





FT2: <u>First-Token-Inspired Online Fault Tolerance on</u> Critical Layers for Generative Large Language Models

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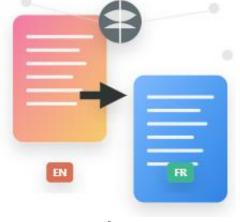
†Rutgers University

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Generative Large Language Models (LLM)

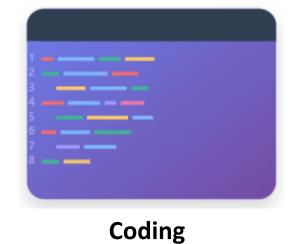


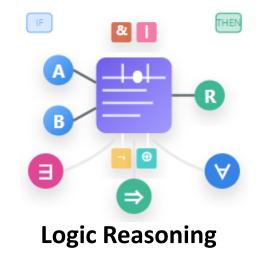




Translation

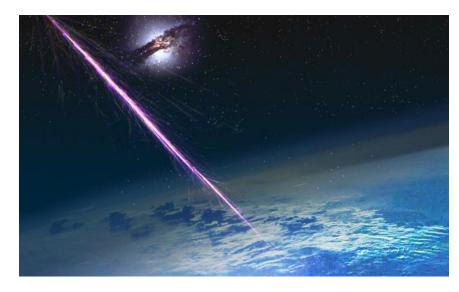




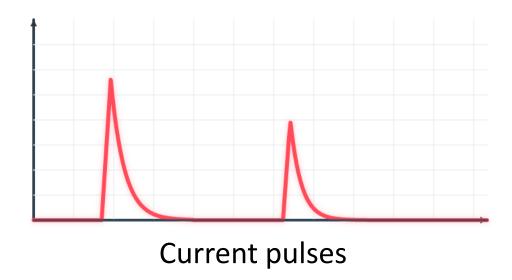


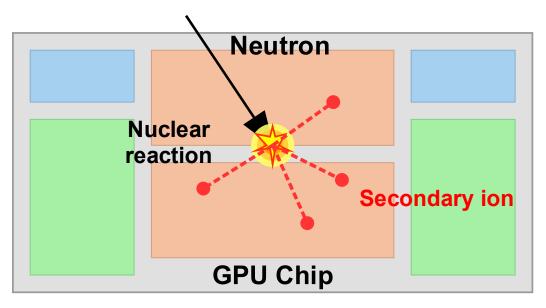


Soft Error

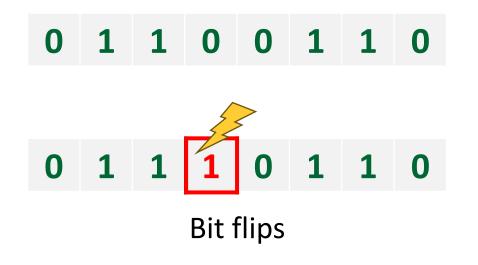


Cosmic ray





Neutrons hit silicon die



Soft Error

There are several consequences...

Text: As of August 2010, Victoria had 1,548 public schools, 489 Catholic schools and 214 independent schools..... Victoria has about 63,519 full-time teachers.

Question: How many full-time teachers does Victoria have?

Reference: 63,519

Fault-free Answer: Victoria has about 63,519 full-time teachers.

Answer with Fault Injection: The number of full-time teachers in Victoria is 63,519.

Answer with Fault Injection: The number is 1548.

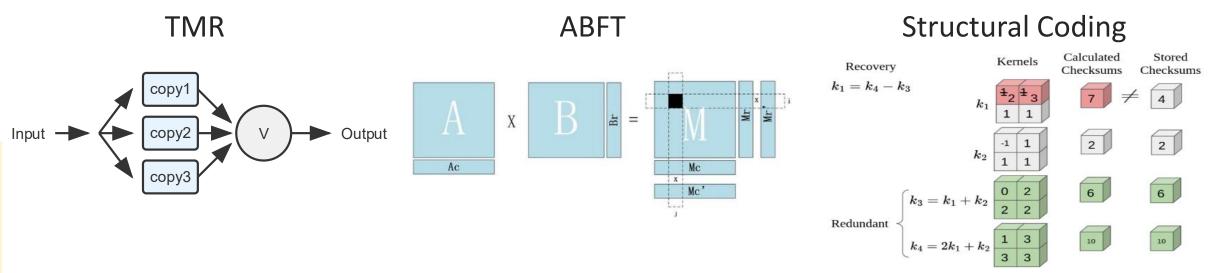
SDC! (Silent Data Corruption)

Harmful and hard to detect

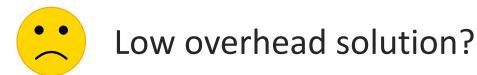
Existing Protection

TMR: Triple Modular Redundancy

ABFT: Algorithm-Based Fault Tolerance

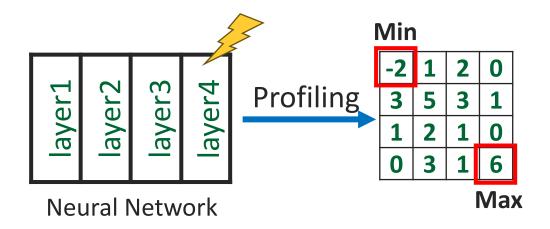


High overhead for LLMs → Larger

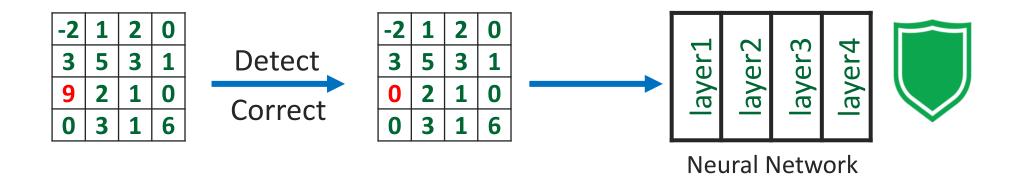


Ranger!

Ranger



Layer	Max	Min
1	-4	3
2	-3	8
3	-1	5
4	-2	6



Two limitations to apply on LLMs

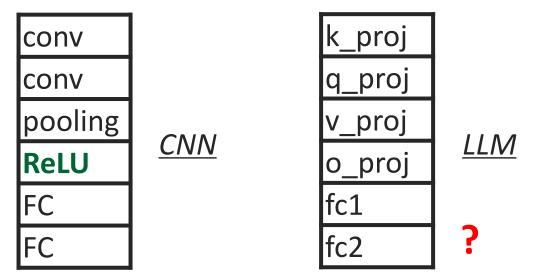


Insufficient protection Require bound profiling

Limitation 1:

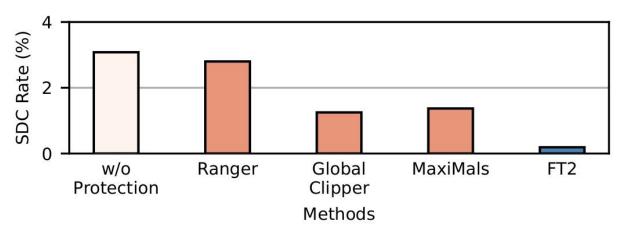
Insufficient Protection

Different layers



If choose layer unwisely

Undesirable SDC rate reduction

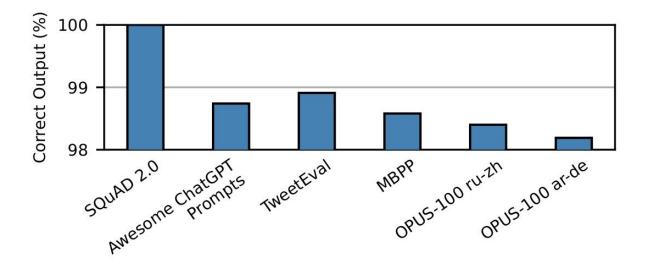


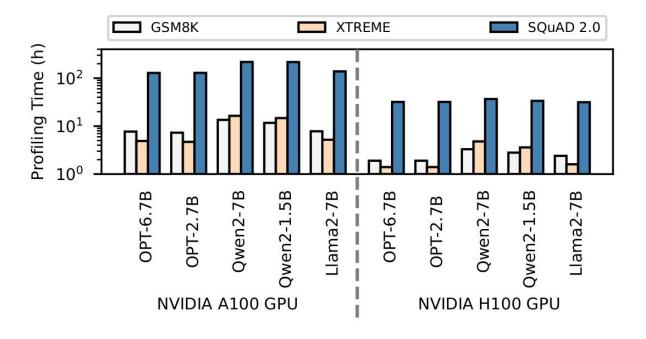
Limitation 2:

Bound Profiling

Lack of training datasets

High profiling cost





For these two limitations to apply Ranger on LLMs

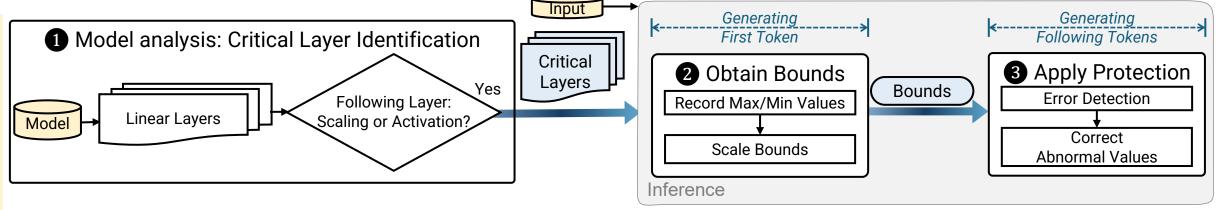
How to overcome?

- Lack of training dataset
- High profiling cost

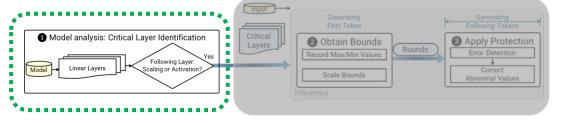
Our Methodology: FT2

FT2: <u>First-Token-Inspired Online</u> <u>Fault Tolerance on Critical Layers</u>

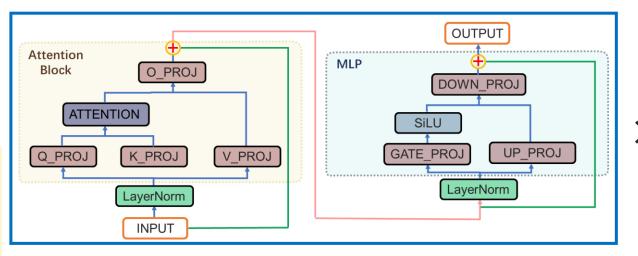
- Better Protection
- No profiling required



Identify Critical Layers



Critical layers: High SDC rate if not specifically protected

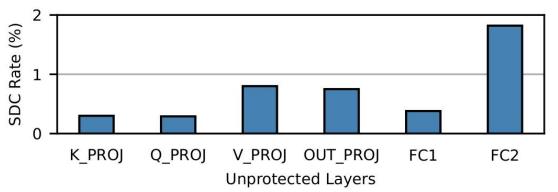


Protect all — High overhead

 $\times N$

Which layers are critical?

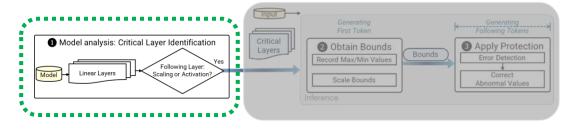
- Fault injection experiments



Model: GPTJ-6B Dataset: SQuAD2.0 Fault model: 1-bit

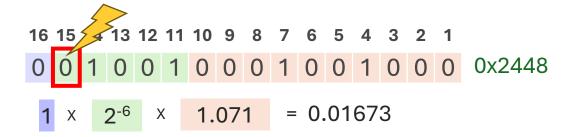
Why Critical?

Identify Critical Layers

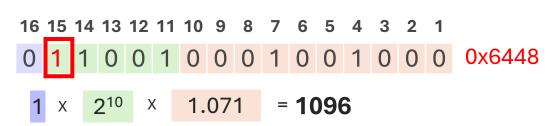


There are two types of abnormal values caused by bit flips

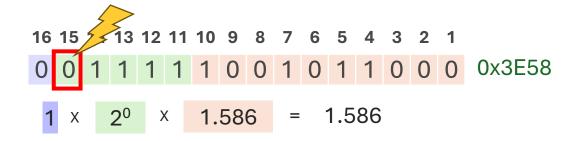
1 Extreme value



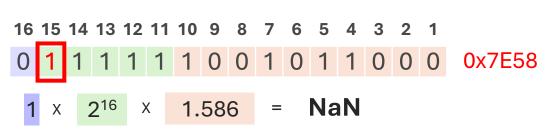




② Not a number (NaN)







Identify Critical Layers

Model analysis: Critical Layer Identification

Following Tokens

Obtain Bounds

Record Max/Min Values

Scale Bounds

Scale Bounds

Inference

Generating
First Token

Following Tokens

Scale Bounds

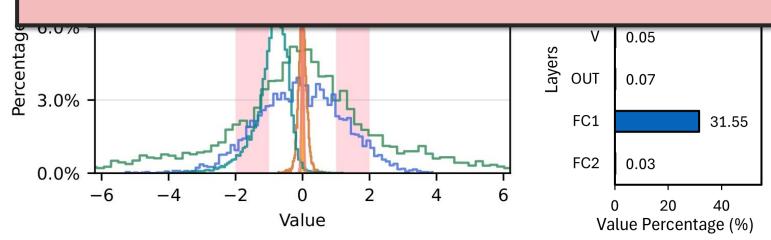
Bounds

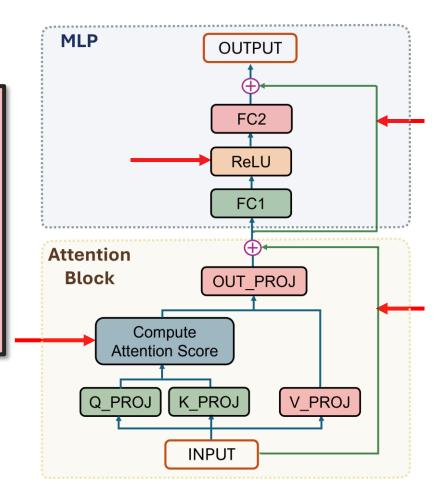
Error Detection

Correct
Abnormal Values

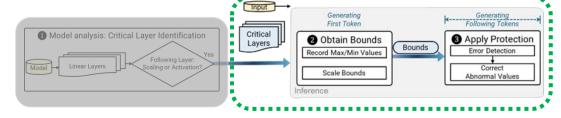
- Different neuron value distributions
 - Scaling operations

A heuristic: a layer is critical if no scaling operation or activation layer is behind.

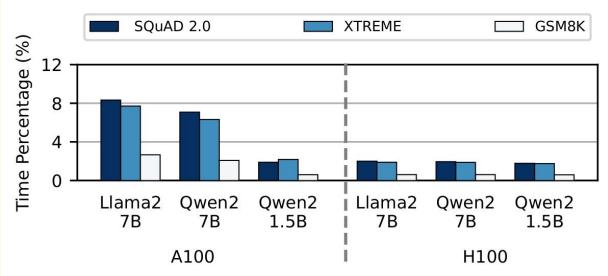


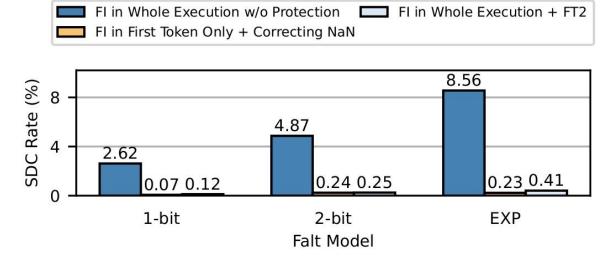


Obtain Bounds Online



- Obtain bounds from the first token generation
 - Input → *Longer*
 - Information → More
 - Bounds → More accurate
- The impact of not protecting this process is negligible





The percentage of execution time is low

The resilience is high

Evaluation: Experimental Set-up

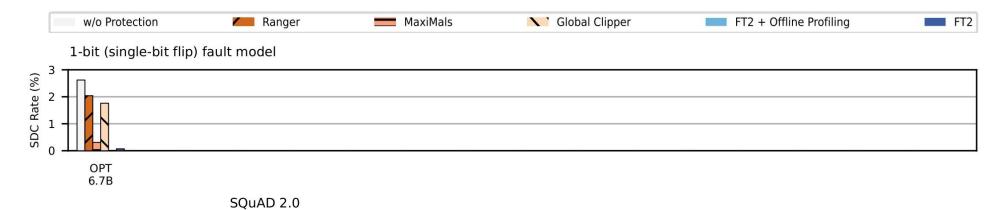
Model Name	# of Parameters	Task Type
OPT-6.7B	6.66B	QA
OPT-2.7B	2.65B	QA
GPTJ-6B	6.05B	QA
Llama2-7B	6.74B	QA/MATH
Vicuna-7B	6.74B	QA
Qwen2-7B	7.62B	QA/MATH
Qwen2-1.5B	1.54B	QA

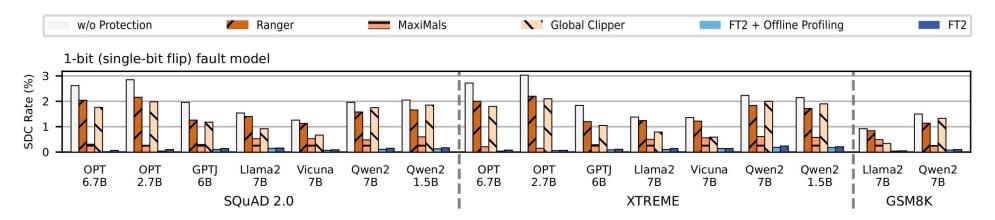
- 7 models covering 2 architectures
- 3 datasets from 2 tasks
- *Datatype*: FP16 and FP32
- 2 GPU configurations: NVDIA A100 and H100 GPU
- 3 fault models: 1-bit, 2-bit and EXP

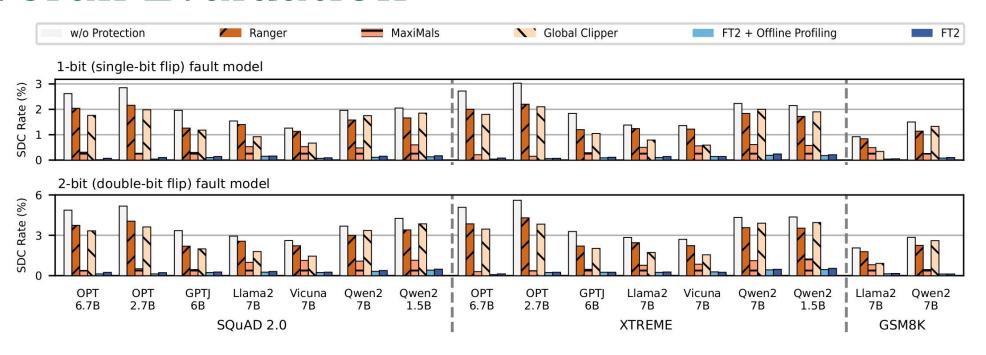


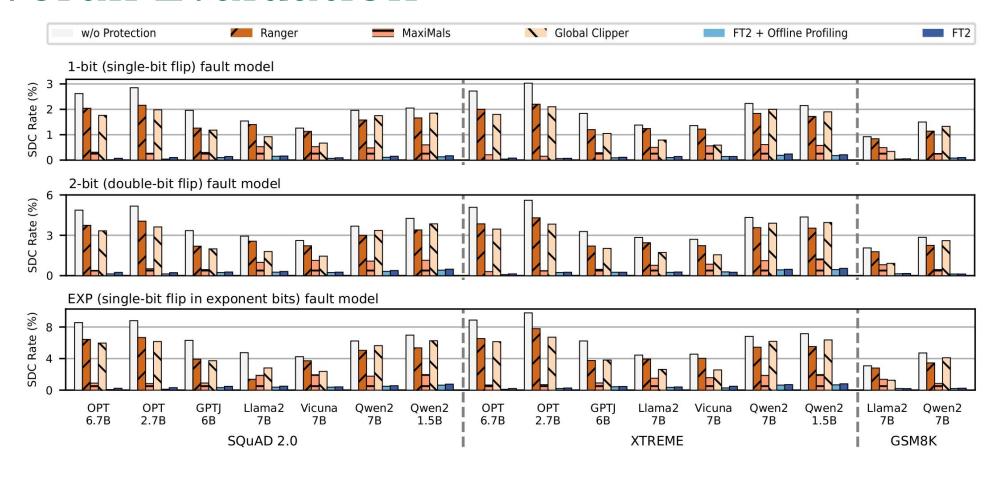






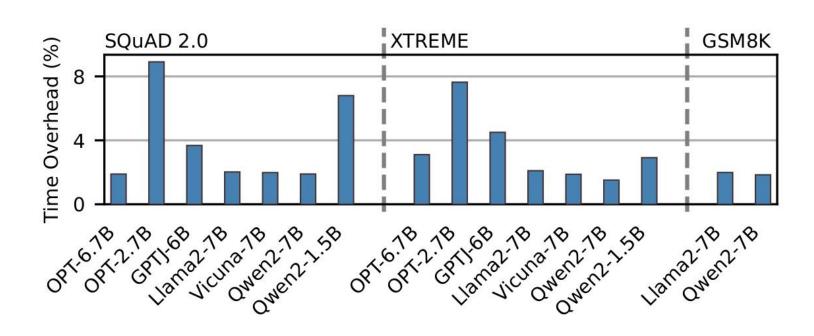






- FT2 outperforms all baselines among all models, datasets, and fault models
- The average SDC rate reduction is 92.92%

Evaluation: Overhead

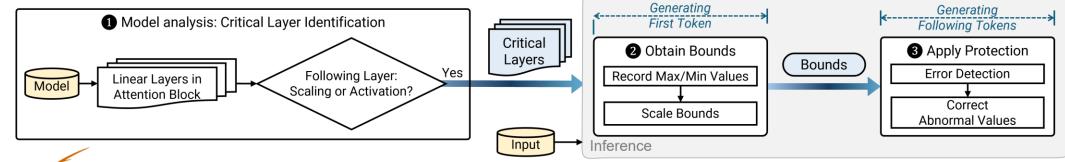


- FT2 introduces 3.42% runtime overhead on average
- Memory overhead is negligible (288 512 Bytes, <0.2% for all models)

Conclusion

- LLMs suffer from soft errors
 - Leads to SDC → Harmful and hard to detect
- Ranger has limitations applying to LLMs
 - Insufficient protection
 - Require bound profiling
- Our method: FT2
 - Identify and protect critical layers → high efficiency and low overhead
 - Obtain bounds during first token generation → no offline profiling
- Achieve 92.92% SDC rate reduction
- Only 3.42% overhead on average
- Code at https://github.com/pipijing13/FT2-LLM-inference-protection





Thank you



Pacific Northwest

FT2: <u>First-Token-Inspired Online Fault Tolerance on</u> Critical Layers for Generative Large Language Models











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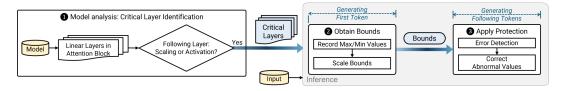


Resilience Estimation

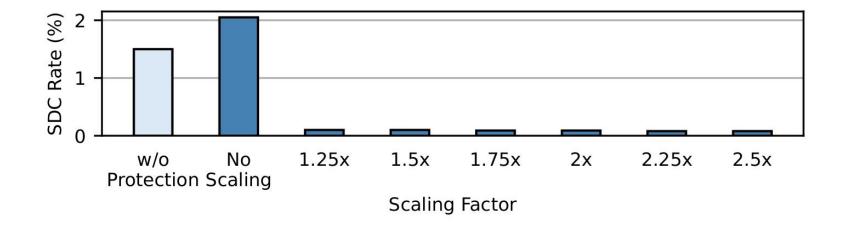
ALUs: Arithmetic Logic Units ECC: Error Correction Code

- Computational faults
- Affect computational hardware components such as ALUs
- Memory faults are protected by ECC
- Fault models
- <u>1-bit</u>: single-bit flip
- <u>2-bit</u>: double-bit flip
- *EXP*: single-bit flip in **Exponent** bits (most severe)
- Inference phase
- Fault injection
- Into neurons which represent computation results
- Random select fault sites (block, layer, neuron, bit)

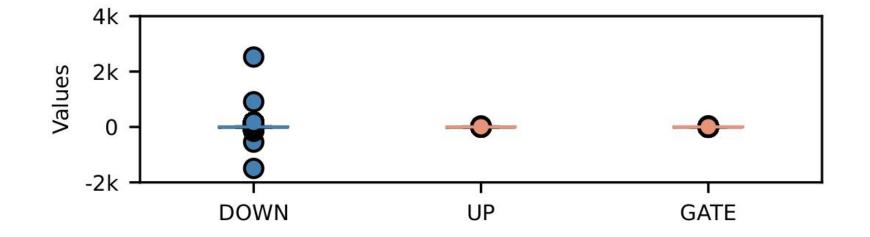
Apply Protection



Scale the bounds



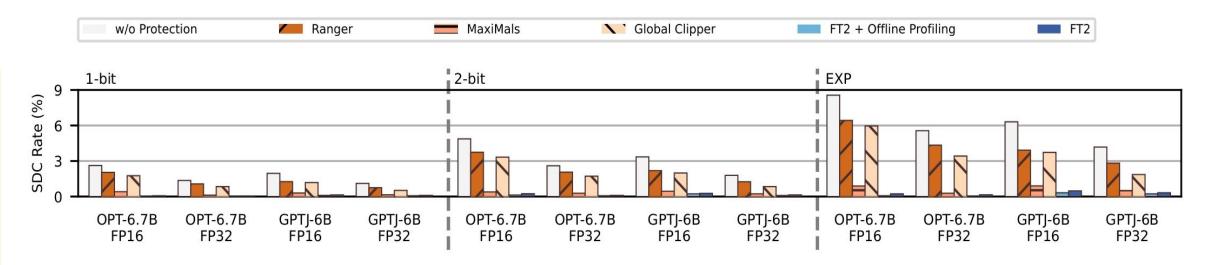
- Clip to bounds



Evaluation: Data Type

FT2 can effectively protect both FP16 and FP32 LLM inference

(Animations here)



Evaluation: GPU Configurations

FT2 is feasible among different generations of NVIDIA GPUs (A100 and H100)

(Animations here)

