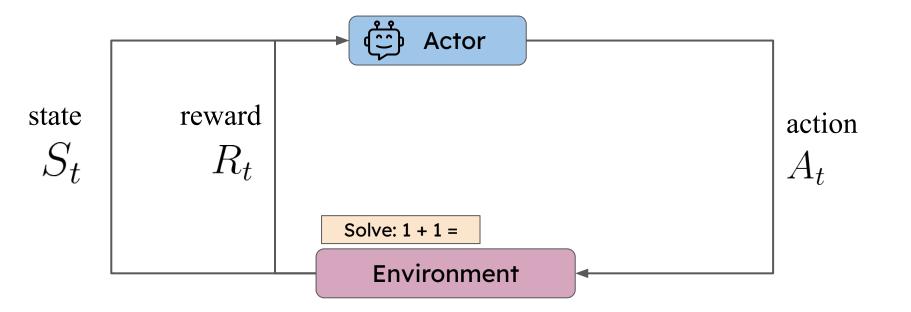
Optimizing RLHF Training for Large Language Models with Stage Fusion

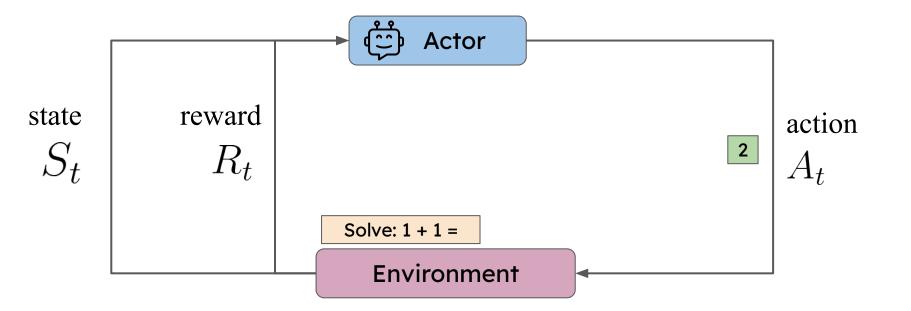
Yinmin Zhong¹ Zili Zhang¹ Bingyang Wu¹ Shengyu Liu¹ Yukun Chen² Changyi Wan² Hanpeng Hu² Lei Xia² Ranchen Ming² Yibo Zhu² Xin Jin¹

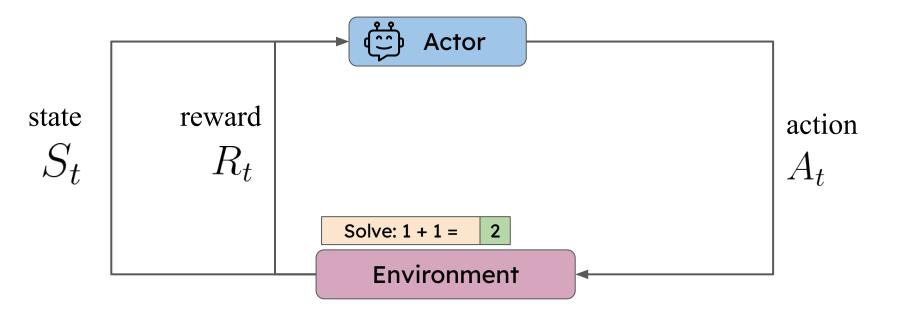
¹Peking University ²StepFun

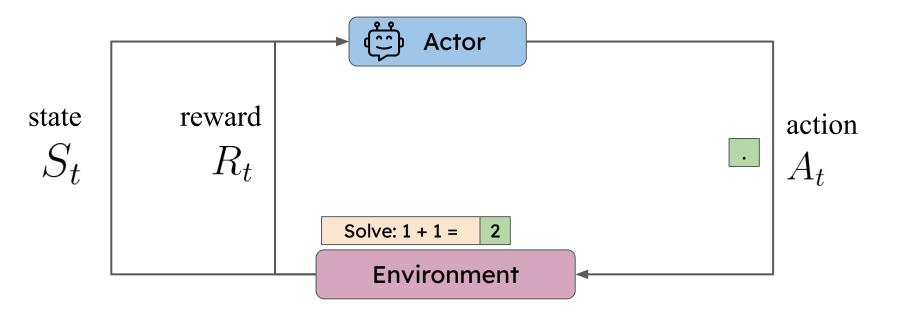


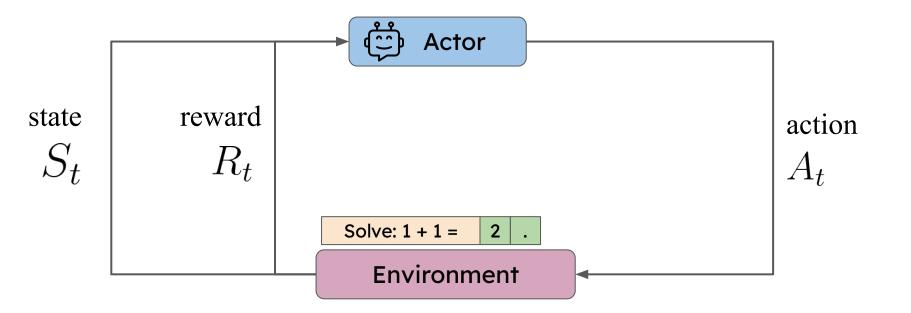


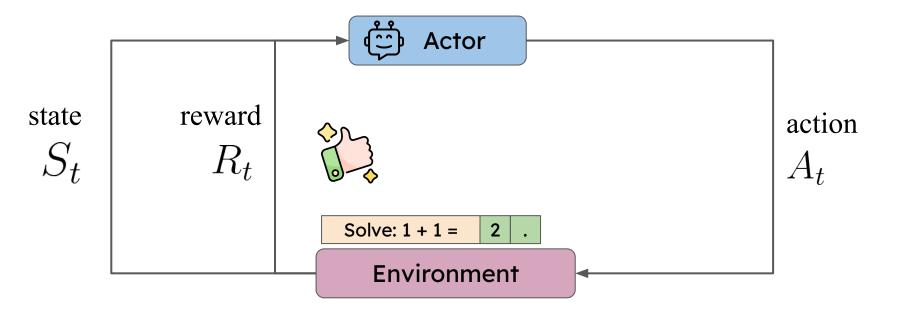


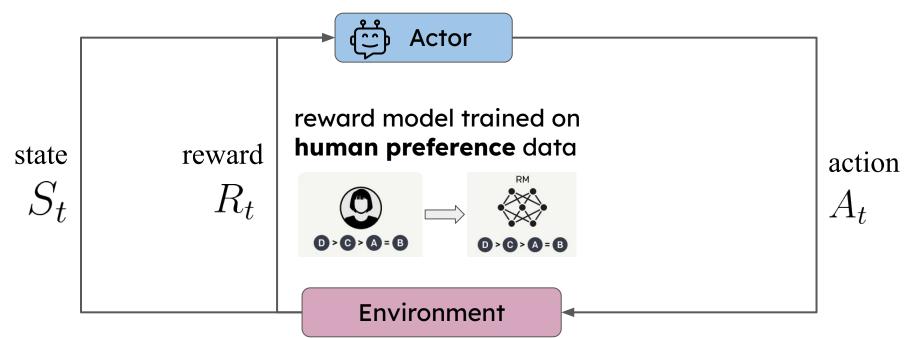








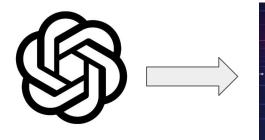




Why use RLHF?

- Human preference
- Safety and robustness
- Hallucination alleviation
- Reasoning ability
- Complex tasks

•

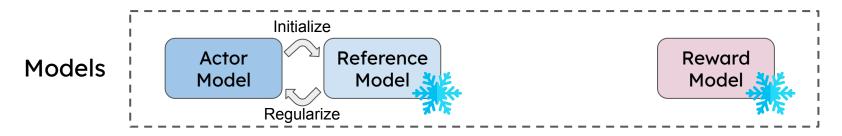


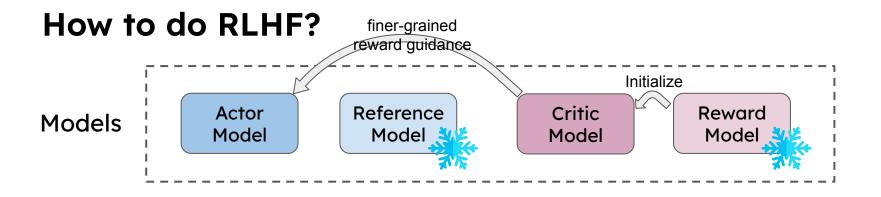
GPT-4

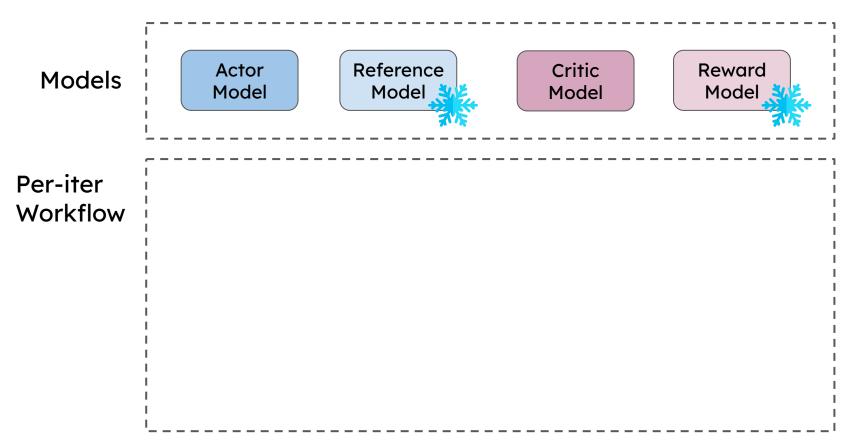


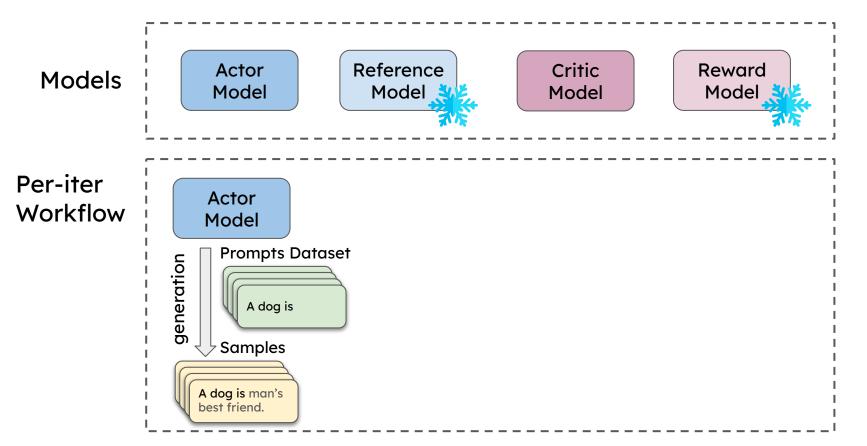
ChatGPT

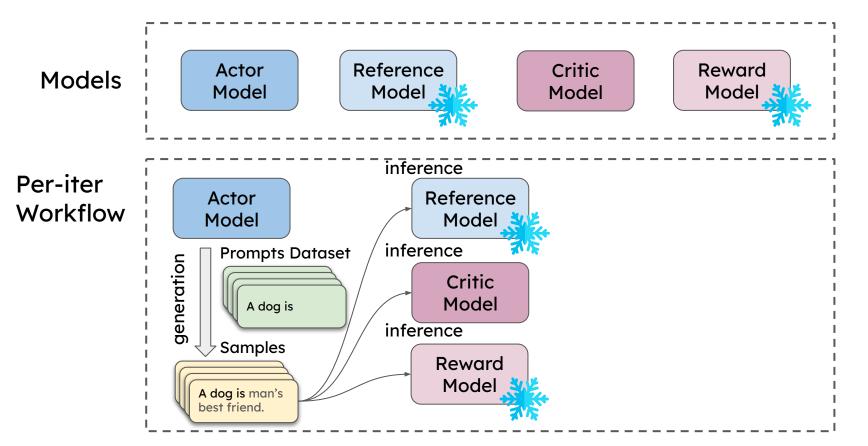


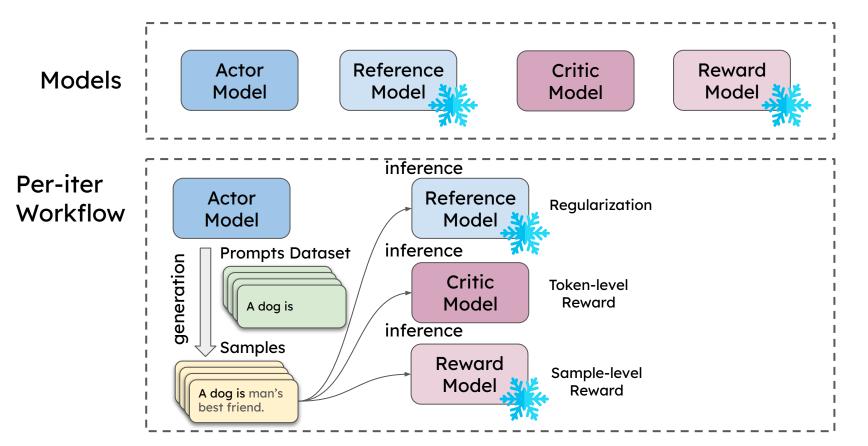


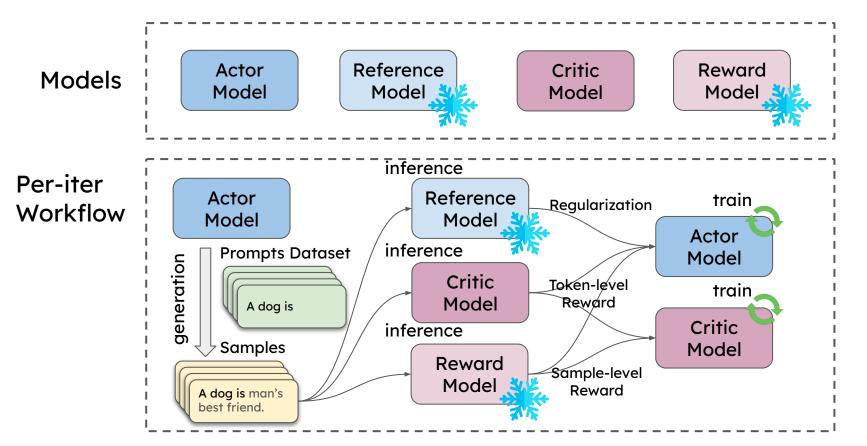








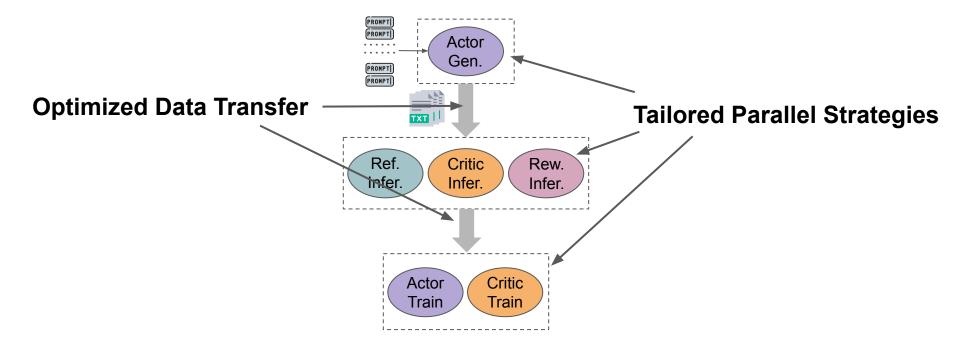




Summary

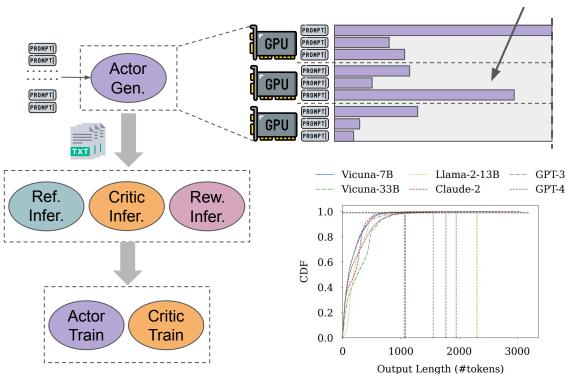
- Four unique models
 - each can have billions of parameters
 - huge computation and memory requirement
- Three distinct stages
 - generation => inference => training
 - different computation pattern
- Six individual tasks
 - \circ complex workflow
 - o data, weights, and communication orchestration

Optimizations in existing systems



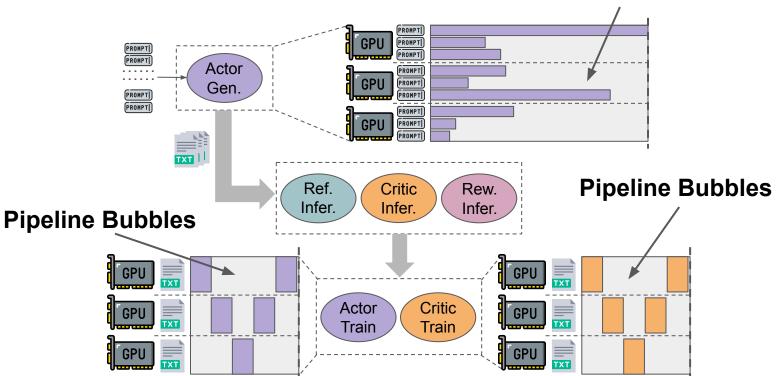
Problems in existing systems

Data Skewness



Problems in existing systems

Data Skewness



The fundamental problem

Existing RLHF training systems view **each task** as the **smallest execution unit**, failing to delve into the **inherent characteristics and structure** inside the tasks.

The fundamental problem

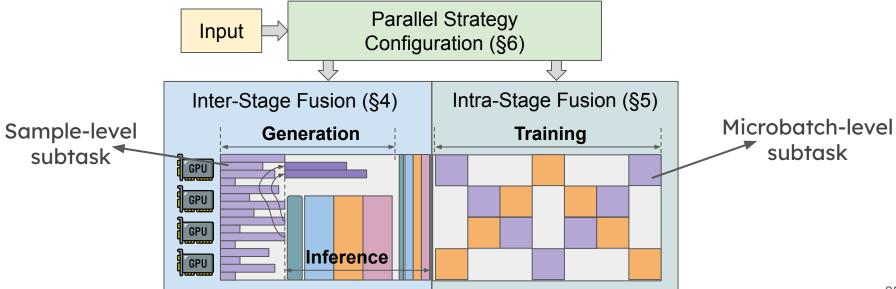
Existing RLHF training systems view **each task** as the **smallest execution unit**, failing to delve into the **inherent characteristics and structure** inside the tasks.

Opportunities

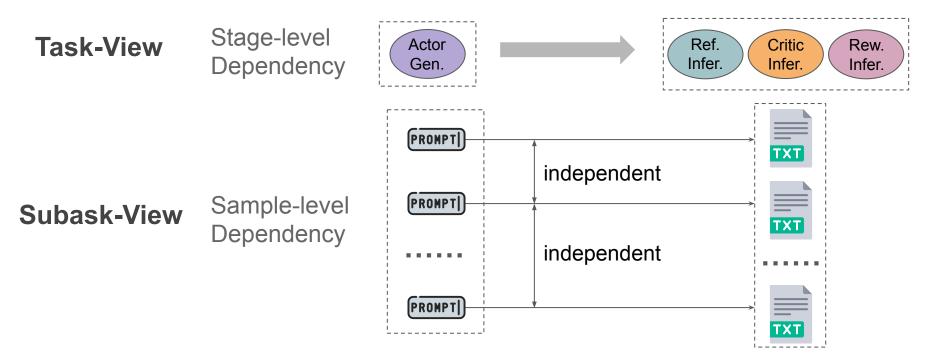
- Generation Stage: each **sample** can be viewed as a subtask
- Training Stage: each **micro-batch** can be viewed as a subtask

RLHFuse Overview

RLHFuse breaks the traditional view of RLHF workflow as a composition of individual tasks, splitting each task into **finer-grained subtasks**, and performs **stage fusion** to improve GPU utilization.

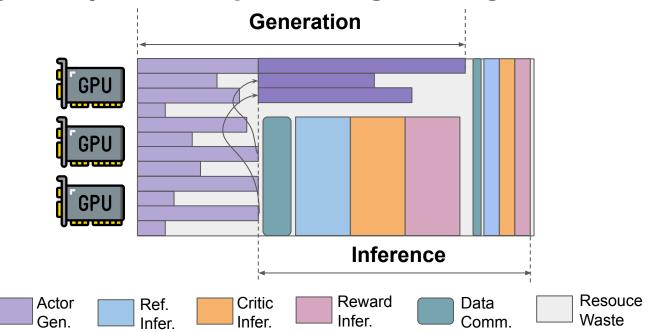


Core observation 1: Sample-level Dependency



Data-aware Inter-stage Fusion

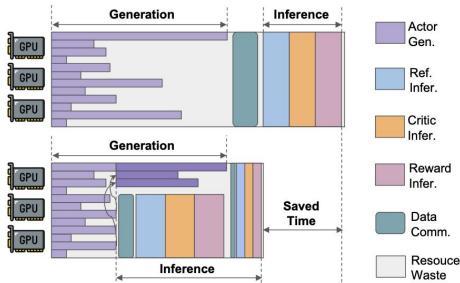
Migrate long-tailed samples together and start inference stage early to overlap with long-tailed generation.



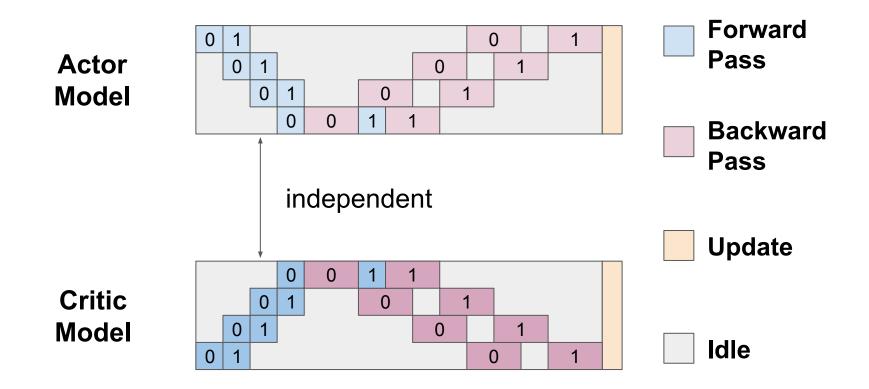
Data-aware Inter-stage Fusion

Algorithm Sketch:

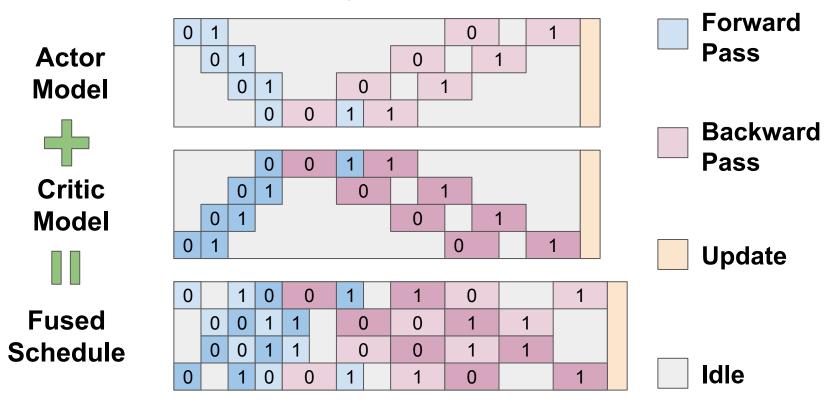
- Migration timing
 - \circ determine migration ratio R_t
- Migration destination
 - latency/memory constraint
 - minimize #migration
- Migration mechanism
 - migrate key-value cache
 - migrate token



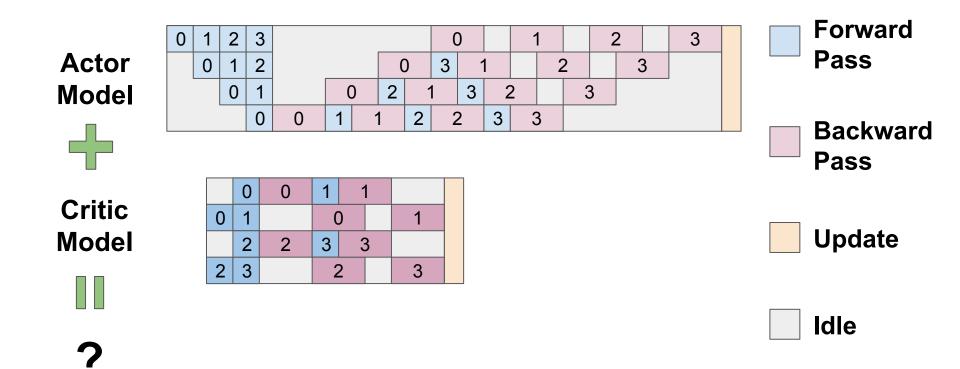
Core observation 2: Independent Training Tasks



Model-aware Intra-stage Fusion

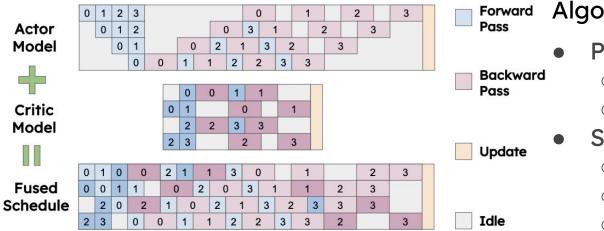


Model-aware Intra-stage Fusion



Model-aware Intra-stage Fusion

Fuse any two different pipeline schedules to achieve optimal latency and memory usage.



Algorithm Sketch:

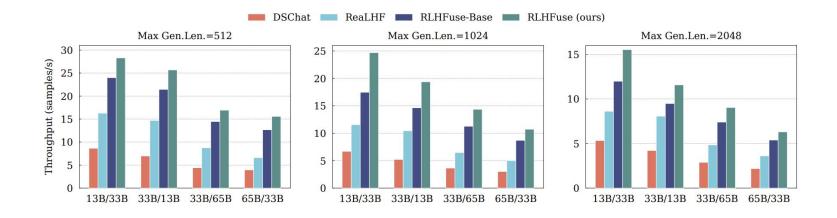
- Problem transformation
 - tackle different tp
 - fusion factor (K1, K2)
- Simulated Annealing
 - swap adjacent subtasks
 - first optimize latency
 - then optimize memory

Evaluation – Setup

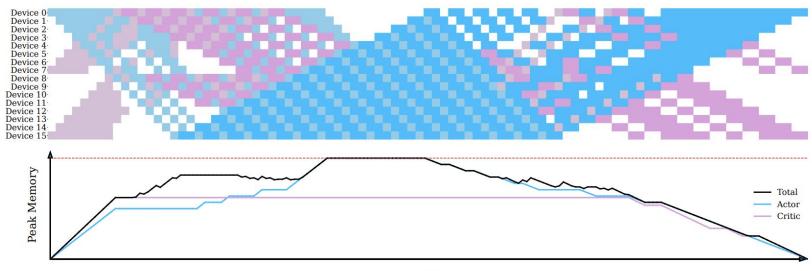
- Cluster: 32 nodes with 256 H800-80GB GPUs
- Models: LLaMA-13B, LLaMA-33B, LLaMA-65B
- Dataset: HH-RLHF
- Settings:
 - Critic/Actor: 13B/33B, 33B/13B, 33B/65B, 65B/33B
 - Maximum generation length: 512, 1024, 2048
- Baselines:
 - DeepSpeed-Chat
 - ReaLHF
 - RLHFuse-Base

Evaluation – End-to-end

RLHFuse achieves 2.5×-3.7× higher end-to-end throughput.



Evaluation – Case Study



Timeline

Takeaway

- RLHFuse
 - breaks the RLHF workflow as a composition of **individual tasks**
 - splits generation task into **sample-level subtasks**
 - splits training task in **microbatch-level substasks**
 - uses inter- and intra-stage fusion to achieve higher GPU utilization
 - achieves up to **3.7x** higher throughput compared with SOTA systems



