# **Algorithms for Big Data (III)**

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**Review of the Last Lecture** 

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We constructed a 2-universal universal family of Hash functions.

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The family

$$\mathcal{H} = \{h_{a,b} : 1 \le a \le p - 1, 0 \le b \le p - 1\},\$$

where each  $h_{a,b} : [m] \rightarrow [n]$  is defined as

 $h_{a,b}(x) = (ax + b \mod p) \mod n.$ 

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We proved that for every  $x \neq y$ ,

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So  $\mathcal{H}$  is a 2-universal Hash function family.

Recall that if we further require that for any *u*, *v*,

$$\mathbf{Pr}_{h\in\mathcal{H}}\left[h(x)=u\wedge h(y)=v\right]=\frac{1}{n^2},$$

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In this case, we have

$$\mathcal{H} = \{h_{a,b}(x) = ax + b \mod p : 0 \le a, b \le p - 1\}.$$

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The equation  $ax + b = 0 \mod p$  has unique solution (in  $\mathbb{F}_p$ ) if  $a \neq 0$  and p is a prime.

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$$a = \frac{y_2 - y_1}{x_2 - x_1} \mod p, \quad b = y_1 - ax_1 \mod p.$$

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Therefore,

$$\mathbf{Pr}_{h_{a,b}\in H}[h_{a,b}(x_1)=y_1\wedge h_{a,b}(x_2)=y_2]=\frac{1}{p^2}.$$

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For every  $\bar{a} = (a_0, a_1, \dots, a_{k-1})$ , with  $0 \le a_i \le p - 1$  and  $0 \le b \le p - 1$ , define

$$h_{\bar{a},b}(x) = \left(\sum_{i=0}^{k-1} a_i x_i + b\right) \mod p.$$

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Then

$$\mathcal{H} = \{h_{\bar{a},b} : 0 \le a_i \le p - 1, 0 \le b \le p - 1\}.$$

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$$\begin{cases} a_i x_i + b = \left(u - \sum_{j \neq i} a_j x_j\right) \mod p \\ a_i y_i + b = \left(v - \sum_{j \neq i} a_j y_j\right) \mod p \end{cases}$$

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For fixed *x*, *y*, *u*, *v* and  $\{a_j\}_{j \neq i}$ , a unique pair  $(a_i, b)$  (out of  $p^2$  pairs) is determined. Therefore,

$$\mathbf{Pr}_{h_{\bar{a},b}\in\mathcal{H}}\left[h_{\bar{a},b}(x)=u\wedge h_{\bar{a},b}(y)=v\right]=\frac{1}{p^2}.$$

**Counting Distinct Elements** 

It defines a frequency vector  $\mathbf{f} = (f_1, \ldots, f_n)$  where  $f_i = |\{k \in [m] : a_k = i\}|$ .

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We want to compute the number  $d = |\{i \in [n] : f_i > 0\}|$ .

The value *d* is the number of distinct elements in the stream.

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$$\operatorname{zero}(p) \triangleq \max\left\{i: 2^i \text{ divides } p\right\}.$$

Algorithm AMS Algorithm for Counting Distinct Elements

#### Init:

```
A random Hash function h : [n] \rightarrow [n] from a 2-universal family Z \leftarrow 0
```

#### **On Input** *y*:

```
if zero(h(y)) > Z then

Z \leftarrow zero(h(y))

end if
```

# Output:

 $\widehat{d} = 2^{Z + \frac{1}{2}}.$ 

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We now turn this intuition into a rigorous proof.

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For every  $k \in [n]$ , we denote  $X_{k,r}$  as the indicator that h(k) has at least r trailing zeros, then  $Y_r = \sum_{k \in [n]: f_k > 0} X_{k,r}$ .

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Using this decomposition, it is not hard to see that  $\mathbf{E}[Y_r] = \frac{d}{2^r}$  and  $\mathbf{Var}[Y_r] \le \frac{d}{2^r}$ .

$$\mathbf{Pr}\left[Y_r > 0\right] = \mathbf{Pr}\left[Y_r \ge 1\right] \le \mathbf{E}\left[Y_r\right] = \frac{d}{2^r}.$$

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Applying Chebyshev's inequality, we obtain

$$\mathbf{Pr}\left[Y_r=0\right] \leq \mathbf{Pr}\left[\left|Y_r-\mathbf{E}\left[Y_r\right]\right| \geq \frac{d}{2^r}\right] \leq \frac{2^r}{d}.$$

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We know that  $Y_r > 0$  for all  $r \le Z$  and  $Y_r = 0$  for all r > Z.

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Therefore, Z cannot be too far from  $\log_2 d$ :

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- if  $Z \ll \log_2 d$ , we can find a small *r* with  $Y_r = 0$ , which happens with small probability;
- if  $Z \gg \log_2 d$ , we can find a big *r* with  $Y_r > 0$ , which happens with small probability.

$$\mathbf{Pr}\left[\widehat{d} \le \frac{d}{3}\right] = \mathbf{Pr}\left[Z \le r\right] = \mathbf{Pr}\left[Y_{r+1} = 0\right] \le \frac{2^{r+1}}{d} \le \frac{\sqrt{2}}{3}.$$

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If  $\hat{d} \ge 3d$ , let *r* be the smallest integer with  $2^{r+\frac{1}{2}} \ge 3d$ .

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The algorithm costs  $O(\log n)$  bits of memory.

# MEDIAN

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We can apply the standard Median trick to the AMS algorithm. (Excercise)

We can apply the standard Median trick to the AMS algorithm. (Excercise) Using  $O(\log \frac{1}{\delta} \log n)$  bits of memory, we can obtain

$$\Pr\left[\frac{d}{3} \le \hat{d} \le 3d\right] \ge 1 - \delta.$$

# THE BJKST ALGORITHM

The following improvement of AMS is due to Bar-Yossef, Jayram, Kumar, Sivakumar and Trevisan.

Algorithm BJKST Algorithm for Counting Distinct Elements

**Init:** Random Hash functions  $h : [n] \rightarrow [n], g : [n] \rightarrow [b\varepsilon^{-4} \log^2 n]$ , both from 2-universal families;  $Z \leftarrow 0, B \leftarrow \emptyset$ 

```
On Input y:

if zero(h(y)) \ge Z then

B \leftarrow B \cup \{(g(y), zeros(h(y)))\}

while |B| \ge c/\varepsilon^2 do

Z \leftarrow Z + 1

Remove all (\alpha, \beta) with \beta < Z from B

end while

end if

Output: \hat{d} = |B| 2^Z
```