Introduction to Ray for distributed and machine learning applications in Python

Jules S. Damji - @2twitme

April 26, 2023, Seattle, WA

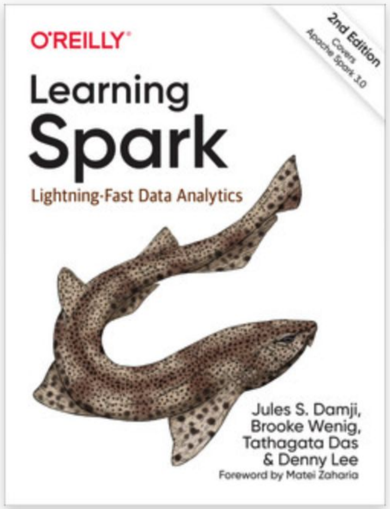
Few Important URLs

Keep these URLs open in your browser tabs

→ Ray Core Class Survey: https://bit.ly/pydata-seatte-2023
→ GitHub: https://bit.ly/pydata-seattle-tutorial-2023
→ Ray Documentation: https://bit.ly/ray-core-docs

$whoami

- Lead Developer Advocate, Anyscale & Ray Team
- Sr. Developer Advocate, Databricks, Apache Spark/MLflow Team
- Led Developer Advocacy, Hortonworks
- Held Software Engineering positions:
  - Sun Microsystems
  - Netscape
  - @Home
  - Loudcloud/Opsware
  - Verisign



Who we are: Original creators of Ray

What we do: Unified compute platform to develop, deploy, and manage scalable AI & Python applications with Ray

Why do it: Scaling is a necessity, scaling is hard; make distributed computing easy and simple for everyone

Agenda

- Why & What’s Ray & Ray Ecosystem
- Ray Architecture & Components
- Ray Core Design & Scaling Patterns & APIs
- Modules [1] Hand-on in class
- Modules [2-3] Extra Curriculum at home

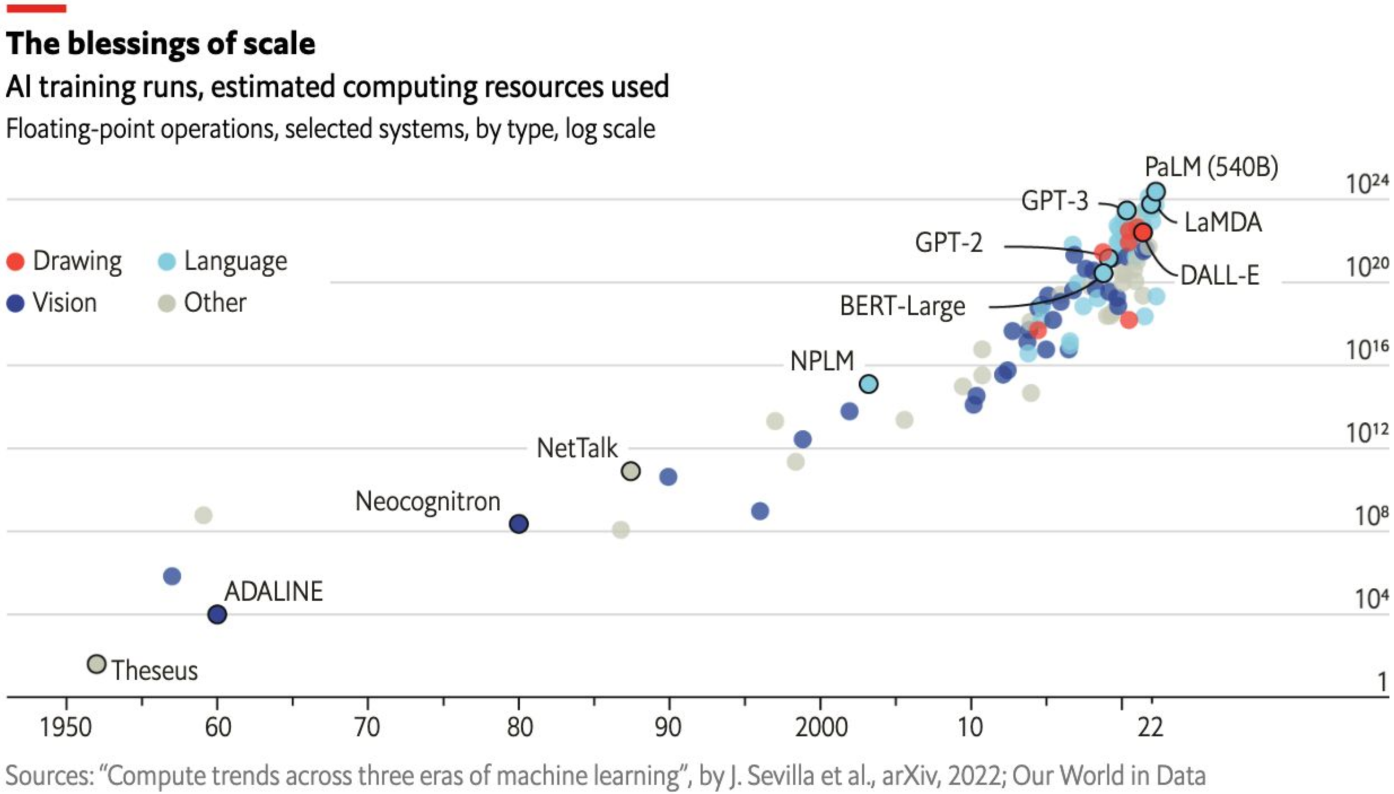
Why Ray

Machine learning is pervasive

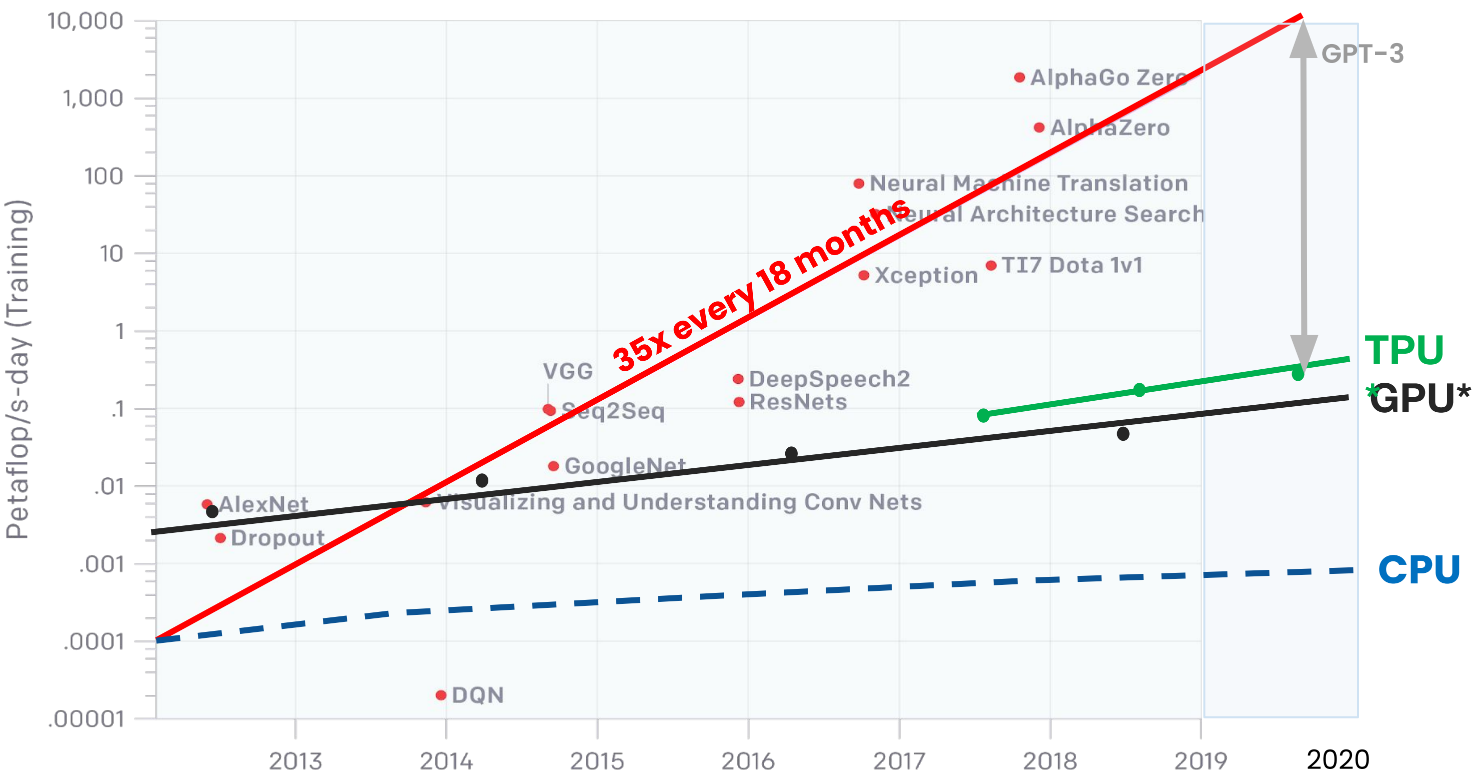
Distributed computing is a necessity

Python is the default language for DS/ML

Blessings of scale …

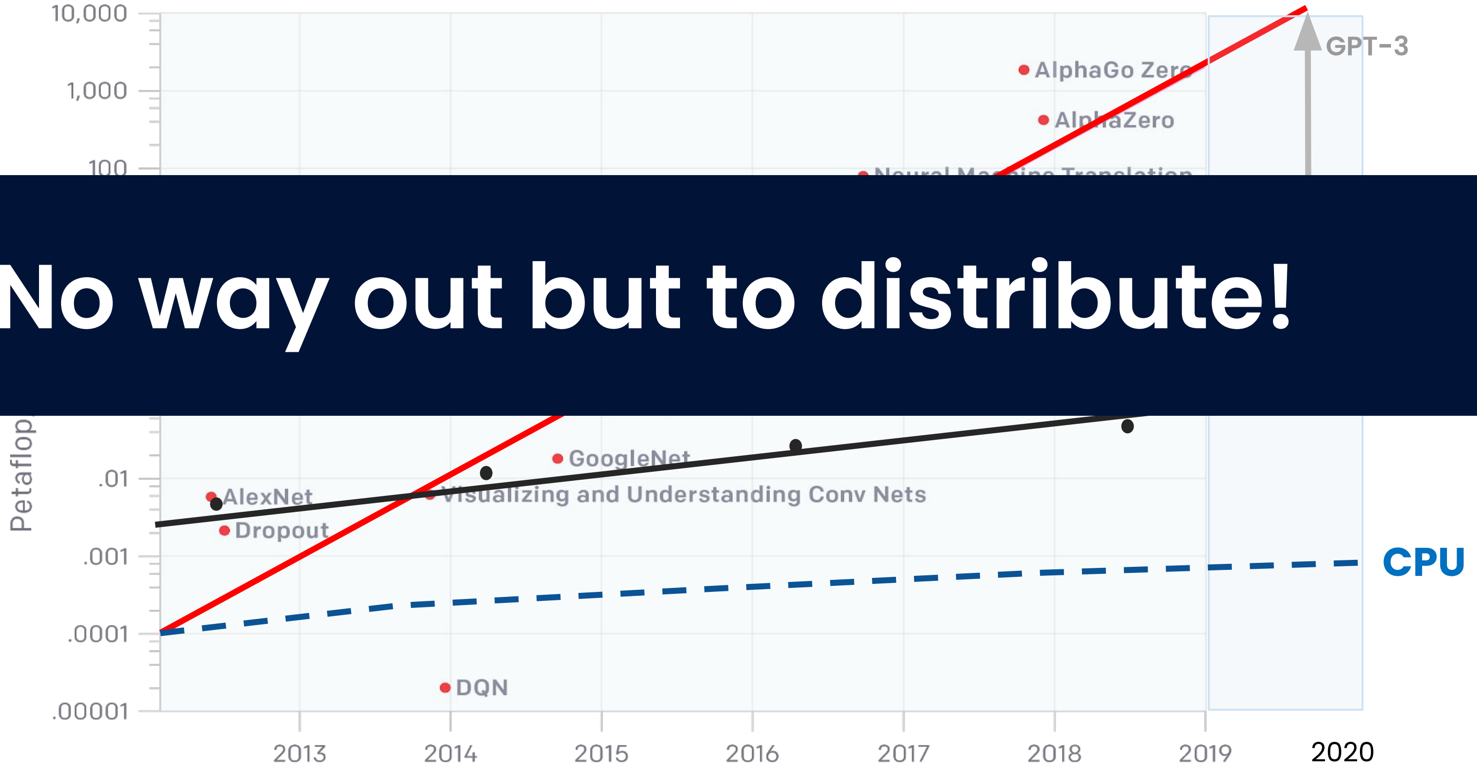


Compute - supply demand problem



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

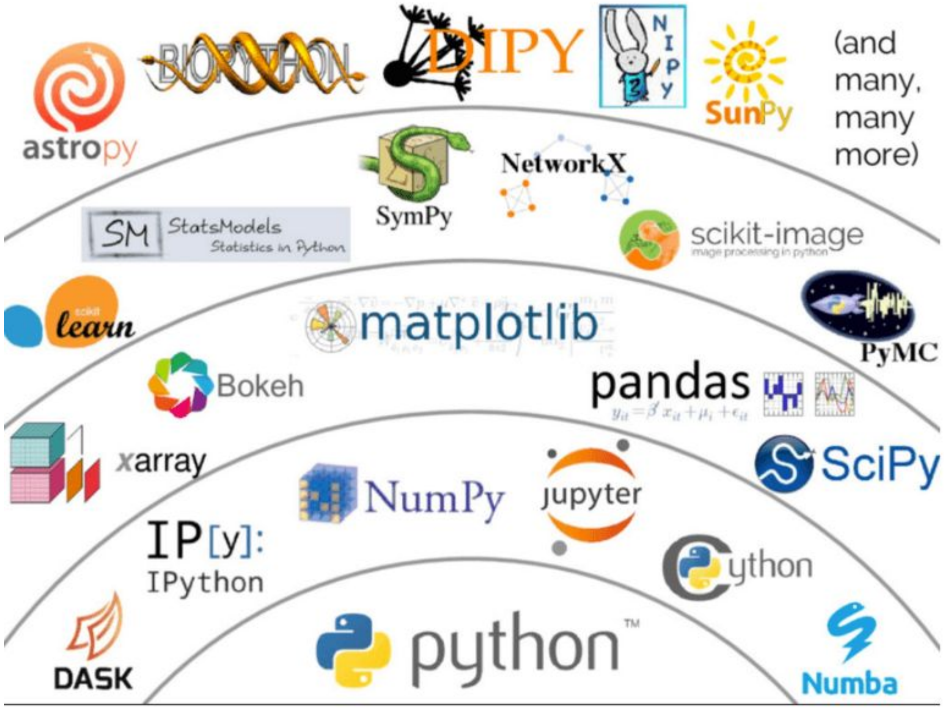
Specialized hardware is not enough



No way out but to distribute!

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

Python data science ecosystem

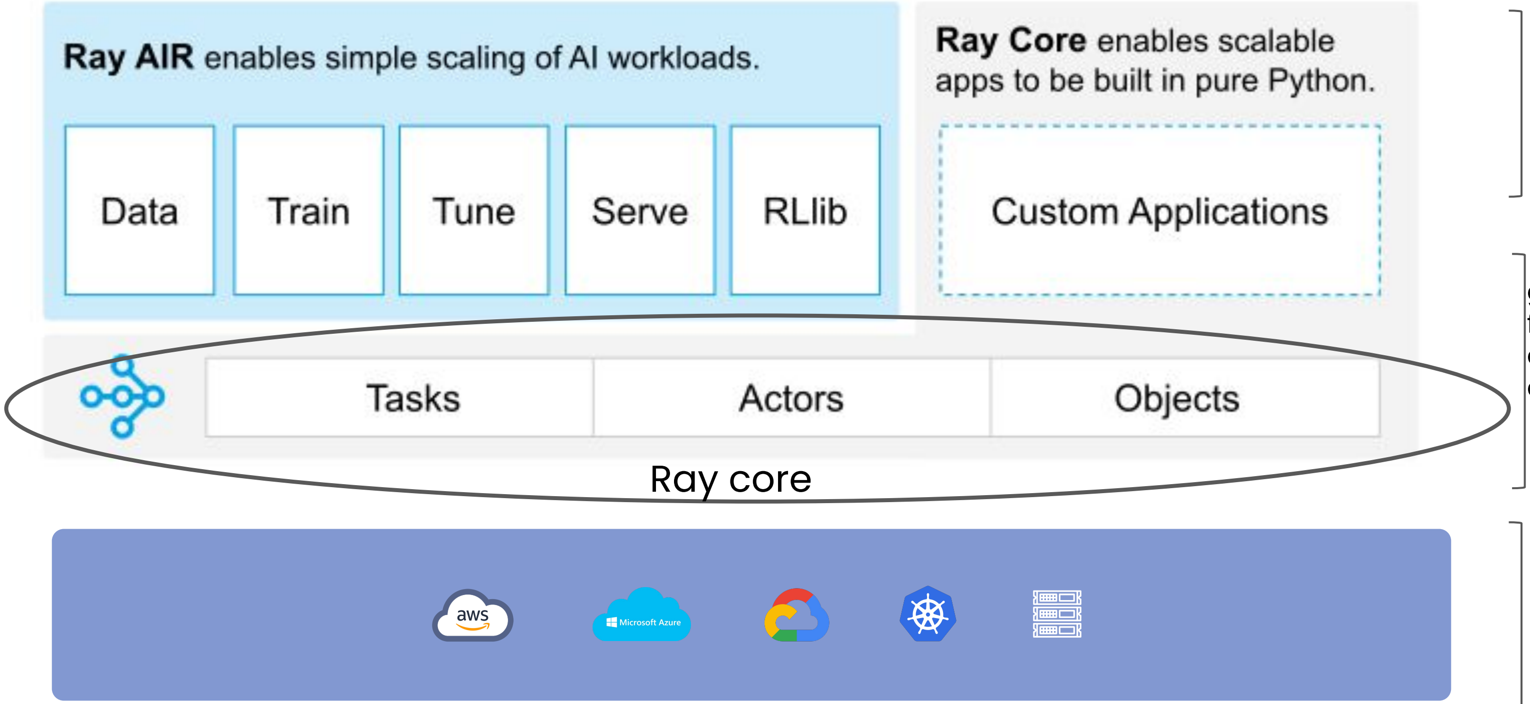


What is Ray

- A ***simple/general-purpose*** 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

A Layered Cake and Ecosystem

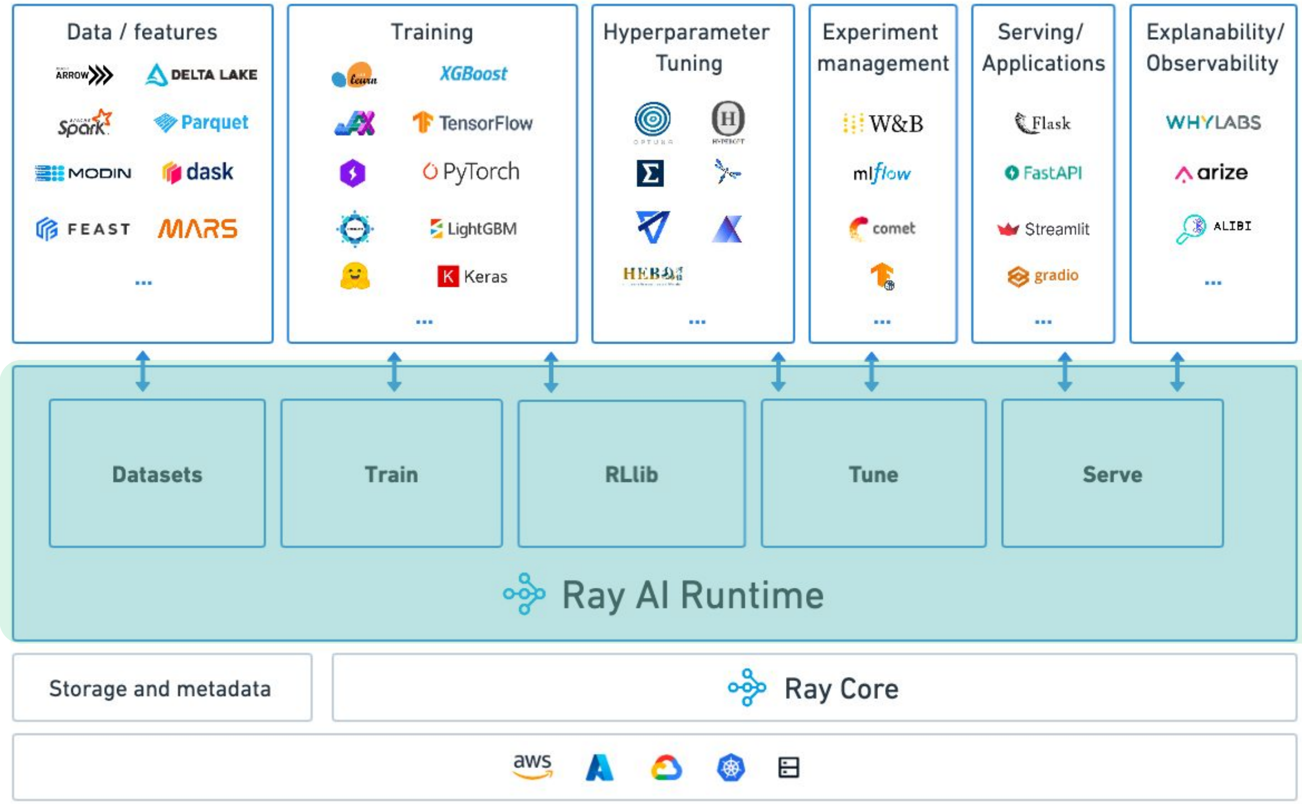


Library + app ecosystem

general-purpose framework for distributed computing

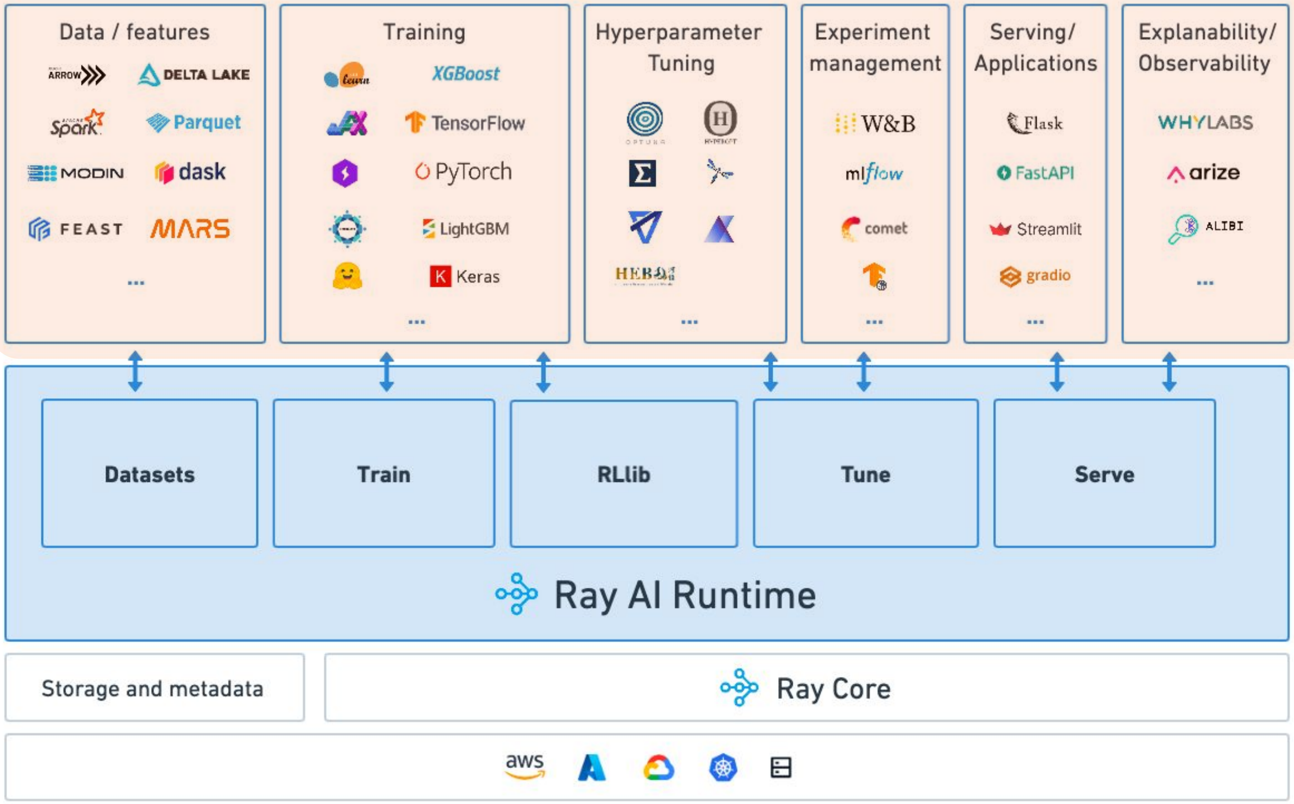
Run anywhere

Ray AI Runtime (AIR) is a scalable runtime for end-to-end ML applications



High-level libraries that make scaling easy for both data scientists and ML engineers.

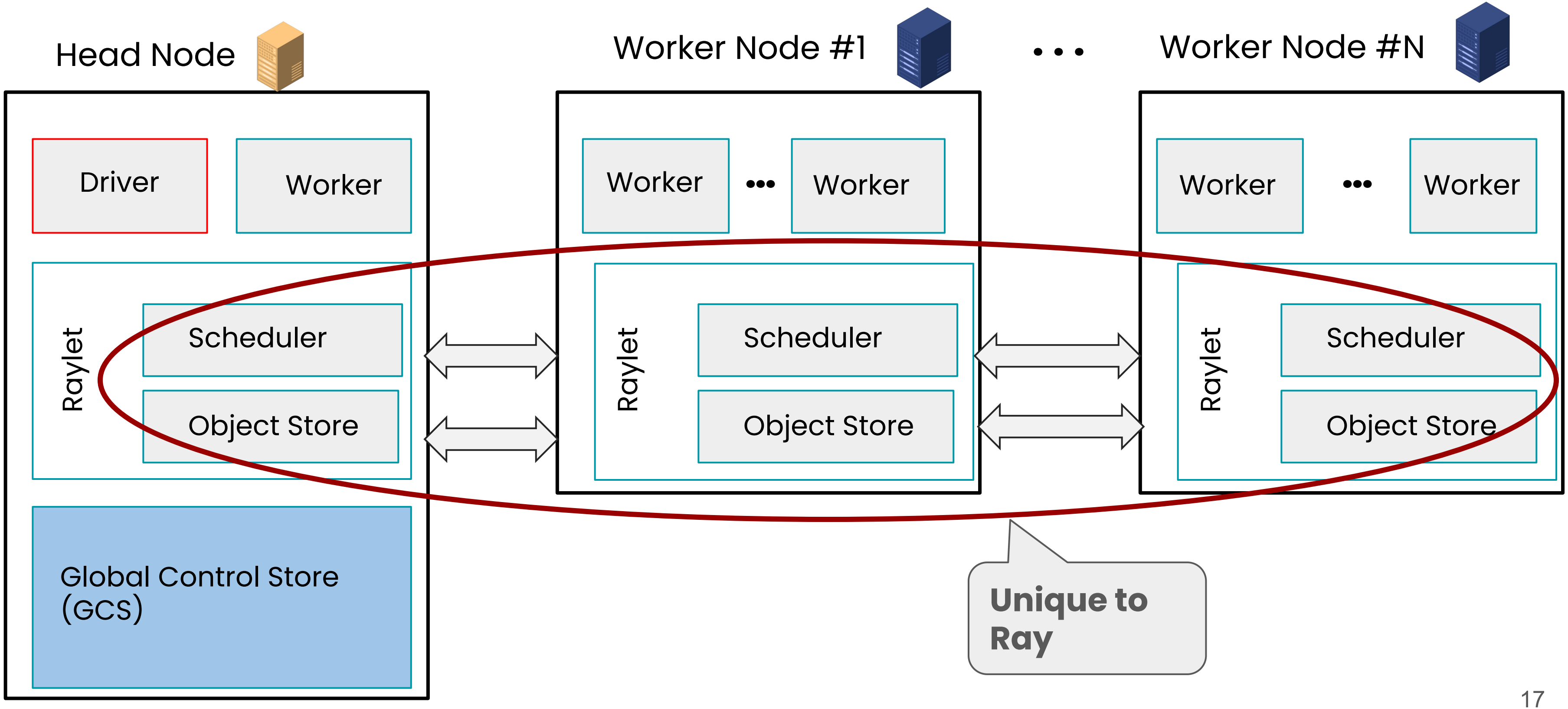
Ray AI Runtime (AIR) is a scalable toolkit for end-to-end ML applications



Scalable integrations with best-of-breed libraries/MLOps tools

Ray Architecture & Components

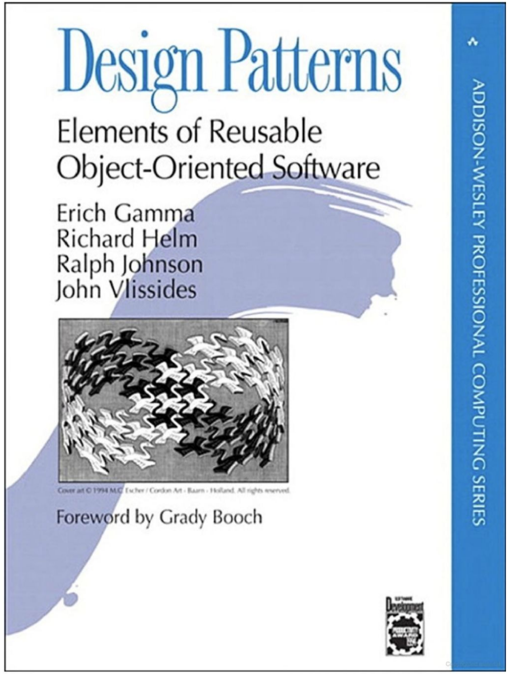
An anatomy of a Ray cluster



Ray distributed design & scaling patterns & APIs

Ray Basic Design Patterns

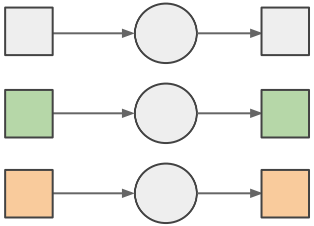
- Ray Parallel Tasks
  - Functions as stateless units of execution
  - Functions distributed across the cluster as tasks
- Ray Objects as Futures
  - Distributed (immutable objects) store in the cluster
  - Fetched when materialized
  - Enable massive asynchronous parallelism
- Ray Actors
  - Stateful service on a cluster
  - Enable Message passing



1. Patterns for Parallel Programming
2. Ray Design Patterns
3. Ray Distributed Library Integration Patterns

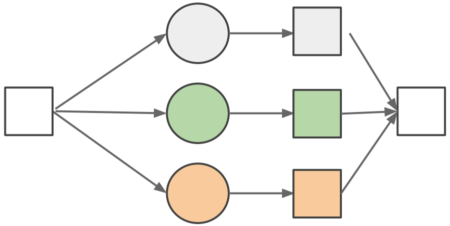
Scaling Design Patterns

Batch Training / Inference



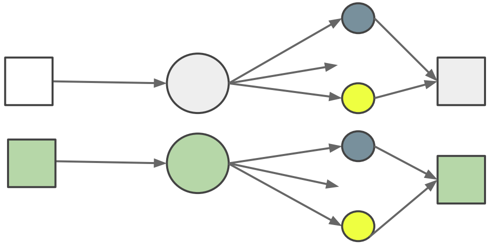
Different data / Same function

AutoML

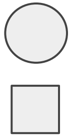


Same data / Different function

Batch Tuning



Different data / Same function /



Compute

Data

Python → Ray APIs

```
def f(x):
   # do something with
x:
   y = …
   return y
```

Task

```
@ray.remote
def f(x):
   # do something with
x:
   Y = …
   return y
f.remote()
```

Distributed

f() Node ••• f() Node

```
class Cls():
  def
__init__(self, x):
  def f(self, a):
      …
  def g(self, a):
      …
```

Actor

```
@ray.remote
class Cls():
  def __init__(self,
x):
  def f(self, a):
      …
  def g(self, a):
      …
cls = Cls.remote()
cls.f.remote(a)
```

Distributed

Cls Node ••• Cls Node

```
import numpy as np
a= np.arange(1, 10e6)
b = a * 2
```

Distributed immutable object

```
import numpy as np
a = np.arange(1, 10e6)
obj_a = ray.put(a)
b = ray.get(obj_a) * 2
```

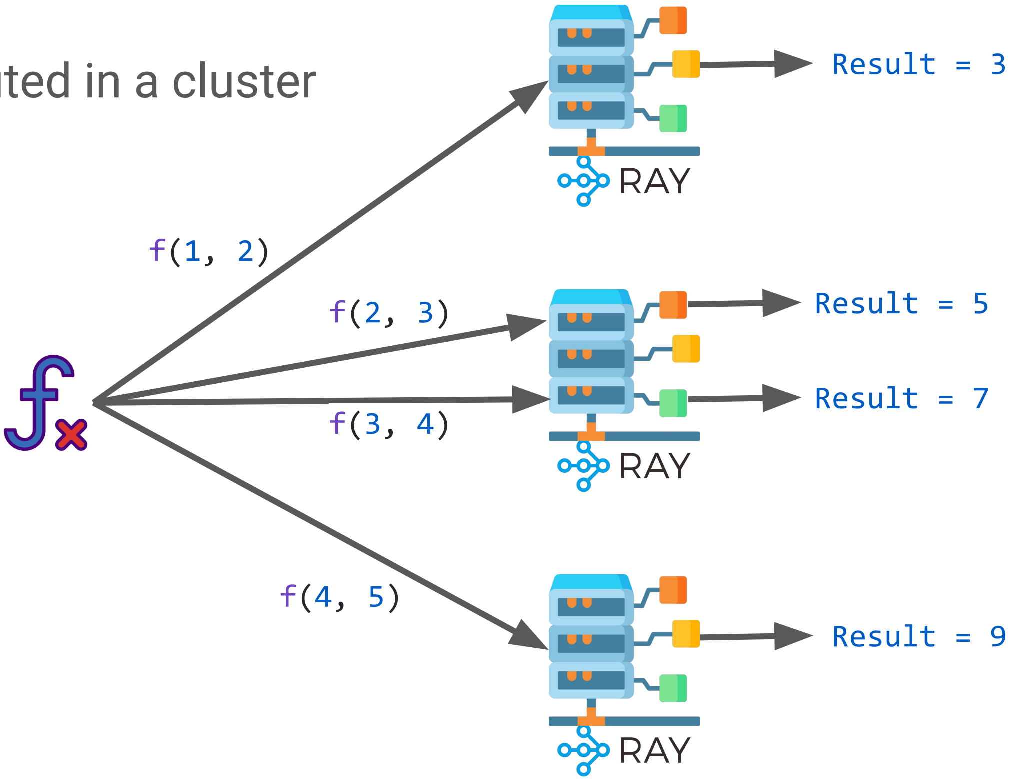
Distributed

a Node ••• a Node

Ray Task

A **function** remotely executed in a cluster

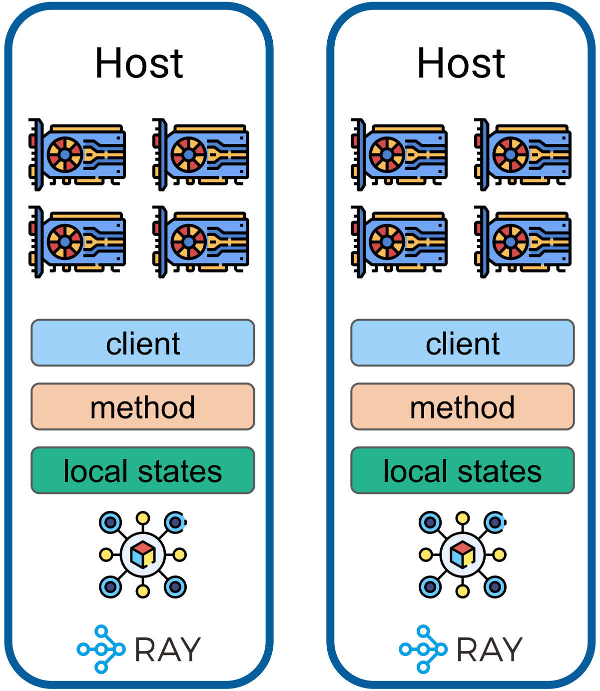
```python
@ray.remote(num_cpus=2)
def f(a, b):
    return a + b

f.remote(1, 2) # returns 3
```



Ray Actor

A **class** remotely executed in a cluster

```python
@ray.remote(num_gpus=4)
class HostActor:
    def __init__(self):
        self.num_devices = os.environ["CUDA_VISIBLE_DEVICES"]

    def f(self, output):
        return f"{output} {self.num_devices}"


actor = HostActor.remote()  # Create an actor
actor.f.remote("hi")  # returns "hi 0,1,2,3"
```



Function → Task

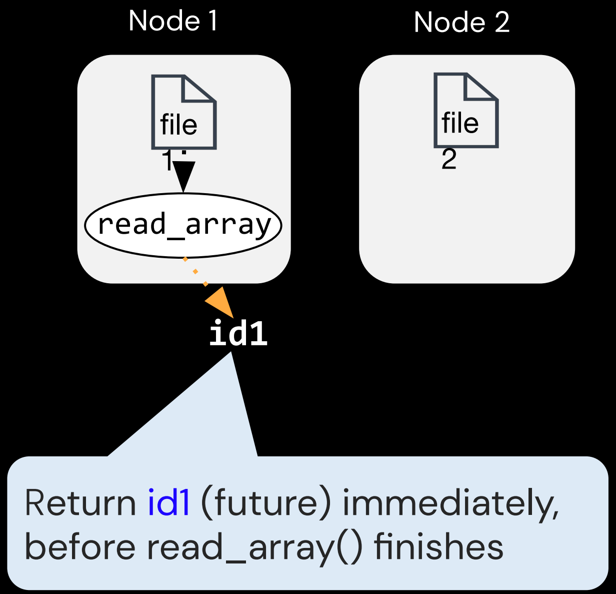
Class → Actor

```python
@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)
```

```python
@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()
```

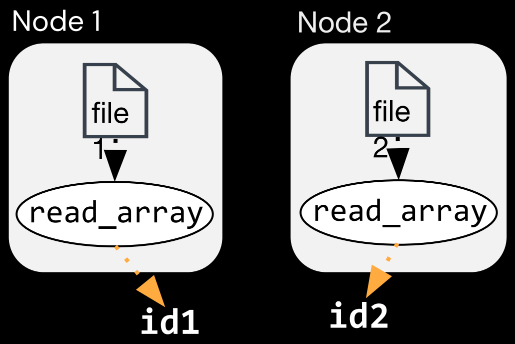
Task API

```
@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)
```



Task API

```python
@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)
```

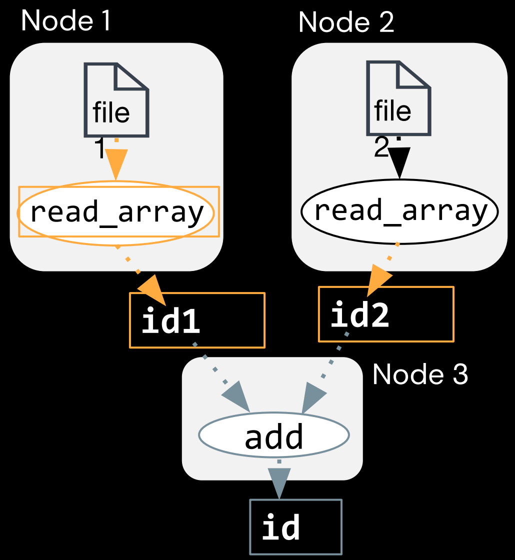


Dynamic task graph: build at runtime

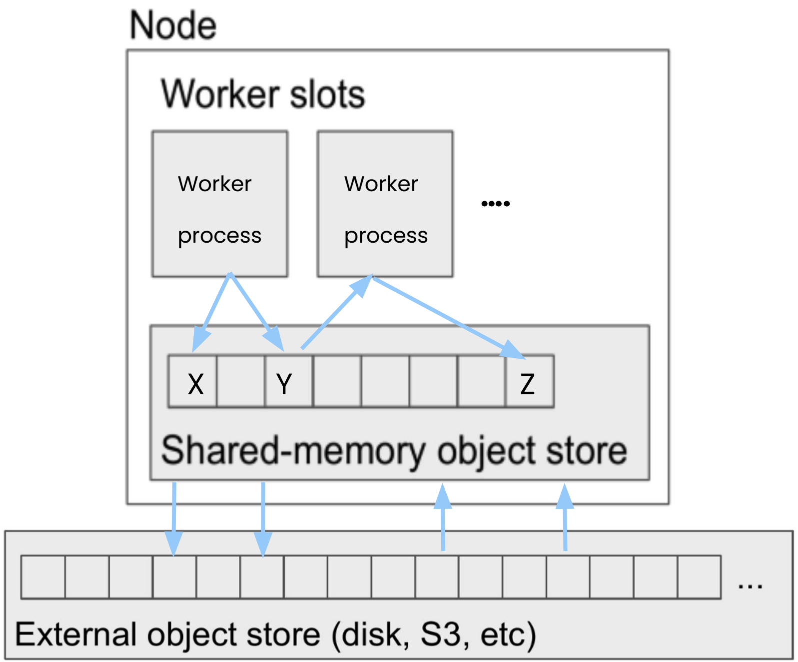
Task API

```
@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)
```

ray.get() block until result available

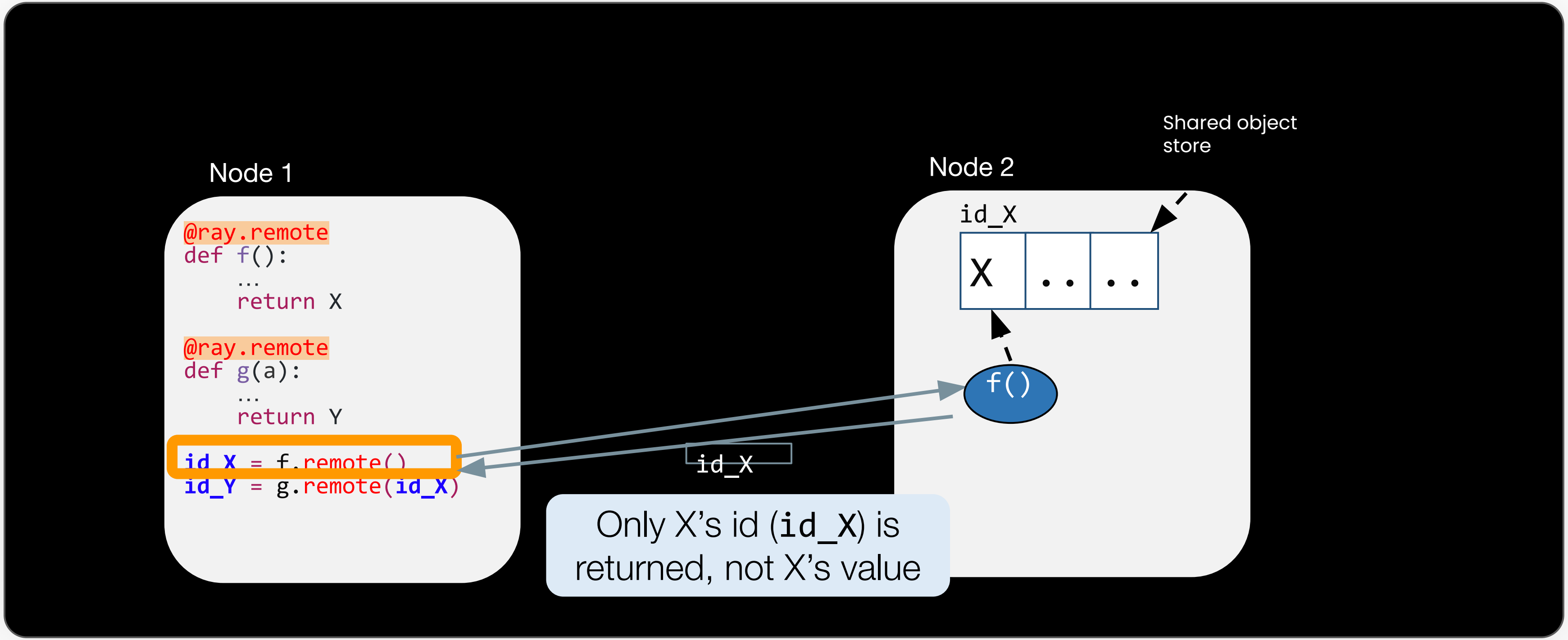


Distributed Immutable object store

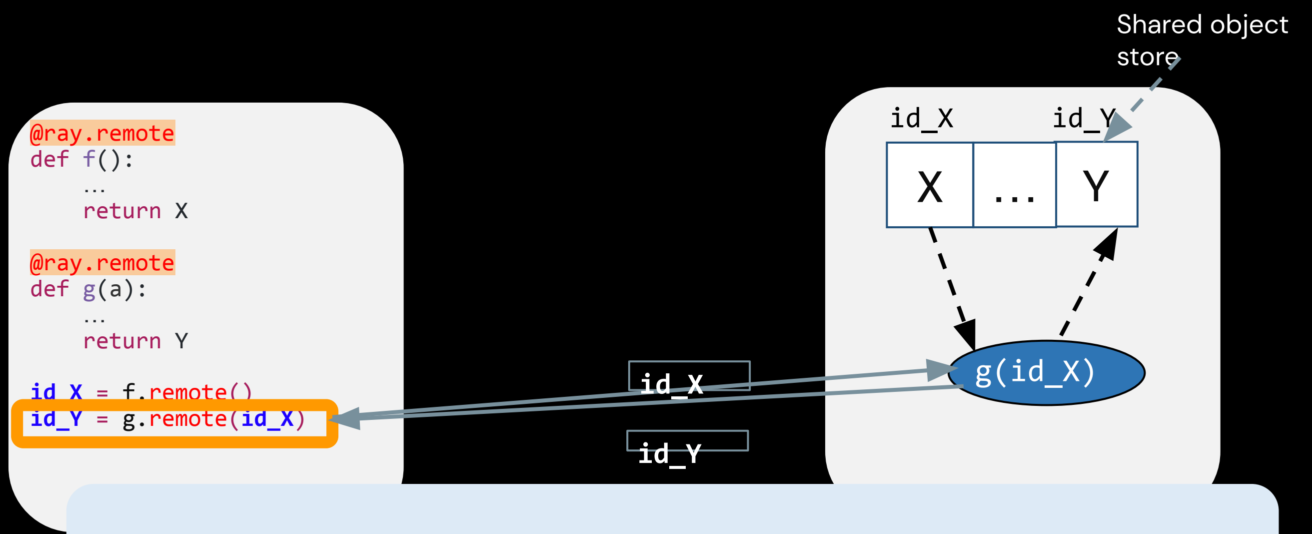


Spill over to external storage

Distributed object store



Distributed object store



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

Examples of Distributed Applications with Ray

Distributed Applications with Ray

ML Libraries

- Ray AI Runtime
- Distributed scikit-learn/Joblib
- Distributed XGBoost on Ray
- Ray Multiprocess Pool

All using Ray core APIs & patterns

Monitoring Services

- WhyLabs
- Arize AI
- W & B

All using Ray core APIs & patterns

ML Platforms & Integrations

- Merlin (Shopify)
- Meta (PyTorch)
- MLflow, Comet
- AirFlow, Prefect
- HuggingFace
- Pycaret
- Ludwig AI
- Uber
- Instacart
- Spotify

All using Ray core APIs & patterns

Ray Ecosystem: https://docs.ray.io/en/latest/ray-overview/ray-libraries.html

What model LLM stack for Generative AI?

What about Generative AI?

How Ray solves common production challenges for generative AI infrastructure

By Antoni Baum, Eric Liang, Jun Gong, Kai Fricke and Richard Liaw | March 20, 2023

This is part 1 of our generative AI blog series. In this post, we talk about how to use Ray to productionize common generative model workloads. An upcoming blog will deep dive into why projects like **Alpa** are using Ray to scale large models.

Training 175B Parameter Language Models at 1000 GPU scale with Alpa and Ray

By Jiao Dong, Hao Zhang, Lianmin Zheng, Jun Gong, Jules S. Damji and Phi Nguyen | March 22, 2023

This is part 2 of our generative AI blog series. Here we cover how Ray empowers large language models (LLM) frameworks such as Alpa. To learn how to use Ray to productionize generative model workloads, see **part 1**.

Faster stable diffusion fine-tuning with Ray AIR

By Kai Fricke | March 28, 2023

*This is part 3 of our generative AI blog series that dives into a concrete example of how you can use Ray to scale the training of generative AI models. To learn more using Ray to productionize generative model workloads, see **part 1**. To learn about how Ray empowers LLM frameworks such as Alpa, see **part 2**.*

How to fine tune and serve LLMs simply, quickly and cost effectively using Ray + DeepSpeed + HuggingFace

By Waleed Kadous, Jun Gong, Antoni Baum and Richard Liaw | April 10, 2023

This is part 4 of our blog series on Generative AI. In the previous blog posts we explained **why Ray is a sound platform for Generative AI, we showed how it can push the performance limits**, and **how you can use Ray for stable diffusion.**

Sample of Companies Who Use Ray in their Machine Learning Platform

RIDECELL
lyft
Uber
cruise
instacart

Meta
Google
OpenAI
Microsoft

ANT GROUP
shopify
amazon
STITCH FIX

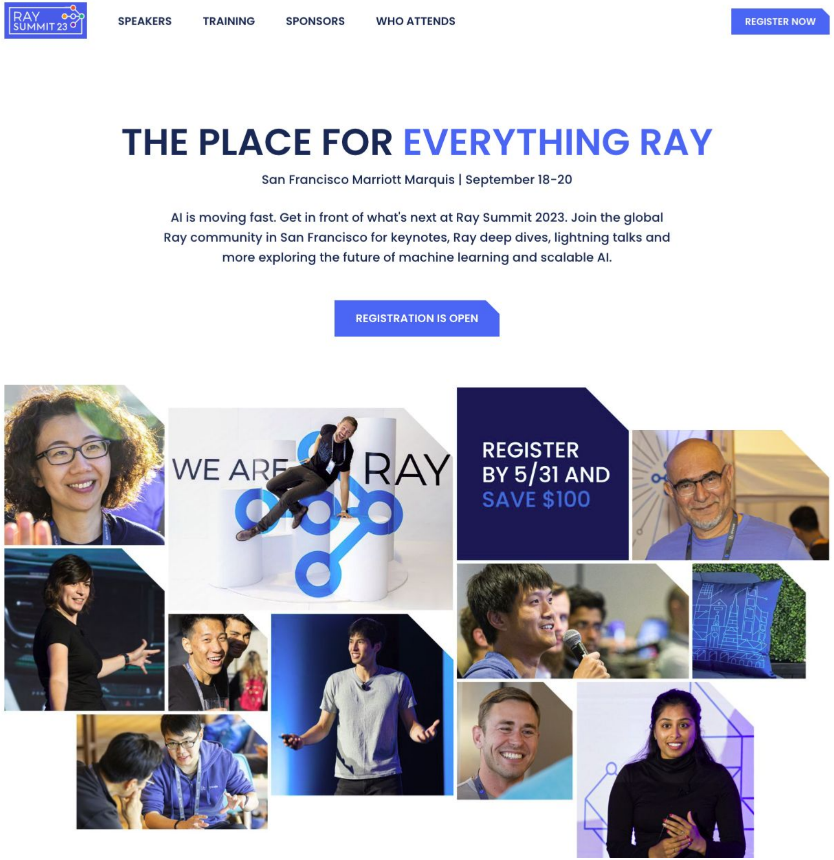
RIOT GAMES
NETFLIX
Spotify
ByteDance

DOW
intel
IBM
Hugging Face
co:here

Key Takeaways

- Distributed computing is a necessity & norm
- Ray's vision: make distributed computing simple
  - Don't have to be distributed programming expert
- Build your own disruptive apps & libraries with Ray
- Scale your ML workloads with Ray libraries (Ray AIR)
- Ray offers the compute substrate for Generative AI workloads

Ray Summit 2023



https://bit.ly/raysummit2023

Let's go with

https://bit.ly/pydata-seattle-tutorial-2023

Thank you!

Questions?

email: jules@anyscale.com

twitter: @2twitme