Progressive Federated Dictionary Learning

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***Abstract*—This research presents an innovative method for federated learning that integrates dictionary learning approaches to tackle intra-class variation. Based on the concept of curriculum learning, we provide a gradual approach to dictionary learning that enhances the initialization of the dictionary in each local model. The process involves developing a neural network architecture using Convolutional Neural Networks in a federated learning configuration, where a curriculum is applied separately to each client. The global model combines local dictionaries by making use of averaging techniques, hence improving the representation of attributes throughout the full federated dataset. The experimental findings validate the effectiveness of the suggested methodology, wherein the integration of curriculum learning leads to enhanced precision. The study also compares the results obtained with and without the utilisation of dictionary learning and curriculum learning, demonstrating the beneficial influence on the performance of the model.**

***Index Terms*—federated learning, dictionary learning, curriculum learning**

I. Introduction

We propose incorporating dictionary learning into federated learning would be helpful when there is intra-class variability in the data. To improve dictionary initialization at every local model, we created a progressive dictionary learning paradigm inspired by curriculum learning. This enables the dictionary to first extract the essential structures and patterns from the data, then proceed to more difficult cases that show the intra-class variation. Dictionary learning enables local clients to share more information about their features rather than simply sharing the weights. This has the potential to address intra-class variation in the dataset present at the local level. Moreover, we used curriculum learning to train our local models to gradually update the local dictionary.

Every local dictionary contains basis vectors as columns and it captures a specific feature or pattern present in the data. The learned dictionary is then utilised to represent data in an informative and sparse manner.

II. Related Work

The authors of the paper "Federated Dataset Dictionary Learning for Multi-Source Domain Adaptation" present a methodology called FedDaDiL to address the problem of federated domain adaptation. This is a situation in which there is a distributional shift among clients. The FedDaDiL framework combines federated learning with dictionary learning of empirical distributions. In this context, the client distributions represent specific domains, and FedDaDiL collectively trains a federated dictionary of these empirical distributions.

In their paper, "A Federated Dictionary Learning Method for Process Monitoring with Industrial Applications," the authors suggest a novel approach to federated learning by incorporating dictionary learning techniques. Local nodes in the network separately learn dictionaries using the K-SVD approach and broadcast these dictionaries to a central fusion centre. The fusion centre then computes a global dictionary using an optimal federated average technique. This global dictionary is utilised in decentralised industrial applications for process monitoring, estimating reconstruction errors and control limitations, and providing effective monitoring while retaining data privacy.

III. Methodology

A. Algorithm

1) **Neural Network Architecture - CNN** as the base model for every local client. The neural network architecture is specifically designed for the purpose of image classification tasks. The model uses ReLU activations to extract features. Fully connected layers process flattened representations.
2) **Federated Learning - 5 clients system** is trained with Curriculum Learning applied independently to each client.
3) **Global Model** which aggregates local dictionaries using averaging techniques. The convolutional layer of each local model then receives this global dictionary application, which modifies the model's features according to the combined knowledge acquired by all clients.

B. Working Of Model

The key steps involved in our algorithm are:

1) Local Dictionary Learning
   - Local dictionaries are learned by using the K-SVD algorithm to image patches from the client's data. These patches are then converted to flattened vectors, giving a matrix of local feature representations.
   - Dictionary initialization with Curriculum Learning
2) Dictionary Aggregation
   - The global dictionary comprises weighted averages of the corresponding elements in the local dictionaries, improving the comprehensive representation

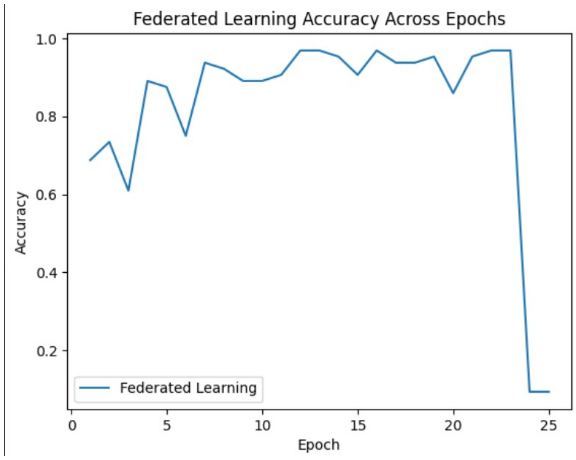

Fig. 1. Results without Dictionary Learning & Curriculum Learning

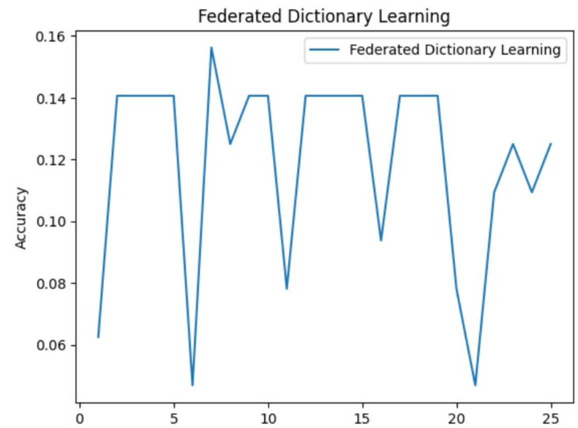

Fig. 2. Results with Dictionary Learning & without Curriculum Learning

of characteristics throughout the entire federated dataset.

3) Dictionary reshaping and distribution
   - The process of reshaping using linear layers involves converting the information in the global dictionary into a form that is compatible with the specific architecture of the convolutional layer in each device's local model.

IV. Experimental Setup

A. Training Model

- The curriculum determines the order of training classes. This curriculum selects easier classes early in training based on class difficulty.
- Local models are trained on each client's dataset, and a local dictionary is obtained.
- The global dictionary which combines the combined knowledge of all clients is then created by averaging the local dictionaries.
- This global dictionary is applied to the convolutional layer of each local model.
- The procedure is iterated over several epochs, with the accuracy of the global model being assessed after each training round.
- The system aims to improve overall performance by federated learning and dictionary adaptation, iteratively fine-tuning the global model based on contributions from several local datasets.

V. Results

A. Inference

- We can see that applying Curriculum Learning in Federated Dictionary Learning has increased the accuracy up to 75%.
- Our Global Model performed poorly on Dictionary Learning without Curriculum Learning as the initialization of the dictionary was random.

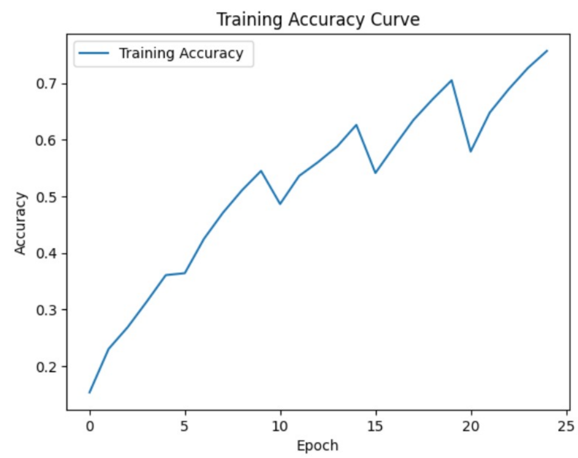

Fig. 3. Results with Dictionary Learning & Curriculum Learning

- Introducing curriculum learning, updated the local dictionary step by step preventing increasing the complexity in one go.

VI. Conclusion

A. Potential Issues

- With the increase in the size of the dictionary, it may become difficult to share and aggregate them with feasible amenities and limited resources.

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