Distributed Machine Learning with Ray

Scaling AI Applications in Python with the Ray Framework

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Learning Outcomes

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Learning Outcomes

- Basics of distributed machine learning

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- Use cases that **Ray** is especially well-suited to solve

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- Differences between **Ray** vs. other frameworks
- Internals of **Ray** and its execution model

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Learning Outcomes

- Basics of distributed machine learning
- Use cases that **Ray** is especially well-suited to solve
- Differences between **Ray** vs. other frameworks
- Internals of **Ray** and its execution model
- Context of the larger **Ray** ecosystem.

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Getting the Materials

https://sr.ht/~hyphaebeast/ray-live-training/

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Do you have any experience with machine learning?

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Have you used a distributed computing framework?
(like Spark, Flink, Hadoop, etc.)

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Why Scale?

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A Brief History

In terms of size [of transistors] you can see that we're approaching the size of atoms which is a fundamental barrier, but it'll be two or three generations before we get that far—but that's as far out as we've ever been able to see.

— Gordon Moore (2006)

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A Brief History

We have another 10 to 20 years before we reach a fundamental limit. By then they'll be able to make bigger chips and have transistor budgets in the billions.

— Gordon Moore (2006)

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Big Data

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Big Data

- **Long Data**: Large # of instances/records/rows/etc.

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Big Data

- **Long Data**: Large # of instances/records/rows/etc.
- **Wide Data**: High dimensionality

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Big Models

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Big Models

- **Large Parameter Spaces**: Models with large number of parameters to learn

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Big Models

- **Large Parameter Spaces**: Models with large number of parameters to learn
- **Prediction Cascades**: Complex pipeline of multiple prediction tasks

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Small Latencies

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Small Latencies

- Real-time predictions (i.e. website ad serving)

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Small Latencies

- Real-time predictions (i.e. website ad serving)
- Prediction Cascades... again (i.e. self-driving cars)

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What Scale?

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What Scale?

- Memory

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What Scale?

- Memory
- Computation

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Introduction to distributed systems

Distributed programming is the art of solving the same problem that you can solve on a single computer using multiple computers.

— Mikito Takada[1]

[1] Distributed systems: for fun and profit

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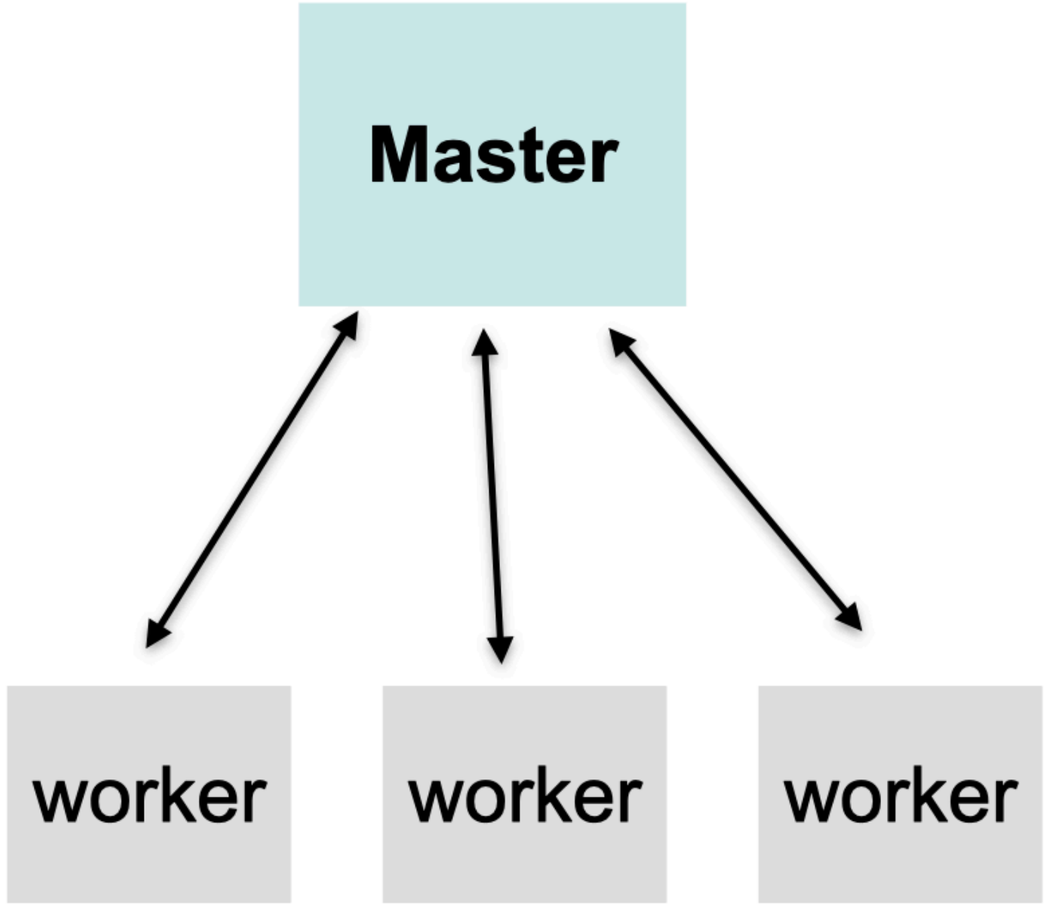
Local

Single Machine

Distributed



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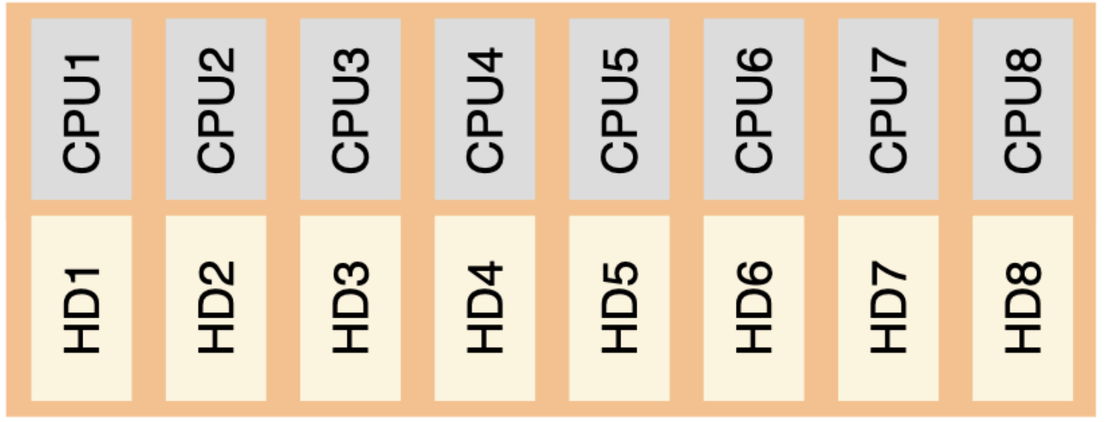
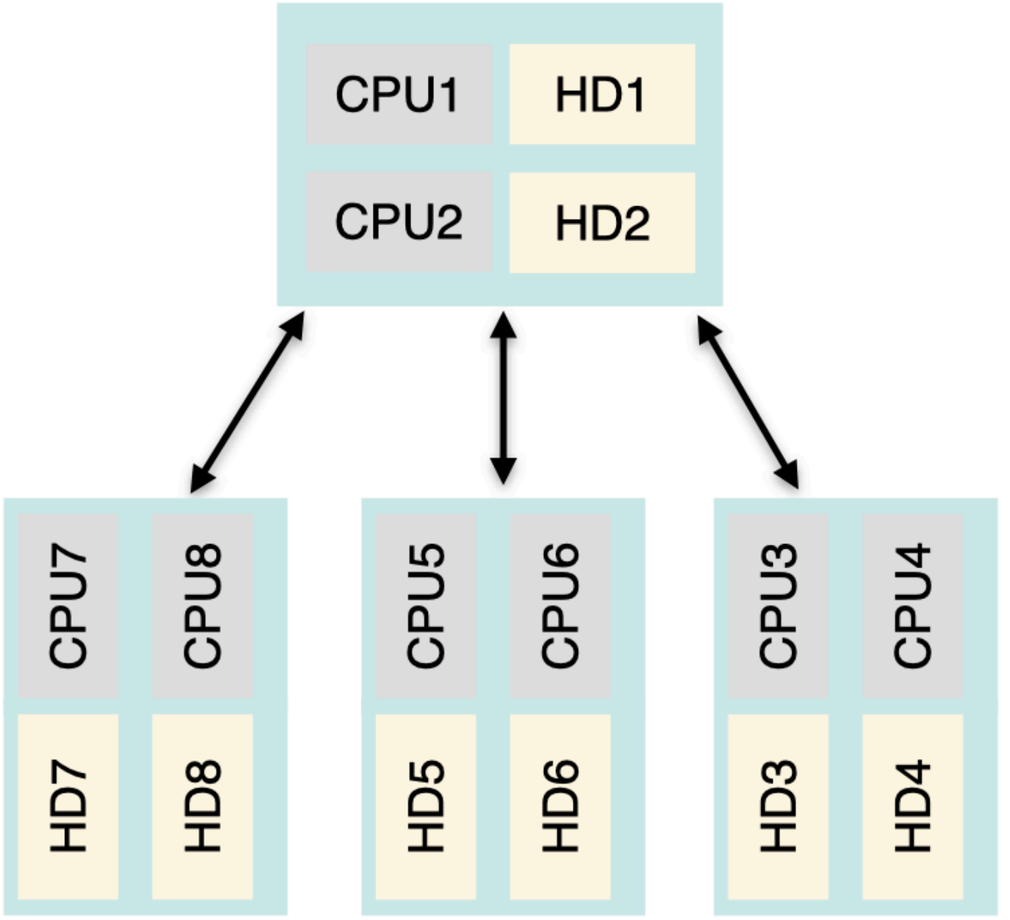
How to Distribute

Local



Distributed



Storage: Hard drives

Computation: CPUs

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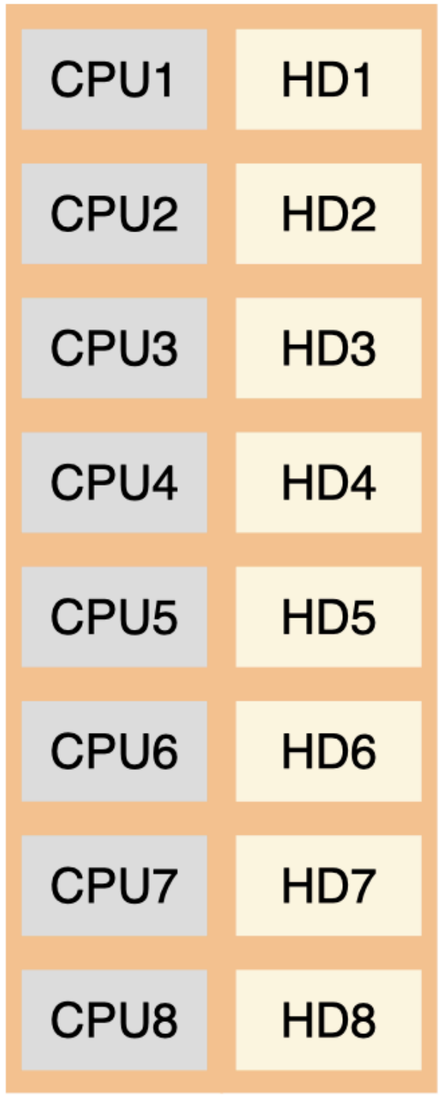
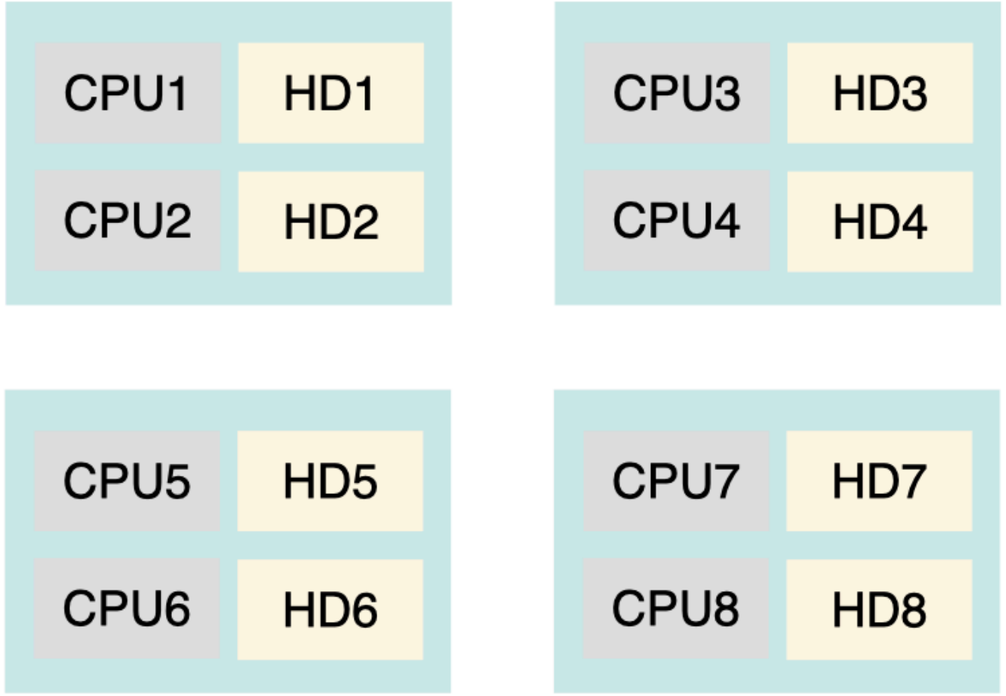
Scale Up versus Out



Up

Out



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Streaming Algorithms

we won't talk about these now....

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Paralellism

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Paralellism

- **Data Parallelism**: Split instances between machines

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Paralellism

- **Data Parallelism**: Split instances between machines
- **Model Paralellism**: Split parameters between machines

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Paralellism

- **Data Parallelism**: Split instances between machines
- **Model Paralellism**: Split parameters between machines
- **Task Paralellism**: Split algorithms between machines

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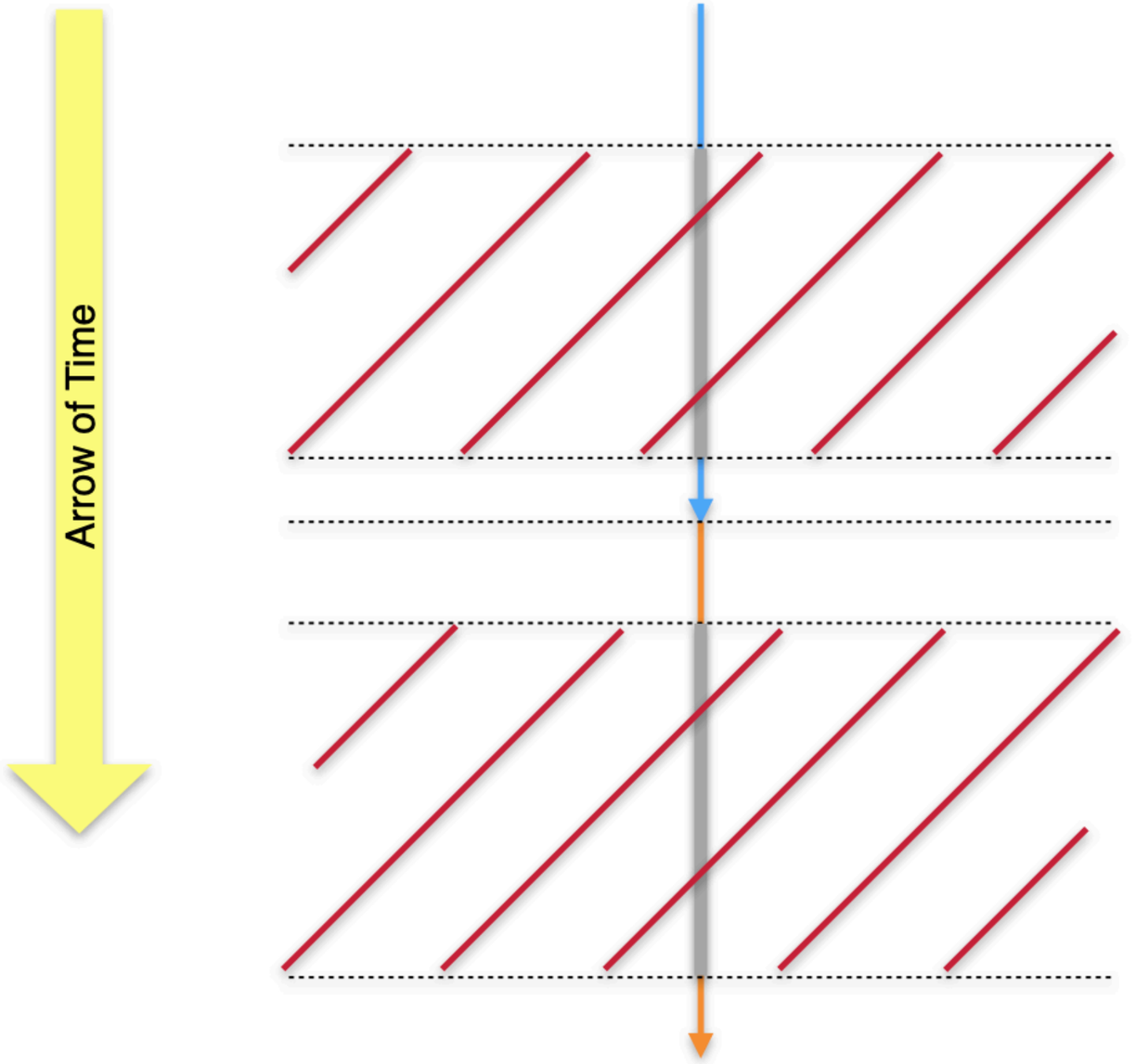
Sequential



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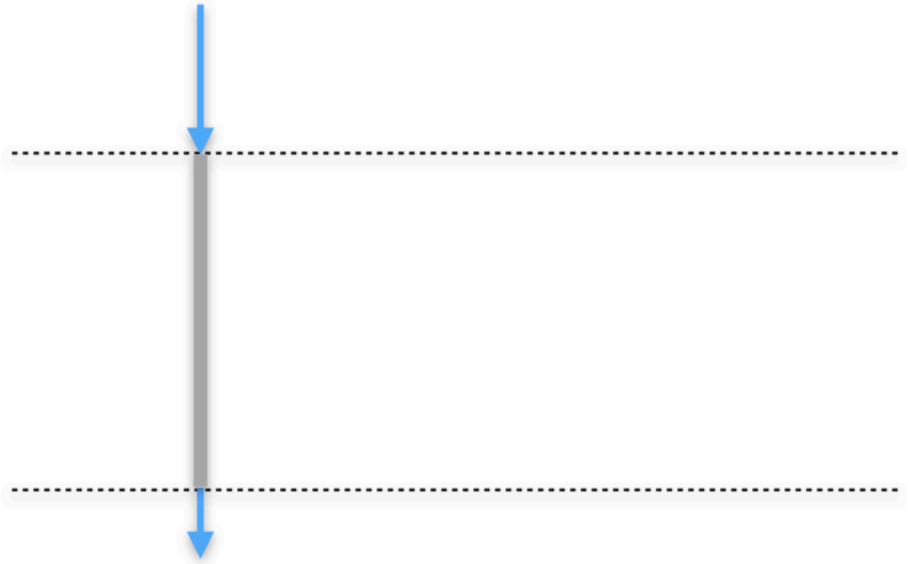
Concurrent



Parallel

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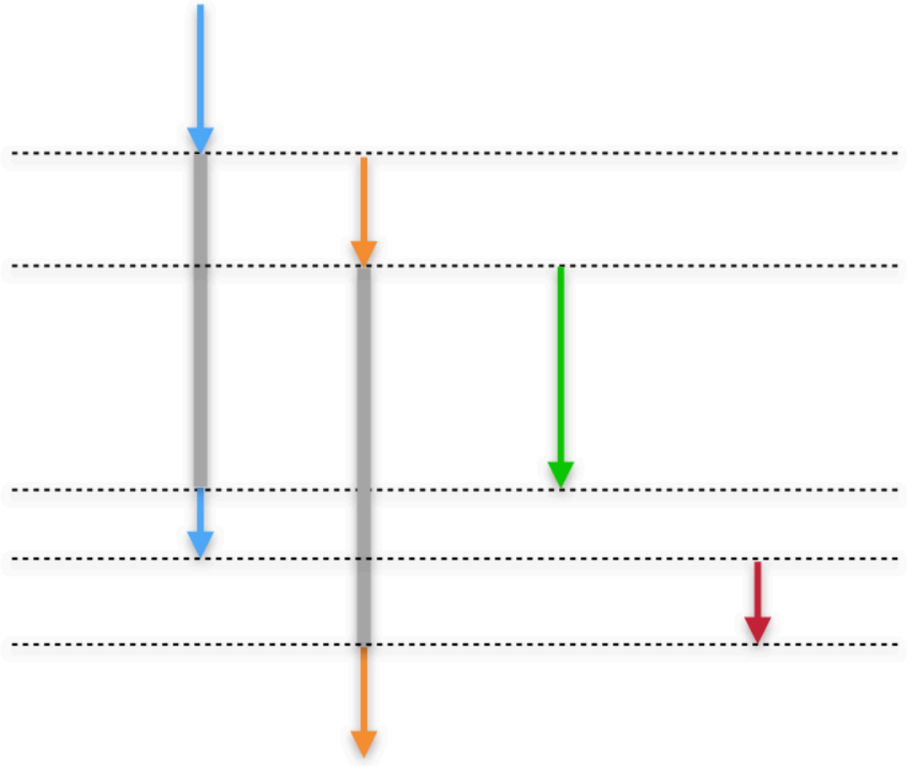
Concurrent



Parallel

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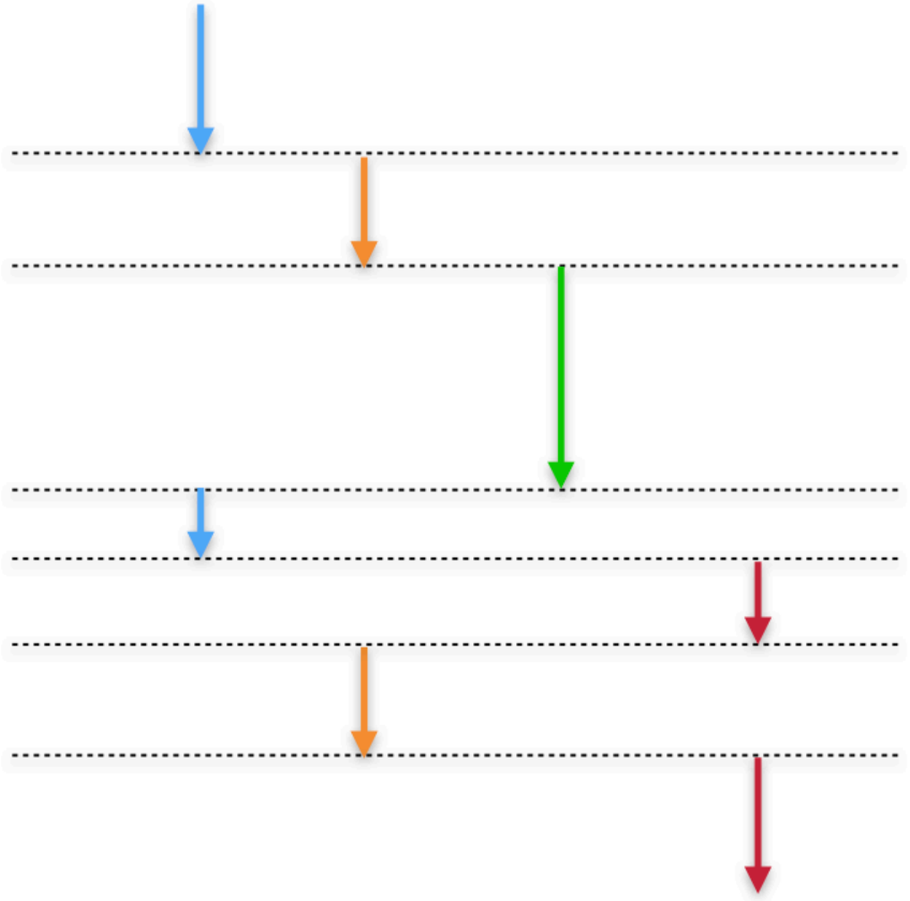
Concurrent



Parallel

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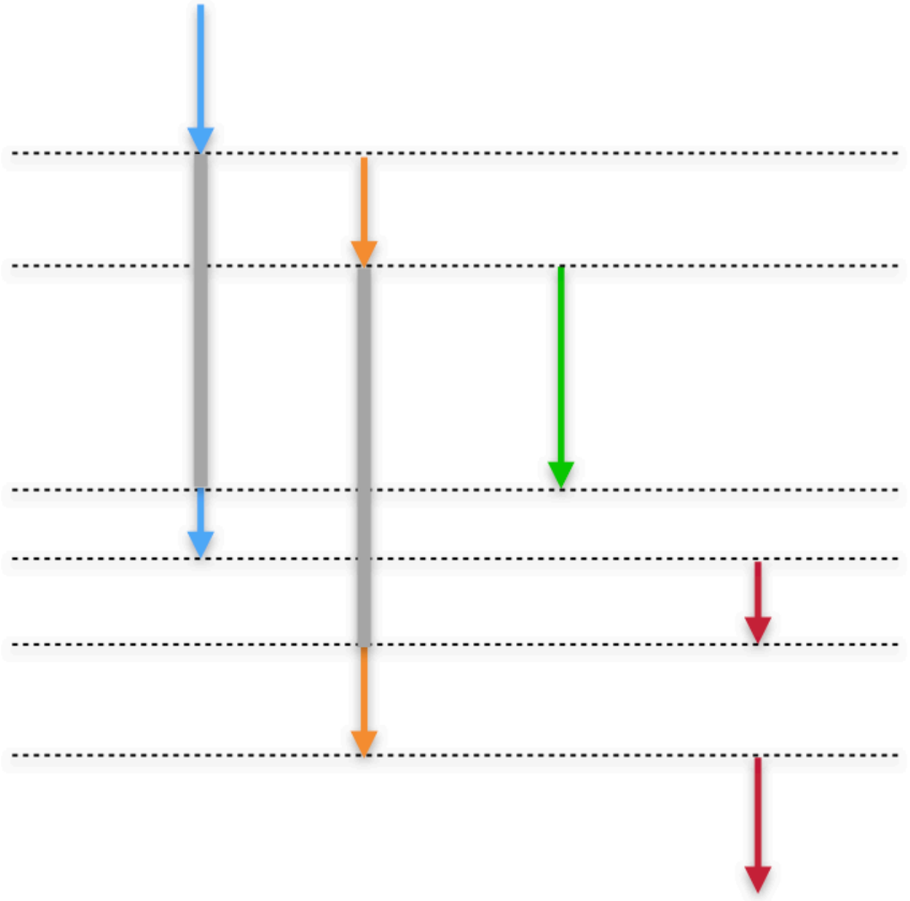
Concurrent



Parallel

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Problem Solved?

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Problem Solved?

- Coordination: what happens when and to whom? And how do you synchronize these events

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Problem Solved?

- *Coordination*: what happens when and to whom? And how do you synchronize these events
- *Communication*: how do the different nodes in your system talk to one another? And how do you talk to your nodes?

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Problem Solved?

- *Coordination*: what happens when and to whom? And how do you synchronize these events
- *Communication*: how do the different nodes in your system talk to one another? And how do you talk to your nodes?
- *Fault Tolerance*: is your system robust to network and machine failures (because they will happen)?

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This is what Ray helps us with 👇

- *Coordination*: what happens when and to whom? And how do you synchronize these events
- *Communication*: how do the different nodes in your system talk to one another? And how do you talk to your nodes?
- *Fault Tolerance*: is your system robust to network and machine failures (because they will happen)?

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CAP Theorem[2]

Consistency: all nodes see the same data at the same time

Availability: every request receives a response about whether it succeeded or failed

Partition tolerance: the system continues to operate despite arbitrary partitioning due to network failures

[2] Choose two: except you can't really sacrifice *P*!

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Break

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Why Ray?

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Why Ray?

- *Distributed computing framework* meant for a new generation of AI applications.

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- *Distributed computing framework* meant for a new generation of AI applications.
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- *Distributed computing framework* meant for a new generation of AI applications.
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- *More generic* programming model than Spark/Flink/Hadoop/etc.

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Why Ray?

- *Distributed computing framework* meant for a new generation of AI applications.
- Emerged from *RL applications*
- *More generic* programming model than Spark/Flink/Hadoop/etc.
- More *fault tolerant* than MPI

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multiprocess meets RPC....

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The Ray programming model

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The Ray programming model

- Tasks (remote functions)

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The Ray programming model

- Tasks (remote functions)
- Actors (remote classes)

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Tasks

```
@ray.remote
def index(url):
    return requests.get(url)

futures = [index.remote(site) for site in internet]
print(ray.get(futures))
```


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Live Code

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Actors

```
@ray.remote
class Child(object):
    def __init__(self):
        self.name = random.choice(baby_names)
        self.age = 1

    def grow(self):
        self.age += 1

    def greet(self):
        return (
            f'My name is {self.name} '
            f'and I am {self.age} years old'
        )
```

```
children = [Child.remote() for i in range(4)]
[c.grow.remote() for c in children]
futures = [c.greet.remote() for c in children]
print(ray.get(futures))
```


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Live Code

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Break

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Distributed Training Architectures

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Distributed Training Architectures

- Parallelized Stochastic Gradient Descent (2010)

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Distributed Training Architectures

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- Hogwild! (2011)

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Distributed Training Architectures

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- AllReduce (2014)

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Distributed Training Architectures

- Parallelized Stochastic Gradient Descent (2010)
- Hogwild! (2011)
- Downpour SGD (DistBelief) (2012)
- AllReduce (2014)
- Parameter Server (2014)

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Will paralellization help me?

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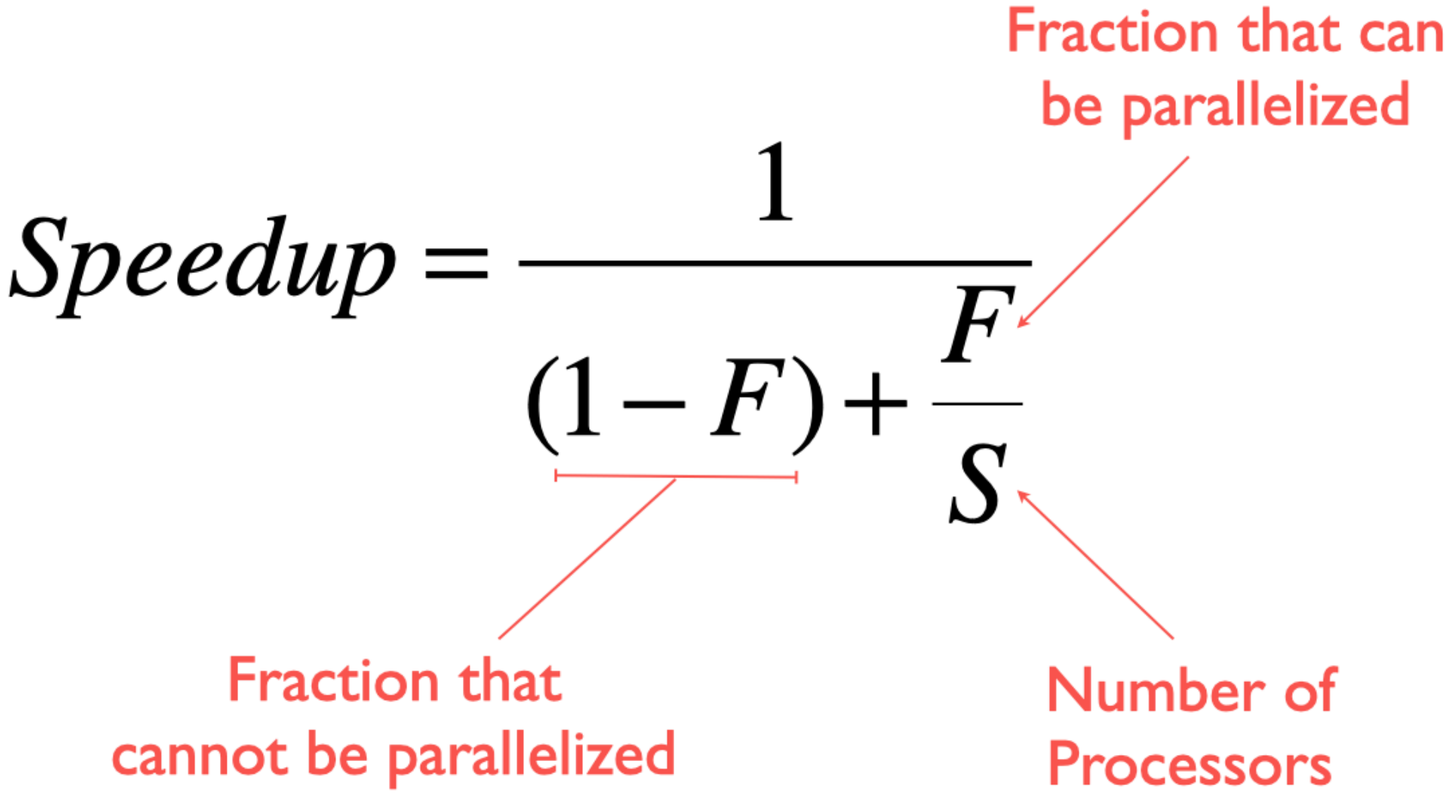
Amdahl's Law



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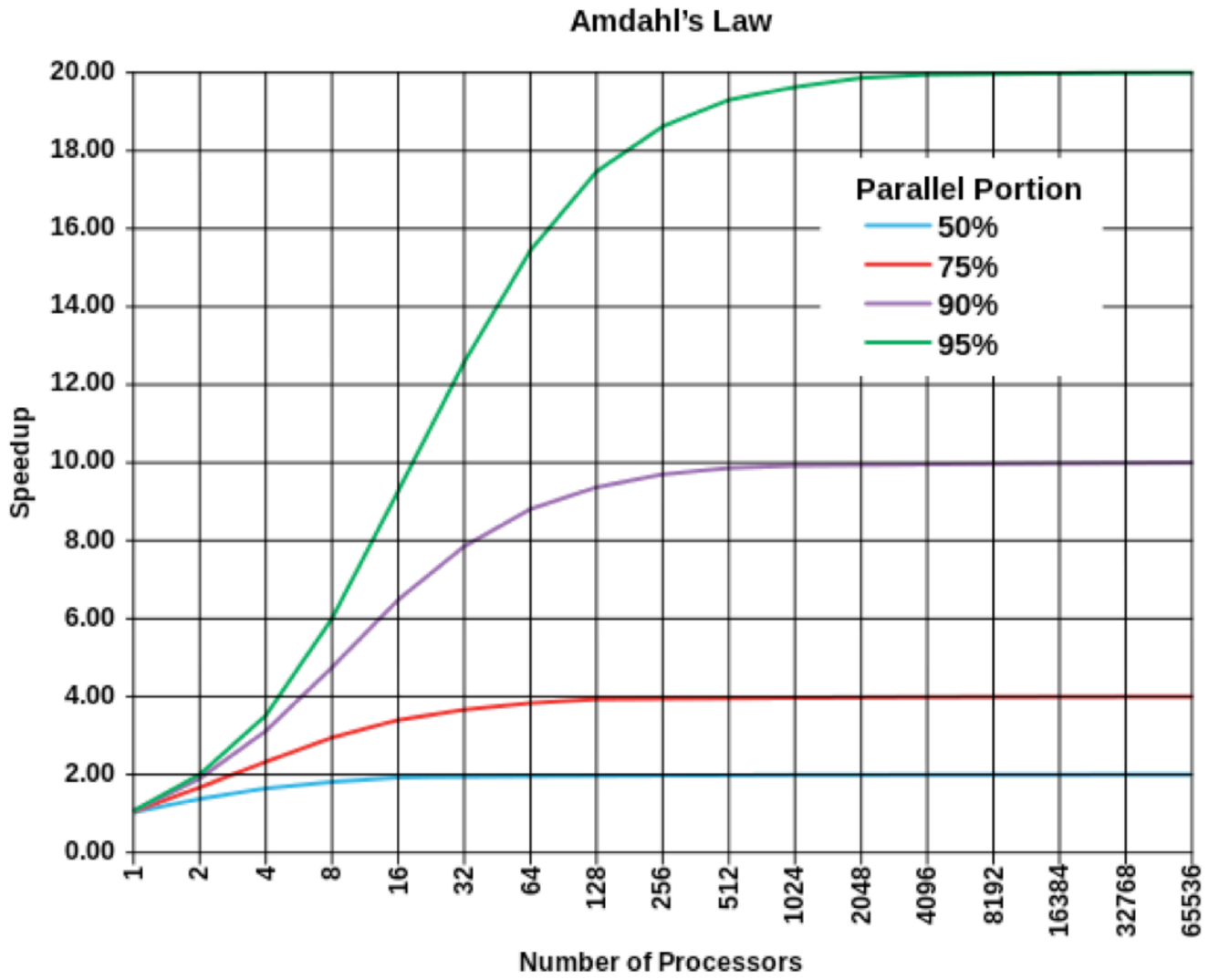
Amdahl's Law



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Amdahl's Law

20x improvement
25% of the time

Fraction that can be parallelized

$$Speedup = \frac{1}{(1 - 0.25) + \frac{0.25}{20}}$$

Fraction that cannot be parallelized

Number of Processors

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Amdahl's Law

20x improvement
25% of the time

Only 1.3x Speedup!

$$Speedup = \frac{1}{0.75 + \frac{0.25}{20}} = 1.31$$

Even with 20 processors

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Moral?

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It doesn't how many machines you throw at a problem... at some point it is just not going to run any faster

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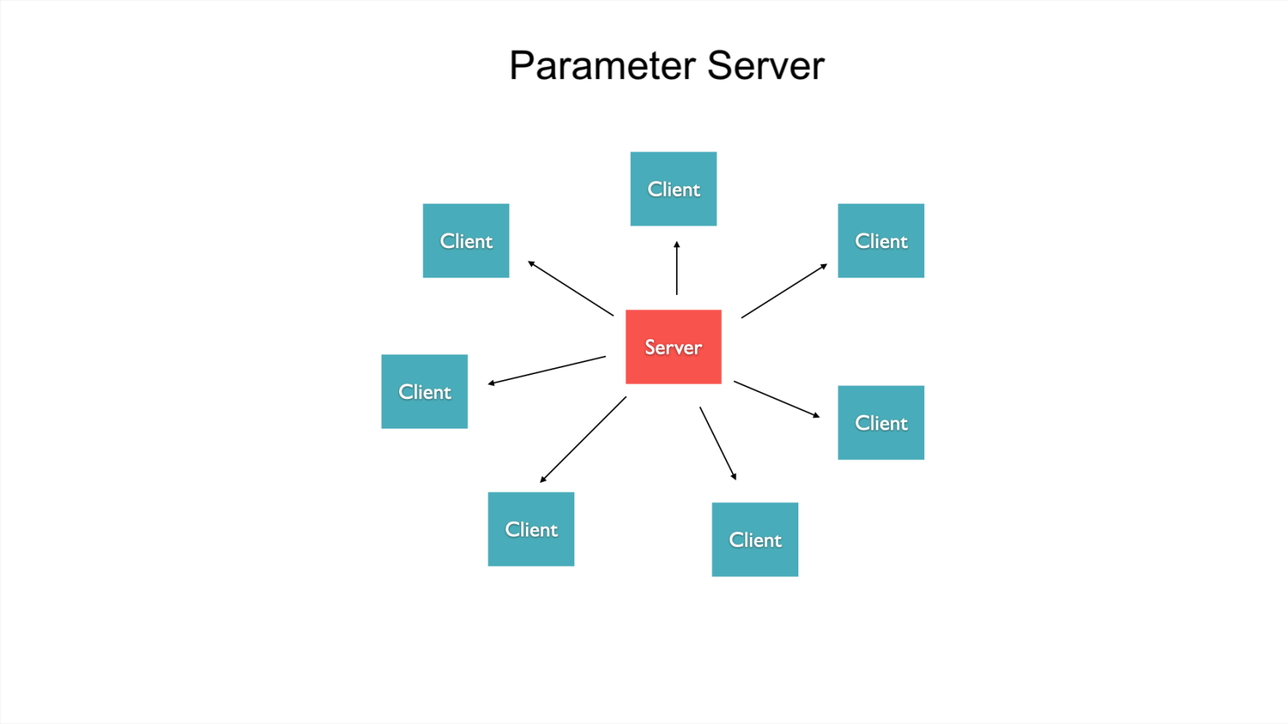
Distributed training with the parameter server



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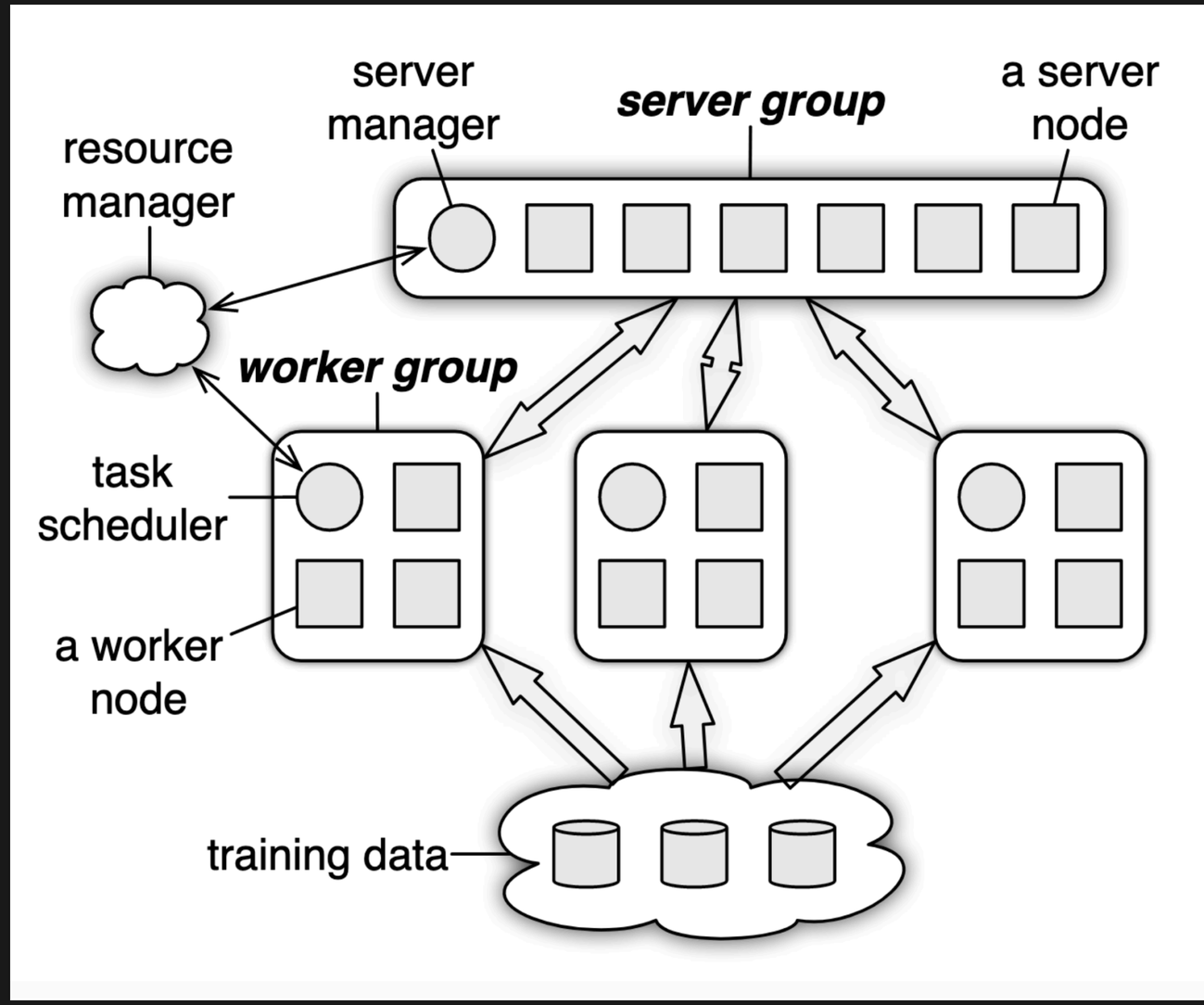
System rather than algorithm[3]



[3] Scaling Distributed Machine Learning with the Parameter Server

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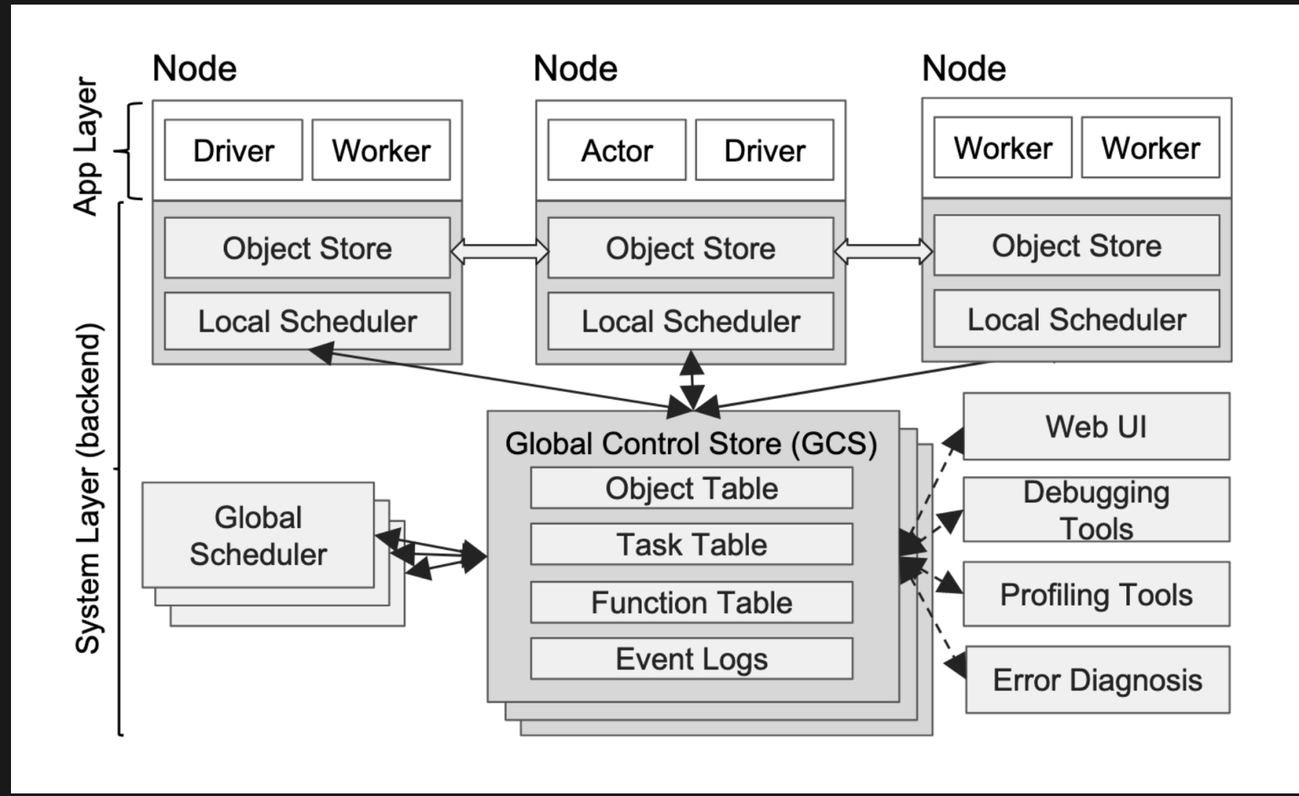
Ray internals[4]



[4] Ray: A Distributed Framework for Emerging AI Applications

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Live Code

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Deploying ML

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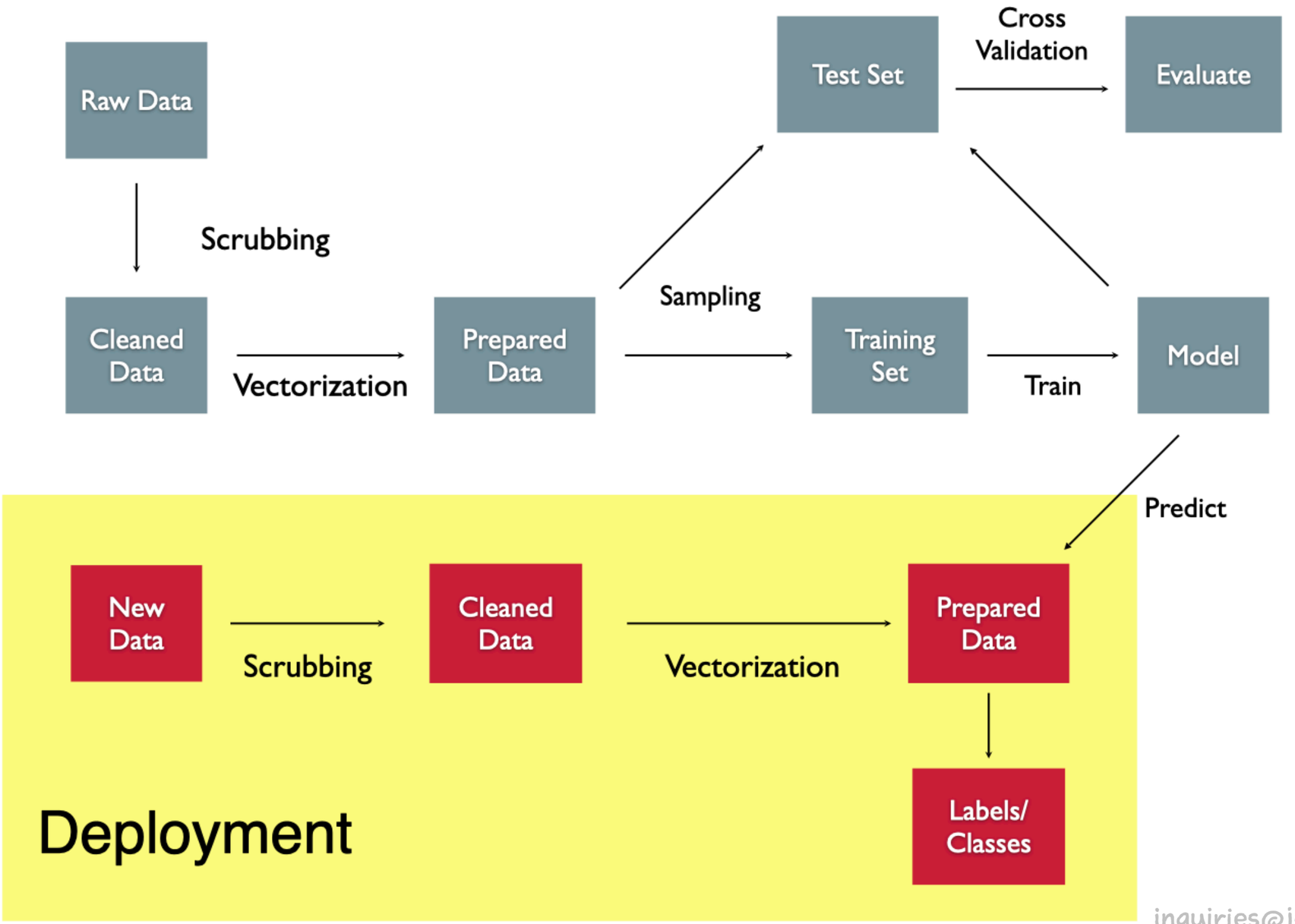

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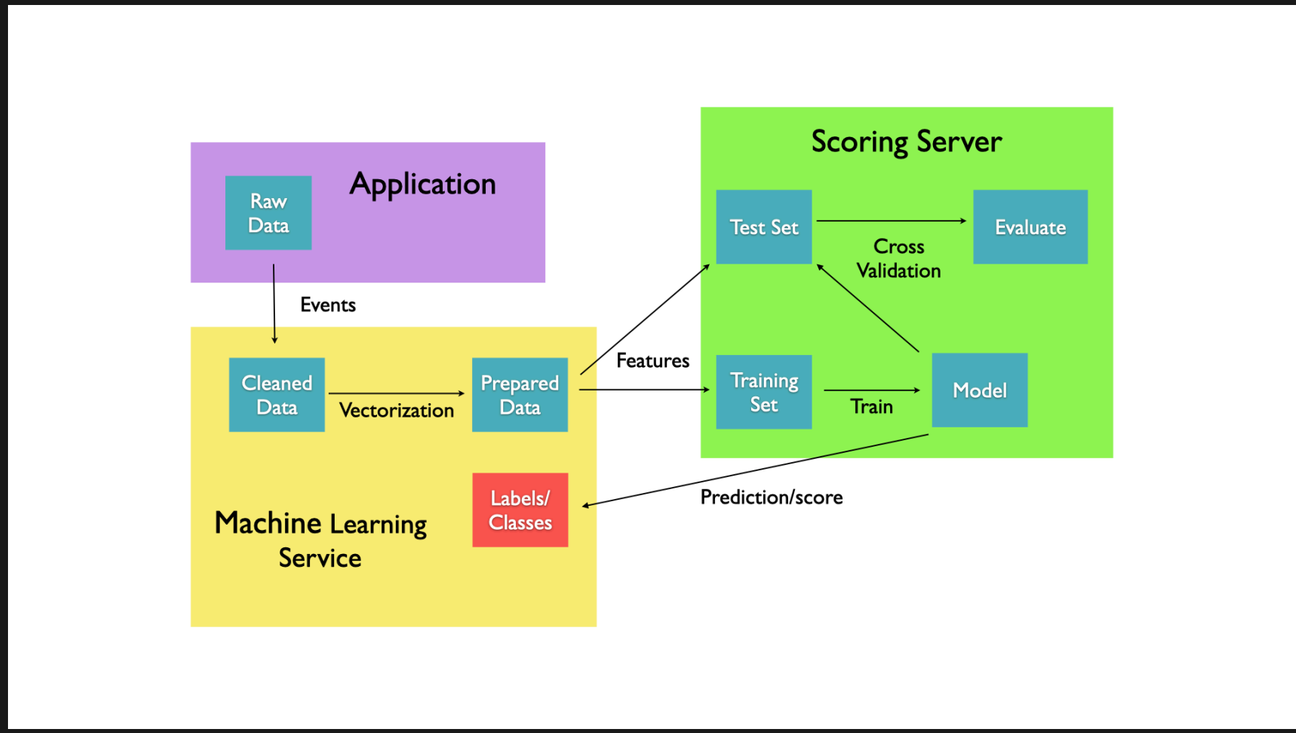
ML infrastructure is varied



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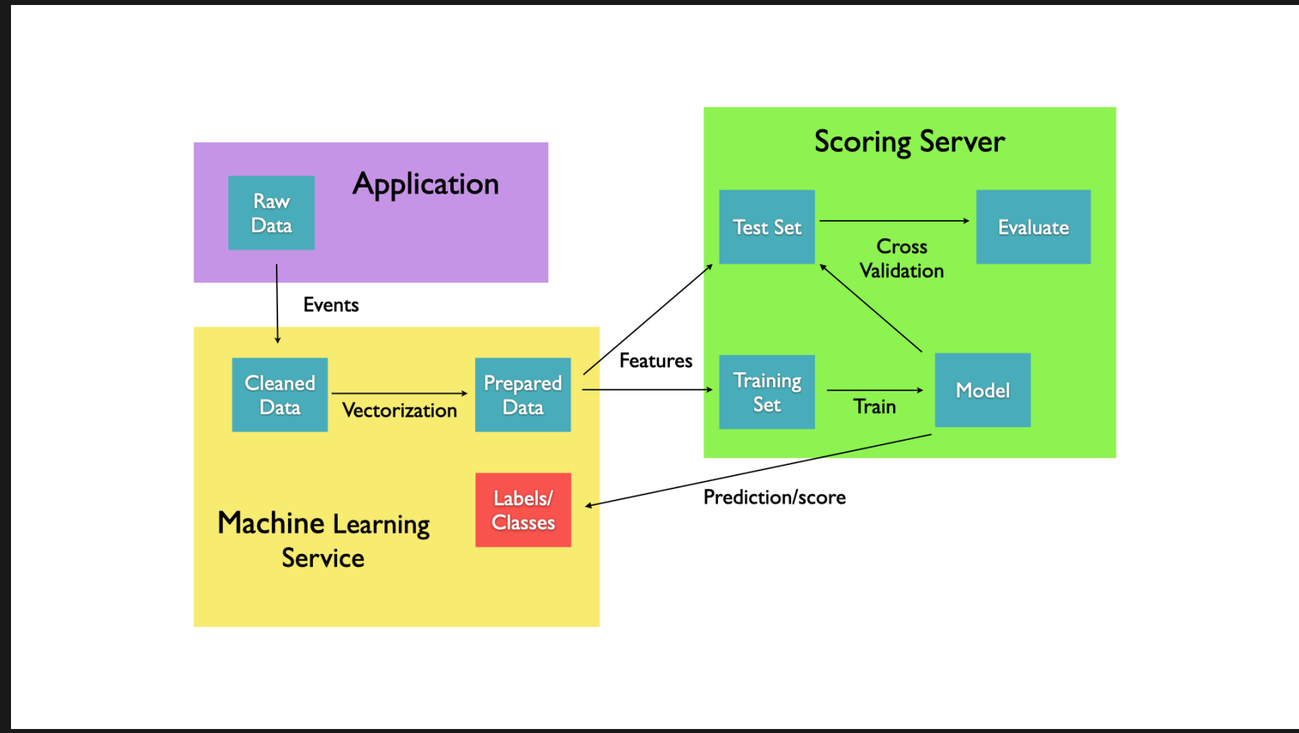
ML infrastructure is varied

- MLaaS (SageMaker, Google AutoML, etc.)



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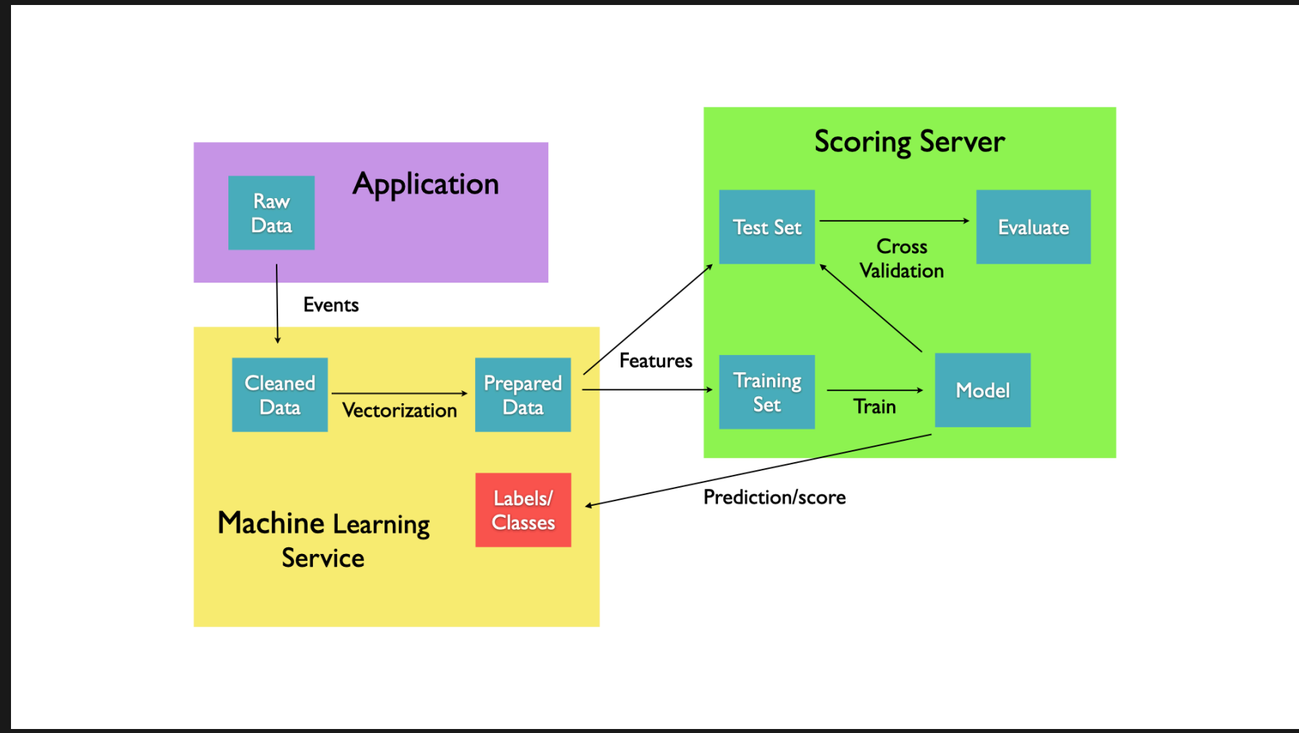
ML infrastructure is varied

- MLaaS (SageMaker, Google AutoML, etc.)
- Containers (Fargate, GKE, etc.)



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ML infrastructure is varied

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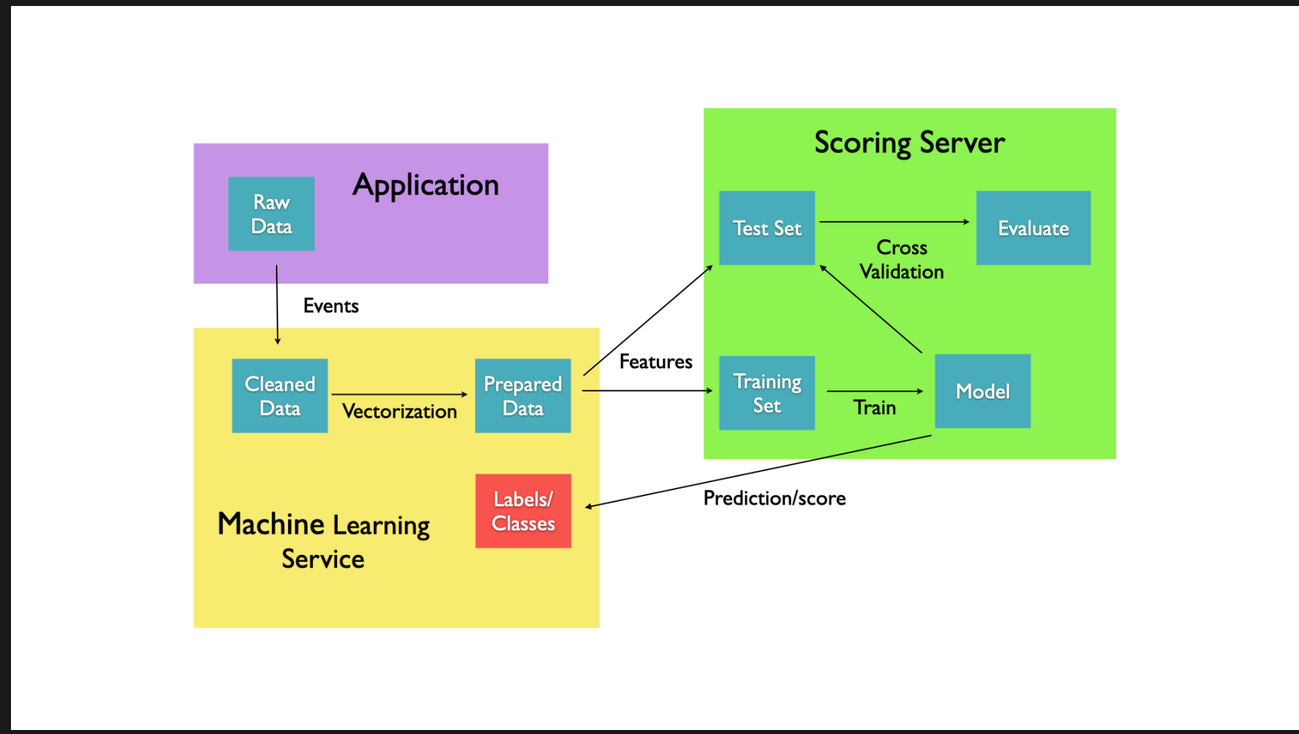
- IaaS (Ec2, GCP, etc.)



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ML infrastructure is varied

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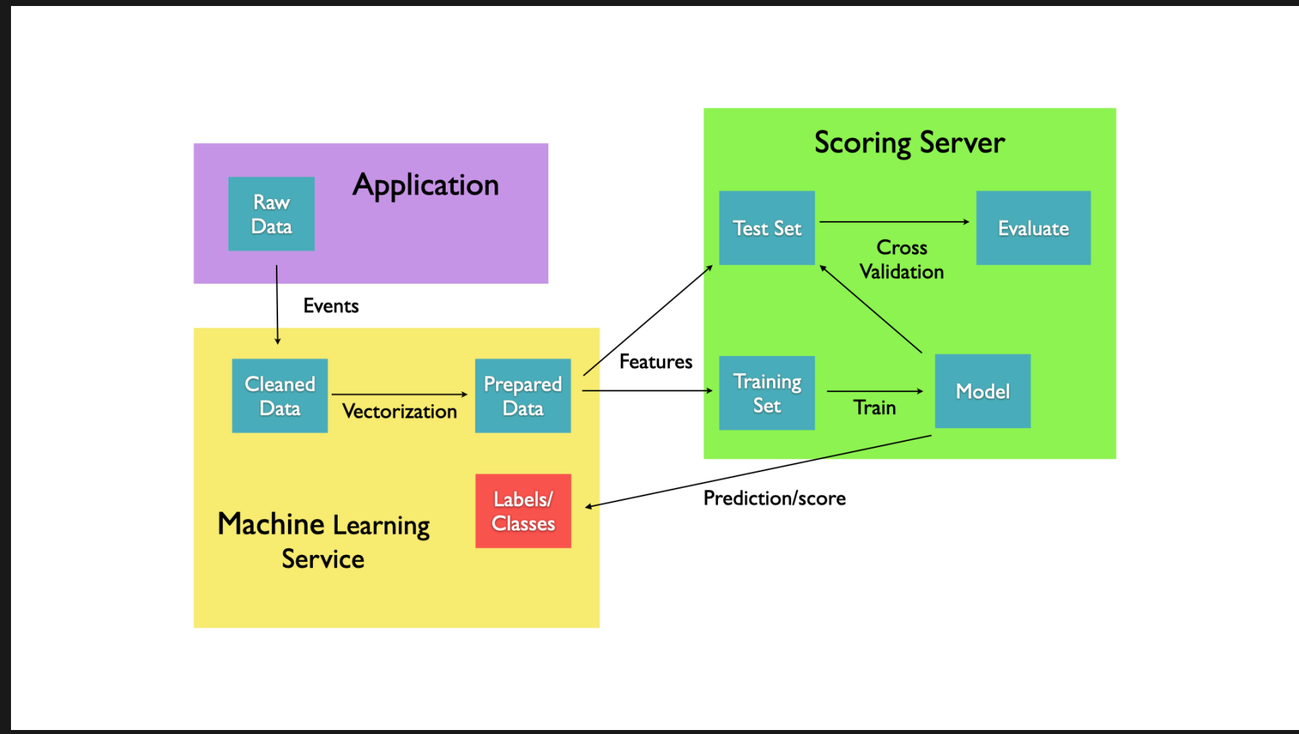
- Containers (Fargate, GKE, etc.)
- IaaS (Ec2, GCP, etc.)
- On premise/data center



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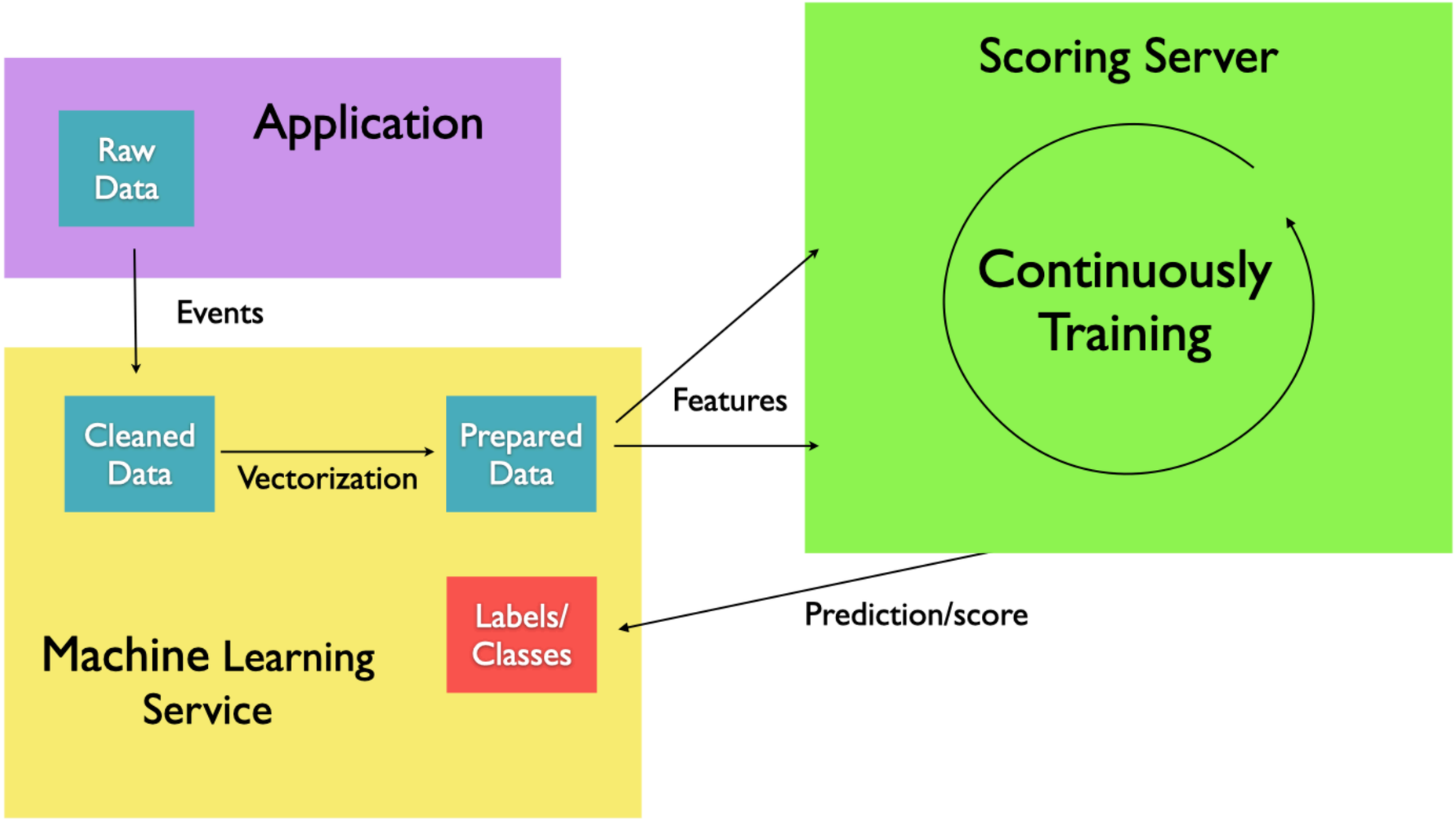

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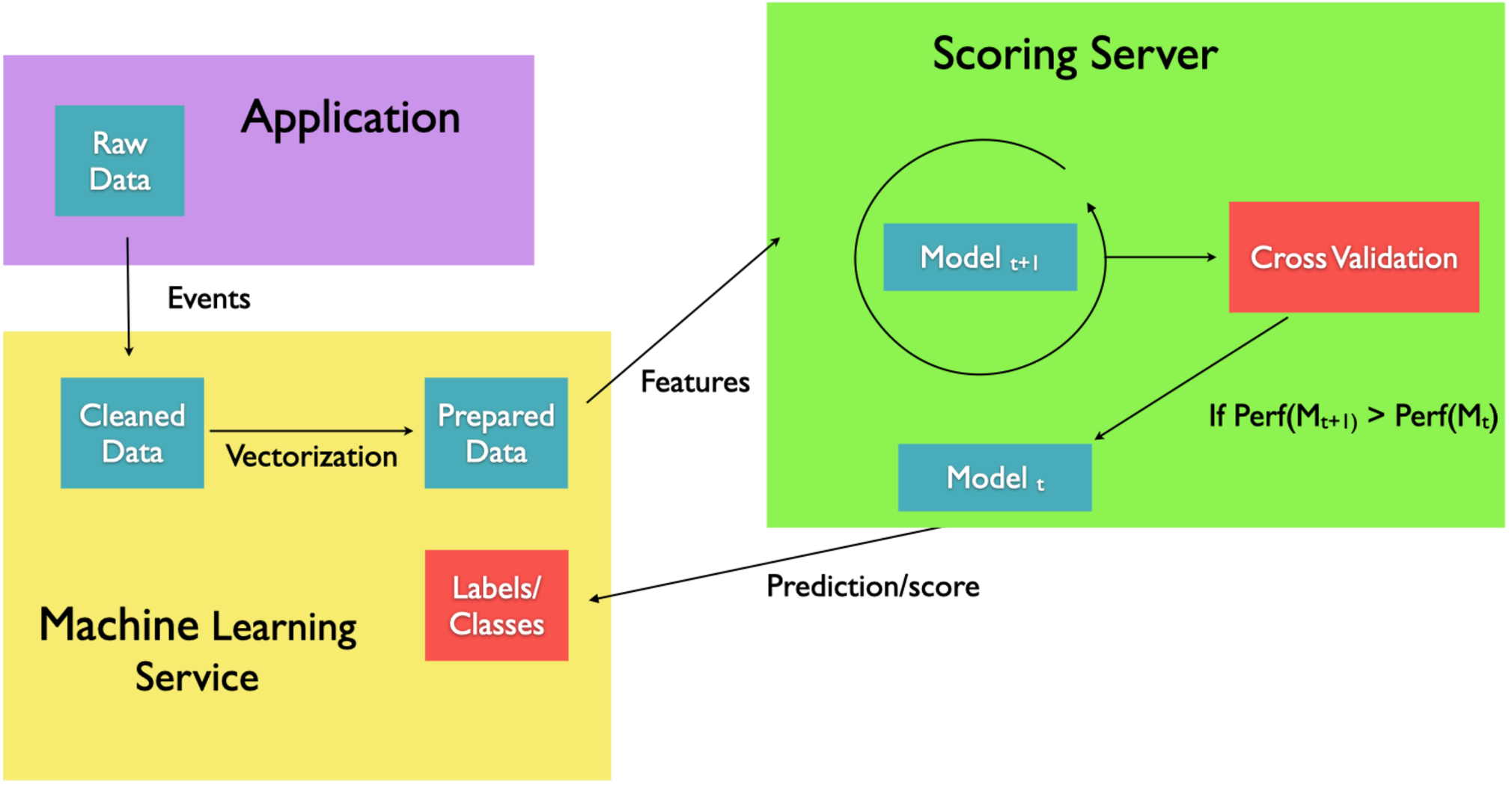

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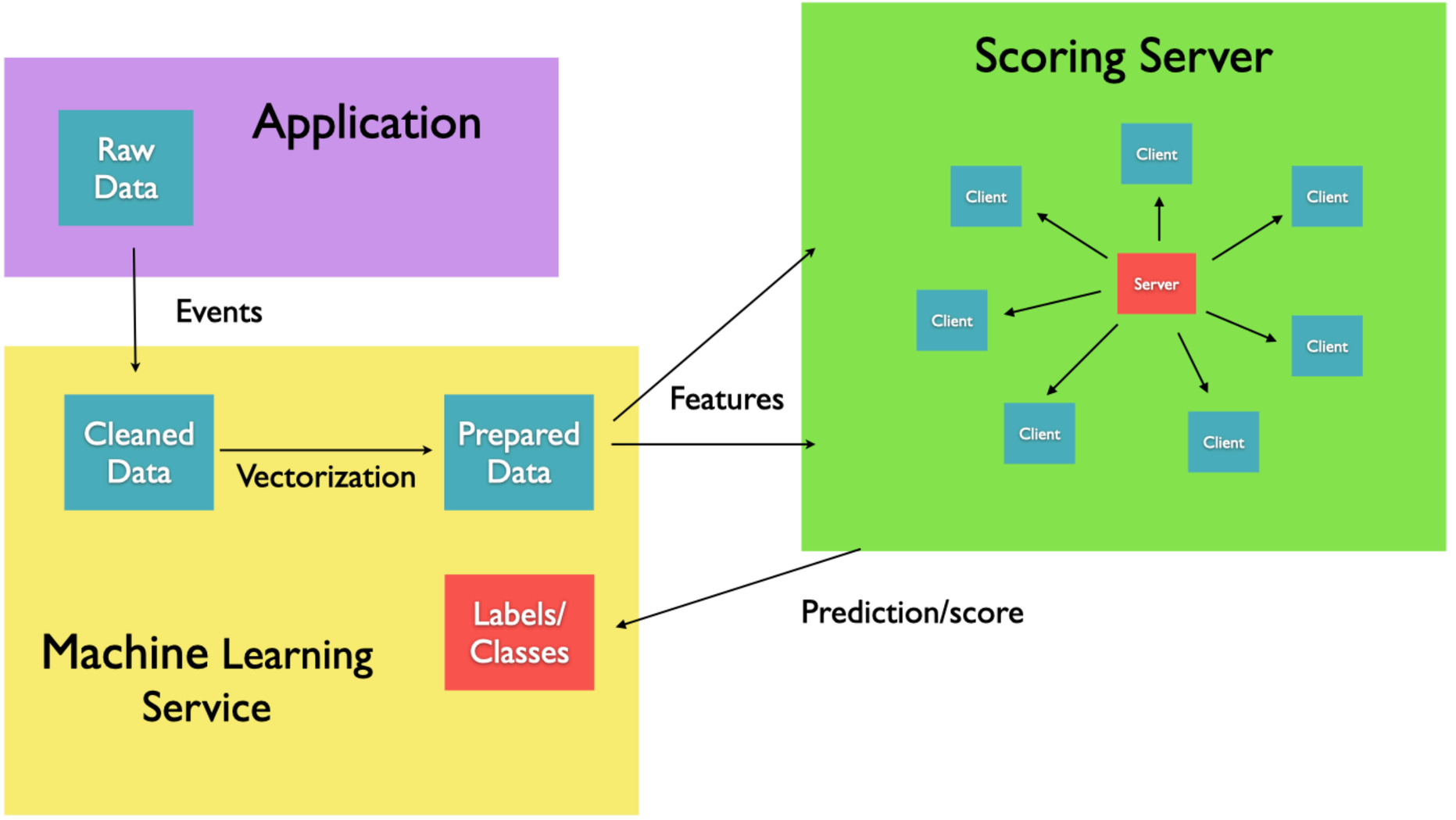

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Next Steps

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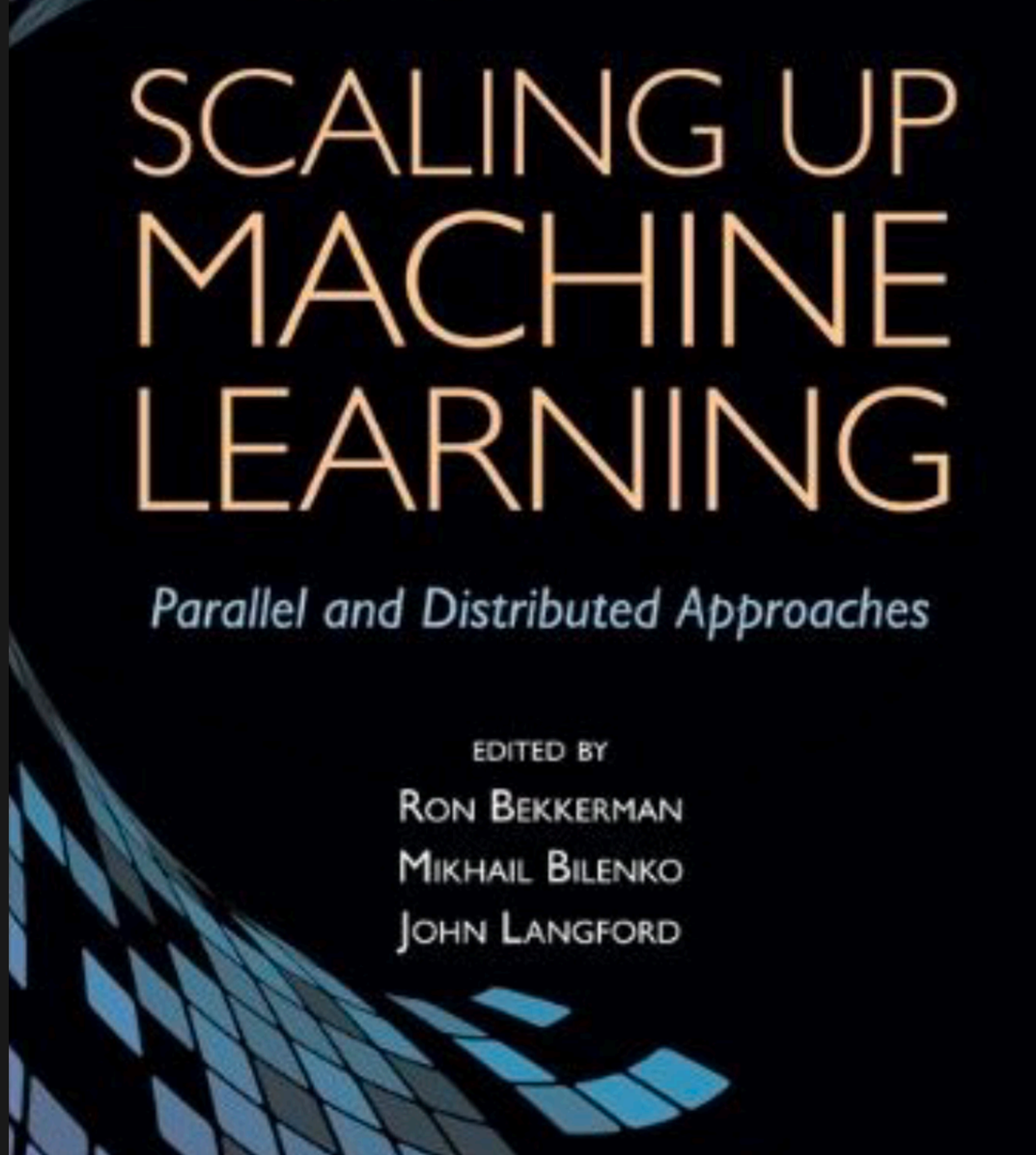
Learning More DistML

Scaling up Machine Learning



Future Live Training

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Future Live Training

- Bayesian Hyperparameter Optimization (Sept. 10)

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Q & A

Materials, mailing list, questions, feedback 👇

https://sr.ht/~hyphaebeast/ray-live-training/

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