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}, $\mathcal{L}_B$, τ

Ensure: X^B

Initialization: $X^B = \emptyset$, $\mathcal{L}_B^{\text{predict}} = \{(\mu_q, f_q^B) \in \mathcal{L}_B \mid u_q > \tau\}$

for $(\mu_q, f_q^B) \in \mathcal{L}_B^{\text{predict}}$ **do**

  $X_{al}^{B} = \{x_i^B\}_{i=1}^{n_{al}}$

  $X_{nl}^{B} = \{x_i^B\}_{i=n_{al}+1}^{n_B}$

  $p = \text{VFPU-M}(X_{al}^{A}, X_{nl}^{A}, X_{al}^{B}, X_{nl}^{B}, f_q^B)$

  $X^B = X^B \cup \{p\}$

end forreturn X^B

Algorithm 2 VFPU-M Algorithm

Require: X_{al}^A, X_{nl}^A, X_{al}^B, X_{nl}^B, y, α, k, T

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

Initialize the federated model f_θ

$\mathcal{D}_L^{(0)} = \{X_{al}^A, X_{al}^B, y\}$

$\mathcal{D}_U^{(0)} = \{X_{nl}^A, X_{nl}^B\}$

for $t = 1$ **to** T **do**

  Federated Model Training:

  $\theta^{(t)} \leftarrow \arg\min_\theta \sum_{(\mathbf{x}^A, \mathbf{x}^B, y) \in \mathcal{D}_L^{(t)}} \ell(f_\theta(\mathbf{x}^A, \mathbf{x}^B), y)$

  Confidence Calculation:

  For $\forall(\mathbf{x}_j^A, \mathbf{x}_j^B) \in \mathcal{D}_U^{(t)}$, calculate the confidence:

  $s_j = \begin{cases} \max_c \mathbb{P}(y = c | f_{\theta^{(t)}}(\mathbf{x}_j^A, \mathbf{x}_j^B)) & \text{Classification task} \\ 1 - \frac{|\hat{y}_j - \mu_t|}{\sigma_t} & \text{Regression task} \end{cases}$

  Where μ_t, σ_t are the current predicted mean and standard deviation

  Sample Selection:

  $\mathcal{C}^{(t)} = \{(\mathbf{x}_j^A, \mathbf{x}_j^B) \in \mathcal{D}_U^{(t)} | s_j \geq \alpha\}$

  Select the top k proportion of samples after sorting by confidence:

  $\mathcal{S}^{(t)} = \text{TopK}(\mathcal{C}^{(t)}, k)$

  Pseudo-label Generation:

  $\forall(\mathbf{x}_j^A, \mathbf{x}_j^B) \in \mathcal{S}^{(t)}, \quad \hat{y}_j = \begin{cases} \arg\max_c \mathbb{P}(y = c | f_{\theta^{(t)}}(\mathbf{x}_j^A, \mathbf{x}_j^B)) & \text{Classification} \\ f_{\theta^{(t)}}(\mathbf{x}_j^A, \mathbf{x}_j^B) & \text{Regression} \end{cases}$

  Dataset Update:

  $\mathcal{D}_L^{(t+1)} \leftarrow \mathcal{D}_L^{(t)} \cup \{(\mathbf{x}_j^A, \mathbf{x}_j^B, \hat{y}_j)\}_{j \in \mathcal{S}^{(t)}}$

  $\mathcal{D}_U^{(t+1)} \leftarrow \mathcal{D}_U^{(t)} \setminus \mathcal{S}^{(t)}$

end for

$\mathbf{y}^{\text{pseudo}} = \left[y, \bigcup_{t=1}^{T} \{\hat{y}_j\}_{j \in \mathcal{S}^{(t)}}\right]$ **return** $\mathbf{y}^{\text{pseudo}}$