



PyData

New York City 2022

Distributed Python with Ray: Hands on with the Ray 2.0 APIs
for scaling Python Workloads

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Few Important URLs

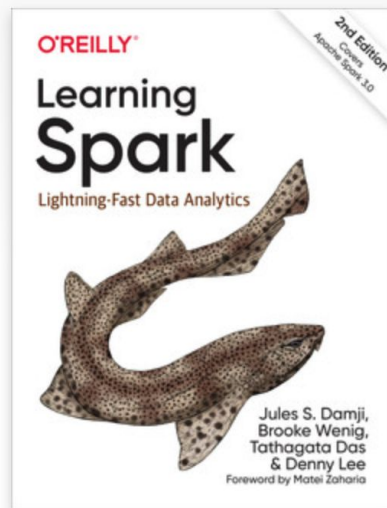
Keep these URLs open in your browser tabs

- Ray Core Class Survey: <https://bit.ly/pydata-nyc-2022>
- GitHub: <https://bit.ly/pydata-nyc-tutorial-2022>
- 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 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

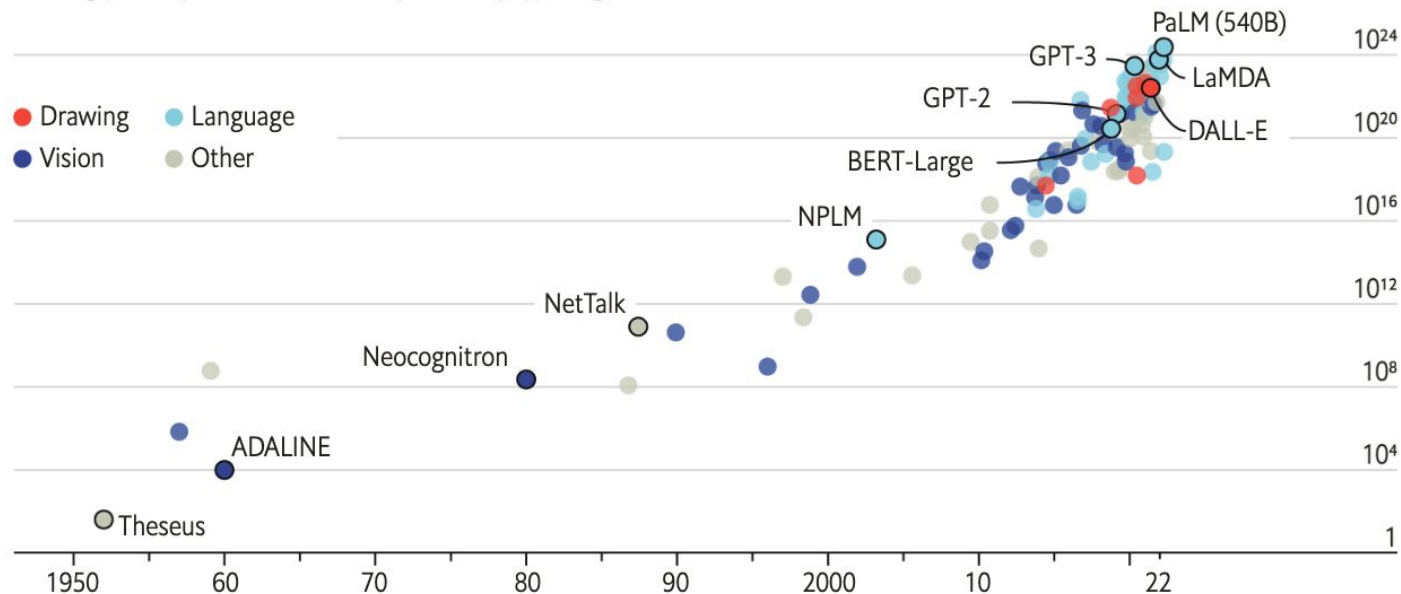
Python is the
default
language for
DS/ML

Blessings of scale ...

The blessings of scale

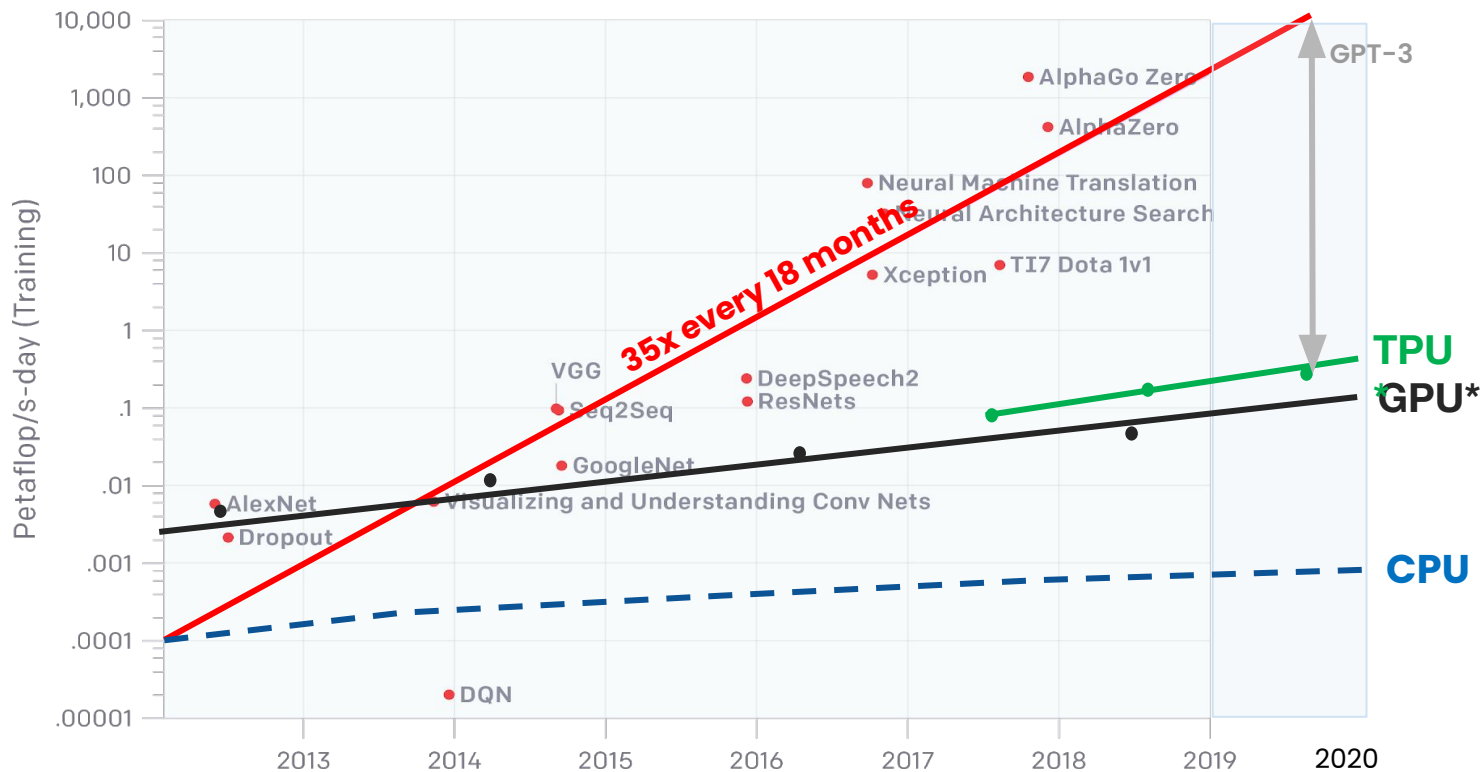
AI training runs, estimated computing resources used

Floating-point operations, selected systems, by type, log scale

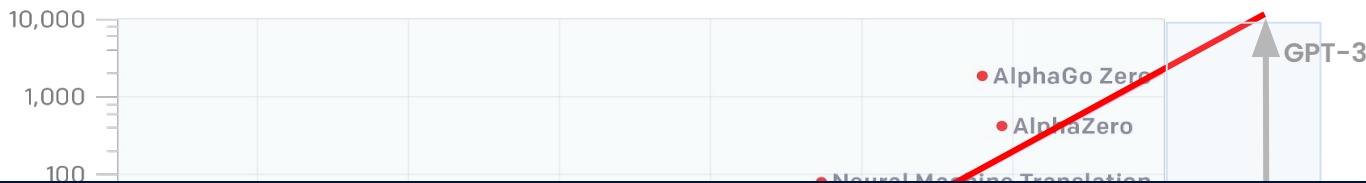


Sources: "Compute trends across three eras of machine learning", by J. Sevilla et al., arXiv, 2022; Our World in Data

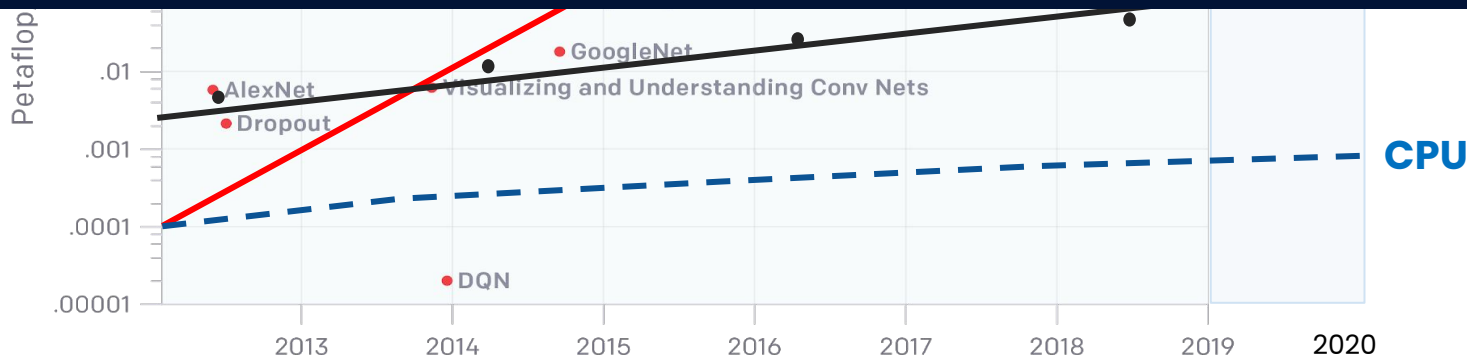
Compute - supply demand problem



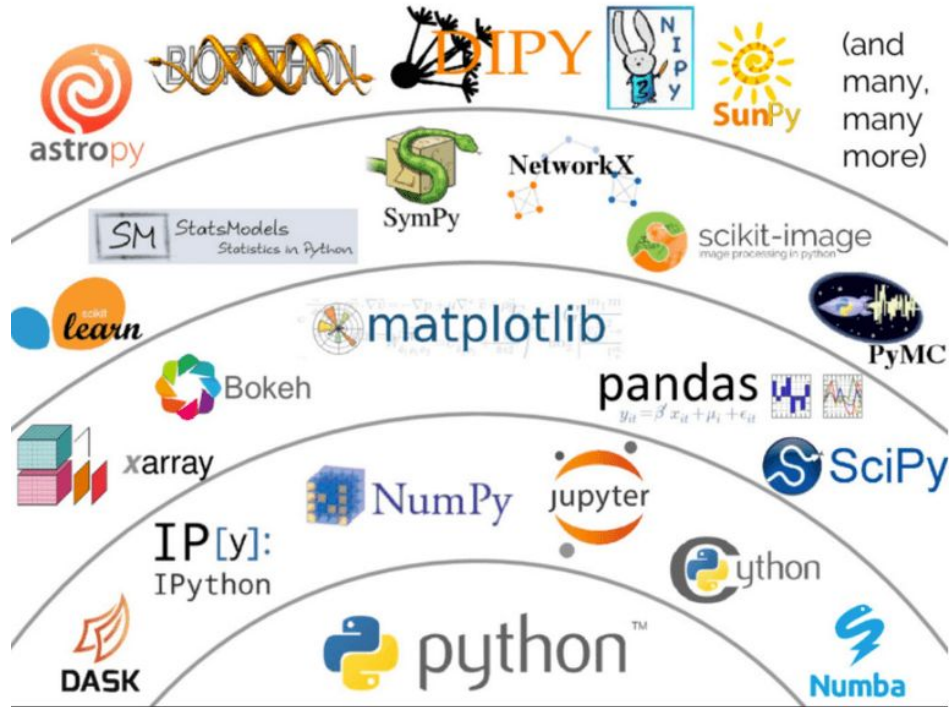
Specialized hardware is not enough



No way out but to distribute!



Python data science ecosystem



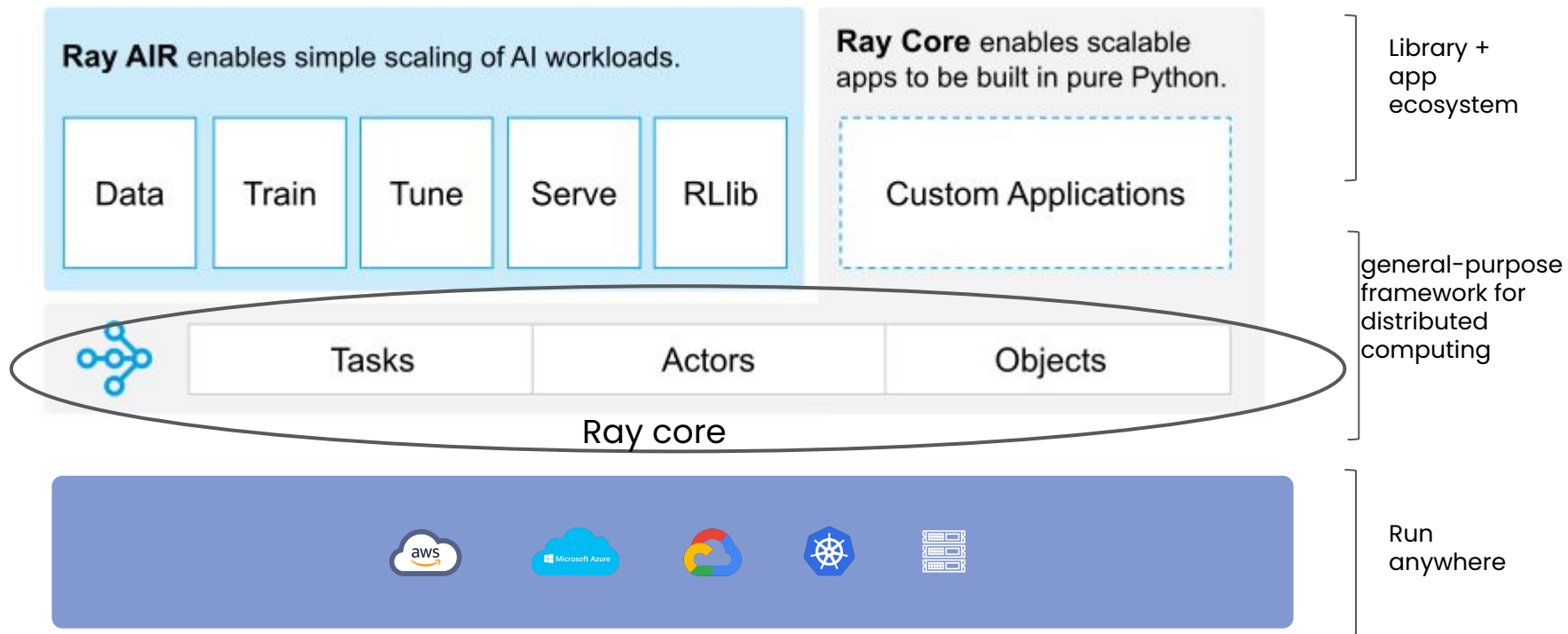
What is Ray



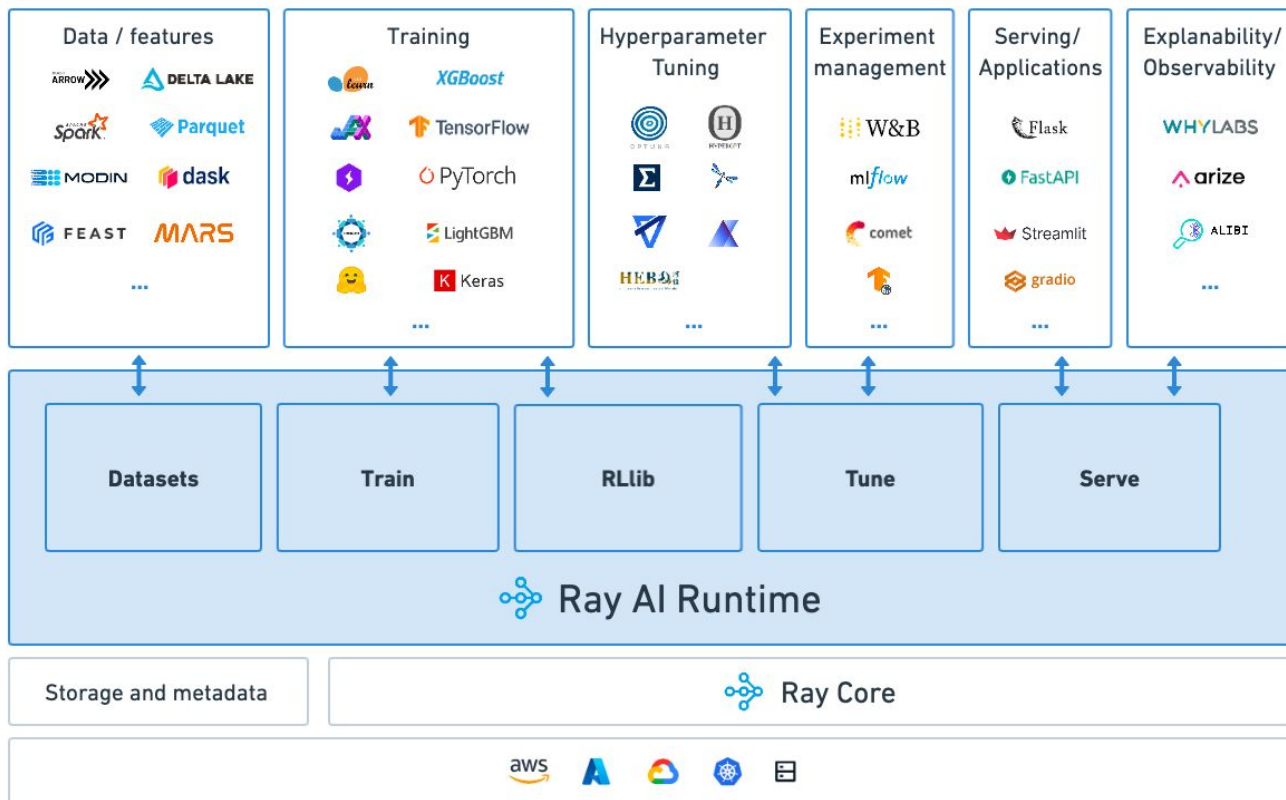
- A simple/general-purpose library for distributed computing
- An ecosystem of Python libraries (for scaling ML and more)
- Runs on laptop, public cloud, K8s, on-premise

A layered cake of functionality and capabilities for scaling ML workloads

A Layered Cake and Ecosystem



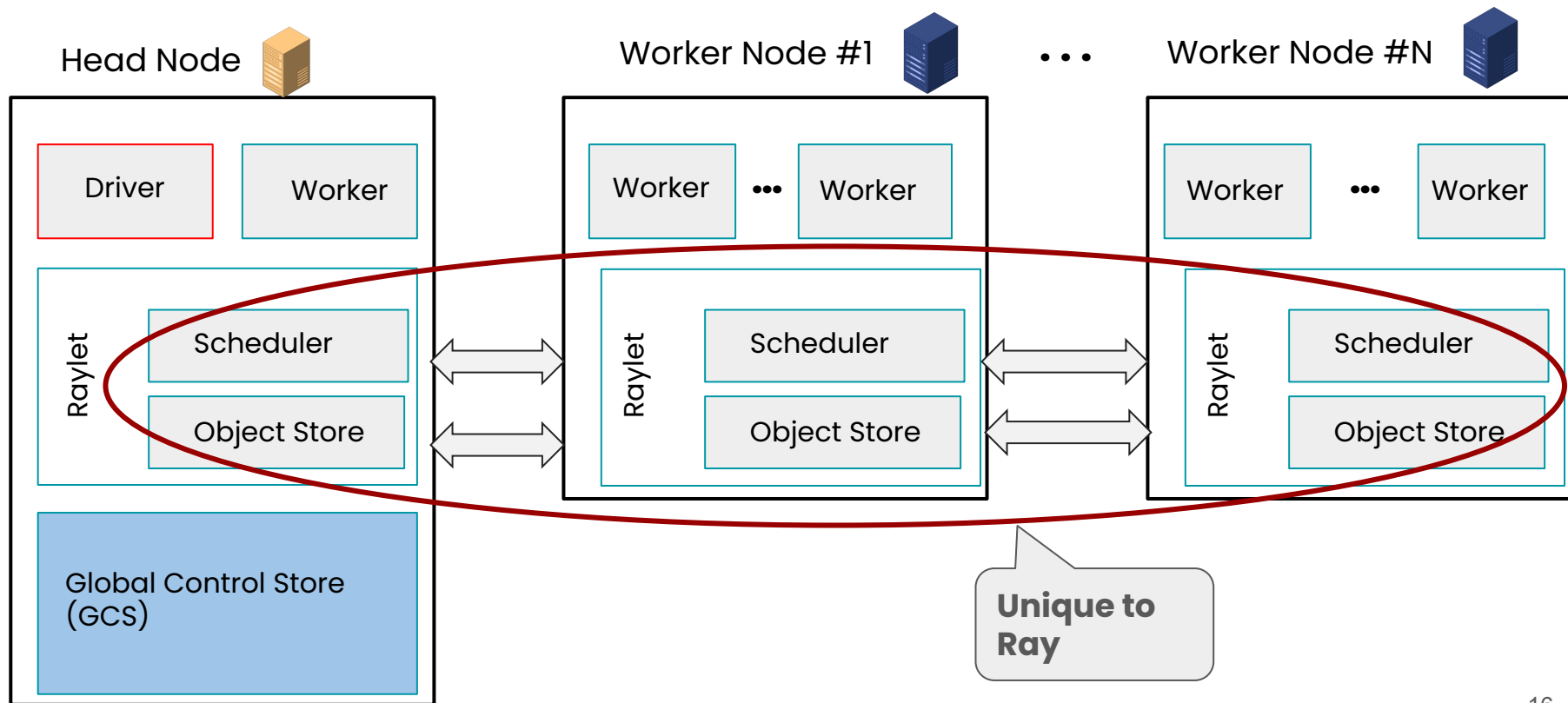
Ray AI Runtime (AIR) is a scalable runtime for end-to-end ML applications



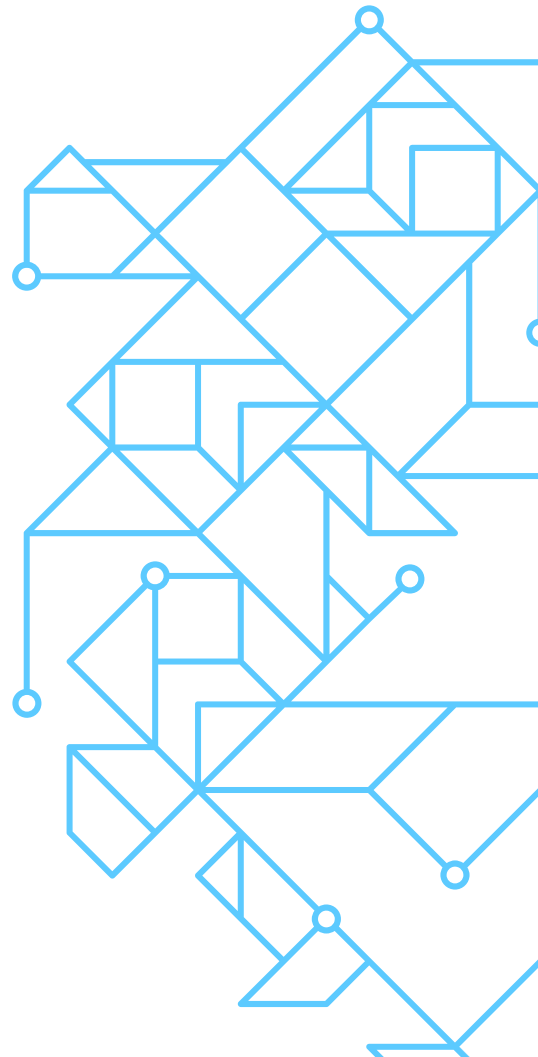
Ray Architecture & Components



An anatomy of a Ray cluster



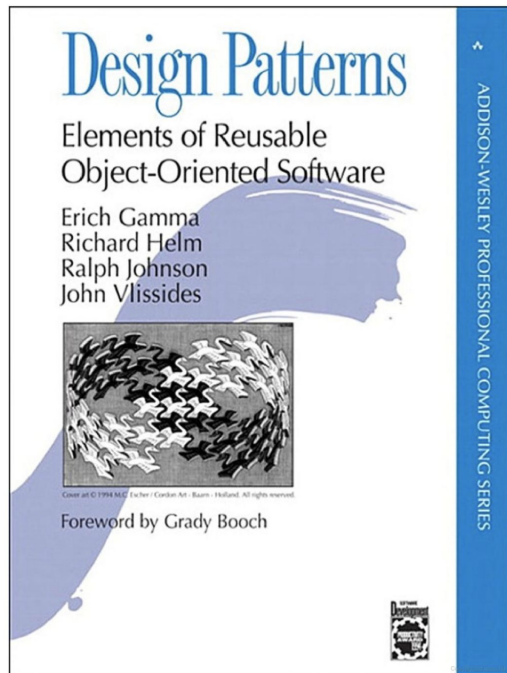
Ray distributed design patterns & APIs



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



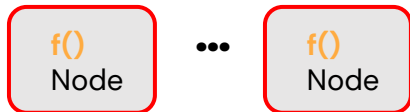
```
def f(x):  
    # do something with  
    x:  
    y = ...  
    return y
```

Task



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

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



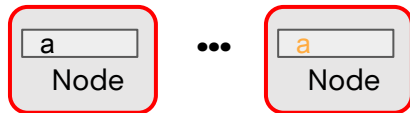
```
import numpy as np  
a = np.arange(1, 10e6)  
b = a * 2
```

Distributed
immutable
object



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

Distributed



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
```

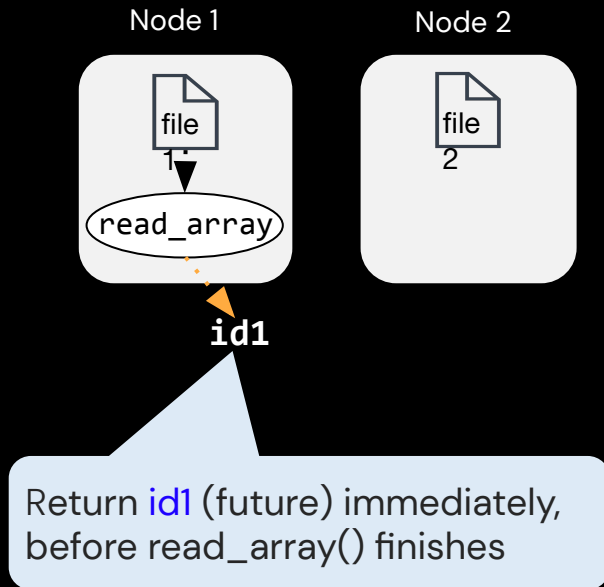
```
c = Counter.remote()
id4 = c.inc.remote()
id5 = c.inc.remote()
```

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)
```

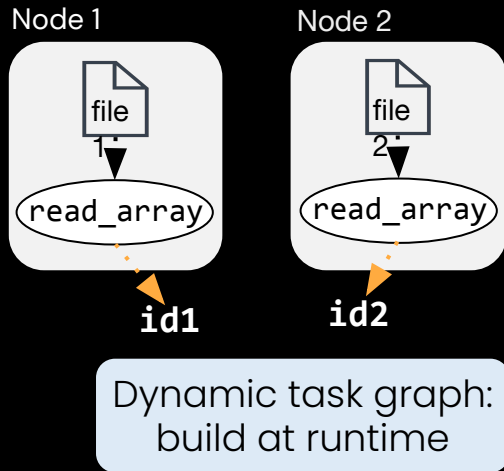


Task API

```
@ray.remote
def read_array(file):
    # 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)
```



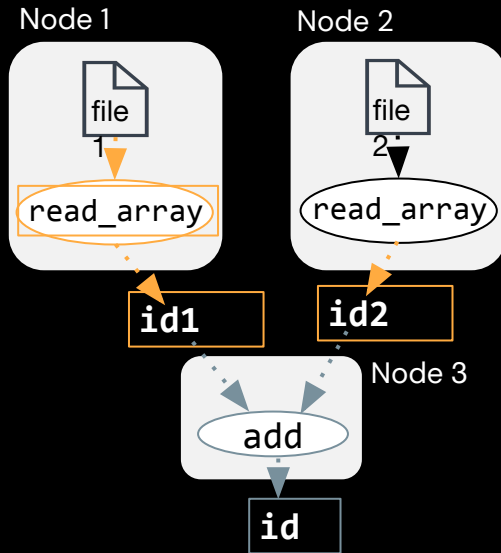
Task API

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

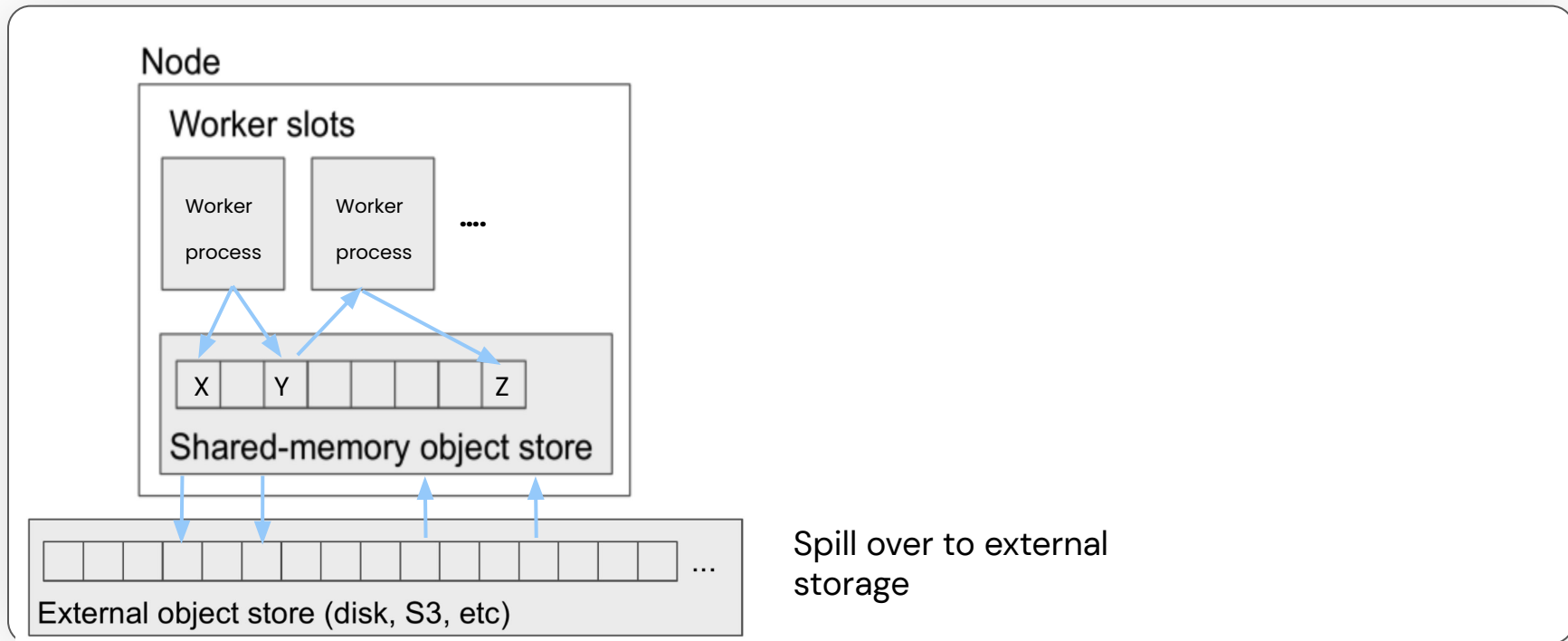
@ray.remote
def add(a, b):
    return np.add(a, b)
```

```
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



Distributed object store

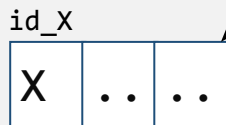
Node 1

```
@ray.remote  
def f():  
    ...  
    return X
```

```
@ray.remote  
def g(a):  
    ...  
    return Y
```

```
id_X = f.remote()  
id_Y = g.remote(id_X)
```

Node 2



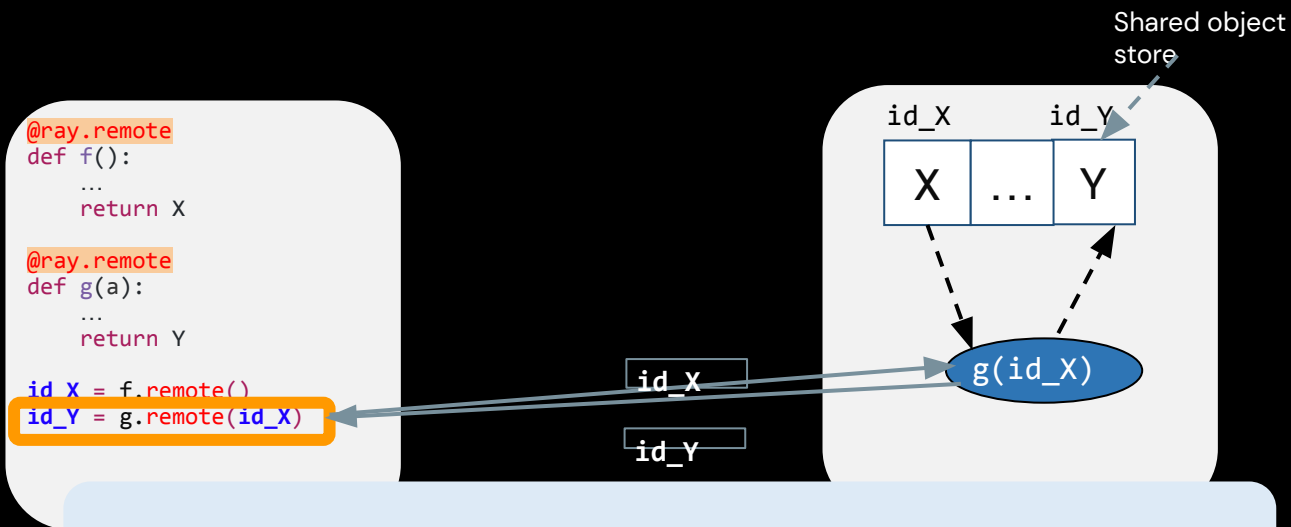
Shared object
store

f()

id_X

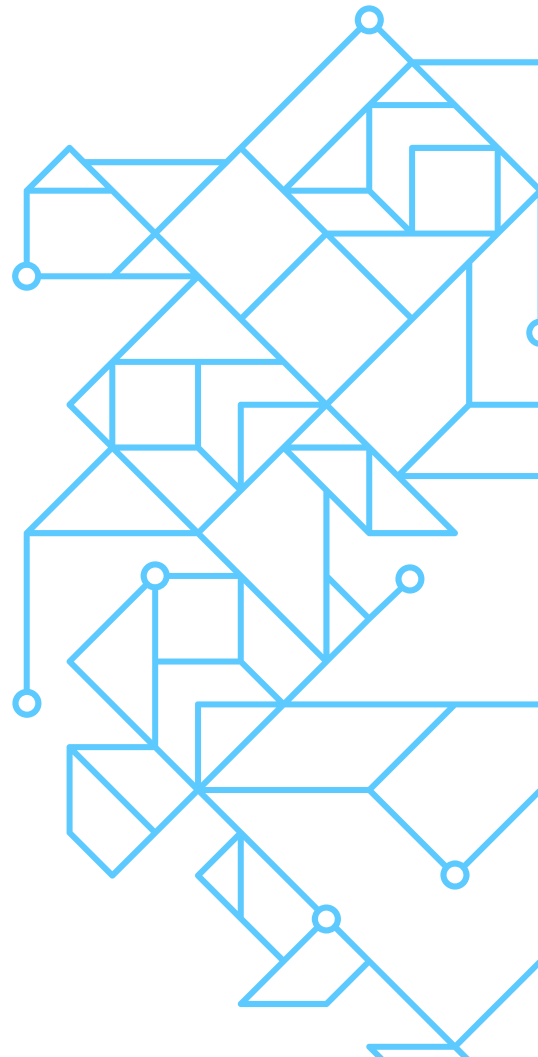
Only X's id (id_X) is
returned, not X's value

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
- Ray native libraries
- 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)
- Zero Copy (IBM)
- Meta
- MLflow, Comet
- AirFlow
- HuggingFace
- Pycaret
- Ludwig AI
- Uber
- Instacart
- Shopify
- Spotify

All using Ray core APIs & patterns

Sample of Companies Who Use Ray in their Machine Learning Platform

RIDECELL



Uber

cruise

instacart

Meta

Google

OpenAI

Microsoft

ANT GROUP

shopify

amazon

STITCH FIX

RIOT GAMES

NETFLIX

Spotify

ByteDance



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)

Let's go with



<https://bit.ly/pydata-nyc-tutorial-2022>



Thank you!

Questions?

email: jules@anyscale.com

twitter: [@2twitme](https://twitter.com/2twitme)

