Introduction to Ray Core & Ray Ecosystem

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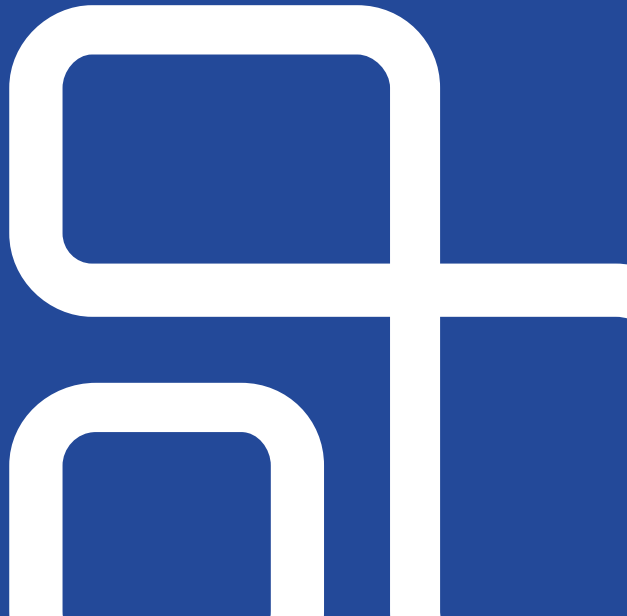
TBD

Software Engineer Ray Core , Anyscale



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Overview

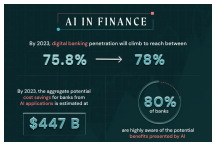
- What, Why Ray & Ray Ecosystem
- Ray Architecture & Components
- Ray Core APIs
- Demo
- Q & A

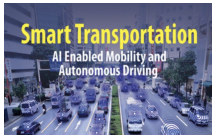
Why Ray?

- **Machine learning is pervasive in every domain**
- Distributed machine learning is becoming a necessity
- Distributed systems is notoriously hard

Apps increasingly incorporate AI/ML

AI/ML apps





Proliferated & Incorporated across Industries

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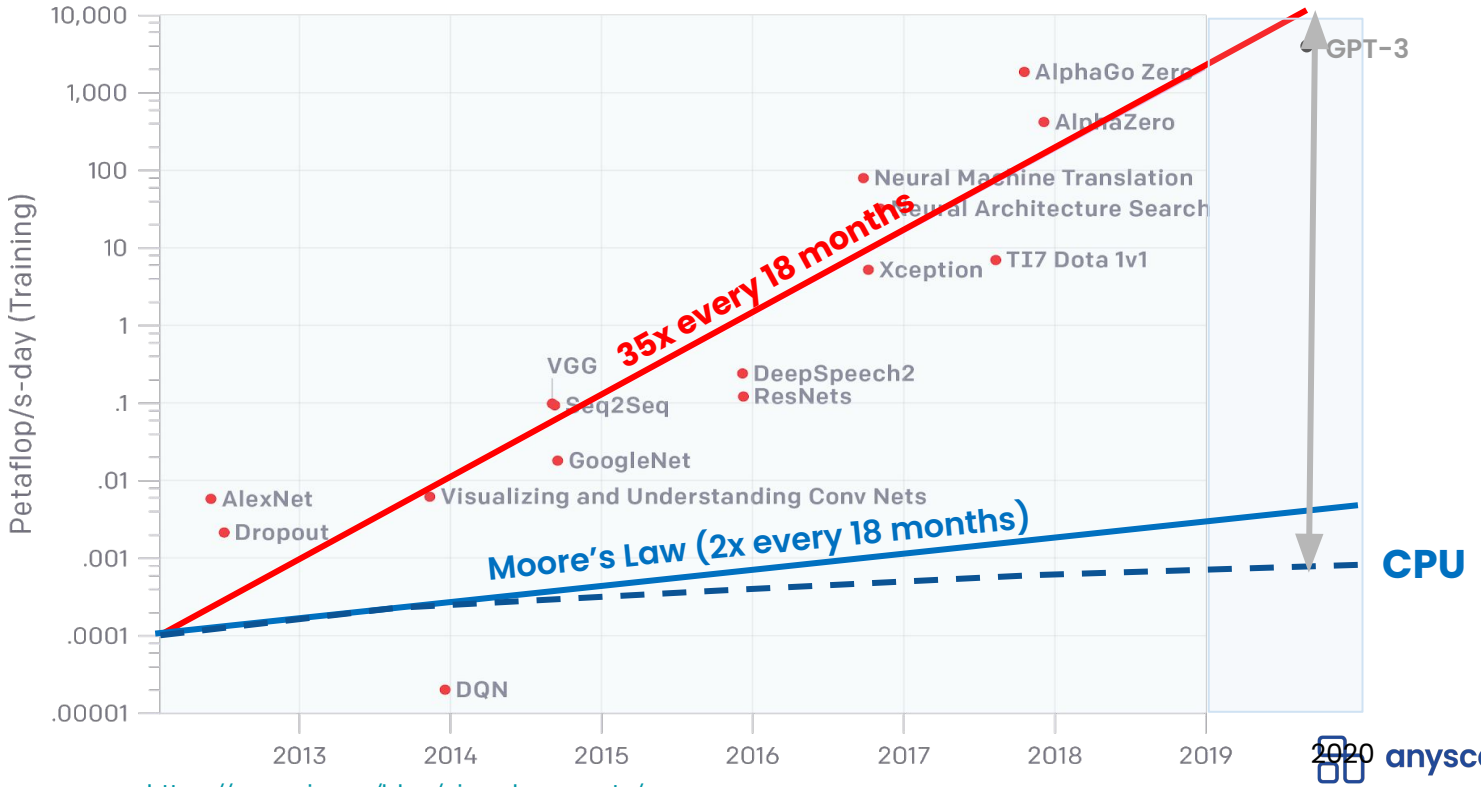
Why Ray?

- Machine learning is pervasive in every domain
- **Distributed machine learning is becoming a necessity**
- Distributed systems is notoriously hard

Compute demand growing faster than supply



https://openai.com/blog/ai-and-compute/

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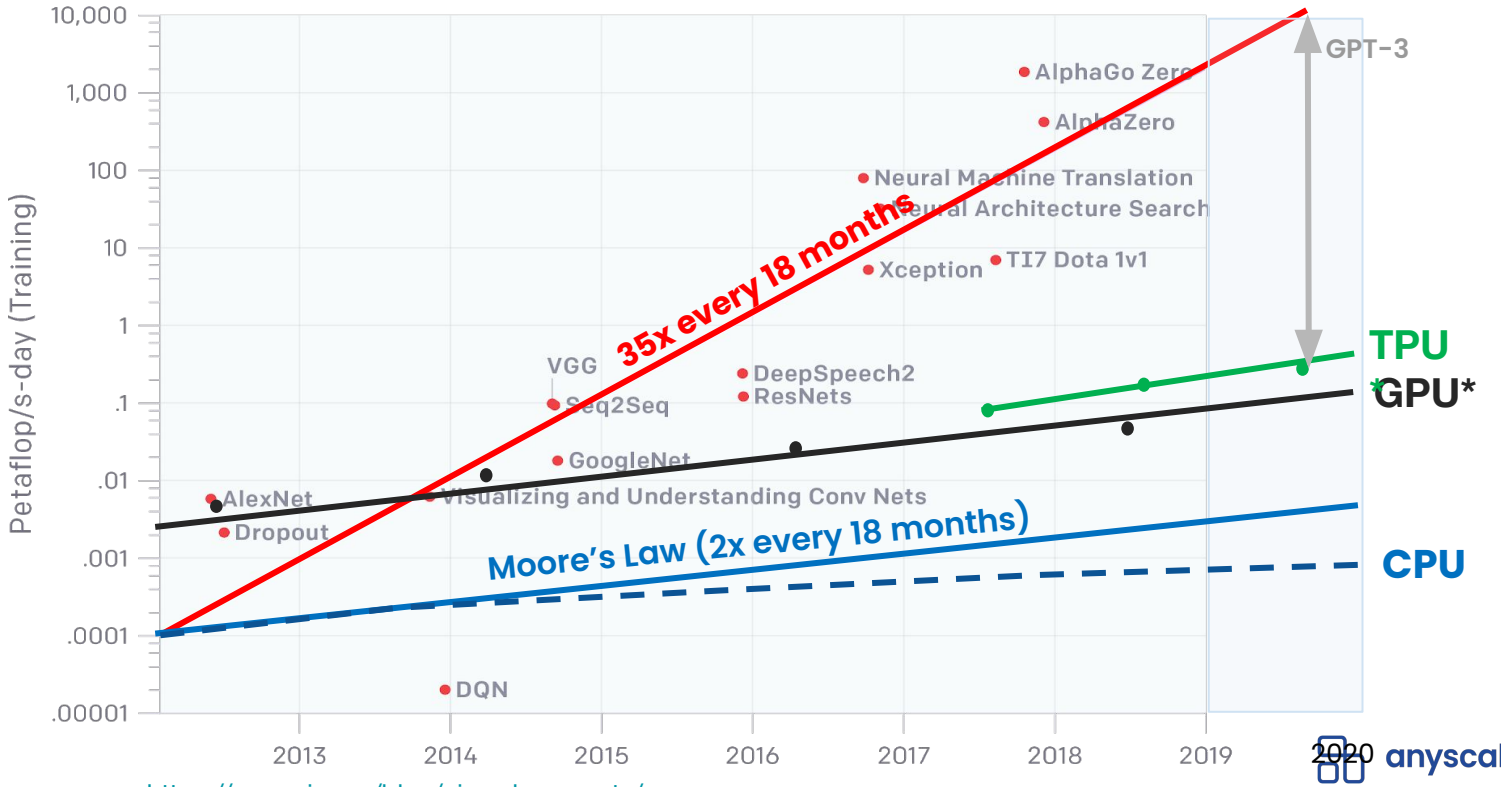
Specialized hardware is also not enough



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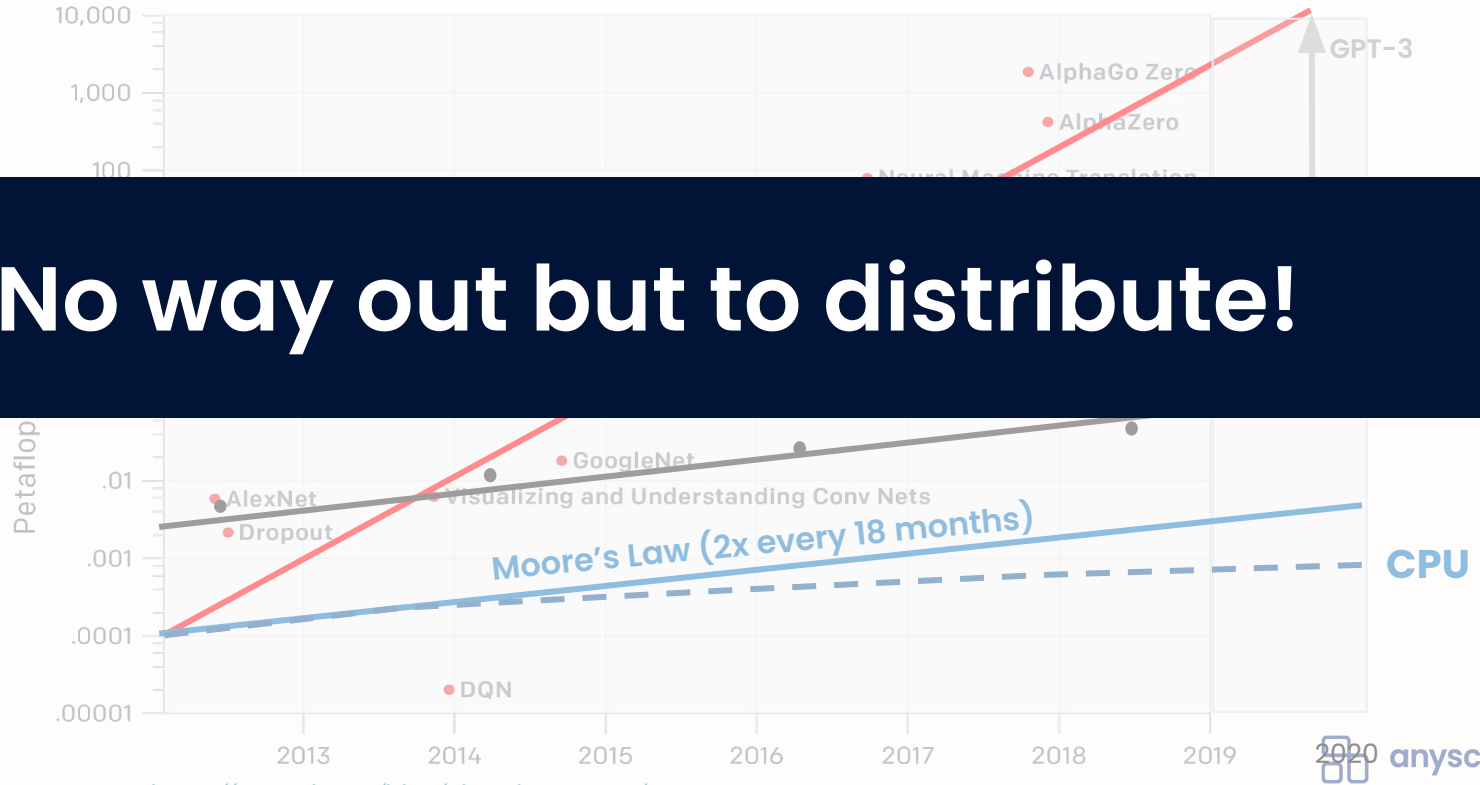
Specialized hardware is also not enough



No way out but to distribute!

https://openai.com/blog/ai-and-compute/

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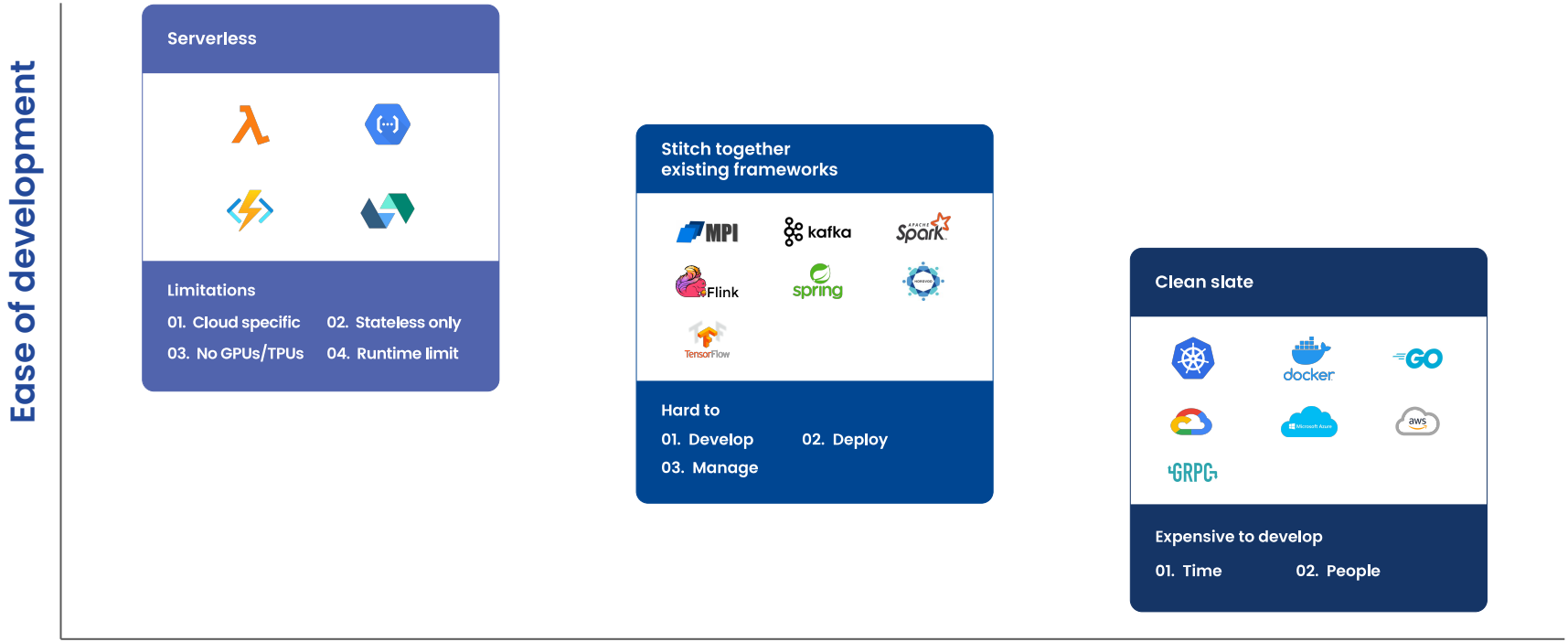
Why Ray?

- Machine learning is pervasive in every domain
- Distributed machine learning is becoming a necessity
- **Distributed systems are notoriously hard**

Existing solutions have may tradeoffs



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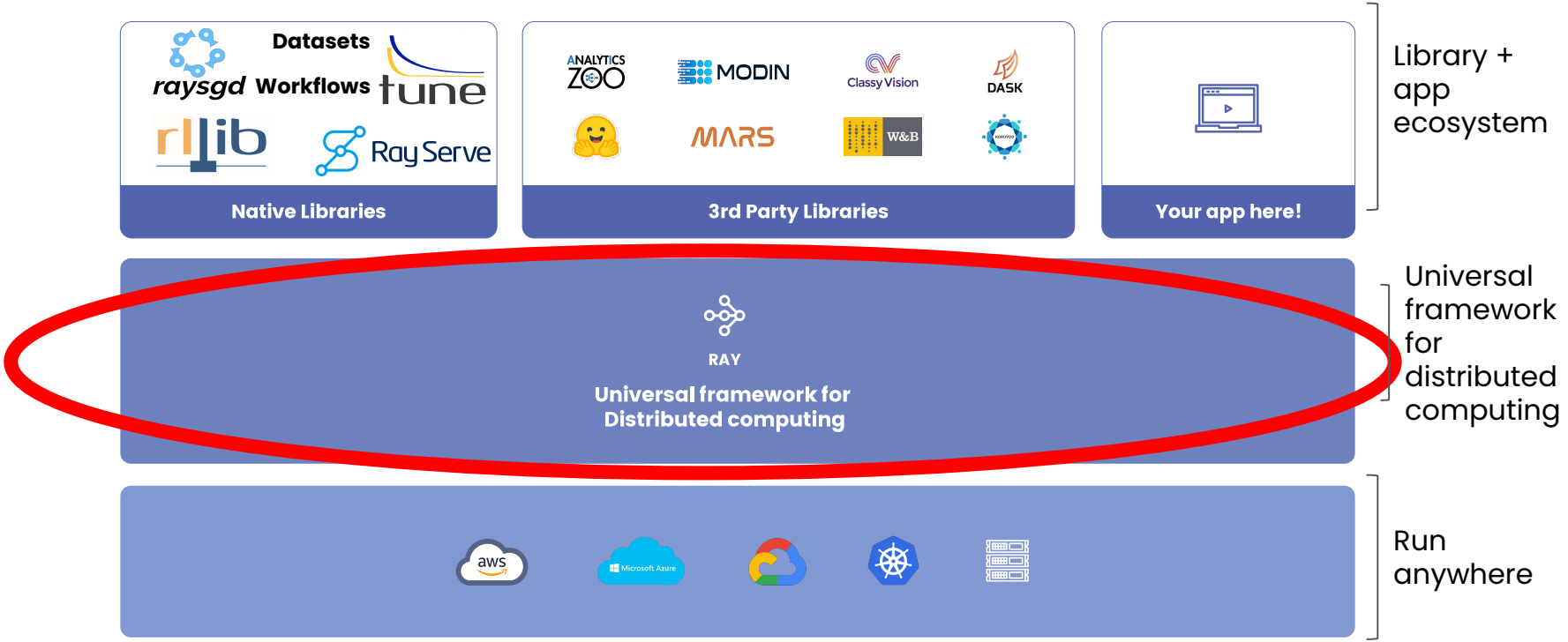
Why Ray?

- Machine learning is pervasive in every domain
- Distributed machine learning is becoming a necessity
- Distributed systems are notoriously hard

Ray's vision:

Make distributed computing accessible to every developer

The Ray Layered Cake and Ecosystem



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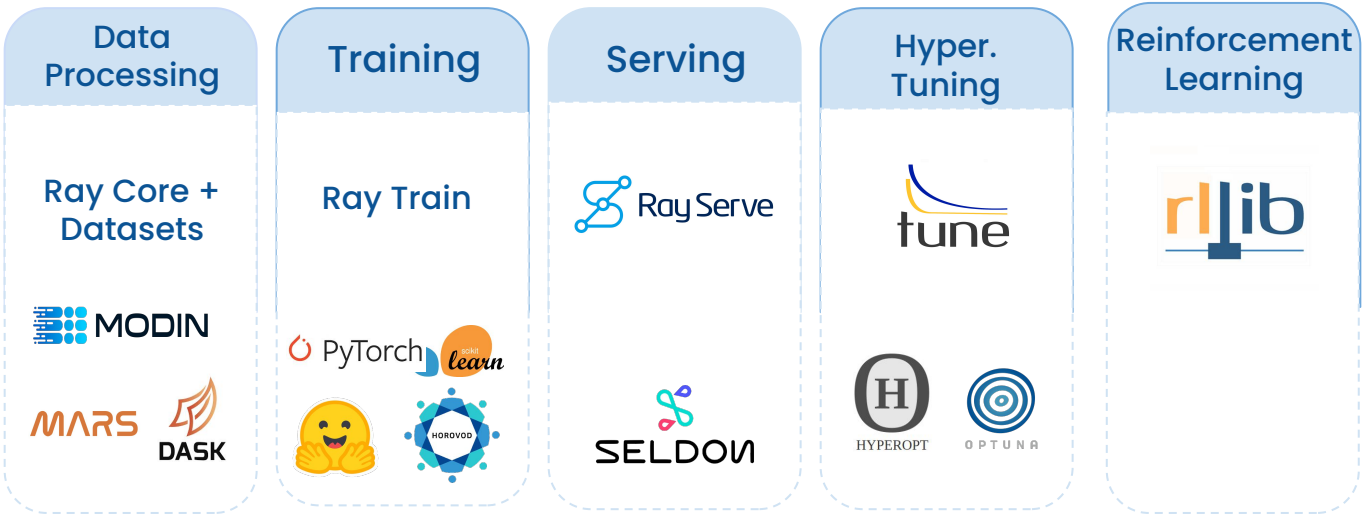
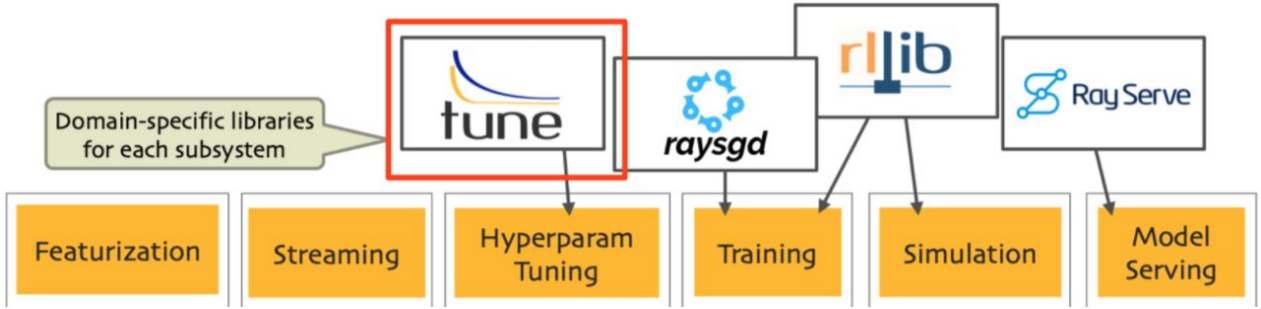
Rich ecosystem for scaling ML workloads



Integrate Ray only based on your needs!

Capitalize on Ray Ecosystem



Library + app ecosystem

RAY

Universal framework for distributed computing

aws
Microsoft Azure

Run anywhere

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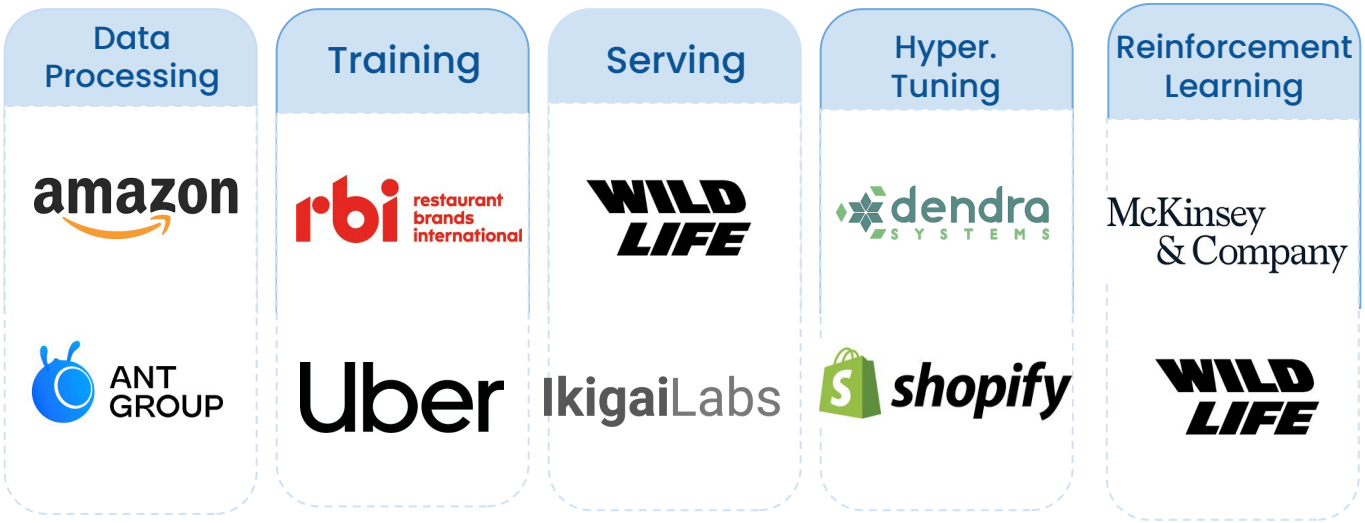
Companies scaling ML with Ray

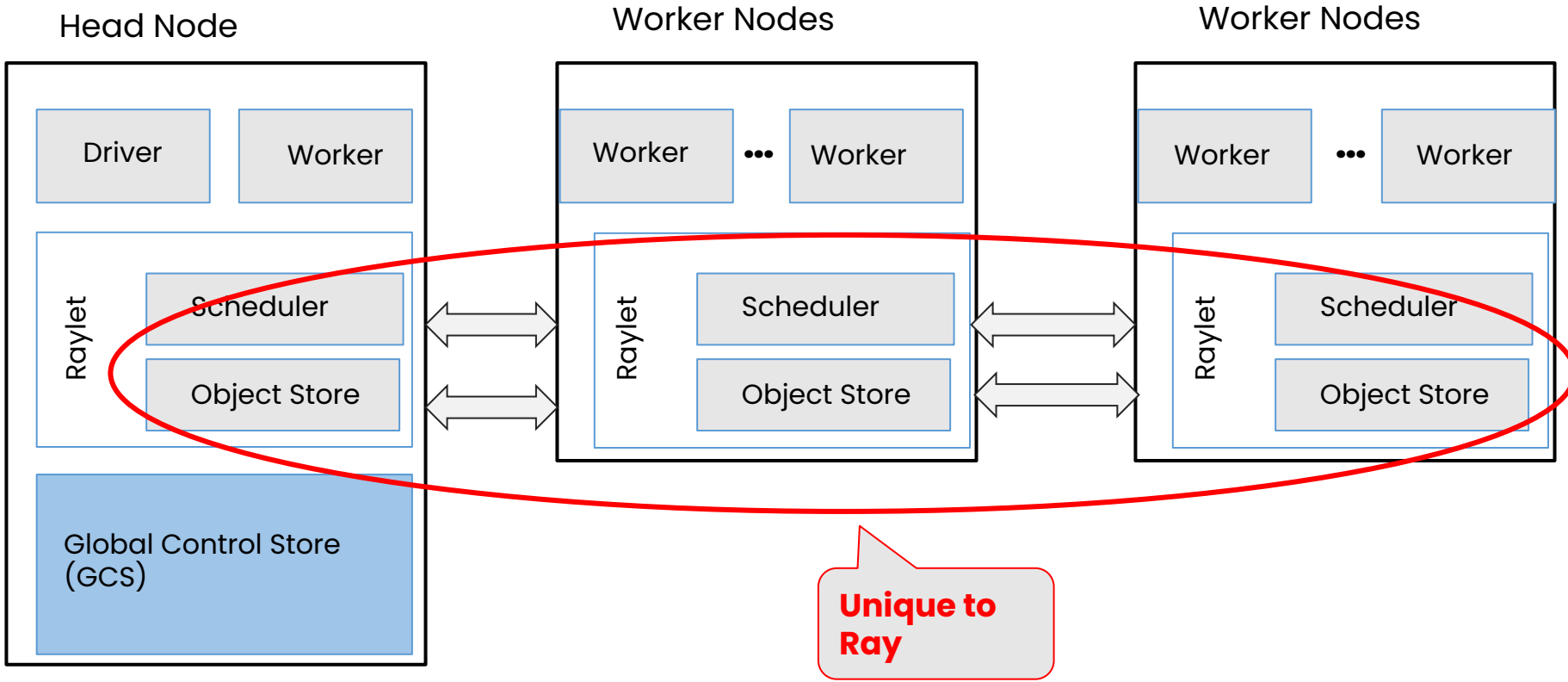
Companies scaling ML with Ray

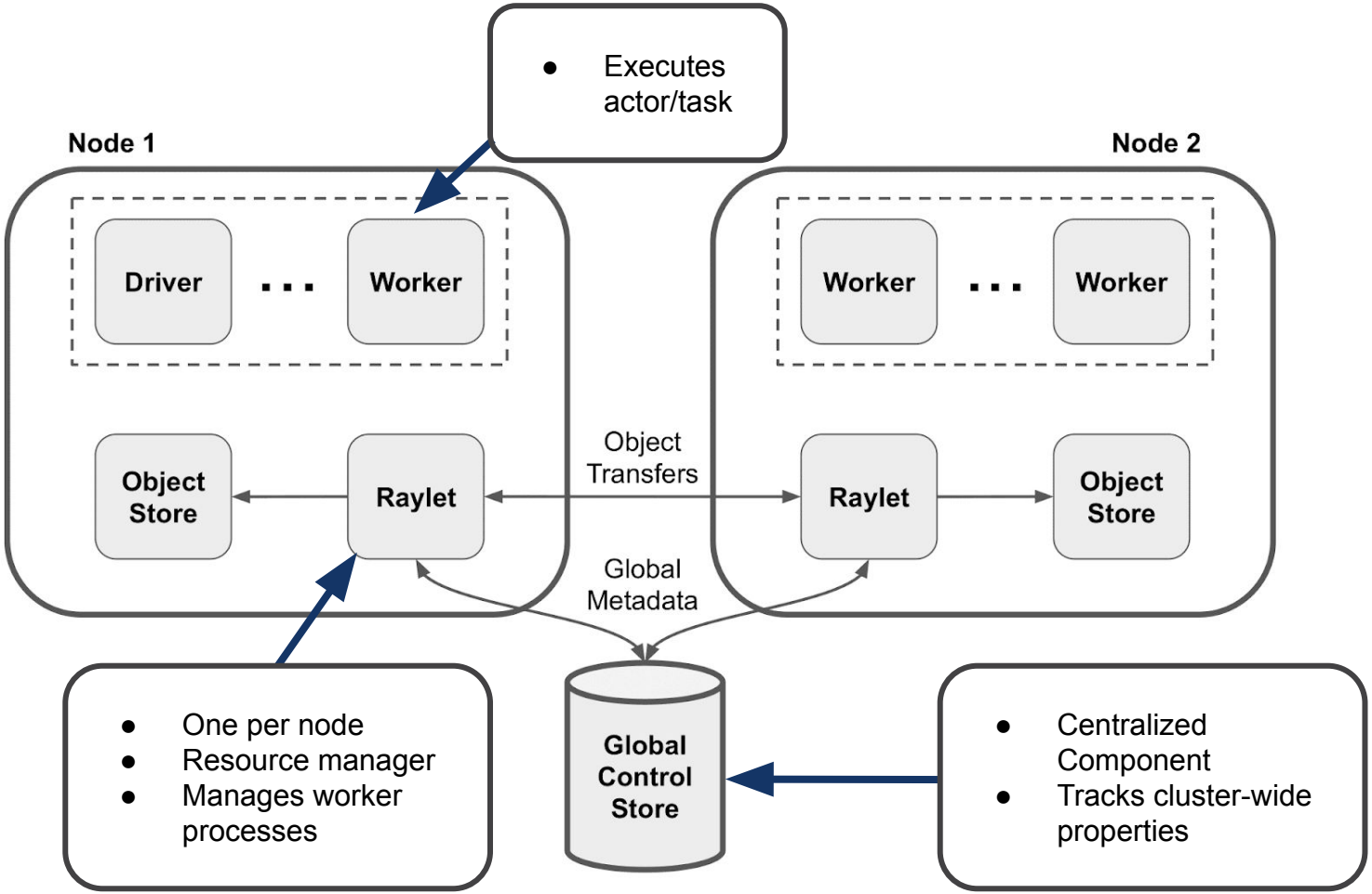


- https://eng.uber.com/horovod-ray/
- https://www.anyscale.com/blog/wildlife-studios-serves-in-game-offers-3x-faster-at-1-10th-the-cost-with-ray
- https://www.ikigailabs.com/blog/how-ikigai-labs-serves-interactive-ai-workflows-at-scale-using-ray-serve

Ray Architecture & Components

What does Ray Cluster Looks Like …

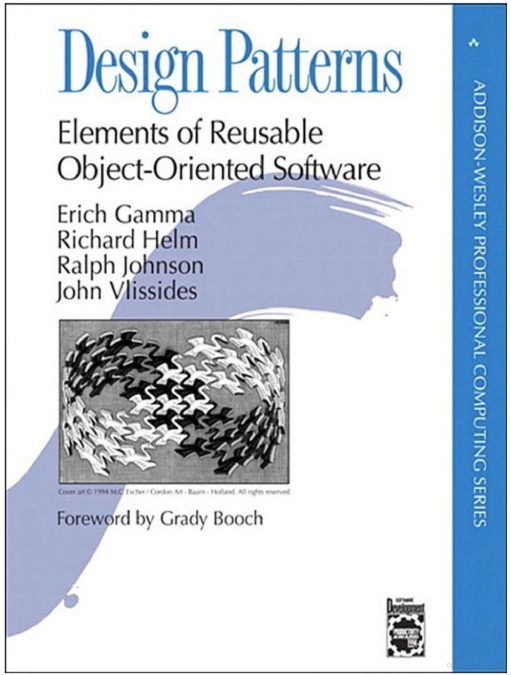



Executes actor/task
Node 1
Node 2
Driver
Worker
Worker
Worker
Object Store
Raylet
Object Transfers
Raylet
Object Store
Global Metadata
One per node
Resource manager
Manages worker processes
Global Control Store
Centralized Component
Tracks cluster-wide properties

Ray Distributed Design Patterns & APIs

Ray Basic Design Patterns

- Ray Parallel Tasks
  - Functions as stateless units of execution
  - Functions distributed across a clusters as tasks
- Ray Objects or Futures
  - Distributed (immutable) Object stored in cluster
  - Retrievable when available
  - Enable asynchronous execution of
- Ray Actors
  - Stateful service on a cluster
  - Message passing and maintains state



1. Patterns for Parallel Programming
2. Ray Design Patterns

Python → Ray Basic Patterns

Function → Task → Node

Class → Actor → Node

Object → (Distributed immutable) Object → Node

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Function

```
def read_array(file):
    # read ndarray “a”
    # from “file”
    return a


def add(a, b):
    return np.add(a, b)

a = read_array(file1)
b = read_array(file2)
sum = add(a, b)
```

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()
```

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Function → Task

```
@ray.remote
def read_array(file):
    # read ndarray “a”
    # from “file”
    return a

@ray.remote
def add(a, b):
    return np.add(a, b)

a = read_array(file1)
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Class → Actor

```
@ray.remote
class Counter(object):
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c = Counter()
c.inc()
c.inc()
```

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Function → Task

```
@ray.remote
def read_array(file):
    # read ndarray “a”
    # from “file”
    return a

@ray.remote
def add(a, b):
    return np.add(a, b)

id1 = read_array.remote(file1)
id2 = read_array.remote(file2)
id = add.remote(id1, id2)
sum = ray.get(id)
```

Class → Actor

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

c = Counter.remote()
id4 = c.inc.remote()
id5 = c.inc.remote()
```

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Task API

Blue variables are ObjectRef IDs (similar to futures)

```
@ray.remote
def read_array(file):
    # read ndarray “a”
    # from “file”
    return a

@ray.remote
def add(a, b):
    return np.add(a, b)

id1 = read_array.remote(file1)
id2 = read_array.remote(file2)
id = add.remote(id1, id2)
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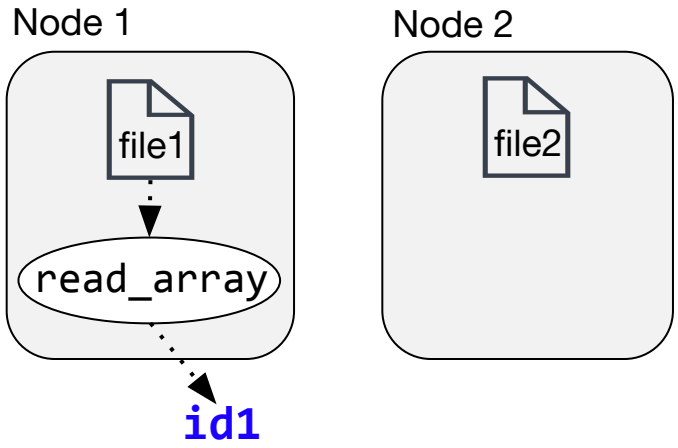
```



Return id1 (future) immediately, before **read_array()** finishes

Task API

```
@ray.remote
def read_array(file):
    # read ndarray “a”
    # from “file”
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def add(a, b):
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id1 = read_array.remote(file1)
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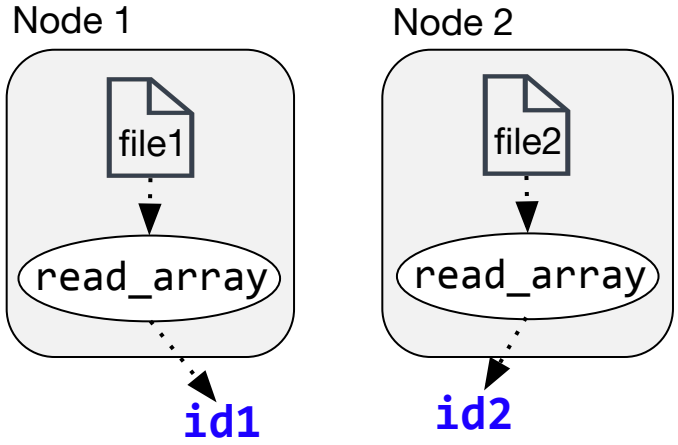
Blue variables are Object IDs (similar to futures)



Dynamic task graph: build at runtime

Task API

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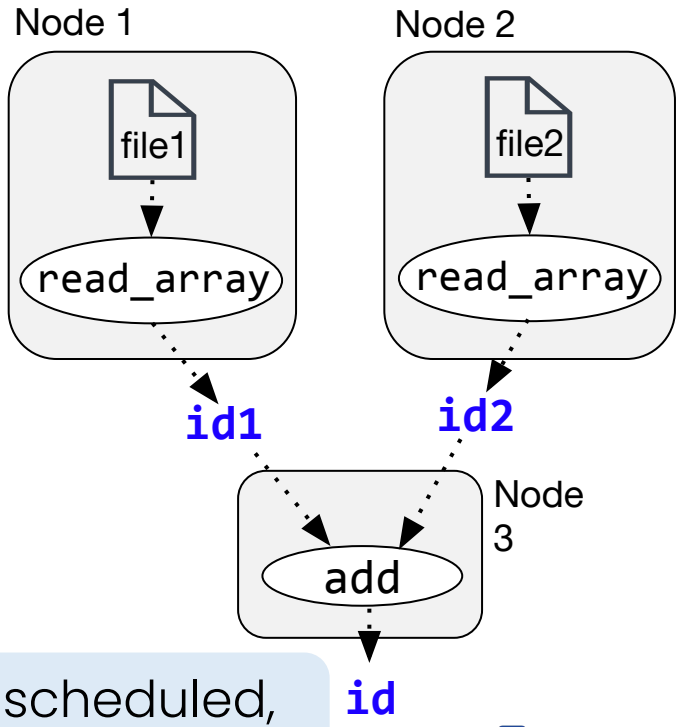

Every task scheduled, but not finished yet

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Task API

Blue variables are Object IDs (similar to futures)

```
@ray.remote
def read_array(file):
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id1 = read_array.remote(file1)
id2 = read_array.remote(file2)
id = add.remote(id1, id2)
sum = ray.get(id)
```
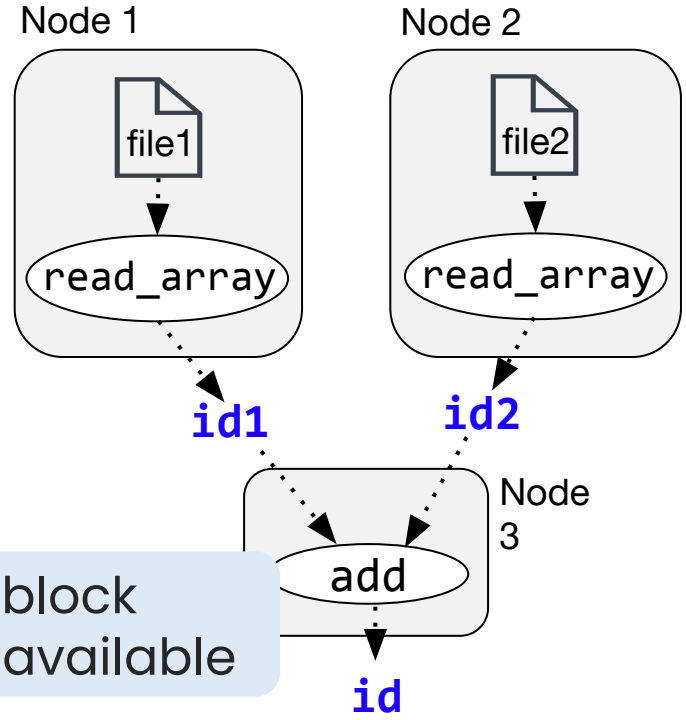

ray.get() block until result available



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Task API

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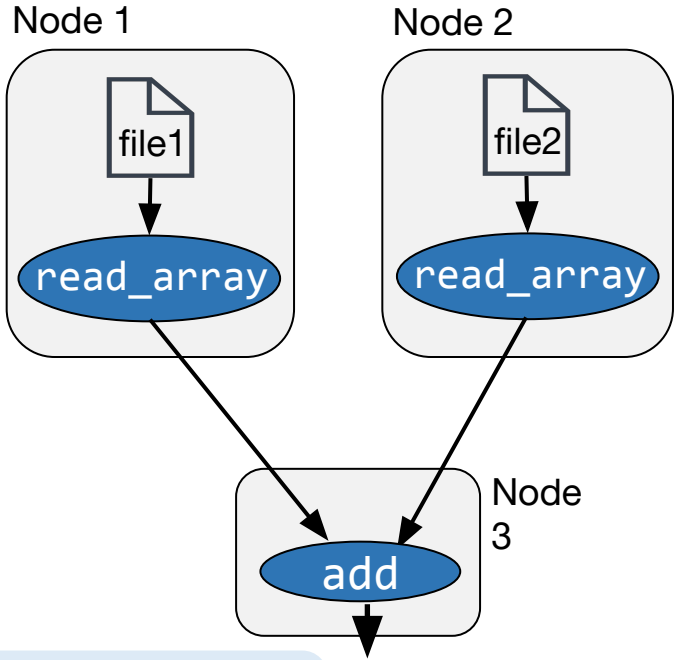

Task graph executed to compute `sum`

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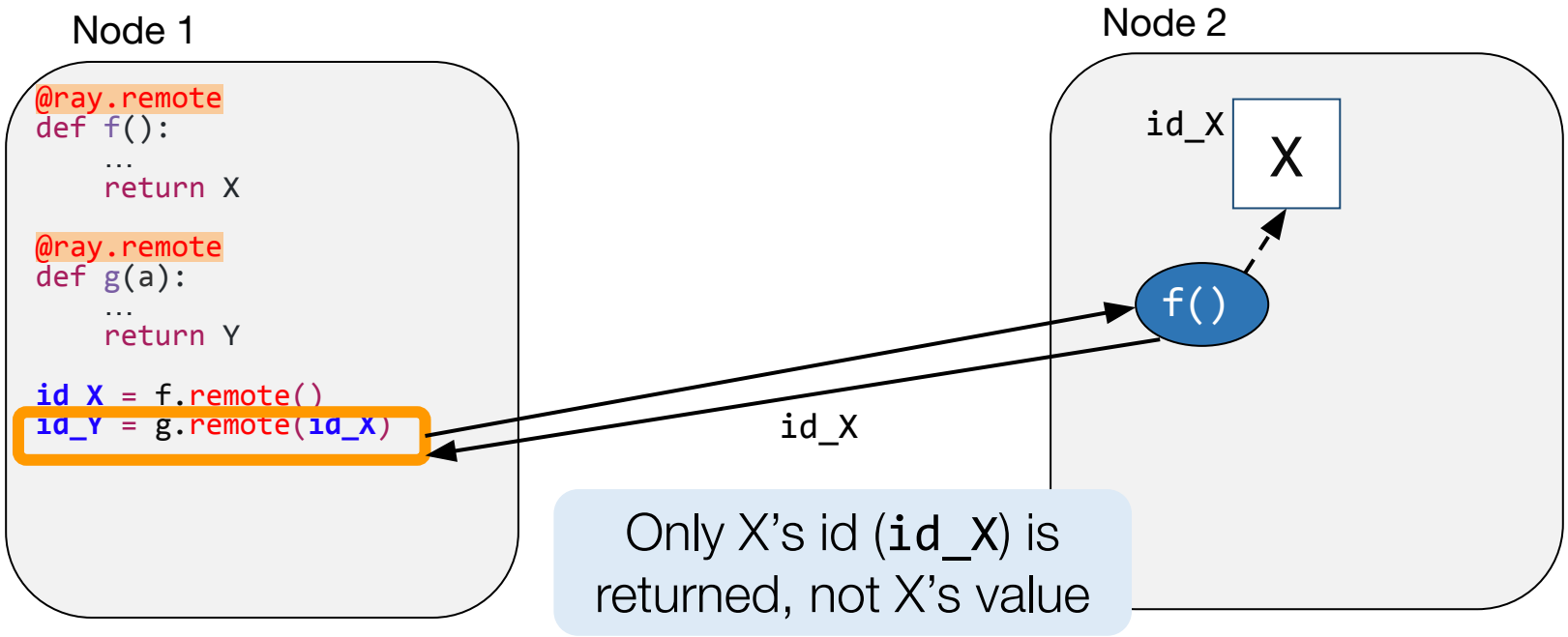
Distributed Immutable object store



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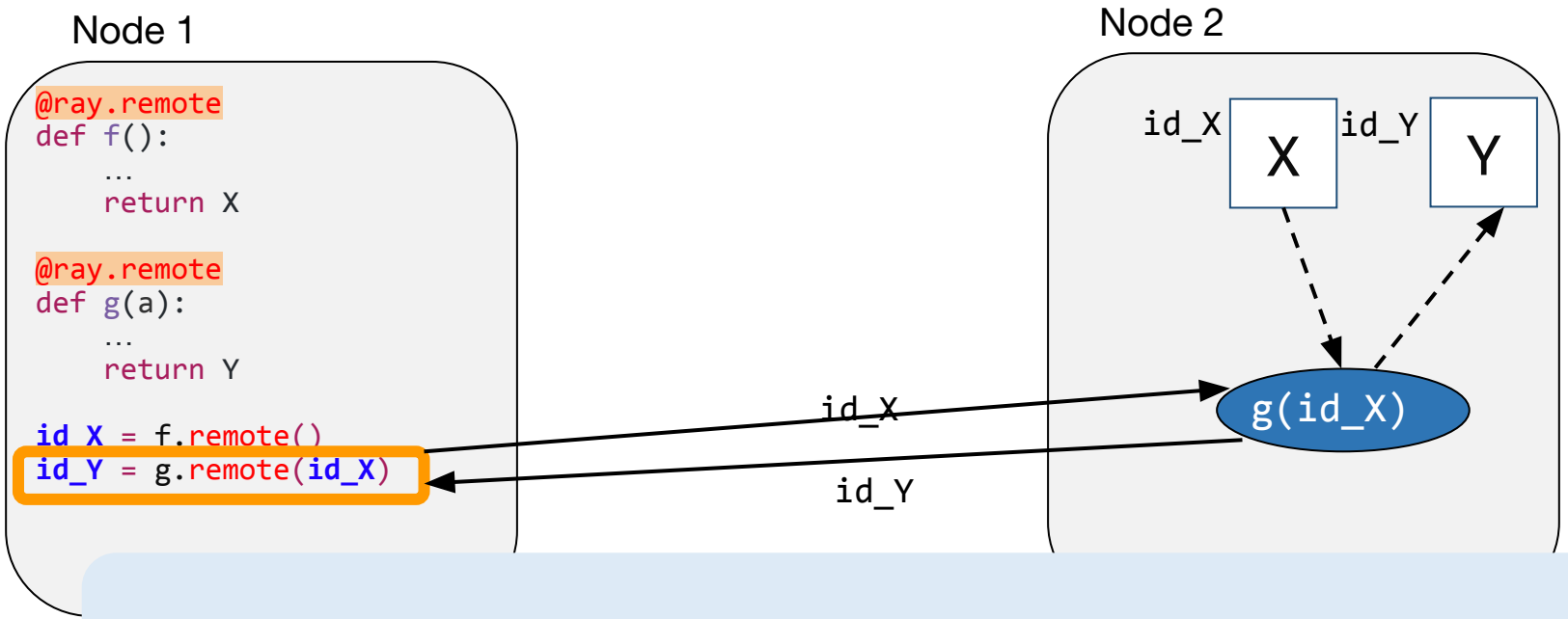
Distributed object store



`g(id_X)` is scheduled on same node, so `X` is never transferred

Takeaways

- Distributed computing is a necessity & norm
- Scale your ML workloads with Ray Libraries
- Ray's vision: make distributed programming simple
- Don't have to be distributed systems expert. Just use @ray.remote :)

RAY

Meetup In 2022

https://tinyurl.com/ray-meetup-jan2022

Jan 19 th @ 6:00 PM PST

Demo

https://tinyurl.com/ray-core-demo

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You might be interested in …

- How to scale ML workloads with Ray
- How to Effectively tune HPO with Ray Tune
- How to Scale Model Serving with Ray Serve
- Scalable RL training & serving in the cloud with Ray
- Let us know what you are looking for ….

Start learning Ray and contributing …

Getting Started:

Documentation (docs.ray.io)
Quick start example, reference guides, etc

Join Ray Meetup
Revive in Jan 2022. Publish recording to the members
https://www.meetup.com/Bay-Area-Ray-Meetup/

Forums (discuss.ray.io)
Learn / share with broader Ray community, including core team

Ray Slack
Connect with the Ray team and community

Social Media (@raydistrtibuted, @anyscalecompute)
Follow us on Twitter and linkedIn

GitHub
*Check out sources, file an issue, become a contributor, give us a **Star** :)*
https://github.com/ray-project/ray

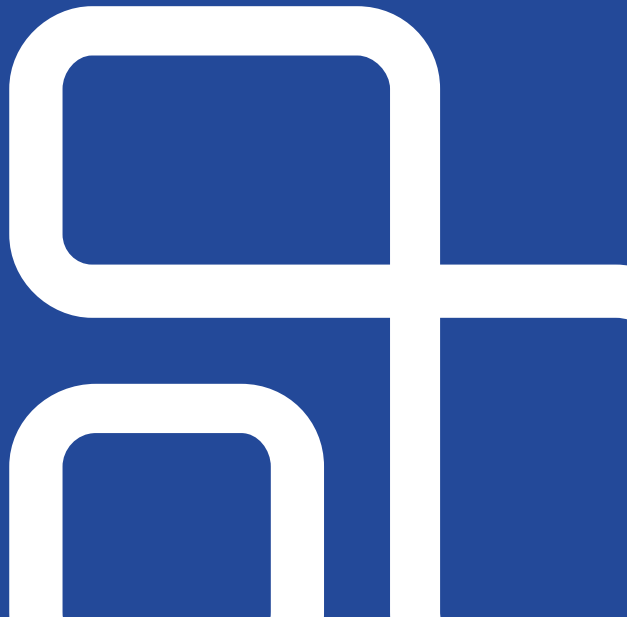
https://github.com/dmatrix/ray-core-tutorial

Thank you!

Let's stay in touch:

jules@anyscale.com
https://www.linkedin.com/in/dmatrix/

@2twitme



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Extras

ray.wait() non-blocking usage

```
c = Counter.remote()
increment_refs = [c.inc.remote() for _ in range(5)]
while len(increment_refs) > 0:
   return_n = 2 if len(increment_refs) > 1 else 1
   ready_refs, remaining_refs = ray.wait(increment_refs,
                                         num_returns=return_n,
                                            timeout=10.0)

   if len(ready_refs > 0:
      print(ray.get(ready_refs))
   # Update the remaining ones
   increment_refs = remaining_refs
```

```
[1, 2]
[3, 4]
[5]
```

Object Ownership