# CS162
# Operating Systems and Systems Programming
# Lecture 25

## Ray and vLLM

December 2nd, 2024

Prof. Ion Stoica

http://cs162.eecs.Berkeley.edu

# Lecturers Today

**Simon**

**Woosuk**

- 4th-year PhD advised by Ion
- Research interests : Systems + AI

# Some projects We've worked on in Berkeley's Labs


MemGPT

Chatbot Arena


Vicuna

Applications

---

Alpa

AlpaServe

vLLM

Optimizers
(optimize ML workloads)

---

Apache Spark


RAY

Distributed Frameworks
(dev & run distributed apps)

---


Apache MESOS


SkyPilot


Skyplane

Infra & Orchestration Layer
(allocate resources)

# Last lecture


MemGPT

Chatbot Arena


Vicuna

Applications

---

Alpa

AlpaServe

vLLM

Optimizers
(optimize ML workloads)

---



Distributed Frameworks
(dev & run distributed apps)

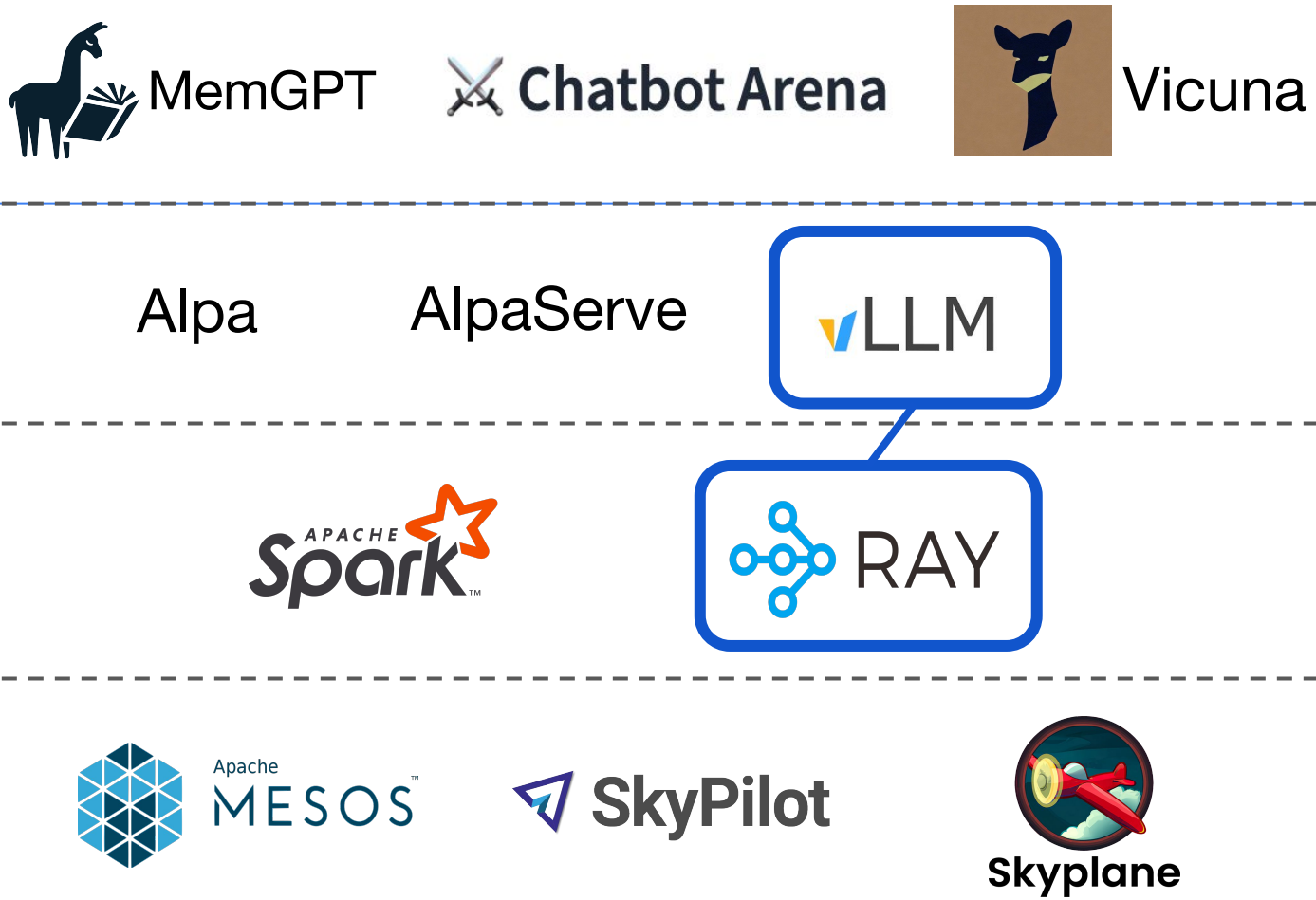
---


Apache MESOS

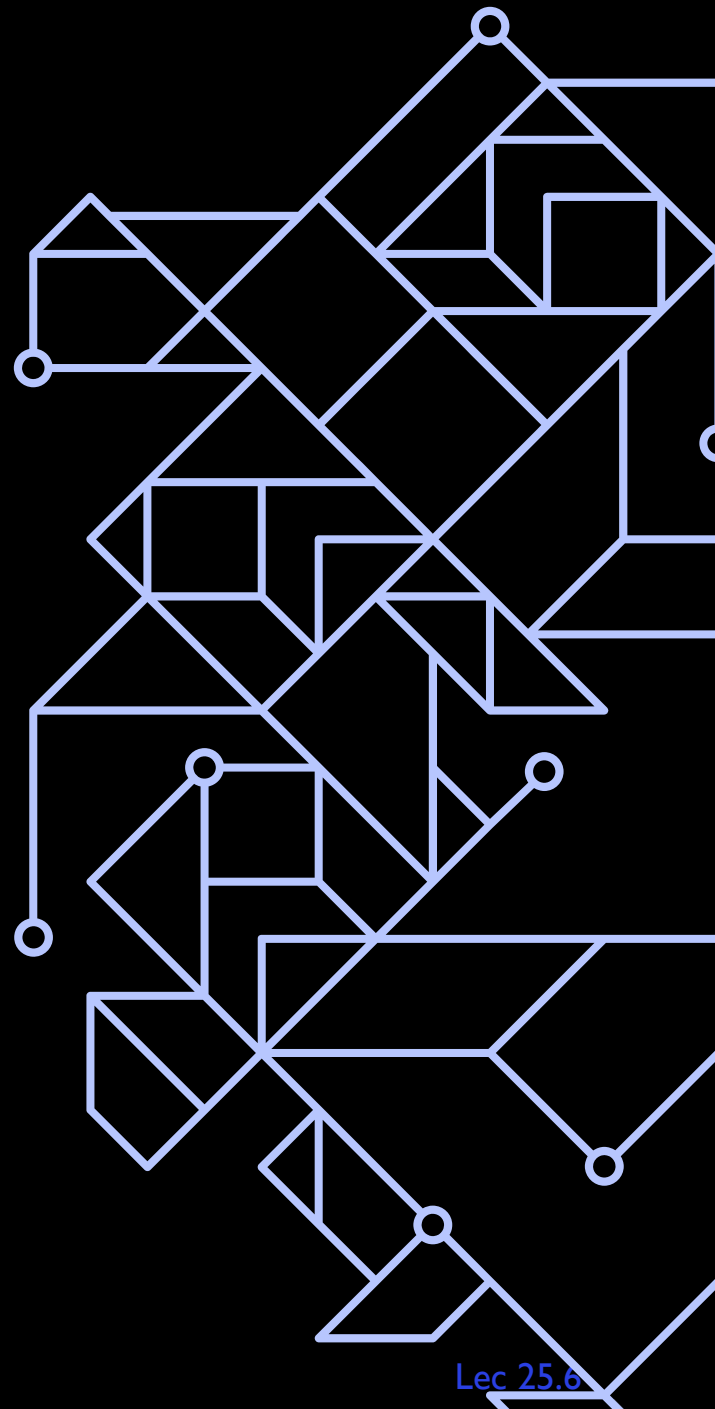


Infra & Orchestration Layer
(allocate resources)

# This Lecture



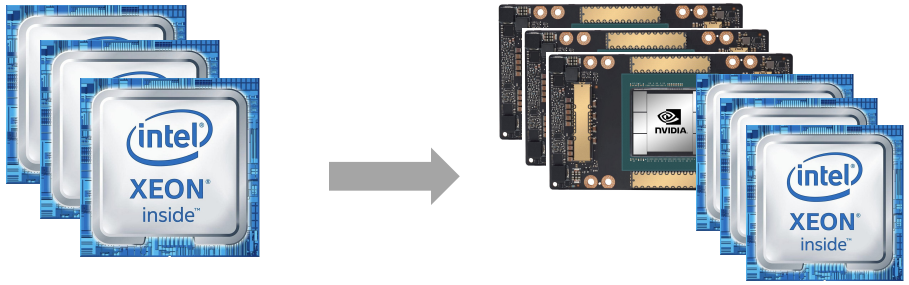
# Ray (2016 - )



# Some historical trends

**2009 (Spark)**

**2016 (Ray)**




- Big Data & Classic ML
- Homogeneous clusters

+ DL & RL
- Heterogeneous clusters

# CS 262a – Fall 2015

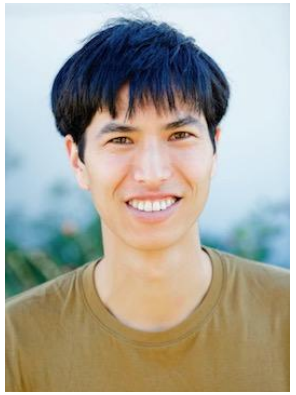
Two ML students

They wanted to train
neural networks distributedly

Ion asked them to train on Spark

- Why reinvent the wheel?

And they did it!



Rober
t

Philip
p

SPARKNET: TRAINING DEEP NETWORKS IN SPARK

**Philipp Moritz, Robert Nishihara, Ion Stoica, Michael I. Jordan**
Electrical Engineering and Computer Science
University of California
Berkeley, CA 94720, USA
{pcmoritz,rkn,istoica,jordan}@eecs.berkeley.edu

ABSTRACT

Training deep networks is a time-consuming process, with networks for object recognition often requiring multiple days to train. For this reason, leveraging the resources of a cluster to speed up training is an important area of work. However, widely-popular batch-processing computational frameworks like MapReduce and Spark were not designed to support the asynchronous and

**ICLR, 2014**

# But pretty soon some issues

Spark was based on JVM, since this is what the Big Data ecosystem was based on, e.g., Hadoop, Kafka, Flink, etc

- JVM doesn't have support for GPUs

The DNN software stack: Python and C++, e.g., Tensorflow, PyTorch, etc

- Very good support for GPUs

BSP (Bulk Syhnchronuous Processing) model great for data, but not flexible enough for AI workloads

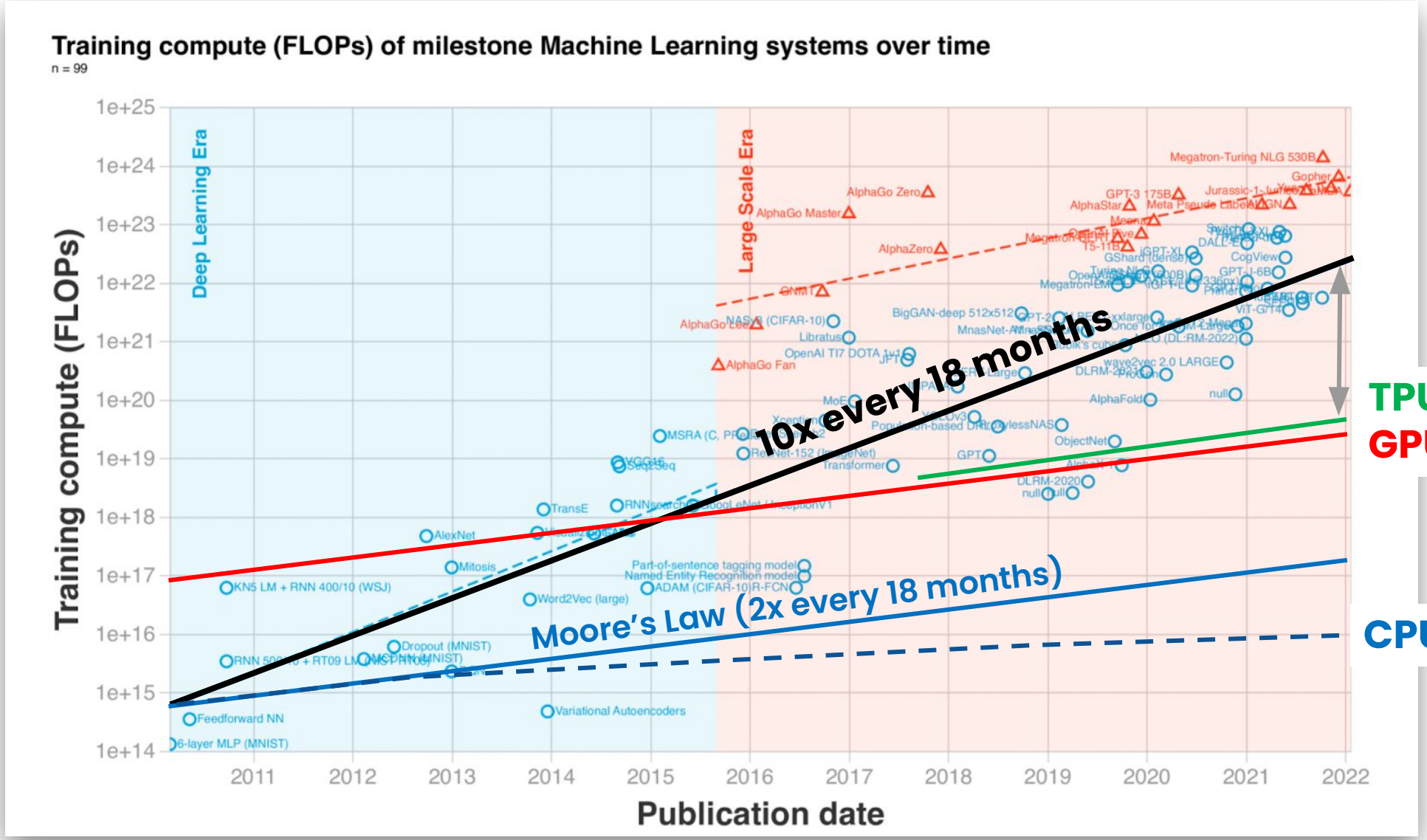
# Trends when we started Ray

AI demands growing faster than single node capabilities

Clusters becoming heterogeneous: GPUs + CPUs

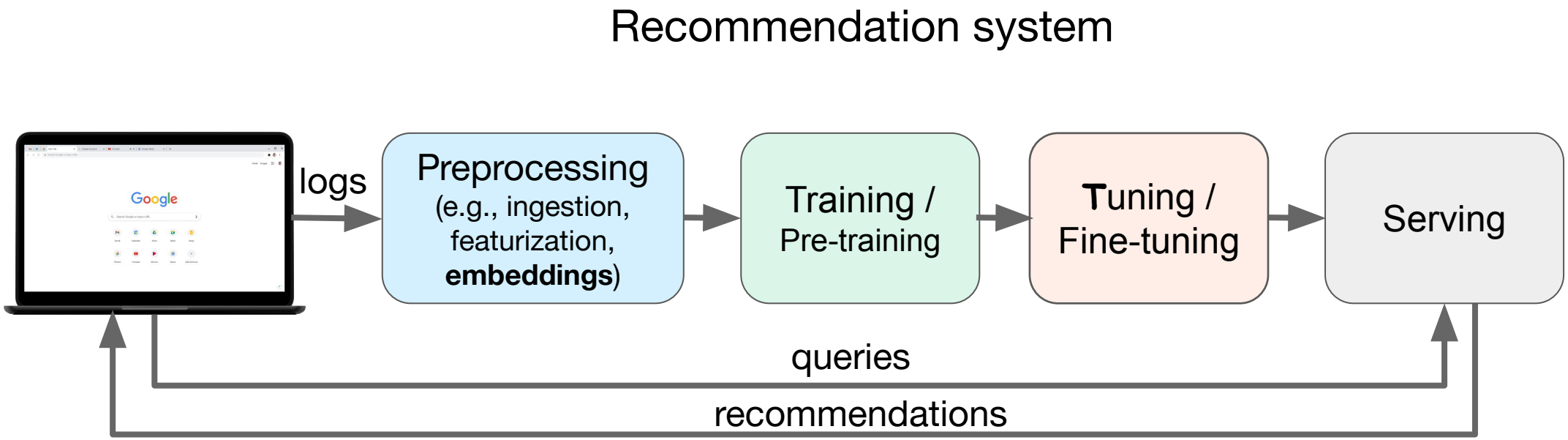
AI workloads becoming more complex

# AI Demands growing faster than hardware capabilities

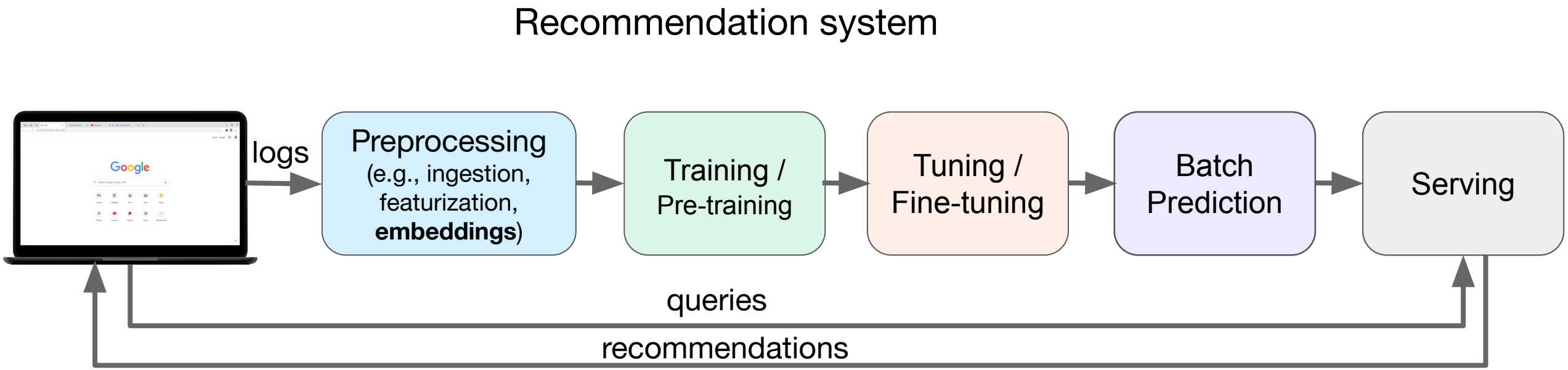



"Compute trends across three eras of machine learning", J. Sevilla, https://ar5iv.labs.arxiv.org/html/2202.05924

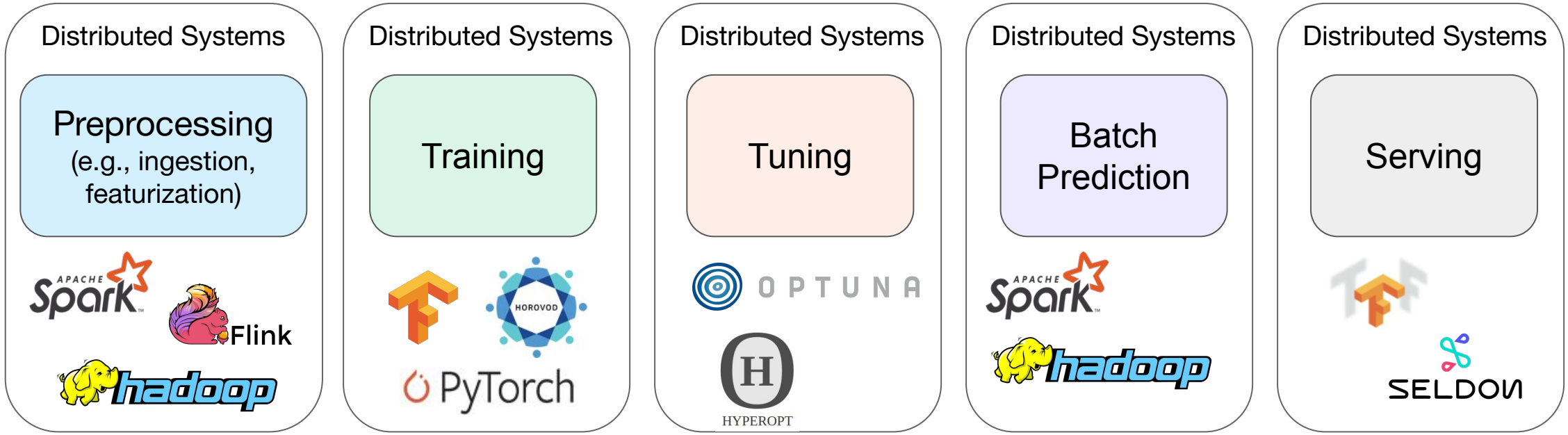
# AI workloads becoming more complex



# AI workloads becoming more complex



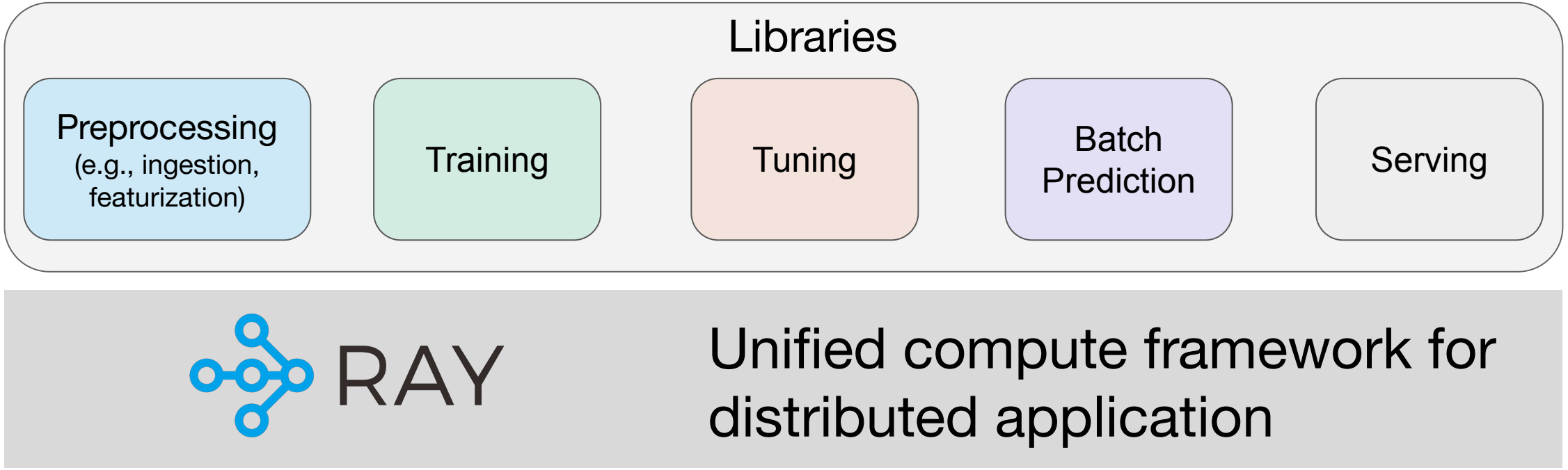
# Challenge: need to scale every stage!




Need to stitch together a bunch of disparate systems

- **Hard** to develop
- **Hard** to deploy
- **Hard** to manage
- **Slow**

# Ray: **One** system to support all these workloads



# Minimalist API

| | |
|---|---|
| ray.init() | Initialize Ray context. |
| @ray.remote | Function or class decorator specifying that the function will be executed as a task or the class as an actor in a different process. |
| .remote | Postfix to every remote function, remote class declaration, or invocation of a remote class method. Remote operations are *asynchronous*. |
| ray.put() | Store object in object store, and return its ID. This ID can be used to pass object as an argument to any remote function or method call. This is a *synchronous* operation. |
| ray.get() | Return an object or list of objects from the object ID or list of object IDs. This is a *synchronous* (i.e., blocking) operation. |
| ray.wait() | From a list of object IDs returns (1) the list of IDs of the objects that are ready, and (2) the list of IDs of the objects that are not ready yet. |

# The FAST Compute Model

# The FAST Compute Model

**Actors:** remote class instance (object)

**Tasks:** remote functions

# The **FAST** Compute Model

**Futures:** reference to objects (possible not created yet)

**Actors:** remote class instance (object)

**Tasks:** remote functions

# The **FAST** Compute Model

**Futures:** reference to objects (possible not created yet)

**Actors:** remote class instance (object)

**S**hared in-memory distributed object store

**T**asks: remote functions

# Python example

```
def f(x):
    # compute...for 1s
    return r
```

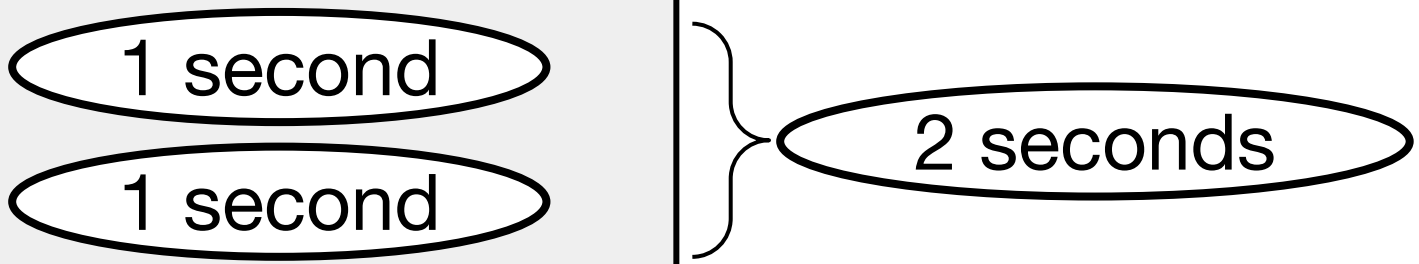
# Python example

```
def f(x):
    # compute...for 1s
    return r

x = f(a)
```

1 second

# Python example

```
def f(x):
    # compute...for 1s
    return r

x = f(a)
y = f(b)
```



# Ray

```
@ray.remote
def f(x):
    # compute...for 1s
    return r
```

# Ray: Function → Task

```
@ray.remote
def f(x):
    # compute...for 1s
    return r

x_ref = f.remote(a)
y_ref = f.remote(b)
ray.get([x_ref, y_ref])
```

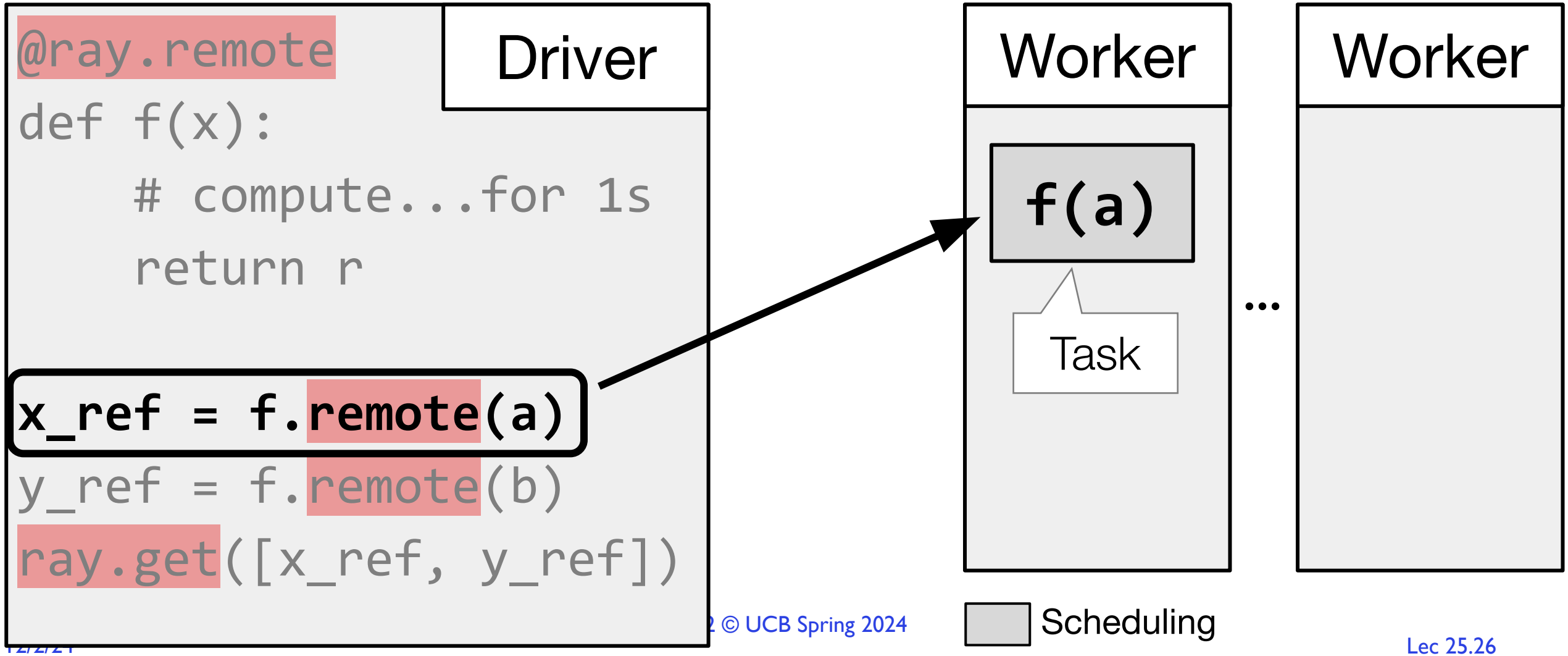
Driver

Worker

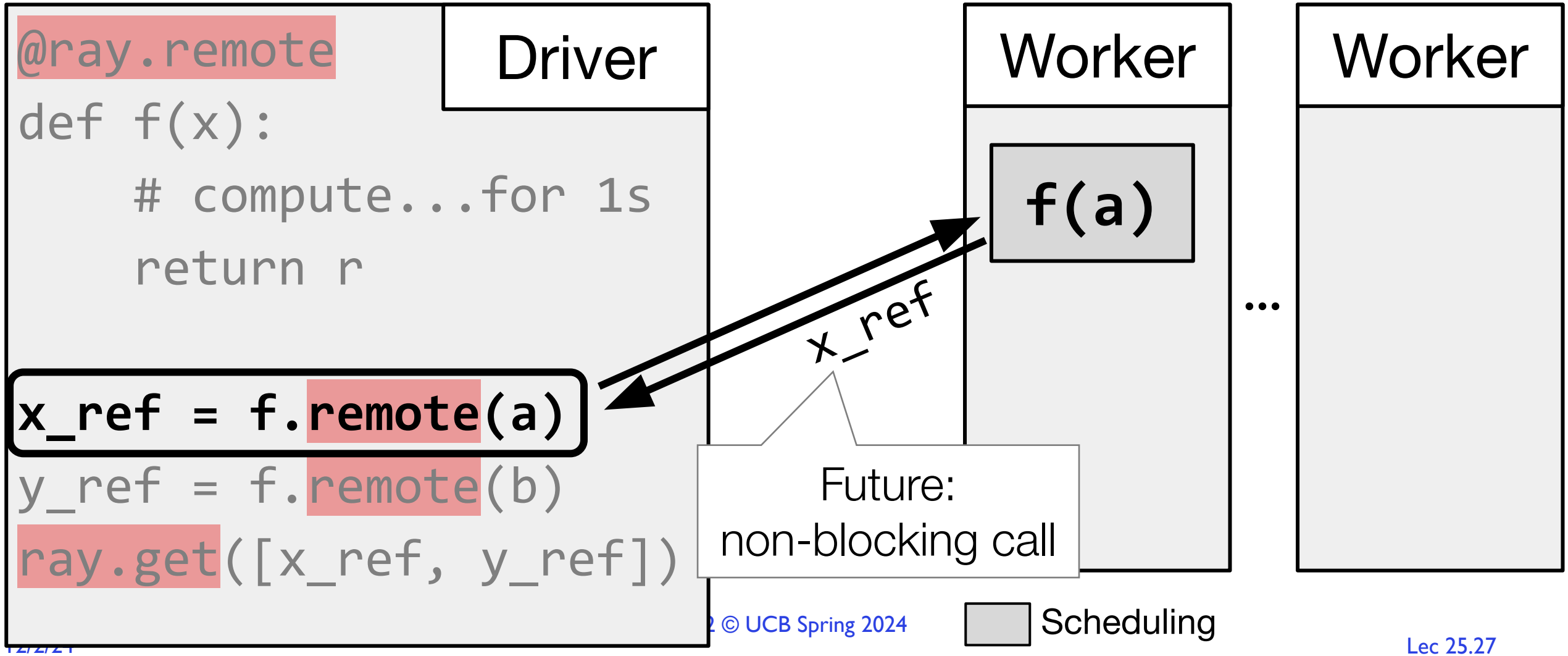
Worker

...

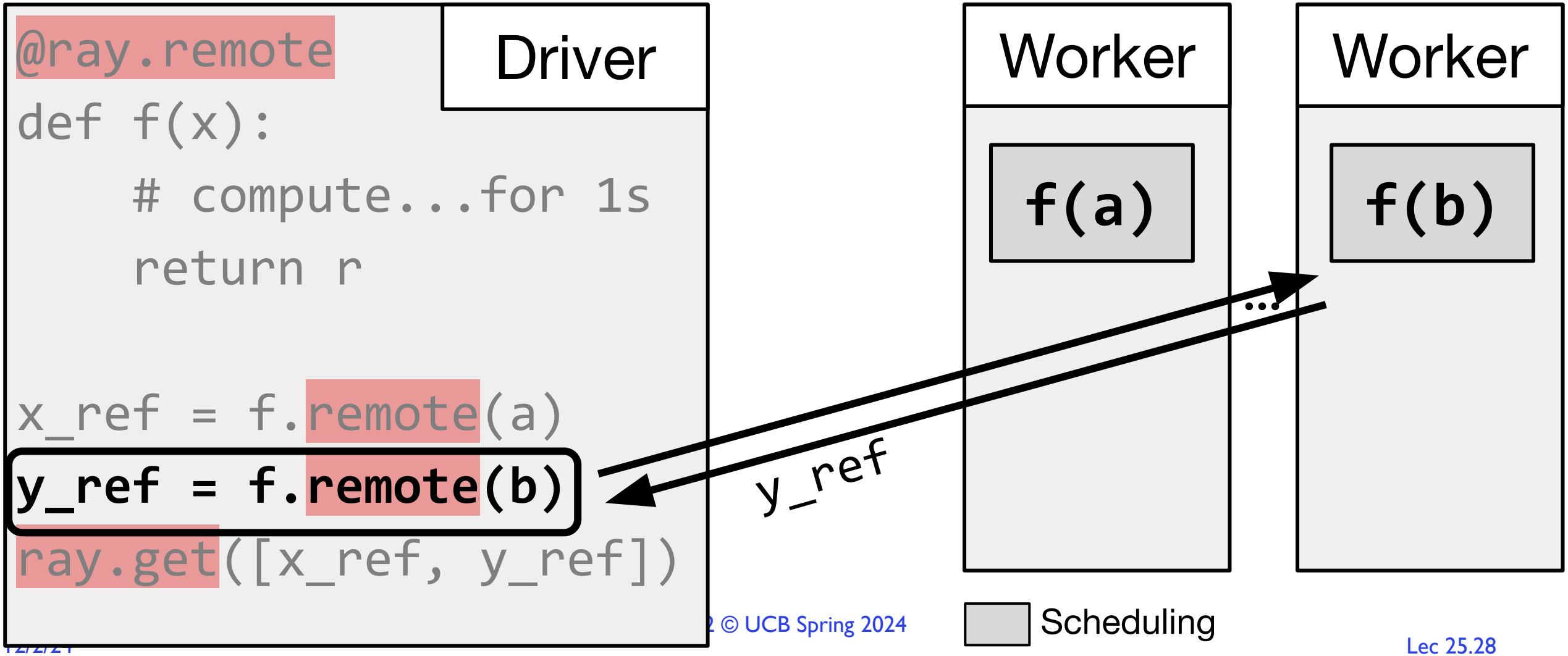
# Ray: Function → Task



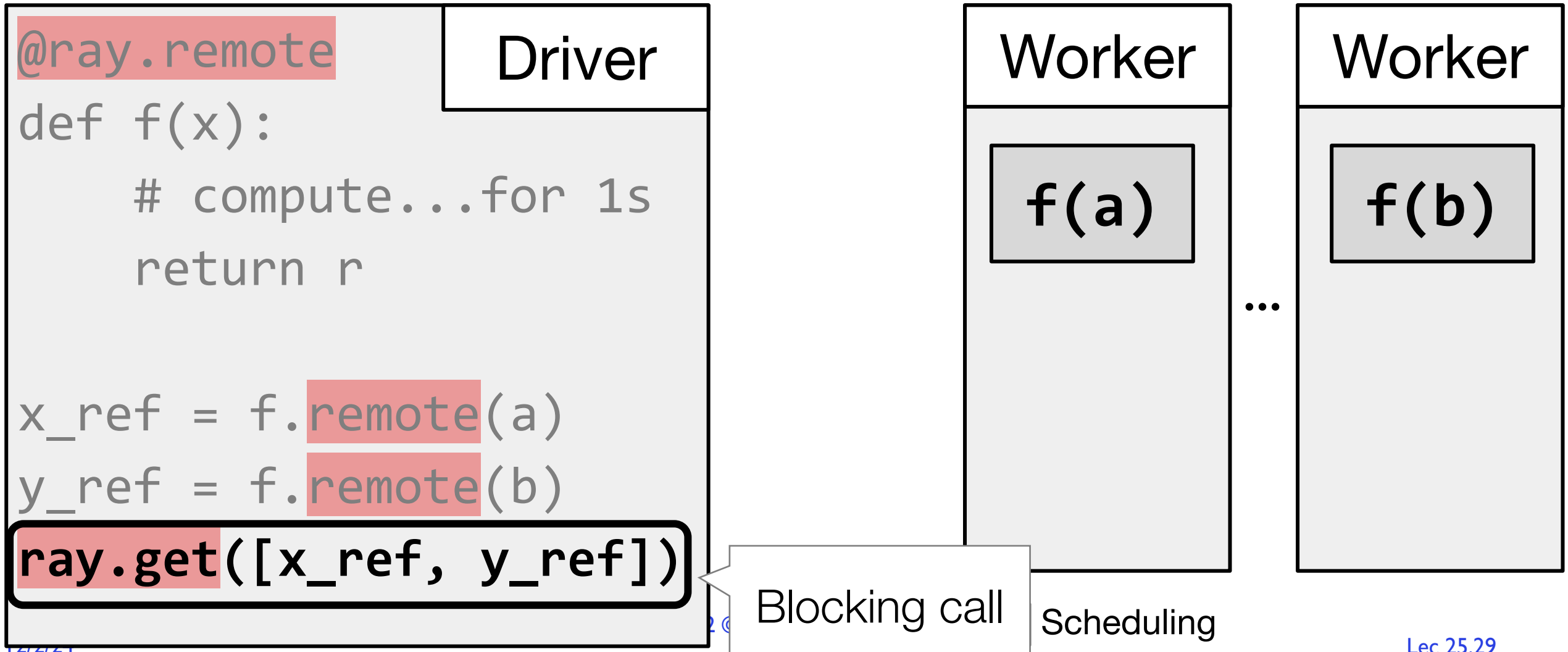
# Ray: Function → Task



# Ray: Function → Task



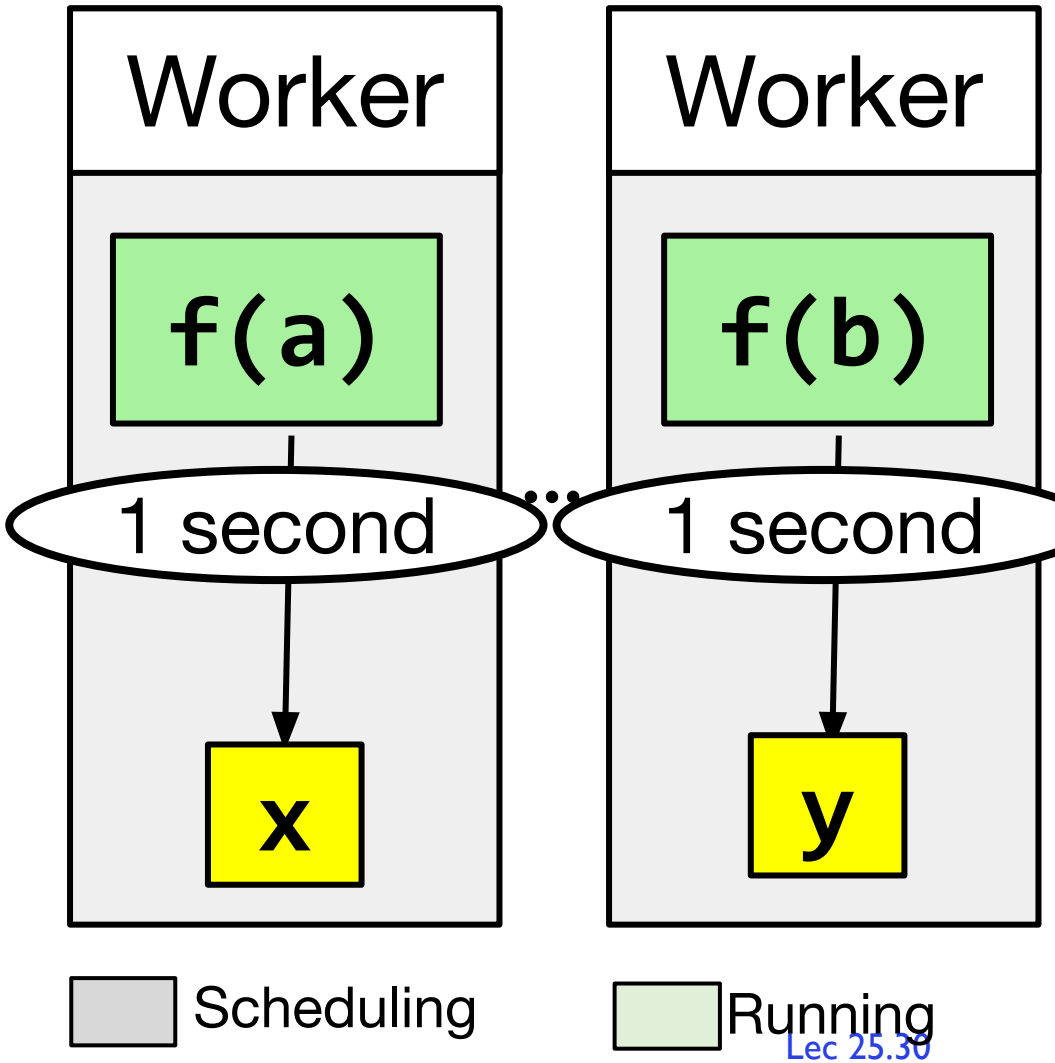
# Ray: Function → Task



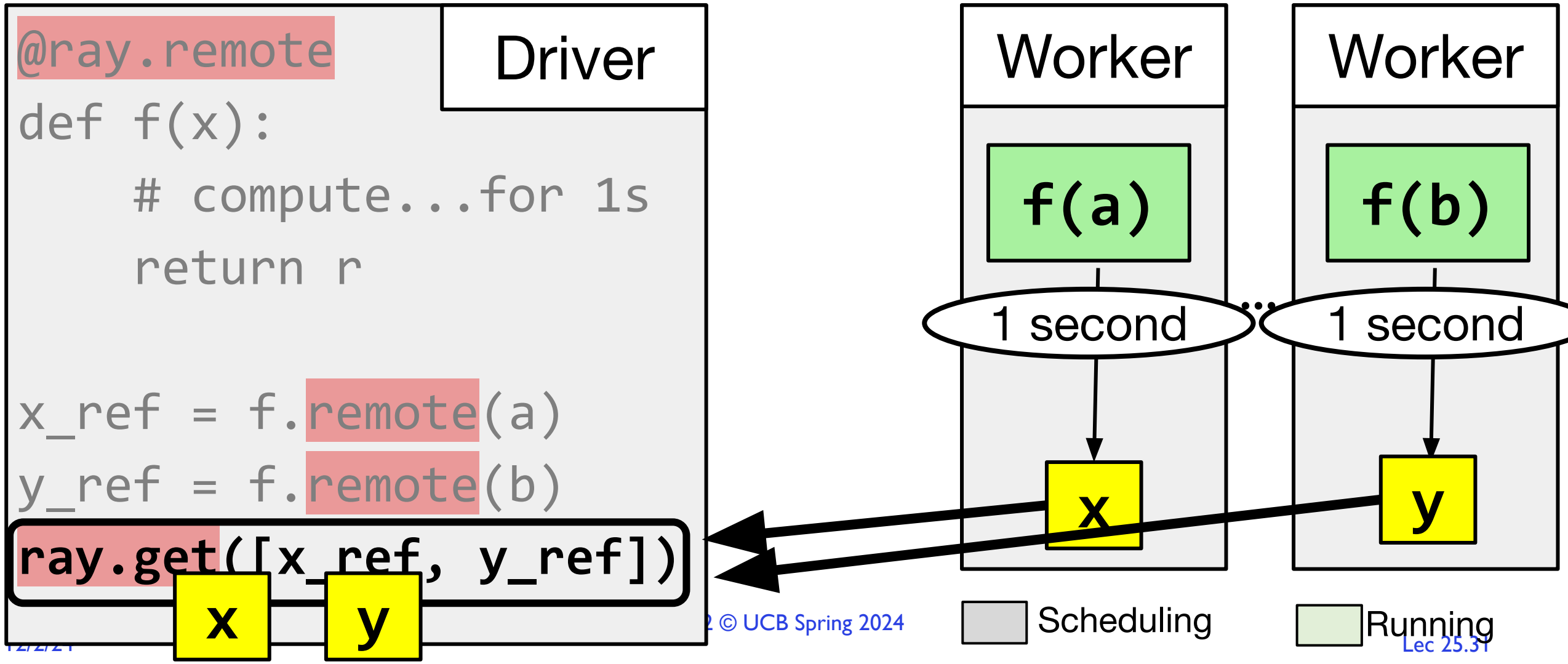
# Ray: Function → Task

Driver

```
@ray.remote
def f(x):
    # compute...for 1s
    return r

x_ref = f.remote(a)
y_ref = f.remote(b)
ray.get([x_ref, y_ref])
```



# Ray: Function → Task



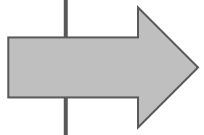
# Python Class

```
class Counter(object):
    def __init__(self):
        self.value = 0
    def inc(self):
        self.value += 1
        return self.value

c = Counter()
c.inc()
c.inc()
```

# Python Class

# Ray: Class → Actor

```
class Counter(object):
    def __init__(self):
        self.value = 0
    def inc(self):
        self.value += 1
        return self.value

c = Counter()
c.inc()
c.inc()
```

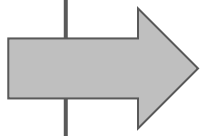


```
@ray.remote
class Counter(object):
    def __init__(self):
        self.value = 0
    def inc(self):
        self.value += 1
        return self.value

c = Counter.remote()
x_ref = c.inc.remote()
y_ref = c.inc.remote()
```

# Python Class

# Ray: Class → Actor

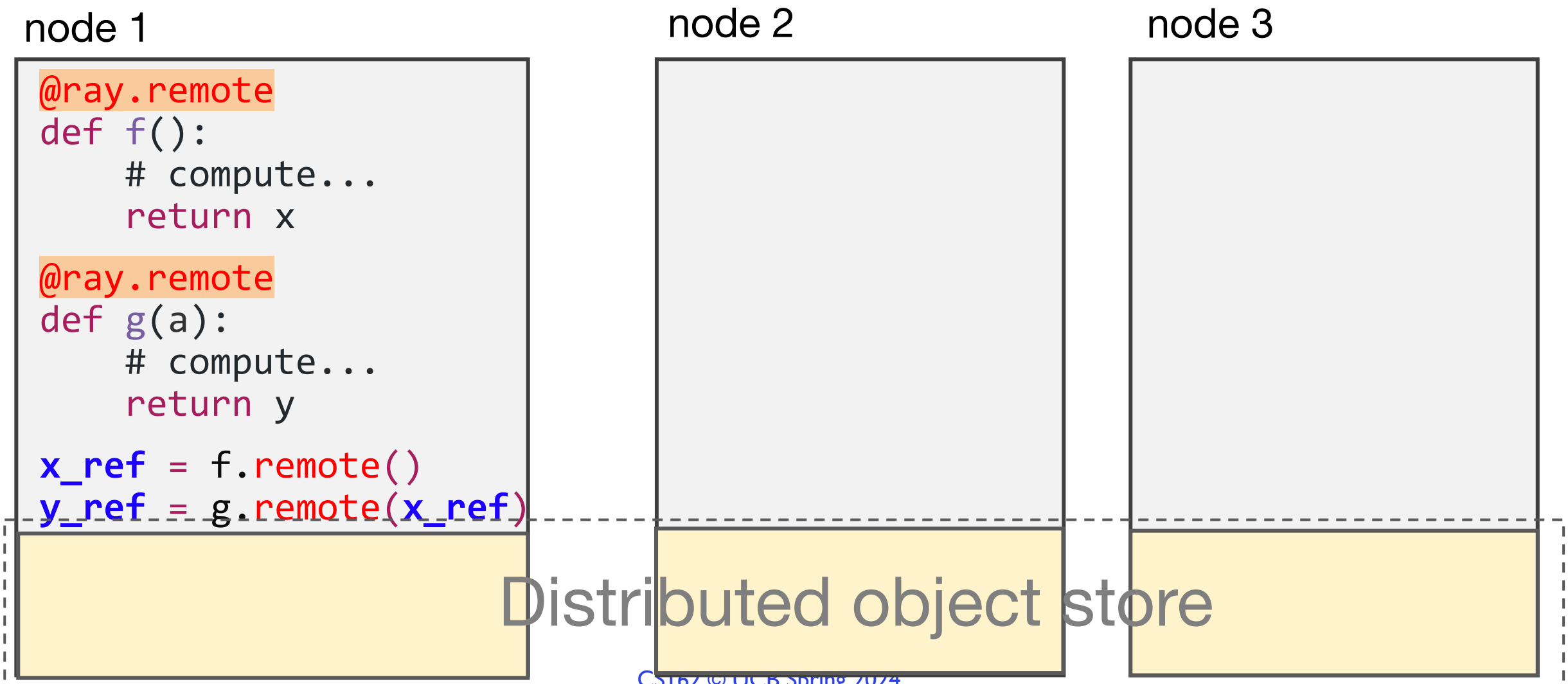
```
class Counter(object):
    def __init__(self):
        self.value = 0
    def inc(self):
        self.value += 1
        return self.value

c = Counter()
c.inc()
c.inc()
```



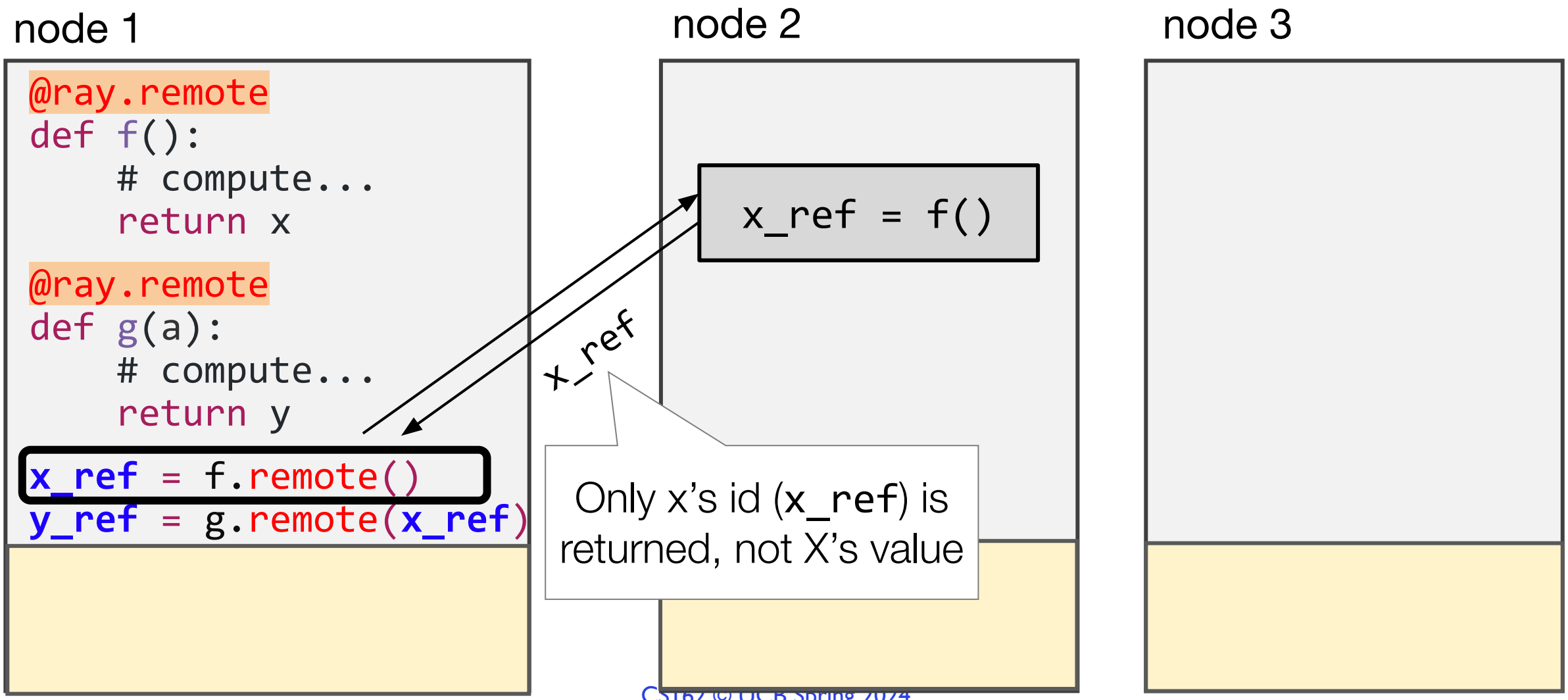
```
@ray.remote(num_cpus=2, num_gpus=1)
class Counter(object):
    def inc(self):
        self.value += 1
        return self.value

c = Counter.remote()
x_ref = c.inc.remote()
y_ref = c.inc.remote()
```

can specify resource demands; support heterogeneous hardware

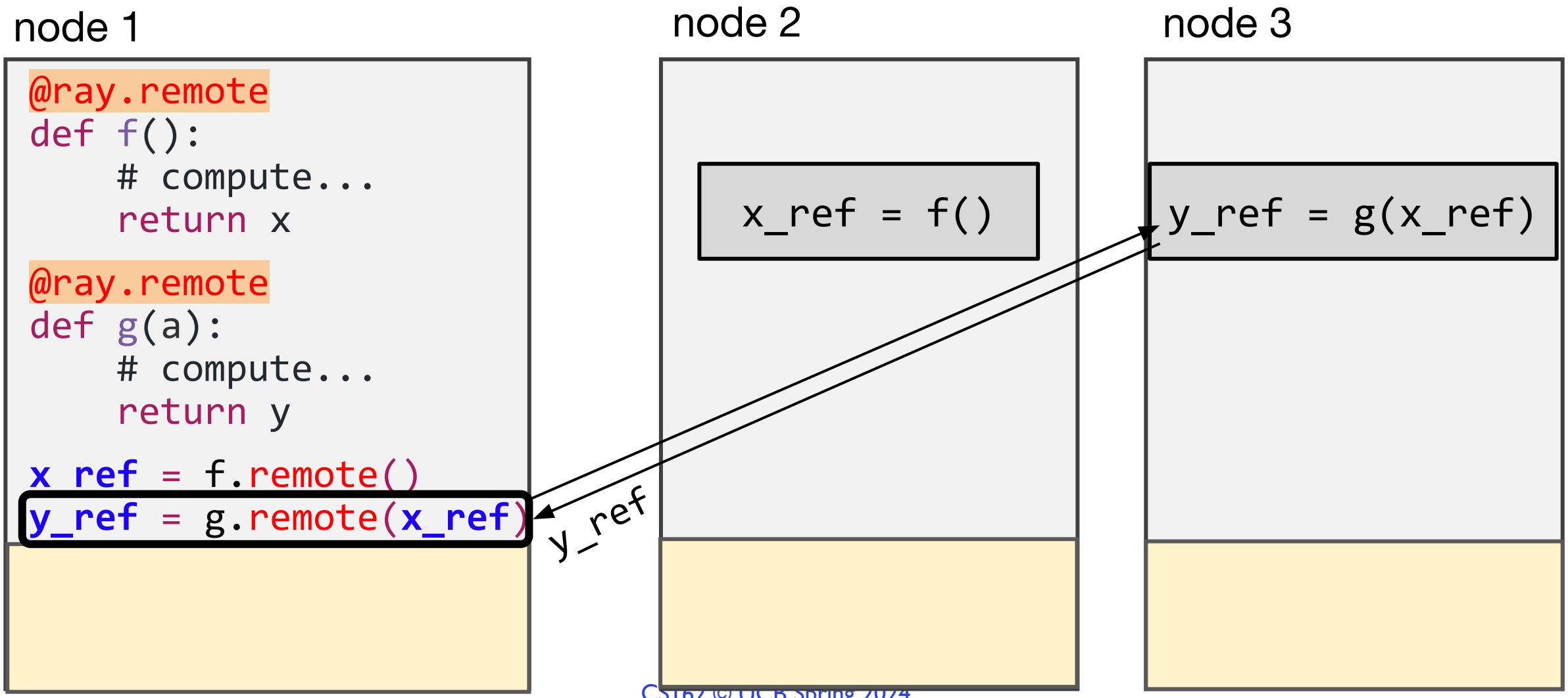
# Shared in-memory object store



# Shared in-memory object store



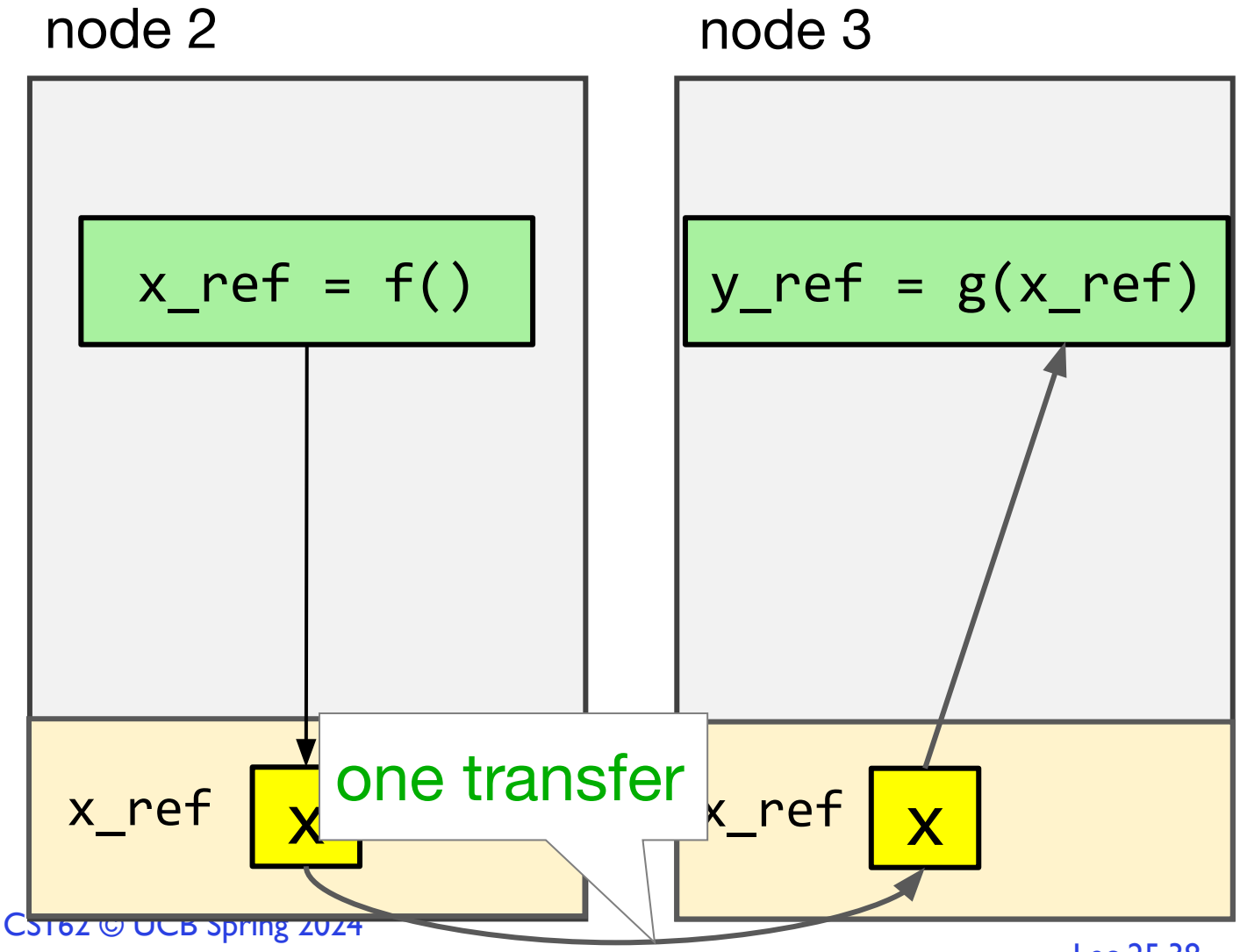
# Shared in-memory object store



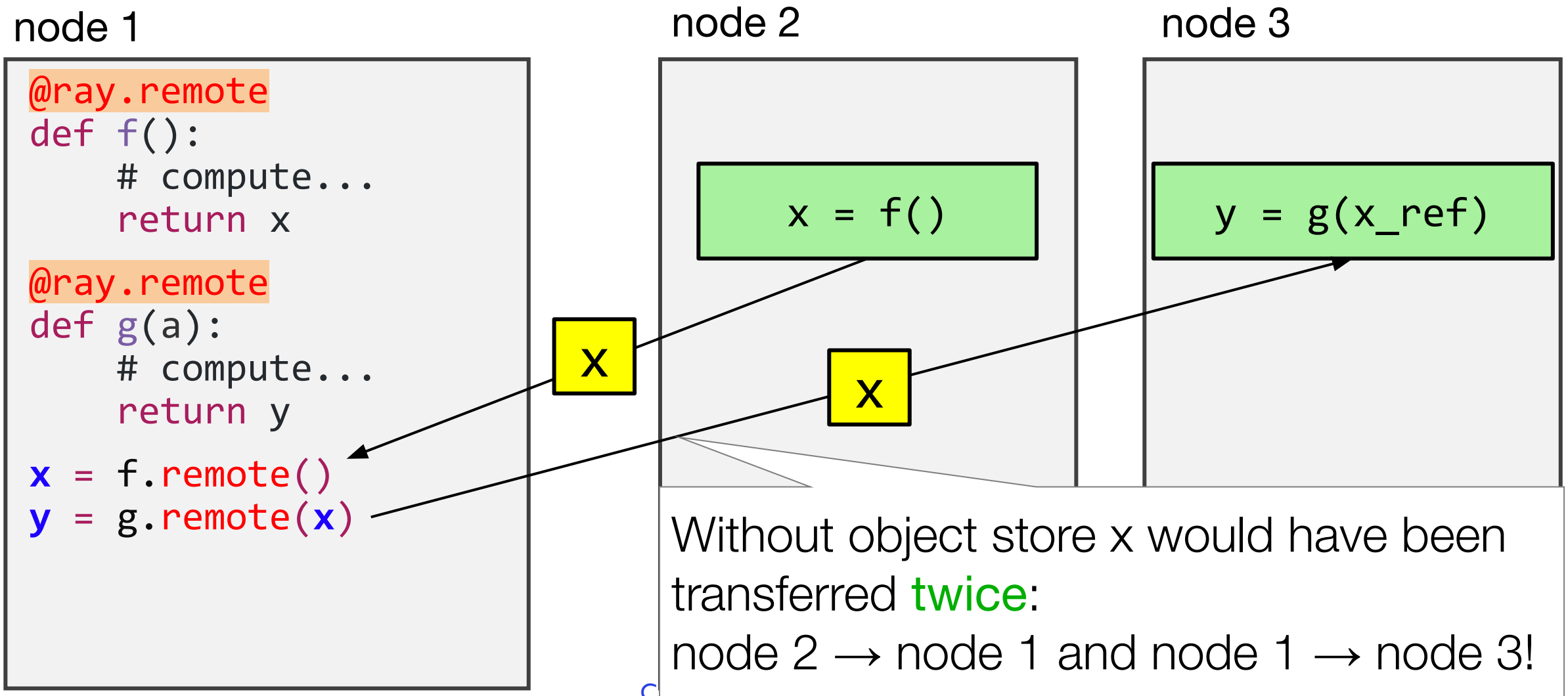
# Shared in-memory object store

node 1

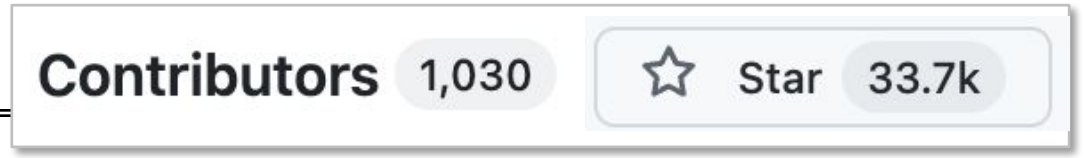
```
@ray.remote
def f():
    # compute...
    return x

@ray.remote
def g(a):
    # compute...
    return y

x_ref = f.remote()
y_ref = g.remote(x_ref)
```



# No object store: object x transferred twice!



# Ray Ecosystem




**Ray AI Libraries** enables simple scaling **of AI** workloads

Data | Train | Tune | Serve | RLlib

**Ray core** enables generic scalable Python applications.

Custom applications

RAY Core

**Unified computing framework for distributed apps**

Tasks | Actors | Object Store

# Ray emerging as the compute framework for Modern AI infrastructure

**Ray breaks the $1/TB barrier as the world's most cost-efficient sorting system**

By Frank Sifei Luan, UC Be

How Ray, a Distributed AI Framework, ps Power ChatGPT

**The Magic of Merlin: Shopify's New Machine Learning Platform**

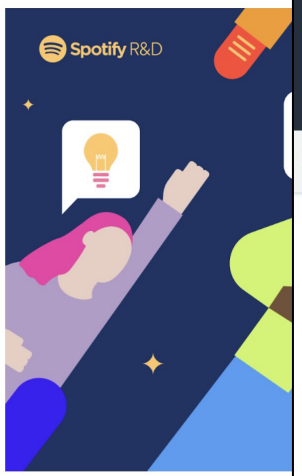
by Isaac Vidas • Data Science & Engineering

Google Cloud Blog

**Large Scale Deep Learning Training and Tuning with Ray at Uber**

Xu Ning, Di Yu, Michael Mui

Unleashing ML Innovation at Spotify with Ray




Han Li

Mar 17 · 9 min read · Listen

**Distributed Machine Learning at Instacart**

How Instacart uses distributed Machine Learning to efficiently thousands of models in production

aws

Contact Us Support My Acc

re:Invent Products Solutions Pricing Documentation Le

Blog Home Category Edition

AWS Big Data Blog

**Introducing AWS Glue for Ray: Scaling your data integration workloads using Python**

by Zach Mitchell, Ishan Gaur, Kinshuk Pahare, and Derek Liu | on 28 NOV

Autho

Netflix Technology Blog

Feb 13 · 11 min read · Listen

**Scaling Media Machine Learning at Netflix**

# Foundation models trained on Ray

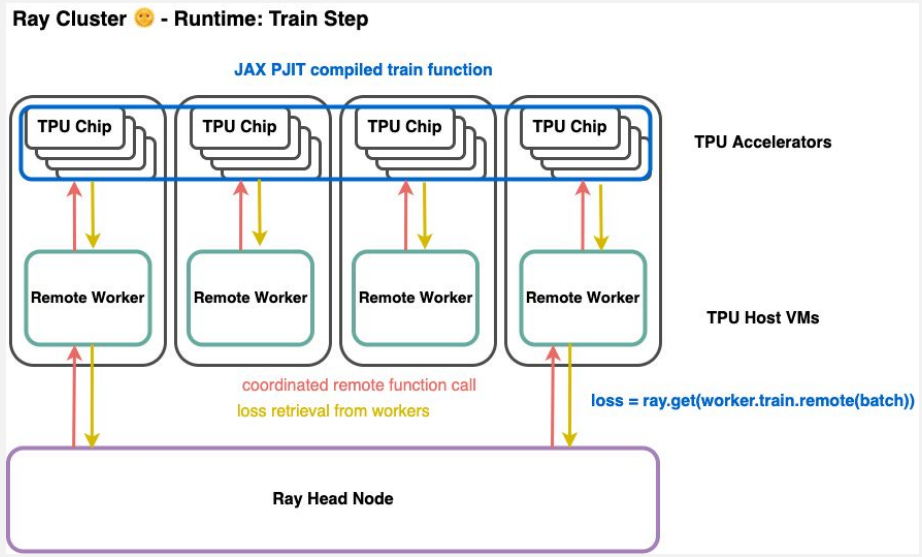
OpenAI

*"We use Ray to train our largest models including ChatGPT"*

**Greg Brockman, Co-founder and President, OpenAI**

co:here

***Use JAX and TPU to train their LLM models***

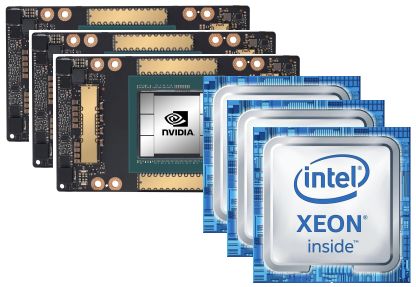


# Some historical trends

**2009 (Spark)**


- Big Data & Classic ML
- Homogeneous clusters

**2016 (Ray)**




+ DL & RL
- Heterogeneous clusters

**2022**


+ LLMs
- Increased cluster heterogeneity; increase vertical integrations (e.g. TPU pods)

# Ray classic API: weak support for GPUs

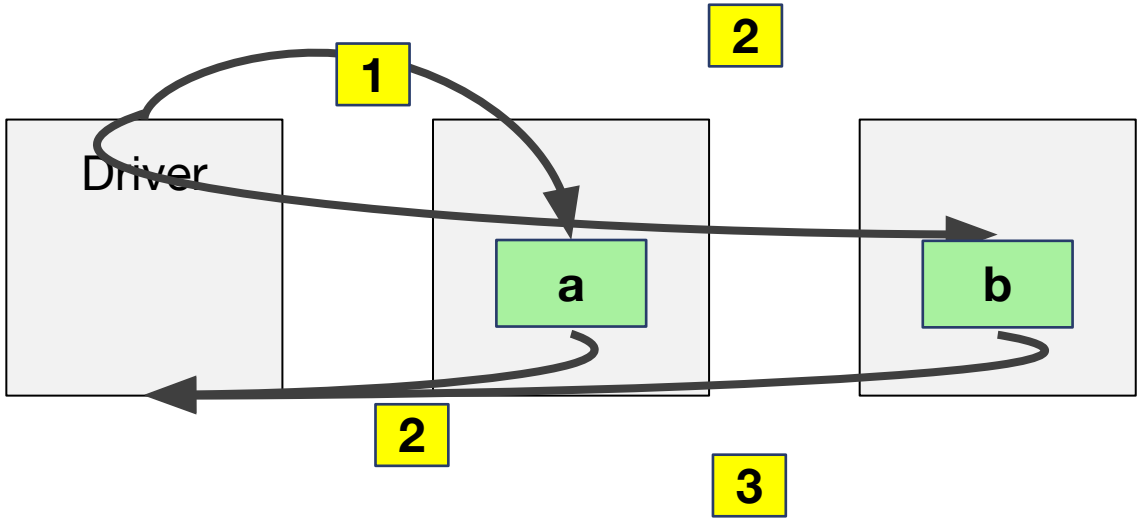
**Trend**: rapid transition CPU-centric  accelerator-centric world

Ray, very dynamic and flexible, but high overhead for small tasks

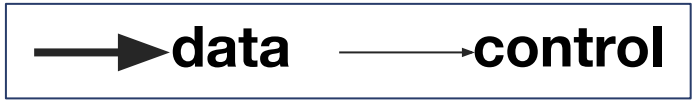
- Pay the cost of RPC
- Pay the cost of dynamic memory allocation
- Difficult to efficiently support p2p protocols like RDMA or NCCL
  - Require upfront resource allocation on all peers to avoid deadlock

# A simple example: RPC-like Execution

```
import ray

@ray.remote
class IncrementActor:
  def inc(self, value):
    return value + 1

a = IncrementActor.remote()
b = IncrementActor.remote()

res_ref = a.echo.remote(1)
res_ref = b.echo.remote(msg_ref)
print(ray.get(res_ref))
```

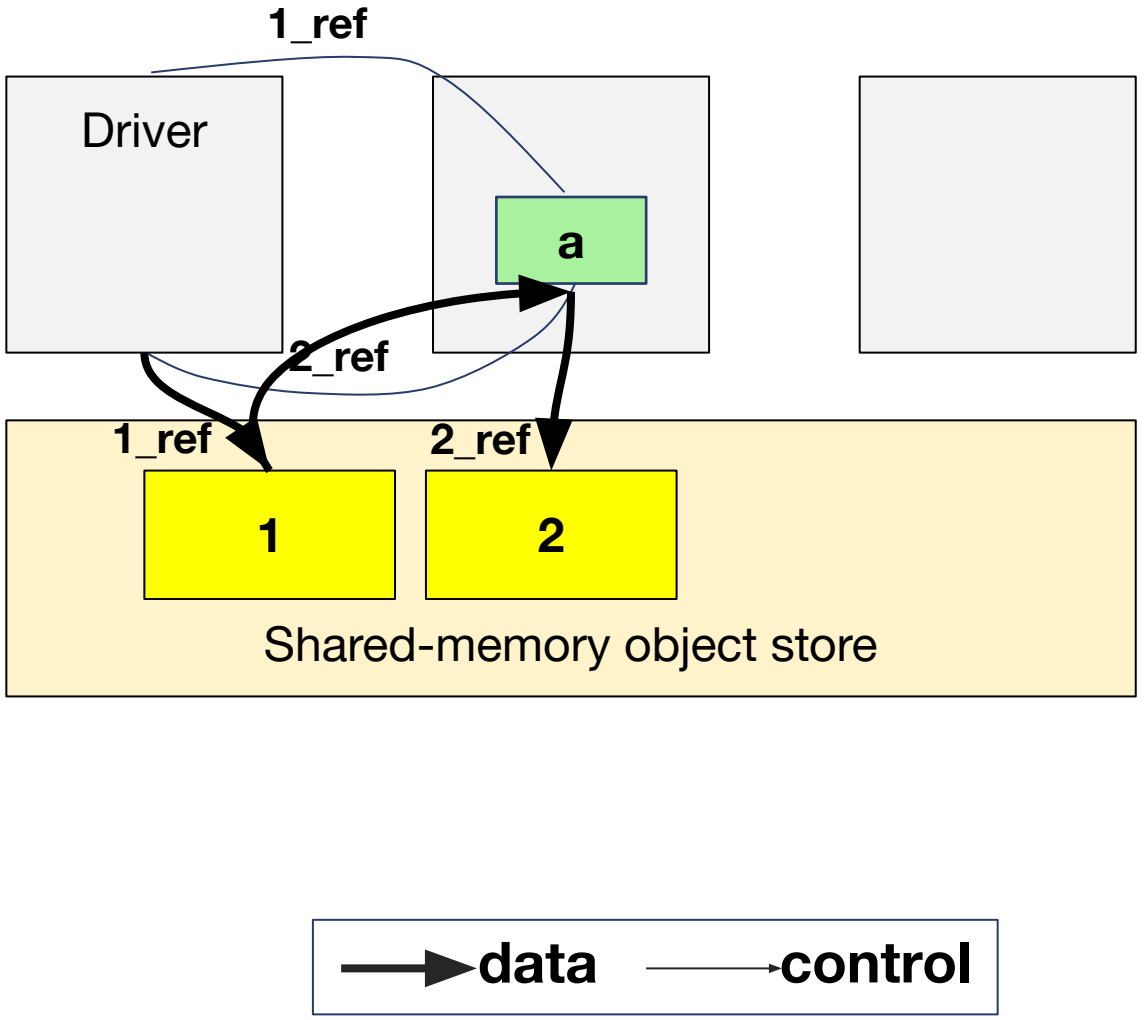



- Four data copies



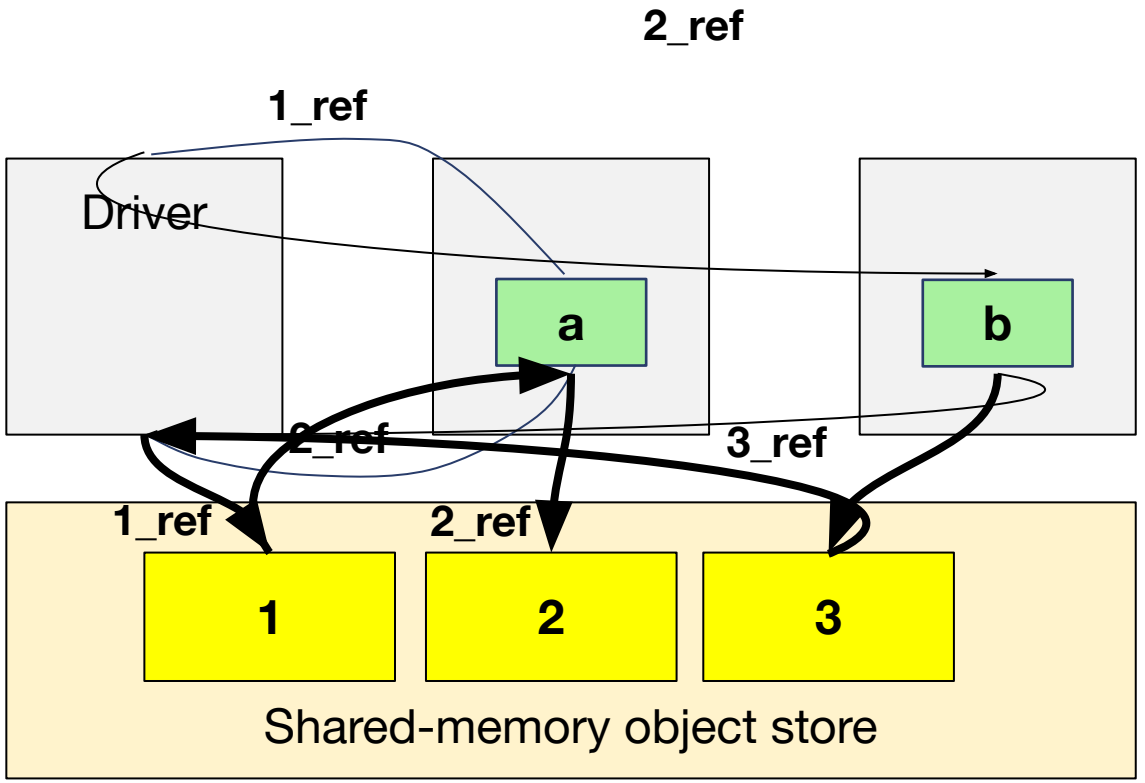
# Default execution with Ray Core

```
import ray

@ray.remote
class IncrementActor:
  def inc(self, value):
    return value + 1

a = IncrementActor.remote()
b = IncrementActor.remote()

res_ref = a.echo.remote(1)
res_ref = b.echo.remote(msg_ref)
print(ray.get(res_ref))
```

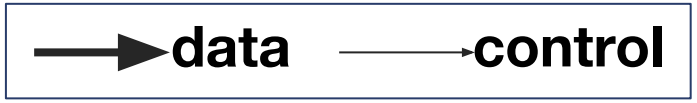


# Default execution with Ray Core

```
import ray

@ray.remote
class IncrementActor:
  def inc(self, value):
    return value + 1

a = IncrementActor.remote()
b = IncrementActor.remote()

res_ref = a.echo.remote(1)
res_ref = b.echo.remote(msg_ref)
print(ray.get(res_ref))
```




- Two data copies (good for large/shared data)
- 6 RPCs & dynamic memory allocation



# Compiled Graphs

Goals

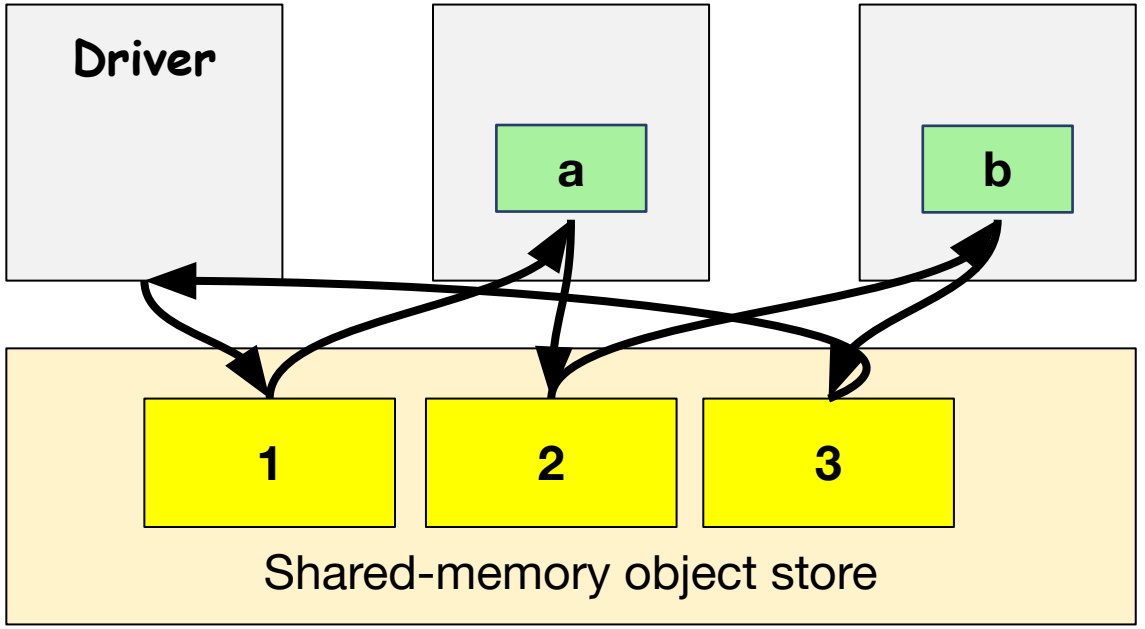
- Run tasks that are 1-10ms with <1% system overhead
- GPU-GPU data transfers with <10us system overhead per op.

What are compiled graphs? Static task graphs with Ray Core-like API

- Allocate resources once, reuse them for multiple executions
- Declare p2p communication schedule before execution

# Ideal execution with Ray

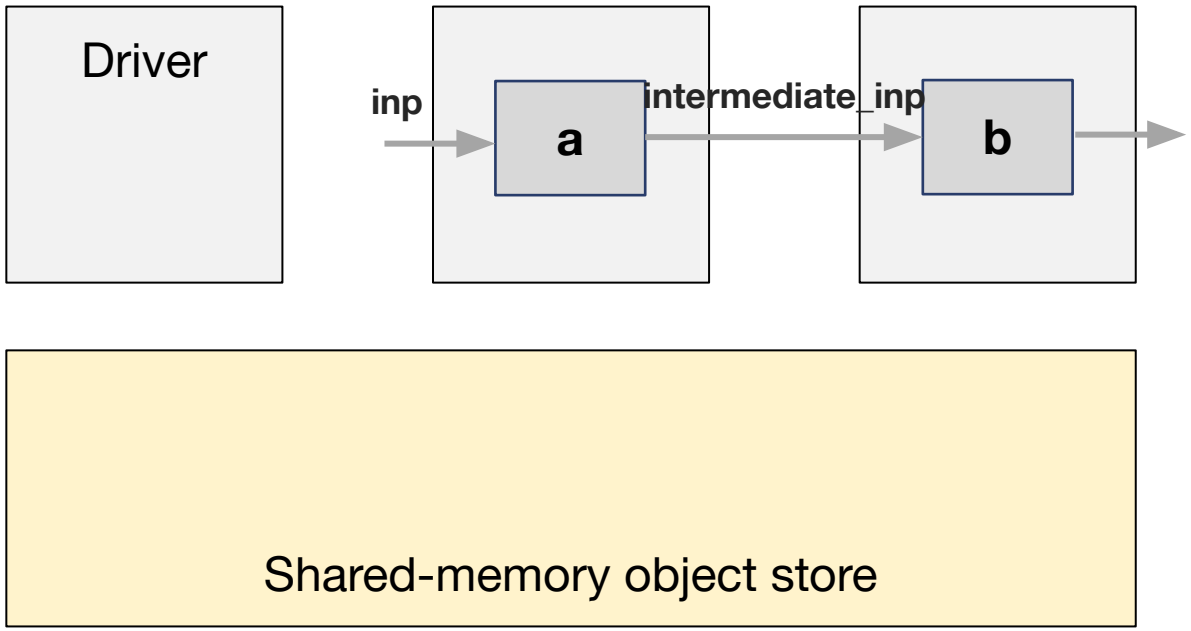
```
import ray

@ray.remote
class IncrementActor:
  def inc(self, value):
    return value + 1

a = IncrementActor.remote()
b = IncrementActor.remote()

res_ref = a.echo.remote(1)
res_ref = b.echo.remote(msg_ref)
print(ray.get(res_ref))
```




- Get rid of control RPCs for each invocation
- Avoid dynamic memory allocation

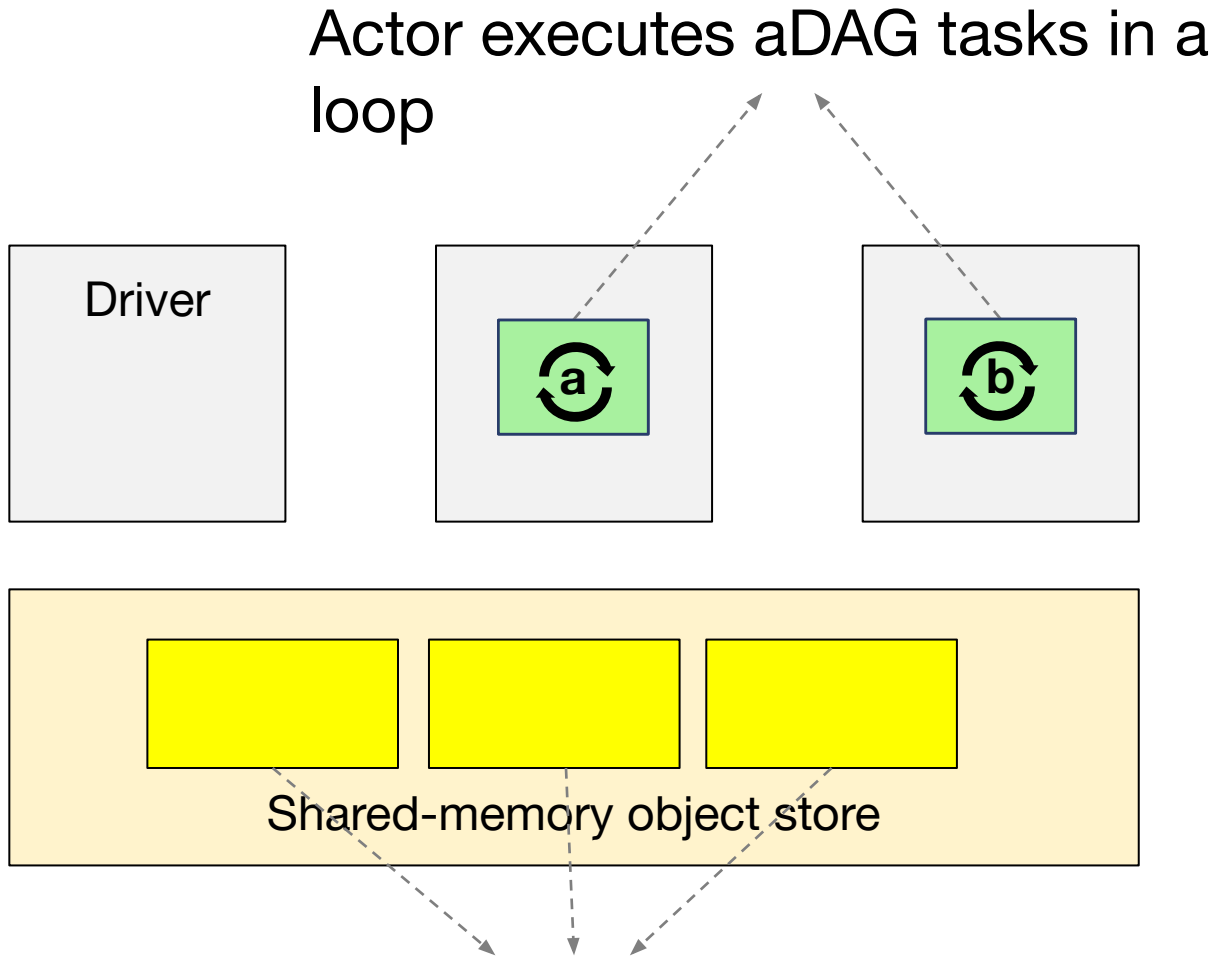
# Ray **compiled graphs**: Compilation

```
a = IncrementActor.remote()
b = IncrementActor.remote()
```



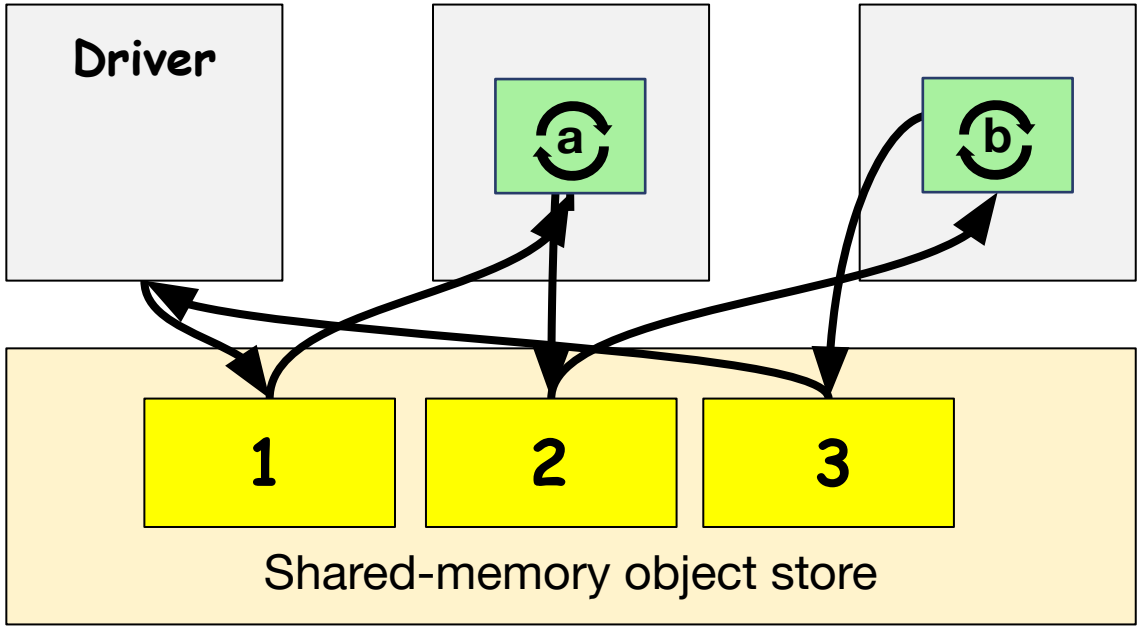
# Ray **compiled graphs**: Compilation

```
a = IncrementActor.remote()
b = IncrementActor.remote()

# Using DAG for lazy execution.
with ray.dag.InputNode() as inp:
  # Bind the actor task to an
  # input placeholder.
  intermediate_inp = a.inc.bind(inp)
  dag = b.inc.bind(intermediate_inp)
```



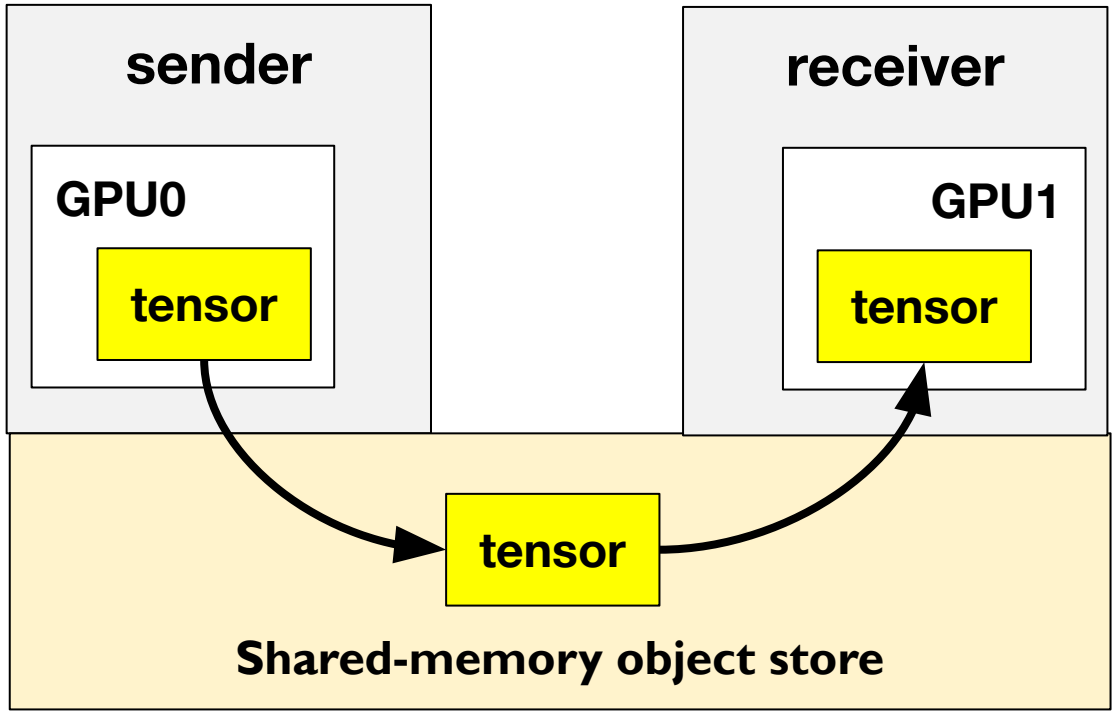
# Ray **compiled graphs**: Compilation

```
adag = dag.experimental_compile()
```



# GPU-GPU transfers: default execution with Ray

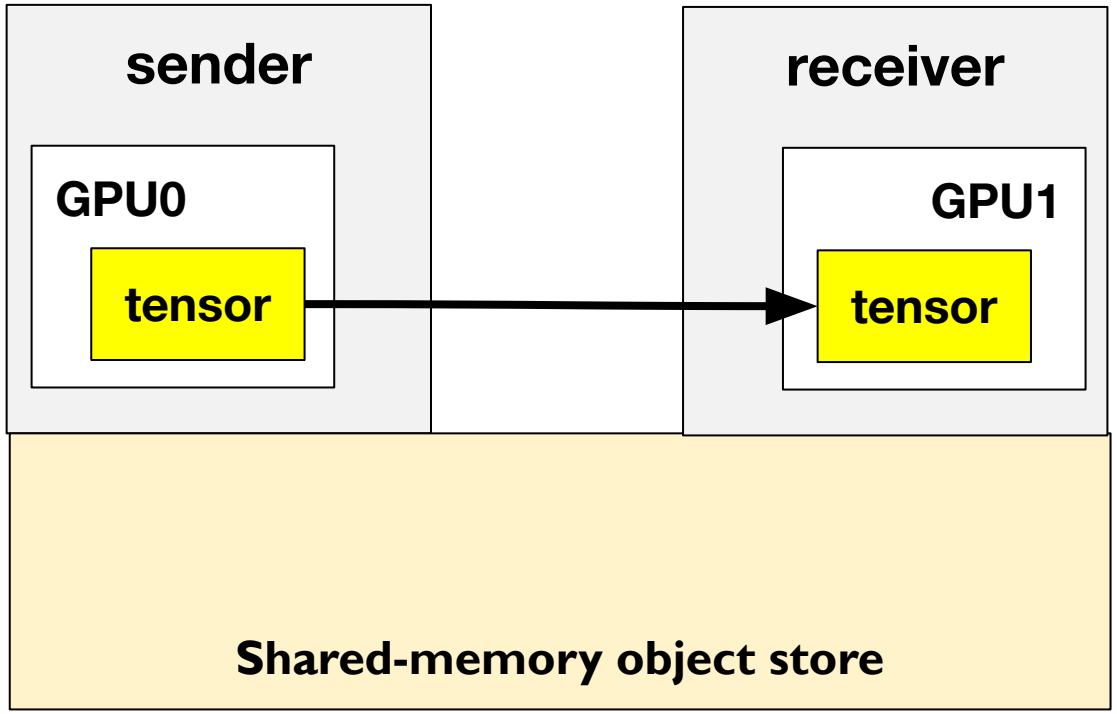
```
@ray.remote(num_gpus=1)
class GPUSender:
  def send(self, shape):
    return torch.zeros(shape,
      device="cuda")

@ray.remote(num_gpus=1)
class GPUReceiver:
  def recv(self, tensor: torch.Tensor):
    assert tensor.device.type == "cuda"
    return tensor.shape
```




- **Must copy through host memory**
- **Naive implementation also requires multiple other copies**

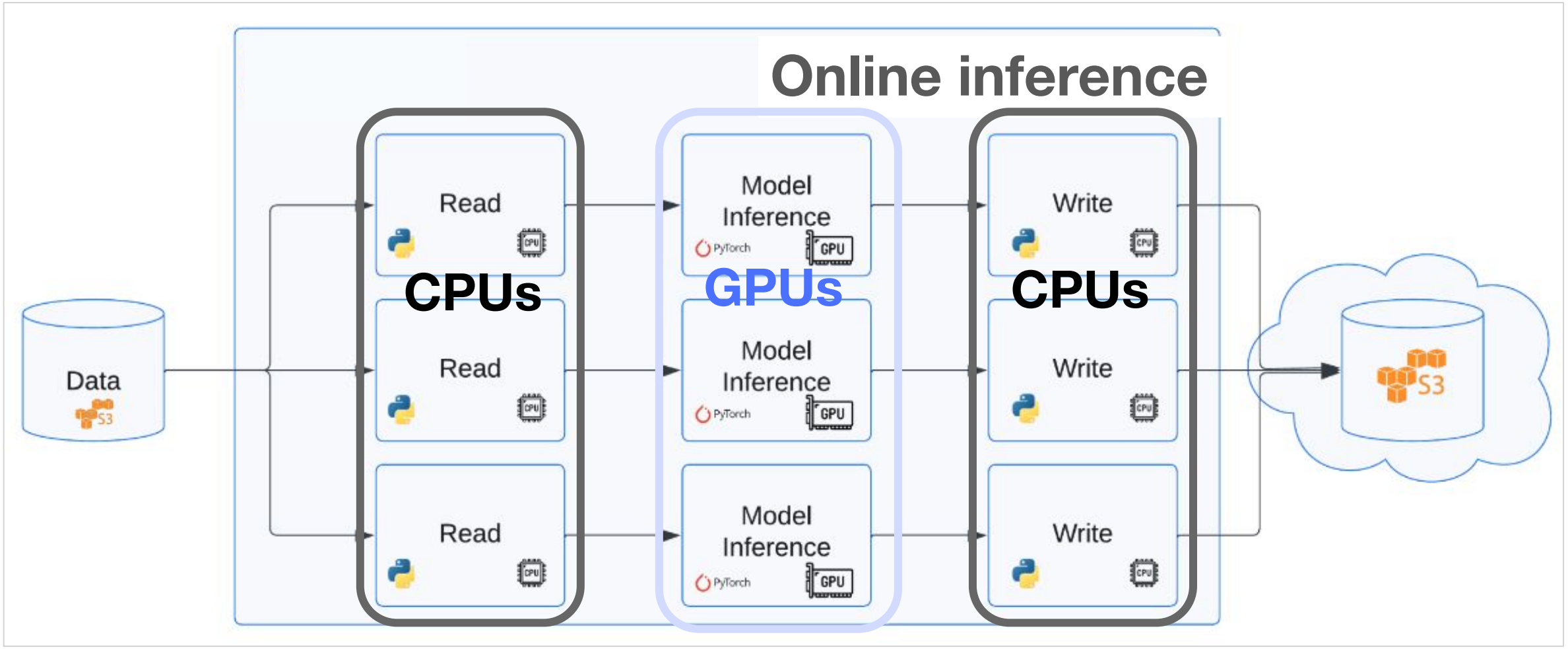
# GPU-GPU transfers with Ray compiled graphs

```
from ray.experimental.channel.torch_tensor_type
  import TorchTensorType

with ray.dag.InputNode() as inp:
  dag = sender.send.bind(inp)
  dag = dag.with_type_hint(TorchTensorType(
      transport="nccl",
  ))
  dag = receiver.recv.bind(dag)

adag = dag.experimental_compile()
adag.execute((100, ))
```



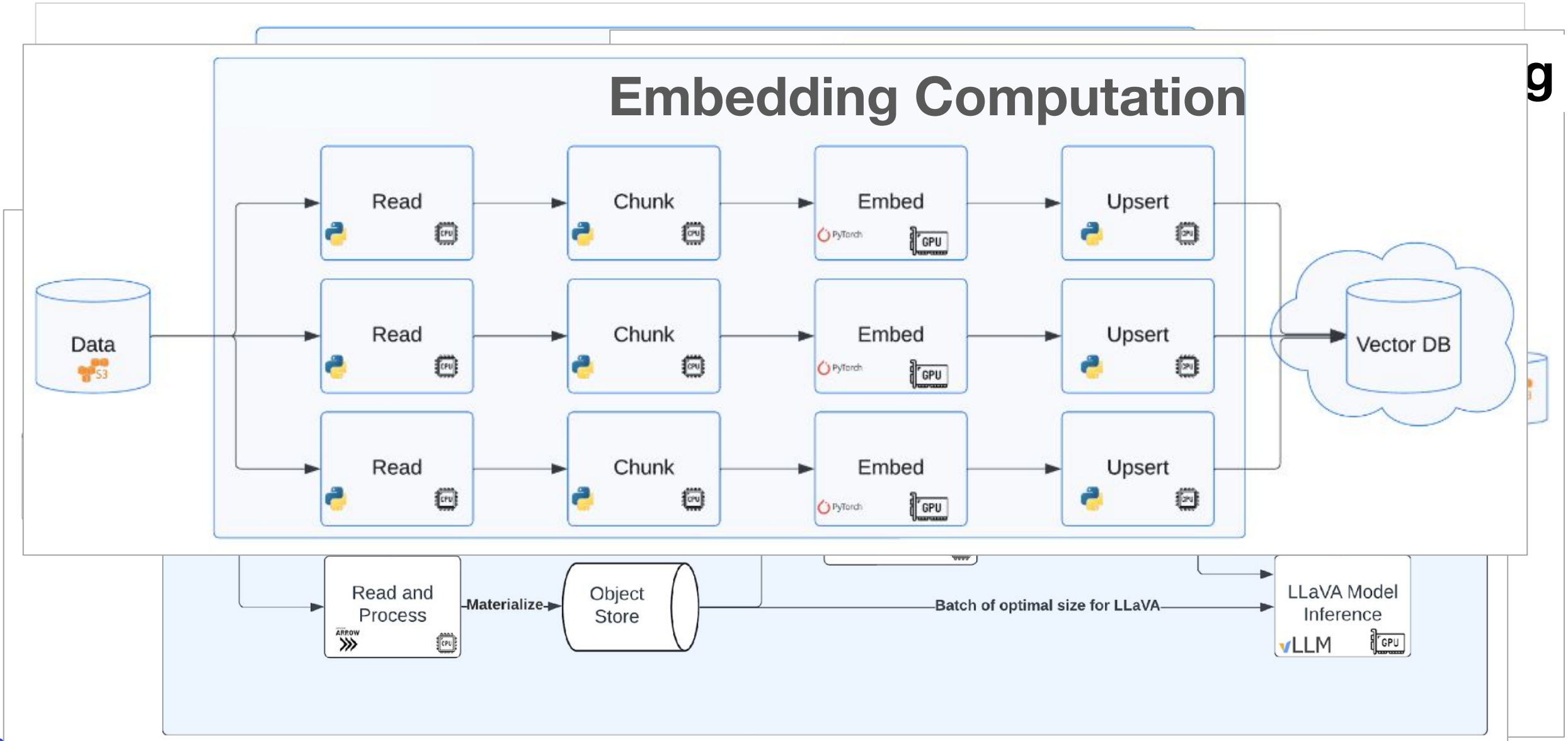

- **Schedule determined at compile tir**
- **Future: collective ops, overlapping with compute**

# Application examples

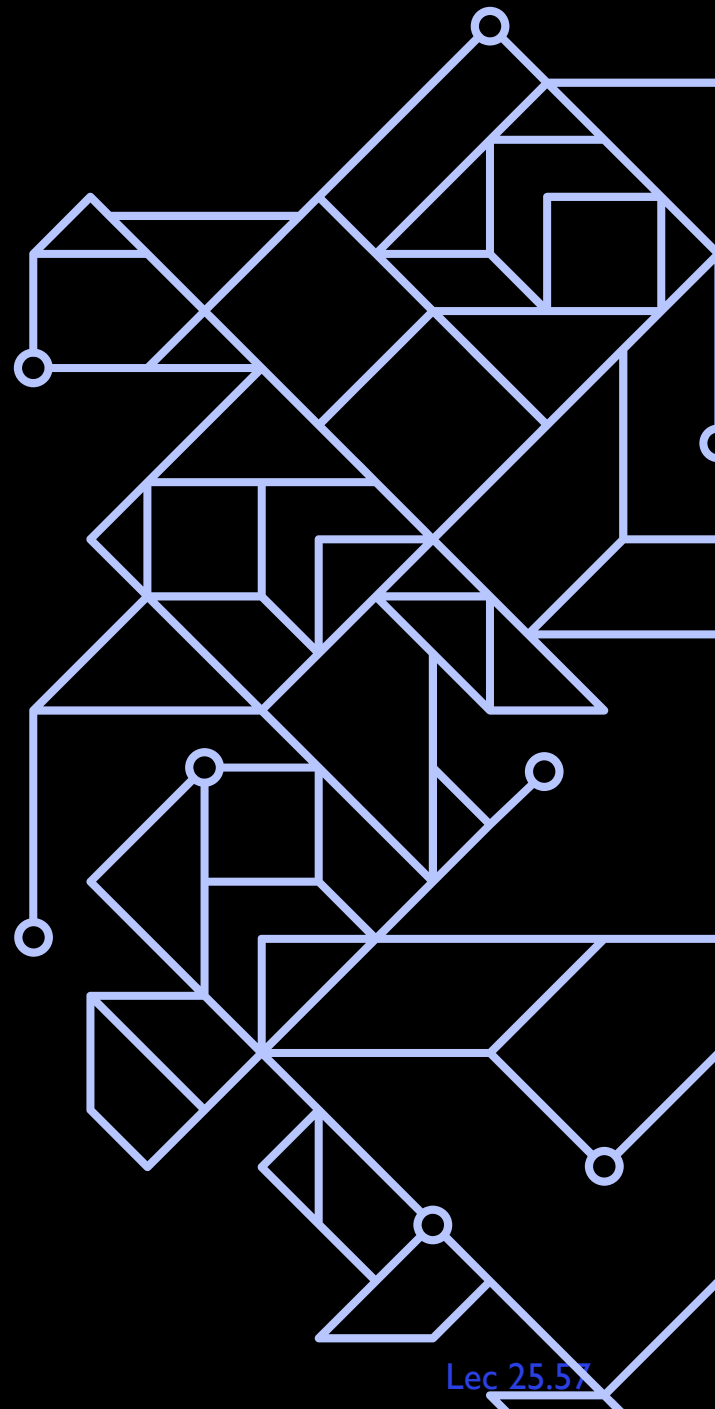



**Exploiting CPU/GPU heterogeneity can reduce cost by 10x !**

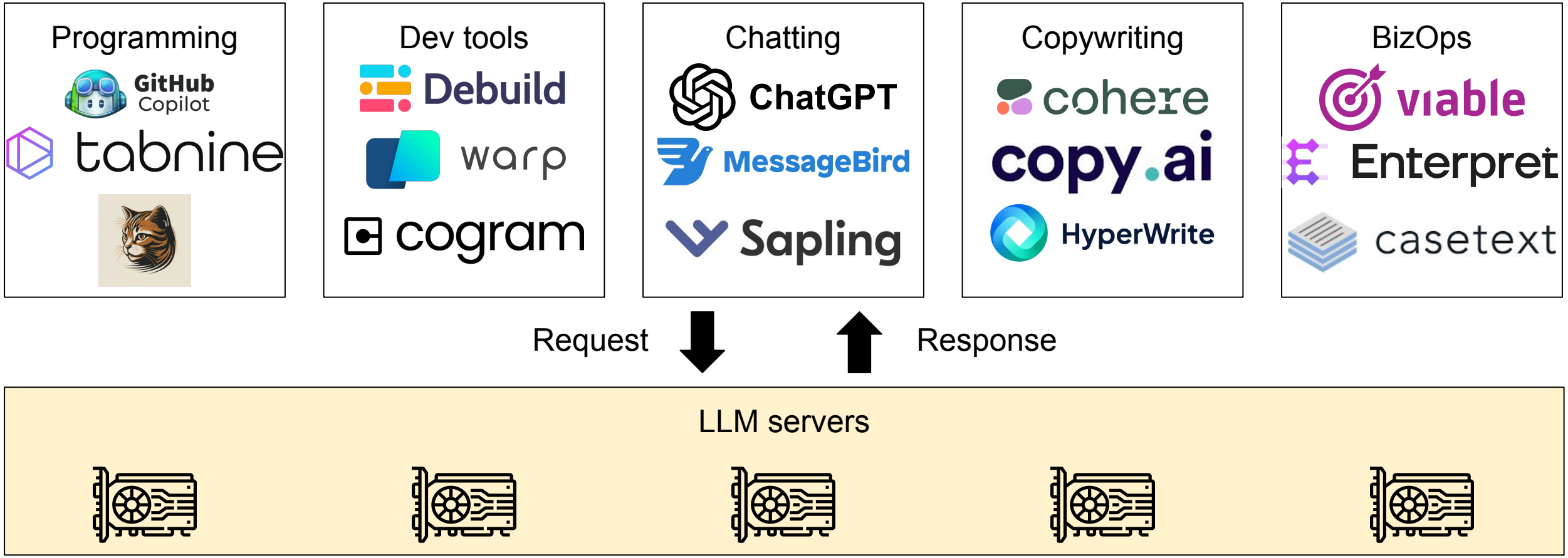
# Application examples



# vLLM (2023- )



# Growing number of LLM-powered services



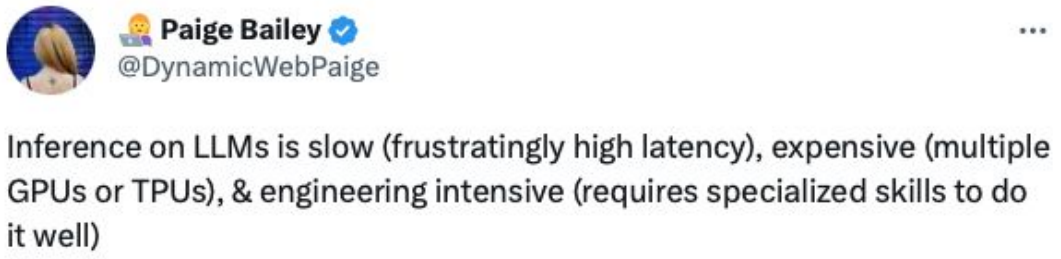
# Problem: Serving LLMs very expensive

LLMs run on high-end GPUs such as NVIDIA A100 and H100

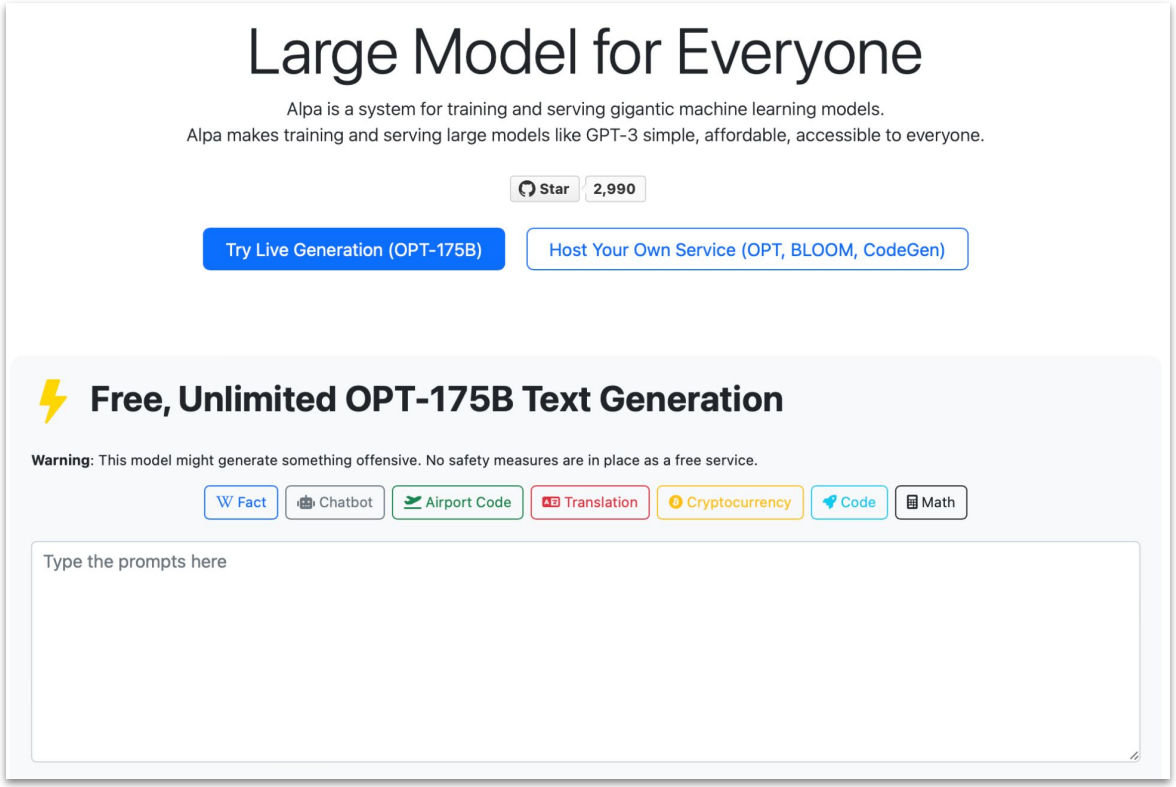
Each GPU can only serve a handful of requests/sec

- For LLaMA-13B, one A100 can process just a few requests/sec

Huge # of GPUs are required for production-scale LLM services




# May 2022 – OPT-175B Serving Demo




Our lab created a free inference service for OPT-175B, the largest open LLM at the time.

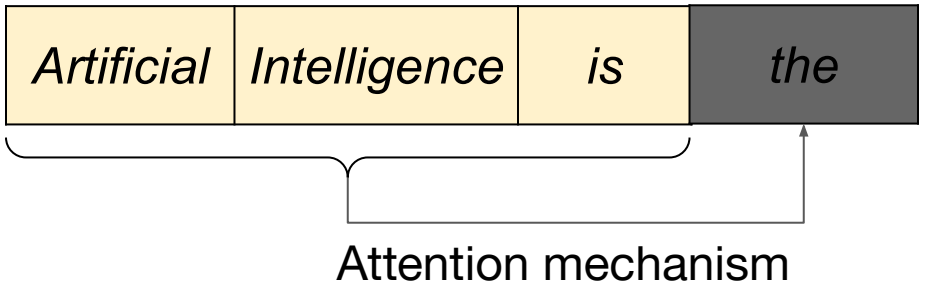
- 16 A100 GPUs per model instance

However, users experienced long queueing time, because of low serving throughput.

# LLM query processing

Given a prompt:

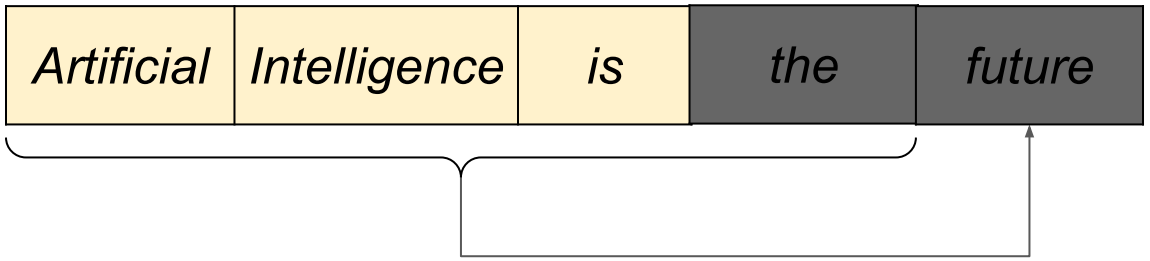
- Generate words (tokens) sequentially
- Each token is based on all previous tokens



# LLM query processing

Given a prompt:

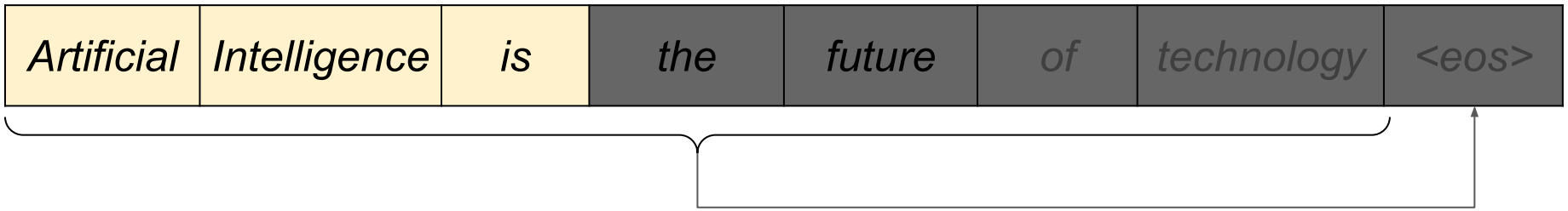
- Generate words (tokens) sequentially
- Each token is based on all previous tokens



# LLM query processing

Given a prompt:

- Generate words (tokens) sequentially
- Each token is based on all previous tokens



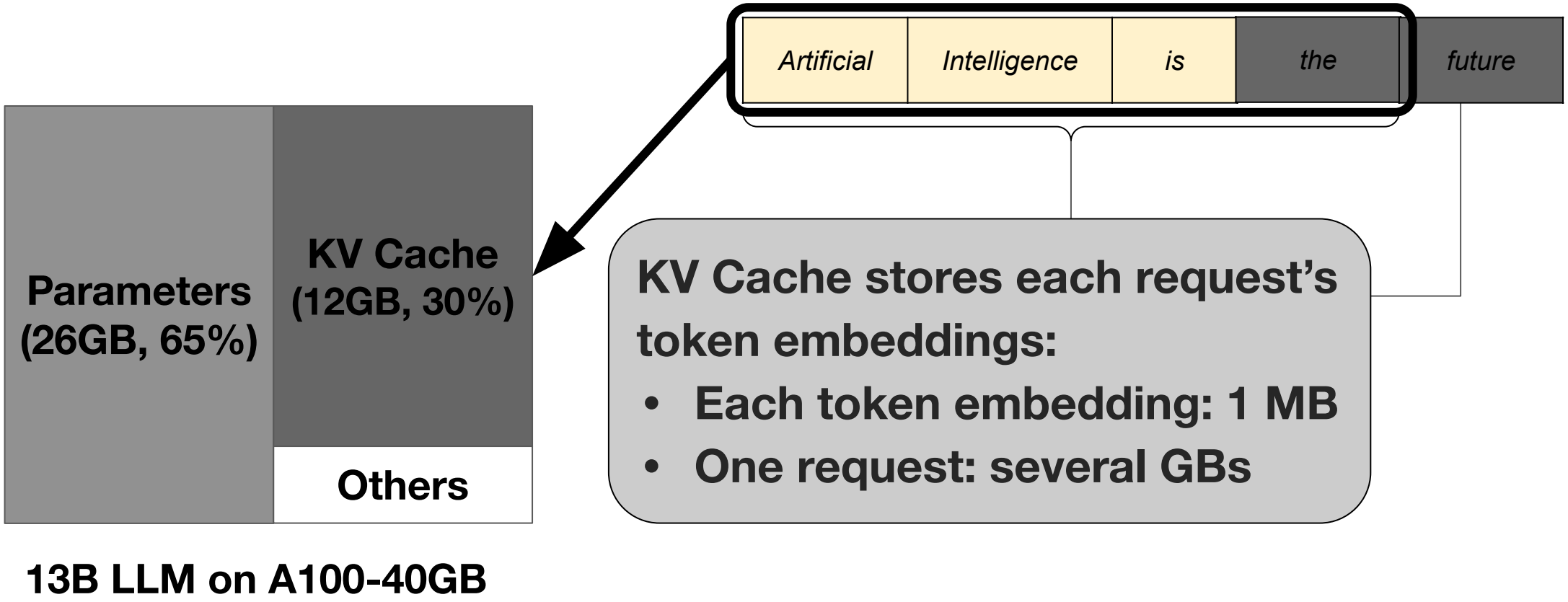
# Challenge: low throughput  high cost

Generating one token at a time doesn't use GPU parallelism

Solution: process multiple requests at the same time (batch)

Challenge: run out of memory!

# Where does the memory go?



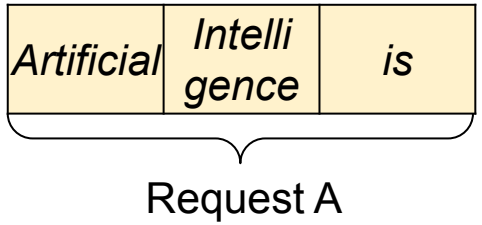
# Memory management in previous systems

Stores a sequence's token states in contiguous memory space

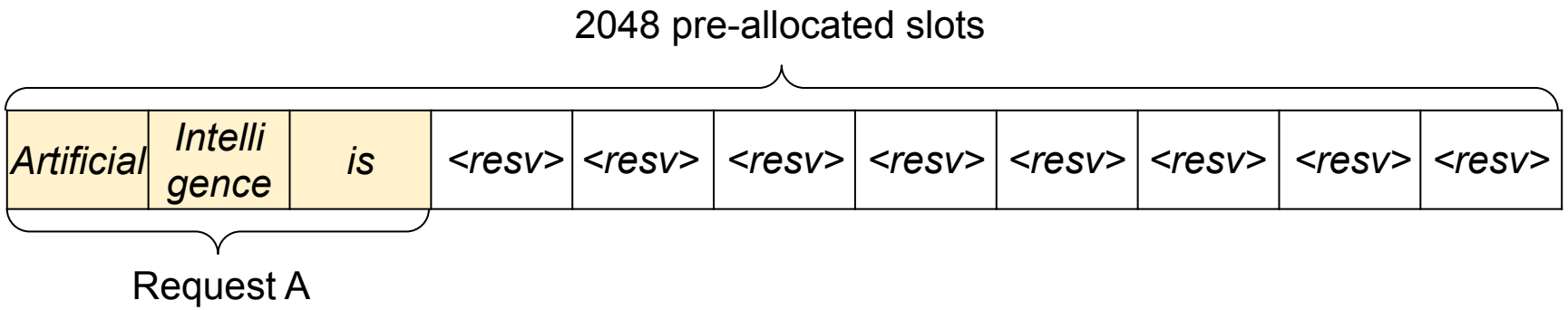
- Convention in traditional DNN workloads

Pre-allocate (reserve) the space for future token states, to handle unknown output lengths

# Memory waste in KV Cache

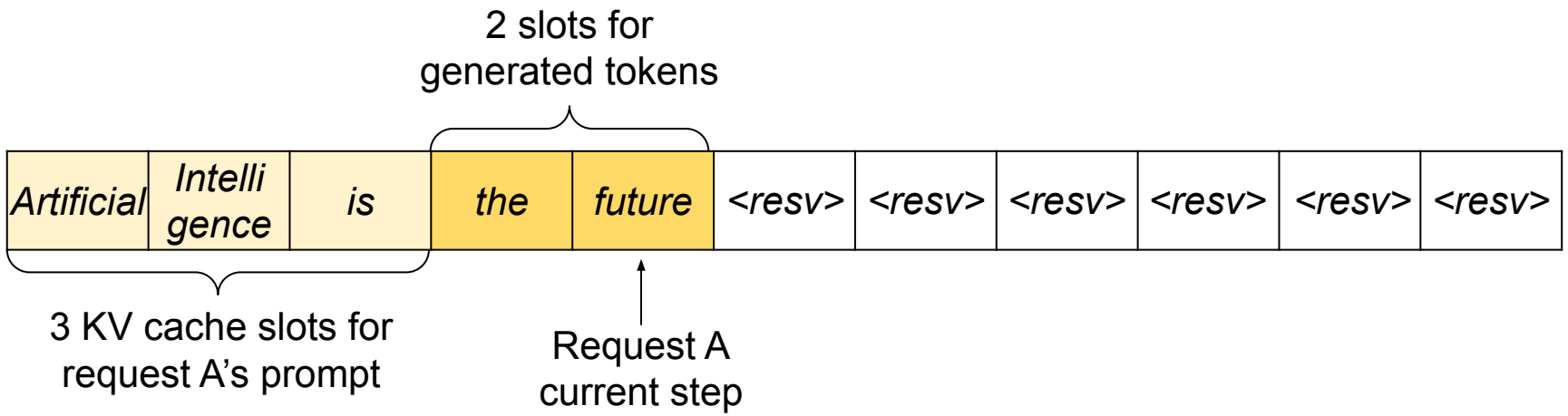


# Memory waste in KV Cache



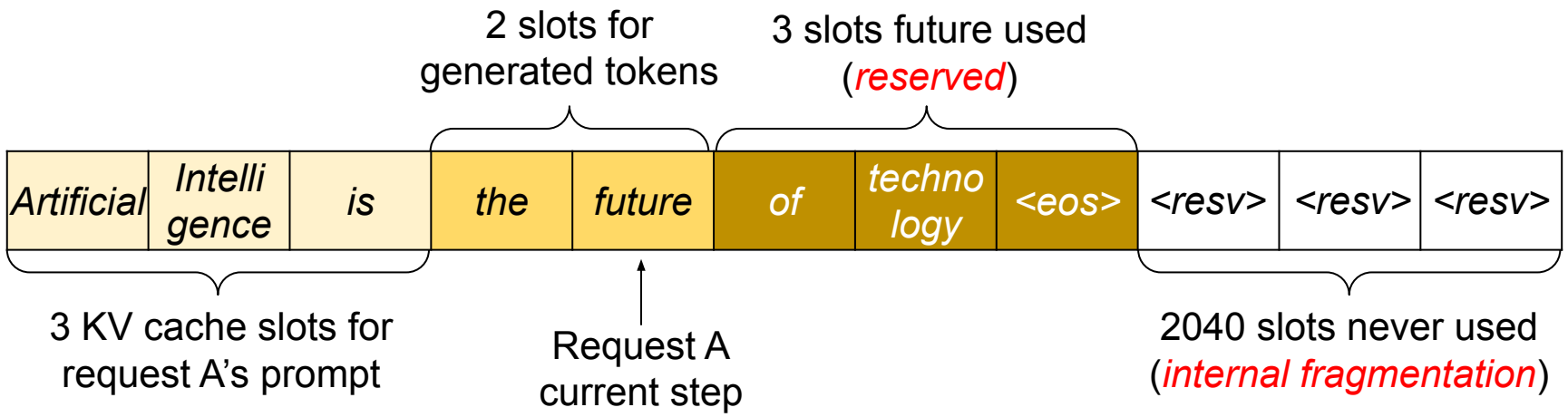

Internal fragmentation: over-allocated due to the unknown output length

# Memory waste in KV Cache




Internal fragmentation: over-allocated due to the unknown output length

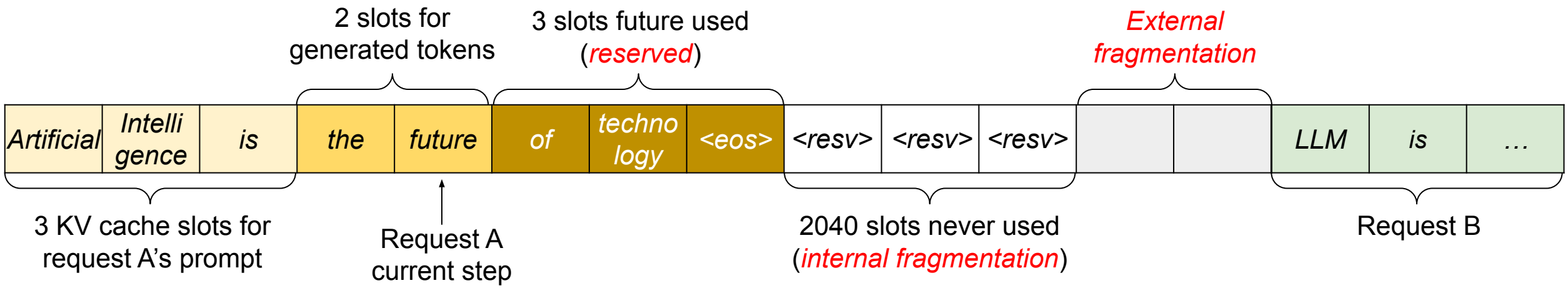
# Memory waste in KV Cache




Internal fragmentation: over-allocated due to the unknown output length

Reservation: not used at the current step but used in the future (this fragmentation happens even if output length is known)

# Memory waste in KV Cache



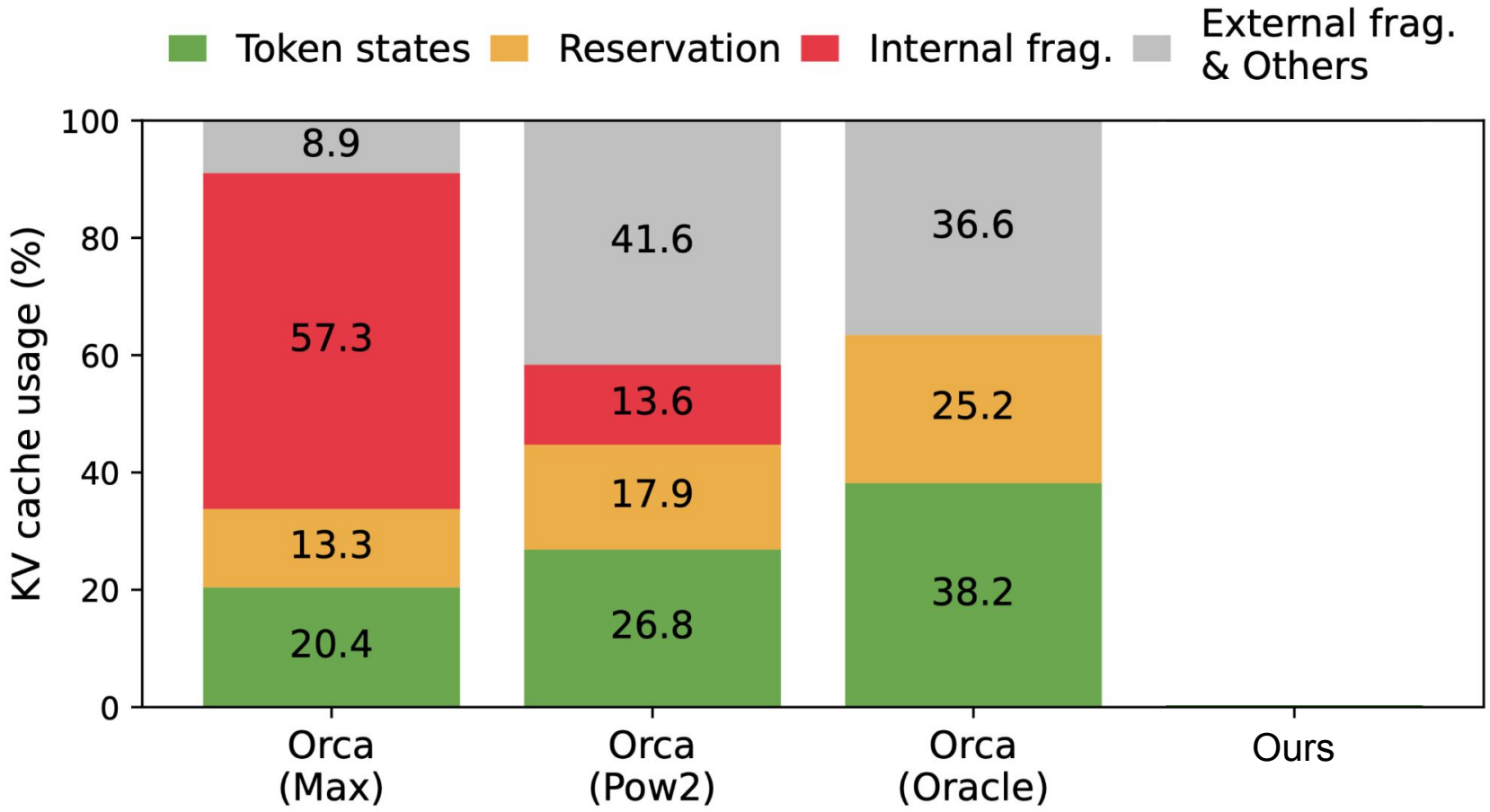

Internal fragmentation: over-allocated due to the unknown output length

Reservation: not used at the current step but used in the future (this fragmentation happens even if output length is known)

External fragmentation: due to different allocation lengths

# Significant memory waste

Only 20–40% of KV cache is utilized to store token states

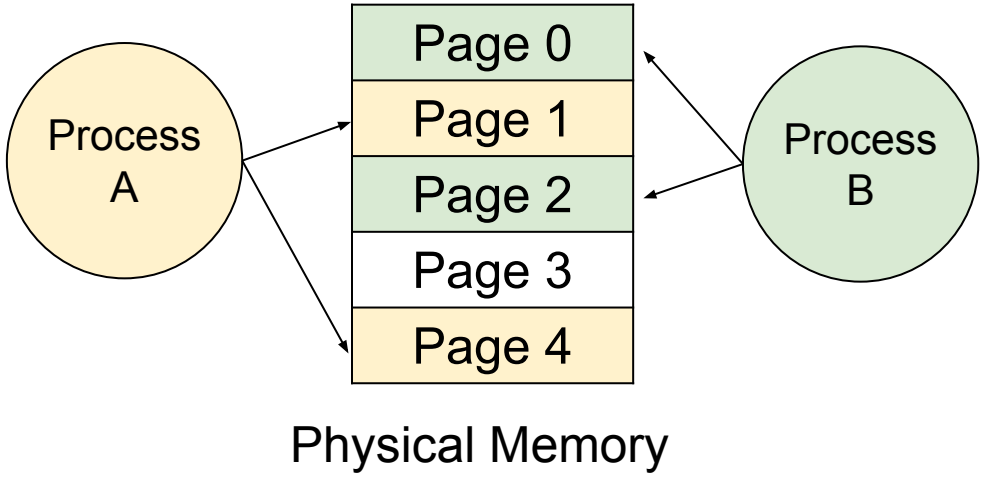



* Yu et al. "Orca: A Distributed Serving System for Transformer-Based Generative Models" (OSDI 22).

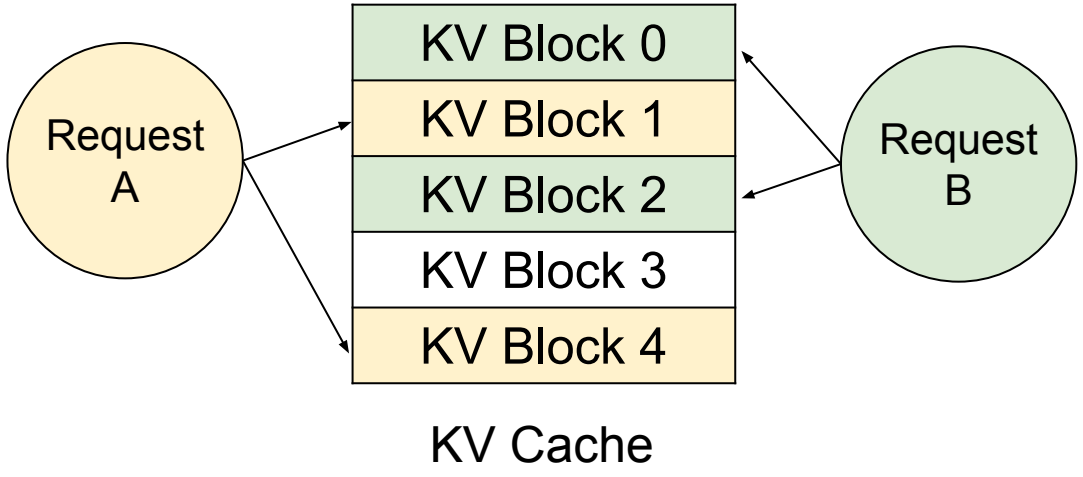
# vLLM: Efficient memory management for LLM inference

Inspired by virtual memory and paging

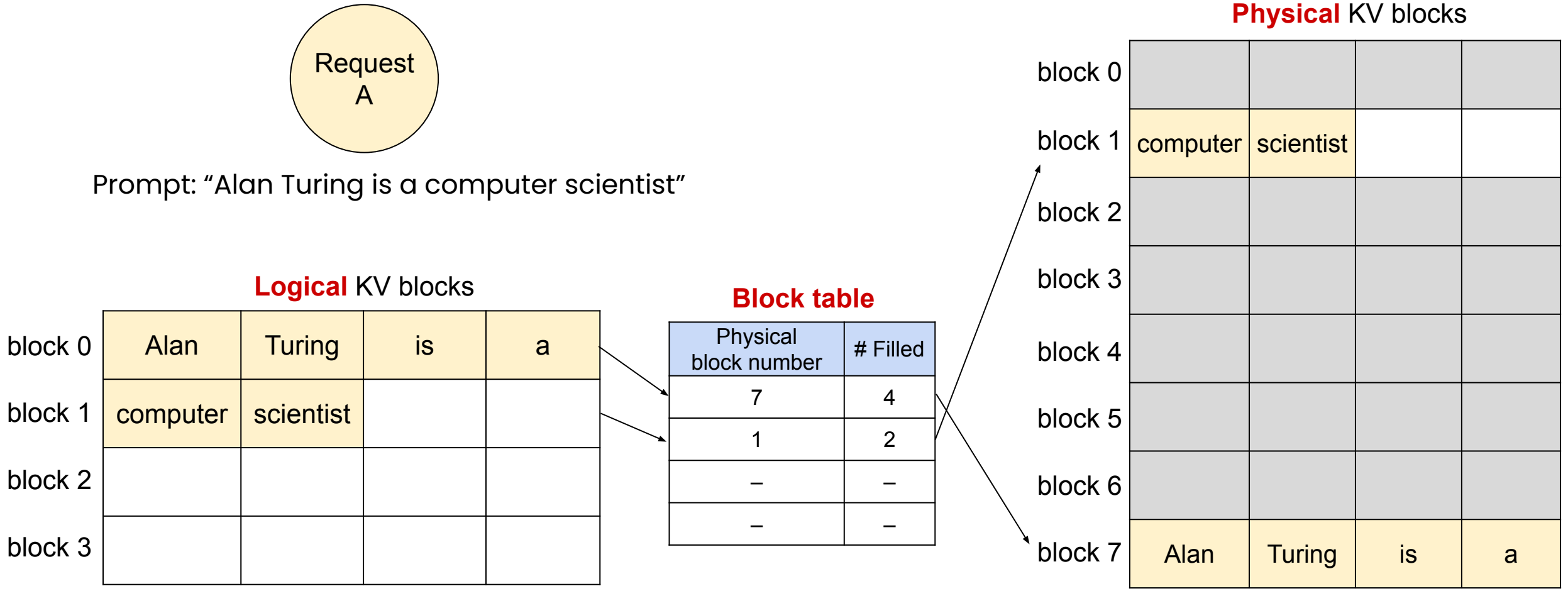
**Memory management in OS**



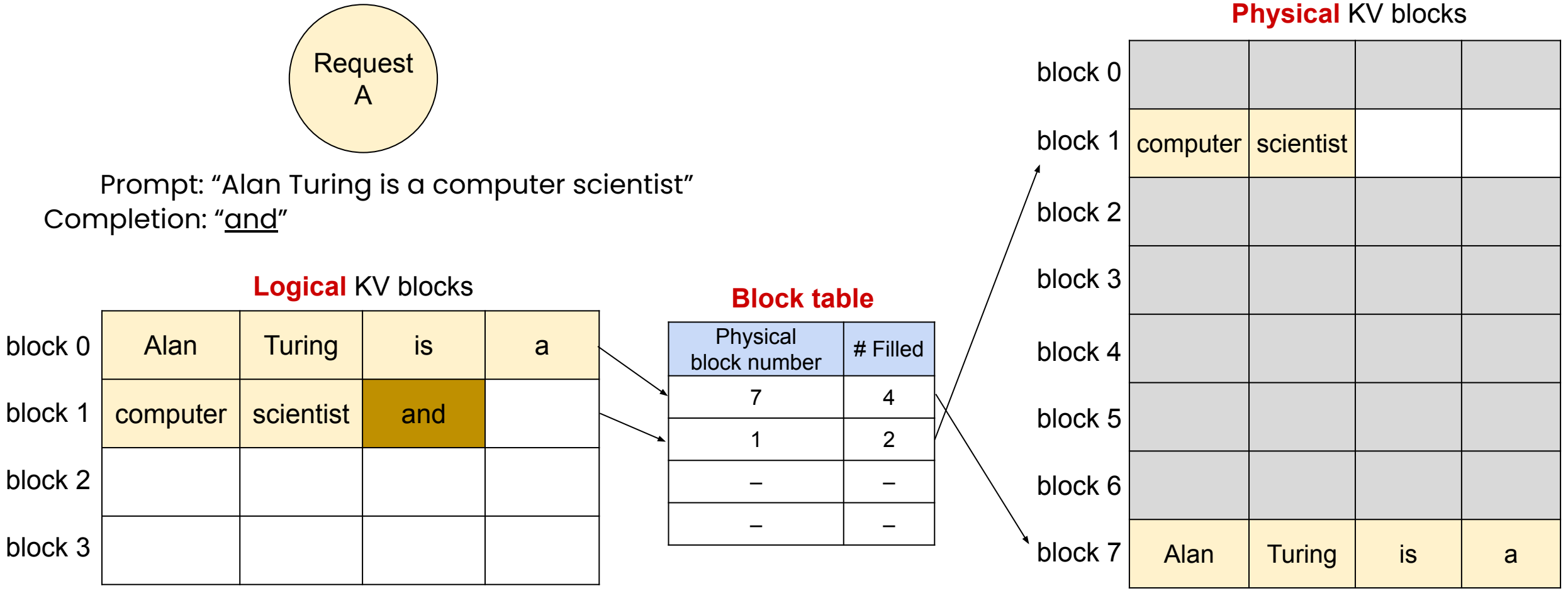

**Memory management in vLLM**



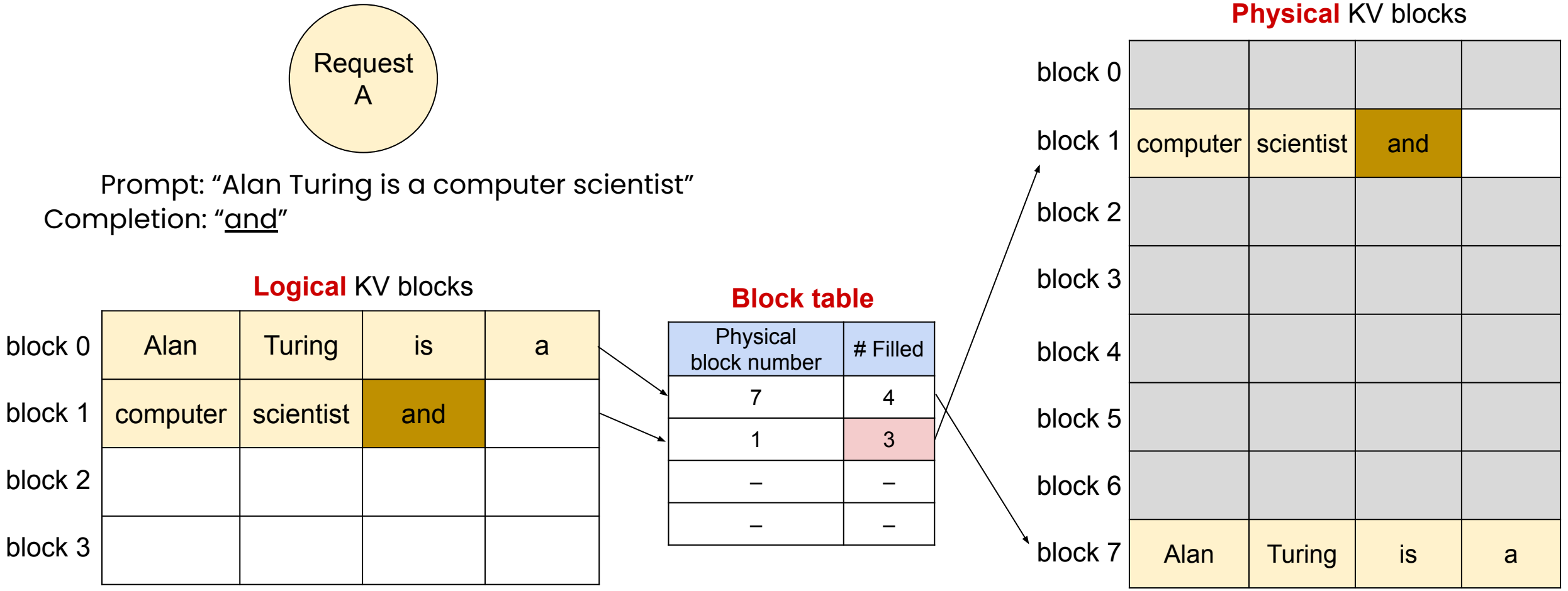
# PagedAttention



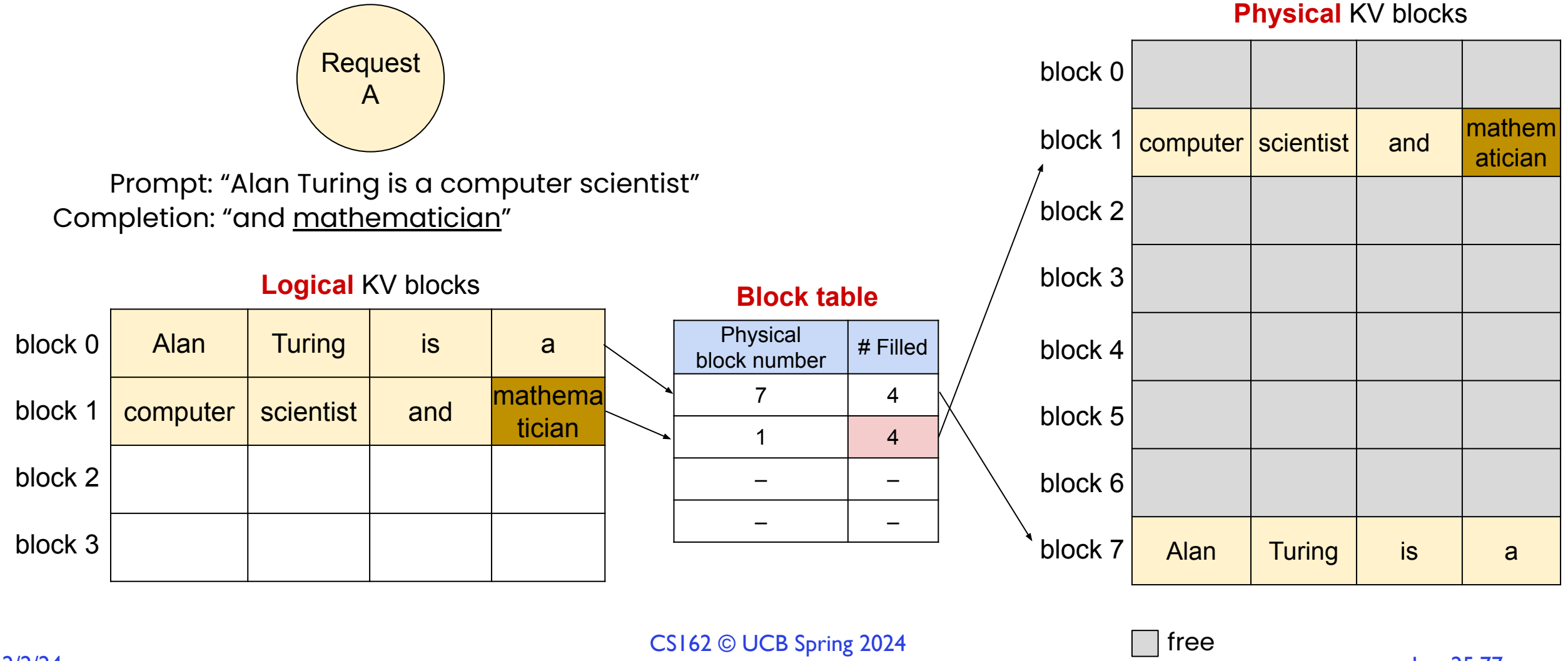
# PagedAttention



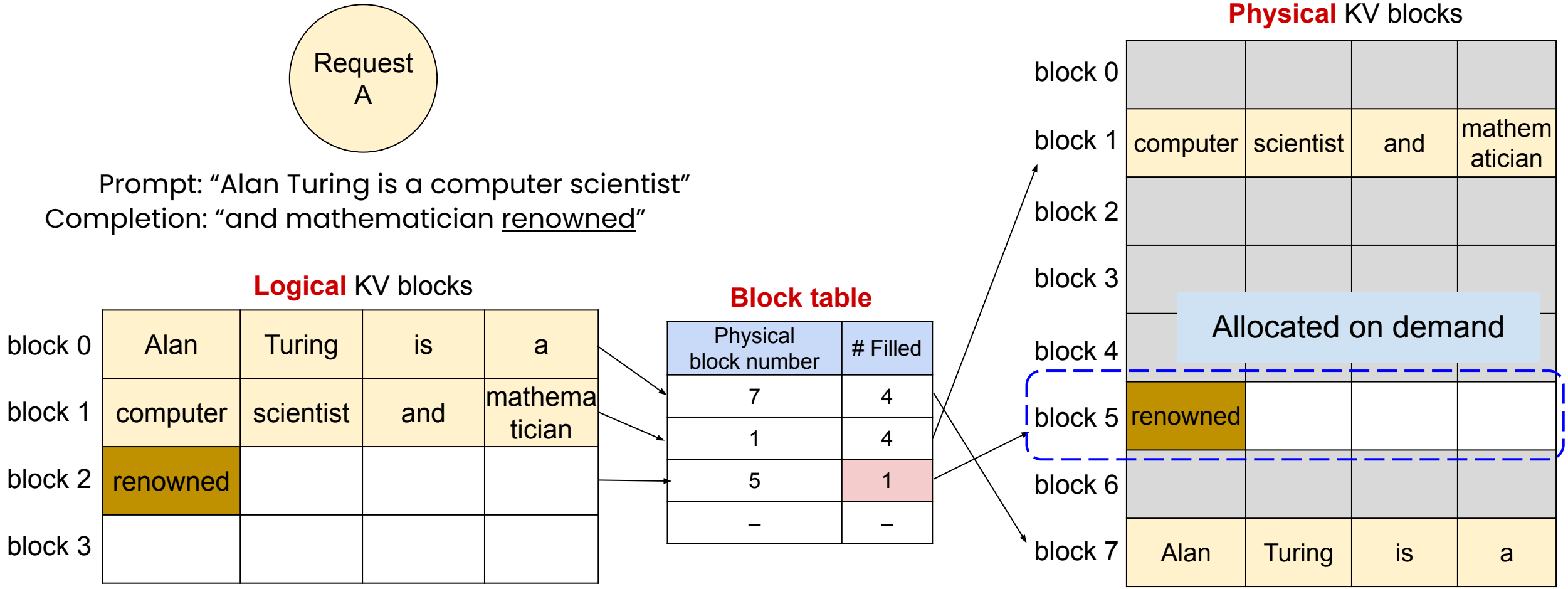
# PagedAttention



# PagedAttention



# PagedAttention

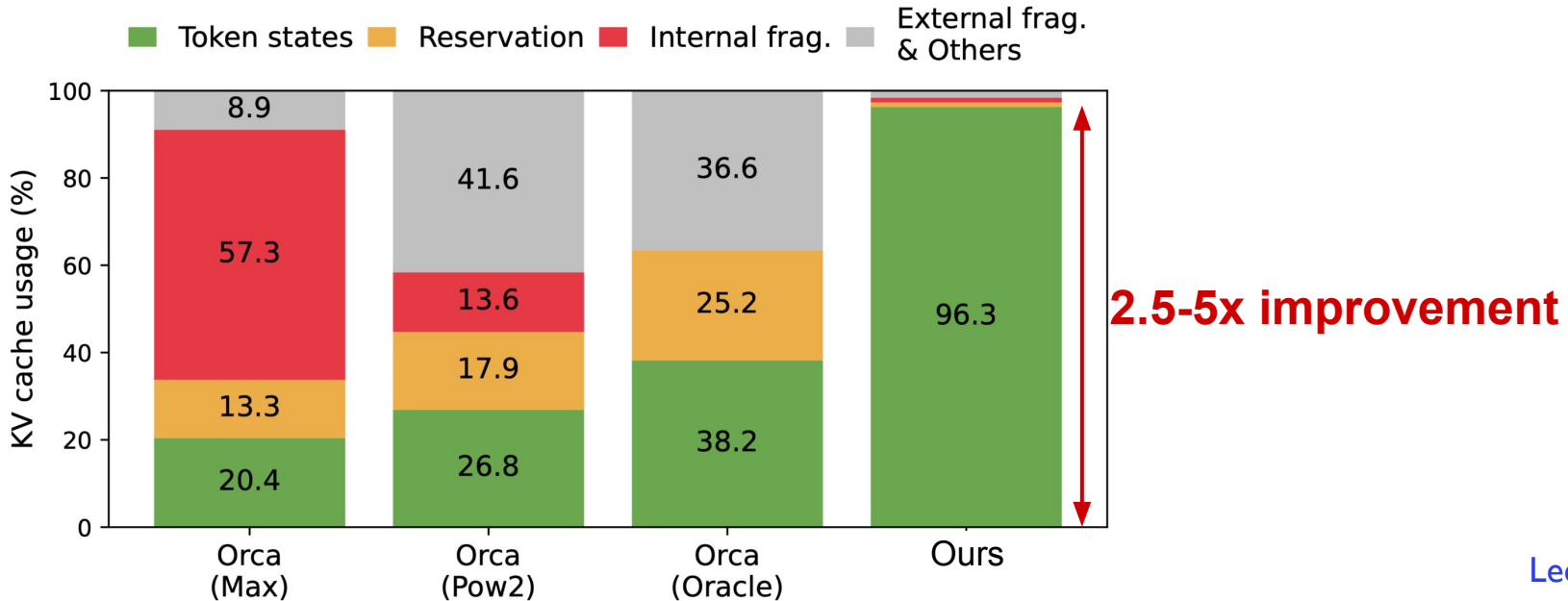


# Memory efficiency of PagedAttention

- Minimal internal fragmentation
  - Only happens at the last block of a sequence
  - # wasted tokens / seq < block size
    - Sequence: O(100) – O(1000) tokens
    - Block size: 16 or 32 tokens
- No external fragmentation

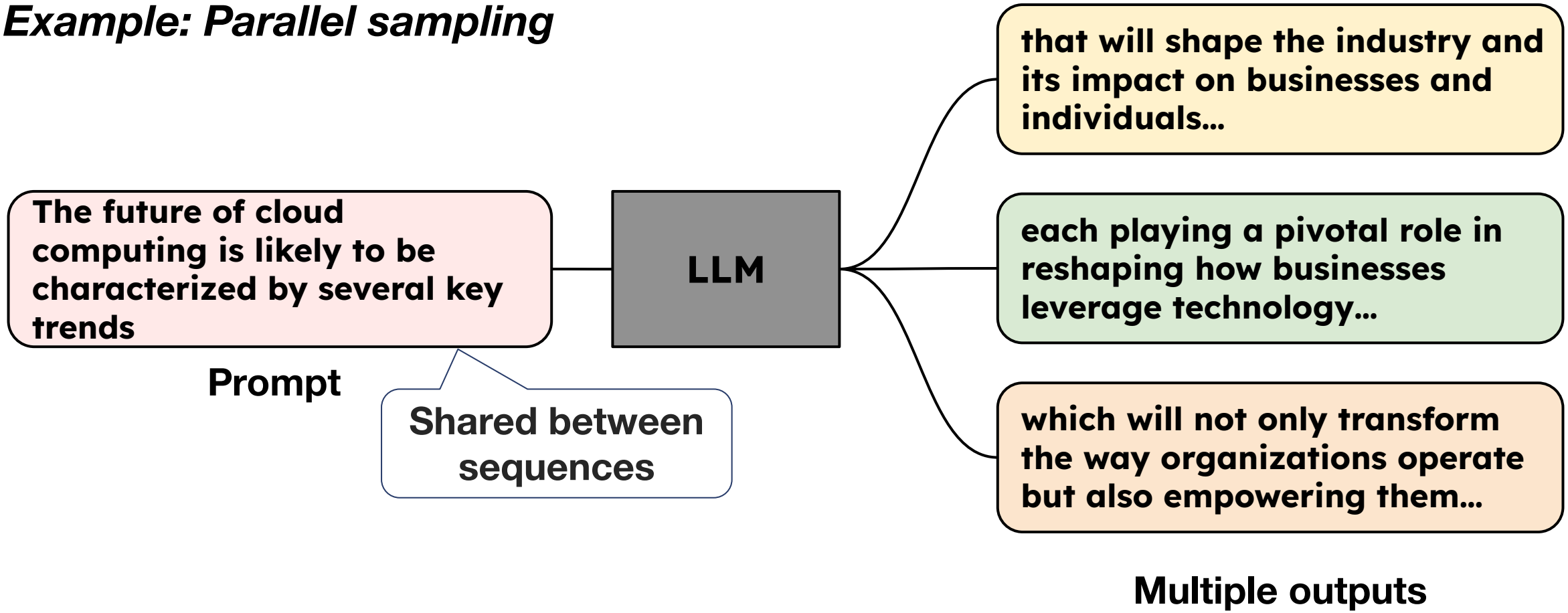
| Alan | Turing | is | a |
|---|---|---|---|
| computer | scientist | and | mathematic ian |
| renowned | | | |

Internal fragmentation

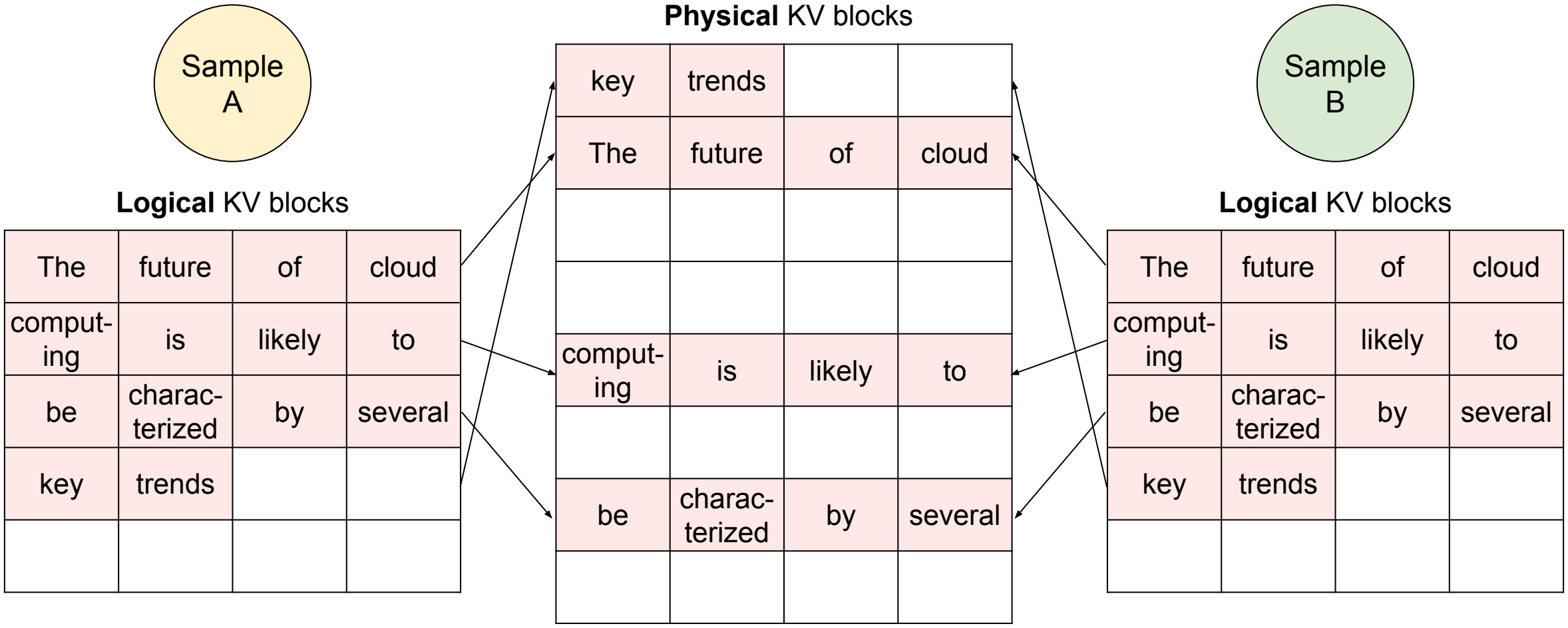


# Paging enables sharing

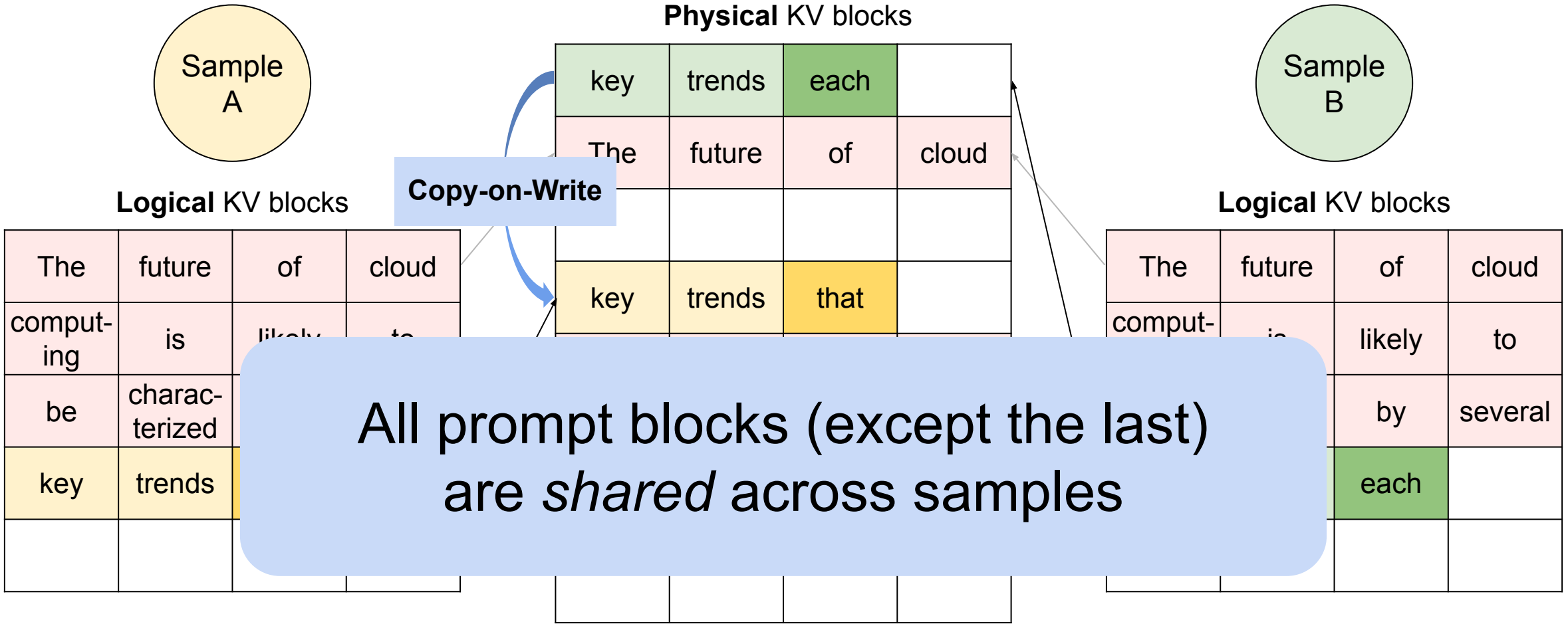
***Example: Parallel sampling***



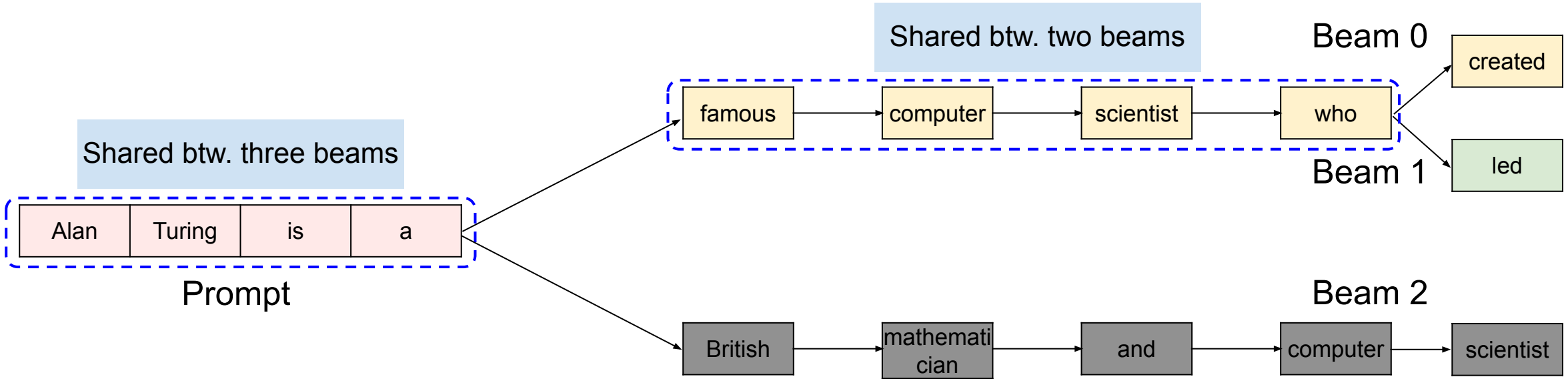
# Sharing KV blocks



# Sharing KV blocks

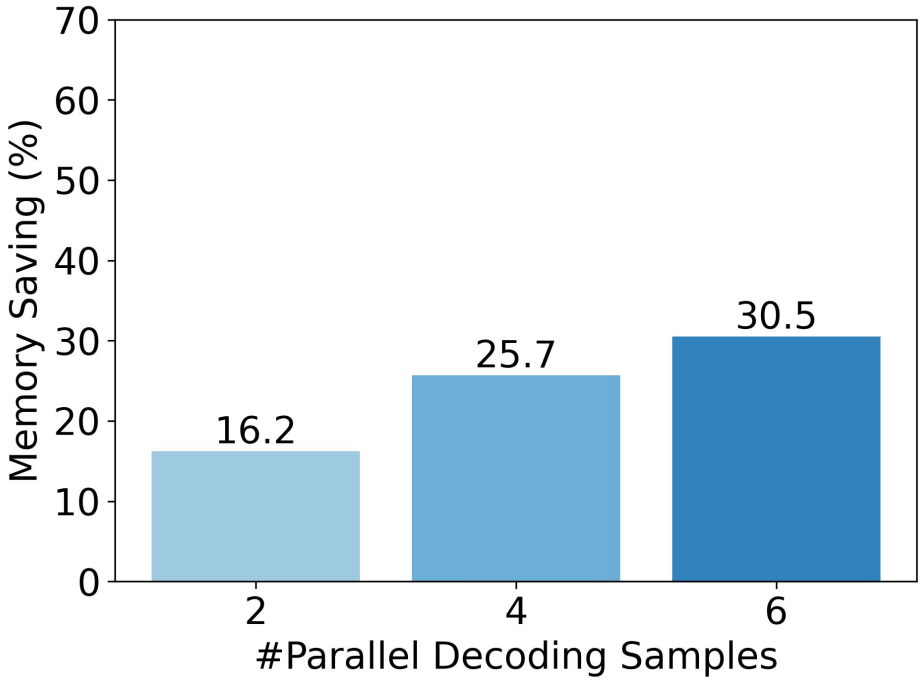


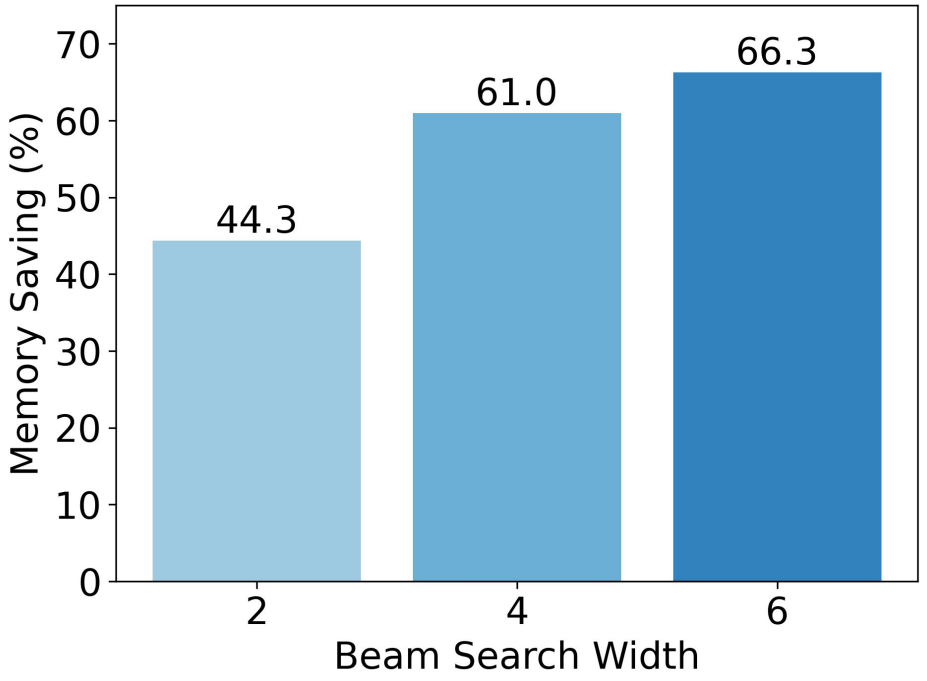
# More complex sharing: beam search




- Similar to process tree (fork & kill)
- Efficiently supported by paged attention and copy-on-write mechanism

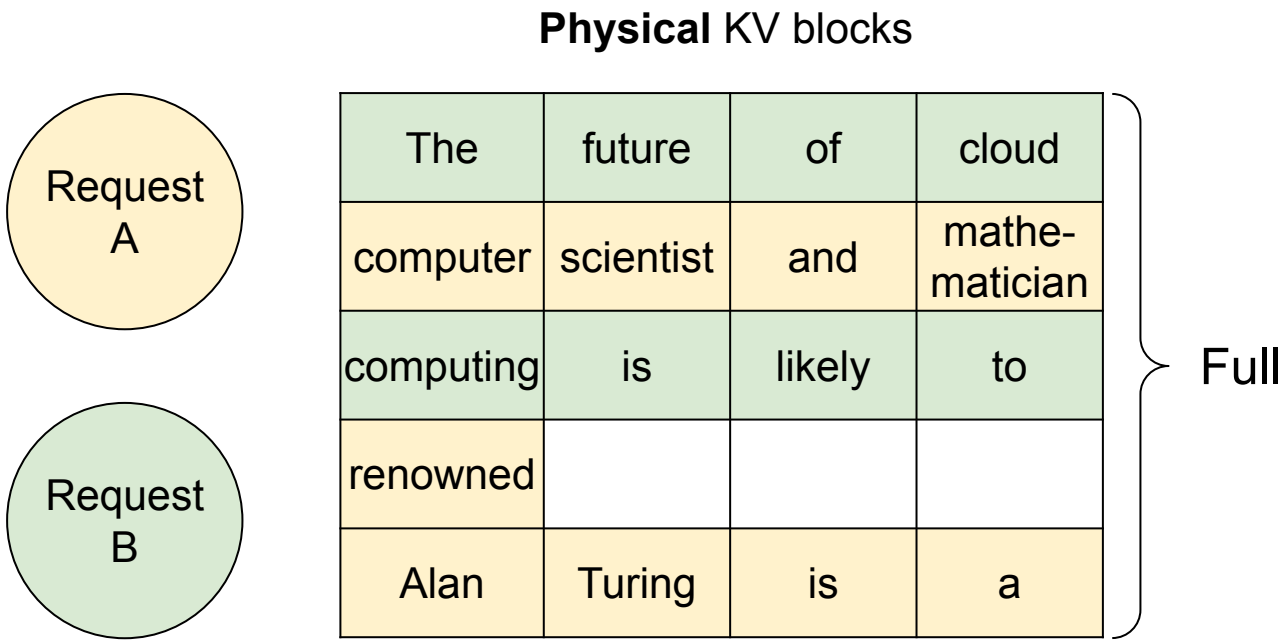
# Memory saving via sharing



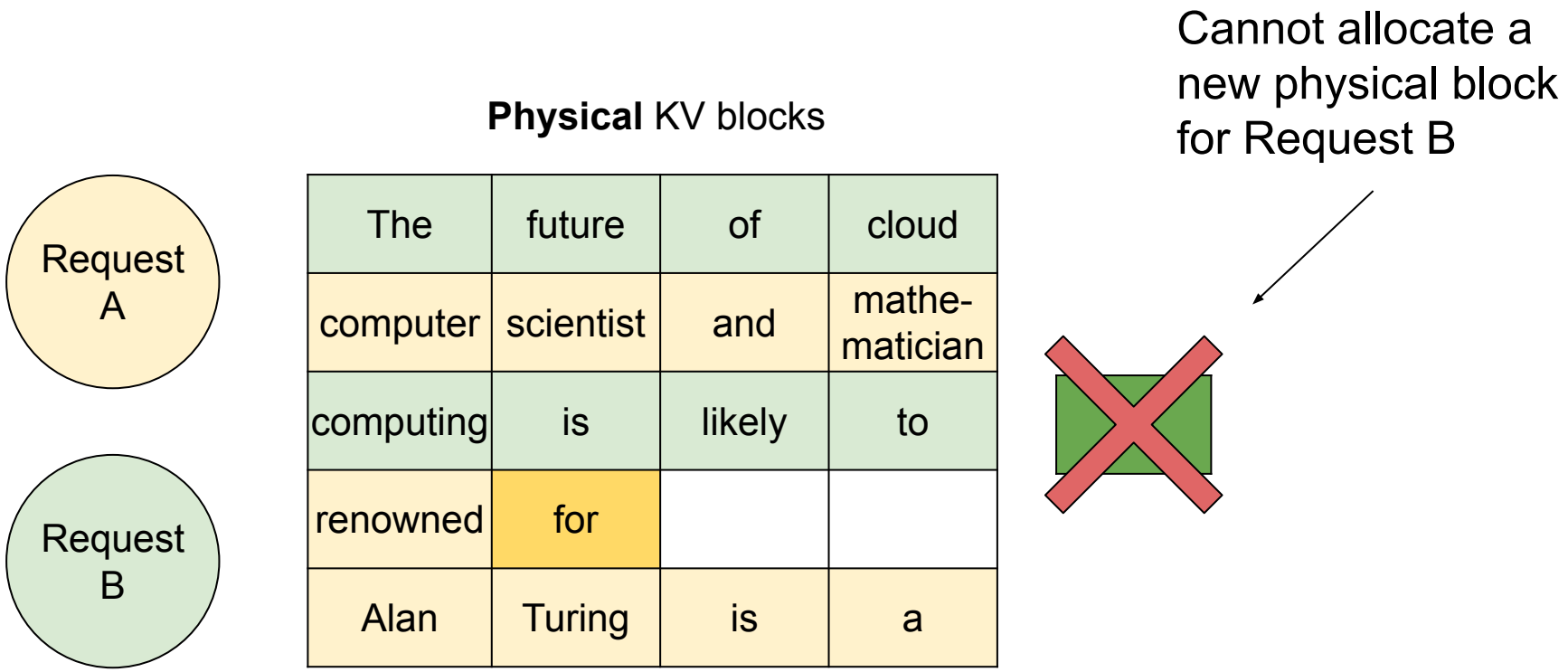




*Percentage = (#blocks saved by sharing) / (#total blocks without sharing)*
*OPT-13B on 1x A100-40G with ShareGPT dataset*

# Out of KV Cache Memory



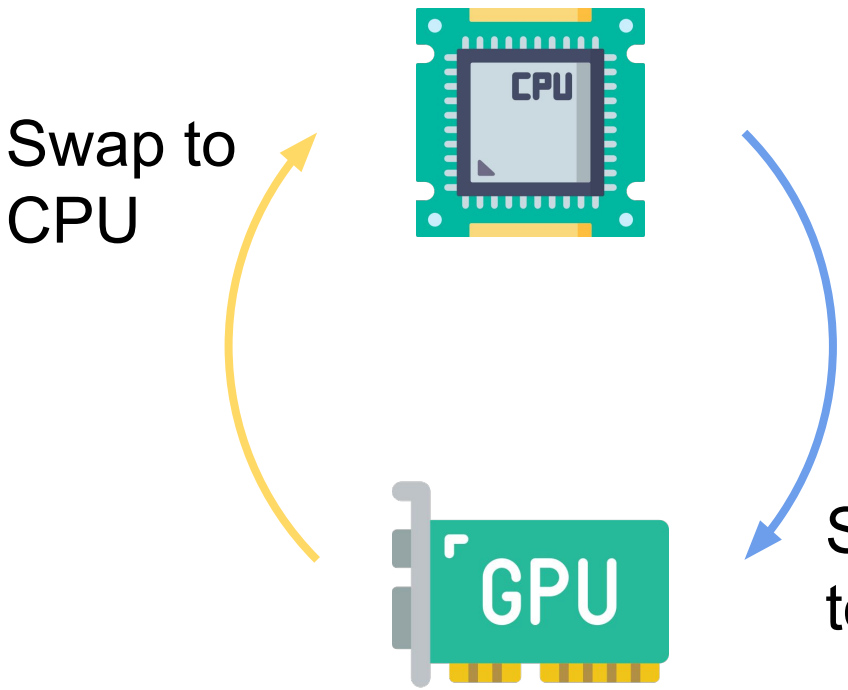
# Out of KV Cache Memory



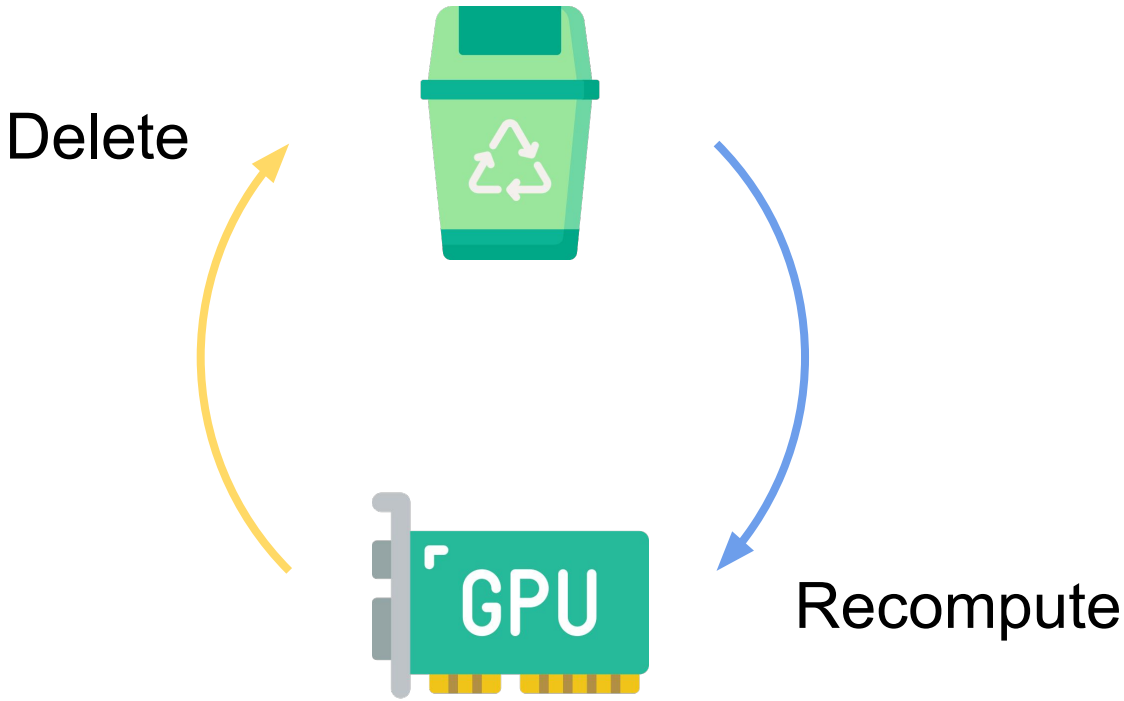
# Request Preemption & Recovery

**Goal:** Free some requests' KV cache to let others run first.

## Option 1: Swapping




## Option 2: Recomputation



# PagedAttention vs operating system virtual memory

## Analogies

**OS pages ↔ KV blocks**

- Reduce memory fragmentation

**Shared pages across processes ↔ Shared KV blocks across samples**

- Reduce memory waste via sharing

## Differences

**Eviction**

- Request-level vs page-level eviction

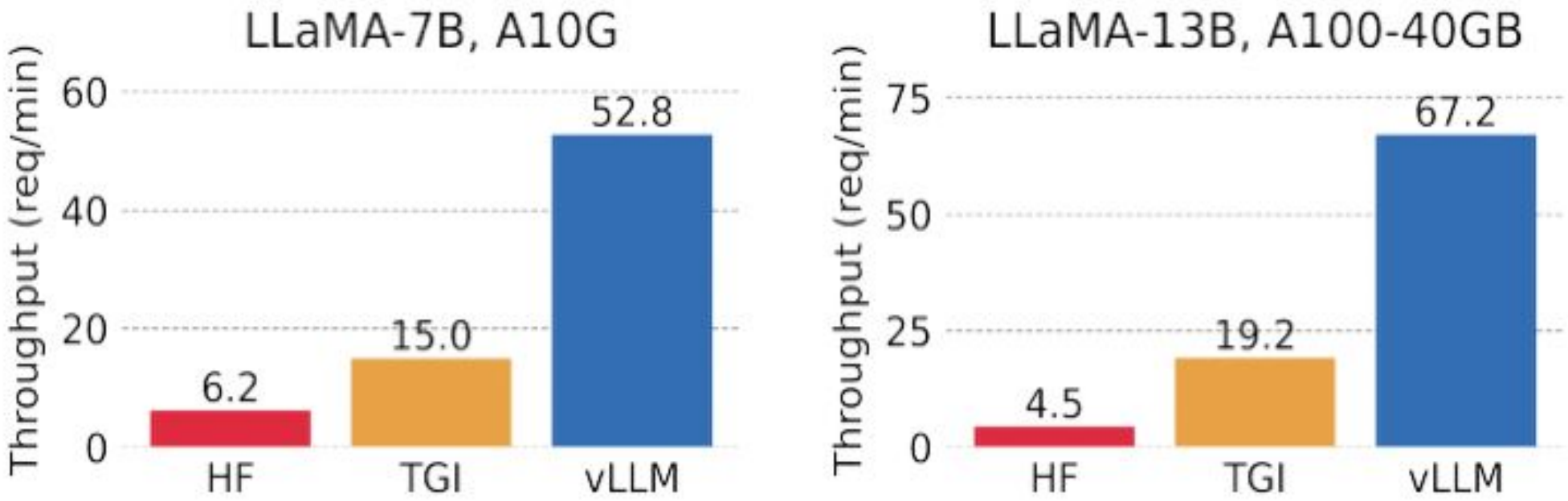
**Loading blocks/pages back to memory**

- Recompute blocks vs saving them to CPU RAM and bringing them back

# Throughput benefit of vLLM

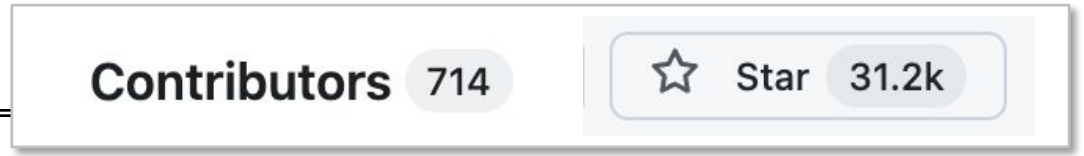
Up to 24x higher throughput than HuggingFace (HF)

Up to 3.5x higher throughput than Text Generation Inference (TGI)




*Serving throughput when each request asks for 3 output completions.*

# vLLM Adoption




## Open-Source Projects


lm-sys/FastChat

OPENCHAT

allenai/open-instruct

SkyPilot


WizardLM

...

## Companies

anyscale

Uber

databricks

Google Cloud

Meta

Modal

Replicate

scale

Lepton AI

...

## Accelerator Support

NVIDIA

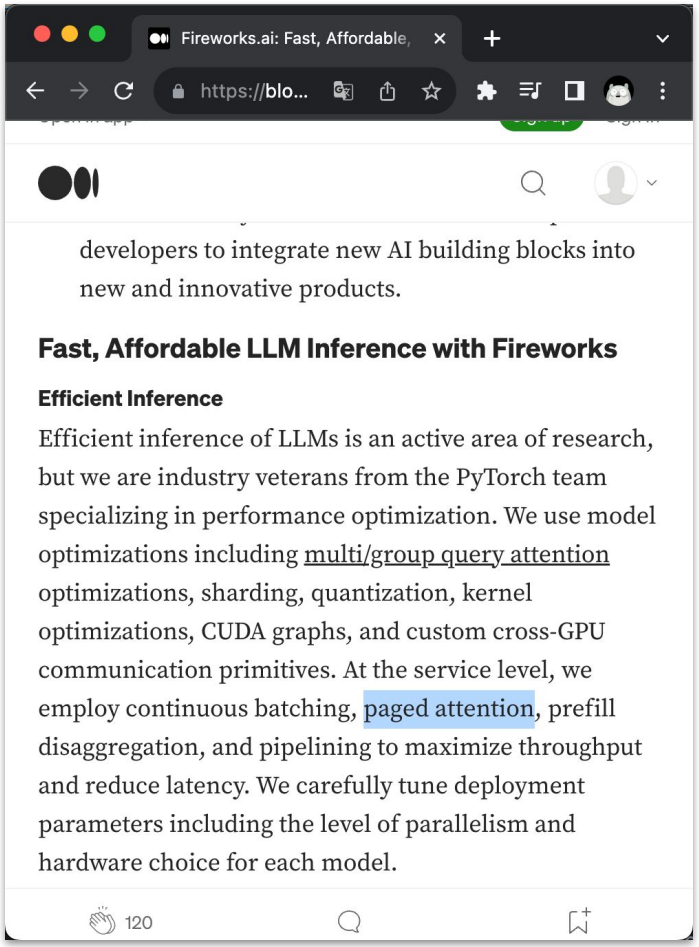
AMD

intel

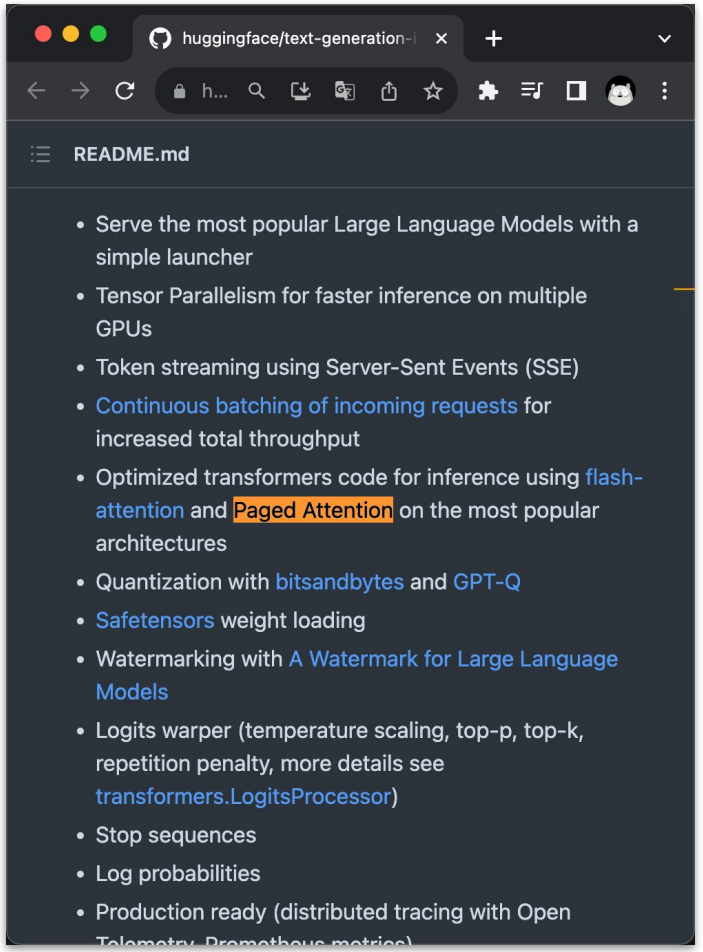
aws Inferentia

Google TPU

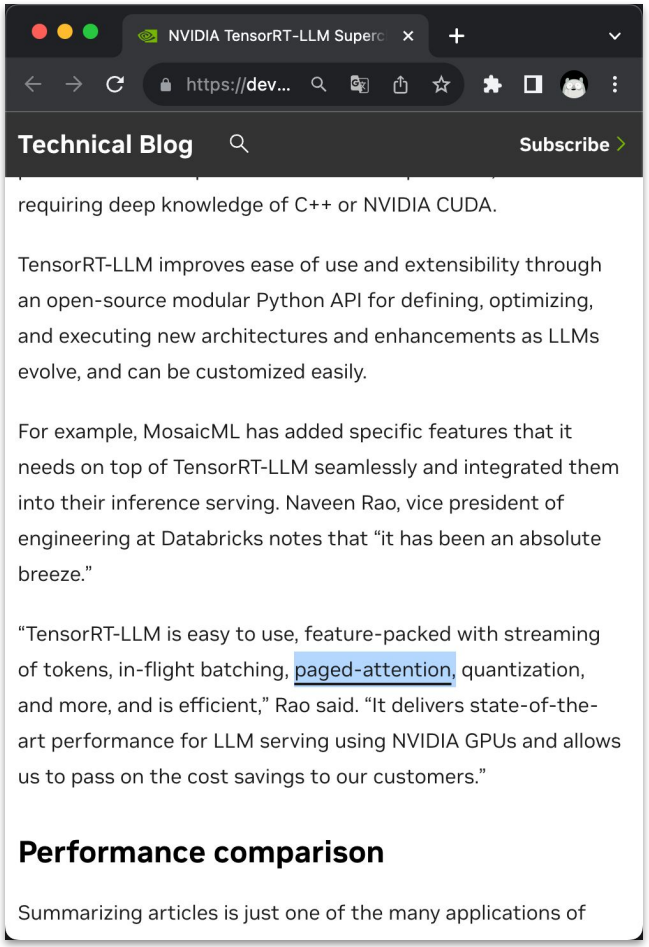
# PagedAttention is becoming an industry standard




Fireworks.ai




HuggingFace TGI




NVIDIA TRT-LLM

. . .

# Summary

The open-source is the future of AI/LLM stack

Two projects covered today (among many):

- Ray: scale and productize AI workloads
- vLLM: high throughput LLM inference engine

Just scratching the surface: many more challenges at the intersection between systems & AI/LLMs