GRAPHCORE OVERVIEW AND ONBOARDING TRAINING FOR TAMU

May 25, 2022

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WORKSHOP GOALS

- Explore and execute code for TensorFlow1, TensorFlow2 and PyTorch
- First insights into how to visualize and optimize IPU code
- Idea of difference of IPU and other hardware and how it might benefit your research

Disclaimer: This is my first coding lab and Graphcore's first large-scale workshop. Bear with us.

THE TEAM

Mario

Alex

Lisa

Brian

Richard

AGENDA

- Introduction to Graphcore, IPU, and Poplar
  - Hands-on: ssh into the POD, enable the SDK, clone tutorials, binary caching, run example
- TensorFlow1
  - Hands-on: Port a basic model, add infeeds, loop on device, profile a sharded/pipelined model
- TensorFlow2
  - Hands-on: Port a Keras script, leverage loop on device, replicate and run data-parallel, pipeline
- PyTorch
  - Hands-on: PopTorch example, DataLoader, options to optimize performance
- Research directions on the IPU

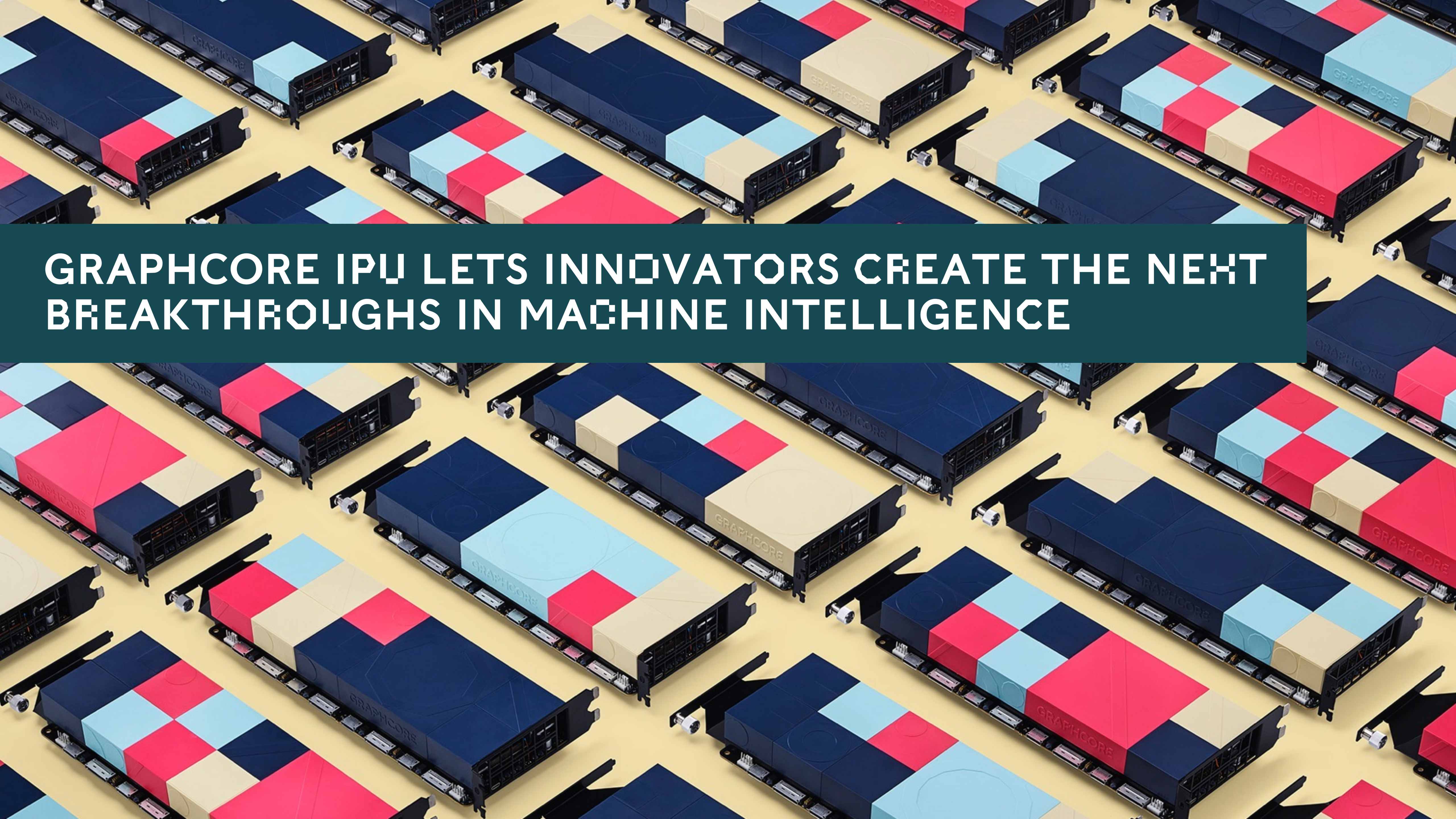
GRAPHCORE OVERVIEW

GRAPHCORE ENABLING MACHINE INTELLIGENCE

- Founded in 2016
- Technology: Intelligence Processor Unit (IPU)
- Team: 650+ globally
- Offices: UK, US, China, Norway, Poland
- Raised >$710M

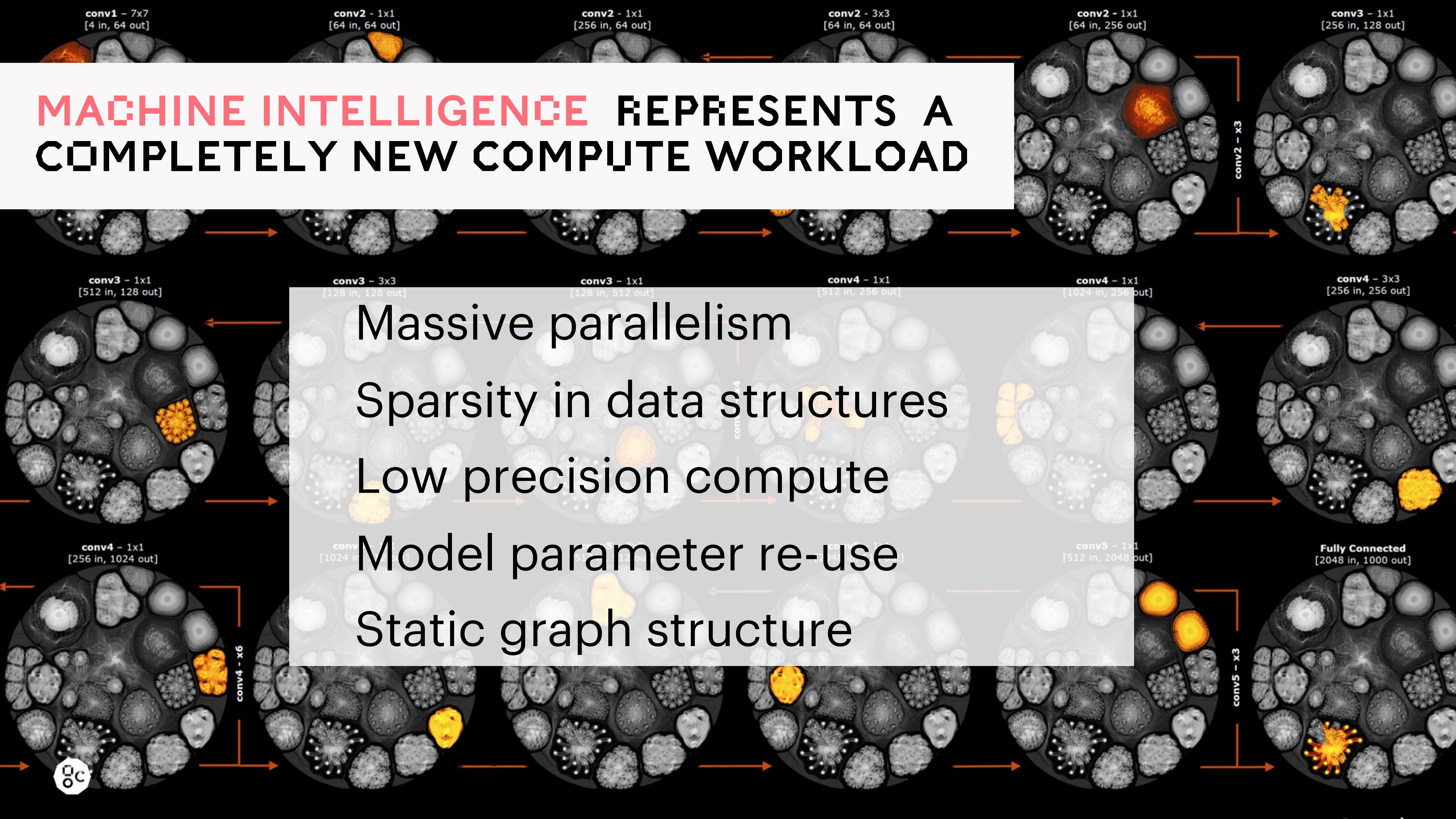
SEQUOIA ATOMICO SOFINA Microsoft
BMW i VENTURES DELL BOSCH SAMSUNG Merian GLOBAL INVESTORS
Amadeus Capital Partners pitango VENTURE CAPITAL draperesprit Foundation CAPITAL

GRAPHCORE IPU LETS INNOVATORS CREATE THE NEXT BREAKTHROUGHS IN MACHINE INTELLIGENCE



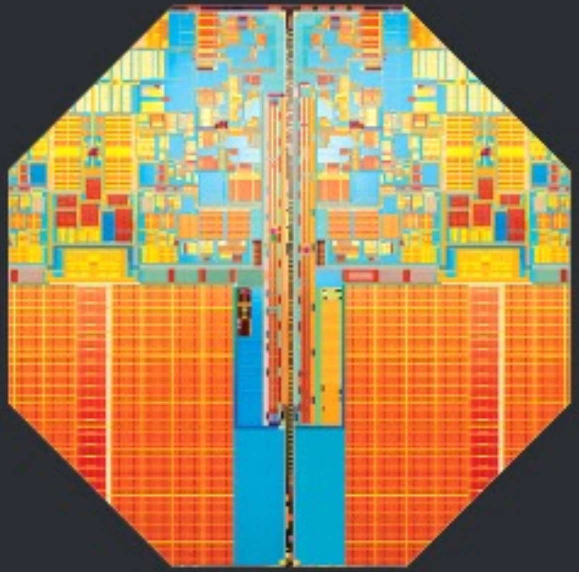
IPU ARCHITECTURE OVERVIEW

MACHINE INTELLIGENCE REPRESENTS A COMPLETELY NEW COMPUTE WORKLOAD



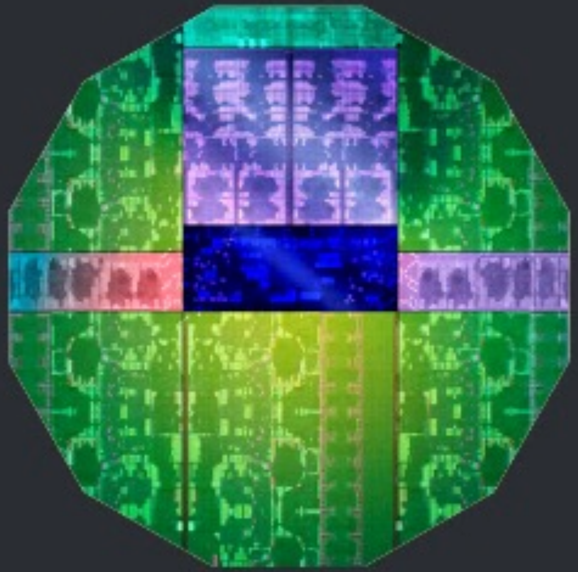
- Massive parallelism
- Sparsity in data structures
- Low precision compute
- Model parameter re-use
- Static graph structure

LEGACY PROCESSOR ARCHITECTURES HAVE BEEN REPURPOSED FOR ML



CPU

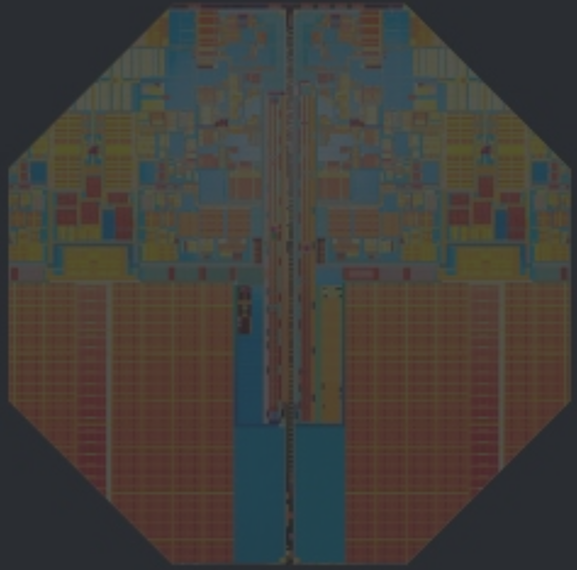
Apps and Web/
Scalar



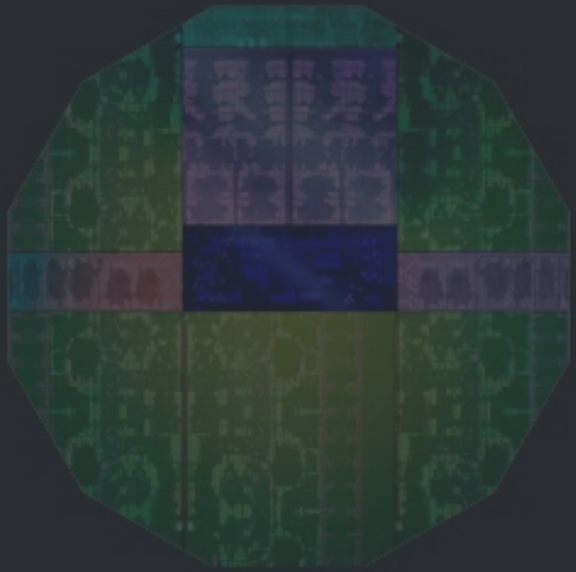
GPU

Graphics and HPC/
Vector

A NEW PROCESSOR IS REQUIRED FOR THE FUTURE



CPU
Apps and Web/
Scalar



GPU
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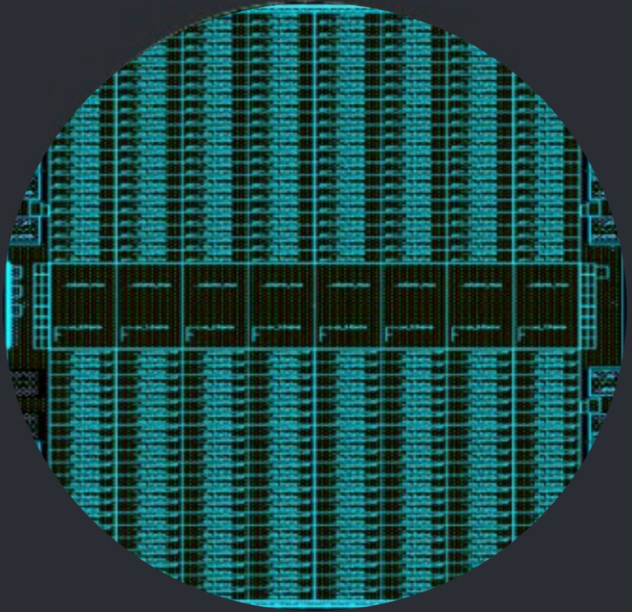
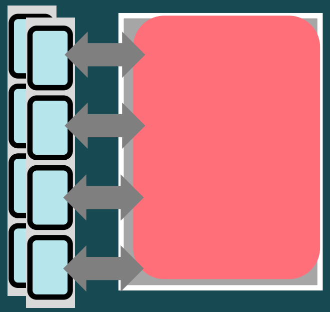
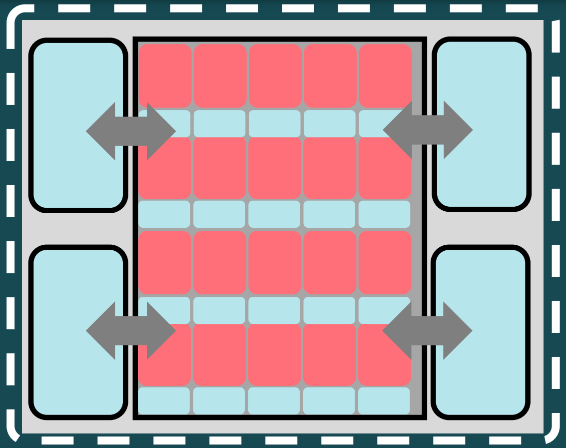
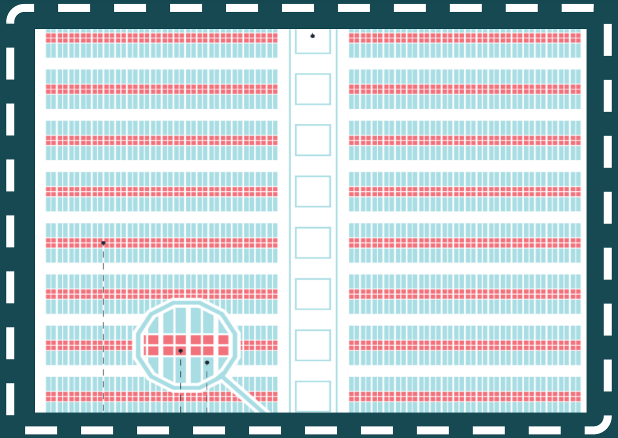


IPU
Artificial Intelligence/
Graph

MASSIVE PARALLELISM WITH ULTRAFAST MEMORY ACCESS

	CPU	GPU	IPU
Parallelism	Designed for scalar processes	SIMD/SIMT architecture. Designed for dense contiguous data	Massively parallel MIMD. Ideal for ML workloads
			
Memory Access	Off-chip memory	Model and Data spread across off-chip and small on-chip cache and shared mem.	Model & Data in tightly coupled large locally distributed SRAM
	1x	5x – 32x	320x

Processor Memory

Generalised comparisons & illustrative diagrams

BOW IPU PROCESSOR

Deep Trench Capacitor

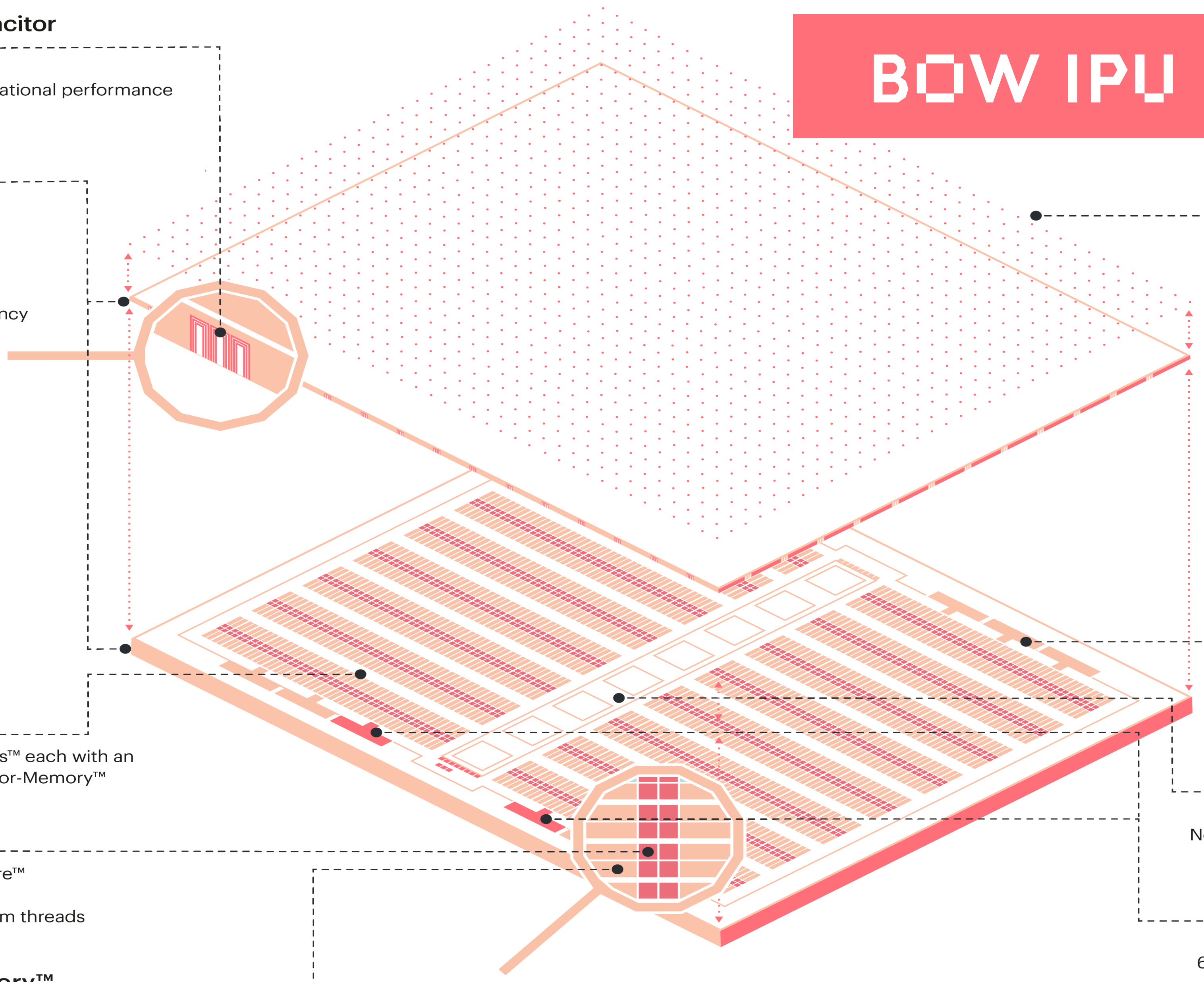
Efficient power delivery
Enables increase in operational performance

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

BOW-2000 IPU MACHINE

4 x Bow 3D Wafer-on-Wafer IPUs

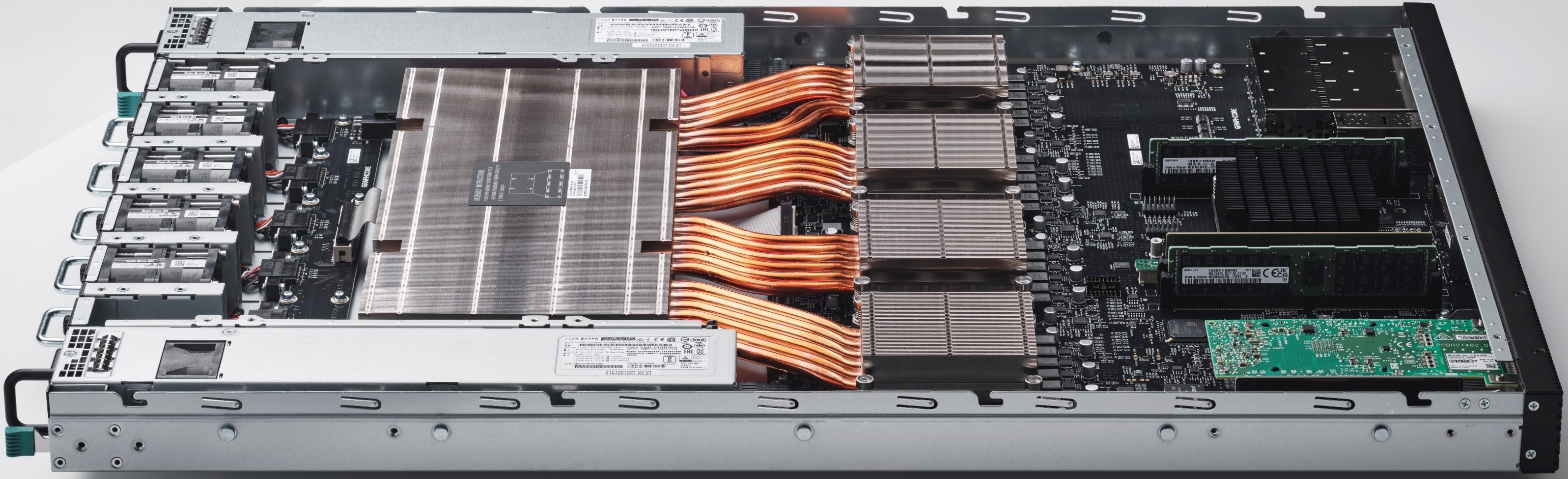
Up to 256 GB IPU Streaming Memory

1.4 PetaFLOPS AI Compute

2.8 Tbps IPU-Fabric™

3.6 GB In-Processor-Memory @ 260TB/s

Same 1U blade form factor



GRAPHCORE

Ideal for both Training & Inference

GRAPHCORE SOFTWARE MATURITY

ML APPLICATIONS

- NLP/TRANSFORMERS
- IMAGE CLASSIFICATION/CNNS
- OBJECT DETECTION
- LARGE MODELS
- MLPERF
- CONDITIONAL SPARSITY
- GNNS

DEVELOPER ECOSYSTEM

- TUTORIALS
- CODE EXAMPLES
- DOCUMENTATION
- VIDEOS
- NATIVE IPU CODERS PROGRAM
- APPS PORTFOLIO

POPLAR® SDK

FRONTENDS
- JUPYTER NOTEBOOKS
- INFERENCE DEPLOYMENT TOOLKIT

FRAMEWORKS
- Keras
- ONNX
- HALO
- PaddlePaddle

FW BACKENDS
- XLA
- POPART+
- POPDIST
- PARTITIONER
- POPIR
- POPIT

POPLAR®
- POPLIBS
- GCL
- POPLAR
- GRAPH ENGINE
- GRAPH COMPILER

DRIVERS
- GC DEVICE ACCESS LAYER
- IPUOF DRIVER
- PCIe DRIVER

POPVISION TOOLS

- GRAPH ANALYZER
- SYSTEM ANALYZER
- DEBUGGER
- DEVELOPMENT ENVIRONMENT

SYSTEM SOFTWARE

- V-IPU
- SYSTEM MONITORING
  - PROMETHEUS
  - GRAFANA
- JOB DEPLOYMENT
  - K8S
  - SLURM

GROWING MODEL GARDEN

POPVISION TOOLS

COMPUTER VISION

IMAGE CLASSIFICATION
- ResNet50 v1.5
- EfficientNet-B0
- EfficientNet-B4
- ResNeXt-101
- MobileNet v2
- MobileNet v3
- ViT NEW

OBJECT DETECTION
- YOLO v3
- YOLO v4
- Faster RCNN NEW

OBJECT SEGMENTATION
- Unet (Industrial)
- Unet (Medical) NEW

GNN
- TGN NEW
- MPNN NEW

PROBABILISTIC
- MCMC
- Sales Forecast

REINFORCEMENT
- RL

Reinforcement Learning

NLP
- BERT-Base
- BERT-Large
- GroupBERT
- GPT2 NEW

SPEECH

STT (ASR)
- RNN-T NEW
- Conformer NEW

TTS
- DeepVoice3
- FastSpeech2 NEW

GENERATIVE
- Autoencoder
- VAE

OTHER
- ETO
- DIN
- Mini DALL-E NEW
- DIEN

Images from text

GRAPHCORE

https://www.graphcore.ai/resources/model-garden

BENCHMARK CODE

- We publish performance benchmarks for some models on our website:

  https://www.graphcore.ai/performance-results

- The command lines needed to reproduce these performance benchmarks should be in a README in the GitHub repo.

INTRO:

GETTING STARTED

COMMAND LINE TOOLS

POPLAR SDK

- Access updates through Graphcore support portal: https://downloads.graphcore.ai/
- Unpack SDK tar and source the shell scripts to update several environment variables on your evaluation machine:

```
$ cd poplar_sdk-[os]-[ver]
$ source poplar-[os]-[ver]/enable.sh
$ source popart-[os]-[ver]/enable.sh
```

where [os] is the host OS (Ubuntu), [ver] is the current software version number.

You need to source the PopART enable script if you are using PopART or PopTorch.

NOTE: each of these scripts must be sourced every time the Bash shell is reset. If you attempt to run any Poplar software without having first enabled these scripts you'll get an error like:

```
fatal error: 'poplar/Engine.hpp' file not found
```

SAMPLE START UP COMMANDS

```
# Consider adding these to ~/.profile
source /opt/gc/poplar_sdk-ubuntu_18_04-2.5.1+1001-64add8f33d/poplar-ubuntu_18_04-2.5.0+4748-e94d646535/enable.sh
source /opt/gc/poplar_sdk-ubuntu_18_04-2.5.1+1001-64add8f33d/popart-ubuntu_18_04-2.5.1+4748-e94d646535/enable.sh

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

export POPLAR_LOG_LEVEL=INFO
export POPLIBS_LOG_LEVEL=INFO
```

INSTALL TF2 WHEEL AND RUN AN EXAMPLE

```
# Create and activate a Python virtual env
virtualenv venv_tf2 -p python3.6
source ~/venv_tf2/bin/activate
# Install AMD TF2 wheel for IPU
pip install /opt/gc/poplar_sdk-ubuntu_18_04-2.5.1+1001-64add8f33d/tensorflow-
2.5.2+gc2.5.1+193132+4673d3afb3b+amd_znver1-cp36-cp36m-linux_x86_64.whl

# Clone repo, install reqs, run example
git clone https://github.com/graphcore/tutorials.git
cd tutorials/simple_applications/tensorflow2/mnist/
pip install -r requirements.txt
python mnist.py

# Sample output:
# Epoch 4/4
# 2000/2000 [==============================] - 1s 320us/step - loss: 0.2542
```

HANDOUT

bit.ly/tamu220525

GRAPHCORE COMMAND LINE TOOLS

gc-info Determines what IPU cards are present in the system.

gc-inventory Lists device IDs, physical parameters and firmware version numbers.

gc-reset Resets an IPU device after reboot. Note that each IPU must be reset after the host machine is rebooted.

gc-exchangetest Allows you to test the internal exchange fabric in an IPU.

gc-memorytest Tests all the memory in an IPU, reporting any tiles that fail.

gc-links Displays the status and connectivity of each of the IPU-Links that connect the C2 IPU-Processor cards together. See also *IPU-Link channel mapping*.

gc-powertest Tests power consumption and temperature of the C2 IPU-Processor cards.

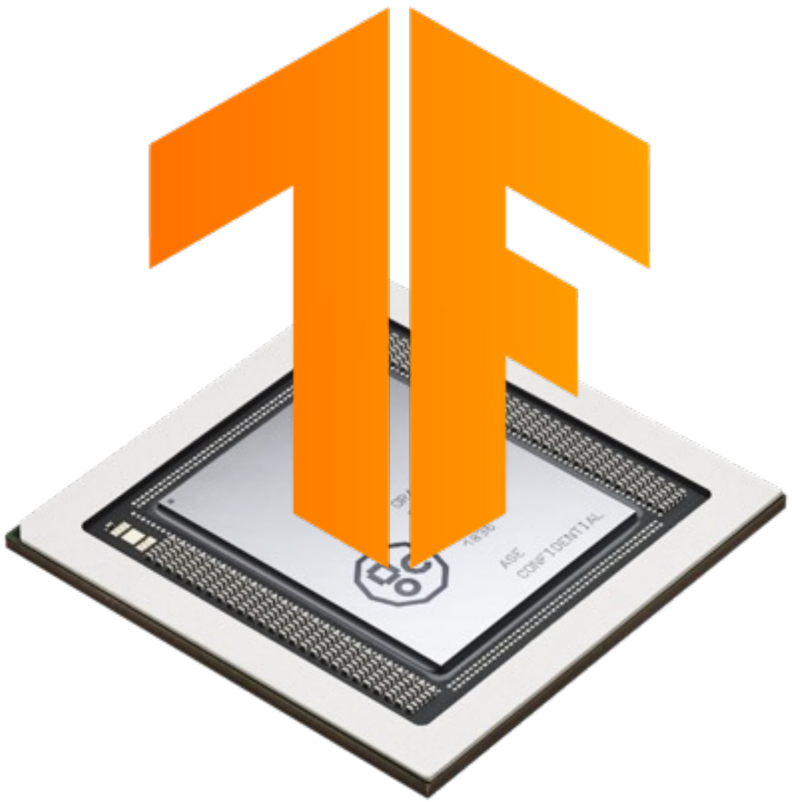
gc-hosttraffictest Allows you to test the data transfer between the host machine and the IPUs (in both directions).

gc-iputraffictest Allows you to test the data transfer between IPUS.

gc-docker Allows you to use IPU devices in Docker containers.

See: https://documents.graphcore.ai/

TENSORFLOW ON THE IPU



- Graphcore supplies its own branch of TensorFlow that supports the IPU.
- TensorFlow 1.15 and TensorFlow 2.4 are supported.
- There are 2 main differences in the Graphcore implementation of TensorFlow:

(1) Some machine-learning ops are optimised for the IPU hardware. For example, our custom dropout op is designed to use less memory by not storing the dropout mask between forward and backward passes.

(2) It provides extra IPU-specific functions, such as those for selecting and configuring IPUs.

PYTORCH ON THE IPU

PyTorch + GRAPHCORE

- PopTorch is a set of extensions for PyTorch to enable PyTorch models to run directly on Graphcore IPU hardware.
- PopTorch supports both inference and training. To run a model on the IPU, you wrap your existing PyTorch model in either a PopTorch inference wrapper or a PopTorch training wrapper.

POPART – POPLAR ADVANCED RUNTIME

- PopART enables you to import models using the Open Neural Network Exchange (ONNX) and run them using the Poplar tools.
- PopART has three main features:

1) It can import ONNX graphs into a runtime environment.
2) It provides a simple interface for constructing ONNX graphs without needing a third party framework.
3) It runs imported graphs in inference, evaluation or training modes, by building a Poplar engine, connecting data feeds and scheduling the execution of the Engine.

PROGRAMMING ON IPU

- DOCS AND TUTORIALS
- USEFUL ENV VARIABLES
- MULTI-IPU CONSTRUCTS
- FRAMEWORKS
- POPVISION

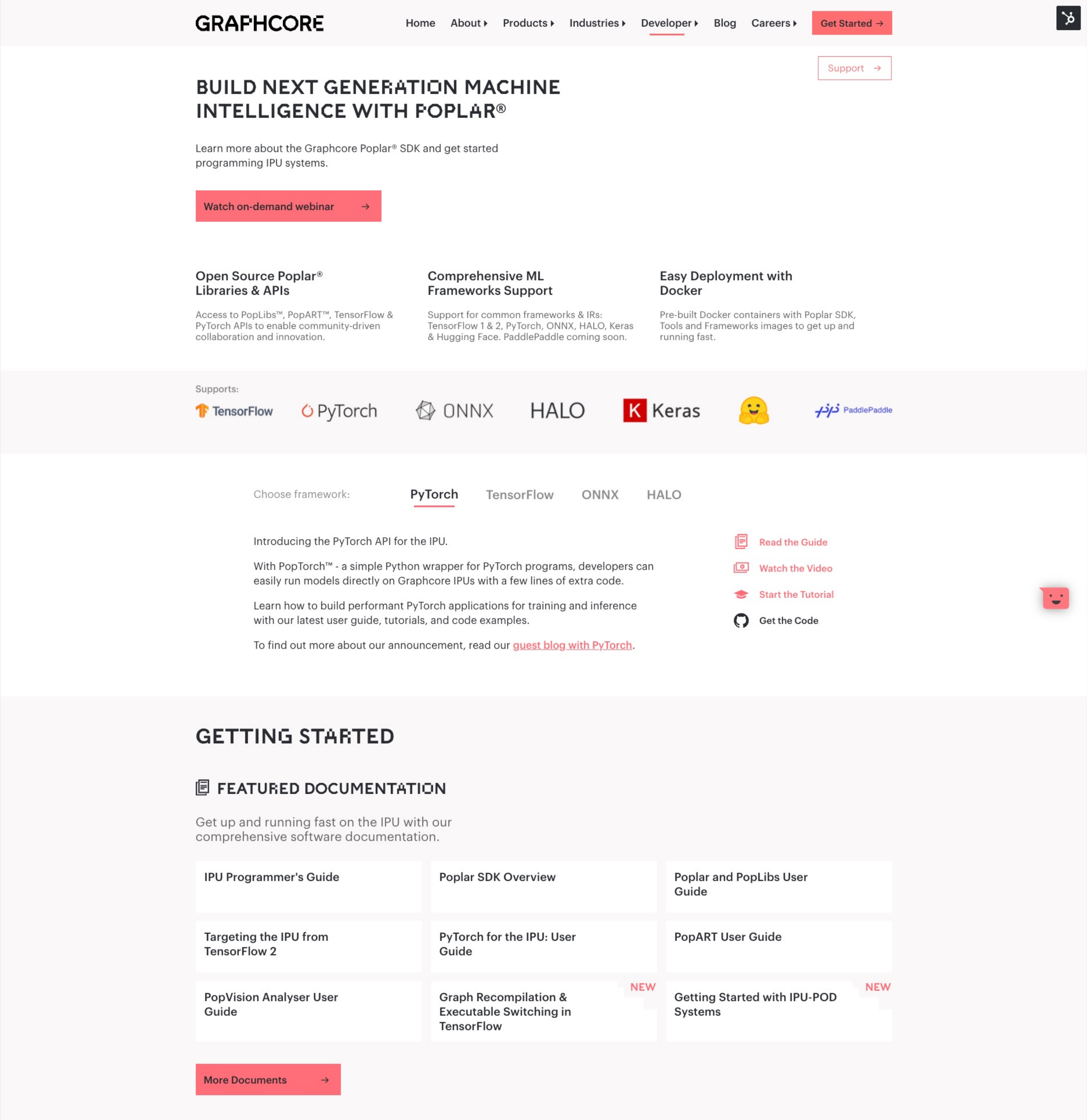
DEVELOPER RESOURCES

CONFIDENTIAL

DEVELOPER PORTAL

graphcore.ai/developer

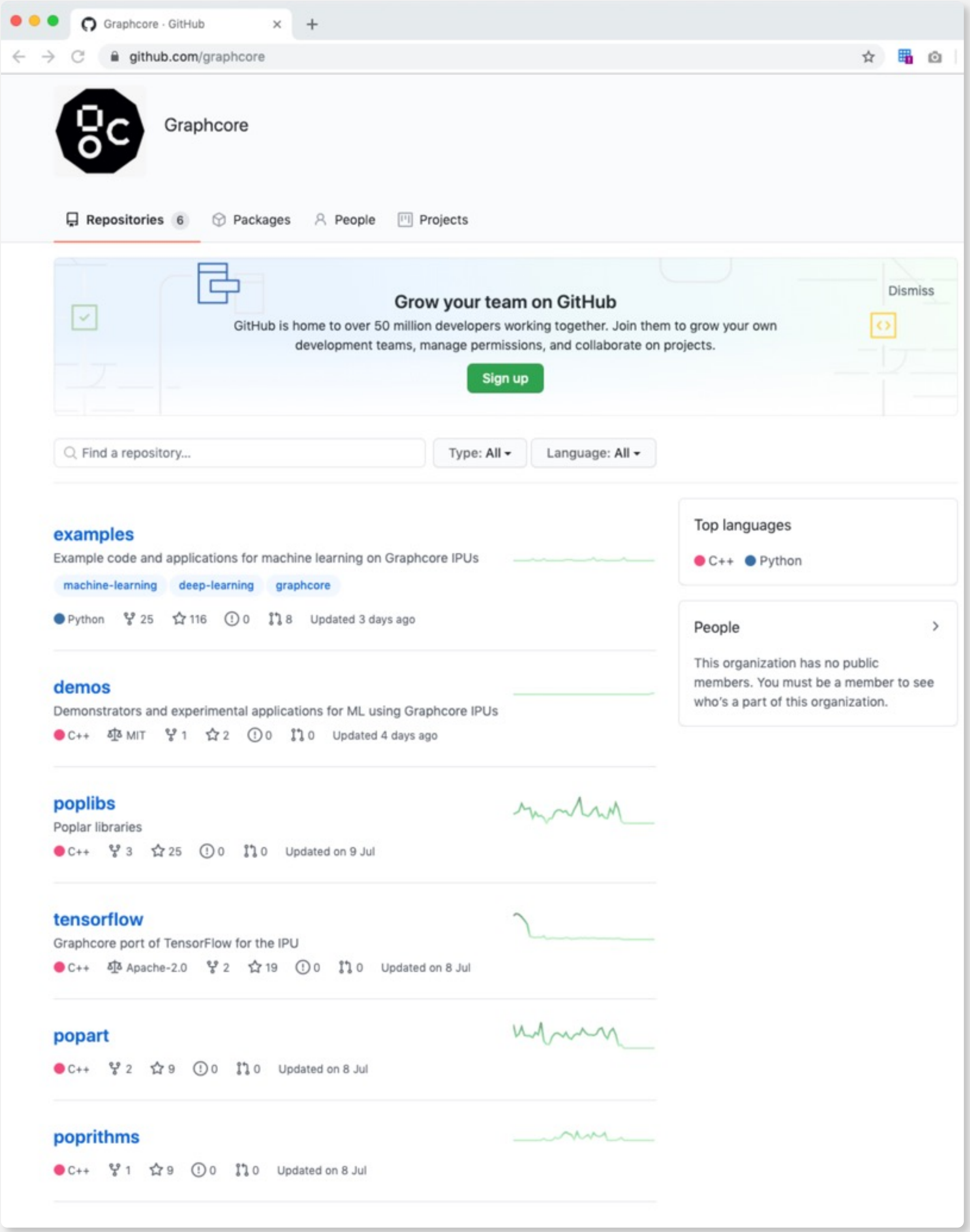
- Graphcore developer portal launched in May 2020
- Public hub for developers to access:
  - Software documentation
  - How-to videos
  - Code tutorial walkthroughs
  - Performance Benchmarks
  - Community support
  - Developer news
- Learn about the Poplar® SDK and how to easily run ML models on IPU systems



OPEN SOURCE

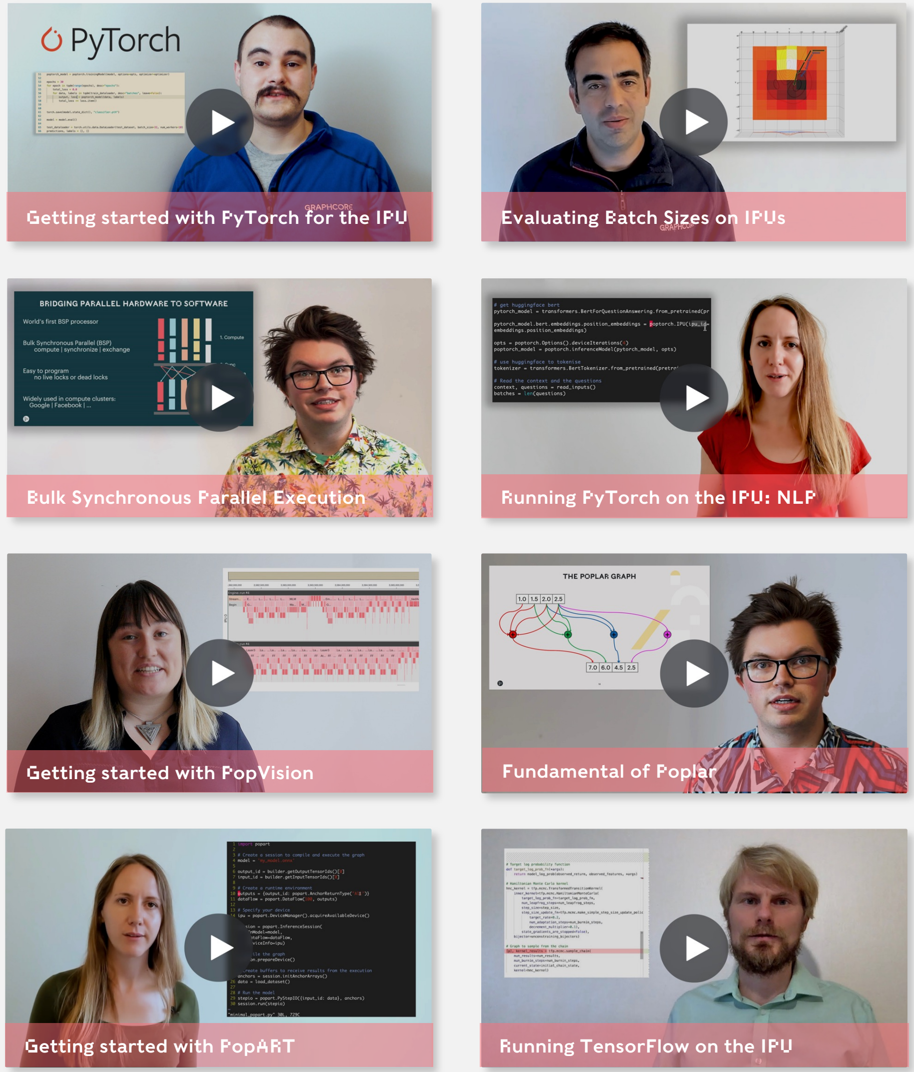
github.com/graphcore

- As part of our ethos to put power in the hands of AI developers, Graphcore open sourced in July 2020
- PopLibs™, PopART, PyTorch & TensorFlow for IPU fully open source and available on GitHub
- Our code is public and open for code contributions from the wider ML developer community



VIDEO + GITHUB TUTORIALS

A comprehensive set of online developer training materials and educational content



TUTORIALS

Learn how to create and run programs using Poplar and PopLibs with our hands-on programming tutorials.

Programs and Variables	Using PopLibs	Writing Vertex Code
Profiling Output	Basic Machine Learning Example	Matrix-Vector Multiplication
Matrix-Vector Multiplication Optimisation	Simple PyTorch for the IPU NEW	

Tutorial 1: programs and variables

Copy the file `tut1_variables/start_here/tut1.cpp` to your working directory and open it in an editor. The file contains the outline of a C++ program including some Poplar library headers and a namespace.

Graphs, variables and programs

All Poplar programs require a `Graph` object to construct the computation graph. Graphs are always created for a specific target (where the target is a description of the hardware being targeted, such as an IPU). To obtain the target we need to choose a device.

The tutorials use a simulated target by default, so will run on any machine even if it has no Graphcore hardware attached. On systems with accelerator hardware, the header file `poplar/DeviceManager.hpp` contains API calls to enumerate and return `Device` objects for the attached hardware.

Simulated devices are created with the `IPUModel` class, which models the functionality of an IPU on the host. The `createDevice` function creates a new virtual device to work with. Once we have this device we can create a `Graph` object to target it.

- Add the following code to the body of `main` :

```
// Create the IPU Model device
IPUModel ipuModel;
Device device = ipuModel.createDevice();
Target target = device.getTarget();

// Create the Graph object
Graph graph(target);
```

Any program running on an IPU needs data to work on. These are defined as *variables* in the graph.

- Add the following code to create the first variable in the program:

Tutorial 5: a basic machine learning example

This tutorial contains a complete training program that performs a logistic regression on the MNIST data set, using gradient descent. The files for the demo are in `tut5_ml` . There are no coding steps in the tutorial. The task is to understand the code, build it and run it. You can build the code using the supplied makefile.

Before you can run the code you will need to run the `get_mnist.sh` script to download the MNIST data.

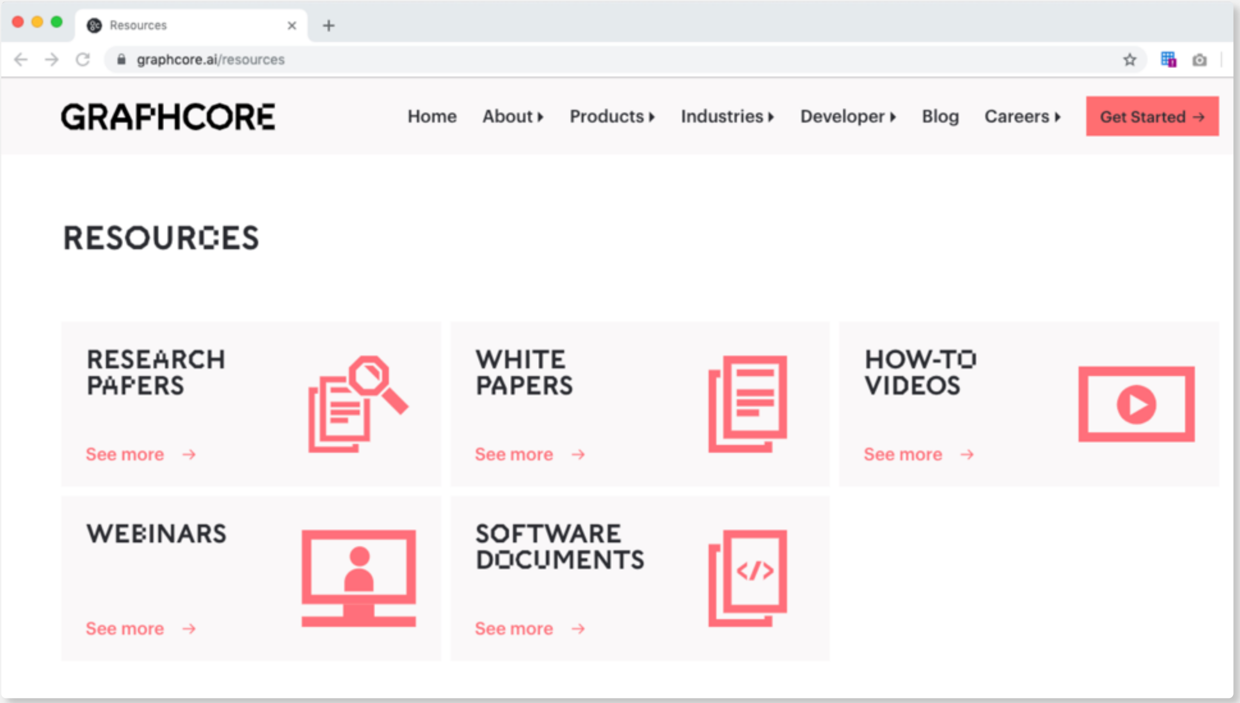
The program accepts an optional command line argument to make it use the IPU hardware instead of a simulated IPU.

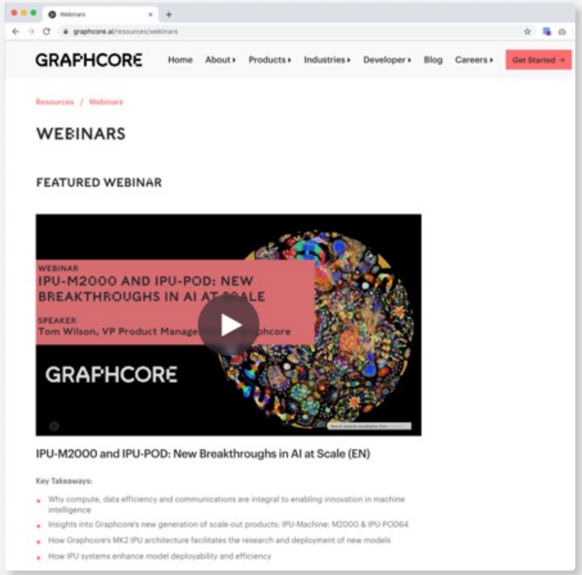
As you would expect, training is significantly faster on the IPU hardware.

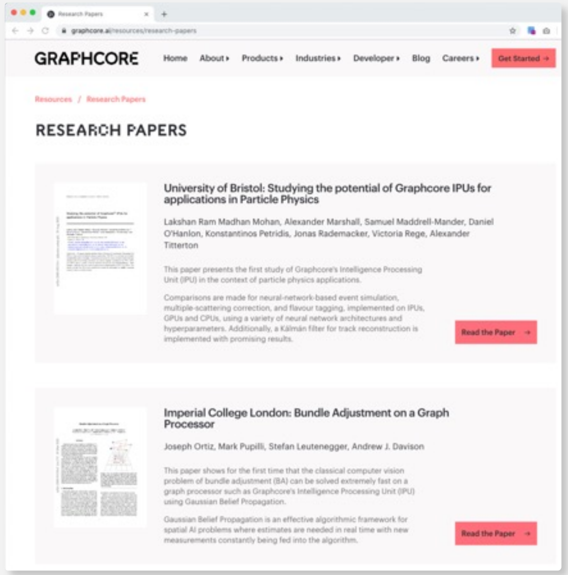
RESOURCES CENTRE

graphcore.ai/resources

- New resources hub made available in September 2020
- Central source of research papers, white papers, videos, on-demand webinars and documentation
- Product resources for ML Engineers & IT / Infrastructure Managers now available







USEFUL ENV VARIABLES

USEFUL ENV VARIABLES

LOGGING

Logging messages can be generated when your program runs. This is controlled by the environment variables described below. For more detailed information see the docs:
https://docs.graphcore.ai/projects/poplar-user-guide/en/latest/env-vars.html

POPLAR_LOG_LEVEL: Enable logging for Poplar

POPLAR_LOG_DEST: Specify the destination for Poplar logging (“stdout”, “stderr” or a file name)

“OFF”	No logging information. The default.
“ERR”	Only error conditions will be reported.
“WARN”	Warnings when, for example, the software cannot achieve what was requested (for example, if the convolution planner can’t keep to the memory budget, or Poplar has determined that the model won’t fit in memory but the debug.allowOutOfMemory option is enabled).
“INFO”	Very high level information, such as PopLibs function calls.
“DEBUG”	Useful per-graph information.
“TRACE”	The most verbose level. All useful per-tile information.

SYNTHETIC-DATA

TF_POPLAR_FLAGS= "--use_synthetic_data --synthetic_data_initializer=random"

Used for measuring the IPU-only throughput and disregards any host/CPU activity.

USING POPVISION (MORE ON THIS LATER)

POPLAR_ENGINE_OPTIONS='{"autoReport.all":"true", "autoReport.directory":"./tommyFlowers"}’

- The PopVision Graph Analyser uses report files generated during compilation and execution by the Poplar SDK.
- These files can be created using POPLAR_ENGINE_OPTIONS.
- In order to capture the reports needed for the PopVision Graph Analyser you only need to set POPLAR_ENGINE_OPTIONS='{"autoReport.all":"true"}' before you run a program. By default this will enable instrumentation and capture all the required reports to the current working directory.

A NOTE ON COMPILE TIME AND EXECUTABLE CACHING

- Our compiler technology consumes input from the high-level frameworks e.g. PyTorch, and generates a massively parallel computational graph. This graph is then compiled down to target the IPUs MIMD architecture.
- It can take a long time to compile a large fused graph into an executable suitable for the IPU. E.g. ~20 mins for BERT-L pre-training on IPU-POD16.
- Reducing compile time is something we are focused on this year.
- To prevent the need for compiling every time a new process is started, you can enable an executable cache: more on the next slide.

EXECUTABLE CACHE

If you often run the same models you might want to enable executable caching to save time:

POPTORCH:

- You can do this by either setting the POPTORCH_CACHE_DIR environment variable or by calling poptorch.Options.enableExecutableCaching.

TENSORFLOW:

- You can use the flag --executable_cache_path to specify a directory where compiled files will be placed. Fused XLA/HLO graphs are hashed with a 64-bit hash and stored in this directory.

Warning
The cache directory might grow large quickly. Poplar doesn't evict old models from the cache and, depending on the number and size of your models and the number of IPUs used, the executables might be quite large.
It is the your responsibility to delete the unwanted cache files.

PRECOMPILATION

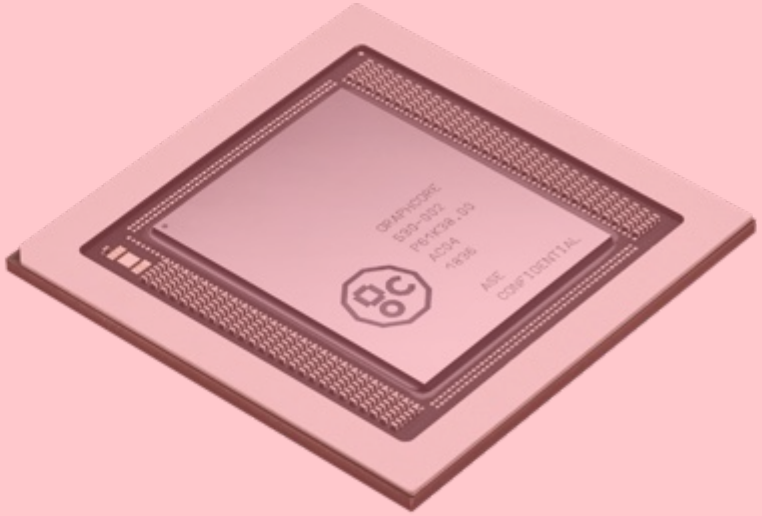
- PopTorch and TensorFlow support precompilation: This means you can compile your model on a machine which doesn’t have an IPU and export the executable to a file. You can then reload and execute it on a different machine which does have an IPU.

More details in the documentation.

TFI FOR IPU

TENSORFLOW PROGRAMS ON THE IPU

Minimum code to run on IPU



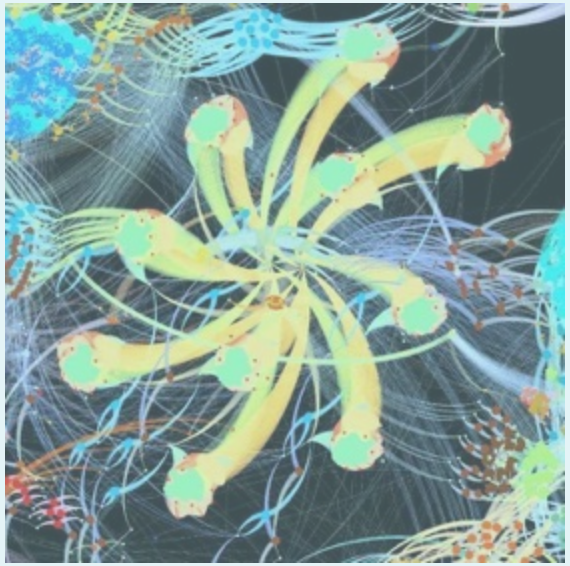
Configure the IPU

Single or multiple IPUs. Graph optimization and profiling options.

Compile graph to XLA

Fix input and output tensors. Compiles static graph to Poplar executable.

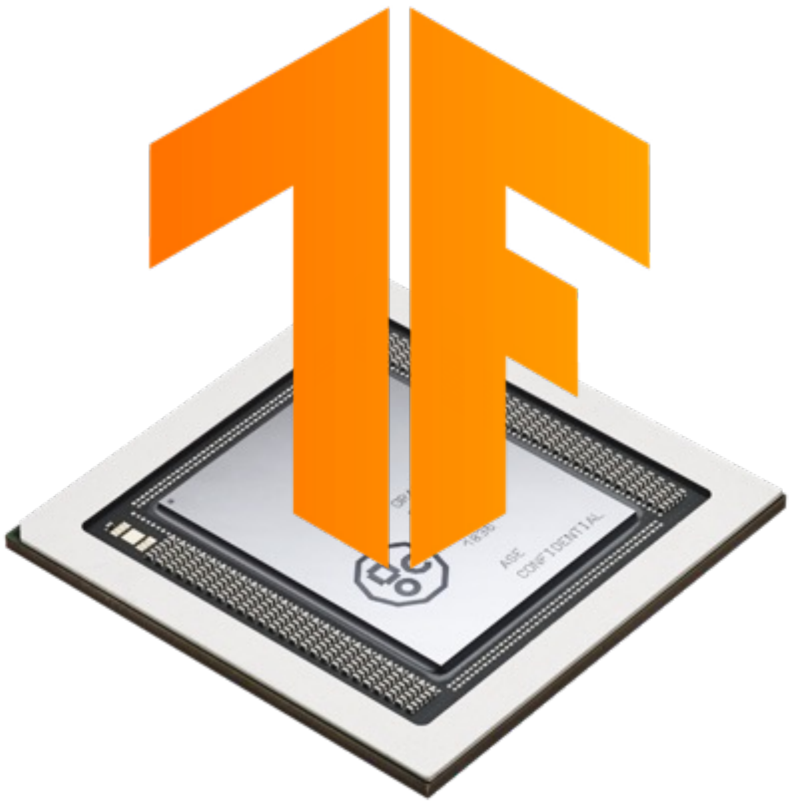
Now, run it fast



Optimise data flow

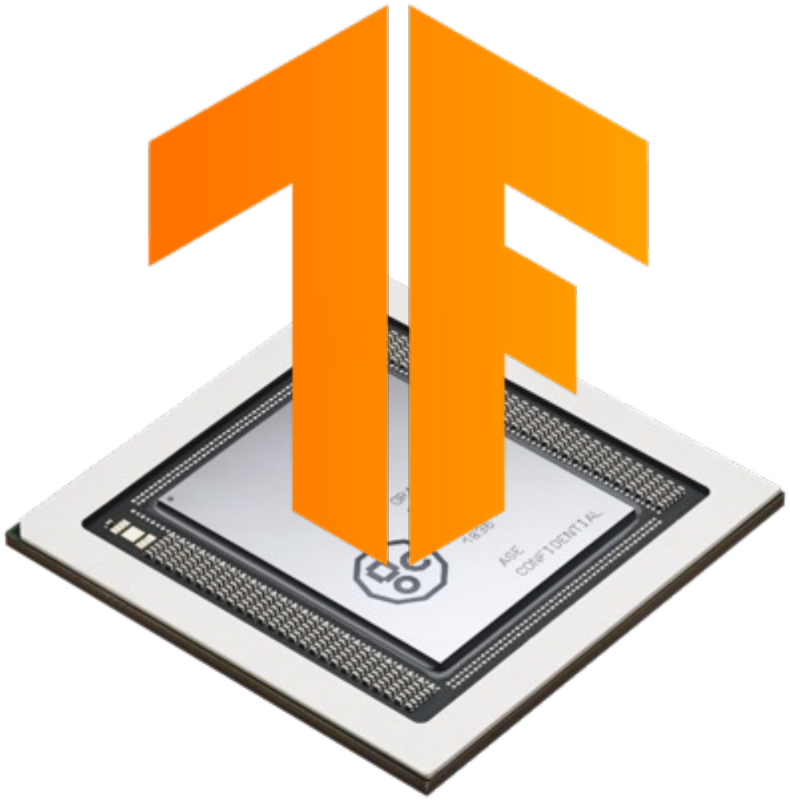
Minimise host IO by looping on IPU. Use Datasets, infeeds & outfeeds.

MINIMUM CODE CHANGES TO RUN ON IPU



1. Configure IPU system
2. Functionalize your model to be placed on IPU
3. Compile on IPU

MINIMUM CODE CHANGES TO RUN ON IPU



1. Configure IPU system

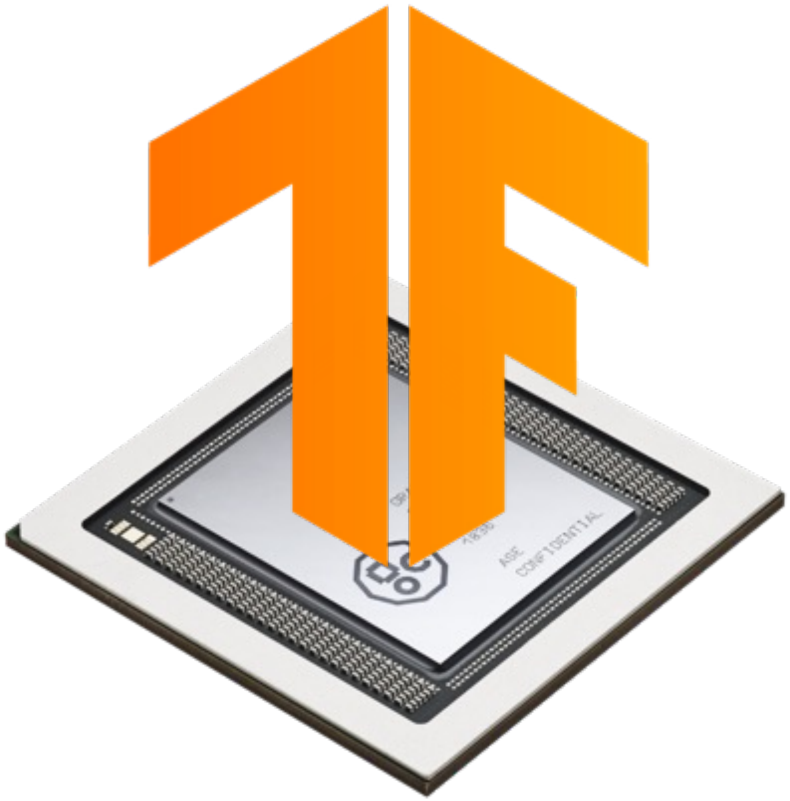
```
from tensorflow.python import ipu


# Create a default configuration
ipu_configuration = ipu.config.IPUConfig()

# Select an IPU automatically
ipu_configuration.auto_select_ipus = 1

# Apply the configuration
ipu_configuration.configure_ipu_system()
```

MINIMUM CODE CHANGES TO RUN ON IPU

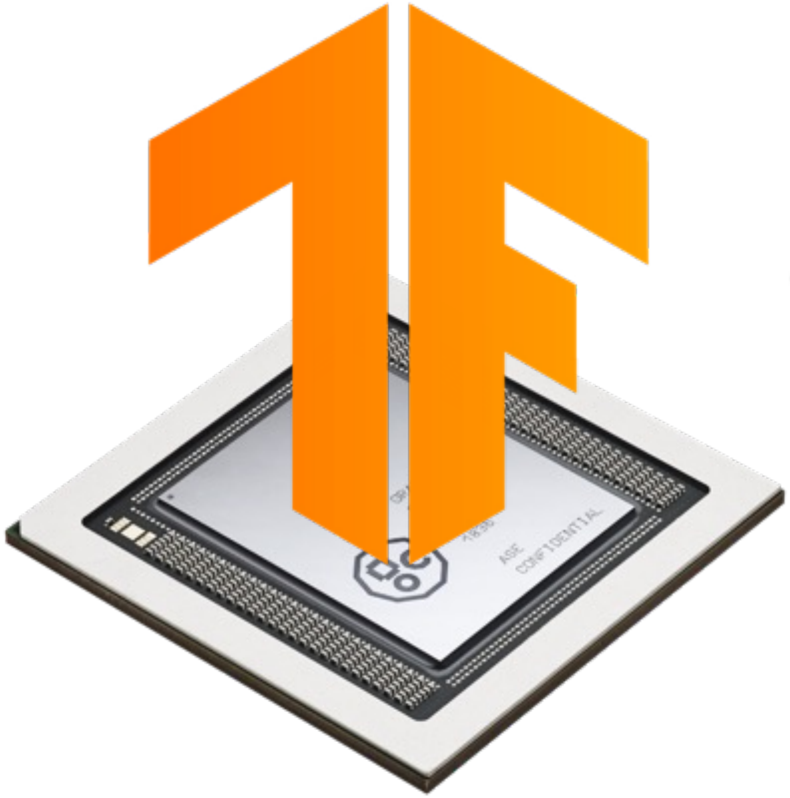


2. Functionalize your model to be placed on IPU

```
# Do basic addition with tensors
o1 = pa + pb
o2 = pa + pc
simple_graph_output = o1 + o2
```

```
def basic_graph(pa, pb, pc):
  # Do basic addition with tensors
  o1 = pa + pb
  o2 = pa + pc
  simple_graph_output = o1 + o2
  return simple_graph_output
```

MINIMUM CODE CHANGES TO RUN ON IPU



3. Compile on IPU

```
from tensorflow.python.ipu.scopes import ipu_scope
```

```
with ipu_scope("/device:IPU:0"):
  xla_result = ipu.ipu_compiler.compile(basic_graph, [pa, pb, pc])
```

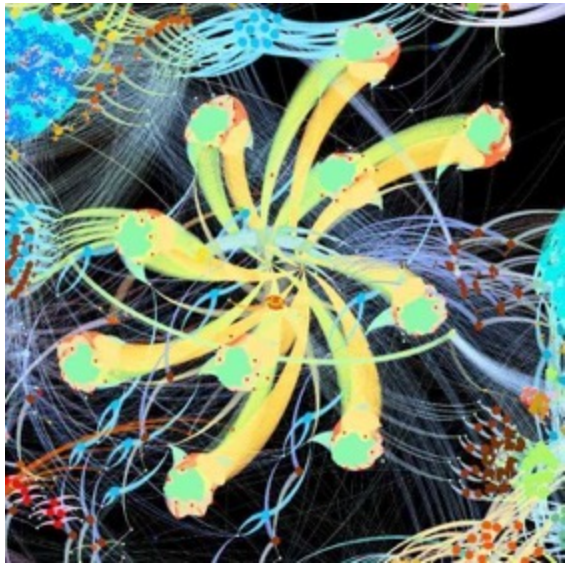
TENSORFLOW PROGRAMS ON THE IPU

Configure the IPU

Single or multiple IPUs. Graph optimization and profiling options.

Compile graph to XLA

Fix input and output tensors. Compiles static graph to Poplar executable.



Optimise data flow

Minimise host IO by looping on IPU. Use Datasets, infeeds & outfeeds.

WHY DO WE NEED TRAINING LOOPS?

- Communication between the host and IPU is slow compared to execution on-device, so we see this overhead if calling the hardware for each batch.

- By placing the training operations inside a loop, they can be executed multiple times without returning control to the host.

WHY DO WE NEED DATA FEEDS?

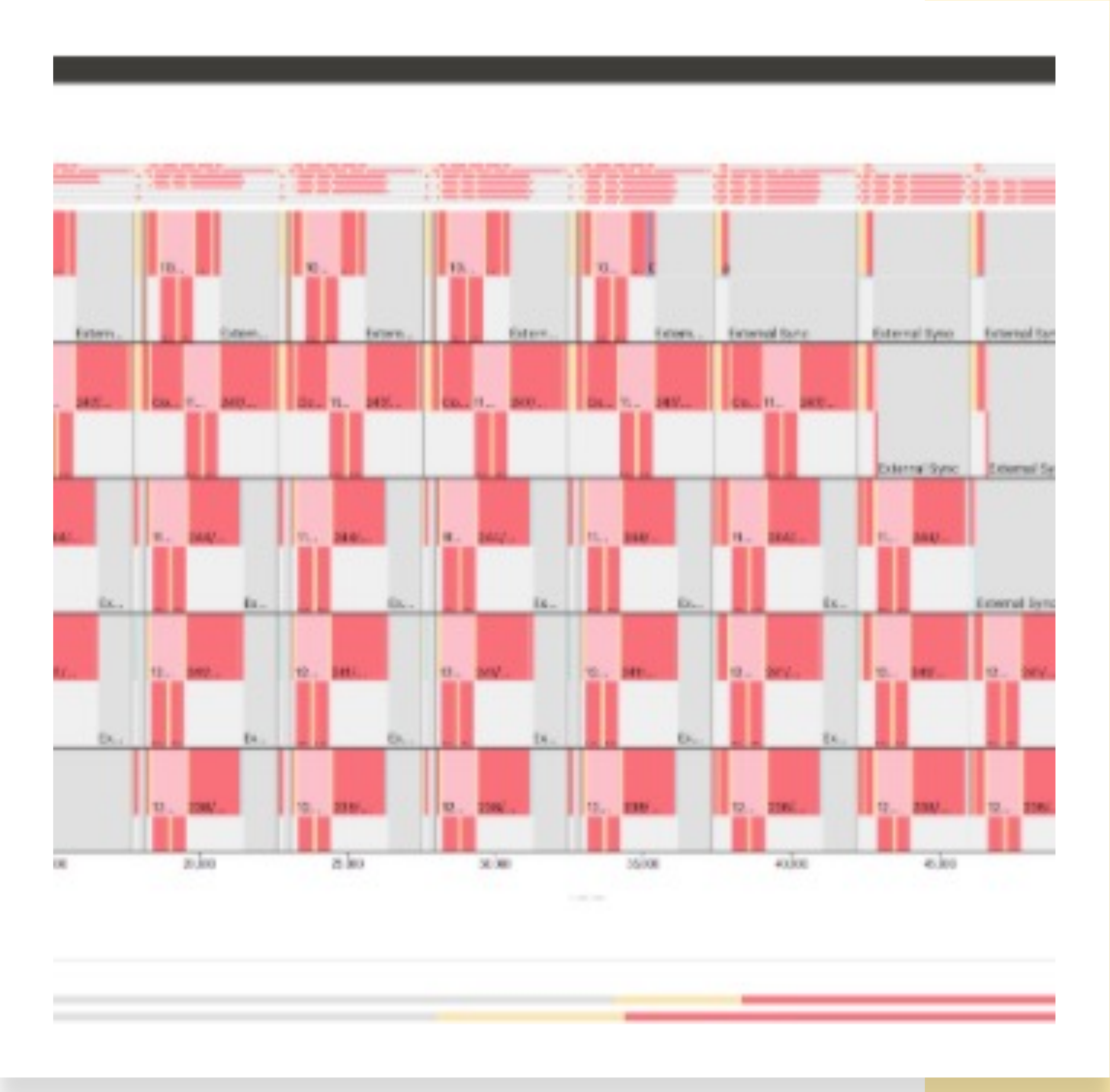
- When a training operation is placed into a loop, the inputs to that training operation need to provide a stream of values.

- Standard TensorFlow Python feed dictionaries cannot provide data in this form, so when training in a loop, data must be fed from a TensorFlow DataSet.

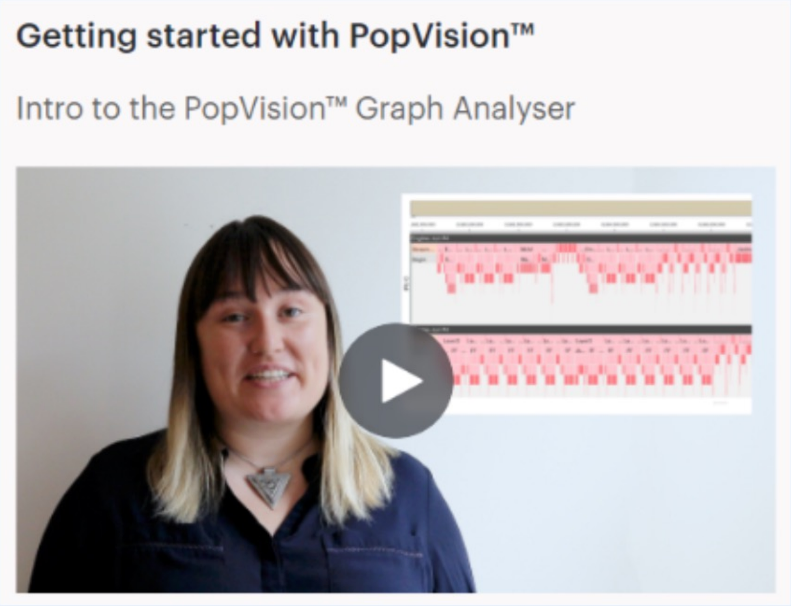
POPVISION™ TOOLS

POPVISION GRAPH ANALYSER

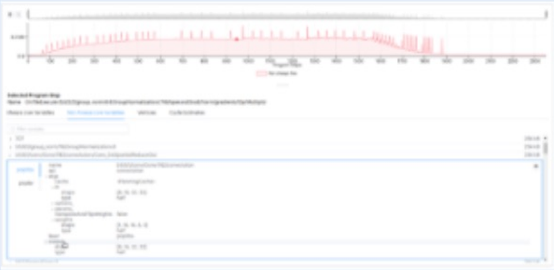
- You can use the PopVision Graph Analyser tool to debug IPU programs and generate reports on compilation and execution of the program.
- This tool can be downloaded from the Graphcore customer support portal: https://downloads.graphcore.ai/.
- There is a built-in help system within the tool for any questions you might have about producing and analysing reports.



PopVision Graph Analyser v2.2



Getting started video available on the developers portal



Several new features including:

- A new file format for the graph and execution profile, resulting in a 50% file size reduction
- Enhanced PopLibs debug information

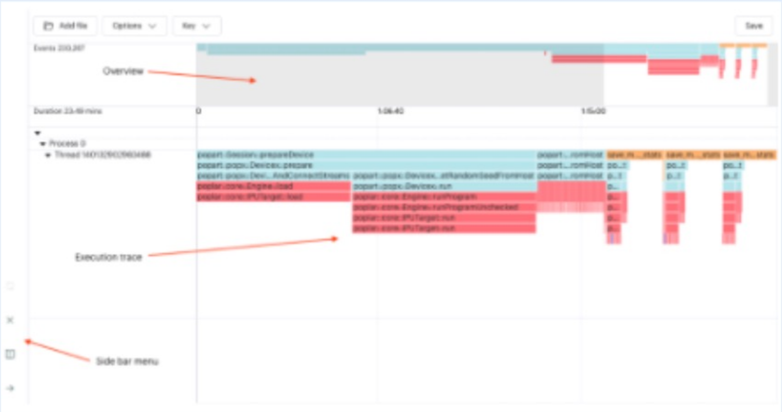
Liveness Report

The debug information shown for a variable now displays enhanced information. For each variable that has debug information, you can now see the PopLibs API that created it, its arguments and its outputs.

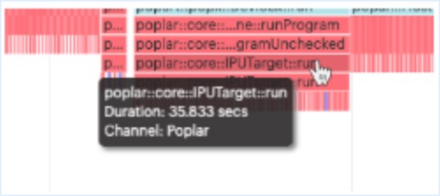
Enhanced debug information has been added to program steps. Program steps show Poplar and PopLibs debug information such as which PopLibs API created that program step, its arguments and its outputs.

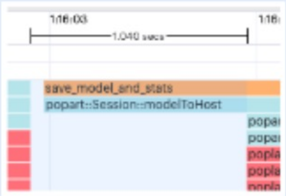
Check out the integrated help or visit our developer portal for more information

PopVision System Analyser v1.0



Show the execution of the software on the host processor enabling users to identify bottlenecks in execution between CPU & IPU(s).





Provide profile insights as you scale models to multiple CPUs / IPUs.

The PopVision System Analyser allows developers to understand the execution of programs running on the host processor which control the IPU(s). The System Analyser shows the interaction between the host and the IPU(s) so that developers can understand where the bottlenecks are in the execution of their applications.

The PopVision System Analyser visualises the information collected by the PopVision Trace Instrumentation Library which is part of the Poplar SDK.

Visit our developer portal for more information and the latest documentation:

https://www.graphcore.ai/developer

BULK SYNCHRONOUS PARALLEL (BSP)

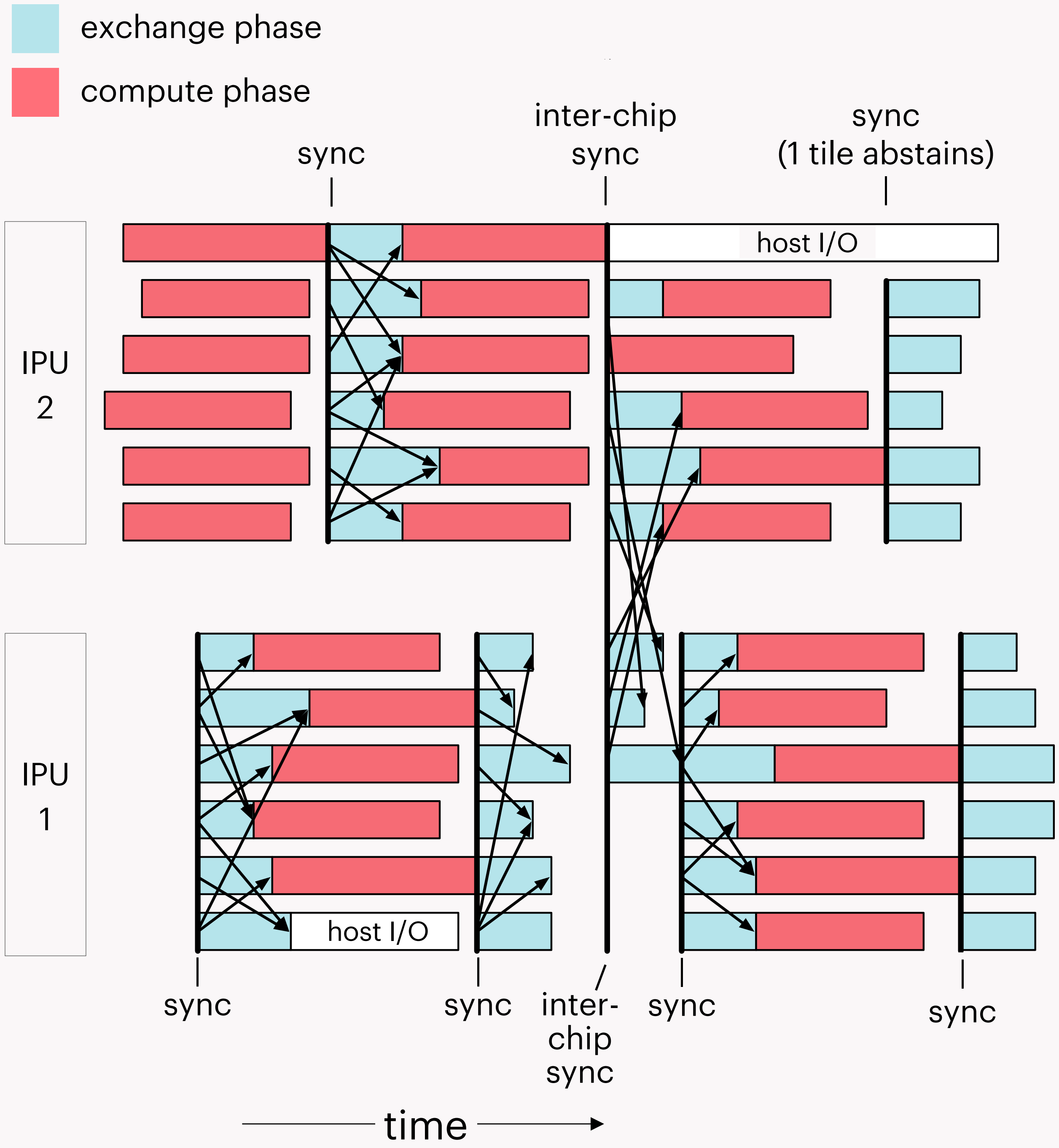
BSP software bridging model – massively parallel computing with no concurrency hazards

3 phases: compute, sync, exchange

Easy to program – no live-locks or dead-locks

Widely-used in parallel computing – Google, FB, ...

First use of BSP inside a parallel processor



TF2/KERAS ON IPU

KERAS ON IPU

- IPU optimized Keras `Model` and `Sequential` are available for the IPU. These have the following features:

  * On-device training loop for reduction of communication overhead.
  * Gradient accumulation for simulating larger batch sizes.
  * Automatic data-parallelisation of the model when placed on a multi-IPU device.

gpu_cnn_keras.py ↔ ipu_cnn_keras.py tf_keras

Keras

GPU

```python
as tf
ras.layers import *

(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
x_train = x_train.astype('float32') / 255.0
y_train = tf.keras.utils.to_categorical(y_train, 10)
ds_train = tf.data.Dataset.from_tensor_slices((x_train, y_train)).batch(64, drop_remainde

model = tf.keras.Sequential([
    Conv2D(32, (3, 3), padding='same', input_shape=x_train.shape[1:]),
    Activation('relu'),
    Conv2D(32, (3, 3)),
    Activation('relu'),
    MaxPooling2D(pool_size=(2, 2)),
    Dropout(0.25),
    Conv2D(64, (3, 3), padding='same'),
    Activation('relu'),
    Conv2D(32, (3, 3)),
    Activation('relu'),
    MaxPooling2D(pool_size=(2, 2)),
    Dropout(0.25),
    Flatten(),
    Dense(512),
    Activation('relu'),
    Dropout(0.5),
    Dense(10),
    Activation('softmax')
    ])

model.compile(loss='categorical_crossentropy',
    optimizer=tf.optimizers.SGD(learning_rate=0.016),
    metrics=['accuracy'])

model.fit(ds_train, epochs=40)
```

IPU

```python
import tensorflow as tf
from tensorflow.keras.layers import *
+ from tensorflow.python import ipu

+ cfg = ipu.config.IPUConfig()
+ cfg.auto_select_ipus = 1
+ cfg.configure_ipu_system()
+ with ipu.ipu_strategy.IPUStrategy().scope():
    (x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()
    x_train = x_train.astype('float32') / 255.0
    y_train = tf.keras.utils.to_categorical(y_train, 10)
    ds_train = tf.data.Dataset.from_tensor_slices((x_train, y_train)).batch(64, drop_rema

    model = tf.keras.Sequential([
        Conv2D(32, (3, 3), padding='same', input_shape=x_train.shape[1:]),
        Activation('relu'),
        Conv2D(32, (3, 3)),
        Activation('relu'),
        MaxPooling2D(pool_size=(2, 2)),
        Dropout(0.25),
        Conv2D(64, (3, 3), padding='same'),
        Activation('relu'),
        Conv2D(32, (3, 3)),
        Activation('relu'),
        MaxPooling2D(pool_size=(2, 2)),
        Dropout(0.25),
        Flatten(),
        Dense(512),
        Activation('relu'),
        Dropout(0.5),
        Dense(10),
        Activation('softmax')
        ])

    model.compile(loss='categorical_crossentropy',
        optimizer=tf.optimizers.SGD(learning_rate=0.016),
        metrics=['accuracy'])

    model.fit(ds_train, epochs=40)
```

alext — ubuntu@ip-172-31-6-210: ~/gpu2ipu_tf

```
(tensorflow2_p36) ubuntu@ip-172-31-6-210:~/gpu2ipu_tf/keras$
$ python3 gpu_keras_cnn.py
```

GPU

alext — alext@IPU4D70: ~/gpu2ipu_tf/keras — ssh -i ~/.ssh/gc_rsa alext@

```
(gc_virtualenv_TF2) alext@IPU4D70:~/gpu2ipu_tf/keras$
$ python3 ipu_keras_cnn.py
```

IPU

alext — ubuntu@ip-172-31-6-210: ~/gpu2ipu_tf

GPU

```
(tensorflow2_p36) ubuntu@ip-172-31-6-210:~/gpu2ipu_tf/keras$
$ python3 gpu_keras_cnn.py
Train for 1560 steps
Epoch 1/40
1560/1560 [==============================] - 8s 5ms/step            2.1685
Epoch 2/40
1560/1560 [==============================] - 5s 3ms/step - loss: 1.8803
Epoch 3/40
1560/1560 [==============================] - 5s 3ms/step - loss: 1.6523
Epoch 4/40
  75/1560 [>.............................] - ETA: 5s - loss: 1.5328 - a
```

alext — alext@IPU4D70: ~/gpu2ipu_tf/keras — ssh -i ~/.ssh/gc_rsa alext@

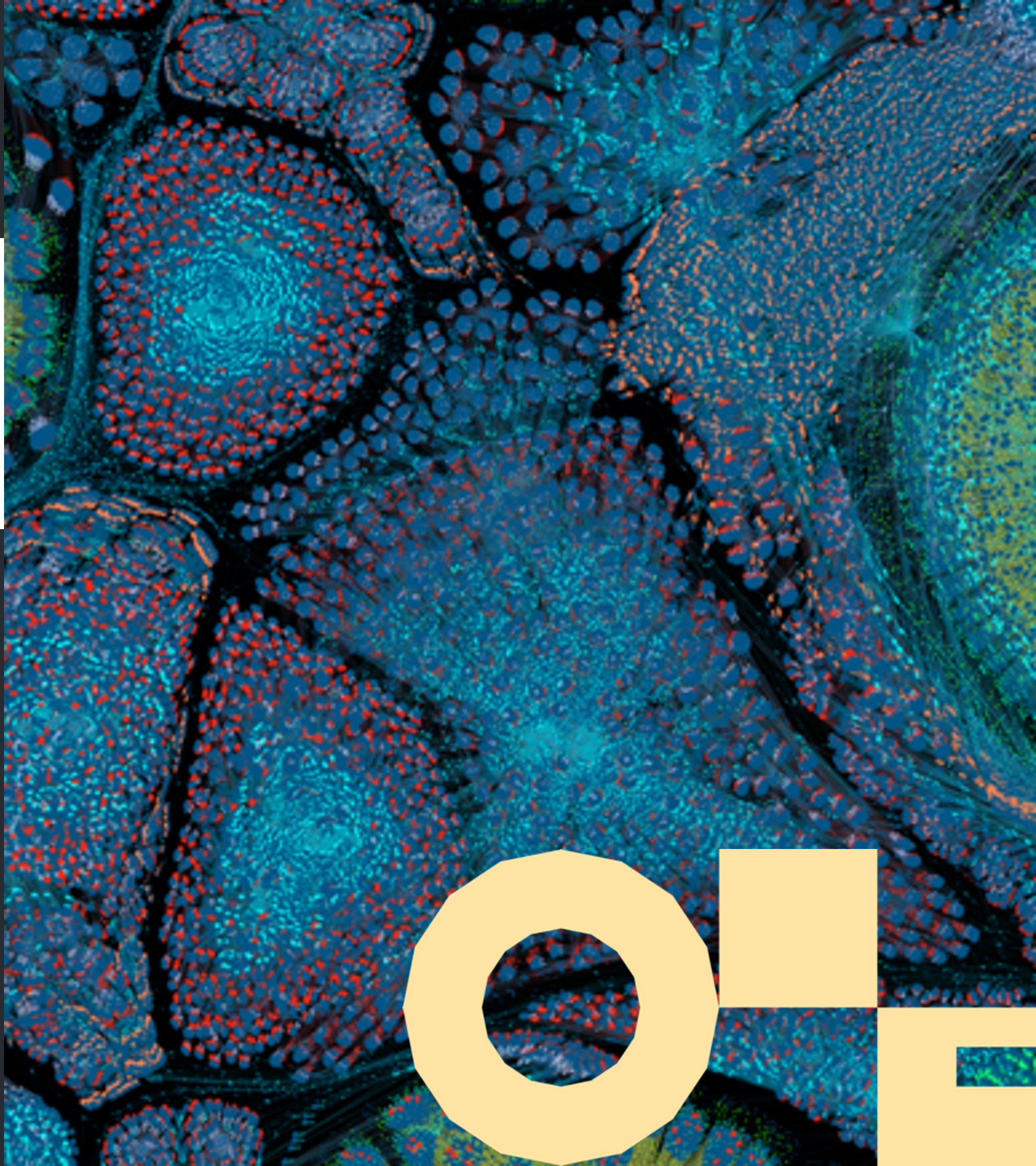
IPU

```
$ python3 ipu_keras_cnn.py
2020-05-12 16:40:32.449285: I tensorflow/compiler/plugin/poplar/driver/poplar_plat
r package: f666ae4ce3)
2020-05-12 16:40:34.523582: I tensorflow/core/platform/pro       ils/cpu_utils.cc
2020-05-12 16:40:35.357131: I tensorflow/compiler/plugin/p       river/poplar_exec
Epoch 1/40
2020-05-12 16:40:35.898895: I tensorflow/compiler/jit/xla_compilation_cache.cc:254
 most once for the lifetime of the process.
1560/1560 [==============================] - 2s 2ms/step - loss: 0.0500 - accuracy
Epoch 2/40
1560/1560 [==============================] - 1s 593us/step - loss: 0.0408 - accura
Epoch 3/40
1560/1560 [==============================] - 1s 592us/step - loss: 0.0357 - accura
Epoch 4/40
1560/1560 [==============================] - 1s 597us/step - loss: 0.0325 - accura
Epoch 5/40
1560/1560 [==============================] - 1s 600us/step - loss: 0.0299 - accura
Epoch 6/40
1560/1560 [==============================] - 1s 600us/step - loss: 0.0278 - accura
Epoch 7/40
1560/1560 [==============================] - 1s 599us/step - loss: 0.0258 - accura
Epoch 8/40
1560/1560 [==============================] - 1s 598us/step - loss: 0.0241 - accura
Epoch 9/40
1560/1560 [==============================] - 1s 600us/step - loss: 0.0224 - accura
Epoch 10/40
1560/1560 [==============================] - 1s 600us/step - loss: 0.0208 - accura
Epoch 11/40
1560/1560 [==============================] - 1s 601us/step - loss: 0.0193 - accura
Epoch 12/40
1560/1560 [==============================] - 1s 608us/step - loss: 0.0178 - accura
Epoch 13/40
1560/1560 [==============================] - 1s 601us/step - loss: 0.0164 - accura
Epoch 14/40
1560/1560 [==============================] - 1s 601us/step - loss: 0.0150 - accura
Epoch 15/40
1560/1560 [==============================] - 1s 598us/step - loss: 0.0136 - accura
Epoch 16/40
1560/1560 [==============================] - 1s 601us/step - loss: 0.0122 - accura
Epoch 17/40
```

KERAS TUTORIAL

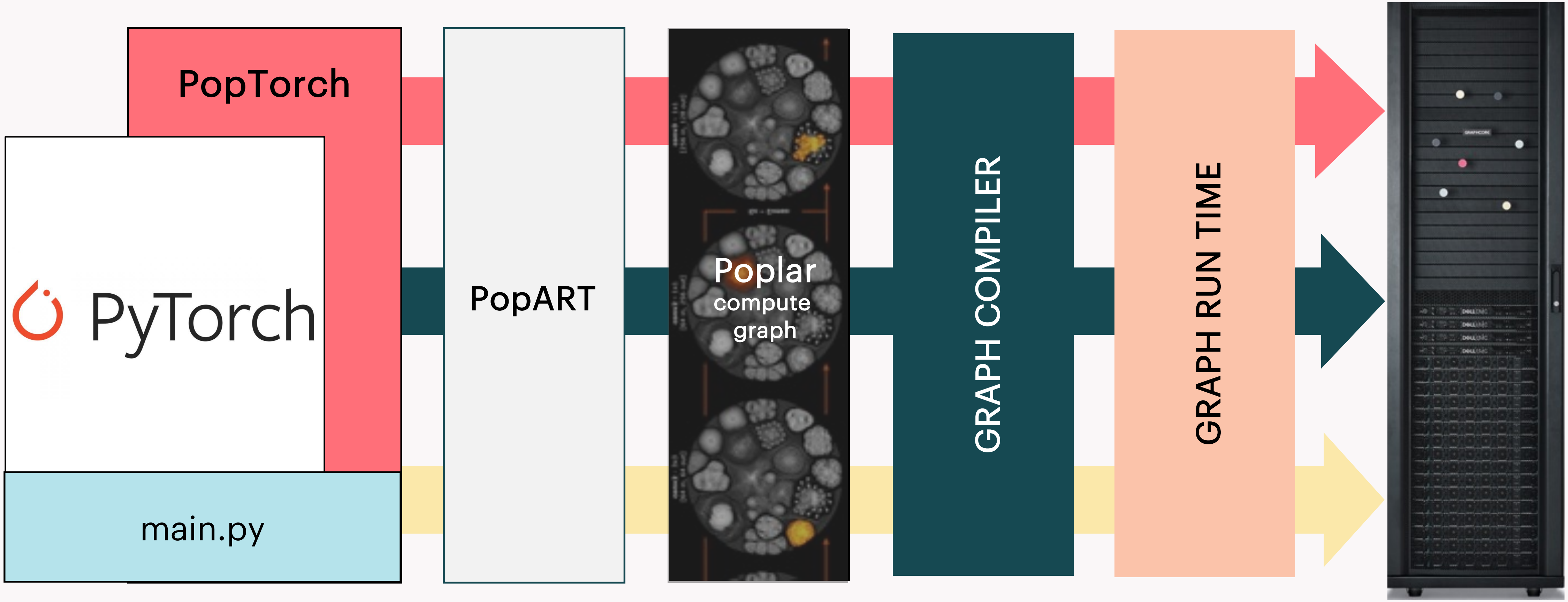
https://github.com/graphcore/tutorials/tree/master/tutorials/tensorflow2/keras

INTRO TO POPTORCH



GRAPHCORE

WHAT IS POPTORCH?



WHAT IS POPTORCH?

- PopTorch is a set of extensions for PyTorch to enable PyTorch models to run on Graphcore's IPU hardware.
- PopTorch supports both inference and training. To run a model on the IPU you wrap your existing PyTorch model in either a PopTorch inference wrapper or a PopTorch training wrapper.
- You can provide further annotations to partition the model across multiple IPUs. Using the user-provided annotations, 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.
- Under the hood PopTorch uses TorchScript, an intermediate representation (IR) of a PyTorch model, using the torch.jit.trace API. To learn more about TorchScript and JIT, you can go through PyTorch’s tutorial: https://pytorch.org/tutorials/beginner/Intro_to_TorchScript_tutorial.html
- Not all PyTorch operations have been implemented by the backend yet and you can find the list of supported operations here: https://docs.graphcore.ai/projects/poptorch-user-guide/en/latest/supported_ops.html

PYTORCH FOR IPU

Define a model within PyTorch

↓

Create an IPU execution wrapper around the model and run as normal

↓

PopTorch uses the **torch.jit.trace** API to trace the model to PyTorch IR

↓

Compile the graph in PopART and then run on one or more IPUs

Examples available from
https://github.com/graphcore/examples

GETTING STARTED: TRAINING A MODEL

TRAINING A MODEL

1. Import packages

PopTorch is a separate package from PyTorch, and must be imported.

2. Load dataset using torchvision.datasets and poptorch.DataLoader

In order to make data loading easier and more efficient, PopTorch offers an extension of `torch.utils.data.DataLoader` class:
`poptorch.DataLoader` class is specialised for the way the underlying PopART framework handles batching of data.

3. Define model and loss function using torch API

The only difference here from pure PyTorch is the loss computation, which has to be part of the forward function. This is to ensure the loss is computed on the IPU and not on the CPU, and to give us as much flexibility as possible when designing more complex loss functions.

TRAINING A MODEL

4. Prepare training

Instantiate compilation and execution options, these are used by PopTorch's wrappers such as `poptorch.DataLoader` and `poptorch.trainingModel`.

5. Train the model

Define the optimizer using PyTorch's API.

Use poptorch.trainingModel wrapper, to wrap your PyTorch model. This wrapper will trigger the compilation of our model, using TorchScript, and manage its translation to a program the IPU can run. Then run your training loop.

PyTorch

GPU

```python
    _, ind = torch.max(predictions, 1)
    # provide labels only for samples, where prediction is available (during the training, not
    ions.size()[0]:]
    ch.eq(ind, labels)).item() / labels.size(                 0

if __name__ == '__main__':
    parser = argparse.ArgumentParser(description='MNIST training in PopTorch')
    parser.add_argument('--batch-size', type=int, default=8, help='batch size for training (de
    parser.add_argument('--test-batch-size', type=int, default=8, help='batch size for testing
    parser.add_argument('--epochs', type=int, default=10, help='number of epochs to train (def
    parser.add_argument('--lr', type=float, default=0.05, help='learning rate (default: 0.05)'

    args = parser.parse_args()

    training_data = torch.utils.data.DataLoader(

                        torchvision.datasets.MNIST('mnist_data/', train=True, download=True, t
                        batch_size=args.batch_size, shuffle=True, drop_last=True)
    test_data = torch.utils.data.DataLoader(
                        torchvision.datasets.MNIST('mnist_data/', train=False, download=True,

    model = Network()
    training_model = TrainingModelWithLoss(model)
    optimizer=optim.SGD(model.parameters(), lr=args.lr)


    # Run training
    for _ in range(args.epochs):
        for data, labels in training_data:
            preds, losses = training_model(data, labels)
            optimizer.zero_grad()
            losses.backward()
            optimizer.step()

    # Run validation
    sum_acc = 0.0
    with torch.no_grad():
        for data, labels in test_data:
            output = model(data)
            sum_acc += accuracy(output, labels)
    print("Accuracy on test set: {:0.2f}%".format(sum_acc / len(test_data)))
```

IPU

```python
    _, ind = torch.max(predictions, 1)
    # provide labels only for samples, where prediction is available (during the training, not
    labels = labels[-predictions.size()[0]:]
    accuracy = torch.sum(torch.eq(ind, labels)).item() / labels.si              100.0
    return accuracy

if __name__ == '__main__':
    parser = argparse.ArgumentParser(description='MNIST training in PopTorch')
    parser.add_argument('--batch-size', type=int, default=8, help='batch size for training (de
    parser.add_argument('--test-batch-size', type=int, default=8, help='batch size for testing
    parser.add_argument('--epochs', type=int, default=10, help='number of epochs to train (def
    parser.add_argument('--lr', type=float, default=0.05, help='learning rate (default: 0.05)'
    parser.add_argument('--device-iterations', type=int, default=50, help='device iterations (
    args = parser.parse_args()

    opts = poptorch.Options().deviceIterations(args.device_iterations)
    training_data = poptorch.DataLoader(opts,
                        torchvision.datasets.MNIST('mnist_data/', train=True, download=True, trans
                        batch_size=args.batch_size, shuffle=True, drop_last=True)
    test_data = poptorch.DataLoader(opts,
                        torchvision.datasets.MNIST('mnist_data/', train=False, download=True, trar

    model = Network()
    training_model = TrainingModelWithLoss(model)
    optimizer=optim.SGD(model.parameters(), lr=args.lr)
    training_model = poptorch.trainingModel(training_model, opts, optimizer=optimizer)
    inference_model = poptorch.inferenceModel(model)

    # Run training
    for _ in range(args.epochs):
        for data, labels in training_data:
            preds, losses = training_model(data, labels)

    # Detach the training model so that the same IPU could be used for validation
    training_model.detachFromDevice()

    # Run validation
    sum_acc = 0.0
    with torch.no_grad():
        for data, labels in test_data:
            output = inference_model(data)
            sum_acc += accuracy(output, labels)
    print("Accuracy on test set: {:0.2f}%".format(sum_acc / len(test_data)))
```

POPTORCH TUTORIAL

https://github.com/graphcore/tutorials/tree/master/tutorials/pytorch/tut1_basics

POPTORCH.OPTIONS

- The compilation and execution on the IPU can be controlled using `poptorch.Options`
- Full list of options available here: https://docs.graphcore.ai/projects/poptorch-user-guide/en/latest/overview.html#options
- Some examples:

  (i) **`deviceIterations`**

  This option specifies the number of batches that is prepared by the host (CPU) for the IPU. The higher this number, the less the IPU has to interact with the CPU, for example to request and wait for data, so that the IPU can loop faster. However, the user will have to wait for the IPU to go over all the iterations before getting the results back. The maximum is the total number of batches in your dataset, and the default value is 1.

  (ii) **`replicationFactor`**

  This is the number of replicas of a model. We use replicas as an implementation of data parallelism. To achieve the same behavior in pure PyTorch, you'd wrap your model with torch.nn.DataParallel, but with PopTorch, this is an option.

INFERENCE

- To run inference, you use `poptorch.inferenceModel` class, which has a similar API to `poptorch.trainingModel` except that it doesn't need an optimizer.
- See tutorial example here: https://github.com/graphcore/tutorials/tree/master/tutorials/pytorch/tut1_basics#running-our-model-for-inference-on-an-ipu

MORE INFO

- PyTorch for the IPU: User Guide
https://docs.graphcore.ai/projects/poptorch-user-guide/en/latest/

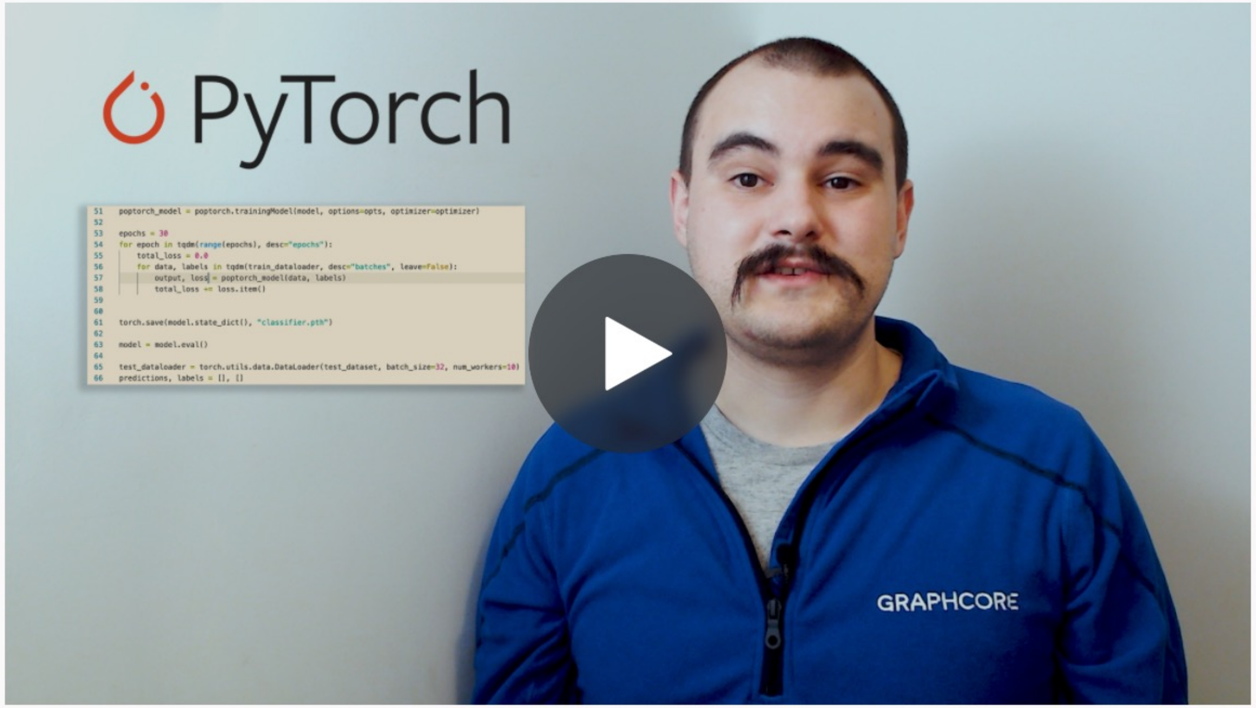
- GitHub tutorial
https://github.com/graphcore/examples/tree/master/tutorials/pytorch/tut1_basics

- Code examples on GitHub
https://github.com/graphcore/examples/tree/master/code_examples/pytorch/mnist

- Video tutorial on our developer page
https://www.graphcore.ai/developer

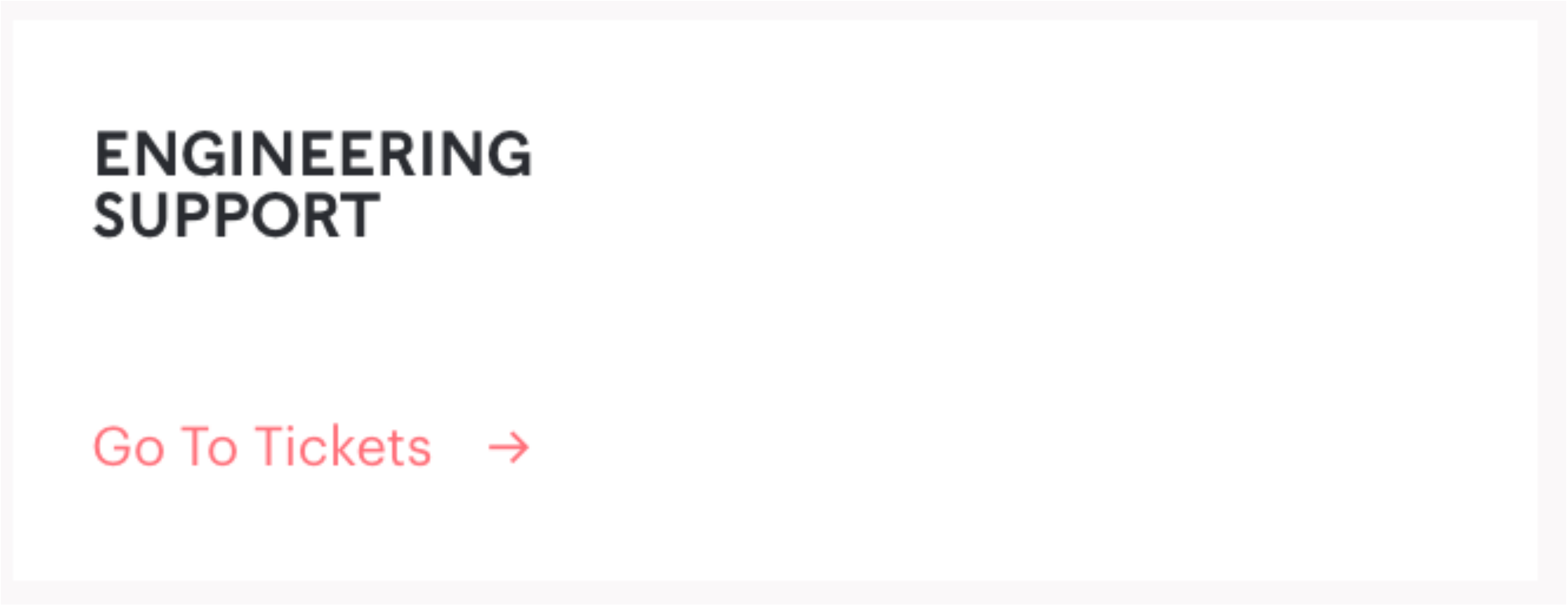
Getting started with PyTorch for the IPU

Running a basic model for training and inference



ANY QUESTIONS, REQUESTS, BUGS...

https://www.graphcore.ai/support



THANK YOU

Mario Michael Krell
mariok@graphcore.ai