

Takum: A New Tapered Precision Machine Number Format

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IEEE 754 Floating-Point

versus Desirable Design Criteria (1/2)



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versus Desirable Design Criteria (1/2)

- ▶ Represented numbers should reflect those used in computations



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versus Desirable Design Criteria (1/2)

- ▶ Represented numbers should reflect those used in computations: Observations



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versus Desirable Design Criteria (1/2)

- ▶ Represented numbers should reflect those used in computations: Observations:
 - ▶ Dynamic Range



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versus Desirable Design Criteria (1/2)

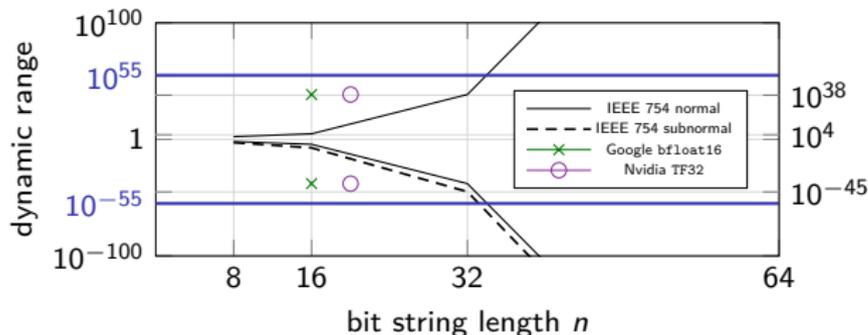
- ▶ Represented numbers should reflect those used in computations: Observations:
 - ▶ Dynamic Range: General purpose $10^{\pm 55}$ (SI units, constants, etc.)

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versus Desirable Design Criteria (1/2)

- ▶ Represented numbers should reflect those used in computations: Observations:
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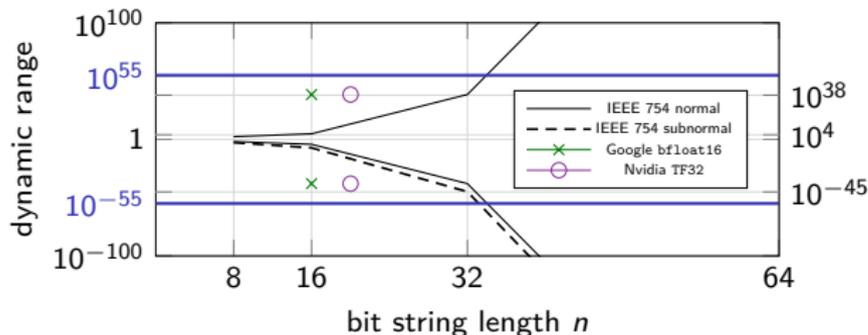


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versus Desirable Design Criteria (1/2)

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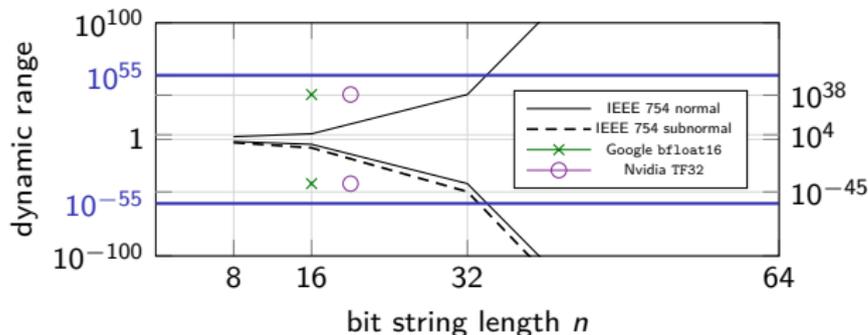
Violated:

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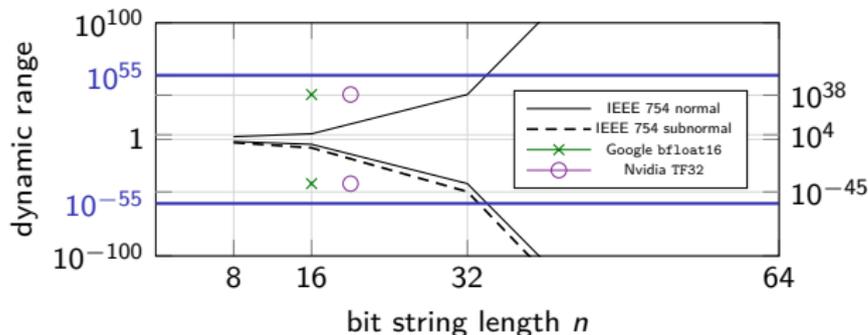
Violated: too small for $n \leq 32$, too large for $n \geq 64$

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- ▶ Represented numbers should reflect those used in computations: Observations:
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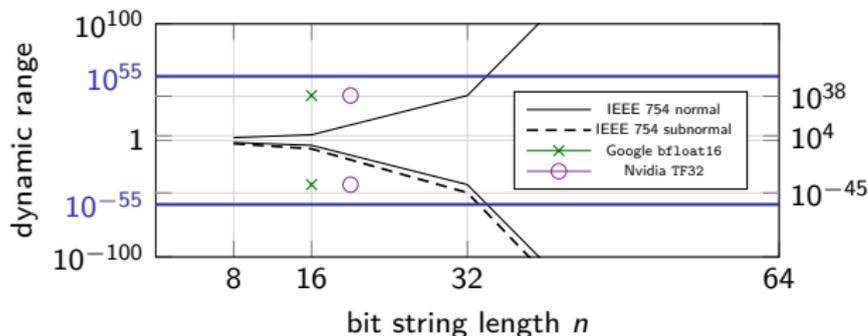
- ▶ Tapering

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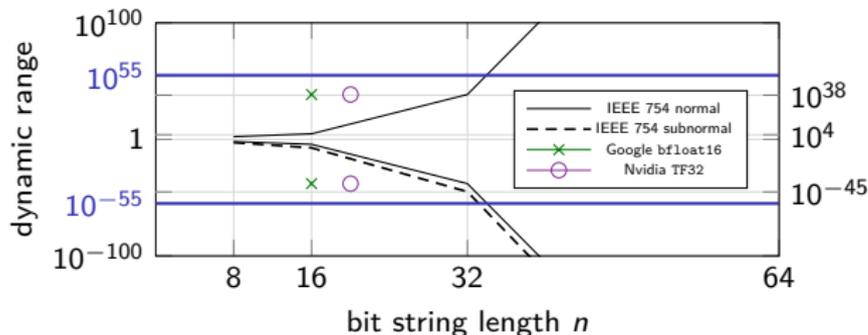
- ▶ **Violated:** too small for $n \leq 32$, too large for $n \geq 64$
- ▶ **Tapering:** Numbers in magnitude close to one are used much more frequently than very large or very small numbers

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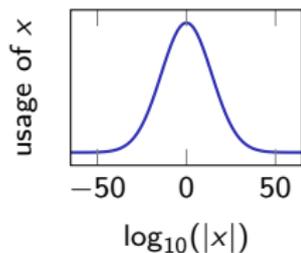
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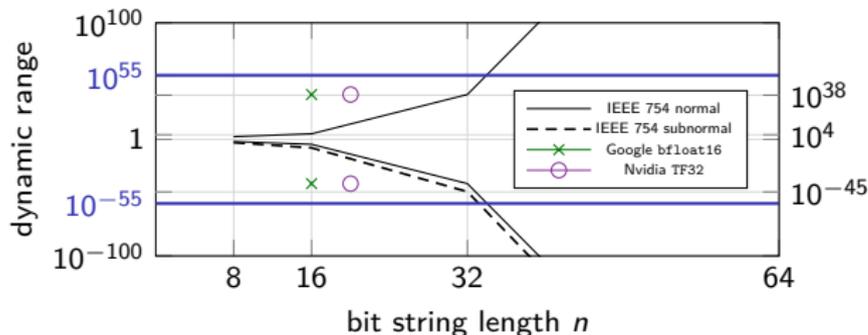


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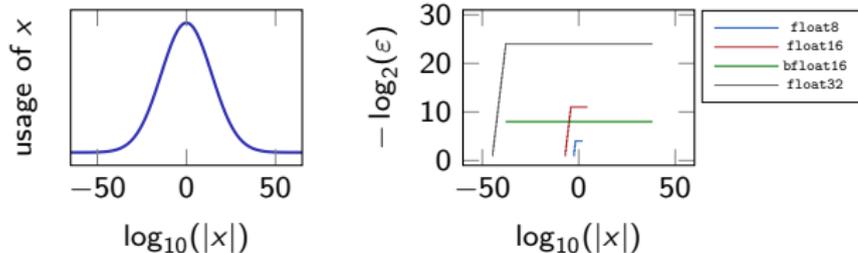
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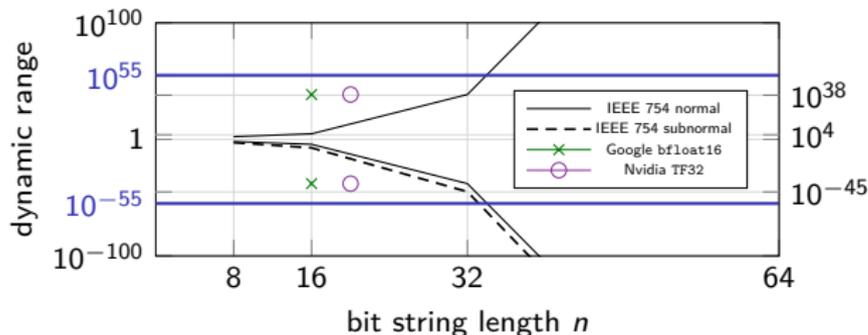


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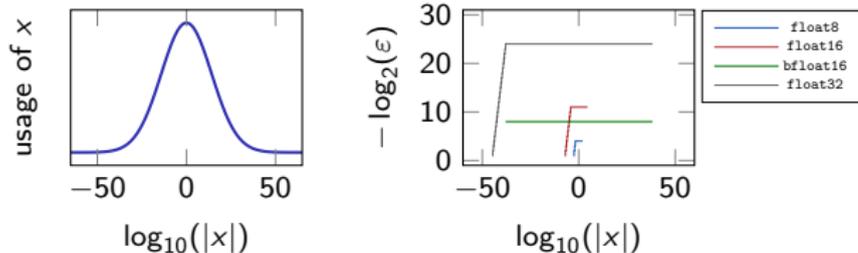
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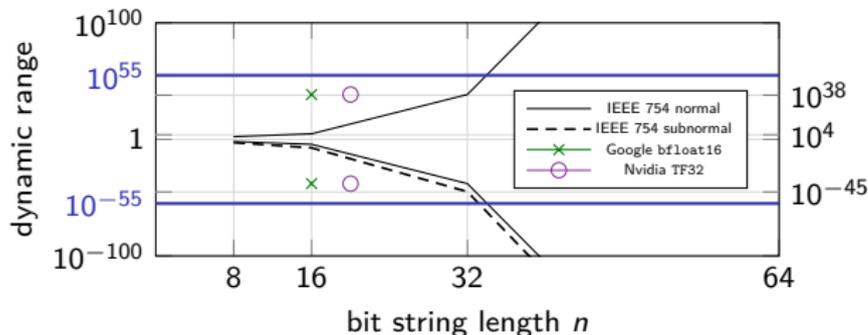
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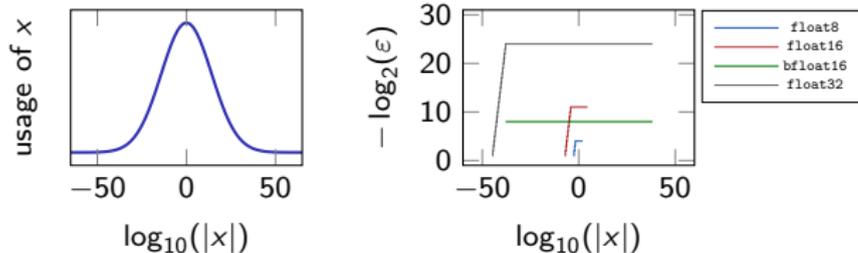
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- ▶ **Tapering:** Numbers in magnitude close to one are used much more frequently than very large or very small numbers



Violated: no tapering, uniform density (except subnormals)

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versus Desirable Design Criteria (2/2)



IEEE 754 Floating-Point

versus Desirable Design Criteria (2/2)

- ▶ No redundant encodings



IEEE 754 Floating-Point

versus Desirable Design Criteria (2/2)

- ▶ No redundant encodings
Violated



IEEE 754 Floating-Point

versus Desirable Design Criteria (2/2)

- ▶ No redundant encodings
Violated: signed zero



IEEE 754 Floating-Point

versus Desirable Design Criteria (2/2)

- ▶ No redundant encodings
Violated: signed zero, redundant NaNs



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versus Desirable Design Criteria (2/2)

- ▶ No redundant encodings

Violated: signed zero, redundant NaNs, excess numbers ($n \geq 64$)



IEEE 754 Floating-Point

versus Desirable Design Criteria (2/2)

- ▶ No redundant encodings

Violated: signed zero, redundant NaNs, excess numbers ($n \geq 64$)



format	float8	float16	bfloat16	TF32	float32	float64	float128
waste/%	5.08	3.12	0.78	0.78	0.39	82.03	98.88

IEEE 754 Floating-Point

versus Desirable Design Criteria (2/2)



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- ▶ Defined for bit strings of any length

IEEE 754 Floating-Point

versus Desirable Design Criteria (2/2)



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IEEE 754 Floating-Point

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IEEE 754 Floating-Point

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IEEE 754 Floating-Point

versus Desirable Design Criteria (2/2)



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Violated: Requires exponent-reencoding

- ▶ Simple/efficient hardware implementation (transistor count, energy efficiency, latency, throughput, etc.)

IEEE 754 Floating-Point

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Violated: Special cases complicate hardware

IEEE 754 Floating-Point

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Violated: Special cases complicate hardware

- ▶ Subnormals (increase FPU energy consumption by 20%)

IEEE 754 Floating-Point

versus Desirable Design Criteria (2/2)



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IEEE 754 Floating-Point

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Violated: Special cases complicate hardware

- ▶ Subnormals (increase FPU energy consumption by 20%)
- ▶ Signed zero ($0 = -0$)

IEEE 754 Floating-Point

versus Desirable Design Criteria (2/2)



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Violated: Special cases complicate hardware

- ▶ Subnormals (increase FPU energy consumption by 20%)
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versus Desirable Design Criteria (2/2)



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- ▶ Subnormals (increase FPU energy consumption by 20%)
- ▶ Signed zero ($0 = -0$, $\sqrt{-0} = -0$, etc.)
- ▶ Signaling/quiet NaN

IEEE 754 Floating-Point

versus Desirable Design Criteria (2/2)



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IEEE 754 Floating-Point

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IEEE 754 Floating-Point

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- ▶ Four rounding modes

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Conclusion

IEEE 754 Floating-Point

Conclusion

End of 'double precision everywhere' era

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- ▶ Deep learning/LLMs

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- ▶ Deep learning/LLMs
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End of 'double precision everywhere' era

- ▶ Deep learning/LLMs
- ▶ Mixed Precision
- ▶ Hardware/energy constraints (IoT, green HPC)

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The standard is failing

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Conclusion

End of 'double precision everywhere' era

- ▶ Deep learning/LLMs
- ▶ Mixed Precision
- ▶ Hardware/energy constraints (IoT, green HPC)

The standard is failing

- ▶ Not suitable for low precision applications ($n \leq 16$)

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Conclusion

End of 'double precision everywhere' era

- ▶ Deep learning/LLMs
- ▶ Mixed Precision
- ▶ Hardware/energy constraints (IoT, green HPC)

The standard is failing

- ▶ Not suitable for low precision applications ($n \leq 16$)
- ▶ Dilution with proprietary formats: bfloat16 and TF32, however still suffer from inherent issues

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- ▶ A lot of new hardware (e.g. GPUs) openly violates the standard

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The race is on

- ▶ IEEE 754 is a dead end with very high inertia
- ▶ Machine Numbers are the backbone of all computations, even small improvements have large high-level effects

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- ▶ A lot of new hardware (e.g. GPUs) openly violates the standard

The race is on

- ▶ IEEE 754 is a dead end with very high inertia
- ▶ Machine Numbers are the backbone of all computations, even small improvements have large high-level effects
- ▶ Time for a new paradigm?

Tapered Precision Machine Numbers

Motivation

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- ▶ Consider general floating-point format



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Posit Arithmetic

Definition

¹ John L. Gustafson et al. 'Standard for Posit Arithmetic (2022)'. Mar. 2022

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Posit Arithmetic

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Posit Arithmetic

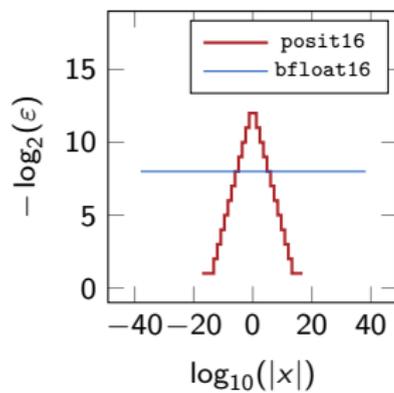
Discussion

Tapering

Posit Arithmetic

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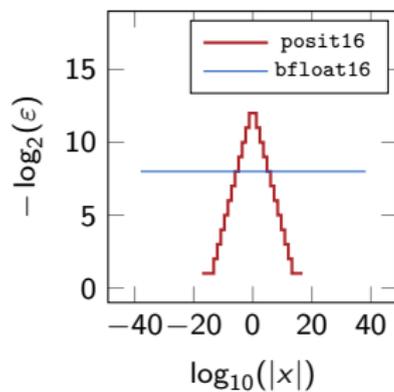


Posit Arithmetic

Discussion

Tapering

- ▶ Linear tapering

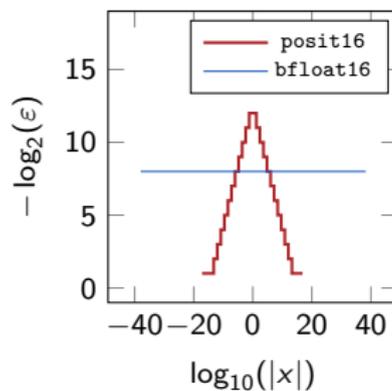


Posit Arithmetic

Discussion

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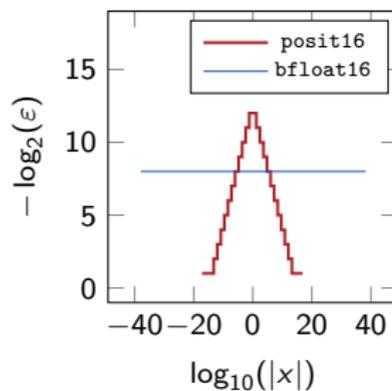
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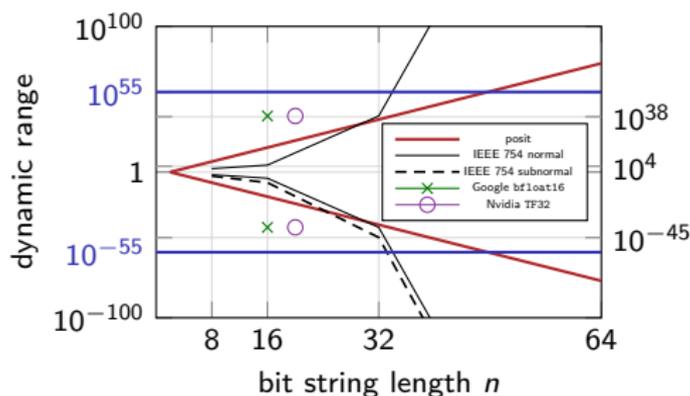
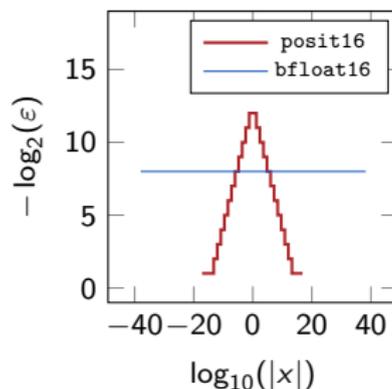
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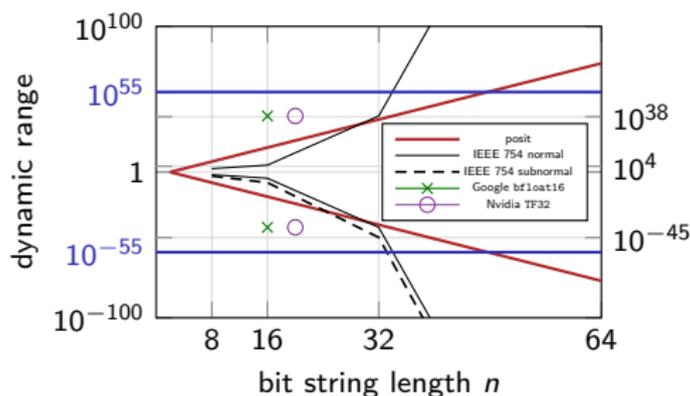
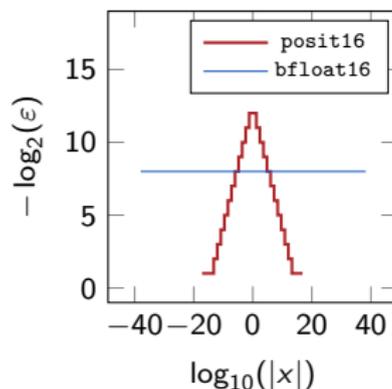
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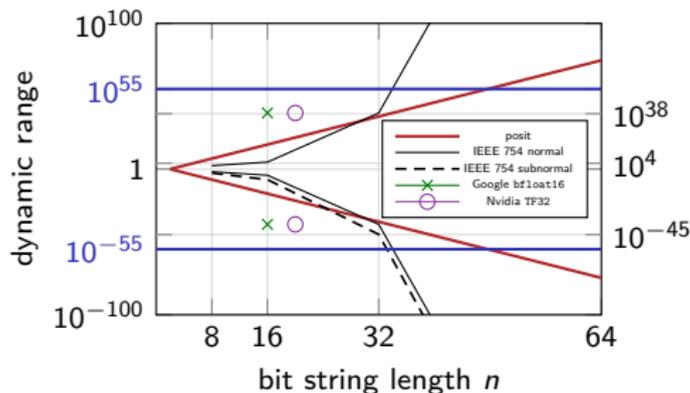
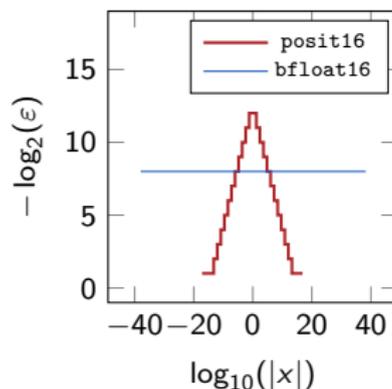
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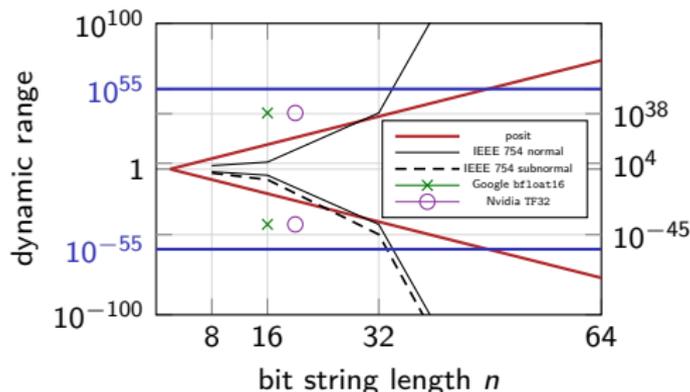
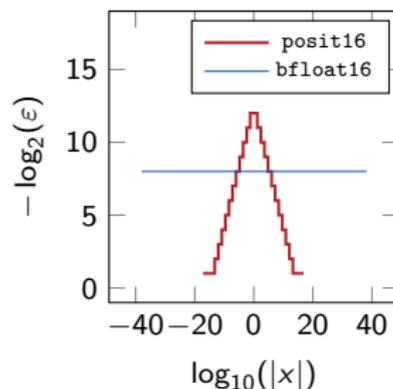
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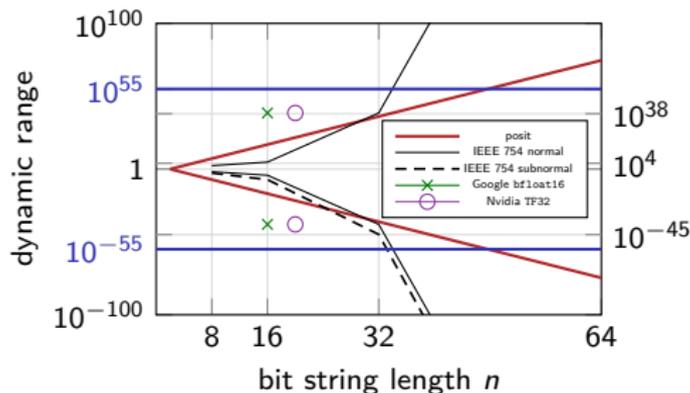
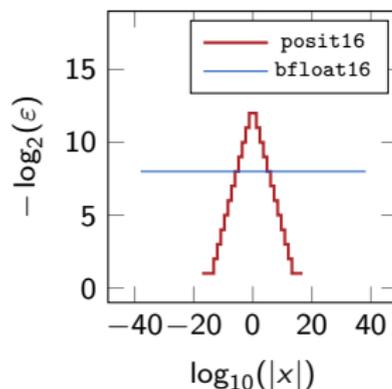
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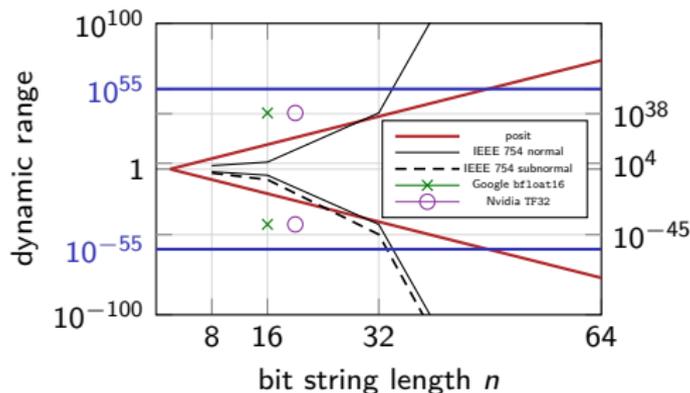
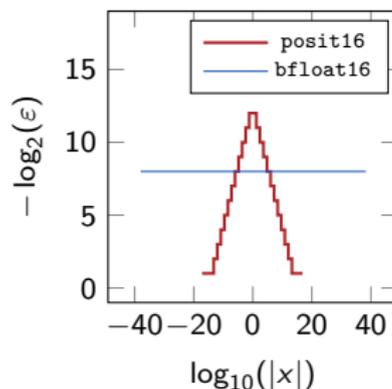
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- ▶ interesting properties
- ▶ not for general purpose arithmetic



Takum Arithmetic

Overview and Exponent Coding

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Logarithmic Number System

² Jeff Johnson. 'Rethinking floating point for deep learning'. arXiv: 1811.01721 (Nov. 2018)

³ J. Nicholas Coleman and Rizalafande Che Ismail. 'LNS with Co-Transformation Competes with Floating-Point'. In: IEEE Transactions on Computers 65.1 (2016), pp. 136-146. DOI: 10.1109/TC.2015.2409059

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- ▶ Advantages
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Logarithmic Number System

- ▶ Used internally at Meta for AI-ASICs (MTIA)
- ▶ Instead of $(-1)^s(1+f) \cdot 2^e$ express numbers as $(-1)^s b^{e+f} =: (-1)^s b^\ell$ for basis $b > 1$ (usually $b = 2$)
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Define takum as LNS with pure base \sqrt{e} (transform to and from base e with ℓ -shift)

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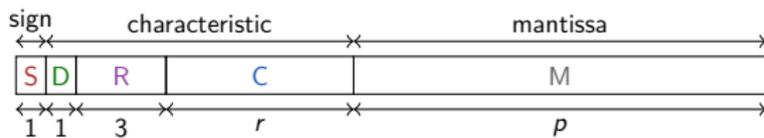
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Takum

Definition

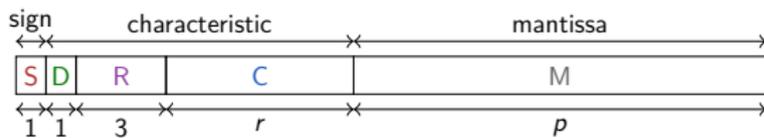
Takum

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Takum

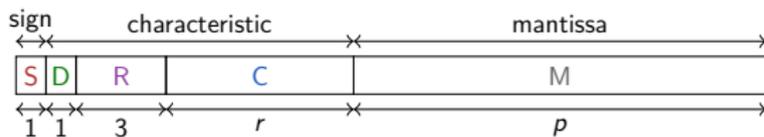
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Sign bit S , direction bit D , regime bits R , characteristic bits C , mantissa bits M

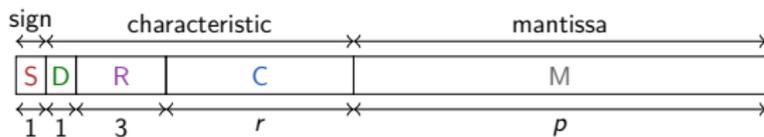
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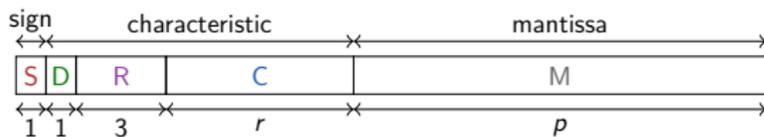
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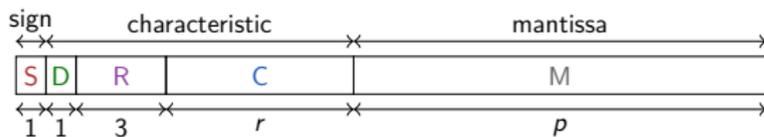


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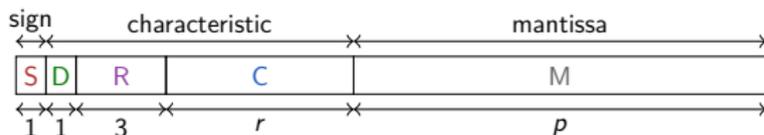
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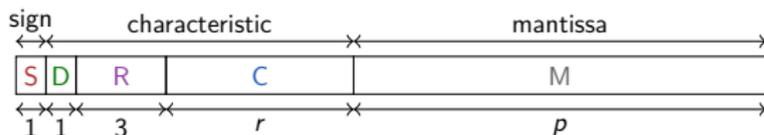
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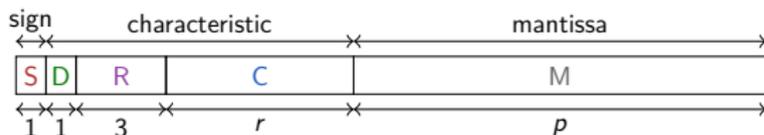
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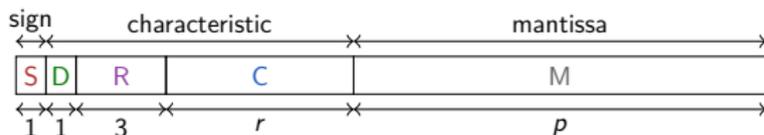
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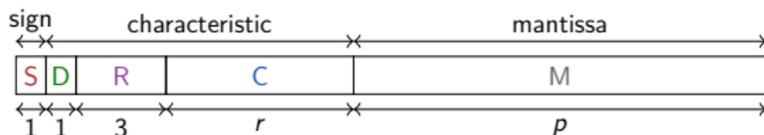
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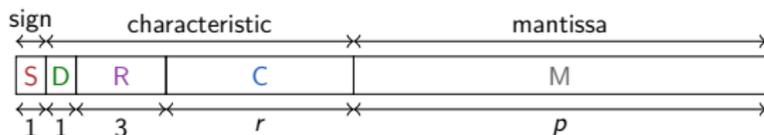
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- ▶ Computation of c is conditional negation, bitwise OR and increment

Takum

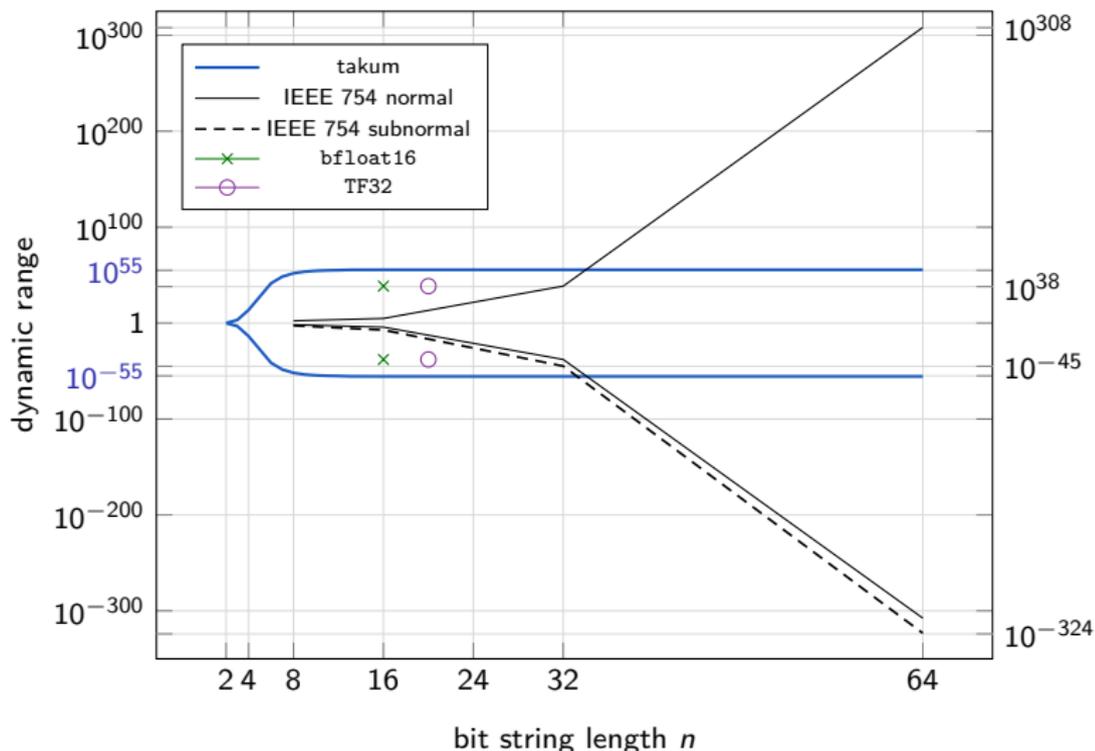
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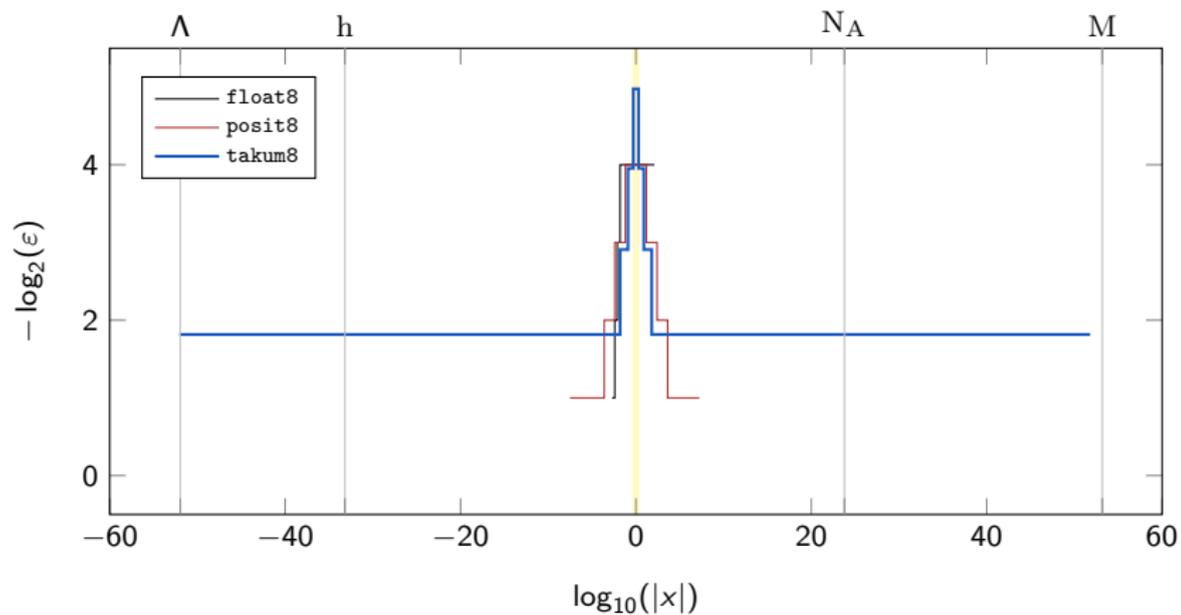
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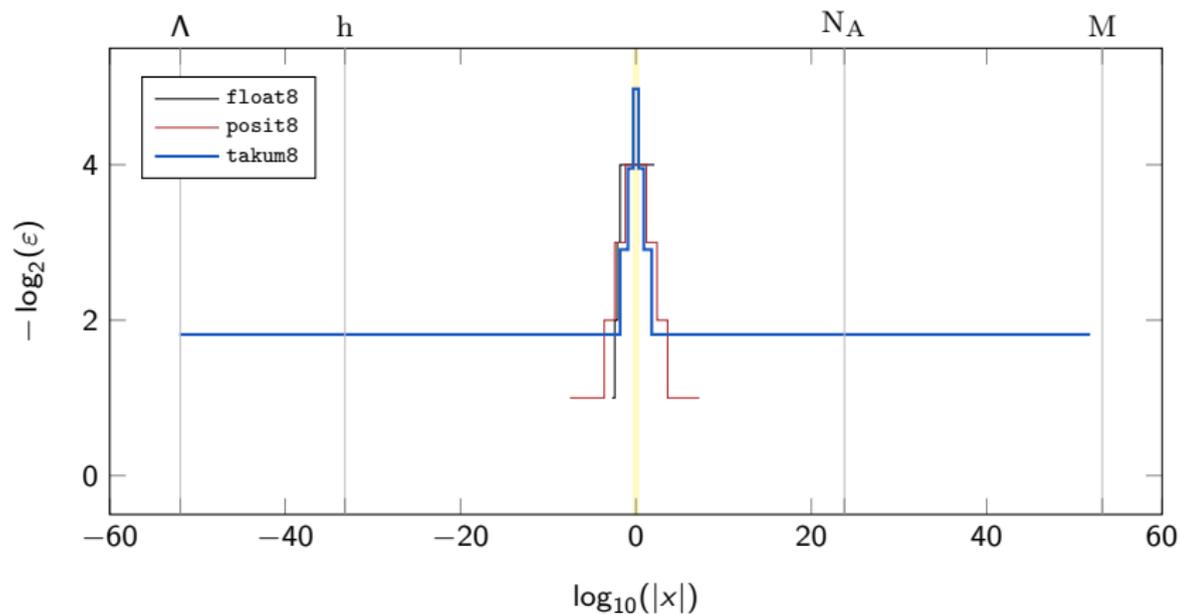
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Density (8 Bit)



Takum

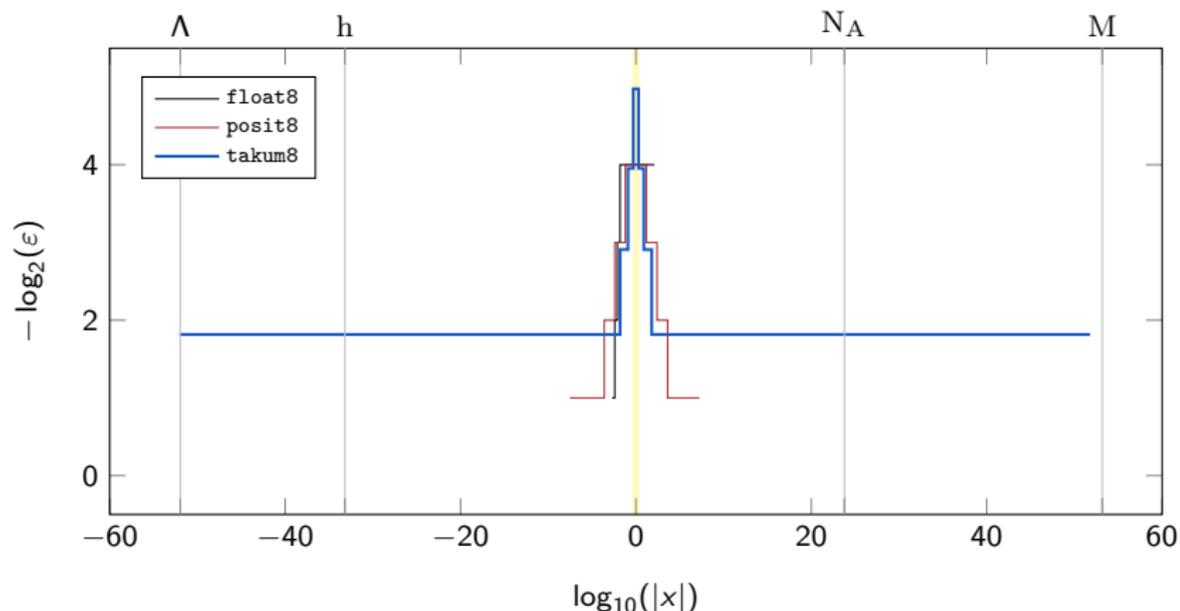
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- ▶ takum8 exceeds float8 ('golden zone') and posit8 near unity (2 times denser)

Takum

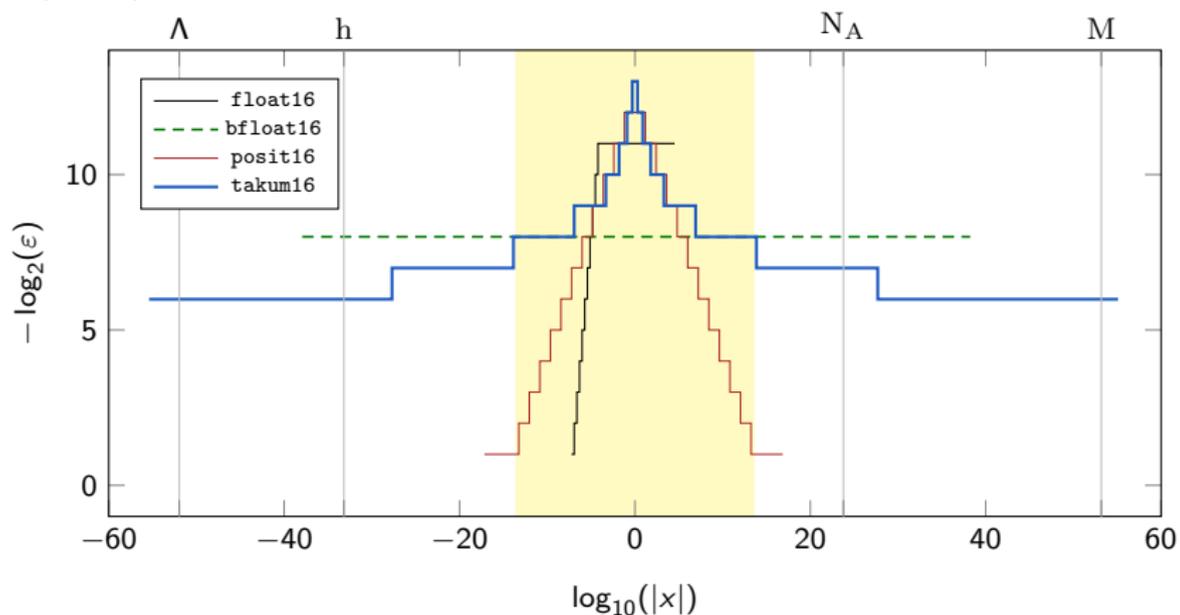
Density (8 Bit)



- ▶ takum8 exceeds float8 ('golden zone') and posit8 near unity (2 times denser)
- ▶ Almost full dynamic range across benchmark constants Λ (cosmological constant), h (PLANCK constant), N_A (AVOGADRO constant), M (mass of the universe)

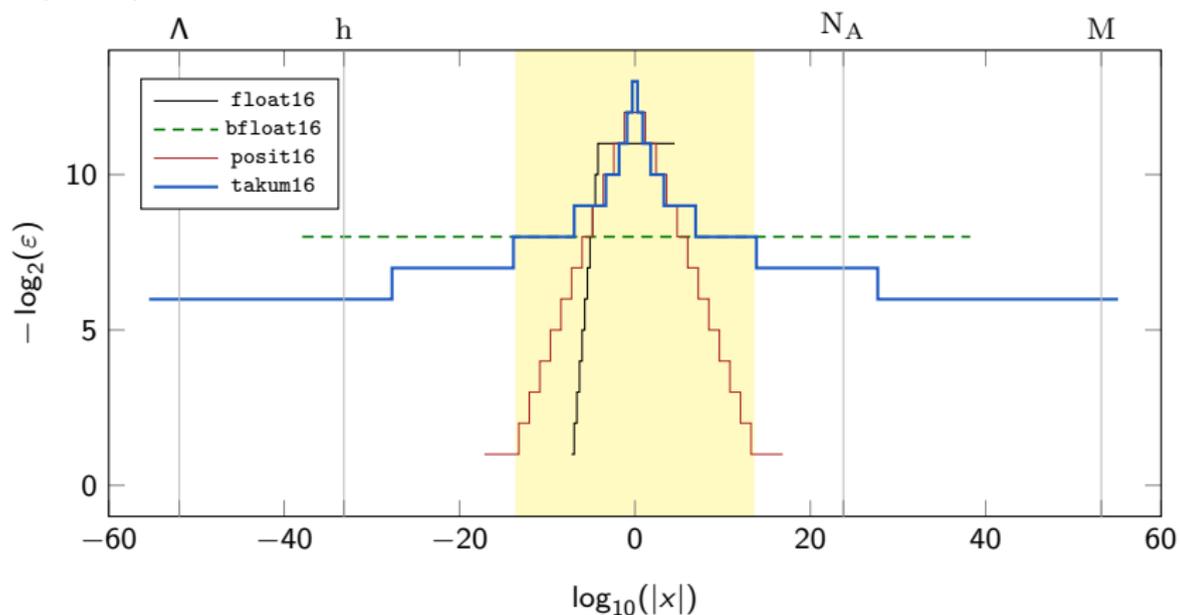
Takum

Density (16 Bit)



Takum

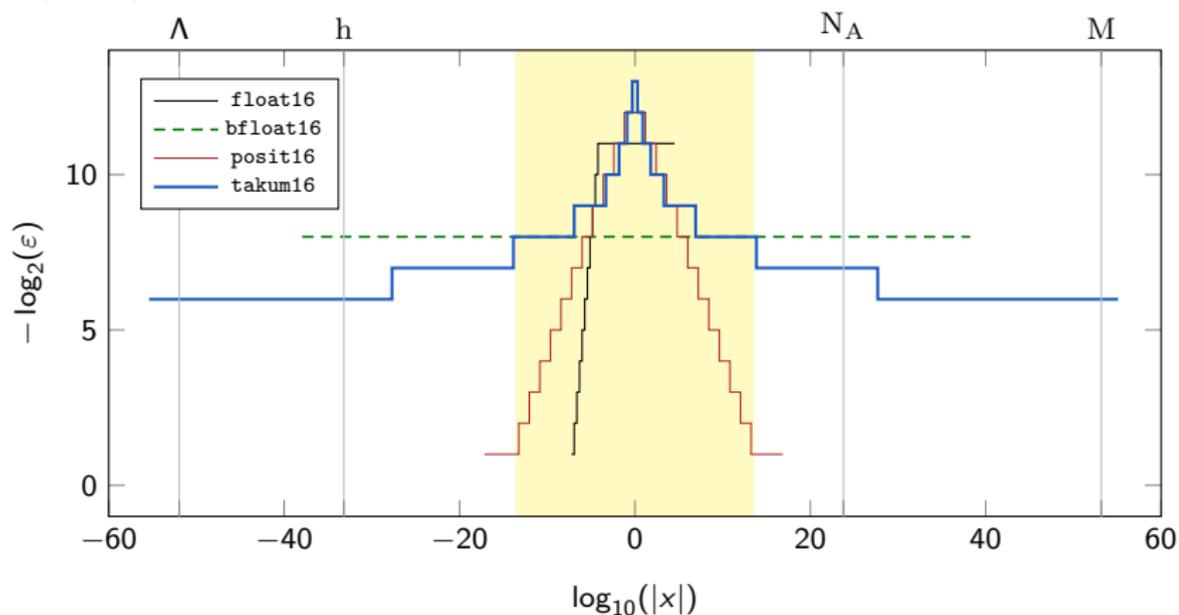
Density (16 Bit)



- Perfect logarithmic tapering

Takum

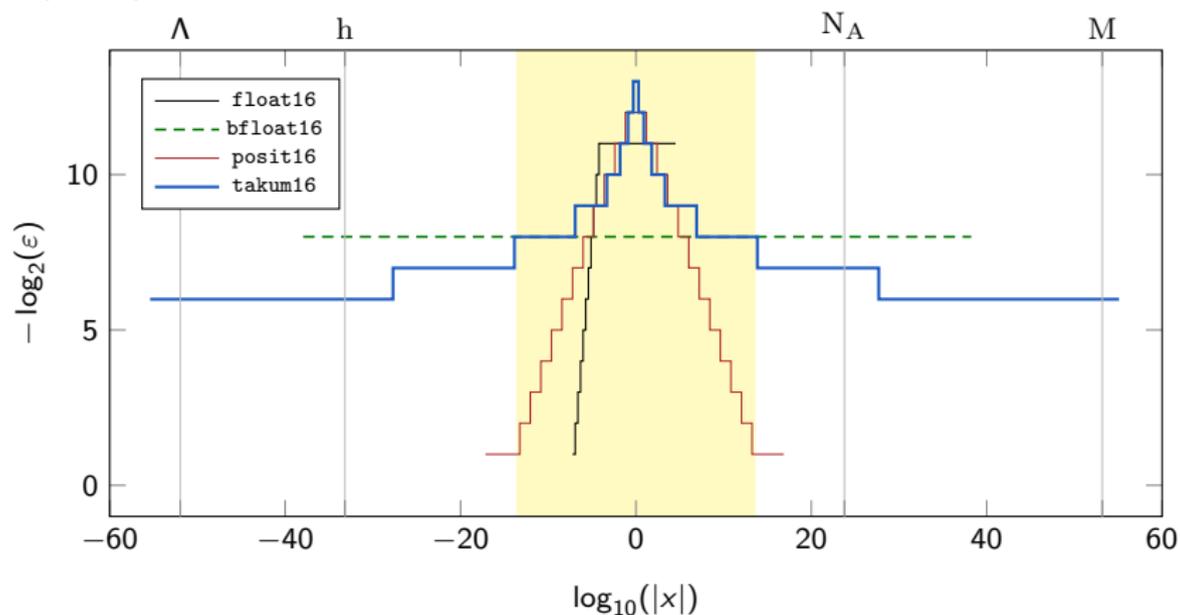
Density (16 Bit)



- ▶ Perfect logarithmic tapering
- ▶ At least the same density as bfloat16 in 'golden zone' ($10^{-17}, 10^{17}$), up to 32 times denser

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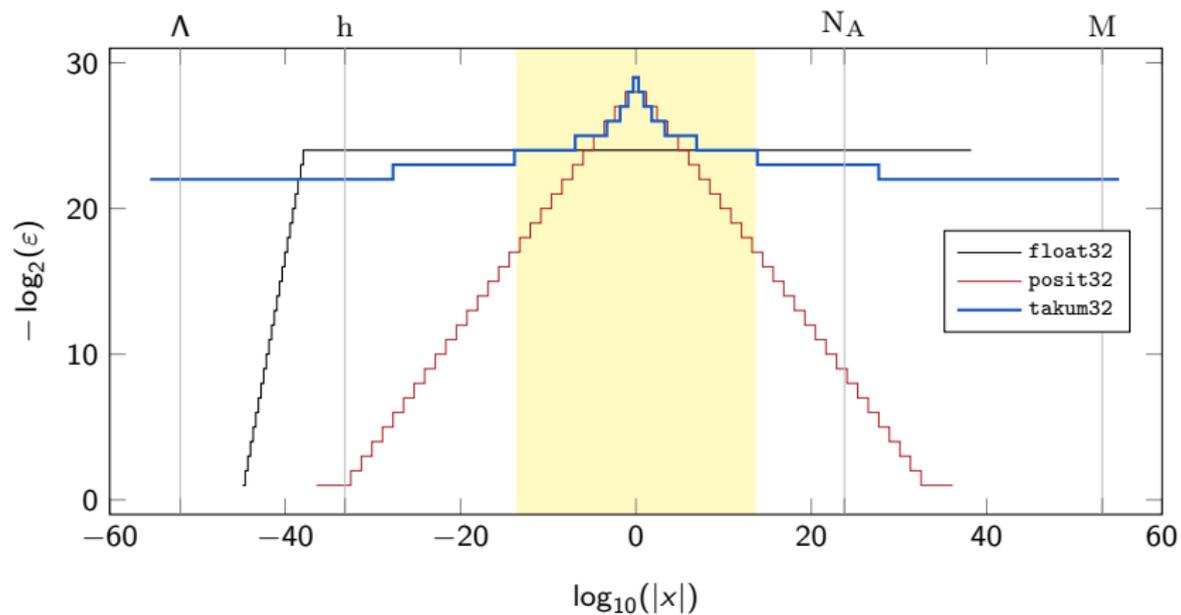
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- ▶ Up to 2 times denser than posit16

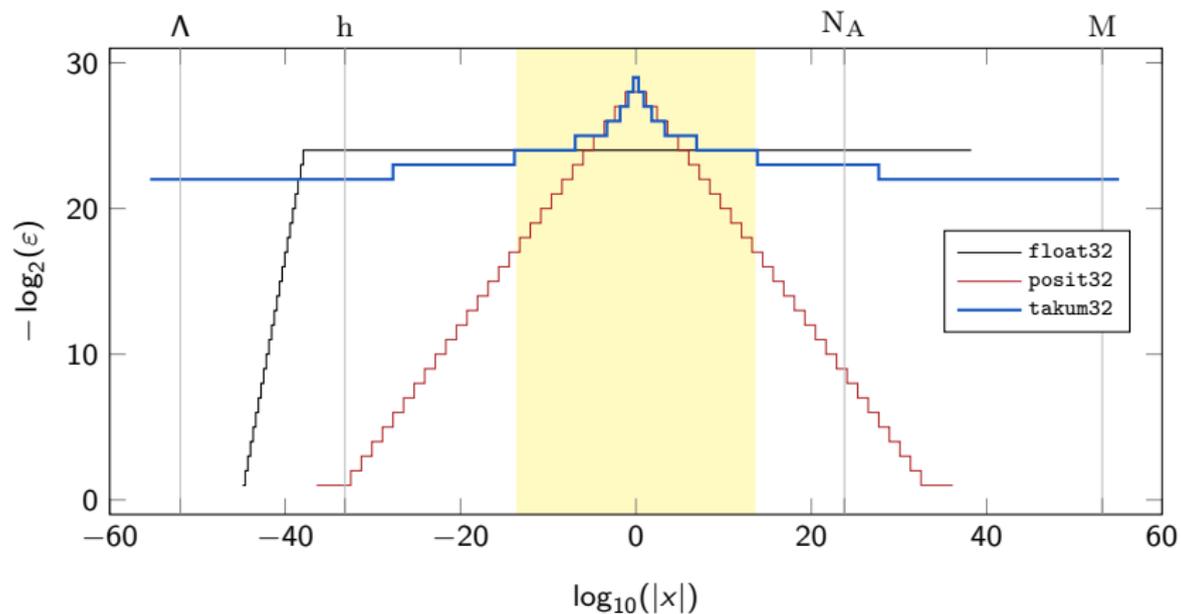
Takum

Density (32 Bit)



Takum

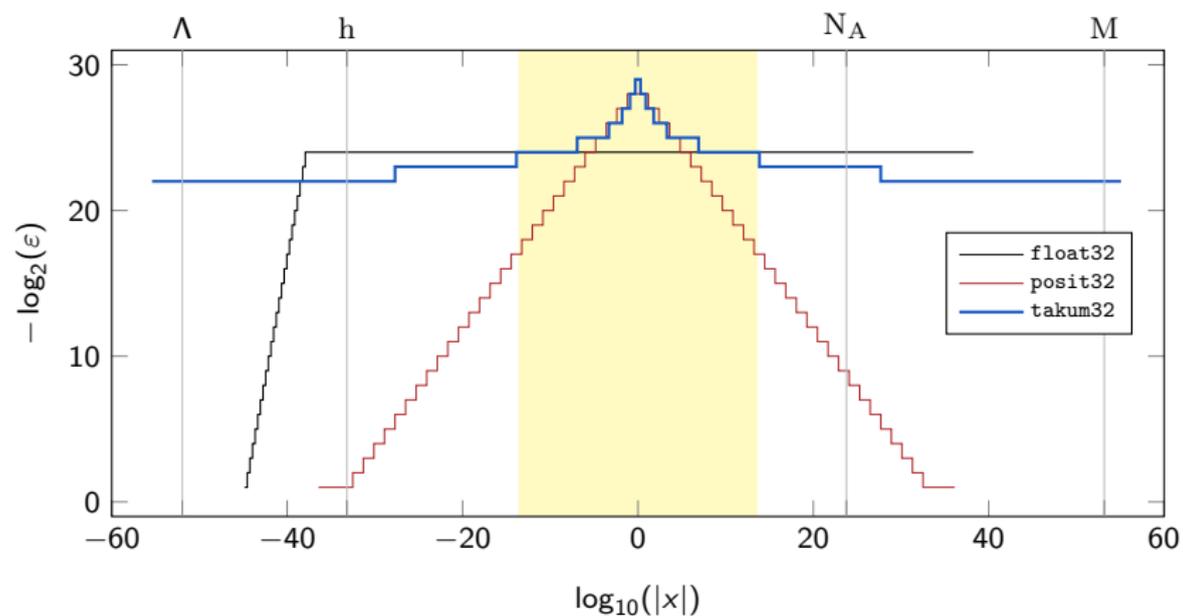
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- ▶ Same golden zone as with $n = 16$

Takum

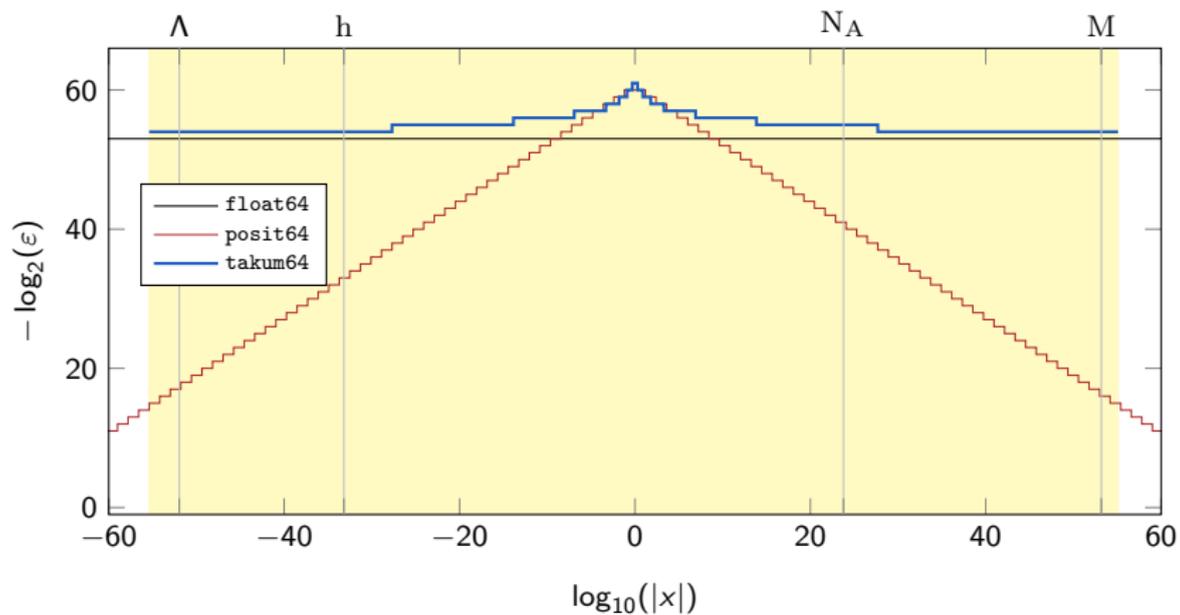
Density (32 Bit)



- ▶ Same golden zone as with $n = 16$
- ▶ Up to 32 times denser than float32

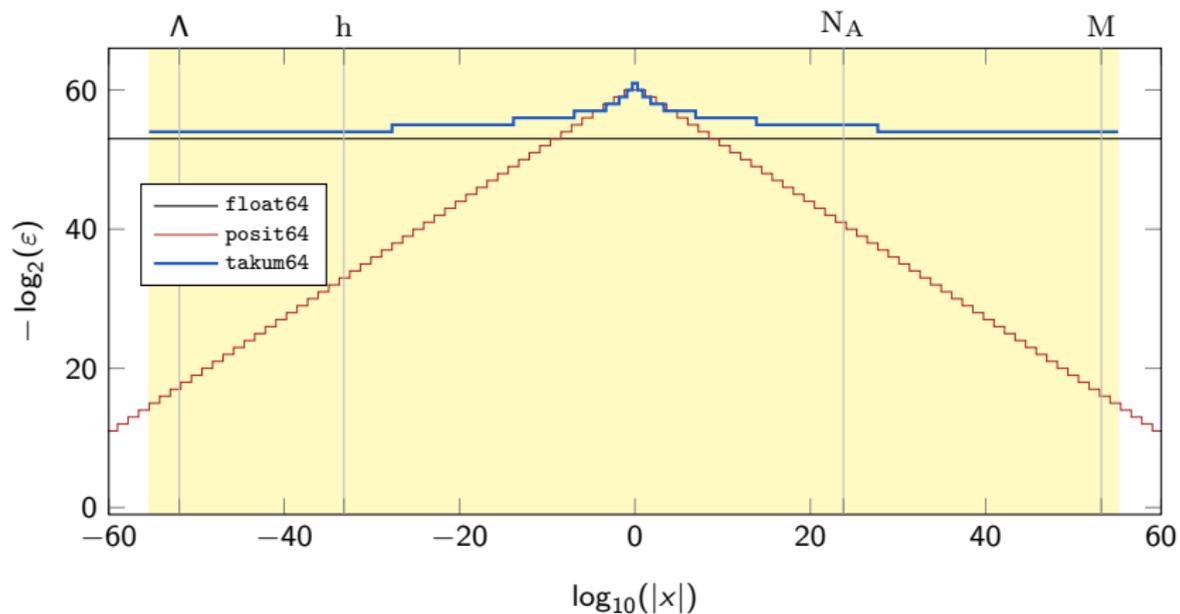
Takum

Density (64 Bit)



Takum

Density (64 Bit)



- ▶ At least 2 and up to 256 times denser than float64

Takum

Further Properties

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- ▶ Defined for all n , conversion between lengths simple rounding or expansion

FPGA Implementation (Artix 7 (100 MHz), VHDL)

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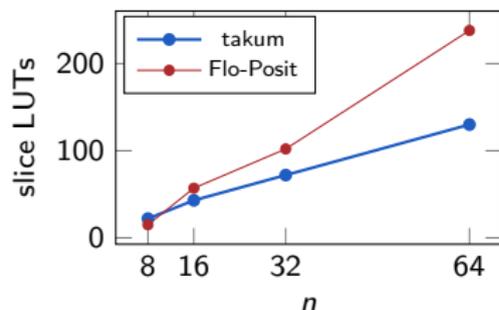
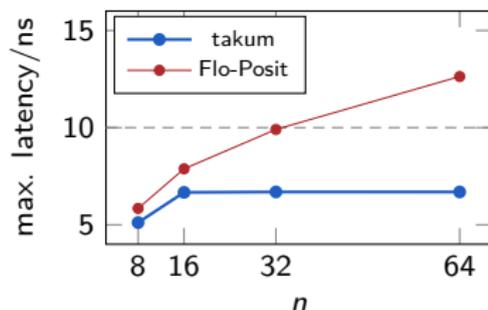
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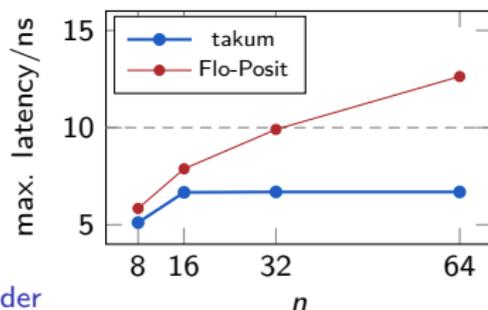


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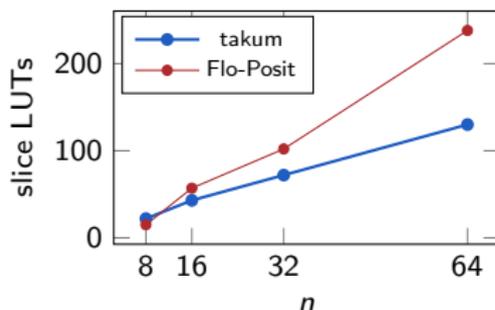
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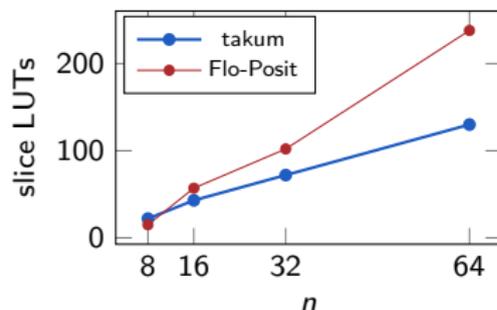
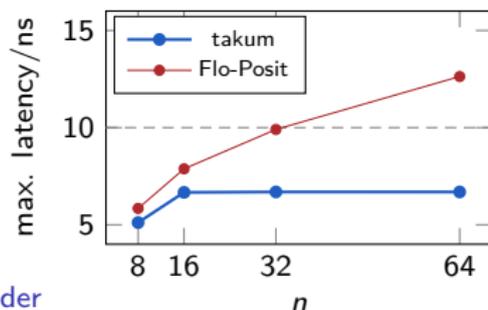


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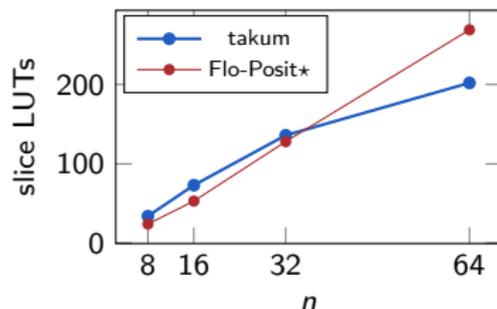
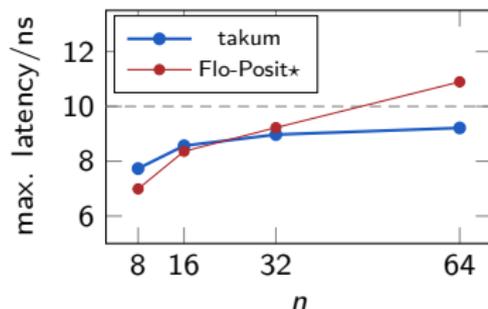
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Time for a new paradigm?

