

Modern Distributed Data-Parallel Large-Scale Pre-training Strategies For NLP models

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Junior, Computer Engineering

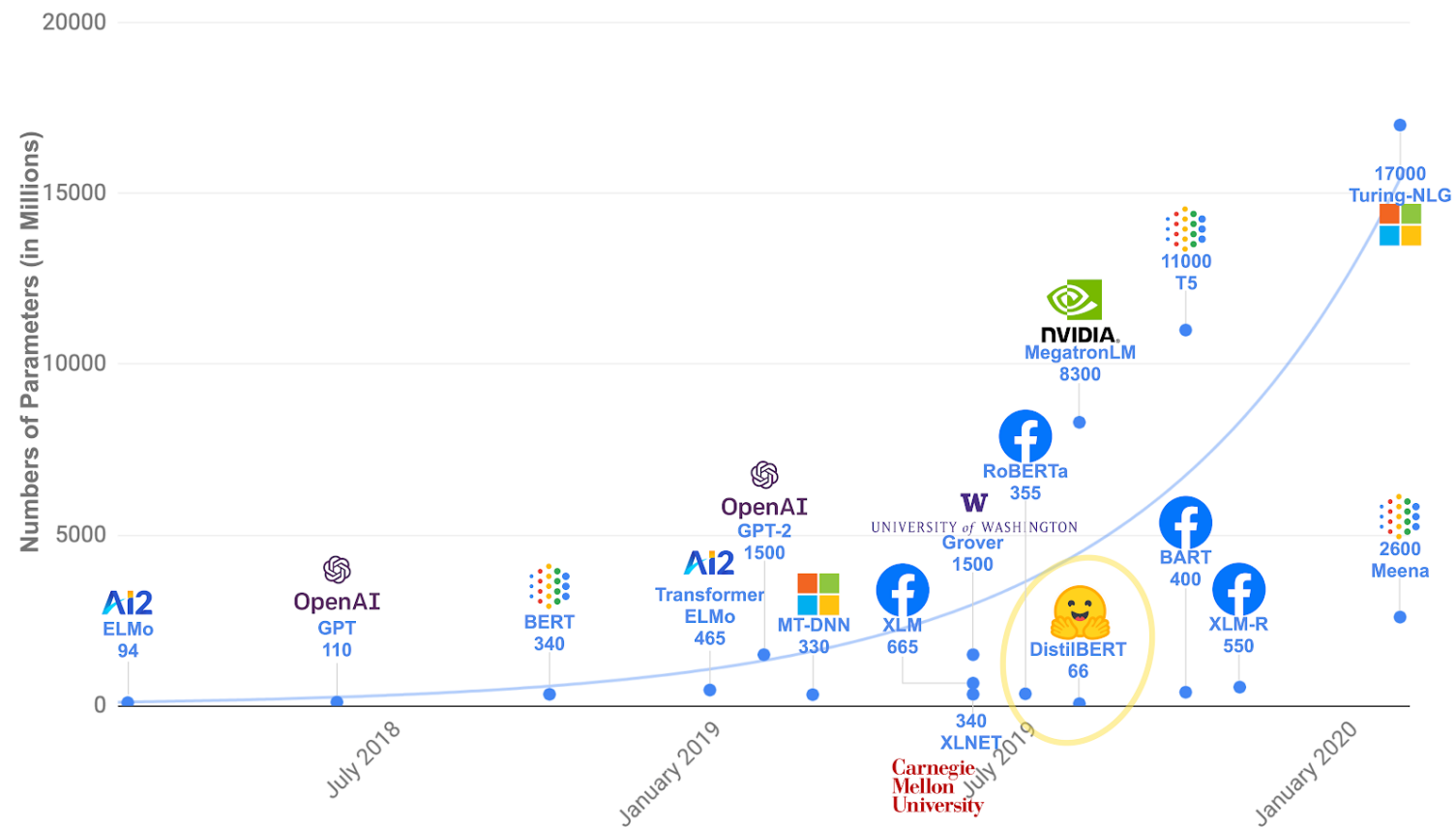
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Author & Supervisor

- AUTHOR | Jack Bai (Junior UG, CompE, UIUC)
 - Take a look at my profile at <https://www.jackgethome.com/>
 - My paper preprint is on ArXiv: <https://arxiv.org/pdf/2206.06356.pdf>
- ADVISOR | Volodymyr Kindratenko (Assistant Director at NCSA)
 - Research interests mainly in HPC
 - Take a look at his profile at <https://ece.illinois.edu/about/directory/faculty/kindrtnk>
 - Has lots of supercomputers, much acknowledge to my prof

Why do we
pick an NLP
pre-trained
model?



Pain...

I'm sure everyone who used
PyTorch or TensorFlow
experiences this kind of pain.

NVIDIA-SMI 375.66					Driver Version: 375.66				
GPU	Name	Persistence-M	Bus-Id	Disp.A	Volatile	Uncorr.	ECC		
Fan	Temp	Perf	Pwr:Usage/Cap	Memory-Usage	GPU-Util	Compute	M.		
0	GeForce GTX 108...	Off	0000:02:00.0	Off			N/A		
30%	53C	P2	63W / 250W	8779MiB / 11172MiB	6%		Default		
1	GeForce GTX 108...	Off	0000:04:00.0	Off			N/A		
30%	53C	P2	59W / 250W	8663MiB / 11172MiB	6%		Default		
2	GeForce GTX 108...	Off	0000:83:00.0	Off			N/A		
31%	55C	P2	62W / 250W	8663MiB / 11172MiB	4%		Default		
3	GeForce GTX 108...	Off	0000:84:00.0	Off			N/A		
28%	50C	P2	61W / 250W	8989MiB / 11172MiB	6%		Default		
Processes:									
GPU	PID	Type	Process name	GPU Memory Usage					
0	85736	C	python	8777MiB					
1	85736	C	python	8661MiB					
2	85736	C	python	8661MiB					
3	85736	C	python	8987MiB					

Dream?

How to improve the volatile GPU utility like this?

```
xiongyu@ubuntu:~$ watch nvidia-smi
  0      47741      C      ./mtcnn_c      461M
Every 2.0s: nvidia-smi

Fri Jun 29 11:25:43 2018

+-----+
| NVIDIA-SMI 390.48                  Driver Version: 390.48 |
+-----+-----+
| GPU  Name            Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. E |
| Fan  Temp   Perf    Pwr:Usage/Cap|      Memory-Usage | GPU-Util  Compute  |
+-----+-----+
|  0   Tesla M40      On          | 00000000:03:00.0 Off |           99%      Defau |
|  0%   57C    P0     217W / 250W | 10806MiB / 11448MiB |           99%      Defau |
+-----+-----+
|  1   Tesla M40      On          | 00000000:04:00.0 Off |           99%      Defau |
|  0%   58C    P0     200W / 250W | 9992MiB / 11448MiB |           99%      Defau |
+-----+-----+
|  2   Tesla M40      On          | 00000000:84:00.0 Off |           99%      Defau |
|  0%   56C    P0     222W / 250W | 9955MiB / 11448MiB |           99%      Defau |
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|  3   Tesla M40      On          | 00000000:85:00.0 Off |           98%      Defau |
|  0%   57C    P0     203W / 250W | 9960MiB / 11448MiB |           98%      Defau |
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| Processes:                                     GPU Memo |
|  GPU       PID   Type   Process name                  Usage    |
+-----+-----+
|    0      35346    C     python2                      110M     |
|    0      55323    C     python                      10673M   |
|    1      55323    C     python                      9970M    |
+-----+-----+
```

Model Parallel And Data Parallel

Not exactly a dream.

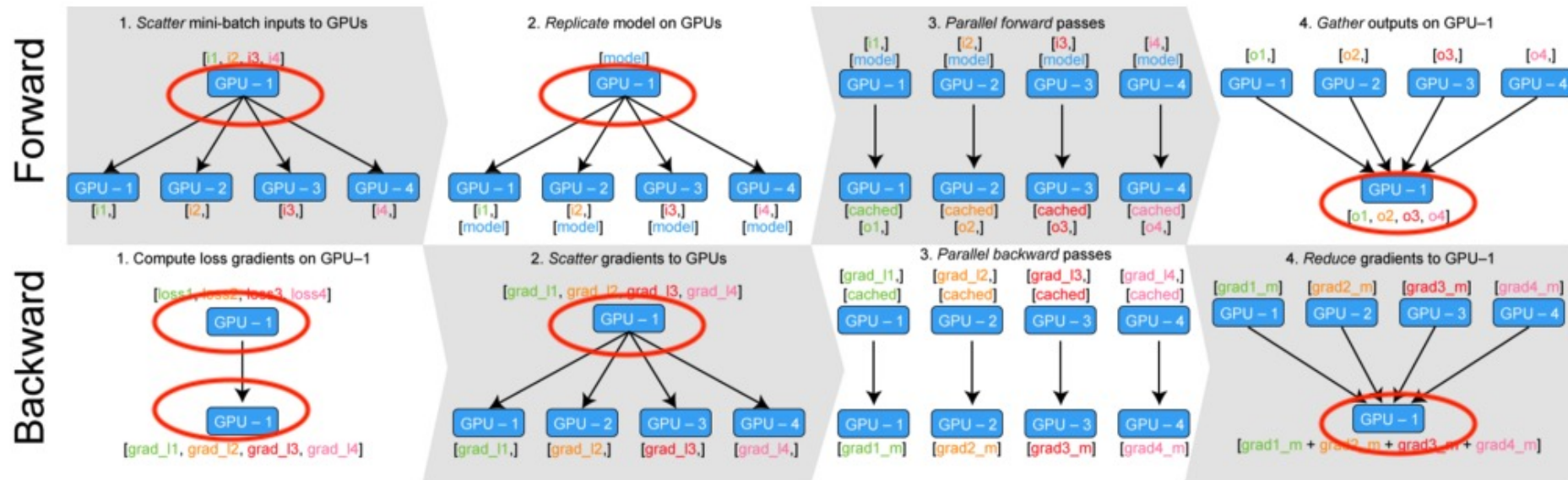
We have model
parallel and data
parallel to help.

Model parallel: parts
of model on
different GPUs.

Data parallel: scatter
and gather data on
different GPUs.

Data Parallel In PyTorch

- Let's take PyTorch for example.
- **Who encountered to use nn.DataParallel library?**
- I'm sure you're worried about the performance. When you're doing a Kaggle, you get anxious about your code.



Forward and Backward passes with `torch.nn.DataParallel`

Bottleneck

- It's not exactly your fault. We've got similar results.
- Why? Because it's Single Parameter Server training. Can you get the bottleneck?
- Yes, it's even slower than the baseline with only 1 GPU. Don't use it that way!

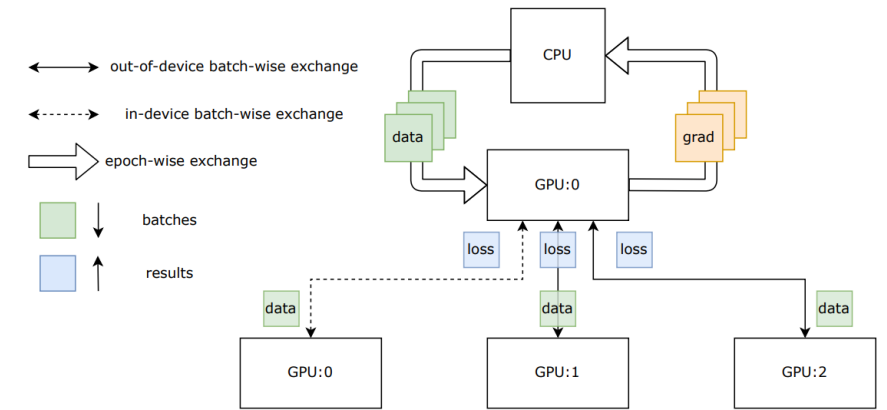


Figure 3: Conceptual architecture of Single Parameter Server parallization approach.

Parallel Type	PrmSrv	GPU0	GPU1	GPU2	GPU3	Total
Baseline	0	85%	0	0	0	0.94
SPS	1	17%	13%	11%	14%	0.55

nn.DistributedDataParallel (DPS)

- Distributed Data Parallel (DPS) helps with the problem.
- No surprise. Think about why it's faster. Does it solve the bottleneck here?
- All-reduce algorithm to synchronize the training process.

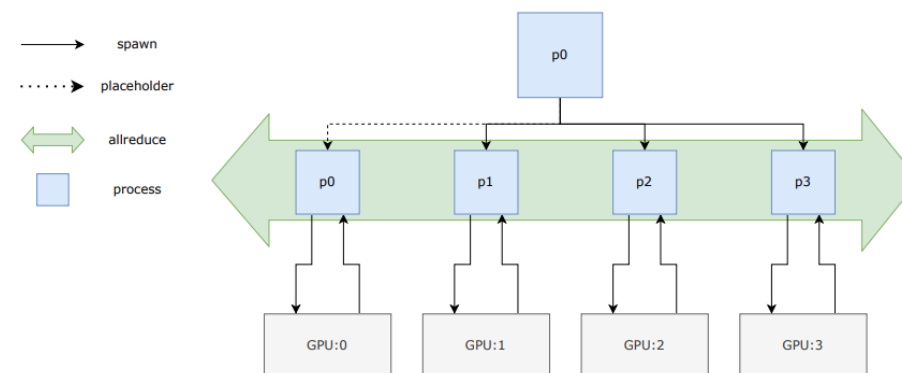


Figure 4: Conceptual architecture of Distributed Parameter Server parallization approach.

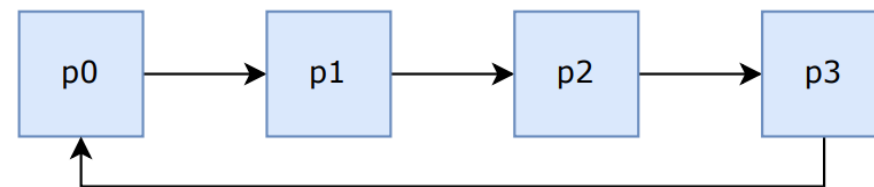
Parallel Type	PrmSrv	GPU0	GPU1	GPU2	GPU3	Total
Baseline	0	85%	0	0	0	0.94
SPS	1	17%	13%	11%	14%	0.55
DPS	4	94%	94%	89%	94%	<u>3.71</u>

Good
approches
come with
price...

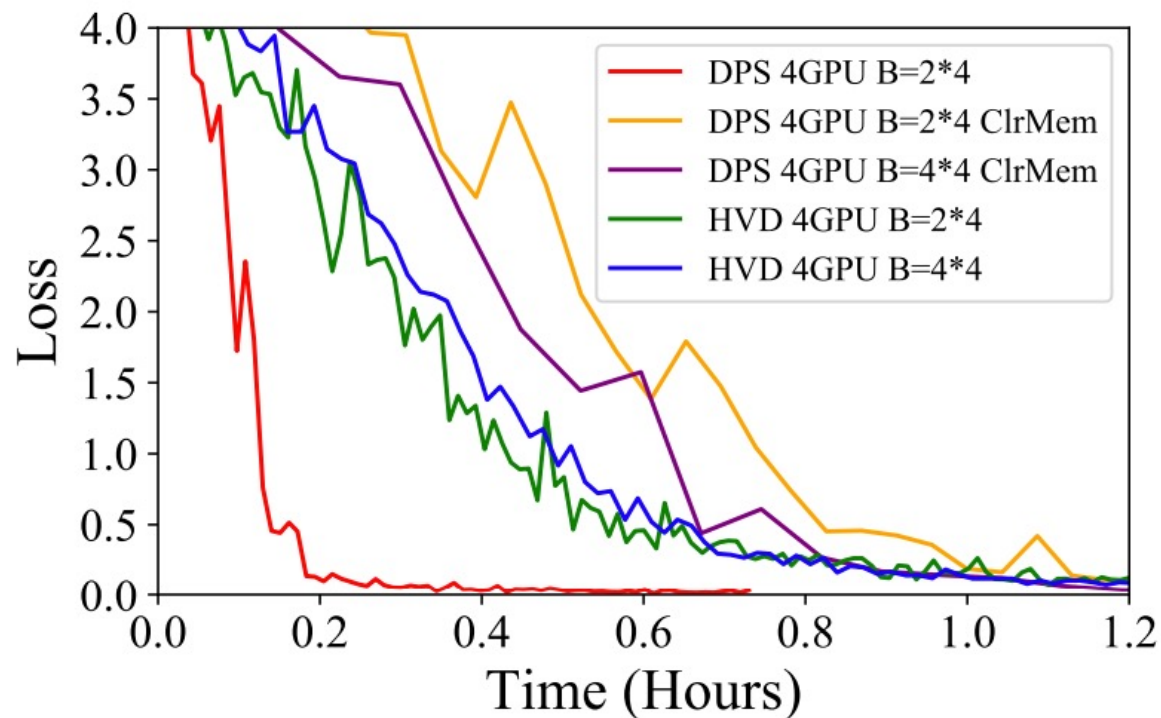
- Good on one node, hard on multiple nodes.
- Because you have to launch the script on every node.
- Any frameworks solving this problem?

Horovod

- Yes! Let's use Horovod, a distributed deep learning framework.
- Install it on all the nodes, so they share the same backend (MPI).
- Launch on one node, then all the nodes can work together.
- Ring-allreduce: optimized synchronization strategy.



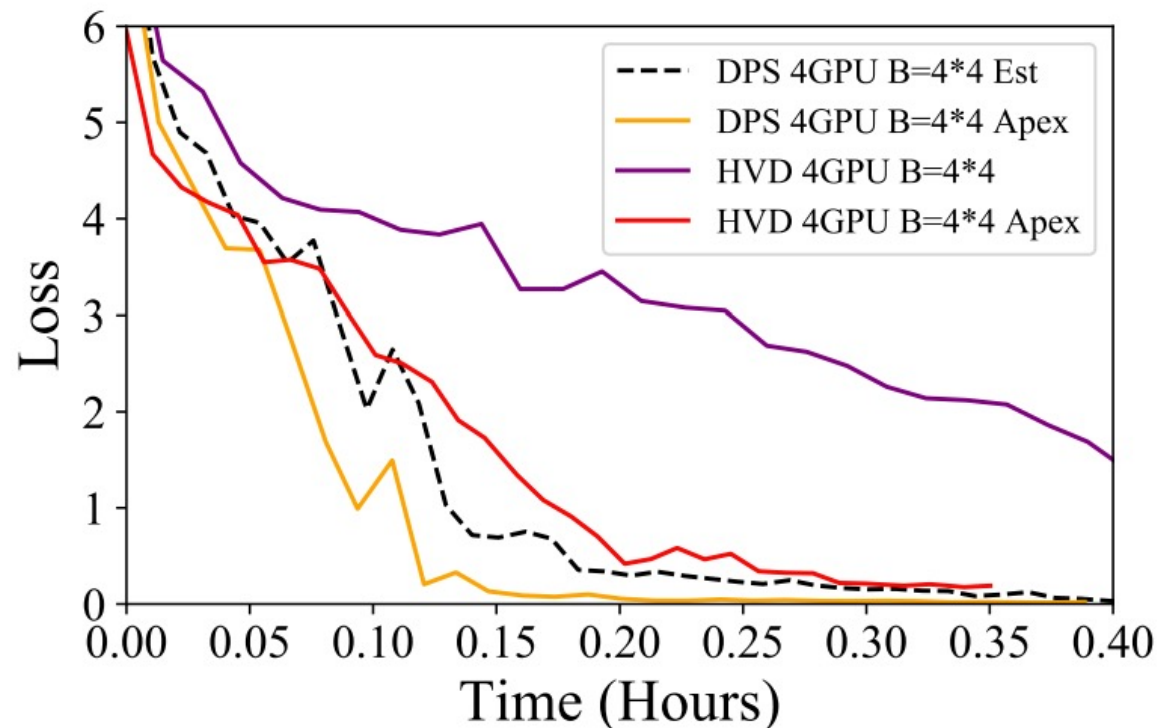
Comparison of DPS and Horovod on one node



(a) Loss curve for DPS (after adding the memory cleaning code) and Horovod, both with respect to a batch size of 8 and 16.

- Look into source code: Horovod is basically a **wrapper** around DPS.
- DPS is faster on one node, but allreduce introduces asymmetry.
- Horovod is slower on one node, but has built-in cache cleaning techniques and ring-allreduce algorithm eliminates asymmetry.

Big brother: Apex mixed Precision (fp16+fp32)



(d) Loss curve for DPS and Horovod before and after applying Apex fp16-fp32 mixed training.

- Extreme performance boosting: 2x faster for DPS, 4x faster for Horovod (i.e. nice compatibility with Horovod)
- Half the memory used to store batches, so DPS 4*4 can now run!
- Requires TensorCore to use. Try to persuade your boss to buy one for you!
- V100+ (V100, A100...)
- Details look at the GPU specs page.

Code? Open-source!

```
n_ctx = model_config.n_ctx
if args.bpe_token:
    full_tokenizer = get_encoder(args.encoder_json, args.vocab_bpe)
else:
    full_tokenizer = tokenization_bert.BertTokenizer(vocab_file=args.t
full_tokenizer.max_len = 999999

#####
# construct GPU network
torch.distributed.init_process_group(
    backend='nccl'
)
local_rank = torch.distributed.get_rank()
torch.cuda.set_device(local_rank)
device = torch.device("cuda", local_rank)
#####
print('using device:', device)
```

- Feel free to copy and paste.
- Easy to follow! '#####' is used to mark the parallel code added to the initial code.
- <https://github.com/BiEchi/DistributedTrainingGPT2>

Thank you!

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NVIDIA-SMI 352.79 Driver Version: 352.79									
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GPU Name Persistence-MI Bus-Id Disp.A Volatile Uncorr. ECC									
Fan Temp Perf Pwr:Usage/Cap Memory-Usage GPU-Util Compute M.									
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23% 62C P2 224W / 250W 11769MiB / 12287MiB 98% Default									
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