

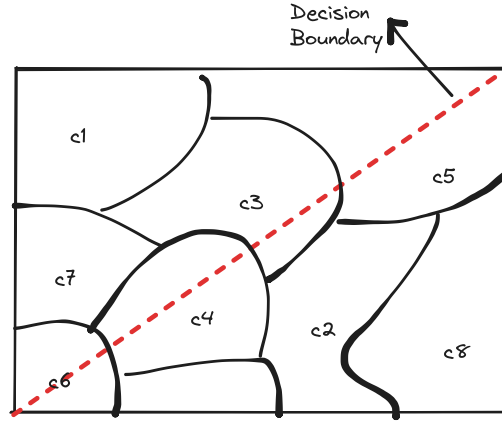
# Active Client Selection - Update Report

## 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:

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

where  $y_{\ell}$  ranges over all possible labels. We can calculate the entropy metric for client  $c_i$  as follows:

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

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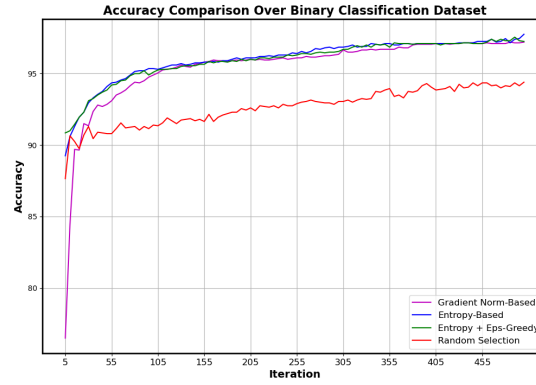
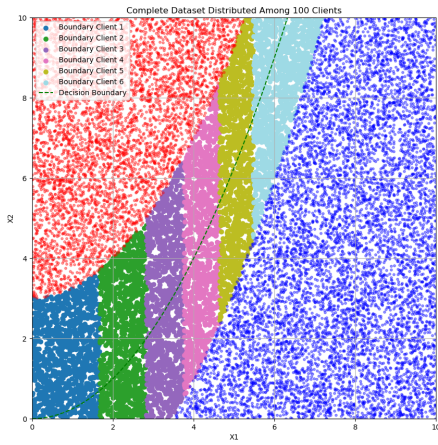
## Experimental Objectives

We consider two variants of our proposed approach:

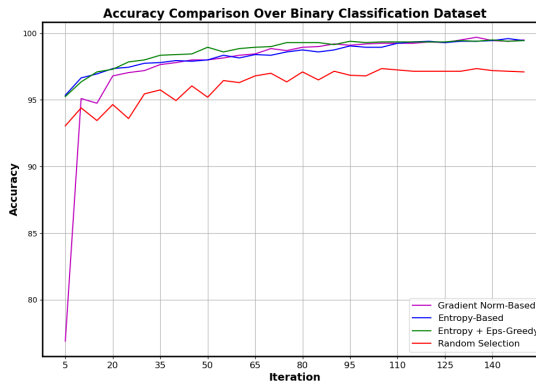
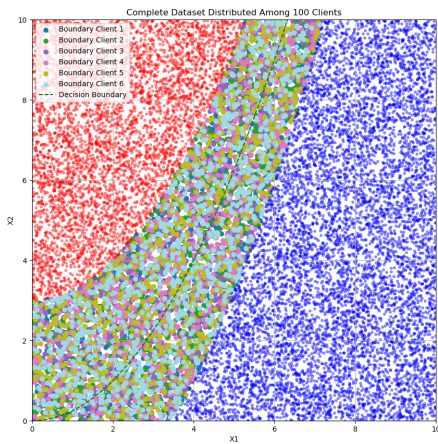
1. Epsilon greedy parameter  $\epsilon = 0.1$ . In our plots we label this as **Entropy+Eps-Greedy**.
2. Epsilon greedy parameter  $\epsilon = 0 \implies$  Pure exploitation. In our plots we label this as **Entropy Based**.
3. We compare our proposed approach against the following baseline client selection 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**.

We demonstrate the performance of our algorithm along with other baselines on three different data distribution settings over a binary classification task. In all three experiments, the number of clients that contribute to efficient learning of the decision boundary is very less ( 6 – 10) compared to the total number of clients (100). In all data distribution plots, **dotted green** represents the decision boundary.

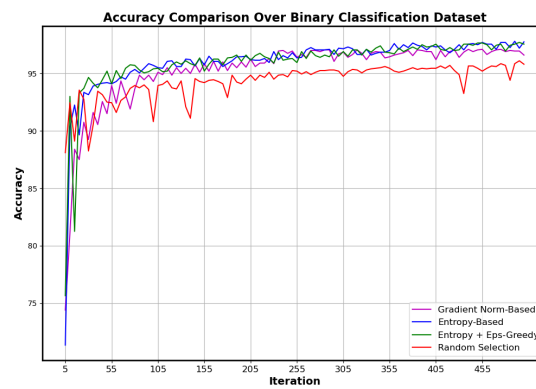
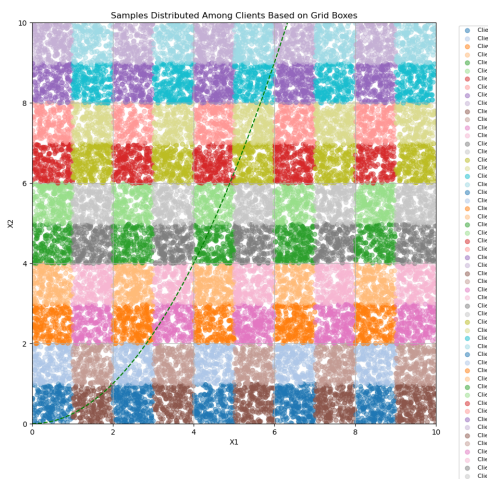
## Experiment 1



## Experiment 2



## Experiment 3



### Remarks:

- In all three data distribution scenarios, random client selection consistently underperforms in comparison to the proposed method.
- Furthermore, while the gradient norm-based client selection achieves comparable results, the proposed method demonstrates superior performance, notably achieving faster convergence.

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## 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  $t + 1$ .
- $\alpha_i$ : 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**  $i \in \{1, 2, \dots, n\}$ :
  - **Client** receives global model parameters  $\mathbf{w}_t$  from the server.
  - **Client** computes the selection metric  $\alpha_i$  based on its local model (see, compute sample entropy equation.).
  - **Client** sends  $\alpha_i$  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  $\{1, 2, \dots, n\}$  without considering  $\alpha_i$ .**Else**  $r > \epsilon$  (exploitation step):
    - Select the top  $m$  clients with the highest  $\alpha_i$  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.