GRAPHCORE OVERVIEW AND ONBOARDING TRAINING FOR TAMU

February 21, 2023

Alexander Tsyplikhin

AGENDA

- Introduction to Graphcore, IPU, and Poplar
  - Hands-on: ssh into the POD, enable the SDK, clone tutorials, binary caching, run example
- 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

GRAPHCORE OVERVIEW

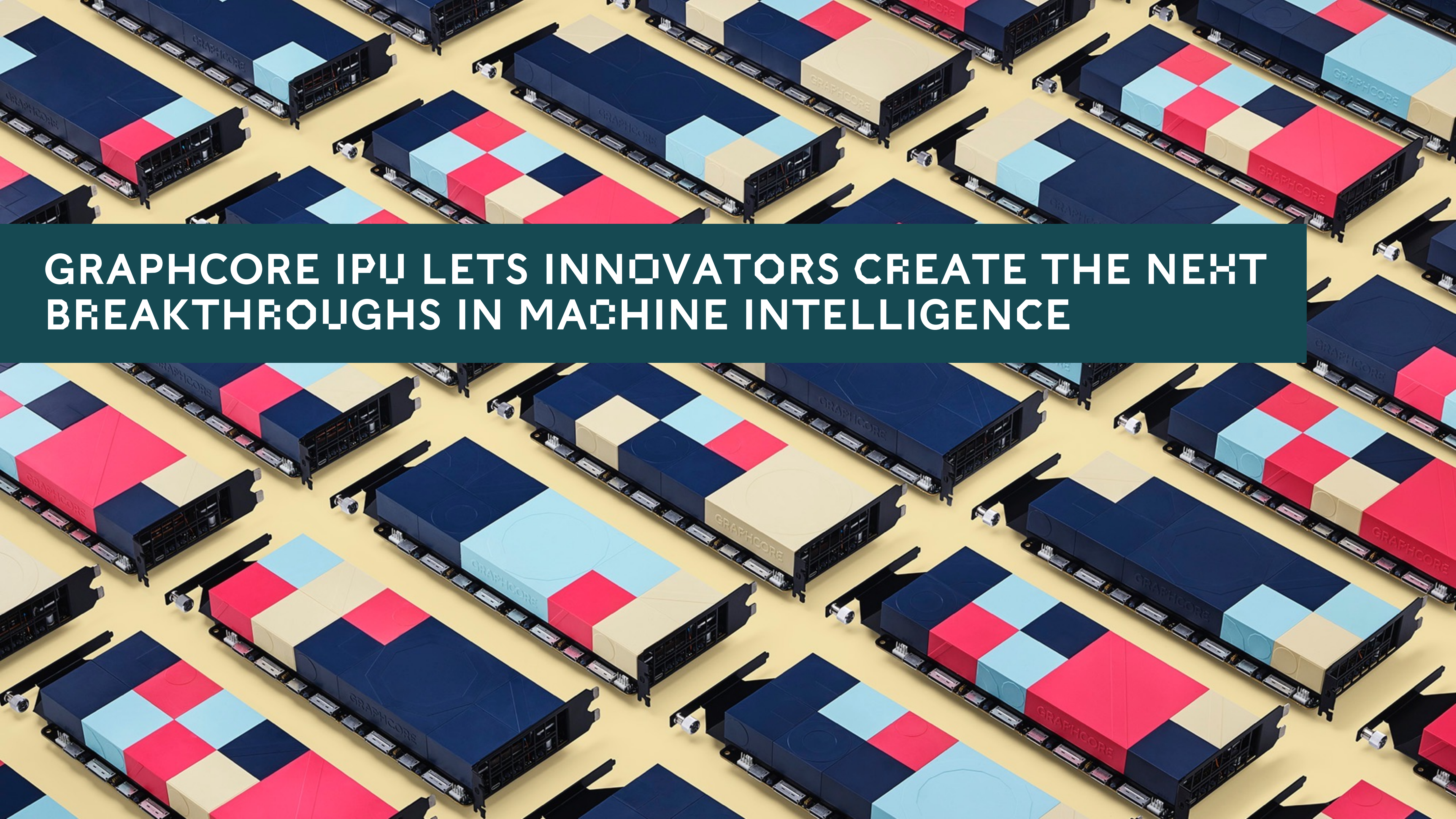
GRAPHCORE ENABLING MACHINE INTELLIGENCE

- Founded in 2016
- Technology: Intelligence Processor Unit (IPU)
- Team: ~500
- Offices: UK, US, China, Poland
- Raised >$710M

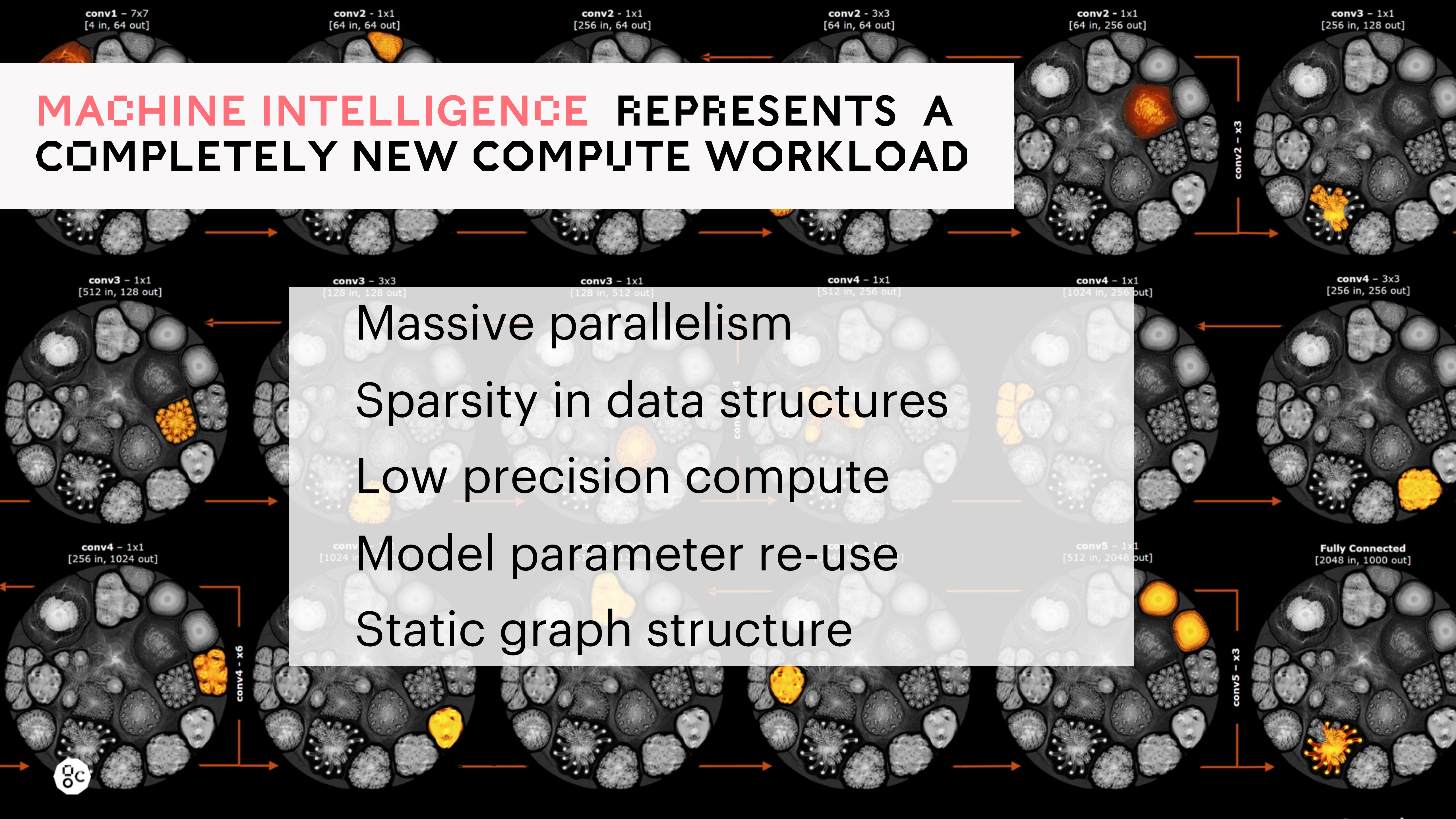
SEQUOIA ATOMICO SOFINA Microsoft

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

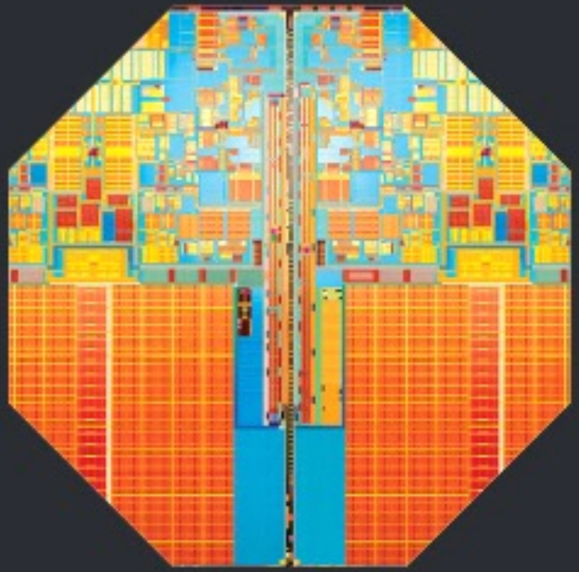
IPU ARCHITECTURE OVERVIEW



MACHINE INTELLIGENCE REPRESENTS A COMPLETELY NEW COMPUTE WORKLOAD

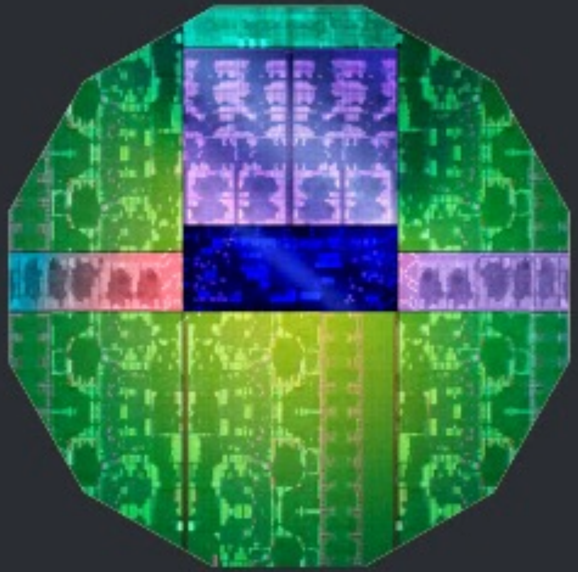
- Massive parallelism
- Sparsity in data structures
- Low precision compute
- Model parameter re-use
- Static graph structure

LEGACY PROCESSOR ARCHITECTURES HAVE BEEN REPURPOSED FOR ML



CPU

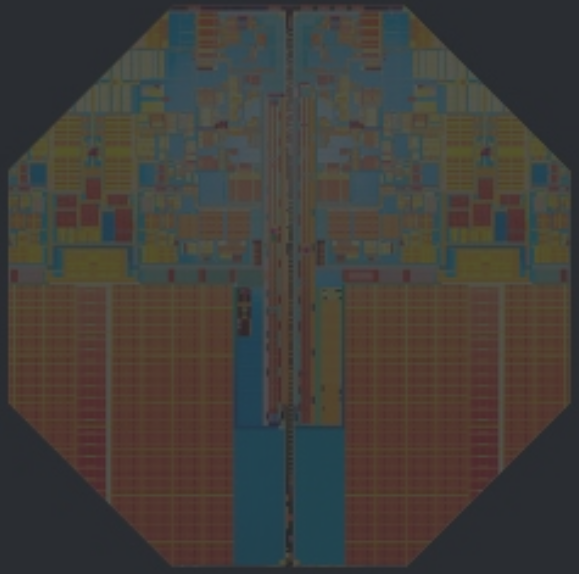
Apps and Web/
Scalar



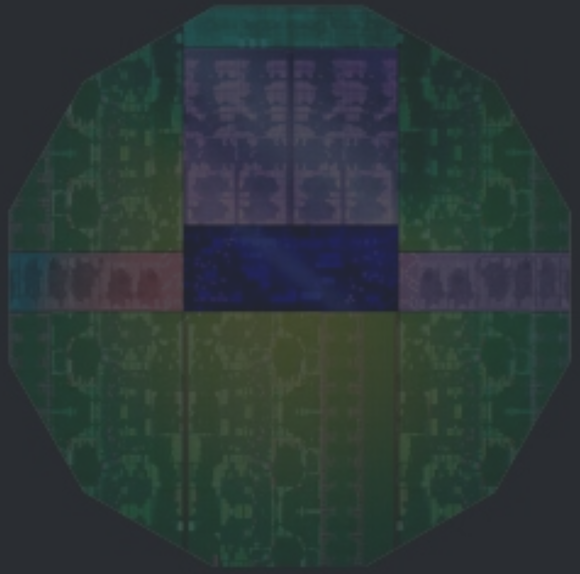
GPU

Graphics and HPC/
Vector

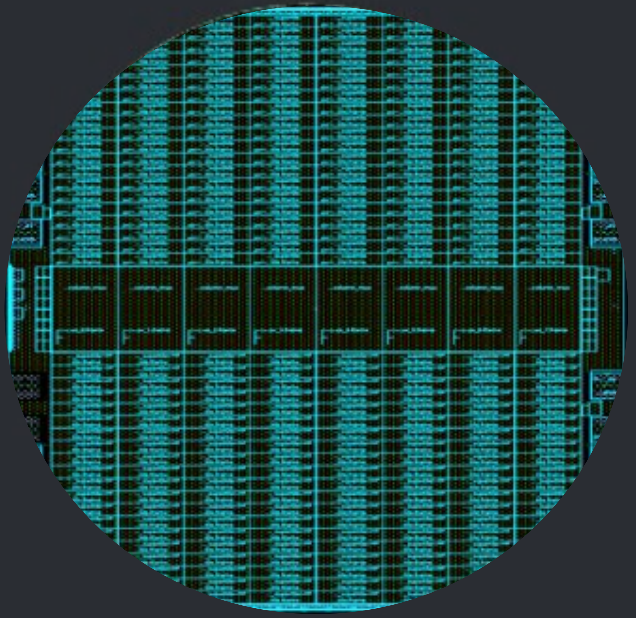
A NEW PROCESSOR IS REQUIRED FOR THE FUTURE



CPU
Apps and Web/
Scalar



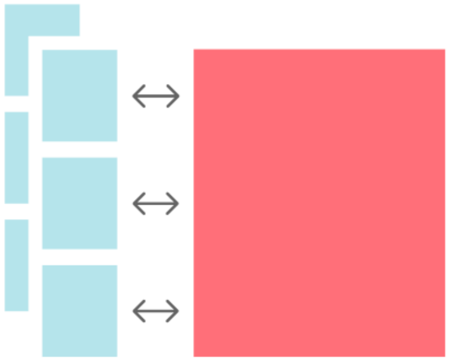
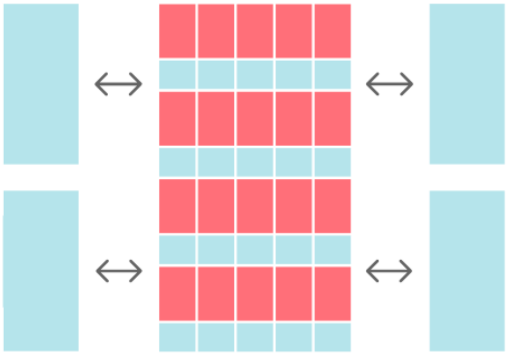
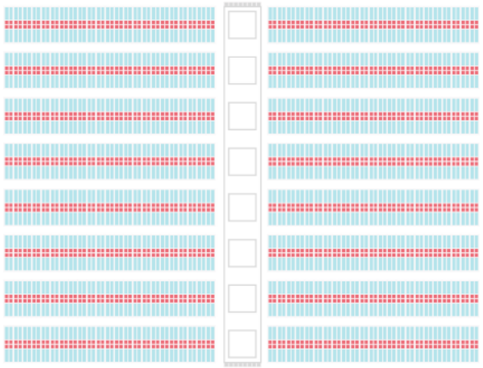
GPU
Graphics and HPC/
Vector



IPU
Artificial Intelligence/
Graph

IPU – ARCHITECTURED FOR AI

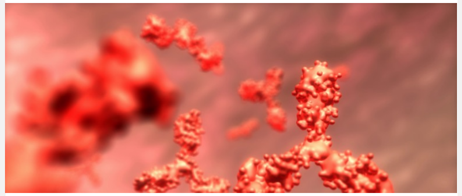
Massive parallelism with ultrafast memory access

	CPU	GPU	IPU
Parallelism	Designed for scalar processes	SIMD/SIMT architecture. Designed for large blocks of dense contiguous data	Massively parallel MIMD. Designed for fine-grained, high-performance computing
Processors Memory			
Memory Access	Off-chip memory	Model and data spread across off-chip and small on-chip cache, and shared memory	Model and data tightly coupled, and large locally distributed SRAM

PROVEN IPU ADVANTAGE
SELECT CASE STUDIES ACROSS MANY INDUSTRIES & FIELDS

LabGenius

HEALTHCARE



CASE STUDY : NLP >

Man

FINANCE – OPTION PRICING

CASE STUDY : SIM >

pienso

AI SaaS – TEXT ANALYTICS

CASE STUDY : NLP >

Argonne NATIONAL LABORATORY

RESEARCH / BIG LABS

CASE STUDY >

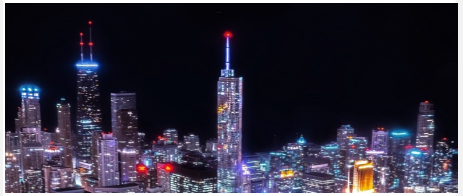
Pacific Northwest NATIONAL LABORATORY

COMPUTATIONAL CHEMISTRY

CASE STUDY : GNN >

SENSORO

SMART CITY



CASE STUDY : CV >

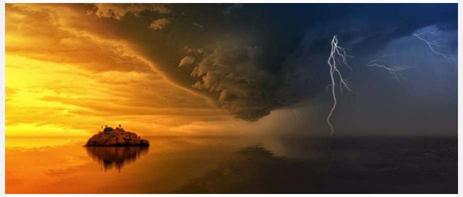
TRACTABLE

FINANCE - INSURANCE

CASE STUDY : CV >

ECMWF

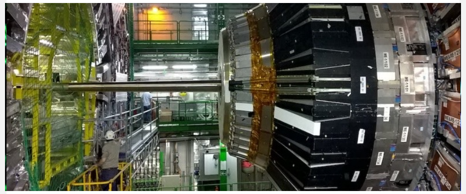
WEATHER FORECASTING



CASE STUDY : SIM >

SLAC NATIONAL ACCELERATOR LABORATORY

HIGH ENERGY PHYSICS



CASE STUDY >

UNIVERSITY OF OXFORD

DYNAMIC GRAPHS

CASE STUDY : GNN >

IPU COMPUTATIONAL ADVANTAGES

Heterogeneous gather/scatter operations. E.g. GNNs

Group and depthwise convolutions. E.g. ResNeXt, EfficientNet

Vector operations with low arithmetic intensity. E.g. Sparse matmuls

Dense as well as Sparse Matrix Multiplication. E.g. Transformers

Hardware accelerated Random Number Generation. E.g. Random Projections

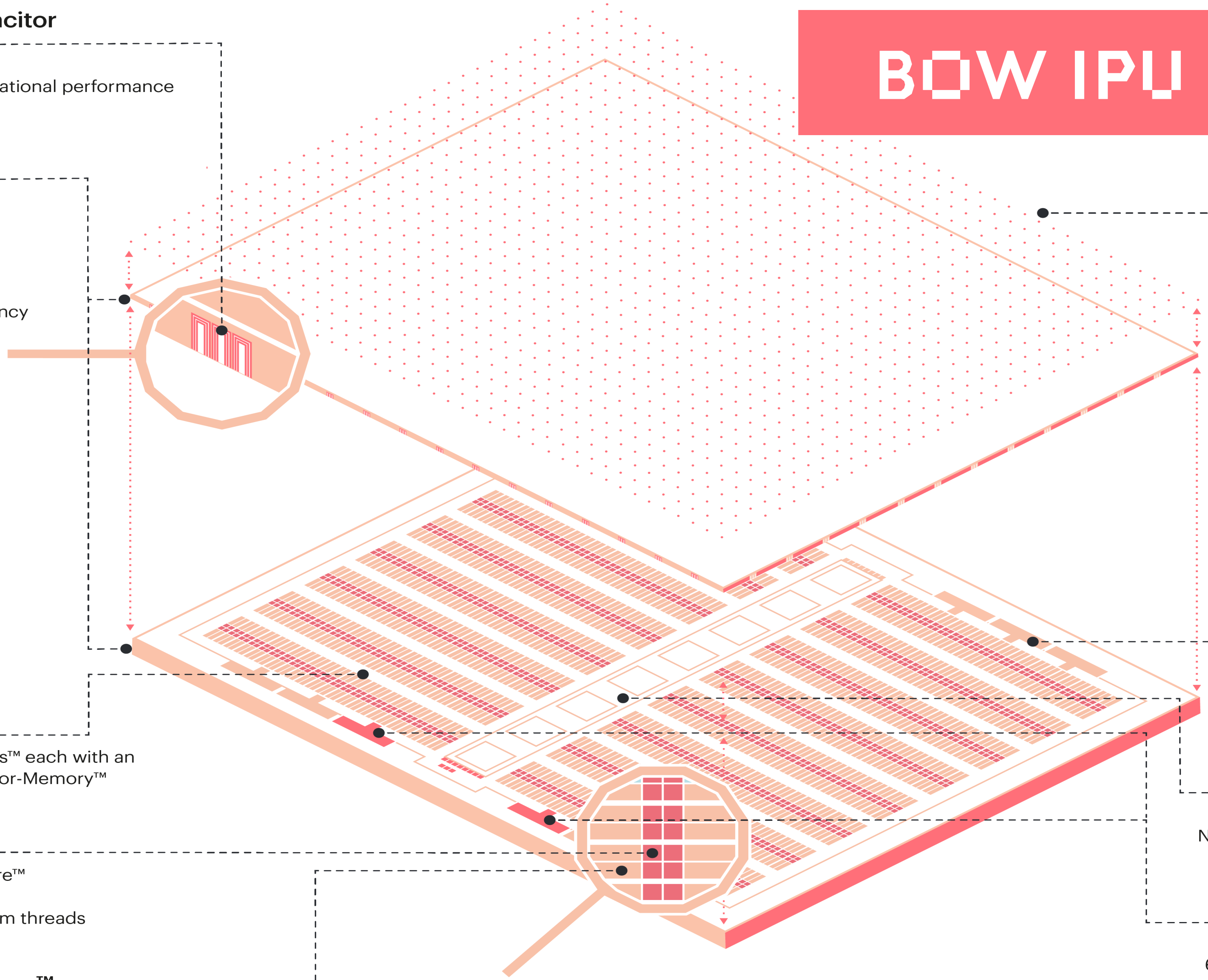
Hard to vectorize workloads. E.g. CRR algorithm for option pricing

References:
https://www.graphcore.ai/performance-results
https://www.graphcore.ai/posts/how-we-made-efficientnet-more-efficient
https://www.graphcore.ai/posts/delving-deep-into-modern-computer-vision-models
https://www.graphcore.ai/posts/training-neural-networks-in-low-dimensional-random-bases
https://www.graphcore.ai/posts/man-group-unlocks-massively-parallel-option-pricing-with-graphcore-ipu

WORKLOADS THAT CAN'T EASILY BE VECTORIZED

- Workloads with while loops that continue until convergence is achieved e.g. ray tracing
- Workloads where different compute paths are required depending on the inputs e.g. CRR model
- Tree-based models with unbalanced trees of different depth

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™

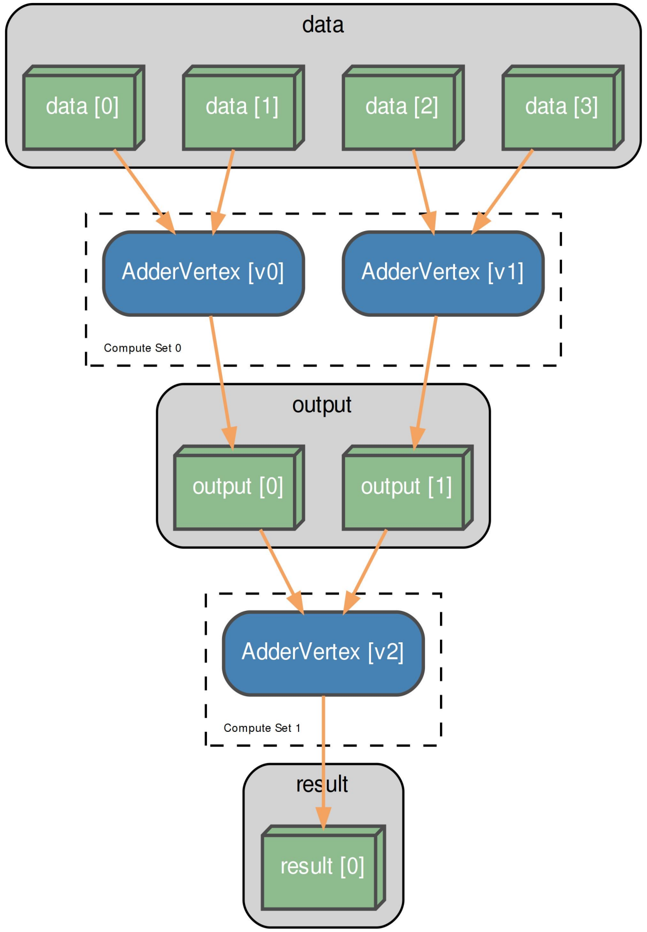
11 TB/s all to all IPU-Exchange™
Non-blocking, any communication pattern

PCIe

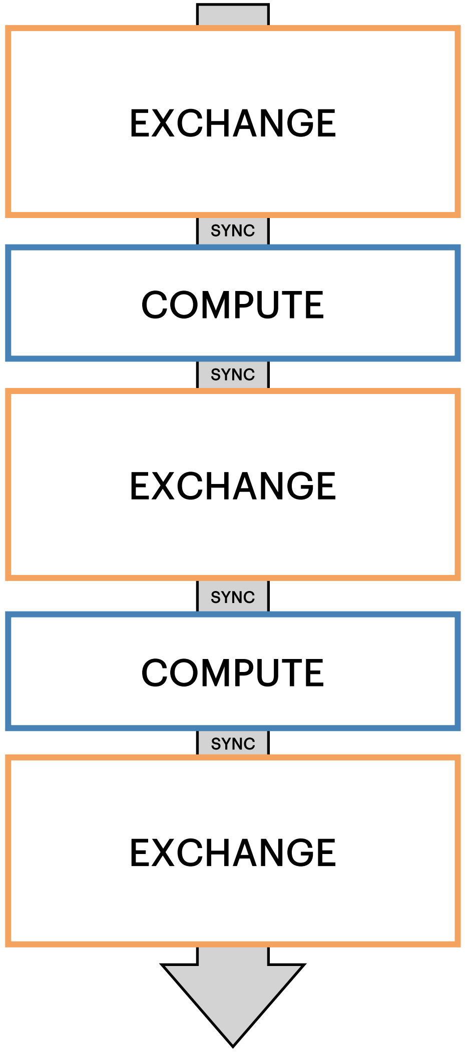
PCI Gen4 x16
64 GB/s bidirectional bandwidth to host

EXECUTION MODEL

COMPUTATIONAL GRAPH

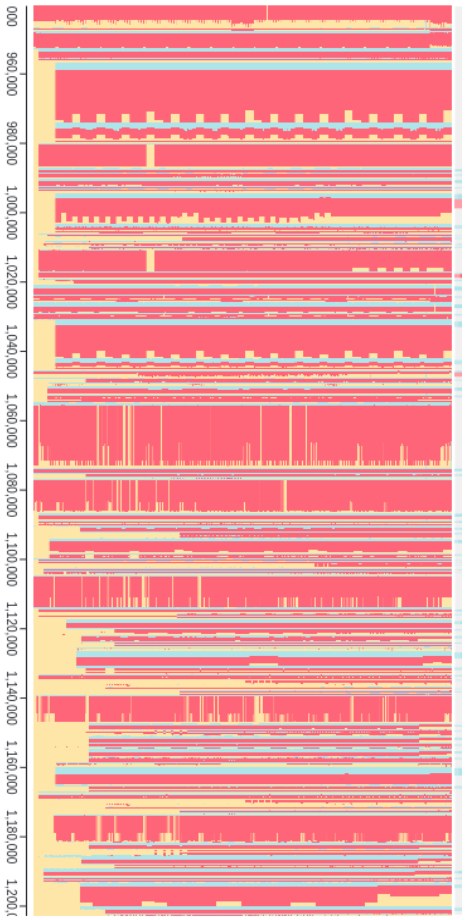


BSP SCHEDULE



OPTIMIZED IPU EXECUTION

BSP EXECUTION TRACE - IPU TILES 0 - 1215



OUTPUT FROM POPVISION GRAPH ANALYSER

BOW-2000 IPU MACHINE

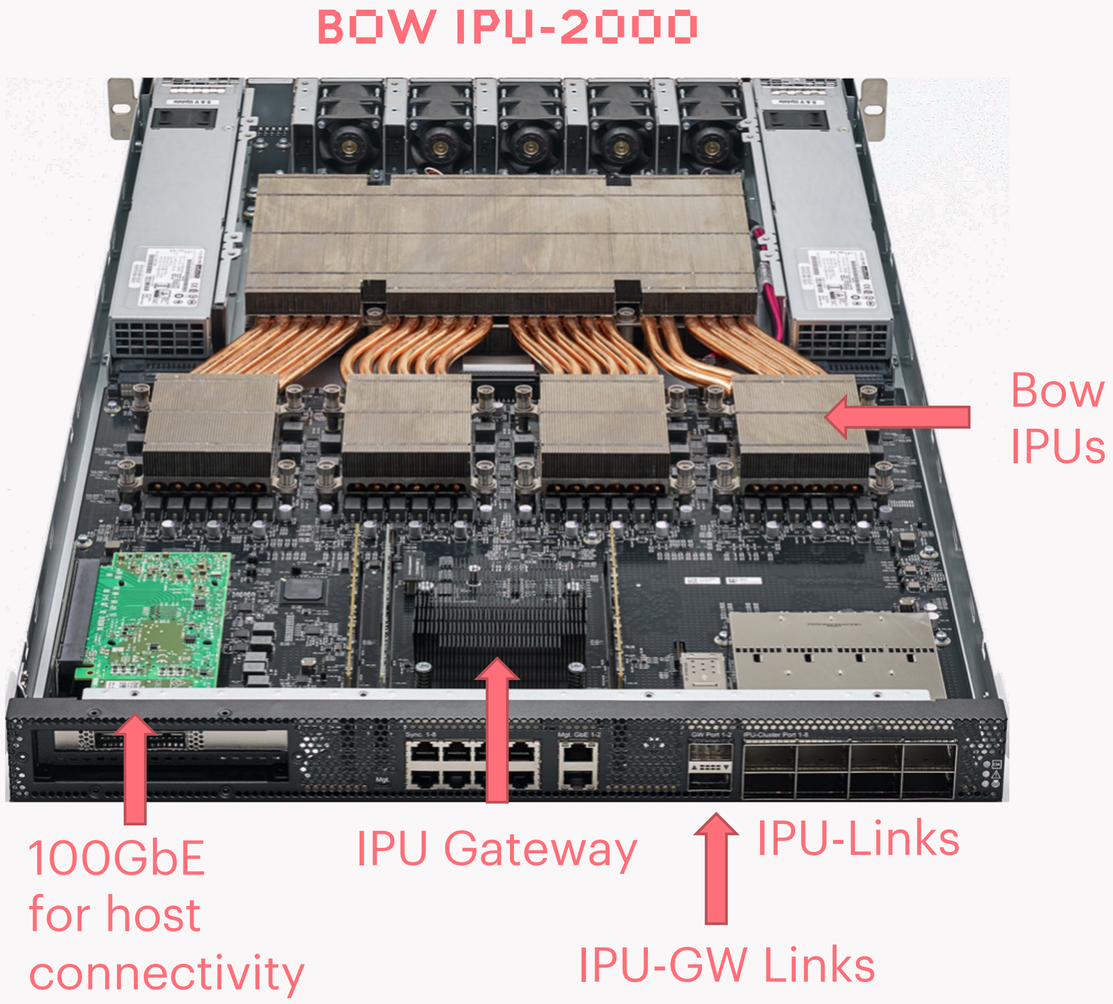
IU blade form factor delivering 1.4 PetaFLOPS AI Compute

Disaggregated AI/ML accelerator platform

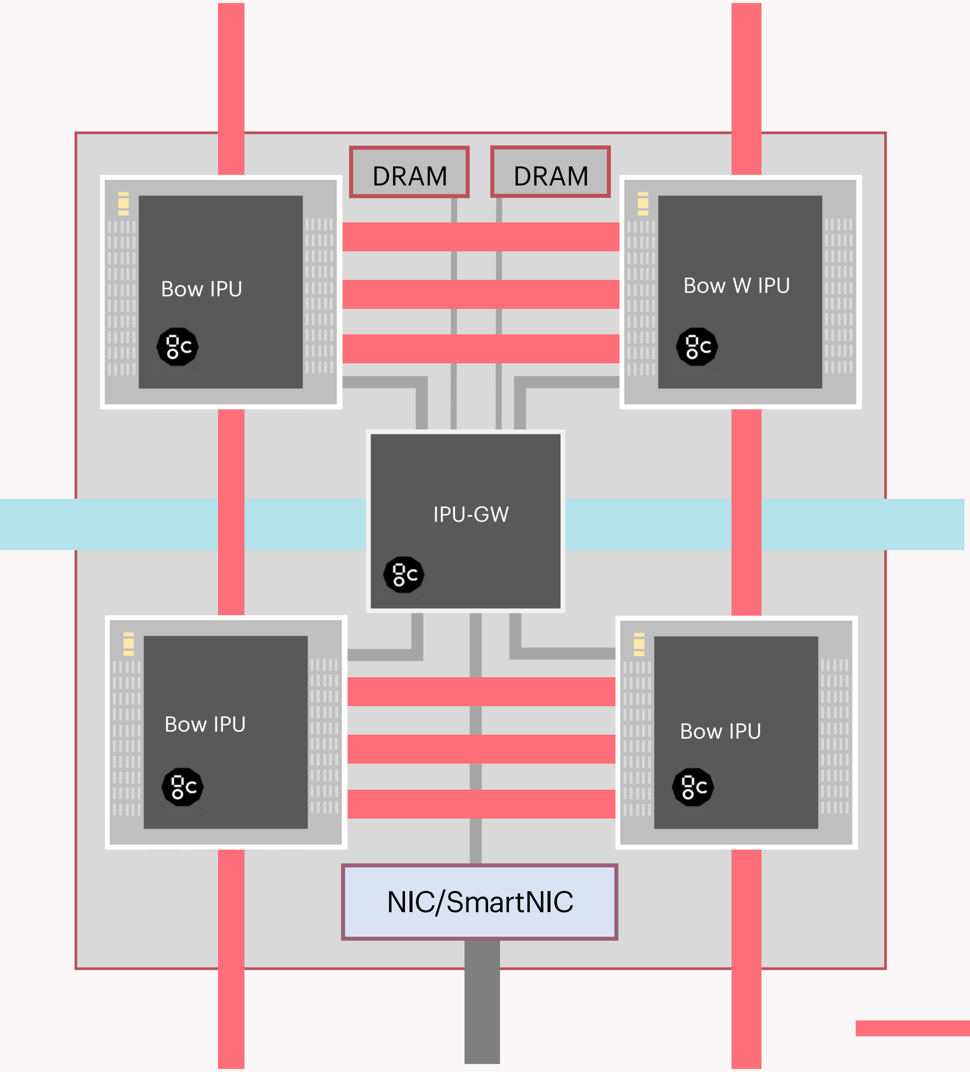
Excellent performance & TCO leveraging In-Processor memory & IPU-Exchange

IPU-Links scale to Bow Pod64

Expansion to Bow Pod256 and beyond with IPU-GW Links



BOW-2000: THE BUILDING BLOCK OF LARGE PODS



x16 IPU-Link [64GB/s]

Host-Link Network I/F [100Gbps]

IPU-GW Link [100Gbps]

x8 PCIe G4 [32GB/s]

COMPUTE

4x Bow IPUs

- 1.4 PFLOP_{16} compute
- 5,888 processor cores
- > 35,000 independent parallel threads

DATA

Exchange Memory

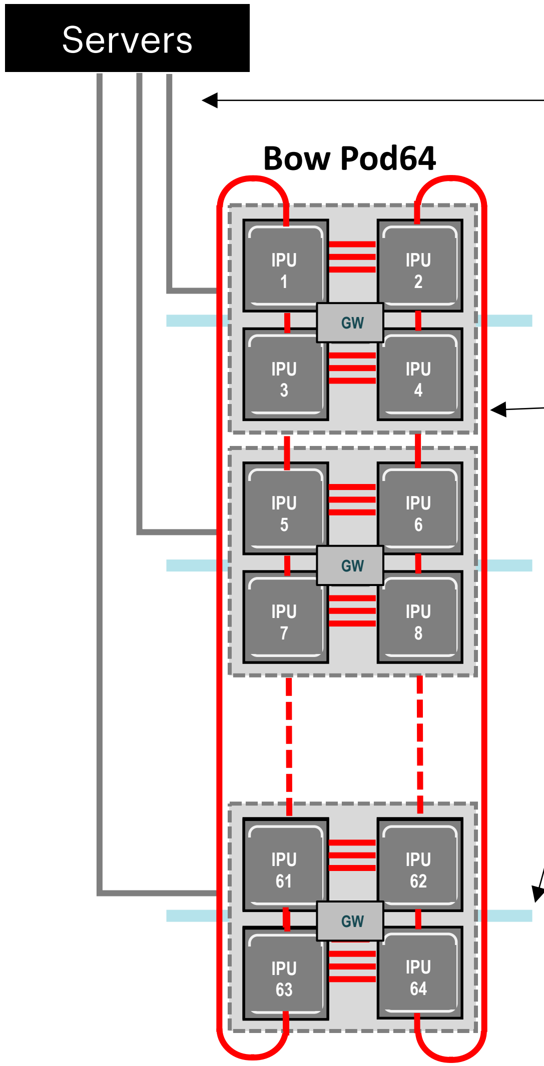
- 3.6GB In-Processor Memory @ 260 TB/s
- 128GB Streaming Memory DRAM (up to 256GB)

COMMUNICATIONS

IPU-Fabric managed by IPU-GW

- Host-Link – 100GE to Poplar Server for standard data center networking
- IPU-Link – 2D Torus for intra-POD64 communication
- GW-Link - 2x 100Gbps Gateway-Links for rack-to-rack – flexible topology

HOST AND IPU-FABRIC ENABLES LARGE SCALEOUT PODS



Host-Links:
100Gbps connectivity for each Bow-2000 to host server

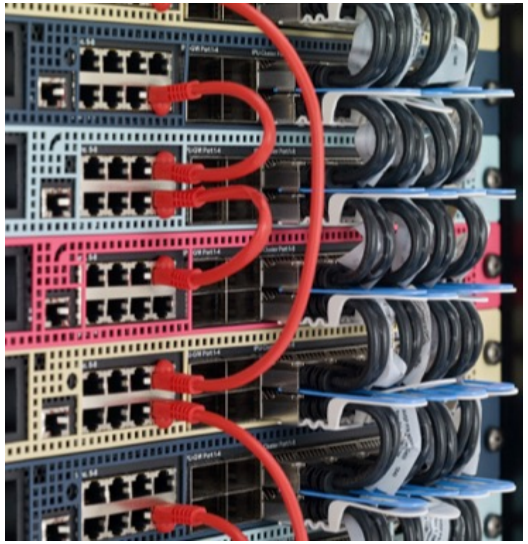
Enabling disaggregation of host server, with optimal server/Bow-2000 ratio.

IPU-Links (part of IPU-Fabric):
2D Torus for IPU communication

Providing high bandwith connectivity across IPUs up to Pod64

GW-Links (part of IPU-Fabric):
2x 100Gbps Gateway-Links for rack-to-rack communication

Redundant rack-to-rack communication for large scaleout beyond Pod64



2.8 Tbps* ultra-low latency fabric designed for AI

x16 IPU-Link 64GB/s

100Gbps Host-Link Network I/F

100Gbps IPU-GW Link

x8 PCIe G4 32GB/s

*Bandwidth for a Bow-2000

HANDS-ON:

GET STARTED

RUN AN EXAMPLE

HANDOUT

bit.ly/tamu230221

MODELS AND SOFTWARE

GRAPHCORE

STANDARD ML FRAMEWORK SUPPORT

Develop models using standard high-level frameworks or port existing models

PyTorch

TensorFlow

PyTorch Lightning

HUGGING FACE

PyG

Keras

PaddlePaddle

HALO

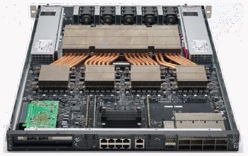
TensorFlow PyTorch HUGGING FACE PyG Keras PyTorch Lightning PaddlePaddle HALO

Existing models on alternative platforms

Easy port of high-level framework models

TensorFlow PyTorch HUGGING FACE PyG Keras PyTorch Lightning PaddlePaddle HALO

POPLAR®



IPU-Processor Platforms

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
- JUPYTER NOTEBOOKS
- INFERENCE DEPLOYMENT TOOLKIT

FRAMEWORKS
- ONNX
- HALO
- Keras
- 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 workload manager
  - SLURM

PROGRAMMING ON IPU

DOCS AND TUTORIALS

USEFUL ENV VARIABLES

FRAMEWORKS

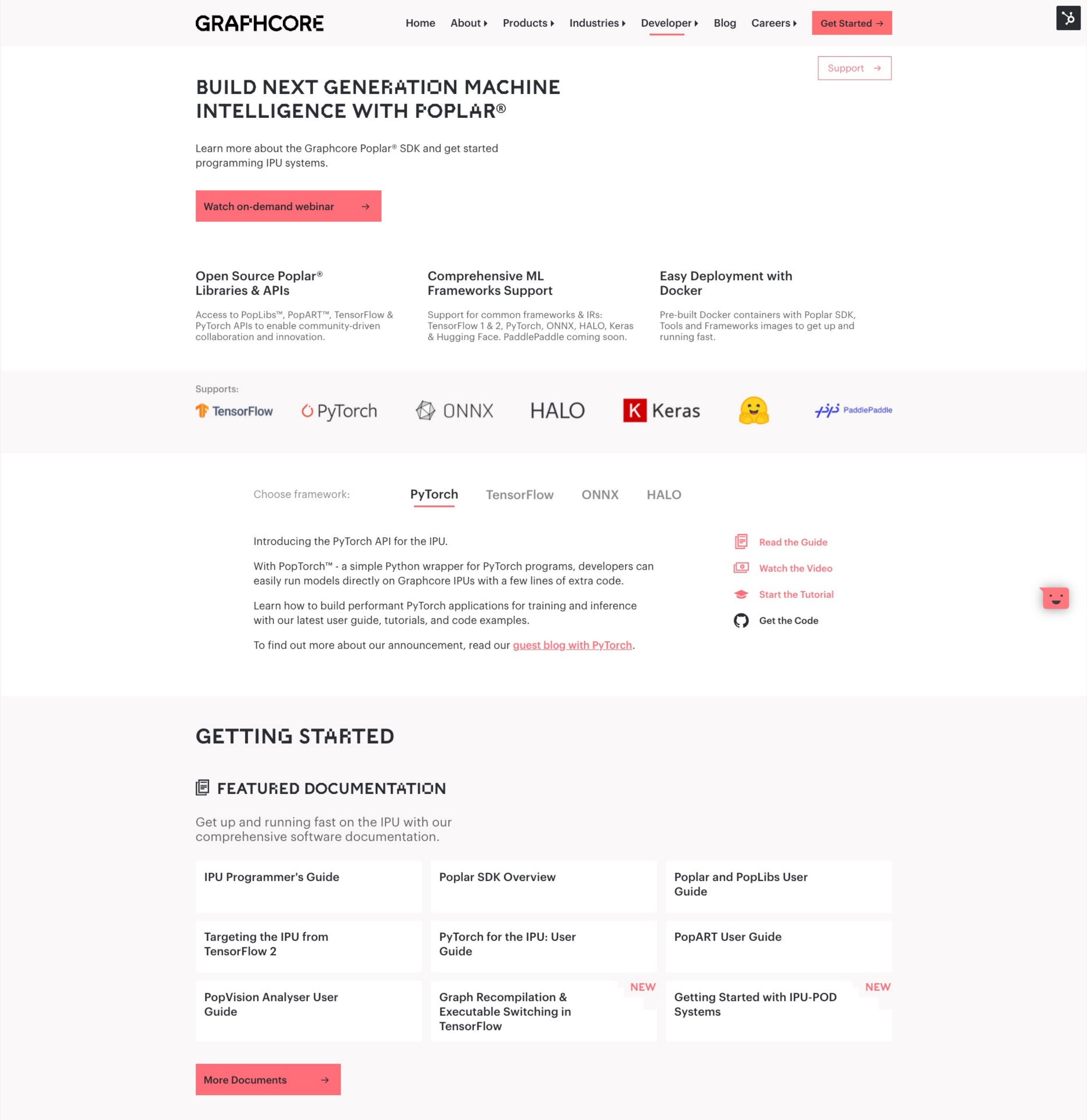
POPVISION

DEVELOPER RESOURCES

DEVELOPER PORTAL

graphcore.ai/developer

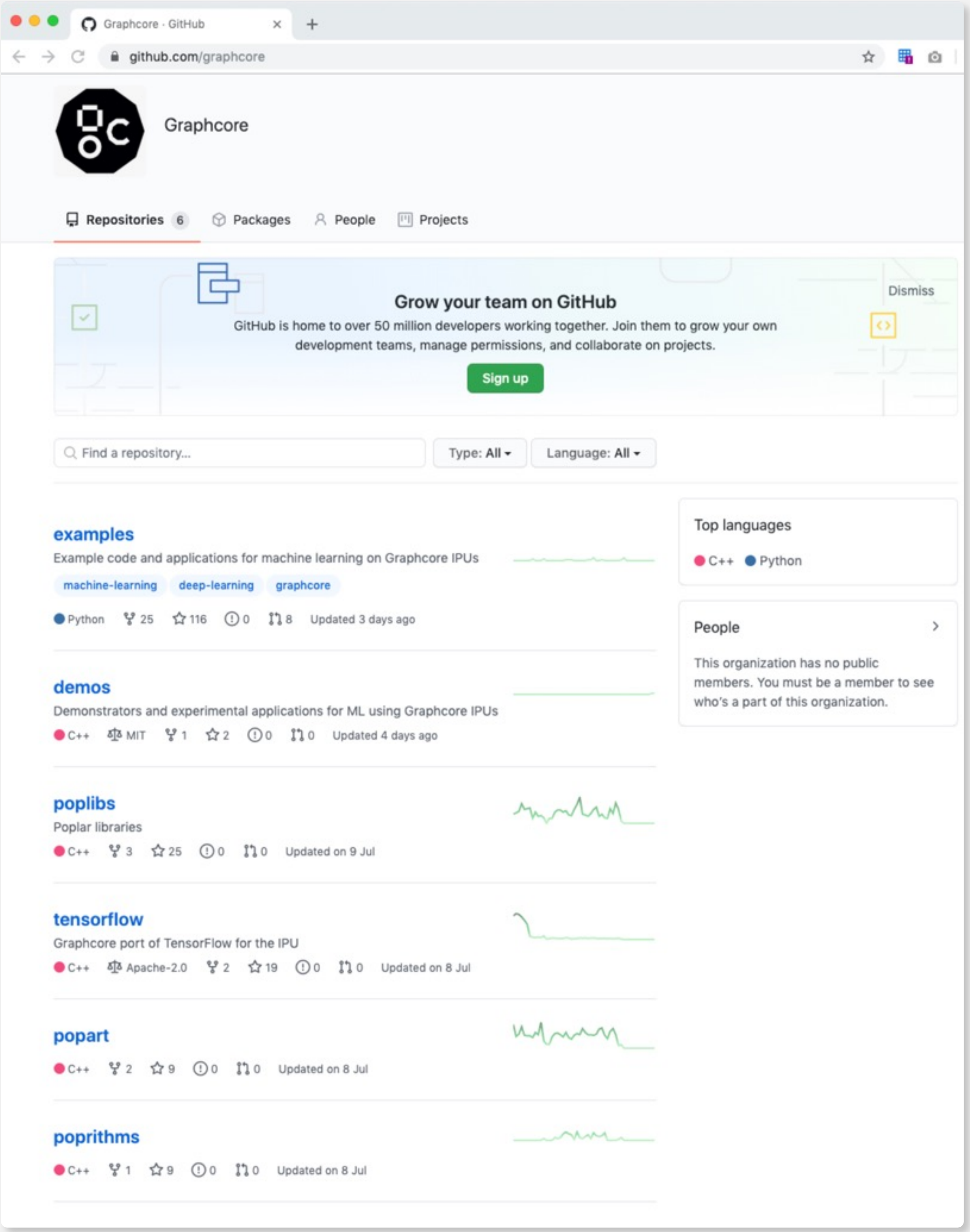
- Public hub for developers to access:
  - Software documentation
  - How-to videos
  - Code tutorial walkthroughs
  - Performance Benchmarks
  - Community support
  - Developer news
- Learn about the Poplar® SDK and how to easily run ML models on IPU systems



OPEN SOURCE

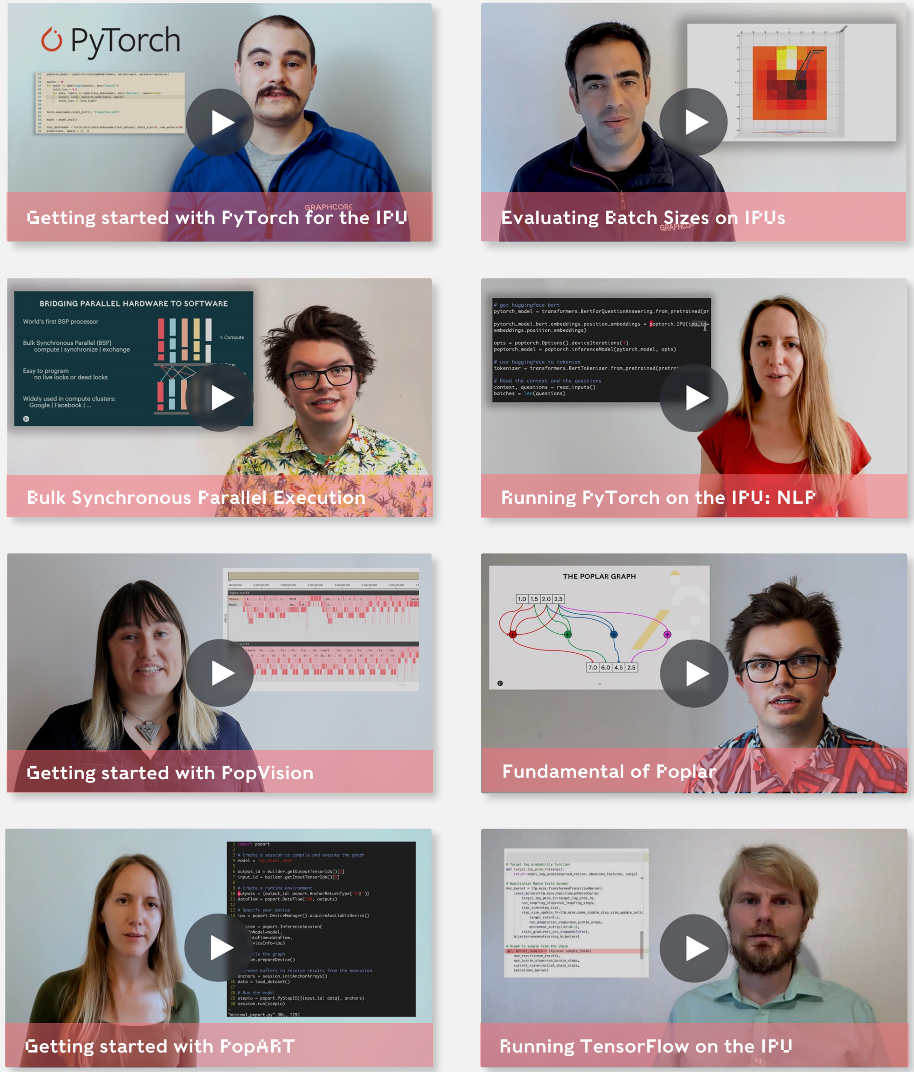
github.com/graphcore

- As part of our ethos to put power in the hands of AI developers, Graphcore open sourced in 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

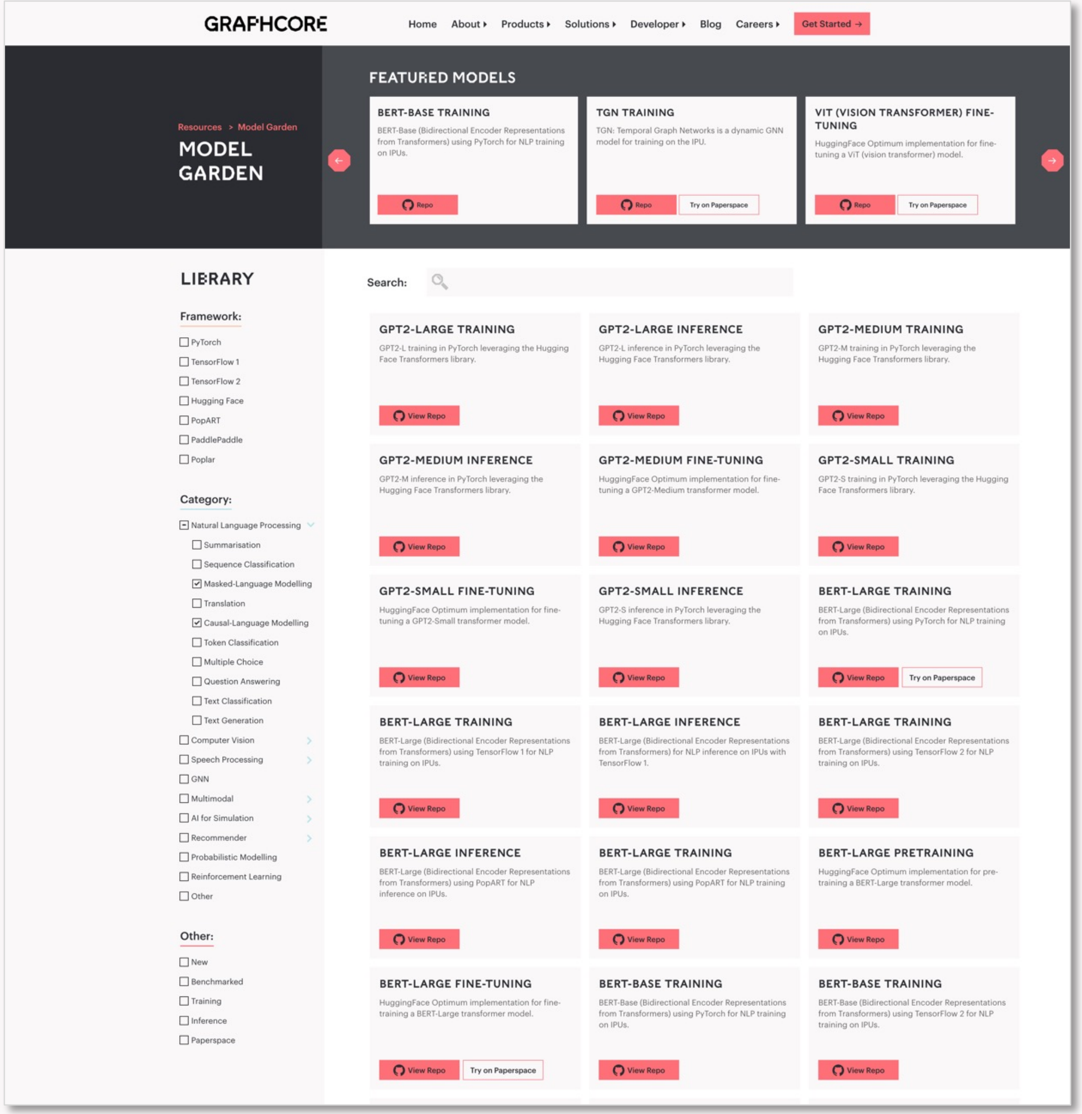
This tutorial contains a complete training program that performs a logistic regression on the MNIST data set, using gradient descent. The files for the demo are in `tut5_ml`. There are no coding steps in the tutorial. The task is to understand the code, build it and run it. You can build the code using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

ENHANCED MODEL GARDEN



PUBLIC ACCESS TO WIDE VARIETY OF MODELS, READY TO RUN ON IPU

NEW FILTER/SEARCH CAPABILITY

DIRECT ACCESS TO GITHUB

PAPERSPACE NOTEBOOK LINKS

MODEL GARDEN COVERAGE

COMPUTER VISION

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

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

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

GNN
- TGN
- MPNN-GIN
- GPS++ NEW
- Cluster-GCN
- SchNet
- Distr. KGE NEW

AI FOR SIMULATION
- DeepMD
- DeepDriveMD
- ETO
- CosmoFlow
- ABC Covid-19

REINFORCEMENT
- RL

Reinforcement Learning

PROBABILISTIC
- MCMC
- VAE

NLP
- BERT-Base
- BERT-Large
- GroupBERT
- PackedBERT
- GPT2
- RoBERTa
- Deberta
- BART
- T5
- Hubert
- DistilBERT NEW

SPEECH

STT (ASR)
- RNN-T
- Conformer

TTS
- DeepVoice3
- FastSpeech2
- FastPitch

RECOMMENDER
- Autoencoder
- DIN
- DIEN

MULTIMODAL
- LXMERT
- CLIP
- Mini DALL-E
- Frozen In Time NEW
- Stable Diffusion NEW

OTHER
- Sales Forecast
- Neural Image Fields

TensorFlow

PyTorch

Hugging Face

Keras

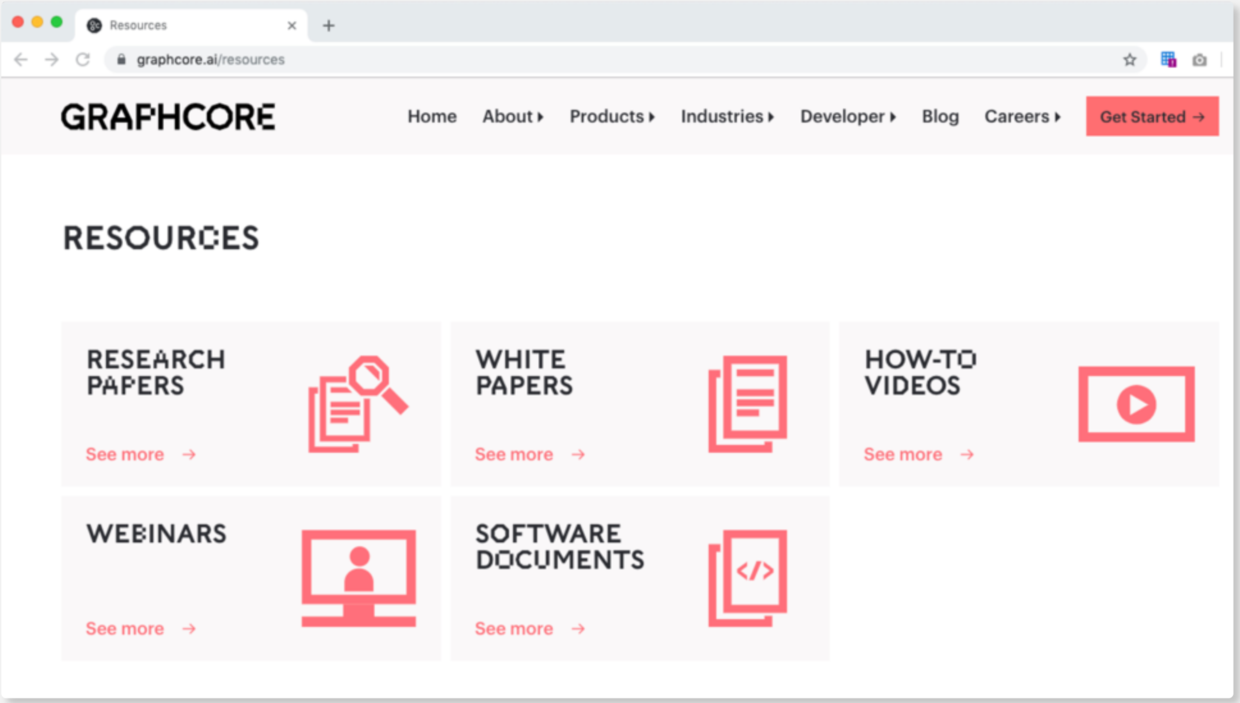
PaddlePaddle

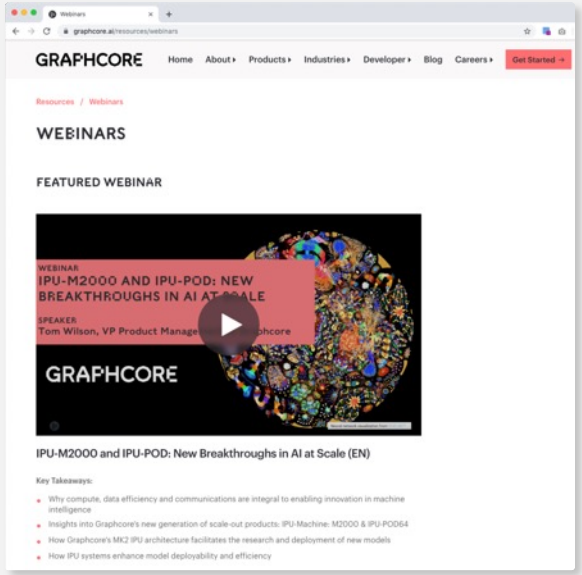
POPART

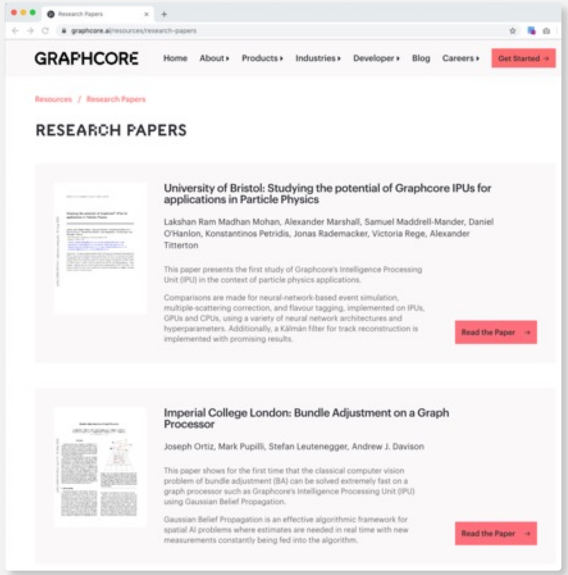
RESOURCES CENTRE

graphcore.ai/resources

- 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.

CREATE EXECUTION PROFILE

```
POPLAR_ENGINE_OPTIONS='{"autoReport.all":"true", "autoReport.directory":"./report"}'
```

- 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.

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.

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.

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          2.168
Epoch 2/40
1560/1560 [==============================] - 5s 3ms/step - loss: 1.880
Epoch 3/40
1560/1560 [==============================] - 5s 3ms/step - loss: 1.652
Epoch 4/40
  75/1560 [>.............................] - ETA: 5s - loss: 1.5328 -
```

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

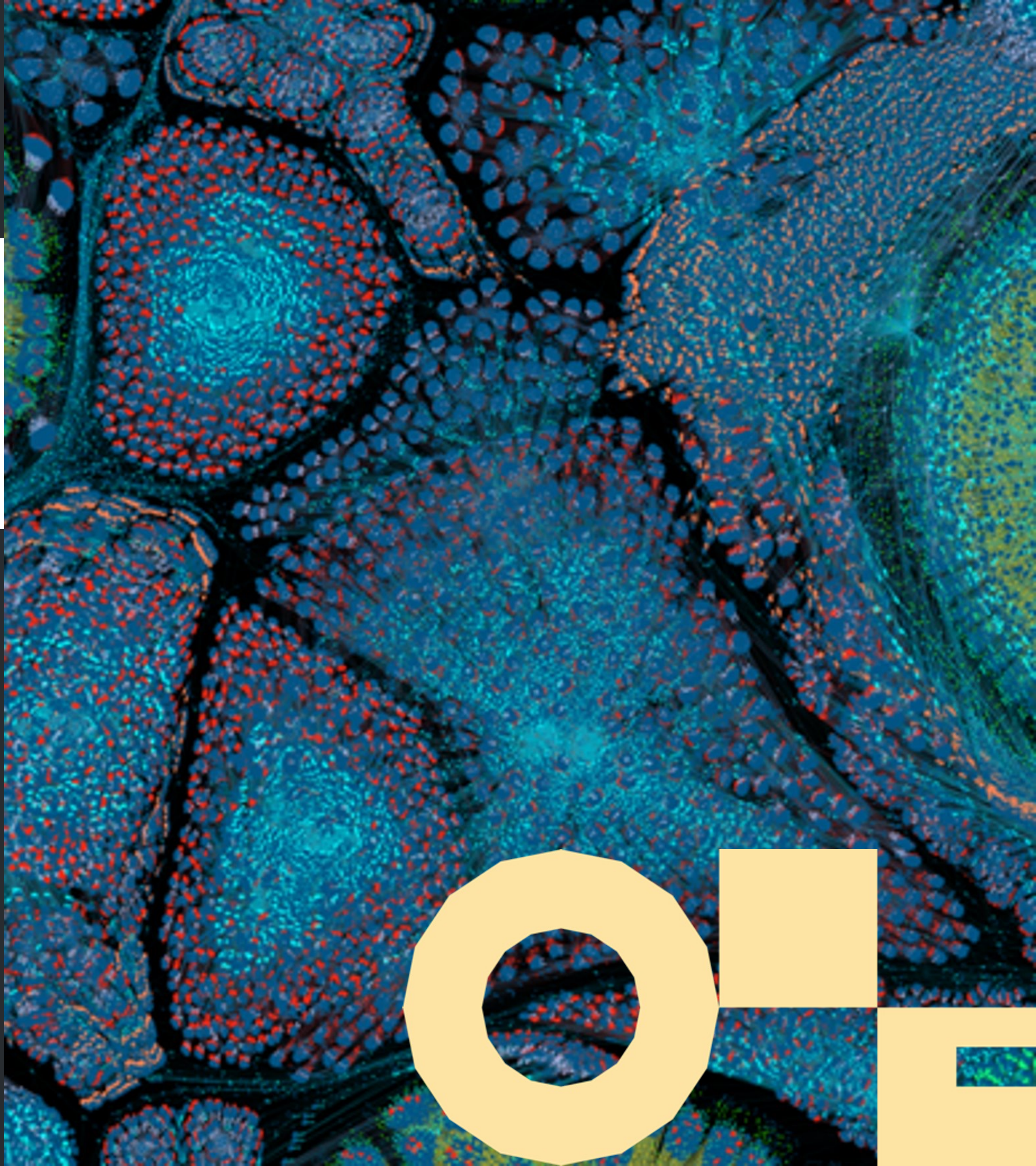
IPU

```
$ 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_exe
Epoch 1/40
2020-05-12 16:40:35.898895: I tensorflow/compiler/jit/xla_compilation_cache.cc:25
 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

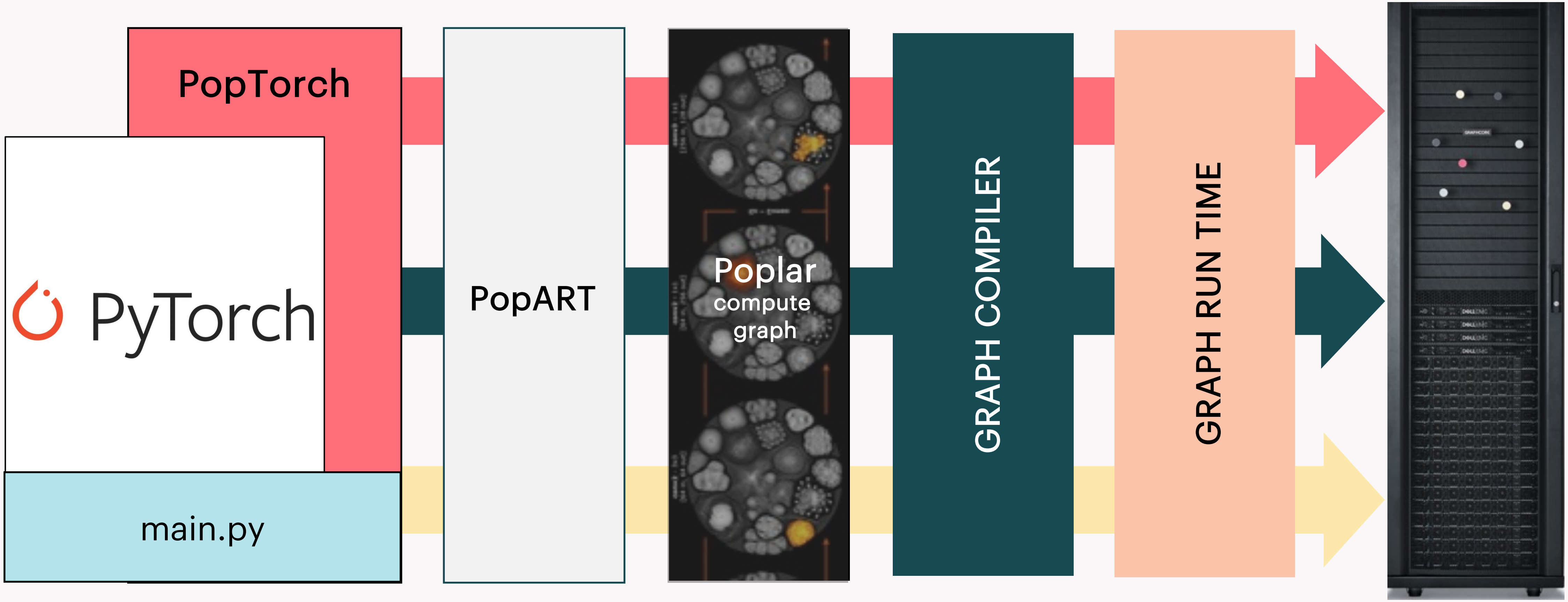
https://github.com/graphcore/tutorials/tree/master/tutorials/tensorflow2/keras

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 (de
    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 (de
    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/

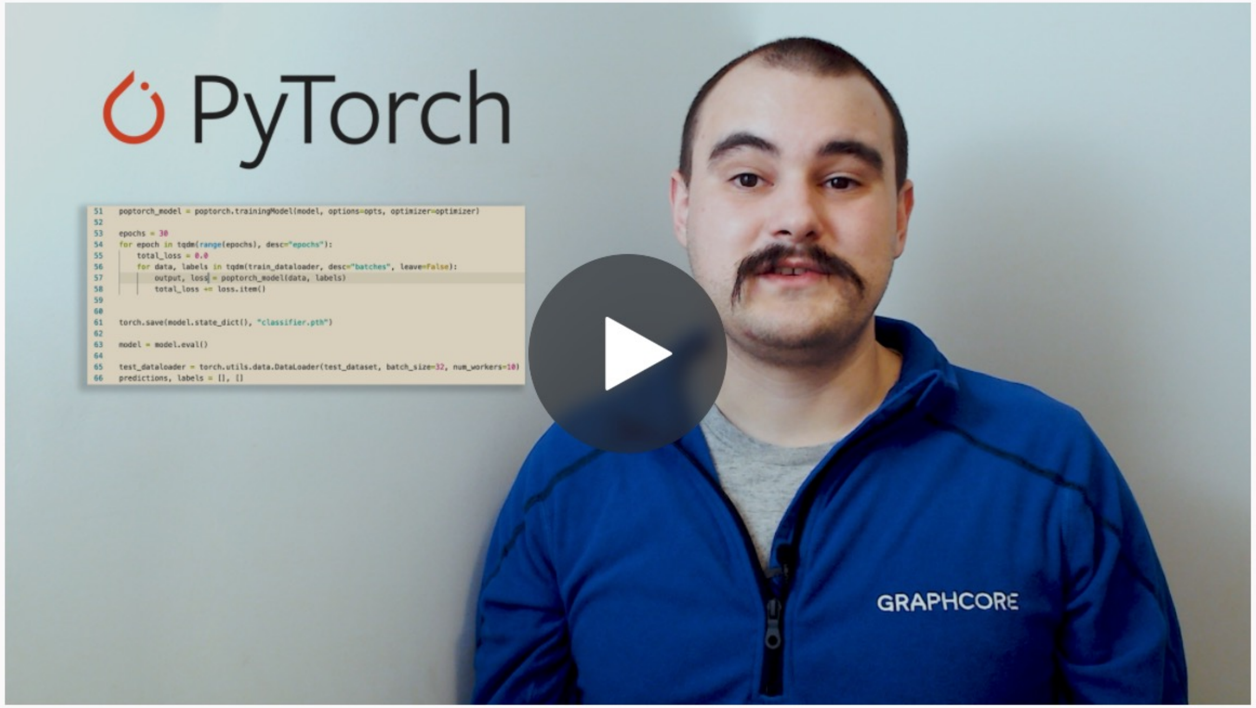
- GitHub tutorial
https://github.com/graphcore/examples/tree/master/tutorials/pytorch/tut1_basics

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

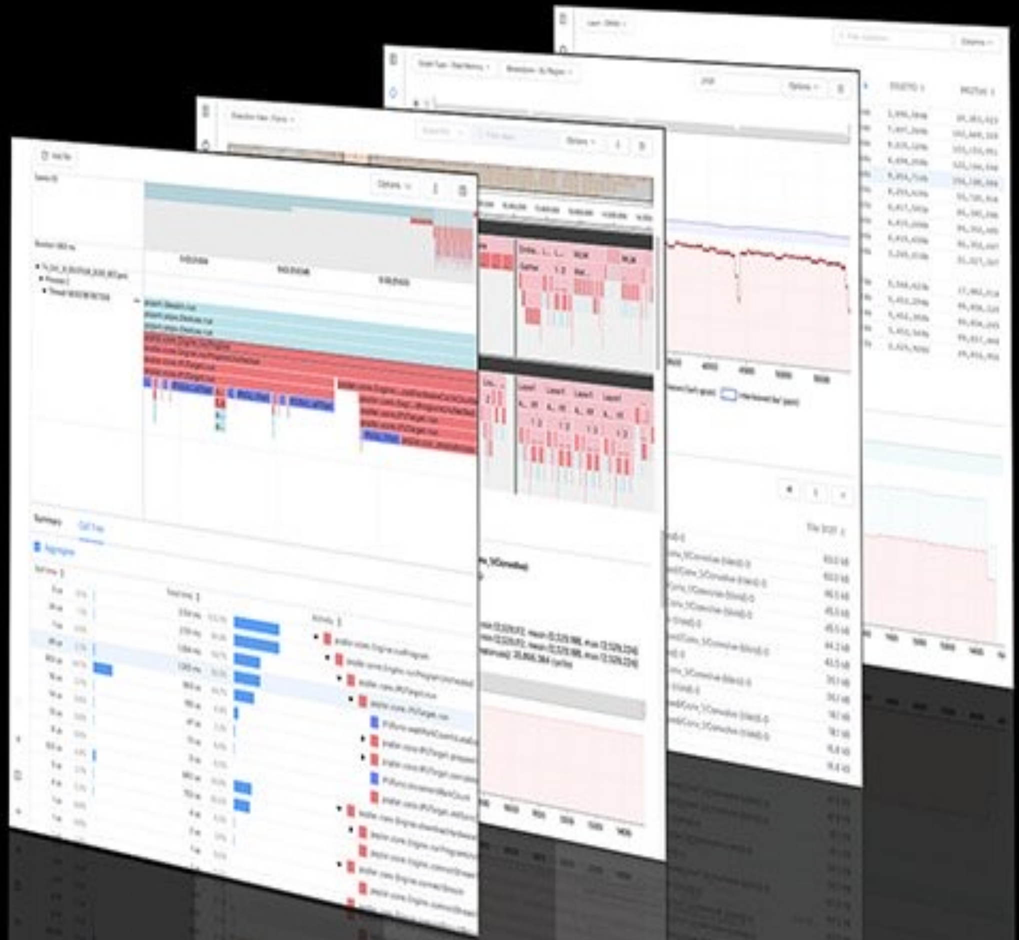
- Video tutorial on our developer page
https://www.graphcore.ai/developer

Getting started with PyTorch for the IPU

Running a basic model for training and inference



POPVISION™ TOOLS



GRAPH ANALYSER

Useful for analysing and optimising the memory use and execution performance of ML models on the IPU

SYSTEM ANALYSER

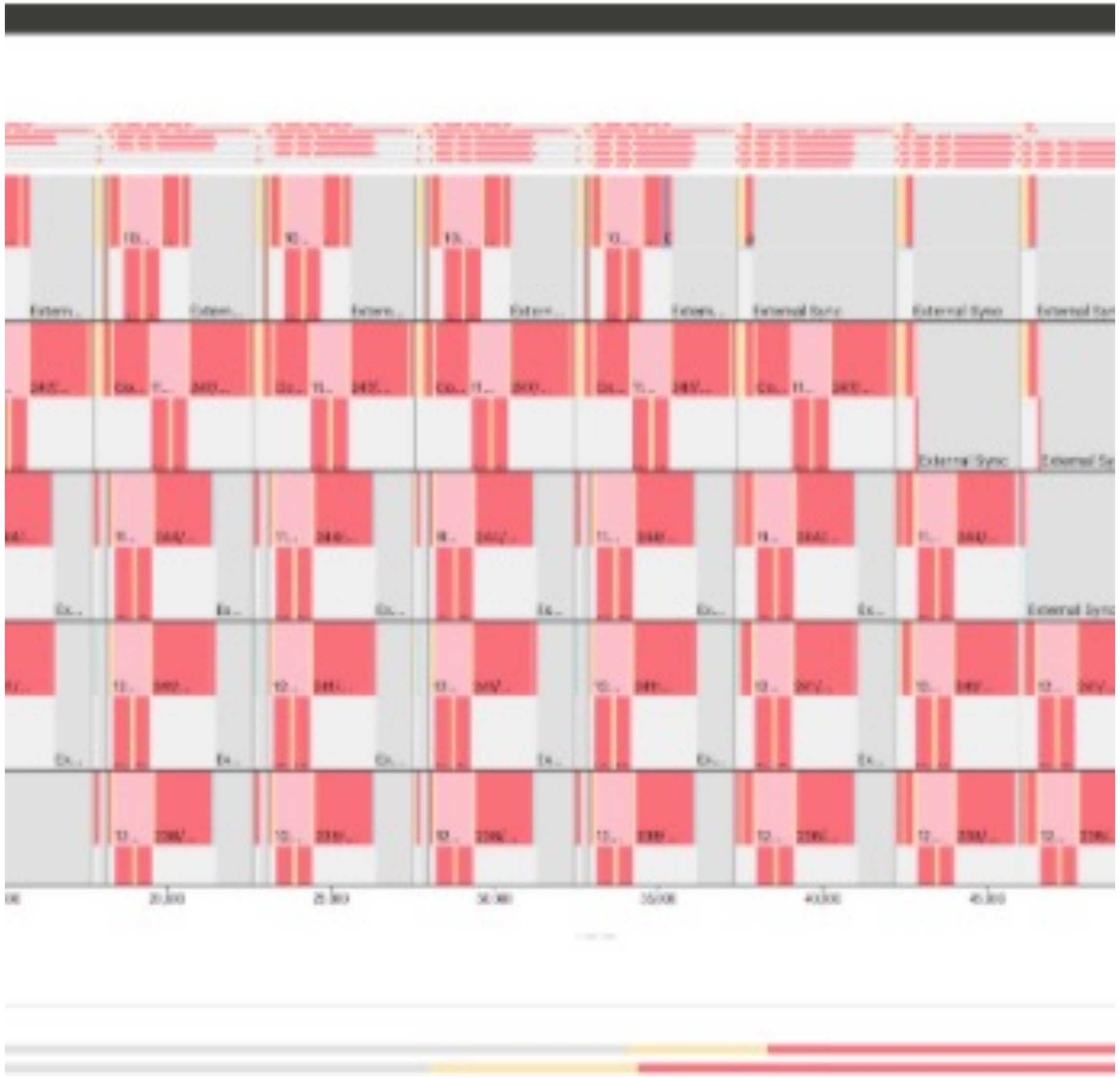
Graphical view of the timeline of host-side application execution steps

"Our team was very impressed by the care and effort Graphcore has clearly put into the PopVision graph and system analysers. It's hard to imagine getting such a helpful and comprehensive profiling of the code elsewhere, so this was really a standout feature in our IPU experience."

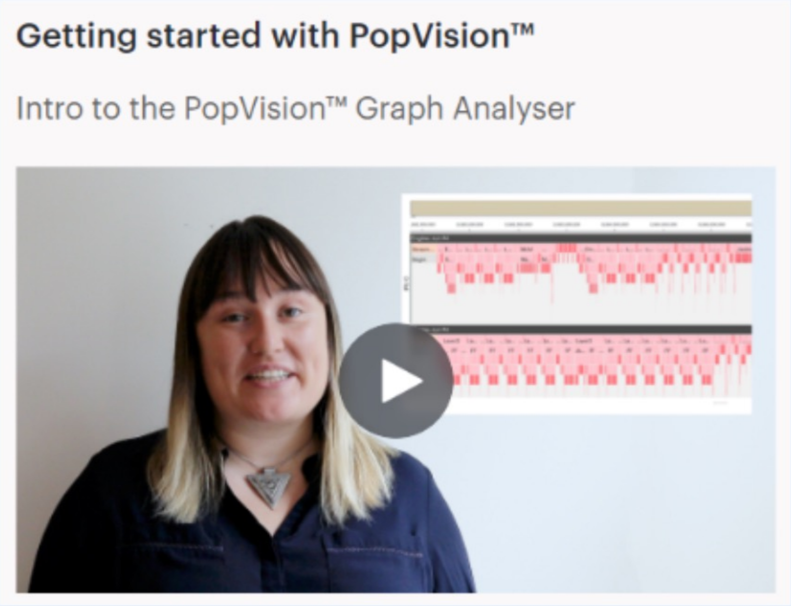
Dominique Beaini, Valence Discovery, a leader in AI-first drug design

POPVISION GRAPH ANALYSER

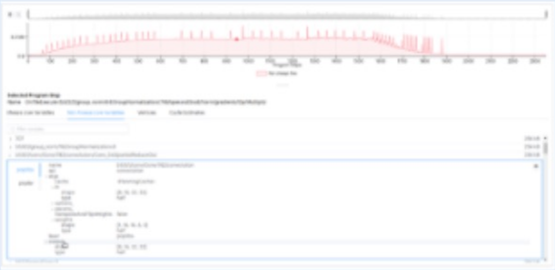
- You can use the PopVision Graph Analyser tool to debug IPU programs and generate reports on compilation and execution of the program.
- This tool can be downloaded from the Graphcore customer support portal: https://downloads.graphcore.ai/.
- There is a built-in help system within the tool for any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



PopVision Graph Analyser



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.

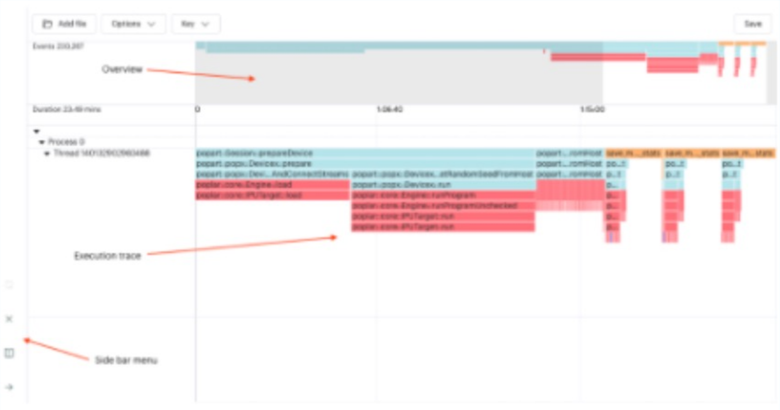
Enhanced debug information has been added to program steps. Program steps show Poplar and PopLibs debug information such as which PopLibs API created that program step, its arguments and its outputs.

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

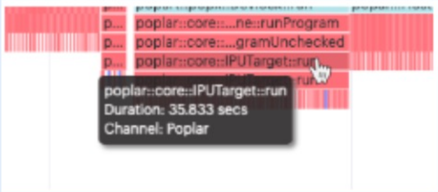
PopVision System Analyser

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.



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.

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

https://www.graphcore.ai/developer

ANY QUESTIONS, REQUESTS, BUGS...

https://www.graphcore.ai/support

ENGINEERING
SUPPORT

Go To Tickets →

THANK YOU

Alexander Tsyplikhin
alext@graphcore.ai