Matrix Sketching

STREAMING ALGORITHMS FOR LOW-RANK MATRIX APPROXIMATIONS



Review ...

- Last time
 - Singular Value Decomposition
 - ▶ Randomized SVD
- ▶ Today
 - ▶ Matrix Sketching



Upcoming Lectures

- Next Lecture
 - Security aspects of Big-Data
 - Guest lecture by Prof. Denning
- Next Week
 - Spark tutorial by TA
- Next Assignment
 - ▶ Choice of programming model
 - ► MPI, Hadoop, Spark
 - ► Low-rank approximation
 - ▶ Stochastic Gradient Descent, Randomized SVD, Sketching



Matrix Sketching

- Data is usually represented as a matrix
- For most Big Data applications, this matrix is too large for one machine
- In many cases, the matrix is too large to even fit in distributed memory
- Need to optimize for data access
 - Similar to our arguments for SGD for UV decomposition
- Streaming algorithm
 - ▶ Generate approximation by accessing (streaming) data once



Matrix Sketching

▶ Efficiently compute a concisely representable matrix *B* such that

$$B \approx A$$
 or $BB^T \approx AA^T$

- Working with B is often "good enough"
 - Dimension reduction
 - Classification
 - Regression
 - Matrix Multiplication (approximate)
 - Recommendation systems



Frequent Directions (Edo Liberty '13)

▶ Efficiently maintain a matrix B with only $l = 2/\epsilon$ columns such that,

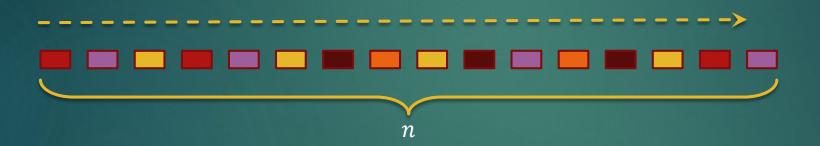
$$||AA^T - BB^T||_2 \le \epsilon ||A||_f^2$$

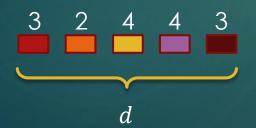
- Intuitive approach > extend frequent items
 - How to estimate the frequency of (frequent) items in a streaming fashion?



Frequent Items

Obtain the frequency f(i) of each item in the stream



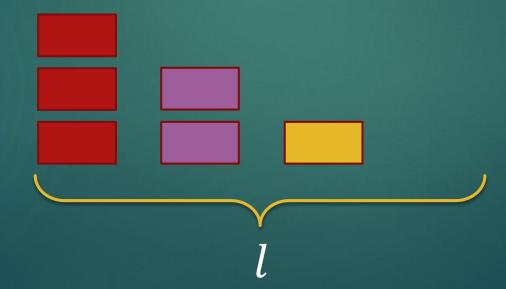


$$f(\square) = 4$$



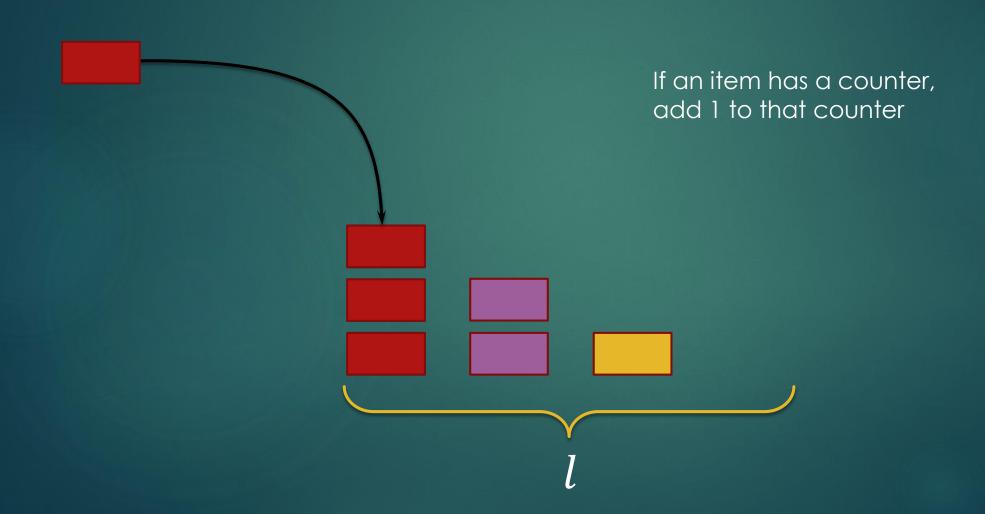
Frequent Items

Lets maintain less than l < d counters (Misra-Gries) With at least 1 empty counter



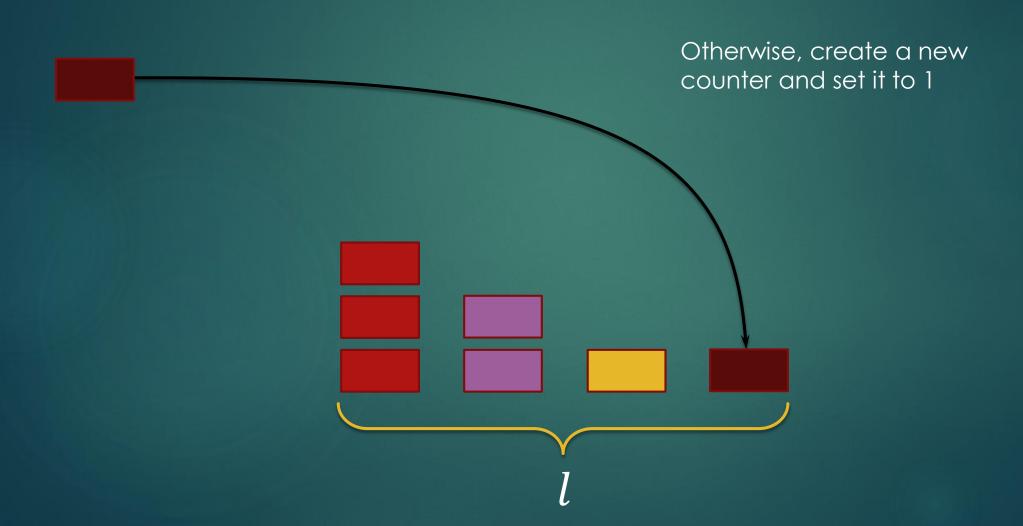


Frequent Items





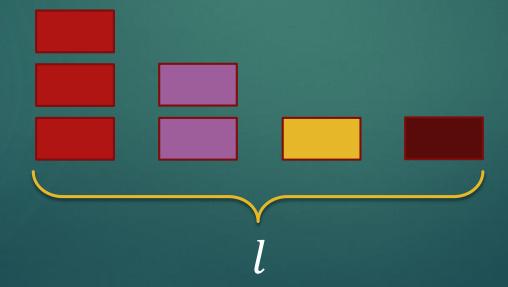
Frequent Items





Frequent Items

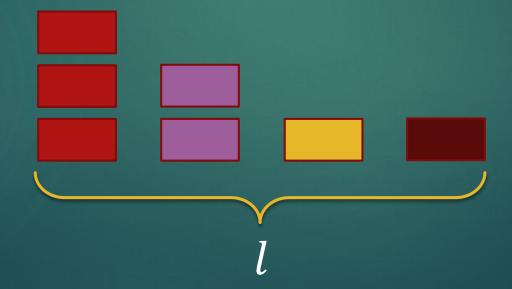
But now we don't have less than l counters





Frequent Items

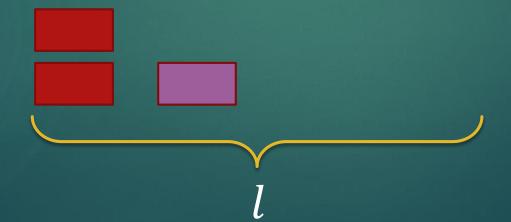
Let δ be the median counter value at time t





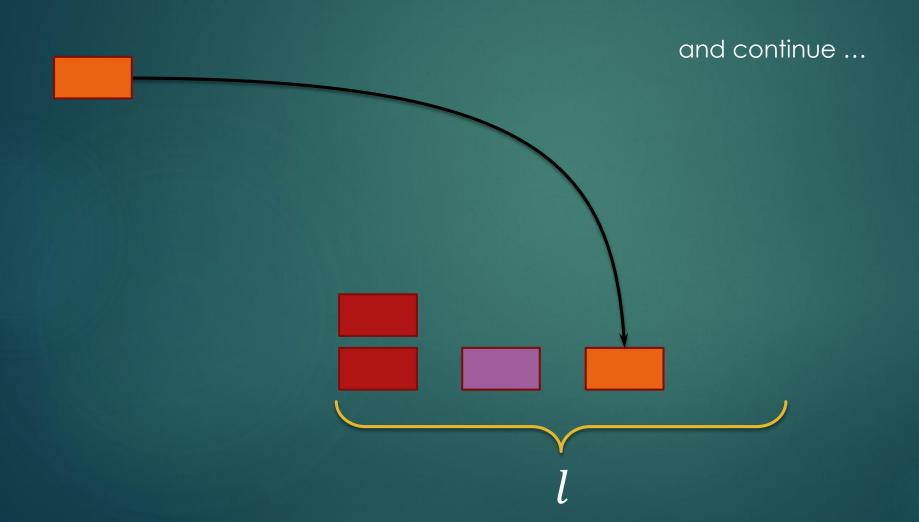
Frequent Items

Decrease all counters by δ





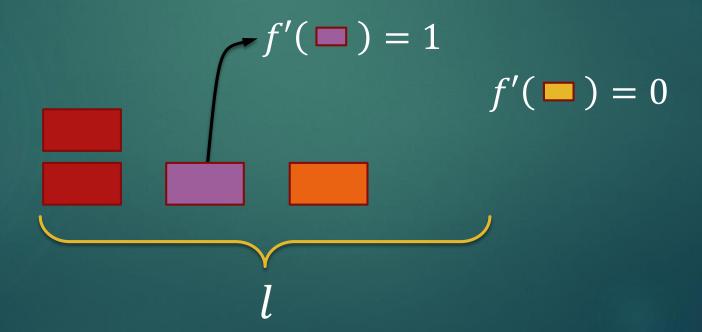
Frequent Items





Frequent Items

The approximated counts are f'





Frequent Items

▶ We increase the count by only 1 for each item appearance

$$f'(i) \le f(i)$$

ightharpoonup Because we decrease each counter by at most δ_t at time t

$$f'(i) \ge f(i) - \sum_{t} \delta_t$$

Calculating the total approximate frequencies:

$$0 \le \sum_{i} f'(i) \le \sum_{t} 1 - \frac{l}{2} \delta_{t} = n - \frac{l}{2} \sum_{t} \delta_{t}$$

$$\sum_{t} \delta_{t} \le \frac{2n}{l}$$

▶ Setting $l = 2/\epsilon$ gives us

$$|f(i) - f'(i)| \le \epsilon n$$



Frequent Directions (Liberty 2013)

maintain a sketch of at most *l* columns

maintain the invariant that some columns are empty (zero-valued)

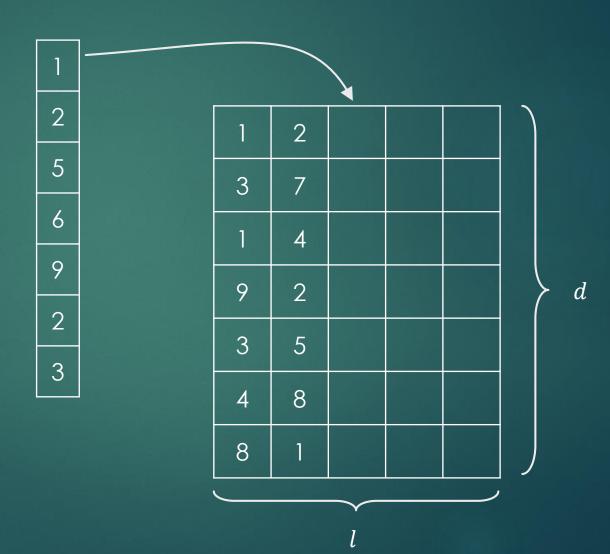
1	2					
3	7					
1	4					
9	2	Te		134	}	d
3	5					
4	8					
8	1					
		1				



Frequent Directions

Stream in matrix A one column at a time

Input vectors are simply stored In empty columns





Frequent Directions

When the sketch is 'full'
We need to zero out some
columns

1	2	3	8	6		
3	7	5	7	0	7	
1	4	4	3	3		
9	2	2	3	7		a
3	5		- 1 1 - 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	1		и
	LI N	6	6	Trace		
4	8	1	5	4		
8	1	2	6	2		



Frequent Directions

 $B = U\Sigma V^T$

Using SVD, compute

$$B = U\Sigma V^T$$

And set

$$B_{new} = U\Sigma$$

-9.2	-0.4	-5.1	1.5	0.9	
-10.4	-4.4	2.0	0.5	0.3	
-6.5	-1.9	-1.1	-0.9	-1.9	
-9.9	6.7	0.1	-1.1	-1.4	
-9.6	-3.2	1.1	1.5	-1.4	
-10.1	-0.8	0.3	-4.0	1.6	
-9.0	3.8	2.1	2.7	1.3	

 $B_{new} = U\Sigma$







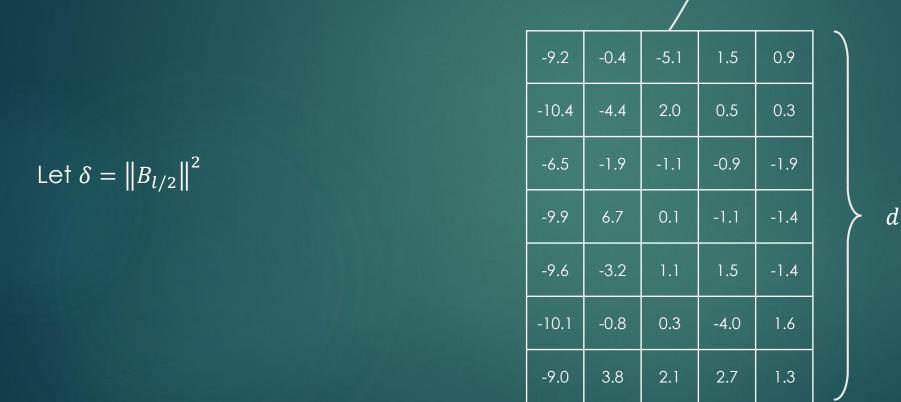
Frequent Directions

The columns of *B* are now orthogonal and in decreasing magnitude

	B_{ne}	$r_{w} = U$	JΣ			
-9.2	-0.4	-5.1	1.5	0.9		
-10.4	-4.4	2.0	0.5	0.3		
-6.5	-1.9	-1.1	-0.9	-1.9		
-9.9	6.7	0.1	-1.1	-1.4		d
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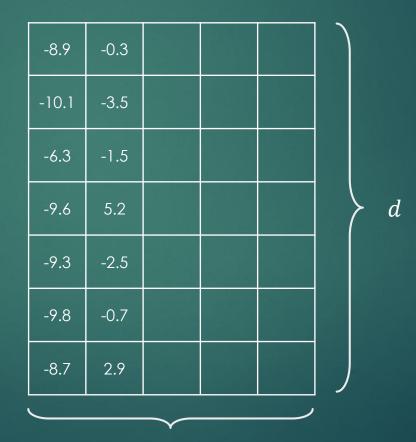
Frequent Directions





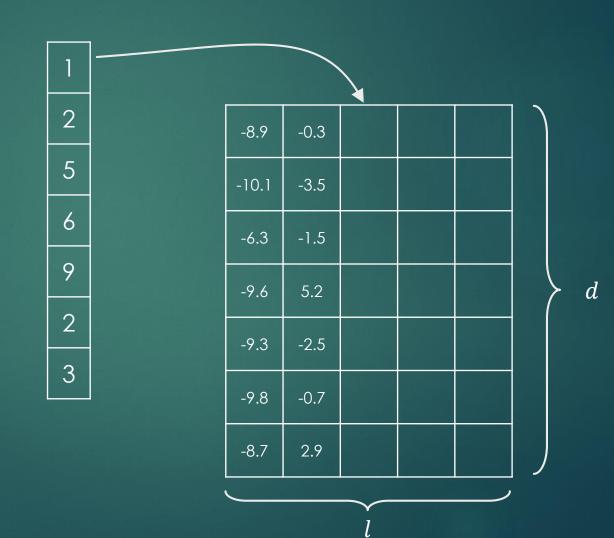
Frequent Directions

Reduce column l_2^2 -norms by δ





Frequent Directions



Start aggregating columns again



Frequent Directions

```
Input: l, A \in \mathbb{R}^{d \times n}
B \leftarrow \text{all zeros matrix} \in \mathbb{R}^{d \times l}
for i \in [n] do
       Insert A_i into a zero valued column of B
       if B has no zero valued columns then
              [U, \Sigma, V] \leftarrow SVD(B)
             \delta \leftarrow \sigma_{l/2}^2
             \hat{\Sigma} \leftarrow \sqrt{\max(\Sigma^2 - I_l \delta, 0)}
              B \leftarrow U\hat{\Sigma}
```

Return: B



Bounding the error

We first bound $||AA^T - BB^T||$

$$\sup_{\|x\|=1} \|xA\|^2 - \|xB\|^2 = \sup_{\|x\|=1} \sum_{t=1}^n [\langle x, A_t \rangle^2 + \|xB^{t-1}\|^2 - \|xB^t\|^2]$$

$$= \sup_{\|x\|=1} \sum_{t=1}^n [\|xC^t\|^2 - \|xB^t\|^2]$$

$$\leq \sum_{t=1}^n \|C^{t^T}C^t - B^{t^T}B^t\| \cdot \|x\|^2$$

$$= \sum_{t=1}^n \delta_t$$

Which gives,

$$||AA^T - BB^T|| \le \sum_{t=1}^n \delta_t$$



Bounding the error

We compute the Frobenius norm of the final sketch,

$$0 \le \|B\|_f^2 = \sum_{t=1}^n [\|B^t\|_f^2 - \|B^{t-1}\|_f^2]$$

$$= \sum_{t=1}^n [(\|C^t\|_f^2 - \|B^{t-1}\|_f^2) - (\|C^t\|_f^2 - \|B^t\|_f^2)]$$

$$= \sum_{t=1}^n \|A_t\|^2 - tr(C^{t^T}C^t - B^{t^T}B^t)$$

$$\le \|A\|_f^2 - \frac{l}{2}\sum_{t=1}^n \delta_t$$

Which gives,

$$\sum_{t=1}^{n} \delta_t \le \frac{2\|A\|_f^2}{l}$$



Bounding the error

We saw that:

$$||AA^T - BB^T|| \le \sum \delta_t$$

and,

$$\sum \delta_t \le \frac{2\|A\|_f^2}{I}$$

setting $l = \frac{2}{\epsilon}$ gives us,

$$||AA^T - BB^T|| \le \epsilon ||A||_f^2$$



Divide & Conquer

- Sketching can be implemented in a divide & conquer fashion as well
- ▶ Let $A = [A_1; A_2]$
- ▶ Compute the sketches B_1 , B_2 of matrices A_1 , A_2
- ▶ Compute the sketch C of the matrix $[B_1; B_2]$
- ▶ It can be shown that

$$||AA^T - CC^T|| \le \frac{2||A||_f^2}{l}$$





Streaming Matrices

Can we compute the covariance matrix from a stream?

$$AA^T = \sum_{i=1}^n A_i A_i^T$$

- Naïve solution
 - \blacktriangleright For A of size $d \times n \rightarrow AA^T$ of size $d \times d$
 - ▶ Compute in $O(nd^2)$ with storage $O(d^2)$