

Asymptotic Properties for Bayesian Neural Network in Besov Space - Theorem 2

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정리 2

아래의 정리는 Polson and Ročková [2018]의 정리 6.2를 베소프 공간으로 확장한 것입니다. 해당 정리는 베이즈 ReLU 신경망이 spike-and-slab 사전분포 하에서 평활 모수를 모르는 경우에도 최적의 베이즈 추론이 가능함을 의미합니다.

정리 (Theorem 2 in Lee and Lee [2022]). *Assume model*

$$y_i = f_0(X_i) + \xi_i, \quad \xi_i \stackrel{iid}{\sim} N(0, \sigma^2) \quad i = 1, \dots, n,$$

Let

$$\tilde{L}_n(H) = \lceil H(\log n) \rceil \vee 1, \quad \tilde{W}_n(H, N) = HN, \quad \tilde{S}_n(H, N) = HN\tilde{L}_n(H), \quad \tilde{B}_n(H, N) = N^H. \quad (1)$$

Consider the following prior

$$N \stackrel{d}{=} 1 \vee \lceil Z/(\log n)^2 \rceil, \quad \pi_Z(Z) = \frac{\lambda_N^Z}{Z!(e^{\lambda_N} - 1)} \quad \text{for } Z = 1, 2, \dots, \quad (2)$$

and prior distribution

$$\pi(\theta_j | \gamma_j, L, W, S, B) = \gamma_j \tilde{\pi}(\theta_j | L, W, S, B) + (1 - \gamma_j) \delta_0(\theta_j),$$

$$\pi(\gamma | L, W, S, B) = 1 / \binom{T}{S},$$

$$\pi(L = L_n) = \pi(W = W_n) = \pi(S = S_n) = \pi(B = B_n) = 1.$$

of θ given $\tilde{L}_n(H_n)$, $\tilde{W}_n(H_n, N)$, $\tilde{S}_n(H_n, N)$, $\tilde{B}_n(H_n, N)$ on the function space

$$\Phi = \bigcup_{n=1}^{\infty} \bigcup_{N=1}^{\infty} \Phi(\tilde{L}_n(H_n), \tilde{W}_n(H_n, N), \tilde{S}_n(H_n, N), \tilde{B}_n(H_n, N)) \quad (3)$$

for any $H_n \rightarrow \infty$ and $\lambda_N > 0$. Suppose that $0 < F < \infty$, $0 < p, q \leq \infty$ and $d(1/p - 1/2)_+ < s < \min\{m, m - 1 + 1/p\}$. The posterior distribution concentrates at the true function with a rate $\epsilon_n = n^{-s/(2s+d)}(\log n)^{3/2}$. That is,

$$\Pi(f_\theta \in \Phi \cap \mathcal{UB}(F) : \|f_\theta - f_0\|_n > M_n \epsilon_n | \mathbb{D}_n) \rightarrow 0$$

in $P_{f_0}^{(n)}$ -probability as $n \rightarrow \infty$ for any $M_n \rightarrow \infty$.

Proof. Let $\mathcal{F} = \Phi \cap \mathcal{UB}(F)$. From **Lemma 3**, it is enough to show that there exist a constant $C' > 2/\sigma^2$ and $\mathcal{F}_n \subset \mathcal{F}$ which satisfy

- (a) $\sup_{\epsilon > \epsilon_n} \log N(\epsilon/36, A_{\epsilon,1} \cap \mathcal{F}_n, \|\cdot\|_n) \leq n\epsilon_n^2$
- (b) $-\log \Pi(A_{\epsilon_n,1}) \leq C'n\epsilon_n^2$
- (c) $\Pi(\mathcal{F} - \mathcal{F}_n) = o\left(e^{-(C'\sigma^2+2)n\epsilon_n^2}\right)$

for sufficiently large n . From

$$L_n = O(\log n), \quad W_n = O(N_n), \quad S_n = O(N_n \log n), \quad (4)$$

we can choose

$$H_0 > \sup_n \{L_n / \log n, W_n / N_n, S_n / (N_n \log n), \Xi\}. \quad (5)$$

Let $\tilde{N}_n = C_N N_n$,

$$\mathcal{F}_n = \mathcal{UB}(F) \cap \left(\bigcup_{N=1}^{\tilde{N}_n} \Phi(\tilde{L}_n(H_0), \tilde{W}_n(H_0, N), \tilde{S}_n(H_0, N), \tilde{B}_n(H_0, N)) \right)$$

for sufficiently large $C_N > 0$ and $\pi_N(N)$ be a density function of N . First, show that (a) holds. From

Lemma 4,

$$\begin{aligned} & N\left(\frac{\epsilon_n}{36}, \mathcal{F}_n, \|\cdot\|_{L^\infty}\right) \\ & \leq \sum_{N=1}^{\tilde{N}_n} \left(\frac{72}{\epsilon_n} \tilde{L}_n(H_0) (\tilde{B}_n(H_0, N) \vee 1)^{\tilde{L}_n(H_0)} (\tilde{W}_n(H_0, N) + 1)^{2\tilde{L}_n(H_0)} \right)^{\tilde{S}_n(H_0, N)+1} \\ & \leq \tilde{N}_n \left(\frac{72}{\epsilon_n} \tilde{L}_n(H_0) (\tilde{B}_n(H_0, \tilde{N}_n) \vee 1)^{\tilde{L}_n(H_0)} (\tilde{W}_n(H_0, \tilde{N}_n) + 1)^{2\tilde{L}_n(H_0)} \right)^{\tilde{S}_n(H_0, \tilde{N}_n)+1} \end{aligned} \quad (6)$$

and

$$\begin{aligned}
& \sup_{\epsilon > \epsilon_n} \log N \left(\frac{\epsilon}{36}, A_{\epsilon,1} \cap \mathcal{F}_n, \|\cdot\|_n \right) \\
& \leq \sup_{\epsilon > \epsilon_n} \log N \left(\frac{\epsilon}{36}, A_{\epsilon,1} \cap \mathcal{F}_n, \|\cdot\|_{L^\infty} \right) \\
& \leq \sup_{\epsilon > \epsilon_n} \log N \left(\frac{\epsilon}{36}, \mathcal{F}_n, \|\cdot\|_{L^\infty} \right) \\
& \leq \log N \left(\frac{\epsilon_n}{36}, \mathcal{F}_n, \|\cdot\|_{L^\infty} \right) \\
& \leq \log \tilde{N}_n \\
& \quad + \left[\tilde{S}_n(H_0, \tilde{N}_n) + 1 \right] \log \left(\frac{72}{\epsilon_n} \tilde{L}_n(H_0) (\tilde{B}_n(H_0, \tilde{N}_n) \vee 1)^{\tilde{L}_n(H_0)} (\tilde{W}_n(H_0, \tilde{N}_n) + 1)^{2\tilde{L}_n(H_0)} \right) \\
& \lesssim \tilde{N}_n (\log n)^3 \\
& \lesssim n \epsilon_n^2.
\end{aligned} \tag{7}$$

for sufficiently large n . Next, show that (b) holds. Note $N_n (\log n)^3 \lesssim n \epsilon_n^2$ and

$$L_n \leq \tilde{L}_n(H_n), \quad W_n \leq \tilde{W}_n(H_n, N_n), \quad S_n \leq \tilde{S}_n(H_n, N_n), \quad B_n \leq \tilde{B}_n(H_n, \tilde{N}_n) \tag{8}$$

for N_n, L_n, W_n, S_n, B_n in **Theorem 1** and sufficiently large n . Thus, there exists a constant $D > 0$ such that

$$\pi_N(N_n) \gtrsim \exp \left(-N_n (\log n)^2 \log \frac{N_n}{\lambda_N} \right) \gtrsim \exp(-Dn\epsilon_n^2) \tag{9}$$

and

$$\begin{aligned}
& \Pi(f_\theta \in \mathcal{F}_n : \|f - f_0\|_n \leq \epsilon_n) \\
& \geq \pi_N(N_n) \Pi(f_\theta \in \Phi(L_n, W_n, S_n, B_n) : \|f_\theta - f_0\|_n \leq \epsilon_n |N_n) \\
& \gtrsim \exp(-(C+D)n\epsilon_n^2)
\end{aligned} \tag{10}$$

holds for sufficiently large n . (b) holds for $C' = \max\{C+D, 1+2/\sigma^2\}$. From

$$\Pi(\mathcal{F} - \mathcal{F}_n) \leq \pi_N(N > \tilde{N}_n)$$

and *Chernoff bound*, for any positive number $t, Z_0 > 0$,

$$P(Z > Z_0) < e^{-t(Z_0+1)} \mathbb{E}[e^{tZ}] \lesssim e^{-t(Z_0+1)} (\exp(e^t \lambda_N) - 1). \tag{11}$$

Letting $t = \log Z_0$, we get

$$P(Z > Z_0) \lesssim e^{-(Z_0+1) \log Z_0} (\exp(Z_0 \lambda_N) - 1). \tag{12}$$

Thus,

$$\begin{aligned}
& \pi_N(N > \tilde{N}_n) \lesssim e^{-[(\tilde{N}_n+1) \log \tilde{N}_n + \tilde{N}_n \lambda_N] (\log n)^2}, \\
& (C'\sigma^2 + 2)n\epsilon_n^2 + \lambda_N \tilde{N}_n (\log n)^2 - (\tilde{N}_n + 1) \log \tilde{N}_n (\log n)^2 \rightarrow -\infty
\end{aligned} \tag{13}$$

for sufficiently large $C_N > 0$. (c) holds.

참고문헌

- K. Lee and J. Lee. Asymptotic properties for bayesian neural network in besov space. In *Advances in Neural Information Processing Systems*, 2022.
- N. G. Polson and V. Ročková. Posterior concentration for sparse deep learning. *Advances in Neural Information Processing Systems*, 31, 2018.