Schrödinger's FP: Dynamic Adaptation of Floating-Point Containers for Deep Learning Training

Miloš Nikolić, Enrique Torres Sanchez, Jiahui Wang, Ali Hadi Zadeh,
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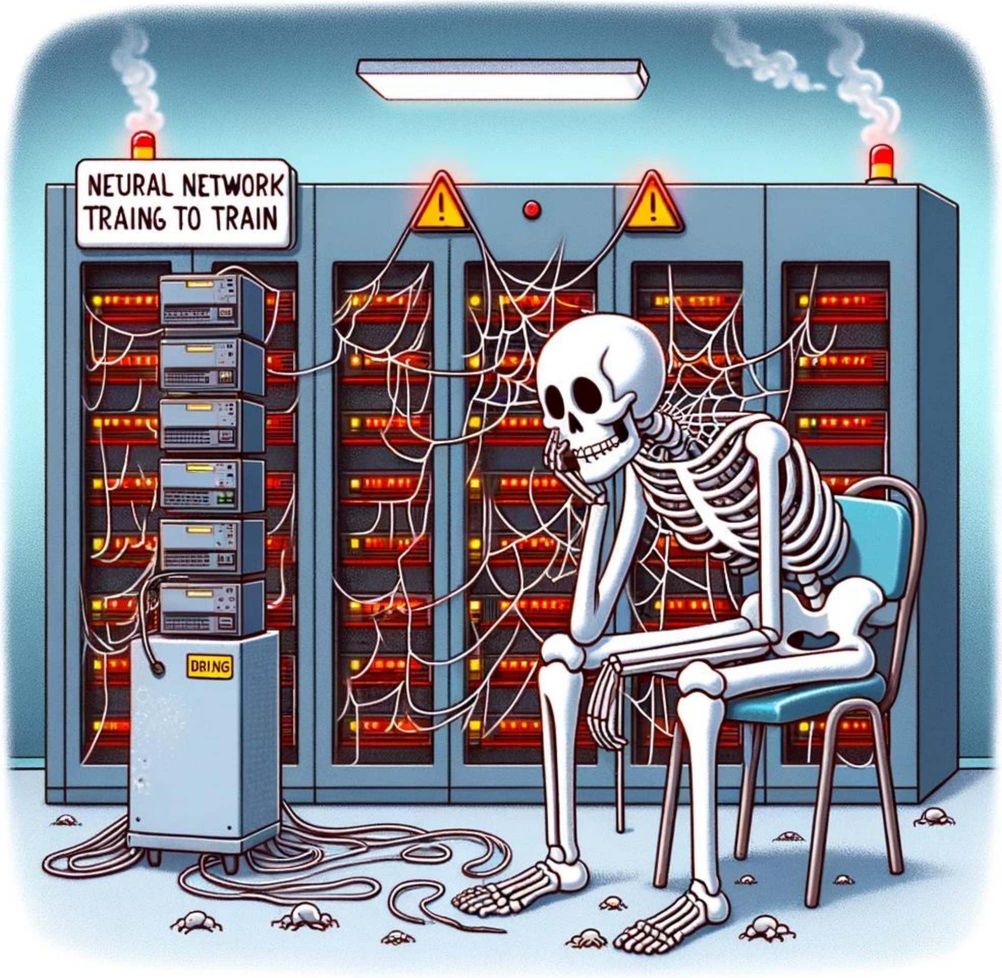
Training is Expensive!

- Neural Networks are becoming ubiquitous
- But they are expensive
  - Energy
  - Time



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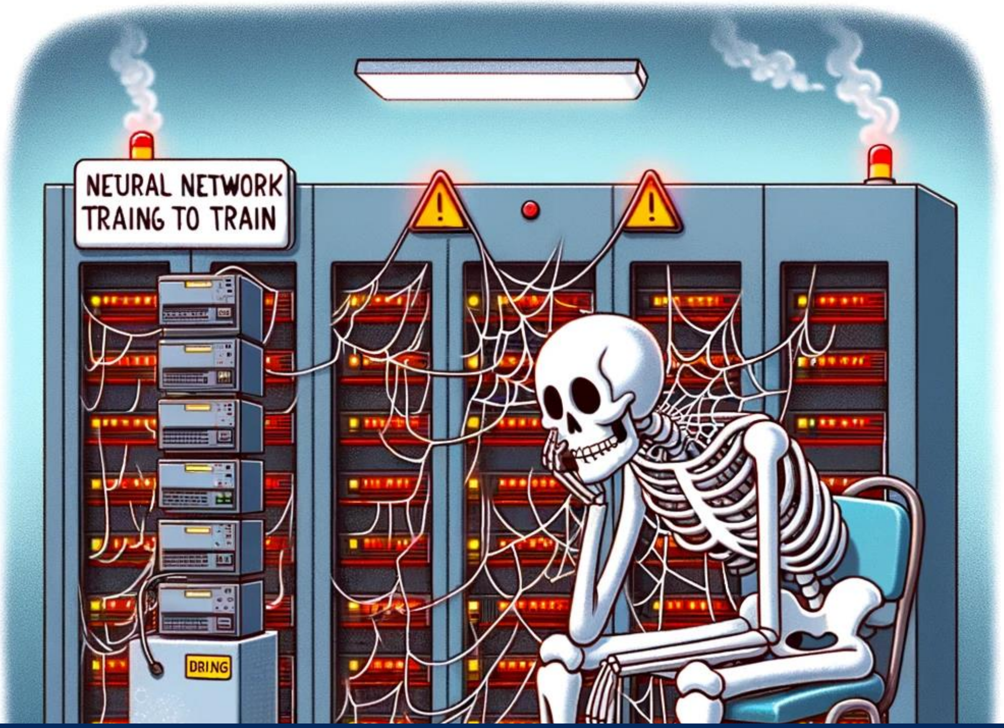
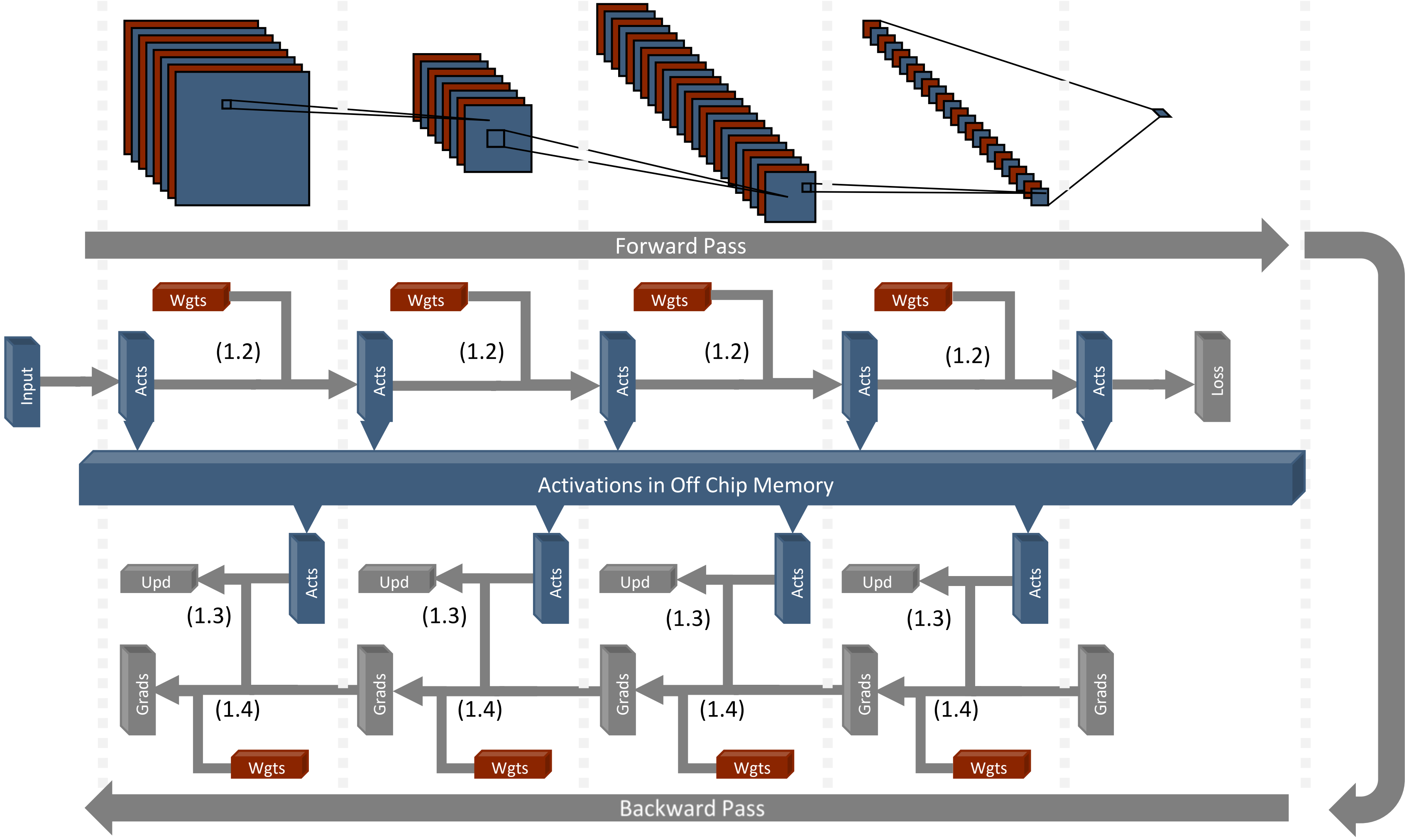


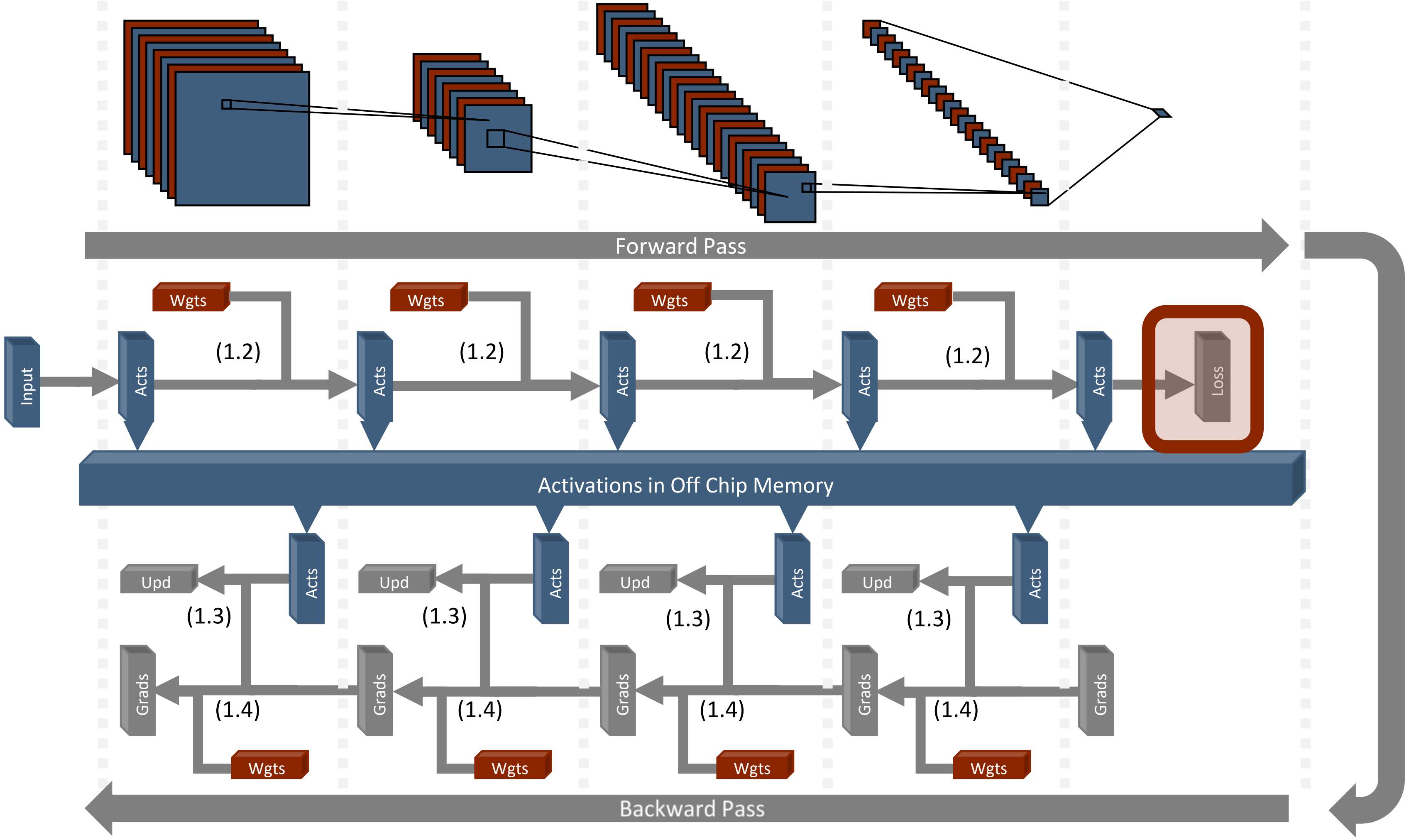
Goal: Improve energy efficiency and performance of Training

Gradient Descent – Overview



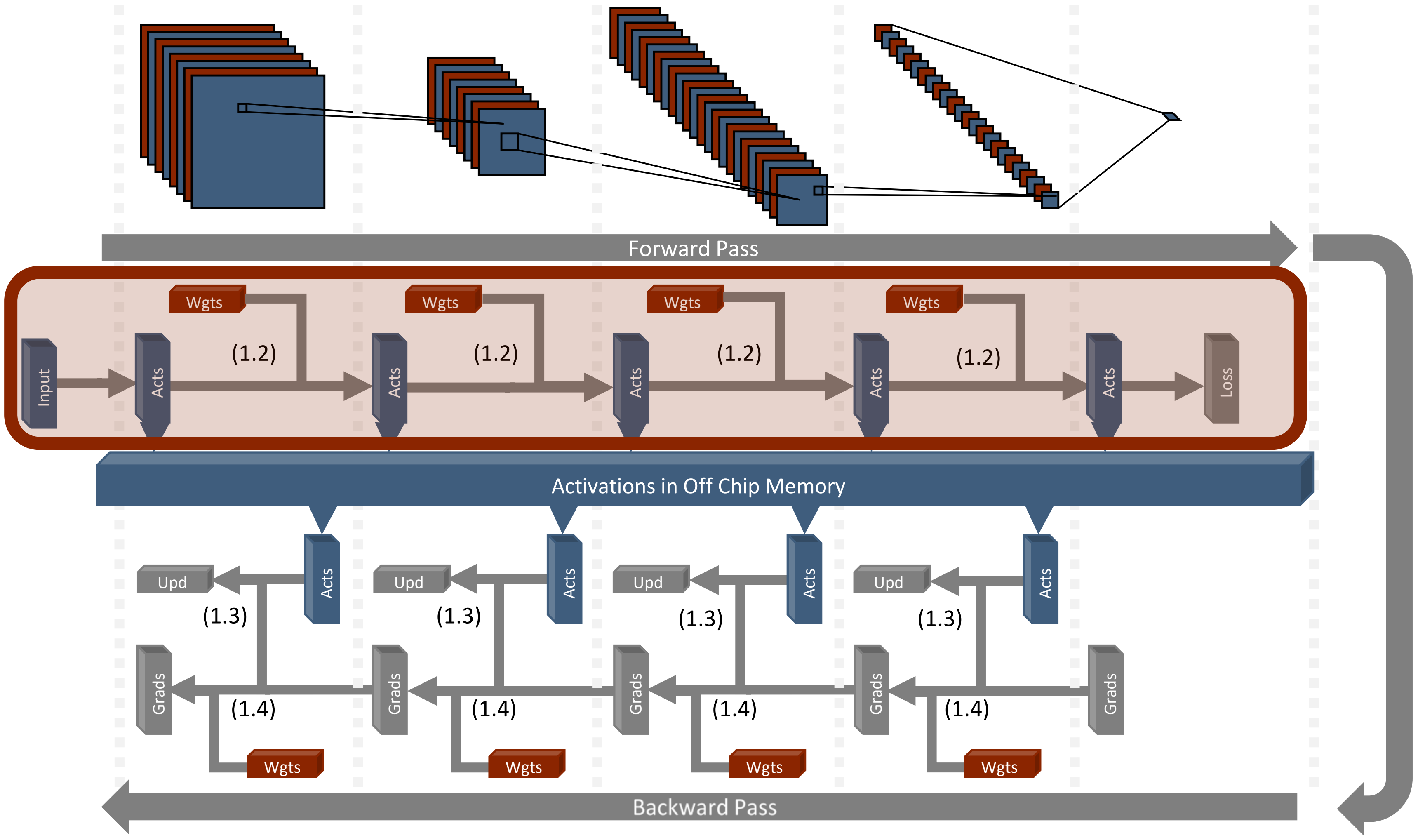
Gradient Descent – Overview

- Loss function



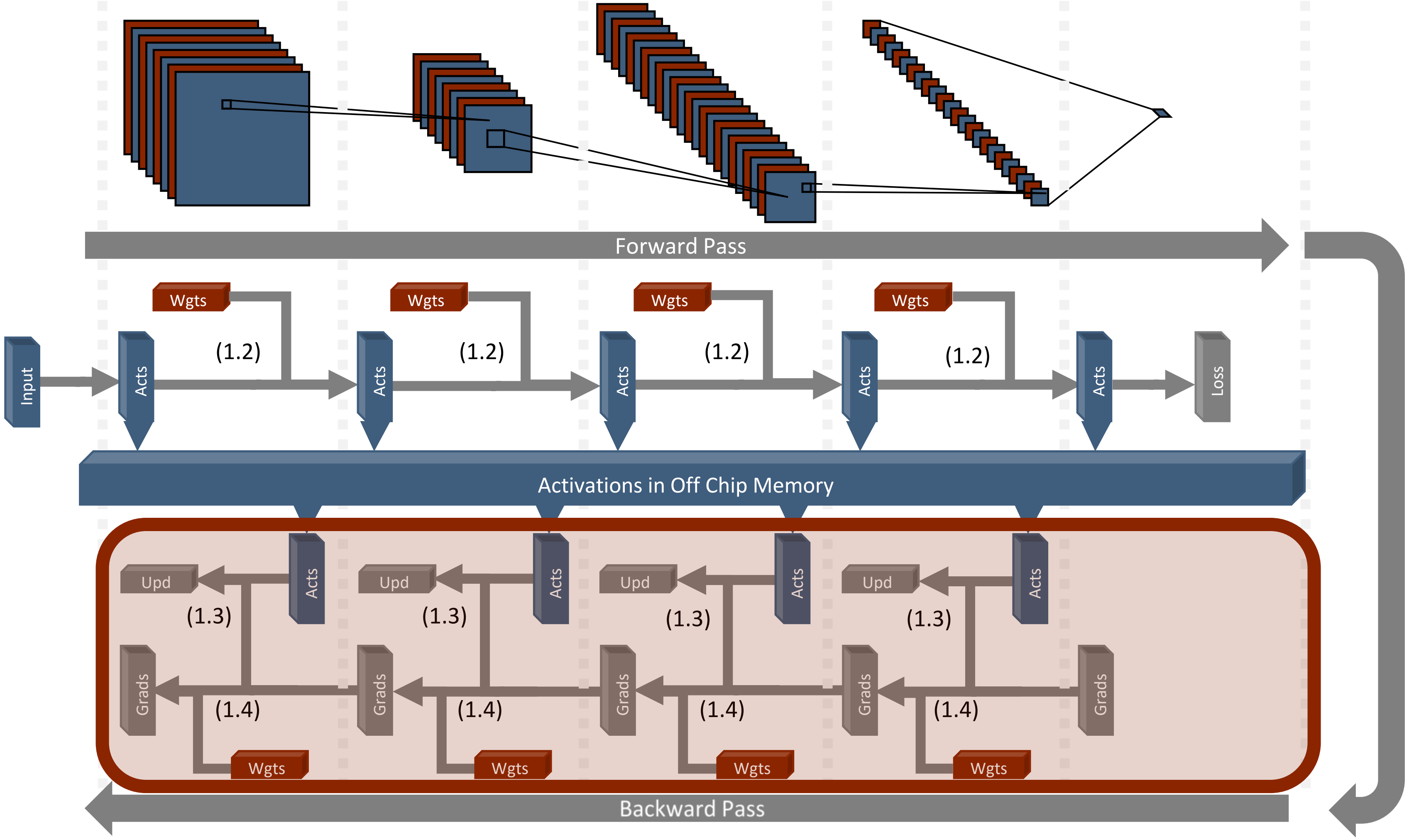
Gradient Descent – Overview

- Loss function
- Forward pass



Gradient Descent – Overview

- Loss function
- Forward pass
- Backward pass
    - Update
    - Gradient



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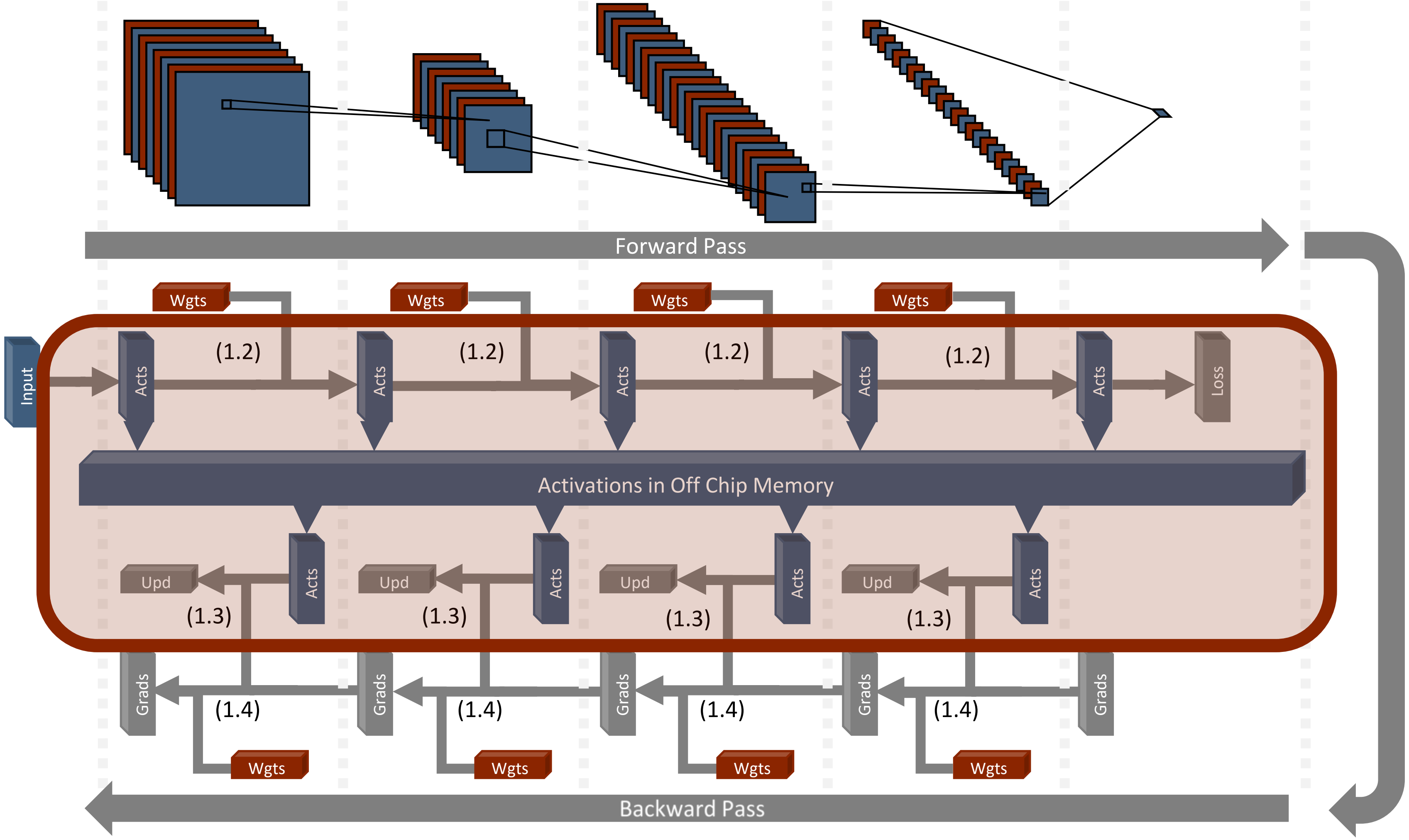

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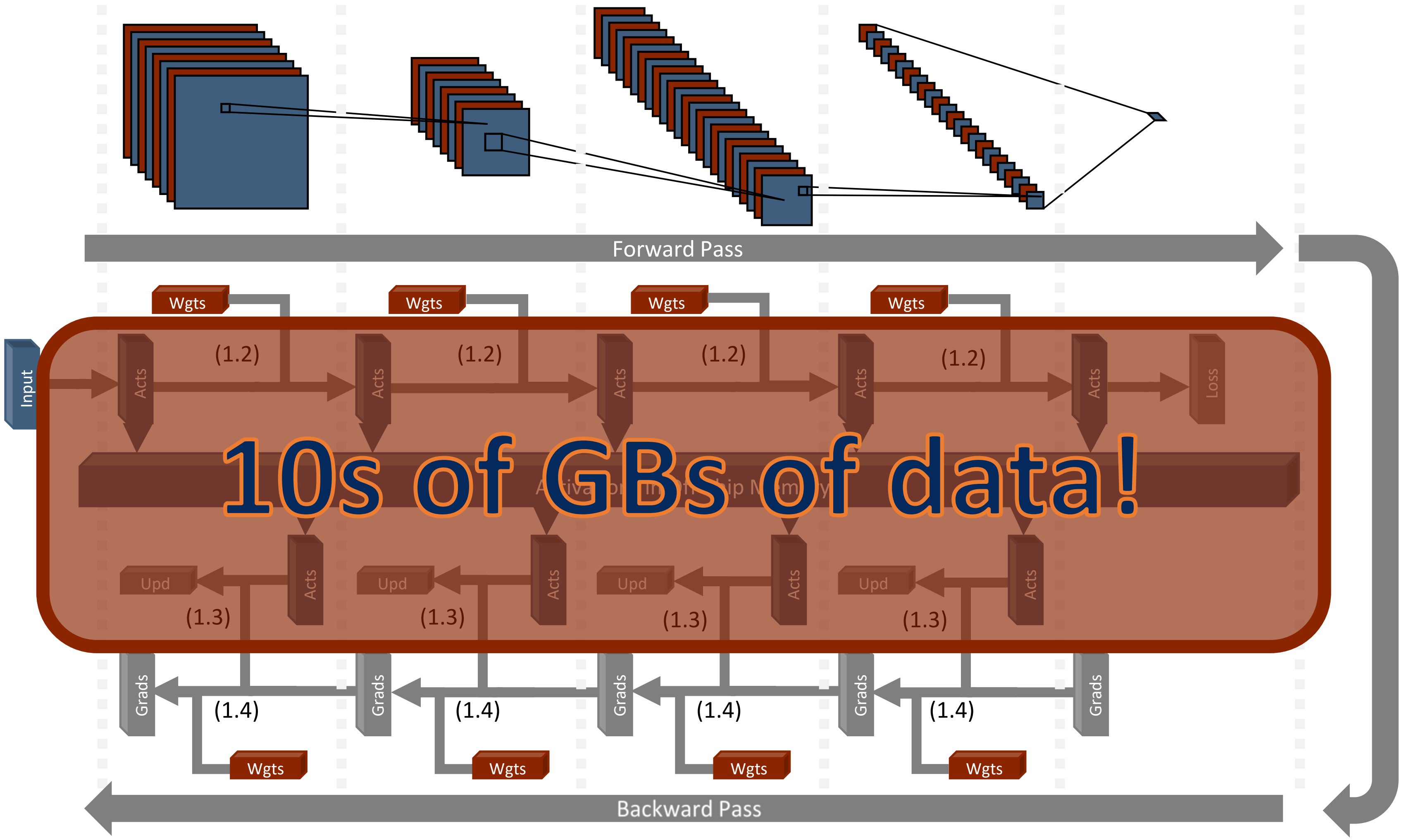

10s of GBs of data!

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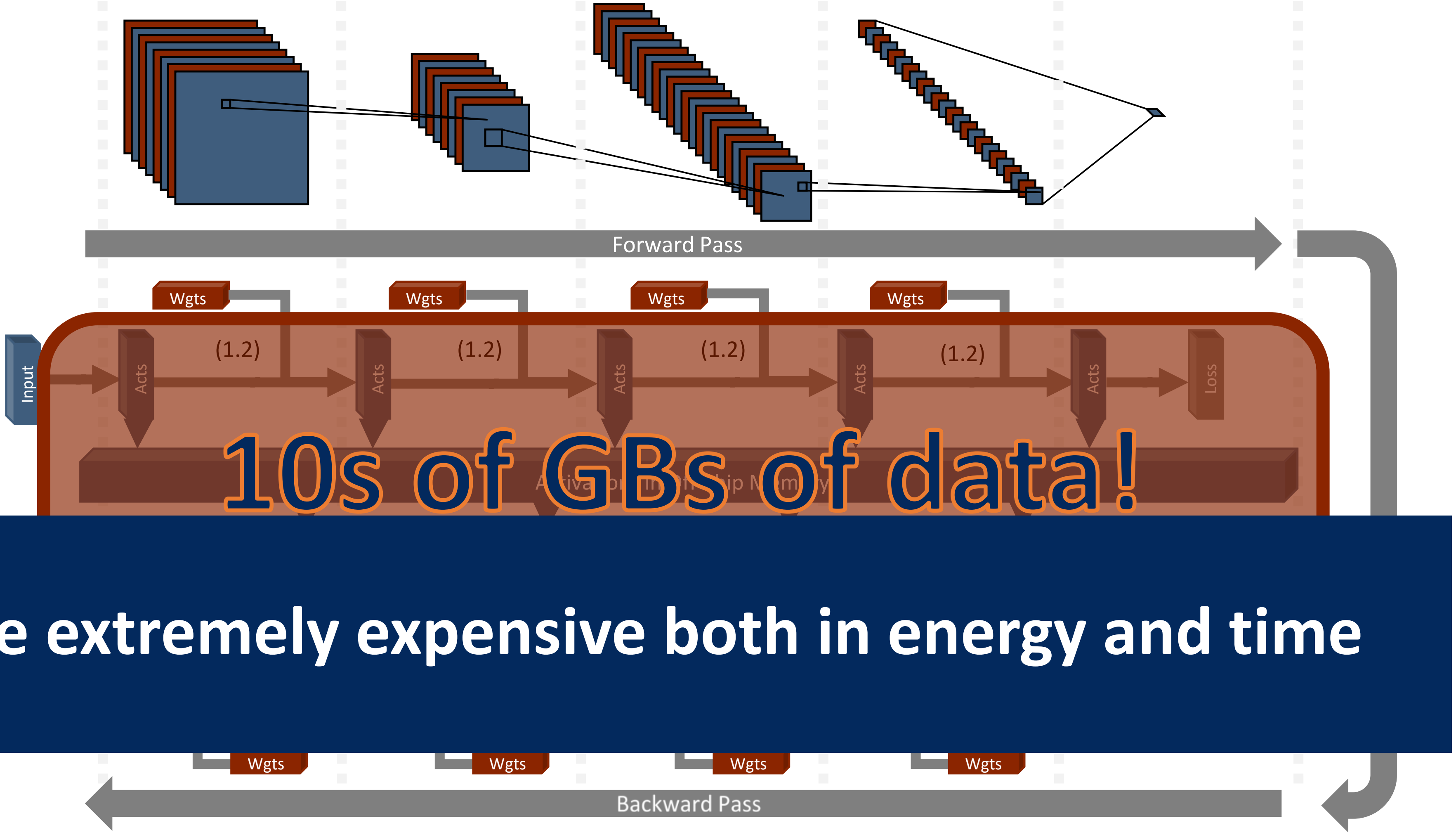

10s of GBs of data!

Off-chip accesses are extremely expensive both in energy and time

Narrow Datatypes can help

- Efficient Datatype reduce costs!
  - Memory
  - Compute

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FP32

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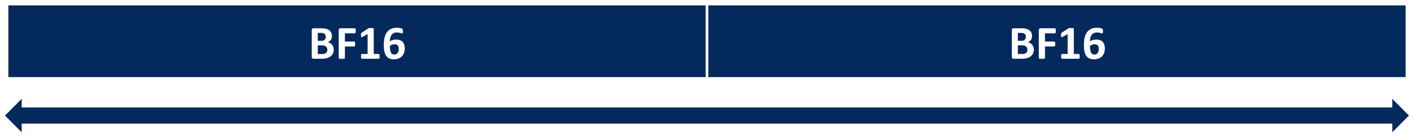

BF16

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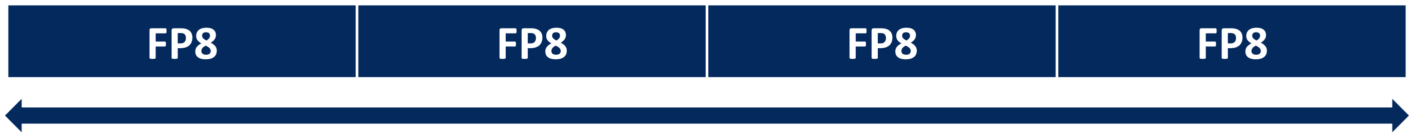

FP8	FP8	FP8	FP8

Narrow Datatypes can help

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FP6 | FP6 | FP6 | FP6 | FP6 | …

Which Datatype? Where? When?

- There are many great options

Published as a conference paper at ICLR 2018

MIXED PRECISION TRAINING

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ABSTRACT

Training DNNs with Hybrid Block Floating Point

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Abstract

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Naigang Wang, Jungwook Choi, Daniel Brand, Chia-Yu Chen and Kailash Gopalakrishnan
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Abstract

…of novel techniques and numerical repres… time, the precision of training systems … To enable this advance, … (GradScale) that addres… …zed gradients as … model trainin…

The 28th IEEE Int. Symp. on High-Performance Computer Architecture (HPCA-28), February 2022

FAST: DNN Training Under Variable Precision Block Floating Point with Stochastic Rounding

Sai Qian Zhang[1], Bradley McDanel[2], and H.T. Kung[1]
[1]Harvard University
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Fig. 1. (left) Overview of the proposed FAST system for DNN … variable precision BFP with stochastic rounding. A group of … converted to a BFP group with a selected mantissa width base… error tolerance (see Algorithm 1). (right) FAST incrementall… BFP precision across both layer depths and training iteratio… on corresponding empirical data obtained via DNN trainin…

FP8 FORMATS FOR DEEP LEARNING

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ABSTRACT

FP8 is a natural progression for accelerating deep learning training inferen… formats common in modern processors. In this paper we propose an 8-bi… interchange format consisting of two encodings - E4M3 (4-bi… (5-bit exponent and 2-bit mantissa). While E5M2 f… special values, E4M3's dynamic range i… mantissa bit-pattern for NaNs… and language tasks… study cov…

…9.05433v2 [cs.LG] 29 Sep 2022

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…stract—This paper introduces Block Data Representations …R), a framework for exploring and evaluating a wide spec… …n of narrow-precision formats for deep learning. It enables …parison of popular quantization standards, and … …R, new formats based on …

Many data formats have been proposed, and the … space of possible new idea…

Which Datatype? Where? When?

- There are many great options
- But it’s a trade-off
  - Accuracy vs. Efficiency
  - All have edge cases

Mixed Precision Training

Training DNNs with Hybrid Block Floating Point

Training Deep Neural Networks with 8-bit Floating Point Numbers

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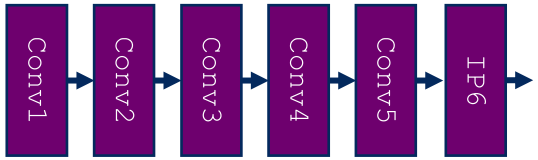
BF16	✓					✓
FP8		✓		✓		
FP6			✓		✓	



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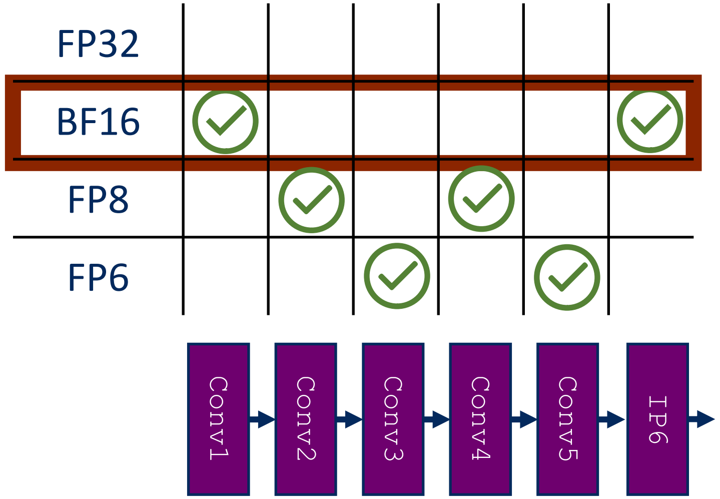

	Conv1	Conv2	Conv3	Conv4	Conv5	IP6
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BF16	✓					✓
FP8		✓		✓		
FP6			✓		✓	

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- Guess
  - Confirm
  - Repeat

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…uhani*, Ritchie Zhao, Venmugil Elango, Rasoul Shafipour, Mathew Hall, Maral Mesmakhosroshahi, …More, Levi Melnick, Maximilian Golub, Girish Varatkar, Lei Shao, Gaurav Kolhe, Dimitry Melts, Jasmine Klar, Renee L'Heureux, Matt Perry, Doug Burger, Eric Chung
Microsoft
Zhaoxia (Summer) Deng, Sam Naghshineh, Jongsoo Park, Maxim Naumov
Meta

…stract—This paper introduces Block Data Representations (BDR), a framework for exploring and evaluating a wide spectrum of narrow-precision formats for deep learning. It enables comparison of popular quantization standards, and … BDR, new formats based on …

Many data formats have been proposed, and the … space of possible new ideas …

Which Datatype? Where? When?

- There are many great options
- But it’s a trade-off
  - Accuracy vs. Efficiency
  - All have edge cases
- Guess
  - Confirm
  - Repeat
- Lost Potential

Published as a conference paper at ICLR 2018

MIXED PRECISION TRAINING

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Baidu Research
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Paulius Micikevicius*, Jonah Alben, David Garcia, Boris Ginsburg, Michael Houston, Oleksii Kuchaiev, Ganesh Venkatesh, Hao Wu
NVIDIA
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Training DNNs with Hybrid Block Floating Point

Mario Drumond, Ecocloud, EPFL, mario.drumond@epfl.ch
Tao Lin, Ecocloud, EPFL, tao.lin@epfl.ch
Martin Jaggi, Ecocloud, EPFL, martin.jaggi@epfl.ch
Babak Falsafi, Ecocloud, EPFL, babak.falsafi@epfl.ch

Training Deep Neural Networks with 8-bit Floating Point Numbers

Naigang Wang, Jungwook Choi, Daniel Brand, Chia-Yu Chen and Kailash Gopalakrishnan
IBM T. J. Watson Research Center
Yorktown Heights, NY 10598, USA
{nwang, choij, danbrand, cchen, kailash}@us.ibm.com

A Study of BFLOAT16 for Deep Learning Training

Dhiraj Kalamkar[1], Dheevatsa Mudigere[2], Naveen Mellempudi*[1], Dipankar Das[1], Kunal Banerjee[1], Sasikanth Avancha[1], Dharma Teja Vooturi†[1], Nataraj Jammalamadaka†[1], Jianyu Huang[2], Hector Yuen[2], Jiyan Yang[2], Jongsoo Park[2], Alexander Heinecke[1], Evangelos Georganas[1], Sudarshan Srinivasan[1], Abhisek Kundu[1], Misha Smelyanskiy[2], Bharat Kaul[1], and Pradeep Dubey[1]
[1]Parallel Computing Lab, Intel Labs
[2]Facebook, 1 Hacker Way, Menlo Park, CA

Ultra-Low Precision 4-bit Training of Deep Neural Networks

Xiao Sun, Naigang Wang, Chia-yu Chen, Jia-min Ni, Ankur Agrawal, Xiaodong Cui, Swagath Venkataramani, Kaoutar El Maghraoui, Vijayalakshmi Srinivasan, Kailash Gopalakrishnan
IBM T. J. Watson Research Center, Yorktown Heights, NY 10598, USA

The 28th IEEE Int. Symp. on High-Performance Computer Architecture (HPCA-28), February 2022

FAST: DNN Training Under Variable Precision Block Floating Point with Stochastic Rounding

Sai Qian Zhang[1], Bradley McDanel[2], and H.T. Kung[1]
[1]Harvard University
[2]Franklin and Marshall College

FP8 FORMATS FOR DEEP LEARNING

Paulius Micikevicius, Dusan Stosic, Patrick Judd, John Kamalu, Stuart Oberman, Mohammad Shoeybi, Michael Siu, Hao Wu
NVIDIA
Neil Burgess, Sangwon Ha, Richard Grisenthwaite
Arm
Naveen Mellempudi, Marius Cornea, Alexander Heinecke, Pradeep Dubey
Intel

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Microsoft
Meta

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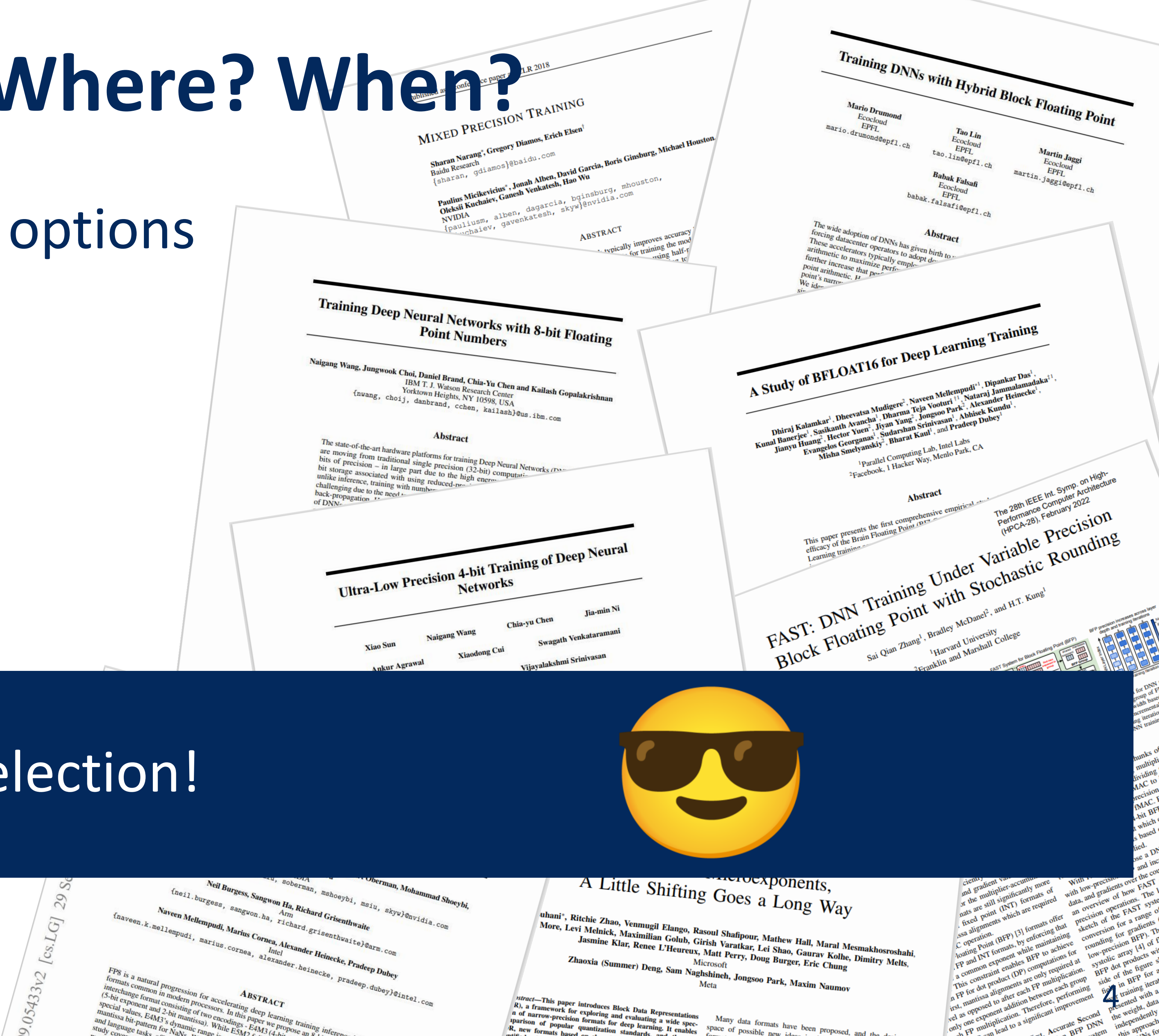
  - Repeat



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ABSTRACT

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A Little Shifting Goes a Long Way

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Intel

ABSTRACT

Automate the datatype selection! 😎

Our Goal

- Oracle?

Our Goal

- Oracle?
- Learn the Datatype
  - Use gradient descent

Our Goal

- Oracle?
- Learn the Datatype
  - Use gradient descent
- Monitor Loss
  - Adapt accordingly

Our Goal

- Oracle?
- Learn the Datatype
  - Use gradient descent
- Monitor Loss
  - Adapt accordingly
- Result
  - Less bits
  - Less energy
  - Less time
  - Bigger models

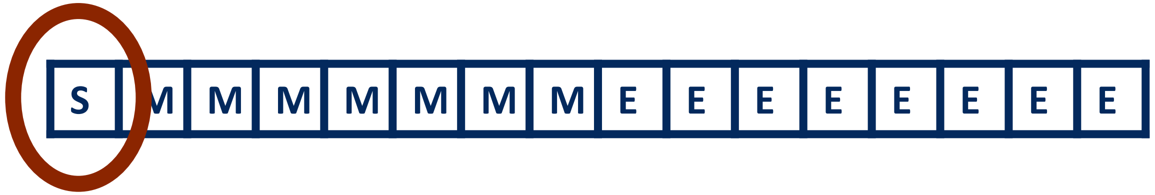
Datatype – Floating Point

- $Value = (-1)^{S} \times M \times 2^{E}$

S	M	M	M	M	M	M	M	E	E	E	E	E	E	E	E

Datatype – Floating Point

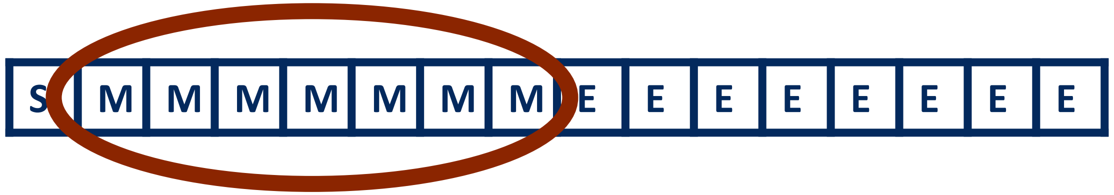
- $Value = (-1)^S \times M \times 2^E$
- Sign is trivial



S	M	M	M	M	M	M	M	E	E	E	E	E	E	E	E

Datatype – Floating Point

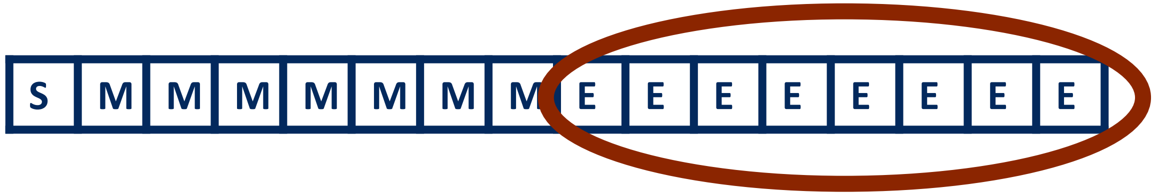
- $Value = (-1)^S \times M \times 2^E$
- Sign is trivial
- Mantissa
  - Precision



S	M	M	M	M	M	M	M	E	E	E	E	E	E	E	E

Datatype – Floating Point

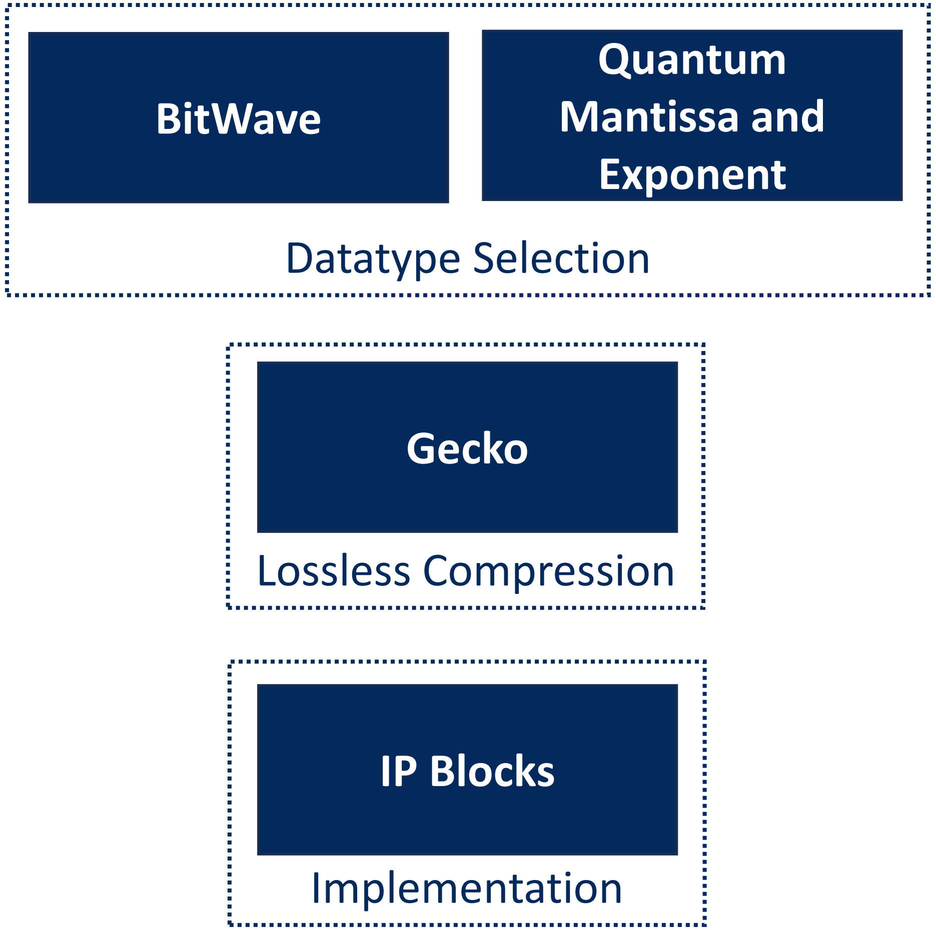
- $Value = (-1)^S \times M \times 2^E$
- Sign is trivial
- Mantissa
  - Precision
- Exponent
  - Range



S	M	M	M	M	M	M	M	E	E	E	E	E	E	E	E

Schrödinger’s FP

- Machine Learning
  - *Quantum Mantissa and Exponent* (**4.7x** reduction)
- Black Box Sampling
  - *BitWave* (**3.2x** reduction)
- Exponent compression
  - *Gecko* (boost to **5.6x** and **4.6x**)
- Hardware IP blocks



Schrödinger’s FP

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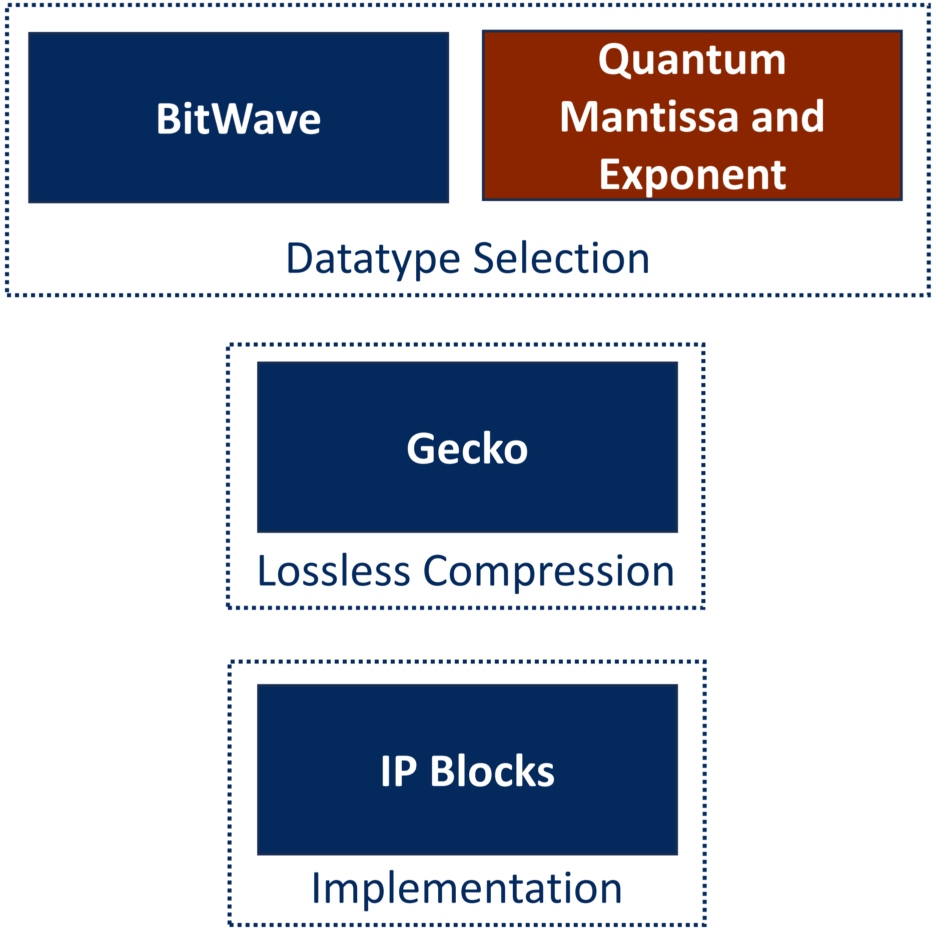
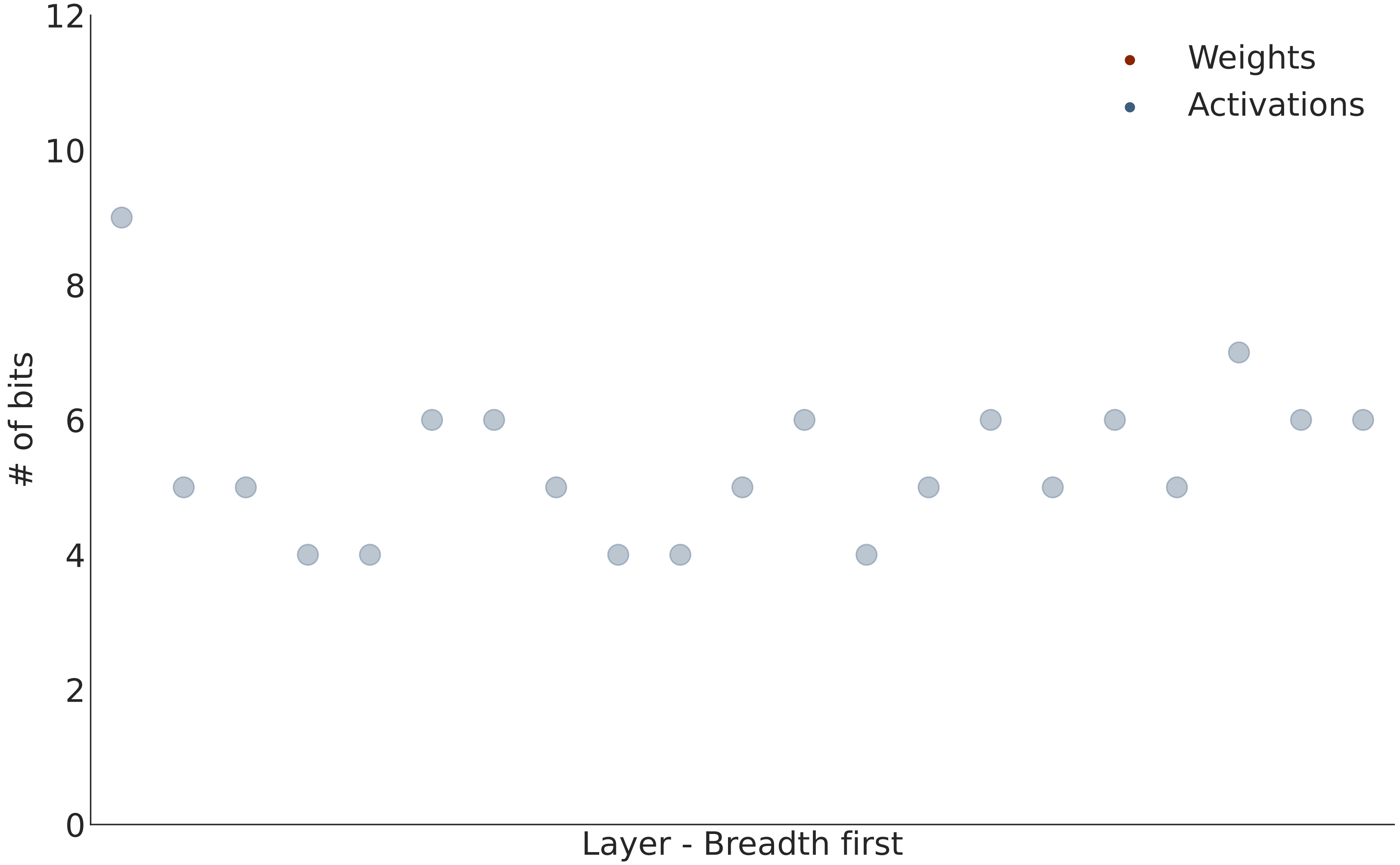


Per Tensor Datatype

- ResNet18
  - Per Tensor?
  - Single datatype?



Per Tensor Datatype

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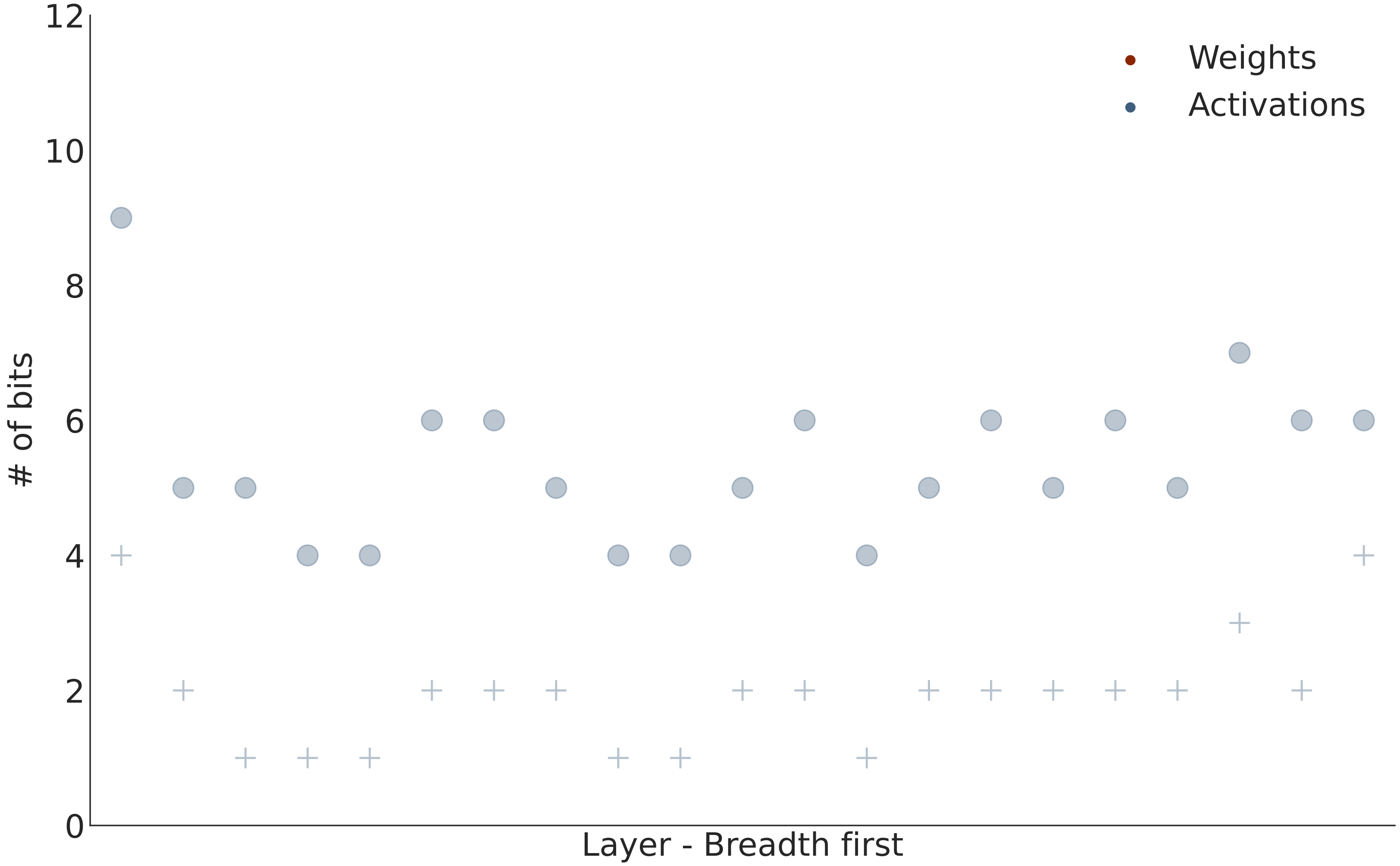

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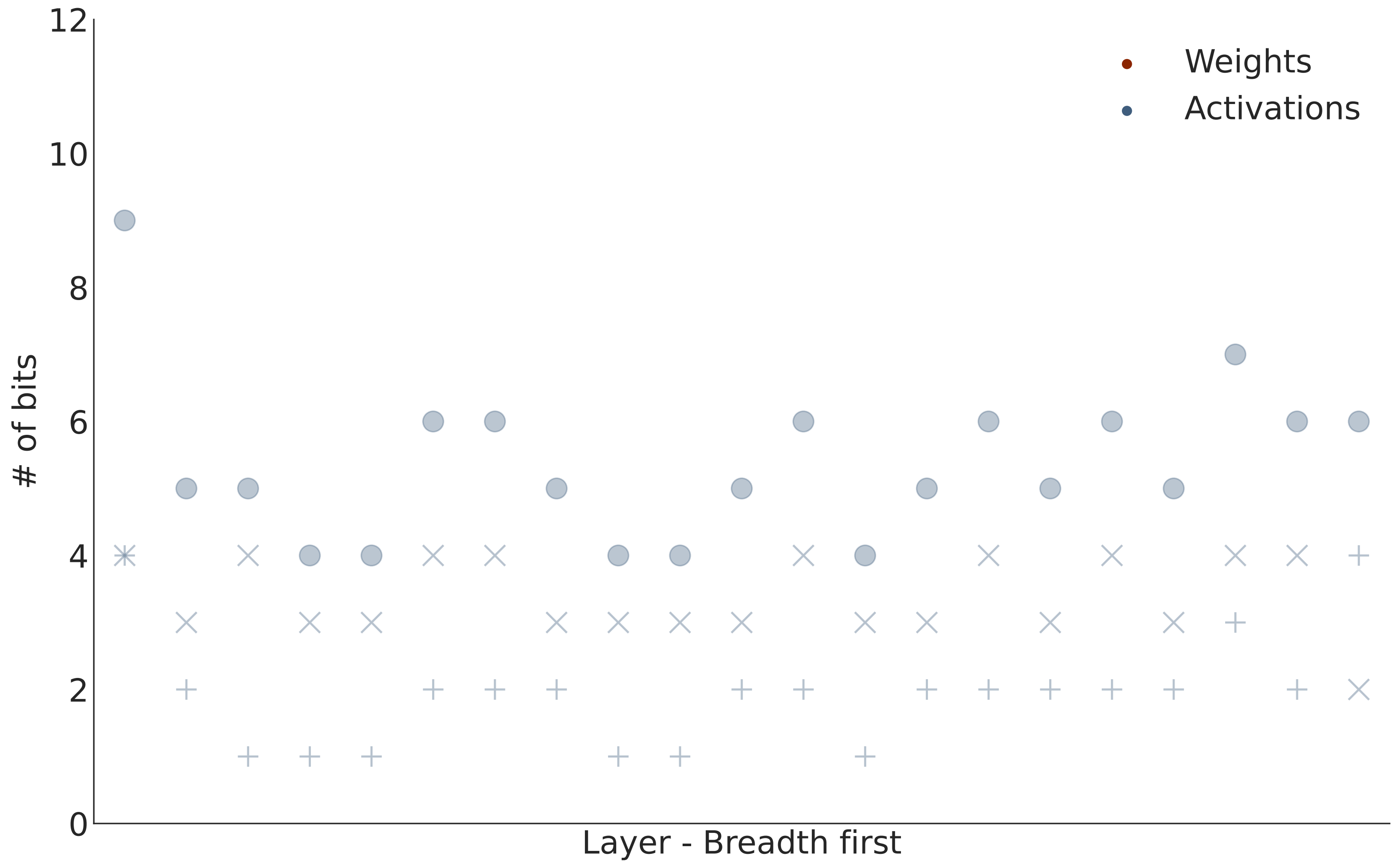

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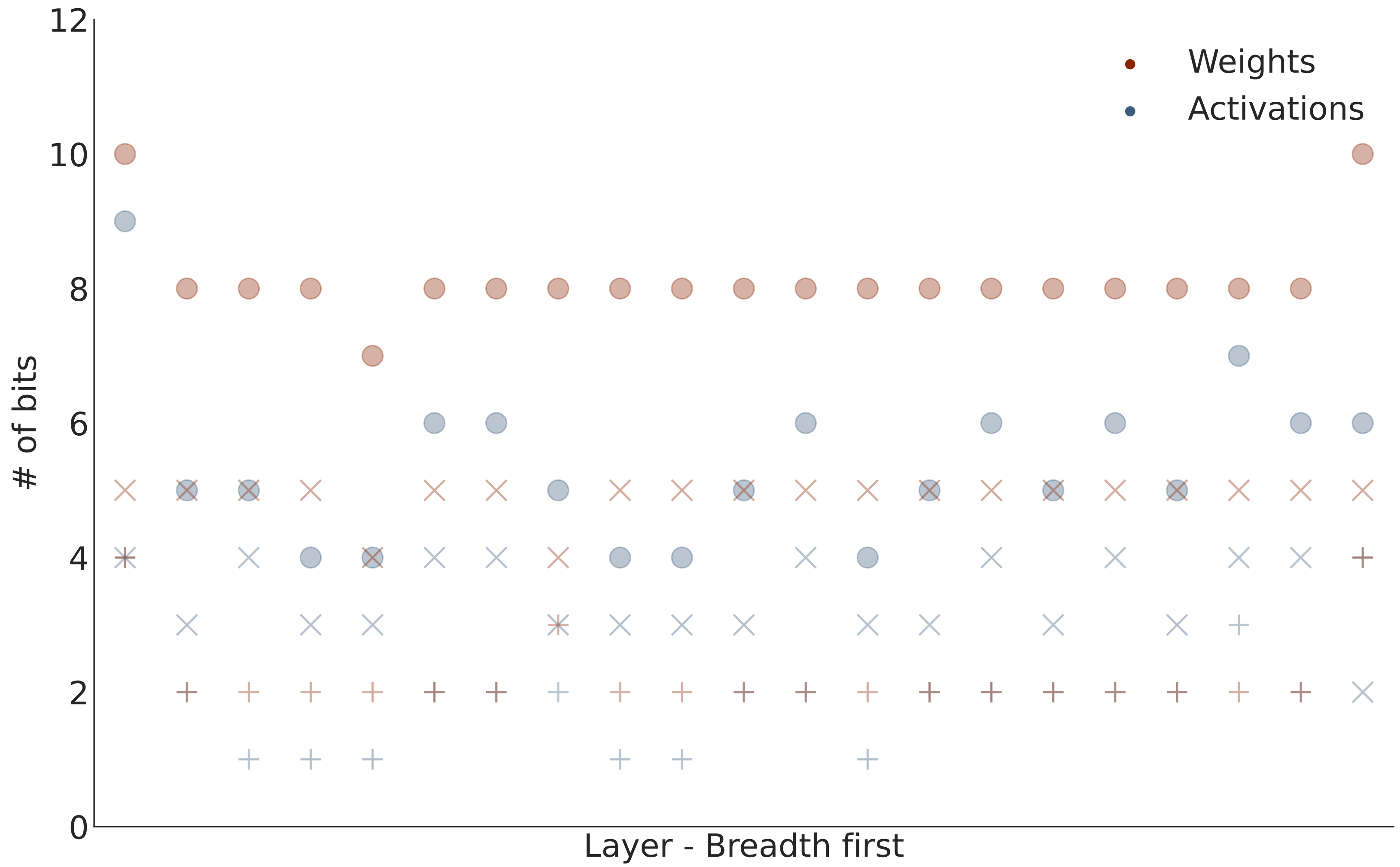

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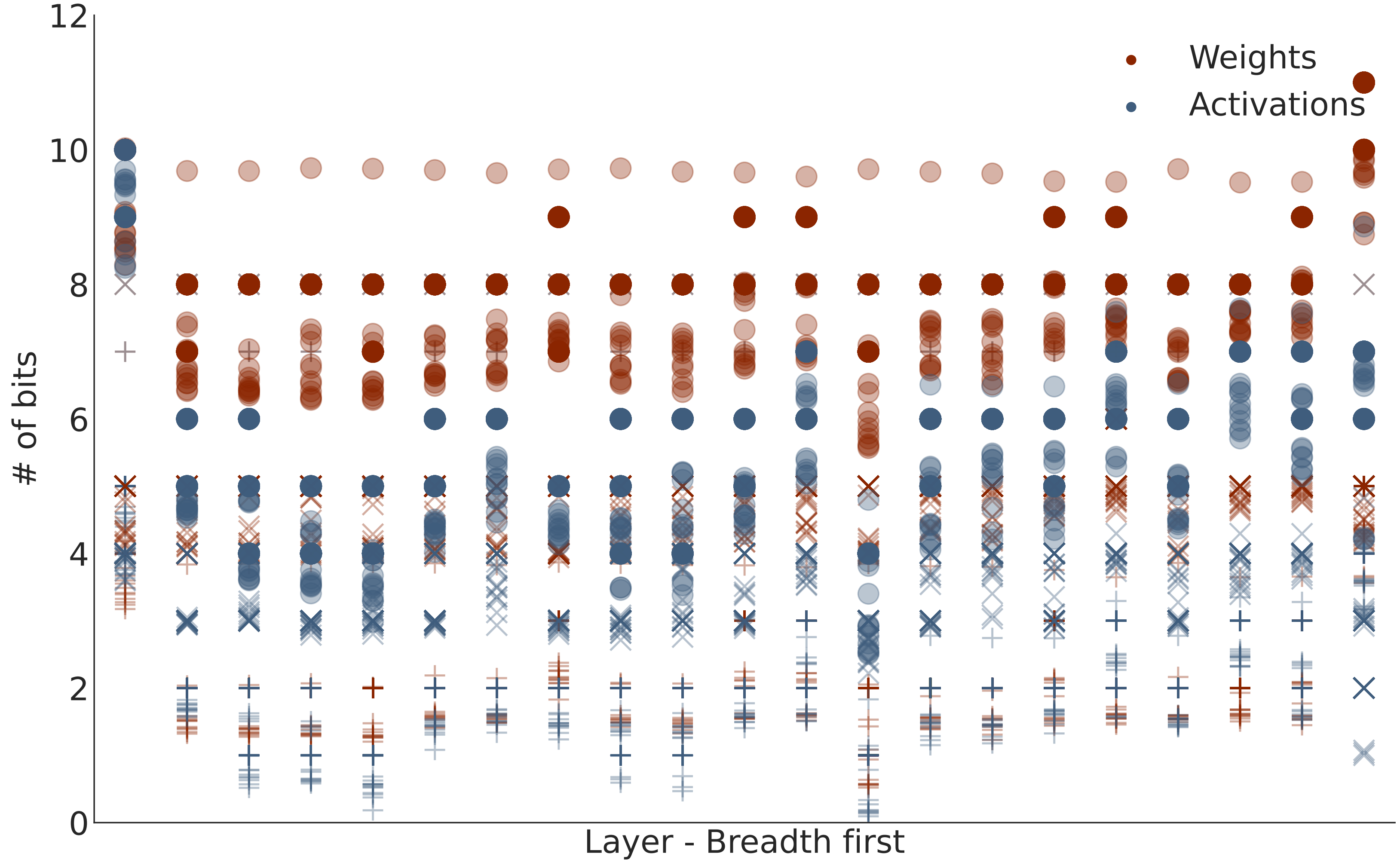
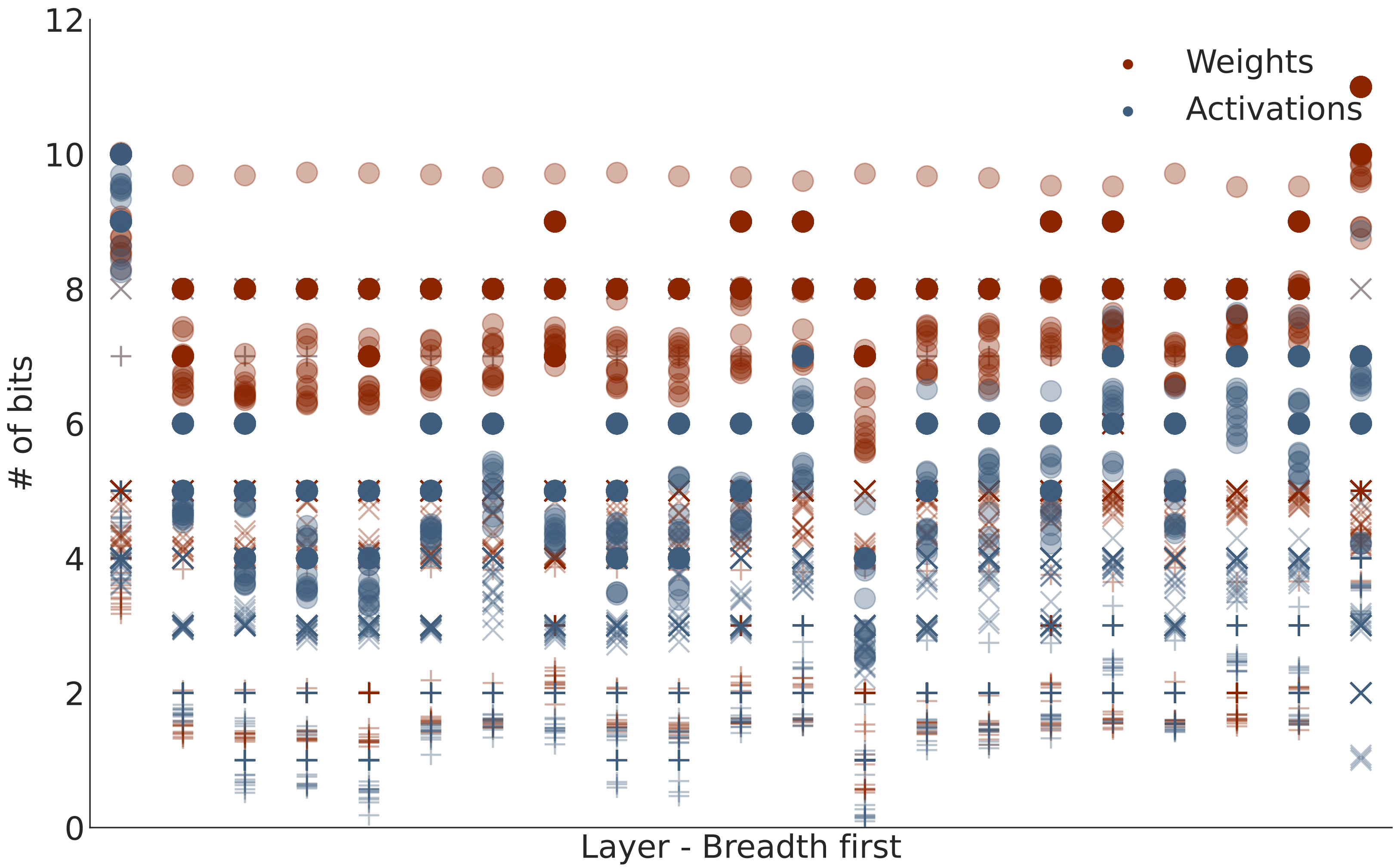


Per Tensor Datatype

- ResNet18
    - Per Tensor?
    - Single datatype?
- Less than 6b on average!
    - Much better than network wide!



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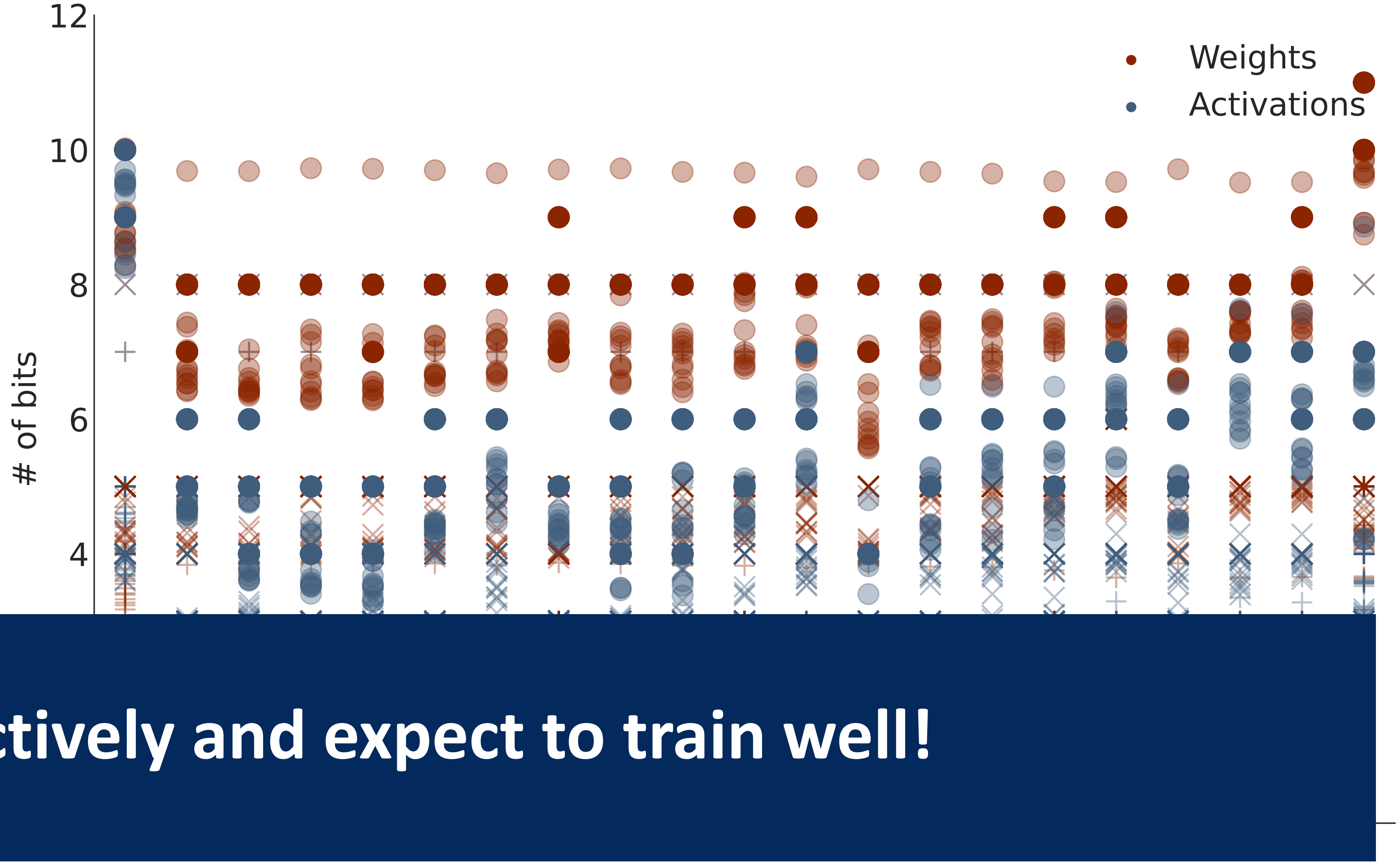


No chance to guess effectively and expect to train well!

Quantum Mantissa Loss

- Our Loss
  - $L = L_O + \gamma \times (\sum \lambda_i \times \alpha_i)$
  - Weighted according to priority
    - Tensor footprint
    - # of operations

Quantum Mantissa Loss

Original Loss

- Our Loss
  - $L = L_O + \gamma \times (\sum \lambda_i \times \alpha_i)$
  - Weighted according to priority
    - Tensor footprint
    - # of operations

Quantum Mantissa Loss

Mantissa Lengths

- Our Loss
  - $L = L_O + \gamma \times (\sum \lambda_i \times \alpha_i)$
  - Weighted according to priority
    - Tensor footprint
    - # of operations

Quantum Mantissa Loss

- Our Loss

  Mantissa Weights

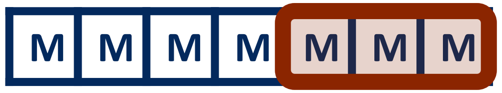
  - $L = L_O + \gamma \times (\sum \lambda_i \times \alpha_i)$
  - Weighted according to priority
    - Tensor footprint
    - # of operations

Quantum Mantissa Loss

- Our Loss
  - $L = L_O + \underset{}{\overset{\textbf{Regularizer Strength}}{\gamma}} \times (\sum \lambda_i \times \alpha_i)$
  - Weighted according to priority
    - Tensor footprint
    - # of operations

Quantum Mantissa Bitlength

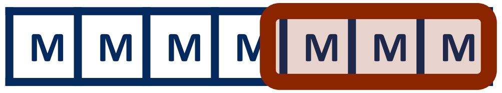
- Int Datatype



M M M M M M M

Quantum Mantissa Bitlength

- Int Datatype
- Non-Int Datatype



Quantum Mantissa Bitlength

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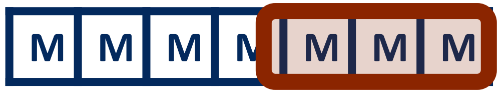

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Quantum Mantissa Bitlength

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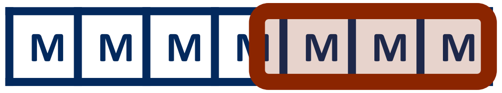

M M M M M M M

Quantum Mantissa Bitlength

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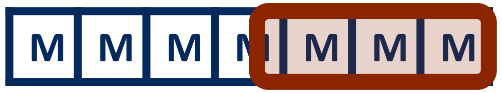
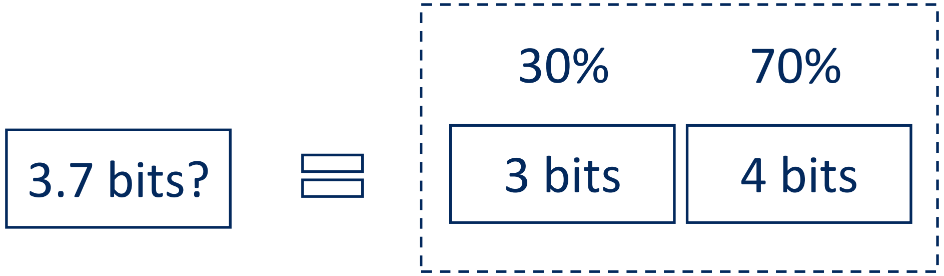
- Non-Int Datatype




3.7 bits?

≡

30%

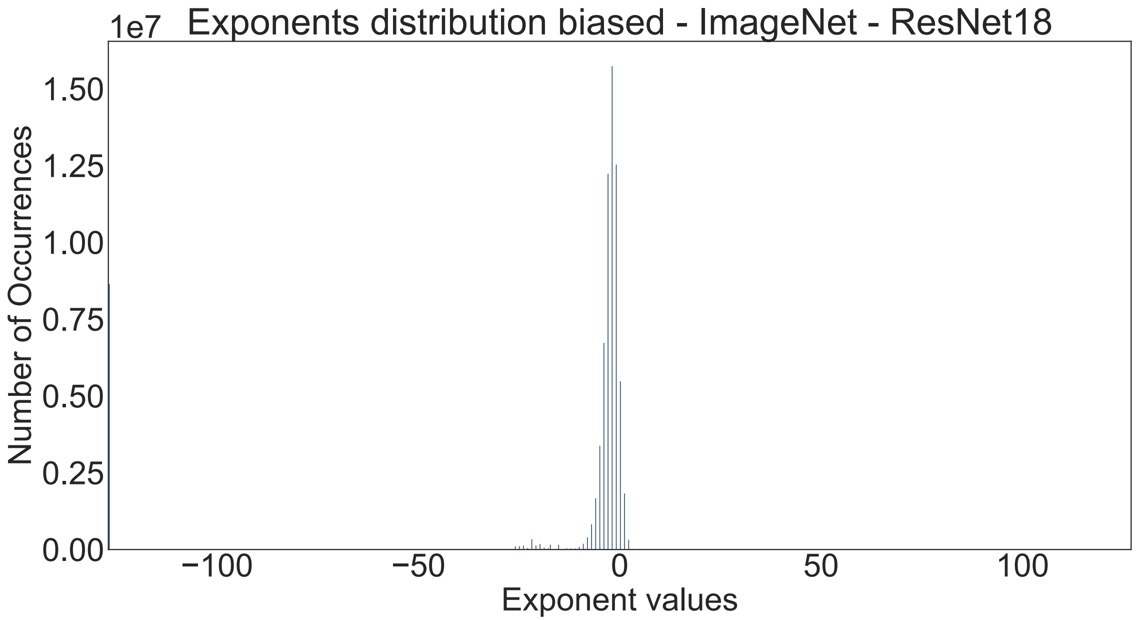
70%

3 bits

4 bits

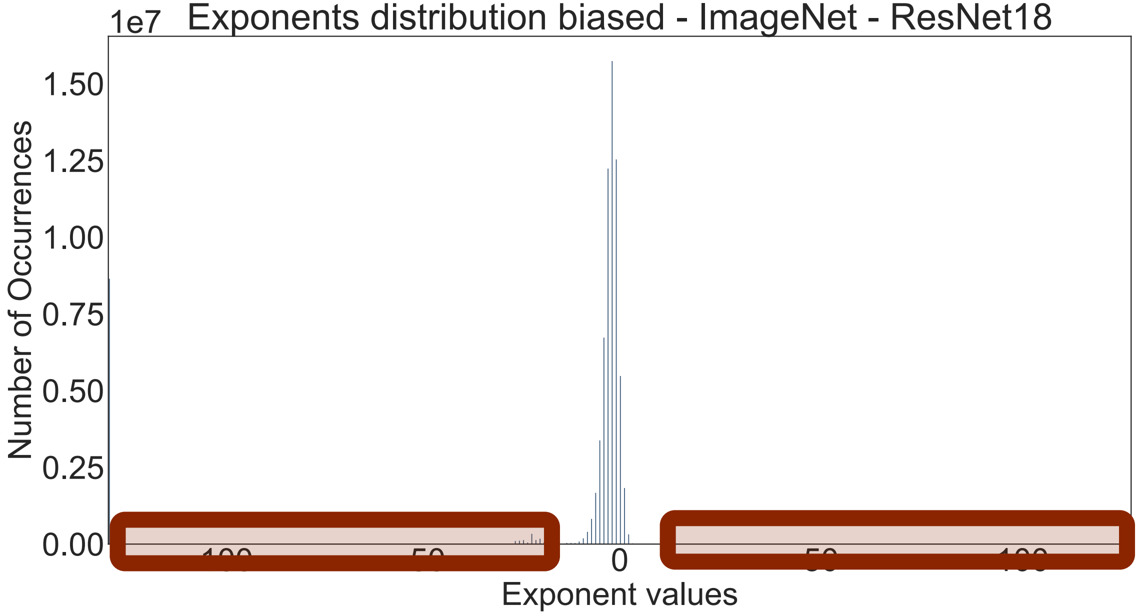
Quantum Exponent Range

- Distribution



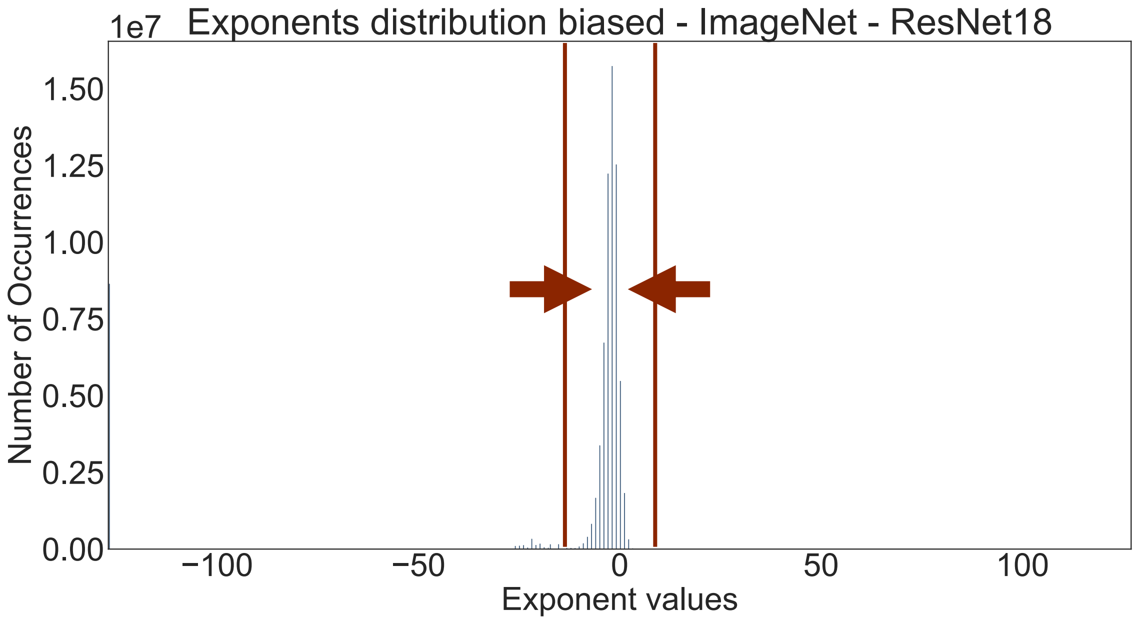
Quantum Exponent Range

- Distribution



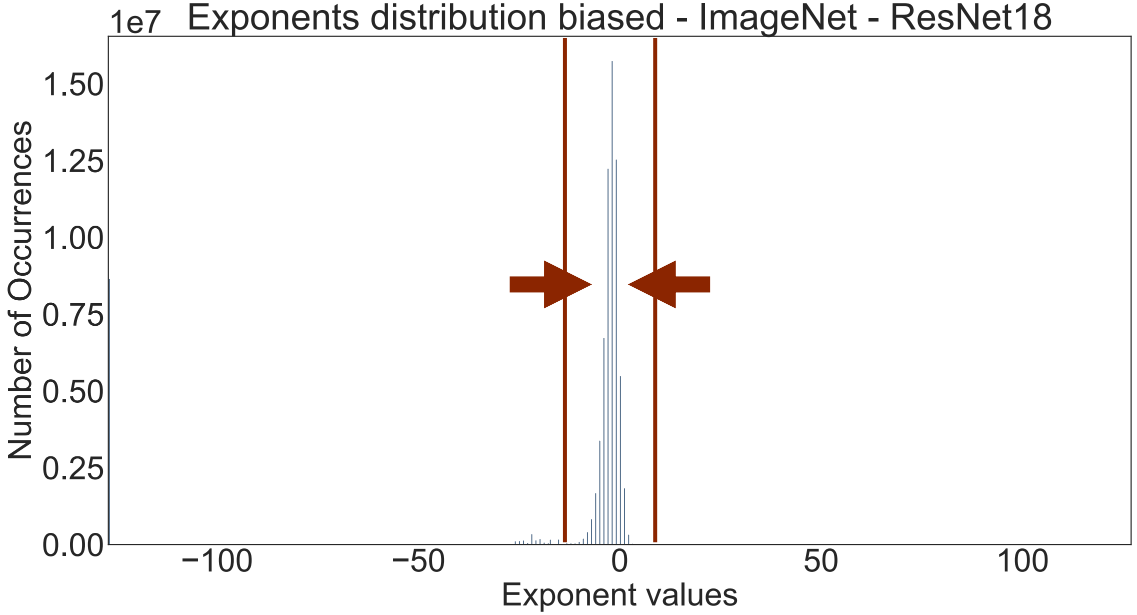
Quantum Exponent Range

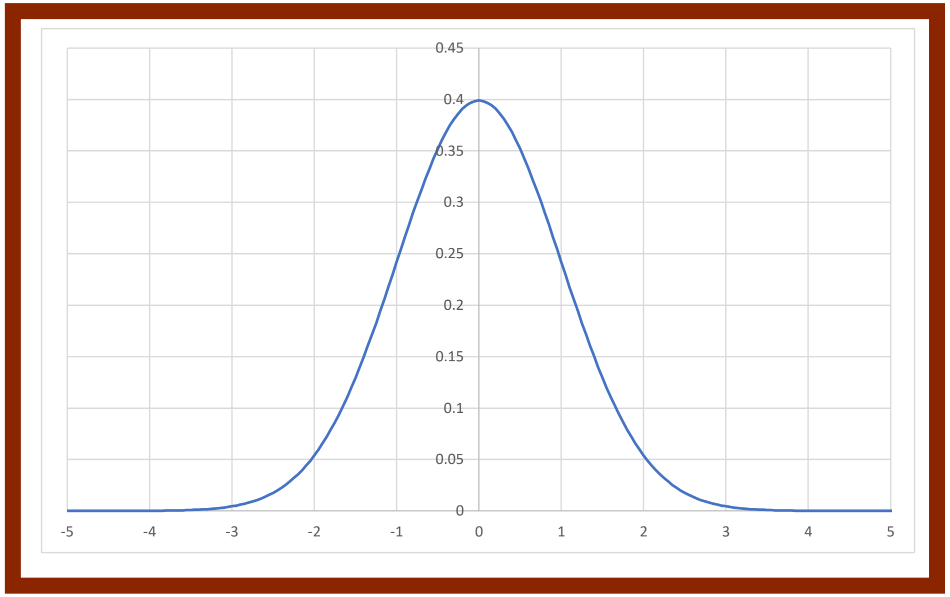
- Distribution
- Compress range



Quantum Exponent Range

- Distribution
- Compress range
- $Value = (-1)^S \times M \times 2^E$





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- Distribution
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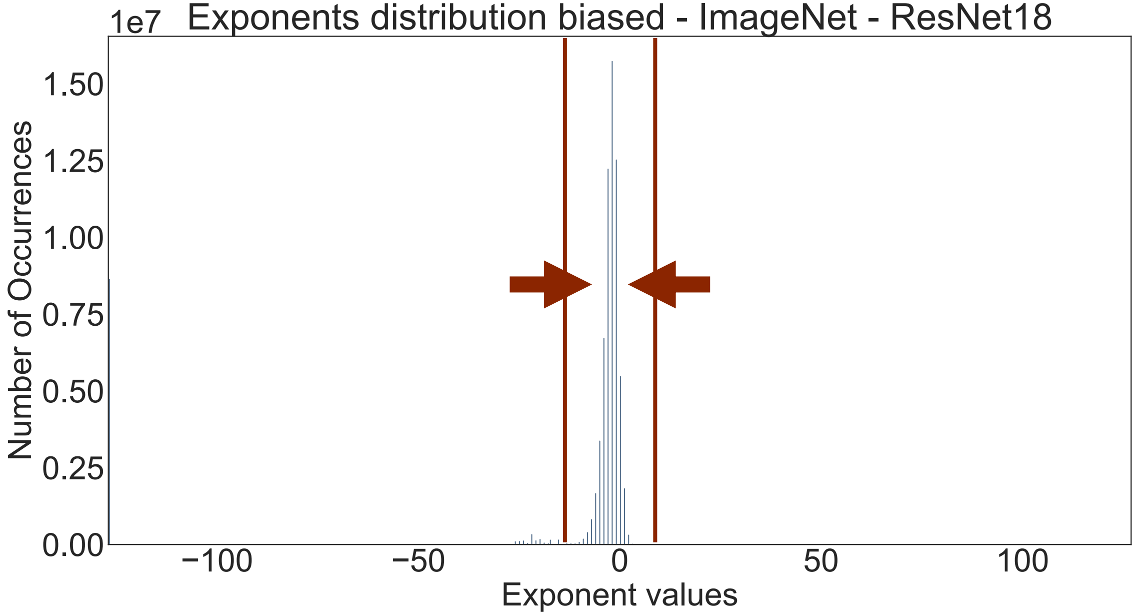
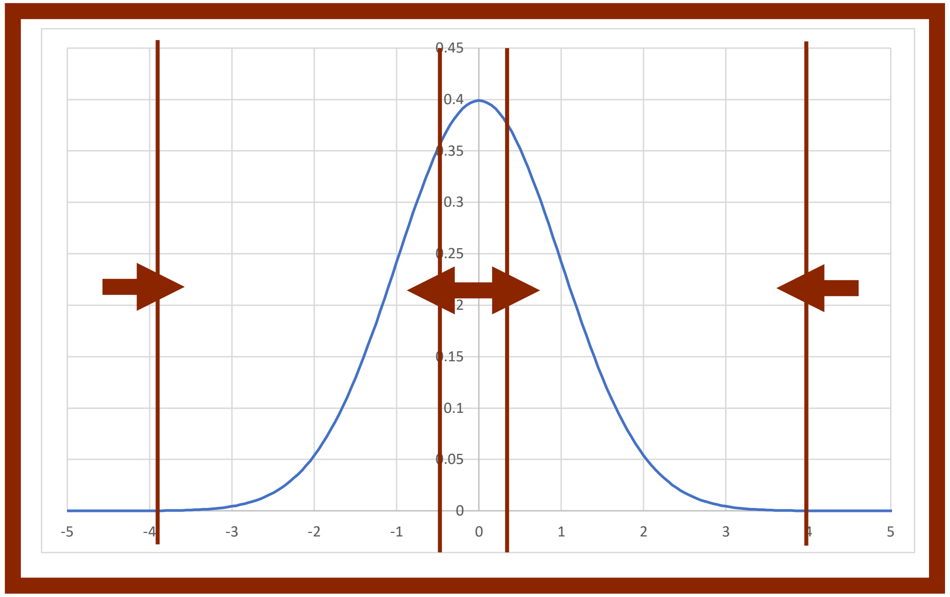
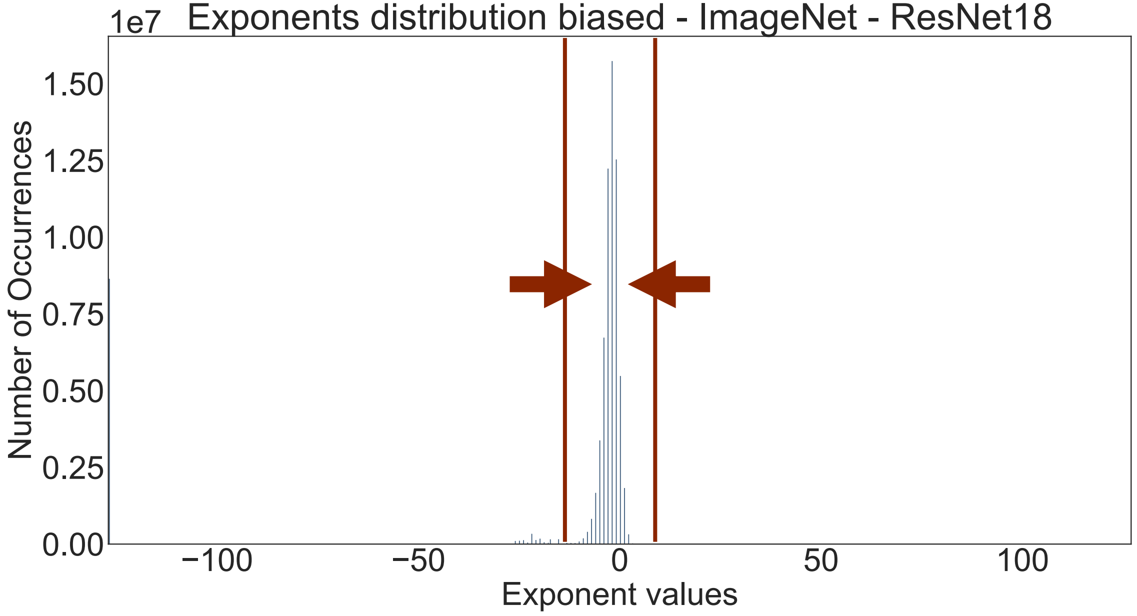
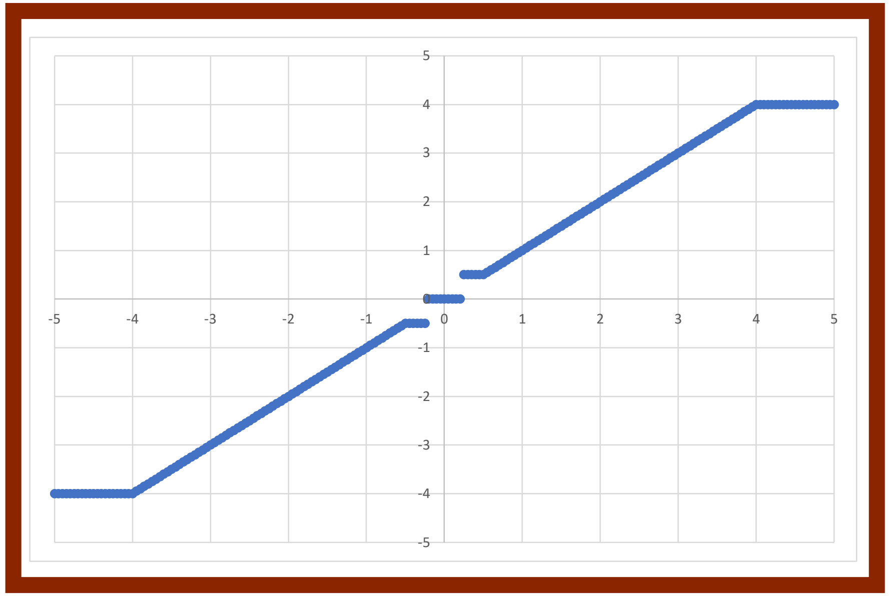


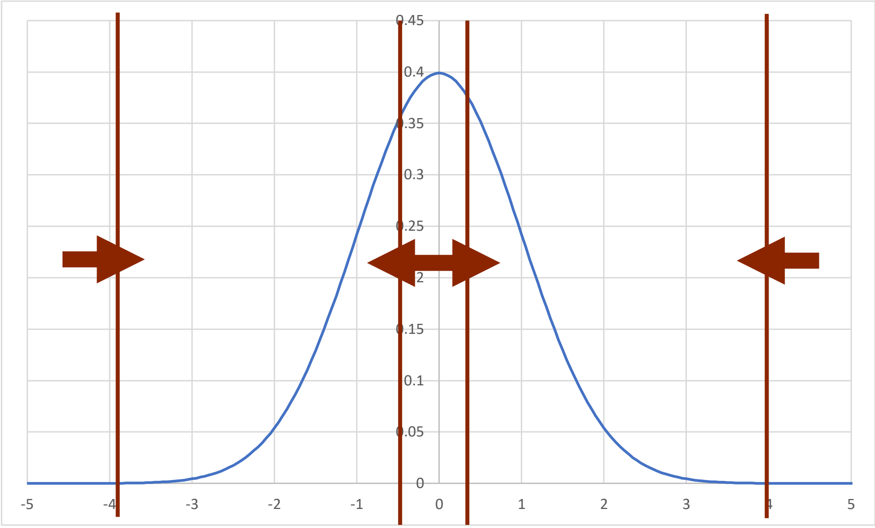


Quantum Exponent Range

- Distribution
- Compress range
- $Value = (-1)^{S} \times M \times 2^{E}$
- Range(x) overlay

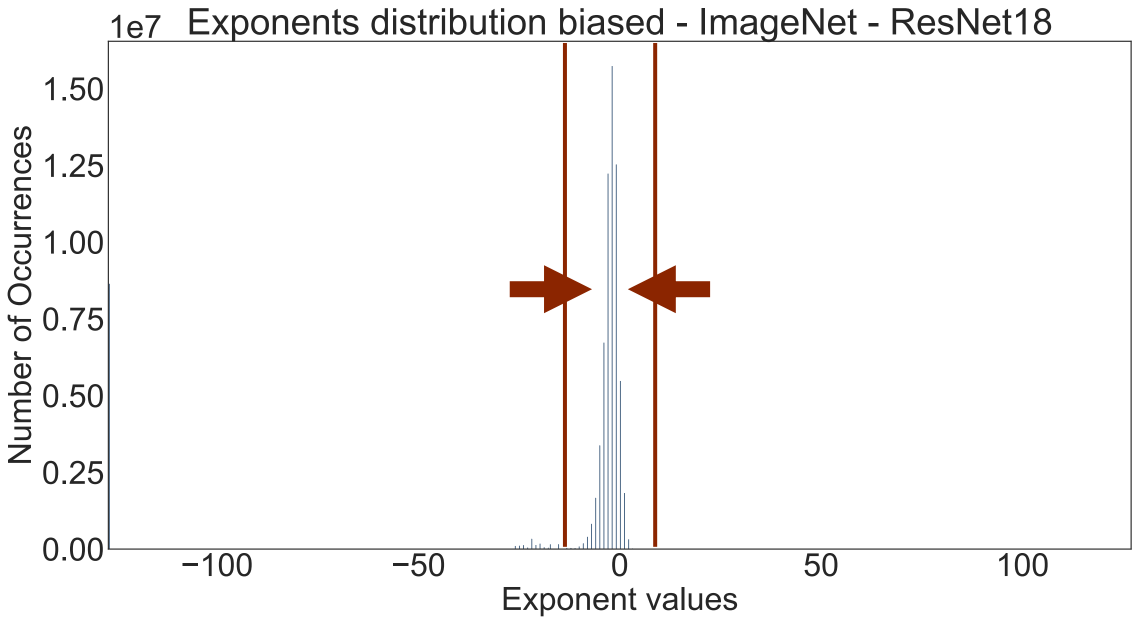


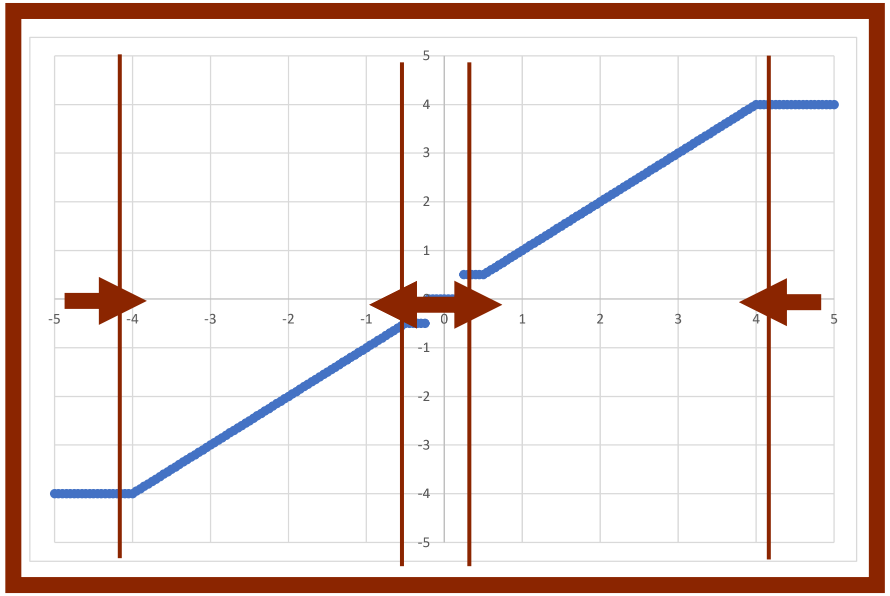


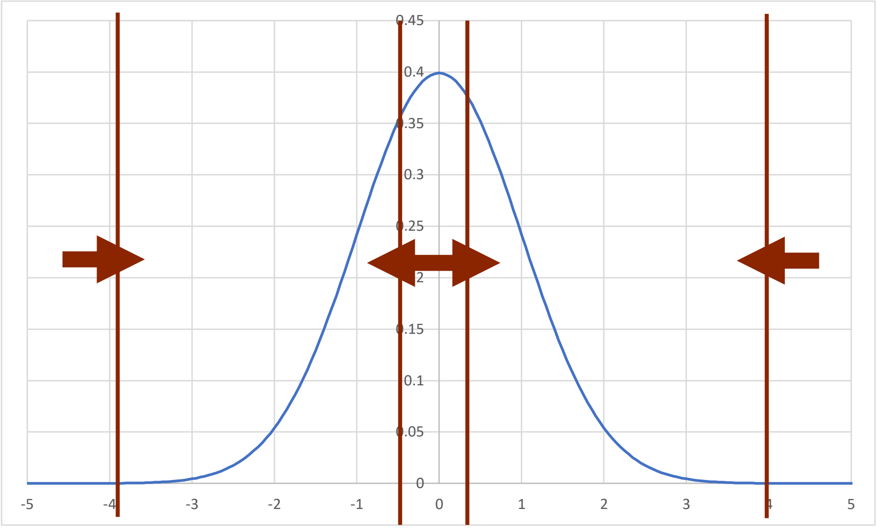


Quantum Exponent Range

- Distribution
- Compress range
- $Value = (-1)^S \times M \times 2^E$
- Range(x) overlay







Quantum Exponent

- Our Loss
    - $L = L_O + \gamma \times (\sum \lambda_i \times \alpha_i)$
    - Weighted according priority

Quantum Exponent

- Our Loss

  Original Loss

  - $L = L_O + \gamma \times (\sum \lambda_i \times \alpha_i)$
  - Weighted according priority

Quantum Exponent

- Our Loss

  Exponent Lengths

  - $L = L_O + \gamma \times (\sum \lambda_i \times \alpha_i)$
  - Weighted according priority

Quantum Exponent

- Our Loss
  - $L = L_O + \gamma \times (\sum \lambda_i \times \alpha_i)$
  - Weighted according priority

Exponent Weights

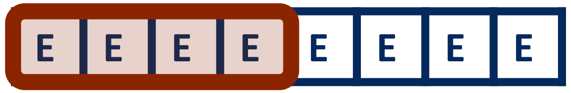
Quantum Exponent

- Our Loss
  - $L = L_O + \gamma \times (\sum \lambda_i \times \alpha_i)$
  - Weighted according priority

Regularizer Strength

Quantum Exponent

- Our Loss
  - $L = L_O + \gamma \times (\sum \lambda_i \times \alpha_i)$
  - Weighted according priority
- Int Datatype



Quantum Exponent

- Our Loss
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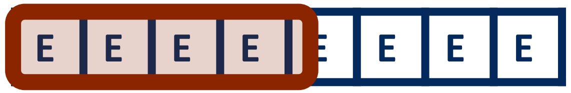
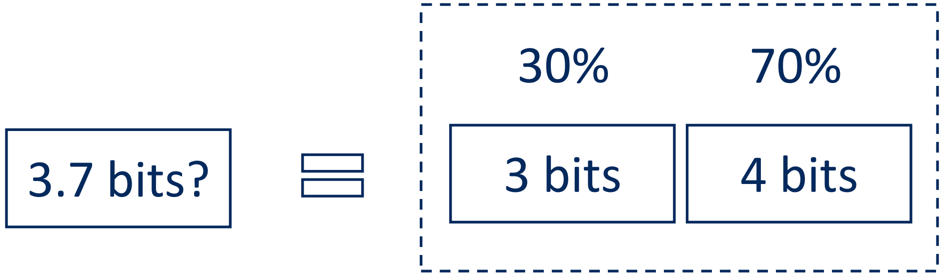
  - Weighted according priority
- Int Datatype
- Non-Int Datatype





3.7 bits?

30%

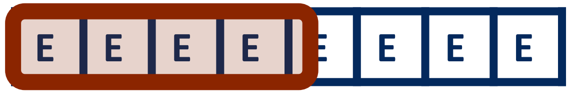
70%

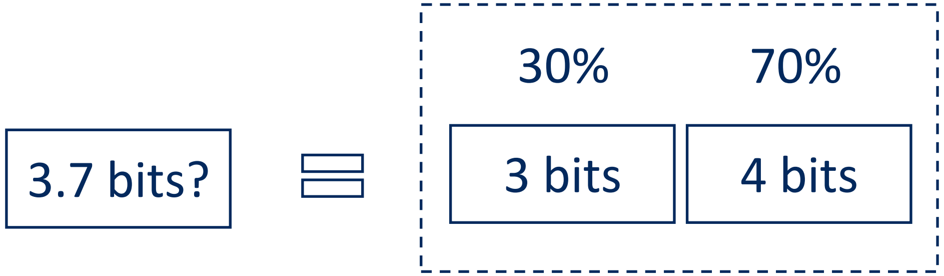
3 bits

4 bits

Quantum Exponent

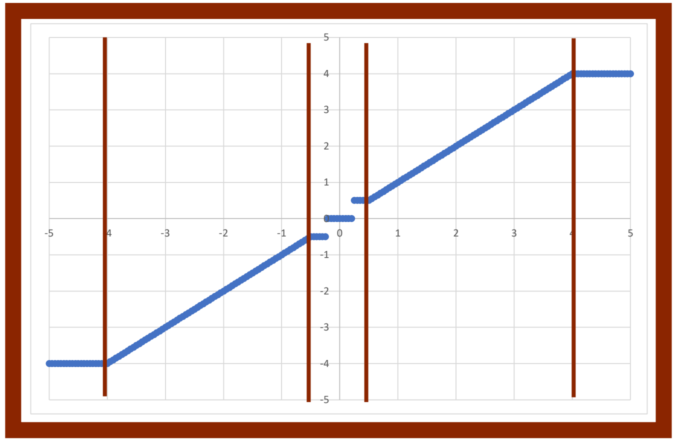
- Our Loss
  - $L = L_O + \gamma \times (\sum \lambda_i \times \alpha_i)$
  - Weighted according priority
- Int Datatype
- Non-Int Datatype
- Determine boundaries




3.7 bits?

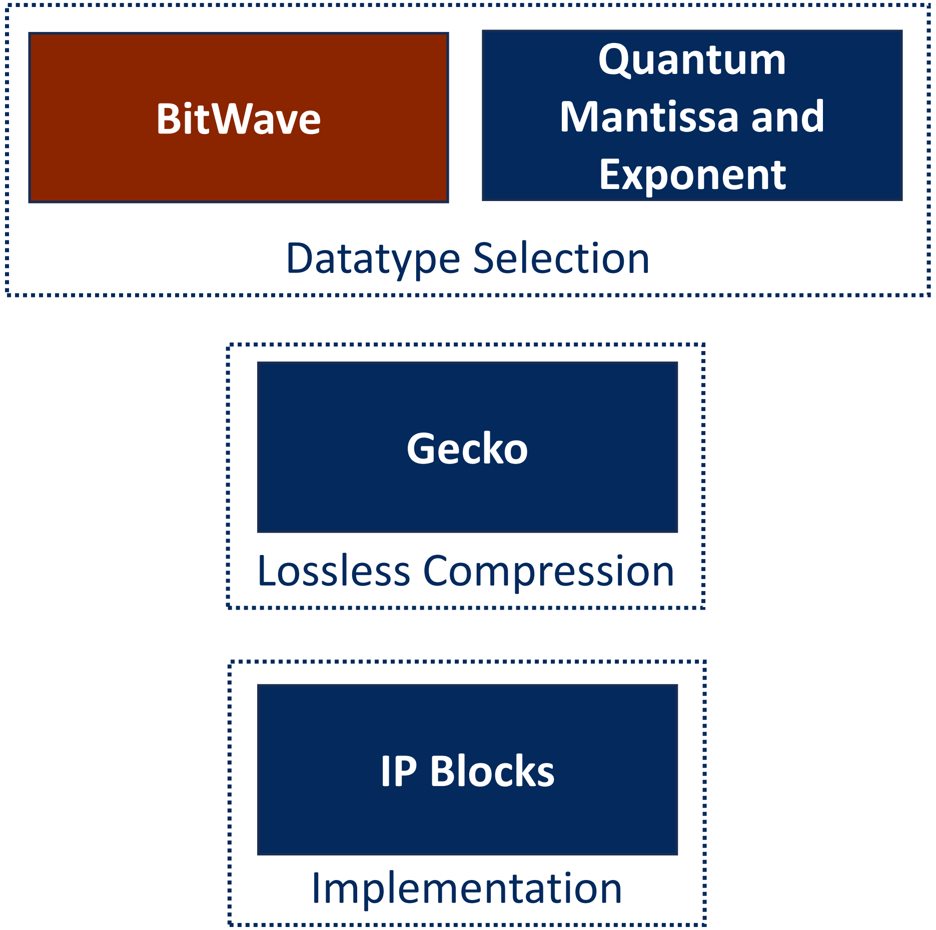
30% 70%

3 bits 4 bits



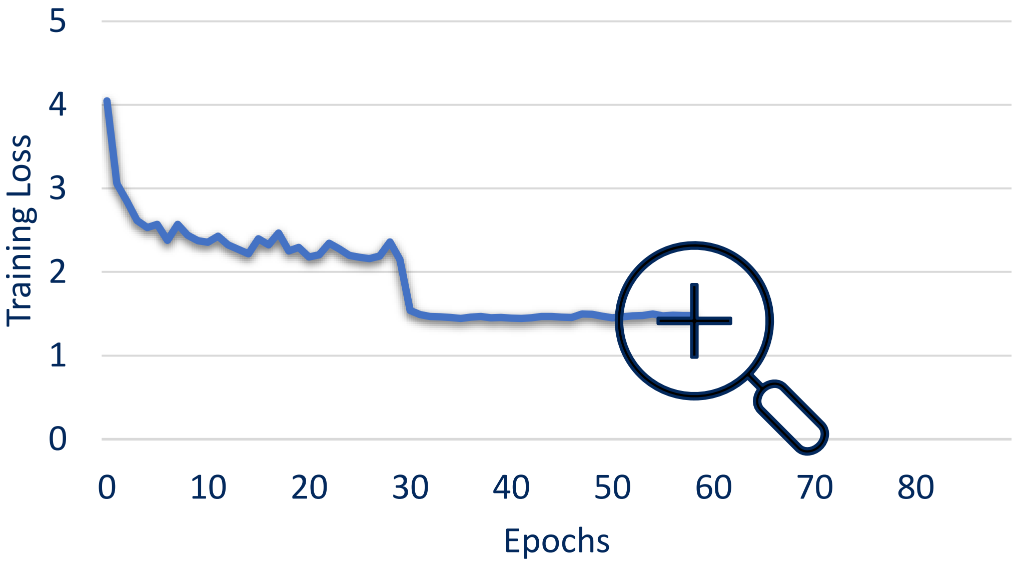
Schrödinger’s FP

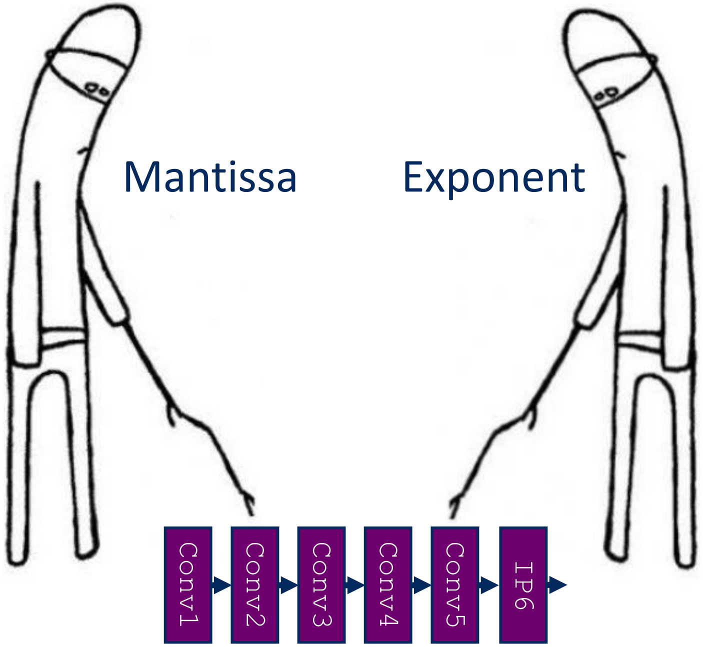
- Machine Learning
  - *Quantum Mantissa and Exponent*
- Black Box Sampling
  - *BitWave*
- Exponent compression
  - *Gecko*
- Hardware IP blocks



BitWave

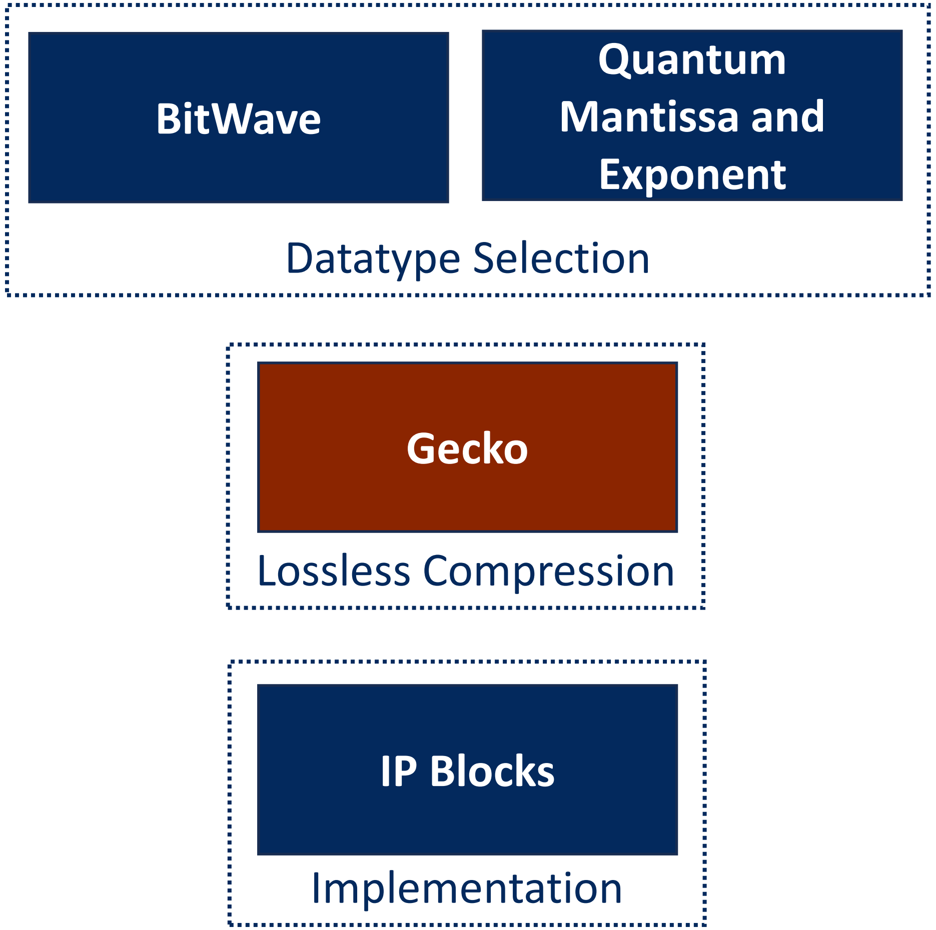
- Observe Loss
  - Adjust bitlengths
    - Mantissa
    - Exponent
- Training is forgiving
- Network wide





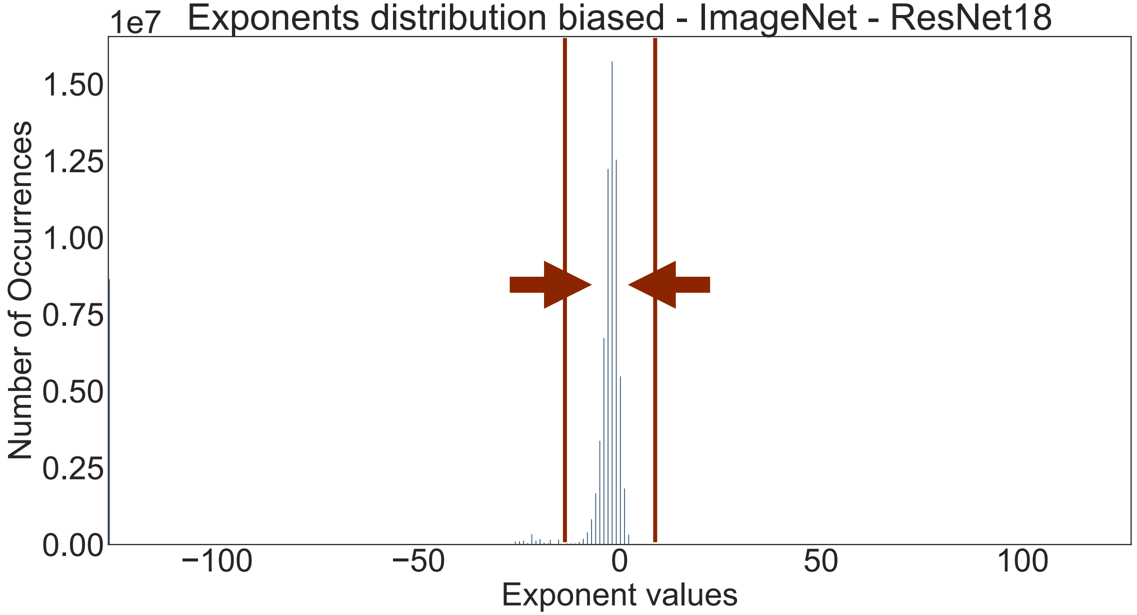
Schrödinger's FP

- Machine Learning
  - *Quantum Mantissa and Exponent*
- Black Box Sampling
  - *BitWave*
- Exponent compression
  - *Gecko*
- Hardware IP blocks



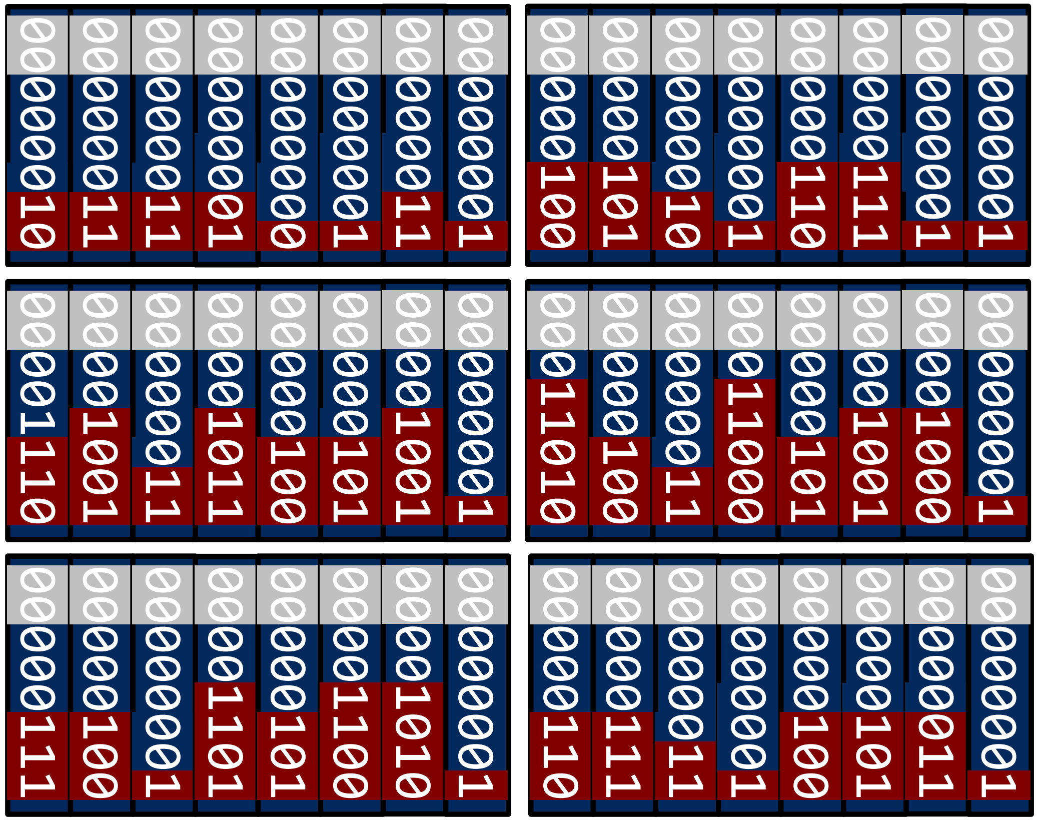
Exponent – *Gecko*

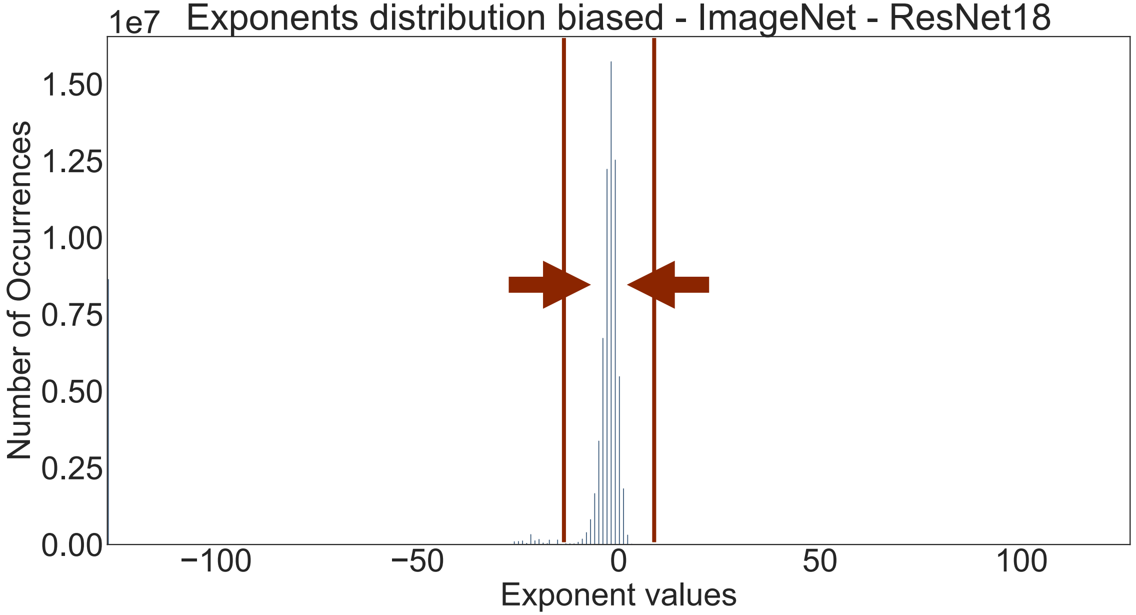
- Distribution



Exponent – *Gecko*

- Distribution
- Group





Exponent – *Gecko*

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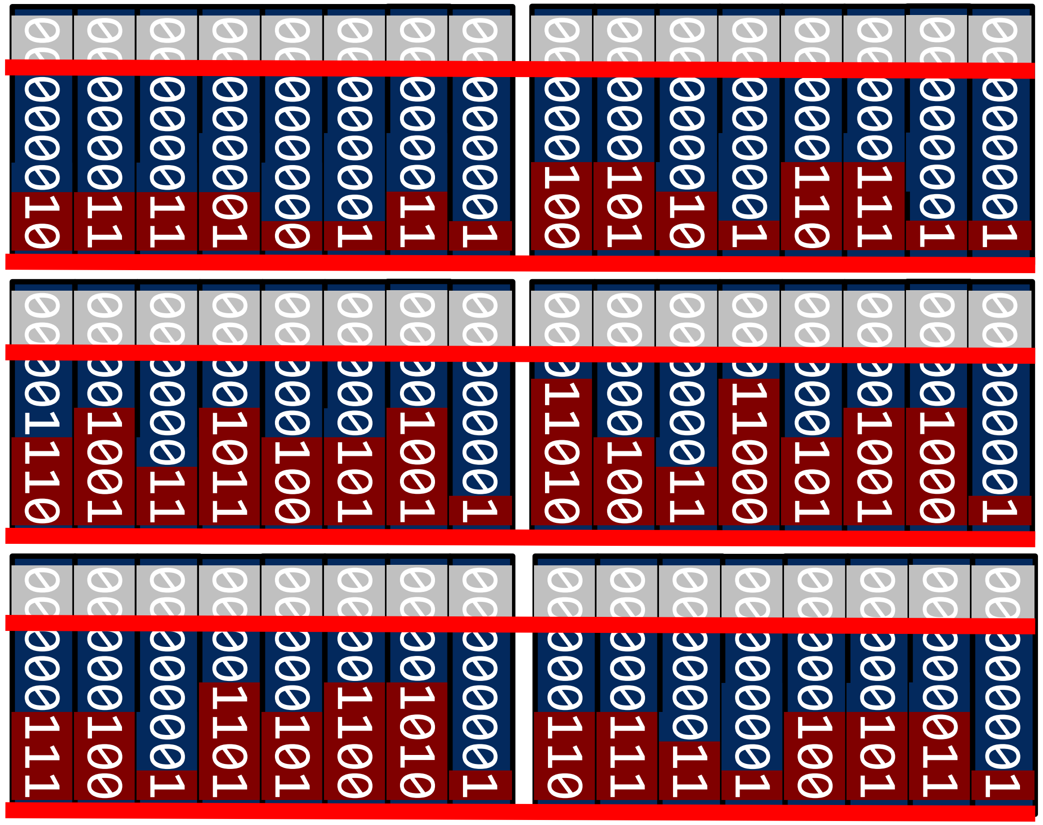

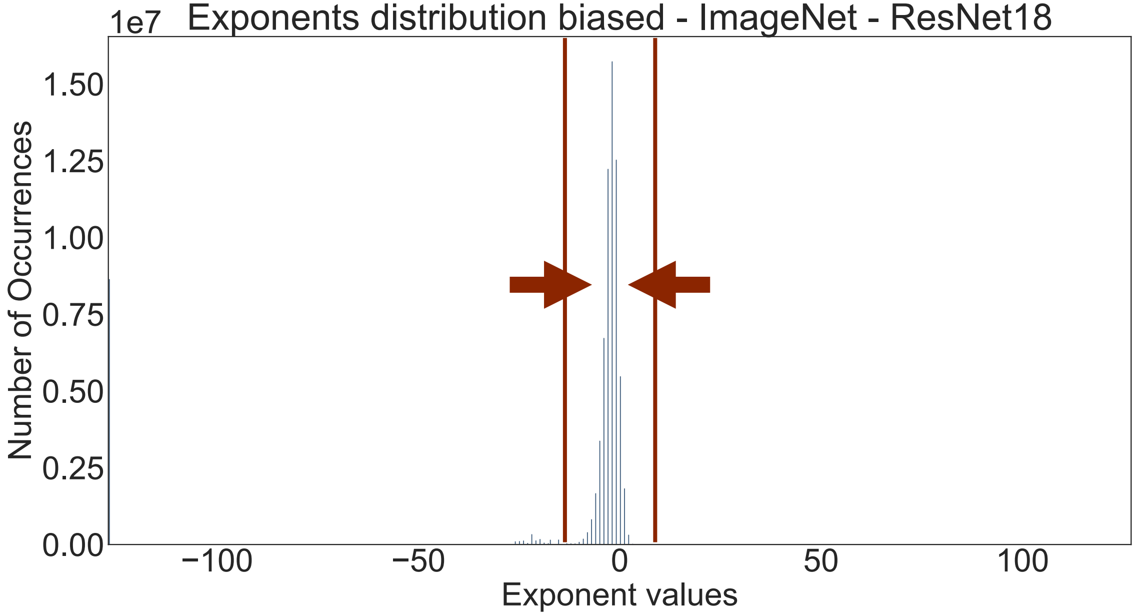

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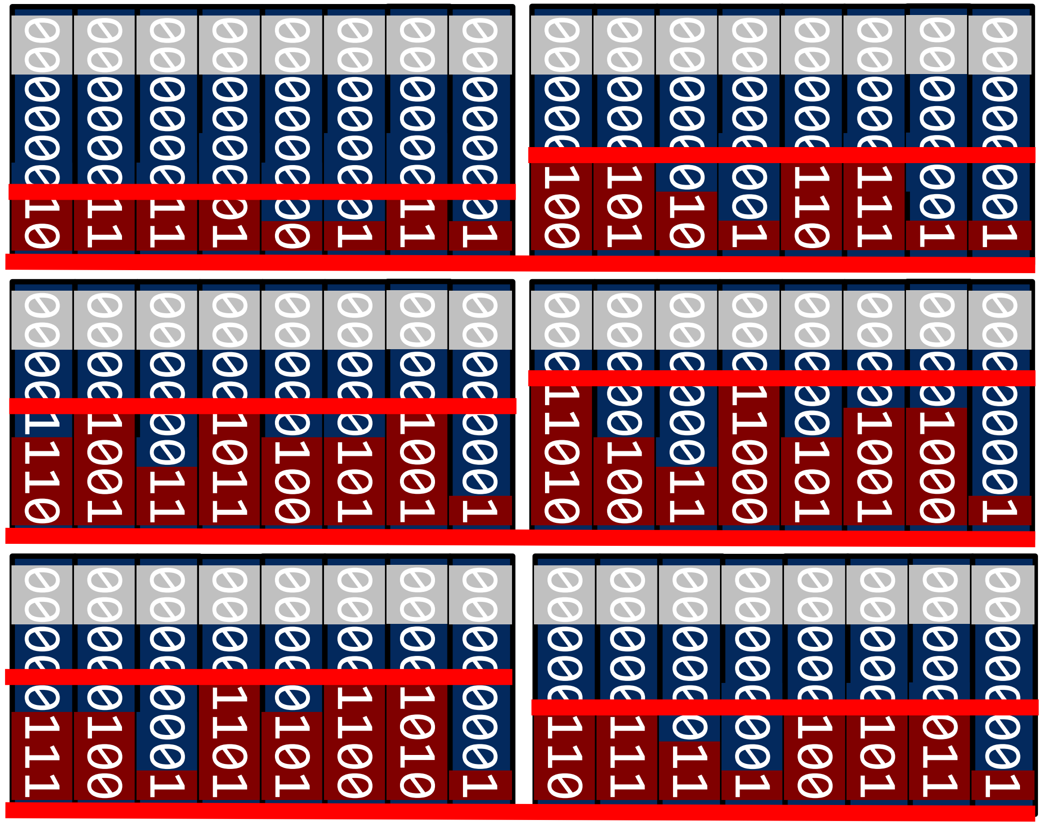
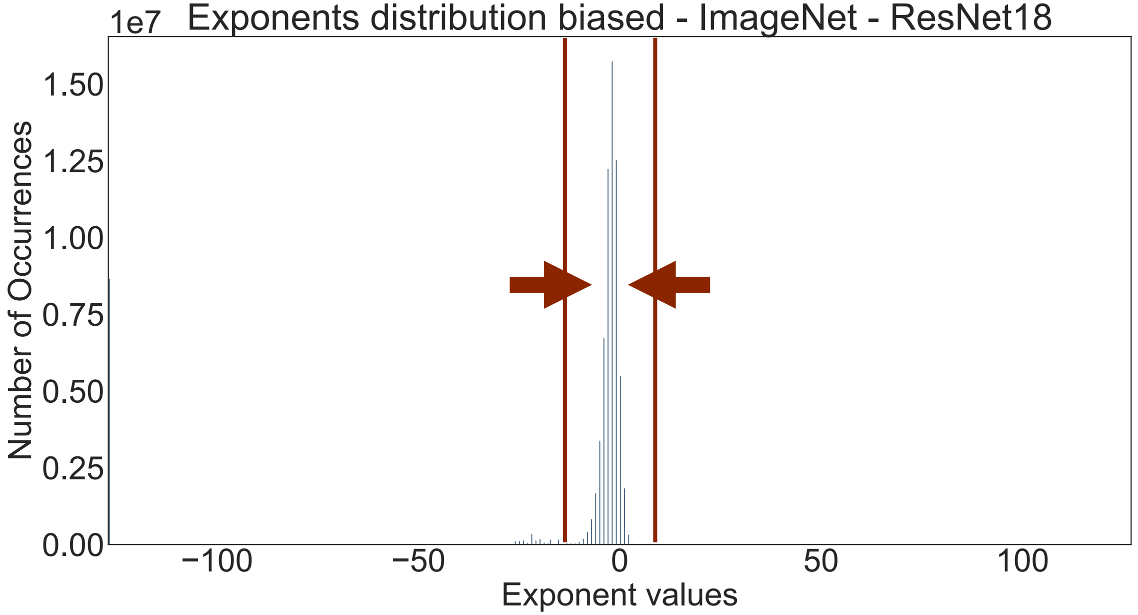
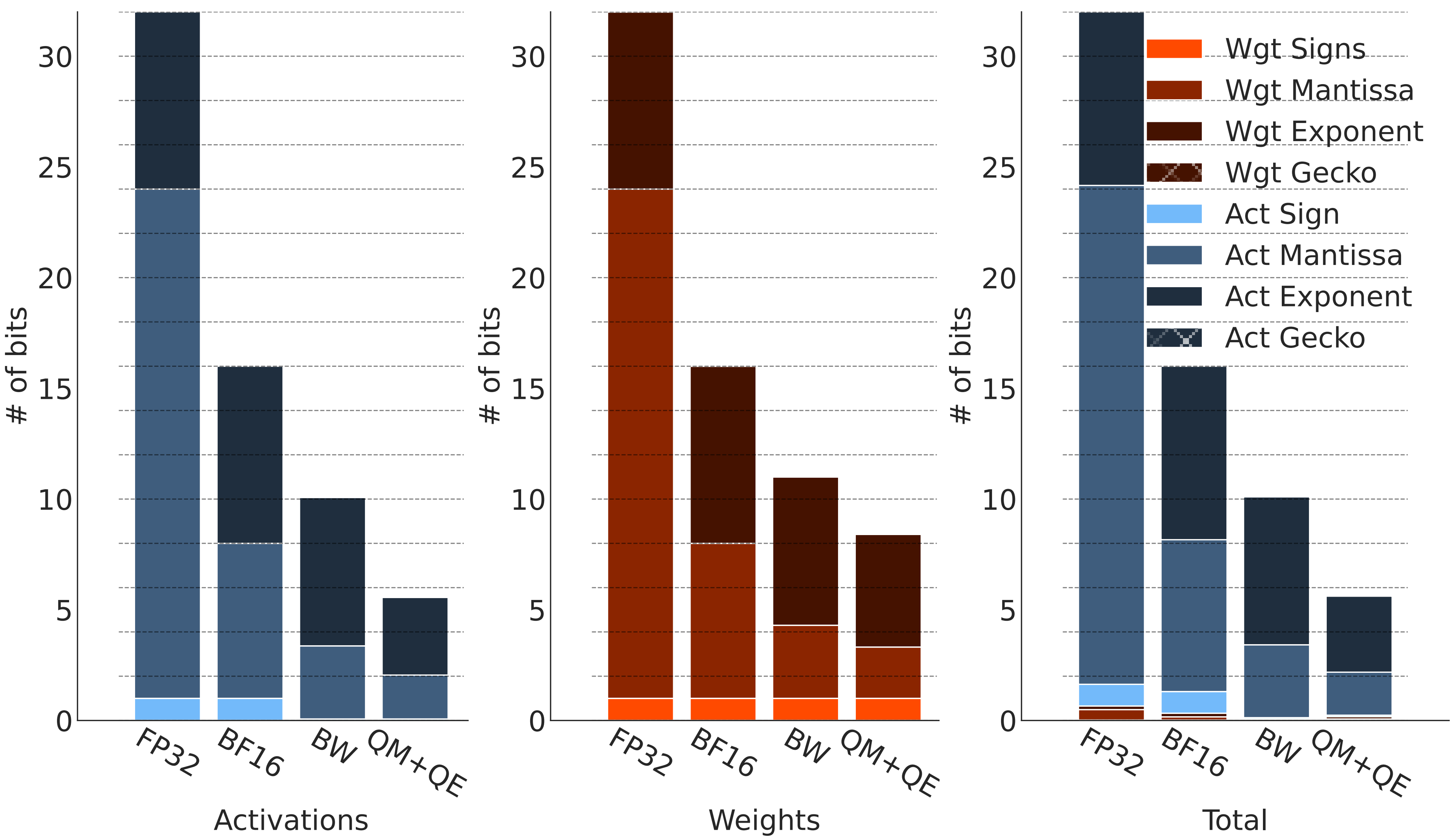




Massive footprint reduction on ResNet18!



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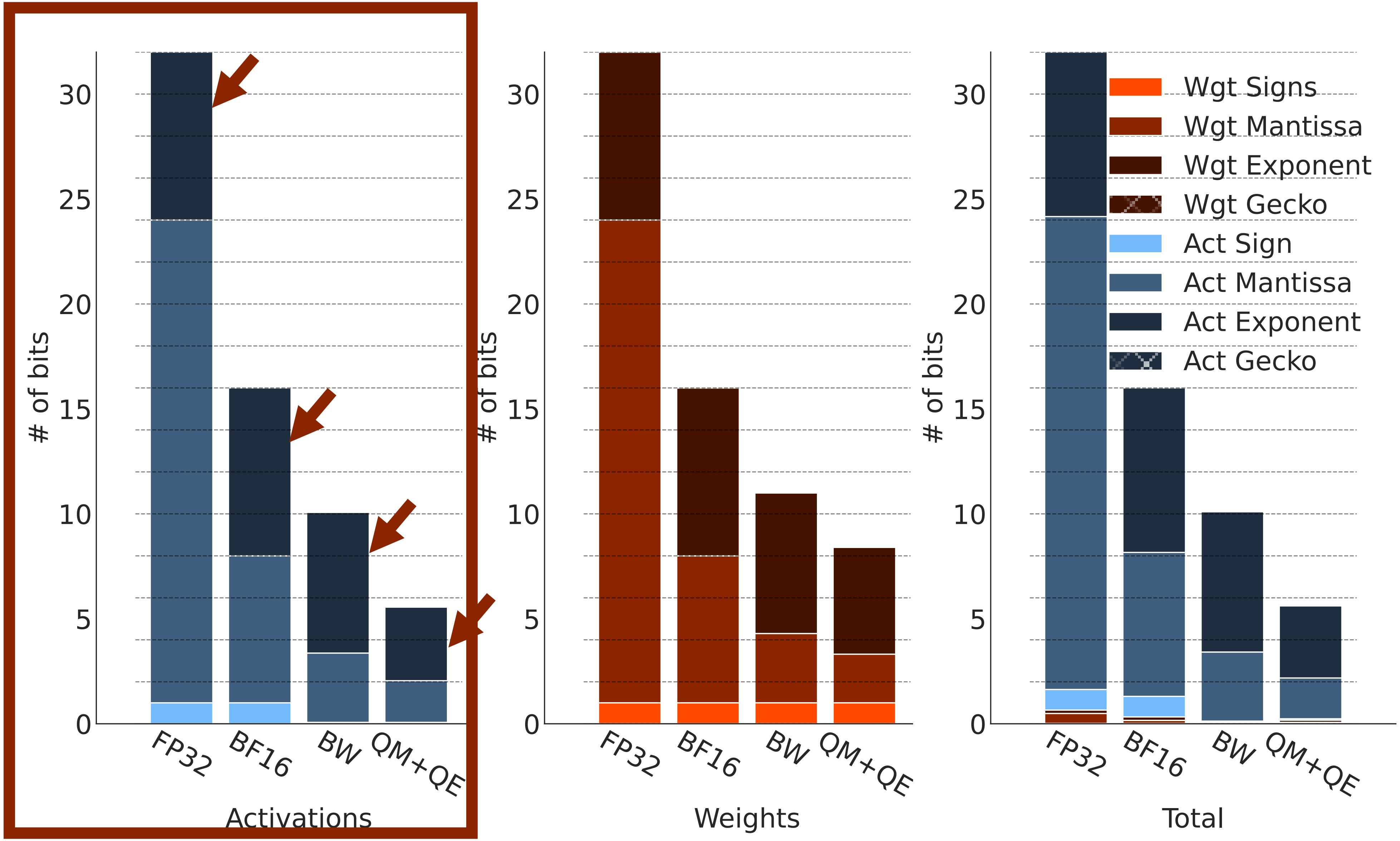

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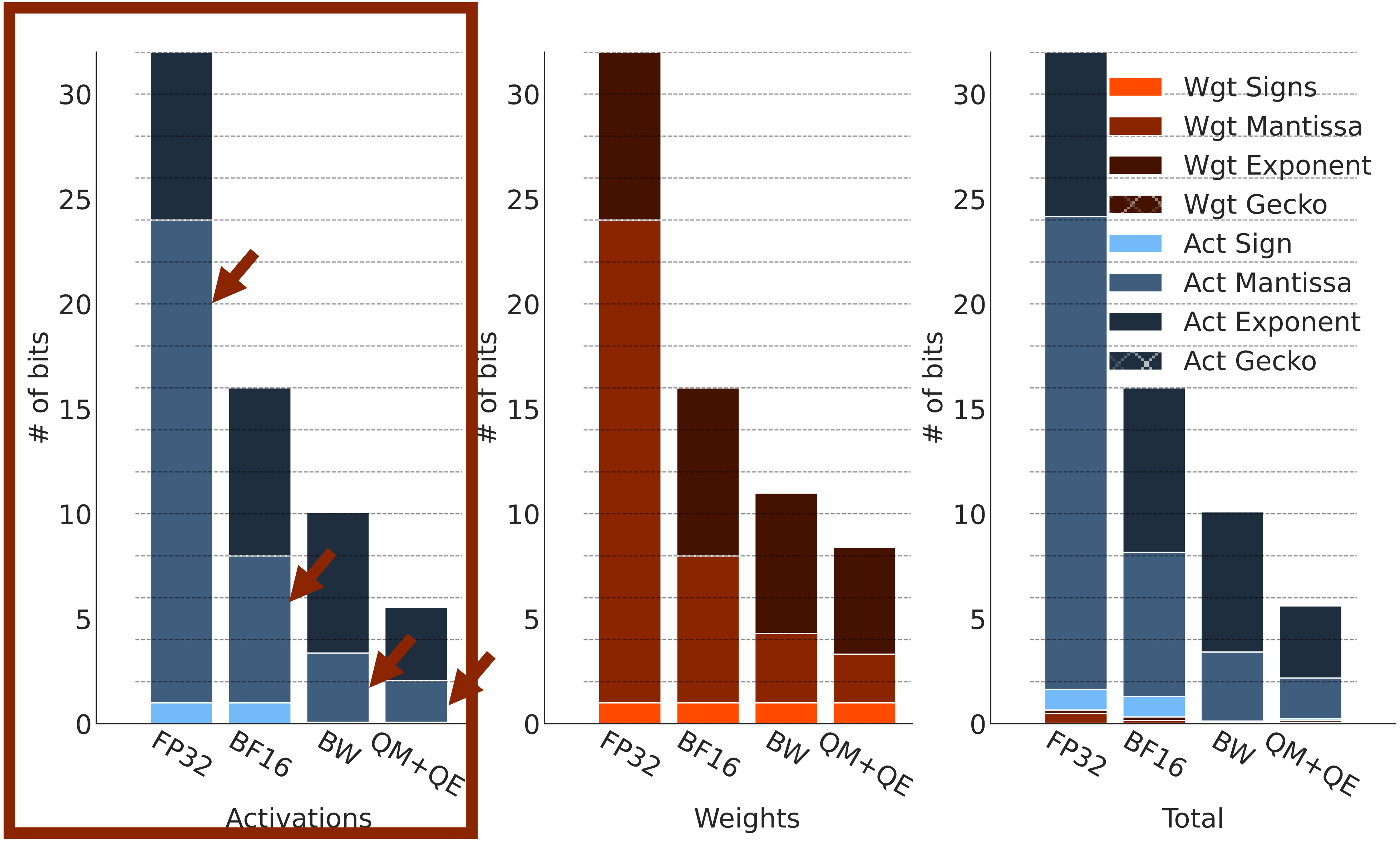

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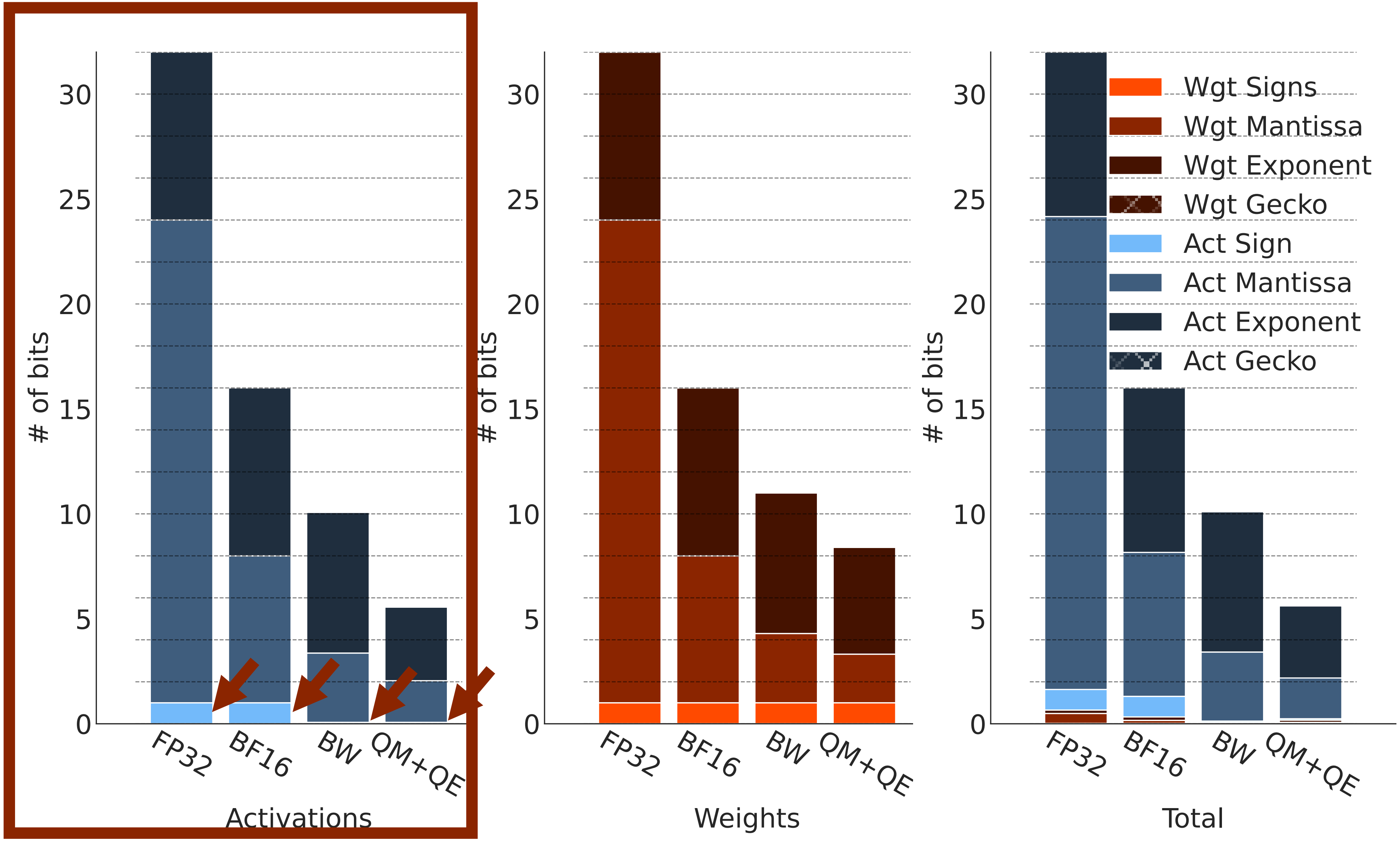

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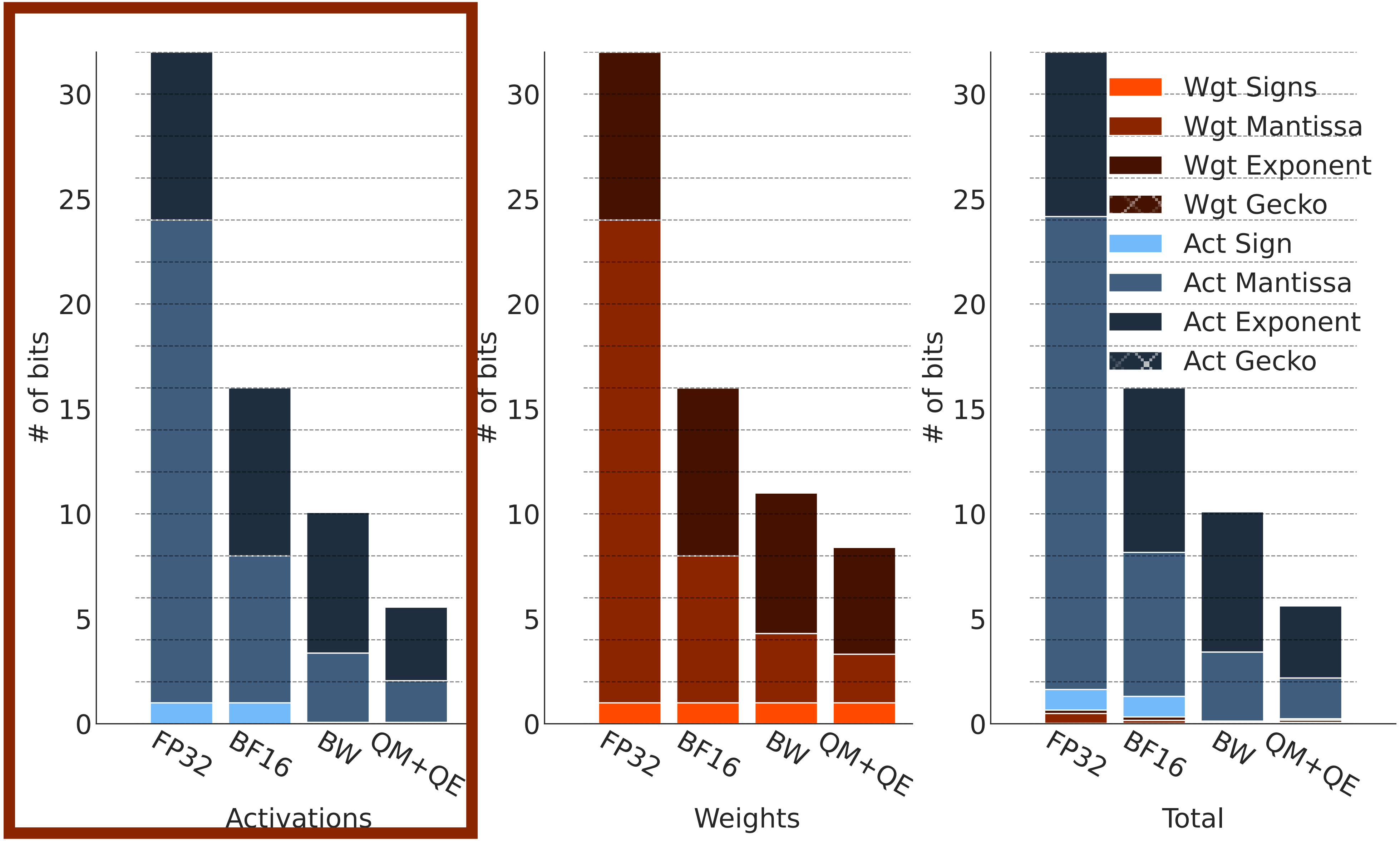

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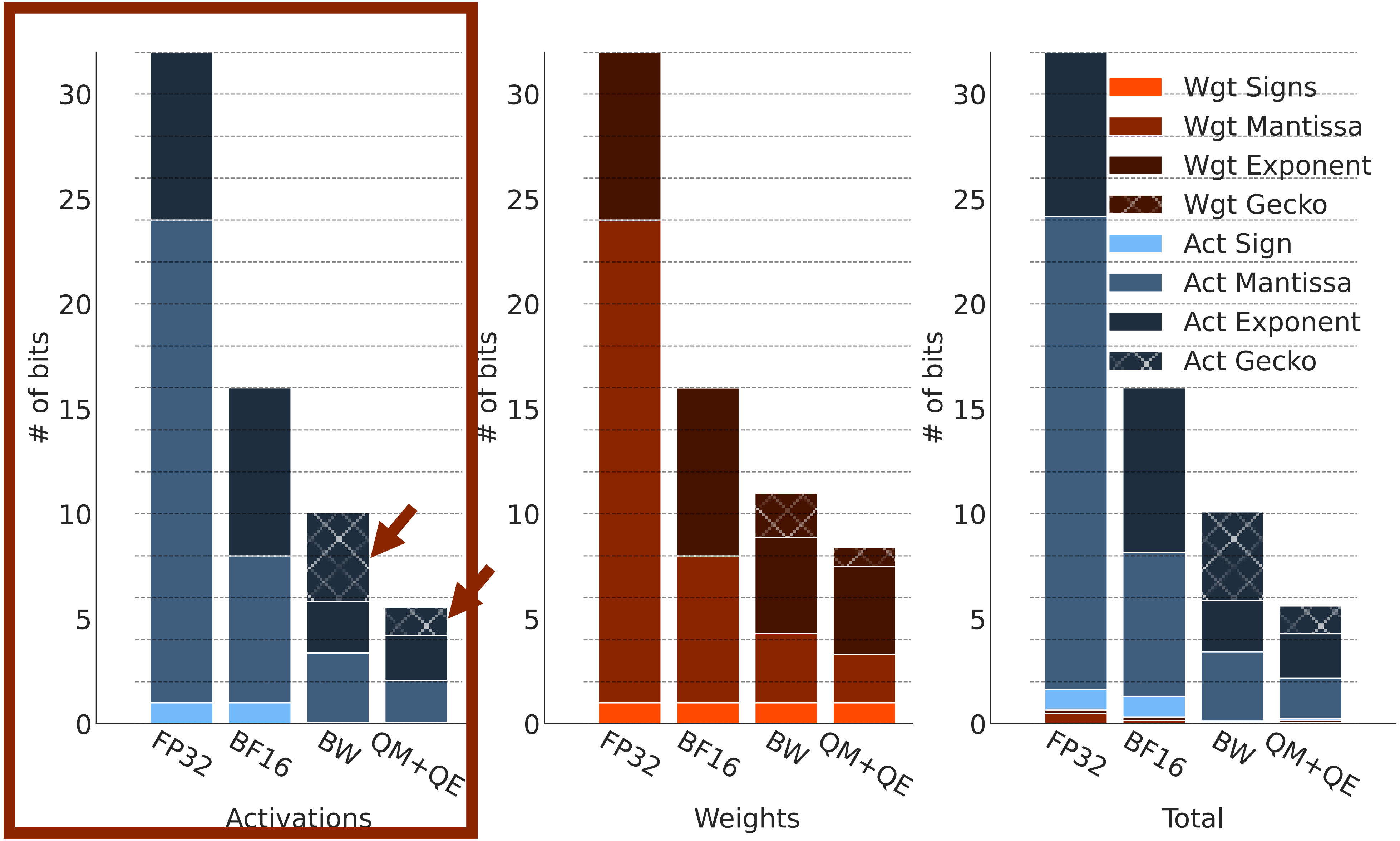

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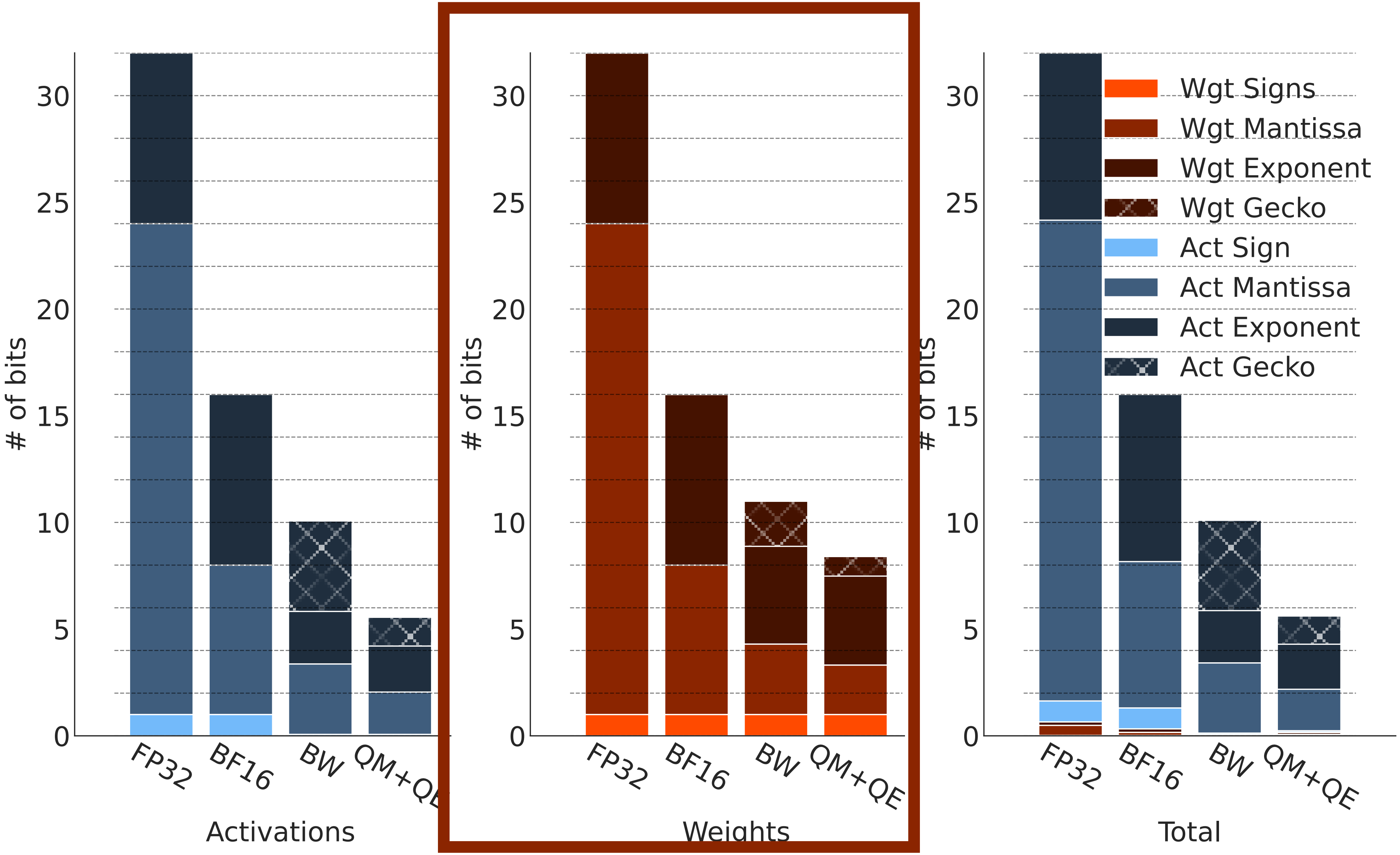

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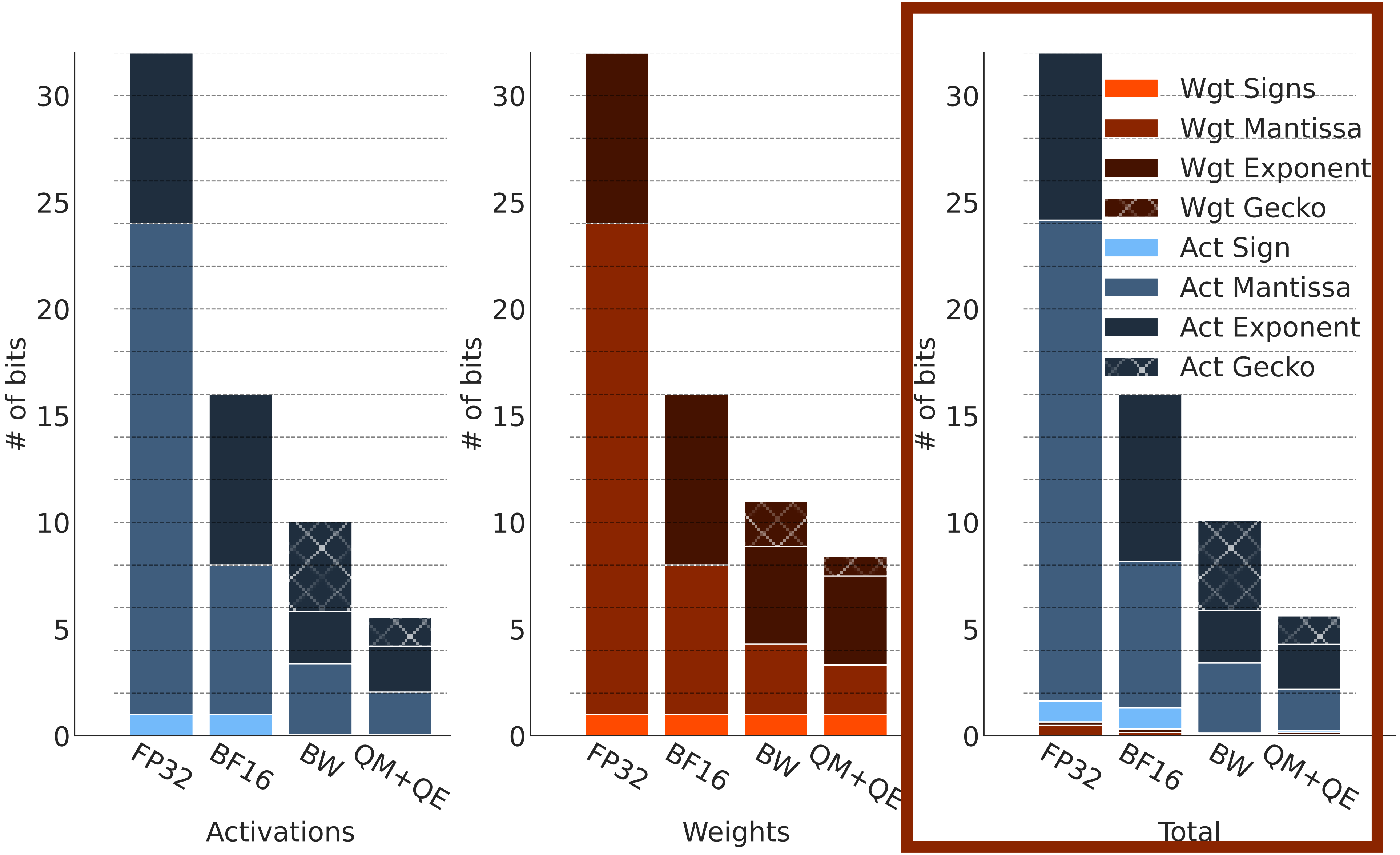
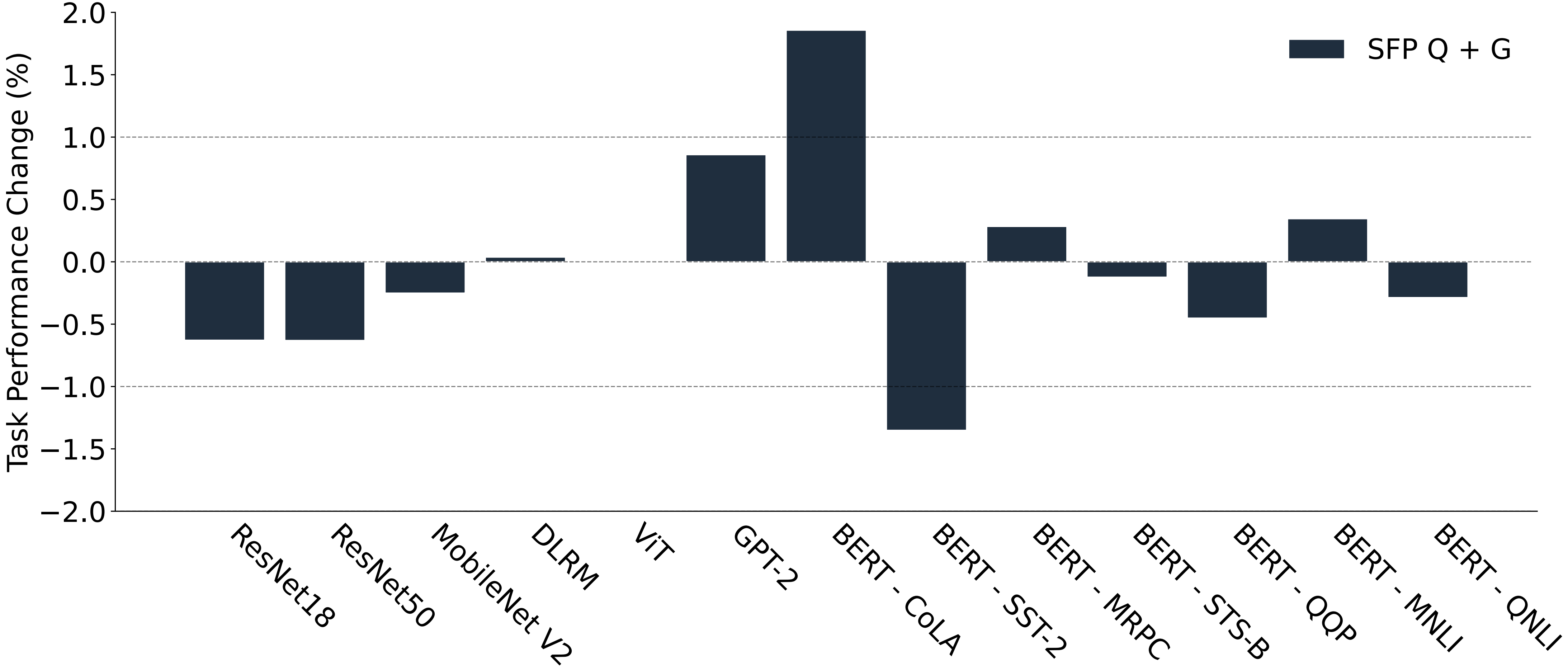


Similar Task Performance!



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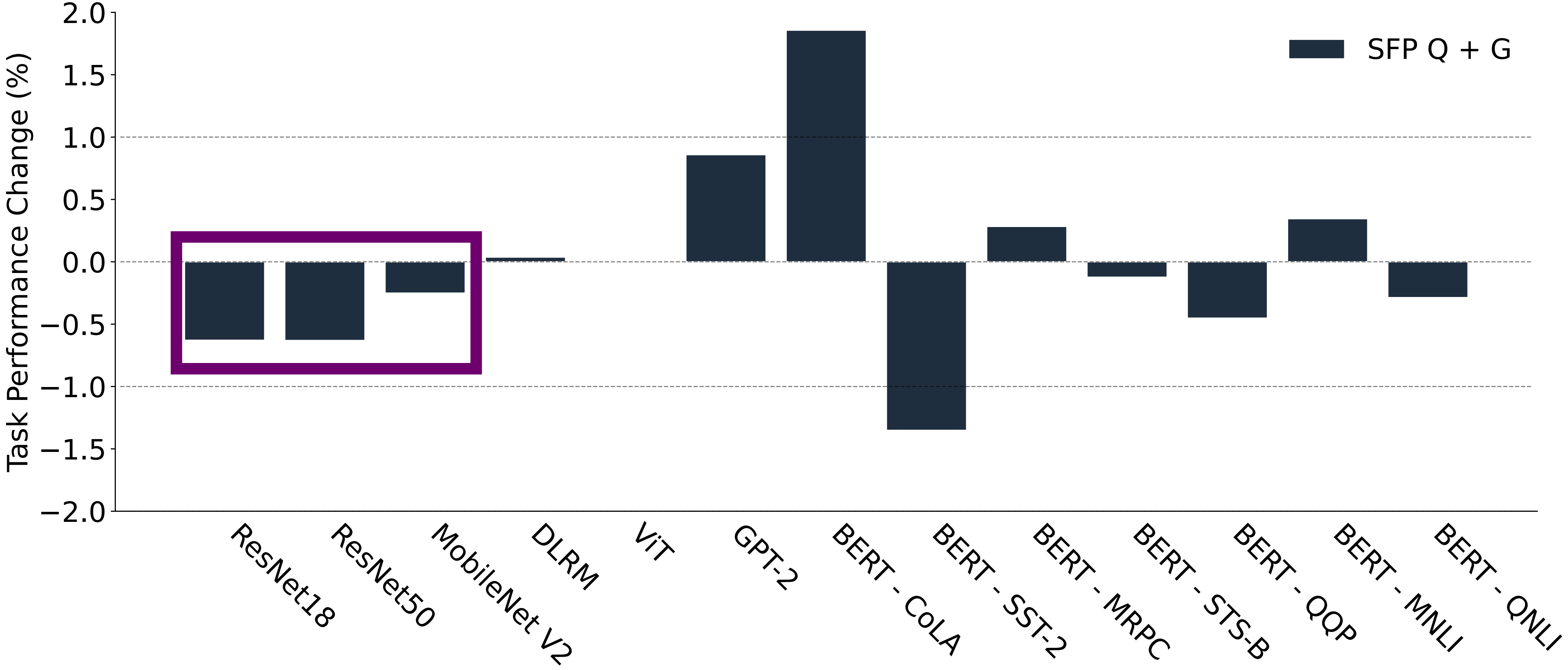

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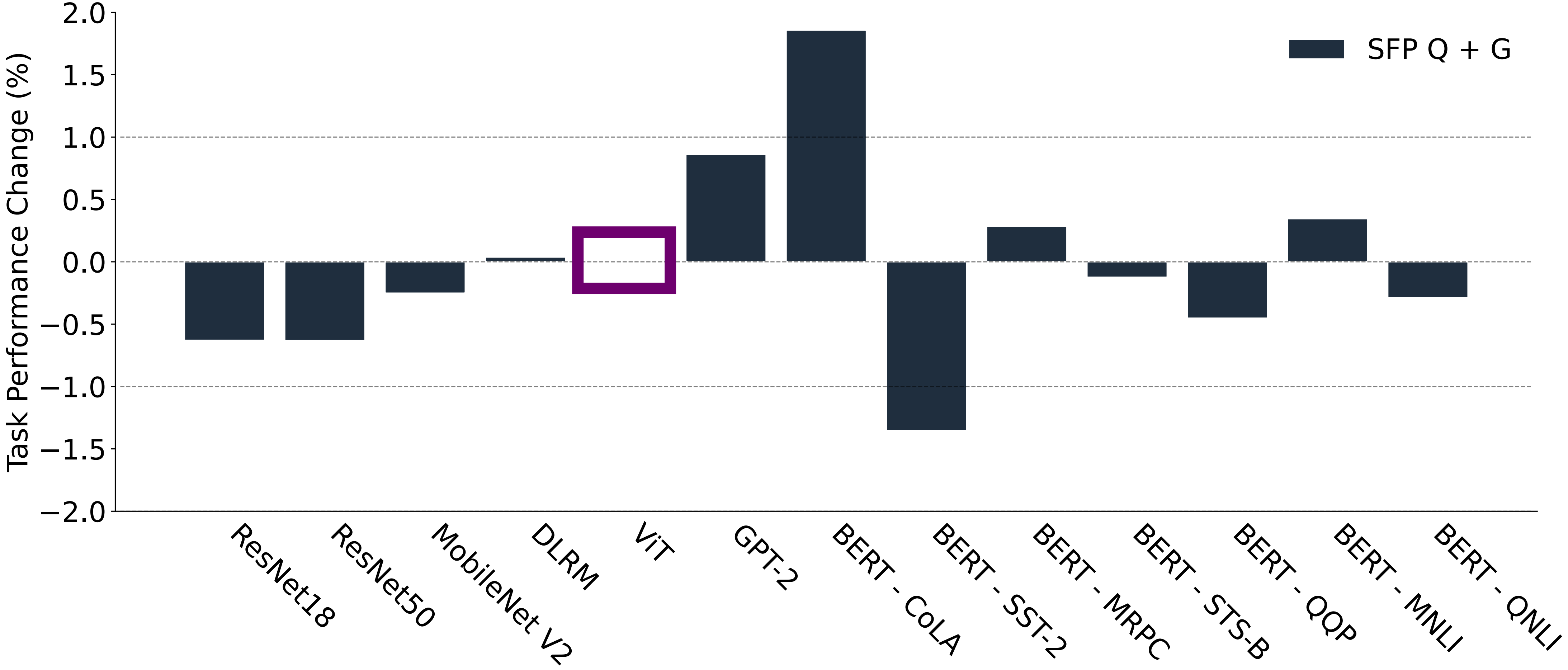

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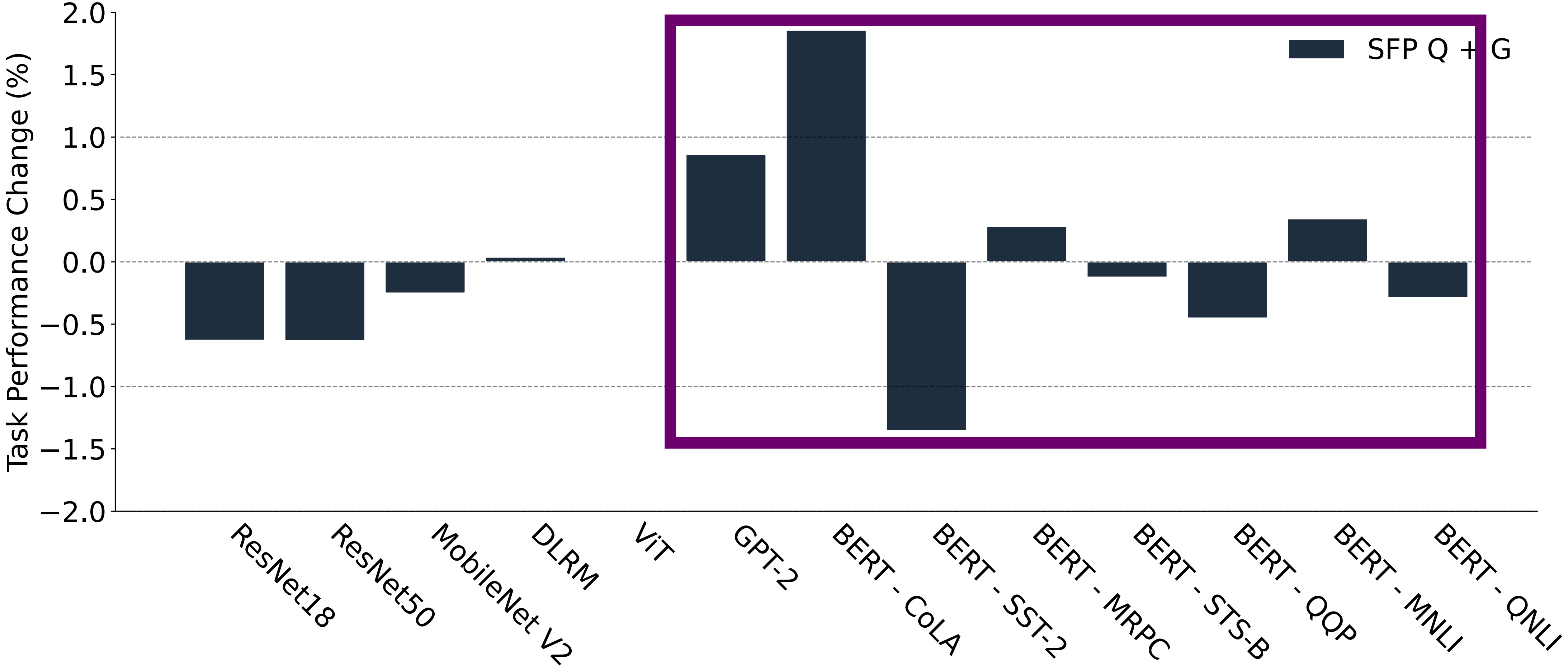

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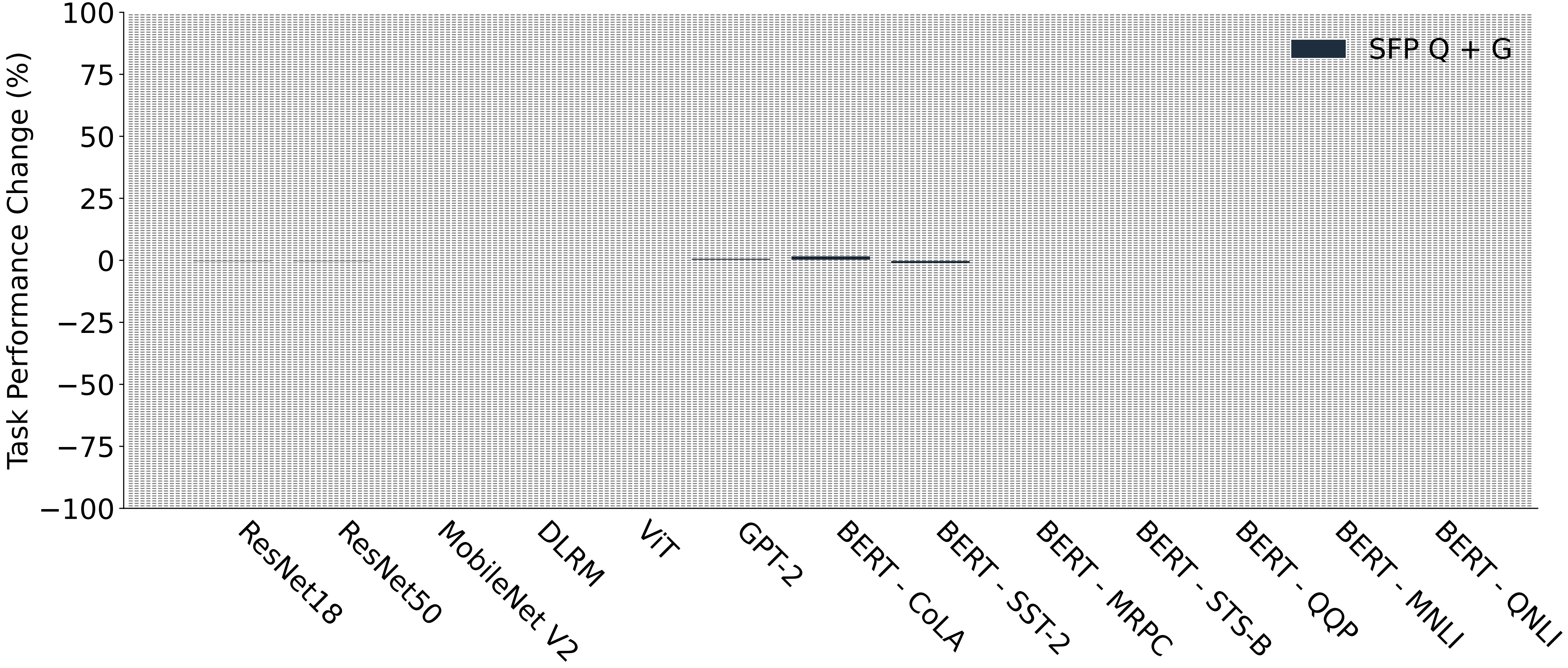
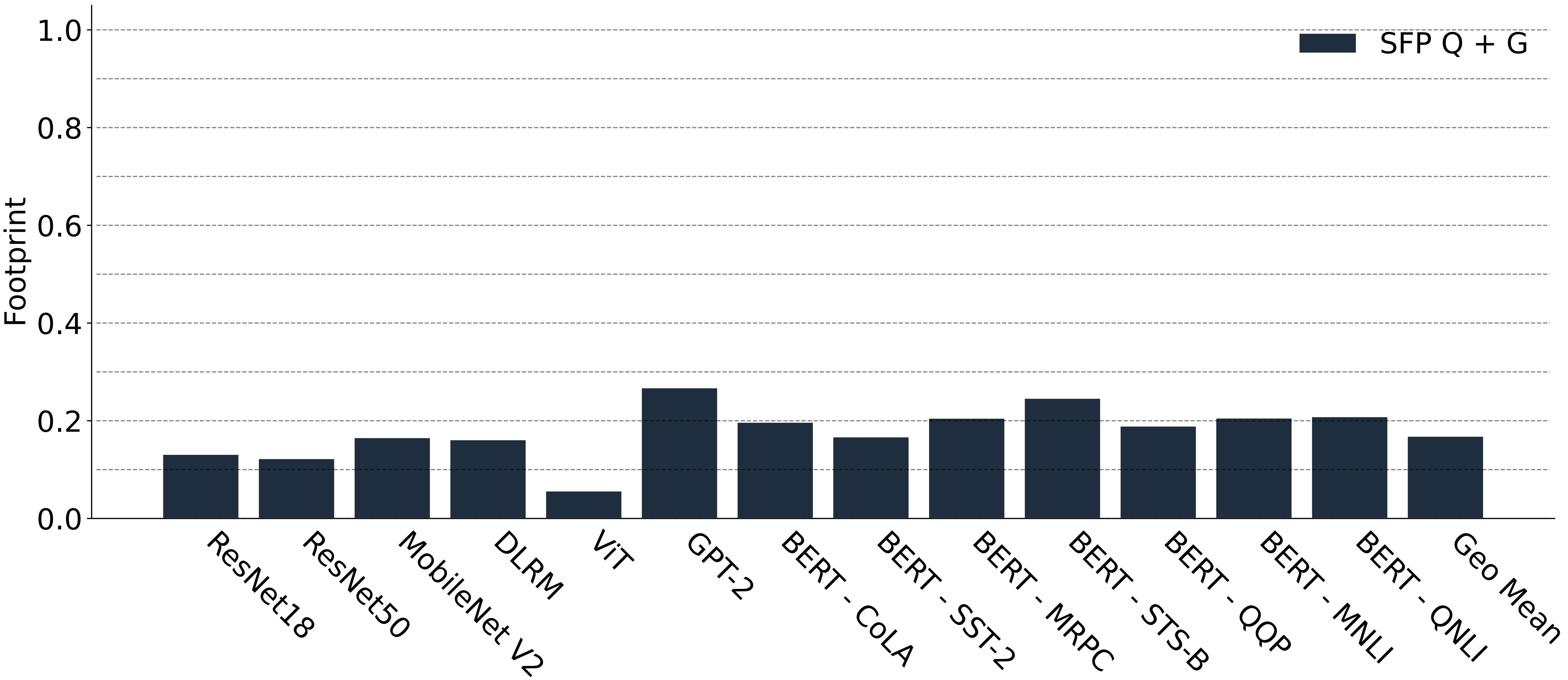


Massive footprint reduction across the board!



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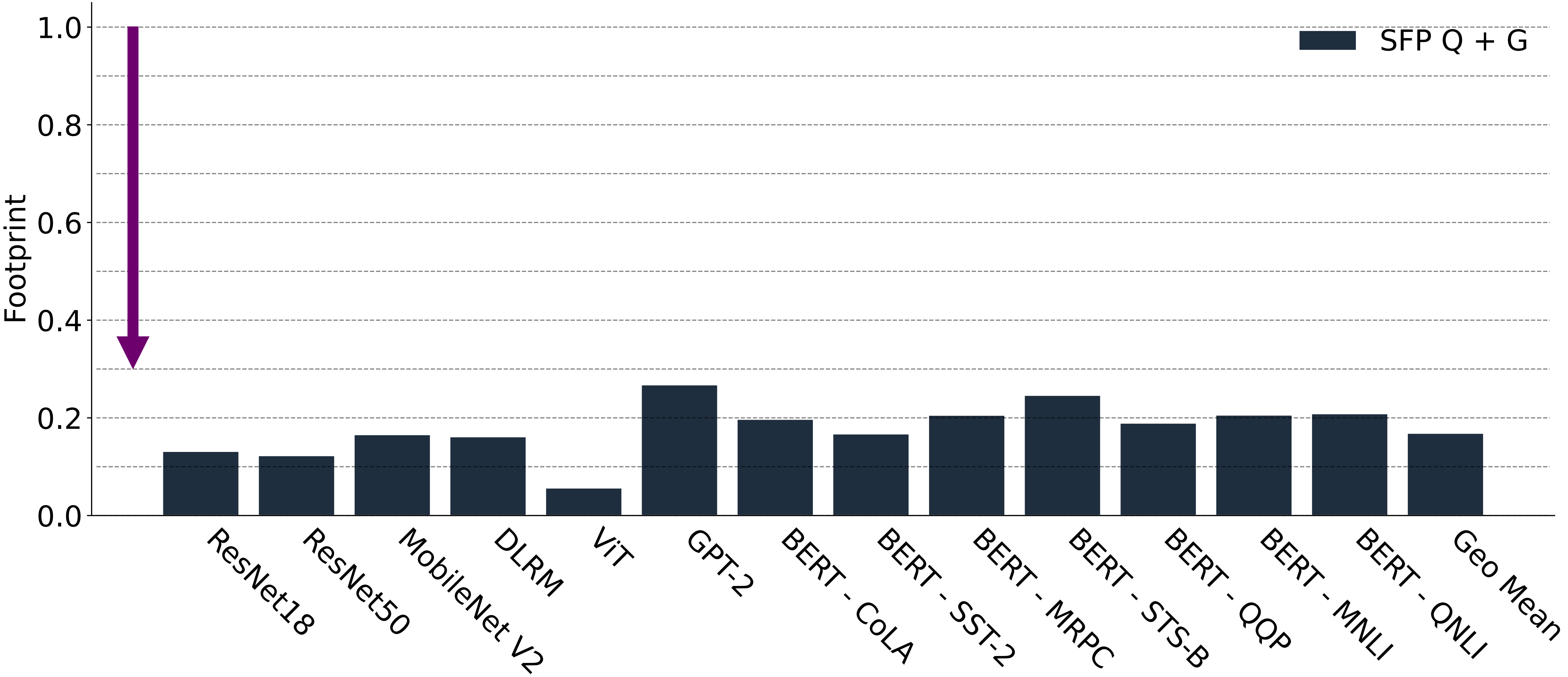

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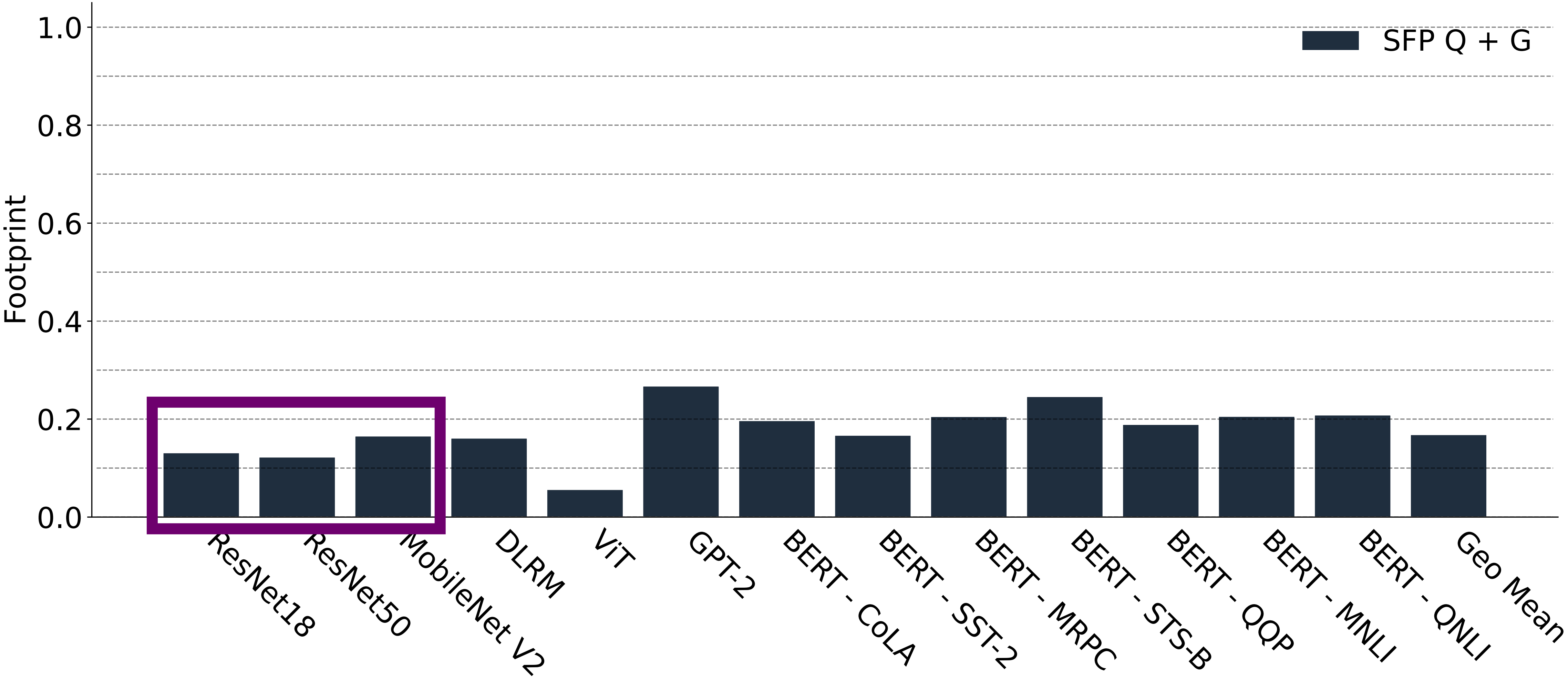

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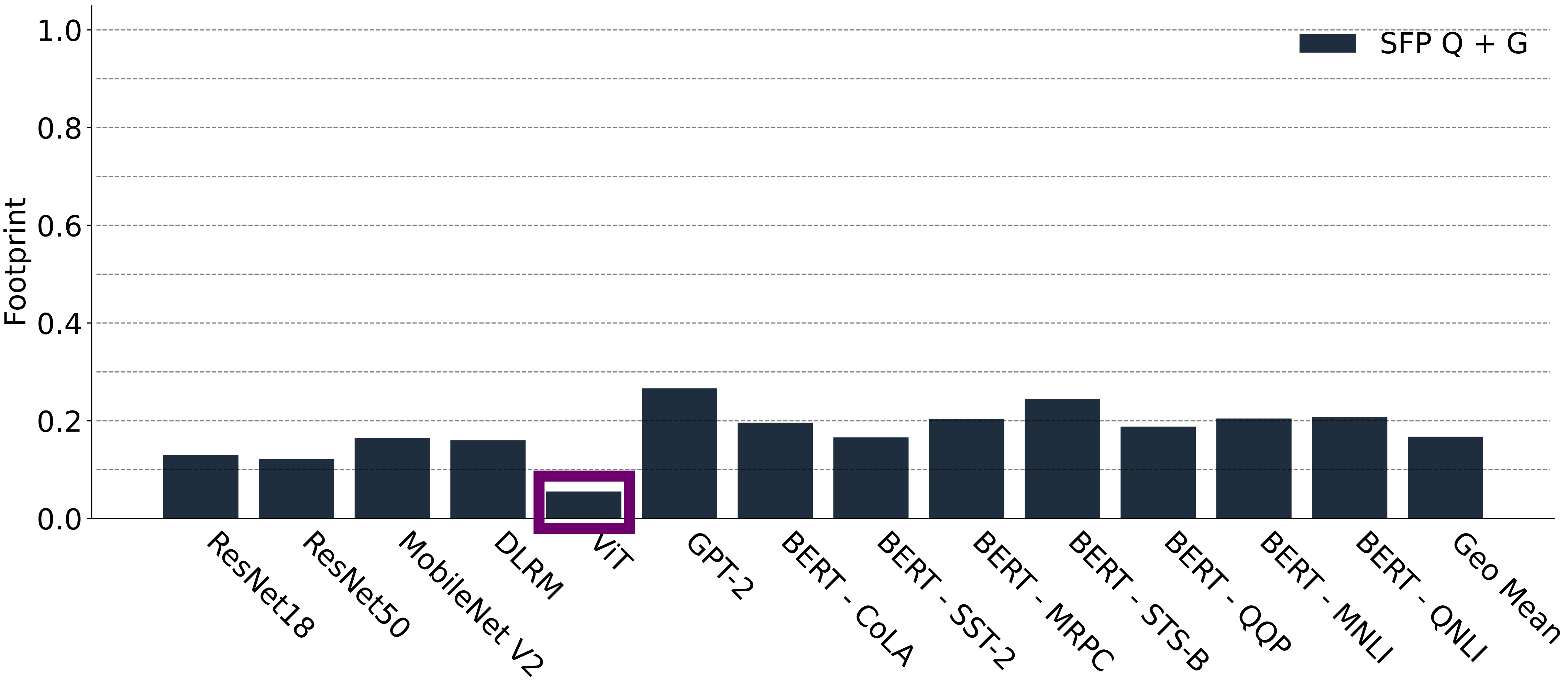

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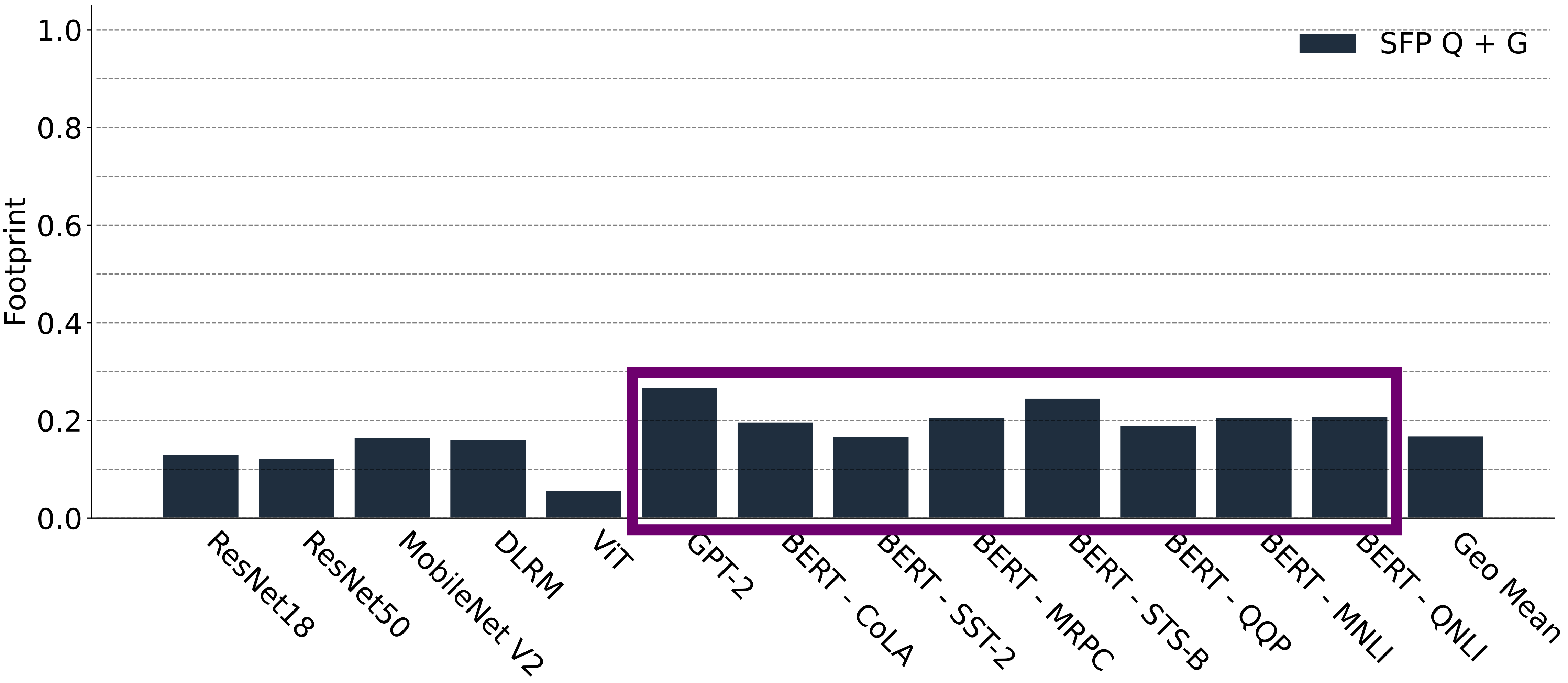

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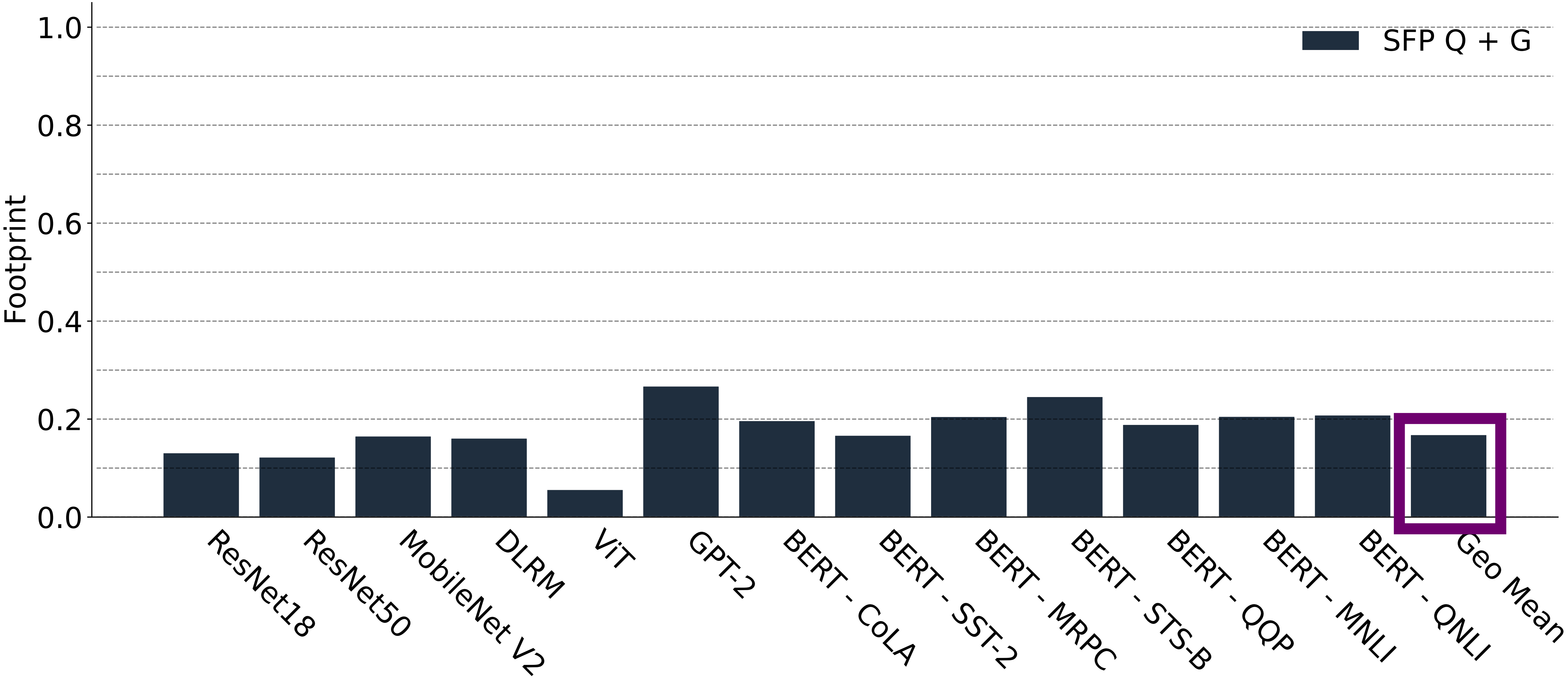

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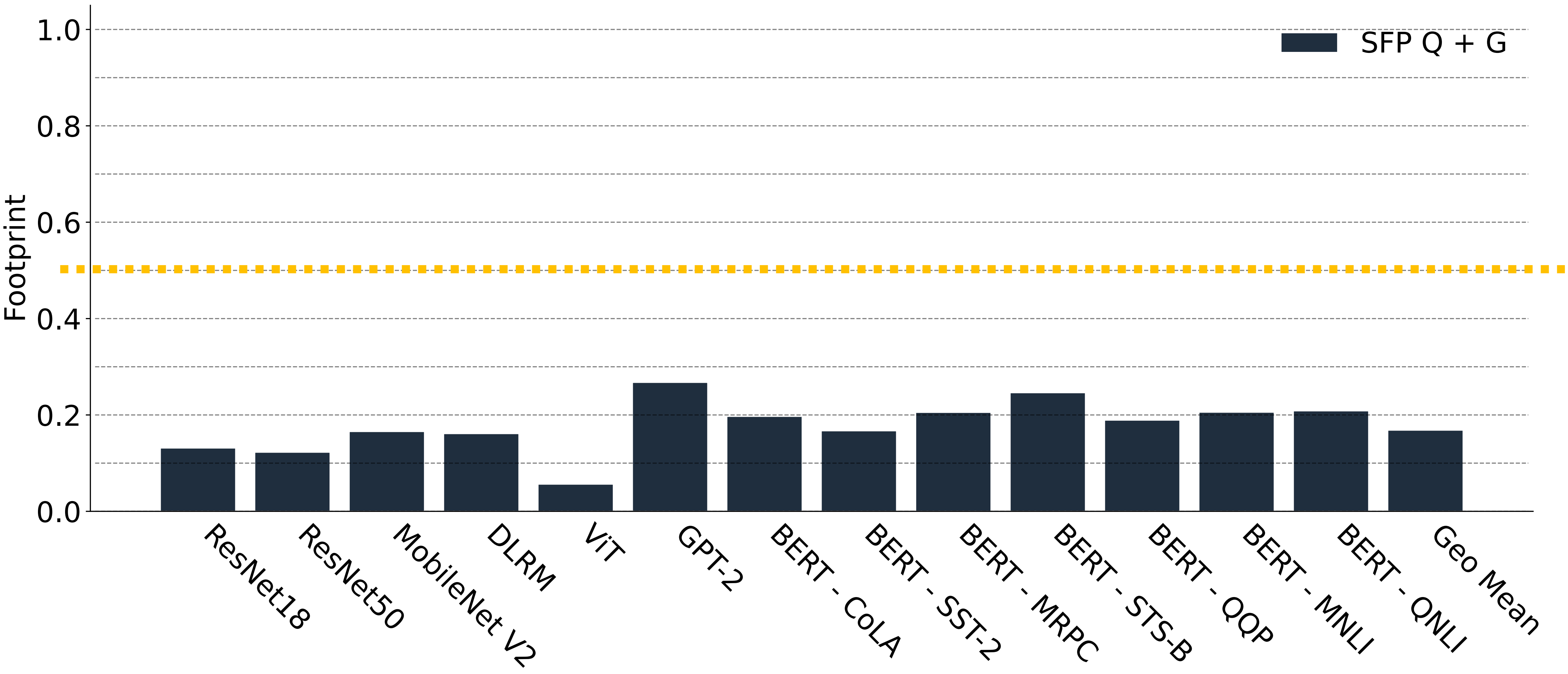

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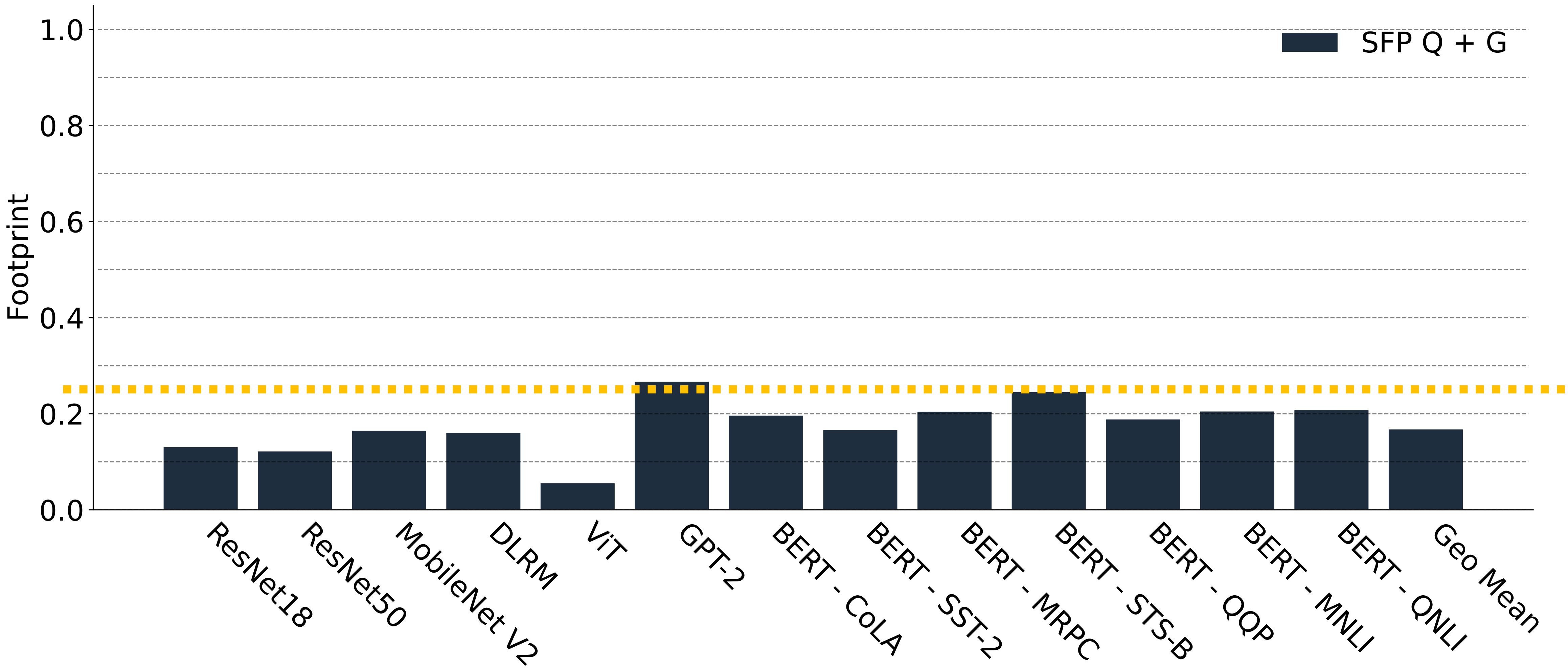
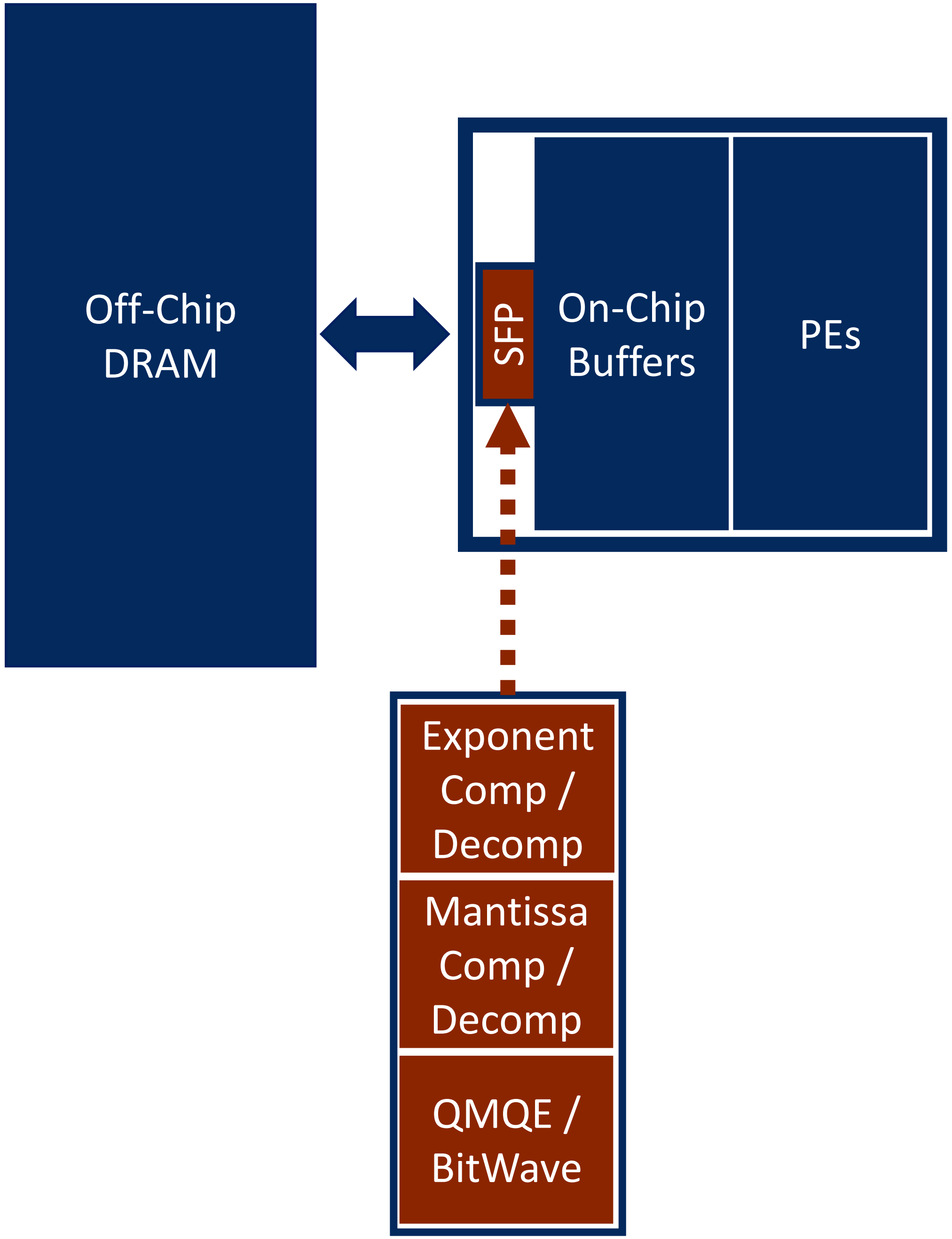


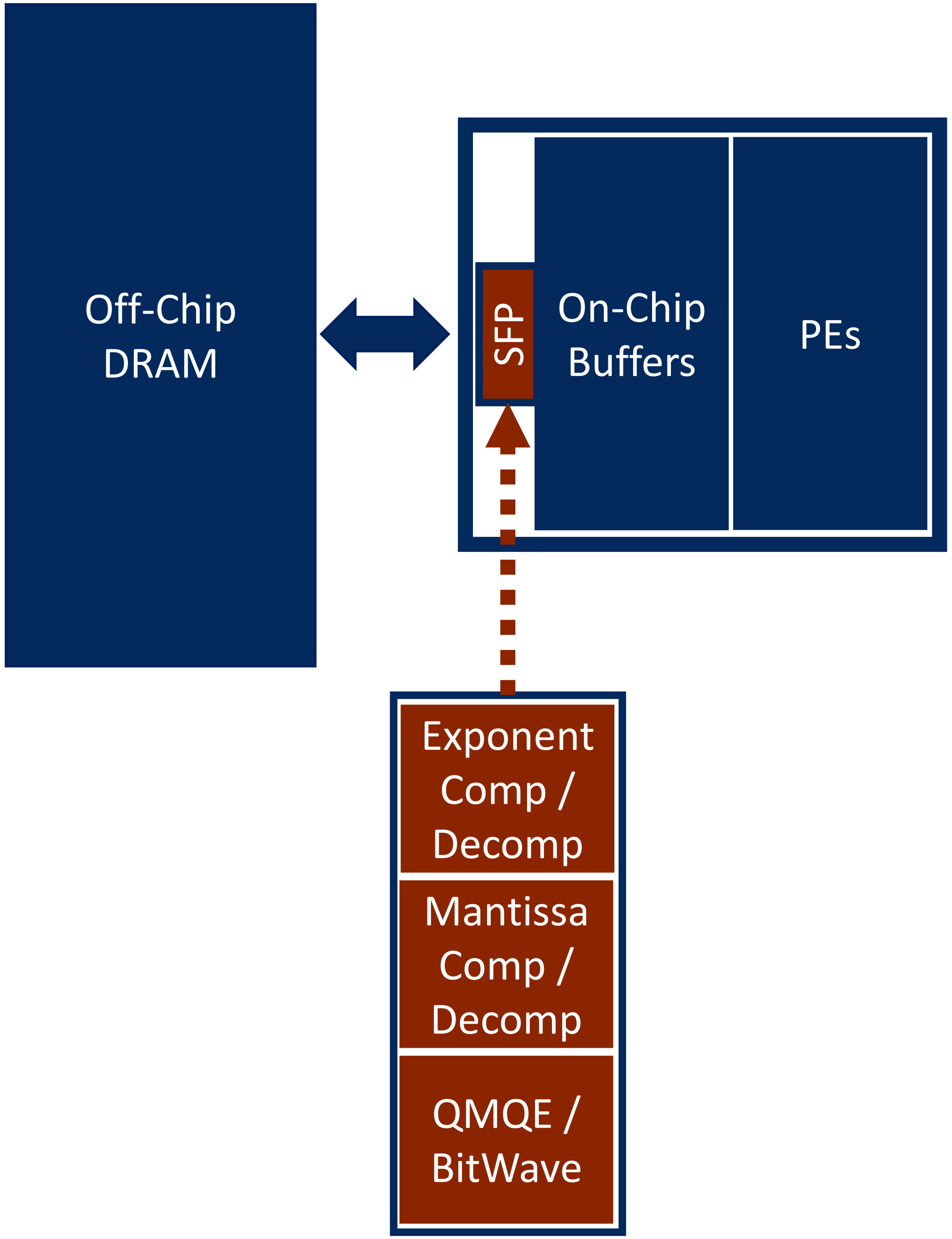
How to exploit?

- Between on- and off-chip memory



How to exploit?

- Between on- and off-chip memory
- Seamless



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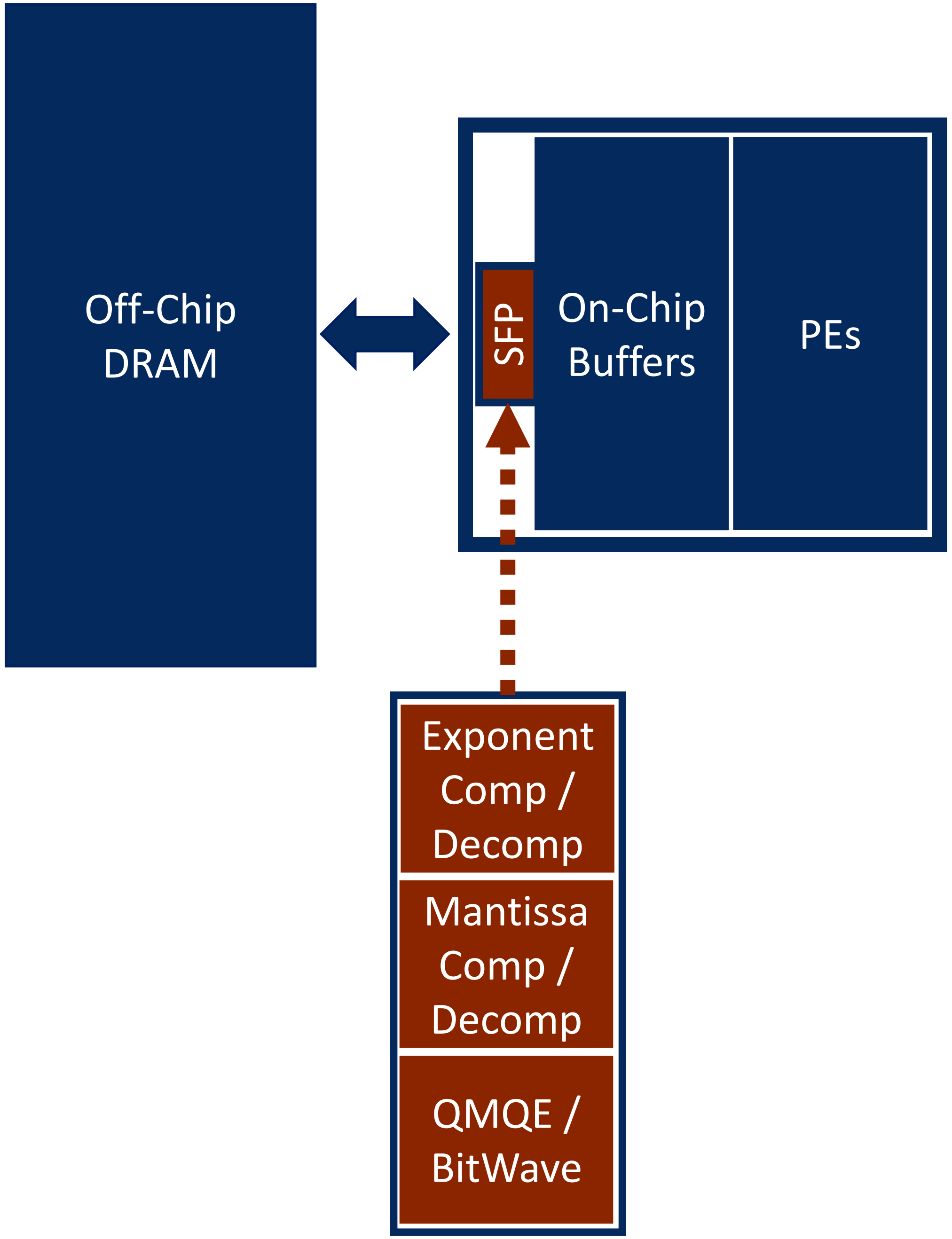
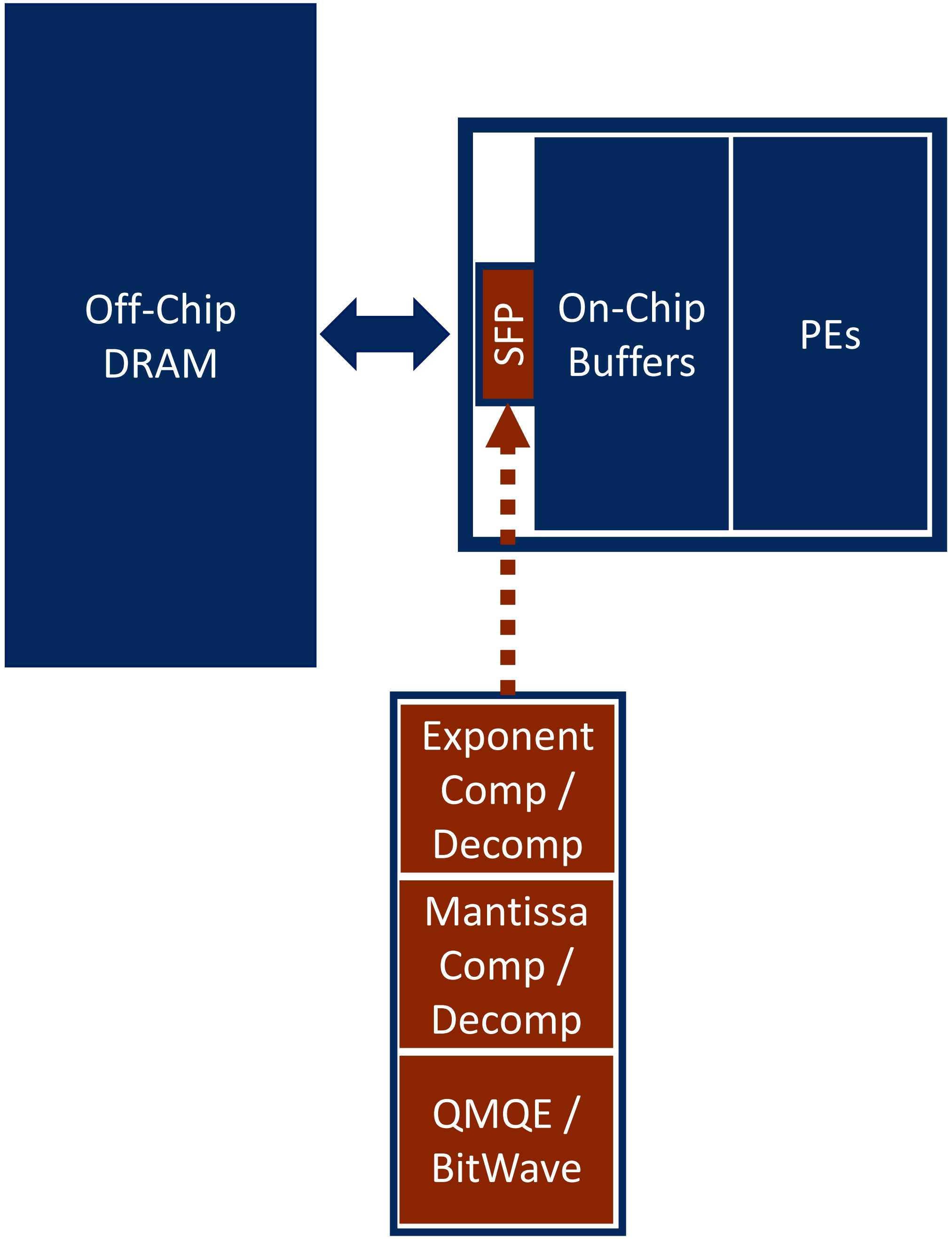


How to exploit?

- Between on- and off-chip memory
- Seamless
- Evaluate in hardware
  - Can be done in software
- vs. FP8 baseline
  - **2.6x** performance
  - **2.3x** energy efficiency



More in the paper!

- *BitWave* description & results
- Behavior through time
- Results for every network
- Hardware IP blocks
- Simulation results
- Simulation details

Conclusion

- **Schrödinger's FP**: Automatic datatype selection and compression methods

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Questions?

Miloš Nikolić <milos.nikolic@mail.utoronto.ca>