### ECE 5997 Hardware Accelerator Design & Automation Fall 2021

# Pipelining



**Cornell University** 



# Announcements

- DNN acceleration tutorial cancelled
  - Slides will be posted on Tuesday

# **Digit Recognition Lab**

- Use a simple machine learning algorithm to recognize handwritten digits
  - 2000 training instances per digit
  - Each training/test instance is a 7x7 bitmap after downsampling



MNIST dataset: http://yann.lecun.com/exdb/mnist/

# **K-Nearest-Neighbor (KNN) Implementation**

```
bit4 digitrec( digit input )
ł
 #include "training_data.h"
 // This array stores K minimum distances per training set
  bit6 knn_set[10][K_CONST];
 // Initialize the knn set
 for ( int i = 0; i < 10; ++i )
   for ( int k = 0; k < K CONST; ++k )
                                            Main compute loop
     // Note that the max distance is 49
                                            (10 cycles per innermost loop)
      knn_set[i][k] = 50;
 L2000: for ( int i = 0; i < TRAINING SIZE; ++i ) {
   L10: for (int j = 0; j < 10; j++) {
     // Read a new instance from the training set
      digit training instance = training data[j * TRAINING SIZE + i];
      // Update the KNN set
      update knn( input, training instance, knn set[j] );
   }
```

~200K cycles by default without optimizations

# **10x Speedup through Parallelization**

```
bit4 digitrec( digit input )
{
 #include "training_data.h"
  // This array stores K minimum distances per training set
  bit6 knn_set[10][K_CONST];
  // Initialize the knn set
  for ( int i = 0; i < 10; ++i )
    for ( int k = 0; k < K CONST; ++k )
      // Note that the max distance is 49
      knn set[i][k] = 50;
 Unroll inner loop completely
 L2000: for ( int i = 0; i < TRAINING_SIZE; ++i ) {
Partition training
   L10: for ( int j = 0; j < 10; j++ ) {
                                                    set into 10 banks
      // Read a new instance from the training set
      digit training_instance = training_data[j * TRAINING_SIZE + i];
      // Update the KNN set
      update_knn( input, training_instance, knn_set[j] );
   }
  }
```

~20K cycles after parallelization

# **Further Speedup through Pipelining**

```
bit4 digitrec( digit input )
{
 #include "training_data.h"
  // This array stores K minimum distances per training set
  bit6 knn_set[10][K_CONST];
  // Initialize the knn set
  for ( int i = 0; i < 10; ++i )
    for ( int k = 0; k < K CONST; ++k )
      // Note that the max distance is 49
                                            Pipeline outer loop
      knn set[i][k] = 50;
 Unroll inner loop completely
  L2000: for ( int i = 0; i < TRAINING_SIZE; ++i
                                                    {
Partition training
   L10: for ( int j = 0; j < 10; j++ ) {
                                                     set into 10 banks
      // Read a new instance from the training set
      digit training_instance = training_data[j * TRAINING_SIZE + i];
      // Update the KNN set
      update_knn( input, training_instance, knn_set[j] );
   }
  }
```

~2K cycles after pipelining

# Outline

- Restrictions of Pipeline Throughput
  - Types of recurrences
- Modulo scheduling concepts
  - Extending SDC formulation for pipelining
- Case studies on HLS pipelining

# **Recap: Restrictions of Pipeline Throughput**

- Resource limitations
  - Limited compute resources
  - Limited Memory resources (esp. memory port limitations)
  - Restricted I/O bandwidth
  - Low throughput of subcomponent

• • •

#### Recurrences

- Also known as feedbacks, carried dependences
- Fundamental limits of the throughput of a pipeline

# **Type of Recurrences**

- Types of dependences
  - True dependences, anti-dependences, output dependences
  - Intra-iteration vs. inter-iteration dependences
- Recurrence if one iteration has dependence on the same operation in a previous iteration
  - Direct or indirect
  - Data or control dependence
- Distance number of *iterations* separating the two dependent operations (0 = same iteration or intra-iteration)

### **True Dependences**

True dependence

1

- Aka flow or RAW (Read After Write) dependence
- S1 →<sup>t</sup>S2
  - Statement S1 precedes statement S2 in the program and computes a value that S2 uses

Example:

# **Anti-Dependences**

- Anti-dependence
  - Aka WAR (Write After Read) dependence
  - S1 →<sup>a</sup> S2
    - S1 precedes S2 and may read from a memory location that is later updated by S2
  - Renaming (e.g., SSA) can resolve many of the WAR dependences

Example:

for (... i++) {  

$$A[i-1] = b - a;$$
  
 $B[i] = A[i] + 1$  Inter-iteration anti-dependence  
on A (distance = 1)  
}

# **Output Dependences**

- Output dependence
  - Aka WAW (Write After Write) dependence
  - S1 precedes S2 and may write to a memory location that is later (over)written by S2
  - Renaming (e.g., SSA) can resolve many of the WAW dependences

Example:  
for 
$$(... i++)$$
 {  
 $B[i] = A[i-1] + 1$   
 $A[i] = B[i+1] + b$   
 $B[i+2] = b - a$   
 $\{distance = 2\}$ 

# **Dependence Graph**

- Data dependences of a loop often represented by a dependence graph
  - Forward edges: Intra-iteration (loopindependent) dependences
  - Back edges: Inter-iteration (loop-carried) dependences
  - Edges are annotated with **distance** values: number of iterations separating the two dependent operations involved
- Recurrence manifests itself as a circuit in the dependence graph



Edges annotated with distance values

# **Modulo Scheduling**

- A regular form of loop (or function) pipelining technique
  - Also applies to software pipelining in compiler optimization
  - Loop iterations use the same schedule, which are initiated at a constant rate
- Advantages of modulo scheduling
  - Easy to analyze: Steady state determines performance & resource
  - Cost efficient: No code or hardware replication
- Optimization objective
  - minimize II under resource constraints
  - minimize resource usage under II constraint

#### NP-hard in general

Optimal polynomial time solution exists without recurrences or resource constraints

# **Modulo Scheduling Example**



# **Algorithmic Scheme for Modulo Scheduling**

- Common scheme of heuristic algorithms
  - Find a lower bound on II: MII = max { ResMII, RecMII }
  - Look for a schedule with the given II
  - If a feasible schedule not found, increase II and try again



# **Calculating Lower Bound of Initiation Interval**

- Minimum possible II (MII)
  - MII = max(ResMII, RecMII)
  - A lower bound, not necessarily achievable
- Resource constrained MII (ResMII)
  - ResMII = max<sub>i</sub> [OPs(r<sub>i</sub>) / Limit(r<sub>i</sub>)]
     OPs(r): number of operations that use resource of type r Limit(r): number of available resources of type r
- Recurrence constrained MII (RecMII)
  - RecMII = max<sub>i</sub>  $\lceil Latency(c_i) / Distance(c_i) \rceil$

Latency( $c_i$ ): total latency in dependence circuit  $c_i$ Distance( $c_i$ ): total distance in dependence circuit  $c_i$ 

# Minimum II due to Resource Limits (ResMII)



- Compute ResMII: Max among all types of resources
  - ResMII = max<sub>i</sub>  $\lceil OPs(r_i) / Limit(r_i) \rceil$

### Minimum II due to Recurrences (RecMII)



- Compute Recurrence Minimum II (RecMII):
  - Max among all circuits of:
     RecMII = max<sub>i</sub> [Latency(c<sub>i</sub>) / Distance(c<sub>i</sub>)]
  - Latency(c) : sum of operation latencies along circuit c
  - **Distance(c)** : sum of dependence distances along circuit *c*

# **Example: Calculating the Minimum II**



#### What is the minimum II (MII) ?

# **SDC-Based Modulo Scheduling**

- The SDC formulation can be extended to support modulo scheduling
  - Unifies intra-iteration and interiteration scheduling constraints in a single SDC
  - Iterative algorithm with efficient incremental SDC update



## **Modeling Loop-Carried Dependence with SDC**

- The dependence between two operations from different iterations is termed inter-iteration (loop-carried) dependence
  - Loop-carried dependence  $u \rightarrow v$  with Dist(u, v) = K

 $s_u + Lat_u \le s_v + K^* II$ 



#### **Modeling Loop-Carried Dependence with SDC**

- The dependence between two operations from different iterations is termed inter-iteration (loop-carried) dependence
  - Loop-carried dependence  $u \rightarrow v$  with Dist(u, v) = K

 $s_u + Lat_u \le s_v + K^* II$ 



# **Case Study: Prefix Sum**

- Prefix sum computes a cumulative sum of a sequence of numbers
  - commonly used in many applications such as radix sort, histogram, etc.

```
void prefixsum ( int in[N], int out[N] )
out[0] = in[0];
for ( int i = 1; i < N; i++ ) {
    #pragma HLS pipeline II=?
    out[i] = out[i-1]+ in[i];
}</pre>
```

```
out[0] = in[0];
out[1] = in[0] + in[1];
out[1] = in[0] + in[1] + in[2];
out[1] = in[0] + in[1] + in[2] + in[3];
```

# **Prefix Sum: RecMII**

- Loop-carried dependence exists between to reads on 'out'
- Assume chaining is not possible on memory reads (Id) and writes (st) due to target cycle time
  - RecMII = 3



#### **Prefix Sum: Code Optimization**

- Introduce an intermediate variable 'tmp' to hold the running sum from the previous 'in' values
- Shorter dependence circuit leads to RecMII = 1



### **Case Study: Convolution for Image Processing**

A common computation of image/video processing is performed over overlapping stencils, termed as <u>convolution</u>

$$(Img \otimes f)_{\left[n+\frac{k-1}{2},m+\frac{k-1}{2}\right]} = \sum_{i=0}^{k-1} \sum_{j=0}^{k-1} Img_{[n+i][m+j]} \cdot f_{[i,j]}$$



# **Achieving High Throughput with Pipelining**

```
for (r = 1; r < R; r++)
for (c = 1; c < C; c++) {
    #pragma HLS pipeline II=?
    for (i = 0; i < 3; i++)
        for (j = 0; j < 3; j++)
            out[r][c] += img[r+i-1][c+j-1] * f[i][j];
    }
```

- Inner loops (i & j) are automatically unrolled
- With a 3x3 convolution kernel, 9 pixels are required for calculating the value of one output pixel
- If the entire input image is stored in an on-chip buffer with two read ports
  - ResMII = ?
  - What about RecMII?

# Achieving II=1 for 3x3 Convolution



 Pixels in line buffer (2 lines stored)
 Pixels in line buffer (2 lines stored)
 Pixels in line buffer (2 lines stored)
 Inew pixels into shift register window 1 new pixel + 2 pixels from line buffer
 Update line buffer by removing the oldest

by removing the oldest pixel and shifting in the new one



New pixel fetched from input stream or frame buffer in off-chip memory

Output pixel produced by one convolution operation

Output Frame

# **Resulting Specialized Memory Hierarchy**

Memory architecture customized for convolution



#### **HLS Code Snippet**

```
LineBuffer<2,C,pixel_t> linebuf;
 1
 \mathbf{2}
     Window<3,3,pixel_t> window;
     for (int r = 1; r < R+1; r++) {
 3
       for (int c = 1; c < C+1; c++) {
 4
         #pragma HLS pipeline II=1
 5
         pixel_t new_pixel = img[r][c];
6
         // Update shift window
7
8
         window.shift_left();
9
         if (r < R \&\& c < C) {
           for (int i = 0; i < 2; i++ )
10
             window.insert(buf[i][c]);
11
         }
12
13
         else { // zero padding
           for (int i = 0; i < 2; i++)
14
             window.insert(0);
15
         }
16
         window.insert(new_pixel);
17
18
         // Update line buffer
         linebuf.shift_up(c);
19
20
         if (r < R \&\& c < C)
           linebuf[1].insert(c, new_pixel);
21
         else // Zero padding
22
23
           linebuf[1].insert(c, 0);
         // Perform 3x3 convolution
24
         out[r-1][c-1] = convolve(window, weights);
25
26
       }
     }
27
```

#### Summary

- Pipelining is one of the most commonly used techniques in HLS to boost performance of the synthesized hardware
- Recurrences and resource restrictions limit the pipeline throughput
- Modulo scheduling
  - A regular form of software pipeline technique
    - Also applies to loop pipelining for hardware synthesis
  - NP-hard problem in general

# **Acknowledgements**

- These slides contain/adapt materials developed by
  - Prof. Ryan Kastner (UCSD)
  - Prof. Scott Mahlke (UMich)
  - Dr. Stephen Neuendorffer (Xilinx)