Johnson-Lindenstrauss Lemma

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1 Johnson-Lindenstrauss Lemma

Lemma 1 let $y = \frac{1}{\sqrt{k}} \mathbf{W} \mathbf{x}$, where $W_{i,j} \sim \mathcal{N}(0,1)$:

$$\Pr((1-\epsilon)\|\mathbf{x}\|^2 \le \|\mathbf{y}\|^2 \le (1+\epsilon)\|\mathbf{x}\|^2) \ge 1 - \frac{2}{2} \exp^{\frac{(2\epsilon^3 - 3\epsilon^2)}{12}k}$$
 (1)

2 Proof of lemma 1

Let $W_{k \times d}$ be the random matrix where $W_{ij} \overset{\text{i.i.d}}{\sim} \mathcal{N}(0,1)$ and $\mathbf{x} \in \mathbb{R}^d$ and:

$$y = \frac{1}{\sqrt{k}} \mathbf{W} \mathbf{x}$$

$$\implies y_i = \frac{1}{\sqrt{k}} \sum_{i=1}^d W_{i,j} x_j$$
(2)

2.1 some helper properties

2.1.1 $\mathbb{E}[\|{\boldsymbol{y}}\|^2] = \|{\mathbf{x}}\|^2$

we know $\mathbb{E}[y_i] = \frac{1}{\sqrt{k}} \sum_{j=1}^d \mathbb{E}[W_{i,j}] x_j = 0$

$$\begin{split} \mathbb{E}[y_i^2] &= \frac{1}{k} \mathbb{E}\Big[\Big(\sum_{j=1}^d W_{i,j} x_j\Big)^2\Big] \\ &= \frac{1}{k} \sum_{j=1}^d \mathbb{E}[W_{i,j}^2] x_j^2 \qquad \text{all terms for } \mathbb{E}[W_{i,j} W_{i,j'}] = 0 \\ &= \frac{1}{k} \sum_{j=1}^d x_j^2 = \frac{1}{k} \|\mathbf{x}\|^2 \end{split} \tag{3}$$

This implies that $y_i \sim \mathcal{N} \left(0, \frac{1}{k} \|\mathbf{x}\|^2 \right)$

$$\mathbb{E}[\|\boldsymbol{y}\|^2] = \mathbb{E}\left[\sum_i y_i^2\right] = \sum_i \mathbb{E}[y_i^2]$$

$$= k \frac{1}{k} \|\mathbf{x}\|^2$$

$$= \|\mathbf{x}\|^2$$
(4)

2.1.2 introduce "normalized" \hat{y} such that $\hat{y} \sim \mathcal{N}(0, \mathbf{I}_k)$:

let
$$\hat{\boldsymbol{y}} = \frac{\sqrt{k}}{\|\mathbf{x}\|} \boldsymbol{y}$$
 be the "normalized" version of \boldsymbol{y}

$$= \frac{\sqrt{k}}{\|\mathbf{x}\|} \frac{1}{\sqrt{k}} \mathbf{W} \mathbf{x} = \frac{1}{\|\mathbf{x}\|} \mathbf{W} \mathbf{x}$$

$$\implies \hat{y}_i = \frac{\sqrt{k}}{\|\mathbf{x}\|} y_i = \frac{1}{\|\mathbf{x}\|^2} W_{i,:} \mathbf{x}$$

$$\sim \mathcal{N}(0, 1) \quad \text{using } y_i \sim \mathcal{N}\left(0, \frac{1}{k} \|\mathbf{x}\|^2\right)$$
(5)

one can interchange ${m y}$ and $\hat{{m y}}$ (no need to use properties above):

$$\hat{\mathbf{y}} = \frac{\sqrt{k}}{\|\mathbf{x}\|} \mathbf{y}$$

$$\|\hat{\mathbf{y}}\|^2 = \frac{k \mathbf{y}^\top \mathbf{y}}{\|\mathbf{x}\|^2}$$

$$= \frac{k \|\mathbf{y}\|^2}{\|\mathbf{x}\|^2}$$

$$\implies \|\mathbf{y}\|^2 = \frac{\|\hat{\mathbf{y}}\|^2 \|\mathbf{x}\|^2}{k}$$
(6)

2.2 prove $\Pr(\|y\|^2 \ge (1+\epsilon)\|\mathbf{x}\|^2) \le \exp^{\frac{(2\epsilon^3-3\epsilon^2)}{12}k}$

$$\Pr(\|\boldsymbol{y}\|^2 \ge (1+\epsilon)\|\mathbf{x}\|^2) \quad \text{not in terms of } k$$

$$= \Pr(\frac{\|\hat{\boldsymbol{y}}\|^2 \|\mathbf{x}\|^2}{k} \ge (1+\epsilon)\|\mathbf{x}\|^2)$$

$$= \Pr(\|\hat{\boldsymbol{y}}\|^2 \ge k(1+\epsilon)) \quad \text{in terms of } k$$

$$(7)$$

using Chernoff bound for $\|\hat{\boldsymbol{y}}\|^2$:

$$\Pr(\|\hat{\boldsymbol{y}}\|^{2} \geq k(1+\epsilon)) \leq \frac{\mathbb{E}\left[\exp\left(\lambda\|\hat{\boldsymbol{y}}\|^{2}\right)\right]}{\exp(\lambda k(1+\epsilon))}$$

$$= \frac{\mathbb{E}\left[\exp\left(\lambda\sum_{i=1}^{k}\hat{y}_{i}^{2}\right)\right]}{\exp(\lambda k(1+\epsilon))} \quad \sum_{i}^{k}\hat{y}_{i}^{2} \sim \chi^{2}(k)$$

$$= \frac{(1-2\lambda)^{-\frac{k}{2}}}{\exp(\lambda k(1+\epsilon))}$$

$$= \left(\frac{1}{\sqrt{1-2\lambda}}\frac{1}{\exp(\lambda(1+\epsilon))}\right)^{k}$$

$$= \left((1+\epsilon)\exp^{-\epsilon}\right)^{\frac{k}{2}}$$

$$(8)$$

this is because, by solving for λ to minimize the bound which obtains $\lambda=\frac{\epsilon}{2(1+\epsilon)}$ and then simplify, one obtains:

$$\frac{1}{\sqrt{1 - 2\frac{\epsilon}{2(1+\epsilon)}}} \exp\left(\frac{\epsilon}{2(1+\epsilon)}(1+\epsilon)\right)$$

$$= \frac{1}{\sqrt{1 - \frac{\epsilon}{1+\epsilon}}} \exp\left(\frac{\epsilon}{2}\right)$$

$$= \frac{1}{\sqrt{\frac{1}{1+\epsilon}}} \exp^{-\frac{\epsilon}{2}}$$

$$= (1+\epsilon)^{\frac{1}{2}} \left(\exp^{-\epsilon}\right)^{\frac{1}{2}}$$

$$= ((1+\epsilon)\exp^{-\epsilon})^{\frac{1}{2}}$$

Derive the fact:

$$\begin{split} \log(1+x) &= \int_x \frac{1}{1+x} \mathrm{d}x = \int_x (1+x)^{-1} \mathrm{d}x \\ &= \int_x (1+0)^{-1} - (1+0)^{-2}x + \frac{2(1+0)^{-3}}{2!} x^2 - \frac{2 \times 3(1+0)^{-4}}{3!} x^3 + \dots \quad \because \text{ Taylor expand about } x = 0 \\ &= \int_x 1 - x + x^2 - x^3 + x^4 \\ &\leq \int_x 1 - x + x^2 \quad \because \ 0 < x < 1 \quad \text{and} \quad (-x^3 + x^4) < 0, \ (-x^5 + x^6) < 0 \dots \\ &= x - \frac{x^2}{2} + \frac{x^3}{3} \end{split}$$

using the fact: $\log(1+x) < x - \frac{x^2}{2} + \frac{x^3}{3}$:

$$(1+\epsilon) < \exp^{\epsilon - \frac{\epsilon^2}{2} + \frac{\epsilon^3}{3}}$$

$$\implies ((1+\epsilon) \exp^{-\epsilon})^{\frac{k}{2}} \le (\exp^{\epsilon - \frac{\epsilon^2}{2} + \frac{\epsilon^3}{3}} \exp^{-\epsilon})^{\frac{k}{2}}$$

$$= (\exp^{-\frac{\epsilon^2}{2} + \frac{\epsilon^3}{3}})^{\frac{k}{2}} \quad \text{alternatively } \le (\exp^{-\frac{\epsilon^2}{2} + \frac{\epsilon^3}{2}})^{\frac{k}{2}} = \exp^{-(\epsilon^2 - \epsilon^3)\frac{k}{4}}$$

$$= (\exp^{\frac{2\epsilon^3 - 3\epsilon^2}{6}})^{\frac{k}{2}}$$

$$= \exp^{\frac{(2\epsilon^3 - 3\epsilon^2)}{12}k}$$
(11)

so we proved that:

$$\Pr(\|\boldsymbol{y}\|^2 \ge (1+\epsilon)\|\mathbf{x}\|^2) = \Pr(\|\hat{\boldsymbol{y}}\|^2 \ge k(1+\epsilon)) \quad \text{from Eq.(7)}$$

$$\le \left((1+\epsilon)\exp^{-\epsilon}\right)^{\frac{k}{2}} \quad \text{from Eq.(8)}$$

$$\le \exp^{\frac{(2\epsilon^3 - 3\epsilon^2)}{12}k} \quad \text{from Eq.(11)}$$

2.3 prove
$$\Pr(\|\mathbf{y}\|^2 \le (1 - \epsilon)\|\mathbf{x}\|^2) \le (\exp^{-\frac{\epsilon^2}{2} + \frac{\epsilon^3}{3}})^{\frac{k}{2}}$$

$$\Pr(\|\mathbf{y}\|^2 \le (1 - \epsilon)\|\mathbf{x}\|^2)$$

$$= \Pr(\frac{\|\hat{\mathbf{y}}\|^2 \|\mathbf{x}\|^2}{k} \le (1 - \epsilon)\|\mathbf{x}\|^2)$$

$$= \Pr(\|\hat{\mathbf{y}}\|^2 \le k(1 - \epsilon))$$

$$= \Pr(\exp^{-\lambda \|\hat{\mathbf{y}}\|^2} \ge \exp^{-\lambda k(1 - \epsilon)}) \quad \lambda > 0$$
(13)

using Chernoff bound:

$$\Pr(\|\hat{\boldsymbol{y}}\|^{2} \leq k(1 - \epsilon)) \leq \frac{\mathbb{E}\left[\exp^{-\lambda \|\hat{\boldsymbol{y}}\|^{2}}\right]}{\exp^{-\lambda k(1 + \epsilon)}} \quad \lambda > 0$$

$$= \frac{\mathbb{E}\left[\exp\left(-\lambda \sum_{i=1}^{k} \hat{y}_{i}^{2}\right)\right]}{\exp(-\lambda k(1 + \epsilon))} \quad \because \sum_{i}^{k} \hat{y}_{i}^{2} \sim \chi^{2}(k)$$

$$= \frac{(1 + 2\lambda)^{-\frac{k}{2}}}{\exp^{\lambda k(1 - \epsilon)}}$$

$$= \left(\frac{1}{\sqrt{1 + 2\lambda}} \exp^{-\lambda(1 - \epsilon)}\right)^{k}$$

$$= ((1 - \epsilon) \exp^{-\epsilon})^{\frac{k}{2}}$$
(14)

this is because, by solving for λ to minimize the bound which obtains $\lambda=\frac{\epsilon}{2(1-\epsilon)}$ and then simplify, one obtains:

$$\frac{1}{\sqrt{1+2\frac{\epsilon}{2(1-\epsilon)}}} \frac{1}{\exp\left(\frac{-\epsilon}{2(1-\epsilon)}(1-\epsilon)\right)}$$

$$= \frac{1}{\sqrt{1-\frac{\epsilon}{1-\epsilon}}} \exp\left(\frac{-\epsilon}{2}\right)$$

$$= \frac{1}{\sqrt{\frac{1}{1-\epsilon}}} \exp^{\frac{\epsilon}{2}}$$

$$= (1-\epsilon)^{\frac{1}{2}} (\exp^{\epsilon})^{\frac{1}{2}}$$

$$= ((1-\epsilon)\exp^{\epsilon})^{\frac{1}{2}}$$

Derive the fact:

$$\log(1-x) < -x - \frac{x^2}{2} < -x - \frac{x^2}{2} - \frac{x^3}{3} \quad \text{for } x > 0$$

$$\implies (1-\epsilon) < \exp^{-\epsilon - \frac{\epsilon^2}{2} - \frac{\epsilon^3}{3}}$$
(16)

the above inequality can be proven as:

$$\log(1-x) = \int_x \frac{-1}{1-x} dx = -\int_x (1-x)^{-1} dx$$

$$= -\int_x (1-0)^{-1} + (1-0)^{-2}x + \frac{2(1-0)^{-3}}{2!}x^2 + \frac{2 \times 3(1+0)^{-4}}{3!}x^3 + \dots \quad \because \text{ Taylor expand about } x = 0$$

$$= \int_x -1 - x - x^2 - x^3 - x^4 - \dots$$

$$\leq \int_x -1 - x - x^2 \quad \because 0 < x < 1$$

$$= -x - \frac{x^2}{2} - \frac{x^3}{3}$$

$$(17)$$

$$\Pr(\|\boldsymbol{y}\|^{2} \leq (1 - \epsilon)\|\mathbf{x}\|^{2}) \leq ((1 - \epsilon) \exp^{\epsilon})^{\frac{k}{2}}$$

$$\leq (\exp^{-\epsilon - \frac{\epsilon^{2}}{2} - \frac{\epsilon^{3}}{3}} \exp^{\epsilon})^{\frac{k}{2}}$$

$$= (\exp^{-\frac{\epsilon^{2}}{2} - \frac{\epsilon^{3}}{3}})^{\frac{k}{2}}$$

$$\leq (\exp^{-\frac{\epsilon^{2}}{2} + \frac{\epsilon^{3}}{3}})^{\frac{k}{2}} \quad :: \epsilon > 0$$

$$\leq \exp^{-(\epsilon^{2} - \epsilon^{3})\frac{k}{4}} \quad :: \text{ alternative version, see Eq.(11)}$$

2.4 Putting together:

$$\Pr(\|\boldsymbol{y}\|^{2} \geq (1+\epsilon)\|\mathbf{x}\|^{2} \cup \|\boldsymbol{y}\|^{2} \leq (1-\epsilon)\|\mathbf{x}\|^{2}) \leq 2 \exp^{\frac{(2\epsilon^{3}-3\epsilon^{2})}{12}k}$$

$$\Rightarrow \Pr(\|\boldsymbol{y}\|^{2} \leq (1+\epsilon)\|\mathbf{x}\|^{2} \cap \|\boldsymbol{y}\|^{2} \geq (1-\epsilon)\|\mathbf{x}\|^{2}) \geq 1 - 2 \exp^{\frac{(2\epsilon^{3}-3\epsilon^{2})}{12}k}$$

$$\Rightarrow \Pr((1-\epsilon)\|\mathbf{x}\|^{2} \leq \|\boldsymbol{y}\|^{2} \leq (1+\epsilon)\|\mathbf{x}\|^{2}) \geq 1 - 2 \exp^{\frac{(2\epsilon^{3}-3\epsilon^{2})}{12}k}$$

$$\Rightarrow \Pr((1-\epsilon)\|\mathbf{x}\|^{2} \leq \|\boldsymbol{y}\|^{2} \leq (1+\epsilon)\|\mathbf{x}\|^{2}) \geq 1 - 2 \exp^{-(\epsilon^{2}-\epsilon^{3})\frac{k}{4}} \quad \text{alternative version}$$

$$(10)$$

another alternative version:

$$\implies \Pr\left((1-\epsilon)\|\mathbf{x}\|^2 \le \|\boldsymbol{y}\|^2 \le (1+\epsilon)\|\mathbf{x}\|^2\right) \ge 1 - \frac{2}{2}\exp^{-(\epsilon^2 - \epsilon^3)\frac{k}{4}} \quad \text{alternative version}$$

$$\ge 1 - \frac{2}{2}\exp^{-\epsilon^2\frac{k}{4}} \quad \text{looser bound}$$
(20)

2.4.1 alternative expression of J-L Lemma

let $\delta = \exp^{\frac{(2\epsilon^3 - 3\epsilon^2)}{12}k}$ or any other variants:

$$\Pr\left((1-\epsilon)\|\mathbf{x}\|^{2} \leq \left\|\frac{1}{\sqrt{k}}W\mathbf{x}\right\|^{2} \leq (1+\epsilon)\|\mathbf{x}\|^{2}\right) \geq 1-2\delta$$

$$\Rightarrow \Pr\left((1-\epsilon) \leq \frac{1}{k}\frac{\|W\mathbf{x}\|^{2}}{\|\mathbf{x}\|^{2}} \leq (1+\epsilon)\right) \geq 1-2\delta$$

$$\Rightarrow \Pr\left(\left|\frac{1}{k}\frac{\|W\mathbf{x}\|^{2}}{\|\mathbf{x}\|^{2}} - 1\right| \leq \epsilon\right) \geq 1-2\delta$$

$$\Rightarrow \Pr\left(\left|\frac{1}{k}\|W\mathbf{x}\|^{2} - \|\mathbf{x}\|^{2}\right| \leq \epsilon\|\mathbf{x}\|^{2}\right) \geq 1-2\delta$$

under special case where $\|\mathbf{x}\| = 1$

$$\implies \Pr\left(\left|\frac{1}{k} \|W\mathbf{x}\|^2 - 1\right| \le \epsilon\right) \ge 1 - 2\delta \tag{22}$$

3 corollary of J-L lemma

3.1 norm preserving for n data points after dimension reduction

Corollary 1.1 let $k \geq \left(\frac{24}{3\epsilon^2 - 2\epsilon^3} \log n\right)$ then: $\exists f: \mathbb{R}^d \to \mathbb{R}^k$, s.t.:

$$(1 - \epsilon) \|\mathbf{x}_i - \mathbf{x}_j\|^2 \le \|f(\mathbf{x}_i) - f(\mathbf{x}_j)\|^2 \le (1 + \epsilon) \|\mathbf{x}_i - \mathbf{x}_j\|^2 \qquad \forall \mathbf{x}_i, \mathbf{x}_j, \quad \forall 0 < \epsilon < 1$$
 (24)

3.1.1 choosing k in terms of n

looking at the (one side) J-L Lemma in Eq.(12). j is the only turnable parameter, so we need to choose an appropriate k. The clever choice is to let $k=\frac{24}{3\epsilon^2-2\epsilon^3}\log n$, so we have:

$$\Pr(\|\mathbf{y}\|^{2} \ge (1+\epsilon)\|\mathbf{x}\|^{2}) \le \exp^{\frac{(2\epsilon^{3}-3\epsilon^{2})}{12}k}$$

$$= \exp^{\frac{(2\epsilon^{3}-3\epsilon^{2})}{12}\left(\frac{24}{3\epsilon^{2}-2\epsilon^{3}}\log n\right)} \qquad \text{let } k = \frac{24}{3\epsilon^{2}-2\epsilon^{3}}\log n$$

$$= \exp^{-2\log n}$$

$$= n^{-2}$$
(26)

3.1.2 back to the dimension reduction case

let
$$\mathbf{y} = f(\mathbf{x}_i) - f(\mathbf{x}_j)$$
 $\mathbf{x} = \mathbf{x}_i - \mathbf{x}_j$:

$$\Pr(\|\mathbf{y}\|^{2} \notin \left\{ (1 - \epsilon) \|\mathbf{x}\|^{2} \cup (1 + \epsilon) \|\mathbf{x}\|^{2} \right\}) \leq \frac{2}{n^{2}}$$

$$\Rightarrow \Pr(\|f(\mathbf{x}_{i}) - f(\mathbf{x}_{j})\|^{2} \notin \left[(1 - \epsilon) \|\mathbf{x}_{i} - \mathbf{x}_{j}\|^{2} \cup (1 + \epsilon) \|\mathbf{x}_{i} - \mathbf{x}_{j}\|^{2} \right]) \leq \frac{2}{n^{2}}$$

$$\Rightarrow \Pr(\|f(\mathbf{x}_{i}) - f(\mathbf{x}_{j})\|^{2} \notin \left[(1 - \epsilon) \|\mathbf{x}_{i} - \mathbf{x}_{j}\|^{2} \cup (1 + \epsilon) \|\mathbf{x}_{i} - \mathbf{x}_{j}\|^{2} \right] \right\}) \leq \binom{n}{k} \frac{2}{n^{2}} \quad \text{union bound}$$

$$= \frac{n(n - 1)}{2} \frac{2}{n^{2}} = \frac{n - 1}{n}$$

$$= 1 - \frac{1}{n} = 1 - \delta$$

$$\Rightarrow \Pr(\forall_{i,j} \left\{ (1 - \epsilon) \|\mathbf{x}_{i} - \mathbf{x}_{j}\|^{2} \leq \|f(\mathbf{x}_{i}) - f(\mathbf{x}_{j})\|^{2} \leq (1 + \epsilon) \|\mathbf{x}_{i} - \mathbf{x}_{j}\|^{2} \right\} \right) \geq \frac{1}{n}$$

$$(27)$$

3.2 inner product

Corollary 1.2 Let $\mathbf{u}, \mathbf{v} \in \mathbb{R}^d$ and that $\|\mathbf{u}\| \le 1$ and $\|\mathbf{v}\| \le 1$. Let $\mathbf{y}(\mathbf{x}) = \frac{1}{\sqrt{k}} \mathbf{W} \mathbf{x}$ where $W_{i,j} \sim \mathcal{N}(0,1)$ (or $W_{i,j} \sim U(-1,+1)$), then:

$$\Pr(|\mathbf{u}^{\top}\mathbf{v} - \mathbf{y}(\mathbf{u})^{\top}\mathbf{y}(\mathbf{v})| \ge \epsilon) \le 4 \exp^{-(\epsilon^2 - \epsilon^3)\frac{k}{4}}$$
(28)

3.2.1 proof

$$\Pr((1-\epsilon)\|\mathbf{x}\|^2 \le \|\mathbf{y}\|^2 \le (1+\epsilon)\|\mathbf{x}\|^2) \ge 1 - 2\exp^{-(\epsilon^2 - \epsilon^3)\frac{k}{4}} \quad \text{alternative version}$$

$$\implies \Pr((1-\epsilon)\|\mathbf{u} - \mathbf{v}\|^2 \le \|\mathbf{u}' - \mathbf{v}'\|^2 \le (1+\epsilon)\|\mathbf{u} - \mathbf{v}\|^2) \ge 1 - 2\exp^{-(\epsilon^2 - \epsilon^3)\frac{k}{4}} \quad \text{let } \mathbf{x} \equiv \mathbf{u} - \mathbf{v} \text{ and } \mathbf{y} \equiv \mathbf{u}' - \mathbf{v}'$$

$$\implies \Pr((1-\epsilon)\|\mathbf{u} + \mathbf{v}\|^2 \le \|\mathbf{u}' + \mathbf{v}'\|^2 \le (1+\epsilon)\|\mathbf{u} + \mathbf{v}\|^2) \ge 1 - 2\exp^{-(\epsilon^2 - \epsilon^3)\frac{k}{4}} \quad \text{let } \mathbf{x} \equiv \mathbf{u} + \mathbf{v} \text{ and } \mathbf{y} \equiv \mathbf{u}' + \mathbf{v}'$$
(29)

therefore, for both of the above last two lines to satisfy simultaneously, we have (union of the complement) with probability of at least $1-4\exp^{-(\epsilon^2-\epsilon^3)\frac{k}{4}}$:

$$(1 - \epsilon) \|\mathbf{u} - \mathbf{v}\|^2 \le \|\mathbf{u}' - \mathbf{v}'\|^2 \le (1 + \epsilon) \|\mathbf{u} - \mathbf{v}\|^2$$
 and
$$(1 - \epsilon) \|\mathbf{u} + \mathbf{v}\|^2 \le \|\mathbf{u}' + \mathbf{v}'\|^2 \le (1 + \epsilon) \|\mathbf{u} + \mathbf{v}\|^2$$
 (30)

when both of these satisfy, then the above implies:

3.2.2 Take left portion

$$(1 - \epsilon) \|\mathbf{u} - \mathbf{v}\|^{2} \le \|\mathbf{u}' - \mathbf{v}'\|^{2} \le \underline{(1 + \epsilon) \|\mathbf{u} - \mathbf{v}\|^{2}} \quad \text{and}$$

$$(1 - \epsilon) \|\mathbf{u} + \mathbf{v}\|^{2} \le \|\mathbf{u}' + \mathbf{v}'\|^{2} \le (1 + \epsilon) \|\mathbf{u} + \mathbf{v}\|^{2})$$
(31)

$$4\mathbf{u'}^{\top}\mathbf{v'} = \|\mathbf{u'} + \mathbf{v'}\|^{2} - \|\mathbf{u'} - \mathbf{v'}\|^{2}$$

$$\geq (1 - \epsilon)\|\mathbf{u} + \mathbf{v}\|^{2} - \|\mathbf{u'} - \mathbf{v'}\|^{2}$$

$$\geq (1 - \epsilon)\|\mathbf{u} + \mathbf{v}\|^{2} - (1 + \epsilon)\|\mathbf{u} - \mathbf{v}\|^{2}$$

$$= (1 - \epsilon)(\|\mathbf{u}\|^{2} + 2\mathbf{u}^{\top}\mathbf{v} + \|\mathbf{v}\|^{2}) - (1 + \epsilon)(\|\mathbf{u}\|^{2} - 2\mathbf{u}^{\top}\mathbf{v} + \|\mathbf{v}\|^{2})$$

$$= (\|\mathbf{u}\|^{2} + 2\mathbf{u}^{\top}\mathbf{v} + \|\mathbf{v}\|^{2} - \|\mathbf{u}\|^{2} + 2\mathbf{u}^{\top}\mathbf{v} - \|\mathbf{v}\|^{2}) - \epsilon(\|\mathbf{u}\|^{2} + 2\mathbf{u}^{\top}\mathbf{v} + \|\mathbf{v}\|^{2} + \|\mathbf{u}\|^{2} - 2\mathbf{u}^{\top}\mathbf{v} + \|\mathbf{v}\|^{2})$$

$$= 4\mathbf{u}^{\top}\mathbf{v} - \epsilon(\|\mathbf{u}\|^{2} + \|\mathbf{v}\|^{2} + \|\mathbf{u}\|^{2} + \|\mathbf{v}\|^{2})$$

$$= 4\mathbf{u}^{\top}\mathbf{v} - 4\epsilon \quad \therefore \|\mathbf{u}\| = 1 \text{ and } \|\mathbf{u}\| = 1$$

$$\implies \mathbf{u'}^{\top}\mathbf{v'} \geq \mathbf{u}^{\top}\mathbf{v} - \epsilon$$
(32)

3.2.3 Combine with the right portion

we also use the two existing conditions in Eq.(30): (therefore no additional union bound is needed):