

# Fano Method

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Thursday 6<sup>th</sup> July, 2017

## Abstract

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## 1 Basic framework

Throughout, we let  $\mathcal{P}$  denote a class of distributions on a sample space  $\mathcal{X}$ , and let  $\theta : \mathcal{P} \rightarrow \Theta$  denote a function defined on  $\mathcal{P}$ , that is, a mapping  $P \mapsto \theta(P)$ . The goal is to estimate the parameter  $\theta(P)$  based on observations  $X_i$  drawn from the distribution  $P$ .

To evaluate the quality of an estimator  $\hat{\theta}$ , we let  $\rho : \Theta \times \Theta \rightarrow \mathbb{R}_+$  denote a semimetric on the space  $\Theta$ , which we use to measure the error of an estimator for the parameter  $\theta$ , and let  $\Phi : \mathbb{R}_+ \rightarrow \mathbb{R}_+$  be a non-decreasing function with  $\Phi(0) = 0$ .

**From estimation to testing** Given an index set  $\mathcal{V}$  of finite cardinality, consider a family of distributions  $\{P_v\}_{v \in \mathcal{V}}$  contained within  $\mathcal{P}$ . This family induces a collection of parameters  $\{\theta(P_v)\}_{v \in \mathcal{V}}$ ; we call the family a  $2\delta$ -packing in the  $\rho$ -semimetric if

$$\rho(\theta(P_v), \theta(P_{v'})) \geq 2\delta \quad \text{for all } v \neq v'.$$

We use this family to define the canonical hypothesis testing problem:

- first, nature chooses  $V$  according to the uniform distribution over  $\mathcal{V}$ ;
- second, conditioned on the choice  $V = v$ , the random sample  $X = X_1^n = (X_1, \dots, X_n)$  is drawn from the  $n$ -fold product distribution  $P_v^n$ .

**Proposition 1.** *The minimax error has lower bound*

$$\mathfrak{M}_n(\theta(\mathcal{P}), \Phi \circ \rho) \geq \Phi(\delta) \inf_{\Psi} \mathbb{P}(\Psi(X_1, \dots, X_n) \neq V).$$

## 2 Metric entropy and packing numbers

- Covering number:  $N(\delta, \Theta, \rho)$
- Metric entropy:  $\log N(\delta, \Theta, \rho)$
- Packing number:  $M(\delta, \Theta, \rho)$

**Lemma 1.**  $M(2\delta, \Theta, \rho) \leq N(\delta, \Theta, \rho) \leq M(\delta, \Theta, \rho)$

**Lemma 2** (Gilbert-Versharnov bound). *Let  $d \geq 1$ . There is a subset  $\mathcal{V}$  of the  $d$ -dimensional hypercube  $\mathcal{H}_d = \{-1, 1\}^d$  of size  $|\mathcal{V}| \geq \exp(d/8)$  such that the  $\ell_1$ -distance*

$$\|v - v'\|_1 = 2 \sum_{j=1}^d \mathbf{1}\{v_j \neq v'_j\} \geq \frac{d}{2}$$

for all  $v \neq v'$  with  $v, v' \in \mathcal{V}$ .

**Lemma 3.** *Let  $\|\cdot\|$  be any norm in  $\mathbb{R}^d$ . Let  $\mathbb{B}$  denote the unit  $\|\cdot\|$ -ball in  $\mathbb{R}^d$ . Then*

$$\left(\frac{1}{\delta}\right)^d \leq N(\delta, \mathbb{B}, \|\cdot\|) \leq \left(1 + \frac{2}{\delta}\right)^d.$$

## 3 Fano inequality

Let  $V$  be a random variable taking values in a finite set  $\mathcal{V}$ , and assume that we observe a random variable  $X$ , and then must estimate or guess the true value of  $\hat{V}$ . That is, we have the Markov chain

$$V \rightarrow X \rightarrow \hat{V}.$$

Let the function  $h_2(p) = -p \log p - (1-p) \log(1-p)$  denote the binary entropy.

**Proposition 2** (Fano inequality). *For any Markov chain  $V \rightarrow X \rightarrow \hat{V}$ , we have*

$$h_2(\Pr(\hat{V} \neq V)) + \Pr(\hat{V} \neq V) \log(|\mathcal{V}| - 1) \geq H(V|\hat{V}).$$

*Proof.* Let  $E$  be the indicator for the event that  $\hat{X} \neq X$ , that is,  $E = 1$  if  $\hat{V} \neq V$  and is 0 otherwise. Then we have

$$\begin{aligned} H(V|\hat{V}) &= H(V, E|\hat{V}) = H(V|E, \hat{V}) + H(E|\hat{V}) \\ &= \Pr(E = 0) \underbrace{H(V|E = 0, \hat{V})}_0 + \Pr(E = 1)H(V|E = 1, \hat{V}) + H(E|\hat{V}) \\ &\leq \Pr(E = 1) \log(|\mathcal{V}| - 1) + H(E) \end{aligned}$$

□

**Remark 1.** During the proof,  $X$  is not needed.

**Corollary 1.** Assume  $V$  is uniform on  $\mathcal{V}$ , then

$$\Pr(\hat{V} \neq V) \geq 1 - \frac{I(V; X) + \log 2}{\log(|\mathcal{V}|)}.$$

*Proof.* Note that  $h_2(\Pr(\hat{V} \neq V)) \leq \log 2$  and

$$H(V|\hat{V}) = H(V) - I(V; \hat{V}) \geq H(V) - I(V; X) = \log(|\mathcal{V}|) - I(V; X).$$

□

## 4 The classical (local) Fano method

**Proposition 3.** Let  $\{\theta(P_v)\}_{v \in V}$  be a  $2\delta$ -packing in the  $\rho$ -semimetric. Assume that  $V$  is uniform on the set  $\mathcal{V}$ , and conditional on  $V = v$ , we draw a sample  $X \sim P_v$ . Then the minimax risk has lower bound

$$\mathfrak{M}(\theta(\mathcal{P}); \Phi \circ \rho) \geq \Phi(\delta) \left( 1 - \frac{I(V; X) + \log 2}{\log |\mathcal{V}|} \right).$$

## References