

Actor-Based Distributed Systems

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Room 4.43, Spring 2024



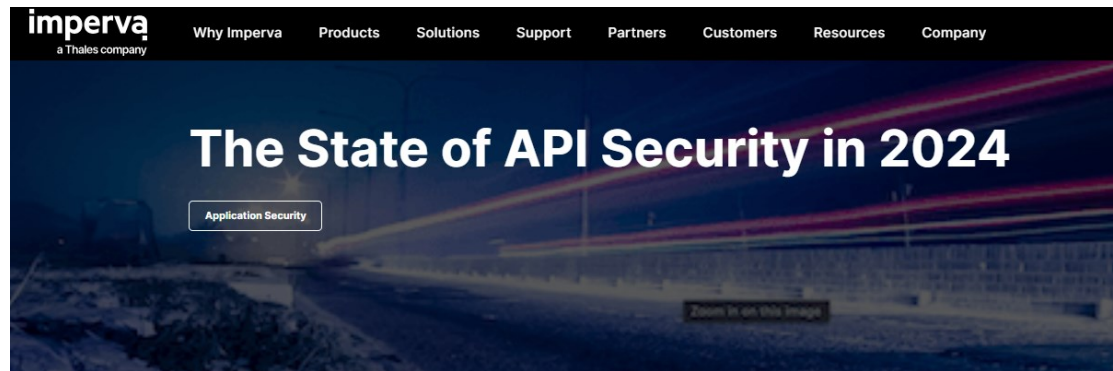
AKADEMIA GÓRNICZO-HUTNICZA
IM. STANISŁAWA STĄSZICA
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Class Logistics

- During our meeting we will use Ray Framework
- Install all required components
 - *pip install -U "ray[default]"*
 - <https://docs.ray.io/en/latest/ray-overview/installation.html>
- Important *pip install ray* is not enough !!!

Notes on REST API

- The most common security issues:
 - Shadow API
 - Deprecated API
 - Unauthorized API



API calls make up a massive 71% of all web traffic

Widespread API usage is expanding the attack surface for bad actors. These threats make it critical for organizations to understand the risks and complexities of APIs and the importance of API Security.

Class Logistics

- Laboratory classes during week 25.3-5.4
 - There is no meeting on Wednesday 3.4
- We will use desktops from Computer Networks Laboratory
 - Select Ubuntu image
- Preliminary plan homework assignment
 - Elastic schedule on week 25-29.4

Class Logistics

- Laboratory grading
 - Showing up => 1 pt
 - UPEL task upload => 1 pt
 - Hard work on lab meeting => 2 pt
 - You need to show me logs of your tasks execution on Ray Dashboard
 - Extra activity, labs improvement => 1 pt

Actors

- Mathematical model of concurrent computation proposed by Carl Hewitt in 1973

Session 8 Formalisms for
Artificial Intelligence

A Universal Modular ACTOR Formalism for Artificial Intelligence

Carl Hewitt

Peter Bishop

Richard Steiger

Abstract

This paper proposes a modular ACTOR architecture and definitional method for artificial intelligence that is conceptually based on a single kind of object: actors [or, if you will, virtual processors, activation frames, or streams]. The formalism makes no presuppositions about the representation of primitive data structures and control structures. Such structures can be programmed, micro-coded, or hard wired in a uniform modular fashion. In fact it is impossible to determine whether a given object is "really" represented as a list, a vector, a hash table, a function, or a process. The architecture will efficiently run the coming generation of PLANNER-like artificial intelligence languages including those requiring a high degree of parallelism. The efficiency is gained without loss of programming generality because it only makes certain actors more efficient; it does not change their behavioral characteristics. The architecture is general with respect to control structure and does not have or need goto, interrupt, or semaphore primitives. The formalism achieves the goals that the disallowed constructs are intended to achieve by other more structured methods.

PLANNER Progress

Actors

- The actor is an object that encapsulates state and behavior
- Originated from
 - Smalltalk, Petri Nets, Channels ...
 - More details on theory in attached document
- More recent
 - *Scheme* made them concrete
 - *Erlang* made them useful
 - *Akka* made them cool
 - *Ray* makes them easy

Actors

- Primitives for concurrency/parallelism
- Entities having a message queue and associated behavior → **And isolated state!!**
- Can exchange messages between each-other
- When an actor receives a message it can:
 - Send a finite number of messages to other actors
 - Create a finite number of new actors
 - Modify its internal behavior on receiving messages

Actors

- Messages between actors are always sent asynchronously
- No requirement on order of message arrival
- Queuing and dequeuing of messages in an actor mailbox are atomic operations
- Fire and Forget approach, **no race conditions anymore**

Origins

- Originated on UC Berkeley
- Group led by Ion Stoica:
 - Apache Messos, Apache Spark (Databricks), Apache Alluxio (Alluxio)
 - Ray is managed by Anyscale

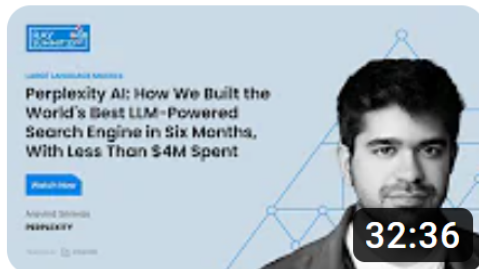


Ray: A Distributed Framework for Emerging AI Applications

Philipp Moritz*, Robert Nishihara*, Stephanie Wang, Alexey Tumanov, Richard Liaw, Eric Liang, Melih Elibol, Zongheng Yang, William Paul, Michael I. Jordan, Ion Stoica
University of California, Berkeley

Origins

The next generation of AI infrastructure is being built and scaled on Ray



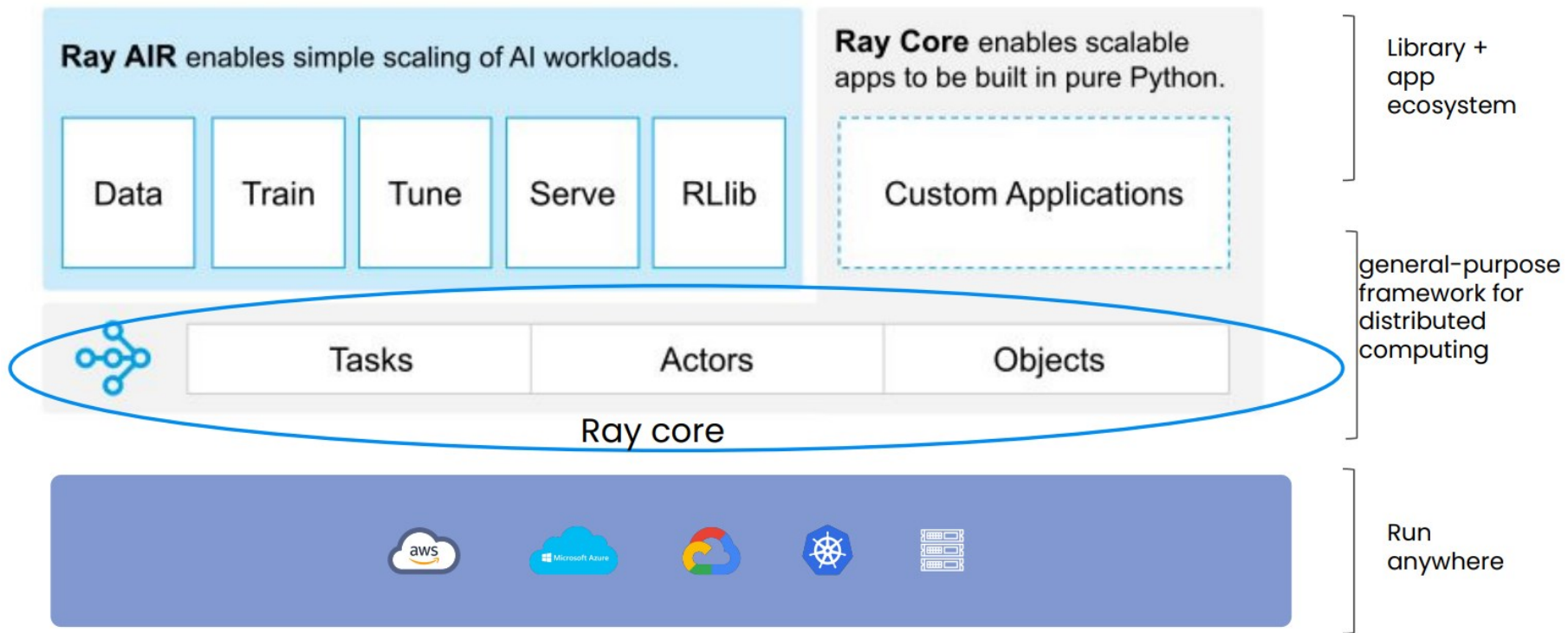
Perplexity AI: How We Built the World's Best LLM-Powered Search Engine in 6 Months, w/ Less Than \$4M

Anyscale • 18K views • 5 months ago

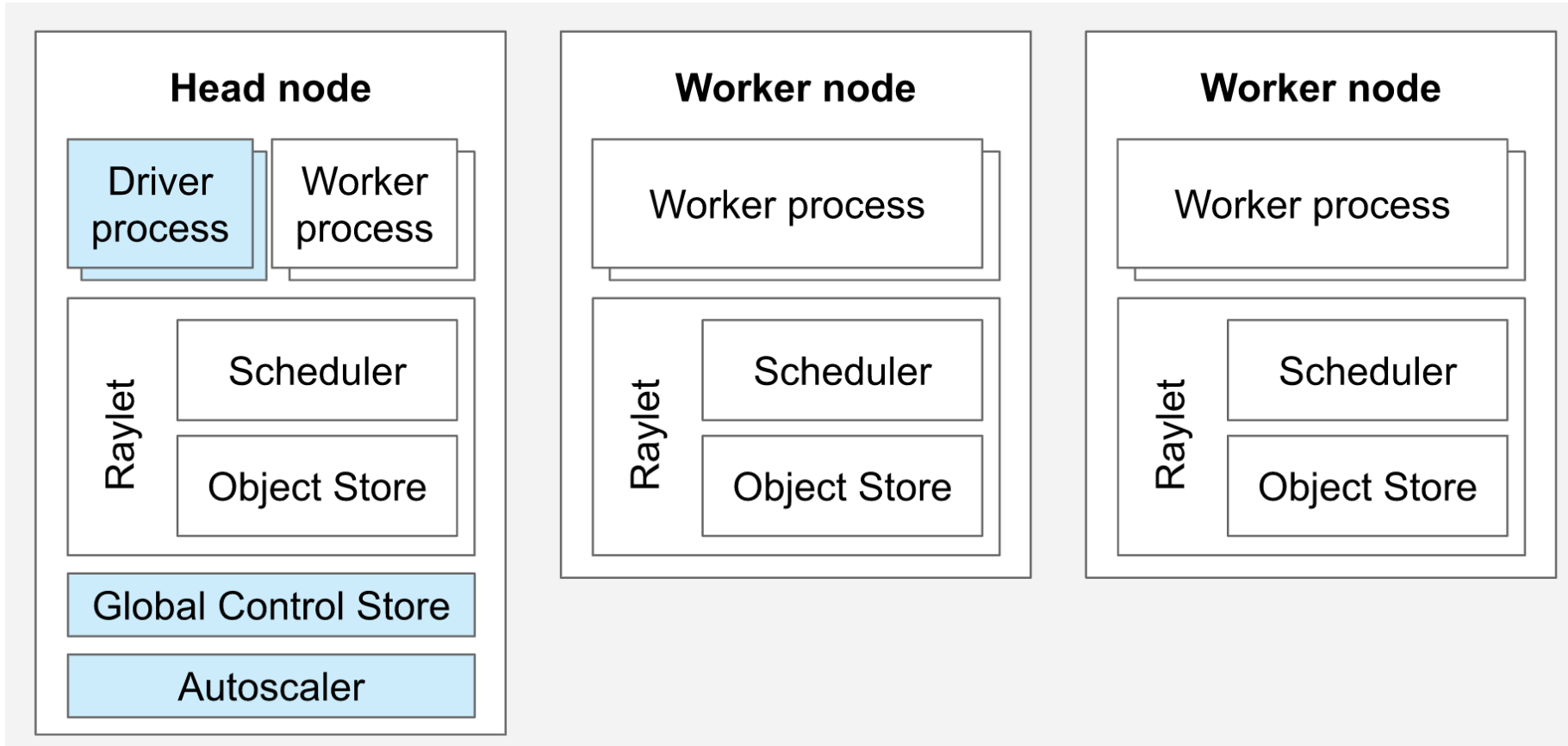
The FAST Compute Model

- **Futures:** references to objects
- **Actors:** remote class instances (objects)
- **Shared in-memory distributed object store**
- **Tasks:** remote functions

What is Ray ?

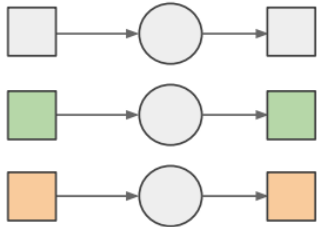


What is Ray ?



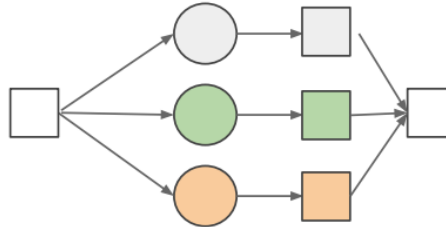
Scaling patterns

Batch Training / Inference



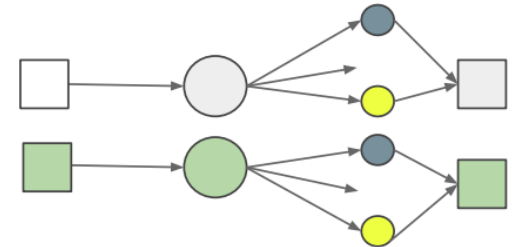
Different data / Same function

AutoML

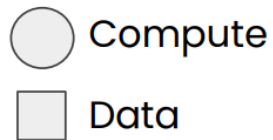


Same data / Different function

Batch Tuning



Different data / Same function



What is Ray ?

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



...



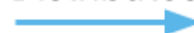
```
class Cls():  
    def __init__(self,  
x):  
    def f(self, a):  
        ...  
    def g(self, a):  
        ...
```

Actor

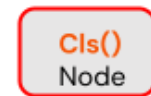


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class Cls():  
    def  
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```

Distributed



...



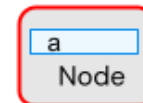
```
import numpy as np  
a= np.arange(1, 10e6)  
b = a * 2
```

Distributed
immutable
object

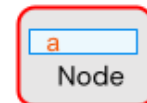


```
import numpy as np  
a = np.arange(1, 10e6)  
obj_a = ray.put(a)  
b = ray.get(obj_a) * 2
```

Distributed



...

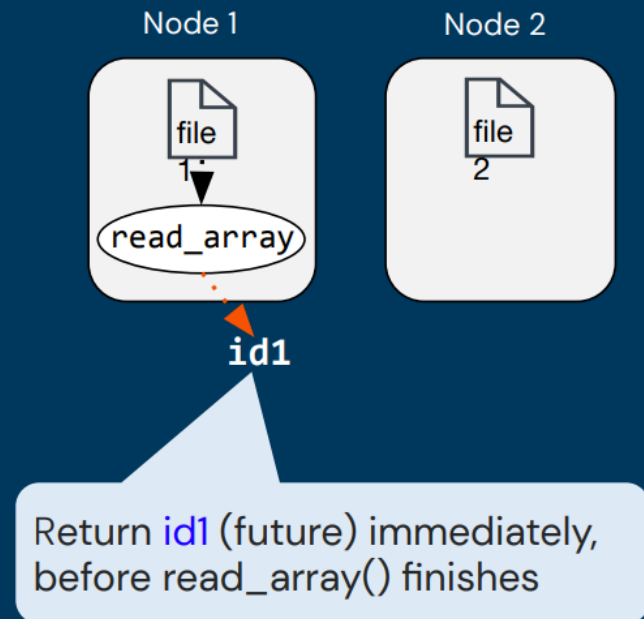


Task API

```
@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)
```

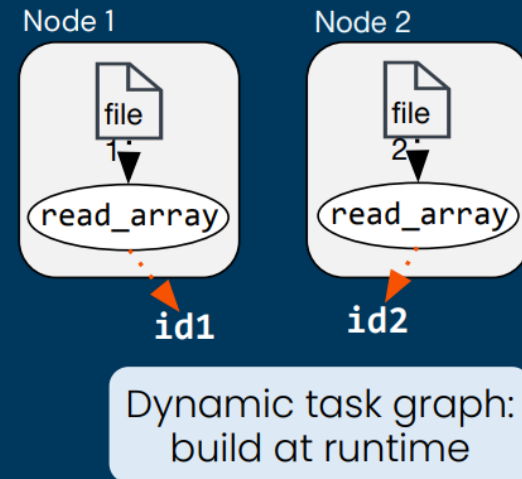


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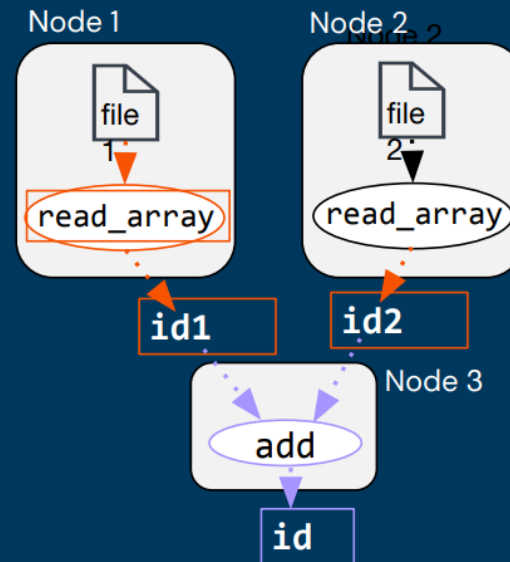
Task API

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```

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

`ray.get()` block until
result available

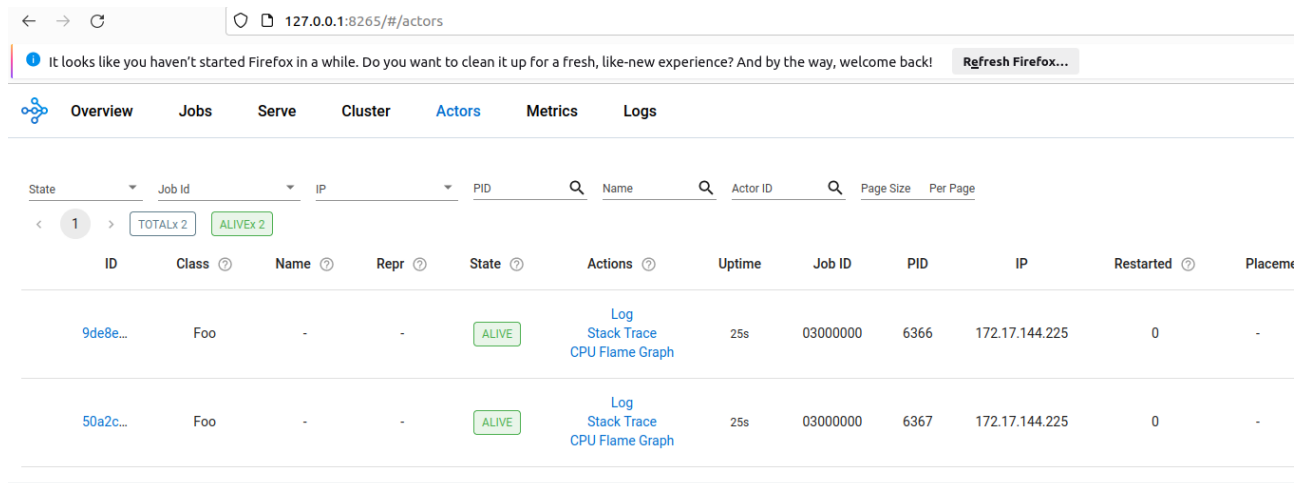


Task 0

- Start a node
 - *ray start --head --port=6379*
- Check the dashboard on :
 - <http://127.0.0.1:8265/>
- Copy notebook to folder and start jupyter service
 - *jupyter notebook*

Task 1

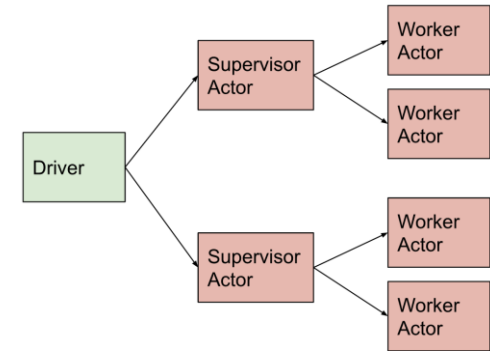
- Open and fill all the gaps in attached notebook
 - All important aspects of ray framework are covered
 - At the end there is main pi computation task
- Your dashboard should look like:



The screenshot shows the Ray dashboard interface. At the top, there's a navigation bar with tabs: Overview, Jobs, Serve, Cluster, Actors (selected), Metrics, and Logs. Below the navigation bar, there's a table of actors. The table has columns: ID, Class, Name, Repr, State, Actions, Uptime, Job ID, PID, IP, Restarted, and Placement. Two actors are listed, both in the 'ALIVE' state.

ID	Class	Name	Repr	State	Actions	Uptime	Job ID	PID	IP	Restarted	Placement
9de8e...	Foo	-	-	ALIVE	Log Stack Trace CPU Flame Graph	25s	03000000	6366	172.17.144.225	0	-
50a2c...	Foo	-	-	ALIVE	Log Stack Trace CPU Flame Graph	25s	03000000	6367	172.17.144.225	0	-

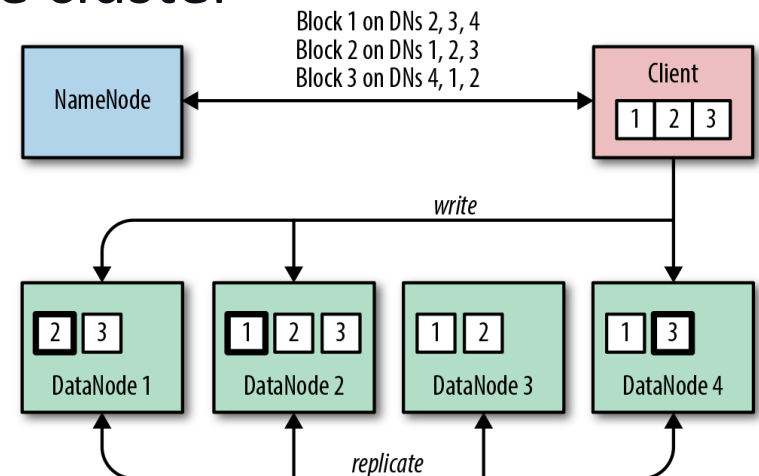
Task 2



- Implement a distributed artifacts storage system:
 - there is one name node and x storage node (all actors)
 - execute it in a separate script in the system terminal/console
 - name node distributes artifacts to storage nodes in chunks/blocks and keeps track of them
 - there are few copies of chunks in the system to improve high availability and speed (similarly as in HDFS)
 - randomly, data storage nodes can fail; the name node keeps track of all chunks and manages the copies (everything should be consistent)
 - provide a list operation of the most important data (e.g. where chunks/blocks are stored)

Task 2

- User can perform the following operations from the interactive shell prompt
 - Artifact consist of name and content (stored as string)
 - upload - by providing a new artifact
 - update the stored artifact content
 - user can delete artifacts present in the storage
 - user can get/download the artifacts from the storage
 - user can list the status of the cluster



Task 2

- Verification tests:
 - upload an artifact, list the status
 - update an artifact, list the status
 - get an artifact, list the status
 - delete an artifact, list the status

Homework

- Tier 1 (4 pts)
 - Prepare and present all exercises from labs from Task 1 => 4 pts
- Tier 2 (6-8 pts)
 - Prepare implementation of the Task 2 from lab
 - Present demo solution and test scenarios => 7 pts
 - Add some additional advanced functionality, select anything from items not discussed on labs (<https://docs.ray.io/en/latest/ray-core/actors.html>) => 8 pts
 - Add distribution of environment (e.g. execute it on cluster based on K8s, docker ...) => 9 pts

Homework

- Tier 3 (9 pts)
 - Prepare sample project with other Ray modules
 - Select 3 different modules
 - Prepare tests form your solution
 - Present how you move it from regular implementation to demo on ray
 - Execute them on top of distributed environment
(+ 1 pt = 10 total)

