

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, $\varphi: Y \rightarrow \mathbb{R}$ and $\sigma: Y \rightarrow Y$. 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 $\varphi: Y \rightarrow \mathbb{R}$. Let $\sigma: Y \rightarrow Y$ 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 $\sigma(Y) \subseteq Q$. \square

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

- ▶ Stein D., Di Gregorio S. and Andres B. Partial Optimality in Cubic Correlation Clustering. ICML 2023
- ▶ 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 $c: \binom{A}{2} \rightarrow \mathbb{R}$,

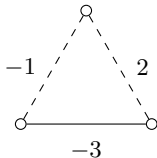
$$Y_A := \left\{ y: \binom{A}{2} \rightarrow \{0, 1\} \mid \forall a \in A \forall b \in A \setminus \{a\} \forall c \in A \setminus \{a, b\}: \right. \\ \left. y_{ab} + y_{bc} - 1 \leq y_{ac} \right\} \quad (1)$$

and $\varphi_c: Y_A \rightarrow \mathbb{R}: y \mapsto \langle c, y \rangle$,

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

is called the instance of the **(clique) partition problem** wrt. A and c , which we abbreviate as $\text{CPP}(A, c)$.

Example 1.



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

$$\partial U := \{ \{u, a\} \in \binom{A}{2} \mid u \in U \wedge a \notin U \} \quad . \quad (3)$$

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

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

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

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

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

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 $c: \binom{A}{2} \rightarrow \mathbb{R}$. If there exists $U \subseteq A$ such that

$$\forall \{a, b\} \in \partial U: \quad 0 \leq c_{ab} \quad , \quad (6)$$

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

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

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

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

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

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

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

$$\stackrel{(6)}{\leq} 0 . \quad (12)$$

The assertion follows by Lemma 1. □

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

$$[r]_+ := \begin{cases} r & \text{if } r \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (13)$$

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

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

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

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

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

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Proof. Let $\xi: Y_A \rightarrow Y_A$ such that for all $y \in Y_A$:

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

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

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

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

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

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

$$\leq -c_{uv} + \sum_{\{a,b\} \in \partial U \setminus \{\{u,v\}\}} [c_{ab}]_- \quad (20)$$

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

The assertion follows by Lemma 1. □

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

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

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

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

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Proof. Let $\xi: Y_A \rightarrow Y_A$ such that for all $y \in Y_A$:

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

For any $y \in Y_A$, $y' := \xi(y)$ and all $\{u, v\} \in \binom{U}{2}$, 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 $\forall \{u, v\} \in \binom{U}{2}: y_{uv} = 1$ then

$\varphi_c(y') - \varphi_c(y) = \varphi_c(y) - \varphi_c(y) = 0 \leq 0$. Otherwise:

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

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

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

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

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

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

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 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: Pseudo-Boolean optimization. Discrete Applied Mathematics 123(1–3): 155–225 (2002)
- ▶ 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

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

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

$$\begin{aligned} J_{22} &= \bigcup_{m=0}^2 \binom{\{1,2\}}{m} \\ &= \binom{\{1,2\}}{0} \cup \binom{\{1,2\}}{1} \cup \binom{\{1,2\}}{2} \\ &= \{\emptyset\} \cup \{\{1\}, \{2\}\} \cup \{\{1, 2\}\} \\ &= \{\emptyset, \{1\}, \{2\}, \{1, 2\}\} \end{aligned}$$

Definition 5. For any $f: A \rightarrow B$ 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 $f: A \rightarrow B$, 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 $d \in \{0, \dots, n\}$ and any $c \in C_{nd}$, the function f_c defined below is called the **PBF defined by c** .

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

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

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

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

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

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

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

Explicitly,

$$\begin{aligned} f(0, 0) &= c_{\emptyset} \\ f(1, 0) &= c_{\emptyset} + c_{\{1\}} \\ f(0, 1) &= c_{\emptyset} \quad \quad \quad + c_{\{2\}} \\ f(1, 1) &= c_{\emptyset} + c_{\{1\}} + c_{\{2\}} + c_{\{1,2\}} . \end{aligned}$$

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

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

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

Now,

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

is written equivalently as

$$\begin{aligned} f(x^\emptyset) &= c_\emptyset \\ \forall J \neq \emptyset: \quad f(x^J) &= c_J + \sum_{J' \subset J} c_{J'}. \end{aligned}$$

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

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

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

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 $f : \{0, 1\}^n \rightarrow \mathbb{R}$, call

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

the instance of the **pseudo-boolean optimization (PBO)** problem wrt. f .

- For any $n \in \mathbb{N}$ and any $f \in F_{n2}$, call

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

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

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

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

$$z = xy \quad \Leftrightarrow \quad xy - 2xz - 2yz + 3z = 0 \quad , \quad (36)$$

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

Proof. By verifying equivalence for all eight cases. □

Algorithm 1 (Boros and Hammer 2001).

Input: $c \in C_{nn}$

Output: $c' \in C_{n2}$

$M := 1 + 2 \sum_{J \subseteq \{1, \dots, n\}} |c_J|$

$m := n$

$c^m := c$

while there exists a $J \subseteq \{1, \dots, n\}$ such that $|J| > 2$ and $c_J^m \neq 0$

 Choose $j, k \in J$ such that $j \neq k$

$c^{m+1} := c^m$

$c_{\{j,k\}}^{m+1} := c_{\{j,k\}}^{m+1} + M$

$c_{\{j,m+1\}}^{m+1} := -2M$

$c_{\{k,m+1\}}^{m+1} := -2M$

$c_{\{m+1\}}^{m+1} := 3M$

for all $\{j, k\} \subseteq J' \subseteq \{1, \dots, n\}$ such that $c_{J'}^{m+1} \neq 0$

$c_{J' - \{j,k\} \cup \{m+1\}}^{m+1} := c_{J'}^{m+1}$

$c_{J'}^{m+1} := 0$

$m := m + 1$

$c' := c^m$

Theorem 1.

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

$$\begin{aligned} & \hat{x} \in \operatorname{argmin}_{x \in \{0,1\}^n} f_c(x) \\ \Rightarrow & \exists \hat{x}' \in \{0,1\}^m \left(\hat{x}'_{\{1,\dots,n\}} = \hat{x}_{\{1,\dots,n\}} \wedge \hat{x}' \in \operatorname{argmin}_{x' \in \{0,1\}^m} f_{c'}(x') \right) . \end{aligned} \quad (38)$$

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 $x_{m+1} = x_j x_k$,

$$f^{m+1}(x_1, \dots, x_{m+1}) = f^m(x_1, \dots, x_n) \leq \max_{x' \in \{0,1\}^n} f^m(x') < M/2 .$$

► If $x_{m+1} \neq x_j x_k$,

$$f^{m+1}(x_1, \dots, x_{m+1}) \geq M/2$$

(by Lemma 5 and by definition of M).

For every iteration m ,

$$|\{J \subseteq \{1, \dots, n\} \mid |J| > 2 \wedge c_J^{m+1} \neq 0\}| < |\{J \subseteq \{1, \dots, n\} \mid |J| > 2 \wedge c_J^m \neq 0\}|$$

which proves the complexity claims. \square

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 $d \in \{0, \dots, n\}$, let

$$K_{nd}^+ := \{(K^1, K^0) \mid K^1, K^0 \subseteq \{1, \dots, n\} \wedge K^1 \cap K^0 = \emptyset \wedge |K^1| + |K^0| = d\}$$

$$J_{nd}^+ := \bigcup_{m=0}^d K_{nm}^+$$

$$C_{nd}^+ := \{c : J_{nd}^+ \rightarrow \mathbb{R} \mid \forall j \in J_{nd}^+ \setminus \{(\emptyset, \emptyset)\} : 0 \leq c_j\}$$

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

Example. For $n = d = 2$,

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

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

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

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

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

$$\begin{aligned} f(x) = & c_{\emptyset \emptyset} \\ & + c_{\{1\} \emptyset} x_1 + c_{\emptyset \{1\}} (1 - x_1) + c_{\{2\} \emptyset} x_2 + c_{\emptyset \{2\}} (1 - x_2) \\ & + c_{\{1,2\} \emptyset} x_1 x_2 + c_{\{1\} \{2\}} x_1 (1 - x_2) + c_{\{2\} \{1\}} (1 - x_1) x_2 \\ & + c_{\emptyset \{1,2\}} (1 - x_1) (1 - x_2) . \end{aligned}$$

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

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

and

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

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

$$\begin{aligned} c_{\emptyset\emptyset} &:= \min_{x \in \{0, 1\}^n} f(x) \\ \forall x \in \{0, 1\}^n \quad c_{K_x^1 K_x^0} &:= f(x) - c_{\emptyset\emptyset} \end{aligned}$$

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

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

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

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

c is a posiform (by definition).

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

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

$$(J^1, J^0) \in \{(\emptyset, \emptyset), (K_x^1, K_x^0)\} \subseteq J$$

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,

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

□

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 $f : \{0, 1\}^n \rightarrow \mathbb{R}$ and any $d \in \{0, \dots, n\}$, let

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

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

Lemma 7.

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

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

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

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

Therefore, the second sum is non-negative.

Thus,

$$\forall x \in \{0, 1\}^n \quad f(x) \geq c_{\emptyset\emptyset} .$$

□

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

$$\begin{aligned} \forall (J^1, J^0) \in J: \quad & (J^1 \cap S = \emptyset \quad \wedge \quad J^0 \cap S = \emptyset) \\ & \vee (\exists j \in J^1 \cap S \quad y_j = 0) \\ & \vee (\exists j \in J^0 \cap S \quad y_j = 1) . \end{aligned} \tag{41}$$

Theorem 2 (partial optimality). For any $n \in \mathbb{N}$, any $f : \{0, 1\}^n \rightarrow \mathbb{R}$, 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

$$\forall j \in S: \quad x_j^* = y_j \quad . \quad (42)$$

Proof. Let $\xi_{Sy} : \{0, 1\}^n \rightarrow \{0, 1\}^n$ such that $\forall x \in \{0, 1\}^n \forall j \in \{1, \dots, n\}$:

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

For any $x \in \{0, 1\}^n$, $x' := \xi_{Sy}(x)$ is such that $\forall j \in S: x'_j = y_j$.

Moreover, ξ_{Sy} is improving for the problem $\min \{f(x) \mid x \in \{0, 1\}^n\}$, by the following argument: Let $J^{\bar{S}} := \{(J^1, J^0) \in J_{nn}^+ \mid J^1 \cap S = J^0 \cap S = \emptyset\}$ and $J^S := J \setminus J^{\bar{S}}$. Thus, for all $x \in \{0, 1\}^n$:

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

Furthermore,

$$\begin{aligned} \forall x \in \{0, 1\}^n: \quad f^S(t_{S,y}(x)) &= 0 && \text{(by definition)} \\ 0 &\leq f^S(x) && \text{(because } (\emptyset, \emptyset) \notin J^S) \\ f^{\bar{S}}(t_{S,y}(x)) &= f^{\bar{S}}(x) && \text{(by definition)} . \end{aligned}$$

□

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
 - ▶ $c \leq f$ is a lower bound on the minimum of f
 - ▶ 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 $x \in \{0, 1\}^n$:

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

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

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

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

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

$$\forall j \in \{1, \dots, n\}: \quad c_{\{j\}} = c'_{\{j\}\emptyset} - c'_{\emptyset\{j\}} + \sum_{k \in \{1, \dots, n\} \setminus \{j\}} (c'_{\{j\}\{k\}} - c'_{\{j,k\}})$$

$$\forall \{j, k\} \in \binom{\{1, \dots, n\}}{2}: \quad c_{\{j,k\}} = c'_{\{j,k\}\emptyset} + c'_{\emptyset\{j,k\}} - c'_{\{j\}\{k\}} - c'_{\{k\}\{j\}}$$

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

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

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

$$\max_{c' : J_{n2}^+ \rightarrow \mathbb{R}} \quad c_{\emptyset} - \sum_{j=1}^n c'_{\emptyset\{j\}} - \sum_{\{j,k\} \in \binom{\{1,\dots,n\}}{2}} c'_{\emptyset\{j,k\}}$$

$$\text{subject to } \forall j \in \{1, \dots, n\}: \quad c_{\{j\}} = c'_{\{j\}\emptyset} - c'_{\emptyset\{j\}} + \sum_{k \in \{1, \dots, n\} - \{j\}} (c'_{\{j\}\{k\}} - c'_{\emptyset\{j,k\}})$$

$$\forall \{j, k\} \in \binom{\{1, \dots, n\}}{2}: \quad c_{\{j,k\}} = c'_{\{j,k\}\emptyset} + c'_{\emptyset\{j,k\}} - c'_{\{j\}\{k\}} - c'_{\{k\}\{j\}}$$

$$\forall J \in J_{n2}^+ - \{(\emptyset, \emptyset)\}: \quad 0 \leq c'_J \quad .$$

Summary:

- For any PBF, a quadratic posiform with maximum floor dual bound $c_{\emptyset\emptyset}$ can be found by solving a linear program.