

Lec 13: Randomized Matrix Multiplication.

Randomized Linear Algebra.

$$AB = \begin{bmatrix} a_1 & \dots & a_r \end{bmatrix} \begin{bmatrix} b_1^T \\ \vdots \\ b_r^T \end{bmatrix} = a_1 b_1^T + \dots + a_r b_r^T$$

Random matrix multiply.

- Probabilities.
- Mean $m \rightarrow AB$ correct.
- Variance $\sigma^2 \rightarrow \text{NOT ZERO!}$
- Lagrange multipliers for $\sum p_j = 1$

[a b]

$p_j = \frac{1}{2}, \frac{1}{2}$, $s=2$ samples Take average. $\frac{1}{s}$

$$\text{mean} = \sum p_i (\text{sample}) = \frac{1}{2} \times (a, 0) + \frac{1}{2} \times (0, b) = \frac{1}{2} (a, b).$$

$s=2$ samples: multiply by 2 $\rightarrow (a, b) = \text{Mean is correct}$

variance: are distance² from mean

$$\sigma_{\text{sample}}^2 = \left(\sum p_i \text{output}^2 \right) - (\text{mean})^2$$

$$= \frac{1}{2} \left[(a, 0) - \left(\frac{a}{2}, \frac{b}{2} \right) \right]^2 + \frac{1}{2} \left[(0, b) - \left(\frac{a}{2}, \frac{b}{2} \right) \right]^2$$

$$= \left(\frac{1}{2} \left[\left(\frac{a}{2} \right)^2 + \left(\frac{b}{2} \right)^2 \right] + \frac{1}{2} \left[\left(\frac{a}{2} \right)^2 + \left(\frac{b}{2} \right)^2 \right] \right) \times 2 = \frac{1}{2} (a^2, b^2)$$



from 2 samples.

$$p_j = \frac{\|a_j\| \|b_j^T\|}{C} \quad \leftarrow C = \sum_1^r \|a_j\| \|b_j^T\|$$

↑
probability of choosing col j of $A \times$ row j of B .

$$\text{approximation } AB = \sum_1^s p_j \left(\frac{a_j b_j^T}{p_j} \right)$$

$$\text{mean of 1 sample } \sum \frac{a_j b_j^T}{s}$$

all. $\sum \frac{a_j b_j^T}{s} = AB.$

variance (will depend on p_1, \dots, p_r).

$$= \sum_1^r \frac{\|a_j\|^2 \|b_j^T\|^2}{s p_j} - \frac{1}{s} \|AB\|_F^2 = \frac{1}{s} [C^2 - \|AB\|_F^2]$$

with optimal p_j

optimize $p_1 \dots p_r$.

$$\text{minimize } \sum \|a_j\| \|b_j^T\|$$

$$\text{minimize } \frac{Q_j^2}{p_j} \quad Q_j = \|a_j\| \|b_j^T\|$$
$$\sum_1^r p_j = 1$$

$$\Leftrightarrow \text{minimize } \frac{\|a_j\| \|b_j^T\|}{p_j} - \lambda (\sum p_j - 1).$$

$$\left. \begin{aligned} \frac{\partial}{\partial p_j} &= -\frac{\|a_j\|^2 \|b_j^T\|^2}{p_j^2} - \lambda = 0. \\ \frac{\partial}{\partial \lambda} &= \sum p_j - 1 = 0. \end{aligned} \right\} \begin{aligned} \lambda &= -\frac{\|a_j\|^2 \|b_j^T\|^2}{p_j^2} \\ \Rightarrow p_j^2 &= \frac{\|a_j\| \|b_j^T\|^2}{\lambda} \text{ for each } j \end{aligned}$$

$$p_j = \frac{\|a_j\| \|b_j^T\|}{\sqrt{\lambda}}$$

$$\sum p_j = 1 \Rightarrow \sum_1^r \|a_j\| \|b_j^T\| = \sqrt{\lambda}$$

C