

# TEXAS A&M IPU WORKSHOP



**GRAPHCORE**



Graphcore Confidential

# GRAPHCORE'S SOLUTION

## Hardware



IPU processor  
designed for AI

## Software



Poplar SDK and  
development tools

## Platform



IPU platforms  
Available in the cloud

# THE INTELLIGENCE PROCESSING UNIT (IPU)

## WHAT MAKES IT DIFFERENT?

CPU

GPU

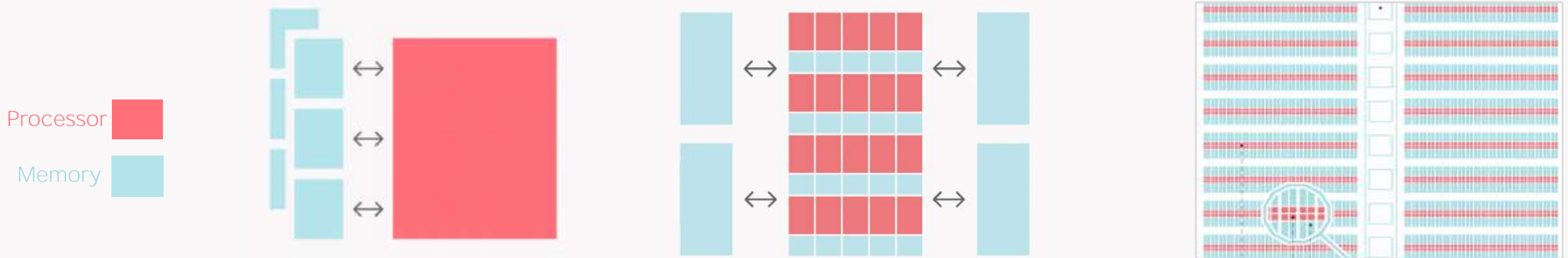
IPU

Parallelism

Designed for  
scalar processing

SIMD/SIMT architecture.  
Designed for large blocks  
of dense contiguous data

Massively parallel MIMD architecture.  
High performance/efficiency  
for future ML trends



Memory  
Bandwidth

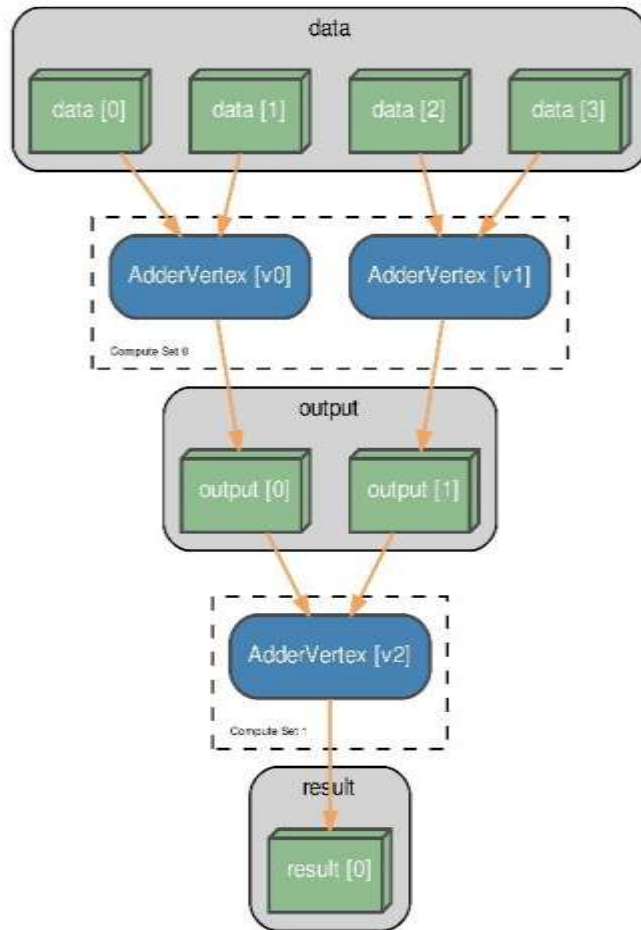
Off-chip  
memory

Model and Data spread across off-chip and  
small on-chip cache and shared memory  
(2TB/s for A100 HBM)

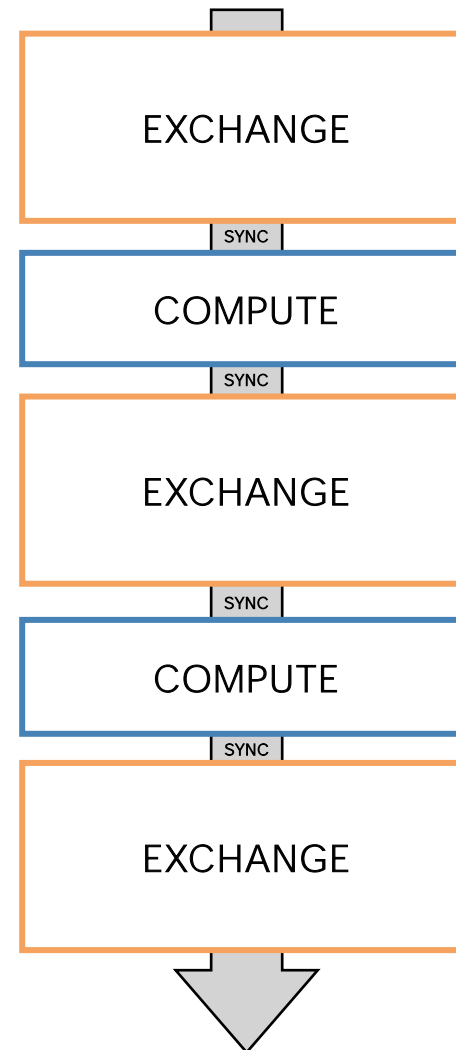
Main Model & Data in tightly coupled  
large locally distributed SRAM  
(~65 TB/s for Bow IPU)

# EXECUTION MODEL

COMPUTATIONAL GRAPH

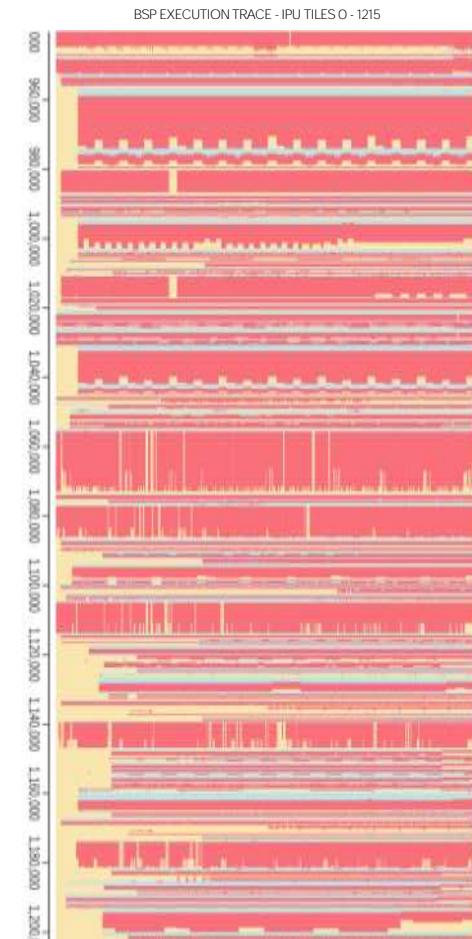


BSP SCHEDULE



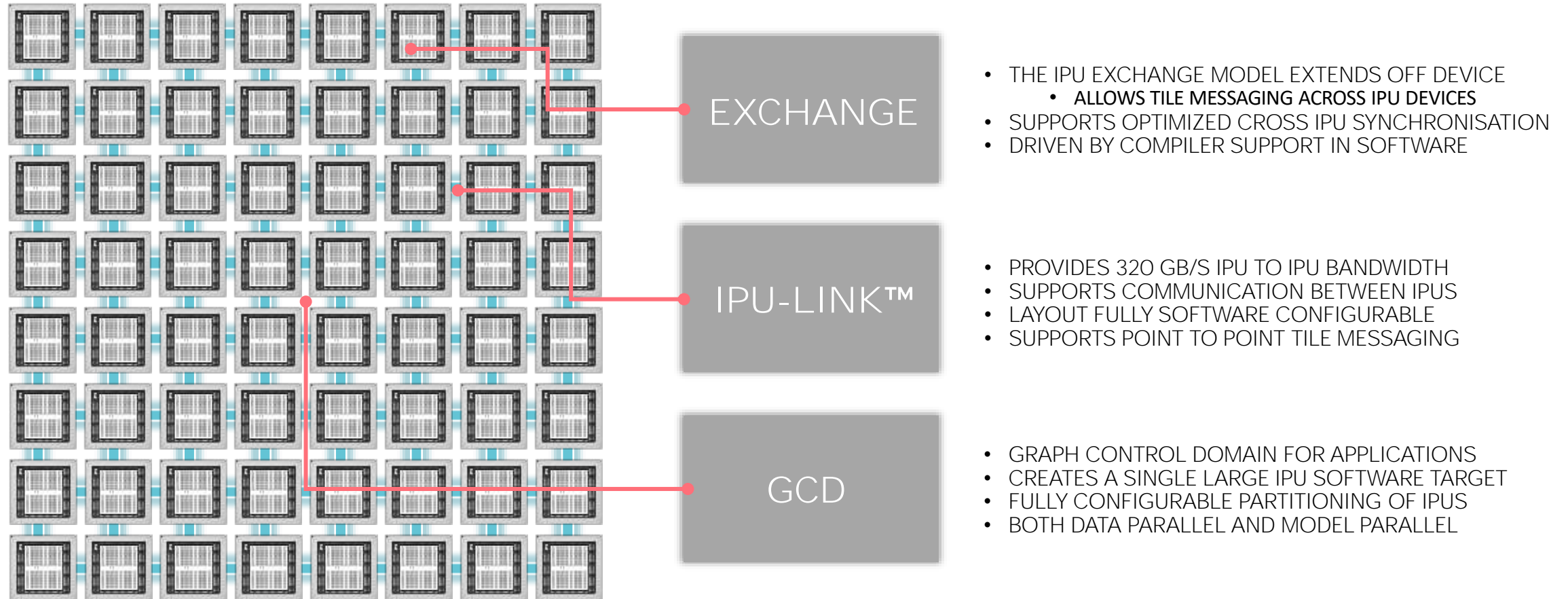
GRAPHCORE

OPTIMIZED IPU EXECUTION



OUTPUT FROM POPVISION GRAPH ANALYSER

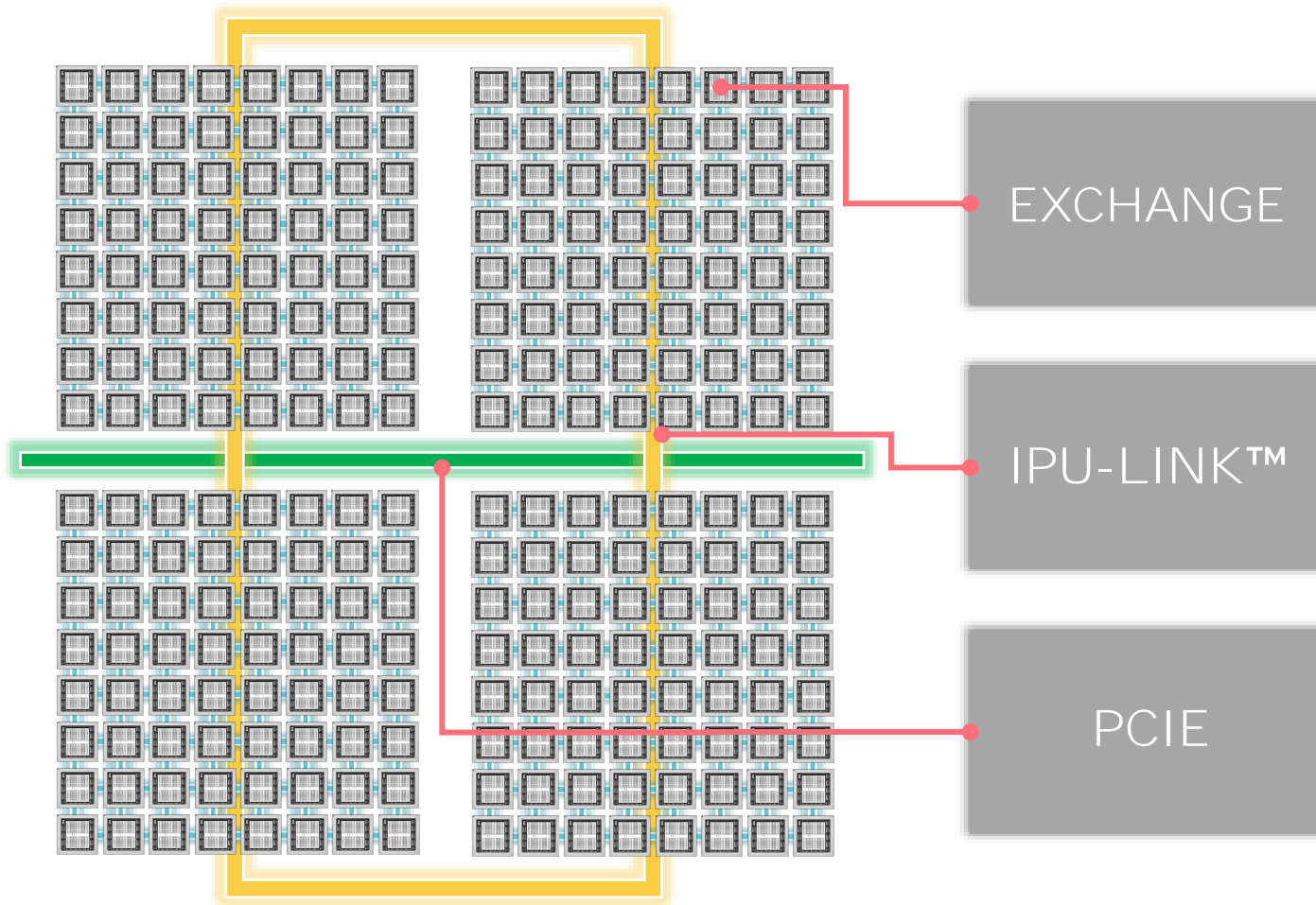
# SCALING ACROSS DEVICES



UP TO 64 IPU DEVICES USABLE AS A SINGLE LARGE IPU FROM APPLICATIONS

565248 FULLY INDEPENDENT WORKERS, 57.6GB IN-PROCESSOR MEMORY™, LEVERAGING OVER 3.8 TRILLION TRANSISTORS

# SCALING ACROSS SYSTEMS



- IPU EXCHANGE SUPPORT ACROSS DOMAINS
  - **DRIVEN BY COMPILER SUPPORT IN SOFTWARE**
- ENABLES APPLICATION COLLECTIVES SUPPORT
- ALLOWS SCALING UP TO 64000 IPU DEVICES

- IPU LINK™ CAN BE EXTENDED ACROSS DOMAINS
- SUPPORTS OPTIMIZED IPU LINK™ COLLECTIVES
- ALLOWS REPLICATION ACROSS SYSTEMS
- SUPPORTS A STANDARD IPU SOFTWARE MODEL

- IPUS CAN ACCESS MEMORY AND DEVICES OVER PCIE
- ALLOWS INTERFACING WITH HOST BASED SOFTWARE
- APPLICATIONS CAN BUILD ON HOST NETWORKING
- ALLOWS SCALING IN STANDARD SERVER PLATFORMS

256 IPU APPLICATION TARGET BUILT FROM INTERCONNECTED 64 IPU DOMAINS

# PRODUCT DETAILS



**GRAPHCORE**



Graphcore Confidential



# 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

## 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



# BOW-2000 IPU MACHINE

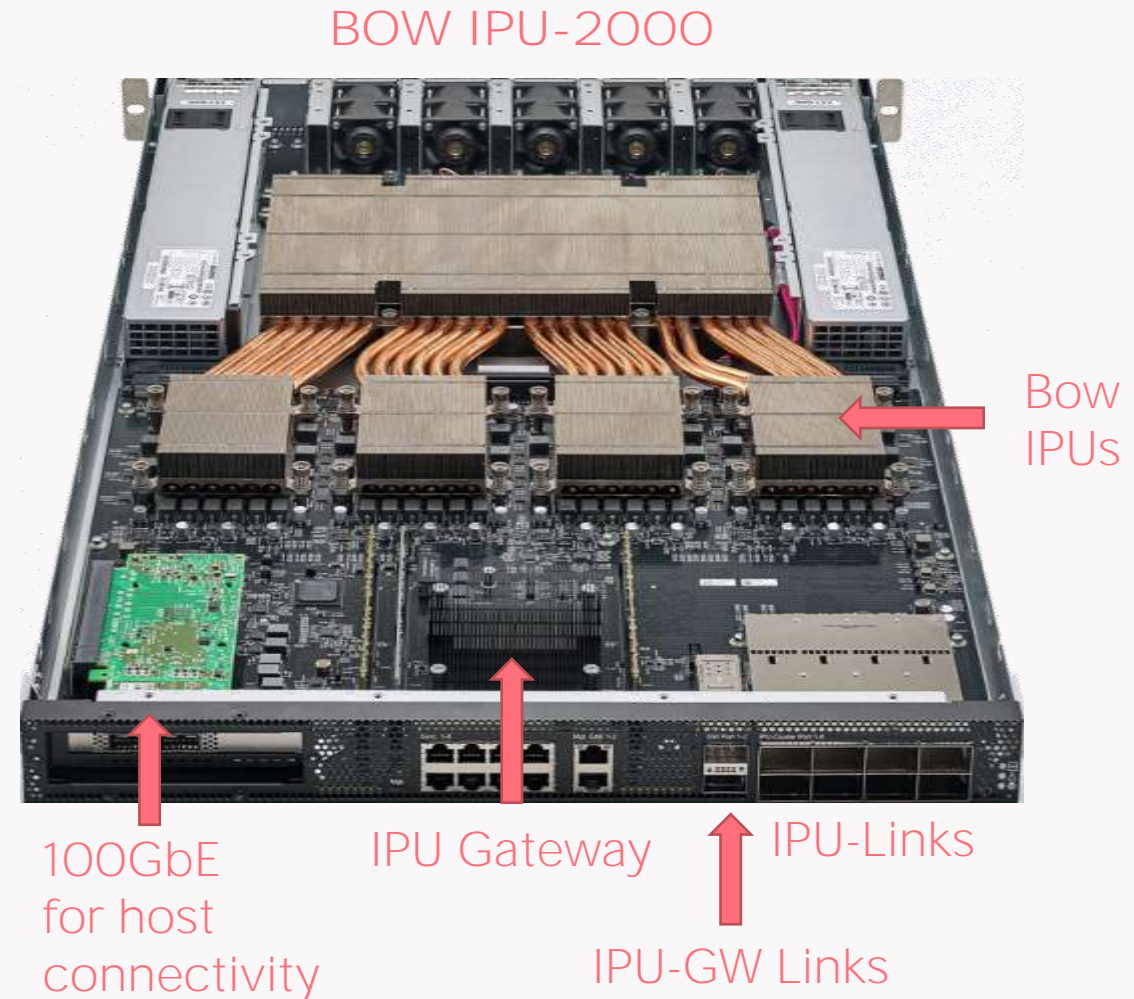
1U blade form factor delivering 1.4 PetaFLOPS AI Compute

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: 3<sup>RD</sup> GENERATION IPU SYSTEMS

## SHIPPING TO CUSTOMERS TODAY



BOW POD<sub>16</sub>

4x Bow-2000  
5.6 PetaFLOPS  
1 CPU server



BOW POD<sub>64</sub>

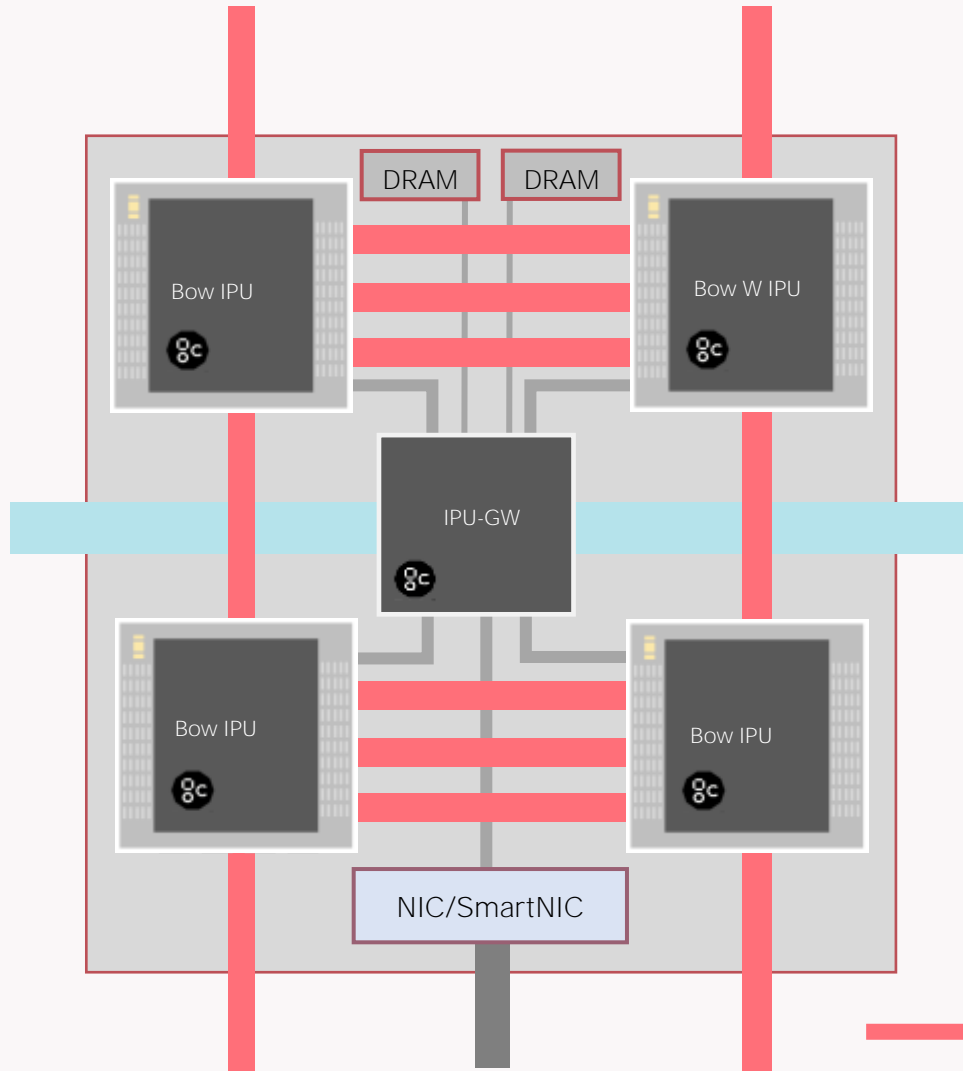
16x Bow-2000  
22.4 PetaFLOPS  
1-4 CPU server(s)



BOW POD<sub>256</sub>

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

# BOW-2000: THE BUILDING BLOCK OF LARGE PODS



COMPUTE

## 4x Bow IPUs

- 1.4 PFLOP<sub>16</sub> 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) @ 20 GB/s



COMMUNICATIONS

## IPU-Fabric managed by IPU-GW

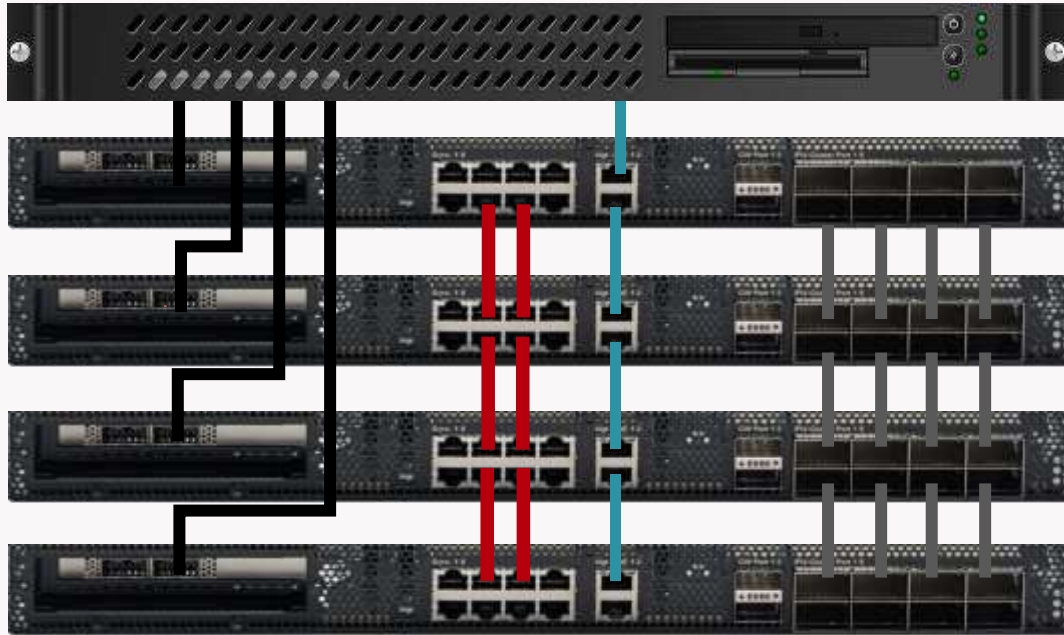
- Host-Link – 100GE to Poplar Server for standard data center networking
- IPU-Link – 2D Torus for intra-POD64 communication
- GW-Link - 2x 100Gbps Gateway-Links for rack-to-rack – flexible topology

-  x16 IPU-Link [64GB/s]
-  Host-Link Network I/F [100Gbps]
-  IPU-GW Link [100Gbps]
-  x8 PCIe G4 [32GB/s]



# BOW POD16 DIRECT ATTACH

Server with x4 Bow-2000



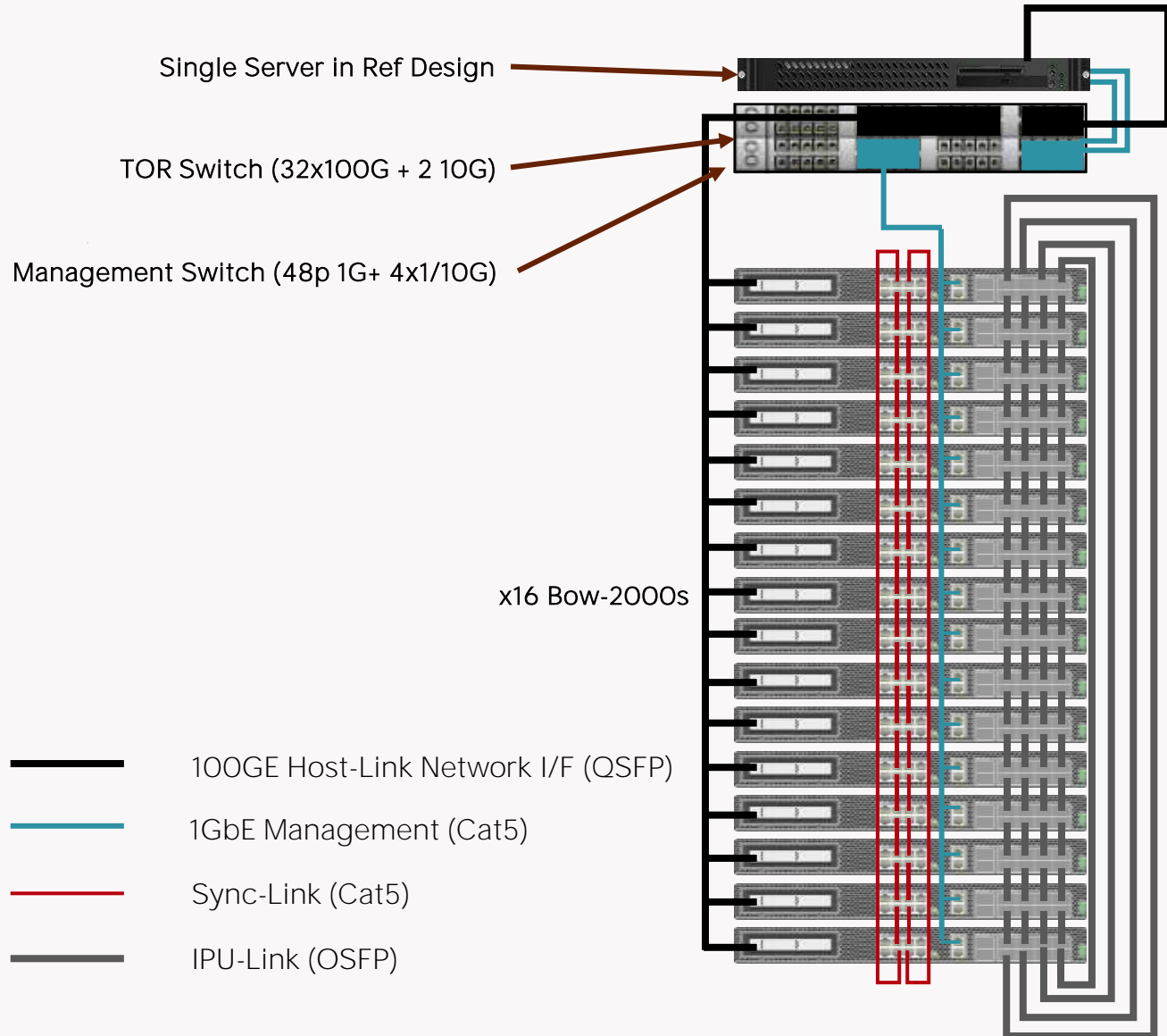
- Convenient cost effective evaluation platform
- Available through Graphcore channel for on-premise or Graphcloud
- Wide range of benchmarks and examples for Bow Pod<sub>16</sub> performance evaluation
- Scale-out with Bow Pod<sub>64</sub> and beyond

- Host-Link 100GE network interface (QSFP, 1.0m)
- 1GbE Management (Cat5, 1.5m)
- Sync-Link (Cat5, 0.15m)
- IPU-Link (OSFP, 0.3m)

# BOW POD64 REFERENCE DESIGN

Pre-Qualified 64-IPU Design with Reference Server and Switches

- Up to 16 Bow-2000 platforms
- Reference architecture supports different server requirements based on workload
- Bow Pod<sub>64</sub> Configuration:
  - 64 IPU
  - 22.4 PFLOPs @ FP16.16
  - ~58GB IPU In-Processor memory
  - ~7TB Streaming Memory
- Bow Pod Host disaggregation
  - Flexibly connect required host server compute over fabric
- 2D-Torus topology
  - Maximizes bandwidth across IPU-Links
  - All-Reduce 2x faster than mesh topology
- Scalable to 64K Bow IPU



# MODELS AND SOFTWARE



**GRAPHCORE**

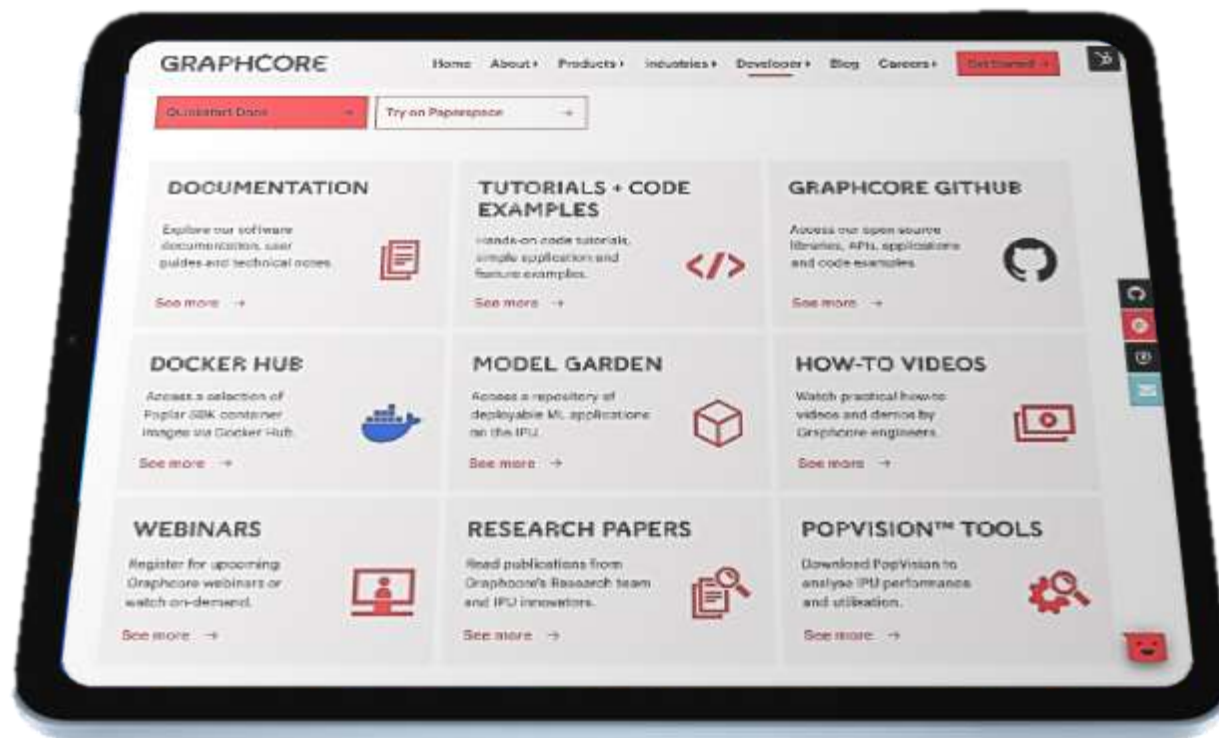


Graphcore Confidential



# GRAPHCORE SOFTWARE ECOSYSTEM

## WORLD CLASS DEVELOPER RESOURCES FOR IPU USERS



[WWW.GRAPHCORE.AI/DEVELOPER](http://WWW.GRAPHCORE.AI/DEVELOPER)

### GRAPHCORE

Graphcore Documents  
Version: Latest

Search docs

- Getting Started
- Software Documents
- Hardware Documents
- Technical Notes and White Papers
- Examples and Tutorials
- Document Updates
- Alphabetical List of All Documents
- Graphcore License Agreements

### GRAPHCORE DOCUMENTS

#### Getting Started

Background information and quick-start guides for Graphcloud and Pod systems

#### Software Documents

Documentation for the Poplar SDK and other software

#### Hardware Documents

Documentation for installing and using IPU-Machines and Pod systems

#### Technical Notes and White Papers

Technical notes and white papers on Graphcore technology

#### Document Updates

The latest news about new documents and examples

#### Examples and Tutorials

Tutorials and application examples for running on the IPU

### Getting started with PyTorch for the IPU

Running a basic model for training and inference

AI Customer Engineer, Chris Bogdankiewicz introduces PyTorch for the IPU. With PopTorch™ - a simple Python wrapper for PyTorch programs, developers can easily run models, directly on Graphcore IPU's with a few lines of extra code.

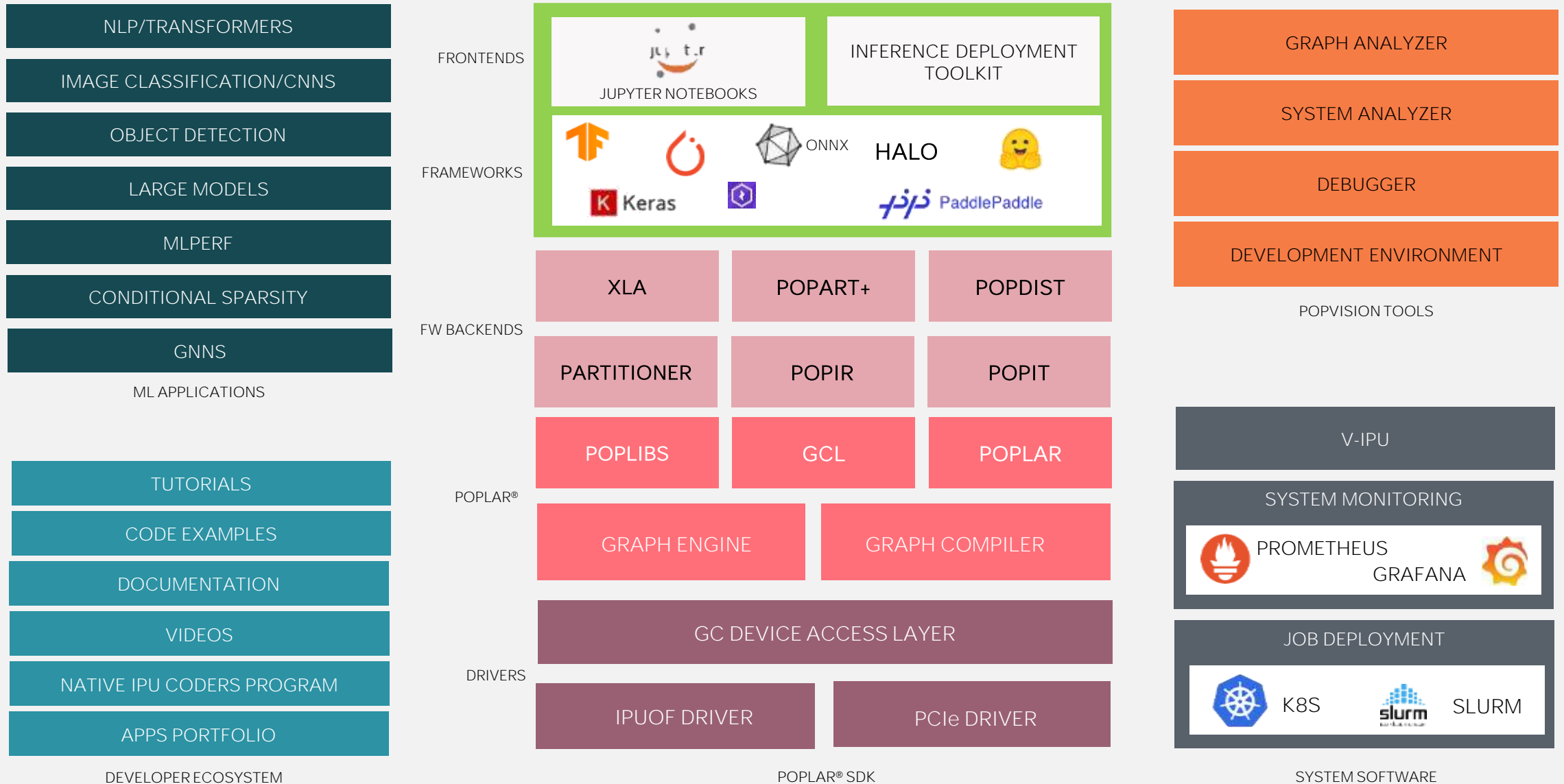
In this video, Chris provides a quick demo on running a basic model for both training and inference using a MNIST based example.

[Get the Code](#)

[Read the Guide](#)



# GRAPHCORE SOFTWARE MATURITY



GRAPHCORE

# POPLIBS GRAPH LIBRARIES

Complete set of open-source libraries of Machine Learning primitives and building blocks

- Over 50 optimized functions for common machine learning models
- More than 750 high performance compute elements
- Simple C++ graph building API
- Implement any application
- Full control flow support

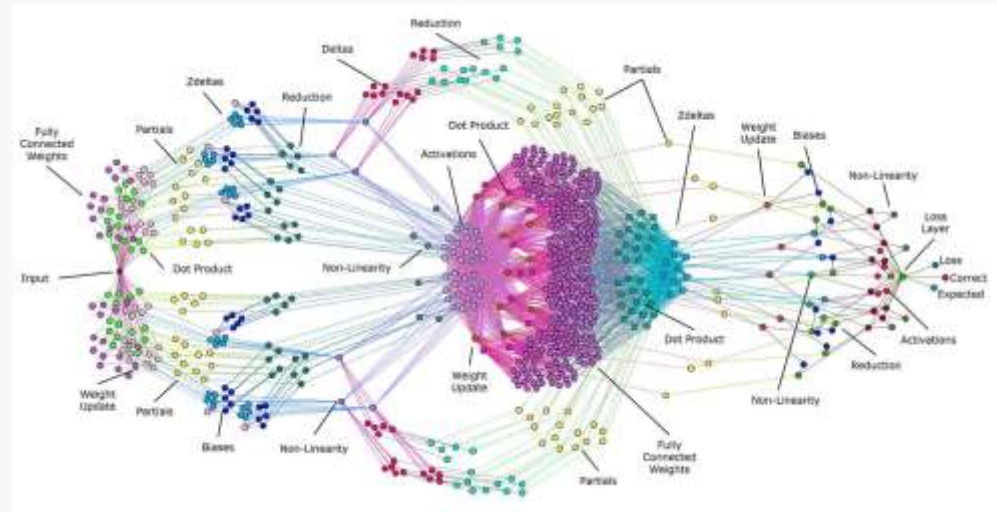
POPNN	FUNCTIONS USED IN NEURAL NETWORKS (NON-LINEARITIES, POOLING, LOSS FUNCTIONS)
POPLIN	OPTIMIZED LINEAR ALGEBRA FUNCTIONS (MATRIX MULTIPLICATION, CONVOLUTIONS)
POPOPS	FUNCTIONS FOR PERFORMING ELEMENTWISE OPERATIONS ON TENSOR DATA
POP RAND	HIGH PERFORMANCE FUNCTIONS FOR POPULATING TENSORS WITH RANDOM NUMBERS
POP UTIL	GENERAL UTILITY FUNCTIONS FOR BUILDING GRAPHS FOR IPU DEVICES
GCL	OPTIMIZED COLLECTIVES LIBRARY SUPPORTING MODEL AND DATA PARALLEL



# GRAPH COMPILER

State of the art compiler for simplified IPU programming

- Handling the scheduling and work partitioning of large parallel programs including memory control:
- Optimized execution of the entire application model to run efficiently on IPU platforms
- Alleviates the burden on developers to manage data or model parallelism
- Code generation using standard LLVM





# POPVISION™ TOOLS

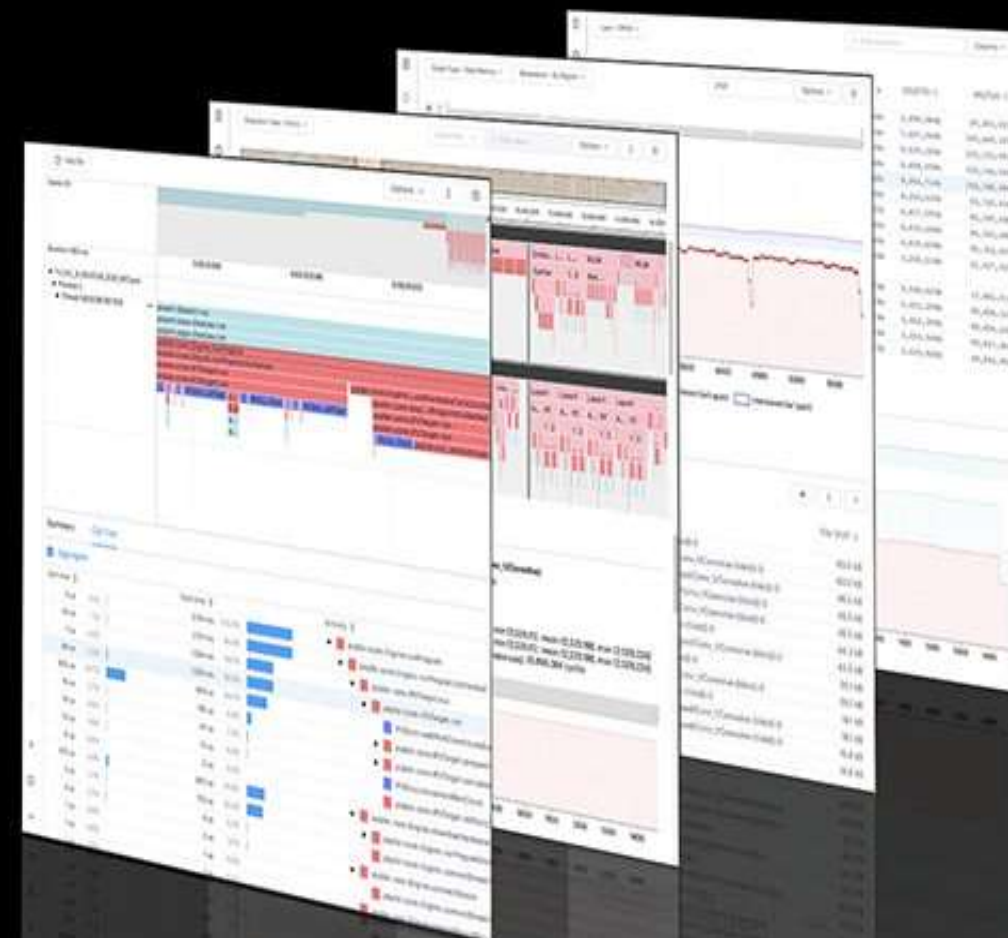
POPLAR™ POPVISION TOOLS

## 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



# STANDARD ML FRAMEWORK SUPPORT

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

 PyTorch

 TensorFlow

 PyTorch Lightning



 PyG

 Keras

 PaddlePaddle

HALO



Existing models on  
alternative platforms

Easy port of  
high-level  
framework  
models



POPLAR®



IPU-  
Processor  
Platforms








# PYTORCH GEOMETRIC FOR IPU

ANNOUNCEMENT | TECHNICAL BLOG | GETTING STARTED

**PyG is the ultimate library for Graph Neural Networks**

Build graph learning pipelines with ease

pyg.org

“The suitability of IPUs for running GNNs and the kind of performance advantage that Graphcore and its customers have demonstrated is really helping to accelerate the uptake of this exciting model class”

**Matthias Fey – PyG creator & founder of Kumo.ai**

Apr 05, 2023 | Poplar, PyTorch, GNN

**GRAPHCORE USERS CAN NOW BUILD AND RUN GNNs WITH PYTORCH GEOMETRIC**

Apr 05, 2023 | Developer, PyTorch, GNN

Written By: **Blazej Banaszewski**

**ACCELERATING PYG ON IPUS: UNLEASH THE POWER OF GRAPH NEURAL NETWORKS**

Apr 05, 2023 | Developer, GNN, Paperspace

Written By: **Blazej Banaszewski, Adam Sanders, Akash Swamy & Mihai Polce**

**GETTING STARTED WITH PYTORCH GEOMETRIC (PYG) ON GRAPHCORE IPUS**

Written By: **Adam Sanders and Arianna Saracino**

```
import torch
import torch.nn.functional as F
from torch_geometric.nn import GNNConv

class PytorchGnnConv(torch.nn.Module):
    def __init__(self, in_channels, out_channels):
        super().__init__()
        self.in_channels = in_channels
        self.out_channels = out_channels
        self.conv = GNNConv(in_channels, out_channels)

    def forward(self, x, edge_index, edge_weight=None):
        x = F.relu(x)
        x = self.conv(x, edge_index, edge_weight)
        x = F.relu(x)
        return x

model = PytorchGnnConv(16, 16)
optimizer = optim.Adam(model.parameters())
trainer = GradientDescentTrainer(model, optimizer)
trainer.train(10, 1000000)
print("Training on PyG")
trainer.evaluate(1000000)
```

RUN GNN MODELS IN PYG ON PAPERSPACE JUPYTER NOTEBOOKS

**Training Dynamic Graphs**  
TGN  
Training

**Training Large Graphs**  
Cluster-GCN  
Training

**Predicting molecular properties**  
SchNet

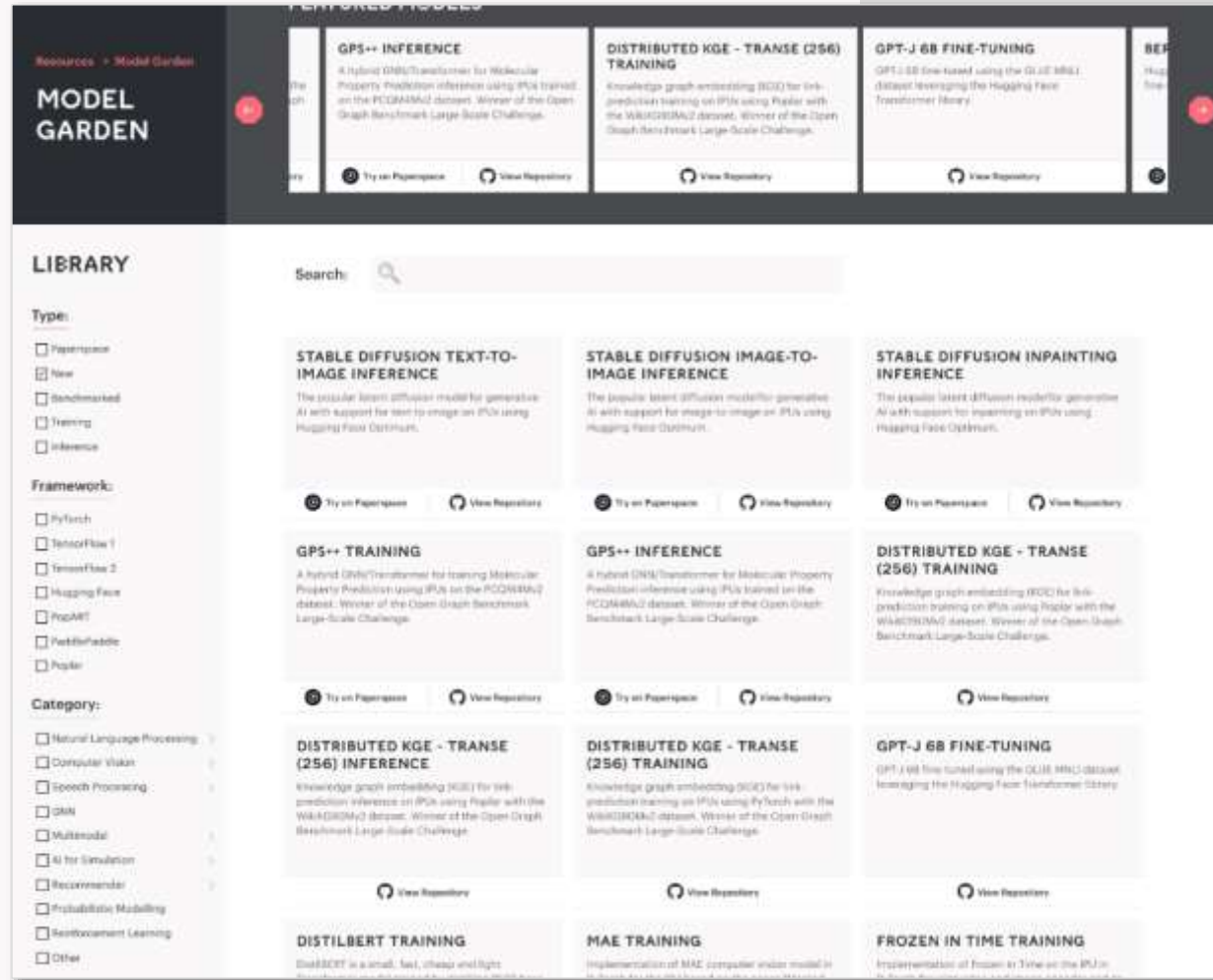
**Predicting molecular properties**  
GIN

**Link Prediction training**  
NBFNet  
Training

# ENHANCED MODEL GARDEN



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

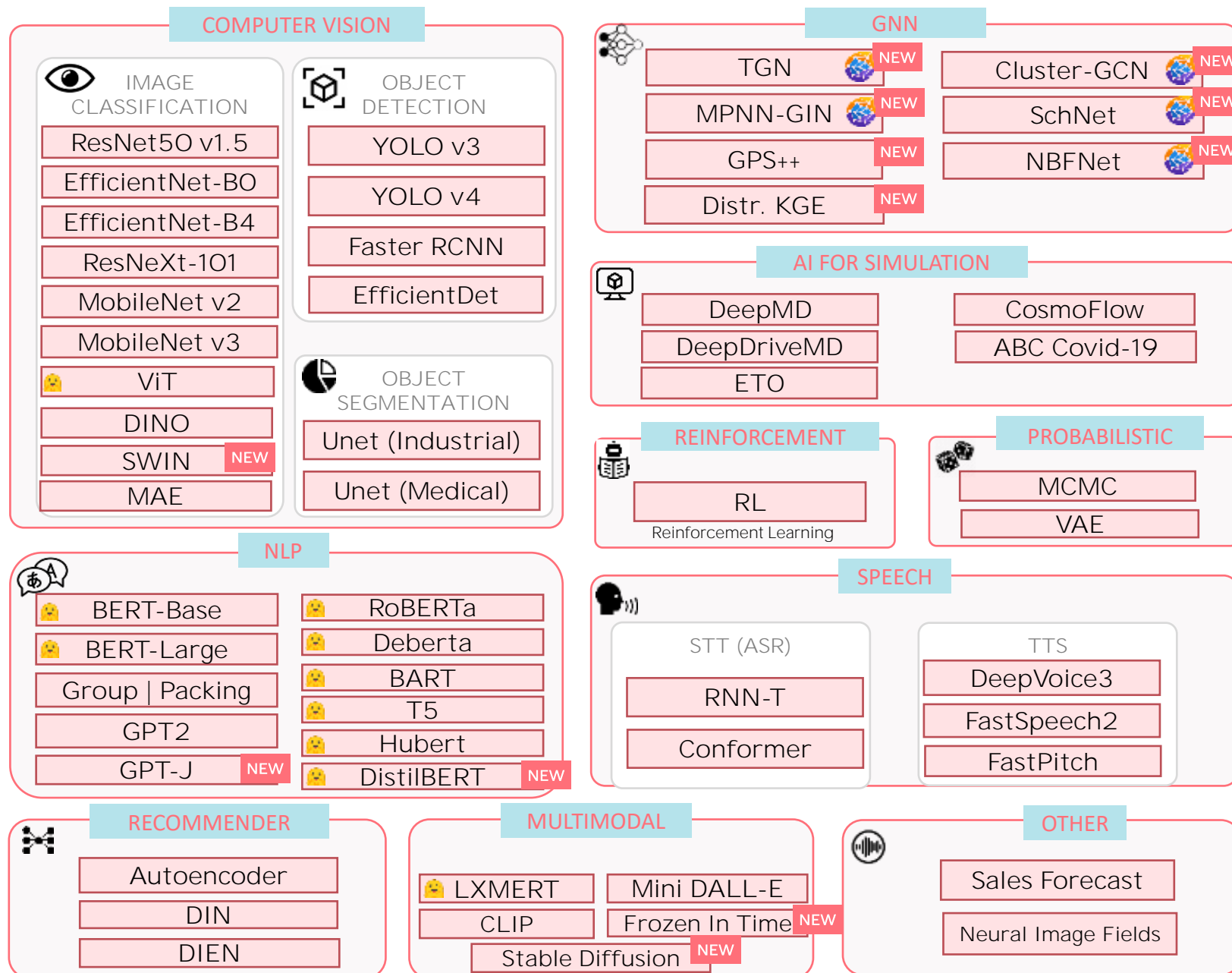
NEW FILTER/SEARCH CAPABILITY

DIRECT ACCESS TO GITHUB

PAPERSPACE NOTEBOOK LINKS



# MODEL GARDEN COVERAGE



POPART

