# Accelerating inference of YOLOv3-tiny model using FPGA

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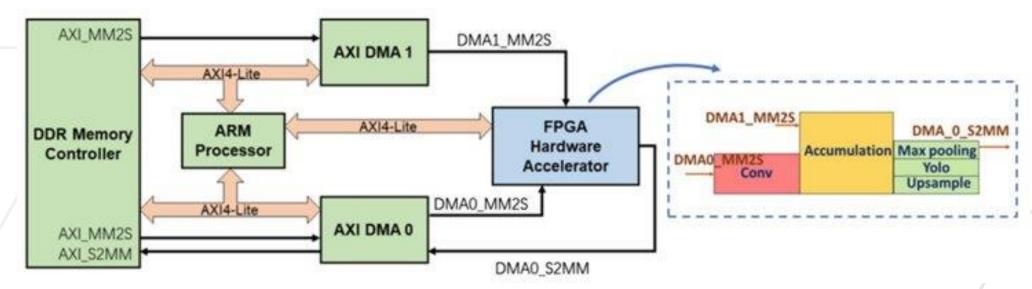
#### **Problem**

- Deploy YOLOv3-tiny on FPGA with minimal reduction in object detection precision
- Limited resources on FPGA (off chip memory required to store parameters and partial DNN inference computation results)
- Low Latency for real time object detection applications on embedded systems



#### Design

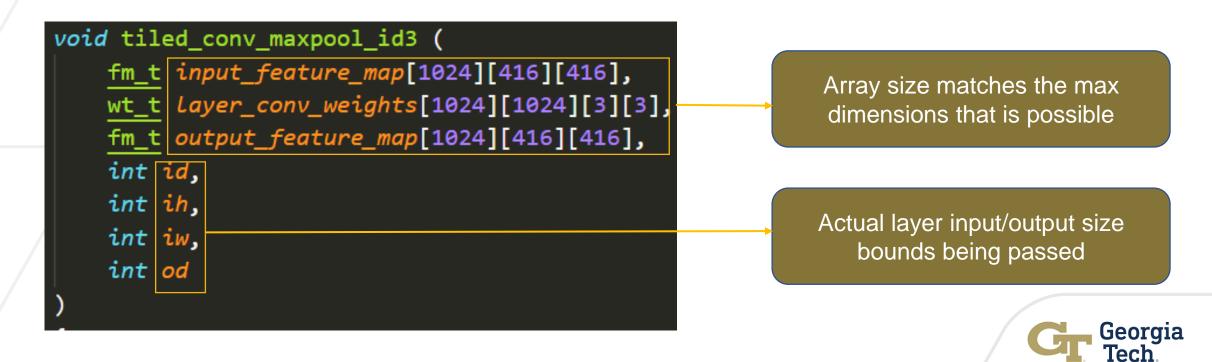
- The FPGA accelerator consists of a three-stage pipeline.
- The first stage of the pipeline supports the execution of the convolution layer, whose output is accumulated in the second stage of the pipeline.
- Depending on the network structure that is executed at a given time, the accumulation results are sent for further processing in the Max pooling, Upsample or Yolo layer





#### Approach

- Worked on a golden C code based off available literature used \*pointers.
- Redid golden C code using Lab2 as base and made modifications to get single layer convolution running for a variable input size.



## Approach

Layer	Type	Filters	Size/Stride	Input	Output
0	Convolutional	16	3 × 3/1	416 × 416 × 3	416 × 416 × 16
1	Maxpool		2 × 2/2	$416\times416\times16$	208 × 208 × 16
2	Convolutional	32	3 × 3/1	208 × 208 × 16	$208\times208\times32$
3	Maxpool		2 × 2/2	$208\times208\times32$	$104\times104\times32$
4	Convolutional	64	3 × 3/1	$104\times104\times32$	$104\times104\times64$
5	Maxpool		2 × 2/2	$104\times104\times64$	$52 \times 52 \times 64$
6	Convolutional	128	3 × 3/1	$52 \times 52 \times 64$	$52 \times 52 \times 128$
7	Maxpool		2 × 2/2	$52 \times 52 \times 128$	$26 \times 26 \times 128$
8	Convolutional	256	3 × 3/1	$26 \times 26 \times 128$	$26 \times 26 \times 256$
9	Maxpool		2 × 2/2	$26 \times 26 \times 256$	$13 \times 13 \times 256$
10	Convolutional	512	3 × 3/1	$13 \times 13 \times 256$	$13 \times 13 \times 512$
11	Maxpool		2 × 2/1	$13 \times 13 \times 512$	$13 \times 13 \times 512$
12	Convolutional	1024	3 × 3/1	$13 \times 13 \times 512$	$13\times13\times1024$
13	Convolutional	256	1 × 1/1	$13\times13\times1024$	$13 \times 13 \times 256$
14	Convolutional	512	3 × 3/1	$13 \times 13 \times 256$	$13 \times 13 \times 512$
15	Convolutional	255	1 × 1/1	$13 \times 13 \times 512$	$13 \times 13 \times 255$
16	YOLO				
17	Route 13				
18	Convolutional	128	1 × 1/1	$13 \times 13 \times 256$	$13 \times 13 \times 128$
19	Up-sampling		2 × 2/1	$13 \times 13 \times 128$	$26 \times 26 \times 128$
20	Route 198				
21	Convolutional	256	3 × 3/1	$13\times13\times384$	$13\times13\times256$
22	Convolutional	255	1 × 1/1	$13 \times 13 \times 256$	13 × 13 × 256
23	YOLO				

- Golden C
  - Implemented all layers YOLO, Convolution, Max Pooling, Upsample and Route
  - Used Lab 2 code as base to develop code.
  - Created a 24-layer network



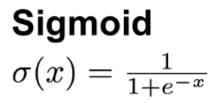
#### **Code Snippets**

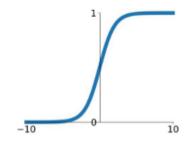
YOLO C-Model code



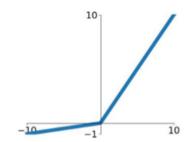
# **HLS Code Approach**

- Had to modify network to implement on FPGA
- Did not implement Batch Normalization on FPGA
- Faced implementation problems for sigmoid and exponential activation – did not implement the YOLO layer on FPGA
- Used Leaky ReLU for convolution





Leaky ReLU max(0.1x, x)





## **Code Snippets**

Max Pooling

```
MAXPOOL_DEPTH:
For (int d = 0; d < 16; d++)
   MAXPOOL_HEIGHT:
    for(int h = 0; h < 208; h++)
        MAXPOOL_WIDTH:
        for(int w = 0; w < 208; w++)
            \max = in\_buf[d][2*h][2*w];
            MAXPOOL WIN DIM1:
            for (int i = 0; i < 2; i++)
                MAXPOOL_WIN_DIM2:
                for(int j = 0; j < 2; j++)
                    if (in_buf[d][(2*h)+i][(2*w)+j] > max)
                        \max = in\_buf[d][(2*h)+i][(2*w)+j];
            out_buf[d][h][w] = max;
```

12	20	30	0			
8	12	2	0	$2 \times 2$ Max-Pool	20	30
34	70	37	4		112	37
112	100	25	12	,		



## **Optimization Strategies**

- Array Partitioning
- Loop Pipelining
- Loop Unroll

```
pragma HLS array_partition variable=X buf dim=1
pragma HLS array_partition variable=X_buf dim=2 factor=3 cyclic
pragma HLS array_partition variable=X_buf dim=3 factor=3 cyclic
pragma HLS array_partition variable=W_buf dim=2
pragma HLS array_partition variable=W_buf dim=3
pragma HLS array partition variable=W buf dim=4
  OUT DEPTH:
  for (int outDepth = 0; outDepth < OUT_BUF_DEPTH; outDepth++)</pre>
       OUT_HEIGHT:
       for (int outHeight = 0; outHeight < OUT BUF HEIGHT; outHeight++)</pre>
           OUT WIDTH:
           for (int outWidth = 0; outWidth < OUT BUF WIDTH; outWidth++)</pre>
#pragma HLS pipeline II=1
               Y buf[outDepth][outHeight][outWidth] = 0;
               fm_t local[IN_BUF_DEPTH];
               IN_HEIGHT:
               for (int kHeight = 0; kHeight < 3; kHeight++)</pre>
                   IN WIDTH:
                   for (int kWidth = 0; kWidth < 3; kWidth++)</pre>
```



#### **Optimization Strategies**

- Loop Tiling
- Ping Pong Buffer

```
outD:
    for (int outDepthOffset = 0; outDepthOffset < 16 / OUT_BUF_DEPTH; outDepthOffset++)</pre>
        // PING PONG
        // PING LOAD
        load input tile block from DRAM(conv_in_buf, input_feature_map, ti, tj, 0);
        load layer params from DRAM(conv_wt_buf, conv_bias_buf, layer_weights, layer_bias, o
    inD:
        for (int inDepthOffset = 0; inDepthOffset < (3 / IN_BUF_DEPTH) - 1; inDepthOffset++)</pre>
            if (inDepthOffset % 2 == 0)
                // PING COMPUTE + PONG LOAD
                conv_3x3(conv_out_buf, conv_in_buf, conv_wt_buf);
                save_partial_output_tile_block(partial_out_fm_buf, conv_out_buf, conv_bias_b
                load_input_tile_block_from_DRAM(conv_in_buf_1, input_feature_map, ti, tj, in
                load layer params from DRAM(conv wt buf 1, conv bias buf 1, Layer weights,
                // PONG COMPUTE + PING LOAD
                conv 3x3(conv out buf, conv in buf 1, conv wt buf 1);
                save_partial_output_tile_block(partial_out_fm_buf, conv_out_buf, conv_bias_b
                load_input_tile_block_from_DRAM(conv_in_buf, input_feature_map, ti, tj, inDe
                load_layer_params_from_DRAM(conv_wt_buf, conv_bias_buf, Layer_weights, Layer
```



#### **Evaluation**

• Unoptimized, Synthesizable Run for all layers:

+	Latency	(cycles)	Latency min	(absolute) max	Int min	erval   max	Pipeline  Type
į	367148894	47550818342	3.671 sec	475.508 sec	367148895	47550818343	none

Accelerated Run:

    -    -	Latency min	(cycles)   max	Latency (	(absolute)     max	Int min	terval max	Pipeline  Type
į	68493294	4029377062	0.685 sec	40.294 sec	68493295	4029377063	none



# **Evaluations – Single layer data**

	Latency (sec)	SpeedUp
Unoptimized	3.2	1
Ping Pong Buffer	2.02	1.584158
Loop Unroll + Pipelining	0.186	17.2043
Array Partitioning	0.0549	58.2878



#### **Evaluation**

#### Accelerated run for four layers:

\_\_\_\_\_\_

== Utilization Estimates

\* Summary:

_						
	Name	BRAM_18K	DSP	FF	LUT	URAM
	DSP	-	4	-	-	- [
	Expression	-	-	0	820	-
	FIFO	-	-	-	-	-
	Instance	225	129	20332	41581	-
	Memory	-	-	-	-	-
	Multiplexer	-	-	-	1151	- [
j	Register	-	-	1099	64	- İ
	Total	225	133	21431	43616	0
	Available	432	360	141120	70560	0
	Utilization (%)	52	36	15	61	0
7						+

#### Latency:

\* Summary:

	Latency	(cycles)	Latency (	(absolute)
	min	max	min	max
ļ +	30498837	30498837	0.305 sec	0.305 sec



## Future Actions to try before submitting code

- Our initial approach caused issues with debugging.
- Use independent functions for all convolution layers.
- Literature search for references with YOLO layer implementation on FPGA

