

i in $[n]$ w.p. p_i
then $Z_k = \max_i | \tilde{f}_i - p_i |$
--> again $k \sim 1/\epsilon^2$

Continuous domains:

Consider any distribution D [draw curve]

Consider any interval I w.p. p_i of having a random sample from D .

$Z_k = \max_{\{I\}} | \tilde{f}_i - p_i |$

Still need $k \sim 1/\epsilon^2$

Works in higher dimensions R^d as well. Instead of intervals -> rectangles, disks, ...

need about $k \sim d/\epsilon^2$

Other error measures:

We consider **worst case bounds** why?

- computer scientists like worst case bounds
- L_1 or L_2 ? (average error, average squared error)
similar results ($k \sim 1/\epsilon^2$) but can be messier
or show variance decreases at about same rate

Tail Bounds:

Markov Inequality

Chernoff-Hoeffding Inequality

How to combine rare events:

The Union Bound

Markov Inequality:

X = random variable, $X > 0$

$\Pr[X > a] \leq E[X]/a$

[draw distribution]

- plot average
- if too much "mass" is too large, then average is too low

Consider if not true: $\gamma = \Pr[X > a]$

$E[X] = (1-\gamma) \cdot 0 + \gamma a = \gamma a > (E[X]/a) \cdot a = E[X]$

Chernoff-Hoeffding Inequality:

r independent random variables $\{X_1, X_2, \dots, X_r\}$

$-\Delta_i \leq X_i \leq \Delta_i$

$$M = \sum_{i=1}^n X_i \quad (\text{average of } X_i)$$

$$E[M] = 0$$

$$\Pr[M > a] \leq 2 \exp(-a^2 / 2 \sum_i \Delta_i^2).$$

idea for proof: (use Markov Inequality)

$$\begin{aligned} \Pr[M > a] &= \Pr[\exp(tM) > \exp(ta)] \\ &\leq E[\exp(tM)] / \exp(ta) \\ &= \prod_{i=1}^n E[\exp(t X_i)] / \exp(ta) \\ &\leq \prod_{i=1}^n \exp(t^2 \Delta_i^2 / 2) / \exp(ta) \\ &= \exp((t^2 / 2) \sum_i \Delta_i^2 - ta) \end{aligned}$$

$$\begin{aligned} \text{choose } t &= a / \sum_i \Delta_i^2 \dots \\ &= \exp(-a^2 / 2 \sum_i \Delta_i^2) \end{aligned}$$

****magic Lemma**** is $E[\exp(t X_i)] \leq \exp(t^2 \Delta_i^2 / 2)$

[draw cumulative density plot]
Central Limit Theorem

Use C-H to prove eps-Sample Bound (for one $\sim f_i$).
Each (of k) trials is a random variable Y_i

$$\begin{aligned} Y_j &= 1 \quad \text{if it chooses } i \text{ in } [n] \\ Y_j &= 0 \quad \text{if it does not choose } i \end{aligned}$$

New random variable X_j

$$\begin{aligned} X_j &= Y_j - 1/n \\ E[X_j] &= 0 \\ \Delta_i &= 1 \quad (-1/n \leq X_j \leq 1-1/n) \end{aligned}$$

$\hat{M} = \sum_{j=1}^k Y_j$ | # random trials with i

$$M = (1/n) \sum_{j=1}^k X_j = (\hat{M} - k) / n$$

fraction of random trials more than expected to have index i

Set $a = \epsilon$, and δ in $(0,1)$

$$\begin{aligned} \Pr[\hat{M} - E[\hat{M}] > \epsilon n] &= \Pr[M > a] \\ &< 2 \exp(-a^2 / 2 \sum_j \Delta_i^2) \\ &= 2 \exp(-\epsilon^2 / 2k) < \delta \end{aligned}$$

Solve for $k \rightarrow k \geq (2/\epsilon^2) \ln(2/\delta)$

Some probability δ of failure. Trade-off between ϵ and δ is exponential!

PAC = "probably approximately correct"

[draw ϵ -($1-\delta$) trade-off cumulative density plot]

For only one $i \in [n]$

Union Bound:

Consider t random variables $\{Z_1, \dots, Z_t\}$

$Z_i = 1$ w.p. p_i and $Z_i = 0$ w.p. $q_i = 1 - p_i$

All random variables = 1

w.p. $p \geq 1 - \sum_{i=1}^t q_i$

Z_i do **not** need to be independent

- add probabilities of failure!

Apply to eps-Samples

n indices to consider

Want bound on k , so $\geq 1 - \delta$ probability of failure on **all** indices.

$k = (2/\epsilon^2) \ln(2/\delta')$ for one index w.p. $1 - \delta'$

Union bound on n indices \rightarrow prob. of failure = $\delta' * n$

\rightarrow prob. of success = $1 - \delta' * n = 1 - \delta$

$\rightarrow \delta' = \delta/n$

$\rightarrow k = (2/\epsilon^2) \ln(2n/\delta)$

eps-sample (at most eps error on **all** indices)

- factor of n , but inside $\ln(\)$

- can remove $\ln(n)$ term (not $\ln(1/\delta)$), but much more complicated

Numbers: Let $\epsilon = 1/10$ so $1/\epsilon^2 = 100$

δ	$\ln(2/\delta)$
.1	3
.05	3.7
.01	5.3
.005	6
.001	7.6
.0005	8.3
.0001	9.9
.00001	12.2
.000001	14.5 (1 in a million)