HIGH PERFORMANCE RESEARCH COMPUTING

ACES: AI/ML Techlab on Graphcore IPUs

03/18/2025

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High Performance
Research Computing
DIVISION OF RESEARCH

ACES
ACCELERATING COMPUTING FOR EMERGING SCIENCES

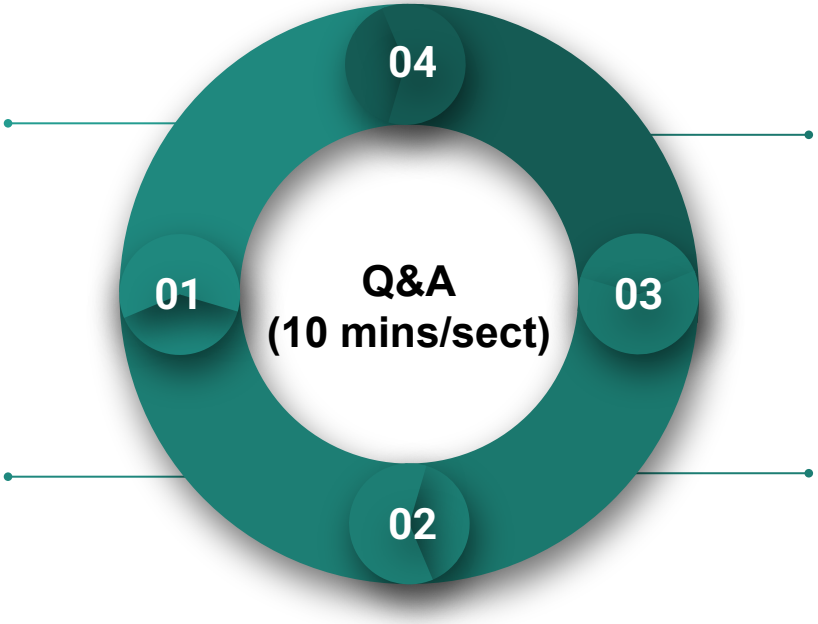
IPU Tutorial Outline

Section I. Intro to IPUs

We will introduce Graphcore IPU architecture, and the IPU systems on TAMU ACES platform.

Section II. Demo on ACES

We will demonstrate how to run models of different frameworks on ACES IPU system.



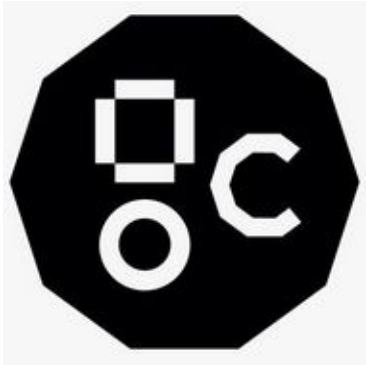
Section IV Porting TensorFlow code to IPU

We will learn to port a Keras MNIST classification model to run on IPU

Section III. Porting PyTorch code to IPU

We will learn to port a PyTorch Fashion-MNIST classification model to run on IPU

Section I. Overview



NSF ACES

Accelerating Computing for Emerging Sciences

Our Mission:

- NSF ACSS CI testbed
- Offer an accelerator testbed for numerical simulations and **AI/ML workloads**
- Provide consulting, technical guidance, and training to researchers
- Collaborate on computational and data-enabled research.

ACES Accelerators

Component	Quantity	Description
Graphcore IPU	32	16 Colossus GC200 IPUs, 16 Bow IPUs. Each IPU group hosted with a CPU server as a POD16 on a 100 GbE RoCE fabric
FPGAs: Intel PAC D5005 BittWare IA-840F	 2 3	 Accelerator with Intel Stratix 10 GX FPGA and 32 GB DDR4 Accelerator with Agilex AGF027 FPGA and 64 GB of DDR4
NextSilicon Coprocessor	2	Reconfigurable accelerator with an optimizer continuously evaluating application behavior.
NEC Vector Engine	8	Vector computing card (8 cores and HBM2 memory)
Intel Optane SSD	48	18 TB of SSDs addressable as memory w/ MemVerge Memory Machine.
NVIDIA GPUs: H100 A30	 30 4	 For HPC, DL Training, AI Inference For AI Inference and Mainstream Compute
Intel PVC GPUs	120	Intel GPUs for HPC, DL Training, AI Inference

Refer to our Knowledge Base for more:
https://hprc.tamu.edu/kb/User-Guides/ACES/Hardware/

BOW IPU PROCESSOR

Deep Trench Capacitor

Efficient power delivery
Enables increase in operational performance

Wafer-On-Wafer

Advanced silicon 3D stacking technology

Closely coupled power delivery die

Higher operating frequency and enhanced overall performance

Solder Bumps

IPU-Links™

10x IPU-Links,
320GB/s chip to chip bandwidth

IPU-Exchange™

11 TB/s all to all IPU-Exchange™
Non-blocking, any communication pattern

PCIe

PCI Gen4 x16
64 GB/s bidirectional bandwidth to host

IPU-Tiles™

1472 independent IPU-Tiles™ each with an IPU-Core™ and In-Processor-Memory™

IPU-Core™

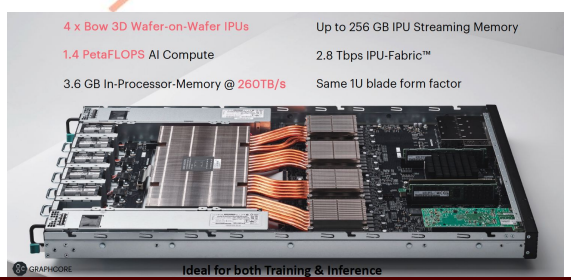
1472 independent IPU-Core™

8832 independent program threads executing in parallel

In-Processor-Memory™

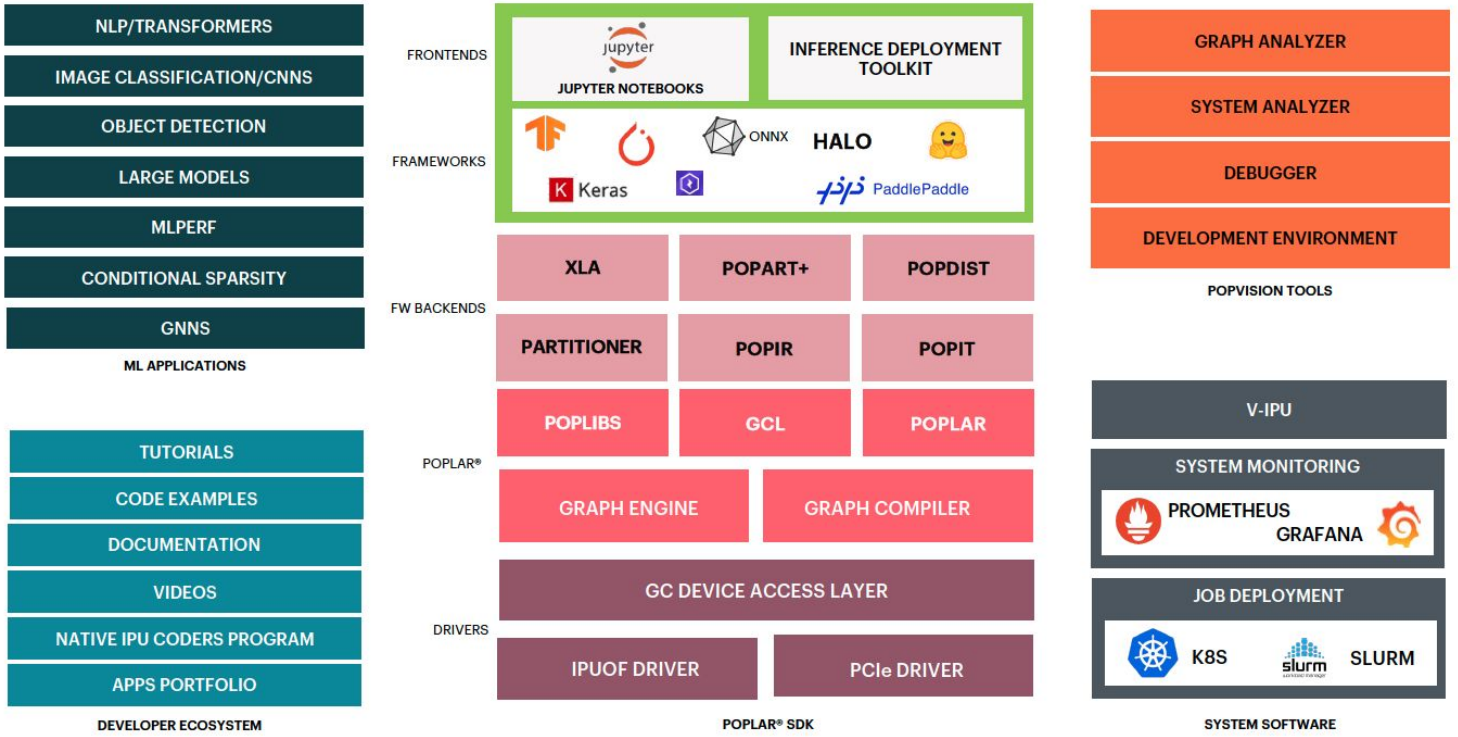
900MB In-Processor-Memory™ per IPU

65.4TB/s memory bandwidth per IPU



Source: Graphcore

Graphcore Software Stack



Source: Graphcore

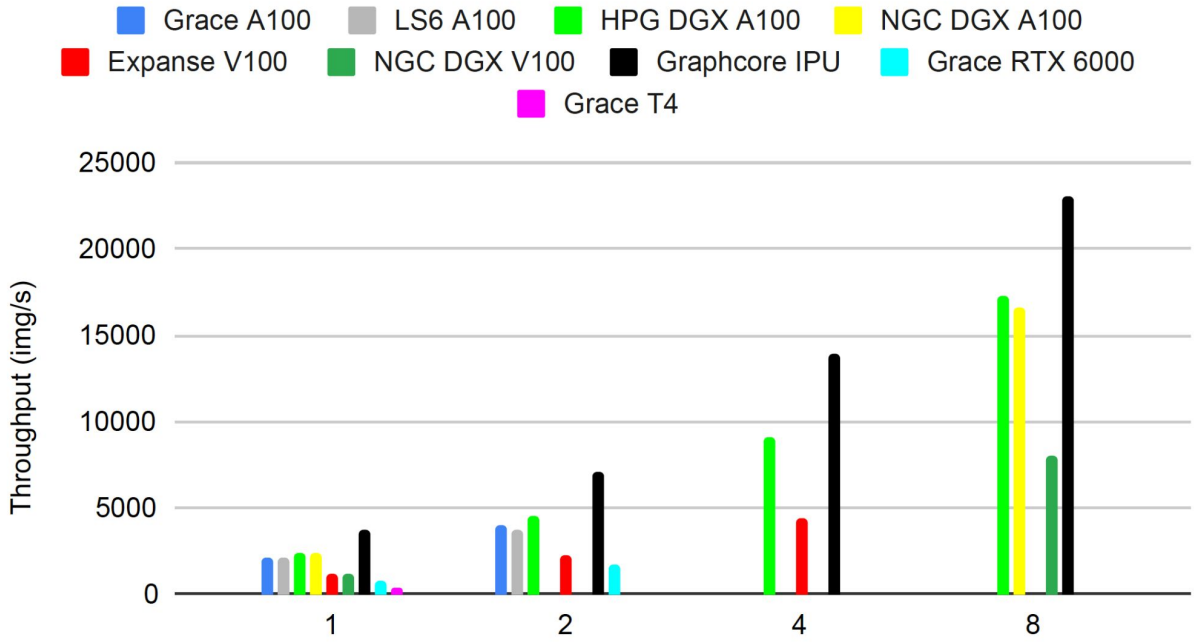
Models on Graphcore GitHub

Vision	ResNet50, EfficientNet, DINO, MAE, Neural Image Fields, SWIN ((Shifted Windows Vision Transformers)), U-Net, ViT (Vision Transformer), YOLOv4, etc.
NLP	BERT, BLOOM-176B (BigScience Large Open-science Open-access Multilingual), GPT-2, GPT-3 2.7B, GPT-3 175B, GPT-J, etc.
Speech	Conformer, FastPitch, etc.
GNN	Cluster-GCN, GIN (Graph Isomorphism Network), NBFnet (Neural Bellman-Ford networks), SchNet, Spektral, TGN (Temporal Graph Networks), etc.
Multi-modal	CLIP, Frozen in time, MAGMA (Multimodal Augmentation of Generative Models through Adapter-based Finetuning), Mini DALL-E, etc.

Source: https://github.com/graphcore/examples

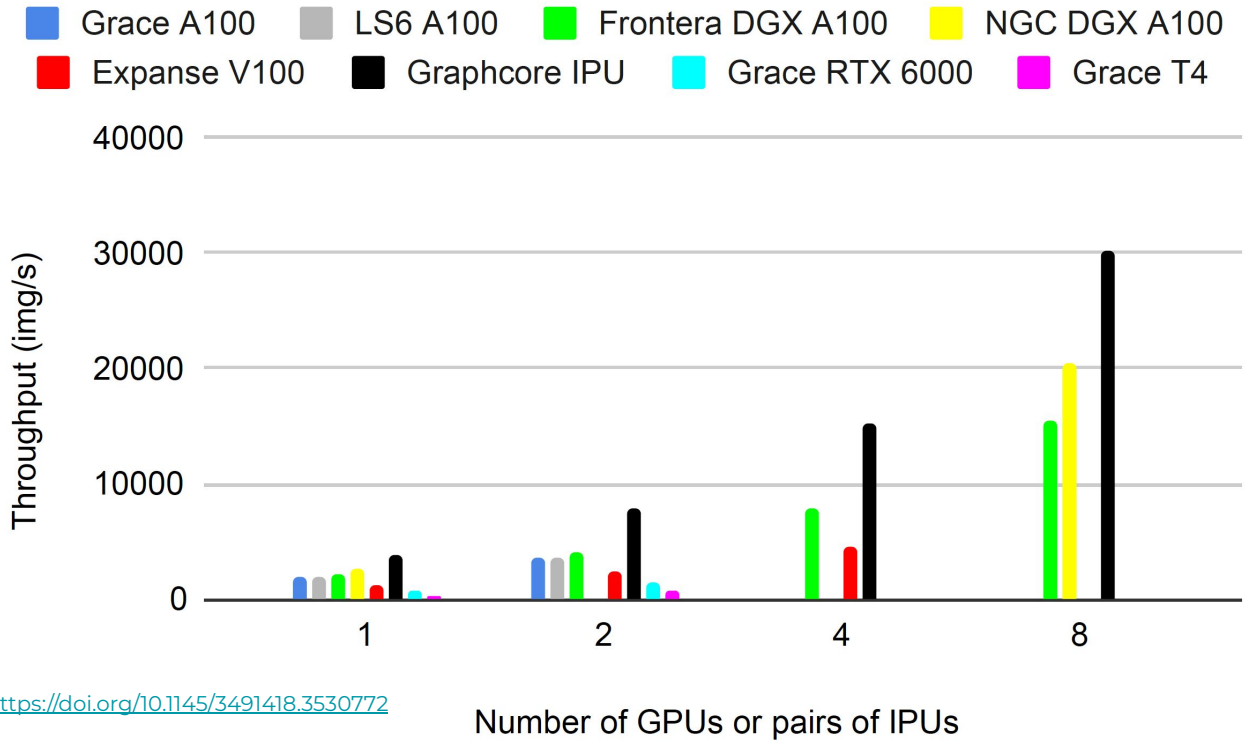
Choosing Between IPUs and GPUs

PyTorch ResNet-50 - GPU vs IPU



Abhinand S. Nasari, et al. https://doi.org/10.1145/3491418.3530772

TensorFlow ResNet-50 - GPU vs IPU



Abhinand S. Nasari, et al. https://doi.org/10.1145/3491418.3530772

Take-home message

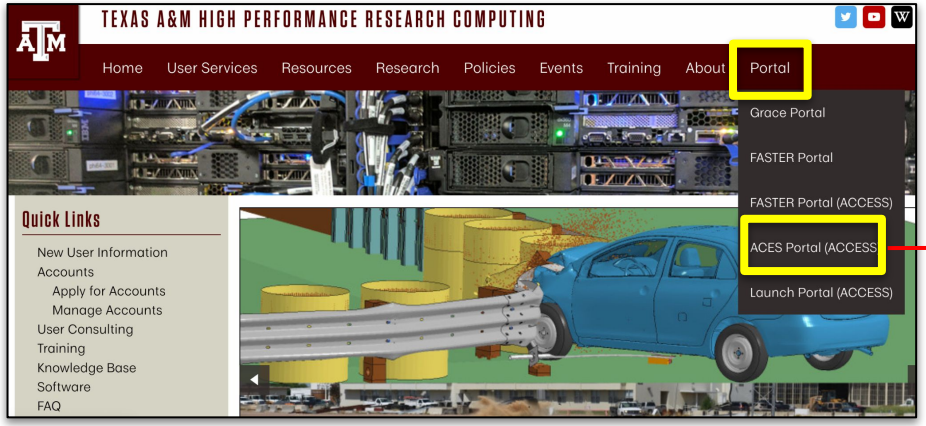
- The performance of ML workflows is highly sensitive to the distributed workflow configuration.
- Increasing the batch size increases the memory pressure and the amount of data that needs to be communicated, but most importantly it usually improves hardware utilization and thus computation.
- IPU has more fine-grained parallelism compared to GPU.

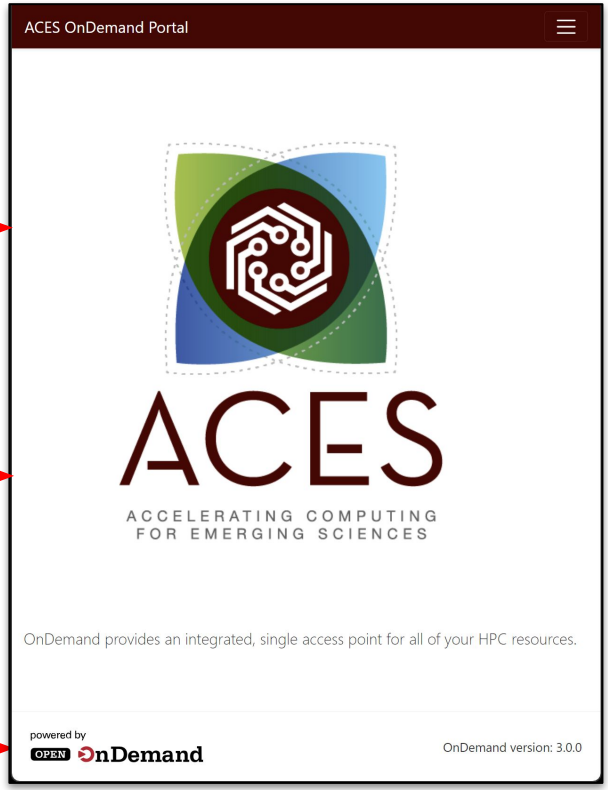
Section II. Demo on ACES

ACES

ACCELERATING COMPUTING
FOR EMERGING SCIENCES

ACES Portal



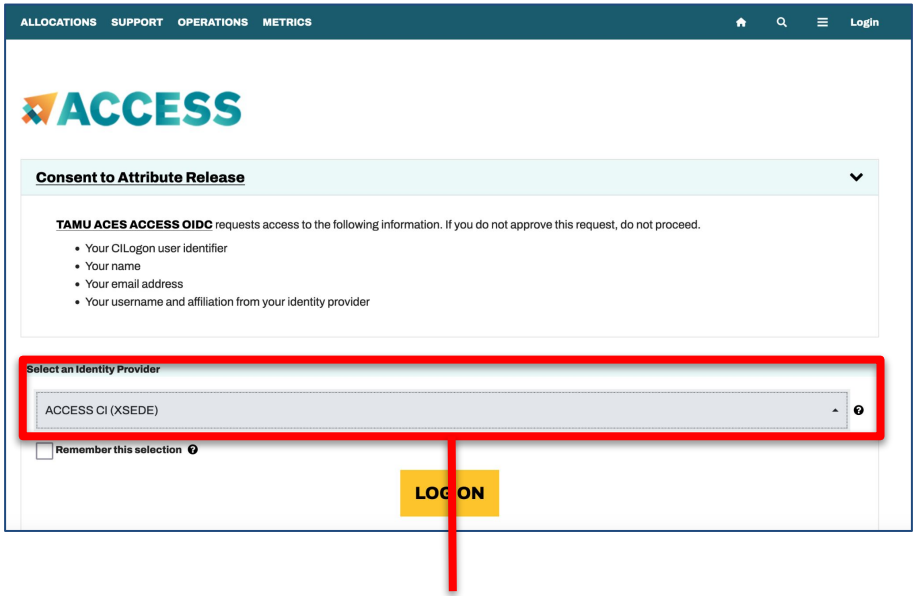


ACES Portal portal-aces.hprc.tamu.edu
is the web-based user interface for the ACES cluster

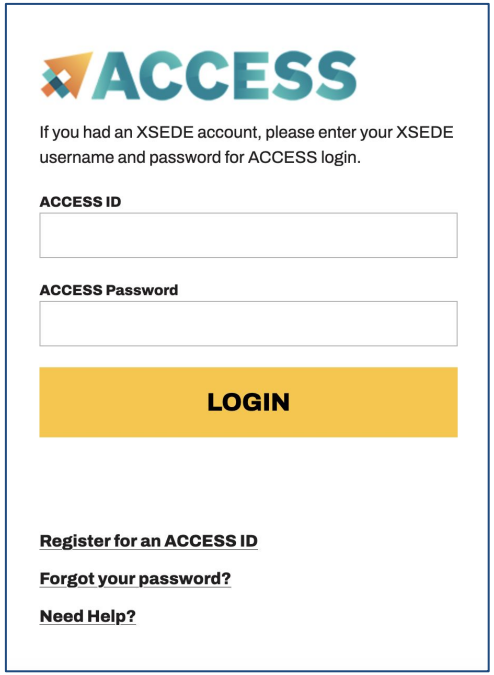
[HPRC Portal YouTube tutorials]

Open OnDemand (OOD) is an advanced web-based graphical interface framework for HPC users

Accessing ACES via the Portal (ACCESS)

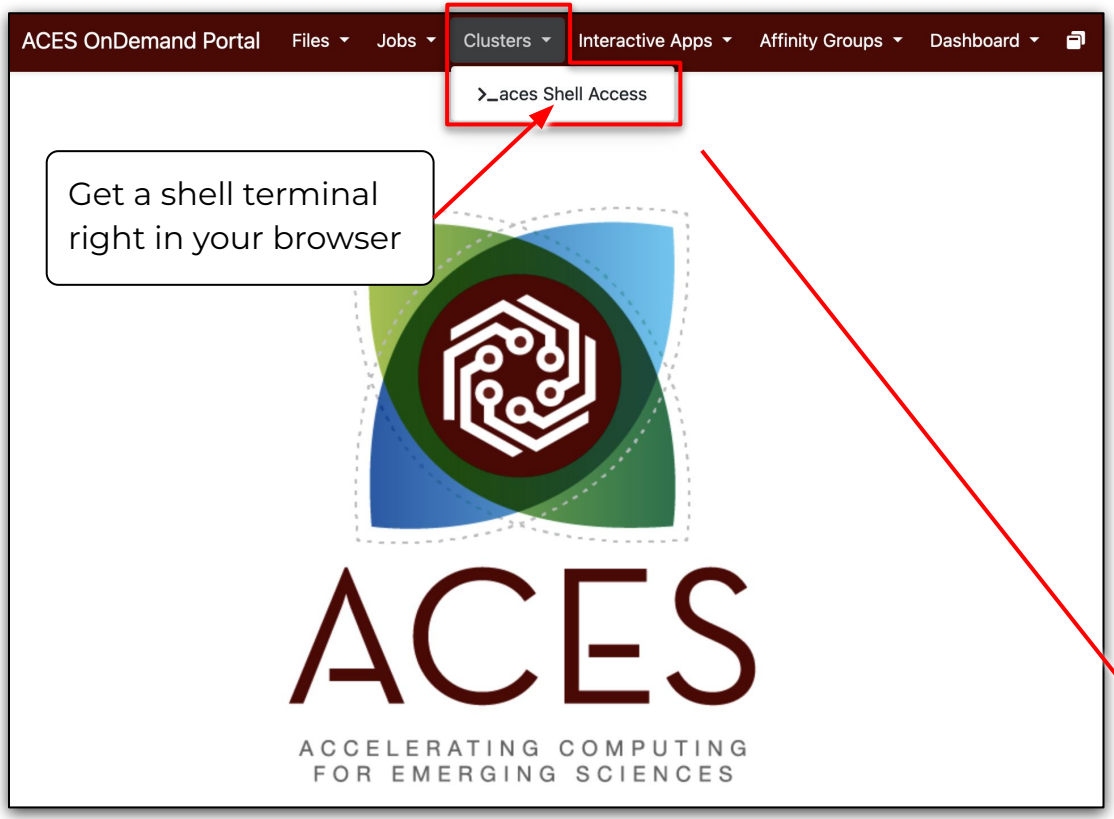


Select the Identity Provider appropriate for your account.



Log in using your ACCESS or institutional credentials.

Shell Access via the Portal



Training Materials

From the ACES login node, ssh into the poplar2 (BOW Pod16) IPU system

```
ssh poplar2
```

Change to your localdata directory:

```
cd /localdata/$USER && mkdir ipu_labs && cd ipu_labs
```

Copy the example materials to your ipu_labs directory:

```
git clone https://github.com/graphcore/examples.git
```

Copy the hands-on exercise materials to your ipu_labs directory:

```
git clone https://github.com/happidence1/IPU-Training.git
```

Poplar SDK setup

```
# activate the poplar SDK
source /usr/local/bin/source.poplar.sh

mkdir -p /localdata/$USER/tmp
export TF_POPLAR_FLAGS=--executable_cache_path=/localdata/$USER/tmp
export POPTORCH_CACHE_DIR=/localdata/$USER/tmp
export TORCH_HOME=/localdata/$USER/tmp/
```

Run a TensorFlow (TF) model on IPU

TF Virtual Environment Setup

```
virtualenv -p python3 venv_tf2

source venv_tf2/bin/activate

python -m pip install
/opt/gc/poplar/poplar_sdk-ubuntu_20_04-3.3.0+1403-208993bbb7/
tensorflow-2.6.3+gc3.3.0+251582+08d96978c7f+intel_skylake512-
cp38-cp38-linux_x86_64.whl
```

Run a TensorFlow model on IPU

```
cd examples/tutorials/tutorials/tensorflow2/keras/completed_demos/

python completed_demo_ipu.py
```

- Deactivate the virtual environment after the model finishes running.

```
deactivate
```

Monitor IPU Usage - *gc-monitor*

- 4 partitions
- 16 IPUs
- Processes

```
watch -n 2 gc-monitor
```

```
Every 2.0s: gc-monitor                                                poplar2: Thu Jul  6 10:33:31 2023

+---------------+--------------------------------------------------------------------------------+
|  gc-monitor   |              Partition: p17 [active] has 16 reconfigurable IPUs                |
+-------------+--------------------+--------+----------------+----------+------+----+------+-------+
|    IPU-M    |       Serial       |IPU-M SW|Server version|  ICU FW  | Type | ID | IPU# |Routing|
+-------------+--------------------+--------+----------------+----------+------+----+------+-------+
|  10.5.5.1   | 0019.0002.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 0  |  3   |  DNC  |
|  10.5.5.1   | 0019.0002.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 1  |  2   |  DNC  |
|  10.5.5.1   | 0019.0001.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 2  |  1   |  DNC  |
|  10.5.5.1   | 0019.0001.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 3  |  0   |  DNC  |
+-------------+--------------------+--------+----------------+----------+------+----+------+-------+
|  10.5.5.2   | 0021.0002.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 4  |  3   |  DNC  |
|  10.5.5.2   | 0021.0002.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 5  |  2   |  DNC  |
|  10.5.5.2   | 0021.0001.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 6  |  1   |  DNC  |
|  10.5.5.2   | 0021.0001.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 7  |  0   |  DNC  |
+-------------+--------------------+--------+----------------+----------+------+----+------+-------+
|  10.5.5.3   | 0013.0002.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 8  |  3   |  DNC  |
|  10.5.5.3   | 0013.0002.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 9  |  2   |  DNC  |
|  10.5.5.3   | 0013.0001.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 10 |  1   |  DNC  |
|  10.5.5.3   | 0013.0001.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 11 |  0   |  DNC  |
+-------------+--------------------+--------+----------------+----------+------+----+------+-------+
|  10.5.5.4   | 0016.0002.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 12 |  3   |  DNC  |
|  10.5.5.4   | 0016.0002.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 13 |  2   |  DNC  |
|  10.5.5.4   | 0016.0001.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 14 |  1   |  DNC  |
|  10.5.5.4   | 0016.0001.8222521  | 2.6.0  |     1.11.0     |  2.5.9   | M2000 | 15 |  0   |  DNC  |
+-------------+--------------------+--------+----------------+----------+------+----+------+-------+
+------------------------------------------------------+------------------------+-----------------+
|         Attached processes in partition p17          |          IPU           |      Board      |
+--------+----------------------+--------+------------+----+----------+--------+--------+--------+
|  PID   |       Command        |  Time  |    User    | ID |  Clock   |  Temp  |  Temp  | Power  |
+--------+----------------------+--------+------------+----+----------+--------+--------+--------+
| 902631 |        python        |  50s   | u.zh108696 | 0  | 1500MHz  | 23.5 C | 21.9 C | 90.3 W |
+--------+----------------------+--------+------------+----+----------+--------+--------+--------+
```

Run a PyTorch (PopTorch) model on IPU

PopTorch Virtual Environment Setup

```
cd /localdata/$USER/ipu_labs

virtualenv -p python3 poptorch_test

source poptorch_test/bin/activate

python -m pip install
/opt/gc/poplar/poplar_sdk-ubuntu_20_04-3.3.0+1403-208993bbb7/
poptorch-3.3.0+113432_960e9c294b_ubuntu_20_04-cp38-cp38-linux
_x86_64.whl
```

Run a PopTorch model on IPU

```
cd examples/tutorials/simple_applications/pytorch/mnist/

python mnist_poptorch.py
```

- Deactivate the virtual environment after the model finishes running.

```
deactivate
```

Monitor IPU Usage - *gc-monitor*

- 4 partitions
- 16 IPUs
- Processes
- IPU used
- Temperature
- Power

```
watch -n 2 gc-monitor
```

```
Every 2.0s: gc-monitor                                          poplar2: Thu Jul  6 10:55:55 2023

+---------------+-----------------------------------------------------------------------------------+
|  gc-monitor   |                Partition: p17 [active] has 16 reconfigurable IPUs                 |
+---------------+-----------------+--------+---------------+----------+--------+----+------+-------+
|     IPU-M     |      Serial     |IPU-M SW|Server version|  ICU FW  | Type   | ID | IPU# |Routing|
+---------------+-----------------+--------+---------------+----------+--------+----+------+-------+
|  10.5.5.1     | 0019.0002.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 0  |  3   |  DNC  |
|  10.5.5.1     | 0019.0002.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 1  |  2   |  DNC  |
|  10.5.5.1     | 0019.0001.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 2  |  1   |  DNC  |
|  10.5.5.1     | 0019.0001.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 3  |  0   |  DNC  |
+---------------+-----------------+--------+---------------+----------+--------+----+------+-------+
|  10.5.5.2     | 0021.0002.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 4  |  3   |  DNC  |
|  10.5.5.2     | 0021.0002.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 5  |  2   |  DNC  |
|  10.5.5.2     | 0021.0001.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 6  |  1   |  DNC  |
|  10.5.5.2     | 0021.0001.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 7  |  0   |  DNC  |
+---------------+-----------------+--------+---------------+----------+--------+----+------+-------+
|  10.5.5.3     | 0013.0002.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 8  |  3   |  DNC  |
|  10.5.5.3     | 0013.0002.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 9  |  2   |  DNC  |
|  10.5.5.3     | 0013.0001.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 10 |  1   |  DNC  |
|  10.5.5.3     | 0013.0001.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 11 |  0   |  DNC  |
+---------------+-----------------+--------+---------------+----------+--------+----+------+-------+
|  10.5.5.4     | 0016.0002.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 12 |  3   |  DNC  |
|  10.5.5.4     | 0016.0002.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 13 |  2   |  DNC  |
|  10.5.5.4     | 0016.0001.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 14 |  1   |  DNC  |
|  10.5.5.4     | 0016.0001.8222521 | 2.6.0  |    1.11.0     |  2.5.9   | M2000  | 15 |  0   |  DNC  |
+---------------+-----------------+--------+---------------+----------+--------+----+------+-------+

+-----------------------------------------------------+-----------------+---------------+
|          Attached processes in partition p17        |       IPU       |     Board     |
+---------+-------------------+--------+--------------+----+-----------+--------+------+--------+
|  PID    |      Command      |  Time  |     User     | ID |   Clock   |  Temp  | Temp | Power  |
+---------+-------------------+--------+--------------+----+-----------+--------+------+--------+
| 907530  |      python       |  17s   | u.zh108696   | 0  | 1500MHz   | 23.5 C | 22.0 C | 90.8 W |
+---------+-------------------+--------+--------------+----+-----------+--------+------+--------+
```

Hands-On Session 1

- Please access ACES and poplar2 now.
- Copy the tutorial materials to your scratch directory.
- Run the TensorFlow and PyTorch (PopTorch) example models on an IPU.

Section III. Porting PyTorch Code to IPU

PopTorch

- PopTorch is a set of extensions for PyTorch released by Graphcore to enable PyTorch models to run on Graphcore's IPU hardware.

- PopTorch will use PopART to parallelise the model over the given number of IPUs. Additional parallelism can be expressed via a replication factor, which enables you to data-parallelise the model over more IPUs.

Training a model on IPU

- Import the packages.

```
import torch
import poptorch
import torchvision
import torch.nn as nn
import matplotlib.pyplot as plt
from tqdm import tqdm
from sklearn.metrics import accuracy_score
```

Load the Data

- PyTorch: `torch.utils.data.DataLoader` class
- PopTorch extension: `poptorch.DataLoader` class,
  - Specialized for the way the underlying PopART framework handles batching of data.

Build the Model

```
class ClassificationModel(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 5, 3)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(5, 12, 5)
        self.norm = nn.GroupNorm(3, 12)
        self.fc1 = nn.Linear(972, 100)
        self.relu = nn.ReLU()
        self.fc2 = nn.Linear(100, 10)
        self.log_softmax =
nn.LogSoftmax(dim=1)
        self.loss = nn.NLLLoss()
```

```
def forward(self, x, labels=None):
        x =
self.pool(self.relu(self.conv1(x)))
        x =
self.norm(self.relu(self.conv2(x)))
        x = torch.flatten(x, start_dim=1)
        x = self.relu(self.fc1(x))
        x = self.log_softmax(self.fc2(x))
        # The model is responsible for the
calculation of the loss when using an IPU.
We do it this way:
        if self.training:
            return x, self.loss(x, labels)
        return x


model = ClassificationModel()
model.train()
```

Prepare training for IPUs

The compilation and execution on the IPU can be controlled using `poptorch.Options`. These options are used by PopTorch's wrappers such as `poptorch.DataLoader` and `poptorch.trainingModel`.

```
opts = poptorch.Options()
train_dataloader = poptorch.DataLoader(
    opts, train_dataset, batch_size=16, shuffle=True, num_workers=20
)
```

Train the model

```
optimizer = poptorch.optim.SGD(model.parameters(), lr=0.001, momentum=0.9)

poptorch_model = poptorch.trainingModel(model, options=opts,
optimizer=optimizer)

epochs = 30
for epoch in tqdm(range(epochs), desc="epochs"):
    total_loss = 0.0
    for data, labels in tqdm(train_dataloader, desc="batches", leave=False):
        output, loss = poptorch_model(data, labels)
        total_loss += loss

poptorch_model.detachFromDevice()

torch.save(model.state_dict(), "classifier.pth")
```

Evaluate the Model

```
model = model.eval()

poptorch_model_inf = poptorch.inferenceModel(model, options=opts)

test_dataloader = poptorch.DataLoader(opts, test_dataset, batch_size=32,
     num_workers=10)

predictions, labels = [], []
for data, label in test_dataloader:
    predictions += poptorch_model_inf(data).data.max(dim=1).indices
    labels += label

poptorch_model_inf.detachFromDevice()

print(f"Eval accuracy: {100 * accuracy_score(labels, predictions):.2f}%")
```

Hands-on Session 2

- Activate the Poptorch virtual environment.

```
cd /localdata/$USER/ipu_labs
source poptorch_test/bin/activate
```

- Change directory to PyTorch.

```
cd IPU-Training/PyTorch
```

- Complete the **#Todo**s in the `fashion-mnist-pytorch-ipu-todo.py`file.
- Run it in the **poptorch_test** virtual environment.

```
pip install -r requirements.txt
python fashion-mnist-pytorch-ipu-todo.py
```

- After finishing the job, you can deactivate the virtual environment.

```
deactivate
```

Section IV. Porting TensorFlow Code to IPU

1. Import the TensorFlow IPU module

Add the following import statement to the beginning of your script:

```
from tensorflow.python import ipu
```

2. Preparing the dataset

- Make sure the sizes of the datasets are divisible by the batch size.

```
def make_divisible(number, divisor):
    return number - number % divisor
```

- Adjust dataset lengths.

```
(x_train, y_train), (x_test, y_test) = load_data()
train_data_len = x_train.shape[0]
train_data_len = make_divisible(train_data_len, batch_size)
x_train, y_train = x_train[:train_data_len], y_train[:train_data_len]
test_data_len = x_test.shape[0]
test_data_len = make_divisible(test_data_len, batch_size)
x_test, y_test = x_test[:test_data_len], y_test[:test_data_len]
```

3. Add IPU configuration

To use the IPU, you must create an IPU session configuration:

```
ipu_config = ipu.config.IPUConfig()
ipu_config.auto_select_ipus = 1
ipu_config.configure_ipu_system()
```

A full list of configuration options is available in the API documentation.

4. Specify IPU strategy

```
strategy = ipu.ipu_strategy.IPUStrategy()
```

The `tf.distribute.Strategy` is an API to distribute training and inference across multiple devices. `IPUStrategy` is a subclass which targets a system with one or more IPUs attached.

5. Wrap the model within the IPU strategy scope

- Creating variables and Keras models within the scope of the `IPUStrategy` object will ensure that they are placed on the IPU.

- To do this, we create a `strategy.scope()` context manager and move all the model code inside it.

Hands-on Session 3

- Activate the TF virtual environment.

```
cd /localdata/$USER/ipu_labs
source venv_tf2/bin/activate
```

- Change the directory to Keras.

```
cd IPU-Training/Keras
```

- Complete the **#Todo**s in the mnist-ipu-todo.py file.
- Run it in the **venv_tf2** virtual environment.

```
python mnist-ipu-todo.py
```

- After finishing the job, you can deactivate the virtual environment.

```
deactivate
```

Section V. Model Replication (optional)

1. Set the number of IPUs and replicas.

```
num_ipus = num_replicas = 2
```

2. Set the steps per execution and adjust data length.

```
(x_train, y_train), (x_test, y_test) = load_data()

train_data_len = x_train.shape[0]
train_steps_per_execution = train_data_len // (batch_size * num_replicas)
train_data_len = make_divisible(train_data_len, batch_size *
num_replicas)
x_train, y_train = x_train[:train_data_len], y_train[:train_data_len]

test_data_len = x_test.shape[0]
test_steps_per_execution = test_data_len // (batch_size * num_replicas)
test_data_len = make_divisible(test_data_len, batch_size * num_replicas)
x_test, y_test = x_test[:test_data_len], y_test[:test_data_len]
```

3. Update the configuration step.

To use the IPU, you must create an IPU session configuration:

```
ipu_config = ipu.config.IPUConfig()
ipu_config.device_connection.type =
ipu.config.DeviceConnectionType.ON_DEMAND
ipu_config.auto_select_ipus = num_ipus
ipu_config.configure_ipu_system()
```

A full list of configuration options is available in the API documentation.

4. Add steps per execution to model compile.

```
 model.compile(
     "sgd",
     "categorical_crossentropy",
     metrics=["accuracy"],
     steps_per_execution=train_steps_per_execution,
 )
```

```
model.compile(
     "sgd",
     "categorical_crossentropy",
     metrics=["accuracy"],
     steps_per_execution=test_steps_per_execution,
 )
```

Hands-on Session 4

- Activate the TF virtual environment.

```
cd /localdata/$USER/ipu_labs
source venv_tf2/bin/activate
```

- Change directory to Keras.

```
cd IPU-Training/Keras
```

- Complete the **#Todo**s in the mnist_ipu_replicated_todo.py file.
- Run it in the **venv_tf2** virtual environment.

```
python mnist_ipu_replicated_todo.py
```

- After finishing the job, you can deactivate the virtual environment.

```
deactivate
```

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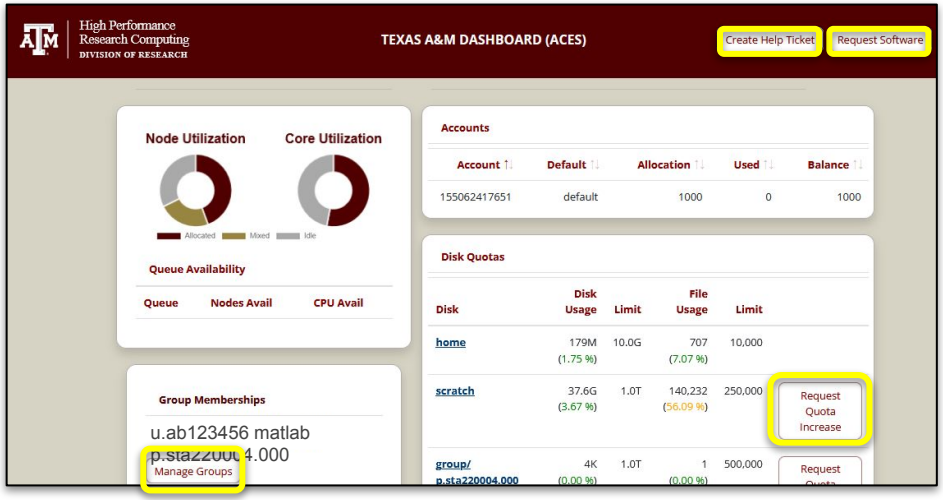
- ACES user Guide: https://hprc.tamu.edu/kb/User-Guides/ACES
- Email your questions to help@hprc.tamu.edu

Remember the Dashboard!



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