Microsecond-scale Preemption for Concurrent GPU-accelerated DNN Inferences

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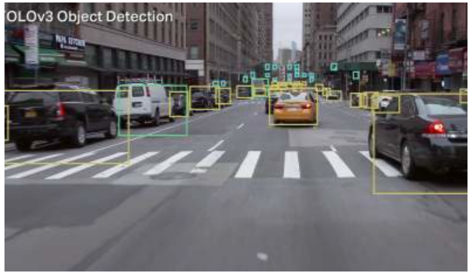
Motivation

DNNs are widely adopted by modern intelligent applications

Motivation



Obstacle Detection

Fatigue Detection

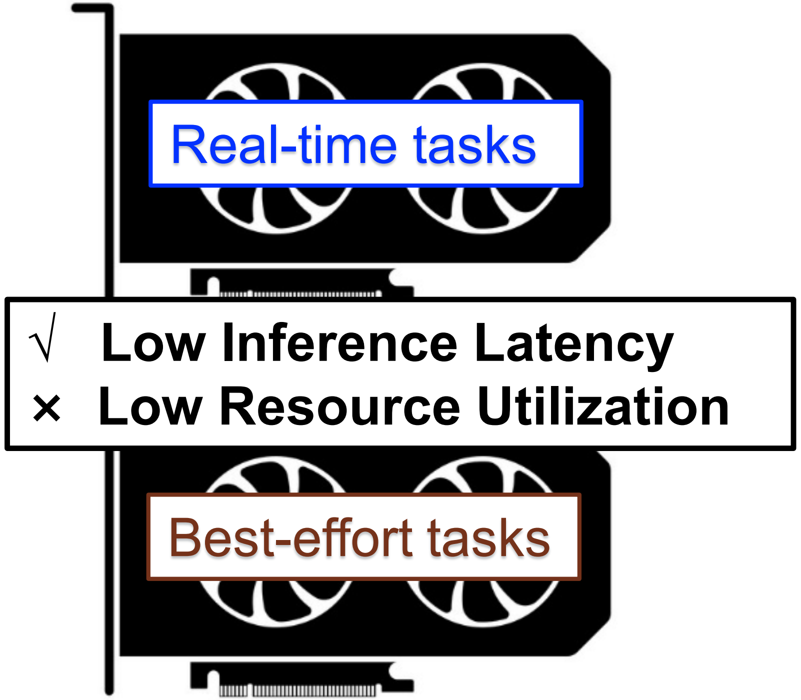
Real-time tasks

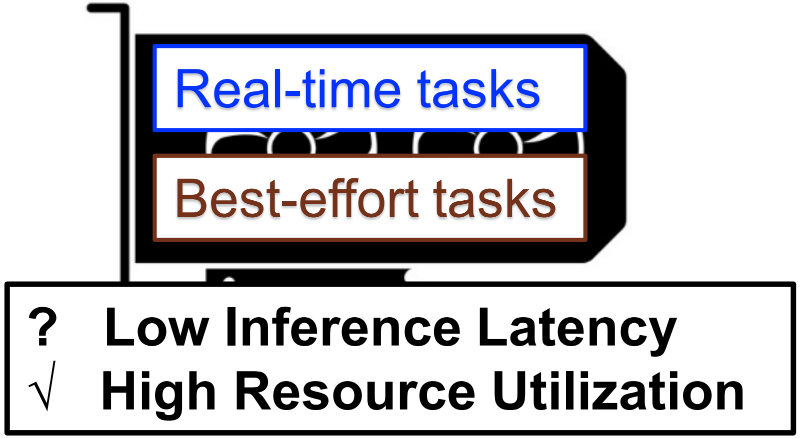
- Latency critical

Best-effort tasks

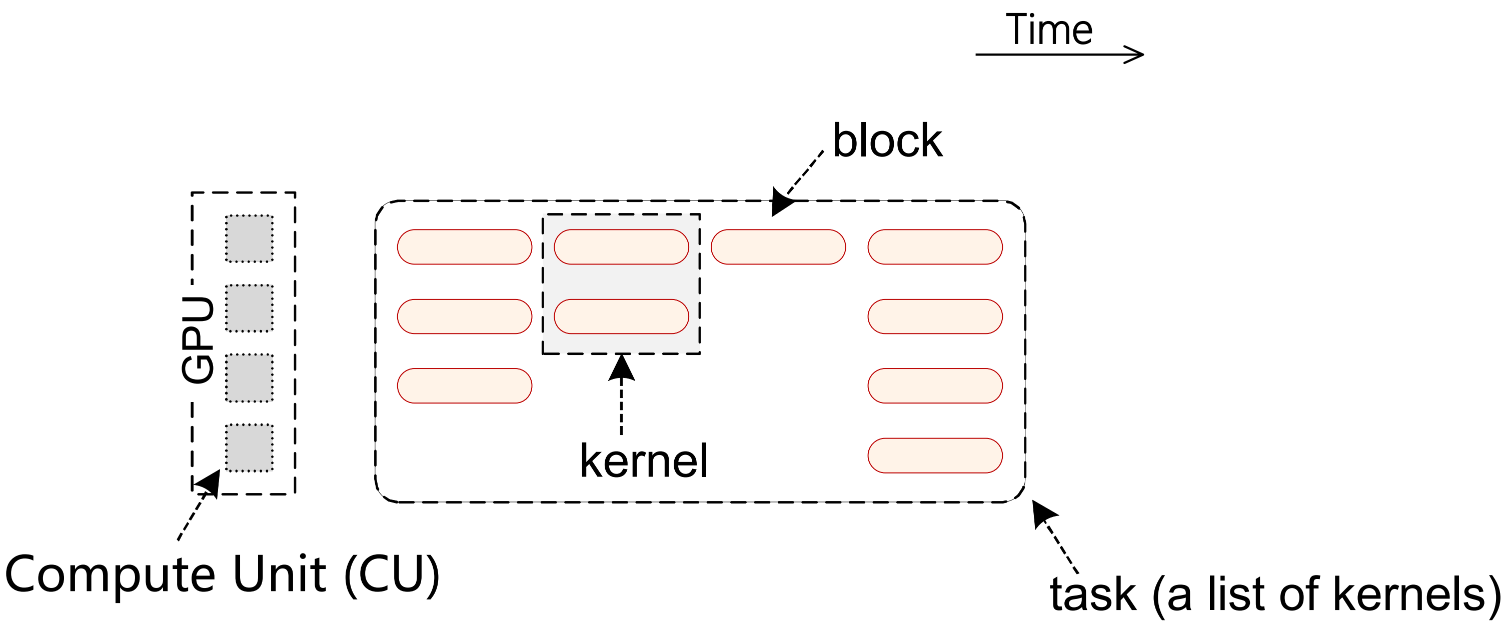
- No hard real-time requirement

Motivation

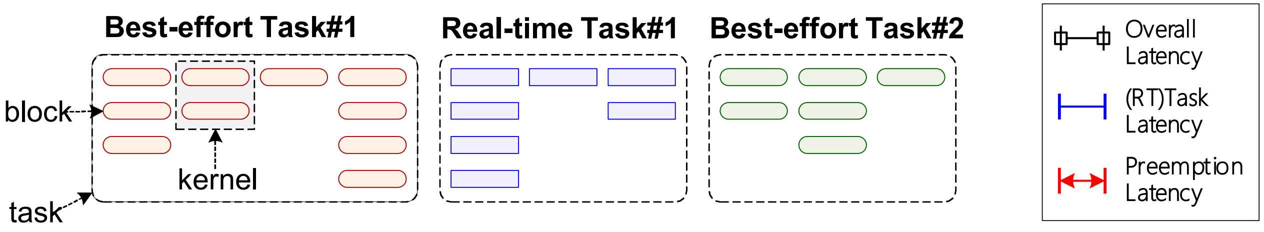

Real-time tasks
√ Low Inference Latency
× Low Resource Utilization
Best-effort tasks


Real-time tasks
Best-effort tasks
? Low Inference Latency
√ High Resource Utilization

GPU-accelerated DNN inference



Existing GPU Task Scheduling



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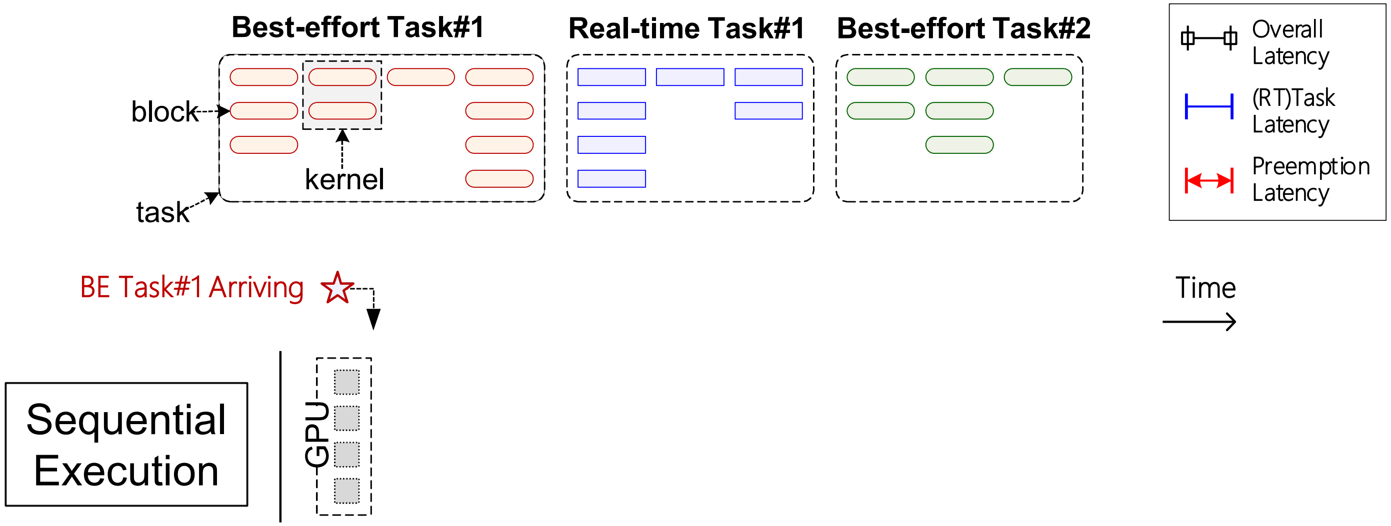

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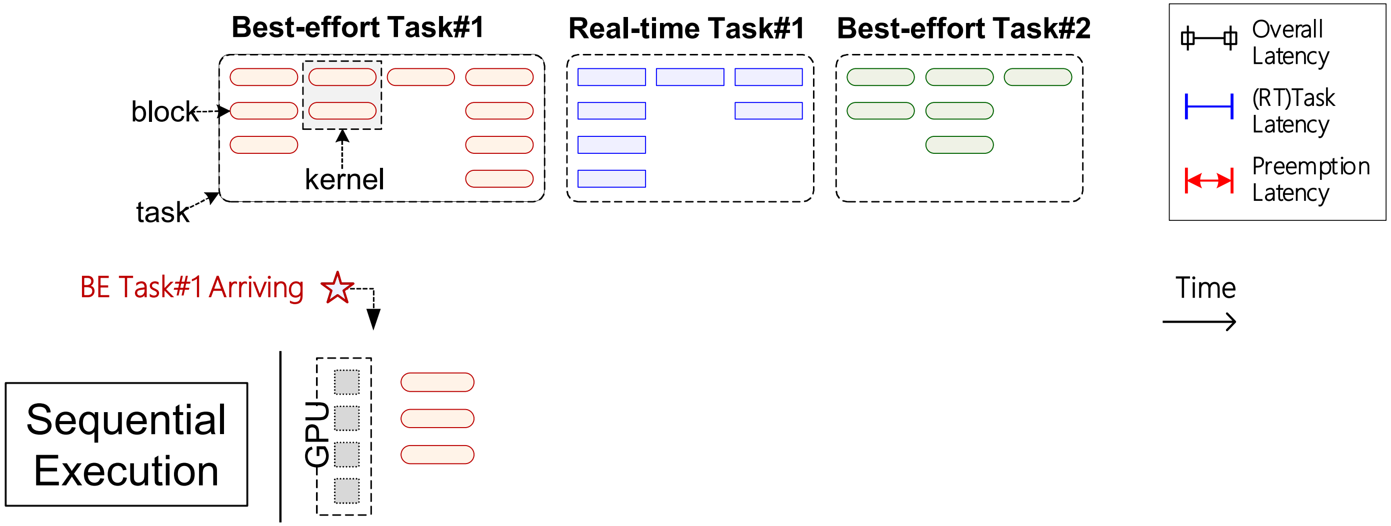

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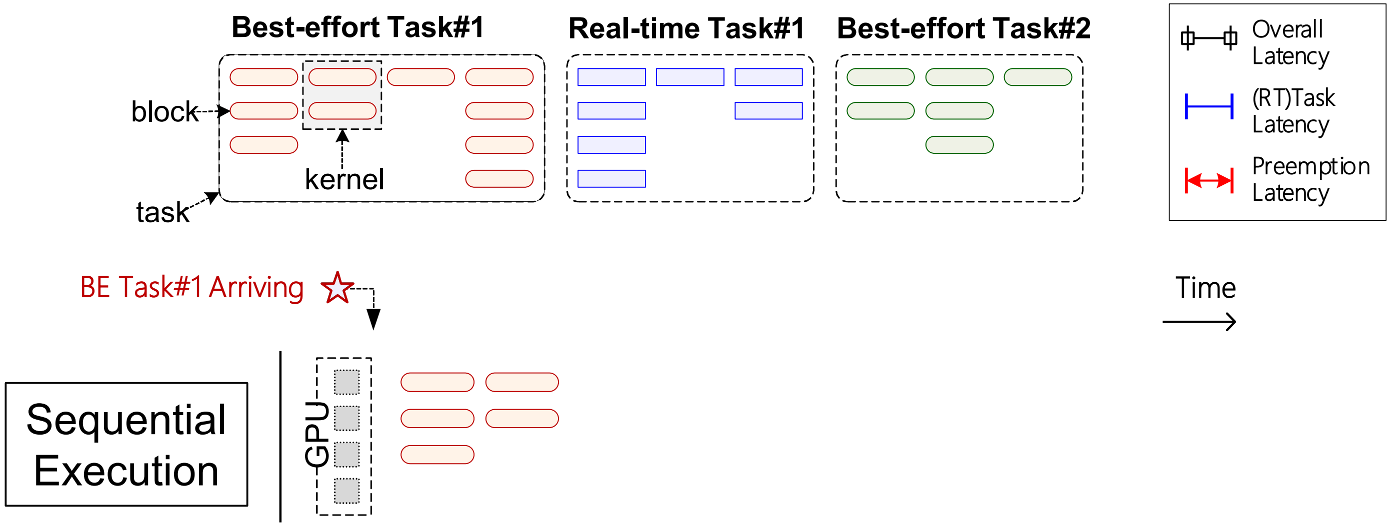

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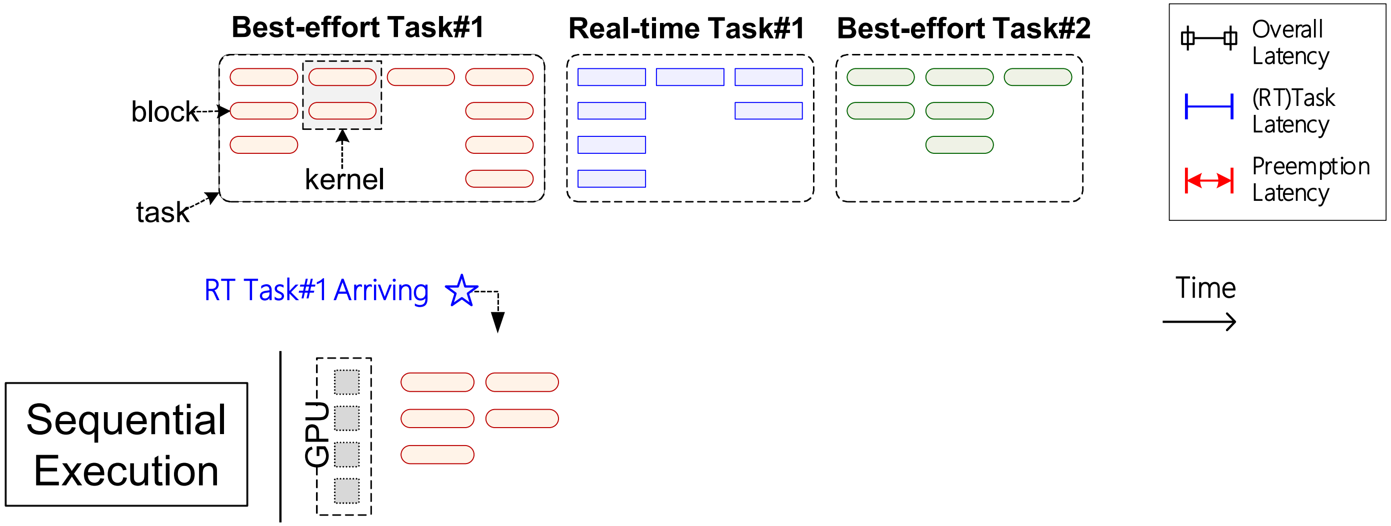

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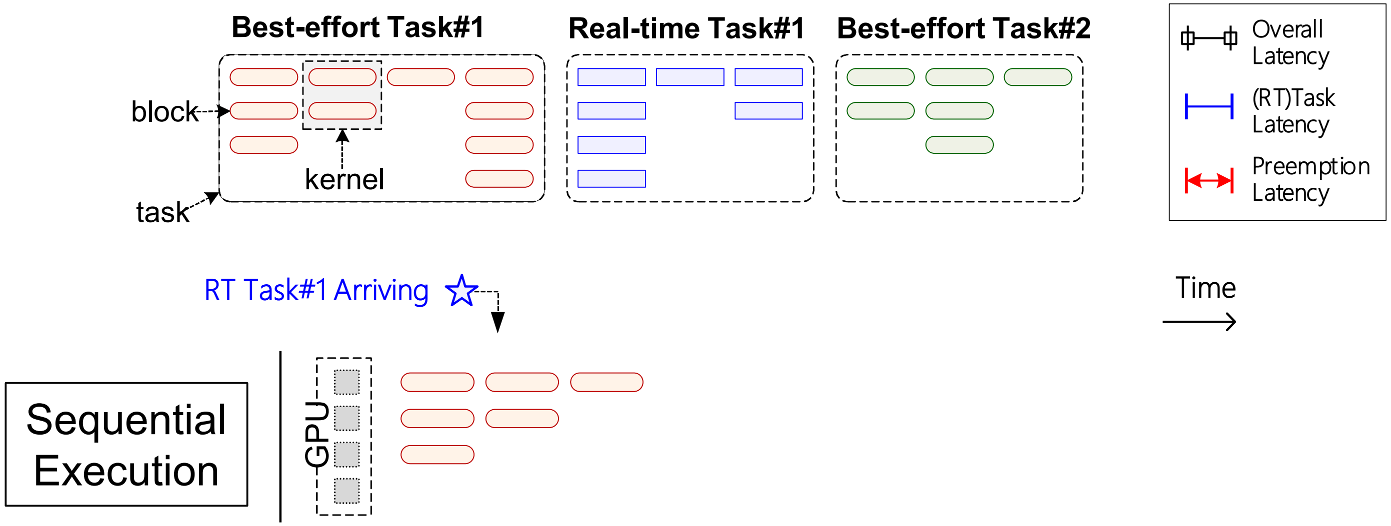

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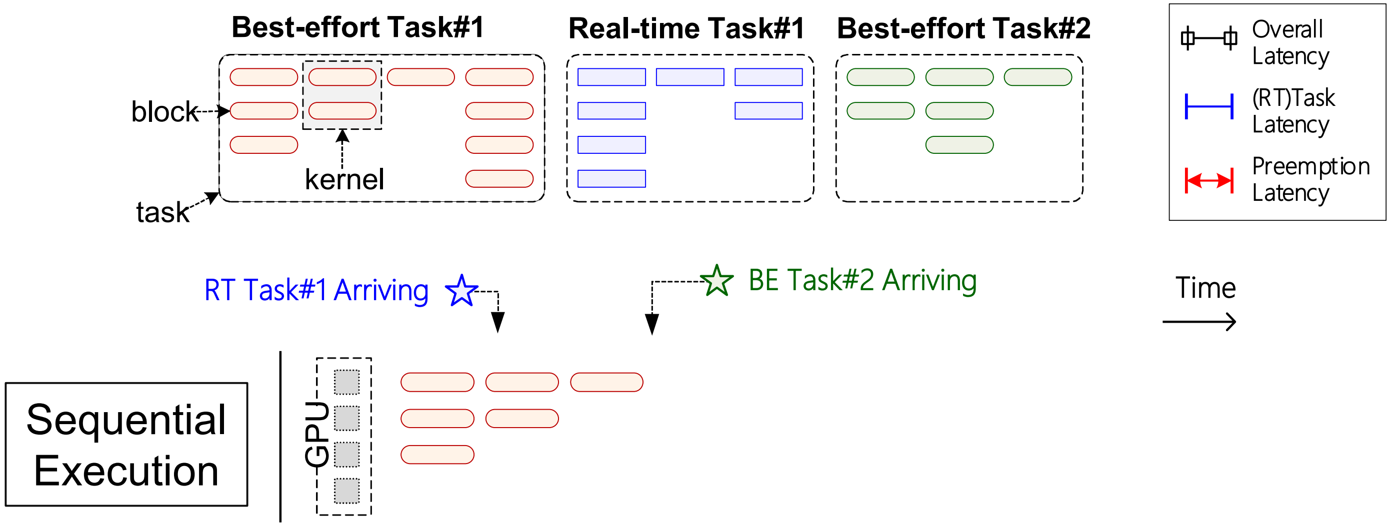

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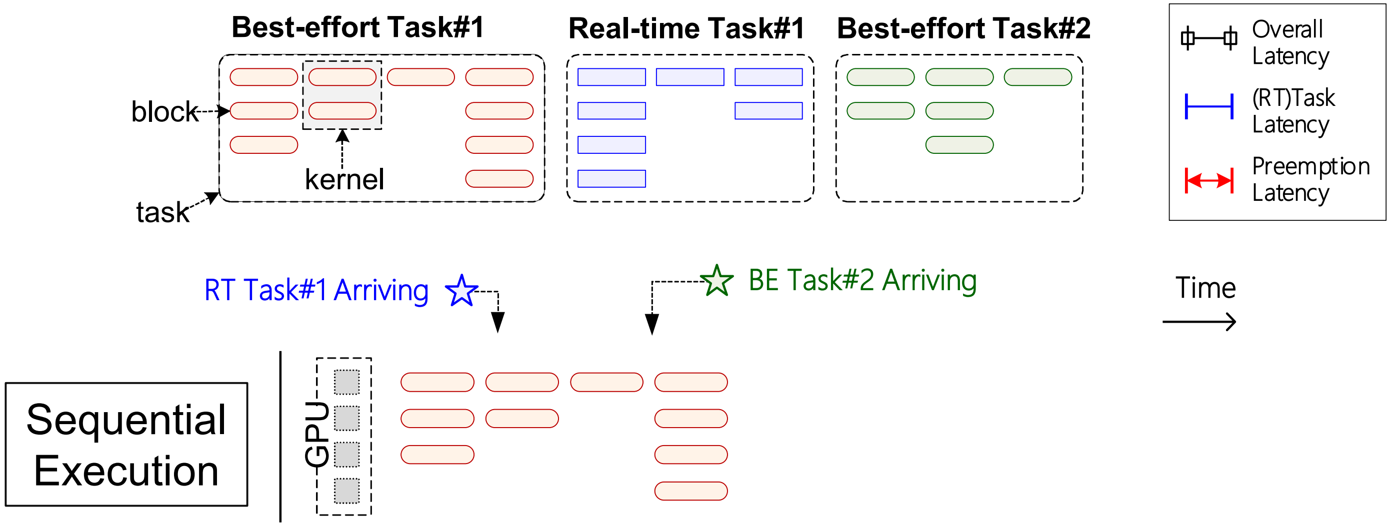

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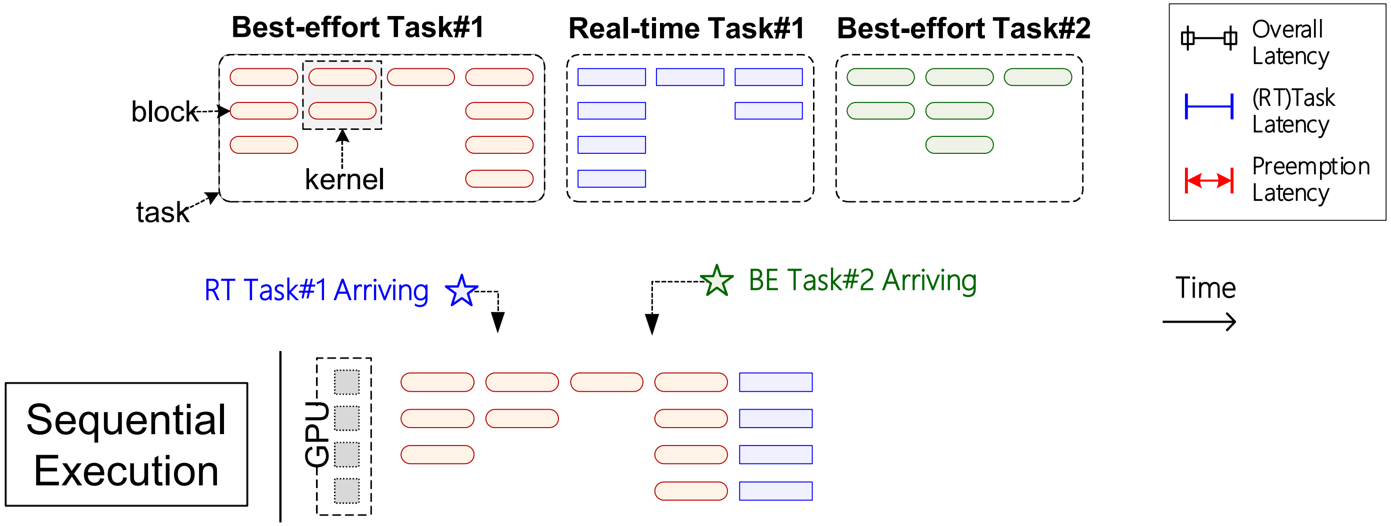

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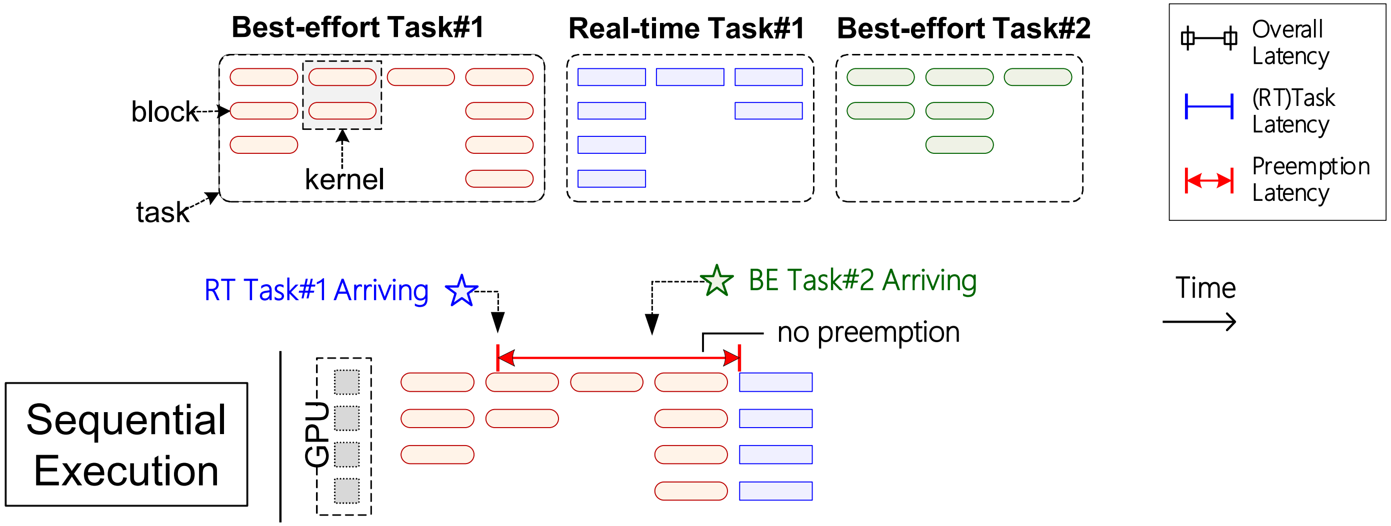

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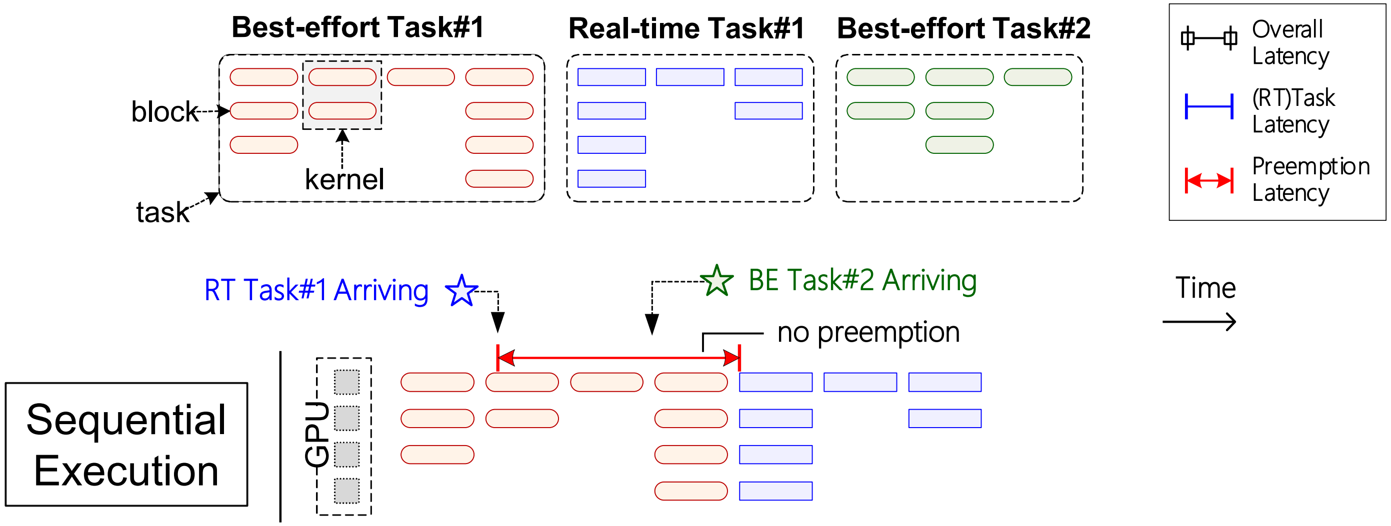

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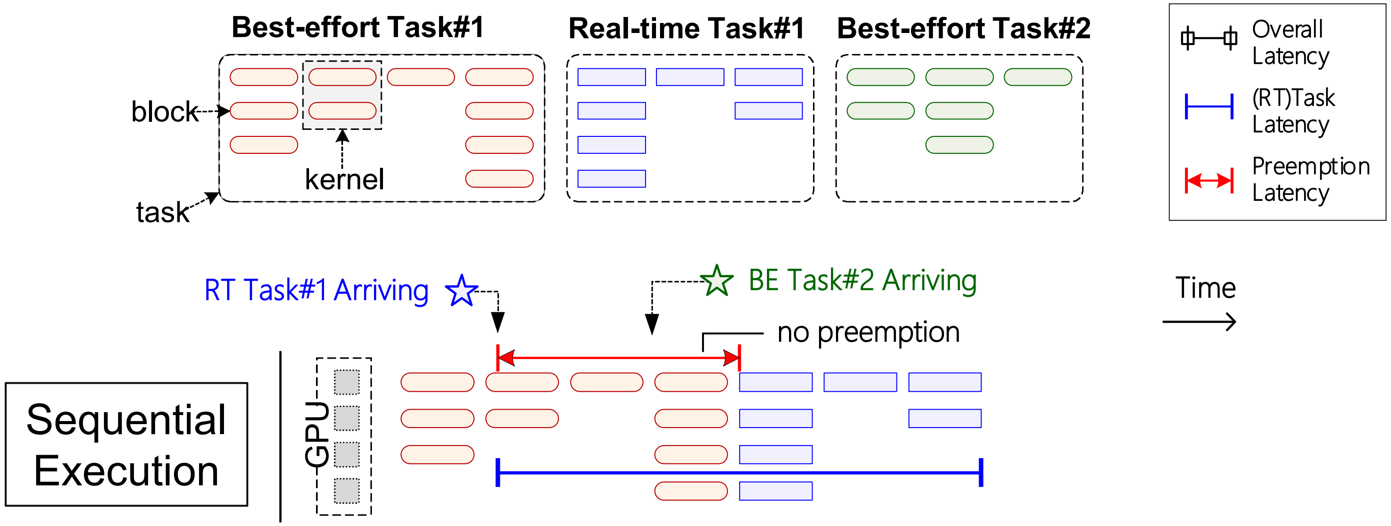

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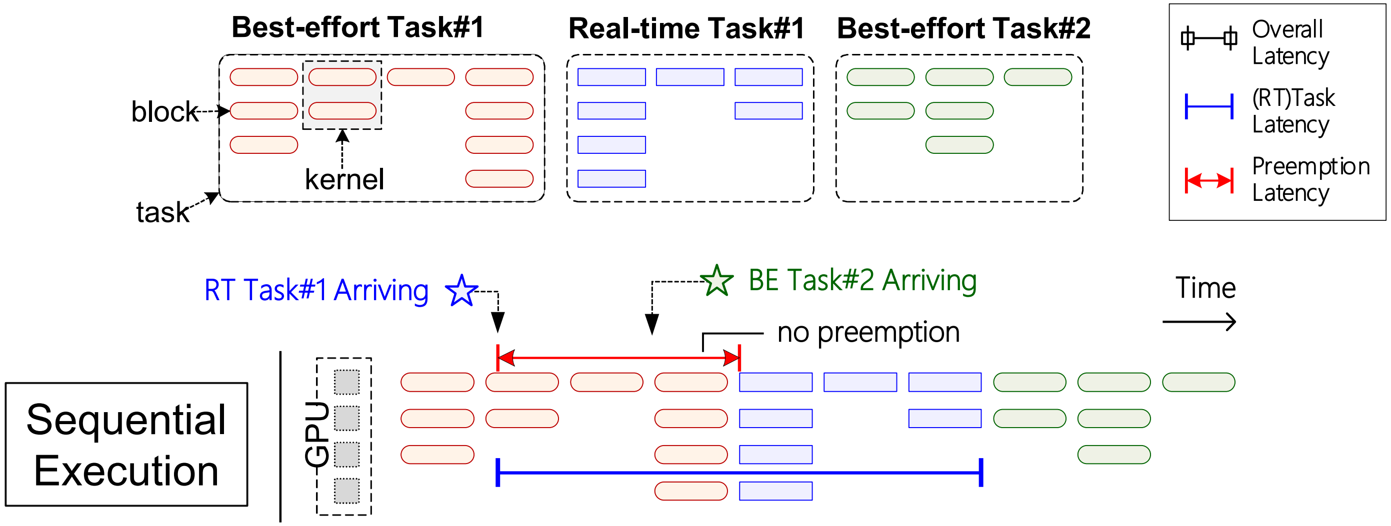

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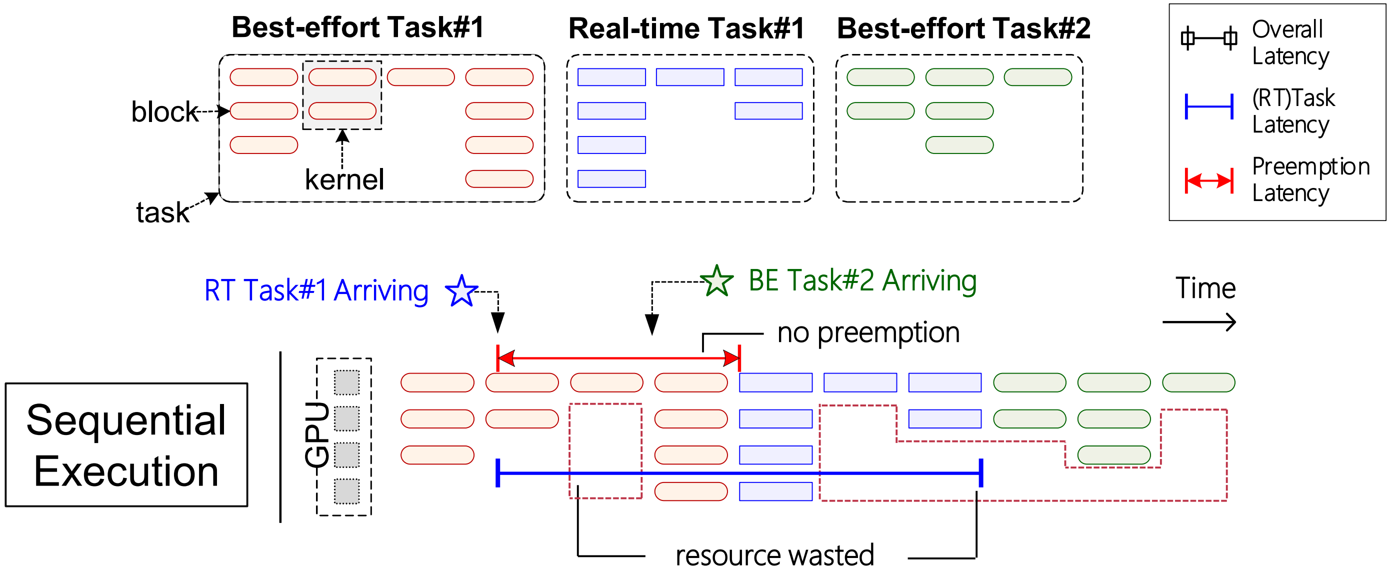

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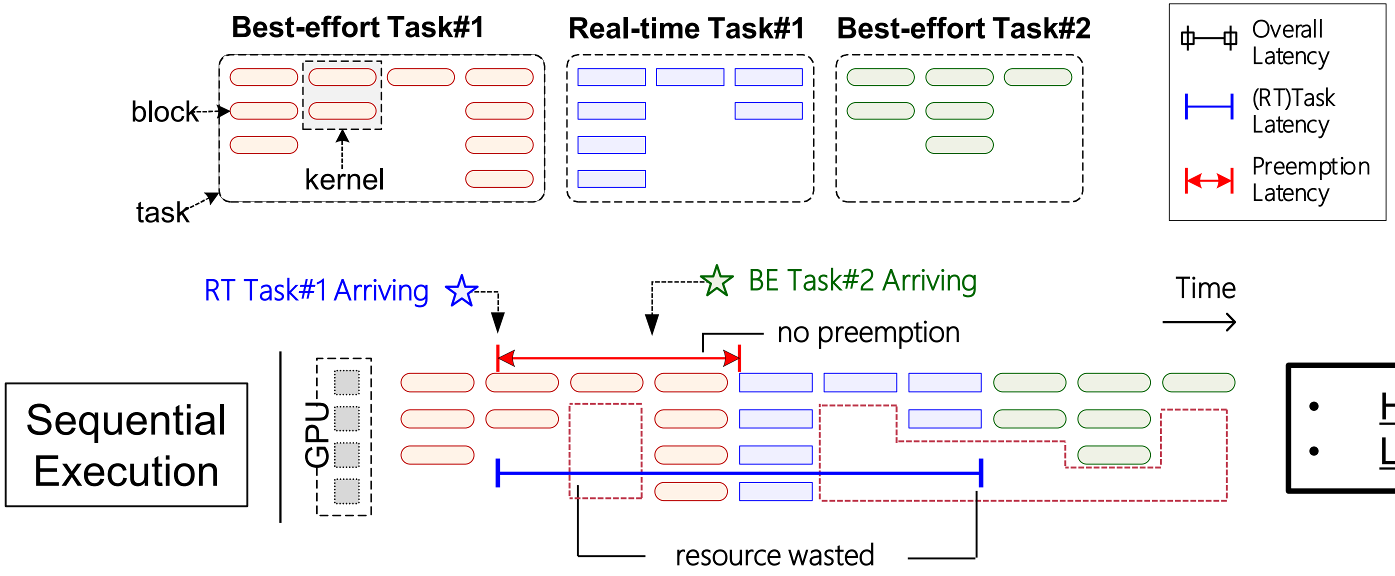
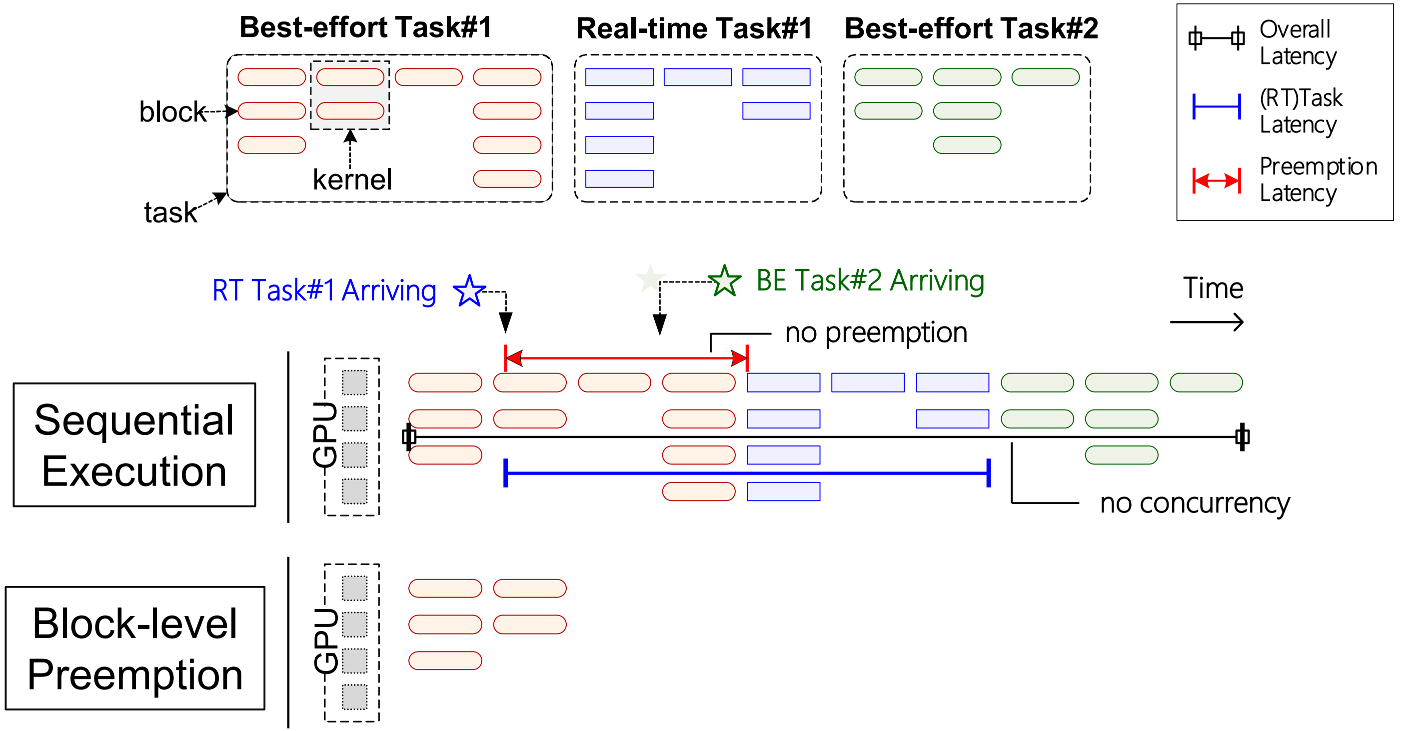


- High latency for **RT** tasks
- Low throughput (not work-conserving)

Existing GPU Task Scheduling



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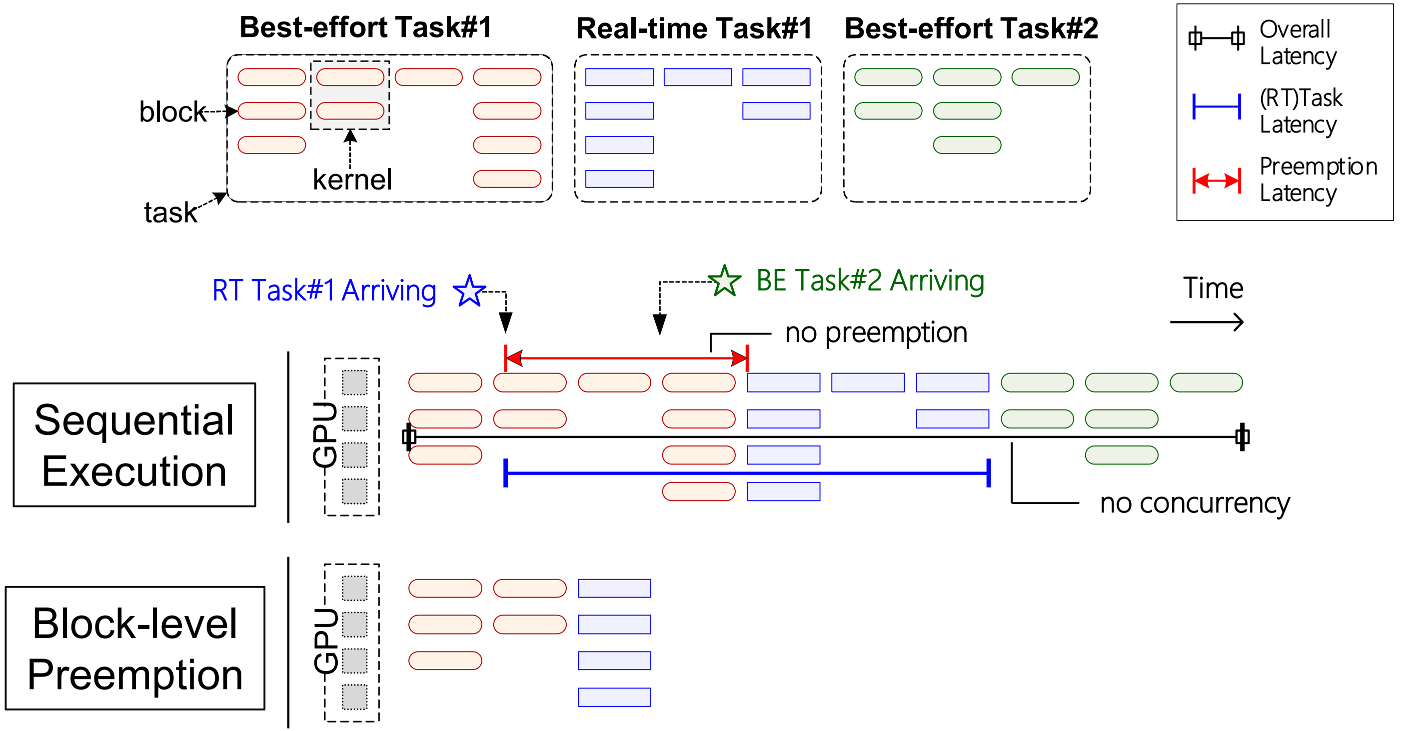

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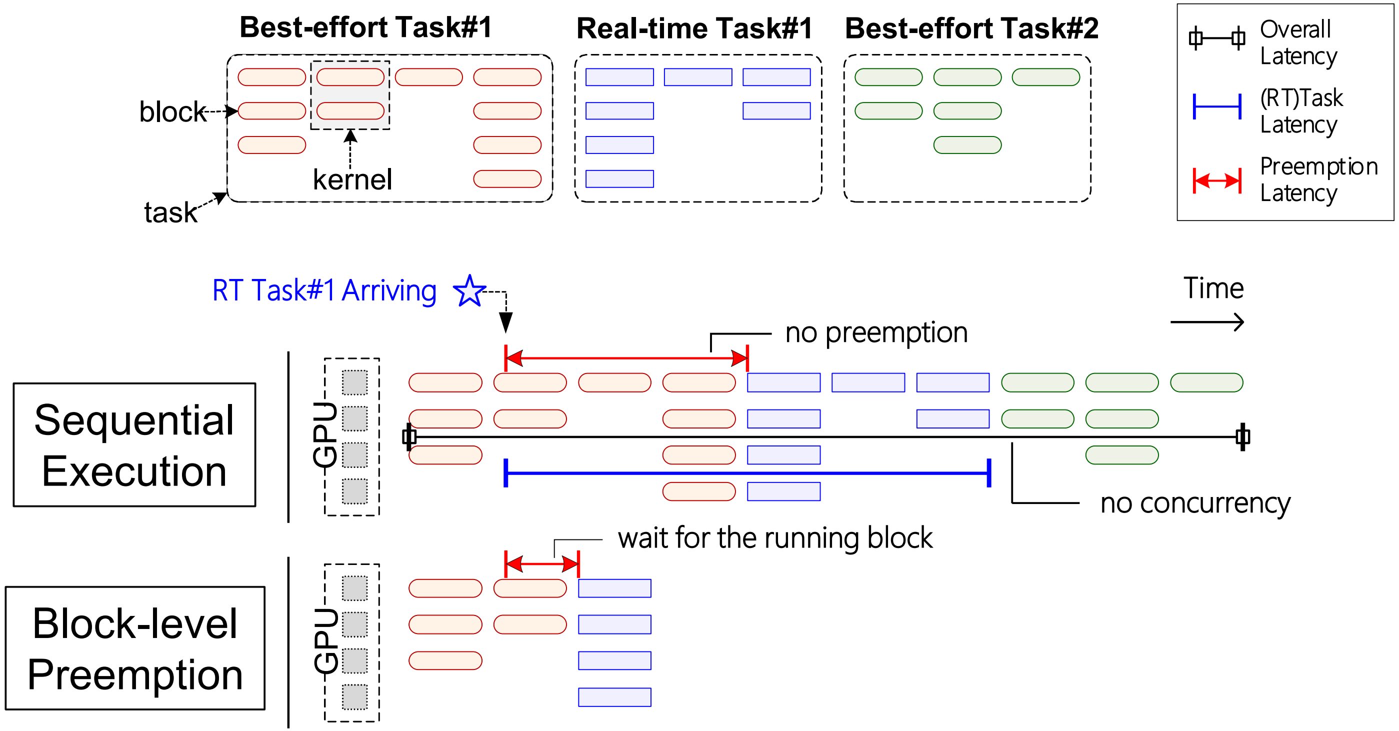

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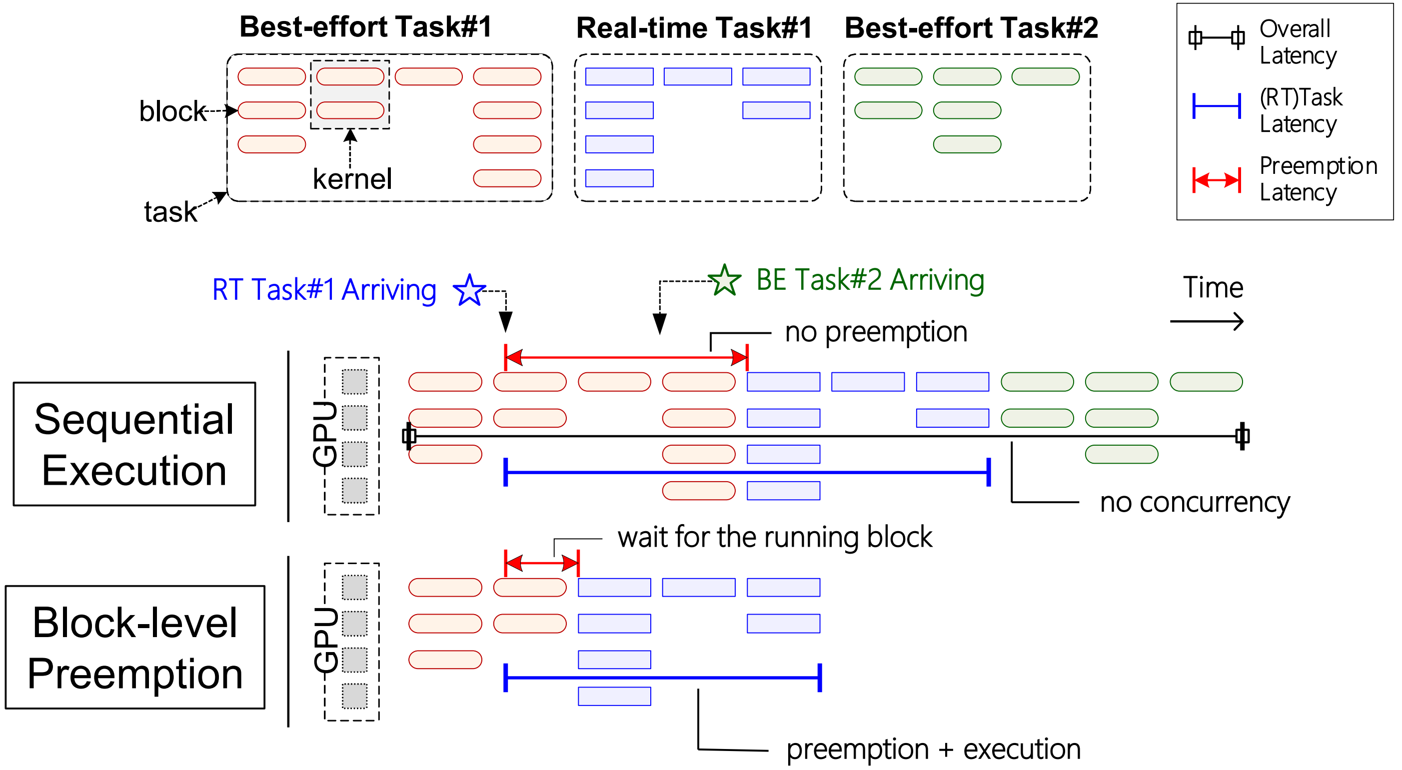

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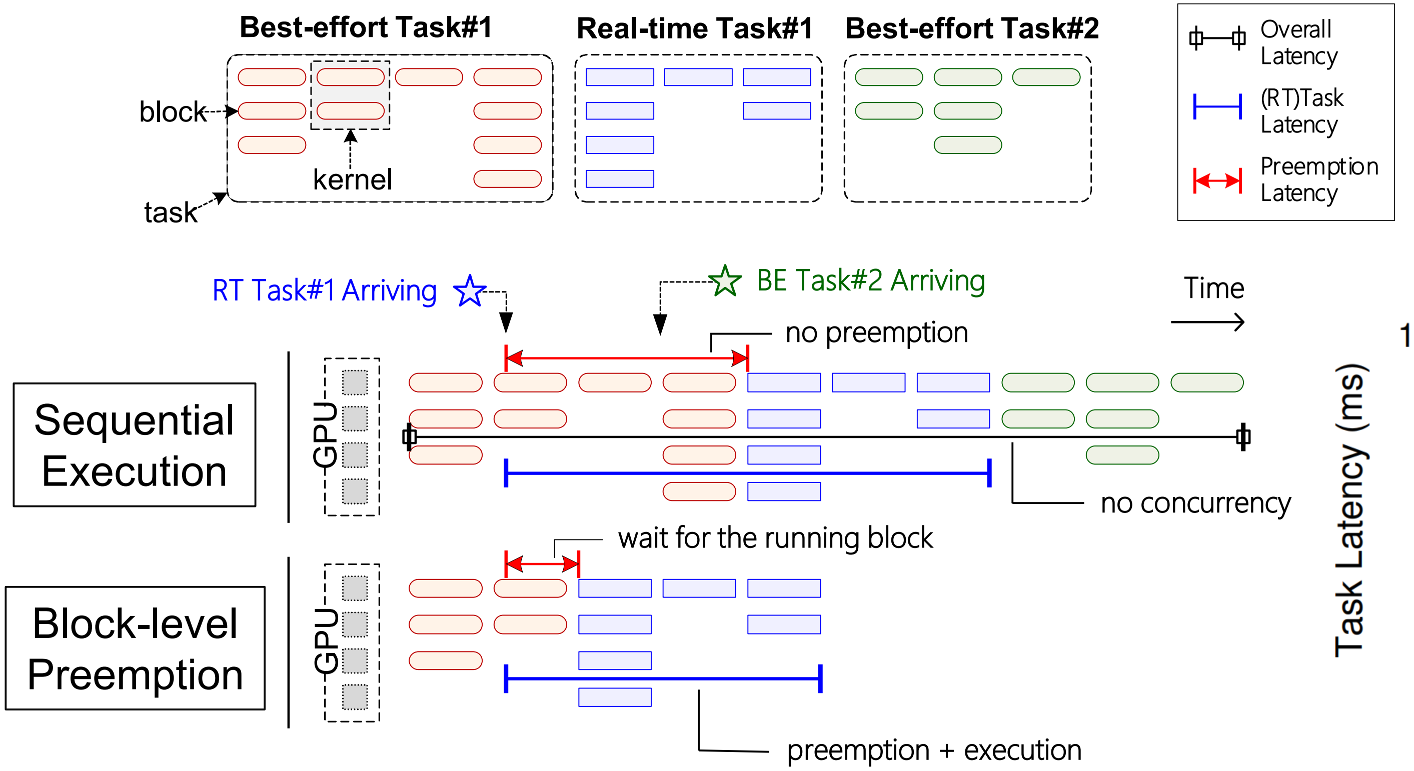

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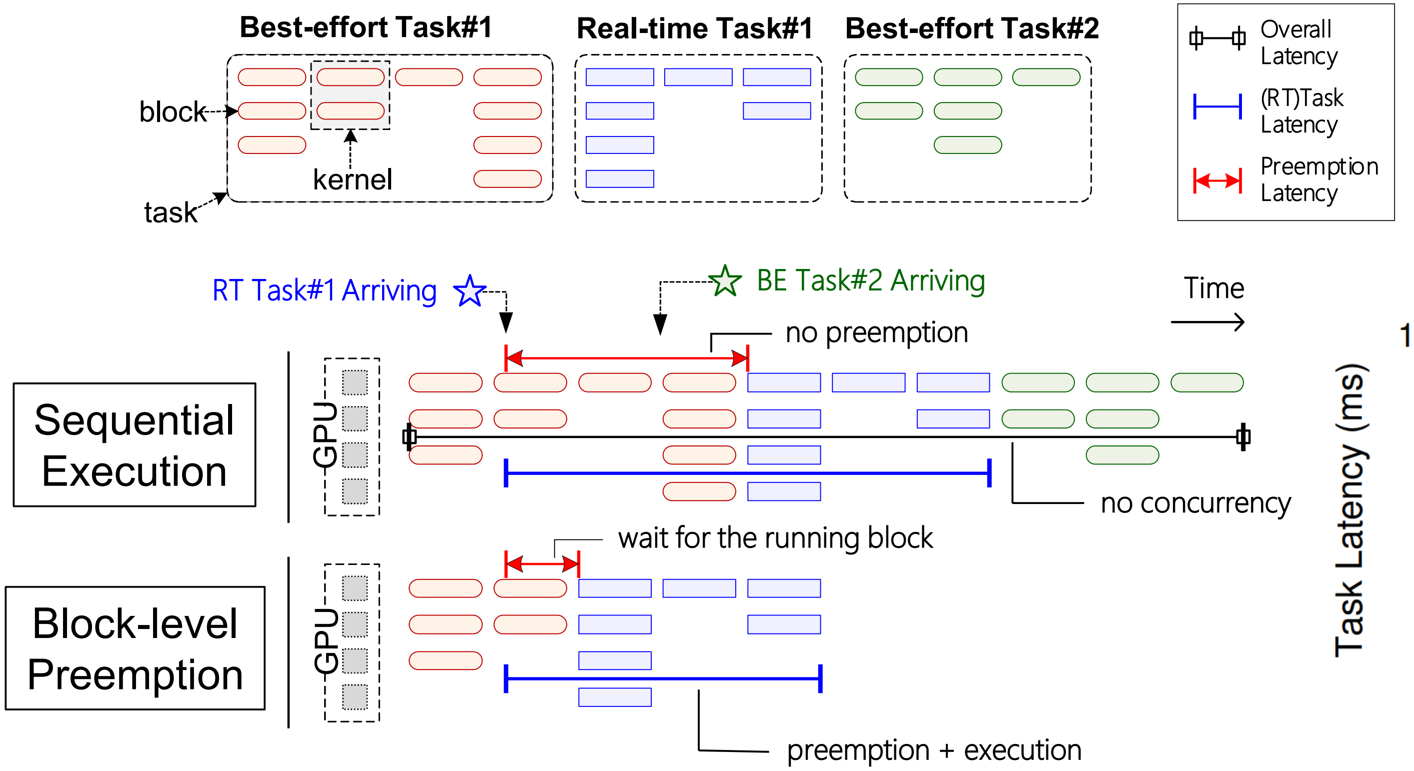

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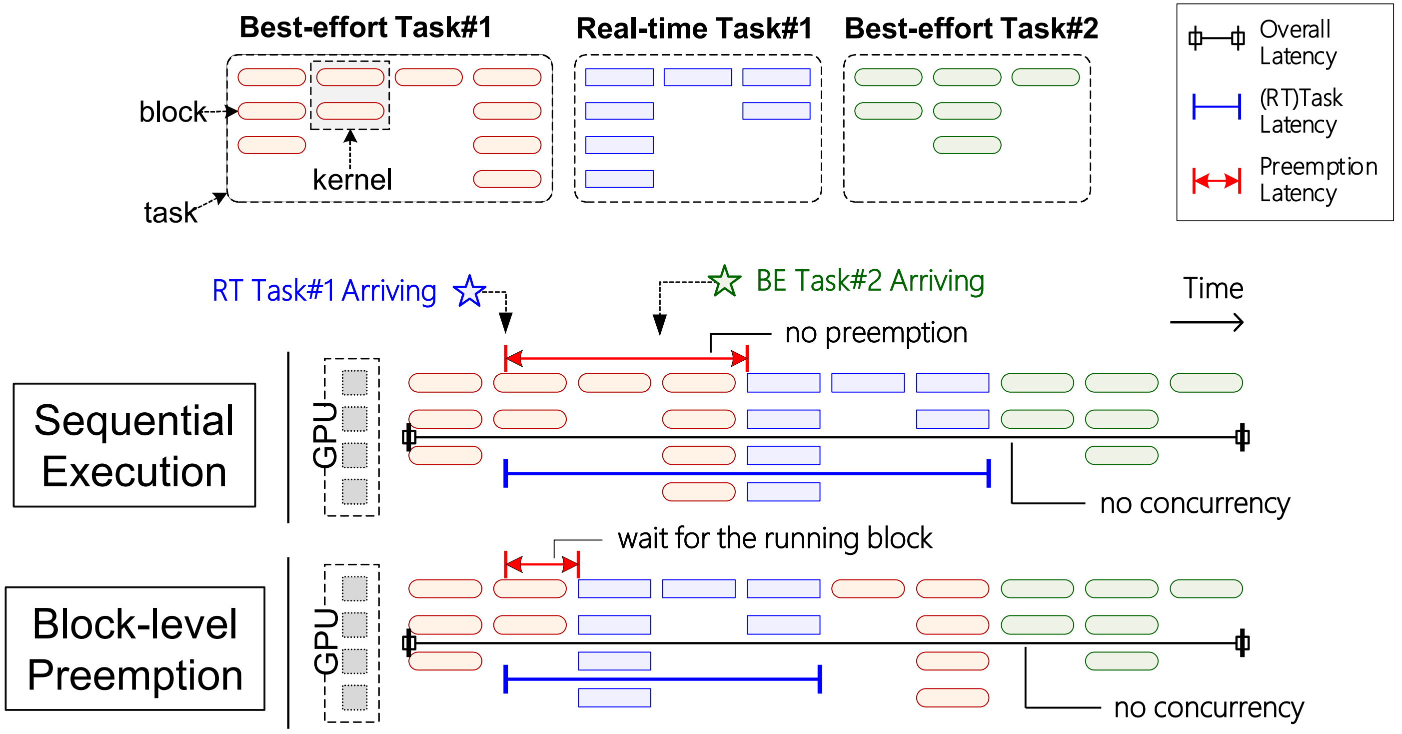

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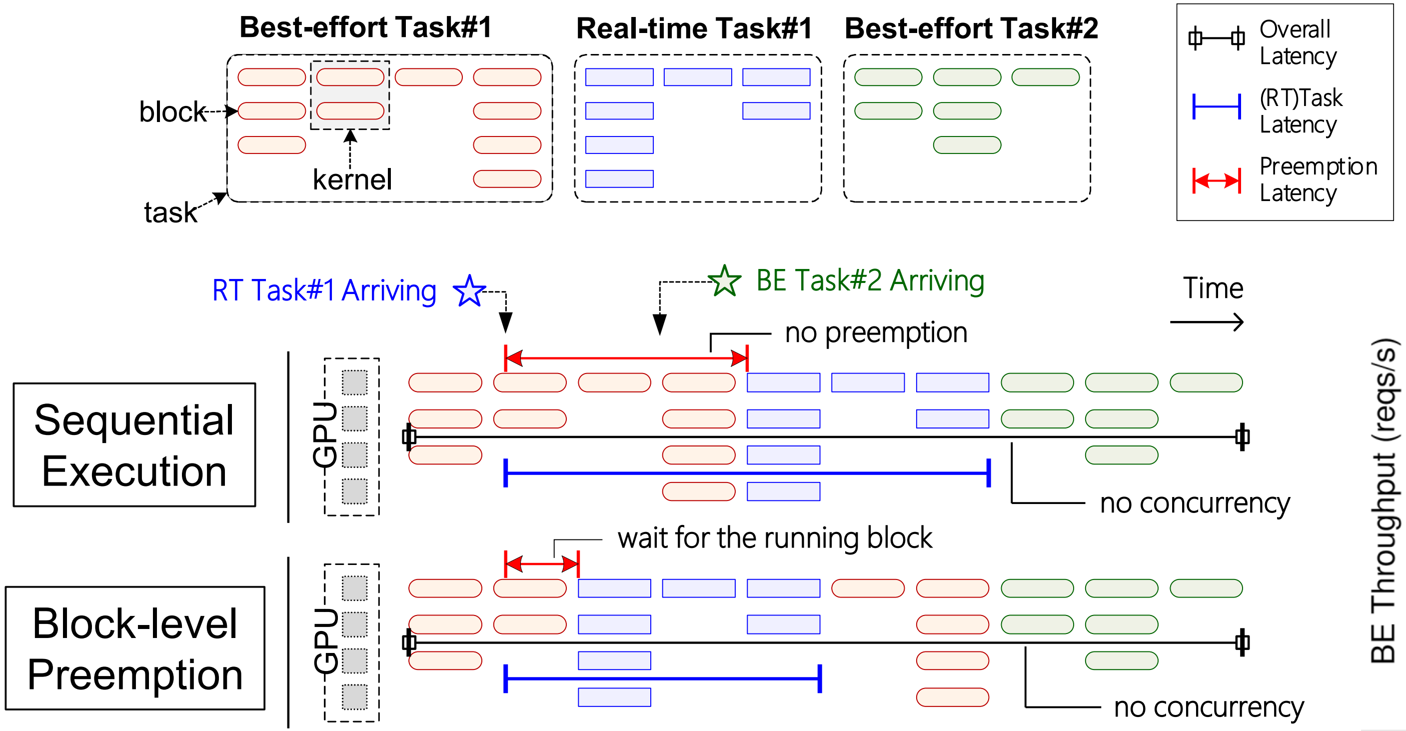

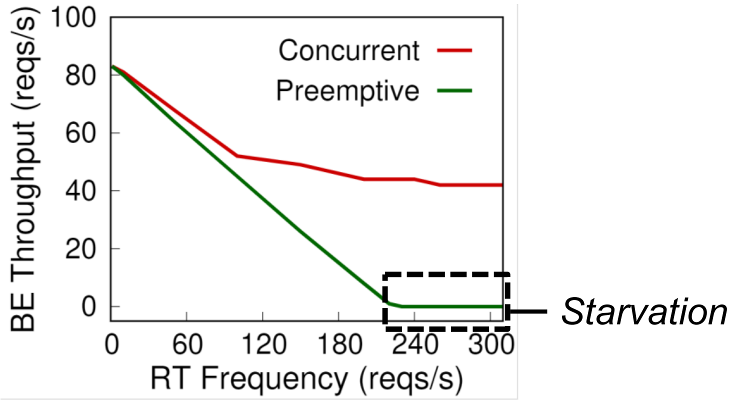

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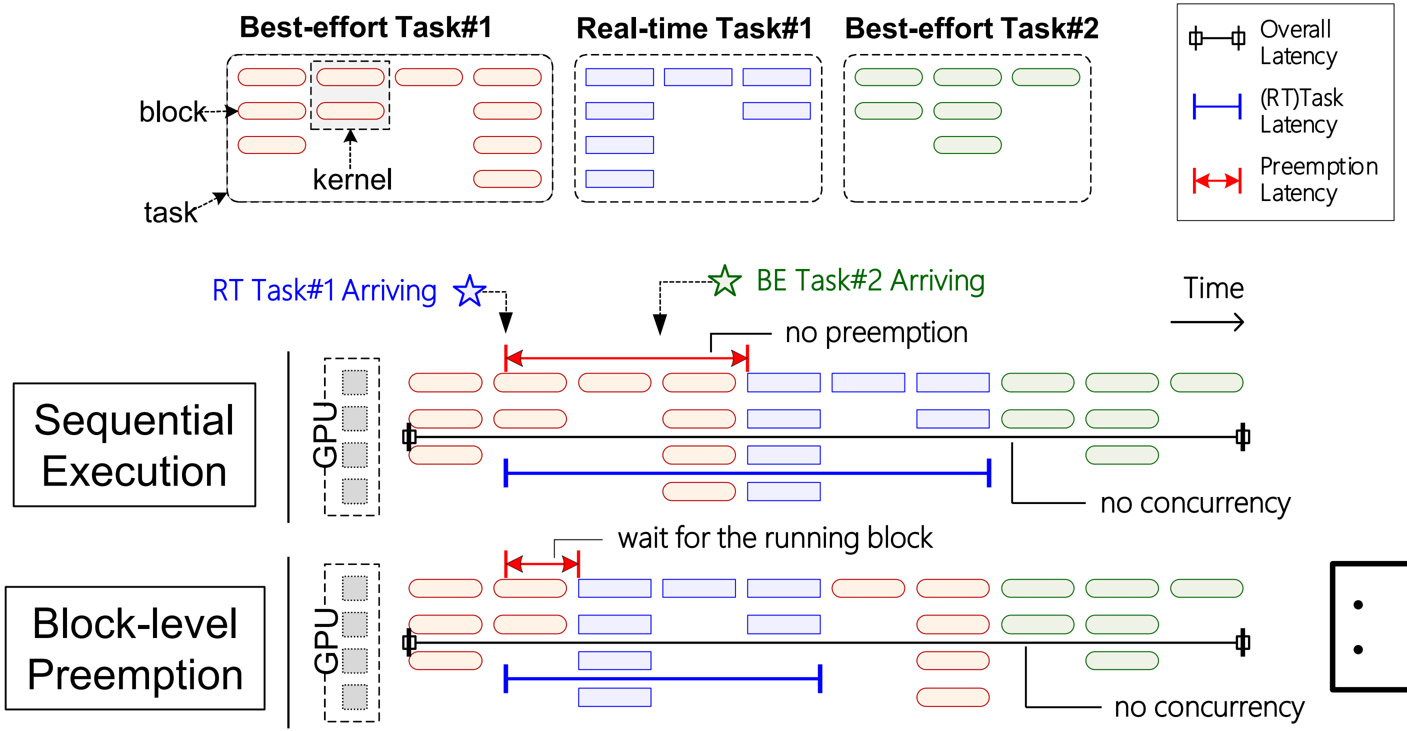

- (Not always) low latency for **RT** tasks
- <u>Low throughput</u> (not work-conserving)

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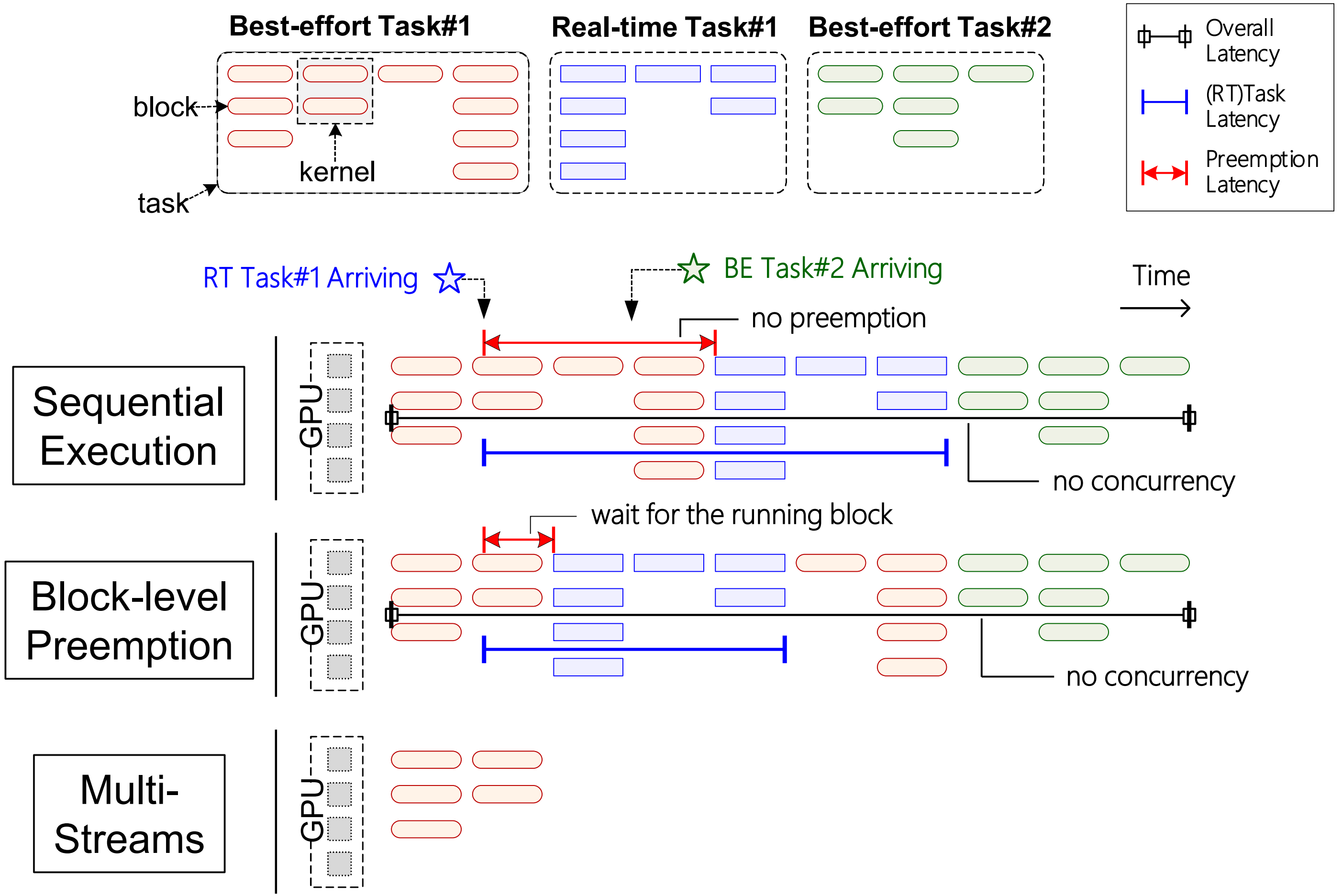

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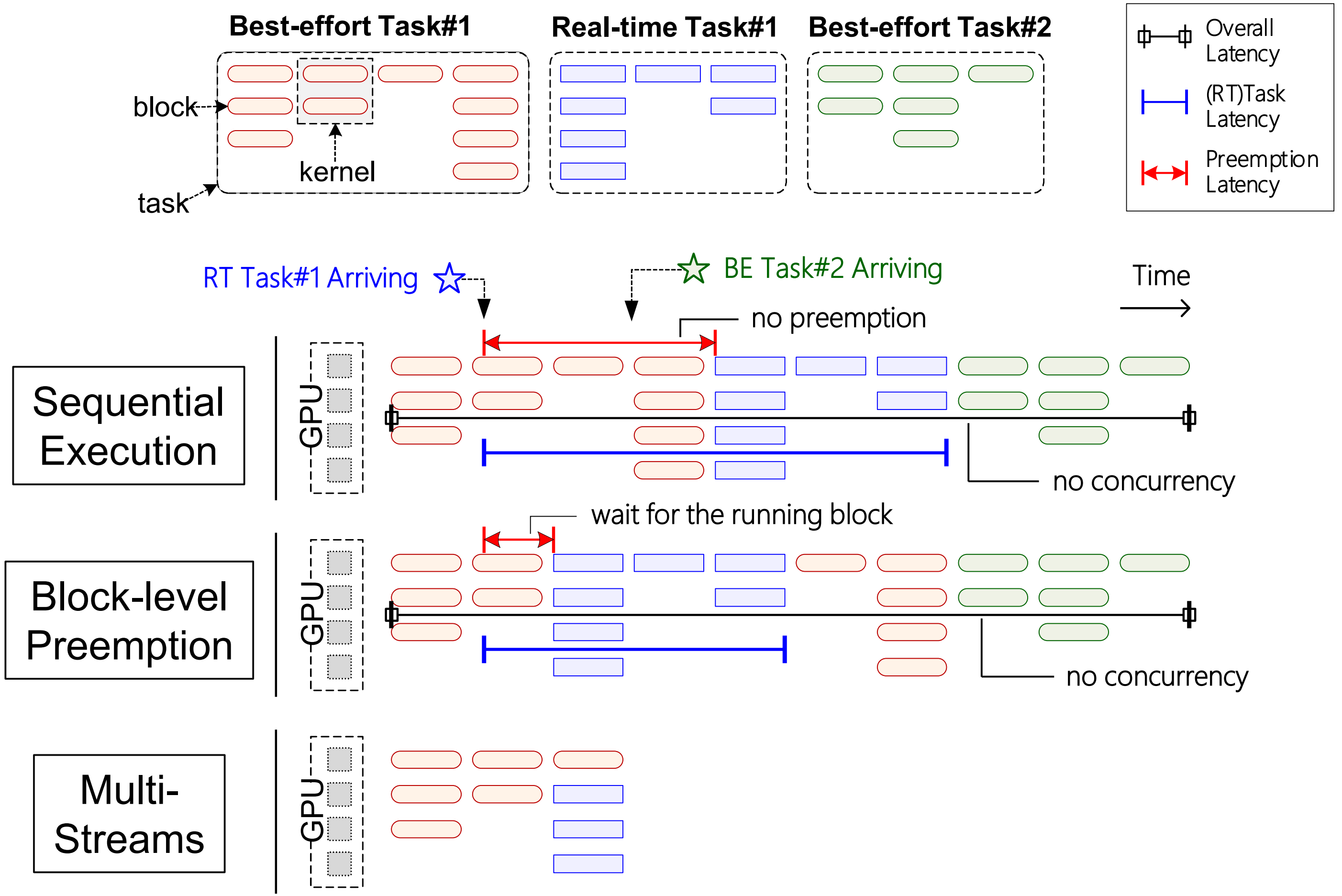

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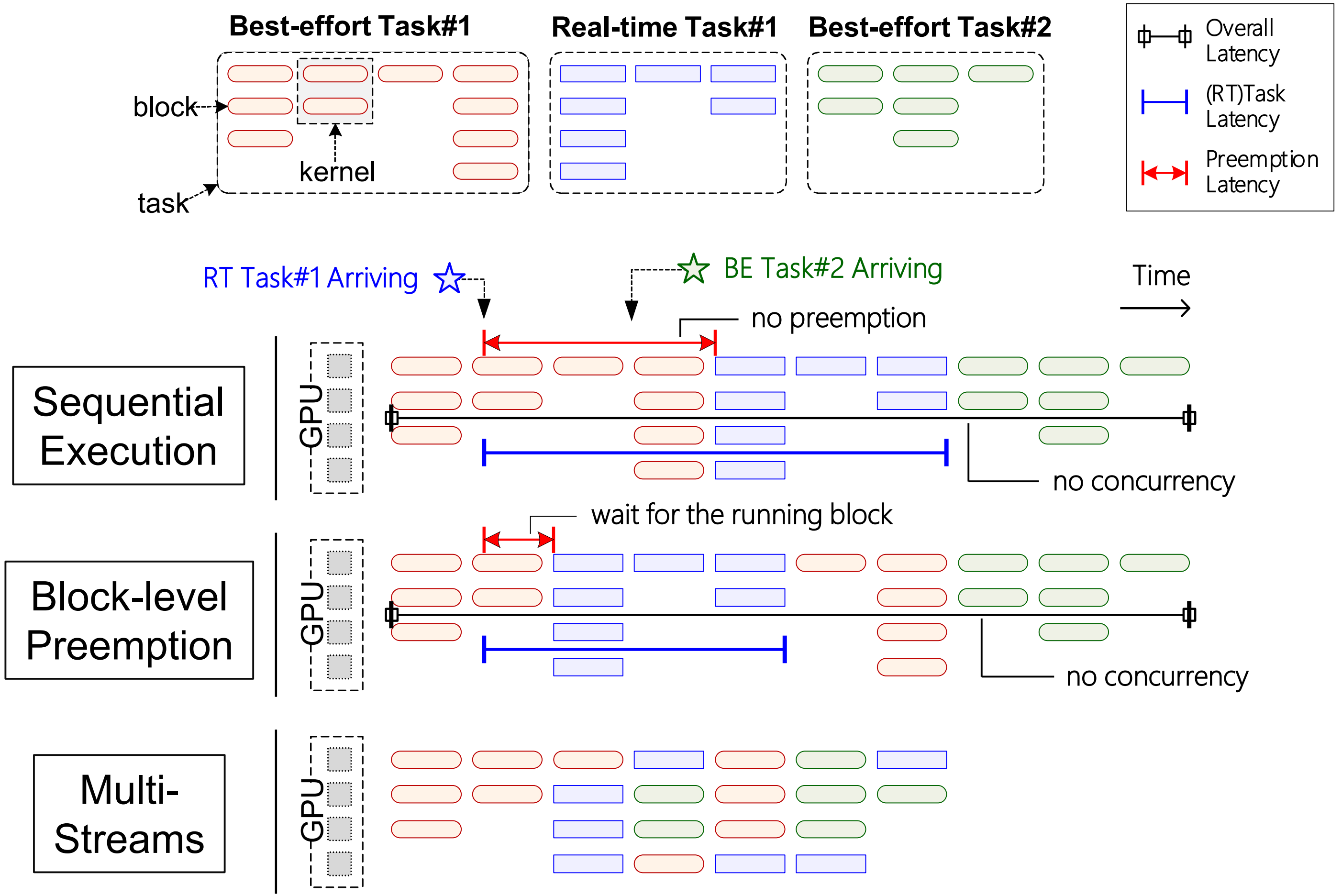

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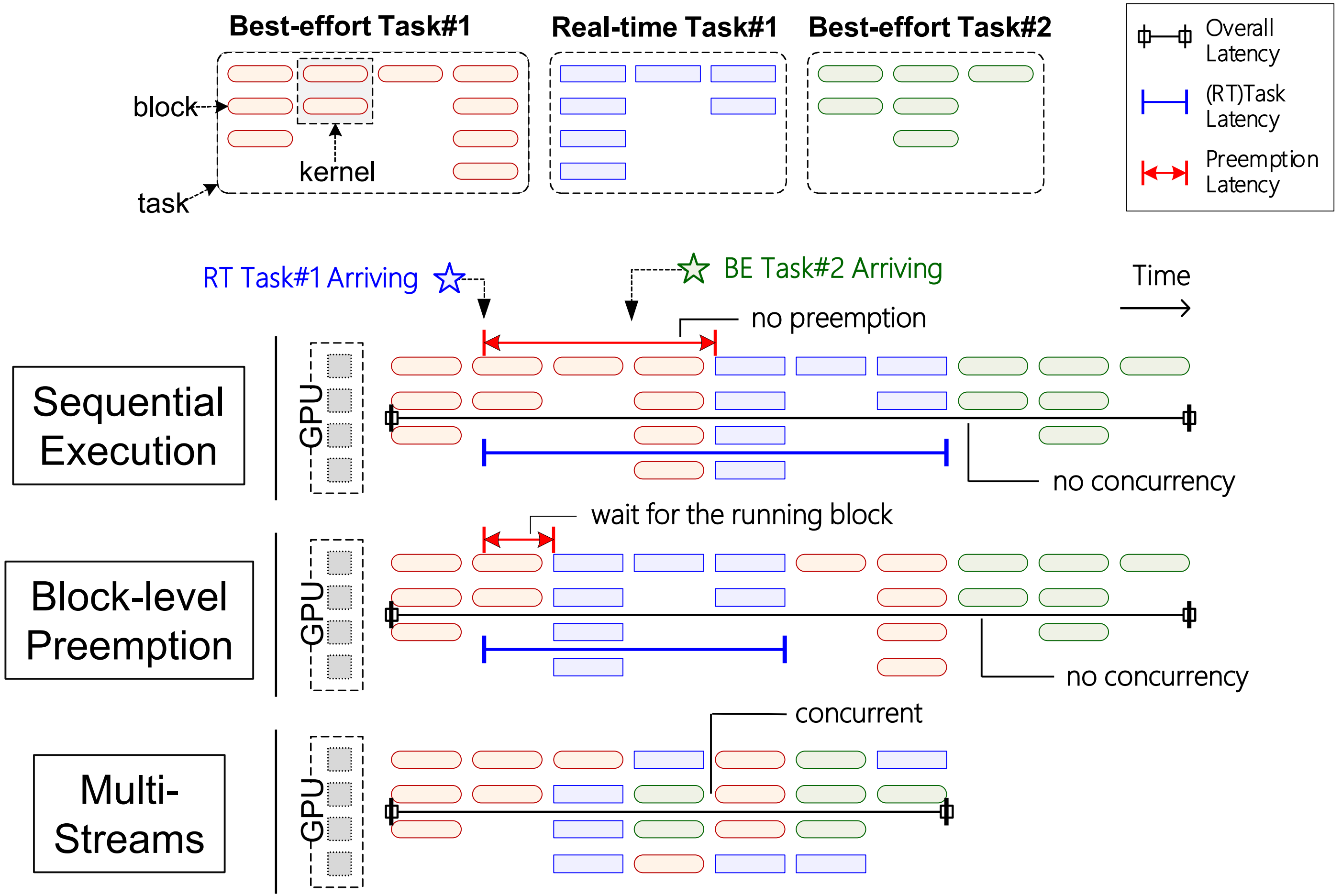

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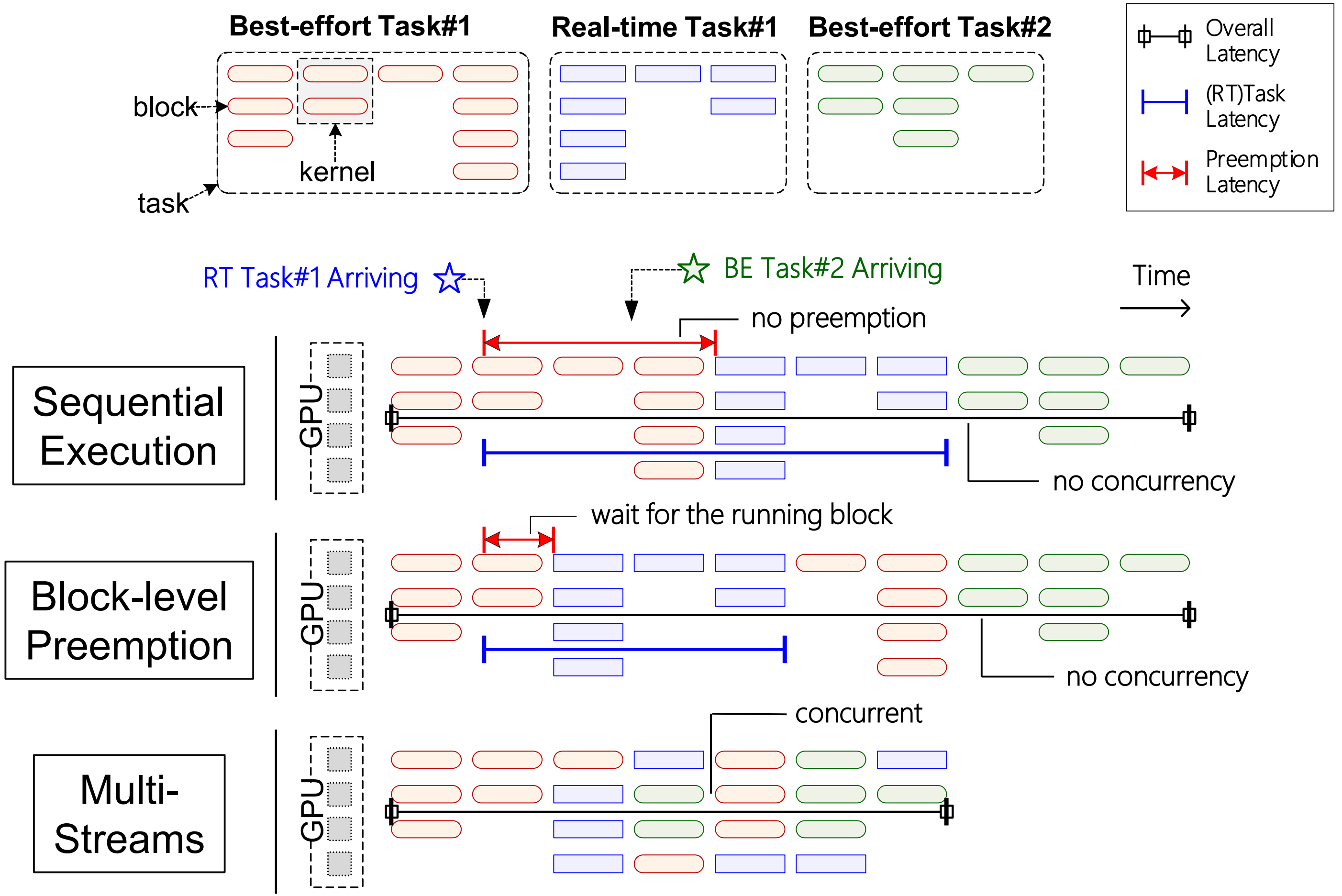

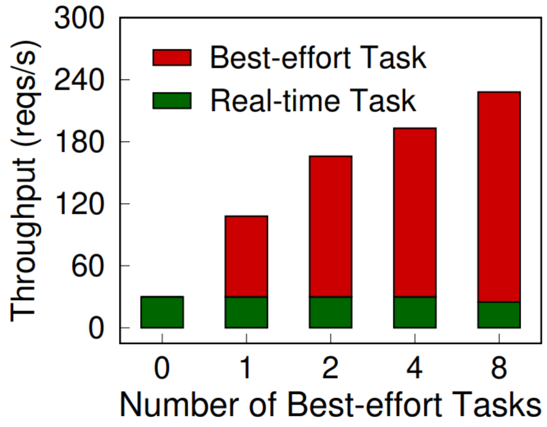

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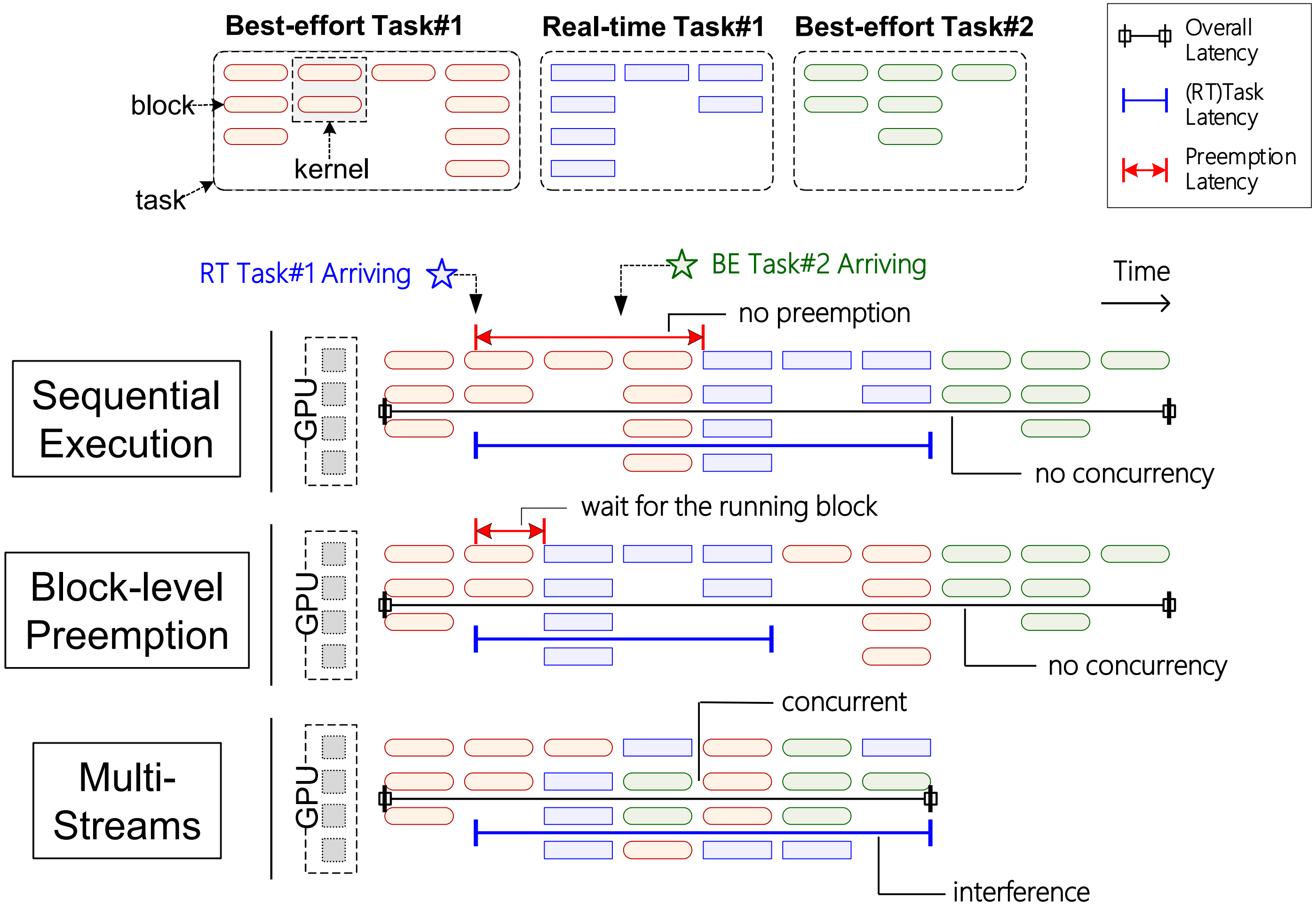

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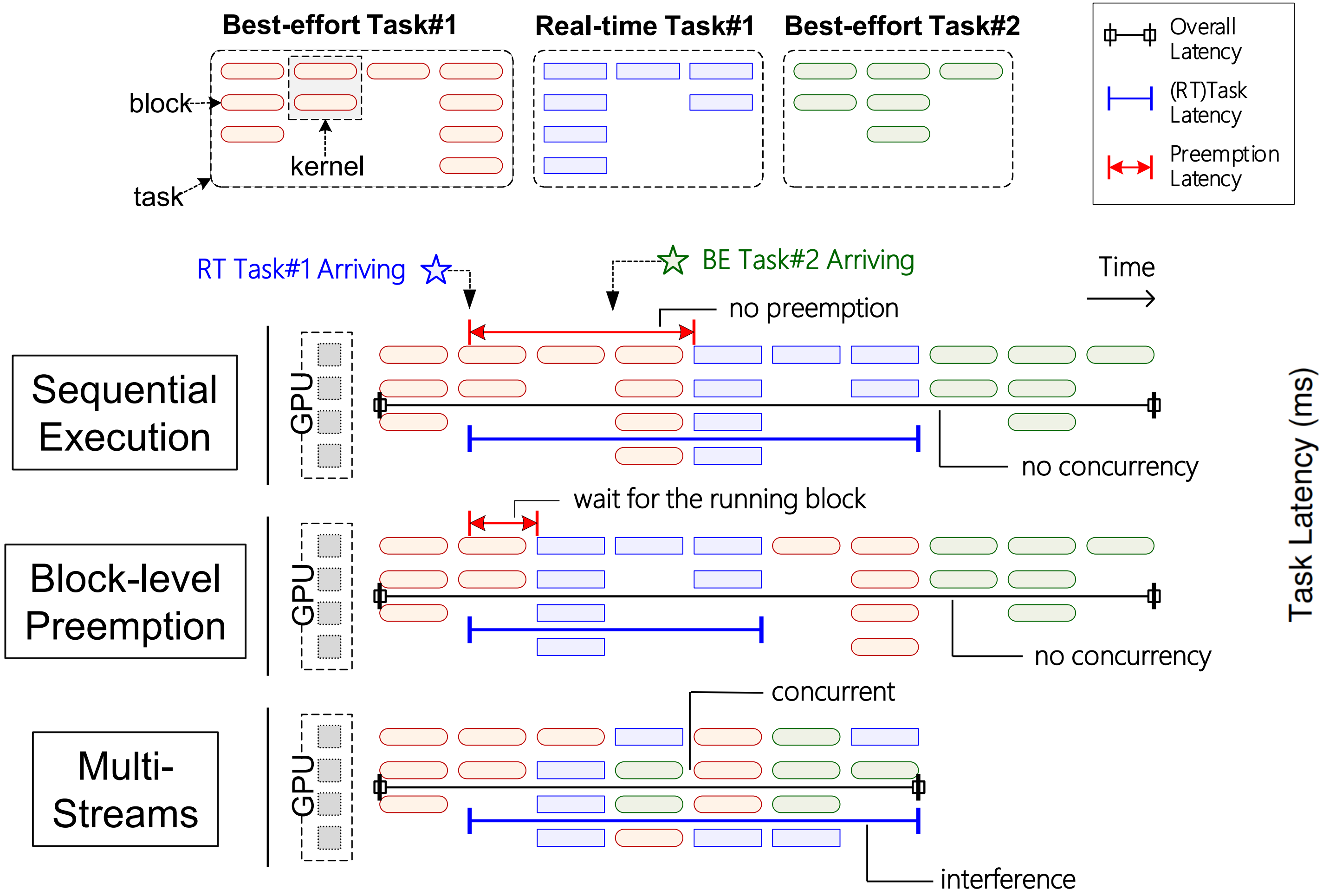

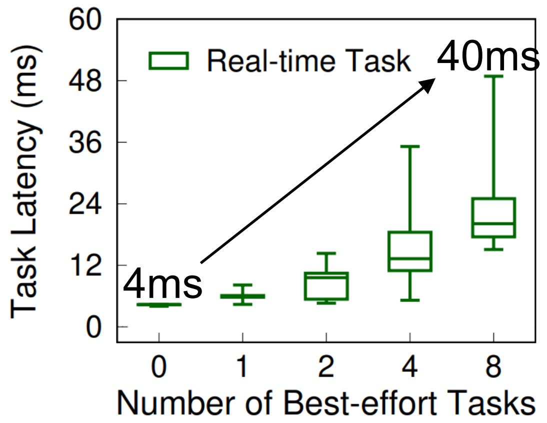

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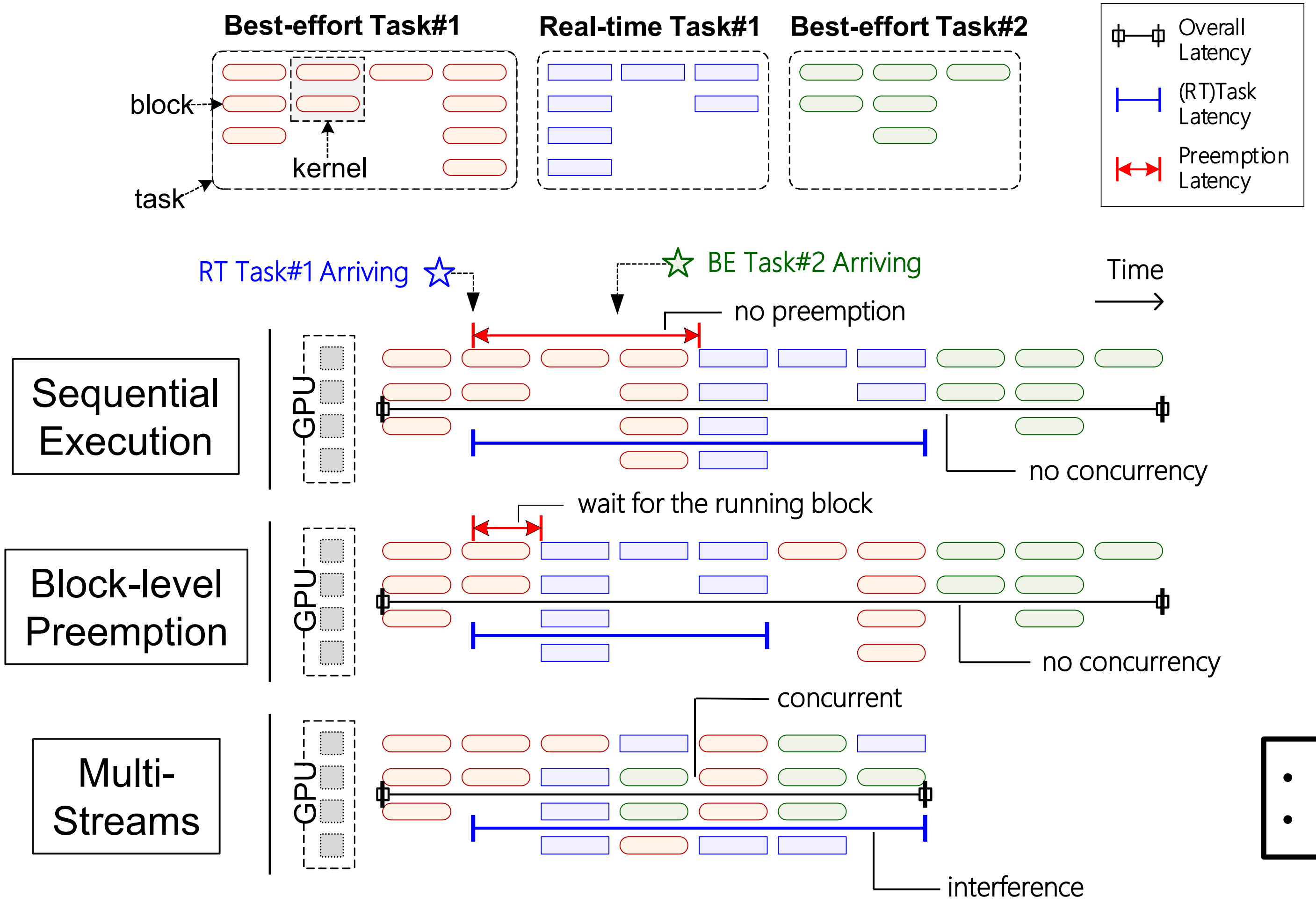
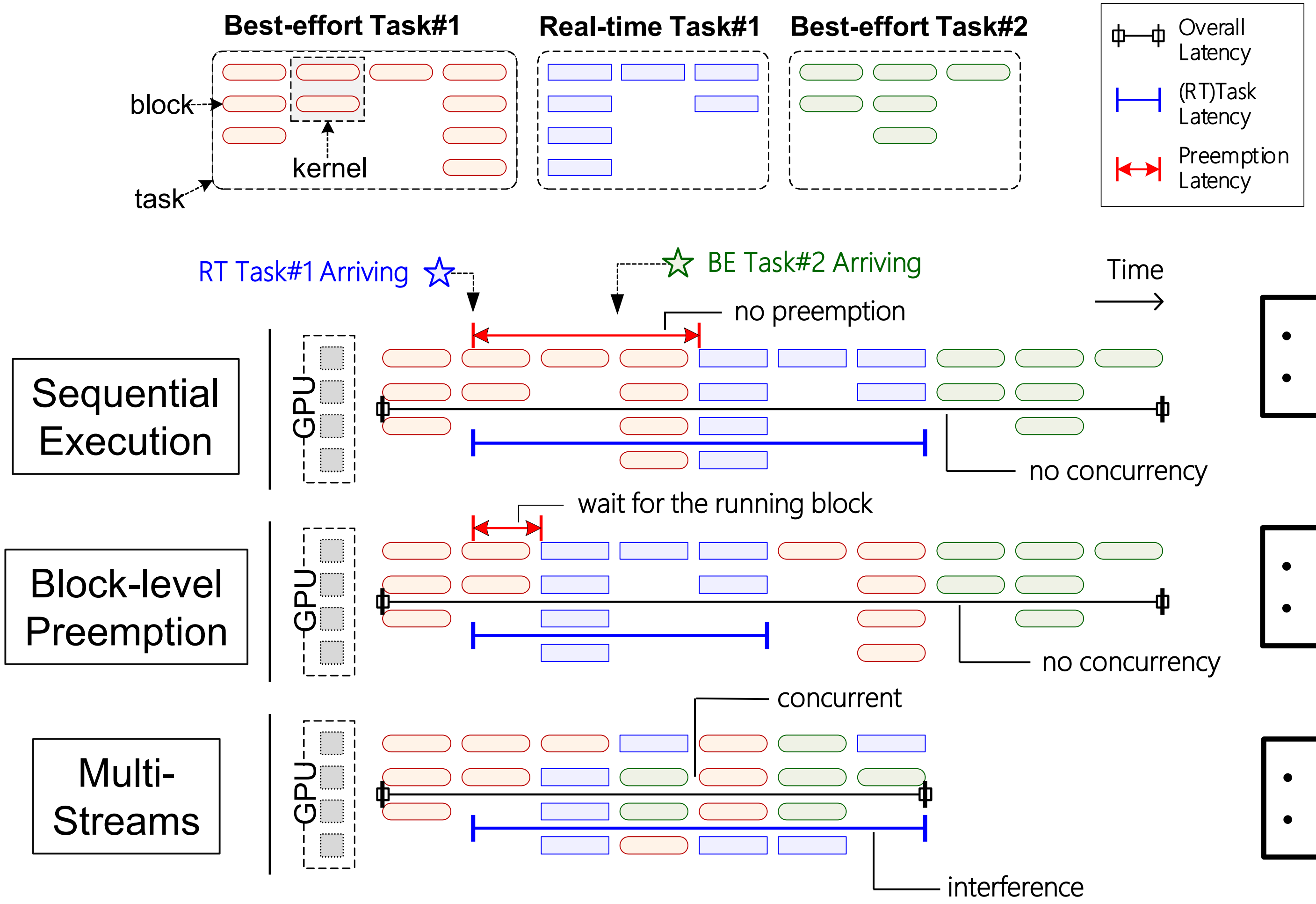


- High latency for **RT** tasks
- High throughput (work-conserving)

Existing GPU Task Scheduling



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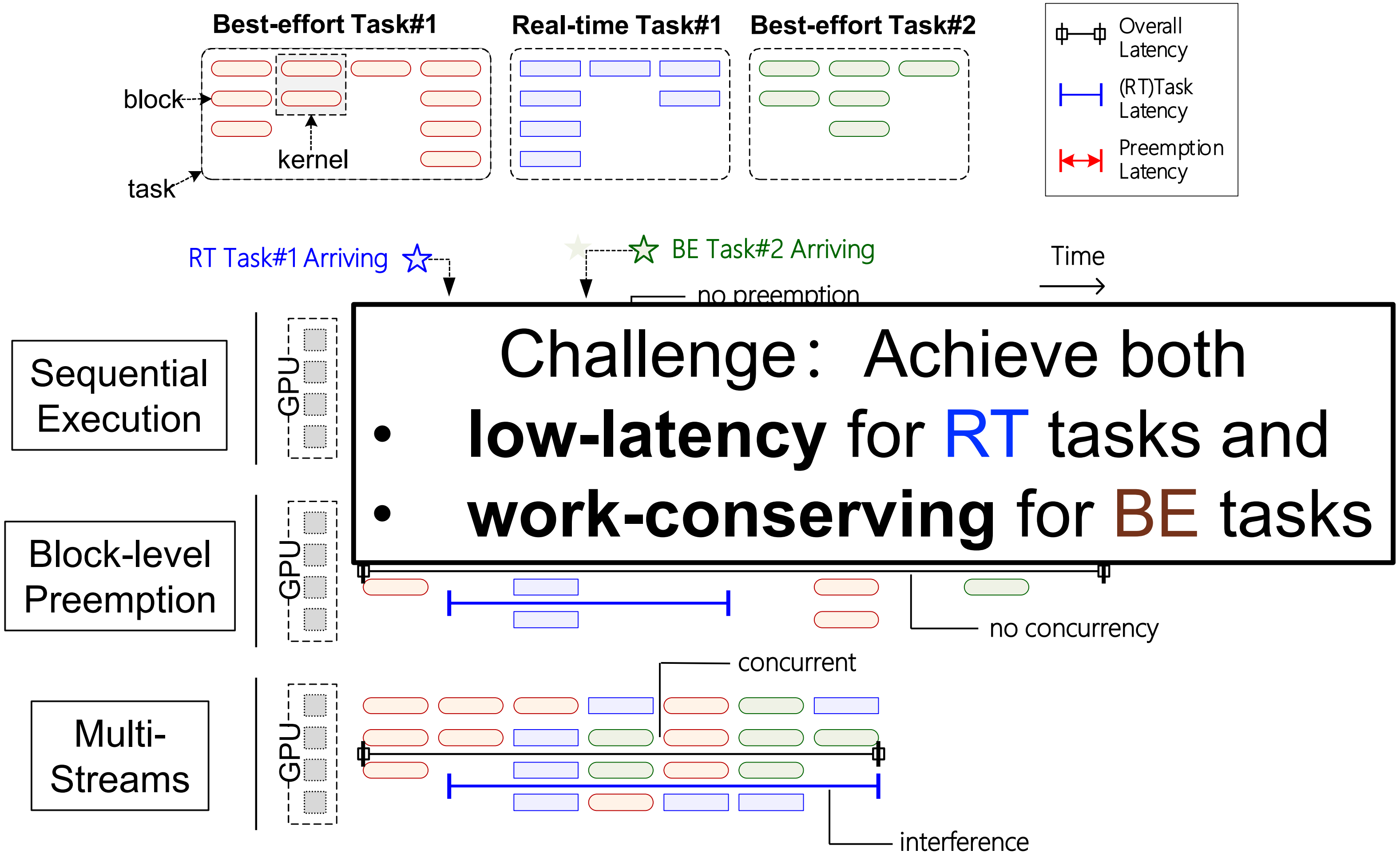
Existing GPU Task Scheduling



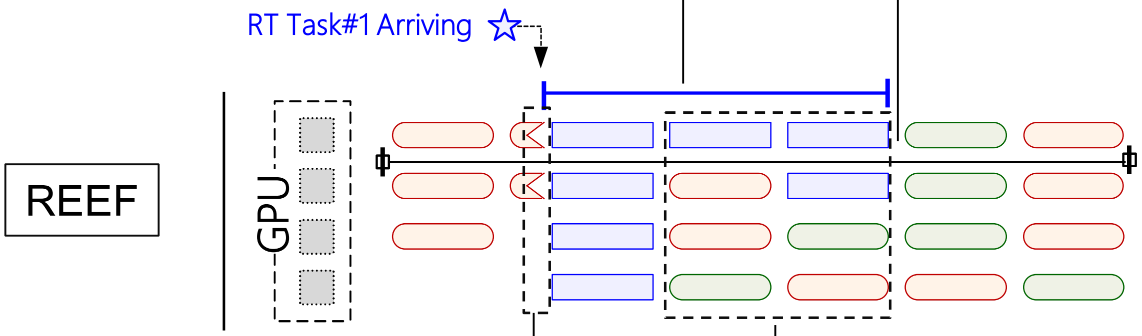
Challenge： Achieve both

- **low-latency** for RT tasks and
- **work-conserving** for BE tasks

REEF: GPU-accelerated DNN Inference System

Design Goal 1:
- Low-latency for real-time tasks

Design Goal 2:
- Work-conserving for best-effort tasks

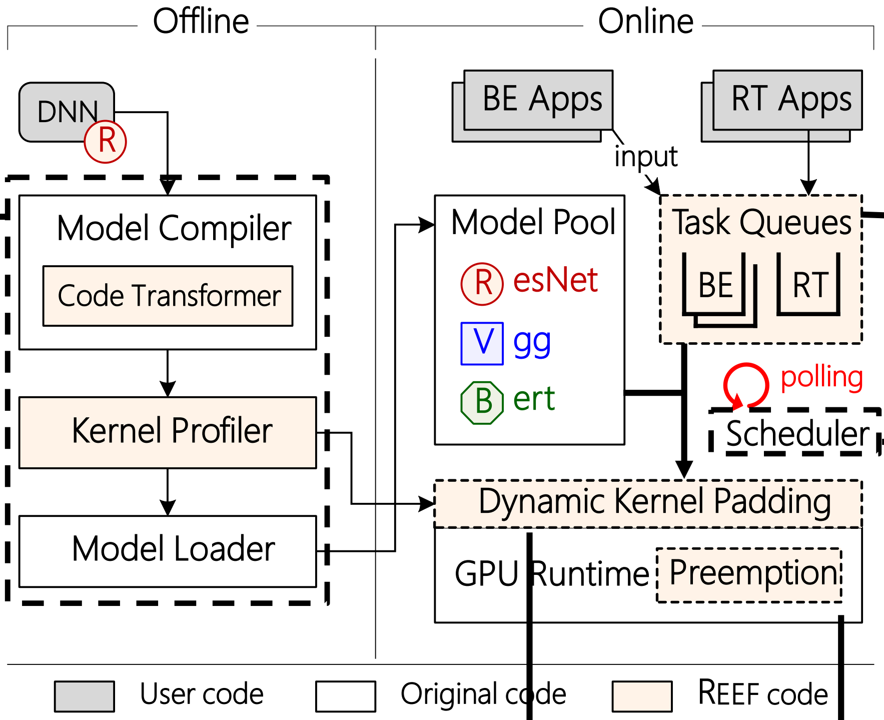


Reset-based Preemption:
- μs-scale preemption based on *idempotence*

Dynamic Kernel Padding:
- controlled concurrent execution based on *latency predictability*

REEF overview: architecture

generate DNN models



Task queues:

- one FIFO queue for **RT** tasks
- several FIFO queues for **BE** tasks

Execution modes:

normal mode:

- no RT task in RT queue
- execute BE tasks concurrently

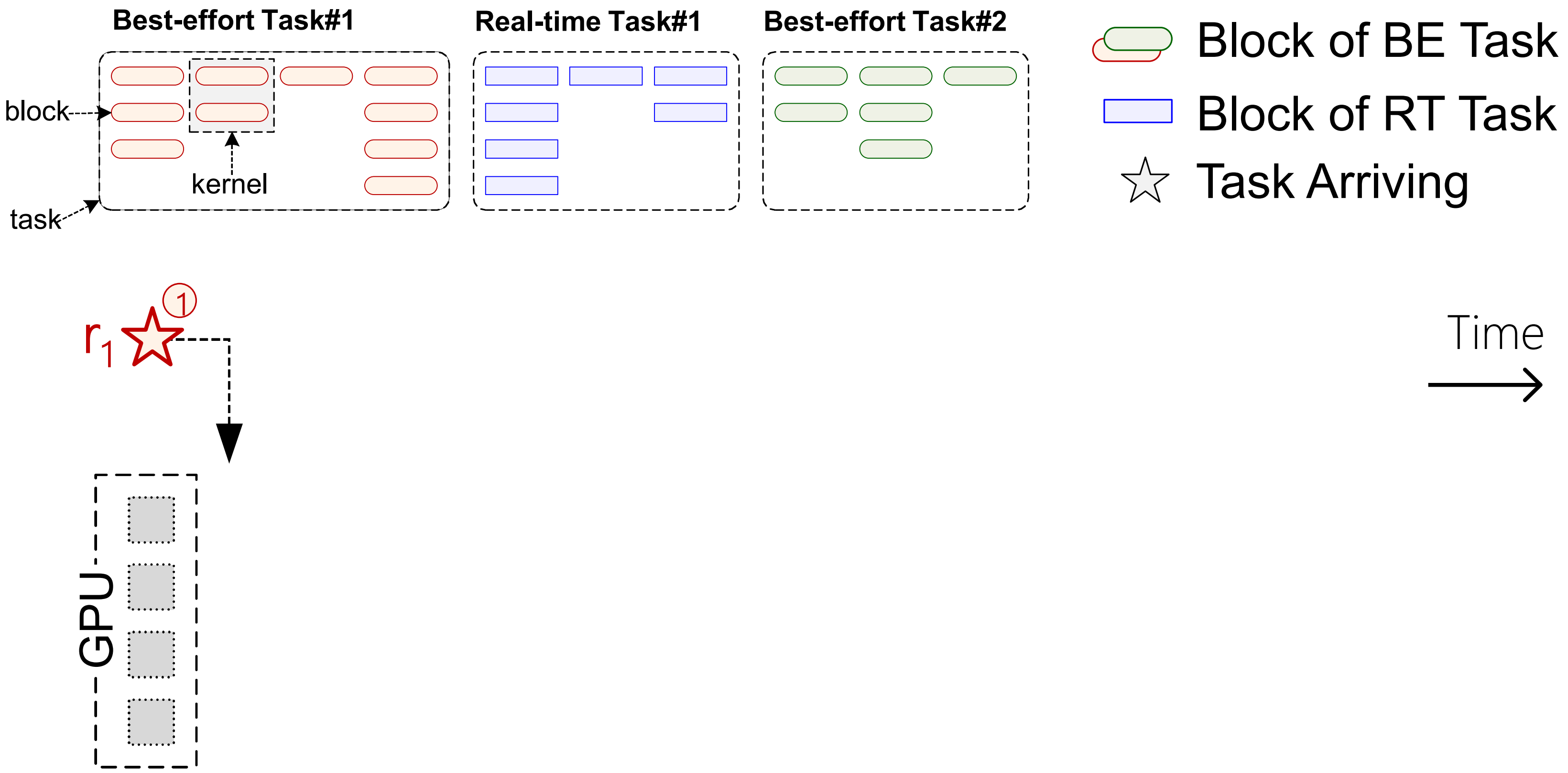
real-time mode:

- at least one RT task in RT queue
- execute one RT task a time

execute both **RT** and **BE** tasks concurrently in ***real-time mode***

preempt **BE** tasks when **RT** task arrives in ***normal mode***

REEF overview: scheduling example



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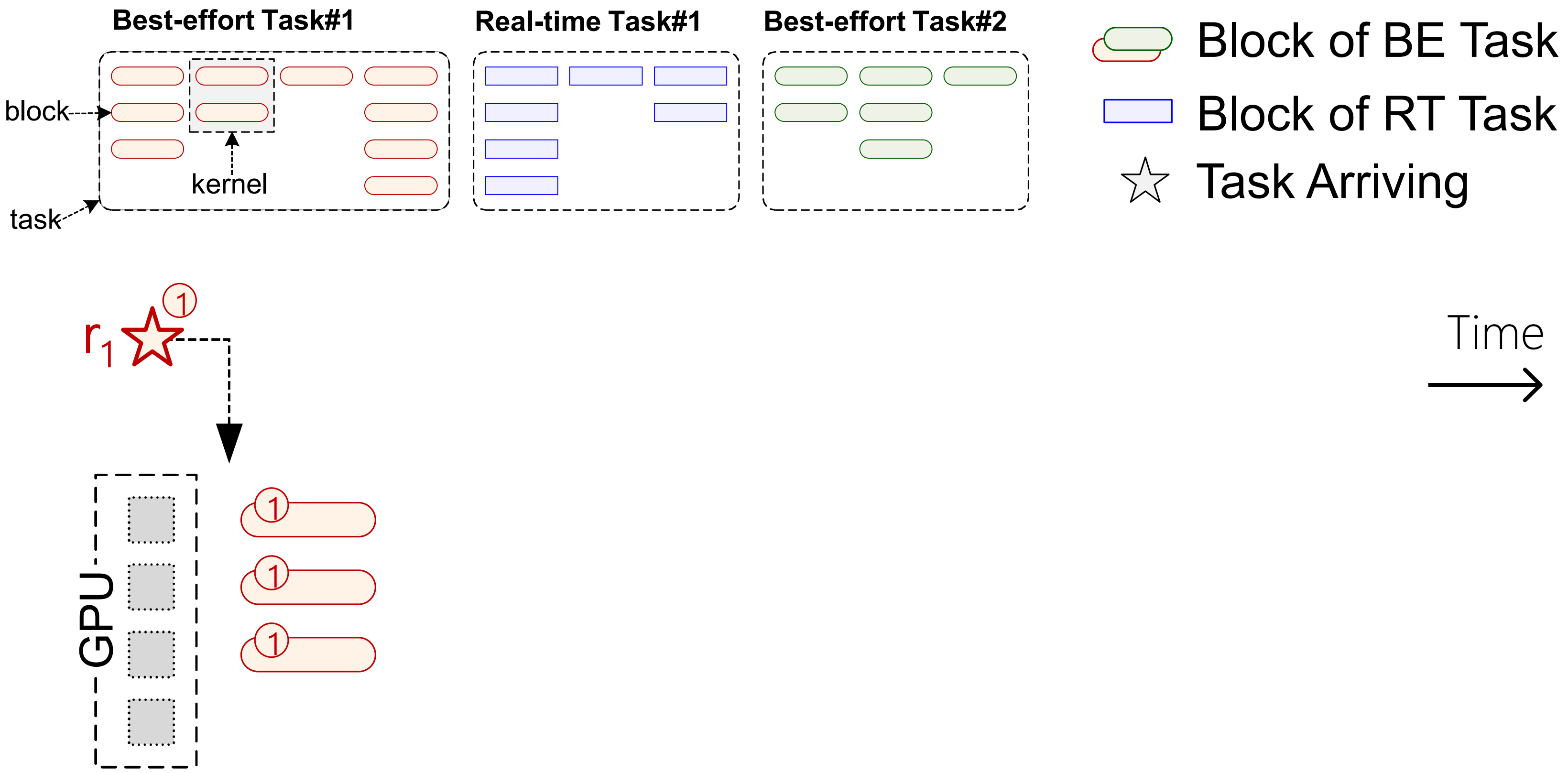

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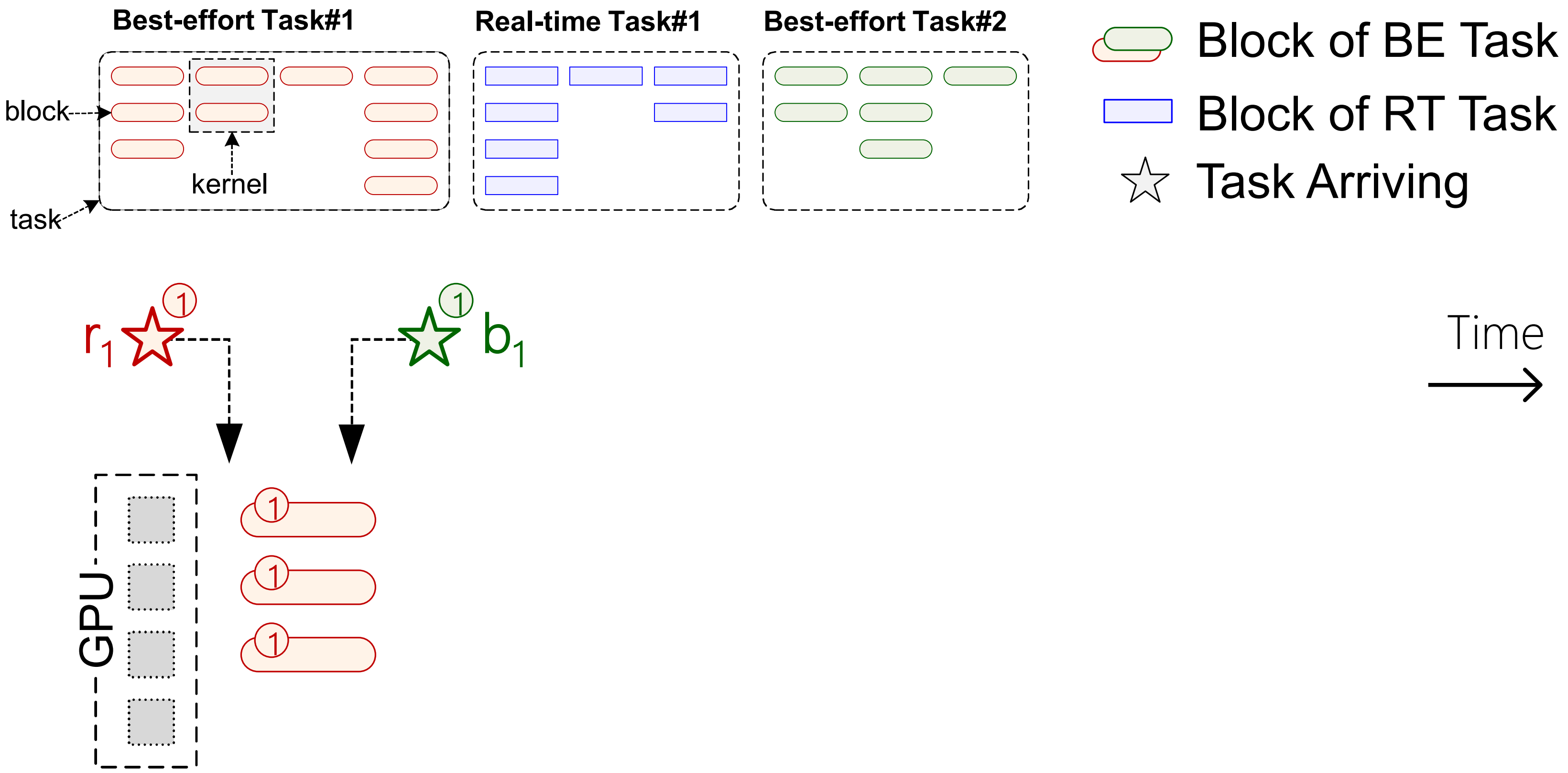

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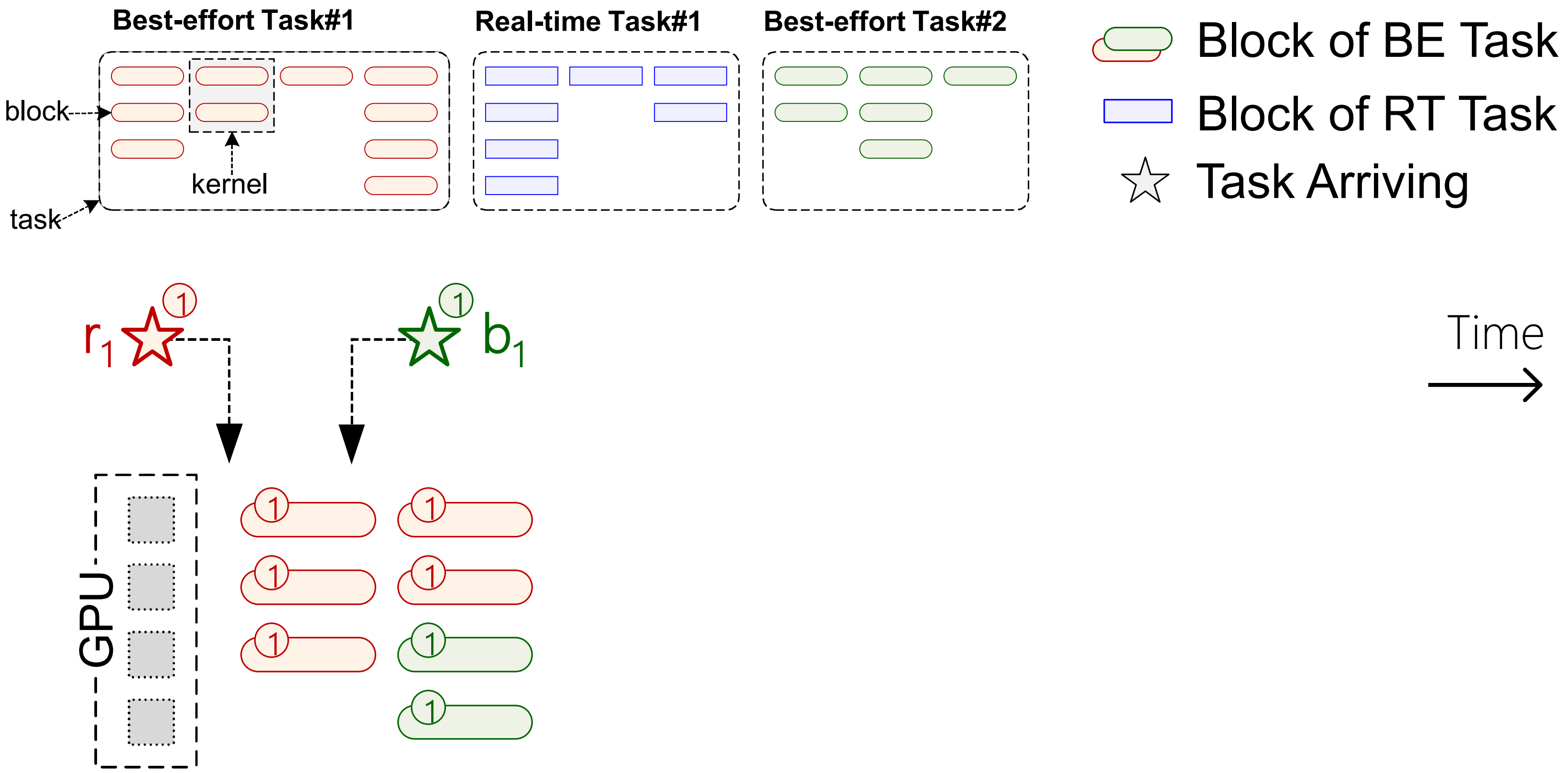

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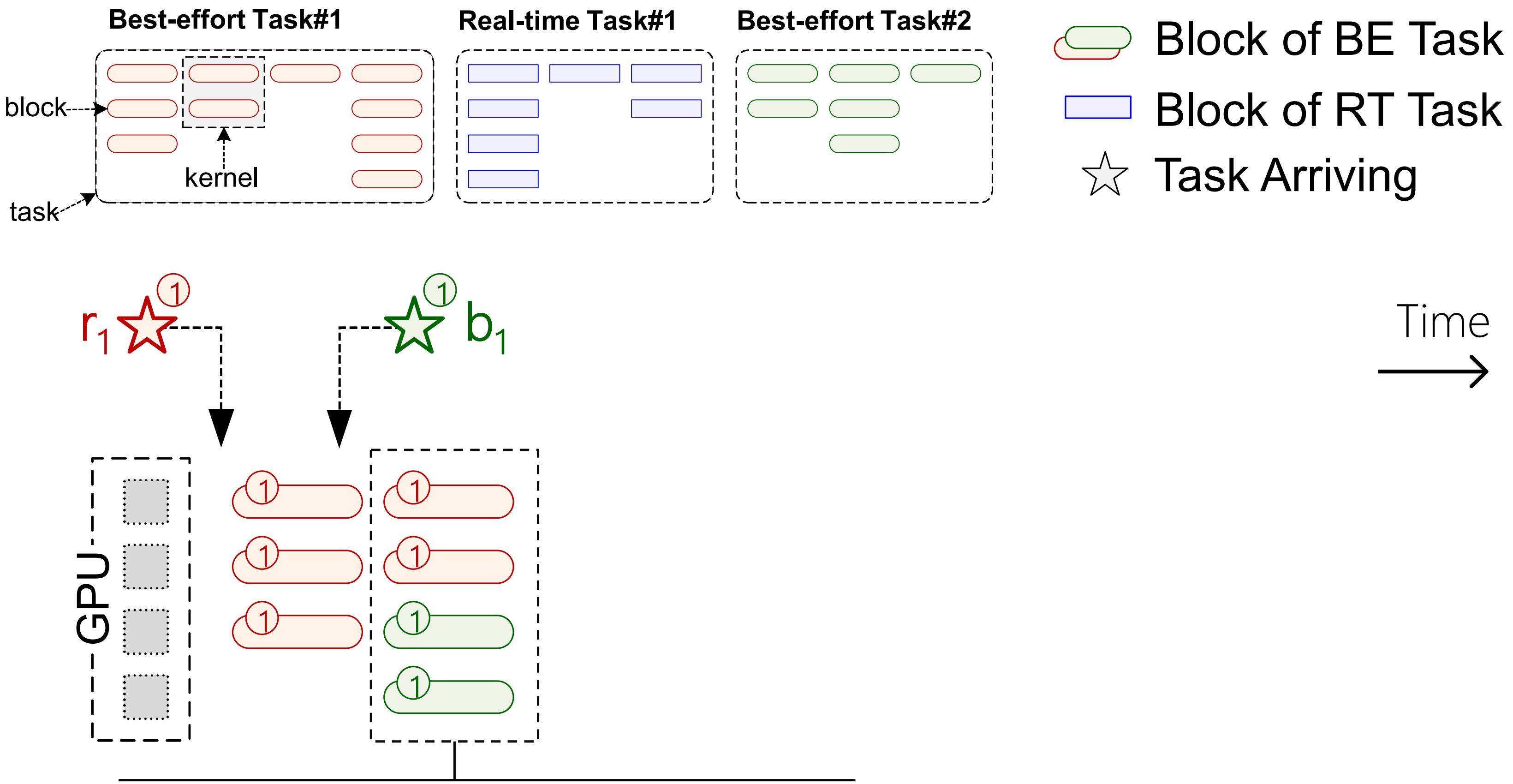
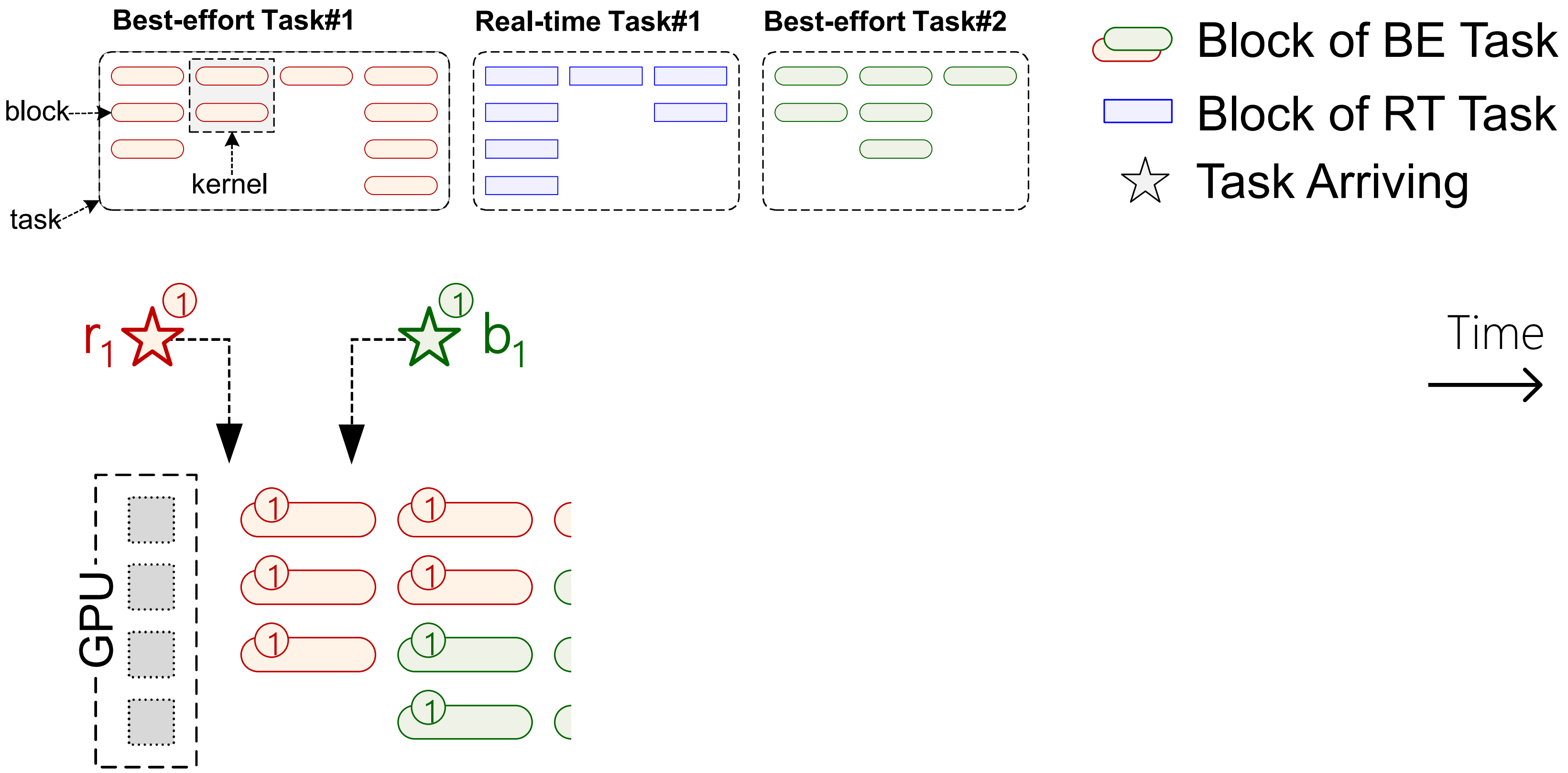


In normal mode, kernels are executed concurrently in **multiple GPU streams**

REEF overview: scheduling example



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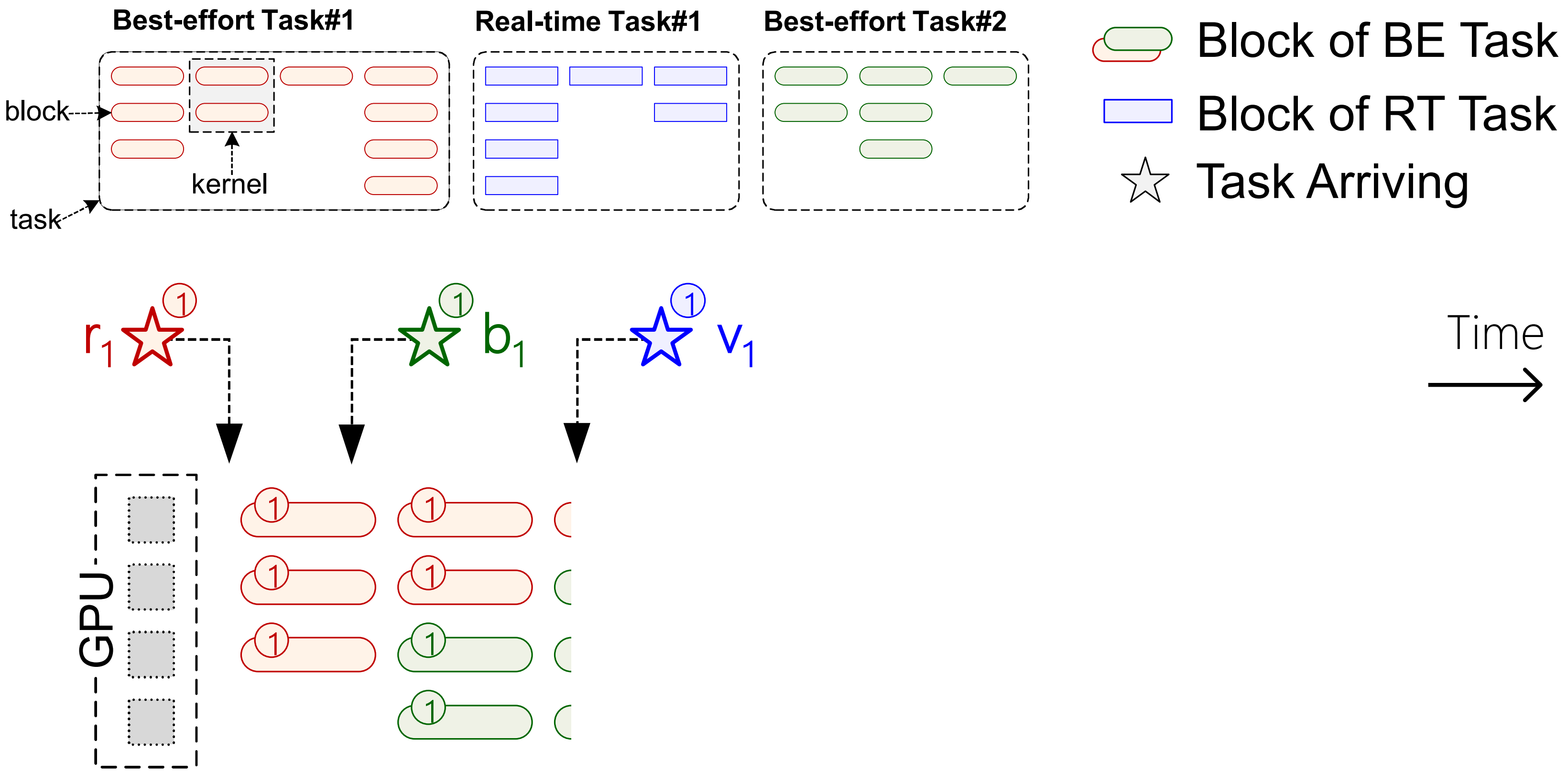

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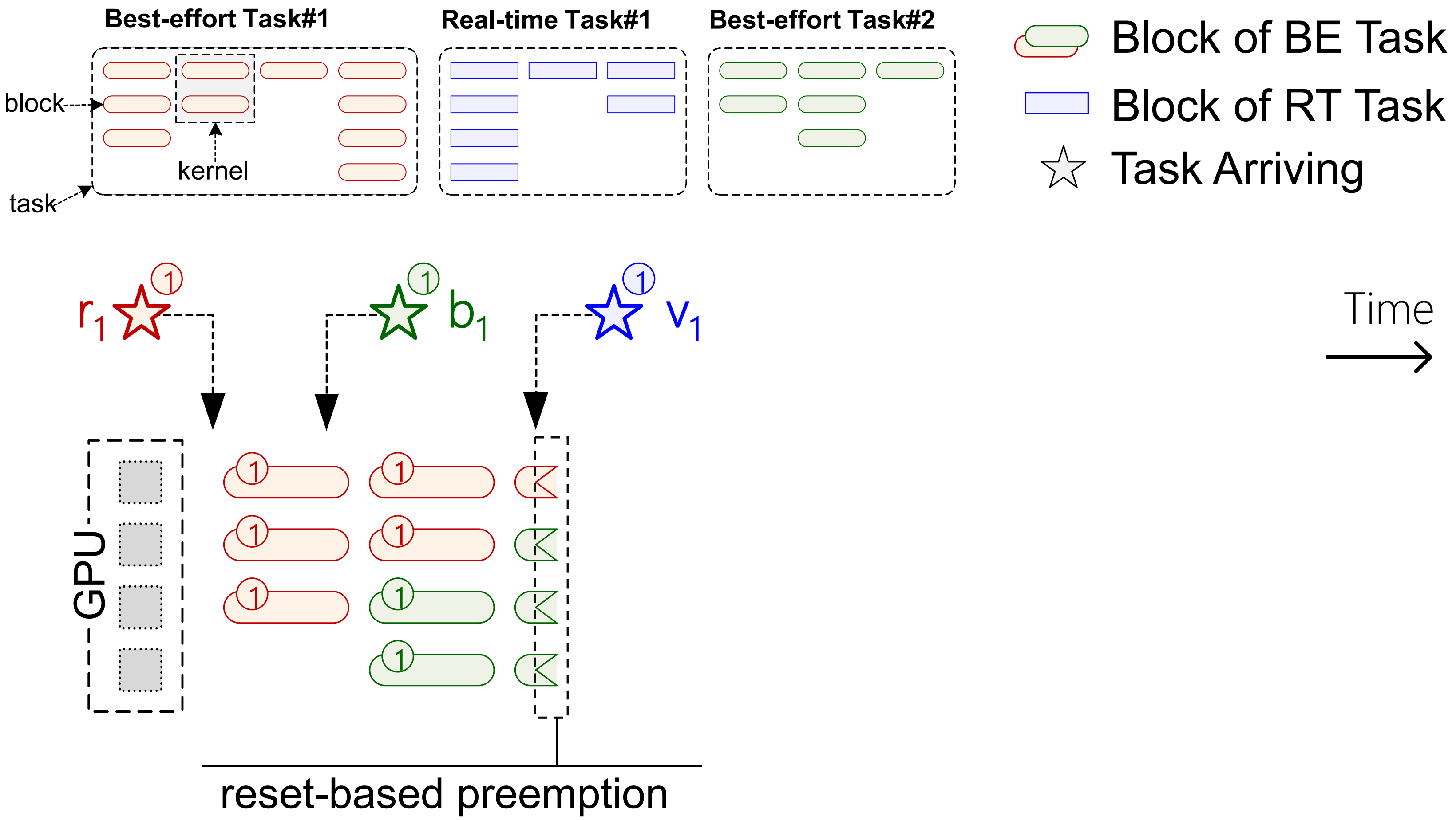

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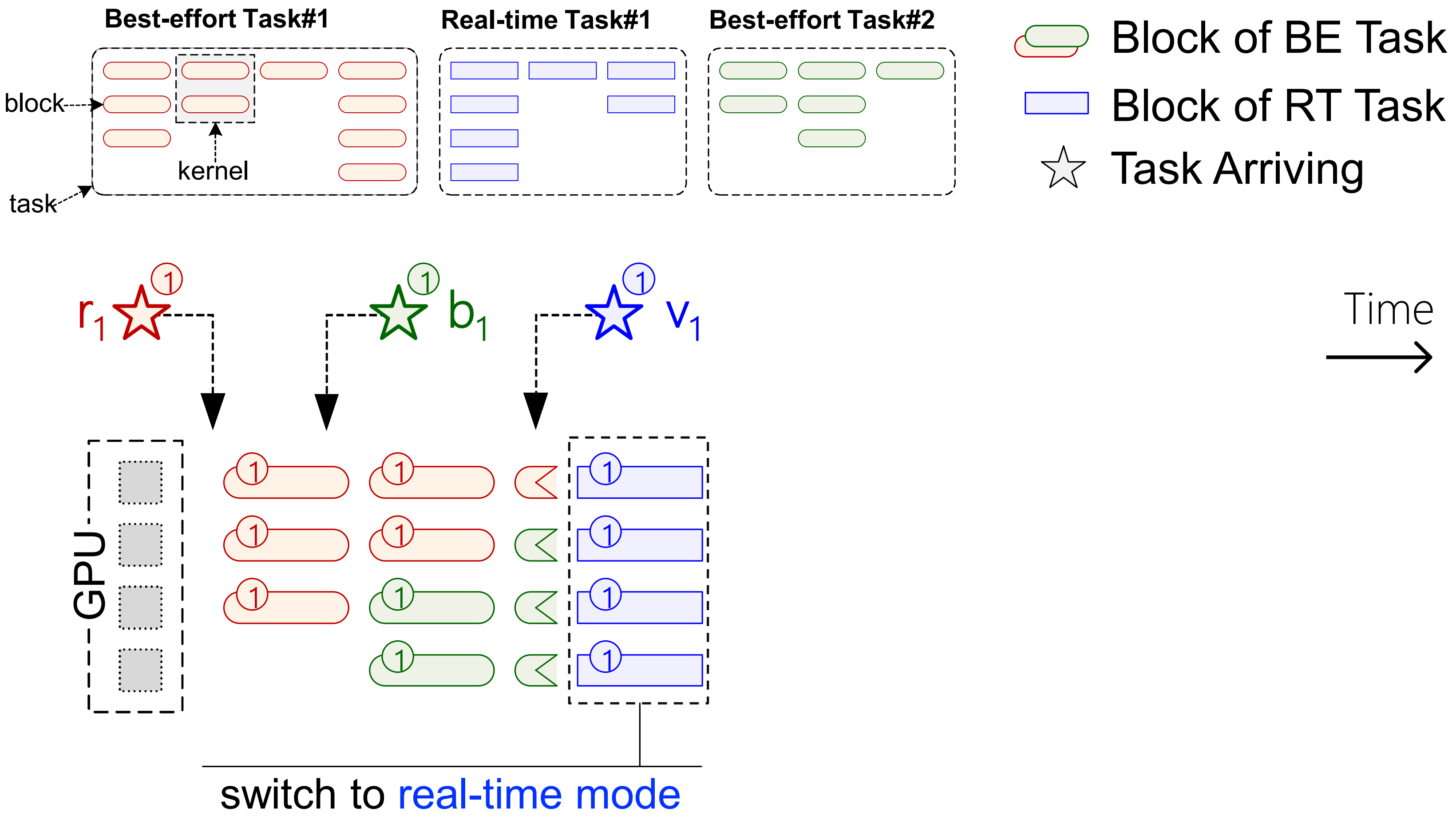

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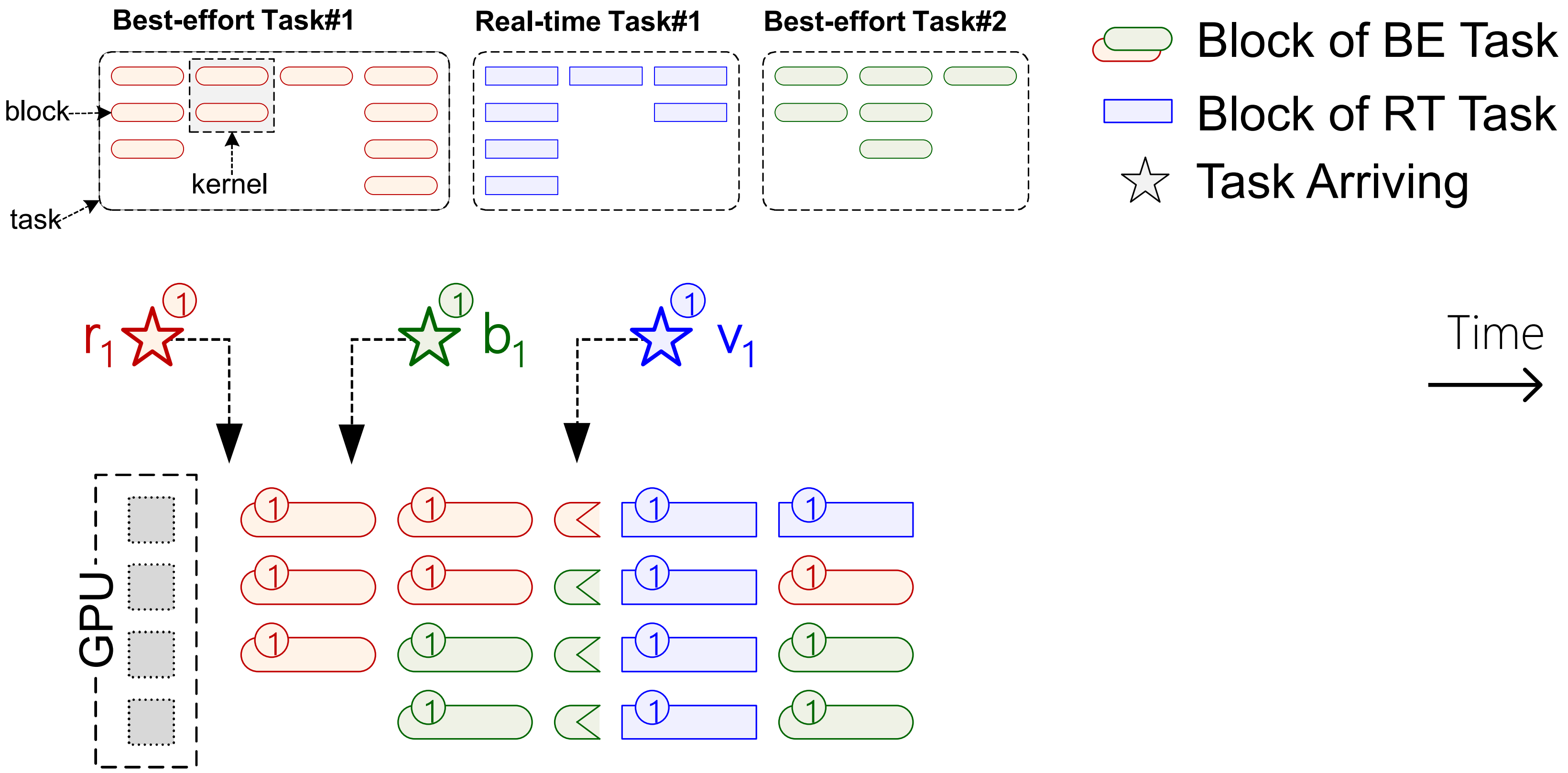

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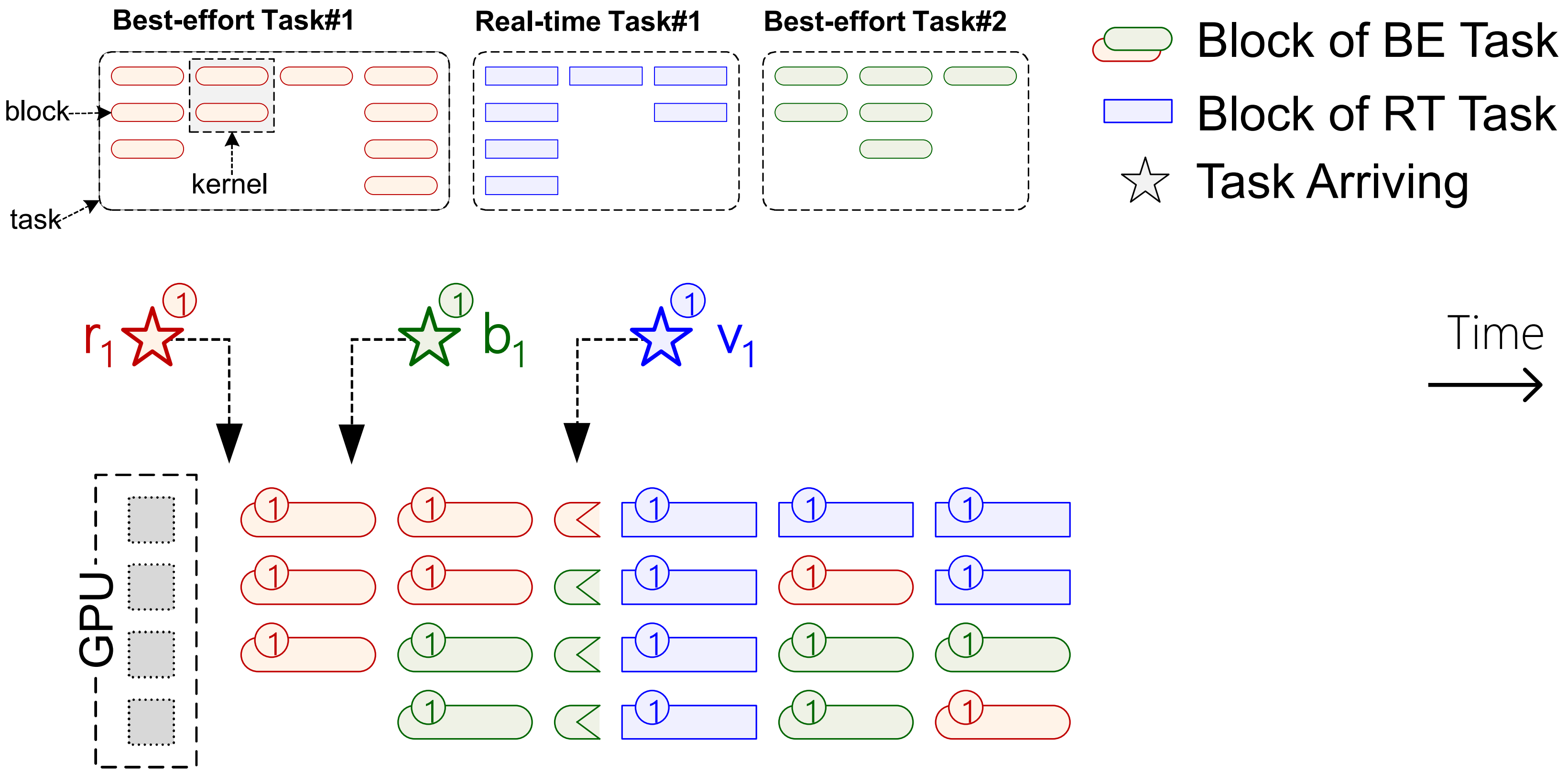

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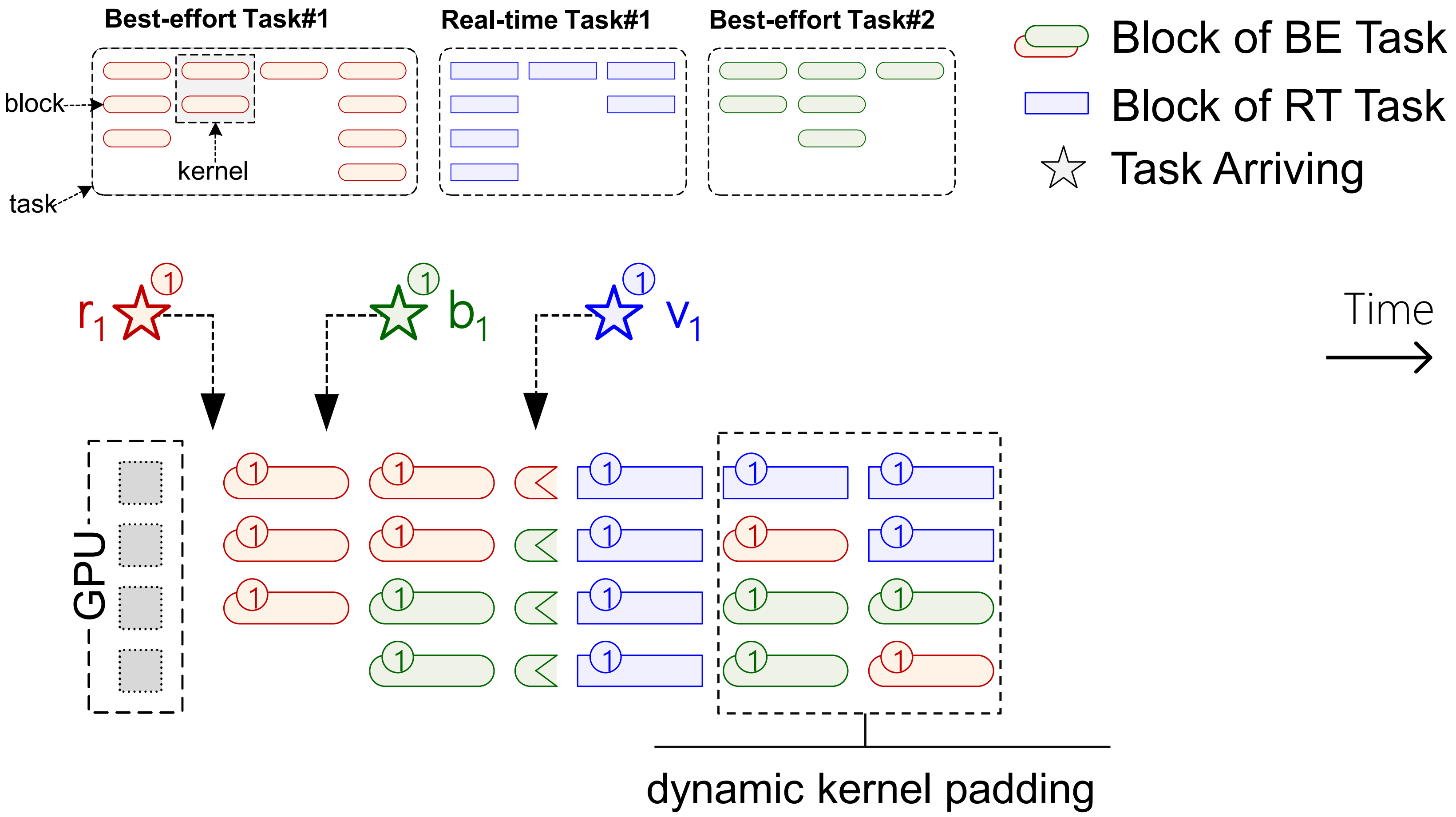

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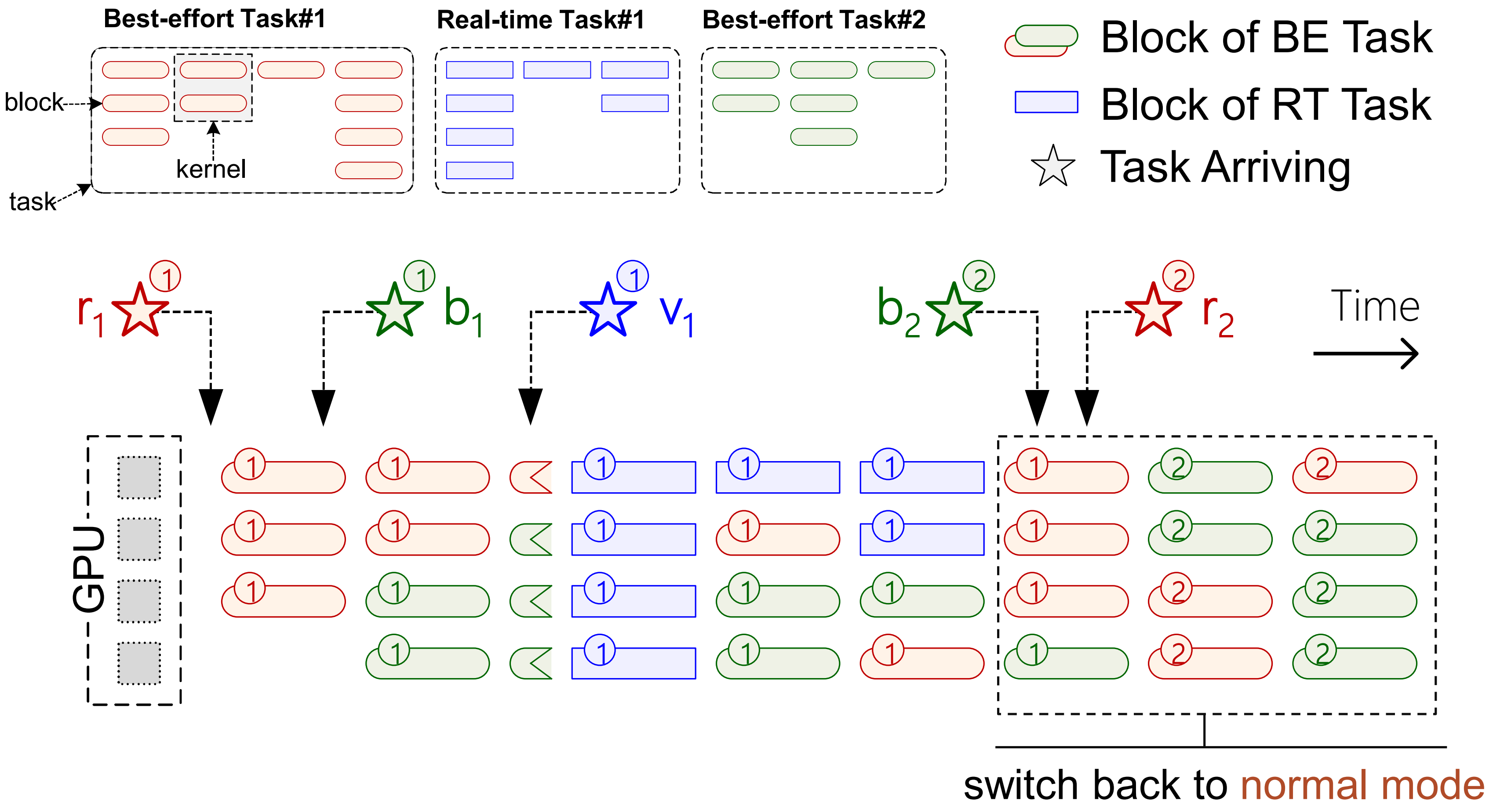

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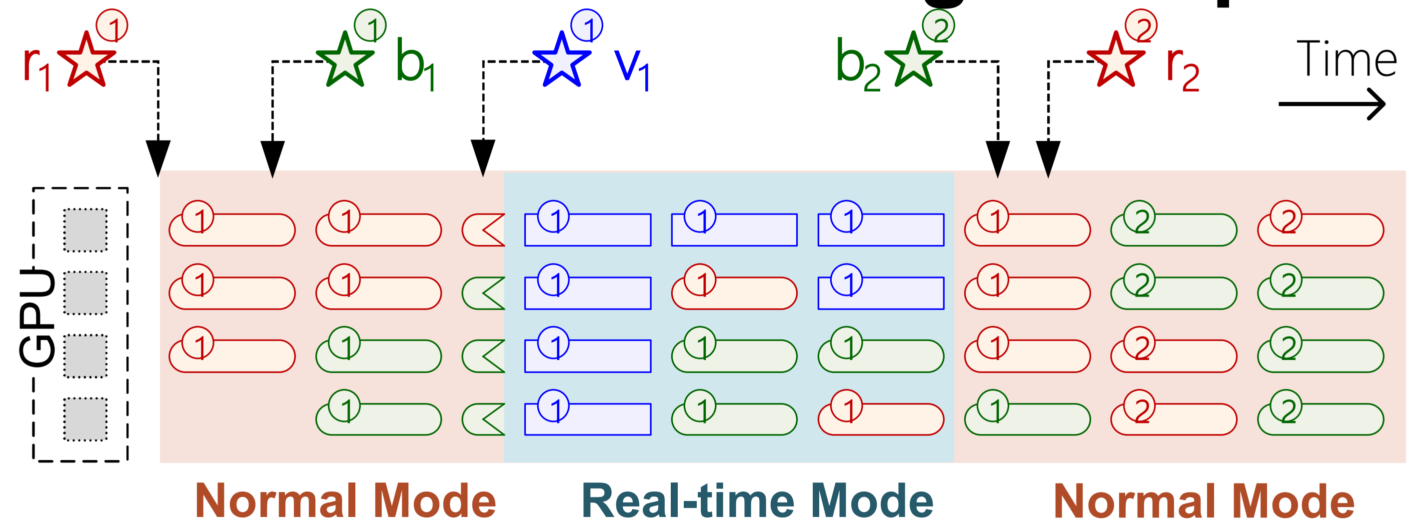
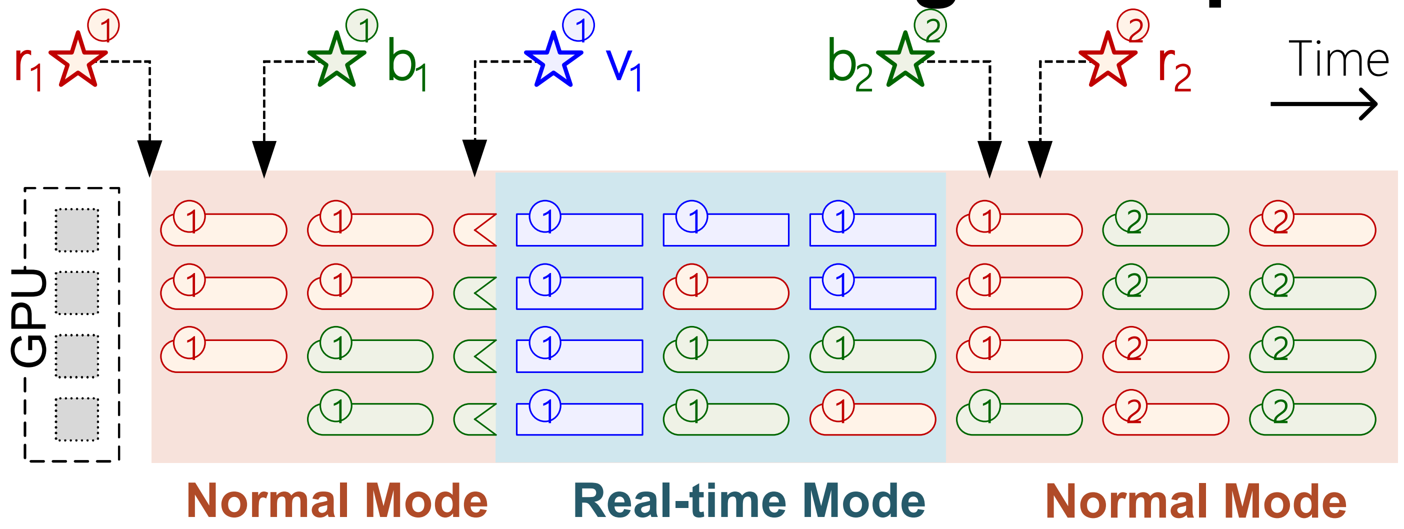


- **Low latency** for real-time tasks
  - **Normal Mode**: preempt best-effort tasks in a few μs.
  - **Real-time Mode**: get the GPU resources as many as possible.
- **Work conserving** for best-effort tasks
  - **Normal Mode**: fully utilize GPU resources by using GPU streams.
  - **Real-time Mode**: use the GPU resources leftover by real-time tasks.

REEF overview: scheduling example



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  - **Normal Mode**: fully utilize GPU resources by using GPU streams
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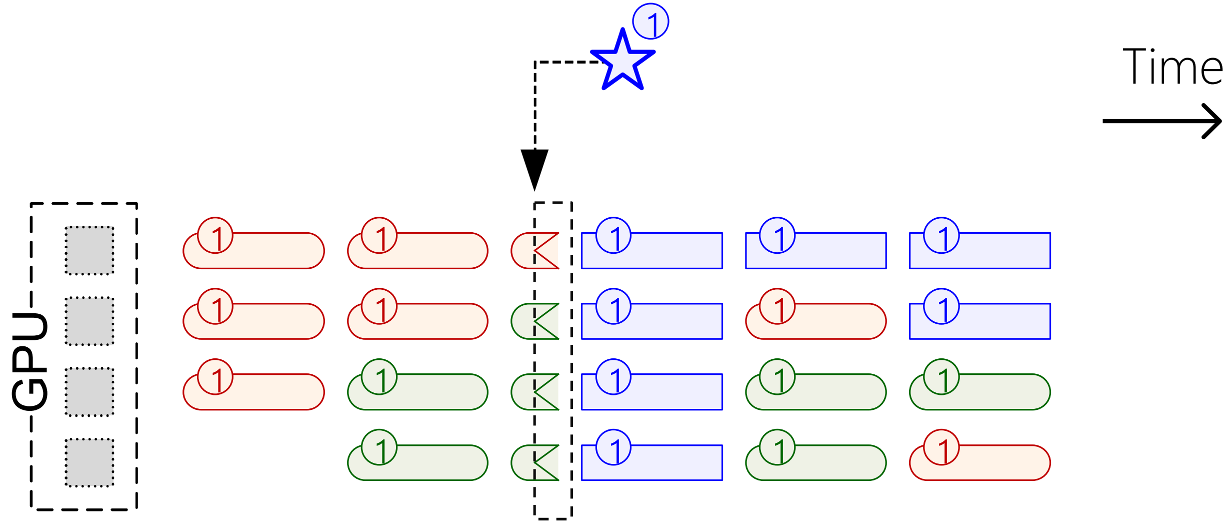
Reset-based Preemption

Dynamic Kernel Padding

Reset-Based Preemption

Design Goal:
Preempt concurrent BE tasks in a few μs



Key Observation

Idempotence

```
# device codes
__global__ void conv_relu(in, weight, out):
    sum = 0;
    for i in range(0,3)
        for j in range(0,3)
            sum += in[..] × weight[..]
    out[..] = ReLU(sum)

__global__ void dense(in, weight, bias, out):
    sum = 0;
    for i in range(0,512)
        sum += in[..] × weight[..]
    out[..] = sum + bias[..]
```

Key Observation

Idempotence

Input (read-only)

Output (write-only)

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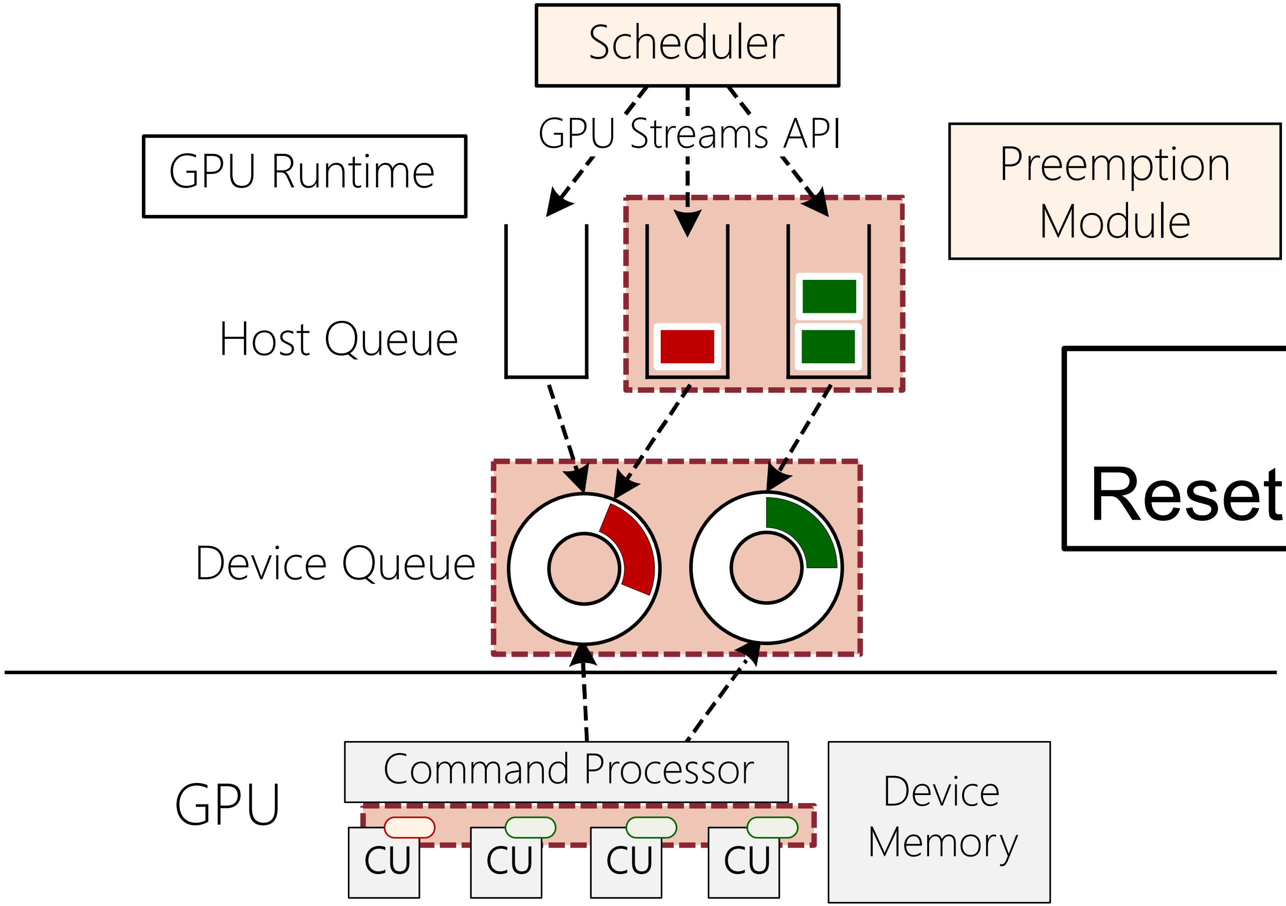
       for j in range(0,3)
          sum += in[..] × weight[..]
    out[..] = ReLU(sum)
...bias, out):
...
       sum += in[..] × weight[..]
    out[..] = sum + bias[..]
```

Basic idea:

- *Preempt* a task by *killing* the running kernels
- *Restore* a task by *re-executing* the preempted kernels

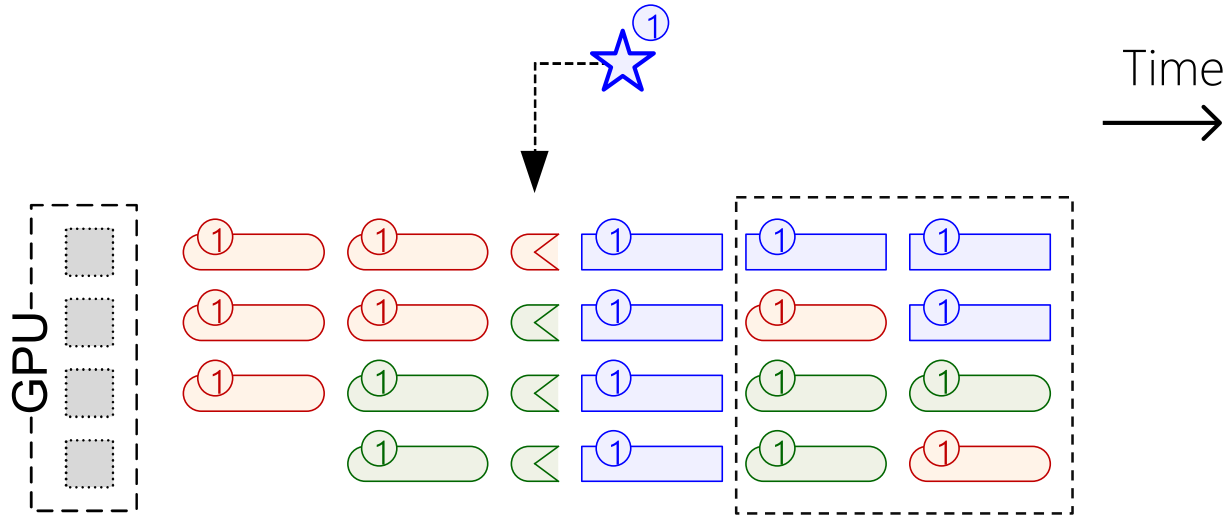
Reset-based Preemption



Key Idea:
Reset kernels in everywhere

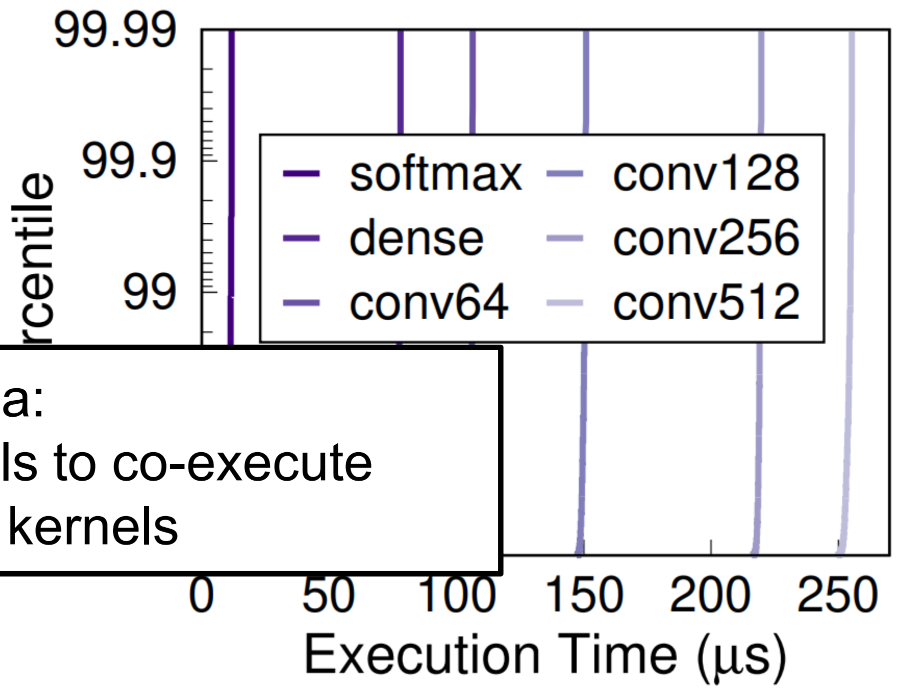
Dynamic Kernel Padding

Design Goal:
Allow RT/BE tasks to execute concurrently
without interference to RT tasks



Key Observation

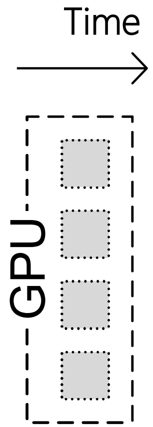
Latency Predictability



Basic Idea:
Allow *shorter* **BE** kernels to co-execute with *longer* **RT** kernels

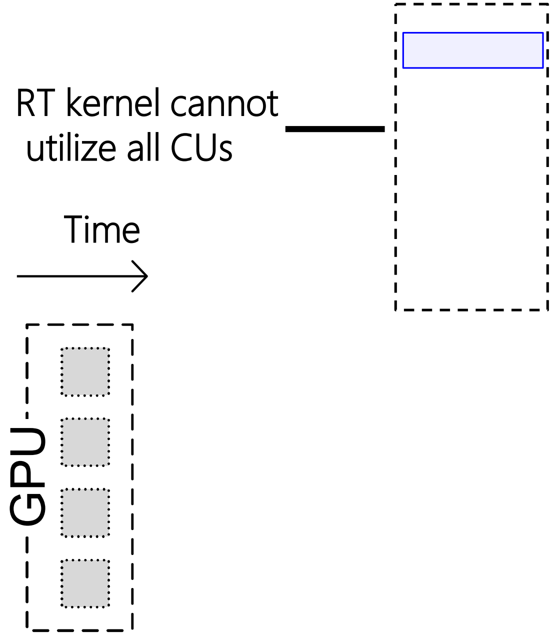
Dynamic Kernel Padding

Key Idea:
Dynamically pad RT kernels with BE kernels



Dynamic Kernel Padding

Key Idea:
Dynamically pad RT kernels with BE kernels



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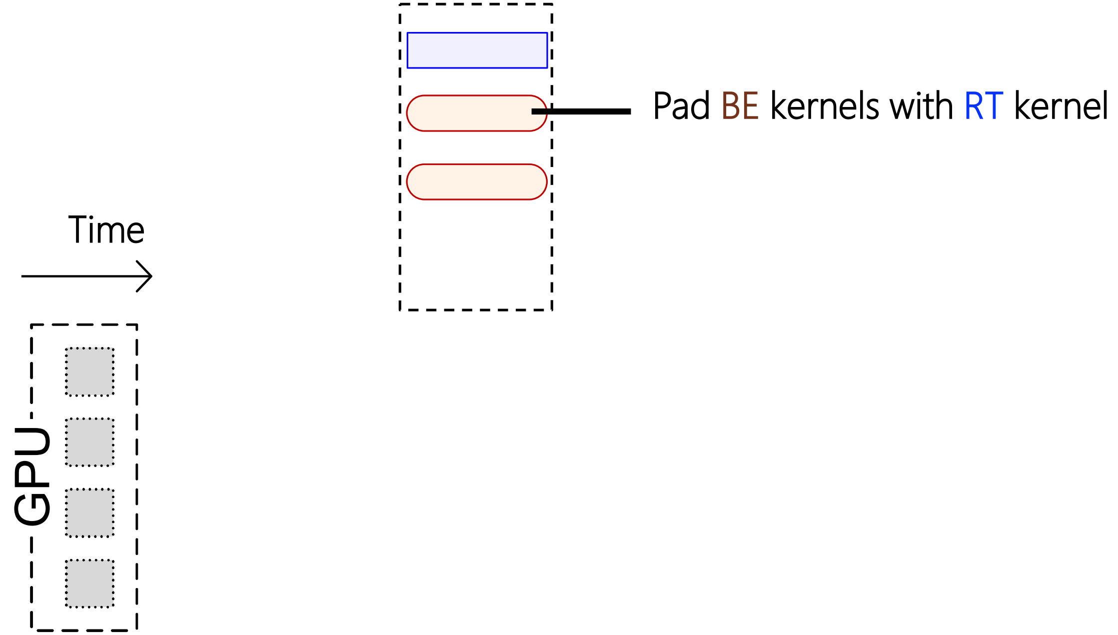

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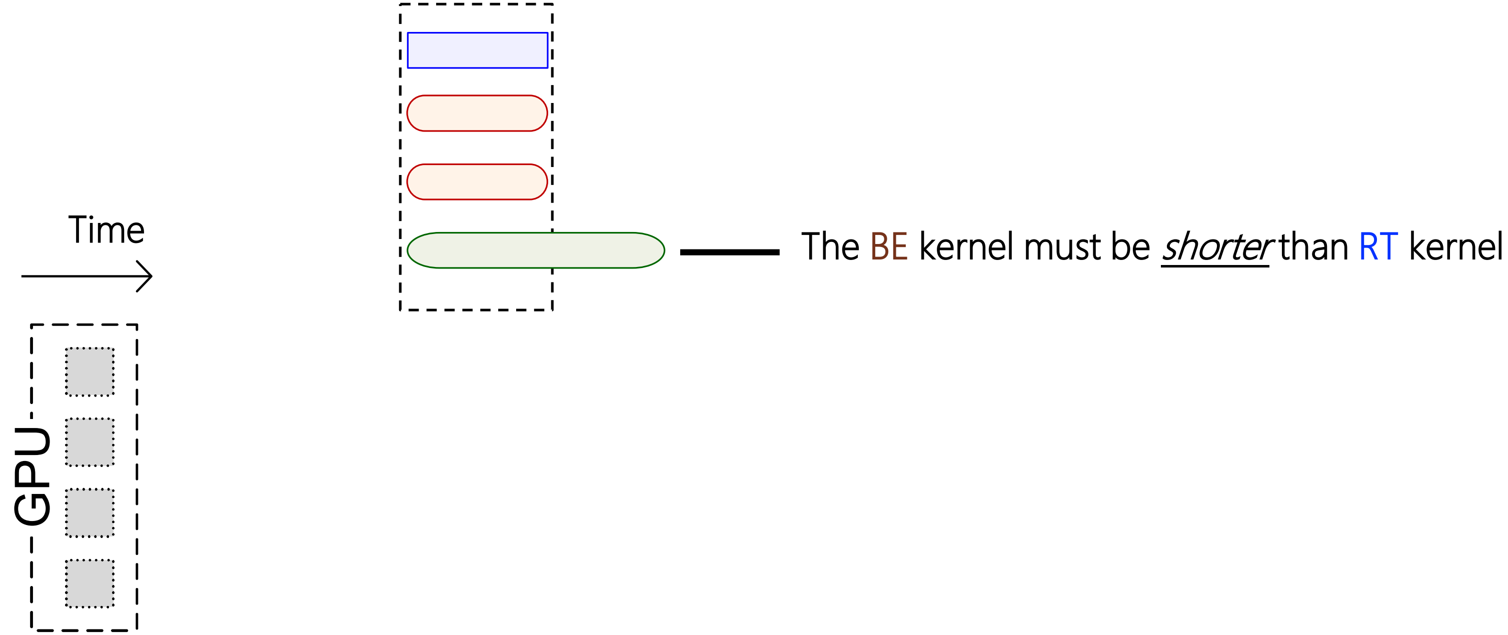

Dynamic Kernel Padding

Key Idea:
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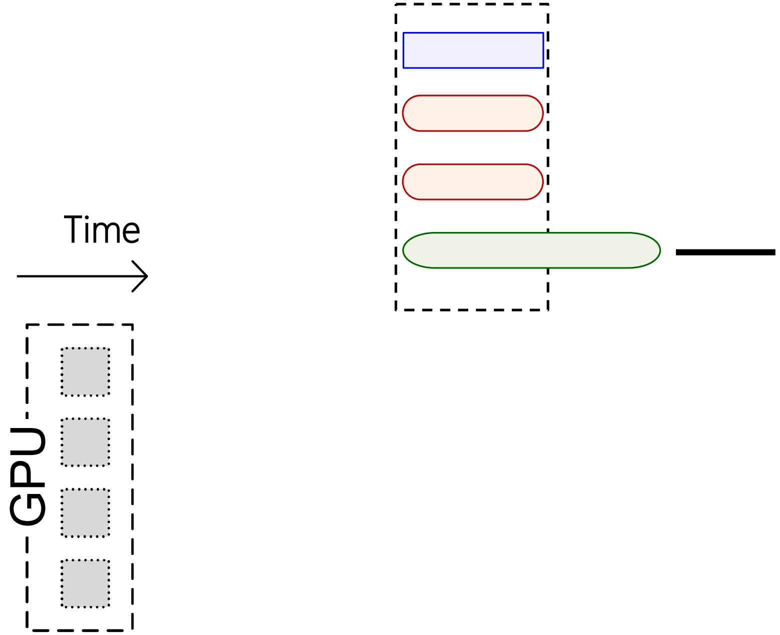
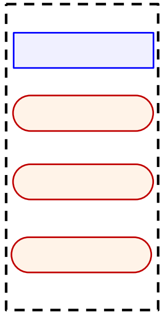


Latency Predictability

The BE kernel must be *shorter* than RT kernel

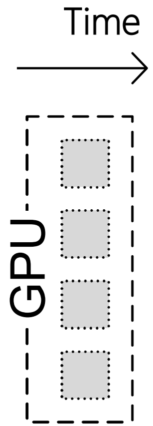
Dynamic Kernel Padding

Key Idea:
Dynamically <u>pad</u> RT kernels with BE kernels



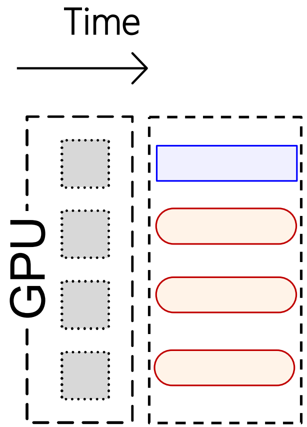
Latency Predictability

The BE kernel must be *<u>shorter</u>* than RT kernel



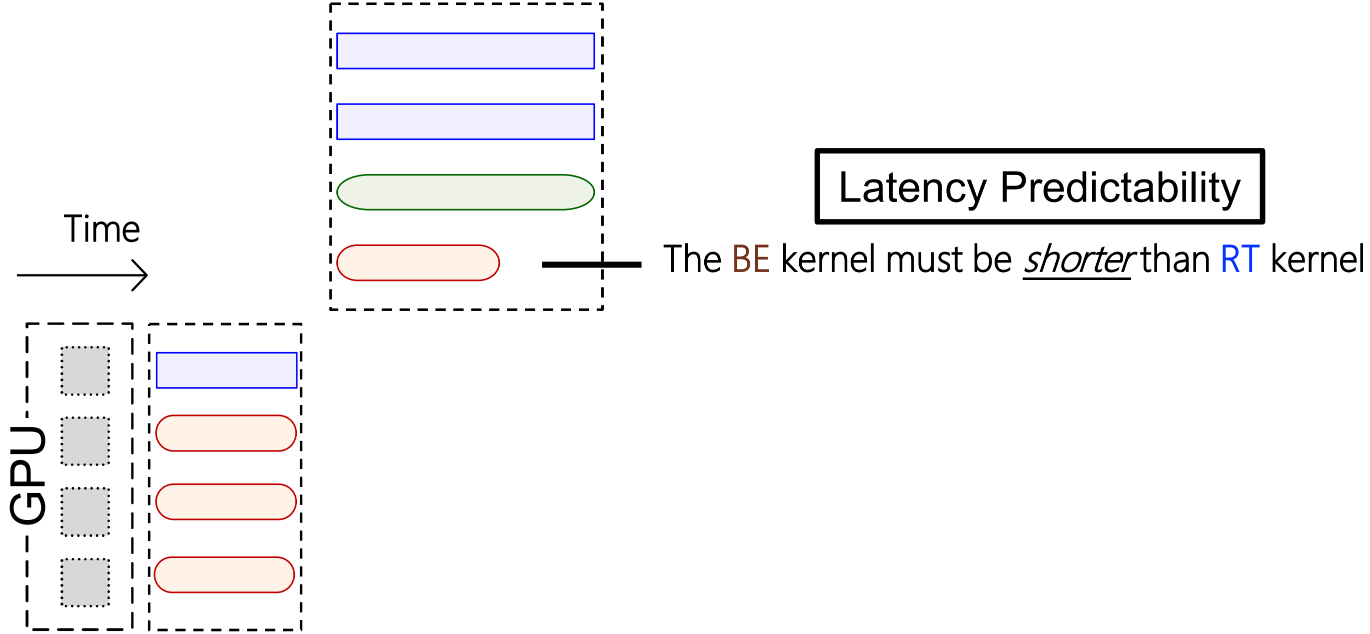
Dynamic Kernel Padding

Key Idea:
Dynamically pad RT kernels with BE kernels



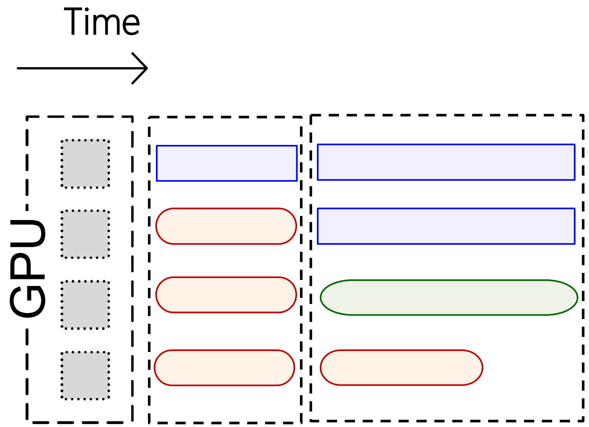
Dynamic Kernel Padding

Key Idea:
Dynamically pad RT kernels with BE kernels



Dynamic Kernel Padding

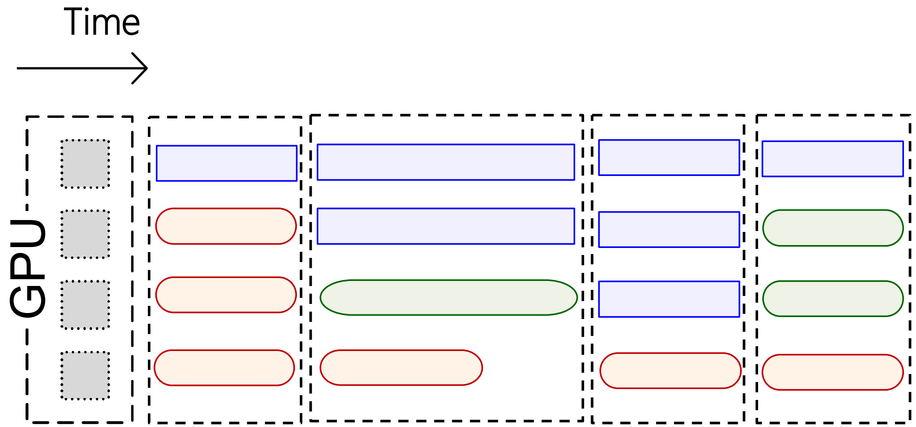
Key Idea:
Dynamically <u>pad</u> RT kernels with BE kernels



Dynamic Kernel Padding

Key Idea:

Dynamically pad RT kernels with BE kernels



Evaluation

- **Hardware Environments**
  - AMD Instinct MI50 GPU (60 CUs and 16 GB memory)
  - Intel Core i7-10700 CPU (8 cores) + 16 GB of DRAM
- **Software Environments**
  - ROCm 4.3.0
  - Apache TVM 0.8.0

Evaluation

- **DNN Inference Serving Benchmark (DISB)**
  - A new benchmark for DNN inferences in real-time scenarios
  - Five representative DNN models:
    - ResNet-152 (RNET), DenseNet-201(DNET) ,VGG-19 (VGG), Inception-v3(IN3), DistilBert(BERT)
  - Five workloads

Issue **RT** inference requests (fixed frequency)

DISB	**A**	**B**	**C**	**D**	**E**
Num. of RT clients	1/VGG	1/VGG	1/VGG	5/ALL	5/ALL
Frequency (reqs/s)	100 [U]	220 [U]	100 [U]	20 [U]	20 [P]
Num. of BE clients	1/RNET	1/RNET	5/ALL	5/ALL	5/ALL

saturate our testbed

Issue **BE** inference requests (close-loop)

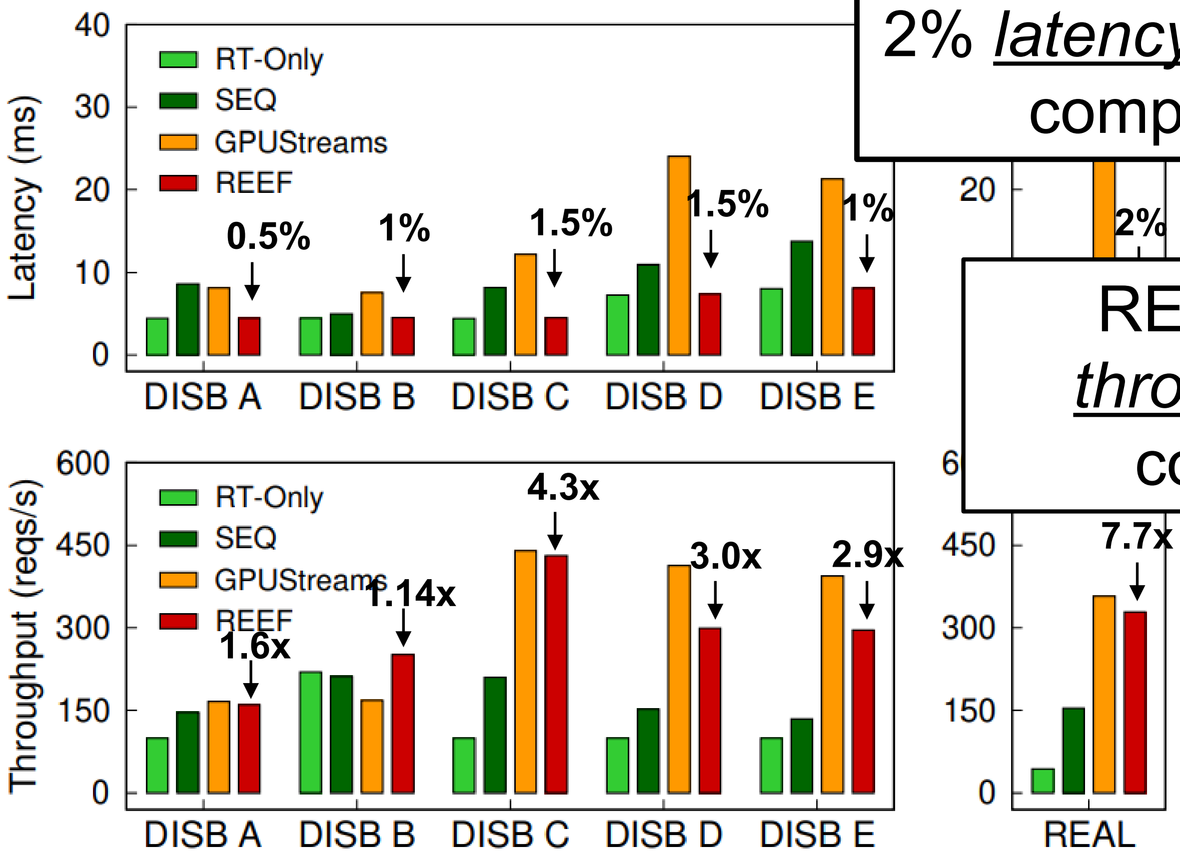
Evaluation

- **DNN Inference Serving Benchmark (DISB)**
  - A new benchmark for DNN inferences in real-time scenarios
  - Five representative DNN models:
    - ResNet-152 (RNET), DenseNet-201(DNET) ,VGG-19 (VGG), Inception-v3(IN3), DistilBert(BERT)
  - Five workloads
- **Real-world Trace**
  - From an open autonomous driving platform (i.e., ApolloAuto)

Evaluation

- **Comparing targets**
  - **RT-Only**: dedicate the GPU for RT tasks
  - **SEQ**: sequentially execute tasks without preemption
  - **GPUStreams**: execute RT/BE tasks concurrently in multiple GPU streams

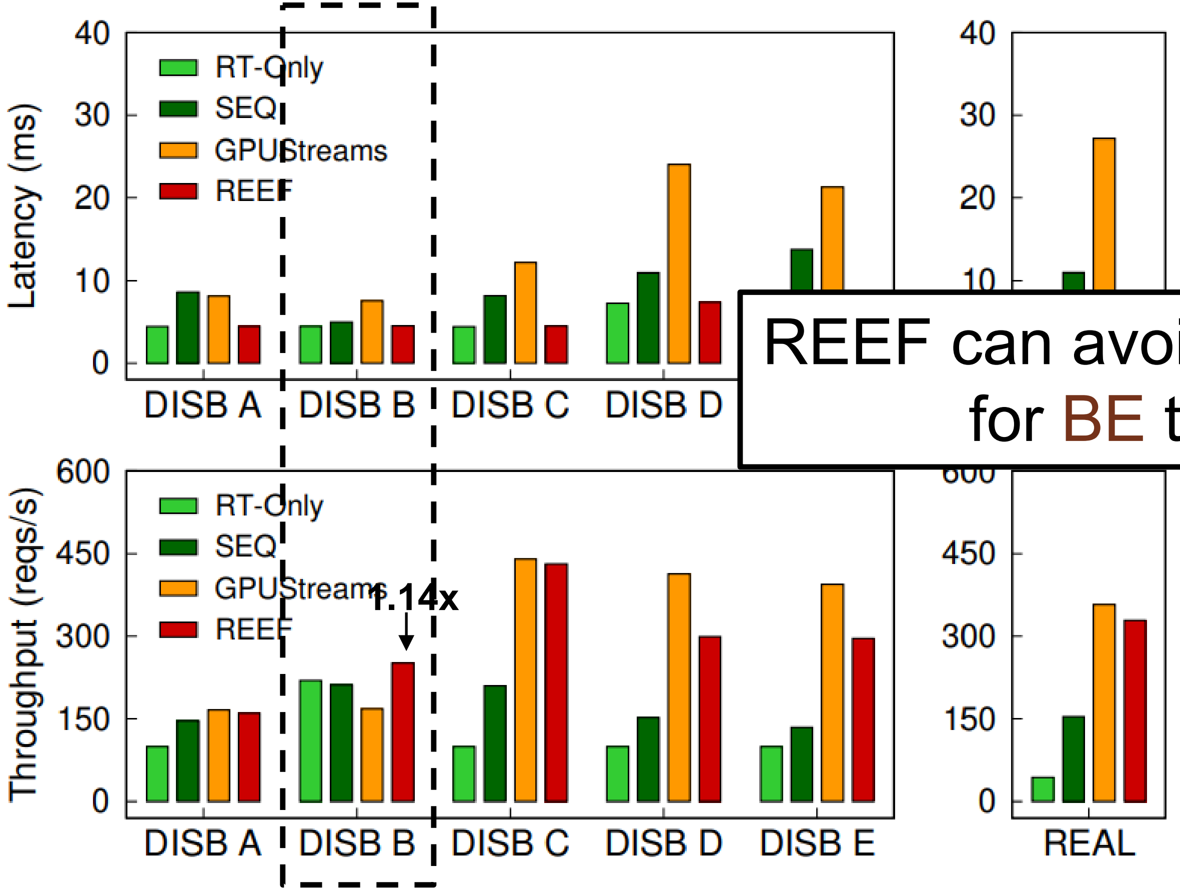
Evaluation



REEF only incurs at most 2% *latency overhead* for RT tasks compared with RT-Only

REEF can improve *overall throughput* by 1.14× ~ 7.7× compared with RT-Only

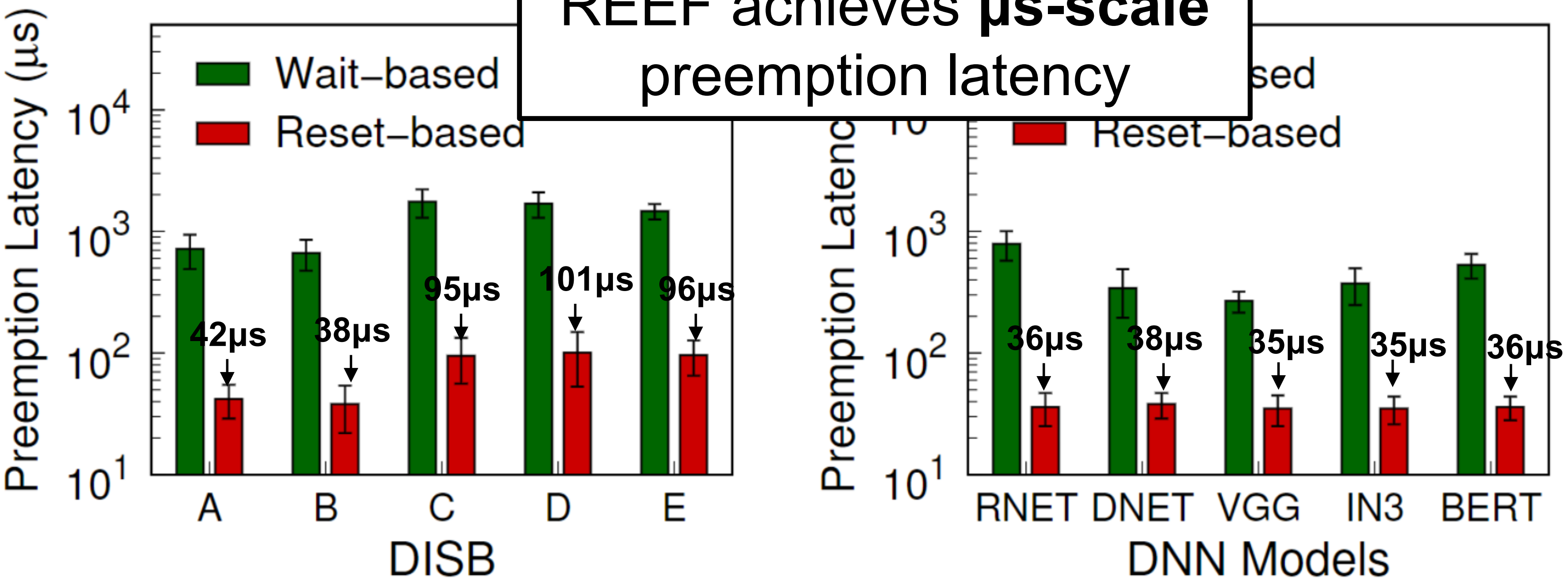
Evaluation



REEF can avoid starvation for BE tasks

Evaluation

REEF achieves **µs-scale** preemption latency



Conclusion

- **REEF: a GPU-accelerated DNN inference serving system**
  - Achieve both low-latency (2% latency overhead for real-time tasks) and work-conserving (1.14x – 7.7x throughput improvement)
  - Reset-based preemption: μs-scale preemption based on ***idempotence***
  - Dynamic kernel padding: controlled concurrent execution based on ***latency predictability***

Thanks & QA