

## Lecture 10 : Fourier-Motzkin elimination, outer bounds of interference channels

Instructor: Rajesh Sundaresan

Scribe: Premkumar K.

**1 Fourier Motzkin elimination:**Solve  $x_1, x_2, \dots, x_n$  such that

$$\sum_{j=1}^n a_{ij}x_j \leq b_i, \quad i = 1, 2, \dots, m.$$

Pick a variable, say  $x_n$ . Eliminate it as follows. Assume  $a_{in} \neq 0$ .

$$a_{in}x_n \leq b_i - \sum_{j=1}^{n-1} a_{ij}x_j, \quad i = 1, 2, \dots, m.$$

If  $a_{in} > 0$ , then upper bound  $x_n \leq \frac{b_i}{a_{in}} - \sum_{j=1}^{n-1} \frac{a_{ij}}{a_{in}}x_j = \beta_i$ , otherwise lower bound  $x_n \geq \alpha_i$ . Eliminate  $x_n$  from all equations; replace by  $\alpha_{i'}$  for every  $i'$ ,  $i$  such that  $i'$  yields a lower bound,  $i$  yields an upper bound. Let  $LB_n$  and  $UB_n$  be the set of indices that yield lower and upper bounds respectively. If this system has a solution in  $n-1$  variables, then that solution with any  $x_n$  in  $[\max_{i \in LB_n} \alpha_i, \min_{i \in UB_n} \beta_i]$  is a solution to the original set.

**2 Gaussian interference channel:**

For the Gaussian interference channel defined earlier,  $\mathcal{P}, \mathcal{P}^*$  depend on the power constraints  $P_1$  and  $P_2$ . Note the following definitions.

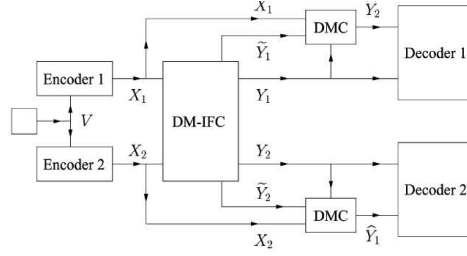
- $\mathcal{P}^*(P_1, P_2) = \{Z \in \mathcal{P}^*, \text{Var}(X_k) \leq P_k, k = 1, 2\}$
- $\mathcal{P}(P_1, P_2) = \{Z \in \mathcal{P}^*(P_1, P_2), \text{ with } |\mathbb{Q}| = 1\}$
- $\mathcal{G} = \text{closure conv } \bigcup_{Z \in \mathcal{P}(P_1, P_2)} \mathcal{R}(Z)$
- $\mathcal{G}^* = \text{closure } \bigcup_{Z \in \mathcal{P}^*(P_1, P_2)} \mathcal{R}(Z)$
- $\mathcal{P}'(P_1, P_2) = \{Z \in \mathcal{P}(P_1, P_2) : U_1, U_2, U_3, U_4 \text{ are Gaussian, } U_1 + U_2 = X_1, U_3 + U_4 = X_2\}$
- $\mathcal{G}' = \text{closure conv } \bigcup_{Z \in \mathcal{P}'(P_1, P_2)} \mathcal{R}(Z)$ .
- Questions: Does correlation in  $U_1U_2U_3U_4$  help? Is  $\mathcal{G}' \subsetneq \mathcal{G}^*$ ? Is  $\mathcal{G}^* \subsetneq \mathcal{G}'$ ?

**3 Outer bounds:**

(1) DMC.

**Definition 1 (II).**

$$\Pi := \{Z = QX_1X_2Y_1Y_2\tilde{Y}_1\tilde{Y}_2\hat{Y}_1\hat{Y}_2 \text{ such that (1) - (2) below hold}\}.$$



**Figure 1:** A statistical model for outer bound.

$$(1) p_Z = p_Q \left( p_{X_1|Q} p_{X_2|Q} \right) \left( p_{Y_1 Y_2 | X_1 X_2} \right) \left( p_{\tilde{Y}_1 \tilde{Y}_2 | X_1 X_2 Y_1 Y_2} \right) \left( p_{\hat{Y}_2 | X_1 Y_1 \tilde{Y}_1} \right) \left( p_{\hat{Y}_1 | X_2 Y_2 \tilde{Y}_2} \right).$$

$$(2) p_{\hat{Y}_2 | X_1 X_2} = p_{Y_2 | X_1 X_2}, p_{\hat{Y}_1 | X_1 X_2} = p_{Y_1 | X_1 X_2}.$$

**Definition 2.**

$$\mathcal{R}_\Pi(Z) := \left\{ (R_1, R_2) \in \mathbb{R}_+^2 : \begin{array}{l} R_1 \leq I(X_1; Y_1 | X_2 Q) \\ R_2 \leq I(X_2; Y_2 | X_1 Q) \\ R_1 + R_2 \leq \min \left\{ I(X_1 X_2; Y_1 \tilde{Y}_1 | Q), I(X_1 X_2; Y_2 \tilde{Y}_2 | Q) \right\} \end{array} \right\}.$$

**Definition 3.**

$$\mathcal{R}_\Pi := \text{closure} \bigcup_{Z \in \Pi} \mathcal{R}_\Pi(Z)$$

**Theorem 1.**  $\mathcal{C}_I \subseteq \mathcal{R}_\Pi$

*Proof.* (1) Fix  $n$ ,  $p_Q(i) = \frac{1}{n}$ ,  $p_{X_1 X_2 Y_1 Y_2 | Q}(x_1 x_2 y_1 y_2 | i) = p_{X_1 i X_2 i Y_1 i Y_2 i}$ . As in the MAC's converse,  $R_1 \leq I(X_1; Y_1 | X_2 Q)$  and  $R_2 \leq I(X_2; Y_2 | X_1 Q)$ .

- (2)
- Now suppose the same codes are used in the new DMC with outputs  $Y_1 \tilde{Y}_1$  at decoder 1 and  $Y_2 \tilde{Y}_2$  at decoder 2.
  - Decoder 1 gets  $X_1^n, \tilde{Y}_1^n, Y_1^n$ ; sends  $\tilde{Y}_1^n$  to DMC  $p_{\tilde{Y}_2 | X_1 Y_1 \tilde{Y}_1}$  to get  $\hat{Y}_2^n$ , applies decoder 2's decode function to get  $\hat{W}_2$  as reliably as decoder 2.
  - Analogously, decoder 2 gets  $\hat{W}_2$  reliably, and moreover  $\hat{W}_1$  as reliably as decoder 1.
  - Using the converse to Ahlswede–Ulrey–Han generalisation, since both can decode, we have a compound DMC that satisfies

$$R_1 + R_2 \leq I(X_1 X_2; Y_1 \tilde{Y}_1 | Q)$$

$$R_1 + R_2 \leq I(X_1 X_2; Y_2 \tilde{Y}_2 | Q)$$

□