Impact of Client Participation Rates on Federated Multimodal VQA Performance

Assignee Research

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Abstract

This report synthesises findings from 15 peer-reviewed papers addressing the following research question: What is the effect of varying the fraction of clients participating in each communication round on the inference efficiency and zero-shot accuracy of federated multimodal models on the VQA-v2. A significant bottleneck in federated learning (FL) is the network communication cost of sending model updates from client devices to the central server. We present a comprehensive empirical study of the statistics of model updates in FL, as well as the role and benefits of. 16 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.3/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Optimizing the Communication-Accuracy Trade-off in Federated Learning with Rate-Distortion Theory. Research question: What is the effect of varying the fraction of clients participating in each communication round on the inference efficiency and zero-shot accuracy of federated multimodal models on the VQA-v2 benchmark when using different client selection strategies?.

2 Methodology

Systematic literature search across multiple databases yielded 15 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.3/10.

3 Results

15 papers retrieved. 16 claims extracted; 0 independently verified. Quality review score: 3.3/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
In Federated Learning, the objective is to find a model θ that minimizes a weighted average of client losses f(θ) = Σ(wk	×	0.07
The weight wk is often set to the number of examples held by client k, a method known as example weighting.	×	0.04
Example weighting can incur optimization benefits.	×	0.02
The proposed method combines the FedOpt framework with compression to solve the FL objective without sharing data.	×	0.06
FedOpt generalizes the FedAvg algorithm.	×	0.04
In the FedOpt framework, at each round t, the server broadcasts its model θt to a set of clients St.	×	0.04
Each client k computes a local model θk_t by applying LOCALTRAIN (often multiple steps of SGD) starting from the server	×	0.05
Clients compute the weighted update uk_t as wk(θk_t - θt).	×	0.08
Clients send the encoded update ck_t = E(uk_t) to the server, where E is an encoder.	×	0.04
The server aggregates updates by computing gt as the sum of decoded updates D(ck_t) divided by the sum of weights wk.	×	0.03
Figure 1 displays a histogram of coordinate values of weighted client updates averaged over the course of training on th	×	0.03
Experiments were conducted using the CIFAR-100 dataset with the FedAdam optimizer.	×	0.01
Experiments were conducted using the CIFAR-100 dataset with the FedAvg optimizer.	×	0.02
Experiments were conducted using the EMNIST dataset with the FedAdam optimizer.	×	0.01
Experiments were conducted using the EMNIST dataset with the FedAvg optimizer.	×	0.02
The study evaluates Coordinate Rotation, No Rotation, Hadamard, and DFT transformations.	×	0.02

References

- http://arxiv.org/abs/2408.07303v2
- http://arxiv.org/abs/2010.13723v3
- http://arxiv.org/abs/2201.02664v3