

FPL'04

Second Order Function Approximation Using a Single Multiplication on FPGAs

Jérémie Detrey

Florent de Dinechin

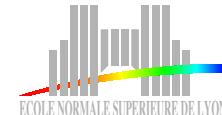
Projet Arénaire – LIP

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INRIA

Overview

- ▶ Context
- ▶ The SMSO method
- ▶ Optimization
- ▶ Results
- ▶ Conclusion

Context

► Context

- Function evaluation
- State of the art
- Objectives

► The SMSO method

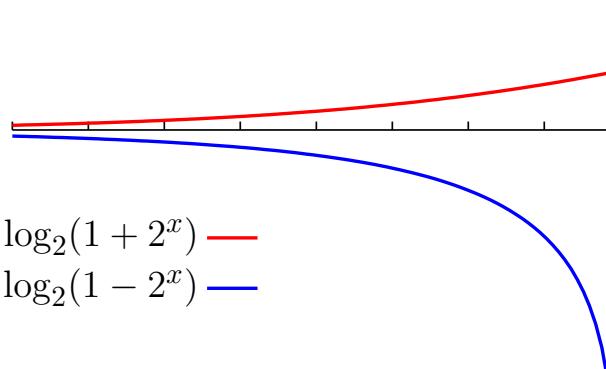
► Optimization

► Results

► Conclusion

Context: function evaluation

- ▶ elementary functions $\sin(x)$, $\cos(x)$, $\log(x)$, e^x , ...
 - signal or image processing
 - neural networks
 - ...
- ▶ special functions:
 - logarithmic number system: $\log_2(1 + 2^x)$ and $\log_2(1 - 2^x)$



Context: function evaluation

► input:

- function $f : [0; 1[\rightarrow [0; 1[$
- input precision w_I
- output precision w_O (usually $w_O = w_I$)

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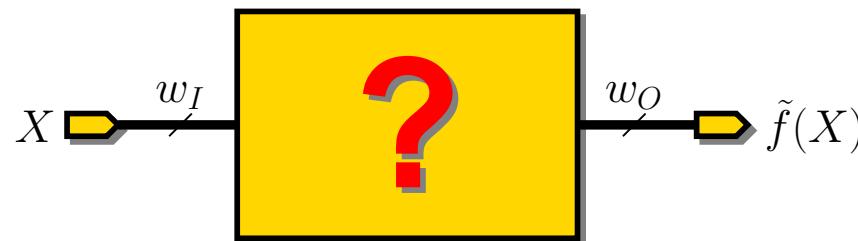
- where $X = .x_1 x_2 \cdots x_{w_I}$
- and $\tilde{f}(X) = Y = .y_1 y_2 \cdots y_{w_O} \approx f(X)$ at the required precision

Context: function evaluation

► input:

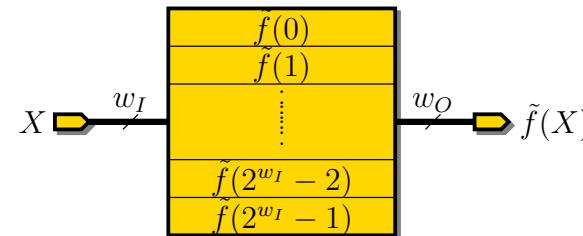
- function $f : [0; 1[\rightarrow [0; 1[$
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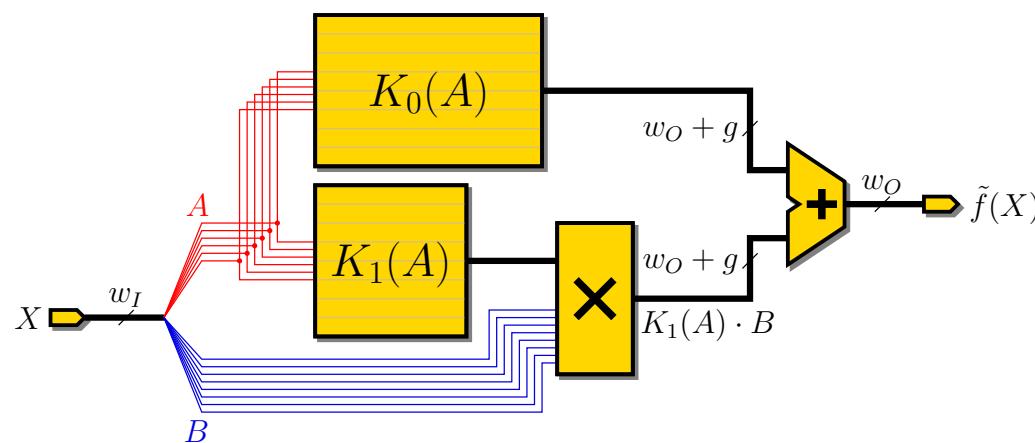
Order 0: direct look-up table



- very short critical path: only 1 table look-up
- huge look-up table: $w_O \times 2^{w_I}$ bits

Order 1: lookup-multiply method

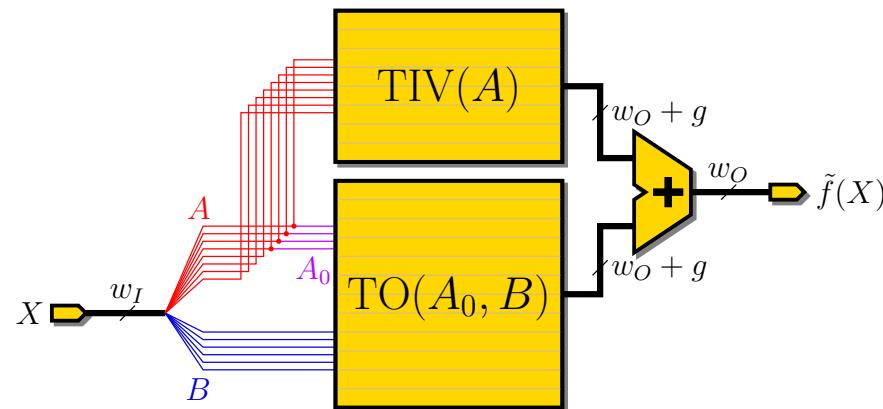
► Mencer, Boullis, Luk and Styles



- smaller tables
- longer critical path: 1 table look-up, 1 mult and 1 add

Order 1: bipartite table method

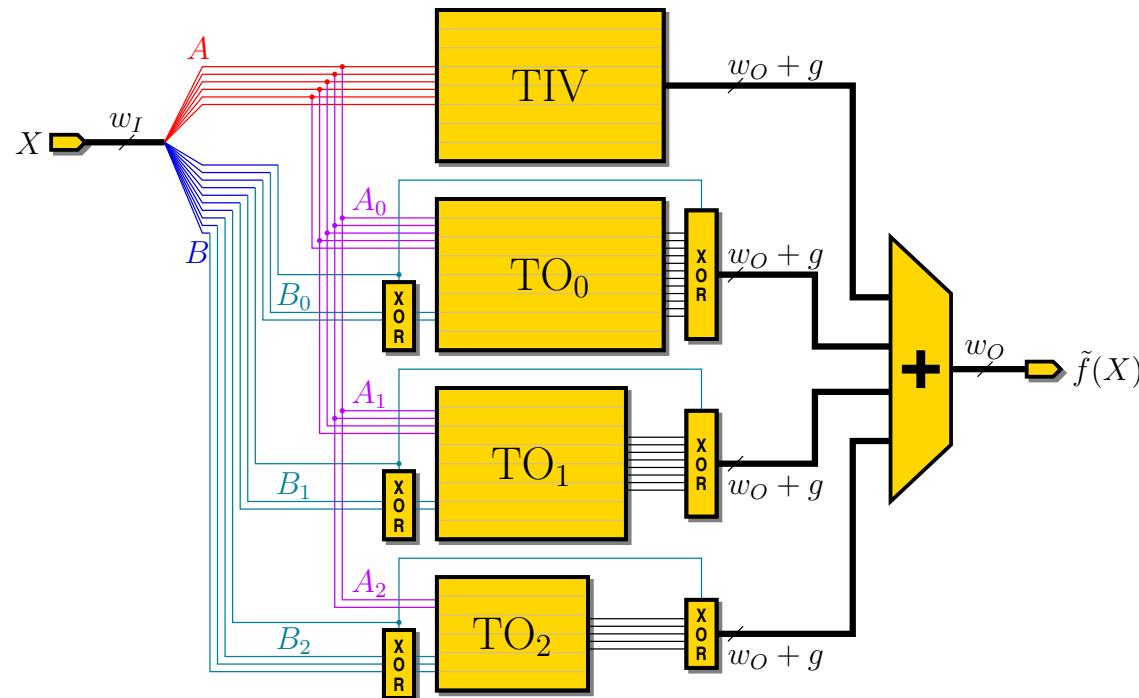
- Das Sarma and Matula, generalized by Schulte and Stine



- shorter critical path: 1 table look-up and 1 add
- slightly larger tables

Order 1: multipartite table method

- ▶ Schulte and Stine, Muller, de Dinechin and Tisserand: generalization and extension of the idea of the bipartite table method



- critical path: 2 XOR stages, 1 table look-up and $\log_2(n)$ adds
- much smaller tables, but adder tree

Higher order methods

- ▶ Hörner evaluation
- ▶ interleaved memory interpolators: [Lewis](#)
- ▶ partial product arrays: [Hassler](#) and [Takagi](#)
- ▶ specialized squaring unit: [Piñero](#), [Bruguera](#) and [Muller](#)
- ▶ simplified order 5 Taylor approximation: [Defour](#), [de Dinechin](#) and [Muller](#)
- ▶ ...

Objectives

- ▶ simplify, generalize and extend Defour's method
- ▶ use ideas from order 1 methods (bipartite and multipartite table) for an order 2 approximation

Objectives

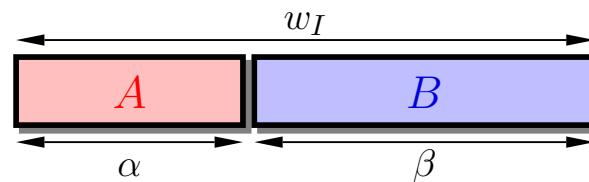
- ▶ simplify, generalize and extend Defour's method
- ▶ use ideas from order 1 methods (bipartite and multipartite table) for an order 2 approximation
- ▶ maintain short critical path while keeping tables as small as possible
- ▶ use only small multipliers (Virtex-II)
- ▶ accurate error analysis for a fine tuning of the operators

The SMSO method

- ▶ Context
- ▶ The SMSO method
 - General idea
 - Architecture
- ▶ Optimization
- ▶ Results
- ▶ Conclusion

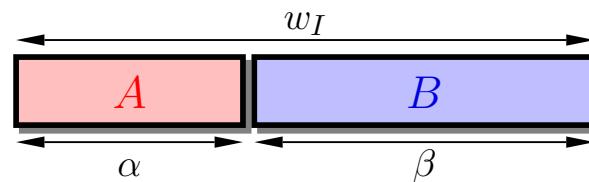
General idea: second order approximation

- ▶ input word decomposition: $X = A + 2^{-\alpha}B = .a_1a_2 \cdots a_\alpha b_1b_2 \cdots b_\beta$



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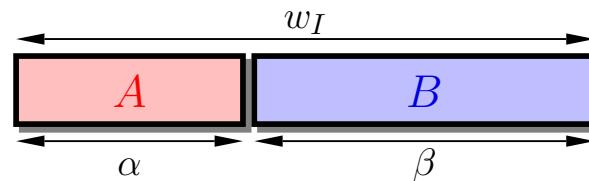


- ▶ order 2 approximation on each interval addressed by A :

$$\tilde{f}(X) = K_0(\textcolor{red}{A}) + K_1(\textcolor{red}{A}) \cdot 2^{-\alpha}B + K_2(\textcolor{red}{A}) \cdot 2^{-2\alpha}B^2$$

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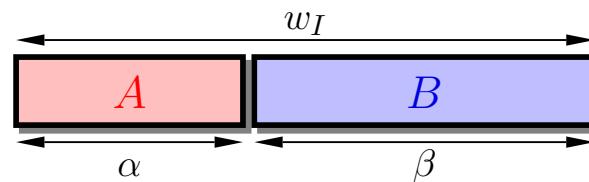
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look-up table
TIV($\textcolor{red}{A}$)

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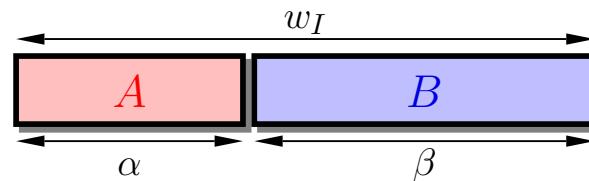


- ▶ order 2 approximation on each interval addressed by A :

$$\tilde{f}(X) = \underbrace{K_0(A)}_{\text{look-up table}} + \underbrace{K_1(A) \cdot 2^{-\alpha}B}_{\text{TIV}(A)} + \underbrace{K_2(A) \cdot 2^{-2\alpha}B^2}_{\text{TO}_2(A, B)}$$

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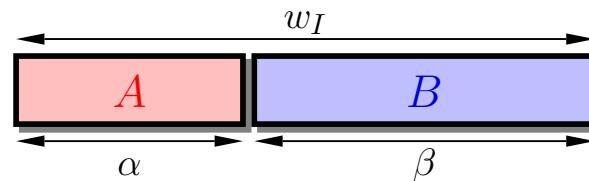


- ▶ order 2 approximation on each interval addressed by A :

$$\tilde{f}(X) = \underbrace{K_0(A)}_{\substack{\text{look-up table} \\ \text{TIV}(A)}} + \underbrace{K_1(A) \cdot 2^{-\alpha}B}_{\substack{\text{multiplier?} \\ \text{look-up table?}}} + \underbrace{K_2(A) \cdot 2^{-2\alpha}B^2}_{\substack{\text{look-up table} \\ \text{TO}_2(A, B)}}$$

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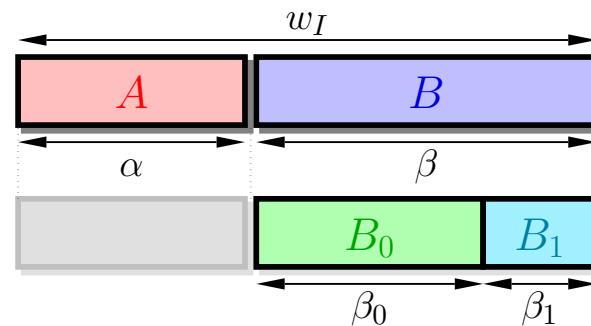


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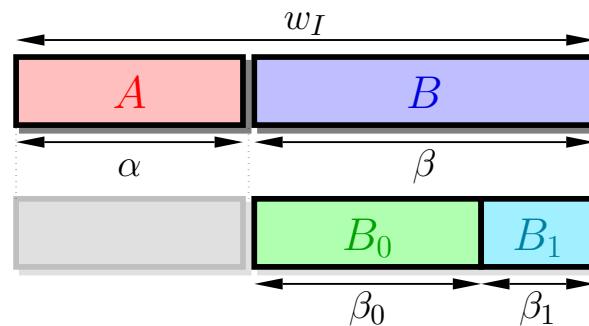
General idea: multiplication vs. look-up table tradeoff

- second decomposition: $B = B_0 + 2^{-\beta_0}B_1 = .b_1b_2 \cdots b_{\beta_0}b_{\beta_0+1} \cdots b_\beta$:



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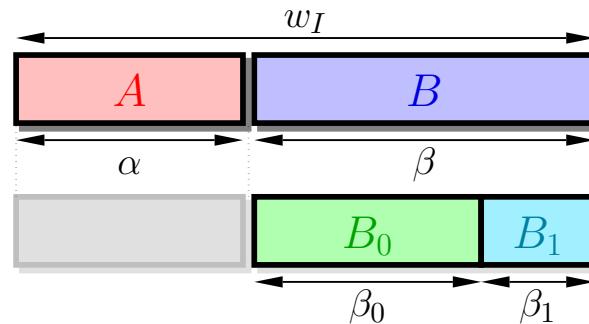


- we obtain:

$$K_1(A) \cdot 2^{-\alpha}B = K_1(A) \cdot 2^{-\alpha}B_0 + K_1(A) \cdot 2^{-\alpha-\beta_0}B_1$$

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- we obtain:

$$K_1(\textcolor{red}{A}) \cdot 2^{-\alpha}B = \underbrace{K_1(\textcolor{red}{A}) \cdot 2^{-\alpha}B_0}_{\begin{array}{c} \text{multiplier} \\ \text{TS}(\textcolor{red}{A}) \times B_0 \end{array}} + \underbrace{K_1(\textcolor{red}{A}) \cdot 2^{-\alpha-\beta_0}B_1}_{\begin{array}{c} \text{look-up table} \\ \text{TO}_1(\textcolor{red}{A}, \textcolor{teal}{B}_1) \end{array}}$$

General idea

► we have 4 tables:

- Table of Initial Values: $TIV(A) = K_0(A)$
- Table of Slopes: $TS(A) = 2^{-\alpha} \cdot K_1(A)$
- Table of Offsets (order 1): $TO_1(A, B_1) = 2^{-\alpha-\beta_0} \cdot K_1(A) \cdot B_1$
- Table of Offsets (order 2): $TO_2(A, B) = 2^{-2\alpha} \cdot K_2(A) \cdot B^2$

General idea

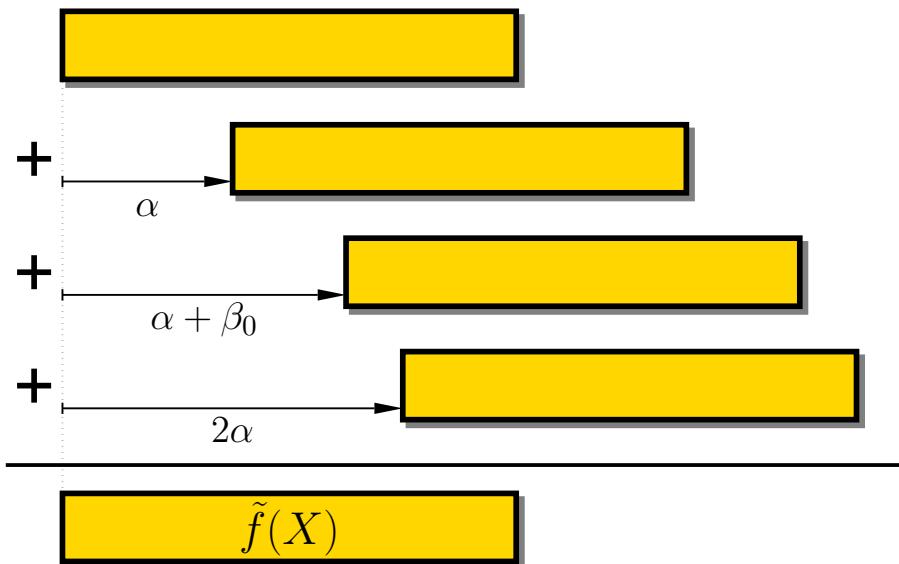
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► we obtain:

$$\tilde{f}(X) = TIV(A) + TS(A) \times B_0 + TO_1(A, B_1) + TO_2(A, B)$$

General idea: degrading accuracy



$$\text{TIV}(A) = K_0(A)$$

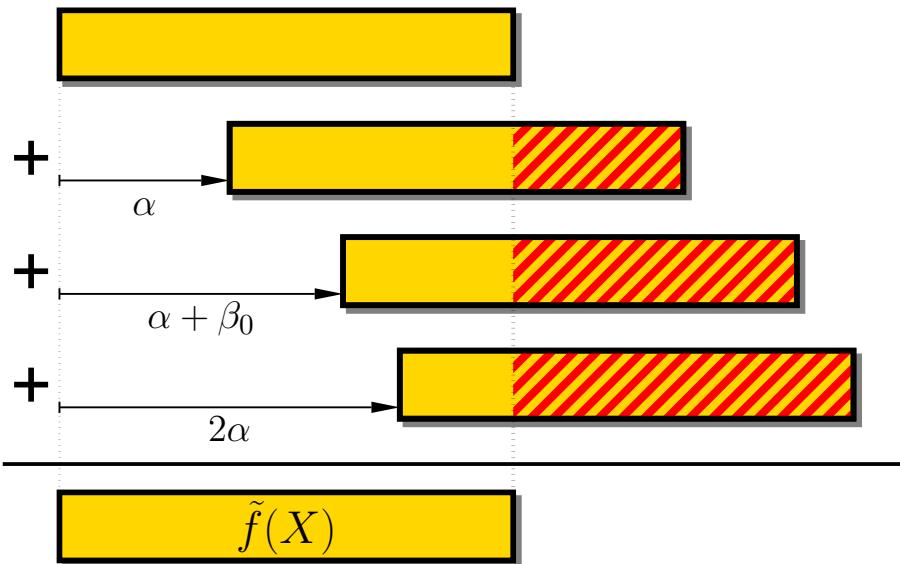
$$\text{TS}(A) \times B_0 = 2^{-\alpha} \cdot K_1(A) \times B_0$$

$$\text{TO}_1(A, B_1) = 2^{-\alpha - \beta_0} \cdot K_1(A) \cdot B_1$$

$$\text{TO}_2(A, B) = 2^{-2\alpha} \cdot K_2(A) \cdot B^2$$

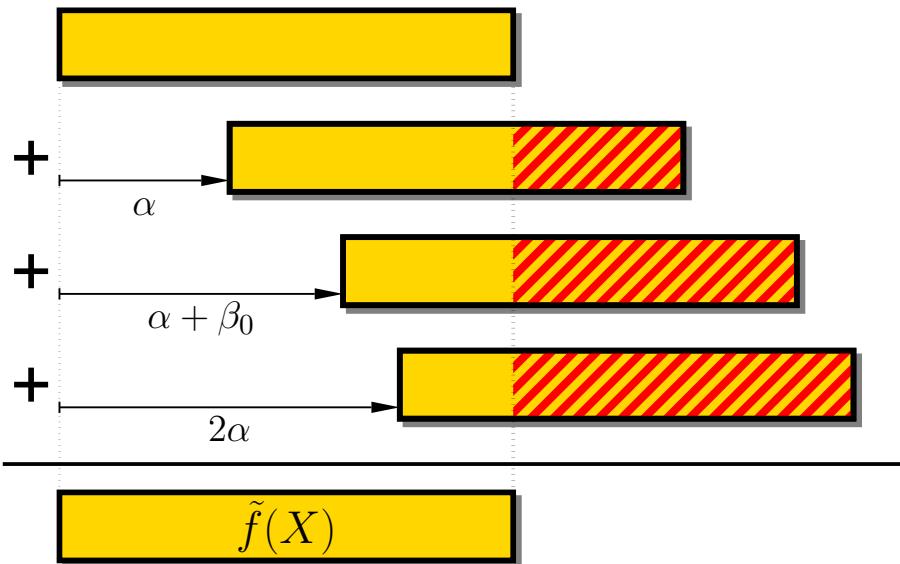
- ▶ some of the terms are **more accurate** than others

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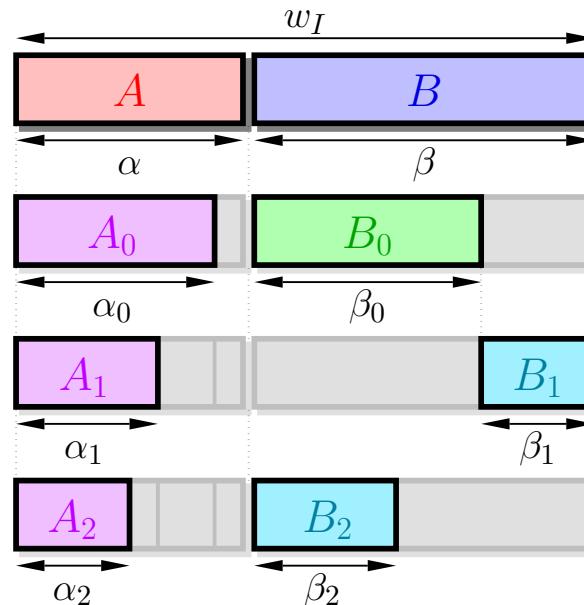
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- ▶ some of the terms are **more accurate** than others
- ▶ we can save **area** by addressing the more accurate tables with **less bits**

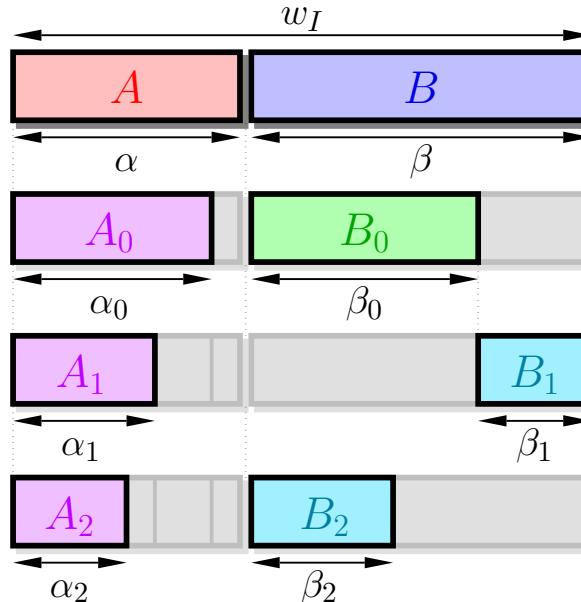
General idea: degrading accuracy

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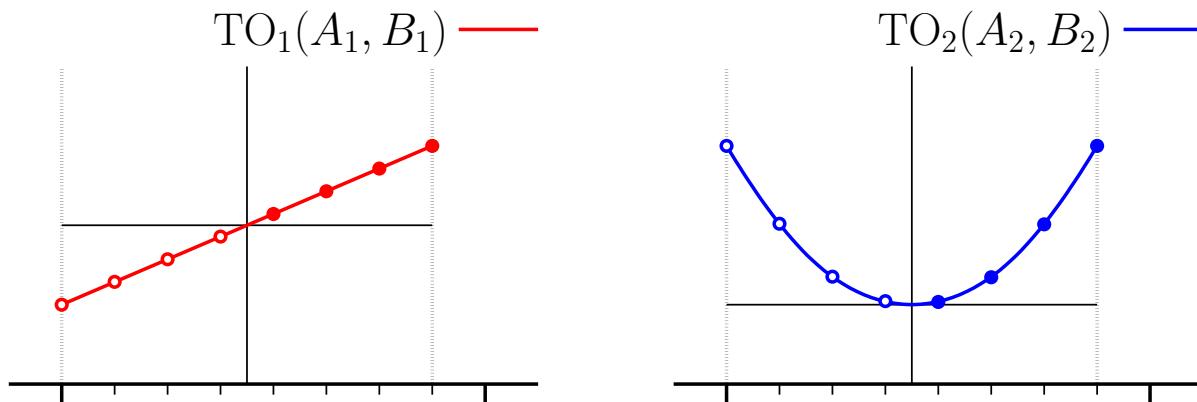
- ▶ we obtain the final SMSO formula:

$$\tilde{f}(X) = \text{TIV}(A) + \text{TS}(A_0) \times B_0 + \text{TO}_1(A_1, B_1) + \text{TO}_2(A_2, B_2)$$

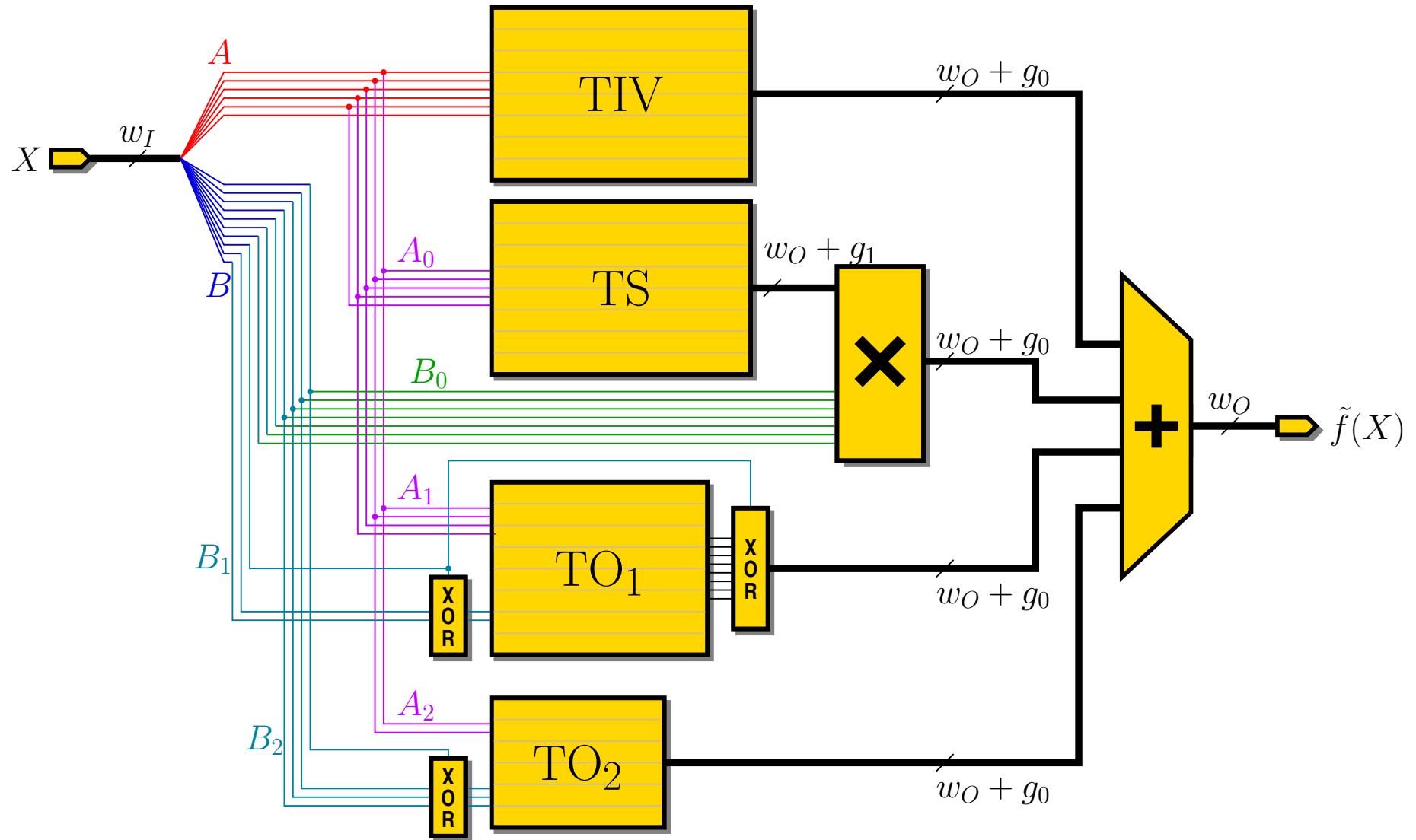
General idea: exploiting symmetry

► both TO_1 and TO_2 have symmetry property:

- $\text{TO}_1(A_1, -B_1) = -\text{TO}_1(A_1, B_1)$
- $\text{TO}_2(A_2, -B_2) = \text{TO}_2(A_2, B_2)$



Architecture



Optimization

- ▶ Context
- ▶ The SMSO method
- ▶ Optimization
 - Rounding considerations
 - Parameter space exploration
- ▶ Results
- ▶ Conclusion

Rounding considerations

- ▶ we want to achieve faithful rounding: $\left| \tilde{f}(X) - f(X) \right| < 2^{-w_O}$

Rounding considerations

- ▶ we want to achieve faithful rounding: $\left| \tilde{f}(X) - f(X) \right| < 2^{-w_O}$
- ▶ the SMSO operator entails several errors:
 - polynomial approximation: ϵ_{poly}
 - degrading table accuracy: ϵ_{tab}
 - rounding table values: $\epsilon_{\text{rt}} < 4 \times 2^{-w_O - g_0 - 1} + 2^{-w_O - g_1 - 1}$
 - final rounding: $\epsilon_{\text{rf}} < 2^{-w_O - 1} \cdot (1 - 2^{-g_0})$

Rounding considerations

- error constraint:

$$\epsilon_{\text{poly}} + \epsilon_{\text{tab}} + \epsilon_{\text{rt}} + \epsilon_{\text{rf}} < 2^{-w_O}$$

Rounding considerations

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$$\epsilon_{\text{poly}} + \epsilon_{\text{tab}} + \epsilon_{\text{rt}} + \epsilon_{\text{rf}} < 2^{-w_O}$$

- ▶ constraint on g_0 and g_1 :

$$\epsilon_{\text{poly}} + \epsilon_{\text{tab}} + 4 \cdot 2^{-w_O - g_0 - 1} + 2^{-w_O - g_1 - 1} + 2^{-w_O - 1} \cdot (1 - 2^{-g_0}) < 2^{-w_O}$$

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- ▶ assuming $g_0 = g_1$, we compute the bound:

$$g_0 > \log_2 \left(\frac{4}{2^{-w_O - 1} - \epsilon_{\text{poly}} - \epsilon_{\text{tab}}} \right) - w_O - 1$$

Parameter space exploration

- ▶ lots of parameters: $\alpha, \beta, \alpha_0, \beta_0, \alpha_1, \beta_1, \alpha_2, \beta_2, g_0, g_1$
- ▶ to find the best decomposition: parameter space exploration

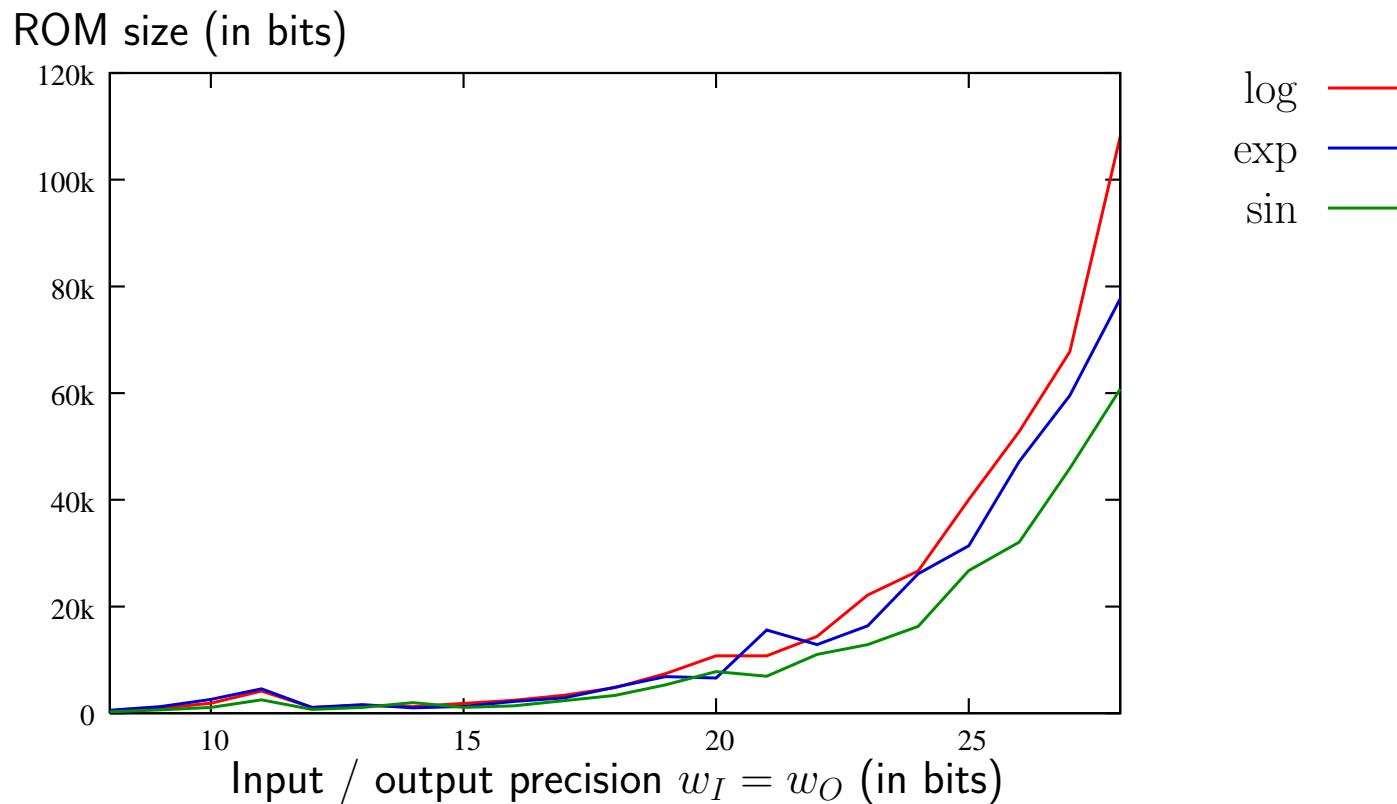
Parameter space exploration

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- ▶ to find the best decomposition: parameter space exploration
- ▶ the parameter space is huge, so we need a heuristic:
 - find all the acceptable decompositions such that $\epsilon_{\text{poly}} + \epsilon_{\text{tab}} < 2^{-w_O - 1}$
 - for each candidate:
 - compute the bounds for g_0 and g_1
 - fill the tables
 - compute the width of the signals
 - apply a user-defined score function (area, latency, multiplier size, ...)
 - the score determines the best decomposition
 - trial-and-error method to decrease g_0 and g_1

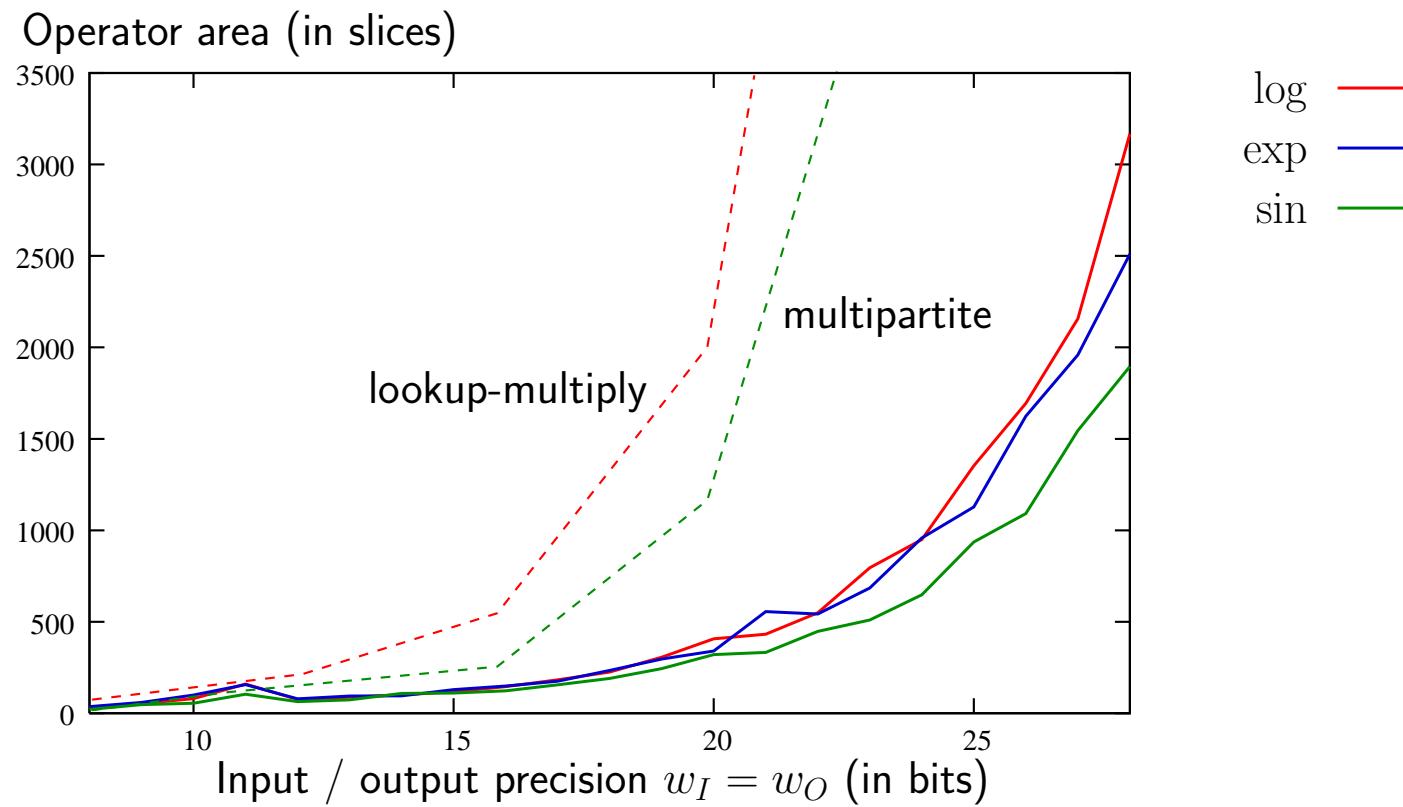
Results

- ▶ Context
- ▶ The SMSO method
- ▶ Optimization
- ▶ **Results**
- ▶ Conclusion

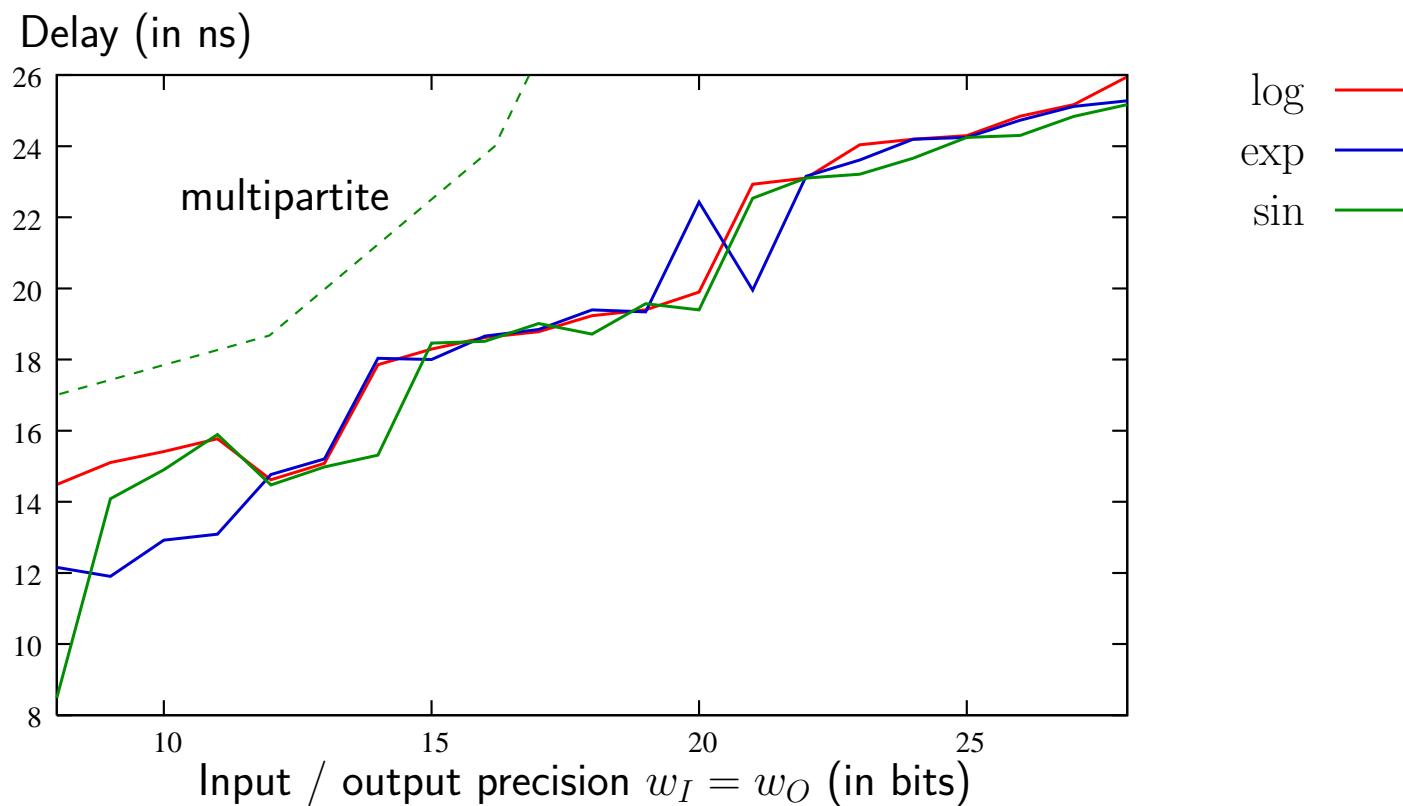
Results: ROM size



Results: operator area



Results: operator latency



Results: using Virtex-II small multipliers

Function		log		
Precision ($w_I = w_O$)		16 bits	20 bits	24 bits
Multiplier bit size		8×11	8×14	14×17
not using block multipliers	area (slices)	148	419	981
	delay (ns)	21	22	27
using block multipliers	area (slices)	102	362	855
	delay (ns)	18	21	25

Function		sin		
Precision ($w_I = w_O$) (bits)		16	20	24
Multiplier bit size		8×13	8×14	14×19
not using block multipliers	area (slices)	124	332	671
	delay (ns)	19	21	25
using block multipliers	area (slices)	71	275	540
	delay (ns)	19	21	25

Conclusion

- ▶ Context
- ▶ The SMSO method
- ▶ Optimization
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Contribution

- ▶ a novel function approximation method:
 - second order: smaller tables
 - only one small multiplier: shorter critical path, and can benefit from recent FPGA technologies (Virtex-II)
- ▶ accurate approximation and rounding error analysis
- ▶ automated exploration of the parameter space according to user-specified criteria

Future work

- ▶ split the TO_i s on several tables, as in the multipartite table method
- ▶ work on table compression techniques
- ▶ extend this method to higher order approximations

Thank you for your attention

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Questions?