

Optimization for Deep Learning

Lecture 13-6: BlueFog Libraries

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BlueFog: An open-source and high-performance python library



https://github.com/Bluefog-Lib/bluefog

BlueFog



• An open-source library to support decentralized communication in optimization and deep learning

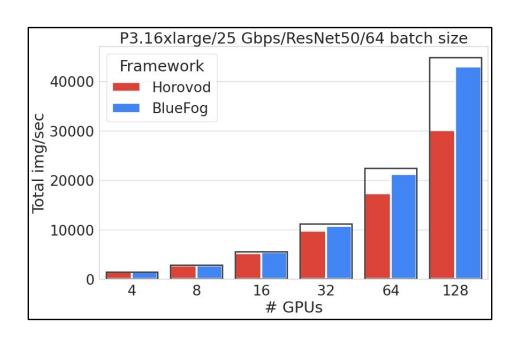
High-performance

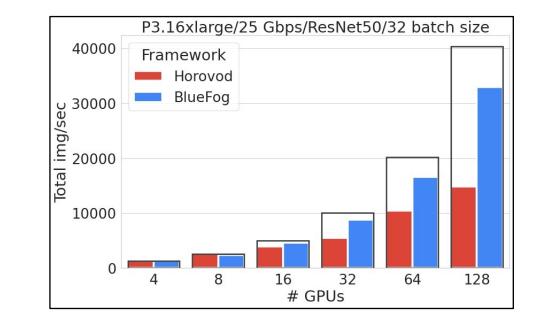
Easy-to-use

High-performance



BlueFog has larger throughput than Horovod (the SOTA DL system implementing PSGD) [YYH+21]





All our research progresses are involved in BlueFog

[YYH+21] B. Ying, K. Yuan, H. Hu, Y. Chen, and W. Yin, ``BlueFog: Make Decentralized Algorithms Practical for Optimization and machine learning", arXiv:2111.04287 [GitHub site: github.com/Bluefog-Lib/bluefog]

Easy-to-use



Writing codes for decentralized methods is as easy as writing equations

Decentralized least-square algorithms

$$y_i^{(k)} = x_i^{(k)} - \gamma A_i^T (A_i x_i^{(k)} - b_i)$$
$$x_i^{(k+1)} = \sum_{j \in \mathcal{N}_i} w_{ij} y_j^{(k)}$$

```
import bluefog.torch as bf

bf.init()  # Initialize the BlueFog

# Set topology as static exponential graph.

G = bf.ExponentialTwoGraph(bf.size())

bf.set_topology(G)

# DGD implementation

for ite in range(maxite):

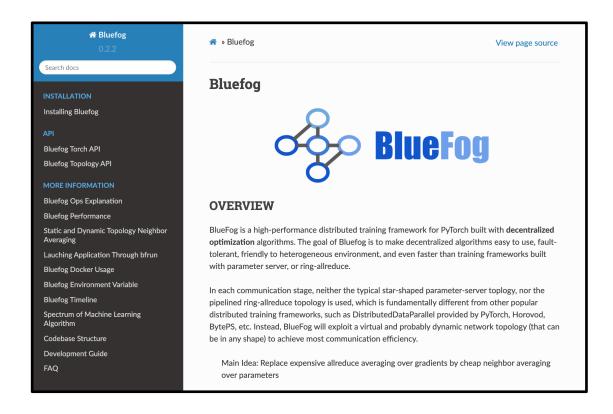
    grad_local = A.t().mm(A.mm(x) - b)  # compute local grad

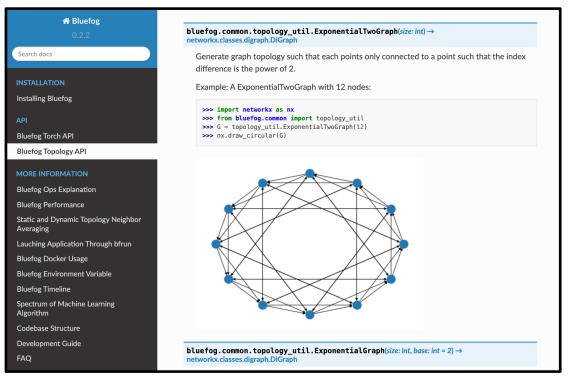
y = x - gamma * grad_local  # local update
x = bf.neighbor_allreduce(y)  # partial averaging
```

Easy-to-use



Abundant documents





Easy-to-use



Detailed tutorials

Contents

1 Preliminary

Learn how to write your first "hello world" program over the real multi-CPU system with BlueFog.

2 Average Consensus Algorithm

Learn how to achieve the globally averaged consensus among nodes in a decentralized manner.

3 Decentralized Gradient Descent

Learn how to solve a general distributed (possibly stochastic) optimization problem in a decentralized manner.

4 Decentralized Gradient Descent with Bias-Correction

Learn how to accelerate your decentralized (possibly stochastic) optimization algorithms with various biascorrection techniques.

5 Decentralized Optimization over directed and time-varying networks

Learn how to solve distributed optimization in a decentralized manner if the connected topology is directed or time-varying.

6 Asynchronous Decentralized Optimization

Learn how to solve a general distributed optimization problem with asynchronous decentralized algorithms.

7 Decentralized Deep Learning

Learn how to train a deep neural network with decentralized optimization algorithms.

2.1.3 Initialize BlueFog and test it

All contents in this section are displayed in Jupyter notebook, and all experimental examples are written with BlueFog and iParallel. Readers not familiar with how to run BlueFog in ipython notebook environment is encouraged to read Sec. [HelloWorld section] first. In the following codes, we will initialize BlueFog and test whether it works normally.

The output of rc.ids should be a list from 0 to the number of processes minus one. The number of processes is the one you set in the ibfrun start -np {X}.

```
import ipyparallel as ipp
rc = ipp.Client(profile="bluefog")
rc.ids
```

Let each agent import necessary modules and then initialize BlueFog. You should be able to see the printed information like:

[stdout:0] Hello, I am 1 among 4 processes

```
In [2]:
    typx
    import numpy as np
    import bluefog.torch as bf
    import torch
    from bluefog.common import topology_util
    import networkx as nx
    bf.init()
    print(f"Hello, I am {bf.rank()} among {bf.size()} processes")
```

Push seed to each agent so that the simulation can be reproduced.

```
dview = rc[:] # A DirectView of all engines
dview.block = True

# Push the data into all workers
# `dview.push({'seed': 2021}, block=True)`
# Or equivalently
dview["seed"] = 2021
```

After running the following code, you should be able to see the printed information like

[stdout:0] I received seed as value: 2021

Final summary



Decentralized algorithms save remarkable communication compared to centralized ones

• Sparse and effective topologies make decentralized optimization practical for deep training

• We propose static exponential, one-peer exponential, and one-peer EquiDyn and justify their superiority with strong theoretical and experimental evidences

• We introduced BlueFog to facilitate research and implementation of decentralized methods

References



L Ding, K Jin, B Ying, K Yuan, W Yin, DSGD-CECA: Decentralized SGD with Communication-Optimal Exact Consensus Algorithm, ICML 2023

Z. Song, W. Li, K. Jin, L. Shi, M. Yan, W. Yin, K. Yuan, Communication-efficient topologies for decentralized learning with O(1) consensus rate, NeurIPS 2022

B Ying, K Yuan, Y Chen, H Hu, P Pan, W Yin, Exponential Graph is Provably Efficient for Decentralized Deep Training, NeurlPS 2021

B Ying, K Yuan, H Hu, Y Chen, W Yin. BlueFog: Make decentralized algorithms practical for optimization and deep learning, arXiv:2111.04287, 2021



Thank you!

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BlueFog homepage: https://github.com/Bluefog-Lib/bluefog