger, Flachs, 2006)

If all arity 2 functions $u_{ij}: K^2 \rightarrow \mathbb{R}$ of a $(\text{Min}, +)$ -problem on a graph are submodular w.r.t. some ordering of K , then the $(\text{Min}, +)$ -problem is equivalent to a MinCut problem and solvable with complexity $\mathcal{O}(V^2 E K^4)$. \square

Transforming a submodular $(\text{Min}, +)$ -problem on a graph (V, E) into a MinCut problem: here, we assume $|K|=2$ for simplicity

(1) Express the $(\text{Min}, +)$ -problem in canonical form, using equivalent transformations

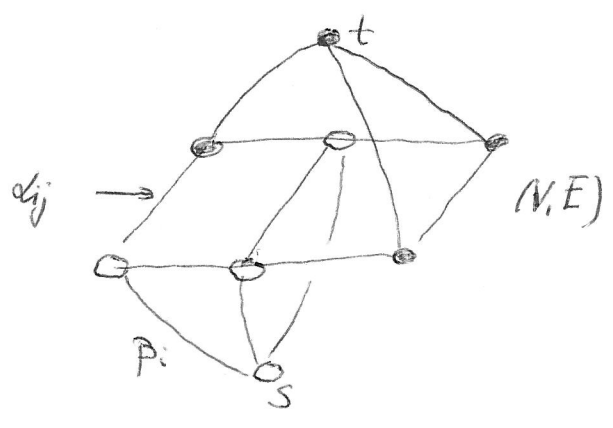
$$\sum_{ij \in E} \alpha_{ij} |s_i - s_j| + \sum_{i \in V} \beta_i s_i \rightarrow \min_{s \in K^V}$$

where $s_i = 0, 1$. Submodularity ensures $\alpha_{ij} \geq 0 \forall ij \in E$

(2) Rewrite the linear terms: Let $V_+ = \{i \in V \mid \beta_i \geq 0\}$, $V_- = V \setminus V_+$

$$\sum_{i \in V} \beta_i s_i = \sum_{i \in V_+} \beta_i s_i + \sum_{i \in V_-} |\beta_i| (1 - s_i) + \text{const}$$

(3) The task is now equivalent to an st -MinCut problem with positive edge weights



$$\tilde{V} = V \cup \{s, t\}$$

$$\tilde{E} = E \cup E_+ \cup E_-$$

$$E_+ = \{ \{s, i\} \mid i \in V_+ \}$$

$$E_- = \{ \{t, i\} \mid i \in V_- \}$$

(4) Solve it by MinCut \Leftrightarrow MaxFlow, e.g.

- augmenting path alg.
- pre-flow push alg.
- V. Kolmogorov's alg.