CS/ECE 570 Project, Winter 2024

Heterogeneous Computing in an AI Context

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Outline

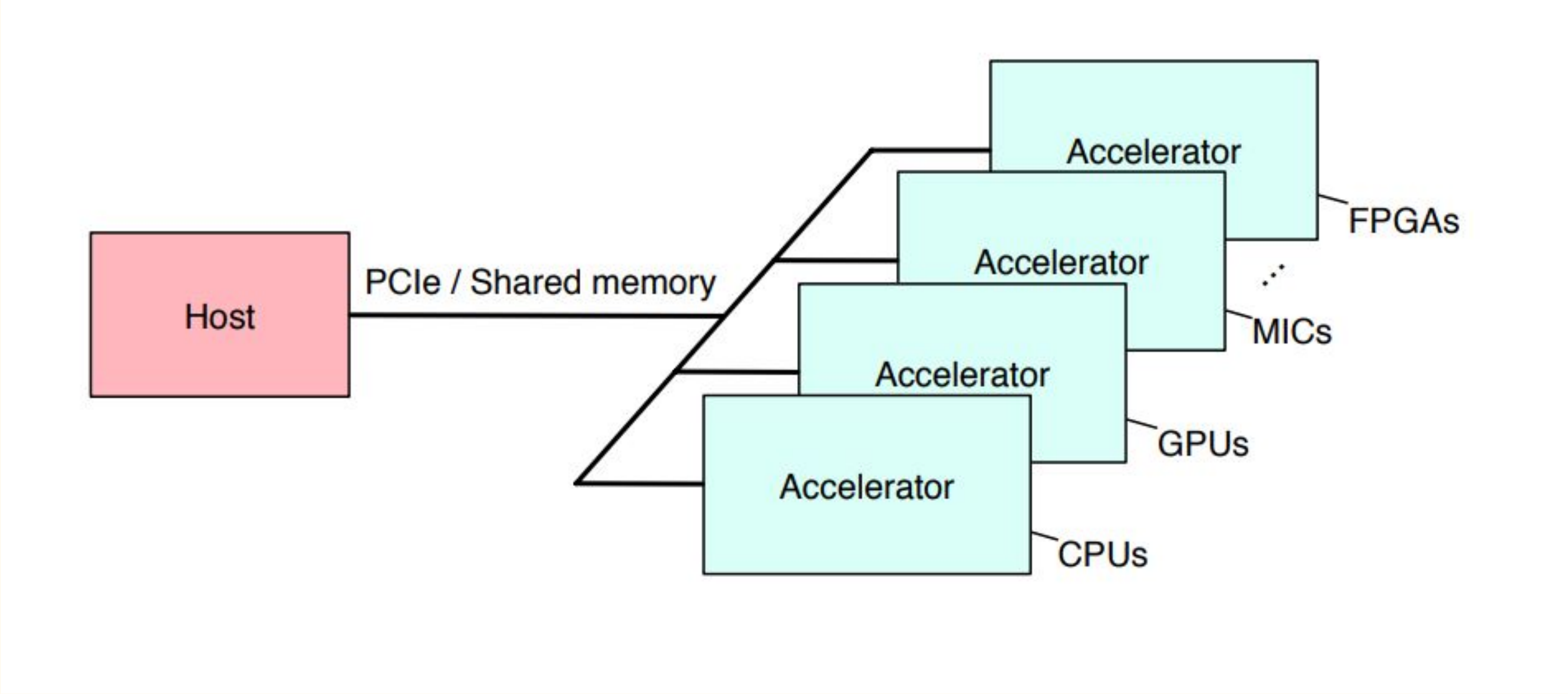
Introduction

- Heterogeneous Computing (HC) and Artificial Intelligence (AI) often go hand in hand
- Uncommon to find AI that doesn't use heterogeneous computing
    - Especially with Machine Learning and Deep Learning
- Survey on different implementations: HC for AI & AI for HC
    - Impact these two topics have on each other
    - challenges, benefits, and limitations
    - Infrastructure and framework: How is it implemented?

Background - Heterogeneous Computing (1)

- Computing architecture
- Incorporates multiple types of processors or cores in one system
- Each specialized for different task
- Leverages strengths of various processing units:
    - CPUs, GPUs, DSPs, and FPGAs
- To optimize:
    - Performance
    - Energy Efficiency
    - Computational Speed
- More effective than homogeneous computing for many applications

Background - Heterogeneous Computing (2)



Background - Heterogeneous Computing (3)

History

- Became more prominent late 2000's early 2010's
- One of the 1st major milestones: NVIDIA's CUDA (Compute Unified Device Architecture)
    - parallel computing platform and programming model
    - Released in 2006
    - Use <u>both</u> CPU and GPU to increase performance
    - Boosted use of heterogeneous computing

Background - Artificial Intelligence (1)

Why is heterogeneous computing relevant to AI?

- Enhance performance, improve energy efficiency, and provide flexibility
- Leverages various types of processors such as:
    - CPUs for general tasks
    - GPUs for parallel processing
    - Specialized accelerators for specific AI functions
- Can handle intensive computational demands
- Helpful for complex and varied applications of AI:
    - Faster processing
    - reduces power consumption
    - supports scalability

Background - Artificial Intelligence (2)

Why is AI relevant to heterogeneous computing?

- Power of AI predictions allow for a decrease in time and monetary costs by using AI to:
    - Design and implement
    - Predict various metrics instead of simulating
- EdgeCortix developed Machine-learning Enhanced Runtime Acceleration (MERA) software and compiler framework:
    - Smart compiler - optimized code is generated for various type of processors [6]
    - Runtime - execution and adaptation of heterogeneous systems is dynamically managed [6]

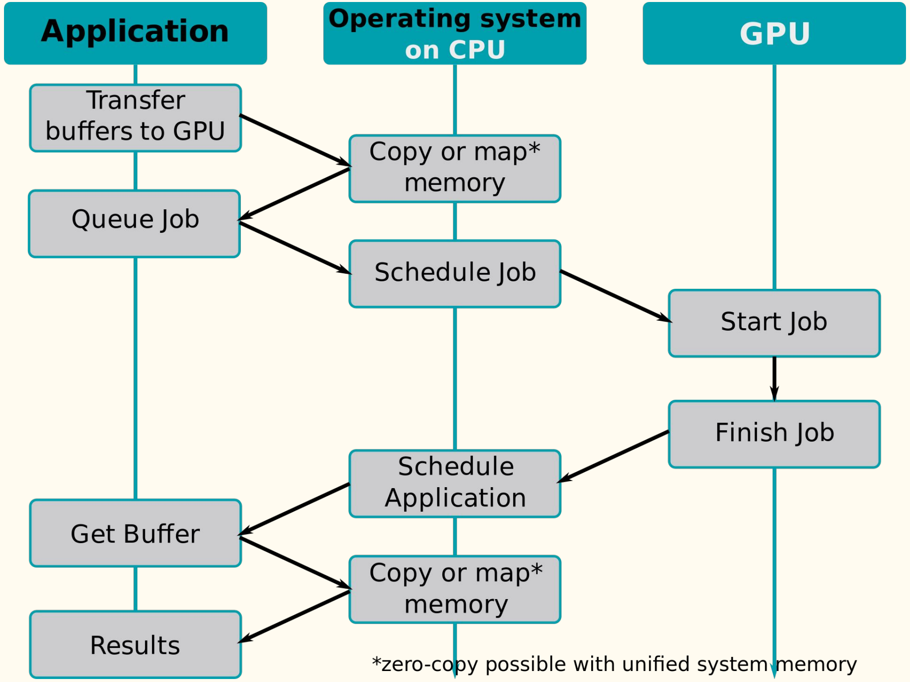
Infrastructure and Frameworks

- Key Architectures/Frameworks
  - **HSA (Heterogeneous System Architecture):** Enables efficient hardware acceleration, integrating CPUs, GPUs for seamless computation.
  - **CUDA (Compute Unified Device Architecture):** NVIDIA's platform for GPGPU, pivotal in AI and deep learning.
  - **OpenCL (Open Computing Language):** Open standard for cross-platform programming across CPUs, GPUs, and more, ensuring flexibility and broad applicability.
  - **TPU Architecture (Tensor Processing Unit):** Google's custom-designed processors optimized for TensorFlow operations, significantly accelerating deep learning computations.
  - **ROCm (Radeon Open Compute):** AMD's open source GPU computing framework.
  - **Intel oneAPI:** A unified programming model by Intel to streamline development across CPUs, GPUs, FPGAs, and AI accelerators.

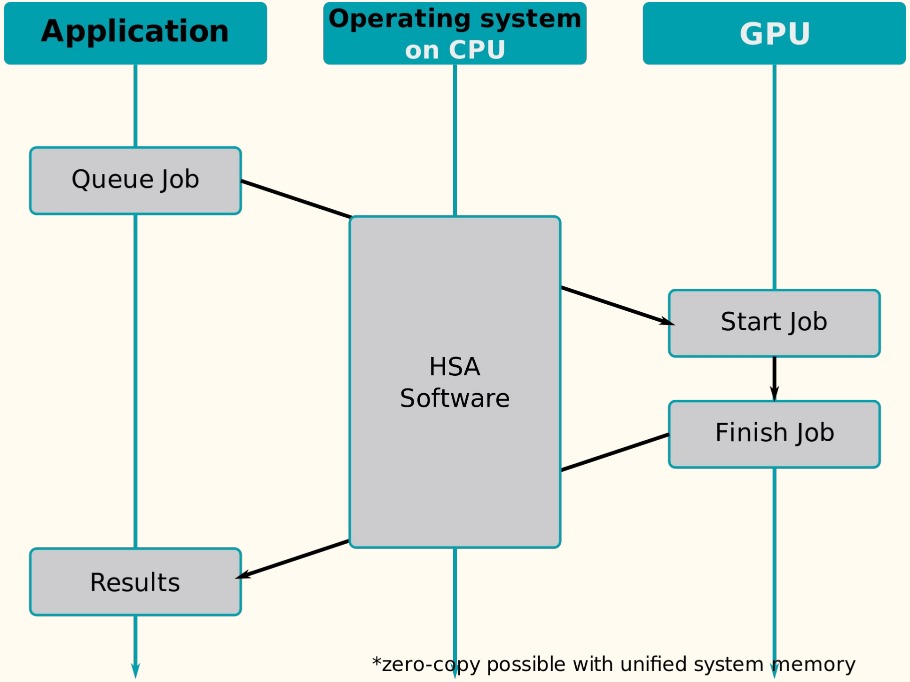
HSA (Heterogeneous System Architecture) (1)

- HSA integrates CPUs and GPUs for shared memory and tasks.
- Led by the HSA Foundation, which includes AMD and ARM.
- Reduces latency between compute devices and simplifies programming.
- Enhances execution performance of programming languages and models like CUDA and OpenCL.
- Enables direct GPU floating point calculations without separate scheduling.

HSA (Heterogeneous System Architecture) (2)



non-HSA system



HSA system

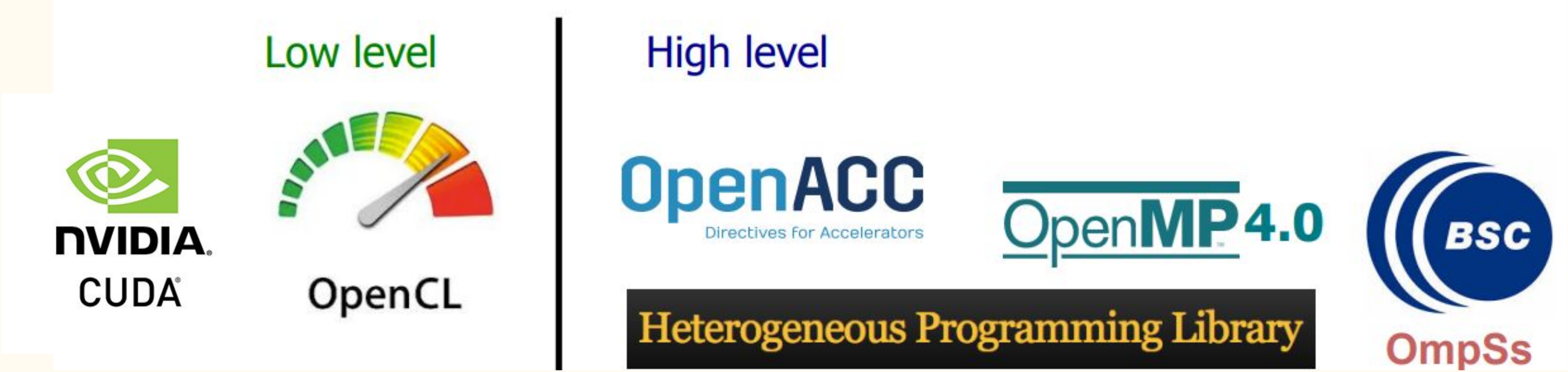
Programming models for Heterogeneous computing (1)

- CUDA
    - NVIDIA proprietary
- OpenCL
    - Open standard, functionally portable across multi-cores
- OpenACC
    - High-level, pragma-based
- Different libraries, programming models, and DSLs for different domains

Level of abstraction increases

Programming models for Heterogeneous computing (2)

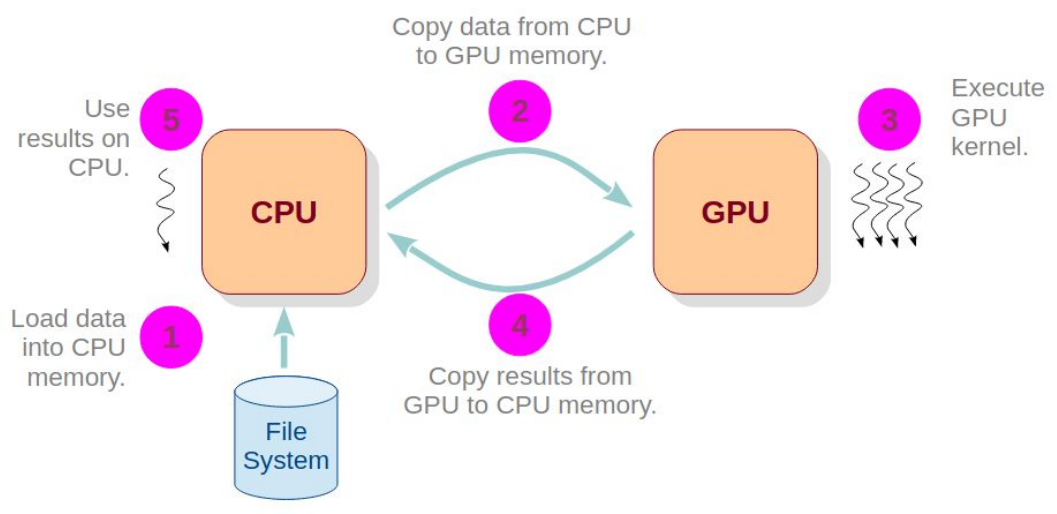
- Mix of programming models
  - One(/several?) for CPUs – OpenMP
  - One(/several?) for GPUs – CUDA
- Single programming model (unified)



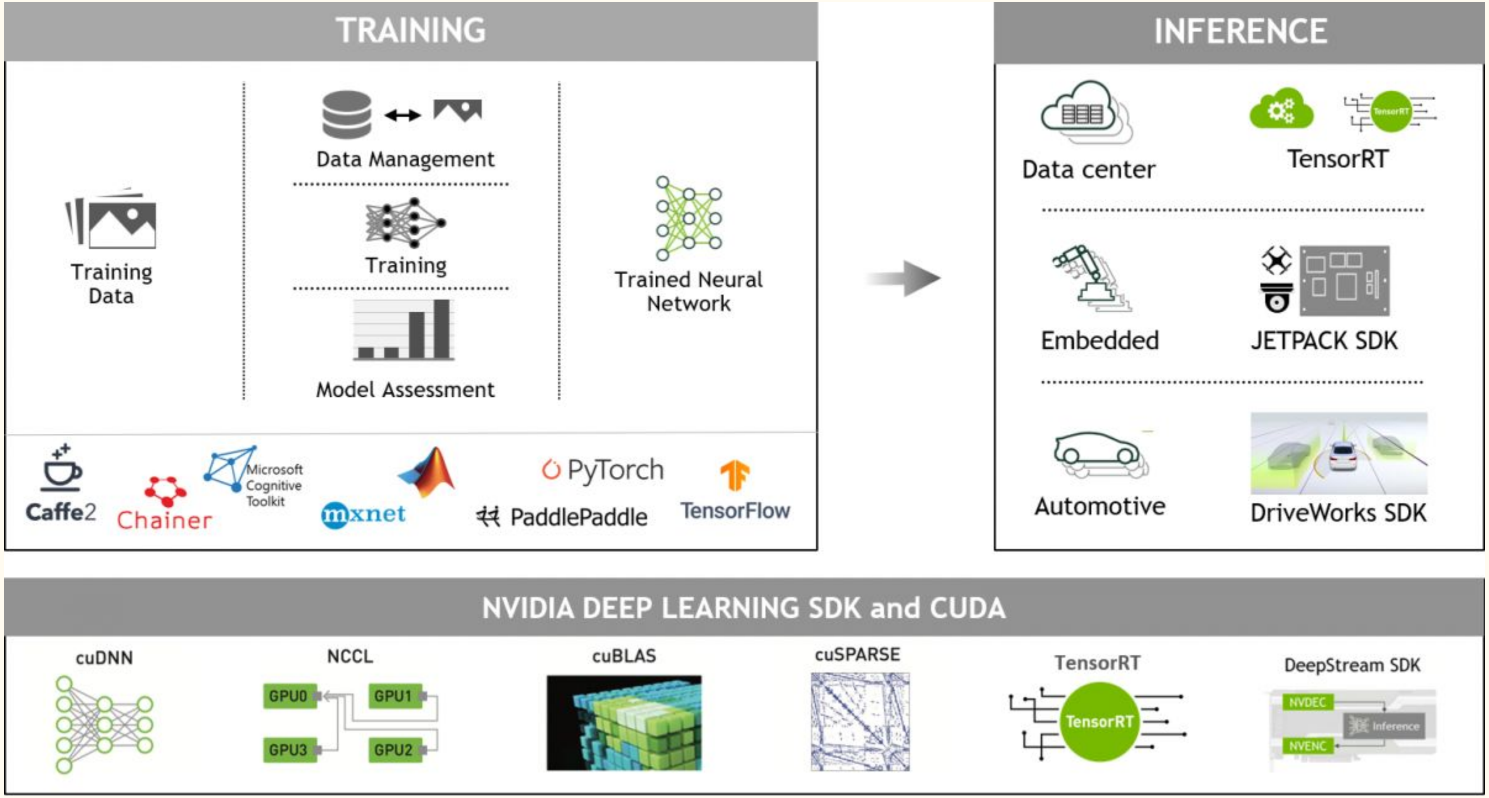
CUDA(Compute Unified Device Architecture) (1)

- NVIDIA's programming platform for GPGPU (General-Purpose computing on Graphics Processing Units).
- Designed for heterogeneous computing: some functions run on the CPU and others on the GPU. Programs typically written in C or C++ with annotations for GPU execution.

Typical CUDA program flow

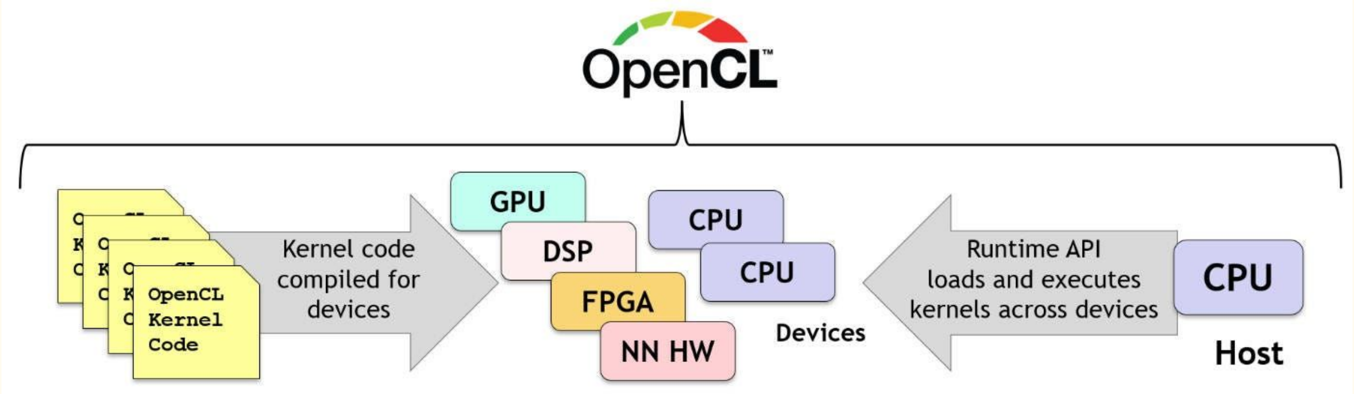


CUDA(Compute Unified Device Architecture) (2)

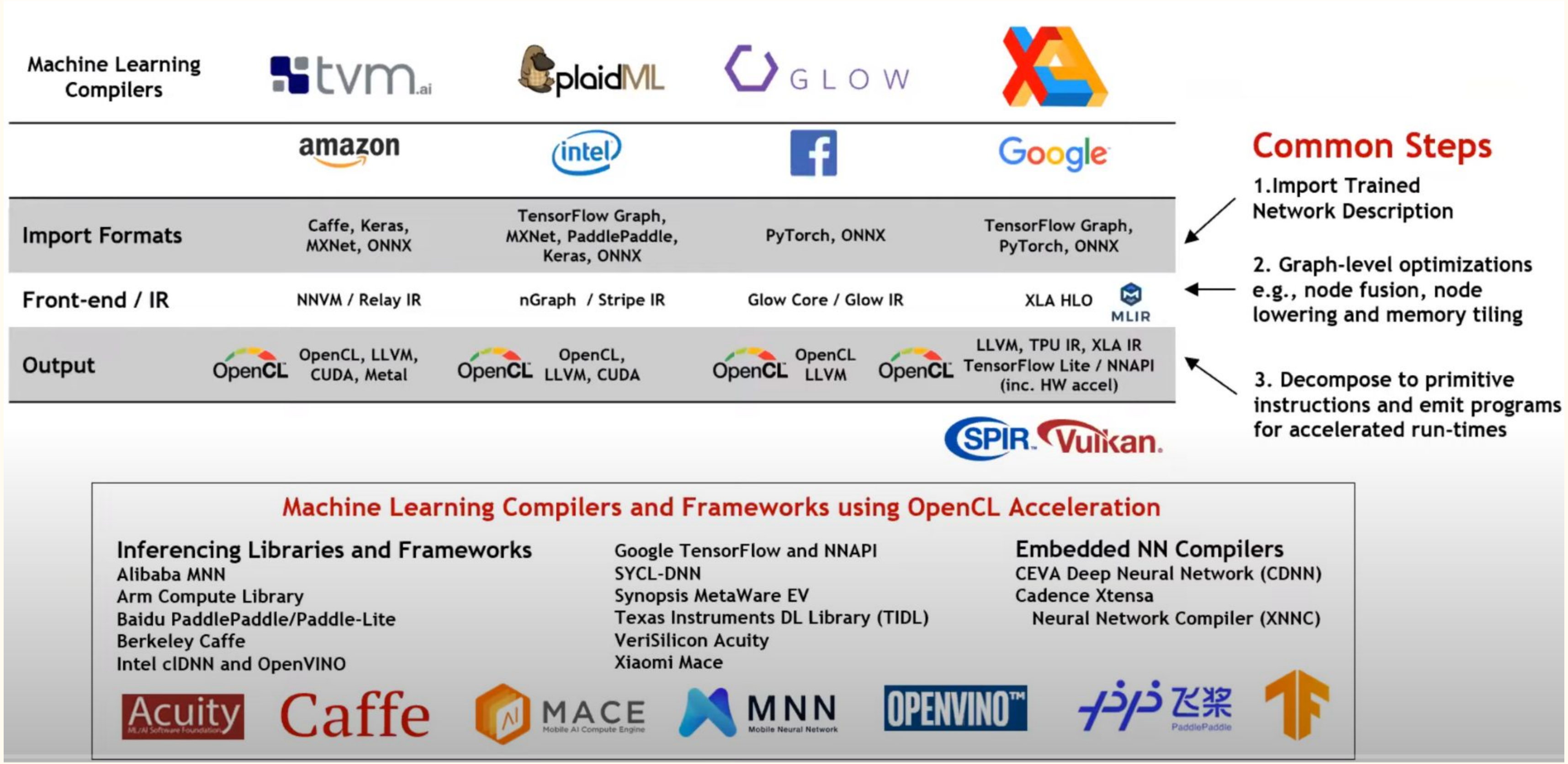


OpenCL (Open Computing Language) (1)

- Cross-Platform Framework: Enables execution of code across different hardware platforms.
- Supports Heterogeneous Systems: Works with various computing devices including CPUs, GPUs, DSPs, and FPGAs.
- Write Once, Run Anywhere: Programs written in OpenCL can run efficiently across multiple hardware architectures supports the OpenCL standard.



OpenCL (Open Computing Language) (2)

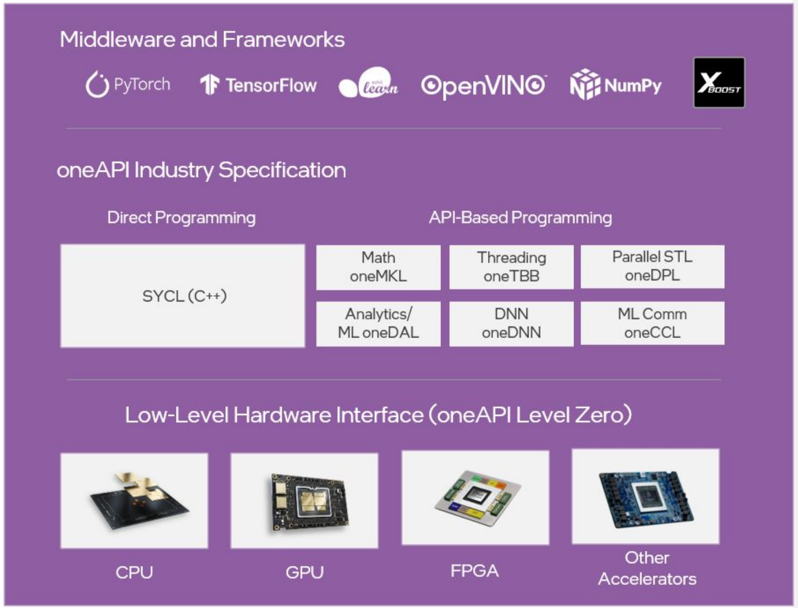


Intel oneAPI (1)

- A unified programming model designed to streamline development across Intel's diverse hardware (CPUs, GPUs, FPGAs, AI accelerators).
- Core Language - DPC++ : Based on ISO C++ and SYCL(a cross-platform abstraction layer that allows algorithms to switch between hardware accelerators—such as CPUs, GPUs, and FPGAs) standards, DPC++ is aimed at leveraging the parallel computing potential of Intel's hardware. `DPC++` = `C++` + `SYCL` + `community extensions`
- Workload Categorization: Classifies workloads into scalar, vector, matrix, and spatial domains to optimize computing across different Intel processors.

Intel oneAPI (2)

- Intel is pitching oneAPI as a viable CUDA alternative.
- There's a growing trend of migrating to oneAPI for its promise of eliminating vendor lock-in and fostering a diverse computing environment.
- Performance Gains: Adopters of oneAPI often report enhanced performance compared to previous implementations.



Performance improvement

- Martínez et al. [12] explored the potential of Intel's oneAPI as a unified programming model for machine learning applications, with a focus on revamping the Caffe framework.
- They performed a comparative performance study for two crucial layers, softmax and convolution, between the original Caffe implementation (with CUDA) and oneAPI implementation on both CPU and GPU platforms.
- Softmax Layer: The oneAPI version showed a 7x speedup on Intel GPUs compared to the CPU baseline and a 1.75x improvement over NVIDIA A100 GPUs.
- Convolution Layer: While GPU comparisons were limited due to compatibility issues(with NVIDIA GPUs), the oneAPI implementation on Intel CPUs outperformed native Caffe implementations for larger datasets.

DL load distribution for Heterogeneous computing

- Let's take the example of Convolutional Neural Network(CNN), a popular image recognition/classification deep learning model.
- CPU:
  - Data Management: Preprocesses input data (decoding, normalization, augmentation).
  - Orchestration: Manages training loop (batch prep, epoch management).
  - Parameter Updates: Updates model weights post-backpropagation.
- GPU:
  - Layer Processing: Speeds up computation of CNN layers (convolutions, activations).
  - Backpropagation: Efficiently computes gradients, enhancing learning speed.
- FPGA:
  - Optimized Operations: Executes custom, efficient CNN operations.
  - Inference: Supports real-time model deployment with low latency.
- TPU:
  - Matrix Operations: Specializes in large-scale matrix computations.
  - Efficient Training/Inference: Boosts both training and inference speeds.

Heterogeneous Computing for Deep Learning (1)

Malita *et al.* [3] explores challenges and advancements in hardware acceleration for deep learning:

- Computational components of Deep Neural Networks (DNNs)
  - Fully connected layers, convolutional layers, pooling layers, softmax layers
  - Significant computational intensity
  - Efficient acceleration for optimal performance very important for DL
- State of the art hardware solutions
  - Reviewed various state-of-the-art hardware solutions - discuss various architecture
    - Intel's Many Integrated Core (MIC) Processors
    - NVIDIA's Graphics Processing units (GPUs)
    - Google's Tensor Processing Units (TPUs)
  - Discussed: performance characteristics, energy efficiency, limitations

Heterogeneous Computing for Deep Learning (2)

Malita *et al.* [3] explores challenges and advancements in hardware acceleration for deep learning:

- Limitations of Specific ASICs like TPU
  - TPUs offer significant computational power → lack flexibility needed for DL
  - Issues regarding:
    - Flexibility, resource utilization, memory hierarchy, architectural suitability
  - Understand limitations to develop strategies to mitigate challenges
- Conclusion and Future Directions
  - Need for innovative architectural designs able to
    - Adapt to evolving landscape of deep learning
    - While optimizing for performance and energy efficiency

AI for Heterogeneous Computing (1)

- Heterogeneous computing is a necessity for AI
- Can AI in turn be used to optimize heterogeneous computing?
  - Implementation: AI for Compiler
    - As seen previously, EdgeCortix's MERA
  - Predict quantifiers: Power, energy use, performance, etc.
    - Useful for understanding system impacts
    - Making design decisions
  - Designing: Finding optimal configuration
    - AI can find a optimal configuration faster or with less energy use

AI for Heterogeneous Computing (2)

Approach 1: Memeti *et al.* [1] use of AI to optimize use of system.

Enumeration and Measurements (ENuM)

vs.

Memeti *et al.* [1] method AI Heuristics with Machine Learning (AML)

ENuM

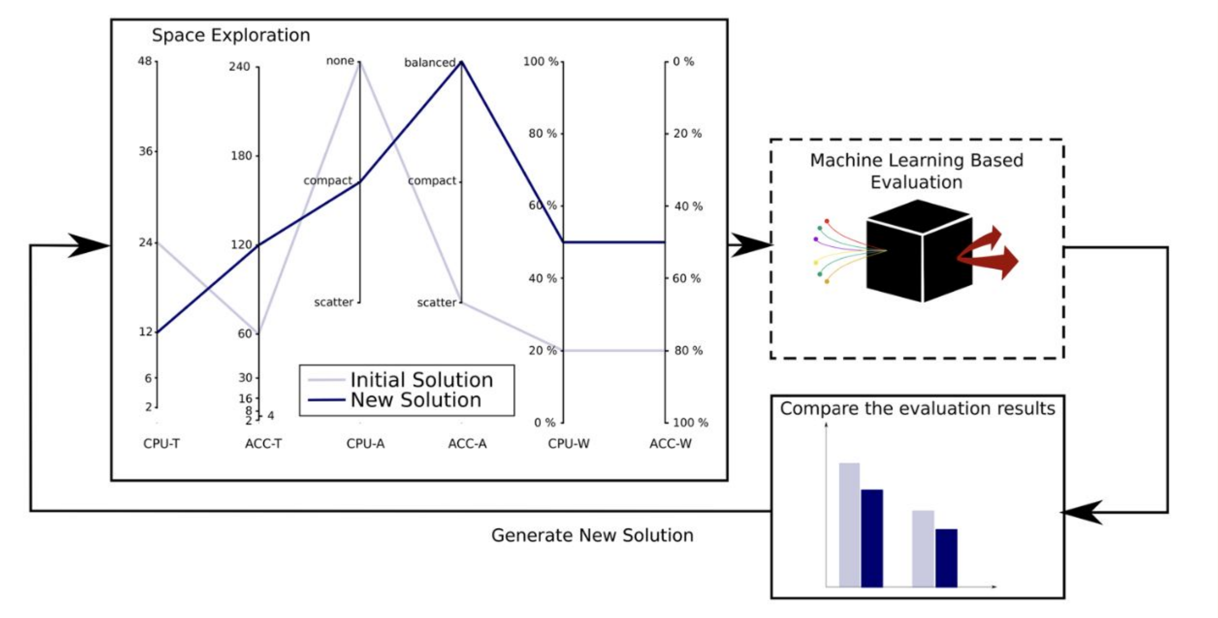
- Brute-force search
- Evaluates every possible option
- Makes a decision based on those options

AML

- Aims to find near optimal system configuration
- To optimize use of heterogeneous system:
    - AI heuristic search in combination with machine learning

AI for Heterogeneous Computing (3)

Approach 1: Memeti *et al.* [1] use of AI to optimize use of system.



- Parameter space
  - Heuristic search as guide
  - Simulated annealing to conduct exploration
- Decision tree regression
  - Supervised Machine Learning model
  - Evaluate system configuration

Results: AML is 1300 times faster than ENuM and achieves similar energy efficiency after only evaluating around 7% of possible configurations.

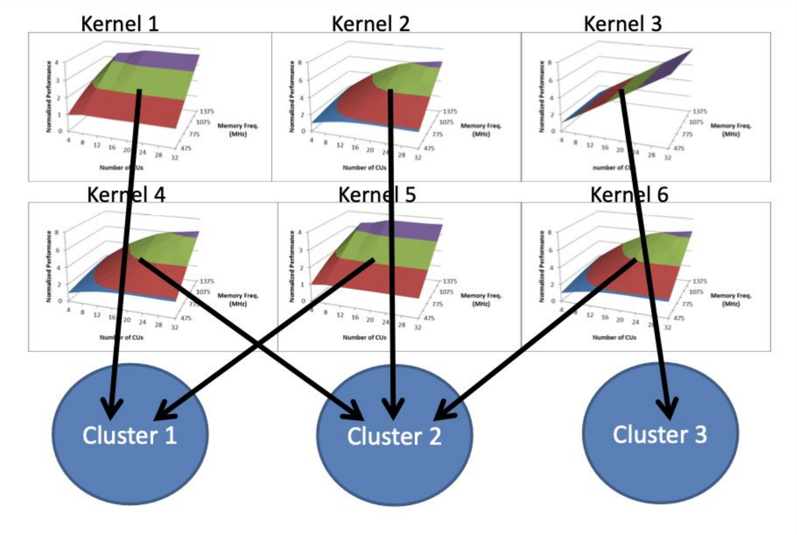
AI for Heterogeneous Computing (4)

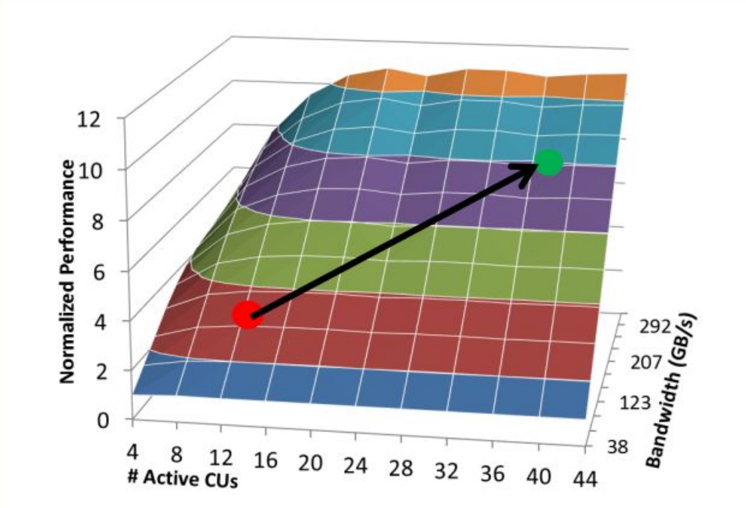
Approach 2: Greathouse *et al.* [2] use AI to predict performance or power.

- Predict an applications performance or power on various heterogeneous systems.
- Designed to lessen cost of simulation for industry professionals
  - When picking system configuration
- Created dataset
  - Running various applications on different combinations of hardware
  - Storing the data
- Fully connected neural network
  - Linear input layer
  - Sigmoid functions for hidden and output layers

AI for Heterogeneous Computing (5)

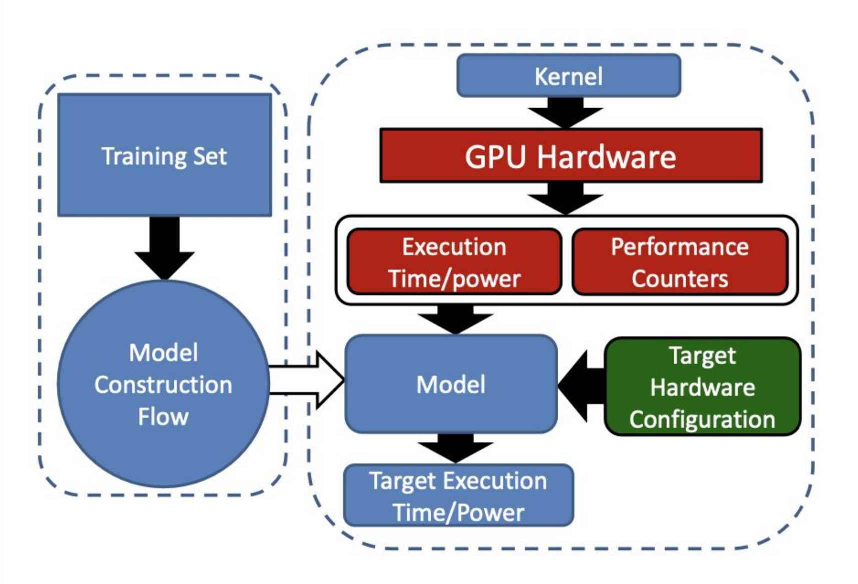
- Kernels are trained and clustered
  - Grouped with similar kernels
  - Kernel with highest value is chosen as cluster representative
  - Within each kernel is a scaling curve





AI for Heterogeneous Computing (6)

- Model is ready to use
  - Application is inserted
  - Cluster is picked based on closest match to application.
  - Scaling curve predicts performance or power of kernel
    - Based on desired configuration
- Results: Use of system is very effective
  - Does not require heavy computations
  - Performance: Model is 85% accurate
  - Power: Model is 90% accurate



Future of Heterogeneous Computing

- Challenges for wider adoption
  - Programming Complexity: writing for various processor types
  - Memory Management: everything is sharing a memory, needs to be effectively managed
  - Task Scheduling: scheduling is done across all processors, needs to be efficient
- Potential for further accelerating AI research and applications
  - Tons of potential with the continued development of AI
    - As AI pushes further it will require more and more from heterogeneous systems
  - Heterogeneous computing being used more push for development
    - Also increase capabilities of heterogeneous computing for AI research and applications

Conclusion

- Heterogeneous Computing
  - Supports the high computational demands of AI processes
  - Allows for scalability
  - Reduces power consumption
- Artificial Intelligence
  - Allows for reduction in time and monetary costs
  - Using AI for design, implementation, prediction of quantifiers
- Infrastructure and Frameworks
  - A lot of organizations are working in the space of developing Heterogeneous Computing ecosystem because of it's promising future.

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Thank you!

Questions?