

A Guided Tour of Ray Core

Paco Nathan @pacoid



derwen.ai



\$(whoami)

- AI in grad school during mid-1980s
- 7 years R&D in *neural networks* (1980s-90s)
- *network engineering* through the **AI Winter**
- “guinea pig” for AWS (2006-ff)
- led early large **Hadoop instance on EC2**, which became a case study for EMR
- **Apache Spark** community evangelist (2014-15)
- lead committer: **kglab**, **pytextrank**
- current focus: **Graph-Based Data Science**



derwen.ai

part 1:

Ray core

Ray Project

The image is a screenshot of a video player interface. On the left, there is a video frame showing a young man with dark hair, Robert Nishihara, speaking. He is wearing a grey t-shirt. The background of the video frame is orange with the "RAY SUMMIT" logo and the text "Presented by Anyscale". To the right of the video frame, the slide content begins.

RAY SUMMIT
Presented by Anyscale

September 30–October 1

Ecosystem

Native Libraries

- rllib
- tune
- RAY SERVE
- raysgd

Third Party Libraries

- HOROVOD PyTorch Azure Machine Learning Weights & Biases
- spaCy emoji Amazon SageMaker ANALYTICS ZOO Joblib
- HYPERTOPT OPTUNA DASK ModelArts SELDON
- MODIN MARS

Ray becoming the go-to framework for scaling libraries

Subscribe

3:18 / 13:31

CC

Keynote: The Future of Ray - Robert Nishihara, Anyscale

Ray Project

A kind of **pattern language** for distributed systems,
as a library in Python, Java, C++ (upcoming):

- **task-parallel** – stateless, data independence
- **remote objects** – key/value store
- **actor pattern** – messages among classes,
managing state
- **parallel iterators** – lazy, infinite sequences
- **multiprocessing.Pool** – drop-in replacement
- **joblib** – e.g., *scikit-learn* back-end
- Dask, Modin, Mars, etc.



Mix and match as needed, without tight coupling
to framework

Closures and Decorators

Ray makes use of *closures* and *decorators* in Python:

- ["Closures and Decorators in Python"](#)
- [PEP 318](#)
- [asyncio](#)

See also:

- ["Ray Design Patterns"](#) (WIP)
- [patterns.eecs.berkeley.edu](#)

Pattern: task-parallel

Remote Functions:

- a `@ray.remote` decorator on a function
- properties: *data independence, stateless*
- patterns: **Task Parallelism, Task Graph**

reference:

Patterns for Parallel Programming

Timothy G. Mattson, Beverly A. Sanders, Berna L. Massingill
Addison-Wesley (2004)

Pattern: task-parallel

```
# A regular Python function.
def my_function():
    return 1

# By adding the `@ray.remote` decorator, a regular Python function
# becomes a Ray remote function.
@ray.remote
def my_function():
    return 1

# To invoke this remote function, use the `remote` method.
# This will immediately return an object ref (a future) and then create
# a task that will be executed on a worker process.
obj_ref = my_function.remote()

# The result can be retrieved with ``ray.get``.
assert ray.get(obj_ref) == 1

@ray.remote
def slow_function():
    time.sleep(10)
    return 1

# Invocations of Ray remote functions happen in parallel.
# All computation is performed in the background, driven by Ray's internal event loop.
for _ in range(4):
    # This doesn't block.
    slow_function.remote()
```

Pattern: task-parallel

Tutorials:

[colab.research.google.com/github/ray-project/tutorial/
blob/master/exercises/colab01-03.ipynb](https://colab.research.google.com/github/ray-project/tutorial/blob/master/exercises/colab01-03.ipynb)

[github.com/ansyscale/academy/blob/master/ray-crash-
course/01-Ray-Tasks.ipynb](https://github.com/ansyscale/academy/blob/master/ray-crash-course/01-Ray-Tasks.ipynb)

Pattern: distributed object store

Remote Objects:

- shared-memory object store
- roughly, akin to parts of **Redis**
- “lives somewhere on the cluster”

reference:

https://en.wikipedia.org/wiki/Shared_memory

Pattern: distributed object store

```
# Put an object in Ray's object store.
y = 1
object_ref = ray.put(y)

# Get the value of one object ref.
obj_ref = ray.put(1)
assert ray.get(obj_ref) == 1

# Get the values of multiple object refs in parallel.
assert ray.get([ray.put(i) for i in range(3)]) == [0, 1, 2]

# You can also set a timeout to return early from a ``get`` that's blocking for too long.
from ray.exceptions import GetTimeoutError

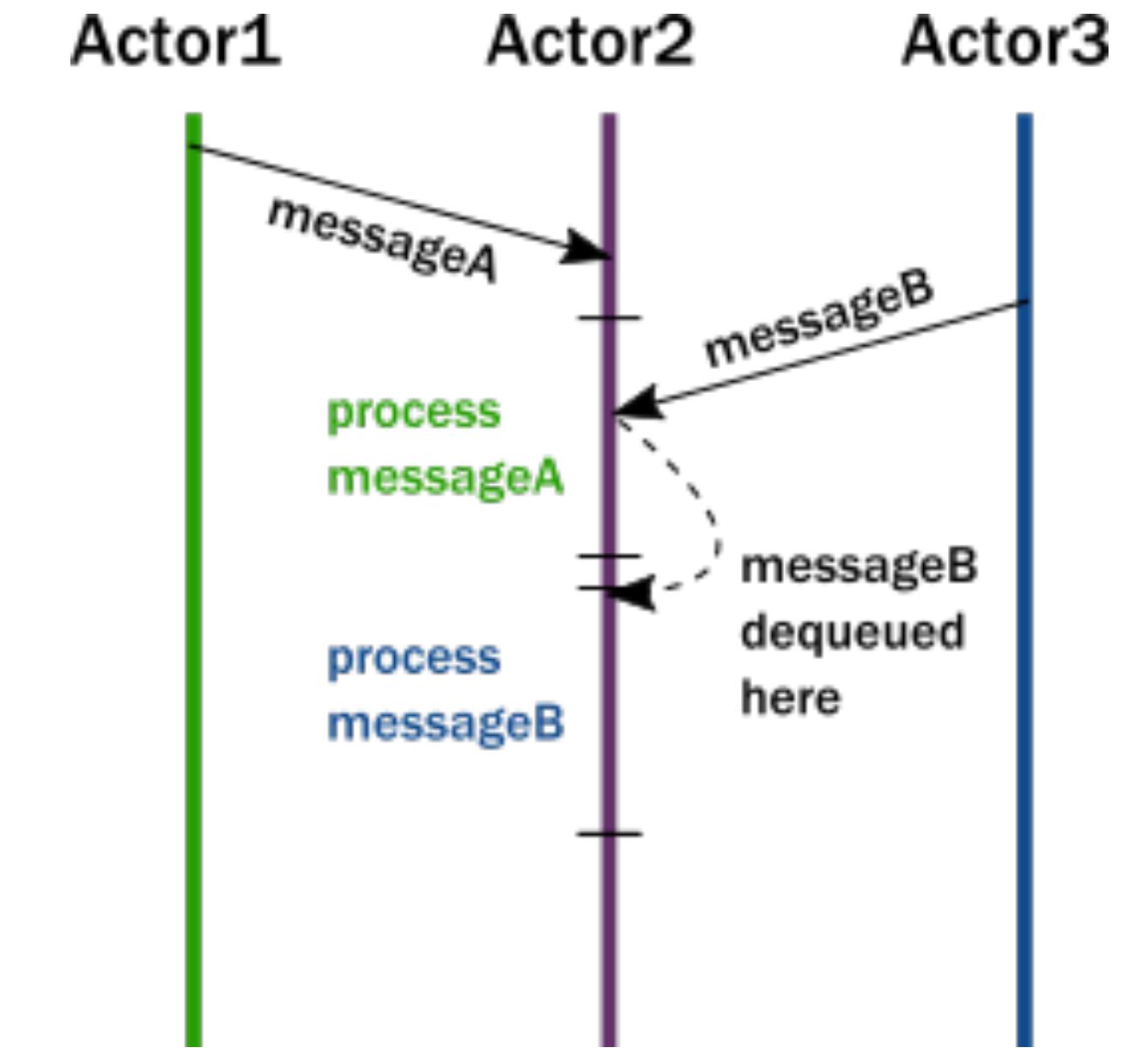
@ray.remote
def long_running_function():
    time.sleep(8)

obj_ref = long_running_function.remote()
try:
    ray.get(obj_ref, timeout=4)
except GetTimeoutError:
    print(``get` timed out.`")
```

Pattern: actors

Remote Classes:

- a `@ray.remote` decorator on a class
- properties: *stateful, message-passing semantics*
- pattern: **Actors**
- “lives somewhere on the cluster”



reference:

“A Universal Modular Actor Formalism for Artificial Intelligence”

Carl Hewitt, Peter Bishop, Richard Steiger

IJCAI (1973)

open: <https://www.ijcai.org/Proceedings/73/Papers/027B.pdf>

Pattern: actors

```
@ray.remote
class Counter(object):
    def __init__(self):
        self.value = 0

    def increment(self):
        self.value += 1
        return self.value

# Create an actor from this class.
counter = Counter.remote()

# Call the actor.
obj_ref = counter.increment.remote()
assert ray.get(obj_ref) == 1
```

Pattern: actors

Tutorials:

[colab.research.google.com/github/ray-project/tutorial/
blob/master/exercises/colab04-05.ipynb](https://colab.research.google.com/github/ray-project/tutorial/blob/master/exercises/colab04-05.ipynb)

[github.com/ansyscale/academy/blob/master/ray-crash-
course/02-Ray-Actors.ipynb](https://github.com/ansyscale/academy/blob/master/ray-crash-course/02-Ray-Actors.ipynb)

Pattern: sharded, lazy iterators

Parallel Iterators:

- API for simple data ingest and processing
- fully serializable
- can operate over infinite sequences of items
- transformations based on method chaining
- passed to remote tasks and actors to represent data shards

Tutorial:

github.com/anyscale/academy/blob/master/ray-crash-course/05-Ray-Parallel-Iterators.ipynb

Pattern: sharded, lazy iterators

```
import ray
import numpy as np

ray.init()

@ray.remote
def train(data_shard):
    for batch in data_shard:
        print("train on", batch) # perform model update with batch

it = (
    ray.util.iter.from_range(1000000, num_shards=4, repeat=True)
    .batch(1024)
    .for_each(np.array)
)

work = [train.remote(shard) for shard in it.shards()]
ray.get(work)
```

Pattern: distributed multiprocessing pool

Distributed multiprocessing.Pool:

- make Python programs distributed, using actors
- easy to scale existing applications that use `multiprocessing.Pool`

```
from ray.util.multiprocessing import Pool

def f(index):
    return index

pool = Pool()
for result in pool.map(f, range(100)):
    print(result)
```

Tutorial:

github.com/anscale/academy/blob/master/ray-crash-course/04-Ray-Multiprocessing.ipynb

Pattern: joblib

Distributed scikit-learn:

- drop-in replacement to parallelize
JobLib (scikit-learn backend)

Tutorial:

github.com/ansyscale/academy/blob/master/ray-crash-course/04-Ray-Multiprocessing.ipynb



Pattern: joblib

```
import numpy as np
from sklearn.datasets import load_digits
from sklearn.model_selection import RandomizedSearchCV
from sklearn.svm import SVC

digits = load_digits()
param_space = {
    'C': np.logspace(-6, 6, 30),
    'gamma': np.logspace(-8, 8, 30),
    'tol': np.logspace(-4, -1, 30),
    'class_weight': [None, 'balanced'],
}

model = SVC(kernel='rbf')
search = RandomizedSearchCV(model, param_space, cv=5, n_iter=300, verbose=10)

import joblib
from ray.util.joblib import register_ray

register_ray()
with joblib.parallel_backend('ray'):
    search.fit(digits.data, digits.target)
```

part 2: “A Berkeley View”

Formal definition of Cloud Computing

Professors **Ion Stoica** and **David Patterson** led EECS grad students to define cloud computing **formally** in 2009

“More than 17,000 citations to this paper...”

2019 follow-up:

“We now predict ... that *Serverless Computing* will grow to dominate the future of cloud computing in the next decade”

The screenshot shows the Ariselab website header with the logo and navigation links: HOME, PEOPLE, PROJECTS, PUBLICATIONS, SPONSORS, DARE, ACADEMICS, NEWS, EVENTS, RISE CAMP, BLOGS, JENKINS. The main content area features the title "Cloud Programming Simplified: A Berkeley View on Serverless Computing" by David Patterson and Ion Stoica, published on FEBRUARY 10, 2019. Below the title is a short bio and a link to the full paper.

Cloud Programming Simplified: A Berkeley View on Serverless Computing

David Patterson and Ion Stoica

The publication of “Above the Clouds: A Berkeley View of Cloud Computing” on February 10, 2009 cleared up the considerable confusion about the new notion of “Cloud Computing.” The paper defined what Cloud Computing was, where it came from, why some were excited by it, what were its technical advantages, and what were the obstacles and research opportunities for it to become even more popular. More than 17,000 citations to this paper and an abridged version in CACM—with more than 1000 in the past year—document that it continues to shape the discussions and the evolution of Cloud Computing.

Evolution of cloud patterns

Initially, cloud services were simplified to make them more recognizable for IT staff accustomed to VMware

- Patterson, et al., developed industry research methodology and eventually also a **pattern language** to describe distributed systems
- **AMPLab** foresaw how cloud use cases would progress in industry over the next decade, which greatly informed **Apache Spark**, etc.

Above the Clouds: A Berkeley View of Cloud Computing



*Michael Armbrust
Armando Fox
Rean Griffith
Anthony D. Joseph
Randy H. Katz
Andrew Konwinski
Gunho Lee
David A. Patterson
Ariel Rabkin
Ion Stoica
Matei Zaharia*

Electrical Engineering and Computer Sciences
University of California at Berkeley

Technical Report No. UCB/EECS-2009-28
<http://www.eecs.berkeley.edu/Pubs/TechRpts/2009/EECS-2009-28.html>

February 10, 2009

Evolution of cloud patterns

Eric Jonas noted >50% of **RISElab** grad students had never used Spark, plus how cloud was evolving in its second decade:

- “Decoupling of computation and storage; they scale separately and are priced independently”
- “The abstraction of executing a piece of code instead of allocating resources on which to execute that code”
- “Paying for the code execution instead of paying for resources you have allocated toward executing the code”

Cloud Programming Simplified: A Berkeley View on
Serverless Computing



*Eric Jonas
Johann Schleier-Smith
Vikram Sreekanti
Chia-Che Tsai
Anurag Khandelwal
Qifan Pu
Vaishaal Shankar
Joao Menezes Carreira
Karl Krauth
Neeraja Yadwadkar
Joseph Gonzalez
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Technical Report No. UCB/EECS-2019-3
<http://www2.eecs.berkeley.edu/Pubs/TechRpts/2019/EECS-2019-3.html>

February 10, 2019

Evolution of cloud patterns

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Cloud Programming Simplified: A Berkeley View on
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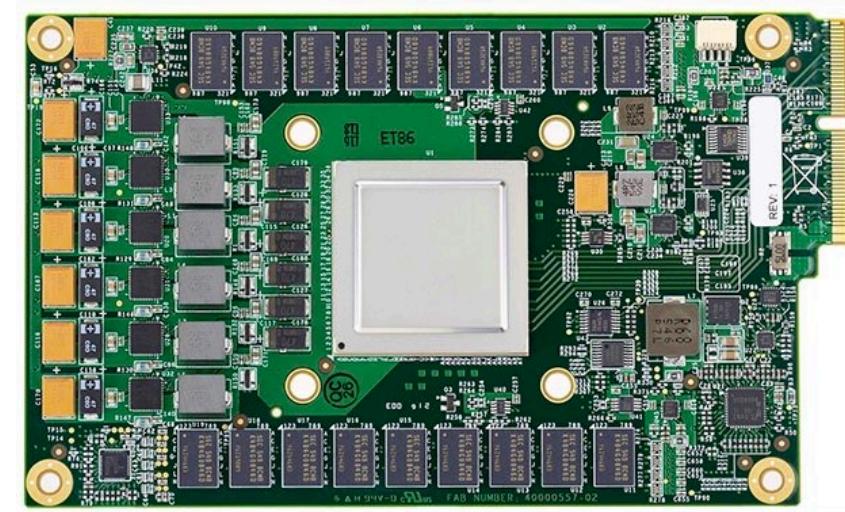
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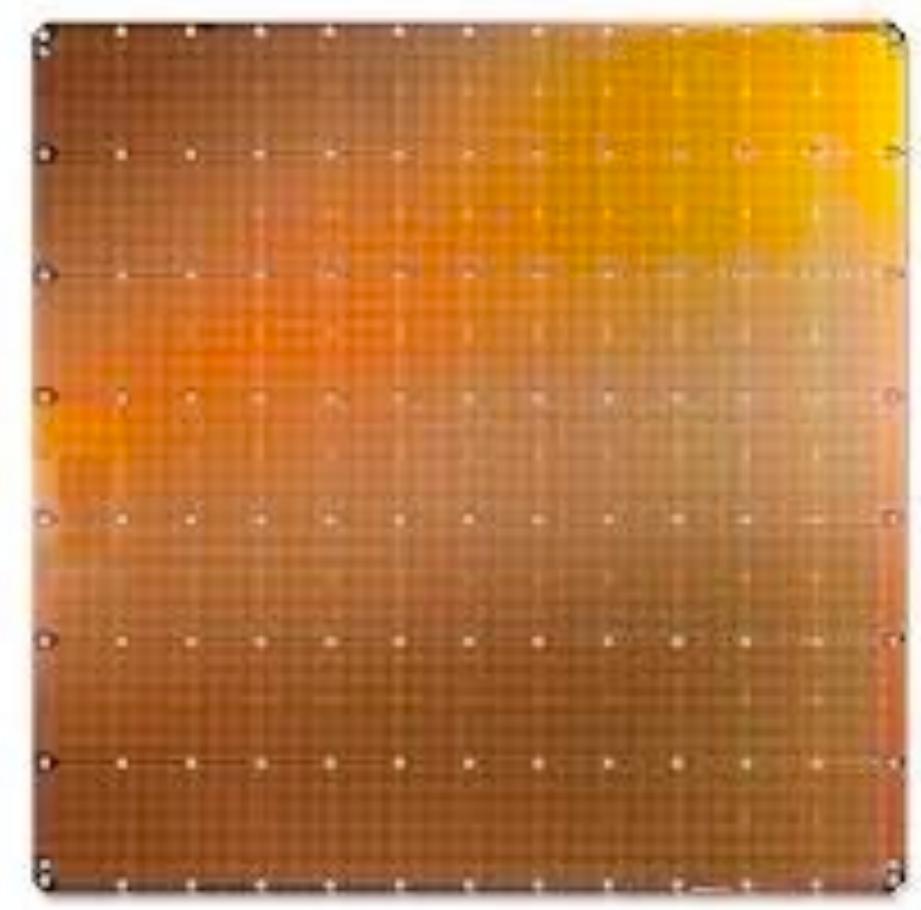
February 10, 2019

Hardware > Software > Process

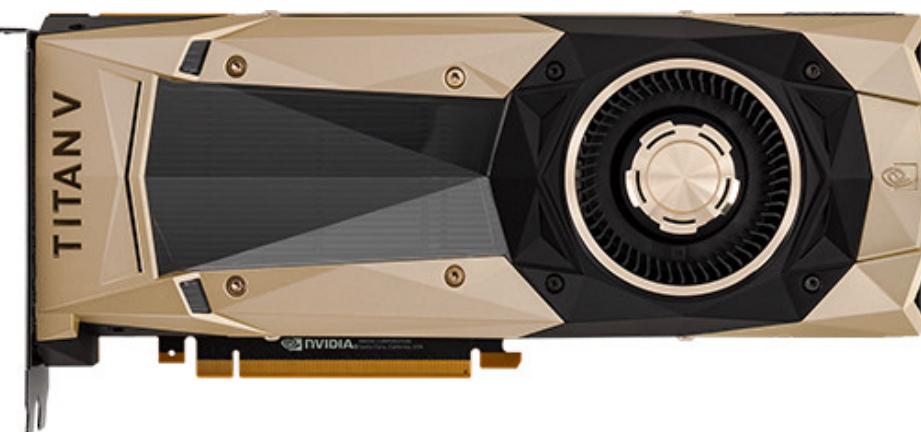
Circa 2005: commodity hardware served Big Data needs: **log file analysis** using **task-parallel**



Circa 2009: data science workloads introduced stateful **actor pattern** through Spark, Akka, etc.



Circa 2013: deep learning placed more demands on s/w + h/w, **differentiating gradients within the context of networked data**



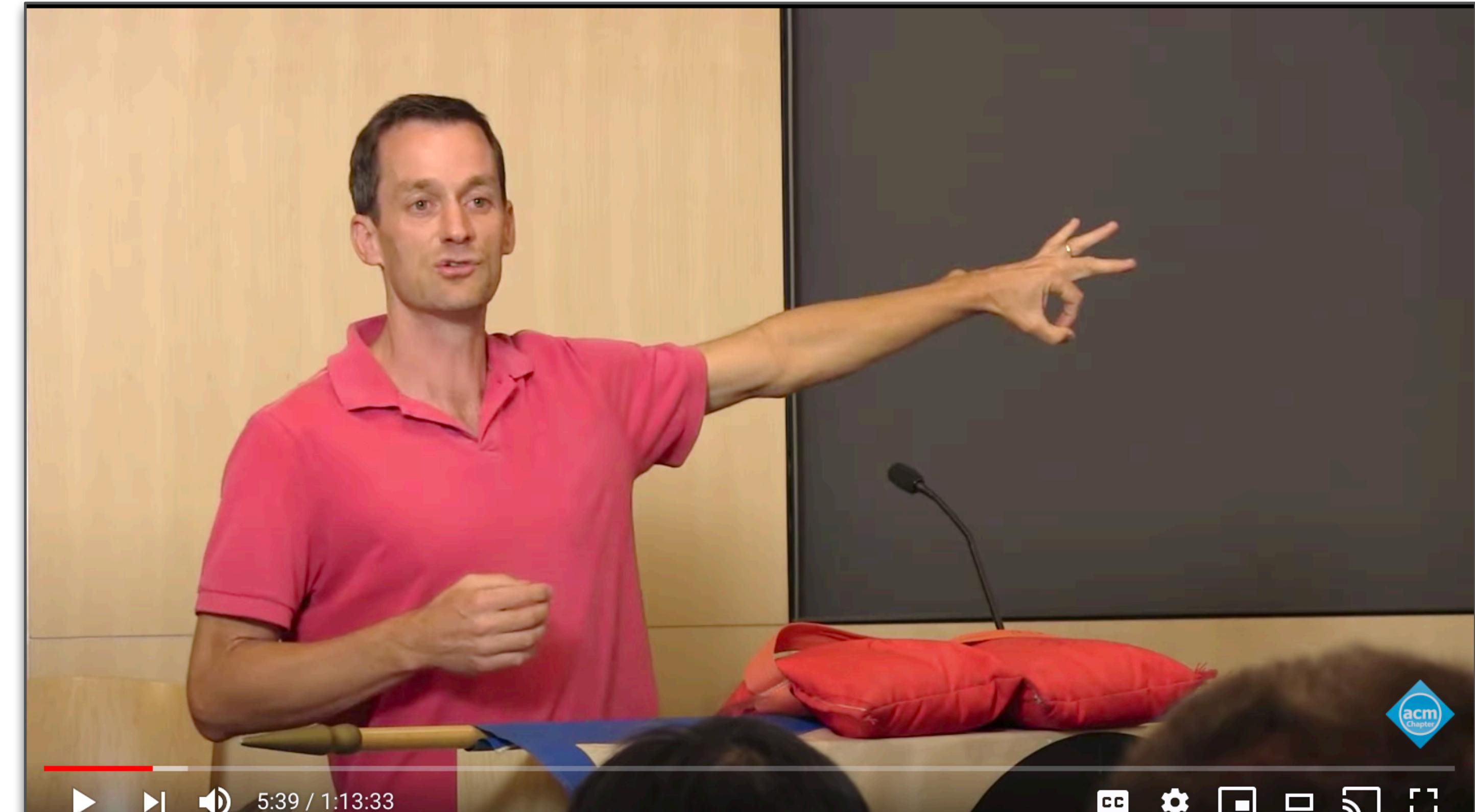
Networks and Gradients

“Taming Latency”
Jeff Dean (2013)

youtu.be/S9twUcX1Zp0

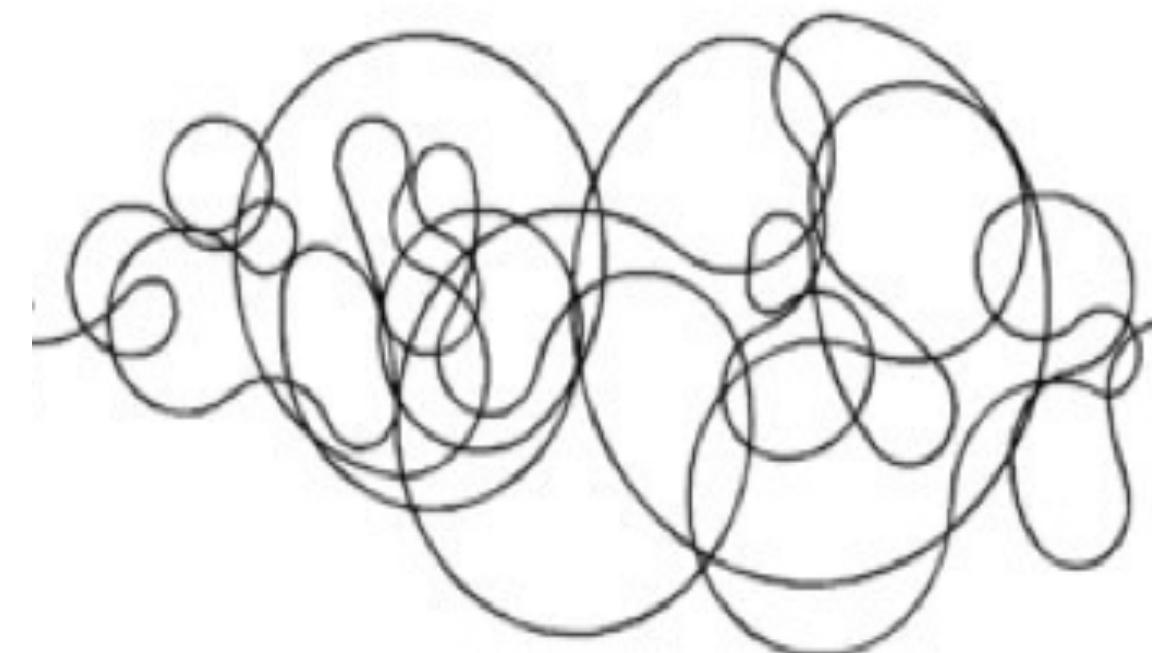
Describing factors within their latest datacenters that drove the design of **TensorFlow**

Optimized to train **networks** (graphs/tensors)

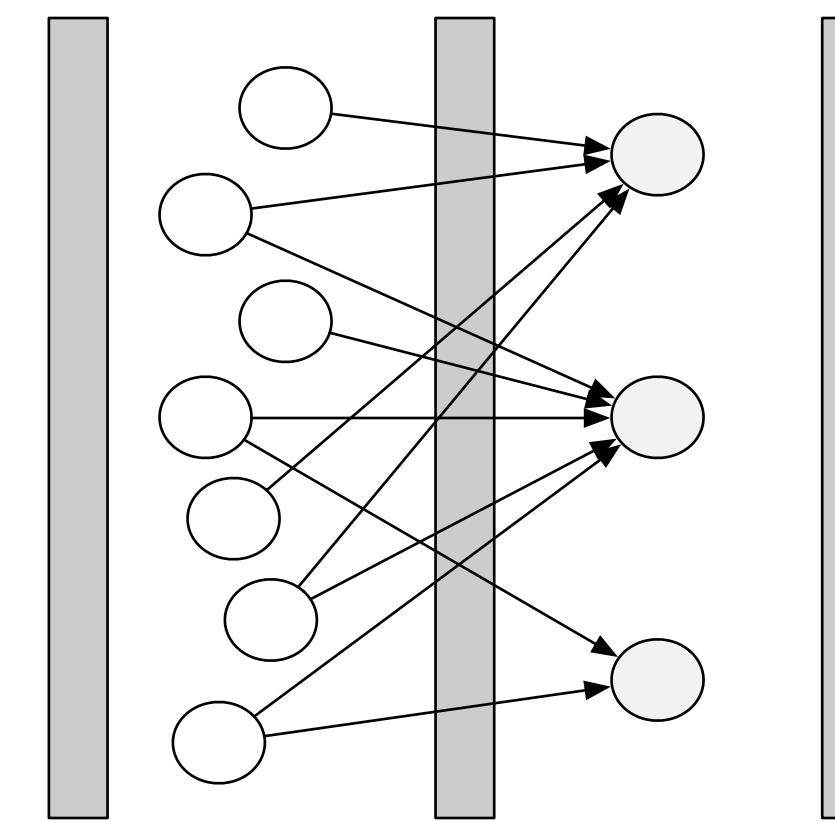


Taming Latency Variability and Scaling Deep Learning, by Jeff Dean, Google, 20131016

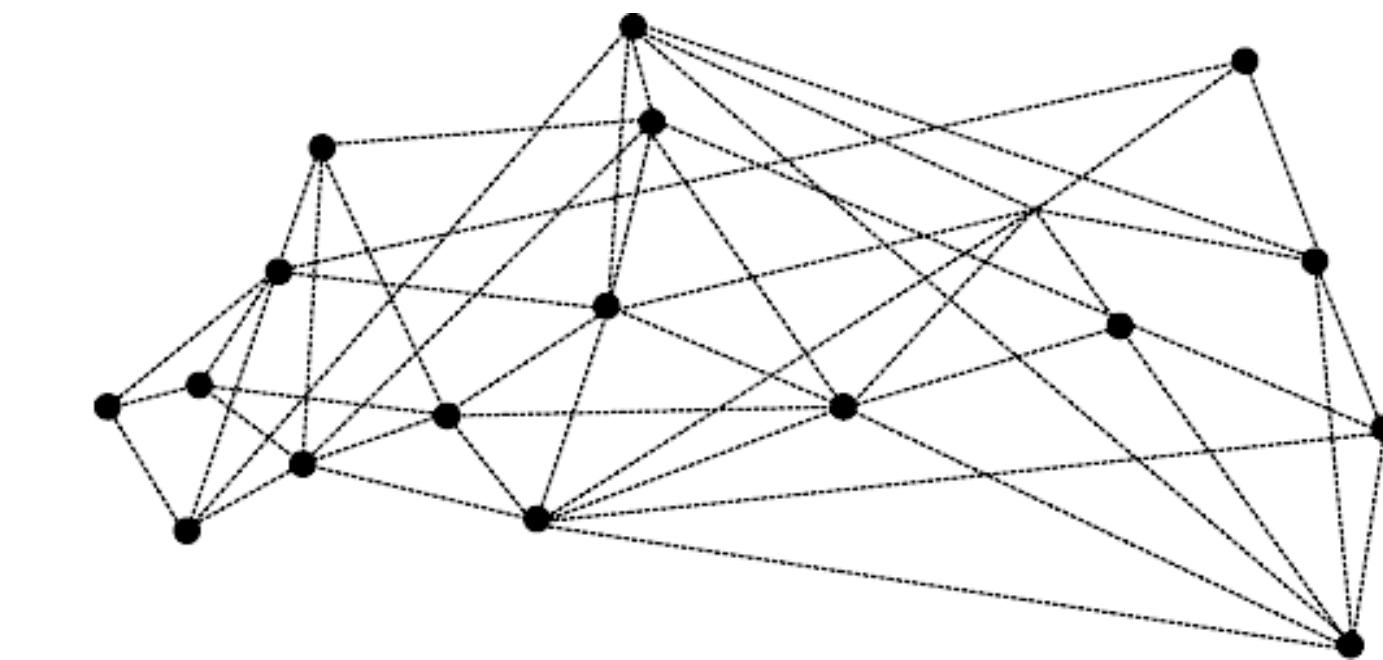
Cluster topologies, by generation



1990s



2000s



current



part 3: resources

Examples in notebooks...

The screenshot shows a GitHub repository page for 'README.md'. The title 'A Guided Tour of Ray Core' is displayed prominently. Below the title, there is a brief description: 'An introductory tutorial about leveraging Ray core features for distributed patterns.' A note follows: 'Note: these examples have been tested using Python 3.7+ on:' followed by a bulleted list: '• Ubuntu 18.04 LTS' and '• macOS 10.13'. A 'Getting Started' section is present with instructions: 'To get started use `git` to clone this public repository:' and a code block containing the command: `git clone https://github.com/DerwenAI/ray_tutorial.git` and `cd ray_tutorial`.

README.md

A Guided Tour of Ray Core

An introductory tutorial about leveraging Ray core features for distributed patterns.

Note: these examples have been tested using Python 3.7+ on:

- Ubuntu 18.04 LTS
- macOS 10.13

Getting Started

To get started use `git` to clone this public repository:

```
git clone https://github.com/DerwenAI/ray_tutorial.git  
cd ray_tutorial
```

https://github.com/DerwenAI/ray_tutorial

A tour through “Ray Design Patterns”

The screenshot shows a Google Document interface with the title "Ray Design Patterns".

Left Sidebar (Table of Contents):

- Ray Design Patterns
 - ★ This is a community maint...
- Basic Patterns
 - Pattern: Tree of Actors
 - Notes
 - Code example
 - Pattern: Tree of Tasks
 - Example use case
 - Code example
 - Pattern: Map and Reduce
 - Example use case
 - Pattern: Using ray.wait to limit t...
 - Code example
- Basic Antipatterns
 - Antipattern: Accessing Global V...
 - Code example

Infinite Laptop

While working, is your **attention** focused on your laptop, or focused somewhere in the cloud?

Why not **both**?

- Ben Lorica explores the emerging architectural pattern of an **Infinite Laptop**
- What RISElab means by the claim “serverless will dominate cloud”



Gradient Flow

Data, Machine Learning, and AI

Newsletter Podcast Blog Reports Video Events



Towards an infinite laptop

The new Anyscale platform offers the ease of development on a laptop combined with the power of the cloud.

During a series of short keynotes at the [Ray Summit](#) this morning, Anyscale¹, the company formed by the creators of Ray, publicly shared their initial product offering.



Dubbed the “infinite laptop”, Anyscale’s platform allows developers to treat their laptop as an “infinite cluster”.

Developers can use their preferred development tools (e.g., IDE, notebook, text editor, etc.) on Anyscale’s platform, and seamlessly burst into a cloud platform when needed.

Infinite Laptop

While working, is your **attention** focused on your laptop, or focused somewhere in the cloud?

Why not both?

- Ben Lorica explores architectural patterns

Infinite Laptop

- What RISElab means by the claim “serverless will dominate cloud”



Gradient Flow

Data, Machine Learning, and AI

Towards an infinite laptop

In other words, what if “cluster” meant a collection of hybrid-, multi-cloud resources?

platform offers the ease of laptop combined with the .

At the Ray Summit this morning, Anyscale¹, the company formed by the creators of Ray, publicly shared their initial product offering.

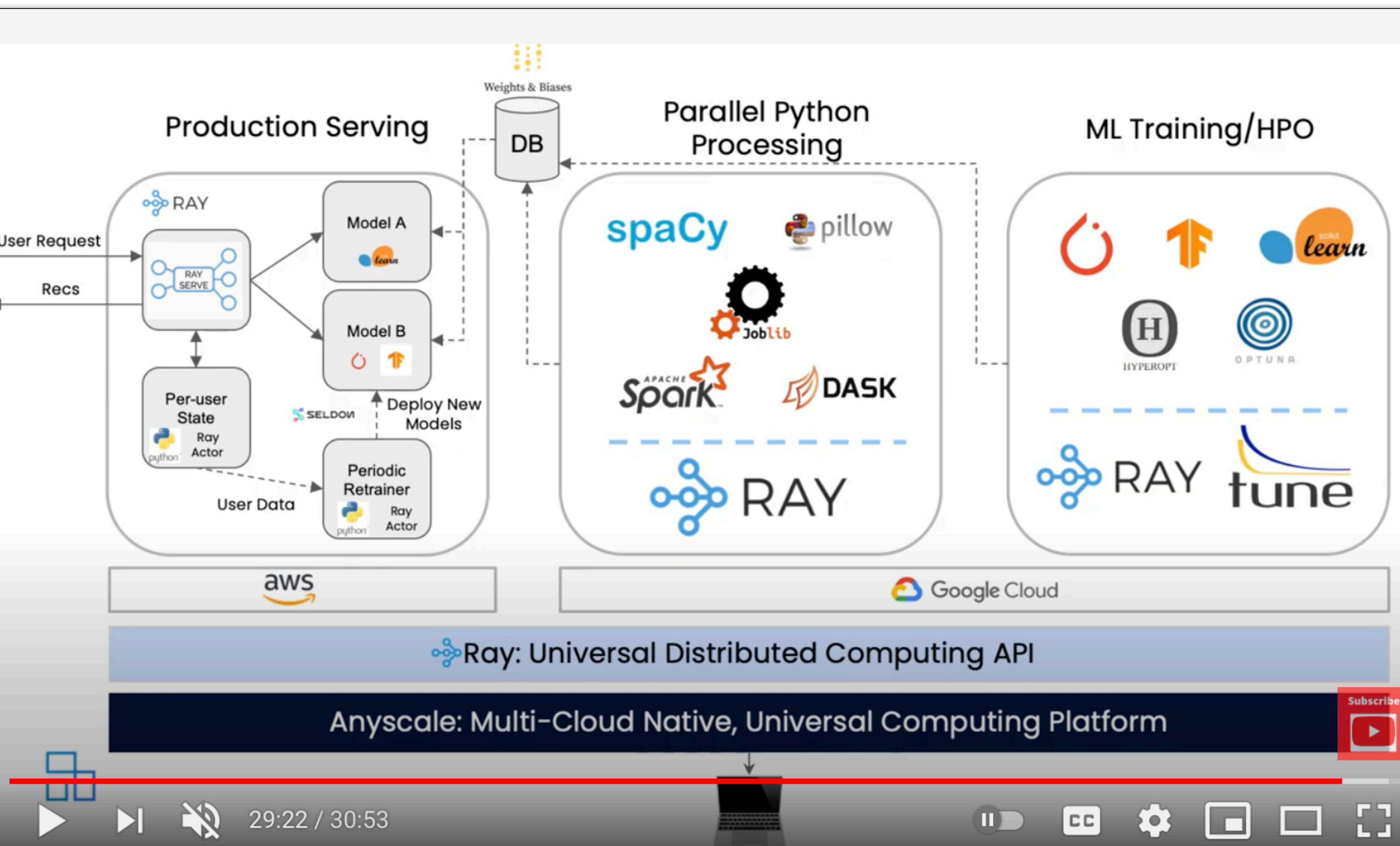
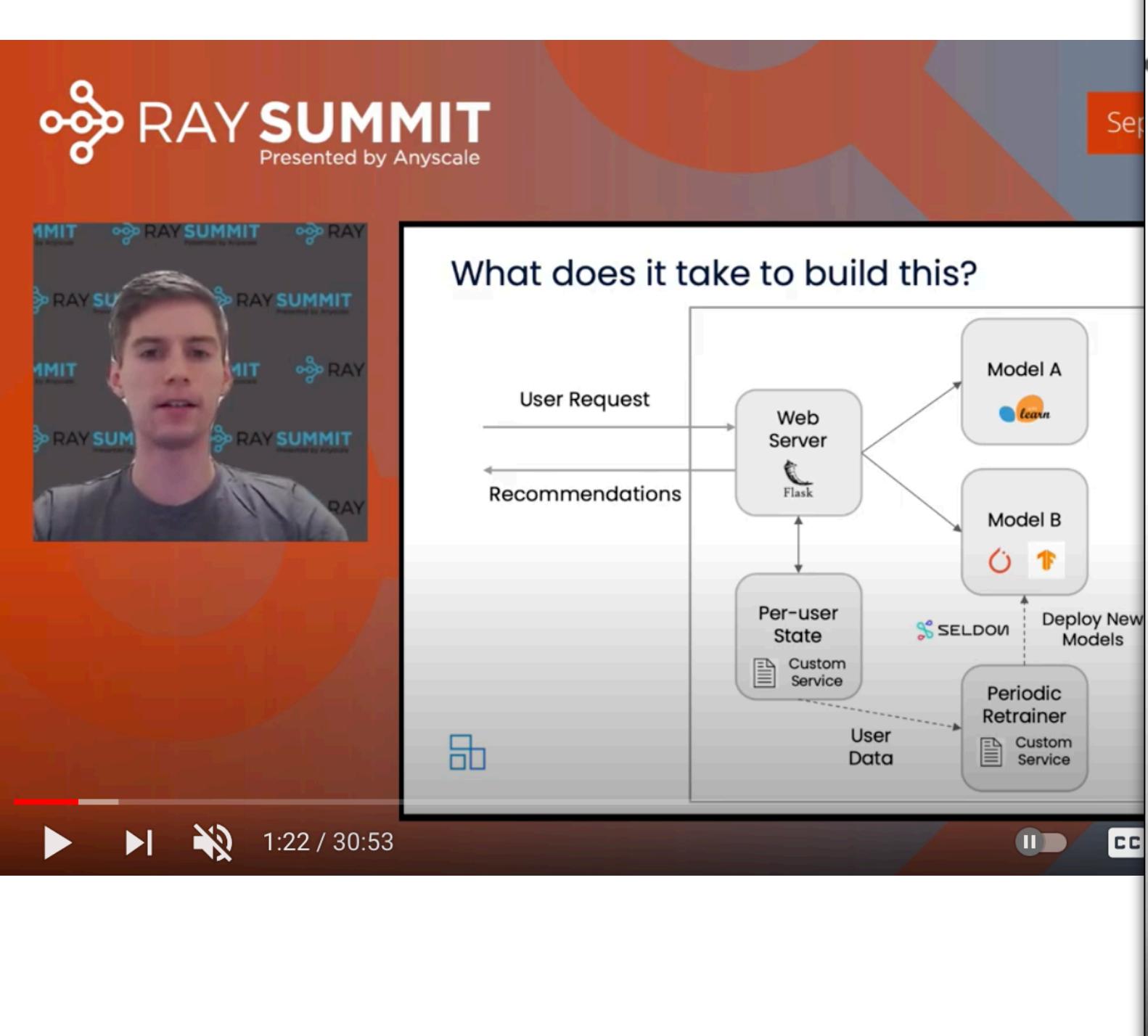


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Edward Oakes demo

youtu.be/8GTd8Y_JGTQ

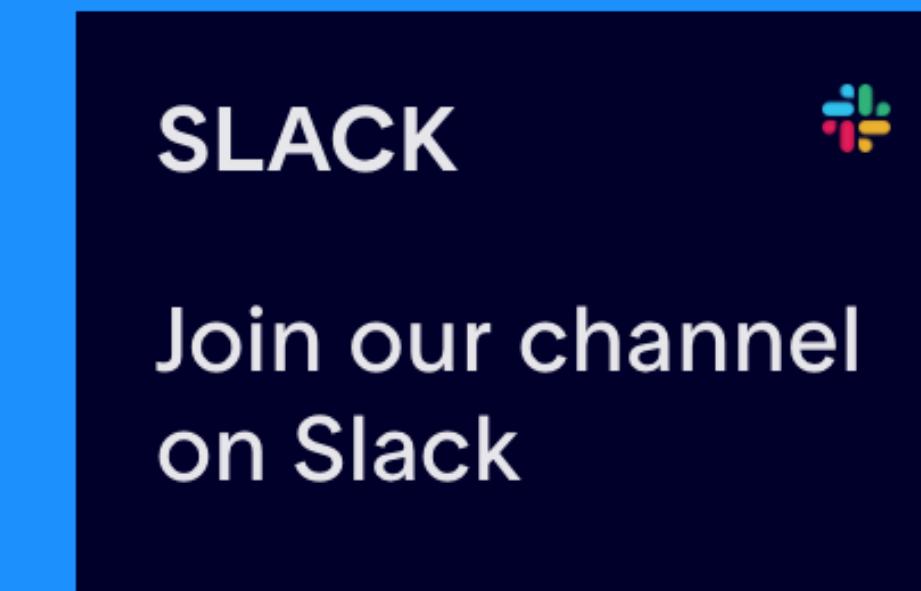
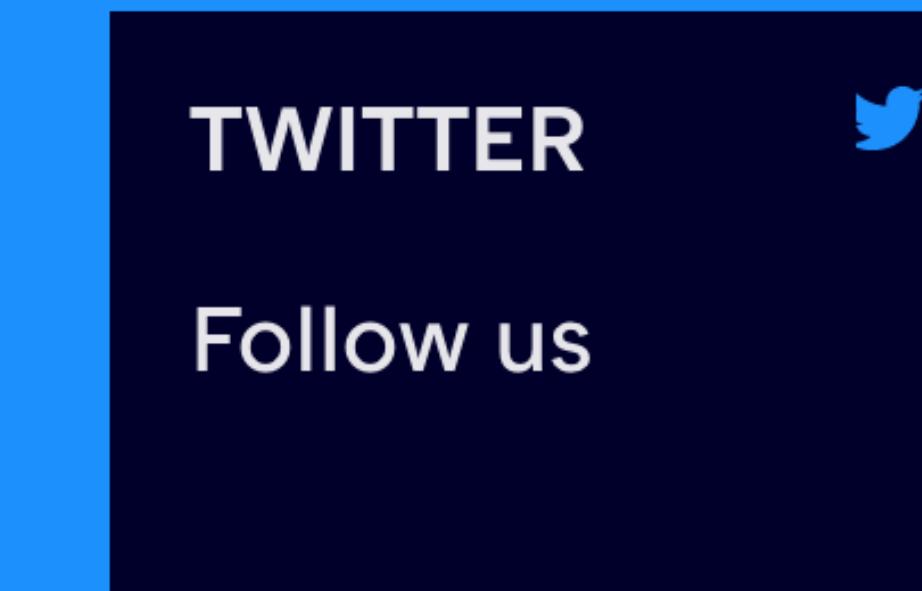
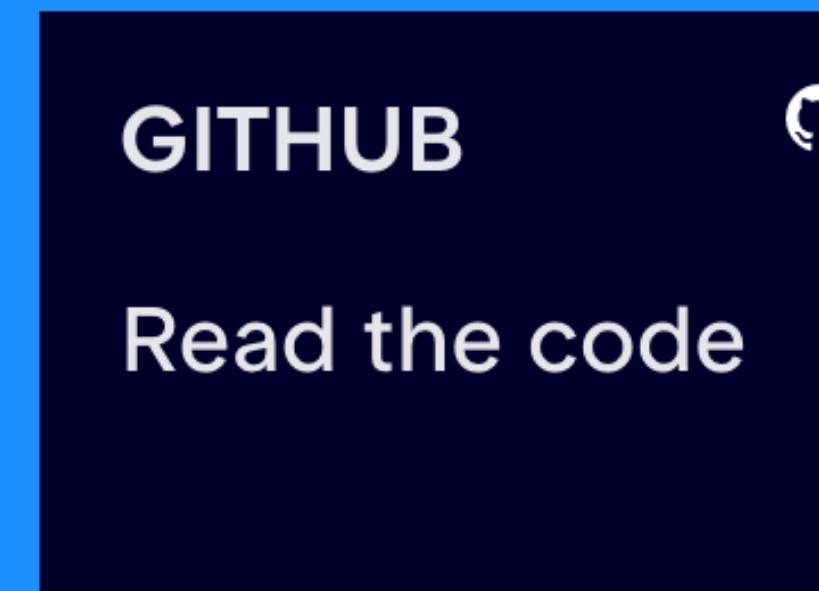
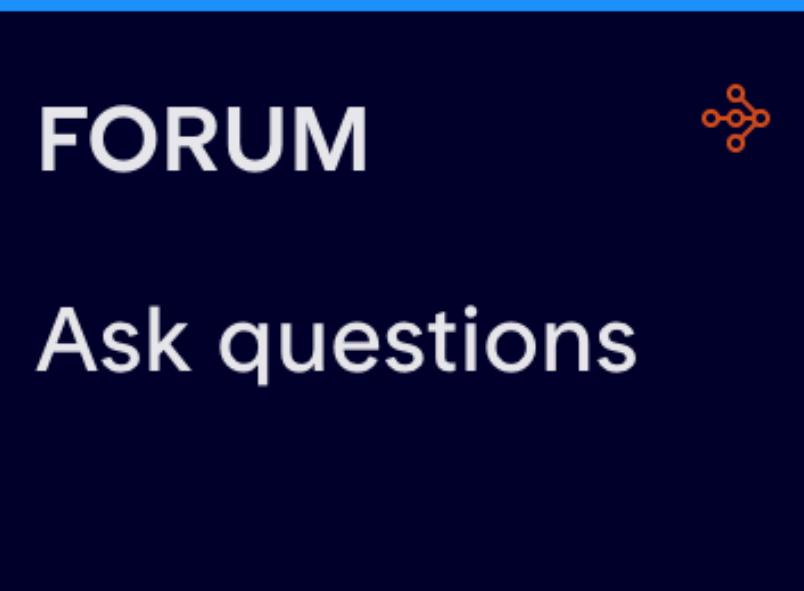


Ray Summit

June 22-24 2021

anyscale.com/ray-summit-2021

Get involved with the Ray community

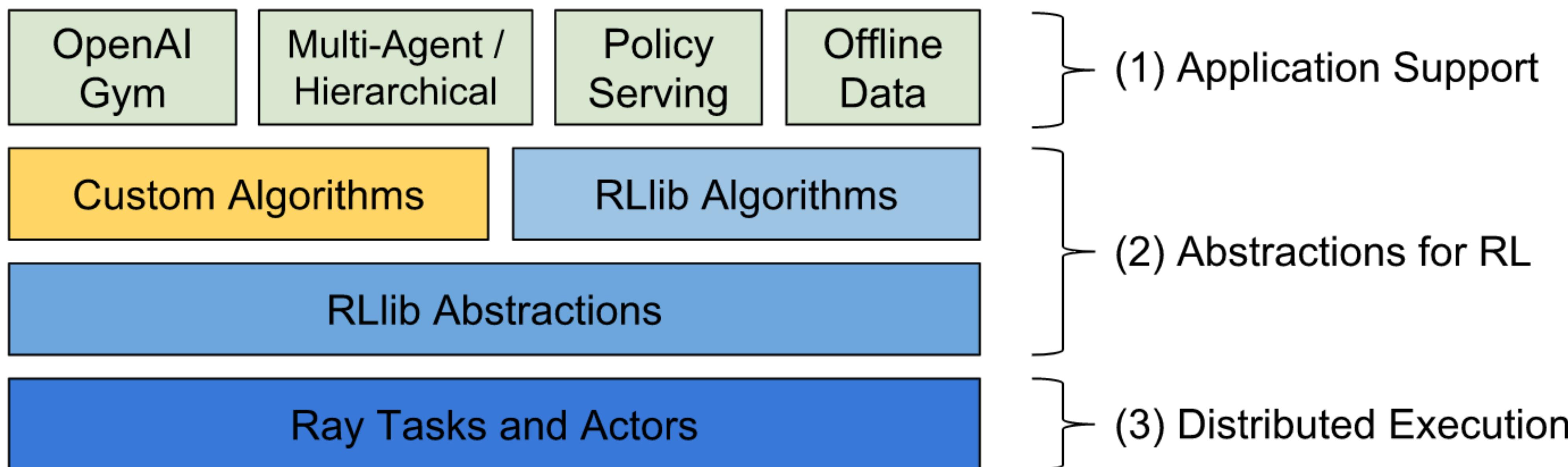


- <https://discuss.ray.io/>
- <https://github.com/ray-project/ray>
- <https://twitter.com/raydistributed>
- <https://tinyurl.com/rayslack>

part 4:
reinforcement learning
(if we have time)

Let's talk about AI...

Ray supplies a much-needed control layer for distributing and optimizing workloads across hybrid architectures, while being mindful about the economics of computing
(*op. cit.*, “A Berkeley View”)



Differentiating Gradients: Part 1

Supervised Learning:

- *loss function* (generalize from patterns)
- *regularization term* (avoid overfitting)

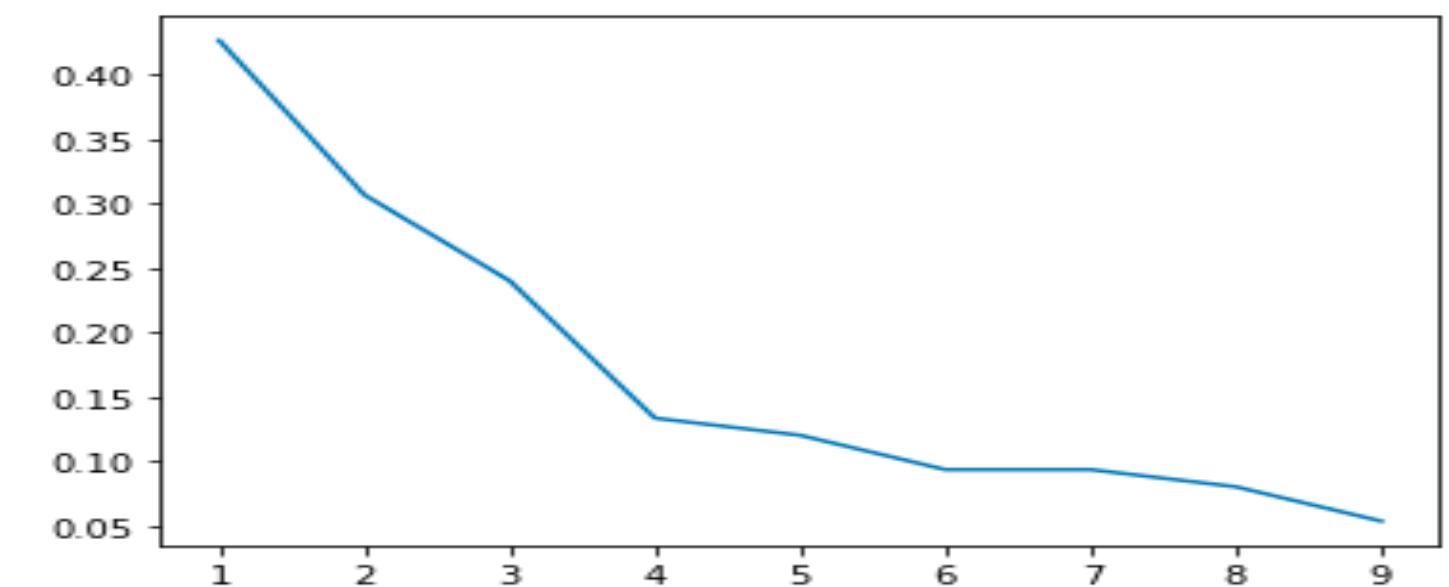
Models generalize from historical data for the **prediction** of future events.

Contextual horizon is typically measured in milliseconds – “**System 1**” thinking that is needed in ecommerce.

However, this is too shallow for the complex, longitudinal decisions which organizations must face.

$$I_G(n) = 1 - \sum_{i=1}^J (p_i)^2$$

$$\min_{f \in H} \left[\sum_{i=1}^N L(y_i, f(x_i)) + \lambda J(f) \right]$$



Differentiating Gradients: Part 2

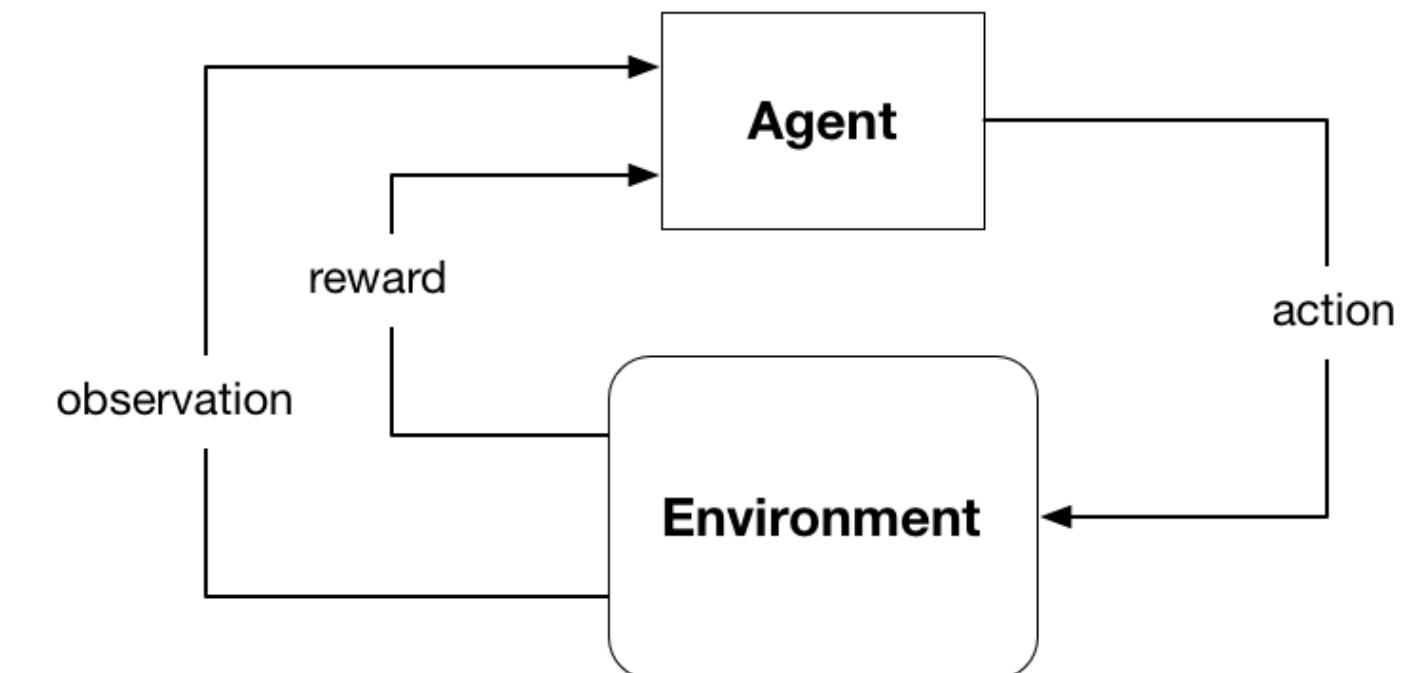
Reinforcement Learning:

- optimal control theory
- augmented by deep learning
- based on markov decision process

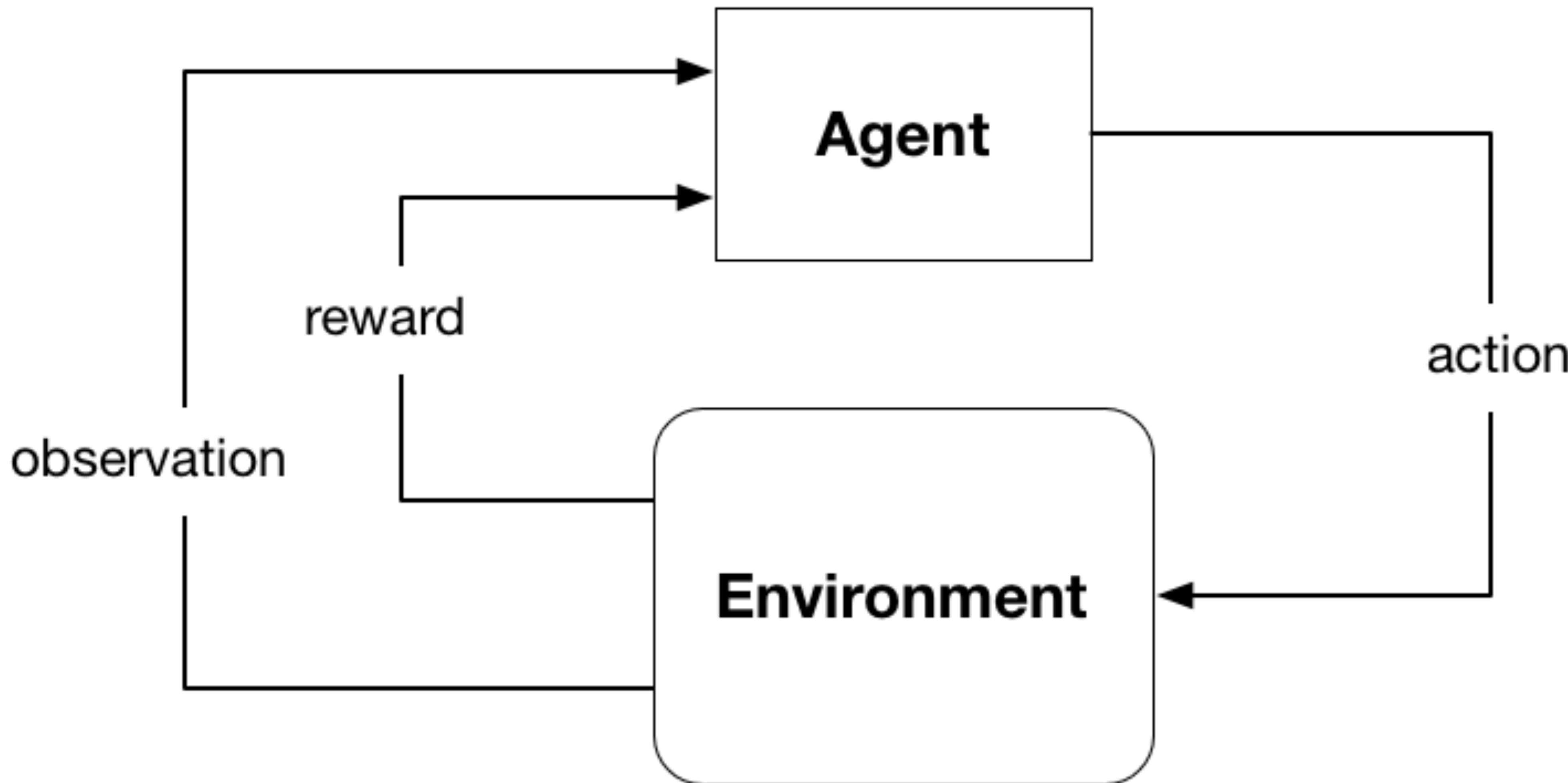
Learned **policies** guide one or more agents within environments.

Agents make sequences of decisions, based on policies, to maximize cumulative rewards: the *exploration/exploitation* trade-off.

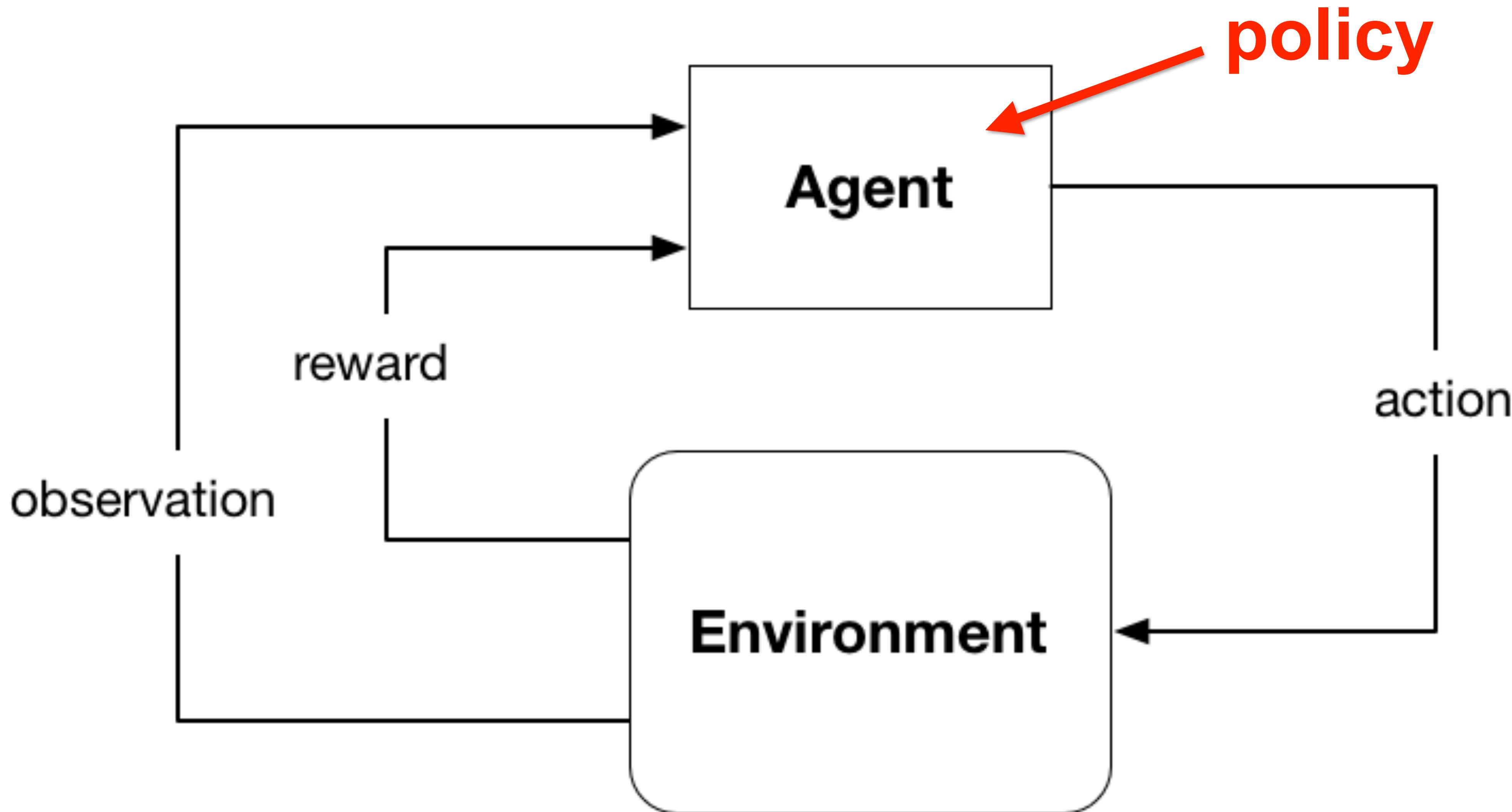
Contextual horizon extends for long periods, leading toward “**System 2**” thinking.



Overview: how RL works...



Overview: how RL works...



Note: that “Environment” component could be just about any **industrial simulation / ops**



For example...

“The AI Economist: Improving Equality and Productivity with AI-Driven Tax Policies”

Stephen Zheng, et al. (2020)

arxiv.org/abs/2004.13332

“We show that AI-driven tax policies improve the trade-off between equality and productivity by 16% over baseline policies.”

- upside: **policy** is a very big word
- downside: RL requires lots of compute + data; how do we avoid **boiling the oceans?**



Getting Started: Four Examples

“Intro to RLlib: Example Environments”

Paco Nathan

Anyscale (2020-07-09)



Taxi



FrozenLake



CartPole



MountainCar

Getting Started: Your Use Cases

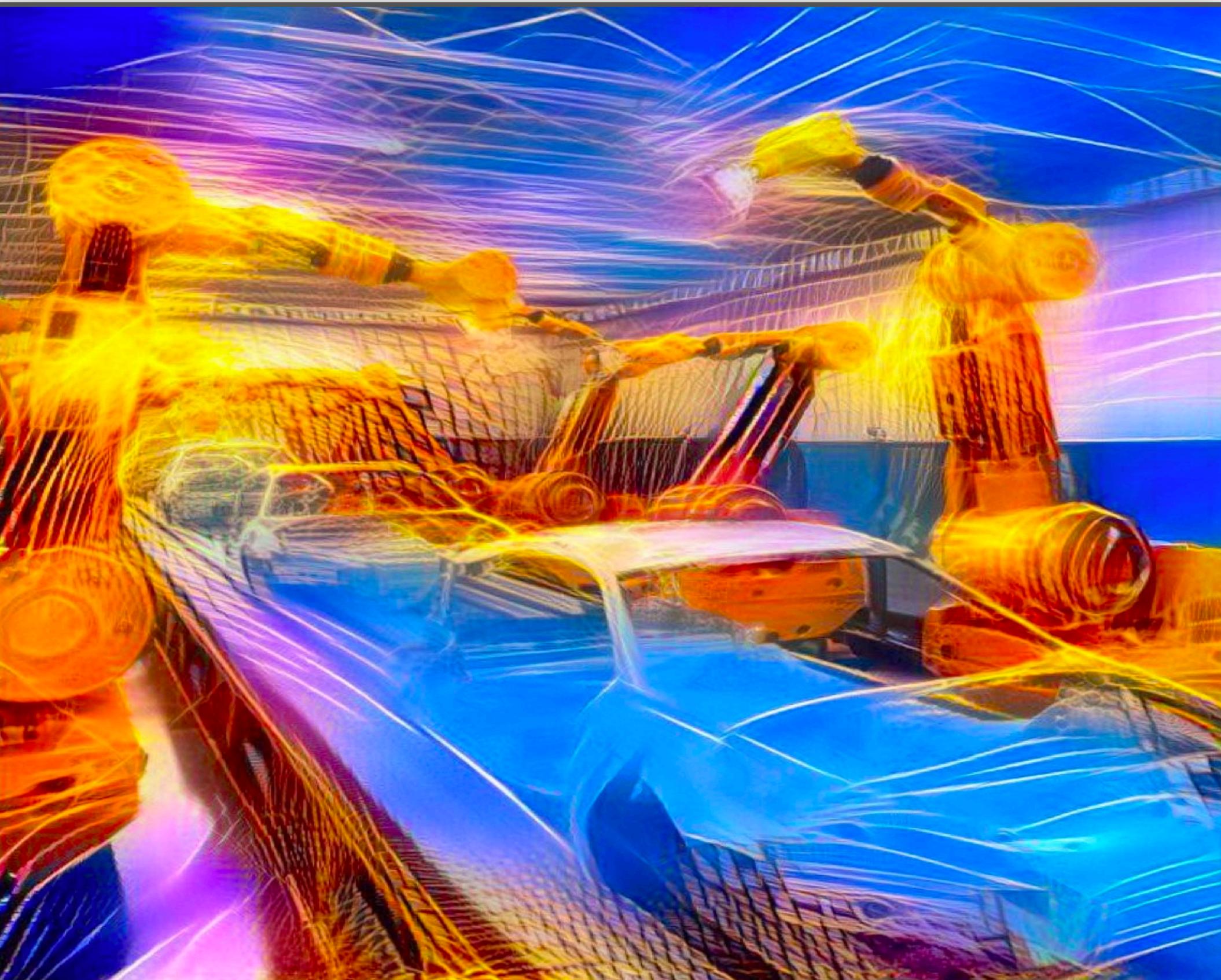
“Anatomy of a custom environment for RLlib”

Paco Nathan

Anyscale (2020-08-27)

Gym + RLlib:

github.com/DerwenAI/gym_example

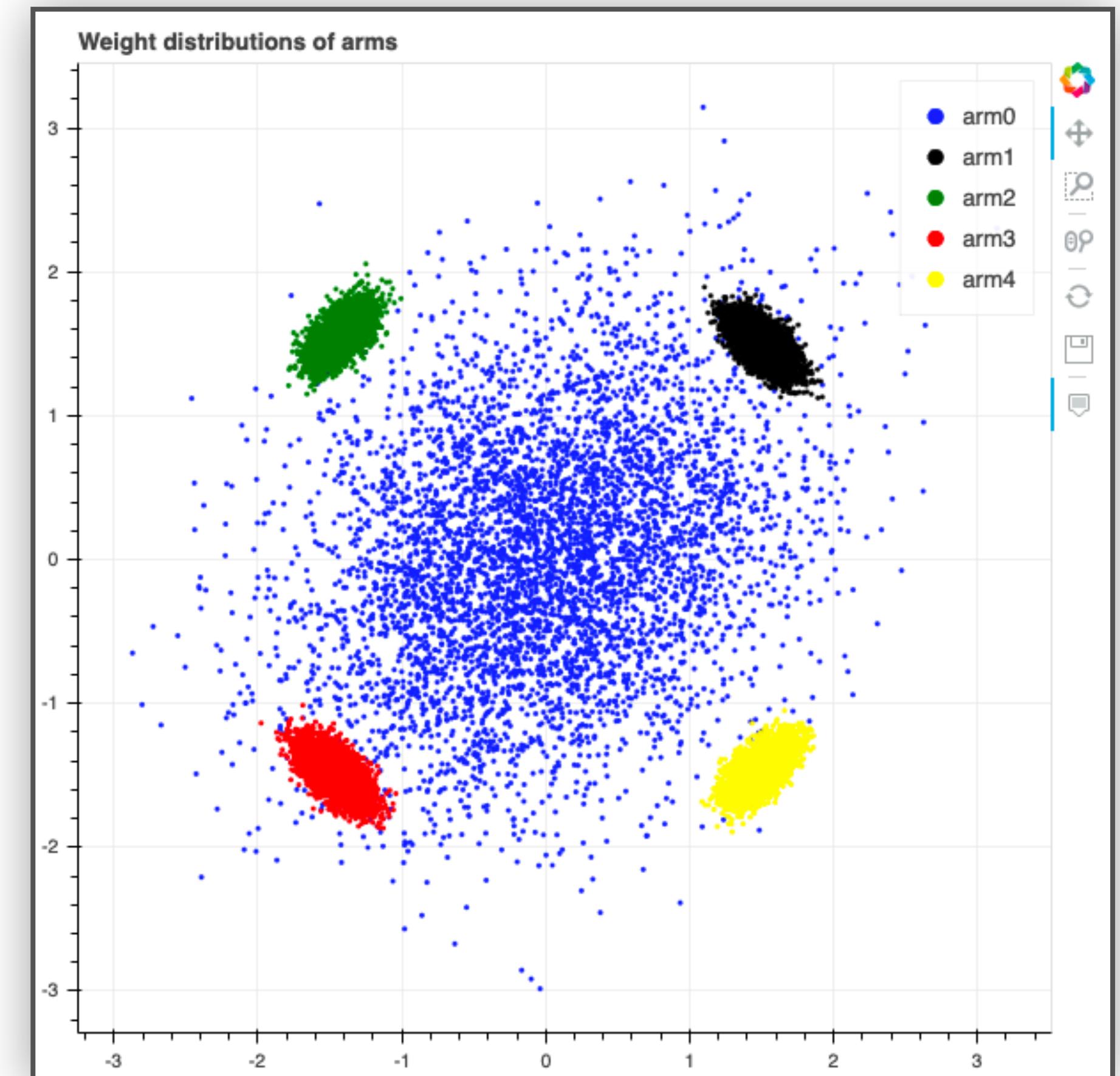


Contextual Bandits

“Market Bandit”

Anyscale Academy

Thompson Sampling for a *contextual bandit* on 93 years of **US financial markets data**, to show developing a policy, as an example of *portfolio optimization*

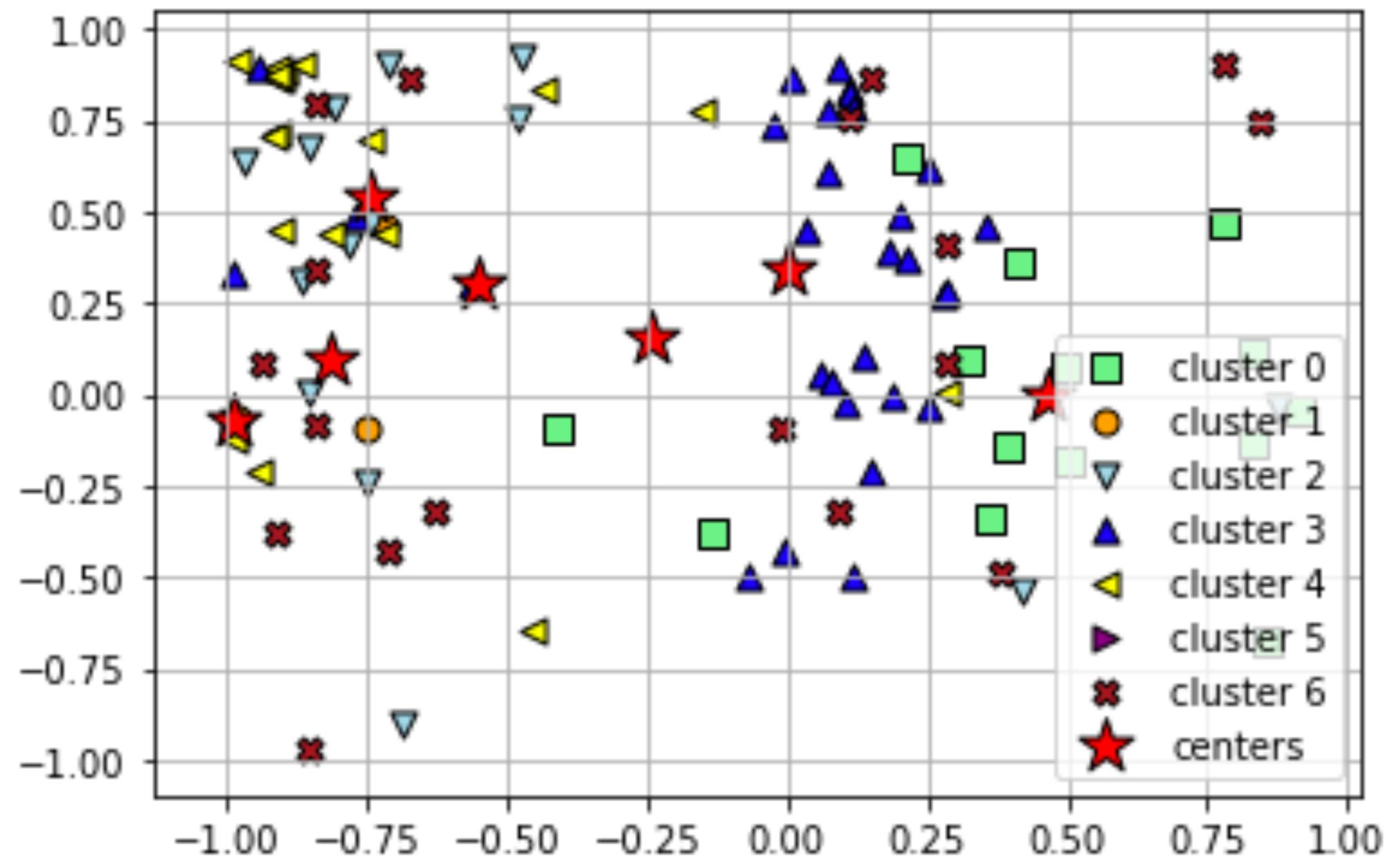


Recommender Systems

“Jester RecSys”

Anyscale Academy

An example of how to apply RL for building
a *recommender system*, based on the
Jester joke ratings database



publications, interviews, conference summaries...

[@pacoid](https://derwen.ai/paco)

Thank you!



derwen.ai