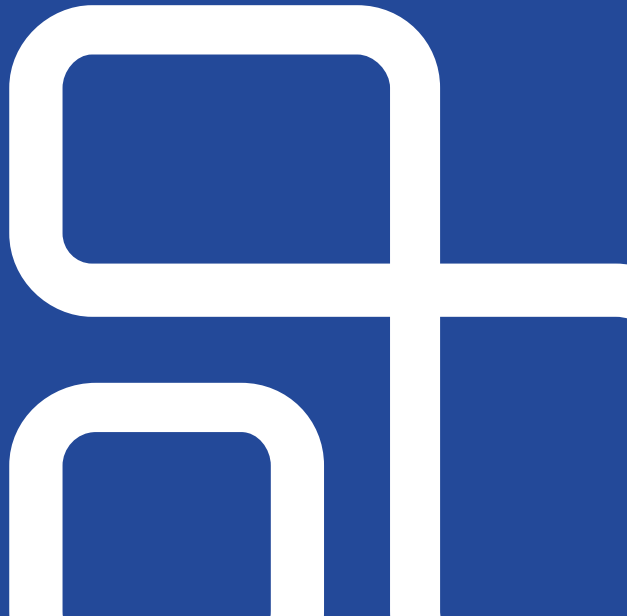
Distributed Python & ML with Ray: Hands-on with Ray Core APIs

Jules S. Damji, @2twitme
Lead Developer Advocate, Ray Team @ Anyscale
PyCon US, Salt Lake City, UT, April 27, 2022



anyscale

$whoami

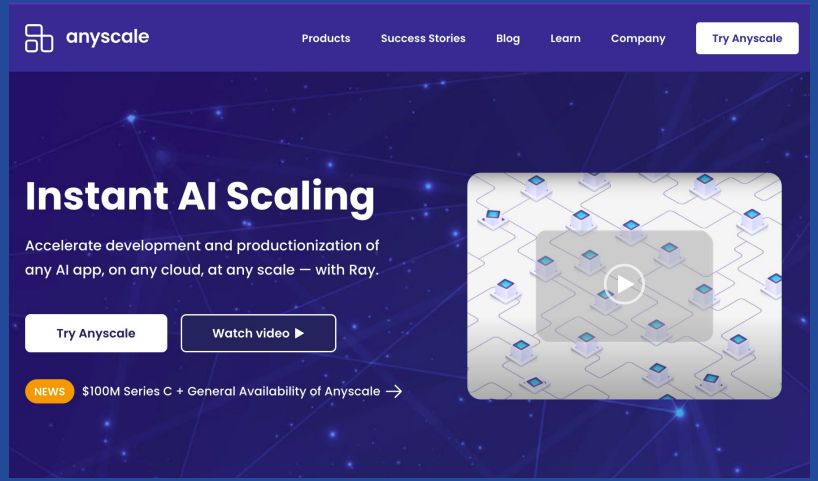
- Lead Developer Advocate @Anyscale
- Senior Developer Advocate @Databricks
- Led Developer Advocacy @Hortonworks
- Held software engineering positions:
  - Sun Microsystems
  - Netscape
  - @Home
  - LoudCloud/Opsware
  - Verisign
  - ProQuest/Ebrary

Anyscale

Who we are: Original creators of Ray

What we do: Provide managed service for Ray on public cloud to scale AI workloads

Why do it: Make distributed computing easy and simple for everyone



anyscale

Overview

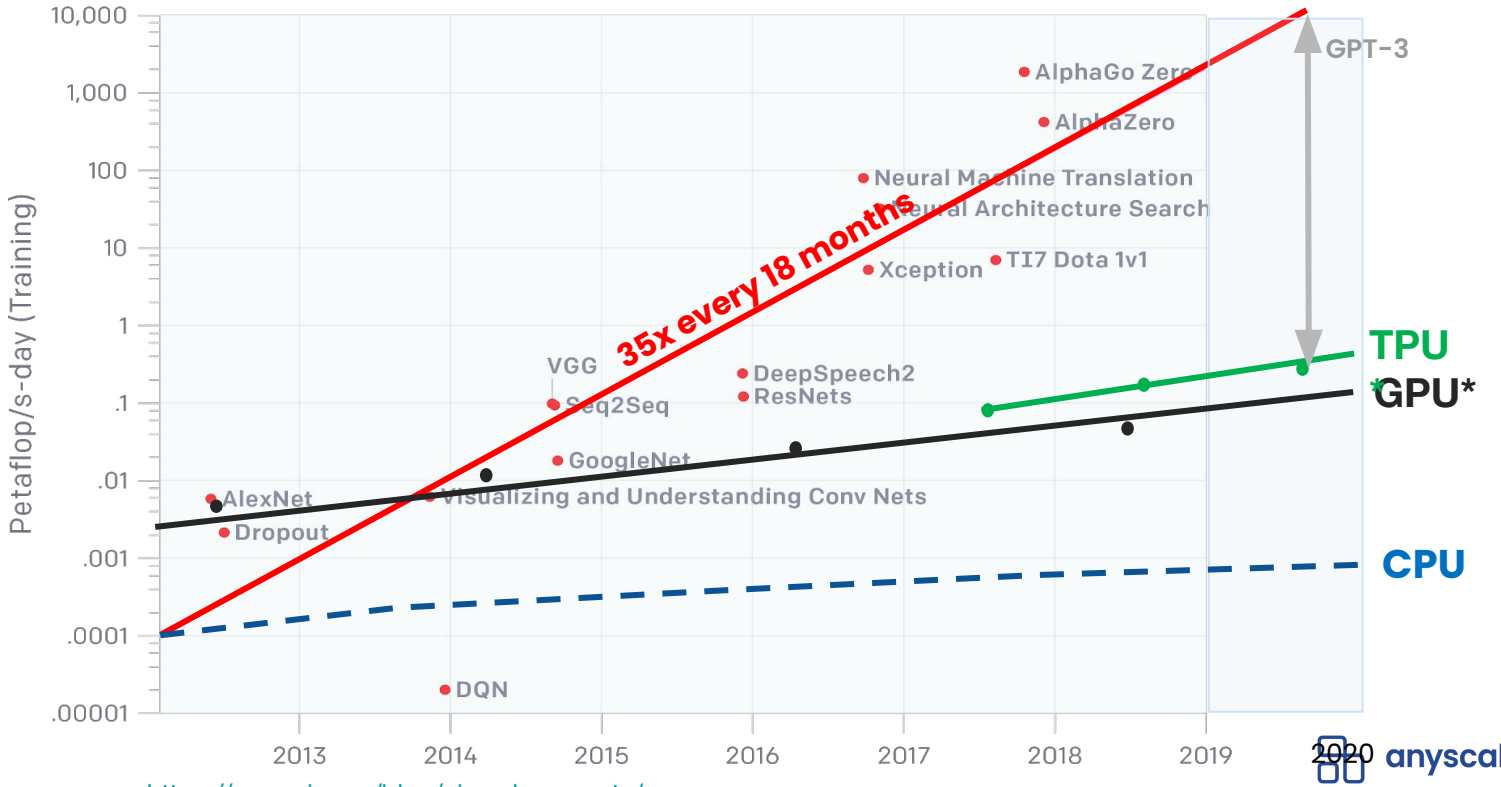
- Why & What's Ray & Ray Ecosystem
- Ray Architecture & Components
- Ray Core Design Patterns & APIs
- Hands-on Tutorials

https://tinyurl.com/pycon-ray-tutorial

Why Ray  ?

-  Machine learning is pervasive in every domain
-  Distributed machine learning is becoming a necessity
-  Python is the default language for DS & ML

Compute Demand - supply problem

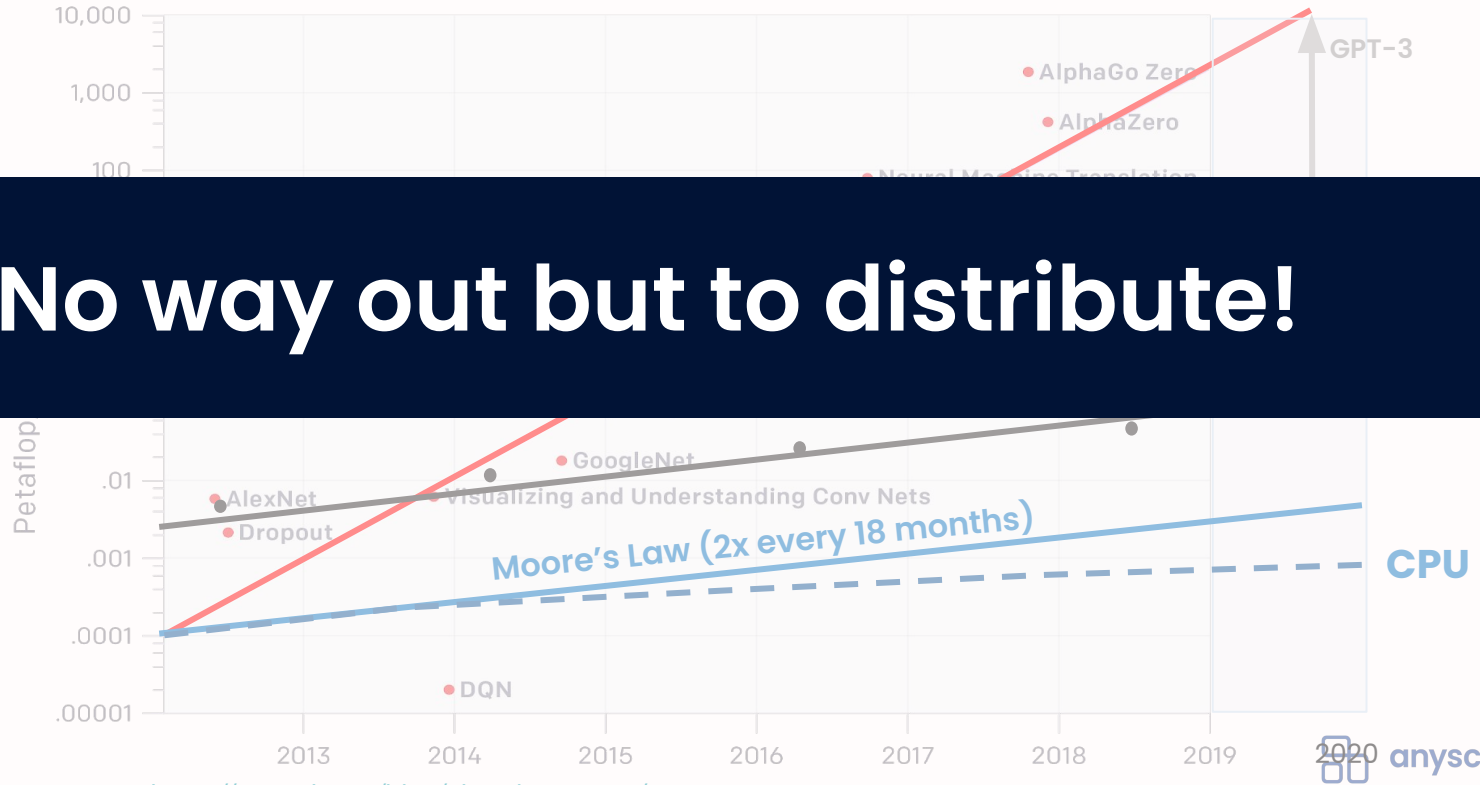


https://openai.com/blog/ai-and-compute/

RAY

anyscale

Specialized hardware is also not enough



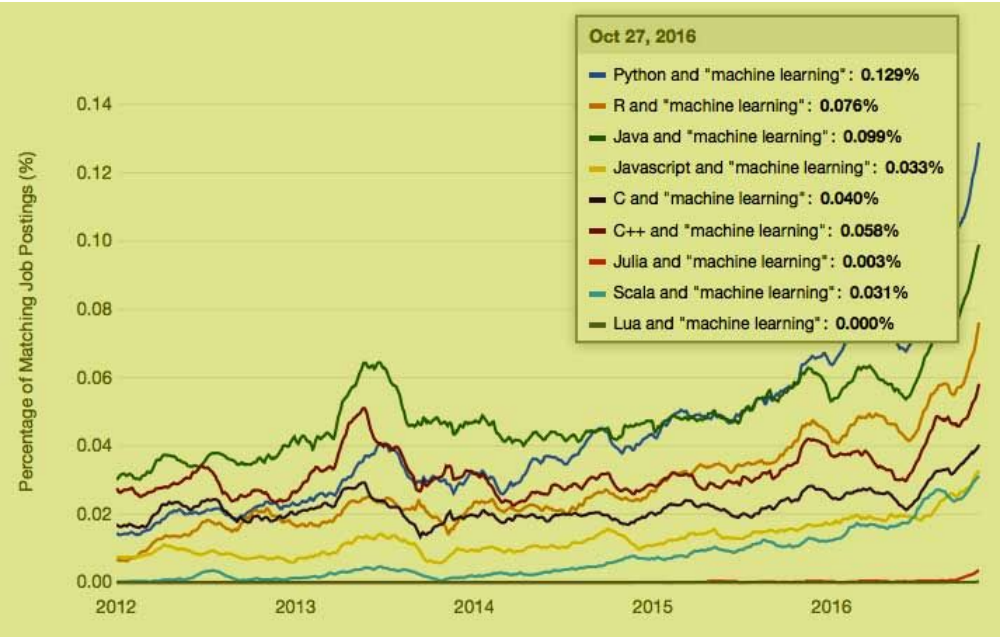
No way out but to distribute!

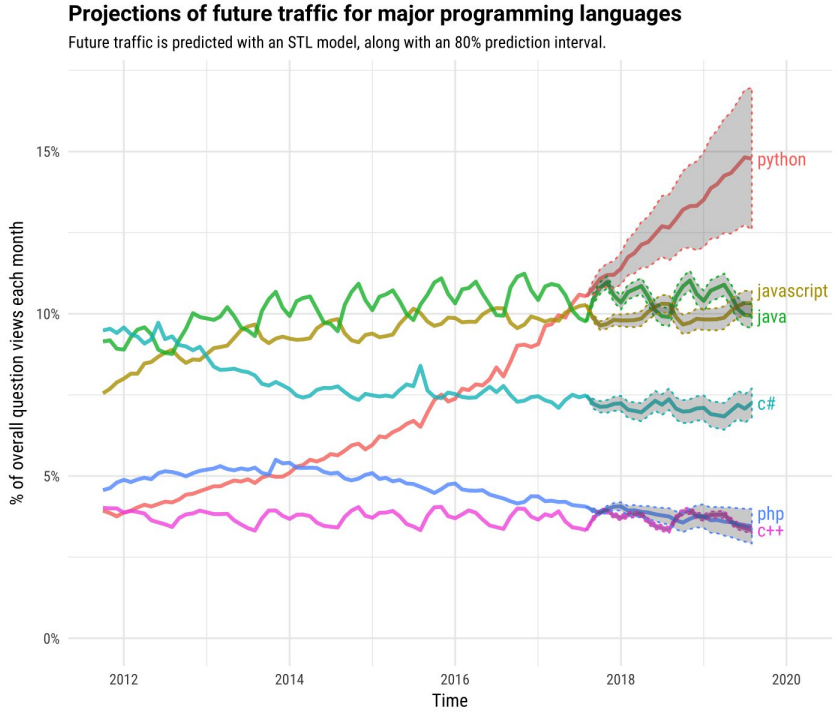
https://openai.com/blog/ai-and-compute/

RAY

anyscale

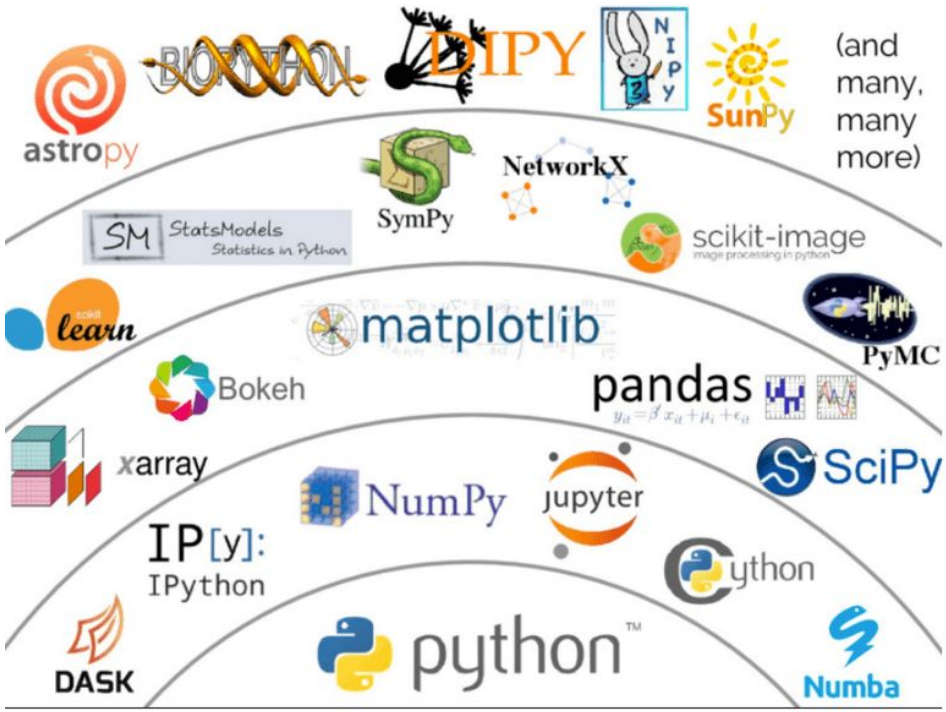
Python's growth as programming language

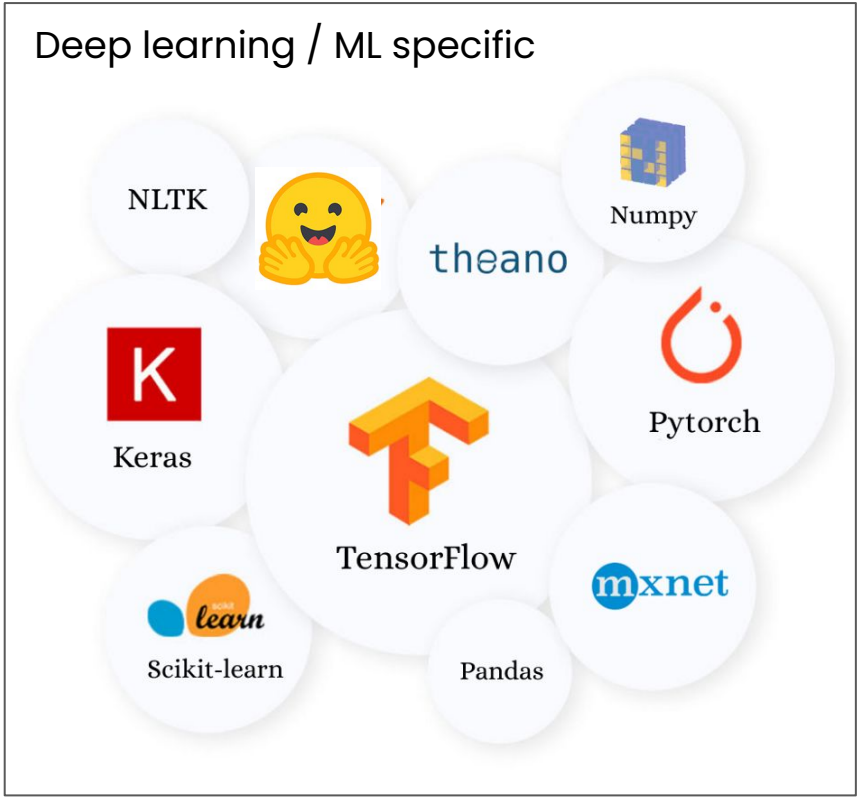




RAY

🐍 Python data science ecosystem dominating



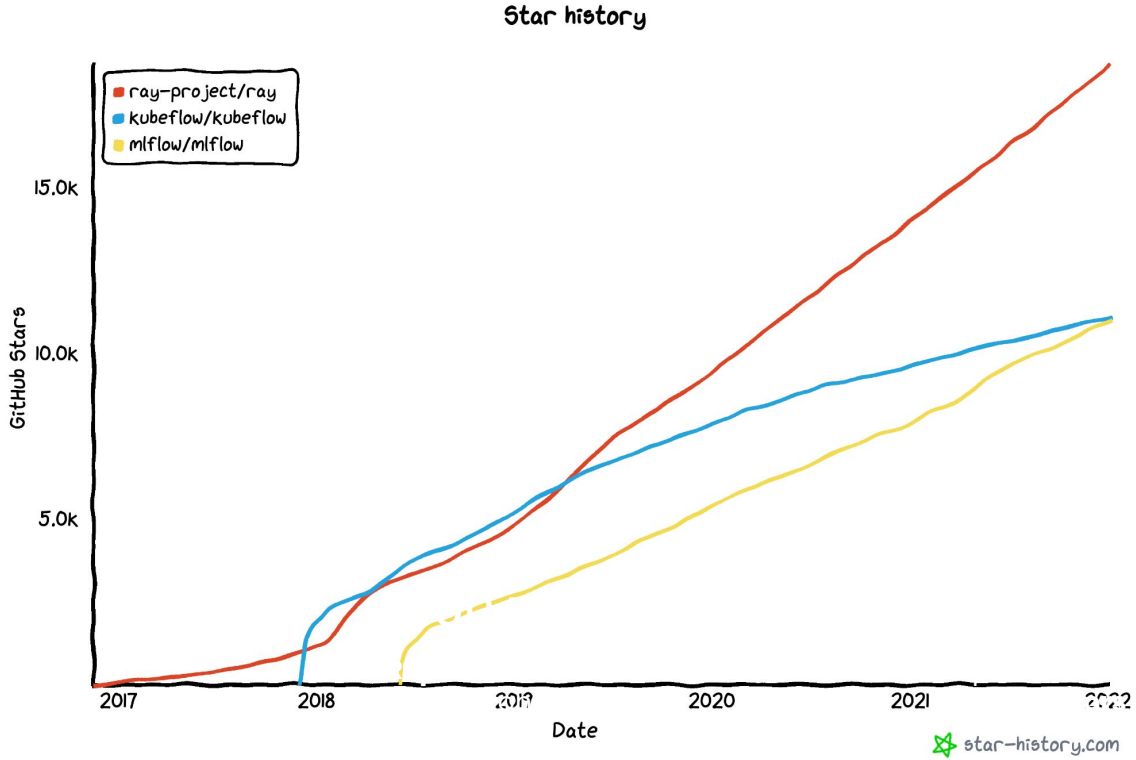


Origins of Ray

Caffe

Apache MESOS

Growth of open-source Ray adoption



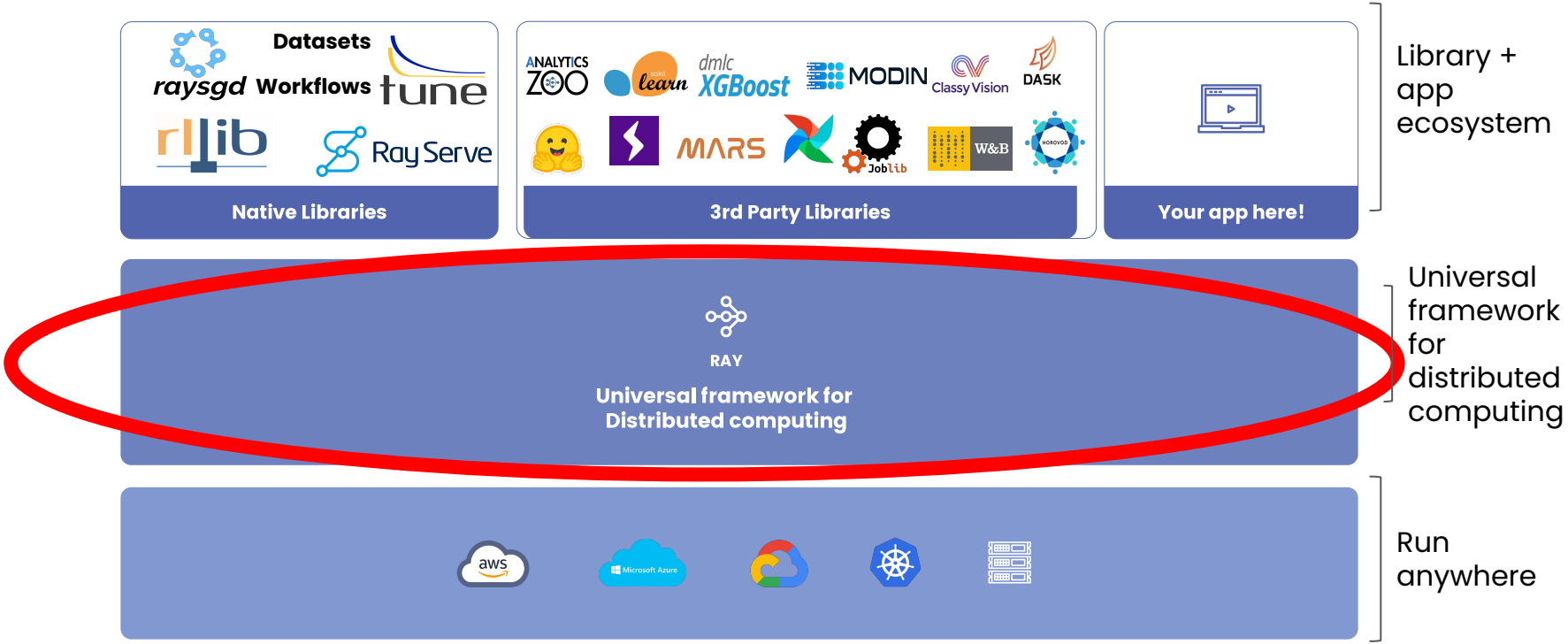
18.7K stars as of 1/1/22

What is Ray? 

- A simple/general library for distributed computing
- An ecosystem of Python libraries (for scaling ML and more)
- Runs on laptop, public cloud, K8s, on-premise

A layered cake of functionality and capabilities for scaling ML workloads

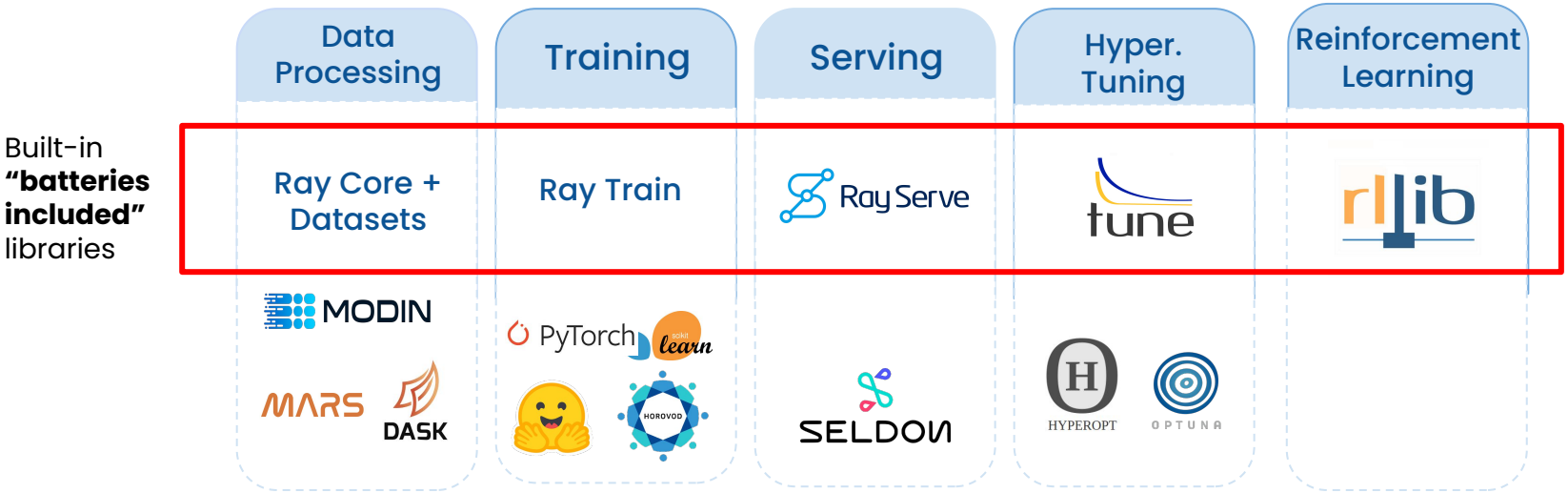
The Ray Layered Cake and Ecosystem



RAY

anyscale

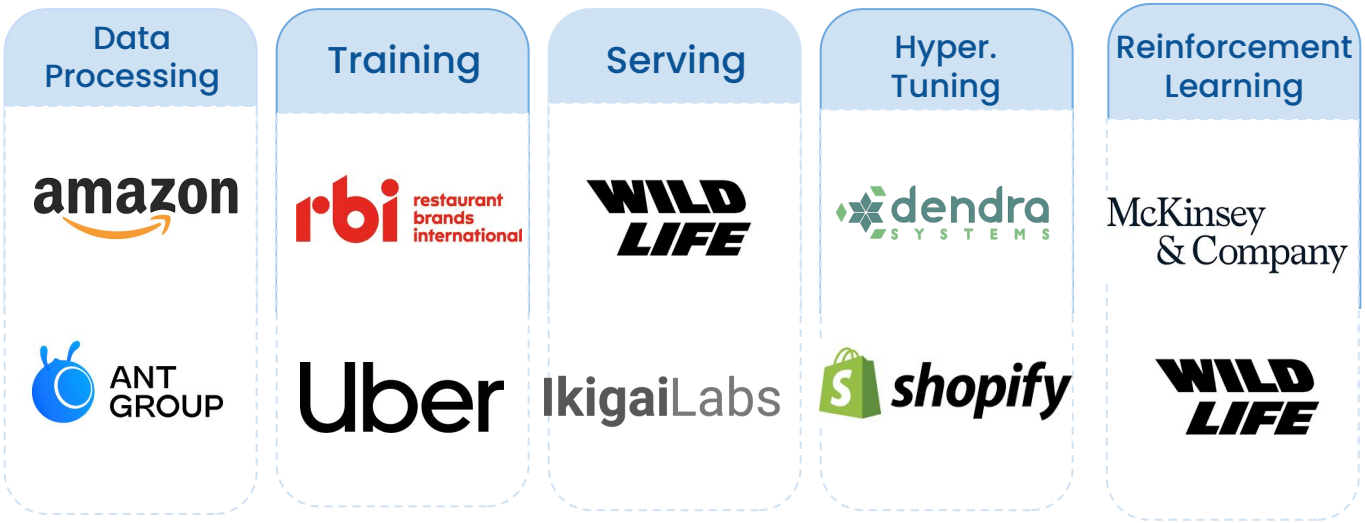
Rich ecosystem for scaling ML workloads



Only use the libraries you need!

Companies scaling ML with Ray

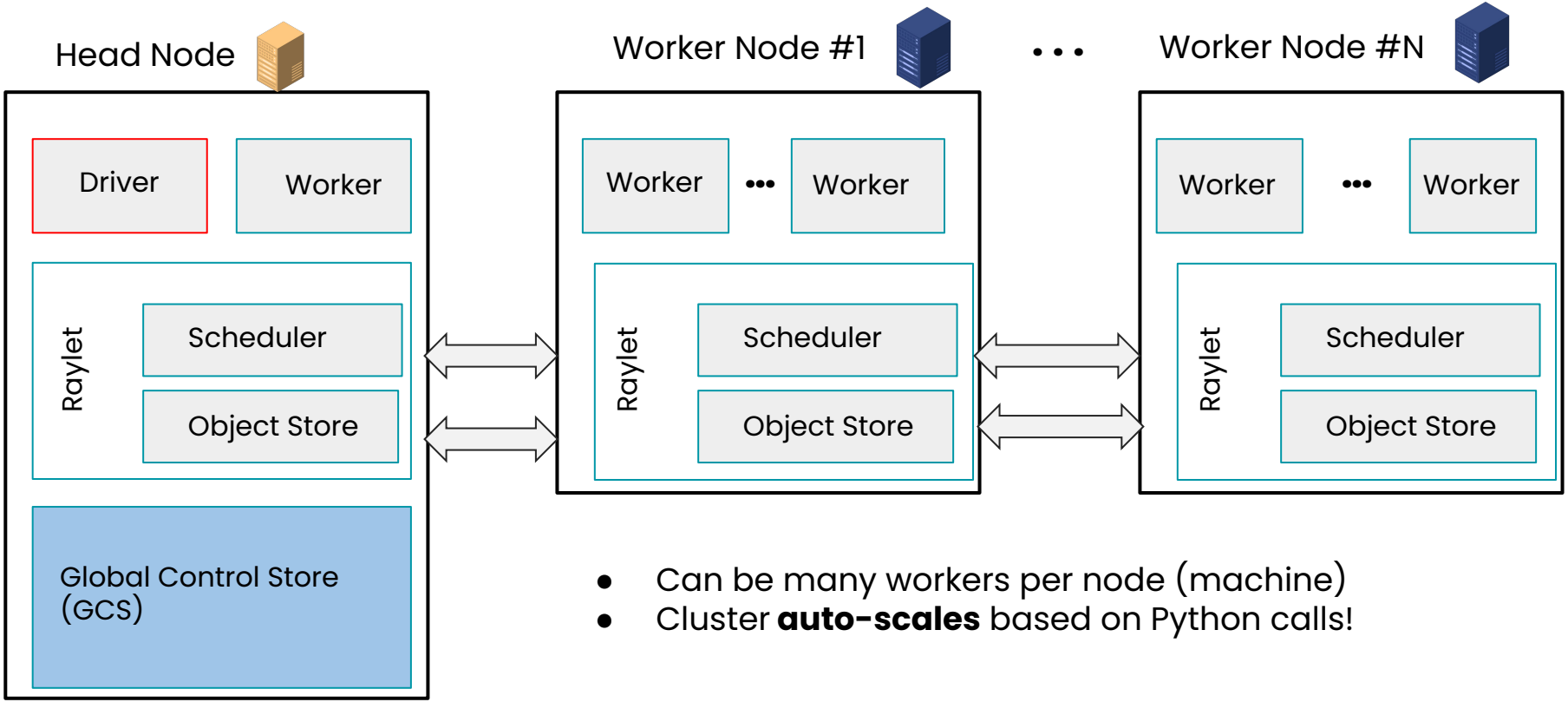
Companies scaling ML with Ray



- 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

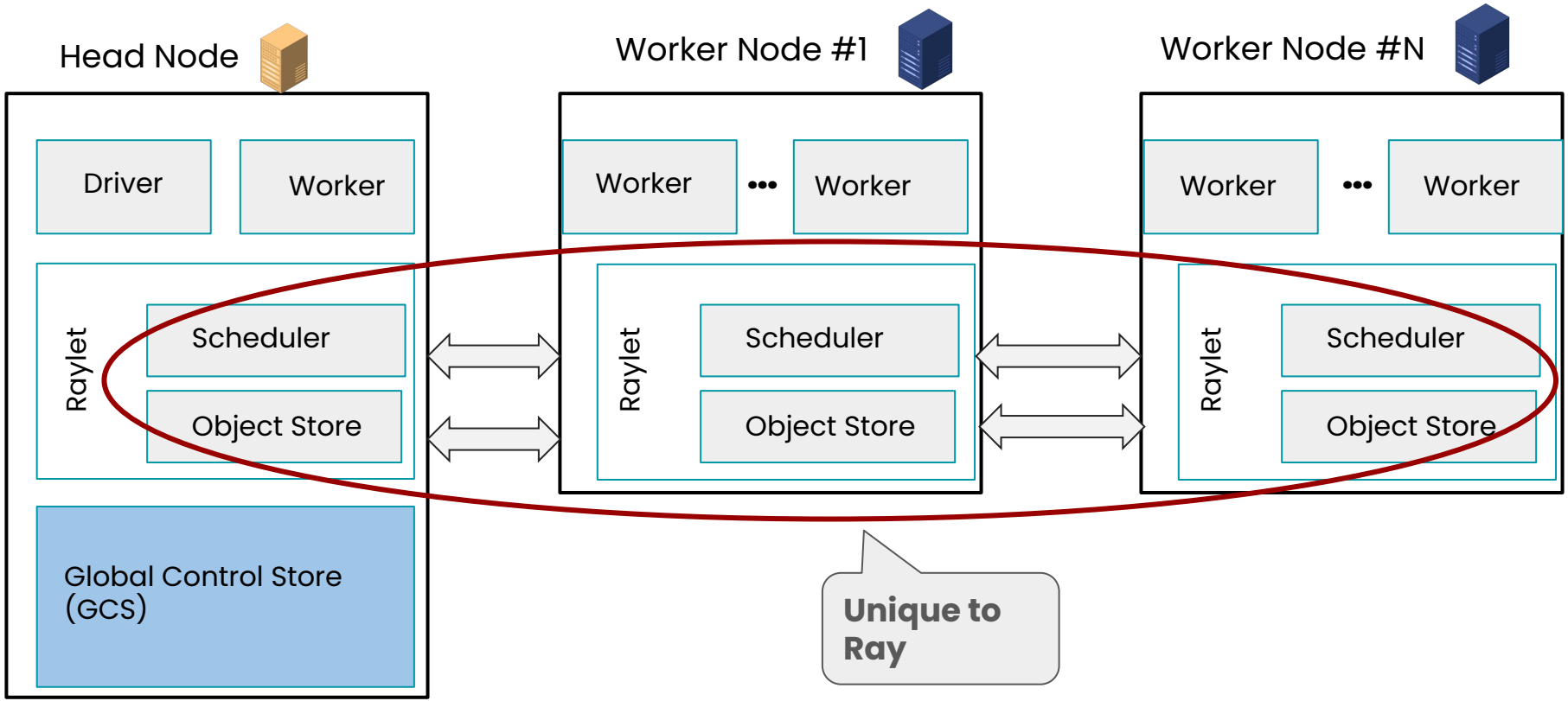
Ray Architecture & Components

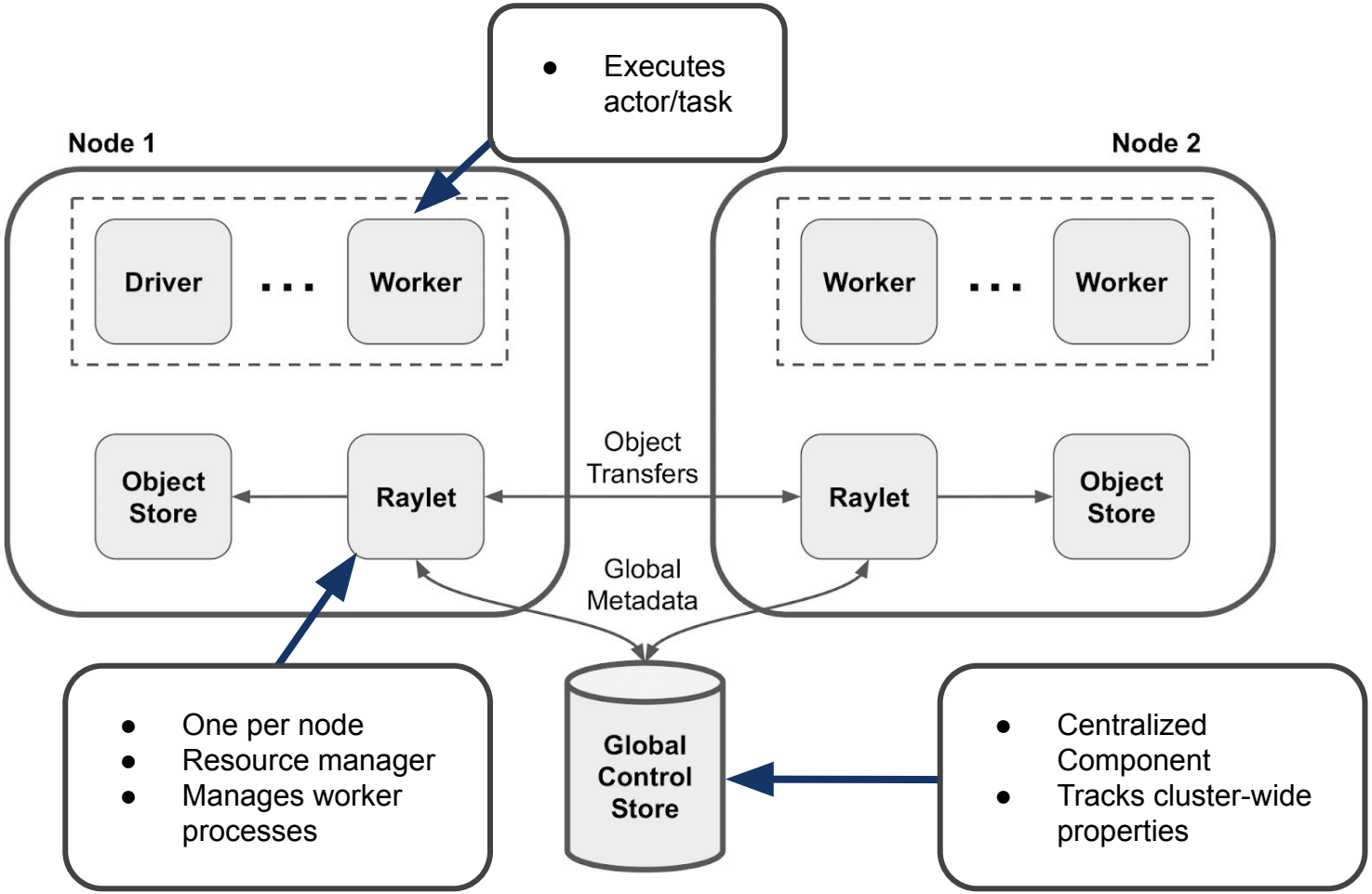
Anatomy of a Ray cluster



- Can be many workers per node (machine)
- Cluster **auto-scales** based on Python calls!

Anatomy of a Ray cluster

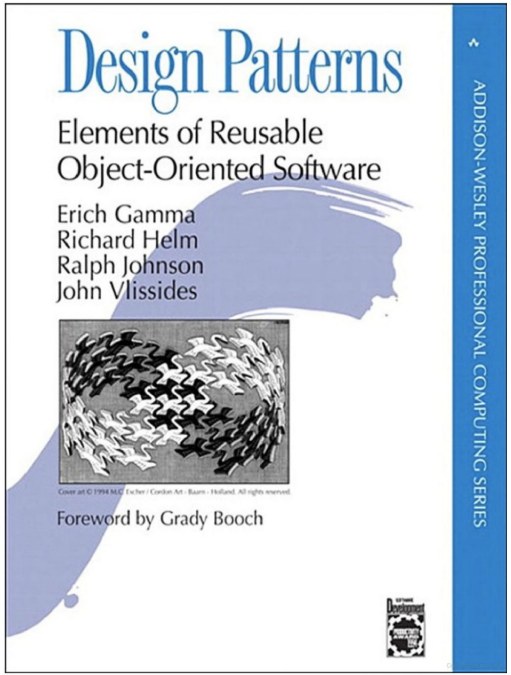



Executes actor/task
Node 1
Node 2
Driver
Worker
Worker
Worker
Object Store
Raylet
Object Transfers
Raylet
Object Store
Global Metadata
One per node
Resource manager
Manages worker processes
Global Control Store
Centralized Component
Tracks cluster-wide properties

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
3. Ray Distributed Library Integration Patterns

Python → Ray Basic Patterns

Function → Task → Node

Class → Actor → Node

Object → (Distributed immutable) Object → Node

RAY

anyscale

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

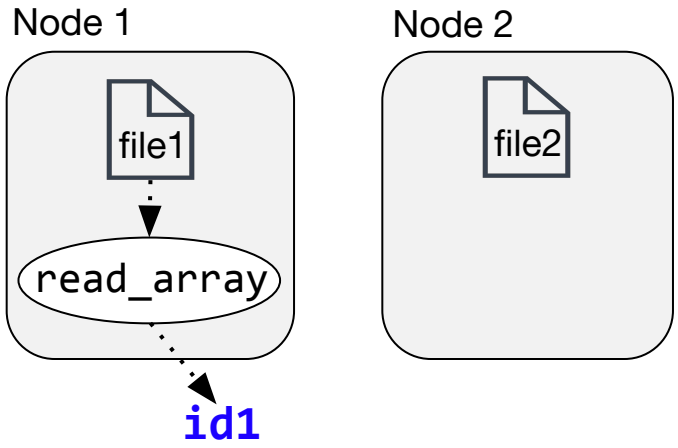
```
@ray.remote(num_gpus=1)
class Counter(object):
    def __init__(self):
        self.value = 0
    def inc(self):
        self.value += 1
        return self.value

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

anyscale

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)
sum = ray.get(id)
```

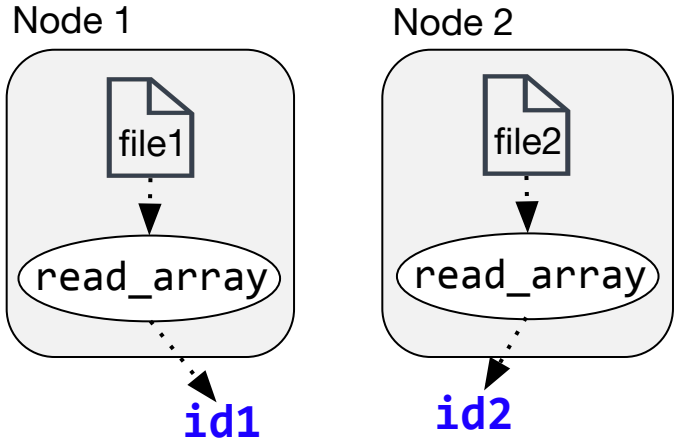


Return id1 (future) immediately, before **read_array()** finishes

Task API

```
@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)
```

Blue variables are Object IDs (similar to futures)

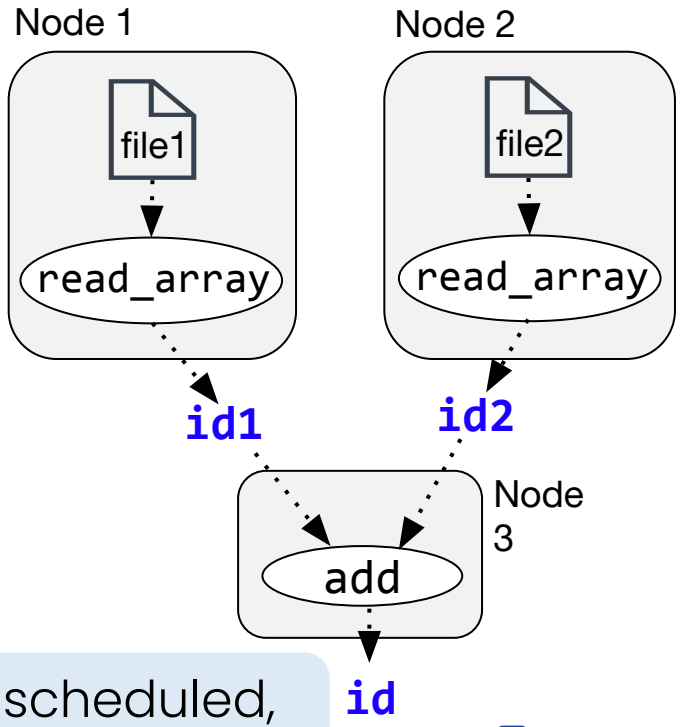


Dynamic task graph: build at runtime

Task API

```
@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)
```

Blue variables are Object IDs (similar to futures)



Every task scheduled, but not finished yet

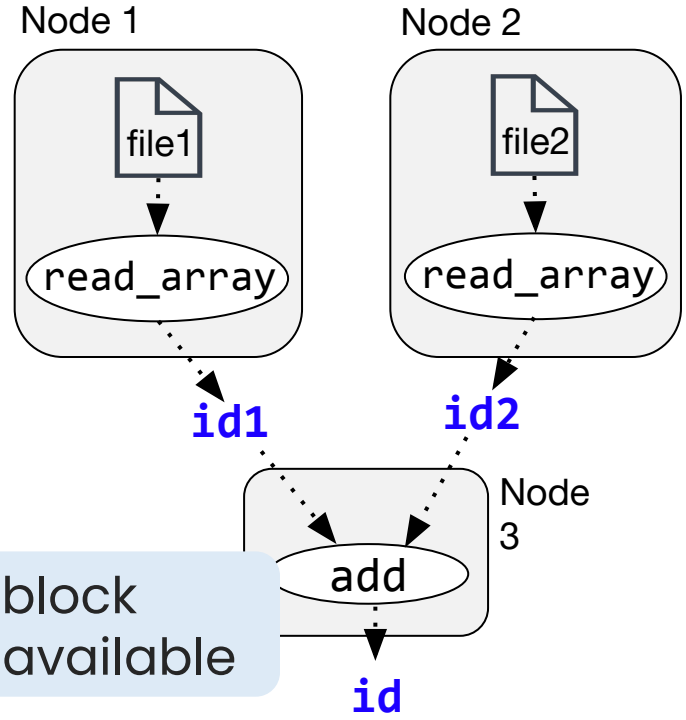
anyscale

Task API

Blue variables are Object 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)
sum = ray.get(id)
```

ray.get() block until result available

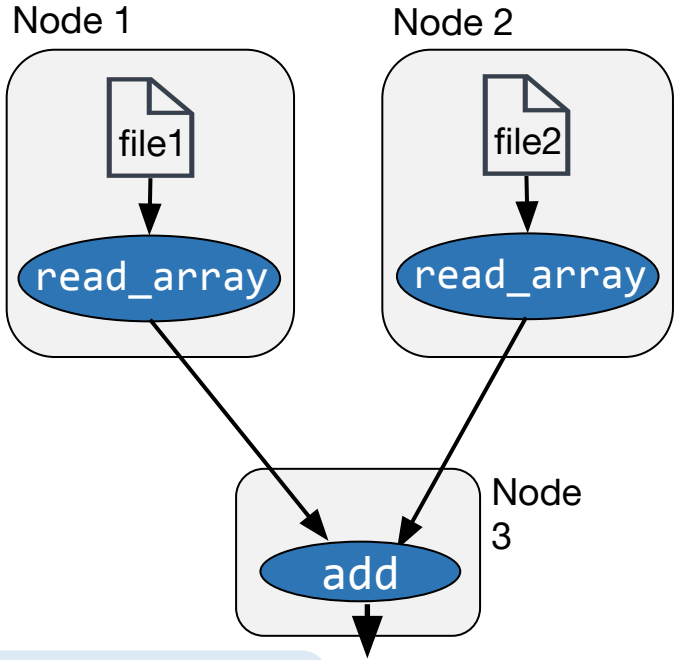


anyscale

Task API

```
@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)
```

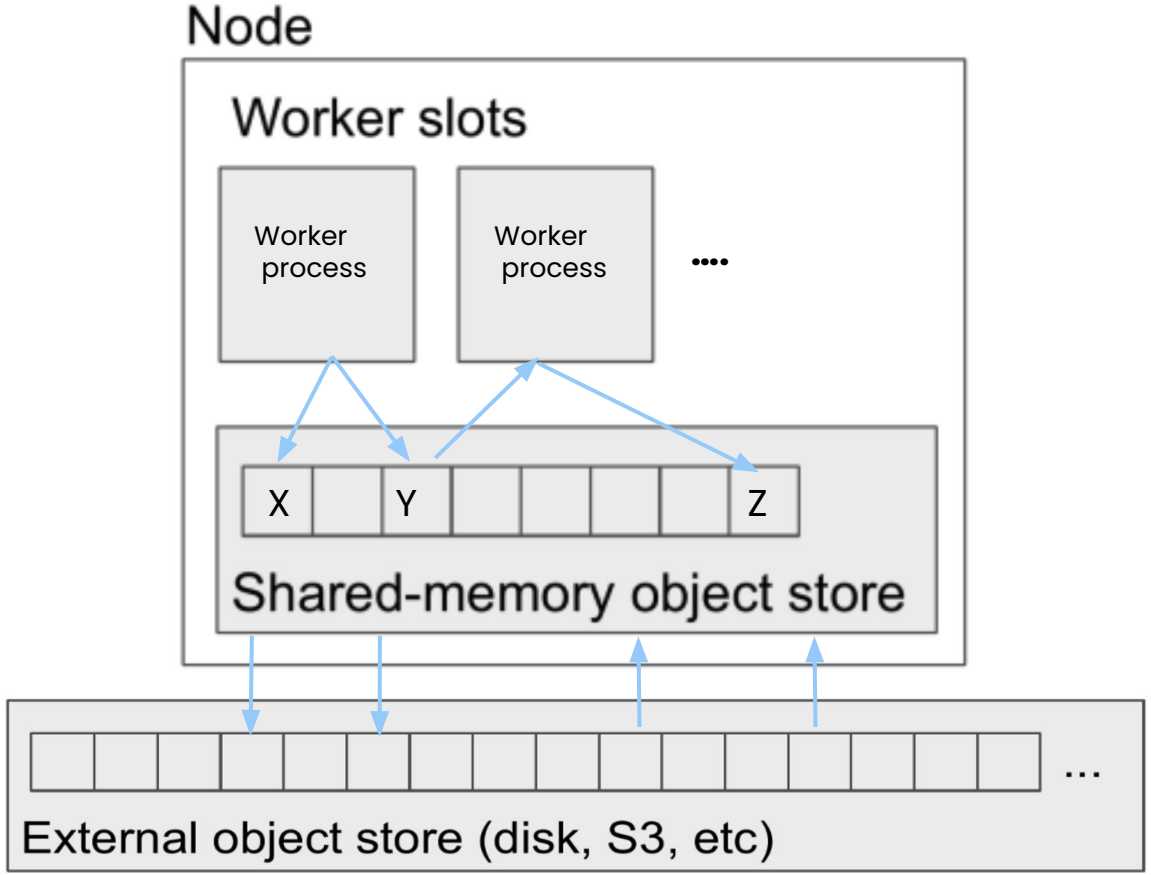
Blue variables are Object IDs (similar to futures)



Task graph executed to compute `sum`

anyscale

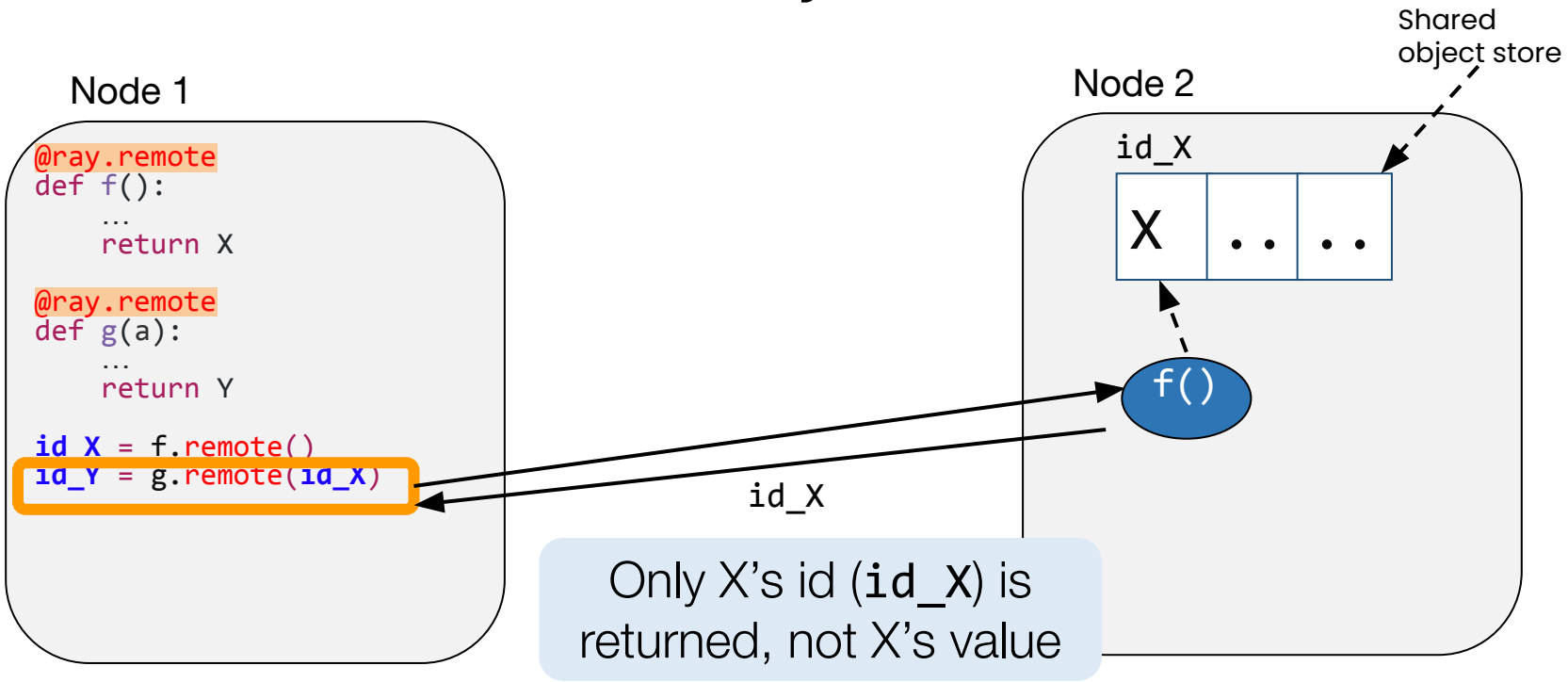
Distributed Immutable object store



Spill over to external storage

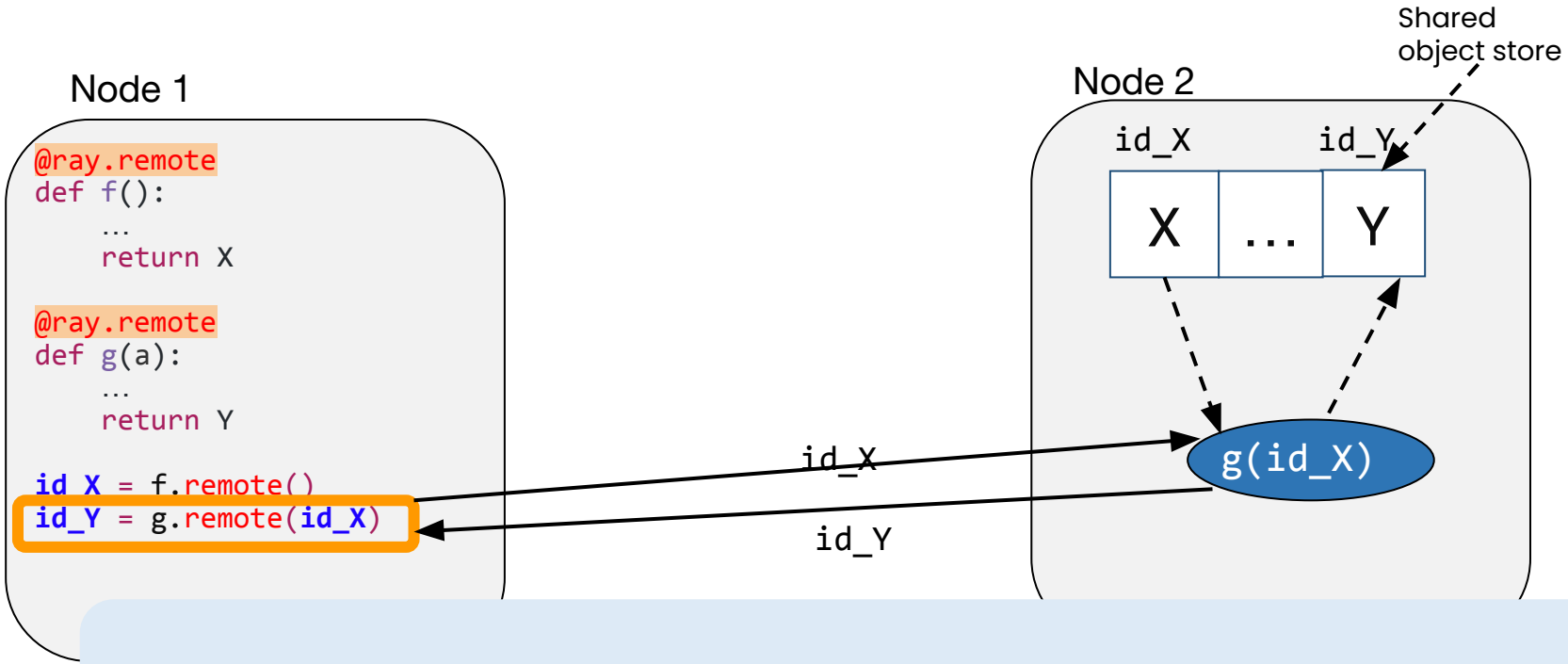
anyscale

Distributed Immutable object store



anyscale

Distributed object store

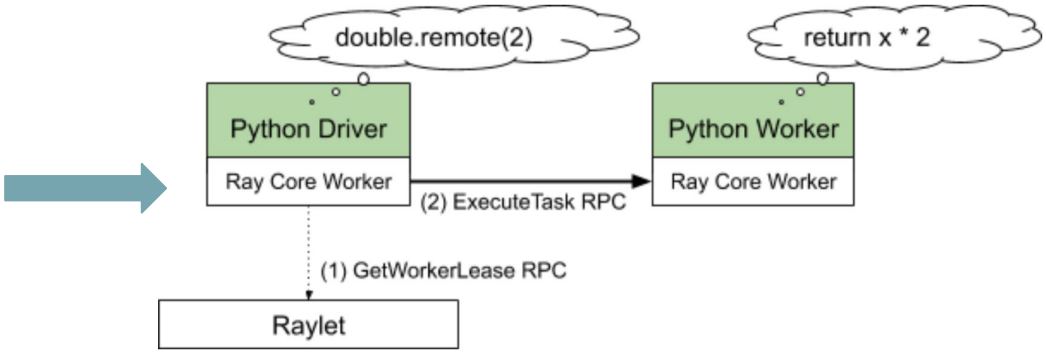


`g(id_X)` is scheduled on same node, so `X` is never transferred

How Raylet Schedules Tasks

Basic Ray Task Call

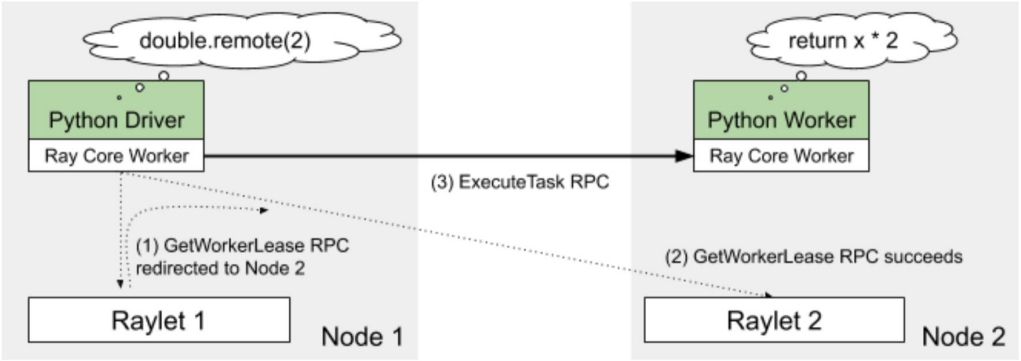
```
@ray.remote
def double(x):
    return x * 2


fut1 = double.remote(2)
assert ray.get(fut1) == 4
```



Components in green boxes represent Python code. Components in white boxes are part of the Ray common runtime written in C++. Joined boxes represent a process. Any Python driver or worker can call into the Ray C++ core worker library to execute further tasks. In this figure, all processes are running on the same machine. Ray uses gRPC as a unified communication layer for both local and remote procedure calls.

Scaling to Multiple Nodes

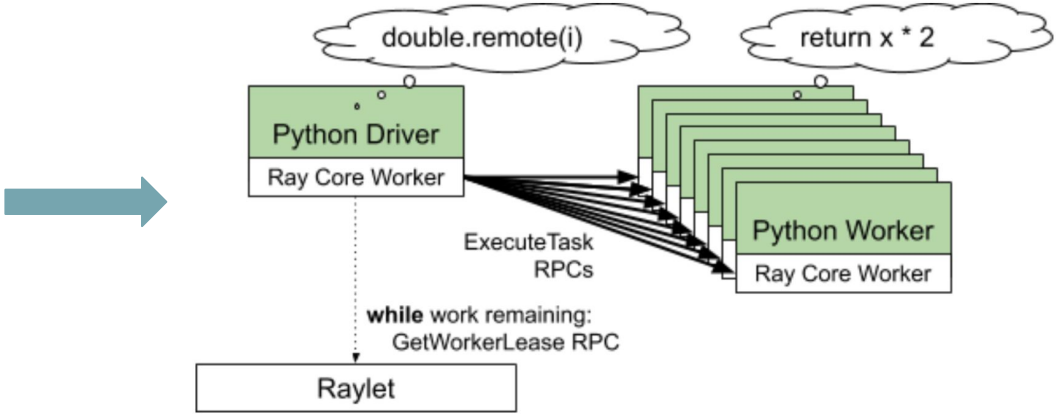
1. The driver asks Raylet 1 for a worker to execute `double`. It has no free workers, but Raylet 1 knows Raylet 2 has free resources, and redirects the request to Raylet 2.
2. The driver sends ExecuteTask to the remote Python worker leased from Raylet 2 over gRPC.



Tasks are sent to remote workers if there are no local resources available, transparently scaling Ray applications out to multiple nodes.

Caching Scheduling Decisions

```
futures = [double.remote(i)
for i in range(10000)]
ray.get(futures)

# [0, 2, 4, 6 ...]
```



Once a scheduling decision is made by the Raylet, the worker returned can be reused for other tasks with the same resource requirements and input dependencies. This amortizes scheduling RPC overhead when executing many similar tasks. To avoid unfair monopolization of workers when there are multiple processes trying to submit tasks, callers are only allowed to reuse workers within a few hundred milliseconds of initial grant.

Takeaways

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

Start learning Ray and contributing …

Getting Started: `pip install ray`

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

Join Ray Meetup
Revived in Jan 2022. Next meetup March 2nd.
Meetup each month and 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

Tutorials

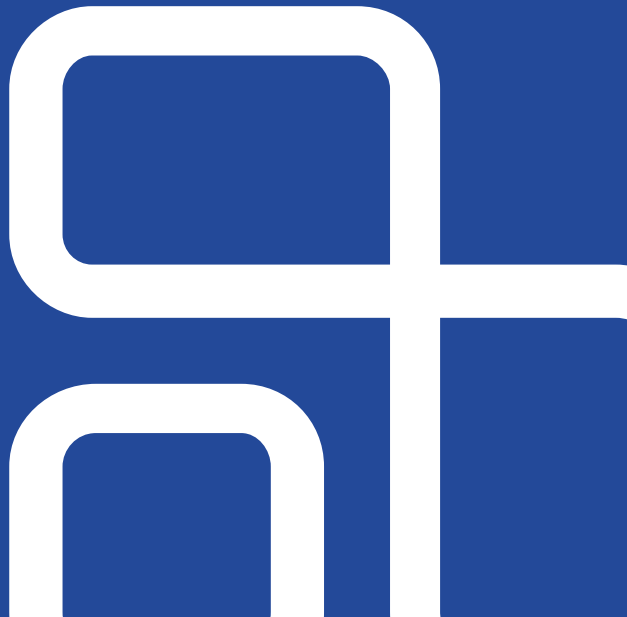
https://tinyurl.com/pycon-ray-tutorial

Thank you!

Let's stay in touch:

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

@2twitme



anyscale