Machine Learning II

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Partial optimality and machine learning

Contents. In this part of the course, we discuss a technique for solving combinatorial optimization problems *partially* and *efficiently*: the construction of *improving maps*.

Definition 1. Let $Y \neq \emptyset$ finite, $\varphi \colon Y \to \mathbb{R}$ and $\sigma \colon Y \to Y$. We call σ improving for the problem $\min\{\varphi(y) \mid y \in Y\}$ iff $\varphi \circ \sigma \leq \varphi$.

Lemma 1. Let $Y \neq \emptyset$ finite and $\varphi: Y \to \mathbb{R}$. Let $\sigma: Y \to Y$ improving for the problem $\min\{\varphi(y) \mid y \in Y\}$. If $Q \subseteq Y$ and $\sigma(Y) \subseteq Q$, there exists a solution y^* such that $y^* \in Q$.

Proof. A solution y' exists because Y is non-empty and finite. $y^* := \sigma(y')$ is also a solution because σ is improving. Moreover, $y^* \in Q$ because $\sigma(Y) \subseteq Q$. \Box

Corollary 1. Let $S \neq \emptyset$ finite, $Y \subseteq \{0,1\}^S$ and $\varphi \colon Y \to \mathbb{R}$. Let $s \in S$ and $q \in \{0,1\}$. If $\sigma \colon Y \to Y$ is improving for the problem $\min\{\varphi(y) \mid y \in Y\}$ such that $\forall y \in Y \colon \sigma(y)_s = q$, there exists a solution y^* such that $y^*_s = q$.

Remark 1. If we can construct such an improving map, we can fix the variable y_s^* to q without compromising optimality.

Contents. In this part of the course, we construct improving maps for the clique partition problem, an inference problem for clustering.

References.

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- Lange J.-H., Andres B. and Swoboda P. Combinatorial persistency criteria for multicut and max-cut. CVPR 2019
- Lange J.-H., Karrenbauer A. and Andres B. Partial Optimality and Fast Lower Bounds for Weighted Correlation Clustering. ICML 2018
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Definition 2. For any $A \neq \emptyset$ finite, any $c: \binom{A}{2} \to \mathbb{R}$,

$$Y_A := \left\{ y \colon \binom{A}{2} \to \{0,1\} \mid \forall a \in A \; \forall b \in A \setminus \{a\} \; \forall c \in A \setminus \{a,b\} \colon y_{ab} + y_{bc} - 1 \le y_{ac} \right\}$$
(1)

and $\varphi_c \colon Y_A \to \mathbb{R} \colon y \mapsto \langle c, y \rangle$,

$$\min\{\varphi_c(y) \mid y \in Y_A\}\tag{2}$$

is called the instance of the (clique) partition problem wrt. A and c, which we abbreviate as CPP(A, c).

Example 1.

For any set A and any $U\subseteq A,$ we write

$$\partial U := \left\{ \{u, a\} \in \binom{A}{2} \mid u \in U \land a \notin U \right\} \quad . \tag{3}$$

Definition 3. Let $A \neq \emptyset$ finite and $U \subseteq A$.

► The elementary cut map wrt. U is the $\sigma_U : Y_A \to Y_A$ such that $\forall y \in Y_A \ \forall \{a, b\} \in \binom{A}{2}$:

$$\sigma_U(y)_{ab} = \begin{cases} 0 & \text{if } \{a, b\} \in \partial U \\ y_{ab} & \text{otherwise} \end{cases}$$
(4)

► The elementary join map wrt. U is the $\sigma'_U: Y_A \to Y_A$ such that $\forall y \in Y_A \ \forall \{a, b\} \in \binom{A}{2}$:

$$\sigma'_{U}(y)_{ab} = \begin{cases} 1 & \text{if } \{a, b\} \in \binom{U}{2} \\ 1 & \text{if } a \in U \land \exists u \in U : y_{ub} = 1 \\ 1 & \text{if } b \in U \land \exists u \in U : y_{ua} = 1 \\ 1 & \text{if } (\exists u \in U : y_{ua} = 1) \land \\ (\exists u \in U : y_{ub} = 1) \\ y_{ab} & \text{otherwise} \end{cases}$$
(5)

Remark 2. σ_U is well-defined, i.e. $\sigma_U(Y_A) \subseteq Y_A$. σ'_U is well-defined. $\sigma'_U \circ \sigma_U$ is well-defined.

To begin with, we establish a trivial partial optimality condition for the CPP:

Lemma 2. Let $A \neq \emptyset$ finite and $c: \binom{A}{2} \to \mathbb{R}$. If there exists $U \subseteq A$ such that $\forall \{a, b\} \in \partial U: \quad 0 \leq c_{ab}$, (6)

there exists a solution y^* to $\operatorname{CPP}(A, c)$ such that

$$\forall \{a, b\} \in \partial U \colon \quad y_{ab}^* = 0 \quad . \tag{7}$$

Proof. For any $y \in Y_A$, $\sigma_U(y)$ satisfies (7). Moreover, σ_U is improving for CPP(A, c) because for any $y \in Y_A$ and $y' := \sigma_U(y)$:

$$\varphi_{c}(y') - \varphi_{c}(y) = \sum_{\{a,b\} \in \binom{A}{2}} c_{ab} \, y'_{ab} - \sum_{\{a,b\} \in \binom{A}{2}} c_{ab} \, y_{ab}$$
(8)
$$= \sum_{\{a,b\} \in \binom{A}{2}} c_{ab}(y'_{ab} - y_{ab})$$
(9)

$$=\sum_{\{a,b\}\in\partial U}c_{ab}(0-y_{ab})$$
(10)

$$= -\sum_{\{a,b\}\in\partial U} c_{ab} \, y_{ab} \tag{11}$$

The assertion follows by Lemma 1.

For any $r \in \mathbb{R}$, we write

$$[r]_{+} := \begin{cases} r & \text{if } r \ge 0\\ 0 & \text{otherwise} \end{cases}$$
(13)
$$[r]_{-} := \begin{cases} 0 & \text{if } r \ge 0\\ -r & \text{otherwise} \end{cases} .$$
(14)

Next, we establish a less trivial partial optimality condition for the CPP:

Proposition 1. Let $A \neq \emptyset$ finite and $c: \binom{A}{2} \to \mathbb{R}$. If there exist $U \subseteq A$ and $\{u, v\} \in \partial U$ such that

$$\sum_{[a,b]\in\partial U\setminus\{\{u,v\}\}} [c_{ab}]_{-} \le c_{uv} , \qquad (15)$$

there exists a solution y^* to CPP(A, c) such that $y^*_{uv} = 0$.

Partial optimality and machine learning – Clustering Proof. Let $\xi: Y_A \to Y_A$ such that for all $y \in Y_A$:

$$\xi(y) = \begin{cases} y & \text{if } y_{uv} = 0\\ \sigma_U(y) & \text{otherwise} \end{cases}$$
(16)

For any $y \in Y_A$ and $y' := \xi(y)$, we have $y'_{uv} = 0$.

Moreover, ξ is improving for CPP(A, c) because for all $y \in Y_A$ and $y' := \xi(y)$, the following holds: If $y_{ab} = 0$ then $\varphi_c(y') - \varphi_c(y) = \varphi_c(y) - \varphi_c(y) = 0 \le 0$. Otherwise:

$$\varphi_c(y') - \varphi_c(y) = \sum_{\{a,b\} \in \binom{A}{2}} c_{ab}(y'_{ab} - y_{ab})$$
(17)

$$= c_{uv}(0-1) + \sum_{\{a,b\} \in \partial U \setminus \{\{u,v\}\}} c_{ab}(0-y_{ab})$$
(18)

$$= -c_{uv} - \sum_{\{a,b\}\in\partial U\setminus\{\{u,v\}\}} c_{ab} \, y_{ab} \tag{19}$$

$$\leq -c_{uv} + \sum_{\{a,b\}\in\partial U\setminus\{\{u,v\}\}} [c_{ab}]_{-}$$

$$(20)$$

$$\stackrel{(15)}{\leq} 0$$
 . (21)

The assertion follows by Lemma 1.

13/45

Next, we establish a non-trivial partial optimality condition for the CPP:

Lemma 3. Let $A \neq \emptyset$ finite and $c \colon {A \choose 2} \to \mathbb{R}$. If there exist $U \subseteq A$ such that

$$\sum_{\{u,a\}\in\partial U} [c_{ua}]_{-} \le \min_{\{s,t\}\in \binom{U}{2}} \min_{\substack{y\in Y_U \\ y_{st}=0}} \sum_{\{u,v\}\in \binom{U}{2}} (-c_{uv})(1-y_{uv}) , \qquad (22)$$

there exists a solution y^* to CPP(A, c) such that $\forall \{u, v\} \in \binom{U}{2}$: $y_{uv}^* = 1$.

Partial optimality and machine learning – Clustering *Proof.* Let $\xi \colon Y_A \to Y_A$ such that for all $y \in Y_A$:

$$\xi(y) := \begin{cases} (\sigma'_U \circ \sigma_U)(y) & \text{if } \exists \{u, v\} \in \binom{U}{2} \colon y_{uv} = 0\\ y & \text{otherwise} \end{cases}$$
(23)

For any $y \in Y_A$, $y' := \xi(y)$ and all $\{u, v\} \in {U \choose 2}$, we have $y'_{uv} = 1$.

Moreover, ξ is improving because for all $y \in Y_A$ and $y' := \xi(y)$, the following condition holds: If $\forall \{u, v\} \in {U \choose 2}$: $y_{uv} = 1$ then $\varphi_c(y') - \varphi_c(y) = \varphi_c(y) - \varphi_c(y) = 0 \le 0$. Otherwise:

$$\varphi_c(y') - \varphi_c(y) = \sum_{\{u,a\} \in \partial U} c_{ua}(0 - y_{ua}) + \sum_{\{u,v\} \in \binom{U}{2}} c_{uv}(1 - y_{uv})$$
(24)

$$\leq \sum_{\{u,a\}\in\partial U} [c_{ua}]_{-} + \max_{\{s,t\}\in\binom{U}{2}} \max_{\substack{y\in Y_U|\\y_{st}=0}} \sum_{\{u,v\}\in\binom{U}{2}} c_{uv}(1-y_{uv})$$
(25)

$$\leq \sum_{\{u,a\}\in\partial U} [c_{ua}]_{-} - \min_{\{s,t\}\in\binom{U}{2}} \min_{\substack{y\in Y_U|\\y_{st}=0}} \sum_{\{u,v\}\in\binom{U}{2}} (-c_{uv})(1-y_{uv})$$
(26)

$$\stackrel{(22)}{\leq} 0$$
 . (27)

The assertion follows by Lemma 1.

Even if set $U \subseteq A$ is given, Condition (22) of Lemma 3 cannot be checked efficiently: In general, the calculation of

$$\min_{\{s,t\} \in \binom{U}{2}} \min_{\substack{y \in Y_U | \\ y_{st} = 0}} \sum_{\{u,v\} \in \binom{U}{2}} (-c_{uv})(1 - y_{uv})$$
(28)

requires solving CPPs with the additional constraint $y_{st} = 0$.

However, in the special case where $\forall \{u, v\} \in {\binom{U}{2}}$: $c_{uv} \leq 0$, these problems become minimum *st*-cut problems that can be solved efficiently.

Hence, an idea toward applying Lemma 3 algorithmically is to work in two steps:

- 1. to heuristically search for a set \boldsymbol{U} such that
 - ▶ inside *U*, all costs are non-positive
 - on the boundary of U, the sum of the negative costs is large.
- 2. to efficiently test (22) from Lemma 3 for these sets U.

Contents: In this part of the course, we discuss partial optimality in the graphical model inference problem.

References:

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- E. Boros, P. L. Hammer, R. Sun, G. Tavares: A max-flow approach to improved lower bounds for quadratic unconstrained binary optimization (QUBO). Discrete Optimization 5(2): 501–529 (2008)

Definition 4. For any $n \in \mathbb{N}$, any $d \in \{0, \dots, n\}$, let

$$J_{nd} := \bigcup_{m=0}^{d} {\binom{\{1,\dots,n\}}{d}} \qquad C_{nd} := \mathbb{R}^{J_{nd}}$$
(29)

and call any $c \in C_{nd}$ an *n*-variate **multi-linear polynomial form** of degree at most *d*.

Example. For n = d = 2, we have

$$J_{22} = \bigcup_{m=0}^{2} {\binom{\{1,2\}}{m}} = {\binom{\{1,2\}}{0} \cup {\binom{\{1,2\}}{1}} \cup {\binom{\{1,2\}}{2}} = \{\varnothing\} \cup \{\{1\}, \{2\}\} \cup \{\{1,2\}\} = \{\varnothing, \{1\}, \{2\}, \{1,2\}\}$$

Definition 5. For any $f: A \to B$ and any $n \in \mathbb{N}$, f is called an *n*-variate pseudo-Boolean function (PBF) iff $A = \{0, 1\}^n$ and $B \subseteq \mathbb{R}$. For any $f: A \to B$, f is called a PBF iff f is an *n*-variate PBF for some $n \in \mathbb{N}$.

Definition 6. For any $n \in \mathbb{N}$, any $d \in \{0, \ldots, n\}$ and any $c \in C_{nd}$, the function f_c defined below is called the **PBF defined by** c.

$$f_c: \quad \{0,1\}^n \to \mathbb{R}: \quad x \mapsto \sum_{m=0}^d \sum_{J \in \binom{\{1,\dots,n\}}{m}} c_J \prod_{j \in J} x_j$$
(30)

Example. For any $c \in C_{22}$, f_c is such that for all $x \in \{0, 1\}^2$:

$$f_c(x_1, x_2) = c_{\varnothing} + c_{\{1\}}x_1 + c_{\{2\}}x_2 + c_{\{1,2\}}x_1x_2 .$$

Lemma 4. Every PBF has a unique multi-linear polynomial form. More precisely,

$$\forall n \in \mathbb{N} \quad \forall f : \{0, 1\}^n \to \mathbb{R} \quad \exists_1 c \in C_{nn} \quad f = f_c \quad . \tag{31}$$

Example. For n = d = 2 and any $f : \{0, 1\}^2 \to \mathbb{R}$, the existence of a $c \in C_{22}$ such that $f = f_c$ means

$$\forall x \in \{0,1\}^2: \quad f(x_1, x_2) = c_{\varnothing} + c_{\{1\}}x_1 + c_{\{2\}}x_2 + c_{\{1,2\}}x_1x_2 \quad .$$

Explicitly,

$$\begin{split} f(0,0) &= c_{\varnothing} \\ f(1,0) &= c_{\varnothing} + c_{\{1\}} \\ f(0,1) &= c_{\varnothing} + c_{\{2\}} \\ f(1,1) &= c_{\varnothing} + c_{\{1\}} + c_{\{2\}} + c_{\{1,2\}} \end{split}$$

In this example, a suitable c exists and is defined uniquely by f.

Proof. For any $J \subseteq \{1, \ldots, n\}$, let $x^J \in \{0, 1\}^n$ such that for all $j \in \{1, \ldots, n\}$:

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$$x_j^J = \begin{cases} 1 & \text{if } j \in J \\ 0 & \text{otherwise} \end{cases}$$

Now,

$$\forall x \in \{0,1\}^n \colon \quad f(x) = \sum_{J \subseteq \{1,\dots,n\}} c_J \prod_{j \in J} x_j$$

is written equivalently as

$$f(x^{\varnothing}) = c_{\varnothing}$$

$$\forall J \neq \varnothing : \quad f(x^J) = c_J + \sum_{J' \subset J} c_{J'} .$$

Thus, c is defined uniquely (by induction over the cardinality of J).

Definition 7. For any $n \in \mathbb{N}$ and any $d \in \{0, \ldots, n\}$, let

$$F_{nd} := \{ f : \{0,1\}^n \to \mathbb{R} \mid \exists c \in C_{nd} : f = f_c \}$$
(32)

and call any $f \in F_{nd}$ an *n*-variate PBF of degree at most *d*. In addition, call any $f \in F_{n2}$ a quadratic PBF (QPBF).

Remark 3. For any $n \in \mathbb{N}$, F_{nn} is the set of all *n*-variate PBFs (by Lemma 4).

Definition 8.

• For any $n \in \mathbb{N}$ and any $f : \{0,1\}^n \to \mathbb{R}$, call

$$\min \{f(x) \mid x \in \{0,1\}^n\}$$
(33)

the instance of the **pseudo-boolean optimization (PBO)** problem wrt. f. For any $n \in \mathbb{N}$ and any $f \in F_{n2}$, call

$$\min \{f(x) \mid x \in \{0,1\}^n\}$$
(34)

the instance of the quadratic pseudo-boolean optimization (QPBO) problem wrt. f.

Is QPBO less complex than PBO?

Definition 9. For any $n \in \mathbb{N}$ and any $c \in C_{nn}$, define the size of c as

$$size(c) := \sum_{J \subseteq \{1,...,n\}: \ c_J \neq 0} |J|$$
 . (35)

Lemma 5. For any $x, y, z \in \{0, 1\}$:

$$z = xy \quad \Leftrightarrow \quad xy - 2xz - 2yz + 3z = 0 \quad , \tag{36}$$

$$z \neq xy \quad \Leftrightarrow \quad xy - 2xz - 2yz + 3z > 0$$
 . (37)

Proof. By verifying equivalence for all eight cases.

Algorithm 1 (Boros and Hammer 2001). Input: $c \in C_{nn}$ **Output**: $c' \in C_{n2}$ $M := 1 + 2 \sum_{J \subset \{1, \dots, n\}} |c_J|$ m := n $c^m := c$ while there exists a $J \subseteq \{1, \ldots, n\}$ such that |J| > 2 and $c_J^m \neq 0$ Choose $j, k \in J$ such that $j \neq k$ $c^{m+1} := c^m$ $\begin{array}{l} c_{\{j,k\}}^{m+1} := c_{\{j,k\}}^{m+1} + M \\ c_{\{j,m+1\}}^{m+1} := -2M \\ c_{\{k,m+1\}}^{m+1} := -2M \\ c_{\{k,m+1\}}^{m+1} := 3M \\ c_{\{m+1\}}^{m+1} := 3M \end{array}$ for all $\{j,k\} \subseteq J' \subseteq \{1,\ldots,n\}$ such that $c_{T'}^{m+1} \neq 0$ $c_{J'-\{j,k\}\cup\{m+1\}}^{m+1} := c_{J'}^{m+1}$ $c_{J'}^{m+1} := 0$ m := m + 1 $c' := c^m$

Theorem 1.

- ► Algorithm 1 terminates in polynomial time in size(c).
- size(c') is polynomially bounded by size(c).
- The multi-linear quadratic form c' is such that $\forall \hat{x} \in \mathbb{R}^n$:

$$\hat{x} \in \underset{x \in \{0,1\}^{n}}{\operatorname{argmin}} f_{c}(x)$$

$$\Rightarrow \quad \exists \hat{x}' \in \{0,1\}^{m} \left(\hat{x}'_{\{1,\dots,n\}} = \hat{x}_{\{1,\dots,n\}} \land \hat{x}' \in \underset{x' \in \{0,1\}^{m}}{\operatorname{argmin}} f_{c'}(x') \right) \quad .$$
(38)

Proof. The algorithm replaces the occurrence of $x_j x_k$ by x_{m+1} and adds the form $M(x_j x_k - 2x_j x_{m+1} - 2x_k x_{m+1} + 3x_{m+1})$. ► If $x_{m+1} = x_j x_k$, $f^{m+1}(x_1, \dots, x_{m+1}) = f^m(x_1, \dots, x_n) \le \max_{x' \in \{0,1\}^n} f^m(x') < M/2$. ► If $x_{m+1} \ne x_j x_k$, $f^{m+1}(x_1, \dots, x_{m+1}) \ge M/2$

(by Lemma 5 and by definition of M). For every iteration m,

 $|\{J \subseteq \{1, \dots, n\}||J| > 2 \land c_J^{m+1} \neq 0\}| < |\{J \subseteq \{1, \dots, n\}||J| > 2 \land c_J^m \neq 0\}|$ which proves the complexity claims.

Summary:

- Every PBF has a unique multi-linear polynomial form.
- ▶ PBO is polynomially reducible to QPBO.

Definition 10. For any $n \in \mathbb{N}$ and any $d \in \{0, \ldots, n\}$, let

$$\begin{split} K_{nd}^+ &:= \{ (K^1, K^0) \mid K^1, K^0 \subseteq \{1, \dots, n\} \wedge K^1 \cap K^0 = \varnothing \wedge |K^1| + |K^0| = d \} \\ J_{nd}^+ &:= \bigcup_{m=0}^d K_{nm}^+ \\ C_{nd}^+ &:= \{ c : J_{nd}^+ \to \mathbb{R} \mid \forall j \in J_{nd}^+ \setminus \{(\varnothing, \varnothing)\} : \ 0 \le c_j \} \end{split}$$

and call any $c \in C_{nd}^+$ an *n*-variate **posiform** of degree at most *d*.

Example. For n = d = 2,

$$\begin{split} J_{22}^+ &= \{ (\varnothing, \varnothing) \} \\ &\cup \{ (\{1\}, \varnothing), \ (\varnothing, \{1\}), \ (\{2\}, \varnothing), \ (\varnothing, \{2\}) \} \\ &\cup \{ \ (\{1, 2\}, \varnothing), \ (\{1\}, \{2\}), \ (\{2\}, \{1\}), \ (\varnothing, \{1, 2\}) \} \end{split}$$

Definition 11. For any $n \in \mathbb{N}$, any $d \in \{0, \ldots, n\}$ and any $c \in C_{nd}^+$, $f_c : \{0, 1\}^n \to \mathbb{R}$ such that

$$\forall x \in \{0,1\}^n \qquad f_c(x) := \sum_{(J^1,J^0) \in J^+_{nd}} c_{J^1J^0} \prod_{j \in J^1} x_j \prod_{j' \in J^0} (1-x'_j)$$
(39)

is called the **PBF defined by** c.

Example. For any $c \in C_{22}^+$, $f_c : \{0,1\}^2 \to \mathbb{R}$ is such that $\forall x \in \{0,1\}^2$:

$$f(x) = c_{\varnothing \varnothing} + c_{\{1\} \varnothing} x_1 + c_{\varnothing \{1\}} (1 - x_1) + c_{\{2\} \varnothing} x_2 + c_{\varnothing \{2\}} (1 - x_2) + c_{\{1,2\} \varnothing} x_1 x_2 + c_{\{1\} \{2\}} x_1 (1 - x_2) + c_{\{2\} \{1\}} (1 - x_1) x_2 + c_{\varnothing \{1,2\}} (1 - x_1) (1 - x_2) .$$

Definition 12. For any $n \in \mathbb{N}$ and any $f : \{0,1\}^n \to \mathbb{R}$, the posiform defined by

$$\forall x \in \{0, 1\}^n : \quad K_x^1 := \{j \in \{1, \dots, n\} | x_j = 1\}$$
$$K_x^0 := \{j \in \{1, \dots, n\} | x_j = 0\}$$

and

$$J := \{(\emptyset, \emptyset)\} \cup \bigcup_{x \in \{0,1\}^n} \{(K_x^1, K_x^0)\}$$

and $c:J\to \mathbb{R}$ such that

$$c_{\varnothing \varnothing} := \min_{x \in \{0,1\}^n} f(x)$$
$$\forall x \in \{0,1\}^n \quad c_{K_x^1 K_x^0} := f(x) - c_{\varnothing \varnothing}$$

is called **min-term posiform** of f.

Lemma 6. For any $n \in \mathbb{N}$ and any $f : \{0, 1\}^n \to \mathbb{R}$, the min-term posiform c of f is such that $f_c = f$.

Corollary 2. For any $n \in \mathbb{N}$ and any $f : \{0,1\}^n \to \mathbb{R}$, there exists a posiform $c \in C_{nn}^+$ such that $f_c = f$.

Proof. Let $n \in \mathbb{N}$ and $f : \{0,1\}^n \to \mathbb{R}$. Moreover, let $c : J \to \mathbb{R}$ the min-term posiform of f.

c is a posiform (by definition).

Let $g:\{0,1\}^n \to \mathbb{R}$ be the PBF defined by this posiform.

Then, for any $x \in \{0,1\}^n$,

$$(J^1, J^0) \in \{(\varnothing, \varnothing), (K^1_x, K^0_x)\} \subseteq J$$

are the only elements of J for which

$$0 \neq \prod_{j \in J^1} x_j \prod_{j' \in J^0} (1 - x'_j) = 1$$
.

Thus,

$$\begin{aligned} \forall x \in \{0,1\}^n \qquad g(x) &= c_{\varnothing \varnothing} + c_{K_x^1 K_x^0} \\ &= c_{\varnothing \varnothing} + f(x) - c_{\varnothing \varnothing} \qquad \text{(by definition of } c\text{)} \\ &= f(x) \ . \end{aligned}$$

34/45

Remark 4. Unlike multi-linear polynomial forms, posiforms of PBFs need not be unique, e.g., $x_1 = x_1x_2 + x_1(1 - x_2)$.

Definition 13. For any $n \in \mathbb{N}$, any $f : \{0,1\}^n \to \mathbb{R}$ and any $d \in \{0,\ldots,n\}$, let

$$C_{nd}^{+}(f) := \left\{ c \in C_{nd}^{+} \mid f_{c} = f \right\} \quad .$$
(40)

Remark 5. For any $n \in \mathbb{N}$ and any $f : \{0,1\}^n \to \mathbb{R}$, $C_{nn}^+(f)$ contains at least the min-term posiform of f.

 $\forall n \in \mathbb{N} \quad \forall f : \{0,1\}^n \to \mathbb{R} \quad \forall c \in C_{nn}^+(f) \quad \forall x \in \{0,1\}^n \colon \quad c_{\varnothing \varnothing} \leq f(x) \ .$

Proof. By definition, we have, for all $x \in \{0, 1\}^n$,

$$\begin{split} f(x) &= \sum_{m=0}^{d} \sum_{(K^{1},K^{0})\in K_{nm}^{+}} c_{K^{1}K^{0}} \prod_{j\in K^{1}} x_{j} \prod_{j'\in K^{0}} (1-x'_{j}) \\ &= c_{\varnothing\varnothing} + \sum_{m=1}^{d} \sum_{(K^{1},K^{0})\in K_{nm}^{+}} c_{K^{1}K^{0}} \prod_{j\in K^{1}} x_{j} \prod_{j'\in K^{0}} (1-x'_{j}) \ , \end{split}$$

and all coefficients $c_{K^1K^0}$ in the second sum are non-negative.

Therefore, the second sum is non-negative.

Thus,

$$\forall x \in \{0,1\}^n \qquad f(x) \ge c_{\varnothing\varnothing} \ .$$

 \square

Definition 14. For any posiform $c: J \to \mathbb{R}$, a pair (S, y) such that $S \subseteq \{1, \ldots, n\}$ and $y: S \to \{0, 1\}$ is called a **contractor** of c iff

$$\forall (J^1, J^0) \in J: \qquad (J^1 \cap S = \varnothing \land J^0 \cap S = \varnothing) \\ \lor (\exists j \in J^1 \cap S \quad y_j = 0) \\ \lor (\exists j \in J^0 \cap S \quad y_j = 1) . \qquad (41)$$

Theorem 2 (partial optimality). For any $n \in \mathbb{N}$, any $f : \{0,1\}^n \to \mathbb{R}$, any posiform $c \in C_{nn}^+(f)$ and any contractor (S, y) of c, there exists a solution x^* to the problem $\min \{f(x) \mid x \in \{0,1\}^n\}$ such that

$$\forall j \in S : \quad x_j^* = y_j \quad . \tag{42}$$

Proof. Let $\sigma_{Sy}: \{0,1\}^n \to \{0,1\}^n$ such that $\forall x \in \{0,1\}^n \ \forall j \in \{1,\ldots,n\}$:

$$\sigma_{Sy}(x)_j = \begin{cases} y_j & \text{if } j \in S \\ x_j & \text{otherwise} \end{cases}$$
(43)

Let $J^{\bar{S}} := \{(J^1, J^0) \in J_{nn}^+ \mid J^1 \cap S = J^0 \cap S = \varnothing\}$ and $J^S := J \setminus J^{\bar{S}}$. Now, $\forall x \in \{0, 1\}^n$:

$$f(x) = \sum_{\substack{(J^1, J^0) \in J^S \\ =:f^S(x)}} c_{J^1 J^0} \prod_{j \in J^1} x_j \prod_{j' \in J^0} (1 - x'_j) + \underbrace{\sum_{\substack{(J^1, J^0) \in J^S \\ =:f^S(x)}} c_{J^1 J^0} \prod_{j \in J^1} x_j \prod_{j' \in J^0} (1 - x'_j)}_{=:f^{\tilde{S}}(x)}$$

Furthermore, $\forall x \in \{0,1\}^n$:

$$\begin{split} f^{S}(\sigma_{Sy}(x)) &= 0 & \text{(by definition)} \\ 0 &\leq f^{S}(x) & \text{(because } (\varnothing, \varnothing) \notin J^{S}) \\ f^{\bar{S}}(\sigma_{Sy}(x)) &= f^{\bar{S}}(x) & \text{(by definition)} \end{split}$$

Adding the lhs. and rhs. shows that σ_{Sy} is improving for the problem $\min \{f(x) \mid x \in \{0,1\}^n\}.$

Summary:

- Every PBF has a posiform
- ► The posiform of a PBF need not be unique
- For every PBF f and every posiform c of f
 - $c_{\varnothing \varnothing}$ is a lower bound on the minimum of f
 - \blacktriangleright partial optimality holds at any contractor of c

For any $n \in \mathbb{N}$, consider *n*-variate **quadratic** forms, i.e.

• any multi-linear polynomial form $c \in C_{n2}$, and f_c , i.e. for all $x \in \{0,1\}^n$:

$$f_c(x) = c_{\varnothing} + \sum_{j \in \{1, \dots, n\}} c_{\{j\}} x_j + \sum_{\{j, k\} \in \binom{\{1, \dots, n\}}{2}} c_{\{j, k\}} x_j x_k$$

• any posiform $c' \in C_{n2}^+$, and f'_c , i.e. for all $x \in \{0,1\}^n$:

$$\begin{aligned} f_{c'}'(x) &= c_{\varnothing\varnothing}' + \sum_{\substack{j \in \{1, \dots, n\} \\ \{j,k\} \in \binom{\{1, \dots, n\}}{2}}} \left(c_{\{j\}\varnothing}' x_j + c_{\varnothing\{j\}}' (1 - x_j) \right) \\ &+ \sum_{\substack{\{j,k\} \in \binom{\{1, \dots, n\}}{2}}} \left(c_{\{j,k\}\varnothing}' x_j x_k + c_{\{j\}\{k\}}' x_j (1 - x_k) \right) \\ &+ c_{\{k\}\{j\}}' x_k (1 - x_j) + c_{\varnothing\{j,k\}}' (1 - x_j) (1 - x_k) \right) \end{aligned}$$

Lemma 8. For any $n \in \mathbb{N}$, any QPBF $f : \{0,1\}^n \to \mathbb{R}$, the $c \in C_{n2}$ such that $f_c = f$ and any $c' \in C_{n2}^+(f)$:

$$c_{\varnothing} = c'_{\varnothing,\varnothing} + \sum_{j=1}^{n} c'_{\varnothing\{j\}} + \sum_{\substack{\{j,k\} \in \binom{\{1,\dots,n\}}{2} \\ \{j,k\} \in \binom{\{1,\dots,n\}}{2} }} c'_{\{j\}} = c'_{\{j\},\varnothing} - c'_{\varnothing\{j\}} + \sum_{\substack{k \in \{1,\dots,n\} \setminus \{j\} \\ k \in \binom{\{1,\dots,n\}}{2} }} c'_{\{j,k\},\emptyset} - c'_{\{j\}\{k\}} - c'_{\{j\}\{k\}} - c'_{\{k\}\{j\}}}$$

Proof. Expansion of the posiform c' yields a quadratic multi-linear polynomial form. Comparison with c yields the conditions stated in the Lemma.

Definition 15 (Complementation). For any $n \in \mathbb{N}$ and any QPBF $f : \{0,1\}^n \to \mathbb{R}$, the real number $\max \{c'_{\varnothing \varnothing} \mid c' \in C^+_{n2}(f)\}$ is called the floor dual of f.

Corollary 3 (of Lemma 8). For any $n \in \mathbb{N}$ and any QPBF $f : \{0, 1\}^n \to \mathbb{R}$, the floor dual is the value of an optimal solution to the linear program

$$\begin{split} \max_{\substack{c':J_{n_{2}}^{+} \to \mathbb{R} \\ \forall j \in \{1, \dots, n\}: \\ \forall \{j, k\} \in \binom{\{1, \dots, n\}}{2}: \\ \forall \{j, k\} = c'_{\{j, k\}} = c'_{\{j, k\} \varnothing} + c'_{\varnothing\{j, k\}} - c'_{\{j\}\{k\}} - c'_{\{k\}\{j\}} \\ \forall J \in J_{n_{2}}^{+} - \{(\varnothing, \varnothing)\}: \\ 0 \le c'_{J} \end{split}$$

Summary:

► For any PBF, a quadratic posiform with maximum floor dual bound c_{ØØ} can be found by solving a linear program.