SWALP: Stochastic Weight Averaging in Low-Precision Training

Guandao Yang, Tianyi Zhang, Polina Kirichenko, Junwen Bai, Andrew Gordon Wilson, Christopher De Sa
Low-precision Computation

- IEEE FP32: Sign, Exponent, Mantissa
- IEEE FP16: Sign, Exponent, Mantissa
- Custom FP8: Sign, Exponent, Mantissa
We study how to leverage low-precision training to obtain a high-accuracy model.
Problem Statement

We study how to leverage low-precision training to obtain a high-accuracy model.

Output model can be higher-precision.
Low-precision Training

Representable Points in Low Precision
SWALP

SWALP model

SGD-LP model

Updating
Every $c$ iterations

Averaging

Updating
Every $c$ iterations

Averaging

Infrequently

SGD-LP model

Updating
Convergence Analysis

Let $T$ be the number of iterations.

**Theorem 1 (quadratic)**
SWALP converges to the optimal solution at a $O(1/T)$ rate.
Convergence Analysis

Let $T$ be the number of iterations.

**Theorem 1 (quadratic)**
SWALP converges to the optimal solution at a $O(1/T)$ rate.

SWALP has the same convergence rate as full precision SGD.
Convergence Analysis

Let $\delta$ be the quantization gap.

**Theorem 2 (strongly convex)**
The expected distance between SWALP solution and the optimal one is bounded by $O(\delta^2)$. 
Convergence Analysis

Let $\delta$ be the quantization gap.

**Theorem 2 (strongly convex)**

The expected distance between SWALP solution and the optimal one is bounded by $O(\delta^2)$.

- The best bound for SGD-LP is $O(\delta)$ (Li et al, NeurIPS 2017).

- SWALP requires half the number of bits to reduce the noise ball by the same factor.
Experiments

CIFAR100 VGG16

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SGD</td>
<td>72.8</td>
</tr>
<tr>
<td>SWA</td>
<td>74.1</td>
</tr>
<tr>
<td>SGDLp</td>
<td>70.4</td>
</tr>
<tr>
<td>SWALP</td>
<td>73.3</td>
</tr>
</tbody>
</table>

IMAGENET ResNet18

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SGD</td>
<td>69.5</td>
</tr>
<tr>
<td>SWA</td>
<td>70.3</td>
</tr>
<tr>
<td>SGDLp</td>
<td>63.4</td>
</tr>
<tr>
<td>SWALP</td>
<td>65.7</td>
</tr>
</tbody>
</table>
Experiments

**CIFAR100 VGG16**

- **SGD**: 72.8%
- **SWA**: 74.1%
- **SGDLP**: 70.4%
- **SWALP**: 73.3%

**IMAGENET ResNet18**

- **SGD**: 69.5%
- **SWA**: 70.3%
- **SGDLP**: 63.4%
- **SWALP**: 65.7%

**Results**

- **CIFAR100 VGG16**
  - 1.3
- **IMAGENET ResNet18**
  - 0.8
  - 2.3
Experiments

CIFAR100 VGG16

IMAGENET ResNet18

Accuracy (%)
Poster @ Pacific Ballroom #58

SWALP Codes

QPyTorch: A Low-Precision Framework