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Quantile estimation,
Reservoir Sampling,
Glivenko-Cantelli

If tokens in a stream come from an ordered set, e.g. $[m]$, we can define the quantile function a.k.a. the empirical CDF

$$q(a) = \frac{\# \{i \mid a_i \leq a\}}{n}$$

stream tokens $\leq a$

total length of stream.

Two goals for quantile sketching.

The algorithm estimates $q(a)$ using estimator $\hat{q}(a)$.

(ϵ, δ) -PAC: $\forall a \quad \Pr(|\hat{q}(a) - q(a)| > \epsilon) < \delta.$

Uniformly (ϵ, δ) -PAC:

$$\Pr(\|\hat{q} - q\|_{\infty} > \epsilon) < \delta$$

where $\|\hat{q} - q\|_{\infty}$ denotes $\max_{a \in [m]} |\hat{q}(a) - q(a)|.$

This lecture in a nutshell:

1. Downsampling the stream —
maintaining in memory a random
sample of $t \approx \frac{1}{\epsilon^2}$ elements —
is a good way to maintain a
quantile sketch.
2. Reservoir sampling achieves downsampling
in $O(t + \log_m(n))$ space.
3. Given $t \approx \frac{1}{\epsilon^2}$ uniformly random
elements of the stream,
the empirical CDF of those t
elements is an ϵ -approx to
the empirical CDF of the entire
stream.

Glivenko-Cantelli Theorem

DKW Inequality

Dvoretzky - Kiefer - Wolfowitz

Reservoir Sampling for $t=1$ random elements

Store a_1 in memory

for $s=2, 3, \dots, n$:

with probability $\frac{1}{s}$ overwrite stored elt with a_s .

Probability that a_i is stored at the end?

— pick a_i and store it when we first see it. $\left(\frac{1}{i}\right)$

— don't pick a_s for all $s > i$.

$$\left(1 - \frac{1}{i+1}\right) \cdot \left(1 - \frac{1}{i+2}\right) \cdot \dots \cdot \left(1 - \frac{1}{n}\right).$$

Product of all these probabilities:

$$\frac{1}{i} \cdot \left(\frac{i}{i+1}\right) \cdot \left(\frac{i+1}{i+2}\right) \cdot \dots \cdot \left(\frac{n-1}{n}\right) = \frac{1}{n}.$$

Generalization to selecting t out of n .

1. Initialize empty buffer of size t .

$$b = (b_1, \dots, b_t) = (\perp, \perp, \dots, \perp).$$

2. for $s = 1, \dots, n$:

if $s \leq t$ store $b_s = a_s$

if $s > t$:

with probability $\frac{t}{s}$:

sample $i \in [t]$ uniformly random

overwrite $b_i \leftarrow a_s$

else: // probability $1 - \frac{t}{s}$

do nothing

Fact. If $n \geq t$ then the buffer contents after processing stream of length n

are a uniformly random t -element subset.

Quantile estimation using reservoir sampling.

Maintain reservoir sample b_1, \dots, b_t in memory.

When queried about $f(a)$ for $a \in [m]$ report

$$\hat{f}(a) = \frac{\# \{i \mid b_i \leq a\}}{t}$$

a.k.a. \hat{f} is the empirical CDF of the reservoir sample.

Analyzing the error $|\hat{f}(a) - f(a)|$

We'll analyze an algorithm where b_1, \dots, b_t are independent, each is uniformly distributed.

Space: $O(t + \log_m(n))$

↑
storing b_1, \dots, b_t

↑
storing the counter $s \in [n]$
when one element of $[m]$ takes $O(1)$ storage.

$$\Pr(|\hat{f}(a) - f(a)| > \epsilon) < 2e^{-2\epsilon^2 t}$$

by Hoeffding Bound.

$$X_i = \begin{cases} 1 & \text{if } b_i \leq a \\ 0 & \text{o.w.} \end{cases} \quad i \in [t]$$

b_i is unif random

$$\mathbb{E}[X_i] = \Pr(b_i \leq a) = \frac{\#\{s \mid a_s \leq a\}}{n} = g(a)$$

Let $X = X_1 + \dots + X_t = t \cdot \hat{g}(a)$

the event $|\hat{g}(a) - g(a)| > \epsilon$ is equiv't to

$$|X - \mathbb{E}X| > \epsilon t.$$

$$b_1, \dots, b_t \text{ indep't} \implies X_1, \dots, X_t \text{ indep't}$$

$$\xRightarrow{\text{(Hoeffding)}} \Pr(|X - \mathbb{E}X| > \epsilon t) < 2e^{-2\epsilon^2 t/t}$$

Summary. For (ϵ, δ) -PAC quantile est
maintain t indep. unif. random samples
from the stream where t is chosen
s.t.

$$2e^{-2\epsilon^2 t} < \delta$$

$$t > \frac{1}{2} \epsilon^{-2} \ln\left(\frac{2}{\delta}\right)$$

Upgrading to a uniform (ϵ, δ) -PAC estimate

Keep same algorithm. Vary the value of t
according to the analysis technique.

Plan 1. Union bound

There are m events of the form

$$|\hat{g}(a) - g(a)| > \epsilon$$

one for each $a \in [m]$.

We can make each have probability less than $\frac{\delta}{m}$ by setting

$$t > \frac{1}{2} \epsilon^{-2} \ln\left(\frac{2m}{\delta}\right).$$

Plan 2. More careful union bound

Lemma. (weak DKW) If b_1, \dots, b_t are independent ident dist'n'b samples from any distribution on \mathbb{R} with CDF $F(a)$ and if

we define the empirical CDF

$$\hat{g}(a) = \frac{\#\{i \mid b_i \leq a\}}{t}$$

then

$$\Pr(\|\hat{g} - F\|_{\infty} > \epsilon) < \frac{4}{\epsilon} e^{-\epsilon^2 t / 2}.$$

Compare with

$$\Pr(\|\hat{f} - F\|_{\infty} > \varepsilon) < 2m e^{-2\varepsilon^2 t}$$

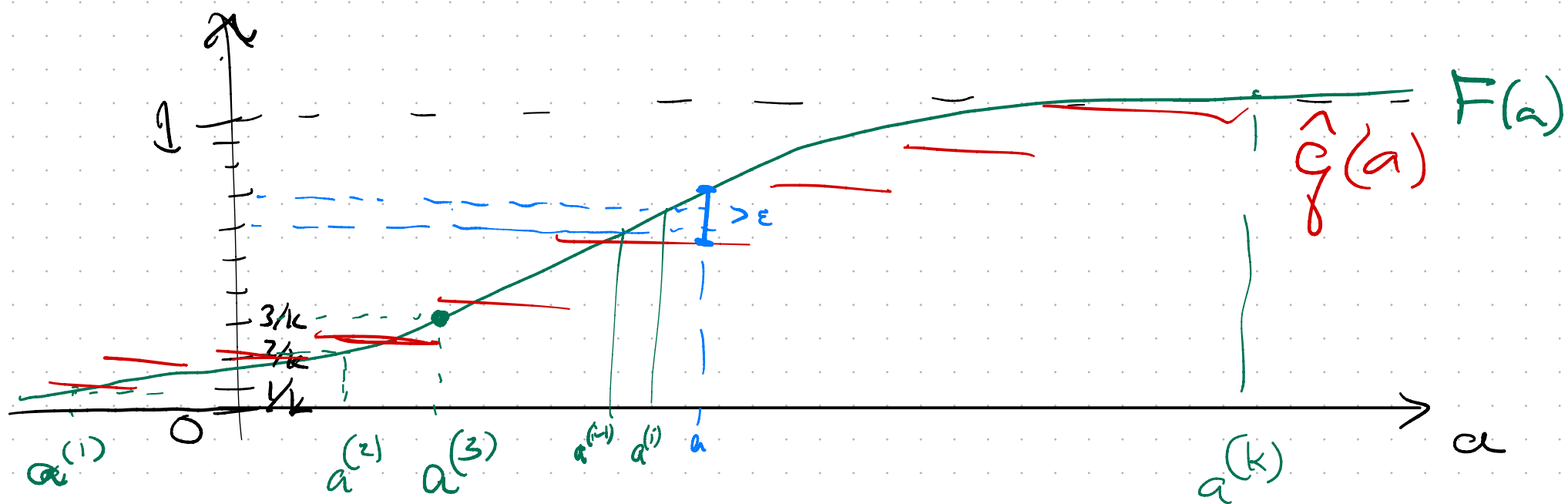
where F supported on $[m]$ and
we use naive union bound
a la Plan 1.

Proof of weak DKW.

$$\text{Let } k = \lceil \frac{2}{\varepsilon} \rceil.$$

We'll find a set of $2(k-1) < \frac{4}{\varepsilon}$
bad events, such that if
none of them happen,

$$\|\hat{g} - F\|_{\infty} \leq \varepsilon.$$



$$a^{(i)} = \sup \left\{ a \mid F(a) < \frac{i}{k} \right\}.$$

Proof shows that if $\exists a$ s.t.

$$|\hat{g}(a) - F(a)| > \epsilon \quad \text{then}$$

$$\exists i \in [k-1] \quad \text{s.t.}$$

$$F(a^{(i)}) - \hat{g}(a^{(i)}) > \epsilon/2 \quad \text{or}$$

$$\hat{g}(a^{(i)}) - F(a^{(i)}) > \epsilon/2$$

$$\sup \{ \hat{g}(a) \mid a < a^{(i)} \}$$

$$\sup \{ F(a) \mid a < a^{(i)} \}$$