Reproduce of ESync

Paper: ESync: Accelerating Intra-Domain Federated Learning in Heterogeneous Data Centers

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Date: 31th / October / 2024

Outline

Background of the paper

Scenario and Feature

- Cross-device FL & Cross-Silo FL
    - Bandwidth-limited **inter-domain** networks (cross WAN),
    - Isolated parties (scale at hundreds or thousands),
    - Uneven and non-i.i.d data distribution.
- Novel scenarios: **intra-domain FL** in heterogeneous data centers
    - Sufficient bandwidth,
    - Highly heterogeneous computing power.

Idea

Combining the ideas of existing either synchronous or asynchronous algorithms, the paper proposes the **ESync** algorithm.

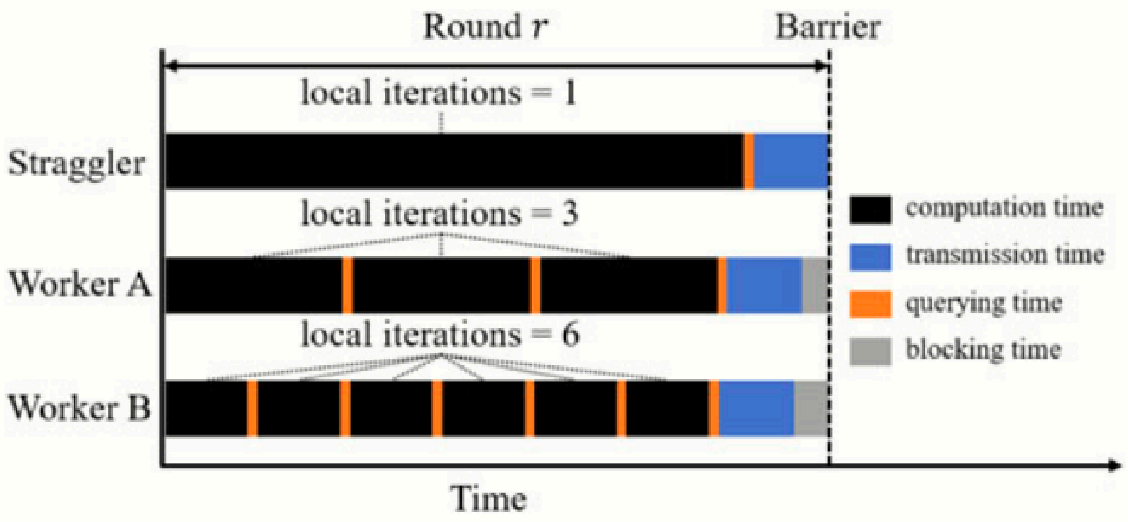


Fig. 7. ESync timeline with adaptive local iterations.

Visualization of the idea

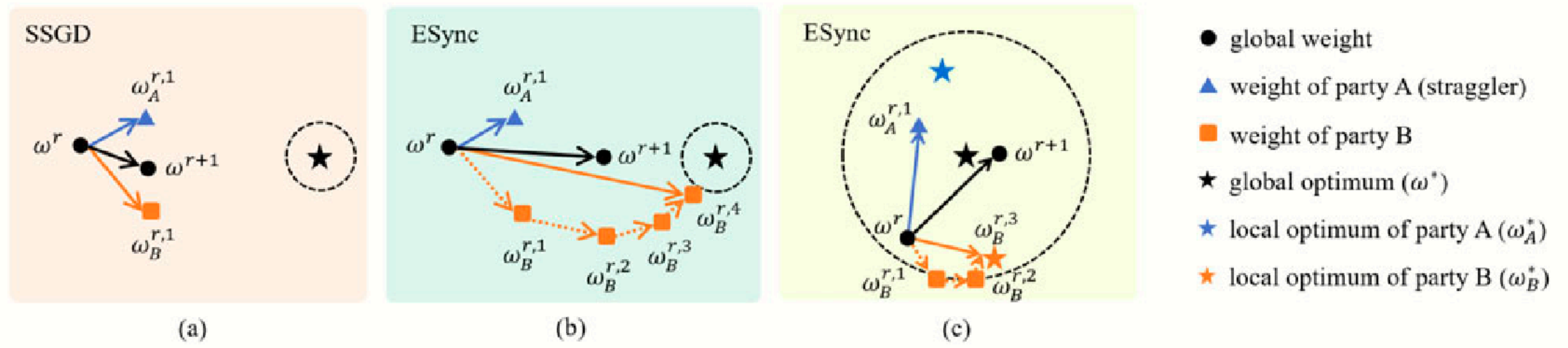


Fig. 6. Illustration of (a) SSGD and (b) ESync in the early training, and (c) ESync in the later training.

How to implement ESync?

- A novel **scheduler**.
- An efficient **synchronization algorithm** (based on SSGD).
- Analyze the **trade-off** between convergence accuracy and communication efficiency.

Architecture Design

Overview

- **State Server**: monitor the status and progress, coordinate the synchronization pace of all workers.
- **Parameter Server**: average the updates and synchronize the averaged updates to all workers.
- **Workers**: perform local updates and send their updates to the parameter server.

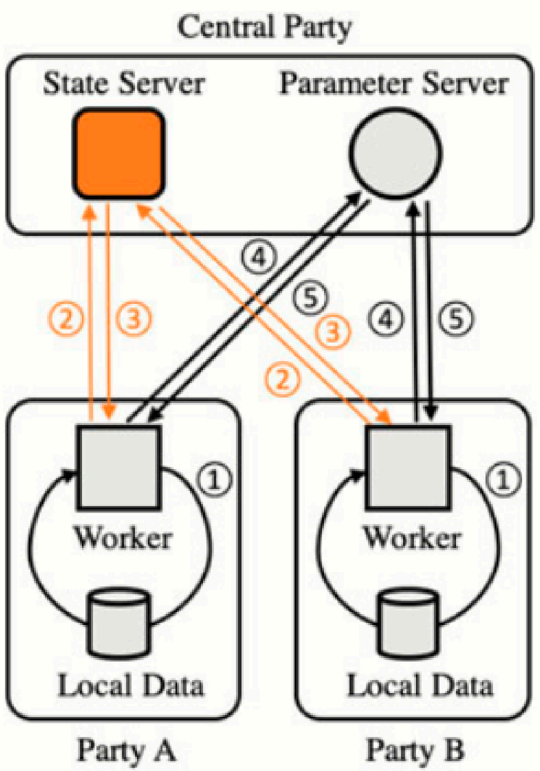


Fig. 2. Overview of the proposed architecture. ① The worker trains a local model on local data. ② The worker queries the next action from the state server. ③ The state server responds with the next action. ④ The worker pushes an update to the parameter server. ⑤ The worker pulls the averaged update from the parameter server.

State Server

State Server contains

- a **message receiver**, a **message sender**,
- a FIFO **message queue**,
  - buffer the received messages.
- a **message router**,
  - forward to the handlers according to `msg_type` field.
- a **state database**,
  - lock-free state table.
- and a set of **message handlers**.

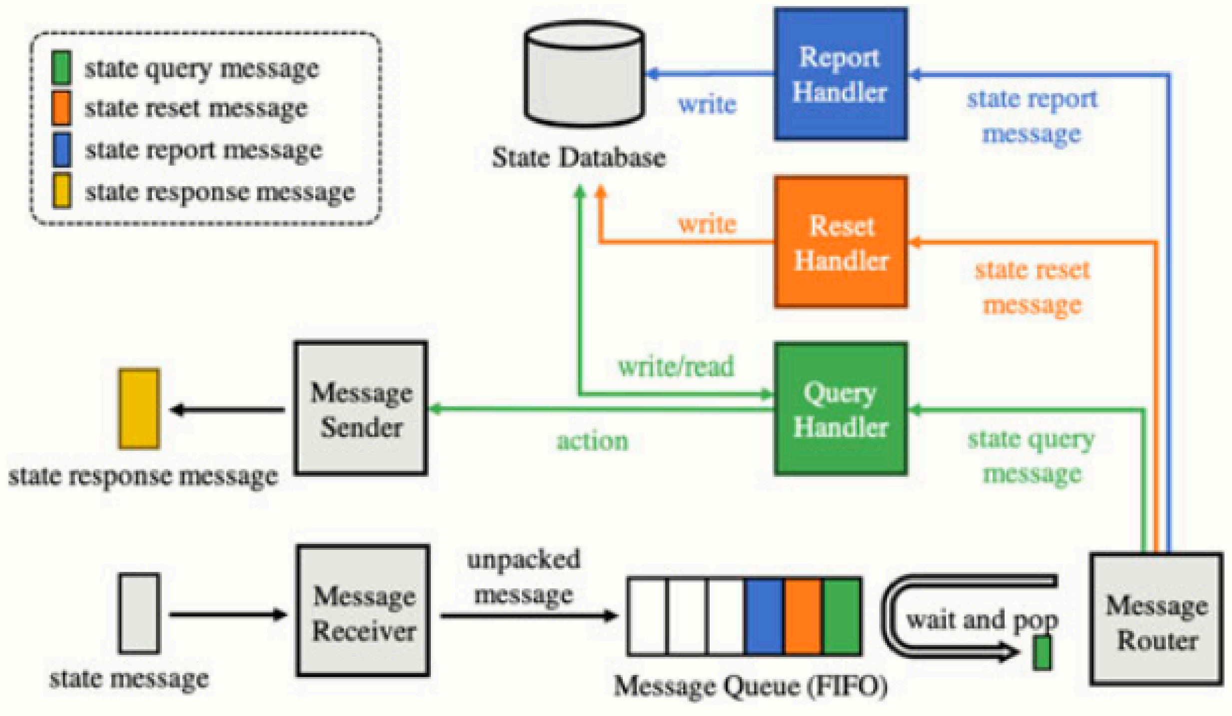


Fig. 3. Implementation of state server.

Message Format & Message Types

- **state reset message**: initiated by the Parameter Server, to initialize the records in the state database.
- ~ **report msg**: initiated by the worker to synchronize its status and progress to State Server.
- ~ **query msg**: initiated by the worker to query State Server for the next action.
- ~ **response msg**: used by State Server to inform the querying worker of the next action.

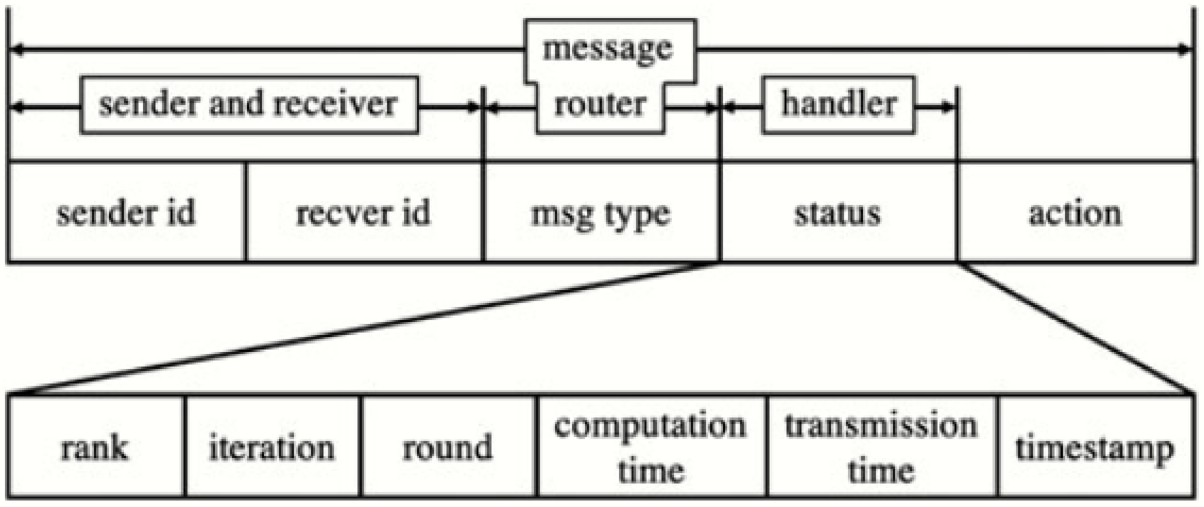


Fig. 4. The structure of message.

Algorithm Implementation

Project Overview

```
ESync-Reproduce
    |—— datasets/
    |—— images/
    |—— logs/
    |—— StateServer/
    |—— models/
    |—— trainer/
    |—— main.py, config.py, draw.py, summary.py, utils.py
```

Dataset Selection

```
ESync-Reproduce
     |——— data/
         |———FashionMNIST/, CIFAR10/, ...
     |——— output/
     |——— logs/
     |——— StateServer/
     |——— models/
     |——— trainer/
     |——— main.py, config.py, draw.py, summary.py, utils.py
```

We chose to test the performance of the **ESync** algorithm in image classification training. So, we use the FashionMNIST, CIFAR10 ,etc. datasets for experiments.

StateServer Implementation

```
|—— StateServer/
    |—— __init__.py
    |—— settings.py
    |—— urls.py # Django URL configuration file.
    |—— wsgi.py # Django Entry Point.
    |—— views.py # Core Functionality.
    |—— manage.py
```

In the `views.py`, we implement the core functionality of the StateServer.

- Global variables: `num_workers`, `records`, `t`, `epsilon`.
- Functions: `init_state_server(request)`, `find_stragglers()`, `apply_for_aggregation(request)`, `reset_state_server(request)`,

Models Implementation

```
|—— models/
    |—— alexnet.py
    |—— resnet.py
    |—— ...
```

Due to the limitation of time, we conducted experiments using only `alexnet` and `resnet` from existing frameworks, adapted for training in federated learning with these frameworks.

Hyperparameters for `resnet`:

- learning rate: 0.001, local lr: 0.001, global lr: 1.0,
- batch size: 64, evaluation duration: 1,
- state server ip: 172.17.73.161, state server port: 9091.

Trainer Implementation

```
|—— trainer/
    |—— esync_trainer.py
    |—— async_trainer.py
    |—— sync_trainer.py
    |—— local_trainer.py
```

Taking `esync_trainer.py` as example, it contains the implementation of a training process for a machine learning model in a distributed environment.

- Imports: `time`, `requests`, `mxnet`, `utils`.
- Variables: `local_lr`, `global_lr`, `batch_size`, etc.
- Training Loop: Batch Processing, Optimization, Global Synchronization.
- State Report, Response Handling, Evaluation(accuracy, loss, time).

Distributed Training

1. Start the StateServer.

```
python3 SimpleStateServer/manage.py runserver 0.0.0.0:10010
```

The state server will listen on port 10010 in the background to wait for the queries from workers.

2. Start the Schedulers.

```
> DMLC_ROLE=scheduler DMLC_PS_ROOT_URI=172.17.73.161 DMLC_PS_ROOT_PORT=9091 DMLC_NUM_SERVER=1 \
DMLC_NUM_WORKER=4 PS_VERBOSE=1 DMLC_INTERFACE=eth0 \
python3 main.py > scheduler.log &
```

Start the scheduler and listen on port 9091 to wait for the messages from workers.

3. Start the Servers.

```
> DMLC_ROLE=server DMLC_PS_ROOT_URI=172.17.73.161 DMLC_PS_ROOT_PORT=9091 DMLC_NUM_SERVER=1 \
 DMLC_NUM_WORKER=4 PS_VERBOSE=1 DMLC_INTERFACE=eth0 \
 python3 main.py > server.log &
```

The parameter server will create a TCP connection to the scheduler and complete registration automatically by specifying **DMLC_PS_ROOT_URI** and **DMLC_PS_ROOT_PORT** (the same as workers). The aggregation operations will be performed on GPU if **cpu** is set to *False*.

4. Start the Workers.

```
> DMLC_ROLE=worker DMLC_PS_ROOT_URI=172.17.73.161 DMLC_PS_ROOT_PORT=9091 DMLC_NUM_SERVER=1 \
DMLC_NUM_WORKER=4 PS_VERBOSE=1 DMLC_INTERFACE=eth0 \
 python3 main.py -m esync -g 0 -n resnet18-v1 -ll 0.001 -b 64 -dcasgd 0 -s 0
```

Dockerization

We provide a Dockerfile to build the image for the StateServer and the worker.

```
FROM python:3.6
COPY . .
RUN pip install -r requirements.txt
ENTRYPOINT ["python", "main.py",  "-dd", "./data/"]
CMD ["-m", "local", "-c", "1", "-e", "1000"]
```

```
tonyzhao@rupa:~/ESync-master$ sudo docker build . -t esync
[sudo] password for tonyzhao:
[+] Building 29.7s (8/8) FINISHED
 => [internal] load build definition from Dockerfile
 => => transferring dockerfile: 271B
 => [internal] load metadata for dockerproxy.net/library/python:3.6
 => [internal] load .dockerignore
 => => transferring context: 2B
 => [internal] load build context
 => => transferring context: 2.58kB
 => CACHED [1/3] FROM dockerproxy.net/library/python:3.6@sha256:f8652afaf88c25f0d22354d547d892591067aa4026a7fa9a6819df9f300af6fc
 => [2/3] COPY . .
 => [3/3] RUN pip install -r requirements.txt -i https://mirrors.sustech.edu.cn/pypi/web/simple
 => exporting to image
 => => exporting layers
 => => writing image sha256:0426194aed524b82aadca7c036f2e11951d1e8c0514556ed04d32008b2d079aa
 => => naming to docker.io/library/esync
```

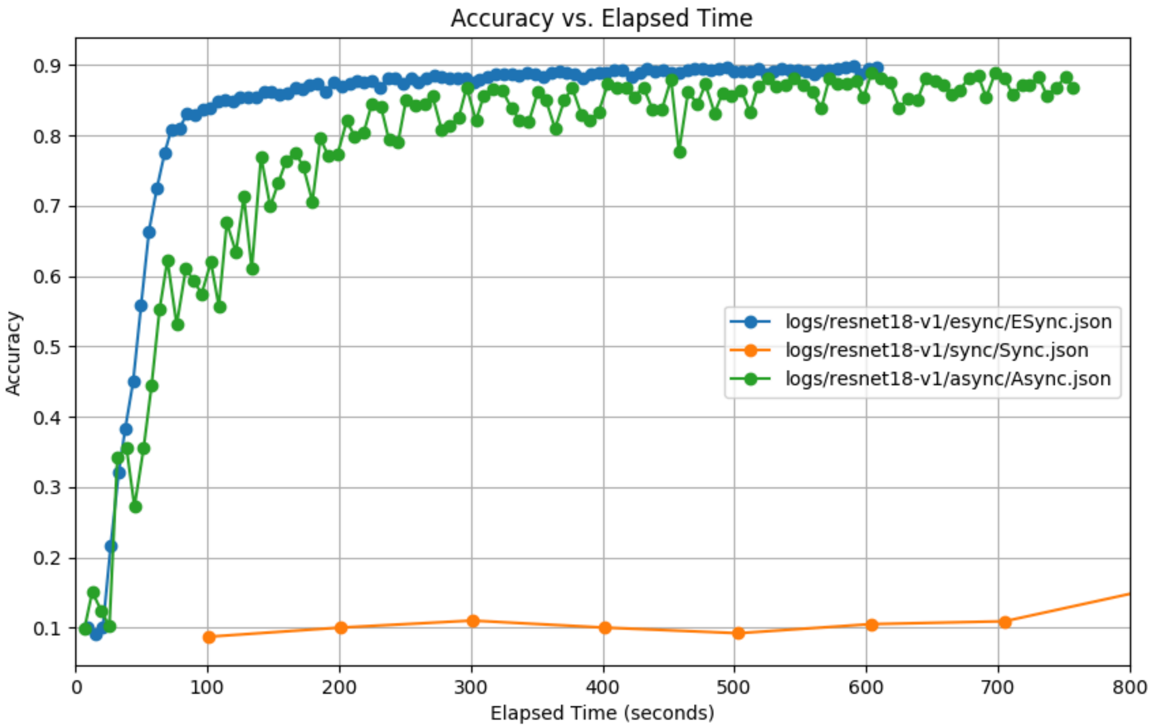
Experimental Evaluation

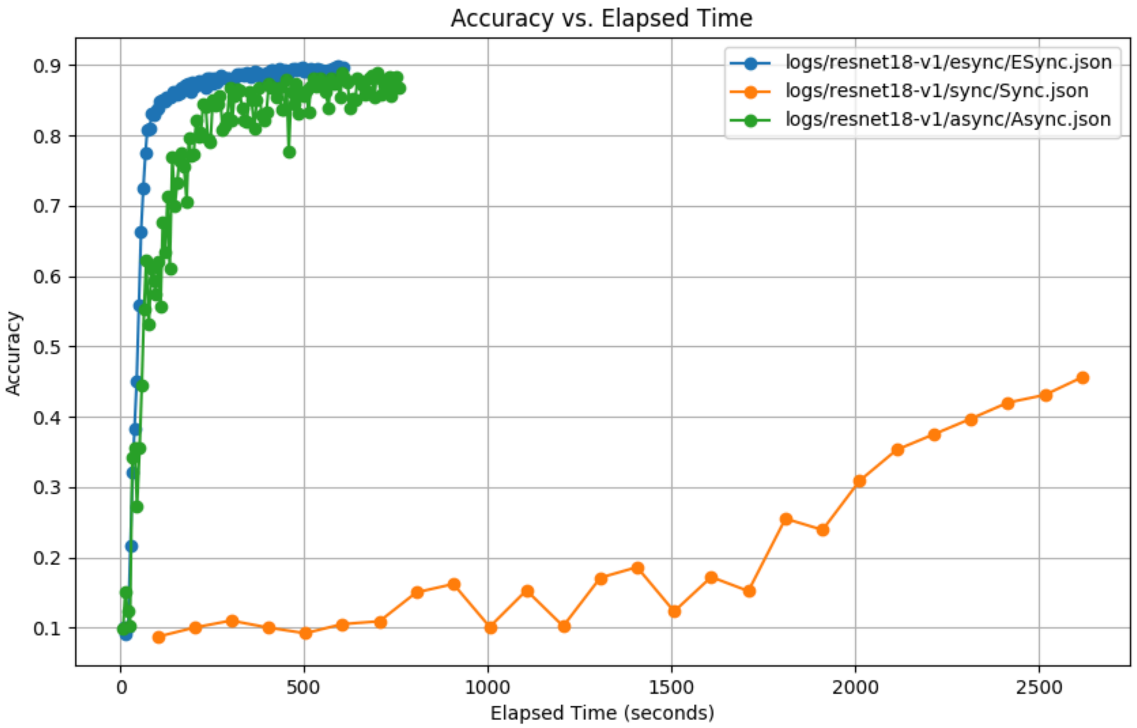
Experimental Setup

- **Environment Setup**:
- **Models and Datasets**: AlexNet, ResNet, CIFAR10, FashionMNist.
- **Benchmark Algorithms**: SSGD, ASGD.
- **Training Hyperparameters**: ...

配置
4核(vCPU) **8** GiB 5 Mbps ecs.e-c1m2.xlarge
2核(vCPU) **8** GiB 5 Mbps GPU： NVIDIA P4 ecs.gn5i-c2g1.large
2核(vCPU) **8** GiB 5 Mbps GPU： NVIDIA P4 ecs.gn5i-c2g1.large

Numerical Results





Thanks for your attention!