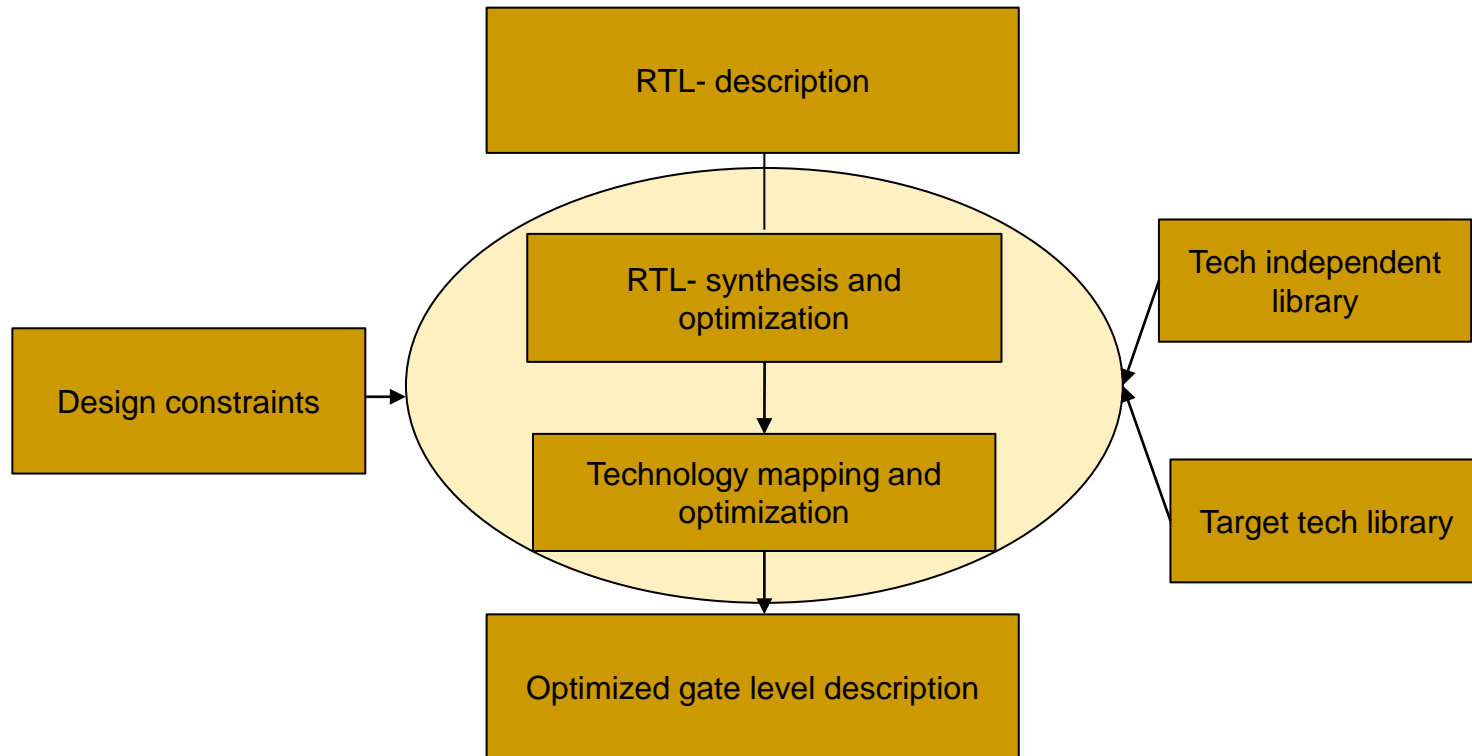


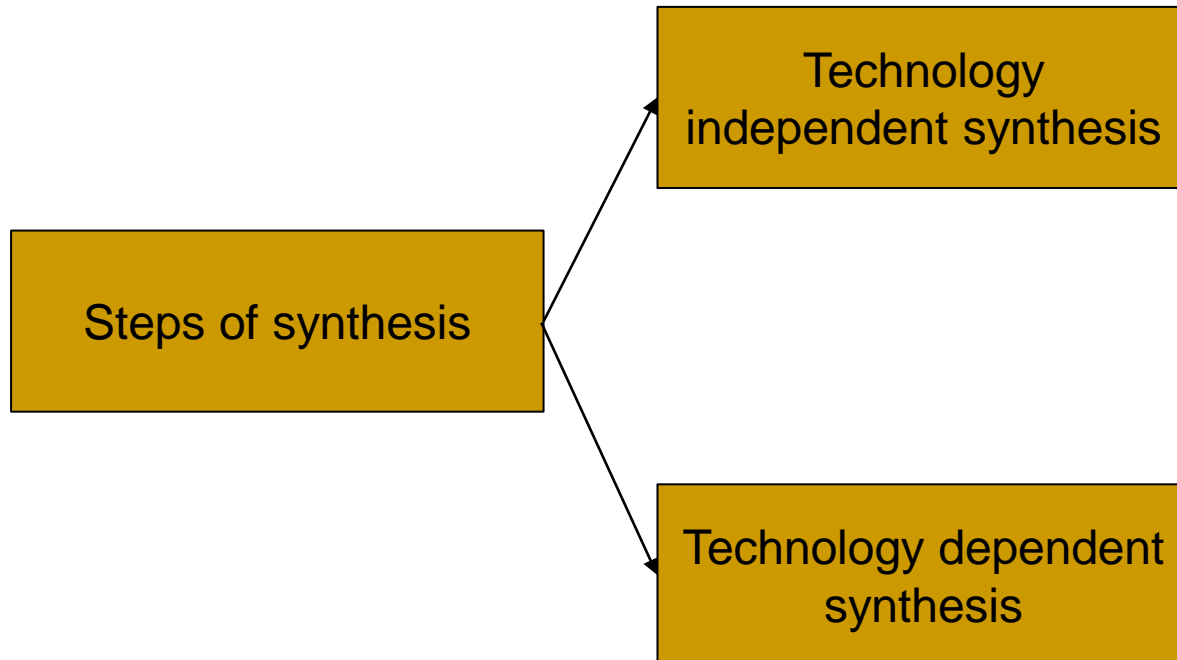
# Process of Synthesis

# Process of Synthesis



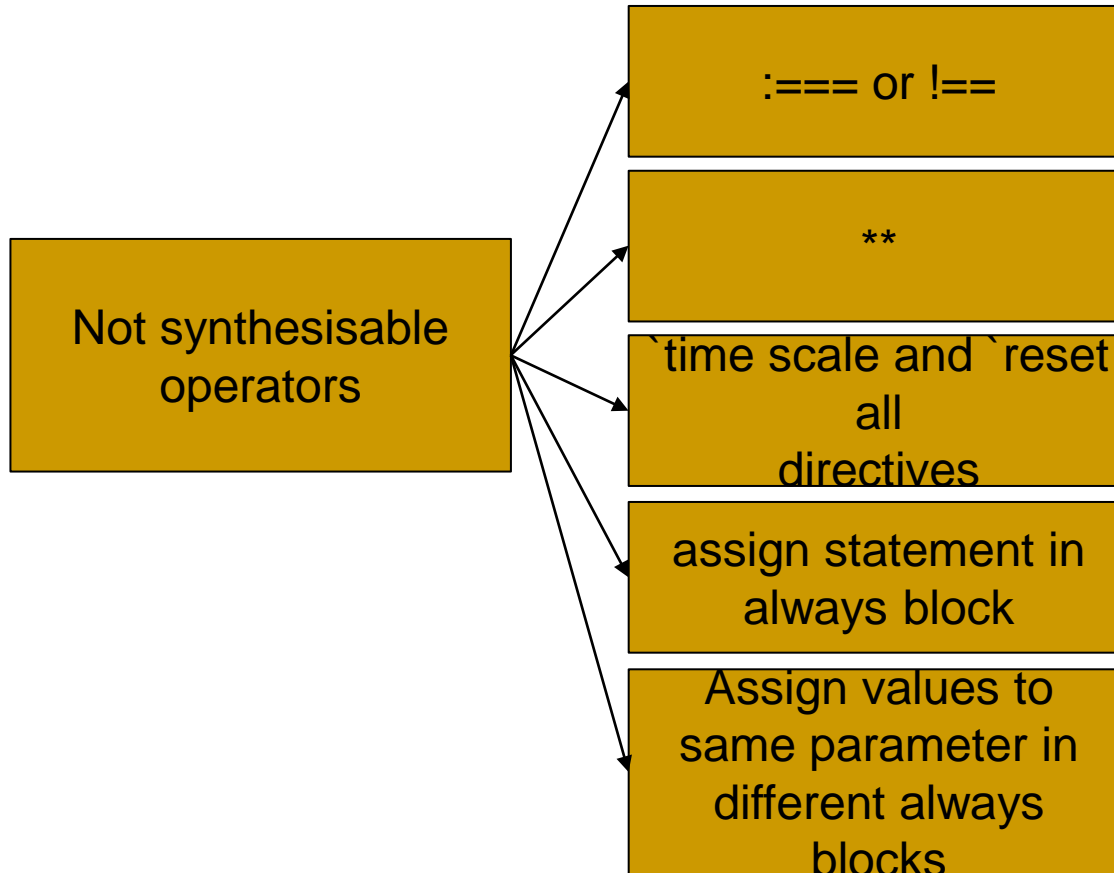
# Steps of Synthesis

---



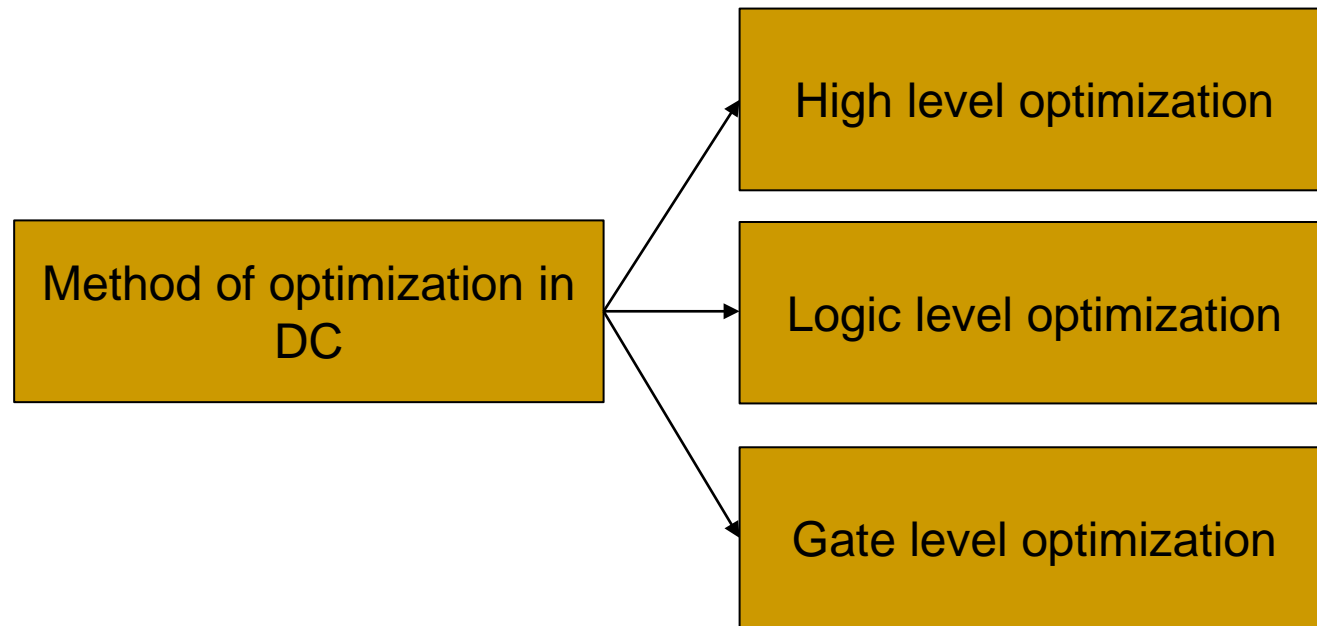
# Not Synthesisable Operators

---



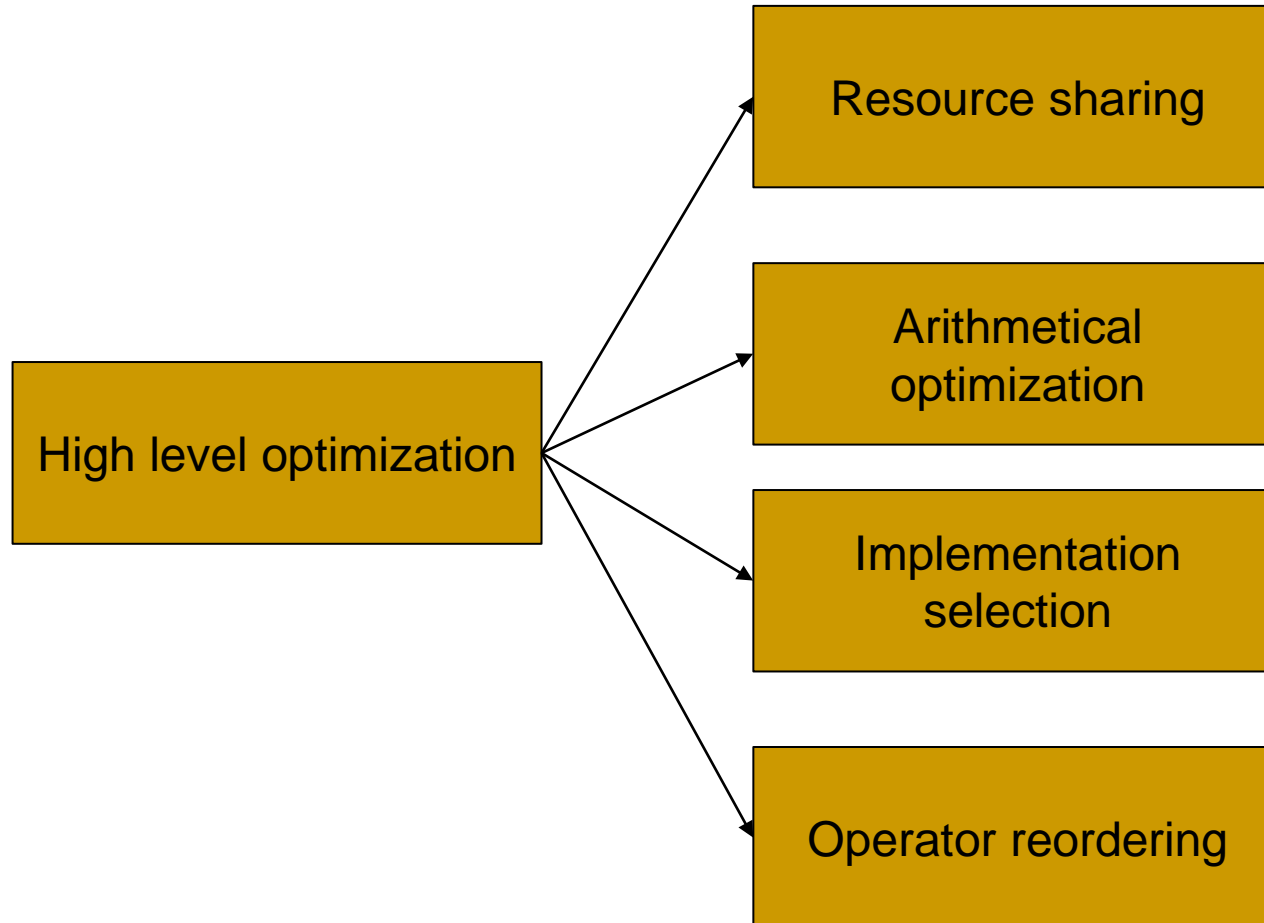
# Optimization Methods in Design Compiler

---



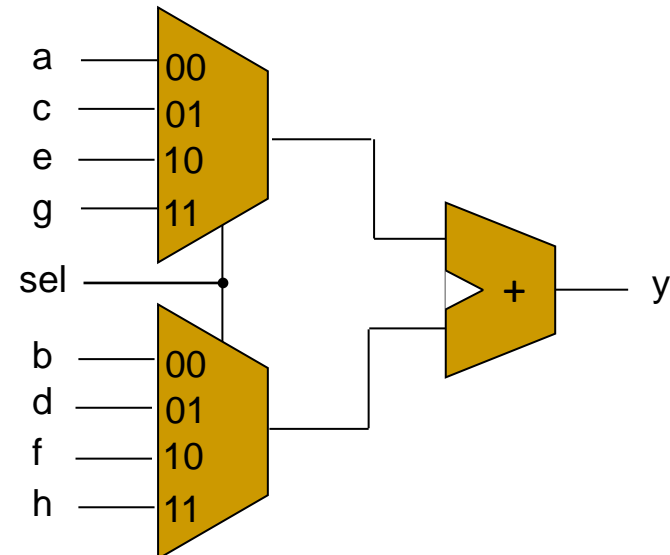
# High Level Optimization

---



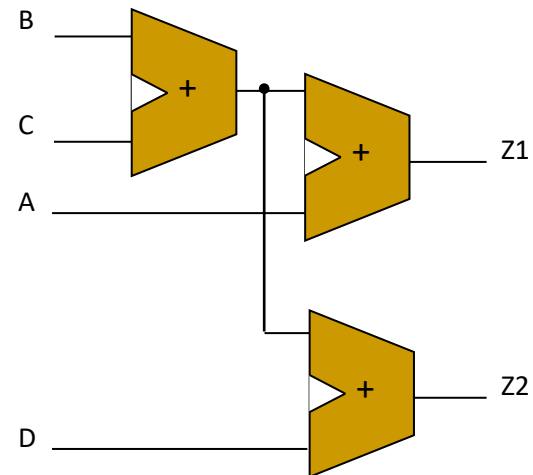
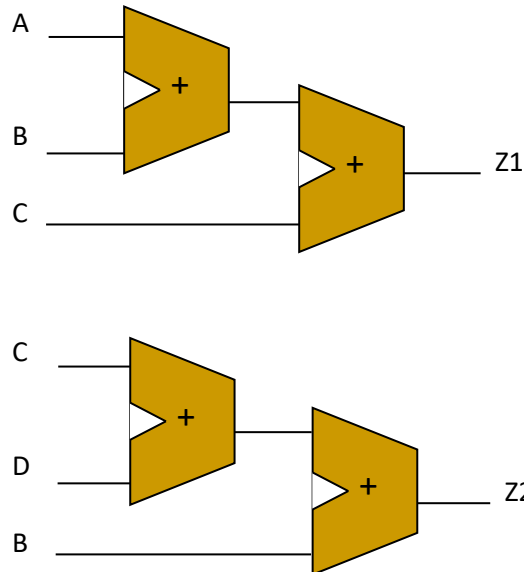
# Resource Sharing

```
if(sel==2'b00) y=a+b;  
else if(sel==2'b01)  
    y=c+d;  
else if(sel==2'b10)  
    y=e+f;  
else y=g+h;  
....
```



# Arithmetical Optimization

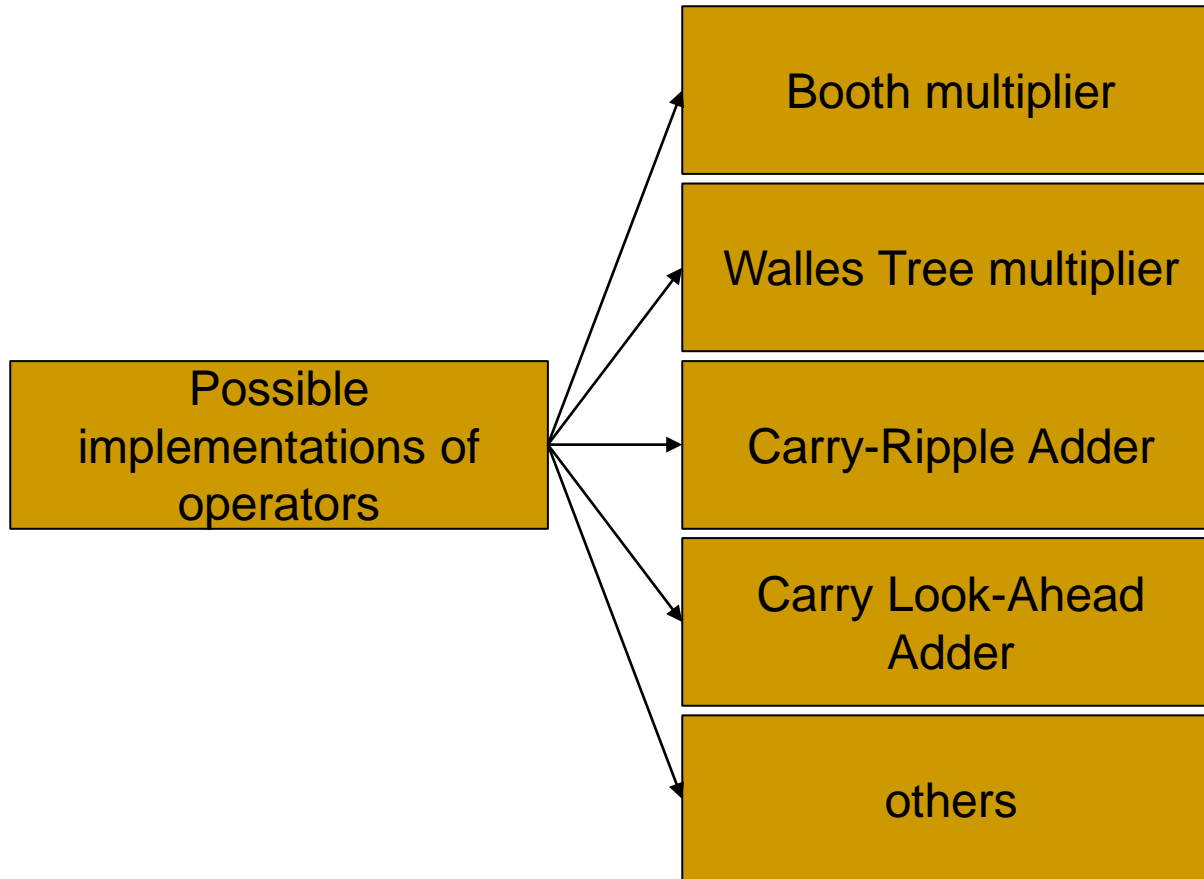
□  $Z1 = A + B + C$   $Z2 = C + D + B$





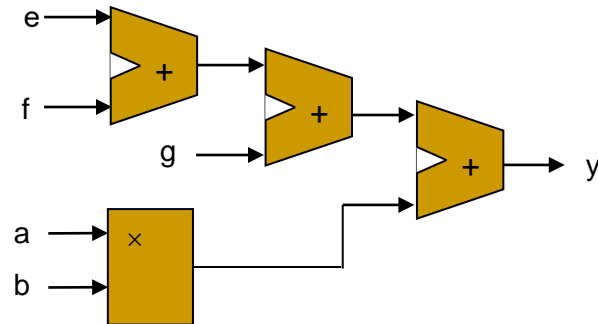
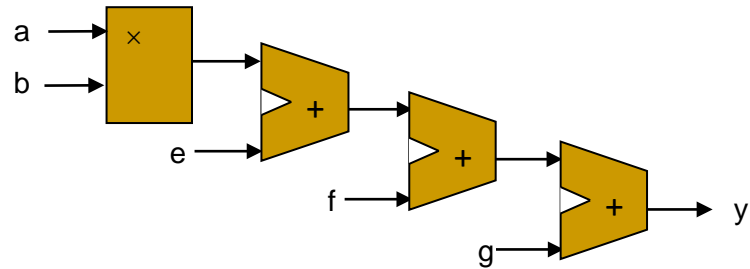
# Implementation Selection

---

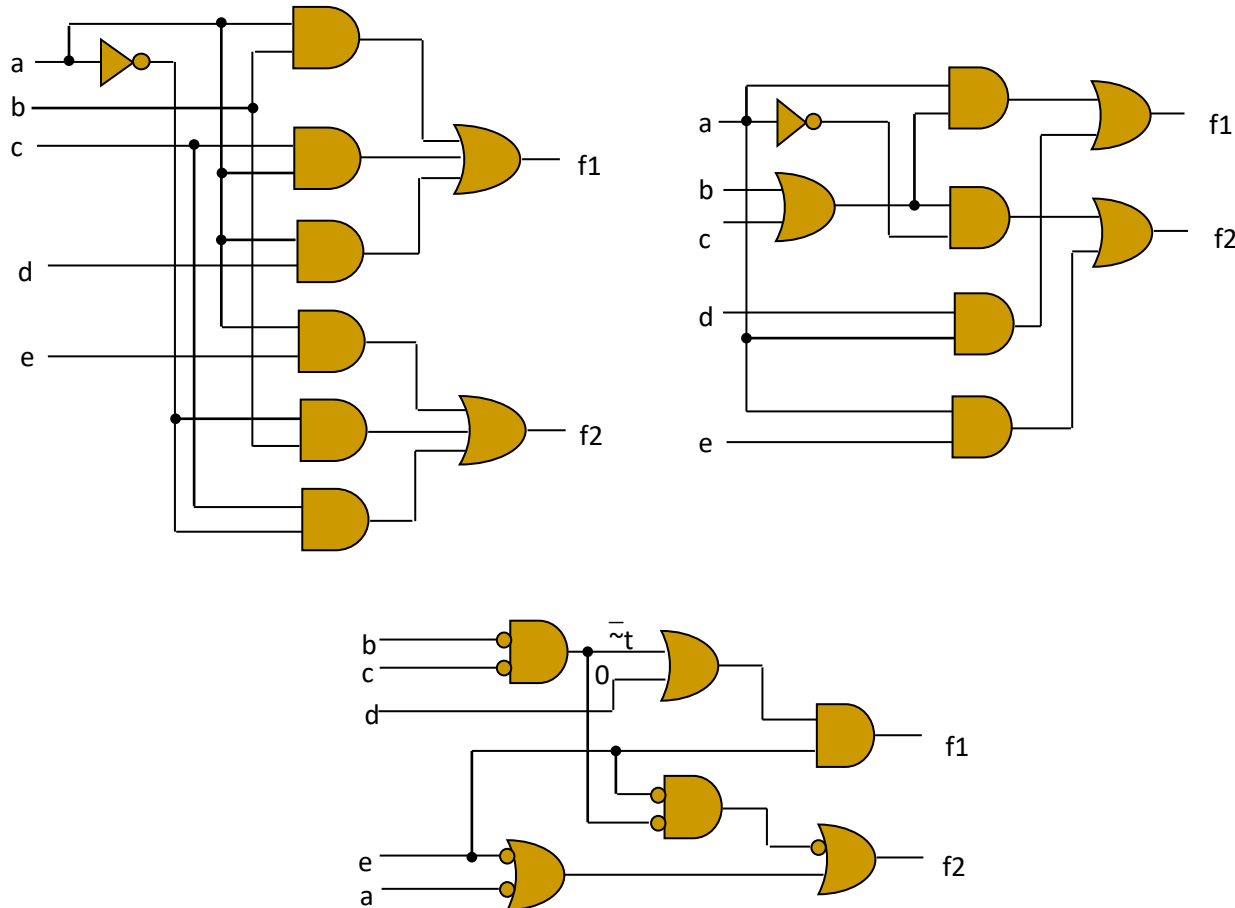


# Operator Reordering

$$Y = a * b + e + f + g$$

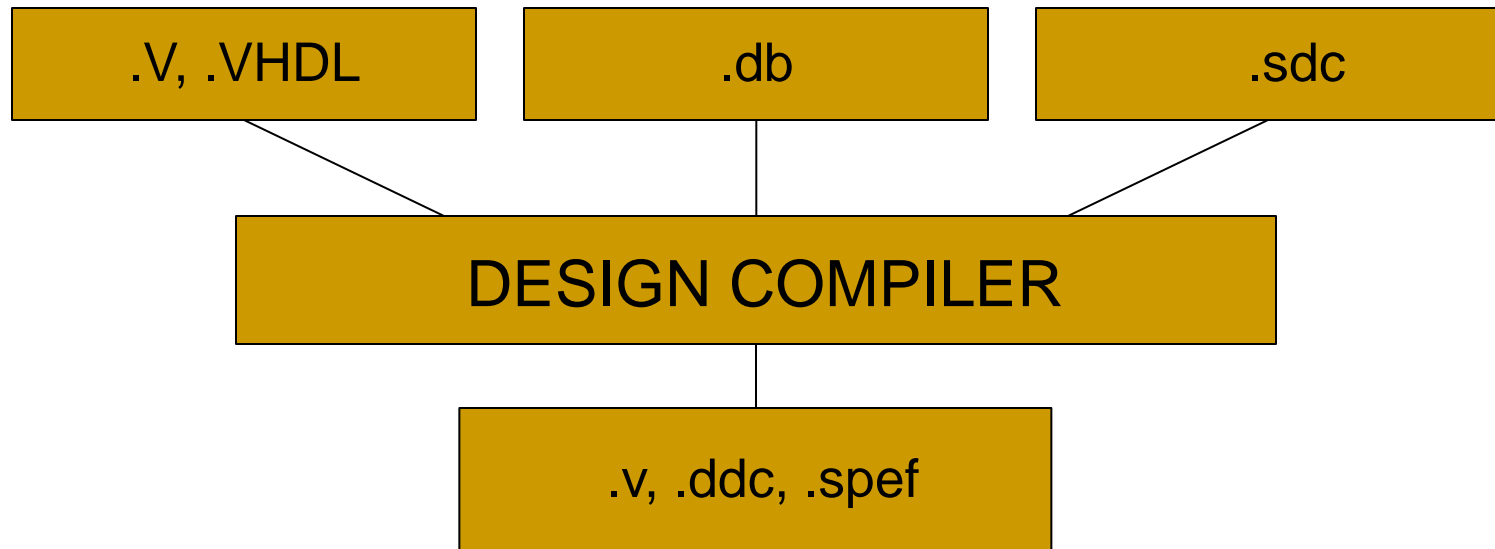


# Gate Level Optimization



# Inputs and Output of Logic Synthesis Tool (DC)

---



# **Systolic Arrays**

# Systolic Arrays: Motivation

---

- ❑ Goal: design an accelerator that has
  - Simple, regular design (keep # unique parts small and regular)
  - High concurrency → high performance
  - Balanced computation and I/O (memory) bandwidth
  
- ❑ Idea: Replace a single processing element (PE) with a regular array of PEs and carefully orchestrate flow of data between the PEs
  - such that they collectively transform a piece of input data before outputting it to memory
  
- ❑ Benefit: Maximizes computation done on a single piece of data element brought from memory

# Systolic Arrays

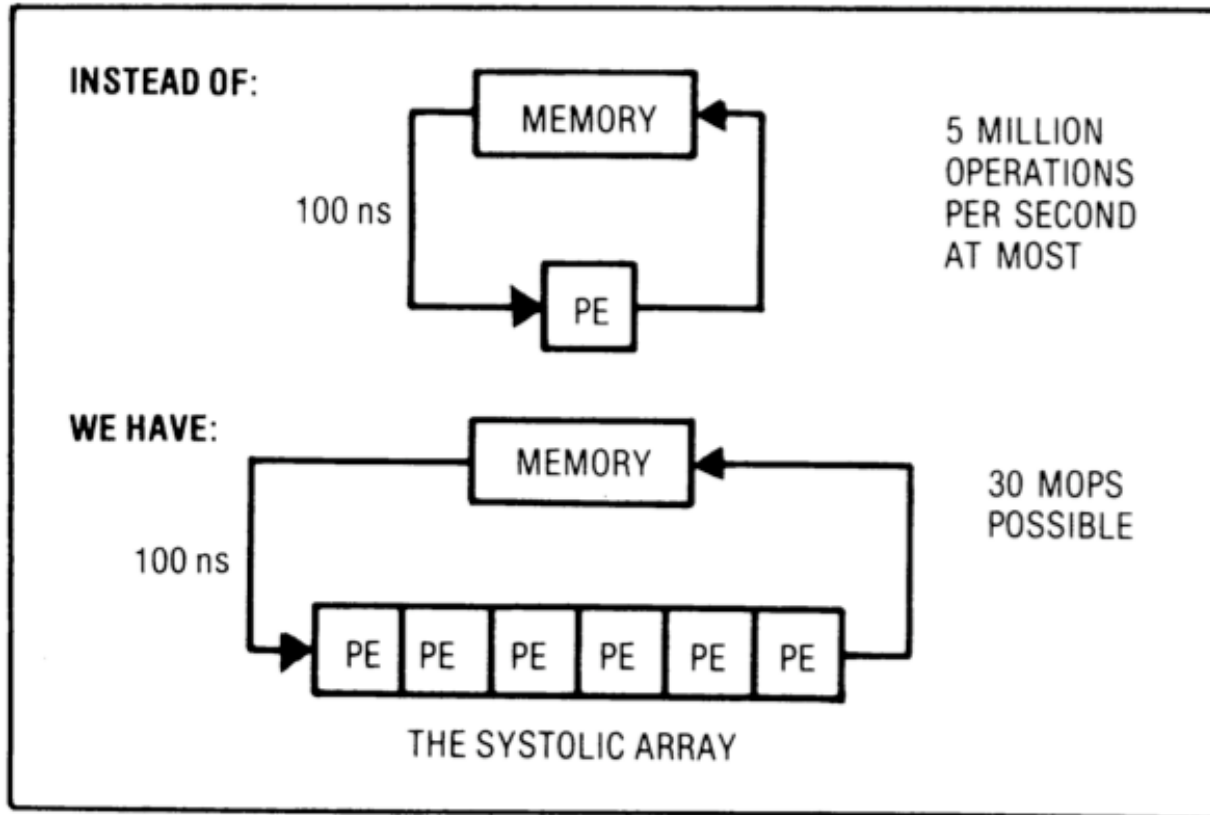
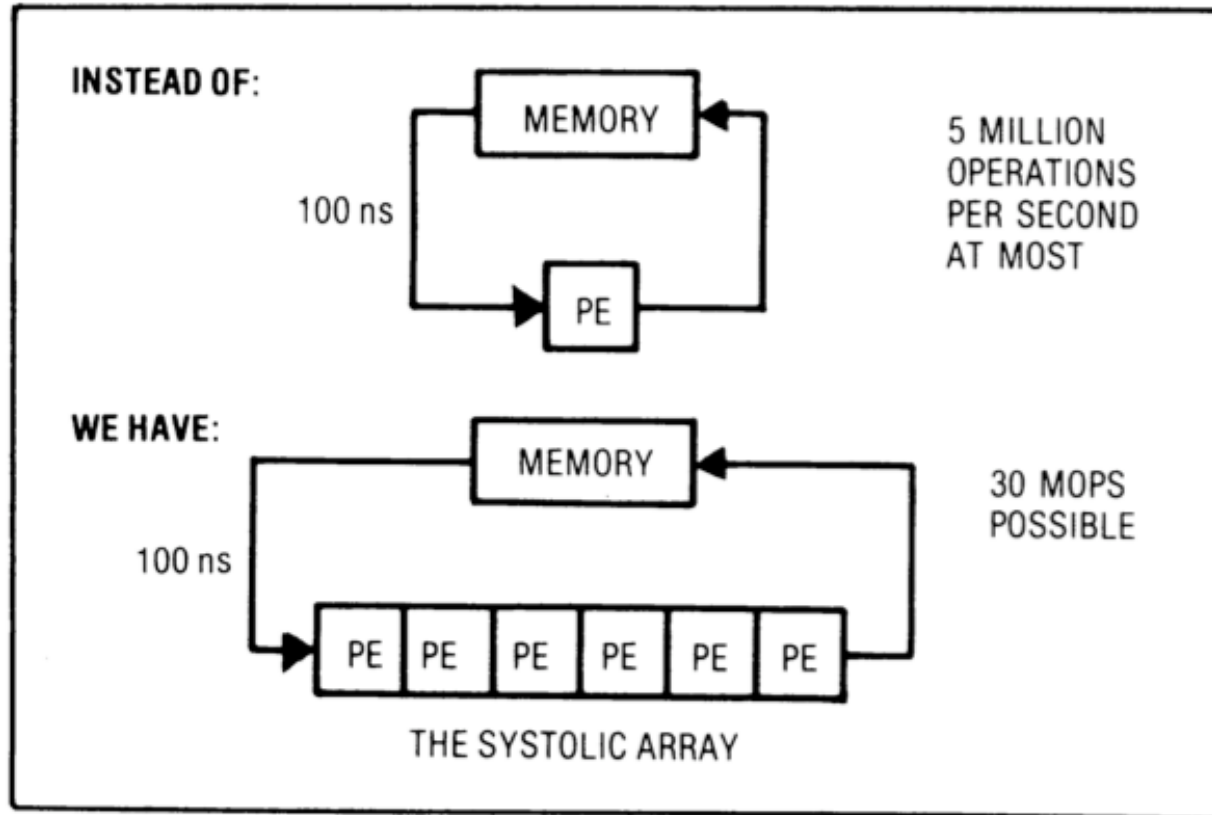


Figure 1. Basic principle of a systolic system.

- H. T. Kung, "[Why Systolic Architectures?](#)," IEEE Computer 1982.

# Systolic Arrays



Memory: heart  
Data: blood  
PEs: cells

Memory pulses  
data through  
PEs

Figure 1. Basic principle of a systolic system.

- H. T. Kung, "[Why Systolic Architectures?](#)," IEEE Computer 1982.



# Why Systolic Architectures?

---

# Why Systolic Architectures?

---

- ❑ Idea: Data flows from the computer memory in a rhythmic fashion, passing through many processing elements before it returns to memory
  - ❑ Similar to blood flow: heart → many cells → heart
    - Different cells “process” the blood
    - Many veins operate simultaneously
    - Can be many-dimensional
  - ❑ Why? Special purpose accelerators/architectures need
    - Simple, regular design (keep # unique parts small and regular)
    - High concurrency → high performance
    - Balanced computation and I/O (memory) bandwidth
-

# Systolic Architectures

- Basic principle: Replace a single PE with a **regular array of PEs** and **carefully orchestrate flow of data** between the PEs

- Balance computation and memory bandwidth

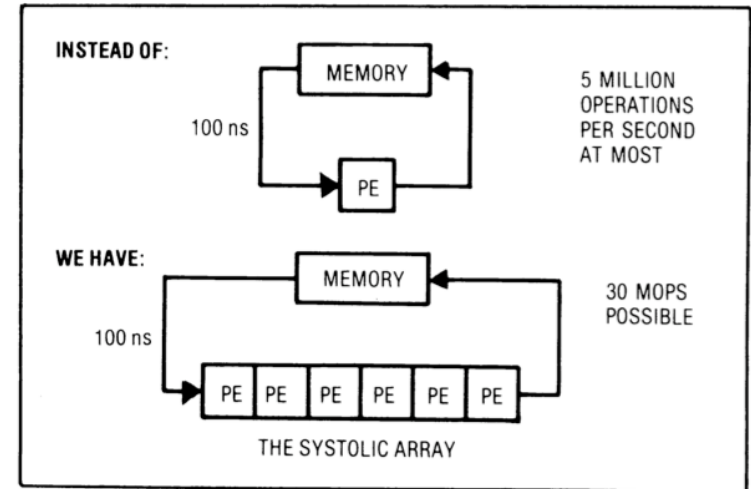


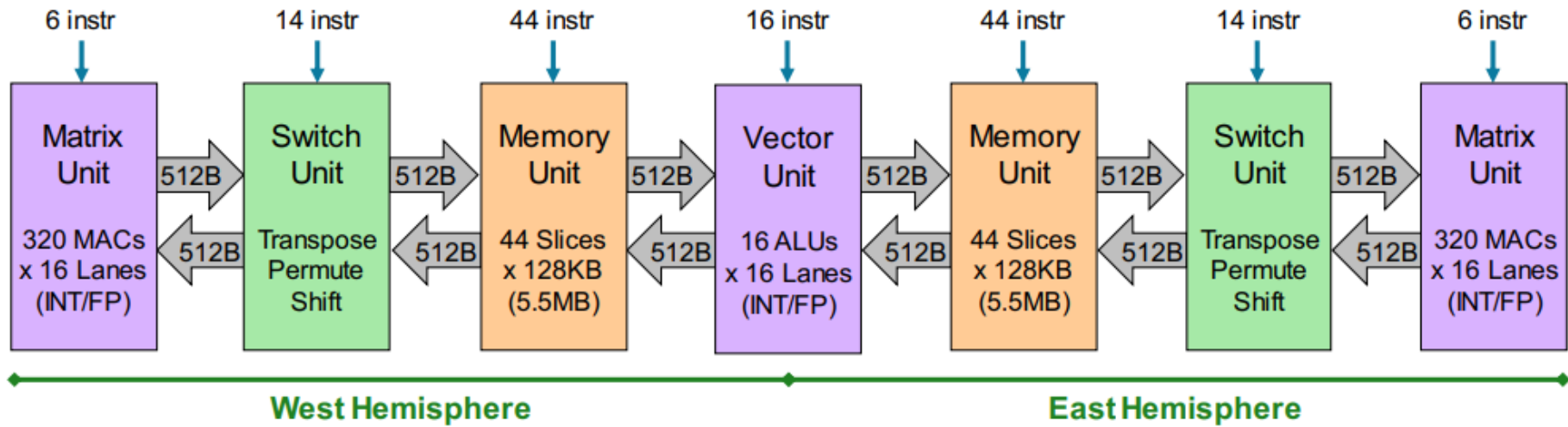
Figure 1. Basic principle of a systolic system.

- **Differences from pipelining:**

- These are individual PEs
- Array structure can be non-linear and multi-dimensional
- PE connections can be multidirectional (and different speed)
- PEs can have local memory and execute kernels (rather than a piece of the instruction)

# Systolic Architectures

- Groq Microarchitecture
  - Neural Networks



**Figure 2. TSP superlane block diagram.** Every superlane is bilaterally symmetric with an east side and a west side. It contains 16 lanes, each of which is 8 bits wide. Data flows from east to west and from west to east.

src: <https://groq.com/wp-content/uploads/2020/04/Groq-Rocks-NNs-Linley-Group-MPR-2020Jan06.pdf>

\_\_\_\_\_

- Neural Networks

[illegible]

**Figure 3. Groq TSP die layout.** Built in 14nm CMOS, the 725mm<sup>2</sup> chip has 20 superlanes plus an extra superlane for redundancy. Instruction control requires only 3% of the die area. Diagram not to scale.

src: <https://groq.com/wp-content/uploads/2020/04/Groq-Rocks-NNs-Linley-Group-MPR-2020Jan06.pdf>

# Systolic Computation Example

---

## □ Convolution

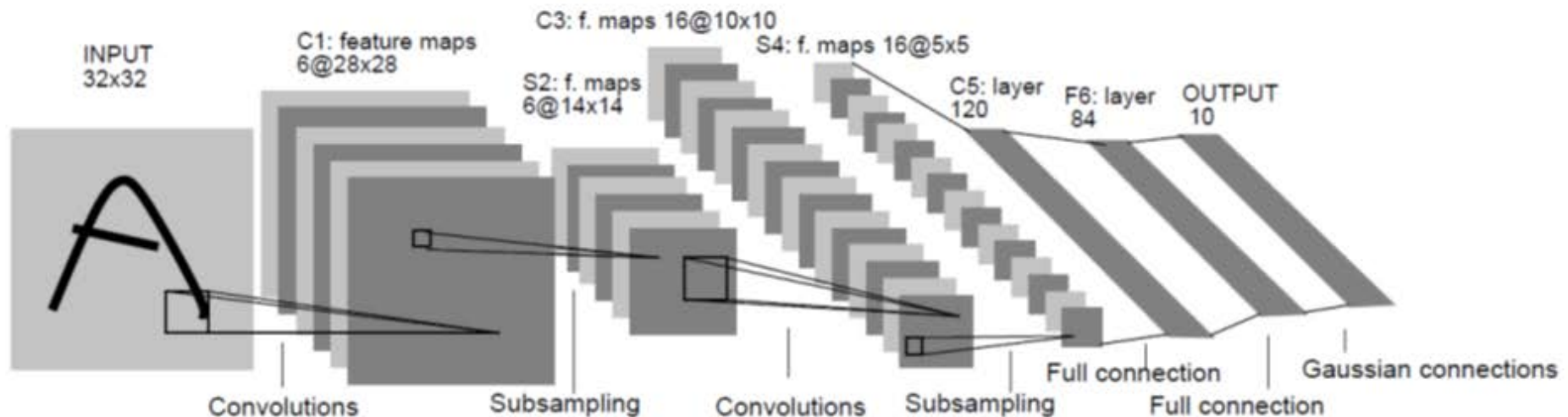
- Used in filtering, pattern matching, correlation, polynomial evaluation, etc ...
- Many **image processing** tasks
- **Machine learning**: up to hundreds of **convolutional layers** in Convolutional Neural Networks (CNN)

**Given** the sequence of weights  $\{w_1, w_2, \dots, w_k\}$   
and the input sequence  $\{x_1, x_2, \dots, x_n\}$ ,  
**compute** the result sequence  $\{y_1, y_2, \dots, y_{n+1-k}\}$   
defined by

$$y_i = w_1x_i + w_2x_{i+1} + \dots + w_kx_{i+k-1}$$

# LeNet-5, a Convolutional Neural Network for Hand-Written Digit Recognition

This is a 1024\*8 bit input, which will have a truth table of  $2^{8196}$  entries



# Convolutional Neural Networks: Demo

[Back to Yann's Home Publications](#)

## LeNet-5 Demos

**Unusual Patterns**  
[unusual styles](#)  
[weirdos](#)

**Invariance**  
[translation](#) (anim)  
[scale](#) (anim)  
[rotation](#) (anim)  
[squeezing](#) (anim)  
[stroke width](#) (anim)

**Noise Resistance**  
[noisy 3 and 6](#)  
[noisy 2](#) (anim)  
[noisy 4](#) (anim)

**Multiple Character**  
[various stills](#)  
[dancing 00](#) (anim)  
[dancing 384](#) (anim)

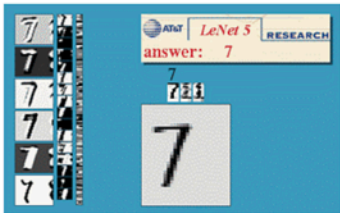
**Complex cases**  
(anim)  
[35 -> 53](#)  
[12 -> 4 -> 21](#)  
[23 -> 32](#)  
[30 + noise](#)  
[31-51-57-61](#)

## LeNet-5, convolutional neural networks

Convolutional Neural Networks are a special kind of multi-layer neural networks. Like almost every other neural networks they are trained with a version of the back-propagation algorithm. Where they differ is in the **architecture**.

Convolutional Neural Networks are designed to recognize visual patterns directly from pixel images with minimal preprocessing. They can recognize patterns with extreme variability (such as handwritten characters), and with robustness to distortions and simple geometric transformations.

LeNet-5 is our latest convolutional network designed for handwritten and machine-printed character recognition. Here is an example of LeNet-5 in action.

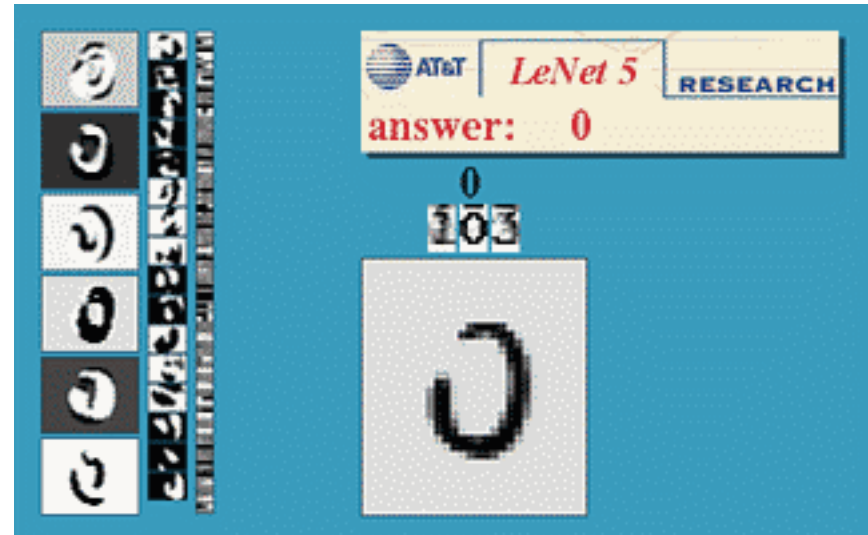


Many more examples are available in the column on the left:

Several papers on LeNet and convolutional networks are available on my [publication page](#):

[LeCun et al., 1998]  
Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner.  
Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, november 1998.  
[ps.gz](#)

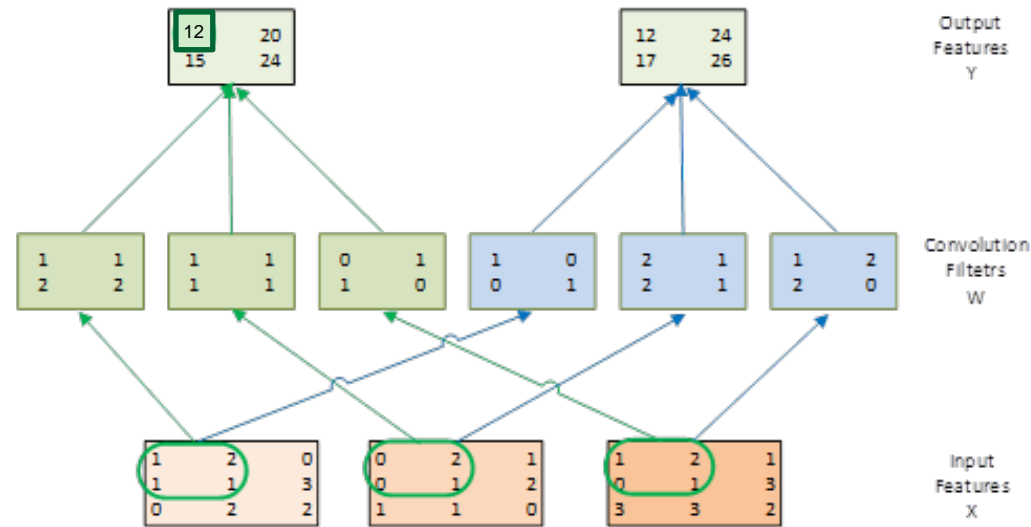
[Bottou et al., 1997]  
L. Bottou, Y. LeCun, and Y. Bengio. Global training of



<http://yann.lecun.com/exdb/lenet/index.html>



# Implementing a Convolutional Layer with Matrix Multiplication



$$\begin{bmatrix} 1 & 1 & 2 & 2 \\ 1 & 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} 1 & 1 & 1 & 1 \\ 2 & 1 & 2 & 1 \end{bmatrix} = \begin{bmatrix} 14 & 20 & 15 & 24 \\ 12 & 24 & 17 & 26 \end{bmatrix}$$

Convolution Filters  $W'$

Input Features  $X_{unrolled}$

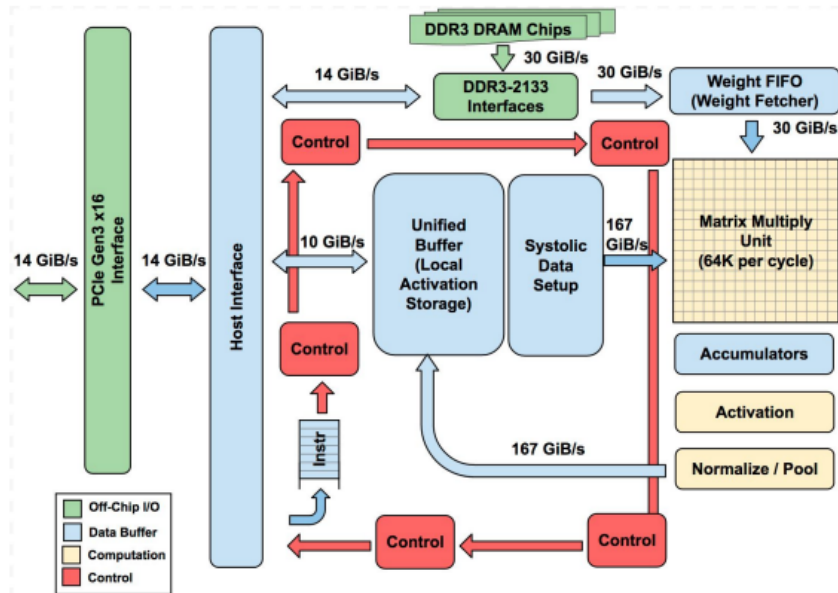
Output Features  $Y$

Slide credit: Hwu & Kirk

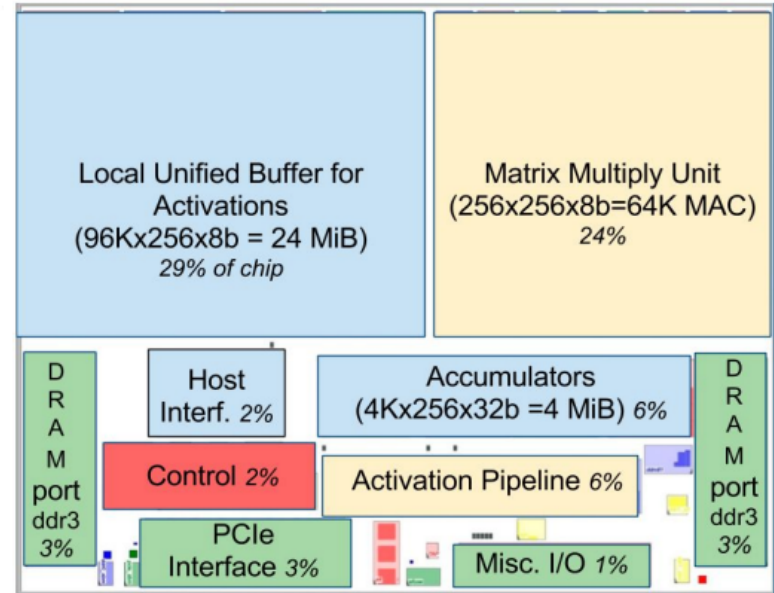
# Google TPU

## Google TPU v1

- N. P. Jouppi, et al. "In-Datacenter Performance Analysis of a Tensor Processing Unit", ISCA 2017



**Figure 1.** TPU Block Diagram. The main computation part is the yellow Matrix Multiply unit in the upper right hand corner. Its inputs are the blue Weight FIFO and the blue Unified Buffer (UB) and its output is the blue Accumulators (Acc). The yellow Activation Unit performs the nonlinear functions on the Acc, which go to the UB.

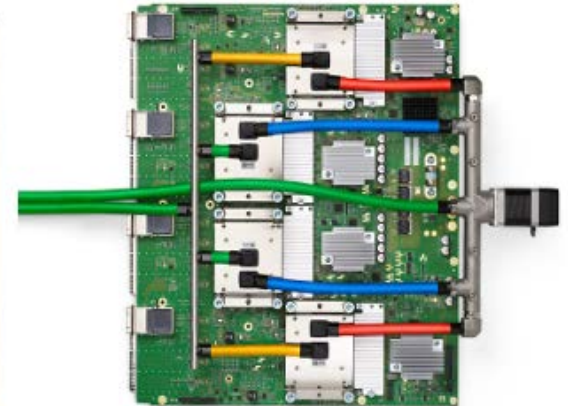


**Figure 2.** Floor Plan of TPU die. The shading follows Figure 1. The light (blue) data buffers are 37% of the die, the light (yellow) compute is 30%, the medium (green) I/O is 10%, and the dark (red) control is just 2%. Control is much larger (and much more difficult to design) in a CPU or GPU

# Google TPU

## Google TPU v4

- N. P. Jouppi, et al.  
"TPUv4: An Optically Reconfigurable Supercomputer for Machine Learning with Hardware Support for Embeddings", ISCA 2023



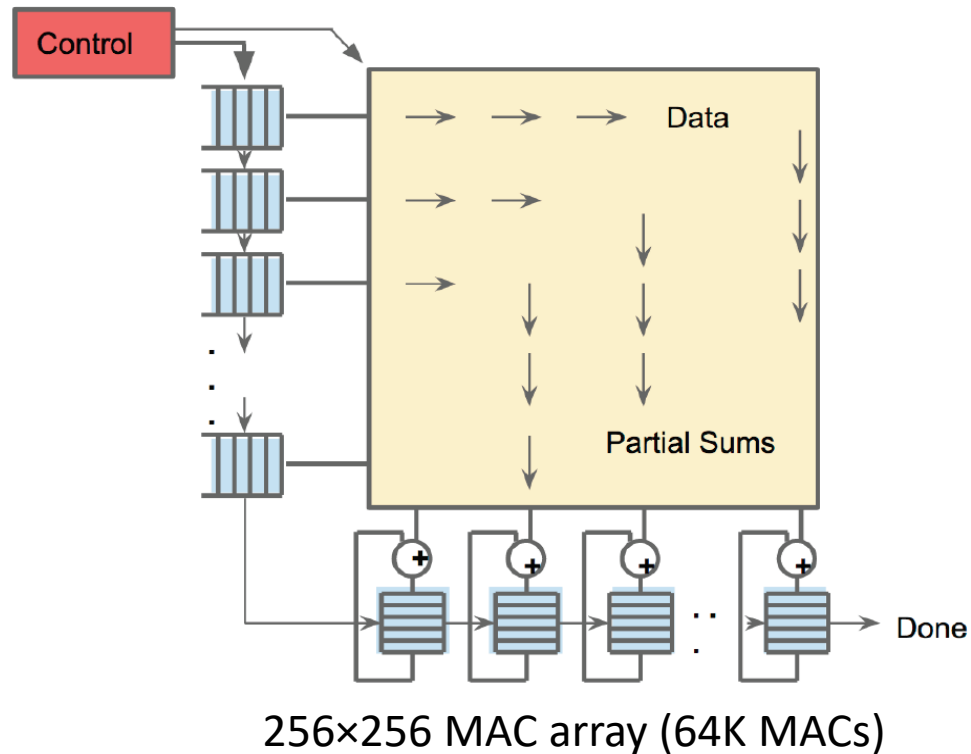
**Figure 2: The TPU v4 package (ASIC in center plus 4 HBM stacks) and printed circuit board with 4 liquid-cooled packages. The board's front panel has 4 top-side PCIe connectors and 16 bottom-side OSFP connectors for inter-tray ICI links.**



**Figure 3: Eight of 64 racks for one 4096-chip supercomputer.**

# Google TPU

## □ Systolic Mac Array



*N. P. Jouppi, et al. "In-Datacenter Performance Analysis of a Tensor Processing Unit", ISCA 2017*

# Systolic Mac Array

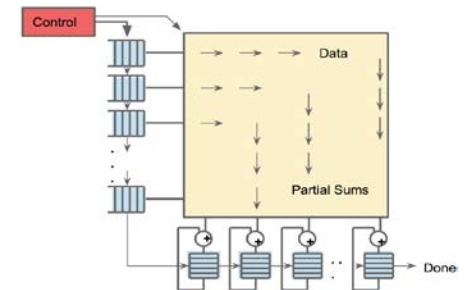
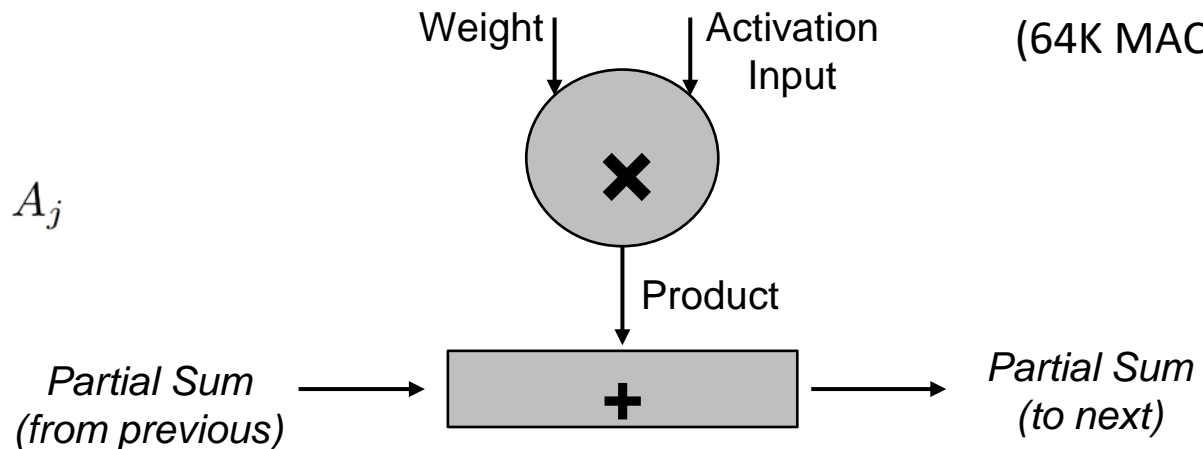
❑ DNN inference: >70% of time in GEMM Operations

❑ MAC Unit

- Multiplier
- Adder
- 8bit weights, activations

❑ Convolution:

$$Y = B + \sum_{j=1}^k W_j \times A_j$$



256×256 MAC array  
(64K MACs)

# Systolic Mac Array

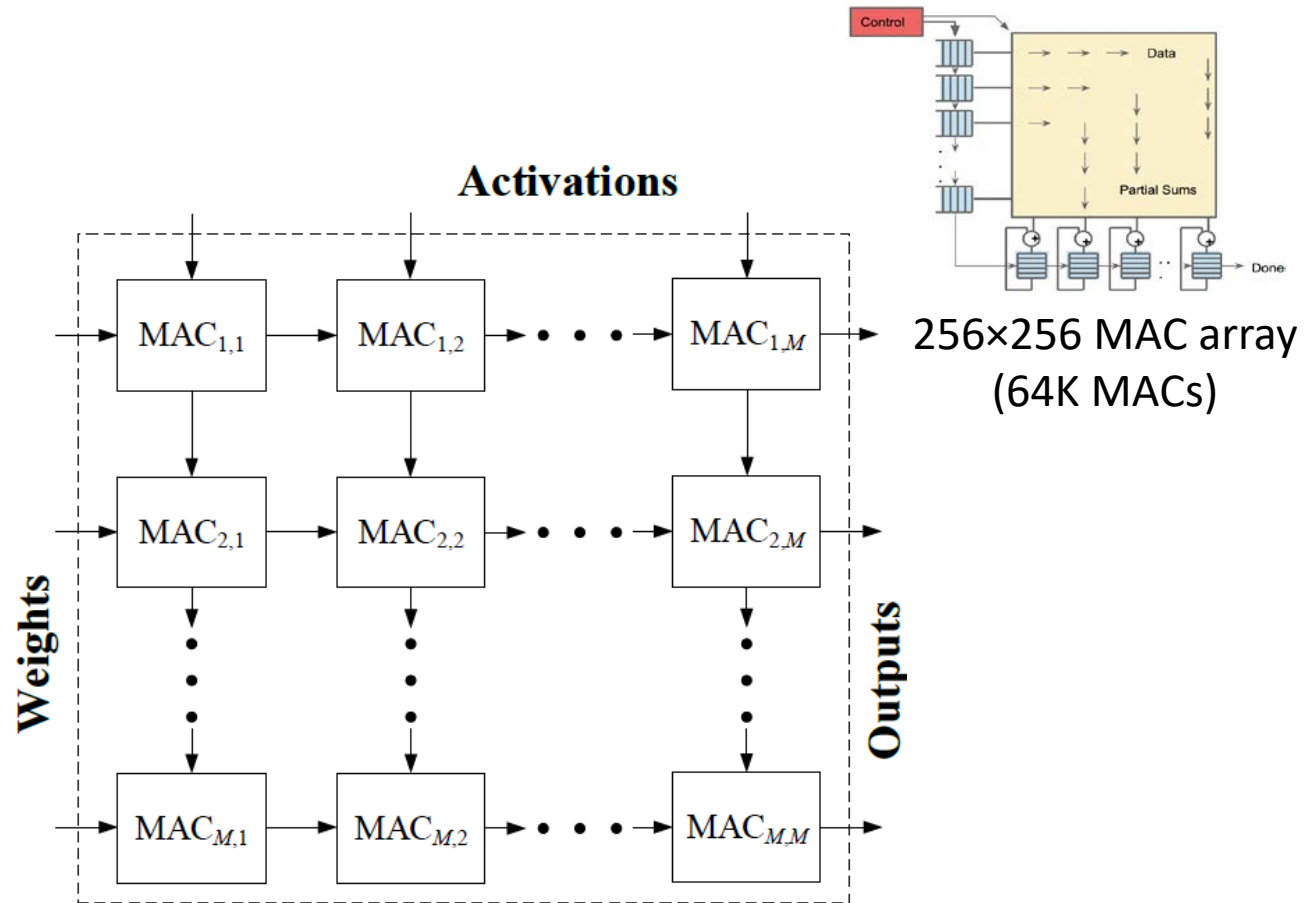
❑ DNN inference: >70% of time in GEMM Operations

❑ MAC Unit

- Multiplier
- Adder
- 8bit weights, acti

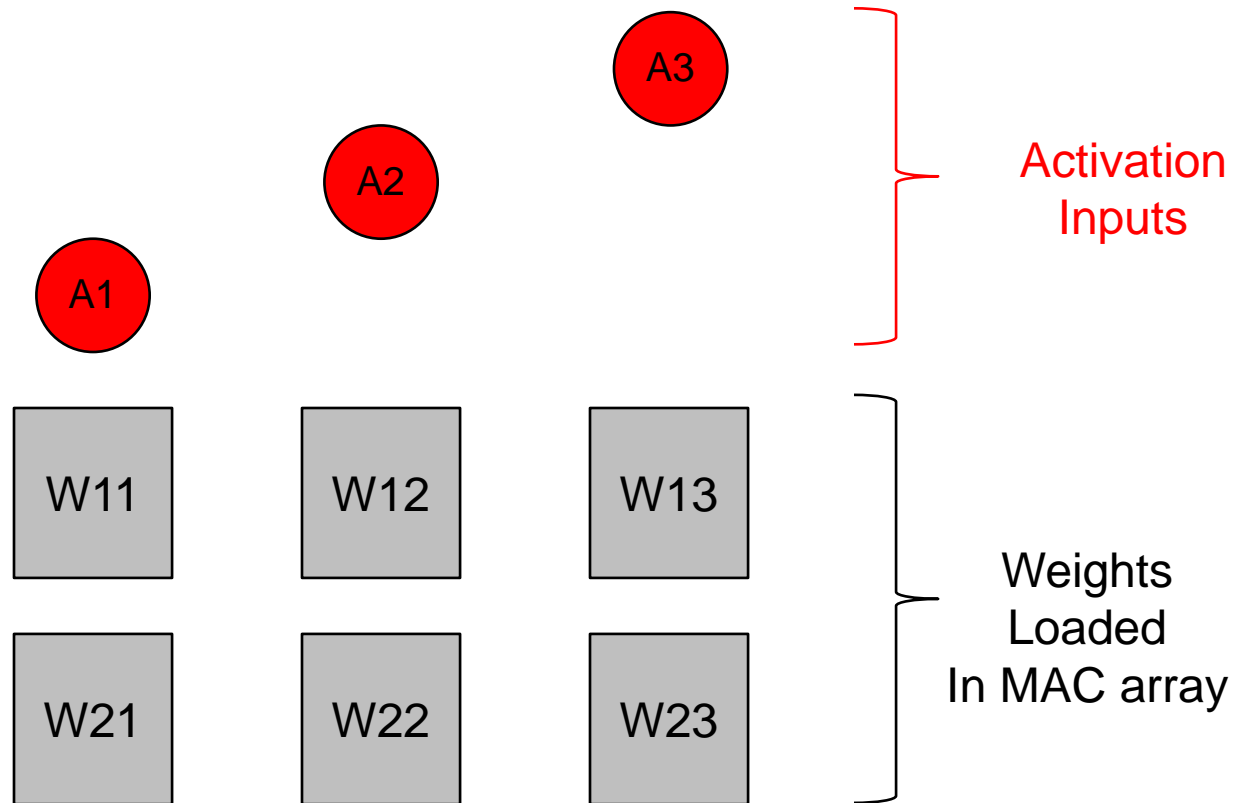
❑ Convolution:

$$Y = B + \sum_{j=1}^k W_j \times .$$



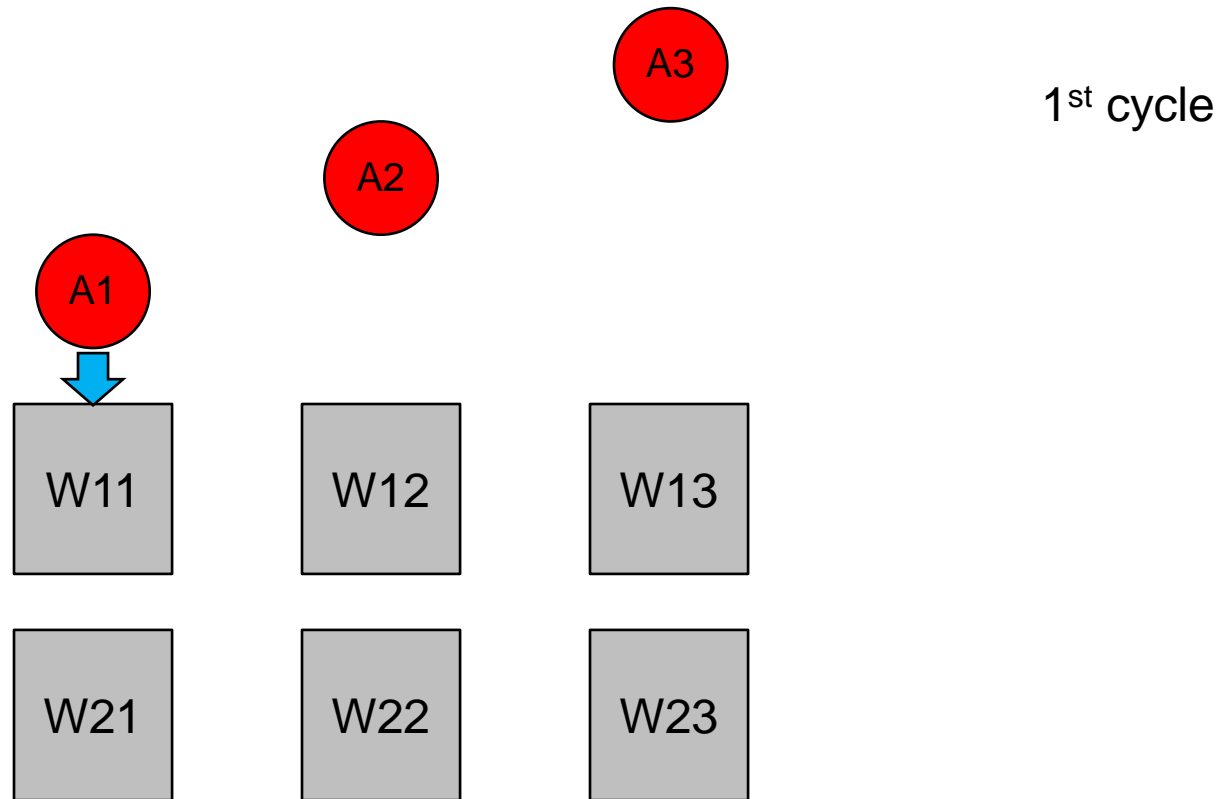
# Systolic Mac Array

---



# Systolic Mac Array

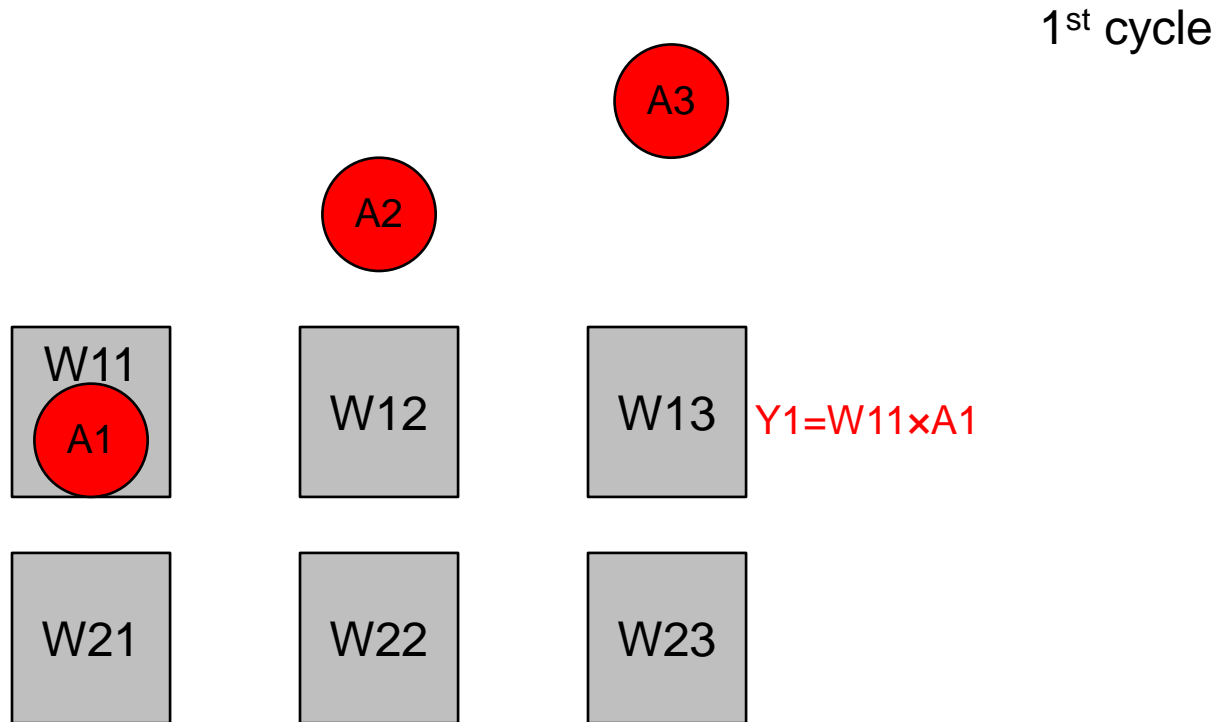
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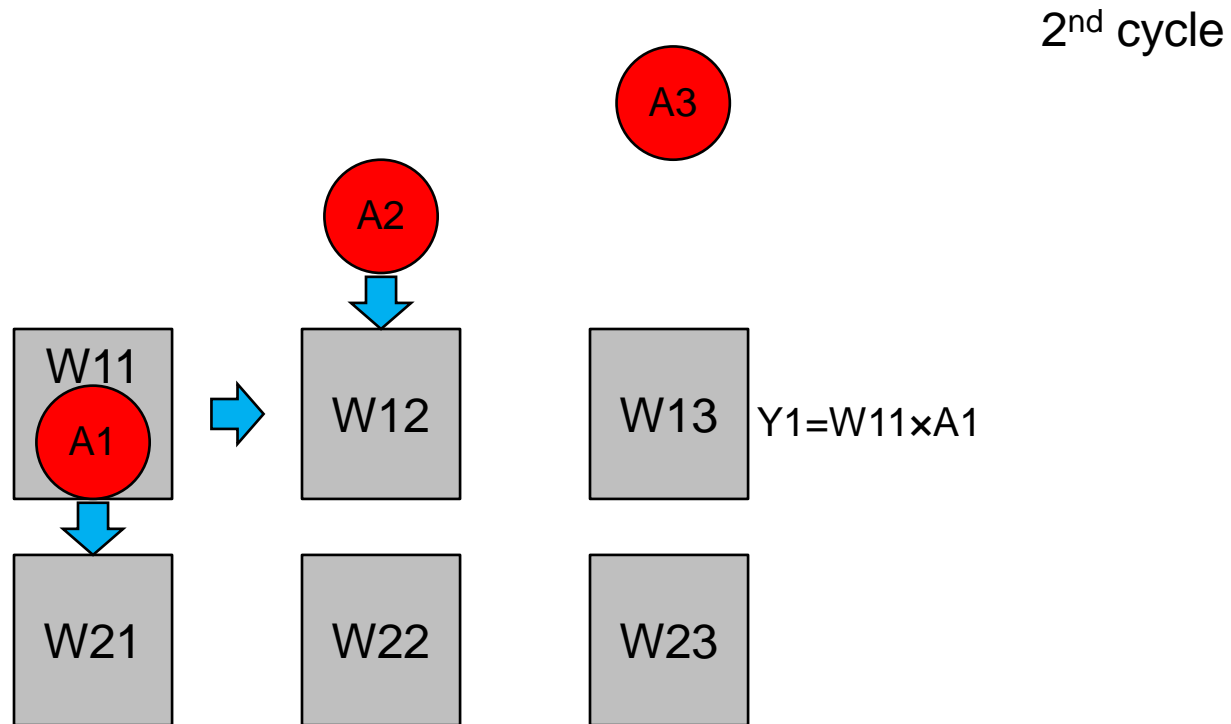
# Systolic Mac Array

---



# Systolic Mac Array

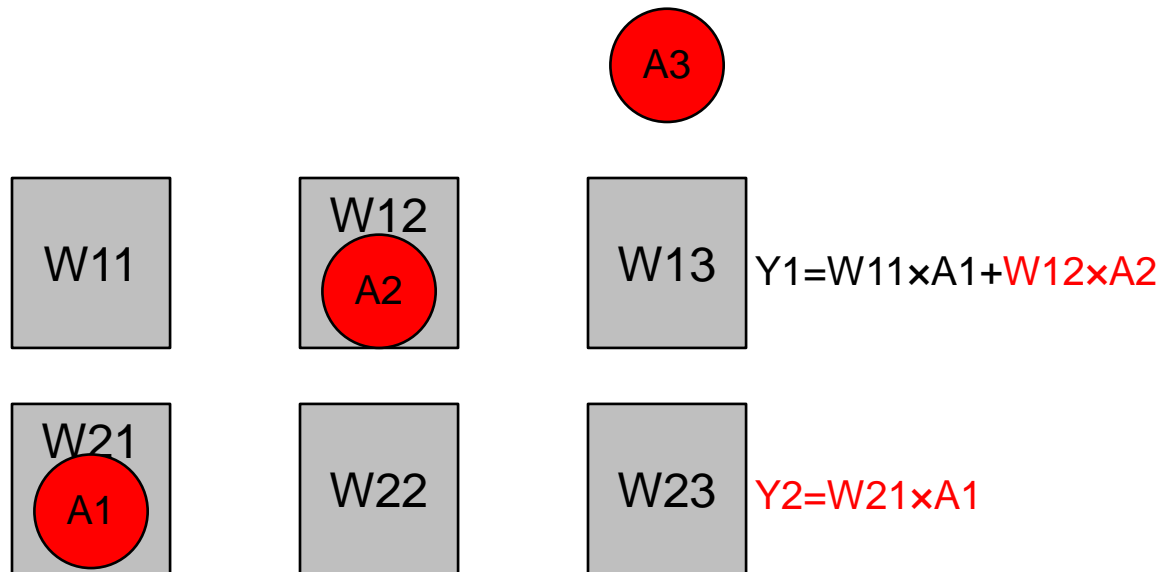
---



# Systolic Mac Array

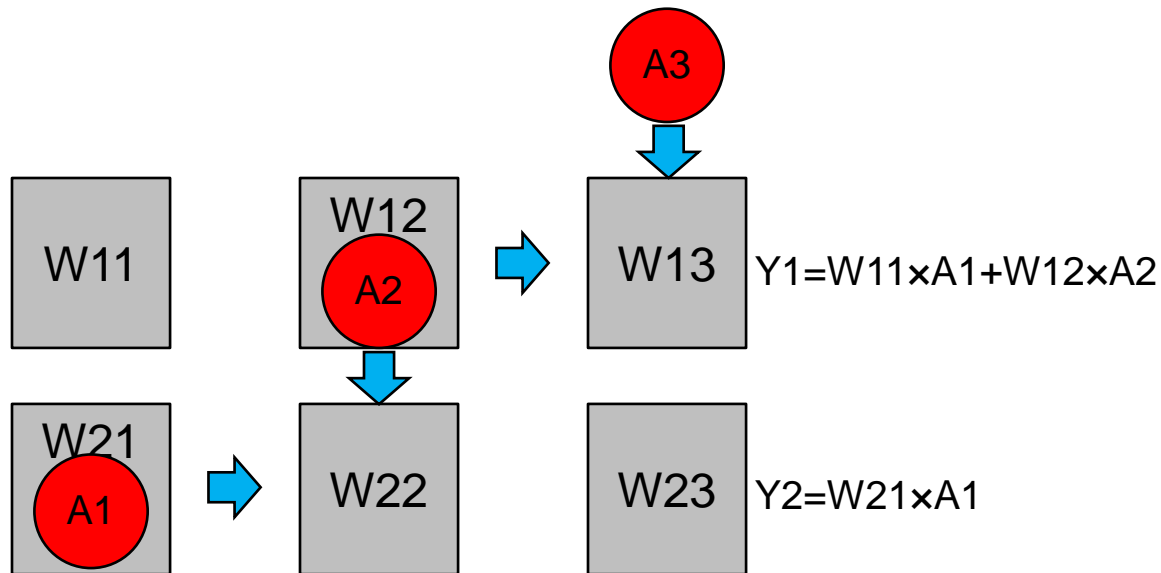
---

2<sup>nd</sup> cycle



# Systolic Mac Array

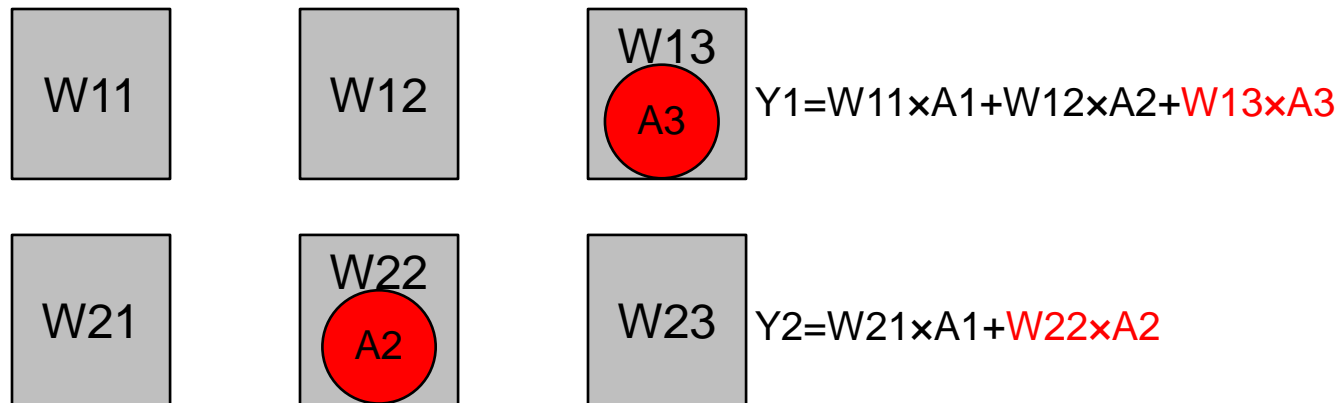
3<sup>rd</sup> cycle



# Systolic Mac Array

---

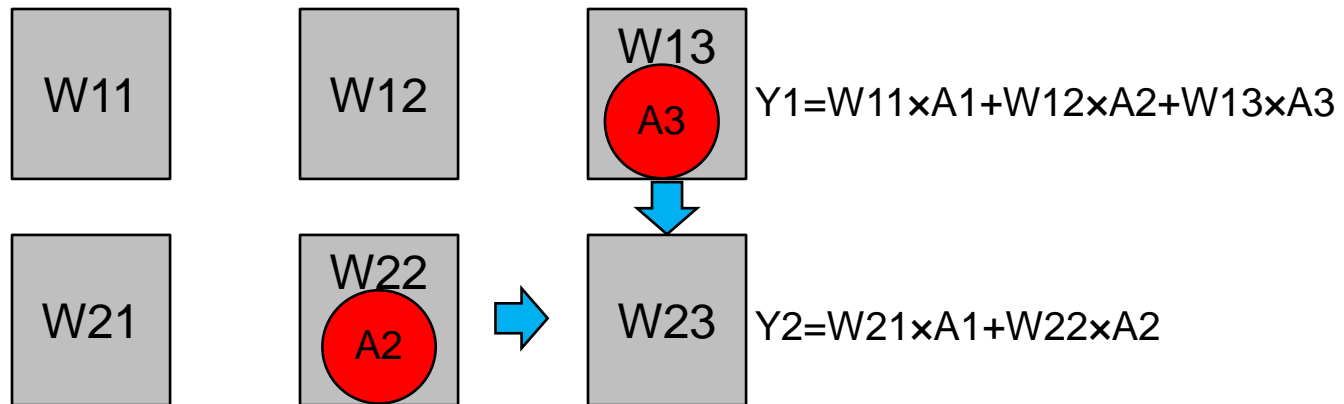
3<sup>rd</sup> cycle



# Systolic Mac Array

---

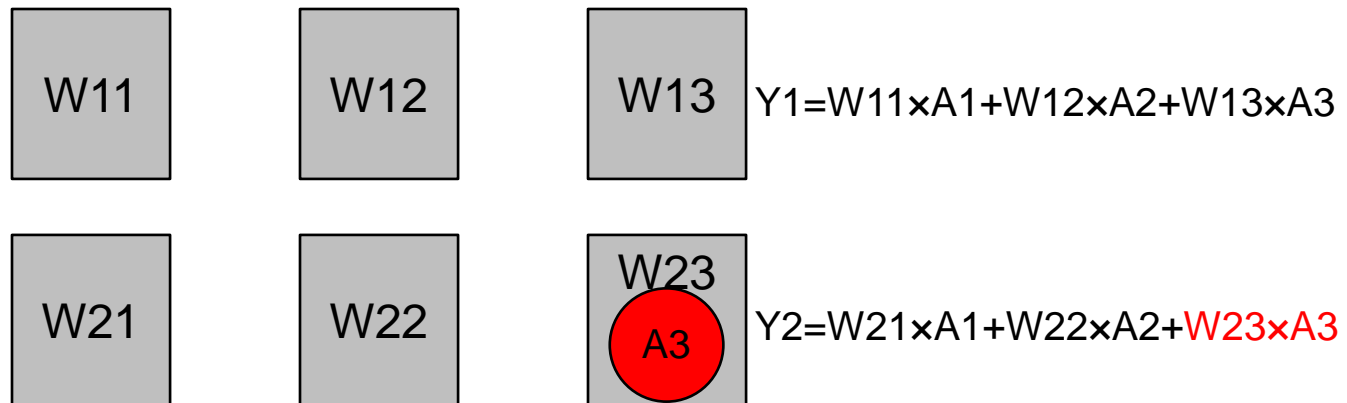
4<sup>th</sup> cycle



# Systolic Mac Array

---

4<sup>th</sup> cycle



# Systolic Mac Array

---

## □ Systolic mac array Verilog example

```
module macarray (clk, rst_n, newWeights_i, weight_i, input_i, OUT_o);
    parameter arrayLines = 16;
    parameter arrayColumns = 16;
    parameter inputWidth = 8;
    parameter weightWidth = 8;
    parameter accumulationWidth=32;

    input clk, rst_n, newWeights_i;
    input [weightWidth*arrayLines*arrayColumns-1:0] weight_i;
    input [inputWidth*arrayColumns-1:0] input_i;
    output [accumulationWidth*arrayLines-1:0] OUT_o;

    wire signed [inputWidth-1:0] activation_w [1:arrayLines+1] [1:arrayColumns+1];
    wire signed [accumulationWidth-1:0] accumulate_w [1:arrayLines+1] [1:arrayColumns+1];
    wire signed [weightWidth-1:0] weight_w [1:arrayLines] [1:arrayColumns+1];
```



# Systolic Mac Array

## □ Systolic mac array Verilog example

```
genvar gi, gj;
generate
//first column zero in
for (gi = 1; gi <= arrayLines; gi=gi+1) begin: firstcolumn
    assign accumulate_w[gi][1] = {accumulationWidth{1'b0}};
end
//activations
for (gj = 1; gj <= arrayColumns; gj=gj+1) begin: firstinpline
    assign activation_w[1][gj] = $signed(input_i[inputWidth*gj-1:inputWidth*(gj-1)]);
end
//weights
for (gj = 1; gj <= arrayColumns; gj=gj+1) begin: firstinpline
    assign weight_w[1][gj] = $signed(weight_i[weightWidth*gj-1:weightWidth*(gj-1)]);
end
// generate macs
for (gi = 1; gi <= arrayLines; gi=gi+1) begin: lines
    for (gj = 1; gj <= arrayColumns; gj=gj+1) begin: columns
        mac #(inputWidth, weightWidth, accumulationWidth) PE (
            .clk(clk), .rst_n(rst_n),
            .newWeights_i(newWeights_i)
            .w_i(weight_w[gi][gj]),
            .in_i(activation_w[gi][gj]),
            .sumIN_i(accumulate_w[gi][gj]),
            .w_o(weight_w[gi+1][gj])
            .in_o(activation_w[gi+1][gj]),
            .sumOUT_o(accumulate_w[gi][gj+1]));
    end
end
//output
for (gi = 1; gi <= arrayLines; gi=gi+1) begin: out
    assign OUT_o[accumulationWidth*gi-1:accumulationWidth*(gi-1)] = accumulate_w[gi][arrayColumns+1];
end
endgenerate
endmodule
```

# Systolic Mac Array

---

## □ MAC unit

```
module mac (clk, newWeights_i, rst_n, w_i, in_i, sumIN_i, w_o, in_o, sumOUT_o);
    parameter inputWidth = 8;
    parameter weightWidth = 8;
    parameter adderWidth=32;
    localparam prodWidth = 2*inputWidth;

    input clk;
    input rst_n;
    input signed [weightWidth-1:0] w_i;
    input signed [inputWidth-1:0] in_i;
    input signed [adderWidth-1:0] sumIN_i;
    output signed [weightWidth-1:0] w_o;
    output signed [inputWidth-1:0] in_o;
    output signed [adderWidth-1:0] sumOUT_o;

    reg signed [weightWidth-1:0] w_reg;
    reg signed [inputWidth-1:0] in_reg;
    reg signed [adderWidth-1:0] sumOUT_reg;

    wire signed [prodWidth-1:0] prod_w;
    wire signed [adderWidth-1:0] sumOUT_w;
```

# Systolic Mac Array

## MAC unit

```
assign sumOUT_w = w_reg * in_i + sumIN_i;

always @ (posedge clk or negedge rst_n) begin
    if (!rst_n) begin
        in_reg <= {multWidth{1'b0}};
        sumOUT_reg <= {adderWidth{1'b0}};
    end
    else begin
        in_reg <= in_i;
        sumOUT_reg <= sumOUT_w;
    end
end

always @ (posedge clk or negedge rst_n) begin
    if (!rst_n) begin
        w_reg <= {weightWidth{1'b0}};
    end
    else begin
        if (newWeights_i) w_reg <= w_i;
    end
end

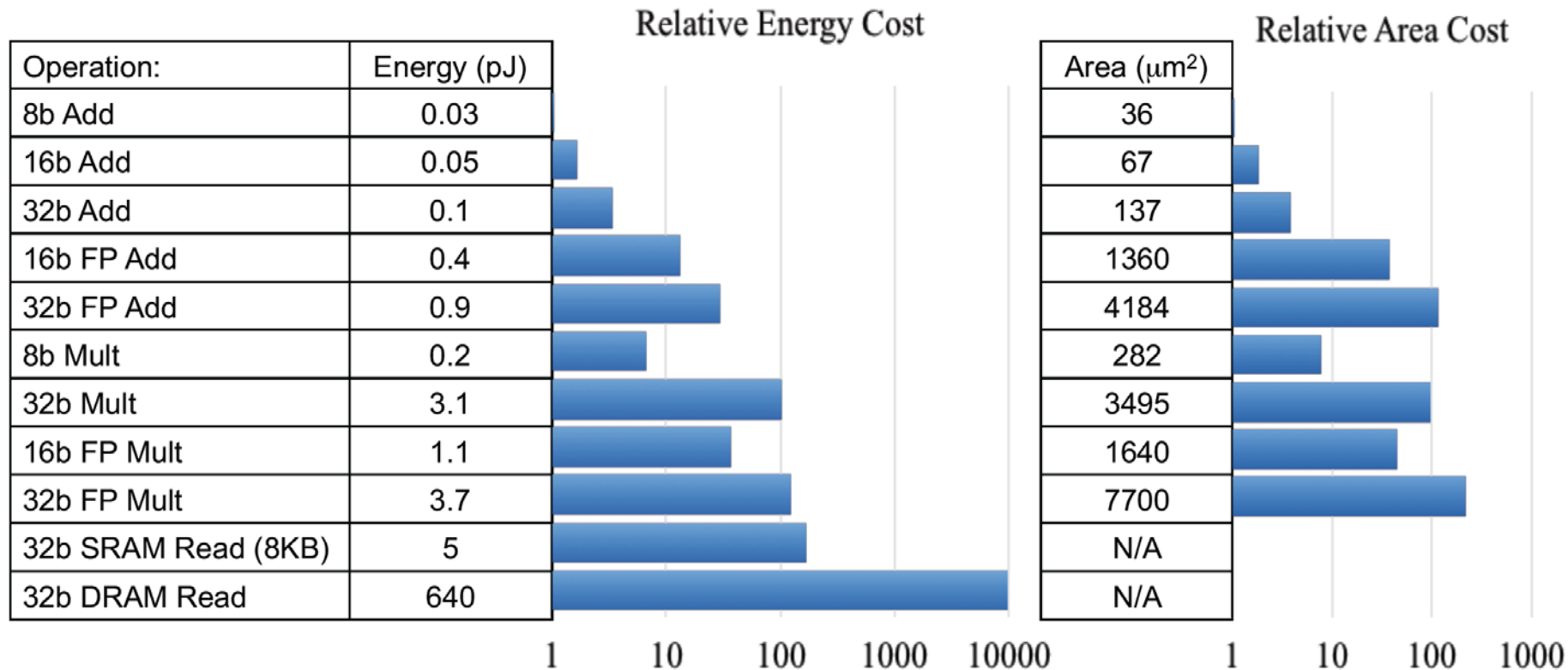
assign in_o = in_reg;
assign sumOUT_o = sumOUT_reg;
assign w_o = w_reg;

endmodule
```

# Number Representation

		Range	Accuracy
FP32	<div> <div>1</div> <div>8</div> <div>23</div> <div>S</div> <div>E</div> <div>M</div> </div>	$10^{-38} - 10^{38}$	.000006%
FP16	<div> <div>1</div> <div>5</div> <div>10</div> <div>S</div> <div>E</div> <div>M</div> </div>	$6 \times 10^{-5} - 6 \times 10^4$	.05%
Int32	<div> <div>1</div> <div>31</div> <div>S</div> <div>M</div> </div>	$0 - 2 \times 10^9$	$\frac{1}{2}$
Int16	<div> <div>1</div> <div>15</div> <div>S</div> <div>M</div> </div>	$0 - 6 \times 10^4$	$\frac{1}{2}$
Int8	<div> <div>1</div> <div>7</div> <div>S</div> <div>M</div> </div>	$0 - 127$	$\frac{1}{2}$

# Cost of Operations

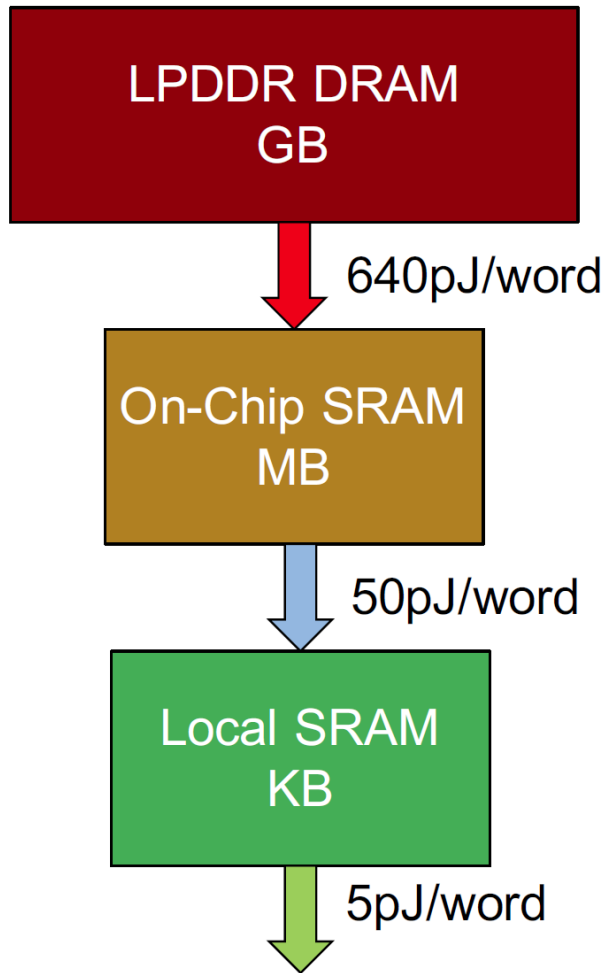


Energy numbers are from Mark Horowitz “Computing’s Energy Problem (and what we can do about it)”, ISSCC 2014

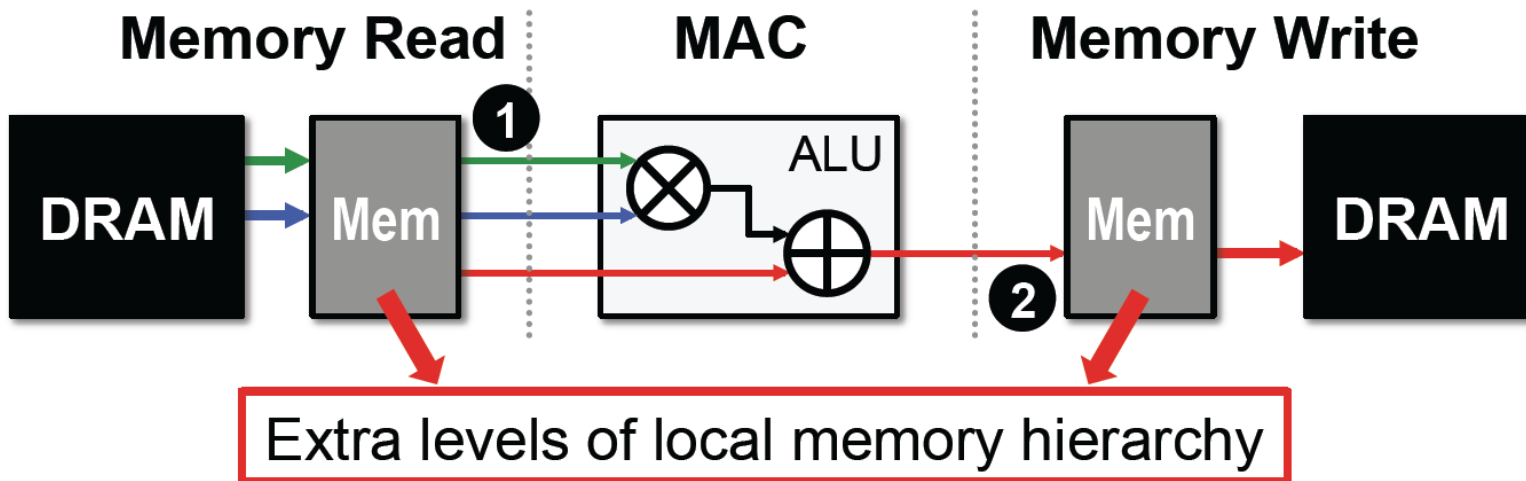
Area numbers are from synthesized result using Design Compiler under TSMC 45nm tech node. FP units used DesignWare Library.

# The Importance of Staying Local

---



# Memory Access is the Bottleneck

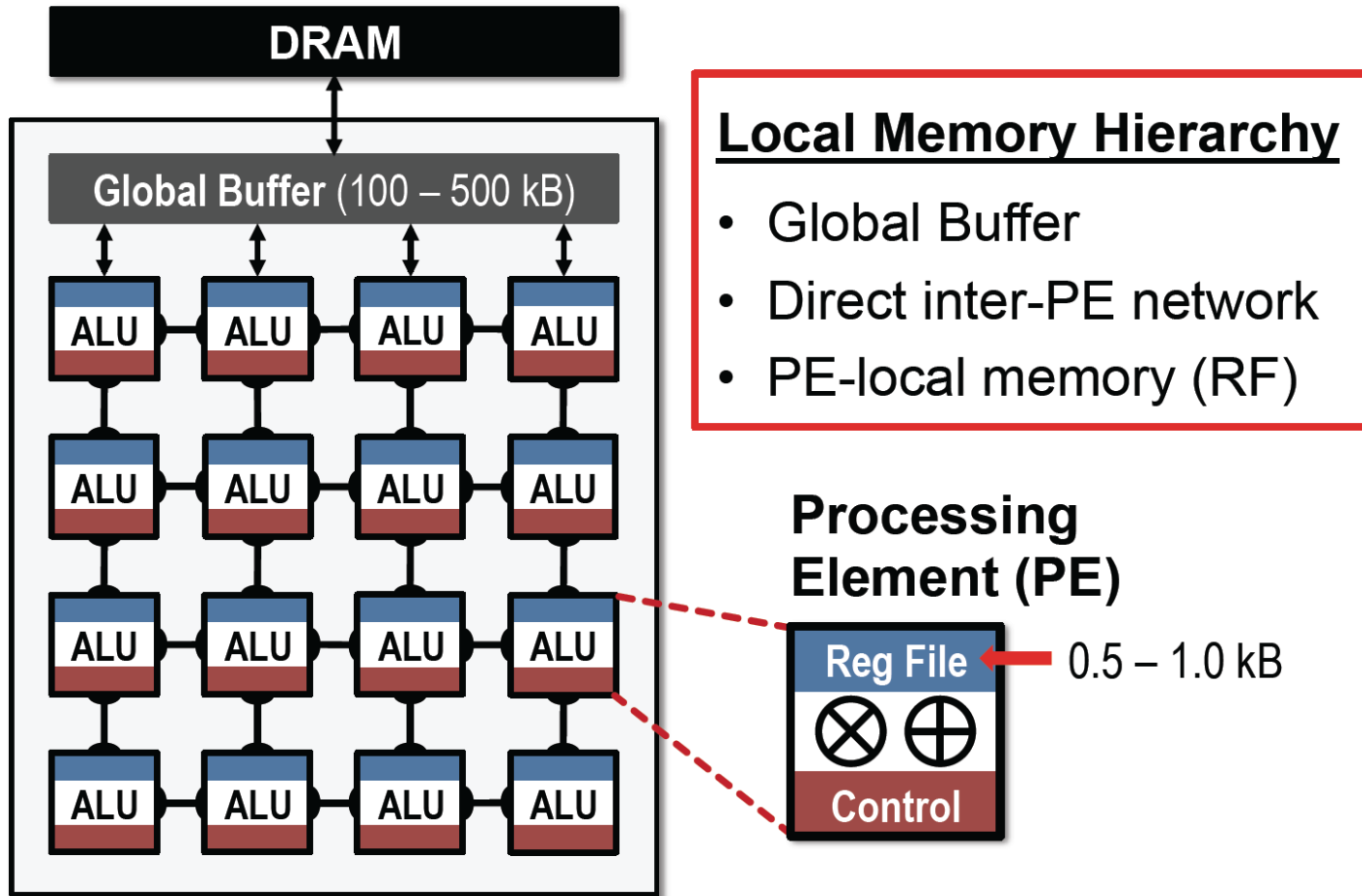


Opportunities: ① data reuse    ② local accumulation

- ① Can reduce DRAM reads of **filter/fmap** by up to **500×**
- ② **Partial sum** accumulation does **NOT** have to access DRAM

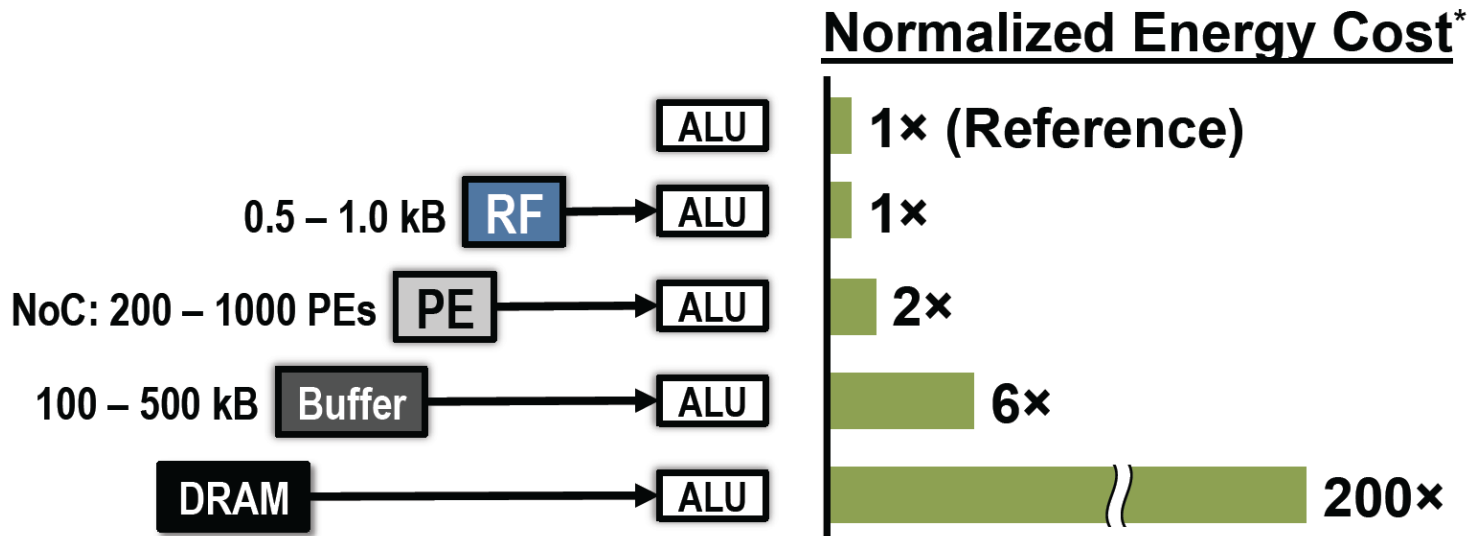
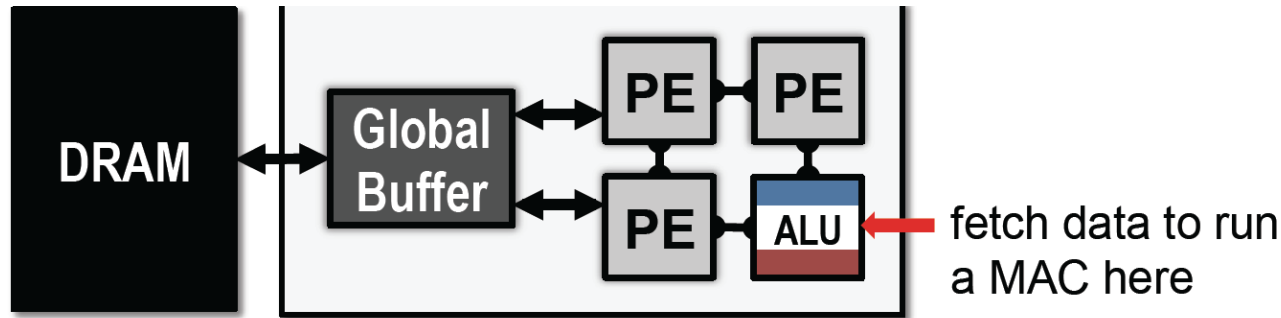
**Example:** AlexNet has **724M** MACs => **2896M** with DRAM accesses which can be reduced to **61M** (best case).

# Spatial Architecture for DNN



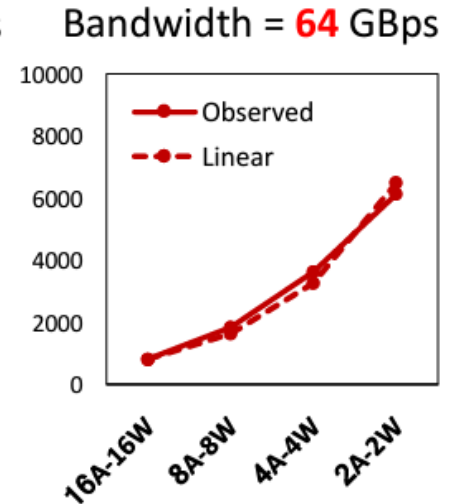
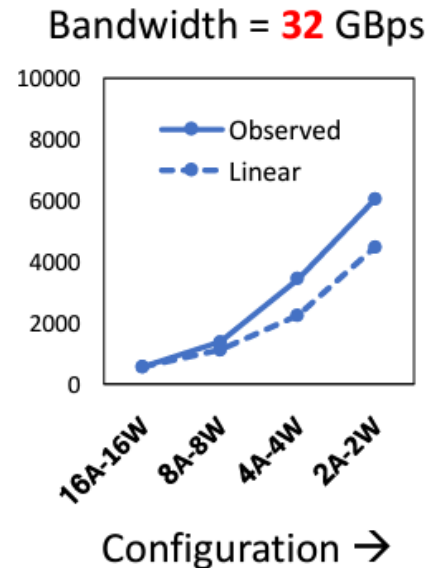
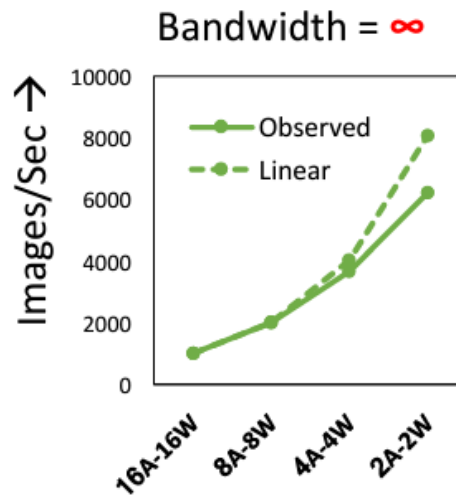
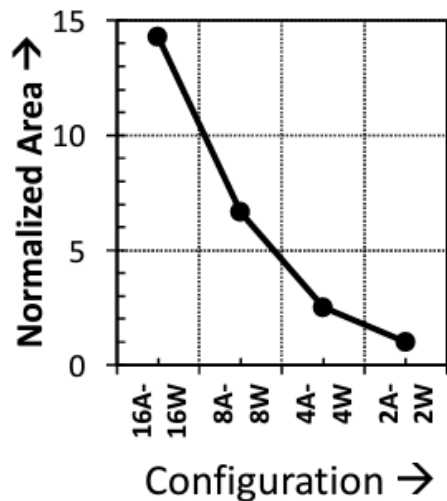


# Low-Cost Local Data Access



\* measured from a commercial 65nm process

# Reduced Precision for Inference



J. Choi, et al., "PACT: Parameterized Clipping Activation for Quantized Neural Networks" 2018

# Reduced Precision for Inference

---

Network	FullPrec	DoReFa				PACT			
		2b	3b	4b	5b	2b	3b	4b	5b
CIFAR10	0.916	0.882	0.899	0.905	0.904	0.897	0.911	0.913	0.917
SVHN	0.978	0.976	0.976	0.975	0.975	0.977	0.978	0.978	0.979
AlexNet	0.551	0.536	0.550	0.549	0.549	0.550	0.556	0.557	0.557
ResNet18	0.702	0.626	0.675	0.681	0.684	0.644	0.681	0.692	0.698
ResNet50	0.769	0.671	0.699	0.714	0.714	0.722	0.753	0.765	0.767

J. Choi, et al., “PACT: Parameterized Clipping Activation for Quantized Neural Networks” 2018

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# Arithmetic Circuits

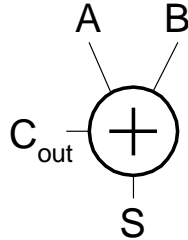
# Adders

# Single-Bit Addition

## Half Adder

$$S = A \oplus B$$

$$C_{\text{out}} = A \cdot B$$

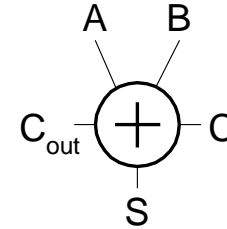


A	B	$C_{\text{out}}$	S
0	0		
0	1		
1	0		
1	1		

## Full Adder

$$S = A \oplus B \oplus C$$

$$C_{\text{out}} = \text{MAJ}(A, B, C)$$



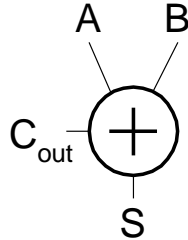
A	B	C	$C_{\text{out}}$	S
0	0	0		
0	0	1		
0	1	0		
0	1	1		
1	0	0		
1	0	1		
1	1	0		
1	1	1		

# Single-Bit Addition

## Half Adder

$$S = A \oplus B$$

$$C_{out} = A \cdot B$$

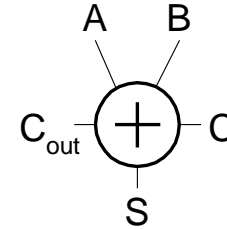


A	B	$C_{out}$	S
0	0	0	0
0	1	0	1
1	0	0	1
1	1	1	0

## Full Adder

$$S = A \oplus B \oplus C$$

$$C_{out} = MAJ(A, B, C)$$



A	B	C	$C_{out}$	S
0	0	0	0	0
0	0	1	0	1
0	1	0	0	1
0	1	1	1	0
1	0	0	0	1
1	0	1	1	0
1	1	0	1	0
1	1	1	1	1

# Single-Bit Addition

## Full adder

a	b	C <sub>in</sub>	S	C <sub>out</sub>
0	0	0	0	0
0	0	1	1	0
0	1	0	1	0
0	1	1	0	1
1	0	0	1	0
1	0	1	0	1
1	1	0	0	1
1	1	1	1	1

S:

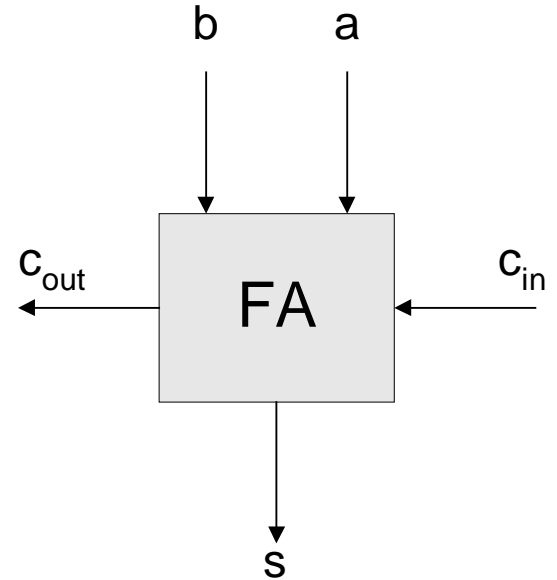
c <sub>in</sub> \ ab	00	01	11	10
0	0	1	0	1
1	1	0	1	0

$$s = c_{in} \bar{a} \bar{b} + \bar{a} \bar{c}_{in} b + b a c_{in} + \bar{c}_{in} a \bar{b}$$

C<sub>out</sub>:

c <sub>in</sub> \ ab	00	01	11	10
0	0	0	1	0
1	0	1	1	1

$$c_{out} = c_{in} b + a b + a c_{in}$$



$$s = a \oplus b \oplus c_{in}$$

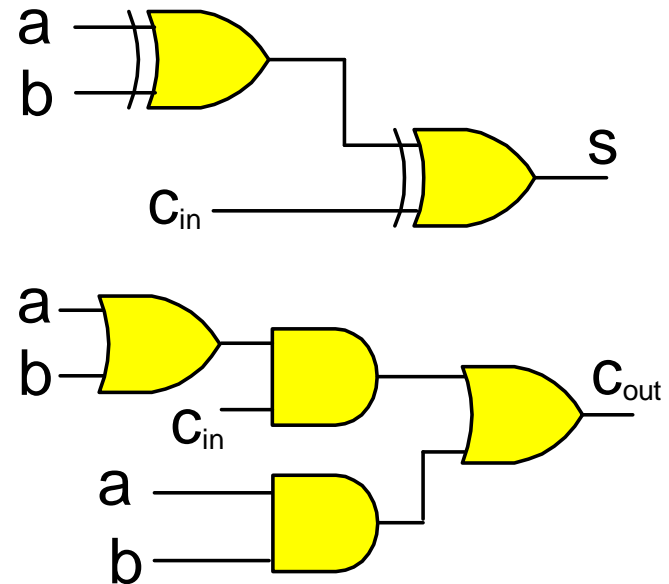
$$c_{out} = ab + ac_{in} + bc_{in}$$



# Full Adder

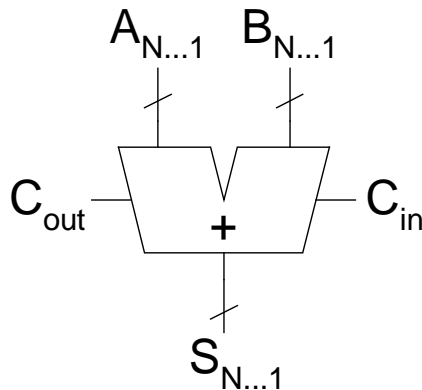
## □ 1 bit adder

$$s = a \oplus b \oplus c_{in}$$
$$c_{out} = ab + c_{in}(a + b)$$



# Carry Propagate Adders

- N-bit adder called CPA
  - Each sum bit depends on all previous carries
  - How do we compute all these carries quickly?



$$\begin{array}{r} \textcircled{0}000\textcircled{0} \\ 1111 \\ +0000 \\ \hline 1111 \end{array}$$

Carry propagation:  $C_{in} \rightarrow \textcircled{0} \rightarrow \textcircled{0} \rightarrow \textcircled{0} \rightarrow \textcircled{0} \rightarrow C_{out}$

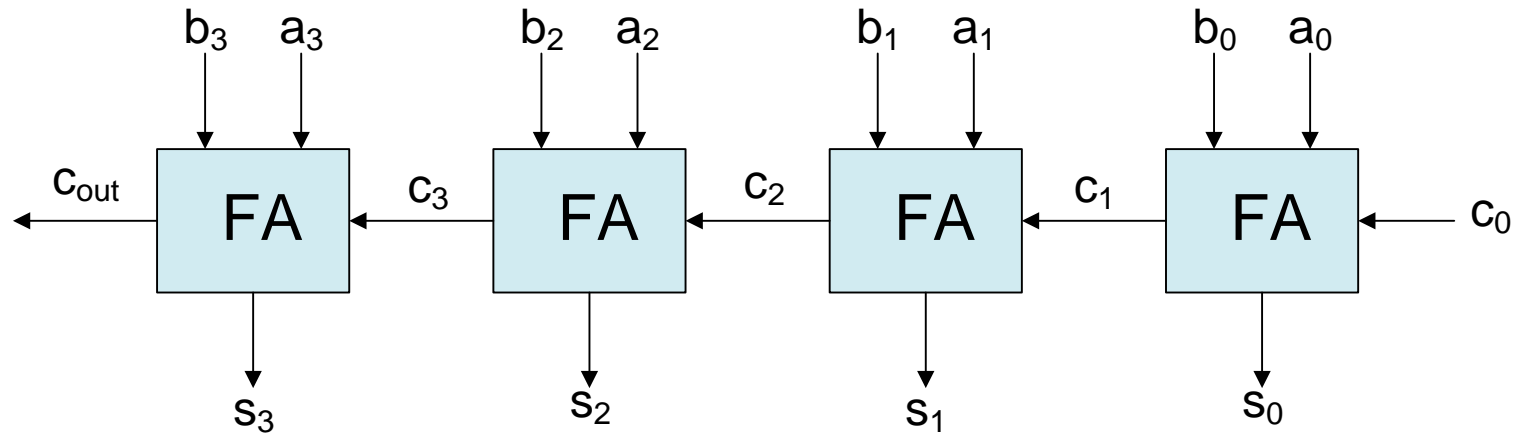
$$\begin{array}{r} \textcircled{1}111\textcircled{1} \\ 1111 \\ +0000 \\ \hline 0000 \end{array}$$

Carry propagation:  $C_{in} \rightarrow \textcircled{1} \rightarrow \textcircled{1} \rightarrow \textcircled{1} \rightarrow \textcircled{1} \rightarrow C_{out}$

carries  
 $A_{4...1}$   
 $B_{4...1}$   
 $S_{4...1}$

# RCA 4-bit

## ❑ 4-bit Ripple Carry Adder (RCA)

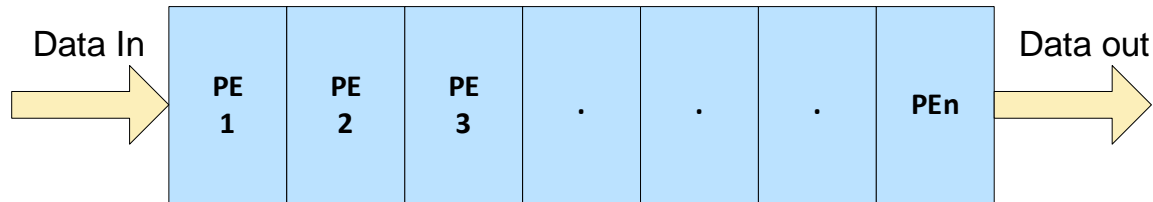


## ❑ $\text{Delay} = n \cdot T_{FA}$

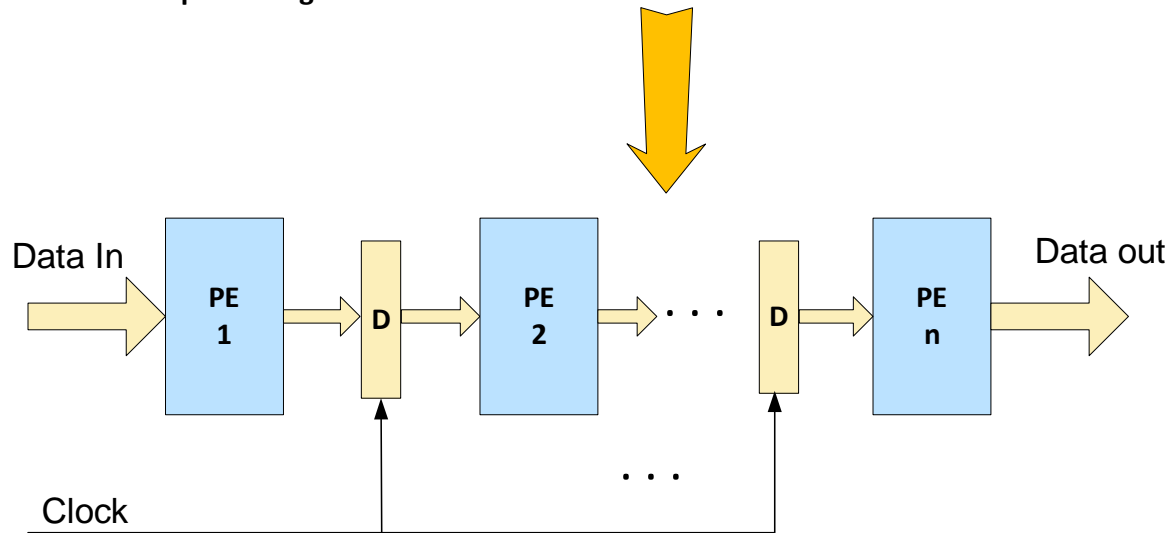
- On average the delay is practically  $\text{Delay} = (\log_2 n) \cdot T_{FA}$
- If the delays of S and Cout are different ( $T_S > T_{Cout}$ ) then  $\text{Delay} = T_S + (n-1) \cdot T_{Cout}$

# Parallel to Systolic

- ❑ Converting a parallel circuit to a systolic one
  - Connections between PEs must pass through registers



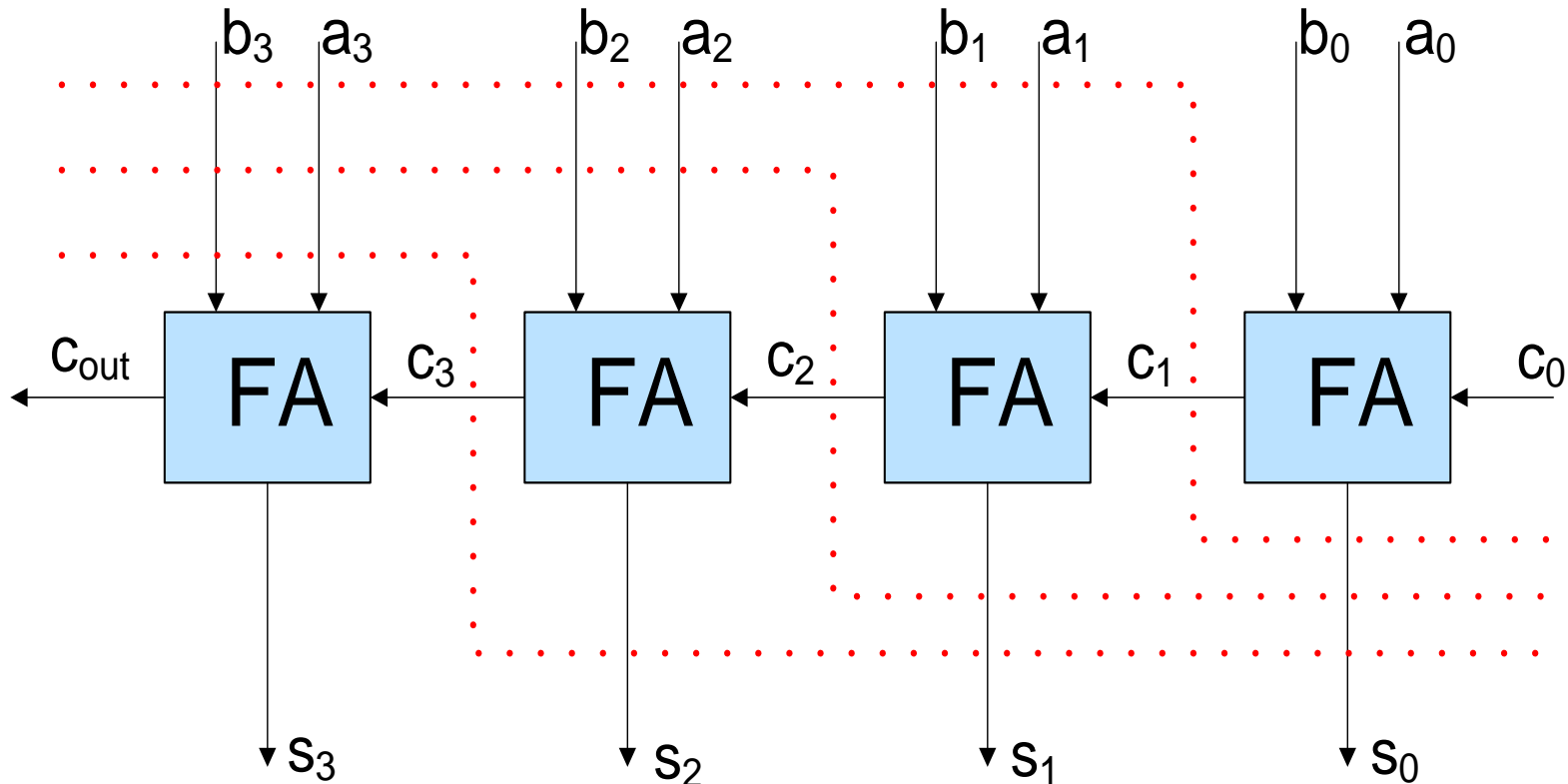
PE: processing element



D: Flip flops

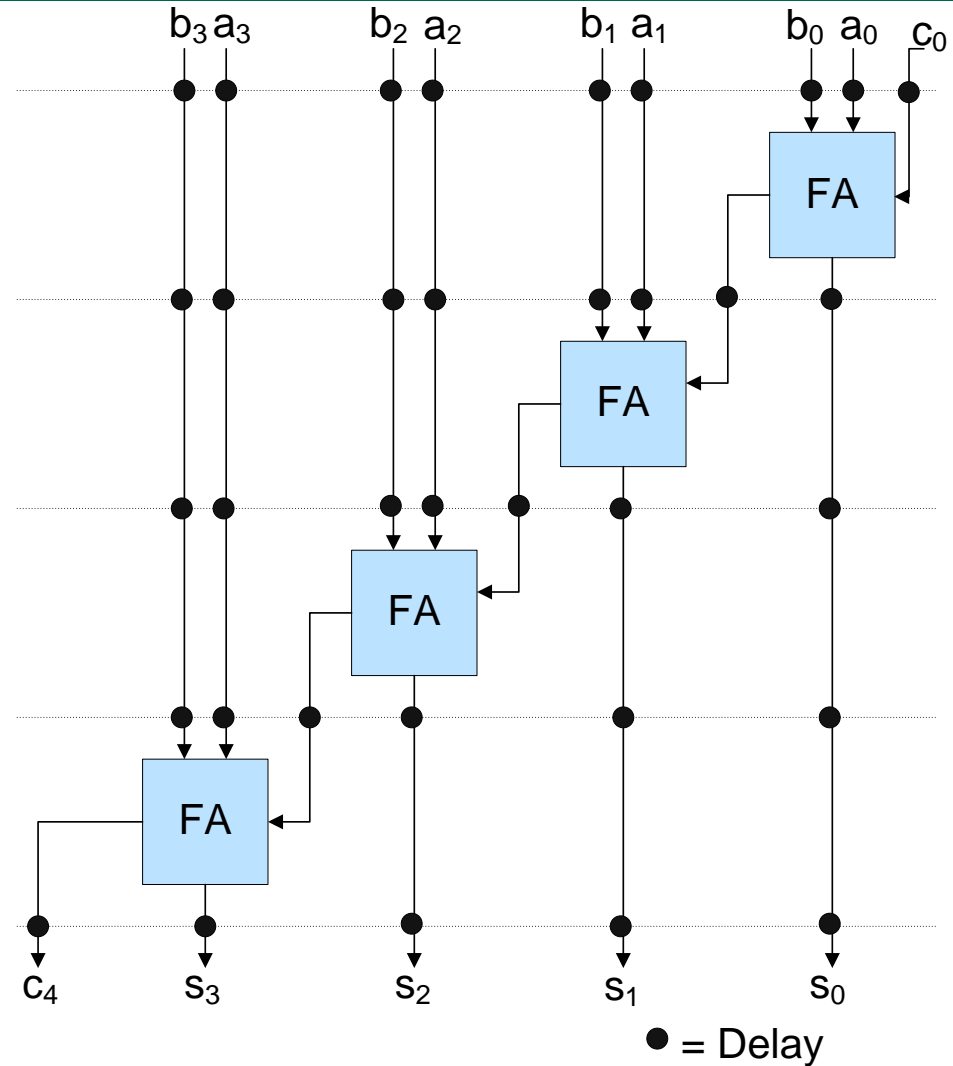
# Parallel to Systolic

- Selecting delay points



# Systolic RCA

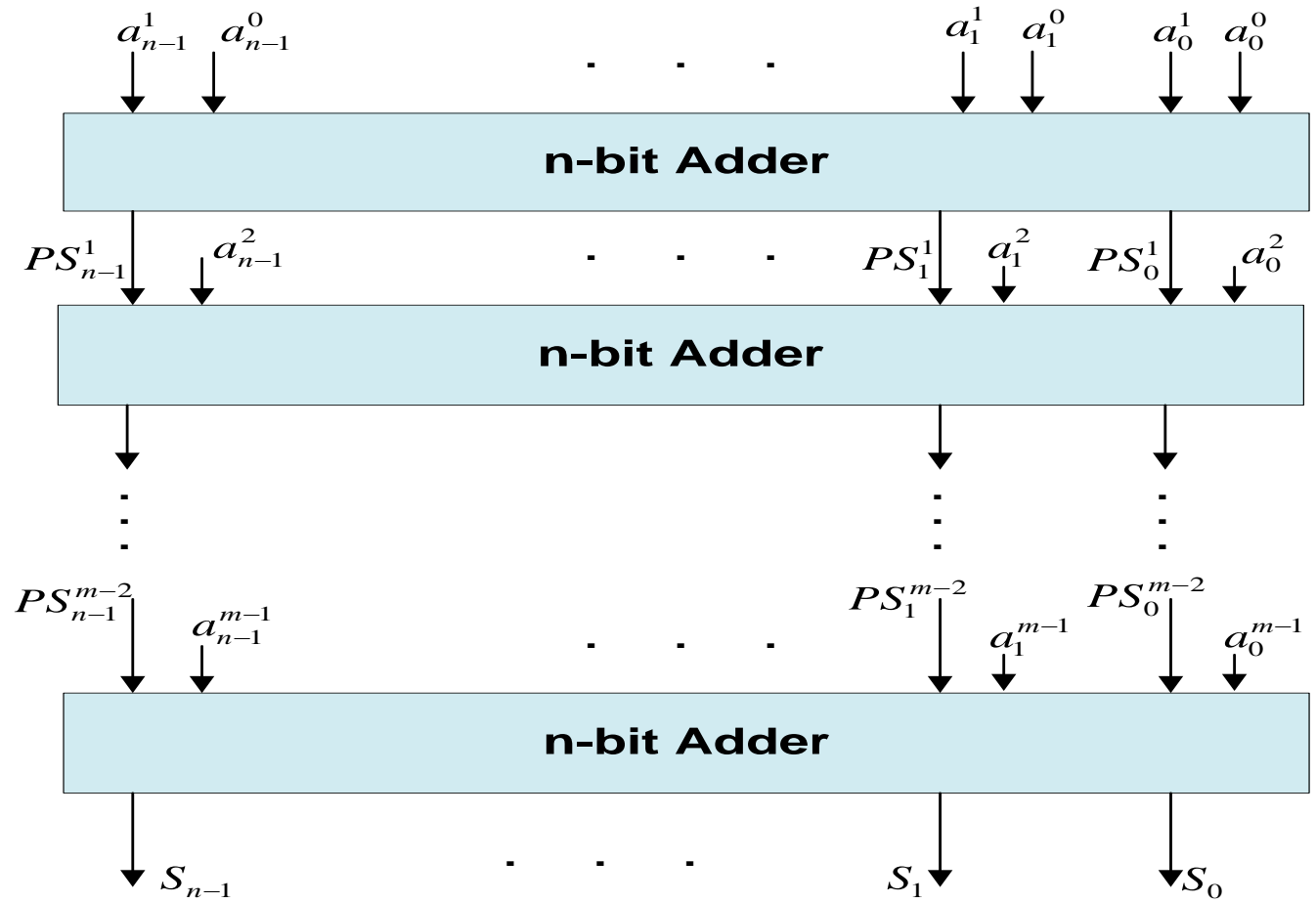
## 4 bit Systolic RCA



# Multi-operand Addition

- Add  $m$   $n$ -bit numbers

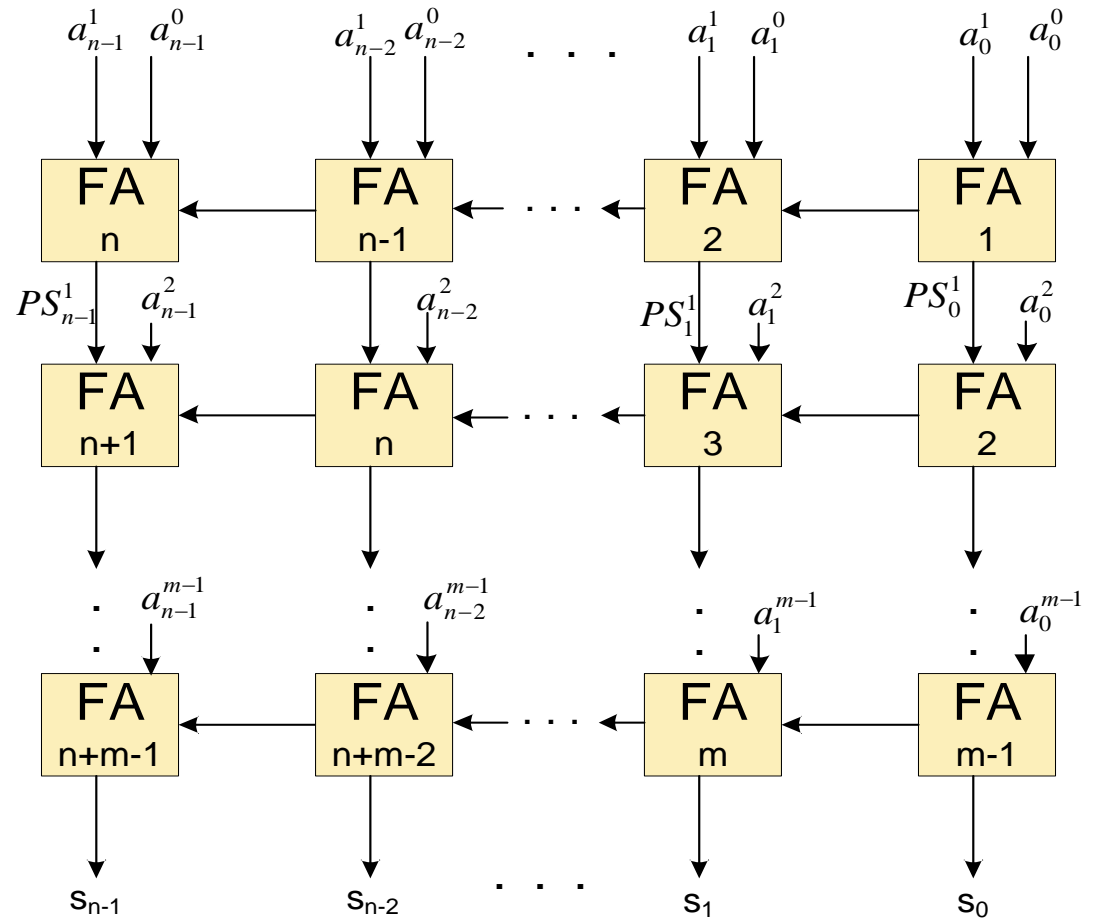
$$S = \sum_{j=0}^{m-1} A^j$$



# Multi-operand Addition

- Delay  $T = (n+m-2)T_{FA}$
- $T = (m-2)T_S + nT_C$

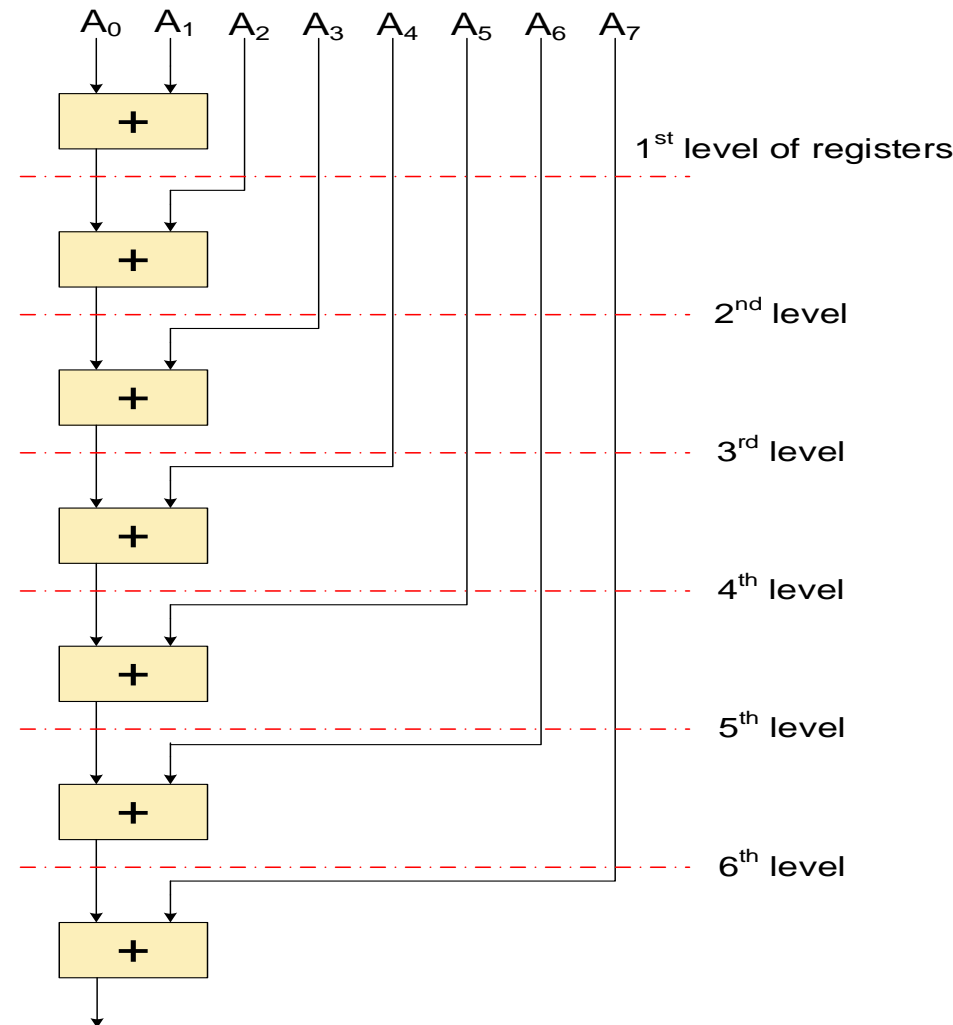
$$S = \sum_{j=0}^{m-1} A^j$$





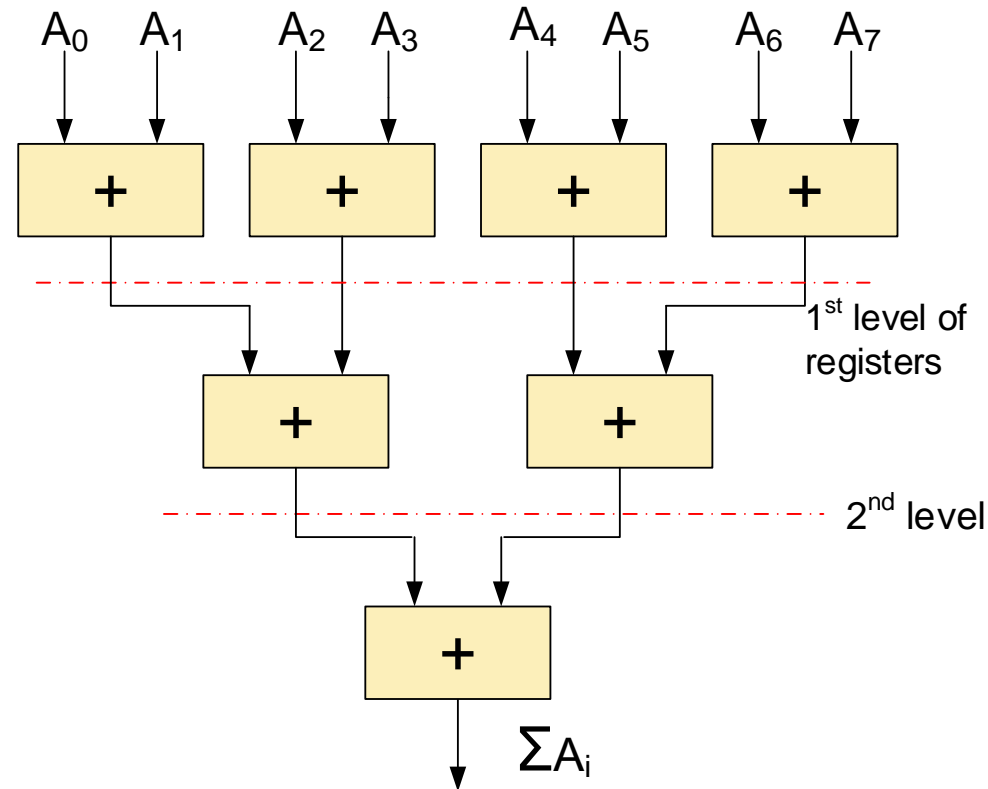
# Systolic Multi-operand Addition

- ❑  $m=8$  summands
- ❑ Number of registers  
 $=m(m-1)/2=28$
- ❑ Latency:  
 $T = (m-1) \cdot T_{\text{Clock}} = 7 \cdot T_{\text{Clock}}$



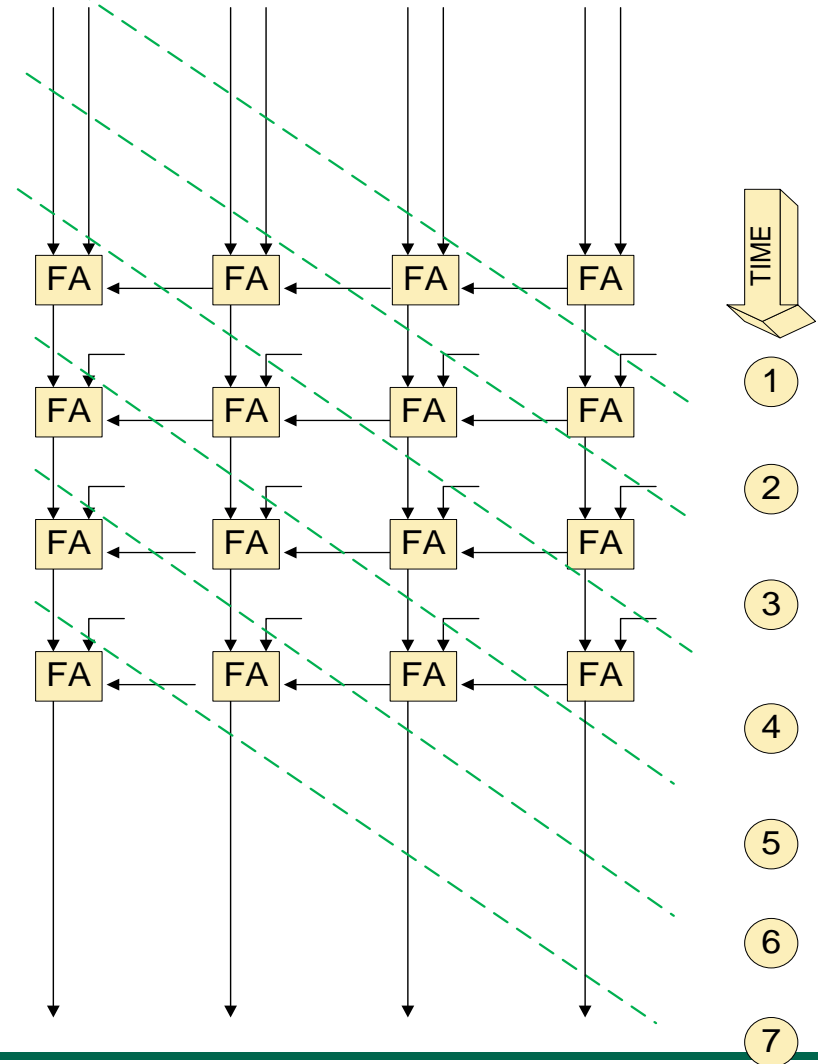
# Systolic Multi-operand Addition

- ❑ Adder Tree
- ❑  $m=8$  summands
- ❑ Number of registers  $= (m-1) = 7$
- ❑ Latency:  
 $T = \log_2 m \cdot T_{\text{clock}} = 3 \cdot T_{\text{clock}}$



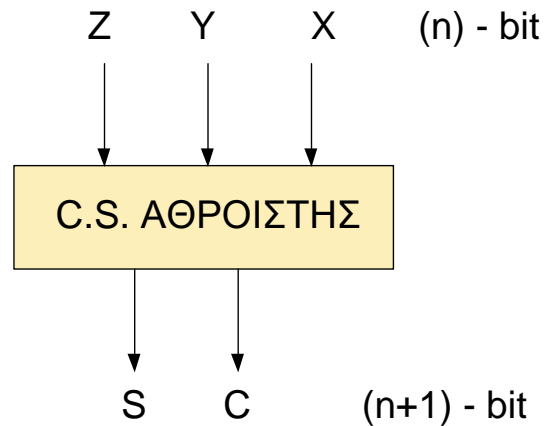
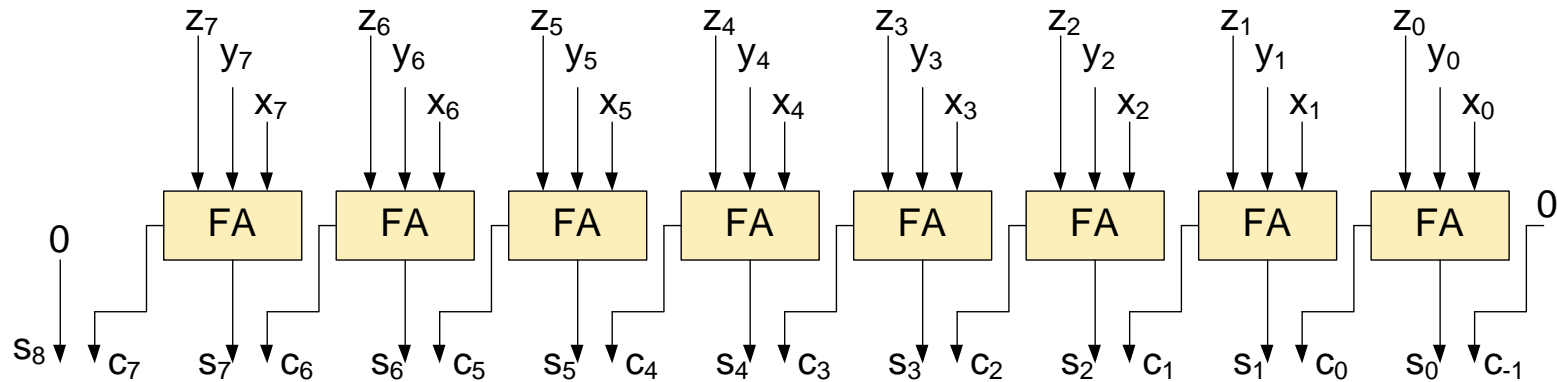
# 5x4 Systolic RCA

- ❑ Latency:  $T = (n+m-2) \cdot T_{\text{clock}}$
- ❑ Frequency:  
 $F = 1/(T_{\text{FA}} + T_{\text{D}}) = 1/T_{\text{clock}}$ 
  - $T_{\text{D}}$  flip-flop induced delay



# Carry-save

## □ Carry-save operation



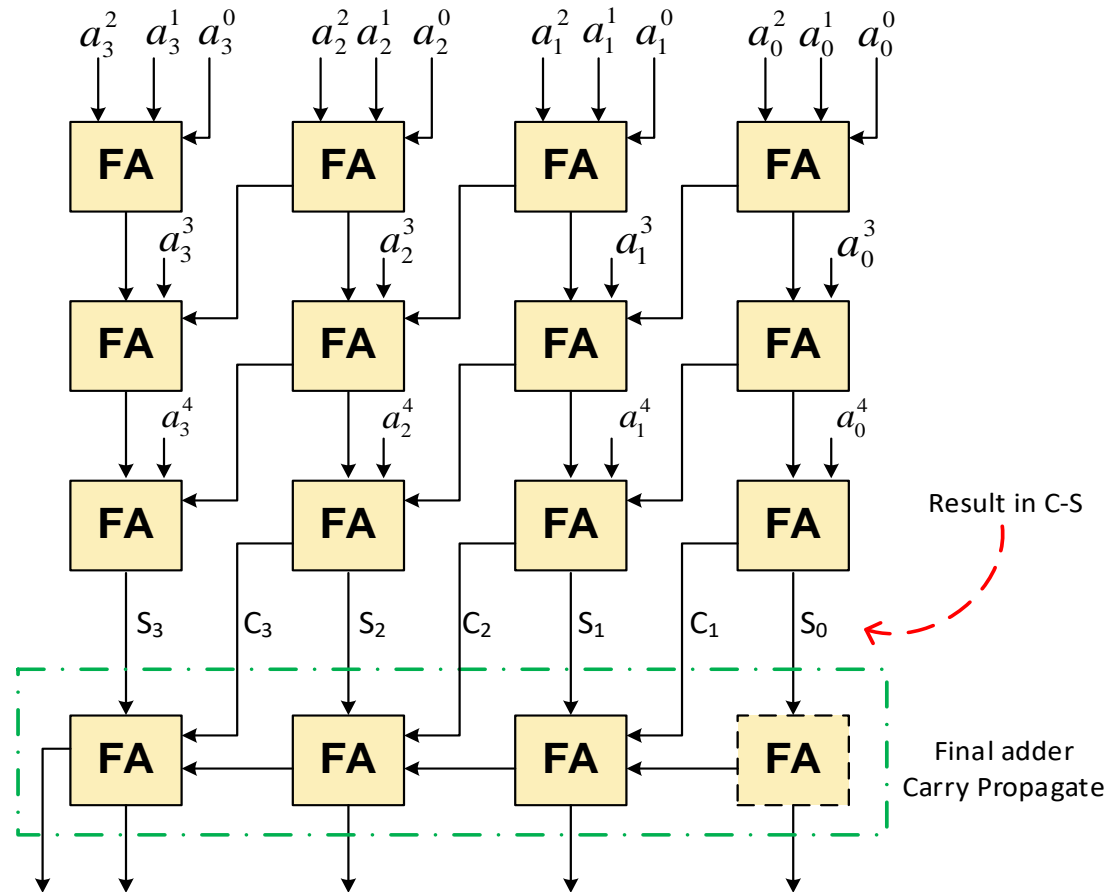
# Carry-save Addition

❑ 5 operand carry-save addition

❑ Delay:

$$T = (m-2)T_{FA} + (n)T_{FA} \\ = (m+n-2)T_{FA}$$

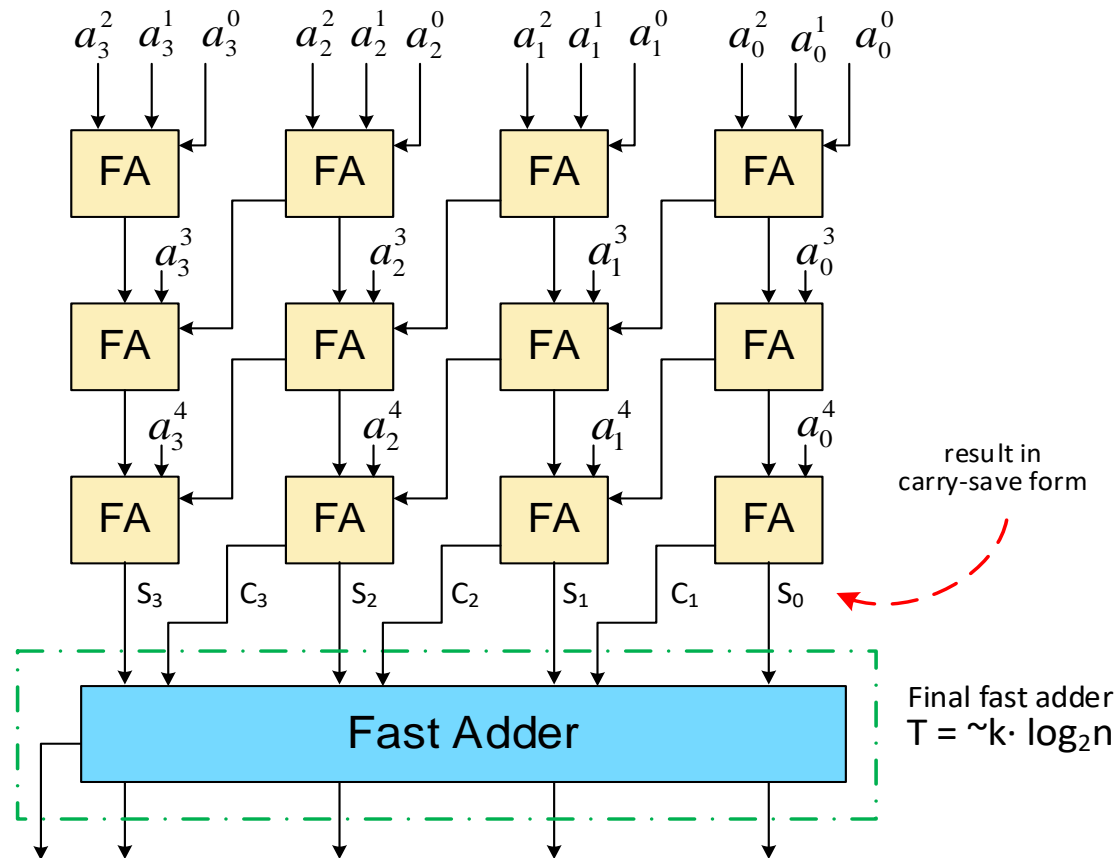
- $m$  = number of summands,  
 $n$  = bit size



# Carry-save Addition

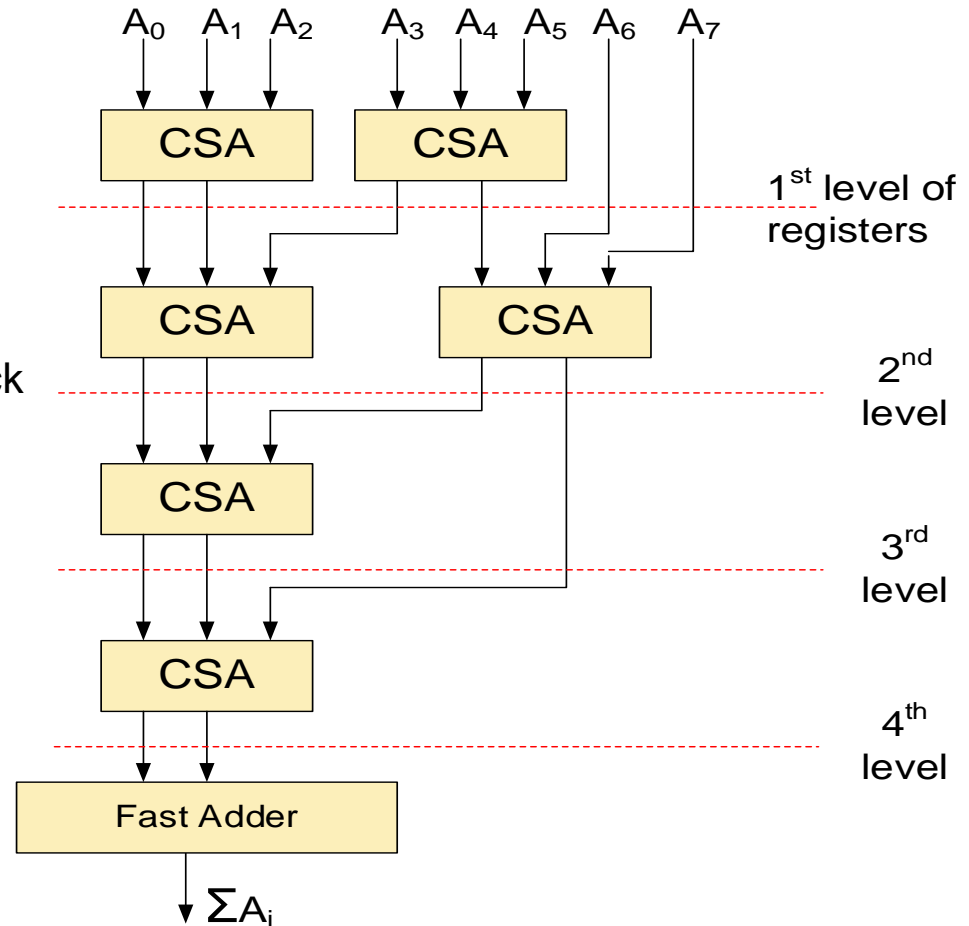
- ❑ 5 operand addition with carry-save
- ❑ Delay:  

$$T = (m-2)T_{FA} + k \cdot \log_2 n T_{FA}$$
  - $m$  = number of summands,
  - $n$  = bit size



# Systolic Carry-save Addition

- 8 operand systolic carry-save addition
- Number of registers  
 $= 2m-3=15$
- Latency  $= \log_{3/2} m \cdot T_{\text{Clock}}$   
 $= 1.7 \log_2 m \cdot T_{\text{Clock}} = 5 \cdot T_{\text{Clock}}$



# Latency

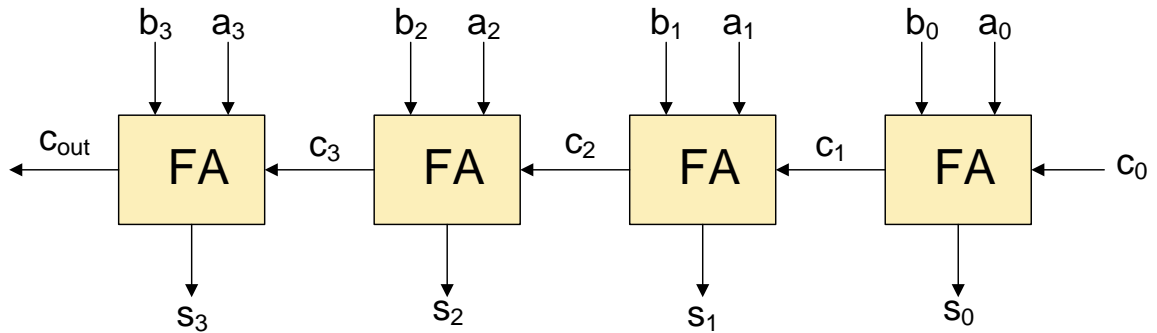
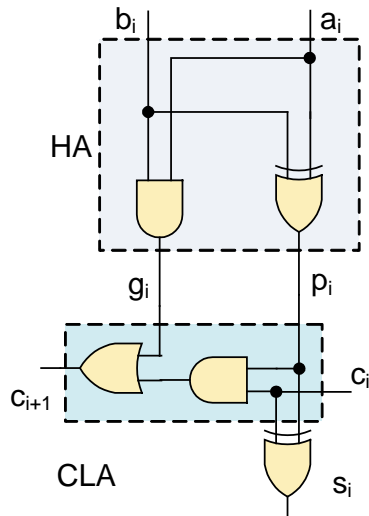
## ❑ Multi-operand addition latency

size $m$	Serial $m-1$	Tree $\log_2 m$	CS Tree $1.7\log_2 m$
8	7	3	5
12	11	4	5
16	15	4	7
32	31	5	9
64	63	6	10



# Carry Propagation

- Full adder:  $s_i = (a_i \oplus b_i) \oplus c_i$  and  $c_{i+1} = a_i \cdot b_i + (a_i + b_i) \cdot c_i$
- Denoting  $p_i = a_i \oplus b_i$  and  $g_i = a_i \cdot b_i$   
 $\rightarrow s_i = p_i \oplus c_i$  and  $c_{i+1} = g_i + p_i \cdot c_i$
- Carry out:
  - If  $g_i = 1 \rightarrow$  a carry is generated
  - If  $p_i = 1 \rightarrow$  carry in is propagated



# PGK

---

- ❑ For a full adder, define what happens to carries
  - Generate:  $C_{out} = 1$  independent of  $C$   
 $G = A \bullet B$
  - Propagate:  $C_{out} = C$   
 $P = A \oplus B$
  - Kill:  $C_{out} = 0$  independent of  $C$   
 $K = \sim A \bullet \sim B$

# Generate / Propagate

---

- Equations often factored into G and P
- Generate and propagate for groups spanning  $i:j$

$$G_{i:j} =$$

$$P_{i:j} =$$

- Base case

$$G_{i:i} \equiv$$

$$P_{i:i} \equiv$$

$$G_{0:0} \equiv$$

$$P_{0:0} \equiv$$

- Sum:

$$S_i =$$

# Generate / Propagate

---

- Equations often factored into G and P
- Generate and propagate for groups spanning i:j

$$G_{i:j} = G_{i:k} + P_{i:k} \cdot G_{k-1:j}$$

$$P_{i:j} =$$

- Base case

$$G_{i:i} \equiv$$

$$P_{i:i} \equiv$$

$$G_{0:0} \equiv$$

$$P_{0:0} \equiv$$

- Sum:

$$S_i =$$

# Generate / Propagate

---

- ❑ Equations often factored into G and P
- ❑ Generate and propagate for groups spanning i:j

$$G_{i:j} = G_{i:k} + P_{i:k} \cdot G_{k-1:j}$$

$$P_{i:j} = P_{i:k} \cdot P_{k-1:j}$$

- ❑ Base case

$$G_{i:i} \equiv$$

$$P_{i:i} \equiv$$

$$G_{0:0} \equiv$$

$$P_{0:0} \equiv$$

- ❑ Sum:

$$S_i =$$

# Generate / Propagate

---

- Equations often factored into G and P
- Generate and propagate for groups spanning i:j

$$G_{i:j} = G_{i:k} + P_{i:k} \cdot G_{k-1:j}$$

$$P_{i:j} = P_{i:k} \cdot P_{k-1:j}$$

- Base case

$$G_{i:i} \equiv G_i = A_i \cdot B_i$$

$$P_{i:i} \equiv$$

$$G_{0:0} \equiv$$

$$P_{0:0} \equiv$$

- Sum:

$$S_i =$$

# Generate / Propagate

---

- Equations often factored into G and P
- Generate and propagate for groups spanning i:j

$$G_{i:j} = G_{i:k} + P_{i:k} \cdot G_{k-1:j}$$

$$P_{i:j} = P_{i:k} \cdot P_{k-1:j}$$

- Base case

$$G_{i:i} \equiv G_i = A_i \cdot B_i$$

$$P_{i:i} \equiv P_i = A_i \oplus B_i$$

$$G_{0:0} \equiv$$

$$P_{0:0} \equiv$$

- Sum:

$$S_i =$$

# Generate / Propagate

---

- ❑ Equations often factored into G and P
- ❑ Generate and propagate for groups spanning  $i:j$

$$G_{i:j} = G_{i:k} + P_{i:k} \cdot G_{k-1:j}$$

$$P_{i:j} = P_{i:k} \cdot P_{k-1:j}$$

- ❑ Base case

$$G_{i:i} \equiv G_i = A_i \cdot B_i$$

$$P_{i:i} \equiv P_i = A_i \oplus B_i$$

$$G_{0:0} \equiv G_0 = C_{in}$$

$$P_{0:0} \equiv$$

- ❑ Sum:

$$S_i =$$



# Generate / Propagate

---

- Equations often factored into G and P
- Generate and propagate for groups spanning i:j

$$G_{i:j} = G_{i:k} + P_{i:k} \cdot G_{k-1:j}$$

$$P_{i:j} = P_{i:k} \cdot P_{k-1:j}$$

- Base case

$$G_{i:i} \equiv G_i = A_i \cdot B_i$$

$$P_{i:i} \equiv P_i = A_i \oplus B_i$$

$$G_{0:0} \equiv G_0 = C_{in}$$

$$P_{0:0} \equiv P_0 = 0$$

- Sum:

$$S_i =$$

# Generate / Propagate

---

- Equations often factored into G and P
- Generate and propagate for groups spanning  $i:j$

$$G_{i:j} = G_{i:k} + P_{i:k} \cdot G_{k-1:j}$$

$$P_{i:j} = P_{i:k} \cdot P_{k-1:j}$$

- Base case

$$G_{i:i} \equiv G_i = A_i \cdot B_i$$

$$P_{i:i} \equiv P_i = A_i \oplus B_i$$

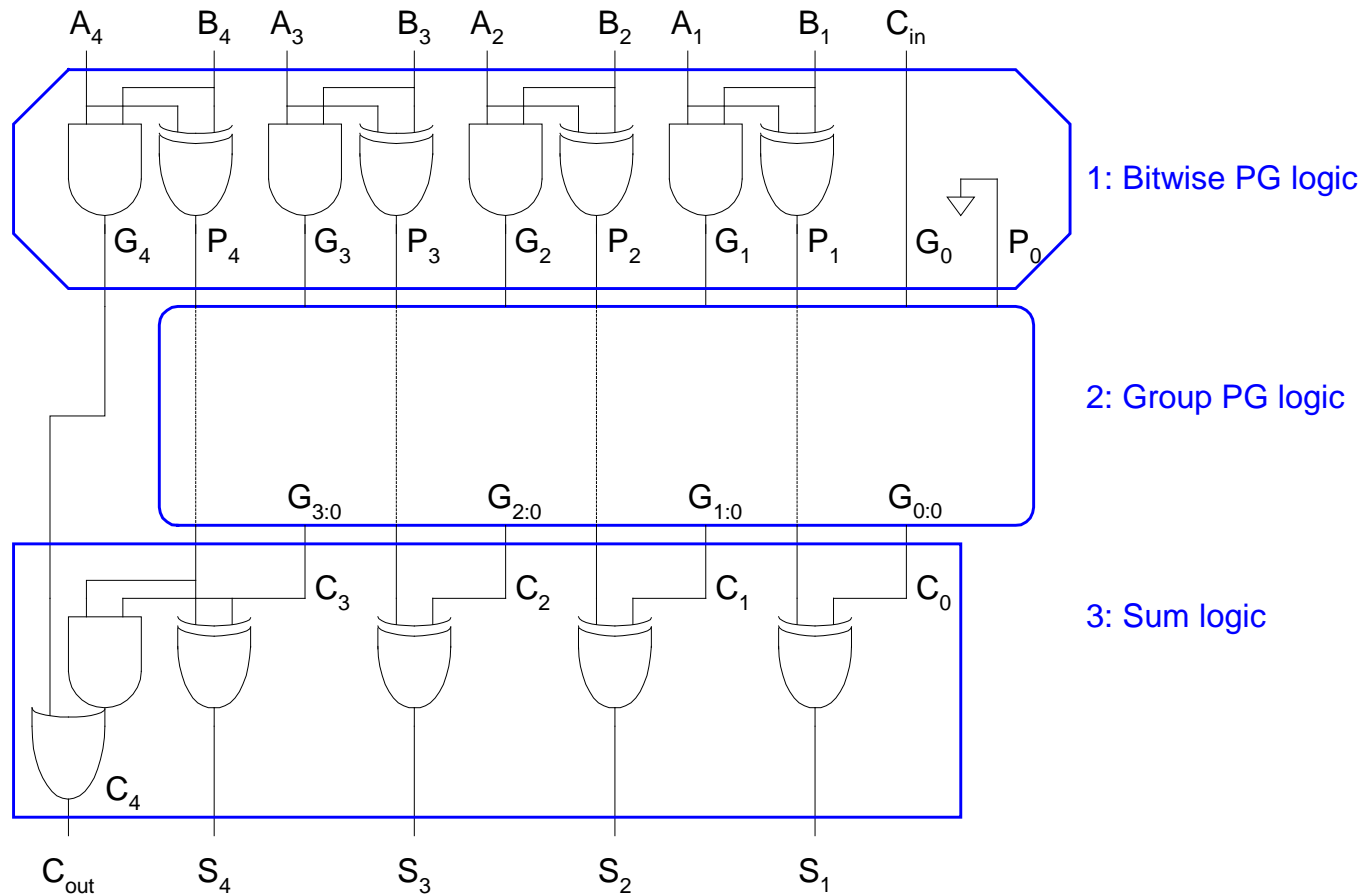
$$G_{0:0} \equiv G_0 = C_{in}$$

$$P_{0:0} \equiv P_0 = 0$$

- Sum:

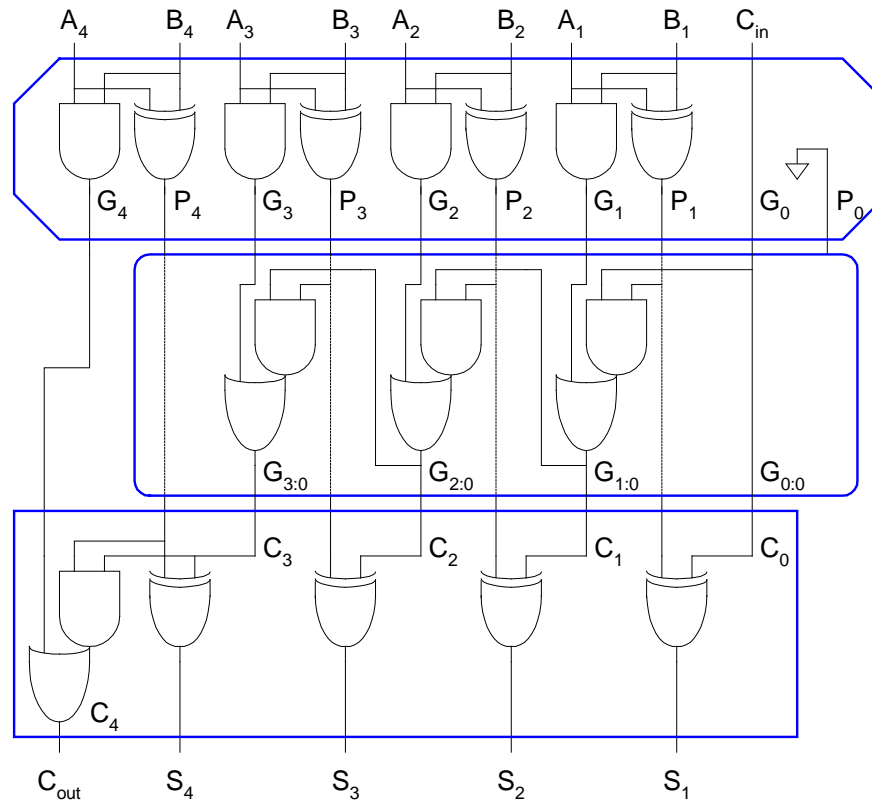
$$S_i = P_i \oplus G_{i-1:0}$$

# PG Logic



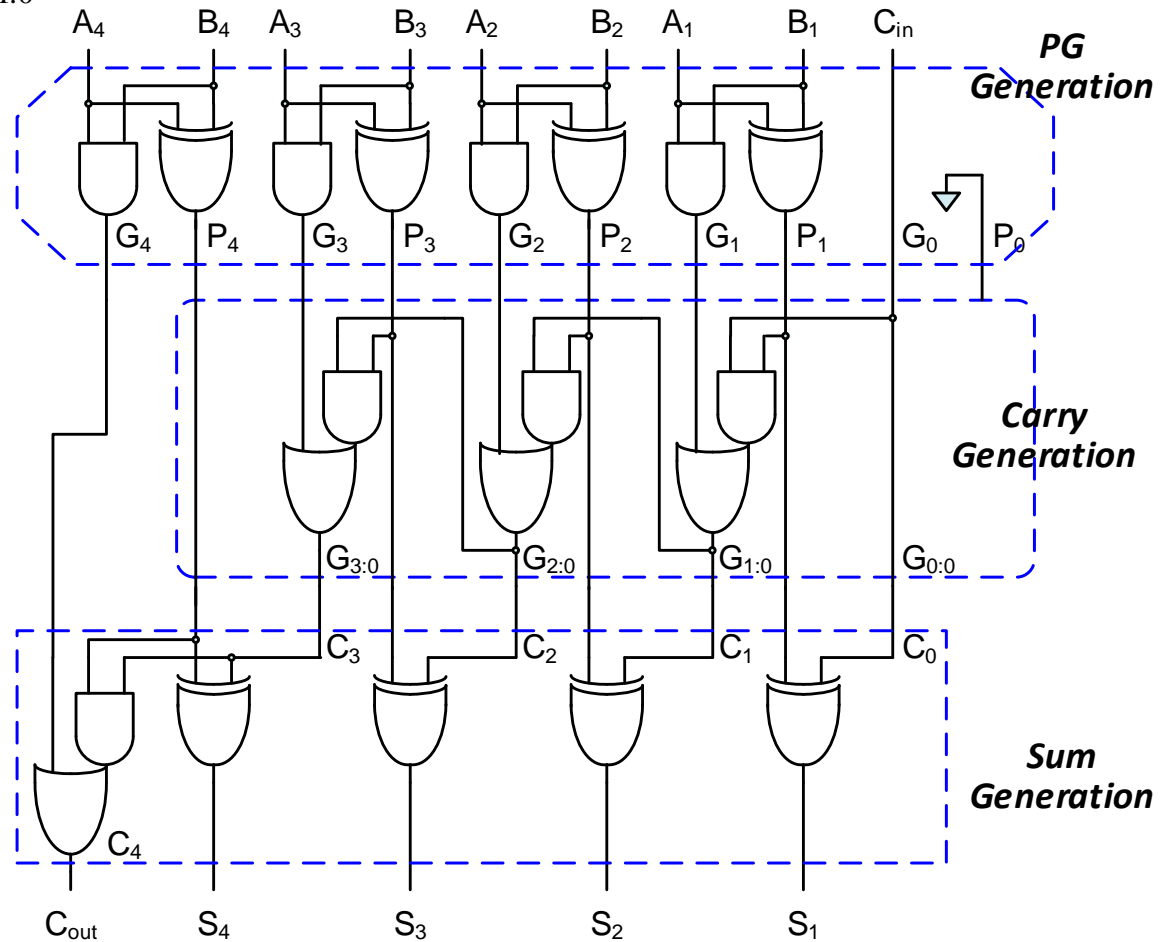
# Carry-Ripple Revisited

□  $G_{i:0} = G_i + P_i \cdot G_{i-1:0}$

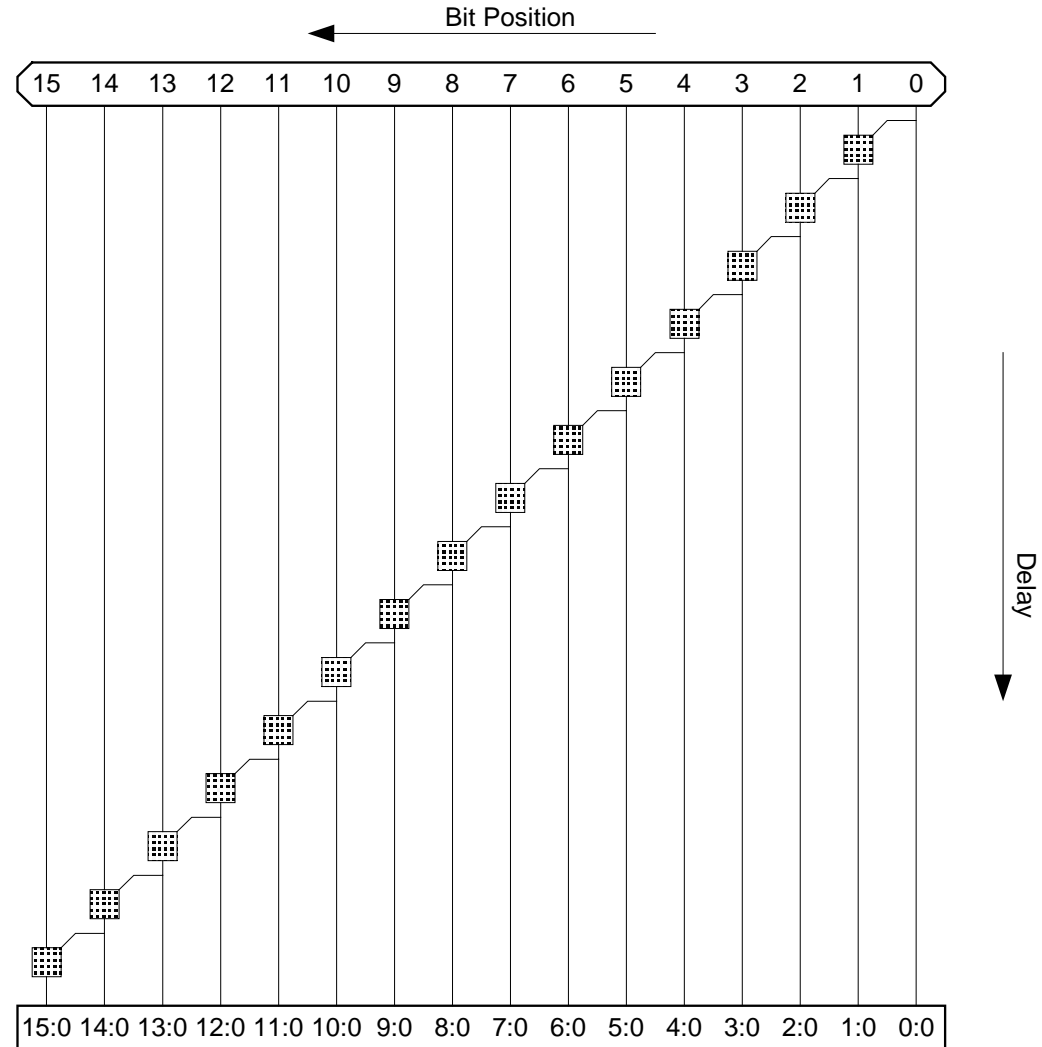


# RCA

□  $G_{i:0} = G_i + P_i \cdot G_{i-1:0}$



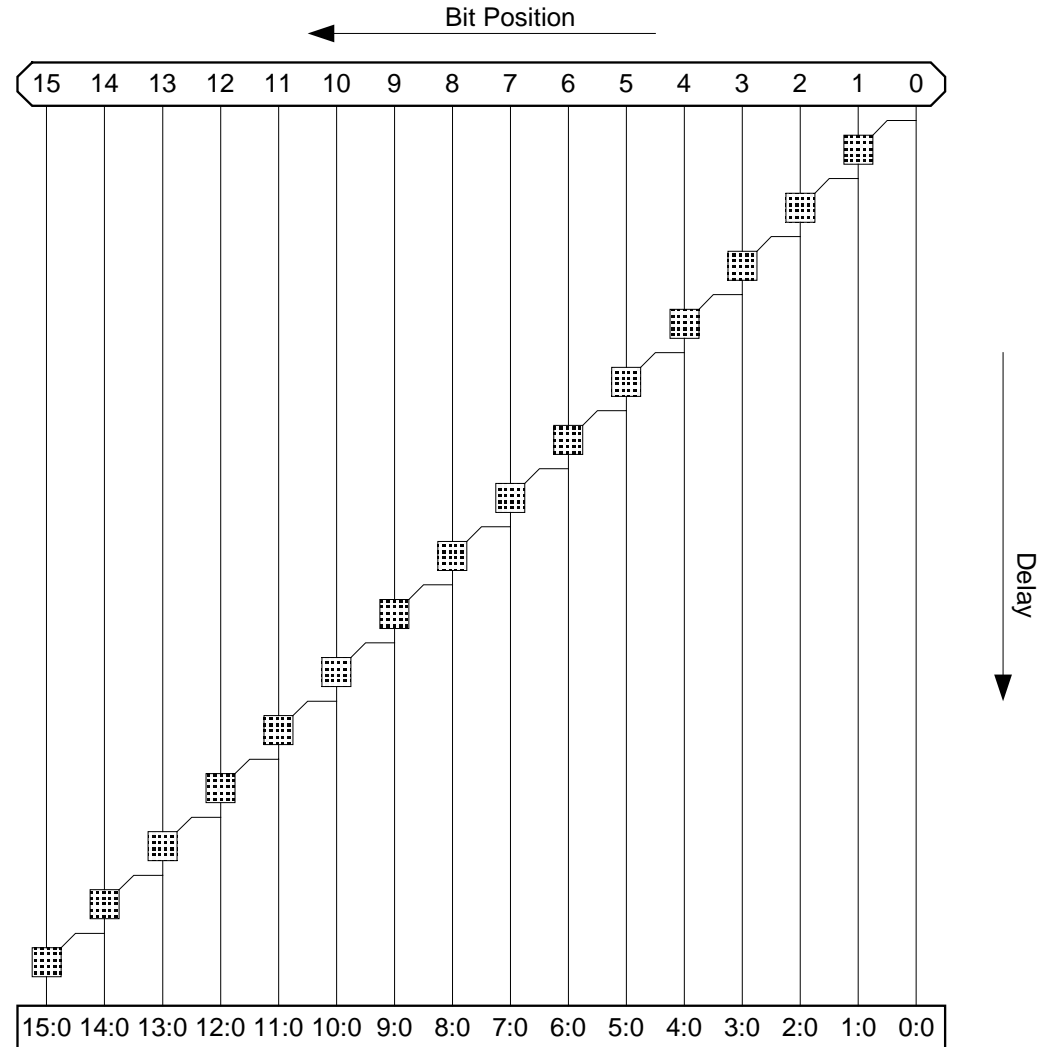
# Carry-Ripple PG Diagram



$t_{\text{ripple}} =$

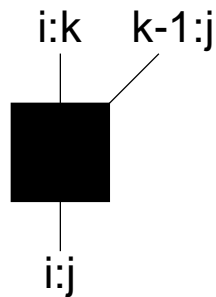
# Carry-Ripple PG Diagram

$$t_{\text{ripple}} = t_{pg} + (N - 1)t_{AO} + t_{\text{xor}}$$

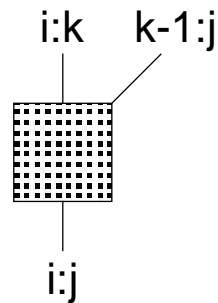


# PG Diagram Notation

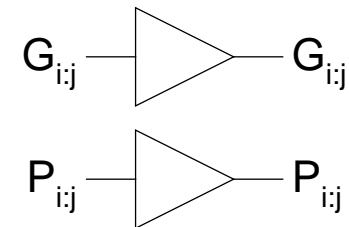
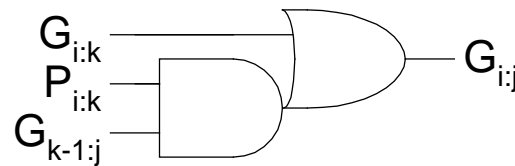
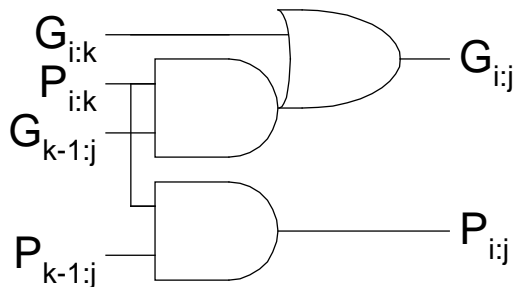
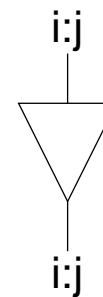
Black cell



Gray cell



Buffer





# Carry Prediction Adders

---

$$C_1 = G_0 + P_0 C_0$$

$$C_2 = G_1 + P_1 G_0 + P_1 P_0 C_0$$

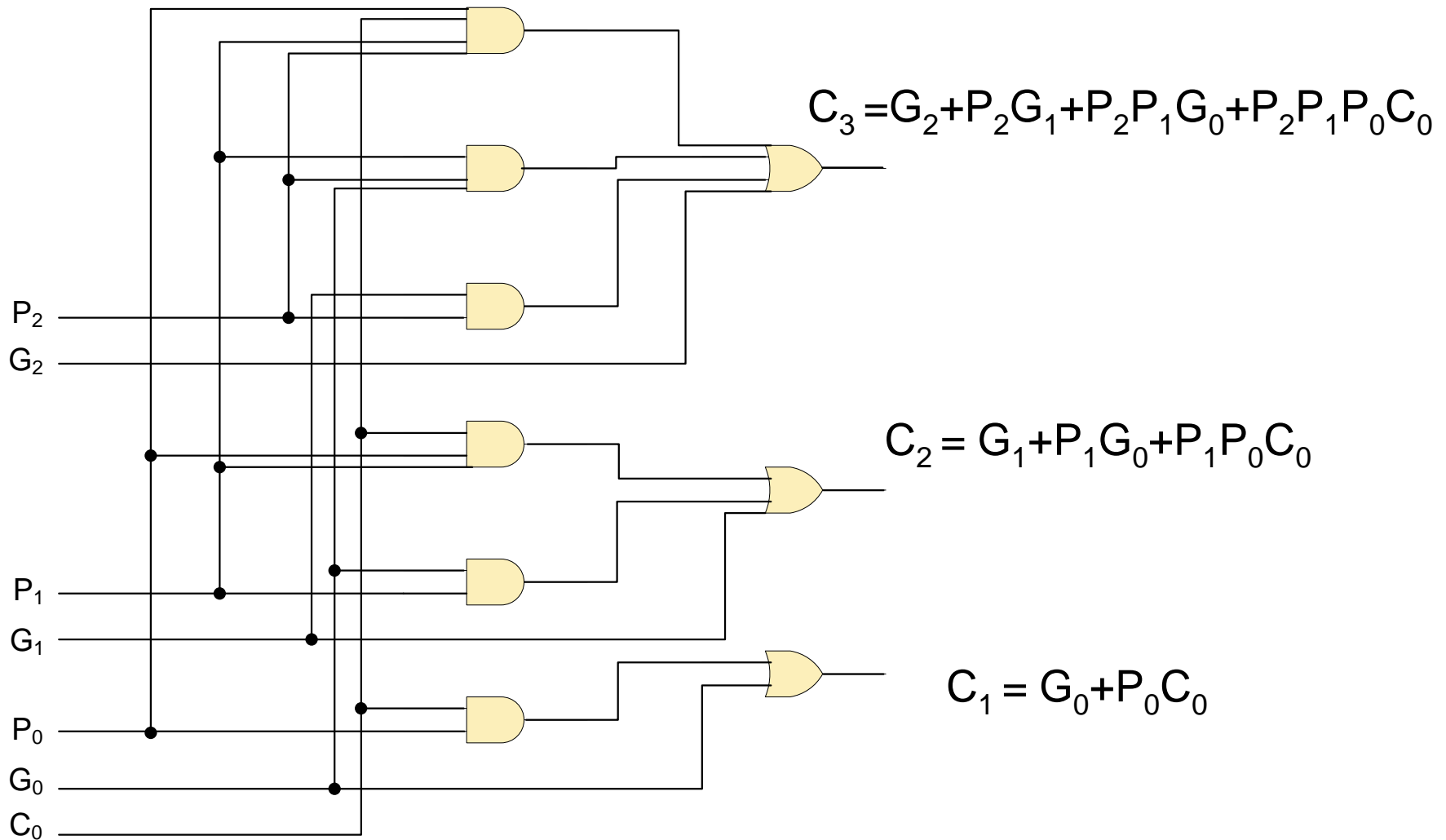
$$C_3 = G_2 + P_2 G_1 + P_2 P_1 G_0 + P_2 P_1 P_0 C_0$$

$$C_4 = G_3 + P_3 G_2 + P_3 P_2 G_1 + P_3 P_2 P_1 G_0 + P_3 P_2 P_1 P_0 C_0$$

For n:

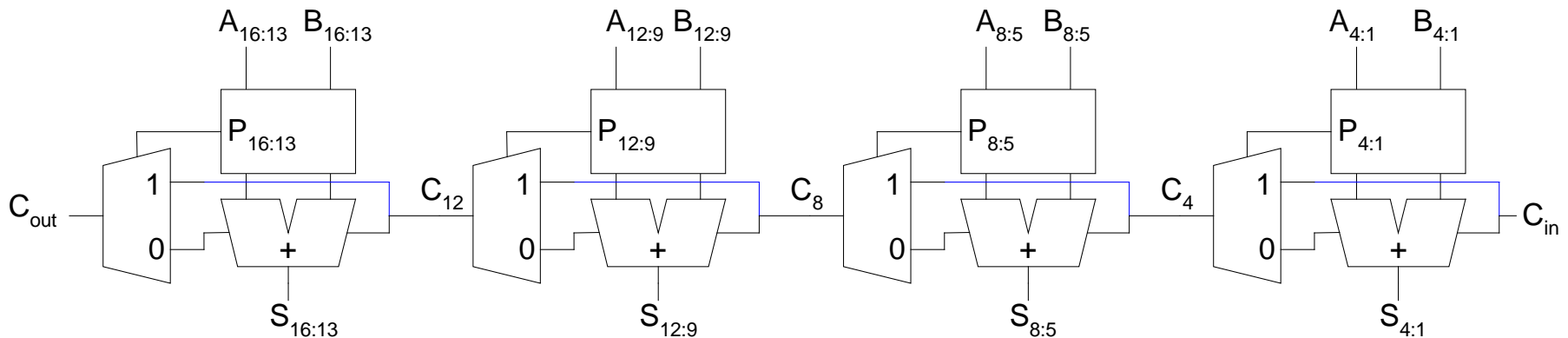
$$\begin{aligned} C_{n+1} &= G_n + P_n (G_{n-1} + P_{n-1} (G_{n-2} + P_{n-2} (G_{n-3} + P_{n-3} (\dots + P_2 (G_1 + P_1 C_1)))))) = \\ &= G_n + P_n G_{n-1} + P_n P_{n-1} G_{n-2} + P_n P_{n-1} P_{n-2} G_{n-3} + \dots + P_n P_{n-1} P_{n-2} \dots P_2 G_1 + P_n P_{n-1} P_{n-2} \dots P_2 P_1 C_1 \end{aligned}$$

# Carry Prediction Adders



# Carry-Skip Adder

- ❑ Carry-ripple is slow through all N stages
- ❑ Carry-skip allows carry to skip over groups of n bits
  - Decision based on n-bit propagate signal

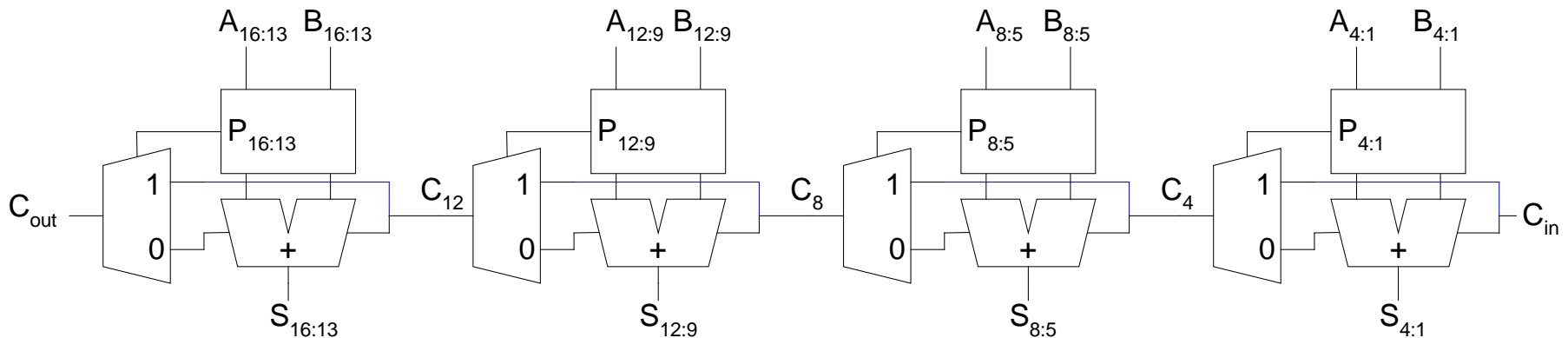


For k n-bit groups ( $N = nk$ )

$$t_{\text{skip}} =$$

# Carry-Skip Adder

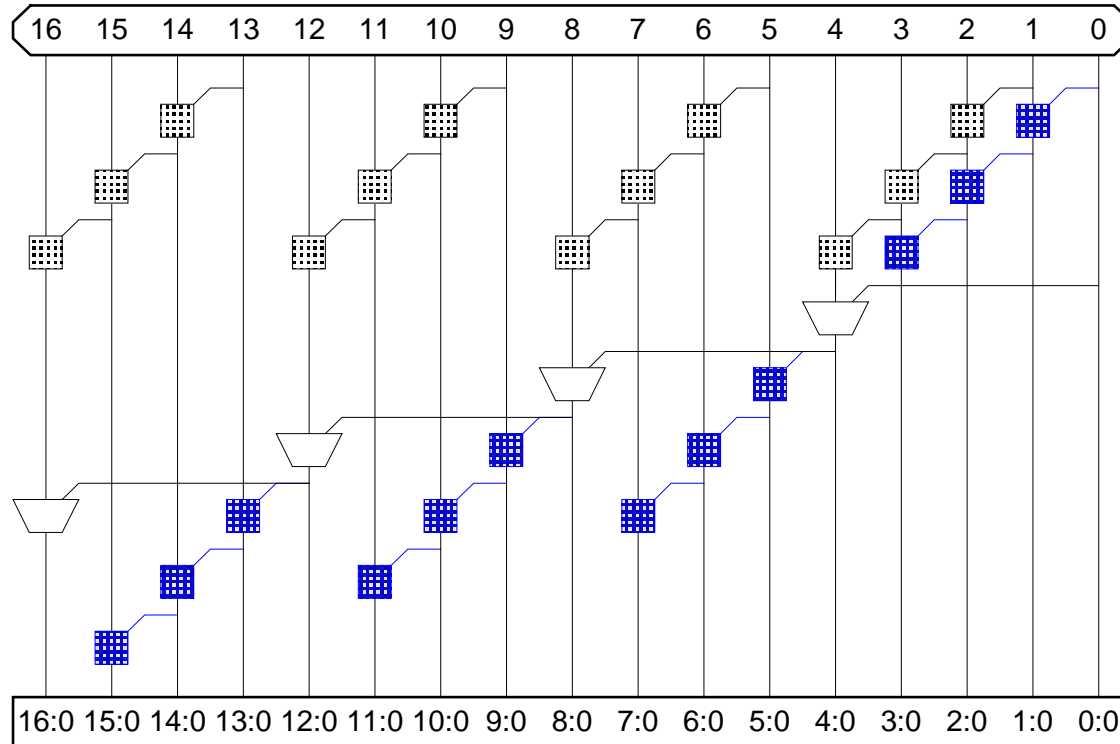
- ❑ Carry-ripple is slow through all N stages
- ❑ Carry-skip allows carry to skip over groups of n bits
  - Decision based on n-bit propagate signal



For k n-bit groups ( $N = nk$ )

$$t_{\text{skip}} = t_{pg} + \left[ 2(n-1) + (k-1) \right] t_{AO} + t_{\text{xor}}$$

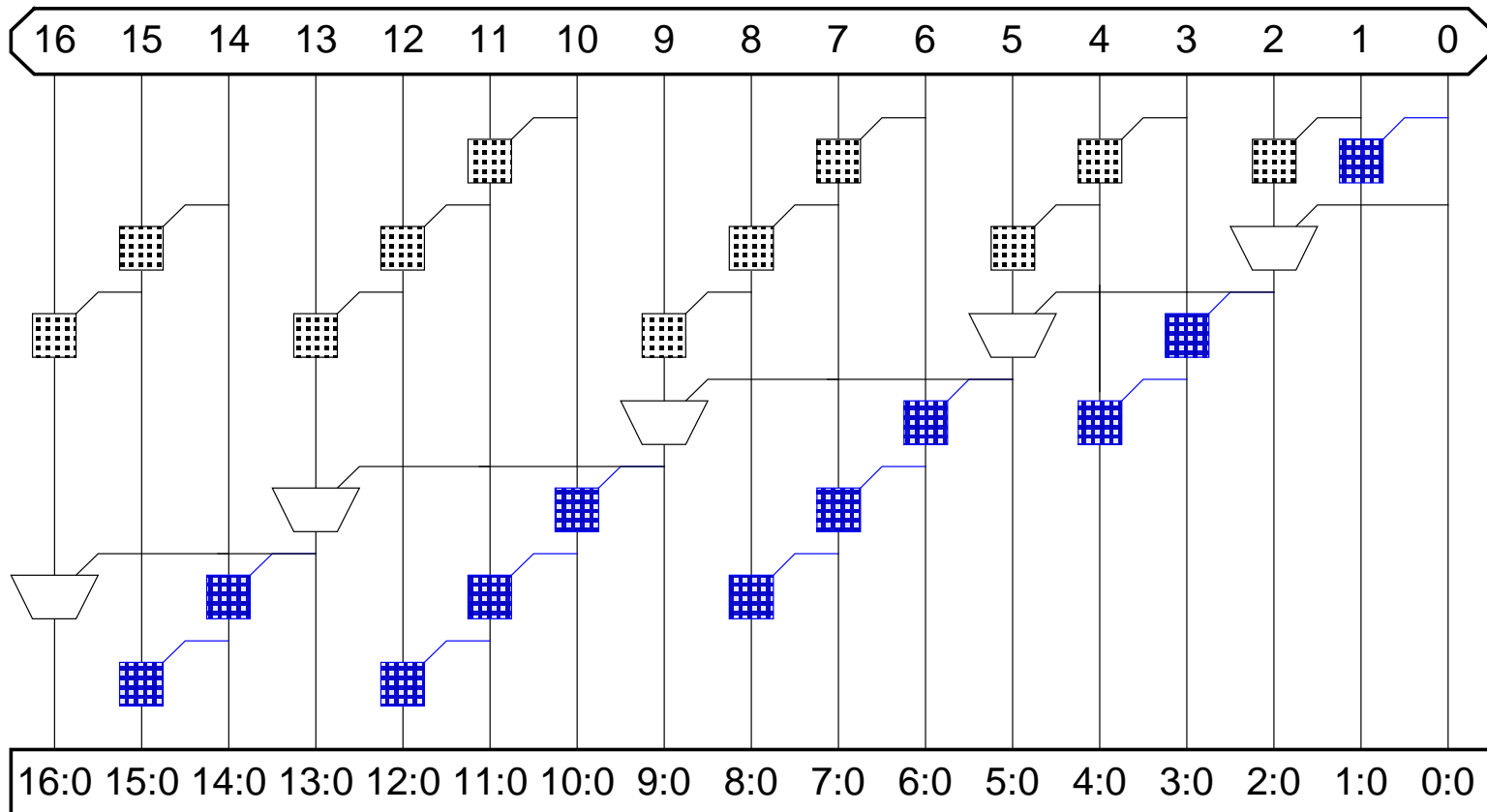
# Carry-Skip PG Diagram



For k n-bit groups ( $N = nk$ )

$$t_{\text{skip}} = t_{pg} + \left[ 2(n-1) + (k-1) \right] t_{AO} + t_{\text{xor}}$$

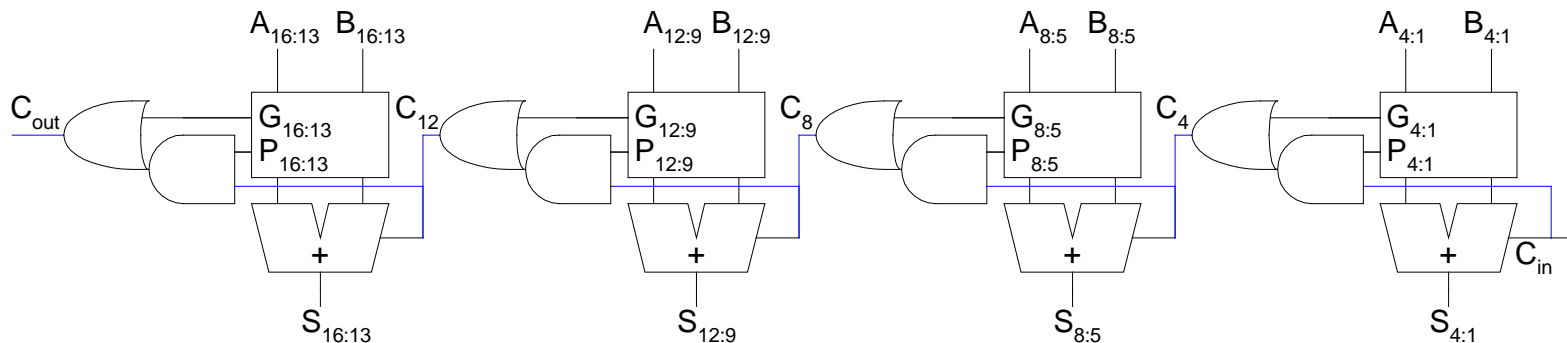
# Variable Group Size



Delay grows as  $O(\sqrt{N})$

# Carry-Lookahead Adder

- ❑ Carry-lookahead adder computes  $G_{i:0}$  for many bits in parallel.
- ❑ Uses higher-valency cells with more than two inputs.

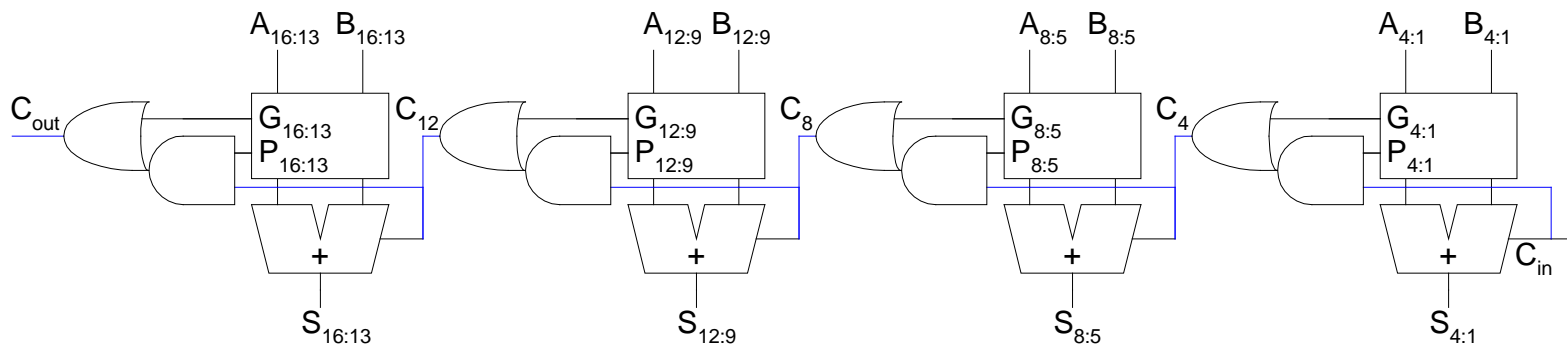


$N = k \cdot b$ ,  $b$ =block size,  $k$ =number of blocks

$t_{\text{add}} =$

# Carry-Lookahead Adder

- Carry-lookahead adder computes  $G_{i:0}$  for many bits in parallel.
- Uses higher-valency cells with more than two inputs.

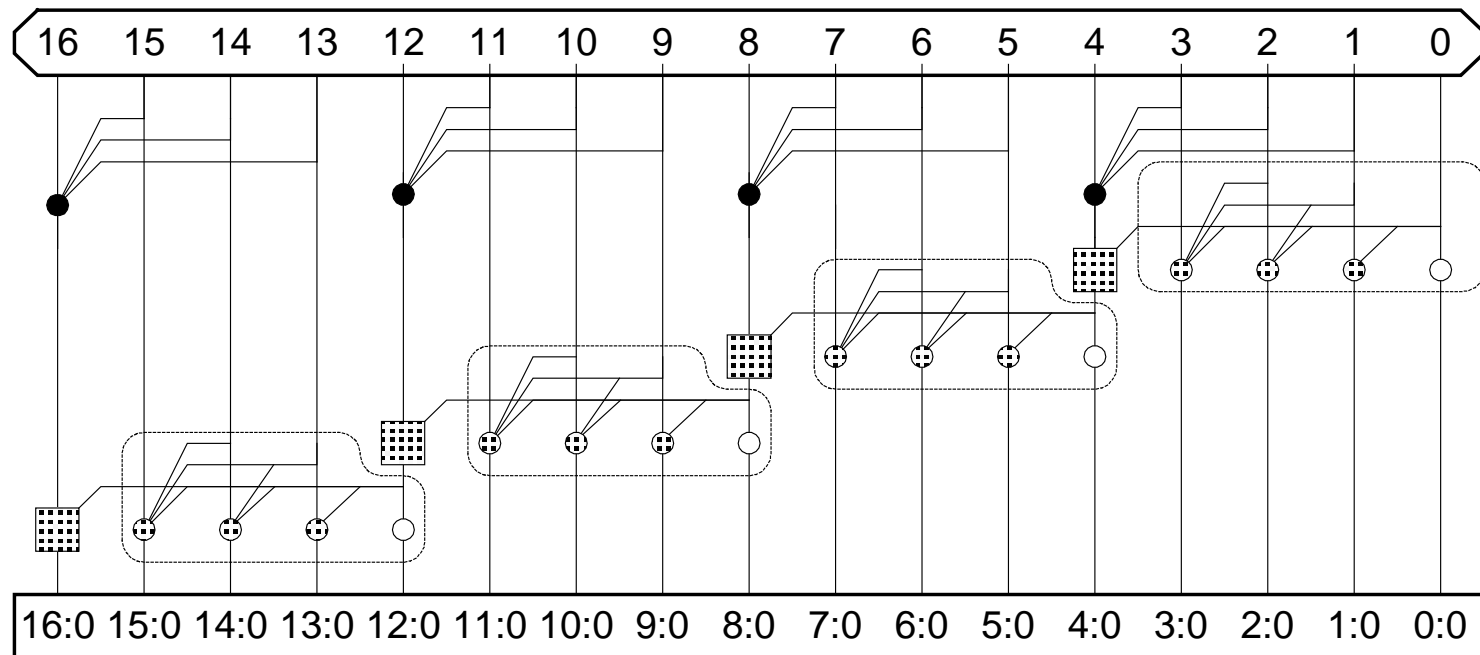


$N = k \cdot b$ ,  $b$ =block size,  $k$ =number of blocks

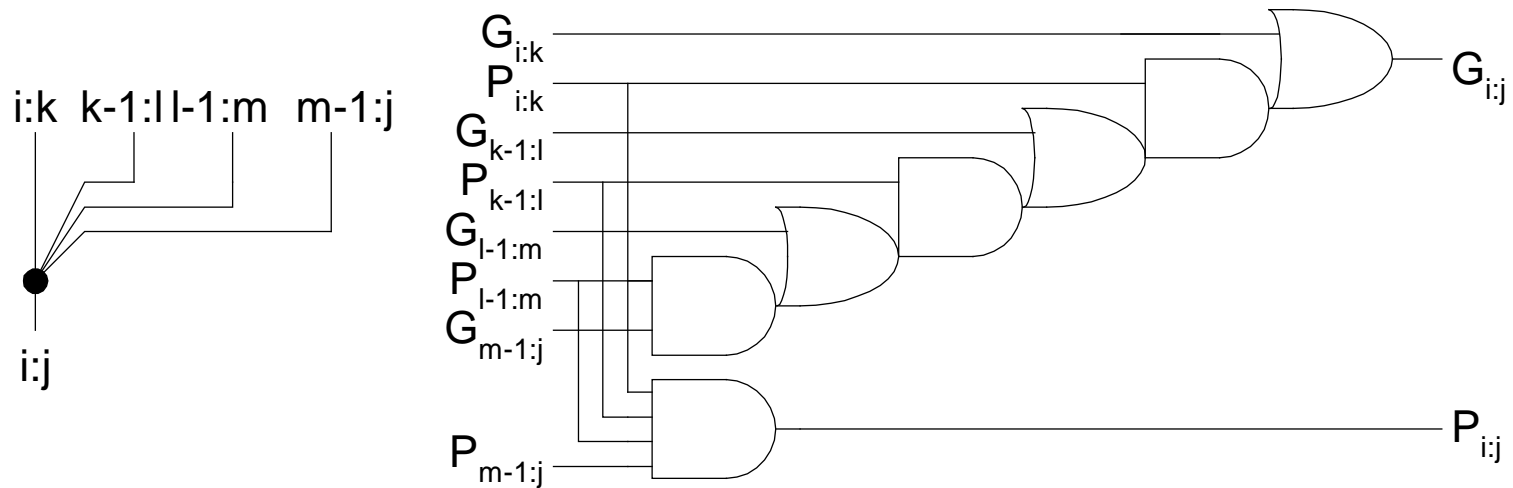
$$t_{add} = t_{pg} + t_{pg(b)} + [(b-1) + (k-1)] \cdot t_{AO} + t_{XOR}$$



# CLA PG Diagram

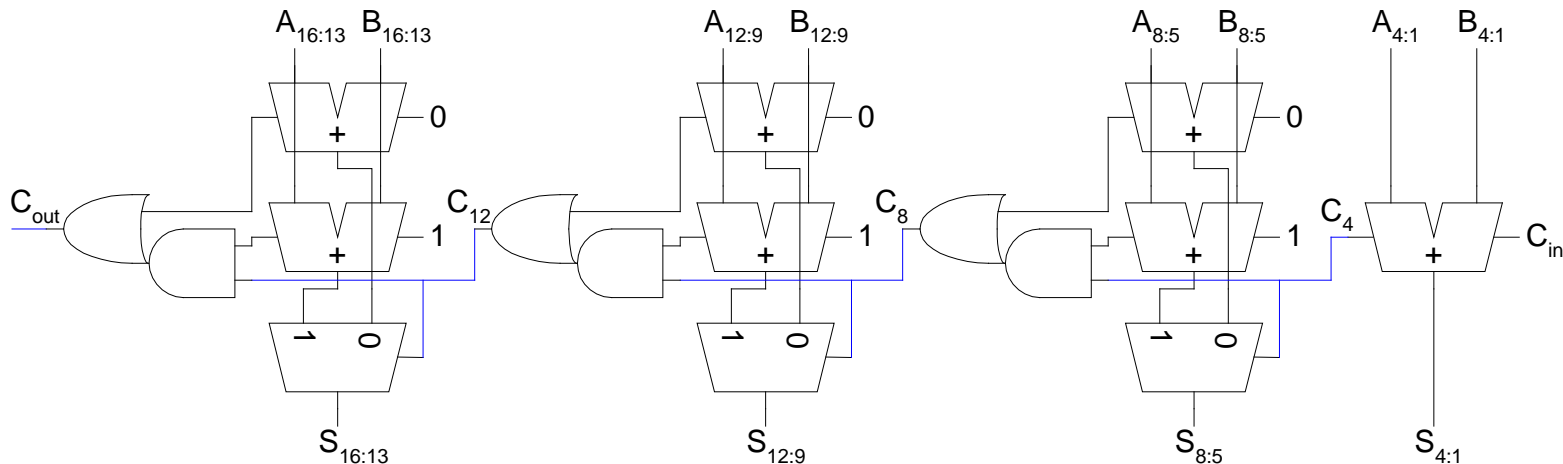


# Higher-Valency Cells



# Carry-Select Adder

- ❑ Trick for critical paths dependent on late input X
  - Precompute two possible outputs for  $X = 0, 1$
  - Select proper output when  $X$  arrives
- ❑ Carry-select adder precomputes n-bit sums
  - For both possible carries into n-bit group

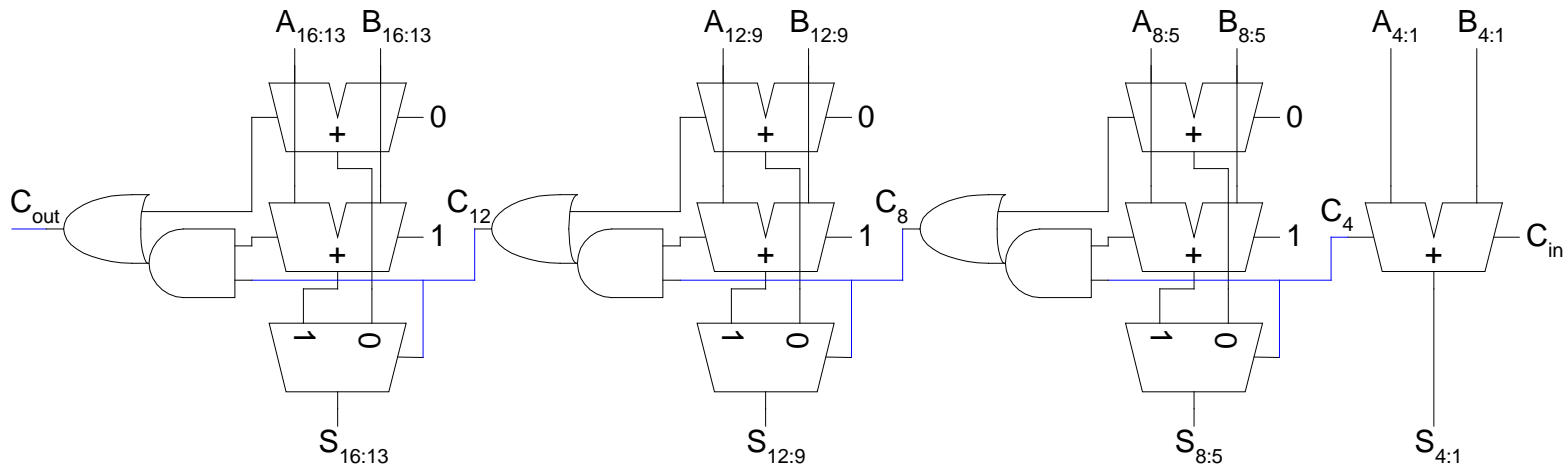


$N = k \cdot b$ ,  $b$  = block size,  $k$  = number of blocks

$t_{add} =$

# Carry-Select Adder

- ❑ Trick for critical paths dependent on late input X
  - Precompute two possible outputs for  $X = 0, 1$
  - Select proper output when  $X$  arrives
- ❑ Carry-select adder precomputes n-bit sums
  - For both possible carries into n-bit group



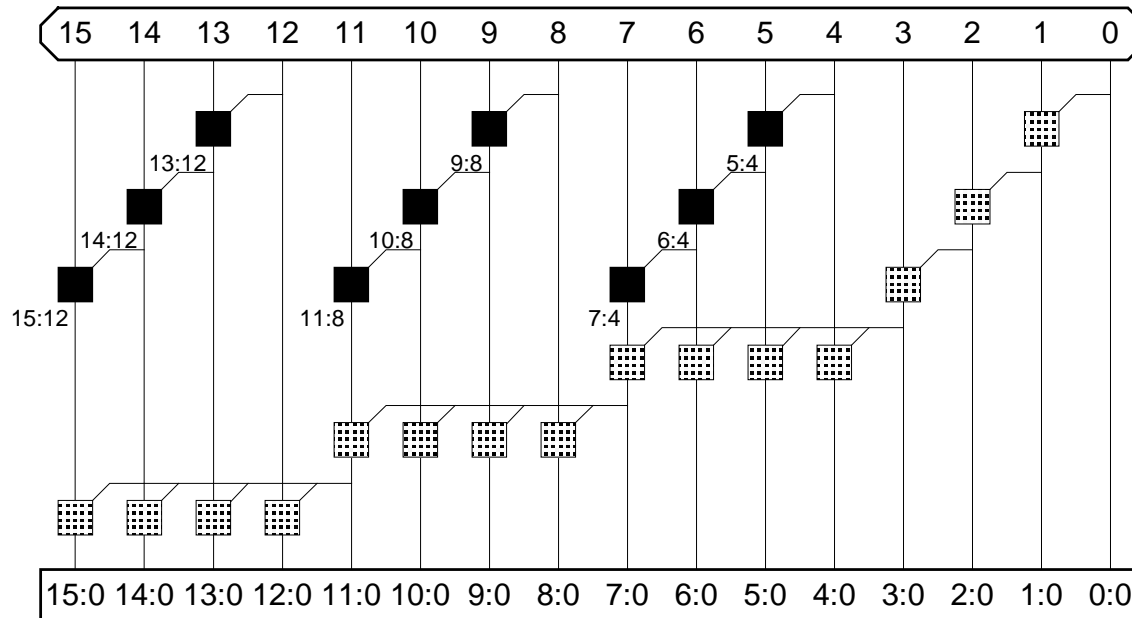
$N = k \cdot b$ ,  $b$ =block size,  $k$ =number of blocks

$$t_{\text{add}} = t_{\text{pg}}$$



# Carry-Increment Adder

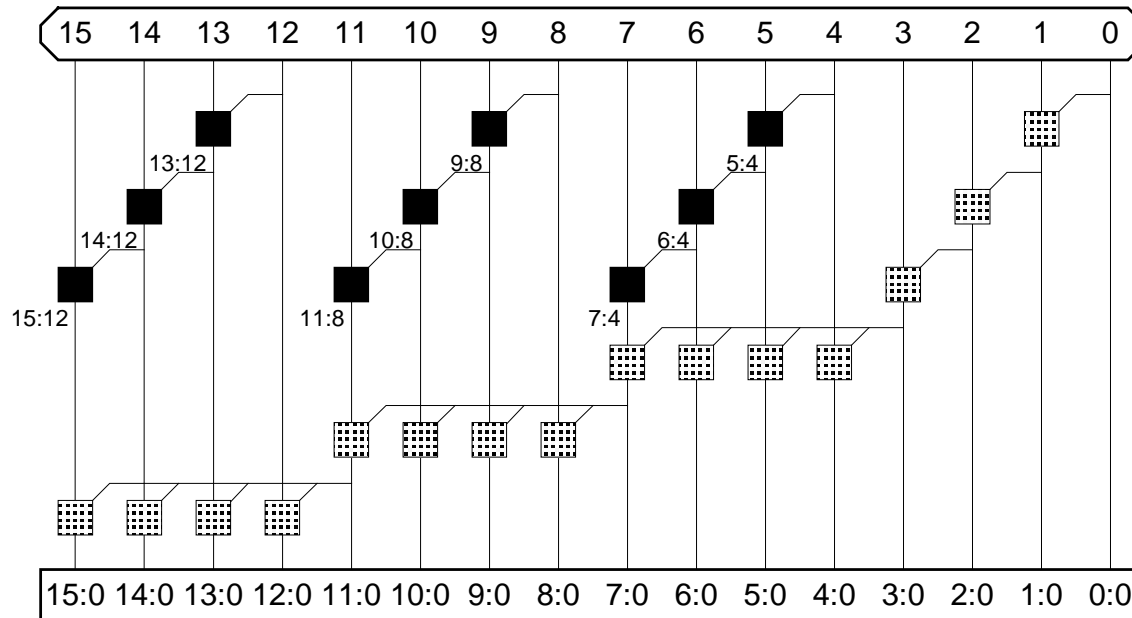
- Factor initial PG and final XOR out of carry-select



$$t_{\text{increment}} =$$

# Carry-Increment Adder

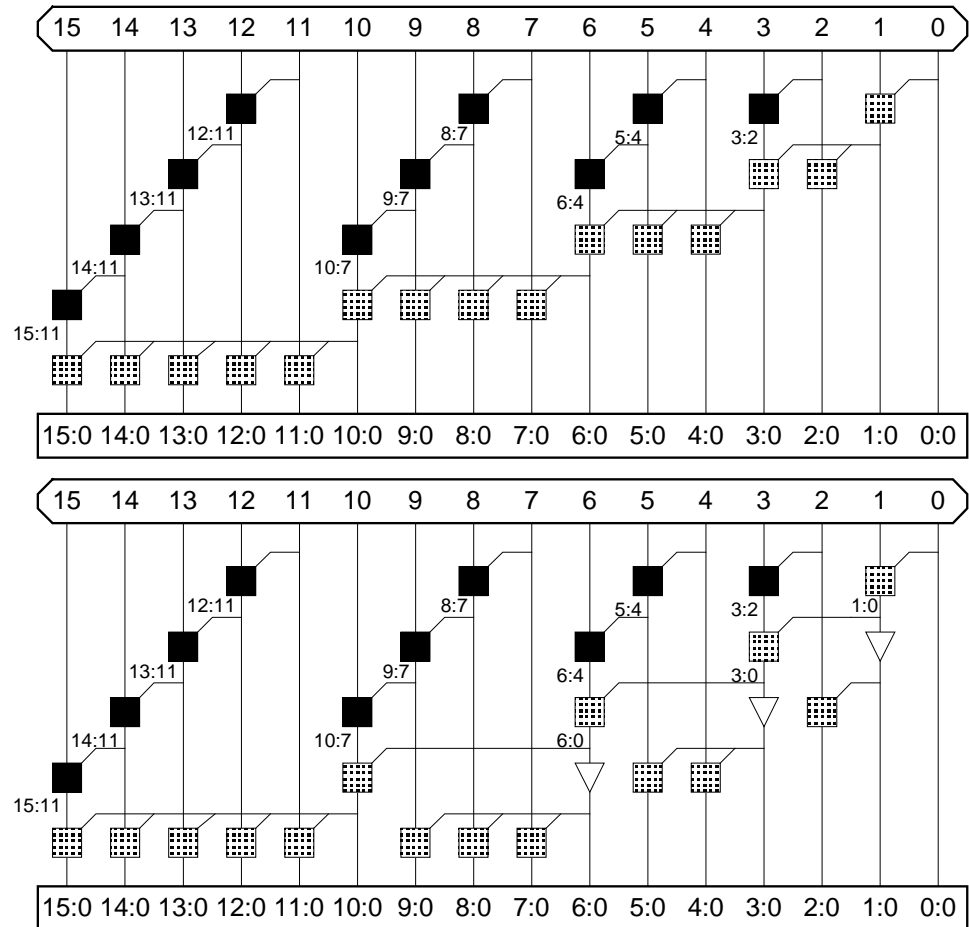
- Factor initial PG and final XOR out of carry-select



$$t_{\text{increment}} = t_{pg} + \left[ (n-1) + (k-1) \right] t_{AO} + t_{\text{xor}}$$

# Variable Group Size

- Also buffer noncritical signals





# Tree Adder

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- ❑ If lookahead is good, lookahead across lookahead!
  - Recursive lookahead gives  $O(\log N)$  delay
- ❑ Many variations on tree adders

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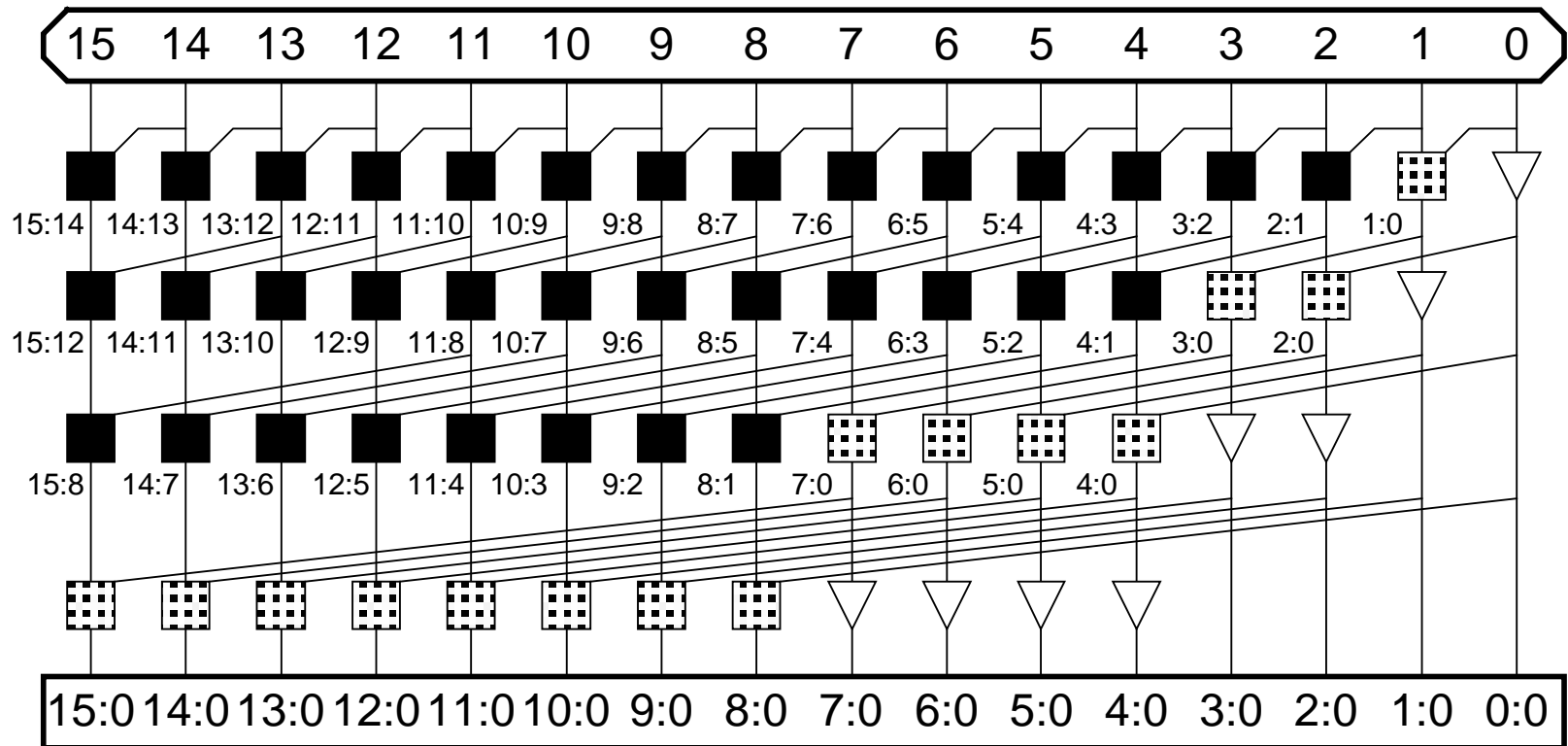
## Section 6: Arithmetic Circuits

**VLSI Systems Design**  
**SS23 | CEID, UPatras**

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# Kogge-Stone



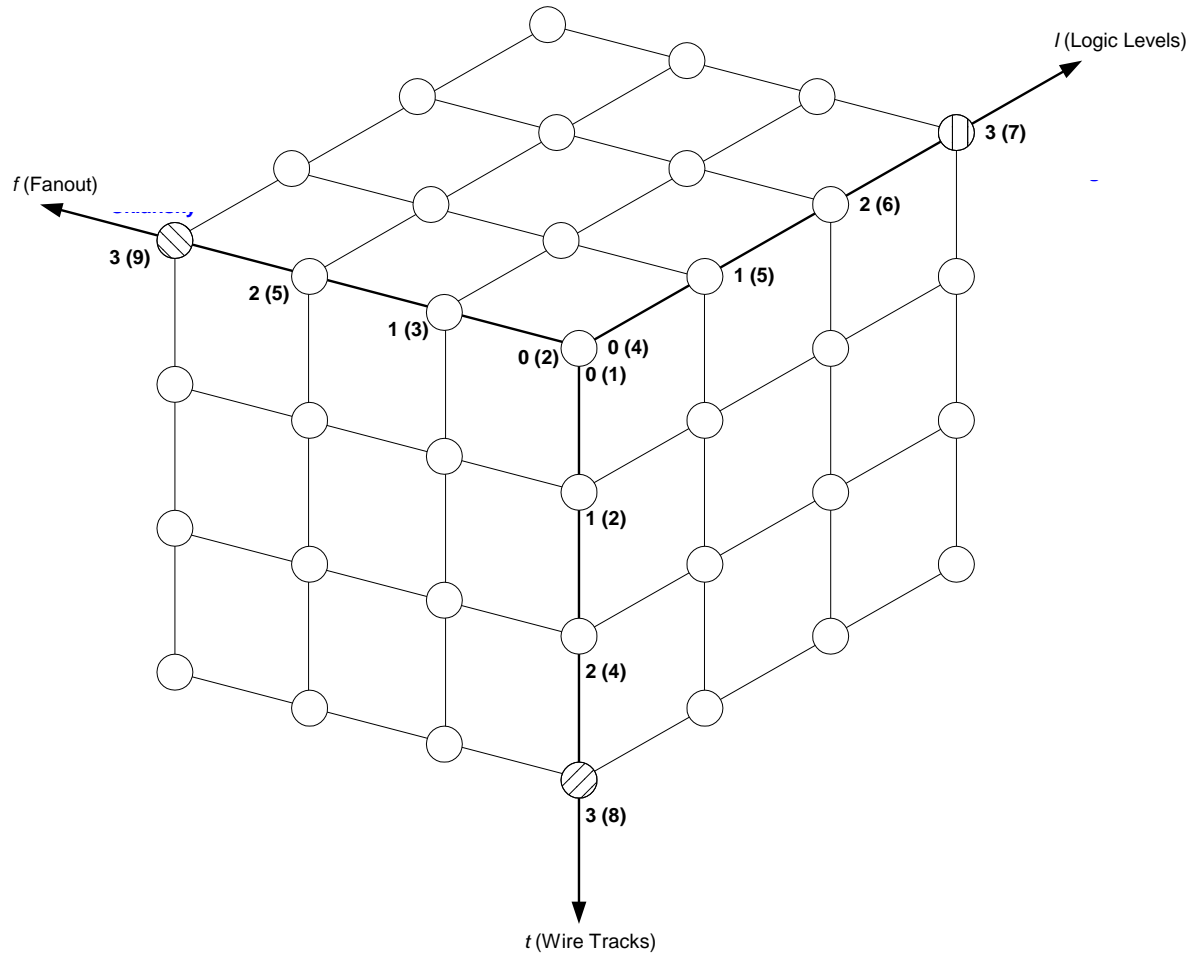
# Tree Adder Taxonomy

---

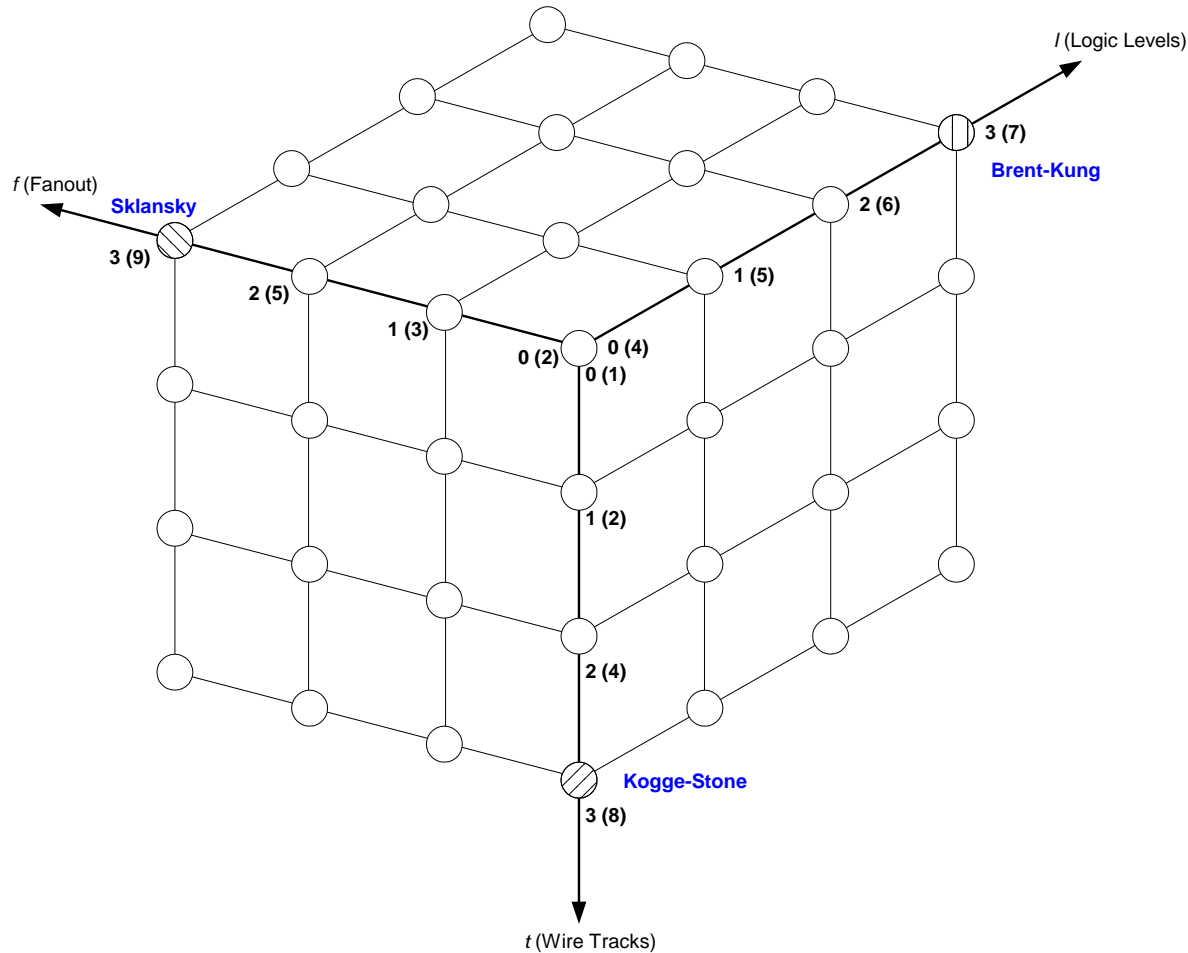
- ❑ Ideal N-bit tree adder would have
  - $L = \log N$  logic levels
  - Fanout never exceeding 2
  - No more than one wiring track between levels
- ❑ Describe adder with 3-D taxonomy ( $l, f, t$ )
  - Logic levels:  $L + l$
  - Fanout:  $2^f + 1$
  - Wiring tracks:  $2^t$
- ❑ Known tree adders sit on plane defined by

$$l + f + t = L - 1$$

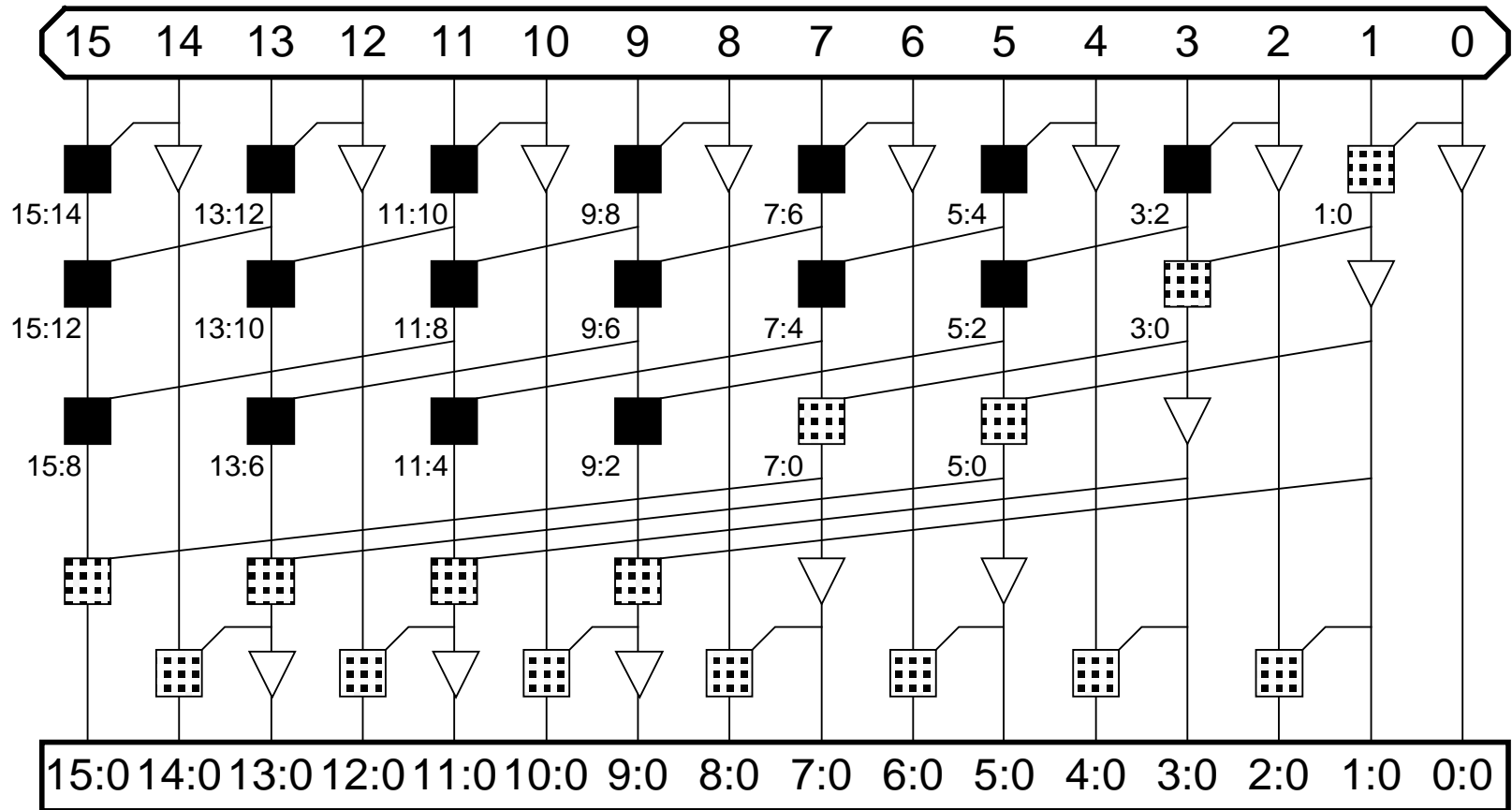
# Tree Adder Taxonomy



# Tree Adder Taxonomy

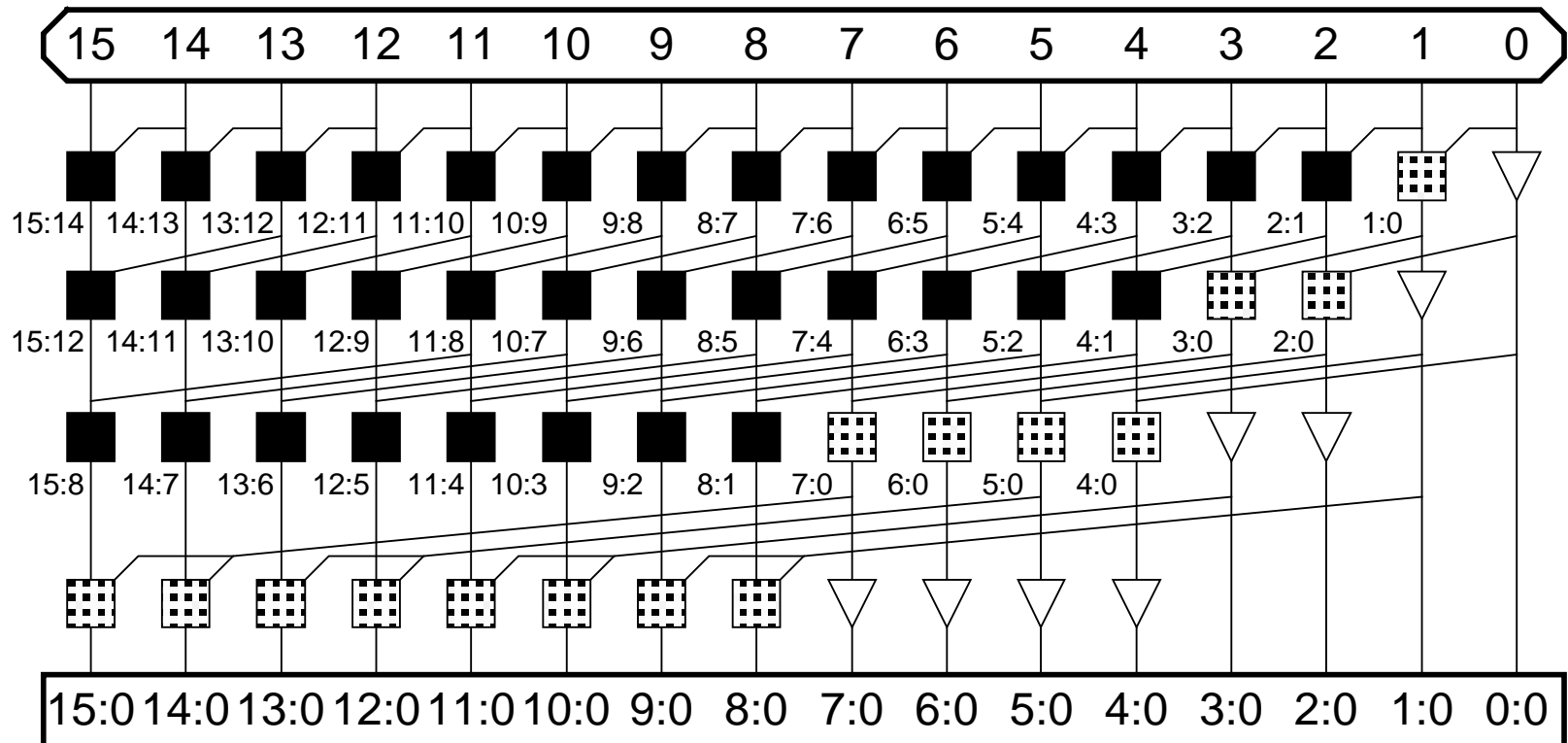


# Han-Carlson

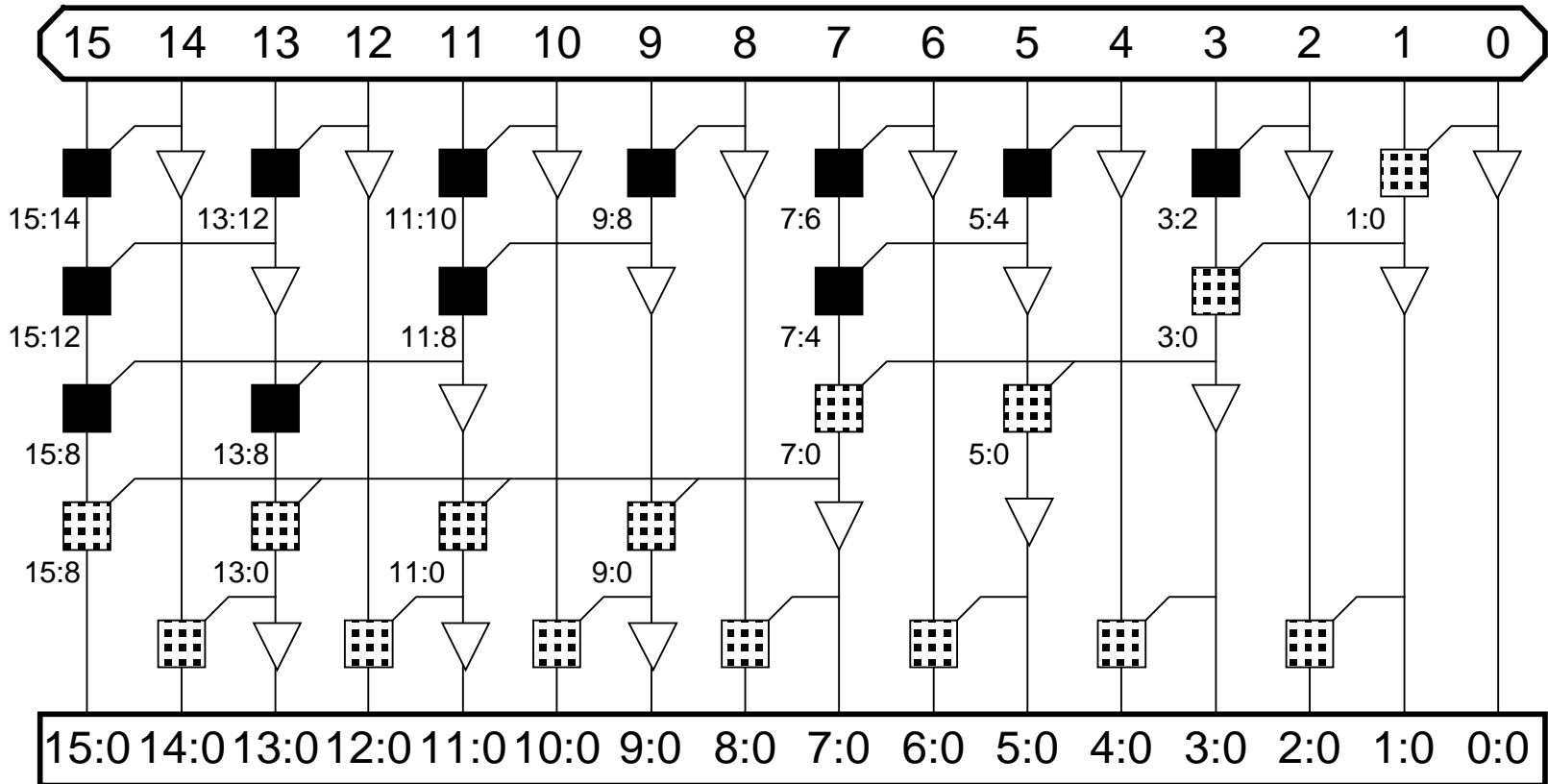




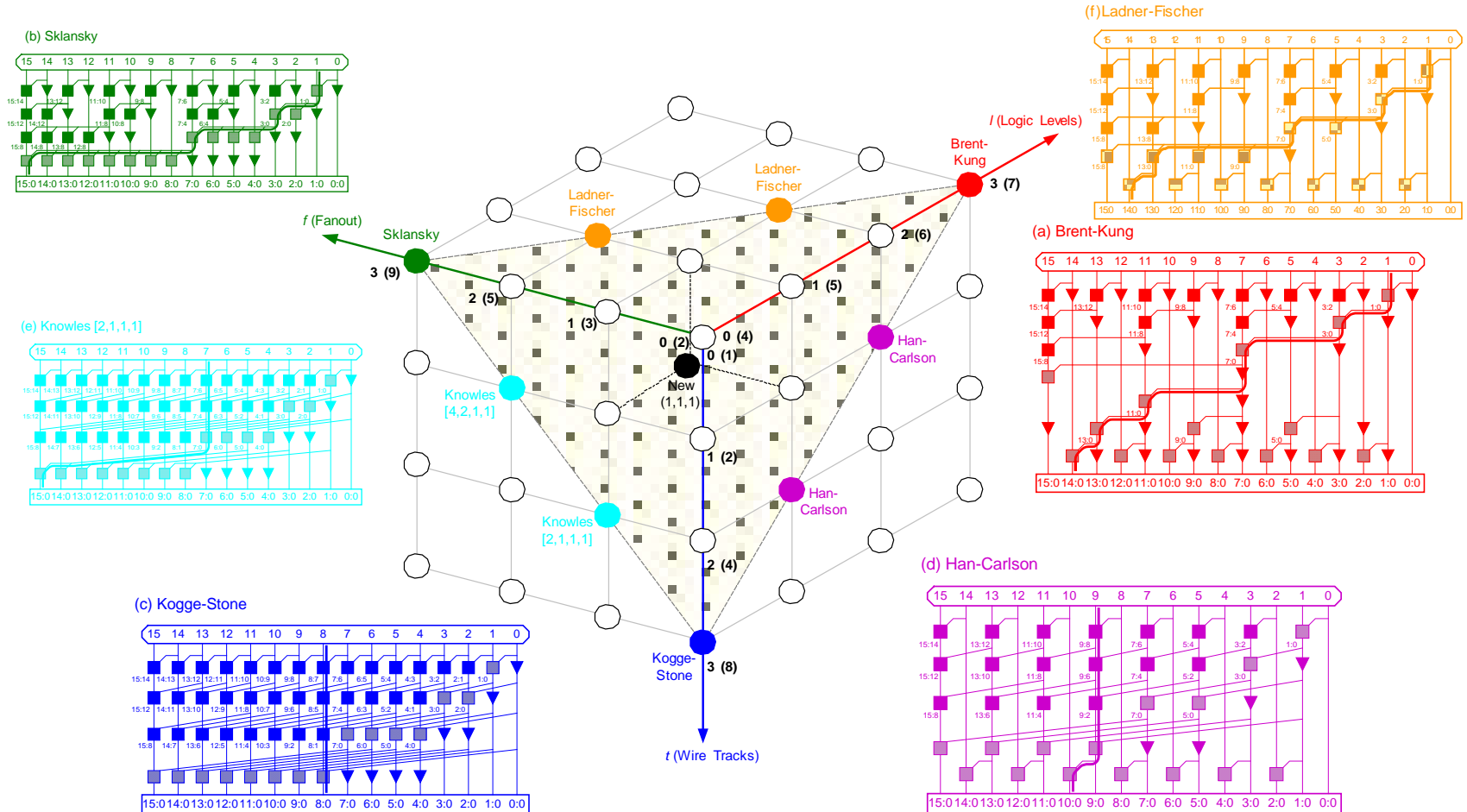
# Knowles [2, 1, 1, 1]



# Ladner-Fischer



# Taxonomy Revisited

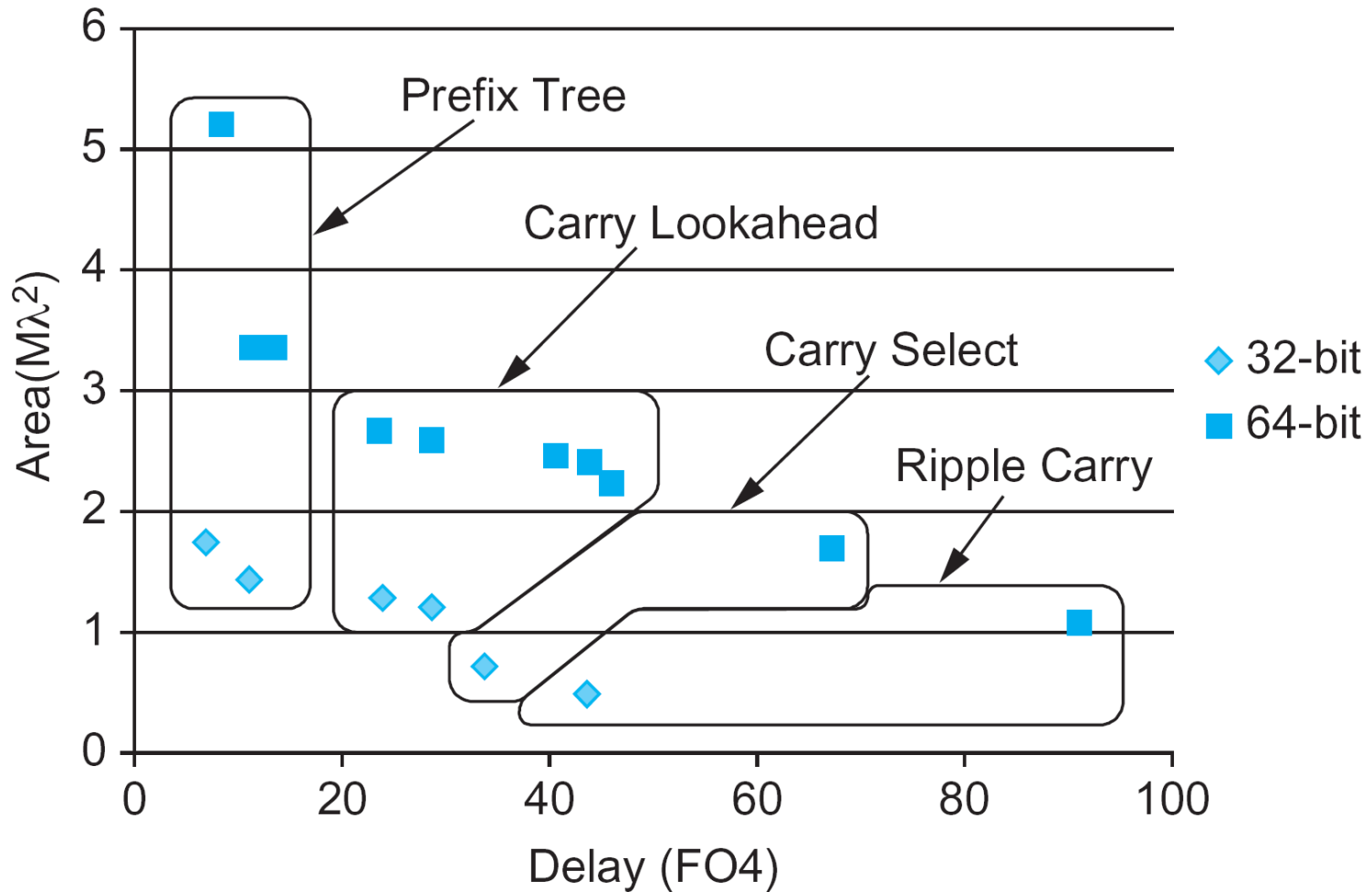


# Summary

- ❑ Adder architectures offer area / power / delay tradeoffs.
- ❑ Choose the best one for your application.

Architecture	Classification	Logic Levels	Max Fanout	Tracks	Cells
Carry-Ripple		$N-1$	1	1	$N$
Carry-Skip $n=4$		$N/4 + 5$	2	1	$1.25N$
Carry-Inc. $n=4$		$N/4 + 2$	4	1	$2N$
Brent-Kung	$(L-1, 0, 0)$	$2\log_2 N - 1$	2	1	$2N$
Sklansky	$(0, L-1, 0)$	$\log_2 N$	$N/2 + 1$	1	$0.5 N \log_2 N$
Kogge-Stone	$(0, 0, L-1)$	$\log_2 N$	2	$N/2$	$N \log_2 N$

# Summary



# Multipliers

# Multiplication

## □ Example:

$$\begin{array}{r} 1100 : 12_{10} \\ \underline{0101 : 5_{10}} \\ \hline \end{array}$$

multiplicand  
multiplier  
partial products  
product

## □ M x N-bit multiplication

- Produce N M-bit partial products
- Sum these to produce M+N-bit product

# Multiplication

## □ Example:

$$\begin{array}{r} 1100 \\ 0101 \\ \hline 1100 \end{array}$$

\_\_\_\_\_

multiplicand  
multiplier  
partial products  
product

## □ M x N-bit multiplication

- Produce N M-bit partial products
- Sum these to produce M+N-bit product



# Multiplication

## □ Example:

$$\begin{array}{r} 1100 : 12_{10} \\ 0101 : 5_{10} \\ \hline 1100 \\ 0000 \\ \hline \end{array}$$

multiplicand  
multiplier  
partial products  
product

## □ M x N-bit multiplication

- Produce N M-bit partial products
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# Multiplication

## □ Example:

$$\begin{array}{r} 1100 : 12_{10} \\ 0101 : 5_{10} \\ \hline 1100 \\ 0000 \\ 1100 \\ \hline \end{array}$$

multiplicand  
multiplier  
partial products  
product

## □ M x N-bit multiplication

- Produce N M-bit partial products
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# Multiplication

## □ Example:

$$\begin{array}{r} 1100 : 12_{10} \\ 0101 : 5_{10} \\ \hline 1100 \\ 0000 \\ 1100 \\ 0000 \\ \hline \end{array}$$

multiplicand  
multiplier  
partial products  
product

## □ M x N-bit multiplication

- Produce N M-bit partial products
- Sum these to produce M+N-bit product

# Multiplication

## □ Example:

$$\begin{array}{r} 1100 : 12_{10} \\ 0101 : 5_{10} \\ \hline 1100 \\ 0000 \\ 1100 \\ 0000 \\ \hline 00111100 : 60_{10} \end{array}$$

multiplicand  
multiplier  
partial products  
product

## □ M x N-bit multiplication

- Produce N M-bit partial products
- Sum these to produce M+N-bit product

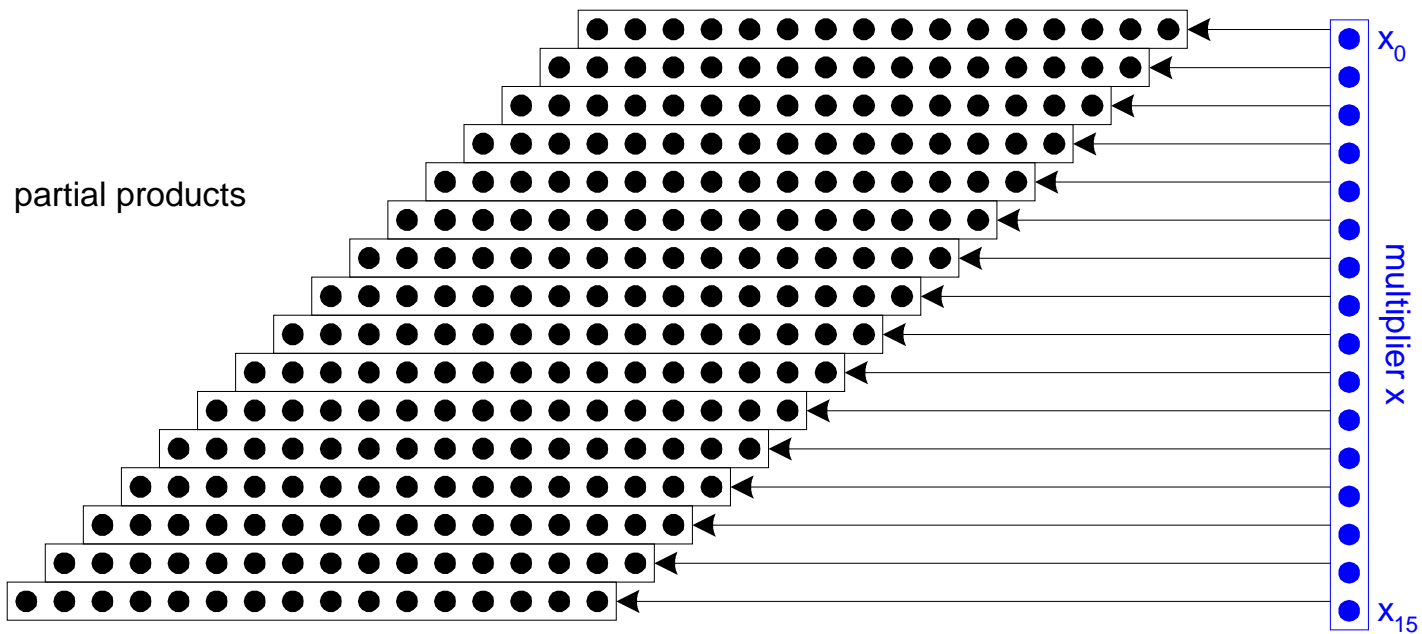
\_\_\_\_\_

-  Product:

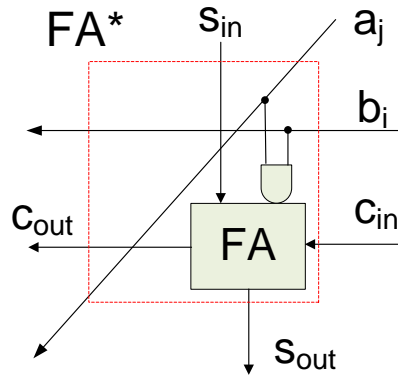
						$y_5$	$y_4$	$y_3$	$y_2$	$y_1$	$y_0$	multiplicand multiplier
						$x_5$	$x_4$	$x_3$	$x_2$	$x_1$	$x_0$	
						$x_0y_5$	$x_0y_4$	$x_0y_3$	$x_0y_2$	$x_0y_1$	$x_0y_0$	partial products
				$x_1y_5$	$x_1y_4$	$x_1y_3$	$x_1y_2$	$x_1y_1$	$x_1y_0$			
		$x_2y_5$	$x_2y_4$	$x_2y_3$	$x_2y_2$	$x_2y_1$	$x_2y_0$					
	$x_3y_5$	$x_3y_4$	$x_3y_3$	$x_3y_2$	$x_3y_1$	$x_3y_0$						
	$x_4y_5$	$x_4y_4$	$x_4y_3$	$x_4y_2$	$x_4y_1$	$x_4y_0$						
$x_5y_5$	$x_5y_4$	$x_5y_3$	$x_5y_2$	$x_5y_1$	$x_5y_0$							product
$p_{11}$	$p_{10}$	$p_9$	$p_8$	$p_7$	$p_6$	$p_5$	$p_4$	$p_3$	$p_2$	$p_1$	$p_0$	

# Dot Diagram

- Each dot represents a bit



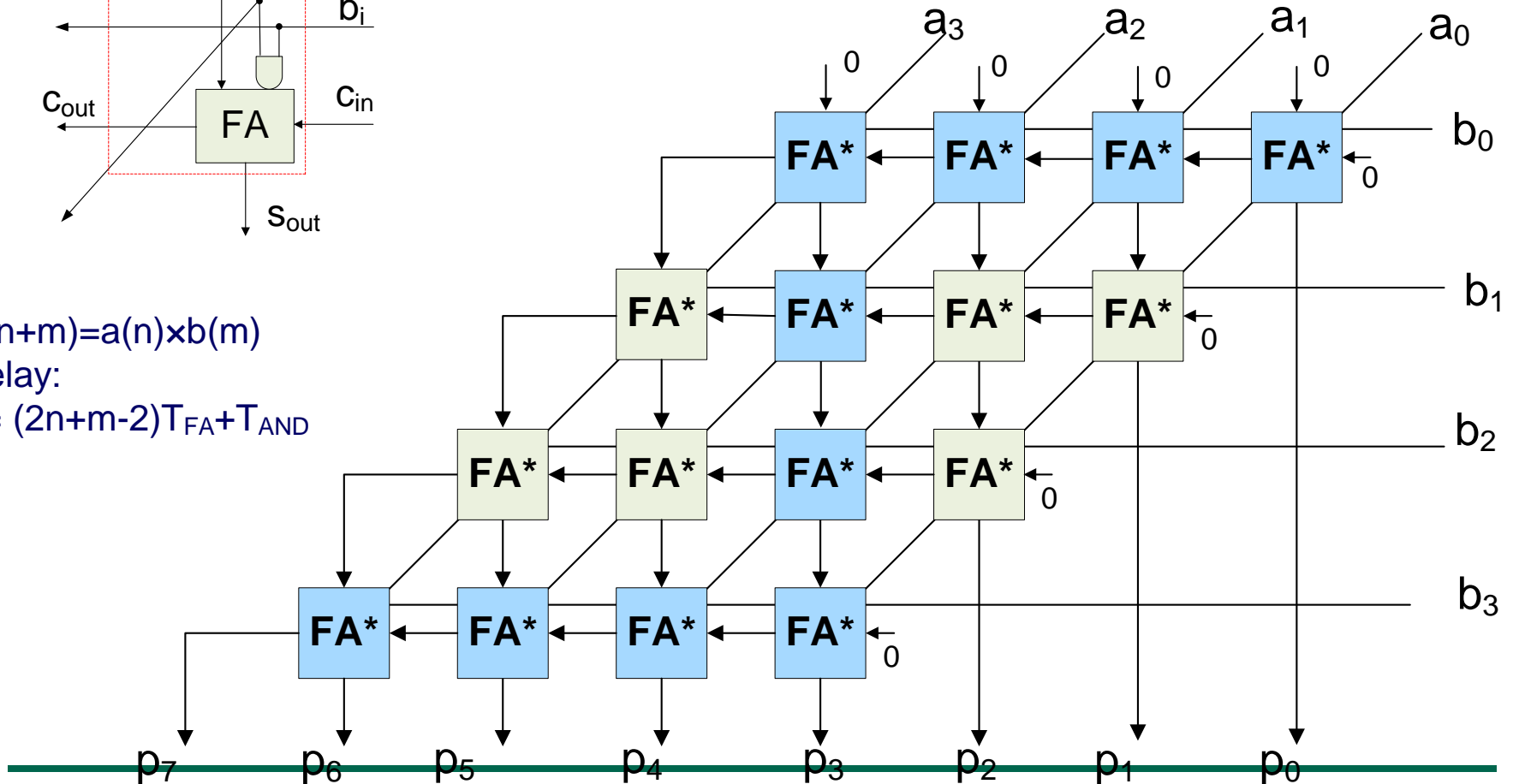
# RCA Array Multiplier



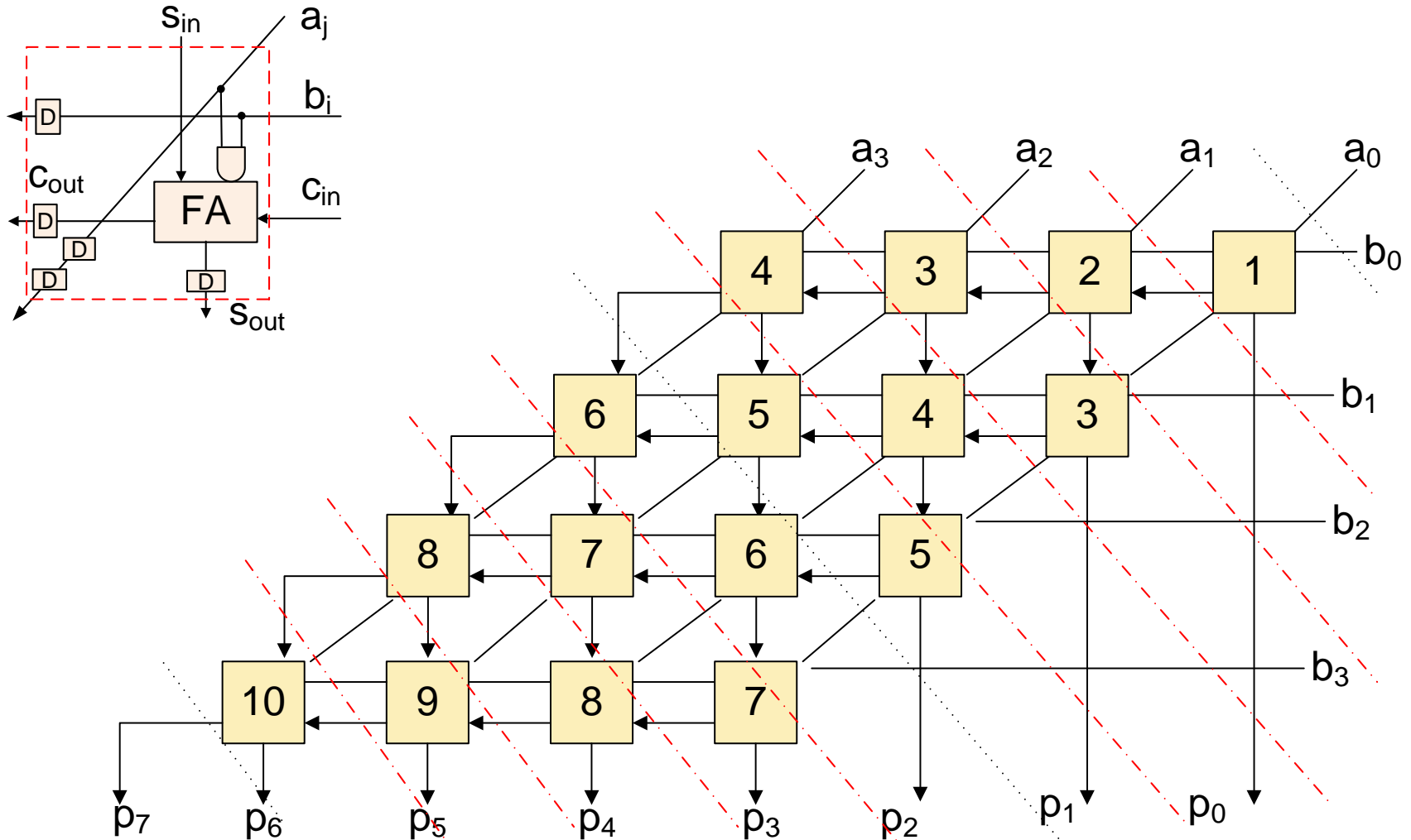
$$P(n+m)=a(n)\times b(m)$$

Delay:

$$T = (2n+m-2)T_{FA} + T_{AND}$$

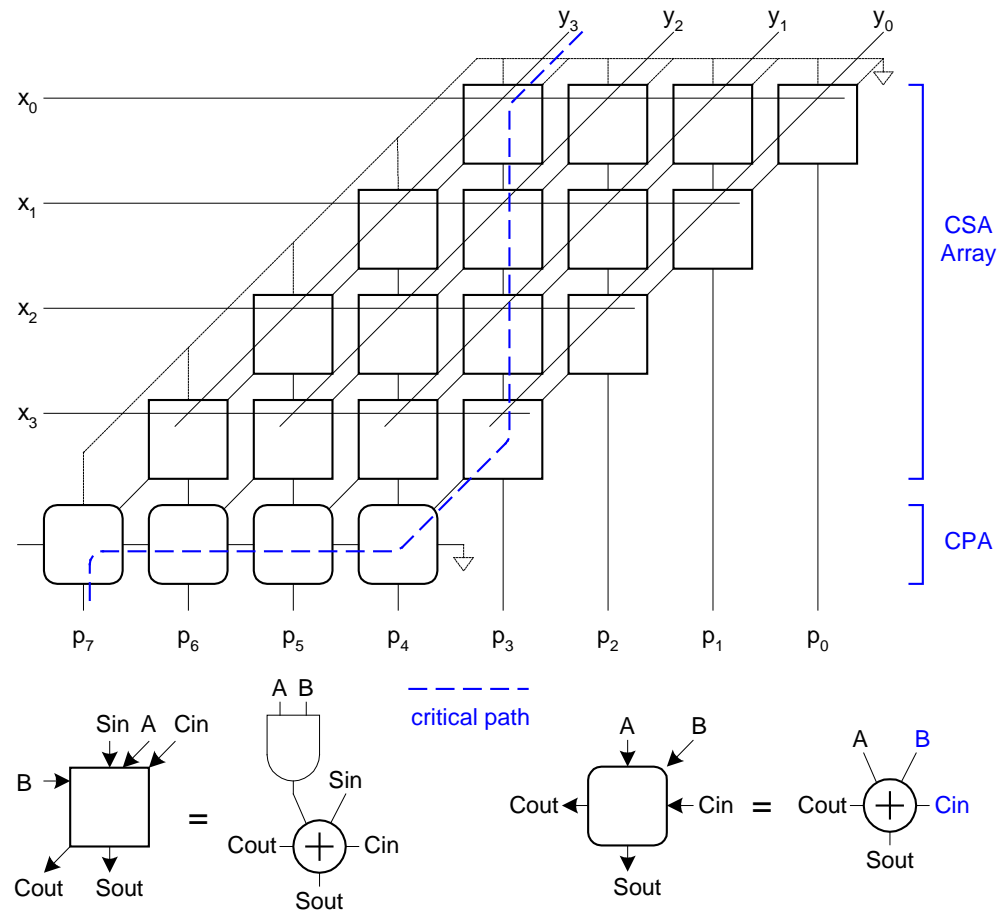


# Systolic RCA Array Multiplier

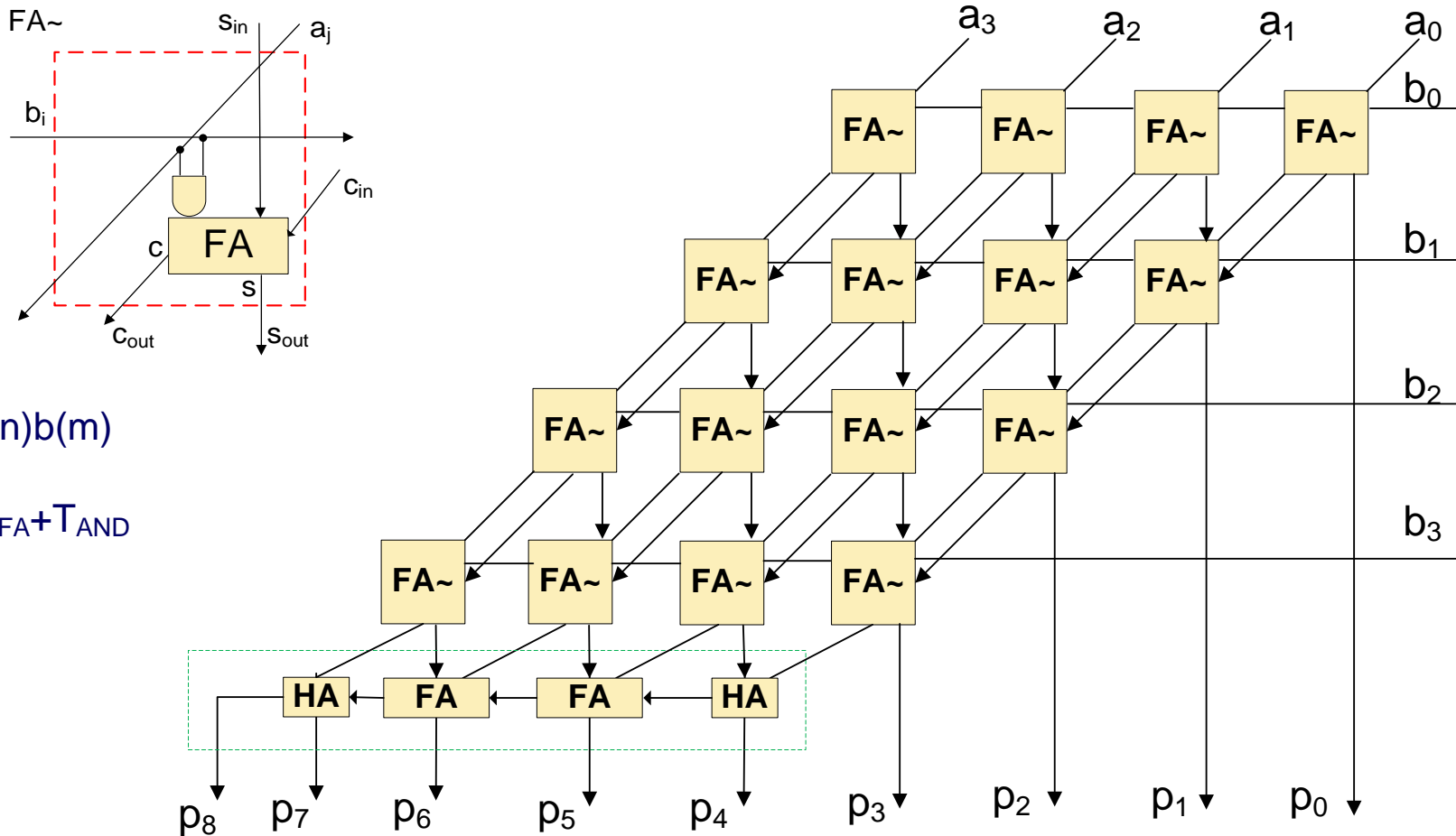




# CSA Array Multiplier



# 4x4 CSA Array Multiplier

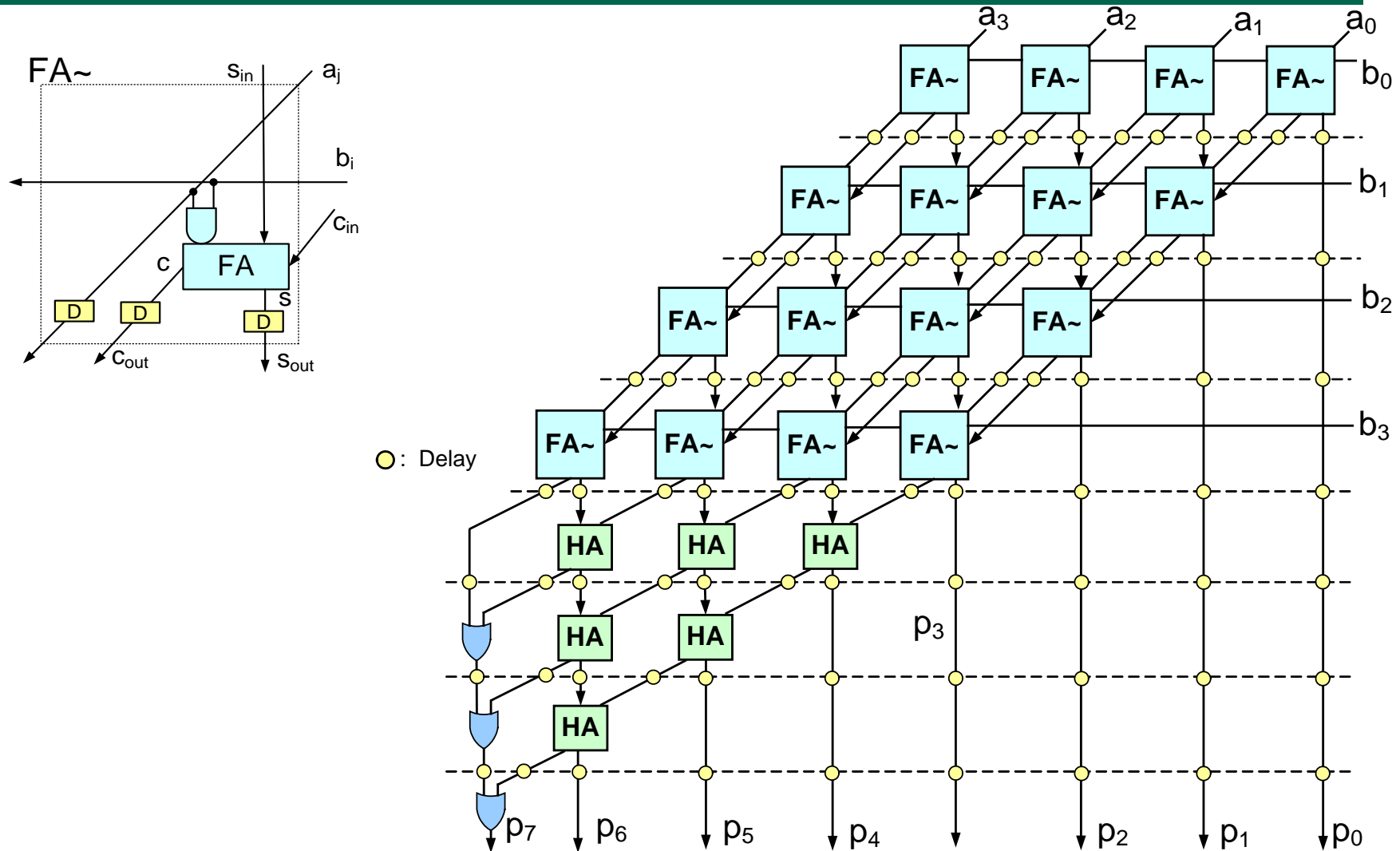


$$P(n+m) = a(n)b(m)$$

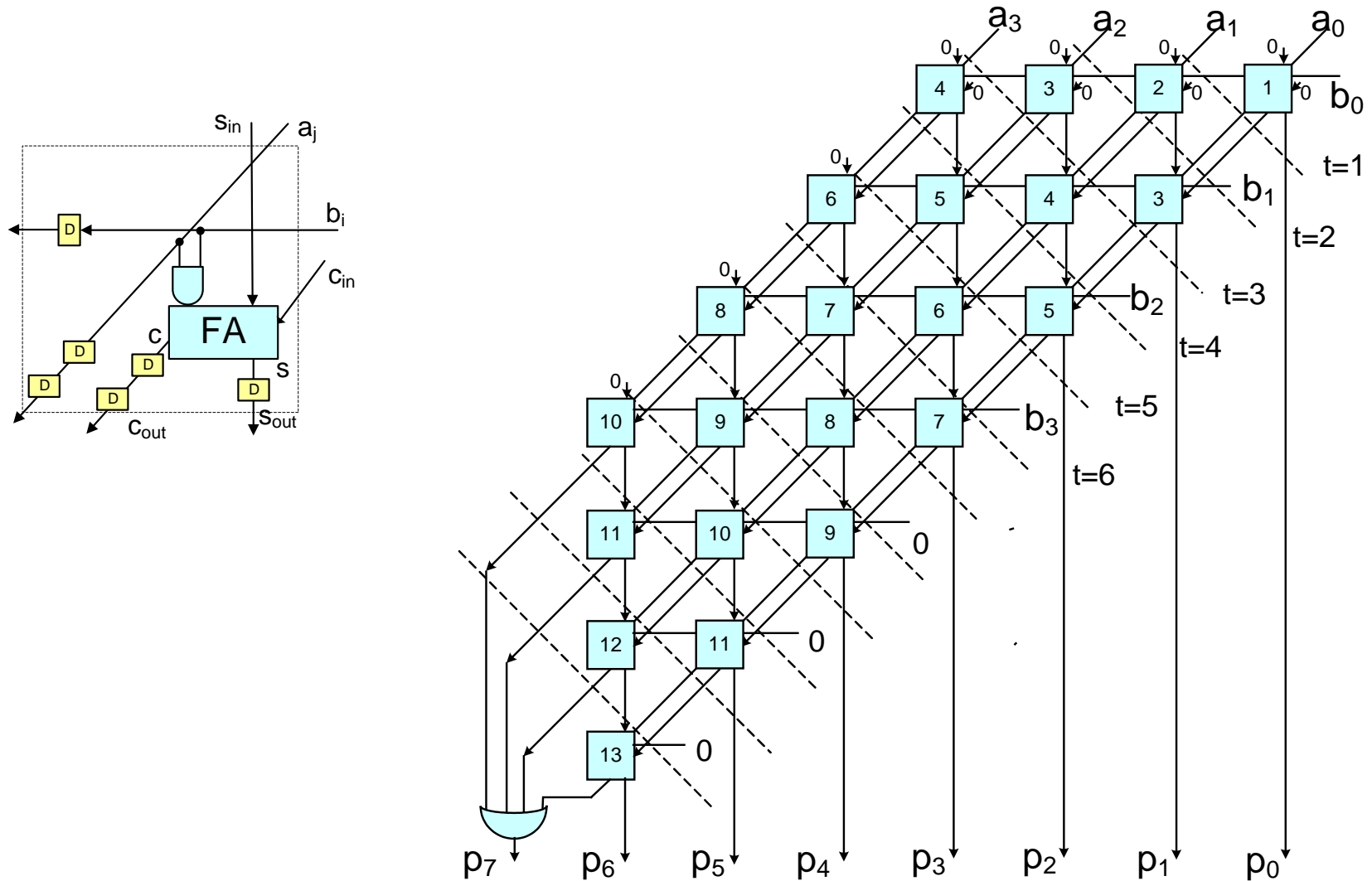
Delay

$$T = (n+m)T_{FA} + T_{AND}$$

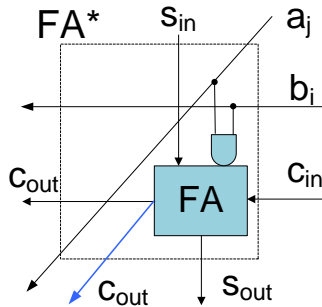
# Pipeline 4x4 CSA Array Multiplier



# Systolic 4x4 CSA Array Multiplier



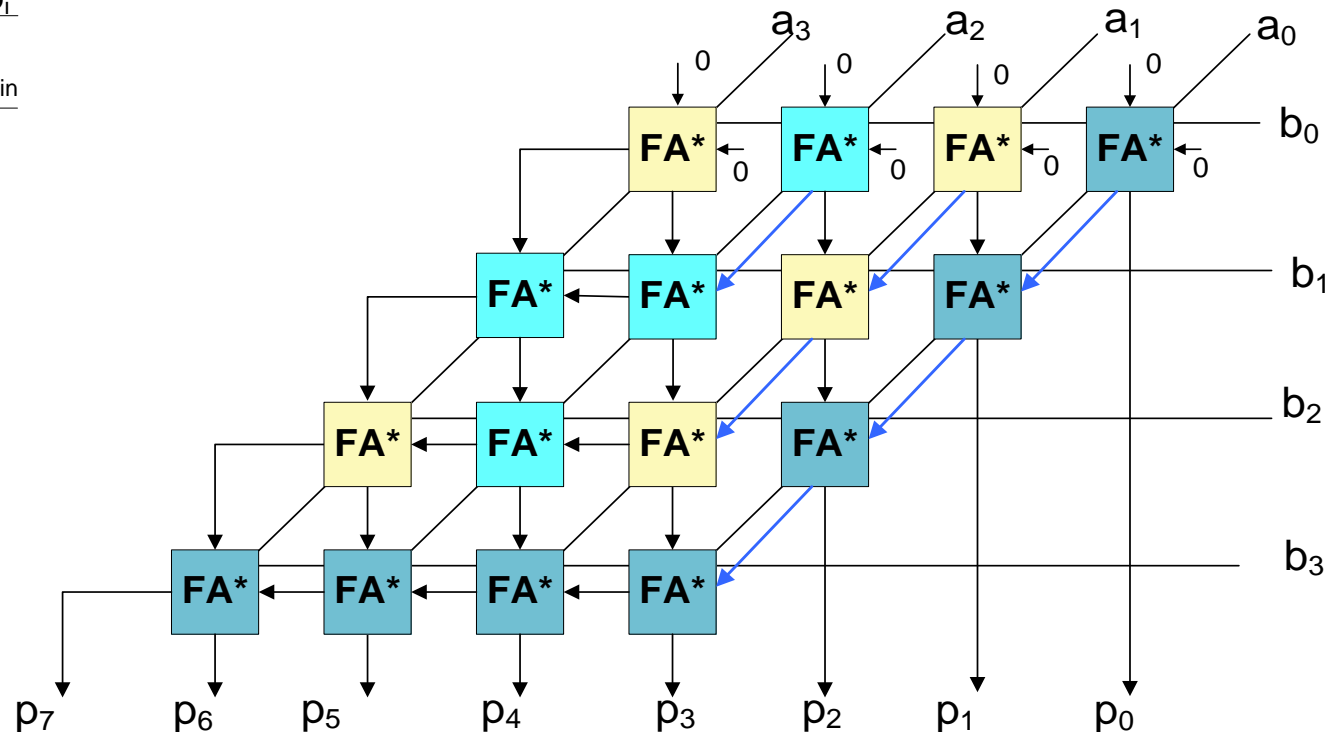
# Array Multiplier w/ RCA & Carry-Save



$$P(n+m)=a(n)b(m)$$

Delay:

$$T = (n+m-1)T_{FA} + T_{AND}$$

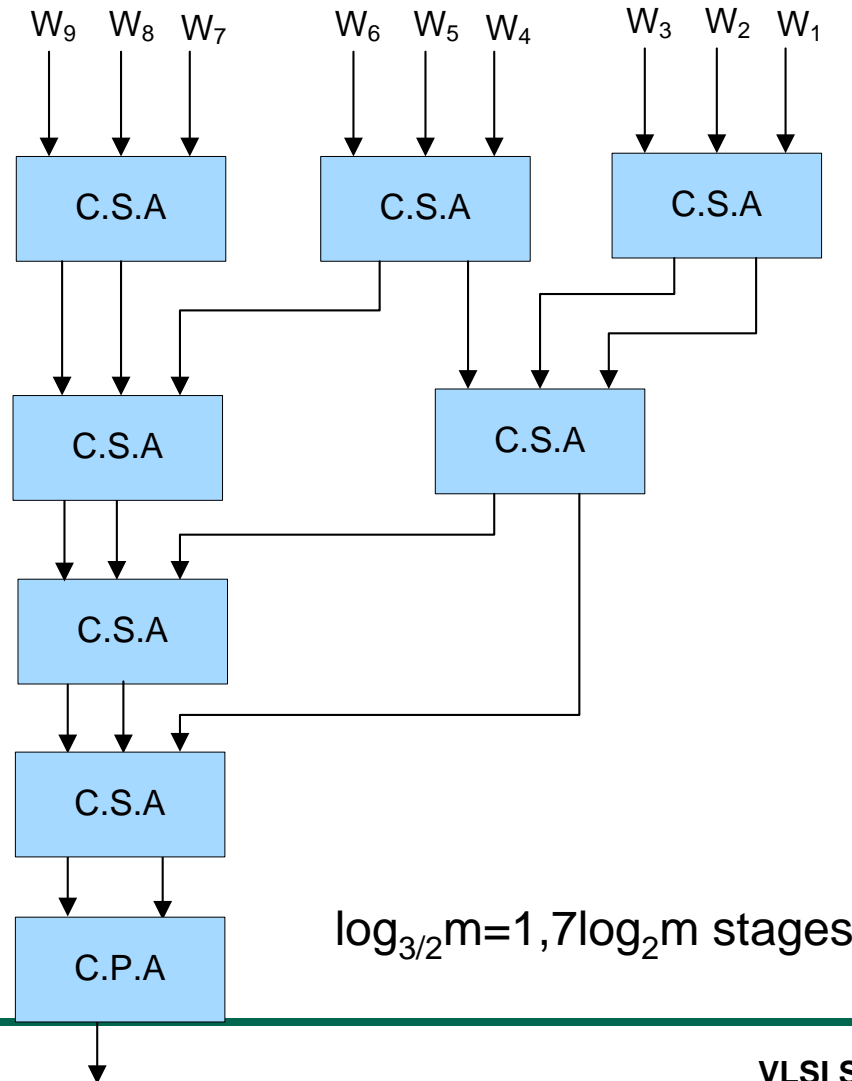


# Wallace Tree

$$P(n+m)=a(n) \cdot b(m)$$

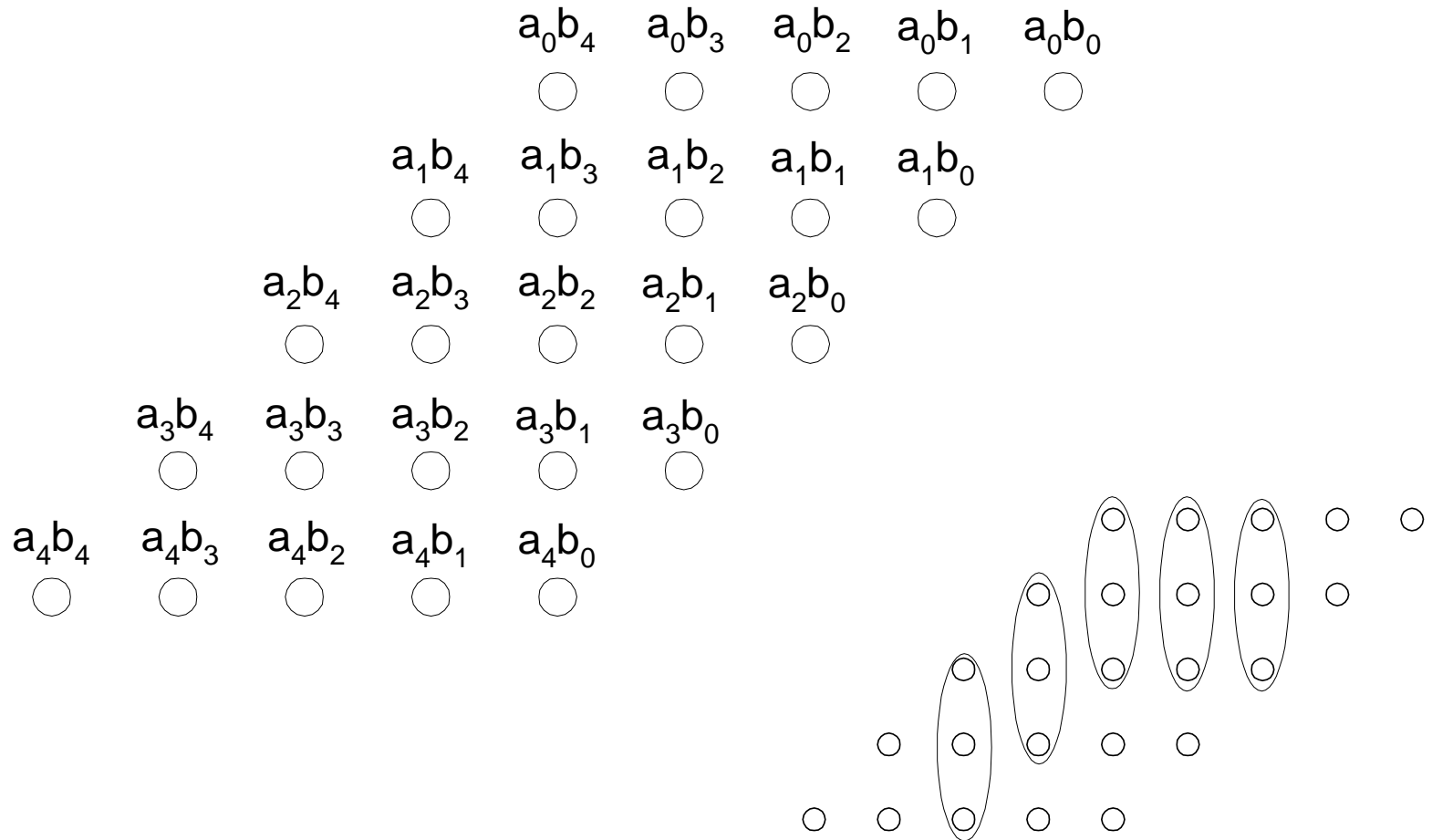
Delay:

$$T=(1,7\log_2 m) \cdot T_{FA} + T_{AND} + \log_2 n \cdot T_{pg}$$

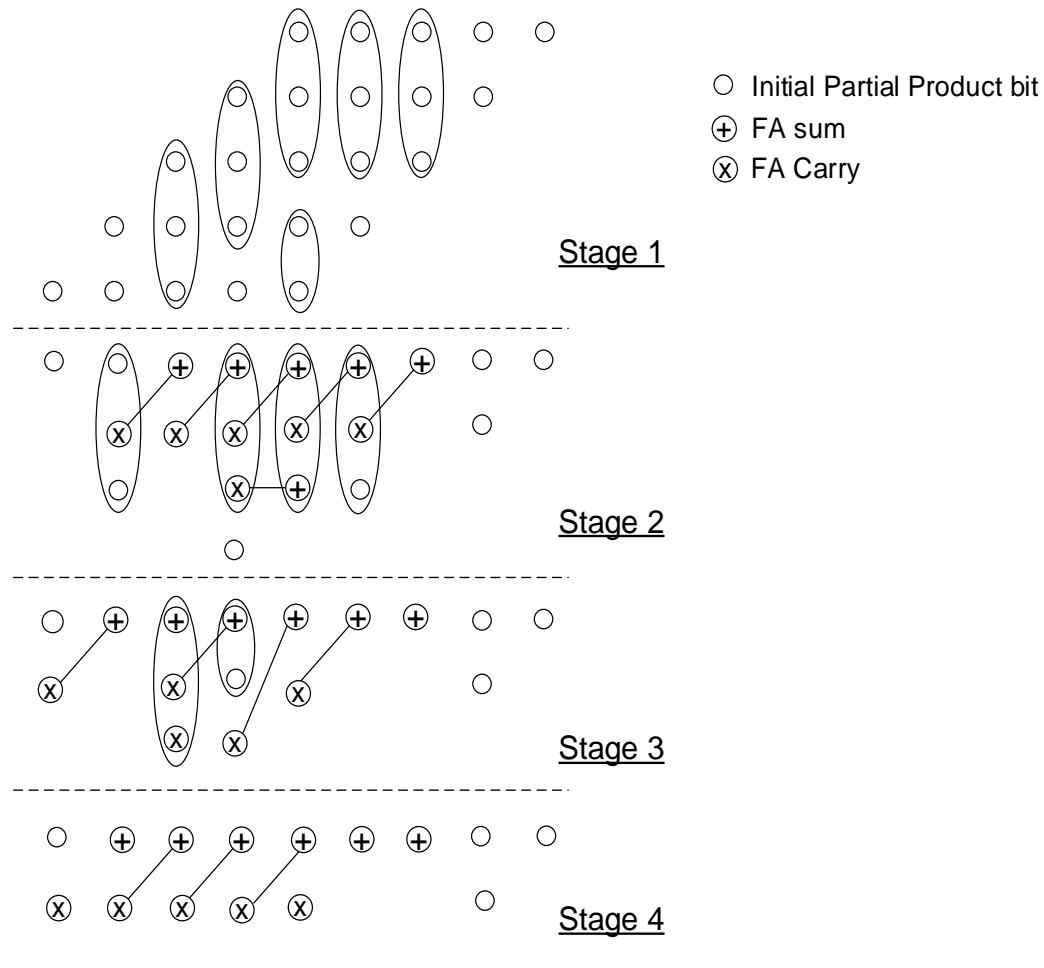


$$\log_{3/2} m = 1,7\log_2 m \text{ stages}$$

# Partial Product Grouping

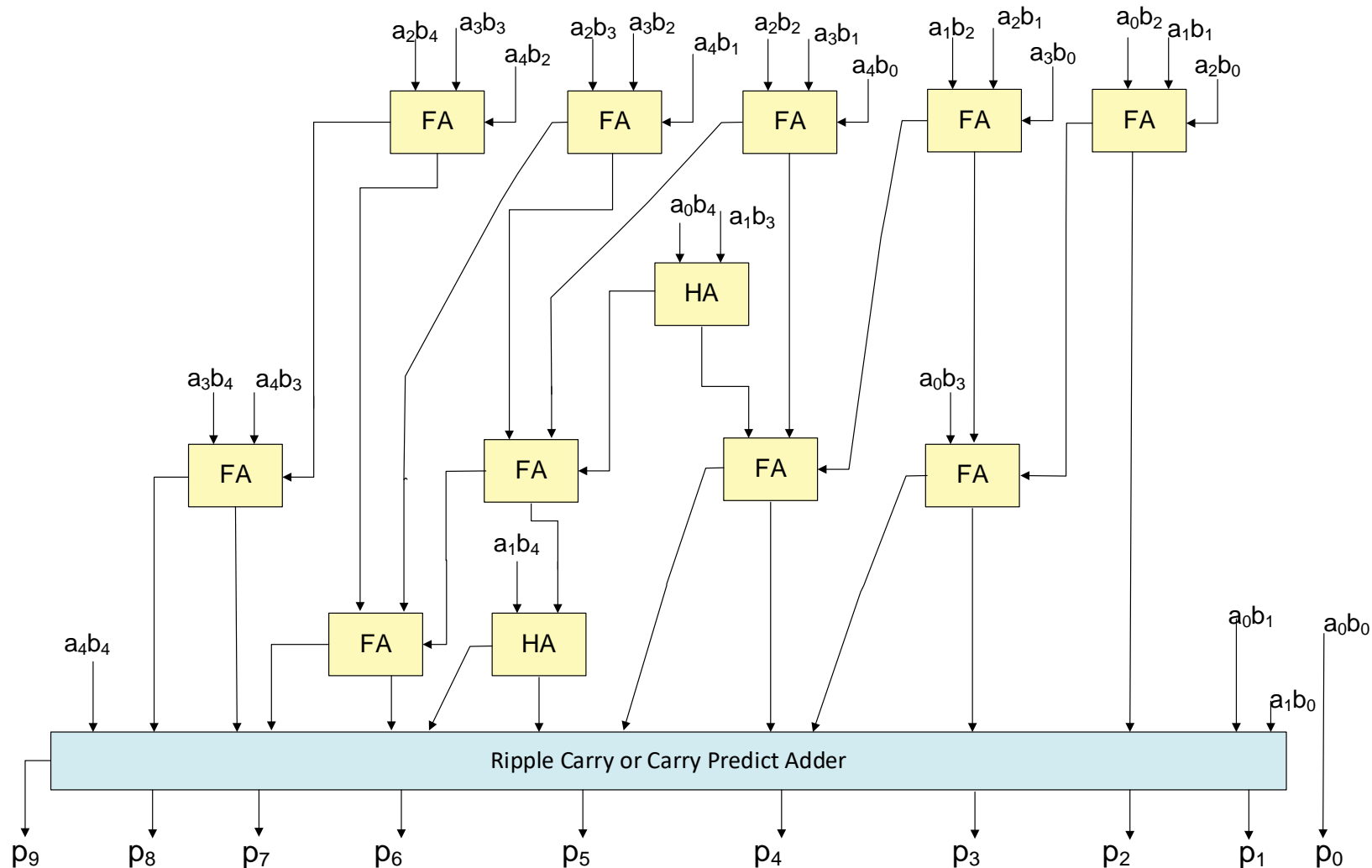


# Wallace Reduction

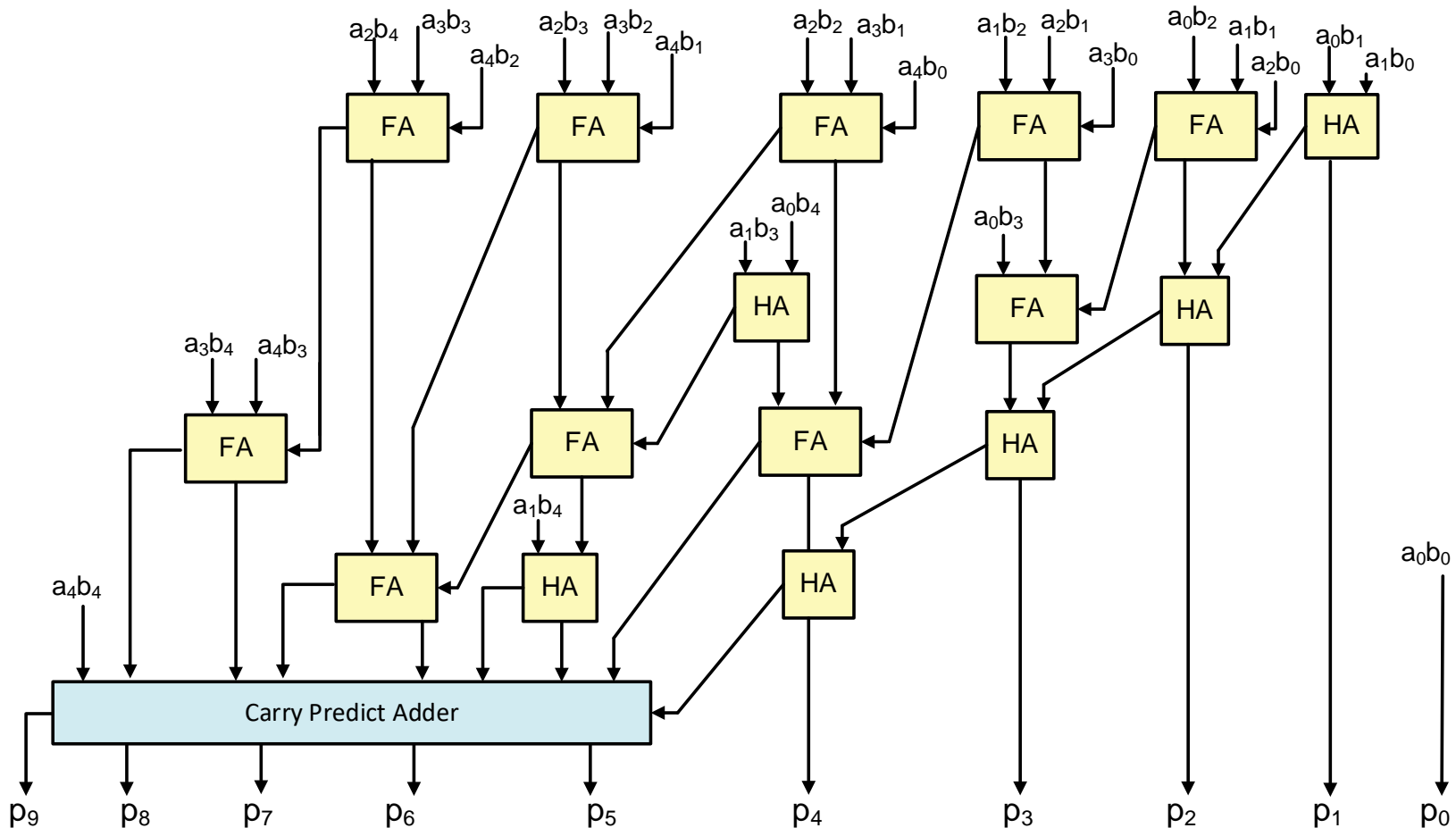




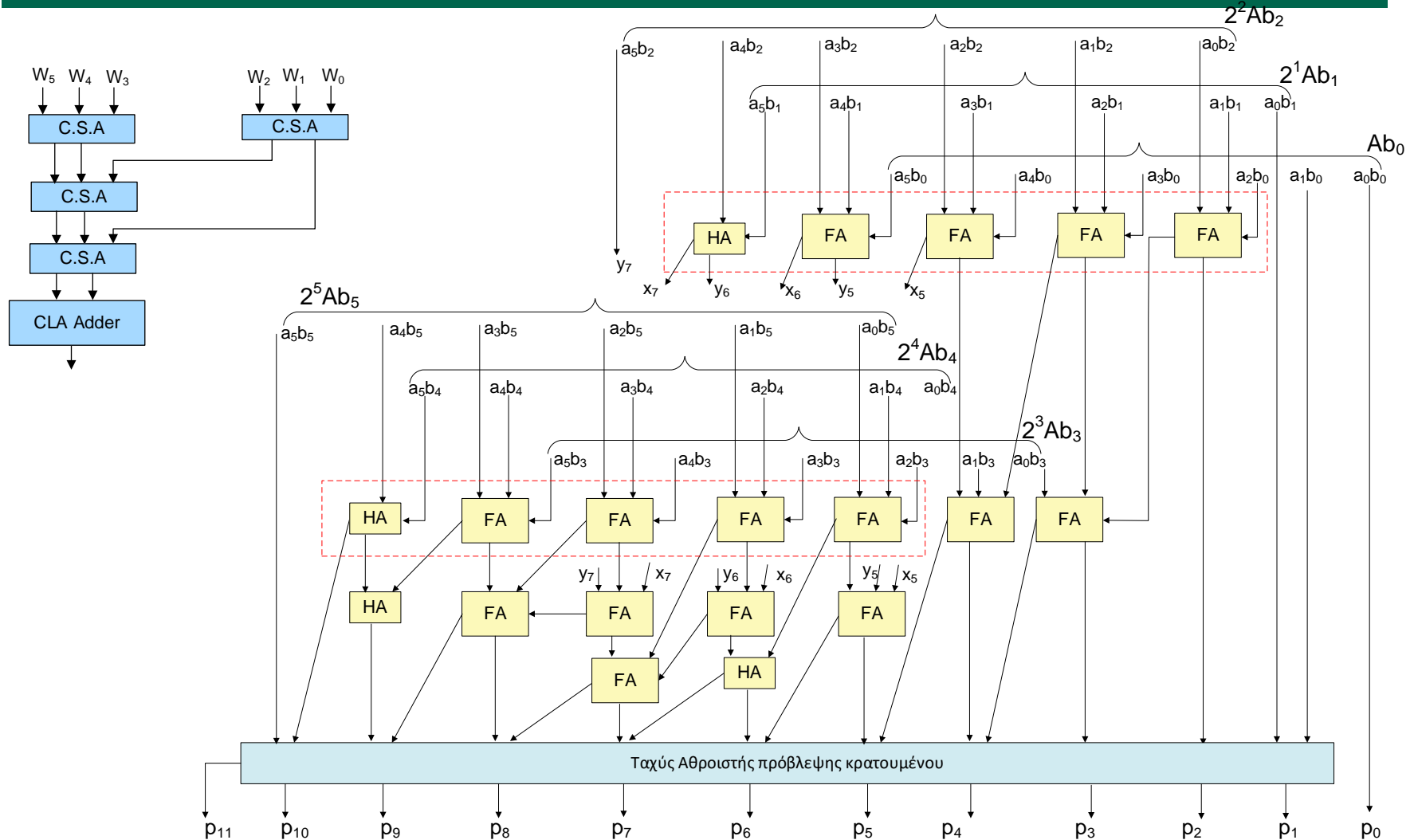
# 5x5 Wallace Multiplier



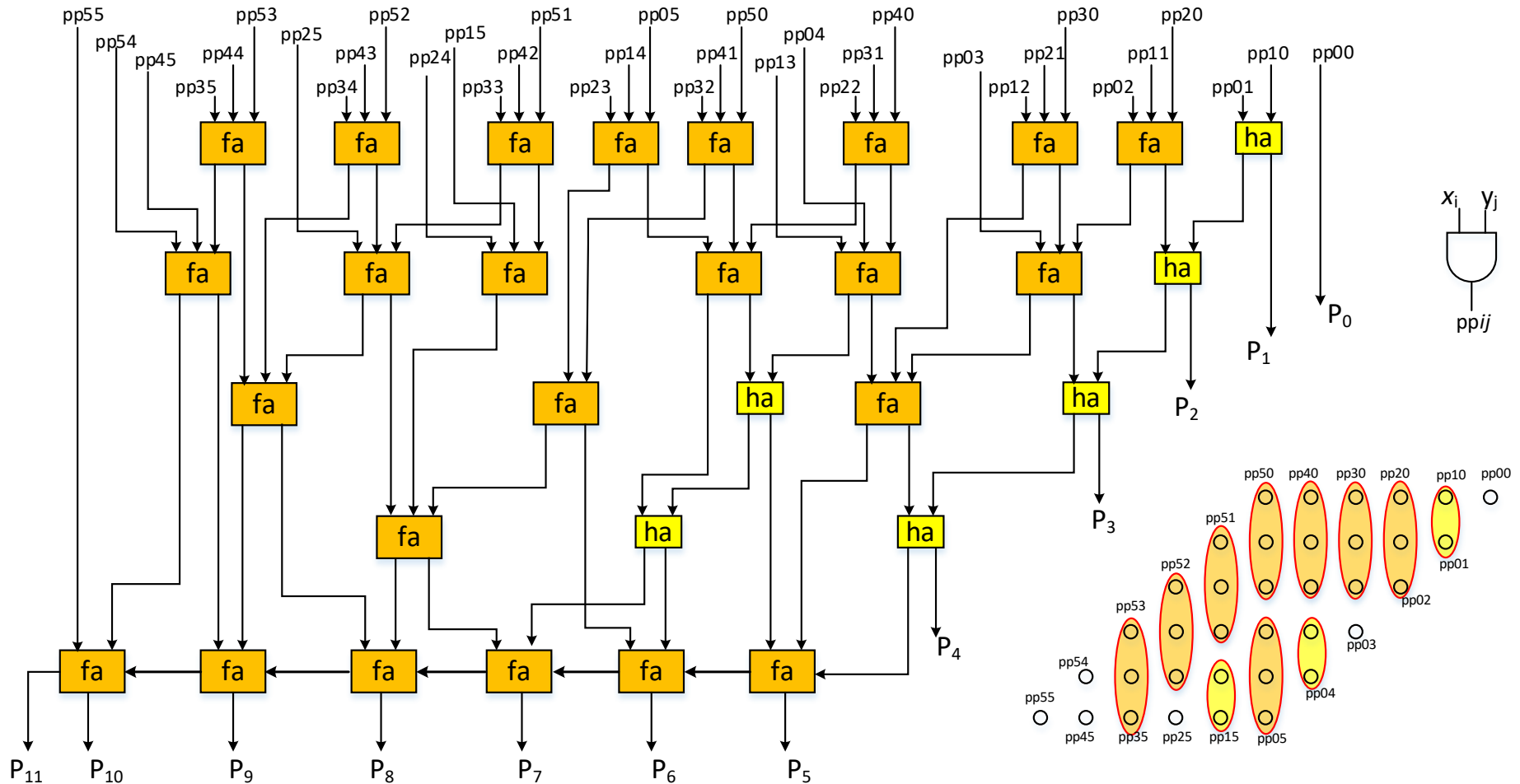
# 5x5 Wallace Multiplier



# 6x6 Wallace Multiplier

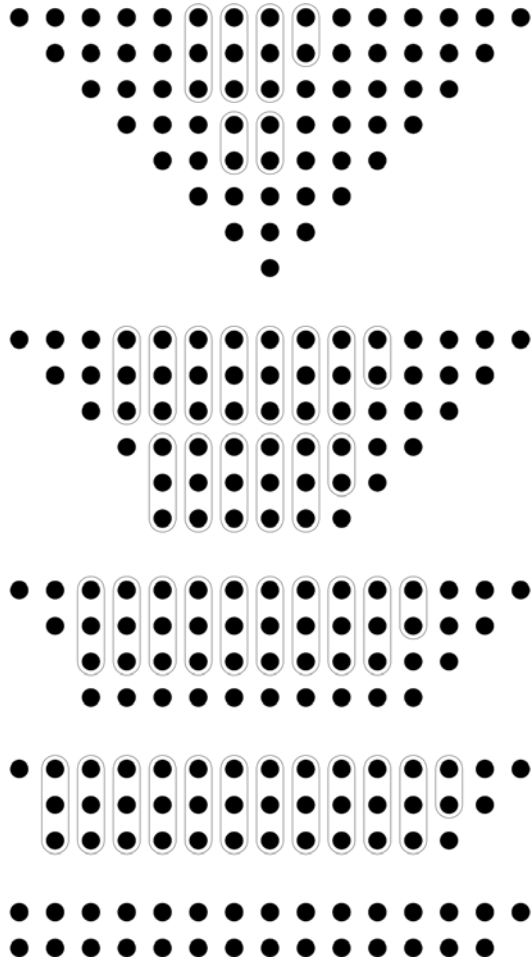


# 6x6 Wallace Multiplier



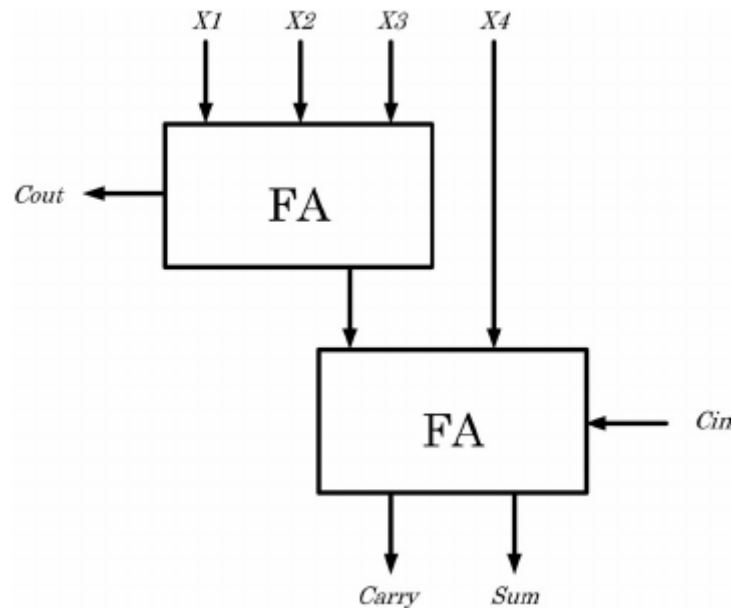
# 8x8 Dadda Multiplier

---

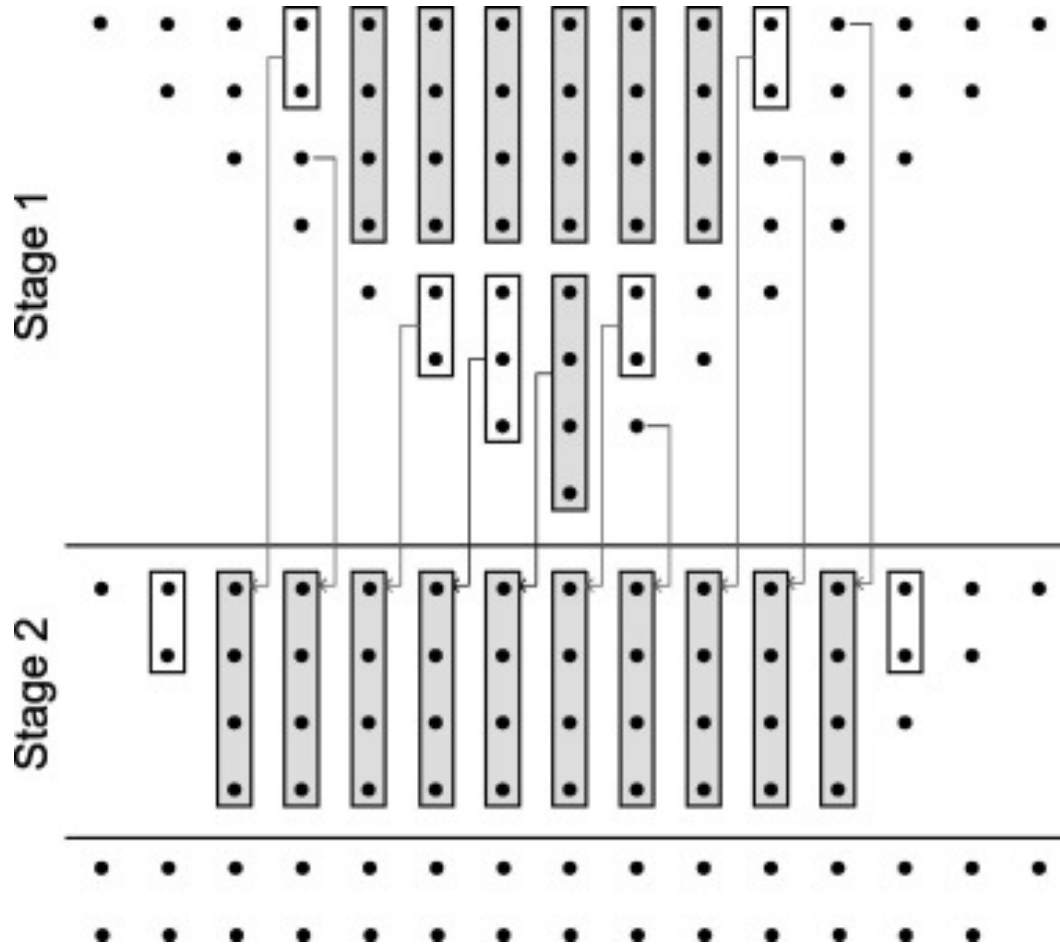


# 4:2 Compressor

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# 8x8 Dadda Multiplier



\_\_\_\_\_

[ ]

$x_5 y_5$

1

1



\_\_\_\_\_

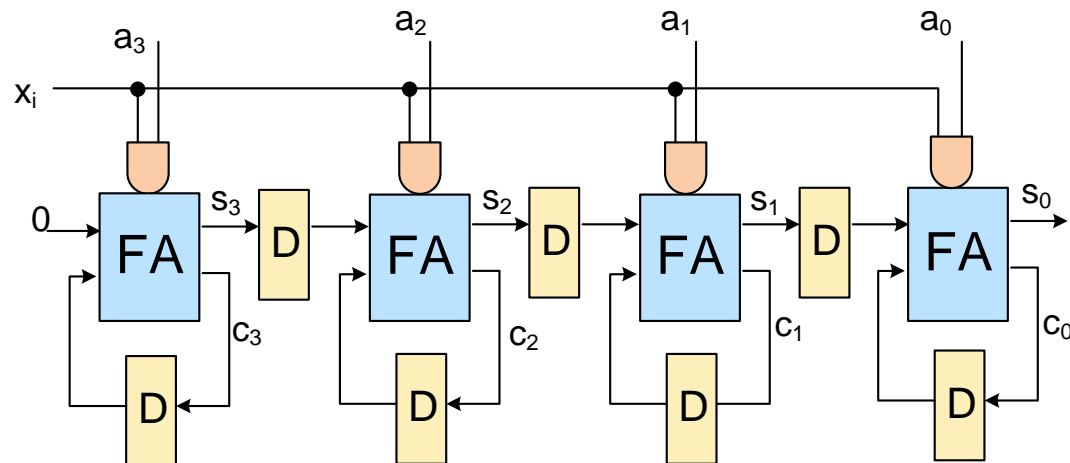
$p_{11}$     $p_{10}$     $p_9$     $p_8$     $p_7$     $p_6$     $p_5$     $p_4$     $p_3$     $p_2$     $p_1$

## Simplified partial products for two's complement multiplier

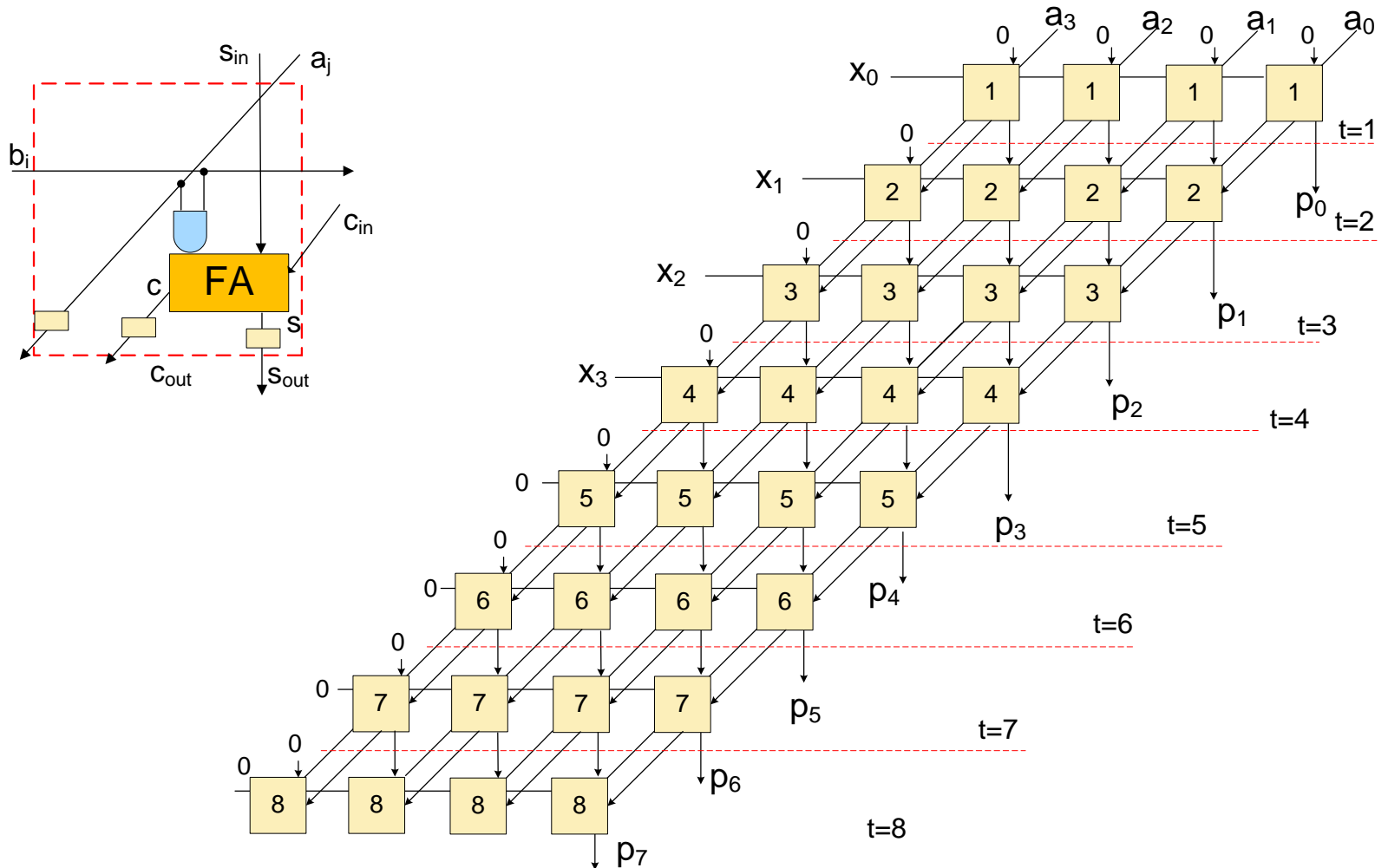
# Serial Array Multiplier

$$AX = Ax_02^0 + Ax_12^1 + Ax_22^2 + Ax_32^3$$

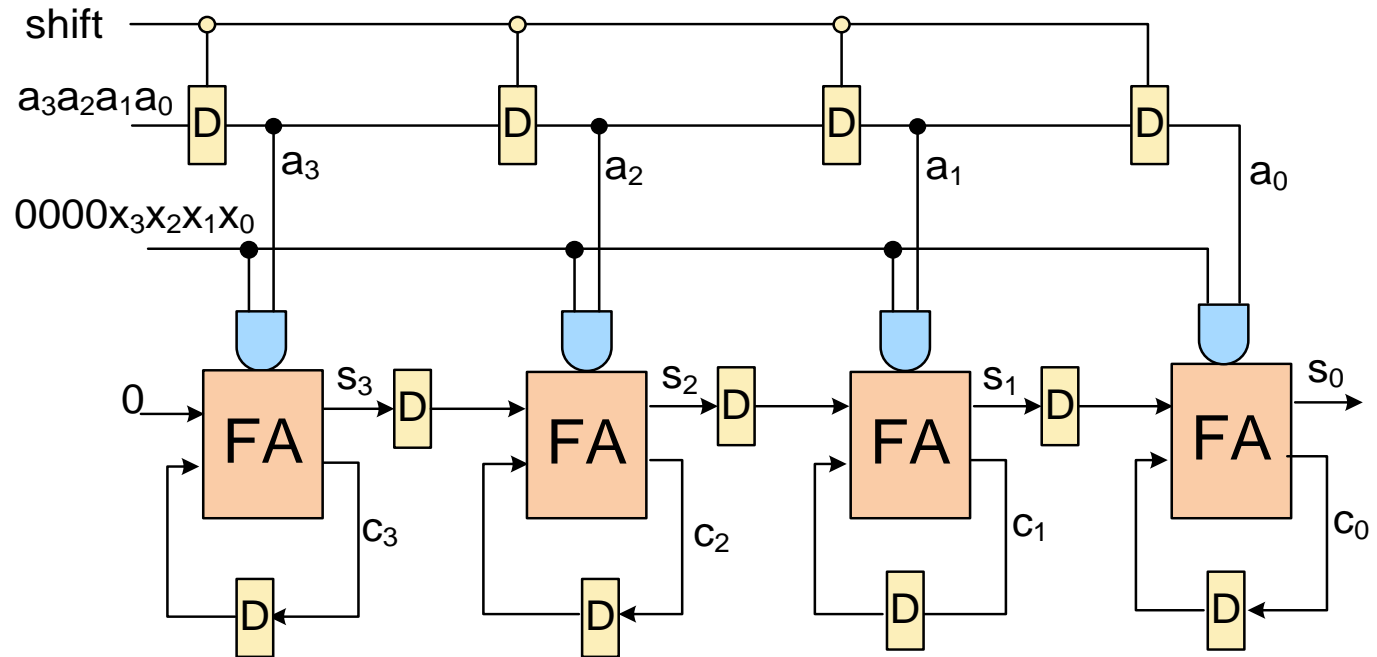
$\begin{array}{r} \phantom{0000} \alpha_3 x_0 \alpha_2 x_0 \alpha_1 x_0 \alpha_0 x_0 \\ \phantom{000} \alpha_3 x_1 \alpha_2 x_1 \alpha_1 x_1 \alpha_0 x_1 \\ \phantom{00} \alpha_3 x_2 \alpha_2 x_2 \alpha_1 x_2 \alpha_0 x_2 \\ \alpha_3 x_3 \alpha_2 x_3 \alpha_1 b_3 \alpha_0 x_3 \end{array}$								
$p_7$	$p_6$	$p_5$	$p_4$	$p_3$	$p_2$	$p_1$	$p_0$	Product



# Unroll in Time



# Save Operand



shift	1 1 1 1 0 0 0 0 1 1 1 1 0 0 0 0
a	a <sub>0</sub> a <sub>1</sub> a <sub>2</sub> a <sub>3</sub> (stable a) a <sub>0</sub> a <sub>1</sub> a <sub>2</sub> a <sub>3</sub>
x	0 0 0 0 x <sub>0</sub> x <sub>1</sub> x <sub>2</sub> x <sub>3</sub> 0 0 0 0 (new x)
p=ax	p <sub>0</sub> p <sub>1</sub> p <sub>2</sub> p <sub>3</sub> p <sub>4</sub> p <sub>5</sub> p <sub>6</sub> p <sub>7</sub> (new p)

# Fewer Partial Products

---

- ❑ Array multiplier requires  $N$  partial products
- ❑ If we looked at groups of  $r$  bits, we could form  $N/r$  partial products.
  - Faster and smaller?
  - Called radix- $2^r$  encoding
- ❑ Ex:  $r = 2$ : look at pairs of bits
  - Form partial products of  $0, Y, 2Y, 3Y$
  - First three are easy, but  $3Y$  requires adder ☹️

# Booth Encoding

- ❑ Instead of  $3Y$ , try  $-Y$ , then increment next partial product to add  $4Y$
- ❑ Similarly, for  $2Y$ , try  $-2Y + 4Y$  in next partial product

Inputs			Partial Product	Booth Selects		
$x_{2i+1}$	$x_{2i}$	$x_{2i-1}$	$PP_i$	$SINGLE_i$	$DOUBLE_i$	$NEG_i$
0	0	0	0	0	0	0
0	0	1	$Y$	1	0	0
0	1	0				
0	1	1				
1	0	0				
1	0	1				
1	1	0				
1	1	1				

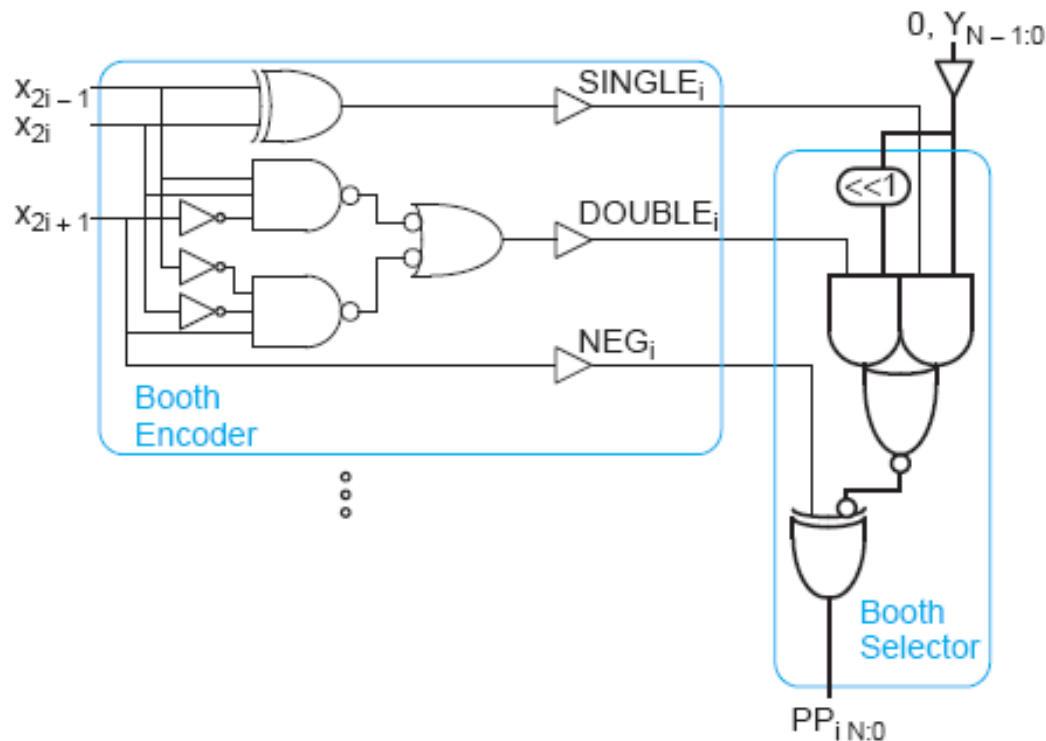
# Booth Encoding

- ❑ Instead of  $3Y$ , try  $-Y$ , then increment next partial product to add  $4Y$
- ❑ Similarly, for  $2Y$ , try  $-2Y + 4Y$  in next partial product

Inputs			Partial Product	Booth Selects		
$x_{2i+1}$	$x_{2i}$	$x_{2i-1}$	$PP_i$	$SINGLE_i$	$DOUBLE_i$	$NEG_i$
0	0	0	0	0	0	0
0	0	1	$Y$	1	0	0
0	1	0	$Y$	1	0	0
0	1	1	$2Y$	0	1	0
1	0	0	$-2Y$	0	1	1
1	0	1	$-Y$	1	0	1
1	1	0	$-Y$	1	0	1
1	1	1	$-0 (= 0)$	0	0	1

# Booth Hardware

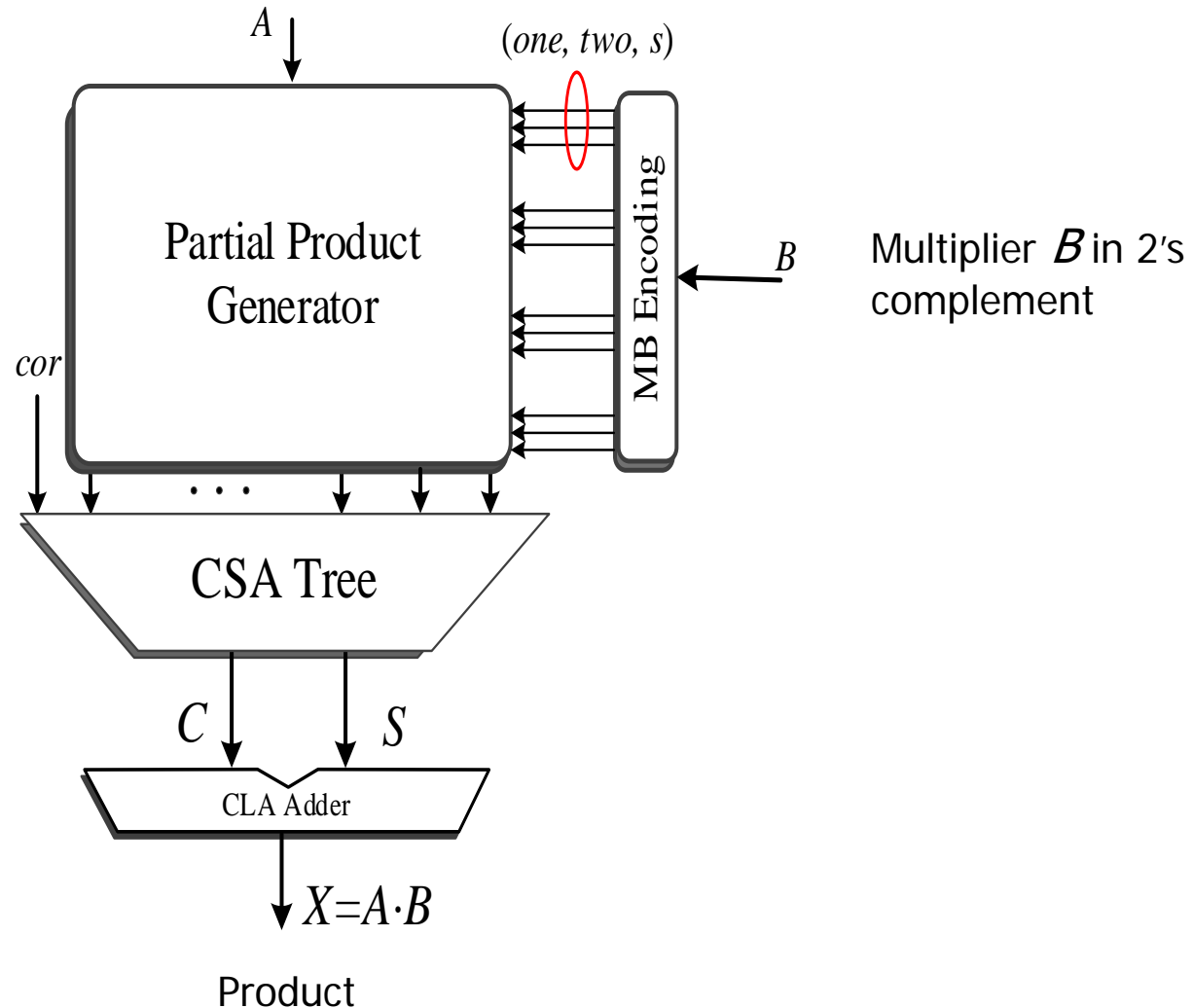
- Booth encoder generates control lines for each PP
  - Booth selectors choose PP bits





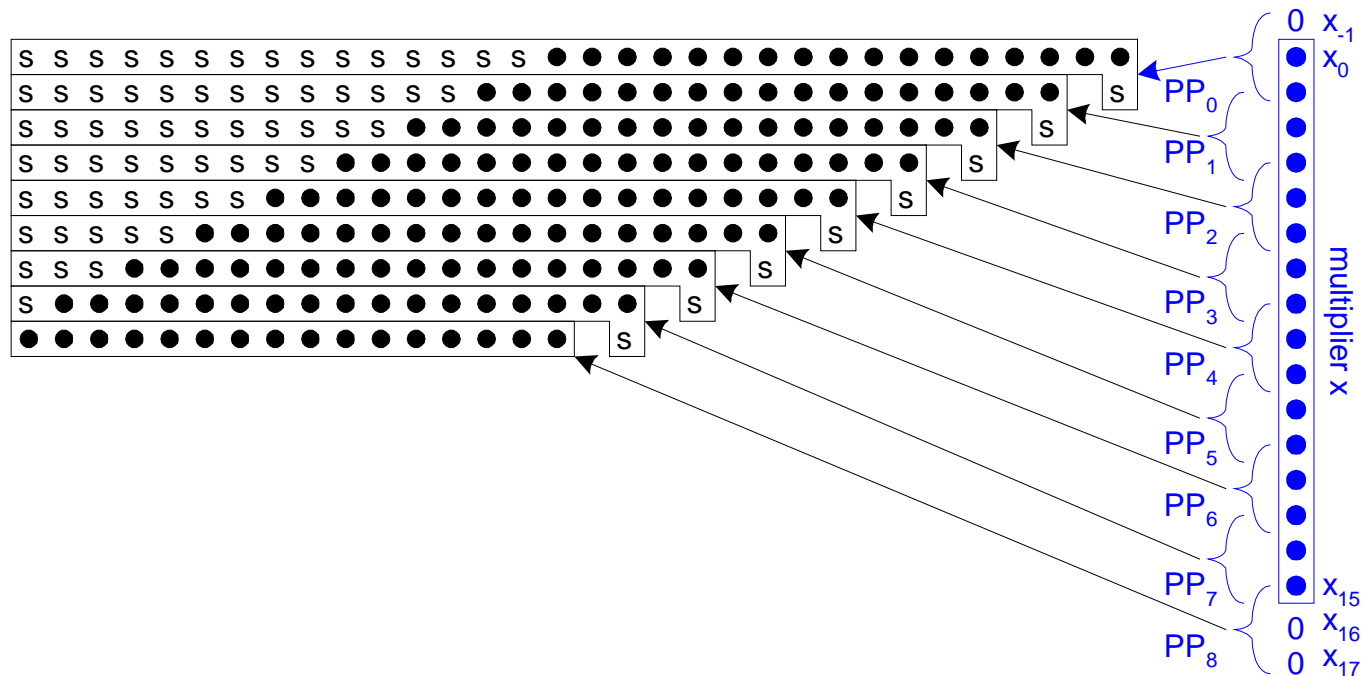
# Modified Booth Multiplier

Multiplicand  $A$  in  
2's complement



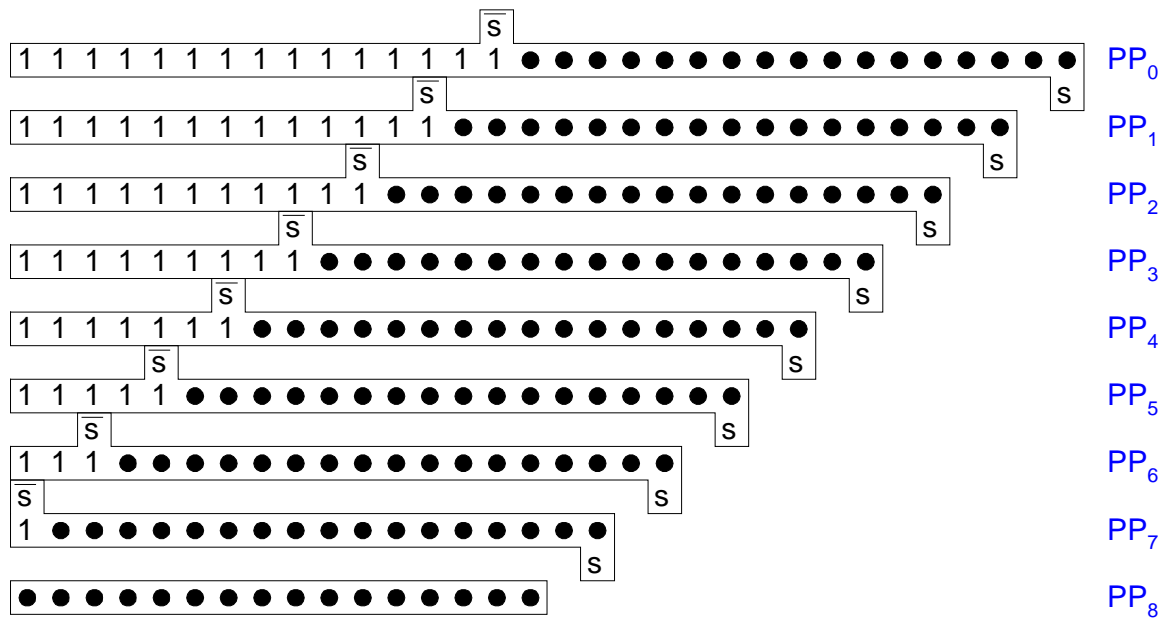
# Sign Extension

- ❑ Partial products can be negative
  - Require sign extension, which is cumbersome
  - High fanout on most significant bit



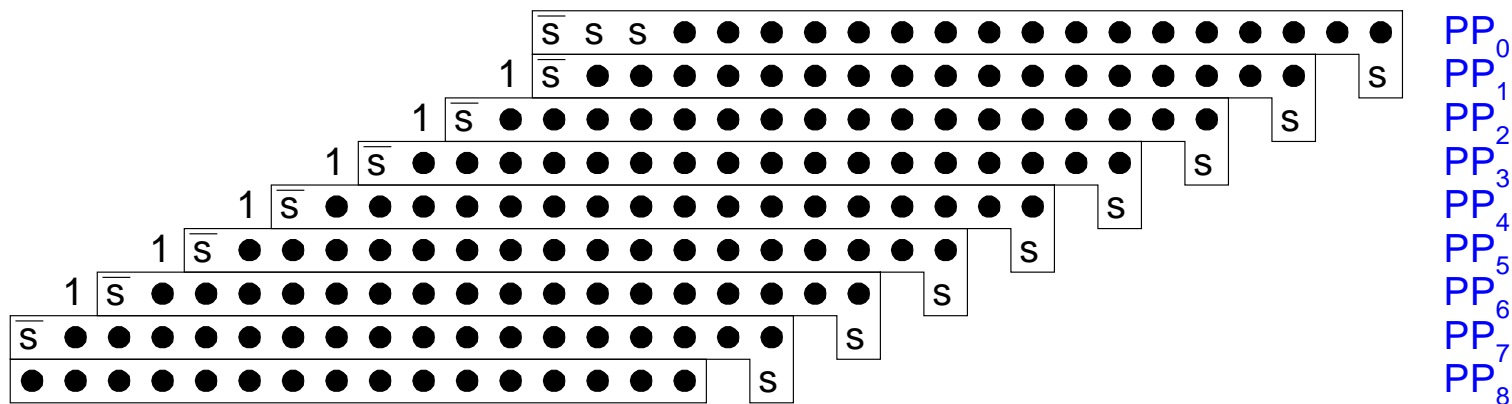
# Simplified Sign Ext.

- ❑ Sign bits are either all 0's or all 1's
  - Note that all 0's is all 1's + 1 in proper column
  - Use this to reduce loading on MSB



# Even Simpler Sign Ext.

- ❑ No need to add all the 1's in hardware
  - Precompute the answer!



# Advanced Multiplication

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- ❑ Signed vs. unsigned inputs
- ❑ Higher radix Booth encoding
- ❑ Array vs. tree CSA networks