We also have

$$\gamma = a_0 \gamma$$

$$= a_0 \sum_{j \in D} \alpha_j C_j(0)$$

$$\geq a_0 \sum_{j \in D} \alpha_j C_j(0) + \sum_{i \in M^{\times}} a_i \left(\sum_{j \in D} \alpha_j C_j(i) \right)$$

$$= \sum_{i \in M} \sum_{j \in D} a_i \alpha_j C_j(i).$$

We now state the duality theorem for linear programming.

Theorem 17.7. Assume that Problems (C, M) and (C, M)' are feasible. Then there exists a program $\{a_i\}_{i\in M}$ for (C, M) and a program $\{\alpha_j\}_{j\in D}$ for (C, M)' such that $g = \gamma$. Moreoever $g_0 = g = \gamma = \gamma_0$.

The proof of Theorem 17.7 can be found in the textbook, pages 110–112.

Next, we consider how to find the programs $\{a_i\}_{i\in M}$ and $\{\alpha_j\}_{j\in D}$ in Theorem 17.7.

Lemma 17.8. Given a program $\{a_i\}_{i\in M}$ for (C,M) and a program $\{\alpha_j\}_{j\in D}$ for (C,M)'. Then $g=\gamma$ if and only if the following (i), (ii) hold:

(i) for $i \in M^{\times}$,

$$a_i \sum_{j \in D} \alpha_j C_j(i) = 0.$$

(ii) for $j \in D^{\times}$,

$$\alpha_j \sum_{i \in M} a_i C_j(i) = 0.$$

Proof. Immediate from the proof of Lemma 17.6.

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Example 17.9. For even d = 2t, the orthogonality graph Ω_d has the same vertex set as the hypercube H(d,2); vertices y,z are adjacent in Ω_d whenever $(y,z) \in R_t$ in H(d,2). A set of vertices Y for Ω_d is called independent whenever no two vertices in Y are adjacent in Ω_d . Our problem is to find the maximal size of an independent set in Ω_d . First assume that t is odd. Recall that H(d,2) is bipartite, and note that either half of the bipartition is an independent set in Ω_d . This independent set has cardinality 2^{d-1} , which is maximal. Next assume that t is even. In this case, the problem is open. The above linear programming

technique gives an upper bound of $g_0 = 2^n/n$ for the size of an independent subset. Thus for H(4,2) we have $g_0 = 16/4 = 4$. For H(4,2) the linear programming details are shown below. We have d = 4. We have $D = \{0,1,2,3,4\}$ and $M = \{0,1,3,4\}$. We take C = Q where

$$Q = \begin{pmatrix} 1 & 4 & 6 & 4 & 1 \\ 1 & 2 & 0 & -2 & -1 \\ 1 & 0 & -2 & 0 & 1 \\ 1 & -2 & 0 & 2 & -1 \\ 1 & -4 & 6 & -4 & 1 \end{pmatrix}.$$

Problem (C, M): Maximize

$$g = a_0 + a_1 + a_3 + a_4$$

subject to

$$a_1 \ge 0$$
, $a_3 \ge 0$, $a_4 \ge 0$, $4a_0 + 2a_1 - 2a_3 - 4a_4 \ge 0$, $6a_0 + 6a_4 \ge 0$, $4a_0 - 2a_1 + 2a_3 - 4a_4 \ge 0$, $a_0 - a_1 - a_3 + a_4 \ge 0$.

Problem (C, M)': Minimize

$$\gamma = \alpha_0 + 4\alpha_1 + 6\alpha_2 + 4\alpha_3 + \alpha_4$$

subject to

$$\alpha_1 \ge 0$$
, $\alpha_2 \ge 0$, $\alpha_3 \ge 0$, $\alpha_4 \ge 0$, $\alpha_0 + 2\alpha_1 - 2\alpha_3 - \alpha_4 \le 0$, $\alpha_0 - 2\alpha_1 + 2\alpha_3 - \alpha_4 \le 0$, $\alpha_0 - 4\alpha_1 + 6\alpha_2 - 4\alpha_3 + \alpha_4 \le 0$.

Suppose we are given a program $\{a_i\}_{i\in M}$ for (C,M) and a program $\{\alpha_j\}_{j\in D}$ for (C,M)' such that $g=\gamma$. Then $a_0=1$ and

$$\alpha_1(4a_0 + 2a_1 - 2a_3 - 4a_4) = 0,$$
 $\alpha_2(6a_0 + 6a_4) = 0,$ $\alpha_3(4a_0 - 2a_1 + 2a_3 - 4a_4) = 0,$ $\alpha_4(a_0 - a_1 - a_3 + a_4) = 0.$

Moreover, $\alpha_0 = 1$ and

$$a_1(\alpha_0 + 2\alpha_1 - 2\alpha_3 - \alpha_4) = 0,$$
 $a_3(\alpha_0 - 2\alpha_1 + 2\alpha_3 - \alpha_4) = 0,$ $a_4(\alpha_0 - 4\alpha_1 + 6\alpha_2 - 4\alpha_3 + \alpha_4) = 0.$

For the above 9 equations, there are 13 solutions (found using Maple). Among these solutions, only one satisfies the inequalities in Problem (C, M) and Problem (C, M). This unique solution is

$$a_0 = 1$$
, $a_1 = 1$, $a_3 = 1$, $a_4 = 1$,
 $\alpha_0 = 1$, $\alpha_1 = 1/4$, $\alpha_2 = 0$, $\alpha_3 = 1/4$, $\alpha_4 = 1$.

For this solution $g = 4 = \gamma$. Therefore $g_0 = 4 = \gamma_0$.

For more information see

E. de Klerk, D. V. Pasechnik.

A note on the stability number of an orthogonality graph. arXiv:math/0505038.

Ferdinand Ihringer, Hajime Tanaka.

The Independence Number of the Orthogonality Graph in Dimension 2^k . arXiv:1901.04860.

18 Subsets of an association scheme

In this section, we investigate the linear programming approach in more detail. Recall the symmetric association scheme $\mathcal{X} = (X, \{R_i\}_{i=0}^d)$ with eigenmatrices P and Q.

Let Y denote a nonempty subset of X.

Definition 18.1. The inner distribution of Y is the row vector $\{a_i\}_{i=0}^d$ where

$$a_i = \frac{|(Y \times Y) \cap R_i|}{|Y|} \qquad (0 \le i \le d).$$

We sometimes let a_Y denote the inner distribution of Y.

The dual distribution of Y is the row vector $\{a_j^*\}_{j=0}^d$ where

$$a_j^* = \sum_{i=0}^d a_i Q_j(i)$$
 $(0 \le j \le d).$

We sometimes let a_Y^* denote the dual distribution of Y.

Observe that

$$a_Y^* = a_Y Q,$$
 $a_Y = |X|^{-1} a_Y^* P.$

Moreover

$$a_j = |X|^{-1} \sum_{i=0}^d a_i^* P_j(i)$$
 $(0 \le j \le d).$

Lemma 18.2. With reference to Definition 18.1,

- (i) $a_0 = 1$;
- (ii) $a_0^* = \sum_{i=0}^d a_i = |Y|$.

Proof. Recall that $Q_0(i) = 1$ for $0 \le i \le d$.

Definition 18.3. By the *characteristic vector of* Y we mean the vector

$$\psi_Y = \sum_{y \in X} \hat{y}.$$

Lemma 18.4. For $0 \le i \le d$ we have

$$a_i = \frac{\psi_Y^t A_i \psi_Y}{|Y|}, \qquad a_i^* = \frac{|X|}{|Y|} \psi_Y^t E_i \psi_Y.$$

Proof. We have

$$\psi_Y^t A_i \psi_Y = \sum_{y,z \in Y} (A_i)_{y,z} = |(Y \times Y) \cap R_i| = |Y| a_i.$$

We also have

$$a_i^* = \sum_{\ell=0}^d a_\ell Q_i(\ell) = |Y|^{-1} \sum_{\ell=0}^d \psi_Y^t A_\ell \psi_Y Q_i(\ell) = |Y|^{-1} \psi_Y^t \left(\sum_{\ell=0}^d Q_i(\ell) A_\ell \right) \psi_Y = \frac{|X|}{|Y|} \psi_Y^t E_i \psi_Y.$$

Corollary 18.5. For $0 \le i \le d$,

$$||E_i\psi_Y||^2 = \frac{|Y|}{|X|} a_i^*.$$

Moreover $a_i^* \geq 0$.

Proof. Use Lemma 18.4 and

$$||E_i\psi_Y||^2 = (E_i\psi_Y)^t E_i\psi_Y = \psi_Y^t E_i^2 \psi_Y = \psi_Y^t E_i \psi_Y.$$

Recall the set $D = \{0, 1, ..., d\}.$

Definition 18.6. We define a matrix B_Y with entries indexed by $X \times D$. For $x \in X$ and $i \in D$ the (x, i)-entry of B_Y is

$$B_Y(x,i) = |Y \cap \Gamma_i(x)|.$$

We call B_Y the outer distribution of Y.

Lemma 18.7. We have

$$a_Y = \frac{\psi_Y^t B_Y}{|Y|}.$$

Proof. For $0 \le i \le d$ the i^{th} entry of either side is equal to

$$|Y|^{-1} \sum_{x \in Y} |Y \cap \Gamma_i(x)|.$$

Lemma 18.8. The following hold for $0 \le i \le d$:

- (i) the vector $A_i \psi_Y$ is equal to column i of B_Y ;
- (ii) the vector $|X|E_i\psi_Y$ is equal to column i of B_YQ .

Proof. (i) For $x \in X$ the x-coordinate of $A_i \psi_Y$ is equal to

$$\sum_{y \in X} (A_i)_{x,y} (\psi_Y)_y = \sum_{y \in Y} (A_i)_{x,y} = \sum_{y \in Y \cap \Gamma_i(x)} 1 = |Y \cap \Gamma_i(x)| = B_Y(x,i).$$

(ii) Use (i) and
$$E_i = |X|^{-1} \sum_{j=0}^{d} Q_i(j) A_j$$
.

Our next general goal is to compute the rank of the matrix B_Y .

We bring in some notation. For any vector $u = (u_1, u_2, \dots, u_r)$ let Δ_u denote the diagonal matrix with diagonal entries u_1, u_2, \dots, u_r .

Theorem 18.9. With the above notation,

$$B_Y^t B_Y = \frac{|Y|}{|X|} P^t \Delta_{a_Y^*} P.$$

Proof. For $0 \le i, j \le d$ we show that the (i, j)-entry of each side is equal to

$$|Y|\sum_{k=0}^{d} p_{i,j}^{k} a_{k}.$$

Using Lemma 18.8 the (i, j)-entry of $B_Y^t B_Y$ is equal to

$$(A_i \psi_Y)^t A_j \psi_Y = \psi_Y^t A_i A_j \psi_Y = \sum_{k=0}^d p_{i,j}^k \psi_Y^t A_k \psi_Y = |Y| \sum_{k=0}^d p_{i,j}^k a_k.$$

The (i,j)-entry of $P^t\Delta_{a_Y^*}P$ is equal to

$$\sum_{\ell=0}^{d} P_{i,\ell}^{t} a_{\ell}^{*} P_{\ell,j} = \sum_{\ell=0}^{d} P_{i}(\ell) a_{\ell}^{*} P_{j}(\ell)$$

$$= \sum_{\ell=0}^{d} a_{\ell}^{*} \sum_{k=0}^{d} p_{i,j}^{k} P_{k}(\ell)$$

$$= \sum_{k=0}^{d} p_{i,j}^{k} \sum_{\ell=0}^{d} a_{\ell}^{*} P_{k}(\ell)$$

$$= |X| \sum_{k=0}^{d} p_{i,j}^{k} a_{k}.$$

Corollary 18.10. The rank of the matrix B_Y is equal to the number of nonzero scalars among $\{a_i^*\}_{i=0}^d$.