Communication-Efficient Learning of Deep Networks from Decentralized Data (Pass 1)

Federated Learning: invented by Google, circa 2017

Useful links:

https://arxiv.org/abs/1602.05629
https://ai.googleblog.com/2017/04/federated-learning-collaborative.html
https://paperswithcode.com/paper/communication-efficient-learning-of-deep

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Category: What type of paper is this?

New algorithm/approach for machine learning

Context: What is it related to?

- Privacy Preserving Machine Learning
- Handling Data from Mobile Devices
- Stochastic Gradient Descent

Correctness: Do the assumptions appear to be valid?

- Communication costs are the principal constraint, which makes sense. The data is decentralized. We don't have access to all data at all times.
- Computation becomes essentially free compared to communication costs. There is no need for a supercomputer. Workload is decentralized on devices.

Contributions: What are the paper's main contributions?

- Presents a practical method for the decentralized machine learning of deep networks
- Provides extensive empirical evaluation, five model architectures and four datasets
- Demonstrates that this approach robust to the unbalanced and non-IID data distributions

Clarity: Is the paper well written?

Sure

Communication-Efficient Learning of Deep Networks from Decentralized Data (Pass 2)

Federated Learning: invented by Google, circa 2017

Problem

- Machine learning on mobile devices
- Processing large amounts of data
    - Non-IID: a particular user's data set will not be representative of population
    - Unbalanced: the amounts of local training data varys
    - Massively Distributed: number of clients participating is much larger than the average number of examples per client
- Limited communication from devices
- Handling privacy sensitive data

Solution

Instead of using a centralized datacenter and learning after aggregating, do the opposite.

- Leave the training data distributed on the devices
- Limit attack surface to only the device not it and the cloud
- Aggregate locally computed updates on a shared model

"since the learning task is solved by a loose federation of participating devices (which we refer to as clients) which are coordinated by a central server. Each client has a local training dataset which is never uploaded to the server. Instead, each client computes an update to the current global model maintained by the server, and only this update is communicated"

This decentralized approach is referred to as "federated learning" of "FL".

Practicality Issues of Solution

- Computing costs
- Communication costs

When using a centralized data center, Computation costs are high while communication costs are small. However, when using a decentralized system, computation costs are essentially free while communication is now costly.

Pseudocode

Federated Machine Learning = Stochastic Gradient Descent + Model Averaging

Synchronous update scheme:

- Server sends the current global state to each of a sample of clients (e.g., the current model parameters)
- Each selected client then performs local computation based on the global state and its local dataset, and sends an update to the server.
- Server then applies these updates to its global state, and the process repeats.

Baseline algorithm: FederatedSGD (or FedSGD), full-batch (non-stochastic) gradient descent
Interested algorithm: FederatedAveraging (or FedAvg), testing different client sample sizes

Algorithm 1 `FederatedAveraging`. The K clients are indexed by k; B is the local minibatch size, E is the number of local epochs, and η is the learning rate.

Server executes:

initialize w_0

for each round $t = 1, 2, \dots$ **do**

$m \leftarrow \max(C \cdot K, 1)$

$S_t \leftarrow$ (random set of m clients)

for each client $k \in S_t$ **in parallel do**

$w_{t+1}^k \leftarrow \text{ClientUpdate}(k, w_t)$

$w_{t+1} \leftarrow \sum_{k=1}^{K} \frac{n_k}{n} w_{t+1}^k$

ClientUpdate(k, w): *// Run on client k*

$\mathcal{B} \leftarrow$ (split $\mathcal{P}_k$ into batches of size B)

for each local epoch i from 1 to E **do**

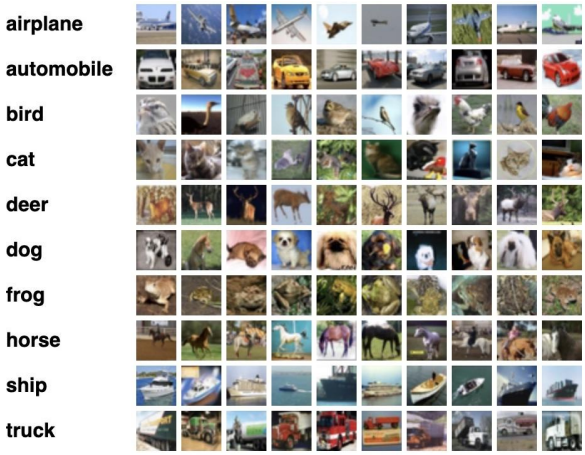
for batch $b \in \mathcal{B}$ **do**

$w \leftarrow w - \eta \nabla \ell(w; b)$

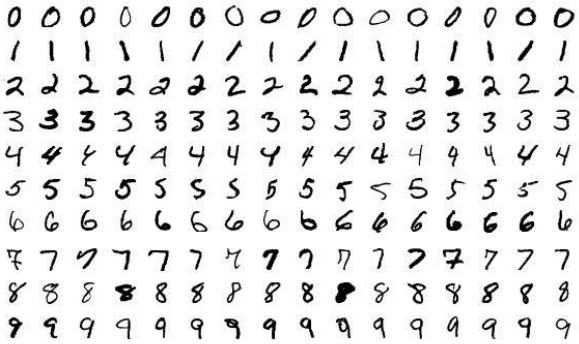
return w to server

Datasets Used:

CIFAR-10 dataset (Canadian Institute for Advanced Research, 10 classes)
https://paperswithcode.com/dataset/cifar-10



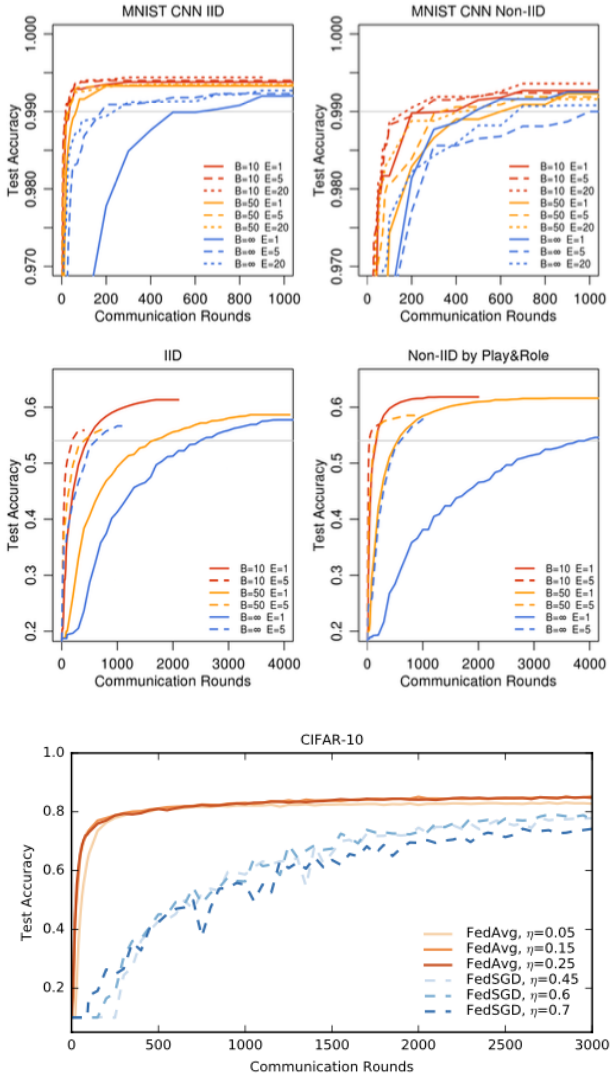
MNIST database (Modified National Institute of Standards and Technology database)
https://paperswithcode.com/dataset/mnist



“For language modeling, we built a dataset from *The Complete Works of William Shakespeare”:*

Conclusions:

I guess it works.



“Our experiments show that federated learning can be made practical, as FedAvg trains high-quality models using rel- atively few rounds of communication, as demonstrated by results on a variety of model architectures: a multi-layer perceptron, two different convolutional NNs, a two-layer character LSTM, and a large-scale word-level LSTM.”

Future Work:

providing stronger privacy guarantees:

- differential privacy
- secure multi-party computation, etc.