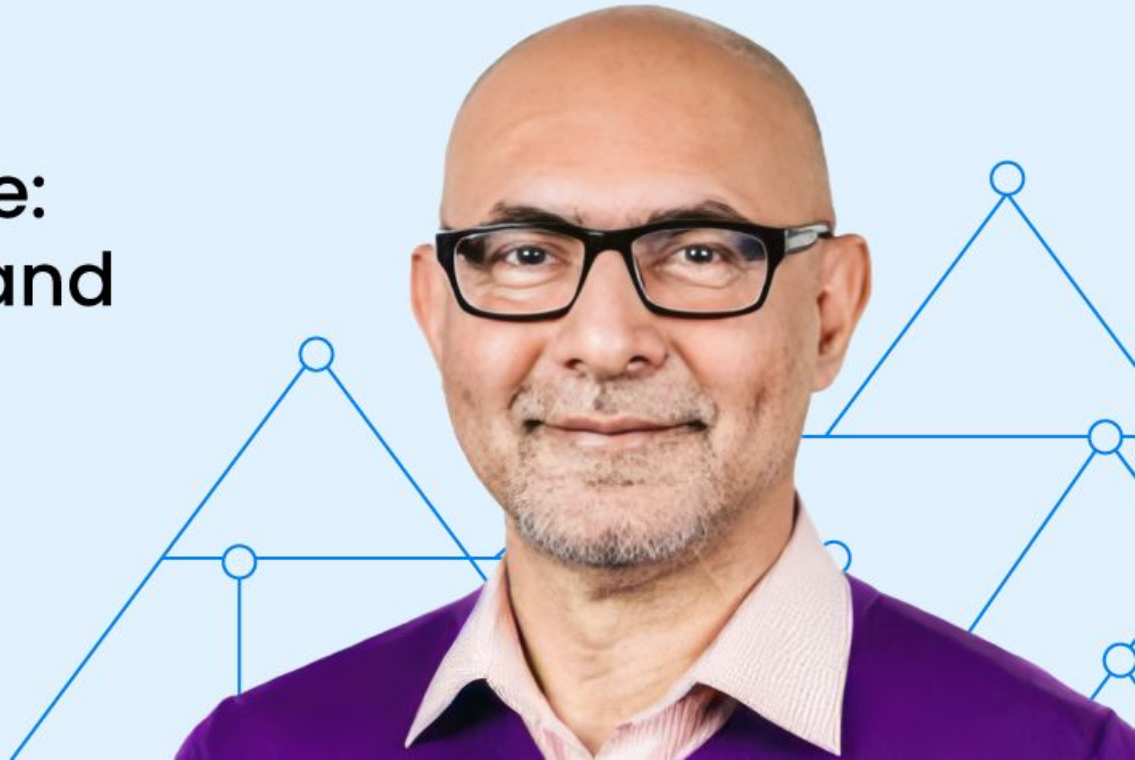
RAY SUMMIT 23

TRAINING

Ray Core Deep Dive: API, Architectures and Best Practices

Jules Damji
Anyscale

presented by anyscale



Meet the TAs!

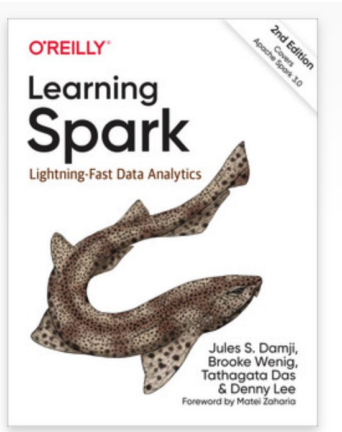
Ruiyang Wang

Ricky Xu

RAY SUMMIT 23

$whoami

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



A few important URLs:

Keep these URLs open in a browser tab:

- GitHub Learning Material: https://bit.ly/ray-core-summit-2023
- Ray Documentation: https://bit.ly/ray-core-docs
- Ray Core Class Survey: bit.ly/ray-summit-feedback

Today's agenda.

- Tech check (slido app, Anyscale clusters, etc)
- Why & What's Ray & Ray Ecosystem
- Ray Architecture & Components
- Ray Core Design & Scaling Patterns & APIs
- Modules [1-3]: Hands-on in class
- Break 2:15 pm - 2:45 PM
- Modules [4-5]: Hands-on in class
- Wrap up...
- Happy Hour Meetup

✅ Tech check.

Participating via app.sli.do

- Join with code **#ray-core**
- Ask questions.
  - Pose your own and upvote others.
  - TAs will be answering questions on a rolling basis.

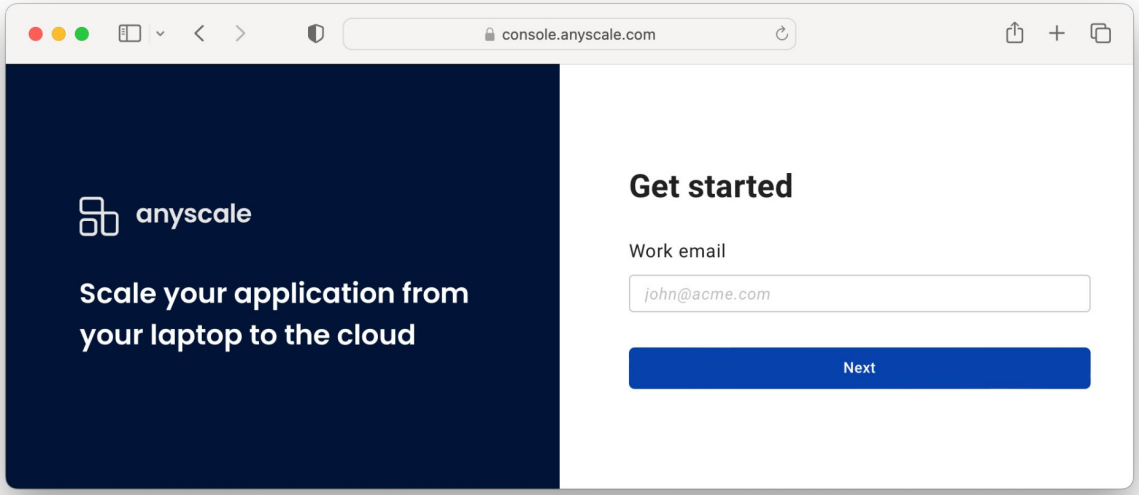
✅ Tech check.

Accessing Anyscale clusters.

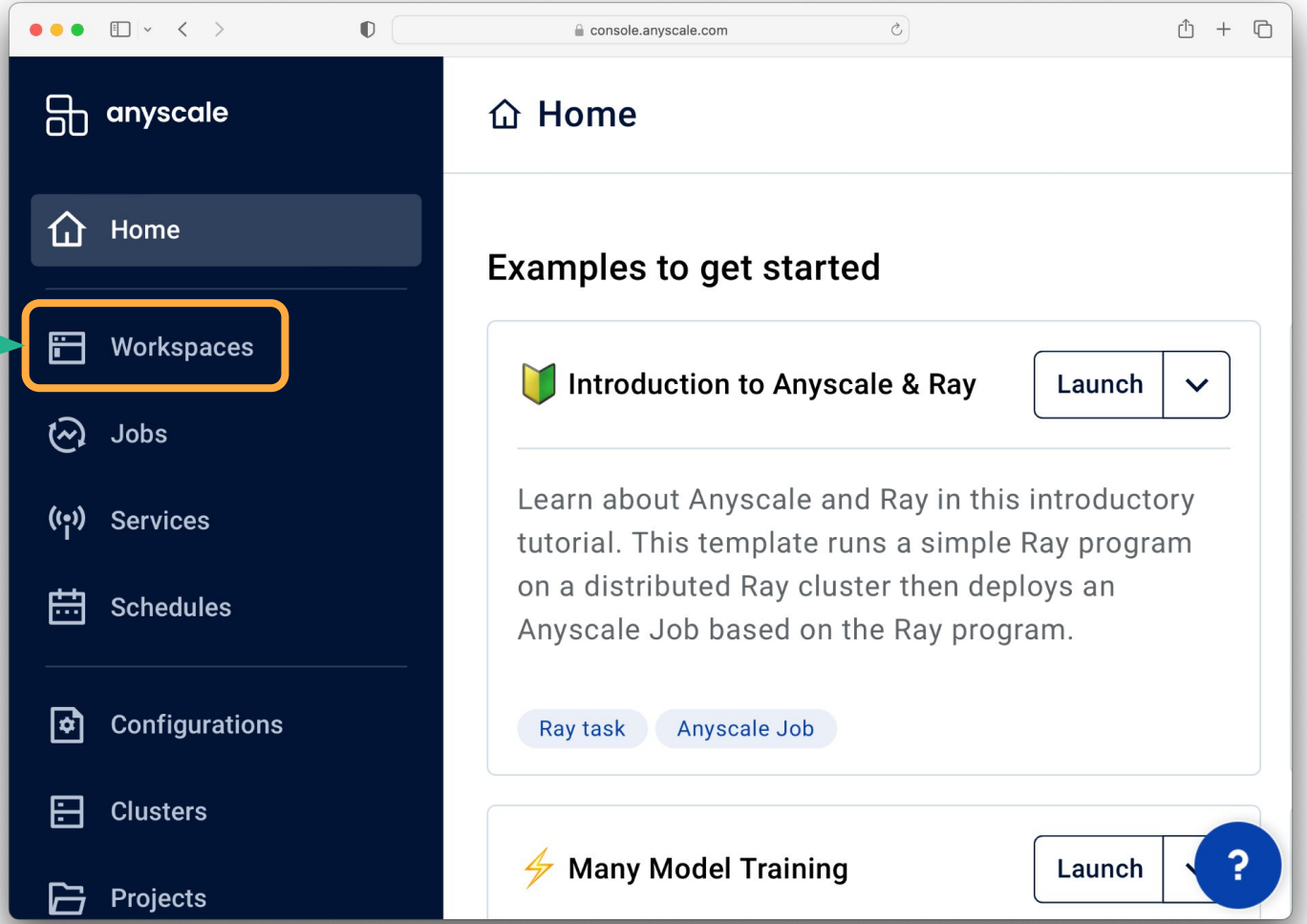
- All work will be in Anyscale provisioned clusters.
- Our GitHub repo will be mounted automatically.
- Access begins now.
  - Check your email for login information.
  - Step-by-step instructions to follow.

Anyscale login

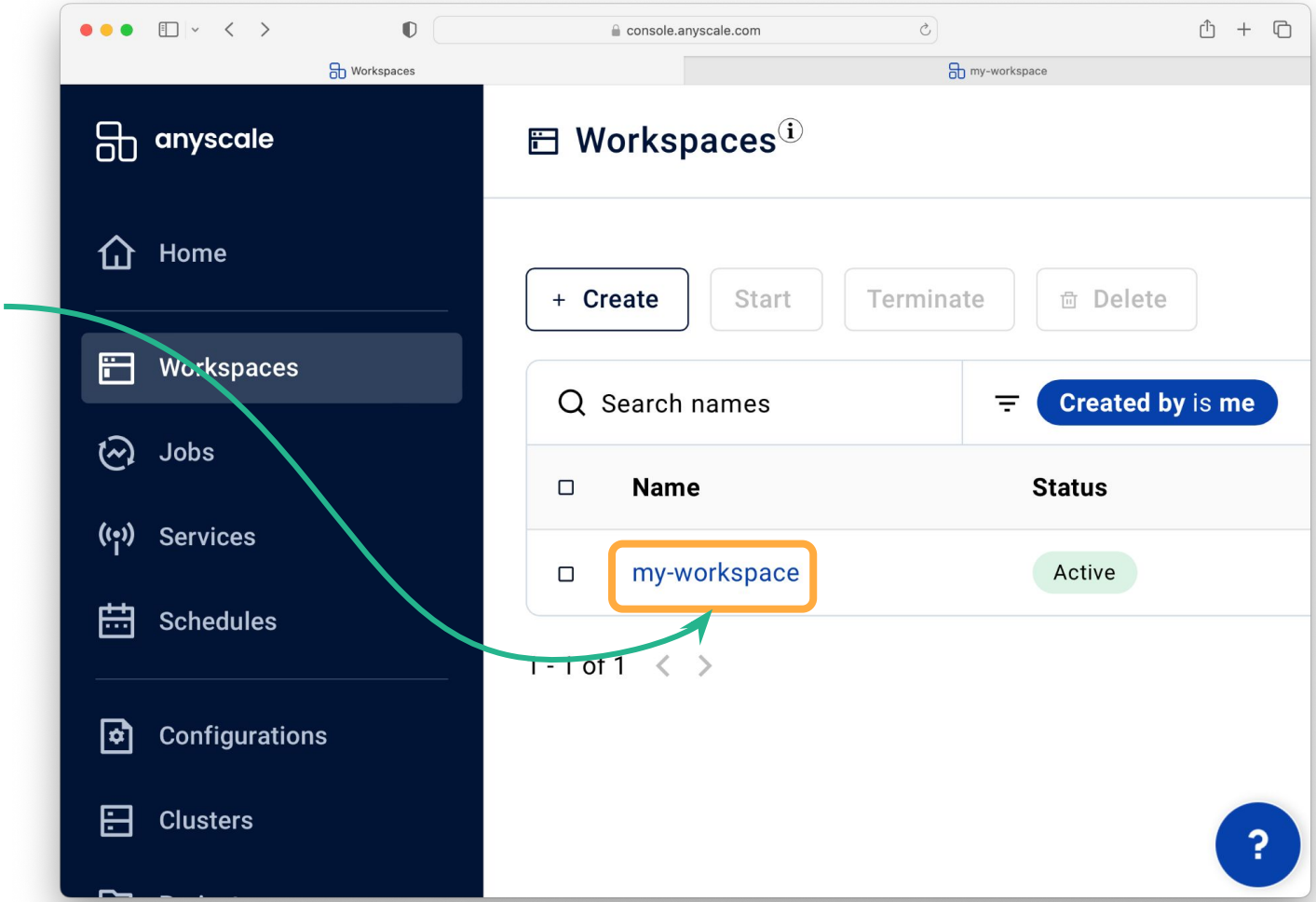
Link to Anyscale cluster: console.anyscale.com



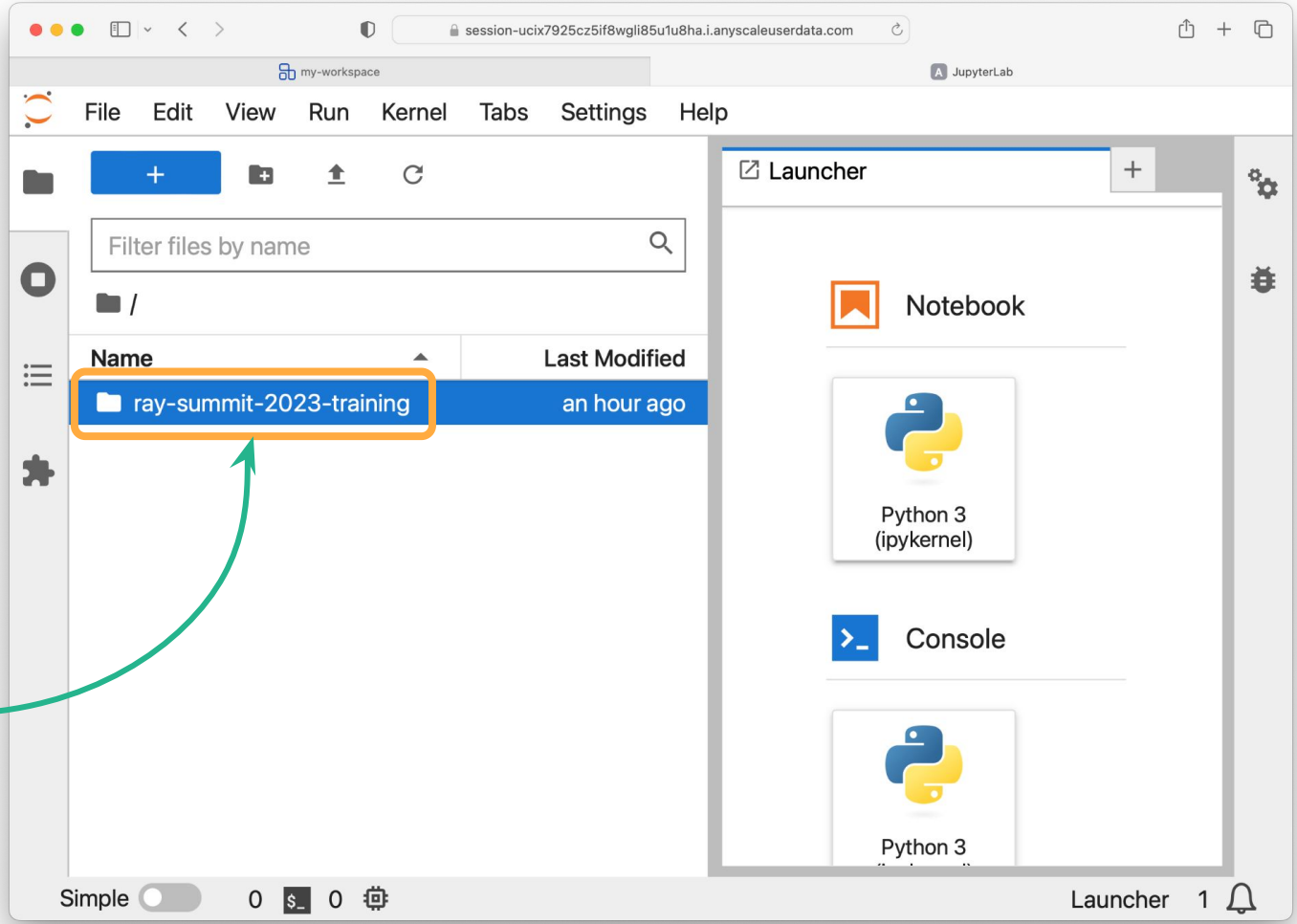
1. Select Workspaces



2. Select Your Workspace



4. Find the content for your class here.



Why Ray + What's Ray

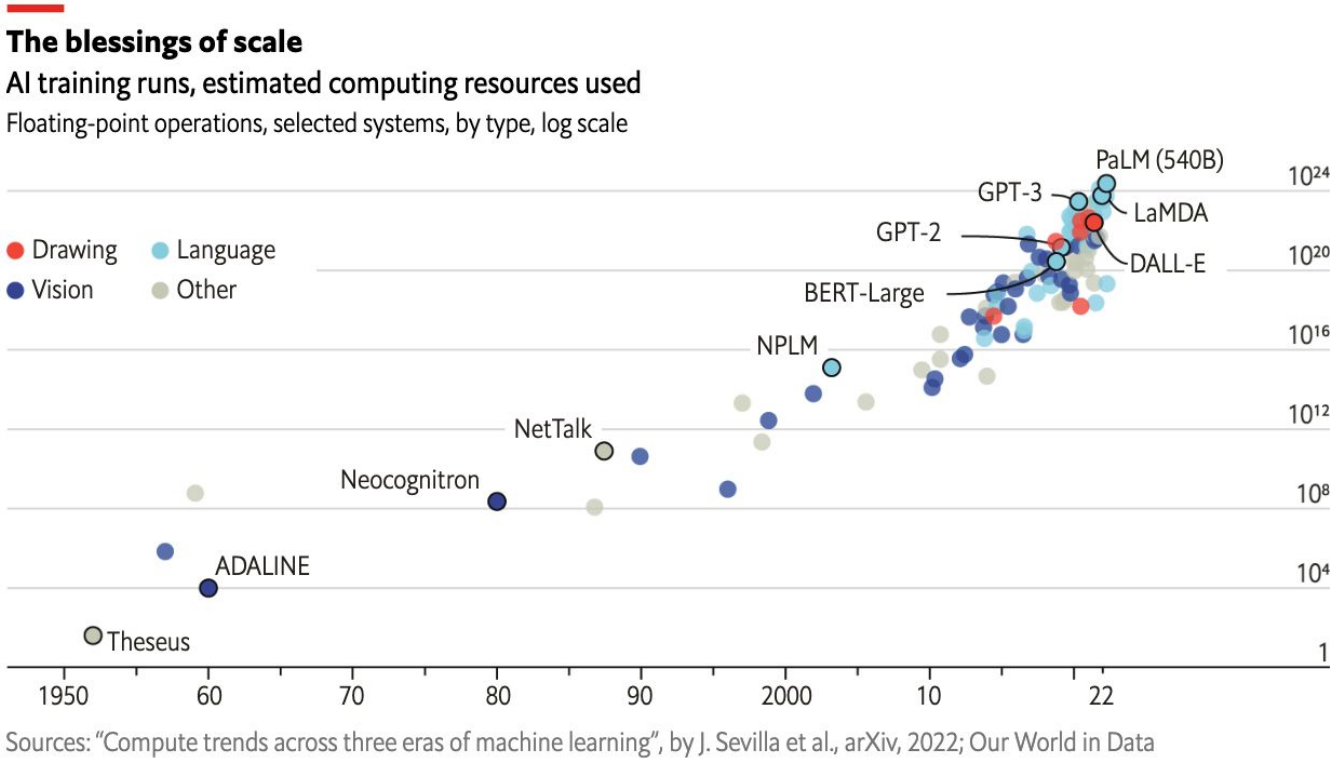
Why Ray

Machine learning is pervasive

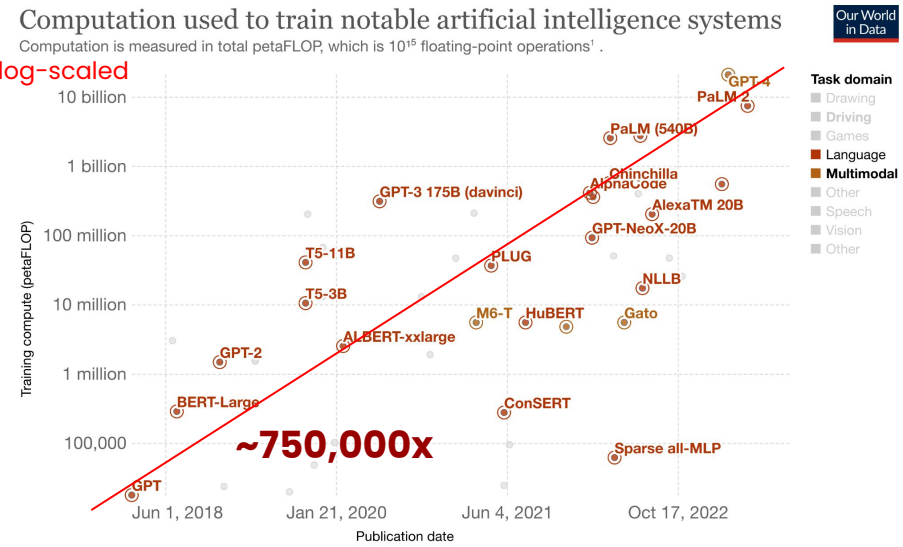
Distributed computing is a necessity

Python is the default language for DS/ML

Blessings of scale ...



Scaling is a Necessity

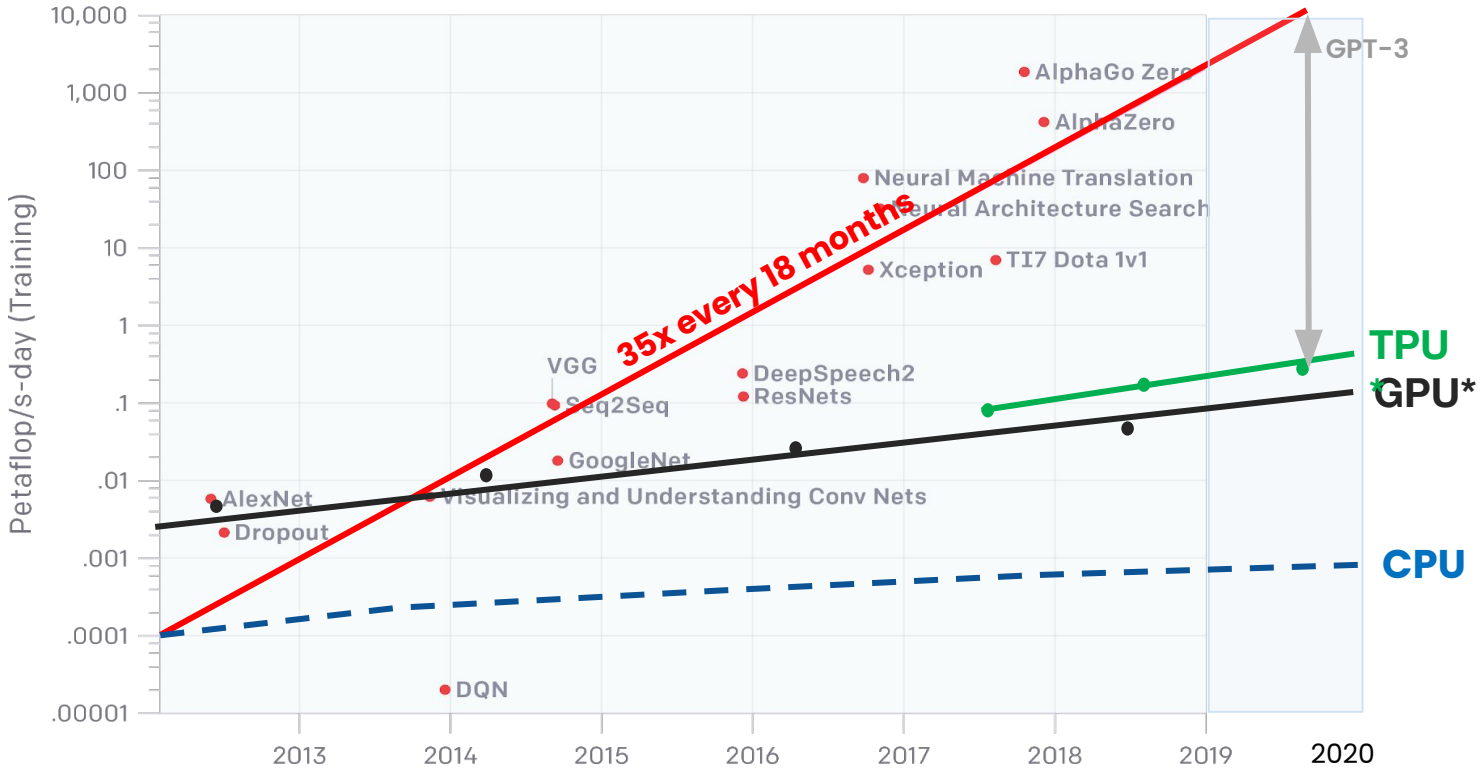


1. **Model size are getting larger**

- Model size is **exponentially** increasing.
- Models are too large to into a single GPU.
- We need to shard the models across multiple GPUs for training
  - e.g. ZeRO, Model Parallel, Pipeline Parallel

BERT(2019): 336M params(1.34GB)
Llama-2 (2023): 70B params(280GB) ~20x
GPT-4: ~1800B >5,000x

Supply-demand problem



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

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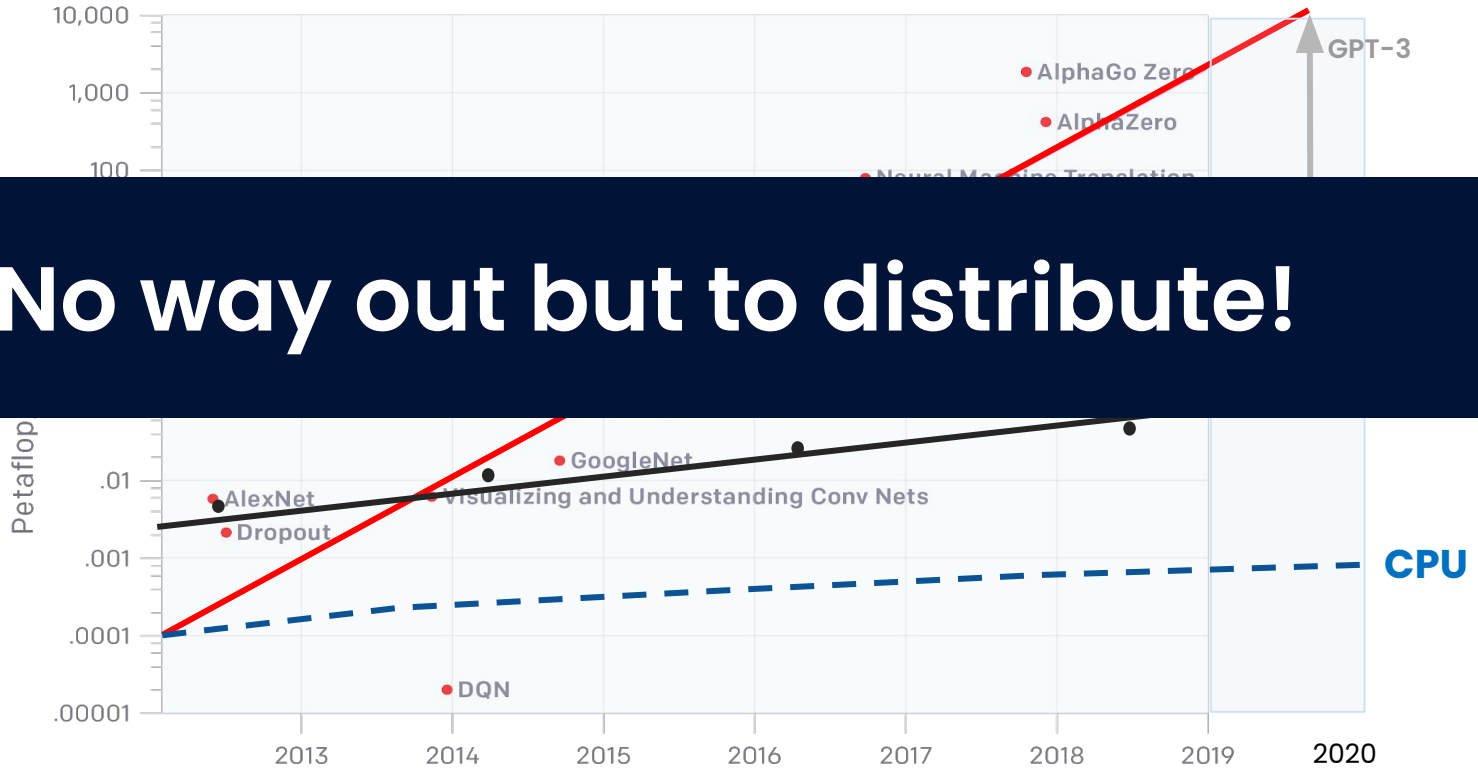
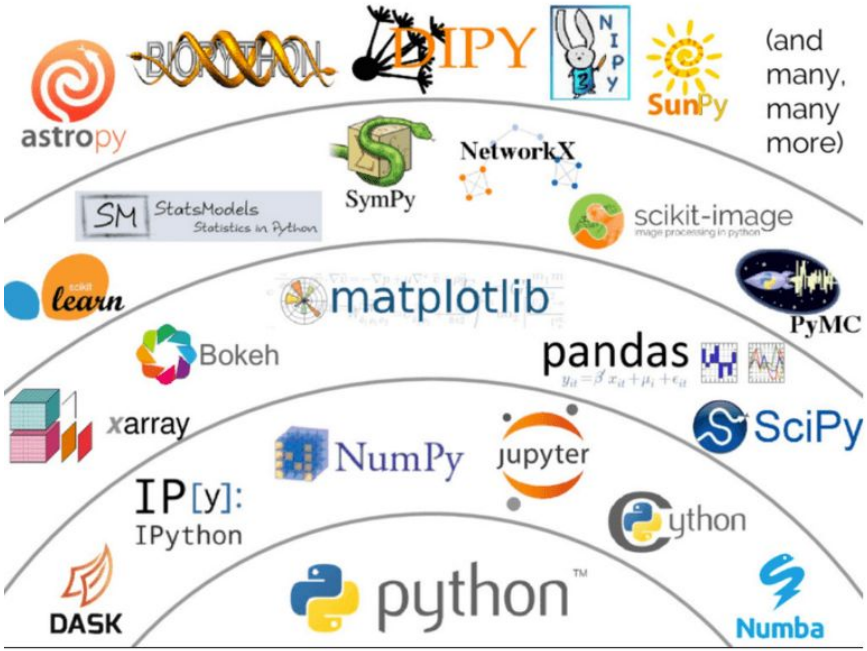
Specialized hardware no enough!

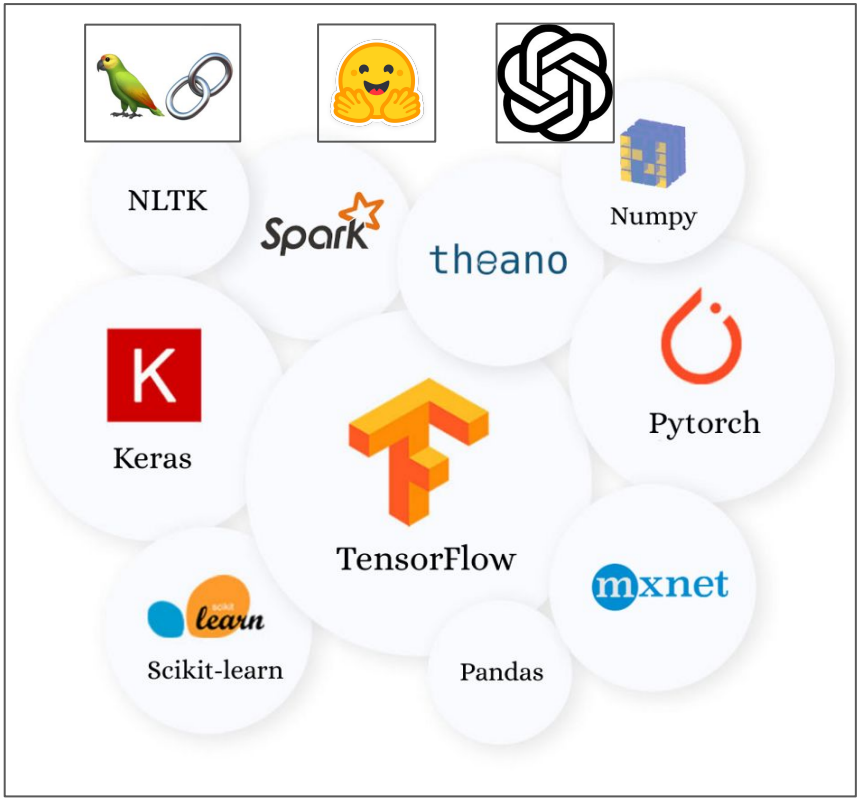


No way out but to distribute!

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

Python DS/ML ecosystem





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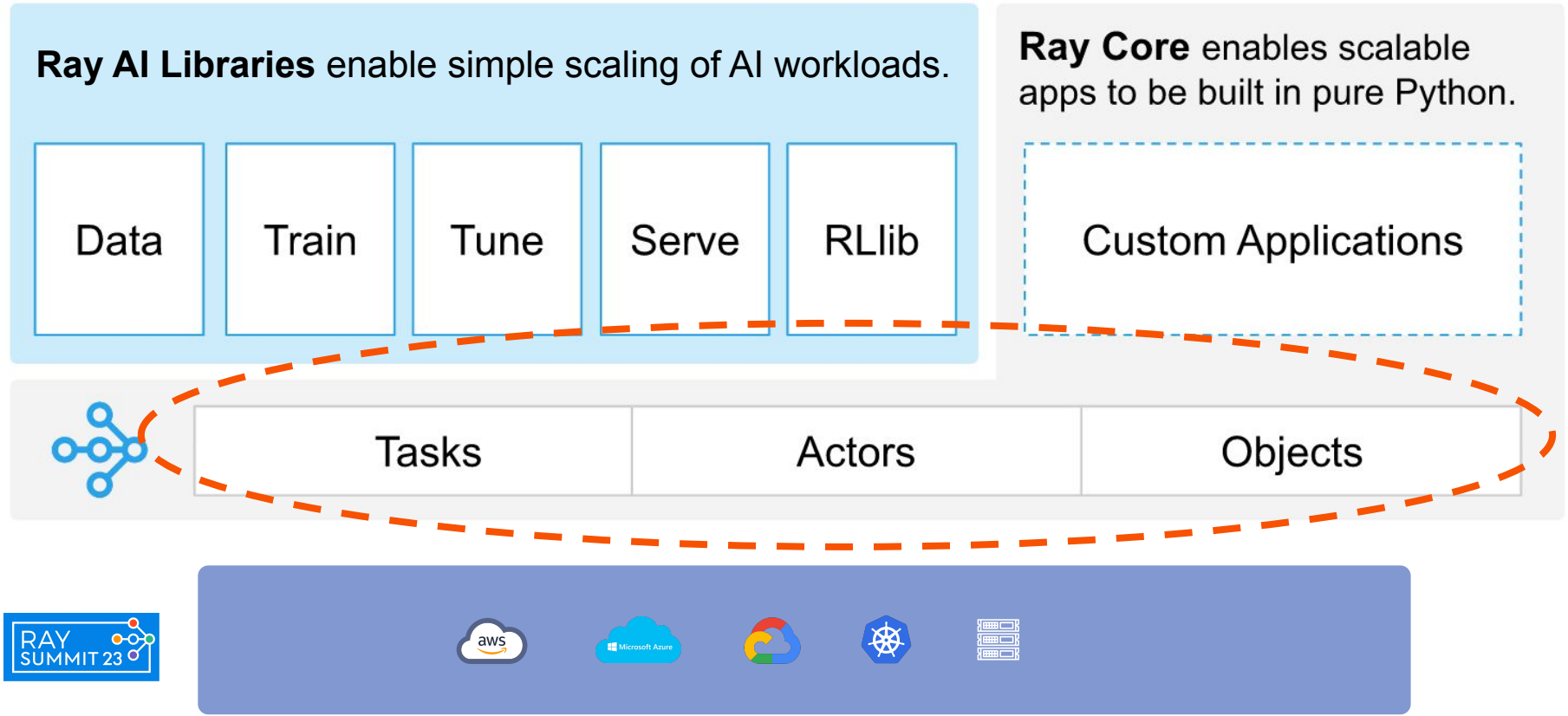
What's Ray?

- A ***simple/general-purpose*** library for distributed computing
- An ecosystem of Python Ray AI libraries (for scaling ML & more)
- Runs on laptop, public cloud, K8s, on-premise
- Easy to install and get started …. *pip install ray[default]*

A layered cake of functionality and capabilities for scaling ML workloads

A Layered Cake and Ecosystem



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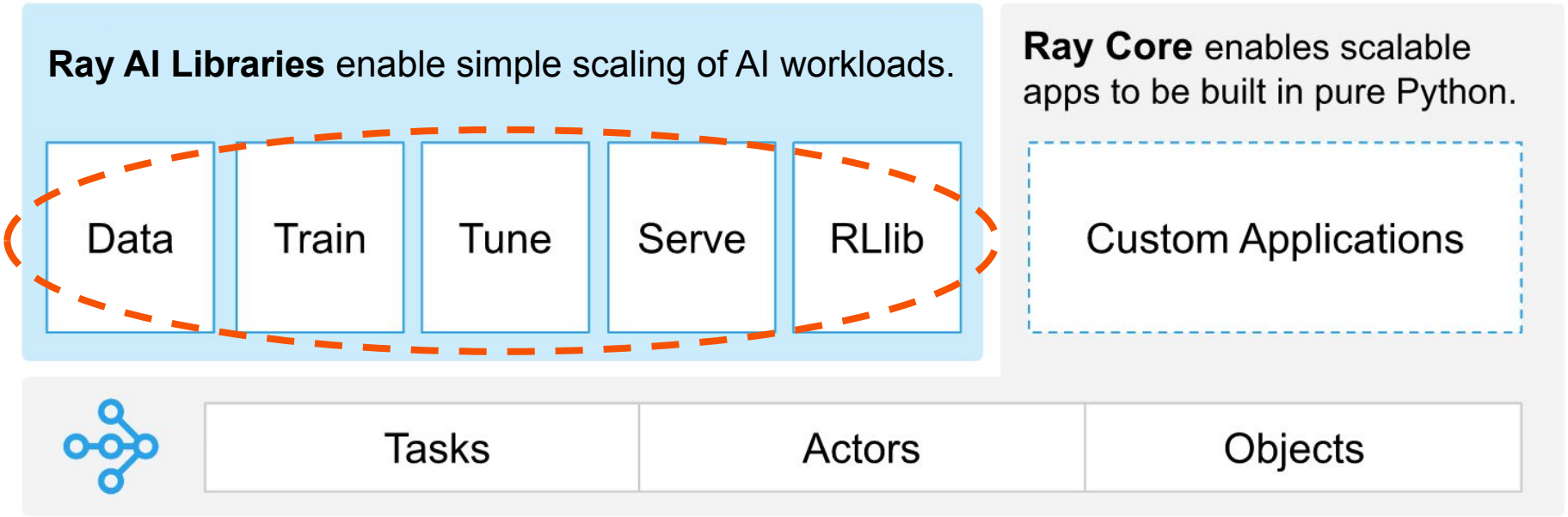
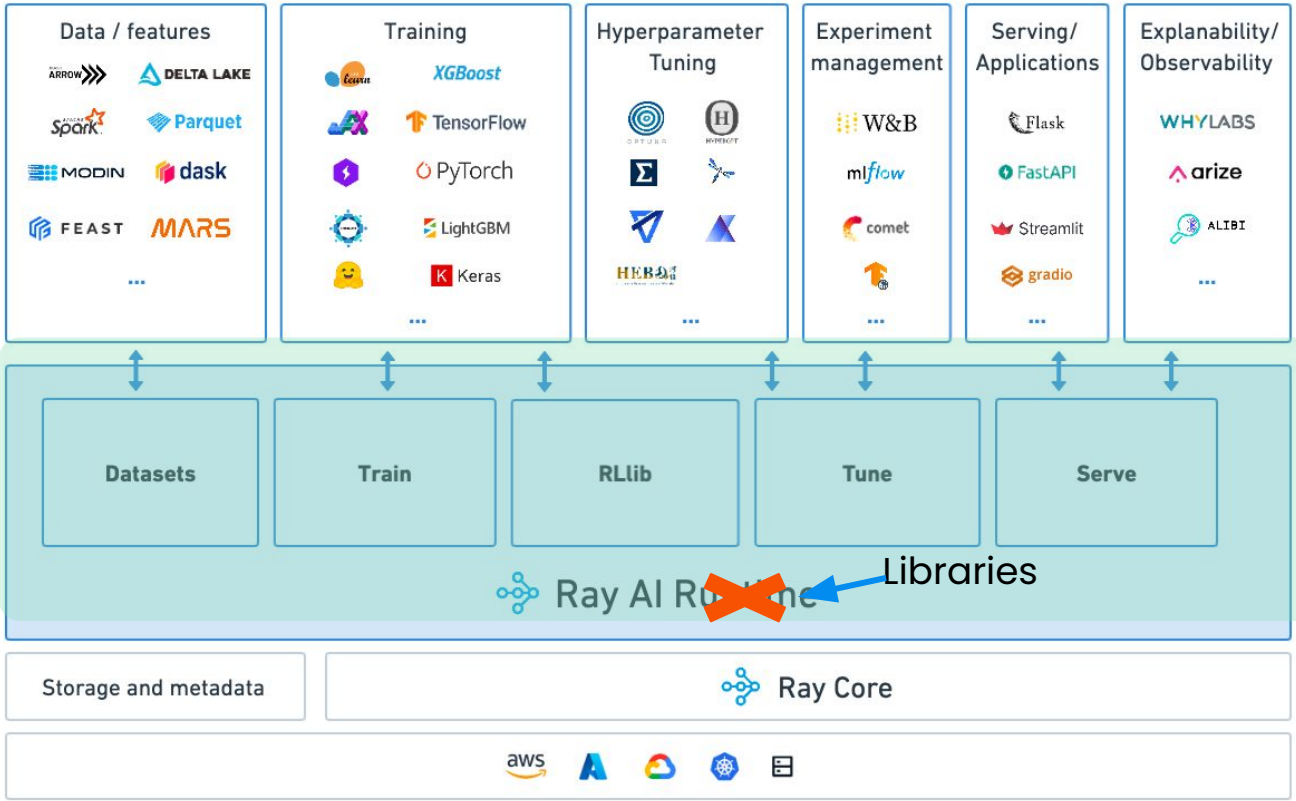
A Layered Cake and Ecosystem



Ray AI Libraries



High-level Ray AI Libraries that make scaling easy for both data scientists and ML engineers.

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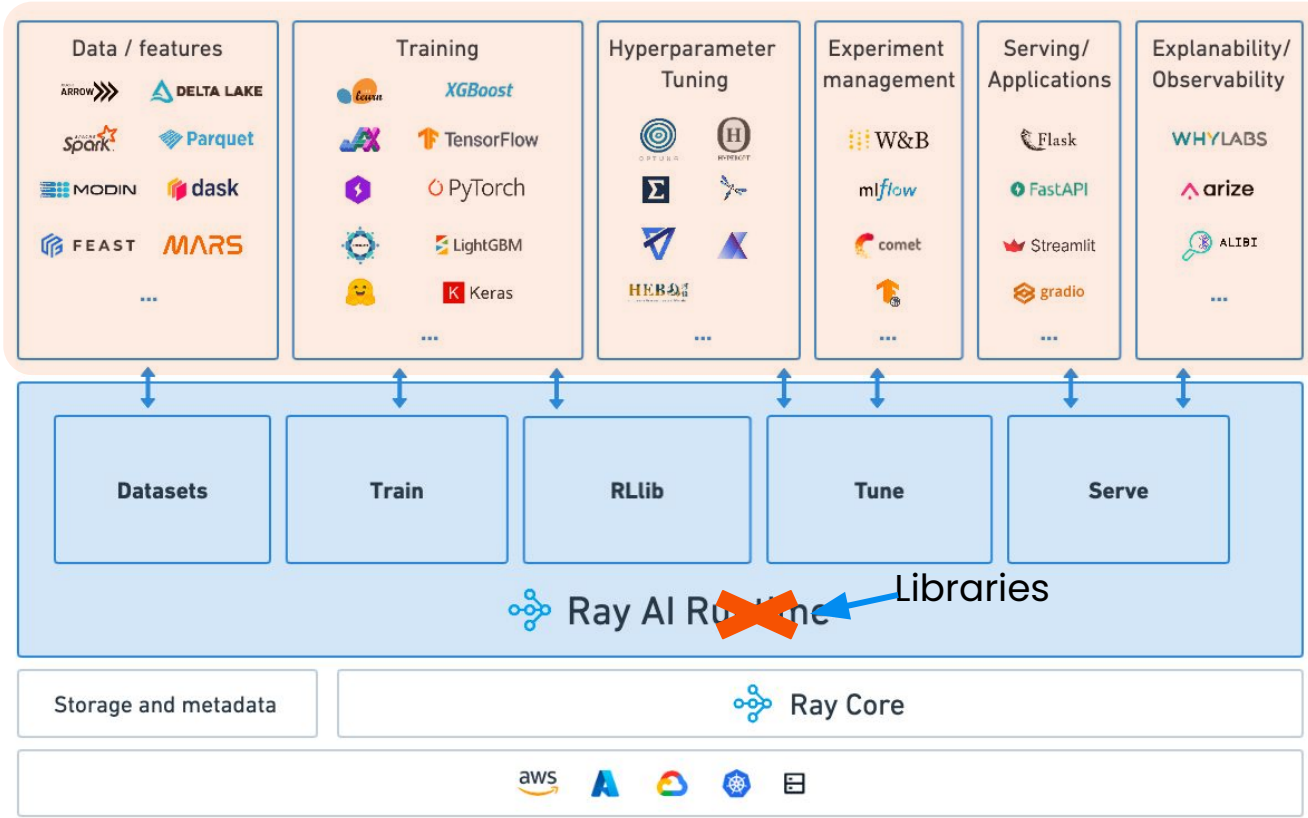
Ray AI Libraries



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

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

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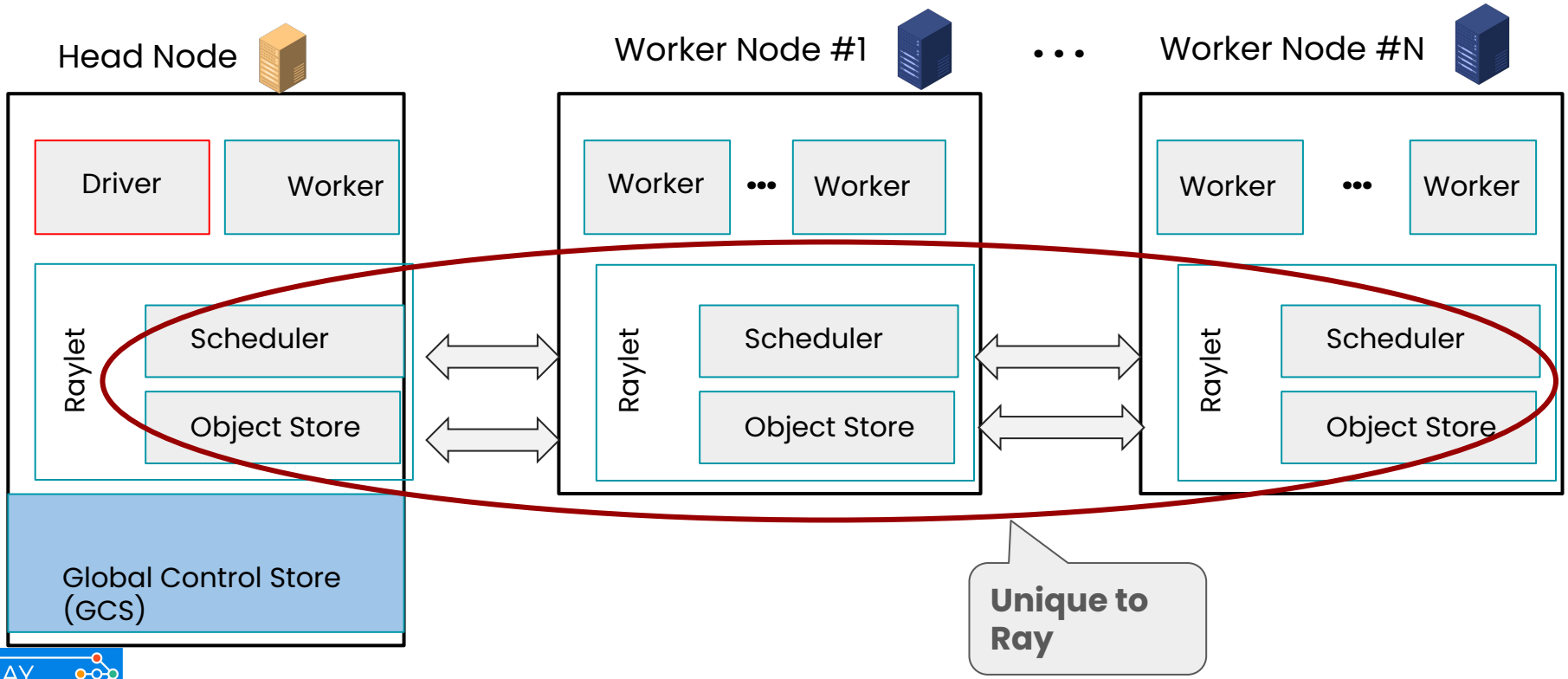
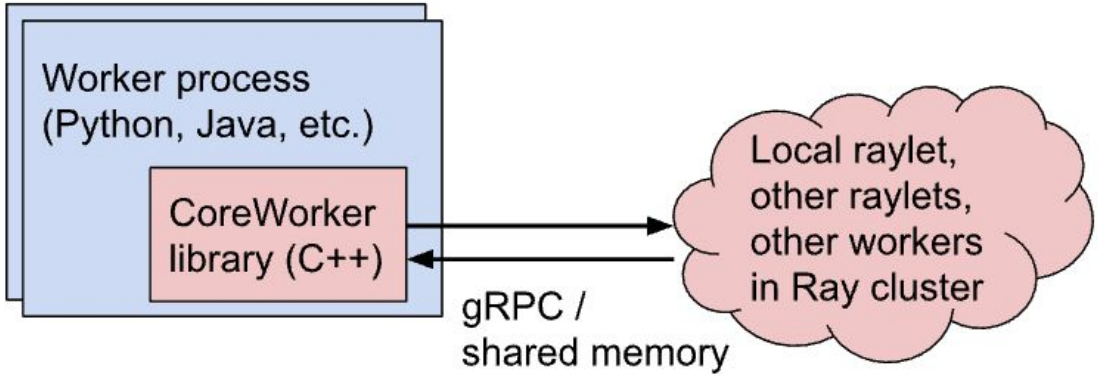
Ray Architecture & Components

Anatomy of a Ray Cluster



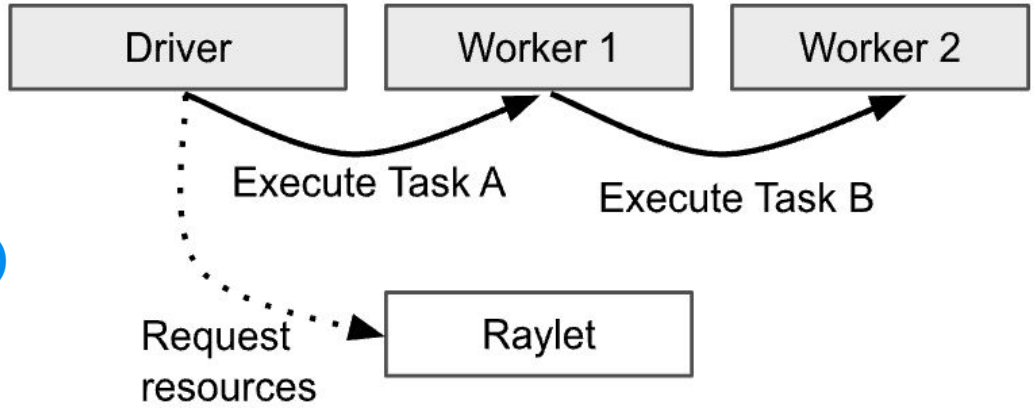
Anatomy of a Ray worker process



Ray workers interact with other Ray processes through the CoreWorker library.

Lifetime of a Ray Task ….

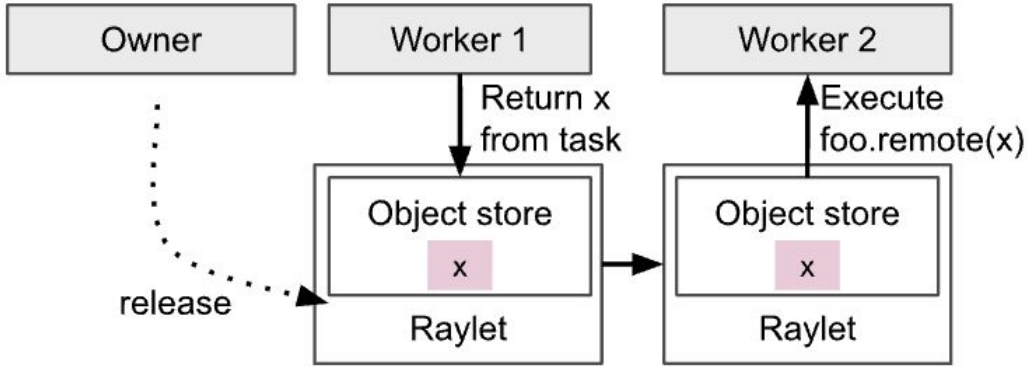
Driver code
…
A_ref = A.remote()



Worker 1 code
…
B = B.remote()
return B

The process that submits a task is considered to be the owner of the result and is responsible for acquiring resources from a raylet to execute the task. Here, the driver owns the result of `A`, and `Worker 1` owns the result of `B`.

Lifetime of a Ray Object

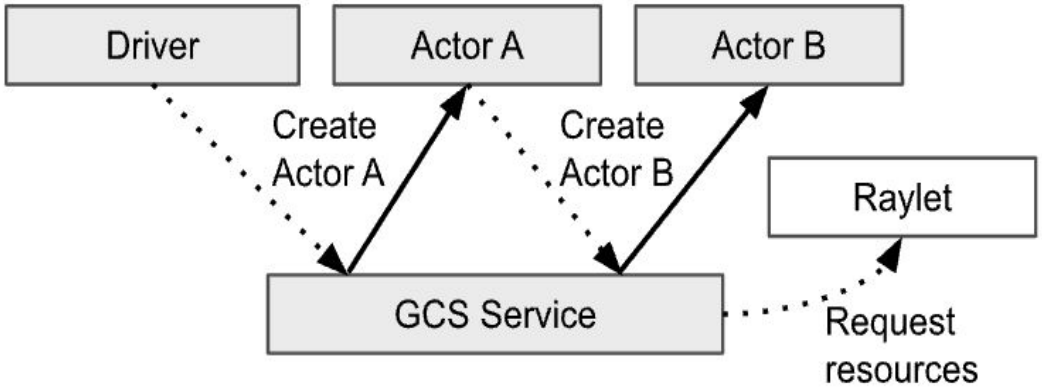


Distributed memory management in Ray. Workers can create and get objects. The owner is responsible for determining when the object is safe to release.

Lifetime of a Ray Actor …

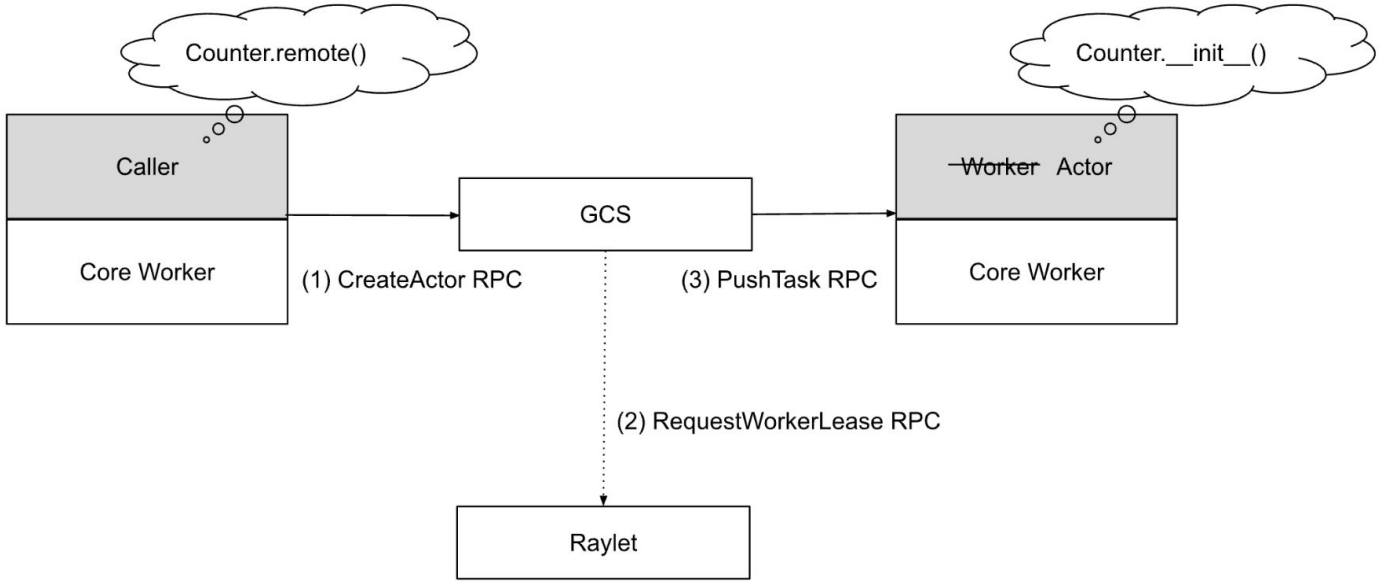
handle_A = ActorA.remote()

handle_B= ActorB.remote()



Unlike task submission, which is fully decentralized and managed by the owner of the task, actor lifetimes are managed centrally by the GCS service.

Actor creation sequence ....

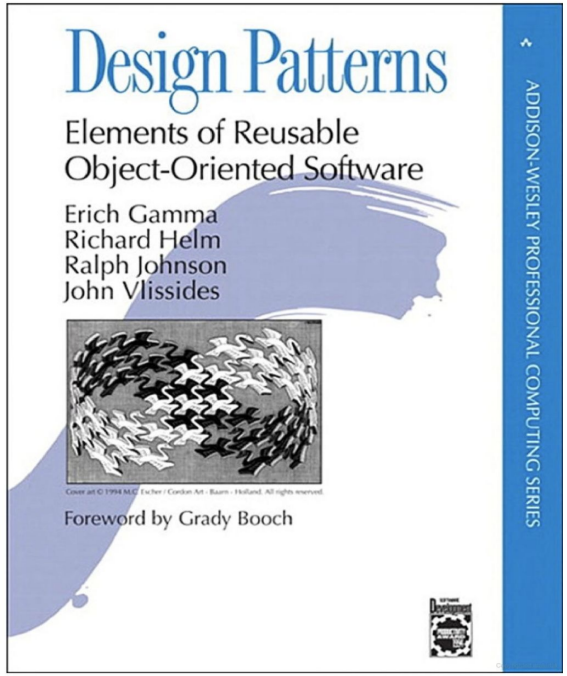


Actor creation tasks are scheduled through the centralized GCS service.

Ray Core Design & Scaling Patterns & APIs

Ray Basic Design Patterns

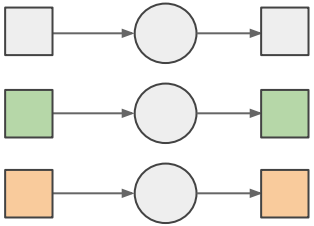
- **Ray Parallel Tasks**
  - Functions as stateless units of execution
  - Functions distributed across the cluster as tasks
- **Ray Objects as Futures**
  - Distributed (immutable objects) store in the cluster
  - Fetched when materialized
  - Enable massive asynchronous parallelism
- **Ray Actors**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



- [Patterns for Parallel Programming]
- [Ray Distributed Library Integration Patterns]

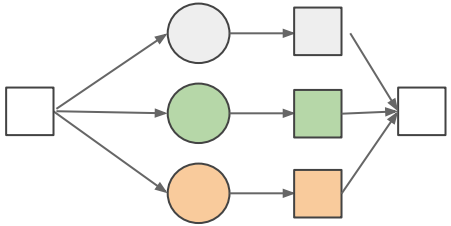
Scaling Design Patterns

Batch Training / Inference



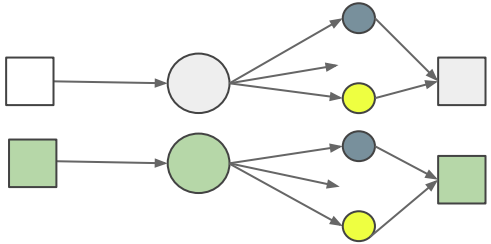
Different data / Same function

AutoML



Same data / Different function

Batch Tuning



Different data / Same function

Compute

Data

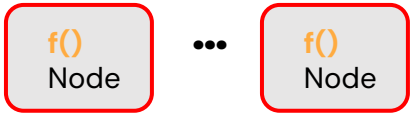
Python → Ray API

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

Task

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

Distributed




```
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)
```

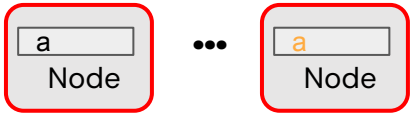
Distributed


```
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



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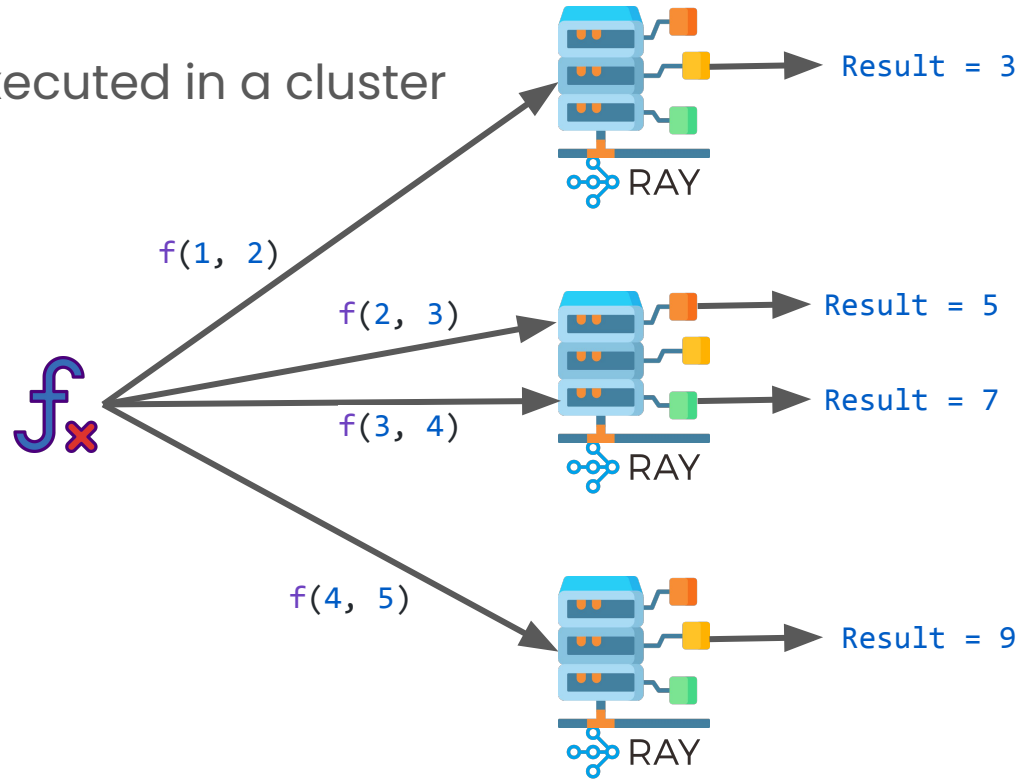
Ray Task

A function f_x remotely executed in a cluster

```
@ray.remote(num_cpus=3)
def f(a, b):
   return a + b

f.remote(1, 2) # returns 3
f.remote(2, 3) # returns 5
f.remote(3, 4) # returns 7
f.remote(4, 5) # returns 9
```

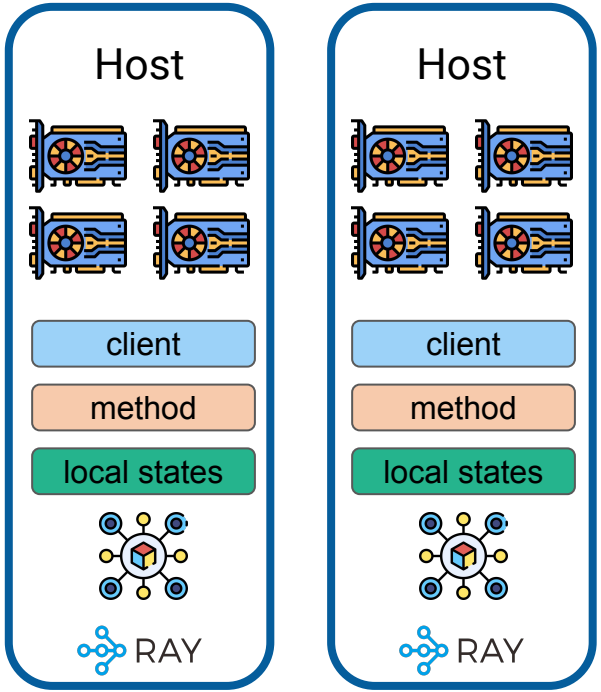


Ray Actor

A class  remotely executed in a cluster

```
@ray.remote(num_gpus=4)
class HostActor:
   def __init__(self):
       self.model  = load_model(“s3://model_checkpoint”)
       self.num_devices = os.environ["CUDA_VISIBLE_DEVICES"]
   def inference(self, data):
        return self.model(data)
   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"
actor.inference(input) # returns predictions…
```



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

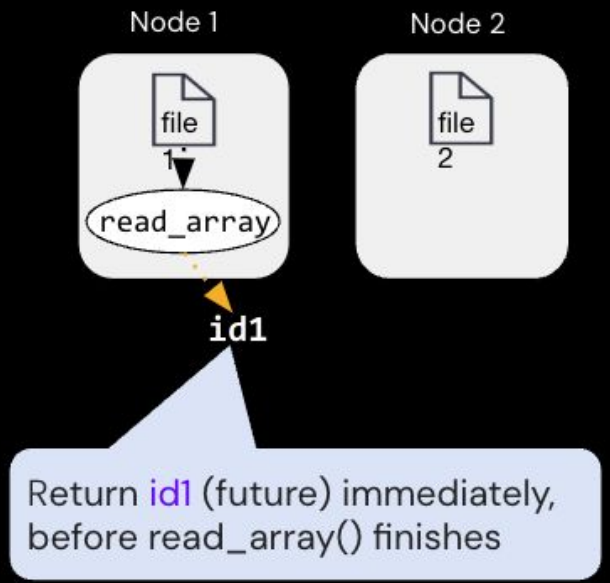
c = Counter.remote()
id4 = c.inc.remote()
id5 = c.inc.remote()
```

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

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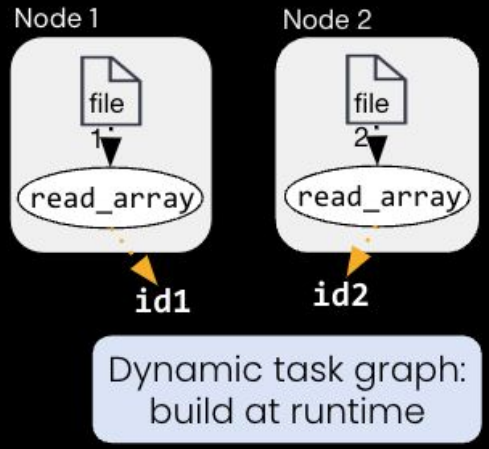
sum = ray.get(id)
```



Task API

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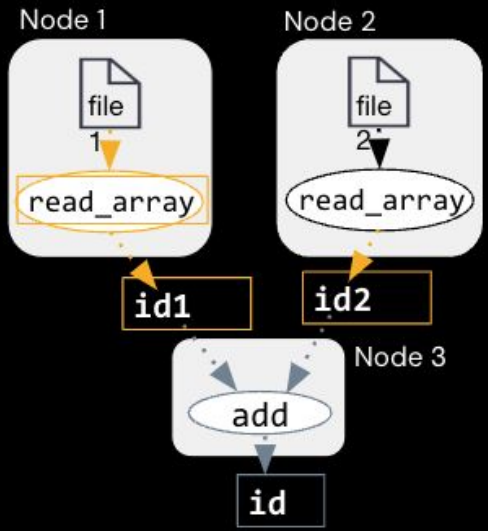
    # from “file”
    return a

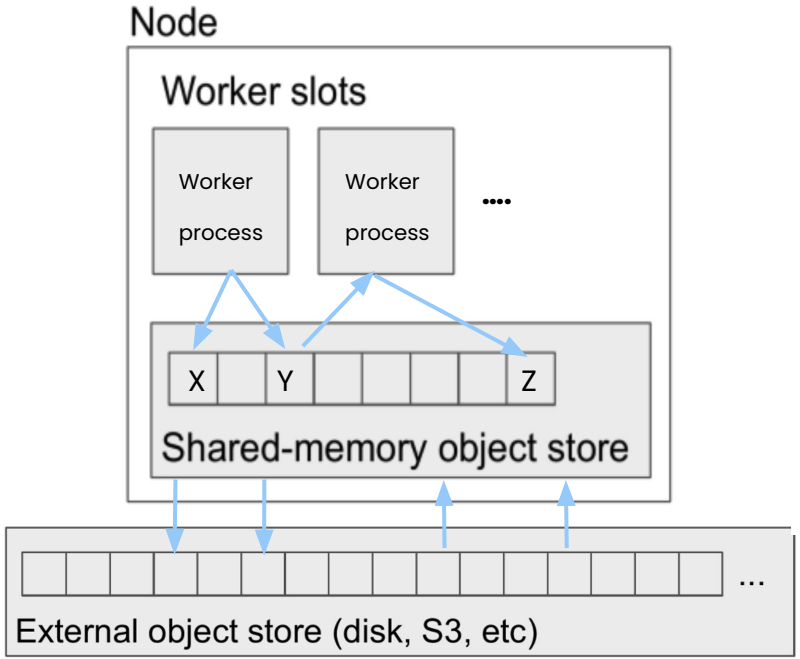
@ray.remote
def add(a, b):
    return np.add(a, b)

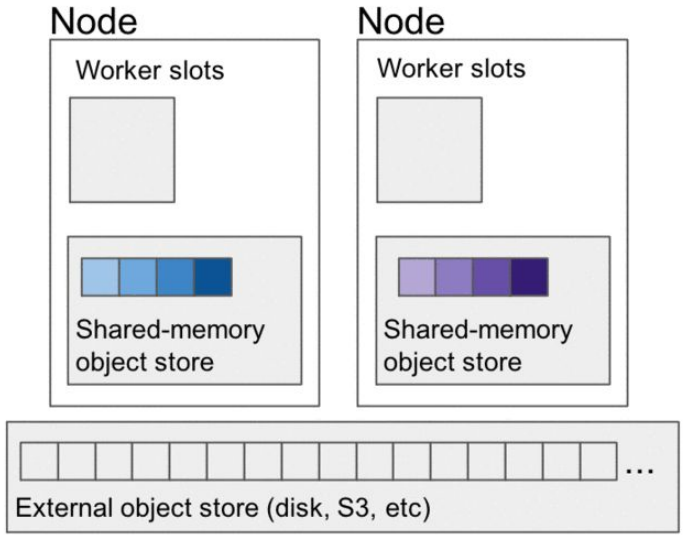
id1 = read_array.remote(file1)
id2 = read_array.remote(file2)
id = add.remote(id1, id2)
sum = ray.get(id)
```

ray.get() block until result available



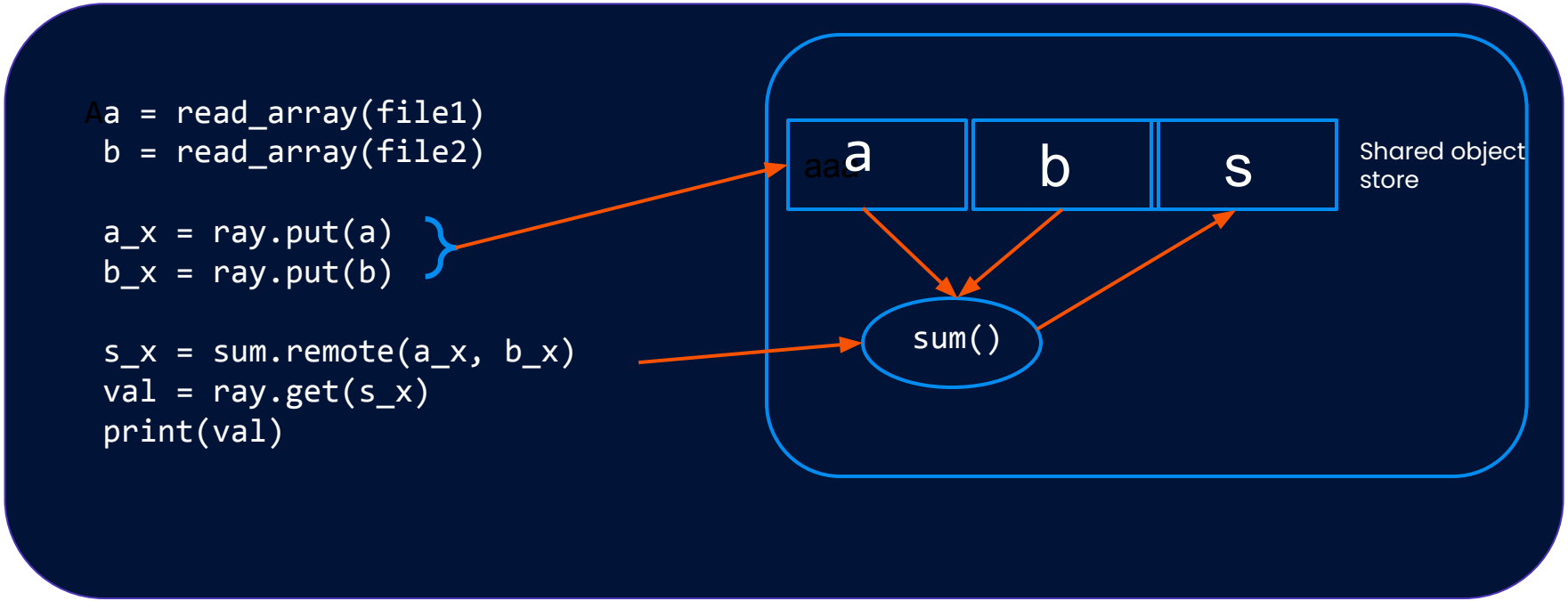
Distributed object store





Spill over to external storage

Distributed object store



Let’s go with Ray

☕ Time for a Break!

☕ Time for a Break!

Recap & More Resources

For further exploration with Ray, Anyscale, and LLMs.

🍎 Recap: Today we learned…

🚂 Why Ray & What's Ray Ecosystem
- Architecture components
  - Role in distributed systems

🔬 Ray Design & Scaling Patterns & APIs
- Ray Tasks, Actors, Objects

🔍 Patterns and Antipatterns
- How to avoid pitfalls
- Use best practices

RAY SUMMIT 23

🍏 Sneak Peek: Self-Paced Ray & Anyscale Education

📧 Access to sharable course materials will be emailed to you after Ray Summit.

🔍 Preview special technical content releases from the whole team!

Fill out the survey.

🔗 Go to bit.ly/ray-summit-feedback

RAY SUMMIT 23

Reading list.

Ray Education GitHub

Access bonus notebooks and scripts about Ray.

Ray documentation

API references and user guides.

Anyscale Blogs

Real world use cases and announcements.

YouTube Tutorials

Video walkthroughs about learning LLMs with Ray.

RAY SUMMIT 23

Bay Area AI + Ray Summit Meetup & Happy Hour

Bay Area AI + Ray Summit Meetup

Hosted By
Alexy K. and 4 others

Details

Our next in-person meetup is held on the last day of the Ray Summit 2023.

We focus on Ray use in AI, such as LLM, and deployment of ML workloads in various use cases. Weights & Biases will host and present, and planned talks include IBM Research and Open-Source Science. We'll also host lightning talks and networking.

Bay Area AI
Public group

Wednesday, September 20, 2023 at 5:00 PM to Wednesday, September 20, 2023 at 7:00 PM PDT
Add to calendar

Microsoft
555 California St #200 · San Francisco, CA

Report this event

https://bit.ly/bayai_ray_meetup

RAY SUMMIT 23

Thank you!

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