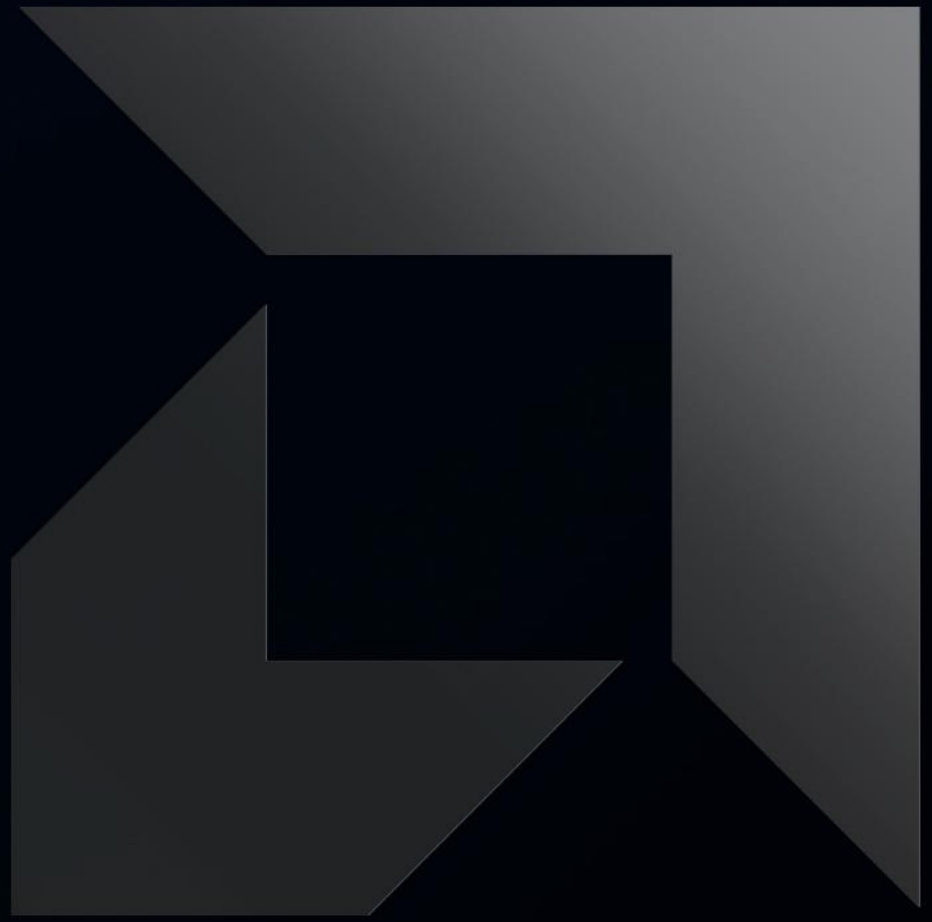


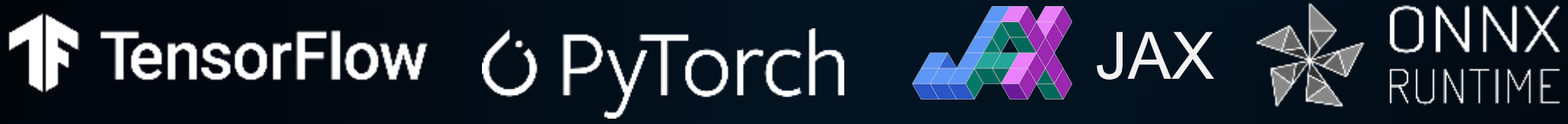
ML and AI on AMD GPUs

Presenter: Bob Robey
AMD @ Tsukuba University
Oct 21-23, 2025

AMD
together we advance_

ML ECOSYSTEM FOR AMD GPUS

SOURCE & BINARY implementations available upstream!



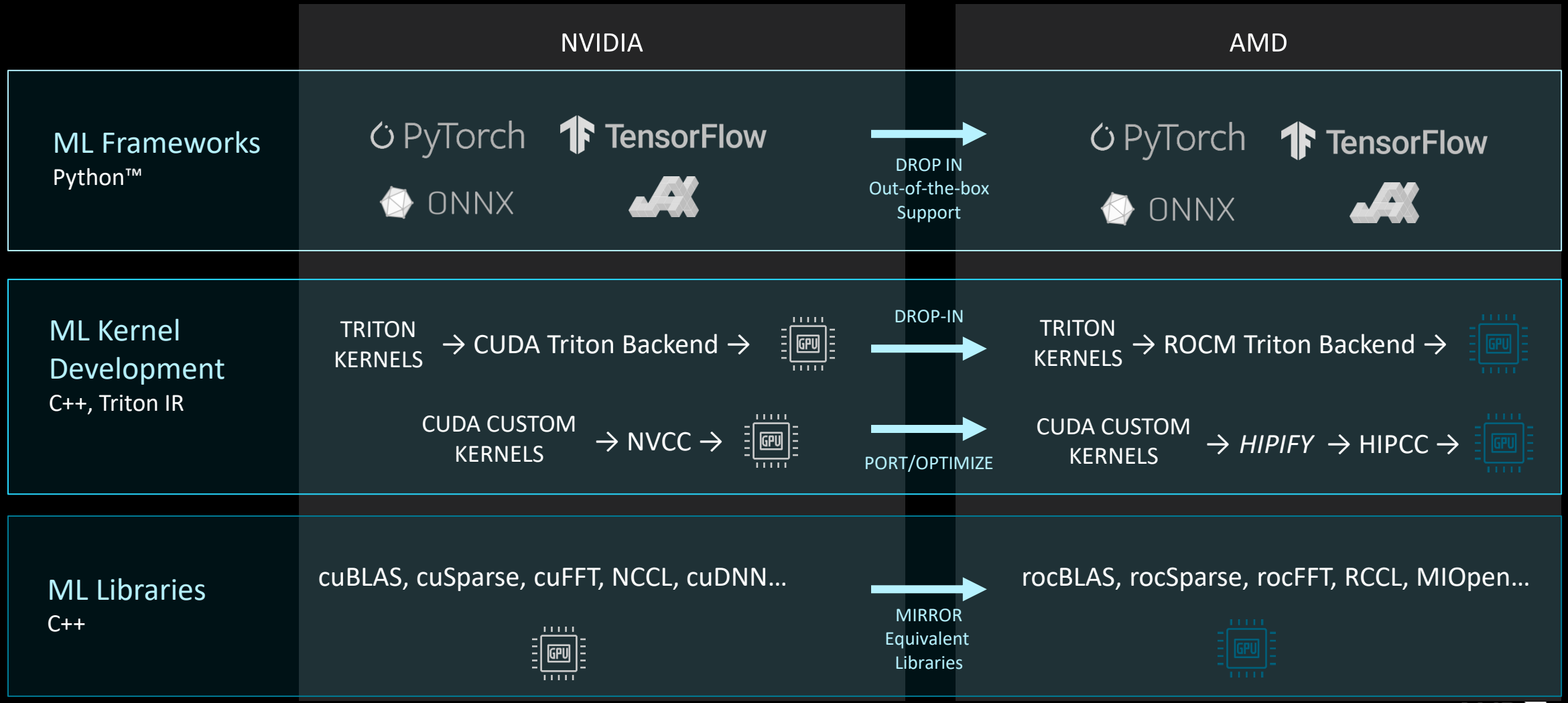
MIOPEN| RCCL | MIVisionX | MIGraphX

DEEPSPEED | AITemplate | openAI Triton|cuPy | XGBoost | hip-Python

flash-attention | vLLM | bitsandbytes

PORTING YOUR ML APPLICATION

NO CHANGES REQUIRED IN MOST CASES



PORTING YOUR ML APPLICATION

API COMPATIBLE LIBRARIES

CUDA Library	ROCm Library	Description
cuBLAS	rocBLAS	Basic Linear Algebra Subroutines
cuFFT	rocFFT	Fast Fourier Transform Library
cuSPARSE	rocSPARSE	Sparse BLAS + SPMV
cuSolver	rocSolver	LAPACK Library
AmgX	rocALUTION	Algebraic Multi-Grid Accelerated Linear Solvers
Thrust	hipThrust	C++ parallel algorithms library
CUB	rocPRIM	Low Level Optimized Parallel Primitives
cuDNN	MIOpen	Deep learning Solver Library
cuRAND	rocRAND	Random Number Generator Library
NCCL	RCCL	Communications Primitives Library based on the MPI equivalents

Linear Algebra Libraries supporting both AMD and NVIDIA GPUs	
Eigen	C++ template library for linear algebra
MAGMA	Dense linear algebra library on GPU and Multicore Architectures
SuperLU_DIST	Direct solution of large, sparse, nonsymmetric systems of linear equation
HYPRE	Scalable Linear Solvers and Multigrid Methods
ELPA	Highly efficient and highly scalable direct eigensolvers for symmetric (hermitian) matrices.
…	

WHERE CAN I GET AI FRAMEWORKS FROM?

BINARY AND SOURCE DISTRIBUTIONS AVAILABLE

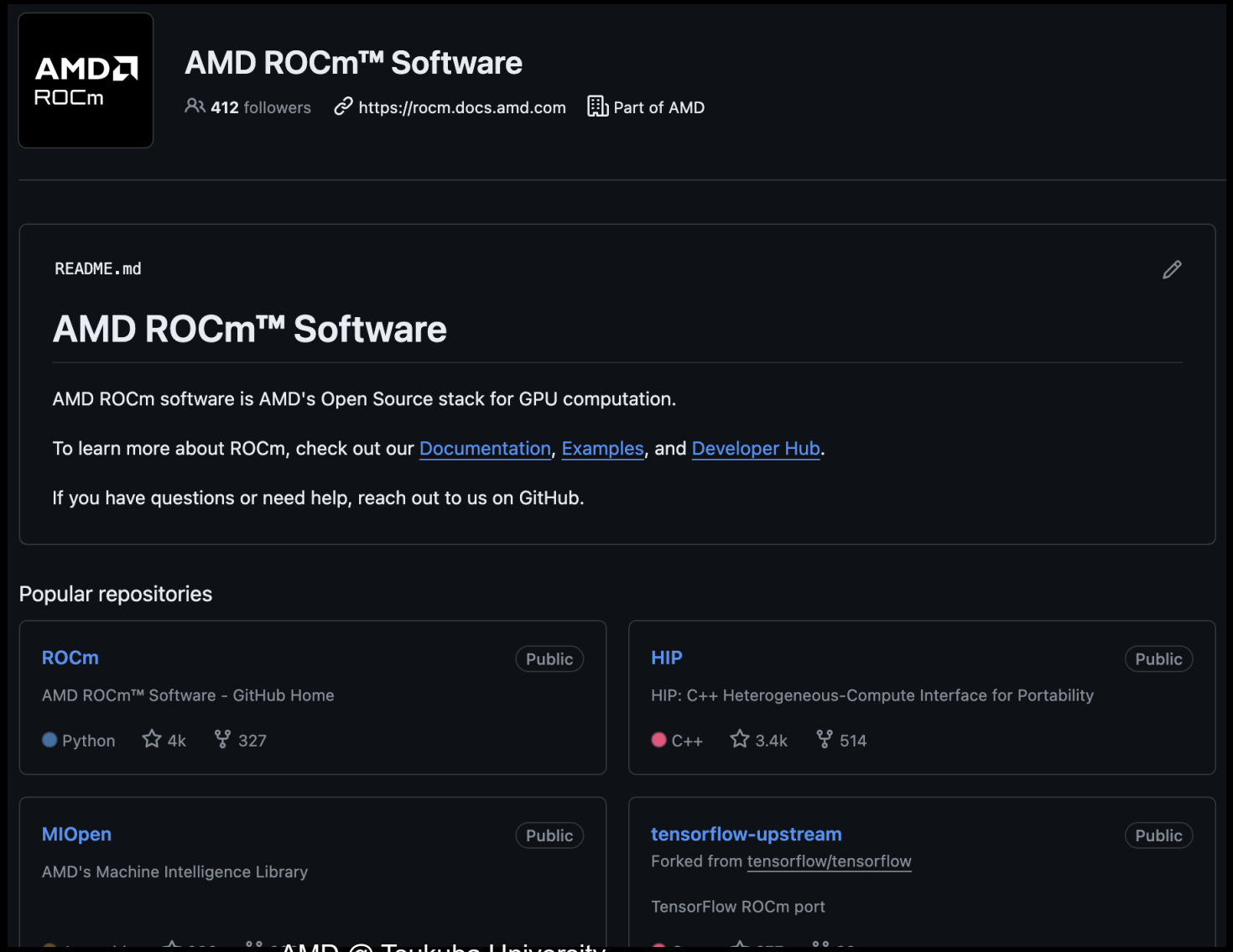
	Source	Container	PIP Wheel
TensorFlow	TensorFlow GitHub	Docker Hub	pypi.org
PyTorch	PyTorch GitHub	Docker Hub	pytorch.org
ONNX RUNTIME	ONNX-RT GitHub	Docker Instructions	onnxruntime.ai
JAX	GitHub public fork	Docker Hub	ROCm GitHub
DeepSpeed	DeepSpeed GitHub	Docker Hub	deepspeed.ai
CuPy	cupy.dev	Docker Hub	cupy.dev

- Source builds can sometimes be……tricky
- Leveraging containers or provided Wheel piles for Python™ installs is recommended if possible!

WHERE CAN I GET AI FRAMEWORKS FROM?

ROCm GITHUB HOSTS MOST AMD GPU PORTS AND LATEST CHANGES

- *https://github.com/ROCm*



ROCm ML FRAMEWORK CONTAINER IMAGES

ROCm DOCKERHUB PROVIDES SEVERAL IMAGES READY TO USE

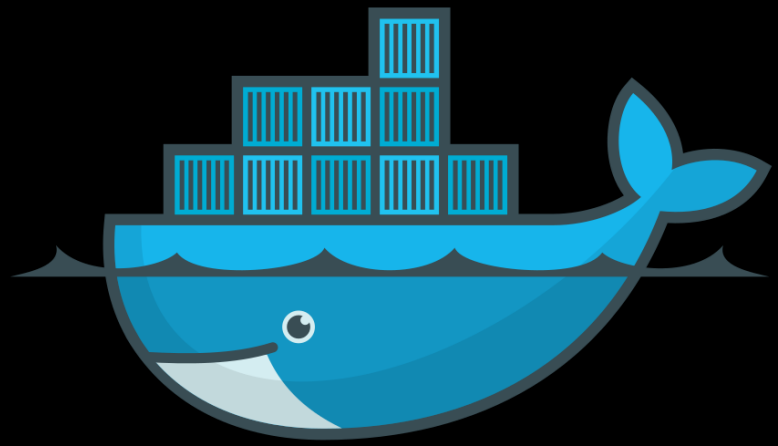
- Docker® command:

```
sudo docker run -it \
 --network=host \
 --device=/dev/kfd \
 --device=/dev/dri \
 --group-add=video \
 --ipc=host \
 --cap-add=SYS_PTRACE \
 --security-opt seccomp=unconfined \
 rocm/<my favorite ML framework>
```

Allow container to access network (dist. learning)

Allow access to the GPU drivers

Security options - may need to be expanded depending on the host system configuration



Replace by your image of choice

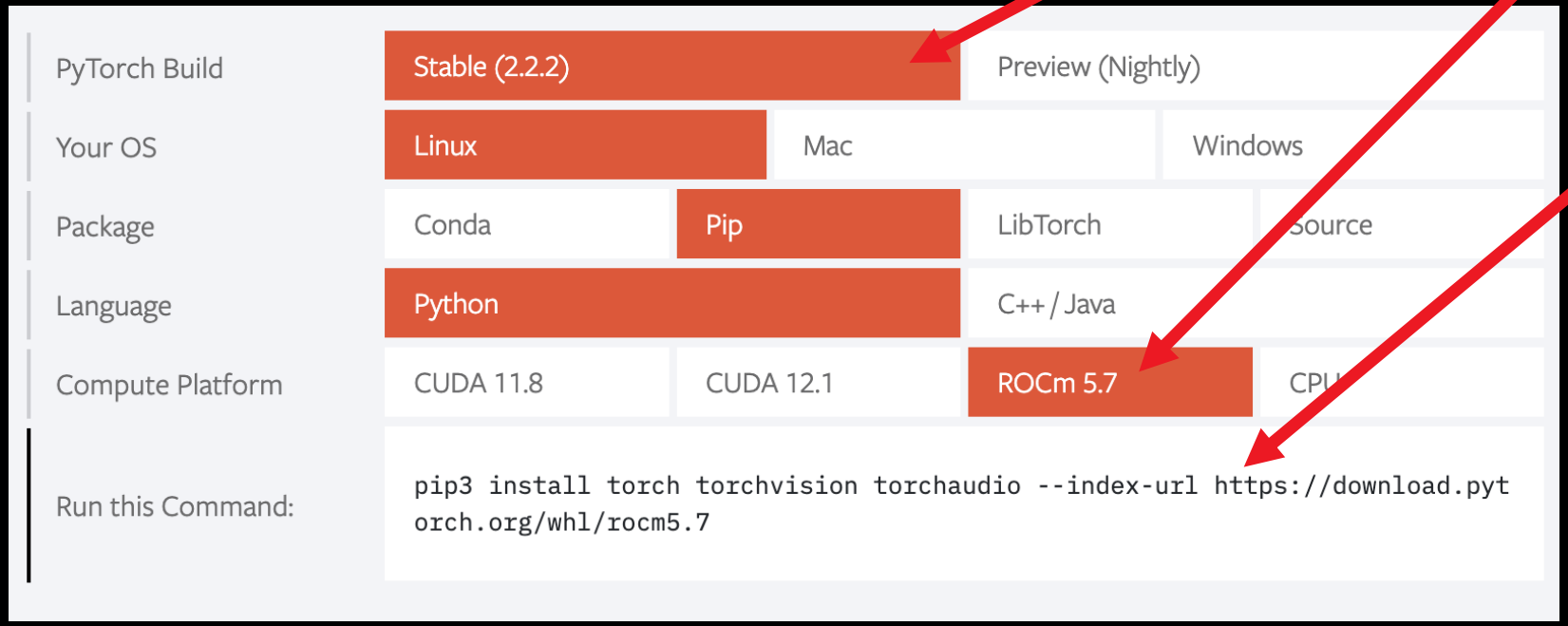
- Some of the available images:
  - PyTorch https://hub.docker.com/r/rocm/pytorch: rocm/pytorch:latest
  - TensorFlow https://hub.docker.com/r/rocm/tensorflow: *rocm/tensorflow:latest*
  - Jax https://hub.docker.com/r/rocm/jax: *rocm/jax:latest*
- Docker images with different tags/versions are available on ROCm DockerHub
- Apptainer and Podman can also be used

Prerequisites

- System dependencies need to be met:
  - GPU drivers
  - ROCm libraries, RCCL, and MIOpen should be installed:
    - rocm-dev
    - hiplibsdk
    - mlsdk
- ROCm and Python™ versions must match the wheel file
- https://rocm.docs.amd.com/en/develop/

Example for PyTorch install

- Pytorch official docs: https://pytorch.org/



- More combinations available! Check here https://download.pytorch.org/whl/torch/
  - E.g. PyTorch 2.2.2 with ROCm 5.6
  - Older versions
- More combinations available in https://repo.radeon.com/rocm/manylinux.

PyTorch install – system Python™

- Native install from PyTorch python wheels

Package install version can mix the PyTorch version as well as the ROCm it was built against.

Where do we want to install things - don't use your home folder!

This is where PyTorch project posts the wheel files - browse it to see what versions and ROCm combinations are available.

```
pip3 install -t $wd/pip-installs --pre torch==2.2.2+rocm5.6          --index-url https://download.pytorch.org/whl/
```

```
Collecting torch==2.2.2+rocm5.6
  Downloading https://download.pytorch.org/whl/rocm5.6/torch-2.2.2%2Brocm5.6-cp310-cp310-linux_x86_64.whl (1570.8 MB)
     ---------------------------------------- 1.6/1.6 GB 88.0 MB/s eta 0:00:01
```

Make the freshly installed PyTorch available to your Python runs

```
PYTHONPATH=$wd/pip-installs \
        srun --jobid=$jobid -n1 --gpus 8 \
        python -c 'import torch; print("I have this many devices:", torch.cuda.device_count())'
```

```
> I have this many devices: 8
```

Should yield the number of GCDs in the node.

PyTorch install – virtual environments

- Virtual environments are convenient to manage python package installation in your user-space

Leverage the venv module to create the virtual environment

We are happy to leverage system's already installed packages

```
python -m venv --system-site-packages cray-python-virtualenv
```

```
source cray-python-virtualenv/bin/activate
```

Activate the environment. It will be leveraged by the install and run.

Install and run as before. No need to specify install location – the environment is doing it for you.

```
pip3 install --pre torch==2.2.2+rocm5.6 --index-url https://download.pytorch.org/whl/
srun --jobid=$jobid -n1 --gpus 8 \
 python -c 'import torch; print("I have this many devices:", torch.cuda.device_count())'
```

PyTorch install – conda environment

- Conda environment adds the package-manager functionality to a virtual environment
- One can tune the Python™ version to use as we won't be leveraging the system one anymore.

```
curl -LO https://repo.anaconda.com/miniconda/Miniconda3-py310_24.1.2-0-Linux-x86_64.sh
bash ./Miniconda3-* -b -p miniconda3 -s
```

Download and install a minimal conda (miniconda).

```
source $wd/miniconda3/bin/activate base
```

Activate the conda environment

```
conda create -y -n pytorch python=3.10
source $wd/miniconda3/bin/activate pytorch
```

Create and activate a conda environment to install PyTorch based on Python 3.10

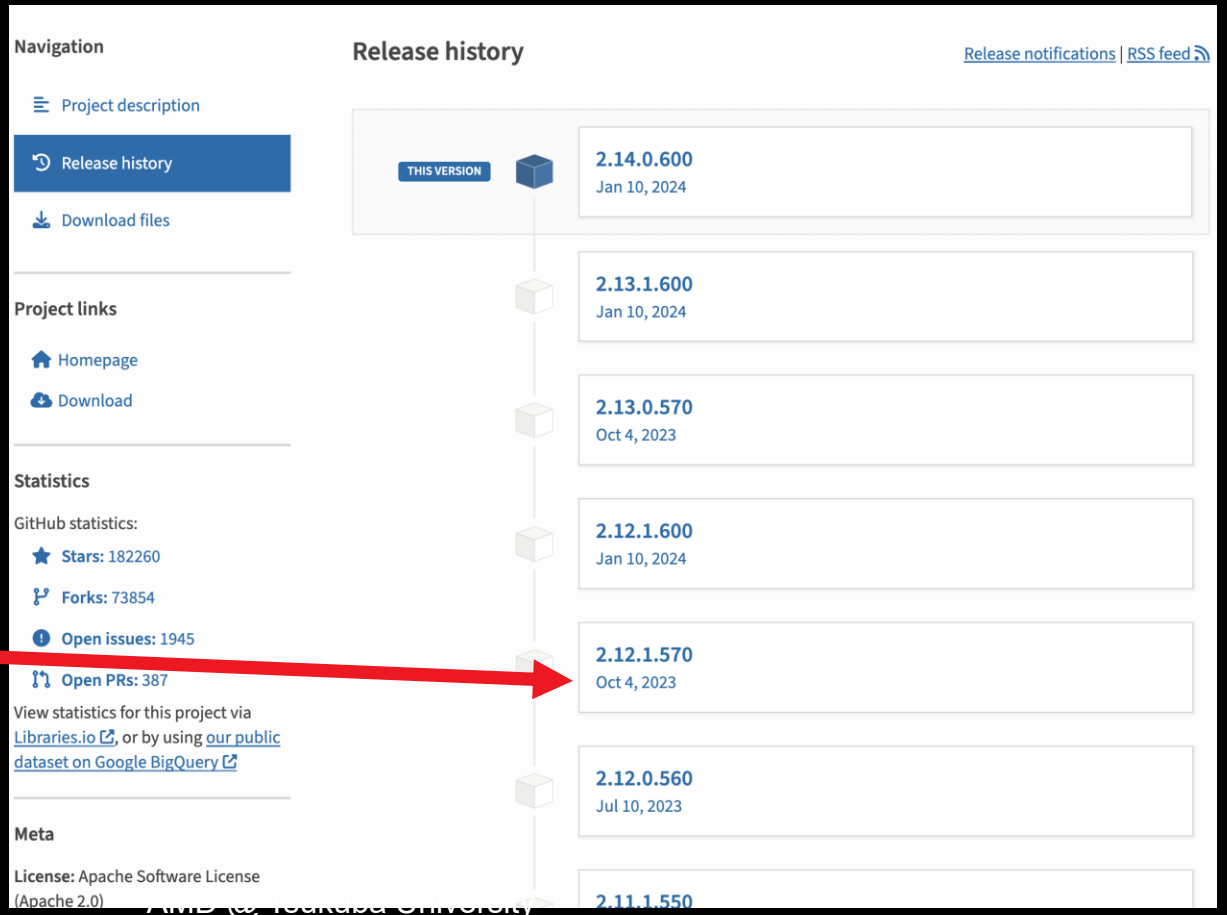
Install and run as before - Conda package manager doesn't have ROCm-enabled PyTorch installs

```
pip3 install --pre torch==2.2.2+rocm5.6 --index-url https://download.pytorch.org/whl/
srun --jobid=$jobid -n1 --gpus 8 \
  python -c 'import torch; print("I have this many devices:", torch.cuda.device_count())'
```

TensorFlow install

- Requirements similar to PyTorch install.
- Unlike PyTorch, TensorFlow packages for ROCm have a specific name:
  - **`tensorflow-rocm`**

Check the available versions from https://pypi.org/project/tensorflow-rocm/#history



Package version example:

- TensorFlow version 2.12.1
- Built on top of ROCm 5.7.0

TensorFlow install

- Installing TensorFlow 2.12.0 for ROCm 5.6.x:
  `pip install tensorflow-rocm==2.12.0.560`

- One can leverage pip command to get the available versions
  `pip install tensorflow-rocm==`

```
ERROR: Could not find a version that satisfies the requirement tensorflow-rocm== (from versions: 2.8.0, 2.8.1, 2.8.2, 2.8.3, 2.8.4, 2.9.
1, 2.9.2, 2.9.3, 2.9.4, 2.10.0.520, 2.10.0.530, 2.10.1.540, 2.10.1.550, 2.11.0.530, 2.11.0.540, 2.11.1.550, 2.12.0.560, 2.12.1.570, 2.12
.1.600, 2.13.0.570, 2.13.1.600, 2.14.0.600)
```

- Checking number of GPUs:
  `python -c 'from tensorflow.python.client import device_lib ; device_lib.list_local_devices()'`

```
Created device /device:GPU:0 with 63922 MB memory:  -> device: 0, name: AMD Instinct MI210, pci bus id: 0000:63:00.0
Created device /device:GPU:1 with 63922 MB memory:  -> device: 1, name: AMD Instinct MI210, pci bus id: 0000:43:00.0
Created device /device:GPU:2 with 63922 MB memory:  -> device: 2, name: AMD Instinct MI210, pci bus id: 0000:03:00.0
Created device /device:GPU:3 with 63922 MB memory:  -> device: 3, name: AMD Instinct MI210, pci bus id: 0000:26:00.0
```

JAX install

- JAX GPU support comes from the package **`jaxlib`**
- **`jaxlib`** requires building from source upstream
- You can leverage the wheel files from ROCm Github:
  - https://github.com/ROCm/jax/releases

JAX install

- Example installing commands:

```
pip install \
 https://github.com/ROCmSoftwarePlatform/jax/releases/download/jaxlib-v0.4.26/
                          jaxlib-0.4.26+rocm600-cp310-cp310-manylinux2014_x86_64.whl
pip install jax==0.4.26
```

JAX package doesn’t have any GPU software dependency

- Checking number of GPUs:

```
python -c 'import jax ; print("I have this many GPUs:", jax.local_device_count())’
```

- Should yield depending on the system:

```
I have this many GPUs: 8
```

PyTorch source install – see HPCTrainingDock script

- Build PyTorch using PyTorch ROCm Docker® image: *rocm/pytorch:latest-base*

```
# Get latest PyTorch docker image - it contains all dependencies needed.
docker pull rocm/pytorch:latest-base

# Start the container
docker run -it \
--cap-add=SYS_PTRACE --security-opt seccomp=unconfined \
--device=/dev/kfd --device=/dev/dri --group-add video --ipc=host \
--shm-size 8G \
rocm/pytorch:latest-base

# Clone the desired version of PyTorch
git clone --recursive https://github.com/pytorch/pytorch.git

# Build targeting a given GPU architecture.
cd pytorch ; PYTORCH_ROCM_ARCH=gfx90a ./.ci/pytorch/build.sh
```

Replace this with this

- Should you prefer not to rely on existing PyTorch ROCm Docker image:

```
# Clone the desired version of PyTorch
git clone --recursive https://github.com/pytorch/pytorch.git

# Build a docker image with the desired version.
cd pytorch/.ci/docker
./build.sh pytorch-linux-ubuntu22.04-rocm6.0-py3.10 -t rocm/pytorch:build_from_dockerfile
```

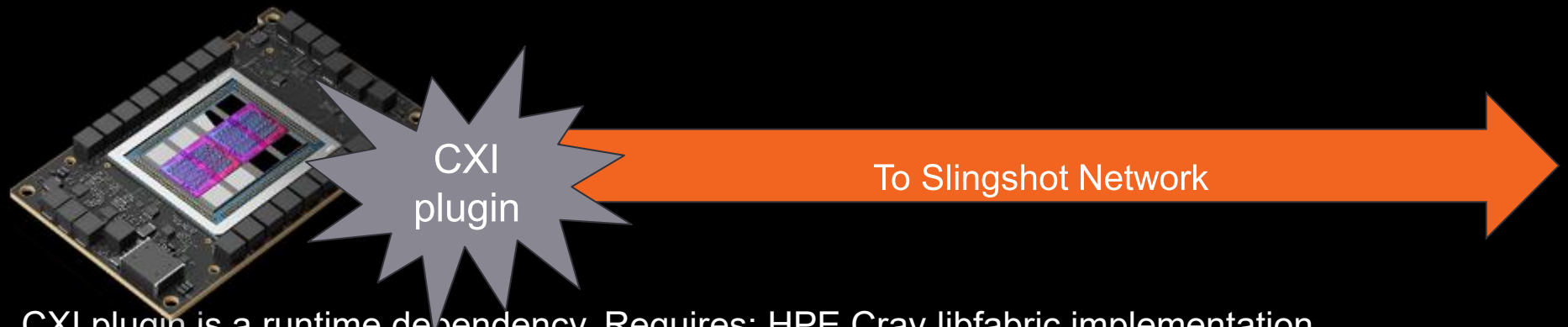
TensorFlow source install

- Build TensorFlow leveraging ROCm Docker® image, e.g. rocm/dev-ubuntu-22.04:6.0-complete

```
# Start the container
docker run -it \
 --cap-add=SYS_PTRACE --security-opt seccomp=unconfined \
 --device=/dev/kfd --device=/dev/dri --group-add video --ipc=host \
 --shm-size 8G \
 rocm/dev-ubuntu-22.04:6.0.2-complete

# Clone desired version of Pytorch
git clone --recursive -b r2.14-rocm-enhanced \
 https://github.com/ROCm/tensorflow-upstream

# Refer to repo available docs: tensorflow-upstream/rocm-doc/tensorflow-build-from-source.md

# Install system and Python™ requirements
apt-get install python3-dev python3-pip openjdk-8-jdk openjdk-8-jre unzip wget git
pip3 install numpy wheel mock future pyyaml setuptools requests keras_preprocessing keras_applications
        jupyter

# Install bazel version from https://github.com/bazelbuild/bazel/releases
cat tensorflow-upstream/.bazelversion

# Build: result wheel file will be in /tmp/tensorflow_pkg
cd tensorflow-upstream \
 ./build_rocm_python3.sh
```

Comms are important! - RCCL AWS-CXI plugin

- LUMI, Frontier (and others) directly attaches AMD Instinct™ MI250x Accelerator to the Cray Slingshot Network
  - Enable collectives computation on devices
  - Minimize the role of the CPU in the control path – expose more asynchronous computation opportunities
  - Lowest latency for network message passing is from GPU HBM memory



- CXI plugin is a runtime dependency. Requires: HPE Cray libfabric implementation
  - https://github.com/ROCm/aws-ofi-rccl
  - 3-4x faster collectives
- **CXI plugin is NOT featured in official DockerHub images! Make sure it exists in your environment!**

```
export NCCL_DEBUG=INFO
export NCCL_DEBUG_SUBSYS=INIT
# and search the logs for:
[0] NCCL INFO NET/OFI Using aws-ofi-rccl 1.4.0
```

Horovod install

- Horovod is a framework to enable distributed deep-learning training with TensorFlow, Keras, PyTorch, and Apache® MXNet. The goal of Horovod is to make distributed deep learning fast and easy to use.

Step 1: configure ROCm details

```
# Configure for ROCm
export HOROVOD_WITHOUT_MXNET=1
export HOROVOD_WITHOUT_GLOO=1
export HOROVOD_GPU=ROCM
export HOROVOD_ROCM_HOME=$ROCM_PATH
export HOROVOD_GPU_OPERATIONS=NCCL
export HOROVOD_CPU_OPERATIONS=MPI
export HOROVOD_WITH_MPI=1
export HOROVOD_ROCM_PATH=$ROCM_PATH
export HOROVOD_RCCL_HOME=$ROCM_PATH/rccl
export RCCL_INCLUDE_DIRS=$ROCM_PATH/rccl/include
export HOROVOD_RCCL_LIB=$ROCM_PATH/rccl/lib
export HCC_AMDGPU_TARGET=gfx90a
export CMAKE_PREFIX_PATH=$MPICH_PATH
```

Step 2: configure for your favorite framework details

```
# Configure for TensorFlow
export HOROVOD_WITH_TENSORFLOW=1
export HOROVOD_WITHOUT_PYTORCH=1

# Configure for PyTorch
export HOROVOD_WITHOUT_TENSORFLOW=1
export HOROVOD_WITH_PYTORCH=1
```

Horovod needs MPI at launch

Step 3: install

```
# Install
pip install --no-cache-dir --force-reinstall --verbose horovod==$HOROVOD_VERSION
```

DeepSpeed install

- DeepSpeed is a framework to optimize distributed deep-learning training and inference

```
DS_BUILD_AIO=0 \
DS_BUILD_CCL_COMM=1 \
DS_BUILD_CPU_ADAM=0 \
DS_BUILD_CPU_LION=0 \
DS_BUILD_EVOFORMER_ATTN=0 \
DS_BUILD_FUSED_ADAM=1 \
DS_BUILD_FUSED_LION=1 \
DS_BUILD_CPU_ADAGRAD=0 \
DS_BUILD_FUSED_LAMB=1 \
DS_BUILD_QUANTIZER=0 \
DS_BUILD_RANDOM_LTD=0 \
DS_BUILD_SPARSE_ATTN=0 \
DS_BUILD_TRANSFORMER=0 \
DS_BUILD_TRANSFORMER_INFERENCE=0 \
DS_BUILD_STOCHASTIC_TRANSFORMER=1 \
pip install deepspeed==0.14.0 \
--global-option="build_ext" --global-option="-j32"

ds_report
```

Select all the optimizations not all are enabled for GPUs.

Allow multiple process builds.

Utility to report supported capabilities.

```
--------------------------------------------------
op name ................ installed .. compatible
--------------------------------------------------
async_io ............... [NO] ....... [NO]
fused_adam ............. [YES] ...... [OKAY]
cpu_adam ............... [NO] ....... [OKAY]
cpu_adagrad ............ [NO] ....... [OKAY]
cpu_lion ............... [NO] ....... [OKAY]
evoformer_attn ......... [NO] ....... [NO]
fused_lamb ............. [YES] ...... [OKAY]
fused_lion ............. [YES] ...... [OKAY]
inference_core_ops ..... [NO] ....... [OKAY]
cutlass_ops ............ [NO] ....... [OKAY]
transformer_inference .. [NO] ....... [OKAY]
quantizer .............. [NO] ....... [OKAY]
ragged_device_ops ...... [NO] ....... [OKAY]
ragged_ops ............. [NO] ....... [OKAY]
random_ltd ............. [NO] ....... [OKAY]
sparse_attn ............ [NO] ....... [NO]
spatial_inference ...... [NO] ....... [OKAY]
transformer ............ [NO] ....... [OKAY]
stochastic_transformer . [YES] ...... [OKAY]
--------------------------------------------------
```

PyTorch example

- What provides distributed capability:
  - PyTorch Distribute Data Parallel (DDP) – Batches of different data run concurrently
  - Other more sophisticated methods available
  - Frameworks like Deepspeed and Horovod can also enable distributed training.

```
import torch.distributed as dist
…
dist.init_process_group(
 backend='nccl',
 init_method='env://',
 world_size=int(os.environ['WORLD_SIZE']),
 rank=int(os.environ['RANK']))
```

Let's use RCCL collectives library.

Well be learning about the distributed setting from the environment

Capture some env vars to adjust my distributed training

- … Epoch 0 Loss 0.148397 Global batch size 2048 on 16 ranks
- … Epoch 1 Loss 0.147906 Global batch size 2048 on 16 ranks
- … Epoch 2 Loss 0.147717 Global batch size 2048 on 16 ranks

Frameworks tend to include information on how the training is distributed.

TensorFlow + Horovod example

- What provides distributed capability: Horovod wraps the TensorFlow operators

```
import tensorflow as tf
import horovod.tensorflow as hvd

# Horovod: initialize Horovod.
hvd.init()

# Horovod: pin GPU to be used to process local rank (one GPU per process)
tf.config.experimental.set_visible_devices(gpus[hvd.local_rank()], 'GPU')

# A local optimizer.
opt = tf.optimizers.SGD(0.01)

# Wrap the Tensorflow operator (e.g. a gradient tape) with the corresponding
# Horovov distributed operator.
tape = tf.GradientTape()
tape = hvd.DistributedGradientTape(tape, compression=compression)

# Apply the gradient information gather from the distributed operator into the local optimizer.
gradients = tape.gradient(loss, model.trainable_variables)
opt.apply_gradients(zip(gradients, model.trainable_variables))
```

Instantiate Horovod implementation for TensorFlow

Horovod requires an initialization similar to what MPI requires: it will leverage MPI dependency to record the information about the ranks

Horovod provides information about local rank useful for GPU binding.

Leverage the results of the distributed operator in the local optimizer.

DISCLAIMERS AND ATTRIBUTIONS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