



2021 OFA Virtual Workshop

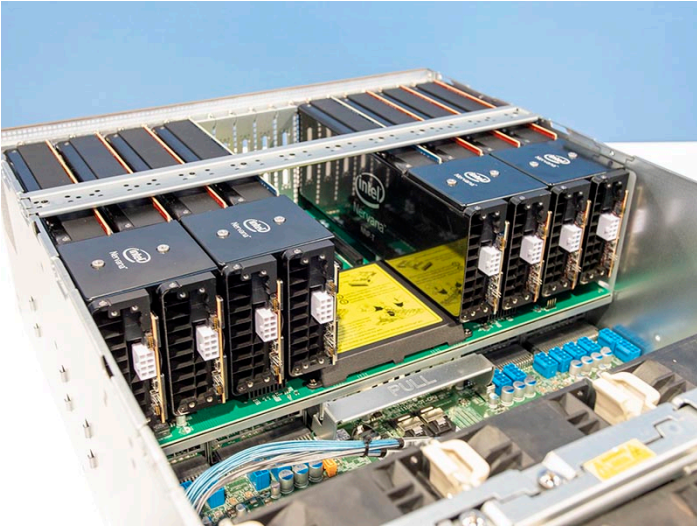
# TRUE ZERO MEMORY COPY DIRECT MEMORY TRANSFER FOR CLUSTERS AND HIGH-PERFORMANCE COMPUTING OVER RDMA USING P2PMEM API'S

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# CLUSTERS AND HIGH-PERFORMANCE COMPUTING



Server with Training Accelerators on board



Server with GPUs on board



Aurora System at Argonne National Laboratory (HPC)

## ■ Cluster/HPC architecture

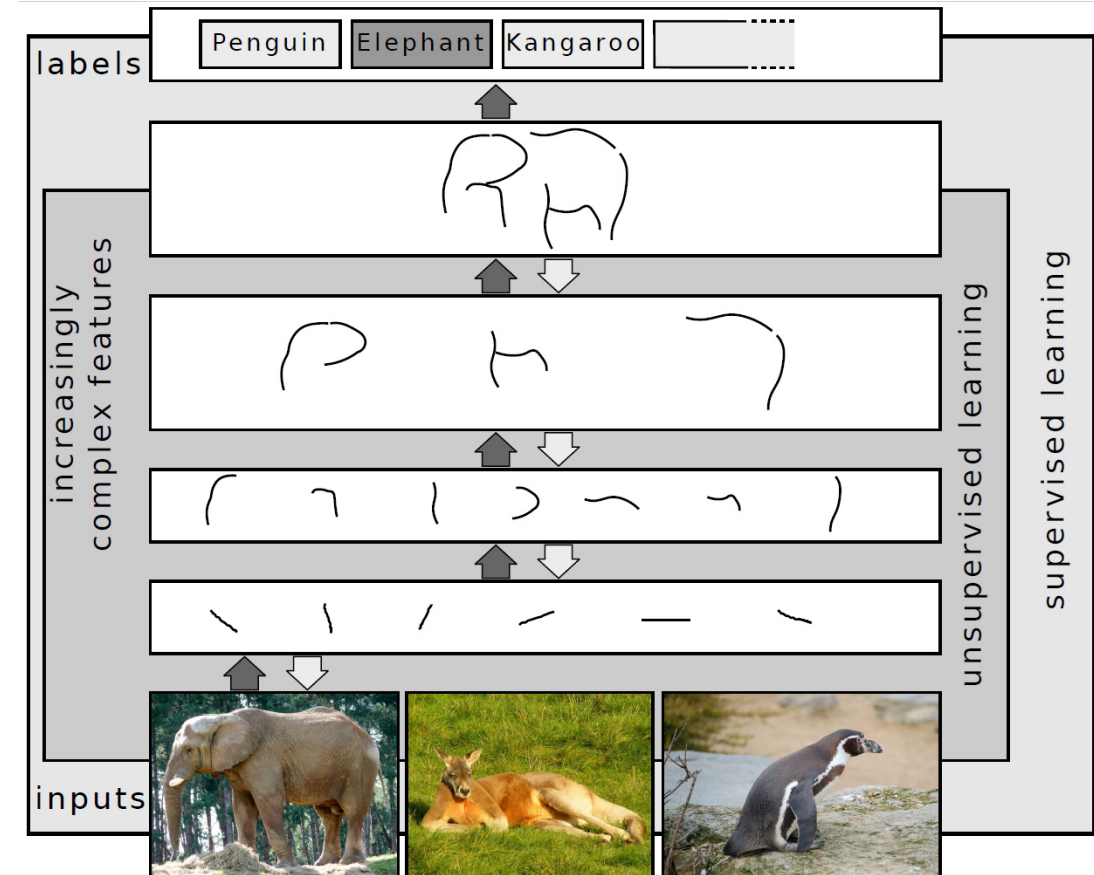
- Node: Servers with PCIe plugins such as Accelerators, Graphical Processing Unit (GPU) and Tensor Processing Unit (TPU) on board.
- Nodes are connected using high-speed links (fabrics) such as IB, Gigabit Ethernet, etc.,

## ■ Cluster/HPC workloads:

- Split and offload their job across PCIe plugins or across nodes
- AI workload, HPC workloads etc.,

# AI WORKLOAD - DEEP LEARNING

- **Progressively extracts higher-level features using multiple layers of the raw input data.**
- **In a typical DL based image processing :**
  - Lower layers may identify the edges
  - Higher layers may identify the concepts relevant to a figures such as digits or letters or faces.
- **DL may be supervised (data with labels) or unsupervised (data only).**
- **DL uses “Deep Neural Network Model” with parameters as weights – learnt through training.**
- **Deep learning training operates on a few samples of data at a time called as mini-batch.**



# DEEP LEARNING TRAINING (DLT) JOB

## ■ Minibatch:

- Comprises of Forward Pass and Backward Pass

## ■ Forward Pass:

- Performs numerical computations on mini batch
- Assigns set of scores based on computations for each mini batch.

## ■ Backward Pass:

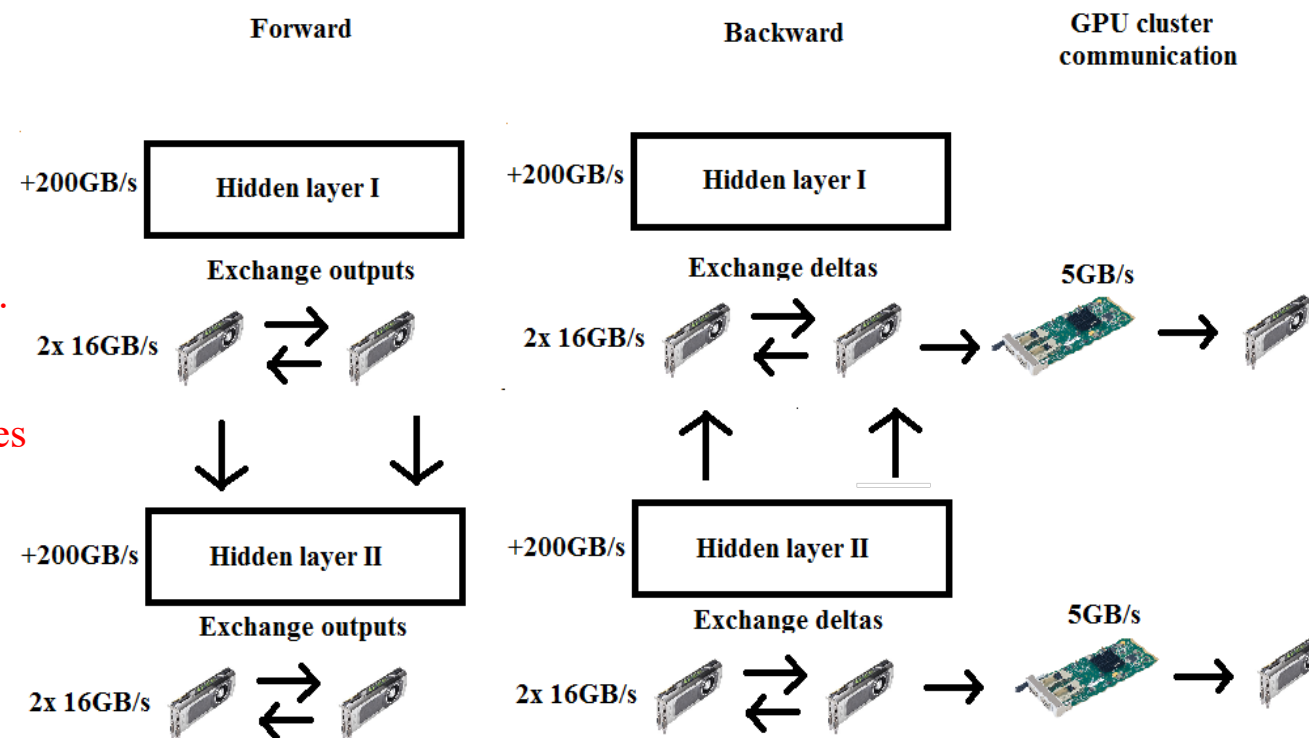
- Objective function that measures the computed and desired scores
- The error is populated via Back Pass over the model.

## ■ Need for Accelerators/GPU/TPU:

- Forward Pass and Backward Pass involve billions of floating point operations.

## ■ Minibatch Iteration:

- Millions of minibatch iterations are performed on large scale datasets to achieve high task accuracy.



# TENSORFLOW AND PYTORCH

## ■ Tensorflow

- Framework **developed by google** for research and productions.
- Open source library for Numerical computation and Large-Scale Machine Learning.
- Bundles together a study of **Machine Learning and Deep learning models**.
- **Provides python API(s) and pip packages.**
- **Underlying math operations are performed by the high performing C/C++ libraries.**

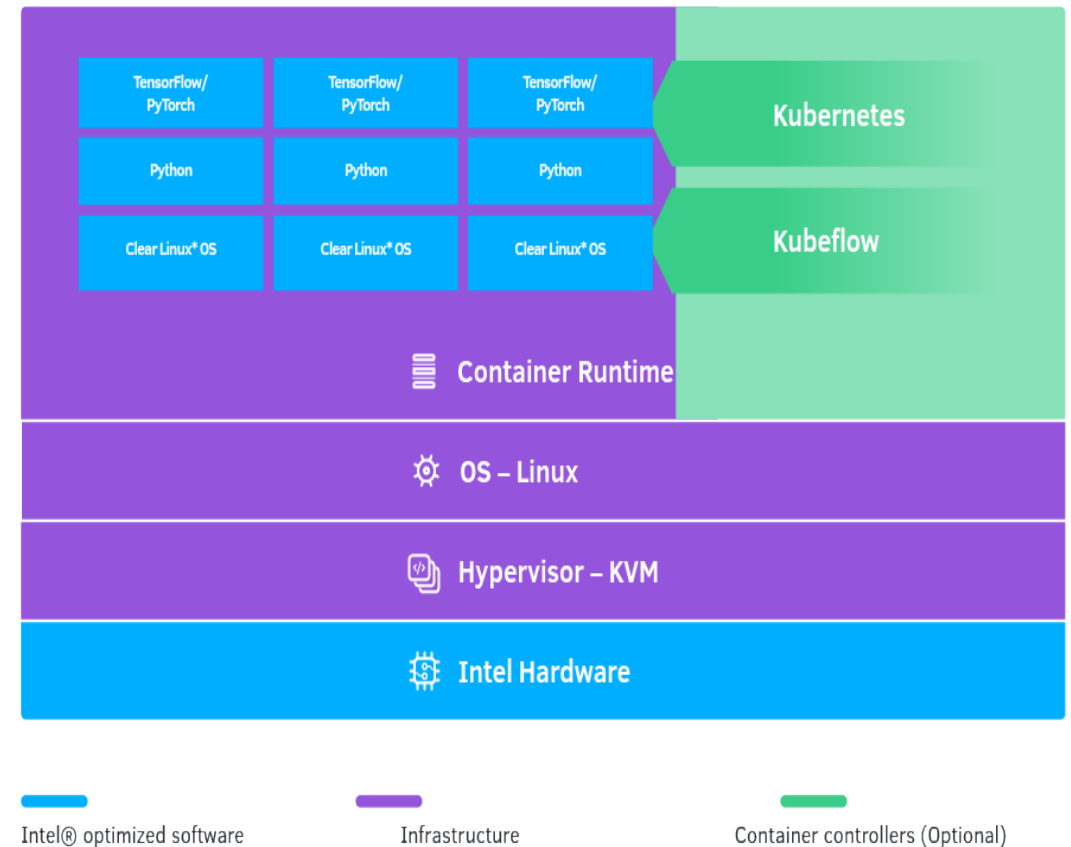
## ■ PYTorch

- Framework **developed and actively used by facebook**
- Open Source machine learning library based on **torch** library.
- **Provides python API(s) and pip packages**
- **Bundles numerous deep learning software on top of PyTorch.**

## ■ Kubernetes

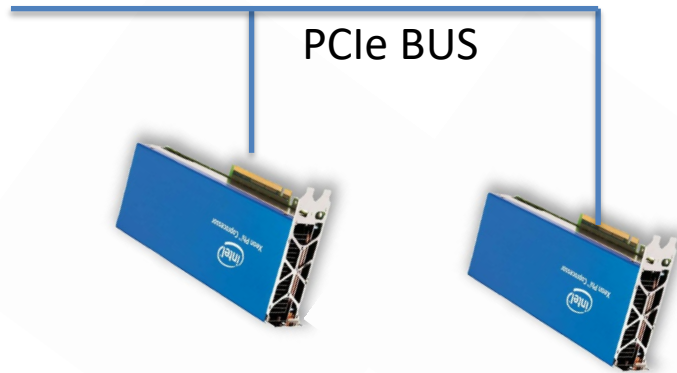
- Open source container-orchestration system for tensor flow application deployment
- Defines a set of building blocks
- Scales applications based on resources such as GPU(s)/Accelerators(s)/Nodes.

## Single node

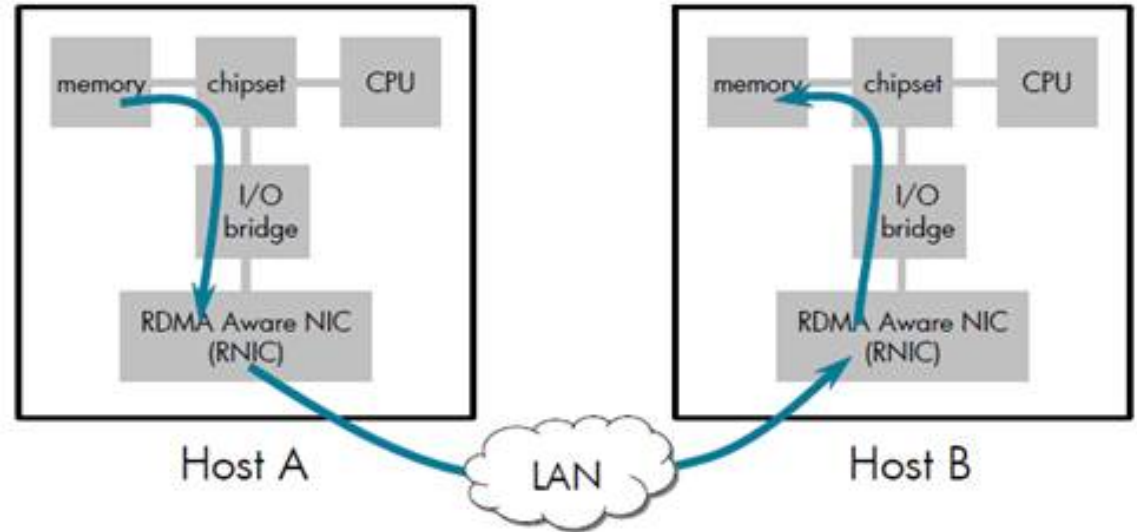




# INTERNODE CLUSTER/HPC AND INTER ACCELERATORS/GPU COMMUNICATION



Node's GPU to GPU communication



## ■ Inter Accelerators/GPU communication:

- Uses Kernel's zero memory copy to transfer data.

## ■ Inter Node communication:

- High speed links are used for communication such as InfiniBand or 100G ethernet
- Remote Direct Memory access (RDMA)
- RDMA end points – memory read/write access.
- Kernel's zero memory copy to transfer data across node's Accelerator/GPU

Key Bottle neck in communication

# CLUSTER/HPC FABRICS AND ACHIEVABLE THROUGHPUT

## ■ Remote Direct Memory Access(RDMA)

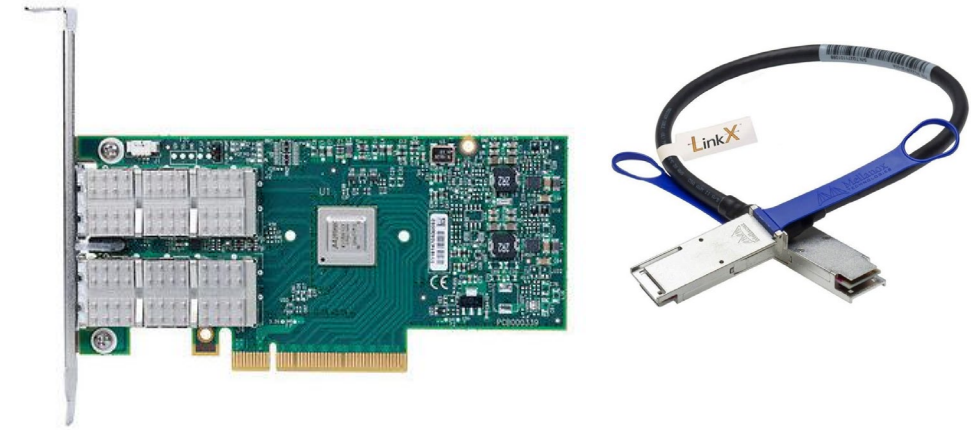
- Direct memory access from one node's memory to another node's memory without involving OS.
- Supports zero-copy networking by enabling network adapter to transfer data from the wire to the application memory directly and vice versa.

## ■ RDMA over Converged Ethernet (RoCE)

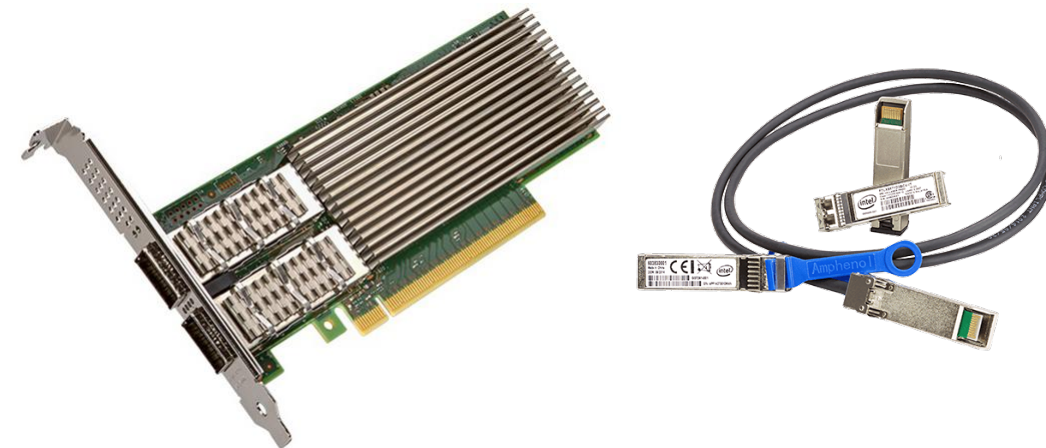
- Network protocol that allows Remote Direct Memory access (RDMA) over ethernet.
- 40 Gigabit Ethernet (40GbE) and 100 Gigabit Ethernet (100GbE) achieves effective throughput of 40 Gb/s and 100 Gb/s respectively

## ■ RDMA over InfiniBand (IB)

- Network protocol that allows RDMA over InfiniBand.
- InfiniBand's SDR, DDR, QDR, FDR, EDR, HDR and NDR achieves effective throughput of 2Gb/s, 4 Gb/s, 8Gb/s, 10 Gb/s, 13 Gb/s, 25 Gb/s, 50 Gb/s and 100 Gb/s respectively.

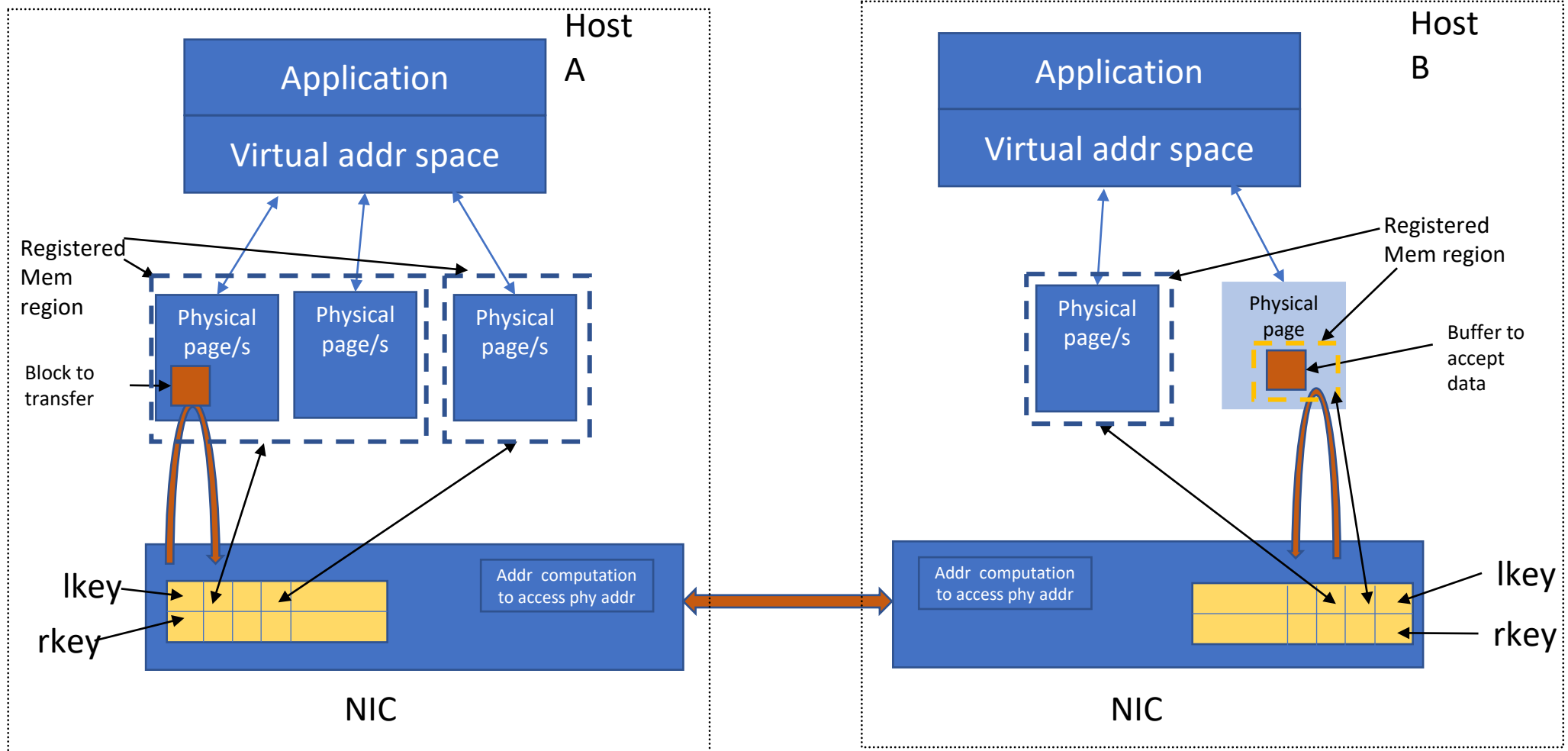


InfiniBand EDR NIC card and cable



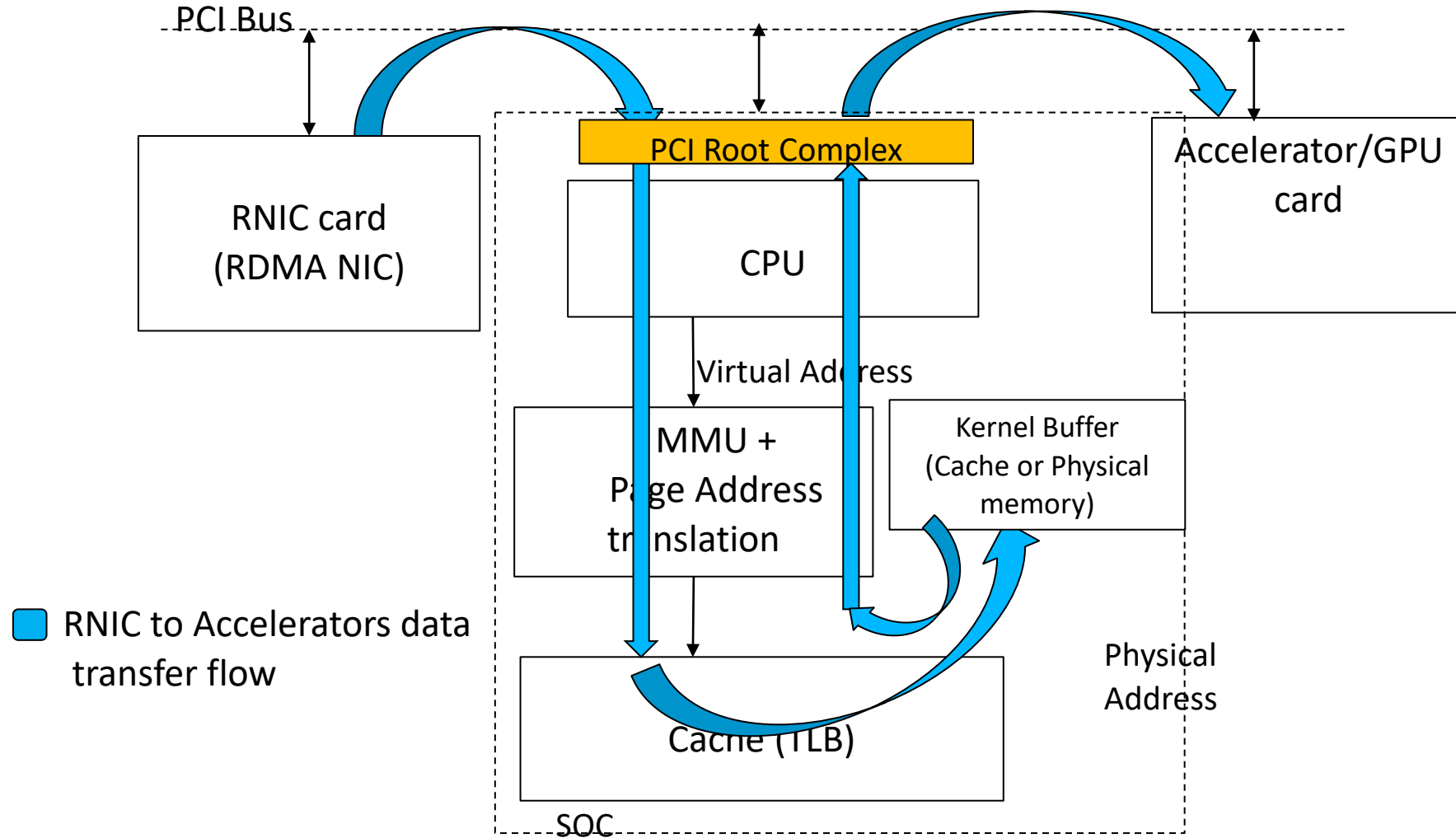
RoCE 100 Gigabit Ethernet and cable

# MEMORY AND TRANSLATION IN RDMA



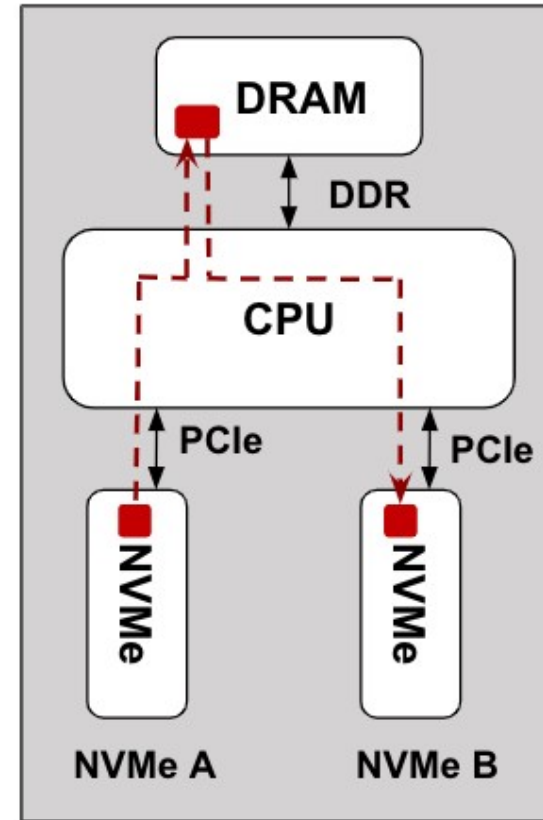


# INTERNODE MEM SHARING USING ZERO MEMORY COPY

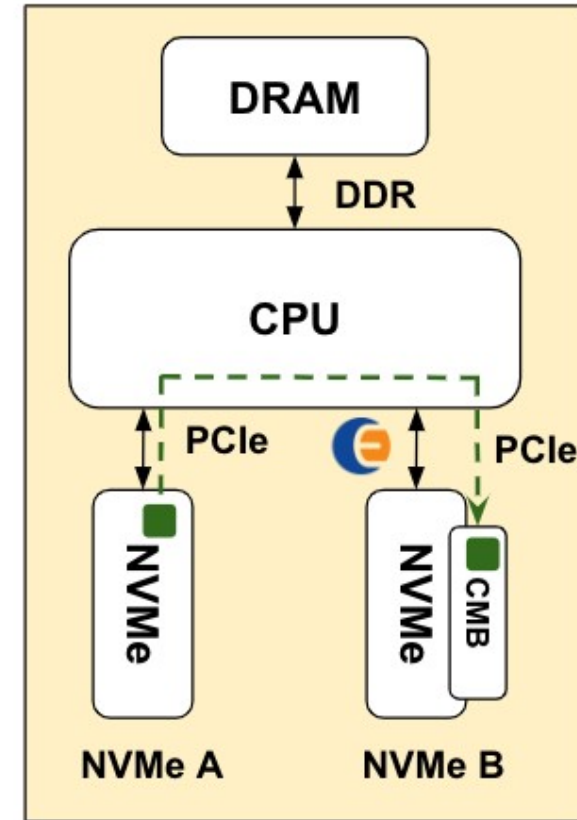


# PEER TO PEER MEMORY

- Framework proposed to bypass extra kernel/user buffer copy for optimization
- Architecture :
  - Shares physical address (no address translation)
  - Publishes desired p2pmem for clients to use
  - Bypasses additional kernel buffer copy and Virtual to Physical Address Translator – expected to perform better than zero buffer copy.
  - Supports broadcast for buffer sharing

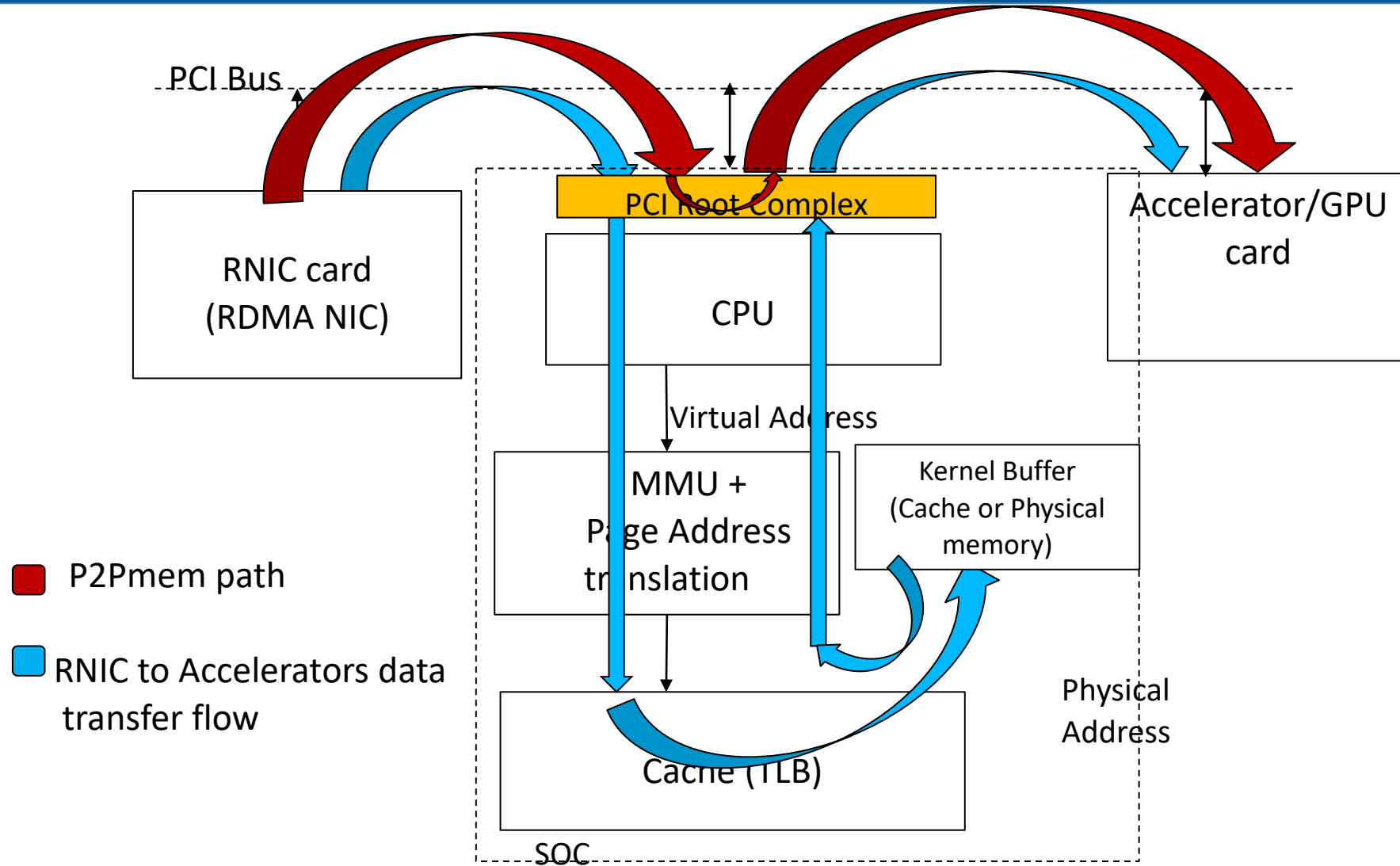


Legacy Datapath



Peer-2-Peer Datapath

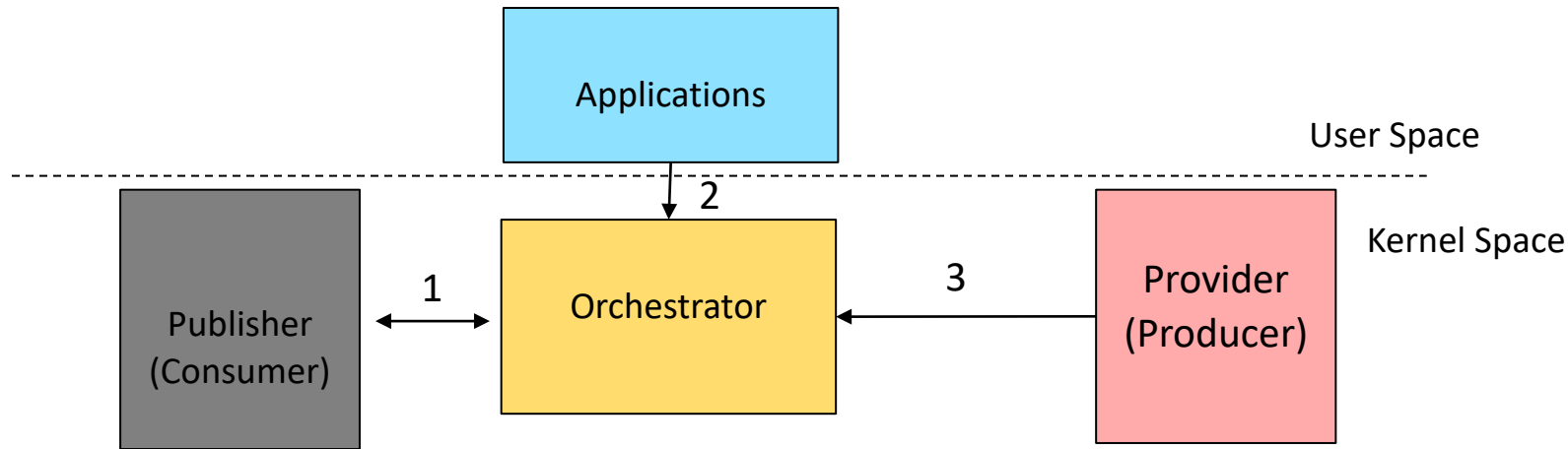
# KERNEL BUFFER COPY VERSUS P2PMEM FLOW COMPARISON



# FACTORS INFLUENCING KERNEL BUFFER COPY & P2PMEM PERFORMANCE

- $\text{Latency}_{\text{Kernel-Buf}} = \text{PCI-root Complex delay} + \text{Virtual Address translation} + \text{Kernel Page translation} + \text{Kernel Buffer Copy} + \text{RDMA to Kernel Page translation} + \text{GPU to kernel page translation}$
- $\text{Latency}_{\text{p2pmem}} = \text{PCI-root Complex delay}$
- **Kernel-Buf incurs additional penalty of cache hit /miss factors**, which flushes the cache to reload the cache with appropriate addresses
- **Common Issue: Multiple PCI cards with multiple DMA access could worsen cache flush incurring delays** (To be quantified with practical data)

# P2PMEM CONTROL AND DATA FLOW



- **Publisher exposes their intended memory bar for P2Pmem transfer** through P2Pmem-publisher API(s)
- Providers consult orchestrator to use the memory.
- **Orchestrator manages the published memory**, and allocates appropriate memory to the providers
- User application will use p2pmem allocator from orchestrator (To be developed) to allocate p2pmemory for RDMA transfer or p2pmem transfer.
- **User Applications can set rules to orchestrator in managing published memory bars.**
- Orchestrator supports list of devices publishing memory bar and the distances between provider and publisher.

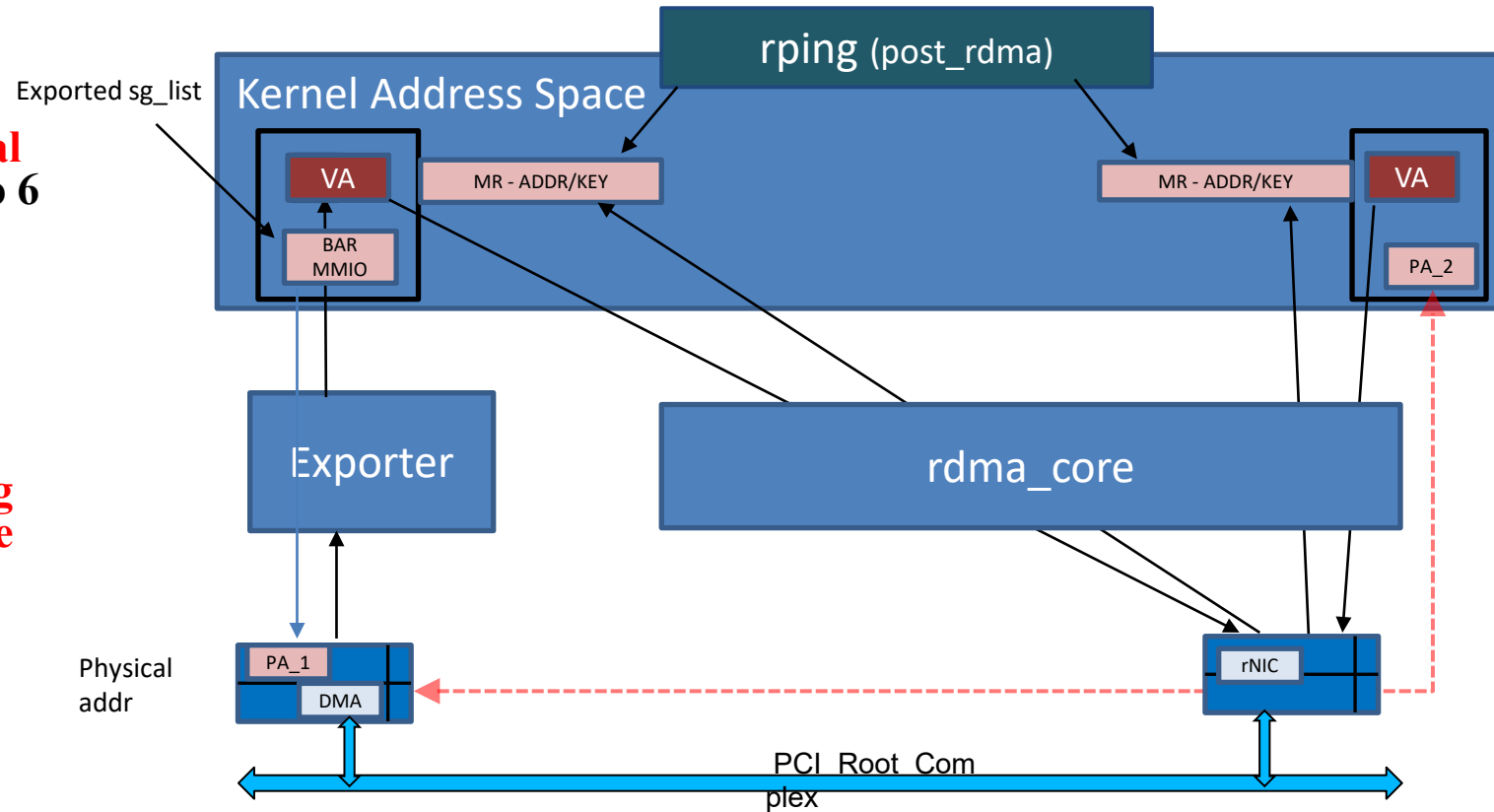


# P2PMEM API(S) SUPPORTED BY UPSTREAM KERNEL

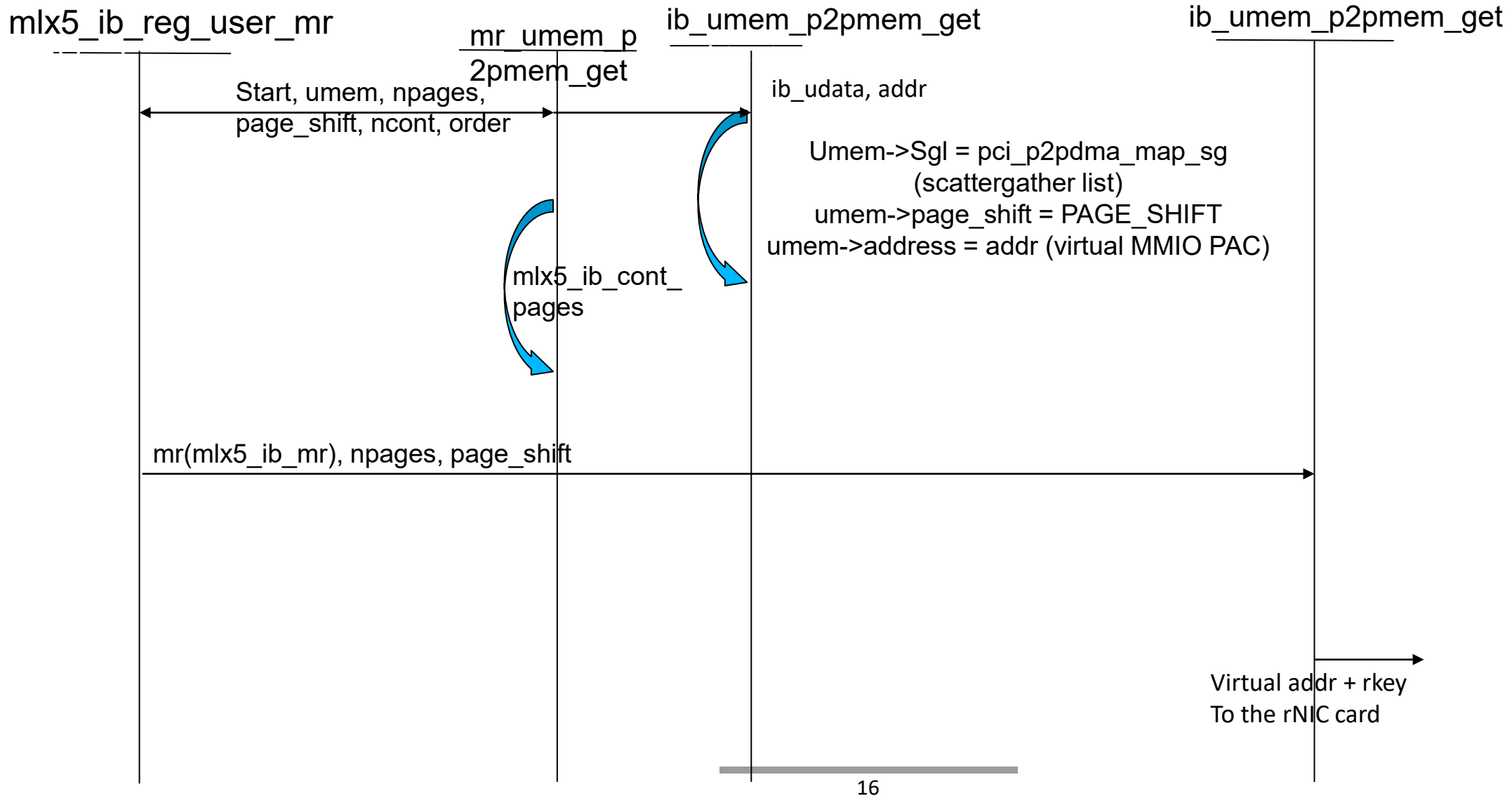
P2Pmem API(s)
<code>pci_alloc_p2pmem()</code> : Allocate P2P DMA memory
<code>pci_p2pdma_add_resource()</code> : Add memory for use as P2P memory
<code>pci_p2pmem_publish()</code> : Publish p2pmem for use by other devices with <code>pci_p2pmem_find()</code>
<code>pci_p2pmem_find_many()</code> : Find a P2P DMA memory device compatible with a specified list of clients with shortest distance
<code>pci_has_p2pmem()</code> : Check if a given PCI has published any p2pmem
<code>pci_p2pmem_alloc_sgl()</code> : Allocate P2P DMA memory in a SGL

# INTEL RDMA (ROCE) SUPPORT FOR RDMA

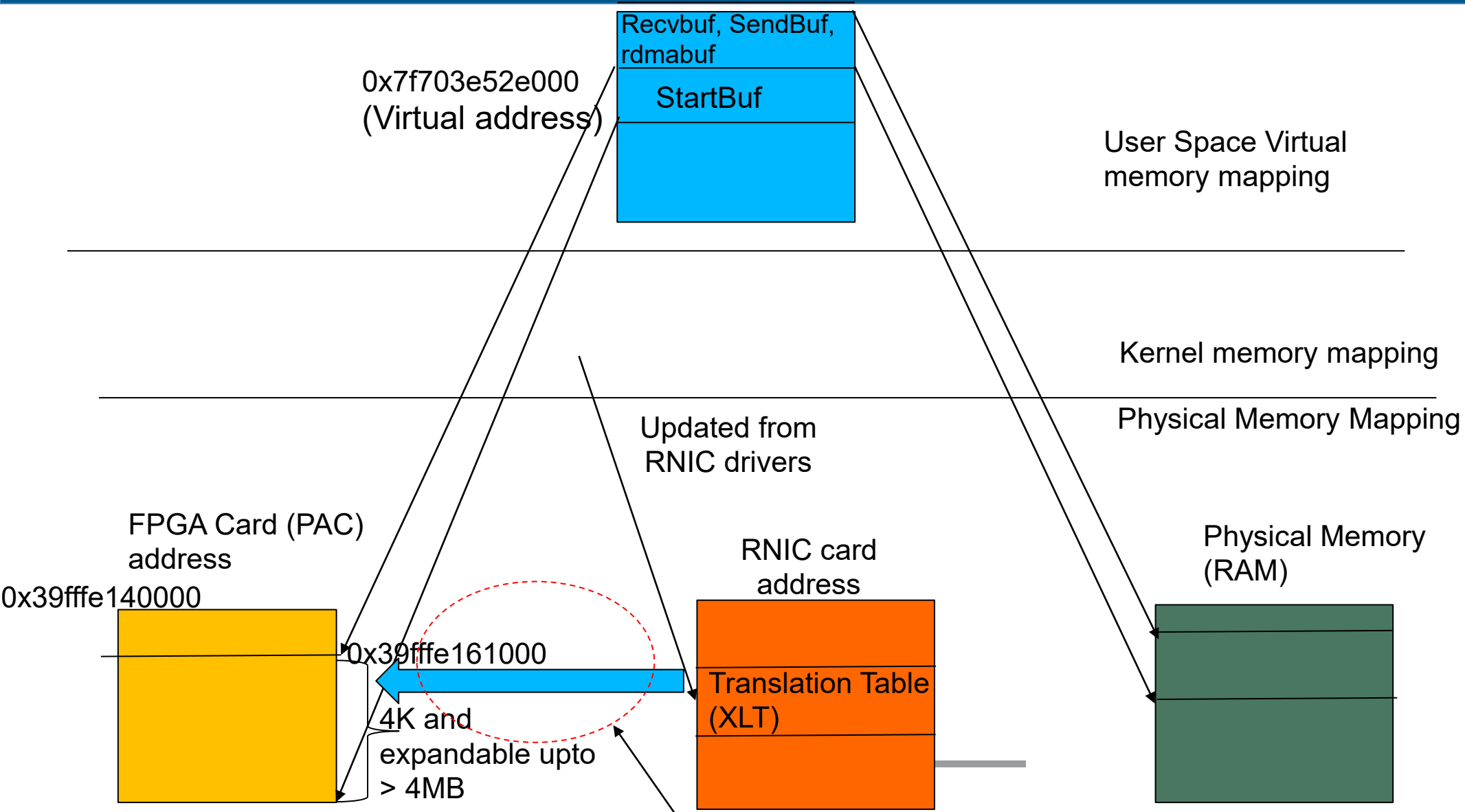
- **Device memory are defined as windows in physical address space BAR (Base Address Register), up to 6 per device**
- **BAR window is usually mapped to kernel/user address space as MMIO addresses**
- **DMA uses physical address. Some address sharing mechanism is needed to allow one driver to get the physical address information of the peer buffer**
- **A few options are available for this purpose**  
peer\_mem, pci\_p2pdma(p2pmem), dma\_buf



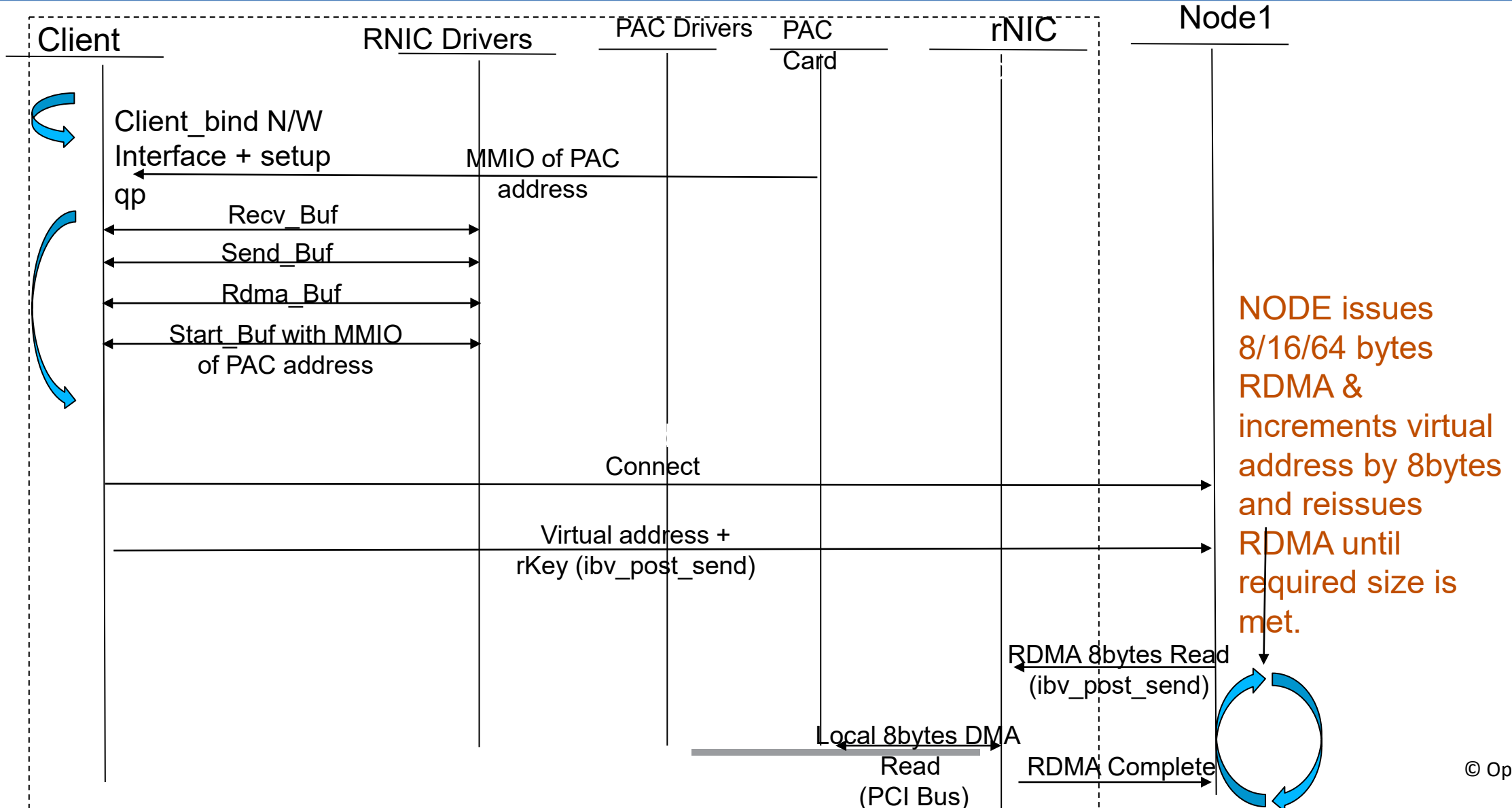
# ROCE/IB MR REGISTRATION FLOW



# ROCE/IB AND PAC SYSTEM MEMORY MAP



# END TO END MR REGISTRATION AND P2PMEM TRANSFER





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**THANK YOU**

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