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Lecture 5: SoS and Robust Regression

$$(x_i, y_i)_{i=1}^N : \text{Corrupted dataset} \quad x_i \in \mathbb{R}^d$$

$$(x_i^*, y_i^*)_{i=1}^N : \text{uncorrupted dataset} \quad y_i \in \mathbb{R}$$

$$a_i^* = \begin{cases} 1 & \text{if } i \text{ is clean} \\ 0 & \text{o.w.} \end{cases}$$

so when $a_i^* = 1$, $(x_i^*, y_i^*) = (x_i, y_i)$

$$y_i^* = \langle w^*, x_i^* \rangle + \zeta_i \sim N(0, \sigma^2)$$

SoS Program

Variables: w (d -dimensional)
 a_1, \dots, a_N (1 -dimensional)

Constraints:

- 1) $a_i^2 = a_i$ (Boolean indicators)
- 2) $\frac{1}{N} \sum a_i \geq 1 - \gamma$ (γ fraction corruptions)

Obj: $\min \tilde{\mathbb{E}} \left[\frac{1}{N} \sum_{i=1}^N a_i (y_i - \langle w, x_i \rangle)^2 \right]$

Clean MSE:

$$\frac{1}{N} \sum_{i=1}^N a_i^* (y_i^* - \langle w, x_i^* \rangle)^2 \leq \frac{1}{N} \sum_{i=1}^N (y_i^* - \langle w, x_i^* \rangle)^2 \quad (\#)$$

Note:

$$1 = a_i a_i^* + a_i (1 - a_i^*) + (1 - a_i)$$

points we correctly identified as clean points we incorrectly identified as clean points we identified as corrupted

So

$$(6) = \frac{1}{N} \sum_i a_i a_i^* (y_i^* - \langle w, x_i^* \rangle)^2 \quad (1)$$

$$+ \frac{1}{N} \sum_i a_i (1-a_i^*) (y_i^* - \langle w, x_i^* \rangle)^2 \quad (2)$$

$$+ \frac{1}{N} \sum_i (1-a_i) (y_i^* - \langle w, x_i^* \rangle)^2 \quad (3)$$

(1): when $a_i^* = 1$, $y_i = y_i^*$ and $x_i = x_i^*$

$$(1) = \frac{1}{N} \sum_i a_i a_i^* (y_i - \langle w, x_i \rangle)^2$$

$$\stackrel{(a_i^* \leq 1)}{\leq} \frac{1}{N} \sum_i a_i (y_i - \langle w, x_i \rangle)^2 \leftarrow \text{objective value}$$

$$\leq \boxed{\text{OPT}} \quad (\text{objective value achieved by } w^*, \text{ i.e. clean MSE})$$

Note: $\{a_i^*\}, w^*$ is feasible solution to SoS program
 $\{x_i^*\}, \{y_i^*\}$

$$(2): \frac{1}{N} \sum_i a_i (1-a_i^*) \underbrace{(y_i^* - \langle w, x_i^* \rangle)^2}_{\text{Cauchy-Schwarz}}$$

$$\leq \left(\frac{1}{N} \sum_i (1-a_i^*)^2 \right)^{1/2} \cdot \left(\frac{1}{N} \sum_i \underbrace{\frac{a_i^2}{\leq 1}}_{\leq 1} (y_i^* - \langle w, x_i^* \rangle)^4 \right)^{1/2}$$

$$\leq \gamma^{1/2} \cdot \left(\frac{1}{N} \sum_i (y_i^* - \langle w, x_i^* \rangle)^4 \right)^{1/2}$$

$$③: \frac{1}{N} \sum_i (1-a_i) (\underbrace{y_i^* - \langle w, x_i^* \rangle}_2)$$

(Cauchy-Schwarz)

$$\leq \left(\frac{1}{N} \sum_i (1-a_i)^2 \right)^{1/2} \cdot \left(\frac{1}{N} \sum_{i=1}^N (y_i^* - \langle w, x_i^* \rangle)^4 \right)^{1/2}$$

$$\text{Note: } \frac{1}{N} \sum_i (1-a_i)^2 \stackrel{\text{(Booleanity)}}{=} \frac{1}{N} \sum_i (1-a_i) \stackrel{(\eta \text{ fraction corruptions})}{\leq} \gamma$$

$$\leq \gamma^{1/2} \cdot \left(\frac{1}{N} \sum_{i=1}^N (y_i^* - \langle w, x_i^* \rangle)^4 \right)^{1/2}$$

How to bound $\frac{1}{N} \sum_{i=1}^N (y_i^* - \langle w, x_i^* \rangle)^4$?

Recall $y_i^* = \langle w^*, x_i^* \rangle + \xi_i \stackrel{N(0, \sigma^2)}{\sim}$ so

$$\frac{1}{N} \sum_{i=1}^N (y_i^* - \langle w, x_i^* \rangle)^4 = \frac{1}{N} \sum_{i=1}^N (\langle w^* - w, x_i^* \rangle + \xi_i)^4$$

Note elementary inequality $(a+b)^4 \leq 8(a^4 + b^4)$,
 So the above

$$\begin{aligned} &\leq \boxed{\frac{8}{N} \sum_{i=1}^N \langle w^* - w, x_i^* \rangle^4} + \underbrace{\frac{8}{N} \sum_{i=1}^N \xi_i^4}_{\approx 8 \mathbb{E}_{\xi \sim N(0, \sigma^2)} [\xi^4]} \\ &= 24 \sigma^4 = O(\sigma^4) \end{aligned}$$

To summarize:

$$\begin{aligned} \text{clean MSE} &\leq \frac{1}{N} \sum_i (y_i^* - \langle w, x_i^* \rangle)^2 \\ &= ① + ② + ③ \\ &= \text{OPT} + 2\gamma^{1/2} \cdot \left(\frac{1}{N} \sum_{i=1}^N (y_i^* - \langle w, x_i^* \rangle)^4 \right)^{1/2} \\ &\leq \text{OPT} + 2\gamma^{1/2} \cdot \left(\frac{8}{N} \sum_i \langle w^* - w, x_i^* \rangle^4 + O(\sigma^4) \right)^{1/2} \\ &\leq \text{OPT} + O(\gamma^{1/2}) \cdot \left[\left(\frac{1}{N} \sum_i \langle w^* - w, x_i^* \rangle^4 \right)^{1/2} + \sigma^2 \right] \end{aligned}$$

• Technically not legit in SOS b/c of fractional power ($1/2$),
 But this step can be made rigorous by writing as
 $(\text{clean MSE} - \text{OPT})^2 \leq O(\gamma) \cdot [\frac{1}{N} \sum_i \langle w^* - w, x_i^* \rangle^4 + \sigma^4]$

To bound $\frac{1}{N} \sum_i \langle w^* - w, x_i^* \rangle^4$, need assumption on distribution:

Def: q is -hypercontractive if

$$\mathbb{E}_{x \sim q} [\langle v, x \rangle^4] \leq \left(C \cdot \mathbb{E}_{x \sim q} [\langle v, x \rangle^2] \right)^2 \quad (\dagger)$$

for all $v \in \mathbb{R}^d$, for some $C = O(1)$.

q is certifiably 4-hypercontractive if (\dagger) has an SOS proof.

Example: Any rotation of a product distribution (e.g. $N(\mu, \Sigma)$) is certifiably 4-hypercontractive.

So for $v = w^* - w$, we get

$$\left(\frac{1}{N} \sum_{i=1}^N \langle w^* - w, x_i^* \rangle^4 \right)^{1/2} \leq \frac{C}{N} \sum_{i=1}^N \langle w^* - w, x_i^* \rangle^2$$

$$= \frac{C}{N} \sum_{i=1}^N (y_i^* - \langle w, x_i^* \rangle - \bar{\xi}_i)^2$$

$$(a+b)^2 \leq 2a^2 + 2b^2$$

$$\leq \frac{2C}{N} \sum_i (y_i^* - \langle w, x_i^* \rangle)^2 + \frac{2C}{N} \sum_i \bar{\xi}_i^2$$

$$\leq \frac{2C}{N} \sum_i (y_i^* - \langle w, x_i^* \rangle)^2 + O(C\sigma^2)$$

So

$$\begin{aligned} \text{clean MSE} &\leq \overbrace{\frac{1}{N} \sum_i (y_i^* - \langle w, x_i^* \rangle)^2} \\ &\leq \text{OPT} + O(\gamma^{1/2}) \left[\overbrace{\frac{2C}{N} \sum_i (y_i^* - \langle w, x_i^* \rangle)^2} + O(C\sigma^2) \right] \end{aligned}$$

Rearranging, we get

$$\begin{aligned} (1 - O(C\gamma^{1/2})) \frac{1}{N} \sum_i (y_i^* - \langle w, x_i^* \rangle)^2 \\ \leq \text{OPT} + O(C\gamma^{1/2}\sigma^2), \end{aligned}$$

so if $C\gamma^{1/2}$ sufficiently small,

$$\text{clean MSE} \leq (\text{OPT} + O(C\gamma^{1/2}\sigma^2))$$