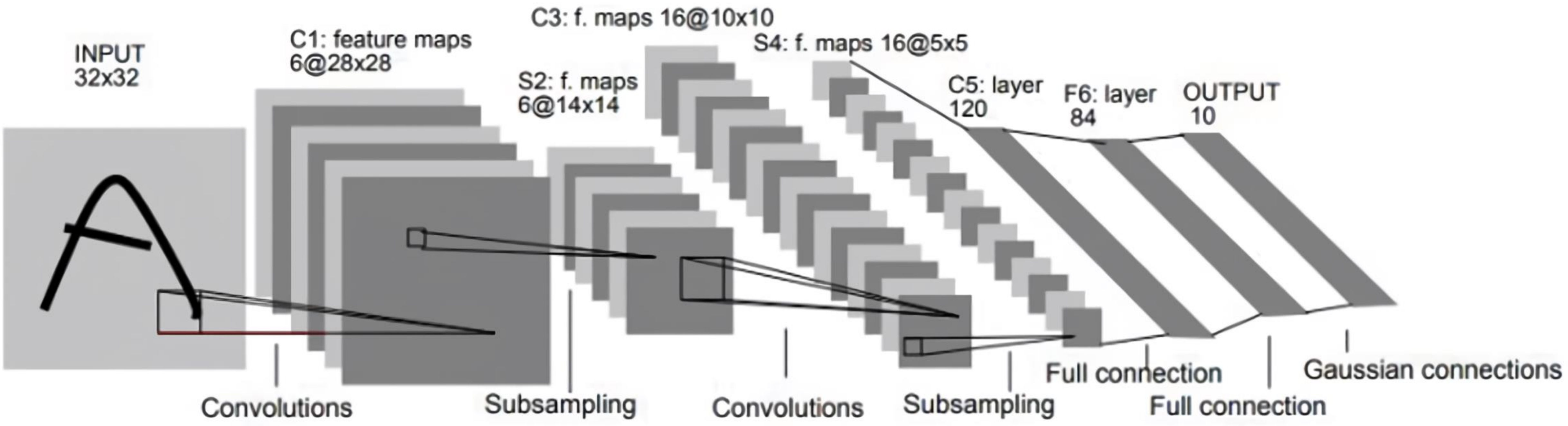
LeNet-5 on ZYBO Z7-10 FPGA

Index

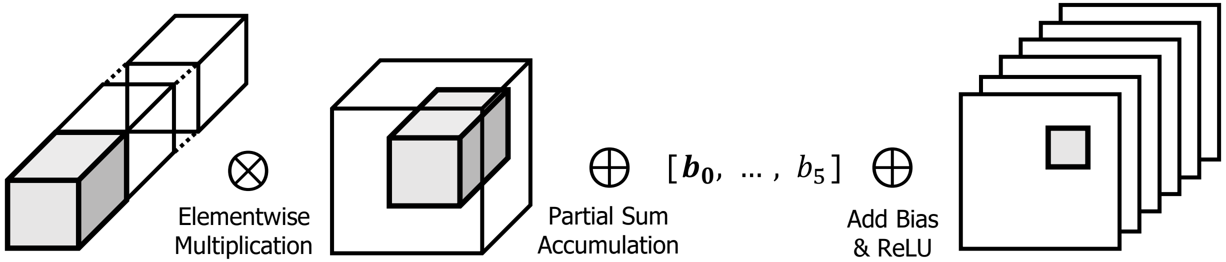
LeNet-5 Introduction

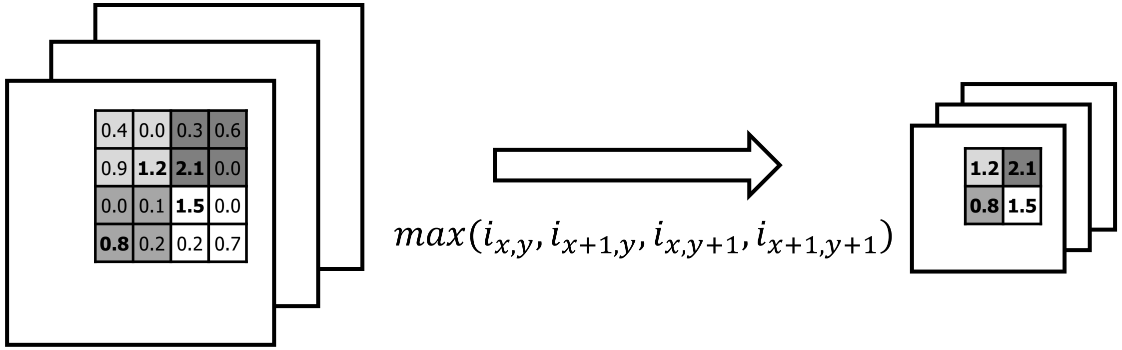


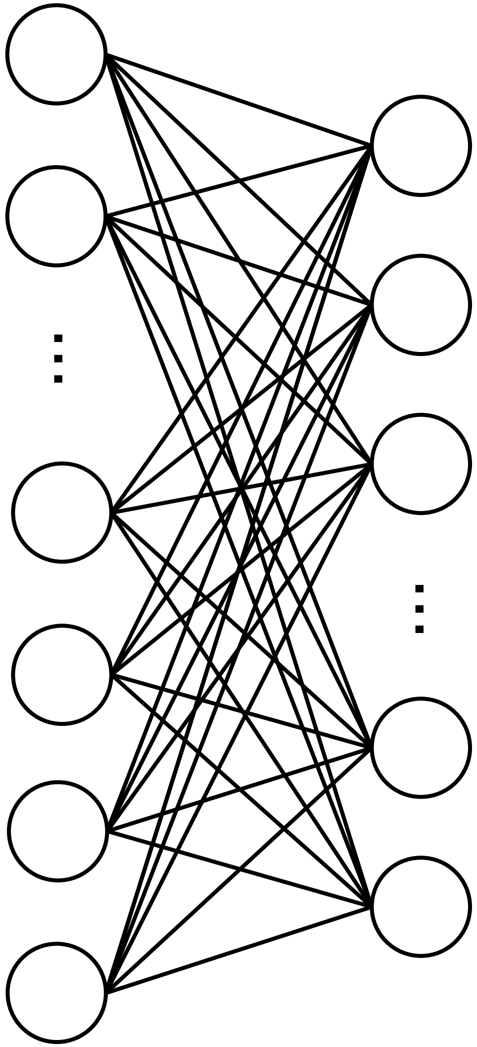
- LeNet-5 is a convolutional neural network (CNN) architecture.
- One of the first neural network architectures to achieve high accuracy on the MNIST handwritten digit recognition.
- Foundational architecture in the development of deep learning.

Components of LeNet-5

- Convolution
- Pooling
- Fully connected
- Activation functions
  - $ReLU$
  - $sigmoid$
  - $tanh$



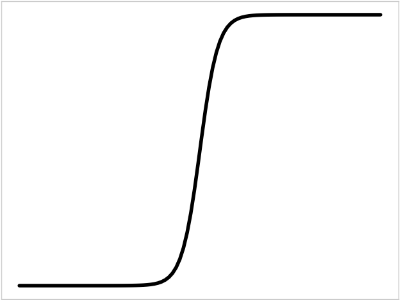


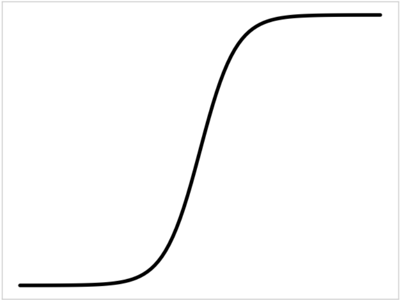


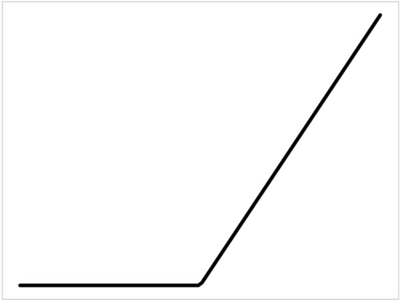
$$tanh(x) = \frac{1 - exp(-x)}{1 + exp(-x)}$$

$$sigmoid(x) = \frac{1}{1 + exp(-x)}$$

$$ReLU(x) = max(x, 0)$$







Parameters of Original LeNet-5

- ZYBO Z7-10 board's resources are not enough to implement Original LeNet-5.
- ZYBO Z7-10 has far fewer resources than the ZYBO Z7-20.

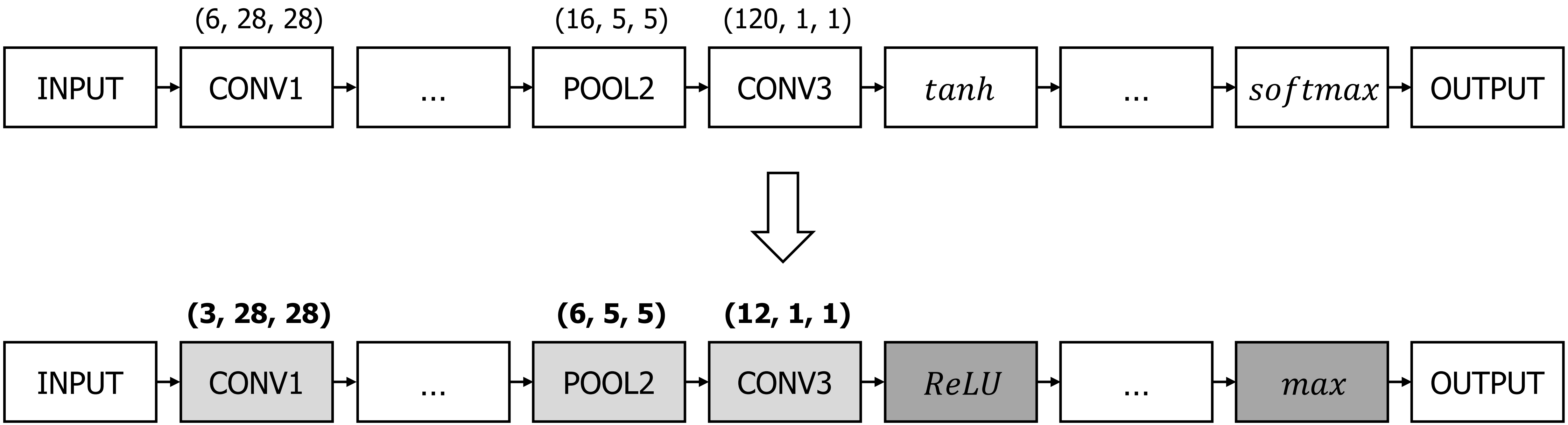
Layer	C	W x H	Kernel	Stride	Activation	Weight + Bias	Feature map
INPUT	1	32 x 32	-	-	-	-	1024
CONV1	6	28 x 28	5x5	1	$tanh$	150 + 6 = 156	4704
A.POOL1	6	14 x 14	2x2	2	$sigmoid$	-	1176
CONV2	16	10 x 10	5x5	1	$tanh$	2400 + 16 = 2416	1600
A.POOL2	16	5 x 5	2x2	2	$sigmoid$	-	400
CONV3	120	1 x 1	5x5	1	$tanh$	48000 + 120 = 48120	120
FC1	-	120	-	-	$tanh$	10080 + 84 = 10164	84
FC2	-	84	-	-	$softmax$	840 + 10 = 850	10
Total	-	-	-	-	-	**61706**	**9118**

	ZYBO Z7-10
LUT	17,600
Flip-Flop	35,200
Block RAM	270 KB
DSP	80
Slice	4,400

	ZYBO Z7-20
LUT	53,200
Flip-Flop	106,400
Block RAM	630 KB
DSP	220
Slice	13,300

Optimization for FPGA Implementation (Model-level)

- Model-level optimization of LeNet-5 from a hardware accelerator perspective.
  - Activation function
  - Model lightening



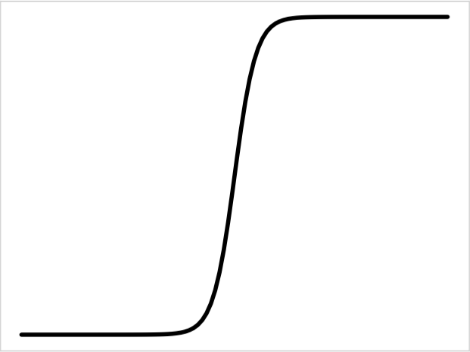
Activation Function ($ReLU$ vs. $tanh$, $sigmoid$)

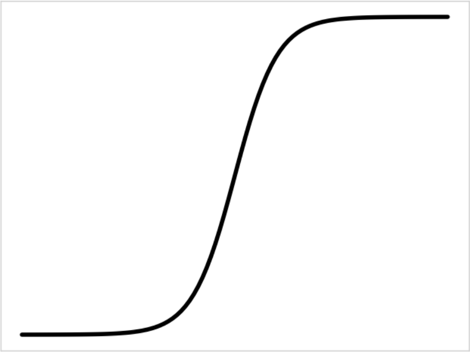
- $tanh(x)$ or $sigmoid(x)$ function in hardware requires additional resources to perform exponentiation and division operations.
- $ReLU(x)$ function can be implemented using basic logical and arithmetic operations, resulting in minimal hardware complexity.
- $ReLU(x)$ helps alleviate the vanishing gradient problem that occurs in activation functions such as $tanh(x)$ or $sigmoid(x)$.

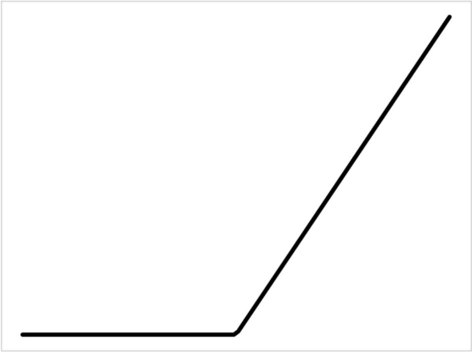
$$tanh(x) = \frac{1 - exp(-x)}{1 + exp(-x)}$$

$$sigmoid(x) = \frac{1}{1 + exp(-x)}$$

$$ReLU(x) = max(x, 0)$$







Activation Function (max vs. $softmax$), Cont'd

- $softmax(\vec{x})$ function in hardware also requires additional resources to perform exponentiation and division operations.
- $max(\vec{x})$ function also can be implemented using basic logical and arithmetic operations, resulting in minimal hardware complexity.
- For both $softmax(\vec{x})$ and $max(\vec{x})$ functions, using the maximum value is the same, so the $max(\vec{x})$ function was used in consideration of efficiency.

$$softmax(\vec{x}) = \frac{exp(x_i)}{\sum_{j=1}^{k} exp(x_j)}, (for\ i = 1, 2, \ldots k)$$

$$max(\vec{x}) = max(x_0, x_1, \ldots, x_k)$$

[0.96 -0.45 … 0.41 -0.5 0.12]

$\Downarrow$ $softmax(\vec{x})$

[**0.97** 0.0 … 0.02 0.0 0.01]

$\Downarrow$ $max(\vec{x})$ & $getIndex(x_{max})$

[**0**]

[**0.96** -0.45 … 0.41 -0.5 0.12]

$\Downarrow$ $max(\vec{x})$ & $getIndex(x_{max})$

[**0**]

Model lightening & Parameters of Light LeNet-5

- Adjust the parameters of each layer to make the model smaller.
- $sigmoid$, $tanh$ are replaced by $ReLU$.
- Weights and biases were reduced by **96%**, and feature maps were reduced by **48%**.

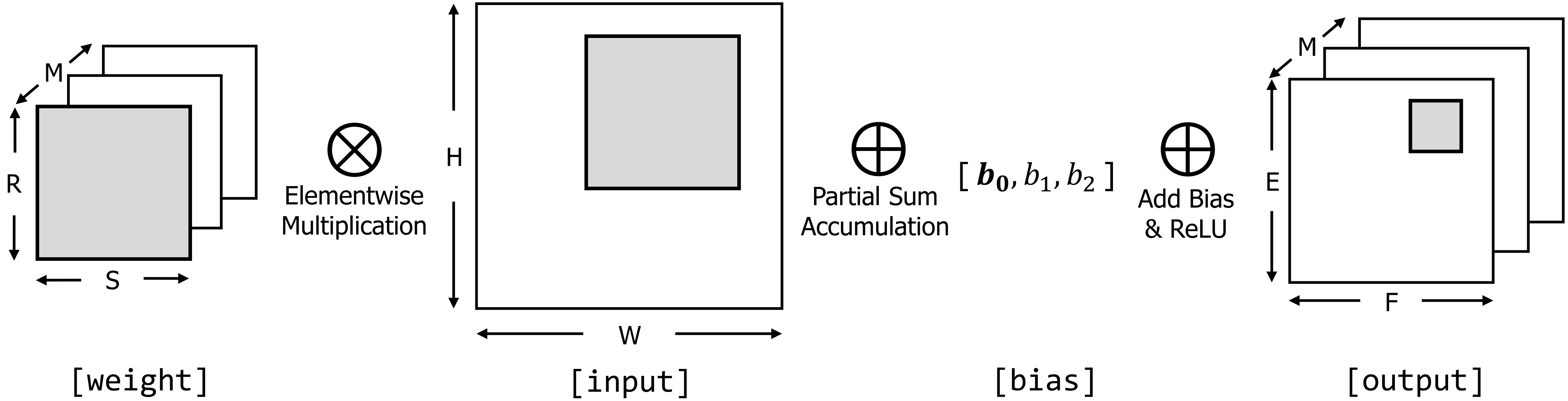
Layer	C	W x H	Kernel	Stride	Activation	Weight + Bias	Feature map
INPUT	1	32 x 32	-	-	-	-	1024
CONV1	3	28 x 28	5x5	1	$ReLU$	75 + 3 = 78	2352
M.POOL1	3	14 x 14	2x2	2	-	-	588
CONV2	6	10 x 10	5x5	1	$ReLU$	450 + 6 = 456	600
M.POOL2	6	5 x 5	2x2	2	-	-	150
CONV3	12	1 x 1	5x5	1	$ReLU$	1800 + 12 = 1812	12
FC1	-	120	-	-	$ReLU$	120 + 10 = 130	10
FC2	-	84	-	-	Max	100 + 10 = 110	10
Total	-	-	-	-	-	**2586**	**4746**

	ZYBO Z7-10
LUT	17,600
Flip-Flop	35,200
Block RAM	270 KB
DSP	80
Slice	4,400

	ZYBO Z7-20
LUT	53,200
Flip-Flop	106,400
Block RAM	630 KB
DSP	220
Slice	13,300

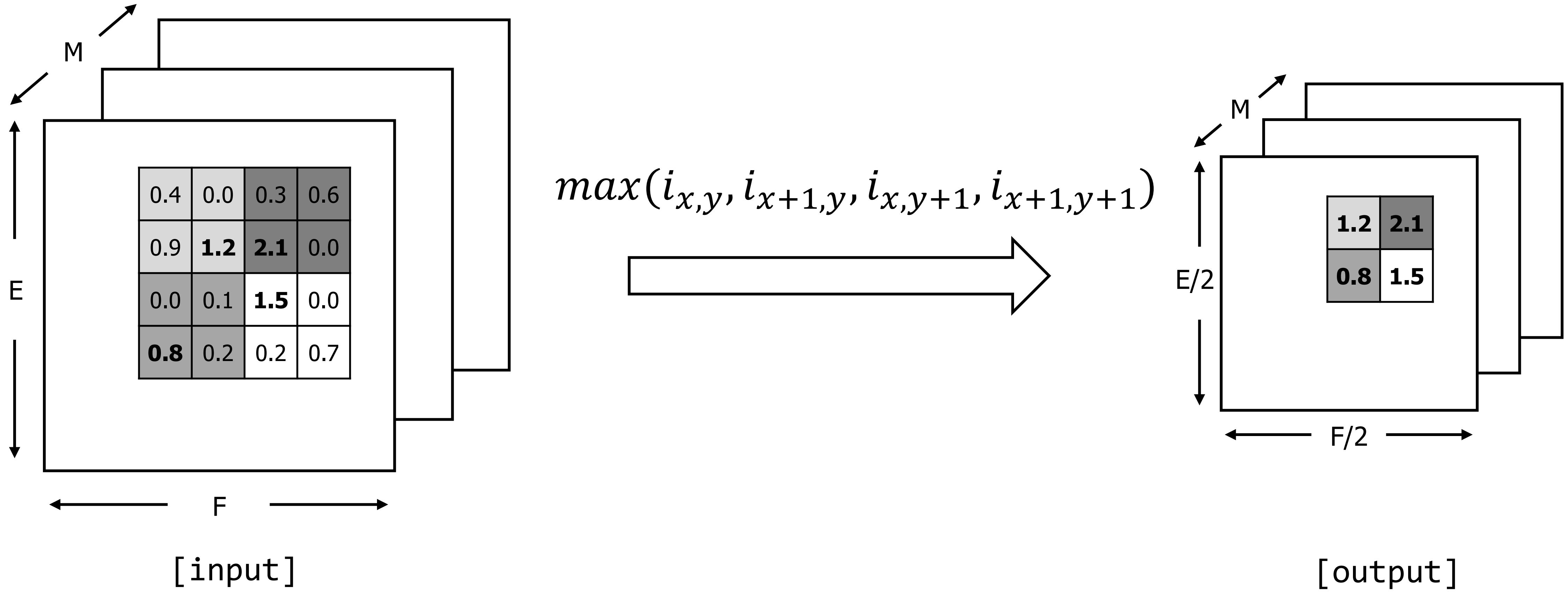
1^{st} Convolution layer

- Input (32 x 32) -> Output (3 x 28 x 28)
- $O[u][x][y] = \sum_{i=0}^{S-1} \sum_{j=0}^{R-1} I[x+i][y+j] * W[u][i][j] + B[u]$
- $0 \le u < M, 0 \le x < F, 0 \le y < E$
- $W = F + S - 1, H = E + R - 1$



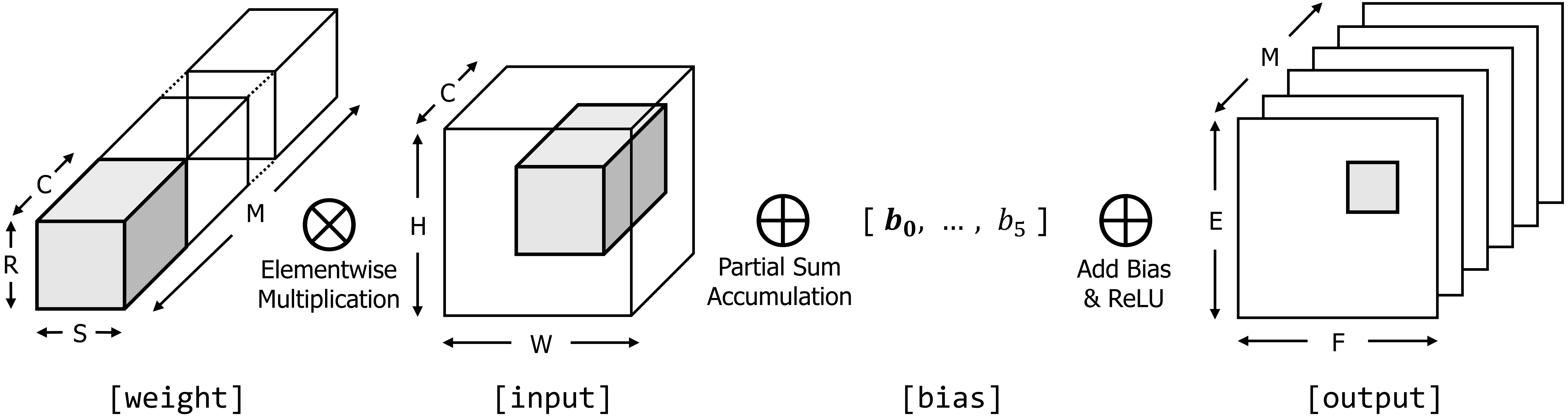
1st Pooling layer

- Input (3 x 28 x 28) -> Output (3 x 14 x 14)
- 2x2 Max pooling, stride 2



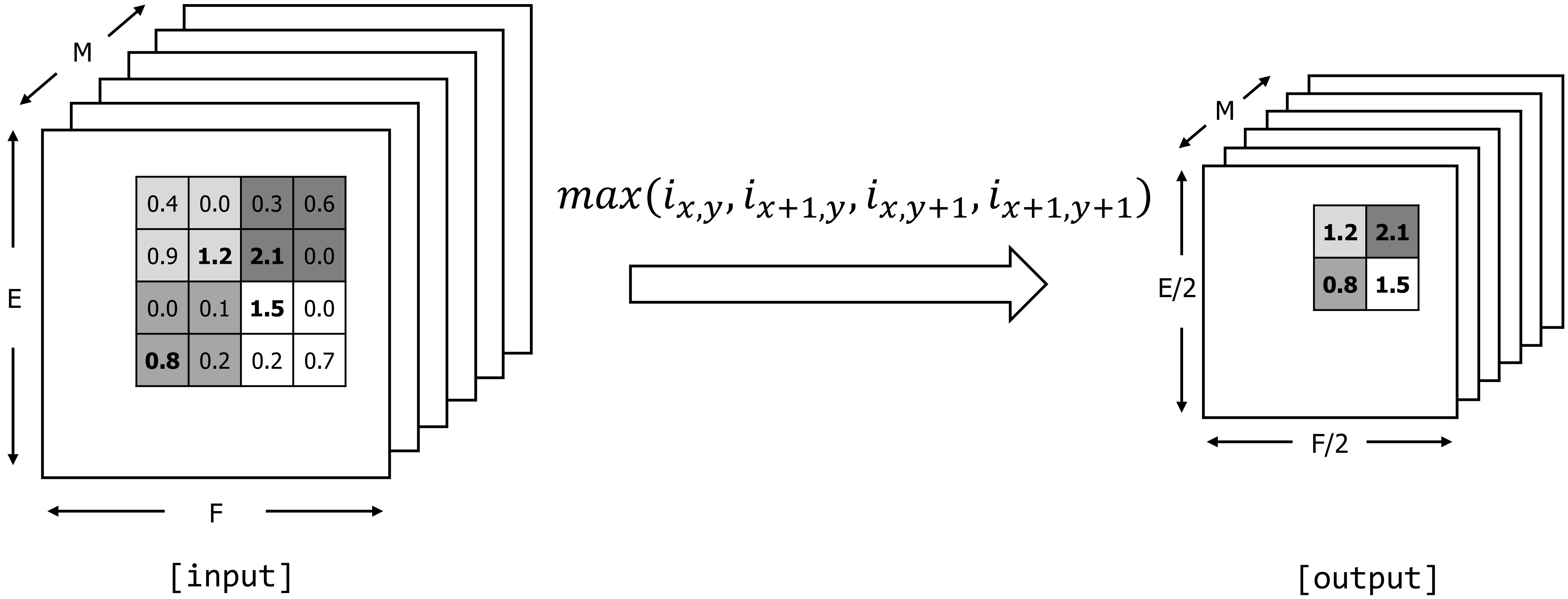
2nd Convolution layer

- Input (3 x 14 x 14) -> Output (6 x 10 x 10)
- $O[u][x][y] = \sum_{k=0}^{C-1} \sum_{i=0}^{S-1} \sum_{j=0}^{R-1} I[k][x+i][y+j] * W[u][k][i][j] + B[u]$
- $0 \leq u < M, 0 \leq x < F, 0 \leq y < E$
- $W = F + S - 1, H = E + R - 1$



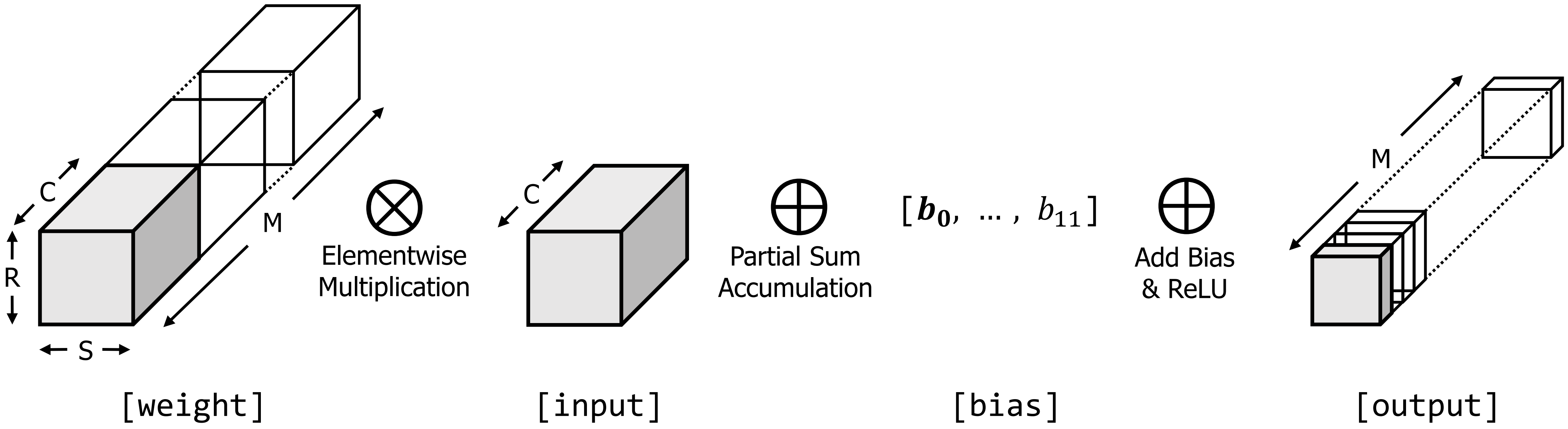
2^{nd} Pooling layer

- Input (6 x 10 x 10) -> Output (6 x 5 x 5)
- 2x2 Max pooling, stride 2



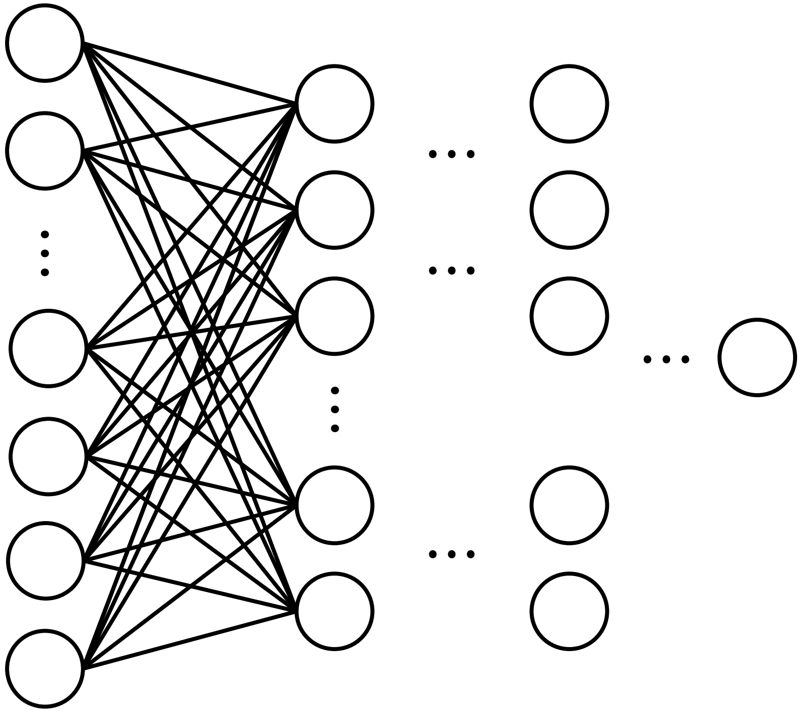
3rd Convolution layer

- Input (6 x 5 x 5) -> Output (12 x 1 x 1)
- $O[u] = \sum_{k=0}^{C-1} \sum_{i=0}^{S-1} \sum_{j=0}^{R-1} I[k][i][j] * W[u][k][i][j] + B[u]$
- $0 \leq u < M$
- $W = S,\ H = R,\ E = F = 1$



1st Fully Connected layer

- Input (12) -> Output (10)
- $O[u] = \sum_{k=0}^{C-1} I[k] * W[u][k] + B[u]$
- $0 \le u < M$



$$\begin{array}{cc} & \xleftarrow{\quad} C \xrightarrow{\quad} \\ M & \begin{bmatrix} \boldsymbol{w_{0,0}} & \cdots & \boldsymbol{w_{0,5}} & \cdots & \boldsymbol{w_{0,11}} \\ \vdots & w_{1,1} & \cdots & w_{1,10} & \vdots \\ w_{4,0} & \cdots & \ddots & \cdots & w_{4,11} \\ \vdots & w_{8,1} & \cdots & w_{8,10} & \vdots \\ w_{9,0} & \cdots & w_{9,5} & \cdots & w_{9,11} \end{bmatrix} \end{array} \otimes \begin{bmatrix} \boldsymbol{I_0} \\ \vdots \\ \boldsymbol{I_5} \\ \vdots \\ \boldsymbol{I_{11}} \end{bmatrix} \oplus \begin{bmatrix} \boldsymbol{b_0} \\ \vdots \\ b_4 \\ \vdots \\ b_9 \end{bmatrix} \oplus \begin{array}{c} \xleftarrow{\quad} M \xrightarrow{\quad} \\ [\boldsymbol{O_0} \quad \cdots \quad O_4 \quad \cdots \quad O_9] \end{array}$$

Elementwise Multiplication

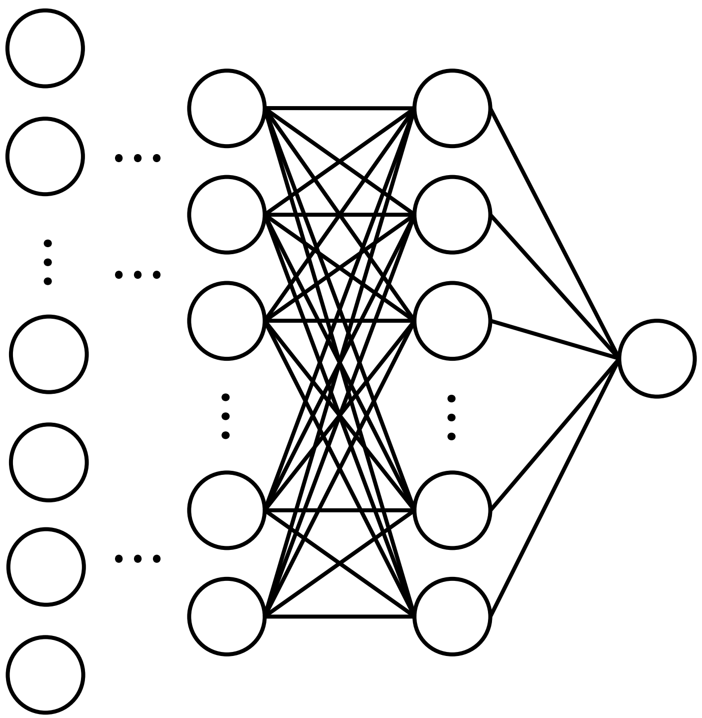
Partial Sum Accumulation

Add Bias & ReLU

[weight] [input] [bias] [output]

2^{nd} Fully Connected layer

- Input (10) -> Output (10)
- $O[u] = \sum_{k=0}^{C-1} I[k] * W[u][k] + B[u]$
- $0 \leq u < M$
- Infer a number by finding index of max value.



$$\begin{array}{cc} & \xleftrightarrow{\qquad\qquad C \qquad\qquad} \\ M \updownarrow & \begin{bmatrix} \boldsymbol{w_{0,0}} & \cdots & \boldsymbol{w_{0,5}} & \cdots & \boldsymbol{w_{0,9}} \\ \vdots & w_{1,1} & \cdots & w_{1,8} & \vdots \\ w_{4,0} & \cdots & \ddots & \cdots & w_{4,9} \\ \vdots & w_{8,1} & \cdots & w_{8,8} & \vdots \\ w_{9,0} & \cdots & w_{9,5} & \cdots & w_{9,9} \end{bmatrix} \end{array} \cdots \begin{bmatrix} \boldsymbol{b_0} \\ \vdots \\ b_4 \\ \vdots \\ b_9 \end{bmatrix} \quad \bigoplus \quad \overset{\xleftrightarrow{\qquad M \qquad}}{[\boldsymbol{O_0} \quad \cdots \quad O_4 \quad \cdots \quad O_9]} \quad \odot \quad [\boldsymbol{N}]$$

Add Bias

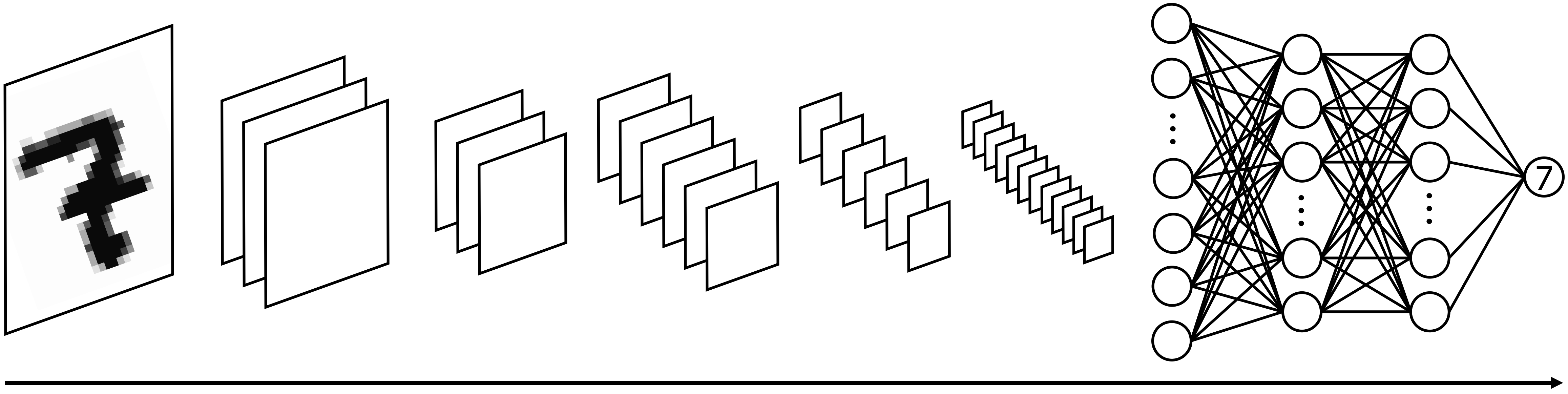
Max index

$0 \leq N \leq 9$

[weight] [bias] [intermediate output] [output]

Overview of Optimized LeNet-5 (Light LeNet-5)

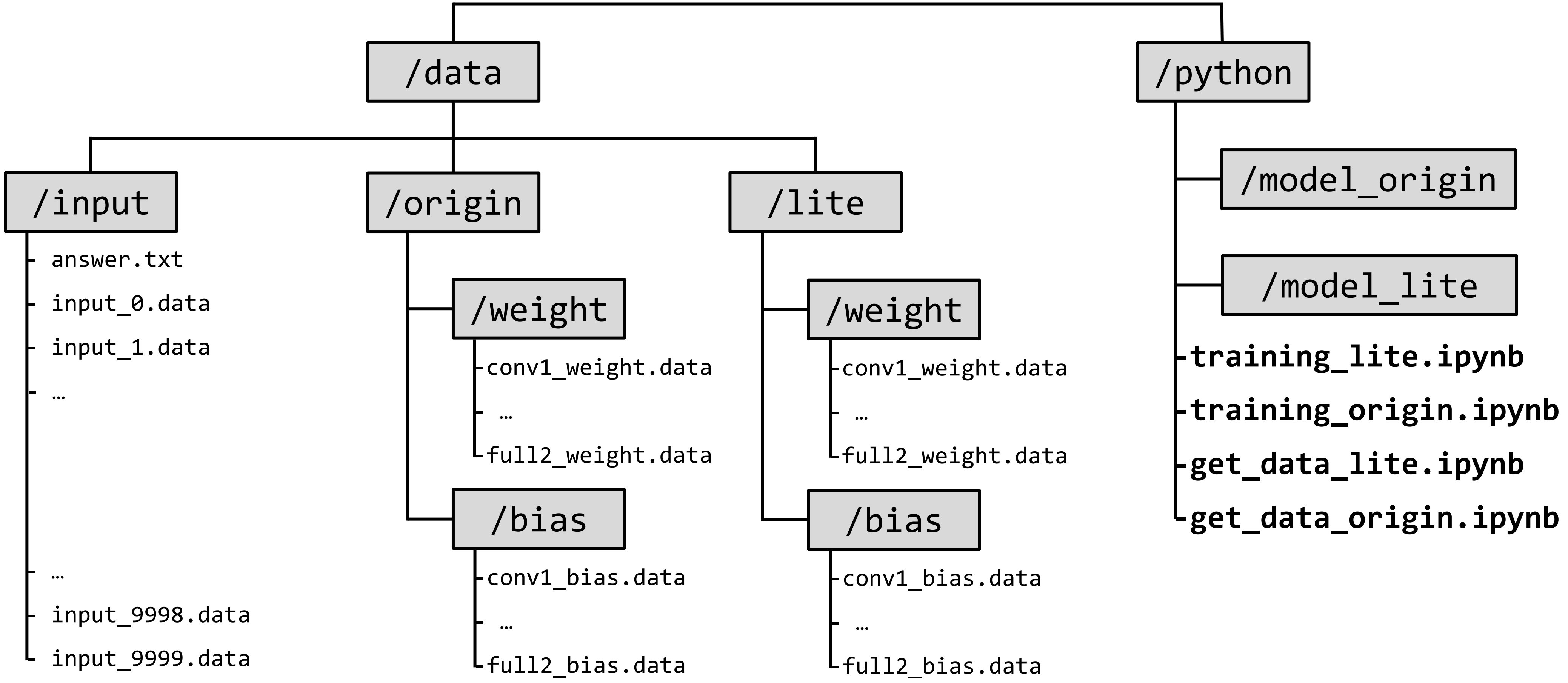
- Feature maps were reduced by **48%,** weights and biases were reduced by **96%**.
- $sigmoid$, $tanh$ are replaced by $ReLU$.



	INPUT	CONV1	POOL1	CONV2	POOL2	CONV3	FULL1	FULL2	OUTPUT
Feature Map	32 x 32	3 @ 28 x 28	3 @ 14 x 14	6 @ 10 x 10	6 @ 5 x 5	12 @ 1 x 1	10	10	1
Weight + Bias	-	78	-	456	-	1812	130	110	-
Activation	-	$ReLU$	-	$ReLU$	-	$ReLU$	$ReLU$	Max	-

Implementation of LeNet-5 using Python, Cont'd

- TensorFlow is used to build LeNet-5.
- Get data such as pre-trained weights and biases.
- Get data such as inputs and answer.



Implementation of LeNet-5 using Python, Cont'd

- In `training_origin.ipynb`, build, train, and evaluate the original model.

```
# Build model using Sequential API
import tensorflow as tf
…
model = models.Sequential()

model.add(layers.Conv2D(6, 5, 'tanh'))
model.add(layers.AveragePooling2D(2))
model.add(layers.Activation('sigmoid'))
model.add(layers.Conv2D(16, 5, 'tanh'))
model.add(layers.AveragePooling2D(2))
model.add(layers.Activation('sigmoid'))
model.add(layers.Conv2D(120, 16, 'tanh'))
model.add(layers.Flatten())
model.add(layers.Dense(10, 'tanh'))
model.add(layers.Dense(10, 'softmax'))


# Training model
model.compile( … )
model.fit( … )


# Get loss value and accuracy
model.evaluate( … )
200/200 [===============] - loss: 0.1888, accuracy: 0.9406
```

```
# Print model information
model.summary()

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1 (Conv2D)              (None, 28, 28, 6)         156

 pool1 (AveragePooling2D)    (None, 14, 14, 6)         0

 activation (Activation)     (None, 14, 14, 6)         0

 conv2 (Conv2D)              (None, 10, 10, 16)        2416

 pool2 (AveragePooling2D)    (None, 5, 5, 16)          0

 activation_1 (Activation)   (None, 5, 5, 16)          0

 conv3 (Conv2D)              (None, 1, 1, 120)         48120

 flatten (Flatten)           (None, 120)               0

 full1 (Dense)               (None, 84)                10164

 full2 (Dense)               (None, 10)                850

=================================================================
Total params: 61,706
Trainable params: 61,706
Non-trainable params: 0
```

Implementation of LeNet-5 using Python, Cont'd

- In `training_lite.ipynb`, build, train, and evaluate light model.

```
# Build model using Sequential API
import tensorflow as tf
…
model = models.Sequential()

model.add(layers.Conv2D(3, 5, 'relu'))
model.add(layers.MaxPooling2D(2))
model.add(layers.Conv2D(6, 5, 'relu'))
model.add(layers.MaxPooling2D(2))
model.add(layers.Conv2D(12, 5, 'relu'))
model.add(layers.Flatten())
model.add(layers.Dense(10, 'relu'))
model.add(layers.Dense(10, 'softmax'))


# Training model
model.compile( … )
model.fit( … )


# Get loss value and accuracy
model.evaluate( … )
200/200 [================] - loss: 0.0773, accuracy: 0.9747
```

```
# Print model information
model.summary()
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1 (Conv2D)              (None, 28, 28, 3)         78

 pool1 (MaxPooling2D)        (None, 14, 14, 3)         0

 conv2 (Conv2D)              (None, 10, 10, 6)         456

 pool2 (MaxPooling2D)        (None, 5, 5, 6)           0

 conv3 (Conv2D)              (None, 1, 1, 12)          1812

 flatten (Flatten)           (None, 12)                0

 full1 (Dense)               (None, 10)                130

 full2 (Dense)               (None, 10)                110

=================================================================
Total params: 2,586
Trainable params: 2,586
Non-trainable params: 0
_________________________________________________________________
```

Implementation of LeNet-5 using Python

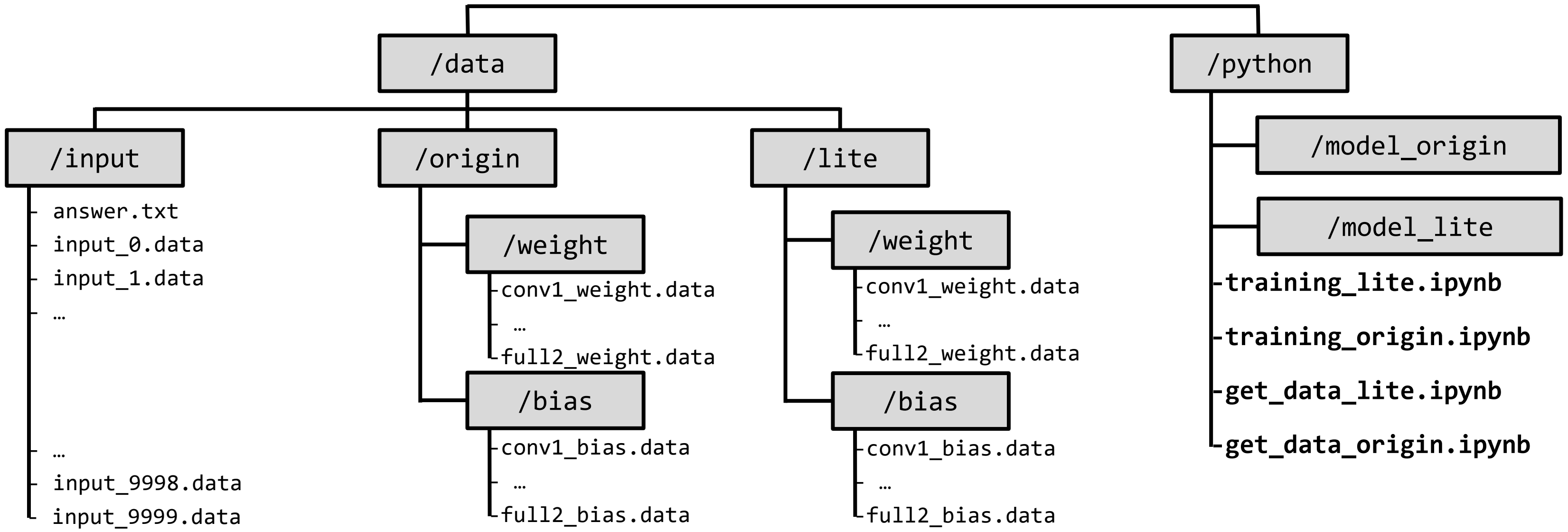
- In `get_data_lite.ipynb`, get the weights and biases processed for ease of use.

```
# Get weights and biases

weight_bias_dict = {}
layer_list = []

for layer in model.layers:
    layer_list.append(layer.name)

    # No trainable params
    if 'pool' in layer.name or 'flatten' in layer.name:
        continue

    weight_bias_dict[layer.name] = layer.get_weights()


# Process weights to use easily in C/C++

for key, value in weight_bias_dict.items():
    if 'conv' in key:
        tp_weight = tf.transpose(value[0])
        weight = tf.transpose(tp_weight, [0,1,3,2])
        value[0] = tf.squeeze(weight)

    if 'full' in key:
        tp_weight = tf.transpose(value[0])
        value[0] = tf.squeeze(tp_weight)
```

```
# Shape of weights and biases before processing
=============================================================
name : conv1  weight shape : (5, 5, 1, 3)   bias shape : (3,)
name : conv2  weight shape : (5, 5, 3, 6)   bias shape : (6,)
name : conv3  weight shape : (5, 5, 6, 12)  bias shape : (12,)
name : full1  weight shape : (12, 10)       bias shape : (10,)
name : full2  weight shape : (10, 10)       bias shape : (10,)
=============================================================


# Shape of weights and biases after processing
=============================================================
name : conv1  weight shape : (3, 5, 5)      bias shape : (3,)
name : conv2  weight shape : (6, 3, 5, 5)   bias shape : (6,)
name : conv3  weight shape : (12, 6, 5, 5)  bias shape : (12,)
name : full1  weight shape : (10, 12)       bias shape : (10,)
name : full2  weight shape : (10, 10)       bias shape : (10,)
=============================================================


# Flatten and save wegihts and biases
for key, value in weight_bias_dict.items()
    value[0] = tf.reshape(value[0], [-1]) # -1 means flatten

    # save as txt file
    np.savetxt('../data/weight/...' value[0], fmt = "%.10f")
    np.savetxt('../data/bias/...'   value[1], fmt = "%.10f")
```

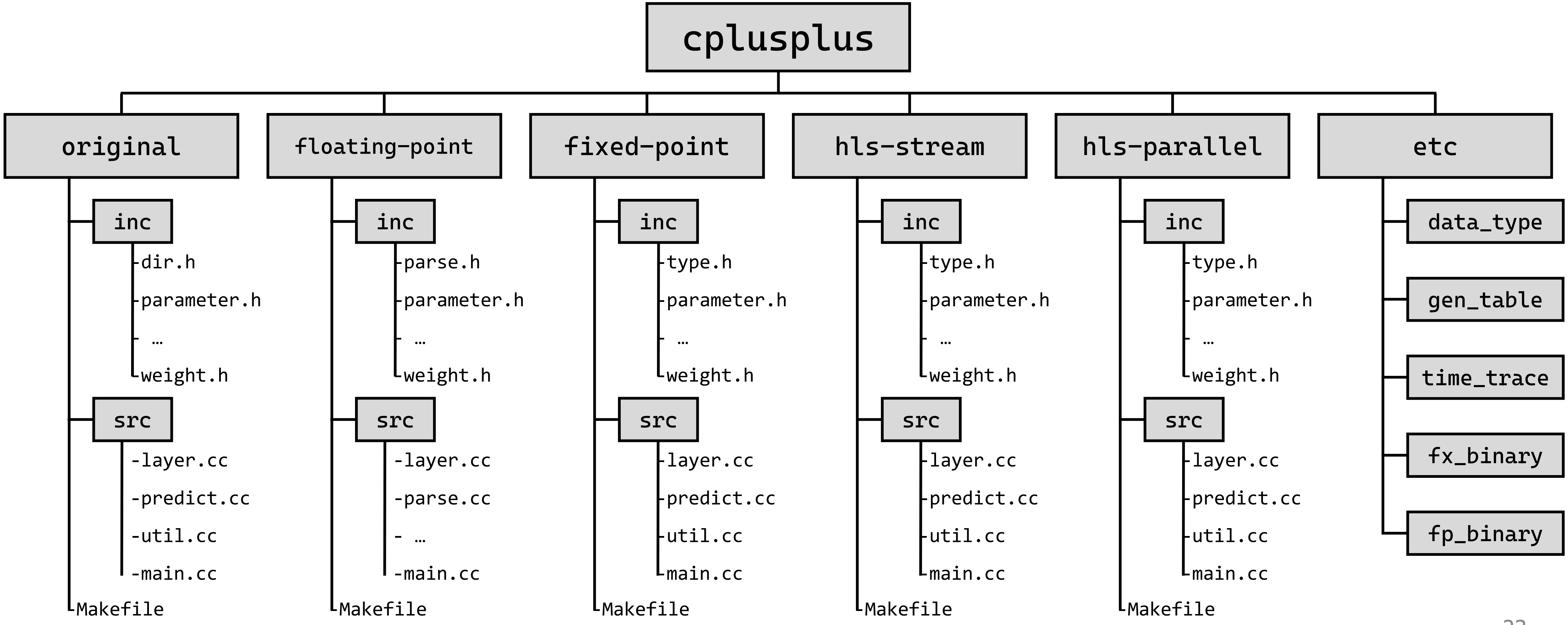
Overview of implementation of LeNet-5 using python

- TensorFlow is used to build LeNet-5.
  - In `training_origin.ipynb`, build, train, and evaluate the original model.
  - In `training_lite.ipynb`, build, train, and evaluate light model.
- Get data such as pre-trained weights and biases.
  - In `get_data_lite.ipynb`, get the weights and biases processed for ease of use.
- Get data such as inputs and answer.
  - In `get_data_lite.ipynb`, get the inputs and answer.



Implementation of LeNet-5 using C/C++

- `cplusplus` directory structure.
- `Makefile` can compile each folder.
- `etc` directory serves to analyze the result, save input txt file as a binary, or generate weight table.



Fixed-Point vs. Floating-Point, Cont'd

- Comparison by data type using *Vivado HLS.*

```
/*
   Tests to determine latency, utilization,
   and max frequency by data type.
*/

#define NUM 32

typedef int data_t;
…
// typedef ap_fixed<32, 16> data_t;
…
// typedef half data_t;

void test(data_t in[NUM], … , data_t out[NUM])
{
    for (int i = 0; i < NUM; i++) {

        data_t result = bias[i];

        for (int j = 0; j < NUM; j++) {
            result += in[j] * weight[i][j];
        }
        out[i] = result;
    }
}
```

[Latency (clock cycles)]

	short	fix16	half	int	fix32	float
Latency	3169	3169	11361	4193	4193	11361

[Resource Usage Implementaion]

	short	fixed16	half	int	fixed32	float
LUT	21	38	166	68	100	330
FF	40	56	280	90	92	460
DSP	1	1	4	3	4	5
SLICE	10	14	96	26	36	184

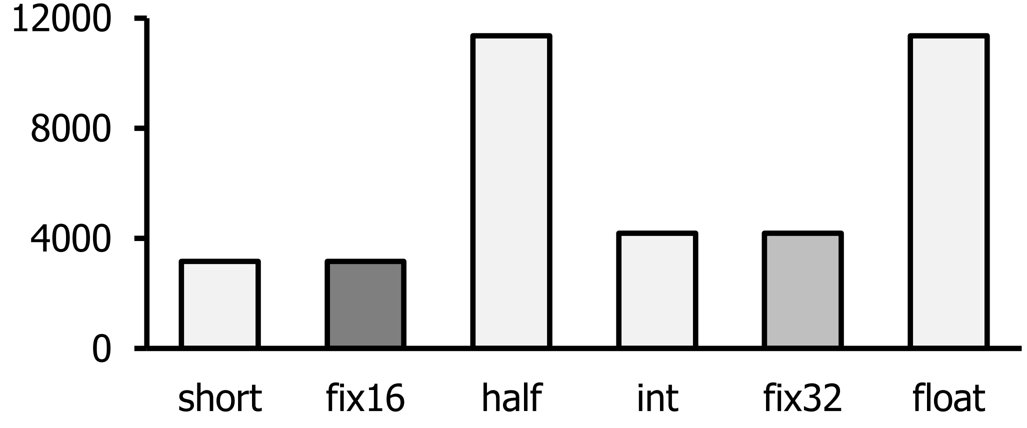
[Final Timing Implementation]

	short	fix16	half	int	fix32	float
CP Req.	10.000	10.000	10.000	10.000	10.000	10.000
Post-Impl	3.884	5.911	8.598	5.692	6.501	8.585

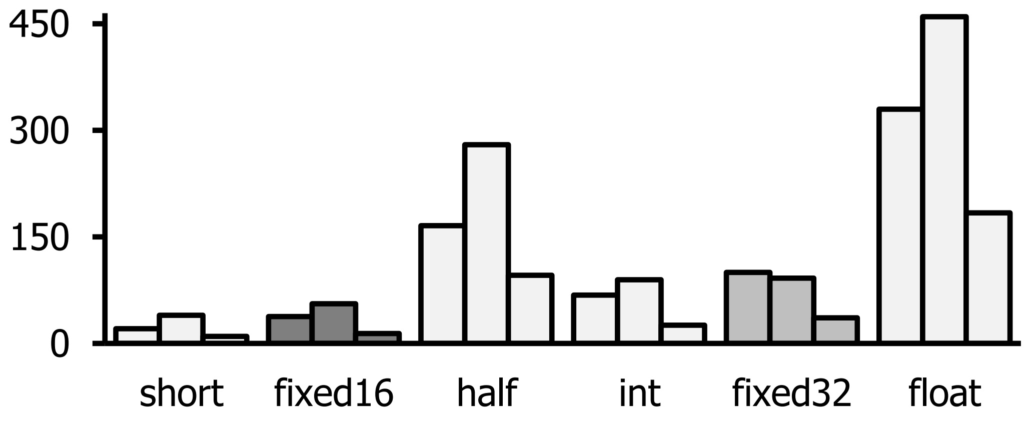
Fixed-Point vs. Floating-Point

- Results of sysnthesis and implementation using *Vivado HLS*.

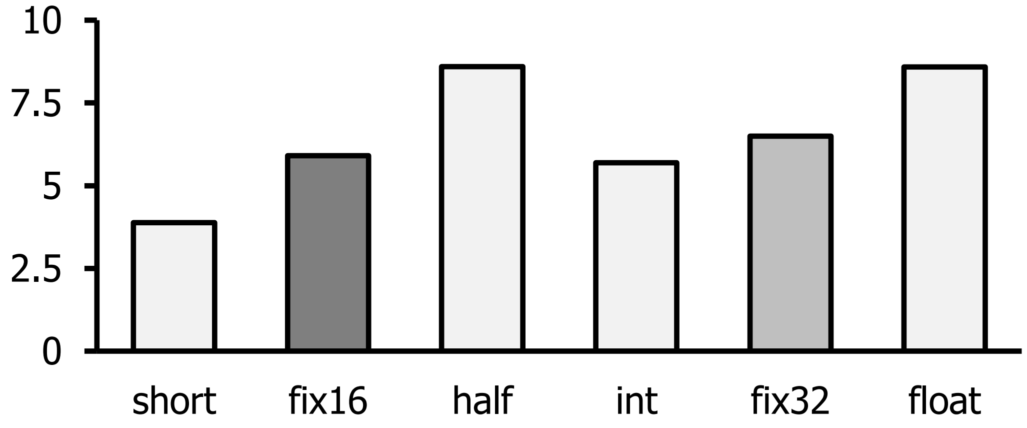
Latency (cycle)



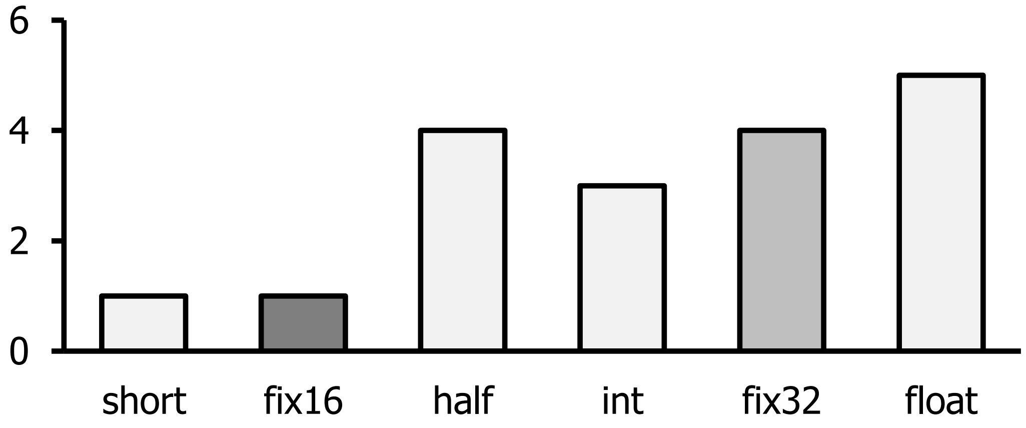
Resource (LUT, FF, Slice)



Max Clock Period (ns)



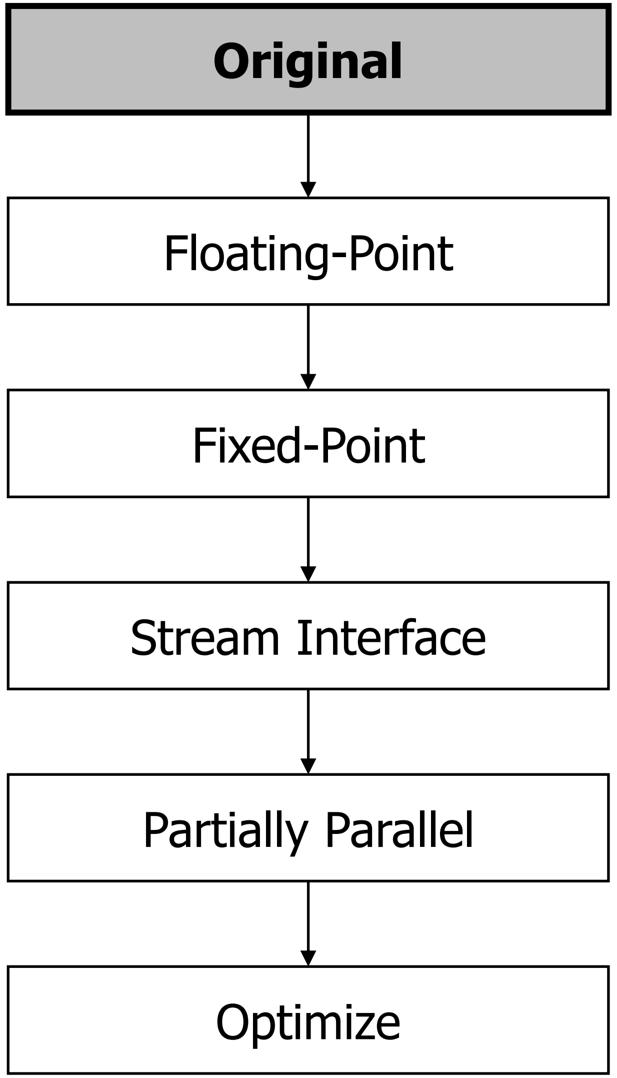
Resource (DSP)



Original LeNet-5 with C/C++, Cont’d

- Implementation of original LeNet-5.
- Check accuracy to ensure that it is implemented correctly.
- Use $tanh$ or $sigmoid$ instead of $ReLU$ for activation function.
- Use Average Pooling instead of Max Pooling.

Layer	C	W x H	Kernel	Stride	Activation	Weight + Bias	Feature map
INPUT	1	32 x 32	-	-	-	-	1024
CONV1	6	28 x 28	5x5	1	$tanh$	150 + 6 = 156	4704
A.POOL1	6	14 x 14	2x2	2	$sigmoid$	-	1176
CONV2	16	10 x 10	5x5	1	$tanh$	2400 + 16 = 2416	1600
A.POOL2	16	5 x 5	2x2	2	$sigmoid$	-	400
CONV3	120	1 x 1	5x5	1	$tanh$	48000 + 120 = 48120	120
FC1	-	120	-	-	$tanh$	10080 + 84 = 10164	84
FC2	-	84	-	-	$softmax$	840 + 10 = 850	10
Total	-	-	-	-	-	**61706**	**9118**



Original LeNet-5 with C/C++, Cont'd

```
/* layer.cc */
…
void full1_layer(float  input[…][…][…],
                  float output[…][…][…])
{
    for (int row = 0; row < … ; …) {

        float acc = full1_bias[row];

        for (int col = 0; col < … ; …) {
            acc += input[col] * full1_weight[row][col];
        }

        output[row] = (float)std::tanh(acc); // tanh activation
    }
}
void pool1_layer(float  input[…][…][…],
                float output[…][…][…])
{
    for (int num = 0; num < … ; …) {
        for (int row = 0; row < … ; …) {
            for (int col = 0; col < … ; …) {
                float avg = 0.0;
                avg += input[num][row][col];
                …
                avg = (float)(avg / 4.0);

               // sigmoid activation
                output[num][row >> 1][col >> 1] = sigmoid(avg);
            }
        }
    }
}
```

```
/* predict.cc */

uint8_t predict(float* input) {

    /* Intermediate outputs */
    float conv1_output[…][…][…] = { 0.0 };
     …
    float full2_output[…] = { 0.0 };

    /* 1st convolution layer */
    conv1_layer(input, conv1_output);

    /* 1st pooling layer */
    pool1_layer(conv1_output, pool1_output);

    /* 2nd convolution layer */
    conv2_layer(pool1_output, conv2_output);

    /* 2nd pooling layer */
    pool2_layer(conv2_output, pool2_output);

    /* 3th convolution layer */
    conv3_layer(pool2_output, conv3_output);

    /* 1st fully connected layer */
    full1_layer(conv3_output, full1_output);

    /* 2nd fully connected layer */
    full2_layer(full1_output, full2_output);

    /* Return result */
    return softmax(full2_output);
}
```

Original LeNet-5 with C/C++

- Similar to the accuracy obtained from python (0.9406)

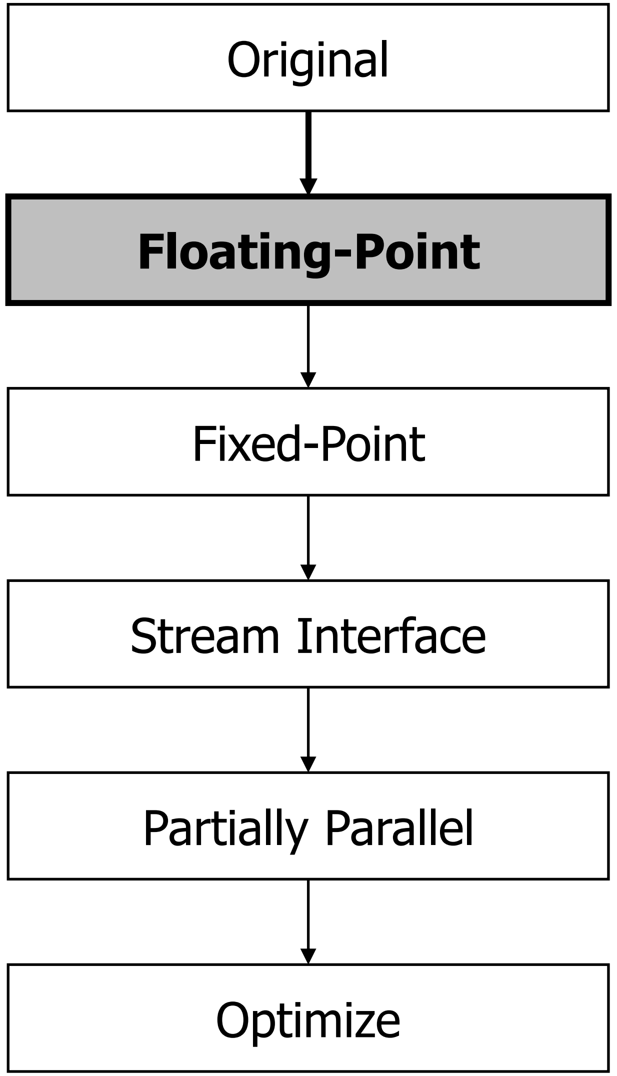
```
/* main.cc */

int main (int argc, char* argv[]) {
    int err_cnt = 0;
    …
    for (size_t i = 0; i < TEST_NUM; i++) {
        …
        my_answer[i] = predict(input_array);
        …
        if (my_answer != answer[i]) {
            err_cnt++;
            cout << "[ FALSE ] " … << "\n";
        }
        else {
            cout << "[ TRUE  ] " … << "\n";
        }
    }

    accuracy = ((float)(TEST_NUM - err_cnt)/(float)TEST_NUM) * 100;
    cout << "\n[Original LeNet-5]\n";
    cout << "Accuracy : " << setw(5) << accuracy << … ;
    cout << "Error    : " << setw(5) << err_cnt  << … ;

    return 0;
}
```

```
# Run all inputs

$ ./main

       Number  Answer  Predict
[TRUE] [   0]  7       7
[TRUE] [   1]  2       2
[TRUE] [   2]  1       1
[TRUE] [   3]  0       0
 …
[TRUE] [9996]  3       3
[TRUE] [9997]  4       4
[TRUE] [9998]  5       5
[TRUE] [9999]  6       6

[Original LeNet-5]
Accuracy : 94.55 [%]
Error    :   545 [cases]
```

Light LeNet-5 with C/C++ (Floating-Point), Cont'd

- Implementation of light LeNet-5 using floating point.
- Use $ReLU$ instead of $sigmoid$ or $tanh$ for activation function.
- Use Max Pooling instead of Average Pooling.
- Use max instead of $softmax$ for output layer.

Layer	C	W x H	Kernel	Stride	Activation	Weight + Bias	Feature map
INPUT	1	32 x 32	-	-	-	-	1024
CONV1	3	28 x 28	5x5	1	$ReLU$	75 + 3 = 78	2352
M.POOL1	3	14 x 14	2x2	2	-	-	588
CONV2	6	10 x 10	5x5	1	$ReLU$	450 + 6 = 456	600
M.POOL2	6	5 x 5	2x2	2	-	-	150
CONV3	12	1 x 1	5x5	1	$ReLU$	1800 + 12 = 1812	12
FC1	-	120	-	-	$ReLU$	120 + 10 = 130	10
FC2	-	84	-	-	Max	100 + 10 = 110	10
Total	-	-	-	-	-	**2586**	**4746**

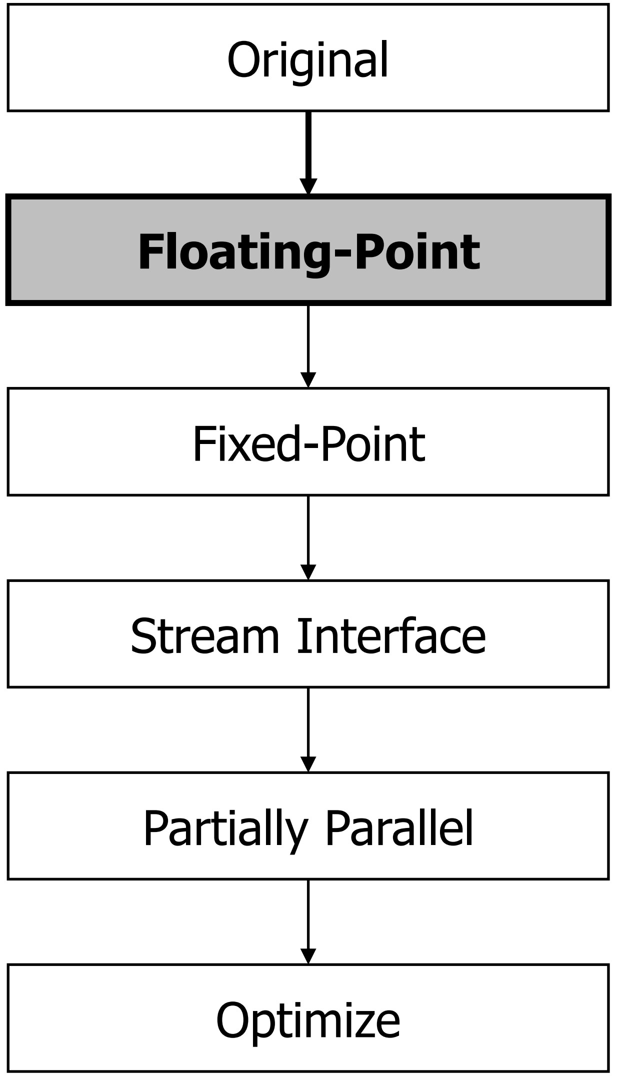


Light LeNet-5 with C/C++ (Floating-Point), Cont'd

- Enble to run with 3 options.
  - Run one input.
  - Run one input + Print intermediate results (Debug).
  - Run all (Chcek accuracy and find Max/Min value).
- Integer part of fixed point can be determined through Run all option.

```
# How to use

$ ./main --help

[Run one input]
Usage : ./main --input=[input.data]
        ./main -i=[input.data]

[Run one input with print option]
Usage : ./main --input=[input.data] --print=[bool]
        ./main -i=[input.data] -p=[bool]

[Run all inputs]
Usage : ./main --all=[bool]
        ./main -a=[bool]

…
```

```
# Run all inputs

$ ./main --all=true


…



# To determine the integer part of fixed point
[CONV1] output  MAX :  4.7115  MIN : - 2.9715
[CONV2] output  MAX : 12.2852  MIN : -20.4851
[CONV3] output  MAX : 36.0140  MIN : -33.7252
[FULL1] output  MAX : 33.5324  MIN : -14.5665
[FULL2] output  MAX : 27.2409  MIN : -30.0438
```



Light LeNet-5 with C/C++ (Floating-Point), Cont'd

```
/* layer.cc */
…
void full1_layer(float input[…], float output[…])
{
    for (int row = 0; row < … ; …) {

        float acc = full1_bias[row];

        for (int col = 0; col < … ; …) {
            acc += input[col] * full1_weight[row][col];
        }
    }
}
… // ReLU function exists to find the MAX/MIN value
void relu4_layer(float input[…], float output[…])
{
    for (int i = 0; i < …; …)
        output[i] = input[i] > 0.0 ? input[i] : 0.0;
}
…
void pool1_layer(float input[…][…][…], float
output[…][…][…])
{
    for (int num = 0; num < … ; …) {
        for (int row = 0; row < … ; …) {
            for (int col = 0; col < … ; …) {

                 max = input[num][row][col];
                … // find max
                output[num][row >> 1][col >> 1] = max;
            }
        }
    }
}
```

```
/* predict.cc */

uint8_t predict(float* input, float* conv1_max, float* conv1_min,
                              …
                              float* full2_max, float* full2_min) {

    /* Intermediate outputs */
    float conv1_output[…][…][…] = { 0.0 };
    float relu1_output[…][…][…] = { 0.0 };
    float pool1_output[…][…][…] = { 0.0 };
    …
    float full2_output[…] = { 0.0 };

    /* 1st convolution layer */
    conv1_layer(input, conv1_output);

    /* 1st ReLU layer */
    relu1_layer(conv1_output, relu1_output);
    …
    /* 2nd fully connected layer */
    full2_layer(relu4_output, full2_output);

    /* Find the MAX/MIN value of each intermediate result.
    *conv1_max = *std::max_element(conv1_output, …);
    …
    *full2_max = *std::max_element(full2_output, …);
    *conv1_min = *std::min_element(conv1_output, …);
    …
    *full2_min = *std::min_element(full2_output, …);

    /* Return result */
    return result(full2_output);
}
```

Light LeNet-5 with C/C++ (Floating-Point), Cont'd

- Enble to run with 3 options. (Run all option)

```
# How to use

$ ./main --help

[Run one input]
Usage : ./main --input=[input.data]
        ./main -i=[input.data]

[Run one input with print option]
Usage : ./main --input=[input.data] --print=[bool]
        ./main -i=[input.data] -p=[bool]

[Run all inputs]
Usage : ./main --all=[bool]
        ./main -a=[bool]

--input=[input] | -i=[input]  File name to run.
                              [input] must be txt file.
                              [input] extension must be *.data.
                              This option is required.

--print=[bool] | -p=[bool]    Determine whether to print intermediate result.
                              [bool] must be true or false with small letters.
                              This option is optional.

--all=[bool] | -a=[bool]      Determine whether run all test cases.
                              [bool] must be true or false with small letters.
                              This option is optional.

--help | -h                   Display this information.
```

```
# Run all inputs

$ ./main --all=true

       Number  Answer  Predict
[TRUE] [   0]  7       7
[TRUE] [   1]  2       2
[TRUE] [   2]  1       1
[TRUE] [   3]  0       0
 …
[TRUE] [9996]  3       3
[TRUE] [9997]  4       4
[TRUE] [9998]  5       5
[TRUE] [9999]  6       6

[Floating-Point]
Accuracy : 97.47 [%]
Error    :    253 [cases]

# To determine the integer part of fixed point
[CONV1] output   MAX :  4.7115   MIN : - 2.9715
[CONV2] output   MAX : 12.2852   MIN : -20.4851
[CONV3] output   MAX : 36.0140   MIN : -33.7252
[FULL1] output   MAX : 33.5324   MIN : -14.5665
[FULL2] output   MAX : 27.2409   MIN : -30.0438
```

Light LeNet-5 with C/C++ (Floating-Point)

- Enble to run with 3 options. (Run one input, Run one input + Print intermediate results options)

 # Run one input

```
$ ./main --input=../../data/input/input_0.data

==========================================================================================
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.33 0.73 0.62 0.59 0.24 0.14 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.87 1.00 1.00 1.00 1.00 0.95 0.78 0.78 0.78 0.78 0.78 0.78 0.78 0.78 0.67 0.20 0.00 0.00
 0.00 0.00 0.26 0.45 0.28 0.45 0.64 0.89 1.00 0.88 1.00 1.00 1.00 0.98 0.90 1.00 1.00 0.55 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.07 0.26 0.05 0.26 0.26 0.26 0.23 0.08 0.93 1.00 0.42 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.33 0.99 0.82 0.07 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.09 0.91 1.00 0.33 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.51 1.00 0.93 0.17 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.23 0.98 1.00 0.24 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.52 1.00 0.73 0.02 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.04 0.80 0.97 0.23 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.49 1.00 0.71 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.29 0.98 0.94 0.22 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.07 0.87 1.00 0.65 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.80 1.00 0.86 0.14 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.15 1.00 1.00 0.30 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.12 0.88 1.00 0.45 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.52 1.00 1.00 0.20 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.24 0.95 1.00 1.00 0.20 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.47 1.00 1.00 0.86 0.16 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.47 1.00 0.81 0.07 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
------------------------------------------------------------------------------------------
==========================================================================================
```

Number : 7

 # Run one input + print intermediate results

```
$ ./main –i=../../data/input/input_0.data --print=true

[CONV1 output] [3][28][28]
 …
==========================================================================================
[POOL1 output] [3][14][14]
 …
==========================================================================================
[CONV2 output] [6][10][10]
 …
==========================================================================================
[POOL2 output] [6][5][5]
 …
 1.72 0.52 0.00 0.00 0.00 0.22 0.41 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
 1.64 1.93 2.15 3.01 3.50 1.82 0.00 0.00 0.00 0.00
 3.83 4.38 5.63 7.22 7.63 3.85 0.00 0.00 0.00 1.00
 0.96 1.25 1.73 2.39 0.96 0.00 0.00 0.00 0.00 2.06
 0.09 0.24 0.74 0.92 0.00 0.00 0.00 0.00 0.10 3.00
 0.18 0.19 0.50 0.00 0.00 0.00 0.00 0.00 1.91 2.51
 0.29 1.23 0.60 0.00 0.00 0.00 0.00 0.53 2.99 1.52
 0.00 0.00 0.00 0.00 0.00 0.00 0.00 2.58 2.39 0.51
 …
==========================================================================================
[CONV3 output] [12]

   0.00   4.09   4.29   1.92  10.52  10.28   8.23   0.00   0.00   2.30   0.00   0.00
==========================================================================================
[FULL1 output] [10]

   8.94   6.80   8.77   0.00   3.41   9.39   0.00   0.00   0.00   0.00
==========================================================================================
[FULL2 output] [10]

  -3.29  -0.61   3.09   2.74  -5.36  -2.09 -13.36  11.65   2.13  -0.26
==========================================================================================
```

Number : 7

Light LeNet-5 with C/C++ (Fixed-Point), Cont'd

- Compare floating-point and fixed-point in terms of :
  - Latency
  - Resource
  - Max frequency

[Latency (clock cycles)]

	short	fix16	half	int	fix32	float
Latency	3169	3169	11361	4193	4193	11361

[Resouce Usage Implementaion]

	short	fixed16	half	int	fixed32	float
LUT	21	38	166	68	100	330
FF	40	56	280	90	92	460
DSP	1	1	4	3	4	5
SLICE	10	14	96	26	36	184

[Final Timing Implementation]

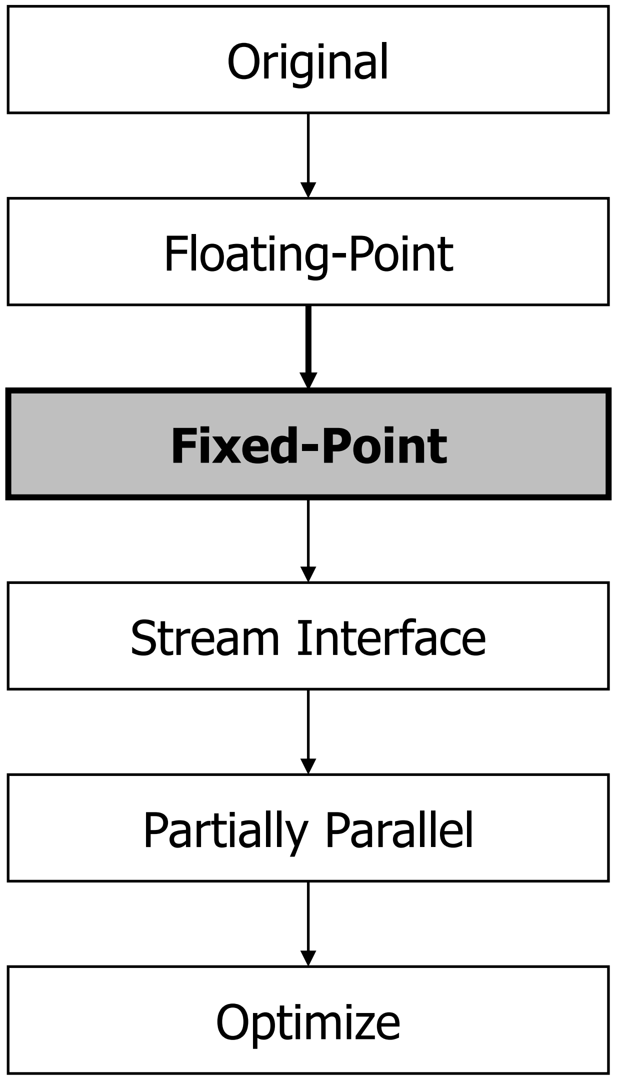
	short	fix16	half	int	fix32	float
CP Req.	10.000	10.000	10.000	10.000	10.000	10.000
Post-Impl	3.884	5.911	8.598	5.692	6.501	8.585

[ZYBO Z7-10 Resource]

	ZYBO Z7-10
LUT	17,600
Flip-Flop	35,200
Block RAM	270 KB
DSP	80
Logic slice	4,400

[ZYBO Z7-20 Resource]

	ZYBO Z7-20
LUT	53,200
Flip-Flop	106,400
Block RAM	630 KB
DSP	220
Logic slice	13,300



Light LeNet-5 with C/C++ (Fixed-Point), Cont'd

- Determine integer part of fixed point.
  - Using `etc/data_type/`
- Include Xilinx HLS library to use `<ap_fixed.h>`
- For the $Round,\ Convert$ formulas,
- Refer to the paper "*Deep Learning with Limited Numerical Precision*"

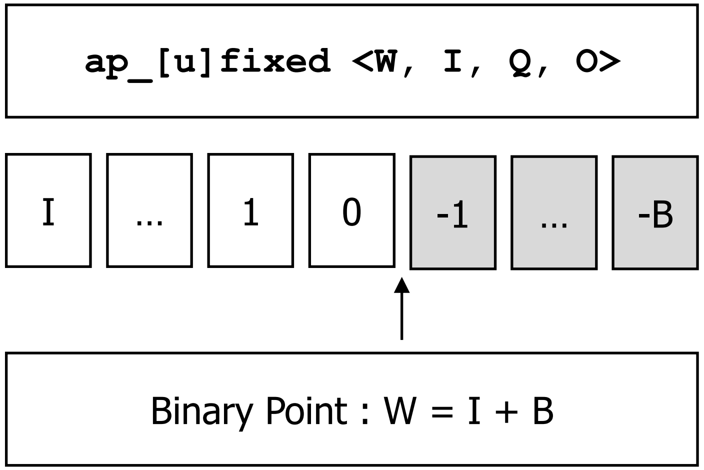
[Round & Saturation formula]

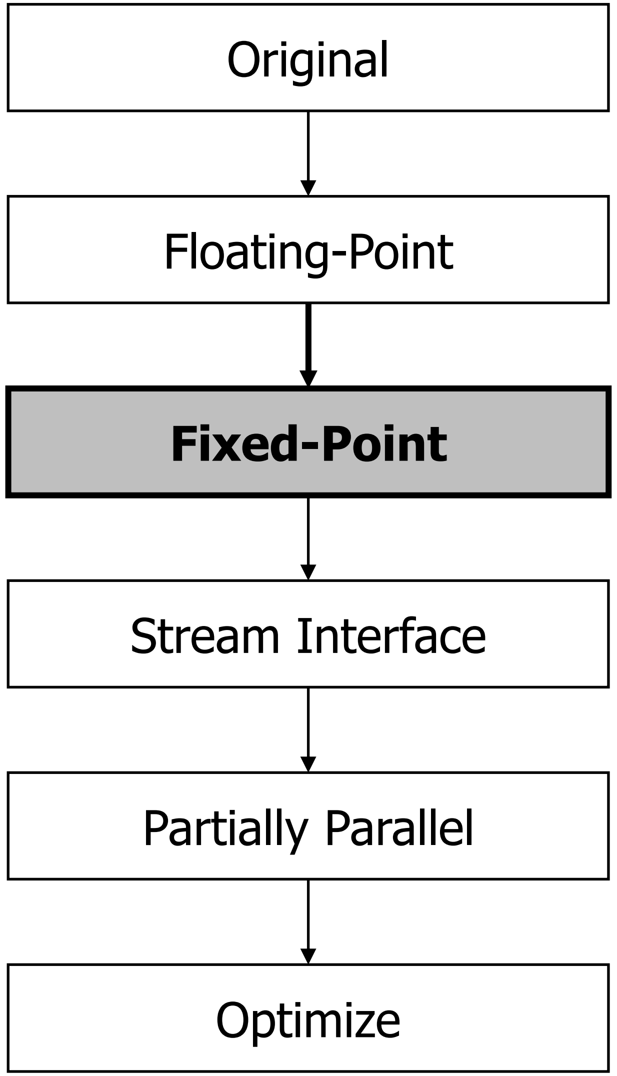
$$Round(x, < I, F >) = \begin{cases} [x] & if\ [x] \le x \le [x] + \frac{\epsilon}{2} \\ [x] + \epsilon & if\ [x] + \frac{\epsilon}{2} < x \le [x] + \epsilon \end{cases}$$

$$where\ \epsilon = 2^{-F}$$

$$Convert(x, < I, F >) = \begin{cases} -2^{I-1} & if\ \ x \le -2^{I-1} \\ 2^{I-1} - 2^{-F} & if\ \ x \ge 2^{I-1} - 2^{-F} \\ Round(x, < I, F >) & otherwise \end{cases}$$

[Fixed point data type]





Light LeNet-5 with C/C++ (Fixed-Point), Cont'd

- Determine integer part of fixed point using `etc/data_type` directory.

```
/* data_type.cc */

// Data from ./main --all=true command output
#define CONV1_MAX   4.71154
#define CONV1_MIN  -2.97152
#define CONV2_MAX   12.2852
#define CONV2_MIN  -20.4851
#define CONV3_MAX   36.0140
#define CONV3_MIN  -33.7252
#define FULL1_MAX   33.5324
#define FULL1_MIN  -14.5665
#define FULL2_MAX   27.2409
#define FULL2_MIN  -30.0438
```

$$QI = ceiling\left(log_2(max(abs[\alpha_{max}, \alpha_{min}]) + 1)\right) + 1$$

```
// Implement the above formula as a function
int fx_integer(float m, float n) {
  int QI;

  QI = ceil(log2(max(abs(m),abs(n)) + 1)) + 1;

  return QI;
}
```

```
/* data_type.cc */

conv1_o = fx_integer(CONV1_MAX, CONV1_MIN);
 …
conv3_w = fx_integer(max_conv3_weight, min_conv3_weight);
 …
full2_b = fx_integer(max_full2_bias, min_full2_bias);

# Run data_type
$ ./data_type

[CONV1_OUTPUT] integer part : 4
[CONV2_OUTPUT] integer part : 6
[CONV3_OUTPUT] integer part : 7
[FULL1_OUTPUT] integer part : 7
[FULL2_OUTPUT] integer part : 6

[CONV1_WEIGHT] integer part : 2
[CONV2_WEIGHT] integer part : 2
[CONV3_WEIGHT] integer part : 2
[FULL1_WEIGHT] integer part : 2
[FULL2_WEIGHT] integer part : 3

[CONV1_BIAS]   integer part : 2
 …
[FULL2_BIAS]   integer part : 2
```

Light LeNet-5 with C/C++ (Fixed-Point), Cont'd

- Refer to *Xilinx User Guide 902*
- Refer to *Deep Learning with Limited Numerical Precision*

```
ap_[u]fixed <W, I, Q, O>
```

I	…	1	0	-1	…	-B

Binary Point : W = I + B

$$Round(x, <I, F>) = \begin{cases} [x] & if\ [x] \le x \le [x] + \frac{\epsilon}{2} \\ [x] + \epsilon & if\ [x] + \frac{\epsilon}{2} < x \le [x] + \epsilon \end{cases}$$

$$where\ \epsilon = 2^{-F}$$

$$Convert(x, <I, F>) = \begin{cases} -2^{I-1} & if\ \ x \le -2^{I-1} \\ 2^{I-1} - 2^{-F} & if\ \ x \ge 2^{I-1} - 2^{-F} \\ Round(x, <I, F>) & otherwise \end{cases}$$

Identifer	Description	
W	Word length in bits	
I	The number of bits used to represent the integer value.	
Q	Quantization mode	
	Mode	Description
	AP_TRN	Truncation to minus infinity (default)
	…	…
	AP_RND	**Rounding to plus inifinity**
O	Overflow mode	
	Mode	Description
	AP_SAT	**Saturation**
	…	…
	AP_WRAP	Wrap around (default)

Light LeNet-5 with C/C++ (Fixed-Point), Cont'd

```
/* layer.cc */
…
void full1_layer(conv3_t input[…], full1_t output[…]) {

    for (int row = 0; row < … ; …) {
        // Temporary enough width accumulate register (32-bit)
        full1_temp acc = full1_bias[row];

        for (int col = 0; col < … ; …) {
            acc += input[col] * full1_weight[row][col];
        }
        if (acc > 0) output[row] = (full1_t)acc;
        else         output[row] = (full1_t)0.0;
    }
}
…
void pool1_layer(conv1_t input[…][…][…], conv1_t output[…][…][…]) {
    for (int num = 0; num < … ; …) {
        for (int row = 0; row < … ; …) {
            for (int col = 0; col < … ; …) {

                conv1_t n1 = input[num][row][col];
                …
                conv1_t n4 = input[num][row+1][col+1];

                conv1_t max1 = std::max(n1, n2);
                conv1_t max2 = std::max(n3, n4);
                conv1_t max  = std::max(max1, max2);
                output[num][row >> 1][col >> 1] = max;
            }
        }
    }
}
```

```
/* predict.cc */

uint8_t predict(float* input) {

    /* Intermediate outputs */
    conv1_t conv1_output[…][…][…] = { 0.0 };
    conv1_t pool1_output[…][…][…] = { 0.0 };
    …
    full2_t full2_output[…] = { 0.0 };

    /* 1st convolution layer */
    conv1_layer(input, conv1_output);

    /* 1st pooling layer */
    pool1_layer(conv1_output, pool1_output);

    /* 2nd convolution layer */
    conv2_layer(pool1_output, conv2_output);

    /* 2nd pooling layer */
    pool2_layer(conv2_output, pool2_output);

    /* 3rd convolution layer */
    conv3_layer(pool2_output, conv3_output);

    /* 1st fully connected layer */
    full1_layer(conv3_output, full1_output);

    /* 2nd fully connected layer */
    full2_layer(full1_output, full2_output);

    /* Return result */
    return result(full2_output);
}
```

Light LeNet-5 with C/C++ (Fixed-Point)

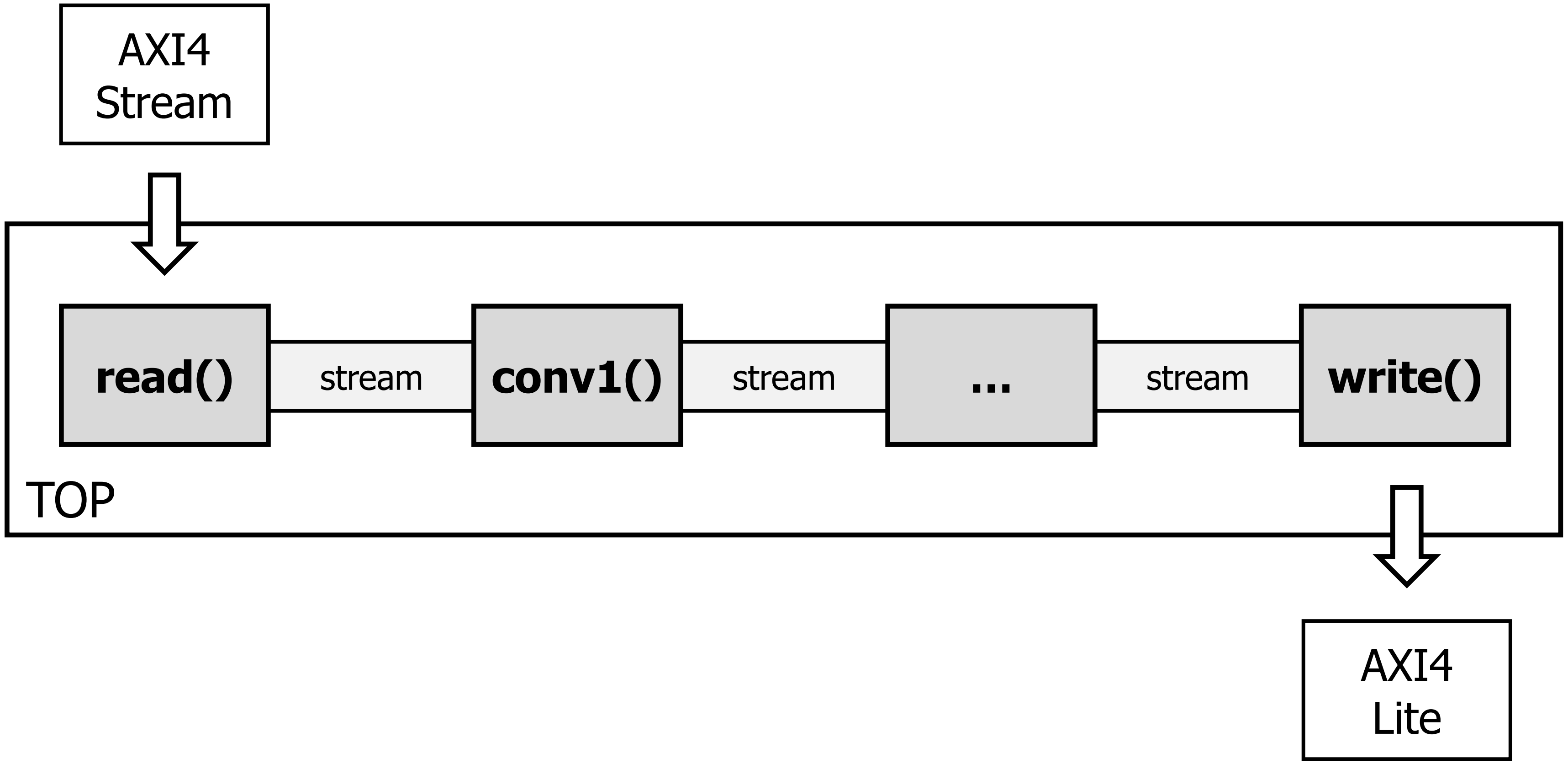
- Include Xilinx HLS library to use `<ap_fixed.h>`

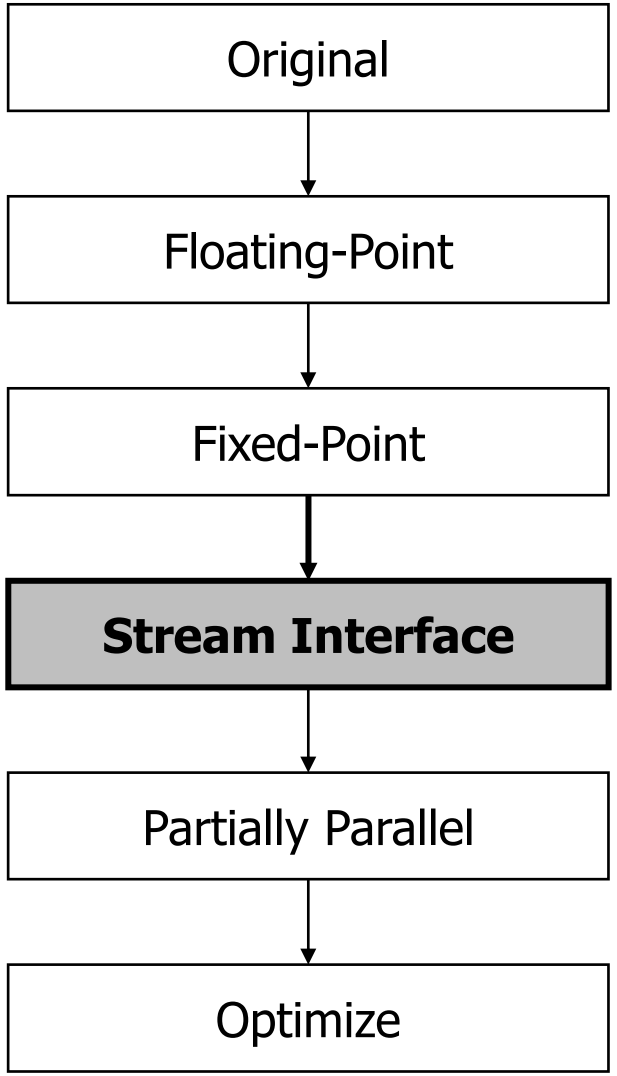
```
/* type.h */

#include <ap_fixed.h> // For fixed-point data type

typedef ap_ufixed<16, 1, AP_RND, AP_SAT> input_t;

typedef  ap_fixed<16, 2, AP_RND, AP_SAT> weight_t;

typedef  ap_fixed<16, 4, AP_RND, AP_SAT> conv1_t;
typedef  ap_fixed<16, 5, AP_RND, AP_SAT> conv2_t;
typedef  ap_fixed<16, 7, AP_RND, AP_SAT> conv3_t;
typedef  ap_fixed<16, 7, AP_RND, AP_SAT> full1_t;
typedef  ap_fixed<16, 7, AP_RND, AP_SAT> full2_t;

/*
  Temporary fixed-point data type with enough width
  to prevent saturation/overflow and avoid any loss of
  precision while accumulating the sum over all products.
  [2*I, 2*F]
*/

typedef  ap_fixed<32,  8, AP_RND, AP_SAT> conv1_temp;
typedef  ap_fixed<32, 10, AP_RND, AP_SAT> conv2_temp;
typedef  ap_fixed<32, 14, AP_RND, AP_SAT> conv3_temp;
typedef  ap_fixed<32, 14, AP_RND, AP_SAT> full1_temp;
typedef  ap_fixed<32, 14, AP_RND, AP_SAT> full2_temp;
```

```
/* Makefile */

CC = g++
CXXLFAGS = -Wall -Wno-comment -g -O2
LIBS += -I $(XILINX_HLS)/include

$(TARGET): $(OBJECTS)
  $(CC) $(CXXLFAGS) $(OBJECTS) -o $(TARGET) $(LIBS)
==================================================
# Run all inputs (just one option)
$ ./main

       Number  Answer  Predict
[TRUE] [   0]  7       7
[TRUE] [   1]  2       2
[TRUE] [   2]  1       1
[TRUE] [   3]  0       0
 …
[TRUE] [9996]  3       3
[TRUE] [9997]  4       4
[TRUE] [9998]  5       5
[TRUE] [9999]  6       6

[Fixed-Point]
Accuracy : 97.47 [%]
Error    :    253 [cases]
```

Light LeNet-5 with HLS (Stream Interface), Cont'd

- Implemented as stream interface instead of array interface as before.
- Closer to *Vivado HLS* canonical form using *DATAFLOW* optimization.
- For improving design throughput and latency.





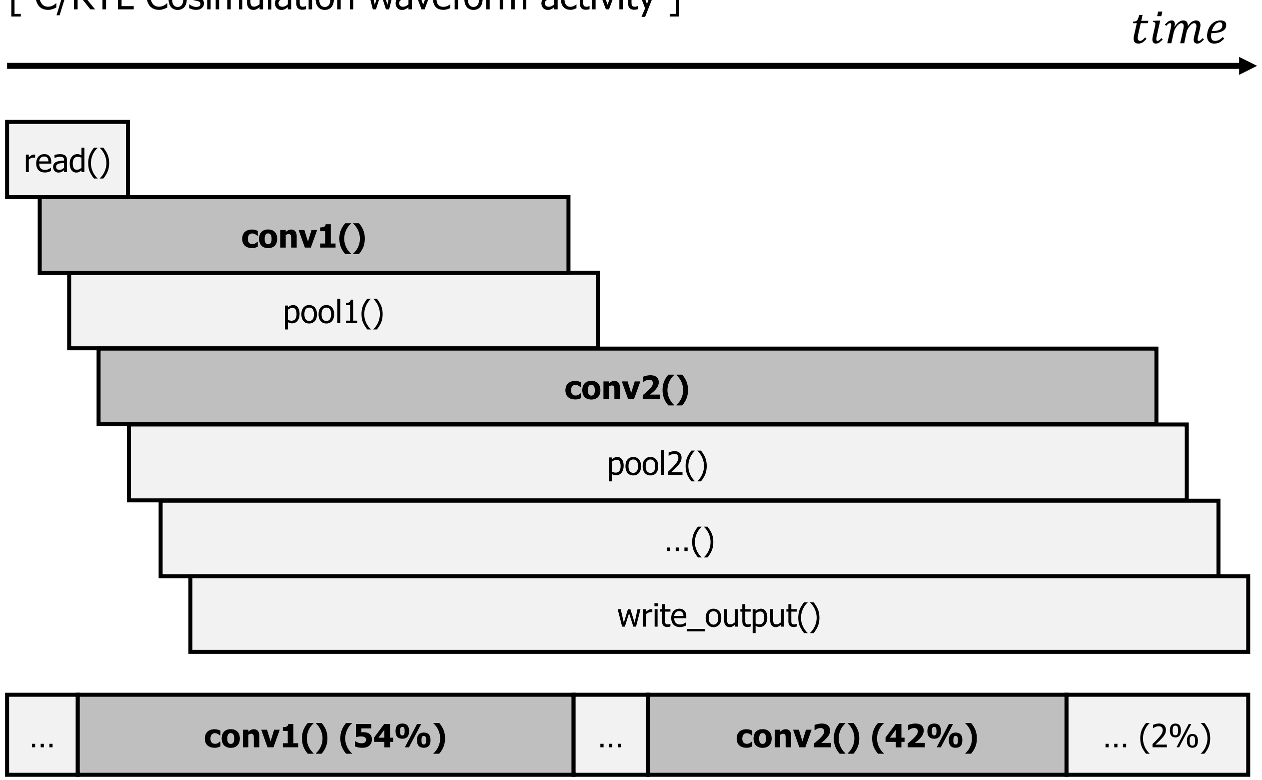
Light LeNet-5 with HLS (Stream Interface), Cont'd

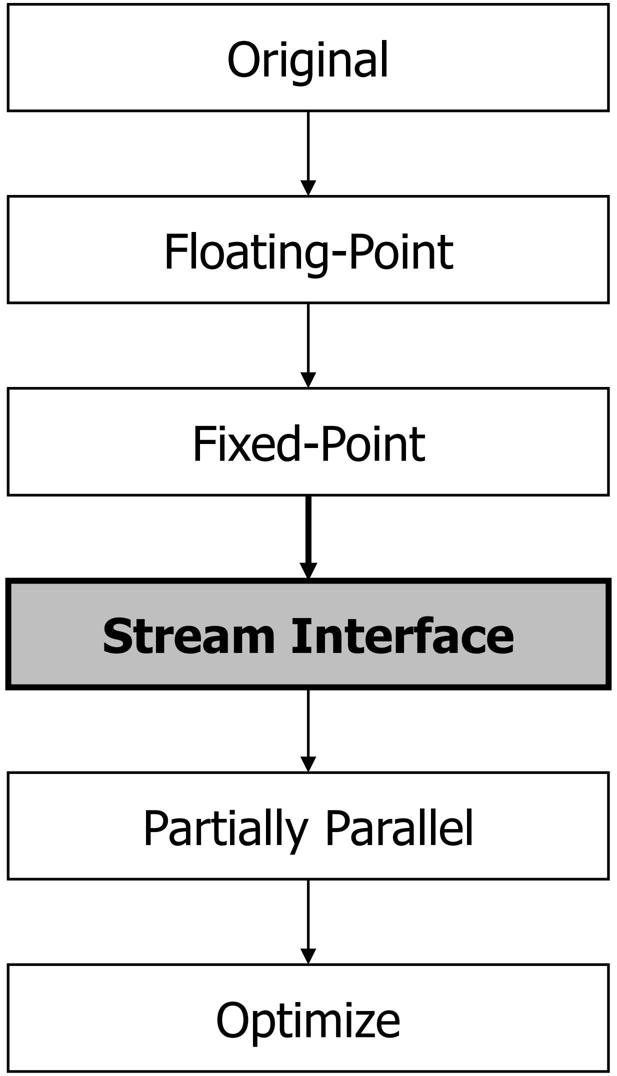
- *Vivado HLS* C/RTL Cosimulation waveform
- *Vivado HLS* Performance Estimates.
- It can be seen that **conv1()** and **conv2()** are the cause of bottleneck.

[Performance Estimates]

	Latency
read()	1025
conv1()	**264691**
pool1()	6734
conv2()	**203618**
pool2()	1856
conv3()	8324
full1()	524
full2()	442
write()	31
Total	**265683**

[C/RTL Cosimulation waveform activity]





Light LeNet-5 with HLS (Stream Interface), Cont'd

- Implemented as stream interface instead of array interface as before.

```
/* type.h */

#include <ap_fixed.h>      // For fixed-point data type
#include <hls_stream.h>    // For stream data type
#include <ap_axi_sdata.h>  // For AXI stream data type

// Data type for AXI streaming with side-channel
typedef  ap_axiu<16, 0, 0, 0>  axis_t;

typedef ap_fixed<16, 1, AP_RND, AP_SAT> input_t;
…
typedef ap_fixed<16, 7, AP_RND, AP_SAT> full2_t;
…
typedef ap_fixed<32, 8, AP_RND, AP_SAT> conv1_temp;
typedef ap_fixed<32,14, AP_RND, AP_SAT> full2_temp;
…

// Stream data type for AXI streaming with side-channel
typedef hls::stream<axis_t> stream_axis;

typedef hls::stream<input_t> stream_input;
typedef hls::stream<conv1_t> stream_conv1;
…
typedef hls::stream<full2_t> stream_full2;
```

```
/* layer.cc */

void read_input(stream_axis &input, stream_input &output) {
    axis_t  temp_axis;
    input_t temp_input;

    for (int i = 0 ; i < IMAGE_SIZE; i++) {
        temp_axis = input.read();

        // range() selects all bits in normal order
        temp_input.range() = temp_axis.data.range();
        output.write(temp_input);
    }
}

…
void write_output(stream_full2 &input, uint8_t* output) {
    full2_t input_1d[…] = { 0, };

    /* Read input */
    for (int i = 0; i < FULL2_OUTPUT_SIZE; i++)
        input_1d[i] = input.read();

    … // Find Max and index
    *output = (uint8_t)max_index;
}
```

Light LeNet-5 with HLS (Stream Interface), Cont'd

- Implemented as stream interface instead of array interface as before.

```
/* layer.cc */
…
void full1_layer(stream_conv3 &input, stream_full1 &output) {

    conv3_t input_1d[CONV3_OUTPUT_NUM] = { 0, };

    /* Read input */
    for (int i = 0; i < CONV3_OUTPUT_NUM; i++) {
        input_1d[i] = input.read();
    }

    /* Compute & Write */
    for (int row = 0; row < … ; …) {

        full1_temp acc = full1_bias[row];

        // Compute
        for (int col = 0; col < … ; …) {
            acc += (full1_temp)(input_1d[col] * full1_weight[…][…]);
        }

        // ReLU Activation & Write
        if (acc > 0) output.write((full1_t)acc);
        else         output.write((full1_t)0.0);
    }
}
```

```
/* predict.cc */

void predict(stream_axis &input, uint8_t* output) {
    #pragma HLS INTERFACE axis port = input

    #pragma HLS INTERFACE s_axilite port = output …
    #pragma HLS INTERFACE s_axilite port = return …
    …
    #pragma HLS DATAFLOW

    stream_input input_stream;

    stream_conv1 conv1_stream;
    …
    stream_full2 full2_stream;

    /* Read input */
    read_input(input, input_stream);

    /* 1st CONV layer */
    conv1_layer(input_stream, conv1_stream);

    …

    /* Write result */
    write_output(full2_stream, output);
}
```

Light LeNet-5 with HLS (Stream Interface)

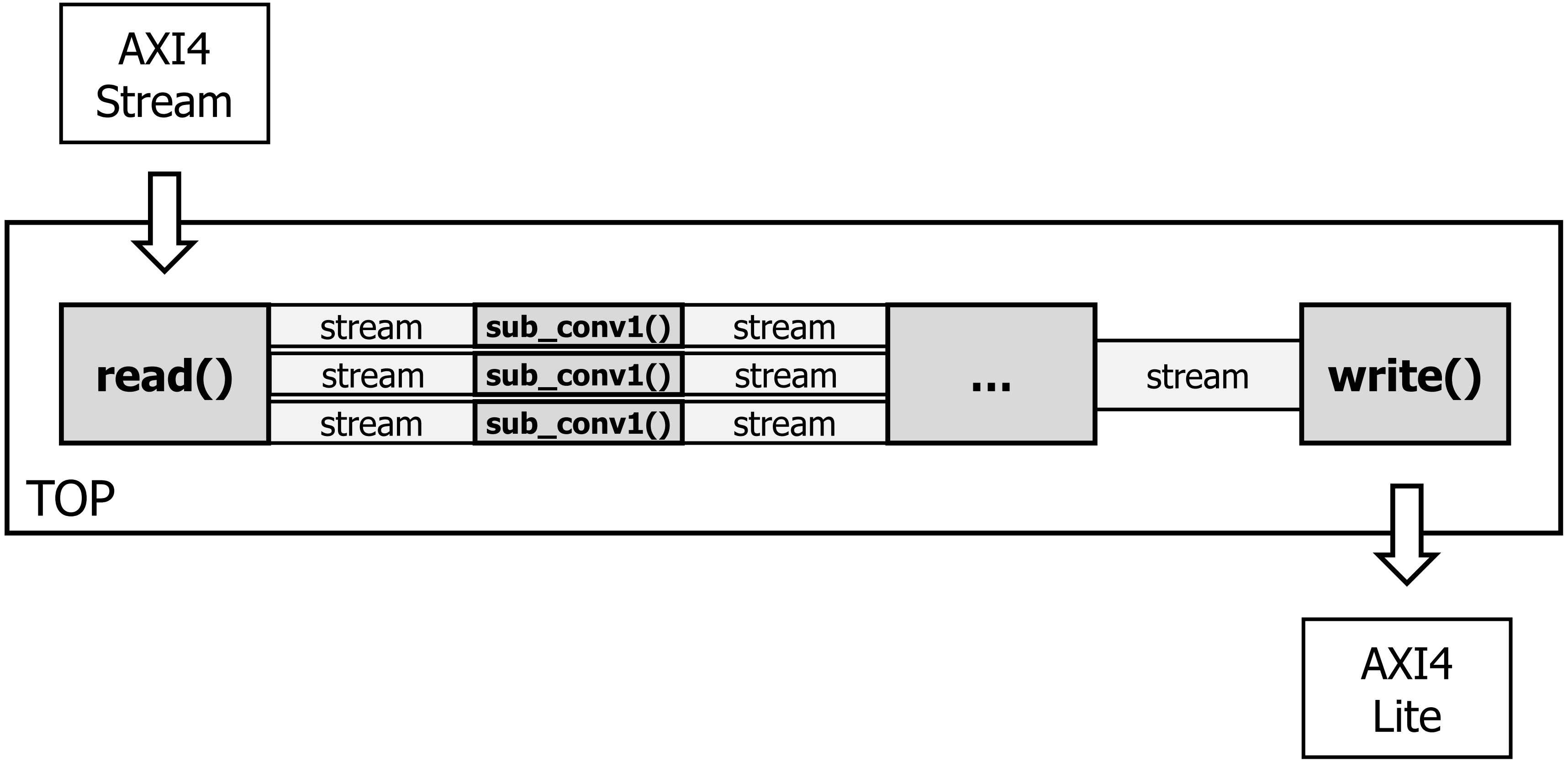
- Implemented as stream interface instead of array interface as before.

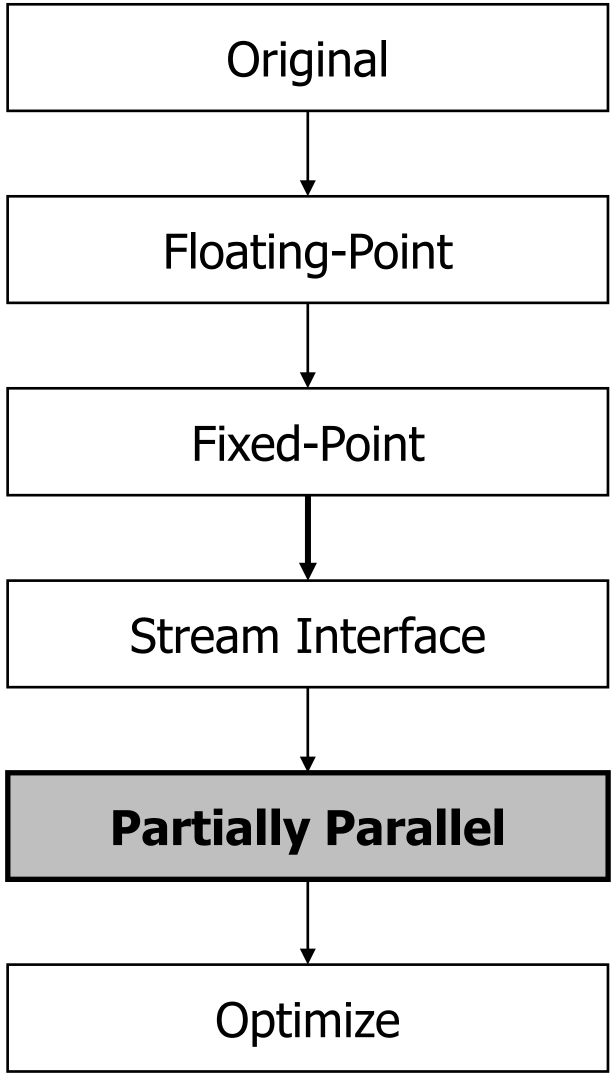
```
/* main.cc or testbench.cc */

int main (int argc, char* argv[]) {

    int err_cnt = 0;
    …
    for (size_t i = 0; i < TEST_NUM; i++) {
        …
        predict(input_axi_stream, &my_answer[i]);
        …
        if (my_answer != answer[i]) {
            err_cnt++;
            cout << "[ FALSE ] " … << "\n";
        }
        else {
            cout << "[ TRUE  ] " … << "\n";
        }
    }

    …
    cout << "\n[Fixed-Point + HLS stream]\n";
    cout << "Accuracy : " << … << accuracy << … ;
    cout << "Error    : " << … << err_cnt  << … ;

    return 0;
}
```

```
# Run all inputs (just one option)

$ ./main

       Number  Answer  Predict
[TRUE] [   0]  7       7
[TRUE] [   1]  2       2
[TRUE] [   2]  1       1
[TRUE] [   3]  0       0
 …
[TRUE] [9996]  3       3
[TRUE] [9997]  4       4
[TRUE] [9998]  5       5
[TRUE] [9999]  6       6

[Fixed-Point + HLS stream]
Accuracy : 97.47 [%]
Error    :    253 [cases]
```

Light LeNet-5 with HLS (Partially Parallel), Cont'd

- Longest latency **conv1()** is divided to be calculated in parallel.
- Since the total latency is bounded by highest latency **conv1()**,
- Reducing the latency by parallelizing **conv1()** will reduce total latency.





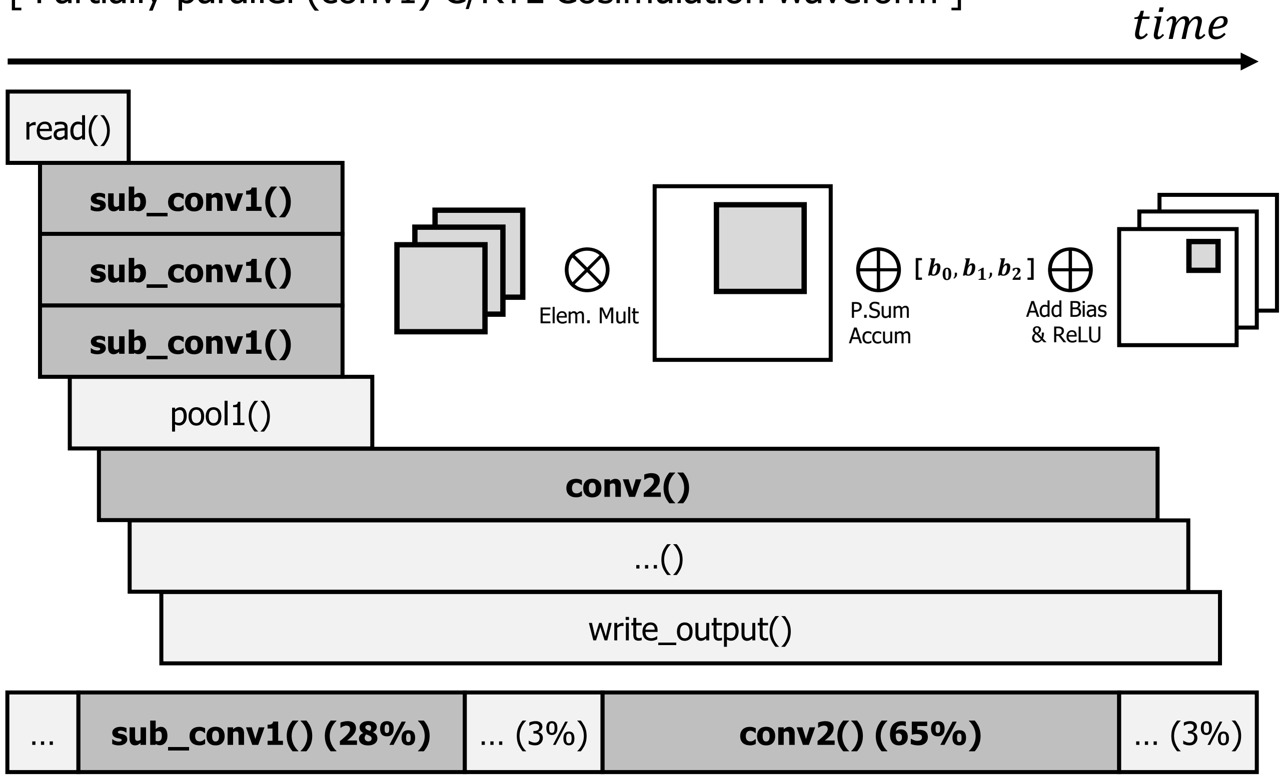
Light LeNet-5 with HLS (Partially Parallel), Cont'd

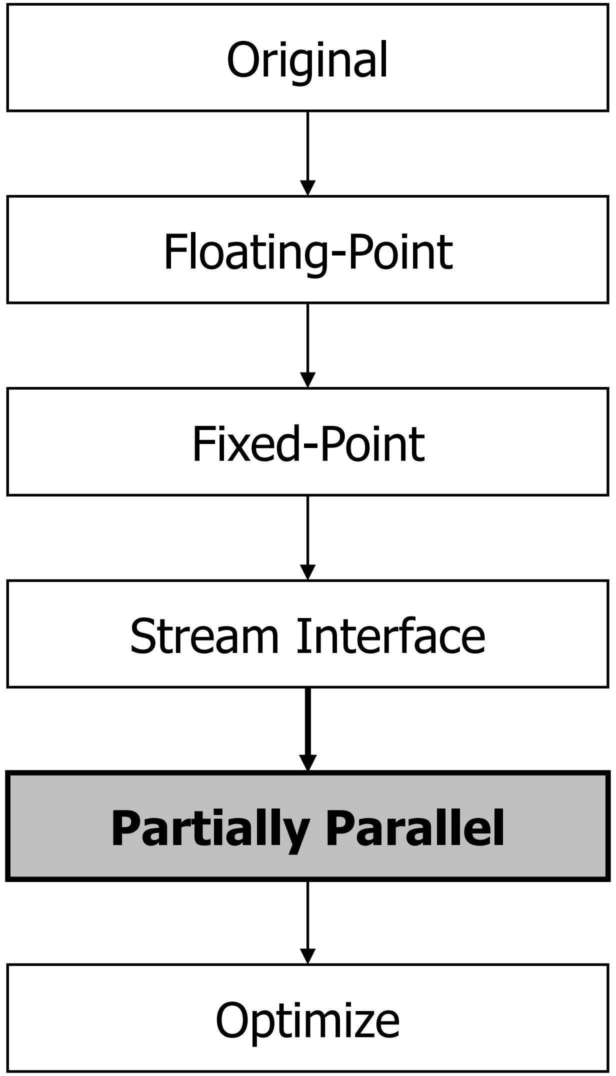
- When **conv1()** was partially parallelized,
- The latency of **conv1()** decreased by **66%**.
- But, the total latency is bounded to new highest latency **conv2()**.

[Performance Estimates]

	Latency
read()	1025
sub_conv1()	**88954**
pool1()	10536
conv2()	**203618**
pool2()	1856
conv3()	8324
full1()	524
full2()	442
write()	31
Total	**207716**

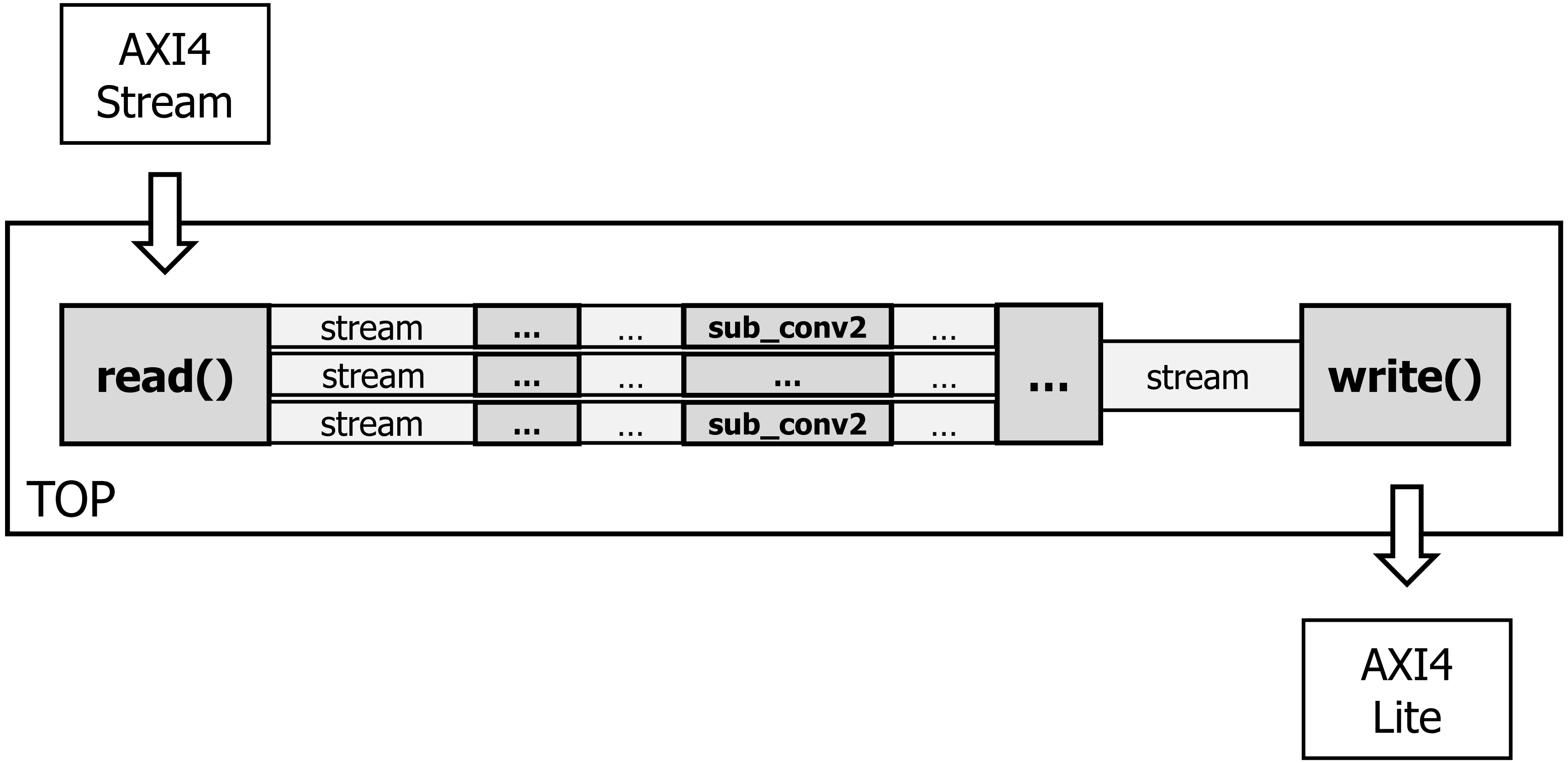
[Partially parallel (conv1) C/RTL Cosimulation waveform]

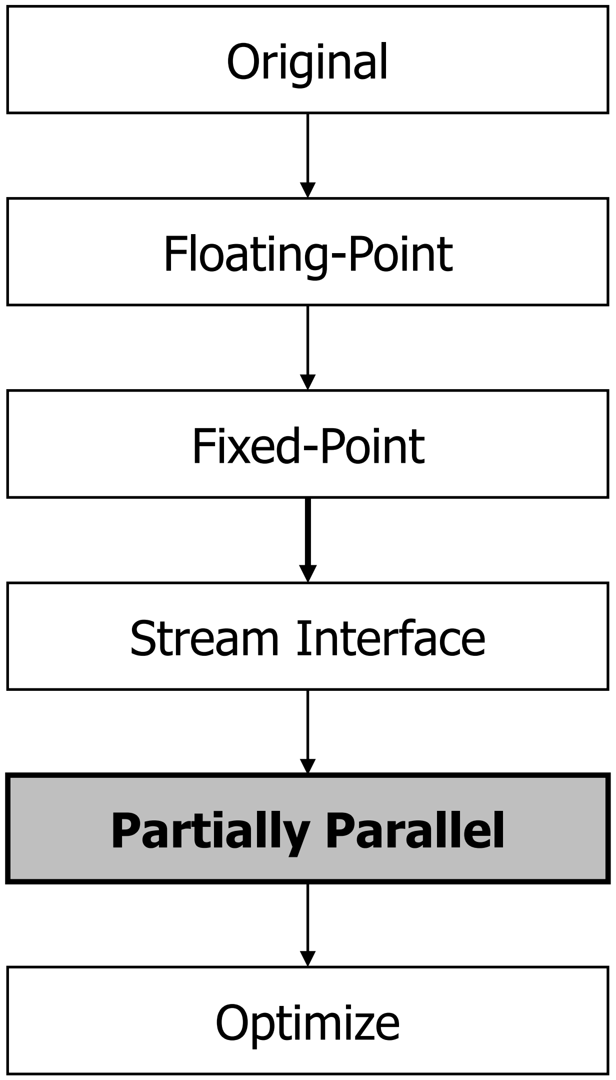




Light LeNet-5 with HLS (Partially Parallel), Cont'd

- New highest latency **conv2()** also divided to be calculated in parallel.
- Since the total latency is bounded by highest latency **conv2()**,
- Reducing the latency by parallelizing **conv2()** will reduce total latency.





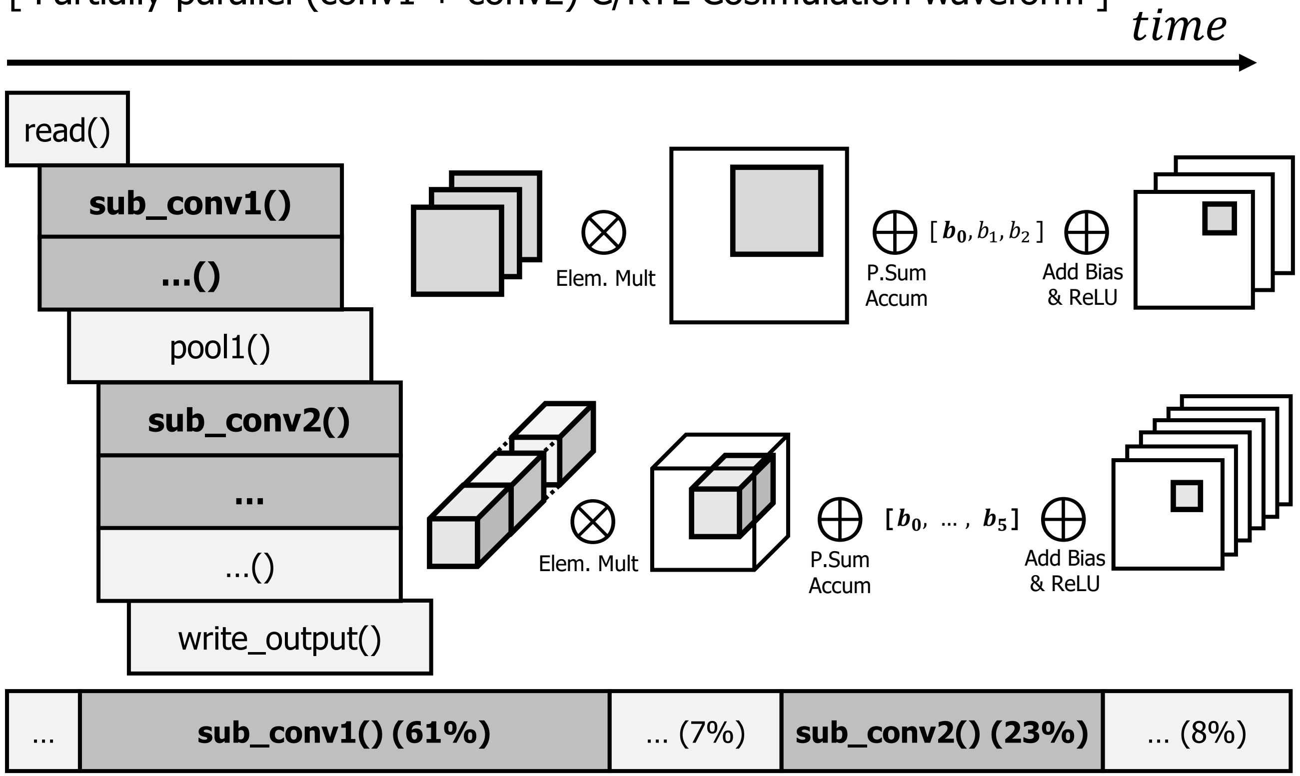
Light LeNet-5 with HLS (Partially Parallel), Cont'd

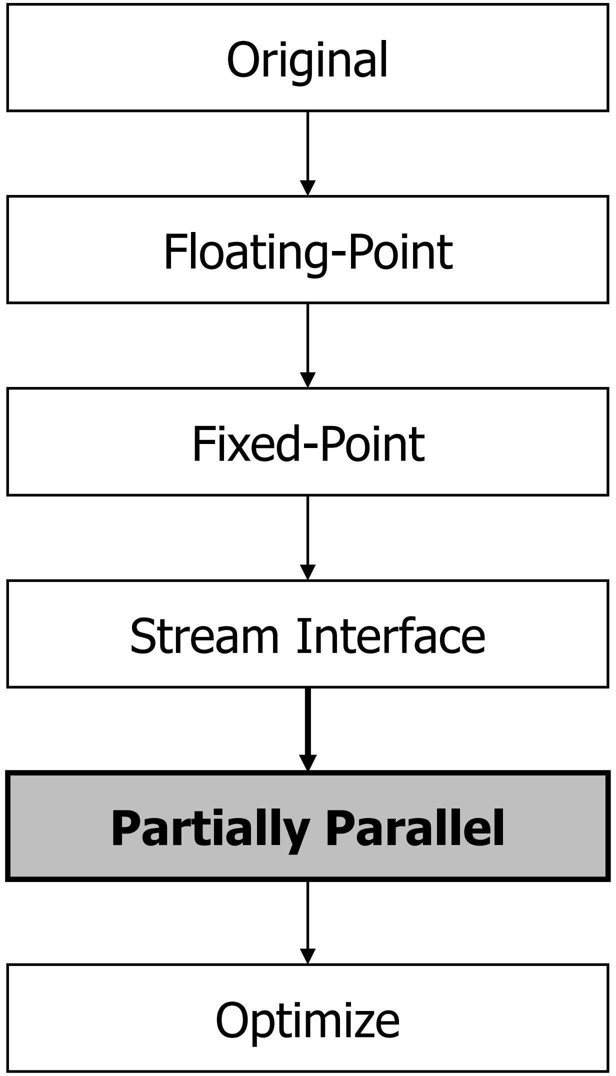
- When **conv2()** was partially parallelized,
- The latency of **conv2()** decreased by **83%**.
- Total latency decreased by **66%** compared to the [Stream Interface].

[Performance Estimates]

	Latency
read()	1025
sub_conv1()	**88954**
pool1()	10536
sub_conv2()	**34500**
pool2()	2544
conv3()	8324
full1()	524
full2()	442
write()	31
Total	**89946**

[Partially parallel (conv1 + conv2) C/RTL Cosimulation waveform]





Light LeNet-5 with HLS (Partially Parallel), Cont'd

- Overview of latency reduction.

[No parallel]

	Latency
read()	1025
conv1()	**264691**
pool1()	6734
conv2()	**203618**
pool2()	1856
conv3()	8324
full1()	524
full2()	442
write()	31
Total	**265683**

66%↓ (conv1) **22%↓** (Total)

[Patially parallel (conv1)]

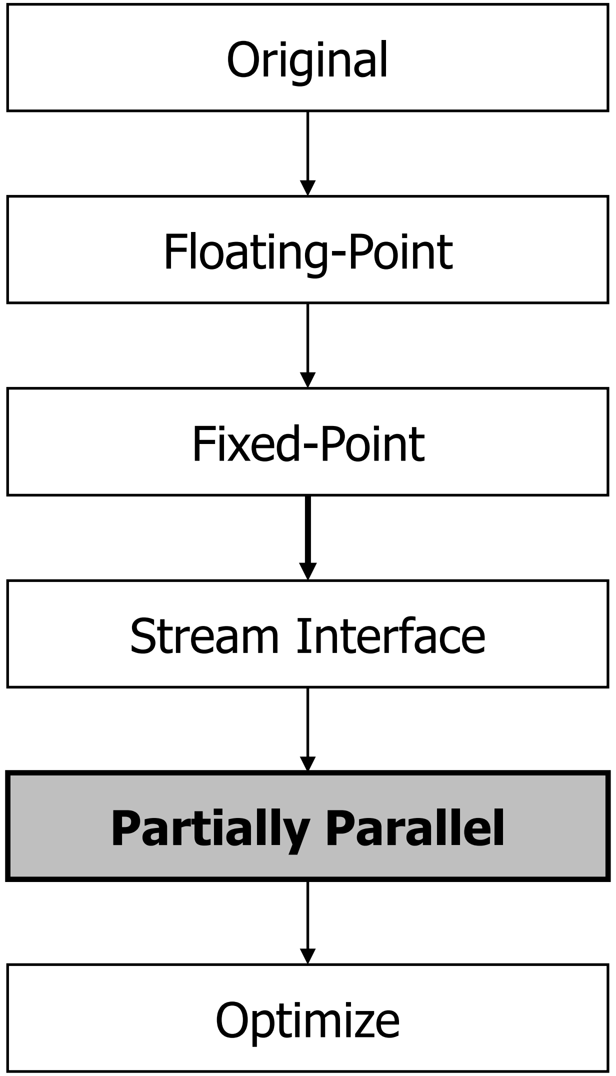
	Latency
read()	1025
sub_conv1()	**88954**
pool1()	10536
conv2()	**203618**
pool2()	1856
conv3()	8324
full1()	524
full2()	442
write()	31
Total	**207716**

83%↓ (conv2) **57%↓** (Total)

[P.P (conv1 + conv2)]

	Latency
read()	1025
sub_conv1()	**88954**
pool1()	10536
sub_conv2()	**34500**
pool2()	2544
conv3()	8324
full1()	524
full2()	442
write()	31
Total	**89946**

Total latency 66%↓



Light LeNet-5 with HLS (Partially Parallel), Cont'd

- Overview of resource utilization.

[No parallel]

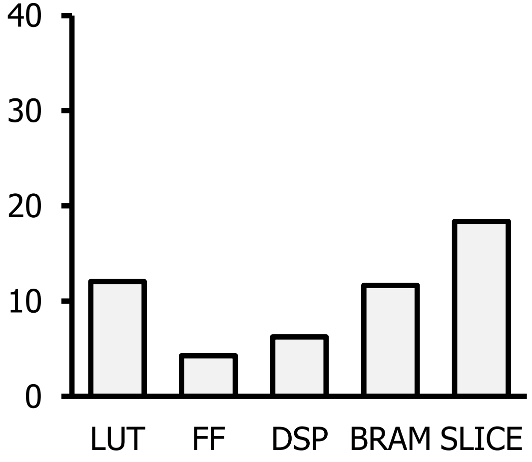
	Usage	Usage (%)
LUT	2125	12.07
FF	1504	4.27
DSP	5	6.25
BRAM	14	11.67
SLICE	808	18.36

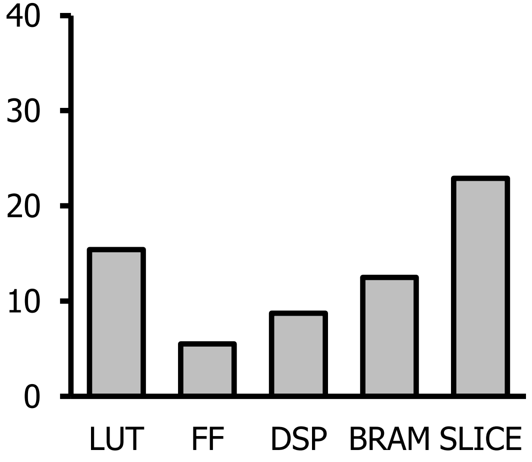
[Patially parallel (conv1)]

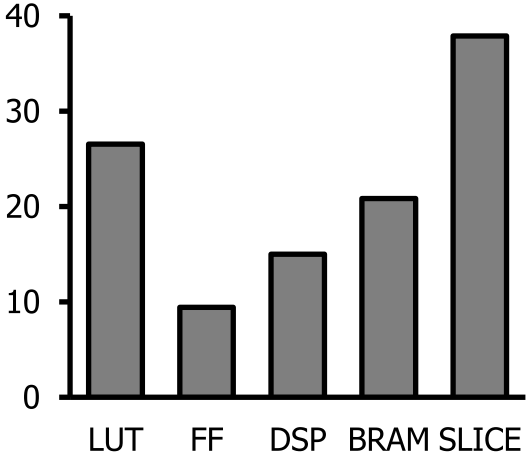
	Usage	Usage (%)
LUT	2713	15.41
FF	1946	5.53
DSP	7	8.75
BRAM	15	12.50
SLICE	1008	22.91

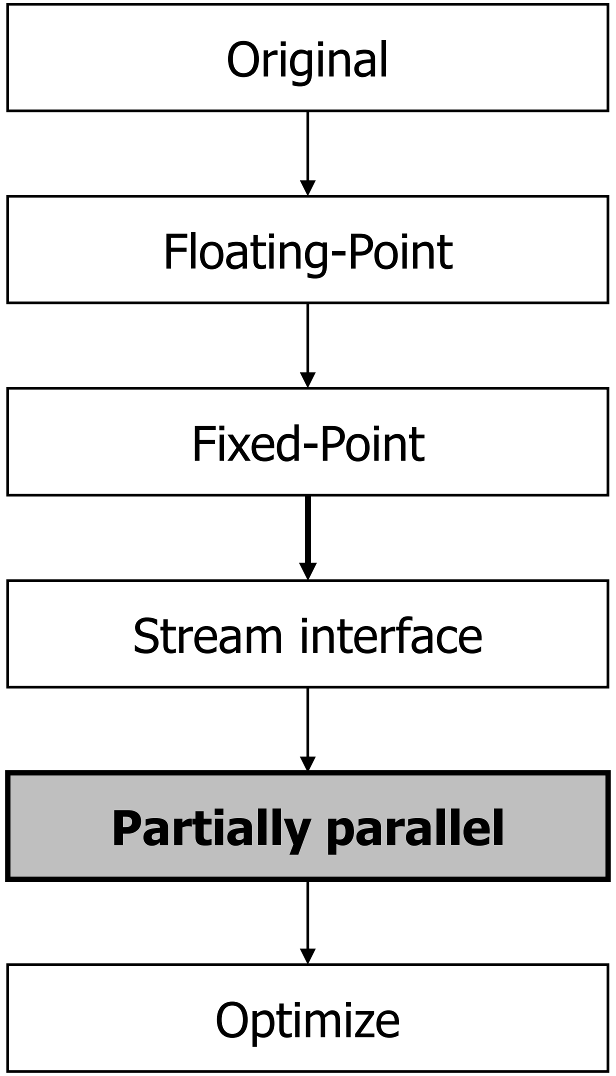
[Patially parallel (conv1 + conv2)]

	Usage	Usage (%)
LUT	4671	26.54
FF	3324	9.44
DSP	12	15.00
BRAM	25	20.83
SLICE	1667	37.89









Light LeNet-5 with HLS (Partially Parallel), Cont'd

- Divide existing functions to be excuted in parallel.

```
/* predict.cc */
void predict(stream_axis &input, uint8_t* output_r) {

    stream_input sub0_input; stream_conv1 sub0_conv1;
    stream_input sub1_input; stream_conv1 sub1_conv1;
    stream_input sub2_input; stream_conv1 sub2_conv1;

    stream_conv1 sub0_pool1;
    …
    stream_conv1 sub5_pool1;

    stream_conv2 sub0_conv2;
    …
    stream_conv2 sub5_conv2;
    …
    read_input(input, sub0_input,
                      sub1_input,
                      sub2_input);

    /* 1st CONV layer */
    sub0_conv1_layer(sub0_input, sub0_conv1);
    sub1_conv1_layer(sub1_input, sub1_conv1);
    sub2_conv1_layer(sub2_input, sub2_conv1);

    /* 1st POOL layer */
    pool1_layer(sub0_conv1, sub1_conv1, sub2_conv1,
                sub0_pool1, sub1_pool1, sub2_pool1,
                sub3_pool1, sub4_pool1, sub5_pool1);
```

```
/* predict.cc */

    …
    /* 2nd CONV layer */
    sub0_conv2_layer(sub0_pool1, sub0_conv2);
    …
    sub5_conv2_layer(sub5_pool1, sub5_conv2);

    /* 2nd POOL layer */
    pool2_layer(sub0_conv2,
                sub1_conv2,
                sub2_conv2,
                sub3_conv2,
                sub4_conv2,
                sub5_conv2, pool2_stream);

    /* 3rd CONV layer */
    conv3_layer(pool2_stream, conv3_stream);

    /* 1st FULL layer */
    full1_layer(conv3_stream, full1_stream);

    /* 2nd FULL layer */
    full2_layer(full1_stream, full2_stream);

    /* Return result */
    write_output(full2_stream, output_r);
}
```

Light LeNet-5 with HLS (Partially Parallel), Cont'd

- Divide existing functions to be excuted in parallel.

```
/* layer.cc */

void read_input(stream_axis &input,
                stream_input &sub0,
                stream_input &sub1,
                stream_input &sub2)
{

    axis_t  temp_axis;
    input_t temp_input;

    for (int i = 0; i < IMAGE_SIZE; i++) {
        temp_axis = input.read();
        temp_input.range() = temp_axis.data.range();

        sub0.write(temp_input);
        sub1.write(temp_input);
        sub2.write(temp_input);
    }
}
```

```
/* layer.cc */

void sub0_conv1_layer(stream_input &input, stream_conv1 &output)
{

  input_t input_2d[IMAGE_ROW][IMAGE_COL] = { 0, };

  /* Read input */
  …
  /* Compute & Write */
  for (int orow = 0; orow < … ; …) {
    for (int ocol = 0; ocol < … ; …) {
      conv1_temp acc = conv1_bias[0];

      for (int wr = 0; wr < … ; …) {
        for (int wc = 0; wc < … ; …) {
          // Compute
          acc += (conv1_temp)(input_2d[…][…] * weight_0[…][…]);
        }
      }
      // ReLU Activation & Write
      if (acc > 0) output.write((conv1_t)acc);
      else         output.write((conv1_t)0.0);
    }
  }
}
```

Light LeNet-5 with HLS (Partially Parallel)

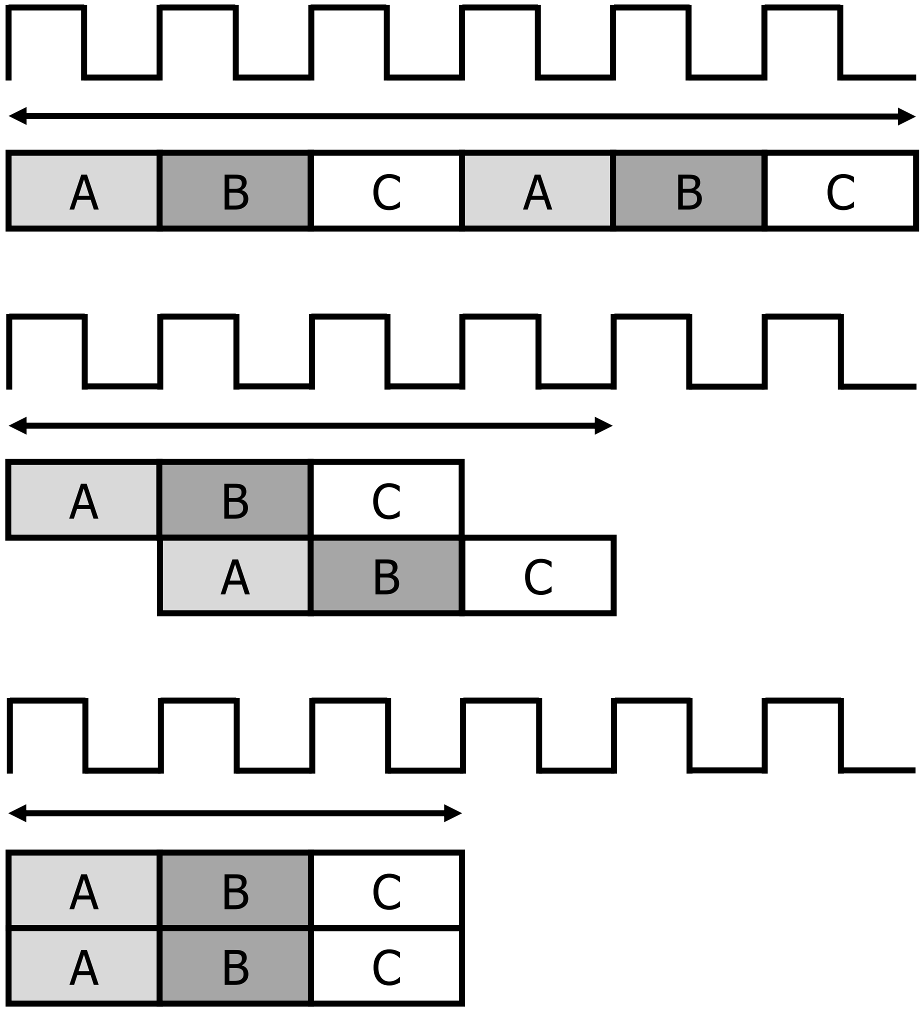
- Divide existing functions to be excuted in parallel.

```
/* layer.cc */

void pool1_layer(stream_conv1  &input0, stream_conv1  &input1, stream_conv1  &input2,
                 stream_conv1 &output0, stream_conv1 &output1, stream_conv1 &output2,
                 stream_conv1 &output3, stream_conv1 &output4, stream_conv1 &output5)
{
    conv1_t input_3d[CONV1_OUTPUT_NUM][CONV1_OUTPUT_ROW][CONV1_OUTPUT_COL] = { 0, };

    /* Read input */
    for (int i = 0; i < … ; …) {
        for (int j = 0; j < … ; …) {
            for (int k = 0; k < … ; …) {
                if      (k == 0) input_3d[k][i][j] = input0.read();
                else if (k == 1) input_3d[k][i][j] = input1.read();
                else             input_3d[k][i][j] = input2.read();
            }
        }
    }

    /* Compute & Write */
    for (int num = 0; num < … ; …) {
        for (int row = 0; row < … ; … ) {
            for (int col = 0; col < … ; …) {
                … // Find Max
                output0.write(max);
                …
                output5.write(max);
            }
        }
    }
}
```

```
# Run all inputs (just one option)

$ ./main

       Number  Answer  Predict
[TRUE] [   0]  7       7
[TRUE] [   1]  2       2
[TRUE] [   2]  1       1
[TRUE] [   3]  0       0
 …
[TRUE] [9996]  3       3
[TRUE] [9997]  4       4
[TRUE] [9998]  5       5
[TRUE] [9999]  6       6

[Fixed-Point + HLS stream + Parallel]
Accuracy : 97.47 [%]
Error    :    253 [cases]
```

Light LeNet-5 with HLS (Optimize), Cont'd

- Compare no pragma, HLS PIPELINE, HLS UNROLL



No pragma

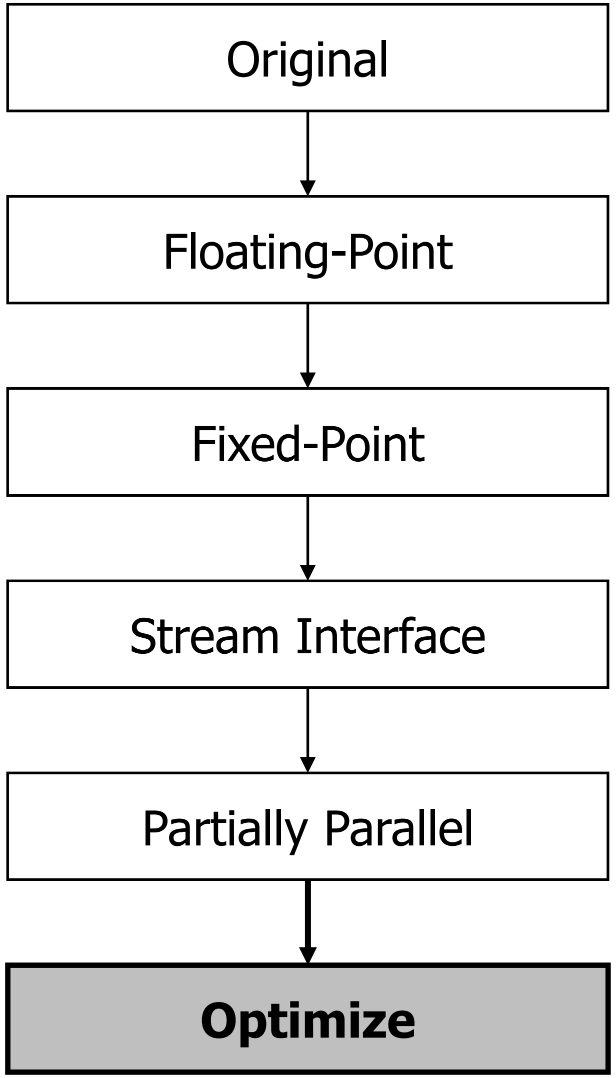
- High latency
- Low resource
- Low throughput

HLS PIPELINE

- Medium latency
- Medium resource
- Medium throughput

HLS UNROLL

- Low latency
- High resource
- High throughput



Light LeNet-5 with HLS (Optimize), Cont'd

- When UNROLL pragma is applied to **conv1()** and **conv2()**,
- The latency of **conv1()** is decreased by **62%.**
- The latency of **conv2()** is decreased by **57%**.
- The **total latency** is decreased by **62%**.

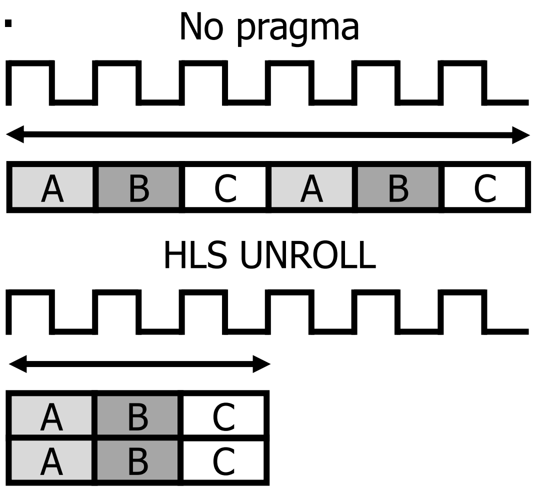
[Before apply pragma]

	Latency
read()	1025
sub_conv1()	**88954**
pool1()	10536
sub_conv2()	**34500**
pool2()	2544
conv3()	8324
full1()	524
full2()	442
write()	31
Total	**89946**

62% ↓ (sub_conv1())
57% ↓ (sub_conv2())
62% ↓ (Total)

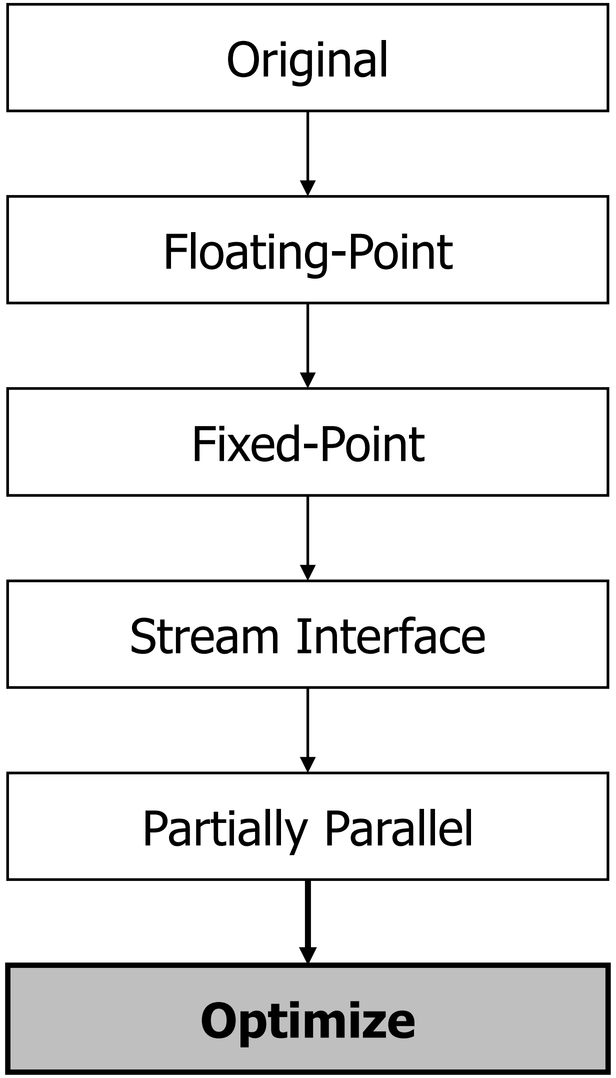
[After apply pragma]

	Latency
read()	1025
sub_conv1()	**34011**
pool1()	10536
sub_conv2()	**14912**
pool2()	2544
conv3()	8324
full1()	524
full2()	442
write()	31
Total	**34011**



[Resource Usage]

	Usage	**Usage (%)**
LUT	8310	47.22
FF	4727	13.43
DSP	48	60.00
BRAM	19	15.83
SLICE	2935	66.70



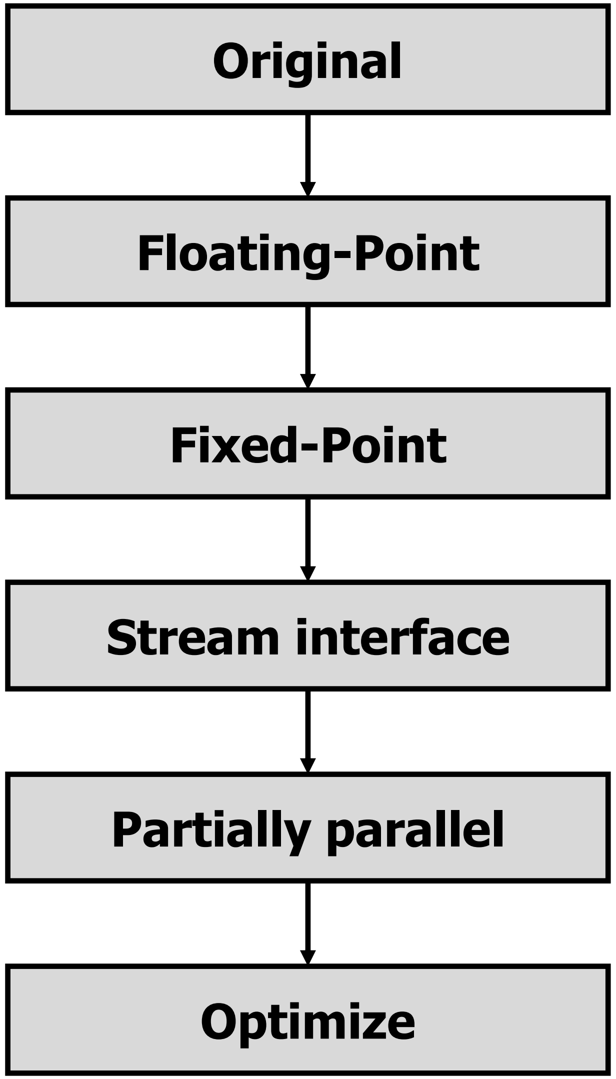
Light LeNet-5 with HLS (Optimize)

- Apply optimization each block.

```
/* layer.cc */

void sub0_conv1_layer(stream_input &input, stream_conv1 &output) {
    input_t input_2d[IMAGE_ROW][IMAGE_COL] = { 0, };

    /* Read input */
    for (int i = 0; i < IMAGE_ROW; i++) {
        for (int j = 0; j < IMAGE_COL; j++) {
            #pragma HLS PIPELINE II=1       // Read input in pipeline manner to reduce this function latency.
            input_2d[i][j] = input.read();
        }
    }

    /* Compute & Write */
    for (int orow = 0; orow < CONV1_OUTPUT_ROW; orow++) {
        for (int ocol = 0; ocol < CONV1_OUTPUT_COL; ocol++) {
            // Compute
            conv1_temp acc = conv1_bias[0];

            for (int wr = 0; wr < WEIGHT_ROW; wr++) {
                for (int wc = 0; wc < WEIGHT_COL; wc++) {
                    #pragma HLS UNROLL      // The loop is unrolled by WEIGHT_COL(5) and fully parallelized.
                    acc += (conv1_temp)(input_2d[orow + wr][ocol + wc] * conv1_weight_sub0[wr][wc]);
                }
            }
            // ReLU Activation & Write
            if (acc > 0) output.write((conv1_t)acc);
            else         output.write((conv1_t)0.0);
        }
    }
}
```

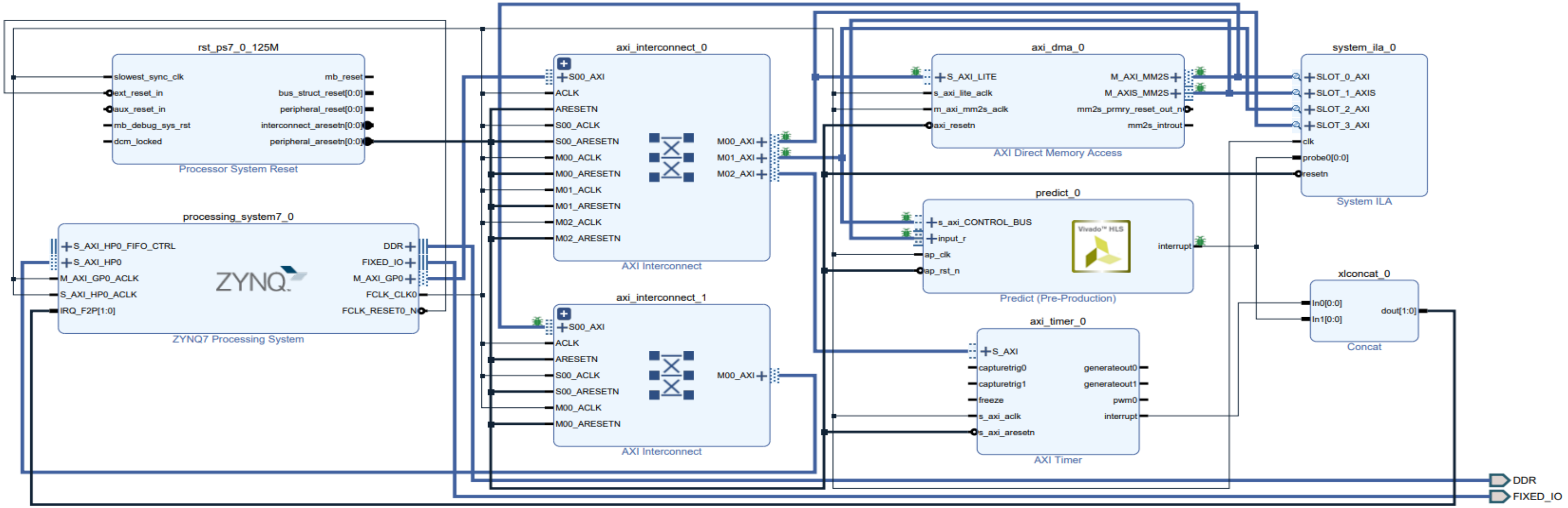
Overview of Impl. of LeNet-5 using C/C++ and HLS

- **Original → Floating-Point**
  - Change activation function ($sigmoid, tanh$ to $ReLU$).
  - Adjust the parameters of each layer to make the model smaller.
- **Floating-Point → Fixed-Point**
  - Confirmed that fixed-point has more benefits than floating-point.
  - Determine fixed-point identifier, for using fixed-point data type.
- **Fixed-Point → Stream interface**
  - Implemented as stream interface instead of array interface as before.
  - Closer to *Vivado HLS* canonical form using *DATAFLOW* optimization.
- **Stream interface → Partially parallel**
  - Reducing the latency by parallelizing conv1() and conv2().
  - Increase the throughput by parallelizing conv1() and conv2().
- **Partially parallel → Optimize**
  - Confirmed that *UNROLL* is more benefits than *PIPELINE*.
  - Apply optimization and confirmed reduced total latency.



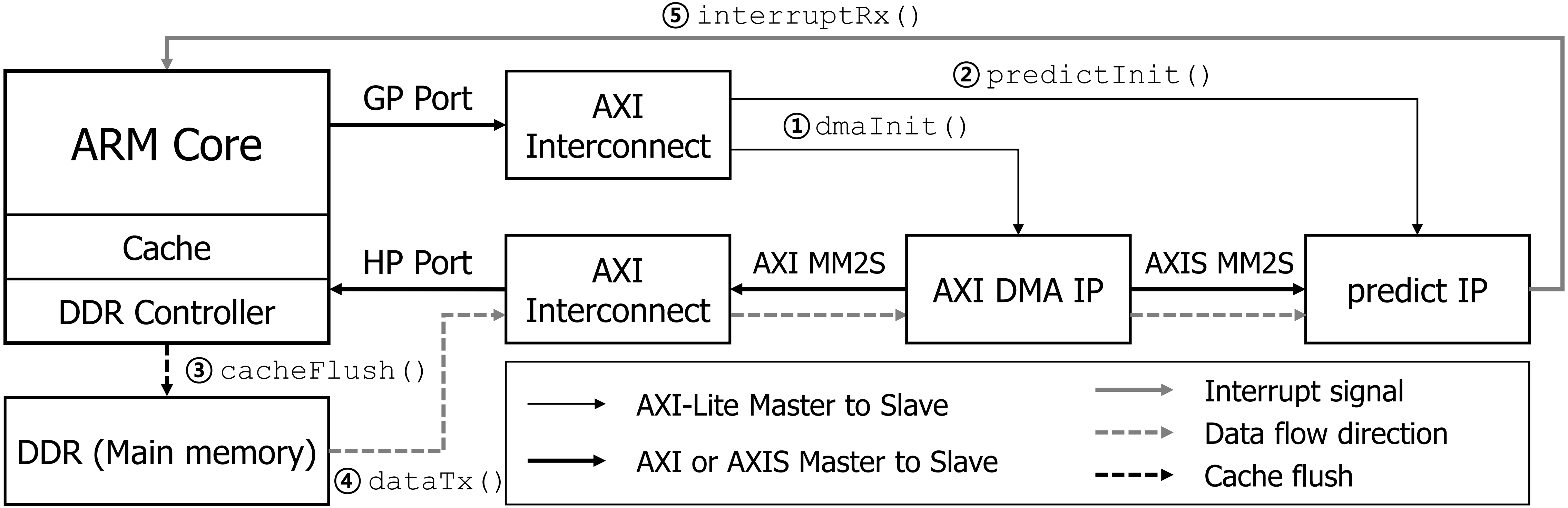
HW Design of LeNet-5 (Programmable Logic), Cont’d

- The AXI DMA provides high-speed data movement between system memory and an AXI4-Stream-based taget IP.
- The Integrated Logic Analyzer (ILA) IP core is logic analyzer core that can be used to monitor the internal signals of a design.
- The AXI Timer provides an AXI4-Lite interface to communicate with the Processing System.
- Interrupt is driven when the `ap_done` or `ap_ready` signals are HIGH.



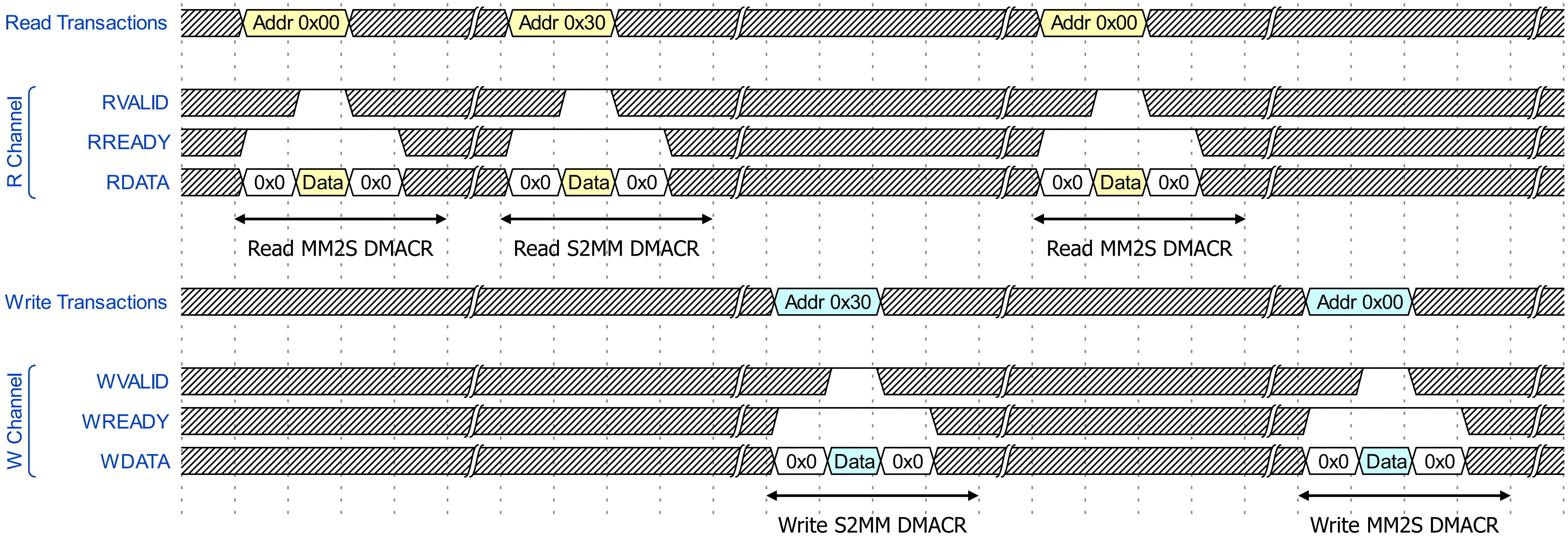
HW Design of LeNet-5 (Programmable Logic), Cont'd

- Initialize AXI DMA IP and predict IP through `dmaInit()` and `predictInit()`.
- Flush the cache before transferring data via DMA through `cacheFlush()`.
- AXI DMA IP reads data through DDR and transfers it to predict IP through `dataTx()`.
- Wait for the predict IP to process, and read the result when interrupt signal is raised.



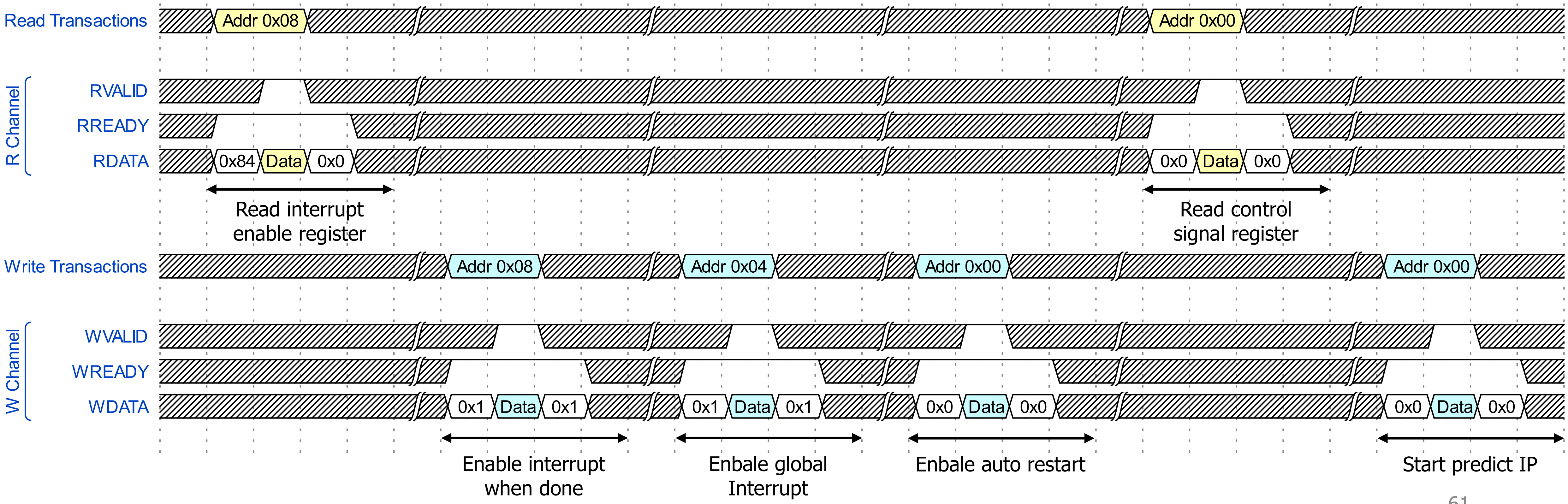
HW Design of LeNet-5 (Programmable Logic), Cont'd

- Waveform in `dmaInit()` part obtained through Integrated Logic Analyzer (ILA).
- Read and write DMA IP config.
- ARM Core ascertain that read channel is open by reading and writing MM2S control register.
- ARM Core ascertain that write channel is not open by reading and writing S2MM control register.



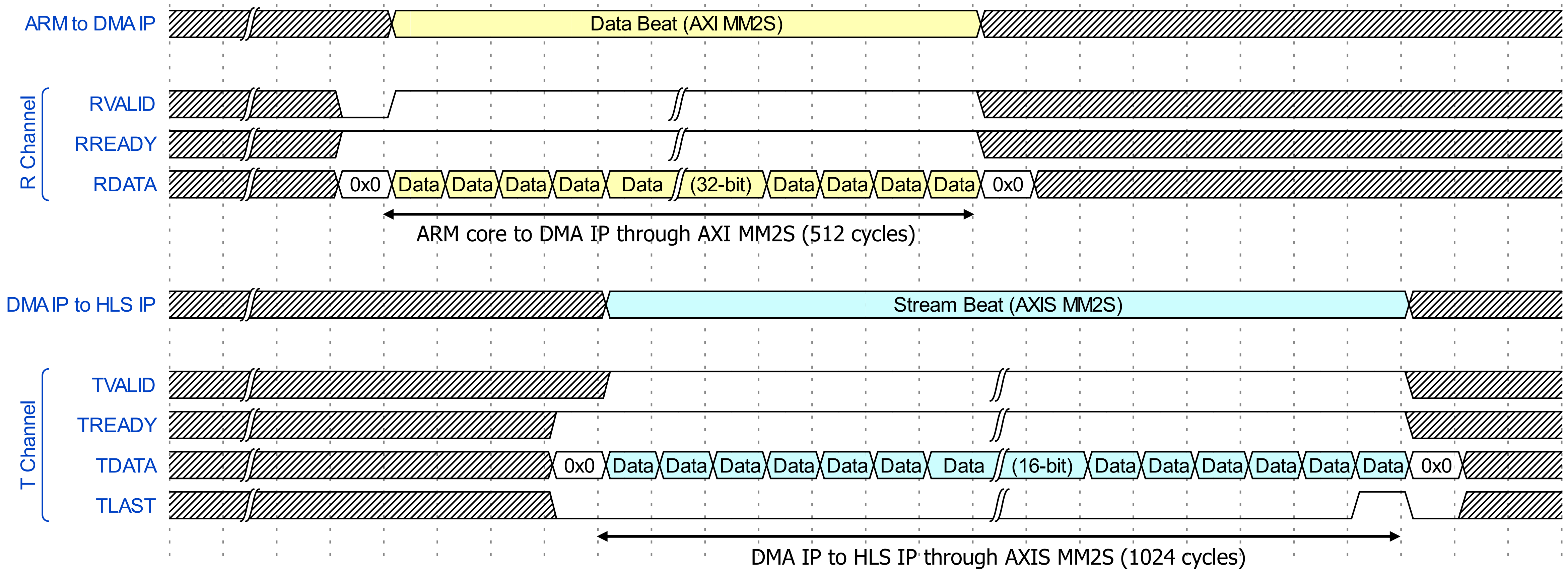
HW Design of LeNet-5 (Programmable Logic), Cont'd

- Waveform in `predictInit()` part obtained through Integrated Logic Analyzer (ILA).
- Read and write predict IP config.
- Set the interrupt signal to be HIGH when the application done.
- Enable predict IP automatically restart and start.



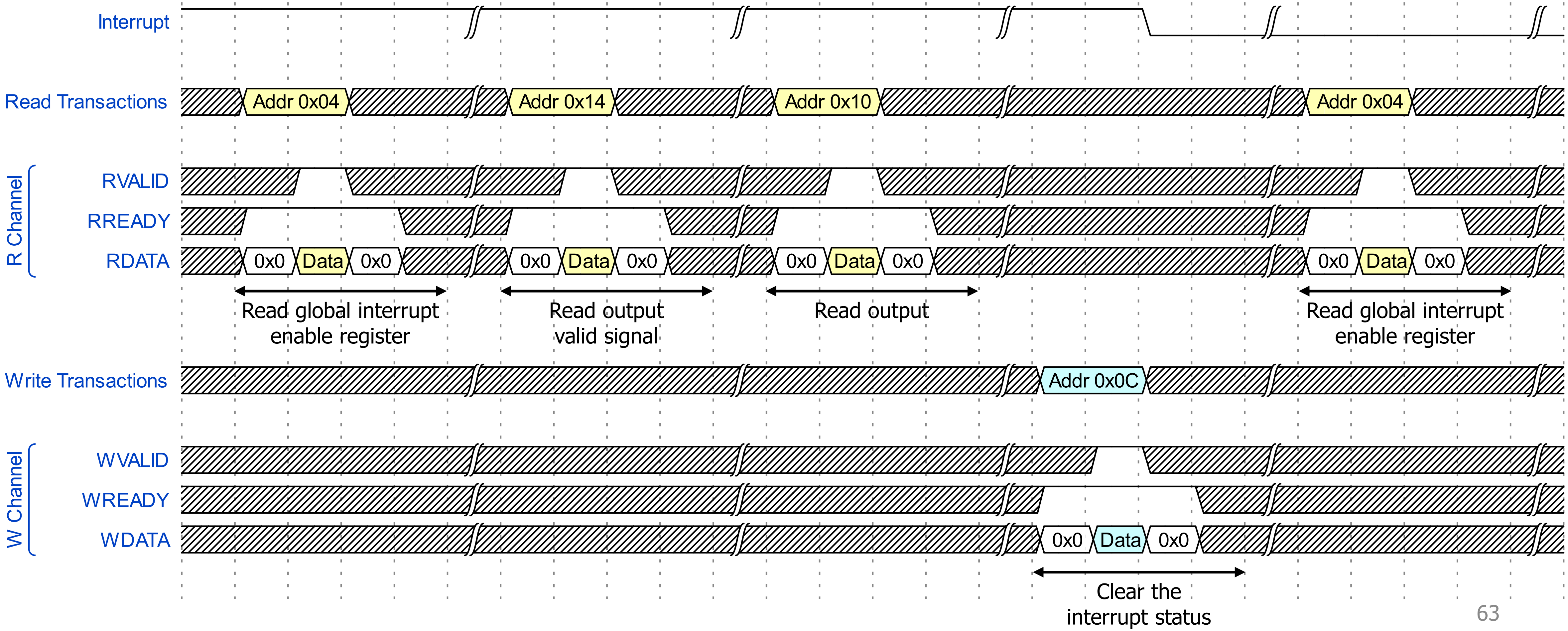
HW Design of LeNet-5 (Programmable Logic), Cont'd

- Waveform in `dataTx()` part obtained through Integrated Logic Analyzer (ILA).
- Data transfer from ARM Core to HLS IP through DMA IP.
- ARM to DMA IP reads data in 32-bit units, while DMA IP to HLS IP reads data in 16-bit units.



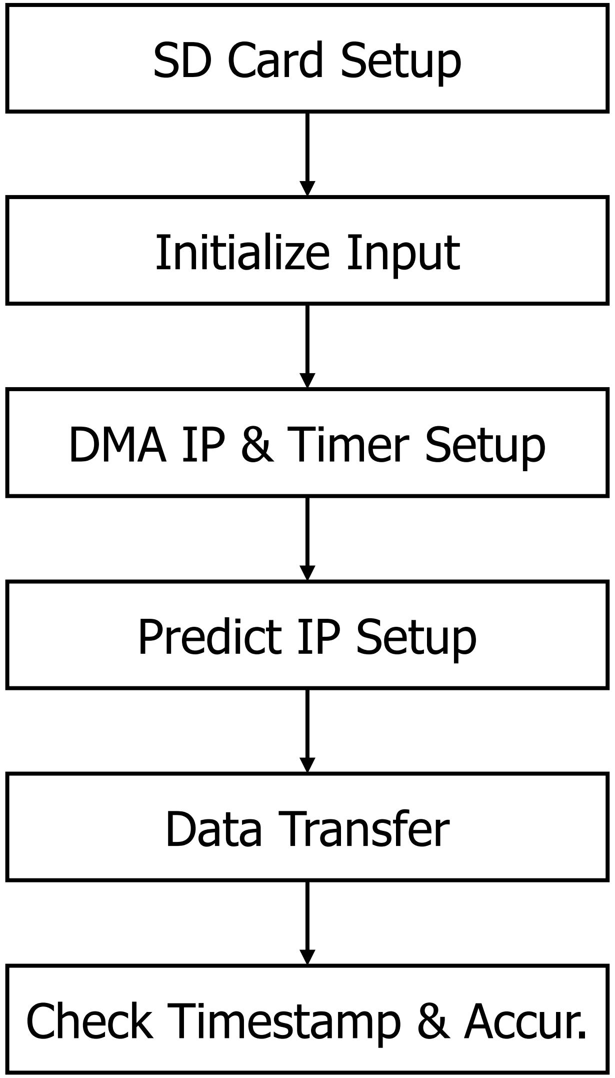
HW Design of LeNet-5 (Programmable Logic)

- Waveform in `interruptRx()` part obtained through Integrated Logic Analyzer (ILA).
- Read predict IP output valid signal and output data when interrupt signal asserted.
- After read output, clear the interrupt status.



SW Driver of LeNet-5 (Processing System)

- Read the input binary file stored in SD card and initialize.
- Input is initialized through the data read from the SD card.
- Configure to use DMA IP, AXI Timer IP, and predict IP.
- Before transferring data, cache flush the data to be transferred.
- Data is transferred using `XAxiDma_SimpleTransfer()` Xilinx API.
- Measure DMA transfer latency, predict IP operataion latency, etc..
- Check the accuracy to make sure predict IP implemented correctly.




```
# UART Terminal output

----------- LeNet-5 Start ----------
[INFO] SD Init PASSED
[INFO] Read 0 binary file PASSED
[INFO] Read 8 binary file PASSED
[INFO] SD Card Read PASSED
[INFO] Input initialize PASSED
[INFO] SD Eject PASSED
[INFO] DMA initialize PASSED
[INFO] AXI Timer initialzed PASSED
[INFO] Predict Core initialized PASSED
 …
[INFO] Timer setup time     : 29 cycles.
[INFO] Loop iteration time  : 44 cycles. (16)
 …
```

```
# UART Terminal output
 …
[INFO] Total [HW] run time   : 1742312 cycles.
[INFO] One sample run time   :  108894 cycles.
 …
[INFO] Start point           : 27
[INFO] 0 DMA Tx Start point  : 92
 …
[INFO] 15 HW ACC Start point : 1231250
[INFO] 15 HW ACC End point   : 1742310
 …
[INFO] End point             : 1742412

[HW Result]
Accuracy : 100.00 [%]
Error    :     0  [cases]
```

Performance analysis, ARM core vs. predict IP, Cont'd

- Result of running the Original model and the Lite model with different compile options on ARM core.

[Original LeNet-5 on ARM core]

No. of input	-O0	-O1	-O2	-O3
1	33.10 ms	6.13 ms	6.12 ms	6.61 ms
4	132.36 ms	24.69 ms	24.25 ms	26.00 ms
16	529.41 ms	96.84 ms	96.86 ms	103.59 ms
64	2116.83 ms	393.79 ms	386.63 ms	414.97 ms
256	8465.10 ms	1576.09 ms	1544.76 ms	1659.93 ms
Average	**33.08** ms	**6.15** ms	**6.05** ms	**6.50** ms

⇨ **81%↓** ⇨ **1%↓** ⇨ **7%↑**

```
# UART Terminal output

----------- LeNet-5 Start ----------
 …

[ORG Result]
Accuracy : 94.55 [%]
Error    :   545 [cases]

------------ LeNet-5 End -----------
```

[Light LeNet-5 on ARM core]

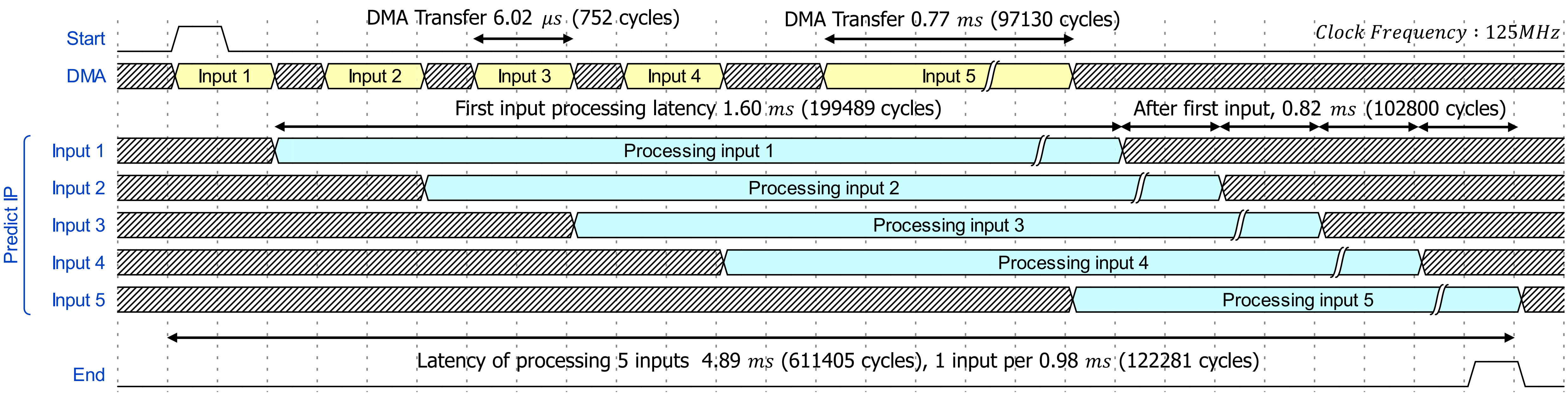
No. of input	-O0	-O1	-O2	-O3
1	13.15 ms	2.31 ms	1.43 ms	1.30 ms
4	52.56 ms	9.20 ms	5.71 ms	5.18 ms
16	210.33 ms	36.76 ms	22.85 ms	20.68 ms
64	839.48 ms	147.09 ms	91.39 ms	82.66 ms
256	3355.89 ms	587.93 ms	364.92 ms	330.59 ms
Average	**13.13** ms	**2.30** ms	**1.43** ms	**1.30** ms

⇨ **82%↓** ⇨ **38%↓** ⇨ **9%↓**

```
# UART Terminal output

----------- LeNet-5 Start ----------
 …

[Lite Result]
Accuracy : 97.47 [%]
Error    :   253 [cases]

------------ LeNet-5 End -----------
```

Performance analysis, ARM core vs. predict IP, Cont’d

- Start and end points are checked through AXI Timer IP.
- For the first input, the latency is high, but it decreases from the second input onwards.
- Predict IP is taking high latency to receive the 5th input as it has not yet consumed the data.
- Because `ap_ctrl_chin` block level protocol is applied to predict IP, the 5th input is back pressured.
- As the number of inputs increases, the latency per one input will decrease.



Performance analysis, ARM core vs. predict IP, Cont'd

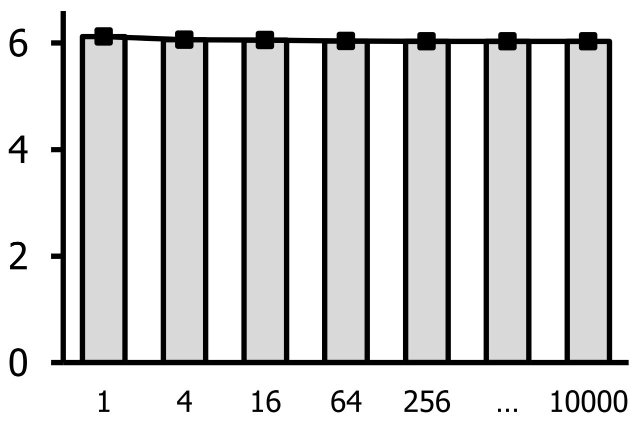
- Although the ARM core operates at $667MHz$ and predict IP operates at $125MHz$,
- Predict IP on programmable logic has the best performance. (**36%** faster than Lite on ARM core)

No. of input	-O2 (Org)	Average
1	6.12 ms	6.12 ms
4	24.25 ms	6.06 ms
16	96.86 ms	6.05 ms
64	386.63 ms	6.04 ms
256	1544.76 ms	6.03 ms
…	24699.98 ms	6.03 ms
10000	60323.51 ms	6.03 ms

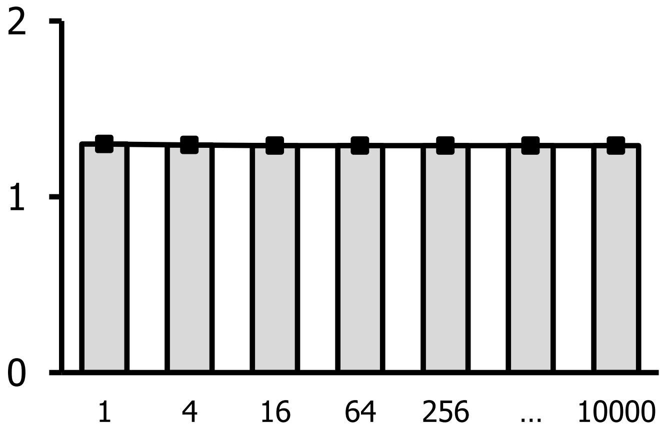
No. of input	-O3 (Lite)	Average
1	1.30 ms	1.30 ms
4	5.18 ms	1.30 ms
16	20.68 ms	1.29 ms
64	82.66 ms	1.29 ms
256	330.59 ms	1.29 ms
…	5290.26 ms	1.29 ms
10000	12915.67 ms	1.29 ms

No. of input	-O0 (predict)	Average
1	1.60 ms	1.60 ms
4	4.06 ms	1.01 ms
16	13.93 ms	0.87 ms
64	53.41 ms	0.83 ms
256	211.31 ms	0.83 ms
…	3369.31 ms	0.82 ms
10000	8224.70 ms	0.82 ms

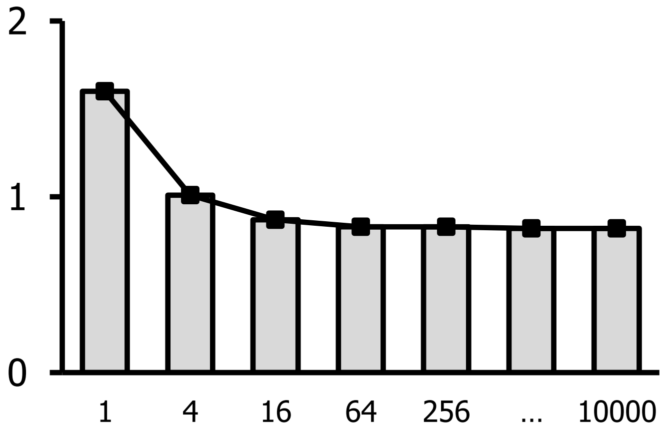
Original Average (-O2)



Lite Average (-O3)



Predict IP

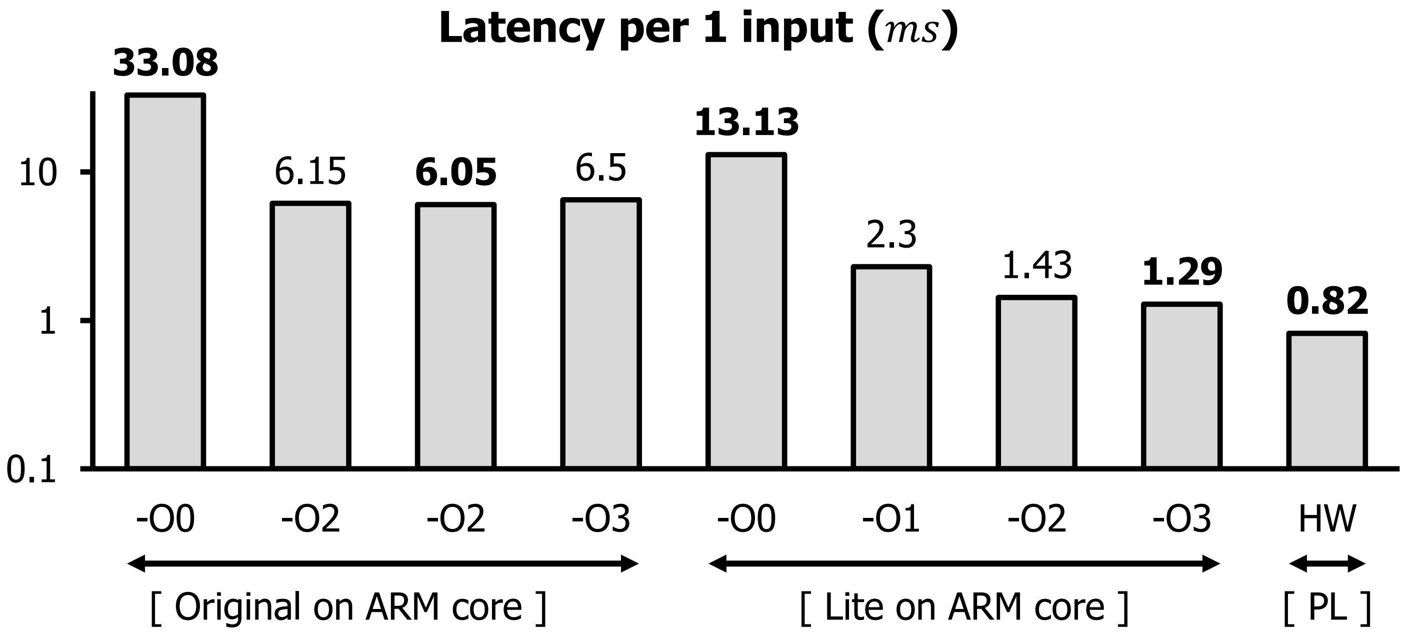


Performance analysis, ARM core vs. predict IP, Cont'd

- Predict IP on PL is **40.34x** faster than Original with **-O0** compile option on PS.
- Predict IP on PL is **7.38x** faster than Original with **-O2** compile option on PS.
- Predict IP on PL is **16.01x** faster than Lite with **-O0** compile option on PS.
- Predict IP on PL is **1.57x** faster than Lite with **-O3** compile option on PS.

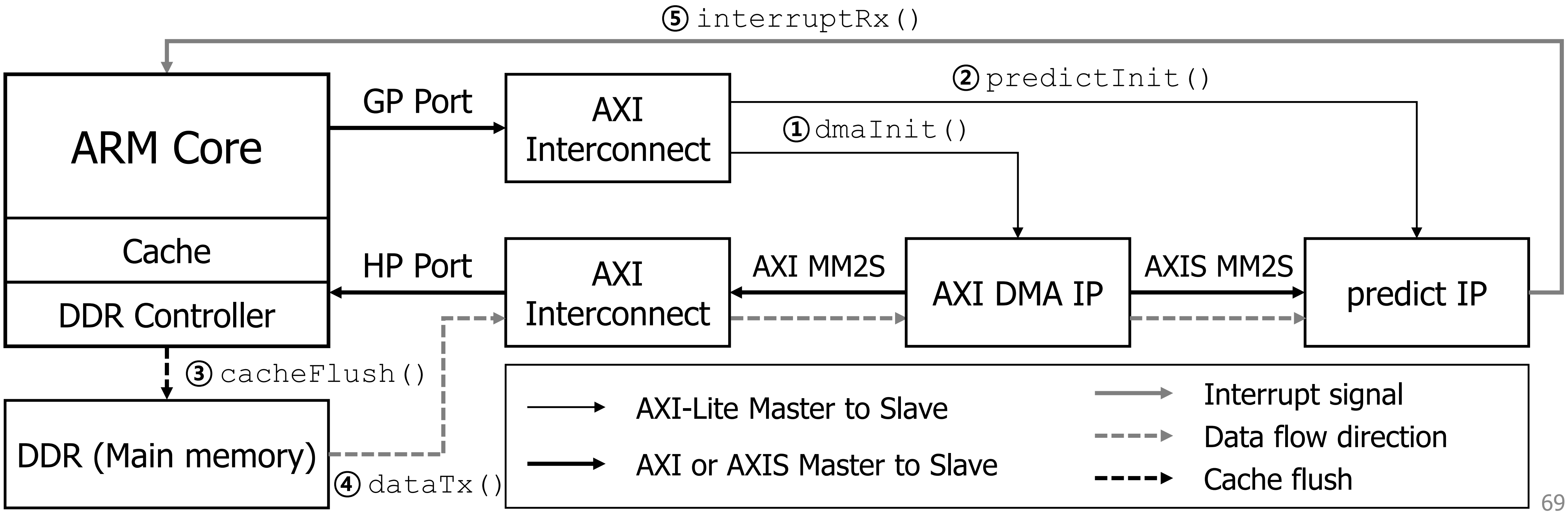
Model	vs. HW
Original (-O0)	**98 % ↓**
Original (-O1)	87 % ↓
Original (-O2)	**86 % ↓**
Original (-O3)	87 % ↓
Lite (-O0)	**94 % ↓**
Lite (-O1)	64 % ↓
Lite (-O2)	42 % ↓
Lite (-O3)	**36 % ↓**

	-O0	-O1	-O2	-O3	-O0	-O1	-O2	-O3	HW
Average	**33.08** ms	6.15 ms	**6.05** ms	6.50 ms	**13.13** ms	2.30 ms	1.43 ms	**1.29** ms	**0.82** ms



Overview of HW Design & SW Driver & Performance

- HW Design
  - Predict IP based on AXI Stream is connected to main memory (DDR) through DMA IP.
- SW Driver
  - When the interrupt signal becomes active HIGH, read the result and measure the latency.
- Performance Analysis
  - Comparing the result of different compile options in PS and the results through predict IP in PL.



References (Xilinx documents)

- Vivado Design Suite User Guide (High-Level Synthesis), UG902 (v2020.1)
- Vivado Design Suite Tutorial (High-Level Synthesis), UG871 (v2015.4)
- Vivado Design Suite AXI Reference Guide, UG1037 (v4.0)
- Vivado Design Suite User Guide (Programming and Debugging) UG908 (v2022.2)
- AXI DMA (v7.1) LogiCORE IP Product Guide, PG021
- AXI Timer (v2.0) LogiCORE IP Product Guide, PG079
- Zynq-7000 SoC Technical Reference Manual, UG585 (v1.13)
- Zynq-7000 All Programmable SoC Software Developers Guide, UG812 (v12.0)
- A Zynq Accelerator for Floating Point Matrix Multiplication Designed with Vivado HLS, XAPP1170 (v2.0)

References (etc.)

- The Zynq Book (Embedded Processing with the ARM Cortex-A9 on the Xilinx Zynq-7000 All Programmable SoC)
- Parallel Programming for FPGAs (The HLS Book)
- ZynqNet : An FPGA-Accelerated Embedded Convolutional Neural Network
- Eyeriss : A Spatial Architecture for Energy-Efficient Dataflow for Convolutional Neural Networks
- Deep Learning with Limited Numerical Precision
- Wavedrom (https://wavedrom.com/)
- Github (https://github.com/wasinsangdam/LeNet-5)

THANK YOU!