

APPENDIX

Proof of Theorem 1

Proof: Let $\vec{W} = \mathbf{A}\vec{X} = [W_1, \dots, W_m]$, since $\vec{X} \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}_{\vec{X}})$ then we have $\vec{W} \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}_{\vec{W}})$, where $\mathbf{\Sigma}_{\vec{W}} = \mathbf{A}\mathbf{\Sigma}_{\vec{X}}\mathbf{A}^\top$. Note that $\mathbf{\Sigma}_{\vec{X}} = \sigma^2\mathbf{I}$, and \mathbf{I} denotes the identity matrix. Let $\vec{Z} = \text{ReLU}(\vec{W}) = \max(\vec{W}, \mathbf{0}) = [Z_1, \dots, Z_m]$, we first discuss the relationship between \vec{W} and \vec{Z} .

Obviously, the variance of W_i can be expressed as $\text{var}(W_i) = (\eta_i\sigma)^2, i = 1, \dots, m$, η_i is related with \mathbf{A} , then the probability density function of W_i , denoted by $f_{W_i}(x)$, is expressed as

$$f_{W_i}(x) = \frac{1}{\sqrt{2\pi}\eta_i\sigma} e^{-\frac{x^2}{2(\eta_i\sigma)^2}}.$$

According to $Z_i = \max(W_i, 0)$, we have the mean and the variance of Z_i as below:

$$\begin{aligned} E(Z_i) &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\eta_i\sigma} e^{-\frac{x^2}{2(\eta_i\sigma)^2}} \max(x, 0) dx \\ &= \int_0^{\infty} \frac{1}{\sqrt{2\pi}\eta_i\sigma} e^{-\frac{x^2}{2(\eta_i\sigma)^2}} x dx = \frac{\eta_i\sigma}{\sqrt{2\pi}}; \\ E(Z_i^2) &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\eta_i\sigma} e^{-\frac{x^2}{2(\eta_i\sigma)^2}} \max(x, 0)^2 dx \\ &= \int_0^{\infty} \frac{1}{\sqrt{2\pi}\eta_i\sigma} e^{-\frac{x^2}{2(\eta_i\sigma)^2}} x^2 dx = \frac{(\eta_i\sigma)^2}{2}; \\ \text{var}(Z_i) &= E(Z_i^2) - E(Z_i)^2 = \frac{\pi - 1}{2\pi}(\eta_i\sigma)^2. \end{aligned}$$

Our purpose is to compute the covariance matrix of \vec{Z} , that is $\mathbf{\Sigma}_{\vec{Z}}$. After computing $\text{var}(Z_i)$, which is on the diagonal position of $\mathbf{\Sigma}_{\vec{Z}}$, we now calculate $\text{cov}(Z_i, Z_j), i \neq j$, by

$$\text{cov}(Z_i, Z_j) = E(Z_i Z_j) - E(Z_i)E(Z_j).$$

Assume that the joint probability density function of W_i and W_j is written as

$$f_{W_i, W_j}(x, y) = \frac{1}{2\pi\eta_i\eta_j\sigma^2\sqrt{1 - \rho_{ij}^2}} p(x, y, \rho_{ij}, \eta_i, \eta_j),$$

where $p(x, y, \rho_{ij}, \eta_i, \eta_j) = e^{-\frac{1}{2(1-\rho_{ij}^2)}\left(\frac{x^2}{(\eta_i\sigma)^2} - \frac{2\rho_{ij}xy}{\eta_i\eta_j\sigma^2} + \frac{y^2}{(\eta_j\sigma)^2}\right)}$, and ρ_{ij} is the correlation coefficient between W_i and W_j . Then,

$$\begin{aligned} E(Z_i Z_j) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{W_i, W_j}(x, y) \max(x, 0) \max(y, 0) dx dy \\ &= \int_0^{\infty} \int_0^{\infty} f_{W_i, W_j}(x, y) xy dx dy \\ &= \int_0^{\infty} \int_0^{\infty} \frac{1}{2\pi\eta_i\eta_j\sigma^2\sqrt{1-\rho_{ij}^2}} p(x, y, \rho_{ij}, \eta_i, \eta_j) xy dx dy. \end{aligned}$$

Furthermore, define $u = \frac{x}{\eta_i\sigma\sqrt{1-\rho_{ij}^2}}, v = \frac{y}{\eta_j\sigma\sqrt{1-\rho_{ij}^2}}$, the computation of $E(Z_i Z_j)$ is transformed to be

$$E(Z_i Z_j) = M_{ij}\sigma^2,$$

where $M_{ij} = \frac{(\sqrt{1-\rho_{ij}^2})^3 \eta_i \eta_j}{2\pi} \int_0^{\infty} \int_0^{\infty} e^{-\frac{1}{2}(u^2 - 2\rho_{ij}uv + v^2)} uv du dv$.

Hence,

$$\begin{aligned} \text{cov}(Z_i, Z_j) &= E(Z_i Z_j) - E(Z_i)E(Z_j) \\ &= M_{ij}\sigma^2 - \frac{\eta_i\eta_j\sigma^2}{2\pi} = (M_{ij} - \frac{\eta_i\eta_j}{2\pi})\sigma^2. \end{aligned}$$

According to the expressions of $\text{var}(Z_i)$ and $\text{cov}(Z_i, Z_j)$, it is clear to see that $\Sigma_{\bar{Z}}$ can be formulated as

$$\Sigma_{\bar{Z}} = \sigma^2 \hat{\Sigma}_{\bar{Z}},$$

where $\hat{\Sigma}_{\bar{Z}}$ is only determined by the matrix \mathbf{A} .

Therefore, the covariance matrix of $\vec{Y} = \vec{B}\vec{Z}$, *i.e.* $\Sigma_{\vec{Y}}$ is written as

$$\Sigma_{\vec{Y}} = \mathbf{B}\Sigma_{\bar{Z}}\mathbf{B}^{\top} = \sigma^2 \mathbf{B}\hat{\Sigma}_{\bar{Z}}\mathbf{B}^{\top}.$$

Due to $E[\|\vec{Y} - E[\vec{Y}]\|_2^2] = \text{tr}(\Sigma_{\vec{Y}}) = \sigma^2 \text{tr}(\mathbf{B}\hat{\Sigma}_{\bar{Z}}\mathbf{B}^{\top})$ ($\text{tr}(\cdot)$ denotes the trace of a matrix) and $E[\|\vec{X} - E[\vec{X}]\|_2^2] = \text{tr}(\Sigma_{\vec{X}}) = n\sigma^2$, then we have

$$E[\|\vec{Y} - E[\vec{Y}]\|_2^2] = \alpha E[\|\vec{X} - E[\vec{X}]\|_2^2],$$

where $\alpha = \frac{\text{tr}(\mathbf{B}\hat{\Sigma}_{\bar{Z}}\mathbf{B}^{\top})}{n}$. That means $E[\|\vec{Y} - E[\vec{Y}]\|_2^2]$ and $E[\|\vec{X} - E[\vec{X}]\|_2^2]$ are linearly related. ■