

Problem 2

We are going to experiment with PyTorch's DataParallel Module, which is PyTorch's Synchronous SGD implementation across a number of GPUs on the same server. In particular, we will train ResNet-18 implementation from <https://github.com/kuangliu/pytorch-cifar> with num workers=2, running up to 4 GPUs with DataParallel (DP) Module. Use SGD optimizers with 0.1 as the learning rate, momentum 0.9, weight decay 5e-4. For this question, you need to do experiment with multiple GPUs on the same server. You may need to execute this on NYU Greene Cluster.

Create a PyTorch program with a DataLoader that loads the images and the related labels from torchvision CIFAR10 dataset. Import CIFAR10 dataset for the torchvision package, with the following sequence of transformations:

- Random cropping, with size 32x32 and padding 4
- Random horizontal flipping with a probability 0.5
- Normalize each image's RGB channel with mean(0.4914, 0.4822, 0.4465) and variance (0.2023, 0.1994, 0.2010)

The DataLoader for the training set uses a minibatch size of 128 and 3 IO processes (i.e., num workers=2). The DataLoader for the testing set uses minibatch size of 100 and 3 IO processes (i.e., num workers =2). Create a main function that creates the DataLoaders for the training set and the neural network.

1

Measure how long does it take to complete 1 epoch of training using different batch size on a single GPU. Start from batch size 32, increase by 4-fold for each measurement (i.e., 32, 128, 512 ...) until single GPU memory cannot hold the batch size. For each run, run 2 epochs, the first epoch is used to warmup CPU/GPU cache; and you should report the training time (excluding data I/O; but including data movement from CPU to GPU, gradients calculation and weights update) based on the 2nd epoch training. (5)

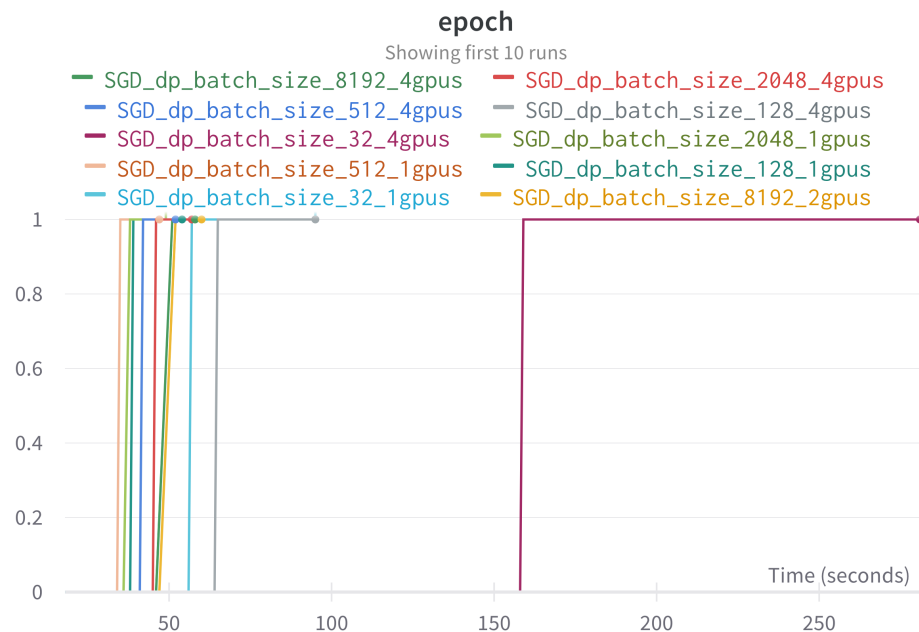
In []:

```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import torchvision.transforms as transforms
import torchvision.datasets as datasets

train_transform = transforms.Compose([transforms.RandomCrop(32, padding=4), #r
                                     transforms.RandomHorizontalFlip(0.5), #r
                                     transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010)), #r
                                     transforms.ToTensor(),]) #convert to ten
train_dataset = datasets.CIFAR10("./cached_datasets/CIFAR10", train=True, download=True)
train_dataloader = torch.utils.data.DataLoader(train_dataset, batch_size=128,
```

Files already downloaded and verified

Please refer to the code in problem2 folder



We use the straight line to calculate the time for each configuration.

```
In [ ]: import pandas as pd
data = pd.read_csv("./problem2/2_1.csv")
```

```
In [ ]: data
```

```
Out [ ]:   Relative Time (Wall)  SGD_dp_batch_size_8192_4gpus  SGD_dp_batch_size_8192_4gpus  SGD_dp_batch_
0      NaN                                           7.5                                           0
```

1 rows x 121 columns

```
In [ ]: import wandb
import pandas as pd
api = wandb.Api()

# Project is specified by <entity/project-name>
runs = api.runs("xiang-pan/NYU_DL_Sys-HW3_problem2")
summary_list = []
config_list = []
name_list = []
res = {}
for run in runs:
    data = run.history()
    log_name = run.name
    res[log_name] = data
```

```
In [ ]: res.keys()
```

```
Out [ ]: dict_keys(['SGD_dp_batch_size_512_2gpus', 'SGD_dp_batch_size_2048_2gpus', 'SGD_dp_batch_size_8192_4gpus', 'SGD_dp_batch_size_2048_4gpus', 'SGD_dp_batch_size_512_4gpus', 'SGD_dp_batch_size_128_4gpus', 'SGD_dp_batch_size_32_4gpus', 'SGD_dp_batch_size_8192_1gpus', 'SGD_dp_batch_size_2048_1gpus', 'SGD_dp_batch_size_512_1gpus', 'SGD_dp_batch_size_128_1gpus', 'SGD_dp_batch_size_32_1gpus', 'SGD_dp_batch_size_8192_2gpus'])
```

```
_512_1gpu', 'SGD_dp_batch_size_128_1gpu', 'SGD_dp_batch_size_32_1gpu', 'SGD_dp_batch_size_8192_2gpu', 'SGD_dp_batch_size_128_2gpu', 'SGD_dp_batch_size_32_2gpu']])
```

In []:

```
res
```

Out[]:

```
{'SGD_dp_batch_size_512_2gpu':      trainer/global_step  _step  _runtime  tra
in_loss_step  epoch  _timestamp  \
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1              1      1          19          2.769084      0  1649128381
2              2      2          19          3.562219      0  1649128381
3              3      3          19          3.776740      0  1649128381
4              4      4          19          3.318298      0  1649128381
..            ...      ...          ...          ...      ...      ...
193            192     193         37          1.172103      1  1649128399
194            193     194         37          1.230016      1  1649128399
195            194     195         37          1.342752      1  1649128399
196            195     196         37          1.132757      1  1649128399
197            195     197         38              NaN      2  1649128400
```

```
train_loss_epoch
0              NaN
1              NaN
2              NaN
3              NaN
4              NaN
..            ...
193            NaN
194            NaN
195            NaN
196            NaN
197            1.342205
```

```
[198 rows x 7 columns],
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in_loss_step  epoch  _timestamp  \
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1              1      1          20          2.558295      0  1649128132
2              2      2          20          2.766725      0  1649128132
3              3      3          20          3.660211      0  1649128132
4              4      4          21          4.084877      0  1649128133
5              5      5          21          3.603554      0  1649128133
6              6      6          21          3.600378      0  1649128133
7              7      7          21          3.024597      0  1649128133
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9              9      9          22          3.080903      0  1649128134
10             10     10          22          2.824992      0  1649128134
11             11     11          23          2.455785      0  1649128135
12             12     12          23          2.284315      0  1649128135
13             13     13          23          2.387378      0  1649128135
14             14     14          24          2.258087      0  1649128136
15             15     15          24          2.535852      0  1649128136
16             16     16          24          2.237878      0  1649128136
17             17     17          25          2.035352      0  1649128137
18             18     18          25          2.010104      0  1649128137
19             19     19          25          2.214593      0  1649128137
20             20     20          26          2.089128      0  1649128138
21             21     21          26          1.944005      0  1649128138
22             22     22          26          1.937898      0  1649128138
23             23     23          27          2.004253      0  1649128139
24             24     24          28          2.022934      0  1649128140
25             24     25          28              NaN      1  1649128140
26             25     26          30          1.917986      1  1649128142
```

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36	35	36	33	1.775432	1	1649128145
37	36	37	33	1.822025	1	1649128145
38	37	38	34	1.789850	1	1649128146
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	train_loss_epoch
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35	NaN
36	NaN

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42          NaN
43          NaN
44          NaN
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47          NaN
48          NaN
49          NaN
50          NaN
51          1.76056 ,
'SGD_dp_batch_size_8192_4gpus': trainer/global_step _step _runtime tra
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1          1          1          41          2.618182          0 1648372569
2          2          2          41          2.409632          0 1648372569
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4          4          4          42          2.854592          0 1648372570
5          5          5          44          4.384065          0 1648372572
6          6          6          46          4.012147          0 1648372574
7          6          7          46          NaN          1 1648372574
8          7          8          51          3.435173          1 1648372579
9          8          9          52          3.664042          1 1648372580
10         9         10          54          3.144501          1 1648372582
11        10        11          54          3.195889          1 1648372582
12        11        12          57          3.081101          1 1648372585
13        12        13          58          2.827945          1 1648372586
14        13        14          58          2.607582          1 1648372586
15        13        15          58          NaN          2 1648372586

train_loss_epoch
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5          NaN
6          NaN
7          2.660240
8          NaN
9          NaN
10         NaN
11         NaN
12         NaN
13         NaN
14         NaN
15          3.263868 ,
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in_loss_step epoch _timestamp \
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1          1          1          36          2.400140          0 1648372483
2          2          2          36          2.707777          0 1648372483
3          3          3          36          3.673821          0 1648372483
4          4          4          36          4.163005          0 1648372483
5          5          5          36          5.222578          0 1648372483
6          6          6          37          4.147680          0 1648372484
7          7          7          37          3.306381          0 1648372484
8          8          8          38          4.035182          0 1648372485
9          9          9          38          2.886489          0 1648372485
10         10         10          39          2.878854          0 1648372486

```

11	11	11	39	3.682711	0	1648372486
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15	15	15	40	3.169637	0	1648372487
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19	19	19	42	2.655234	0	1648372489
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21	21	21	43	2.510918	0	1648372490
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train_loss_epoch	
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19	NaN
20	NaN

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21          NaN
22          NaN
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24          NaN
25      3.039449
26          NaN
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29          NaN
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2          2          2          31          3.141139          0 1648372406
3          3          3          31          4.203696          0 1648372406
4          4          4          31          4.988063          0 1648372406
..          ...          ...          ...          ...          ...
193          192          193          51          1.580170          1 1648372426
194          193          194          51          1.535819          1 1648372426
195          194          195          52          1.507741          1 1648372427
196          195          196          52          1.734261          1 1648372427
197          195          197          52          NaN          2 1648372427

      train_loss_epoch
0          NaN
1          NaN
2          NaN
3          NaN
4          NaN
..          ...
193          NaN
194          NaN
195          NaN
196          NaN
197      1.64051

[198 rows x 7 columns],
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in_loss_step epoch _timestamp \
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1          1          1          34          3.187948          0 1648372290
2          2          2          34          3.783150          0 1648372290

```

3	3	3	34	4.302678	0	1648372290
4	4	4	34	8.475398	0	1648372290
..
517	774	775	94	1.817231	1	1648372350
518	775	776	94	1.216002	1	1648372350
519	779	780	95	1.199796	1	1648372351
520	780	781	95	1.388824	1	1648372351
521	781	783	95	NaN	2	1648372351

train_loss_epoch	
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
..	...
517	NaN
518	NaN
519	NaN
520	NaN
521	1.463055

```
[522 rows x 7 columns],
'SGD_dp_batch_size_32_4gpus':
```

n_loss_step	epoch	_timestamp	trainer/global_step	_step	_runtime	train
0	12	12	38	4.564947	0	1648371922
1	44	44	40	2.453320	0	1648371924
2	46	46	40	2.263949	0	1648371924
3	54	54	41	2.240820	0	1648371925
4	66	66	42	2.397463	0	1648371926
..
485	3089	3090	278	1.161531	1	1648372162
486	3093	3094	278	0.834570	1	1648372162
487	3098	3099	279	0.499158	1	1648372163
488	3114	3115	280	2.188230	1	1648372164
489	3118	3119	280	0.931003	1	1648372164

```
[490 rows x 6 columns],
'SGD_dp_batch_size_8192_1gpus': Empty DataFrame
Columns: []
Index: [],
'SGD_dp_batch_size_2048_1gpus':
```

in_loss_step	epoch	_timestamp	trainer/global_step	_step	_runtime	train
0	0	0	23	2.378599	0	1648371712
1	1	1	24	2.419253	0	1648371713
2	2	2	24	2.778703	0	1648371713
3	3	3	25	3.354625	0	1648371714
4	4	4	25	4.705425	0	1648371714
5	5	5	26	5.723037	0	1648371715
6	6	6	26	6.090533	0	1648371715
7	7	7	27	6.604627	0	1648371716
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9	9	9	28	8.495030	0	1648371717
10	10	10	28	7.792514	0	1648371717
11	11	11	29	6.351874	0	1648371718
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13	13	13	30	3.963925	0	1648371719
14	14	14	30	6.134727	0	1648371719
15	15	15	31	5.324747	0	1648371720
16	16	16	31	4.129182	0	1648371720
17	17	17	32	3.113030	0	1648371721
18	18	18	32	3.248461	0	1648371721
19	19	19	32	2.751126	0	1648371721
20	20	20	33	2.790308	0	1648371722

21	21	21	33	2.772371	0	1648371722
22	22	22	34	2.586316	0	1648371723
23	23	23	34	2.596285	0	1648371723
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25	24	25	36	NaN	1	1648371725
26	25	26	38	2.522918	1	1648371727
27	26	27	39	2.351709	1	1648371728
28	27	28	39	2.585978	1	1648371728
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31	30	31	41	2.326970	1	1648371730
32	31	32	41	2.376224	1	1648371730
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34	33	34	42	2.323020	1	1648371731
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36	35	36	43	2.282800	1	1648371732
37	36	37	43	2.251382	1	1648371732
38	37	38	44	2.217711	1	1648371733
39	38	39	44	2.229835	1	1648371733
40	39	40	45	2.261669	1	1648371734
41	40	41	45	2.194469	1	1648371734
42	41	42	46	2.201263	1	1648371735
43	42	43	46	2.248072	1	1648371735
44	43	44	47	2.173002	1	1648371736
45	44	45	47	2.177445	1	1648371736
46	45	46	48	2.208236	1	1648371737
47	46	47	48	2.183602	1	1648371737
48	47	48	49	2.229931	1	1648371738
49	48	49	49	2.221301	1	1648371738
50	49	50	49	2.225251	1	1648371738
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	train_loss_epoch
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2	NaN
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31          NaN
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4              4      4          21          5.095662      0  1648371678
..            ...      ...          ...            ...      ...
193           192     193          46          1.473887      1  1648371703
194           193     194          47          1.604234      1  1648371704
195           194     195          47          1.577804      1  1648371704
196           195     196          47          1.381406      1  1648371704
197           195     197          47              NaN      2  1648371704

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3              NaN
4              NaN
..            ...
193           NaN
194           NaN
195           NaN
196           NaN
197           1.619874

[198 rows x 7 columns],
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0              1      1          21          3.322361      0  1648371640
1              4      4          21          5.161662      0  1648371640
2              5      5          21          5.269036      0  1648371640
3              9      9          22          3.224431      0  1648371641
4             10     10          22          2.732107      0  1648371641
..            ...      ...          ...            ...      ...
502           776     777          54          1.222841      1  1648371673
503           777     778          54          1.118677      1  1648371673
504           778     779          54          1.203329      1  1648371673
505           780     781          54          1.263283      1  1648371673
506           781     783          54              NaN      2  1648371673

      train_loss_epoch

```

0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
..	...
502	NaN
503	NaN
504	NaN
505	NaN
506	1.468338

```
[507 rows x 7 columns],
'SGD_dp_batch_size_32_1gpu':
```

n_loss_step	epoch	_timestamp	trainer/global_step	_step	_runtime	train_loss
0	14	14	18	5.188556	0	1648371592
1	17	17	18	3.954767	0	1648371592
2	25	25	18	3.013579	0	1648371592
3	35	35	18	3.005083	0	1648371592
4	38	38	18	2.163107	0	1648371592
..
491	3086	3087	94	1.174098	1	1648371668
492	3090	3091	95	1.645498	1	1648371669
493	3097	3098	95	1.174476	1	1648371669
494	3098	3099	95	1.003709	1	1648371669
495	3105	3106	95	1.125607	1	1648371669

```
[496 rows x 6 columns],
'SGD_dp_batch_size_8192_2gpu':
```

in_loss_step	epoch	_timestamp	trainer/global_step	_step	_runtime	train_loss
0	0	0	39	2.343246	0	1648371067
1	1	1	40	2.417241	0	1648371068
2	2	2	41	2.485400	0	1648371069
3	3	3	42	2.576402	0	1648371070
4	4	4	43	3.028359	0	1648371071
5	5	5	44	3.302346	0	1648371072
6	6	6	47	4.070184	0	1648371075
7	6	7	47	NaN	1	1648371075
8	7	8	52	4.775397	1	1648371080
9	8	9	53	4.856526	1	1648371081
10	9	10	55	4.949286	1	1648371083
11	10	11	56	4.184242	1	1648371084
12	11	12	59	3.392799	1	1648371087
13	12	13	60	2.816032	1	1648371088
14	13	14	60	2.903746	1	1648371088
15	13	15	60	NaN	2	1648371088

```
train_loss_epoch
```

0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
5	NaN
6	NaN
7	2.721693
8	NaN
9	NaN
10	NaN
11	NaN
12	NaN
13	NaN
14	NaN
15	4.130736

'SGD_dp_batch_size_128_2gpus':				trainer/global_step	_step	_runtime	trai
n_loss_step	epoch	_timestamp	\				
0	49	0		29	2.181488	0	1648370297
1	99	1		32	2.085283	0	1648370300
2	149	2		34	1.959760	0	1648370302
3	199	3		37	1.864811	0	1648370305
4	249	4		39	1.824337	0	1648370307
5	299	5		42	1.748104	0	1648370310
6	349	6		44	1.689489	0	1648370312
7	390	7		47	NaN	1	1648370315
8	399	8		48	1.787462	1	1648370316
9	449	9		50	1.464020	1	1648370318
10	499	10		53	1.419646	1	1648370321
11	549	11		55	1.453597	1	1648370323
12	599	12		58	1.254473	1	1648370326
13	649	13		60	1.219815	1	1648370328
14	699	14		63	1.319156	1	1648370331
15	749	15		65	1.492566	1	1648370333
16	781	16		67	NaN	2	1648370335

train_loss_epoch

0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
5	NaN
6	NaN
7	1.987961
8	NaN
9	NaN
10	NaN
11	NaN
12	NaN
13	NaN
14	NaN
15	NaN
16	1.462412 ,

'SGD_dp_batch_size_32_2gpus':				trainer/global_step	_step	_runtime	train
_loss_step	epoch	_timestamp	\				
0	49	0		24	3.000532	0	1648370289
1	99	1		27	3.825331	0	1648370292
2	149	2		29	2.502269	0	1648370294
3	199	3		31	2.015135	0	1648370296
4	249	4		33	1.945419	0	1648370298
..
59	2949	59		153	1.278652	1	1648370418
60	2999	60		155	2.211522	1	1648370420
61	3049	61		157	1.409628	1	1648370422
62	3099	62		159	1.205655	1	1648370424
63	3125	63		161	NaN	2	1648370426

train_loss_epoch

0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
..	...
59	NaN
60	NaN
61	NaN
62	NaN
63	1.50301

```
[64 rows x 7 columns]}
```

```
In [ ]: def get_info(log_name):
        gpu_nums = log_name.split('_')[-1]
        batch_size = log_name.split('_')[-2]
        batch_size = int(batch_size)
        gpu_nums = gpu_nums.replace('gpus', '')
        gpu_nums = int(gpu_nums)
        return gpu_nums, batch_size

        def get_time_info(log_name):
            data = res[log_name]
            epoch_1_start_time = data[data["epoch"] == 1].iloc[0]["_timestamp"]
            epoch_1_end_time = data[data["epoch"] == 1].iloc[-1]["_timestamp"]
            t = epoch_1_end_time - epoch_1_start_time
            return t
        get_time_info("SGD_dp_batch_size_8192_4gpus")
```

```
Out[ ]: 12.0
```

batch_size = 8192 can not work in my gpu.

```
In [ ]: df = pd.DataFrame(columns=['gpu_nums', 'batch_size', 'time'])
        for key in res.keys():
            # print(key)
            if "8192" in key:
                continue
            gpu_nums, batch_size = get_info(key)
            t = get_time_info(key)
            df.loc[len(df)] = [gpu_nums, batch_size, t]
        df.sort_values(by=['gpu_nums', 'batch_size'], ascending=True, inplace=True)
        df["gpu_nums"] = df["gpu_nums"].astype(int)
        df["batch_size"] = df["batch_size"].astype(int)
        df.reset_index(inplace=True, drop=True)
```

```
In [ ]: df.to_markdown("problem2/2_1_table_src.md")
```

```
In [ ]: df
```

```
Out[ ]:
```

	gpu_nums	batch_size	time
0	1	32	38.0
1	1	128	16.0
2	1	512	13.0
3	1	2048	13.0
4	2	32	67.0
5	2	128	18.0
6	2	512	9.0
7	2	2048	10.0
8	4	32	121.0
9	4	128	30.0

	gpu_nums	batch_size	time
10	4	512	11.0
11	4	2048	11.0

```
In [ ]: t = df[df["batch_size"] == 32]
t["speedup"] = t["time"].iloc[0]/t["time"]
t
```

/tmp/ipykernel_768624/1156332872.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
t["speedup"] = t["time"].iloc[0]/t["time"] * t["gpu_nums"]
```

```
Out[ ]:   gpu_nums  batch_size  time  speedup
0         1           32   38.0  1.000000
4         2           32   67.0  1.134328
8         4           32  121.0  1.256198
```

```
In [ ]: t = df[df["batch_size"] == 128]
t["speedup"] = t["time"].iloc[0]/t["time"]
t
```

/tmp/ipykernel_768624/3464596280.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
t["speedup"] = t["time"].iloc[0]/t["time"]
```

```
Out[ ]:   gpu_nums  batch_size  time  speedup
1         1          128   16.0  1.000000
5         2          128   18.0  0.888889
9         4          128   30.0  0.533333
```

```
In [ ]: t = df[df["batch_size"] == 512]
t["speedup"] = t["time"].iloc[0]/t["time"]
t
```

/tmp/ipykernel_768624/3178531423.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
t["speedup"] = t["time"].iloc[0]/t["time"]
```

```
Out[ ]:   gpu_nums  batch_size  time  speedup
2         1          512   13.0  1.000000
```

	gpu_nums	batch_size	time	speedup
6	2	512	9.0	1.444444
10	4	512	11.0	1.181818

In []:

```
t = df[df["batch_size"] == 2048]
t["speedup"] = t["time"].iloc[0]/t["time"]
t
```

/tmp/ipykernel_768624/2197254454.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
t["speedup"] = t["time"].iloc[0]/t["time"]
```

Out []:

	gpu_nums	batch_size	time	speedup
3	1	2048	13.0	1.000000
7	2	2048	10.0	1.300000
11	4	2048	11.0	1.181818

In []:

```
l = []
for b in [32, 128, 512, 2048]:
    t = df[df["batch_size"] == b]
    t["speedup"] = t["time"].iloc[0]/t["time"]
    t.to_markdown(f"problem2/2_1_table_src_{b}.md")
    l.append(t)
l = pd.concat(l)
```

/tmp/ipykernel_768624/2183533066.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
t["speedup"] = t["time"].iloc[0]/t["time"]
```

In []:

```
1
```

Out []:

	gpu_nums	batch_size	time	speedup
0	1	32	38.0	1.000000
4	2	32	67.0	0.567164
8	4	32	121.0	0.314050
1	1	128	16.0	1.000000
5	2	128	18.0	0.888889
9	4	128	30.0	0.533333
2	1	512	13.0	1.000000
6	2	512	9.0	1.444444
10	4	512	11.0	1.181818

	gpu_nums	batch_size	time	speedup
3	1	2048	13.0	1.000000
7	2	2048	10.0	1.300000
11	4	2048	11.0	1.181818

```
In [ ]: l[l["batch_size"] == b]
```

```
Out [ ]:
```

	gpu_nums	batch_size	time	speedup
3	1	2048	13.0	1.000000
7	2	2048	10.0	1.300000
11	4	2048	11.0	1.181818

```
In [ ]: # pd.set_option('max_columns',1000)
cols = []
cols.append("gpu_nums")
for b in [32, 128, 512, 2048]:
    cols.append(f"batch_{b}_time")
    cols.append(f"batch_{b}_speedup")
# print(cols)
df = pd.DataFrame(columns=cols)
for g in [1, 2, 4]:
    temp_df = pd.DataFrame(columns=cols)
    temp_df["gpu_nums"] = [g]
    for b in [32, 128, 512, 2048]:
        t = l[l["batch_size"] == b]
        t = t[t["gpu_nums"] == g]
        temp_df[f"batch_{b}_time"] = t["time"].values
        temp_df[f"batch_{b}_speedup"] = t["speedup"].values
    df = pd.concat([df, temp_df])
df.reset_index(inplace=True, drop=True)
df
```

```
Out [ ]:
```

	gpu_nums	batch_32_time	batch_32_speedup	batch_128_time	batch_128_speedup	batch
0	1	38.0	1.000000	16.0	1.000000	
1	2	67.0	0.567164	18.0	0.888889	
2	4	121.0	0.314050	30.0	0.533333	

```
In [ ]: df.to_markdown("problem2/2_1_table_src_all.md")
df.to_csv("problem2/2_1_table_src_all.csv", index=False)
```

That speed up we use $T = \text{epoch_time}$, $T(1) / T(N)$.

According to the [campuswire](#), we are suggested to use $N * T(1) / T(N)$. But the not sure the T definition here.

To clarify, we use $t = \text{batch_time}$ and $T = \text{epoch_time}$.

We can calculate using $n * t(1) / t(N)$ if we would like to use the same problem size.

$\text{Speedup} = T(1) / T(N) = n * t(1) / t(N)$, T is the epoch time, t is the batch time.

	gpu_nums	batch_32_time	batch_32_speedup	batch_128_time	batch_128_speedup	batch_
0	1	38	1	16	1	
1	2	67	0.567164	18	0.888889	
2	4	121	0.31405	30	0.533333	

If we use the $N * T(1) / T(N)$ definition, we can get the following result:

In []:

```
new_df = df.copy(deep=True)

for b in [32, 128, 512, 2048]:
    new_df[f"batch_{b}_speedup"] = new_df[f"batch_{b}_time"] * new_df["gpu_"]
new_df
```

Out[]:

	gpu_nums	batch_32_time	batch_32_speedup	batch_128_time	batch_128_speedup	batch_
0	1	38.0	1.0	16.0	1.0	
1	2	67.0	1.134328	18.0	1.777778	
2	4	121.0	1.256198	30.0	2.133333	

2

Report for each batch size per gpu (i.e., 32, 128, 512 ...), how much time spent in computation (including CPU-GPU transferring and calculation) and how much time spent in communication in 2-GPU and 4-GPU case for one epoch. (hint You could use the training time reported in Question 1 to facilitate your calculation). (5) Expected Answer: First, describe how do you get the compute and communication time in each setup. Second, list compute and communication time in Table 2.

Comment

Expected Answer: Table 1 records the training time and speedup for different batch size up to 4 GPUs. Comment on which type of scaling we are measuring: weak-scaling or strong-scaling? Comment on if the other type scaling was used speedup number will be better or worse than what you we are measuring.

If we follow the definition, T is the epoch time, and we use $T(1) / T(N)$ to calculate the speedup, the we use the stong-scaling (Strong scaling concerns the speedup for a fixed problem size with respect to the number of processors, and is governed by Amdahl's law) to measure the speedup, because we measure the epoch time, and the problem size for one epoch is fixed.

$$\text{Speedup} = 1/(s + p/N), \quad (1)$$

s is the serial part, p is the parallel part, N is the number of processors.

$$\text{Speedup} = T(1)/T(N) \quad (2)$$

If we use the weak-scaling (Weak scaling concerns the speedup for a scaled problem size with respect to the number of processors, and is governed by Gustafson's law.) to measure

the speedup.

$$\text{Speedup} = s + p * N \quad (3)$$

$$\text{Speedup} = N * T(1) / T(N) \quad (4)$$

Considering the larger problem size will be more efficient for more processors, if we use the weak-scaling to measure the speedup, we will get a better speedup efficiency.

Suggested Definition

If we use the $N * T(1) / T(N)$ definition, T is the epoch time, then we are using the weak-scaling to measure the speedup, because we vary the problem size with respect to the number of processors.

Then if we use another definition (strong scaling), the score will be worse.

3

Report for each batch size per gpu (i.e., 32, 128, 512 ...), how much time spent in computation (including CPU-GPU transferring and calculation) and how much time spent in communication in 2-GPU and 4-GPU case for one epoch. (hint You could use the training time reported in Question 1 to facilitate your calculation). (5) Expected Answer: First, describe how do you get the compute and communication time in each setup. Second, list compute and communication time in Table 2.

For one gpu, we consider all the time is used for computation (including CPU-GPU transferring and calculation).

For two gpus or four gpus, the iteration number for each gpu is reduced, thus the computation time is reduced half of the original time, the communication time is the difference between the actual time and the reduced computation time.

```
In [ ]: df = pd.read_csv("problem2/2_1_table_src_all.csv")
cal_col = []
for b in [32, 128, 512, 2048]:
    df.drop(columns=[f"batch_{b}_speedup"], inplace=True)
    cal_col.append(f"batch_{b}_time")
```

```
In [ ]: df
```

```
Out [ ]:
```

	gpu_nums	batch_32_time	batch_128_time	batch_512_time	batch_2048_time
0	1	38.0	16.0	13.0	13.0
1	2	67.0	18.0	9.0	10.0
2	4	121.0	30.0	11.0	11.0

```
In [ ]: communication_col = []
calculation_col = []
for b in [32, 128, 512, 2048]:
    communication_col.append(f"batch_{b}_communication_time")
    calculation_col.append(f"batch_{b}_calculation_time")
```

```
In [ ]: # df["calculation_time"]
communication_time = []
calculation_time = []
for g in [1, 2, 4]:
    if g == 1:
        temp_df = df[df["gpu_nums"] == g]
        temp_df = temp_df[cal_col].to_numpy()[0]
        base_df = temp_df
        communication_time.append(temp_df-temp_df)
        calculation_time.append(base_df)
        continue
    temp_df = df[df["gpu_nums"] == g]
    temp_df = temp_df[cal_col].to_numpy()[0]
    calculation_time.append(base_df / g)
    res_df = temp_df - base_df / g
    communication_time.append(res_df)
df[communication_col] = communication_time
df[calculation_col] = calculation_time
```

```
In [ ]: df
```

```
Out [ ]:
```

	gpu_nums	batch_32_time	batch_32_speedup	batch_128_time	batch_128_speedup	batch
0	1	38.0	1.000000	16.0	1.000000	
1	2	67.0	0.567164	18.0	0.888889	
2	4	121.0	0.314050	30.0	0.533333	

```
In [ ]: df.to_csv('./problem2/2_3.csv', index=False)
df.to_markdown('./problem2/2_3.md')
```

```
In [ ]: display_cols = ["gpu_nums"] + communication_col
df[display_cols]
```

```
Out [ ]:
```

	gpu_nums	batch_32_communication_time	batch_128_communication_time	batch_512_com
0	1	0.0	0.0	
1	2	48.0	10.0	
2	4	111.5	26.0	

```
In [ ]: display_cols = ["gpu_nums"] + calculation_col
df[display_cols]
```

```
Out [ ]:
```

	gpu_nums	batch_32_calculation_time	batch_128_calculation_time	batch_512_calculation_ti
0	1	38.0	16.0	13
1	2	19.0	8.0	6
2	4	9.5	4.0	3

4

Assume PyTorch DP implements the all-reduce algorithm as discussed in the class (reference below), calculate communication bandwidth utilization for each multi-gpu/batch-size-per-gpu setup. (5) Expected Answer: First, list the formula to calculate how long does it take to finish an allreduce. Second, list the formula to calculate the bandwidth utilization. Third, list the calculated results in Table 3.

References:

- PyTorch Data Parallel, Available at https://pytorch.org/docs/stable/modules/torch/nn/parallel/data_parallel.html.
- Bringing HPC Techniques to Deep Learning

Comment

We calculate the all-reduce (ring-allreduce).

P: number of processes

N: total number of model parameters

Scatter-reduce: Each process sends N/P amount of data to $(P-1)$ learners, Total amount sent (per process): $N(P-1)/P$

AllGather: Each process again sends N/P amount of data to $(P-1)$ learners

Total communication cost per process is $2N(P-1)/P$

Batch-size-per-GPU 32	Batch-size-per-GPU 128	Batch-size-per-GPU 512
Bandwidth Utilization(GB/s)	Bandwidth Utilization(GB/s)	Bandwidth Utilization(GB/s)
2-GPU		
4-GPU		

We use the ResNet18 architecture to calculate the bandwidth utilization.

```
In [ ]: from models.resnet import ResNet18
import numpy as np

model = ResNet18()

# calculate model parameters size
model_parameters = filter(lambda p: p.requires_grad, model.parameters())
params_count = sum([np.prod(p.size()) for p in model_parameters])
print(f"Model parameters: {params_count}, {params_count/1e6}M")

N = params_count
```

Model parameters: 11173962, 11.173962M

```
In [ ]: import torch
import torch.nn as nn
import torch.nn.functional as F
```

```

import torch.optim as optim
import torchvision.transforms as transforms
import torchvision.datasets as datasets

train_transform = transforms.Compose([transforms.RandomCrop(32, padding=4), #r
                                     transforms.RandomHorizontalFlip(0.5), #r
                                     transforms.Normalize((0.4914, 0.4822, 0
                                     transforms.ToTensor(),)]#convert to ten
train_dataset = datasets.CIFAR10("./cached_datasets/CIFAR10", train=True, dow
train_dataloader = torch.utils.data.DataLoader(train_dataset, batch_size=128,
dataset_size = len(train_dataset))

```

Files already downloaded and verified

In []:

```
df
```

```
Out[ ]:
```

	gpu_nums	batch_32_time	batch_128_time	batch_512_time	batch_2048_time	batch_32_c
0	1	38.0	16.0	13.0	13.0	
1	2	67.0	18.0	9.0	10.0	
2	4	121.0	30.0	11.0	11.0	

In []:

```

bandwidth_cols = []
communication_count_cols = []
for b in [32, 128, 512, 2048]:
    bandwidth_cols.append(f"batch_{b}_bandwidth")
    communication_count_cols.append(f"batch_{b}_communication_count")
df[bandwidth_cols] = np.nan
df[communication_count_cols] = np.nan

```

In []:

```

import math
append_df = []
# P = 1

for i,P in enumerate([1, 2, 4]):
    if i == 0:
        continue
    for b in [32, 128, 512, 2048]:
        iter_num = math.ceil(dataset_size/b)
        each_iter_communication_count = 2 * N * (P - 1) / P
        communication_count = iter_num * each_iter_communication_count
        communication_time = df["batch_" + str(b) + "_communication_time"][i]
        # print(communication_time)
        # print(f"communication_count: {communication_count}")
        bandwidth_utilization = communication_count / (communication_time * 1e
        df["batch_" + str(b) + "_bandwidth"][i] = bandwidth_utilization
        df["batch_" + str(b) + "_communication_count"][i] = communication_cou

```

/tmp/ipykernel_768624/3602963460.py:16: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
df["batch_" + str(b) + "_bandwidth"][i] = bandwidth_utilization
```

/tmp/ipykernel_768624/3602963460.py:17: SettingWithCopyWarning:
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```
able/user_guide/indexing.html#returning-a-view-versus-a-copy
df["batch_" + str(b) + "_communication_count"][i] = communication_count
```

In []:

```
df
```

Out[]:

	gpu_nums	batch_32_time	batch_128_time	batch_512_time	batch_2048_time	batch_32_c
0	1	38.0	16.0	13.0	13.0	
1	2	67.0	18.0	9.0	10.0	
2	4	121.0	30.0	11.0	11.0	

In []:

```
df[communication_count_cols]
```

Out[]:

	batch_32_communication_count	batch_128_communication_count	batch_512_communication
0	NaN	NaN	
1	1.746490e+10	4.369019e+09	1.0950
2	2.619735e+10	6.553529e+09	1.6425

No communication for gpu_nums = 1

In []:

```
display_cols = ["gpu_nums"] + bandwidth_cols
df[display_cols]
```

Out[]:

	gpu_nums	batch_32_bandwidth	batch_128_bandwidth	batch_512_bandwidth	batch_2048
0	1	NaN	NaN	NaN	
1	2	0.363852	0.436902	0.438019	
2	4	0.234954	0.252059	0.211945	

The bandwidth utilization is calculated by the following formula:

1. Calculate the iteration number
2. Calculate the communication cost per process per iter.
3. Calculate the communication cost per process per epoch.
4. Using the epoch communication time to get the bandwidth utilization.

The above table unit is GB/s.

$$T_{train} = T_{communication} + T_{compute} \quad (5)$$

$$T_{compute} = T_1/N \quad (6)$$

$$T_{communication} = T_{train} - T_1/N \quad (7)$$

We have the $T_{communication}$, and we have all-reduce to get the model transfer size, we can get the bandwidth utilization by

$$\text{Bandwidth Utilization} = \frac{Size_{communication}}{T_{communication}} \quad (8)$$

