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Accelerating Machine Learning inference using FPGAs: the PYNQ framework tested on an AWS EC2 F1 Instance

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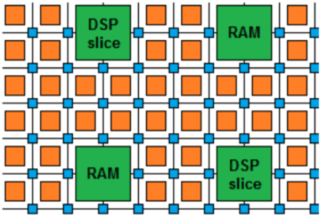
Field Programmable Gate Array

Field Programmable Gate Arrays (FPGAs) → Middle ground between ASICs and multipurpose CPUs:

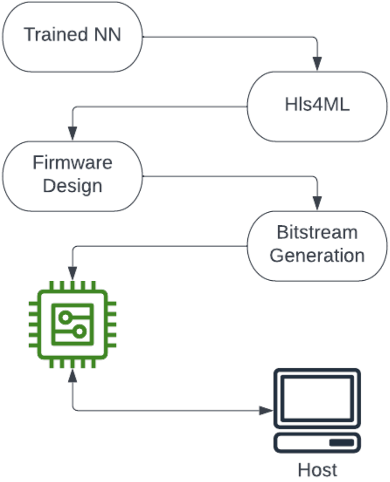
- **Programmables** to perform a wide range of tasks;
- **Low-level/Near-metal** implementation of algorithms → low latency;
- Blend the **benefits of both hardware and software**;
- Internal layout made up of *logic blocks* (**LUTs**, **flipflops**, **Digital Signal Processor** slices), embedded in a **general routing structure**.

FPGA diagram



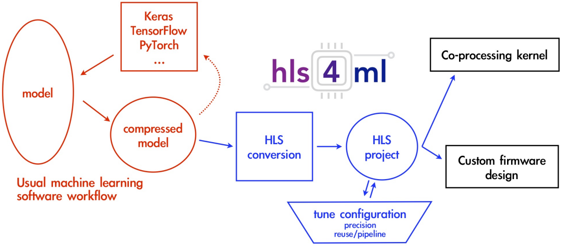
Implementing a Neural Network on an FPGA

- **NN Translation into HLS** (C++) using *hls4ml* (see next slide);
- **Firmware design** (I/O interfaces);
- **Synthesis and implementation** of the design;
- Production of the **bitstream and programming** of the FPGA;
- **Running** of the inference using an application on the **host** machine.



The hls4ml package

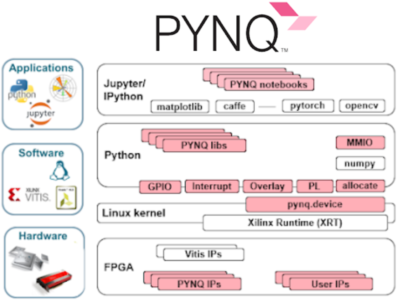
https://fastmachinelearning.org/hls4ml



- Developed by members of the HEP community to translate **ML algorithms** written in **Python** into **High Level Synthesis** code;
- HLS allows the **generation** of **hardware descriptive code** (HDL) from *behavioral descriptions* contained in C++ program;
- The translated Python objects can be injected in the automatic workflow of proprietary software like Vivado from Xilinx Inc.

The PYNQ project

- *PYNQ* is an **open-source** project from Xilinx®;
- It provides a **Jupyter-based framework** with Python APIs for using Xilinx platforms;
- The **Python language** opens up the **benefits of programmable logic** (PL) to people **without** in-depth knowledge of **low-level programming languages**.



https://pynq.readthedocs.io

An introduction to PYNQ

- The **overlay** class is the **core** of the library;
- An overlay object is built providing the **FPGA design** to run on the PL;
- FPGA is **programmed** and relevant **interface** is available through **PYNQ API function** calls;
- It is possible to **accelerate** a software **application**, or to customize the hardware platform for a particular application.

```python
from pynq import Overlay

overlay = Overlay("designbitstream.xclbin") # or .awsxclbin
result = overlay.<function described in FPGA design>
```

The testing ground: AWS F1 Instances

Cloud computing is used to test the capabilities of these tools in preparation for deployment of FPGA accelerator cards in a local server.

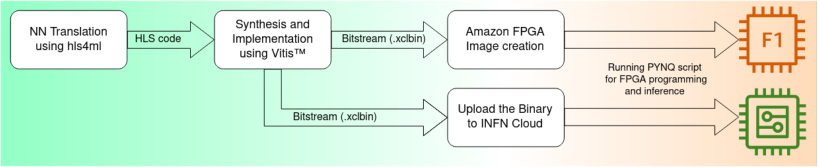
- Part of the **AWS Cloud Computing** catalogue;
- EC2 F1 instances use **FPGAs** to enable **delivery** of **custom hardware accelerations**;
- Packaged with **tools** to **develop**, simulate, debug, and **compile** a design.

Amazon EC2

Deploying on F1

- Follow the *Application Acceleration development flow*, offered by Vitis™, targeting data center acceleration cards;
- **Upload** the **bitstream** to a S3 bucket and request the **creation** of an *Amazon FPGA Image* (AFI) accessible from all F1 instances;
- Write a **Pyhton script** using PYNQ APIs.

A "more traditional" approach is to use **OpenCL** to write the host application: both ways follow the **same** list of **basic instructions**.



From Python to HLS Code

```python
import tensorflow as tf
from qkeras.qlayers import QDense, QActivation

netinputs = tf.keras.layers.Input(shape=(4,),dtype=X_train.dtype,name="input_1")
x = QActivation(activation=quantized_relu(16,6,relu_upper_bound=6.0),
                name='qrelu1')(inputs)
x = QDense(16, kernel_quantizer=quantized_bits(16,5,alpha=1),
            bias_quantizer=quantized_bits(16,5,alpha=1),
            kernel_initializer='random_normal',name='qdense_1')(x)
x = QActivation(activation=quantized_relu(16,6), name='qrelu2')(x)
#...# List of layers and activation functions
output = tf.keras.layers.Activation('softmax', name='soft1')(x)
model = tf.keras.Model(inputs=netinputs,outputs=netoutput,name="model")
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy')
history = model.fit(X_train, Y_train, epochs=num_epochs, validation_data=(X_test, Y_test))
```

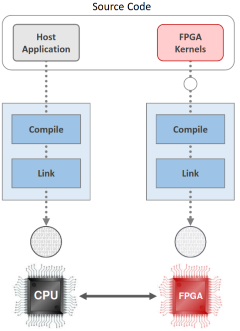
```python
import hls4ml

config = hls4ml.utils.config_from_keras_model(model, granularity='model')
hls_model = hls4ml.converters.convert_from_keras_model(model,
            hls_config=config, part='<id of FPGA model>')
hls_model.compile()
hls_model.build(csim=False,synth=False)
```

Producing the Bitstream with Vitis

The *build* function creates the HLS code to import in the Vitis Software Platform developed by Xilinx.

- An **application project** with the target platform is created;
- The HLS code from *hls4ml* is imported as **source** for the *kernel* of the application;
- A *Hardware function* is associated to the **main C++ function** in the code;
- The **host application** is usually written in OpenCL (see next slide);
- The whole application is build for **hardware deployment** → **Bitstream**.



OpenCL vs PYNQ

The first thing to do in both cases, is to **program the device and initialize** the software context.

```
auto devices = xcl::get_xil_devices();
auto fileBuf = xcl::read_binary_file(binaryFile);
cl::Program::Binaries bins{{fileBuf.data(), fileBuf.size()}};
OCL_CHECK(err, context = cl::Context({device}, NULL, NULL, NULL, &err));
OCL_CHECK(err, q = cl::CommandQueue(context, {device}, CL_QUEUE_PROFILING_ENABLE, &err));
OCL_CHECK(err, cl::Program program(context, {device}, bins, NULL, &err));
OCL_CHECK(err, krnl_vector_add = cl::Kernel(program, "vadd", &err));

```

```
import pynq
ov = pynq.Overlay("model_binary.awsxclbin")
nn = ov.myproject
```

In OpenCL host and FPGA **buffers** need to be handled separately and linked after creation; with PYNQ, the user is only presented with a single interface for both:

```
std::vector<int, aligned_allocator<int>> source_in1(DATA_SIZE);
OCL_CHECK(err, l::Buffer buffer_in1(context,
    CL_MEM_USE_HOST_PTR | CL_MEM_READ_ONLY, vector_size_bytes,
    source_in1.data(), &err))
```

```
inp = pynq.allocate(27, 'u2')
out = pynq.allocate(1, 'u2')
```

OpenCL vs PYNQ (cont'd)

To **initiate data transfers** the direction as a function parameter must be specified in OpenCL, while in PYNQ the same is done with a specific function:

```
OCL_CHECK(err, err = q.enqueueMigrateMemObjects({buffer_input}, 0 /*0 means from host*/,NULL,&eventinp));
```

```
inp.sync_to_device()
```

To **run the kernel** in OpenCL each kernel argument need to be set explicitly using the `setArgs()` function, before starting the execution with `enqueueTask()`; in PYNQ, the `.call()` function does everything in a single line.

```
OCL_CHECK(err, err = myproject.setArg(0, buffer_input));
OCL_CHECK(err, err = myproject.setArg(1, buffer_output));
//[...]
OCL_CHECK(err, err = q.enqueueTask(myproject,NULL,&eventker));
// wait for all kernels to finish their operations
OCL_CHECK(err, err = q.finish());
```

```
nn.call(inp,out)
```

Finally, the **output is retrieved** in both cases similarly to the input transfer:

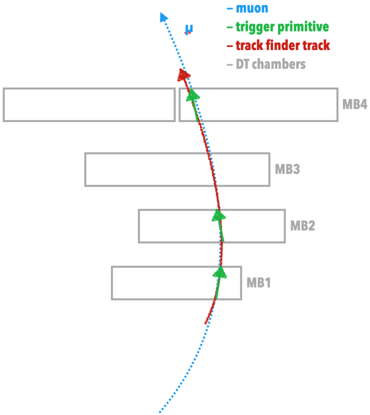
```
OCL_CHECK(err, err = q.enqueueMigrateMemObjects({buffer_output},
CL_MIGRATE_MEM_OBJECT_HOST));
```

```
out.synq_from_device()
```

The tested model

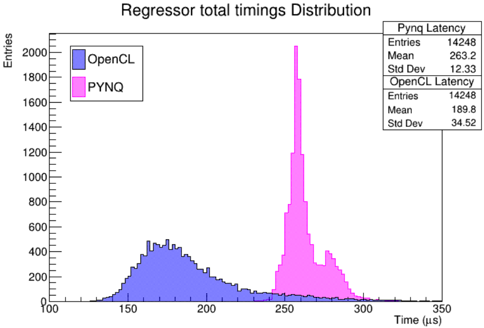
To **test** the **workflow** and the **performance**, **a Neural Network** has been considered:

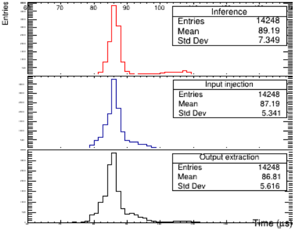
- **Regressor** in the context of Level-1 **triggering** at the CMS experiment at CERN:
  - NN predicts **transverse momentum** of **muons** using their position and direction in the detector.

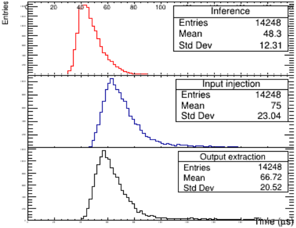


Timing Comparison

A **difference** in **computation times** can be seen between the same algorithm deployed with PYNQ and OpenCL:



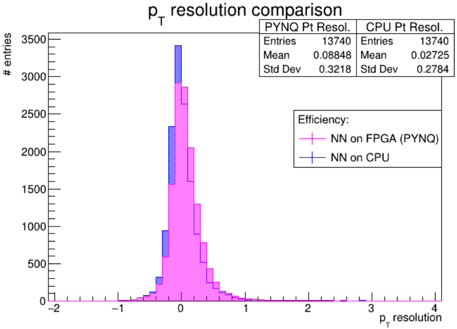




Inference comparison

The **FPGA's output** has been **validated against** the NN run on a consumer **CPU**:

- **small difference** traceable to **quantization** of **floating** point to **fixed** point;
- small bias towards higher values of $\Delta p_T / p_T$.



Summary and conclusions

- This work is still in **progress** (i.e. kernel optimization);
- The possibility of **deploying** a **Neural Network** on a **FPGA** inside an **AWS instance** has been explored;
- A **fast** and **easy-to-use** alternative to host applications written in **OpenCL** has been found in **PYNQ** using the **Python** programming language;
- There seems to be **no important drawbacks** from using this new approach.

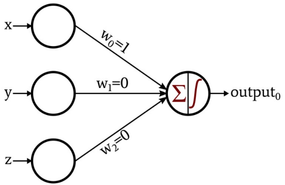
Thank you!

Backup

Artificial Neural Networks

The p_T assignment is currently carried out using **precompiled LUTs**. An alternative was explored using **Artificial Neural Network** (ANN):

- An ANN is a network designed to tackle **non-linear learning problems**;
- The **Fully Connected Multilayer Perceptrons** (MLPs) are made up of single units called *Perceptrons*;
- Perceptrons can be stacked together to **build arbitrarily deep custom networks**;



Graphical representation of a Perceptron.

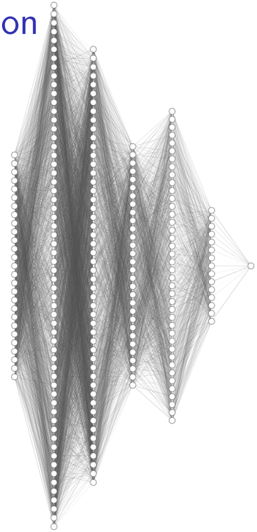
- The NN *learns* during the **training** process by receiving **input patterns** together with the corresponding true target variable and finding the **best set of weights**;
- The weights are used to **predict the output with unseen data**.

Neural Network for regression

A **Fully Connected MLP** was built using QKeras with:

- **Input layer**: 27 features;
- **6 hidden layers**: 35, 20, 25, 40, 20, 15 nodes;
- **Output layer**: returns the p_T value.
- **Activation function**: Rectified Linear Unit;
- **Weight pruned**.

The model was **tested using a consumer CPU** before the hardware implementation.



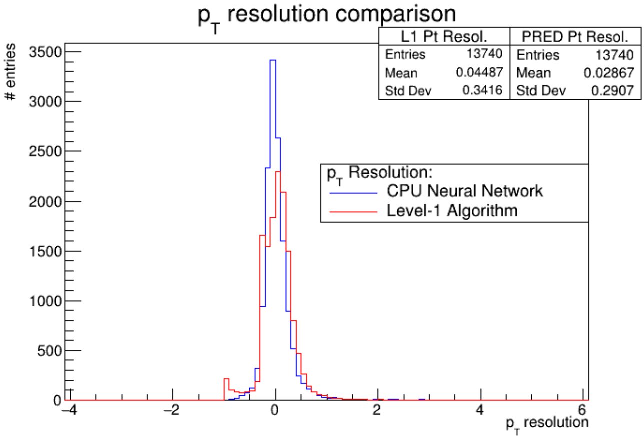
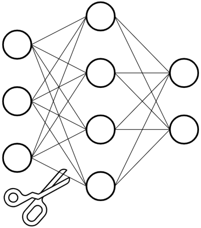


Figure: Transverse momentum resolution histograms computed for the machine learning model (blue) and Level-1 trigger (red) based momentum assignment.

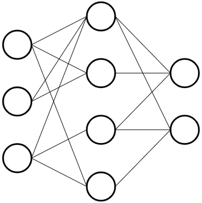
Optimization techniques

To produce an **optimized NN** for **implementation** on an FPGA:

- **Quantization**:
  the parameters were converted **from double precision floating-points to fixed points** to exploit the efficiency of DSPs;
- **Pruning**: **connections** between nodes with low influence were **cut** to **minimize** the number of **paramaters** and operations during inference and **reduce the resources** needed for implementation.



Before pruning

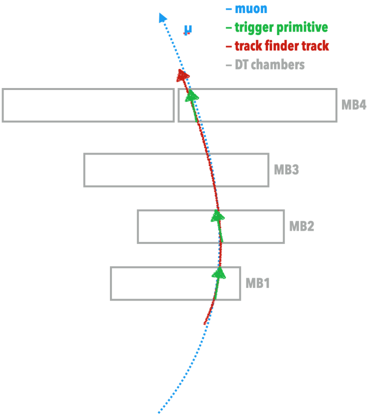


After pruning

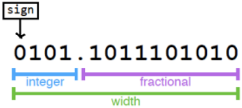
Dataset to train and test the NN

The entire **dataset** contains about **300000 simulated muons** with a range in p_T **from 3 to 200 GeV/c**. A set of **information** is included in order to **predict** the muon p_T:

- **Trigger segments' position** (wheel, sector, ϕ) for each station crossed by the particle;
- Their **direction** in CMS global coordinates (ϕ_b).
- Trigger primitives' **quality** (i.e. number of hits used to build a segment).



Quantization



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In order to produce an **optimized NN** for **implementation** on an FPGA, the models were *quantized*:

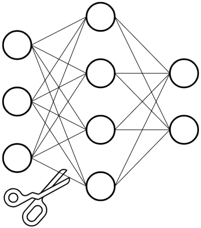
- *Quantization* is the conversion **from high-precision floating-points to normalized low-precision integers** (*fixed-point*) parameters;
- *QKeras* is a Python package developed as a collaboration between Google and HEP researchers to **build NN with quantized parameters**;
- It has an easy-to-use API: there are **drop-in replacements** for the most common layers used with Keras (e.g. Dense → QDense).

```
QDense(64, kernel_quantizer = quantized_bits(6,0),
           bias_quantizer = quantized_bits(6,0)(x))
QActivation('quantized_relu(6,0)')(x)
```

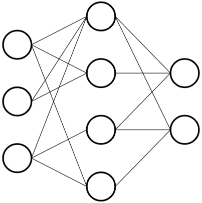
Slimming techniques - Weight Pruning

When building a NN model,
the final hardware platform where the inference computation will be run, has to be considered.

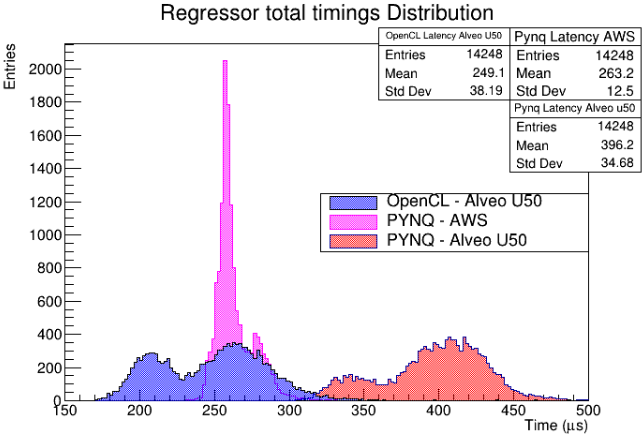
- *Weight Pruning* is the elimination of unnecessary values in the weight tensor;
- Connections between nodes with low influence are "cut" during the synthesis of the HLS design;
- This is aimed at minimizing the number of parameters and operations involved in the inference computation.



Before pruning



After pruning


Regressor total timings Distribution
Entries
Time (µs)
OpenCL Latency Alveo U50
Entries 14248
Mean 249.1
Std Dev 38.19
Pynq Latency AWS
Entries 14248
Mean 263.2
Std Dev 12.5
Pynq Latency Alveo u50
Entries 14248
Mean 396.2
Std Dev 34.68
OpenCL - Alveo U50
PYNQ - AWS
PYNQ - Alveo U50