

Approximate Matrix Multiplication

Lecture 22

November 12, 2020

Matrix data

Lot of data can be viewed as defining a matrix. We have already seen vectors modeling data/signals. More generally we can use tensors too.

n data items and each data item \mathbf{a}_i is a vector over some features (say m features)

\mathbf{A} is the matrix defined by the n data items.

Assuming $\mathbf{a}_1, \dots, \mathbf{a}_n$ are columns then \mathbf{A} is a $m \times n$ matrix

Combinatorial objects such as graphs can also be modeled via graphs

Numerical Linear Algebra

Basic problems in linear algebra:

- Matrix vector product: compute Ax
- Matrix multiplication: compute AB
- Linear equations: solve $Ax = b$
- Matrix inversion: compute A^{-1}
- Least squares: solve $\min_x \|Ax - b\|$
- Singular value decomposition, eigen values, principal component analysis, low-rank approximations
- ...

Fundamental in all areas of applied mathematics and engineering.
Many applications to statistics and data analysis.

Numerical Linear Algebra

NLA has a vast literature

In practice iterative methods are used that converge to an optimum solution. They can take advantage of sparsity in the input data better than exact methods

Some TCS contributions in the recent past:

- randomized NLA for faster algorithms with provable approximation guarantees - sampling and JL based techniques and others
- revisit preconditioning methods for Laplacians and beyond
- Many powerful applications in theory and practice

Norms and matrix norms

Definition

A norm $\|\cdot\|$ in a real vector space V is a real valued function that has three properties: (i) $\|x\| \geq 0$ for all $x \in V$ and $\|x\| = 0$ implies $x = 0$, (ii) $\|ax\| = |a|\|x\|$ for all scalars a (iii) $\|x + y\| \leq \|x\| + \|y\|$

Familiar vector norms: $\|x\|_p = (\sum_i |x_i|^p)^{1/p}$

If A is an injective linear transformation $\|Ax\|$ is also a norm in the original space.

Norms and metrics: $d(x, y) = \|x - y\|$ is a metric

Matrix norms

Consider vector space of all matrices $\mathbf{A} \in \mathbb{R}^{m \times n}$

What are useful norms over matrices?

- Treat matrix like a vector of dimension $m \times n$ and apply vector norm. For instance $\|\mathbf{A}\|_F$ (Frobenius norm) is $(\sum_{i,j} |A_{i,j}|^2)^{1/2}$.
- Treat matrix as linear operator and see what it does to norms of vectors it operates on. Spectral norm is $\sup_{\|x\|_2=1} \|\mathbf{A}x\|_2$.
- Schatten p -norms based on singular values of \mathbf{A}
- Trace norm, nuclear norm, ...
- Norms are related in some cases (different perspective on the same norm)

$$\sup_{\|x\|_2=1} \frac{\|\mathbf{A}x\|_2}{\|x\|_2}$$

Frobenius and Spectral norms

Some other properties:

$$\underline{\underline{\|AB\|_F}} \leq \underline{\underline{\|A\|_F}} \underline{\underline{\|B\|_F}}$$

$$\underline{\underline{\|AB\|_2}} \leq \underline{\underline{\|A\|_2}} \underline{\underline{\|B\|_2}}$$

Matrix Multiplication

Problem: Given matrices $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{n \times h}$ compute the matrix AB

- Standard algorithm based on definition: $O(mnh)$ time
- Faster algorithms via non-trivial Strassen-like divide and conquer.

Matrix Multiplication

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- Standard algorithm based on definition: $O(mnh)$ time
- Faster algorithms via non-trivial Strassen-like divide and conquer.

Approximation: Compute $D \in \mathbb{R}^{m \times h}$ such that $\|D - AB\|$ is small in some appropriate matrix norm.

Two methods

- random sampling
- random projections (fast JL)

Matrix Multiplication

Problem: Given matrices $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{n \times h}$ compute the matrix AB

Notation: $M^{(j)}$ for j 'th column of M and $M_{(i)}$ for i 'th row of M both interpreted as vectors

From textbook definition: $D_{i,j} = \langle A_{(i)}, B^{(j)} \rangle = \sum_{k=1}^n A_{i,k} B_{k,j}$

Consider A^T consisting of m column vectors from \mathbb{R}^n and B as h column vectors from \mathbb{R}^n

We want to compute all mh inner products of these vectors.

$$M_{(i)} \quad i \left[\begin{array}{c} \updownarrow \\ \leftarrow \rightarrow \\ \updownarrow \end{array} \right] \quad M^{(j)}$$

$$\begin{matrix}
 & n & & & h & & h \\
 m & \left[\begin{array}{c} \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \\ \text{---} \end{array} \right] & \times & \begin{matrix} n \\ \left[\begin{array}{c} | \\ | \\ | \\ | \end{array} \right] \end{matrix} & = & \begin{matrix} m \\ \left[\begin{array}{c} \\ \\ \\ \end{array} \right] \end{matrix} & \\
 & A & & & B & & D.
 \end{matrix}$$

$$D_{i,j} = \sum_{k=1}^n A_{i,k} B_{k,j}$$

$\overbrace{m \times h.}^{m \times h.}$

$\langle A_{(i)}, B^{(j)} \rangle$

mh inner products of n-dim. vectors

mh

Want: $D \leq I$
 $\|D - A\|_F$ is small.

Part I

Random Sampling for Approx Matrix Mult

Approximate Matrix Multiplication

Want to approximate AB in the Frobenius norm “additively”.

Want D such that $\|D - AB\|_F \leq \epsilon \|AB\|_F$ but instead will settle for $\|D - AB\|_F \leq \epsilon \|A\|_F \|B\|_F$

Alternate definition of matrix multiplication based on outer product:

$$AB = \sum_{j=1}^n A^{(j)} B_{(j)}$$

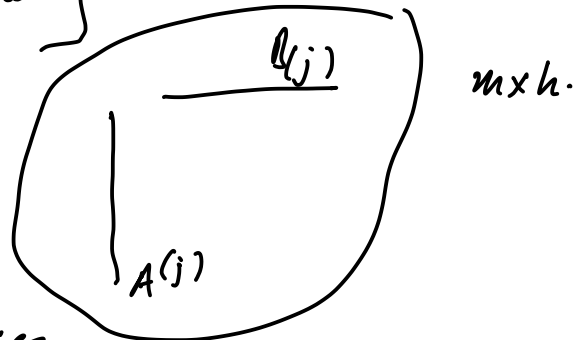
$A^{(j)} B_{(j)}$ is a $m \times h$ matrix of rank 1

$$\begin{bmatrix} \hline A_{(c)} \end{bmatrix} \times \begin{bmatrix} | \\ v_b^{(j)} \end{bmatrix} = \begin{bmatrix} \hline \underline{\underline{D_{c,j}}} \end{bmatrix}$$

Sum of n outer products

$$\begin{bmatrix} | \\ A^{(j)} \end{bmatrix} \cdot \begin{bmatrix} \hline B_{(j)} \end{bmatrix}$$

$$= \sum_{j=1}^n \underline{\underline{A^{(j)} B_{(j)}}} =$$



Sum of n matrices

$$\underline{\underline{(mh)}} \times n$$

Importance Sampling

$$AB = \sum_{j=1}^n A^{(j)} B_{(j)}$$

- Pick a probability distribution over $[n]$, $p_1 + p_2 + \dots + p_n = 1$
- For $\ell = 1$ to t do pick an index $j_\ell \in [n]$ according to distribution p (independent with replacement)
- Output $C = \frac{1}{t} \sum_{\ell=1}^t \frac{1}{p_{j_\ell}} A^{(j_\ell)} B_{(j_\ell)}$

$$C = \frac{1}{t} \sum_{\ell=1}^t \frac{1}{p_{j_\ell}} A^{(j_\ell)} B_{(j_\ell)}$$

$$E[C] = AB.$$

$$C = \frac{1}{p_j} A^{(j)} B_{(j)} \quad \text{if chosen index is } j$$

$$E[C] = \sum_{j=1}^n p_j [j \text{ is chosen}] \cdot \frac{1}{p_j} A^{(j)} B_{(j)}$$

$$= \sum_{j=1}^n p_j \cdot \frac{1}{p_j} A^{(j)} B_{(j)}$$

$$= AB$$

Importance Sampling

$$AB = \sum_{j=1}^n \underbrace{A^{(j)} B_{(j)}}_{\text{circled and underlined}}$$

- Pick a probability distribution over $[n]$, $p_1 + p_2 + \dots + p_n = 1$
- For $\ell = 1$ to t do pick an index $j_\ell \in [n]$ according to distribution p (independent with replacement)
- Output $C = \frac{1}{t} \sum_{\ell=1}^t \frac{1}{p_{j_\ell}} A^{(j_\ell)} B_{(j_\ell)}$

$$C = \frac{1}{t} \sum_{\ell} C_\ell \text{ where } \mathbf{E}[C_\ell] = AB.$$

By linearity of expectation: $\mathbf{E}[C] = AB$

Importance Sampling

Question: How should we choose p_1, p_2, \dots, p_n ?

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Use spectral norm of $A^{(j)} B_{(j)}$ which is $\|A^{(j)} B_{(j)}\|_2$

The diagram shows several handwritten mathematical expressions:

- A vertical vector $\begin{bmatrix} \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \end{bmatrix}$ with a subscript m to its left.
- A horizontal vector $\begin{bmatrix} \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}$ with a subscript n above it.
- A large empty square bracket $[\quad]$.

Importance Sampling

Question: How should we choose p_1, p_2, \dots, p_n ? p_j should correspond to contribution of $A^{(j)} B_{(j)}$ to $\|AB\|_F$

Use spectral norm of $A^{(j)} B_{(j)}$ which is $\|A^{(j)} B_{(j)}\|_2$

Claim: $\|A^{(j)} B_{(j)}\|_2 = \|A^{(j)}\|_2 \|B_{(j)}\|_2$.

Choose $p_j = \frac{\|A^{(j)}\|_2 \|B_{(j)}\|_2}{\sum_{\ell} \|A^{(\ell)}\|_2 \|B_{(\ell)}\|_2}$

Due to [Drineas-Kannan-Mahoney]

$$p_j = \frac{\|A^{(j)}\|_2 \|B_{(j)}\|_2}{\sum_{\ell} (\quad)}$$

Running time

- For all j compute $\|A^{(j)}\|_2$ and $\|B^{(j)}\|_2$. Takes one pass over A and B
- Allows one to compute p_1, p_2, \dots, p_n
- $C = \frac{1}{t} \sum_{\ell=1}^t \frac{1}{p_{i_\ell}} A^{(j_\ell)} B_{(j_\ell)}$
- At most $O(tmh + \underline{N_A} + \underline{N_B})$ time where N_A and N_B is number of non-zeroes in A and B .
- Full computation takes $O(nmh)$ time.

$$\frac{1}{\|x\|_2}$$

$$w_j = \|A^{(j)}\|_2 \|B^{(j)}\|_2$$

cell w_j
values

$$p_j = \frac{w_j}{\sum_{l=1}^n w_l}$$

Analysis of approximation

We would ideally like to know $\Pr[\|C - AB\|_F \geq \epsilon \|AB\|_F]$. Hard to understand $\|AB\|_F$. Instead analyse

$\Pr[\|C - AB\|_F \geq \epsilon \|A\|_F \|B\|_F]$ since $\|AB\|_F \leq \|A\|_F \|B\|_F$.

Analysis of approximation

We would ideally like to know $\Pr[\|C - AB\|_F \geq \epsilon \|AB\|_F]$. Hard to understand $\|AB\|_F$. Instead analyse $\Pr[\|C - AB\|_F \geq \epsilon \|A\|_F \|B\|_F]$ since $\|AB\|_F \leq \|A\|_F \|B\|_F$.

Using Markov:

$$\Pr[\|C - AB\|_F \geq \epsilon \|A\|_F \|B\|_F] \leq \frac{\mathbb{E}[\|C - AB\|_F^2]}{\epsilon^2 \|A\|_F^2 \|B\|_F^2}$$

Lemma

$$\mathbb{E}[\|C - AB\|_F^2] \leq \frac{1}{t} \left(\sum_{j=1}^n \|A^{(j)}\|_2 \|B^{(j)}\|_2 \right)^2 - \frac{1}{t} \|AB\|_F^2$$

Proof later.

Analysis continued

$$\Pr[\|C - AB\|_F \geq \epsilon \|A\|_F \|B\|_F] \leq \frac{\mathbb{E}[\|C - AB\|_F^2]}{\epsilon^2 \|A\|_F^2 \|B\|_F^2}$$

$$\begin{aligned} \mathbb{E}[\|C - AB\|_F^2] &\leq \frac{1}{t} \left(\sum_{j=1}^n \|A^{(j)}\|_2 \|B_{(j)}\| \right)^2 - \frac{1}{t} \|AB\|_F^2 \\ &\leq \frac{1}{t} \|A\|_F^2 \|B\|_F^2. \end{aligned}$$

Thus, if $t = \frac{1}{\epsilon^2 \delta}$ then

$$\Pr[\|C - AB\|_F \geq \epsilon \|A\|_F \|B\|_F] \leq \delta.$$

Compute P_1, P_2, \dots, P_n in $\underline{O(N_A + N_B)}$

Sampling t outer products

C is $\text{rank } t$ matrix $O(\Theta m)$. $\underline{n} \underline{m}$

$$t = \frac{1}{\varepsilon^2 \delta}$$

then $P_n [\|C - A_n\|_F \leq \varepsilon \|A\|_F \text{ with } \leq \underline{\delta}]$

$$t = \underline{\frac{1}{\varepsilon^2 \delta}} \quad \text{is } \underline{n}$$

$$\frac{1}{\varepsilon^2} \ln \frac{1}{\delta}$$

Median trick

Recall that we used median trick to improve dependence on δ from $1/\delta$ to $\log(1/\delta)$.

If $t = \frac{3}{\epsilon^2}$ then

$$\Pr[\|C - AB\|_F \geq \epsilon \|A\|_F \|B\|_F] \leq 1/3.$$

Repeat independently to obtain C_1, C_2, \dots, C_r where $r = \Theta(\log(1/\delta))$

By Chernoff bounds majority of estimators are good. How do we pick the “median” matrix?

Median trick

If $t = \frac{3}{\epsilon^2}$ then

$$\Pr[\|C - AB\|_F \geq \epsilon \|A\|_F \|B\|_F] \leq 1/3.$$

Repeat independently to obtain $\underline{C_1}, \underline{C_2}, \dots, \underline{C_r}$ where
 $r = \Theta(\log(1/\delta))$

For each $1 \leq i \leq r$ compute

$$\underline{\rho_i} = |\{j \mid j \neq i, \|C_i - C_j\|_F \leq \underline{2\epsilon \|A\|_F \|B\|_F}\}|$$

Output $\underline{C_s}$ such that $\underline{\rho_s} \geq r/2$.

[Clarkson-Woodruff]

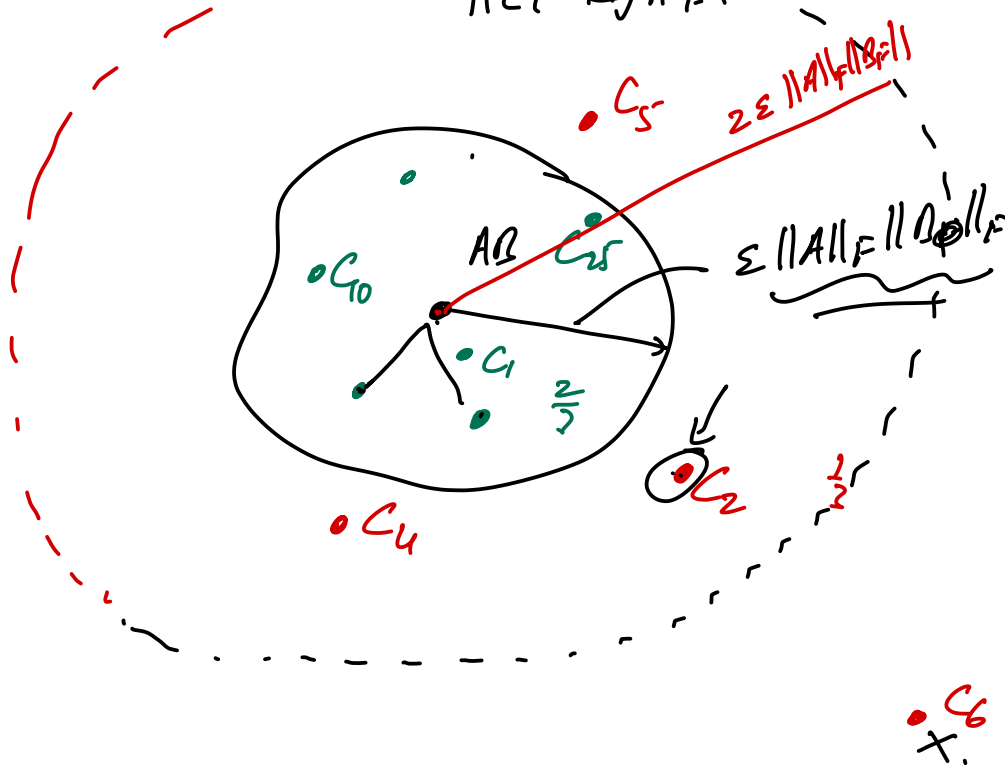
C_1, C_2, \dots, C_n as points in a metric space $d(i,j) = \|C_i - C_j\|_F$

output C_s if

$\exists \frac{\epsilon}{2}$ among the $\{1, 2, \dots, n\}$

$$\text{s.t. } d(s, j) \leq 2\epsilon \|A\|_F \|B\|_F.$$

requires $\binom{n}{2}$ computations of $\|C_i - C_j\|_F$.



Median trick

For each $1 \leq i \leq r$ compute

$$\rho_i = |\{j \mid j \neq i, \|C_i - C_j\| \leq 2\epsilon \|A\|_F \|B\|_F\}|$$

Output C_s such that $\rho_s \geq r/2$

Correctness follows from triangle inequality.

$$\|C_i - C_j\|_F \leq \|C_i - AB\|_F + \|C_j - AB\|_F$$

and

$$\|C_i - C_j\|_F \geq \|C_i - AB\|_F - \|C_j - AB\|_F.$$

Median trick

For each $1 \leq i \leq r$ compute

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$$\|C_i - C_j\|_F \leq \|C_i - AB\|_F + \|C_j - AB\|_F$$

More than half of C_i 's have $\|C_i - AB\|_F < \epsilon \|A\|_F \|B\|_F$. If C_s is good then $\rho_s \geq r/2$.

Median trick

For each $1 \leq i \leq r$ compute

$$\rho_i = |\{j \mid j \neq i, \|C_i - C_j\| \leq 2\epsilon \|A\|_F \|B\|_F\}|$$

Output C_s such that $\rho_s \geq r/2$

Correctness follows from triangle inequality.

$$\|C_i - C_j\|_F \geq \|C_i - AB\|_F - \|C_j - AB\|_F.$$

More than half of C_i 's have $\|C_i - AB\|_F < \epsilon \|A\|_F \|B\|_F$. If C_s is bad ($\|C_s - AB\|_F > 3\epsilon \|A\|_F \|B\|_F$) then $\|C_s - C_j\| > 2\epsilon \|A\|_F \|B\|_F$ which means $\rho_s < r/2$.

Running time again

- For all j compute $\|A^{(j)}\|_2$ and $\|B_{(j)}\|_2$. Takes one pass over A and B
- Allows one to compute p_1, p_2, \dots, p_n
- $C = \frac{1}{t} \sum_{\ell=1}^t \frac{1}{p_{i_\ell}} A^{(j_\ell)} B_{(j_\ell)}$
- At most $O(tmh + N_A + N_B)$ time where N_A and N_B is number of non-zeroes in A and B .
- Full computation takes $O(nmh)$ time.

Either we choose $t = \frac{1}{\epsilon^2 \delta}$ or we choose $t = \frac{1}{\epsilon^2} \ln(1/\delta)$ but then we need to do pairwise matrix computations so effectively $t = \frac{1}{\epsilon^4} \log^2(1/\delta)$.

Proof of Lemma

Lemma

$$\mathbf{E}[\|C - AB\|_F^2] \leq \frac{1}{t} \left(\sum_{j=1}^n \|A^{(j)}\|_2 \|B^{(j)}\|_2 \right)^2 - \frac{1}{t} \|AB\|_F^2$$

Recall C is sum of t independent estimators so the lemma is basically about $t = 1$.

$$\mathbf{E}[\|C - AB\|_F^2] = \sum_{x,y} \mathbf{E}[(C_{x,y} - (AB)_{x,y})^2]$$

Fix x, y . Let $Z = C_{x,y}$. We have $\mathbf{E}[Z] = (AB)_{x,y}$. Hence

$$\text{Var}[Z] = \mathbf{E}[Z^2] - (AB)_{x,y}^2 = \mathbf{E}[(C_{x,y} - (AB)_{x,y})^2]$$

Proof of Lemma

$$\mathbf{E}[Z^2] = \sum_{j=1}^n p_j (A_{x,j} B_{j,y})^2 / p_j^2 = \sum_{j=1}^n (A_{x,j} B_{j,y})^2 / p_j$$

$$\text{Thus } \mathbf{E}[\|C - AB\|_F^2] = \sum_{x,y} \sum_{j=1}^n (A_{x,j} B_{j,y})^2 / p_j - \|AB\|_F^2.$$

Simplifying the first term:

$$\sum_{x,y} \sum_{j=1}^n (A_{x,j})^2 (B_{j,y})^2 / p_j = \sum_{j=1}^n \frac{1}{p_j} \|A^{(j)}\|^2 \|B_{(j)}\|^2$$

Proof of Lemma

$$\mathbf{E}[Z^2] = \sum_{j=1}^n p_j (A_{x,j} B_{j,y})^2 / p_j^2 = \sum_{j=1}^n (A_{x,j} B_{j,y})^2 / p_j$$

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$$\sum_{x,y} \sum_{j=1}^n (A_{x,j})^2 (B_{j,y})^2 / p_j = \sum_{j=1}^n \frac{1}{p_j} \|A^{(j)}\|^2 \|B_{(j)}\|^2$$

$$\text{Recall: } p_j = \frac{\|A^{(j)}\| \|B_{(j)}\|}{\sum_{\ell} \|A^{(\ell)}\| \|B_{(\ell)}\|}$$

$$\text{Thus } \mathbf{E}[\|C - AB\|_F^2] = \left(\sum_{j=1}^n \|A^{(j)}\| \|B_{(j)}\| \right)^2 - \|AB\|_F^2.$$

Proof of Lemma

$$\mathbf{E}[Z^2] = \sum_{j=1}^n p_j (A_{x,j} B_{j,y})^2 / p_j^2 = \sum_{j=1}^n (A_{x,j} B_{j,y})^2 / p_j$$

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Simplifying the first term:

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$$\text{Recall: } p_j = \frac{\|A^{(j)}\| \|B_{(j)}\|}{\sum_{\ell} \|A^{(\ell)}\| \|B_{(\ell)}\|}$$

$$\text{Thus } \mathbf{E}[\|C - AB\|_F^2] = \left(\sum_{j=1}^n \|A^{(j)}\| \|B_{(j)}\| \right)^2 - \|AB\|_F^2.$$

One can show that the choice of p_j values is optimum for reducing variance in the simple importance sampling scheme.

Sampling matrix view

$$AB = \sum_{j=1}^n A^{(j)} B_{(j)}$$

- Pick a probability distribution over $[n]$, $p_1 + p_2 + \dots + p_n = 1$
- For $\ell = 1$ to t do pick an index $j_\ell \in [n]$ according to distribution p (independent with replacement)
- Output $C = \frac{1}{t} \sum_{\ell=1}^t \frac{1}{p_{j_\ell}} A^{(j_\ell)} B_{(j_\ell)}$

$C = (AS^T)(SB)$ where $S \in \mathbb{R}^{n \times t}$ is a sampling matrix:

$$S_{i,j} = \frac{1}{\sqrt{tp_j}} \text{ if column } j \text{ is picked in } i\text{'th sample else } S_{i,j} = 0$$

Part II

Random Projection for Approx Matrix Mult

JL Approach for Approx Matrix Multiplication

[Sarlos]

Output $C = (AS^T)(SB)$ where S is a (fast) JL matrix. Works!

Advantage?

JL Approach for Approx Matrix Multiplication

[Sarlos]

Output $C = (AS^T)(SB)$ where S is a (fast) JL matrix. Works!

Advantage? Oblivious to A, B . Can update them etc.

Recalling JL

Lemma (Distributional JL Lemma)

Fix vector $x \in \mathbb{R}^d$ and let $\Pi \in \mathbb{R}^{k \times d}$ matrix where each entry Π_{ij} is chosen independently according to standard normal distribution $\mathcal{N}(0, 1)$ distribution. If $k = \Omega\left(\frac{1}{\epsilon^2} \log(1/\delta)\right)$, then with probability $(1 - \delta)$ we have $\|\frac{1}{\sqrt{k}}\Pi x\|_2 = (1 \pm \epsilon)\|x\|_2$.

Can choose entries from $\{-1, 1\}$ as well.

Definition

Let \mathcal{D} be a distribution over $m \times n$ matrices. \mathcal{D} is said to have (ϵ, δ) JL moment property if for any unit vector $x \in \mathbb{R}^n$,

$$E_{\Pi \sim \mathcal{D}} \left| \|\Pi x\|_2^2 - 1 \right| \leq \epsilon \delta.$$

JL Property

Lemma

If Π comes from (ϵ, δ) JL moment distribution then for all unit vectors $x, y \in \mathbb{R}^n$, $|\langle \Pi x, \Pi y \rangle - \langle x, y \rangle|^2 \leq c\epsilon^2\delta$.

Using JL

Theorem

Suppose Π is chosen from a distribution \mathcal{D} that satisfies (ϵ, δ) JL moment property then

$$\Pr_{\Pi \sim \mathcal{D}} [\|AB - (A\Pi^T)(B\Pi)\|_F > 3\epsilon\|A\|_F\|B\|_F] \leq \delta.$$

Using JL

Theorem

Suppose Π is chosen from a distribution \mathcal{D} that satisfies (ϵ, δ) JL moment property then

$$\Pr_{\Pi \sim \mathcal{D}} [\|AB - (A\Pi^T)(B\Pi)\|_F > 3\epsilon\|A\|_F\|B\|_F] \leq \delta.$$

Let $C = (A\Pi^T)(B\Pi)$.

$$\Pr[\|AB - C\|_F^2 > 3\epsilon\|A\|_F\|B\|_F^2] \leq \frac{\mathbf{E}[\|AB - C\|_F^2]}{(3\epsilon\|A\|_F\|B\|_F)^2}.$$

Analysis

$$C_{i,j} = \langle \Pi A_{(i)}, \Pi B^{(j)} \rangle \text{ while } (AB)_{i,j} = \langle A_{(i)}, B^{(j)} \rangle$$

Notation: a_i for $A_{(i)}$ and b_j for $B^{(j)}$

Analysis

$$C_{i,j} = \langle \Pi A_{(i)}, \Pi B^{(j)} \rangle \text{ while } (AB)_{i,j} = \langle A_{(i)}, B^{(j)} \rangle$$

Notation: a_i for $A_{(i)}$ and b_j for $B^{(j)}$

$$\|AB - C\|_F^2 = \sum_{i,j} |\langle \Pi a_i, \Pi b_j \rangle - \langle a_i, b_j \rangle|^2$$

Analysis

$$C_{i,j} = \langle \Pi A_{(i)}, \Pi B^{(j)} \rangle \text{ while } (AB)_{i,j} = \langle A_{(i)}, B^{(j)} \rangle$$

Notation: a_i for $A_{(i)}$ and b_j for $B^{(j)}$

$$\|AB - C\|_F^2 = \sum_{i,j} |\langle \Pi a_i, \Pi b_j \rangle - \langle a_i, b_j \rangle|^2$$

Term by term:

$$|\langle \Pi a_i, \Pi b_j \rangle - \langle a_i, b_j \rangle|^2 = \alpha \left| \langle \Pi \frac{a_i}{\|a_i\|_2}, \Pi \frac{b_j}{\|b_j\|_2} \rangle - \langle \frac{a_i}{\|a_i\|_2}, \frac{b_j}{\|b_j\|_2} \rangle \right|^2$$

$$\text{where } \alpha = \|a_i\|_2^2 \|b_j\|_2^2$$

Analysis

$$C_{i,j} = \langle \Pi A_{(i)}, \Pi B^{(j)} \rangle \text{ while } (AB)_{i,j} = \langle A_{(i)}, B^{(j)} \rangle$$

Notation: a_i for $A_{(i)}$ and b_j for $B^{(j)}$

$$\|AB - C\|_F^2 = \sum_{i,j} |\langle \Pi a_i, \Pi b_j \rangle - \langle a_i, b_j \rangle|^2$$

Term by term:

$$|\langle \Pi a_i, \Pi b_j \rangle - \langle a_i, b_j \rangle|^2 = \alpha \left| \langle \Pi \frac{a_i}{\|a_i\|_2}, \Pi \frac{b_j}{\|b_j\|_2} \rangle - \langle \frac{a_i}{\|a_i\|_2}, \frac{b_j}{\|b_j\|_2} \rangle \right|^2$$

where $\alpha = \|a_i\|_2^2 \|b_j\|_2^2$

Applying JL property and linearity of expectation

$$\mathbf{E}[\|AB - C\|_F^2] \leq (c\epsilon)^2 \delta \sum_{i,j} \|a_i\|_2^2 \|b_j\|_2^2 \leq (c\epsilon^2) \delta \|A\|_F^2 \|B\|_F^2$$

Analysis

$$\Pr[\|AB - C\|_F^2 > 3\epsilon\|A\|_F\|B\|_F^2] \leq \frac{\mathbf{E}[\|AB - C\|_F^2]}{(3\epsilon\|A\|_F\|B\|_F)^2}.$$

and

$$\mathbf{E}[\|AB - C\|_F^2] \leq (c\epsilon)^2\delta \sum_{i,j} \|a_i\|_2^2 \|b_j\|_2^2 \leq (c\epsilon^2)\delta \|A\|_F^2 \|B\|_F^2$$

hence

$$\Pr[\|AB - C\|_F^2 > 3\epsilon\|A\|_F\|B\|_F^2] \leq \delta.$$

Running time

Roughly speaking: Π converts vectors of dimension n into vectors of dimension $d = O(\frac{1}{\epsilon^2} \log(1/\delta))$.

Need to compute ΠA^T and ΠB and then compute dot products.

mh inner products of vectors of dimension d which is $O(mhd^2)$ time in the worst case

Using Fast JL with very sparse Π one can improve running time