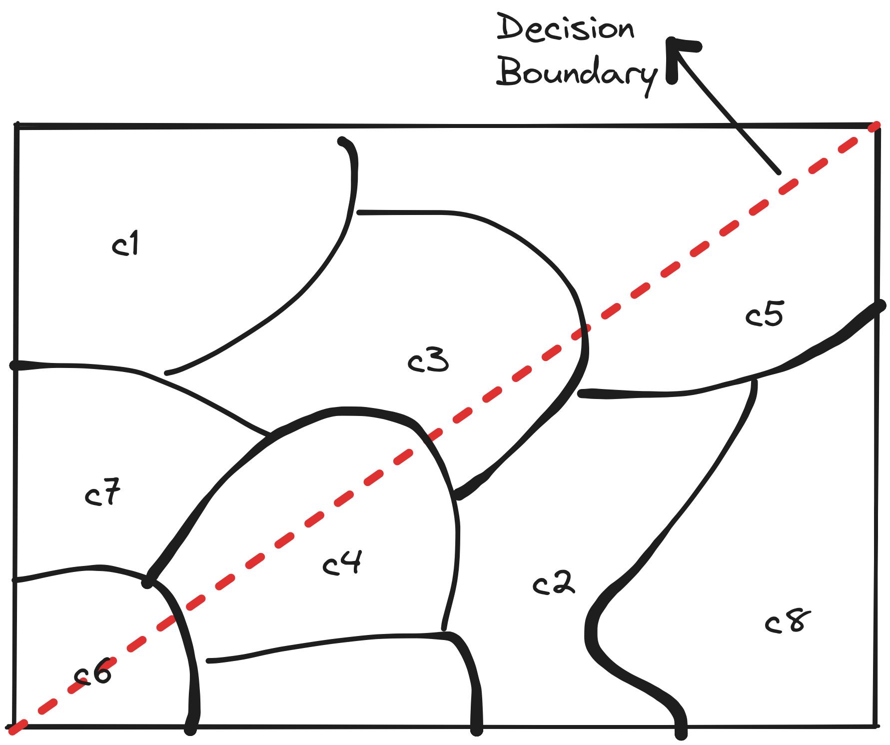
Active Client Selection - Update Report

Introduction

Previously, we proposed a novel algorithm, Federated Proximal Sketching (FPS), to reduce communication overhead in noisy, band-limited wireless channels. We now focusing on reducing computational costs by introducing an adaptive client selection strategy. In federated learning, particularly when data is heterogeneously distributed across clients, only a subset of clients significantly contributes to the global model's learning process. To address this, we propose an active client selection strategy that prioritizes clients based on the uncertainty in their data distribution, thereby reducing overall computational complexity.

Drawing inspiration from the field of active learning, we employ entropy as an information-theoretic measure of uncertainty. At each epoch of federated learning, our client selection strategy involves choosing clients with the highest measured uncertainty. We call this approach Uncertainty-based Active Client Selection for Federated Learning (UACS-FL).

To demonstrate the efficacy of our proposed approach (UACS-FL) consider the following illustration of how data is distributed across different clients. From Figure it is clear that only a fraction of clients (c_3, c_4, c_5 and c_6) contribute significantly to the learning of decision boundary in red.



In order to choose the clients that contribute significant information at each epoch we look to compute the sample entropy at each client c_i. At client c_i, let us denote the dataset as $\mathcal{D}_i$.

The entropy-based metric for a sample x defined as:

$$H(x) = -\sum_{\ell} P_\theta(y_g|x)\log P_\theta(y_g|x)$$

where y_ℓ ranges over all possible labels. We can calculate the entropy metric for client c_i as follows:

$$\alpha_i = \frac{-\sum_{n=1}^{|\mathcal{D}_i|}\sum_g P_\theta(y_\ell^{i,n}|x^{i,n})\log P_\theta(y_\ell^{i,n}|x^{i,n})}{|\mathcal{D}_i|}. \tag{Compute sample entropy}$$

Algorithm

We now describe our UACS-FL method. The algorithm is presented below. UACS-FL is based on FedAvg framework and uses AL metric (entropy) to select clients.

Objective

$$\min_{x}\left[f(x):=\sum_{i=1}^{n}\mathbf{w}_i f_i(x)\right],$$

To keep it simple we choose $\mathbf{w}_i = \frac{1}{n}\,\forall i \in [n]$.

Notation

- $\mathbf{w}_t$: Global model parameters at round t.
- $\mathbf{w}_i^{(t+1)}$: Local model parameters of client i after round $t+1$.
- α_i: Selection metric for client i.
- n: Total number of clients.
- m: Number of clients selected per round.
- D_i: Local dataset of client i.

Initialization

1. **Server** initializes the global model parameters $\mathbf{w}_0$.
2. **Server** sets the number of selected clients m per round.

Federated Learning Round

Active Client Selection

- **For each client** $i \in \{1, 2, \ldots, n\}$:
  - **Client** receives global model parameters $\mathbf{w}_t$ from the server.
  - **Client** computes the selection metric α_i based on its local model (see, compute sample entropy equation.).
  - **Client** sends α_i to the server.
- **Server** selects a set S_t of m clients based on epsilon greedy approach:
  - **Step 1:** Generate a random number $r \in [0, 1]$
  - **Step 2:**
    If $r \leq \epsilon$ (exploration step):
    - Randomly select m clients from the set $\{1, 2, \ldots, n\}$ without considering α_i.
      Else $r > \epsilon$ (exploitation step):
    - Select the top m clients with the highest α_i values.

Client-Side Computation

For each client $i \in S_t$:
- **Client** updates its local model using its local dataset D_i to compute the local model parameters $\mathbf{w}_i^{(t+1)}$.

Server-Side Aggregation

- **Server** aggregates the parameters from the selected m clients:

$$\mathbf{w}_{t+1} = \frac{1}{m}\sum_{i \in S_t}\mathbf{w}_i^{(t+1)}$$

- **Server** broadcasts the updated global model parameters $\mathbf{w}_{t+1}$ to all clients.

Experimental Objectives

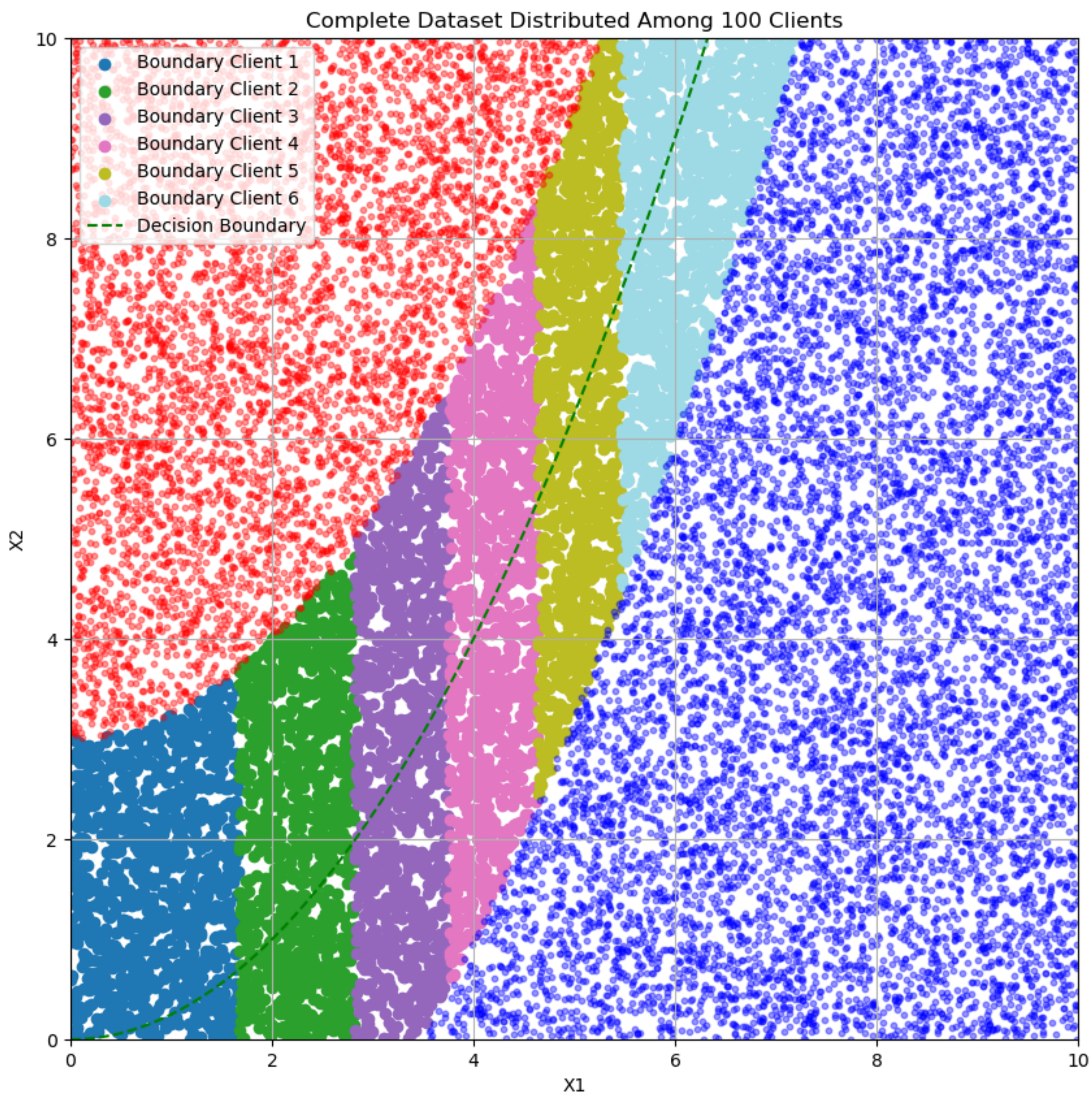
We consider two variants of our proposed approach:

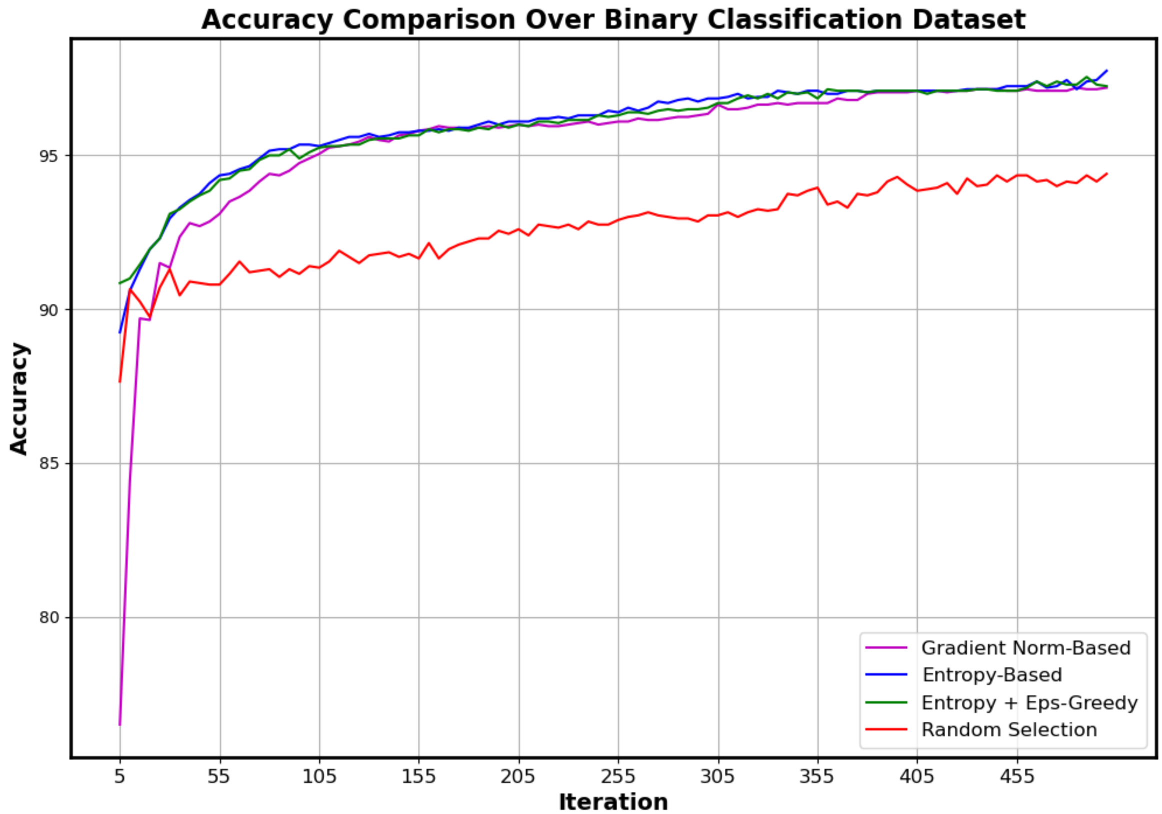
1. Epsilon greedy parameter $\epsilon = 0.1$. In our plots we label this as Entropy+Eps-Greedy.
2. Epsilon greedy parameter $\epsilon = 0 \implies$ Pure exploitation. In our plots we label this as Entropy Based.

We will compare our proposed approach against the following baseline client selection strategies:

- Random Client Selection (RCS). In our plots we label this as Random Selection.

- Gradient Norm-Based Selection (GNCS): Choosing clients with the largest gradient norm values. In our plots we label this as Gradient Norm-Based.




Accuracy Comparison Over Binary Classification Dataset
Accuracy
95
90
85
80
5
55
105
155
205
255
305
355
405
455
Iteration
Gradient Norm-Based
Entropy-Based
Entropy + Eps-Greedy
Random Selection