Dynamic Tensor Rematerialization

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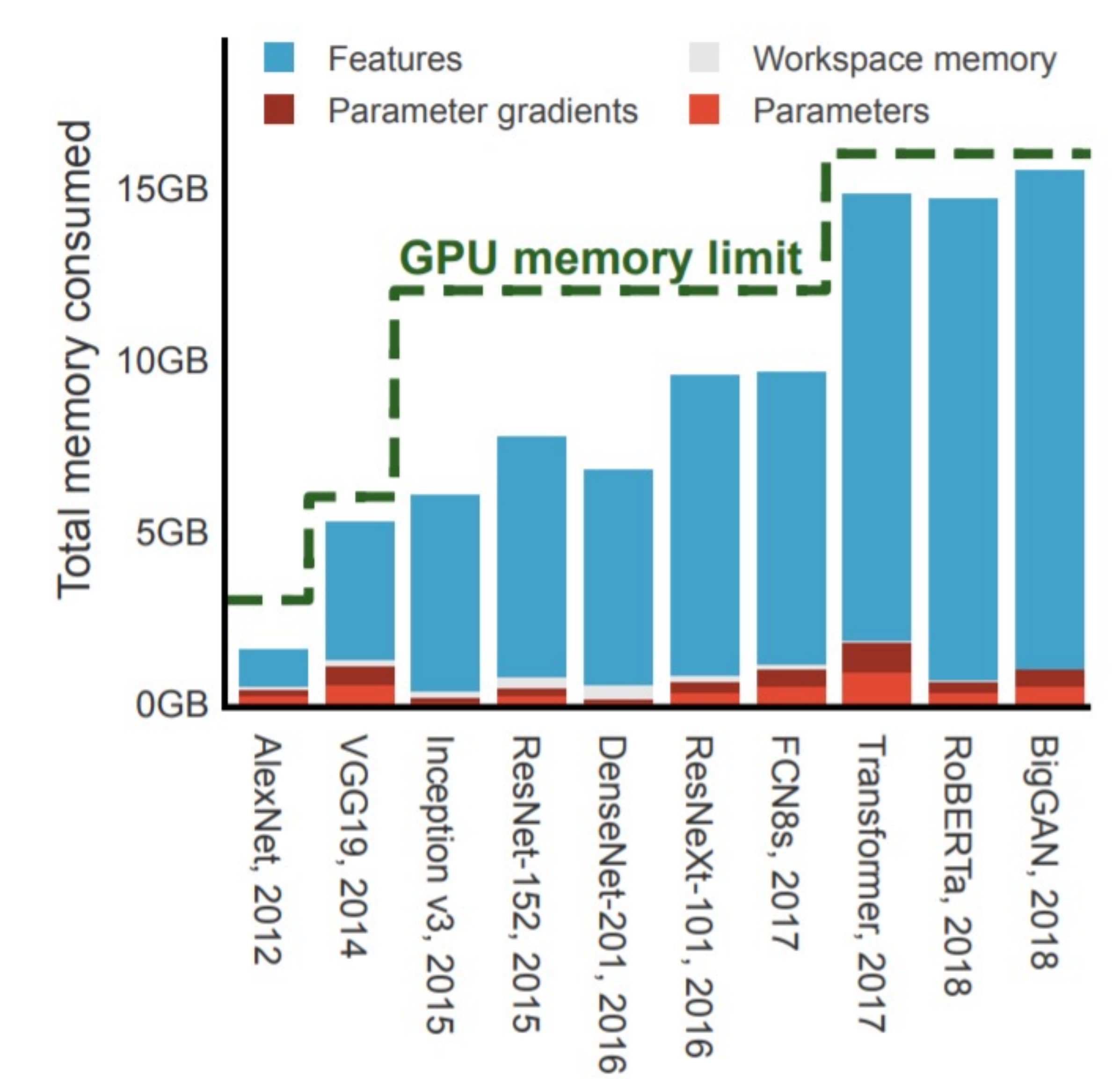
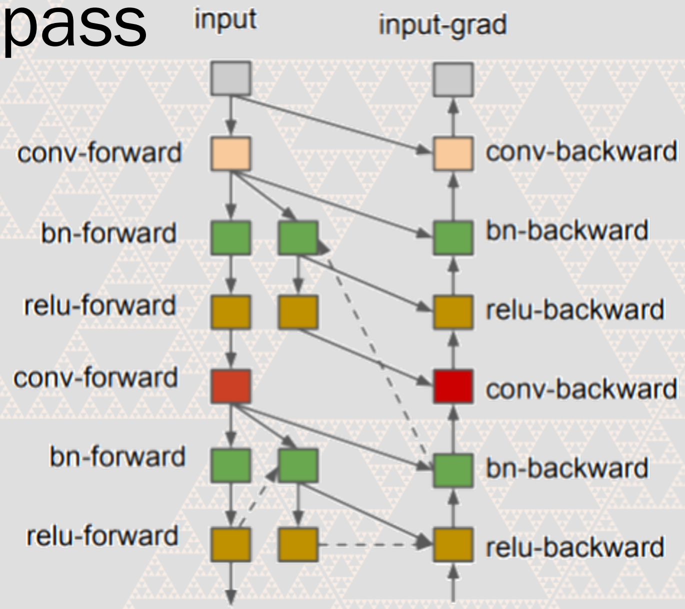
PLSE



Jain *et al.*, “Checkmate: Breaking the Memory Wall With Optimal Tensor Rematerialization” (2020)

Checkpointing: Trade Time for Space

- Recompute activations instead of storing them
- Gradient Checkpointing, Chen *et al.* (2016)
  - Pick segments to recompute in backward pass
  - $O(\sqrt{N})$ memory for $O(N)$ extra ops
  - Many later segmenting approaches
- Checkmate, Jain *et al.* (2020)
  - Rematerialize individual values
  - ILP for optimal(!) planning



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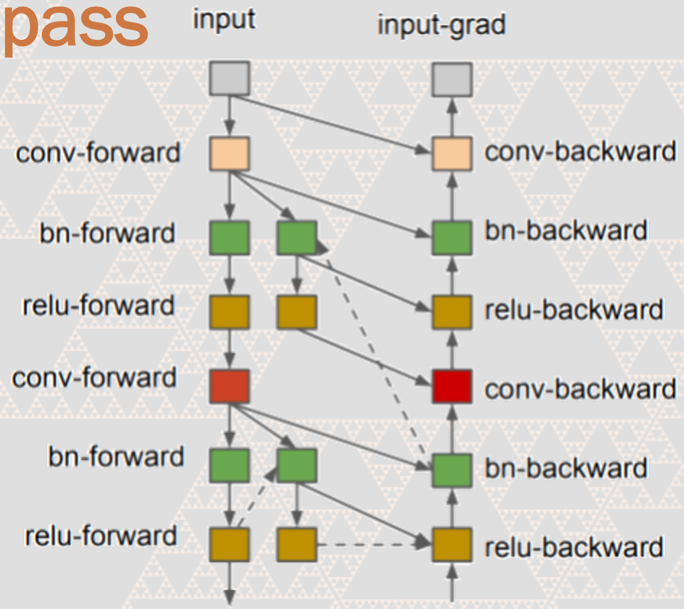

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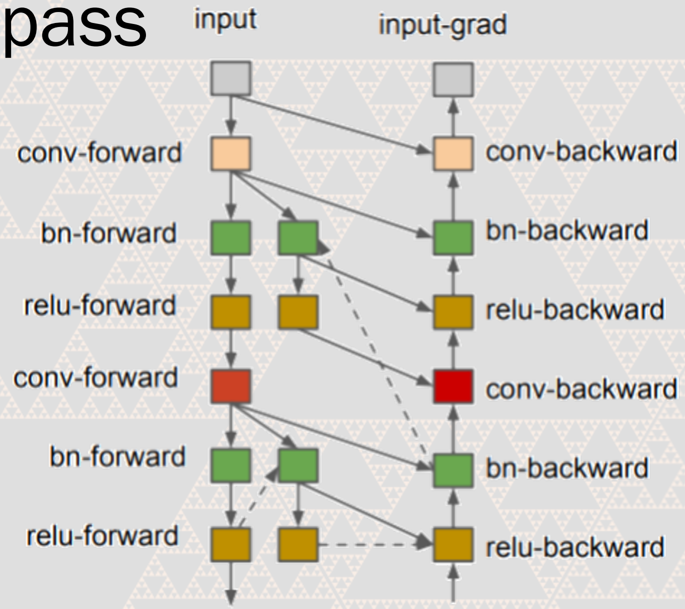


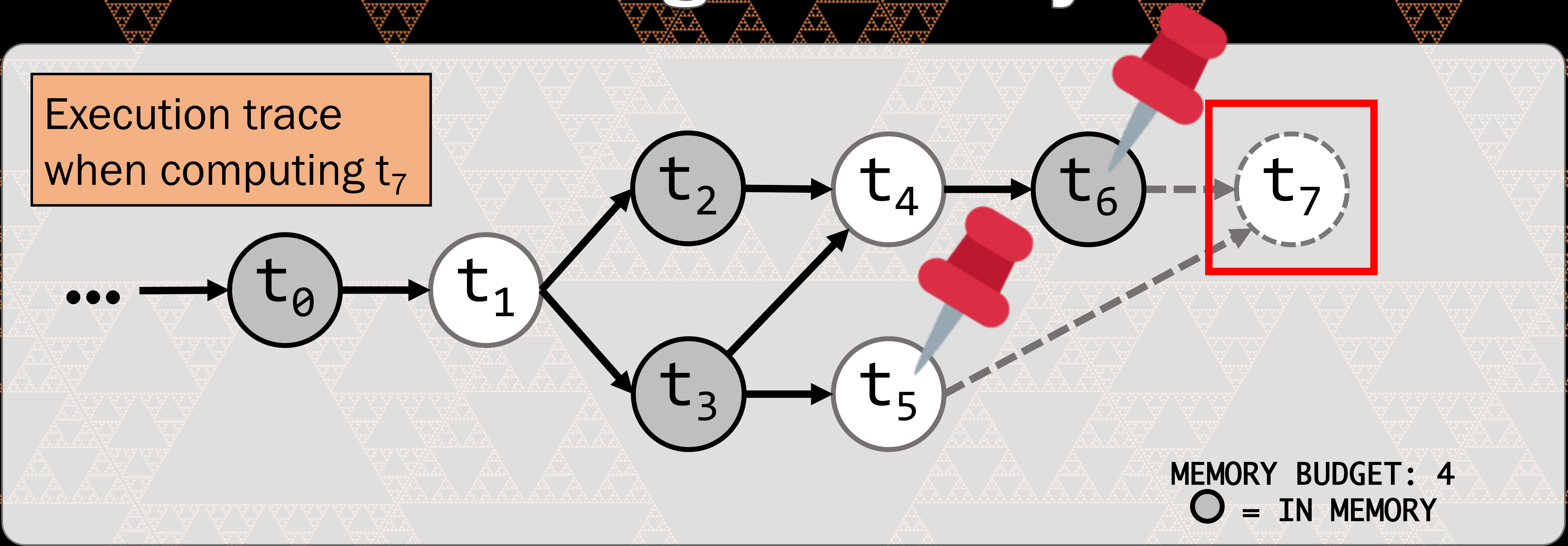
Static Planning is Unnecessary

- Past approaches plan checkpoints in advance
- Require static knowledge of the model
- Planning can be expensive, limits applications
- Our contributions:
    - *Static planning is unnecessary for checkpointing*
    - Still achieve good compute-memory tradeoffs

Dynamic Tensor Rematerialization

- Cache-like approach: A runtime system
  - No static information necessary
  - Greedily allocate, evict and recompute as needed
  - Collects metadata to guide heuristics
  - Operates at a high level of abstraction
- Still competitive with static planning!

Rematerializing on the Fly



Current operation: `PerformOp(op₇, [t₅, t₆])`

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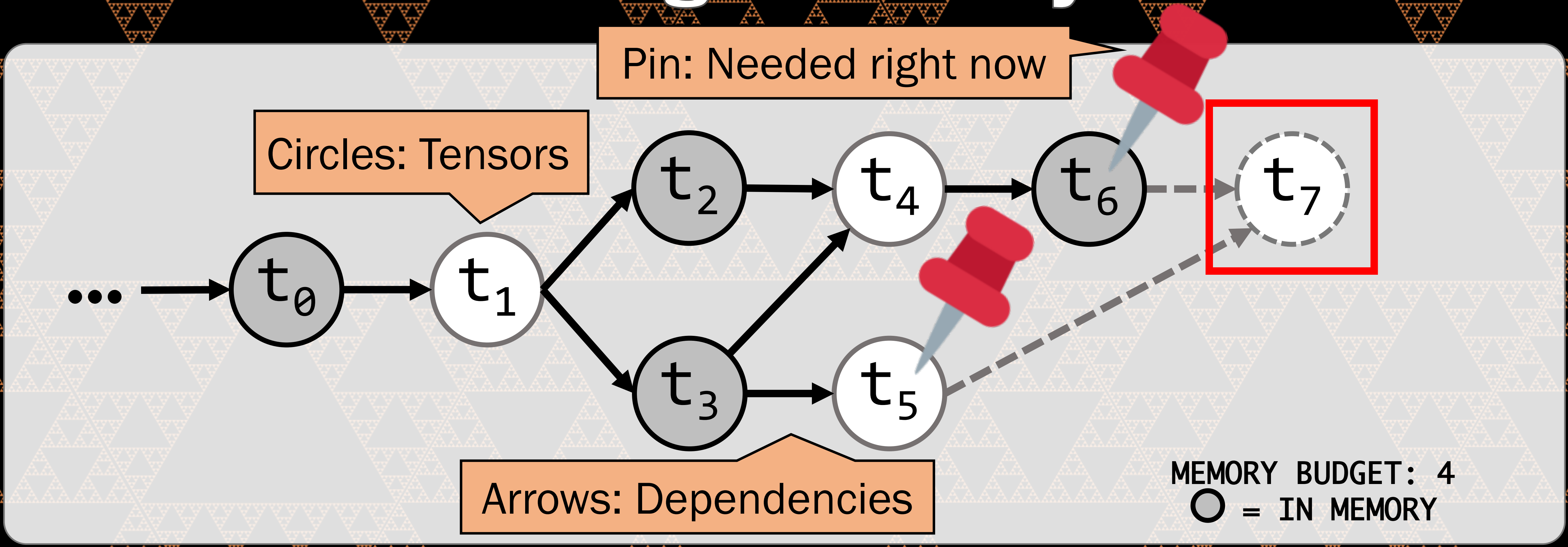

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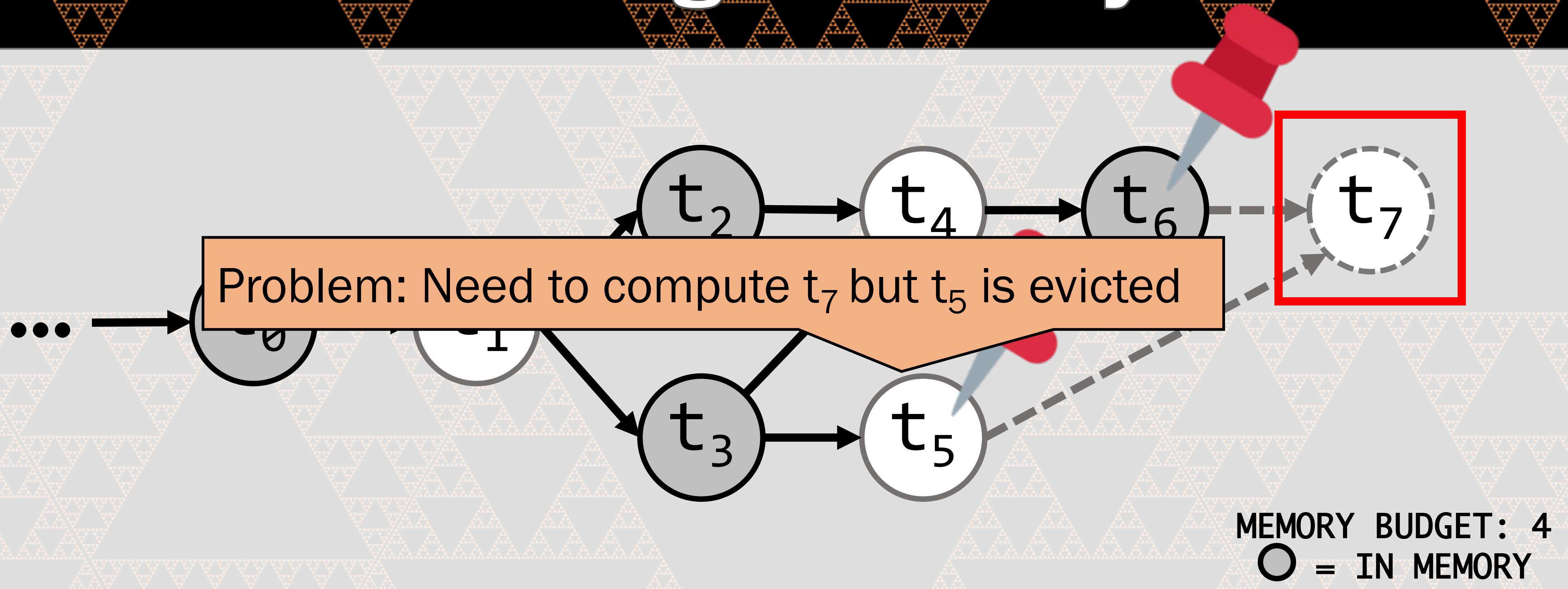
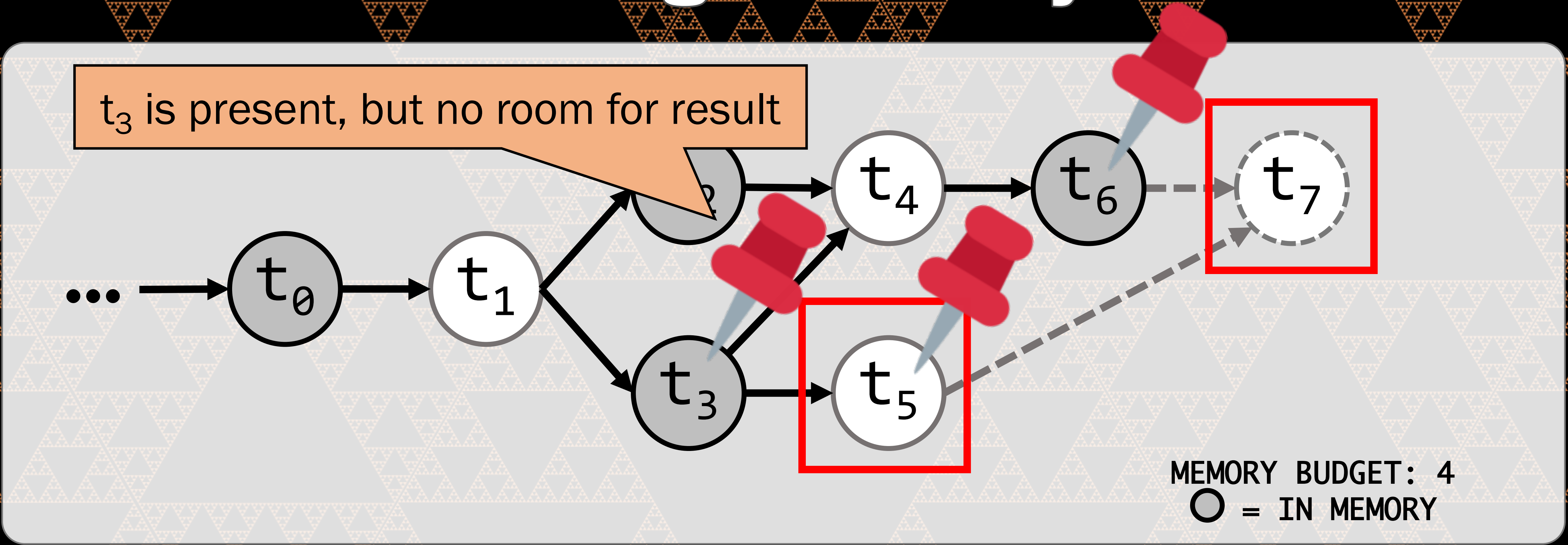


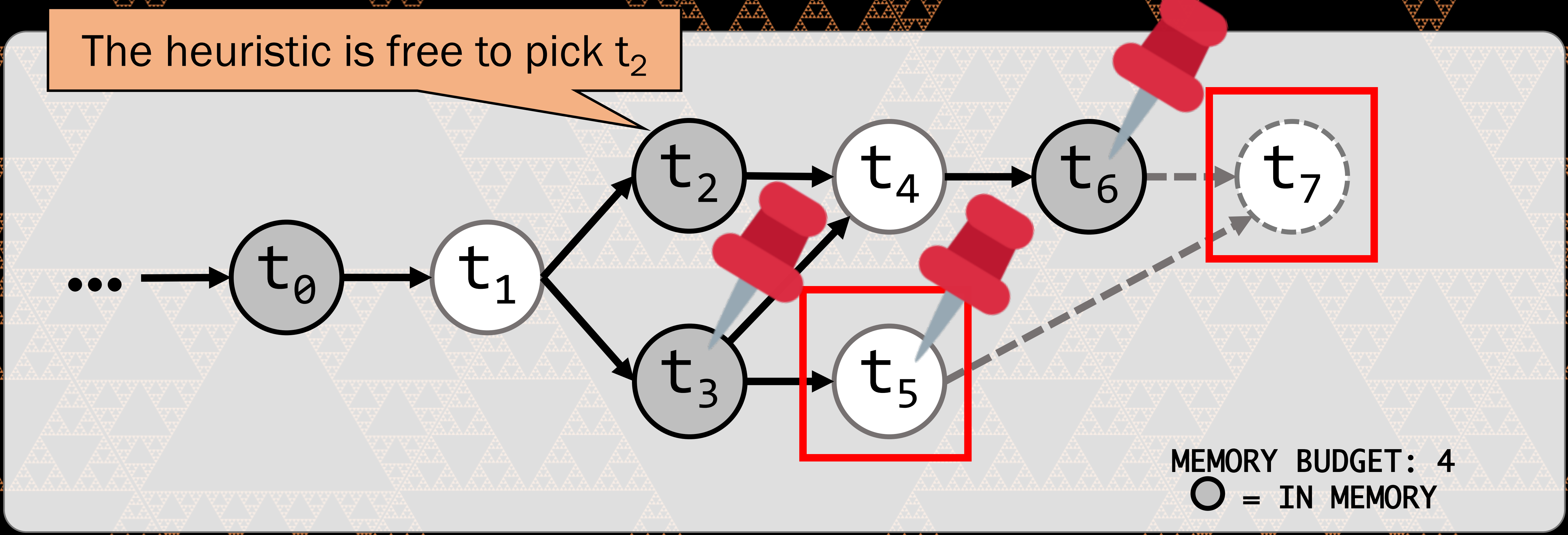
Current operation: `Rematerialize(t₅)`

Rematerializing on the Fly



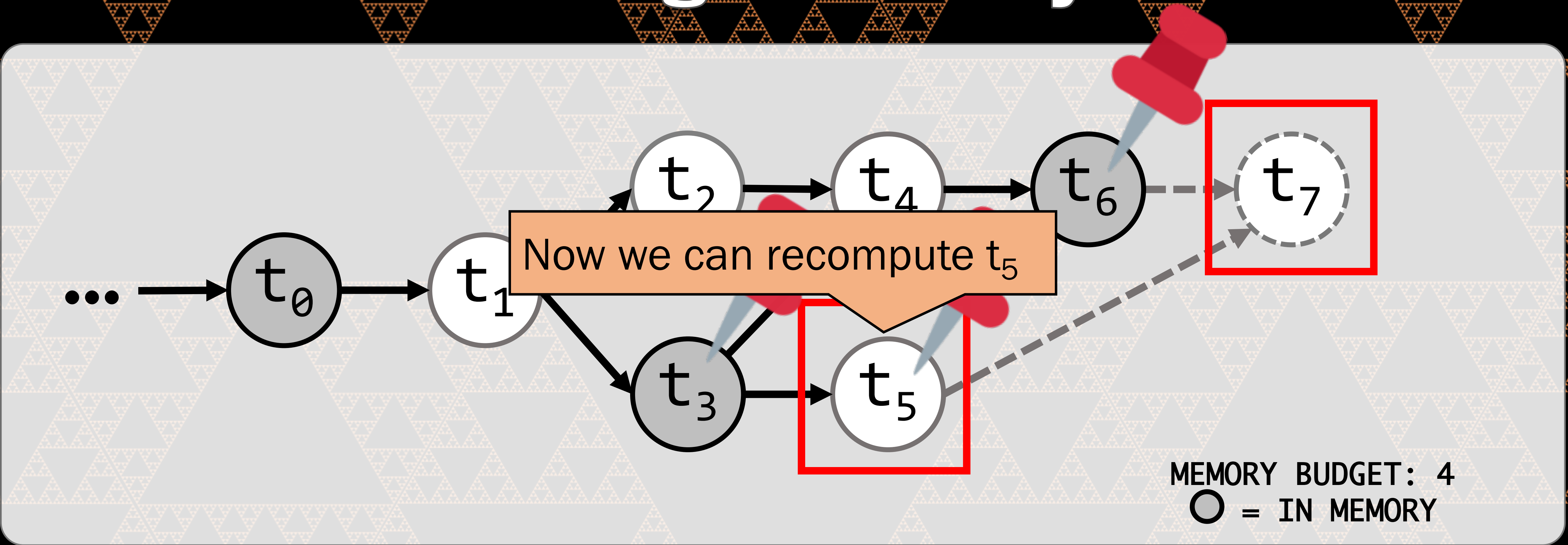
Current operation: `PerformOp(op₅, [t₃])`

Rematerializing on the Fly



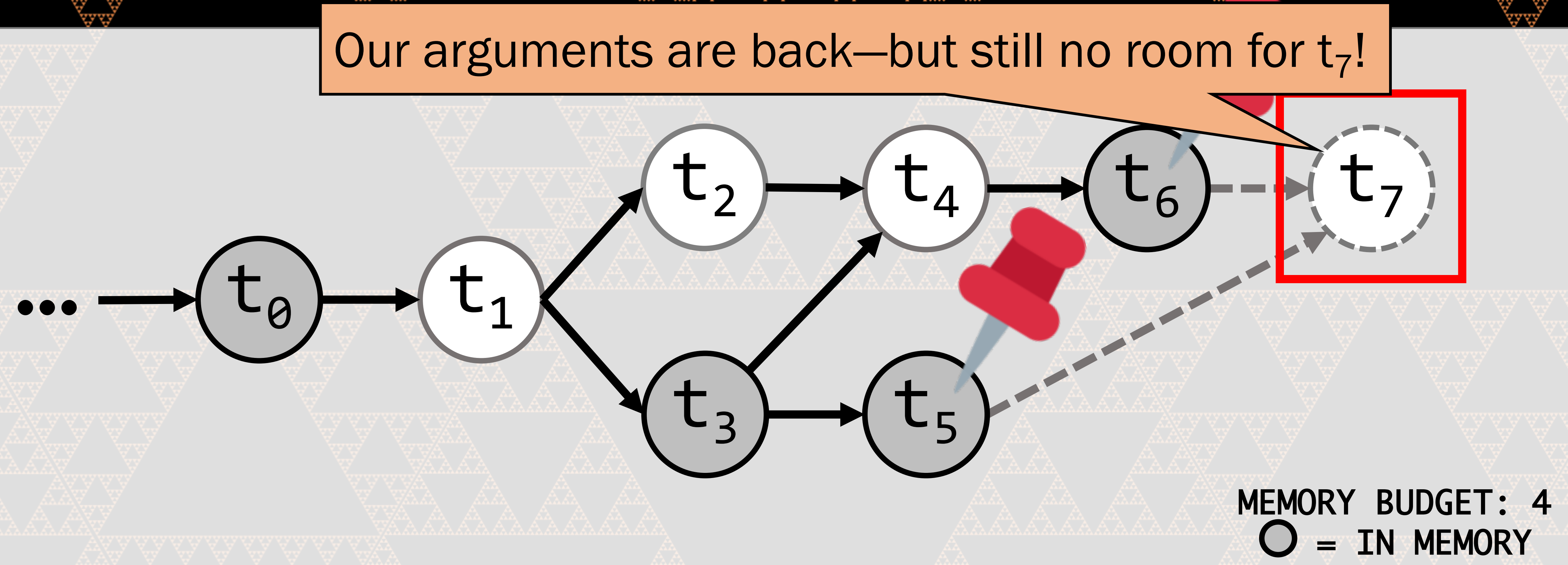
Current operation: `PerformEviction()`

Rematerializing on the Fly



Current operation: `AllocateBuffer(t₅.size); op₅(t₃)`

Rematerializing on the Fly



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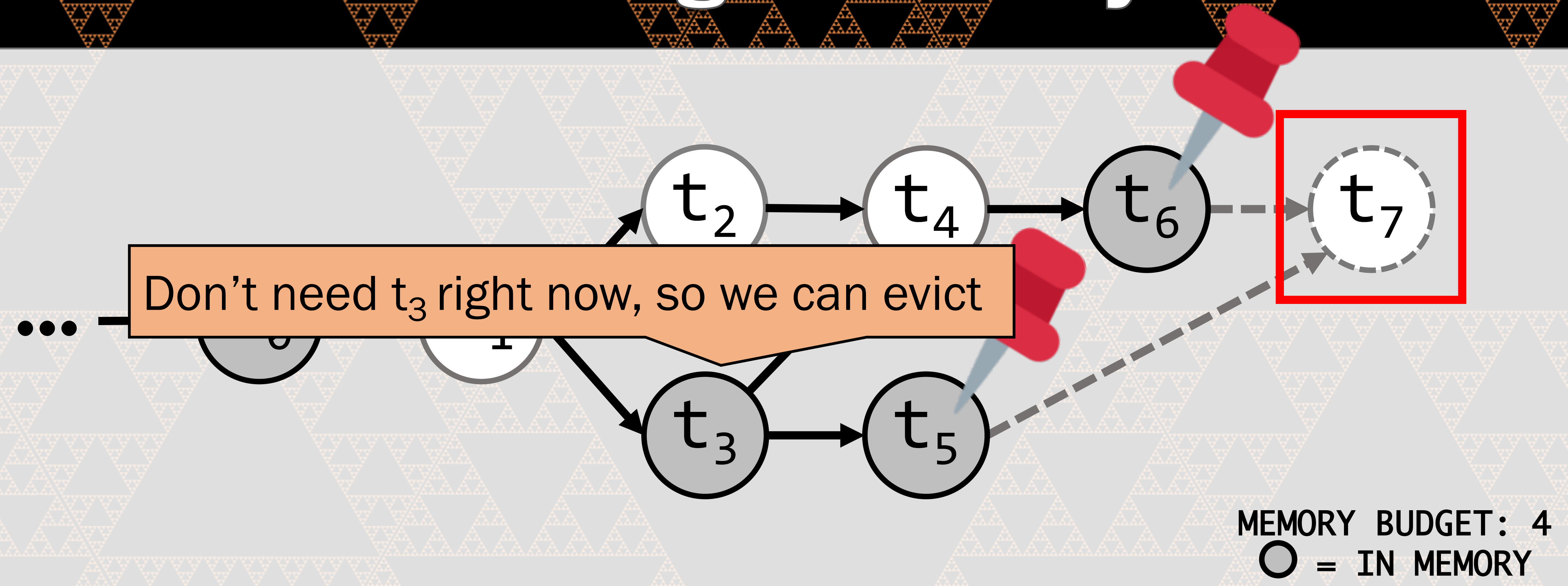

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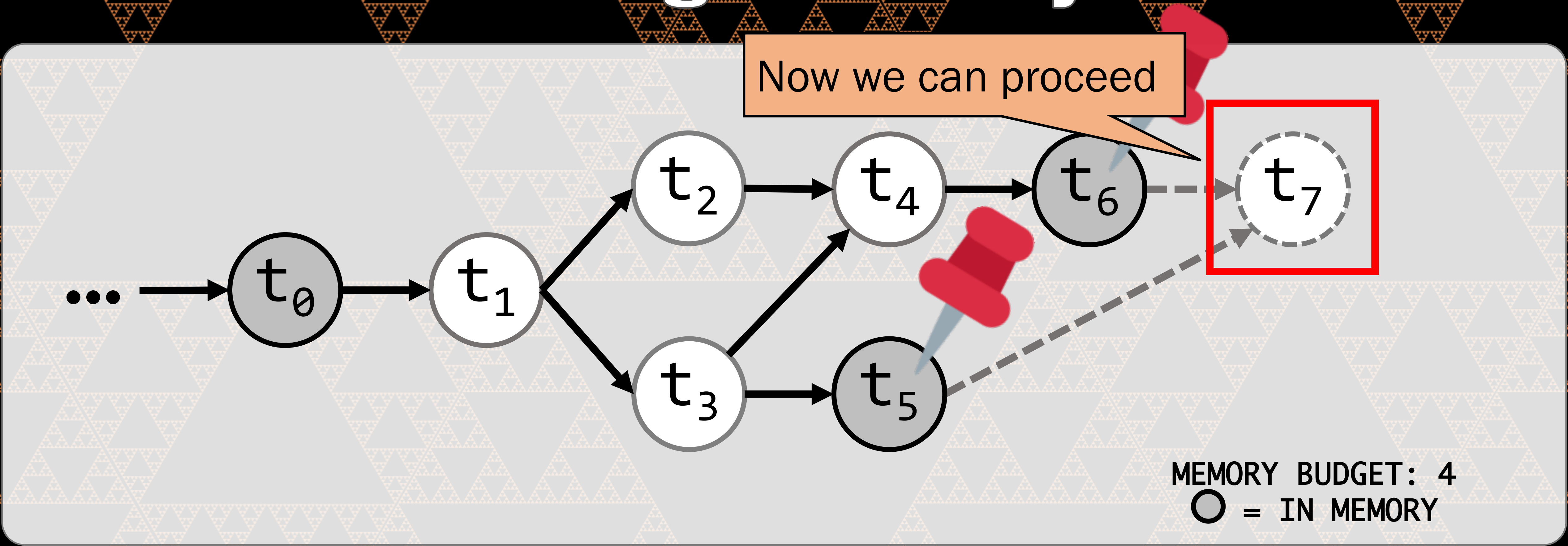
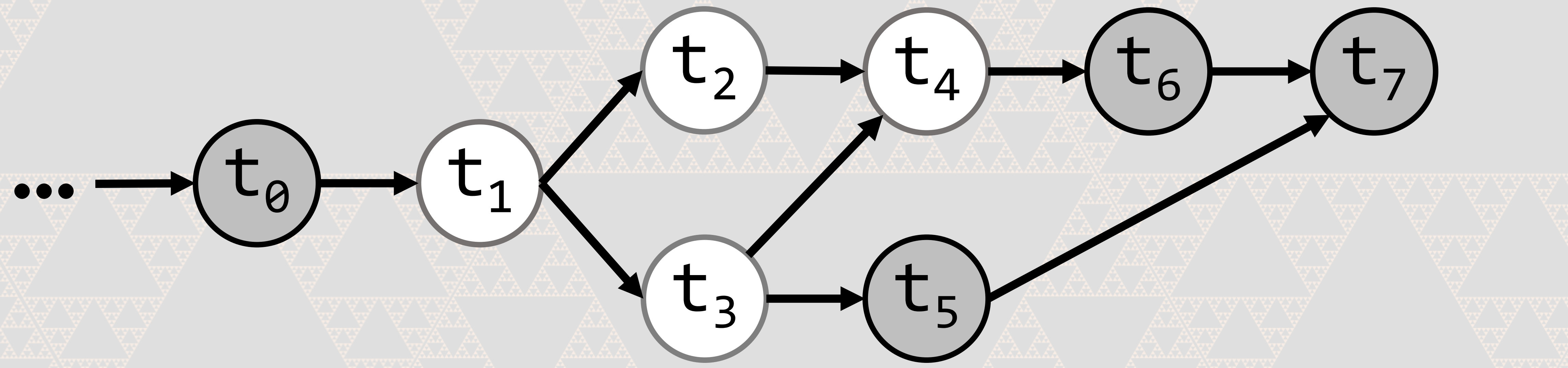
Rematerializing on the Fly



Current operation: $op_7(t_5,\ t_6)$

Rematerializing on the Fly



DTR: Just Some Callbacks

`AllocateBuffer(size)`: Allocate if enough room, else evict until there is

`PerformEviction()`: Heuristic chooses a tensor to evict

`Rematerialize(t)`: Recompute `t` by replaying its parent op (`PerformOp`)

`PerformOp(op, args)`:

- Rematerialize evicted arguments
- Make room for result
- Update metadata

What Do Heuristics Look Like?

- Dynamic prediction of which tensor is least valuable
- Useful metadata, easy to track:
  - Cost $c(t)$: Avoid recomputing expensive tensors
  - Staleness $s(t)$: Recently used $\Longrightarrow$ likely to be used soon
  - Memory $m(t)$: Large tensors are most profitable to evict
- Resulting policy: minimize $h(t) = c(t)/(m(t) \cdot s(t))$
- Others: LRU $\left(\frac{1}{s(t)}\right)$ and largest-first $\left(\frac{1}{m(t)}\right)$

Reasoning About Tensor Cost

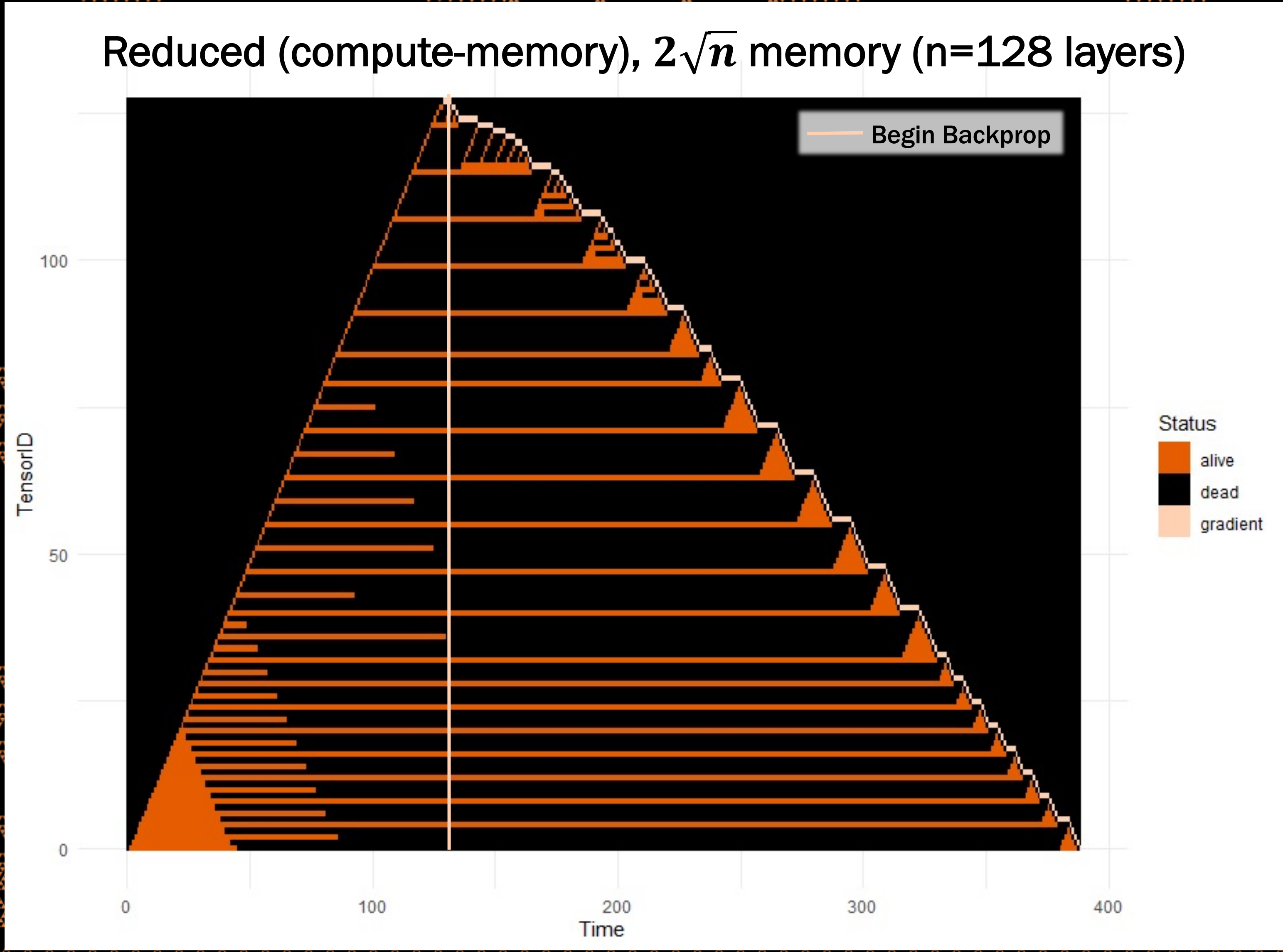
- True cost of a rematerialization includes recursive calls
- Recursively computing exact cost is expensive!
- We approximate evicted components via union-find
  - Keep a running sum for union-find components
  - When tensor rematerialized, map to a new component
  - Leaves “phantom connections” but is fast

Formal Bounds

Performance on N-layer linear feedforward network:

- $\Omega(\sqrt{N})$ memory and $O(N)$ operations
- Same bound as Chen *et al*. (2016)
- No advance knowledge of model!

Proof (Sketch) in Pictures



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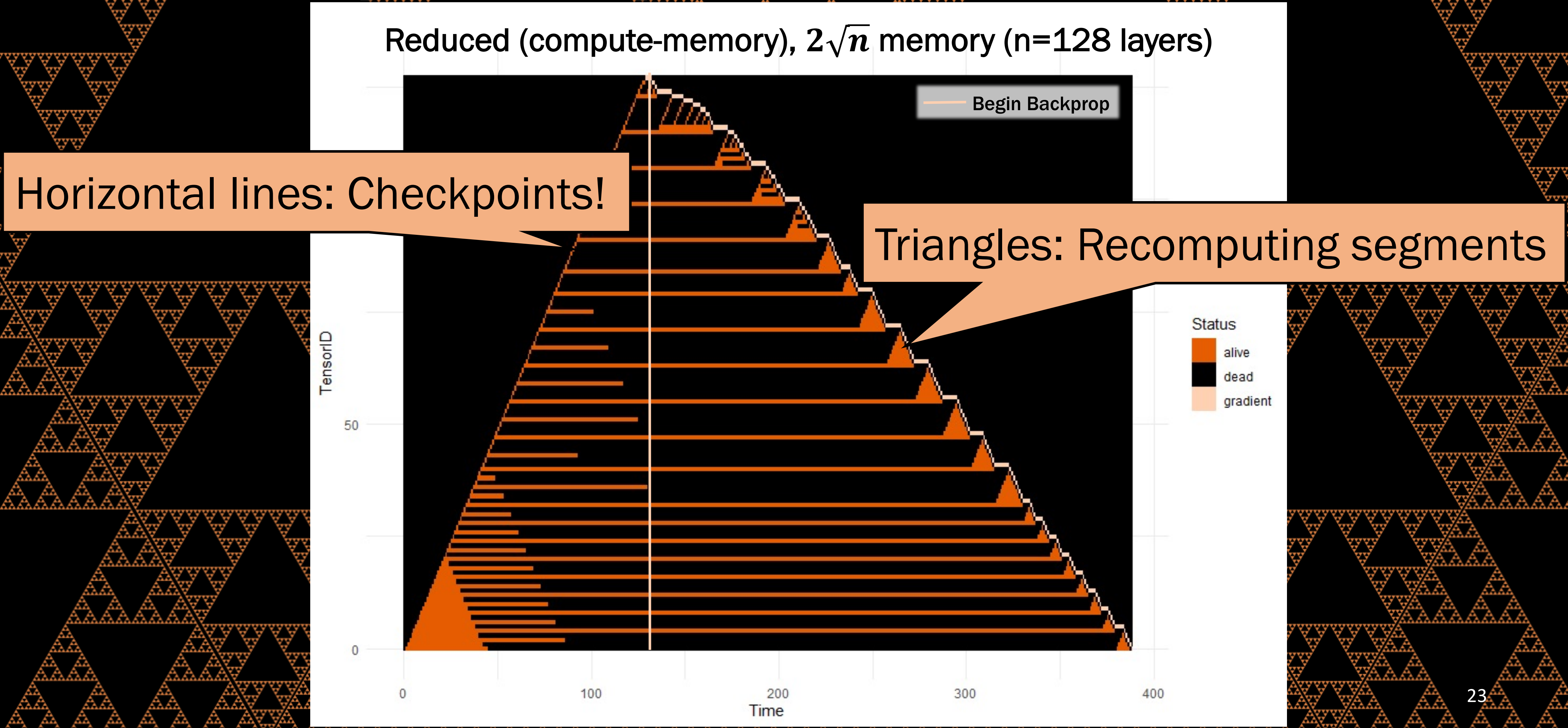

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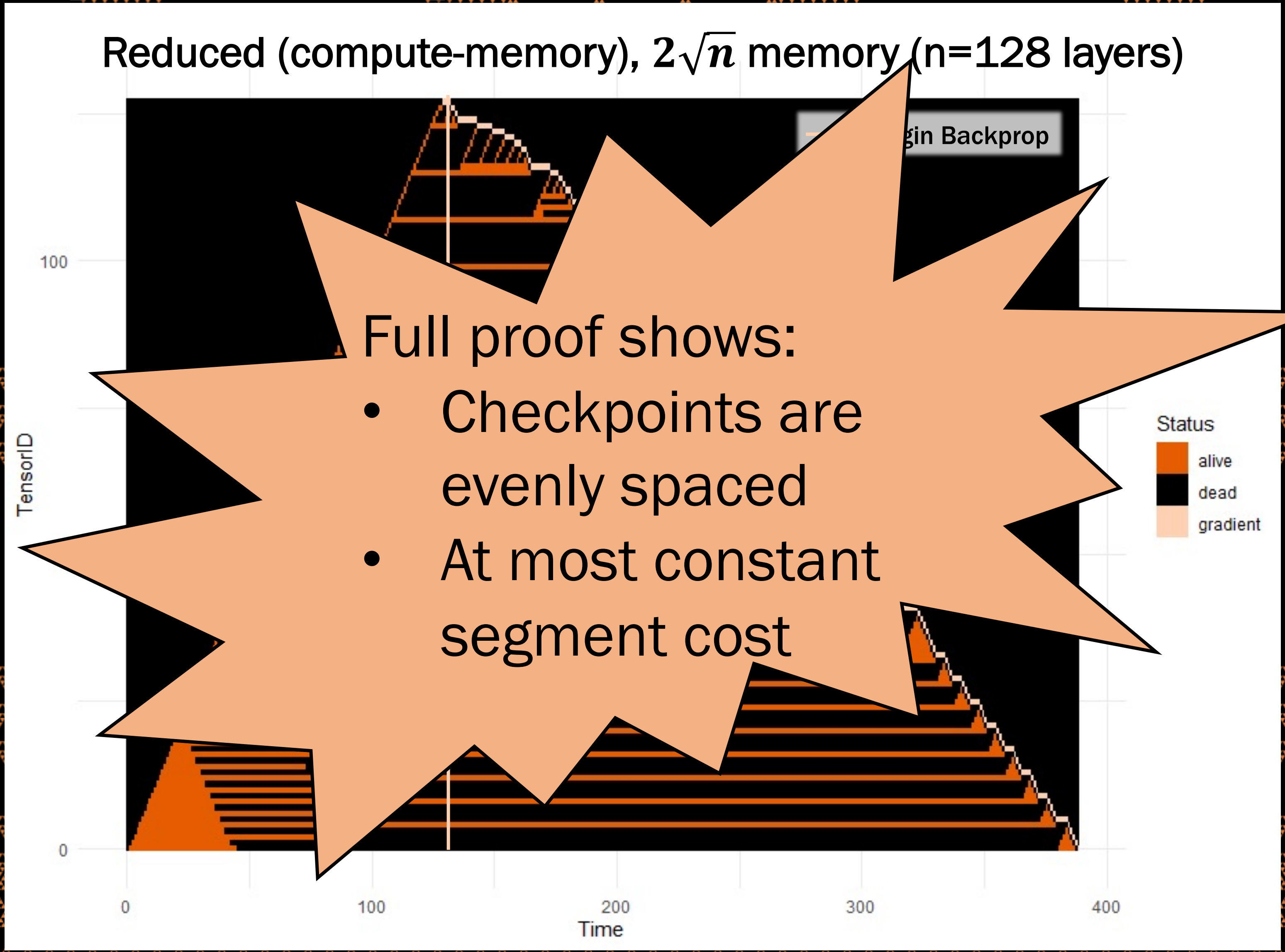

Full proof shows:

- Checkpoints are evenly spaced
- At most constant segment cost

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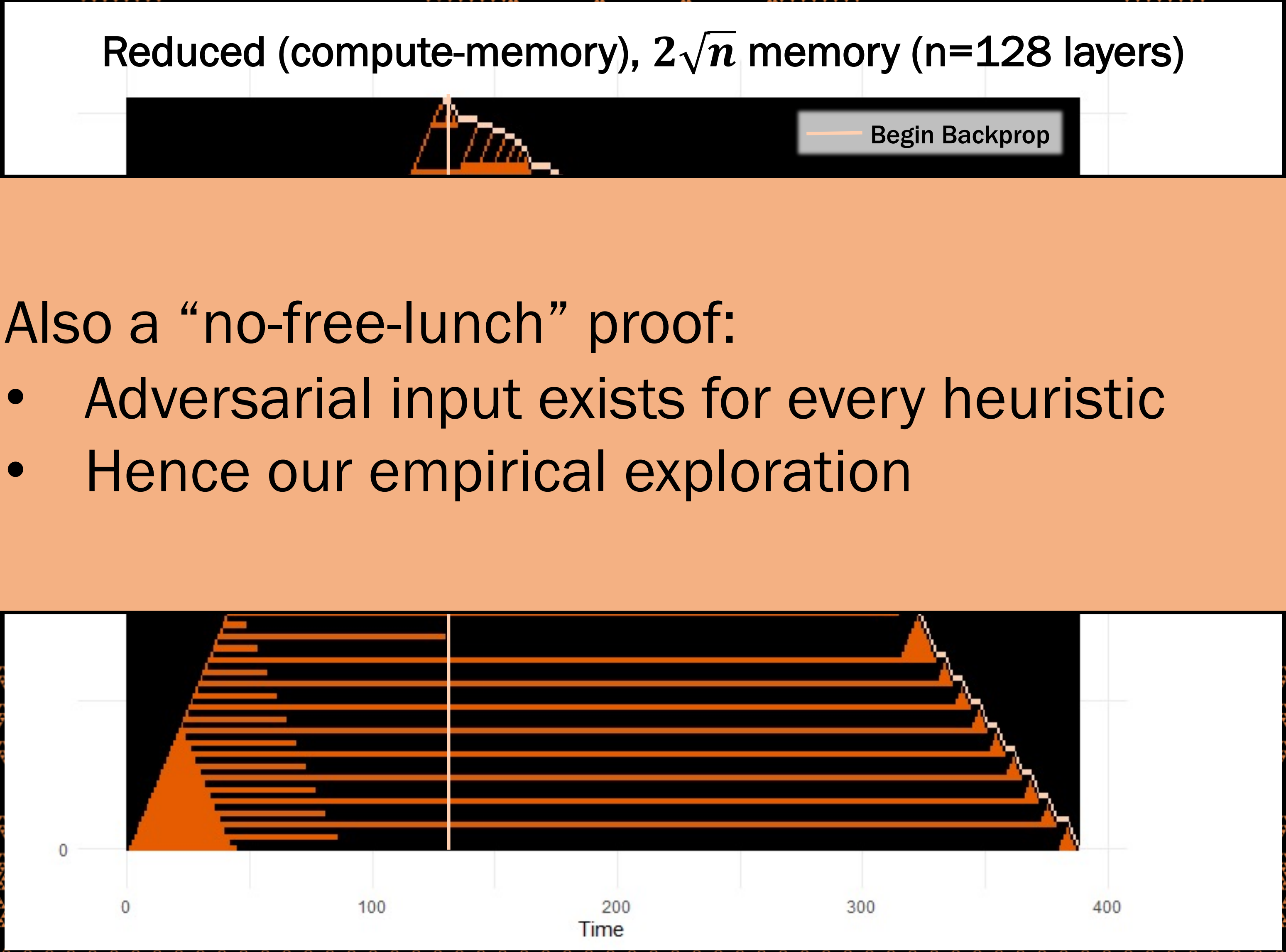
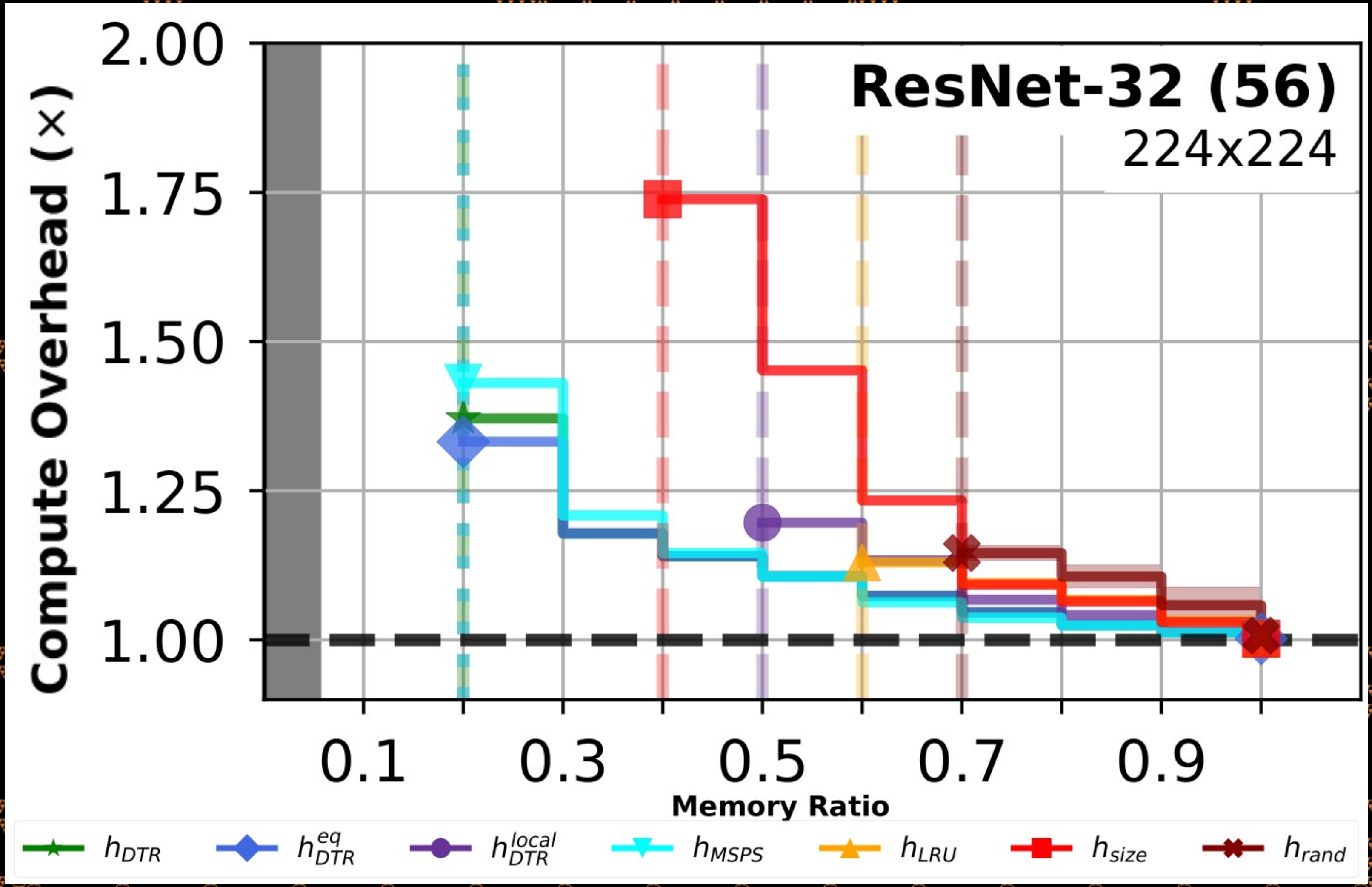


Also a “no-free-lunch” proof:

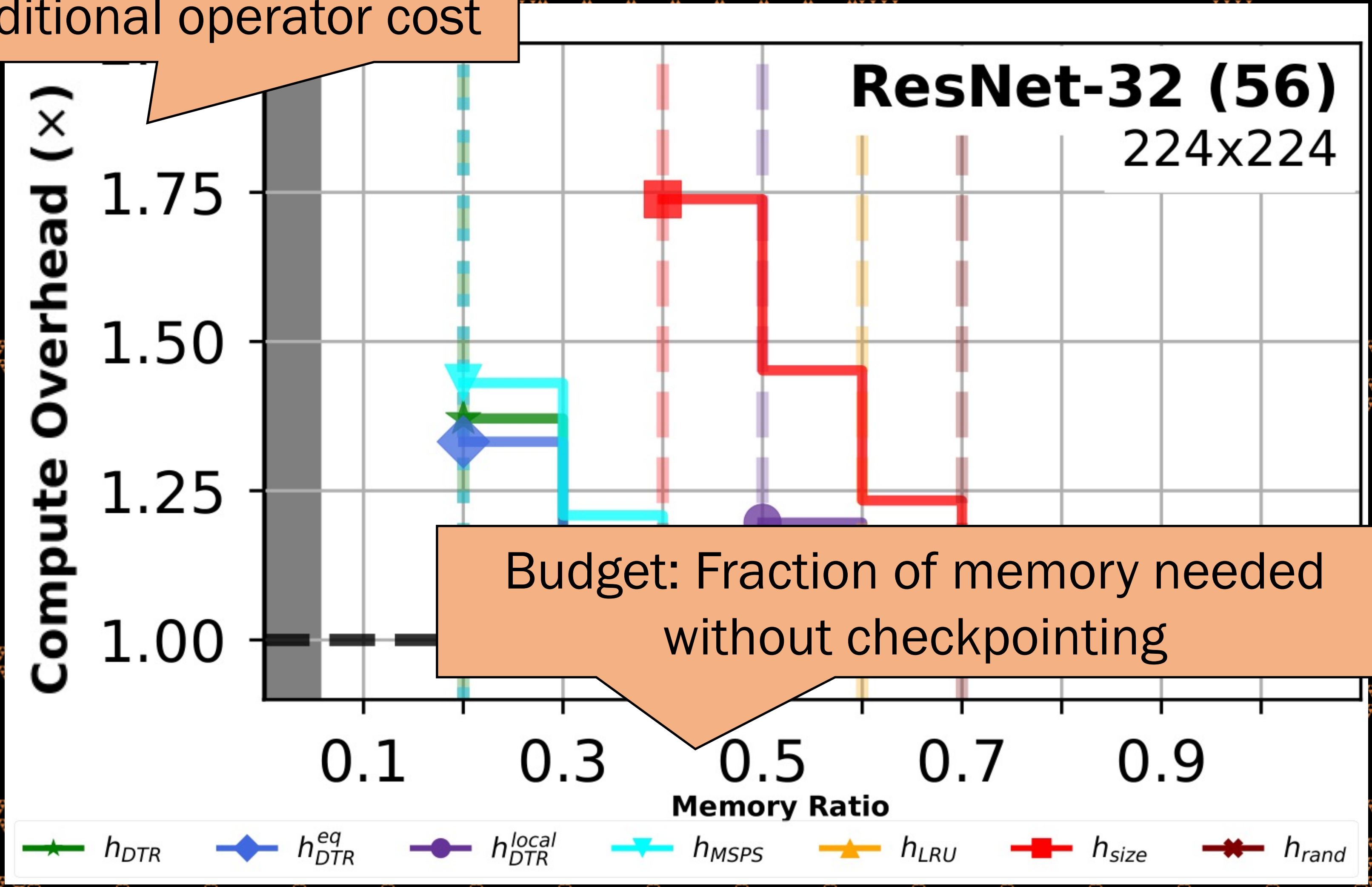
- Adversarial input exists for every heuristic
- Hence our empirical exploration

Comparison of Heuristics (Simulated)



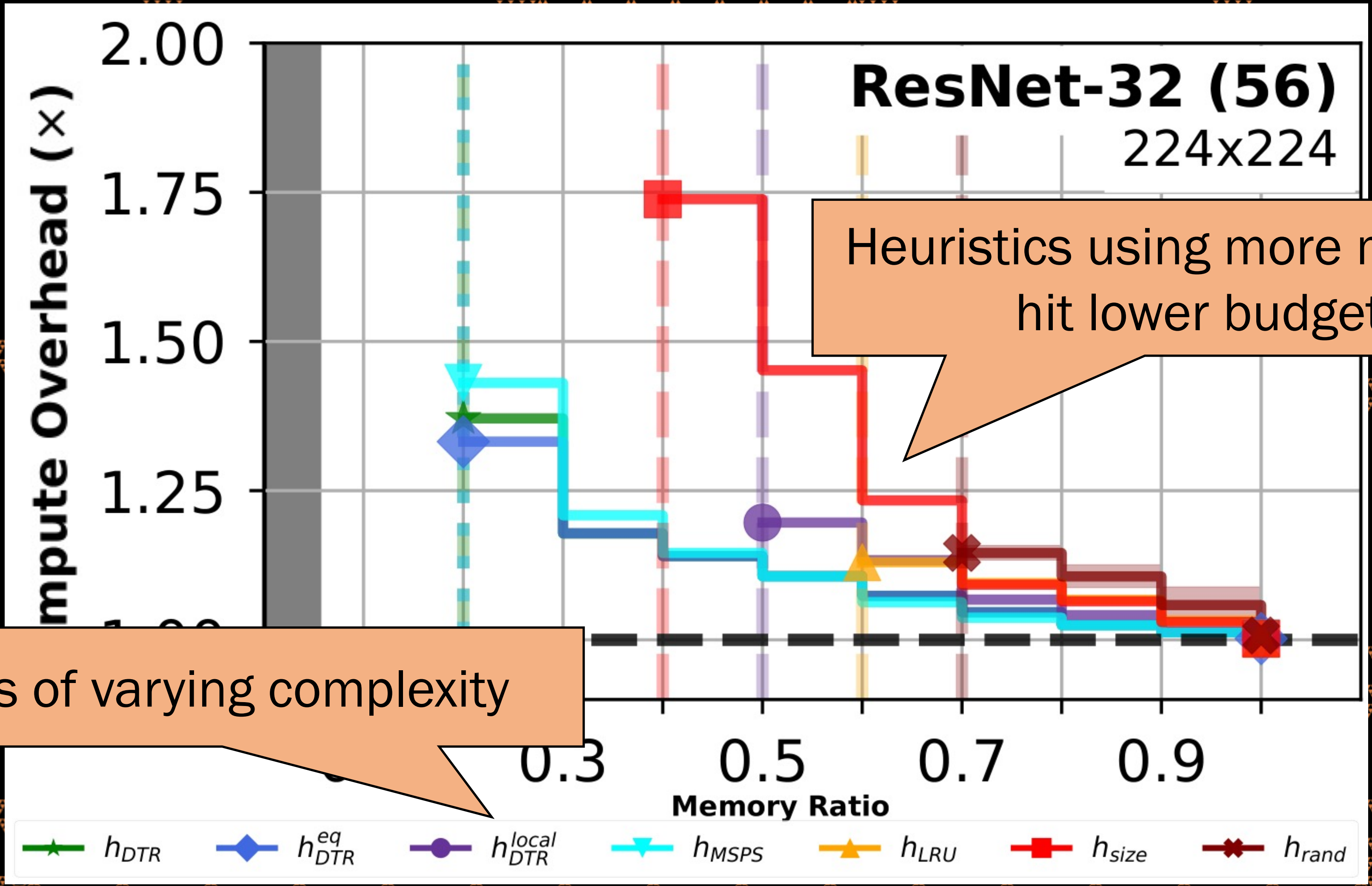
Comparison of Heuristics (Simulated)

Overhead: Additional operator cost



Budget: Fraction of memory needed without checkpointing

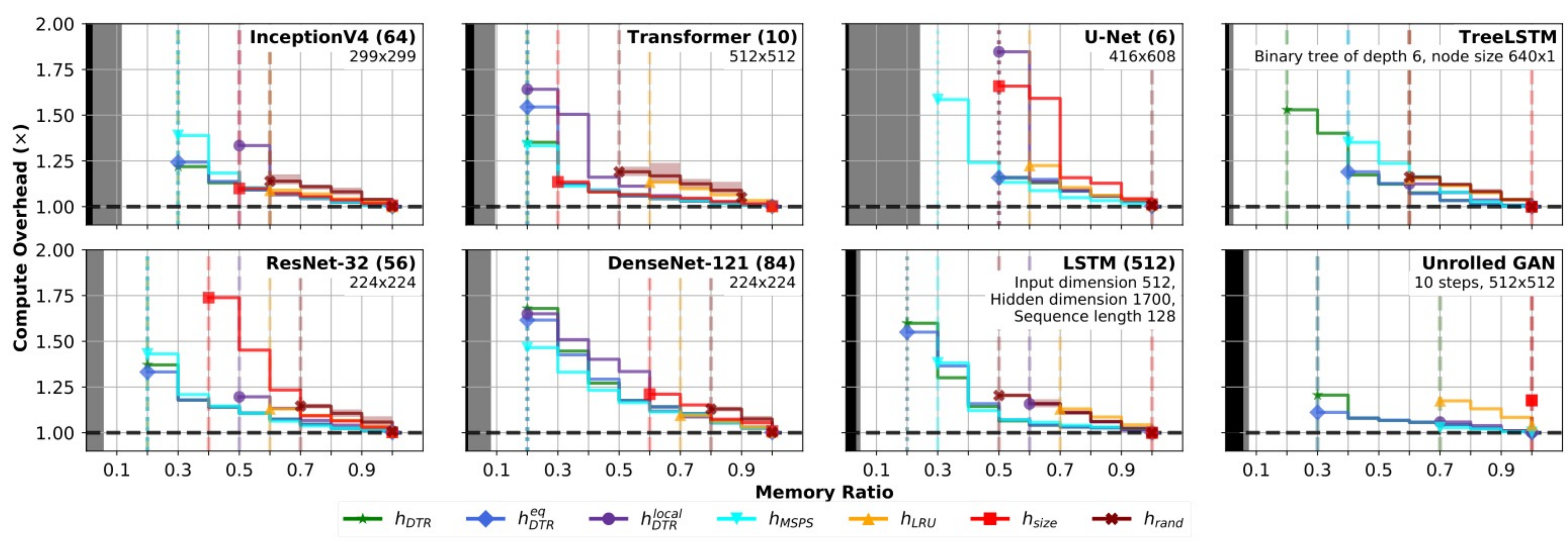
Comparison of Heuristics (Simulated)



Heuristics using more metadata hit lower budgets

Heuristics of varying complexity

Comparison of Heuristics (Simulated)



Similar trend holds across all models examined!

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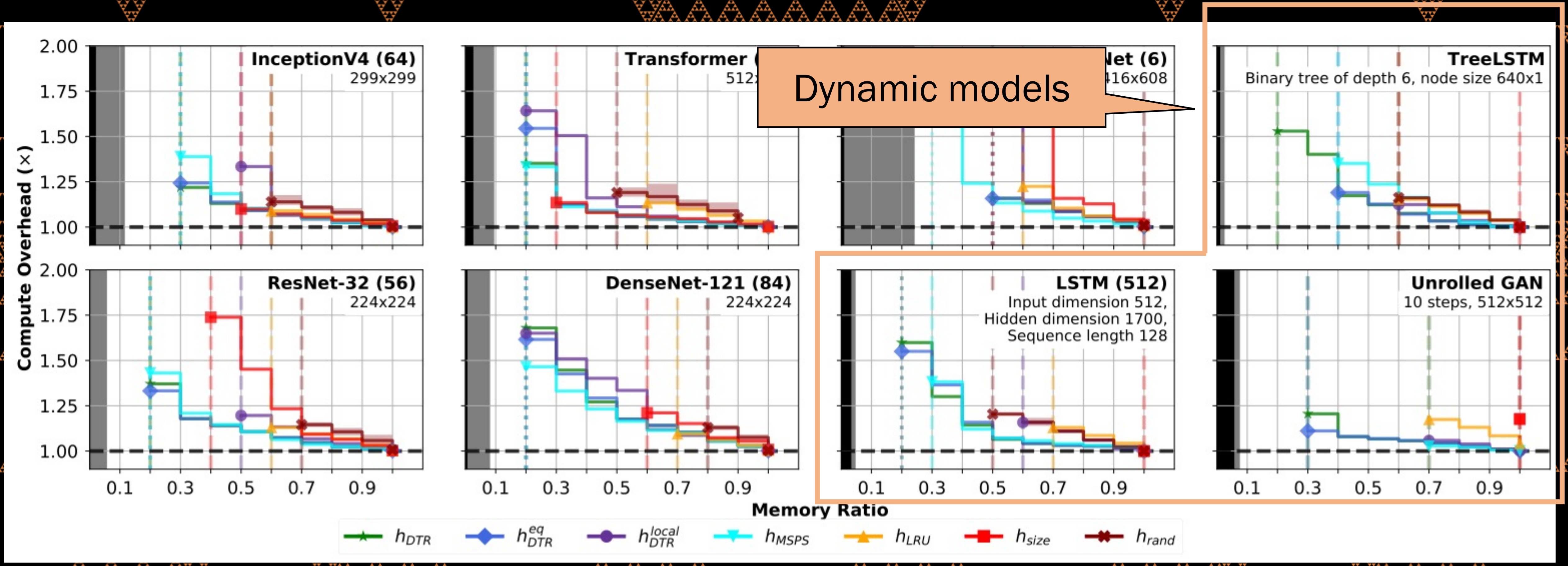

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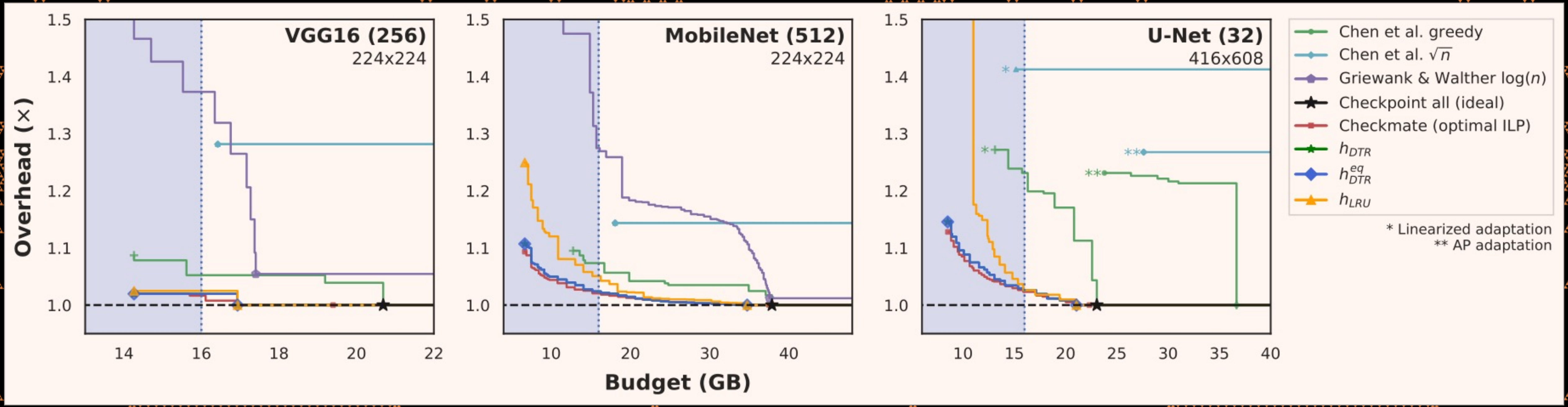
Comparison Against Static Techniques



Simulated comparison via the Checkmate MLSys 2020 artifact

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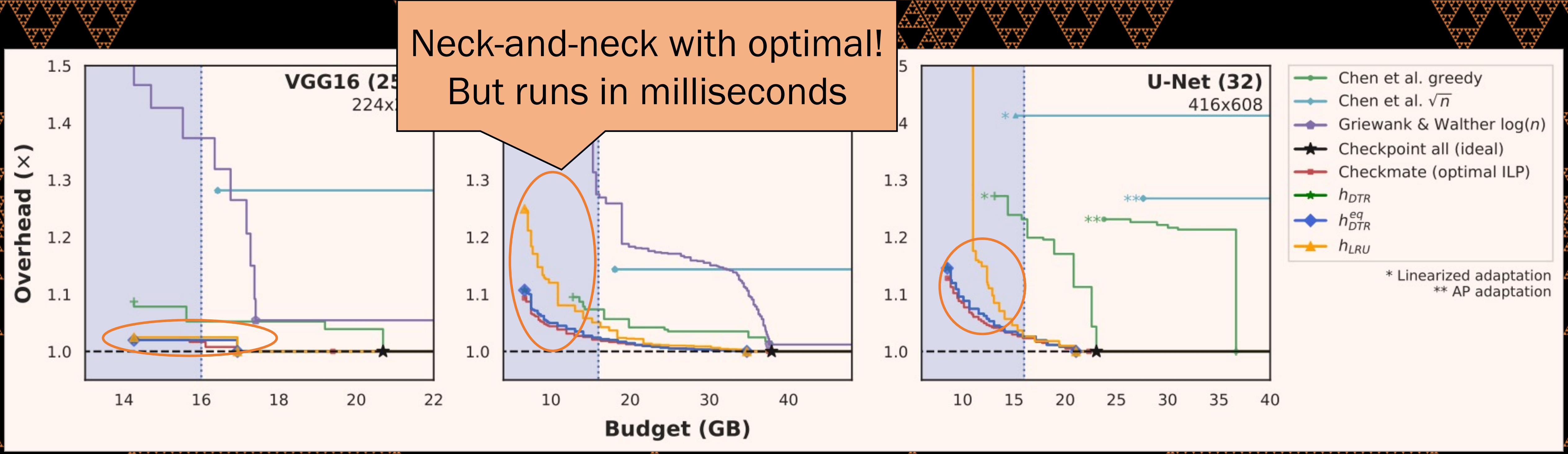

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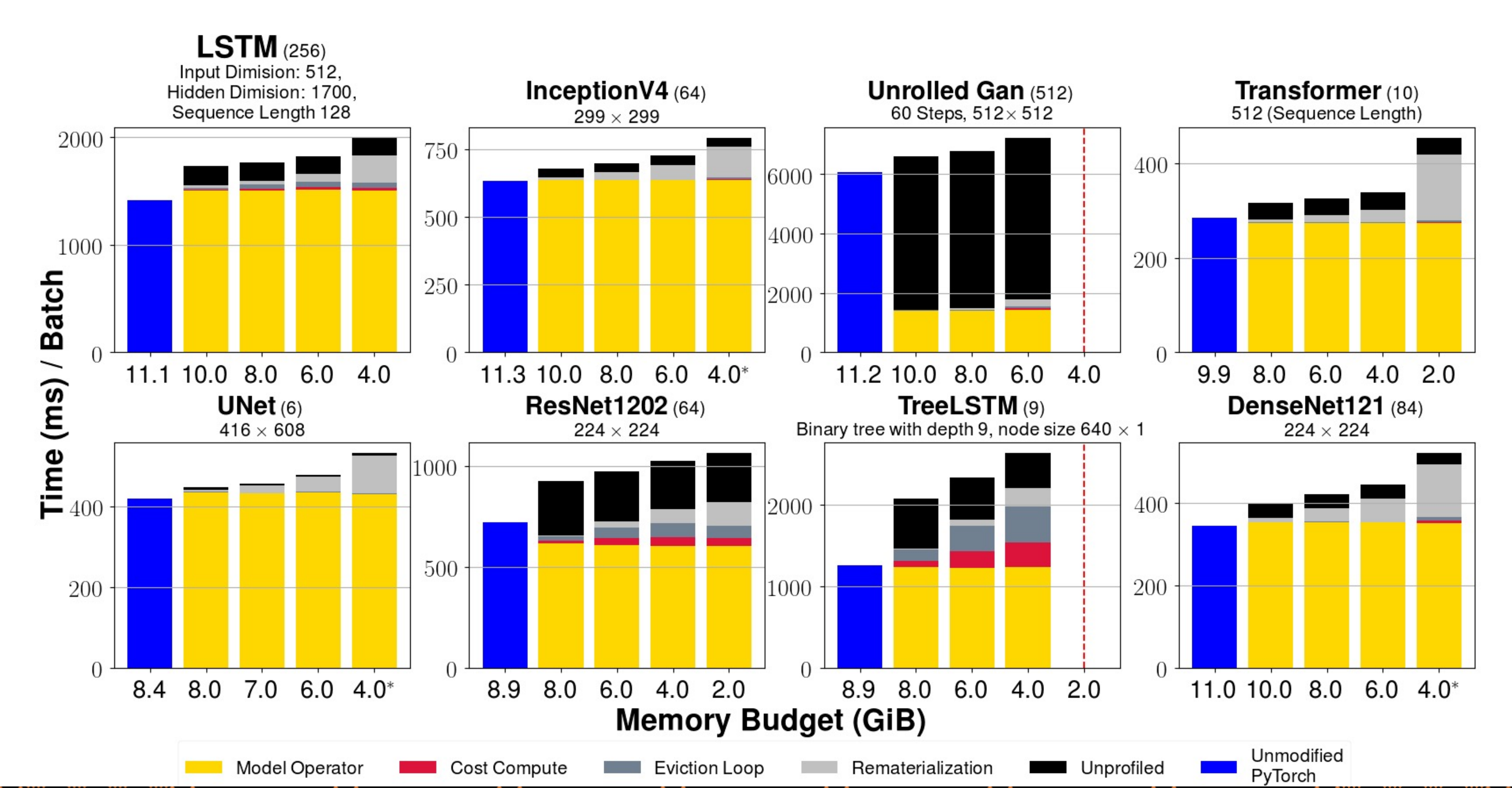
Prototype Implementation in PyTorch



Thin wrapper over tensor operators, core logic a few hundred LOC

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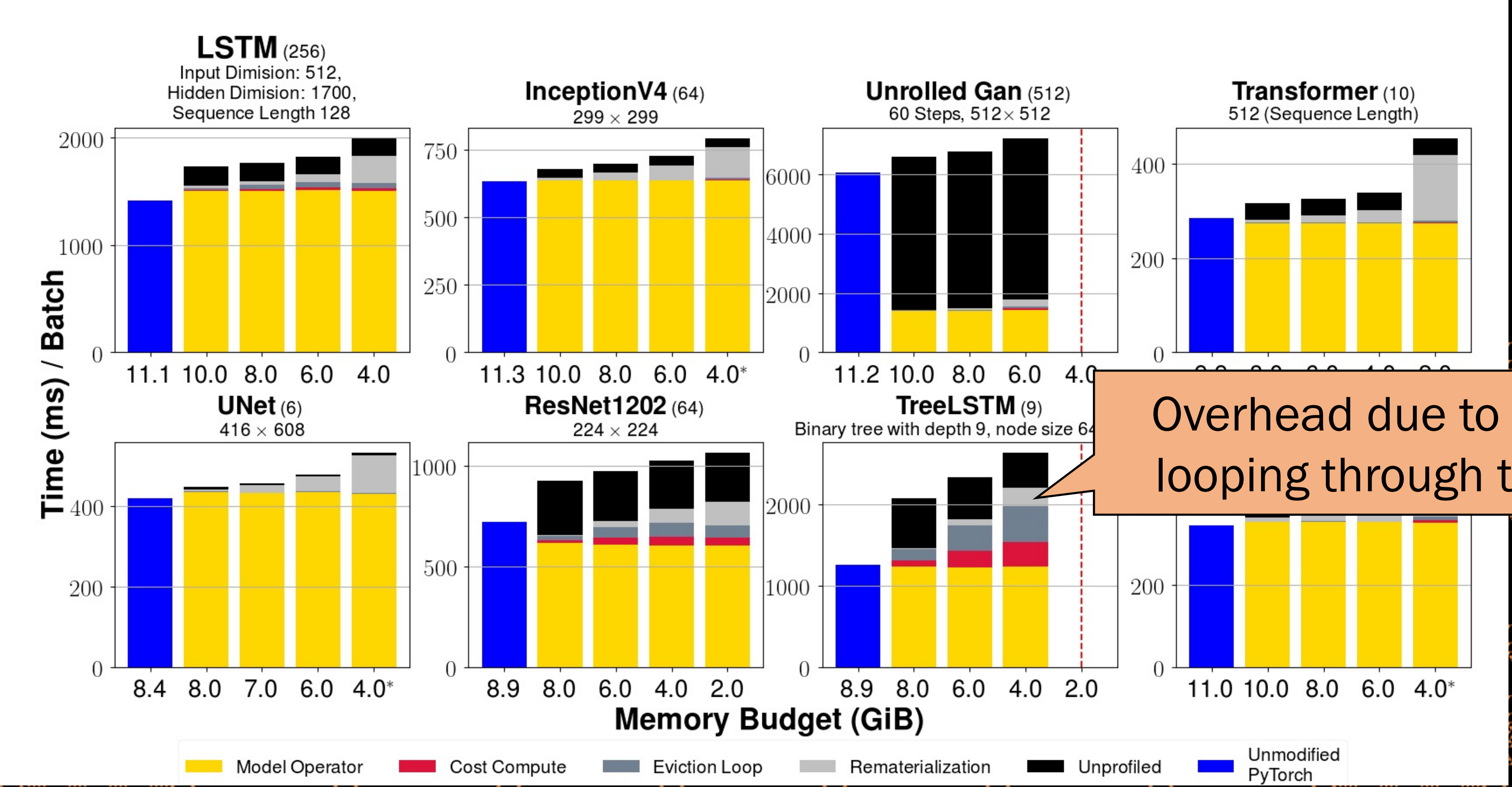

Overhead due to naively looping through tensors

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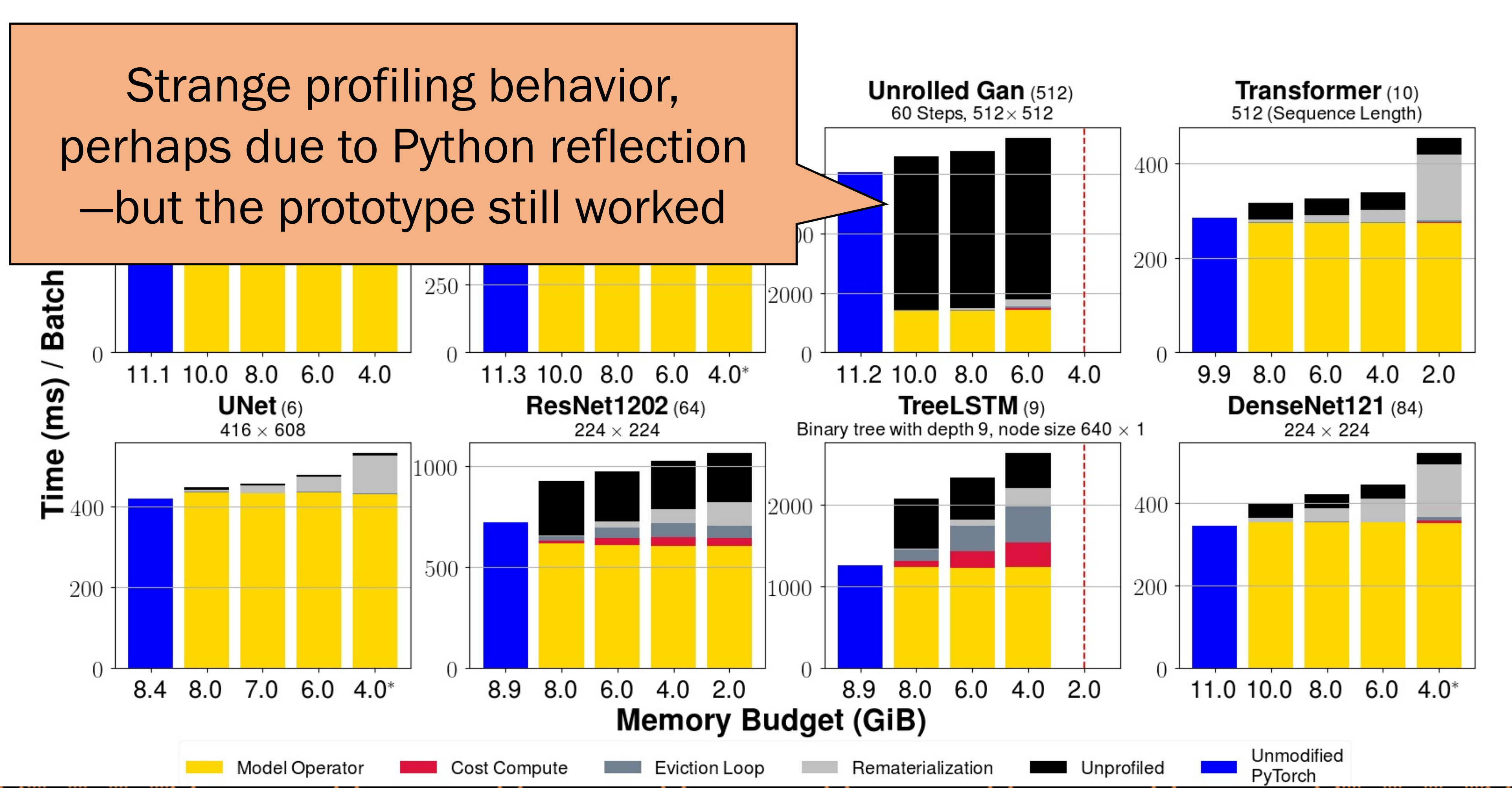

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Conclusion

- Encouraging initial results
- Many possible avenues of future work
  - Distributed settings: DTR per GPU?
  - Combining DTR with swapping
  - Tighter integration into the memory manager
  - Learning heuristics, learn from past batches
- Check out the simulator and prototype! https://github.com/uwsampl/dtr-prototype

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Applications Driving Architectures