Leibniz Supercomputing Centre

of the Bavarian Academy of Sciences and Humanities

AI Training Series
Introduction to the LRZ AI Systems

05.11.2024 | Ajay Navilarekal, Darshan Thummar

Agenda

1. Introduction to the LRZ AI Systems

- Overview of the LRZ AI Systems
- Access to the LRZ AI Systems
- NVIDIA NGC Cloud
- Introduction to Enroot Containers
- Interactive and Batch Jobs
- Open on Demand
- Exercise: Run a job and extend an Enroot container

2. Data Distributed Training

- Introduction to Convolutional Neural Networks
- Exercise: Train VGG-19 on a GPU
- Introduction to Distributed Training
- Exercise: Train VGG-199 on 2 GPUs using DDP

3. Fully Sharded Data Parallel

- Introduction to Fully Sharded Data Parallel
- Exercise: Train VGG-199 on 2 GPUs using FSDP

Planned breaks

- 11:30 – 11:45 Coffee Break I
- 12:30 – 13:30 Lunch break
- 15:00 – 15:15 Coffee Break II

Overview of the LRZ Systems

Data Science Archive (DSA)

Archive and Backup (ABS)

Data Science Storage (DSS)

Multi-purpose cluster systems might be used for AI workloads as well, but have different focus

LRZ Linux Cluster

CoolMUC-2 Teramem-2 CoolMUC-3

lxlogin[1-3].lrz.de

lxlogin8.lrz.de

Designed and Configured for AI

LRZ AI Systems

- “Big Data” CPU nodes
- HPE P100 node
- V100 nodes
- DGX-1 P100, DGX-1 V100
- Multiple DGX A100

login.ai.lrz.de

https://login.ai.lrz.de

Flexible system that copes with almost any workload

LRZ Compute Cloud

LRZ Compute Cloud (w/ some GPUs)

https://cc.lrz.de

Overview of the LRZ AI Systems

	HGX H100 Architecture	DGX A100 Architecture	DGX A100 Architecture MIG	DGX-1 V100 Architecture	DGX-1 P100 Architecture	HPE Intel Skylake + Nvidia Node	V100 GPU Nodes	CPU Nodes
Number of Nodes	30	4	1	1	1	1	4	12
CPU cores per node	96	252	252	76	76	28	19	18 / 28 / 38 / 94
Memory per node	768GB	2 TB	1 TB	512 GB	512 GB	256 GB	368 GB	min. 360 GB
GPUs per node	4 NVIDIA H100	8 NVIDIA A100	8 NVIDIA A100 (16 MIG partitions)	8 Nvidia Tesla V100	8 Nvidia Tesla P100	4 Nvidia Tesla P100	2 Nvidia Tesla V100	--
Memory per GPU	94 GB	80 GB	40 GB (20GB per MIG partition)	16 GB	16 GB	16GB	16 GB	--
SLURM Partition	lrz-hgx-h100-92x4	lrz-dgx-a100-80x8	lrz-dgx-a100-40x8-mig	lrz-dgx-1-v100x8	lrz-dgx-1-p100x8	lrz-hpe-p100x4	lrz-v100x2	lrz-cpu
Nodes	lrz-hgx-h100-[001-030]	lrz-dgx-a100-[001-002,004-005]	lrz-dgx-a100-003	dgx-002	dgx-001	p100-001	gpu-[001-003,005]	cpu-[001-012]

Storage on the LRZ AI Systems

Storage Pool	Designated Use	Top-level Directory	Size Limit	Automated Backup	Expiration	Additional Information
Home directory	unified home directory with the LRZ Linux Cluster, created when LRZ Linux Cluster access is granted Not suitable for heavy and/or high-frequency I/O operations - use the AI Systems DSS instead.	/dss/dsshome1 /.../<user>	100 GB	yes, backup to tape and file system snapshots	lifetime of LRZ project	File Systems and IO on Linux-Cluster
AI Systems DSS	high-bandwidth, low latency I/O, access is granted upon request through the LRZ Servicedesk	/dss/dssfs04	up to 4 TB	no	until further notice	
Linux Cluster DSS	general purpose, long-term data storage	/dss/dssfs02 /dss/dssfs03	up to 10 TB (or 20TB+ with associated costs)	yes for paid DSS / no for the free tier	lifetime of data project	File Systems and IO on Linux-Cluster (or DSS on demand offer with associated costs)
Exclusive/private DSS systems	specified by the system owner, can be purchased, implemented and housed exclusively for a private group of dedicated users	/dsslegfs01 /dsslegfs02 /dssmcmlfs01	specified by the system owner	specified by the system owner	specified by the system owner	Data Science Storage ("joint project offer")

Access to the LRZ AI Systems – How to access?

- User requirements to get the access:
    1. Own / get a Linux Cluster account: https://doku.lrz.de/display/PUBLIC/Access+and+Login+to+the+Linux-Cluster
    2. Submit a service request to LRZ Servicedesk – select "AI topics" and "LRZ AI Systems - Request for Access" from the drop-down lists. Request has to include Linux Cluster account username and a description of the intended usage.

- Login node login.ai.lrz.de accessible via SSH:

```
$ ssh --login_name=xxyyyzz login.ai.lrz.de
```

- Make sure you are connected to the Munich Scientific Network (MWN).
- Provide your LRZ Linux Cluster credentials to log in.

Access to the LRZ AI Systems – Slurm: sinfo, salloc, srun & scancel

$ ssh --login_name=xxyyyzz login.ai.lrz.de

Executes in the login node

$ sinfo

$ squeue --user=xxyyzzz

$ salloc --partition=lrz-v100x2 --gres=gpu:1

$ srun --pty bash

$ scancel job_id

di82hod — ssh login.ai.lrz.de — 82×28

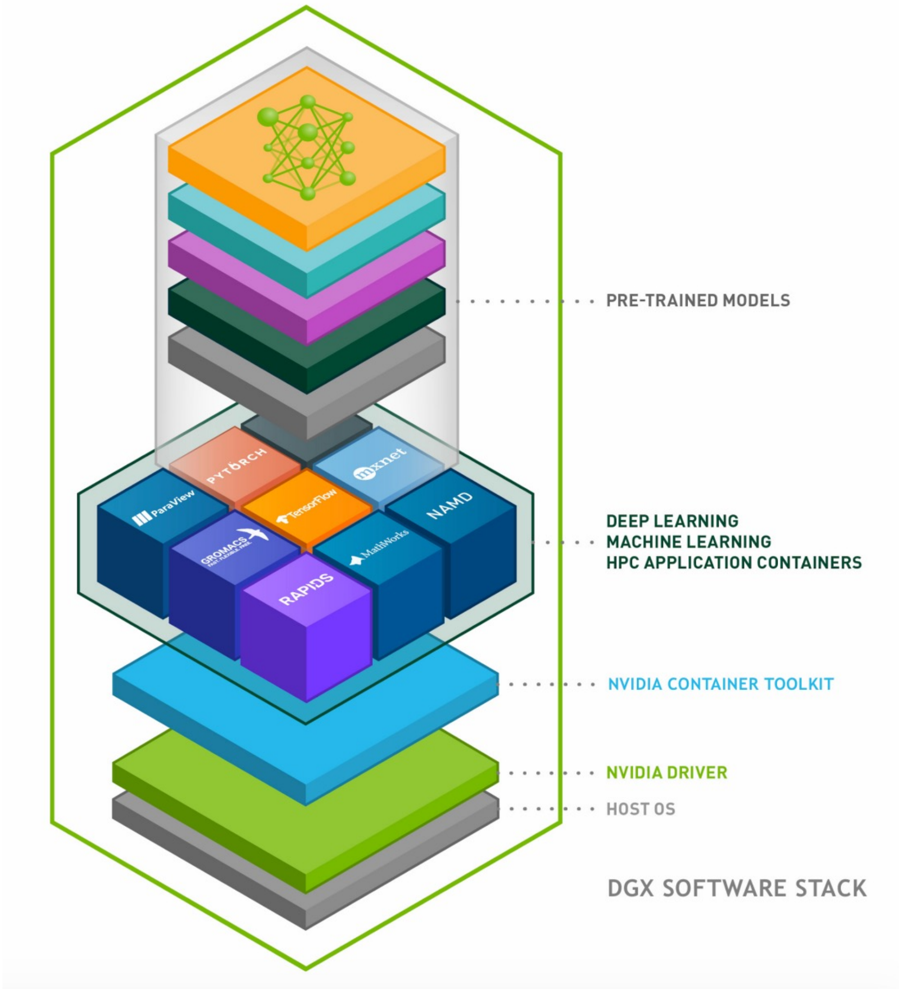
```
di82hod@login-1:~$ sinfo
PARTITION             AVAIL  TIMELIMIT  NODES  STATE NODELIST
lrz-v100x2*              up 14-00:00:0      1    mix gpu-005
lrz-v100x2*              up 14-00:00:0      3  alloc gpu-[001-003]
lrz-hpe-p100x4           up 14-00:00:0      1   idle p100-001
lrz-dgx-1-p100x8         up 14-00:00:0      1 drain* dgx-001
lrz-dgx-1-v100x8         up 14-00:00:0      1  alloc dgx-002
lrz-dgx-a100-80x8        up 14-00:00:0      2    mix lrz-dgx-a100-[002,004]
lrz-dgx-a100-80x8        up 14-00:00:0      2  alloc lrz-dgx-a100-[001,005]
lrz-dgx-a100-40x8-mig    up 14-00:00:0      1    mix lrz-dgx-a100-003
lrz-cpu                  up 14-00:00:0      6    mix cpu-[001-002,004-005,007,009]
lrz-cpu                  up 14-00:00:0      1  alloc cpu-003
lrz-cpu                  up 14-00:00:0      2   idle cpu-[006,008]
mcml-dgx-a100-40x8       up 14-00:00:0      2    mix mcml-dgx-[004,008]
mcml-dgx-a100-40x8       up 14-00:00:0      6  alloc mcml-dgx-[001-003,005-007]
test-v100x2              up 14-00:00:0      1   idle gpu-004
di82hod@login-1:~$ salloc -p lrz-hpe-p100x4 --gres=gpu:2 --time=02:00:00
salloc: Pending job allocation 162333
salloc: job 162333 queued and waiting for resources
salloc: job 162333 has been allocated resources
salloc: Granted job allocation 162333
di82hod@login-1:~$ srun --pty bash
di82hod@p100-001:~$ exit
exit
di82hod@login-1:~$ scancel 162333
di82hod@login-1:~$ salloc: Job allocation 162333 has been revoked.

di82hod@login-1:~$
```

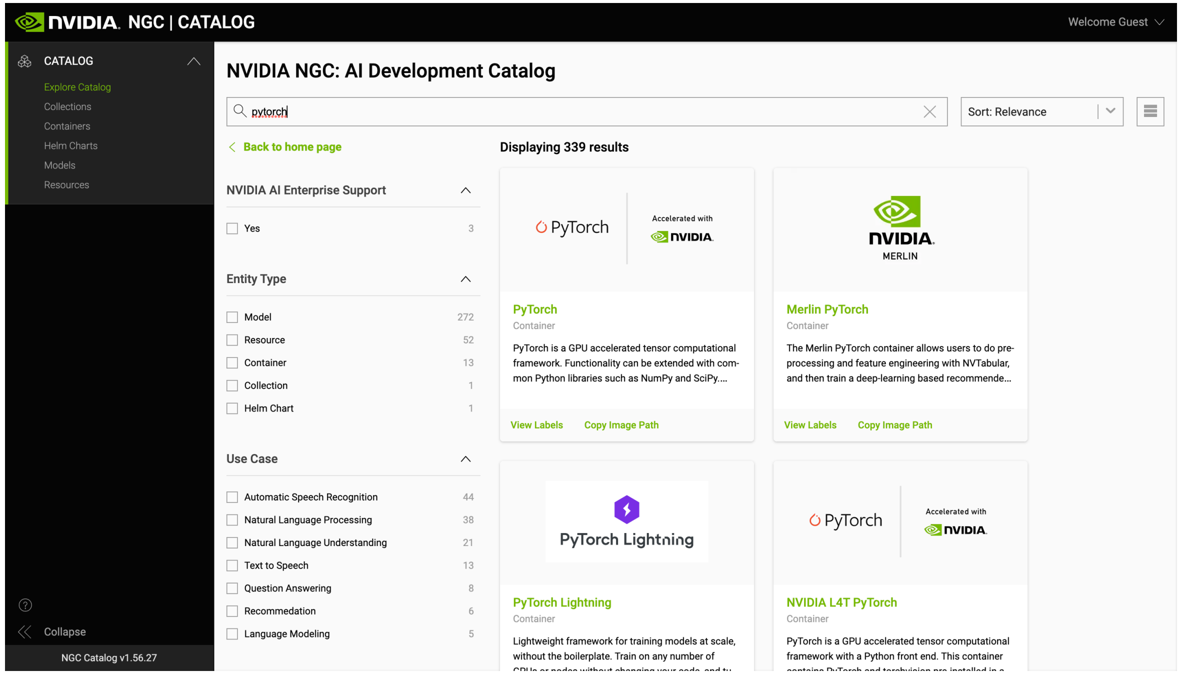
https://slurm.schedmd.com/overview.html

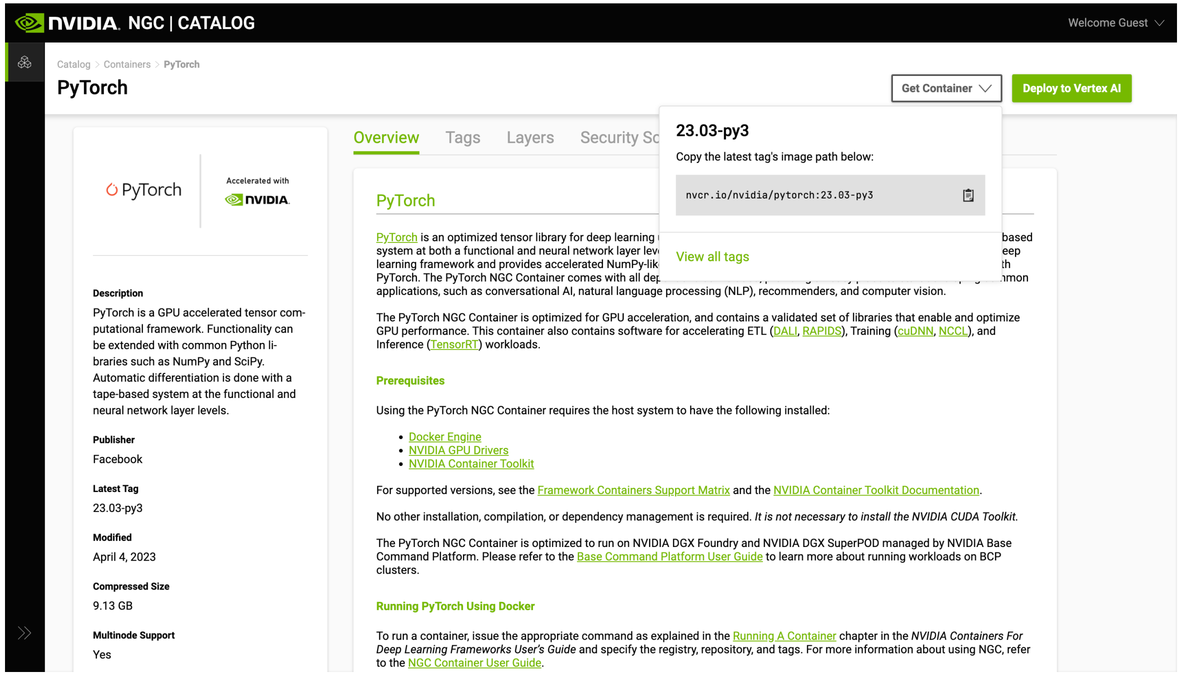
Nvidia NGC Containers

- The NGC catalogue provides access to **GPU accelerated** software that speeds up end-to-end workflows with performance optimized **containers, pretrained AI models, and SDKs** that can be deployed on any NVIDIA's GPU powered systems.
- The **NVIDIA Container Toolkit** includes a container runtime library and utilities to automatically configure containers to leverage NVIDIA GPUs.
- The **NVIDIA CUDA Toolkit**, incorporated within each GPU-accelerated container in NGC, is the development environment for creating high performance NVIDIA GPU-accelerated applications.
- https://catalog.ngc.nvidia.com

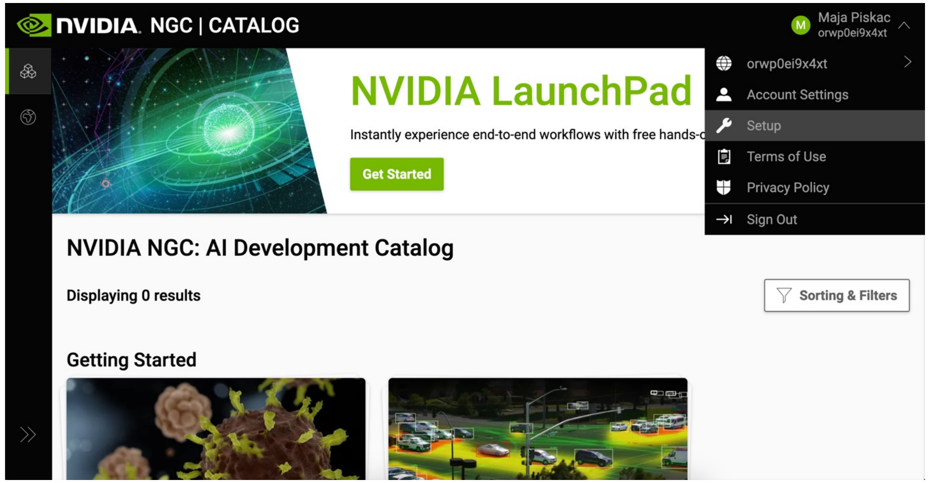


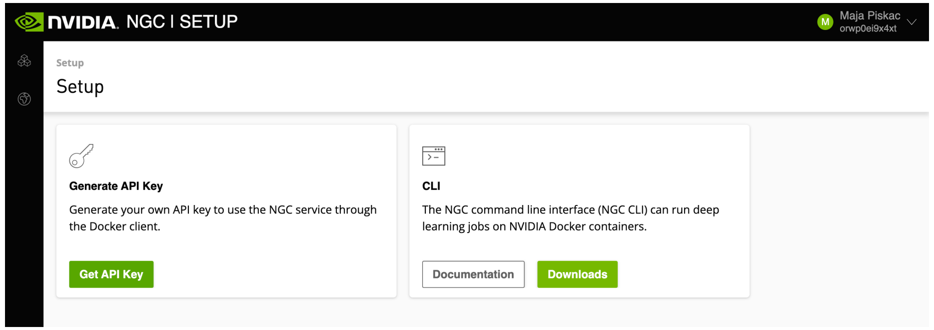
Nvidia NGC Containers

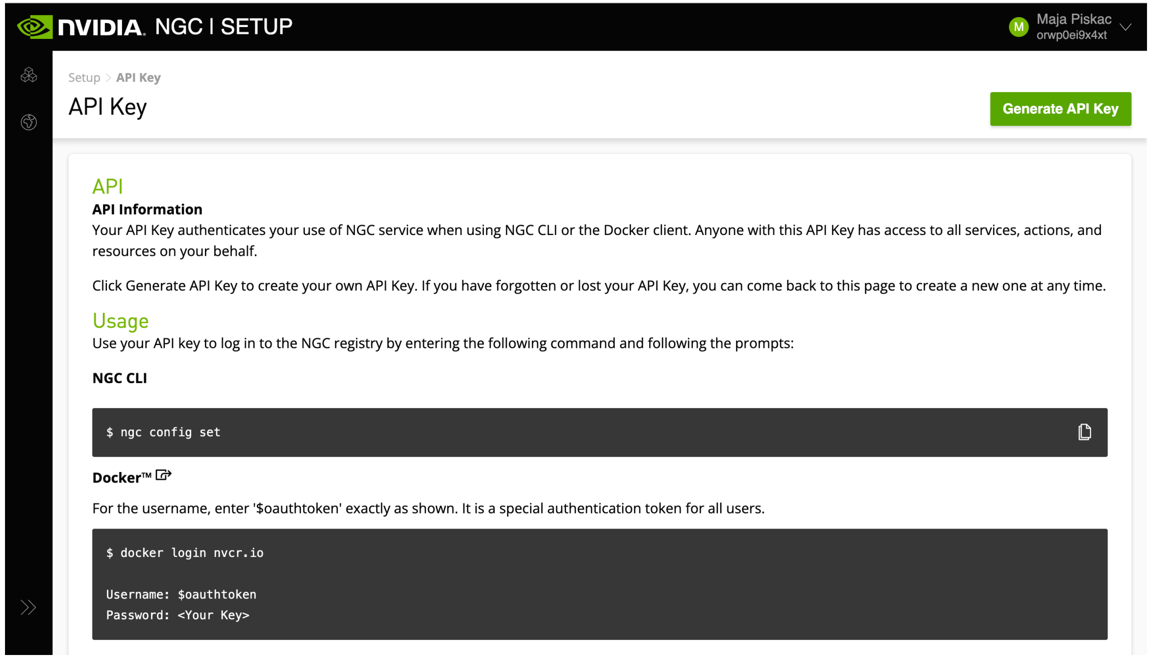




Nvidia NGC Containers – Setting up credentials







Nvidia NGC Containers – Setting up credentials

- Create the file *enroot/.credentials* within your $HOME and insert the following lines in it:

```
machine nvcr.io login $oauthtoken password < KEY>
machine authn.nvidia.com login $oauthtoken password <KEY>
```

- Where <KEY> is the API key generated and copied in the previous step.
- Introduce a new line after < KEY>.

- Now you can import containers from Nvidia NGC on compute nodes of LRZ AI Systems, e.g. a Pytorch container, with:

```
$ enroot import docker://nvcr.io/nvidia/pytorch:24.08-py3
```

Introduction to Enroot: The Software Stack Provider for the AI Systems

- Enroot container runtime operates completely in user space.
- It allows to run containers defined by container images from the NVIDIA NGC Cloud or from the Docker Hub.
- Not available on the login node, but on the compute nodes!
- The Enroot Workflow:
  - **I.** **Import** an Enroot Container Image – resulting in **sqsh** file
  - II. Create an Enroot Container with **create**,
  - III. Run software inside an existing Enroot Container with **start**.

Executes in the login node

```
$ salloc --partition=lrz-hpe-p100x4 --gres=gpu:1
$ srun --pty bash
```

Executes in the allocated compute node

```
$ enroot import docker://nvcr.io/nvidia/pytorch:24.10-py3
$ enroot create nvidia+pytorch+24.10-py3.sqsh
$ enroot start nvidia+pytorch+24.10-py3
```

Running Applications as Interactive Jobs

- Interactive jobs are submitted to an existing allocation of resources using the **srun** command.
- We can **mount** existing data from outside of the container into container.
- Enroot container creation and job submission in a single step can be done via a plugin called *pyxis.*

Executes in the login node

```
$ salloc --partition=lrz-hpe-p100x4 --gres=gpu:1
```

If Enroot Container Image is already imported

```
$ srun --pty \
--container-mounts=./:/workspace \
--container-image=path/to/your/container.sqsh bash
```

If Enroot Container Image has not been imported

```
$ srun --pty \
--container-mounts=./:/workspace \
--container-image=nvcr.io/nvidia/pytorch:24.10-py3 bash
```

Executes in the allocated compute node

```
$ python /workspace/exercise1.py
```

Running Applications as Batch Jobs

- Batch jobs are the preferred and quicker way of using the LRZ AI Systems.
- Batch job is queued and executed when the resources are available.
- It does the allocation and running of the job for you (instead of salloc and srun).

- The **sbatch** command submits jobs described in a **sbatch script file**.
- You need to specify the partition and number of GPUs that you want to use.
- Two additional required arguments: *output* and *error messages* file.

```
#!/bin/bash
#SBATCH -p lrz-hpe-p100x4
#SBATCH --gres=gpu:1
#SBATCH -o exercise1.out
#SBATCH -e exercise1.err

srun \
--container-mounts='./:/workspace' \
--container-image='nvcr.io/nvidia/pytorch:24.10-py3' \
python /workspace/exercise1.py
```

Executes in the login node

```
$ sbatch exercise1.sbatch
```

Dealing with base images from catalogues other than NGC

- If your image does not supply the CUDA Toolkit, do not install it within the image, because this fixes paths to the existing NVIDIA driver on the target machine and might crash if the NVIDIA driver is upgraded.
- Instead add the following **environment variables** within the container, and the container runtime will copy within the container the needed libraries. Refer to https://docs.nvidia.com/datacenter/cloud-native/container-toolkit/latest/docker-specialized.html for more information on the accepted values of these variables.

Executes in the allocated resource

```
$ enroot import docker://some/image-no-cuda
$ enroot create --name base_container some+image-no-cuda.sqsh
$ enroot start base_container bash
echo "NVIDIA_DRIVER_CAPABILITIES=compute,utility" >> /etc/environment
echo "NVIDIA_REQUIRE_CUDA=cuda>=9.0" >> /etc/environment
echo "NVIDIA_VISIBLE_DEVICES=all" >> /etc/environment
$ exit
$ enroot export --output base_image.sqsh base_container
```

Creating an extended Enroot image

- If your workload depends on a package not provided by the used image.

Executes in the allocated resource

```
$ enroot create --name custom_container nvidia+pytorch+24.08-py3.sqsh
```

```
$ enroot start custom_container
```

```
$ pip install --no-cache-dir lightning
$ HOROVOD_GPU_OPERATIONS=NCCL pip install --no-cache-dir horovod
```

```
$ exit
```

```
$ enroot export --output custom_container.sqsh custom_container
```

- For installing some applications you need to be root within the container (e.g., installing software using the apt package manager in Debian and Ubuntu-based containers.) In this case, add the --root flag.

Executes in the allocated resource

```
$ enroot start --root my_container
```

```
$ apt update
$ apt install python3-dev
```

Access to AI Systems through interactive web servers

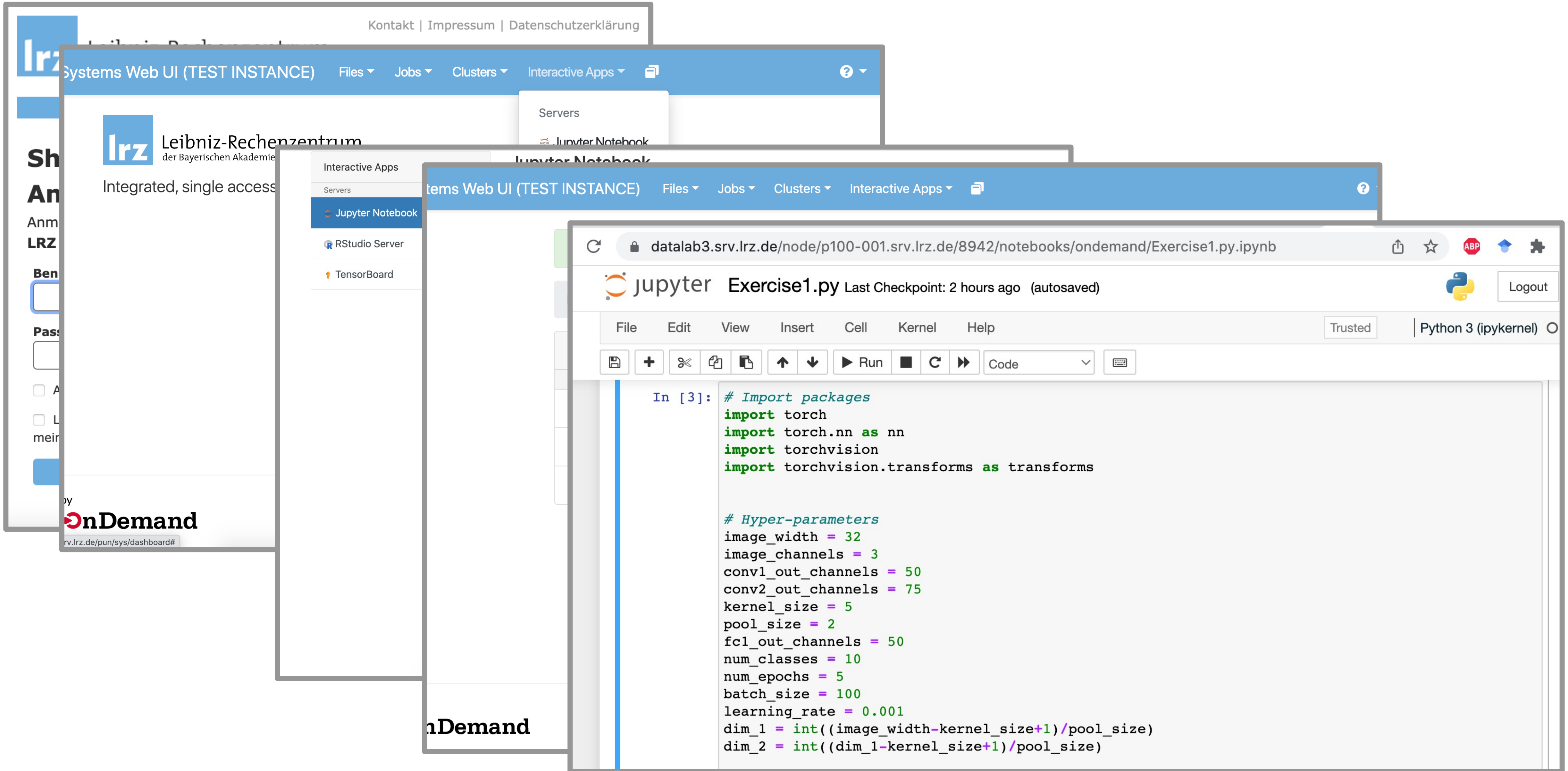
- Jupyter Notebook, JupyterLab, RStudio Server and TensorBoard

- Available at https://login.ai.lrz.de

- To start e.g. a Jupyter Notebook session select from the top panel:
  "Interactive Apps" => “Jupyter Notebook”

- For a typical use-case:
  - select the type of resources (CPU only or CPU + single GPU)
  - specify your workload (a combination of CPU core and RAM requirements)
  - select the container environment you want to work with (e.g. available PyTorch or Tensorflow container, or a custom container)
  - finally, specify the number of hours you plan to work (be aware that your session will be shut down when this time limit is reached, and any unsaved work will then be lost).

Access to AI Systems through interactive web servers



Public Datasets and Containers on the LRZ AI Systems

- Dedicated DSS container for storing public datasets and Enroot container images of interest to researchers.
- Procedure to request the addition of public datasets / Enroot images:
  - make sure the dataset / Enroot image is licensed for public usage and requires no individual license nor registration, and in case of an Enroot image make sure the image is not provided by the Nvidia NGC, Dockerhub or another public repository directly
  - open a ticket with the LRZ Servicedesk, providing the location of the dataset / Dockerfile for building the image, and a justification for public interest (including the expected target audience)
  - provide instructions for downloading the dataset (ideally shell script) / building the image (if non-standard).

Dataset	Location	Version	Licence
AlphaFold	/dss/dssfs04/pn69za/pn69za-dss-0004/datasets/alphafold_2024	Last update March 2024 following the instructions here https://github.com/deepmind/alphafold#genetic-databases	https://github.com/deepmind/alphafold#license-and-disclaimer
COCO-Stuff	dss/dssfs04/pn69za/pn69za-dss-0004/datasets/cocostuff/	2020 Update (train2017.zip, val2017.zip, annoations_trainval2017.zip, stuff_annotations_trainval2017.zip)	https://cocodataset.org/#termsofuse
Visual Genome	dss/dssfs04/pn69za/pn69za-dss-0004/datasets/visualgenome/	Version 1.4 of dataset completed as of July 2017	Creative Commons Attribution 4.0 International License

Summary

Command line

$ ssh -l xxyyyzz login.ai.lrz.de

Interactive job

Executes in the login node login-1

```
$ sinfo
```

```
$ salloc --partition=dgx-1-p100 --gres=gpu:1
```

```
$ srun --pty --container-mounts=./:/workspace \
--container-image=nvcr.io/nvidia/pytorch:24.08-py3 bash
```

Executes in the allocated resource

```
$ python /workspace/exercise1.py
```

Batch job

```
#!/bin/bash
#SBATCH -p lrz-dgx-a100-80x8
#SBATCH --gres=gpu:1
#SBATCH -o exercise1.out
#SBATCH -e exercise1.err

srun --container-mounts=‘./:/workspace’ \
--container-image=‘nvcr.io/nvidia/pytorch:24.08-py3’ \
python /workspace/exercise1.py
```

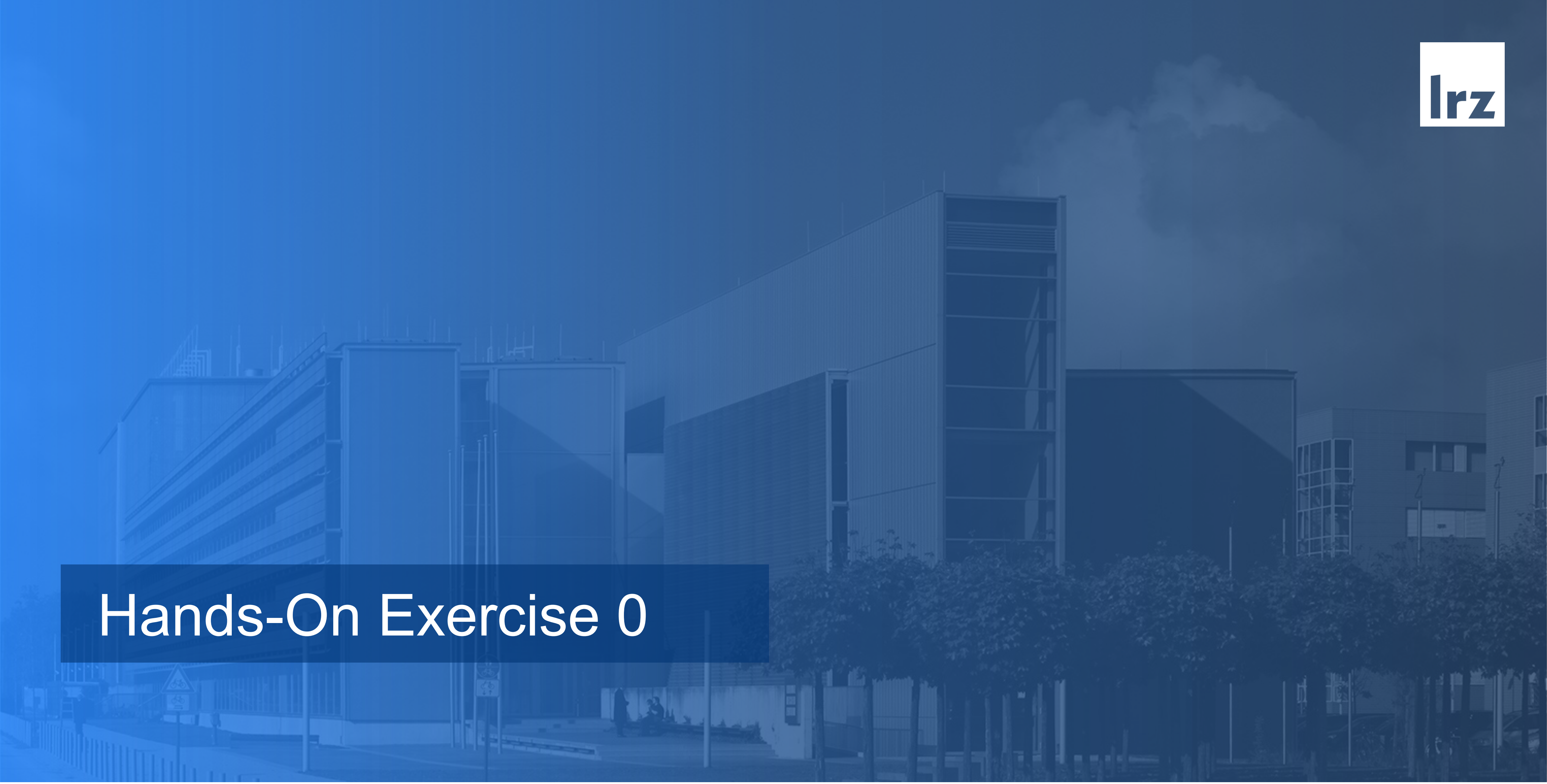
Executes in the login node datalab2

```
$ sbatch exercise1.sbatch
```

Web browser

https://login.ai.lrz.de

https://doku.lrz.de/display/PUBLIC/LRZ+AI+Systems



Hands-On Exercise 0

Hands-On Exercise 0

Creating an extended Enroot image

1. Write a job script to import and extend a container
2. Execute and create your own container

Job script info:

1. partition: lrz-hgx-h100-92x4
2. reservation: aits
3. gpu resources: 1

Agenda

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- Exercise: Run a job and extend an Enroot container

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- Exercise: Train VGG-19 on a GPU
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3. Fully Sharded Data Parallel

- Introduction to Fully Sharded Data Parallel
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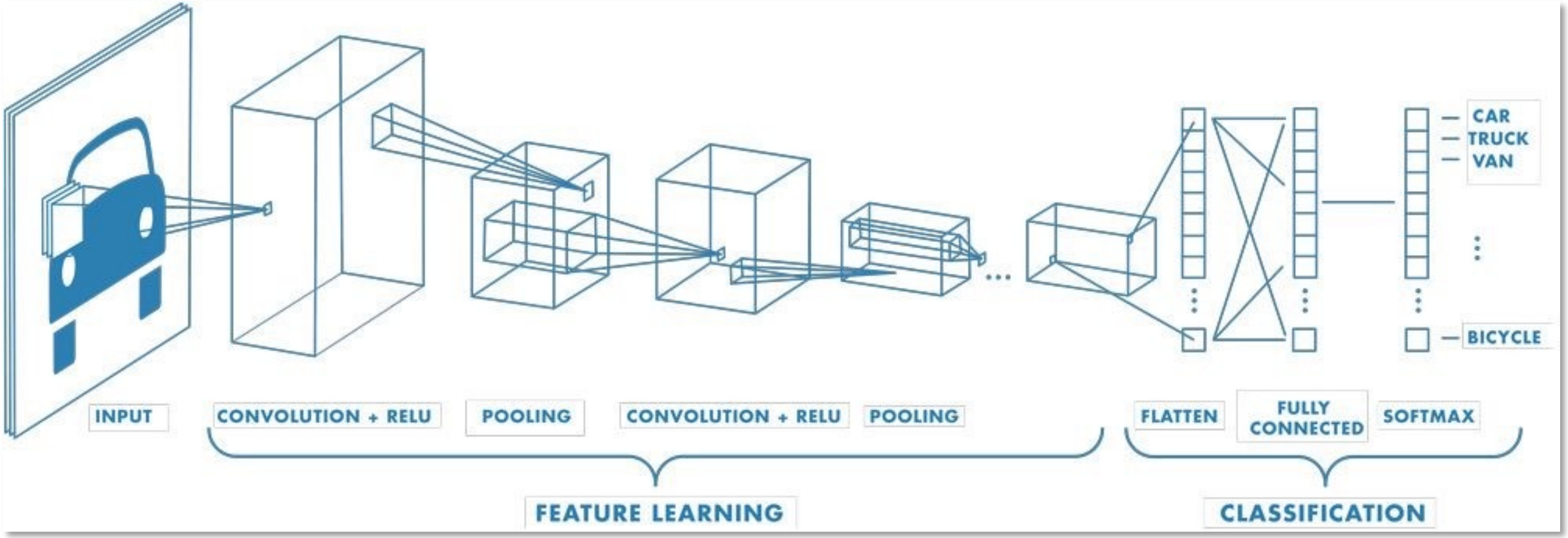
Introduction to Convolutional Neural Networks



https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Convolutional Neural Network Architectures – VGG (Visual Geometry Group)

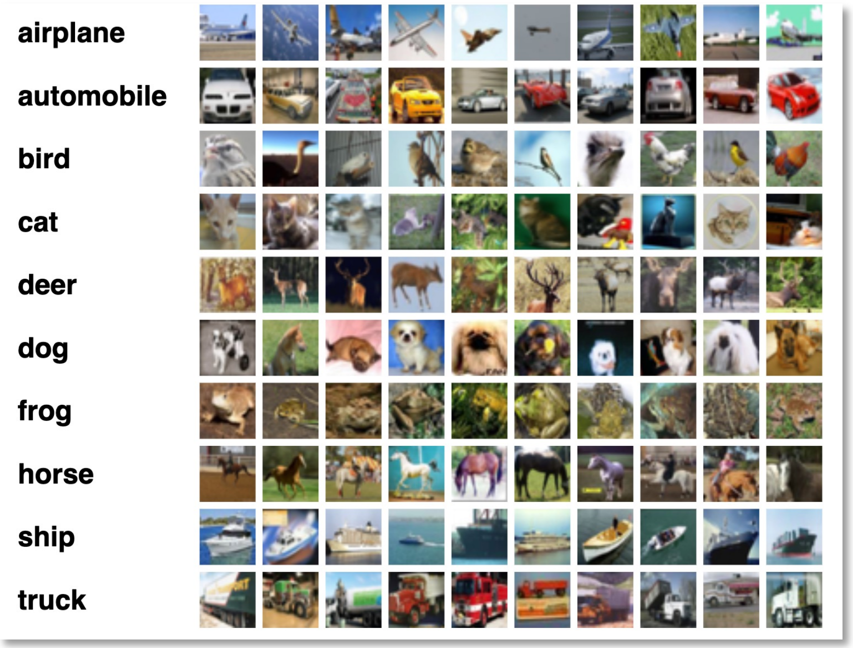
ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

- Main idea: increasing depth of CNNs
- 3 × 3 conv. layers with a stride of 1 - small receptive fields (compared to prev. 11 × 11 with a stride of 4 in AlexNet)
- 1 × 1 conv. to make the decision function more non-linear without changing the receptive fields
- ReLU activation function
- ImageNet dataset – 4 days of training
- 19 layers – 144M parameters

https://arxiv.org/pdf/1409.1556.pdf

CIFAR10 Data

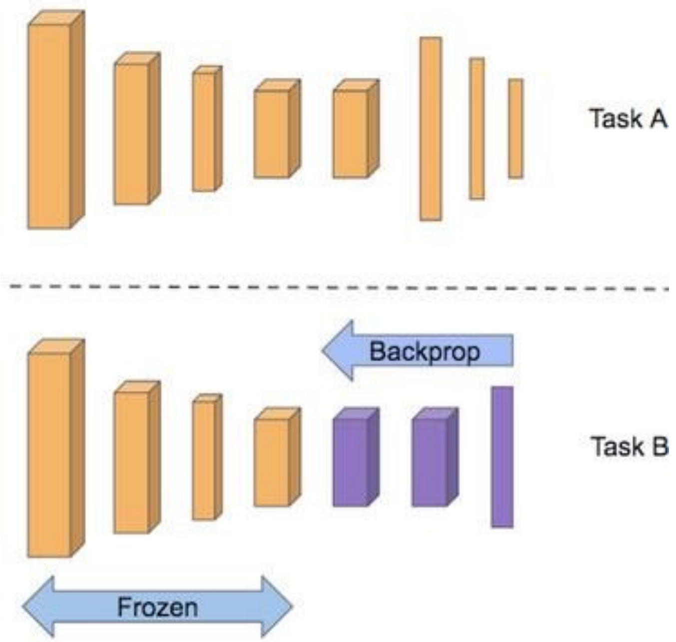
```
# download the data
train_dataset = torchvision.datasets.CIFAR10(root='./data', train=True, transform=transforms.ToTensor(), download=True)
test_dataset = torchvision.datasets.CIFAR10(root='./data', train=False, transform=transforms.ToTensor(), download=True)

# transform to DataLoader
train_loader = torch.utils.data.DataLoader(dataset=train_dataset, batch_size=batch_size, shuffle=True)
test_loader = torch.utils.data.DataLoader(dataset=test_dataset, batch_size=batch_size, shuffle=False)
```



Input size: 32x32x3

https://www.cs.toronto.edu/~kriz/cifar.html

Transfer learning – Pretrained Convolutional Neural Networks



- Pre-trained model is a saved network that was previously trained on a large dataset.
- Feature Extraction: Use the feature maps from the pre-trained model to detect features in the new samples. Add a new classifier, which will be trained from scratch to make predictions.
- Fine-Tuning: Unfreeze a few top layers of a pretrained model and jointly train both the newly-added classifier layers and the last layers of the base model. This allows us "fine-tune" the higher-order feature maps to make them more relevant for the specific task.

```
import torchvision.models as models
model = models.resnet34(weights='IMAGENET1K_V1')
```

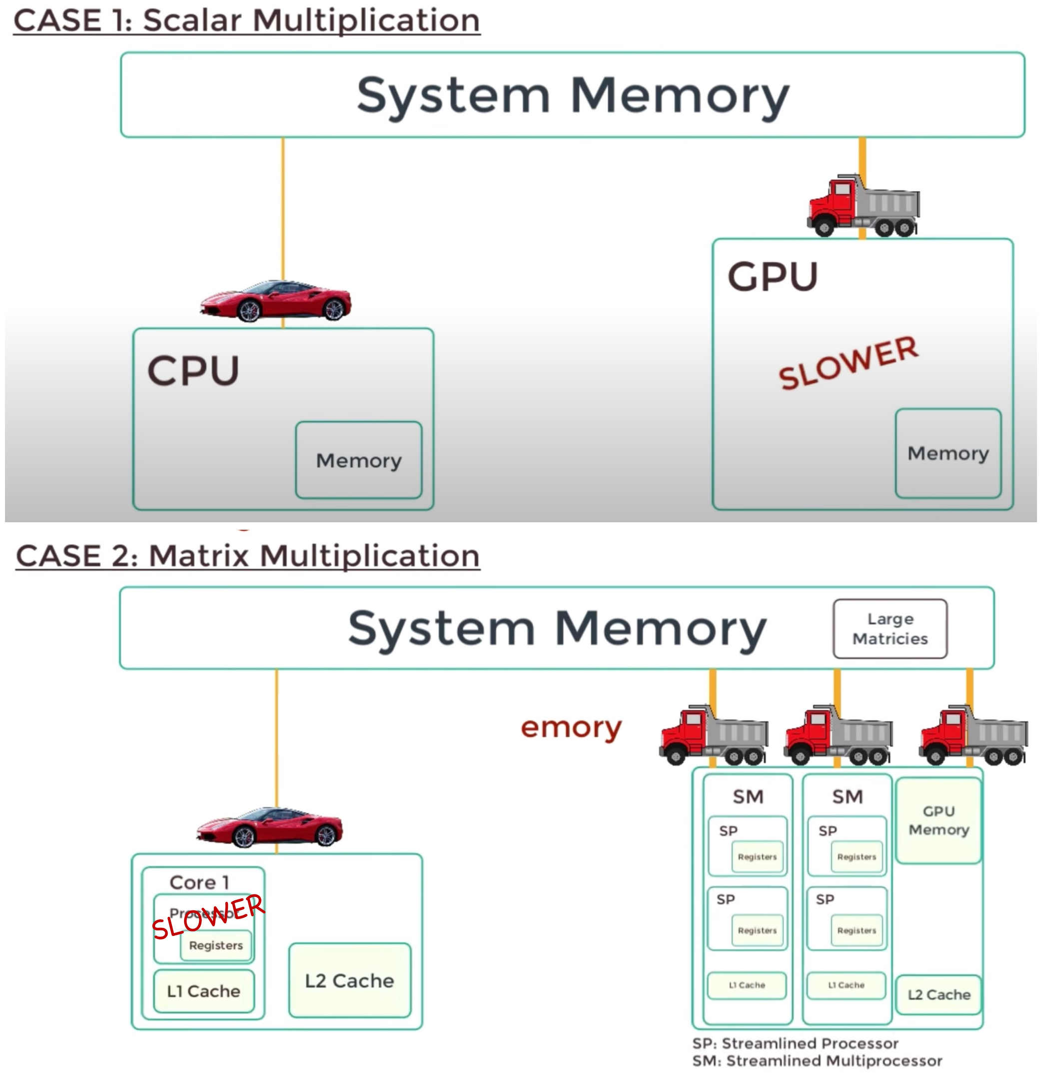
```
import torchvision.models as models
model = models.vgg19(weights='IMAGENET1K_V1')
```

Neural Networks and GPUs - Why?

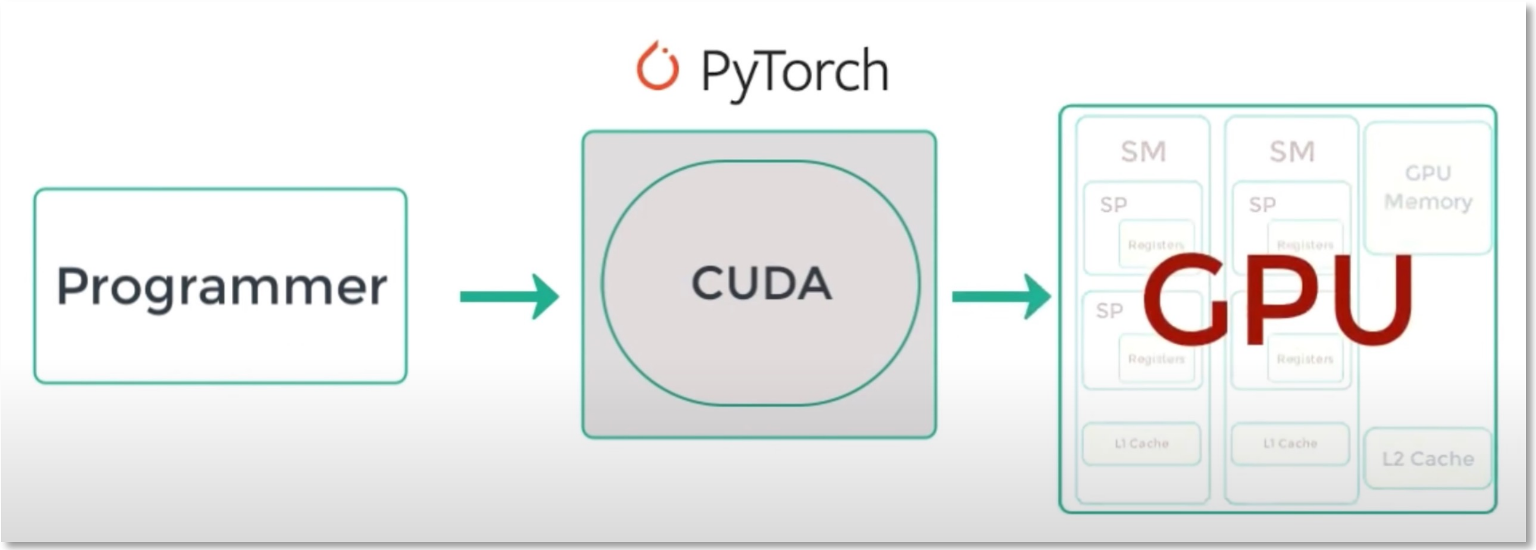
- GPUs in comparison to CPUs:
  - GPU allows parallel running of repetitive calculations within an application
  - CPU can be thought of as the taskmaster of the entire system, coordinating a wide range of general-purpose computing tasks
  - GPU performs a narrower range of more specialized tasks (e.g., matrix multiplications)

- CPUs are faster than GPUs in scalar multiplications.

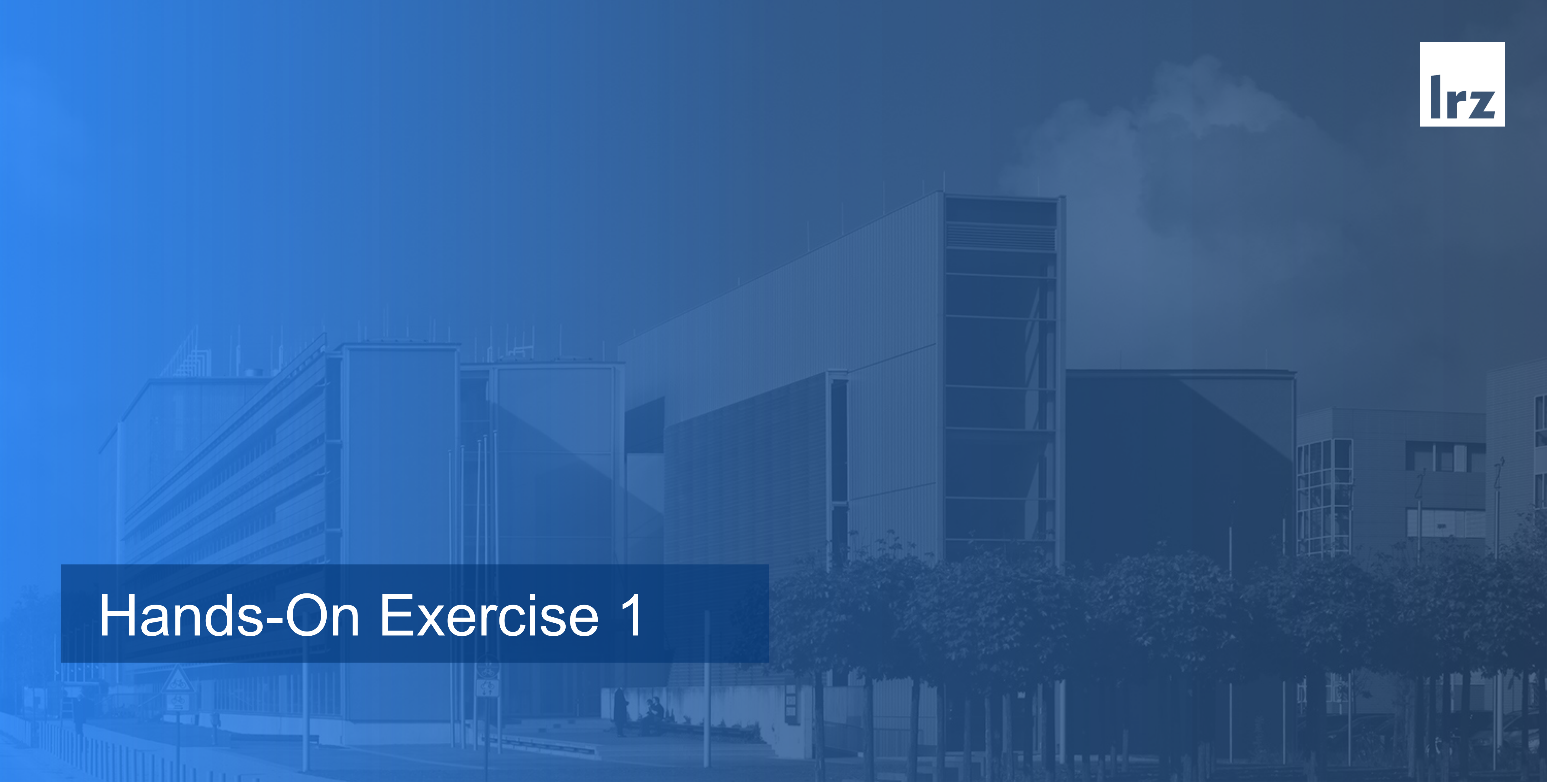
- GPUs are faster than CPUs in matrix multiplications.



Neural Networks and GPUs - How?




```
# Device configuration - cpu
device = torch.device('cpu’)

# Device configuration - gpu
device = torch.device(‘cuda’)

# Model to device
model = model.to(device)

# Data to device
images = images.to(device=device)
labels = labels.to(device=device)
```



Hands-On Exercise 1

VGG-19 + CIFAR10 on a GPU

1. Make a batch-size vs epoch time table
2. Pull the GitHub repo: https://github.com/LRZ-BADW/ai-systems.git
3. Explore the code
4. Write a job script to run the code
5. Play with the batch size and note the time

Batch Size	1 GPU	2 GPU

Job script info:

- partition: lrz-hgx-h100-92x4
- reservation: aits
- gpu resources: 1

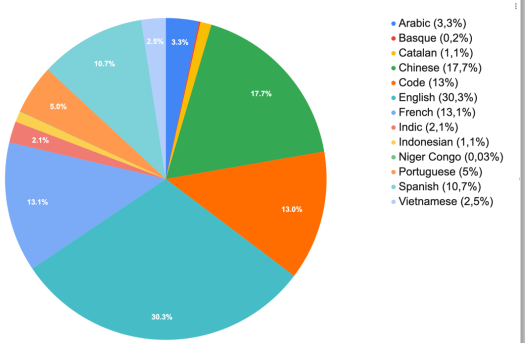
Increasing Amount of Data Available for Deep Learning

ImageNet

14,197,122 images
(150 GB)

https://paperswithcode.com/dataset/imagenet

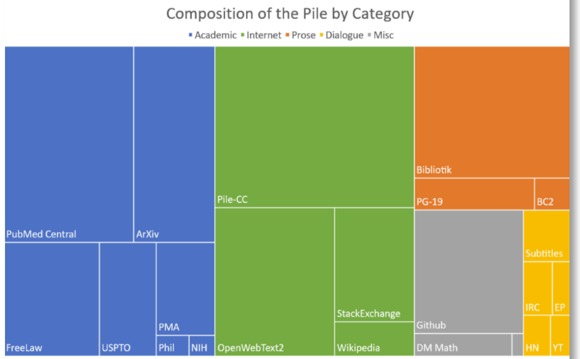
BigScience Multilingual Dataset for Language Modeling



350 billion tokens
(1.5 TB)
46 languages

https://bigscience.huggingface.co/blog/building-a-tb-scale-multilingual-dataset-for-language-modeling

Pile: Dataset of Diverse Text for Language Modeling



800GB

https://arxiv.org/abs/2101.00027

Common Crawl

2.95 billion web pages
(351.844 TB)

https://commoncrawl.org/

2. Data Distributed Training

Pytorch Distributed Data Parallel

- Based on package *torch.distributed* for synchronizing gradients.
- DDP registers a hook for each parameter that fires when the corresponding gradient is computed in the backward pass. That signal is used to trigger gradient synchronization across processes.

- Runs across *multiple GPUs* and across *multiple machines/nodes.*
- Near-linear scalability

Li et al., 2020, arXiv:2006.15704

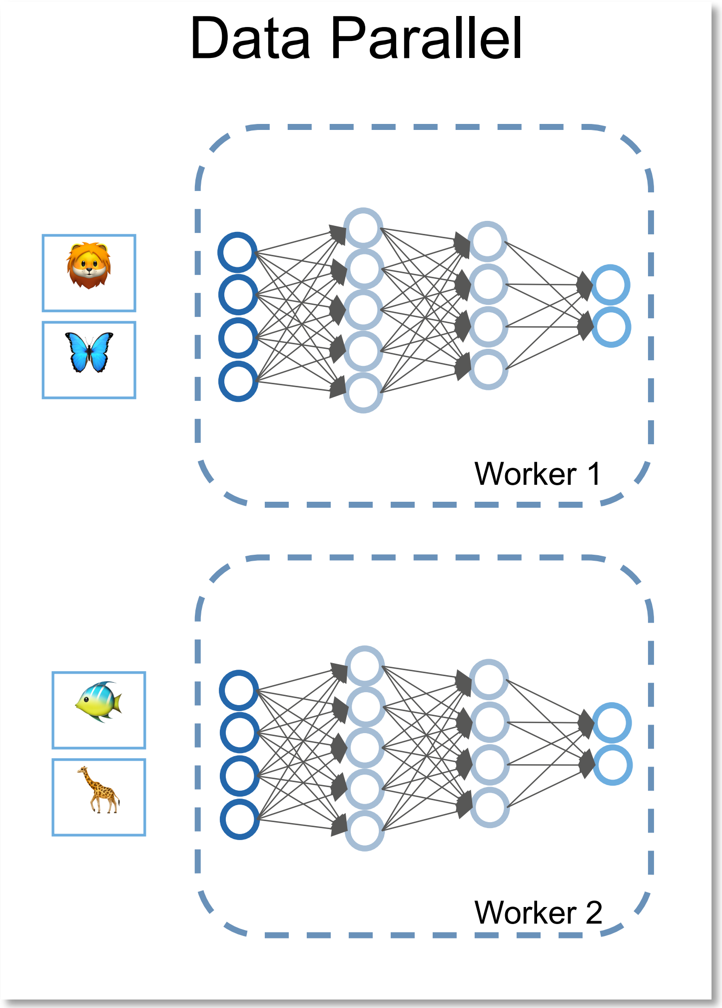
https://pytorch.org/docs/master/notes/ddp.html

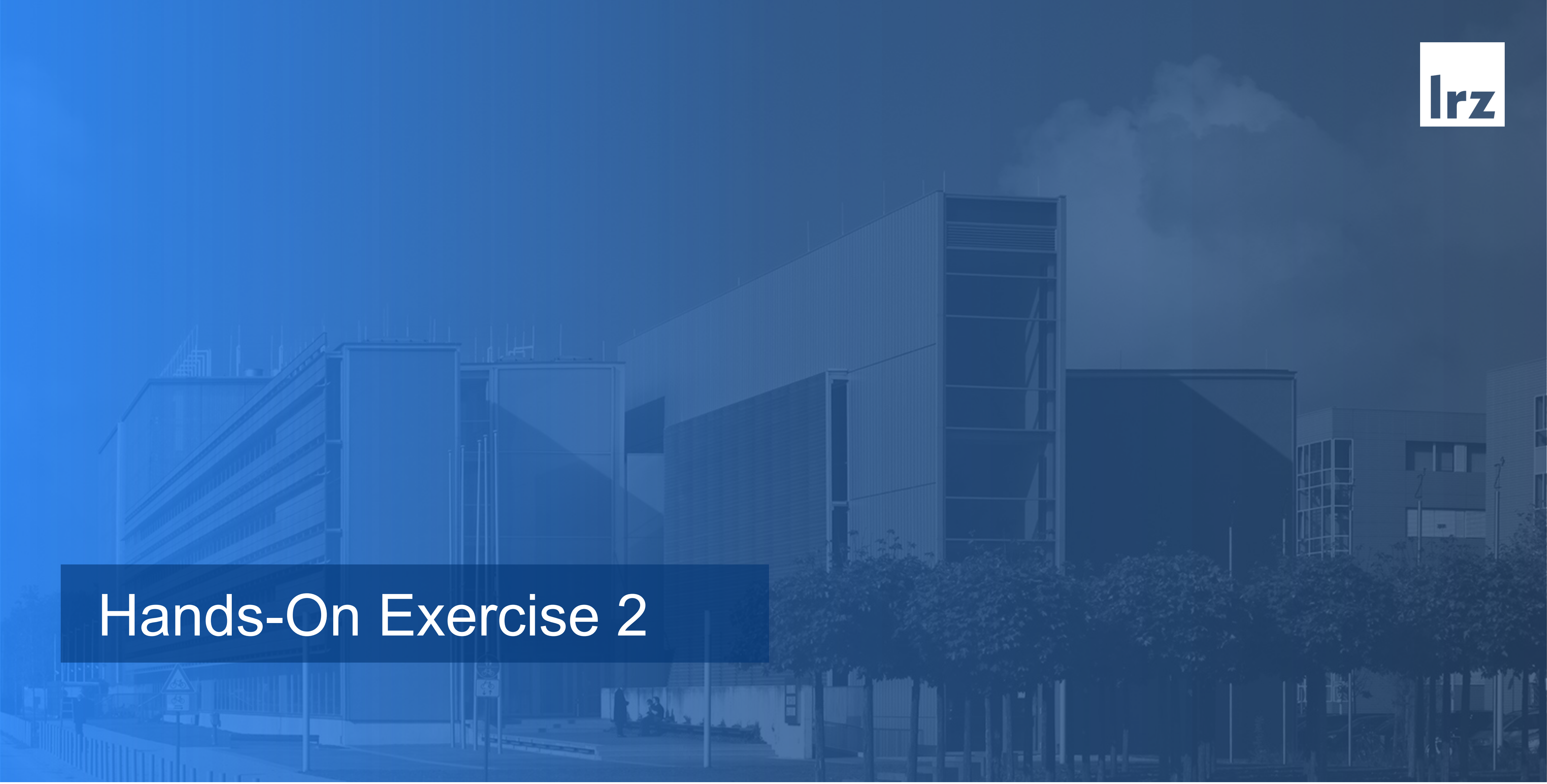
https://pytorch.org/tutorials/intermediate/ddp_tutorial.html#basic-use-case

```
import torch.distributed as dist
import torch.multiprocessing as mp
from torch.nn.parallel import DistributedDataParallel as DDP

def setup(rank, world_size):
    #environment variables for using torch.distributed
    os.environ['MASTER_ADDR'] = 'localhost'
    os.environ['MASTER_PORT'] = '12355'

    #initialize the process group
    dist.init_process_group("nccl", rank=rank, world_size=world_size)

def main(rank, world_size, args):
    #setup DDP
    setup(rank, world_size)
    #create a model…..
    #wrap model in DDP
    ddp_model = DDP(model, device_ids=[rank])
    #define loss function and optimizer…
    #forward pass…
    #backward pass and update parameters….
    #cleanup
    dist.destroy_process_group()

if __name__=="__main__":

    world_size = torch.cuda.device_count()
    batch_size = int(batch_size / world_size)
    mp.spawn(main, args=(world_size, args), nprocs=world_size,
join=True)
```

lrz

Data Distributed Parallel Training of NNs





Hands-On Exercise 2

VGG-19 + CIFAR10 on 2 GPUs - DDP

1. Refer to batch-size vs epoch time table
2. Pull the GitHub repo: https://github.com/LRZ-BADW/ai-systems.git
3. Explore the code
4. Write a job script to run the code
5. Play with the batch size and note the time

Job script info:
- partition: lrz-hgx-h100-92x4
- reservation: aits
- gpu resources: 2

Batch Size	1 GPU	2 GPU

Agenda

1. Introduction to the LRZ AI Systems

- Overview of the LRZ AI Systems
- Access to the LRZ AI Systems
- NVIDIA NGC Cloud
- Introduction to Enroot Containers
- Interactive and Batch Jobs
- Open on Demand
- Exercise: Run a job and extend an Enroot container

2. Data Distributed Training

- Introduction to Convolutional Neural Networks
- Exercise: Train VGG-19 on a GPU
- Introduction to Distributed Training
- Exercise: Train VGG-199 on 2 GPUs using DDP

3. Fully Sharded Data Parallel Training

- Introduction to Fully Sharded Data Parallel
- Exercise: Train VGG-199 on 2 GPUs using FSDP

Fully Sharded Data Parallel

- Inspired by ZeRO Stage 3 from DeepSpeed
- Ideal for training large models that do not fit into a single GPU
- Model parameters, gradients and optimizer states are sharded across GPUs

```
import torch.distributed as dist
import torch.multiprocessing as mp
from torch.distributed.fsdp import FullyShardedDataParallel as FSDP

def setup(rank, world_size):
    #environment variables for using torch.distributed
    os.environ['MASTER_ADDR'] = 'localhost’
    os.environ['MASTER_PORT'] = '12355’

    #initialize the process group
    dist.init_process_group("nccl", rank=rank, world_size=world_size)

def main(rank, world_size, args):
    #setup FSDP
    setup(rank, world_size)
    #create a model…..
    #wrap model in FSDP
    fsdp_model = FSDP(model)
    #define loss function and optimizer…
    #forward pass…
    #backward pass and update parameters….
    #cleanup
    dist.destroy_process_group()

if __name__=="__main__":

    world_size = torch.cuda.device_count()
    batch_size = int(batch_size / world_size)
    mp.spawn(main, args=(world_size, args), nprocs=world_size,
join=True)
```

Fully Sharded Data Parallel

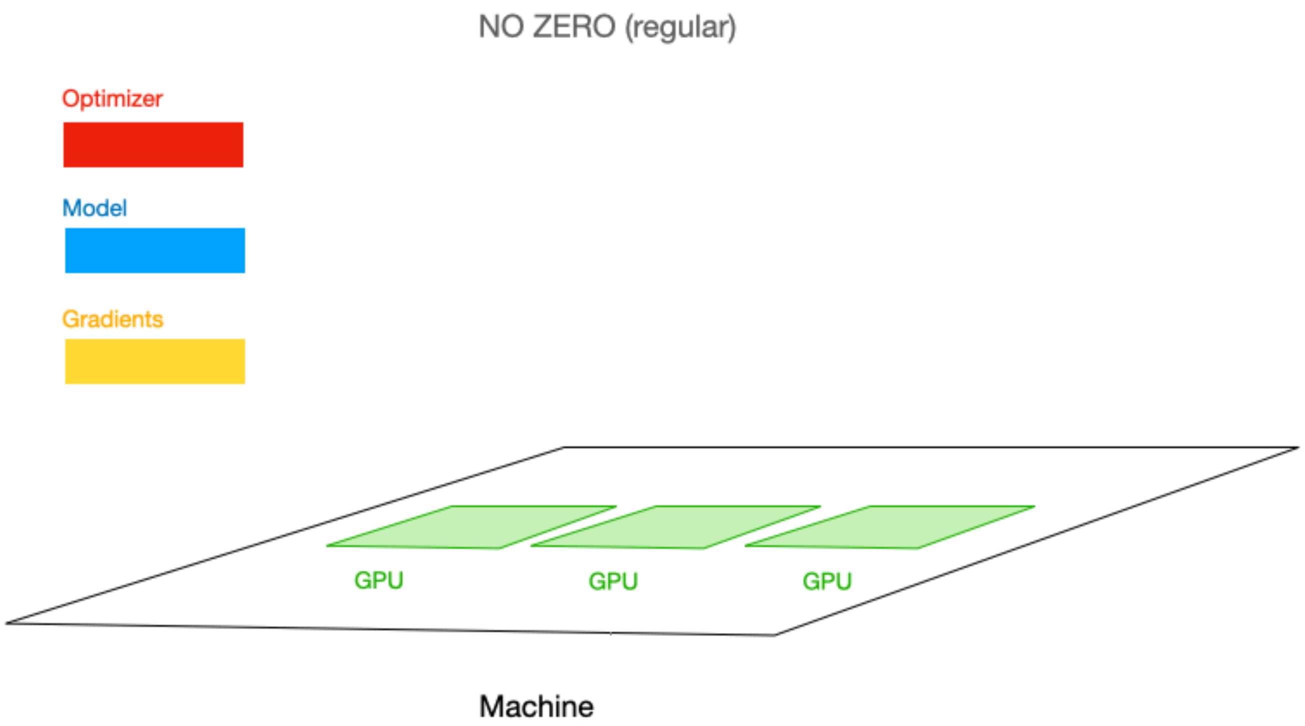
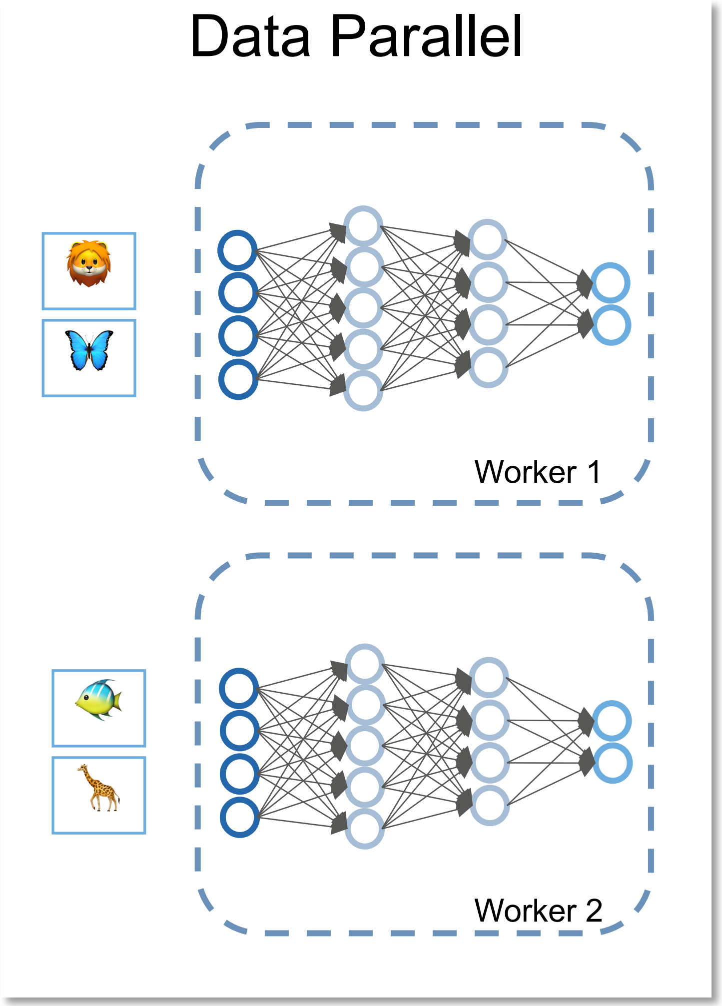
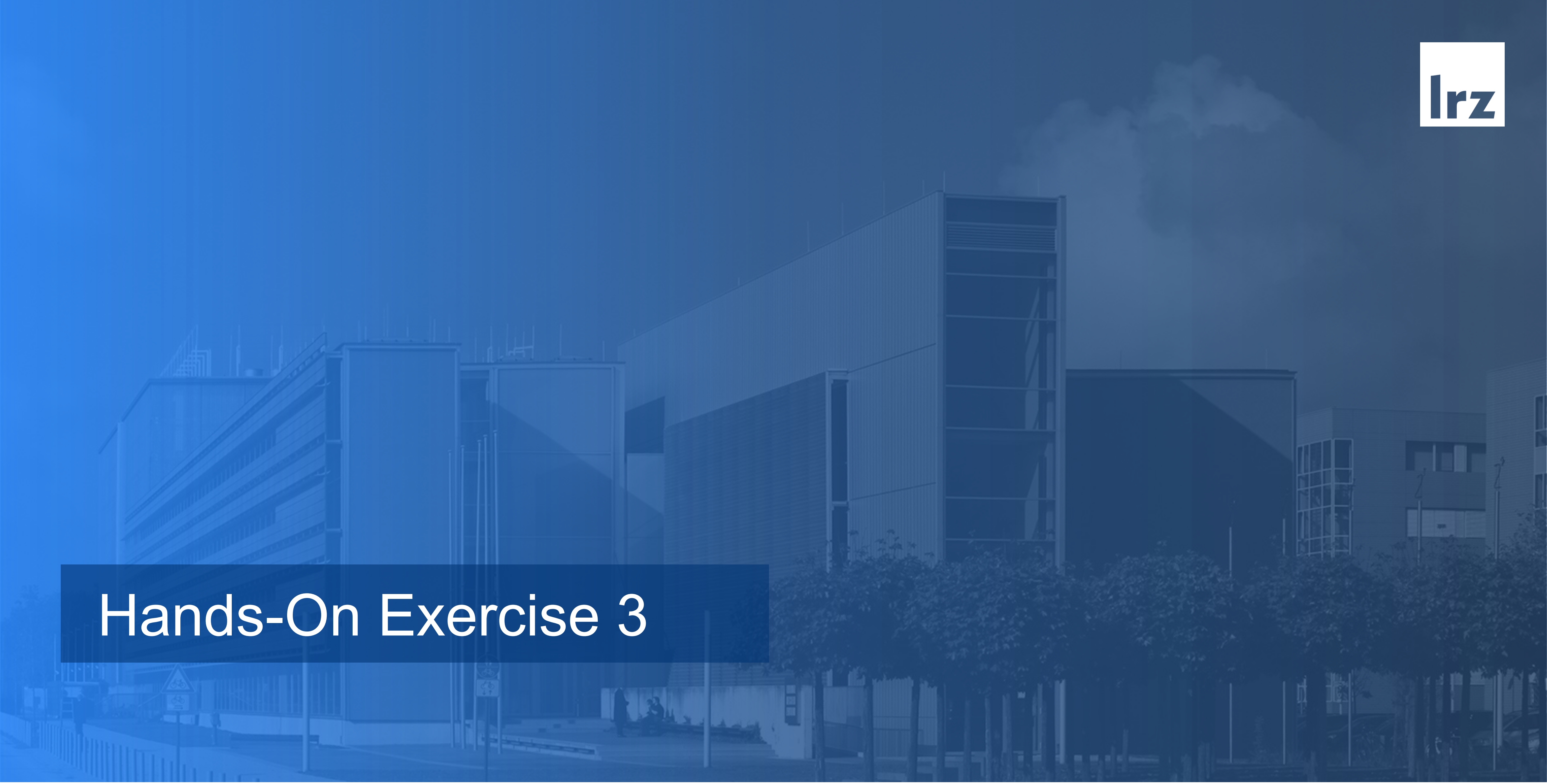


Image from: https://towardsdatascience.com/pytorch-lightning-vs-deepspeed-vs-fsdp-vs-ffcv-vs-e0d6b2a95719

Data Distributed Parallel Training of NNs





Hands-On Exercise 3

VGG-19 + CIFAR10 on 2 GPUs - FSDP

1. Refer to batch-size vs epoch time table
2. Pull the GitHub repo: https://github.com/LRZ-BADW/ai-systems.git
3. Explore the code
4. Write a job script to run the code
5. Play with the batch size and note the time

Batch Size	1 GPU	2 GPU

Job script info:

- partition: lrz-hgx-h100-92x4
- reservation: aits
- gpu resources: 2

The End!

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3. Fully Sharded Data Parallel Training

- Introduction to Fully Sharded Data Parallel
- Exercise: Train VGG-19 on 2 GPUs using FSDP

Announcements

Hackathon

- Half day event
- BYOC – Bring Your Own Code
- Hands-on & mentoring on scaling/parallelizing your code
- Write us at – Ajay.Navilarekal@lrz.de or Darshan.Thummar@lrz.de

Feedback Survey

https://survey.lrz.de/index.php/885115?lang=en