

Estimation of Smoothed Entropy

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Estimation of Smoothed Support

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Problem

- Take n samples from an unknown distribution (i.i.d.)
- Estimate the entropy
- Estimate the support

Many Incarnations

- Shakespeare's vocabulary
- How many species?
- Good-Turing estimator



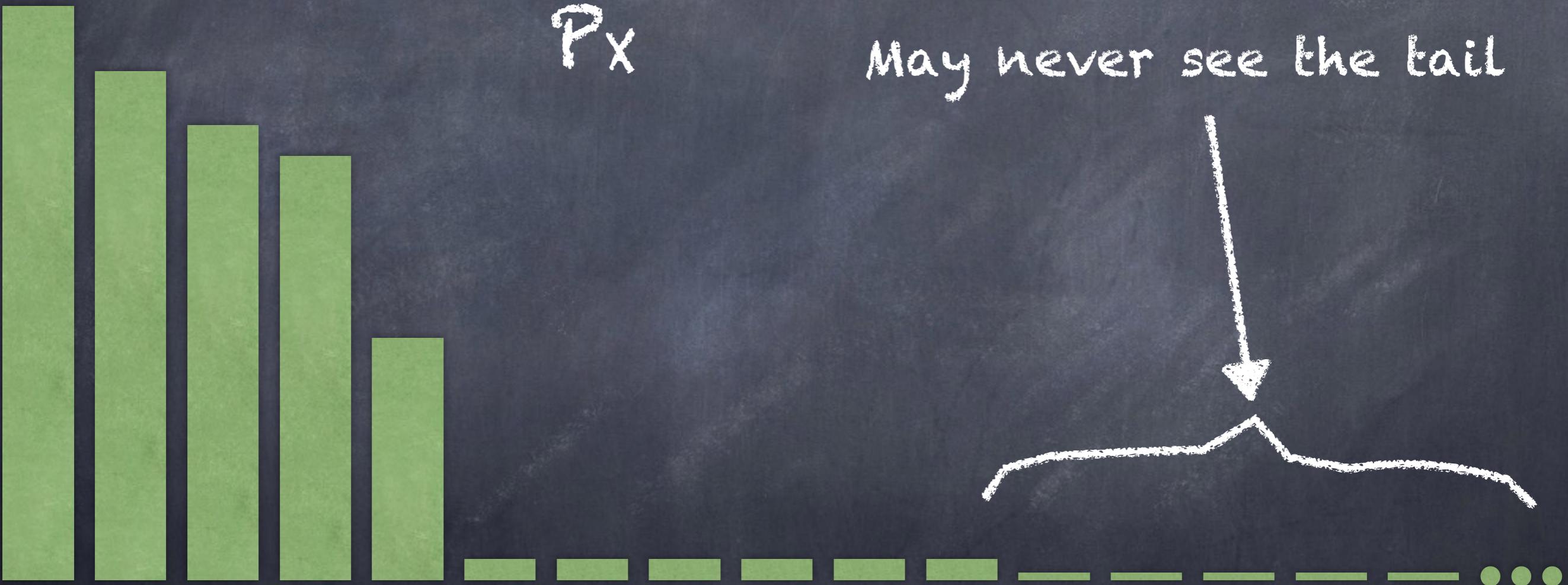
Long History

- Recent:
 - [Valiant-Valiant 10]
 - [Acharya-Jafarpour-Orlitsky-Suresh-Wu 13, 15]
 - [Jiao-Venkat-Han-Weissman 15]

The problem

P_x

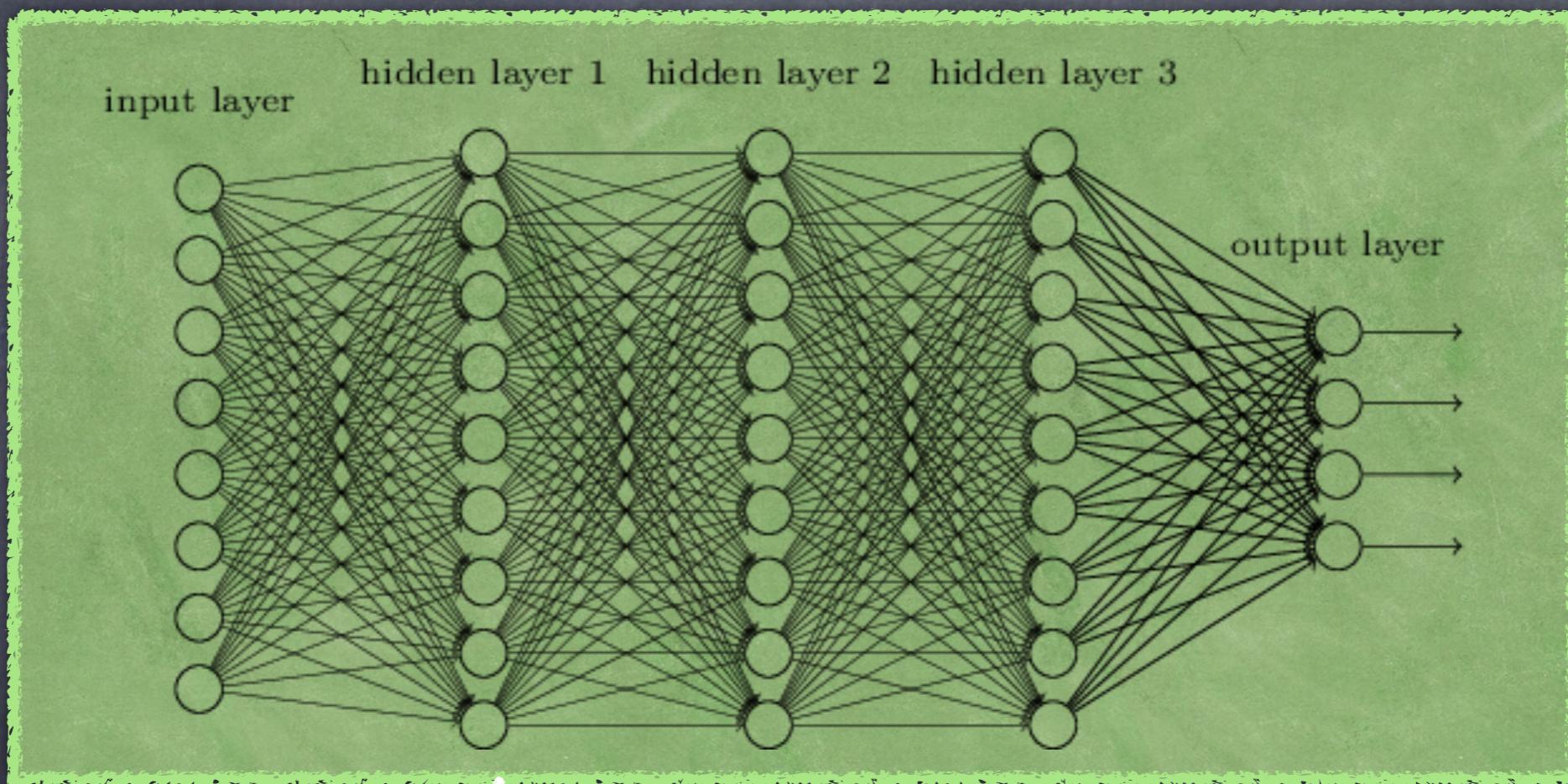
May never see the tail



The usual assumption

- Recent work
- Entropy: assume a bound on the support size (S)
- Support: assume a minimum probability mass ($1/S$)
- Sample complexity: $n \sim \frac{S}{\log S}$

Death by S



$S = 22000$

What can we do
with no assumption?

Perhaps nothing

- Cannot reliably decide that entropy or support is finite.
- Reason: Every distribution has an $H=\infty$ neighbor (in total variation)

Yikes

- After one million samples of seeing only one outcome, can we not say anything?

Two Changes

1. Estimate smoothed entropy/support

$$S_\delta(P_X) = \min_{Q : \|P_X - Q\|_{TV} \leq \delta} |\text{Support}(Q)|$$

2. Confidence bounds: Estimator can fail as long as it knows when it fails

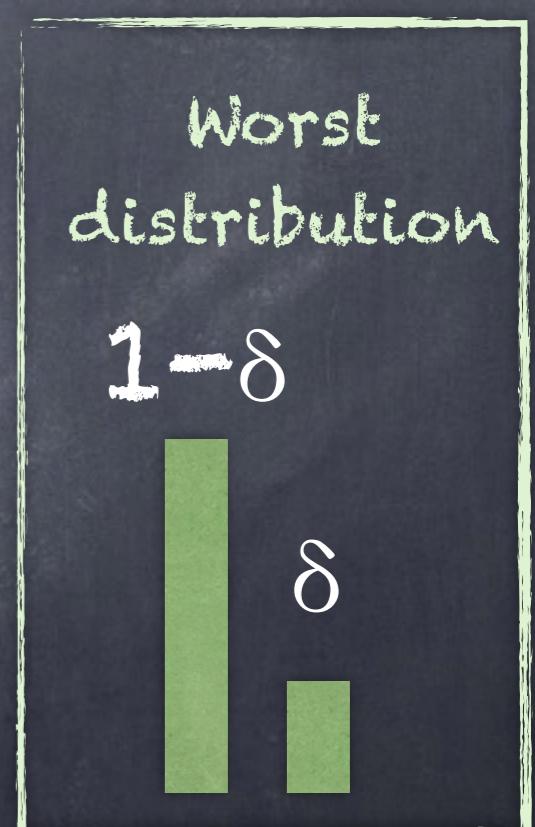
$$\underline{S}_\delta(X^n)$$

$$S_\delta$$

$$\overline{S}_\delta(X^n)$$

ALL Samples the Same

- Conclude: $H=0$, Support=1
- Error prob. $< \epsilon$ if $n \geq \frac{\log \frac{2}{\epsilon}}{\log \frac{1}{1-\delta}}$
- 459 samples (for $\delta=\epsilon=0.01$)



ALL Samples Different

- No upper bound possible
- Lower bound: $\text{Support} = \Omega(n^2)$

ϵ -Achieving

$$\sup_P \mathbb{P} \left(S_\delta(P) \notin [\underline{S}_\delta(X^n), \overline{S}_\delta(X^n)] \right) \leq \epsilon$$

Simple estimator

- Build estimator based on a simple statistic:
- R = fraction of unique samples

Claim

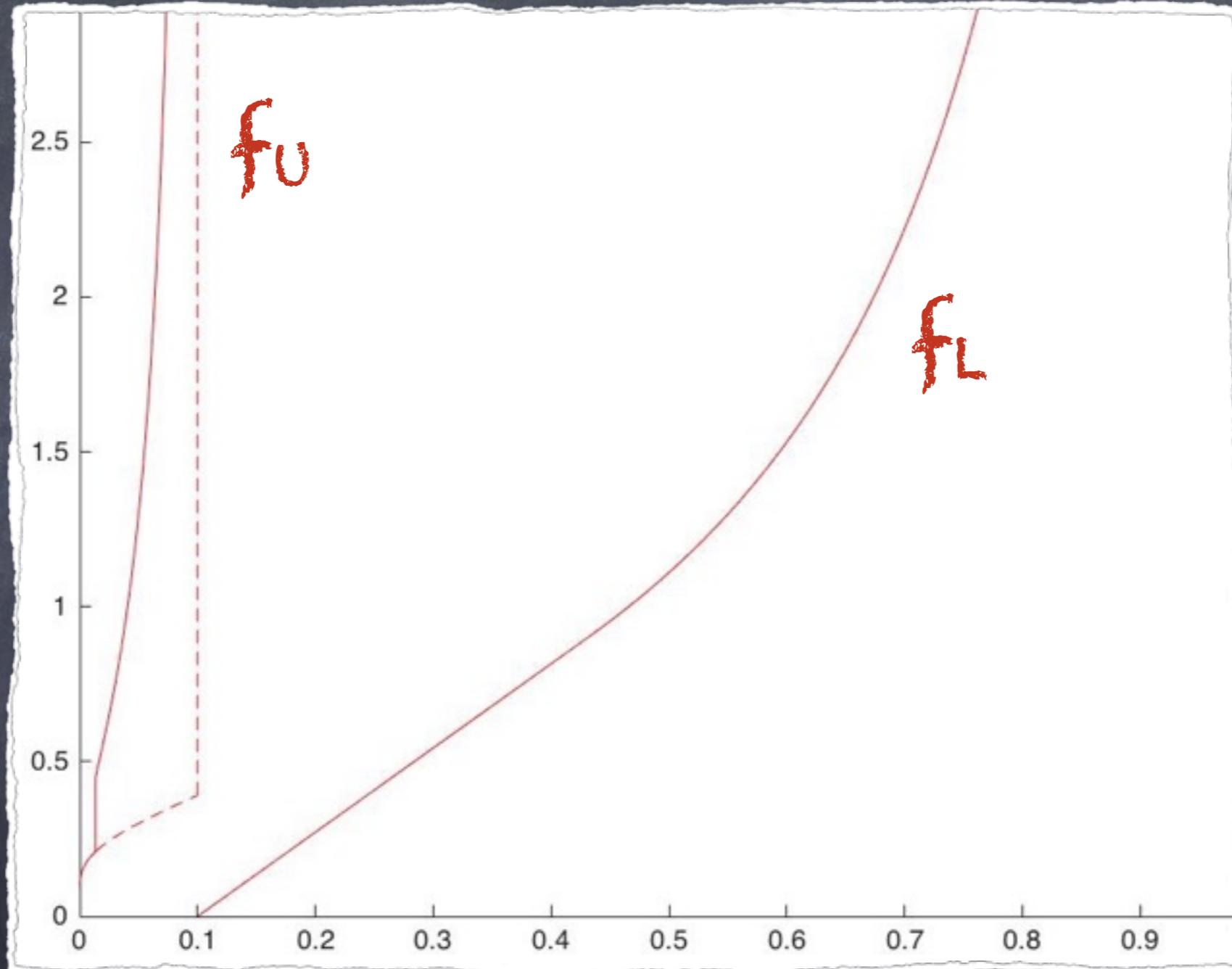
- Choose $c > 3$:
- ε -achieving (for large enough n):

$$\underline{S}_\delta(R) = n f_L \left(R + c \sqrt{\frac{\log n}{n}} \right) \quad \overline{S}_\delta(R) = n f_U \left(R - c \sqrt{\frac{\log n}{n}} \right)$$

$$f_L(r) = \begin{cases} 0 & r \leq \delta \\ e(r - \delta) & \delta < r < \delta + e^{-1}(1 - \delta) \\ \frac{1 - \delta}{\log \frac{1 - \delta}{r - \delta}} & r \geq \delta + e^{-1}(1 - \delta) \end{cases} \quad f_U(r) = \begin{cases} \frac{1 - \delta}{\log \frac{\delta}{r}} & r < \delta \\ \infty & r \geq \delta \end{cases}$$

$\delta=0.1$

$$\frac{S_\delta}{n}$$



R

Best bounds

• Small R :

$$\bar{S}_\delta = O\left(\frac{n}{\log n}\right)$$

• Large R :

$$\bar{S}_\delta = \Omega\left(n^{3/2}\right)$$



Maybe n^2

Proof - 2 Steps

1. Connect to Poisson Approximation
2. Analyze Poisson Approximation

Step 1

Poisson
approximation

Non-discrete part

Discrete

Bernstein

Tail

$$\mathbb{P}(|R - \mathbb{E}_{X^N} R| > 3\Delta) < e\sqrt{n} \left(\exp\left(-\frac{n\Delta^2}{2(1+\Delta)}\right) + \exp\left(-\frac{n\Delta^2}{2}\right) + \exp\left(-\frac{n\Delta^2}{2(1+\Delta/3)}\right) + \frac{1}{n} \right)$$

Plug in $\Delta = \frac{c}{3} \sqrt{\frac{\log n}{n}}$

Step 2

- Define fingerprint: $X \sim P_X$
 $Y = P_X(X) = e^{-\iota_X(X)}$
- P_Y is fingerprint of P_X

$$S_\delta(P_X) = \mathbb{E} \frac{1}{Y} \mathbf{1}\{Y > \mathbb{F}_Y(\delta)\}$$

$$\mathbb{E}_{X^N} R = \mathbb{E} e^{-nY}$$

Sample Complexity

- Choose $c > \epsilon$
- If $n > cS/\delta$ and n large enough:

$$\overline{S}_\delta \leq n(1 - \delta)/2$$

Bottom Line

- With 11 million samples, start to have guarantees
- With 100 million samples, guarantee for $S < 1,797,000$