## Algorithm 1 GuardedLearn (GL)

**Require:** Data set St, threshold  $\lambda$ , data partitions M, N, and learning rate r

Ensure: Benign cluster

- 1: Divide the data set M vertically into n partitions.
- 2: Distribute partition  $M_i$  to participant  $u_i$ .
- 3: Initialize an empty set G.
- 4: Set  $\theta_{t-1}$  as the global model parameters after the previous training round t-1.
- 5: for each neuron i in the final layer |C| do
- 6: **for** each partition j in St **do**
- 7: Update parameters  $\theta_{t,j}$  after training.
- 8: Compute the parameter difference  $\theta_{\Delta,j} = \theta_{t,j} \theta_{t-1}$ .
- 9: Extract parameters  $\theta_{i\Delta,j}$  connected to neuron i in the final layer.
- 10: Convert  $\theta_{i\Delta,j}$  to a numpy array  $X(i)_j$ .
- 11: Transform  $X(i)_i$  to  $X'(i)_i = M_i X(i)_i N$ .
- 12: Add partition  $M_i$  to G.
- 13: end for
- 14: Construct matrix  $Y'(i) = [X'(i)_1, X'(i)_2, ..., X'(i)_n].$
- 15: Perform Singular Value Decomposition (SVD) on Y'(i) to obtain  $U'_i, \Sigma'_i$ , and  $V'^T_i$ .
- 16: Calculate  $U_i = G^T U_i'$ .
- 17: Compute  $bY_i = U_i \Sigma_i'$ .
- 18: Apply Algorithm 2 to  $bY_i$  to classify benign weights.
- 19: end for
- 20: Pass benign updates  $bY_i$  to Algorithm 3 (RFA) for aggregation.

## **Algorithm 2** Clustering using DBSCAN

```
Require: Data matrix M, threshold \epsilon, minimum points MinPts
Ensure: Cluster labels
 1: Initialize an empty list clusters
 2: Initialize an empty set visited
 3: for each data point p in M do
      if p is visited then
        Continue to the next data point
 5:
      end if
 6:
      Mark p as visited
 7:
 8:
      NeighborPts \leftarrow \text{regionQuery}(p, \epsilon)
      if size(NeighborPts) < MinPts then
 9:
        Mark p as noise
10:
      else
11:
        Create a new cluster C and add p to C
12:
        ExpandCluster(M, p, NeighborPts, C, \epsilon, MinPts, visited)
13:
        Add C to clusters
14:
15:
      end if
16: end for
17: return Cluster labels
```

## Algorithm 3 Robust Federated Aggregation (RFA) [1]

```
Require: Initial parameter vector w^{(0)}, total communication rounds T, clients per round
    m, local update iterations \tau, step size \gamma, convergence threshold \varepsilon
 1: for t = 0, 1, \dots, T - 1 do
       Randomly select m clients from the cluster of benign clients
 2:
       for each selected client i in parallel do
 3:
          Set initial local parameter vector w^{(t)}i, 0 = w^{(t)}
 4:
          for k = 0, ..., \tau - 1 do
 5:
            Sample data batch z^{(t)}i, k \sim D_i
 6:
            Update local parameter: w^{(t)}i, k+1 = w^{(t)}i, k-\gamma \nabla f(w^{(t)}i, k; z^{(t)}i, k)
 7:
          end for
 8:
          Set global parameter: w^{(t+1)}i = w^{(t)}i, \tau
 9:
       end for
10:
       Perform federated aggregation: w^{(t+1)} = GM(w^{(t+1)}i)i \in St, (\alpha_i)_{i \in St}, \varepsilon (Refer
11:
       Algo. 2)
12: end for
13: return Updated global parameter vector w^{(T)}
```

## **Bibliography**

[1] Krishna Pillutla, Sham M Kakade, and Zaid Harchaoui. Robust aggregation for federated learning. *IEEE Transactions on Signal Processing*, 70:1142–1154, 2022.