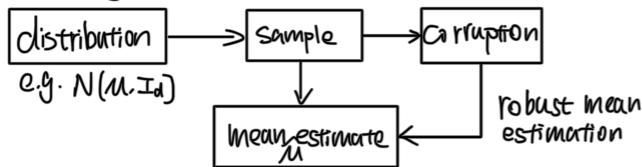


Lecture 12

Robust against adversarial corruptions



Unknown $\mu \in \mathbb{R}^d$, $\Sigma \in \mathbb{R}^{d \times d}$, $0 \leq \Sigma \leq I_d$

sample $y_1^0, \dots, y_n^0 \stackrel{\text{iid}}{\sim} N(\mu, \Sigma)$, $Y^0 = (y_1^0, \dots, y_n^0)$

corruption $C_\epsilon(Y) = \{Z \mid Y - Z \text{ has } \leq \epsilon \cdot n \text{ non-zero columns}\}$

adversarial error estimator $\hat{\mu}(Z)$

$$\sup \{ \|\hat{\mu}(Z) - \mu\|^2 \mid Z \in C_\epsilon(Y^0) \}$$

Inefficient estimator given ϵ -corrupted sample $Z \in C_\epsilon(Y^0)$

- find $Y \in C_\epsilon(Z)$ such that $\text{Cov}(\text{Unif}(\{Y_1, \dots, Y_n\})) \leq 2 \cdot I_d$
- output mean of $\leftarrow$

Lemma Let Y, Y' random vectors. Suppose $\Pr(Y \neq Y') \leq \epsilon$ and $\text{Cov}(Y), \text{Cov}(Y') \leq I$.

Then, $\|E[Y - Y']\| \leq \sqrt{\epsilon}$. * $\text{Cov}(Y), \text{Cov}(Y') \leq \sigma^2 I$, $\|E[Y] - E[Y']\| \leq O(\sqrt{\epsilon}) \cdot \sigma$.

Proof Let $u = Y - Y'$, $\bar{u} = E[u] = E[Y] - E[Y']$

$$\|\bar{u}\|^2 = \langle \bar{u}, \bar{u} \rangle = E[\langle \bar{u}, u \rangle] = E[1_{u \neq 0} \cdot \langle \bar{u}, u \rangle]$$

$$\begin{aligned} &\leq \underbrace{\sqrt{E[1_{u \neq 0}^2]}}_{\leq \epsilon} \cdot \underbrace{\sqrt{E[\langle \bar{u}, u \rangle^2]}}_{\leq \sqrt{\text{Var}(\langle \bar{u}, Y \rangle)} + \sqrt{\text{Var}(\langle \bar{u}, Y' \rangle)} + \|\bar{u}\|^2} \\ &\leq \sqrt{\epsilon} \cdot (2\|\bar{u}\| + \|\bar{u}\|^2) \end{aligned}$$

$$\rightarrow \|\bar{u}\|^2 \leq \frac{2\epsilon^{1/2}}{1-\epsilon^{1/2}} \|\bar{u}\| \rightarrow \|\bar{u}\| \leq \frac{2\epsilon^{1/2}}{1-\epsilon^{1/2}} \leq 4\sqrt{\epsilon}$$

Theorem

$\exists$ estimator $\hat{\mu}$ such that w.h.p. over Y^0 , ϵ -adversarial error $\leq O(\sqrt{\epsilon})$, $n \geq O(d/\epsilon)$.

Proof: By standard concentration bounds, w.h.p.

$$\left\| \frac{1}{n} \sum y_i^0 - \mu \right\| \leq O(\sqrt{\epsilon}) \Rightarrow \|\hat{\mu}^0 - \mu\| \leq O(\sqrt{\epsilon})$$

$$\text{Cov}(\text{Unif}(\{y_1^0, \dots, y_n^0\})) \leq 2 \cdot I$$

estimator $\hat{\mu}(Z)$:

- find $Y = (y_1, \dots, y_n) \in C_\epsilon(Z)$ such that $\text{Cov}(\text{Unif}(\{y_1, \dots, y_n\})) \leq 2 \cdot I$
- output $\hat{\mu}(Z) = \frac{1}{n} \sum_{i=1}^n y_i$

analysis: let $(Y, Y') \sim \text{Unif}(\{(y_1, y_1^0), \dots, (y_n, y_n^0)\})$

$$P(Y \neq Y') = \frac{1}{n} \cdot \# \text{ non-zero columns of } Y - Y^0$$

$$\leq \frac{1}{n} (\# \text{ non-zero columns of } Y - Z + \# \text{ non-zero columns of } Z - Y^0)$$

$$\leq 2\varepsilon$$

$$\xrightarrow{\text{lemma}} \|E[Y] - E[Y']\| \leq O(\sqrt{\varepsilon})$$

$$\rightarrow \|\hat{\mu}^0 - \hat{\mu}(Z)\| \leq O(\sqrt{\varepsilon})$$

$$\rightarrow \|\mu - \hat{\mu}(Z)\| \leq O(\sqrt{\varepsilon})$$

Efficient estimator

polynomial system A with variables

$$- y_1, \dots, y_n \in \mathbb{R}^d$$

$$- \mu \in \mathbb{R}^d$$

$$- w_1, \dots, w_n \in \mathbb{R}$$

$$- R \in \mathbb{R}^{d \times d}$$

$$A = \begin{cases} w_i^2 = w_i, i \in [n] \\ w_i(z_i - y_i) = 0, i \in [n] \\ \sum_{i=1}^n w_i \geq (1-\varepsilon)n \\ \mu = \frac{1}{n} \sum_{i=1}^n y_i \text{ to enforce } \frac{1}{n} \sum_{i=1}^n (y_i - \mu)(y_i - \mu)^T \leq 2I_d \\ \frac{1}{n} \sum_{i=1}^n (y_i - \mu)(y_i - \mu)^T + \boxed{R^T R} = 2I_d \end{cases}$$

$$\xrightarrow{\text{lemma}} \text{if } (Y^0, \mu^0, w^0, R^0) \models A$$

$$(Y, \mu, w, R) \models A$$

$$\text{then } \|\mu - \mu^0\| \leq \sqrt{\varepsilon}$$

* Any two solutions to A are close

* In order to get poly-time estimator, we just need low-degree SOS proofs for the above.

Theorem

$$\text{Let } (Y^0, \mu^0, w^0, R^0) \models A, \text{ then } A \mid_{\frac{Y, \mu, w, R}{8}} \|\mu^0 - \mu\|^2 \leq 100\varepsilon$$

or more general

Theorem

$$A \mid_{\frac{Y, \mu, w, R}{4}} \|\mu - \mu^0\|^2 \leq O(\varepsilon)$$

Proof:

With the SOS meta theorem, there exists $\hat{\mu}(z)$ such that $\|\hat{\mu}(z) - \mu^0\|^2 \leq O(\varepsilon) \implies \|\hat{\mu}(z) - \mu^0\| \leq O(\sqrt{\varepsilon})$

Some useful SOS inequalities

$$- \frac{a \cdot b}{2} \langle a, b \rangle \leq \frac{1}{2} \|a\|^2 + \frac{1}{2} \|b\|^2$$

$$- \frac{a \cdot b}{4} \langle a, b \rangle^2 = \langle a \otimes b, b \otimes a \rangle \leq \frac{1}{2} \|a\|^2 \cdot \|b\|^2 + \frac{1}{2} \|a\|^2 \cdot \|b\|^2 = \|a\|^2 \cdot \|b\|^2$$

$$- C > 0, \{x^2 \leq Cx\} \vdash X < C$$

$$\{x^2 \leq Cx\} \vdash X = \left(\frac{1}{\sqrt{C}} X\right) \cdot \sqrt{C} \leq \frac{X^2}{2C} + \frac{C}{2} \leq \frac{X}{2} + \frac{C}{2}$$

$$A \vdash \frac{1}{n} \sum_{i=1}^n (1 - w_i w_i^*)^2 = \frac{1}{n} \sum_{i=1}^n (1 - w_i w_i^*)$$

$$A \vdash 1 - w_i w_i^* \leq 2 - w_i \cdot w_i^* \rightarrow \frac{1}{n} \sum_{i=1}^n (1 - w_i) + \frac{1}{n} \sum_{i=1}^n (1 - w_i^*)$$

$$\leq 2\varepsilon$$

$$* \sum_{i=1}^n w_i \geq (1-\varepsilon)n$$

$$\Rightarrow \frac{1}{n} \sum_{i=1}^n w_i \geq 1-\varepsilon$$

$$\Rightarrow \frac{1}{n} \sum_{i=1}^n (1 - w_i) \leq \varepsilon$$

$$\begin{aligned}
A \frac{1}{4} \| \mu - \mu^* \|^2 &= \langle \mu - \mu^*, \mu - \mu^* \rangle \\
&= \langle \mu - \mu^*, \frac{1}{n} \sum_{i=1}^n y_i - \frac{1}{n} \sum_{i=1}^n y_i^* \rangle \\
&= \frac{1}{n} \sum_{i=1}^n \langle \mu - \mu^*, y_i - y_i^* \rangle \\
&= \frac{1}{n} \sum_{i=1}^n (1 - w_i w_i^*) \langle \mu - \mu^*, y_i - y_i^* \rangle \\
&= \frac{1}{n} \sum_{i=1}^n (1 - w_i w_i^*) \langle \mu - \mu^*, y_i - \mu + \mu^* - y_i^* + \mu - \mu^* \rangle \\
&\leq \frac{1}{n} \sum_{i=1}^n (1 - w_i w_i^*) \langle \mu - \mu^*, y_i - \mu \rangle \\
&\quad + \frac{1}{n} \sum_{i=1}^n (1 - w_i w_i^*) \langle \mu - \mu^*, \mu^* - y_i^* \rangle + 2\varepsilon \| \mu - \mu^* \|^2
\end{aligned}$$

$$\begin{aligned}
A \frac{1}{8} \| \mu - \mu^* \|^4 &\leq 4 \left(\frac{1}{n} \sum_{i=1}^n (1 - w_i w_i^*) \langle \mu - \mu^*, y_i - \mu \rangle + \frac{1}{n} \sum_{i=1}^n (1 - w_i w_i^*) \langle \mu - \mu^*, \mu^* - y_i^* \rangle \right)^2 \\
&\leq 8 \underbrace{\left(\frac{1}{n} \sum_{i=1}^n (1 - w_i w_i^*) \langle \mu - \mu^*, y_i - \mu \rangle \right)^2}_{\leq 2\varepsilon} + 8 \underbrace{\left(\frac{1}{n} \sum_{i=1}^n (1 - w_i w_i^*) \langle \mu - \mu^*, \mu^* - y_i^* \rangle \right)^2}_{\leq 2\varepsilon} \\
&\leq 16\varepsilon \left(\frac{1}{n} \sum_{i=1}^n \langle \mu - \mu^*, y_i - \mu \rangle \right)^2 + 16\varepsilon \left(\frac{1}{n} \sum_{i=1}^n \langle \mu - \mu^*, \mu^* - y_i^* \rangle \right)^2
\end{aligned}$$

Recall $\frac{1}{n} \sum_{i=1}^n (y_i^* - \mu^*)(y_i^* - \mu^*)^T \preceq 2I_d$, which implies

$$\begin{aligned}
A \frac{1}{2} \frac{1}{n} \sum_{i=1}^n \langle \mu - \mu^*, \mu^* - y_i^* \rangle^2 &= (\mu - \mu^*)^T \left[\frac{1}{n} \sum_{i=1}^n (y_i - \mu)(y_i - \mu)^T \right] (\mu - \mu^*) \\
&= (\mu - \mu^*)^T [2I_d - R^T R] (\mu - \mu^*) \\
&\leq 2 \| \mu - \mu^* \|^2
\end{aligned}$$

together

$$\begin{aligned}
A \frac{1}{8} \| \mu - \mu^* \|^4 &\leq 32\varepsilon \cdot \| \mu - \mu^* \|^2 \\
\Rightarrow A \frac{1}{8} \| \mu - \mu^* \|^2 &\leq 32\varepsilon = O(\varepsilon)
\end{aligned}$$