Welcom to the Megatron GPT bootcamp

Application Expert -- Quantum Chemistry

Dr. Johan Raber

Director of the EuroCC National Competence Center Sweden (ENCCS)

Dr. Lilit Axner

Day 1 - intro & Getting Started

Outline of Day 1 (+3 hour)

Day 1: October 25, 2021 (9:00 AM to 12:00 PM CEST)
09:00 AM - 09:15 AM: Welcome and opening note (Lilit)
09:15 AM - 09:30 AM: Bootcamp Overview
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[for those who finished the challenge early]
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INTRODUCING THE TA

Introducing the lead TAs

J-C Vasnier

Xianchao Wu

Meriem Bendris

INTRODUCING THE TA

Introducing the TAs - ATOS

Giorkallos, Alexis

Tournadre, Maxime

Ulker, Erkan

INTRODUCING THE SPEAKERS OF THE DAY

Day 1's speakers – Dai Yang and Bruno Charrier

Dai Yang

Bruno Charrier

LOGISTICS OF THE BOOTCAMP

Zoom functions | Slack channels | check cluster access

Join Slack : https://tinyurl.com/4and8wsy

Master doc

Login (or access) nodes

Typically a few nodes accessible from the internet. This where you end up when accessing the cluster via SSH or ThinLinc for instance, and is where you transfer files to. These nodes are not meant for heavy computations as they are shared by all users accessing the cluster, but are used to request compute resources (and build code, edit scripts etc) for compute intensive jobs. On berzelius these nodes are called `berzelius1.nsc.liu.se` and `berzelius2.nsc.liu.se` .

https://www.nsc.liu.se/support/systems/berzelius-getting-started/

NVIDIA OpenACC ENCCS

General links:

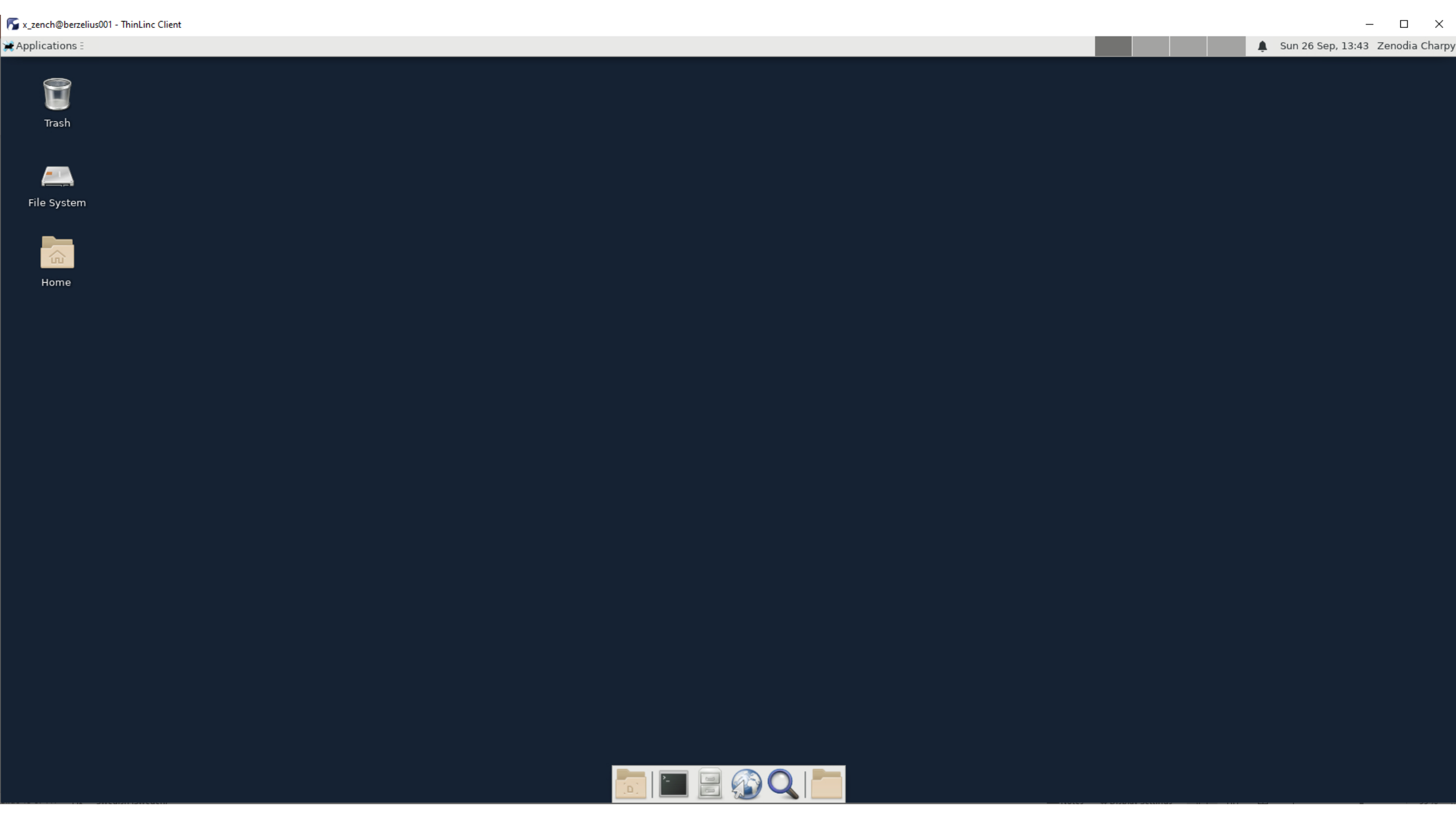
- Link to the Master document: https://tinyurl.com/y85dz3sz
- GPU Hackathons Website: https://gpuhackathons.org/
- Agenda: https://gpuhackathons.org/event/enccs-nsc-megatron-bootcamp
- Slack Channel: https://tinyurl.com/4and8wsy
- Zoom information: https://zoom.us

  Meeting ID: 856 7289 9555
  Passcode: 021869

- Cluster access: https://tinyurl.com/stjcypxy (9:00-15:00)
- Port allocations: Check the 2nd page
- Survey: https://forms.gle/G2WUWcPuiQ6DUTH79

General Guidance

- Be kind. Be understanding. Be flexible.
- Slides will be available after the event.
- Keep yourself muted when not speaking to minimise background noise.
- Zoom chat is disabled; general chat in the **ENCCS & NSC Megatron Bootcamp 2021** Slack workspace.
- Introduce yourself to fellow participants, tell us about your expertise and interests in the


x_zench@berzelius001 - ThinLinc Client
Applications
Sun 26 Sep, 13:43
Zenodia Charpy
Trash
File System
Home

FROM QUESTIONS TO ANSWERS

In this bootcamp, we are trying to address to these questions

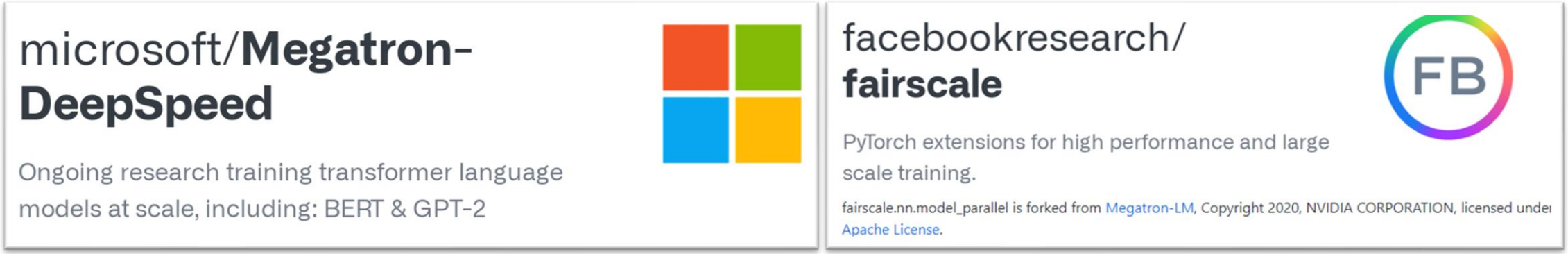
What is Megatron-LM (vs DeepSpeed vs FairScale ?)

Why should I care about training very large NLP models

How to kick-start to train large NLP models with my own language / own dataset


MEGATRON-LM | DEEPSPEED | FAIRSCALE

NVIDIA MEGATRON-LM MPU AS CORE ENGINE



NVIDIA Megatron-LM MPU as core engine

https://github.com/facebookresearch/fairscale

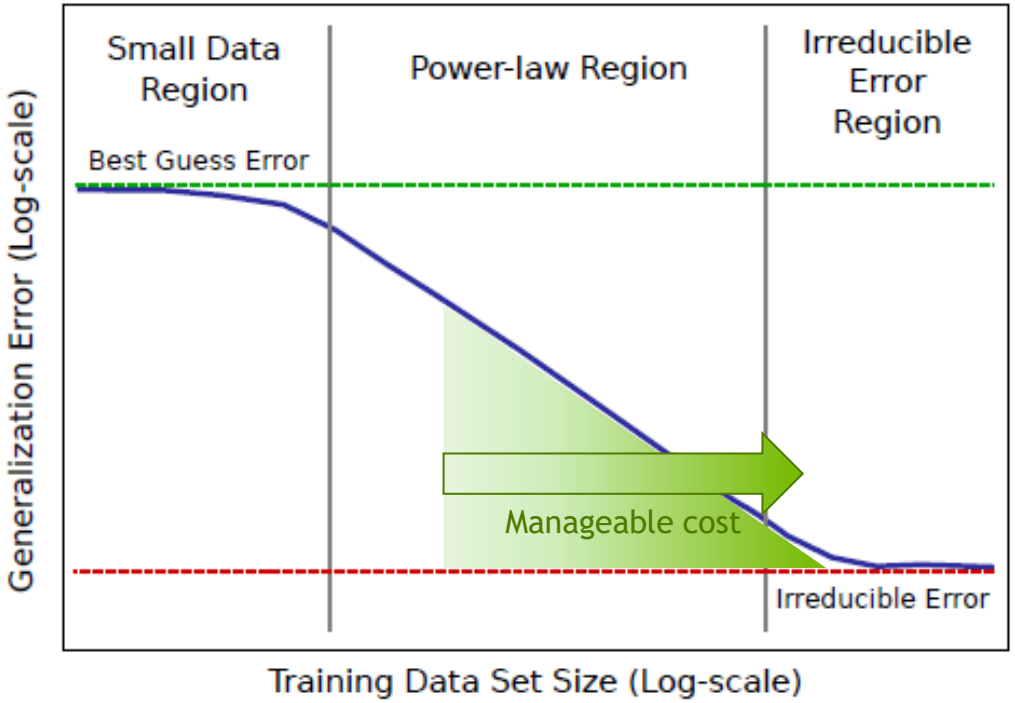
https://www.deepspeed.ai/features/

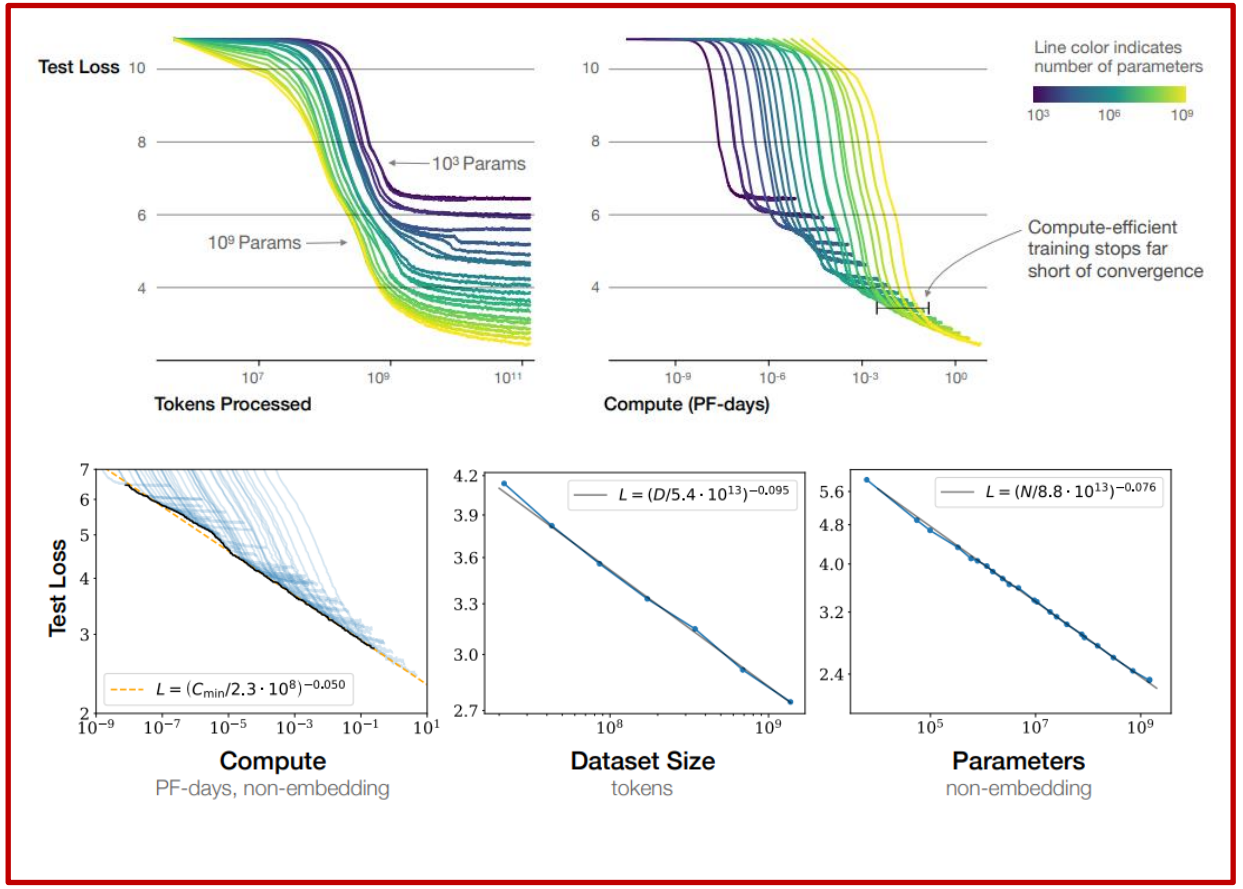
https://github.com/NVIDIA/Megatron-LM

WHY VERY LARGE NLP MODELS ?

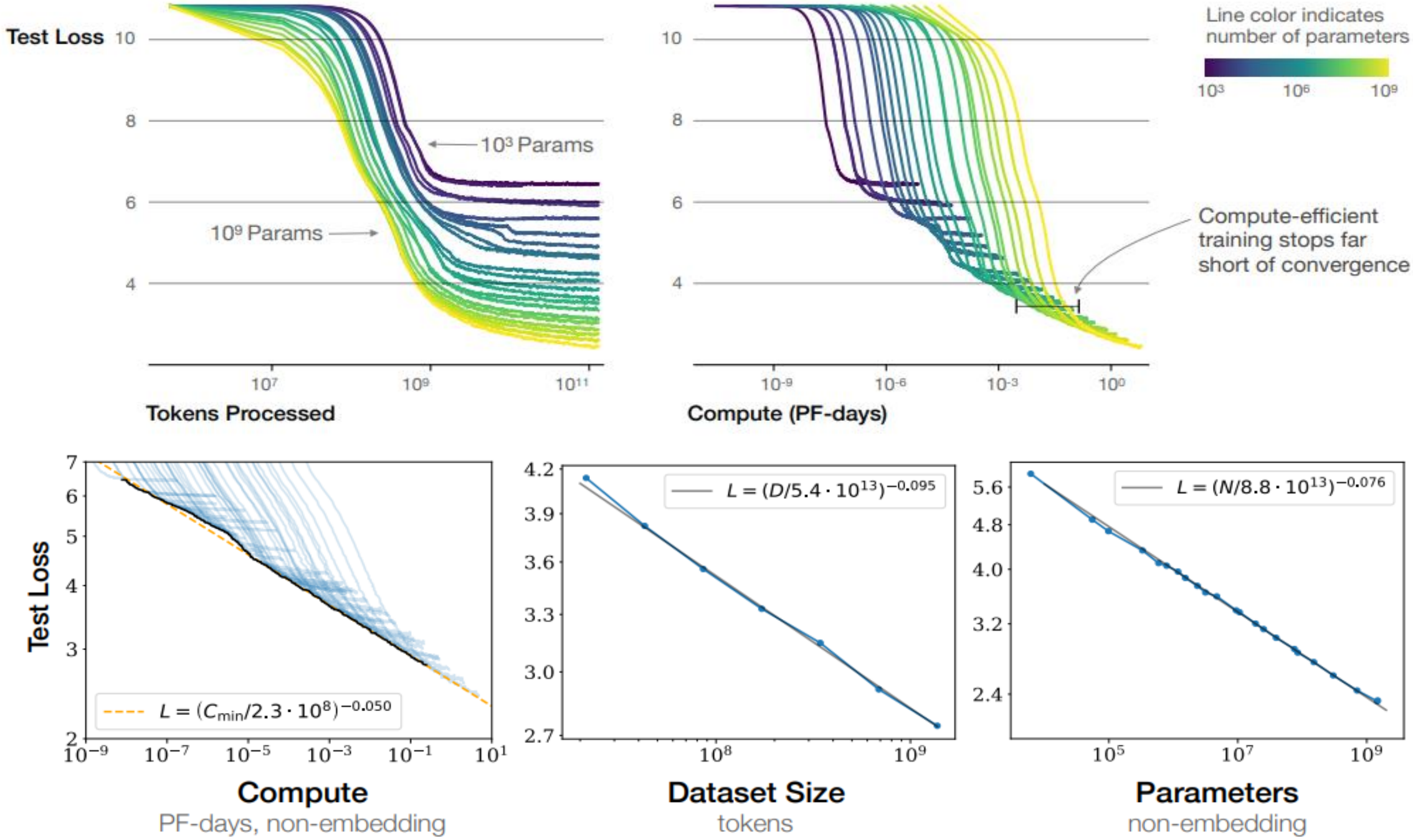
THE PROMISE

Big data + Big model + Big compute



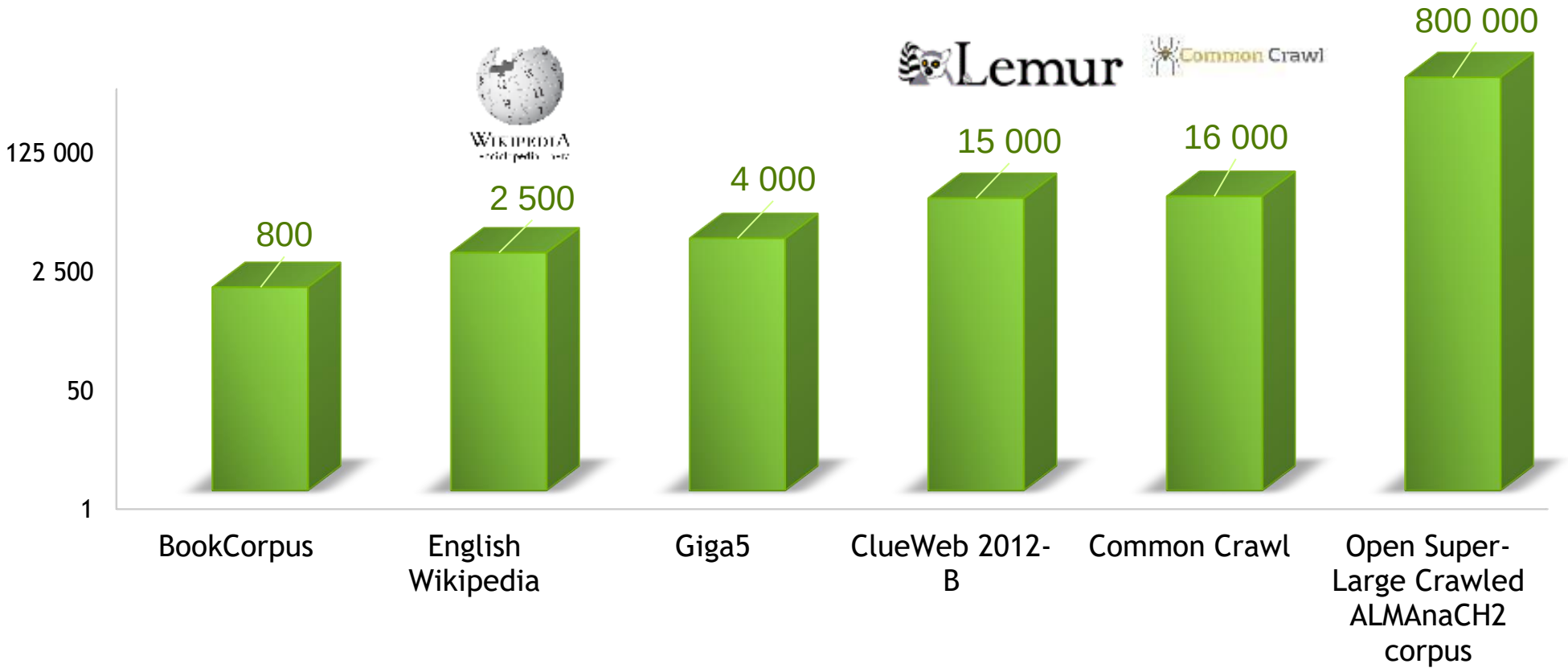


Hestness, J., Narang, S., Ardalani, N., Diamos, G., Jun, H., Kianinejad, H., ... & Zhou, Y. (2017). Deep Learning Scaling is Predictable, Empirically. arXiv preprint arXiv:1712.00409.


Test Loss
10
8
6
4
10^3 Params
10^9 Params
10^7
10^9
10^{11}
Tokens Processed
10
8
6
4
10^{-9}
10^{-6}
10^{-3}
10^0
Compute (PF-days)
Line color indicates number of parameters
10^3
10^6
10^9
Compute-efficient training stops far short of convergence
Test Loss
7
6
5
4
3
2
$L = (C_{min}/2.3 \cdot 10^8)^{-0.050}$
10^{-9}
10^{-7}
10^{-5}
10^{-3}
10^{-1}
10^1
Compute
PF-days, non-embedding
4.2
3.9
3.6
3.3
3.0
2.7
$L = (D/5.4 \cdot 10^{13})^{-0.095}$
10^8
10^9
Dataset Size
tokens
5.6
4.8
4.0
3.2
2.4
$L = (N/8.8 \cdot 10^{13})^{-0.076}$
10^5
10^7
10^9
Parameters
non-embedding

SELF-SUPERVISED LEARNING

Abundance of unlabeled data



THE SCALING LAWS

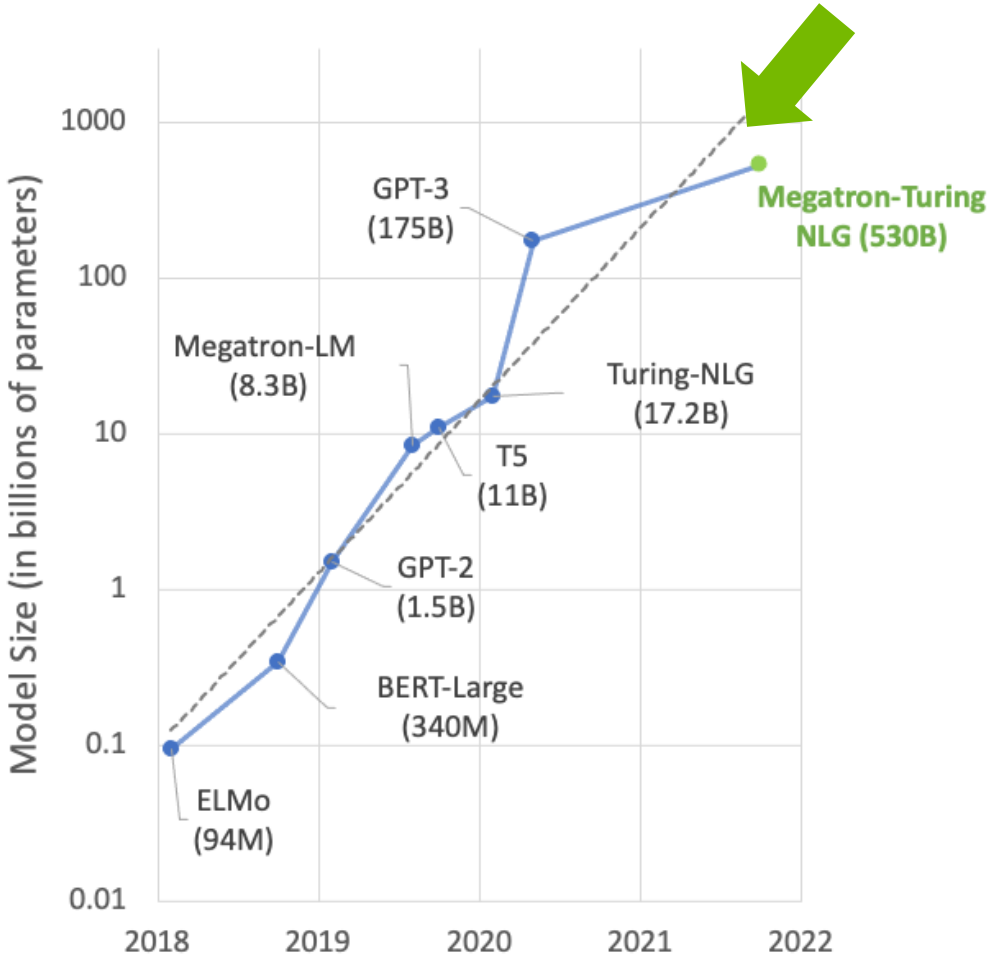
MOST IMPORTANT!!

"… more importantly, we find that the precise architectural hyperparameters are unimportant compared to the overall scale of the language model."

Kaplan, J., McCandlish, S., Henighan, T., Brown, T. B., Chess, B., Child, R., ... & Amodei, D. (2020). Scaling Laws for Neural Language Models. *arXiv preprint arXiv:2001.08361*.

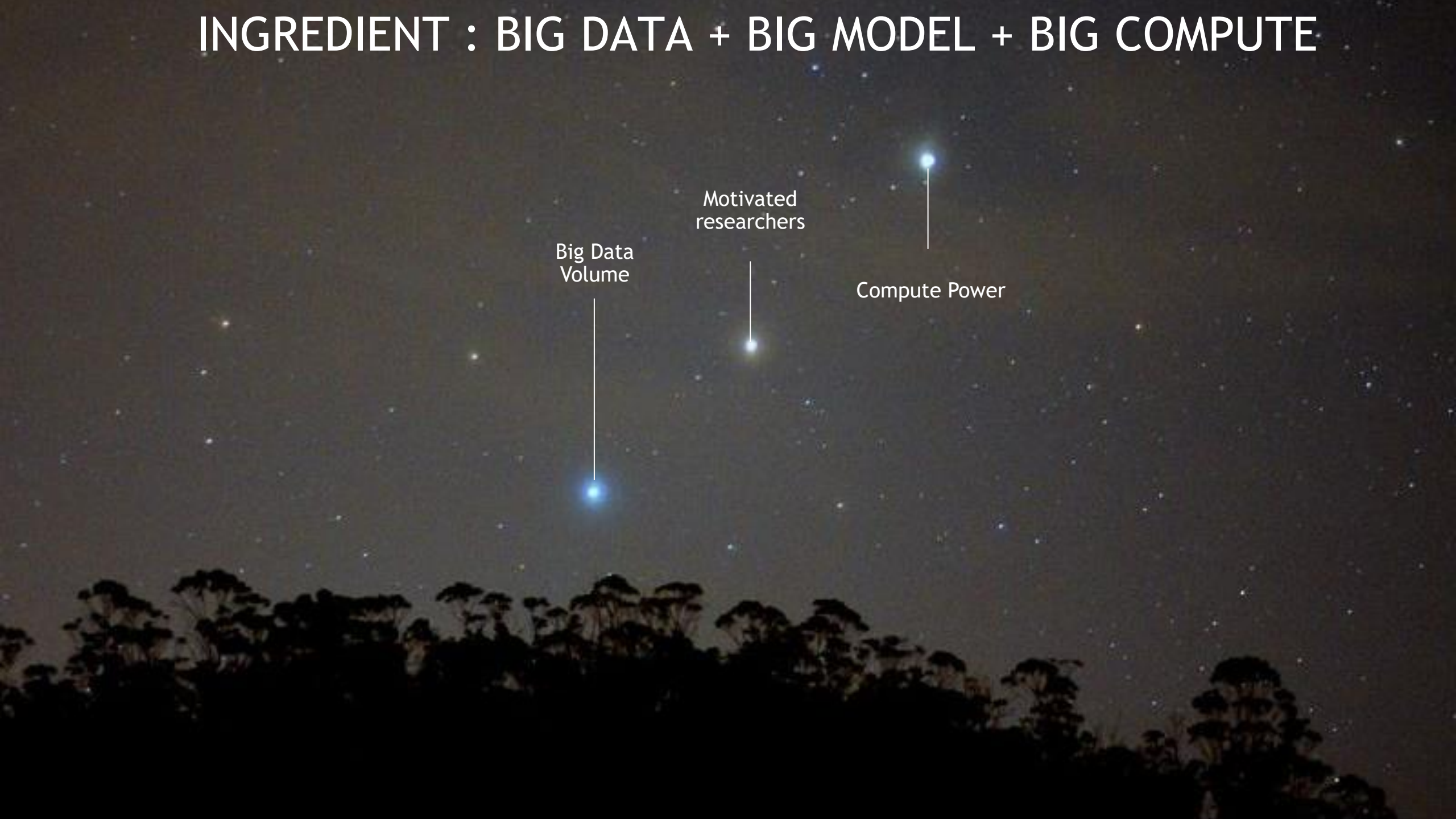
THE SCALING LAWS

Next two years will bring much larger models



https://developer.nvidia.com/blog/using-deepspeed-and-megatron-to-train-megatron-turing-nlg-530b-the-worlds-largest-and-most-powerful-generative-language-model/

INGREDIENT : BIG DATA + BIG MODEL + BIG COMPUTE



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[for those who finished the challenge early]
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OVERVIEW 3 HALF DAYS BOOTCAMP

objective overview

Day 1

- Familiarize with the SuperPOD environment
- Get Megatron to run by default
- Bonus session : the man behind Cambridge-1

Day 2

- Intro to Megatron workflow
- Profiling
- Bonus session : importance of profiling – ask the expert!

Day 3

- Customize Megatron
- On scaling model size
- Bonus session 1: on deploying large NLP models
- Bonus session 2: ask the experts on NVIDIA bigNLP vision

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Day 2 – Run through Megatron GPT

Outline of Day 2 (5.5 hours lunch break)

09:00 AM - 09:15 AM: Environment prep
09:15 AM - 09:45 AM: About compute
09:45 AM - 10:15 AM:
Lab 1 – Acquire data (WebScraping)
Lab 1 – 2_Estimate Time Needed for Compute
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12:00 PM - 12:10 PM: Ask the Experts (Robert Dietrich)
12:10 PM – 13:10 PM: Lunch break
13:10 PM - 13:40 PM: Lab 1 – 6_GPT training config vs GPUs performance
13:40 PM - 14:10 PM: Challenge overview
14:10 PM - 14:30 PM: Discussion & What's up next day

Day 3 – Customize Megatron for Swedish

Outline of Day (6 hour with lunch break)

09:00 AM - 09:15 AM: Recap and Overview of Day 3
09:15 AM - 09:30 AM: About acquiring your own
09:30 AM - 10:20 AM:
Lab 2 – 1_Acquiring data
Lab 2 – 2_data cleaning & filter
10:20 AM - 10:30 AM: train own GPT tokenizer + preprocessing
10:30 AM - 11:00 AM: Lab 2 – 3_train your own GPT tokenizer
11:00 AM - 11:30 AM: Lab 2 – 4_data preprocessing
11:30 AM - 12:00 PM: Lab 2 - 4 Mini challenge
12:00 PM - 12:30 PM: Lunch Break
13:00 PM - 14:00 PM: Lab 2 – 5 Challenge – Go BIG or go home
14:00 PM - 14:30 PM: About deploying Big NLP model with NVIDIA Triton | faster transformer solution
14:30 PM - 15:00 PM: Ask the Experts with NVIDIA data scientists on what's next for NLP
15:00 PM - 15:05 PM: Discussion & Final remarks


LET’S START !

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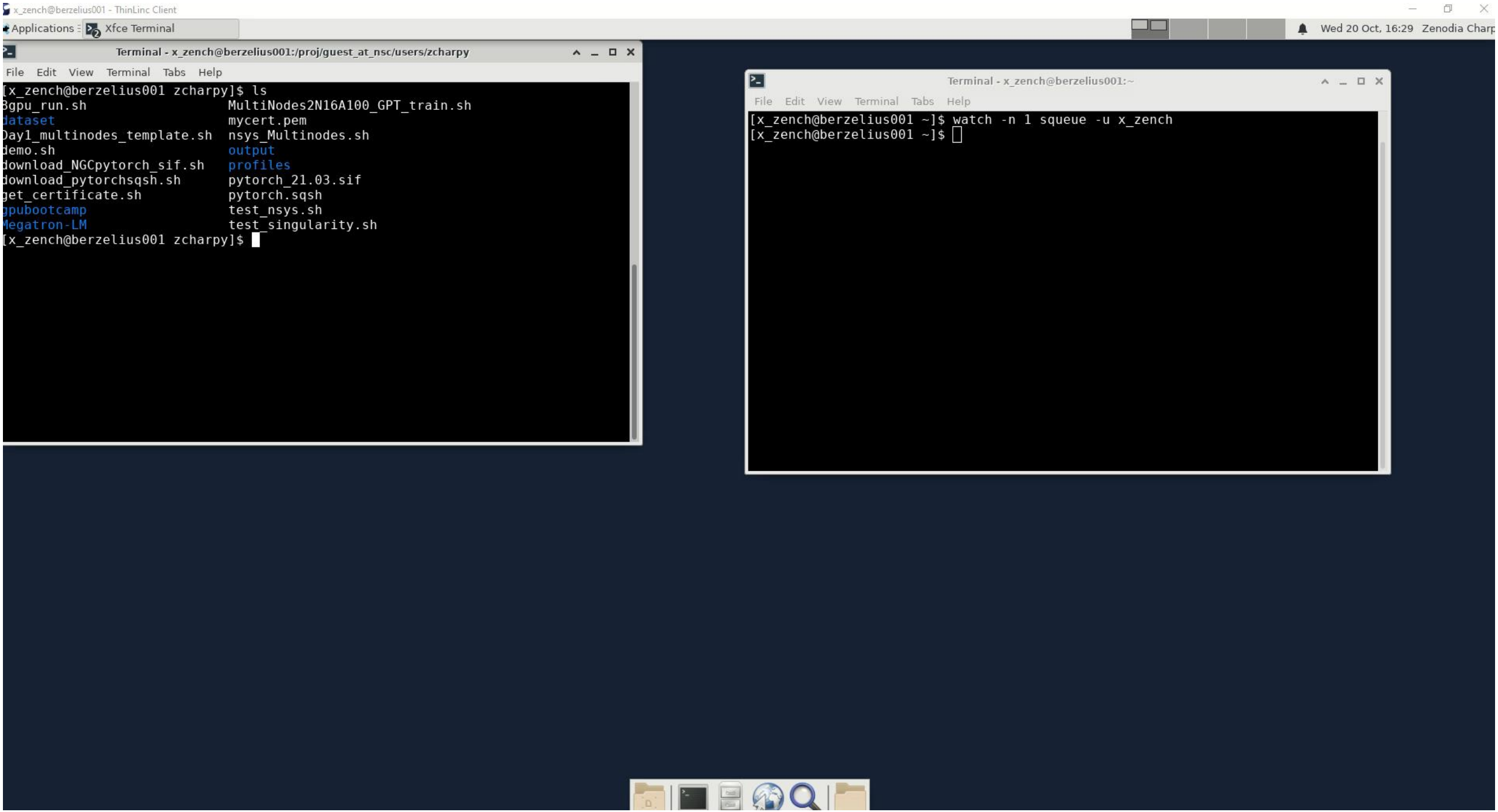
Applications
Wed 20 Oct, 16:20 Zenodia Charp
Trash
File System
Home


MULTI-NODES GPT3
TRAINING DEMO


x_zench@berzelius001 - ThinLinc Client
Applications
Xfce Terminal
Wed 20 Oct, 16:29 Zenodia Charp
Terminal - x_zench@berzelius001:/proj/guest_at_nsc/users/zcharpy
File Edit View Terminal Tabs Help
[x_zench@berzelius001 zcharpy]$ ls
3gpu_run.sh MultiNodes2N16A100_GPT_train.sh
dataset mycert.pem
Day1_multinodes_template.sh nsys_Multinodes.sh
demo.sh output
download_NGCpytorch_sif.sh profiles
download_pytorchsqsh.sh pytorch_21.03.sif
get_certificate.sh pytorch.sqsh
gpubootcamp test_nsys.sh
Megatron-LM test_singularity.sh
[x_zench@berzelius001 zcharpy]$
Terminal - x_zench@berzelius001:~
File Edit View Terminal Tabs Help
[x_zench@berzelius001 ~]$ watch -n 1 squeue -u x_zench
[x_zench@berzelius001 ~]$

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Task :

you will be given a template script which you should modify in order to run Megatron-LM successfully.

Only modify the parameters in the section denoted ---CHANGE ALLOWED---

THE CHALLENGE – MAKE IT RUN !

MULTINODES MEGATRON TRAINING ON BERZELIUS

```
#!/bin/bash
#SBATCH -N 2
#SBATCH --gpus 16
#SBATCH --ntasks-per-node 8
#SBATCH --exclusive
#SBATCH -A berzelius-2021-43
#SBATCH --time=3:00:00
#####################################    Beginning of modifiable section    ##########################################
MY_DIR=
MY_USR_NAME=
NUM_LYS=
HIDDEN_SIZE=
NUM_ATTN_HEADS=
SEQ_LEN=
MAX_POS_EM=
MICRO_BATCH_SIZE=
GLOBAL_BATCH_SIZE=
TENSOR_PARALLEL_SIZE=
PIPELINE_PARALLAL_SIZE=
##############################    end of modifiable sectio, do NOT modify anything below this line    ###################

export NNODES=$SLURM_NNODES
export GPUS_PER_NODE=8
export MASTER_ADDR=`scontrol show hostnames ${SLURM_NODELIST} | head -1`
export MASTER_PORT=8890
export WORLD_SIZE=$(($GPUS_PER_NODE*$NNODES))

DIR='/megatron_workspace'
DATETIME=`date +'date_%y-%m-%d_time_%H-%M-%S'`
CHECKPOINT_PATH=$DIR/output/sv_gpt3_ckpt/
VOCAB_FILE=$DIR/dataset/vocab.json
MERGE_FILE=$DIR/dataset/merges.txt
DATA_PATH=$DIR/dataset/SVGPT_32k_text_document

options="--num-layers ${NUM_LYS} \
                --hidden-size ${HIDDEN_SIZE} \
                --num-attention-heads ${NUM_ATTN_HEADS} \
                --seq-length ${SEQ_LEN} \
                --max-position-embeddings ${MAX_POS_EM} \
                --lr 0.00015 \
                --train-iters 100 \
                --min-lr 0.00001 \
                --lr-decay-iters 99 \
                --lr-warmup-fraction 0.01 \
                --override-lr-scheduler \
                --micro-batch-size ${MICRO_BATCH_SIZE} \
                --global-batch-size ${GLOBAL_BATCH_SIZE} \
```

Modify ***ONLY*** this section please !

Adopted from https://github.com/NVIDIA/Megatron-LM/blob/main/examples/pretrain_gpt3_175B.sh

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END OF DAY 1

Congratulations – you did it !

Day 2 – Run through Megatron GPT

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INTRODUCING THE SPEAKERS OF THE DAY

Day 2's speakers – Robert Dietrich

Robert Dietrich

Expert in Nsight Profiling
EMEA Profiling Champion

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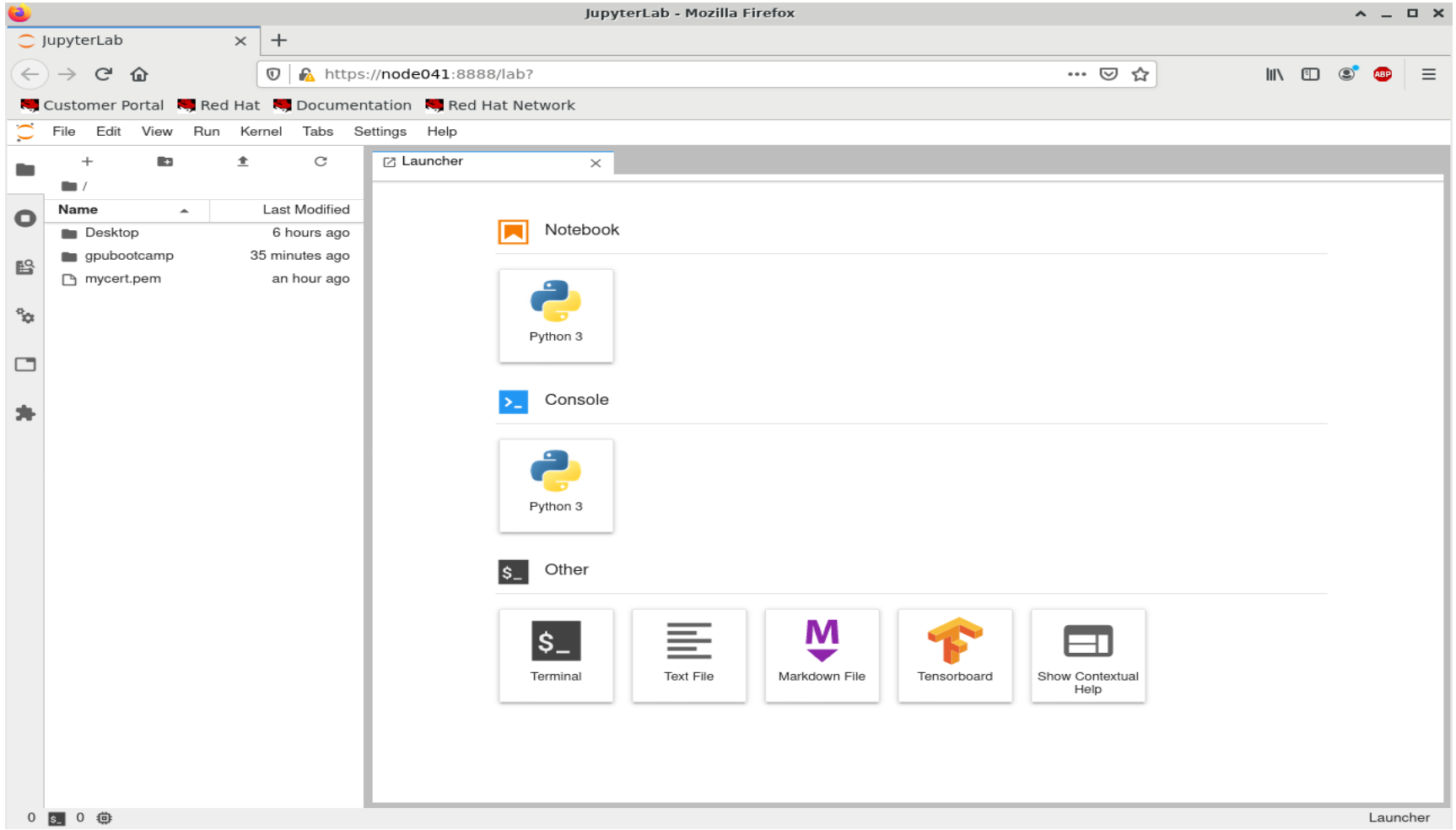
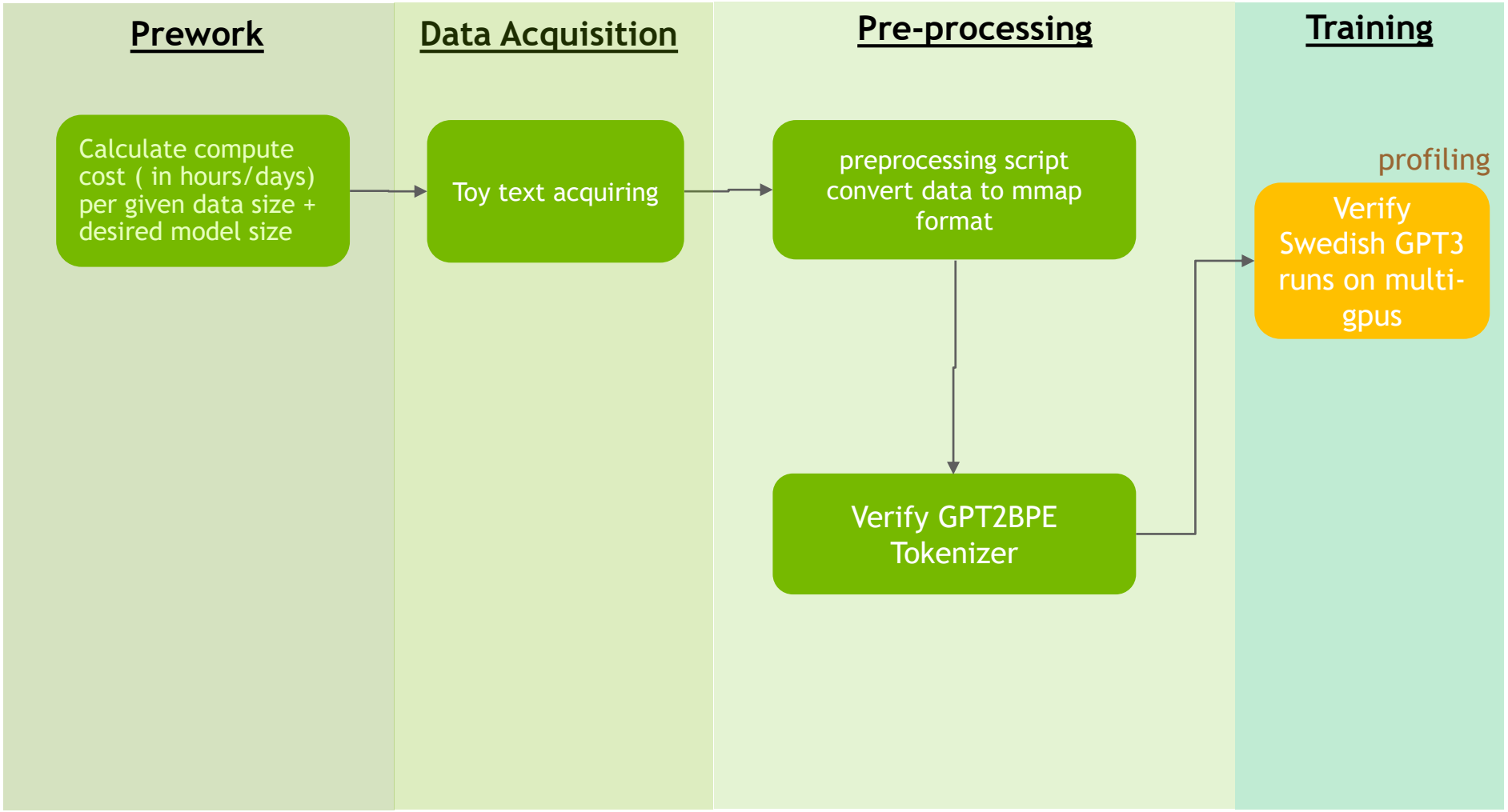
ENV PREP

Download the instruction fron shared google drive :

Following the step-by-step instruction from that PDF file to access the jupyter lab



WORKFLOW OVERVIEW



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DATA | MODEL SIZE | COMPUTE NEED

Massive data volume is necessary as you scale

Model Name	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{head}	Batch Size	Learning Rate
GPT-3 Small	125M	12	768	12	64	0.5M	6.0×10^{-4}
GPT-3 Medium	350M	24	1024	16	64	0.5M	3.0×10^{-4}
GPT-3 Large	760M	24	1536	16	96	0.5M	2.5×10^{-4}
GPT-3 XL	1.3B	24	2048	24	128	1M	2.0×10^{-4}
GPT-3 2.7B	2.7B	32	2560	32	80	1M	1.6×10^{-4}
GPT-3 6.7B	6.7B	32	4096	32	128	2M	1.2×10^{-4}
GPT-3 13B	13.0B	40	5140	40	128	2M	1.0×10^{-4}
GPT-3 175B or "GPT-3"	175.0B	96	12288	96	128	3.2M	0.6×10^{-4}

Table 2.1: Sizes, architectures, and learning hyper-parameters (batch size in tokens and learning rate) of the models which we trained. All models were trained for a total of 300 billion tokens.

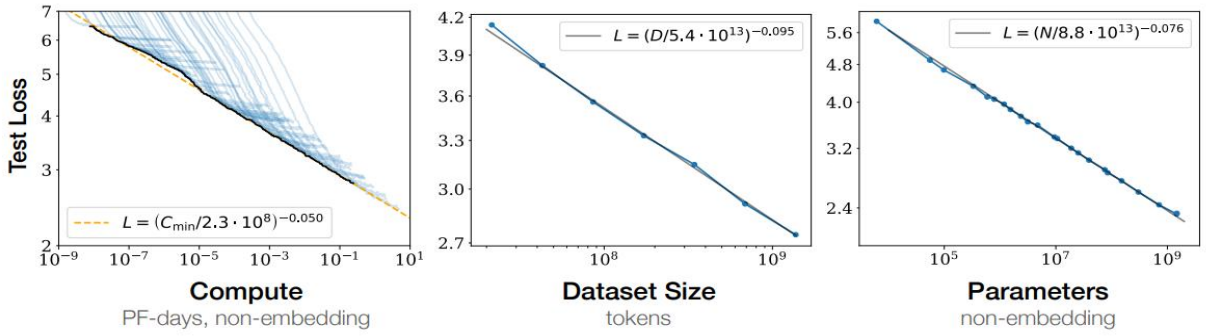

Figure 1 Language modeling performance improves smoothly as we increase the model size, datasetset size, and amount of compute[2] used for training. For optimal performance all three factors must be scaled up in tandem. Empirical performance has a power-law relationship with each individual factor when not bottlenecked by the other two.

ESTIMATE COMPUTE NEEDED

Calculate how many hours/days compute resource need

paper : https://arxiv.org/pdf/2005.14165.pdf

[2]:
```
import numpy as np
T=300*1e+9 #oftokens in the dataset
#P=175*1e+9 # number of model parameters
n= 480 # Berzelius 480 # number of GPUs in the compute cluster

def calculate_days_needed(T , P , n ,x):
    if x is None:
        return '1-2 weeks'
    else:
        #x=140*1e+12 # TeraFlop/s per GPU
        tot=8*T*P
        div=n*x
        compute_sec=tot/div
        #convert compute seconds to days
        to_days=round(compute_sec/(3600*24),1)
        return to_days

GPT3_models_labels=[ 'gpt3_2.7B', 'gpt3_6.7B','gpt3_13B', 'gpt3_175B']
GPT3_model_params=[ 2.7*1e+9, 6.7*1e+9 , 13*1e+9, 175*1e+9,1*1e+12 ]
GPT3_model_params_str=['1.3 Billion' ,'2.7 Billion', '13 Billion', '175 Billion']
#according to the table above
GPT3_X=[127*1e+12, 130*1e+12,135*1e+12,140*1e+12 ]
print("all below are measured with dataset size **300 billion** measured in tokens \n")
for gpt3_name, gpt3_params, gpt3_param_str, x in zip(GPT3_models_labels,GPT3_model_params,G
    days_needed=calculate_days_needed(T,gpt3_params,n,x)
    print(" ----------------------------------------------------------------------------")
    print(" language model :{} with {} number of parameters , it will need {} days to compu
```

```
all below are measured with dataset size **300 billion** measured in tokens

 ----------------------------------------------------------------------------
 language model :gpt3_2.7B with 1.3 Billion number of parameters , it will need 1.2 days to compute

 ----------------------------------------------------------------------------
 language model :gpt3_6.7B with 2.7 Billion number of parameters , it will need 3.0 days to compute

 ----------------------------------------------------------------------------
 language model :gpt3_13B with 13 Billion number of parameters , it will need 5.6 days to compute

 ----------------------------------------------------------------------------
 language model :gpt3_175B with 175 Billion number of parameters , it will need 72.3 days to compute
```

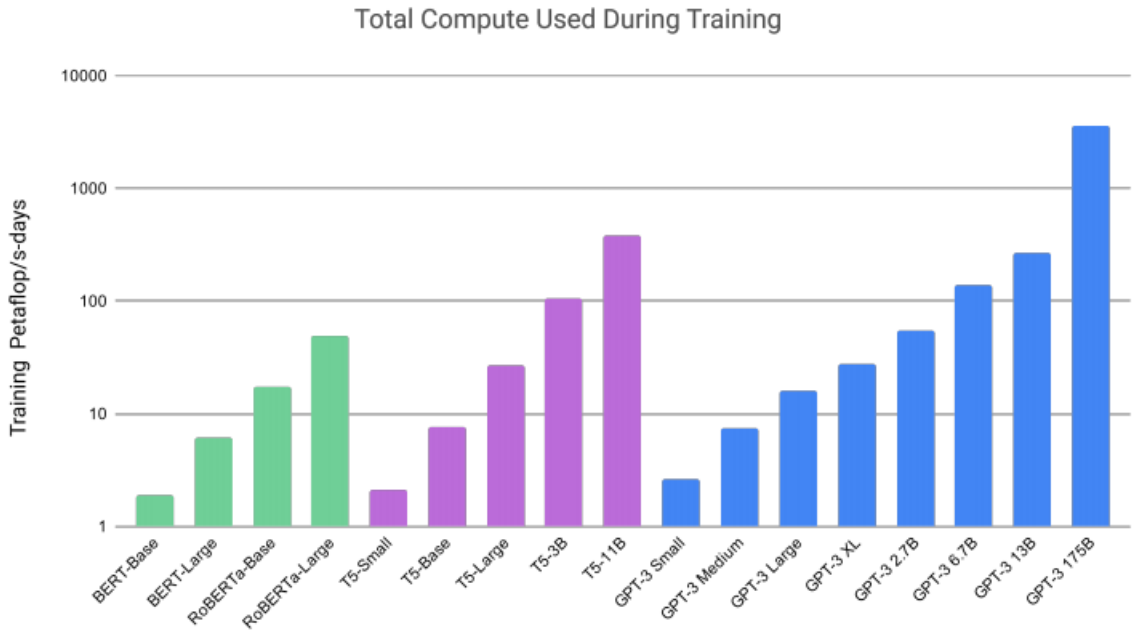

Figure 2.2: Total compute used during training. Based on the analysis in Scaling Laws For Neural Language Models [KMH+20] we train much larger models on many fewer tokens than is typical. As a consequence, although GPT-3 3B is almost 10x larger than RoBERTa-Large (355M params), both models took roughly 50 petaflop/s-days of compute during pre-training. Methodology for these calculations can be found in Appendix D.

Source :https://arxiv.org/pdf/2005.14165.pdf

MEGATRON IS AN EFFICIENT FRAMEWORK TO TRAIN VERY LARGE LANGUAGE MODELS

Model size	Attention heads	Hidden size	Number of layers	Number of parameters (billion)	Model-parallel size	Number of GPUs	Microbatch size	Batch size	Achieved teraFlOP/s per GPU	Percentage of theoretical peak FLOP/s	Achieved aggregate petaFLOP/s
1.7B	24	2304	24	1.7	1	32	16	512	137	44%	4.4
3.6B	32	3072	30	3.6	2	64	16	512	138	44%	8.8
7.5B	32	4096	36	7.5	4	128	16	512	142	46%	18.2
18B	48	6144	40	18.4	8	256	8	1024	135	43%	34.6
39B	64	8192	48	39.1	16	512	4	1536	138	44%	70.8
76B	80	10240	60	76.1	32	1024	2	1792	140	45%	143.8
145B	96	12288	80	145.6	64	1536	2	2304	148	47%	227.1
310B	128	16384	96	310.1	128	1920	1	2160	155	50%	297.4
530B	128	20480	105	529.6	280	2520	1	2520	163	52%	410.2
1T	160	25600	128	1008.0	512	3072	1	3072	163	52%	502.0

Table 1: Weak scaling throughput for GPT models ranging from 1 billion to 1 trillion parameters

GPT3 MODEL VARIENTS

Rule of thumb estimation

													12
Model size	Attention heads	Hidden size	Number of layers	Number of parameters (billion)	Model-parallel size	Number of GPUs	Microbatch size	Batch size	Achieved teraFLOP/s per GPU	Percentage of theoretical peak FLOP/s	Achieved aggregate petaFLOP/s	Training time per epoch (days)	Training time on 12 nodes (days)
1.7B	24	2304	24	1.7	1	32	16	512	137	44%	4.4	10.77	3.5904974
3.6B	32	3072	30	3.6	2	64	16	512	138	44%	8.8	11.32	7.5483092
7.5B	32	4096	36	7.5	4	128	16	512	142	46%	18.2	11.46	15.282668
18B	48	6144	40	18.4	8	256	8	1024	135	43%	34.6	14.79	39.437586
39B	64	8192	48	39.1	16	512	4	1536	138	44%	70.8	15.37	81.983025
76B	80	10240	60	76.1	32	1024	2	1792	140	45%	143.8	14.75	157.2834
145B	96	12288	80	145.6	64	1536	2	2304	148	47%	227.1	17.79	284.65966
310B	128	16384	96	310.1	128	1920	1	2160	155	50%	297.4	28.94	578.89038
530B	128	20480	105	529.6	280	2520	1	2520	163	52%	410.2	35.81	940.12724
1T	160	25600	128	1008	512	3072	1	3072	163	52%	502	55.92	1789.3661

estimation done on draco and selene assumed 300B tokens as data size

Day 2 – Your Turn

Outline of Day 2 (5.5 hours lunch break)

09:00 AM - 09:15 AM: Environment prep
09:15 AM - 09:45 AM: About compute
09:45 AM - 10:15 AM:
Lab 1 - 1_Acquire data (WebScraping)
Lab 1 - 2_Estimate Time Needed for Compute
10:15 AM - 10:30 AM: Lab 1 – 3_Megatron's core MPU (presentation)
10:30 AM - 11:00 AM: Lab 1 – 3_Megatron's core MPU (lab)
11:00 AM - 11:40 AM:
Lab 1 – 4_GPT Vocab+Merge file
Lab 1 – 5_data_preprocessing2mmap
11:40 AM - 12:00 PM: Intro to profiling
12:00 PM - 12:10 PM: Ask the Experts (Robert Dietrich)
12:10 PM – 13:10 PM: Lunch break
13:10 PM - 13:40 PM: Lab 1 – 6_GPT training config vs GPUs performance
13:40 PM - 14:10 PM: Challenge overview
14:10 PM - 14:30 PM: Discussion & What's up next day

FETCH THE TOY DATA

Lab1-1_Website_scrapping.ipynb.ipynb

Get Your Own Data via webcrawling the website / webpages you have permisson to use

note_1 : strongly recommand to consult with your own legal department for compliance before proceeding this step on websites/webpages you have permission to

note_2 : modification needed when applying to different website/webpages

note_3 : use at your own risk !

Learning Objectives

The goal of this lab is to demonstrate the fact that, there are ways to obtain your own data, the example given below is to crawl the webpages, from a seeding url, with the end goal of obtaining the raw texts. Please double check you have permission to extract the content of these webpages.

- Provide a list of urls in a text file via collecting webpages links

the base url used to crawl links from is https://developer.nvidia.com/blog/

- scrap the webpage (in html format) using scrapy and obtain raw text, then concatenate all the raw text per webpage into one text file

In [ ]:
```
!pip install beautifulsoup4
!pip install html5lib
!pip install PyPDF2
!pip install selenium
!pip install Scrapy
```

crawl NVblog landing page and obtain links to the individual blogs

source github repo : https://github.com/x4nth055/pythoncode-tutorials/tree/master/web-scraping/link-extractor

In [2]:
```
!wget https://raw.githubusercontent.com/x4nth055/pythoncode-tutorials/master/web-scraping/link-extractor/link_extractor.py
```

```
--2021-09-15 09:14:55--  https://raw.githubusercontent.com/x4nth055/pythoncode-tutorials/master/web-scraping/link-extractor/link_extracto
r.py
Resolving raw.githubusercontent.com (raw.githubusercontent.com)... 185.199.110.133, 185.199.108.133, 185.199.109.133, ...
Connecting to raw.githubusercontent.com (raw.githubusercontent.com)|185.199.110.133|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 3485 (3.4K) [text/plain]
Saving to: ‘link_extractor.py’

link_extractor.py   100%[===================>]   3.40K  --.-KB/s    in 0.001s

2021-09-15 09:14:56 (3.97 MB/s) - ‘link_extractor.py’ saved [3485/3485]
```

Day 2 – Intro to Megatron MPU

Xianchao Wu

Outline of Day 2 (5.5 hours lunch break)

09:00 AM - 09:15 AM: Environment prep
09:15 AM - 09:45 AM: About compute
09:45 AM - 10:15 AM:
Lab 1 – Acquire data (WebScraping)
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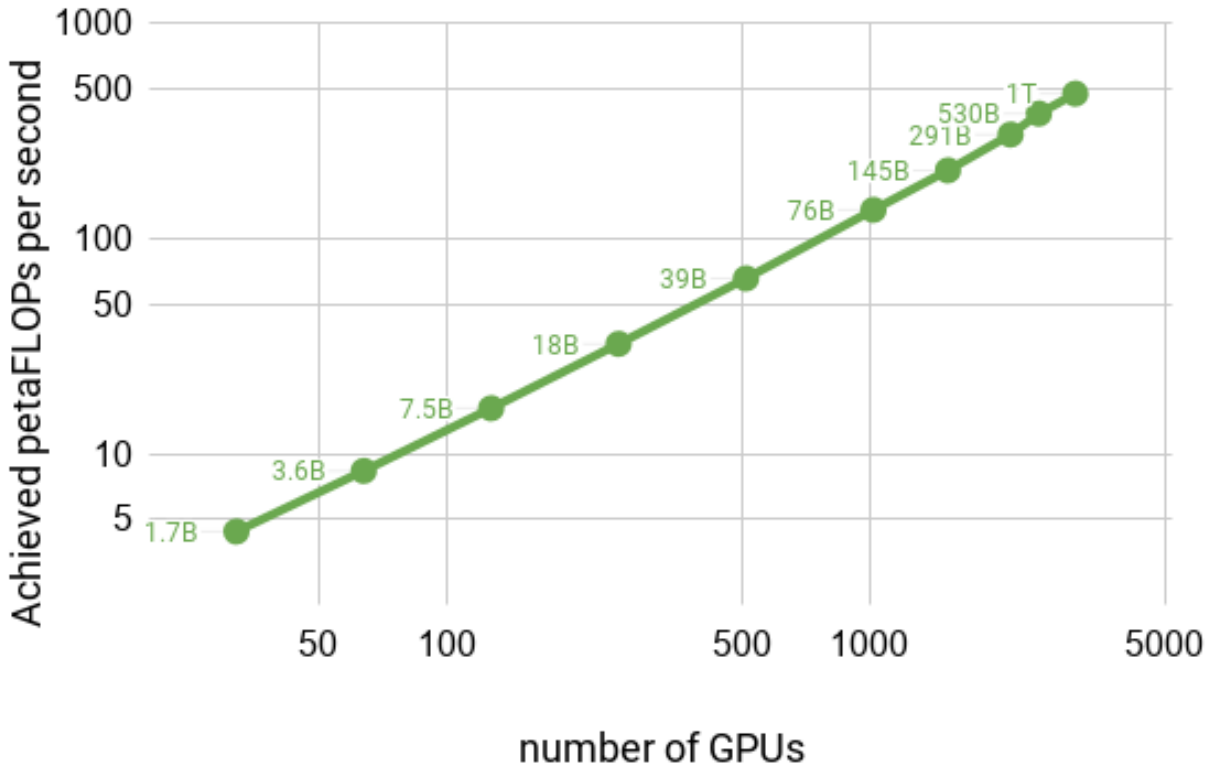
13:40 PM - 14:10 PM: Challenge overview
14:10 PM - 14:30 PM: Discussion & What's up next day

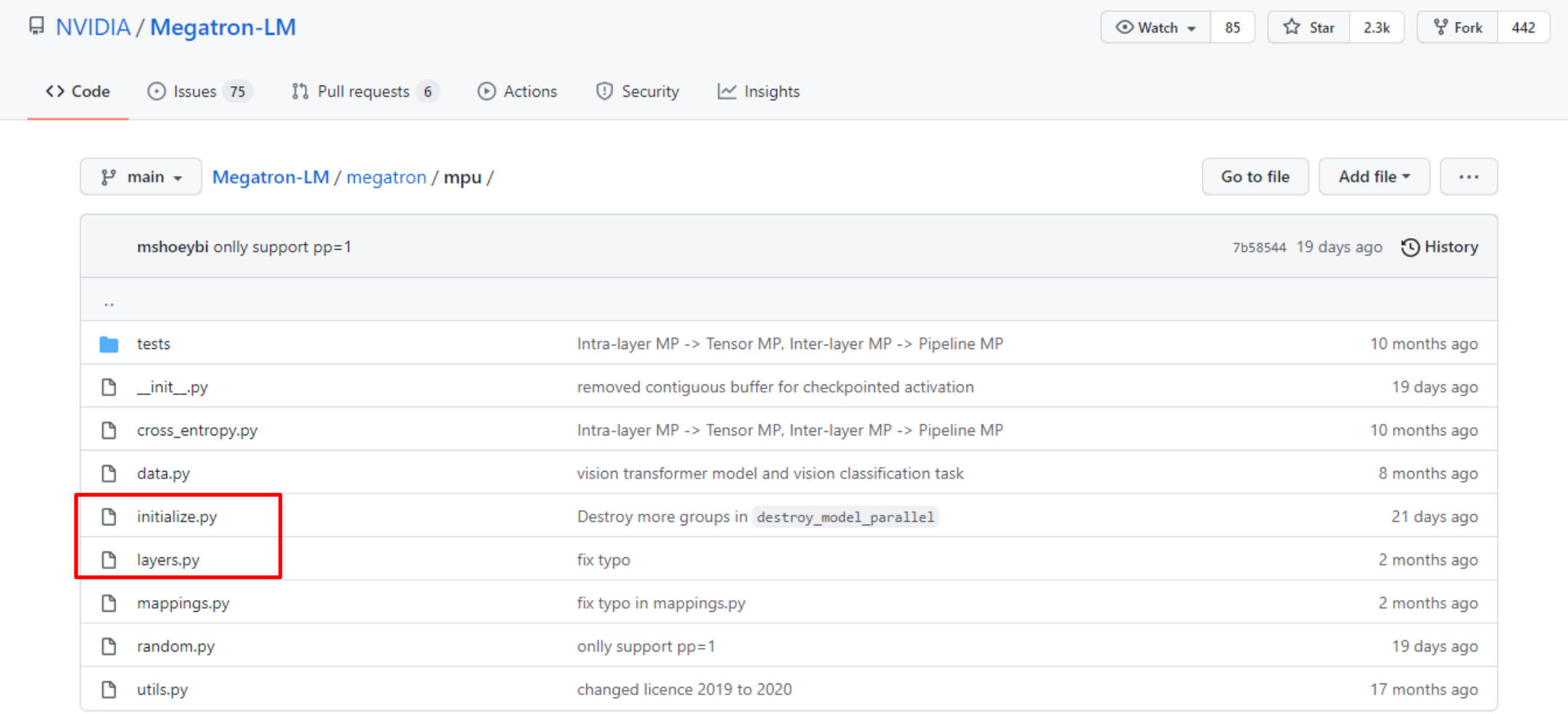
REMEMBER WHY WE CARE



● is the achievable GPT3 model size

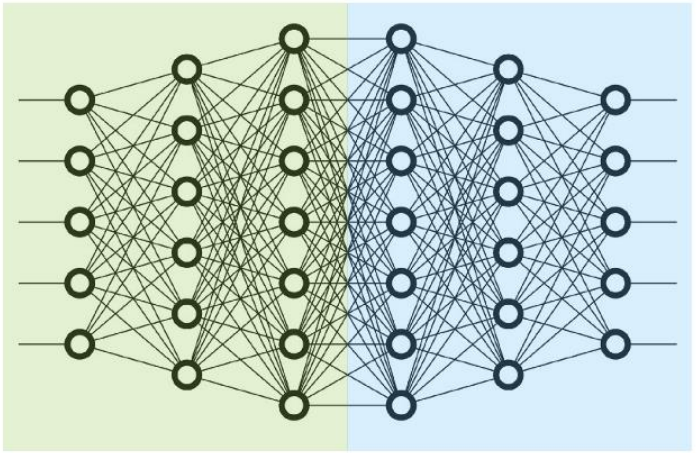
https://arxiv.org/pdf/1909.08053.pdf

MEGATRON CORE MPU

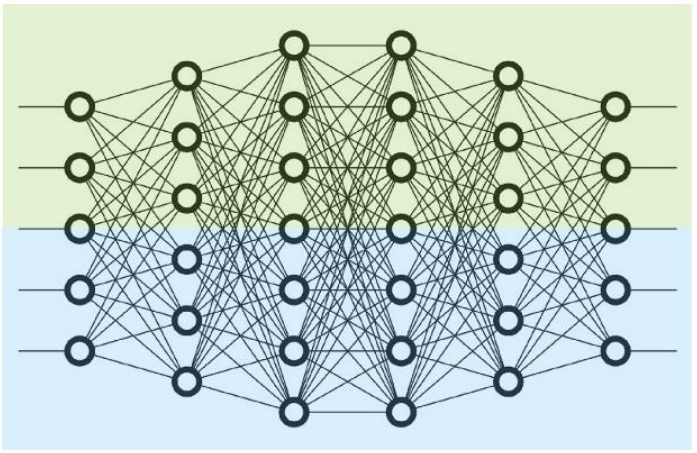


MODEL PARALLELISM

- Pipeline (Inter-Layer) Parallelism
  - Split sets of layers across multiple devices
  - Layer 0,1,2 and layer 3,4,5 are on difference devices

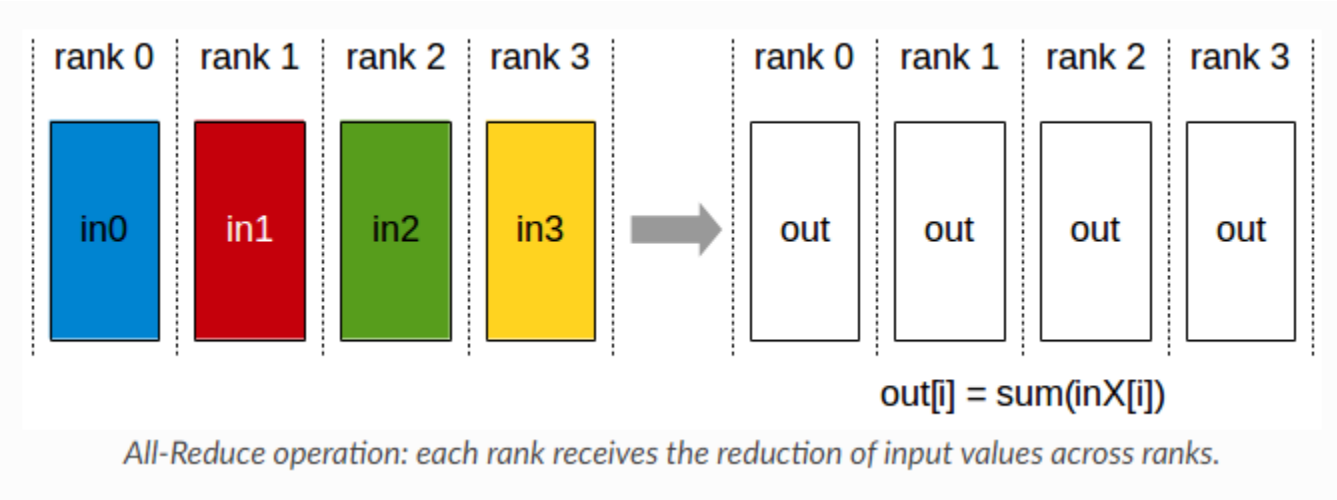


- Tensor (Intra-Layer) Parallelism
  - Split individual layers across multiple devices
  - Both devices compute difference parts of Layer 0,1,2,3,4,5



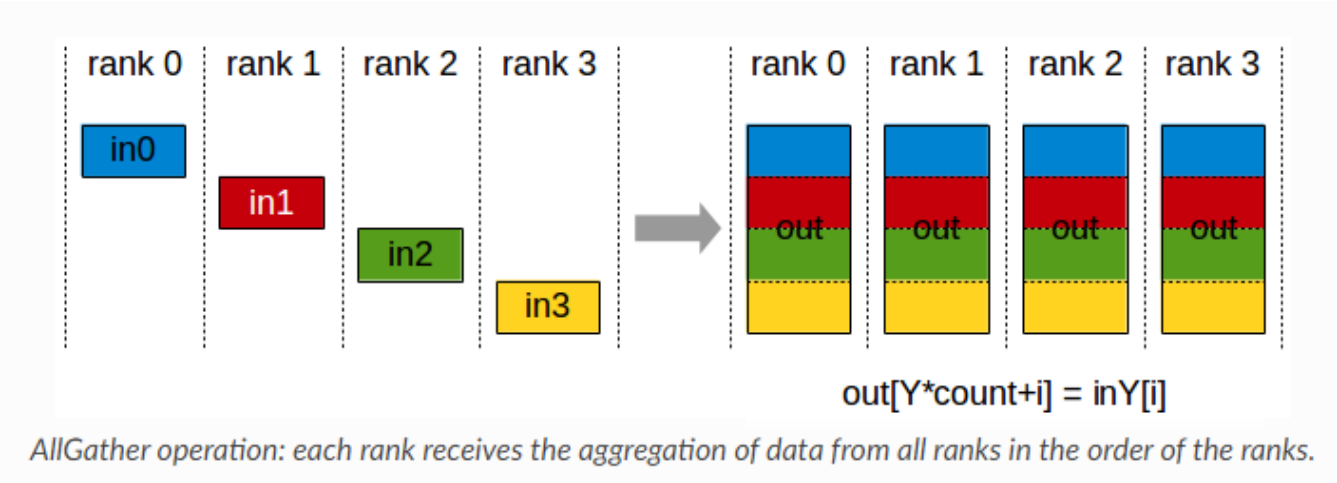
NCCL COLLECTIVE OPERATORS

All reduce



All-Reduce operation: each rank receives the reduction of input values across ranks.

All gather



AllGather operation: each rank receives the aggregation of data from all ranks in the order of the ranks.

https://docs.nvidia.com/deeplearning/nccl/user-guide/docs/usage/operations.html

GELU | ELU | RELU

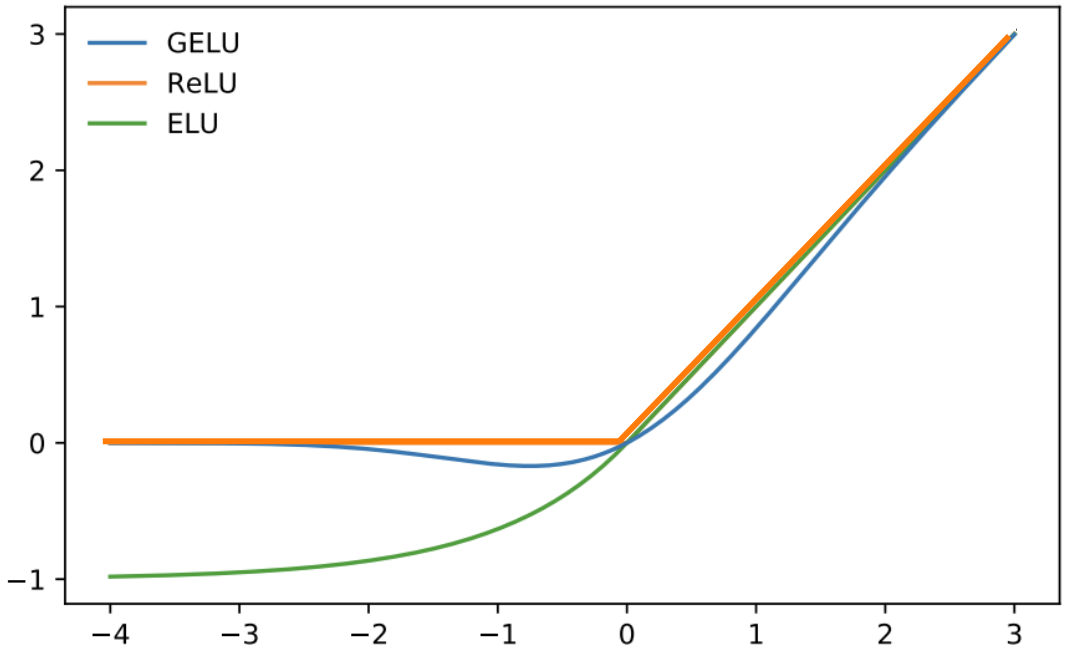
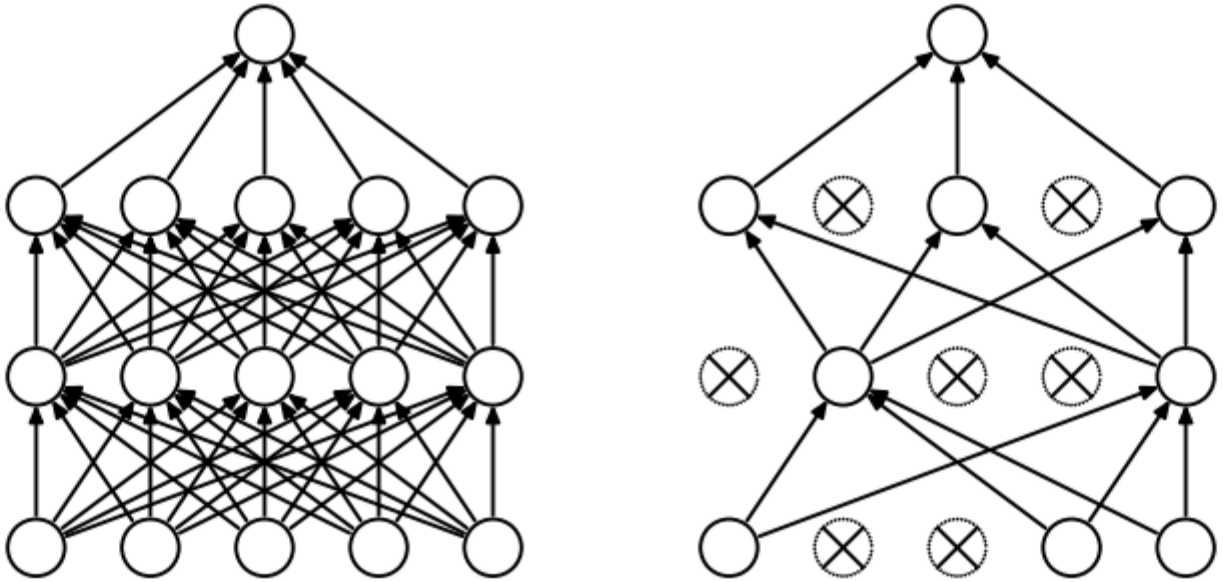


Figure 1: The GELU ($\mu = 0, \sigma = 1$), ReLU, and ELU ($\alpha = 1$).

https://paperswithcode.com/method/gelu

DROPOUT



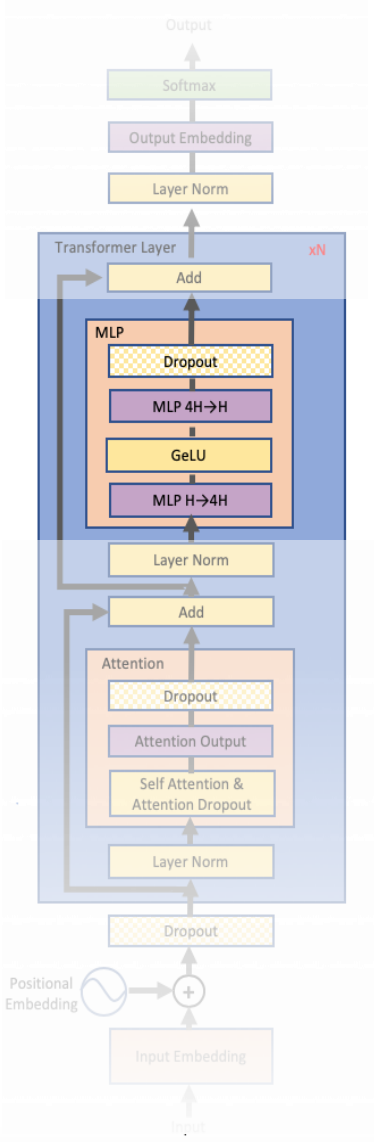
(a) Standard Neural Net (b) After applying dropout.

Figure 1: Dropout Neural Net Model. **Left**: A standard neural net with 2 hidden layers. **Right**: An example of a thinned net produced by applying dropout to the network on the left. Crossed units have been dropped.

https://proceedings.neurips.cc/paper/2013/file/71f6278d140af599e06ad9bf1ba03cb0-Paper.pdf

https://www.jmlr.org/papers/volume15/srivastava14a/srivastava14a.pdf?utm_content=buffer79b43&utm_medium=social&utm_source=twitter.com&utm_campaign=buffer

LET'S BREAK IT DOWN – FIRST UP *MLP*



PARTITIONING MULTI-LAYER PERCEPTRON (MLP)

- MLP:

$$Y = \mathrm{GeLU}(XA)$$
$$Z = \mathrm{Dropout}(YB)$$

- Approach 1: split X column-wise and A row-wise:

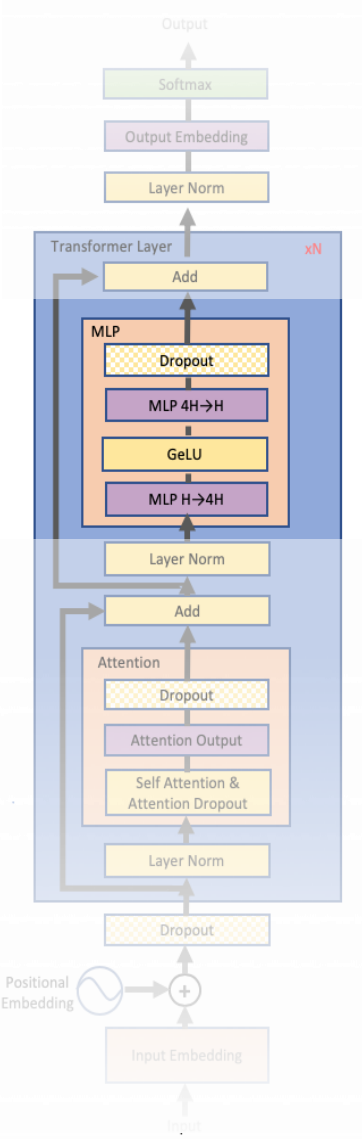
$$X = [X_1, X_2] \quad A = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix} \longrightarrow Y = \mathrm{GeLU}(X_1A_1 + X_2A_2)$$

  - Before GeLU we will need a communication point

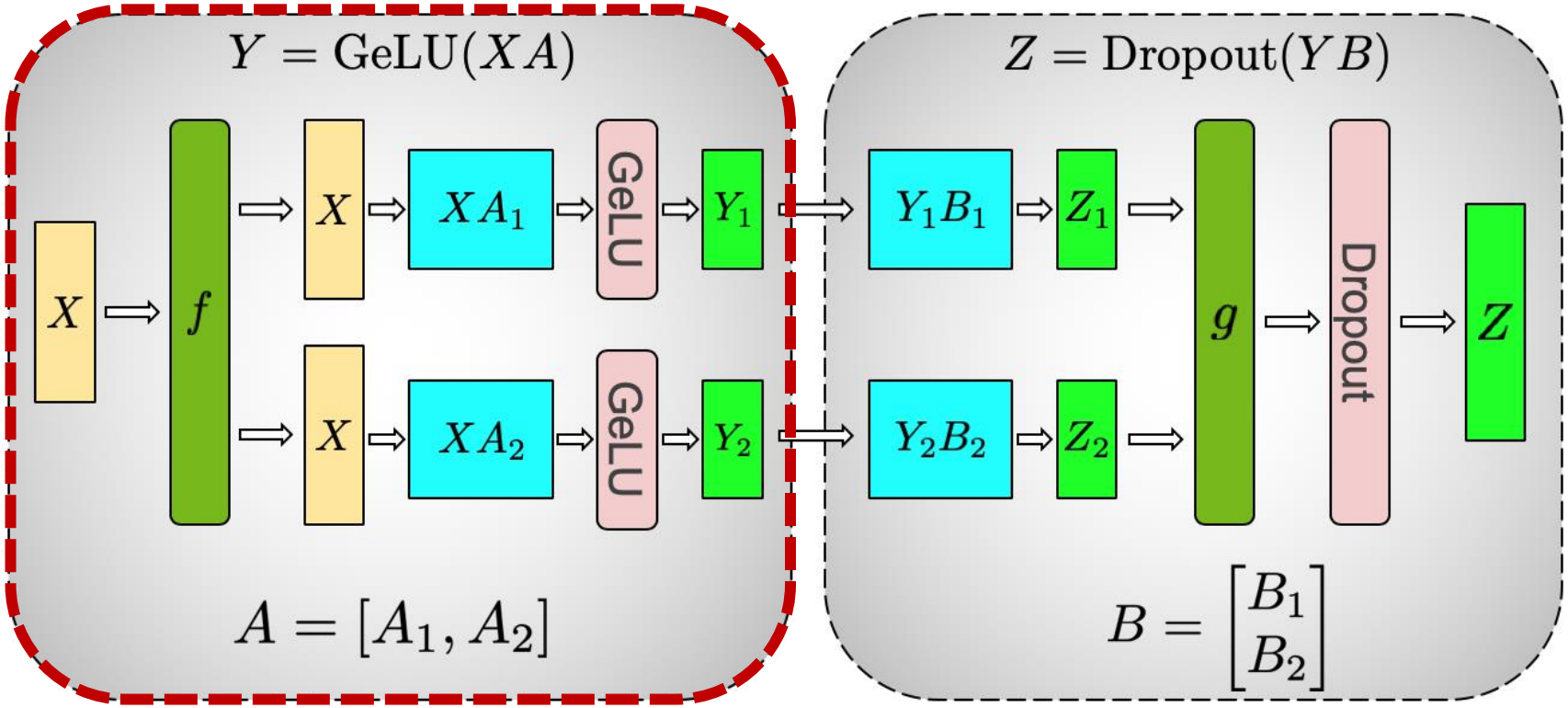
- Approach 2: split A column-wise:

$$A = [A_1, A_2] \longrightarrow [Y_1, Y_2] = [\mathrm{GeLU}(XA_1), \mathrm{GeLU}(XA_2)]$$

  - No communication is required



MLP



f and ***g*** are **conjugate**, ***f*** is **identity** operator in the forward pass and **all-reduce** in the backward pass while ***g*** is **all-reduce** in forward and **identity** in backward.

TENSOR MODEL PARALLEL - *COLUMN* PARALLEL

$$Y = \text{gelu}(XA)$$

If we cut A vertically

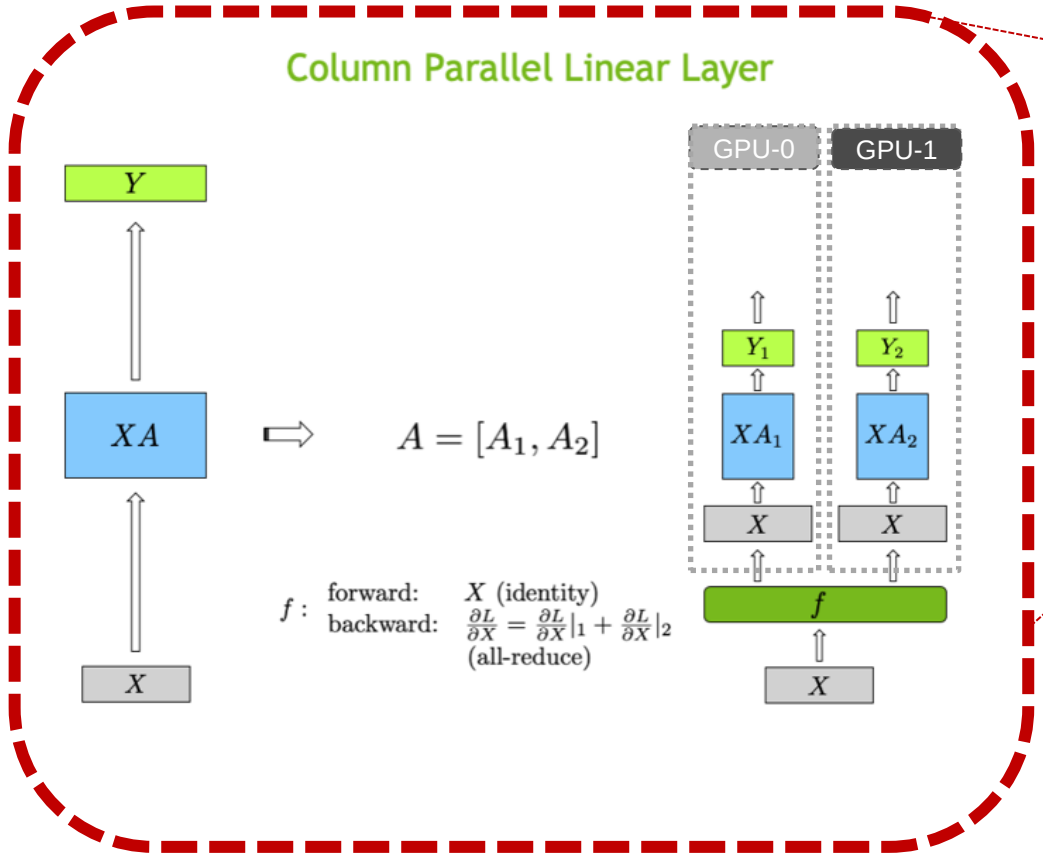
$$A = [A_1, A_2]$$

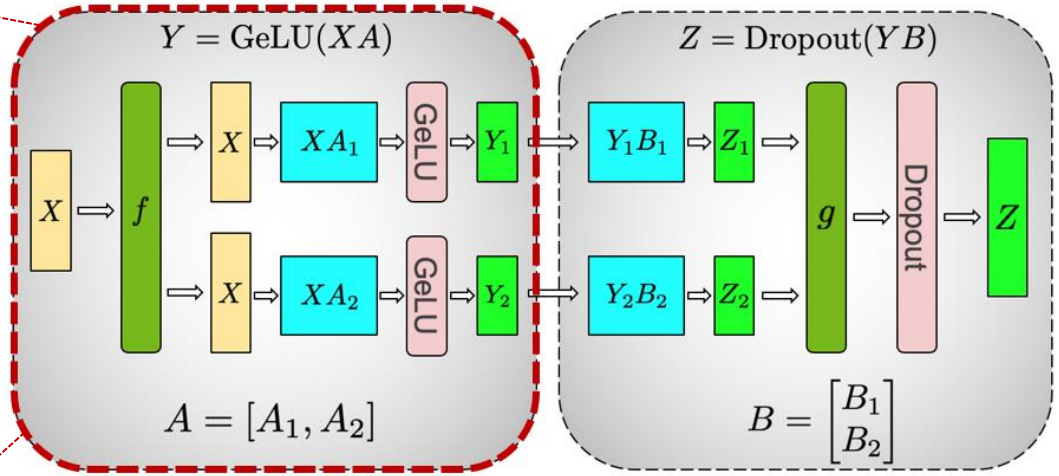
slice	Parameter matrix A	Input tensor X
Column Parallel	$[A_1, A_2]$	X

$$Y = [Y_1, Y_2] = [\text{gelu}(XA_1), \text{gelu}(XA_2)]$$

GPU-0 GPU-1

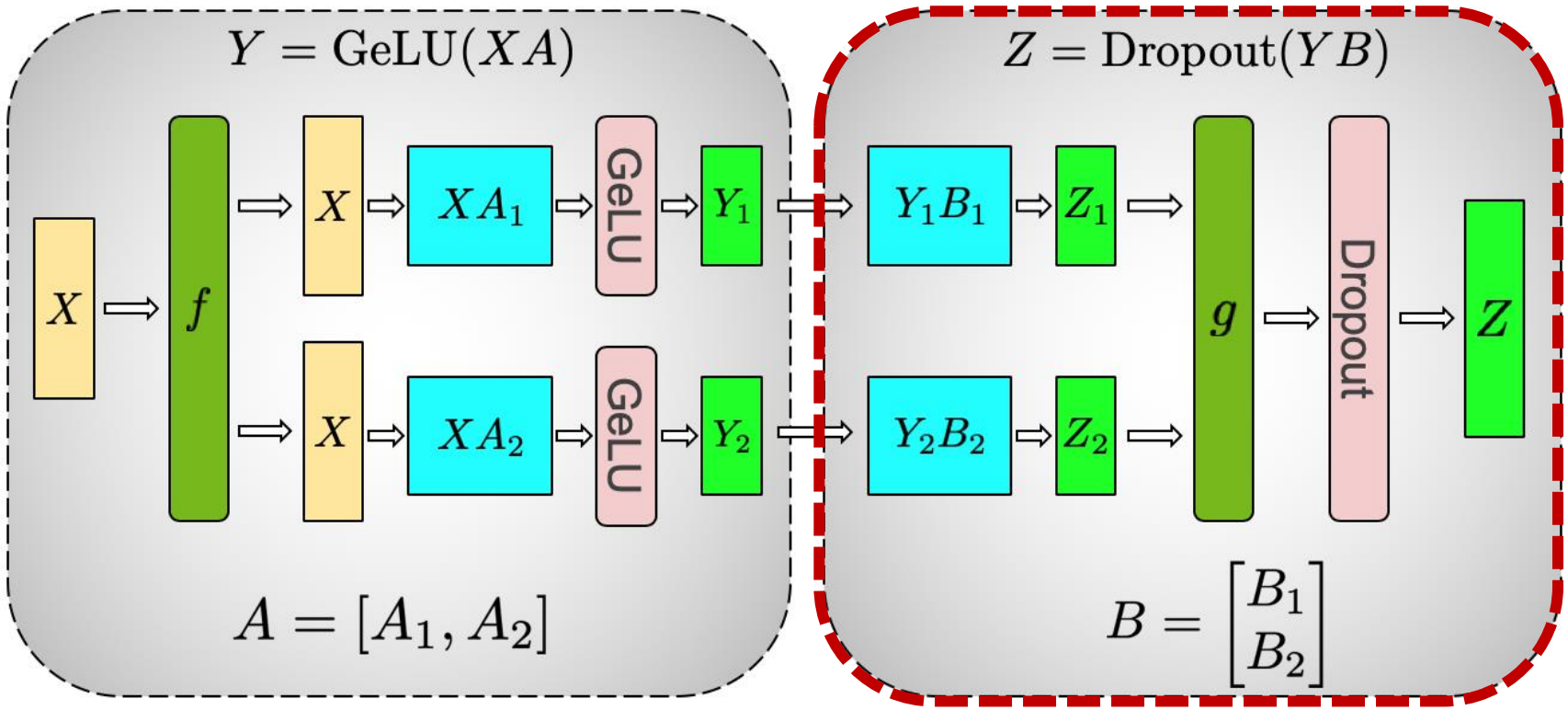
COLUMN PARALLEL - FORWARD | BACKWARD





f and *g* are **conjugate**, *f* is **identity** operator in the forward pass and **all-reduce** in the backward pass while *g* is **all-reduce** in forward and **identity** in backward.

MLP



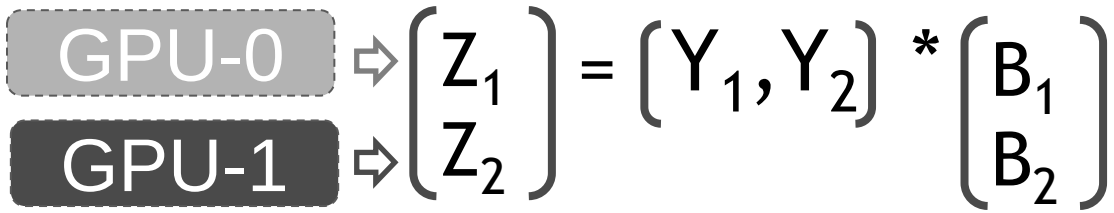
f and ***g*** are **conjugate**, ***f*** is **identity** operator in the forward pass and **all-reduce** in the backward pass while ***g*** is **all-reduce** in forward and **identity** in backward.

TENSOR MODEL PARALLEL - *ROW* PARALLEL

Z=Dropout(YB)

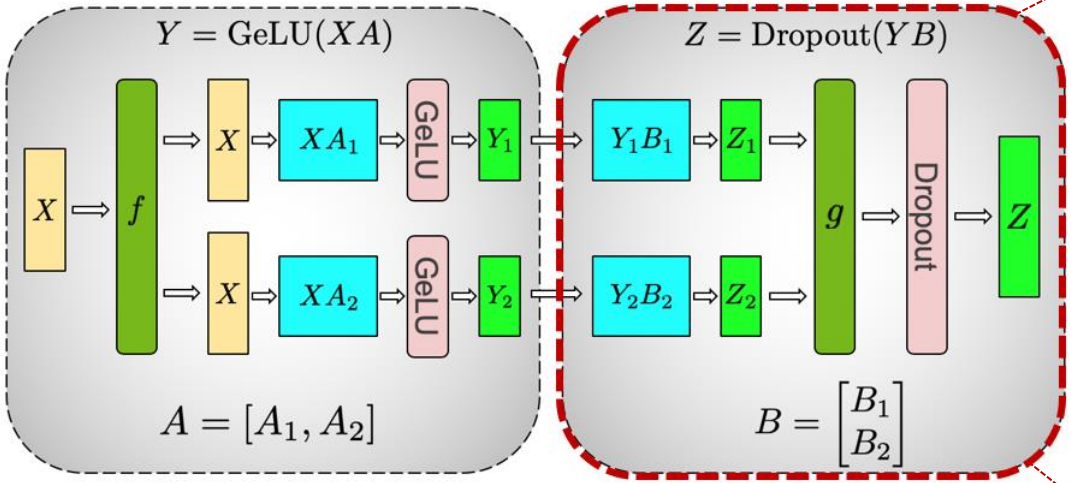
If we cut B horizontally

slice	Parameter Matrix B	output from previous Y
Row Parallel	$[B_1, B_2]$	$[Y_1, Y_2]$

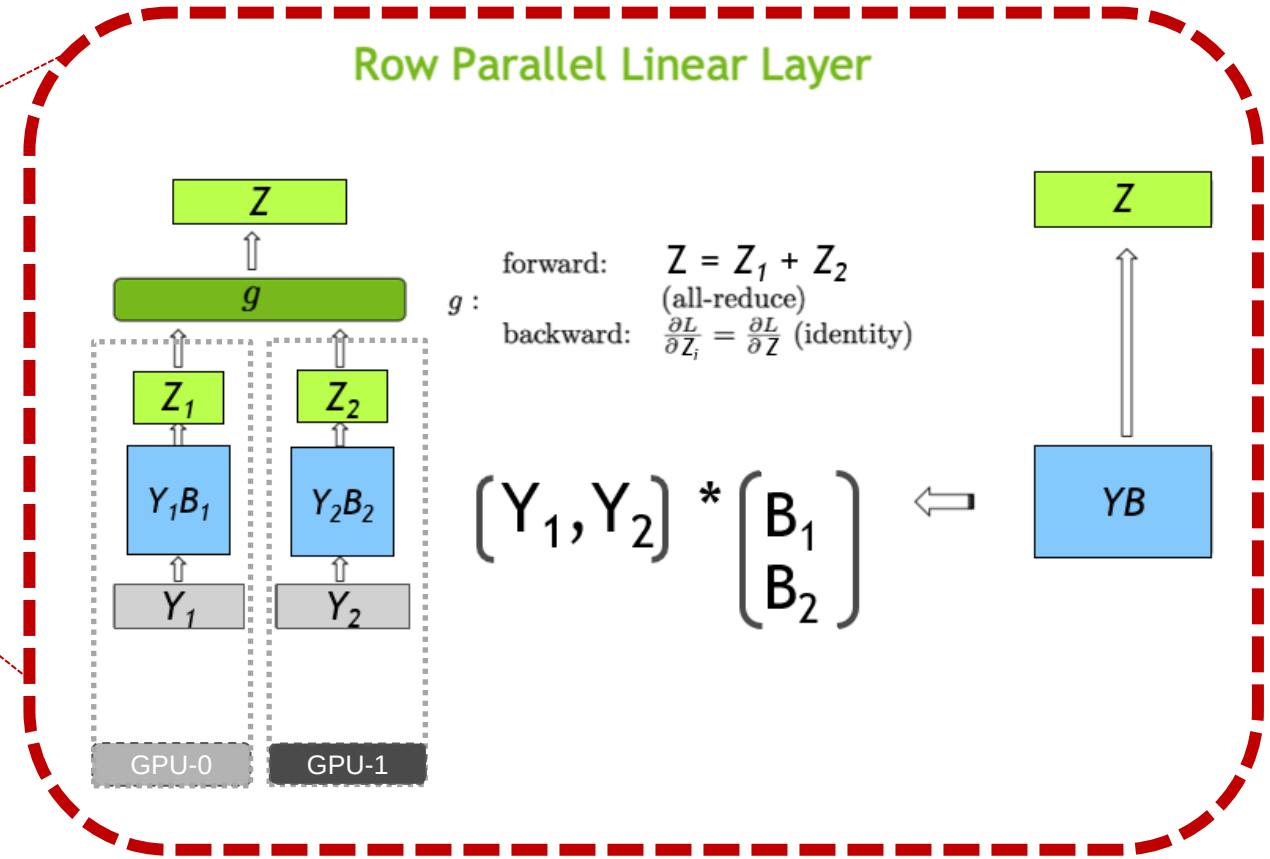


$$Z = Z_1 + Z_2$$

ROW PARALLEL - FORWARD | BACKWARD



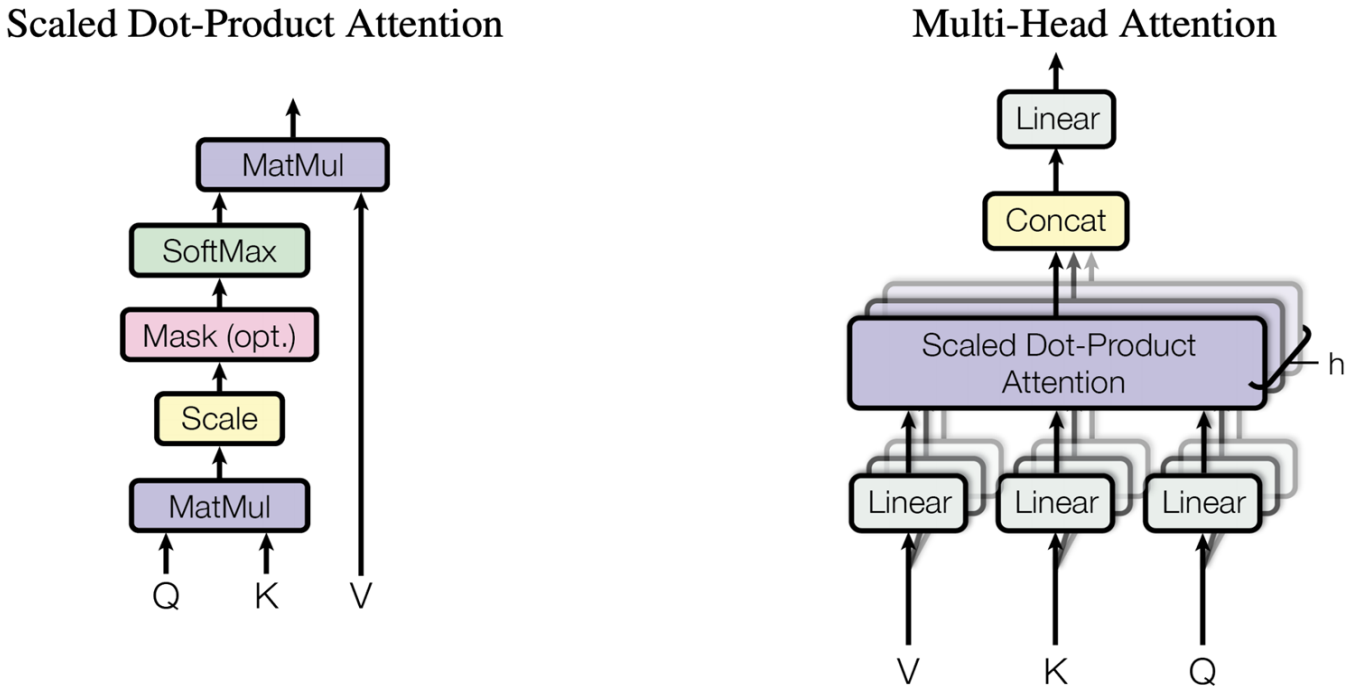
f and *g* are **conjugate**, *f* is **identity** operator in the forward pass and **all-reduce** in the backward pass while *g* is **all-reduce** in forward and **identity** in backward.

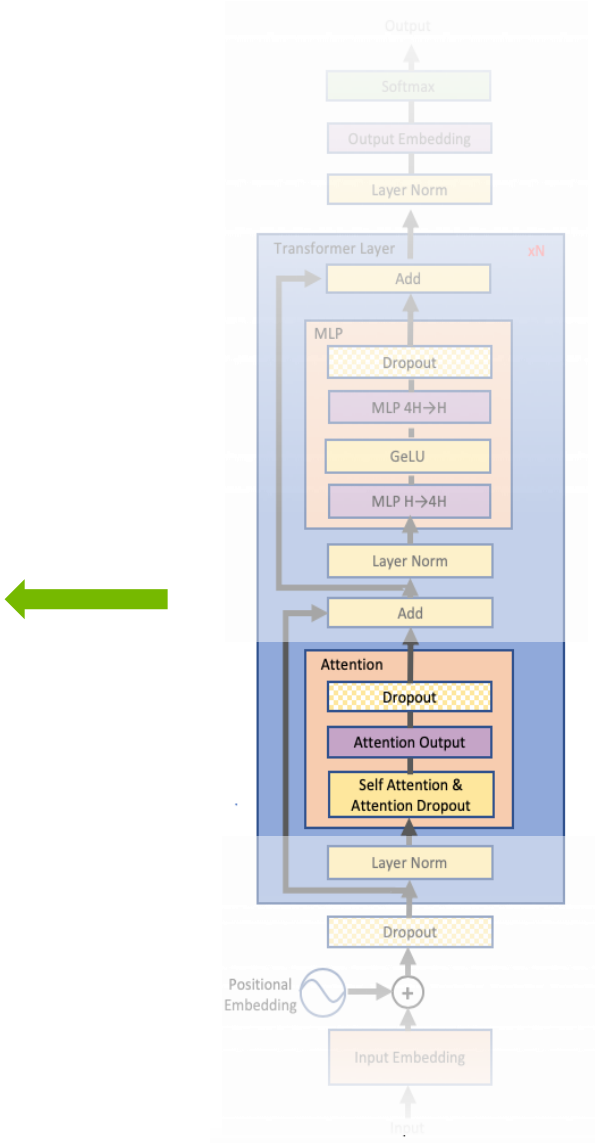


SELF-ATTENTION

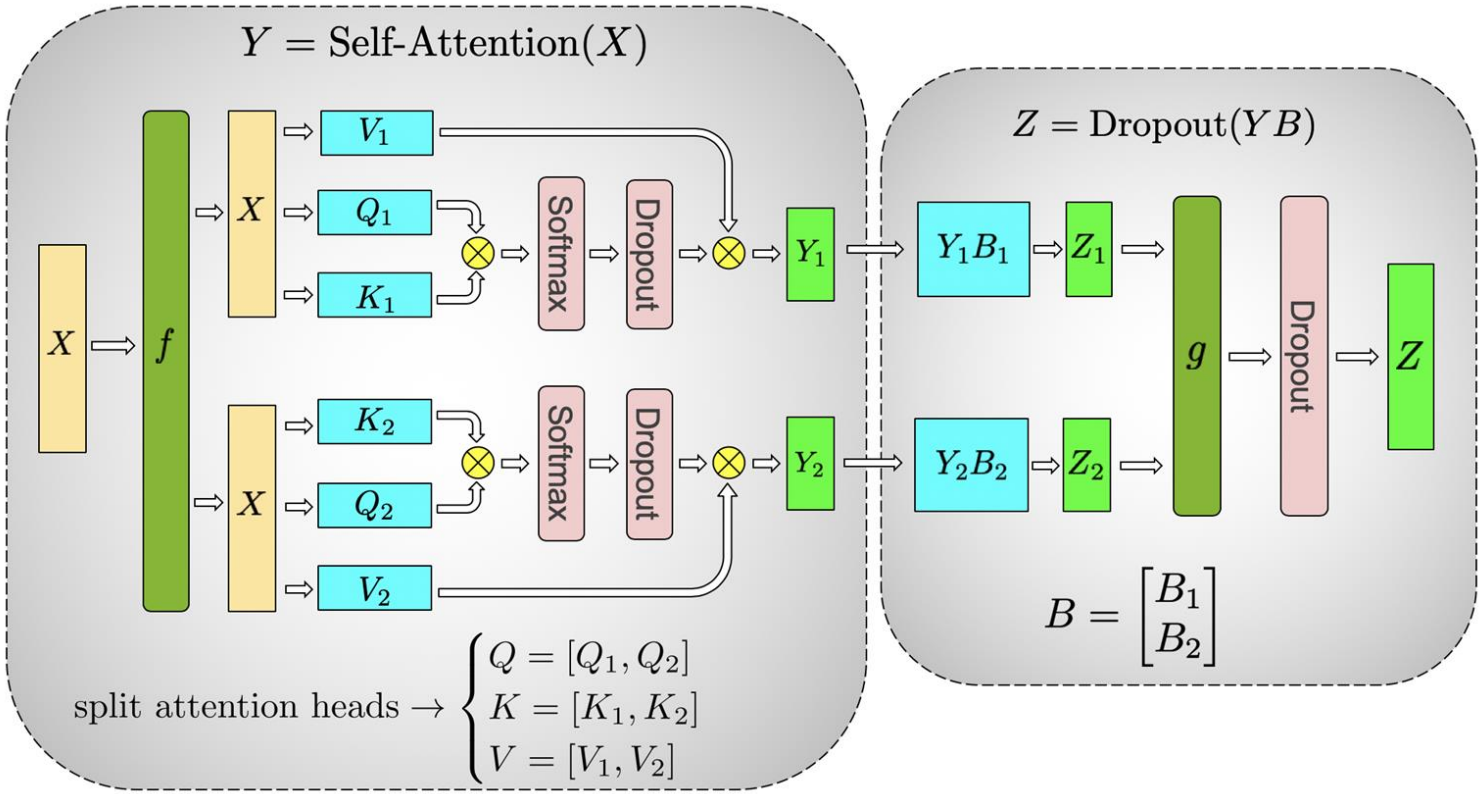
PARTITIONING: SELF-ATTENTION

- Self-attention is more complex than MLP





SELF-ATTENTION – SAME MECHANISM APPLIES



f and ***g*** are **conjugate**, ***f*** is **identity** operator in the forward pass and **all-reduce** in the backward pass while ***g*** is **all-reduce** in forward and **identity** in backward.

COMPARING TENSOR AND PIPELINE PARALLELISM

Tensor Parallelism

Communication expensive

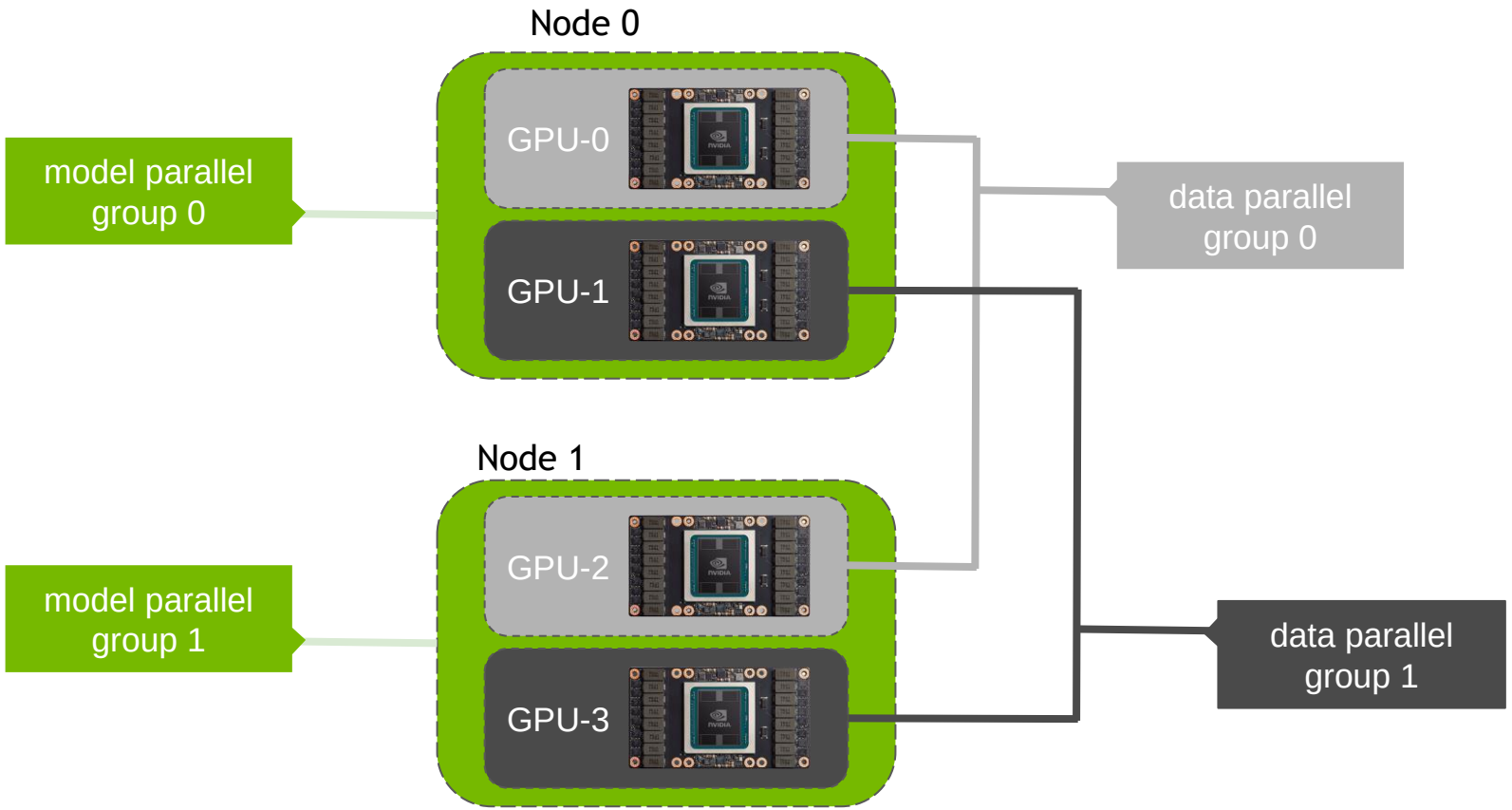
Good performance across batch sizes

Pipeline Parallelism

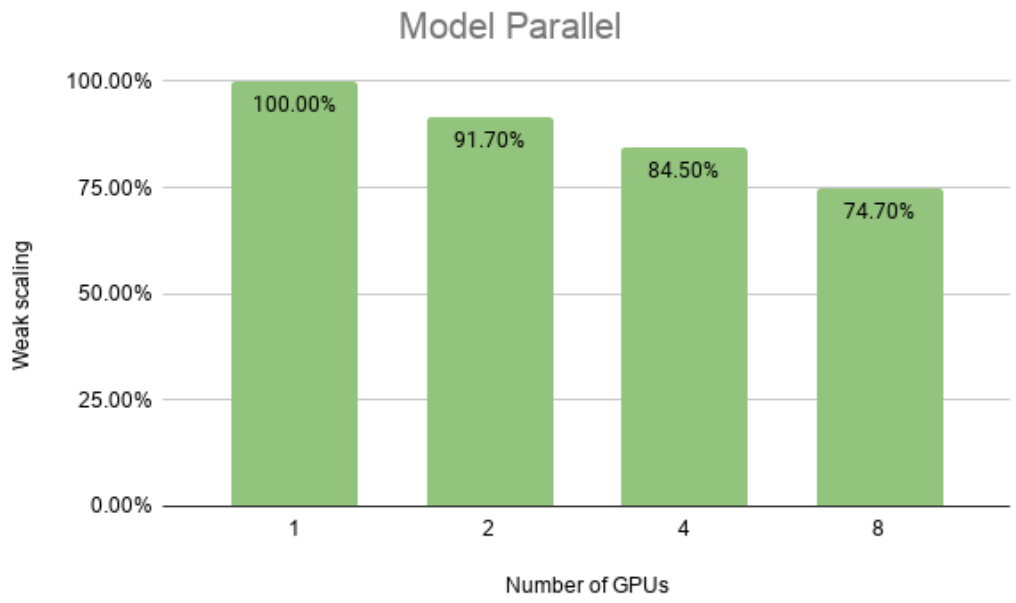
Communication cheap

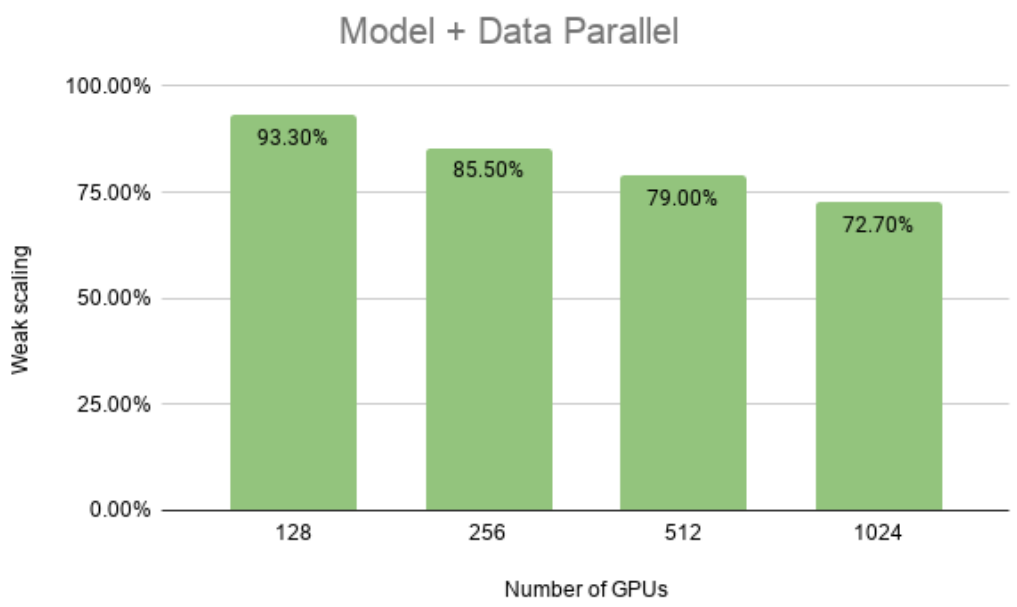
Good performance at larger batch sizes (pipeline stall amortized)

HYBRID MODEL+DATA PARALLELISM



WEAK SCALING EFFICIENCY ON SELENE

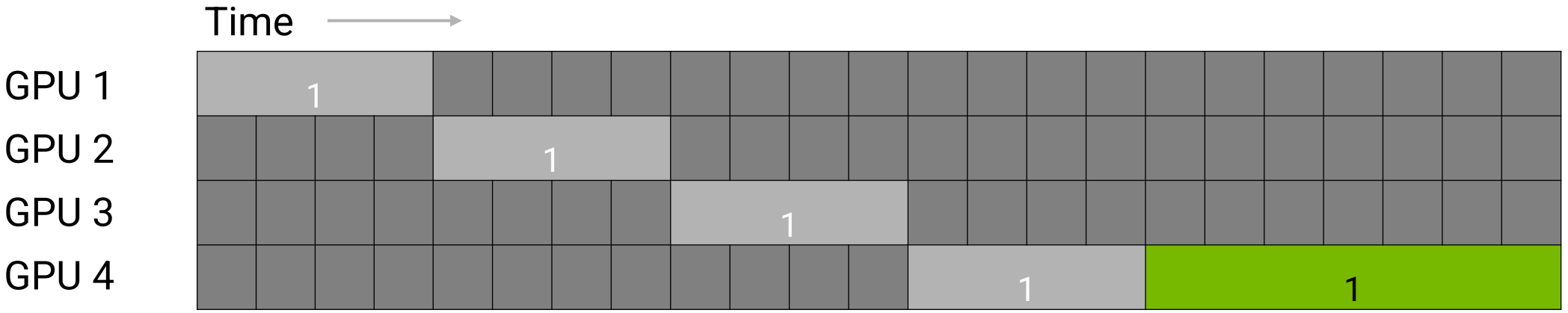




Baseline (1.2B parameters on a single GPU) sustains
149.8 teraFLOPs/sec on a single A100 GPU (48% of the theoretical peak flops) over the entire training process

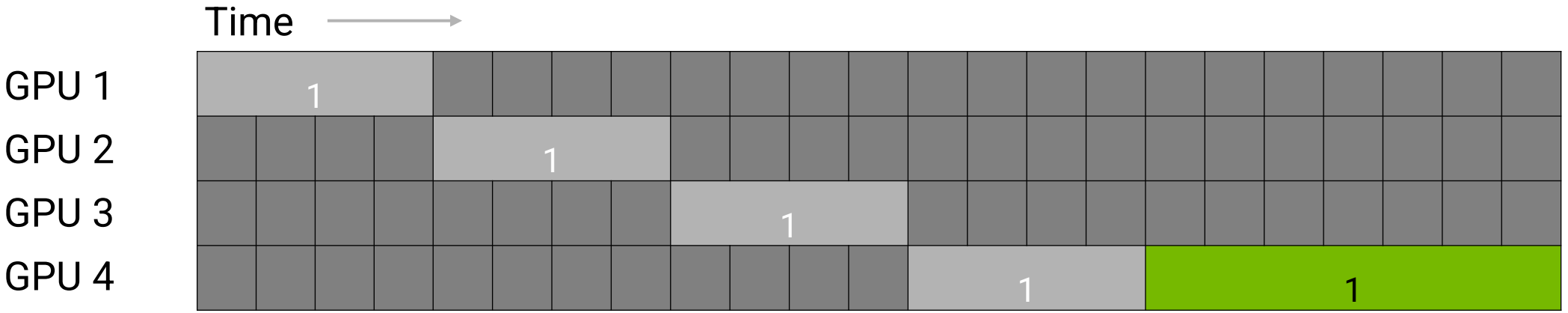
PIPELINING

PIPELINING

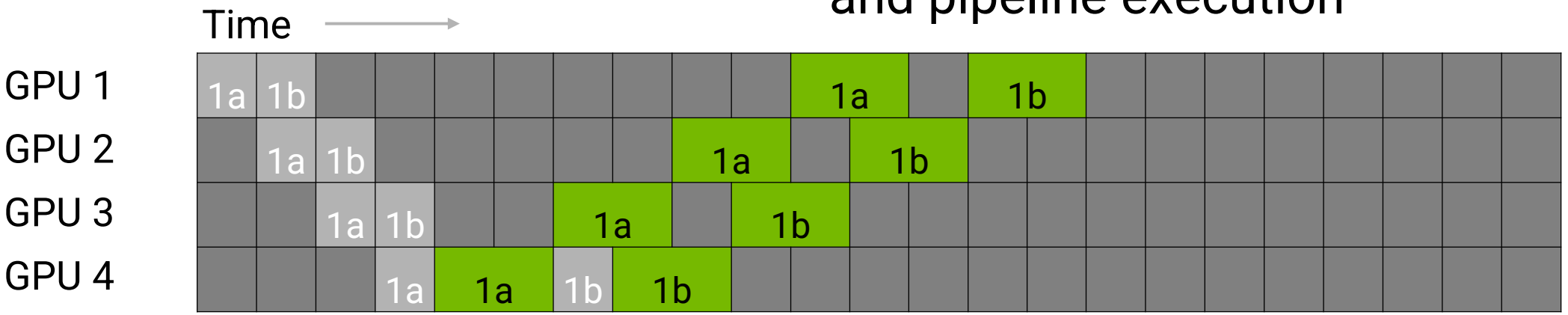


Split batch into microbatches and pipeline execution

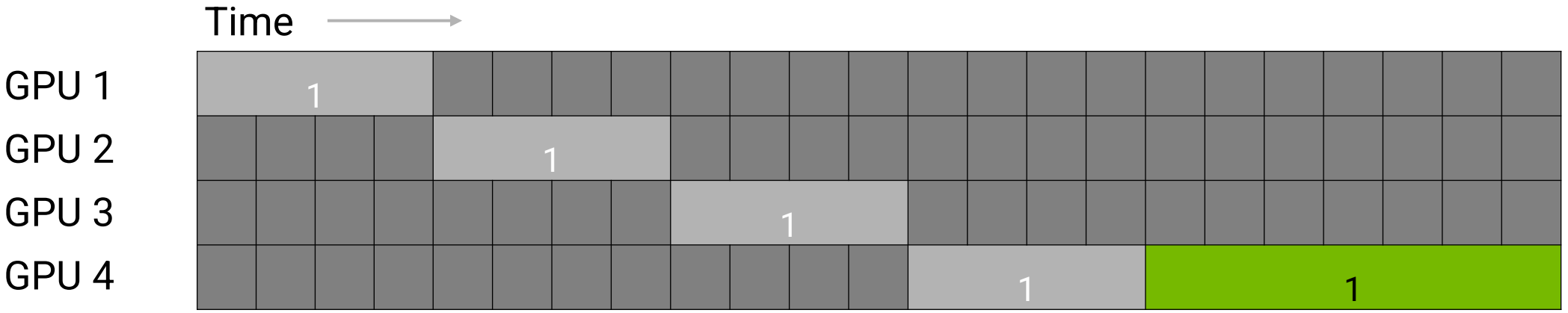
PIPELINING



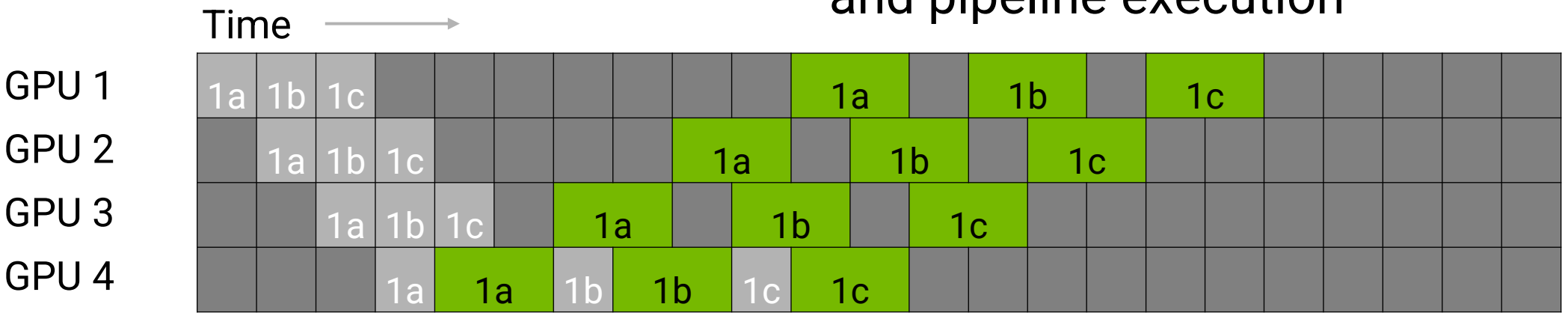
Split batch into microbatches and pipeline execution



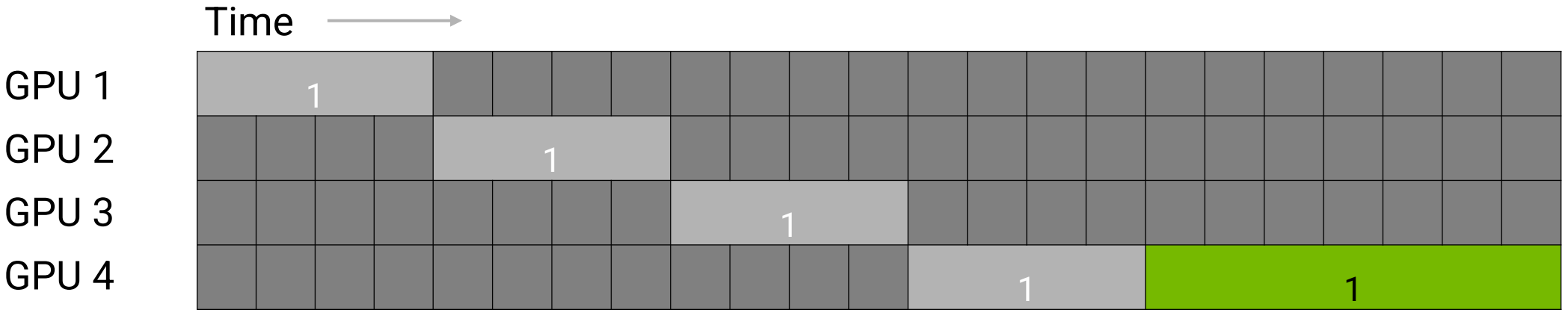
PIPELINING



Split batch into microbatches and pipeline execution



PIPELINING



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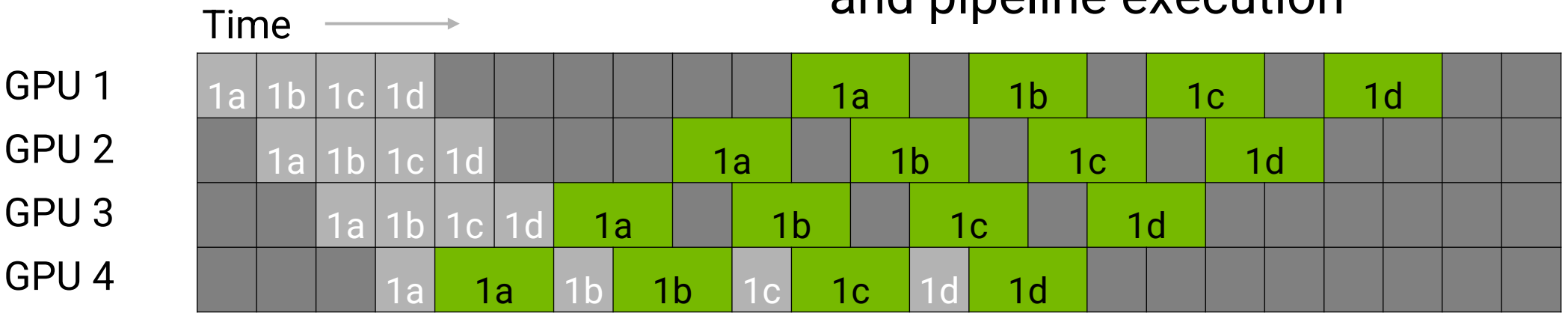
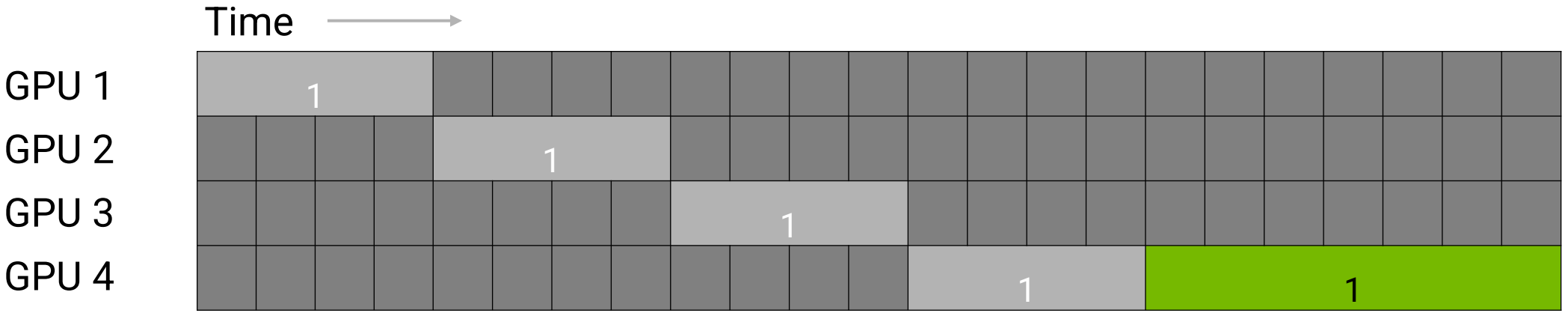


PIPELINING



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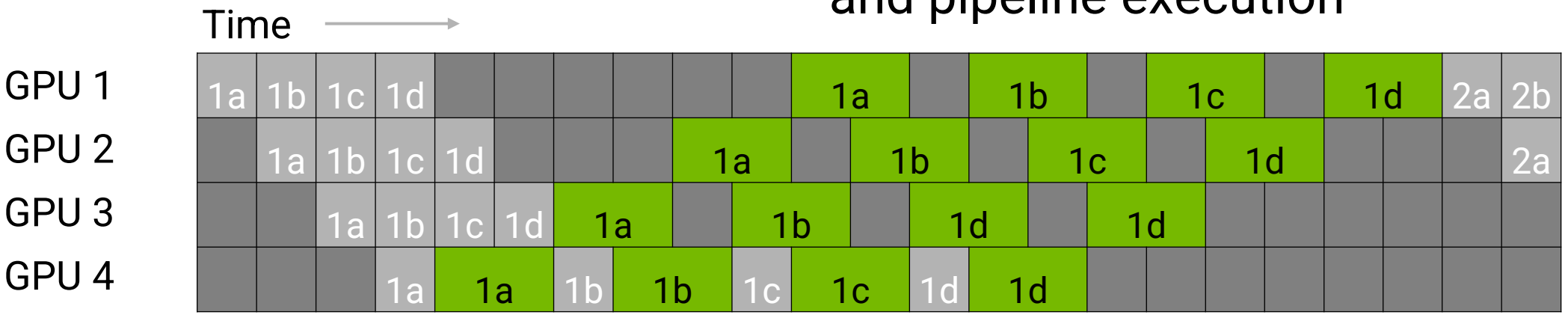
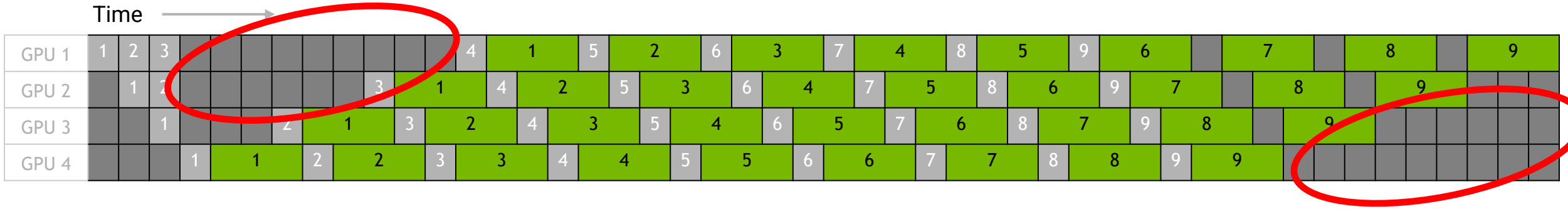


PIPELINE BUBBLES



p : number of pipeline stages

m : number of micro batches

t_f : forward step time

t_b : backward step time

$$\text{total time} = (m + p - 1) \times (t_f + t_b)$$

$$\text{ideal time} = m \times (t_f + t_b)$$

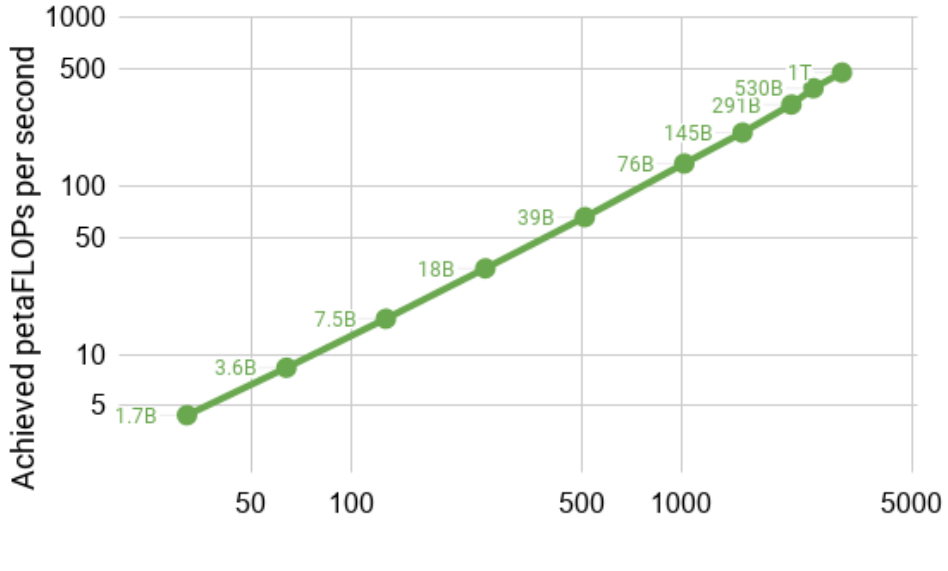
$$\text{bubble time} = (p - 1) \times (t_f + t_b)$$

$$\text{bubble time overhead} = \frac{\text{bubble time}}{\text{ideal time}} = \frac{p-1}{m}$$

SCALING ON SELENE (NVIDIA SUPERPOD)

Sequence length: 2048

Vocabulary size: 51,200



Model size (parameters)	Attention heads	Hidden size	Number layers	Tensor parallel size	Pipeline parallel size	Model parallel size	Data parallel size	Number GPUs	Batch size	% peak flops
1.7B	24	2304	24	1	1	1	32	32	512	44%
3.6B	32	3072	30	2	1	2	32	64	512	42%
7.5B	32	4096	36	4	1	4	32	128	512	41%
18B	48	6144	40	8	1	8	32	256	1024	41%
39B	64	8192	48	8	2	16	32	512	1536	41%
76B	80	10240	60	8	4	32	32	1024	1792	43%
145B	96	12288	80	8	8	64	24	1536	2304	44%
291B	128	16384	90	8	18	144	15	2160	2430	45%
530B	128	20480	105	8	35	280	9	2520	2520	49%
1T	160	25600	128	8	64	512	6	3072	3072	49%

Day 2 – Your turn !

Outline of Day 2 (5.5 hours lunch break)

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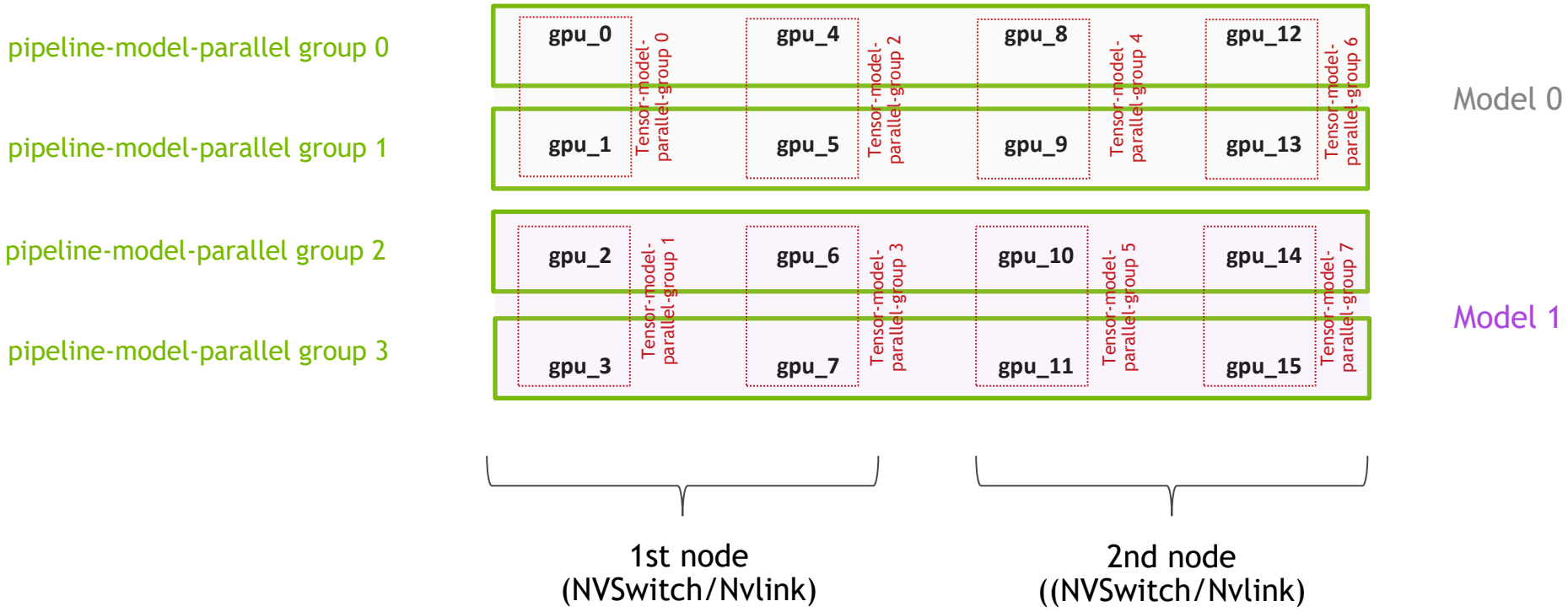
MEGATRON MODEL PARALLISM

GPU affinity grouping

Config set-up ---
Total number of GPUS : 16 GPUs (2 nodes , 8 gpus each node)
Pipeline-model-parallel : 4
Tensor-model-parallel : 2



Day 2 – Run through Megatron GPT

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PREPROCESSING DATA

- Input format: JSON array of dictionaries
  - One element per document
  - Text in the ‘text’ field by default (can also extract other fields)

BERT

```
python tools/preprocess_data.py \
        --input my-corpus.json \
        --output-prefix my-bert \
        --vocab bert-vocab.txt \
        --dataset-impl mmap \
        --tokenizer-type
BertWordPieceLowerCase \
        --split-sentences \
        --workers 80
```

GPT

```
python tools/preprocess_data.py \
        --input my-corpus.json \
        --output-prefix my-gpt \
        --vocab gpt-vocab.txt \
        --merge-file gpt-merges.txt \
        --dataset-impl mmap \
        --tokenizer-type GPT2BPETokenizer \
        --append-eod \
        --workers 80
```

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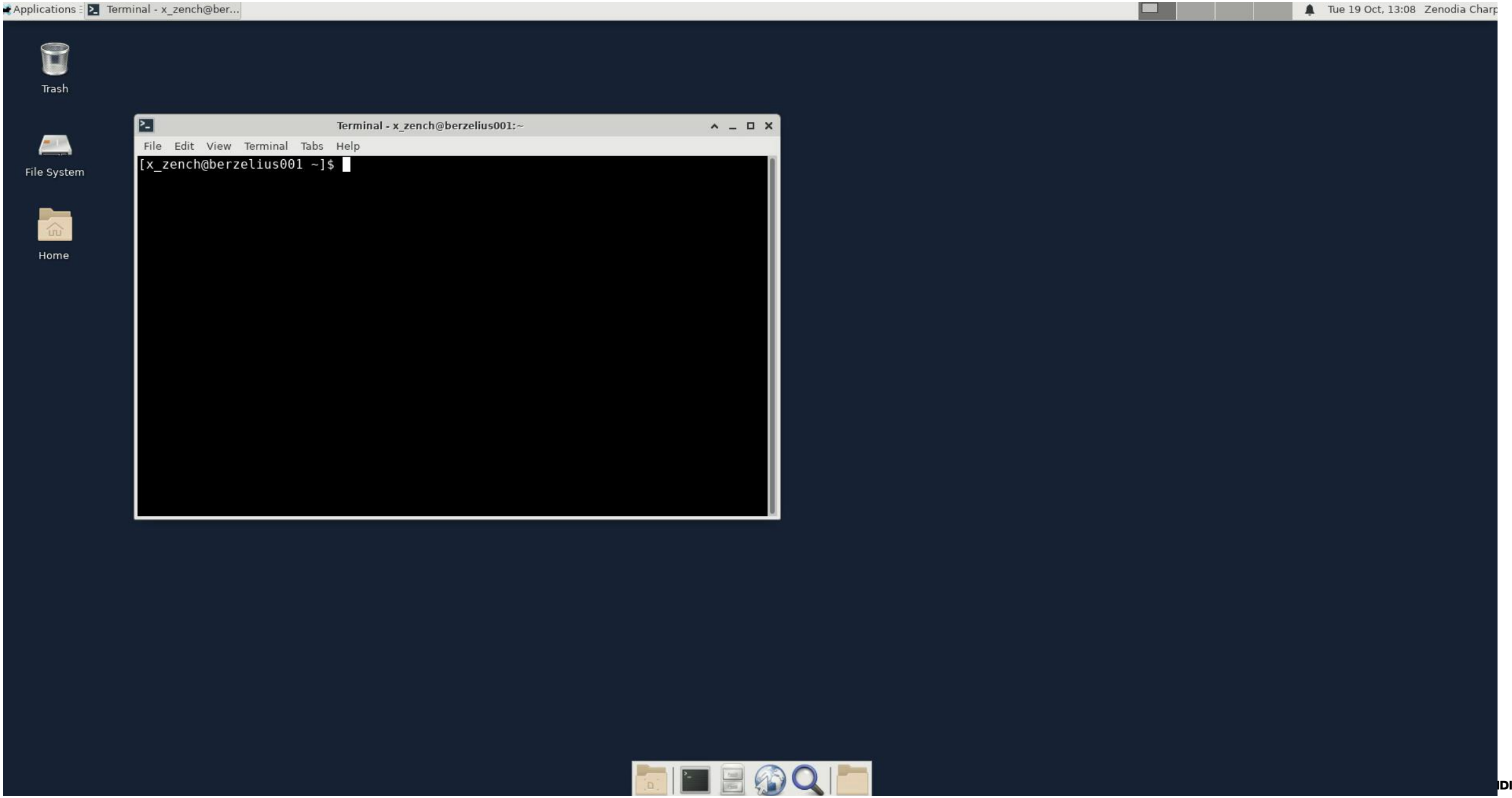
CALL OUT NSIGHT UI AND MONITOR ON BERZELIUS

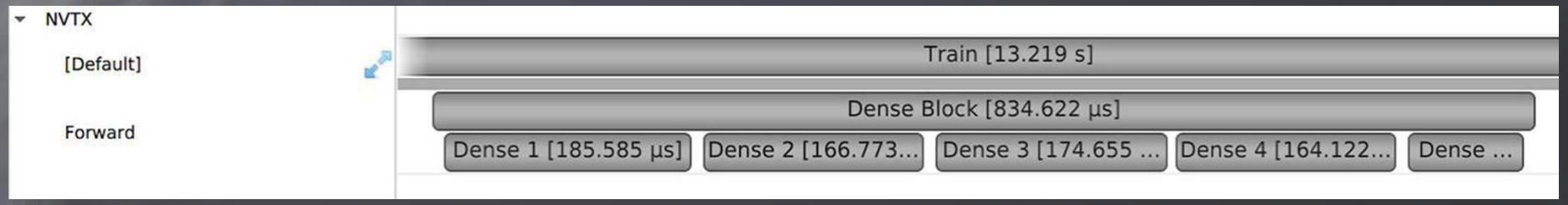


Verify the code runs for a smaller GPT3 variants

Nsight Systems	Nsight Compute

NVTX for Tensorflow	NVTX for PyTorch	NVTX for MXNet

With NVTX tags on Nsight



MANY SHADES OF PROFILING (MEGATRON PROFILING DECK)

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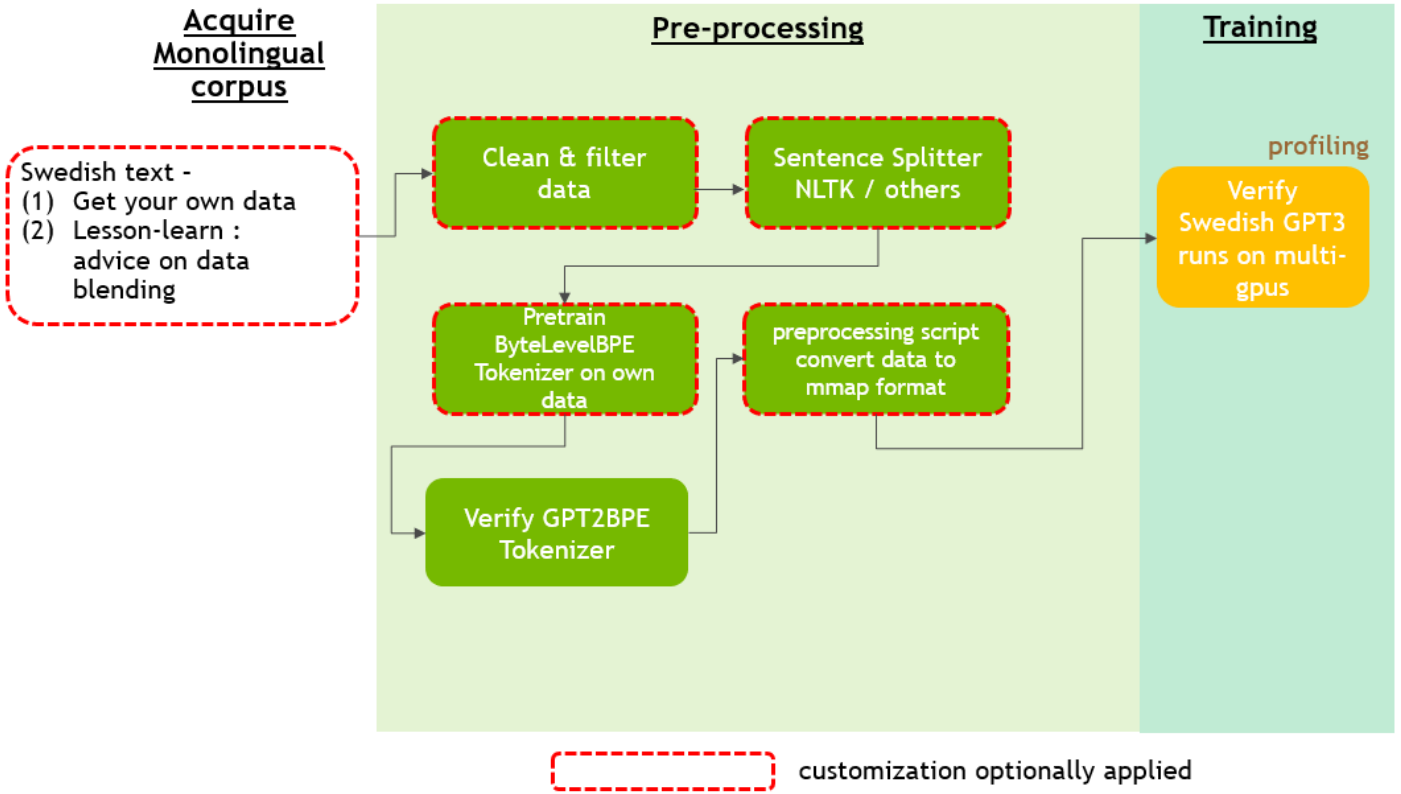
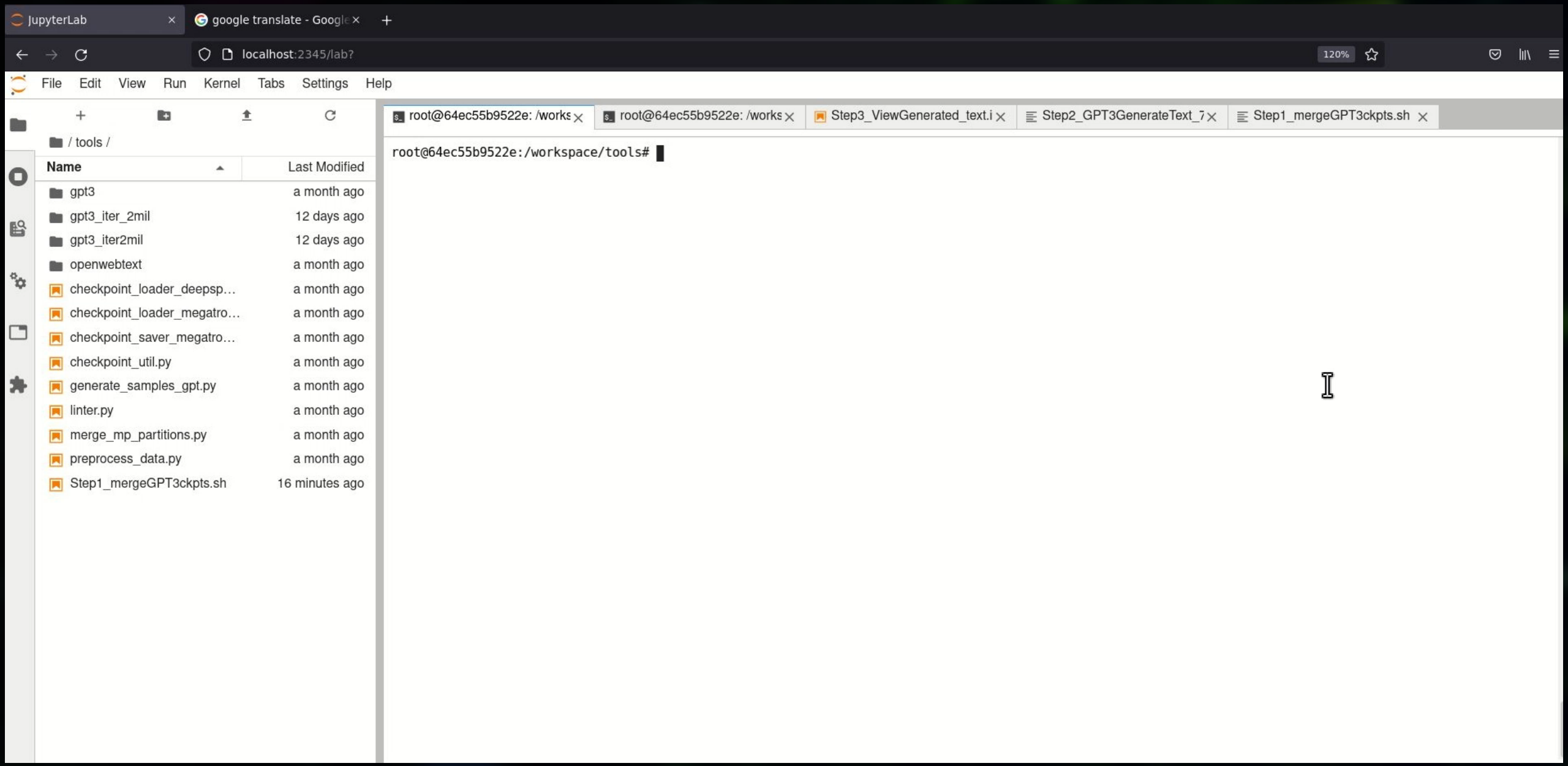
End of Day 2 !

Sneak peak of day 3 !





GENERATING TEXT WITH SWEDISH GPT 760M ITER_1MIL

INTRODUCING THE SPEAKERS OF THE DAY

Day 3's speakers – Denis Timonin &Avinash Kaur & Ashish Sardana

Dennis Timonin

Avinash Kaur

Ashish Sardana

Day 3 – Customize Megatron for Swedish

Outline of Day (6 hour with lunch break)

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09:30 AM - 10:20 AM:
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Lab 2 – 2_data cleaning & filter
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10:30 AM - 11:00 AM: Lab 2 – 3_train your own GPT tokenizer
11:00 AM - 11:30 AM: Lab 2 – 4_data preprocessing
11:30 AM - 12:00 PM: Lab 2 - 4 Mini challenge
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13:00 PM - 14:00 PM: Lab 2 – 5 Challenge – Go BIG or go home
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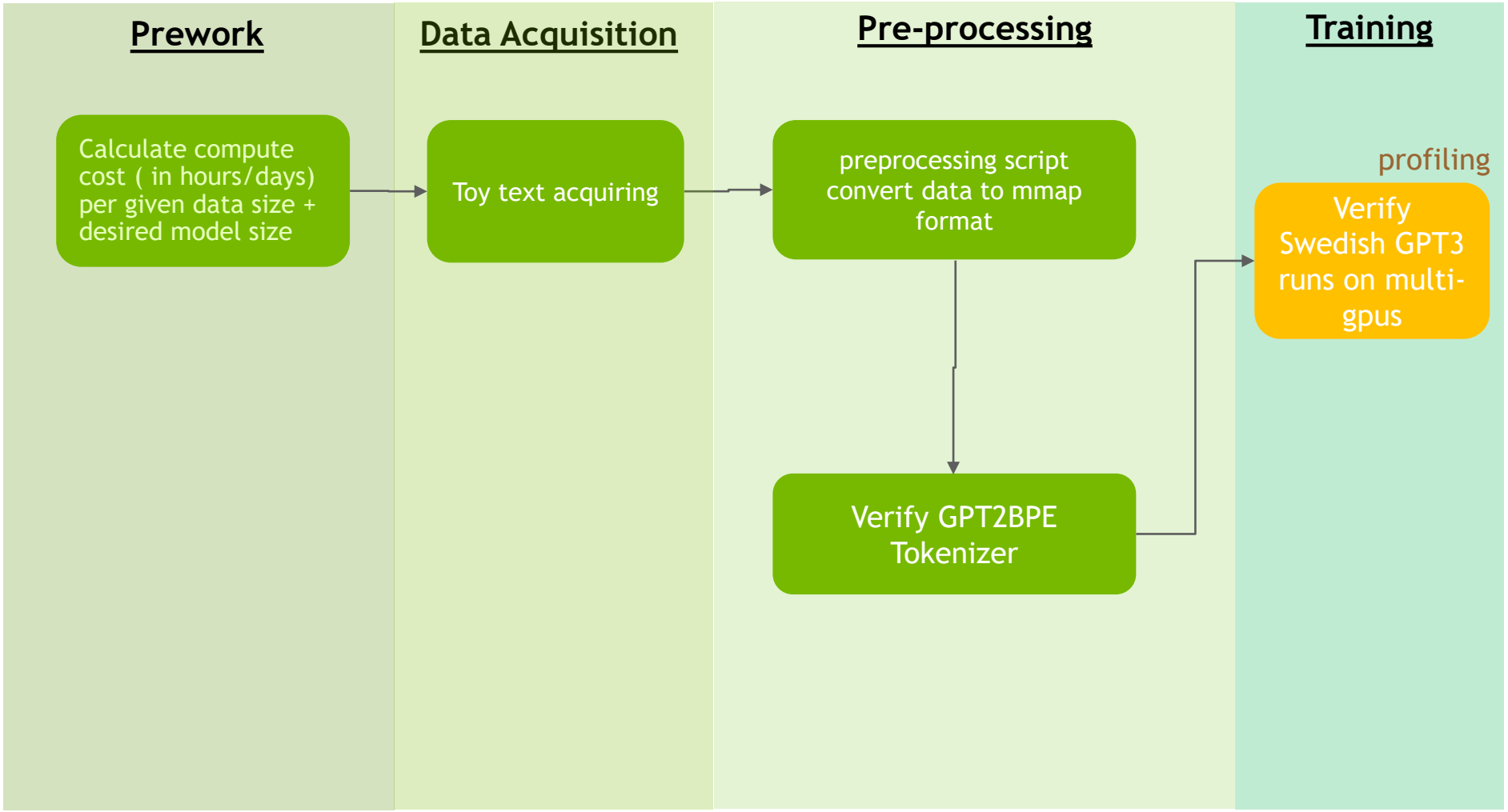
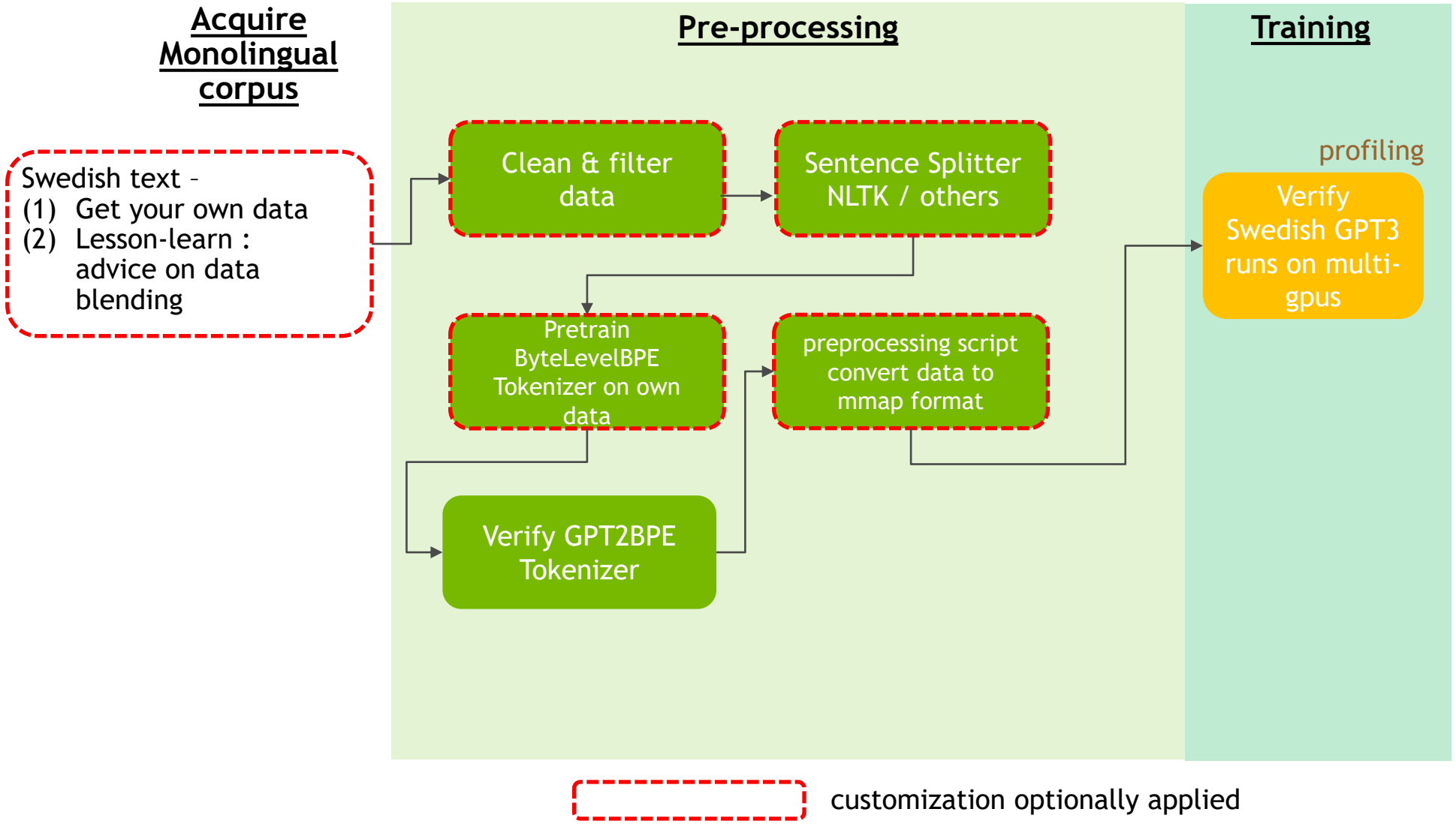
14:30 PM - 14:45 PM: Ask the Experts with NVIDIA data scientists on what's next for NLP
14:45 PM - 15:00 PM: Discussion & Final remarks

DAY 2 - RECAP


Prework
Data Acquisition
Pre-processing
Training
Calculate compute cost (in hours/days) per given data size + desired model size
Toy text acquiring
preprocessing script convert data to mmap format
Verify GPT2BPE Tokenizer
profiling
Verify Swedish GPT3 runs on multi-gpus

DAY 3 - OVERVIEW



Day 3 – Customize Megatron for Swedish

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ABOUT DATA ACQUISITION

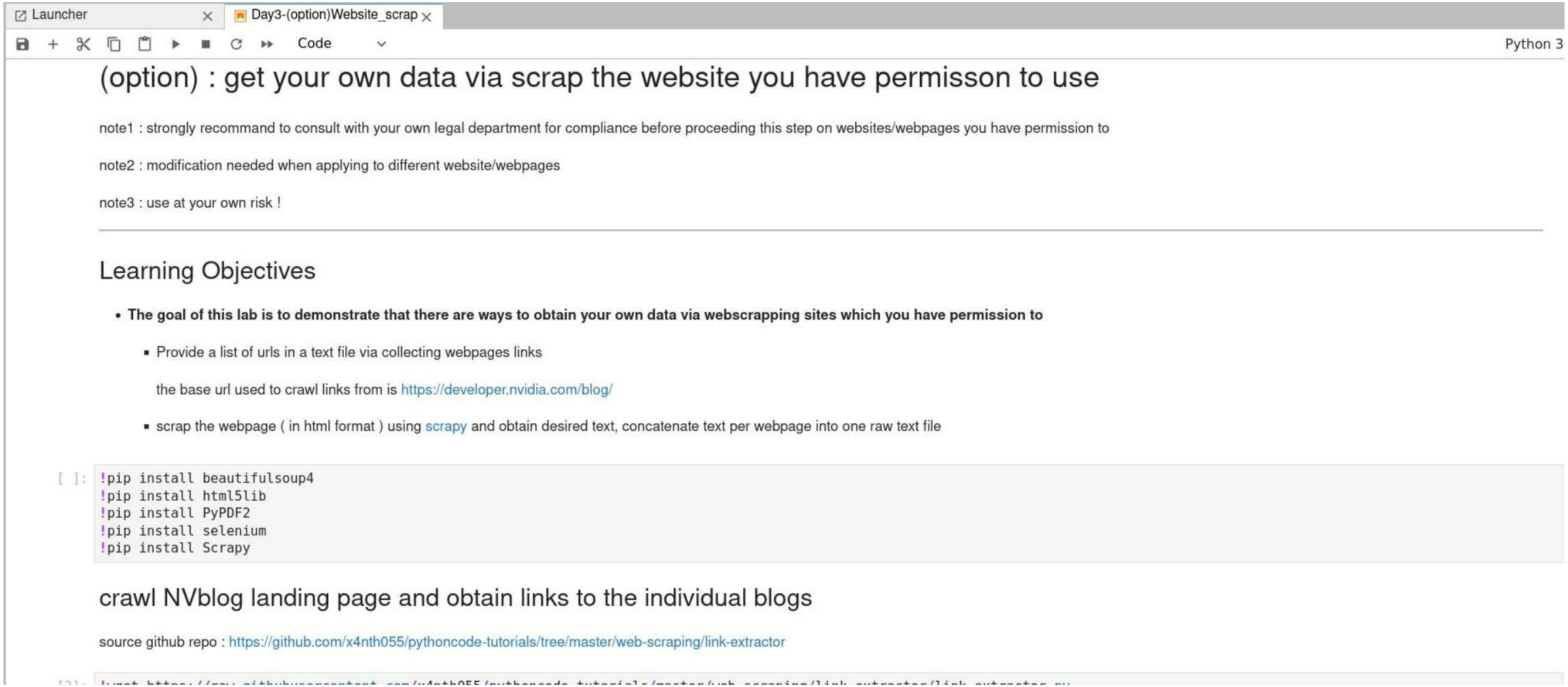
Prioirtize getting large data volume then clean properly

Dataset characteristic –

- Make sure to carefully weight different datasets during model training, for example, commoncrawl data is known for having both high-quality and very bad quality data blended together. If one cannot clean out all the bad data, should consider sampling with less weight during training
- It is tempting to try on a very small dataset first, however, we advice to prioritize getting as much data as possible and do as much cleaning as possible, see section on advice on cleaning
- Get basic stats: # of tokens in the dataset | avg tokens per sentence | avg sentence count per doc

[DEMO] GET YOUR OWN DATA

Scrape the websites/webpages you have permission to



SCRAP OWN PAGES TO OBTAIN OWN DATA

Example of web pages scraping

Scrape webpages

```
!python link_extractor_js.py https://blogs.nvidia.com/blog/category/deep-learning/ -m 2

[*] Crawling: https://blogs.nvidia.com/blog/category/deep-learning/
[W:pyppeteer.chromium_downloader] Starting Chromium d
100%|████████████████████████████████| 109M/1
[W:pyppeteer.chromium_downloader] Chromium download d
[W:pyppeteer.chromium_downloader] chromium extracted
[*] Internal link: https://blogs.nvidia.com/blog/cate
[!] External link: https://www.nvidia.com/en-us/
[*] Internal link: https://blogs.nvidia.com/
[*] Internal link: https://blogs.nvidia.com
[!] External link: https://twitter.com/nvidia
[!] External link: https://www.facebook.com/NVIDIA
[!] External link: https://news.ycombinator.com/submit
[!] External link: https://www.instagram.com/nvidia/
[!] External link: https://www.linkedin.com/company/n
[!] External link: https://www.reddit.com/r/nvidia/
[!] External link: https://feeds.feedburner.com/nvidi
[!] External link: https://www.twitch.tv/nvidia
[!] External link: https://www.youtube.com/nvidia
[*] Internal link: https://blogs.nvidia.com/privacy-c
[!] External link: https://www.nvidia.com/en-us/about
[!] External link: https://www.nvidia.com/en-us/conta
[*] Internal link: https://blogs.nvidia.com/blog/cate
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[*] Internal link: https://blogs.nvidia.com/blog/tag/
[*] Internal link: https://blogs.nvidia.com/ai-podcas
[*] Internal link: https://blogs.nvidia.com/blog/2021/
[*] Internal link: https://blogs.nvidia.com/blog/2021/
ggraph/
[*] Internal link: https://blogs.nvidia.com/blog/2021/08/11/omniverse-making-of-gtc/
[*] Internal link: https://blogs.nvidia.com/blog/2021/08/11/lending-a-helping-hand-jules-anh-tuan-nguyen-on-building-a-neuroprosthetic/
[*] Internal link: https://blogs.nvidia.com/blog/2021/08/12/geforce-now-thursday-august-12/
[*] Internal link: https://blogs.nvidia.com/blog/2021/08/11/cloudxr-google-cloud-demo/
[*] Internal link: https://blogs.nvidia.com/blog/2021/08/10/omniverse-connector-extension-plugin-siggraph/
```

Parse text from individual webpages and concate into one .txt file

```
!head -1 /home/zcharpy/bootcamp/jupyter_notebook/Megatron-LM/dataset/EN/extractedNVblogs.txt

Scientists searching the universe for gravitational waves just got a boost thanks to a new study and AI. The research, recently published
in Nature Astronomy, creates a deployable AI framework for detecting gravitational waves within massive amounts of data—at several magnit
udes faster than real time. Created by a group of scientists from Argonne National Laboratory, the University of Chicago, the University
of Illinois at Urbana-Champaign, NVIDIA, and IBM, the work highlights how AI and supercomputing can accelerate reproducible, data-driven
discoveries.“As a computer scientist, what’s exciting to me about this project is that it shows how, with the right tools, AI methods can
be integrated naturally into the workflows of scientists. Allowing them to do their work faster and better. Augmenting, not replacing, hu
man intelligence,” study senior author Ian Foster, director of Argonne’s Data Science and Learning division said in a press release.In 20
15, the advanced Laser Interferometer Gravitational-Wave Observatory (LIGO) first detected gravitational waves when two black holes, 1.3
billion light-years away, collided and merged. These waves occur when massive objects quickly accelerate (such as a star exploding or mas
sive objects colliding) creating a ripple through space time.The notable discovery confirmed part of Einstein’s theory of relativity, hyp
othesizing that space and time are linked. It also marked the start of gravitational wave astronomy, which could result in a deeper under
standing of the cosmos, including dark energy, gravity, and neutron stars. It also holds potential for scientists to step back through ti
me to the moments around the Big Bang.Since 2015, many more gravitational wave sources have been detected from LIGO. As the observatory c
ontinues with sensor upgrades and refinements, the expanse of detectors within the universe will also grow, creating large amounts of dat
a for processing. Quickly computing these data streams remains key to gravitational wave astronomy advancements and discoveries.In 2018 E
liu Huerta, lead for Translational AI at Argonne, demonstrated the capability of machine learning to detect gravitational waves from mult
iple LIGO detector data streams.In this study, the researchers further refined the model, which uses the cuDNN-accelerated deep learning
framework distributed over 64 NVIDIA GPUs. They tested the model against LIGO data from 2017 and found it accurately identified four bina
ry black hole mergers—without any misclassifications. It also processed a month’s worth of data in under 7 minutes. “In this study, we’ve
used the combined power of AI and supercomputing to help solve timely and relevant big-data experiments. We are now making AI studies ful
ly reproducible, not merely ascertaining whether AI may provide a novel solution to grand challenges,” Huerta said.The team’s models are
open-source and readily available. Read the full article in Nature Astronomy >>Read more >>  Have a story to share? Submit an idea.Get t
he developer news feed straight to your inbox.
```

CLEAN - REMOVE UNWANTED LANGUAGE

Remove unwanted language blended in the sentence of raw corpus

1. detect and filter undesired langauge in the raw text corpus

[1]:
```
from langdetect import detect
swe_raw_text='Under fredagsförmiddagen höll polis och räddningstjänst presskonferens tillsammans med en representanter från flygplatsens egna räddningsenhet och Örebro kommun.'
detect(swe_raw_text)
```

[1]:
```
'sv'
```

[2]:
```
danish_text='1. januar 2021 var folketallet 5.840.045. Ved den første folketælling i 1735 var der 718.000 danskere.'
detect(danish_text)
```

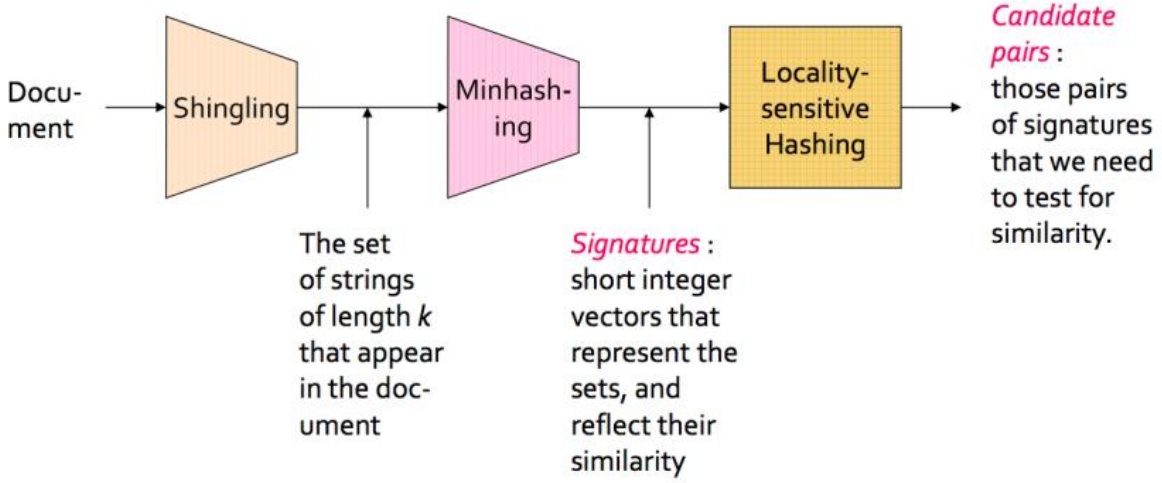
[2]:
```
'da'
```

[3]:
```
finnish_text='Jokaisella on oikeus vapaasti osallistua yhteiskunnan sivistyselämään, nauttia taiteista sekä päästä osalliseksi tieteen edistyksen mukanaan tuomista eduista.'
detect(finnish_text)
```

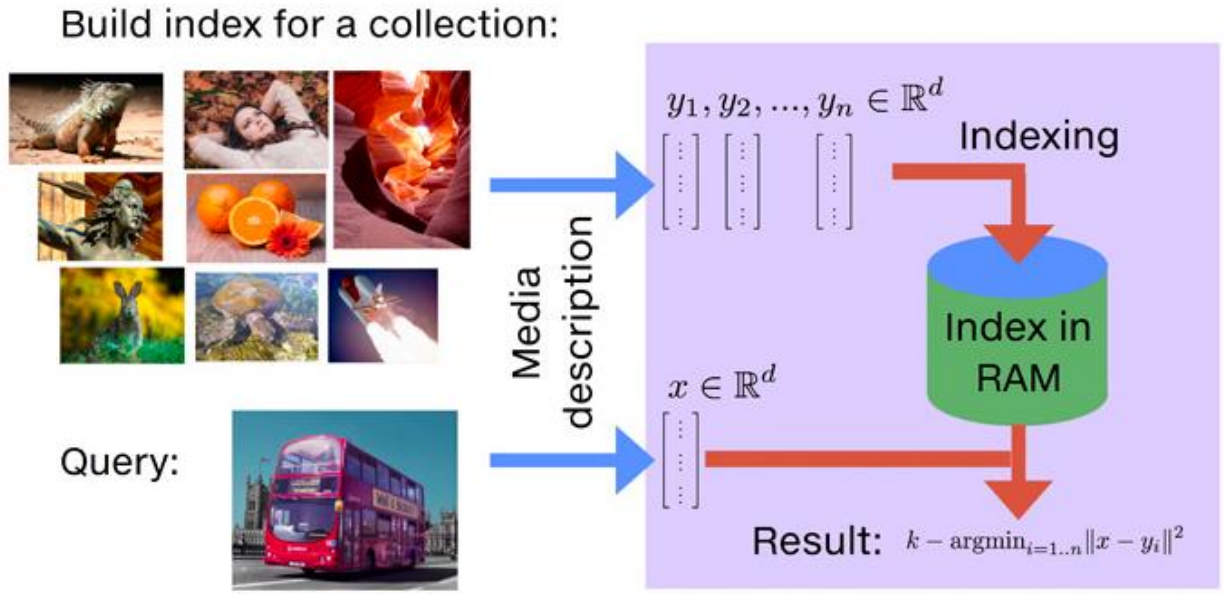
[3]:
```
'fi'
```

CLEAN - METHODS OF DE-DUPLICATE

laternatives of computing similarity score



Source : MinHash



Source : Facebook Faiss

CLEAN - DEDUPLICATION

Shingles → MinHash → LSH

deduplicate text based on similarity score

In [1]:
```
import itertools
from lsh import cache, minhash # https://github.com/mattilyra/lsh

# a pure python shingling function that will be used in comparing
# LSH to true Jaccard similarities
def shingles(text, char_ngram=5):
    return set(text[head:head + char_ngram] for head in range(0, len(text) - char_ngram))


def jaccard(set_a, set_b):
    intersection = set_a & set_b
    union = set_a | set_b
    return len(intersection) / len(union)


def candidate_duplicates(document_feed, char_ngram=5, seeds=100, bands=5, hashbytes=4):
    char_ngram = char_ngram
    sims = []
    hasher = minhash.MinHasher(seeds=seeds, char_ngram=char_ngram, hashbytes=hashbytes)
    if seeds % bands != 0:
        raise ValueError('Seeds has to be a multiple of bands. {} % {} != 0'.format(seeds, bands))

    lshcache = cache.Cache(num_bands=bands, hasher=hasher)
    for i_line, line in enumerate(document_feed):
        line = line.decode('utf8')
        docid, headline_text = line.split('\t', 1)
        fingerprint = hasher.fingerprint(headline_text.encode('utf8'))

        # in addition to storing the fingerpring store the line
        # number and document ID to help analysis later on
        lshcache.add_fingerprint(fingerprint, doc_id=(i_line, docid))

    candidate_pairs = set()
    for b in lshcache.bins:
        for bucket_id in b:
            if len(b[bucket_id]) > 1:
                pairs_ = set(itertools.combinations(b[bucket_id], r=2))
                candidate_pairs.update(pairs_)

    return candidate_pairs
```

```
    # reset file pointer and do LSH
    fh.seek(0)
    feed = itertools.islice(fh, 1000)

    candidates = candidate_duplicates(feed, char_ngram=char_ngram, seeds=seeds, bands=bands, hashbytes=hashbytes)

# go over all the generated candidates comparing their similarities
similarities = []
for ((line_a, docid_a), (line_b, docid_b)) in candidates:
    doc_a, doc_b = lines[line_a], lines[line_b]
    shingles_a = shingles(lines[line_a])
    shingles_b = shingles(lines[line_b])

    jaccard_sim = jaccard(shingles_a, shingles_b)
    fingerprint_a = set(hasher.fingerprint(doc_a.encode('utf8')))
    fingerprint_b = set(hasher.fingerprint(doc_b.encode('utf8')))
    minhash_sim = len(fingerprint_a & fingerprint_b) / len(fingerprint_a | fingerprint_b)
    similarities.append((docid_a, docid_b, jaccard_sim, minhash_sim))

for a,b,jsim, msim in random.sample(similarities, k=2 ):
    print("pair of similar sentences with jaccard_sim score:{} and minhash_sim score:{} --- \n".format(str(jsim),str(msim)))
    a=int(a)
    b=int(b)
    text_a=df2.iloc[a,1]
    text_b=df2.iloc[b,2]
    if text_a==text_b:
        print("100% duplicates \n")
    print("text_a:", text_a.split(' ')[:5])
    print("text_b:", text_b.split(' ')[:5])
    print('-----'*10)
    import random

print('\nThere are **{}** candidate duplicates in total\n'.format(len(candidates)))
random.sample(similarities, k=1)
```

```
pair of similar sentences with jaccard_sim score:0.6978398983481575 and minhash_sim score:0.5037593984962406 ---

text_a: ['Researchers,', 'developers,', 'and', 'engineers', 'worldwide']
text_b: ['Edge', 'computing', 'has', 'been', 'around']
--------------------------------------------------
pair of similar sentences with jaccard_sim score:0.9133693568066934 and minhash_sim score:0.9047619047619048 ---

text_a: ['The', 'NGC', 'team', 'is', 'hosting']
text_b: ['The', 'first', 'post', 'in', 'this']
--------------------------------------------------

There are **31** candidate duplicates in total
```

CLEAN - SENTENCE BOUNDARY

alternatives of sentence-splitter for Swedish

[1]:
```
import nltk
from nltk.tokenize import sent_tokenize
text='Har någon funderat på varför man inte får inomhusteperaturens kurva synlig i grafen? Är det någon som frågat Thermia? Skulle det inte vara väsentligt att kunna kolla historiken på den då man skall s
print("original doc is :\n ", text)
sents=sent_tokenize(text)
i=0
for sent in sents:
    print("------- sentence {} -------".format(str(i)))
    print(sent)
    i+=1
```

```
original doc is :
  Har någon funderat på varför man inte får inomhusteperaturens kurva synlig i grafen? Är det någon som frågat Thermia? Skulle det inte vara väsentligt att kunna kolla historiken på den då man skall stäl
la in kurvan?
------- sentence 0 -------
Har någon funderat på varför man inte får inomhusteperaturens kurva synlig i grafe
------- sentence 1 -------
Är det någon som frågat Thermia?
------- sentence 2 -------
Skulle det inte vara väsentligt att kunna kolla historiken på den då man skall stä
```

[2]:
```
from sentence_splitter import SentenceSplitter, split_text_into_sentences
splitter = SentenceSplitter(language='sv', non_breaking_prefix_file='custom_engl
sents=splitter.split(text=text)
i=0
for sent in sents:
    print("------- sentence {} -------".format(str(i)))
    print(sent)
    i+=1
```

```
------- sentence 0 -------
Har någon funderat på varför man inte får inomhusteperaturens kurva synlig i gra
------- sentence 1 -------
Är det någon som frågat Thermia?
------- sentence 2 -------
Skulle det inte vara väsentligt att kunna kolla historiken på den då man skall ställa in kurvan?
```

[45]:
```
import re
def custom_sentence_cutter(text):
    sents=re.split(',|\.',text)
    return sents
sents=custom_sentence_cutter(sv[rn])
sents=[s for s in sents if len(s)>1]
i=0
for sent in sents:
    print("------- sentence {} -------".format(str(i)))
    print(sent)
    i+=1
```

```
------- sentence 0 -------
Hela anslutningsförfarandet har präglats av andra krav som vi menar är oacceptabla
------- sentence 1 -------
 t
------- sentence 2 -------
ex
------- sentence 3 -------
 diskriminering när det gäller rörligheten för arbetstagare och lika tillgång till EU-finansiering liksom de ensidiga skyddsklausuler som kan använda
s mot dessa länders
------- sentence 4 -------
 och enbart dessa länders
------- sentence 5 -------
 intressen
```

[DEMO] DATA CLEANING AND FILTERING

File Edit View Run Kernel Tabs Settings Help

root@dd533a7e3b90: /works × data_cleaning_demo.ipynb ×

Code Python 3

get the blended dataset

```
[ ]: import random
import os
txt_dir='./txt/'
text_files=os.listdir(txt_dir)
text_files=[t for t in text_files if t.endswith('.txt') ]
tot=0
def get_lines(f_name):
    f=open(txt_dir+f_name,'r')
    lines=f.readlines()
    return lines

for cur_f in text_files:
    if cur_f.endswith('.txt'):
        if 'da' in cur_f:
            da_line=get_lines(cur_f)
            print("Dannish ", len(da_line))
        elif 'fi' in cur_f :
            fi_line=get_lines(cur_f)
            print("Finnish ", len(fi_line))
        elif 'de' in cur_f:

            de_line=get_lines(cur_f)
            print('German ', len(de_line))
        else:
            sv_line=get_lines(cur_f)
            print("Swedish ", len(sv_line))
```

```
[ ]: sv=random.sample(sv_line,100)
da=random.sample(da_line,573) # these are the language we want to filtered out
de=random.sample(de_line,611) # these are the language we want to filtered out
fi=random.sample(fi_line,520) # these are the language we want to filtered out
```

DATA COLLECTION

Dataset Weighting

Dataset	Tokens (billions)	Weights (%)	Epochs
Books3	25.7	14.3	1.5
OpenWebText2	14.8	19.3	3.6
Stack Exchange	11.6	5.7	1.4
PubMed Abstracts	4.4	2.9	1.8
Wikipedia	4.2	4.8	3.2
Gutenberg (PG-19)	2.7	0.9	0.9
BookCorpus2	1.5	1.0	1.8
NIH ExPorter	0.3	0.2	1.8
Pile-CC	49.8	9.4	0.5
ArXiv	20.8	1.4	0.2
GitHub	24.3	1.6	0.2
CC-2020-50	68.7	13.0	0.5
CC-2021-04	82.6	15.7	0.5
RealNews	21.9	9.0	1.1
CC-Stories	5.3	0.9	0.5

https://developer.nvidia.com/blog/using-deepspeed-and-megatron-to-train-megatron-turing-nlg-530b-the-worlds-largest-and-most-powerful-generative-language-model/

DATA CLEANSING ADVISE

Summary

1. Prioritize getting as large raw dataset as possible
2. Clearn it aggresively – OpenAI raw data is 45TB --> after cleaned is 570GB
    1. Detect and remove undesired language inside the raw corpus
    2. Do NOT include downstream tasks' datasets into training dataset, deduplicate training dataset against downstream datasets
    3. Find best suited alternatives to de-duplication at the ***document*** level, within and across datasets, to prevent redundancy and preserve the integrity of original dataset's characteristics
    4. Add known high-quality reference corpora to the training mix whenever possible
    5. Consider filter by # of characters in a sentences within a document
3. Megatron-LM repo provide some basic data cleansing scripts

source: https://arxiv.org/pdf/2005.14165.pdf

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TRAIN YOUR OWN GPT3 VOCAB + MERGE

train your own GPT compatible tokenizer

```
import os , sys
from tokenizers import Tokenizer
from tokenizers import Tokenizer, models, pre_tokenizers, trainers
from tokenizers.decoders import ByteLevel as ByteLevelDecoder
from tokenizers.trainers import BpeTrainer
from tokenizers.normalizers import NFKC, Sequence
from tokenizers.pre_tokenizers import Whitespace
import argparse
import os

if __name__ == '__main__':
    parser = argparse.ArgumentParser()
    parser.add_argument('--infile', default=None, type=str,  help='path to the txt files')
    parser.add_argument('--bpe_path', default=None, type=str, help='output bpe path')
    parser.add_argument('--load_pretrained', action='store_true', help='load pretrained BPE model')
    parser.add_argument('--incl_special_toks', action='store_true', help='load pretrained BPE model')
    parser.add_argument('--vocab_size', default=None, type=int,
                        help='specify the vocab_size when training HF BPE for chinese usually 8k/16k/32k/48k/64k')
    args = parser.parse_args()
    tokenizer = Tokenizer(models.BPE())
    if args.load_pretrained :
        print("loading gpt2bpe english vocab and merge \n")
        vocab_file='/workspace/SVdata/gpt2bpe/gpt2-vocab.json'
        merge_file='/workspace/SVdata/gpt2bpe/gpt2-merges.txt'
        tokenizer.model = models.BPE.from_file(vocab_file, merge_file)

    tokenizer.pre_tokenizer = pre_tokenizers.ByteLevel()
    tokenizer.decoder = ByteLevelDecoder()
    if args.incl_special_toks:
        special_tokens = ['[CLS]','[BOS]','[EOS]','[SEP]','[PAD]','[MASK]','[UNK]','[EOD]']
        print("including special tokens :", special_tokens)
    else:
        print("include minimal special token end of text ")
        special_tokens= ["<|endoftext|>"]

    # Set the training hyperparameters
    trainer = trainers.BpeTrainer(
        vocab_size=args.vocab_size,
        special_tokens=special_tokens,
        initial_alphabet=pre_tokenizers.ByteLevel.alphabet()
    )
    # Train it with either files or an iterator:
    tokenizer.train([args.infile], trainer=trainer)
    print("Trained vocab size: {}".format(tokenizer.get_vocab_size()))
    # You will see the generated files in the output.
    print("saving trained BPE model to : ", args.bpe_path)
    tokenizer.model.save(args.bpe_path)
    print("model saved ! \n\n\n")
```

PREPROCESSING DATA

- Input format: JSON array of dictionaries
  - One element per document
  - Text in the ‘text’ field by default (can also extract other fields)

BERT

```
python tools/preprocess_data.py \
        --input my-corpus.json \
        --output-prefix my-bert \
        --vocab bert-vocab.txt \
        --dataset-impl mmap \
        --tokenizer-type BertWordPieceLowerCase \
        --split-sentences \
        --workers 80
```

GPT

```
python tools/preprocess_data.py \
        --input my-corpus.json \
        --output-prefix my-gpt \
        --vocab gpt-vocab.txt \
        --merge-file gpt-merges.txt \
        --dataset-impl mmap \
        --tokenizer-type GPT2BPETokenizer \
        --append-eod \
        --workers 80
```

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MEGATRON COMMAND LINE ARGUMENTS

Model Architecture Arguments

--num-layers	Number of transformer layers
--hidden-size	Hidden size between layers
--num-attention-heads	Number of attention heads
--seq-length	Maximum sequence length
--max-position-embeddings	Maximum position embeddings

Distributed training arguments

--tensor-model-parallel-size	Degree of tensor parallelism
--pipeline-model-parallel-size	Degree of pipeline parallelism
--num-layers-per-virtual-pipeline-stage	Allows interleaved schedule

MEGATRON COMMAND LINE ARGUMENTS

Training Arguments

--micro-batch-size	Batch size passed through the model
--global-batch-size	Batch size of each iteration, including data parallelism and gradient accumulation
--fp16	Train with fp16, required to fit any reasonably large model

MEGATRON COMMAND LINE ARGUMENTS

dataset Arguments

either

--train-iters

or

--train-samples

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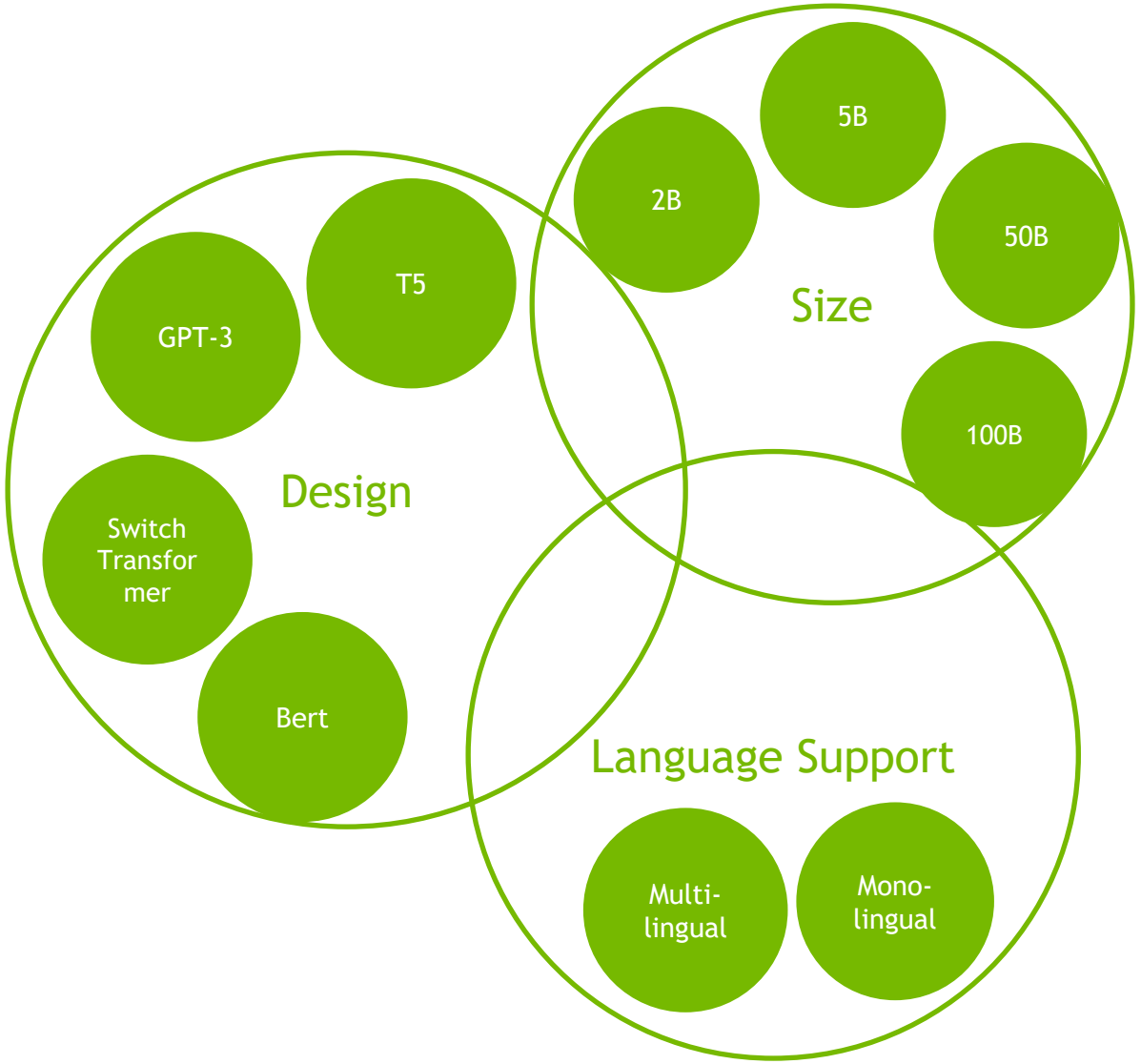
09:00 AM - 09:15 AM: Recap and Overview of Day 3
09:15 AM - 09:30 AM: About acquiring your own
09:30 AM - 10:20 AM:
Lab 2 – 1_Acquiring data
Lab 2 – 2_data cleaning & filter
10:20 AM - 10:30 AM: train own GPT tokenizer + data preprocessing
10:30 AM - 11:00 AM: Lab 2 – 3_train your own GPT tokenizer
11:00 AM - 11:30 AM: Lab 2 – 4_data preprocessing
11:30 AM - 12:00 PM: Lab 2 - 4 Mini challenge
12:00 PM - 12:30 PM: Lunch Break
13:00 PM - 14:00 PM: Lab 2 – 5 Challenge – Go BIG or go home (lab)
14:00 PM - 14:30 PM: About deploying Big NLP model with NVIDIA Triton | faster transformer solution
14:30 PM - 14:45 PM: Ask the Experts with NVIDIA data scientists on what's next for NLP
14:45 PM - 15:00 PM: Discussion & Final remarks

MODEL ARCHITECTURE

Open question – what is the right architecture for your problem



MEGATRON 760M GPT TEXT GENERATION

Training Arguments

root@64ec55b9522e: /works | view_generated_text.ipynb | GPT3GenerateText_760Mgp | 5a_GeneratingGPTtext_step | generate_samples_gpt.py

Code | Python 3

[1]:
```
import json
f=open('samples_760Miter1mil.json','r')
ls=[json.loads(l) for l in f.readlines() ]
i=0
for txt in [item['text'] for item in ls ]:
    print("generated text sample {} : {} \n".format(str(i),txt))
    i+=1
```

```
generated text sample 0 : Produkter med detta motiv Vit I Love Can - over stone T-

generated text sample 1 : Raspberry Ketone Plus verkar vara potenta vikt förlust och vikt hantering komplement som kan motivera en massa mä
nniskor i Kristianstad Sverige anta en hälsosammare mer aktiv livsstil och därmed få alla fördelar denna hallon keton extrahera så rikligt
ger

generated text sample 2 : Restauranger i närheten av Iforway

generated text sample 3 : Sök efter hotell i
```

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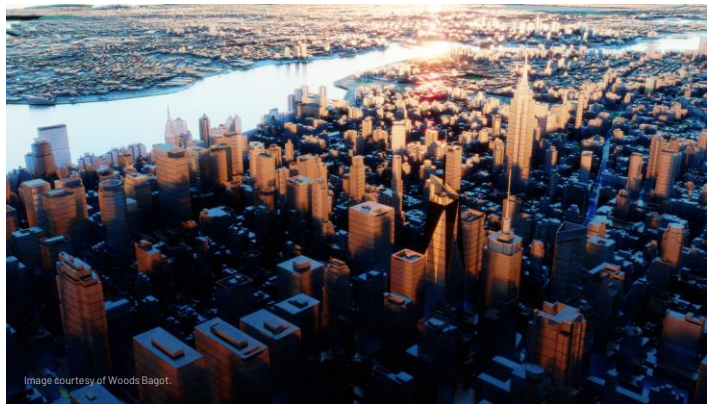

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