Introduction to Ray for Distributed Applications

Jules Damji, Anyscale
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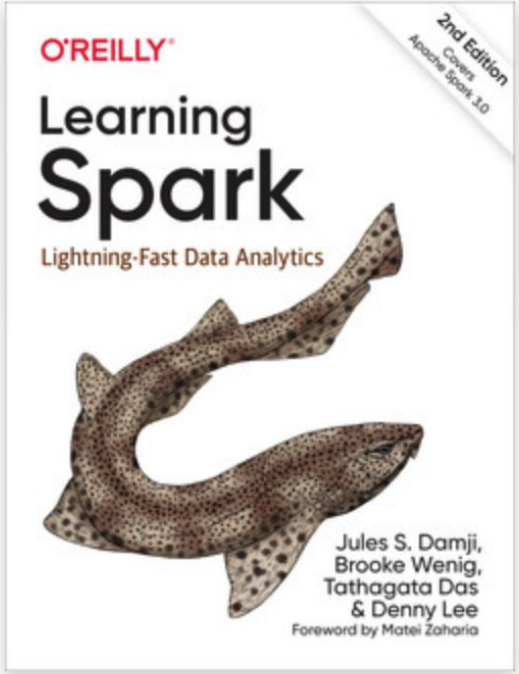
TAs: Stephanie Wang, Jiajun Yao, Sangbin Cho

$whoami (Jules)

- → Lead Developer Advocate @Anyscale
- → Senior Developer Advocate @Databricks
- → Led Developer Advocacy @Hortonwork
- → Held SWE positions:
  - + Sun Microsystems
  - + Netscape
  - + @Home
  - + Loudcloud/Opsware
  - + Verisign



Anyscale

Who we are: Original creators of Ray, a unified framework for scalable computing

What we do: Scalable compute for AI And Python

Why we 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 Patterns & APIs
- → Modules [1 - 3]
- → Closing Q & A with Committers
- → Happy Hour 🍻 + Meetup

Ray Summit Meetup Seacliff foyer

Meetup

Ray Summit Meetup Community Talks

Monday, August 22
6:00 PM - 8:00 PM

We are delighted to host an exclusive Ray Summit Meetup, hosted by Anyscale with Ray community talks, on the eve of the summit. Invited Ray community speakers will share how they use Ray to scale and solve challenging ML problems.

You don't have to be registered for the Ray Summit to attend. The meetup is free for the community. Join us for the Ray Summit Happy Hour from 5:00 - 6:00 p.m., followed immediately by the meetup.

Agenda (The times are not strict; they may vary slightly.)

- 5:00 - 6:00 p.m. Ray Summit Community Happy Hour (in Seacliff Foyer)
- 6:00 p.m. Welcome remarks, announcements, and agenda - Jules Damji, Anyscale
- 6:05 p.m. Talk 1: Ray + Arize: Close the ML infrastructure loop - Aparna Dhinakaran, Arize AI
- 6:35 p.m. Q & A
- 6:40 p.m. Talk 2: Maintaining long-running distributed Ray clusters - Jaehyun Sim, Ikigai Labs
- 7:20 p.m. Q & A
- 7:25 p.m. Talk 3: Large-scale distributed approximate nearest neighbor search with Ray - Daniel Acuna, Syracuse University
- 7:50 p.m. Q & A

Talk 1: Ray + Arize: Close the ML infrastructure loop Detecting, diagnosing, and resolving ML model performance can be difficult for even the most sophisticated ML engineers. As more machine learning models are deployed into production, it is imperative we have tools to monitor, troubleshoot, and explain model decisions. Join Aparna Dhinakaran, chief product officer at Arize AI, in a discussion on the state of commonly seen ML production monitoring challenges. Learn how to use ML Observability from training through production environments to find upstream model issues faster, monitor your models in real time at scale, and improve model interpretability and explainability.

Daniel Acuna
Associate Professor, Computer Science Department, University of Colorado

Jaehyun Sim
Director of Engineering, Ikigai Labs, Inc.

Aparna Dhinakaran
Chief Product Officer, Arize AI

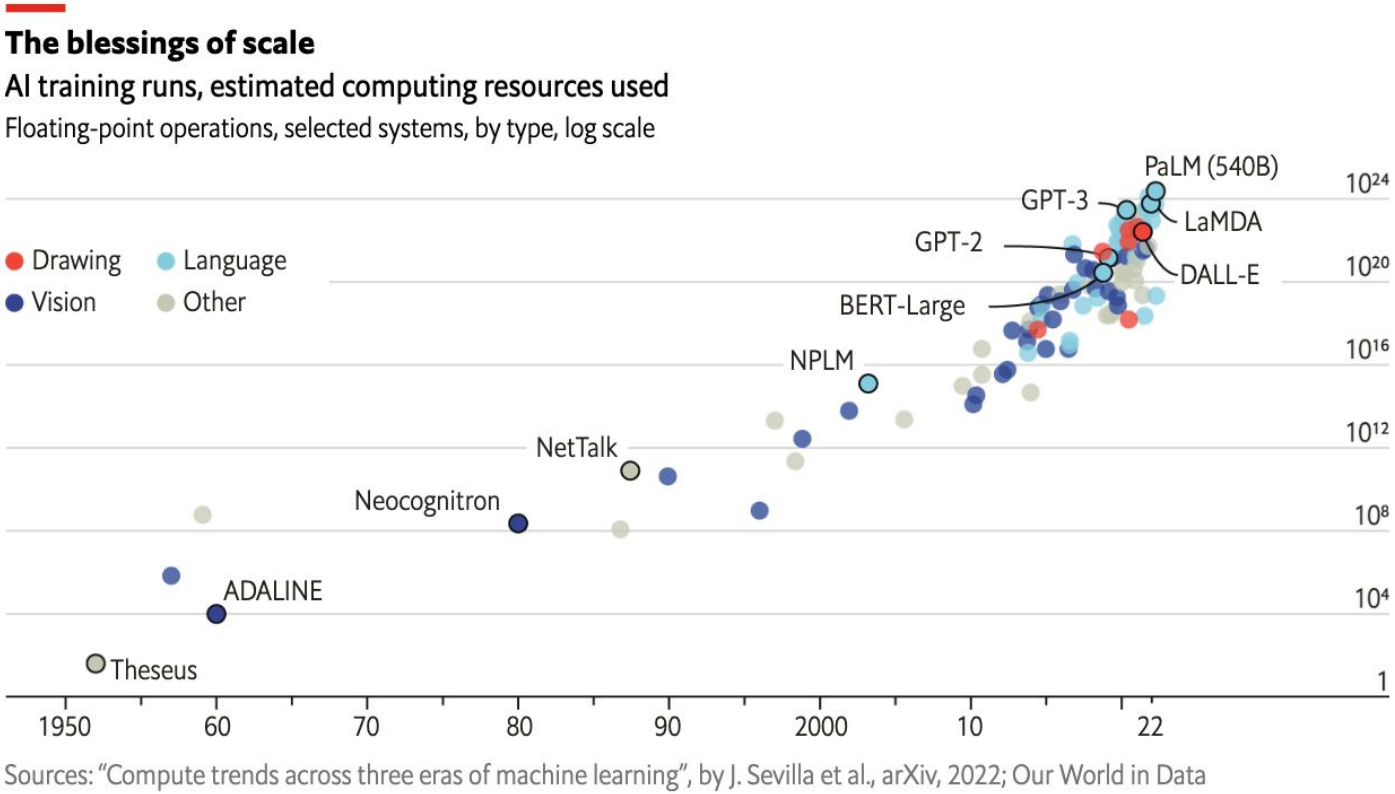
Jules Damji
Lead Developer Advocate, Anyscale

RAY SUMMIT 22

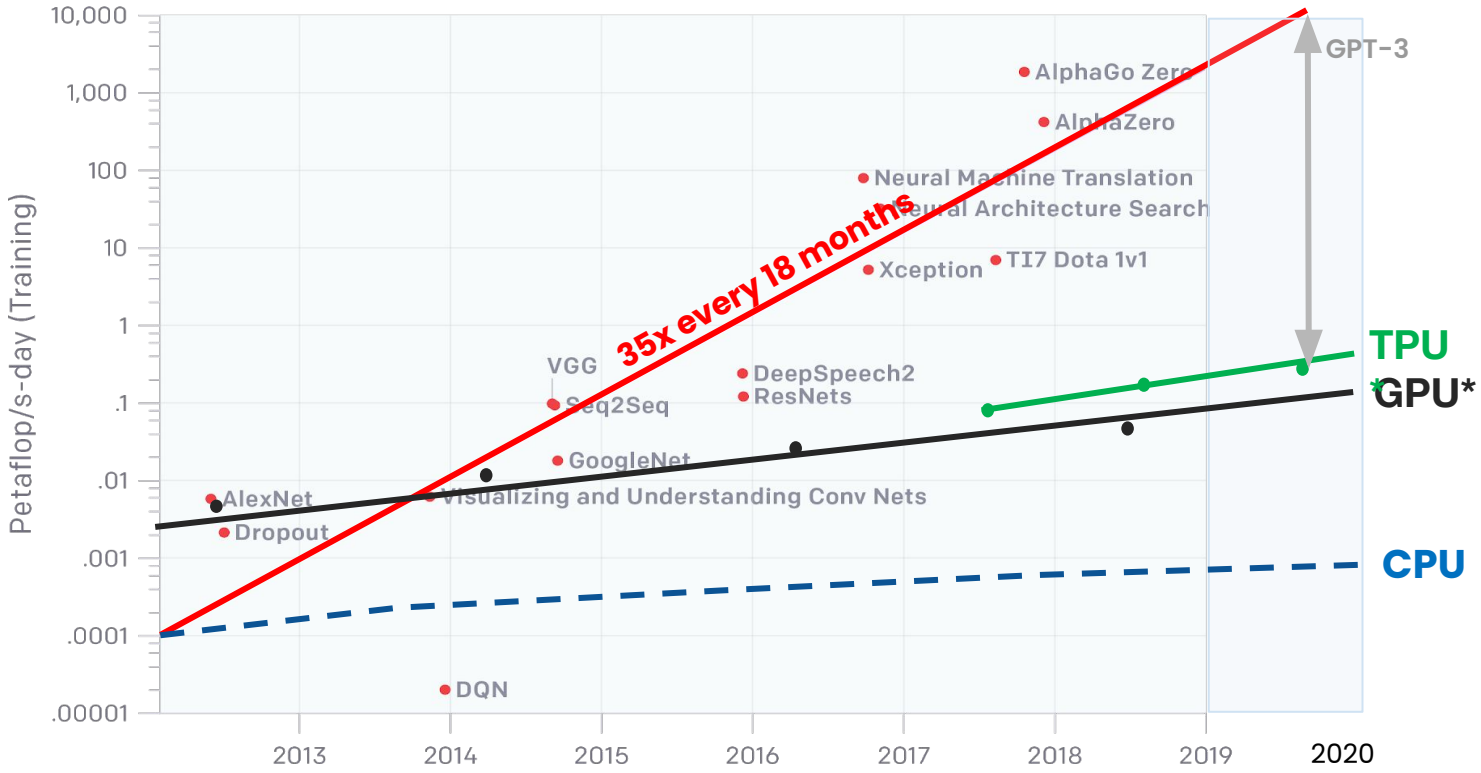
Why Ray 

→ Machine learning is pervasive
→ Distributed computing is a necessity
→ Python is the default language for DS/ML

Blessings of scale …

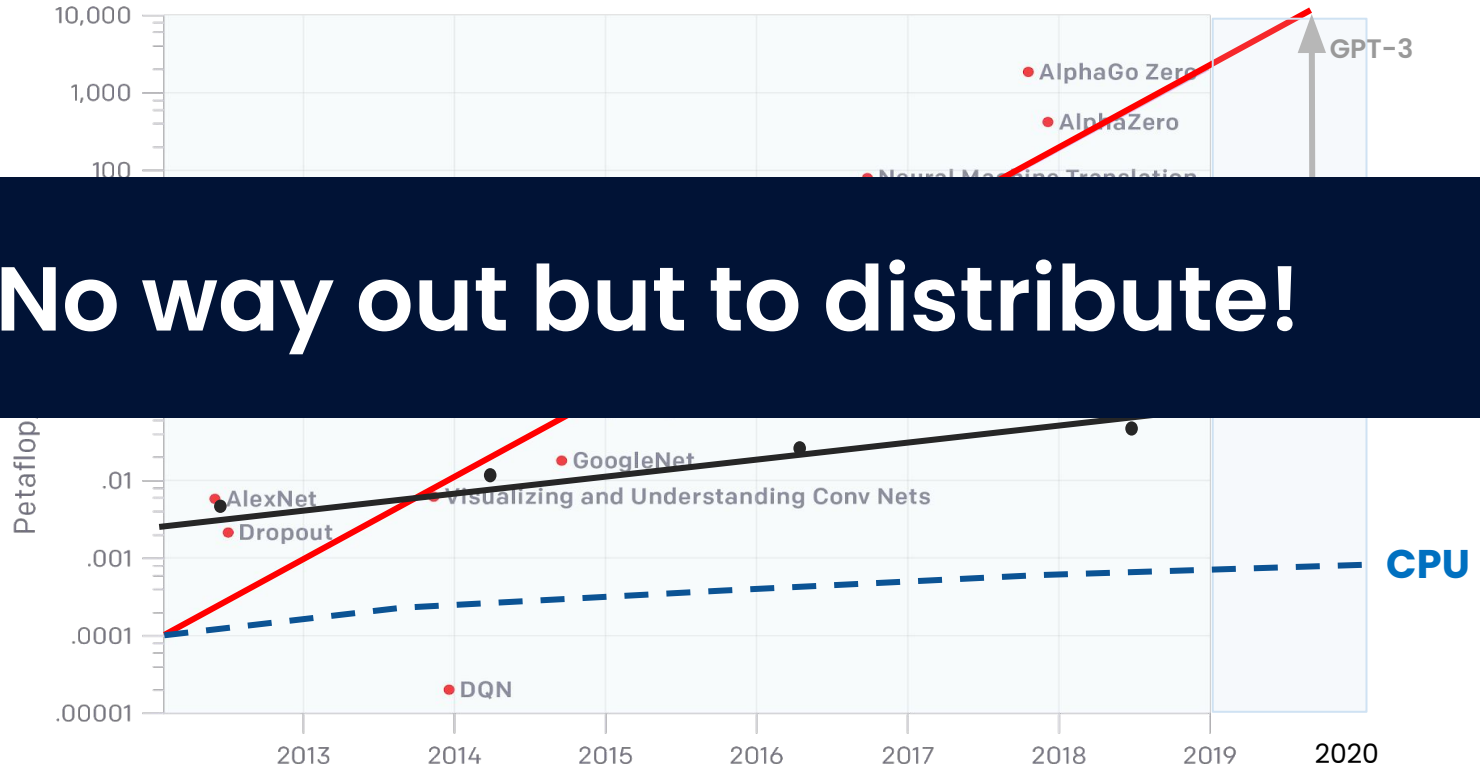


Compute - supply demand problem



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

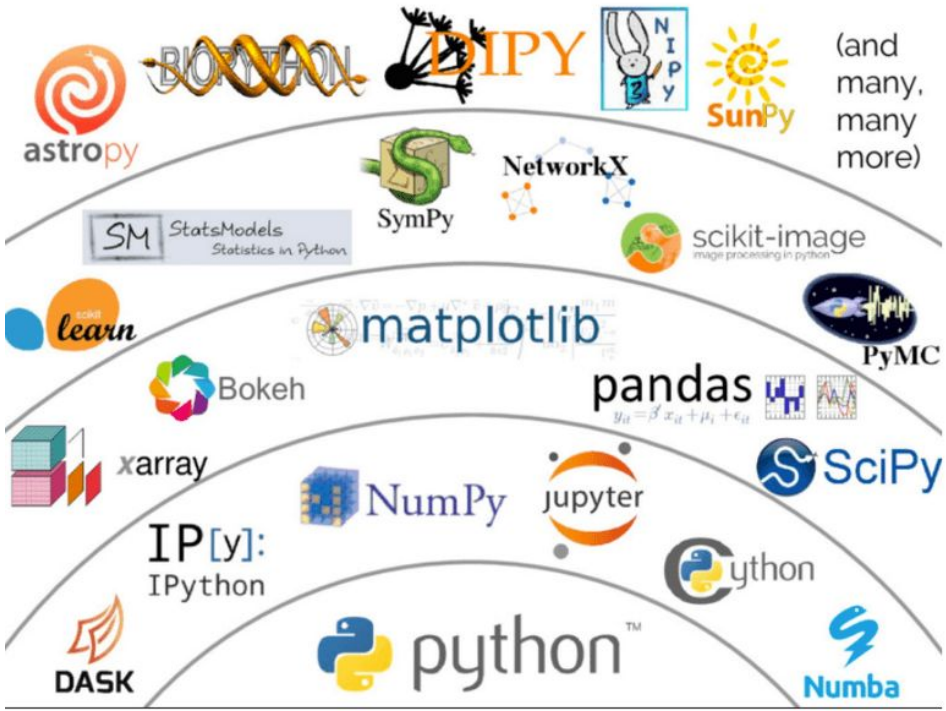
Specialized hardware is not enough

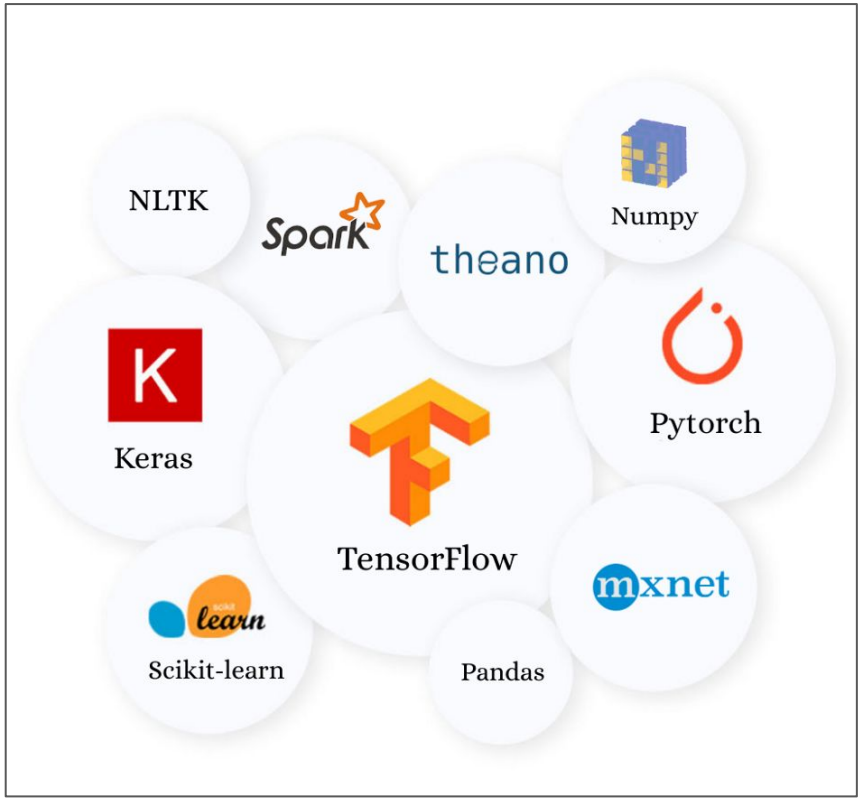


No way out but to distribute!

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

Python data science ecosystem



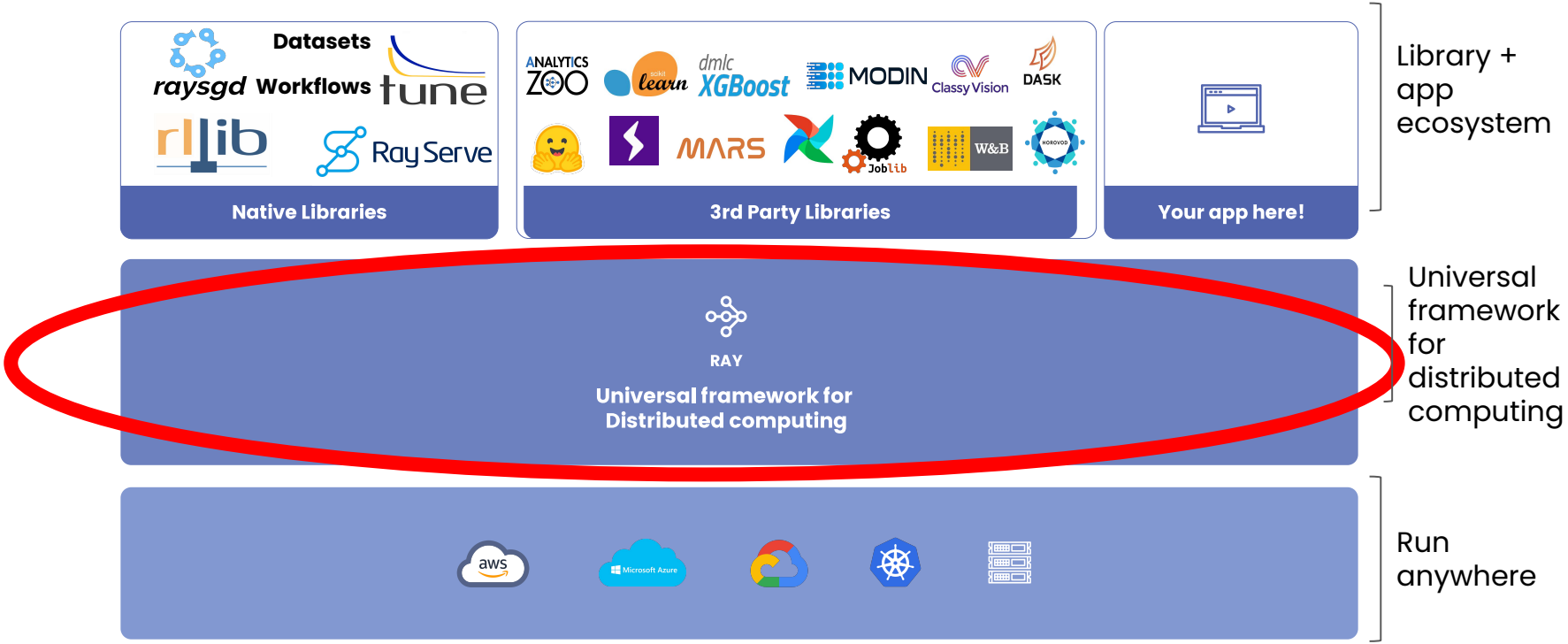


What is Ray 

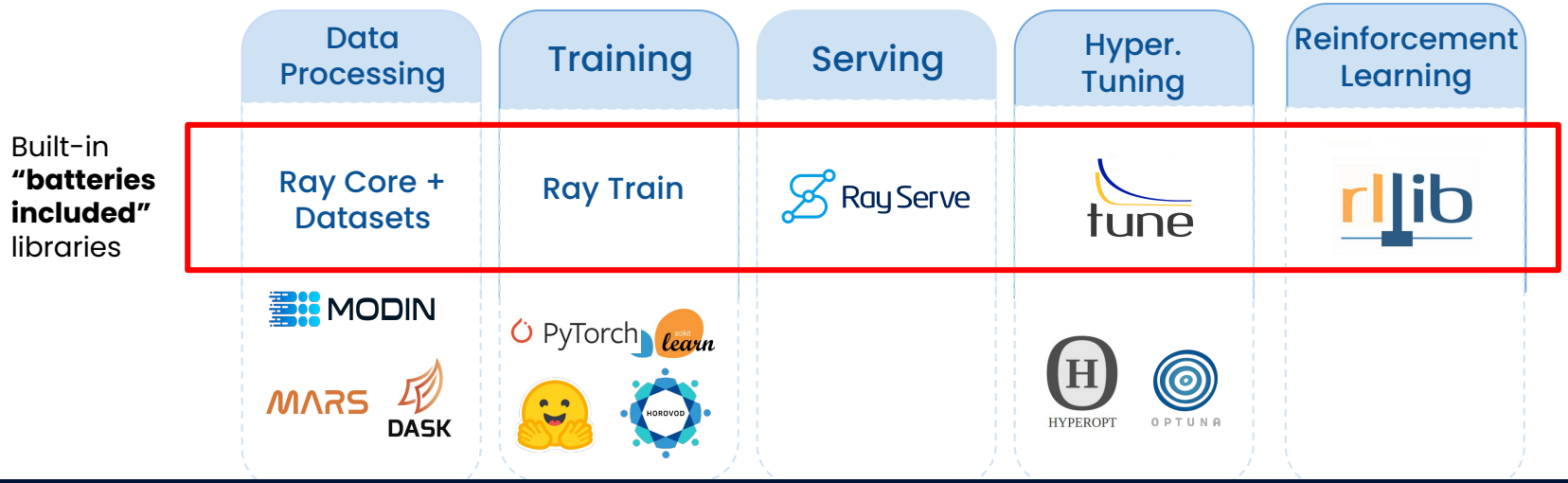
→ A simple/general-purpose library for distributed computing
→ An ecosystem of Python libraries (for scaling ML and more)
→ Runs on laptop, public cloud, K83, on-premise

A layered cake of functionality and capabilities for scaling ML workloads

A Layered Cake and Ecosystem

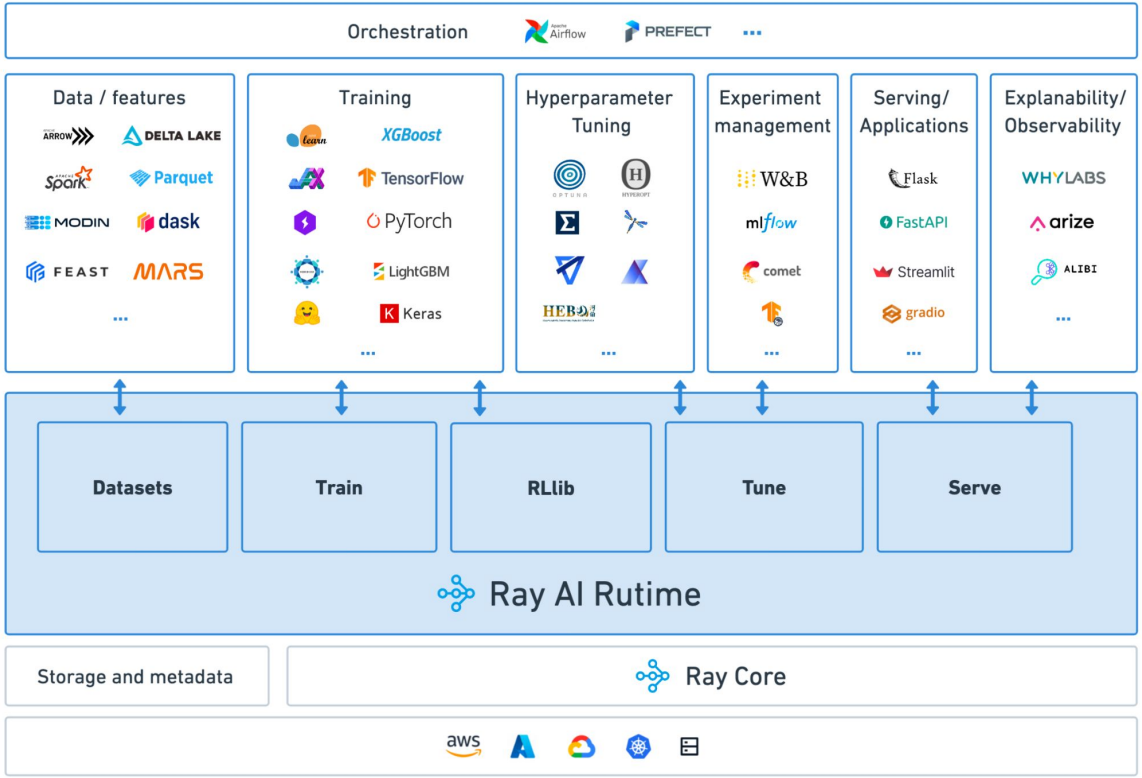


Rich ecosystem of scaling ML workloads



Only use the libraries you need!

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



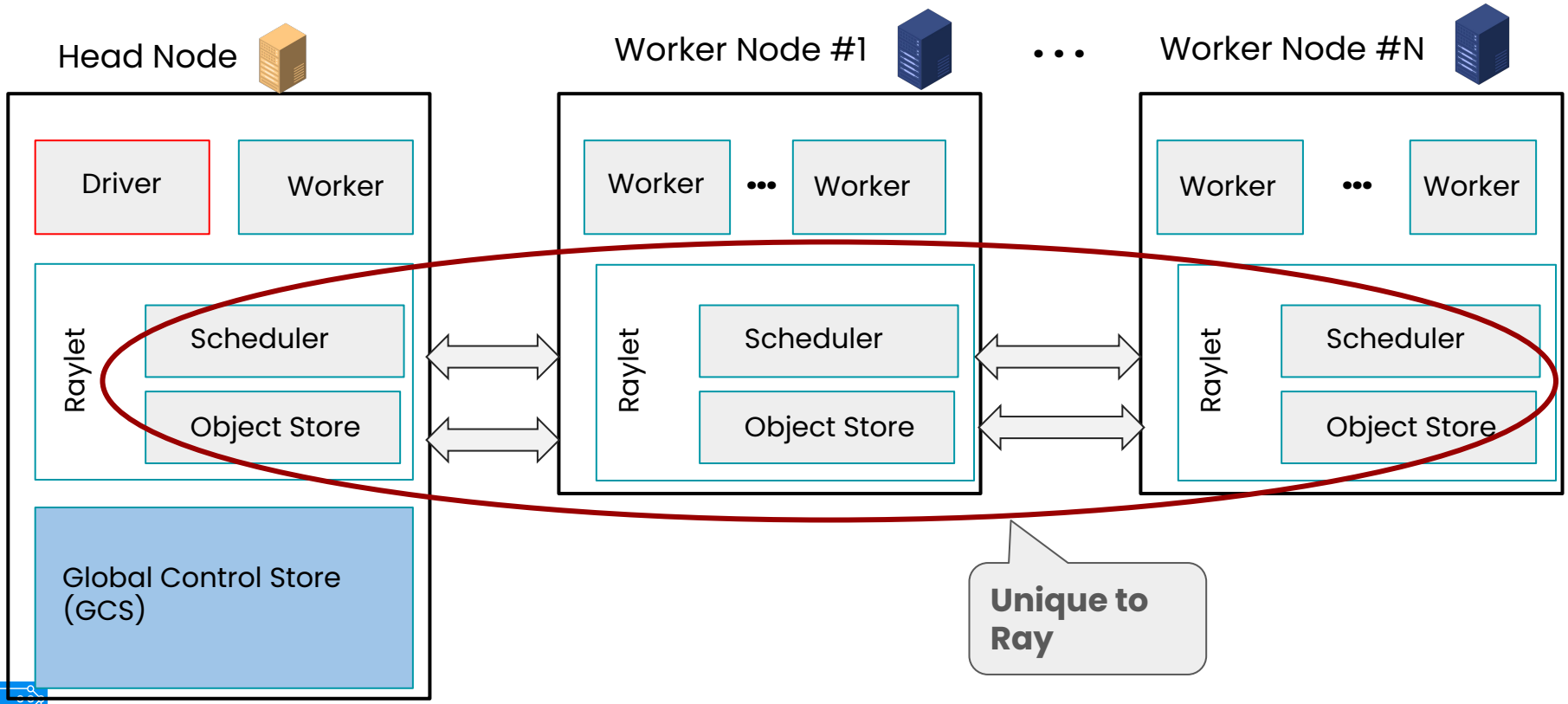
Ray 2.0 & Ray AIR sessions

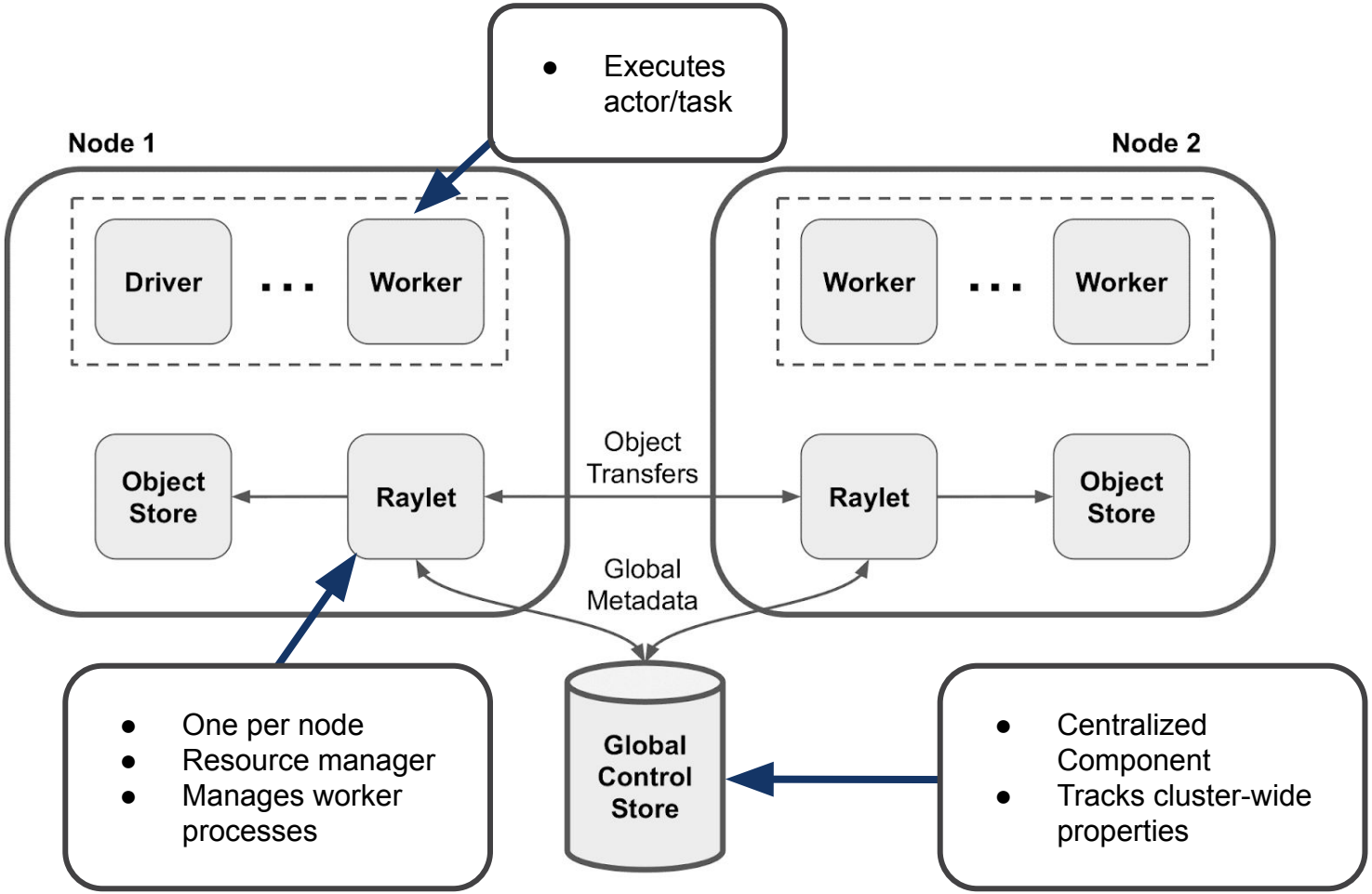
→ Introduction Ray AI Runtime
→ State of Ray Serve in 2.0
→ Shuffling 100TB with Ray Datasets
→ Ray Observability: Present & future
→ Many others in Ray Deep Dives track …

Who's using it

Ray Architecture & Components

An 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

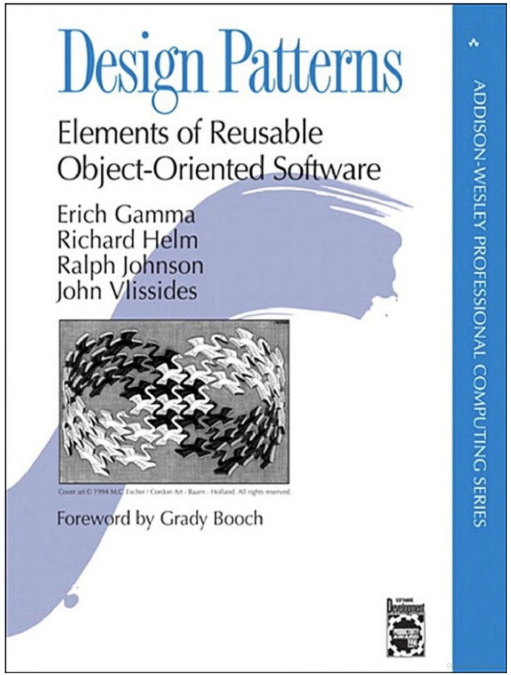
Ray distributed design patterns & APIs

Ray Basic Design Patterns

→ Ray Parallel Tasks
  + Functions as stateless units of execution
  + Functions distributed across 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

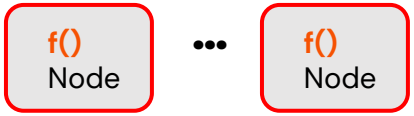
Python → Ray APIs

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

Task

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

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):
        ...
```

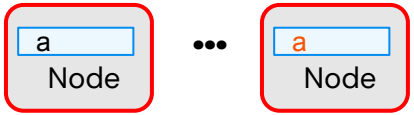
Distributed


```
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



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

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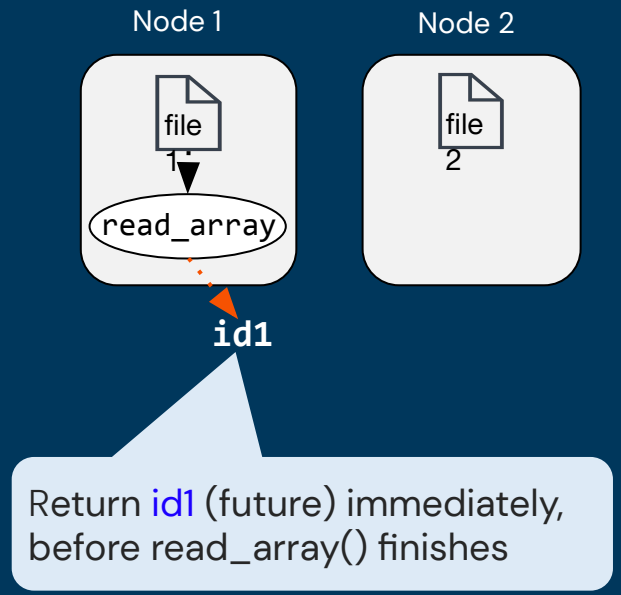

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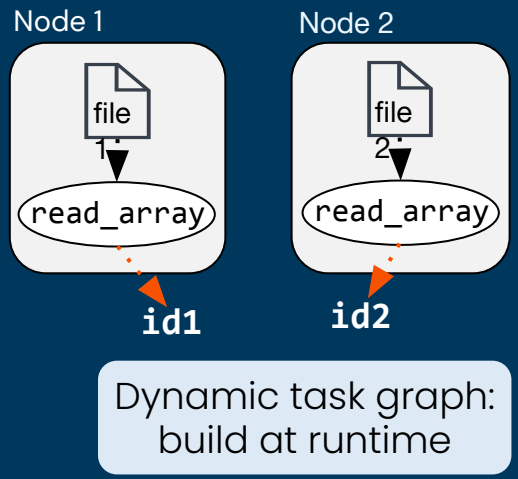

Task API

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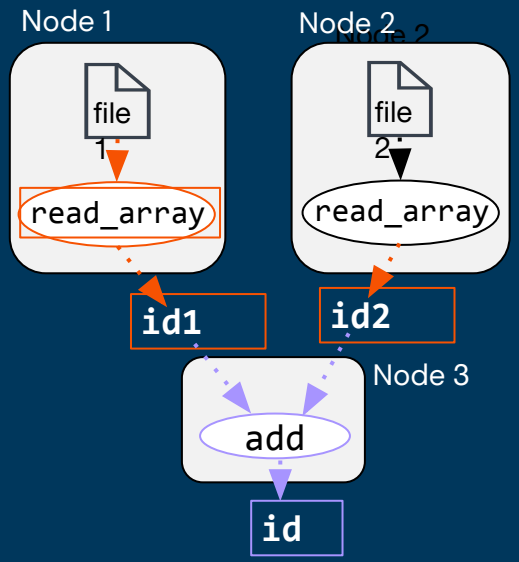
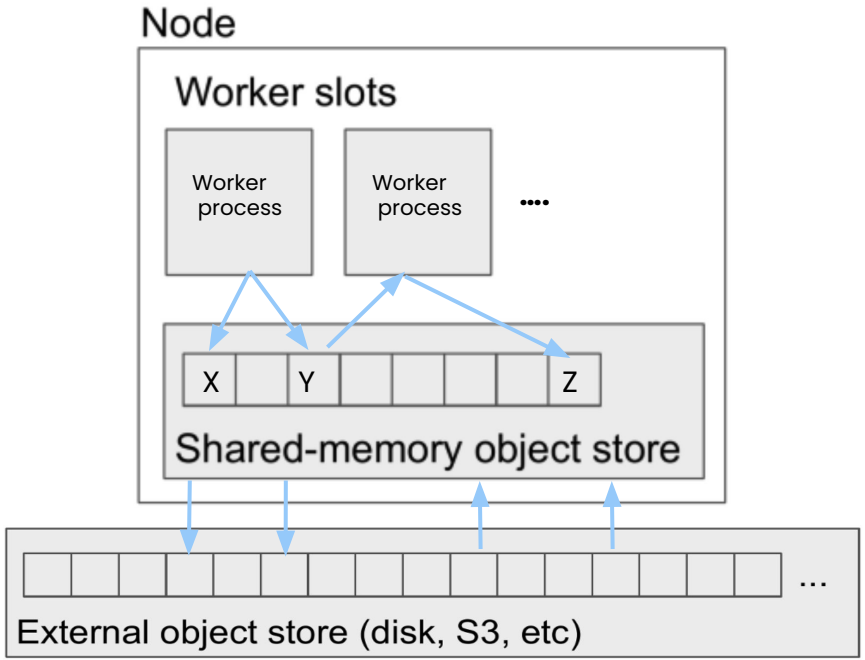
sum = ray.get(id)
```

ray.get() block until result available

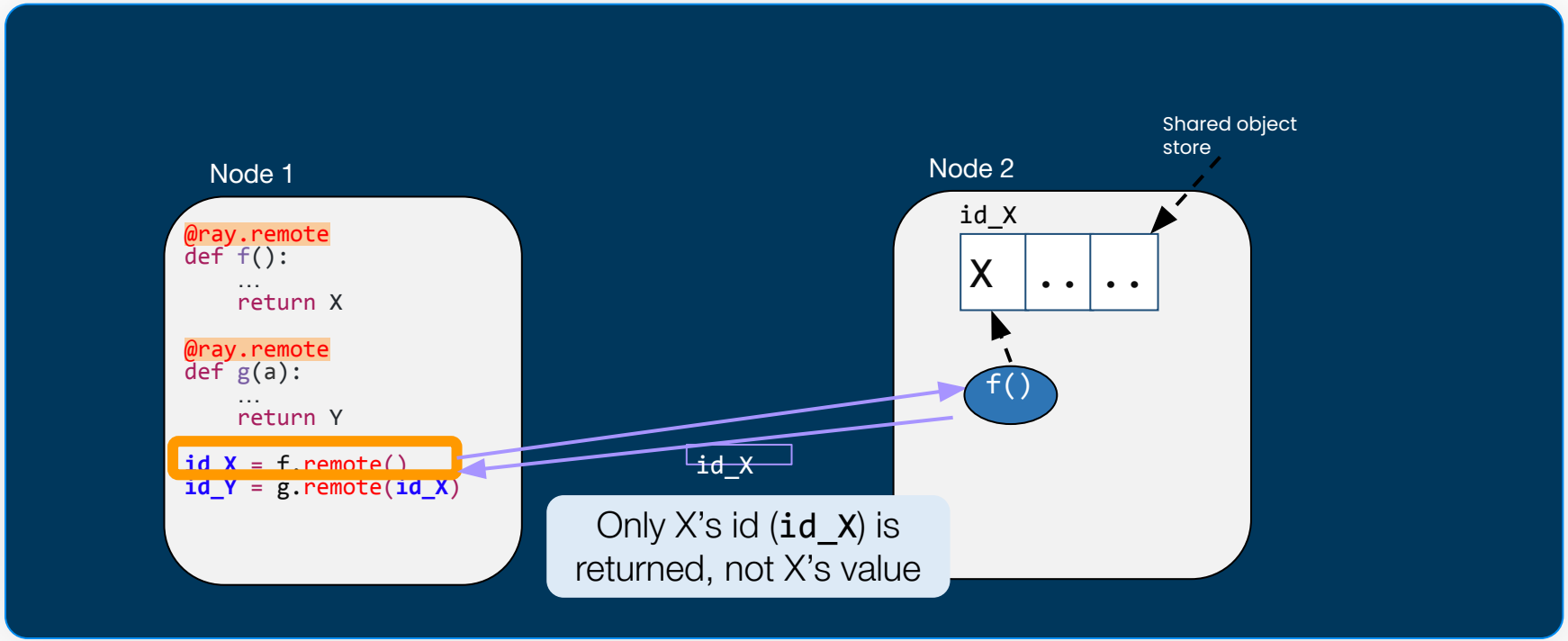


Distributed Immutable object store

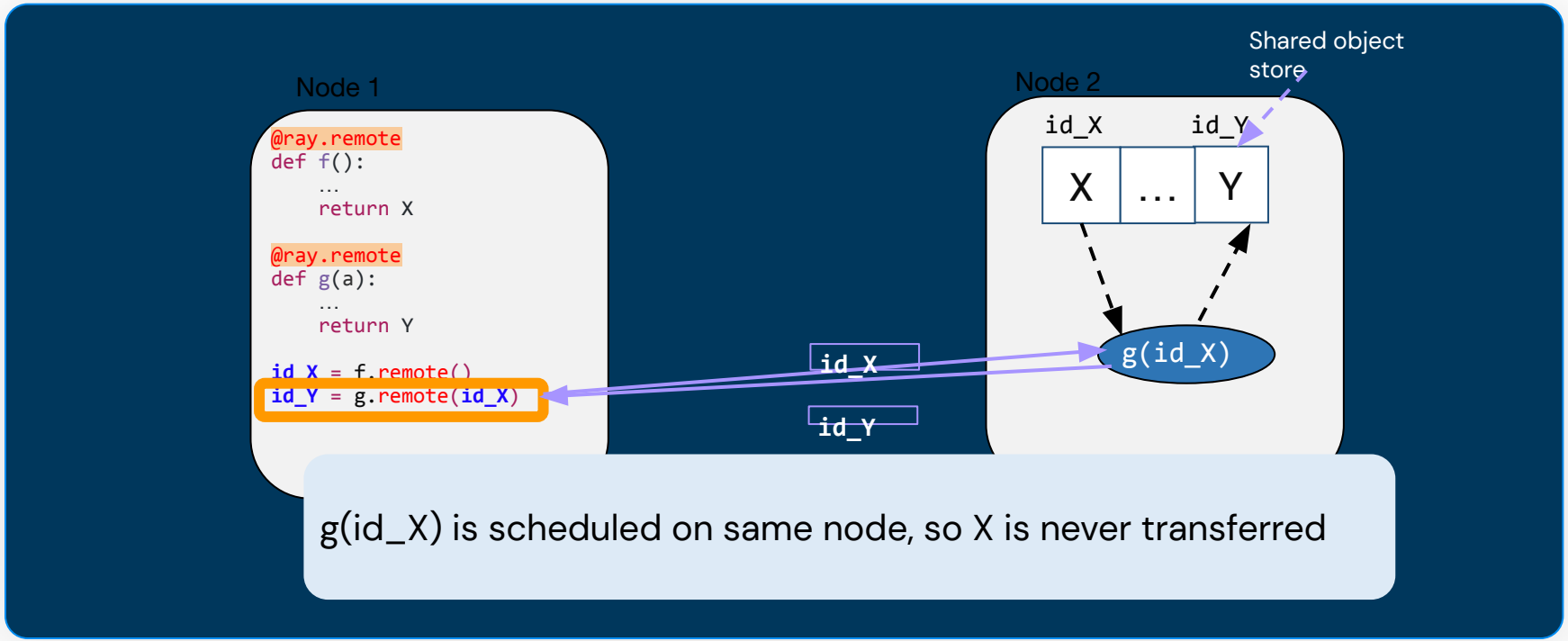


Spill over to external storage

Distributed object store



Distributed object store



Examples of Distributed Applications with Ray

Distributed Applications with Ray

ML Libraries

- Ray AI Runtime
  - Ray Data, Tune, Train, Serve, RLlib
- Distributed scikit-learn/Joblib
- Distributed XGBoost on Ray
- Dask on Ray
- Modin on Ray

All using Ray design patterns

Monitoring Services

- WhyLabs
- Arize AI
- W & B

All using Ray design patterns

ML Platforms & Integrations

- Merlin (Shopify)
- Zero Copy (IBM)
- TorchX
- MLflow, Comet
- AirFlow
- HuggingFace
- Pycaret
- Ludwig AI

All using Ray design patterns

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

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)

Let’s go with

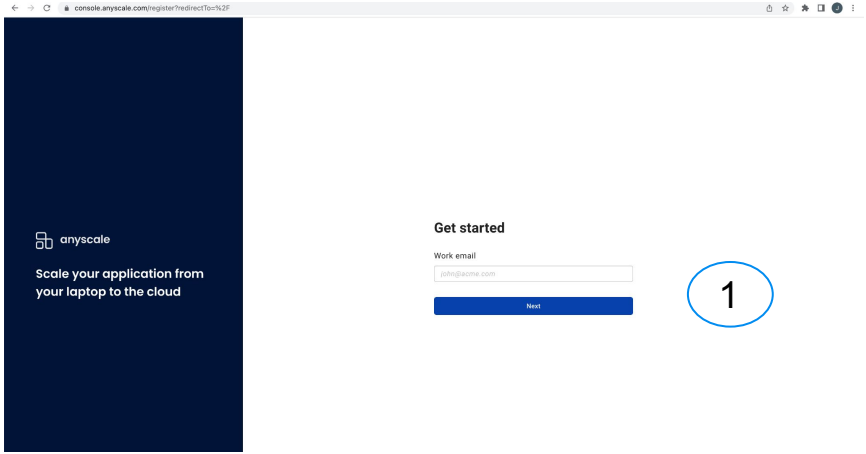
Anyscale User/Password

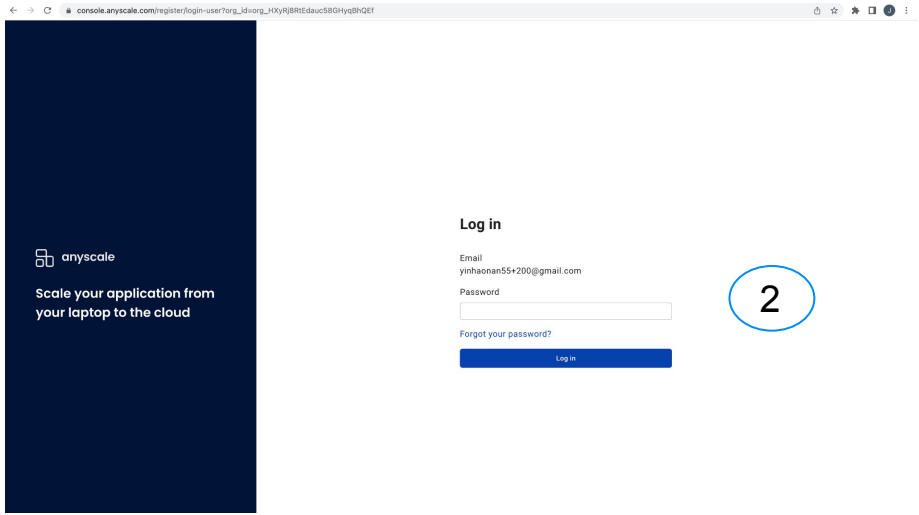
https://bit.ly/rsummit2022-class-logins

- Choose any line from spreadsheet under your class name: “Introduction to Ray for Distributed Applications”
- In column “Account” switch “Not Available”
- For example, Username/password: `yinhaonan55+520@gmail.com/tutorialpassword520`

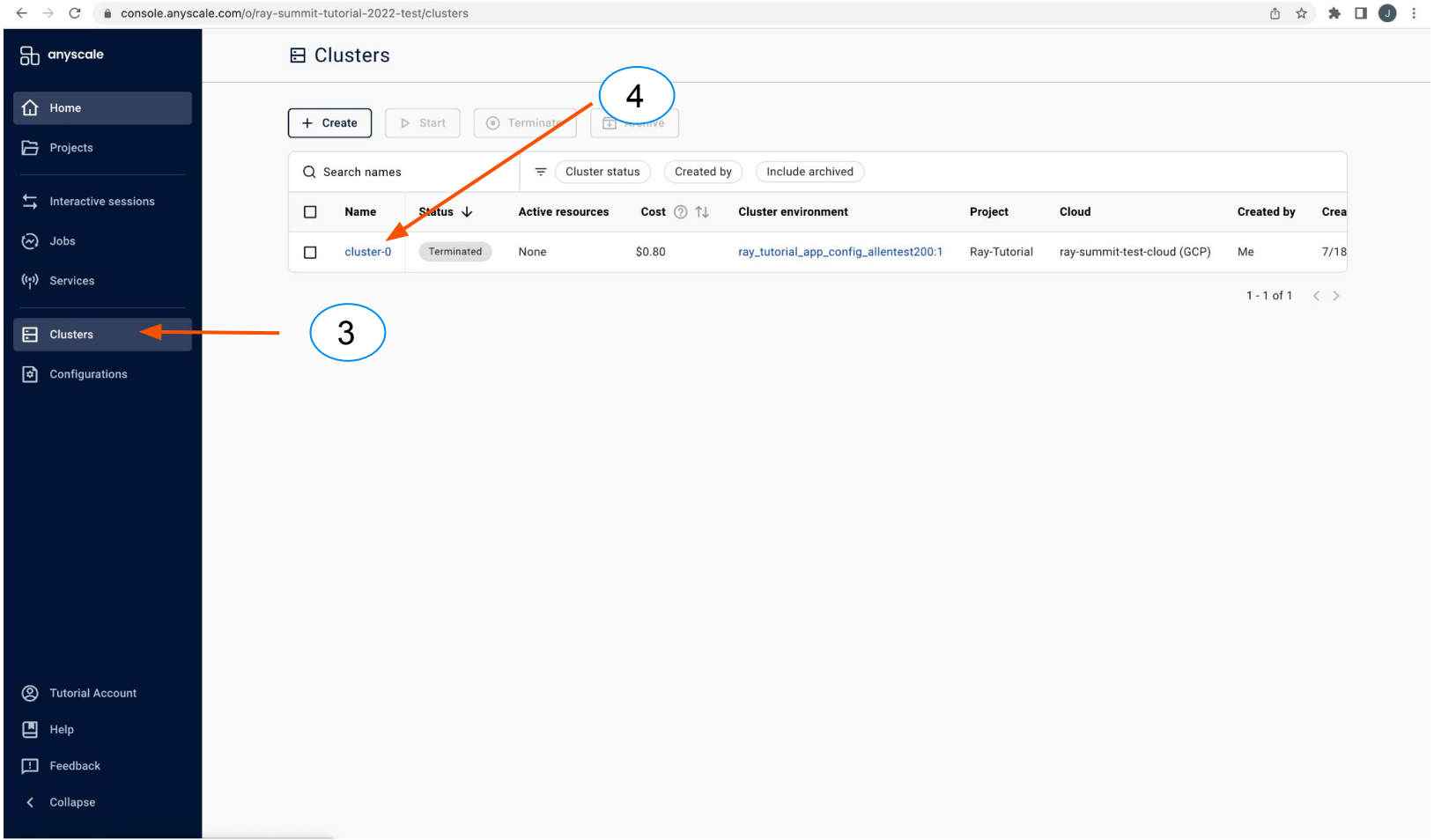
Your Anyscale Cluster

→ Console: http://console.anyscale.com/
→ User name: <username@gmail.com>
→ Password : password

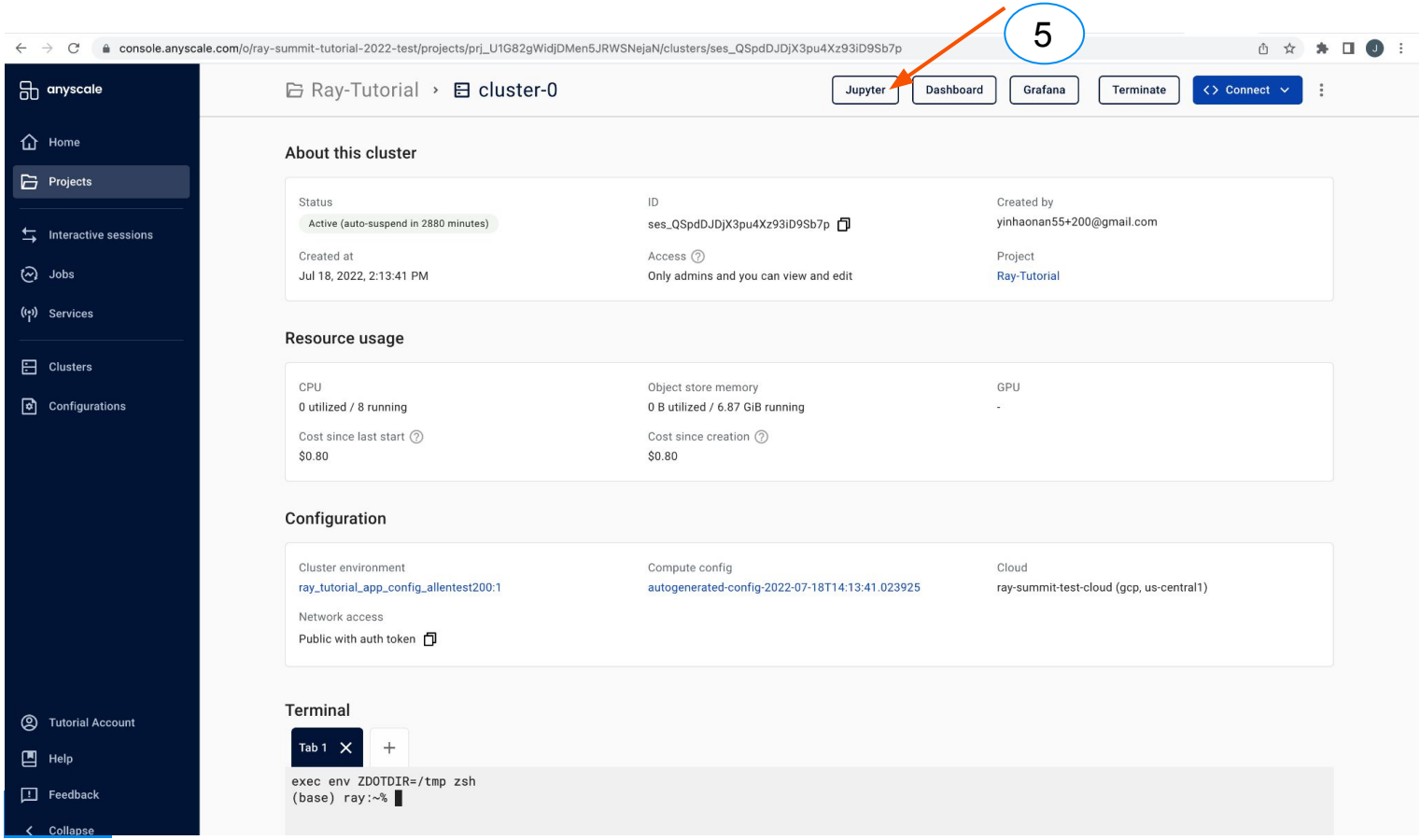




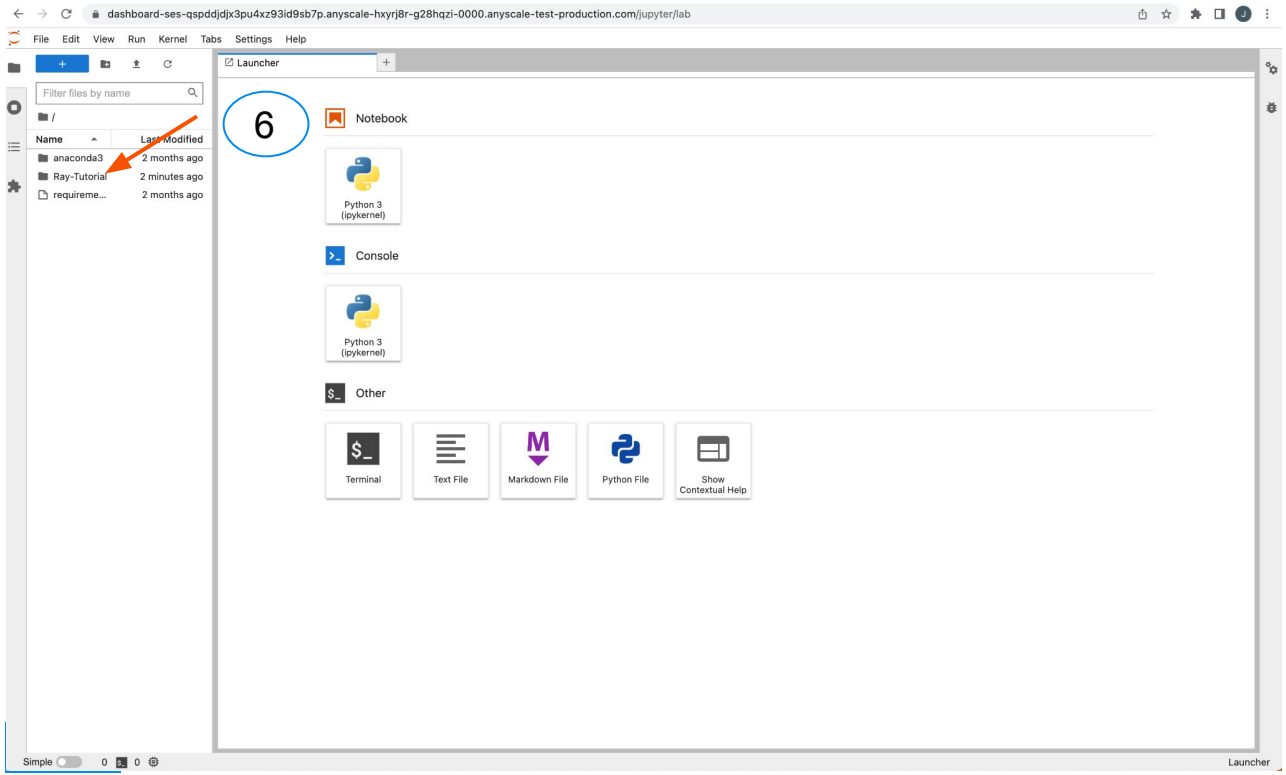
Your Anyscale Cluster



Your Anyscale Cluster



Your Anyscale Cluster



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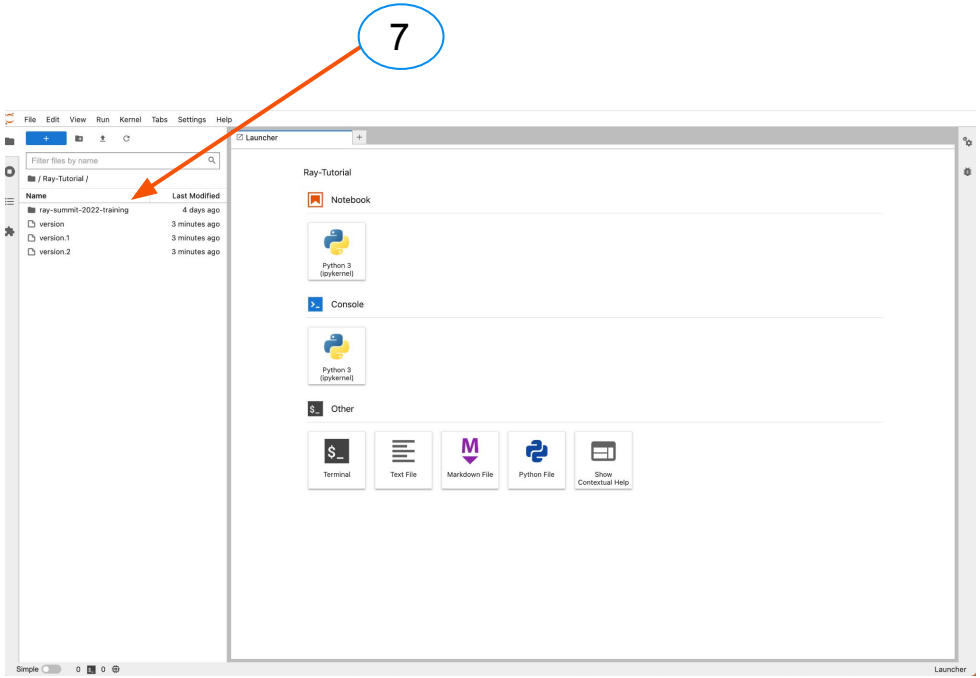

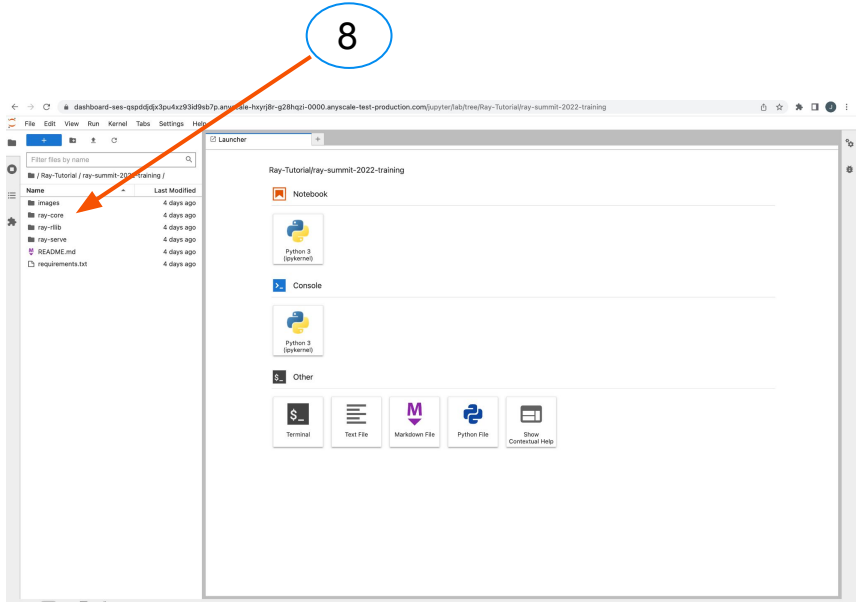

Thank you.

Tell us what you think...

https://bit.ly/ray-core-summit2022

Tell us what you think...

https://bit.ly/ray-core-summit2022

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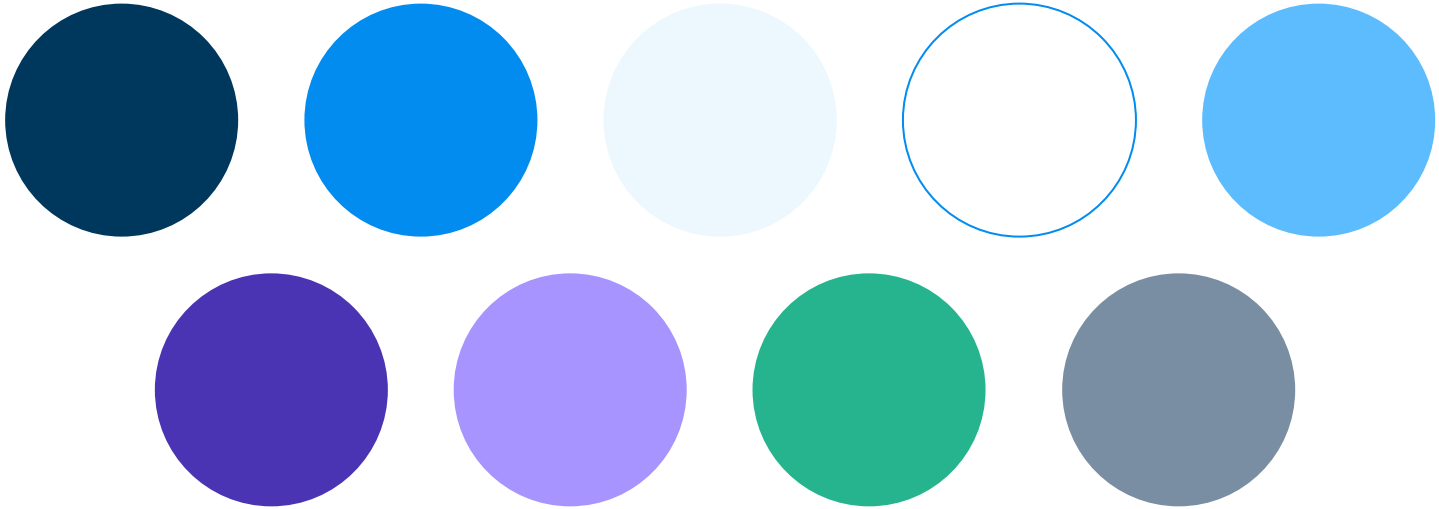
Firstname Lastname, Company

Colors



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Here is a Basic Light Slide

How about a slide with 2 options?

Here is an info card

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Thank you.

Follow up information can go here.