

# ACES Tutorial for using Graphcore Intelligence Processing Units (IPUs) for AI/ML workflows

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High Performance  
Research Computing  
DIVISION OF RESEARCH

**PEARC** 23



# IPU Tutorial

## Section I. Intro to IPUs

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

## Section IV. Porting PyTorch code to IPU

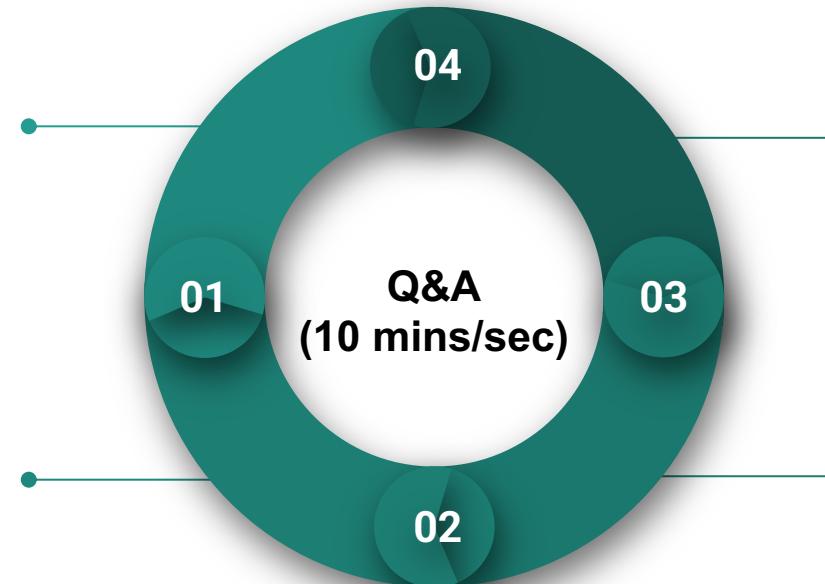
We will learn to port a PyTorch Fashion-MNIST classification model to run on IPU

## Section II. Demo on ACES

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

## Section III Porting TensorFlow code to IPU

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



Structure of the IPU Tutorial.

# Section I. ACES and IPU Systems Overview



# ACES

## Accelerating Computing for Emerging Sciences

Mission:

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



Credit: [towardsdatascience.com](https://towardsdatascience.com)

# 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

## 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

## Solder Bumps

## IPU-Links™

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

## IPU-Exchange™

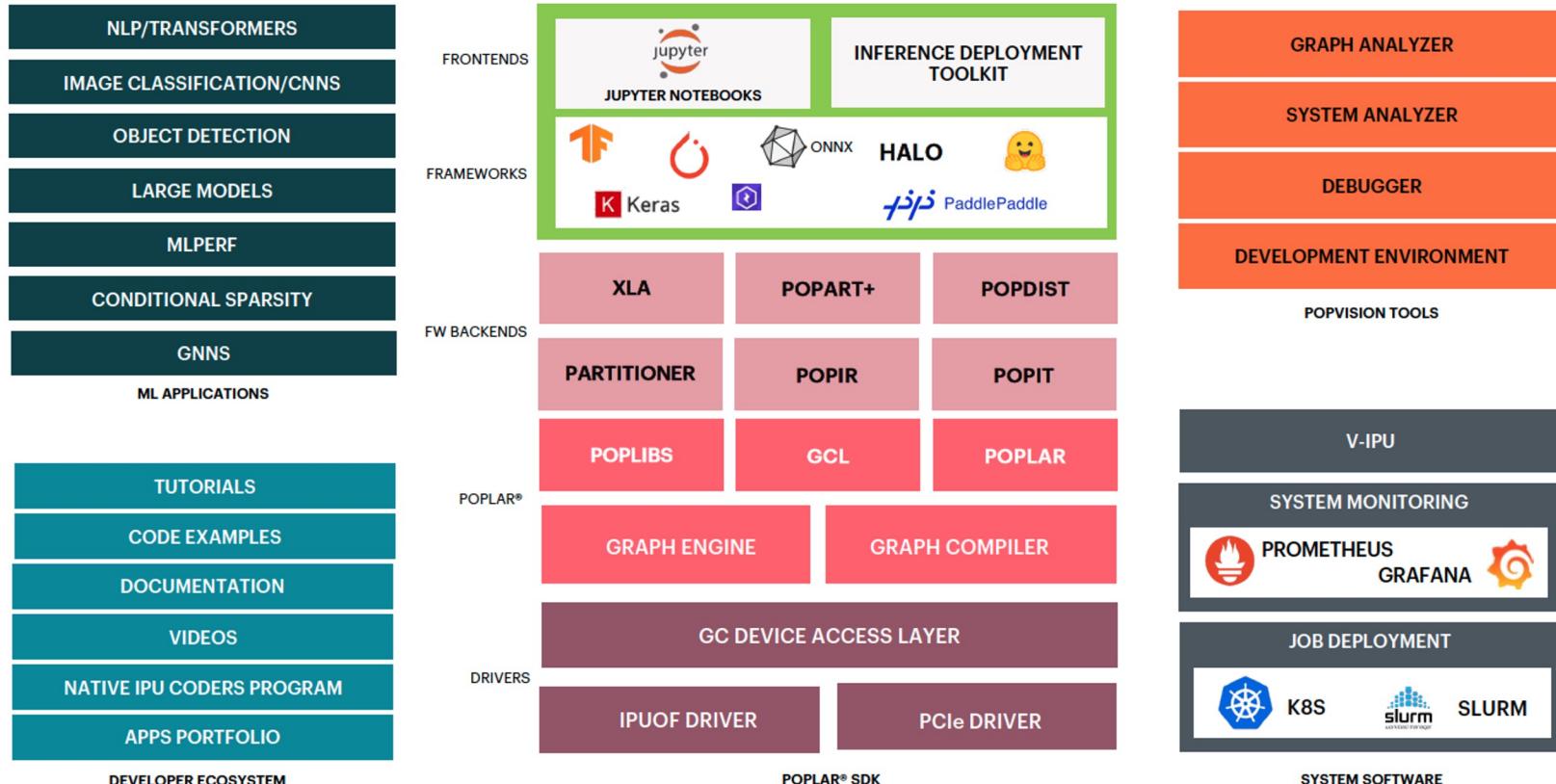
11 TB/s all to all IPU-Exchange™  
Non-blocking, any communication pattern

## PCIe

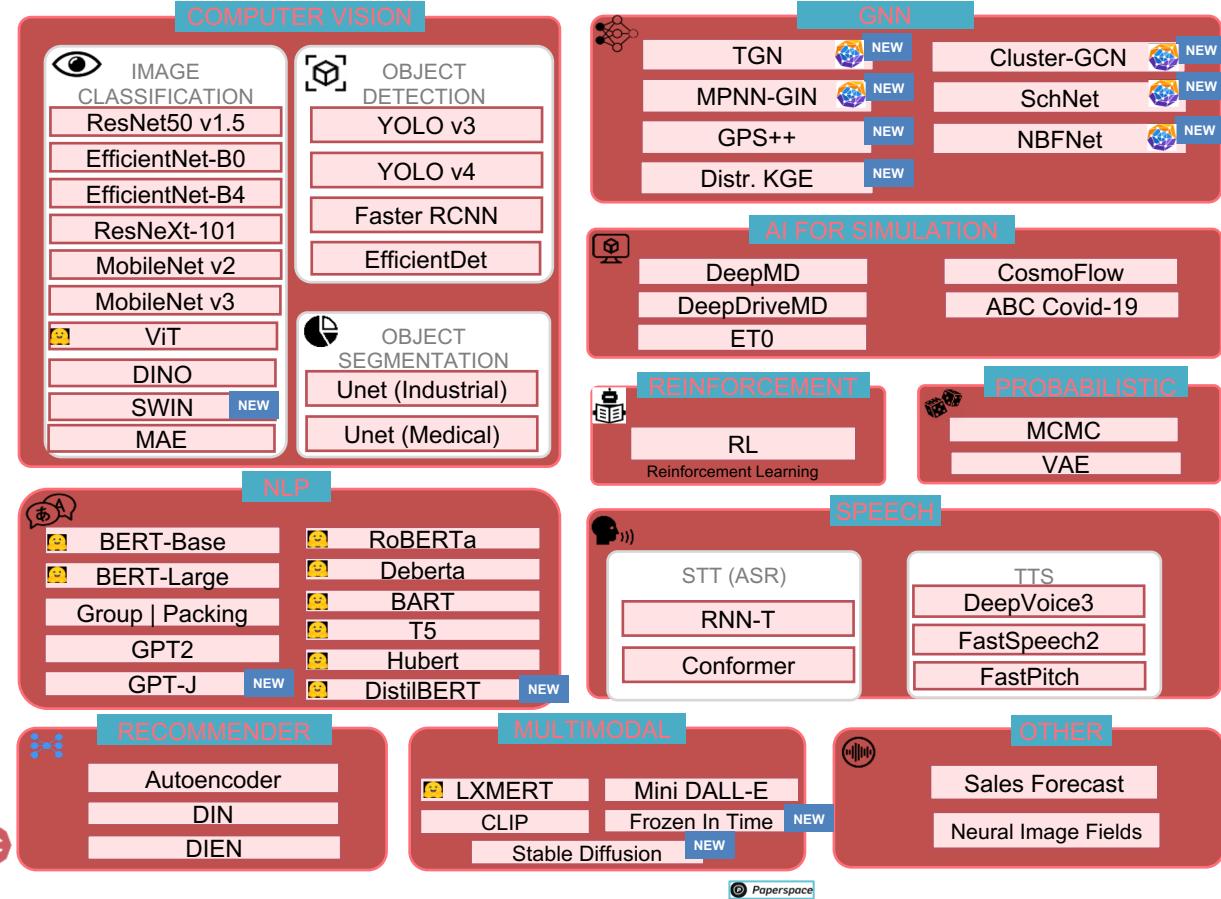
PCI Gen4 x16  
64 GB/s bidirectional bandwidth to host



# Graphcore Software Stack



# MODEL GARDEN COVERAGE

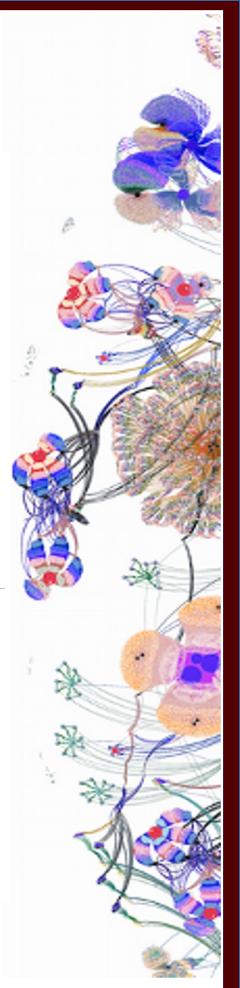


PyG  
 PyTorch  
 TensorFlow  
 Hugging Face

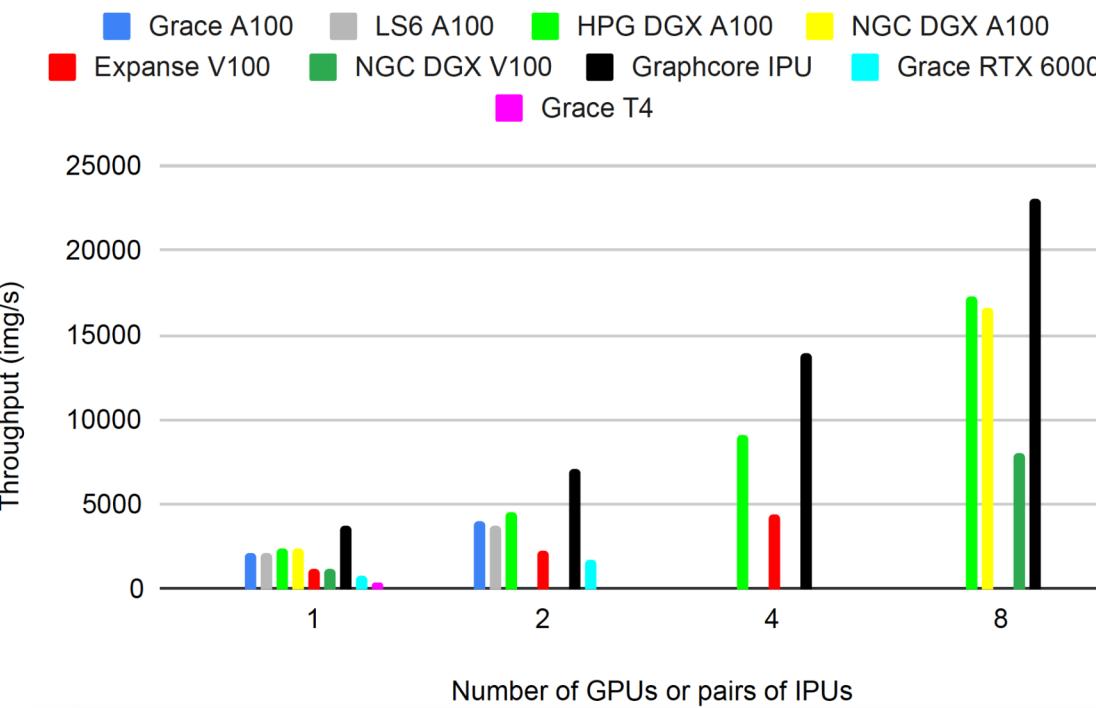
Keras

PaddlePaddle

POPART

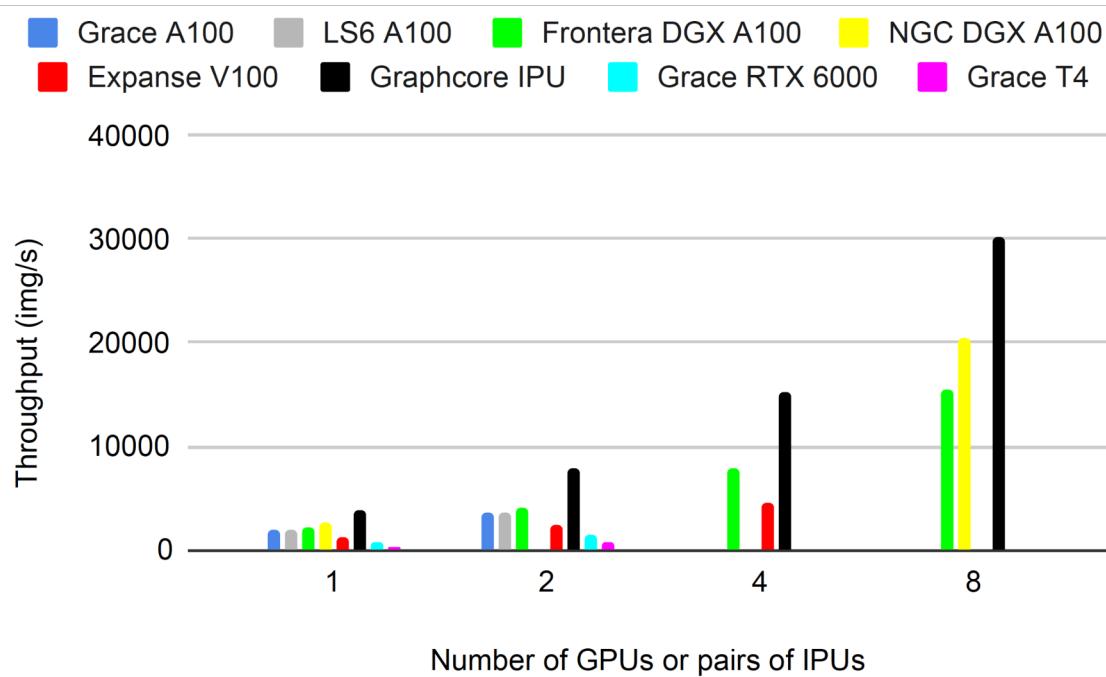


# PyTorch ResNet50 - GPU vs IPU



Abhinand S. Nasari, Hieu T. Le, Richard Lawrence, Zhenhua He, Xin Yang, Mario M. Krell, Alex Tsyplykhin, Mahidhar Tatineni, Tim Cockerill, Lisa M. Perez, Dhruba K. Chakravorty and Honggao Liu. 2022. Benchmarking the Performance of Accelerators on National Cyberinfrastructure Resources for Artificial Intelligence / Machine Learning Workloads. In Practice and Experience in Advanced Research Computing (PEARC '22), July 10-14, 2022, Boston, MA, USA. ACM, New York, NY, USA, 13 Pages. <https://doi.org/10.1145/3491418.3530772>

# TensorFlow ResNet50 - GPU vs IPU



Abhinand S. Nasari, Hieu T. Le, Richard Lawrence, Zhenhua He, Xin Yang, Mario M. Krell, Alex Tsyplykin, Mahidhar Tatineni, Tim Cockerill, Lisa M. Perez, Dhruva K. Chakravorty and Honggao Liu. 2022. Benchmarking the Performance of Accelerators on National Cyberinfrastructure Resources for Artificial Intelligence / Machine Learning Workloads. In Practice and Experience in Advanced Research Computing (PEARC '22), July 10-14, 2022, Boston, MA, USA. ACM, New York, NY, USA, 13 Pages. <https://doi.org/10.1145/3491418.3530772>

# Section II. Demo on ACES



# ACES

ACCELERATING COMPUTING  
FOR EMERGING SCIENCES

# Log into ACES Using the HPRC Portal

- HPRC webpage: <https://hprc.tamu.edu/>, Portal dropdown menu

The screenshot shows the Texas A&M High Performance Research Computing (HPRC) website. The header features the HPRC logo and the text "TEXAS A&M HIGH PERFORMANCE RESEARCH COMPUTING". Below the header is a navigation bar with links: Home, User Services, Resources, Research, Policies, Events, Training, About, and Portal. The "Portal" link is highlighted with a yellow box. A dropdown menu appears from the "Portal" link, listing "Terra Portal", "Grace Portal", "FASTER Portal", "FASTER Portal (ACCESS)", and "ACES Portal (ACCESS)". The "ACES Portal (ACCESS)" option is also highlighted with a yellow box. The background of the page features a photograph of server racks and a colorful abstract graphic at the bottom.

- Terra Portal
- Grace Portal
- FASTER Portal
- FASTER Portal (ACCESS)
- ACES Portal (ACCESS)**



# Accessing ACES via the ACES Portal (ACCESS)

Log-in using your ACCESS credentials.

ACCESS

Powered By CILogon CI

Consent to Attribute Release

TAMU FASTER ACCESS OOD requests access to the following information. If you do not approve this request, do not proceed.

- Your CILogon user identifier
- Your name
- Your email address
- Your username and affiliation from your identity provider

Select an Identity Provider

ACCESS CI (XSEDE)

Remember this selection ?

**Log On**

By selecting "Log On", you agree to the [privacy policy](#).

For questions about this site, please see the [FAQs](#) or send email to [help@cielogon.org](mailto:help@cielogon.org).  
Know your responsibilities using the CILogon Service.  
See acknowledgement of support for this site.

Select an Identity Provider

ACCESS CI (XSEDE)

Select the Identity Provider appropriate for your account.

ACCESS

CI Logon

Login to CILogon

ACCESS Username

ACCESS Password

Don't Remember Login

**Login**

If you had an XSEDE account, please enter your XSEDE username and password for ACCESS login  
Register for an ACCESS Account  
Forgot your password?  
Need Help?

Click Here for Assistance

# Shell access via the HPRC Portal

Access through (most) web browsers

-Top Banner Menu “Clusters” -> “Shell Access”



# ACES

ACCELERATING COMPUTING  
FOR EMERGING SCIENCES



# Training Materials

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

```
ssh poplar2
```

- Change to your scratch directory:

```
cd $SCRATCH
```

- Copy the **example** materials to your scratch directory:

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

- Copy the hands-on **exercise** materials to your scratch directory:

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

# Poplar SDK setup

```
source /opt/gc/poplar/poplar_sdk-ubuntu_20_04-3.3.0+1403-  
208993bbb7/poplar-ubuntu_20_04-3.3.0+7857-  
b67b751185/enable.sh
```

```
source /opt/gc/poplar/poplar_sdk-ubuntu_20_04-3.3.0+1403-  
208993bbb7/popart-ubuntu_20_04-3.3.0+7857-  
b67b751185/enable.sh
```

```
mkdir -p $SCRATCH/tmp  
export TF_POPLAR_FLAGS=--executable_cache_path=$SCRATCH/tmp  
export POPTORCH_CACHE_DIR=$SCRATCH/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 -U pip  
  
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 the IPU usage with gc-monitor command

```
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 $SCRATCH

virtualenv -p python3 poptorch_test

source poptorch_test/bin/activate

python -m pip install -U pip

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 $SCRATCH/examples/tutorials/simple_applications/pytorch/mnist/  
pip install -r requirements.txt  
python mnist_poptorch.py
```

- Deactivate the virtual environment after the model finishes running.

```
deactivate
```

# Monitor the IPU usage with gc-monitor command

```
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 IPU

# Section III. Porting TensorFlow Code to IPU



TensorFlow



Keras

# 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 2

- Activate the TF virtual environment

*cd \$SCRATCH*

*source venv\_tf2/bin/activate*

- Change directory to Keras

*cd IPU-Training/Keras*

- Complete the **#Todos** 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 IV. Porting PyTorch Code to IPU



PyTorch

# 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

PopTorch offers an extension of `torch.utils.data.DataLoader` class with its `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 3

- Activate the TF virtual environment

*cd \$SCRATCH*

*source poptorch\_test/bin/activate*

- Change directory to PyTorch

*cd IPU-Training/PyTorch*

- Complete the **#Todos** in the `fashion-mnist-pytorch-ipu-todo.py` file.
- Run it in the **poptorch\_test** virtual environment.

*pip install scikit-learn*

*python fashion-mnist-pytorch-ipu-todo.py*

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

*deactivate*



# References

- <https://www.graphcore.ai/>
- <https://github.com/graphcore/examples/tree/v3.2.0/tutorials/tutorials/tensorflow2/keras>
- <https://github.com/graphcore/examples/tree/v3.2.0/tutorials/tutorials/pytorch/basics>
- [https://hprc.tamu.edu/wiki/Main\\_Page](https://hprc.tamu.edu/wiki/Main_Page)



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Phone: 979-845-0219

Help us help you. Please include details in your request for support, such as, Cluster (ACES, Faster, Grace, Terra, ViDaL), Job information (Job id(s), Location of your jobfile, input/output files, Application, Module(s) loaded, Error messages, etc), and Steps you have taken, so we can reproduce the problem.



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