

LaTeX

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1 Algorithm

Algorithm 1 Process of Generating Data Using Vertical Federated Semi-supervised Method

Require: $X_{al}^A, X_{nl}^A, \mathcal{L}_B, \tau, n_{al}, n_{nl}$

Ensure: $X^{B_{predict}}$

- 1: Initialization: $X^{B_{predict}} = \emptyset, \mathcal{L}_B^{\text{predict}} = \{(\mu_q, \phi_q^B) \in \mathcal{L}_B \mid u_q > \tau\}$
 - 2: **for** $(\mu_q, \phi_q^B) \in \mathcal{L}_B^{\text{predict}}$ **do**
 - 3: $X_{al}^{B_{predict}} = \{x_i^{B_{predict}}\}_{i=1}^{n_{al}}$
 - 4: $X_{nl}^{B_{predict}} = \{x_i^{B_{predict}}\}_{i=n_{al}+1}^{n_{al}+n_{nl}}$
 - 5: $p = \text{VFPU-M}(X_{al}^A, X_{nl}^A, X_{al}^{B_{predict}}, X_{nl}^{B_{predict}}, \phi_q^B)$
 - 6: $X^{B_{predict}} = X^{B_{predict}} \cup \{p\}$
 - 7: **end for**
 - 8: **return** $X^{B_{predict}}$
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Algorithm 2 VFPU-M Algorithm

Require: X_{al}^A : Aligned data of party A, X_{nl}^A : Non-aligned data of party A, X_{al}^B : Aligned data of party B, X_{nl}^B : Non-aligned data of party B, y : Labels for the aligned data, α : Confidence threshold, k : Proportion of data selected per iteration, T : Number of iterations.

Ensure: $\mathbf{y}^{\text{pseudo}}$

- 1: Initialize the federated model f_θ
 - 2: $\mathcal{D}_L^{(0)} = \{X_{al}^A, X_{al}^B, y\}$
 - 3: $\mathcal{D}_U^{(0)} = \{X_{nl}^A, X_{nl}^B\}$
 - 4: **for** $t = 1$ **to** T **do**
 - 5: **Federated Model Training:**
 - 6: $\theta^{(t)} \leftarrow \arg \min_\theta \sum_{(\mathbf{x}^A, \mathbf{x}^B, y) \in \mathcal{D}_L^{(t)}} \ell(f_\theta(\mathbf{x}^A, \mathbf{x}^B), y)$
 - 7: **Confidence Calculation:**
 - 8: For $\forall(\mathbf{x}_j^A, \mathbf{x}_j^B) \in \mathcal{D}_U^{(t)}$, calculate the confidence:
 - 9: $s_j = \begin{cases} \max_c \mathbb{P}(y = c | f_{\theta^{(t)}}(\mathbf{x}_j^A, \mathbf{x}_j^B)) & \text{Classification task} \\ 1 - \frac{|\hat{y}_j - \mu_t|}{\sigma_t} & \text{Regression task} \end{cases}$
 - 10: Where μ_t, σ_t are the current predicted mean and standard deviation
 - 11: **Sample Selection:**
 - 12: $\mathcal{C}^{(t)} = \{(\mathbf{x}_j^A, \mathbf{x}_j^B) \in \mathcal{D}_U^{(t)} | s_j \geq \alpha\}$
 - 13: Select the top k proportion of samples after sorting by confidence:
 - 14: $\mathcal{S}^{(t)} = \text{TopK}(\mathcal{C}^{(t)}, k)$
 - 15: **Pseudo-label Generation:**
 - 16: $\forall(\mathbf{x}_j^A, \mathbf{x}_j^B) \in \mathcal{S}^{(t)}, \hat{y}_j = \begin{cases} \arg \max_c P(y = c | f_{\theta^{(t)}}(\mathbf{x}_j^A, \mathbf{x}_j^B)) & \text{Classification} \\ f_{\theta^{(t)}}(\mathbf{x}_j^A, \mathbf{x}_j^B) & \text{Regression} \end{cases}$
 - 17: **Dataset Update:**
 - 18: $\mathcal{D}_L^{(t+1)} \leftarrow \mathcal{D}_L^{(t)} \cup \{(\mathbf{x}_j^A, \mathbf{x}_j^B, \hat{y}_j)\}_{j \in \mathcal{S}^{(t)}}$
 - 19: $\mathcal{D}_U^{(t+1)} \leftarrow \mathcal{D}_U^{(t)} \setminus \mathcal{S}^{(t)}$
 - 20: **end for**
 - 21: $\mathbf{y}^{\text{pseudo}} = \left[y, \bigcup_{t=1}^T \{\hat{y}_j\}_{j \in \mathcal{S}^{(t)}} \right]$ **return** $\mathbf{y}^{\text{pseudo}}$
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