Adaptive stochastic optimization using trajectory cues

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Motivation

- Modern machine learning involves minimizing the prediction error of a model using stochastic gradient descent (SGD) and its variants
- SGD is difficult to use because one must select a tuning parameters (the learning rate) for each problem instance

Project Description

- Eliminate the learning rate tuning parameter from SGD
- Eliminate other tuning parameters from more sophisticated variants of SGD

Context

- Current practice for using SGD involves searching over a user specified grid of learning rates
- There is much work exploring the adaptive methods under the assumption that data points are chosen by an adversary instead of stochastically
- By devising an automatic tuning algorithm for the stochastic case we believe we can better results.

What is a trajectory cue?

- The trajectory refers to the path of an algorithm
- Trajectory cues are information that we get from running the algorithm
- An example of a trajectory cue is the distance travelled by the algorithm
- There has been no research explicitly studying how trajectory cues can be used to choose tuning parameters of stochastic optimization algorithms



Training machine learning models requires users to select many tuning parameters. These parameters are hard to select.

This project aims to eliminate these parameters by using information inferred from training algorithm trajectories. This will make training machine learning models less time consuming and more userfriendly.





Preliminary results: training CIFAR-10 with a CNN. Comparison is with a range of different fixed step sizes and with our method called DoG, note step sizes not displayed diverge.

Project Deliverables

- Funding from NSF
- Publication of several papers developing the theory and practice of adaptive stochastic optimization using trajectory cues
- The development of practical software

Potential Impact

- The most efficient way to remove tuning parameters from SGD is a major outstanding problem in optimization theory
- Better understanding of the differences between between adversarial and stochastic optimization
- If we can translate our theory into practice this will make training machine learning models faster and easier