소규모 셀 네트워크에서 통신 효율적 연합학습을 위한 기지국 밀도

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Required Base Station Density for Communication-Efficient Federated Learning in Small-Cell Networks

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요 약

Federated Learning (FL) generates massive benefits of shared machine learning models without violating security and privacy requirements, making this setting relevant for many wireless applications. In this paper, we comprehensively investigate the effects of geographic node deployment on the model aggregation in federated learning on the basis of stochastic geometry-based analysis. Based on the coverage probability expression derived with stochastic geometry framework, we derive and discuss the minimum required base station density for achieving a target model aggregation rate in small-cell networks with algorithms for optimizing the target transmission rate and the base station density.

Ⅰ. 서 론

Federated learning with wireless edge devices has been attracting great attention as an effective tool to mitigate the data privacy problem and computation concentration in deep learning. [1-3]. In this paper, we derive the closed-form expression of coverage probability in small-cell networks with tractable approximations. Based on this, we propose the two-step iterative method to numerically solve the minimum base station density required to guarantee a target value of the expected number of aggregated bits of trained models in a single transmission interval. Our analysis and simulation results provide insightful information for understanding the behaviors of federated learning in small-cell networks, and it can be exploited as a guideline for designing the network facilitating the wireless federated learning.

Ⅱ. 본론

We consider small-cell networks where base stations (BSs) and users (UEs) located in the Euclidean plane according to homogeneous PPPs of densities λ_b and λ_u. At a typical BS with a distance r from a typical serving UE, the received power of the desired signal is $hr^{-\alpha}$ with $h \sim exp(\mu)$, where $1/\mu$ denotes the constant transmit power.

The cumulative interference power is given by:

$$I_r = \sum_{i \in \Phi} g_i R_i^{-\alpha},$$

where $g_i \sim exp(\mu)$ and R_i denote the power of small-scale fading and a distance with an interferer i, respectively.

The received SINR at a typical BS is expressed as:

$$\text{SINR} = \frac{hr^{-\alpha}}{I_r + \sigma^2}$$

With equal bandwidth allocation in a cell, the coverage probability is defined as

$$\mathbf{P}\left[\frac{B}{K}\log_2(1+\text{SINR}) \geq u\right] \Leftrightarrow p_c \triangleq \mathbf{P}\left[\text{SINR} > 2^{\frac{uK}{B}} - 1\right],$$

where B denotes the total bandwidth, K denotes the number of UEs in a typical cell, u denotes the target transmission rate.

We derive the closed-form expression of the p_c in a high SNR regime, with $\alpha = 4$ as

$$p_c \approx \frac{1}{1 + \left(1 - \left(1 + \frac{\lambda_u}{c\lambda_b}\right)^{-c}\right)\sqrt{2^{u\frac{\lambda_u}{B\lambda_b}} - 1}\ \arctan\sqrt{2^{u\frac{\lambda_u}{B\lambda_b}} - 1}}. \quad (1)$$

For given network area A_{net}, the expected number of aggregated bits of trained models in a single transmission interval is represented as $Q_{network} = A_{net}\lambda_u u p_c$. To accelerate the training and reduce communication resources for update parameter report, we solve optimization problems in two different scenarios.

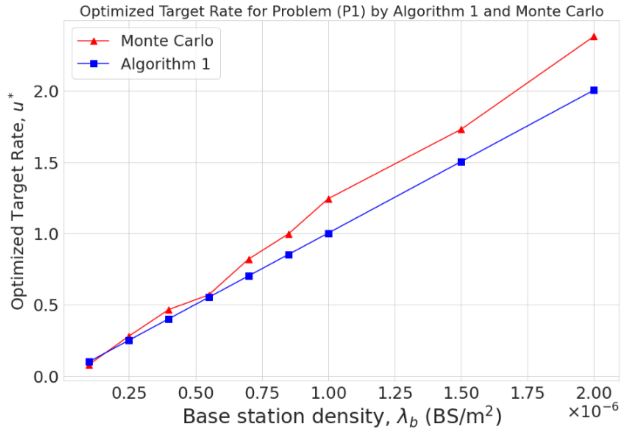

Fig. 1. Comparison of the optimized $\boldsymbol{u}$ in (P1).

In the first scenario, we optimize the target transmission rate u to maximize the aggregated bits for given base station density λ_b

$$\underset{u}{\text{maximize}} \quad Q_{network} \tag{P1}$$

To solve (P1), we apply the bisection method to the derivative of the approximated coverage probability (2).

In the second scenario, we can control λ_b as well as u to find the minimum base station deployment for achieving a target bit aggregation Q_{target}

$$\begin{aligned} \underset{\lambda_b, u}{\text{minimize}} \quad & \lambda_b \\ \text{subject to} \quad & Q_{network} \geq Q_{target}. \end{aligned} \tag{P2}$$

To solve (P2), we propose the two-step iterative method by iteratively solving equation (2) and equation $g(\lambda_b) = Q_{target}/(A_{net}\lambda_u)$ using the bisection method until convergence.

We validate our analysis by comparisons with Monte Carlo simulation in high SNR regime. We consider a homogeneous PPP deployment in a network area of 20km x 20km. We set $\lambda_u = 0.00005$ user/m^2, $\alpha = 4$, $B = 20$ MHz, $1/\mu = 10$, and $\sigma^2 = -104$ dBm. We implement 2,000 deployments and sample 10,000 times of channel realizations in each deployment.

Figure 1 shows the optimized u in (P1), which are produced by Monte Carlo simulation and high SNR approximation (1) with the bisection method. It is shown that the optimal u is monotonic increasing function of λ_b. Furthermore, the error caused by the high SNR approximation in (1) does not have significant impact on the optimized u when $\lambda_b \ll \lambda_u$. Based on the above validation, figure 2 plots the minimum required λ_b in (P2) with respect to λ_u. It is shown that the required λ_b for achieving the target performance is monotonic increasing functions of Q_{target} and λ_u. In addition, the required λ_b increases more significantly when $\lambda_u \leq 2.5 \times 10^{-5}$ and become saturated when $\lambda_u > 2.5 \times 10^{-5}$. Figure 3 plots the optimized u in (P2) with respect to λ_u. As Q_{target} increases, the optimized u increases, but the gap decreases when λ_u increases. Also, the optimized u is a decreasing function of λ_u.

Ⅲ. 결론

In this paper, we consider the model aggregation for federated learning in small-cell cellular networks

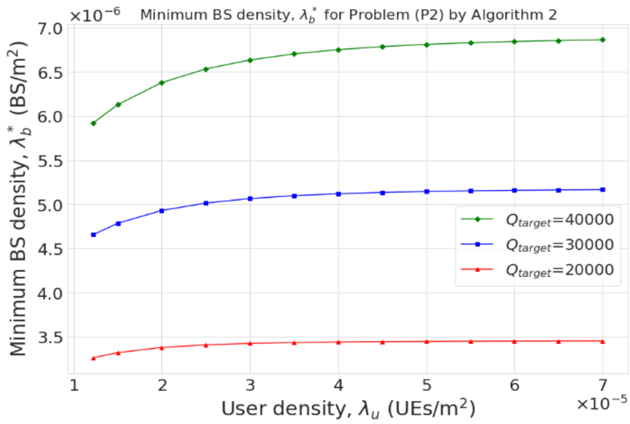

Fig. 2. The required $\boldsymbol{\lambda_b}$ in (P2) with the optimized $\boldsymbol{u}$.

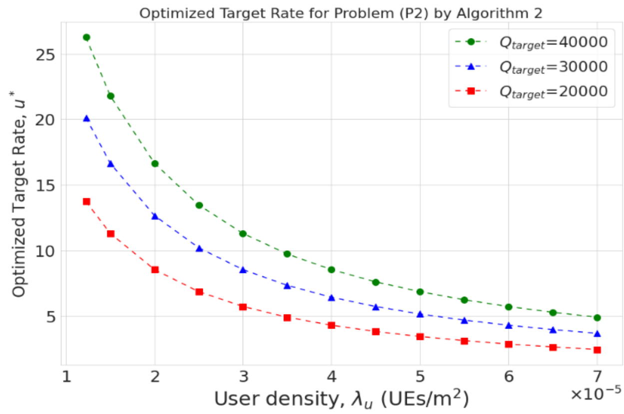

Fig. 1. The optimized $\boldsymbol{u}$ in (P2).

where multiple BSs and UEs are located according to PPPs. We derive the closed-form expression of coverage probability and propose the two-step iterative method to find the minimum required BS density to achieve a target performance. The simulation results confirm the analysis result well characterize the system performance in high SNR regime and show the effect of system parameters on the behavior of the federated learning in cellular networks.

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