Federated Learning under Heterogeneous Resource Constraints

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Background: Federated learning is a class of algorithms that produce predictive models on data distributed over many devices. This technique is useful when dealing with information that is too sensitive to share or at a quantity too expensive to transport. This is accomplished by delegating computation to participating devices. Prior work has shown that system heterogeneity of participating devices can have negative impacts on such an algorithm's efficiency by extending round latency or dropping parameter updates [1]. System heterogeneity can worsen predictive accuracy in the presence of statistical heterogeneity [1,2]. One way varying local training workload is by reducing the amount of parameters a local device has to update [3]. Parameter convergence has been shown to converge non-uniformly, allowing for fine-grained updates [4] as well as various compression approaches of reducing message sizes between machines.

Hypothesis: Since model parameters converge non-uniformly, updates to some parameters are more important than others. Instead of compressing the updates after they've been calculated, there might be methods of predicting that some updates are unnecessary. We would like to build a scheduler that generates tasks tailored to the capacity of each device while taking into consideration the non-uniform convergence of parameters.

Timeline:

1. February: Investigate the convergence order of parameters, local data distribution, and parameter state.
2. March: Learn and evaluate a model to predict convergence order.
3. April: Write about our findings and experimental results.

References:

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