Optimizing FPGA-based Accelerator Design for Deep Convolutional Neural Network

Chen Zhang¹, Peng Li³, Guangyu Sun^{1,2}, Yijin Guan¹, Bingjun Xiao³, Jason Cong^{1,2,3}

¹Peking University ²PKU/UCLA Joint Research Institution ³University of California, Los Angeles



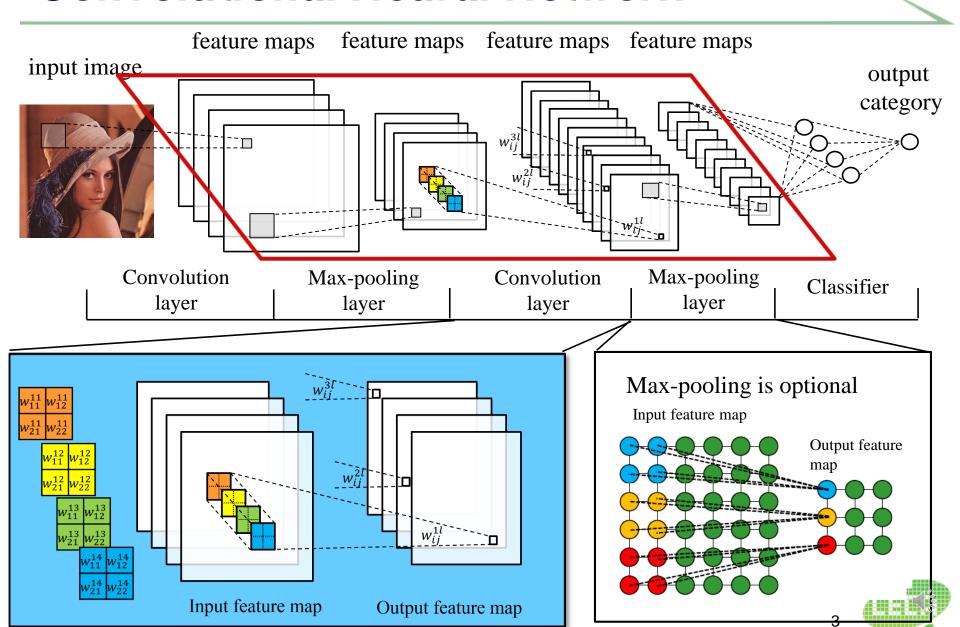
Convolutional Neural Network



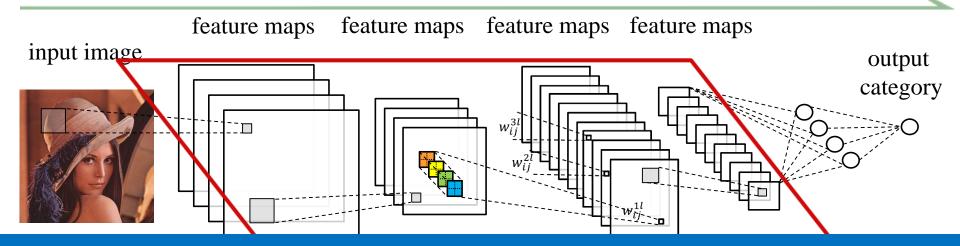
a person sitting at a

table

Convolutional Neural Network

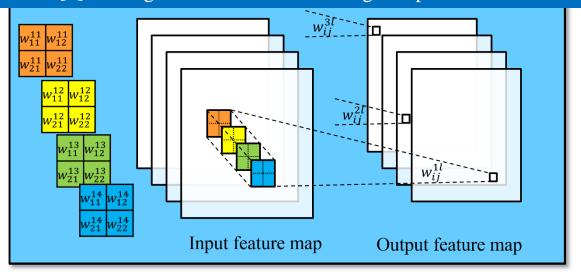


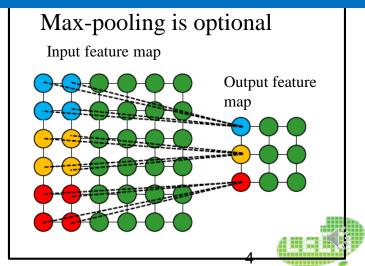
Convolutional Neural Network



Convolutional layers account for over 90% computation

[1] A. Krizhevsky, etc. Imagenet classification with deep convolutional neural networks. NIPS 2012. [2] J. Cong and B. Xiao. Minimizing computation in convolutional neural networks. ICANN 2014



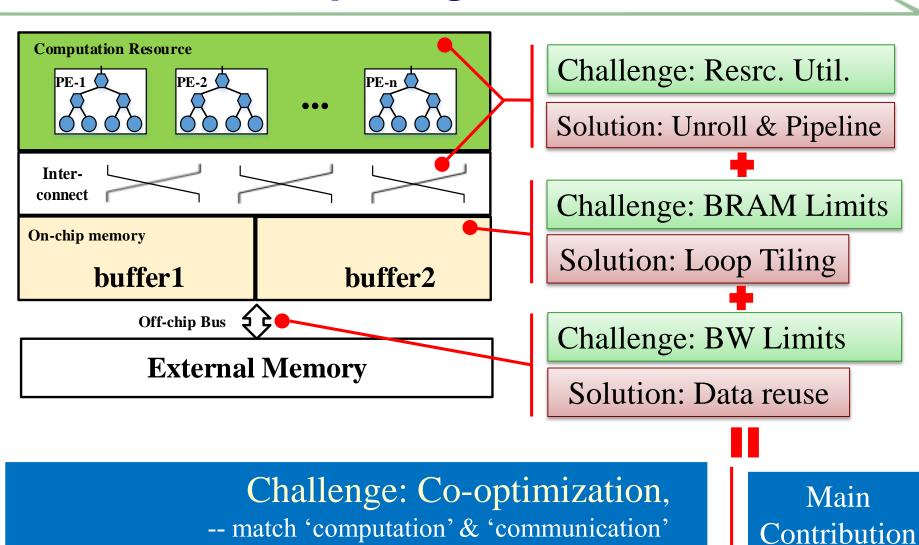


Related Work

- 1. CNP: An FPGA-based processor for convolutional networks. FPL 2009;
- 2. A massively parallel coprocessor for convolutional neural networks. ASAP 2009;
- 3. A programmable parallel accelerator for learning and classification. PACT 2010;
- 4. A Dynamically Configurable Coprocessor for Convolutional Neural Networks. ISCA 2010;
- 5. Design and Implementation of an FPGA-based Real-Time Face Recognition System. (short paper) FCCM 2011;
- 6. A massively parallel digital learning processor. NIPS 2008;
- 7. NeuFlow: A Runtime Reconfigurable Dataflow Processor for Vision. CVPRW 2011;
- 8. Accelerating deep neural networks on mobile processor with embedded programmable logic. (Poster) NIPS 2013;
- 9. Memory-Centric Accelerator Design for Convolutional Neural Networks. ICCD 2013.

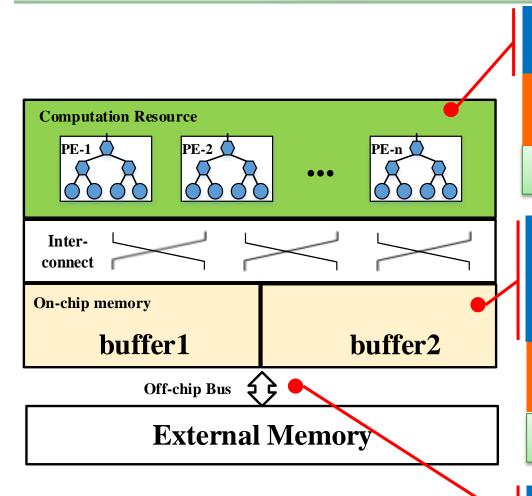


Hardware Computing on FPGA



Solution: Roofline Model

FPGA design in Roofline Model



Computational Perf.

 $= \frac{total\ number\ of\ operations}{execution\ cycles}$

GFLOP/S

Computation To Communication Ratio

 $= \frac{Total\ number\ of\ operations}{Amount\ of\ external\ data\ access}$

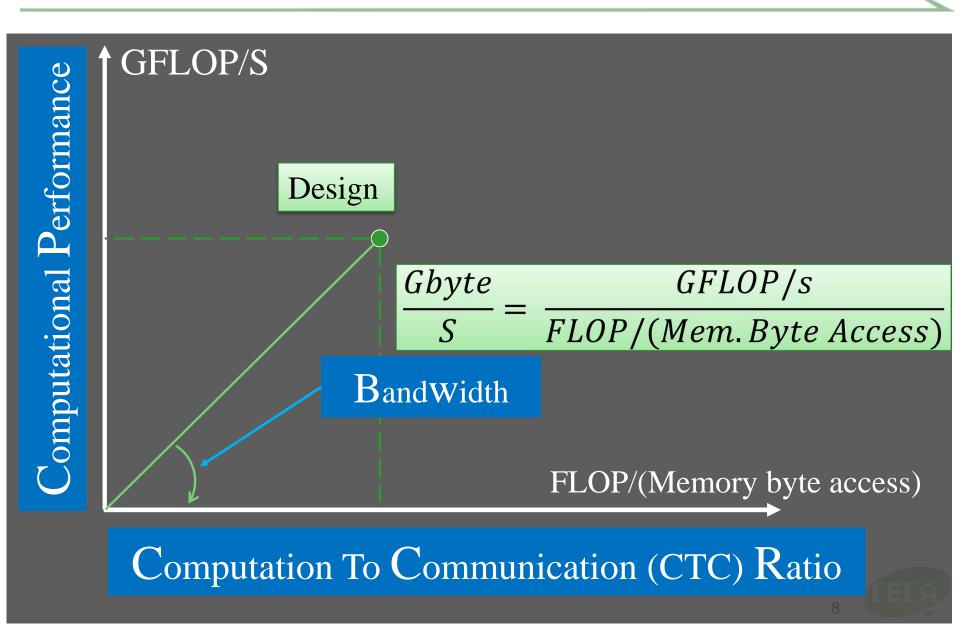
FLOP / (Mem. Byte Access)

BandWidth

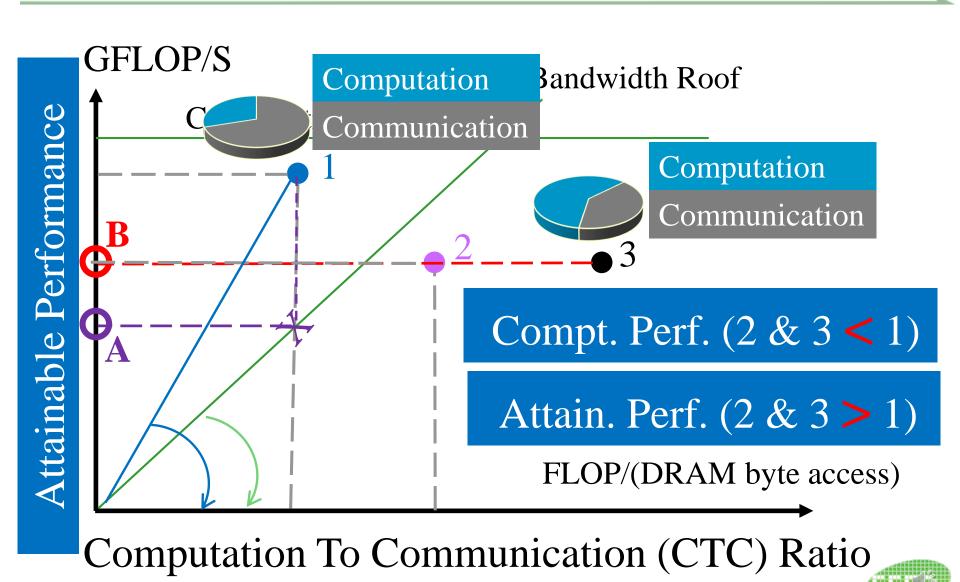
Gbyte/S



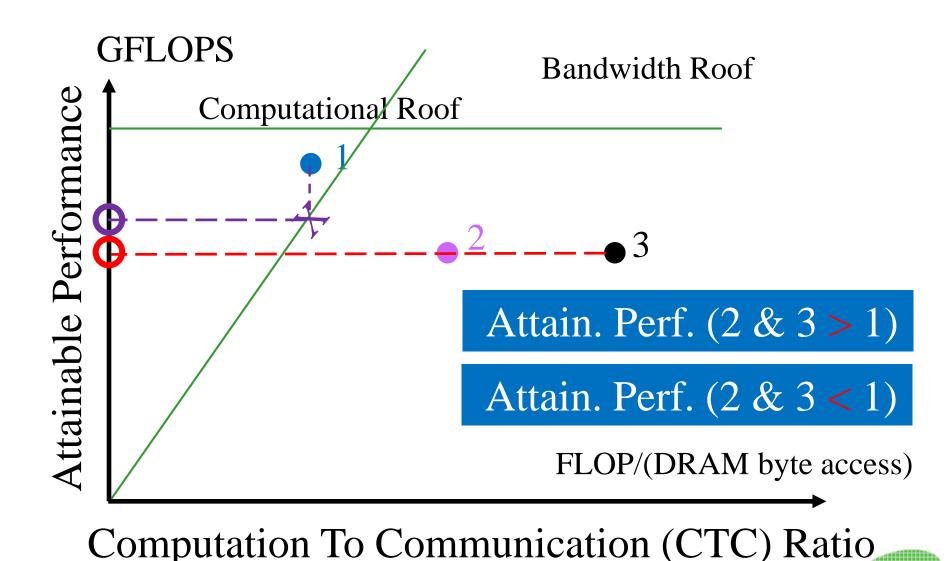
FPGA design in Roofline Model



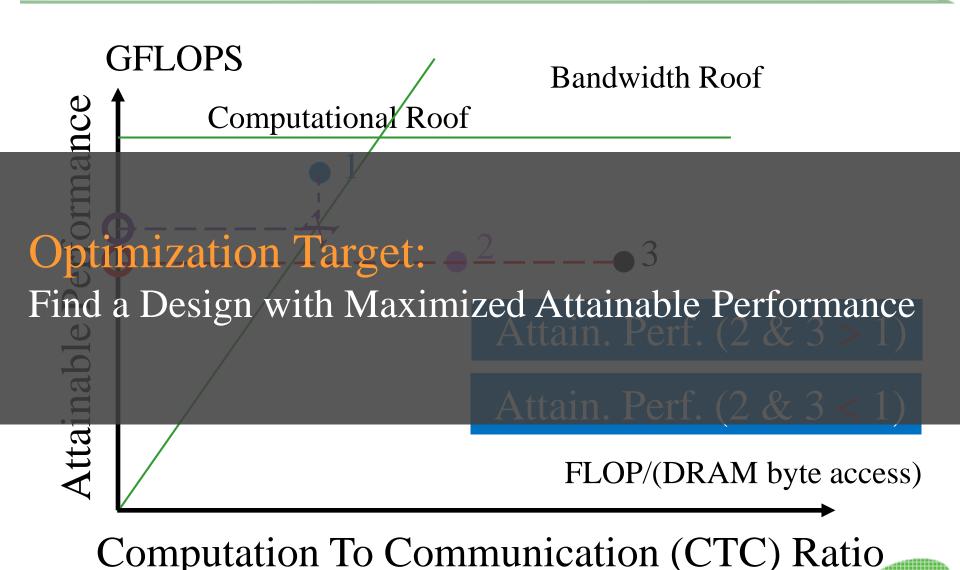
Attainable Performance



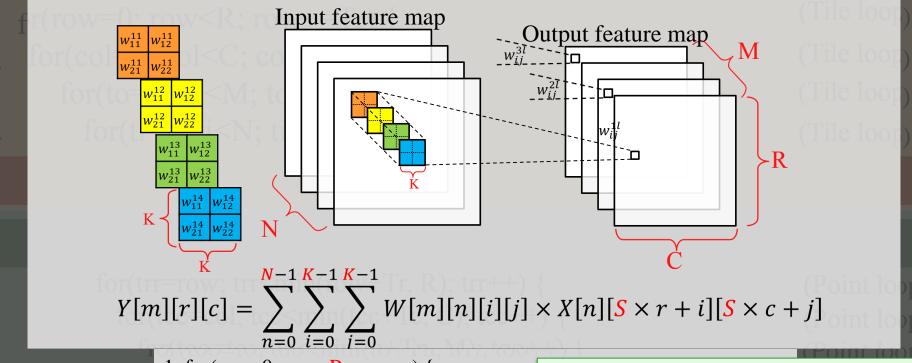
Attainable Performance



Attainable Performance



Loop tiling



```
1 for(row=0; row<R; row++) {
2  for(col=0; col<C; col++) {
3  for(to=0; to<M; to++) {
4  for(ti=0; ti<N; ti++) {
5  for(j=0; j<K; j++) {
6  output_fm[to][row][col] +=
  weights[to][ti][i][j]*input_fm[ti][S*row+i][S*col+j];
}}
```

Loop tiling

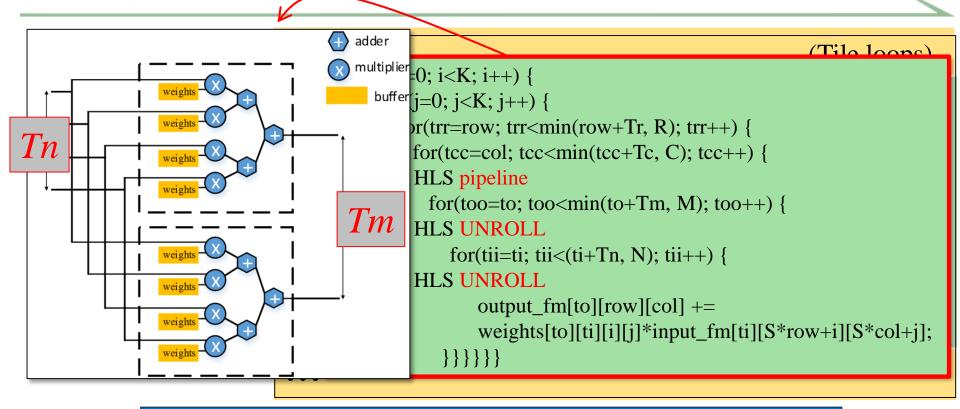
```
(Tile loop)
  for(row=0; row<R; row+=Tr) {
    for(col=0; col<C; col+=Tc) {
                                                                  (Tile loop)
      for(to=0; to<M; to+=Tm) {
3
                                                                  (Tile loop)
        for(ti=0; ti<N; ti+=Tn) {
                                                                  (Tile loop)
          Off-chip Data Transfer: Memory Access Optimization
                On-chip Data: Computation Optimization
         for(trr=row; trr<min(row+Tr, R); trr++) {
                                                                   (Point loop)
```

```
for(tcc=col; tcc<min(tcc+Tc, C); tcc++) {
                                                                             (Point loop)
               for(too=to; too<min(to+Tn, M); too++) {
                                                                             (Point loop)
                for(tii=ti; tii<(ti+Tn, N); tii++) {
                                                                             (Point loop)
                  for(i=0; i<K; i++) {
                                                                             (Point loop)
                    for(j=0; j< K; j++) {
10
                                                                              (Point loop)
                       output_fm[to][row][col] +=
                       weights[to][ti][i][j]*input_fm[ti][S*row+i][S*col+j];
            }}}}
```

Computation Optimization

```
(Tile loops)
```

Computation Optimization



total number of operations Computational Performance = execution cycles

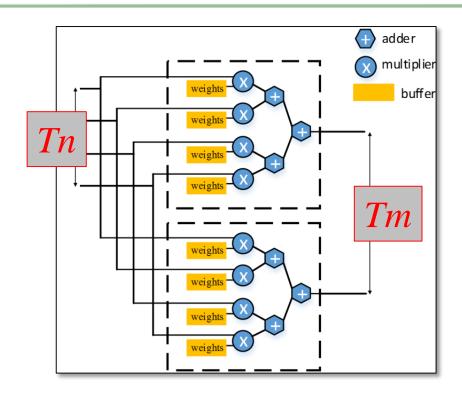
execution cycles =
$$\frac{R}{Tr} \times \frac{C}{Tc} \times \left[\frac{M}{Tm}\right] \times \left[\frac{N}{Tn}\right] \times (K \times K \times Tc \times Tr + P)$$

$$\approx \left[\frac{M}{Tm}\right] \times \left[\frac{N}{Tn}\right] \times R \times C \times K \times K$$





Computational Performance

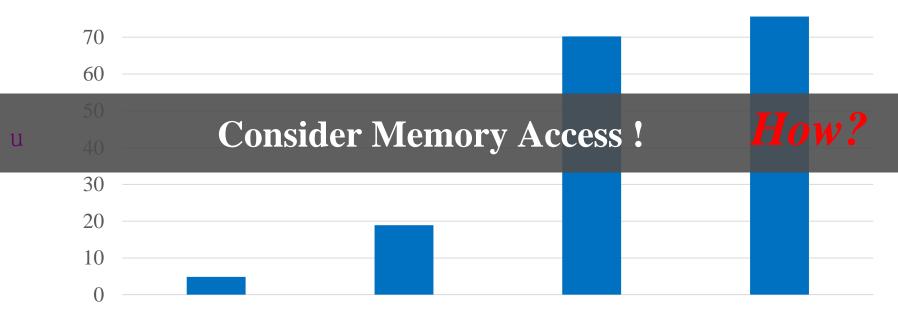


	Design 1	Design 2	Design 3	Design 4
Output (Tm)	5	10	20	30
Input (Tn)	5	10	20	15
DSPs	125	500	2000	2250



Computational Performance

 $\label{eq:computational} \text{Computational Performance} = \frac{total \ number \ of \ operations}{execution \ cycles}$



	Design 1	Design 2	Design 3	Design 4
Output (Tm)	5	10	20	30
Input (Tn)	5	10	20	15
DSPs	125	500	2000	2250



Memory Access Optimization

Memory Access Optimization

```
for(row=0; row<R; row+=Tr) {
                                             for(row=0; row<R; row+=Tr) {
 for(col=0; col< C; col+=Tc) 
                                              for(col=0; col< C; col+=Tc)
    for(to=0; to < M; to +=Tm) {
                                               for(to=0; to< M; to+=Tm) {
      for(ti=0; ti<N; ti+=Tn) {
                                                  load output feature map
                                                  for(ti=0; ti<N; ti+=Tn) {
load output feature map
                                              S: foo(output_fm(to, row, col));
S: foo(output_fm(to, row, col));
store output feature map
                                                store output feature map
                                           }}}
                                               After local memory promotion
```

Before local memory promotion

$$= 2 \times \frac{R}{Tr} \times \frac{C}{Tc} \times \frac{M}{Tm} \times \frac{N}{Tn} \times \frac{Size_{array}}{T}$$

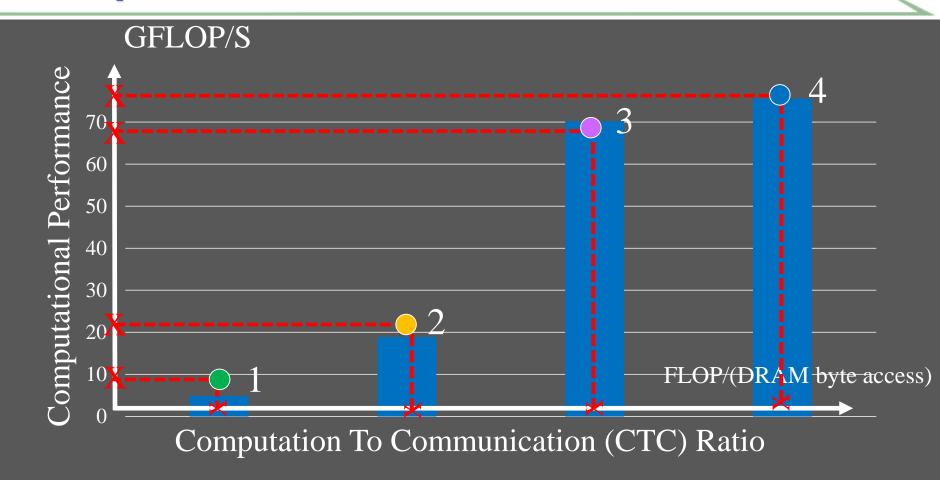
'output_fm' memory access

$$= 2 \times \frac{R}{Tr} \times \frac{C}{Tc} \times \frac{M}{Tm} \times Size_{array}$$

Total number of operations Total amount of external data access

Computation to Communication Ratio =

Computation To Communication Ratio



	Design 1	Design 2	Design 3	Design 4
Output (Tm)	5	10	20	30
Input (Tn)	5	10	20	15

Design Space

Computation Engine:

Constraints for CNN configurations:

$$Tm \in (Integer, 1 < Tm < M)$$
 N=128
 $Tn \in (Integer, 1 < Tn < N)$ N=192

Constraints for FPGA resource:

$$Tn \times Tm \in (Integer, 1 < Tm \times Tn < \# \text{ of PE})$$

of PE = 450

Legal Solutions of Tm & Tn:

2097

Communication:

of memory access methods

Legal Solutions:

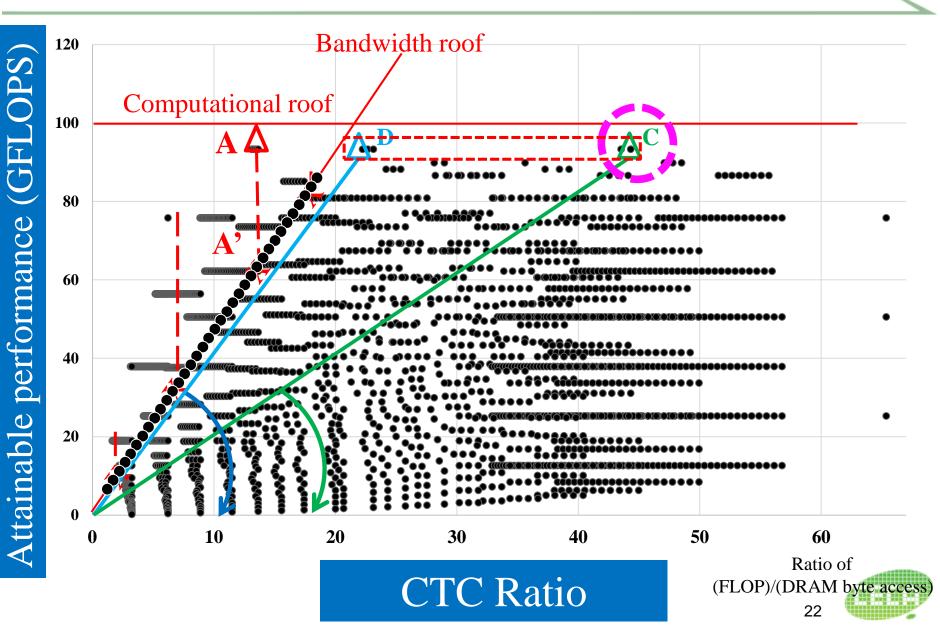
3

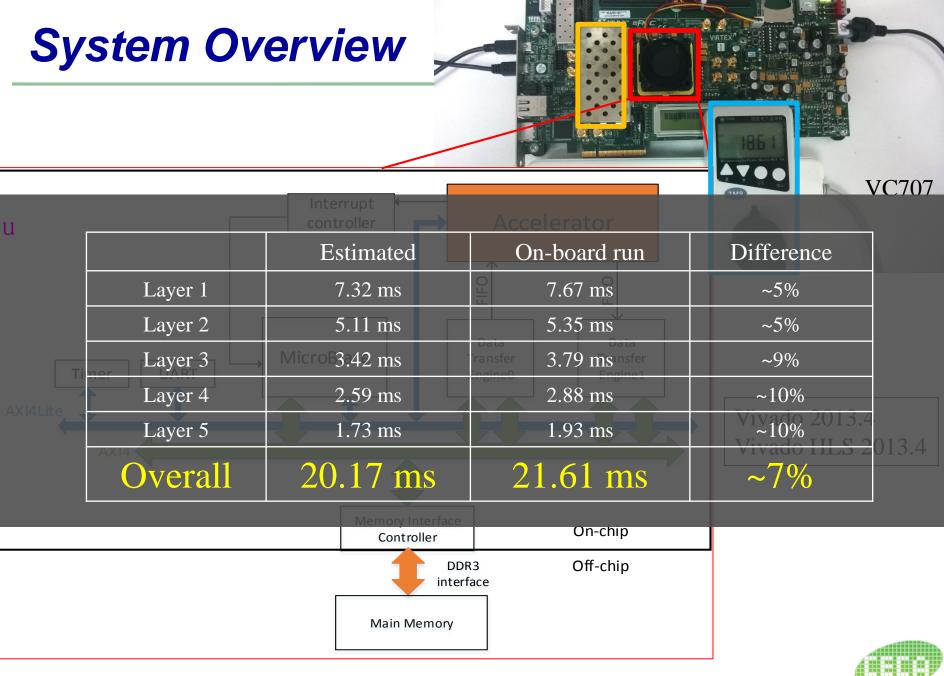


Total Legal Solutions:

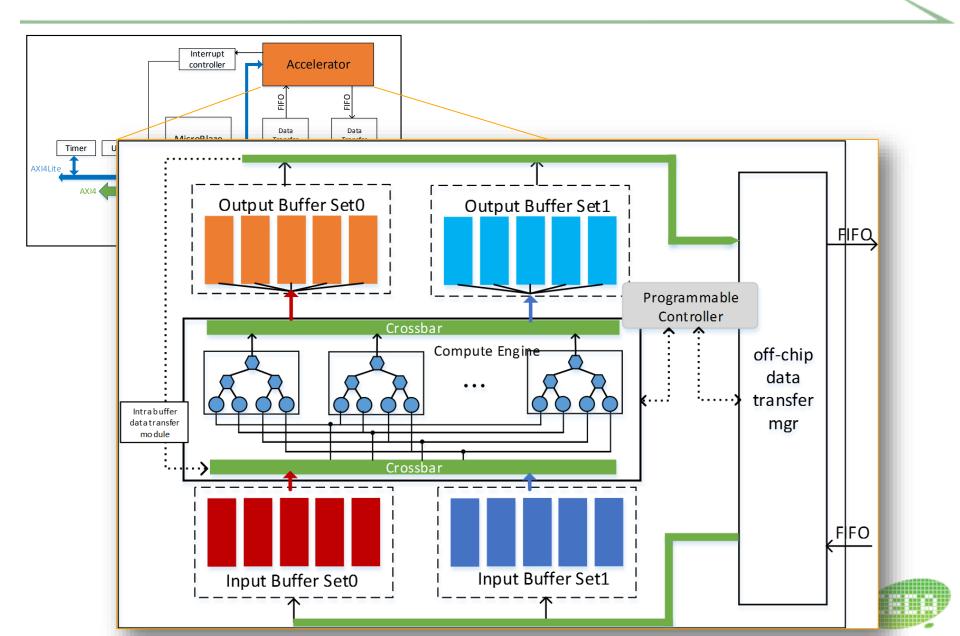
6291

Design Space Exploration

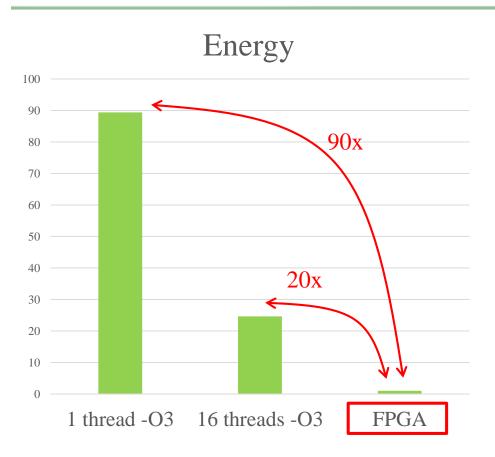


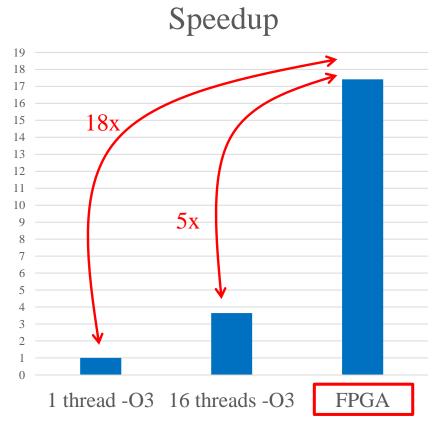


Accelerator



Experimental Results: vs. CPU



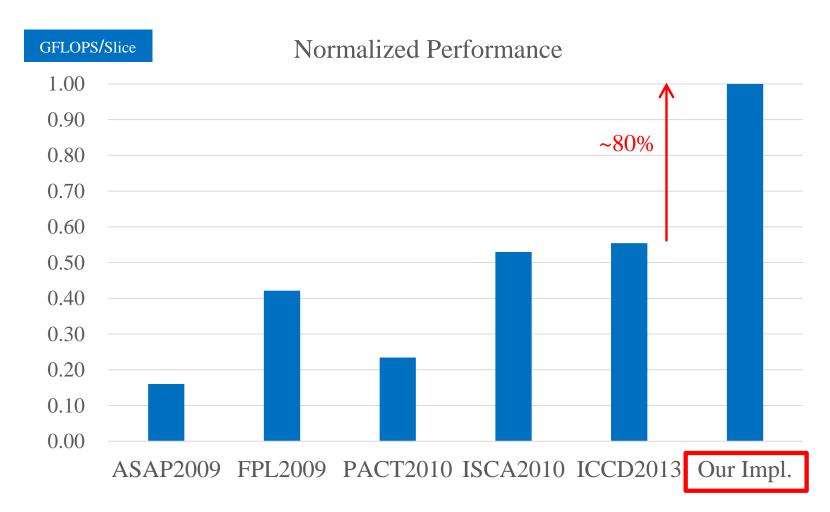


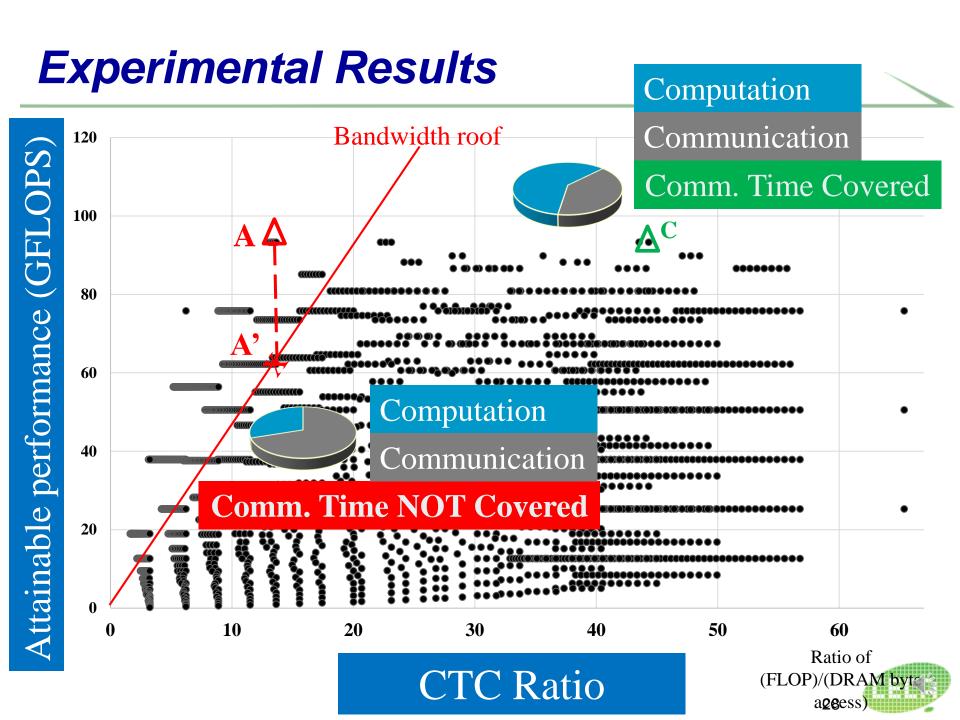
CPU	Xeon E5-2430 (32nm)	16 cores	2.2 GHz	gcc 4.7.2 –O3 OpenMP 3.0
FPGA	Virtex7-485t (28nm)	448 PEs	100MHz	Vivado 2013.4 Vivado HLS 2013.4

Experimental Results: vs. Other FPGAs

FPL2009	ASAP2009	PACT2010	ISCA2010	ICCD2013	Our Impl.
Virtex 4	Virtex 5	Virtex 5	Virtex 5	Virtex 6	Virtex 7
125MHz	115MHz	125MHz	200MHz	150MHz	100MHz
5.25 GOPS	6.74 GOPS	7 GOPS	16 GOPS	17 GOPS	61.6 GOPS

Experimental Results: vs. Other FPGAs





Conclusions

■ An accelerator for convolutional neural network

- **Contribution:**
 - >Accurate Analytical model for computation & communication
 - Find the best solution with roofline model
- **Result:**
 - **≻On-board run implementation**
 - >~3.5x better performance over other FPGA implementations
 - >~80% performance/area improvement



Thank You Q & A