

Minimax Lower Bounds via f-divergences

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f-divergences

$$D_f(P\|Q) = \int f\left(\frac{dP}{dQ}\right) dQ$$

P, Q probs; $P \ll Q$

f convex on $[0, \infty)$
 $f(1)=0$

KL, χ^2 (chi-squared), Total
Variation, Hellinger etc.

Estimation

F finite
size N

To estimate $\theta \sim \text{unif}(F)$

Observe $X \sim p(x|\theta)$ or p_θ or P_θ

$T(X)$: estimator for θ based on X

$$P_e(T) = P(T(X) \neq \theta) = \frac{1}{N} \sum_{\theta \in F} P_\theta(T(X) \neq \theta)$$

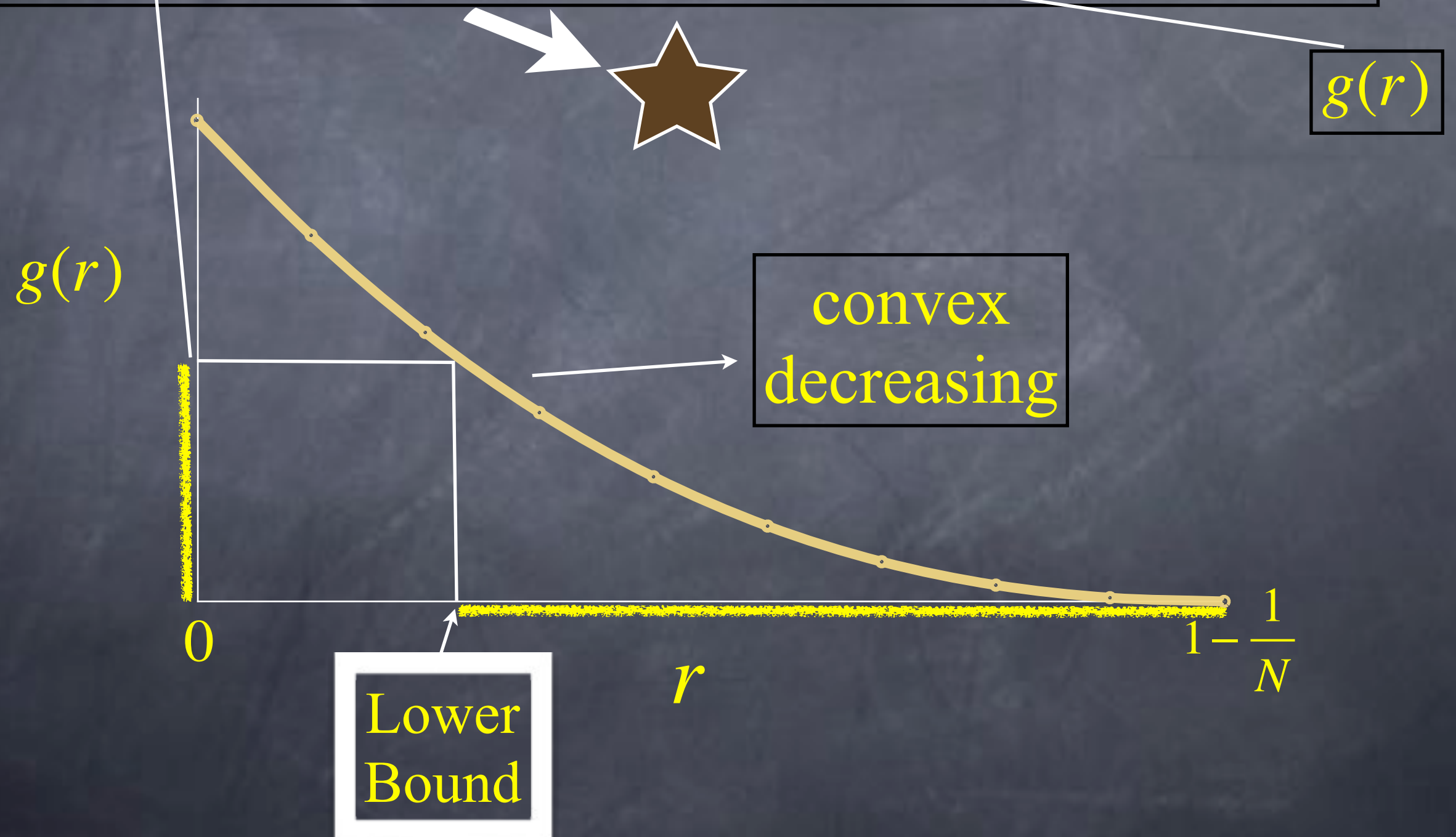
$$r = \inf_T P_e(T)$$

We'll lower bound r using f-divergences

$$r = 1 - \frac{1}{N} \int \max_{\theta \in F} p_\theta \leq 1 - \frac{1}{N}$$

Implicit Lower Bound for r

$$\inf_Q \sum_{\theta \in F} D_f(P_\theta \| Q) \geq f(N(1-r)) + (N-1)f\left(\frac{Nr}{N-1}\right)$$



Proof of CONVEXITY

$$b > 0$$

$$\sum_{\theta \in F} f(ba_{\theta}) \geq f(bm) + (N-1)f\left(\frac{b(1-m)}{N-1}\right)$$

$$a_{\theta} \geq 0; \sum_{\theta \in F} a_{\theta} = 1$$

$$m := \max_{\theta \in F} a_{\theta}$$

$$b = \frac{\sum p_{\theta}}{q}; ba_{\theta} = \frac{p_{\theta}}{q}$$

Integrate with Q
Jensen's Inequality

$$r = 1 - \frac{1}{N} \int \max_{\theta \in F} p_{\theta}$$



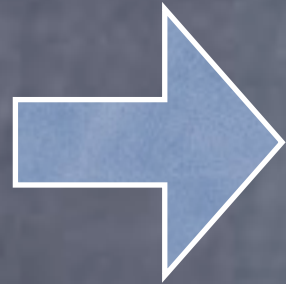
$$\inf_Q \sum_{\theta \in F} D_f(P_{\theta} \parallel Q) \geq f(N(1-r)) + (N-1)f\left(\frac{Nr}{N-1}\right)$$

$f(x) := x \log x$; Fano

$$\frac{1}{N} \inf_Q \sum_{\theta \in F} D(P_\theta \parallel Q) = \frac{1}{N} \sum_{\theta \in F} D(P_\theta \parallel \bar{P}) =: I(\theta, X)$$

KL

Mutual
Information



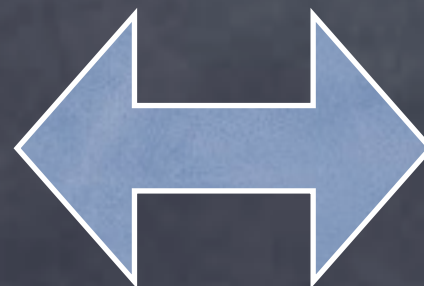
$$I(\theta, X) \geq (1 - r) \log N - H(r)$$



$$r \geq 1 - \frac{\log 2 + I(\theta; X)}{\log N}$$

$\leq \log 2$

Binary
Entropy



Fano's
Inequality

$$\underline{f(x) = x^2 - 1; \text{chi-squared}}$$

Right Hand Side of   $N^2 \left(r - \left(1 - 1/N \right) \right)^2$



$$r \geq 1 - \frac{1}{\sqrt{N}} \sqrt{\inf_Q \frac{1}{N} \sum_{\theta \in F} \chi^2(P_\theta \| Q)} - \frac{1}{N}$$

χ^2 -analogue of
Mutual Information

$$N = 2$$

$$r = 1 - \frac{1}{2} \int \max(p_1, p_2) = \frac{1-V}{2}$$

$$V := \frac{1}{2} \int |p_1 - p_2|$$

Total
Variation

$$\inf_Q \left[D_f(P_1 || Q) + D_f(P_2 || Q) \right] \geq f(1+V) + f(1-V)$$

$$f(x) = x \log x$$

$$f(1+V) + f(1-V) \geq V^2$$

Topsøe (2000)

SHARP

$$P_1\{1\} = P_2\{2\} = \frac{1+V}{2}$$

$$P_1\{2\} = P_2\{1\} = \frac{1-V}{2}$$

$$Q\{1\} = Q\{2\} = \frac{1}{2}$$

Pinsker's
Inequality



Upper Bound for $\inf_Q \sum_{\theta \in F} D_f(P_\theta \| Q)$

$I(\theta, X)$

$$\inf_Q \frac{1}{N} \sum_{\theta \in F} D(P_\theta \| Q) \leq \log M_{KL}(\varepsilon) + \varepsilon^2$$

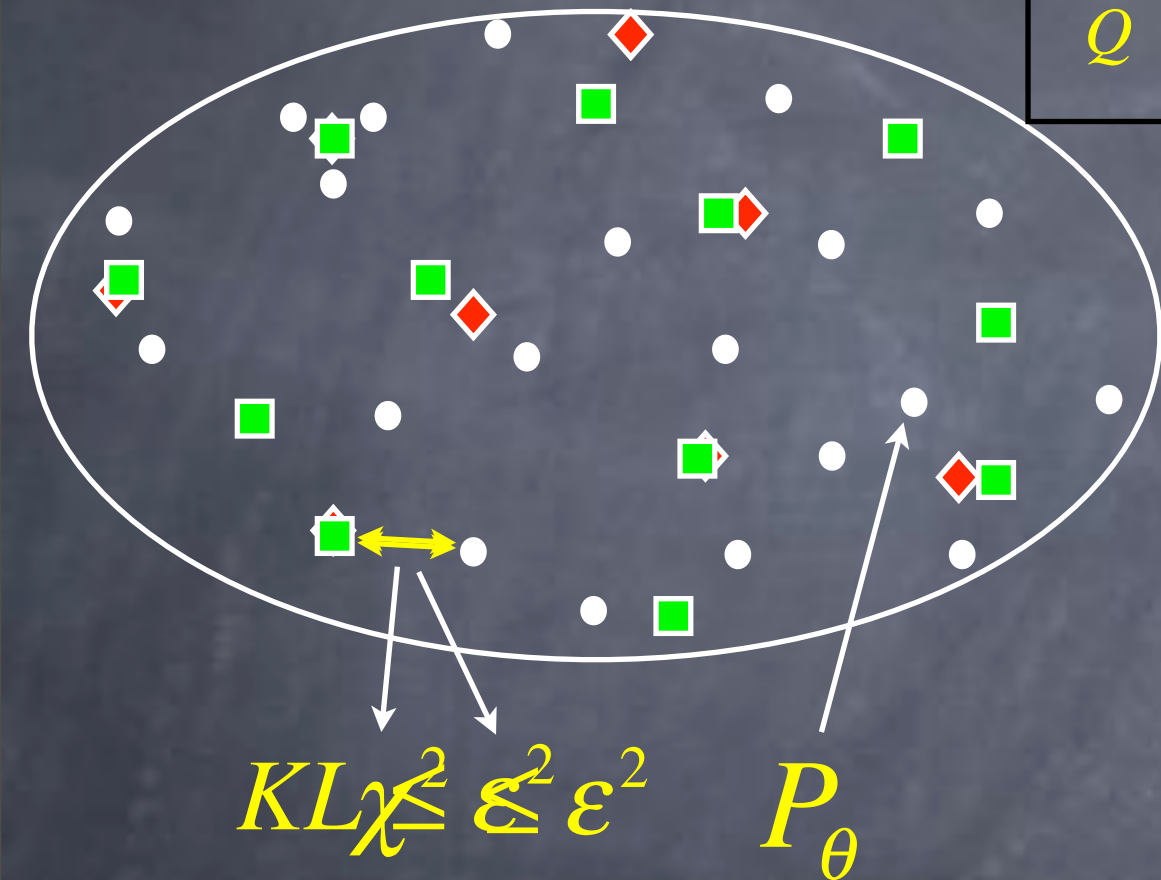
Yang and Barron (1999)

Covering Number
Bounds

$KL \chi^2 \leq \varepsilon^2 \varepsilon^2$

P_θ

$$\inf_Q \frac{1}{N} \sum_{\theta \in F} \chi^2(P_\theta \| Q) \leq M_C(\varepsilon)(1 + \varepsilon^2)$$



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General Estimation Problem

To estimate $\theta \in \Theta$ (Θ, ρ) metric space

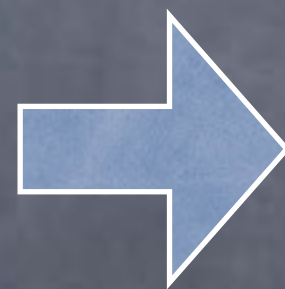
Observe $X \sim p(x|\theta)$ or p_θ or P_θ

$U(X)$: estimator for θ based on X

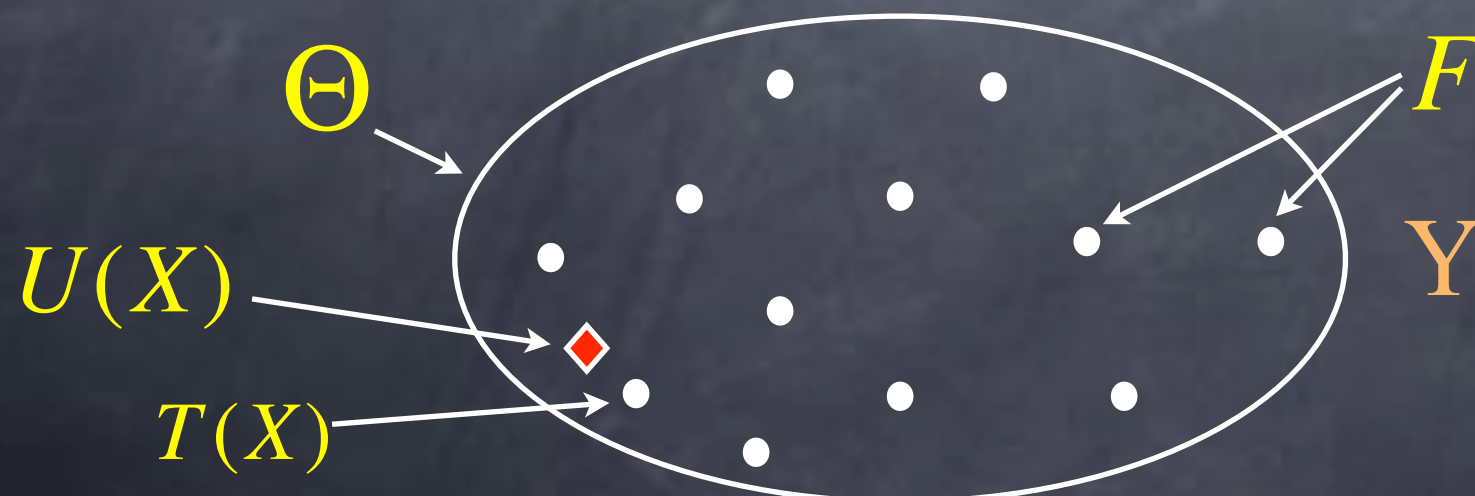
$$P_e(U) = \sup_{\theta \in \Theta} E_\theta (\rho(U(X), \theta))^2$$

$$R = \inf_U P_e(U) \quad \begin{array}{l} \text{Minimax} \\ \text{Risk} \end{array}$$

$F \subseteq \Theta$ finite & η -separated



$$R \geq \left(\frac{\eta}{2}\right)^2 r$$



Yang and Barron (1999)

Global Entropy Bounds

$$R \geq \left(\frac{\eta}{2}\right)^2 \left[1 - \frac{\log M_{KL}(\varepsilon) + \varepsilon^2 + \log 2}{\log N(\eta)} \right]$$

Yang and Barron (1999)

Size of any
 η -separated
subset of Θ

$$R \geq \left(\frac{\eta}{2}\right)^2 \left[1 - \sqrt{\frac{M_C(\varepsilon)(1 + \varepsilon^2)}{N(\eta)}} - \frac{1}{N(\eta)} \right]$$

Optimize over η and ε

Convenient when global covering/packing
numbers are available

Example: Parametric Estimation

$$\Theta = [1, 2]$$

$$\rho(\theta, \theta') = |\theta - \theta'|$$

$$N(\eta) = \frac{c_1}{\eta}$$

$$M_{KL}(\varepsilon) = c_2 \frac{\sqrt{n}}{\varepsilon}$$

$$M_C(\varepsilon) = c_3 \frac{\sqrt{n}}{\sqrt{\log(1 + \varepsilon^2)}}$$

eg. $X_1, X_2, \dots, X_n \sim \exp(\theta)$ or $N(\theta, 1)$

$$R \geq o\left(\frac{1}{n}\right) \leftarrow \text{KL}$$

$$\chi^2 \rightarrow$$

$$R \geq \frac{c}{n}$$

Conclusion

- New Lower Bound for Estimation using f -divergences.
- Special cases include Fano's inequality and Pinsker's inequality.
- The lower bound involves a version of Mutual Information for f -divergences, which can be bounded from above using global covering numbers.
- Global entropy numbers determine the parametric minimax lower bound as well.

References

- Y. Yang and A. Barron, “Information-theoretic determination of minimax rates of convergence,” *Annals of Statistics*, vol. 27, pp. 1564-1599, 1999.
- F. Topsøe, “Some inequalities for information divergence and related measures of discrimination,” *IEEE Trans. Inform. Theory*, vol. 46, pp. 1602-1609, 2000.
- A. Guntuboyina, “Lower bounds for the minimax risk using f-divergences and applications,” 2010, [Online]. Available: <http://arxiv.org/abs/1002.0042v1>.