FPGAs-as-a-Service Toolkit (FaaST)

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Sixth International Workshop on Heterogeneous High-performance Reconfigurable Computing (H²RC’20)
• Computing projections for high energy physics (HEP) greatly outpace CPU growth, interest in ML rapidly increasing

• We see FPGAs as possible solution

• How can we best use FPGAs for ML computing tasks in HEP?
  • → As-a-service computing
Applications

• FPGA compute as-a-service not only beneficial for our particular experiments

• Gravitational waves

• Neutrinos

• Multi-messenger astronomy
As-a-service Computing

- As a user, I just want my workflow to run quickly

- On-demand computing
  - Client communicates with server CPU, server CPU communicates with coprocessor
  - Many existing tools from industry, cloud
As-a-service Computing

- Can provide large speed up w.r.t traditional computing model
  - Scheduling important to improvement
- Machine learning is particularly well-suited for as-a-service
  - Small number of inputs relative to large number of operations
- Large speedups w.r.t CPU
FPGAs-as-a-Service Toolkit

- Have developed cohesive set of implementations for range of hardware/ML models - refer to as **FPGAs-as-a-Service Toolkit (FaaST)**
- For fast inference we focus on gRPC protocol
  - Open source remote procedure call (RPC) system developed by Google

1. Runs the inference
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1. Formats inputs
2. Sends asynchronous, non-blocking gRPC call
3. Interprets response
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1. Initializes model on coprocessor
2. Receives and schedules inference request
3. Sends inference request to FPGA
4. Outputs and send results
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Tools:

- hls4ml
- Xilinx VITIS
- Xilinx ML Suite
SONIC

- FaaS compatible with Services for Optimized Network Inference on Coprocessors (SONIC) framework
- Integration of as-a-service requests into HEP workflows
  - Works with any accelerator
- Requests are asynchronous, non-blocking

```
External Processor

Workflow Module
```

```
Coprocessor
```

```
Event data
```

```
acquire()
other_work()
produce()
```

```
Callback
```
FaaST Server

- Triton inference server developed by Nvidia for as-a-service inference on GPUs
  - Supports gRPC protocol
- FaaST designed to use same message protocol as Triton
- Server designed using various tools for different benchmarks
  - **FACILE:** ![Xilinx Vitis + hls4ml](Alveo U250 & AWS f1)
  - **ResNet-50:** ![Xilinx](AWS f1)
  - **ResNet-50:** ![Azure Machine Learning Studio](Azure Stack Edge)
• Standard HEP data processing proceeds event-by-event

• Batch sizes limited by event characteristics \(\rightarrow\) smaller batches

2k
parameters

batch 16000

10M
parameters

batch 10/batch 1

- **FACILE**
  - calorimeter energy regression
  - 3-layer MLP

- **ResNet-50**
  - top quark image classification
  - Large CNN

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**Benchmarks**
Gains

Where should we gain from coprocessors?

- FACILE
- Large gain
- ResNet
- Small gain
• hls4ml is a software package for creating implementations of neural networks for FPGAs and ASICs

• https://fastmachinelearning.org/hls4ml/

• arXiv:1804.06913

• Supports common layer architectures and model software, options for quantization/pruning

• Output is a fully ready high level synthesis (HLS) project

• Customizable output

• Tunable precision, latency, resources
- Use Vitis Accel to manage data transfers, kernel execution

- Basic scheduling:
  - Copy batch 16000 inputs from host to FPGA DDR
  - Run hls4ml kernel
    - Tuned for low latency, pipelined, ~104 ns/inference
  - Copy 16000 batch outputs from FPGA DDR to host
  - Server responsible for transferring input to dedicated buffers in host memory

- Set up for Alveo U250, AWS f1
FACILE Server (XILINX VITIS + hls4ml)

- Large amount of server optimization
- Can create multiple copies of hls4ml inference kernel on separate SLRs
- Can create buffer in DDR for multiple inputs, cycle through buffers
ResNet Server

- Similar server interface designed for ResNet / Xilinx ML Suite
- Set up for AWS f1
ResNet Server ( )

- Microsoft Azure Machine Learning Studio works with Azure Stack Edge server
  - Intel Arria 10 FPGA
  - Predefined list of ML models (including ResNet-50)
  - Out-of-the-box solution accepts gRPC calls
  - Installed locally at Fermilab
Server Optimization

- Many settings to tune
- **FACILE**: scan of CU duplication and DDR buffer size
- **ResNet**: streaming gRPC inference calls found to greatly increase throughput
- Both: proxies to manage requests, distribute to multiple gRPC server endpoints
Throughput Tests

- What is the maximum throughput of the server?

- Start server (local/cloud), create N client processes at Fermilab computing cluster
  - Workflow contains only accelerated processing module

- All processes begin running at the same time
  - Fixed number of events

- Measure time/throughput for each process
Throughput Tests

- With small **FACILE** network, server able to process over 5000 events/s

- Limitation from CPU

- **ResNet** performance depends on hardware/specs
Scalability Test

• How many processes can a single server realistically serve?

• Start server, create N client processes

  • Running realistic HEP high level trigger (HLT) workflow

  • HLT is fast reconstruction during data-taking traditionally performed using large CPU farm

• Compare standard HLT to HLT with calorimeter reconstruction replaced by FaasST server running FACILE

• Use HEPCloud to manage clients
Scalability Test

• 10% reduction in computing time operating as-a-service
  
  • Consistent with fraction of time spent on calorimeter reconstruction w.r.t total HLT time
  
  • → Maximal achievable reduction for this single algorithm
  
  • No increase in latency until **1500 clients**
    
    • Single FPGA can service **1500 HLT instances**
  
  • Limited by AWS bandwidth (25 Gbps)
    
    • On Alveo U250, without network limit, estimate saturation at ~3300 clients
• Comparison of results to GPUaaS results (arXiv:2007.10359)

• **FaaST** greatly outperforms **GPUaaS** for **FACILE**

• Small network, large batch is ideally suited for FPGA

• Comparable performance between **FaaST** and **GPUaaS** for **ResNet**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Platform</th>
<th>Number of Devices</th>
<th>Batch Size</th>
<th>Inf./s [Hz]</th>
<th>Bandwidth [Gbps]</th>
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<tbody>
<tr>
<td>FACILE</td>
<td>AWS EC2 F1</td>
<td>1</td>
<td>16,000</td>
<td>36 M</td>
<td>23</td>
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<td>250</td>
<td>1.2</td>
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</tbody>
</table>
Conclusions

- FPGAs have been used in HEP for decades

- As-a-service paradigm, recent developments in ML inference, provide opportunity to leverage FPGA compute for many additional applications

- FPGAs-as-a-Service Toolkit (FaaST) can help facilitate integration of FPGA compute into existing workflows
  - Our results focus on HEP (and LHC particularly)
  - Applicable many other fields
    - Astronomy, neutrinos, gravitational waves
  - Look forward to the growth of heterogeneous computing for science
Thanks!

Institute for AI and Fundamental Interactions

Fast Machine Learning Lab
BACKUP
FACILE Optimization

Alveo U250

AWS f1

Throughput (events/sec)

Size of DDR buffer (# of inputs)

# of CUs = 1
# of CUs = 2
# of CUs = 3
# of CUs = 4

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Size of DDR buffer (# of inputs)

# of CUs = 1
# of CUs = 2
# of CUs = 3