IPU HANDS-ON SESSION

Minkyu Kim
Field AI Engineer

GRAPHCORE

Reinforcement Learning Neural network visualization from POPLAR™

BERT LARGE – POPLAR GRAPH VISUALIZATION FROM POPART

Day01

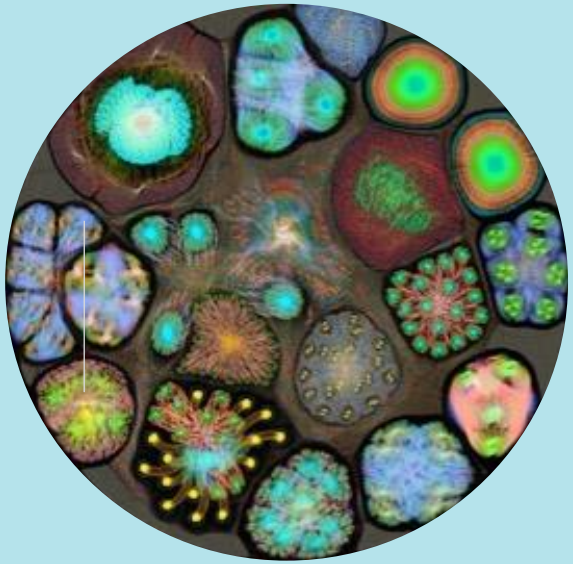
1. IPU HW
2. Poplar SDK
3. Basic porting guide w/ a simple model
   - Pytorch
   - Tensorflow

ABOUT US...

Hardware

IPU processors
designed for AI

Software



Poplar® software stack &
development tools

Platforms

M2000 and Server
IPU-POD$_{64}$ scale-out

The Hardware Lottery

Sara Hooker

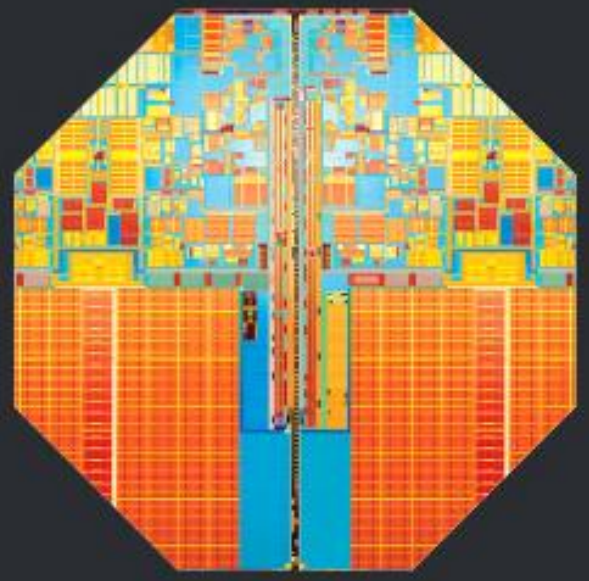
Google Research, Brain Team
shooker@google.com

Abstract

Hardware, systems and algorithms research communities have historically had different incentive structures and fluctuating motivation to engage with each other explicitly. This historical treatment is odd given that hardware and software have frequently determined which research ideas succeed (and fail). This essay introduces the term hardware lottery to describe when a research idea wins because it is suited to the available software and hardware and *not* because the idea is superior to alternative research directions. Examples from early computer science history illustrate how hardware lotteries can delay research progress by casting successful ideas as failures. These lessons are particularly salient given the advent of domain specialized hardware which make it increasingly costly to stray off of the beaten path of research ideas. This essay posits that the gains from progress in computing are likely to become even more uneven, with certain research directions moving into the fast-lane while progress on others is further obstructed.

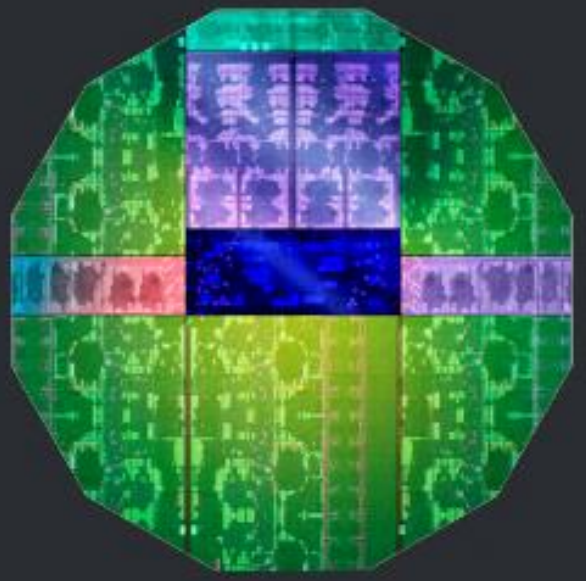
OUR IPU LETS INNOVATORS CREATE THE NEXT BREAKTHROUGHS IN MACHINE INTELLIGENCE

LEGACY PROCESSOR ARCHITECTURES HAVE BEEN REPURPOSED FOR ML



CPU

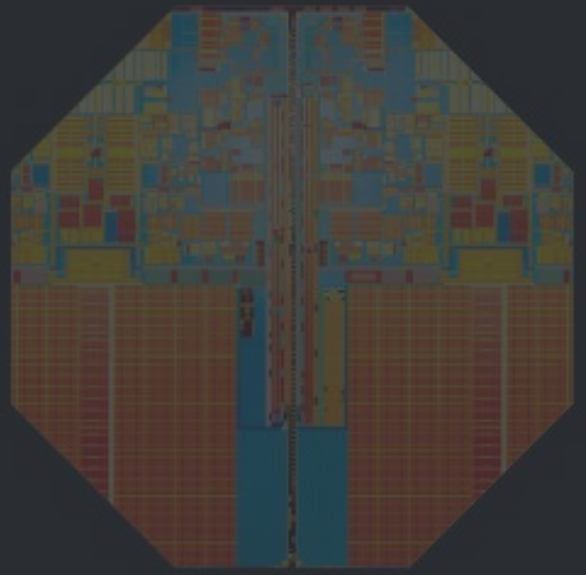
Apps and Web/
Scalar



GPU

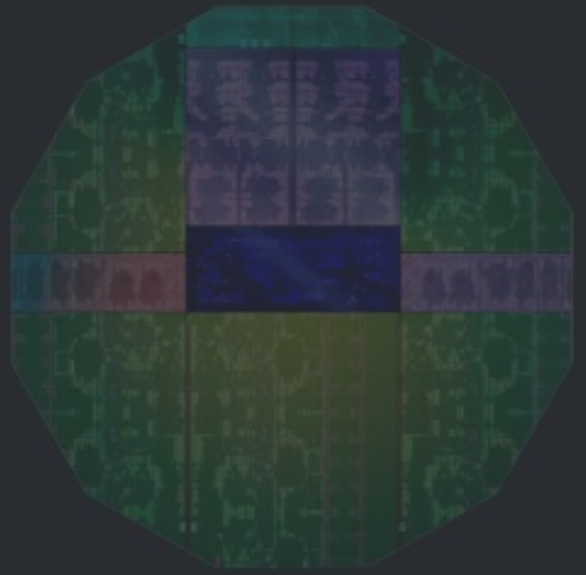
Graphics and HPC/
Vector

A NEW PROCESSOR IS REQUIRED FOR THE FUTURE



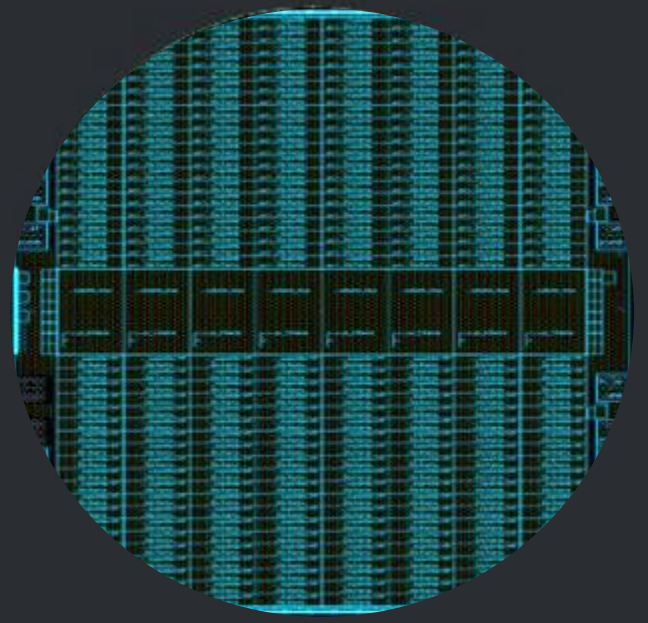
CPU

Apps and Web/
Scalar



GPU

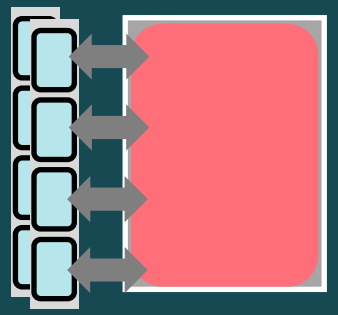
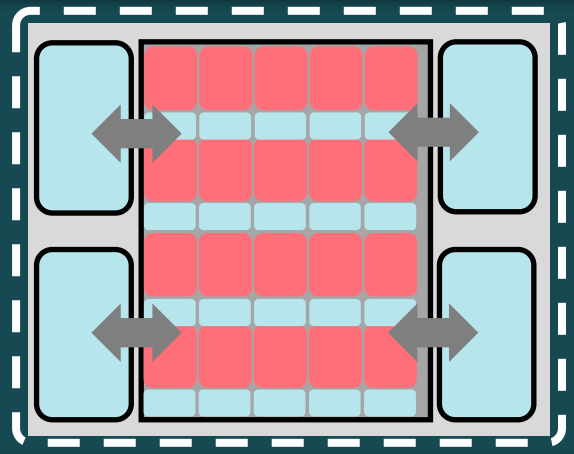
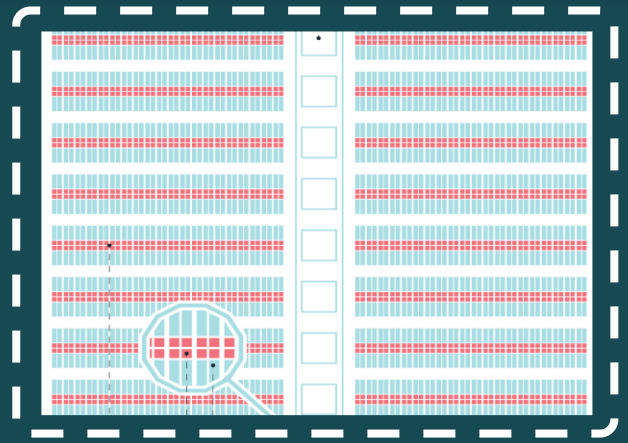
Graphics and HPC/
Vector



IPU

Artificial Intelligence/
Graph

MACHINE LEARNING REQUIRES 2 KINDS OF COMPUTE INNOVATION

	CPU	GPU	IPU
Parallelism	Suitable for scalar processes	SIMD/SIMT architecture. Suitable for large blocks of dense contiguous data	**Massively parallel MIMD. High performance/efficiency as ML trends to sparsity & small kernels**
			
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

GC200 IPU PROCESSOR

IPU-Tiles™

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

IPU-Core™

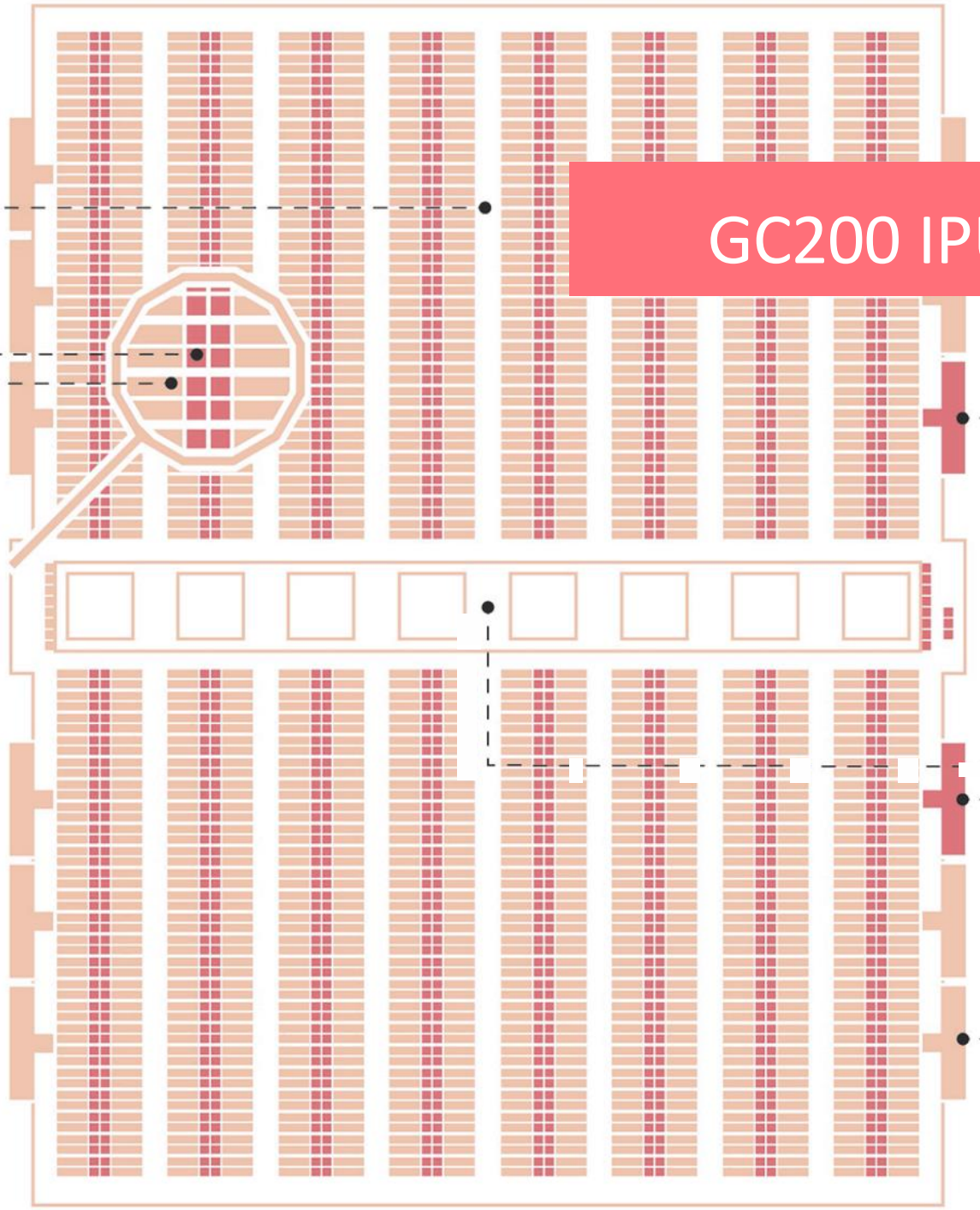
1472 independent IPU-Core™

8832 independent program threads executing in parallel

In-Processor-Memory™

900MB In-Processor-Memory™ per IPU

47.5TB/s memory bandwidth per IPU



IPU-Exchange™

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

PCIe

PCI Gen4 x16
64 GB/s bidirectional bandwidth to host

IPU-Links™

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

COMPUTE

COLOSSUS MK2

the worlds most complex processor

59.4Bn transistors, TSMC 7nm @ 823mm^2

250TFlops AI-Float | 900MB In-Processor-Memory™

1472 independent processor cores

8832 separate parallel threads

>8x step-up in system performance vs Mk1

GC200 IPU

INTRODUCING THE BOW IPU
WORLD'S FIRST 3D WAFER-ON-WAFER PROCESSOR

3D silicon wafer stacked processor

Optimized silicon **power delivery**

350 TeraFLOPS AI compute

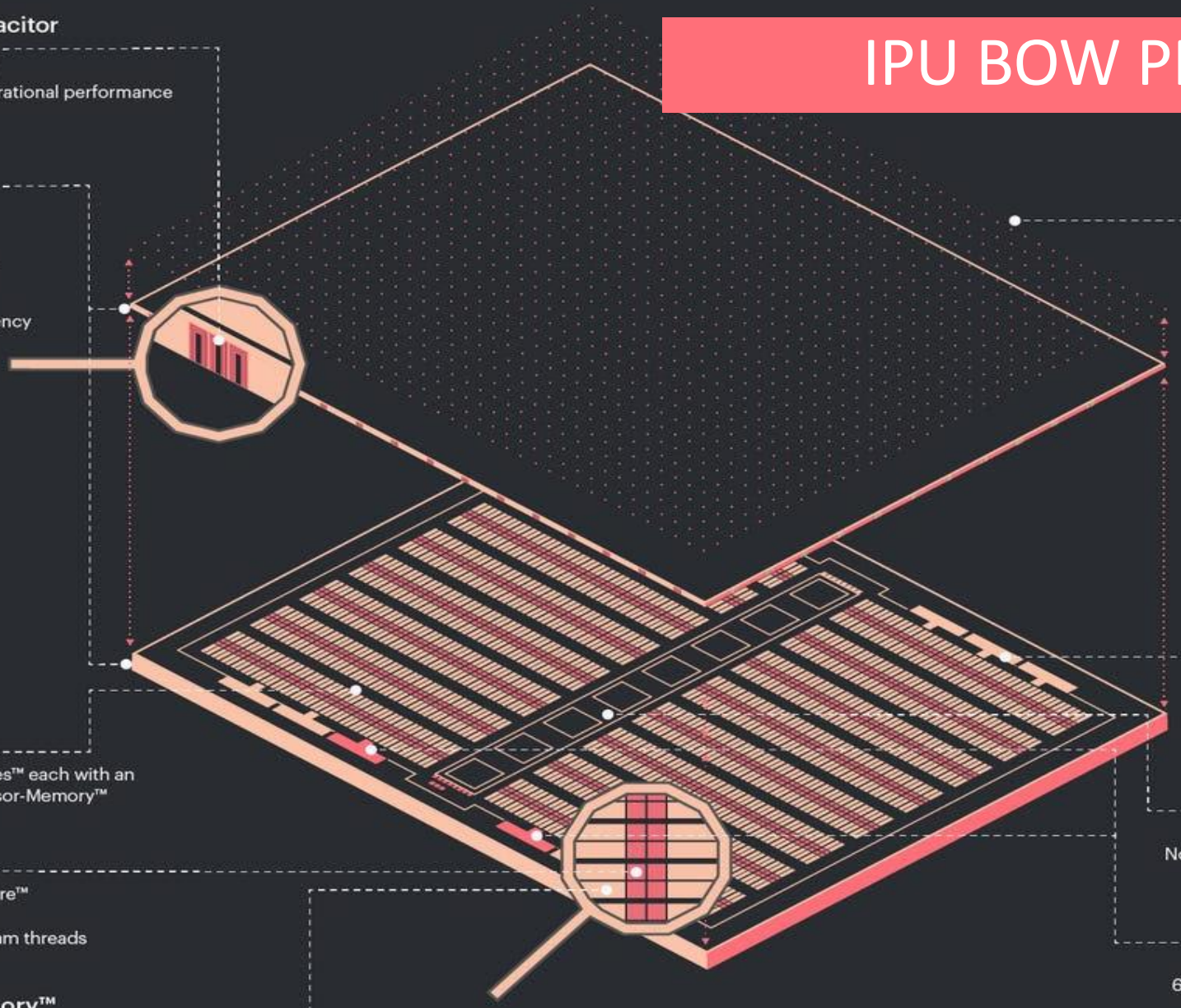
0.9 GigaByte In-Processor-Memory @ **65TB/s**

1,472 independent processor cores

8,832 independent parallel programs

10x IPU-Links™ delivering 320GB/s

IPU BOW 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

GRAPHCORE

BOW-2000 IPU MACHINE

4 x Bow 3D Wafer-on-Wafer IPUs

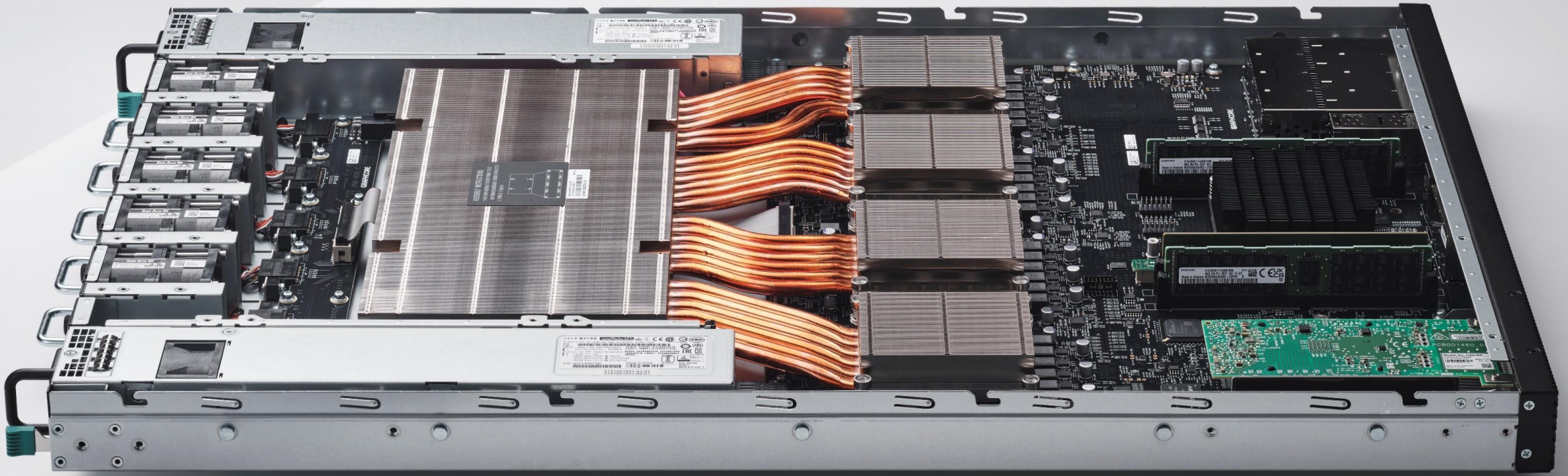
1.4 PetaFLOPS AI Compute

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

Up to 256 GB IPU Streaming Memory

2.8 Tbps IPU-Fabric™

Same 1U blade form factor



GRAPHCORE

BOW: 3RD GENERATION IPU SYSTEMS

BOW POD16

4x Bow-2000
5.6 PetaFLOPS
1 CPU server

BOW POD32

8x Bow-2000
11.2 PetaFLOPS
1 CPU server

BOW POD64

16x Bow-2000
22.4 PetaFLOPS
1-4 CPU server(s)

BOW POD256

64x Bow-2000
89.6 PetaFLOPS
4-16 CPU server(s)

BOW POD1024

256x Bow-2000
358.4 PetaFLOPS
16 - 64 CPU server(s)
Early access

100% SOFTWARE COMPATIBLE

No code changes to run existing IPU applications

Full support in Poplar SDK and reference applications

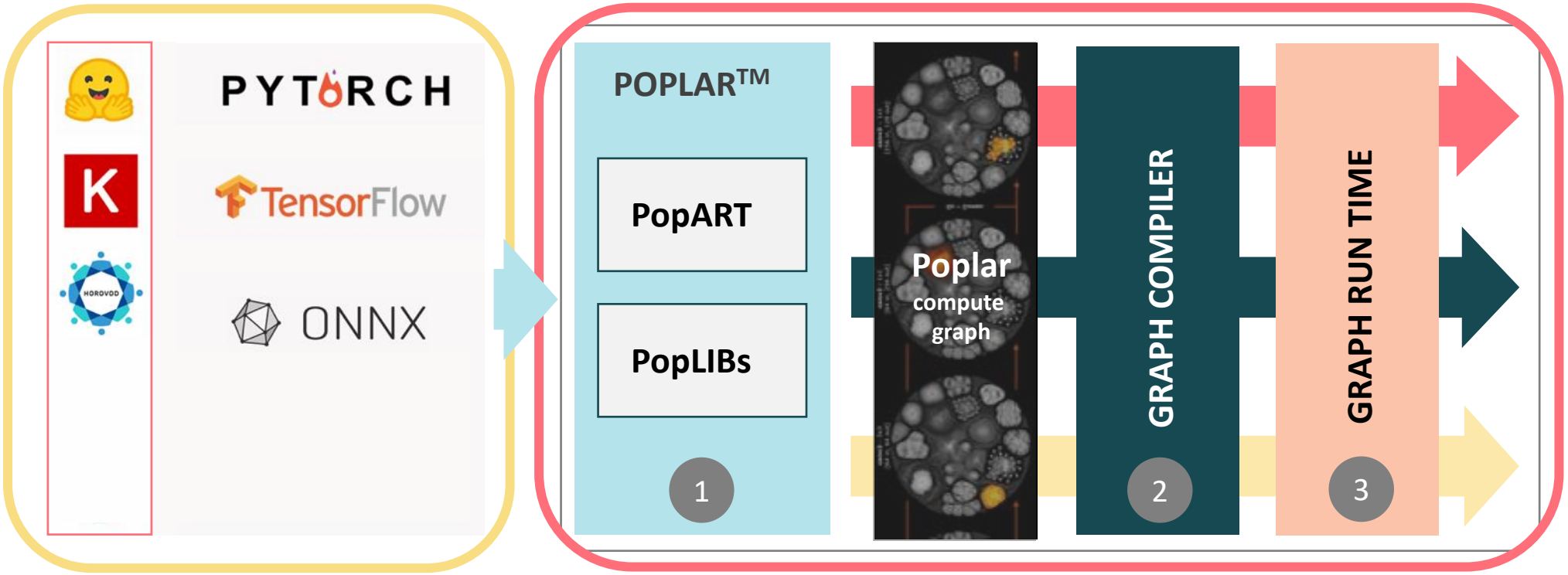
Seamless integration into IPU software ecosystem

THE POPLAR® SDK

BERT LARGE – POPLAR GRAPH VISUALIZATION FROM POPART

POPLAR-SDK

유저 : 일반적인 high-level 프레임워크 사용



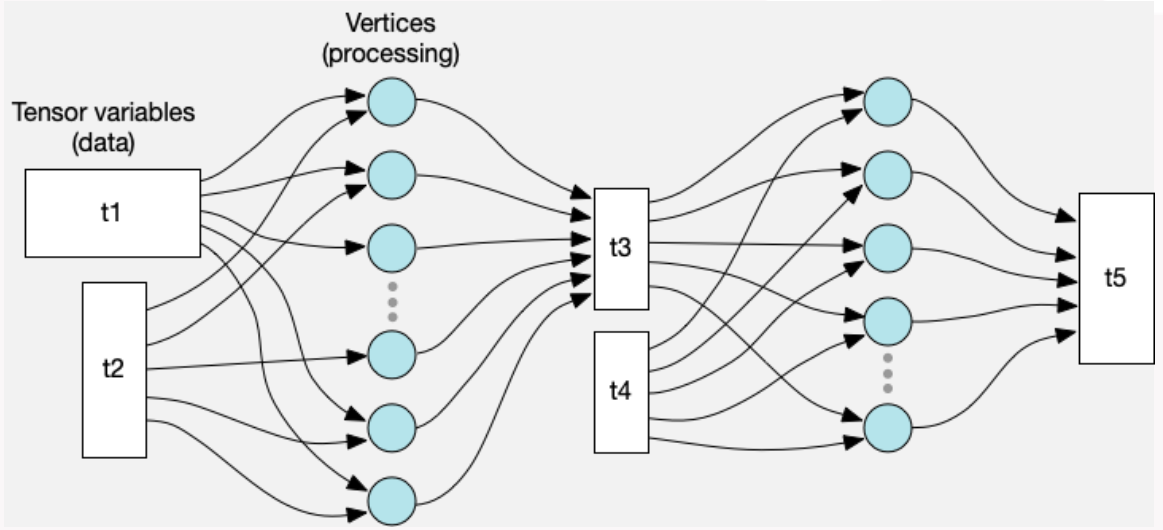
Poplar SDK : 연산 그래프 생성 + IPU 연산 계획 수립 + 실행

POPLAR 내부동작

Poplar 라이브러리 종류

Library	Description
poplin	Linear algebra functions (matrix multiplications, convolutions)
popnn	Functions used in neural networks (for example, non-linearities, pooling and loss functions)
popops	Functions for operations on tensors in control programs (elementwise functions and reductions)
poprand	Functions for populating tensors with random numbers
popsparse	Functions for operating on sparse tensors
poputil	General utility functions for building graphs

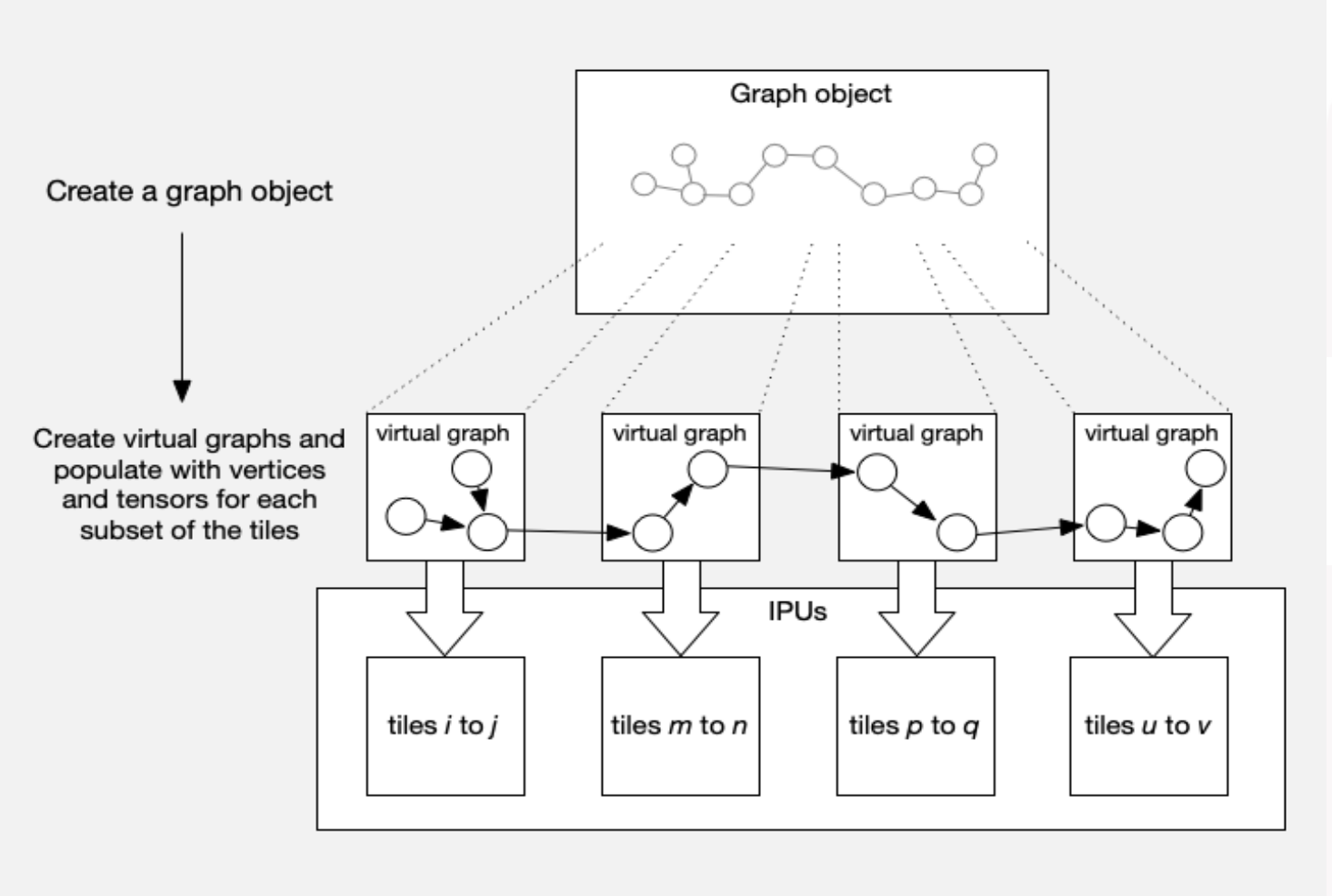
Compute Graph (연산 그래프)



- Vertex (Codelet) : 단일 타일에서 한 번에 수행되는 연산
- Edge (Data) : 로컬 타일 혹은 다른 타일의 데이터
  - 로컬 타일 : 로컬 메모리로의 Read/Write
  - 다른 타일 : 타일 간의 Exchange

POPLAR 내부동작

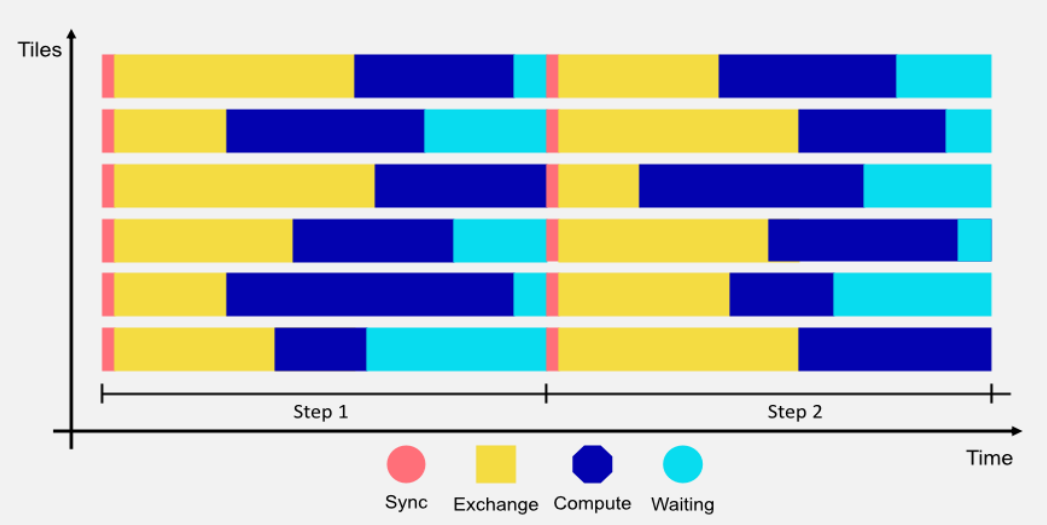
- Graph compiler



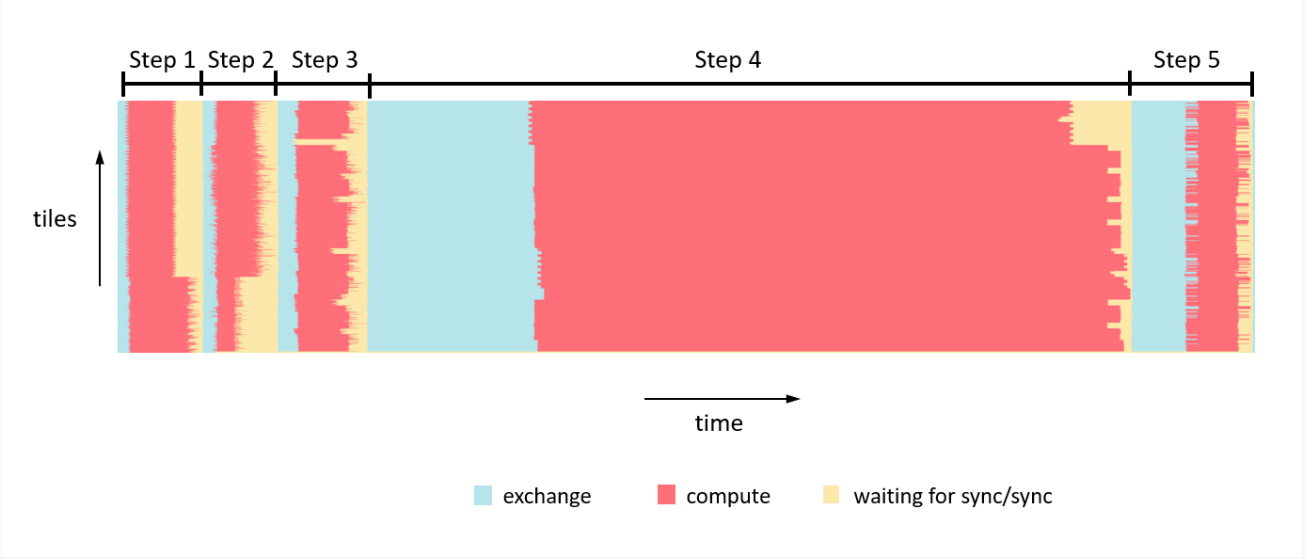
https://docs.graphcore.ai/projects/ipu-programmers-guide/en/latest/

POPLAR 내부동작

BSP (Bulk Synchronous Parallel)



- Local compute : 모든 타일들의 병렬 연산
- Global synchronization : 모든 타일의 연산 종료 대기
- Data exchange : 타일 간의 데이터 전송



실제 BSP 시각화 예시

ML FRAMEWORKS SUPPORTED TODAY

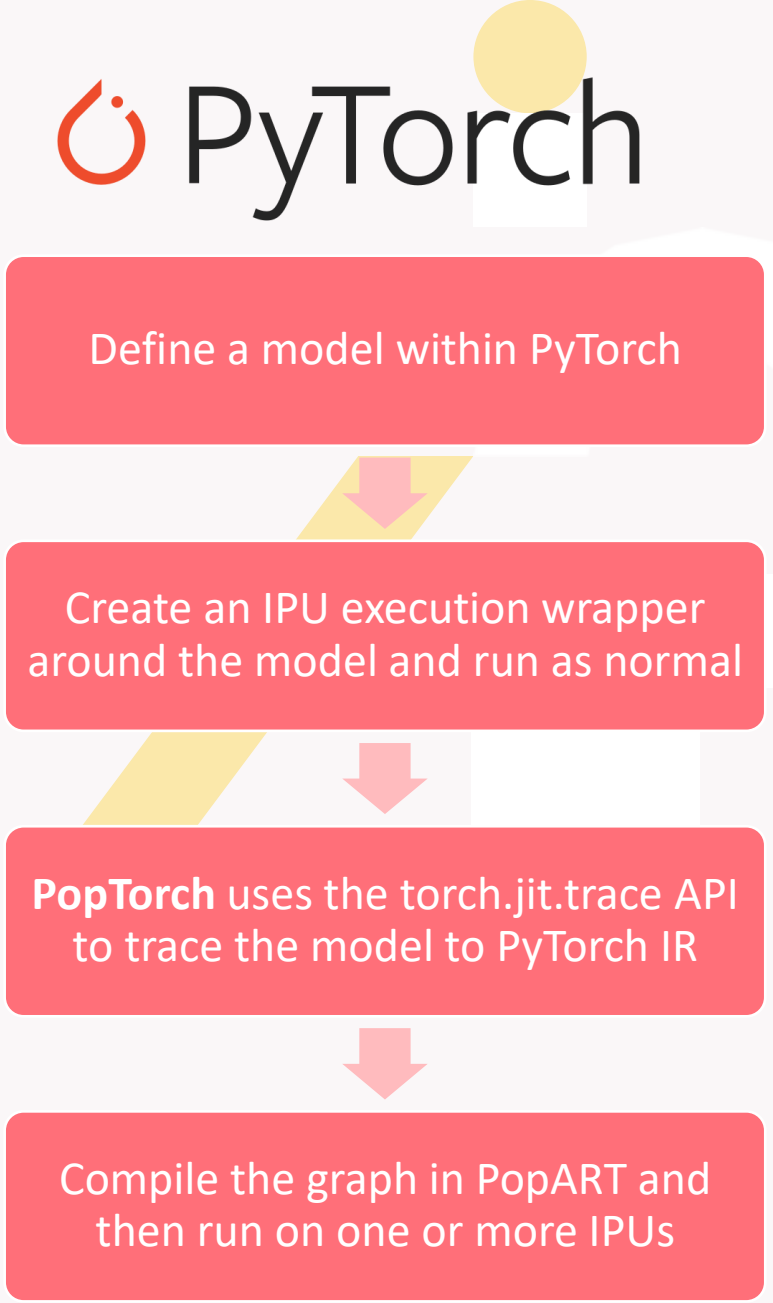
TENSORFLOW FOR THE IPU

TensorFlow

- Graphcore supplies its own branch of TensorFlow that supports the IPU
- Full backend with extensive feature coverage
- Enable TensorFlow to target the IPU directly via Poplar
- TensorFlow 1.15 support
- TensorFlow 2.5 support
- Inference and training
- Full integration with PopVision analysis tools

PYTORCH FOR THE IPU

- PopTorch is a set of extensions for PyTorch
- PopTorch enables native PyTorch models to run directly on IPUs
- Minimal changes to PyTorch code
- PyTorch 1.10.0+cpu
- Inference and training
- Full integration with PopVision analysis tools



POPART: ONNX SUPPORT FOR THE IPU

The Poplar Advanced Runtime

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.
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.

What is ONNX?

- Open Neural Network Exchange
- ONNX is a serialisation format for neural network systems that can be created and read by several frameworks including Caffe2, PyTorch and MXNet.

IMPORTING A MODEL INTO POPART VIA ONNX

Your model

Chainer mxnet Caffe2
Microsoft CNTK TensorFlow Keras
GLUON PYTORCH theano

Convert to ONNX format

Caffe	apple/coremltools and onnx/onnxmltools	Example
Caffe2	part of caffe2 package	Example
Chainer	chainer/onnx-chainer	Example
Cognitive Toolkit (CNTK)	built-in	Example
CoreML (Apple)	onnx/onnxmltools	Example
Keras	onnx/keras-onnx	Example
LibSVM	onnx/onnxmltools	Example
LightGBM	onnx/onnxmltools	Example
MATLAB	Deep Learning Toolbox	Example
ML.NET	built-in	Example
MXNet (Apache)	part of mxnet package docs github	Example
PyTorch	part of pytorch package	Example1, Example2, export for Windows ML, Extending support
SciKit-Learn	onnx/sklearn-onnx	Example
SINGA (Apache) - Github (experimental)	built-in	Example
TensorFlow	onnx/tensorflow-onnx	Examples

https://github.com/onnx/tutorials

ONNX model

Training & Inference

Poplar graph

Poplar

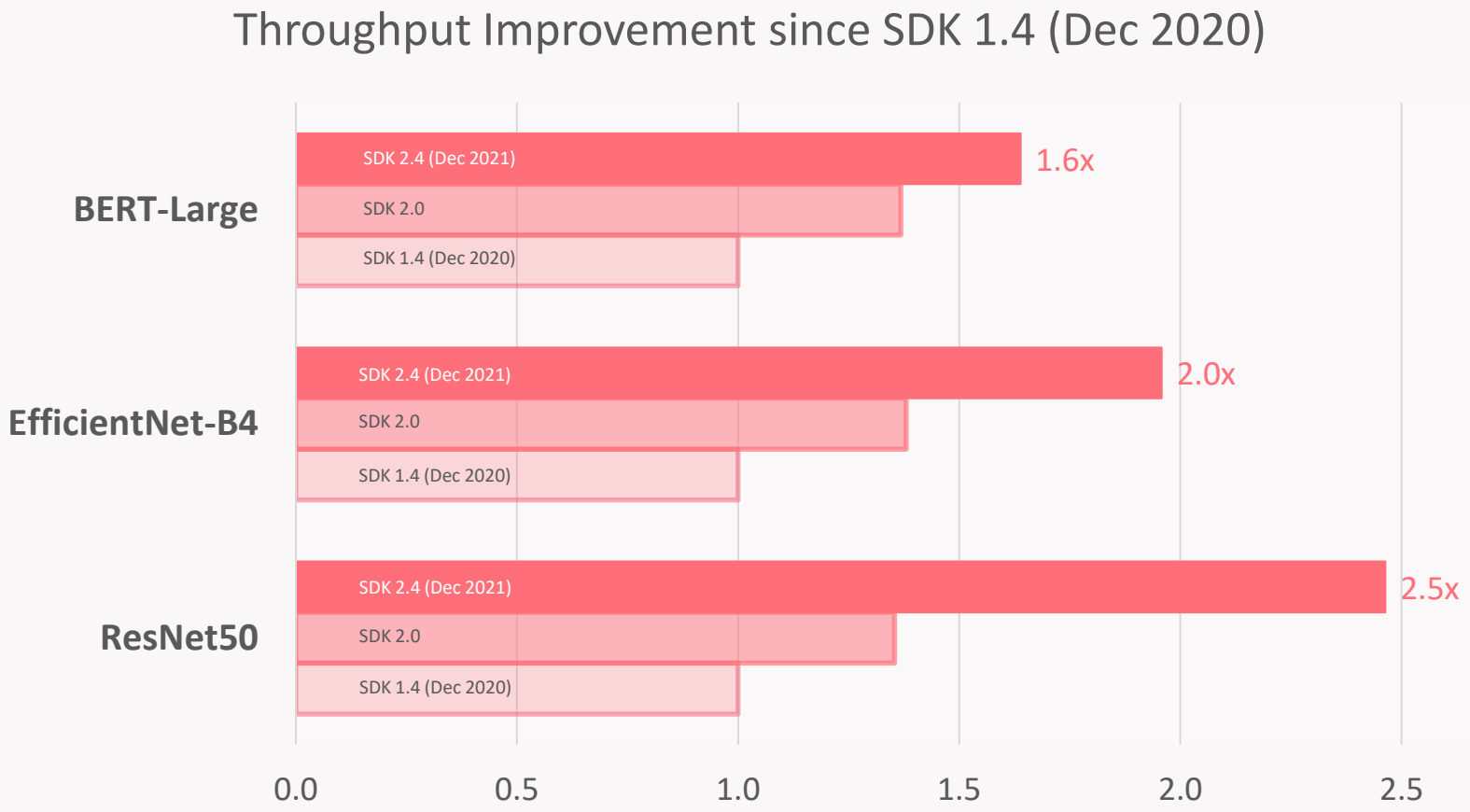
PopART

Data

PopART session

GC200 IPU

SDK 2.4 PERFORMANCE IMPROVEMENT



BERT-Large Phase 1 Pre-Training (SL128) Throughput
G16- EfficientNet-B4 Training Throughput
ResNet50 v1.5 Training Throughput
https://www.graphcore.ai/performance-results

DEVELOPER ECOSYSTEM ENGAGEMENT

TensorFlow

Keras

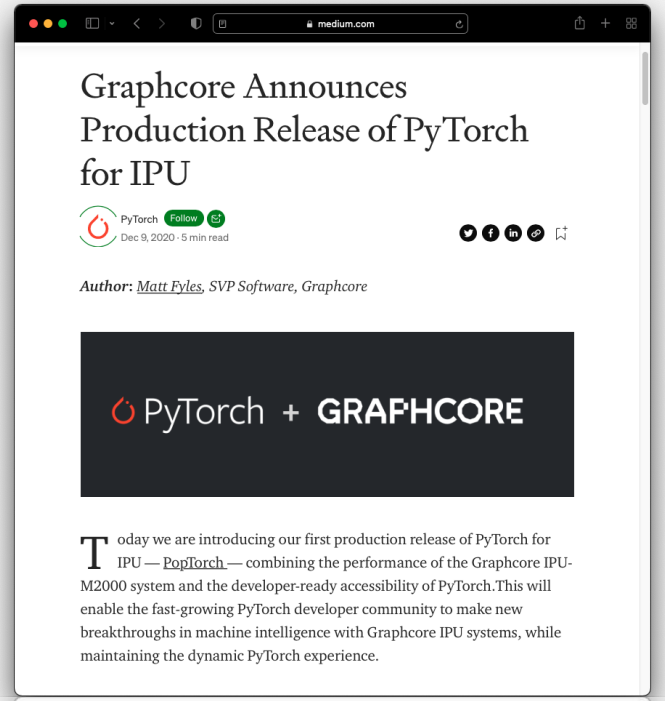
PaddlePaddle

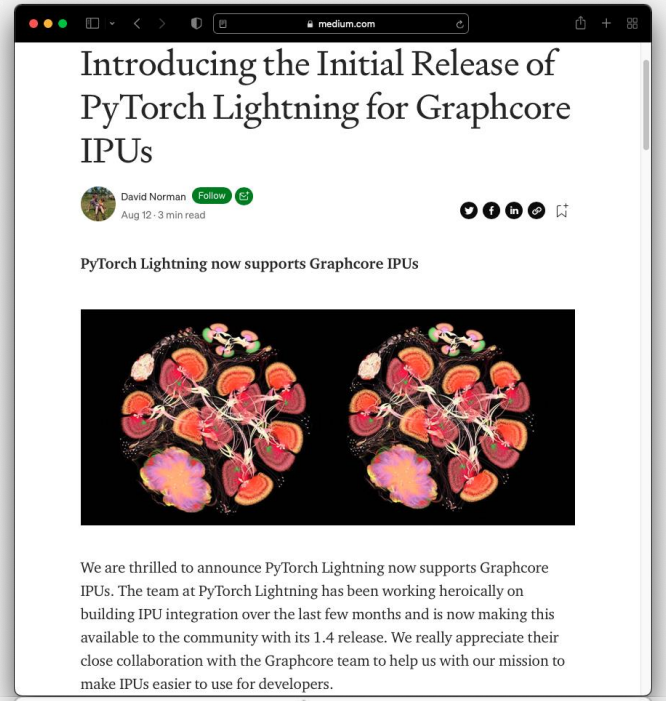
PyTorch

PyTorch Lightning

HALO

jupyterhub





HUGGING FACE

vmware

Weights & Biases

docker

SPELL

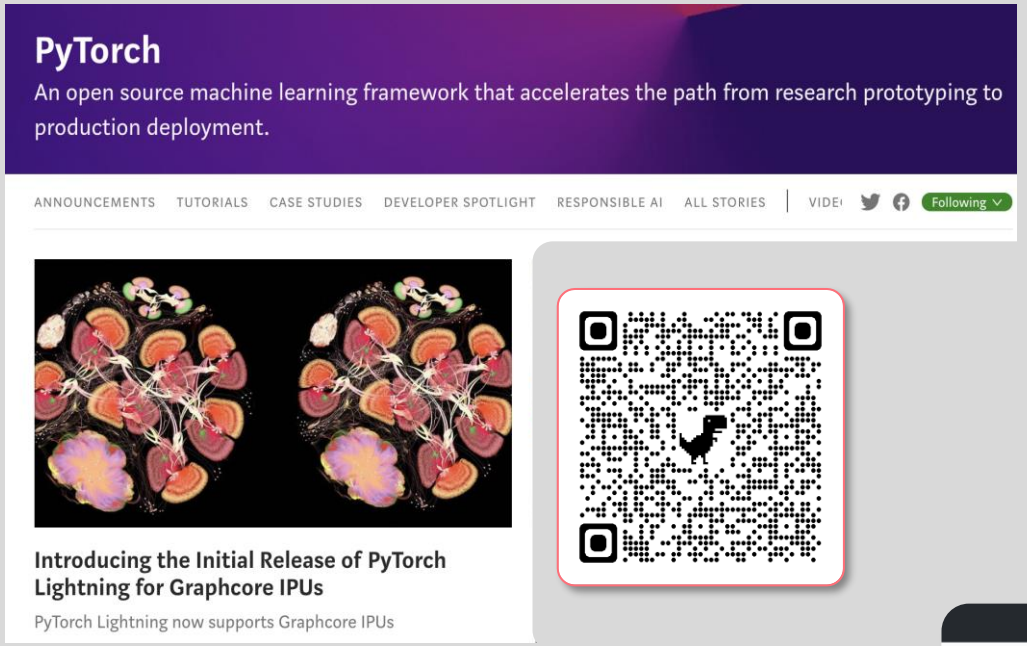
openstack

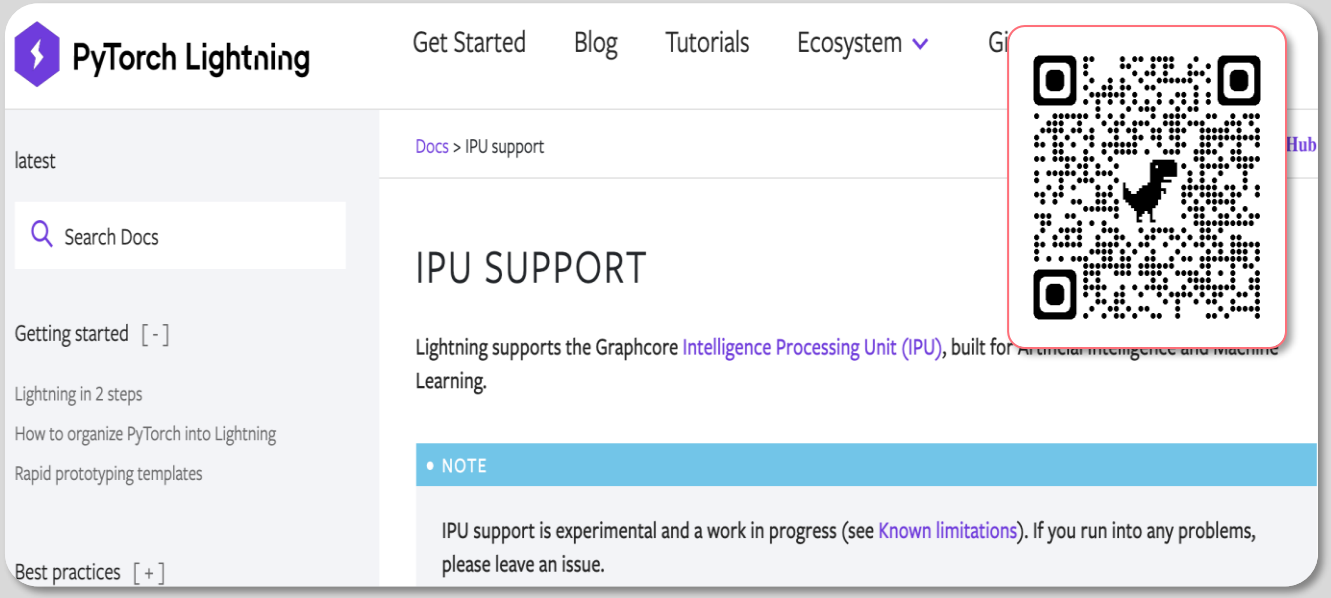
gradient by Paperspace

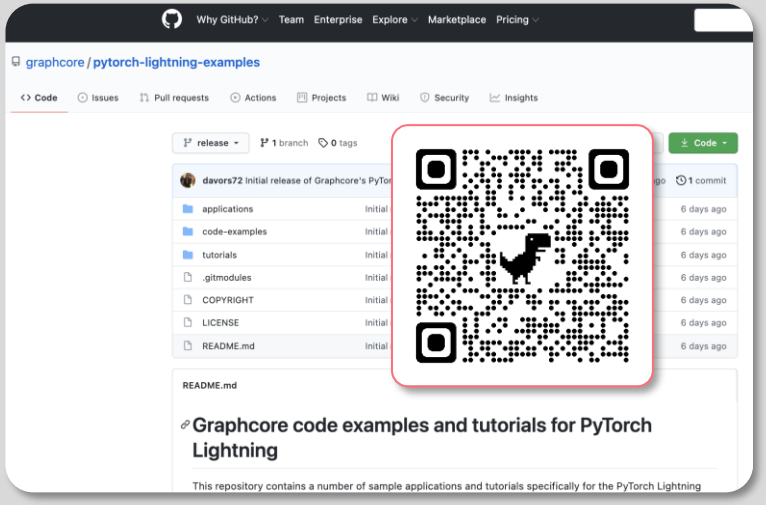
GitHub

GRAPHCORE

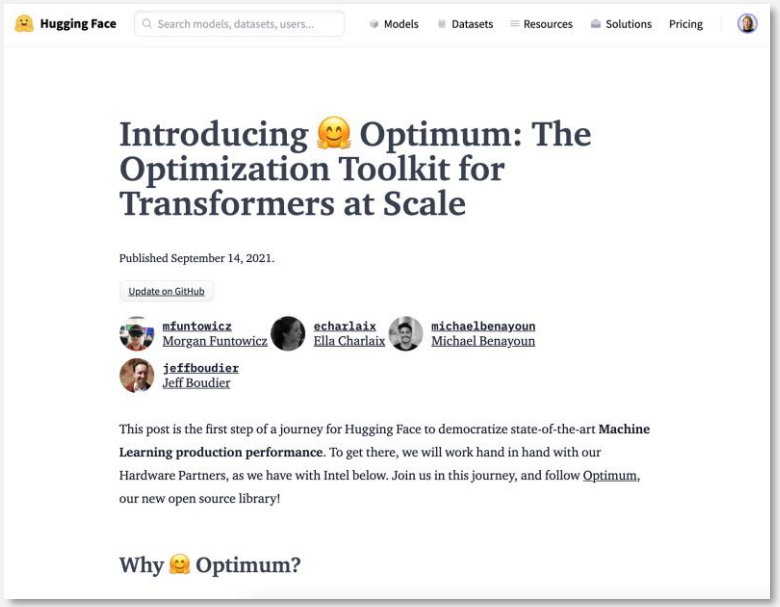
PYTORCH LIGHTNING ON IPU
RESOURCES

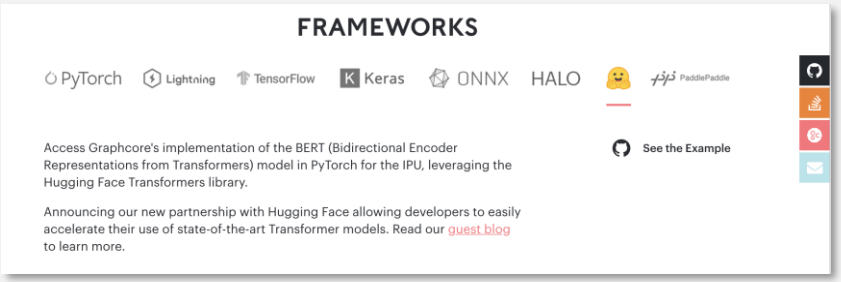


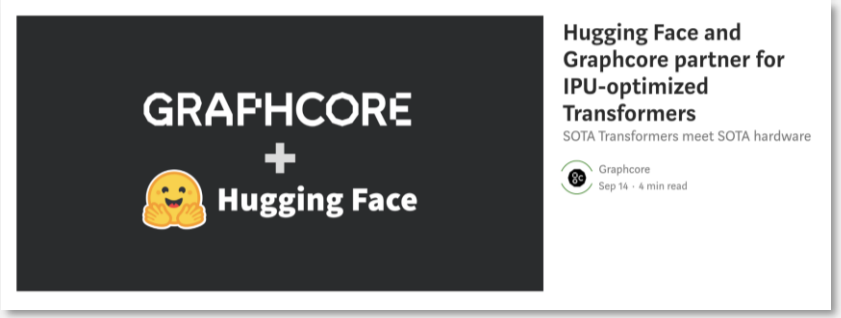


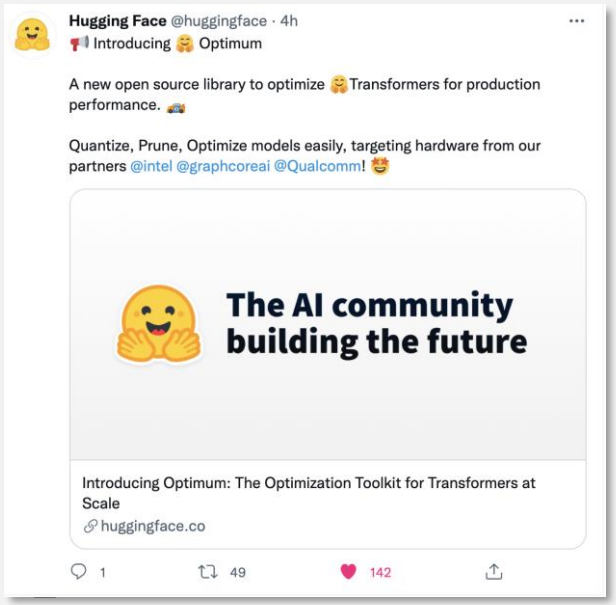


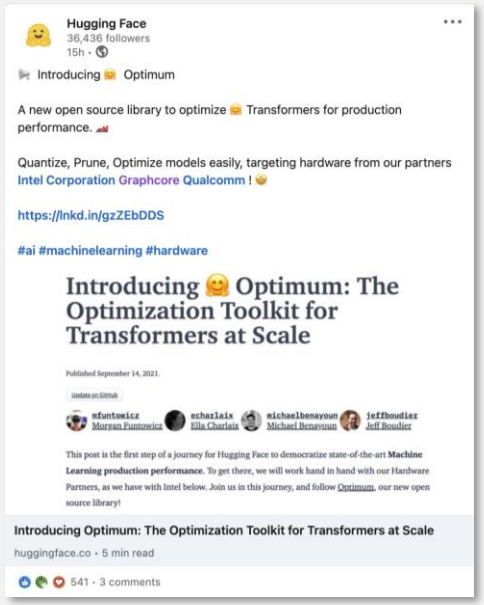
GRAPHCORE X HUGGING FACE











3. Train

Train models faster than ever before with Graphcore Intelligence Processing Units (IPUs), the latest generation of AI dedicated hardware, leveraging the built-in IPUTrainer API to train or finetune transformers models (coming soon)

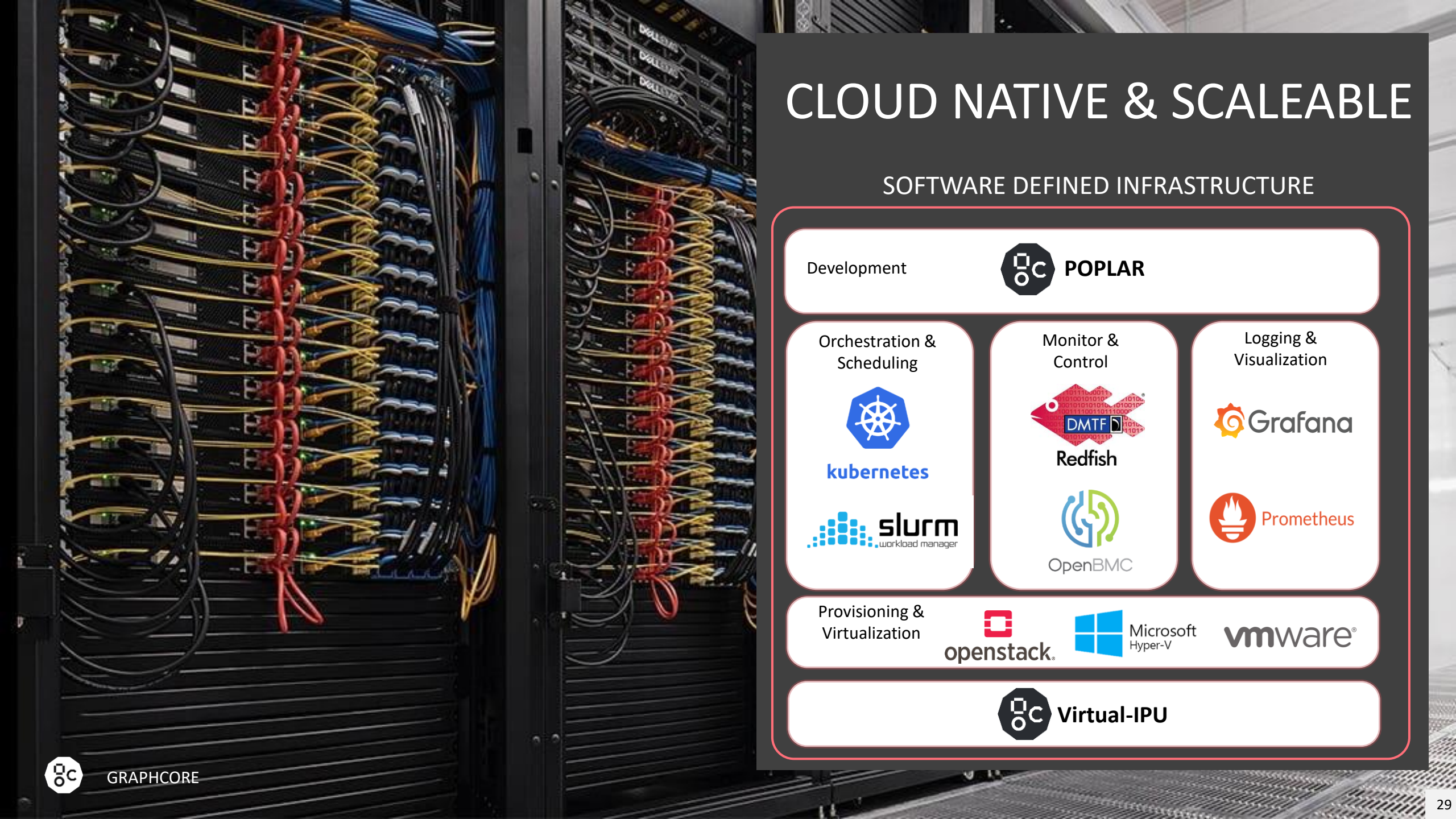
```python
from optimum.graphcore import IPUTrainer
from optimum.graphcore.bert import BertIPUConfig
from transformers import BertForMaskedLM, BertTokenizer
from poptorch.optim import AdamW

# Allocate model and tokenizer as usual
tokenizer = BertTokenizer.from_pretrained("bert-base-cased")
model = BertForMaskedLM.from_pretrained("bert-base-cased")

# Trainer + poptorch custom configuration optional
ipu_config = BertIPUConfig()
trainer = IPUTrainer(model, trainings_args, config=ipu_config)
optimizer = AdamW(model.parameters)

# This is hidden from the user, it will be handled by the Trainer
with trainer.compile(some_data_loader) as model_f:
    for steps in range(...):
        outputs = trainer.step(optimizer)

# Save the model and/or push to hub
model.save_pretrained("...")
model.push_to_hub("...")
```



CLOUD NATIVE & SCALEABLE

SOFTWARE DEFINED INFRASTRUCTURE

Development — POPLAR

Orchestration & Scheduling — kubernetes; slurm workload manager

Monitor & Control — DMTF Redfish; OpenBMC

Logging & Visualization — Grafana; Prometheus

Provisioning & Virtualization — openstack; Microsoft Hyper-V; vmware

Virtual-IPU

GRAPHCORE

GROWING MODEL GARDEN

POPVISION TOOLS

MODEL GARDEN

Framework: PyTorch | TensorFlow | PopART

Category: Natural Language Processing | Computer Vision | Speech Processing | Probabilistic Modelling | Reinforcement Learning | Generative | Other

INFERENCE MODELS

BERT-Large Inference
BERT-Large (Bidirectional Encoder Representations from Transformers) for NLP inference on IPUs.
View on GitHub →
Natural Language Processing | PopART

BERT-Base Inference
BERT-Base (Bidirectional Encoder Representations from Transformers) for NLP inference on IPUs.
View on GitHub →
Natural Language Processing | PopART

ResNet-50 Inference
Image classification inference on IPUs using the CNN (Convolutional Neural Network) model ResNet-50.
View on GitHub →
Computer Vision | PyTorch

ResNet-50 Inference
Image classification inference on IPUs using the CNN (Convolutional Neural Network) model ResNet-50.
View on GitHub →
Computer Vision | TensorFlow

EfficientNet-B0/B4 Inference
CNN (Convolutional Neural Network) image classification inference on IPUs with EfficientNet.
View on GitHub →
Computer Vision | PyTorch

ResNeXt-101 Inference
Image classification inference on IPUs using the CNN (Convolutional Neural Network) model ResNeXt-101.
View on GitHub →
Computer Vision | PyTorch

ResNeXt-101 Inference
Image classification inference on IPUs using the CNN (Convolutional Neural Network) model ResNeXt-101.
View on GitHub →
Computer Vision | TensorFlow

ResNeXt-101 Inference
Image classification inference on IPUs using the CNN (Convolutional Neural Network) model ResNeXt-101.
View on GitHub →
Computer Vision | PopART

DIEN Inference
DIEN (Deep Interest Evolution Network) inference on IPUs - a recommendation model for click-through rate prediction.
View on GitHub →
Other | TensorFlow

DIN Inference
DIN (Deep Interest Network) inference on IPUs - a recommendation model for click-through rate prediction.
View on GitHub →
Other | TensorFlow

YOLOv3 Inference
YOLOv3 - You Only Look Once - is a convolutional neural network model that performs object detection tasks on IPUs.
View on GitHub →
Computer Vision | TensorFlow

YOLOv4 Inference
YOLOv4 - You Only Look Once - is a convolutional neural network model that performs object detection tasks on IPUs.
View on GitHub →
Computer Vision | PyTorch

MobileNetv2 Inference
MobileNetv2 - Convolutional neural network inference for classification, detection and segmentation.
View on GitHub →
Computer Vision | TensorFlow

MobileNetv3 Inference
MobileNetv3 - Convolutional neural network inference for classification, detection and segmentation.
View on GitHub →
Computer Vision | PyTorch

Autoencoder Inference
Custom autoencoder inference model on the IPU to perform collaborative filtering in recommender systems.
View on GitHub →
Generative | TensorFlow

TRAINING MODELS

BERT-Large Training
BERT-Large (Bidirectional Encoder Representations from Transformers) for NLP training on IPUs.
View on GitHub →
Natural Language Processing | TensorFlow

BERT-Large Training
BERT-Large (Bidirectional Encoder Representations from Transformers) for NLP training on IPUs.
View on GitHub →
Natural Language Processing | PopART

BERT-Large Training
BERT-Large (Bidirectional Encoder Representations from Transformers) for NLP training on IPUs.
View on GitHub →
Natural Language Processing | PyTorch

BERT-Base Training
BERT-Base (Bidirectional Encoder Representations from Transformers) for NLP pre-training and training on IPUs.
View on GitHub →
Natural Language Processing | PyTorch

BERT-Base Training
BERT-Base (Bidirectional Encoder Representations from Transformers) for NLP pre-training and training on IPUs.
View on GitHub →
Natural Language Processing | TensorFlow

BERT-Base Training
BERT-Base (Bidirectional Encoder Representations from Transformers) for NLP pre-training and training on IPUs.
View on GitHub →
Natural Language Processing | PopART

ResNet-50 Training
Image classification training on IPUs using the CNN (Convolutional Neural Network) model ResNet-50.
View on GitHub →
Computer Vision | PyTorch

ResNet-50 Training
Image classification training on IPUs using the CNN (Convolutional Neural Network) model ResNet-50.
View on GitHub →
Computer Vision | TensorFlow

EfficientNet-B0 Training
CNN (Convolutional Neural Network) image classification training on IPUs with EfficientNet.
View on GitHub →
Computer Vision | PyTorch

EfficientNet-B4 Training
CNN (Convolutional Neural Network) image classification training on IPUs with EfficientNet.
View on GitHub →
Computer Vision | TensorFlow

ResNeXt-101 Training
Image classification training on IPUs using the CNN (Convolutional Neural Network) model ResNeXt-101.
View on GitHub →
Computer Vision | TensorFlow

MCMC Training
Markov Chain Monte Carlo (MCMC) training on IPUs using standard TensorFlow Probability.
View on GitHub →
Probabilistic Modelling | TensorFlow

Deep Voice 3 Training
Text-To-Speech training on IPUs using a Convolutional Sequence Learning technique.
View on GitHub →
Speech Processing | PopART

DIEN Training
DIEN (Deep Interest Evolution Network) training on IPUs - a recommendation model for click-through rate prediction.
View on GitHub →
Other | TensorFlow

DIN Training
DIN (Deep Interest Network) training on IPUs - a recommendation model for click-through rate prediction.
View on GitHub →
Other | TensorFlow

YOLOv3 Training
YOLOv3 - You Only Look Once - is a convolutional neural network model that performs object detection tasks on IPUs.
View on GitHub →
Computer Vision | TensorFlow

MobileNetv3 Training
MobileNetv3 - Convolutional neural network training for classification, detection and segmentation.
View on GitHub →
Computer Vision | PyTorch

Autoencoder Training
Custom autoencoder model on the IPU to train collaborative filtering in recommender systems.
View on GitHub →
Generative | TensorFlow

Contrastive Divergence VAE Training
Train a Variational Autoencoder / Markov Chain Monte Carlo hybrid model on IPUs.
View on GitHub →
Generative | TensorFlow

Reinforcement Learning Training
How to train a deep reinforcement learning model on multiple IPUs with synchronous data parallel training.
View on GitHub →
Reinforcement Learning | TensorFlow

Sales Forecasting Training
How to train a sales forecasting machine learning model on Graphcore's IPUs.
View on GitHub →
Probabilistic Modelling | TensorFlow

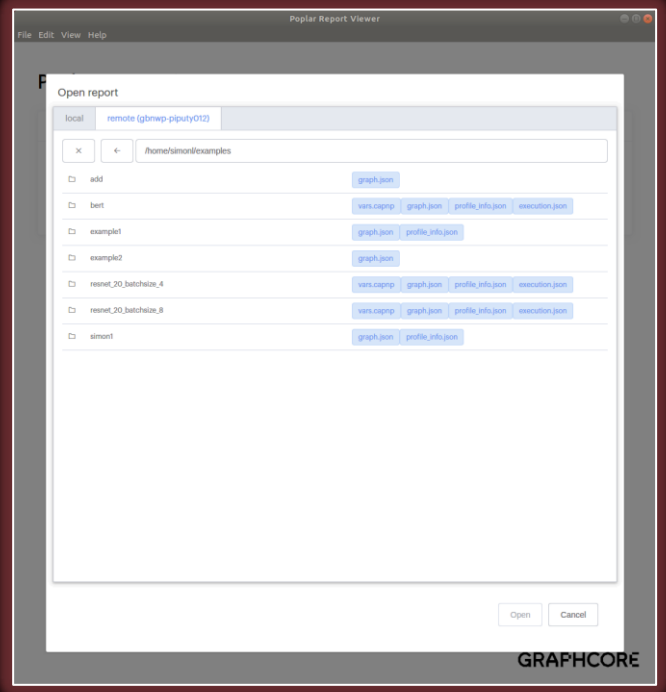
UNet Industrial Training
How to run a UNet Industrial training example for image segmentation
View on GitHub →
Computer Vision | TensorFlow

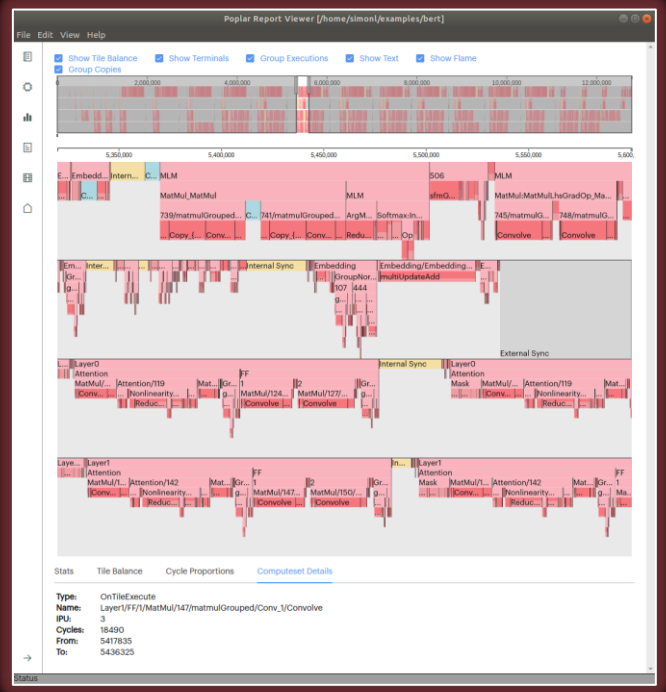
GRAPHCORE

GRAPHCORE

POPVISION ANALYSIS TOOLS

GRAPH ANALYSER 2.4 RELEASED WITH POPLAR SDK 2.1





VERSION 1.0 SCREENSHOTS

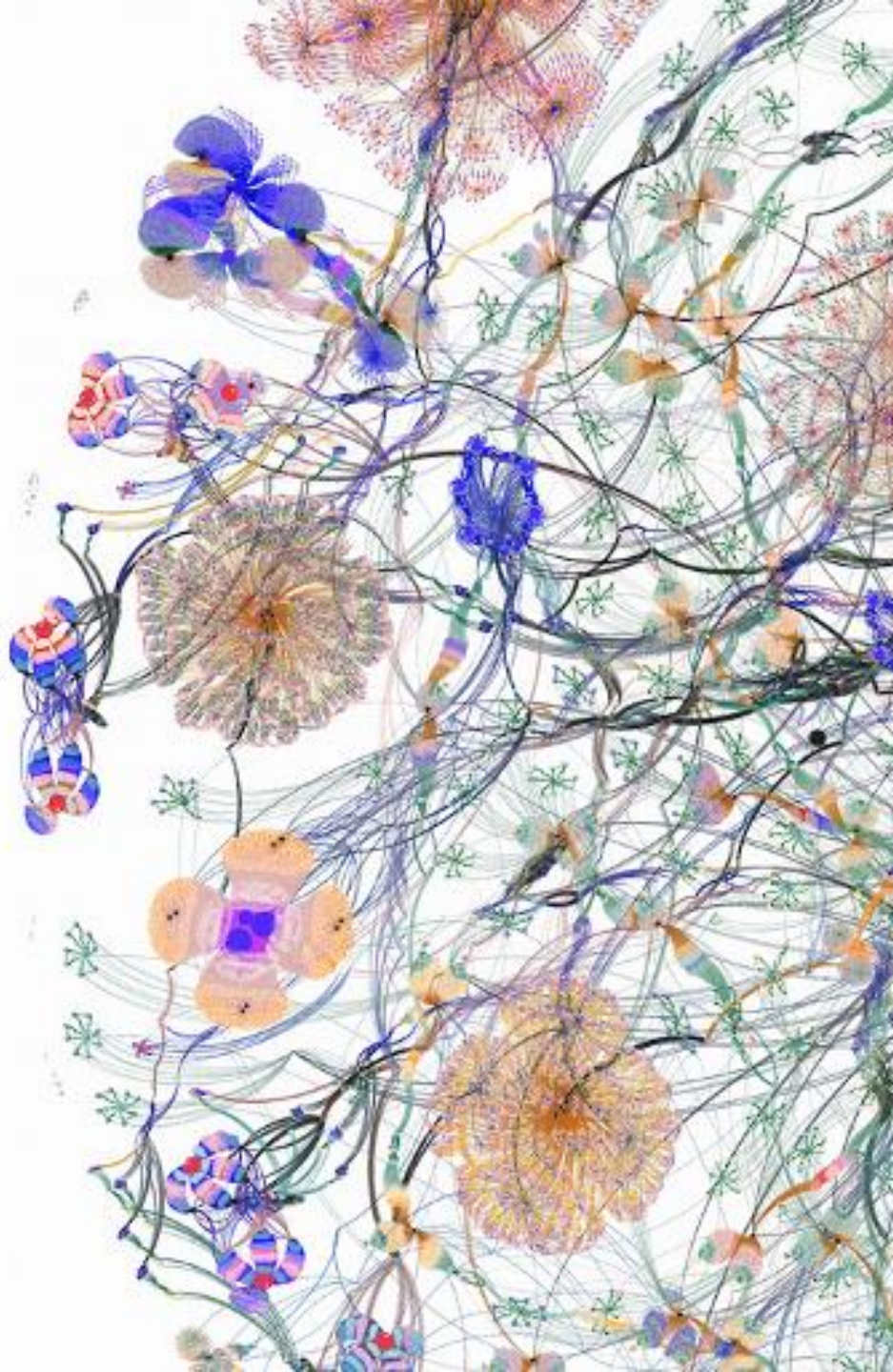
LOCAL AND REMOTE FILE ACCESS

- SUPPORT FOR LOCAL FILE VIEWING AND ANALYSIS OF PROFILE REPORTS OFFLINE
- SUPPORT FOR REMOTE SERVER CONNECTION AND ANALYSIS OF FILES ON A SERVER CONTAINING HARDWARE

IPU APPLICATION PROFILE VISUALISATION

- PRODUCT VERSION OF GC-PROFILE, SUPPORTED AND DEVELOPED WITH ROADMAP FOR FUTURE FEATURES
- VISUALIZE DETAILED INFORMATION ABOUT IPU APPLICATION EXECUTION
- VIEW APPLICATION MEMORY USAGE, LIVENESS ANALYSIS, PROGRAM TREE, EXECUTION TRACE FOR IPU DEVICES
- NEW SUPPORT FROM INTERNAL TOOL TO VIEW PROGRAM SYMBOL INFORMATION

BASIC PORTING GUIDE - PYTORCH



FROM PYTORCH TO POPTORCH

Model

```
class CustomModel(nn.Module):
    def __init__(self):
        super().__init__()

        # down-sampling layer
        self.MaxPool = nn.MaxPool2d(kernel_size=2, stride=2)
        self.Conv2d_1_64 = nn.Conv2d(1, 64, 7, 2, 3)
        self.Conv2d_64_128_1 = nn.Conv2d(64, 128, 3, 2, 1)


    def forward(self, x):
        # down
        # print(x.shape)
        x = self.Conv2d_1_64(x)
        x = self.BatchNorm2d_64(x)
        x = self.ReLU(x)


        return x
```

```
class CustomModel(nn.Module):
    def __init__(self):
        super().__init__()

        # down-sampling layer
        self.loss = nn.BCELoss()
        self.MaxPool = nn.MaxPool2d(kernel_size=2, stride=2)
        self.Conv2d_1_64 = nn.Conv2d(1, 64, 7, 2, 3)


    def forward(self, x, targets=None):
        # down
        # print(x.shape)
        x = self.Conv2d_1_64(x)
        x = self.BatchNorm2d_64(x)
        x = self.ReLU(x)


        if targets is not None:
            return x, self.loss(x, targets)
        return x
```

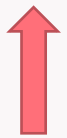
You should place loss function inside the model definition in order to use PopTorch training wrapper

FROM PYTORCH TO POPTORCH

Model

```
5   import torch
6   from efficientnet_pytorch import EfficientNet

72      model = EfficientNet.from_pretrained('efficientnet-b0', num_classes=18)
75      criterion = torch.nn.CrossEntropyLoss()
78      model_with_loss = ModelWithLoss(model, criterion)
```



```
5   class ModelWithLoss(torch.nn.Module):
6       def __init__(self, net, loss):
7           super(ModelWithLoss, self).__init__()
8           self.net = net
9           self.loss = loss
10
11      def forward(self, x, target=None):
12          outputs = self.net(x)
13          if target is not None:
14              return outputs, self.loss(outputs, target)
15          return outputs
```

Alternatively, you can use a simple wrapper class to add loss function at the end of the model

FROM PYTORCH TO POPTORCH

Model

```
model = densenet.densenet201(num_classes=args.num_classes).eval(
).cuda()
```

```
model = densenet.densenet201(num_classes=args.num_classes).eval()

opts = poptorch.Options()
opts.deviceIterations(args.device_iteration)
opts.replicationFactor(args.replication_factor)
```

You can change how PopTorch compiles and executes models using poptorch.Options

```
poptorch_model = poptorch.inferenceModel(model, options=opts)
```

This function wraps a PyTorch model, yielding a PopTorch model that can be run on the IPU in inference mode.

FROM PYTORCH TO POPTORCH

Model

PopTorch doesn't use torch.device to target the IPU device.

```
    net = CustomModel()

    device = torch.device('cuda:' + args.gpu_num if
torch.cuda.is_available() else 'cpu')


    optimizer = optim.SGD(net.parameters(), args.lr, weight_decay=1e-5)
    criterion = torch.nn.BCELoss()
    net.to(device=device).train()

    train = BasicDataset(dir_train, dir_train2, args.scale)
    n_train = len(train)
    train_loader = DataLoader(
        train, batch_size=args.batchsize, shuffle=True, drop_last=True,
        num_workers=args.num_workers, pin_memory=True
```

```
from poptorch import optim
from poptorch import DataLoader

    net = CustomModel()

    opts = poptorch.Options()
    opts.replicationFactor(args.replication_factor)
    opts.Training.gradientAccumulation(args.gradient_accumulation)

    optimizer = optim.SGD(net.parameters(), args.lr, weight_decay=1e-5)
    poptorch_model = poptorch.trainingModel(net, options=opts,
optimizer=optimizer)

    train = BasicDataset(dir_tr
    n_train = len(train)
    train_loader = DataLoader(
        opts, train, batch_size=args.batchsize, shuffle=True,
drop_last=True,
        num_workers=args.num_workers, pin_memory=True,
mode=poptorch.DataLoaderMode.Async
    )
```

You can change how PopTorch compiles and executes models using poptorch.Options

This function wraps a PyTorch model, yielding a PopTorch model that can be run on the IPU in training mode.

FROM PYTORCH TO POPTORCH

Optimizer

```
from torch import optim
from torch.utils.data import DataLoader

    net = CustomModel()

    device = torch.device('cuda:' + args.gpu_num if
 torch.cuda.is_available() else 'cpu')


    optimizer = optim.SGD(net.parameters(), args.lr, weight_decay=1e-5)
    criterion = torch.nn.BCELoss()
    net.to(device=device).train()

    train = BasicDataset(dir_train, dir_train2, args.scale)
    n_train = len(train)
    train_loader = DataLoader(
        train, batch_size=args.batchsize, shuffle=True, drop_last=True,
        num_workers=args.num_workers, pin_memory=True
```

```
from poptorch import optim
from poptorch import DataLoader

    net = CustomModel()

    opts = poptorch.Options()
    opts.replicationFactor(ar
    opts.Training.gradientAcc

    optimizer = optim.SGD(net.parameters(), args.lr, weight_decay=1e-5)
    poptorch_model = poptorch.trainingModel(net, options=opts,
 optimizer=optimizer)

    train = BasicDataset(dir_train, dir_train2, args.scale)
    n_train = len(train)
    train_loader = DataLoader(
        opts, train, batch_size=args.batchsize, shuffle=True,
 drop_last=True,
        num_workers=args.num_workers, pin_memory=True,
 mode=poptorch.DataLoaderMode.Async
    )
```

PopTorch optimizers have features to support float16 precision, such as loss scaling, velocity scaling, bias correction and accumulator types.

FROM PYTORCH TO POPTORCH

DataLoader

Poptorch provides a thin wrapper around the traditional torch.utils.data .DataLoader to abstract away some of the batch sizes calculations.
If poptorch.DataLoader is used in a distributed execution environment, it will ensure that each process uses a different subset of the dataset.

```
from torch import optim
from torch.utils.data import DataLoader

    net = CustomModel()

    device = torch.device('cuda:' + args.gpu_num if
 torch.cuda.is_available() else 'cpu')


    optimizer = optim.SGD(net.parameters(), args.lr, weight_decay=1e-5)
    criterion = torch.nn.BCELoss()
    net.to(device=device).train()

    train = BasicDataset(dir_train, dir_train2, args.scale)
    n_train = len(train)
    train_loader = DataLoader(
        train, batch_size=args.batchsize, shuffle=True, drop_last=True,
        num_workers=args.num_workers, pin_memory=True
```

```
from poptorch import DataLoader

    net = CustomModel()

    opts = poptorch.Options()
    opts.replicationFactor(args.replication_factor)
    opts.Training.gradientAccumulation(args.gradient_accumulation)

    optimizer = optim.SGD(net.parameters(), args.lr, weight_decay=1e-5)
    poptorch_model = poptorch.trainingModel(net, options=opts,
optimizer=optimizer)

    train = BasicDataset(dir_train, dir_train2, args.scale)
    n_train = len(train)
    train_loader = DataLoader(
        opts, train, batch_size=args.batchsize, shuffle=True,
drop_last=True,
        num_workers=args.num_workers, pin_memory=True,
mode=poptorch.DataLoaderMode.Async
    )
```

FROM PYTORCH TO POPTORCH

DataLoader

```
from torch import optim
from torch.utils.data import DataLoader

    net = CustomModel()

    device = torch.device('cuda:' + args.gpu_num if
 torch.cuda.is_available() else 'cpu')


    optimizer = optim.SGD(net.parameters(), args.lr, weight_decay=1e-5)
    criterion = torch.nn.BCELoss()
    net.to(device=device).train()

    train = BasicDataset(dir_train, dir_train2, args.scale)
    n_train = len(train)
    train_loader = DataLoader(
        train, batch_size=args.batchsize, shuffle=True, drop_last=True,
        num_workers=args.num_workers, pin_memory=True
```

```
from poptorch import optim
from poptorch import DataLoader

    net = CustomModel()

    opts = poptorch.Options()
    opts.replicationFactor(args.replication_factor)
    opts.Training.gradientAccumulation(args.gradient_accumulation)

    optimizer = optim.S
    poptorch_model = po
optimizer=optimizer)

    train = BasicDataset(dir_train, dir_train2, args.scale)
    n_train = len(train)
    train_loader = DataLoader(
        opts, train, batch_size=args.batchsize, shuffle=True,
drop_last=True,
        num_workers=args.num_workers, pin_memory=True,
mode=poptorch.DataLoaderMode.Async
    )
```

To reduce host overhead, you can offload the data loading process to a separate thread by specifying mode=poptorch.DataLoaderMode.Async in the DataLoader constructor.

FROM PYTORCH TO POPTORCH

Training / Inference loop

```
        pbar = tqdm(loader, desc=f'Epoch [{epoch + 1:0{digits}d} /
{args.num_epochs}]')
        for images, labels in pbar:
            images, labels = images.to(device), labels.to(device)
            start = time.time()
            if args.command == 'train':
                optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            if args.command == 'train':
                loss.backward()
                optimizer.step()
```

Setting gradients to zero

forward pass

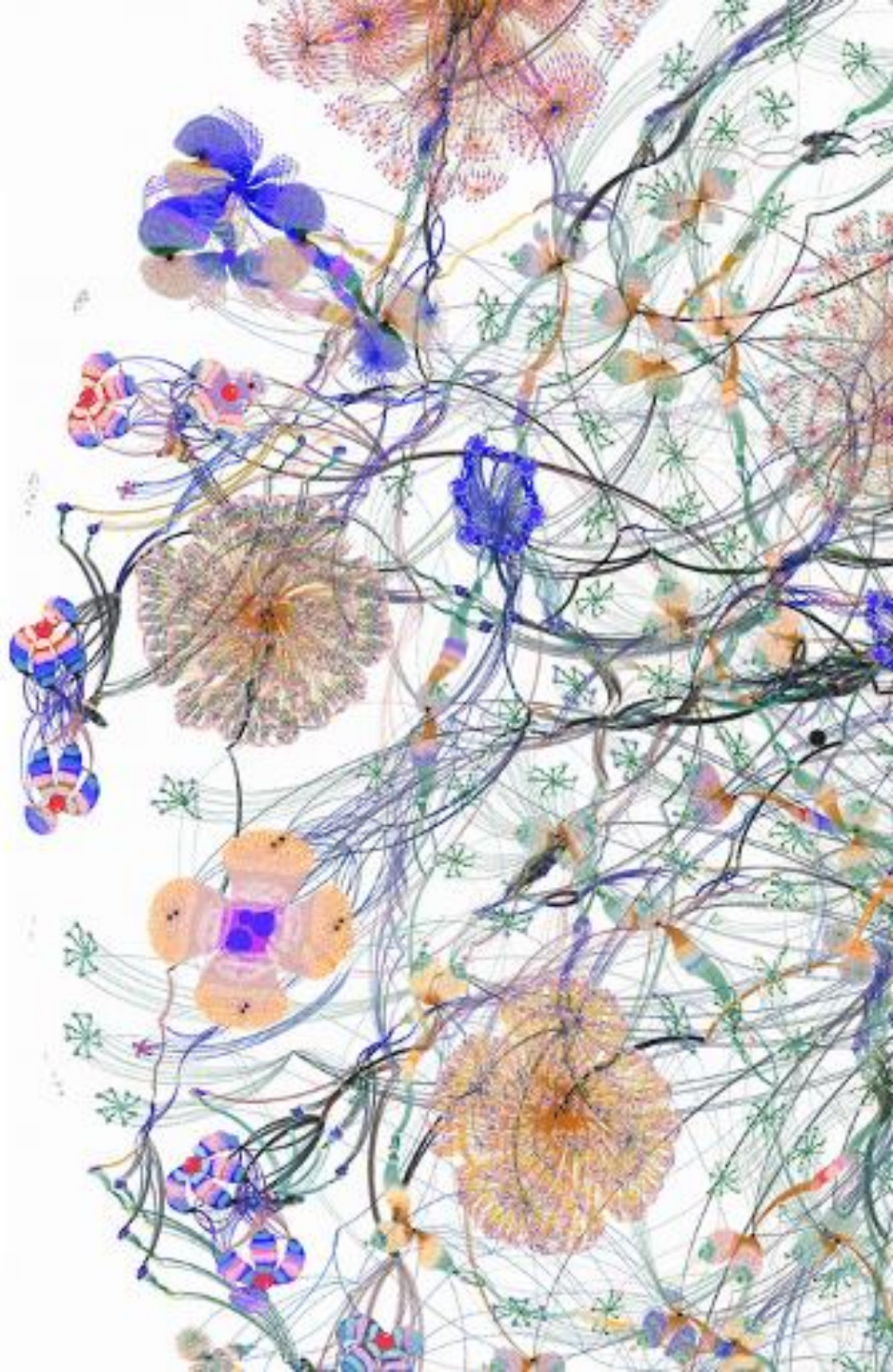
backward pass

weight update

Combined into single step

```
        pbar = tqdm(loader, desc=f'Epoch [{epoch + 1:0{digits}d} /
{args.num_epochs}]')
        for images, labels in pbar:
            start = time.time()
            outputs, loss = poptorch_model(images, labels)
```

BASIC PORTING GUIDE - TENSORFLOW2



TENSORFLOW 2 FOR THE IPU

[Tensorflow 2 User Guide – 3.1. IPUStrategy]

Use the **IPUStrategy** context to ensure that everything within that context will be compiled for the IPU device. You should do this instead of using the tf.device context:

```
import tensorflow as tf
from tensorflow.python import ipu

# Configure the IPU device.
config = ipu.config.IPUConfig()
config.auto_select_ipus = 1
config.configure_ipu_system()


# Create a simple model.
def create_model():
  return tf.keras.Sequential([
      tf.keras.layers.Flatten(),
      tf.keras.layers.Dense(256, activation='relu'),
      tf.keras.layers.Dense(128, activation='relu'),
      tf.keras.layers.Dense(10)
  ])


# Create a dataset for the model.
def create_dataset():
  mnist = tf.keras.datasets.mnist

  (x_train, y_train), (_, _) = mnist.load_data()
  x_train = x_train / 255.0

  train_ds = tf.data.Dataset.from_tensor_slices(
      (x_train, y_train)).shuffle(10000).batch(32, drop_remainder=True)
  train_ds = train_ds.map(lambda d, l:
                          (tf.cast(d, tf.float32), tf.cast(l, tf.int32)))

  return train_ds.repeat().prefetch(16)


dataset = create_dataset()

# Create a strategy for execution on the IPU.
strategy = ipu.ipu_strategy.IPUStrategy()
with strategy.scope():
  # Create a Keras model inside the strategy.
  model = create_model()

  # Compile the model for training.
  model.compile(
      loss=tf.keras.losses.SparseCategoricalCrossentropy(),
      optimizer=tf.keras.optimizers.RMSprop(),
      metrics=["accuracy"],
  )

  model.fit(dataset, epochs=2, steps_per_epoch=100)
```

TENSORFLOW2

IPUConfig : device selection을 비롯한 system configuration 세팅

```
from tensorflow.python import ipu

cfg = ipu.config.IPUConfig()
# Select multi-IPU with device ID 30, which contains all 16 IPUs of a 16-IPU system.
cfg.select_ipus = 30
cfg.configure_ipu_system()
```

- select_ipus : 특정 IPU ID 지정
- auto-select_ipus : 사용할 IPU 개수를 지정하면 자동으로 할당
- configure_ipu_system() : 세팅된 configuration 적용

https://docs.graphcore.ai/projects/tensorflow-user-guide/en/latest/tensorflow/keras_tf2.html#keras-with-ipus

TENSORFLOW2

IPUStrategy : context 내의 모델을 poplar XLA를 통해 IPU에서 동작시키는 역할

(Keras의 fit()을 사용하는 경우)

```
strategy = ipu.ipu_strategy.IPUStrategy()
with strategy.scope():
  # Create a Keras model inside the strategy.
  model = create_model()

  # Compile the model for training.
  model.compile(
      loss=tf.keras.losses.SparseCategoricalCrossentropy(),
      optimizer=tf.keras.optimizers.RMSprop(),
      metrics=["accuracy"],
  )

  model.fit(dataset, epochs=2, steps_per_epoch=100)
```

IPUStrategy의 scope 내에서 모델 생성 및 실행

https://docs.graphcore.ai/projects/tensorflow-user-guide/en/latest/tensorflow/keras_tf2.html#keras-with-ipus

TENSORFLOW2

IPUStrategy : context 내의 모델을 poplar XLA를 통해 IPU에서 동작시키는 역할

(custom training loop을 사용하는 경우)

IPU에서 동작시킬 부분에 @tf.function 데코레이터 사용

```
@tf.function(experimental_compile=True)
def training_step(num_iterations, iterator, in_model, optimizer):

  for _ in tf.range(num_iterations):
    features, labels = next(iterator)
    with tf.GradientTape() as tape:
      predictions = in_model(features, training=True)
      prediction_loss = tf.keras.losses.sparse_categorical_crossentropy(
          labels, predictions)
      loss = tf.reduce_mean(prediction_loss)
      grads = tape.gradient(loss, in_model.trainable_variables)
      optimizer.apply_gradients(zip(grads, in_model.trainable_variables))
```

IPUStrategy의 scope 내에서 strategy.run()을 통해 실행

```
strategy = ipu.ipu_strategy.IPUStrategyV1()
with strategy.scope():
    # Run the custom training loop over the dataset.
    strategy.run(training_step,
                 args=[NUM_ITERATIONS, train_iterator, model, opt])
```

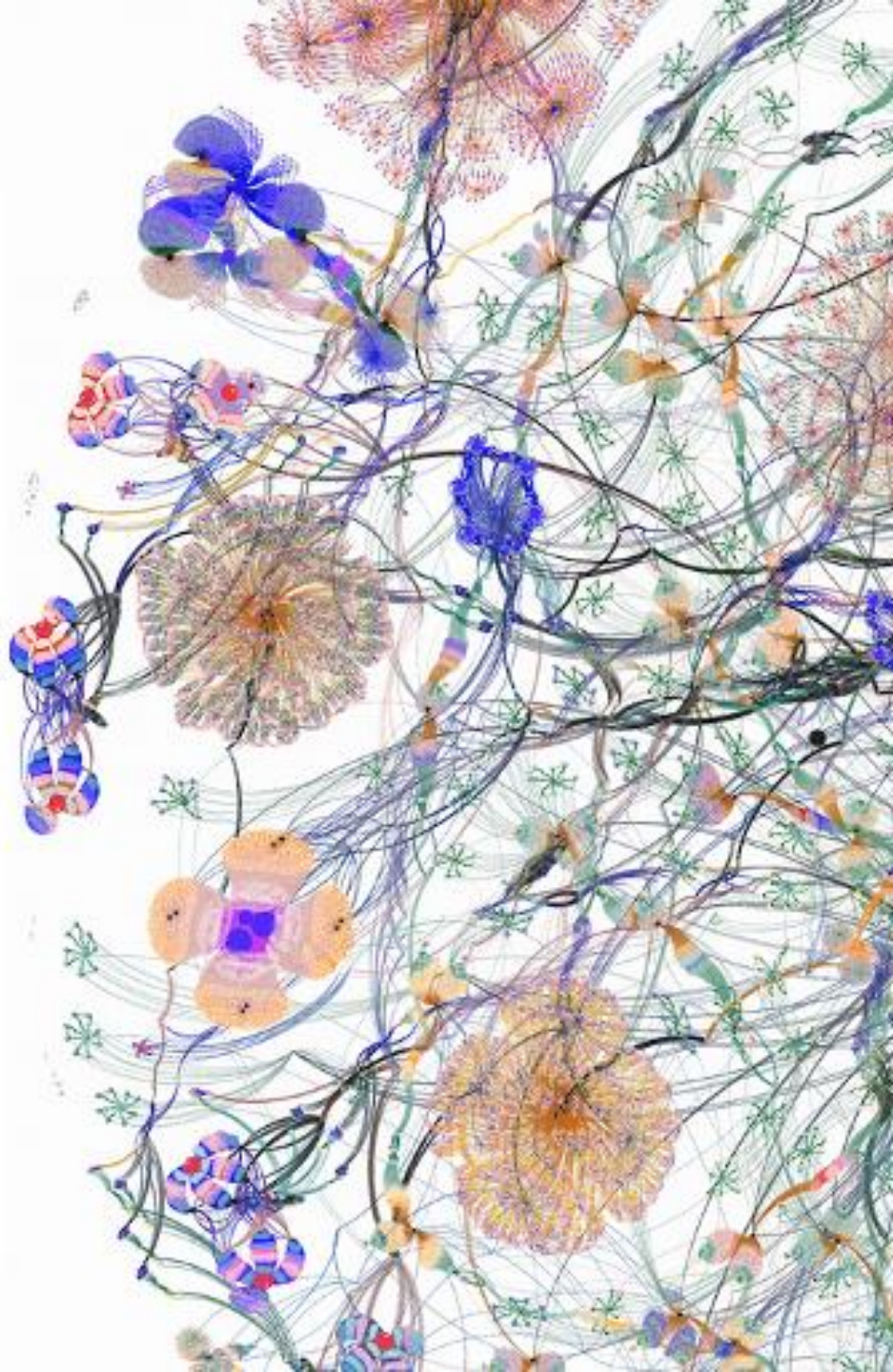
https://docs.graphcore.ai/projects/tensorflow-user-guide/en/latest/tensorflow/targeting_tf2.html#on-device-loops

TENSORFLOW 2

IPU-optimized operations

[Tensorflow 2 User Guide – 12. IPU-optimized operations]

HANDS-ON TUTORIAL



GRAPHCORE COMMAND LINE TOOLS

- gc-monitor : 현재 파티션 내 ipu 하드웨어 정보 및 ipu 프로세스 확인

```
(venv_tutorial) minkyuk@pod642:~/projects/NHN/hands_on_tutorials/day01$ gc-monitor
+-------------+-----------------------------------------------------------------------------------------------------------+
| gc-monitor  |                          Partition: 'pt-minkyuk-16-ipus' has 16 reconfigurable IPUs                       |
+-------------+-------------------+----------+------+--------------+----+--------+-------+-----------------------------+
|    IPU-M    |       Serial      | ICU FW   | Type |Server version| ID | PCIe ID |Routing|             GWSW            |
+-------------+-------------------+----------+------+--------------+----+--------+-------+-----------------------------+
| 10.1.5.21   | 0046.0002.8204521 | 2.4.4    |M2000 |    1.9.0     | 0  |    3   | DNC   |             2.4.2           |
| 10.1.5.21   | 0046.0002.8204521 | 2.4.4    |M2000 |    1.9.0     | 1  |    2   | DNC   |             2.4.2           |
| 10.1.5.21   | 0046.0001.8204521 | 2.4.4    |M2000 |    1.9.0     | 2  |    1   | DNC   |             2.4.2           |
| 10.1.5.21   | 0046.0001.8204521 | 2.4.4    |M2000 |    1.9.0     | 3  |    0   | DNC   |             2.4.2           |
+-------------+-------------------+----------+------+--------------+----+--------+-------+-----------------------------+
| 10.1.5.22   | 0012.0002.8204521 | 2.4.4    |M2000 |    1.9.0     | 4  |    3   | DNC   |             2.4.2           |
| 10.1.5.22   | 0012.0002.8204521 | 2.4.4    |M2000 |    1.9.0     | 5  |    2   | DNC   |             2.4.2           |
| 10.1.5.22   | 0012.0001.8204521 | 2.4.4    |M2000 |    1.9.0     | 6  |    1   | DNC   |             2.4.2           |
| 10.1.5.22   | 0012.0001.8204521 | 2.4.4    |M2000 |    1.9.0     | 7  |    0   | DNC   |             2.4.2           |
+-------------+-------------------+----------+------+--------------+----+--------+-------+-----------------------------+
| 10.1.5.23   | 0040.0002.8204521 | 2.4.4    |M2000 |    1.9.0     | 8  |    3   | DNC   |             2.4.2           |
| 10.1.5.23   | 0040.0002.8204521 | 2.4.4    |M2000 |    1.9.0     | 9  |    2   | DNC   |             2.4.2           |
| 10.1.5.23   | 0040.0001.8204521 | 2.4.4    |M2000 |    1.9.0     | 10 |    1   | DNC   |             2.4.2           |
| 10.1.5.23   | 0040.0001.8204521 | 2.4.4    |M2000 |    1.9.0     | 11 |    0   | DNC   |             2.4.2           |
+-------------+-------------------+----------+------+--------------+----+--------+-------+-----------------------------+
| 10.1.5.24   | 0050.0002.8204521 | 2.4.4    |M2000 |    1.9.0     | 12 |    3   | DNC   |             2.4.2           |
| 10.1.5.24   | 0050.0002.8204521 | 2.4.4    |M2000 |    1.9.0     | 13 |    2   | DNC   |             2.4.2           |
| 10.1.5.24   | 0050.0001.8204521 | 2.4.4    |M2000 |    1.9.0     | 14 |    1   | DNC   |             2.4.2           |
| 10.1.5.24   | 0050.0001.8204521 | 2.4.4    |M2000 |    1.9.0     | 15 |    0   | DNC   |             2.4.2           |
+-------------+-------------------+----------+------+--------------+----+--------+-------+-----------------------------+
+-----------------------------------------------------------------------------------------+
|                                  No attached processes                                  |
+-----------------------------------------------------------------------------------------+
```

- vipu-admin list partitions : IPU-POD 내 파티션 정보 확인

https://docs.graphcore.ai/projects/command-line-tools/en/latest/index.html

SETUP

1. Poplar SDK 활성화
   - source SDK_PATH/poplar*/enable.sh
   - source SDK_PATH/popart*/enable.sh

2. 가상환경 생성 및 활성화
   - virtualenv -p python3 venv_tutorial
   - source venv_tutorial/bin/activate

3. 패키지 설치
   - (pytorch)pip install SDK_PATH/poptorch*.whl
   - (tensorflow)pip install SDK_PATH/tensorflow-2*amd*.whl (tf1/tf2, amd/intel 지정)

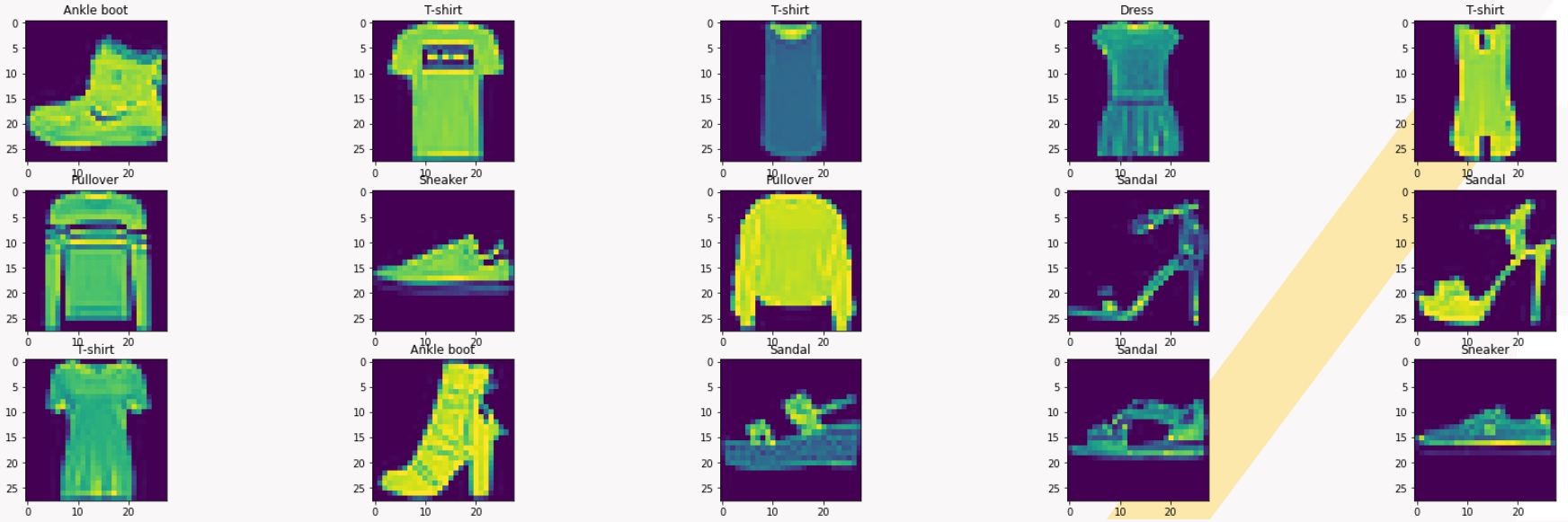
```
Package              Version
-------------------- -----------
dataclasses          0.8
importlib-resources  5.4.0
pip                  21.3.1
pkg_resources        0.0.0
poptorch             2.4.0+40669
setuptools           59.6.0
torch                1.10.0+cpu
tqdm                 4.64.0
typing_extensions    4.1.1
wheel                0.37.1
zipp                 3.6.0
```

poptorch 설치 시 호환되는 torch 버전 자동으로 함께 설치

```
(venv_tutorial) minkyuk@pod642:~/projects/NHN/hands_on_tutorials/day01$ ls ~/sdks/2.4.0/tensorflow-
tensorflow-1.15.5+gc2.4.0+139618+803bd5d97f3+amd_znver1-cp36-cp36m-linux_x86_64.whl       tensorflow-2.4.4+gc2.4.0+139613+8debb698097+amd_znver1-cp36-cp36m-linux_x86_64.whl
tensorflow-1.15.5+gc2.4.0+139620+803bd5d97f3+intel_skylake512-cp36-cp36m-linux_x86_64.whl  tensorflow-2.4.4+gc2.4.0+139619+8debb698097+intel_skylake512-cp36-cp36m-linux_x86_64.whl
```

PYTORCH TUTORIAL

FASHION MNIST EXAMPLE



- pytorch_gpu.py : GPU 코드 (IPU-POD에서 실행 시 CPU로 동작)
- pytorch_ipu.py : 최소한의 코드 변환으로 IPU 동작하는 코드
- requirements.txt : pip install -r requirements.txt

PYTORCH TUTORIAL

FASHION MNIST EXAMPLE

- 패키지 import

```
3  import torch
4  import torchvision
5  import torch.nn as nn
6  import matplotlib.pyplot as plt
7  from tqdm import tqdm
8  from sklearn.metrics import accuracy_score, confusion_matrix
9- from torch.utils import data as torch_data
```

```
3  import torch
4  import torchvision
5  import torch.nn as nn
6  import matplotlib.pyplot as plt
7  from tqdm import tqdm
8  from sklearn.metrics import accuracy_score, confusion_matrix
9+ import poptorch
```

- Training 시에는 Loss를 함께 리턴하는 wrapper class 정의

```
33+
34+ class ModelwithLoss(nn.Module):
35+     def __init__(self, model, criterion):
36+         super().__init__()
37+         self.model = model
38+         self.criterion = criterion
39+
40+     def forward(self, x, labels=None):
41+         output = self.model(x)
42+         if labels is not None:
43+             loss = self.criterion(output, labels)
44+             return output, poptorch.identity_loss(loss, reduction='sum')
45+         return output
46+
47+
```

PYTORCH TUTORIAL

FASHION MNIST EXAMPLE

- Device를 cuda로 세팅하는 부분 제거

```
33 if __name__ == '__main__':
34-    device = torch.device('cuda' if torch.cuda.is_available() else 'cpu'
35-    print(device)
36-
```

```
48 if __name__ == '__main__':
```

```
52     model = ClassificationModel()
53     model.train()
54-    model = model.to(device)
```

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

- IPU 옵션 세팅

```
64+    opts = poptorch.Options()
65+    opts.enableExecutableCaching('cache')
66+
```

- Poptorch의 DataLoader / Optimizer 사용

```
56-    train_dataloader = torch_data.DataLoader(train_dataset,
57                                             batch_size=16,
58                                             shuffle=True)
59
60-    optimizer = torch.optim.SGD(model.parameters(), lr=0.001, momentum=0
```

```
70+    train_dataloader = poptorch.DataLoader(opts,
71+                                           train_dataset,
72                                             batch_size=16,
73                                             shuffle=True)
74
75+    optimizer = poptorch.optim.SGD(model.parameters(), lr=0.001, momentum=0.9)
```

PYTORCH TUTORIAL

FASHION MNIST EXAMPLE

- Poptorch의 trainingModel / inferenceModel 생성

```
78+    model = ModelwithLoss(model, criterion)
79+    poptorch_model = poptorch.trainingModel(model,
80+                                            options=opts,
81+                                            optimizer=optimizer)
82+
```

- Training Loop 불필요한 부분 제거

```
64     for epoch in range(1, epochs + 1):
65         bar = tqdm(train_dataloader, total=len(train_dataloader))
66         bar.set_description(f'[Epoch {epoch:02d}]')
67         for data, labels in bar:
68-            data = data.to(device)
69-            labels = labels.to(device)
70-
71-            optimizer.zero_grad()
72-            output = model(data)
73-            loss = criterion(output, labels)
74-            loss.backward()
75-            optimizer.step()
76-
77             bar.set_postfix({"Loss": torch.mean(loss).item()})
```

```
84     for epoch in range(1, epochs + 1):
85         bar = tqdm(train_dataloader, total=len(train_dataloader))
86         bar.set_description(f'[Epoch {epoch:02d}]')
87         for data, labels in bar:
88+            output, loss = poptorch_model(data, labels)
89             bar.set_postfix({"Loss": torch.mean(loss).item()})
```

PYTORCH TUTORIAL

FASHION MNIST EXAMPLE

- poptorch.identity_loss()

```python
class ModelwithLoss(nn.Module):
    def __init__(self, model, criterion):
        super().__init__()
        self.model = model
        self.criterion = criterion

    def forward(self, x, labels=None):
        output = self.model(x)
        if labels is not None:
            loss = self.criterion(output, labels)
            return output, poptorch.identity_loss(loss, reduction='sum')
        return output
```

- poptorch의 backward() 에서 자동으로 인식하기 위해 해당 텐서가 Loss 임을 명시
- 일반적인 torch의 Loss 객체를 바로 사용하는 경우는 불필요하지만 Custom Loss의 경우 필수

poptorch.identity_loss(*x*, *reduction*)

Marks a tensor as being part of the loss calculation and, as such, will backpropagate through it in the PopTorch autograd.

This function should be called on the (final) loss of a model so that it is used as the start of backpropagation. This is equivalent to calling `x.backward()` on a tensor `x` when running on the CPU.

This function is necessary to combine multiple losses into a custom loss. It ensures that the tensor is part of the loss calculation and, as such, should be part of the backpropagation in PopTorch autograd.

Multiple calls to `identity_loss` can be made inside the same model provided they are all dependant: all marked losses must be traceable into a single final tensor itself marked by a call to `identity_loss` otherwise an error is raised.

Parameters:
- **x** (*torch.Tensor*) – The calculated loss.
- **reduction** (*str*) – Reduce the loss output as per PyTorch loss semantics. Supported values are:
  - `"sum"`: Sum the losses.
  - `"mean"`: Take the mean of the losses.
  - `"none"`: Don't reduce the losses.

Returns: The loss tensor with the specified reduction applied.

Return type: torch.Tensor

PYTORCH TUTORIAL

FASHION MNIST EXAMPLE

- enableExecutableCaching()

```
opts = poptorch.Options()
opts.enableExecutableCaching('cache')
```

- 컴파일된 연산 그래프를 캐싱하고 이 후 동일한 연산 그래프 호출 시 컴파일 없이 바로 로드하여 사용

`enableExecutableCaching(path)`

Load/save Poplar executables to the specified `path`, using it as a cache, to avoid recompiling identical graphs.

Parameters: **path** (*str*) – File path for Poplar executable cache store; setting path to None`` disables executable caching.

Return type: poptorch.Options

TENSORFLOW2 TUTORIAL

MNIST EXAMPLE

- tensorflow_gpu.py : GPU 코드 (IPU-POD에서 실행 시 CPU로 동작)
- tensorflow_ipu.py : 최소한의 코드 변환으로 IPU 동작하는 코드
- tensorflow_ipu_custom_training.py : custom training loop 예시 코드

TENSORFLOW2 TUTORIAL

MNIST EXAMPLE

- IPUOutfeedQueue()

```
#
# The host side queue
#
outfeed_queue = ipu.ipu_outfeed_queue.IPUOutfeedQueue()


#
# A custom training loop
#
@tf.function(experimental_compile=True)
def training_step(steps_per_execution, iterator, in_model, optimizer):
  for _ in tf.range(steps_per_execution):
    features, labels = next(iterator)
    with tf.GradientTape() as tape:
      predictions = in_model(features, training=True)
      prediction_loss = tf.keras.losses.sparse_categorical_crossentropy(
          labels, predictions)
      loss = tf.reduce_mean(prediction_loss)
      grads = tape.gradient(loss, in_model.trainable_variables)
      optimizer.apply_gradients(zip(grads, in_model.trainable_variables))

    outfeed_queue.enqueue(loss)
```

class `tensorflow.python.ipu.ipu_outfeed_queue.IPUOutfeedQueue`(*outfeed_mode=None, device_ordinal=None, buffer_depth=1, optimise_latency=False*)

Generates and adds outfeed enqueue/dequeue operations to the graph.

An outfeed is the counterpart to an infeed and manages the transfer of data (like tensors, tuples or dictionaries of tensors) from the IPU graph to the host.

The queue has two modes of operation - outfeed all or outfeed last. In outfeed all mode every element that is enqueued will be stored for a subsequent dequeue. All of the enqueued elements will be returned when the dequeue operation is run. This is the default behaviour.

In outfeed last mode only the last enqueued element is stored. The dequeue operation will in this case return a single element.

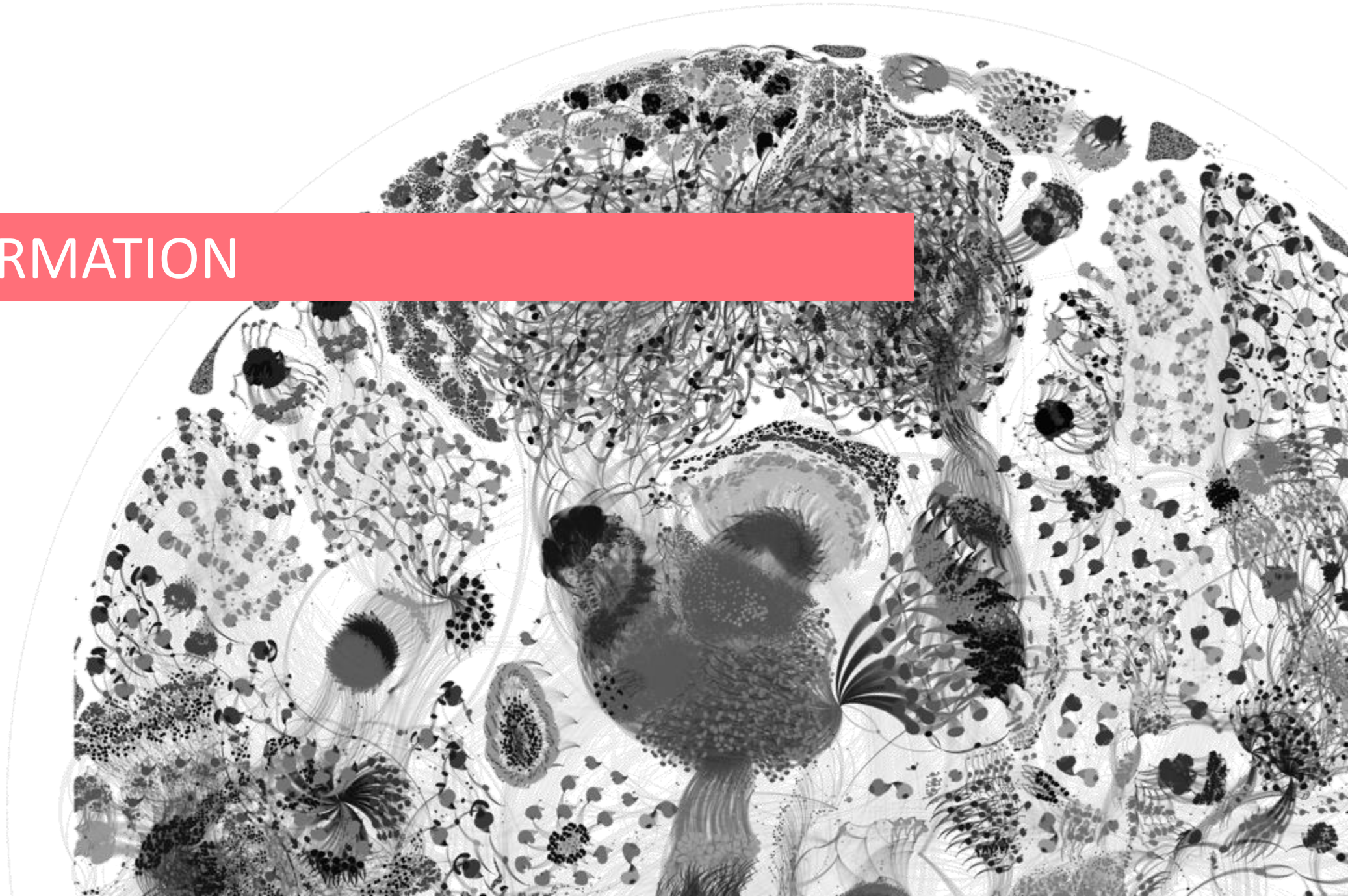
`__init__`(*outfeed_mode=None, device_ordinal=None, buffer_depth=1, optimise_latency=False*)

Creates an IPUOutfeedQueue object.

- IPU 연산의 결과값을 호스트로 리턴하는 경우
- IPUOutfeedQueue를 활용

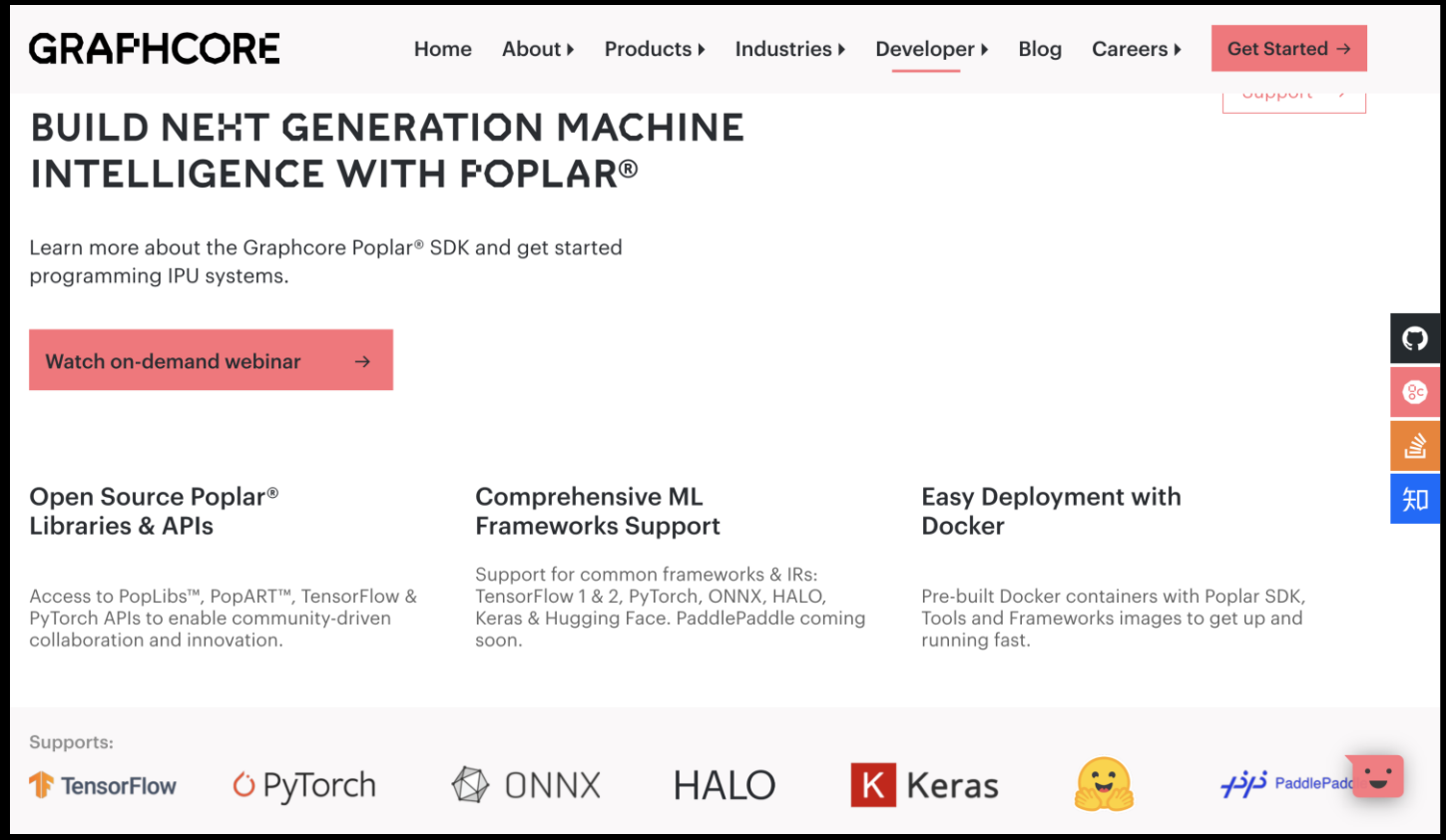
https://docs.graphcore.ai/projects/tensorflow-user-guide/en/latest/tensorflow/targeting_tf2.html#on-device-loops

MORE INFORMATION



DEVELOPER PORTAL

https://graphcore.ai/developer

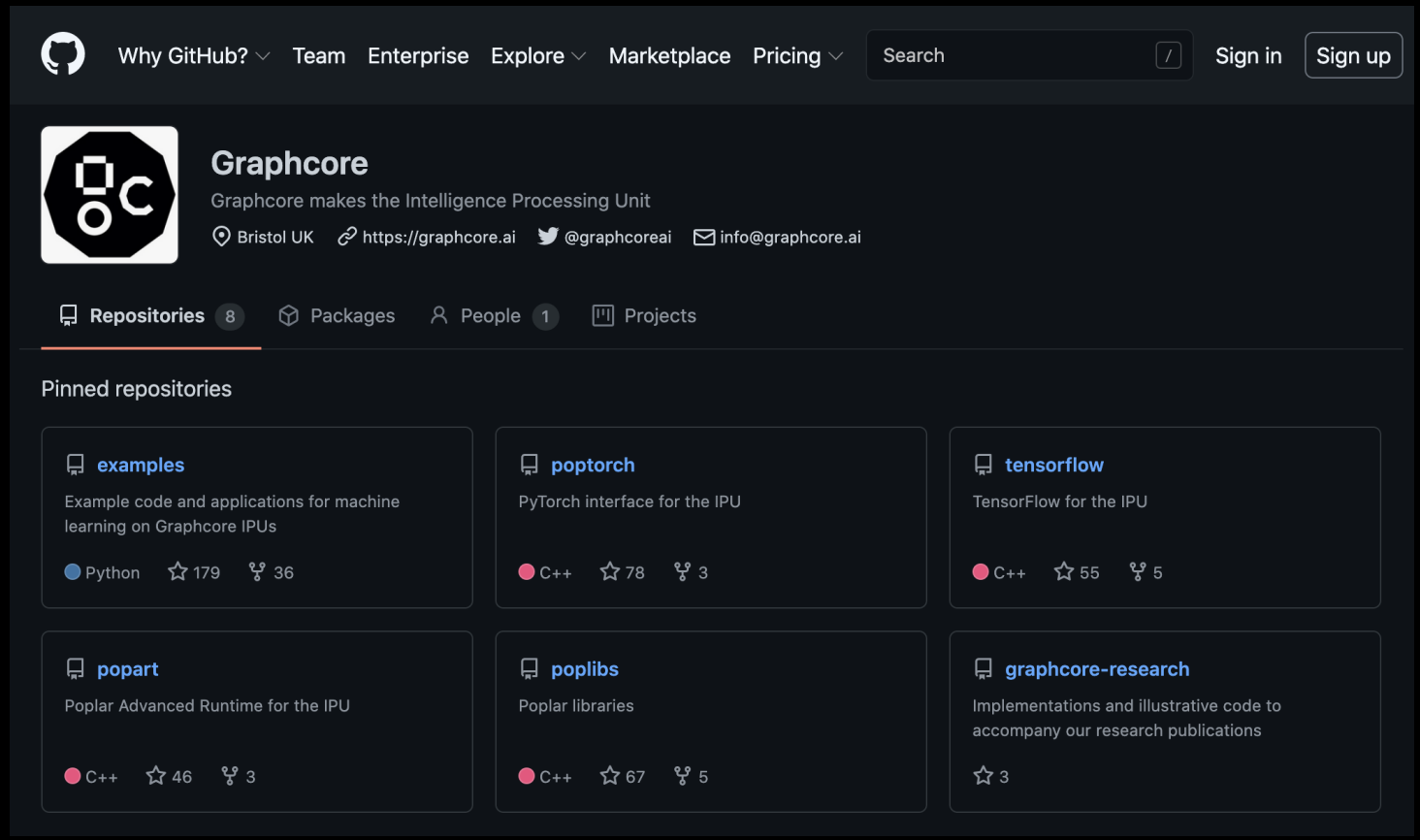


GRAPHCORE DOCUMENTS

https://docs.graphcore.ai

GRAPHCORE GITHUB

https://github.com/graphcore



THANK YOU

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