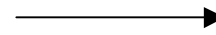


Adversary



# Lower Bounds in Streaming

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# Streaming Algorithms

- Norm estimation:  $(1+\varepsilon)$ -approximation of  $\|x\|_p$ ,  $x \in \mathbb{R}^m$ , under a sequence of  $n$  updates
  - $O(\log(n+m)/\varepsilon^2)$  bits for  $p \in (0, 2]$   
(excluding randomness)
- Heavy hitters/sparse approximations
- Question: are these algorithms (nearly) optimal ?

# Lower Bounds in Streaming

- Two techniques:
  - Pigeonhole principle: need enough space to distinguish “different” inputs
  - Communication complexity
- PP is really a special case of CC (but is often easier to apply)
- Today:
  - Randomness and approximation are both necessary for estimating  $\|x\|_0$  in  $\text{polylog}(n+m)$  space (even in the insertions-only case)
  - Need  $\Omega(1/\varepsilon^2)$  bits to  $(1+\varepsilon)$ -approximate  $\|x\|_2$
  - Need  $\Omega(k \log(m/k))$  measurements for the  $l_1/l_1$  guarantee [Indyk-Khanh-Price'08]



New!

# Pigeonhole Principle

# Estimating $\|x\|_0$

- Warmup theorem: any **deterministic exact** algorithm for computing  $\|x\|_0$  needs  $\Omega(m)$  bits of space
- Proof:
  - Assume there is an algorithm  $A$  using  $M=O(m)$  bits of space
  - Take any vector  $y \in \{0,1\}^m$ ,  $\|y\|_0 = m/2$
  - Feed the coordinates of  $y$  to  $A$
  - Let  $A[y]$  be the state of  $A$  at the end of this process, and  $E$  be the estimation of  $\|y\|_0$  (i.e.,  $E = \|y\|_0$ )
  - We can decode  $y$  from  $A[y]$ :
    - For any  $z \in \{0,1\}^m$ ,  $\|z\|_0 = m/2$ , feed  $z$  to  $A$  in state  $A[y]$ , obtaining  $A[y \circ z]$
    - The algorithm computes an estimation  $E'$  of  $\|y+z\|_0$  (i.e.,  $E' = \|y+z\|_0$ )
    - We have  $y=z$  iff  $E=E'$
  - Therefore
$$2^M \geq \text{number of } y\text{'s} = \exp(\Omega(m))$$

# Estimating $\|x\|_0$ , ctd.

- Upgraded theorem: any **deterministic c-approximate** algorithm for computing  $\|x\|_0$  needs  $\Omega(m)$  bits of space, for  $c < 2$ 
  - Estimation  $E$  such that  $\|x\|_0 \leq E < c\|x\|_0$
- Proof:
  - For any  $y \in \{0,1\}^m$ , let  $ECC(y) \in \{0,1\}^{m'}$ ,  $m' = O(m)$  be such that:
    - $\|ECC(y)\|_0 = m'/a$ ,  $a = \Theta(1)$
    - For any  $y \neq z$ , the distance  $\|ECC(y) - ECC(z)\|_0 \geq 2m'(c-1)/a$   
(which implies that  $\|ECC(y+z)\|_0 \geq m'/a + m'(c-1)/a = m'c/a$ )
  - Take any  $y$
  - Feed the coordinates of  $ECC(y)$  to  $A$
  - The remainder of the argument essentially as before  
(except that  $y=z$  iff  $E' < m'c/a$ )

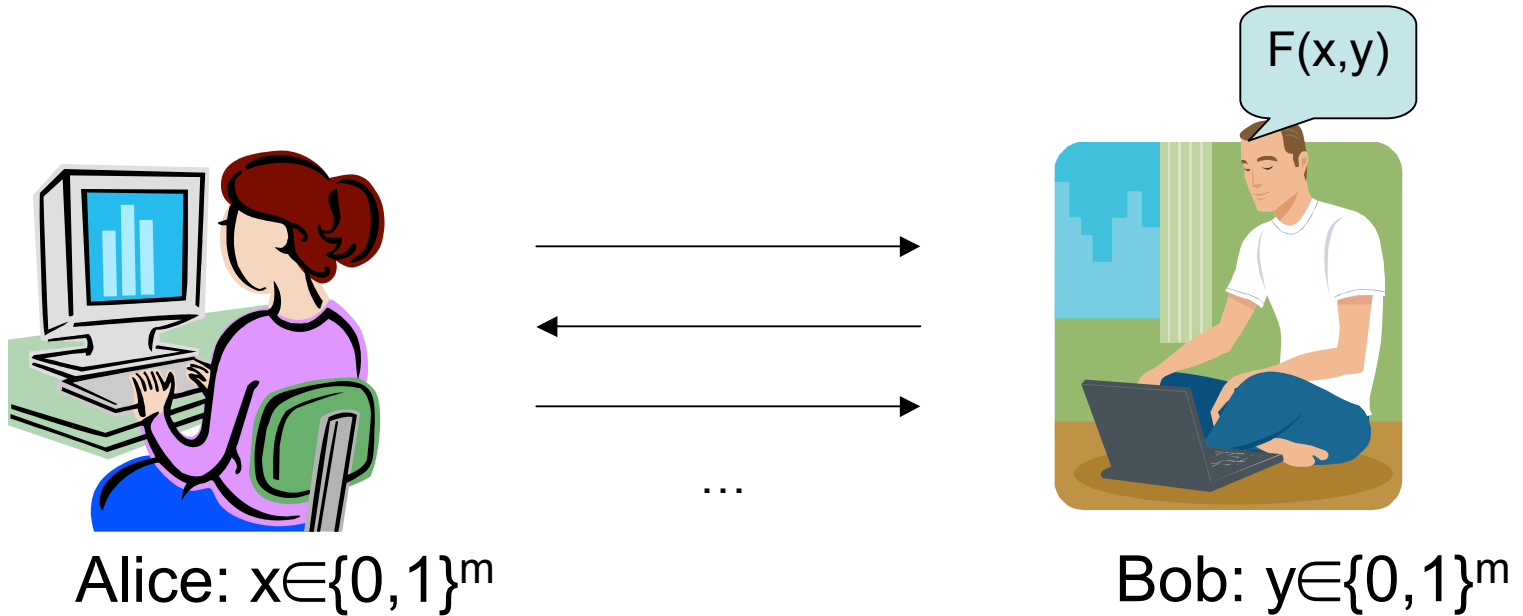
# Estimating $\|x\|_0$ , ctd.

- Upgraded theorem 2: any randomized exact algorithm for computing  $\|x\|_0$  needs  $\Omega(m)$  bits of space
- Proof:
  - Assume  $o(m)$  space, and the probability of error  $< 1/8$
  - Take any ECC with minimum distance  $m'/4$
  - Take any  $y$
  - Feed the coordinates of  $\text{ECC}(y)$  to  $A$
  - With prob.  $1/2$  we can recover  $z$  such that  $\|z - \text{ECC}(y)\|_0 < m'/4$
  - can recover  $y$ 
    - In parallel, for any  $i=1..m'$ , feed  $e_i$  to  $A$  with state  $A[\text{ECC}(y)]$ , obtaining estimate  $E_i$
    - Set  $z_i=0$  iff  $E_i > m/a'$  (works correctly with prob.  $1-1/8$ )
    - Markov inequality implies that the fraction of errors is  $< 1/4$  with prob.  $1/2$
  - There is a choice of random coin tosses which works for half of the vectors  $y$  (i.e., for those  $y$ 's, we can recover  $y$  from  $A[\text{ECC}(y)]$ )
  - The rest of the argument as before

# Communication Complexity



# Communication Complexity



- Resources:
  - # bits
  - # rounds
    - Today, we will be only interested in one-round protocols
- Probability of error: some constant  $\delta > 0$
- See [Kushilevitz-Nisan] for more  
(and there is much more)

# Indexing

- (Balanced) indexing problem:
  - Alice: a vector  $x \in \{0,1\}^m$ ,  $\|x\|_0 = m/2$
  - Bob: an index  $i = 1 \dots m$
  - Goal: compute  $f(x,i) = x_i$
- Theorem: any randomized one-round protocol for indexing has  $\Omega(m)$  bit complexity
- Proof: pigeonhole principle as applied earlier

# Gap Dot Product

- (Gap) parameter  $\Delta$
- Alice: a vector  $u \in \mathbb{R}^m$ ,  $\|u\|_2=1$  (with  $O(\log m)$  bits)
- Bob: a vector  $v \in \mathbb{R}^m$ ,  $\|v\|_2=1$
- Goal:
  - If  $u^*v=0$ , return 0
  - If  $u^*v \geq \Delta$ , return 1
- Theorem: the randomized one-round CC of GDP with gap  $\Delta=1/(m/2)^{1/2}$  is  $\Omega(m)$
- Proof: via reduction from indexing:
  - Alice: computes  $u = \Delta x$
  - Bob: computes  $v = e_i$
  - Fact:  $u^*v = \Delta x_i$

# Space complexity of $L_2$ norm estimation

- Theorem: any streaming algorithm for estimating the  $L_2$  norm of an  $m$ -dimensional vector  $x$  up to a factor of  $1 \pm \Delta$ ,  $\Delta = c/m^{1/2}$ , requires  $\Omega(m)$  bits for some constant  $c > 0$  (even if coordinates of  $x$  have  $O(\log m)$  bits)
- Proof:
  - Assume we have an  $M$ -space streaming algorithm that computes  $(1 \pm \Delta) \|x\|_2$
  - Then we have an  $M$ -space streaming algorithm that, given a stream  $u \circ v$ ,  $\|u\|_2 = \|v\|_2 = 1$ , computes  $u^*v \pm O(\Delta)$  (Lecture 4)
    - Using the equality  $\|u-v\|_2^2 = \|u\|_2^2 + \|v\|_2^2 - 2u^*v$
  - Then we have an  $M$ -bit one-round protocol that solves GDP with gap  $1/(m/2)^{1/2}$  (assuming  $c$  small enough)
  - Ergo,  $M = \Omega(m)$

# Back to Pigeonhole Principle

# Lower bound for $l_1/l_1$

- Compressive sensing setup: want an  $M \times m$  sketch matrix  $A$  such that:
  - Given:  $Ax$  for an arbitrary vector  $x$
  - Can obtain: an approximation  $x^*$  such that
$$\|x^* - x\|_1 \leq C \text{Err}_1^k(x)$$
where  $\text{Err}_1^k(x) = \min_{x'} \|x' - x\|_1$  over all  $x'$  that are  $k$ -sparse
- Will show that  $M = \Omega(k \log(m/k))$   
(if  $C$  is an absolute constant)

# Error-correcting code

- Let  $E \subseteq \{0,1\}^m$  be a set of  $k$ -sparse vectors such that for any distinct  $y_1, y_2 \in E$  we have

$$\|y_1 - y_2\|_1 > k$$

- We can have  $|E| > \exp(c k \log(m/k))$  for some absolute constant  $c$
- Define  $r = k/(2C+2)$
- We consider signals  $x = y + z$  where  $y \in E$  and  $\|z\|_1 \leq r$ 
  - Clearly,  $\text{Err}_1^k(x) \leq \|z\|_1 \leq r$

# Distinctness

- Lemma: For any  $x_1=y_1+z_1$  and  $x_2=y_2+z_2$  as in the earlier slide, we have

$$Ax_1 \neq Ax_2$$

- Proof:
  - Suppose we have  $Ax_1 = Ax_2$
  - We know:
    - Given  $Ax_1$ , our algorithm decodes  $x_1^*$  s.t.  $\|x_1-x_1^*\|_1 \leq Cr$
    - Given  $Ax_2$ , our algorithm decodes  $x_2^*$  s.t.  $\|x_2-x_2^*\|_1 \leq Cr$
  - But if  $Ax_1 = Ax_2$  then  $x_1^* = x_2^*$
  - This would imply  $\|x_1-x_2\|_1 \leq 2Cr$
  - Therefore  $\|y_1-y_2\|_1 \leq 2Cr+2r=k$  - a contradiction
- Corollary: Let  $B=B_1(0,r)$ . Then for any distinct  $y_1, y_2 \in E$  the “affine balls”  $A(y_1+B)$  and  $A(y_2+B)$  are disjoint



# Pigeonhole

- All “affine balls”  $A(y_1+B)$  and  $A(y_2+B)$  are disjoint
- At the same time, for all  $y \in E$  we have

$$y+B \subseteq BB = B_1(0,R),$$

where  $R=k+r = (2C+3)r$

- Therefore,  $A(y+B) \subseteq A(BB)$ , so  $\text{vol}(A(BB)) \geq |E| \text{vol}(A(B))$

- Altogether

$$\exp(c k \log(m/k)) < |E| \leq \text{vol}(A(BB)) / \text{vol}(A(B)) \leq (2C+3)^M$$

- After applying logarithm on both sides we get

$$M = \Omega(k \log(m/k))$$