RAY

Distributed Systems and AI

Ray: Programming at Any Scale

https://github.com/ray-project/ray

Robert Nishihara

riselab
UC Berkeley

A Growing Number of Use Cases

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The Machine Learning Ecosystem

Machine Learning Ecosystem

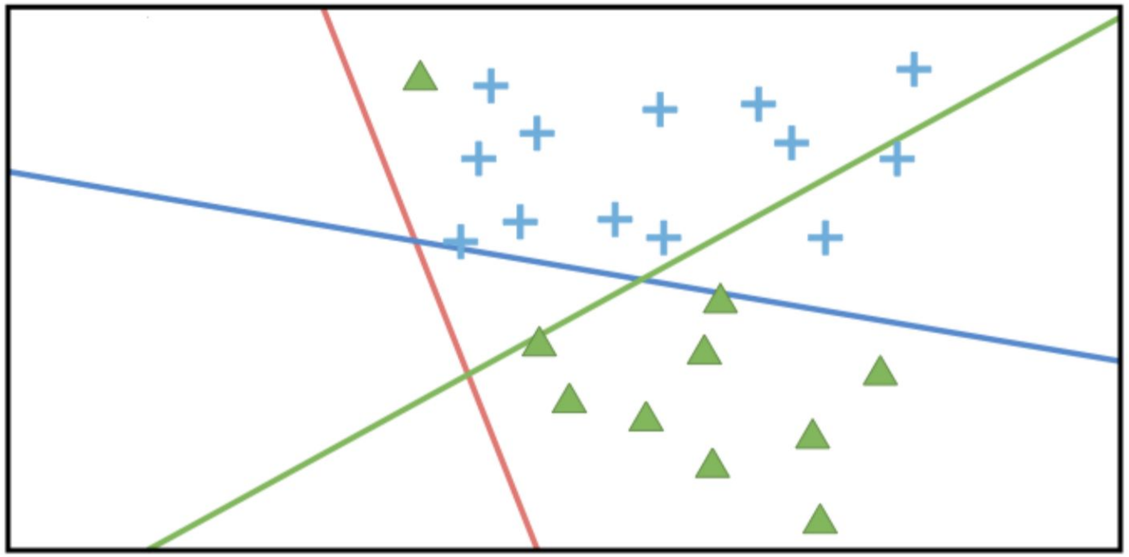
The Machine Learning Ecosystem

The Machine Learning Ecosystem

Training

Multiclass (more than 2) Classification

- **One-vs-rest** train separate binary classifiers for each class



Machine Learning Ecosystem

The Machine Learning Ecosystem

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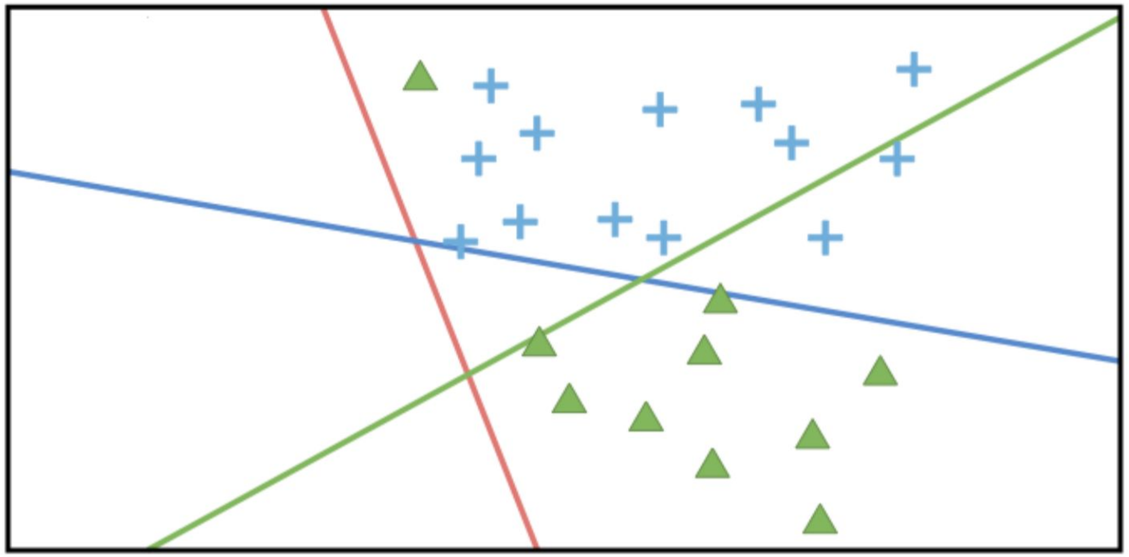
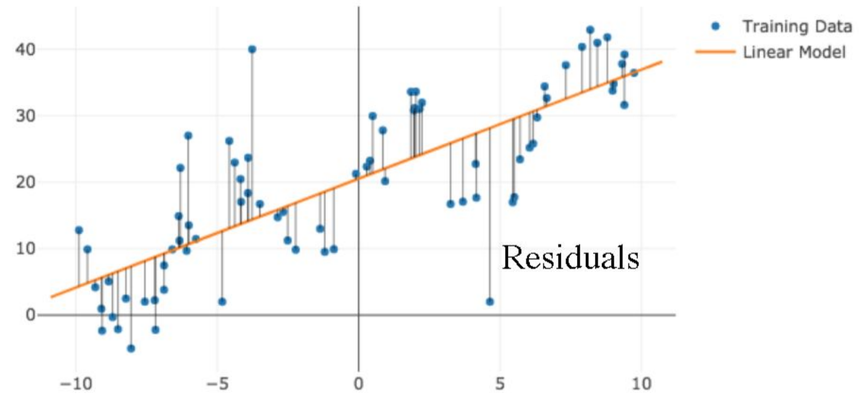


Training

Diagnosing Fit
→ The Residuals



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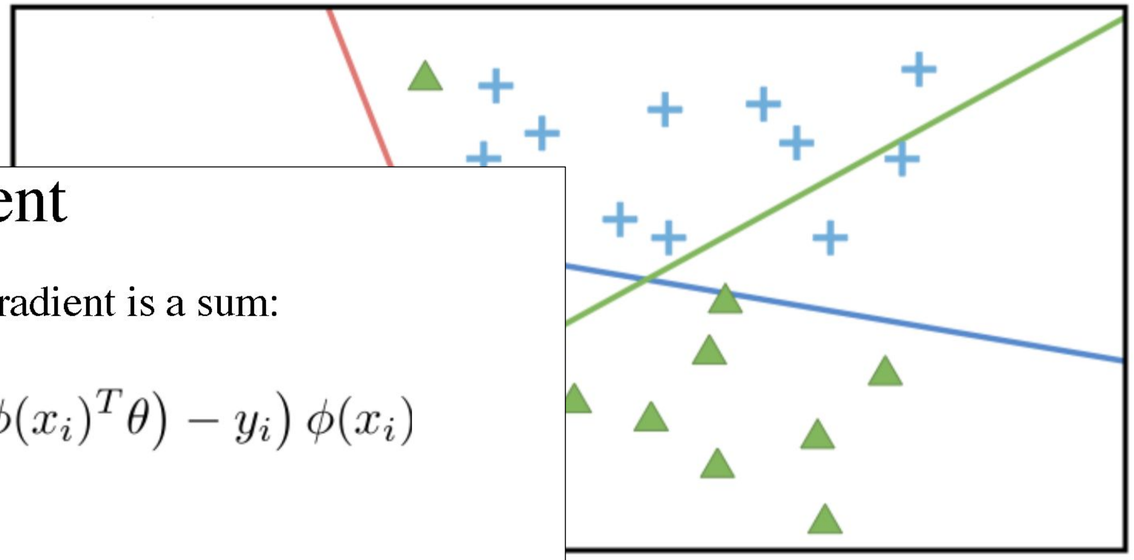

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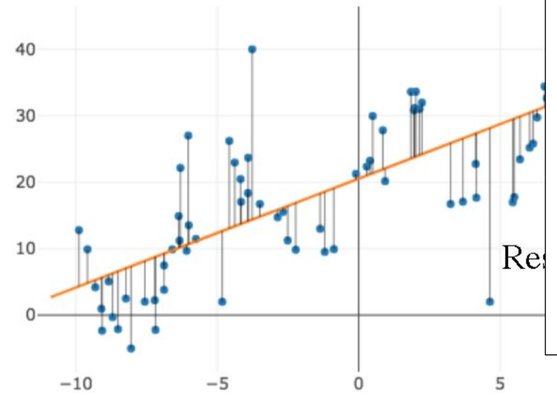

Stochastic Gradient Descent

- For many learning problems the gradient is a sum:

$$\nabla_\theta \mathbf{L}(\theta) = \frac{1}{n}\sum_{i=1}^{n}\left(\sigma\left(\phi(x_i)^T\theta\right) - y_i\right)\phi(x_i)$$

  - For large n this can be costly

- What if we approximated the gradient by looking at a few random points:

$$\nabla_\theta \mathbf{L}(\theta) \approx \frac{1}{|\mathcal{B}|}\sum_{i\in\mathcal{B}}\left(\sigma\left(\phi(x_i)^T\theta\right) - y_i\right)\phi(x_i)$$

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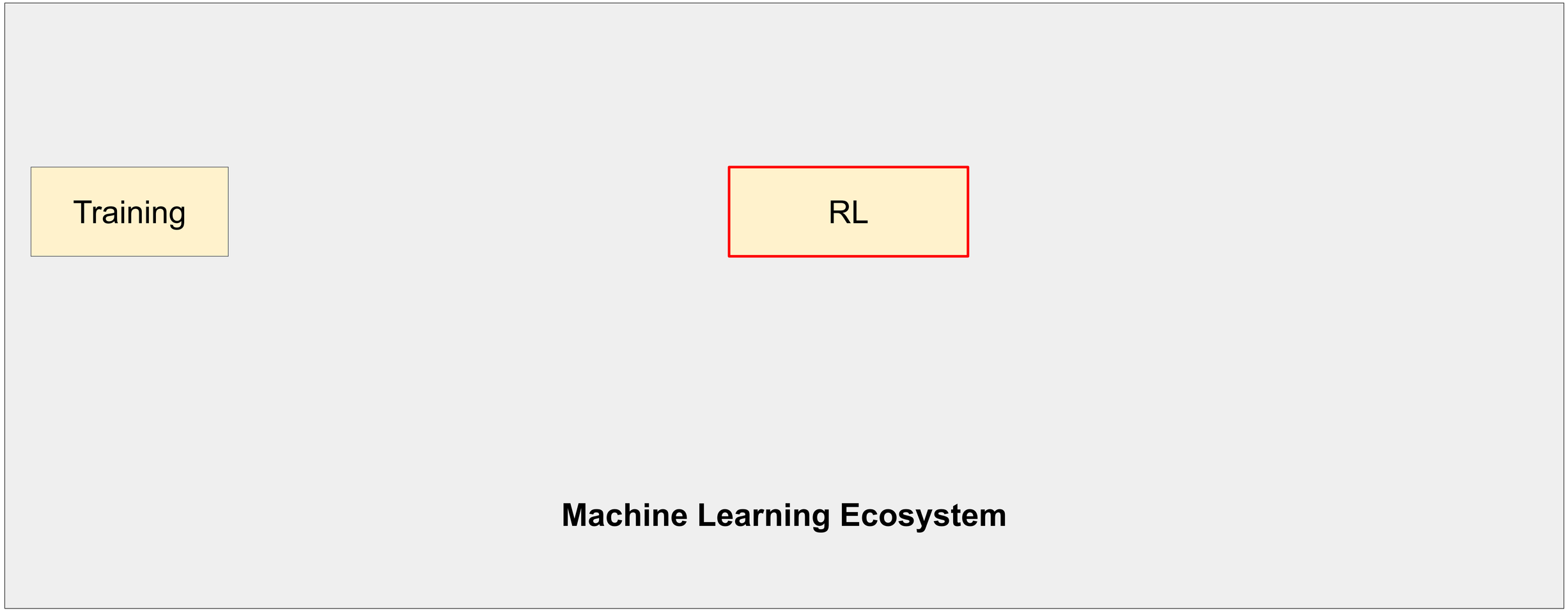
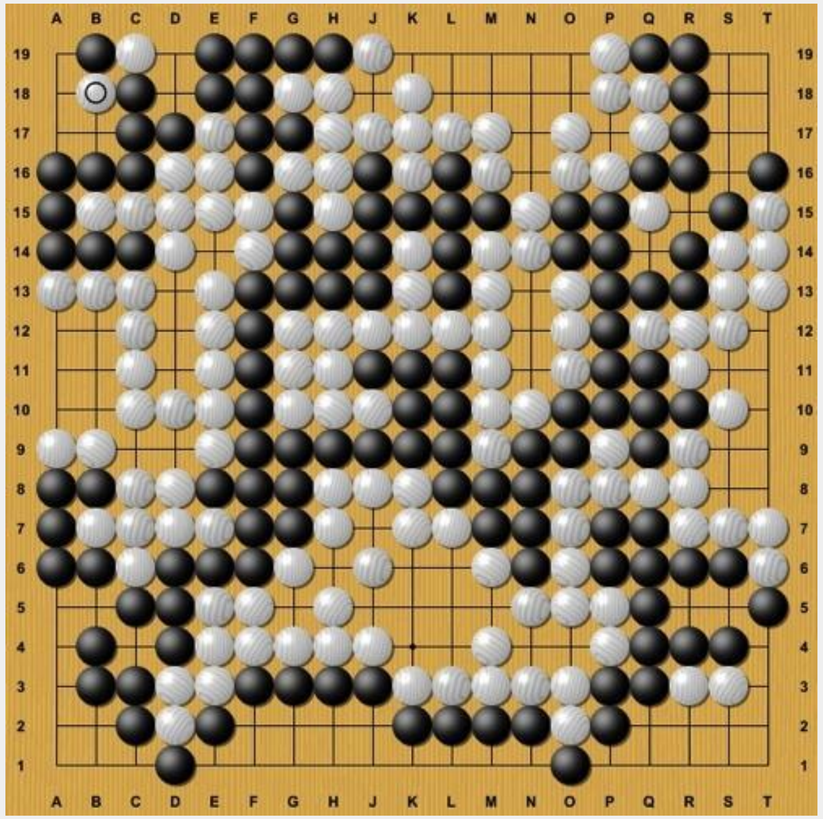


The Machine Learning Ecosystem

Training

RL



Machine Learning Ecosystem

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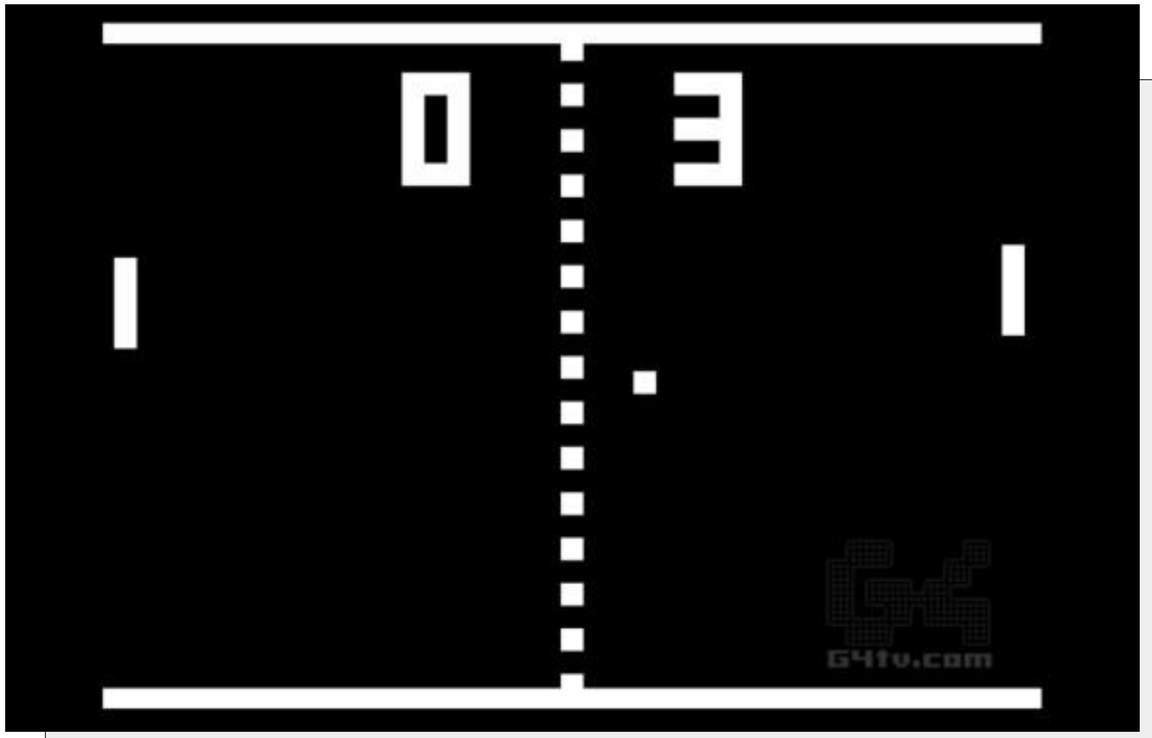
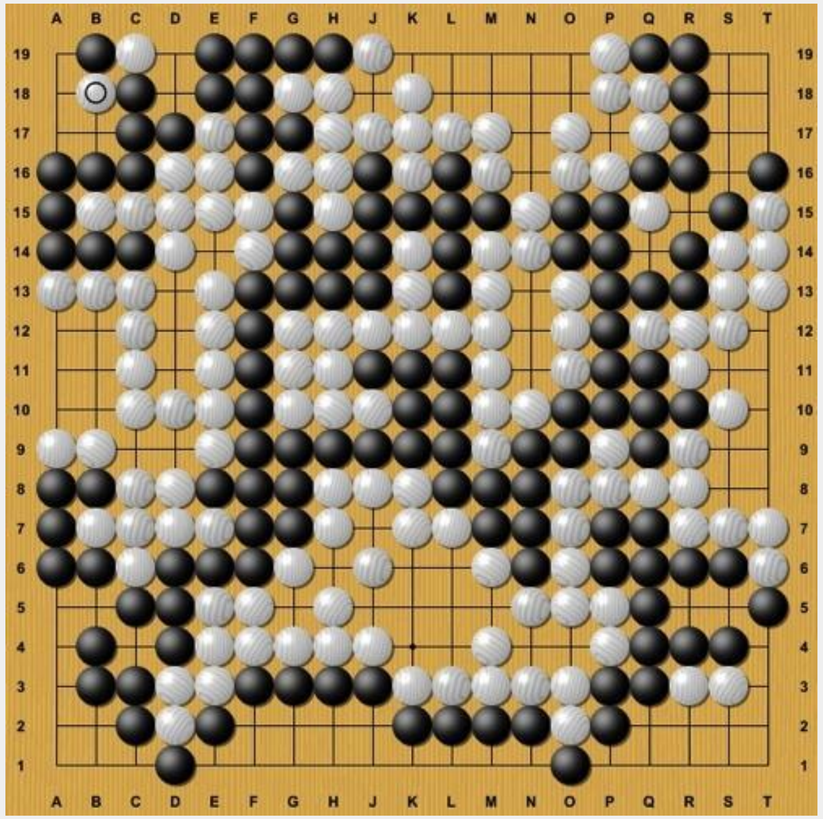


RL



Machine Learning Ecosystem

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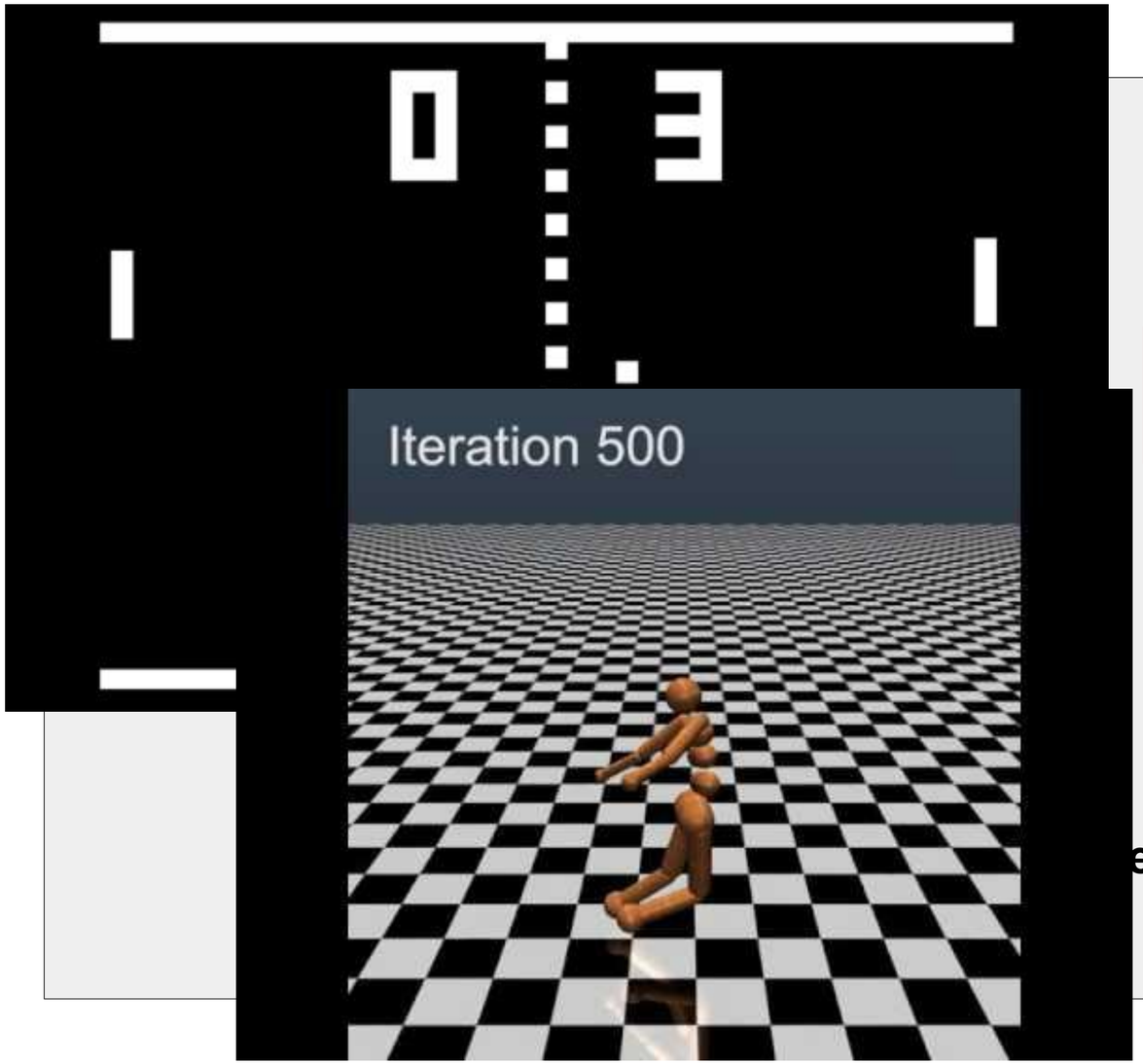

RL

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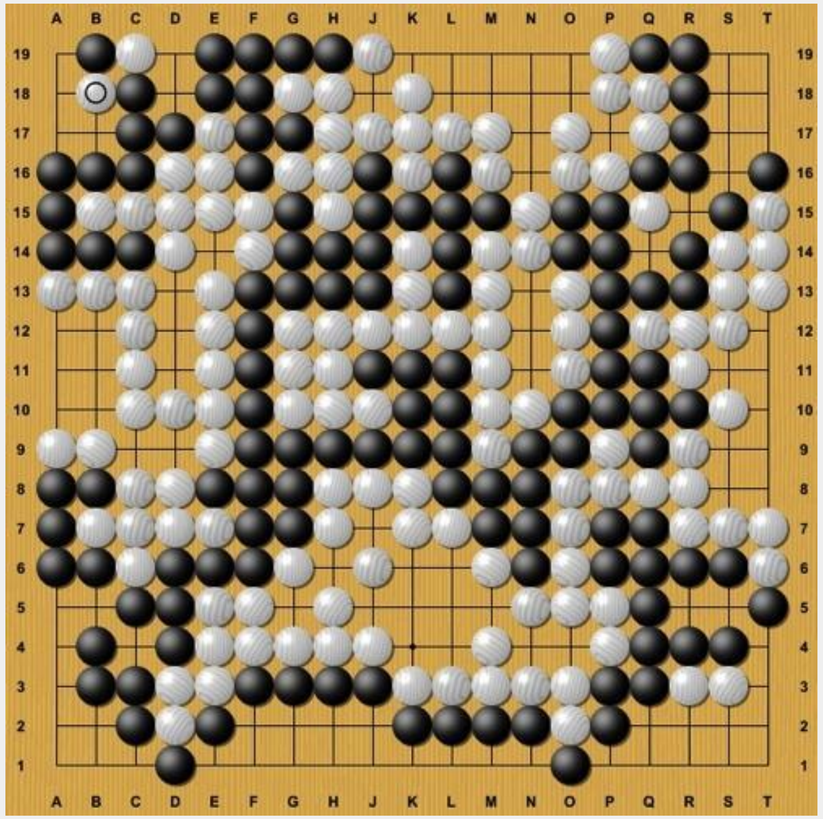
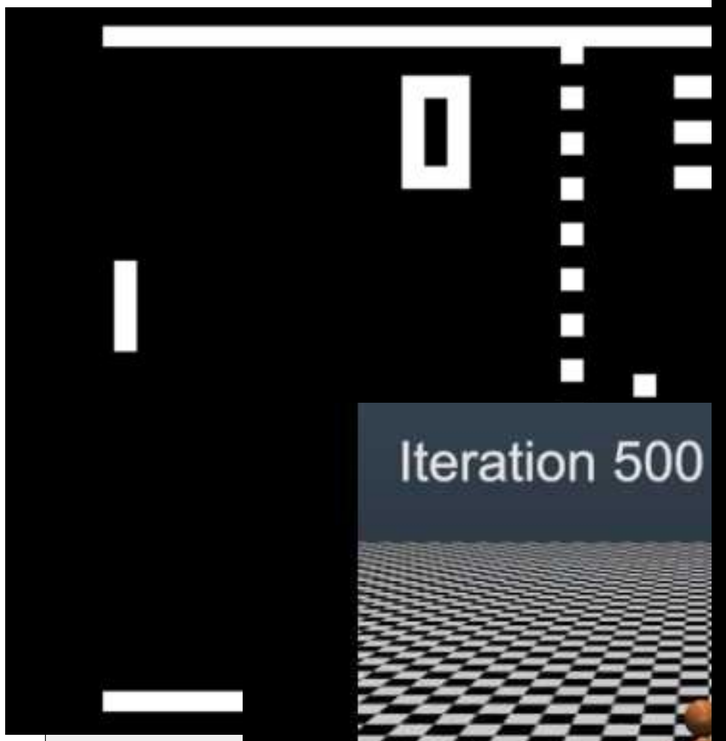
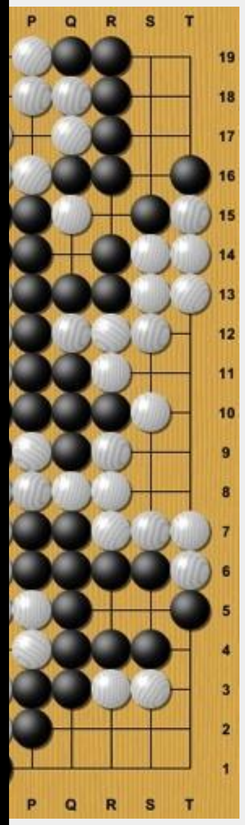


The Machine




Iteration 500


P Q R S T
19
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P Q R S T

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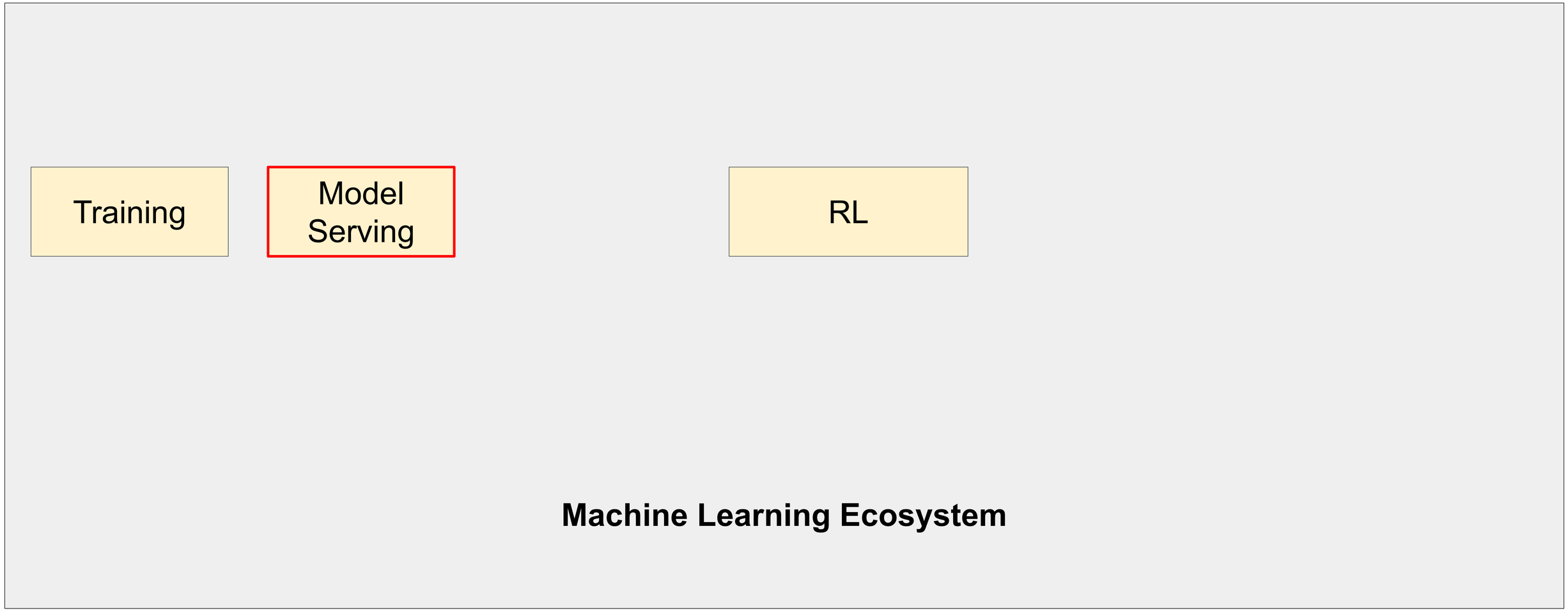

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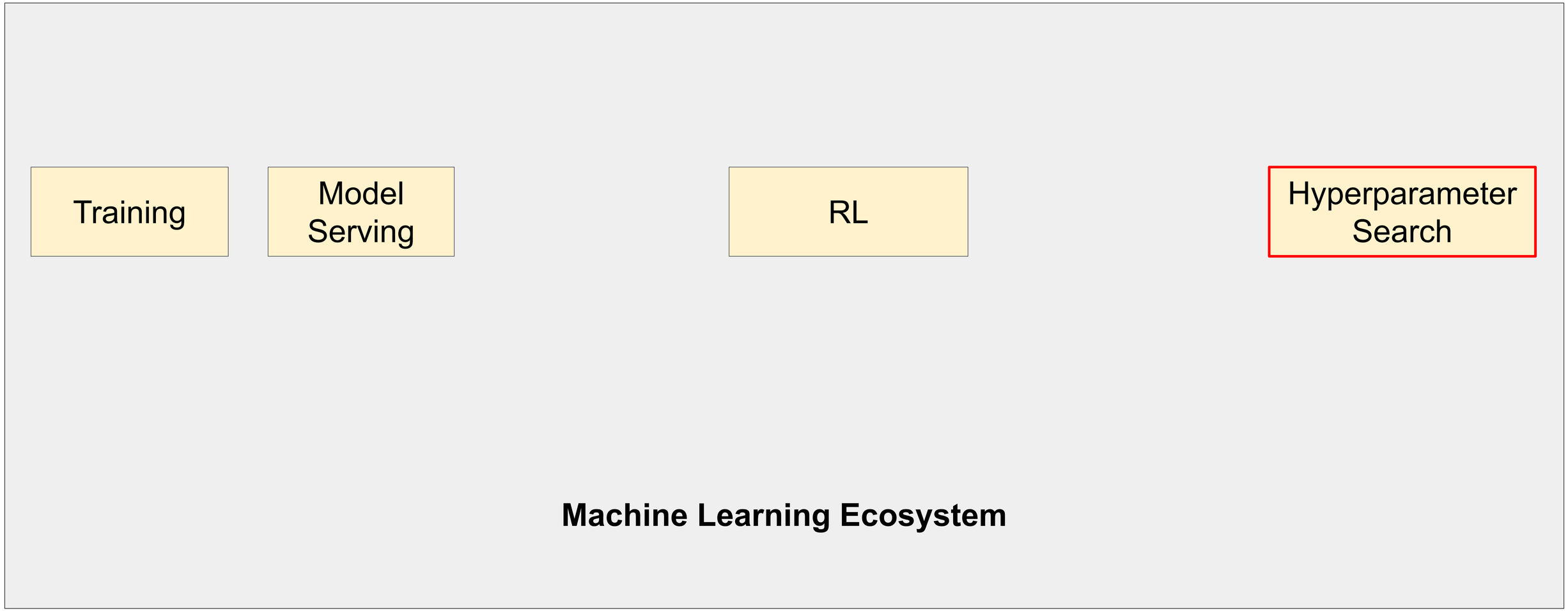

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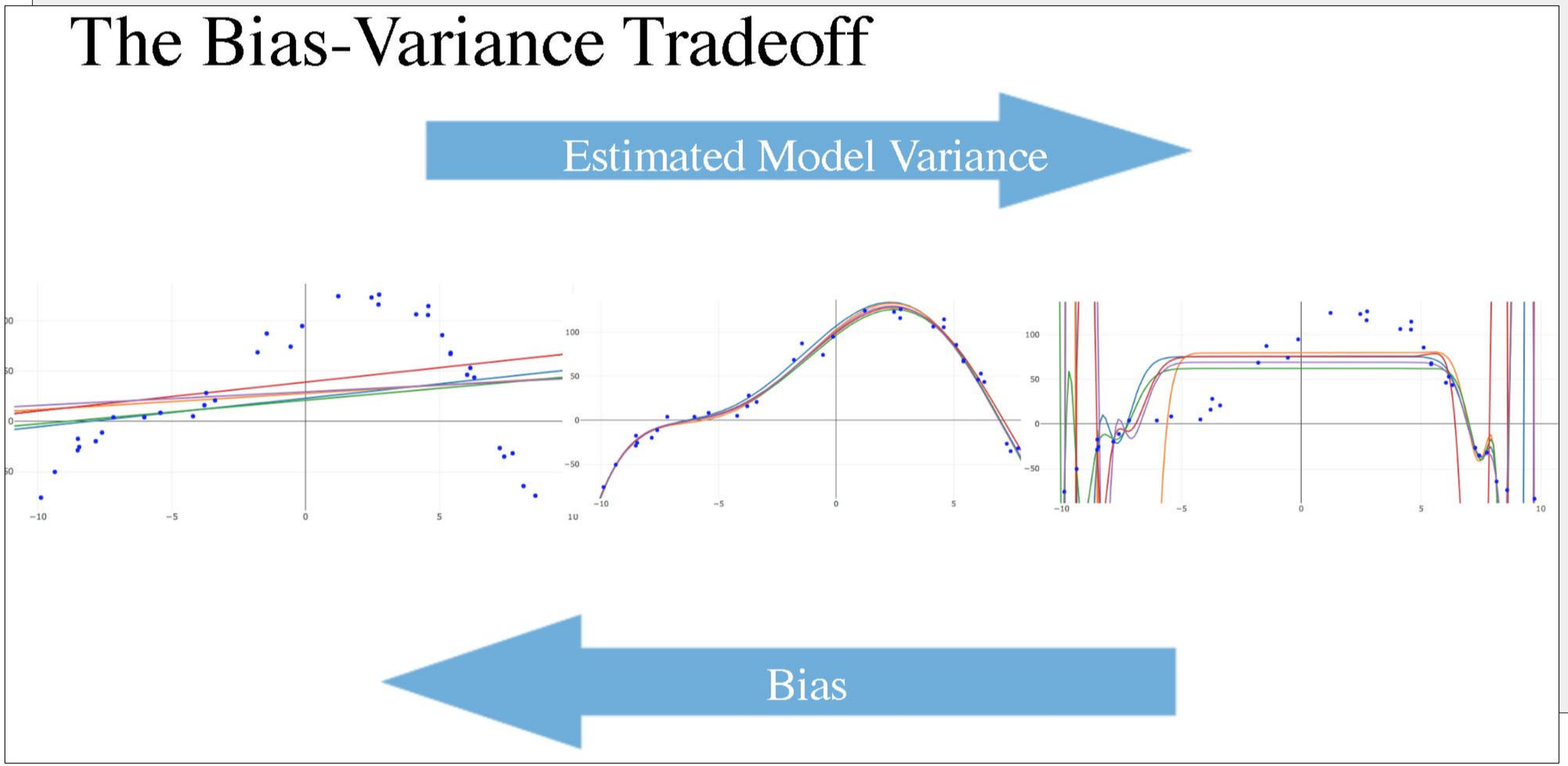
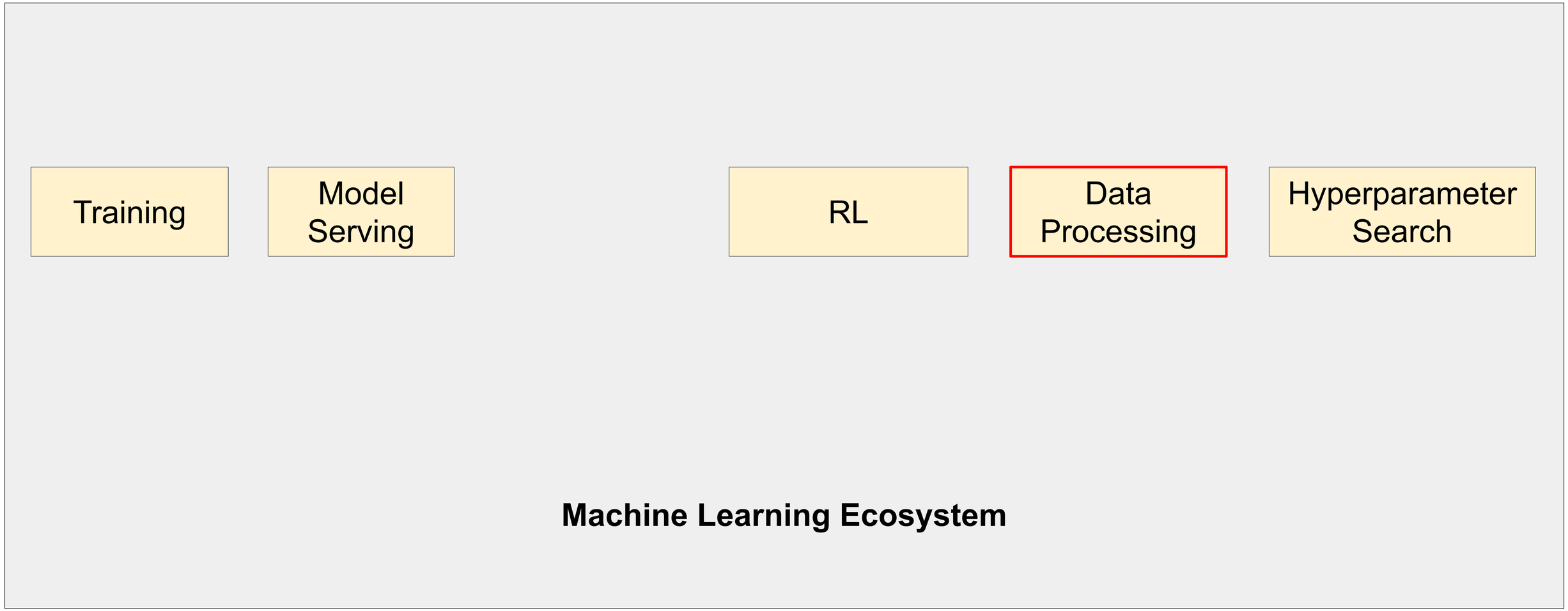
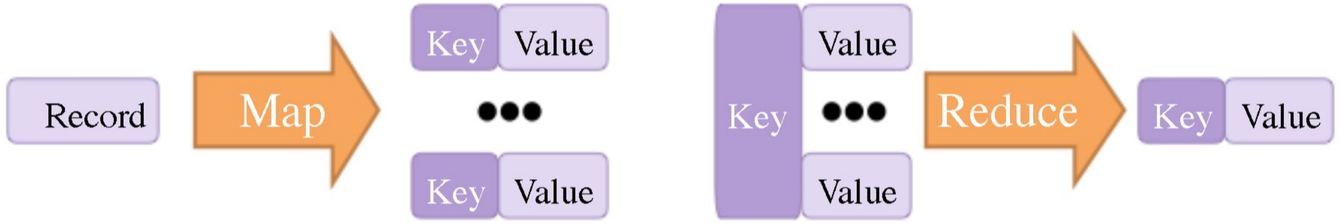


Hyperparameter Search

The Machine Learning Ecosystem



The Map Reduce Abstraction (Simpler)



Example: *Word-Count*

```
Map(book):
 for (word in book):
  emit (word, 1)
```

Key | Value

```
Reduce(word, counts) {
 sum = 0
 for count in counts:
    sum += count
 emit (word,
SUM(counts))
}
```

Data Processing

Hyperparameter Search

Machine Learning Ecosystem

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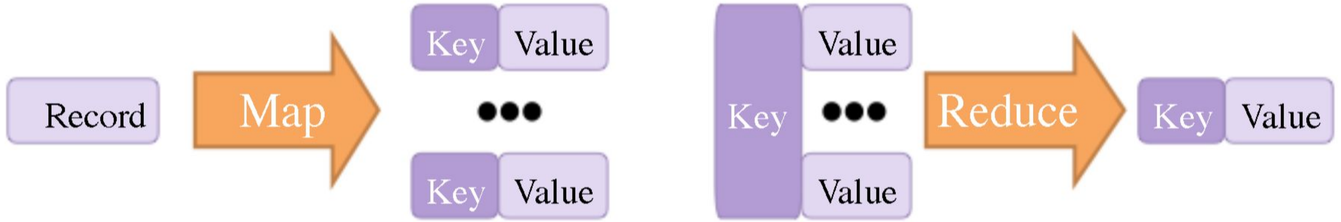


Example: *Word-Count*

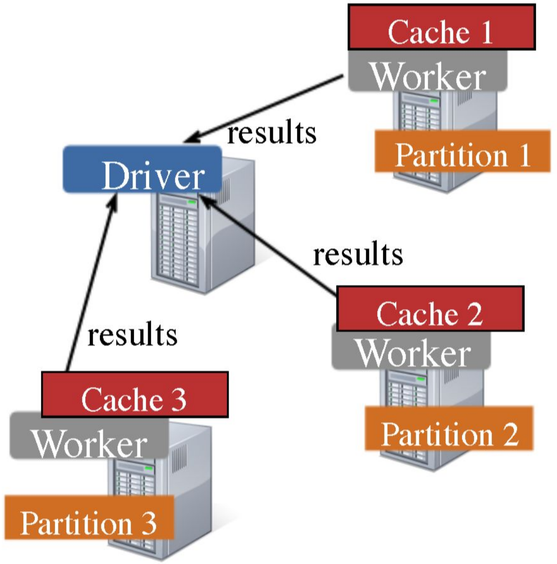
Reduce(word, counts) {

Example: Log Mining

Load error messages from a log into memory, then interactively search for various patterns

```
lines = spark.textFile("hdfs://file.txt")
errors = lines.filter(lambda s: s.startswith("ERROR"))
messages = errors.map(lambda s: s.split("\t")[2])
messages.cache()

messages.filter(lambda s: "mysql" in s).count()
messages.filter(lambda s: "php" in s).count()
```



Data Processing

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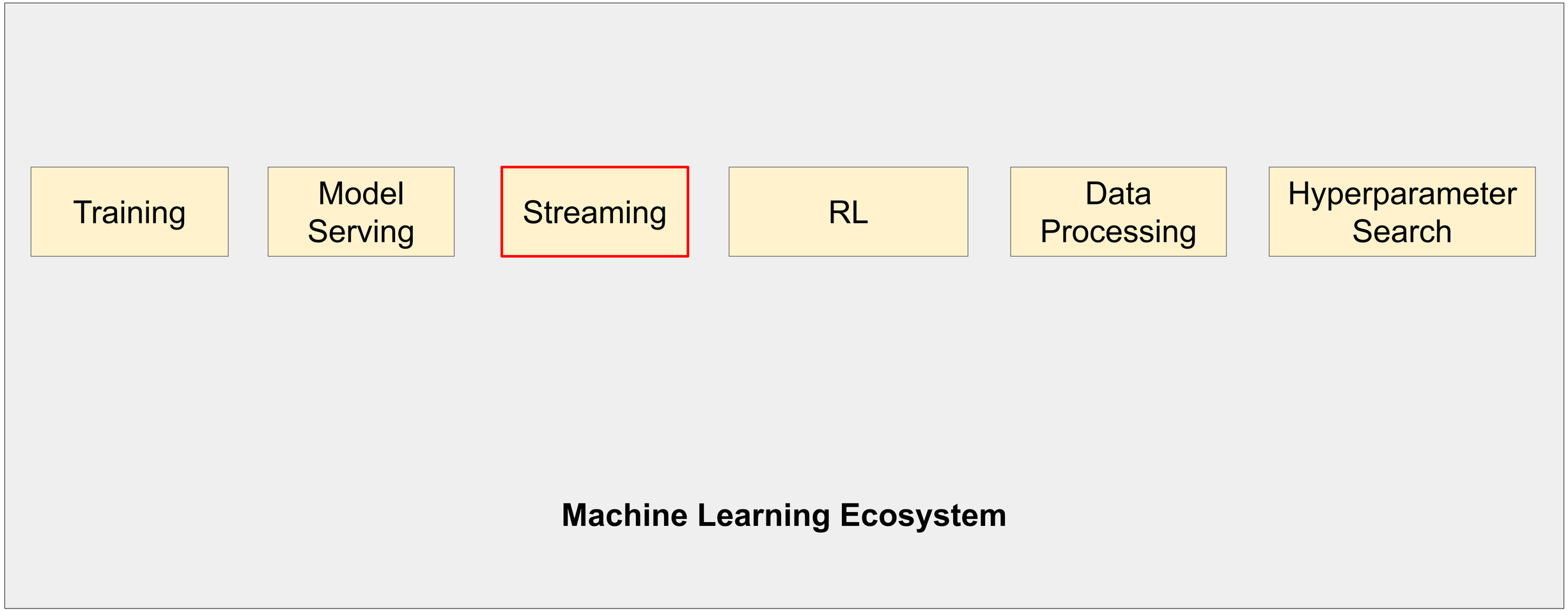

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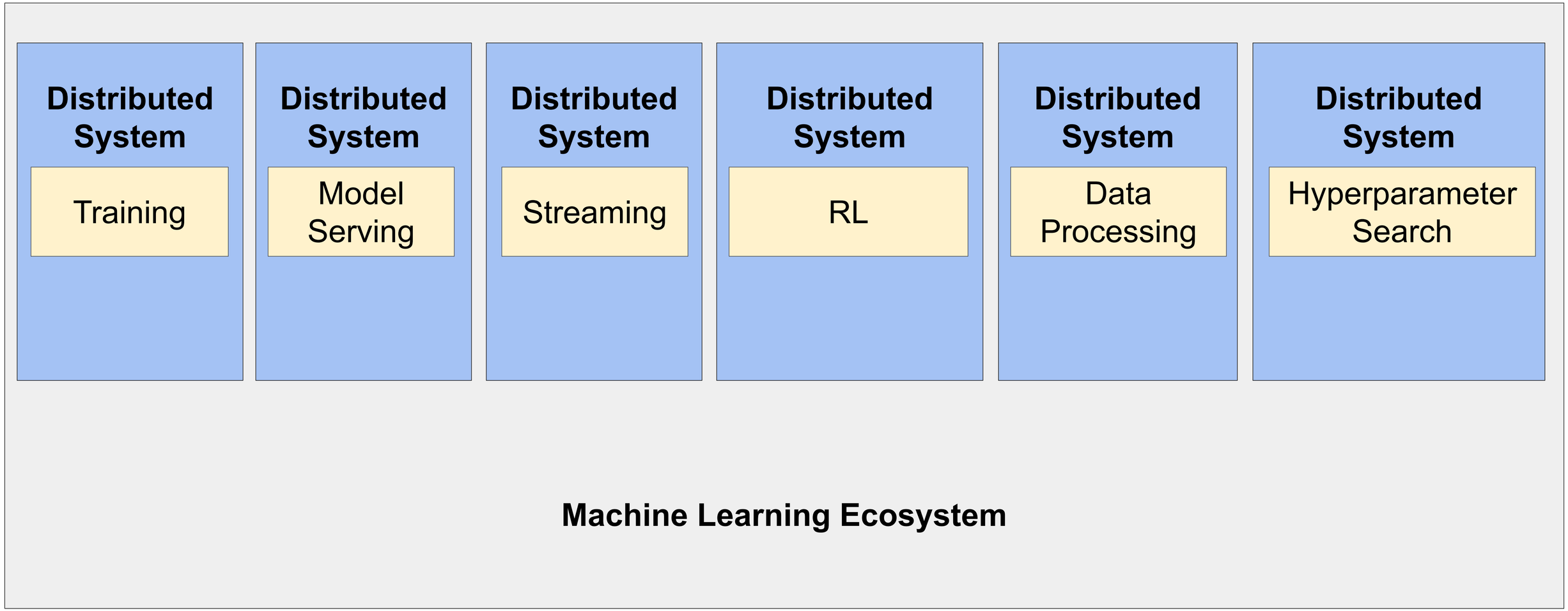

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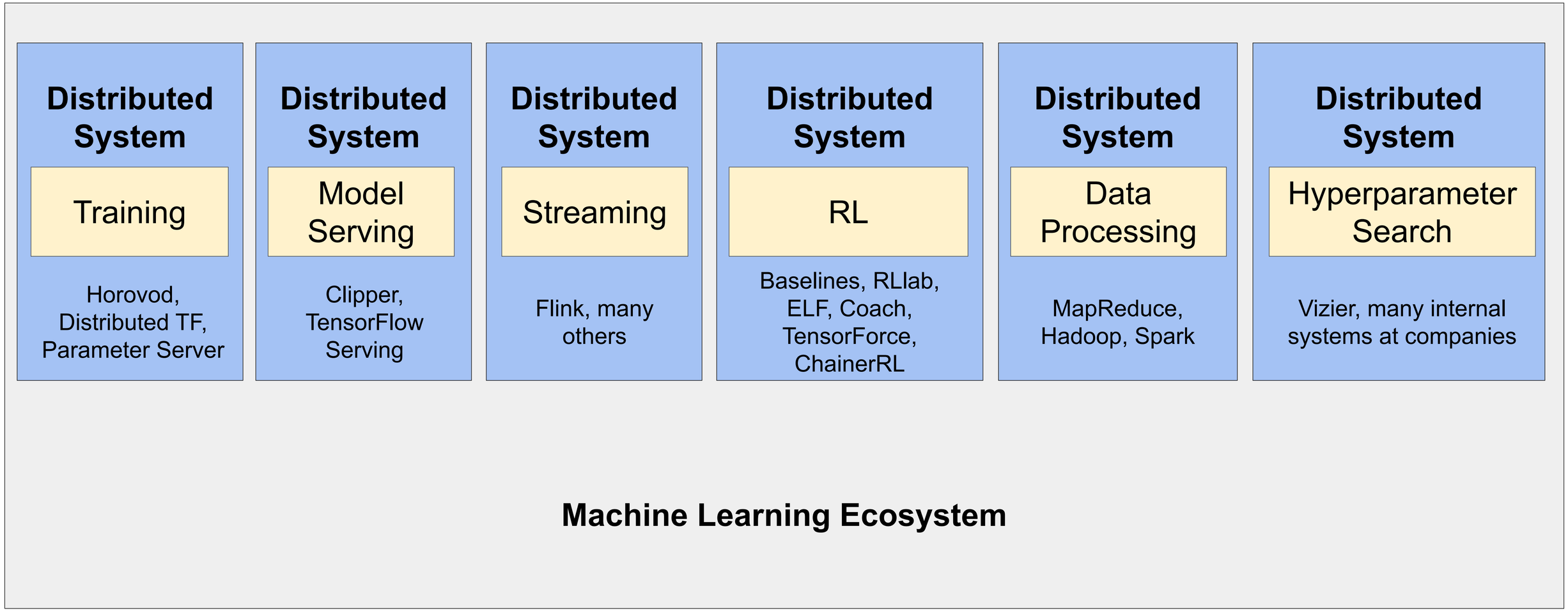

The Machine Learning Ecosystem

Distributed System

Training

Horovod, Distributed TF, Parameter Server

Distributed System

Model Serving

Clipper, TensorFlow Serving

Distributed System

Streaming

Flink, many others

Distributed System

RL

Baselines, RLlab, ELF, Coach, TensorForce, ChainerRL

Distributed System

Data Processing

MapReduce, Hadoop, Spark

Distributed System

Hyperparameter Search

Vizier, many internal systems at companies

<u>Why distributed systems?</u>

The Machine Learning Ecosystem

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- More **work** (computation) than one machine can do in a reasonable amount of time.
- More **data** than can fit in one machine.

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- Units of work “tasks” executed in parallel
- Scheduling (which tasks run on which machines and when)
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The Machine Learning Ec

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What is Ray?

Training | Model Serving | Streaming | RL | Data Processing | Hyperparameter Search

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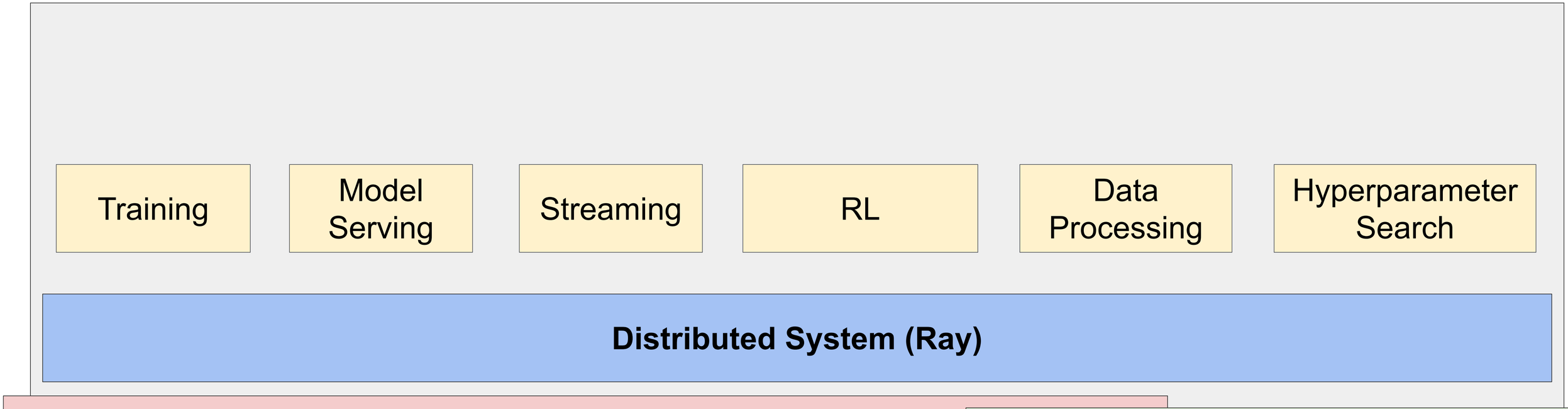

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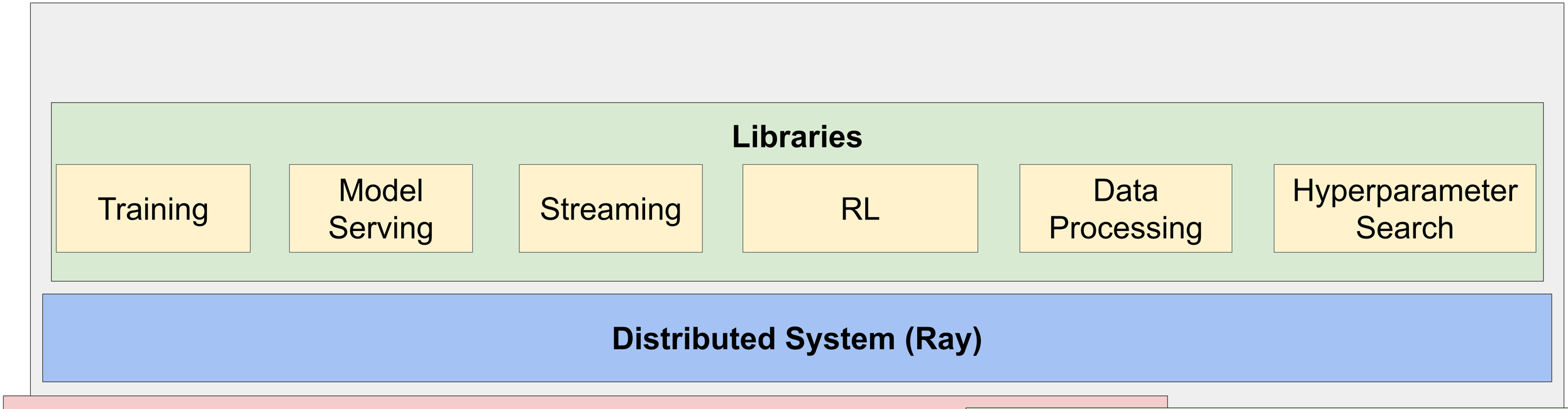

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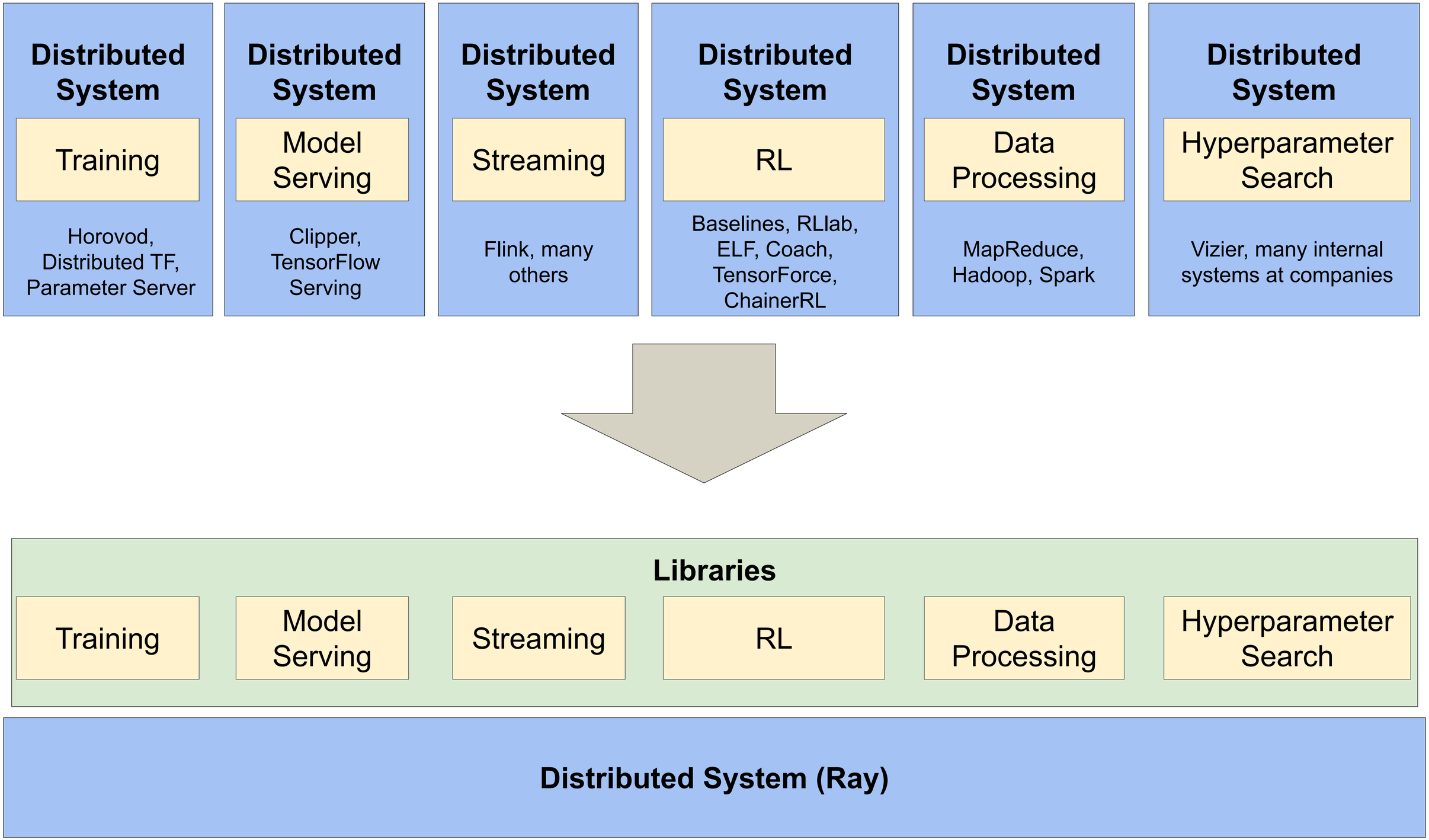
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Libraries
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Distributed System (Ray)

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This requires a very **general** underlying distributed system.

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Distributed System (Ray)

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This requires a very **general** underlying distributed system.

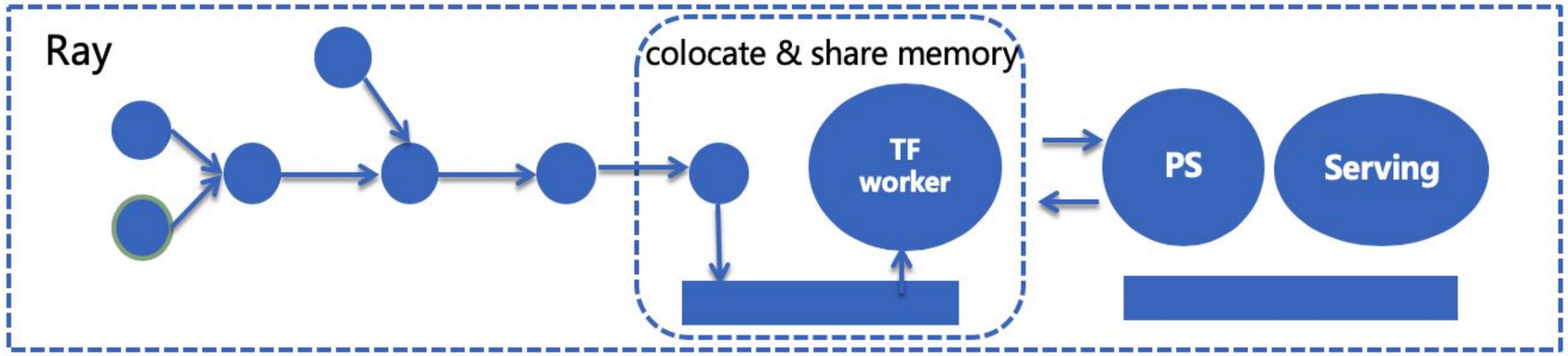
Generality comes from **tasks (functions)** and **actors (classes).**

Libraries

Training	Model Serving	Streaming	RL	Data Processing	Hyperparameter Search

Distributed System (Ray)

Use Case: Online Machine Learning



- 3 min, streaming + model training, from feature / label to model output
- 5 min, streaming + training + serving, from feature / label to model deploy
- 5% CTR improvement comparing to offline model; 1% CTR improvement comparing to blink solution

Ray API

Functions -> Tasks

```
def read_array(file):
    # read array “a” from “file”
    return a


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

Ray API

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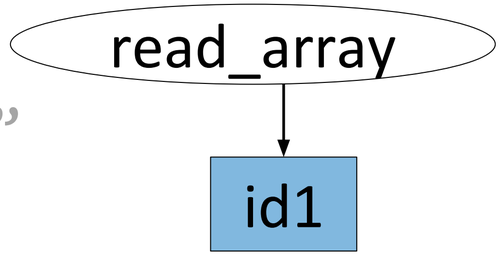
```



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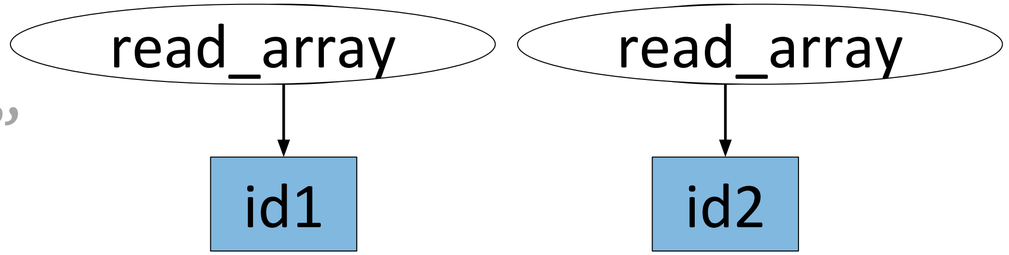

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id3 = add.remote(id1, id2)
```

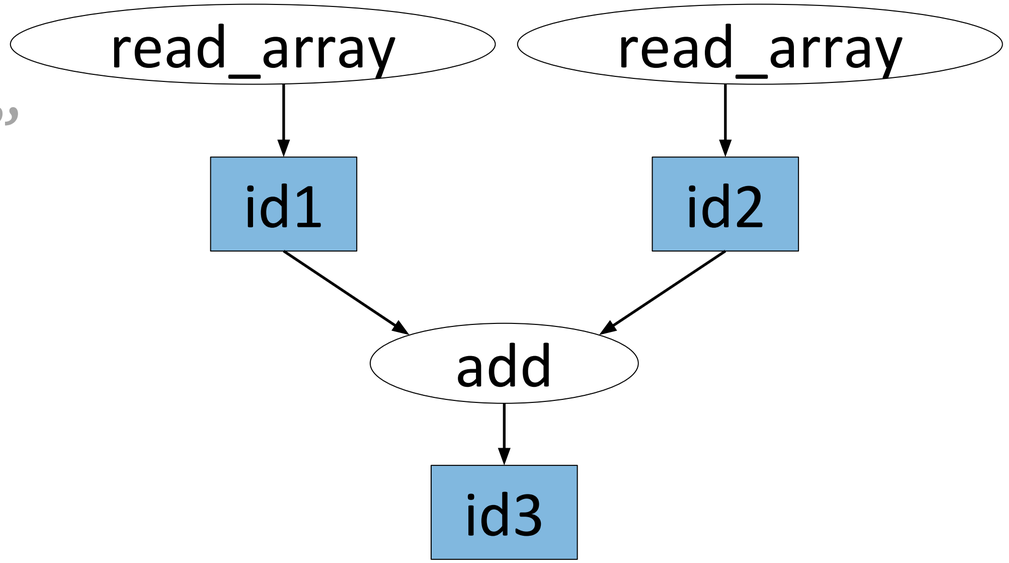

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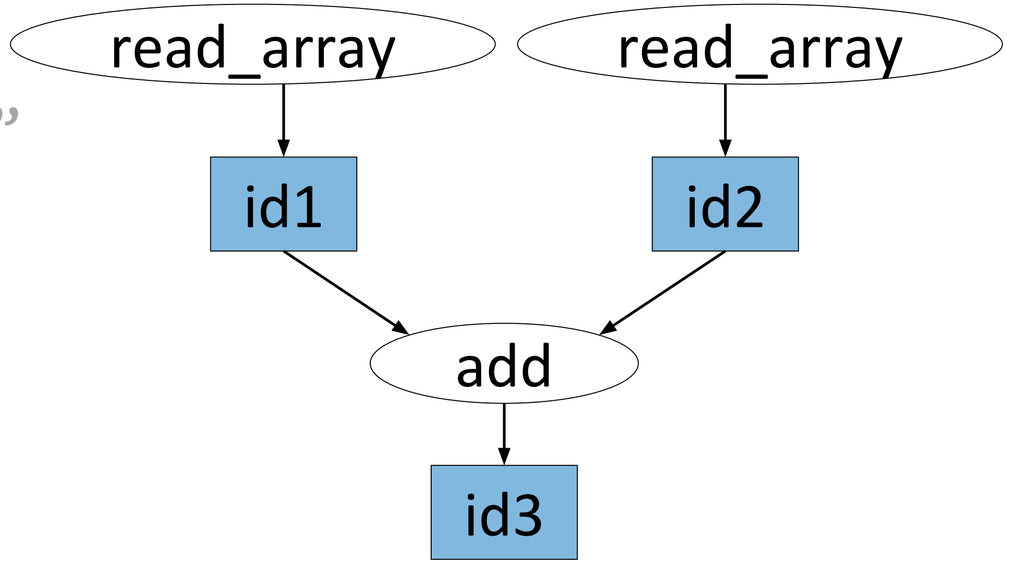
id2 = read_array.remote([5, 5])
id3 = add.remote(id1, id2)
ray.get(id3)
```



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```

Classes -> Actors

Ray API

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id3 = add.remote(id1, id2)
ray.get(id3)
```

Classes -> Actors

```
@ray.remote(num_gpus=1)
class Counter(object):
    def __init__(self):
        self.value = 0
    def inc(self):
        self.value += 1
        return self.value
```

Ray API

Functions -> Tasks

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        return self.value

c = Counter.remote()
id4 = c.inc.remote()
id5 = c.inc.remote()
ray.get([id4, id5])
```

Parallelism Example: Tree Reduction

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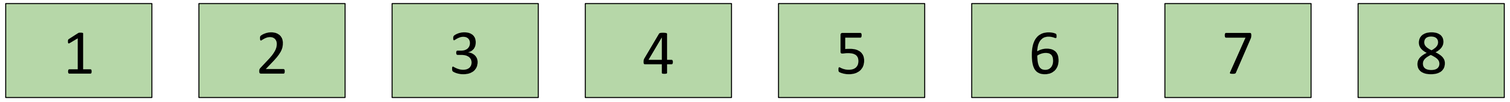

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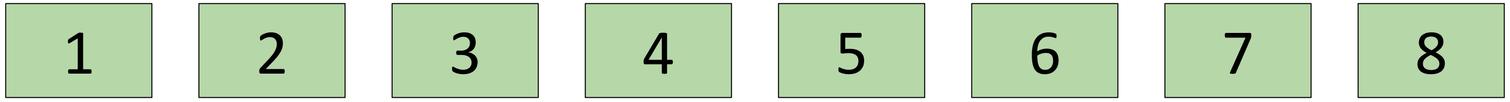


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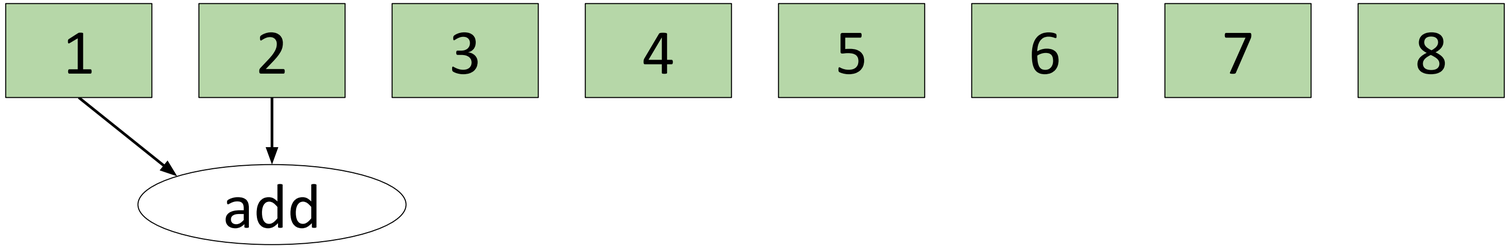


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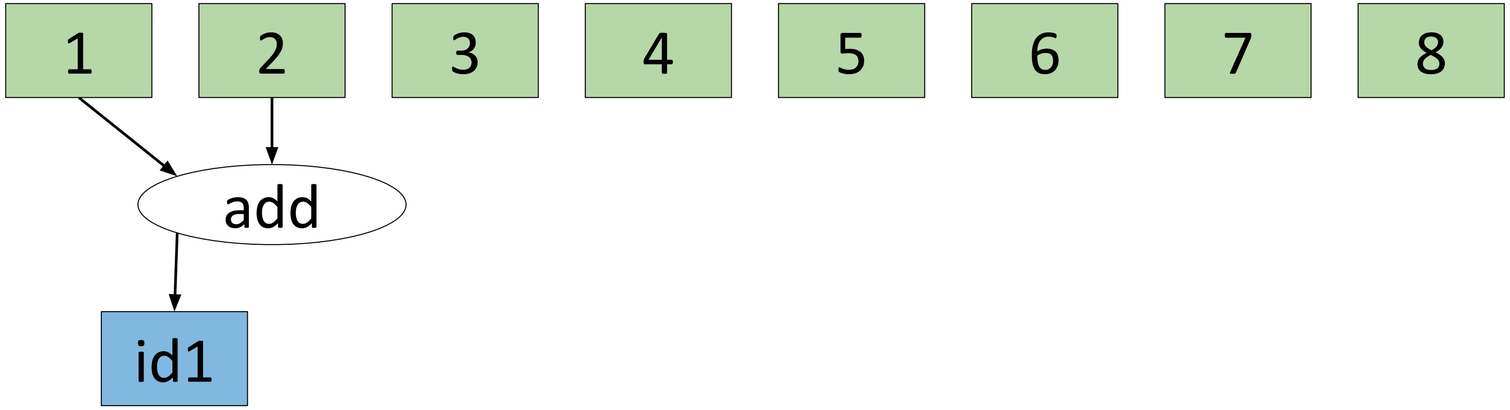


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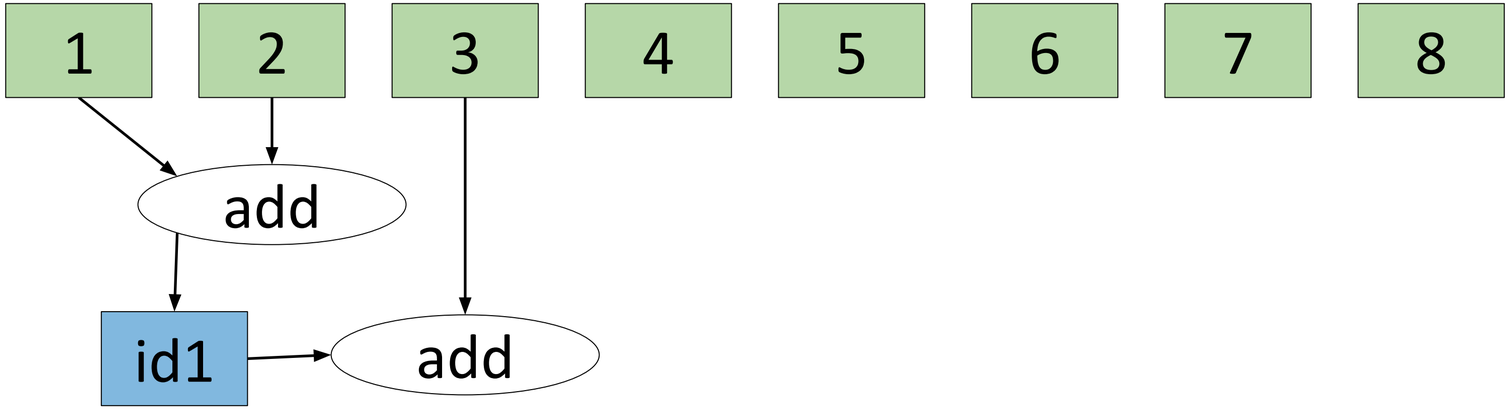


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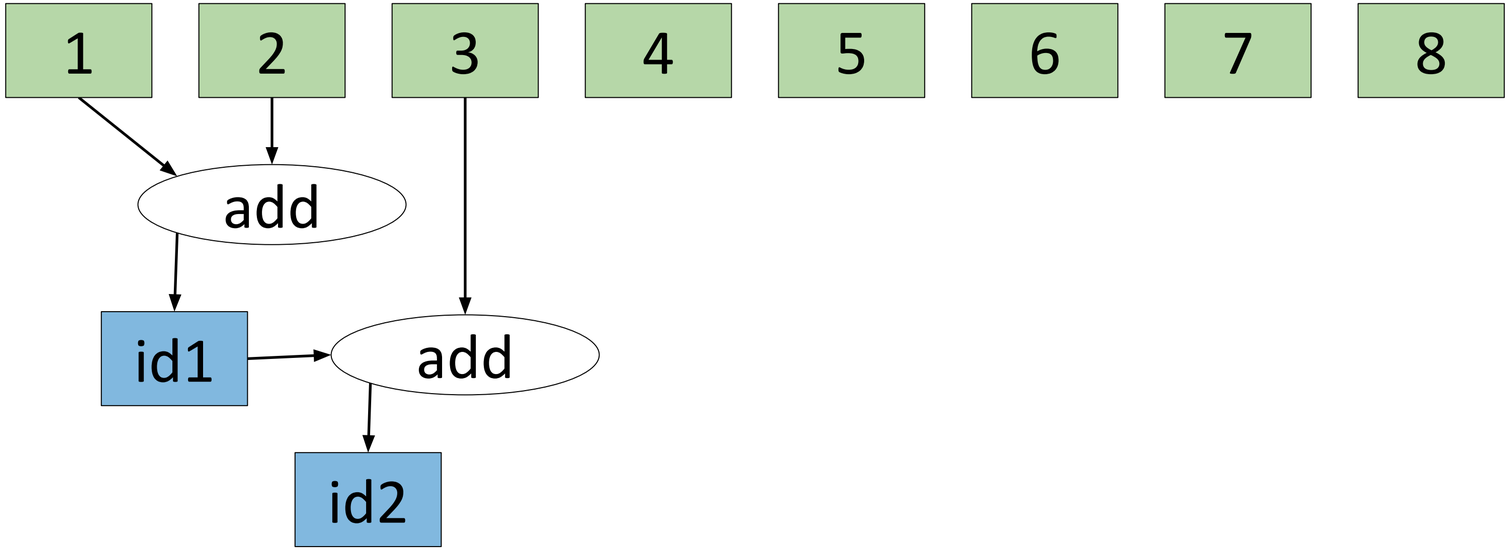


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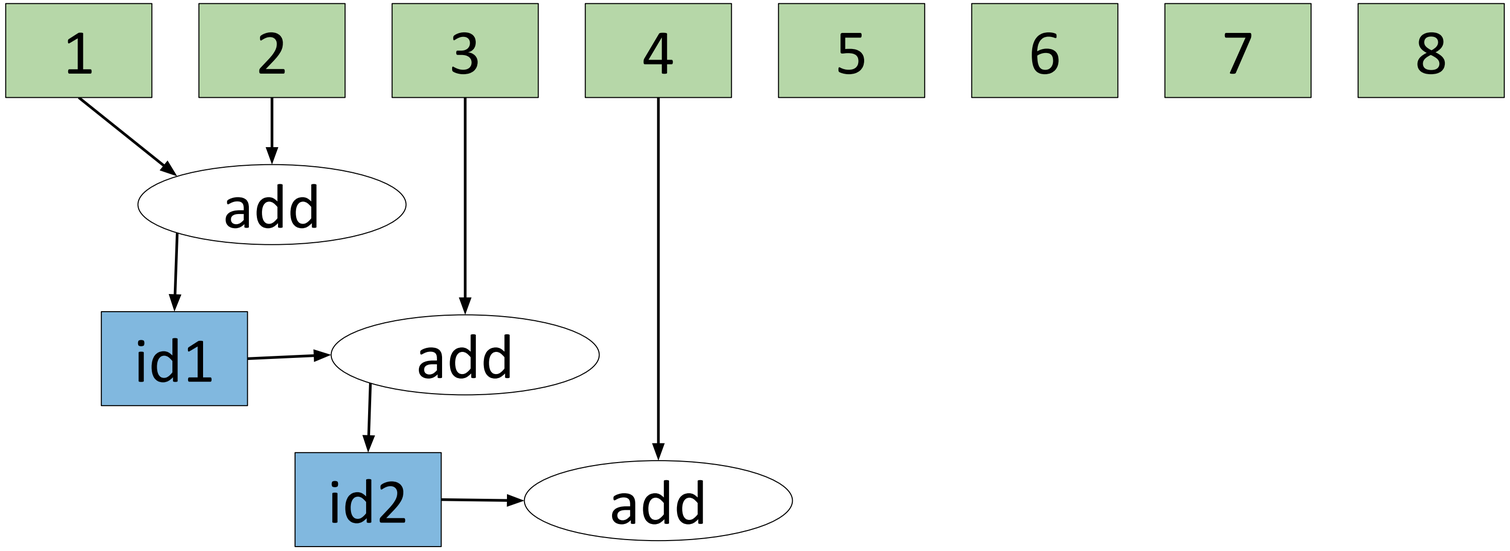


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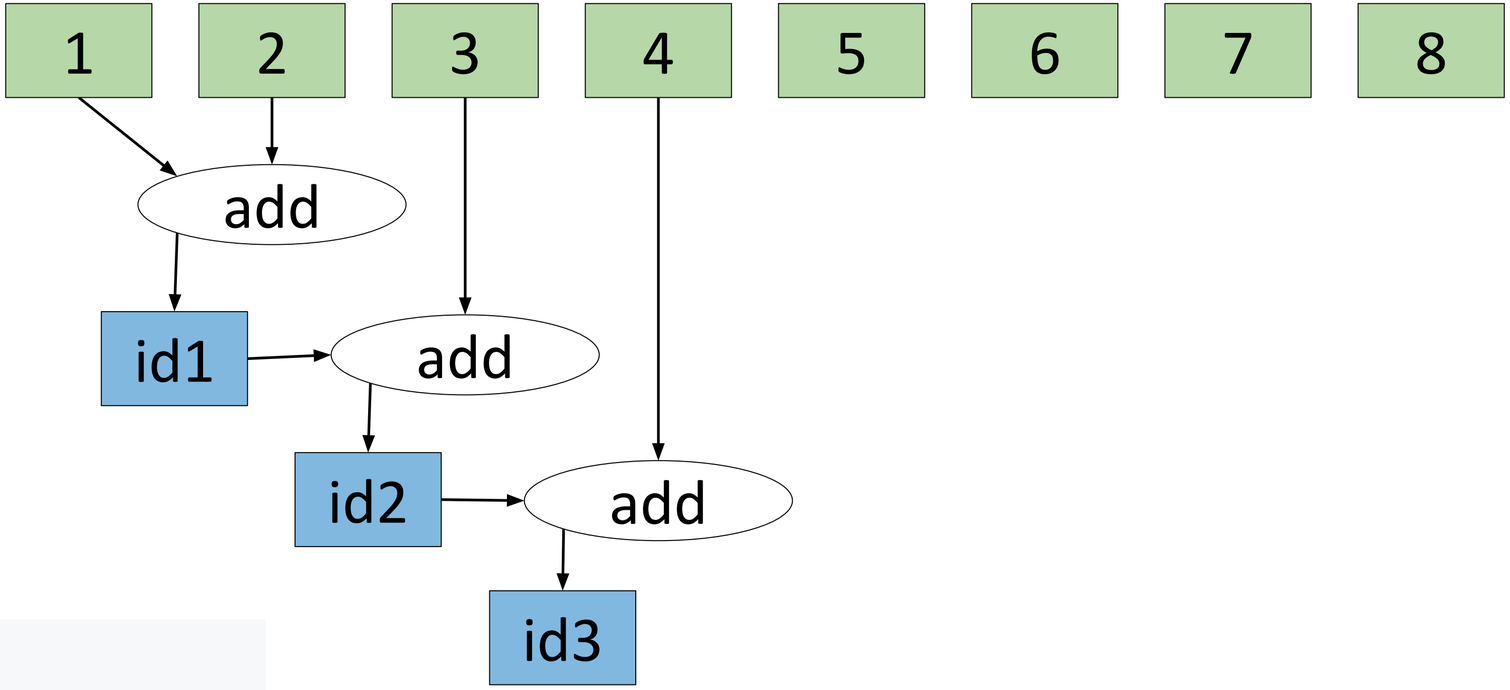


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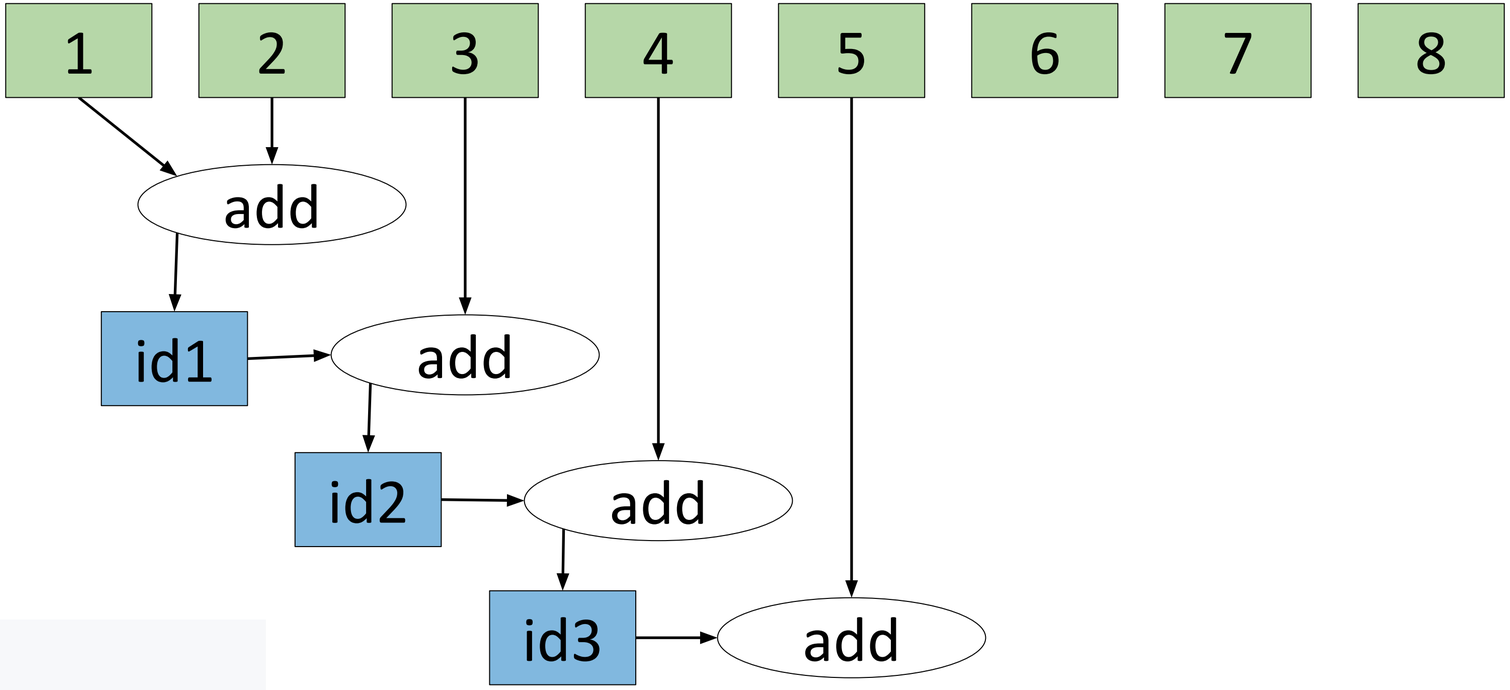


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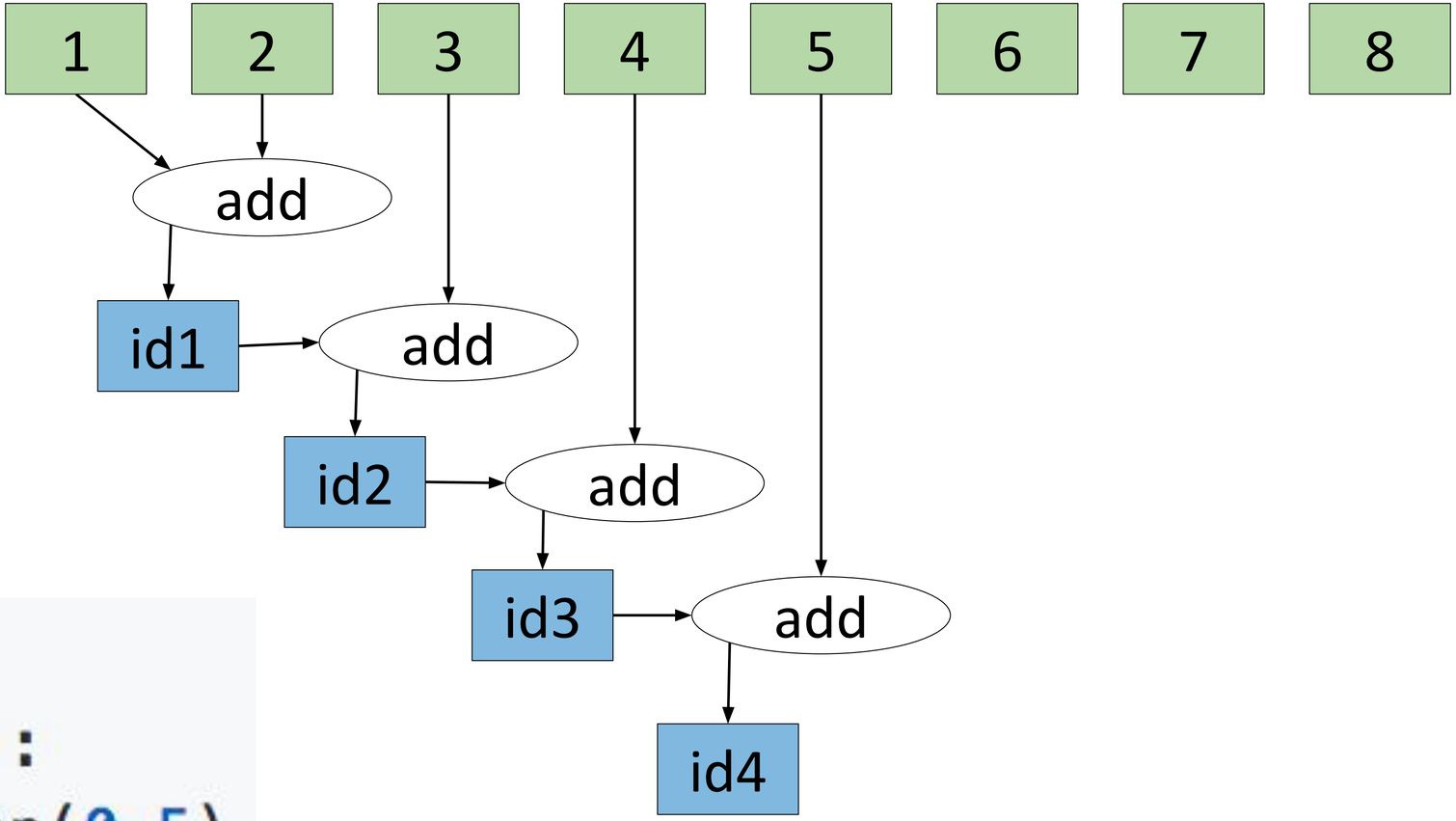


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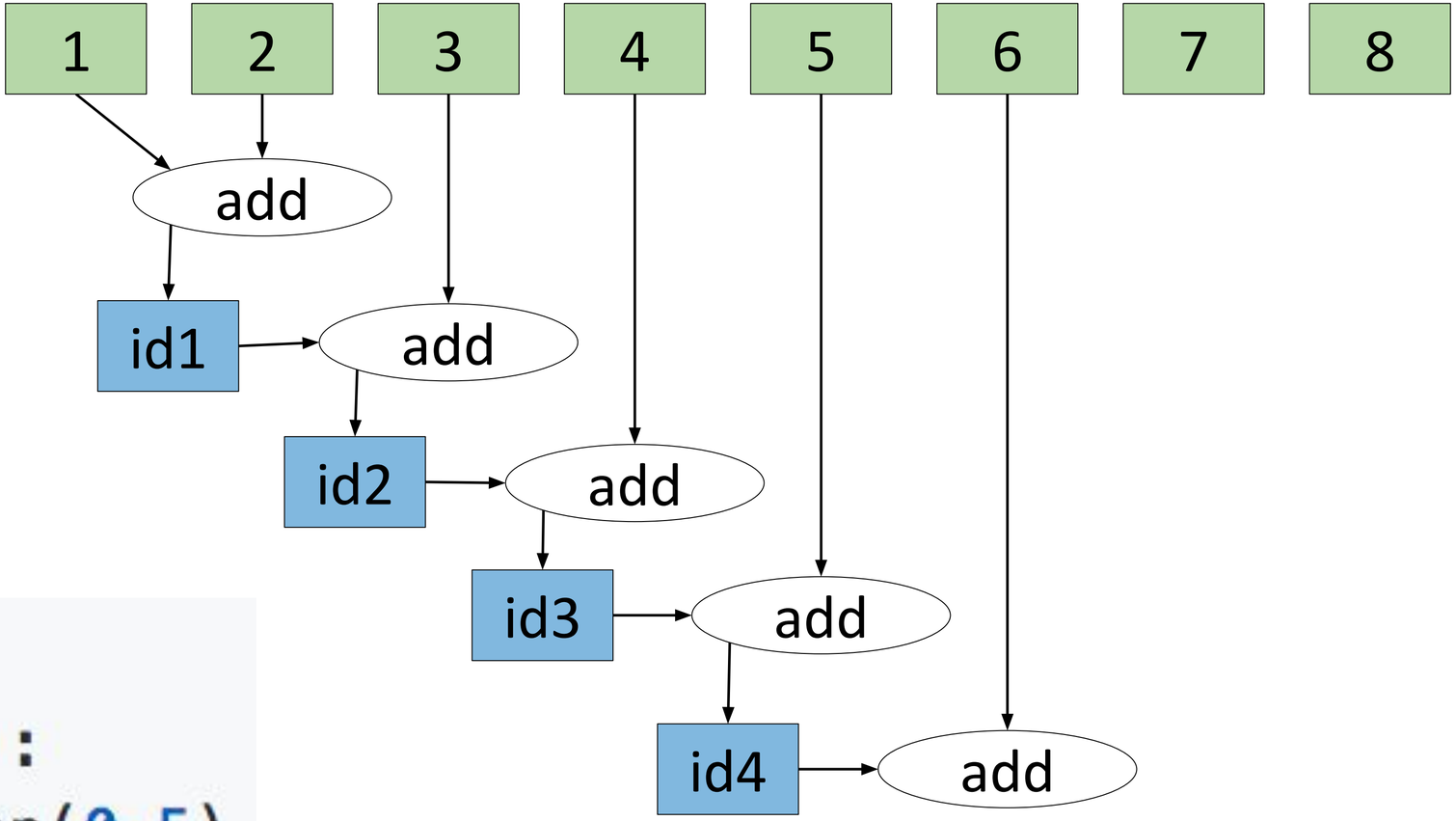


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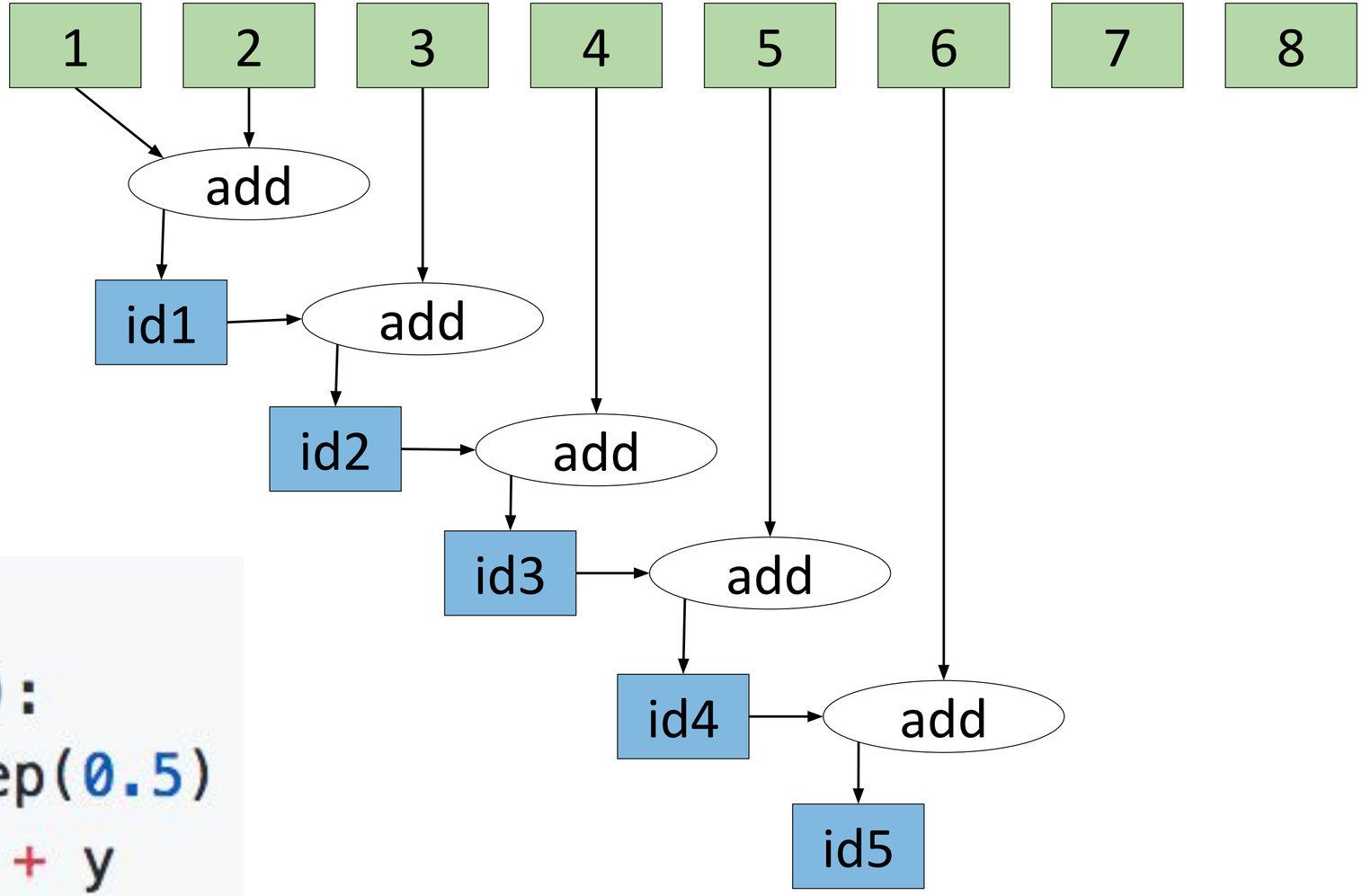


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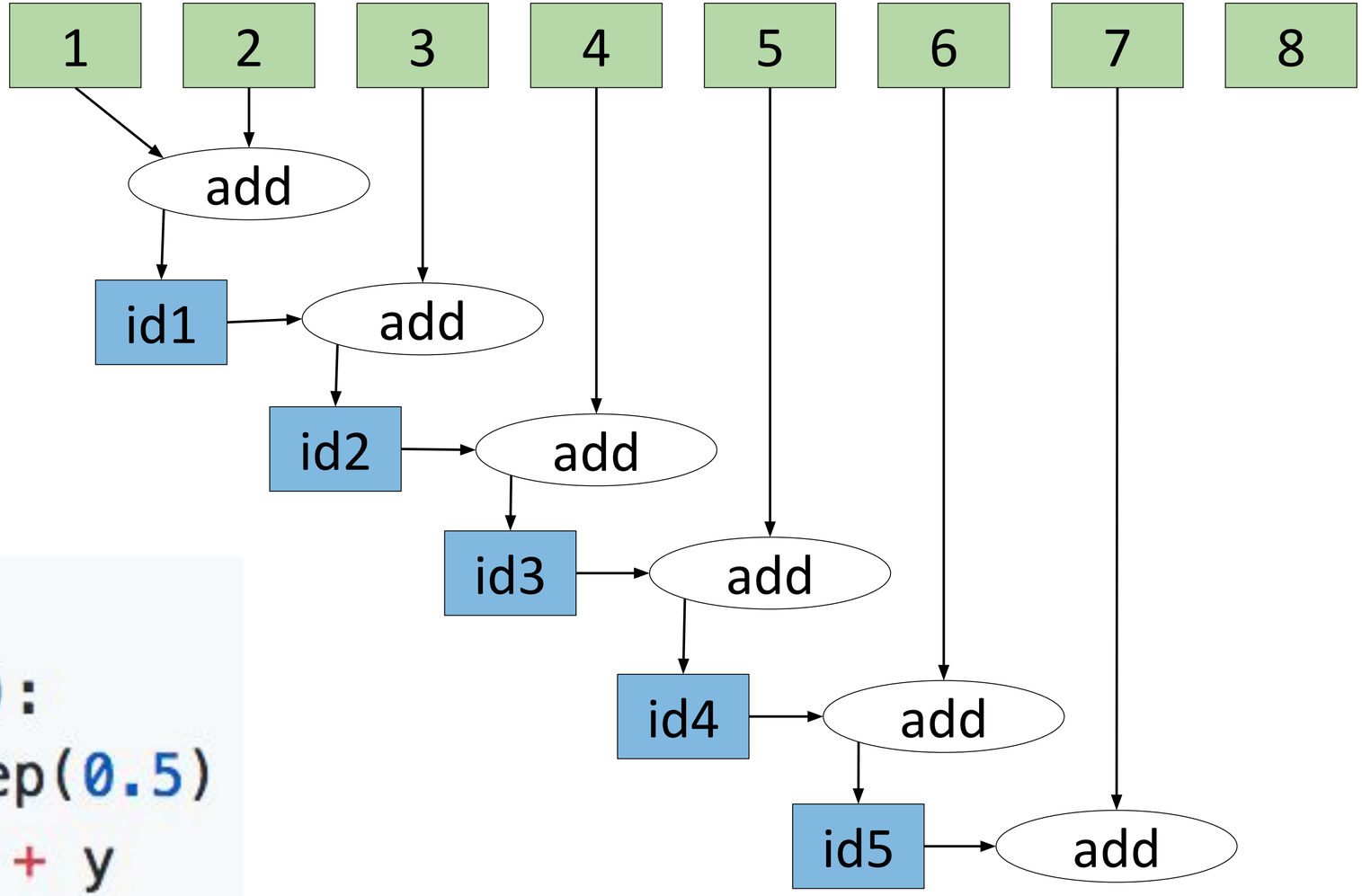


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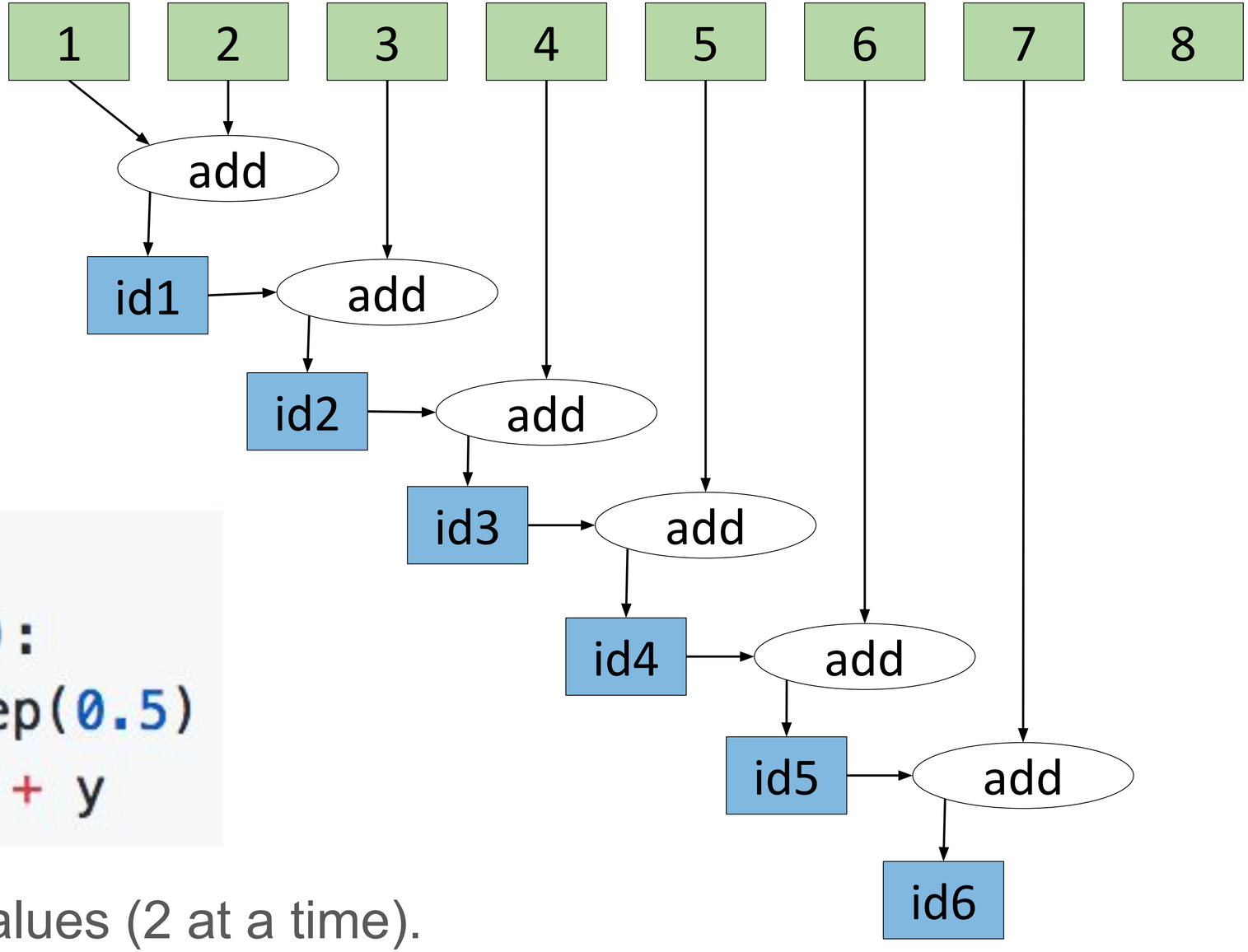


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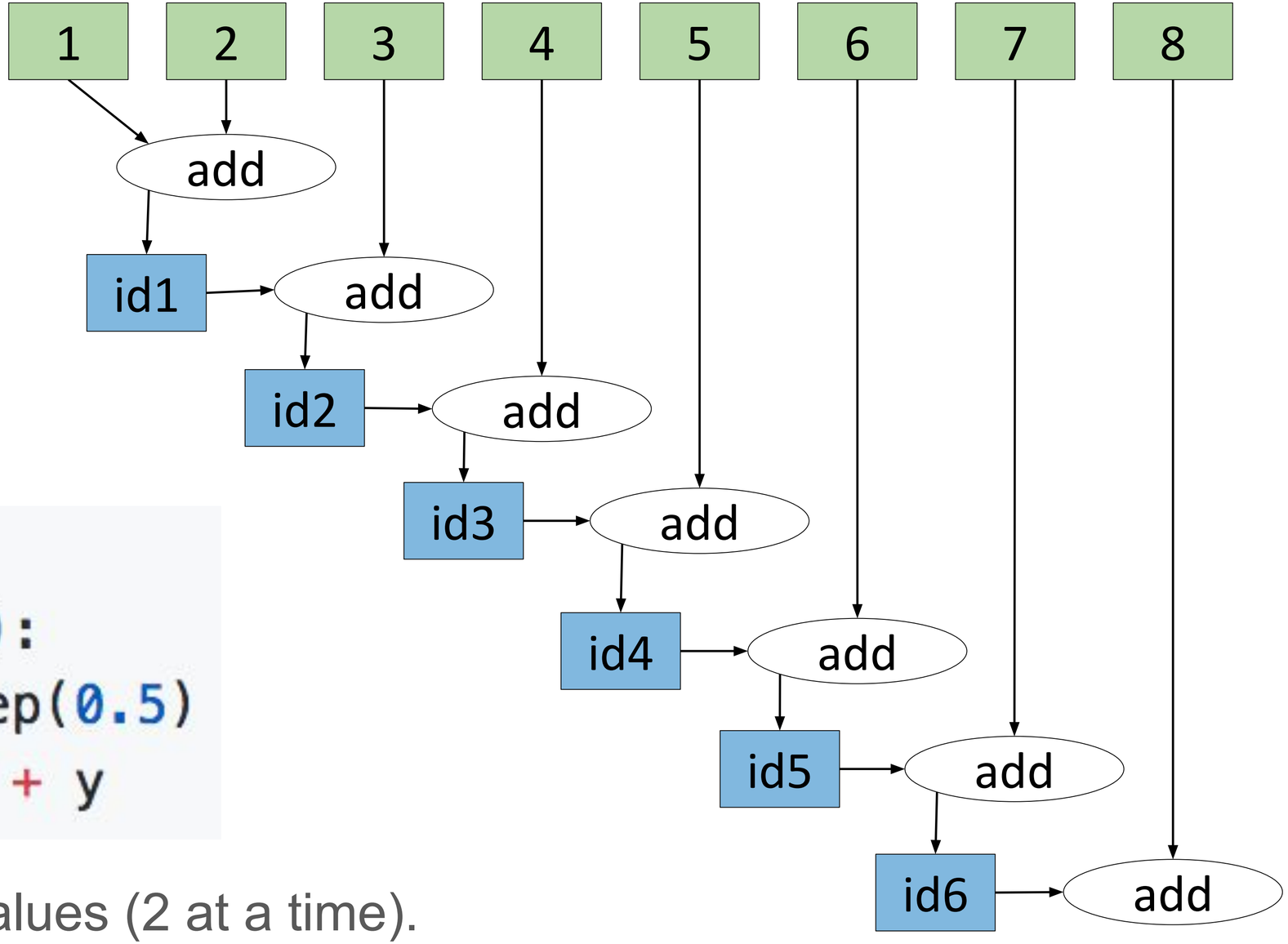


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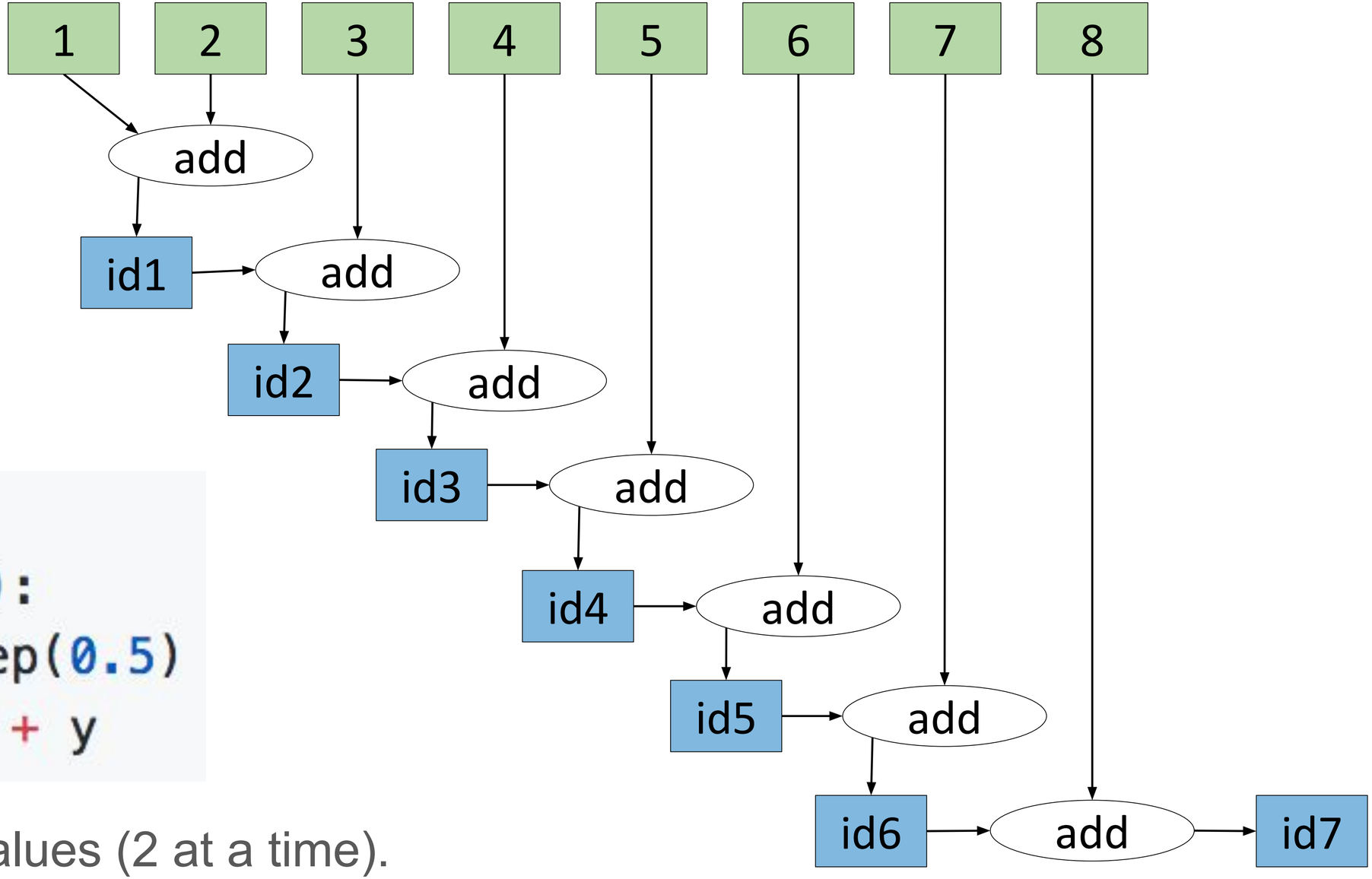


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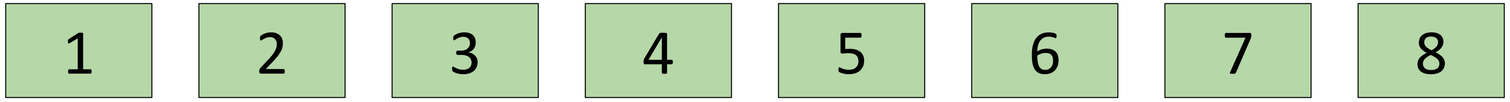


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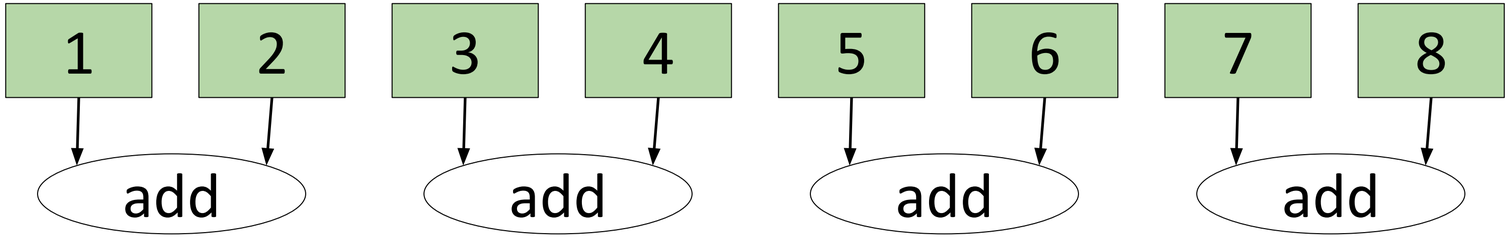


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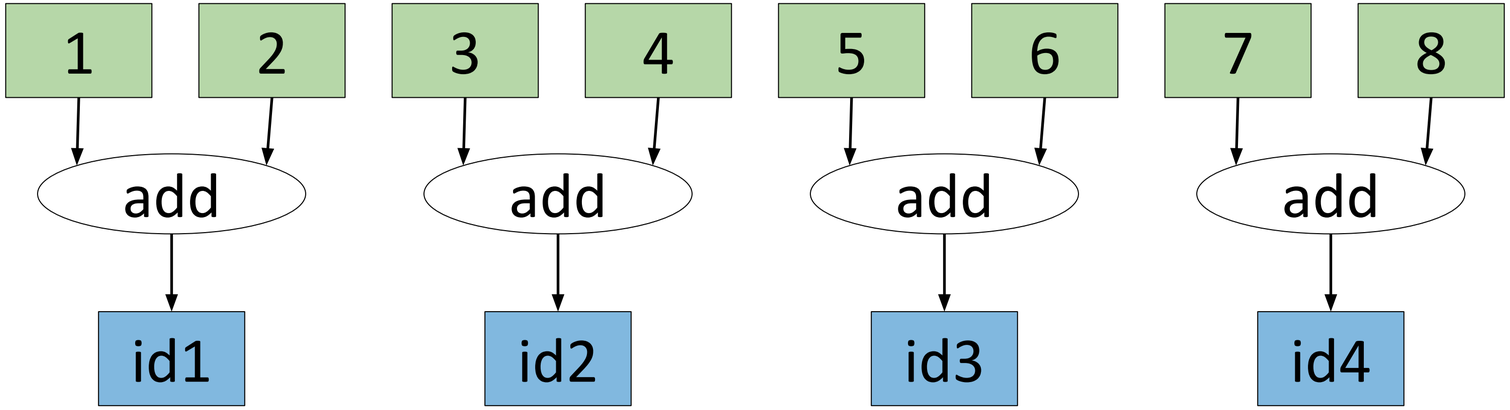


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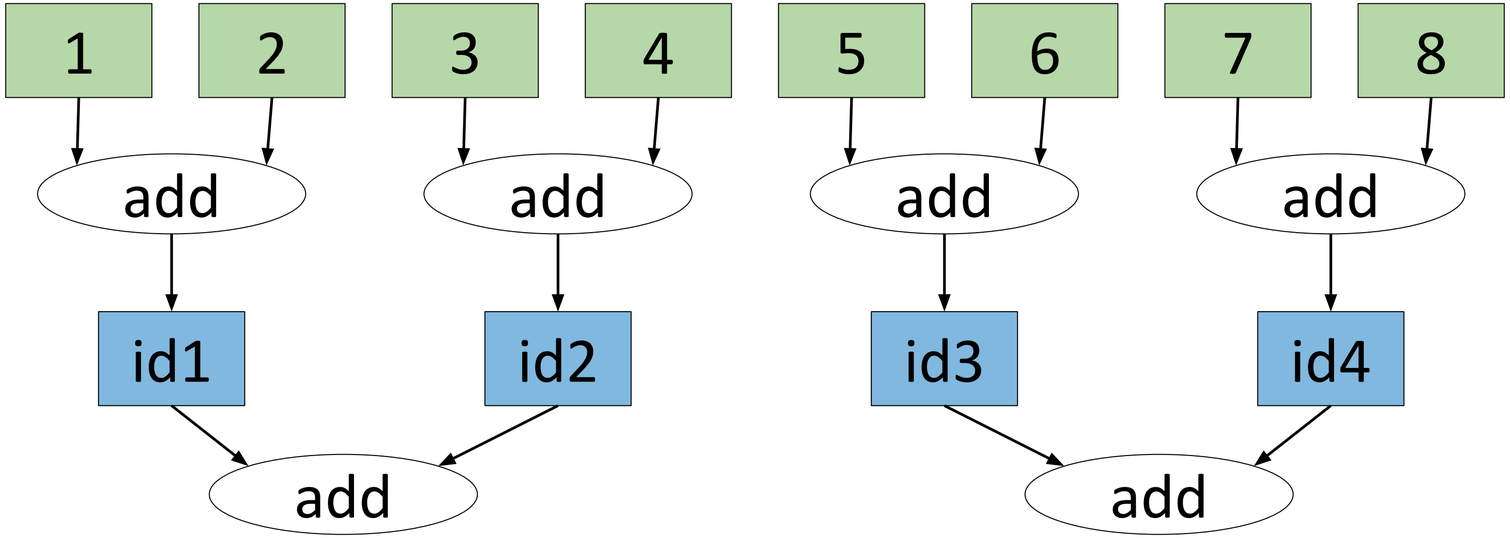


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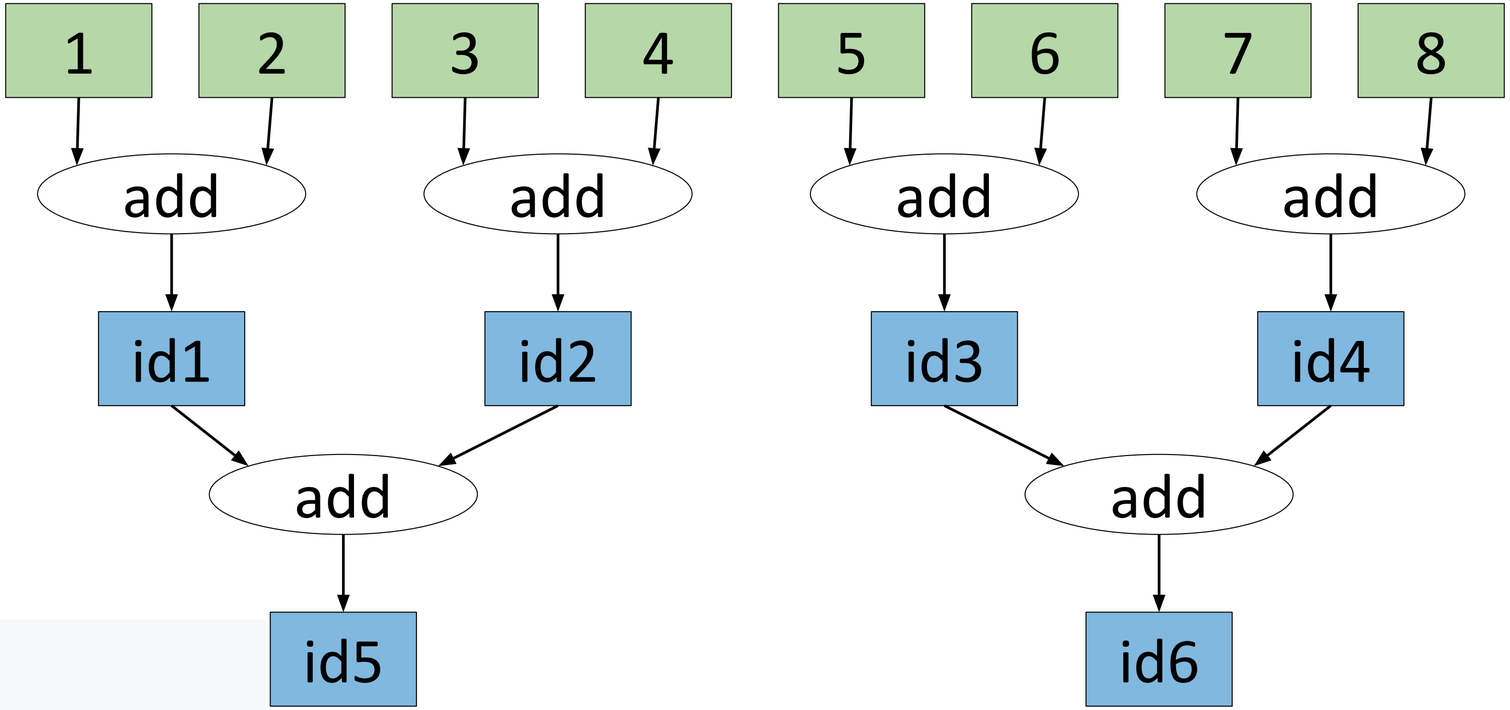


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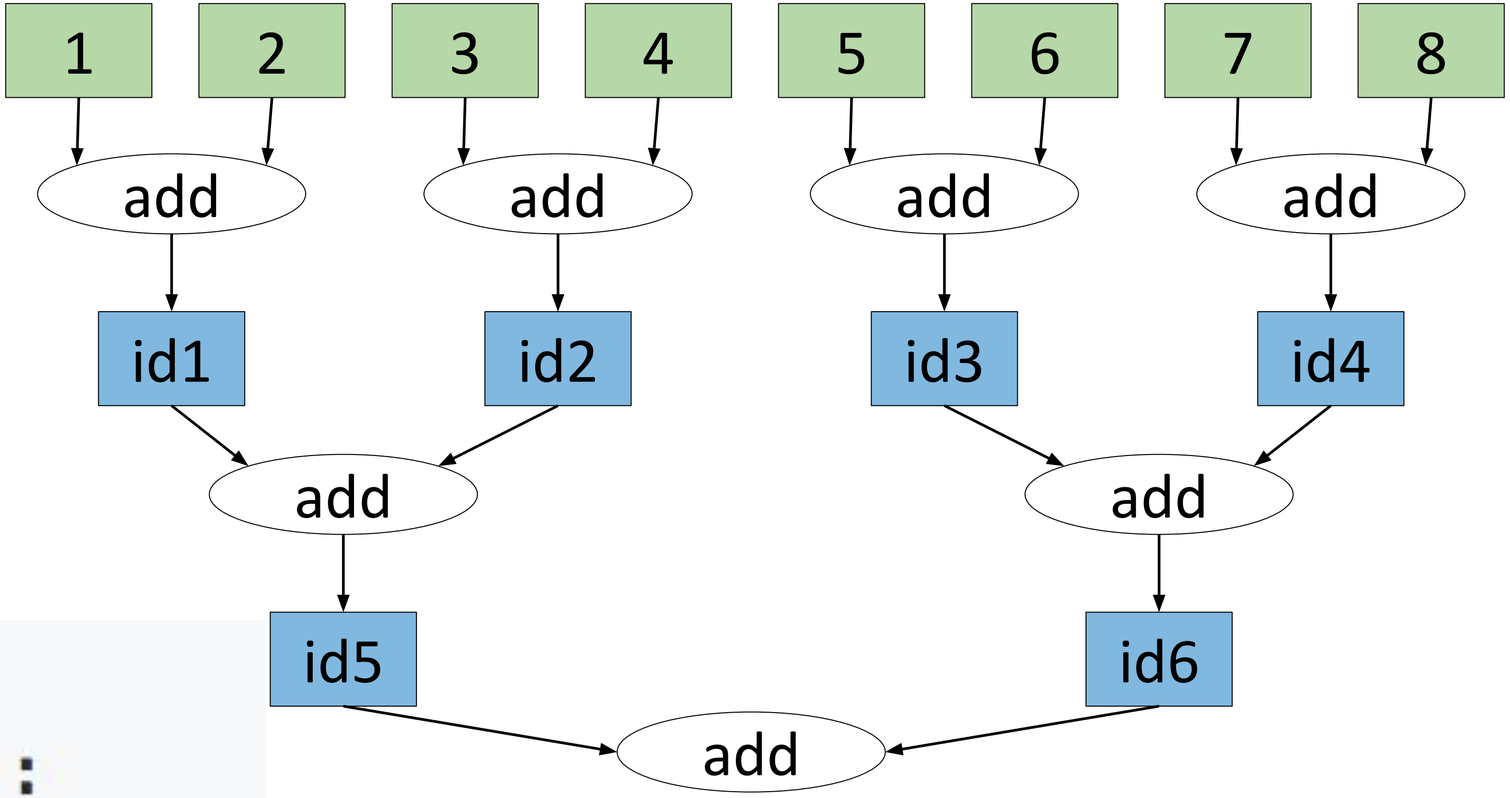


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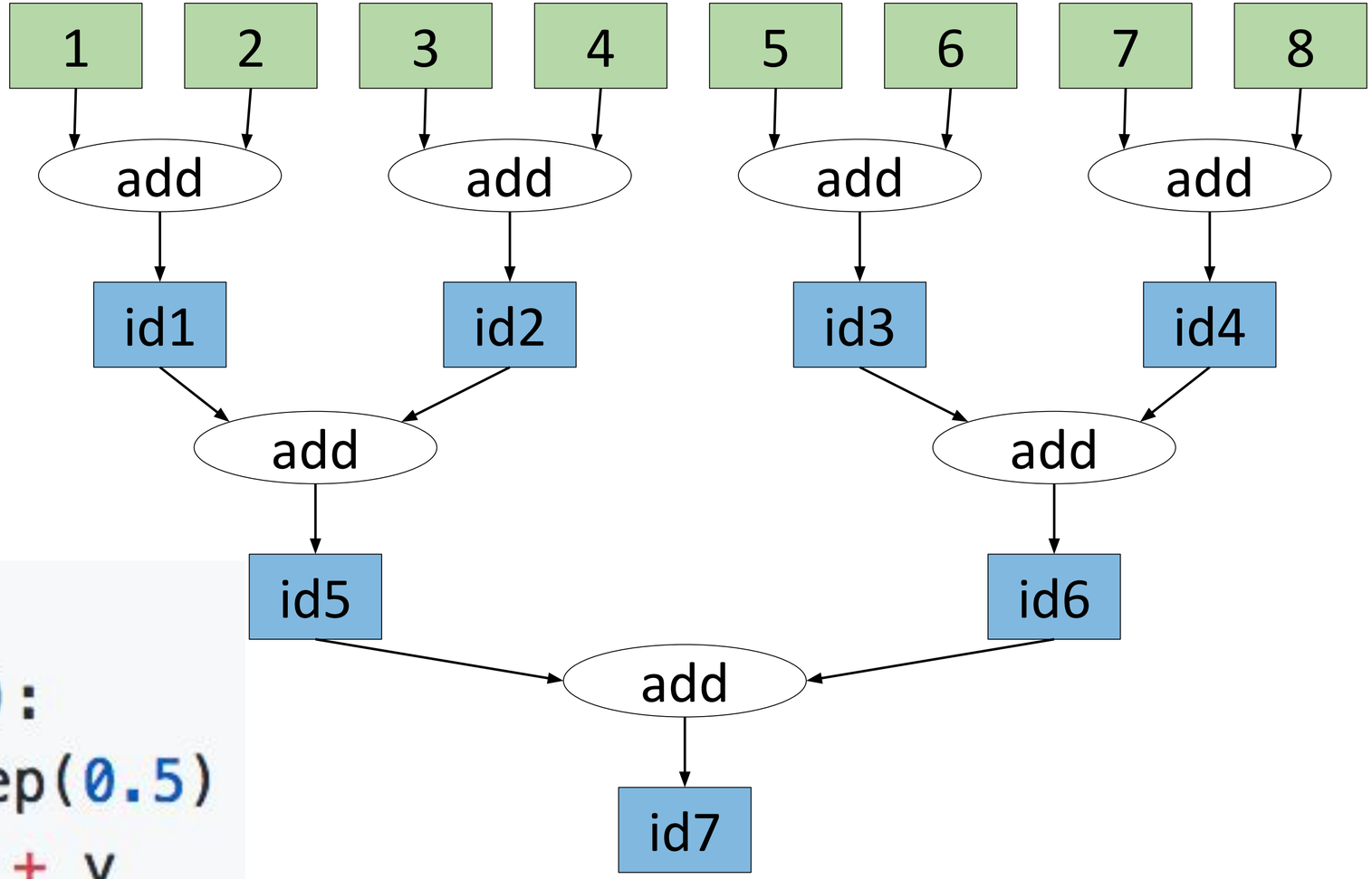


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Actors: Parameter Server Example

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@ray.remote
class ParameterServer(object):
    def __init__(self):
        self.params = np.zeros(10)
    def get_params(self):
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    def update_params(self, grad):
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@ray.remote(num_gpus=1)
def worker(ps):
    while True:
        params = ray.get(ps.get_params.remote())
        grad = ...  # Use TensorFlow
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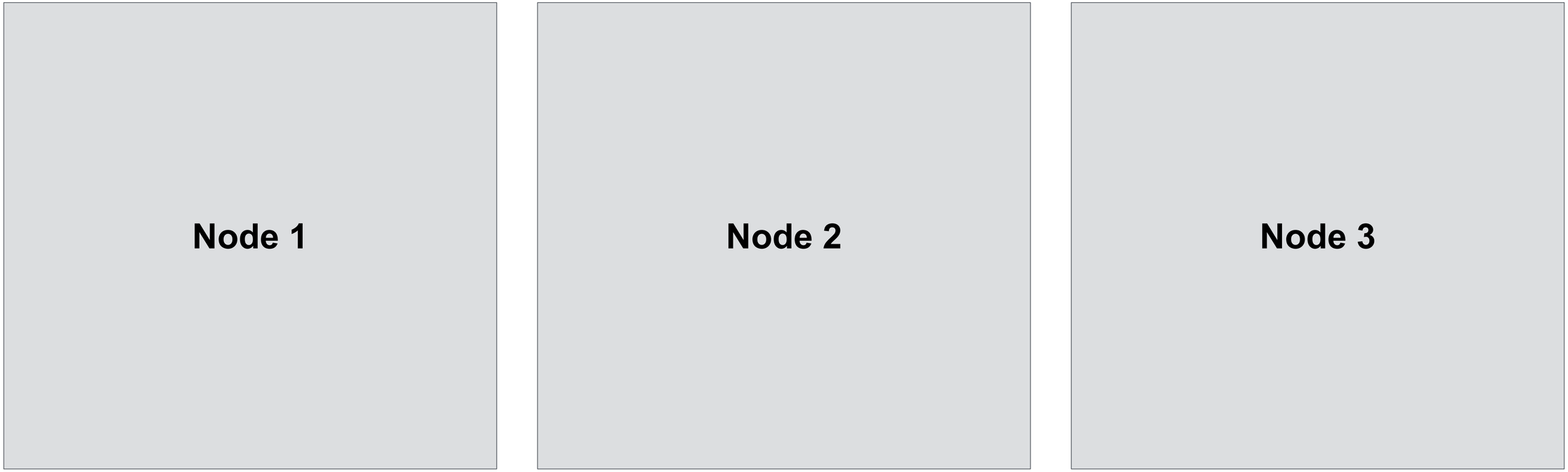

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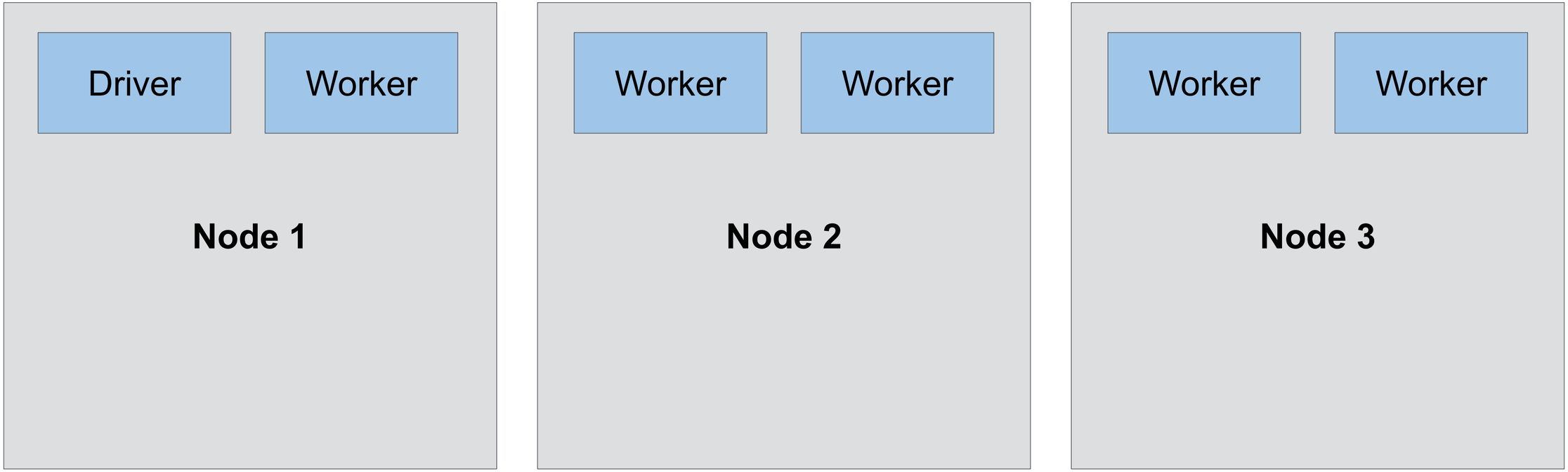

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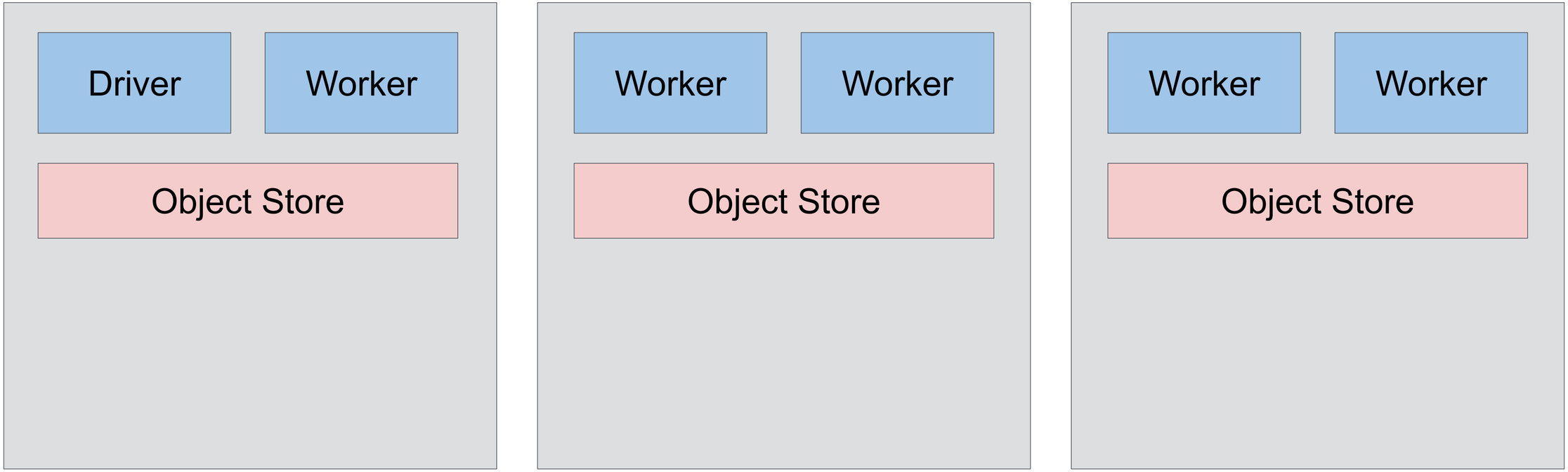

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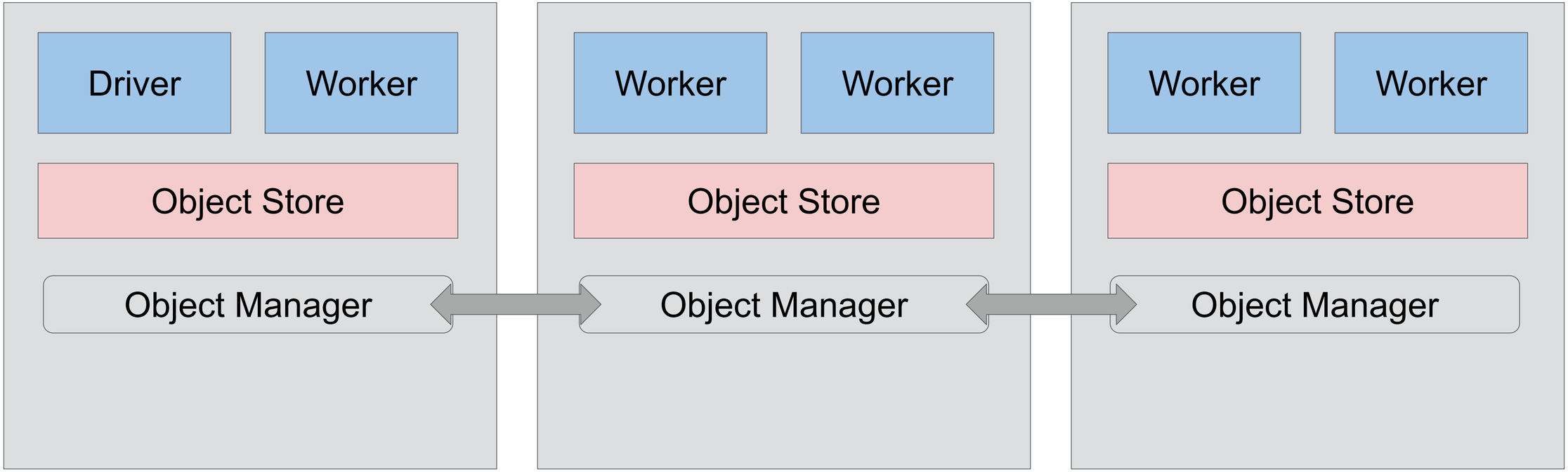

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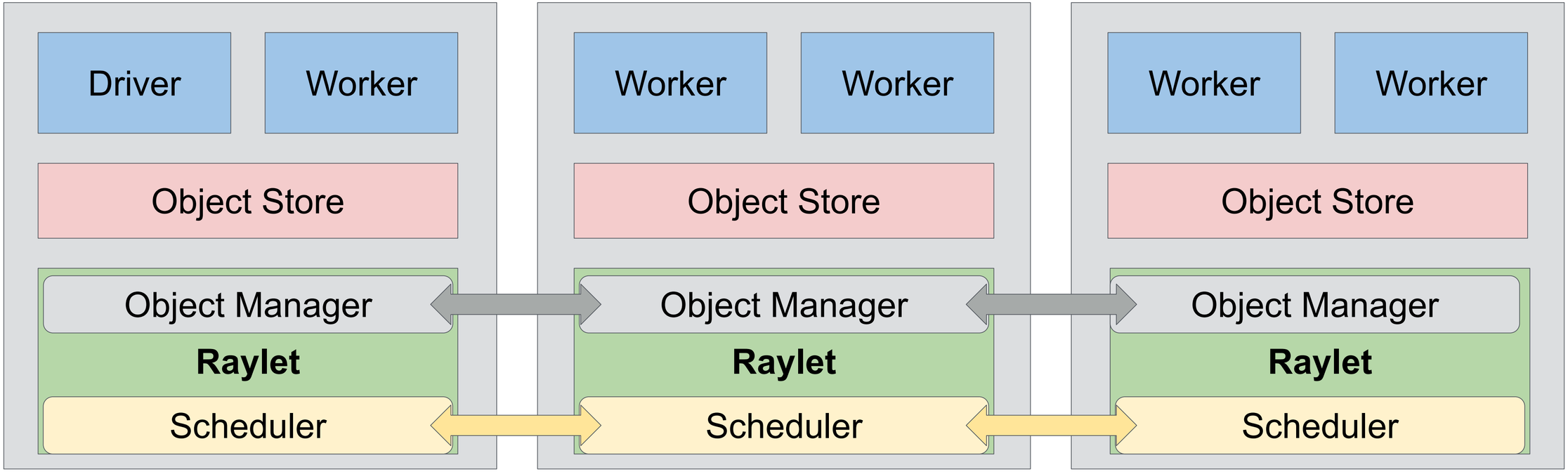

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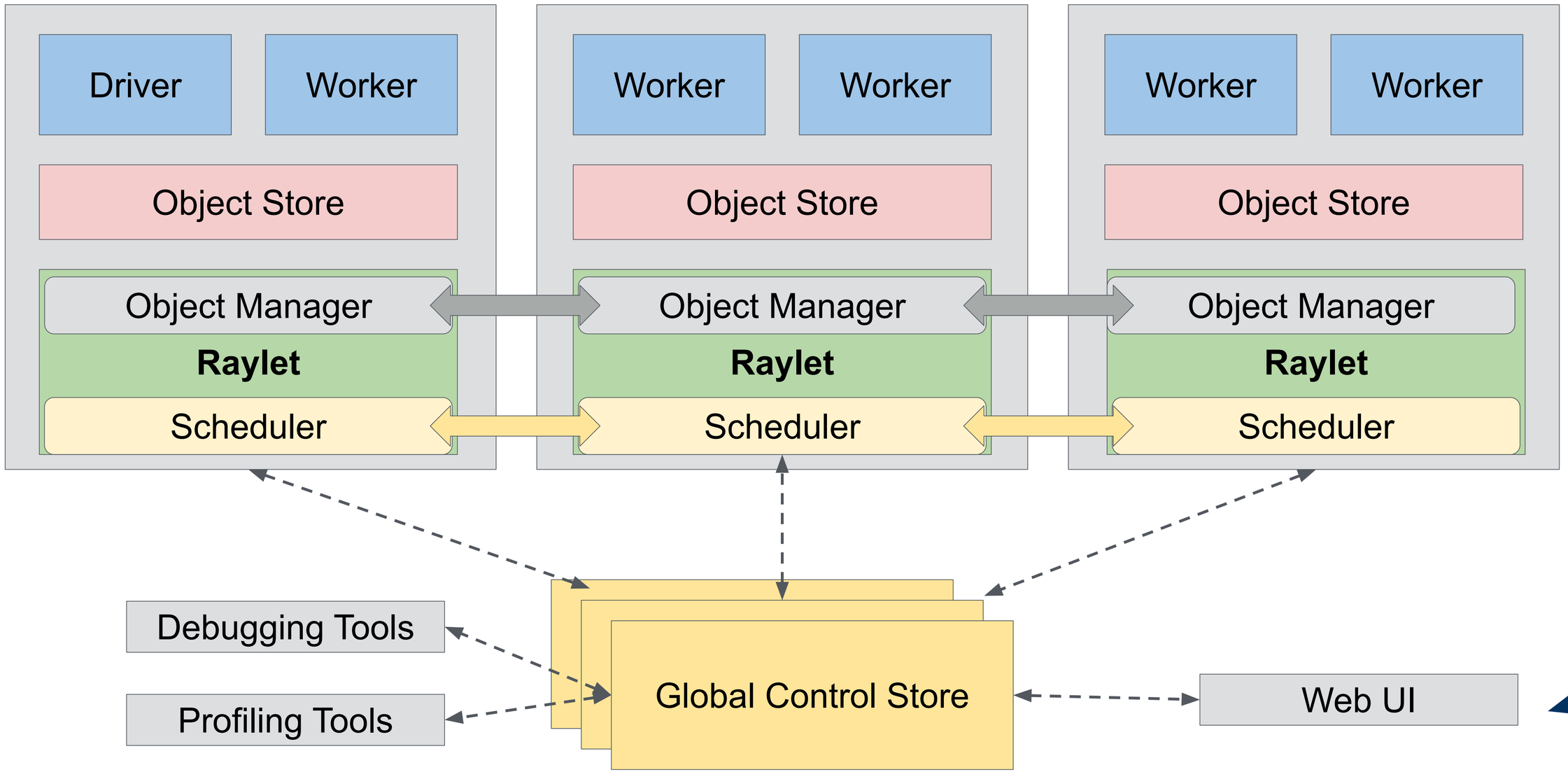

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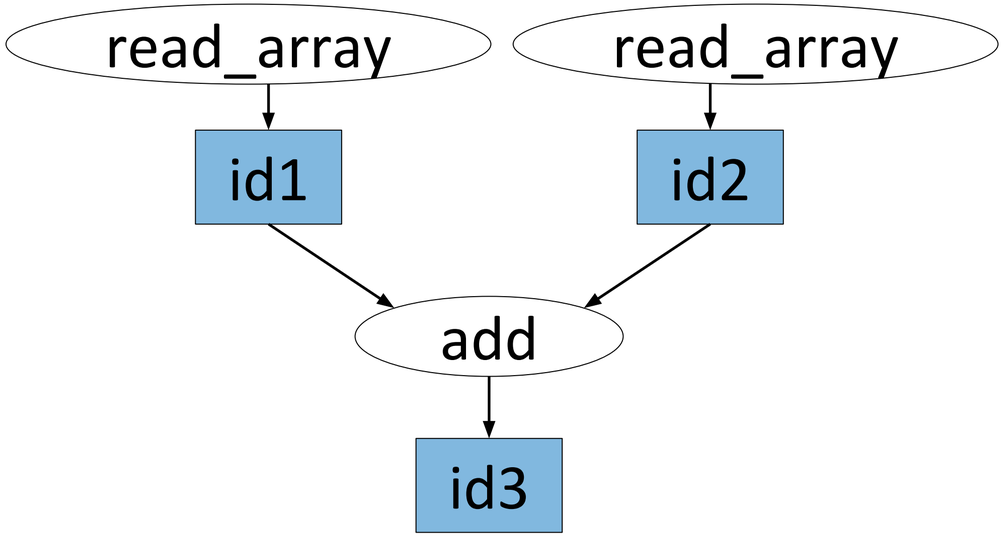
Tasks

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

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

id1 = read_array.remote([5, 5])
id2 = read_array.remote([5, 5])
id3 = add.remote(id1, id2)
ray.get(id3)
```



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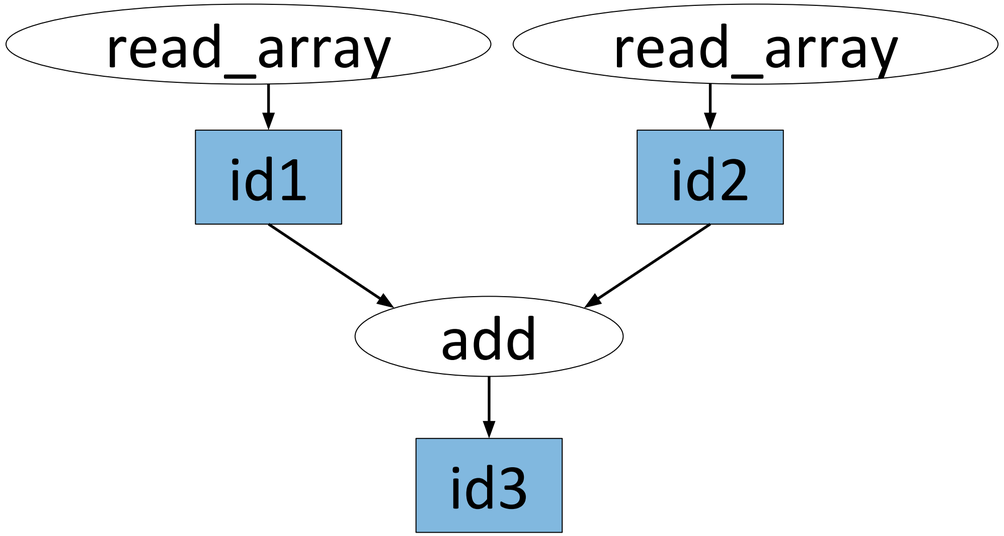

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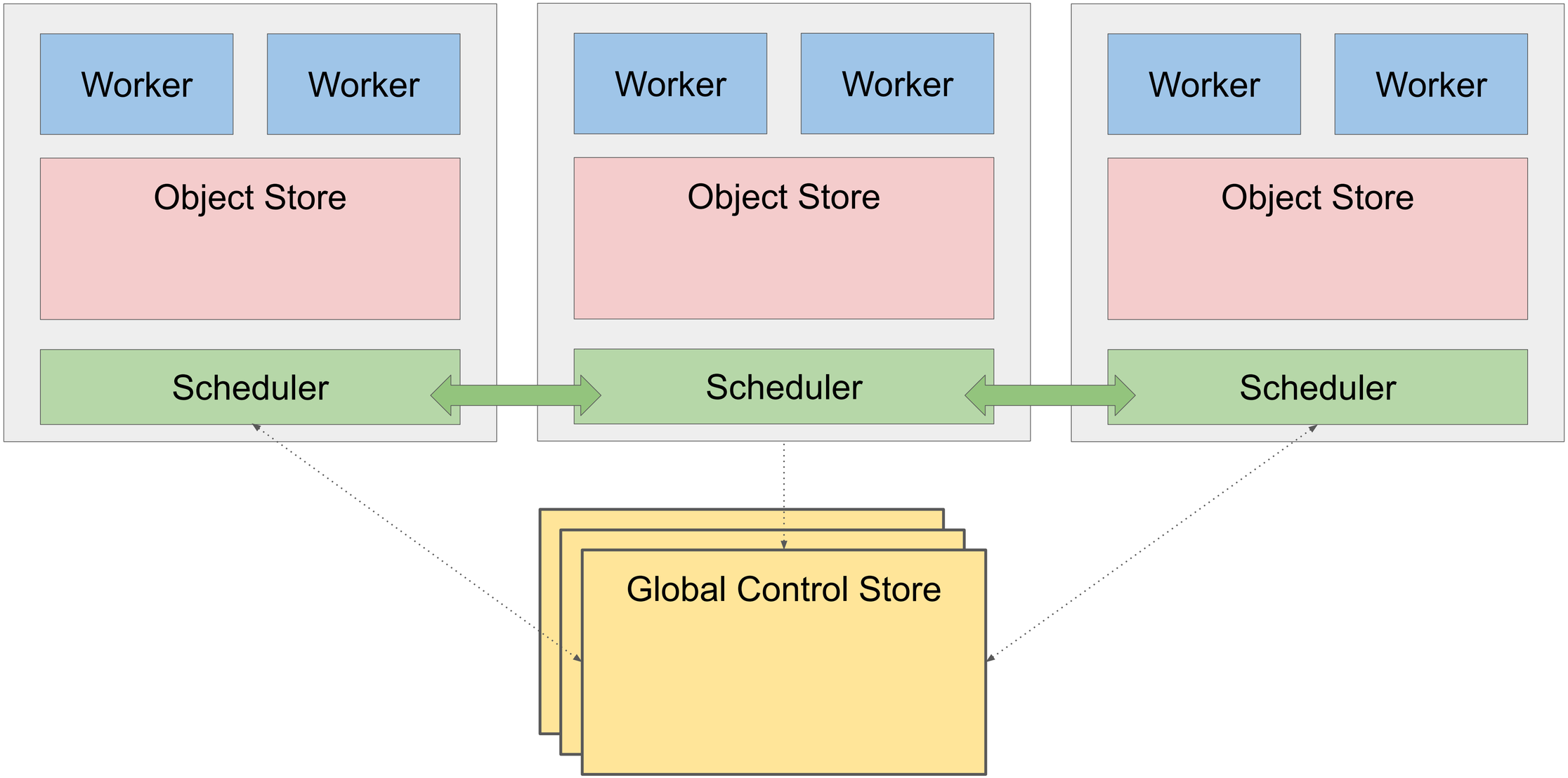

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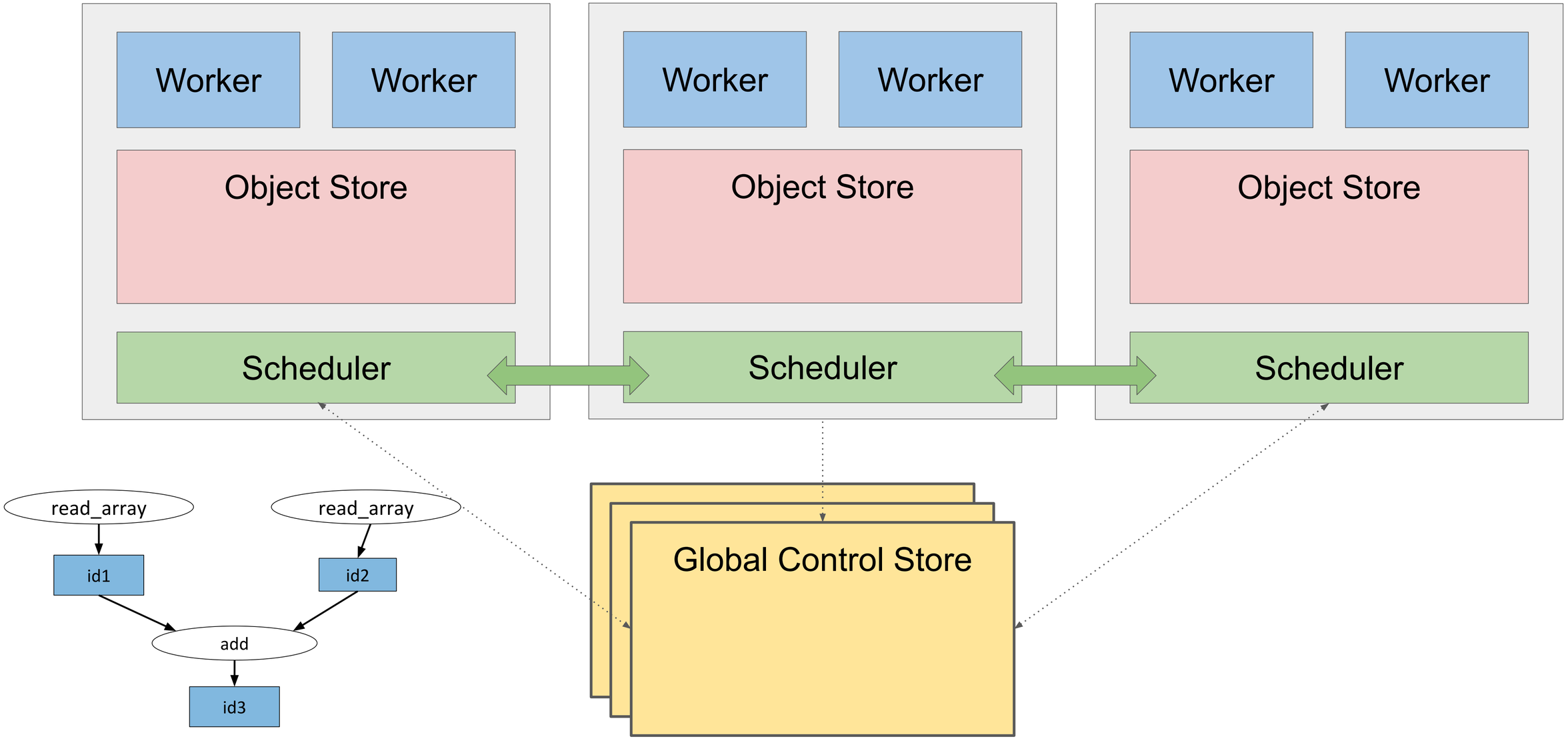

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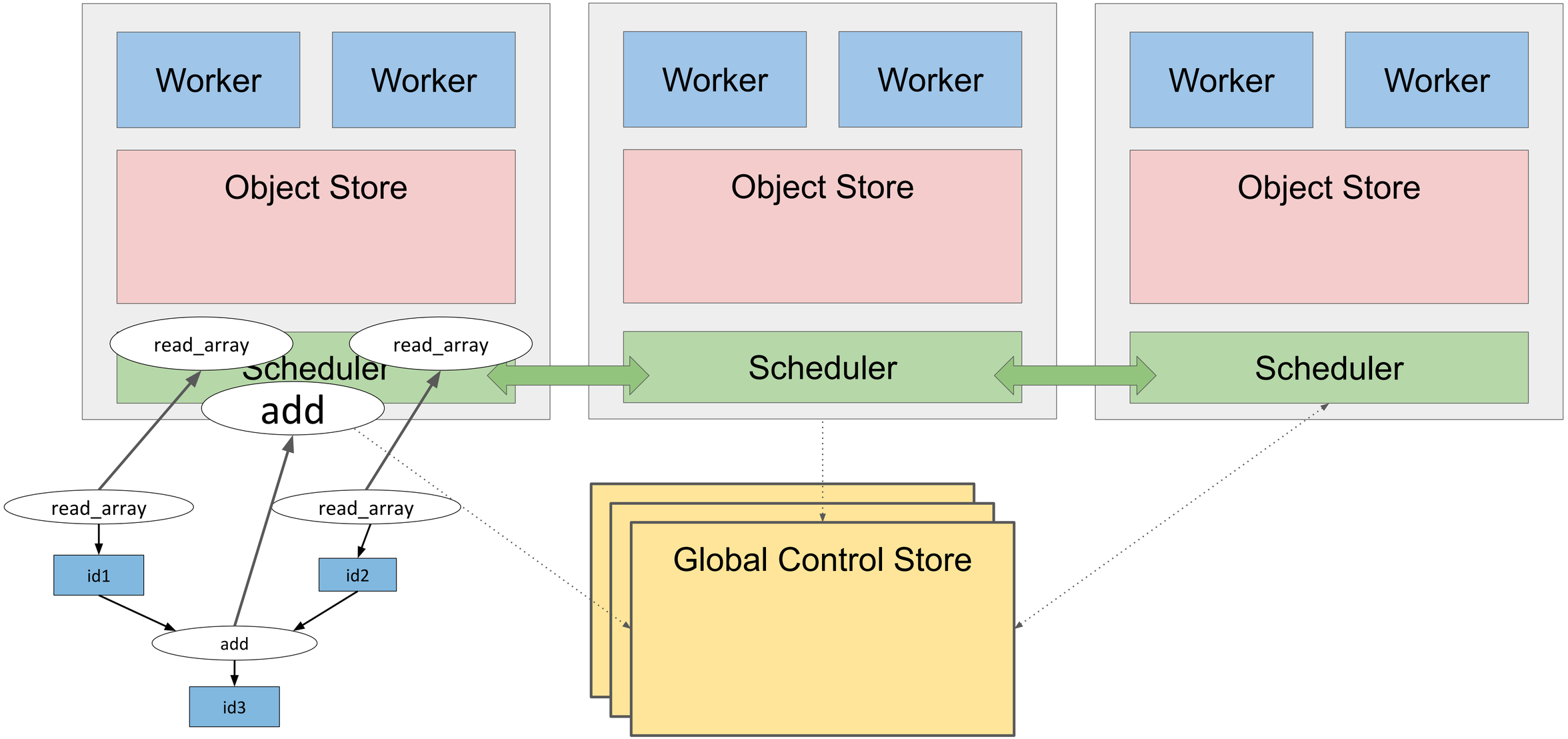

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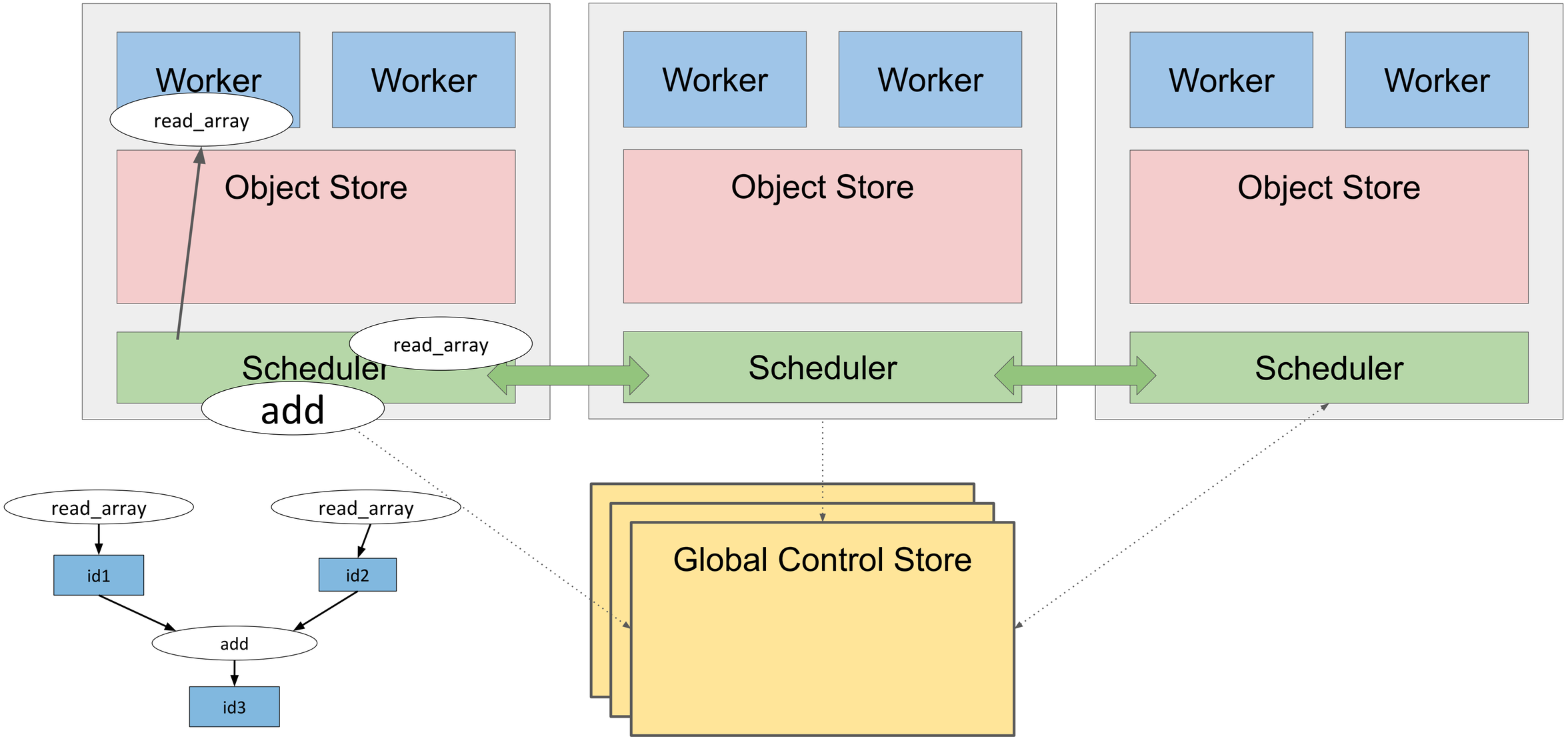

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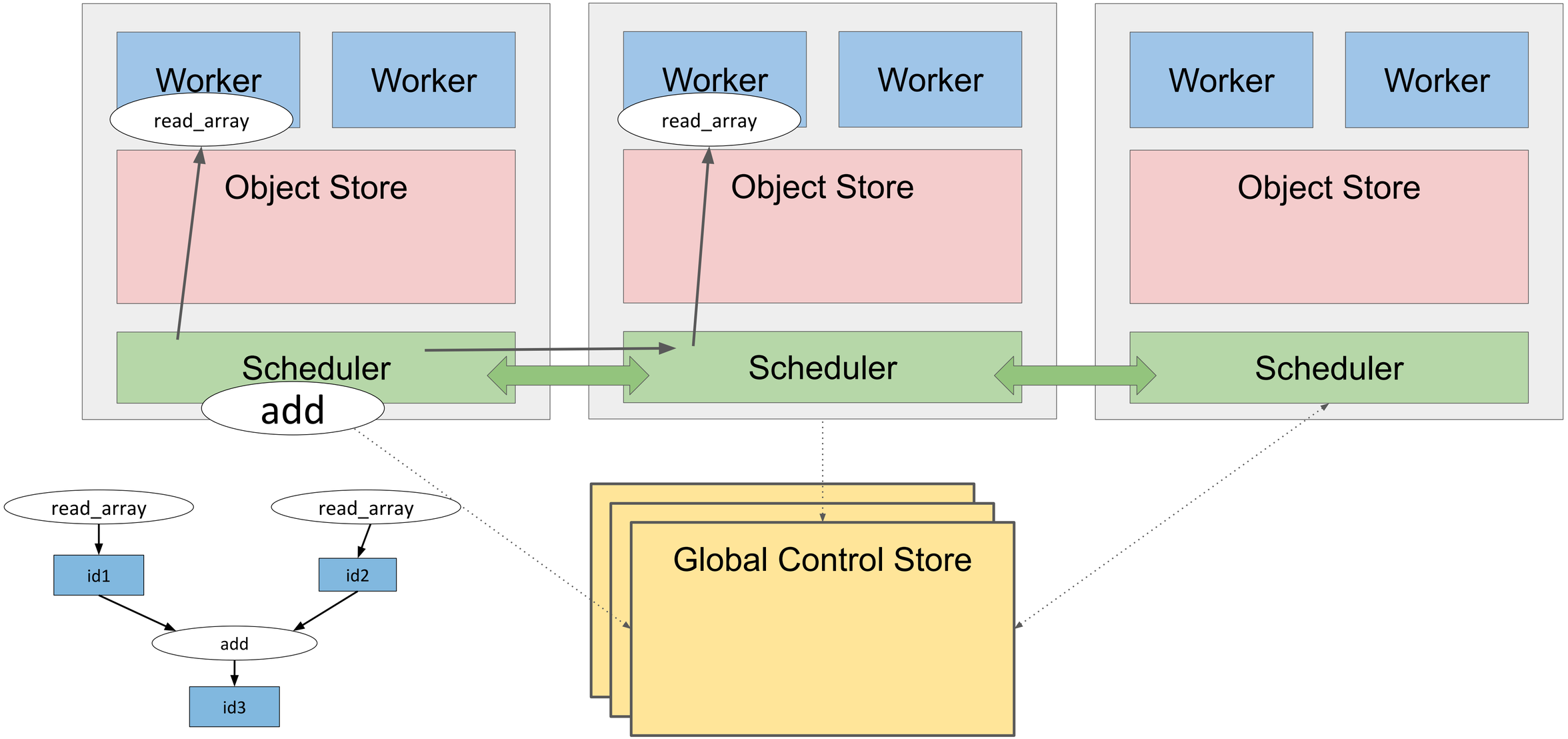

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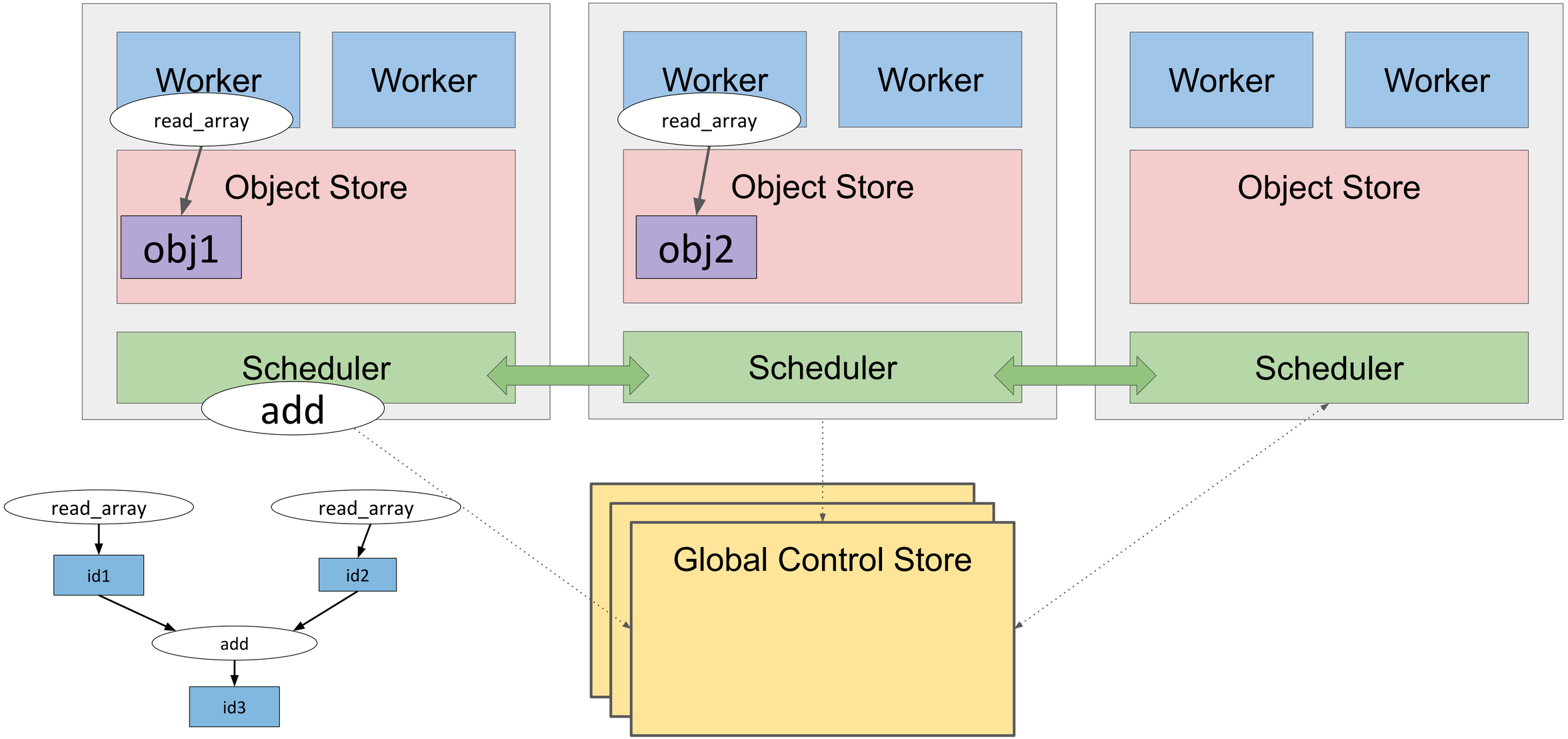

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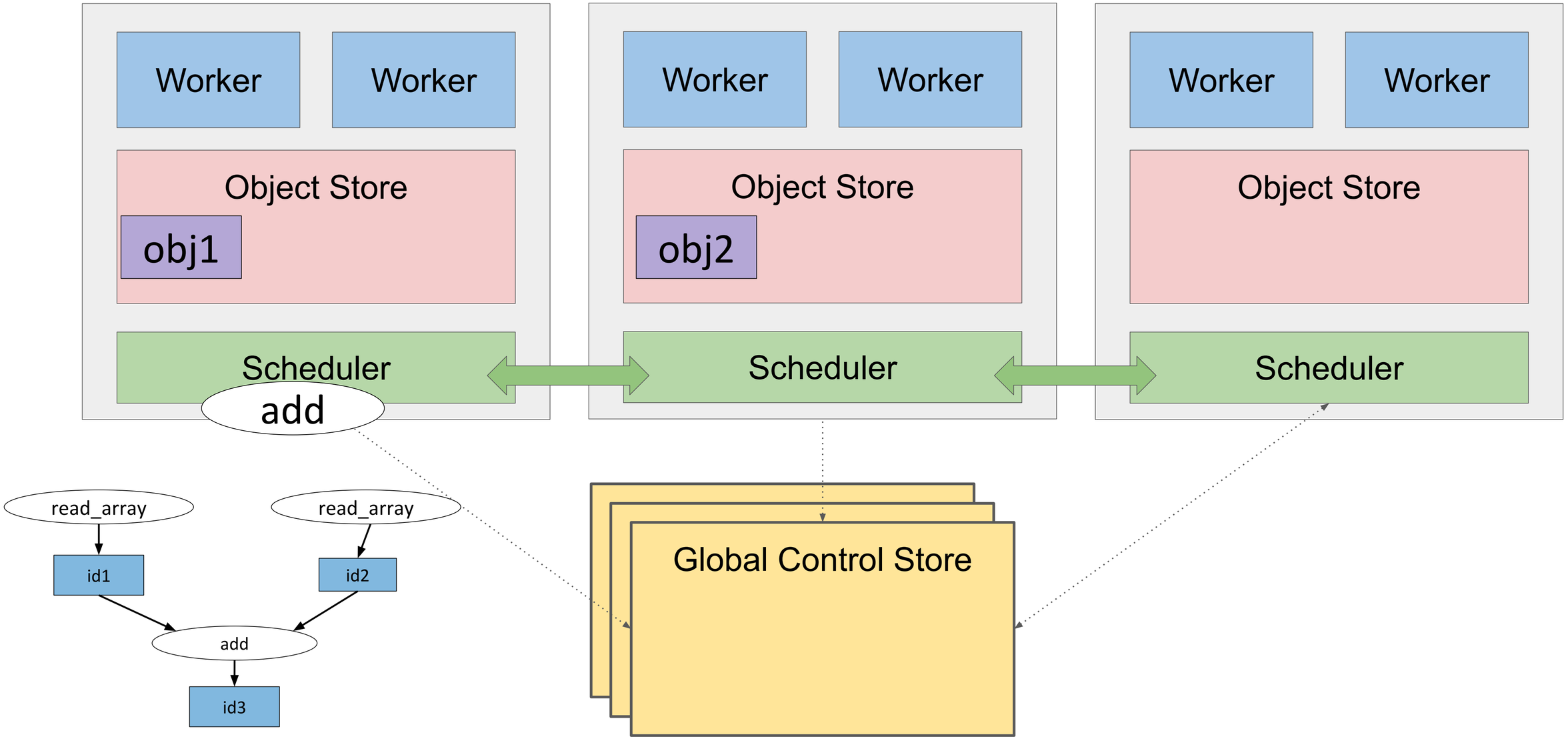

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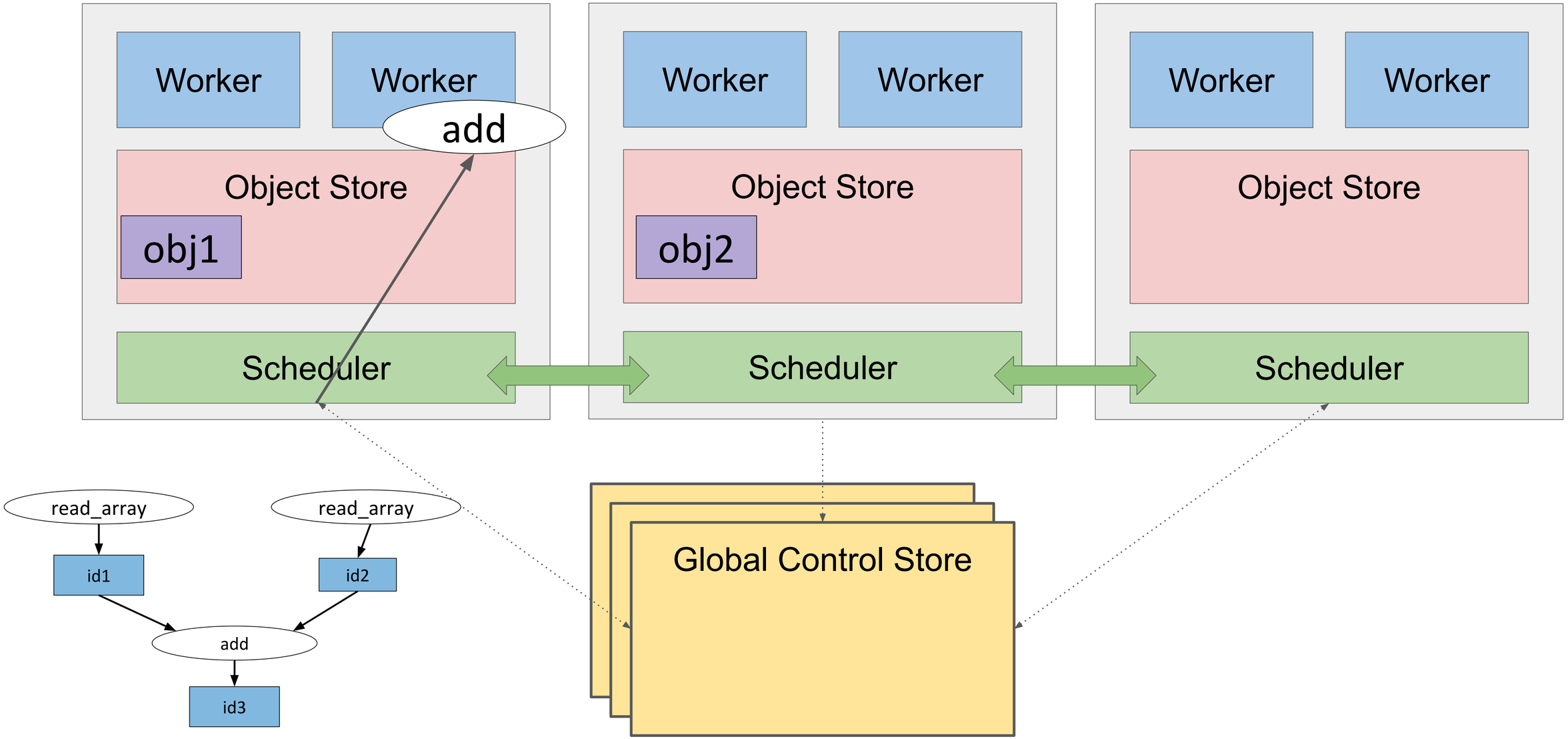

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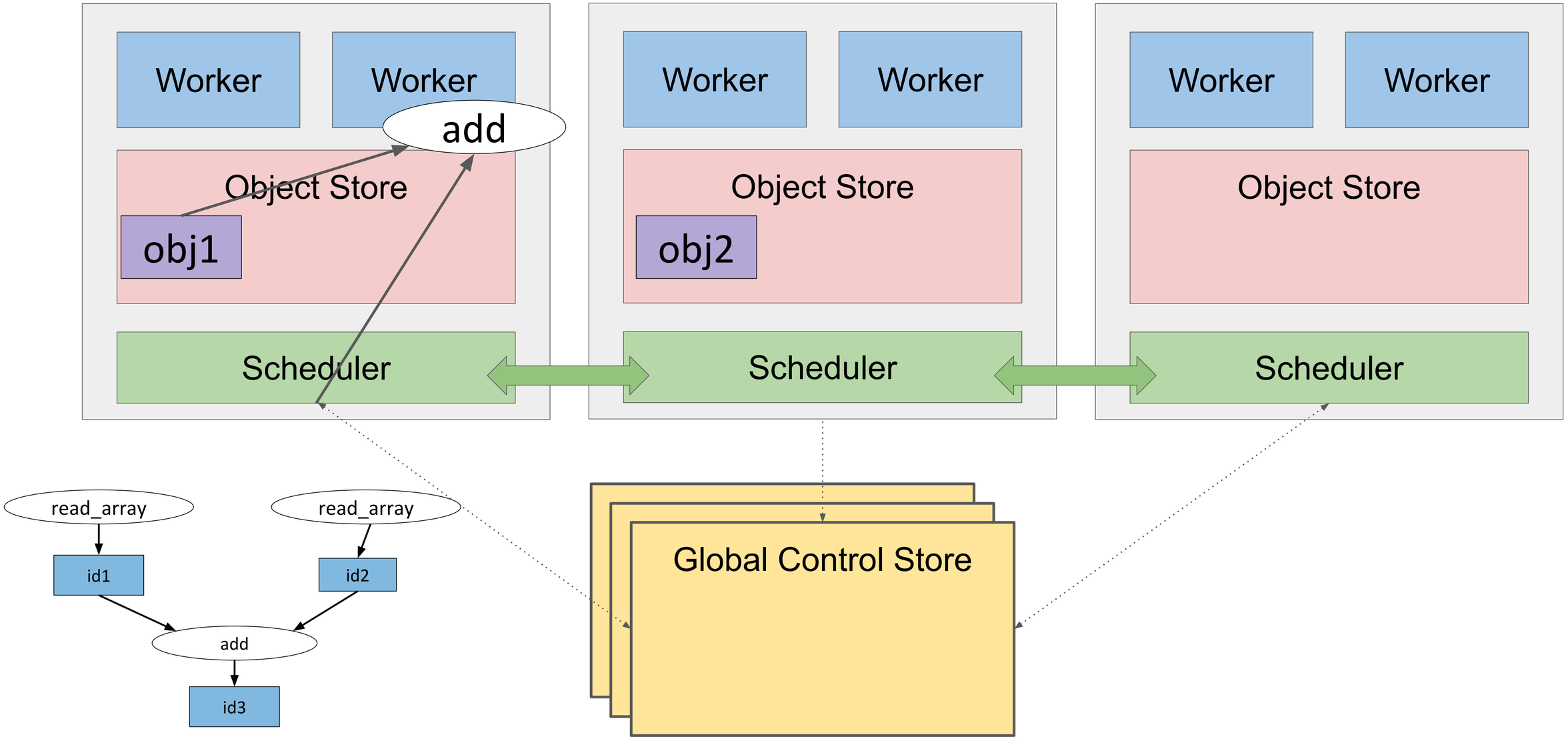

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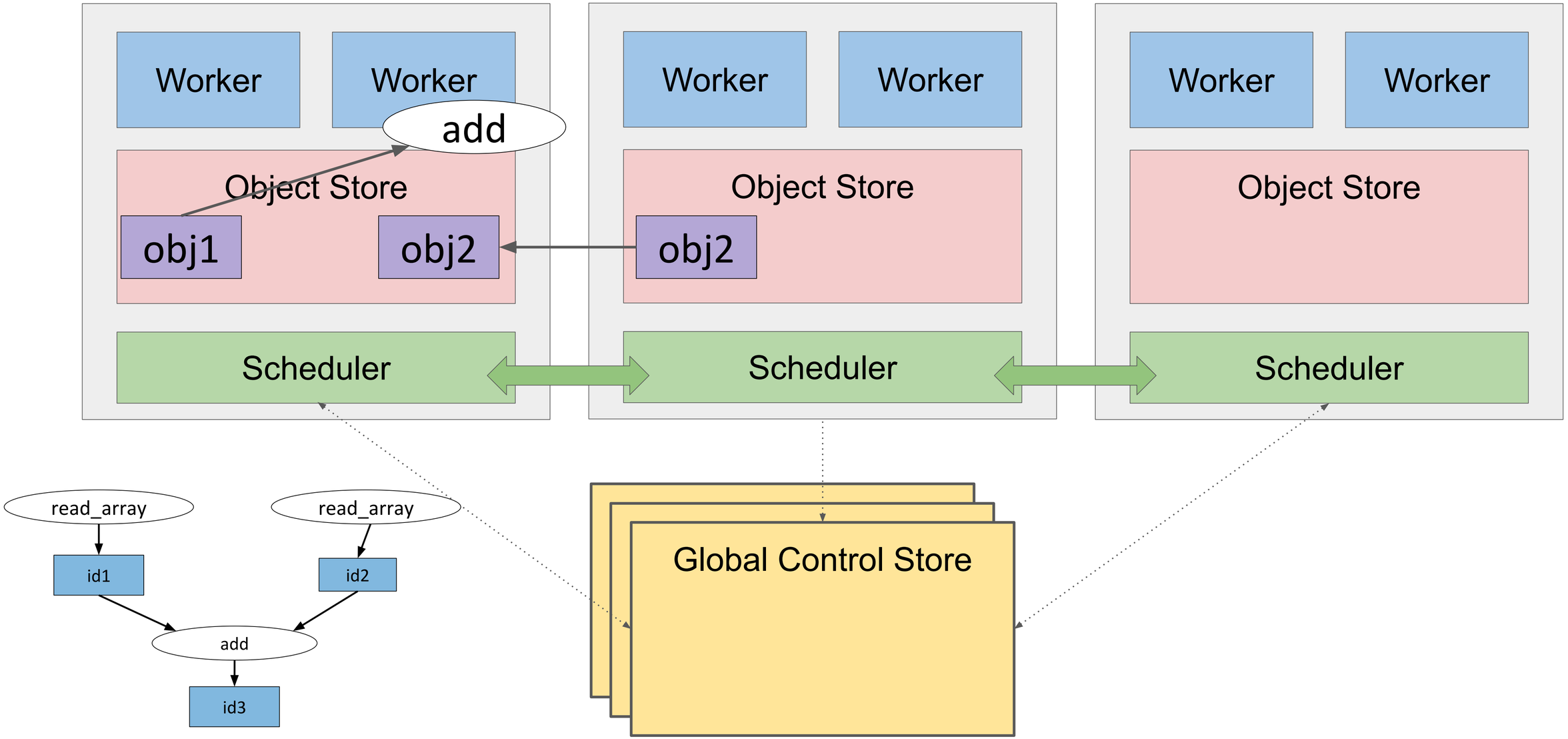
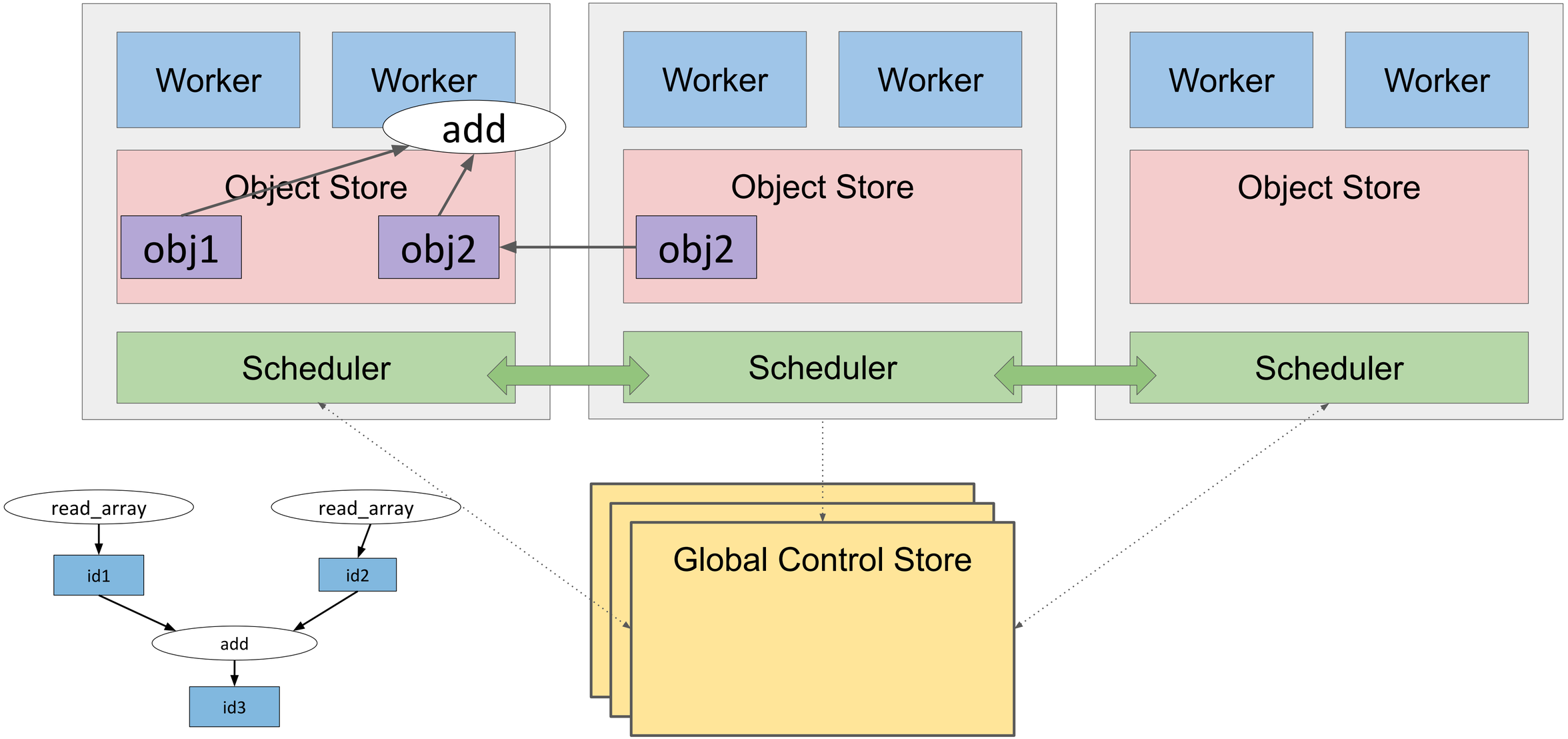
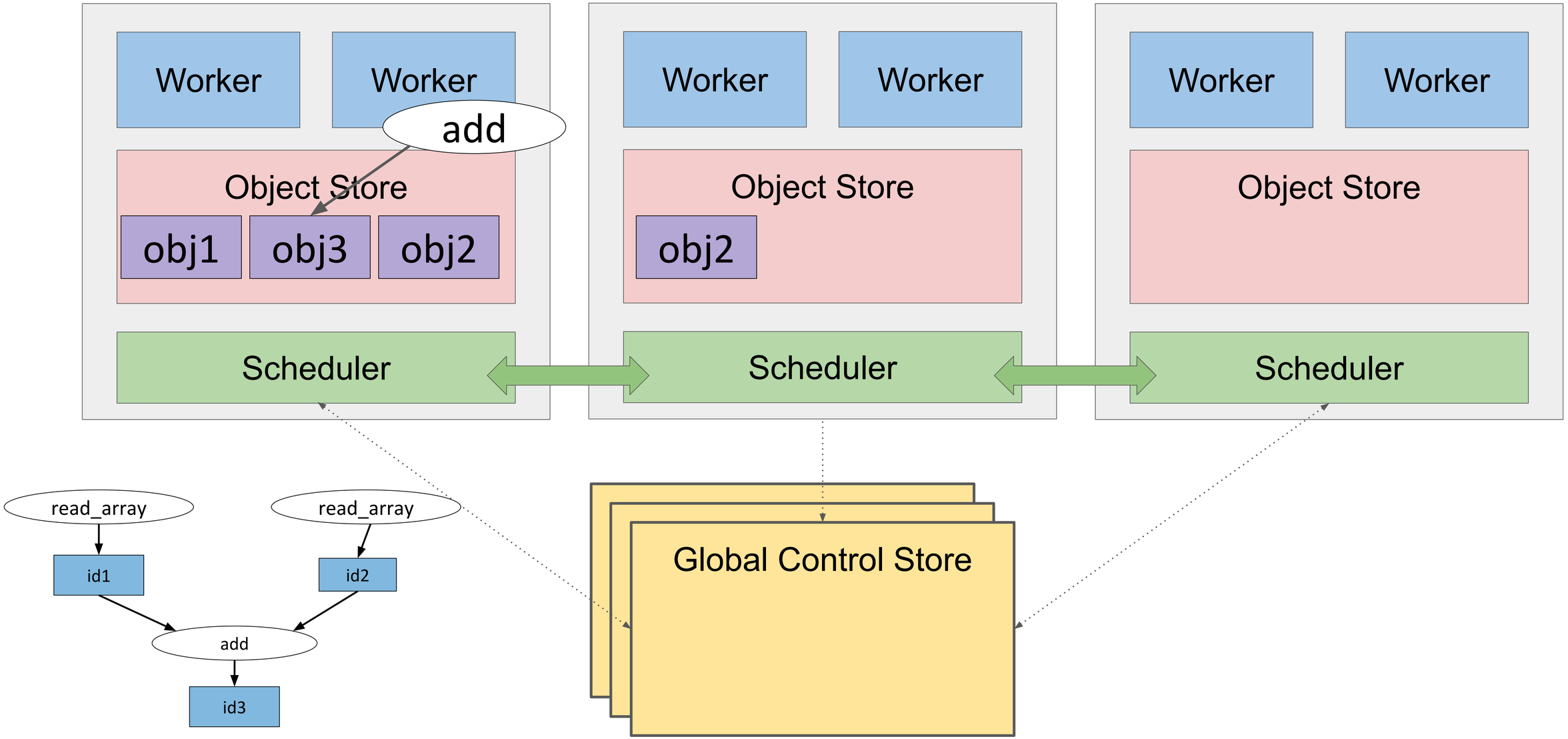


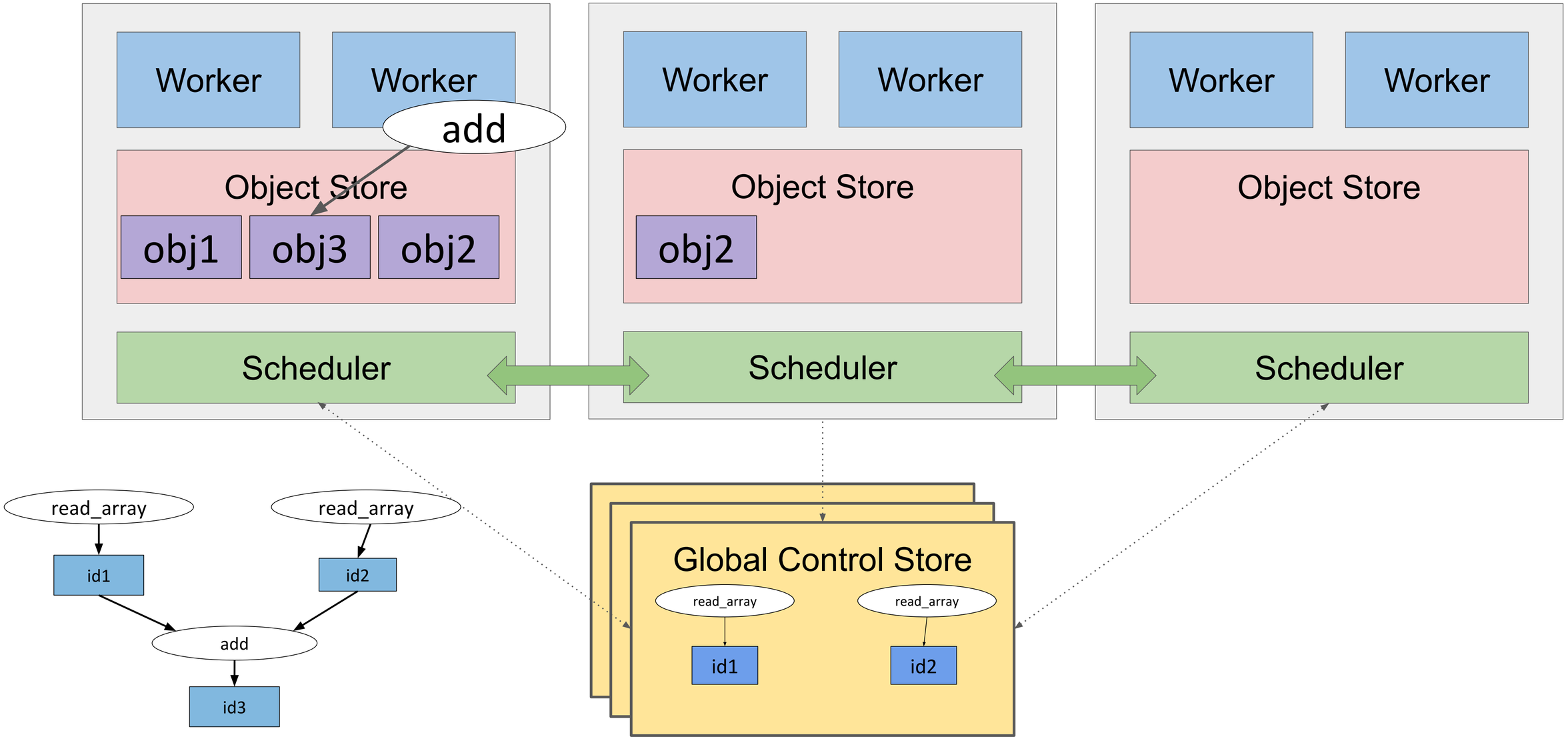
The Ray Architecture



The Ray Architecture



The Ray Architecture



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