FlexInfer: Breaking Memory Constraint via Flexible and Efficient Offloading for On-Device LLM Inference

EuroMLSys '25, March 31, 2025, Rotterdam, Netherlands

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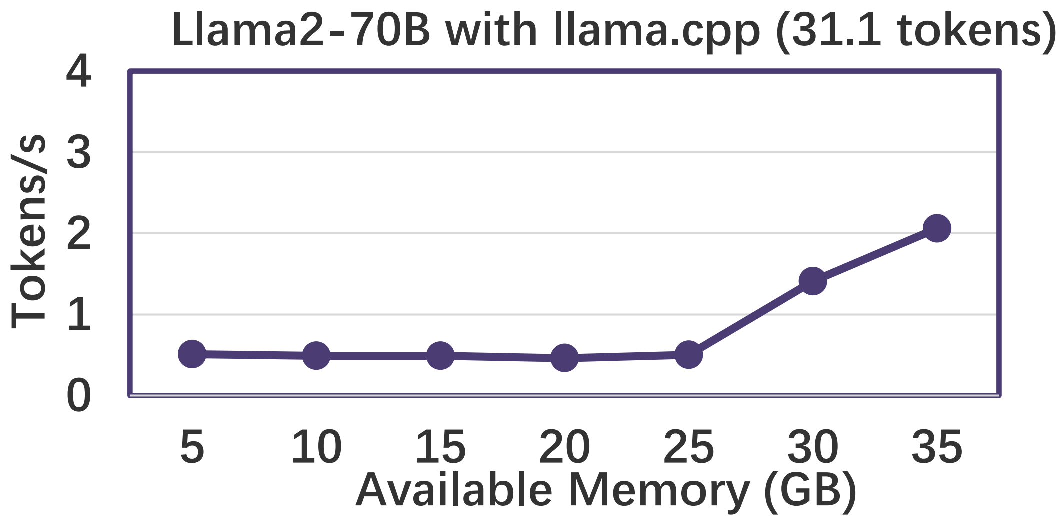
Background: On-Device LLM Inference Challenges

- **LLMs demand high memory, exceeding device capacity**
  - E.g., 36.2GB for 4-bits quantized Llama2-70B
- **Cloud deployment raises privacy and customization issues**



Limitations of Current Solutions:

1. Model compression **sacrifices accuracy**
2. Offloading to storage causes **high I/O overhead**
3. Cannot adapt to **varying memory budgets**

Question: How can we achieve efficient and flexible on-device LLM inference?

Motivation: Optimizing Offloading for On-Device LLMs

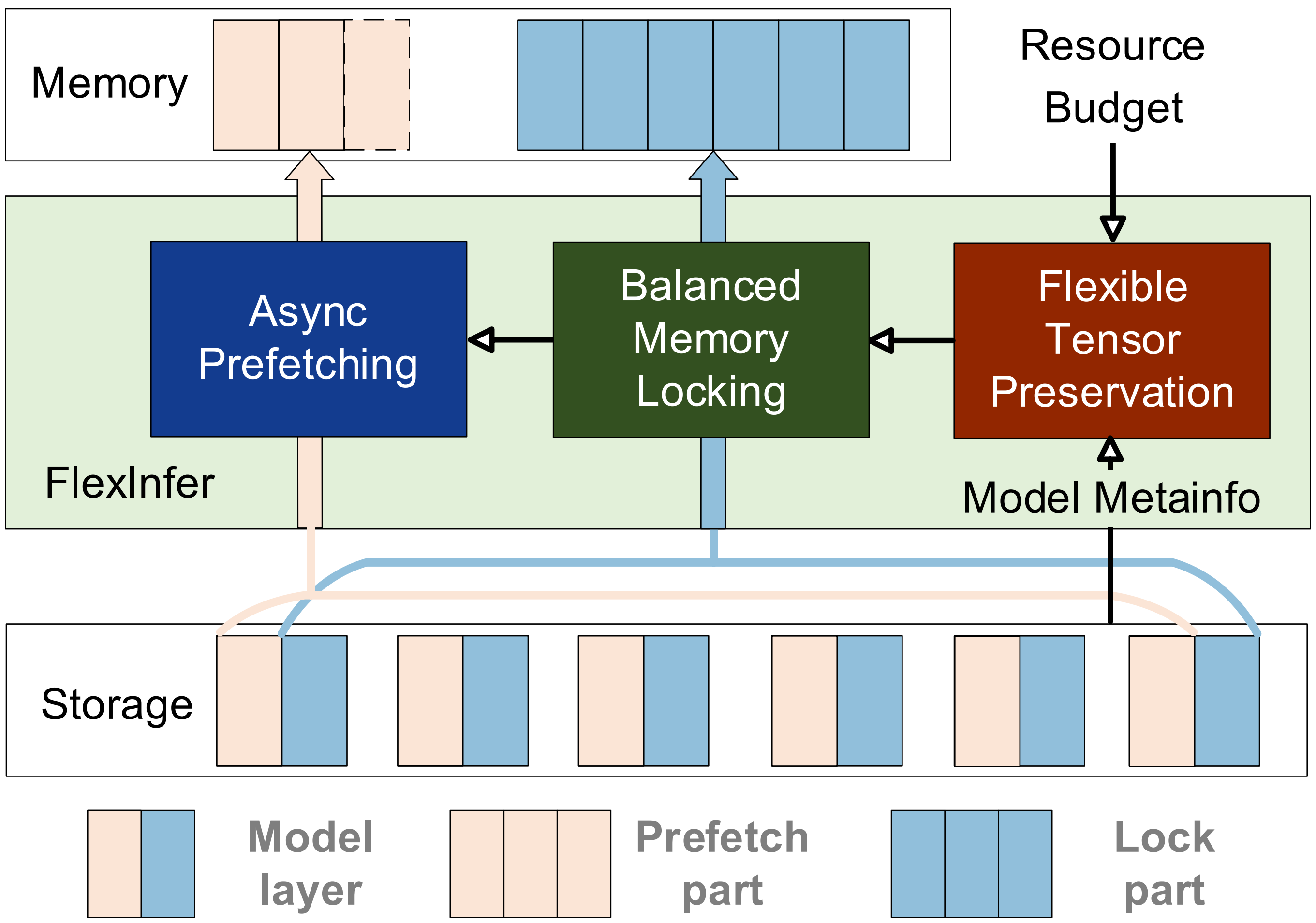
- **Current offloading suffers from high I/O overhead**
  - $T_{IO} = \frac{Size_{model}}{BW}$, $\mathrm{P}_{sync} = \frac{1}{T_{IO} + T_{CPU}}$, $\mathrm{P}_{async} = \frac{1}{\max(T_{IO}, T_{CPU})}$
  - **Key factors**: Improve I/O performance (BW) and parallelism
- **Need flexibility to adapt to varying memory budgets**
  - Maximize performance with available memory
  - **Requirement**: Adaptive fine-grained memory management method
- **FlexInfer**
  - Optimize IO performance with targeted asynchronous prefetching
  - Enhance parallelism via careful parameter partitioning
- **Targets:**
  - Performance close to the theoretical upper limit
  - Scales linearly with available memory

Outline

FlexInfer: Flexible and Efficient Offloading

- **Overview**
  - Layer-wise prefetch to optimize I/O performance
  - Tensor-level memory management for flexibility
- **Key Components**
  - 🚀 **Async Prefetching**: Overlap I/O & compute to hide latency
  - ⚖️ **Balanced Locking**: Uniform allocation to maximize parallelism
  - 🔧 **Flexible Preservation**: Retain critical tensors for any memory budget

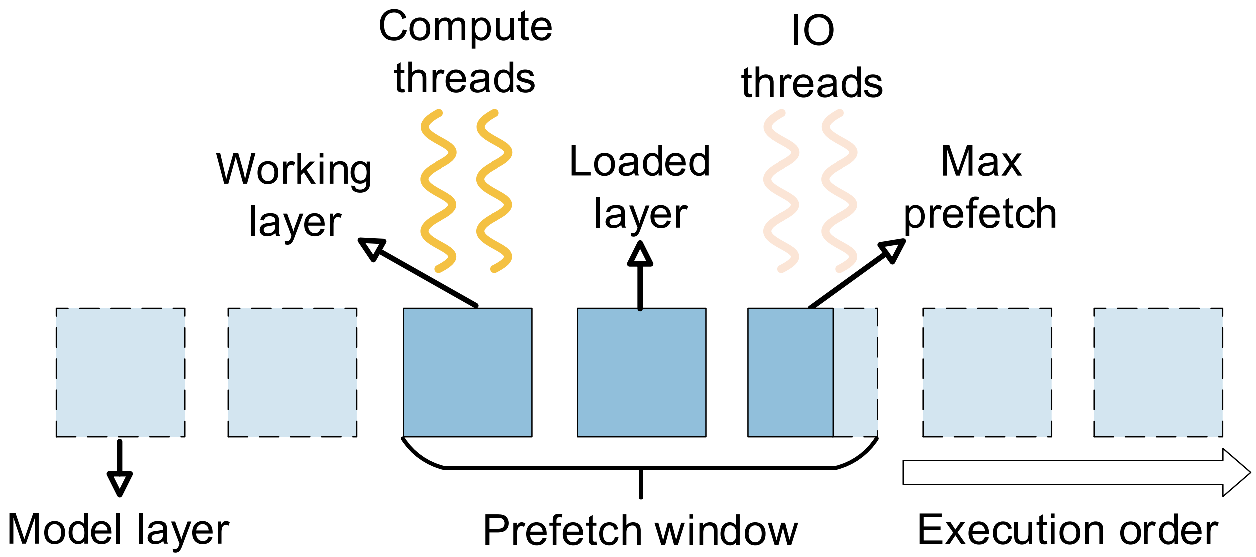
FlexInfer Workflow Overview



FlexInfer: Asynchronous Prefetching

- **Goal:** Maximize the IO efficiency of the prefetch threads
- **Mechanism**
  - 🧵 **Multi-threading**: Dedicated I/O threads prefetch next layers
  - 🗑️ **Memory Release**: Free parameters immediately after use
  - 🔒 **Atomic Sync**: Ensure correct execution order

Asynchronous Prefetching Workflow



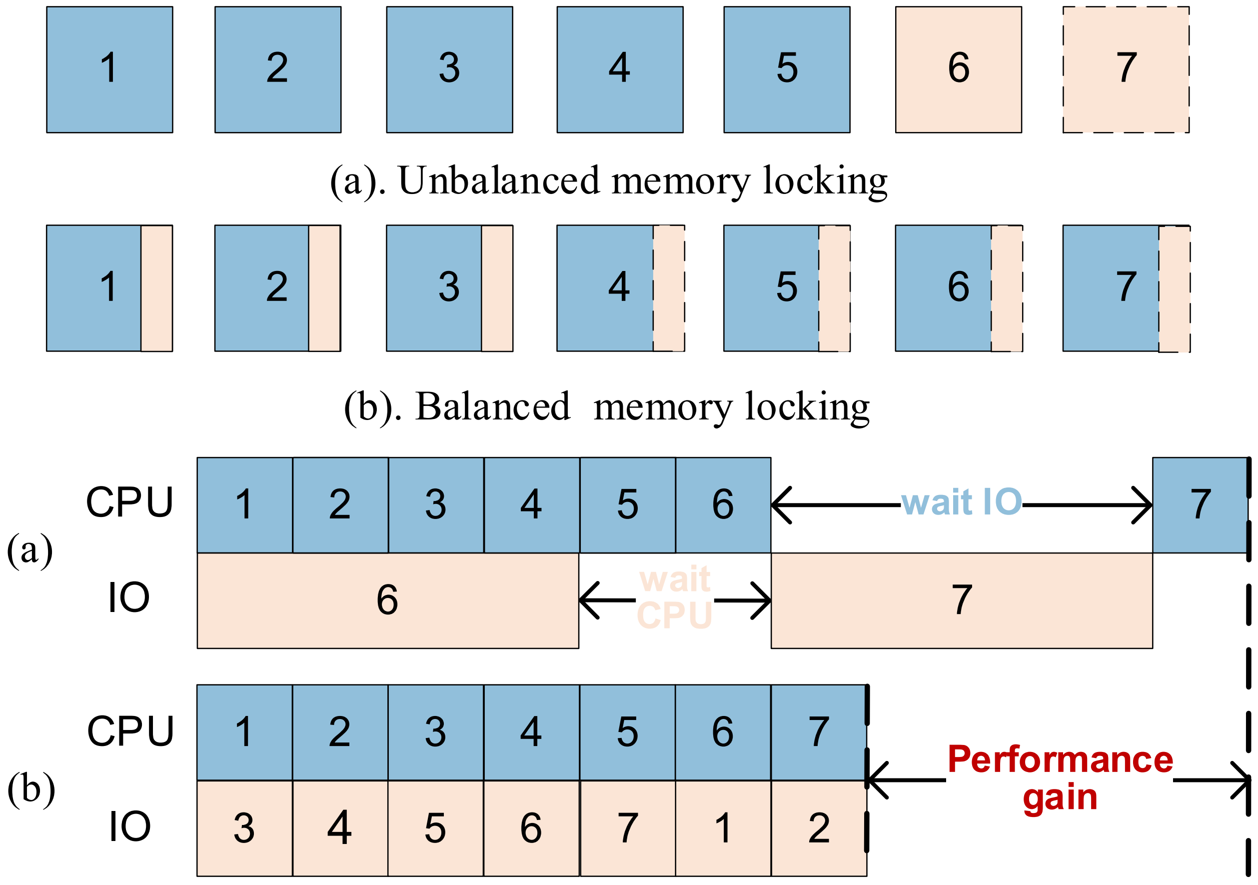
2.6~3x IO efficiency compared to mmap

34.8~59.4% faster by parallelizing computation and IO

FlexInfer: Balanced Memory Locking

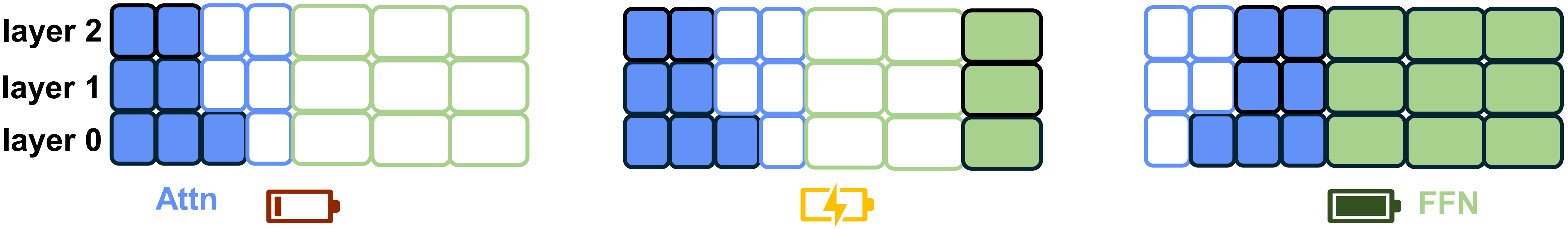
- **Mechanism:** Lock parameters using available memory
- **Key points:** Uniform allocation to maximize parallelism
- **Policy**
  1. **Unbalanced (Fails)**
     ❌ **Fixed layers cause I/O waits, reducing parallelism**
  2. **Balanced (Succeeds)**
     ✅ **Uniform splitting enables full parallelism**
     ✅ **Up to 56.8~83.3% throughput improvement over unbalanced locking**

Unbalanced vs. Balanced Locking



FlexInfer: Flexible tensor preservation

- **Observations**
  - **Attn** and **FFN** tensors impact performance differently under varying memory budgets
- **Key points:** Adopt **different lock policy** under different memory budget
  - High memory: Keep **FFN** first to keep IO uniform
  - Low memory: Keep **Attn** to reduce IO number
  - Intermediate case: Mix **FFN** and **Attn** with heuristic selection
- **Result**: Up to **21.9%** improvement compared to static policy



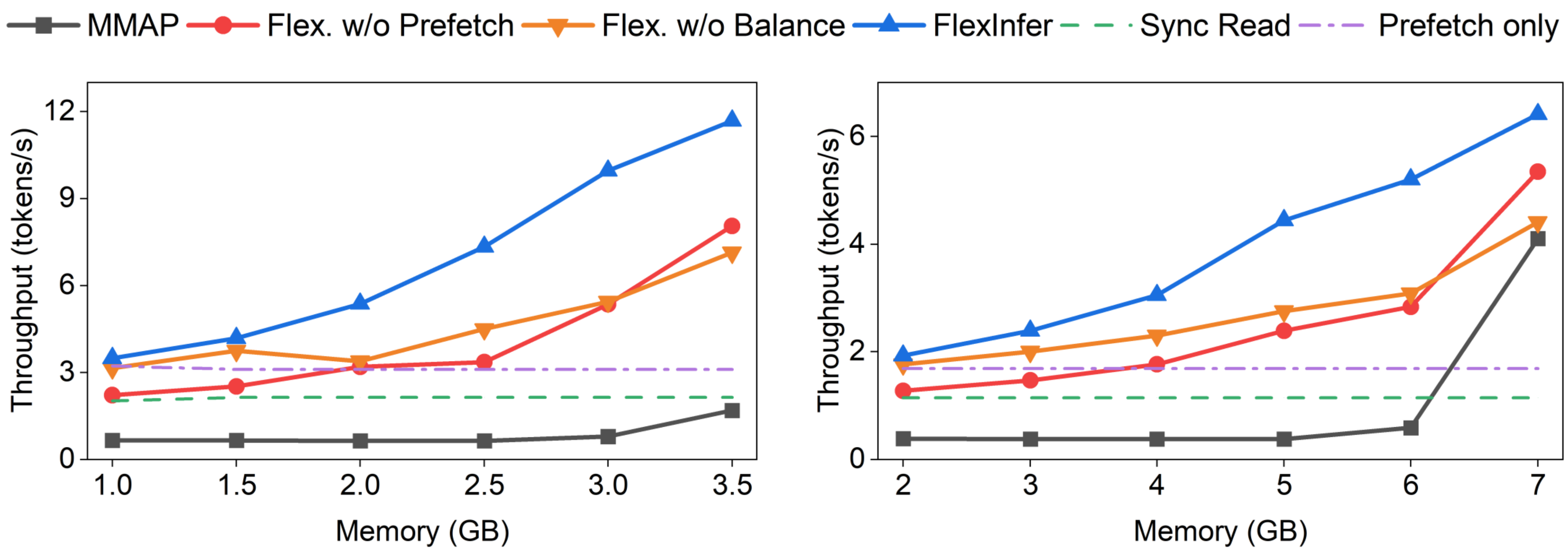
Outline

- Background and Motivation
- FlexInfer: Flexible and Efficient Offloading for LLM Inference
- Evaluation
- Conclusion

Evaluation Setup

- **Environment**
  - ⚙️ Hardware: AMD 7995WX CPU, 512GB DDR5 DRAM, 2TB Crucial T700 SSD
  - 🖥️ Software: Extended llama.cpp
    - Taskset and cgroup to simulate resource-constrained devices
- **Models & Baselines**
  - 🦙 Llama2-7B/13B/70B, Codellama-34B under 4-bit quantized
  - 🆚 MMAP, FlexInfer w/o x, Sync Read, Prefetch only
- **Metrics**
  - 🚀 Throughput (tokens/s)
- **Configurations**
  - 📥 Prefetch Window = 3 layers
  - 🛠️ CPU core number = 8 cores

Evaluation Results: Throughput

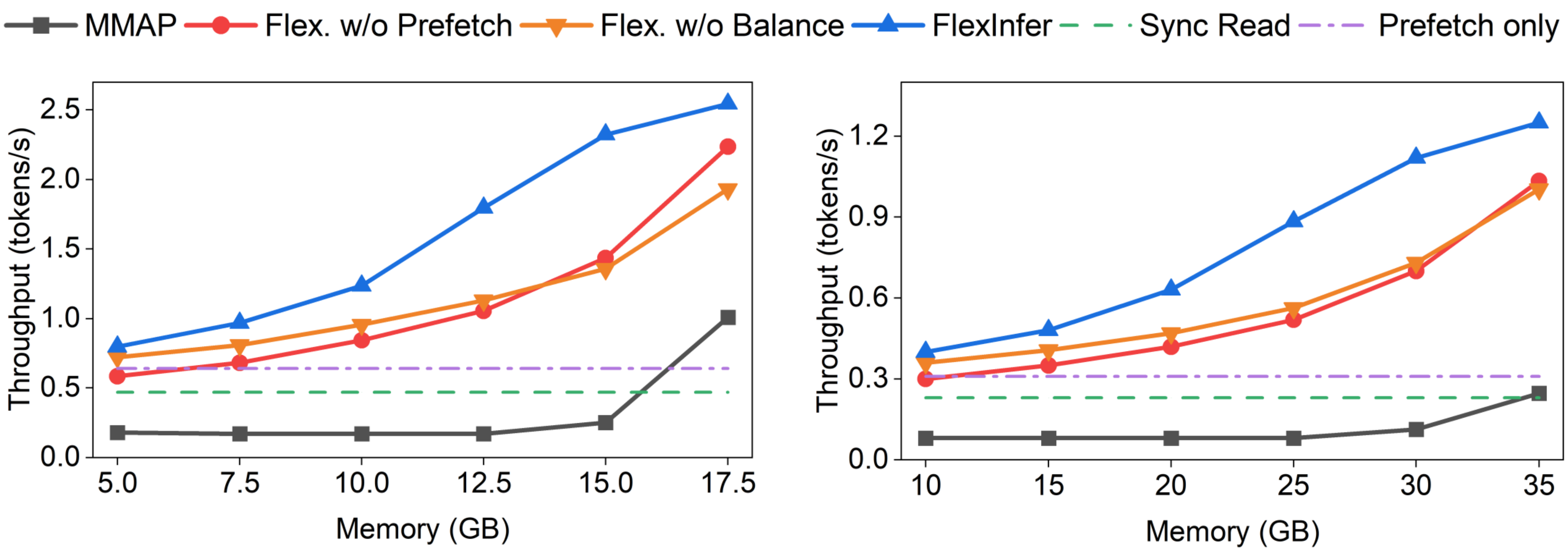


Llama2-7B (3.8GB, 12.72 tokens/s)

Llama2-13B (7.3GB, 6.74 tokens/s)

FlexInfer achieves performance improvement of 5.2-12.5x, 5-11.8x for 7B and 13B models, with nearly linear scalability

Evaluation Results: Throughput



Codellama-34B (17.9GB, 2.6 tokens/s)

Llama2-70B (36.4GB, 1.3 tokens/s)

FlexInfer achieves performance improvement of 4.2-10.6x, 5-11x for 34B and 70B models, with nearly linear scalability

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Conclusion

FlexInfer Achieves:

- 🚀 2.6~3x Faster than MMAP under **Asynchronous Prefetching**
- ⚖️ Up to **56.8~83.3%** improvement via **Balanced Locking**.
- 🔧 **Any budget adaptation** with **Flexible Preservation**.

Evaluation results show that FlexInfer achieve **10.6-12.5** times inference speedup compared to mmap-based offloading

Democratizing LLMs for every edge device.

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