

### Frequent Items:

Keep  $k$  counters. If all are non-zero, subtract one from all of them. (for distinct elements).

[If elements exist increment counter; if not put element in empty space.]

Fact: each estimate  $\leq$  actual count and underestimate by at most  $n/k$ .

$$\hat{f}_i \leq f_i \quad f_i - \frac{n}{k} \leq \hat{f}_i \leq f_i$$

BTW: suppose measure error by total loss.

$(f_1 \geq f_2 \geq \dots \geq f_m)$

Optimal: underestimate 
$$OPT = \sum_{i=k+1}^m f_i$$

Suppose we maintain  $l$  counters: - and then ops  $d$  decrements. then

$$l \text{ counters} = \sum_{i=1}^m f_i - l(d). \quad \sum_{i=1}^k f_i \geq \sum_{i=1}^k (f_i - d) \Rightarrow d \leq \frac{OPT}{l-k}$$

$\Rightarrow$  if we output the top  $k$  estimates then  $\hat{f}_1 \geq \hat{f}_2 \geq \dots \geq \hat{f}_k$

$$\begin{aligned} \Rightarrow \text{total loss} &= \sum_{i=1}^m f_i - \left( \sum_{i=1}^k \hat{f}_i \right) \leq \sum_{i=1}^m f_i - \left( \sum_{i=1}^k (f_i - d) \right) \\ &= \cancel{OPT} + kd \leq OPT + k \frac{OPT}{l-k} \\ &= OPT \left( \frac{l}{l-k} \right) \end{aligned}$$

$\Rightarrow$  if  $l = O(k/\epsilon)$  then loss =  $(1 + O(\epsilon)) OPT$ .

So if we maintain  $l$  different counters and outputs the best  $k$ , loss is small compared to  $OPT$ .

Similar to: suppose we find a matrix  $B$  that's a good approximation and

$P_{B,k}$  be the projection onto the top  $k$  right singular vectors, then

$$\text{want } \|A - AP_{B,k}\|_F^2 \leq (1 + \epsilon) \|A - A_k\|_F^2$$

$\left\{ \begin{array}{l} \text{if } B = UV^T \\ \text{then } P_{B,k} = V_k V_k^T \end{array} \right.$

Would be cool if we could get such a guarantee.

Liberty, et al:

Input:  $A, K, \epsilon = K/\ell$ .  $A = \mathbb{R}^{n \times d}$   
 Start with  $B \leftarrow 0^{\ell \times d}$ . // invariant:  $B\epsilon$  is all zeros vector.

When  $a_t$  arrives  $B\epsilon \leftarrow a_t$ .

let  $B = U\Sigma V^T$  (assume  $\Sigma \in \mathbb{R}^{d \times d}$ . pad with zeros as necessary).

$C = \Sigma V^T$ ,  $\delta_i \leftarrow \sigma_i^2$ . (last singular value squared).

$B \leftarrow (\sqrt{\Sigma^2 - \delta I}) \cdot V^T$

Return  $B$ .

Let  $B_t, C_t, \delta_t$  be these quantities at end of iteration  $t$ .  $\Delta = \sum_t \delta_t$  is total "loss".

Property 1:  $\forall x \quad 0 \leq \|Ax\|^2 - \|Bx\|^2 \leq \Delta$ . (each coordinate is off by at most  $\frac{\Delta}{d}$ )

Property 2:  $\|A\|_F^2 - \|B\|_F^2 \geq \Delta \ell$  (total mass lost =  $d\ell$ )

Thm 1.1:  $\forall x \quad 0 \leq \|Ax\|^2 - \|Bx\|^2 \leq \frac{\|A - A_k\|_F^2}{(\ell - k)}$

$\Leftrightarrow 0 \leq x^T (A^T A - B^T B) x \leq \dots$

$\Leftrightarrow \|A^T A - B^T B\| \leq \frac{\|A - A_k\|_F^2}{\ell - k}$

( $y_i =$  right singular vectors of  $A$ )  
 $d$ -dimensional

pf:  $\Delta \ell \leq \|A\|_F^2 - \|B\|_F^2$   
 $= \sum_{i=1}^k |Ay_i|^2 + \sum_{i=k+1}^d |Ay_i|^2 - \|B\|_F^2$

$= \sum_{i=1}^k |Ay_i|^2 + \|A - A_k\|_F^2 - \|B\|_F^2$

$\leq \|A - A_k\|_F^2 + \sum_{i=1}^k (|Ay_i|^2 - |By_i|^2) \leq \|A - A_k\|_F^2 + k\Delta$ . by PPM #1.

$\Rightarrow \Delta \leq \frac{\|A - A_k\|_F^2}{(\ell - k)}$

$0 \leq \|Ax\|^2 - \|Bx\|^2$



Thm 1.2: Let  $B = UZV^T$  and  $V_k =$  top  $k$  singular values (right) of  $B$ .

$$P = V_k V_k^T$$

$$\text{then } \|A - AP\|_F^2 \leq \left(1 + \frac{k}{l-k}\right) \|A - A_k\|_F^2.$$

Pf:  $\|A - AP\|_F^2 = \|A\|_F^2 - \|AP\|_F^2$  (Pythagoras)

$$= \|A\|_F^2 - \sum_{i=1}^k |Av_i|^2$$

$$\leq \|A\|_F^2 - \sum_{i=1}^k |Bv_i|^2 \quad (\text{Prop 1})$$

$$\leq \|A\|_F^2 - \sum_{i=1}^k |By_i|^2 \quad (\text{Eckart-Young})$$

$$\leq \|A\|_F^2 - \left(\sum_{i=1}^k |By_i|^2 - \Delta\right) \quad (\text{Prop 1})$$

$$= \|A - A_k\|_F^2 + \Delta k \leq \|A - A_k\|_F^2 \left(1 + \frac{k}{l-k}\right).$$

↑ (by Thm 1.1.)

$y_i \leftarrow$  right sing. of  $A$

$v_i \leftarrow$  right sig of  $B$ .

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(Recall)

$$\text{error} = \sum_i f_i - \sum_{i=1}^k \hat{f}_i \leq \sum_i f_i - \left(\sum_{i=1}^k f_i - d\right) = \text{OPT} + dk \leq \text{OPT} \left(1 + \frac{k}{l-k}\right).$$

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