Tackling Data Heterogeneity in Federated Learning via Loss Decomposition (Supplementary Material)

Algorithm 1 FedLD

return w_t^i to server

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Input: number of clients selected in each round m, number of communication rounds
            T, number of local epochs E, local batch size B, learning rate \eta, regularization
            hyperparameter \lambda, number of eigenvectors selected L, number of local samples
            for each client n_i and n = \sum_{i=1}^m n_i
Output: global model w_T
Server executes: Initialize w_0
 for each round t = 1, ..., T do
     S_t \leftarrow \text{Random selected } m \text{ local clients}
     Receive local gradients G = [\boldsymbol{g}_1, \cdots, \boldsymbol{g}_m] from S_t
     \hat{\boldsymbol{g}} = \frac{1}{m} \sum_{i=1}^{m} \boldsymbol{g}_i for z = 1, \dots, m do
           \lambda_z, \boldsymbol{e}_z = \mathrm{SVD}_z\left(\frac{1}{m}\boldsymbol{G}^{\top}\boldsymbol{G}\right) \setminus \text{refer to Eq.}(4)
           \boldsymbol{v}_z = \boldsymbol{G} e_z \setminus \text{refer to Eq.}(5)
           \bar{\boldsymbol{v}}_z = \boldsymbol{v}_z, if \langle \boldsymbol{v}_z, \hat{\boldsymbol{g}} \rangle \geq 0; -\boldsymbol{v}_z, otherwise \\ refer to Eq.(6)
     Select the principal gradients with the top L largest eigenvalues, \{\bar{\pmb{v}}_1,\cdots,\bar{\pmb{v}}_L\}
     for i=1,\cdots,m do
           ar{m{g}} = \sum_{i=1}^m rac{n_i}{n} m{g}_i^{revise} Update the global model m{w}_t \leftarrow m{w}_{t-1} with ar{m{g}}
end
Clients update(i, w_t):
oldsymbol{w}_t^i \leftarrow oldsymbol{w}_t
\mathcal{B} \leftarrow (\text{split local dataset of client } i \text{ into batches of size } B)
for local epoch e = 1, \dots, E do
     for batch \ b = \{x,y\} \in \mathcal{B} \ \mathbf{do}
           l = l_{CE}\left(y, f_{\boldsymbol{w}_{t}^{i}}(x)\right) + \lambda \log \left(1 + \left\|f_{\boldsymbol{w}_{t}^{i}}\left(x\right)\right\|_{2}^{2}\right)
           w_t^i \leftarrow w_t^i - \eta \nabla \ell
     \mathbf{end}
end
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