

Supplementary material - Bilinear Random Projections for Locality-Sensitive Binary Codes

April 16, 2015

1 Outline

In this supplementary material, we provide the proof of Lemma 3 and Theorem 3 described in the paper. Note that Lemma 3 and Theorem 3 in the paper are renamed as Lemma 2 and Theorem 1 in this supplementary material, respectively.

2 Bounds on the Expected Hamming Distance

Lemma 1 [1] For any $u, v \in [-1, 1]$, $P_t\{sgn(u+t) \neq sgn(v+t)\} = |u - v|/2$.

Lemma 2 (Lemma 2 in the paper)

$$\mathbb{E}_{\mathbf{w}, \mathbf{v}, b, t} [\mathbb{I}_{h(\mathbf{X}) \neq h(\mathbf{Y})}] = \frac{8}{\pi^2} \sum_{m=1}^{\infty} \frac{1 - \kappa_{bi}(m\mathbf{X} - m\mathbf{Y})}{4m^2 - 1},$$

where $h(\mathbf{X}) \triangleq \frac{1}{2}(1 + sgn(\cos(\mathbf{w}^\top \mathbf{X} \mathbf{v} + b) + t))$, $\mathbf{w}, \mathbf{v} \sim \mathcal{N}(0, \mathbf{I})$, $b \sim \text{Unif}[0, 2\pi]$, and $t \sim \text{Unif}[-1, 1]$.

Proof. Using Lemma 1, we can show that $\mathbb{E}_{\mathbf{w}, \mathbf{v}, b, t} [\mathbb{I}_{h(\mathbf{X}) \neq h(\mathbf{Y})}] = \frac{1}{2} \mathbb{E}_{\mathbf{w}, \mathbf{v}, b} |\cos(\mathbf{w}^\top \mathbf{X} \mathbf{v} + b) - \cos(\mathbf{w}^\top \mathbf{Y} \mathbf{v} + b)|$. By using a trigonometry identity,

$$\frac{1}{2} \mathbb{E}_{b, \mathbf{w}, \mathbf{v}} |\cos(\mathbf{w}^\top \mathbf{X} \mathbf{v} + b) - \cos(\mathbf{w}^\top \mathbf{Y} \mathbf{v} + b)| = \frac{2}{\pi} \mathbb{E}_{\mathbf{w}, \mathbf{v}} |\sin\left(\frac{\mathbf{w}^\top (\mathbf{X} - \mathbf{Y}) \mathbf{v}}{2}\right)|.$$

By [1], we use Fourier series of $g(\tau) = |\sin(\tau)|$:

$$g(\tau) = \frac{4}{\pi} \sum_{m=1}^{\infty} \frac{1 - \cos(2m\tau)}{4m^2 - 1}.$$

This formula leads to the following equation:

$$\mathbb{E}_{\mathbf{w}, \mathbf{v}, b, t} [\mathbb{I}_{h(\mathbf{X}) \neq h(\mathbf{Y})}] = \frac{8}{\pi^2} \sum_{m=1}^{\infty} \frac{1 - \mathbb{E}_{\mathbf{w}, \mathbf{v}} [\cos(m\mathbf{w}^\top (\mathbf{X} - \mathbf{Y}) \mathbf{v})]}{4m^2 - 1}$$

According to the proof of Lemma 1 described in the paper, we know that $\mathbb{E}_{\mathbf{w}, \mathbf{v}} \cos(m\mathbf{w}^\top (\mathbf{X} - \mathbf{Y}) \mathbf{v}) = \kappa_{bi}(m\mathbf{X} - m\mathbf{Y})$, which completes the proof. Q.E.D.

3 Bounds on the Covariance by Bilinear Projections

Lemma 3 Given a datum as $\mathbf{X} \in \mathcal{R}^{d_1 \times d_2}$ and bilinear projections, $\mathbf{w}, \mathbf{v}_1, \mathbf{v}_2$, are drawn from the $\mathcal{N}(\mathbf{0}, \mathbf{I})$, $\mathbb{E}_{\mathbf{w}, \mathbf{v}_1, \mathbf{v}_2} [\cos(m\mathbf{w}^\top \mathbf{X}\mathbf{v}_1)\cos(n\mathbf{w}^\top \mathbf{X}\mathbf{v}_2)] = \kappa_{bi}(\sqrt{(m^2 + n^2)}\mathbf{X})$.

Proof.

$$\begin{aligned}
& \mathbb{E}_{\mathbf{w}, \mathbf{v}_1, \mathbf{v}_2} [\cos(m\mathbf{w}^\top \mathbf{X}\mathbf{v}_1)\cos(n\mathbf{w}^\top \mathbf{X}\mathbf{v}_2)] \\
&= \int \left[\int \cos(m\mathbf{w}^\top \mathbf{X}\mathbf{v}_1)p(\mathbf{v}_1)d\mathbf{v}_1 \right] \left[\int \cos(n\mathbf{w}^\top \mathbf{X}\mathbf{v}_2)p(\mathbf{v}_2)d\mathbf{v}_2 \right] p(\mathbf{w})d\mathbf{w} \\
&= \int \kappa_g(m\mathbf{w}^\top \mathbf{X})\kappa_g(n\mathbf{w}^\top \mathbf{X})p(\mathbf{w})d\mathbf{w} \quad (\text{by Lemma 1 in the paper}) \\
&= \int \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}(\mathbf{w}^\top [\mathbf{I} + m^2\mathbf{X}\mathbf{X}^\top + n^2\mathbf{X}\mathbf{X}^\top]\mathbf{w})\right) d\mathbf{w} \\
&= |\mathbf{I} + (m^2 + n^2)\mathbf{X}\mathbf{X}^\top|^{-\frac{1}{2}} \triangleq \kappa_{bi}(\sqrt{(m^2 + n^2)}\mathbf{X}).
\end{aligned}$$

Theorem 1 (Theorem 3 in the paper) Given the hash functions $h_1(\cdot)$ and $h_2(\cdot)$, the upper bound on the covariance between the two bits is derived as

$$cov(\cdot) \leq \left(\frac{64}{\pi^4} \right) \left[\left(\sum_{m=1}^{\infty} \frac{\kappa_g(vec(\mathbf{X} - \mathbf{Y}))^{0.79m^2}}{4m^2 - 1} \right)^2 - \left(\sum_{m=1}^{\infty} \frac{\kappa_g(vec(\mathbf{X} - \mathbf{Y}))^{m^2}}{4m^2 - 1} \right)^2 \right],$$

where $\kappa_g(\cdot)$ is the Gaussian kernel and $cov(\cdot)$ is the covariance between two bits defined as

$$\begin{aligned}
cov(\cdot) &= \mathbb{E}_{\mathbf{w}, \mathbf{v}_1, \mathbf{v}_2, b_1, b_2, t_1, t_2} [\mathbb{I}_{h_1(\mathbf{X}) \neq h_1(\mathbf{Y})} \mathbb{I}_{h_2(\mathbf{X}) \neq h_2(\mathbf{Y})}] \\
&\quad - \mathbb{E}_{\mathbf{w}, \mathbf{v}_1, b_1, t_1} [\mathbb{I}_{h_1(\mathbf{X}) \neq h_1(\mathbf{Y})}] \mathbb{E}_{\mathbf{w}, \mathbf{v}_2, b_2, t_2} [\mathbb{I}_{h_2(\mathbf{X}) \neq h_2(\mathbf{Y})}], \\
h_1(\mathbf{X}) &= sgn(\cos(\mathbf{w}^\top \mathbf{X}\mathbf{v}_1 + b_1) + t_1), \\
h_2(\mathbf{X}) &= sgn(\cos(\mathbf{w}^\top \mathbf{X}\mathbf{v}_2 + b_2) + t_2).
\end{aligned}$$

Proof. First, we want to derive the first term in the covariance in terms of $\kappa_{bi}(\cdot)$.

$$\begin{aligned}
& \mathbb{E}_{\mathbf{w}, \mathbf{v}_1, \mathbf{v}_2, b_1, b_2, t_1, t_2} [\mathbb{I}_{h_1(\mathbf{X}) \neq h_1(\mathbf{Y})} \mathbb{I}_{h_2(\mathbf{X}) \neq h_2(\mathbf{Y})}] \\
&= \frac{1}{4} \mathbb{E}_{\mathbf{w}, \mathbf{v}_1, \mathbf{v}_2, b_1, b_2} [|\cos(\mathbf{w}^\top \mathbf{X}\mathbf{v}_1 + b_1) - \cos(\mathbf{w}^\top \mathbf{Y}\mathbf{v}_1 + b_1)| |\cos(\mathbf{w}^\top \mathbf{X}\mathbf{v}_2 + b_2) - \cos(\mathbf{w}^\top \mathbf{Y}\mathbf{v}_2 + b_2)|] \quad (\because \text{Lemma 1}) \\
&= \frac{4}{\pi^2} \mathbb{E}_{\mathbf{w}, \mathbf{v}_1, \mathbf{v}_2} [|\sin(\frac{\mathbf{w}^\top (\mathbf{X} - \mathbf{Y})\mathbf{v}_1}{2}) \sin(\frac{\mathbf{w}^\top (\mathbf{X} - \mathbf{Y})\mathbf{v}_2}{2})|] \\
&= \left(\frac{64}{\pi^4} \right) \sum_{m, n=1}^{\infty} \mathbb{E}_{\mathbf{w}, \mathbf{v}_1, \mathbf{v}_2} \left[\left(\frac{1 - \cos(m\mathbf{w}^\top (\mathbf{X} - \mathbf{Y})\mathbf{v}_1)}{4m^2 - 1} \right) \left(\frac{1 - \cos(n\mathbf{w}^\top (\mathbf{X} - \mathbf{Y})\mathbf{v}_2)}{4n^2 - 1} \right) \right]
\end{aligned}$$

Using the Lemma 2, the first term in the covariance can be represented in terms of $\kappa_{bi}(\cdot)$:

$$\begin{aligned}
& \mathbb{E}_{\mathbf{w}, \mathbf{v}_1, b_1, b_2, t_1, t_2} [\mathbb{I}_{h_1(\mathbf{X}) \neq h_1(\mathbf{Y})} \mathbb{I}_{h_2(\mathbf{X}) \neq h_2(\mathbf{Y})}] \\
&= \left(\frac{64}{\pi^4} \right) \sum_{m, n=1}^{\infty} \frac{1}{4m^2 - 1} \frac{1}{4n^2 - 1} (1 - \kappa_{bi}(m\mathbf{X} - m\mathbf{Y}) - \kappa_{bi}(n\mathbf{X} - n\mathbf{Y}) + \kappa_{bi}(\sqrt{(m^2 + n^2)}(\mathbf{X} - \mathbf{Y})))
\end{aligned}$$

The second term in the covariance is also represented in terms of $\kappa_{bi}(\cdot)$:

$$\begin{aligned}
& \mathbb{E}_{\mathbf{w}, \mathbf{v}_1, b_1, t_1} [\mathbb{I}_{h_1(\mathbf{X}) \neq h_1(\mathbf{Y})}] \mathbb{E}_{\mathbf{w}, \mathbf{v}_2, b_2, t_2} [\mathbb{I}_{h_2(\mathbf{X}) \neq h_2(\mathbf{Y})}] \\
&= \left(\frac{64}{\pi^4} \right) \sum_{m, n=1}^{\infty} \frac{1}{4m^2 - 1} \frac{1}{4n^2 - 1} (1 - \kappa_{bi}(m(\mathbf{X} - \mathbf{Y})) - \kappa_{bi}(n(\mathbf{X} - \mathbf{Y})) + \kappa_{bi}(m(\mathbf{X} - \mathbf{Y}))\kappa_{bi}(n(\mathbf{X} - \mathbf{Y})))
\end{aligned}$$

Therefore, the covariance between two bits is computed as

$$\begin{aligned}
\text{cov}(\cdot) &= \left(\frac{64}{\pi^4}\right) \sum_{m,n=1}^{\infty} \frac{1}{4m^2-1} \frac{1}{4n^2-1} [\kappa_{bi}(\sqrt{(m^2+n^2)}(\mathbf{X}-\mathbf{Y})) - \kappa_{bi}(m(\mathbf{X}-\mathbf{Y}))\kappa_{bi}(n(\mathbf{X}-\mathbf{Y}))] \\
&\leq \left(\frac{64}{\pi^4}\right) \sum_{m,n=1}^{\infty} \frac{1}{4m^2-1} \frac{1}{4n^2-1} [\kappa_g(\text{vec}(\sqrt{(m^2+n^2)}(\mathbf{X}-\mathbf{Y})))^{0.79} - \kappa_g(\text{vec}(m\mathbf{X}-m\mathbf{Y}))\kappa_g(\text{vec}(n\mathbf{X}-n\mathbf{Y}))] \\
&= \left(\frac{64}{\pi^4}\right) \sum_{m,n=1}^{\infty} \frac{1}{4m^2-1} \frac{1}{4n^2-1} [\kappa_g(\text{vec}(\mathbf{X}-\mathbf{Y}))^{0.79(m^2+n^2)} - \kappa_g(\text{vec}(\mathbf{X}-\mathbf{Y}))^{m^2} \kappa_g(\text{vec}(\mathbf{X}-\mathbf{Y}))^{n^2}] \\
&= \left(\frac{64}{\pi^4}\right) \left[\left(\sum_{m=1}^{\infty} \frac{\kappa_g(\text{vec}(\mathbf{X}-\mathbf{Y}))^{0.79m^2}}{4m^2-1} \right)^2 - \left(\sum_{m=1}^{\infty} \frac{\kappa_g(\text{vec}(\mathbf{X}-\mathbf{Y}))^{m^2}}{4m^2-1} \right)^2 \right],
\end{aligned}$$

where the second inequality is given by Lemma 1 in the paper ($\kappa_g(\text{vec}(\mathbf{X}-\mathbf{Y})) \leq \kappa_{bi}(\mathbf{X}-\mathbf{Y}) \leq \kappa_g(\text{vec}(\mathbf{X}-\mathbf{Y}))^{0.79}$) and the third equality is given by $\kappa_g(\text{vec}(m\mathbf{X}-m\mathbf{Y})) = \kappa_g(\text{vec}(\mathbf{X}-\mathbf{Y}))^{m^2}$. The lower bound can be derived in a similar way.

Corollary 1 *Given the hash functions $h_1(\cdot)$ and $h_2(\cdot)$, the lower bound on the covariance between the two bits is derived as*

$$\text{cov}(\cdot) \geq \left(\frac{64}{\pi^4}\right) \left[\left(\sum_{m=1}^{\infty} \frac{\kappa_g(\text{vec}(\mathbf{X}-\mathbf{Y}))^{m^2}}{4m^2-1} \right)^2 - \left(\sum_{m=1}^{\infty} \frac{\kappa_g(\text{vec}(\mathbf{X}-\mathbf{Y}))^{0.79m^2}}{4m^2-1} \right)^2 \right],$$

where $\kappa_g(\cdot)$ is the Gaussian kernel and $\text{cov}(\cdot)$ is the covariance between two bits defined as

$$\begin{aligned}
\text{cov}(\cdot) &= \mathbb{E}_{\mathbf{w}, \mathbf{v}_1, \mathbf{v}_2, b_1, b_2, t_1, t_2} [\mathbb{I}_{h_1(\mathbf{X}) \neq h_1(\mathbf{Y})} \mathbb{I}_{h_2(\mathbf{X}) \neq h_2(\mathbf{Y})}] \\
&\quad - \mathbb{E}_{\mathbf{w}, \mathbf{v}_1, b_1, t_1} [\mathbb{I}_{h_1(\mathbf{X}) \neq h_1(\mathbf{Y})}] \mathbb{E}_{\mathbf{w}, \mathbf{v}_2, b_2, t_2} [\mathbb{I}_{h_2(\mathbf{X}) \neq h_2(\mathbf{Y})}], \\
h_1(\mathbf{X}) &= \text{sgn}(\cos(\mathbf{w}^\top \mathbf{X} \mathbf{v}_1 + b_1) + t_1), \\
h_2(\mathbf{X}) &= \text{sgn}(\cos(\mathbf{w}^\top \mathbf{X} \mathbf{v}_2 + b_2) + t_2).
\end{aligned}$$

References

[1] M. Raginsky and S. Lazebnik. Locality-sensitive binary codes from shift-invariant kernels. In *Advances in Neural Information Processing Systems (NIPS)*, volume 22. MIT Press, 2009.