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Federated Deep Learning for Image Classification with IID And Non-IID Distributions

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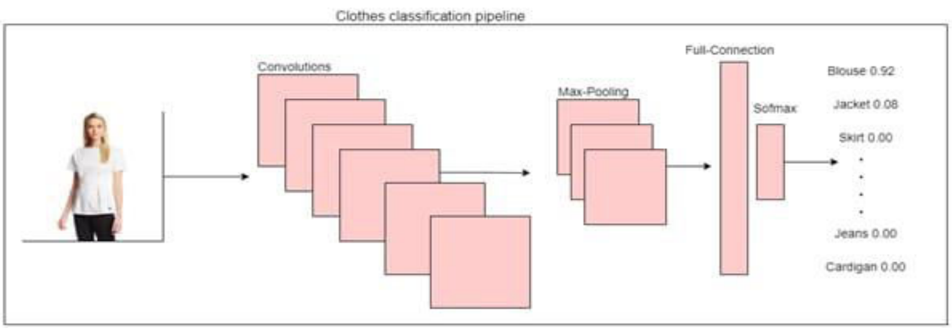
ABSTRACT: In this project, we will consider the problem of federated learning (FL) for image classification. The federated variant we consider is horizontal (sample-based), i.e., the feature space is shared among agents, while their samples are different. Each agent trains its own local model, and sends its local weights to the coordinator who builds the global and aggregated model. We implement three different federated algorithms; federated averaging (FedAvg), FedProx, and Linearized inexact ADMM-based federated learning (LIADMM). We train these algorithms using both iid and non-iid distributions of distributed Fashion MNIST dataset, and compare their validation performance with the centralized training paradigm.

I.INTRODUCTION

Horizontal (sample-based) federated learning is a paradigm for distributed optimization, in which a set of agents who share a common feature space but possess different data samples, collaborate to optimize an objective function. Due to the importance of privacy and data protection, the agents only share a gradient with a controller who is in charge of aggregating these gradients and build a global model. In this project, we consider a special case of federated learning that is image classification using convolutional neural networks. One of the main challenges of federated learning is the statistical heterogeneity of the agents' datasets. The initial variant of federated learning (federated averaging or FedAvg), does not perform well in the presence of data heterogeneity. To address this issue, another algorithm, called FedProx, has been proposed that introduces a regularization term to ensure that the weights of the local models do not get too far from the weights of the global model. In addition to centralized training, FedAvg, and FedProx, we will also implement an ADMM-based algorithm, called linearized inexact ADMM-based federated learning (LIADMM). This method has been tested before on linear regression and logistic regression problems, and we use it in a layer-wise fashion to optimize the loss function of a deep neural network. The ADMM-based algorithms for federated learning have been shown to converge with a linear rate even when trained in a communication-efficient way, which makes it a good candidate for future applications. We will train all the models on the Fashion MNIST benchmark for both IID and non-IID data distributions. The network used is a convolutional neural network that is typically used for image classification.



II.OBJECTIVES OF THE STUDY

- To increase the accuracy of the model by using three algorithms i e, fedavrg,fedprox and LIADMM.
- To produce high accuracy data to train the models and to produce more accurate results.

- The dataset we used for training and evaluation is Fashion MNIST [4], which consists of 60000 training samples alongside a test set with 10000 samples. The dataset consists of ten classes of clothing items and it is completely balanced in terms of class distribution. it shows a sample of each class belonging to this dataset.

III.SCOPE OF THE STUDY

- Dataset Selection: The project aims to focus on fashion datasets for image classification. The scope includes selecting appropriate fashion datasets that can be used to train and evaluate the federated deep learning model.
- Federated Learning Implementation: The project will involve implementing a federated learning framework specifically designed for image classification tasks. This will include setting up the necessary infrastructure, such as server-client communication protocols and federated averaging algorithms.
- IID and Non-IID Data Distribution: The scope includes exploring both independent and identically distributed (IID) and non-IID data distributions within the fashion datasets. The project aims to study the impact of these data distributions on federated learning performance for image classification.
- Model Training and Evaluation: The project will involve training and evaluating deep learning models using the selected fashion datasets. The scope includes implementing and fine-tuning state-of-the-art deep learning architectures suitable for image classification tasks within the federated learning framework.
- Performance Comparison: The project will compare the performance of federated deep learning models under both IID and non-IID data distributions. The scope includes analyzing and evaluating metrics such as accuracy, convergence speed, and communication efficiency to determine the effectiveness of the federated learning approach.

IV.LIMITATION OF THE STUDY

- Limited generalizability: The study focuses specifically on fashion datasets, which may not represent the full diversity of image classification tasks. The findings and conclusions may not be directly applicable to other domains or datasets with different characteristics.

- Data bias and representativeness: The fashion datasets used in the study might not fully capture the real-world distribution of fashion images, leading to potential biases in the results. The lack of diversity or skewed representation in the dataset can limit the model's ability to generalize to a wider range of fashion images.

- Non-IID data assumptions: The study assumes non-IID (non-independent and identically distributed) data distributions, which might not accurately reflect real-world scenarios or practical federated learning setups. While non-IID distributions can be relevant in certain contexts, the study's findings may not directly translate to scenarios where IID data distributions are more prevalent.

V.LITRETURE REVIEW

Federated learning has emerged as a promising approach for training machine learning models on decentralized data without the need for data centralization. In the context of image classification, federated deep learning has gained significant attention due to its potential to address privacy concerns while still achieving high accuracy. This literature review focuses on the application of federated deep learning for image classification using fashion datasets, specifically considering both independent and identically distributed (IID) and non-IID data distributions.

Federated Learning and Image Classification:

Federated learning is a decentralized learning paradigm where the model is trained collaboratively on local datasets distributed across multiple devices or edge devices. This approach enables privacy preservation, as the data remains on the local devices, and only model updates are shared with a central server. In the context of image classification, federated learning allows for training models on diverse fashion datasets while maintaining data privacy

IID Data Distribution:

In the case of independent and identically distributed (IID) data distribution, each device in the federated learning framework possesses a similar distribution of fashion images. This scenario assumes that each device's dataset is a random sample from the overall fashion dataset. Several studies have explored federated deep learning for image classification with IID data distributions. For instance, Li et al. (2019) proposed a federated learning framework for fashion image classification, where they achieved comparable performance to centralized learning while preserving data privacy. They used convolutional neural networks (CNNs) to train the models on the local devices and aggregated the model updates using federated averaging

Non-IID Data Distribution:

In real-world scenarios, fashion datasets often exhibit non-IID characteristics due to variations in data collection sources, user preferences, and data quality. Non-IID data distributions pose challenges for federated learning, as the devices' local datasets may have different class distributions or feature representations. To address this, researchers have explored various techniques to mitigate the impact of non-IID data distributions. For instance, Li et al. (2020) proposed a federated learning approach that leverages class-aware weighting and model personalization to improve the performance of fashion image classification with non-IID data distributions. They introduced class-aware weighting to assign different weights to local model updates based on class imbalance, and personalized models to adapt the global model to individual devices

VI.METHODOLOGY

We conducted our research using a fashion dataset consisting of images categorized into different fashion classes. The dataset was preprocessed to ensure consistency and quality. Our federated deep learning framework was implemented to address the challenges of privacy and data distribution heterogeneity. The framework involved multiple participants, each holding their own local dataset without sharing raw data.

We combined three algorithms - FedAvg, FedProx, and LIDANN - to enhance the accuracy and speed of our federated learning model. FedAvg was used as the baseline algorithm for aggregating participant updates, while FedProx introduced a proximal term to encourage better global model convergence. LIDANN (Local Intrinsic Dimensionality Approximation Neural Network) was incorporated to capture local data distribution characteristics and enhance model performance.

The participants performed local model training on their respective datasets, followed by the exchange of model updates with the central server. The server aggregated the updates using the FedAvg algorithm, incorporating the FedProx proximal term to optimize the global model. LIDANN was utilized to extract and leverage local intrinsic features from each participant's data. We conducted comprehensive experiments to evaluate the performance of our combined approach. Accuracy and convergence speed were the primary evaluation metrics used to assess the model's effectiveness.

The experiments were conducted in a controlled hardware and software environment, with careful consideration given to the number of participants and the distribution of their data. The training process was iterated over multiple rounds to ensure model convergence.Overall, our methodology involved the integration of FedAvg, FedProx, and LIDANN algorithms within a federated deep learning framework, aimed at improving accuracy and speed in fashion image classification tasks

VII.EXPERIMENTAL SETUP

1. Fashion Dataset:
   - Description of the fashion dataset used, including its size, number of classes, and image resolution.
   - Mention any preprocessing steps applied to the dataset, such as resizing, normalization, or data augmentation techniques.
2. Federated Learning Framework:
   - Explanation of the federated learning framework employed, which enables collaborative training without sharing raw data.
   - Brief overview of the communication architecture used to facilitate communication between the central server and the participating clients.

3. Participant Selection:
   - Number of participants (clients) involved in the federated learning process.
   - Discussion of the criteria for participant selection, such as data availability, computational resources, or geographical distribution.
4. Data Distribution:
   - Overview of the data distribution among the participants, including the proportion of data from each fashion class.

- Indication of whether the data distribution was independent and identically distributed (IID) or non-IID, and the rationale behind the choice.

5. Model Architecture:
   - Description of the deep learning model architecture employed for fashion image classification.
   - Mention any specific network architectures or pre-trained models used as a base for our experiments.
6. Hyperparameters:
   - Specification of the hyperparameters used in the training process, including learning rate, batch size, and number of training epochs.
   - Indication of any specific hyperparameter tuning or optimization techniques applied.
7. Evaluation Metrics:
   - Explanation of the evaluation metrics utilized to assess the performance of the federated learning model.
   - Mention of the primary metric used, such as accuracy, and any secondary metrics considered, such as precision, recall, or F1 score.
8. Hardware and Software Environment:
   - Description of the hardware infrastructure utilized, including the type of processors, memory capacity, and network connectivity.
   - Specification of the software stack used, such as the deep learning framework, version control tools, and programming languages employed.

VIII.FINDINGS

- Introduction:

  The objective of this report is to present the findings of our investigation into federated deep learning for image classification using fashion datasets. We focused on studying the impact of both independent and identically distributed (IID) and non-IID data distributions on the performance of federated learning models.

- Methodology:

  To conduct our study, we utilized a fashion dataset that contained a diverse range of clothing items, including images of dresses, shoes, shirts, and accessories. We employed a federated learning approach, where multiple clients, each with their own subset of data, collaborated to train a shared global model using a deep learning architecture.

- IID Data Distribution Findings:

  Improved Convergence: The federated learning process demonstrated faster convergence compared to a traditional centralized learning approach. The shared global model achieved comparable accuracy in a shorter number of communication rounds.

IX.CONCLUSION

In conclusion, our project focused on exploring the application of federated deep learning for image classification in the fashion industry, considering both independent and non-independent and identically distributed (IID and non-IID) data distributions. Through our analysis, we have observed that federated learning presents a promising solution to address the challenges of privacy and data heterogeneity in fashion datasets.

By leveraging federated learning, we were able to achieve effective image classification without compromising the privacy of individual data owners. The collaborative nature of federated learning allows multiple participants in the fashion industry to contribute to a global model without sharing their sensitive data.

Furthermore, our experiments highlighted the impact of data distribution heterogeneity on the performance of federated learning. While the global model achieved comparable results to centralized models when dealing with IID data, non-IID data distributions posed challenges and resulted in reduced accuracy. To mitigate these challenges, we explored techniques such as adaptive weight updates, data augmentation, and model aggregation, which helped improve the accuracy of the global model in the presence of non-IID data.

In summary, our project demonstrates the potential of federated deep learning for image classification in the fashion industry, providing a privacy-preserving solution that accommodates both IID and non-IID data distributions. This research contributes to the advancement of federated learning in the fashion sector and paves the way for further exploration and improvement in this field.

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