goto;

GOTO CHICAGO 2023

#GOTOchgo

Reinforcement Learning: ChatGPT, Games, and More

goto;

Don't forget to
vote for this session
in the **GOTO Guide app**

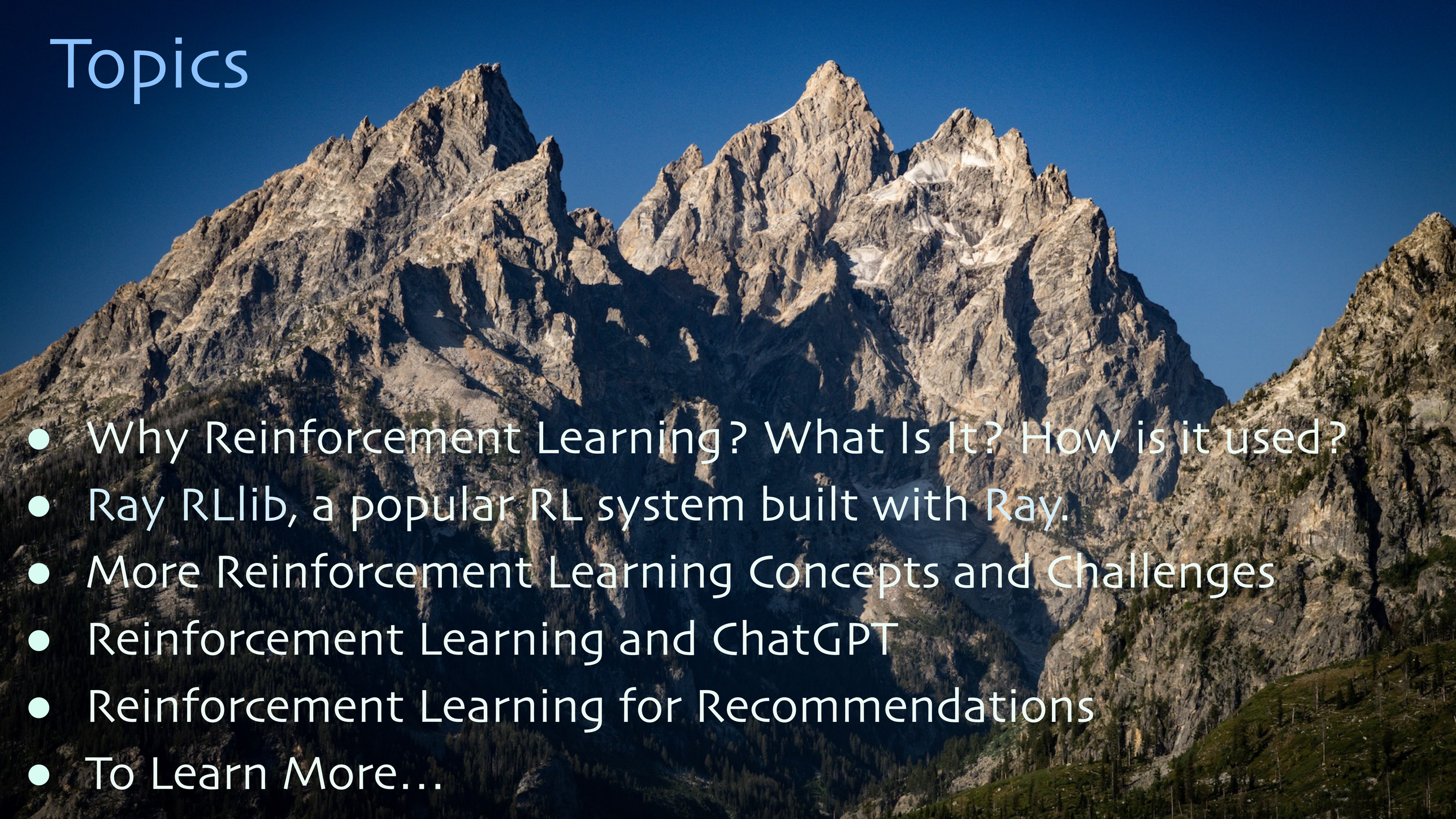
Reinforcement Learning: ChatGPT, Games, and More



dean@deanwampler.com
deanwampler.com/talks
IBM Research
@discuss.systems@deanwampler
@deanwampler

© Dean Wampler, 2022-2023, except where noted. Photos from the Wind River Range, Grand Teton NP, and Yellowstone NP, Wyoming

Topics

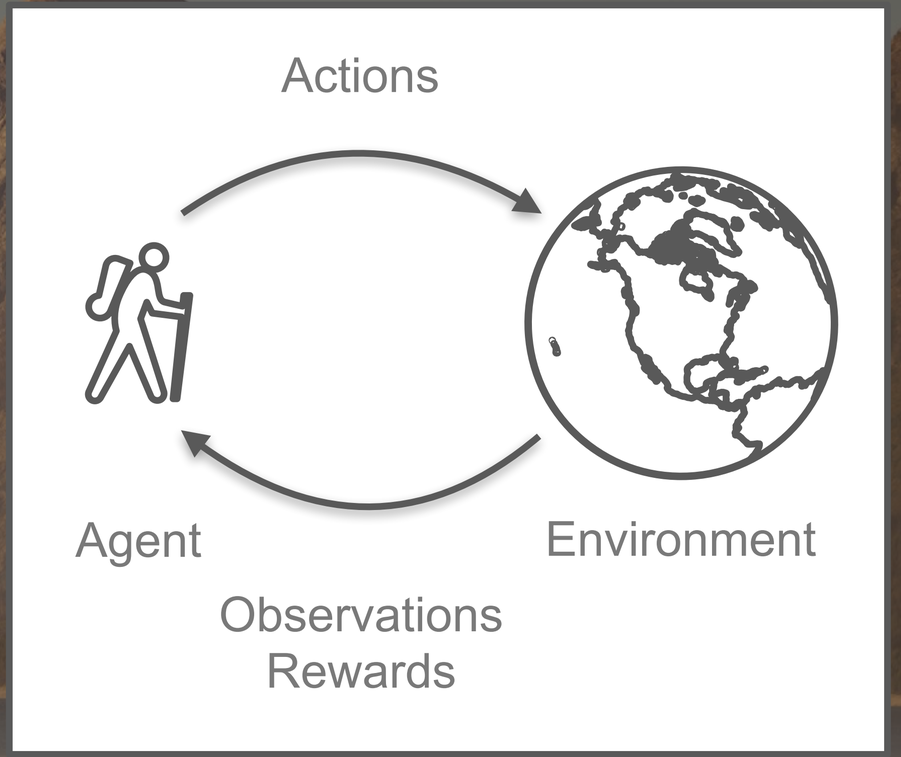


- Why Reinforcement Learning? What Is It? How is it used?
- Ray RLlib, a popular RL system built with Ray.
- More Reinforcement Learning Concepts and Challenges
- Reinforcement Learning and ChatGPT
- Reinforcement Learning for Recommendations
- To Learn More…

The Agent choses an Action, then Observes any changes to the Environment and a Reward received, if any.

Through a sequence of these steps, the Agent learns a Policy for maximizing the cumulative Reward.

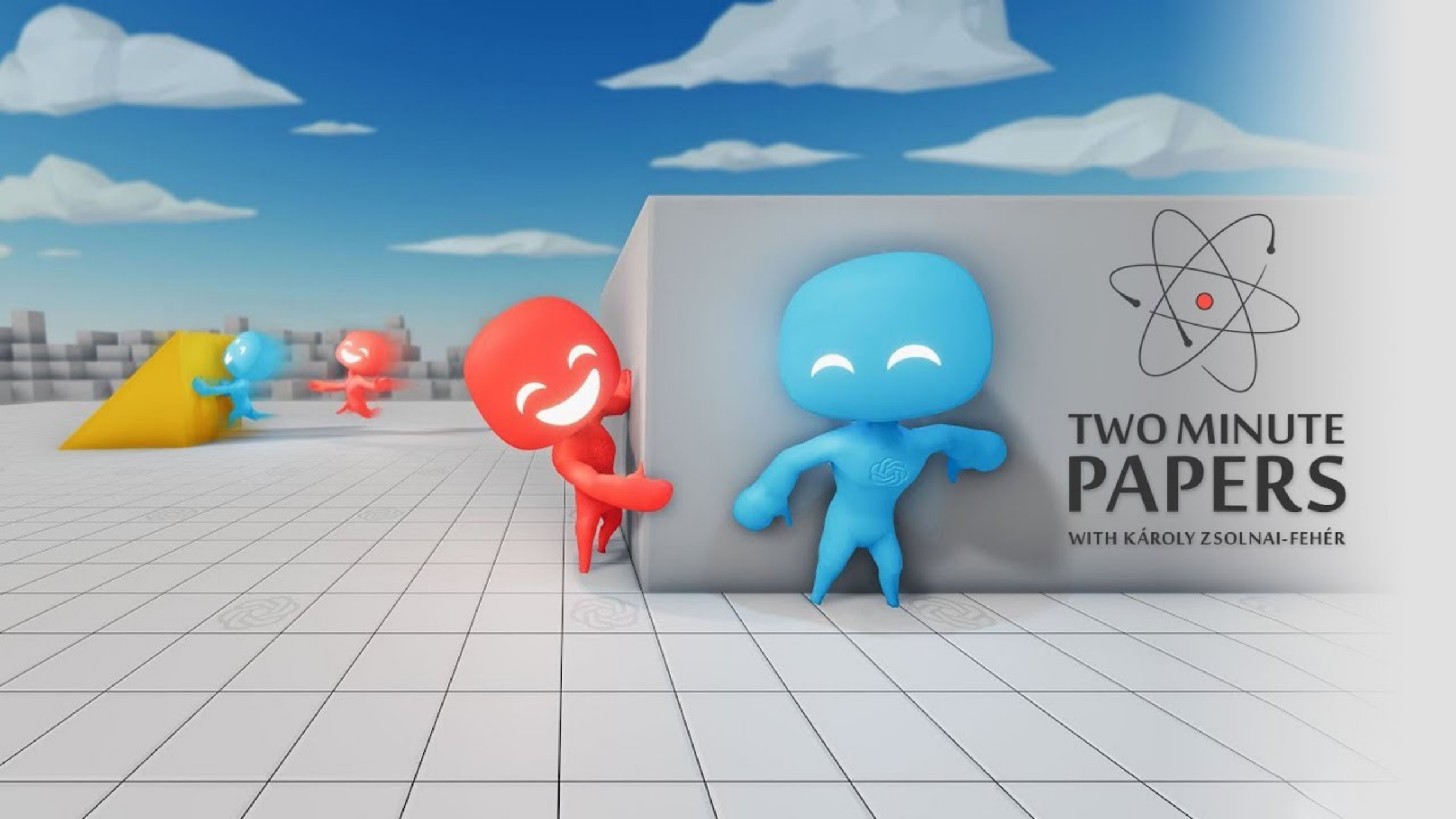
Each sequence is an Episode. It takes many Episodes to learn a good Policy.



Some systems return a Reward after each Action. Others, only at the Episode end.

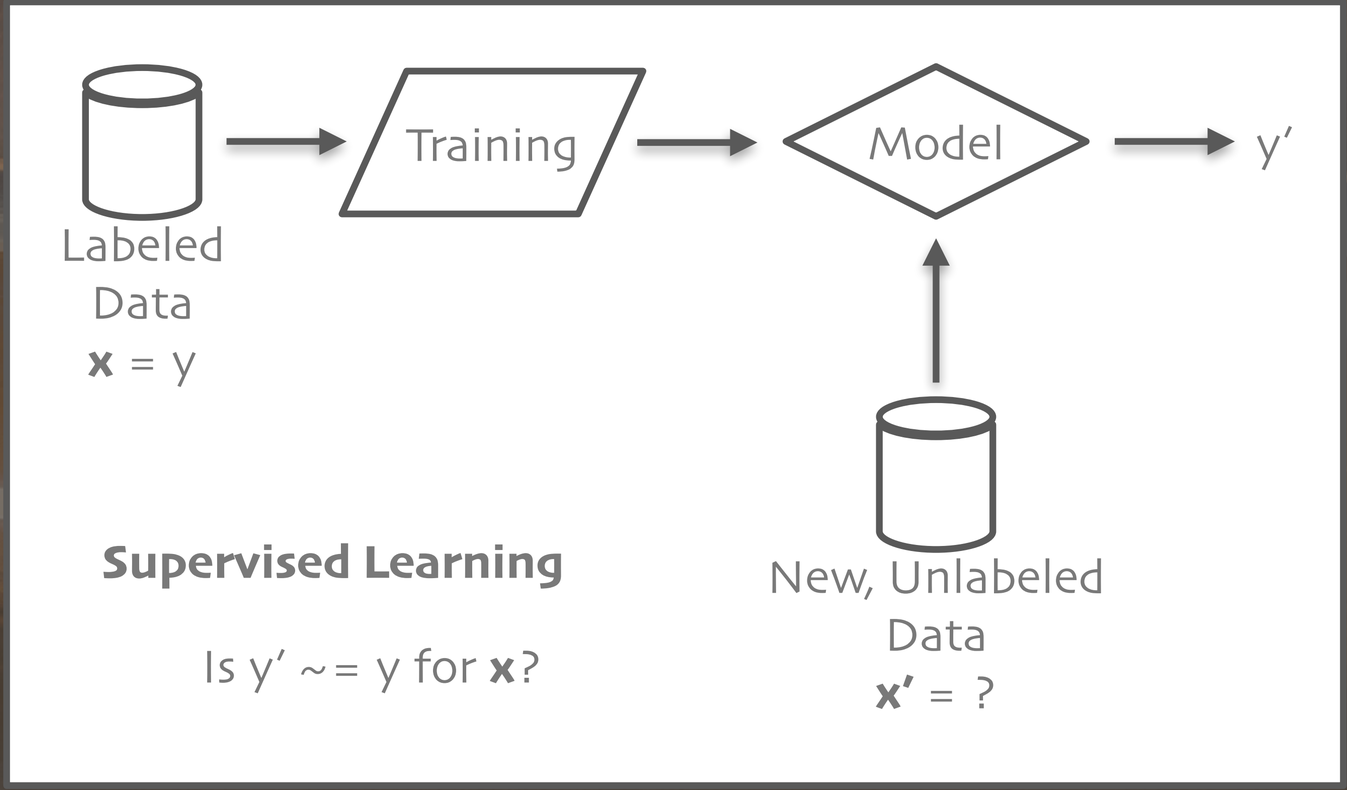


Why Reinforcement Learning?


TWO MINUTE
PAPERS
WITH KÁROLY ZSOLNAI-FEHÉR

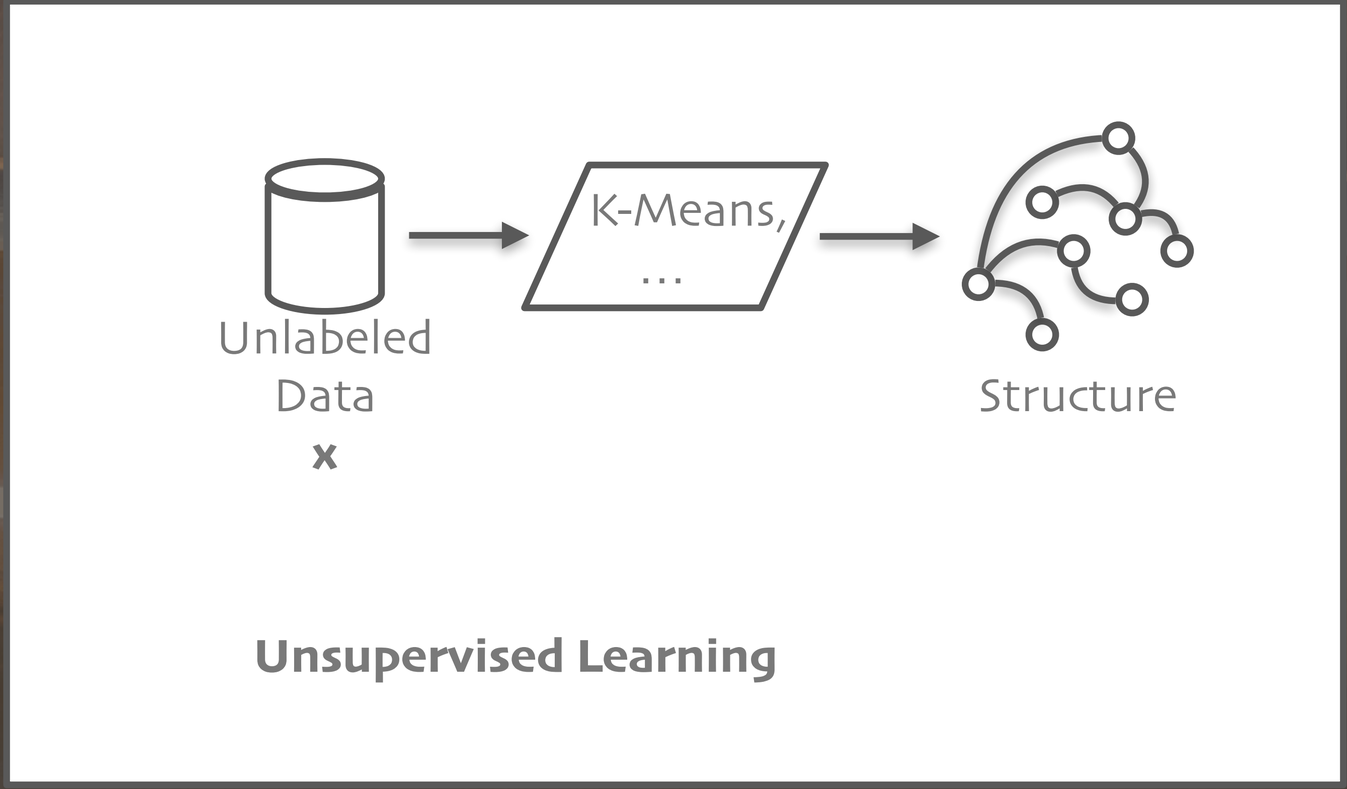
Compared to Supervised Learning





Compared to Unsupervised Learning





RL Applications

Games

Robotics, Autonomous Vehicles

Industrial Processes

System Optimization

Advertising, Recommendations

Finance



Common Theme:

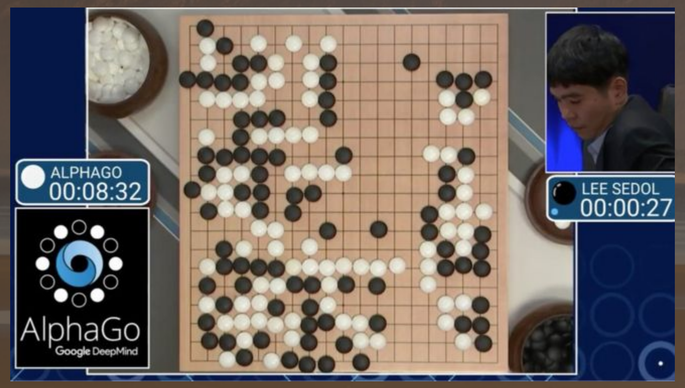
The ideal applications have sequential, evolving state for the environment plus the agent.

RL Applications

AlphaGo, Atari, OpenAI Gym/ Gymnasium, …

- Games
- Robotics, Autonomous Vehicles
- Industrial Processes
- System Optimization
- Advertising, Recommendations
- Finance



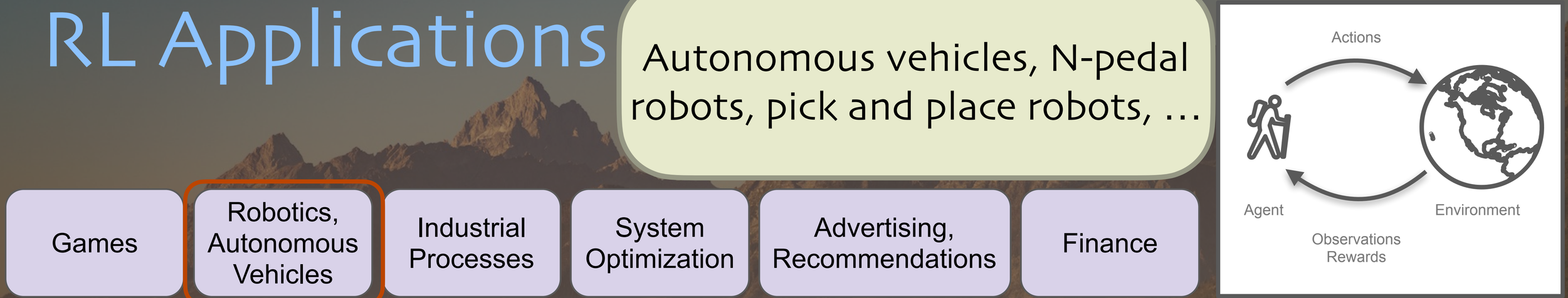


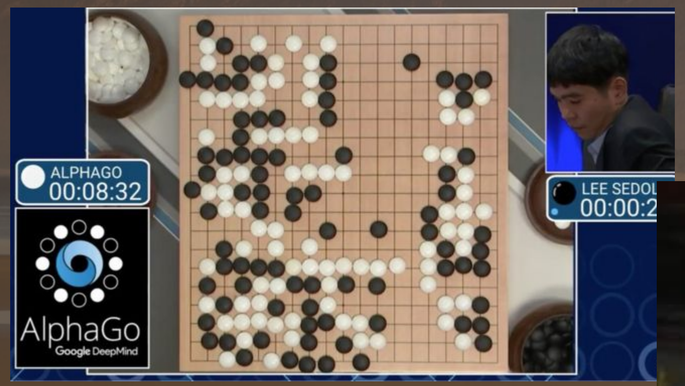


RL Applications

Autonomous vehicles, N-pedal robots, pick and place robots, …

Games | Robotics, Autonomous Vehicles | Industrial Processes | System Optimization | Advertising, Recommendations | Finance











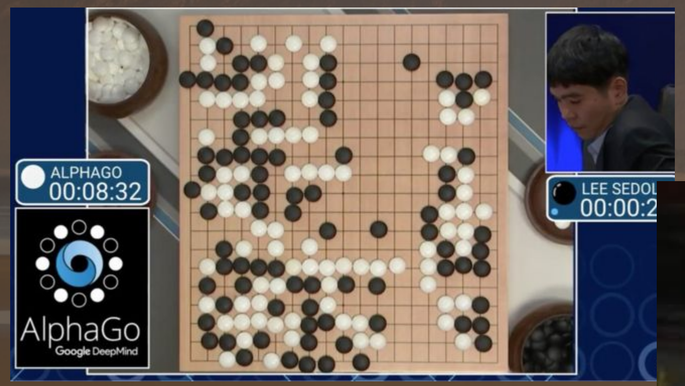


RL Applications

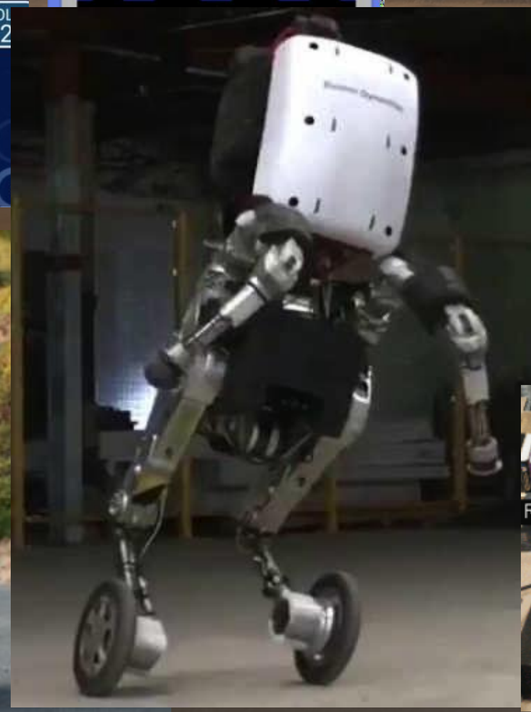
Assembly lines, warehouse and delivery routing, …



Games | Robotics, Autonomous Vehicles | Industrial Processes | System Optimization | Advertising, Recommendations | Finance

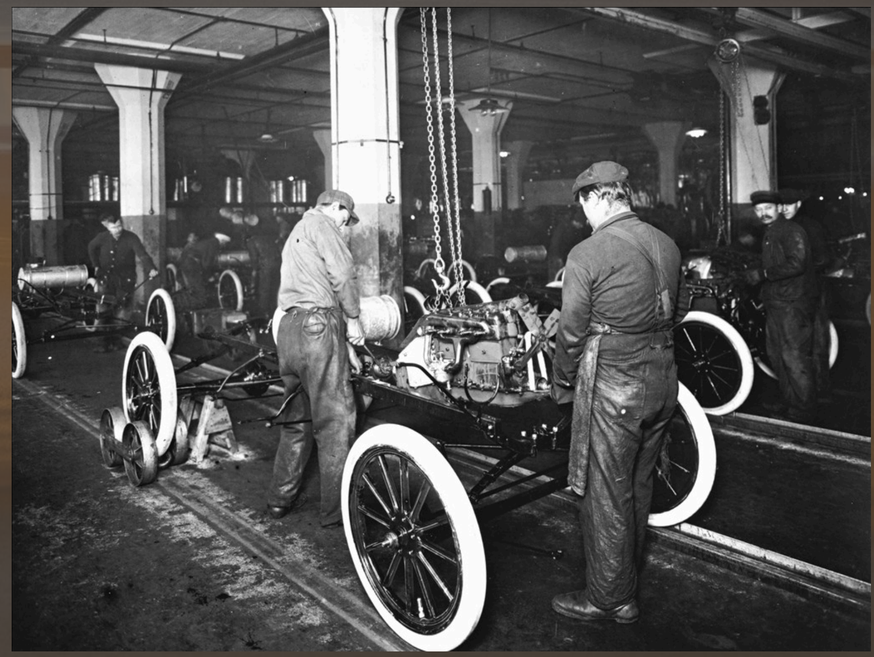








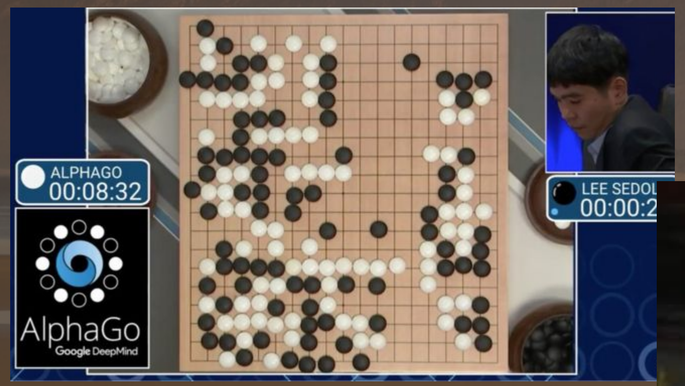




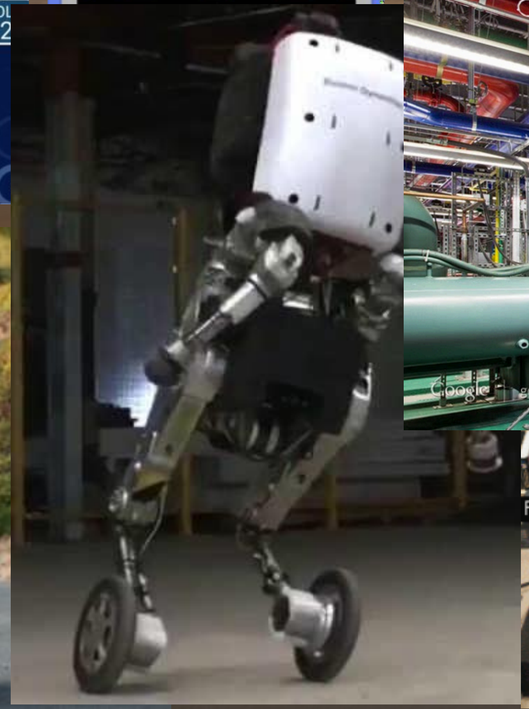
RL Applications

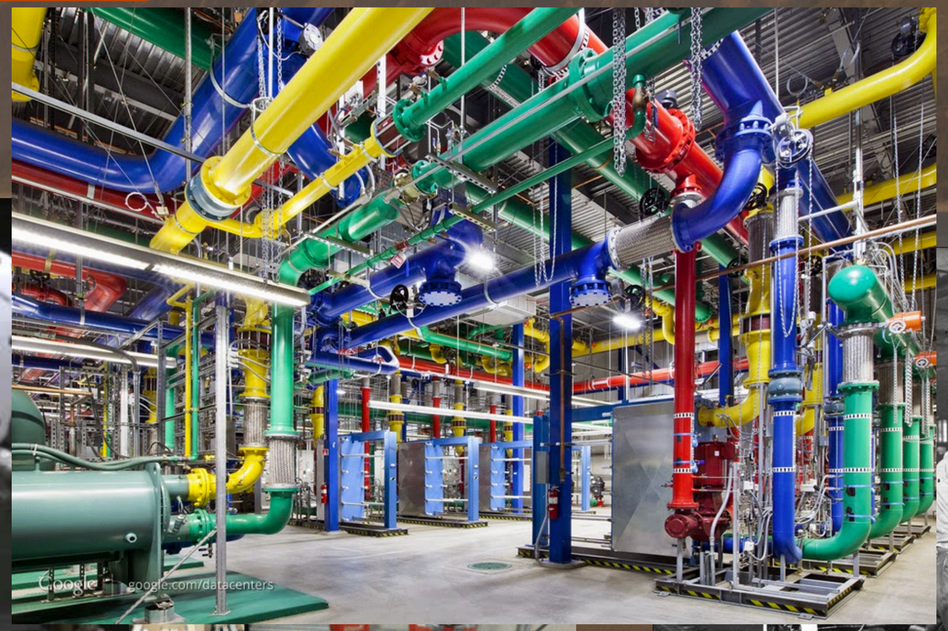
HVAC optimization, networks, business processes, …

Games | Robotics, Autonomous Vehicles | Industrial Processes | System Optimization | Advertising, Recommendations | Finance





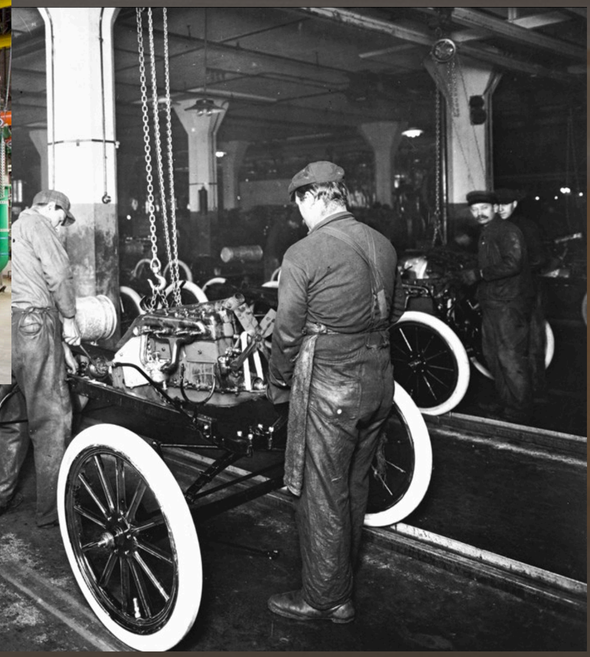












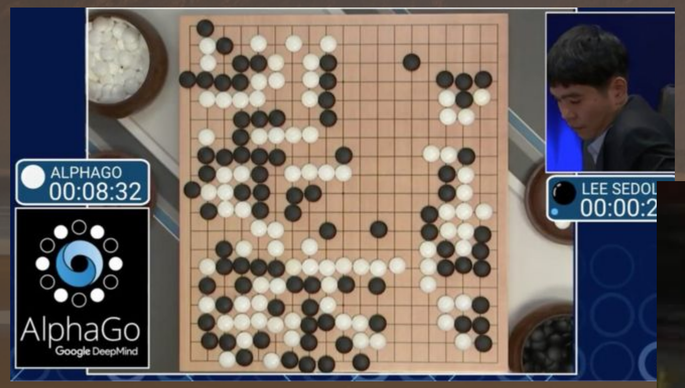


RL Applications

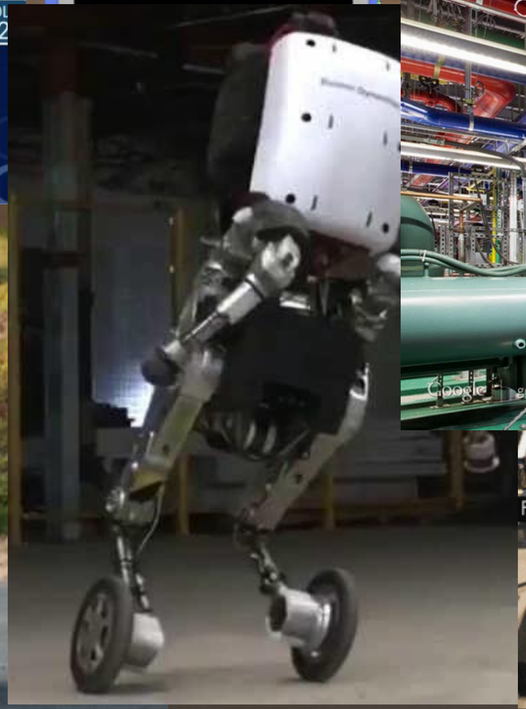
Better recommendations, ad placements, …

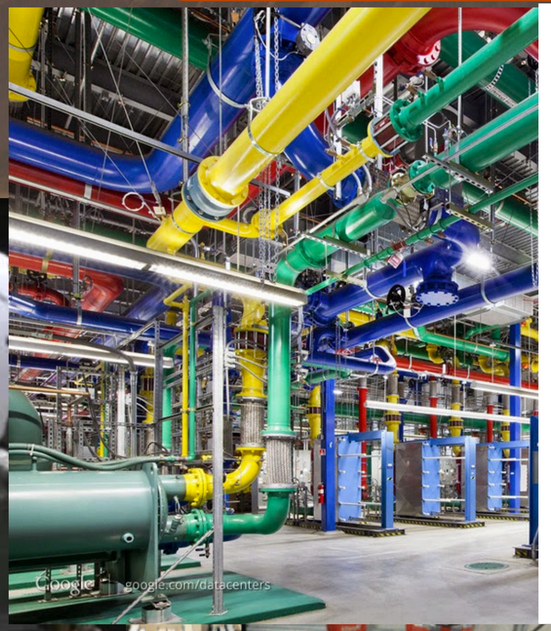
Games | Robotics, Autonomous Vehicles | Industrial Processes | System Optimization | Advertising, Recommendations | Finance

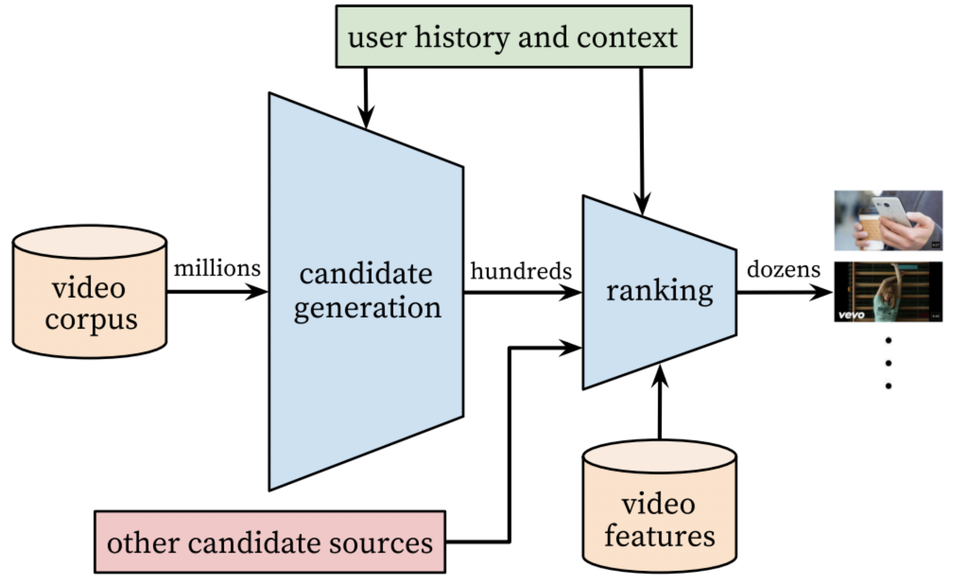
















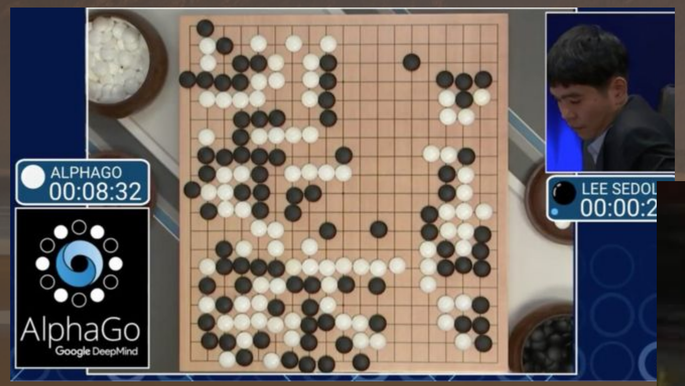


RL Applications

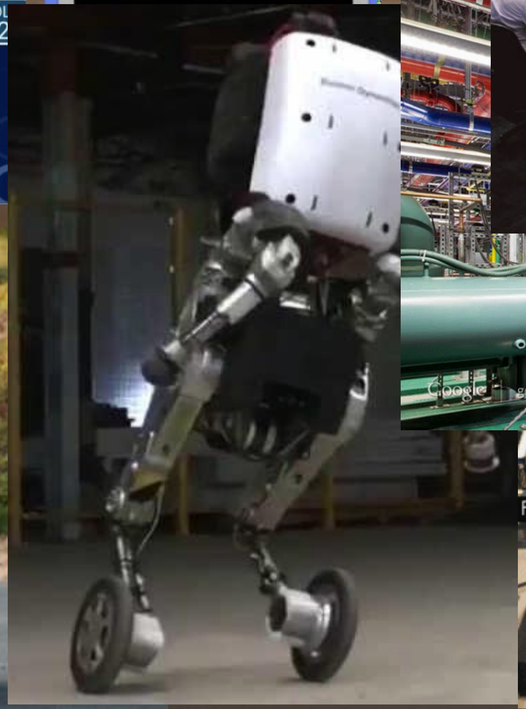
Market trends, timing of trades, …

Games | Robotics, Autonomous Vehicles | Industrial Processes | System Optimization | Advertising, Recommendations | Finance

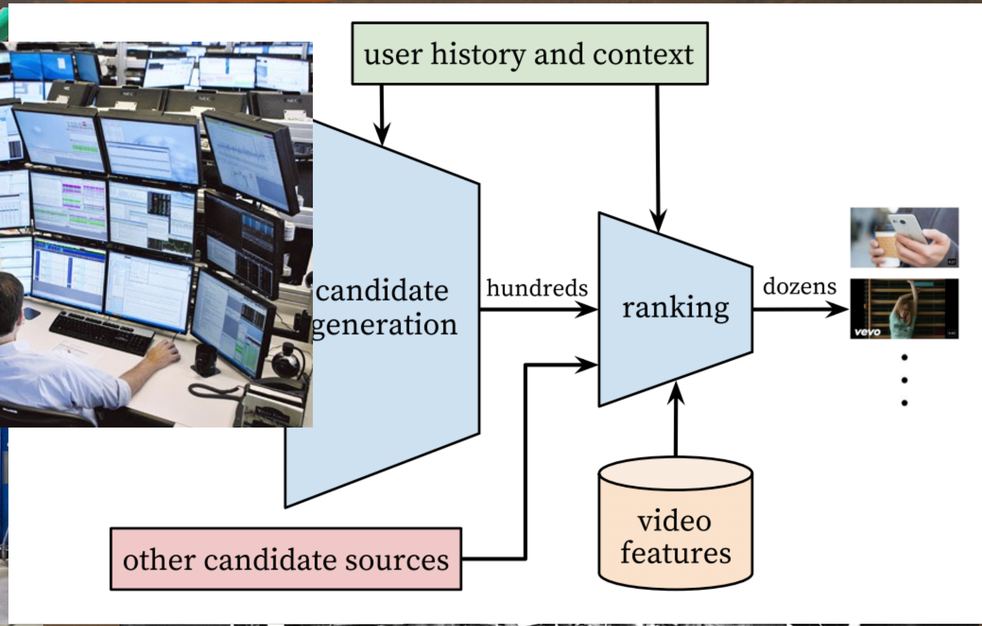


















RL Applications

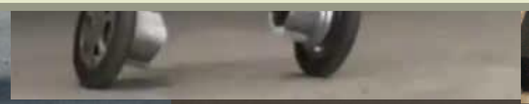
Market trends, timing of trades,

Games

Rob
Auton
Veh

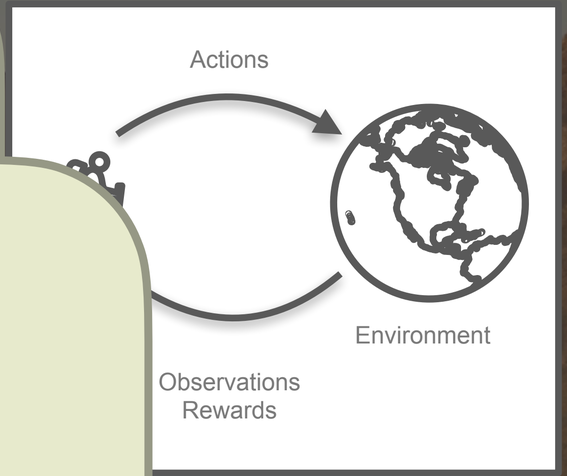


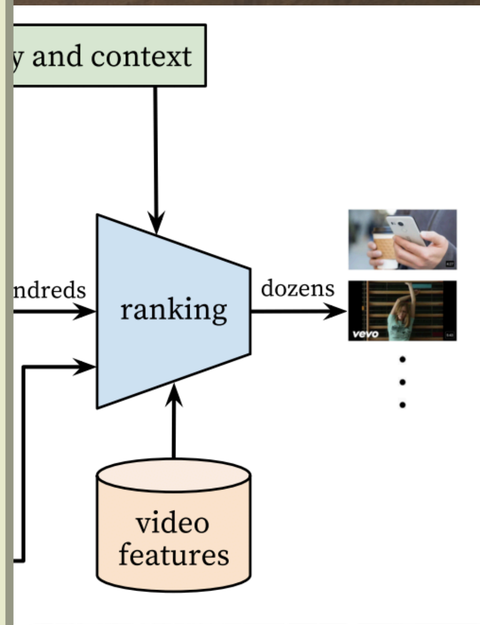












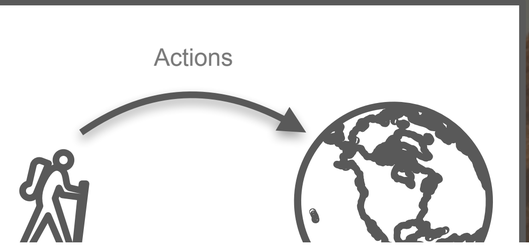
Common Theme:

The ideal applications have sequential, evolving state for the environment plus the agent.

RL Applications

ChatGPT!

https://openai.com/blog/chatgpt/



https://openai.com/blog/chatgpt/

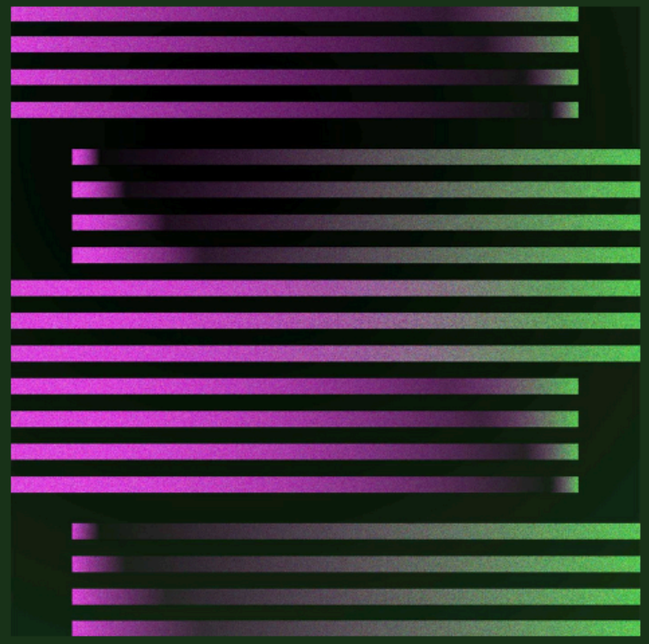
Introducing ChatGPT research release Try↗ Learn more›

OpenAI API RESEARCH BLOG ABOUT

ChatGPT: Optimizing Language Models for Dialogue

We've trained a model called ChatGPT which interacts in a conversational way. The dialogue format makes it possible for ChatGPT to answer followup questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests. ChatGPT is a sibling model to InstructGPT, which is trained to follow an instruction in a prompt and provide a detailed response.

TRY CHATGPT ↗

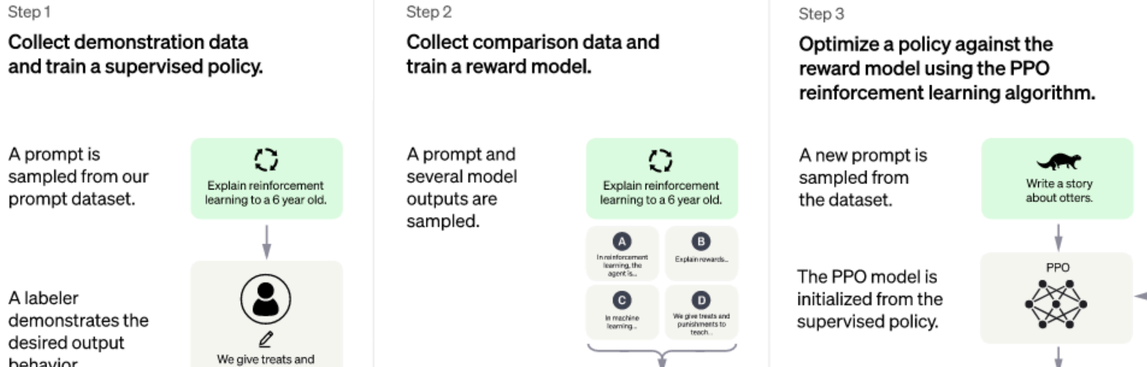


November 30, 2022
13 minute read

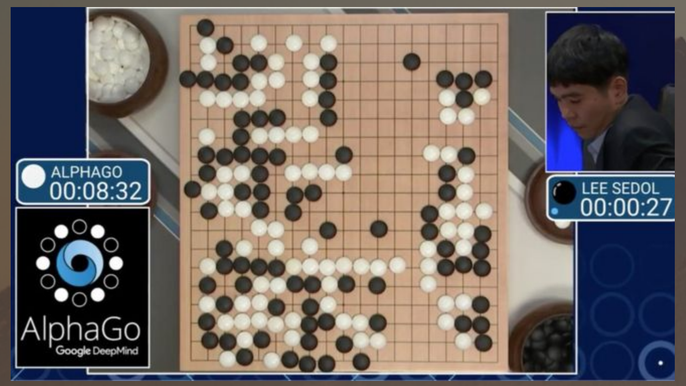
Methods

We trained this model using Reinforcement Learning from Human Feedback (RLHF), using the same methods as InstructGPT, but with slight differences in the data collection setup. We trained an initial model using supervised fine-tuning: human AI trainers provided conversations in which they played both sides—the user and an AI assistant. We gave the trainers access to model-written suggestions to help them compose their responses. We mixed this new dialogue dataset with the InstructGPT dataset, which we transformed into a dialogue format.

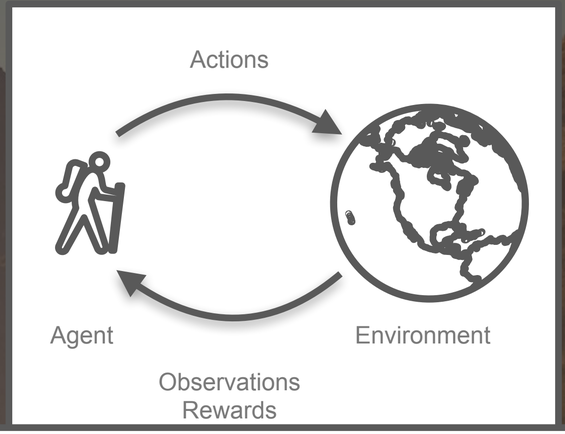
To create a reward model for reinforcement learning, we needed to collect comparison data, which consisted of two or more model responses ranked by quality. To collect this data, we took conversations that AI trainers had with the chatbot. We randomly selected a model-written message, sampled several alternative completions, and had AI trainers rank them. Using these reward models, we can fine-tune the model using Proximal Policy Optimization. We performed several iterations of this process.



AlphaGo example

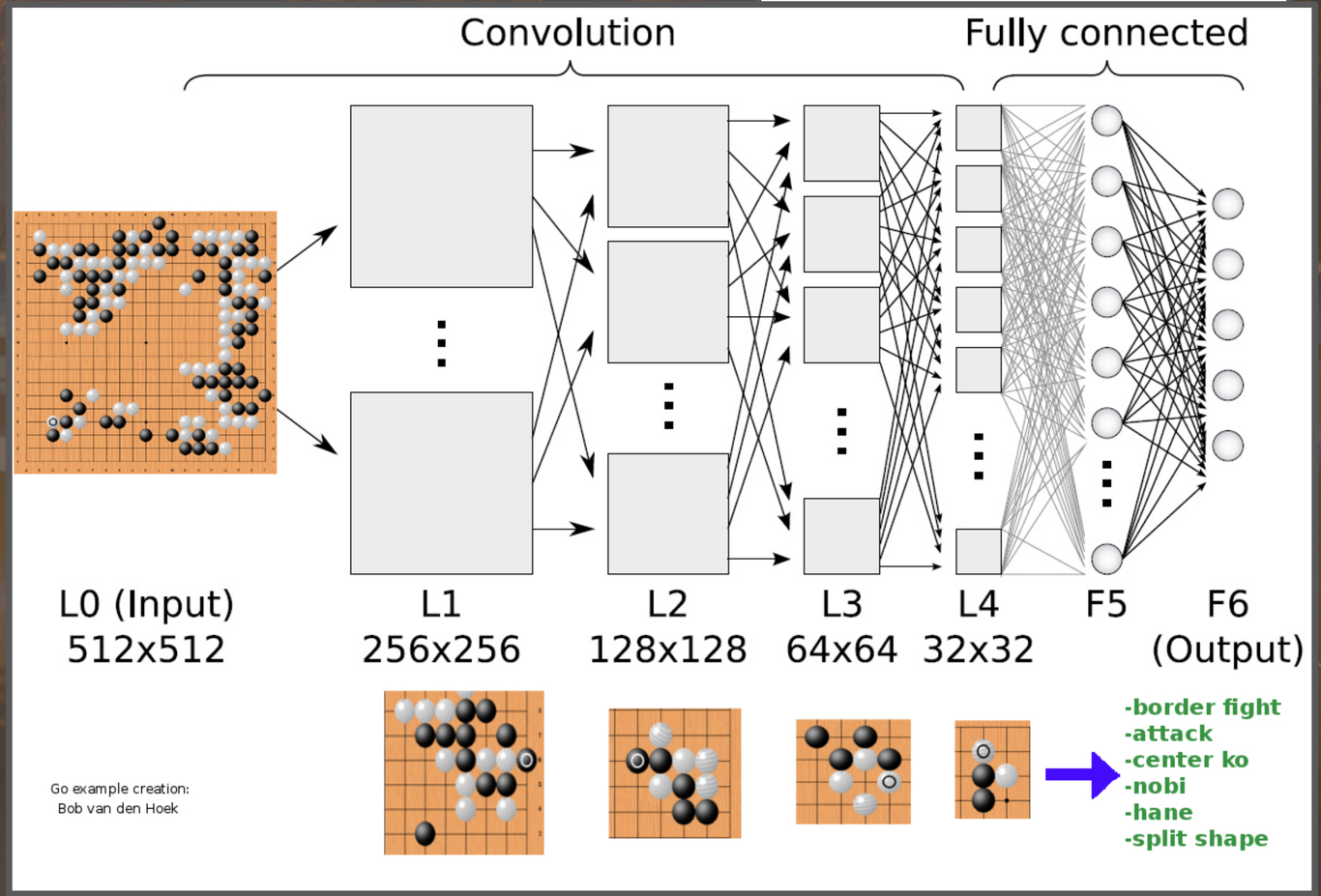


Deep Reinforcement Learning



AlphaGo (Silver et al. 2016)

- **Observations**:
  - board state
- **Actions**:
  - where to place the stones
- **Rewards**:
  - 1 if you win
  - 0 otherwise




Ray RLlib

https://docs.ray.io/en/master/rllib/index.html

RAY Get started Use cases Libraries Docs Resources

Ray 3.0.0.dev0

Search the docs ...

OVERVIEW

Getting Started Guide

Installing Ray

Ray Use Cases

The Ray Ecosystem

RAY AI RUNTIME

What is Ray AI Runtime (AIR)?

Key Concepts

User Guides

Examples

Ray AIR API

Benchmarks

RAY LIBRARIES

Ray Data

Ray Train

Ray Tune

Ray Serve

Ray RLlib

Getting Started with RLlib

Key Concepts

Environments

Algorithms

User Guides

Examples

Ray RLlib API

RLlib: Industry-Grade Reinforcement Learning



RLlib is an open-source library for reinforcement learning (RL), offering support for production-level, highly distributed RL workloads while maintaining unified and simple APIs for a large variety of industry applications. Whether you would like to train your agents in a **multi-agent** setup, purely from **offline** (historic) datasets, or using **externally connected simulators**, RLlib offers a simple solution for each of your decision making needs.

If you either have your problem coded (in python) as an RL environment or own lots of pre-recorded, historic behavioral data to learn from, you will be up and running in only a few days.

RLlib is already used in production by industry leaders in many different verticals, such as climate control, industrial control, manufacturing and logistics, finance, gaming, automobile, robotics, boat design, and many others.

RLlib in 60 seconds



It only takes a few steps to get your first RLlib workload up and running on your laptop.

RLlib does not automatically install a deep-learning framework, but supports **TensorFlow** (both 1.x with static-graph and 2.x with eager mode) as well as **PyTorch**. Depending on your needs, make sure to install either TensorFlow or PyTorch (or both, as shown below):

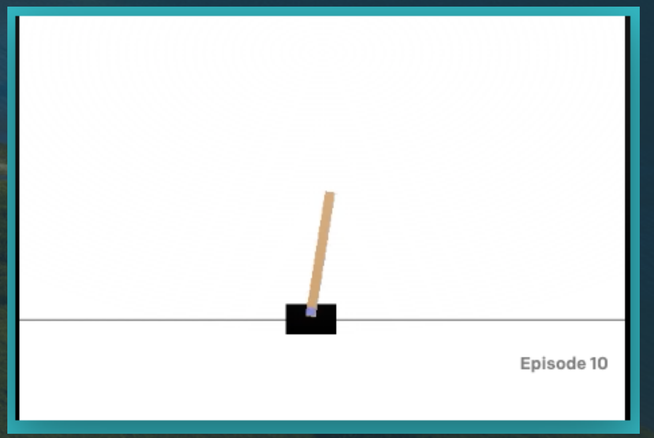
rllib.io


To Try It Out...

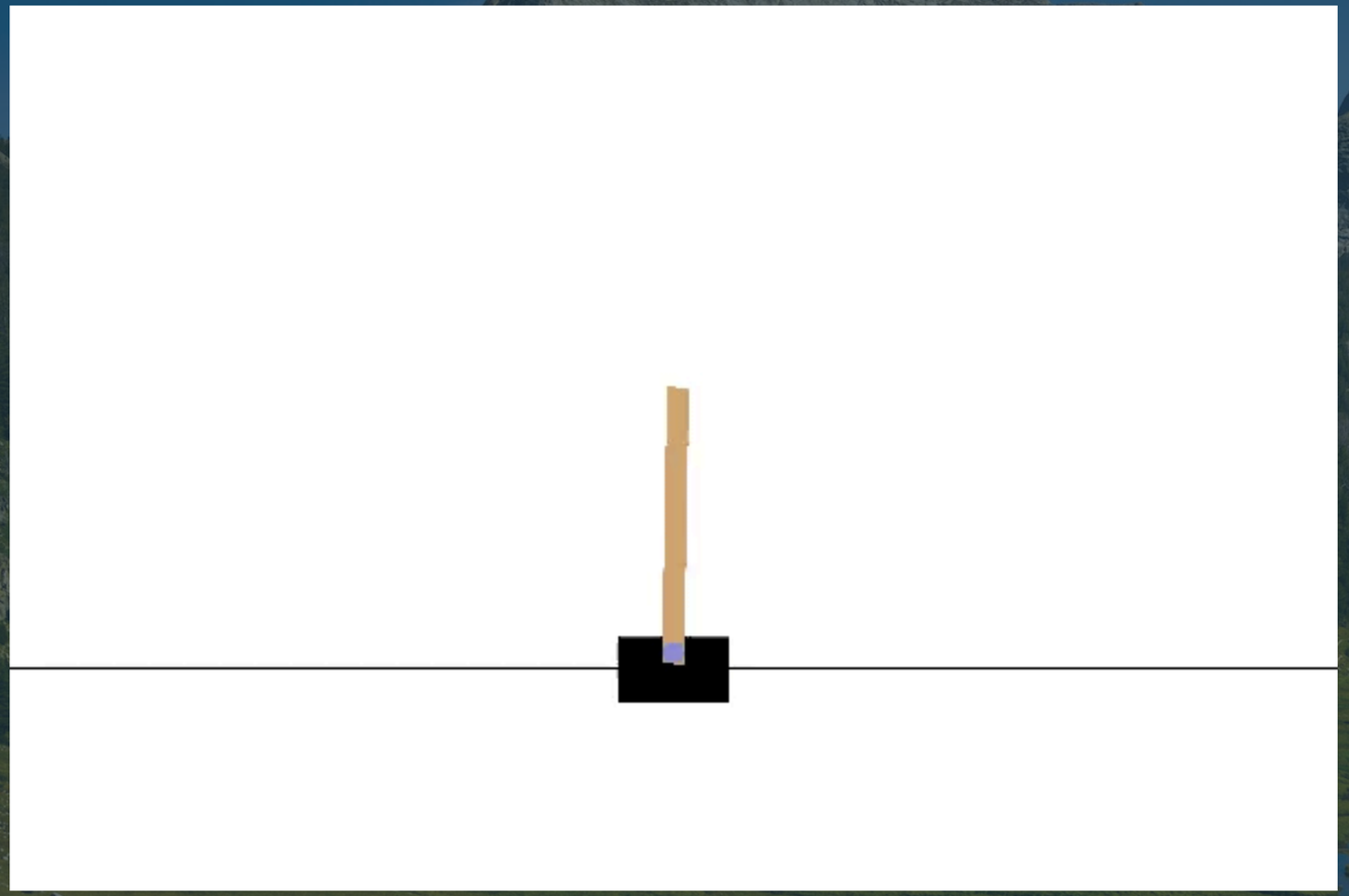
```
# Install what we need:
$ pip install "ray[rllib]" tensorflow \
  tensorflow-probability pygame

# Train CartPole using DQN, stop after 100 iterations:
# At end, will print the next command to run:
$ rllib train --algo DQN --env 'CartPole-v1' \
  --stop '{"training_iteration": 200}'

# Run CartPole and see how well it goes:
$ rllib evaluate /path/to/checkpoint --algo DQN
```

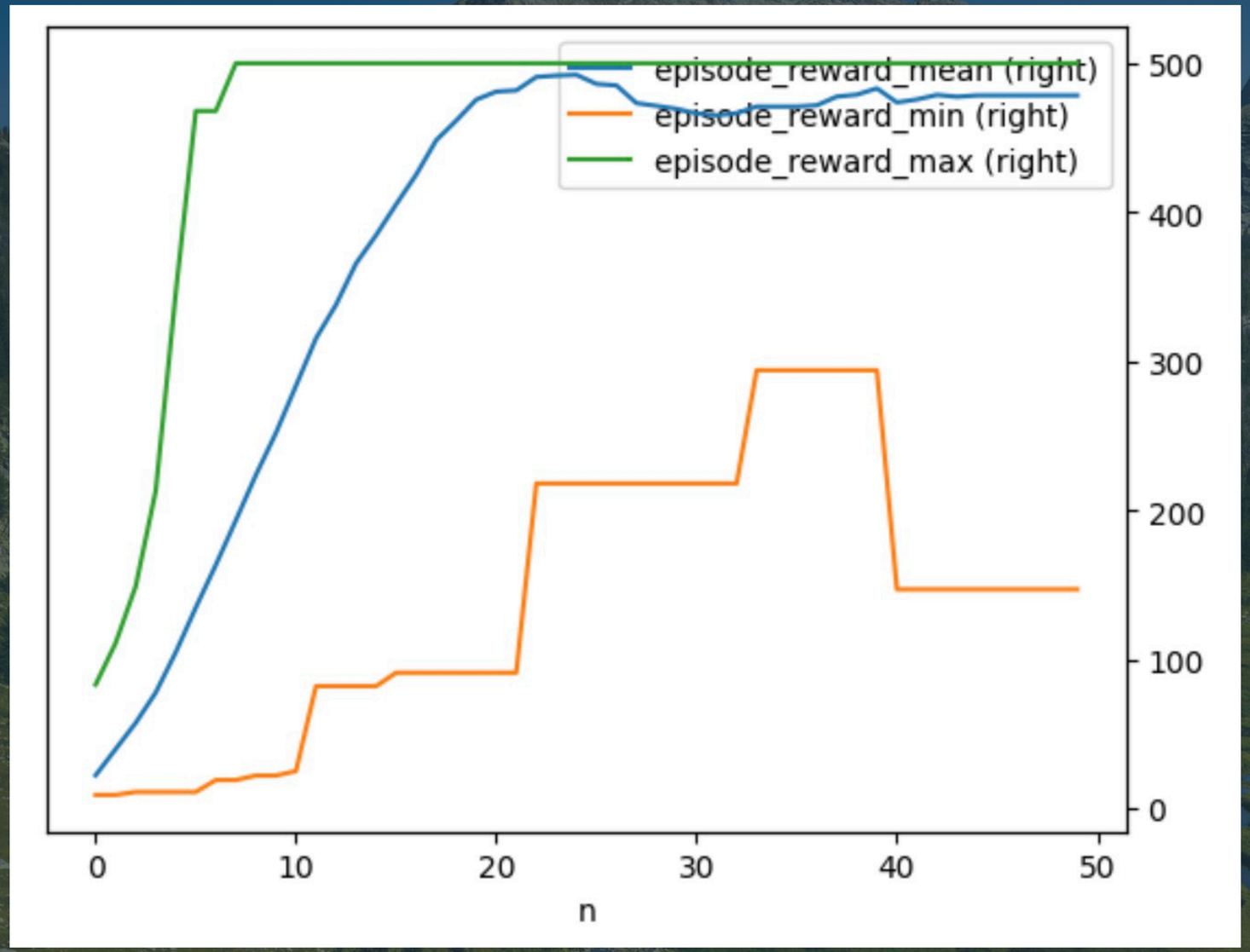


To Try It Out...



Example episode after training.

To Try It Out…



Training n=50 episodes with PPO. Max score is 500. Note that the average actually dips above 20 episodes. Probably overfitting?

To Try It Out…

RLlib Benefits

- Rich set of RL algorithms
  - … and features for building your own.
- Integrated with OpenAI Gym/Gymnasium
  - … and you can build your own environments.
- Integrated with PyTorch and TensorFlow.
- Excellent performance… from Ray!

More Reinforcement Learning Concepts and Challenges



Exploitation vs. Exploration

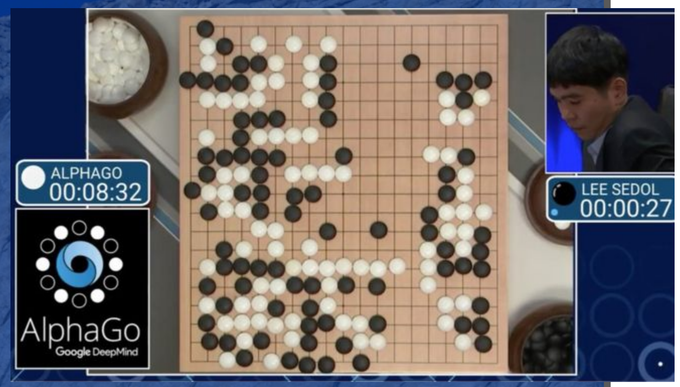


What if the agent finds an action with a good short-term reward? Should it keep exploiting it?

Or, should it explore other actions, in case even better options exist?

The "Exploitation vs. Exploration Tradeoff"

What Makes a Good Reward?





Games often only provide a reward at the end of the episode - win or lose.

What about intermediate rewards?

Crafting rewards is hard. Intermediate rewards can lead to greedy optimization and local optima rather than the desired global optima - the cumulative reward.

Environments and Offline RL



What if you want to train a system for optimizing a chemical plant?

You can't let a naïve policy drive your plant while it learns!! The plant might be too complex to simulate, too. The higher the stakes, the greater the fidelity required.

However, since the environment "generates" data in normal RL, what about using historical data, instead?

Offline RL works with historical data instead of interacting with the environment.



Reinforcement Learning and ChatGPT

“Reinforcement Learning from Human Feedback” (RLHF)

Useful references:

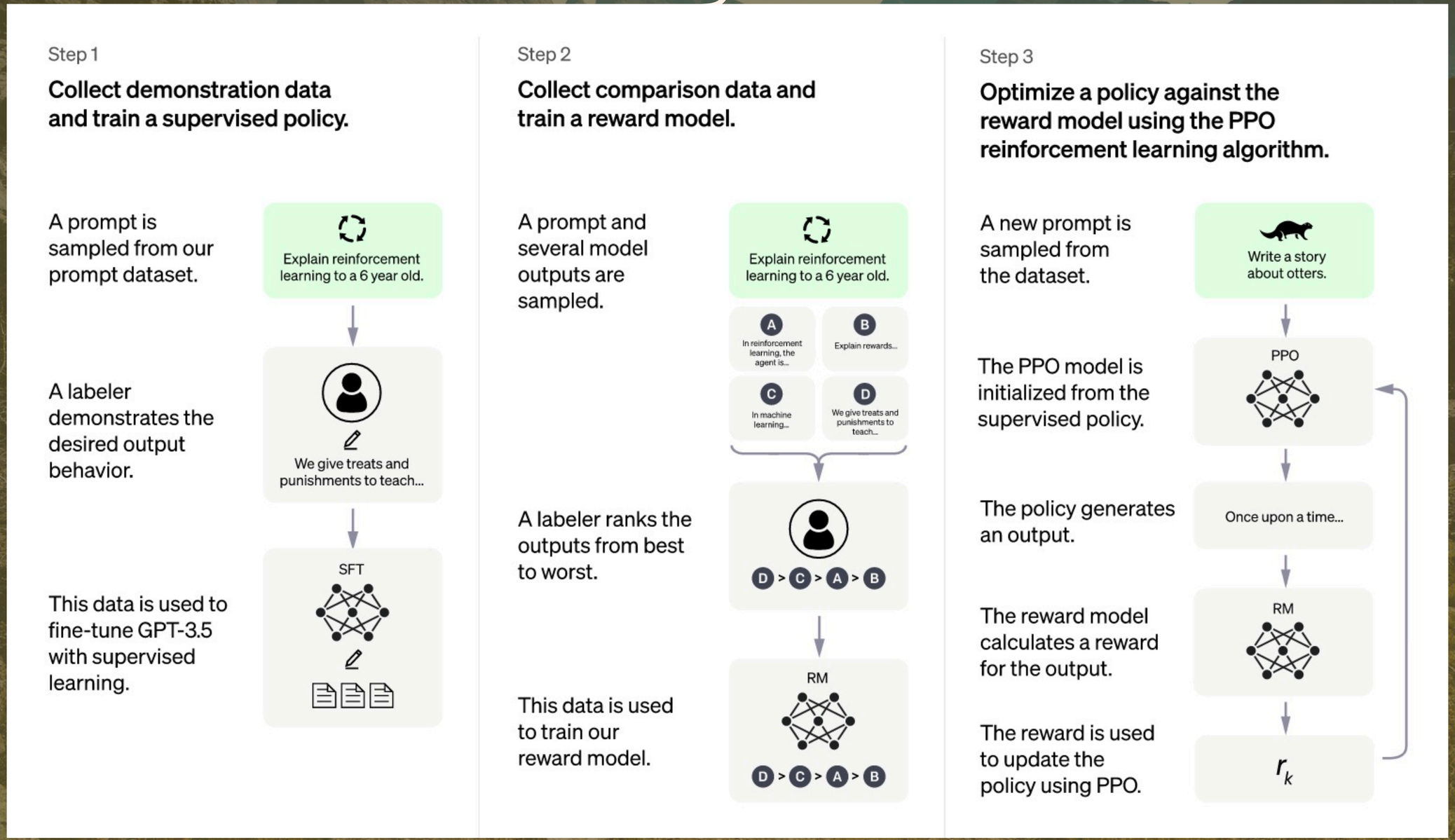
- https://openai.com/blog/chatgpt
- huggingface.co/blog/rlhf



Writing a loss function to capture these attributes seems intractable and most language models are still trained with a simple next token prediction loss (e.g. cross entropy). To compensate for the shortcomings of the loss itself people define metrics that are designed to better capture human preferences such as BLEU or ROUGE. While being better suited than the loss function itself at measuring performance these metrics simply compare generated text to references with simple rules and are thus also limited. Wouldn't it be great if we use human feedback for generated text as a measure of performance or go even one step further and use that feedback as a loss to optimize the model? That's the idea of Reinforcement Learning from Human Feedback (RLHF); use methods from reinforcement learning to directly optimize a language model with human feedback. RLHF has enabled language models to begin to align a model trained on a general corpus of text data to that of complex human values.

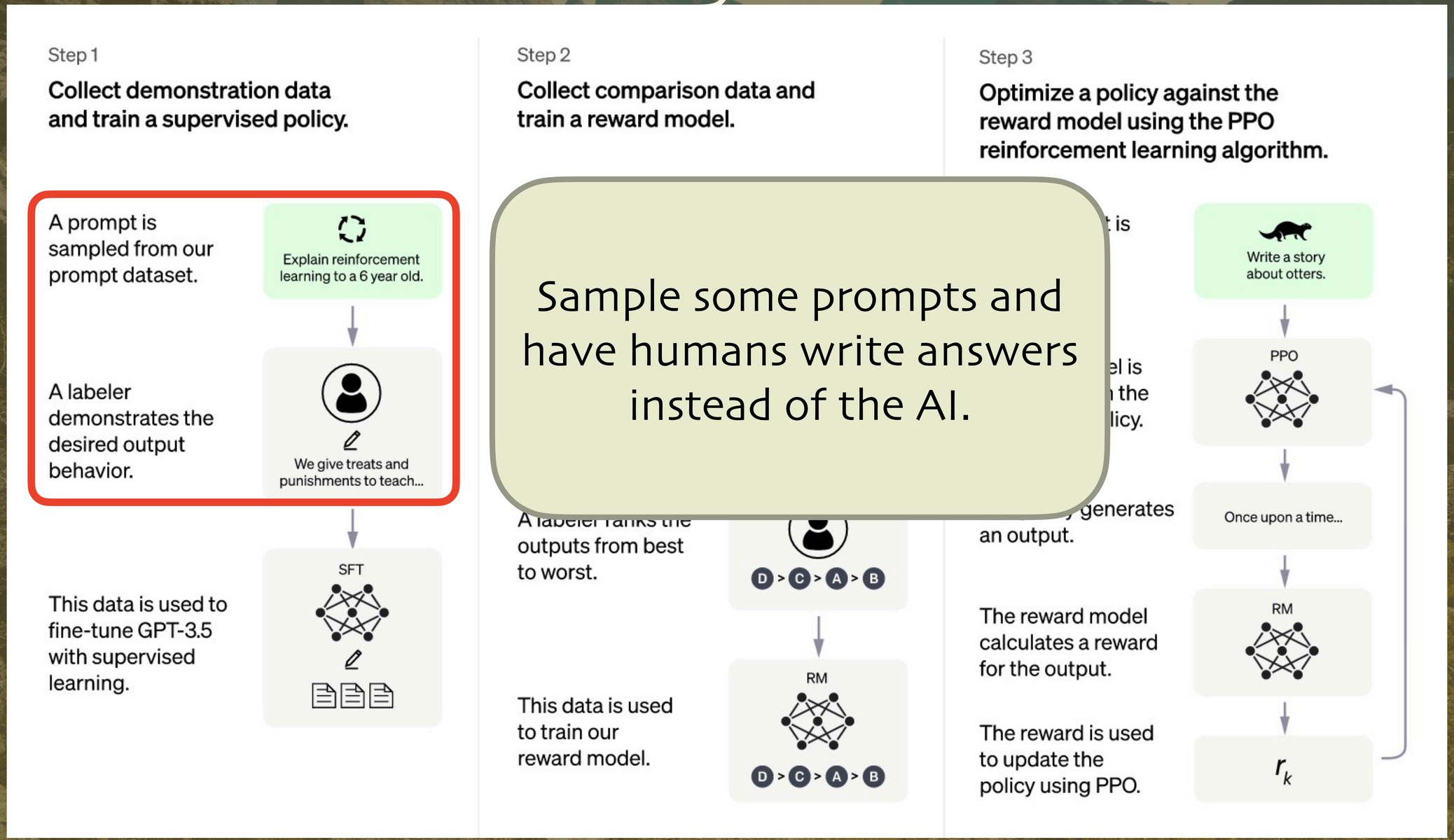


Reinforcement Learning from Human Feedback



Credit: openai.com/blog/chatgpt

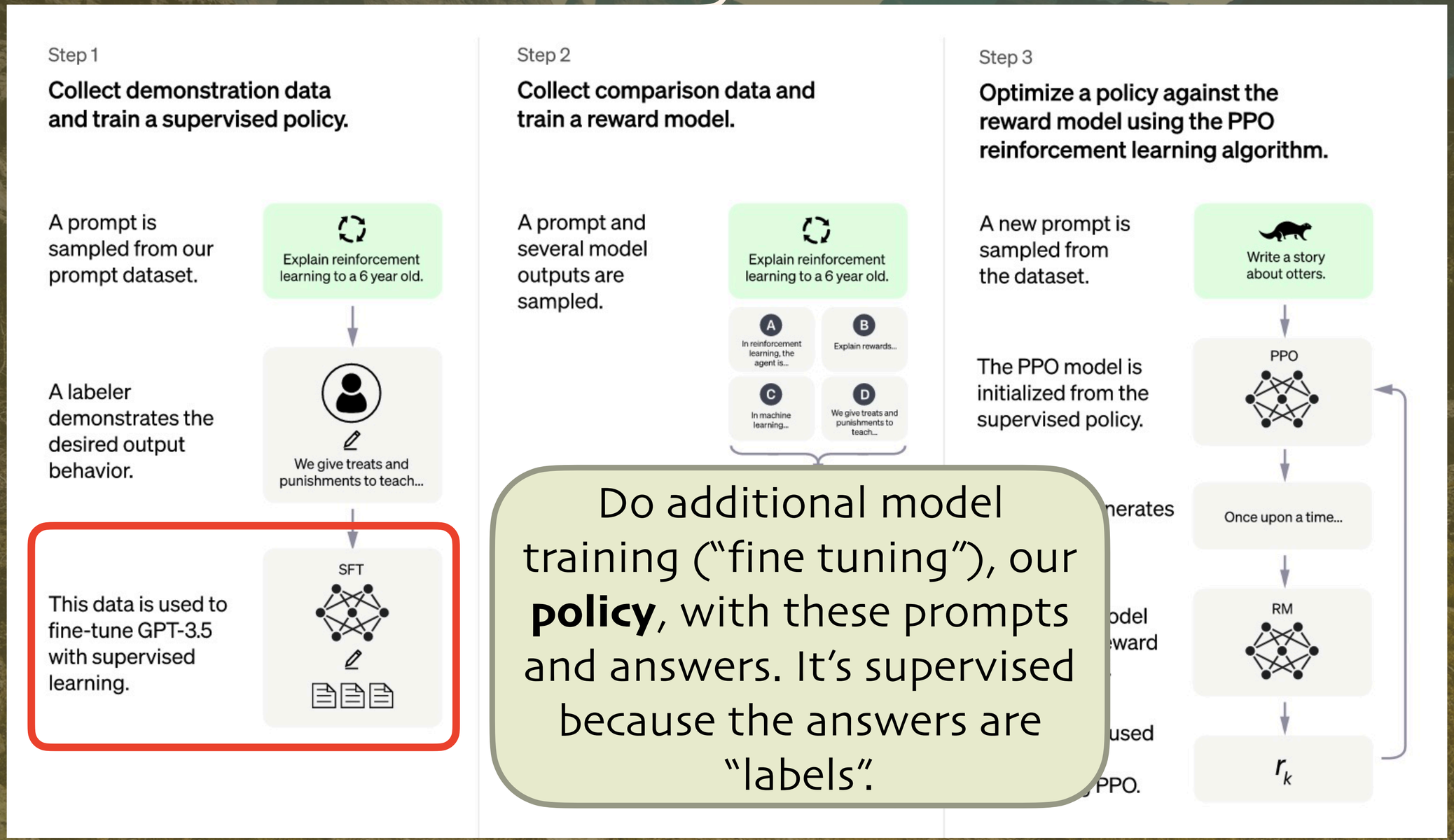
Reinforcement Learning from Human Feedback



Sample some prompts and have humans write answers instead of the AI.

Credit: openai.com/blog/chatgpt

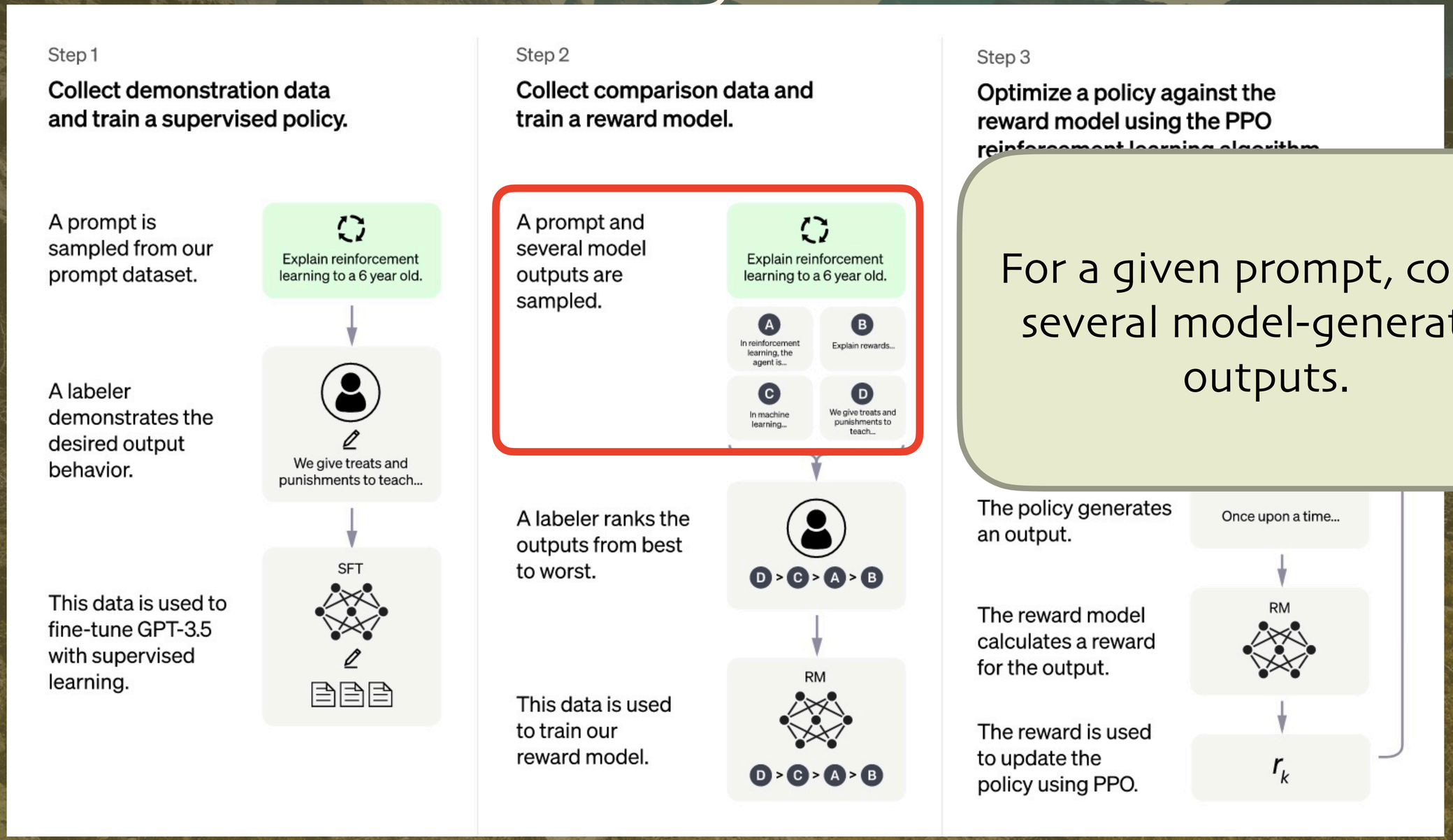
Reinforcement Learning from Human Feedback



Do additional model training ("fine tuning"), our **policy**, with these prompts and answers. It's supervised because the answers are "labels".

Credit: openai.com/blog/chatgpt

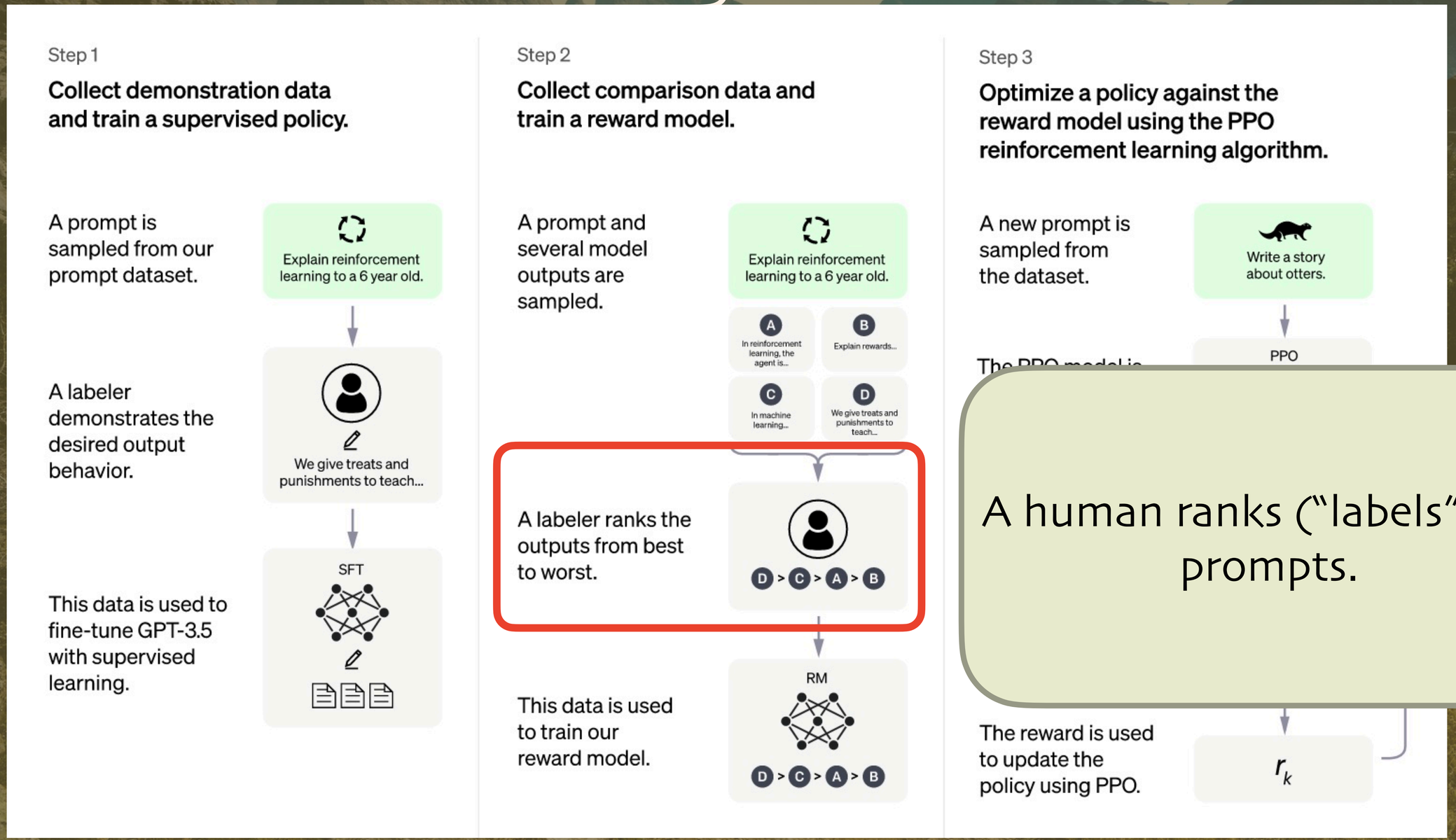
Reinforcement Learning from Human Feedback



For a given prompt, collect several model-generated outputs.

Credit: openai.com/blog/chatgpt

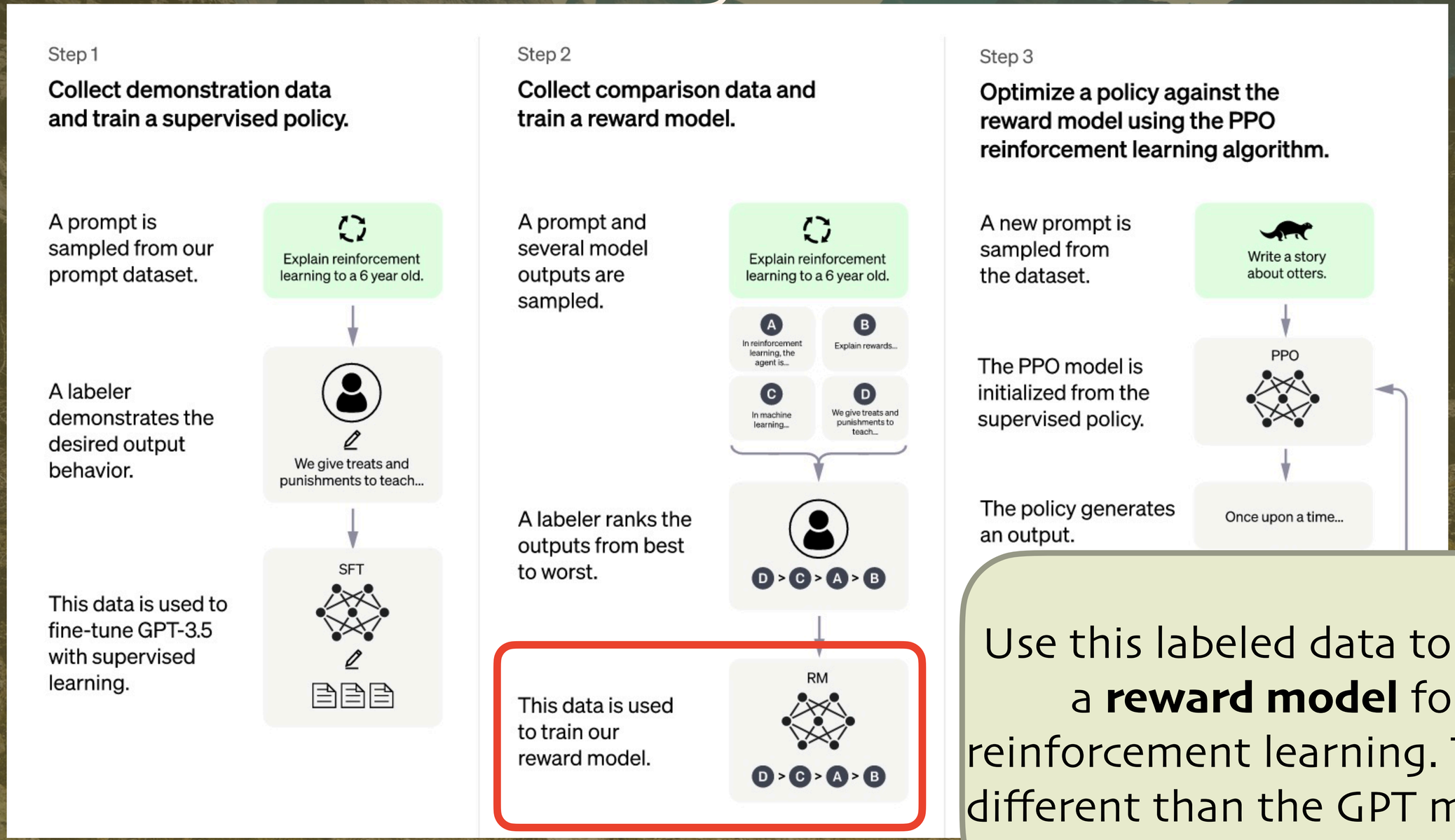
Reinforcement Learning from Human Feedback



A human ranks ("labels") the prompts.

Credit: openai.com/blog/chatgpt

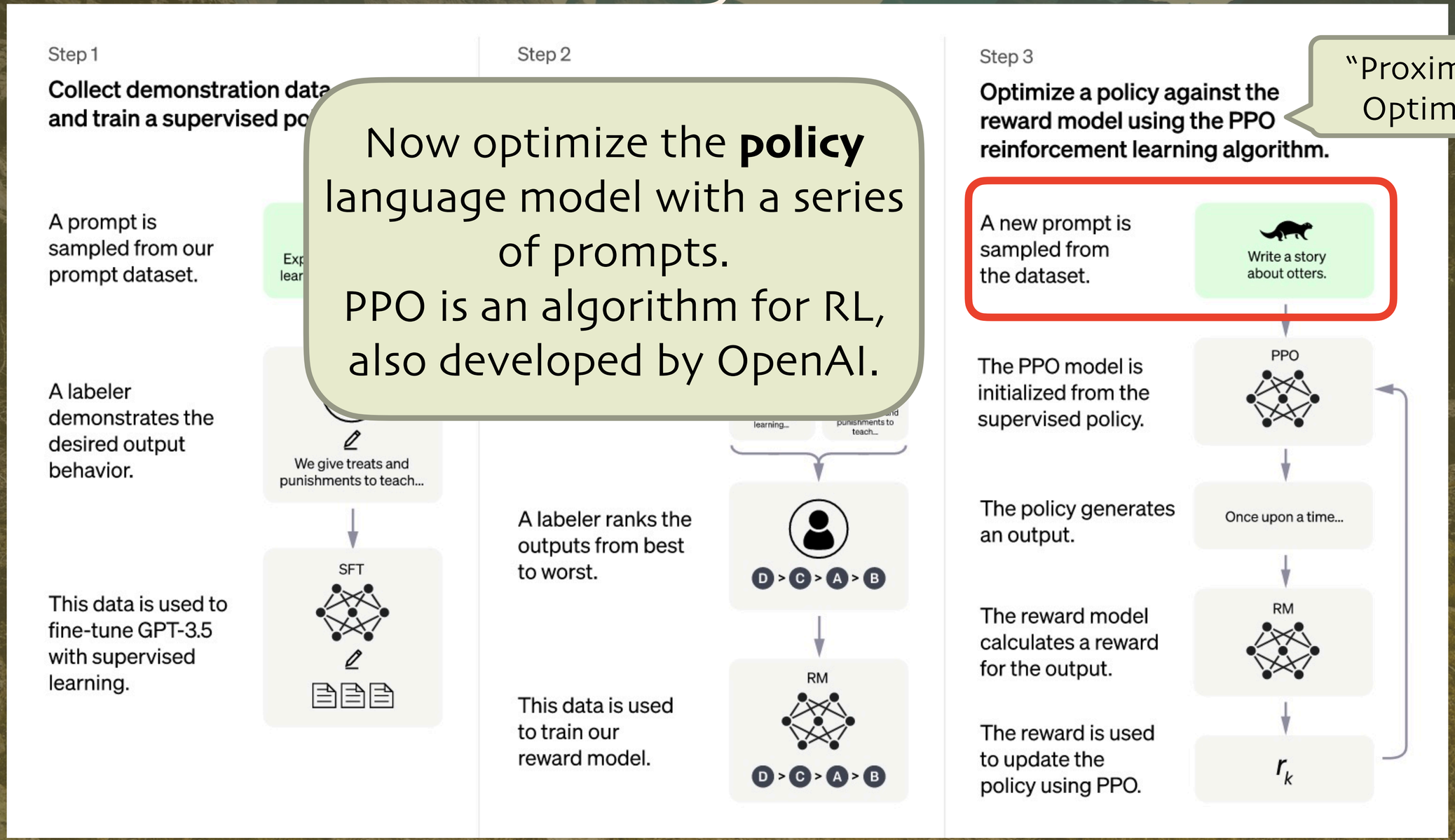
Reinforcement Learning from Human Feedback



Use this labeled data to train a **reward model** for reinforcement learning. This is different than the GPT model!

Credit: openai.com/blog/chatgpt

Reinforcement Learning from Human Feedback

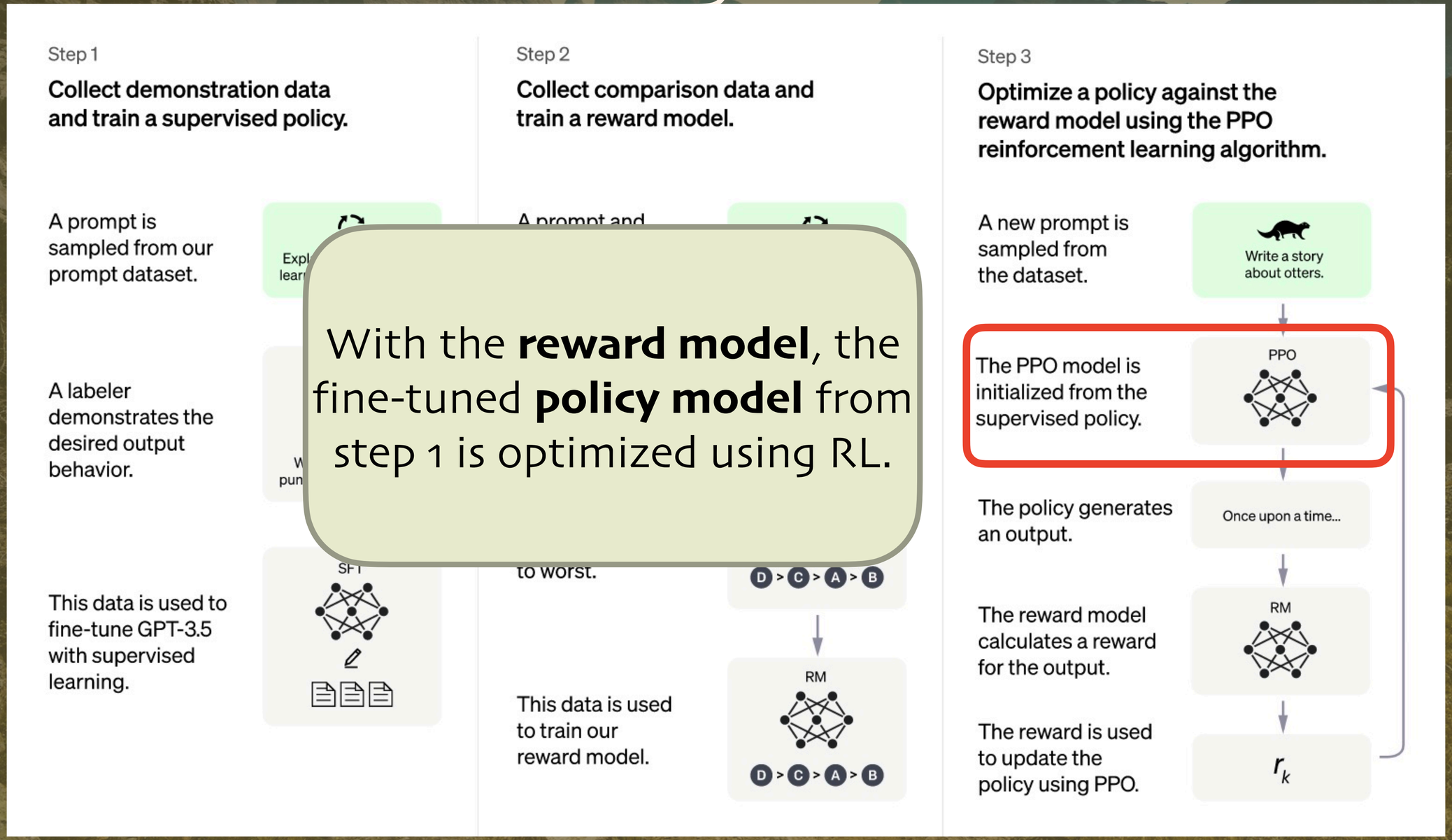


Now optimize the **policy** language model with a series of prompts.
PPO is an algorithm for RL, also developed by OpenAI.

"Proximal Policy Optimization"

Credit: openai.com/blog/chatgpt

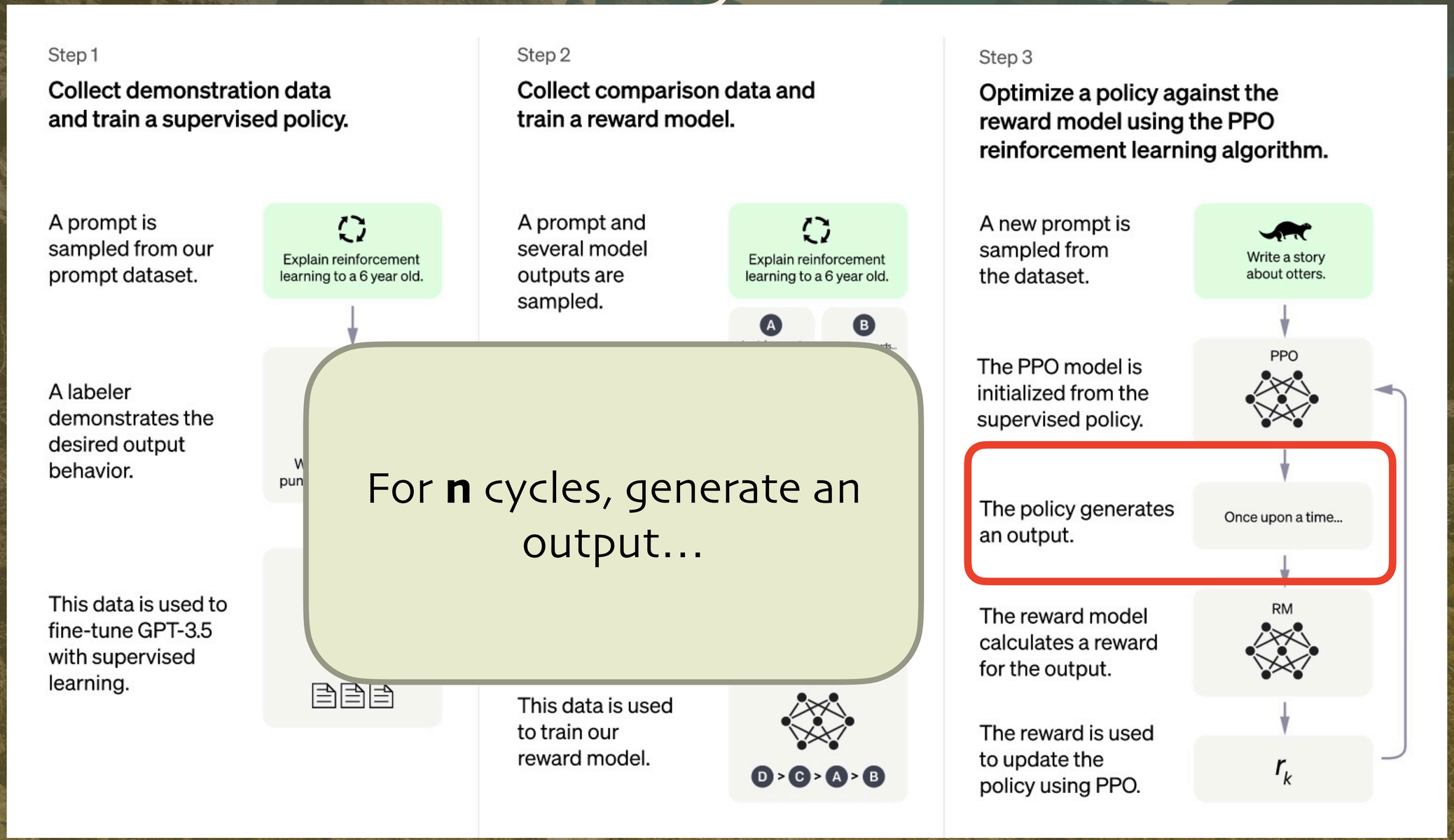
Reinforcement Learning from Human Feedback



With the **reward model**, the fine-tuned **policy model** from step 1 is optimized using RL.

Credit: openai.com/blog/chatgpt

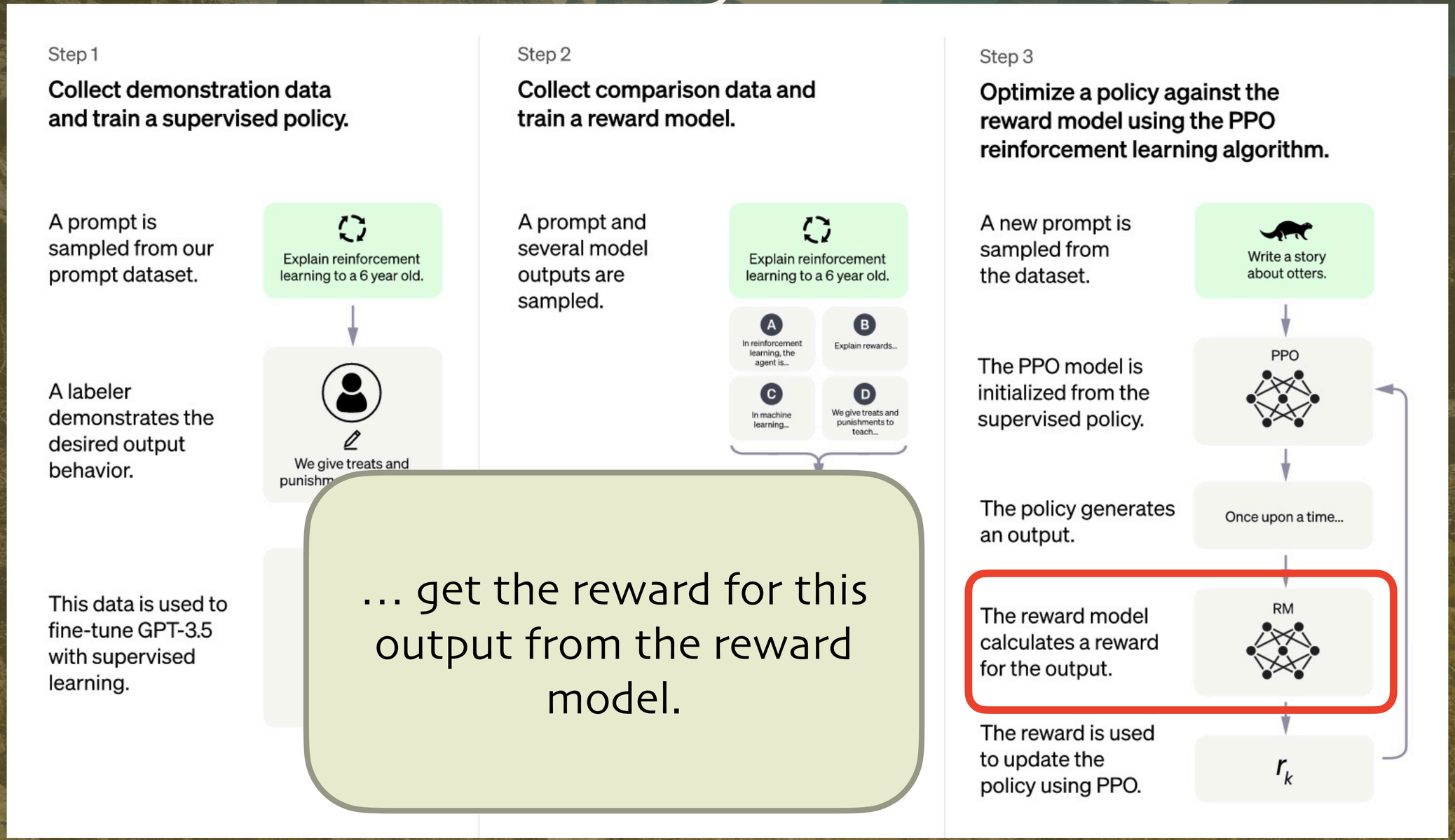
Reinforcement Learning from Human Feedback



For **n** cycles, generate an output…

Credit: openai.com/blog/chatgpt

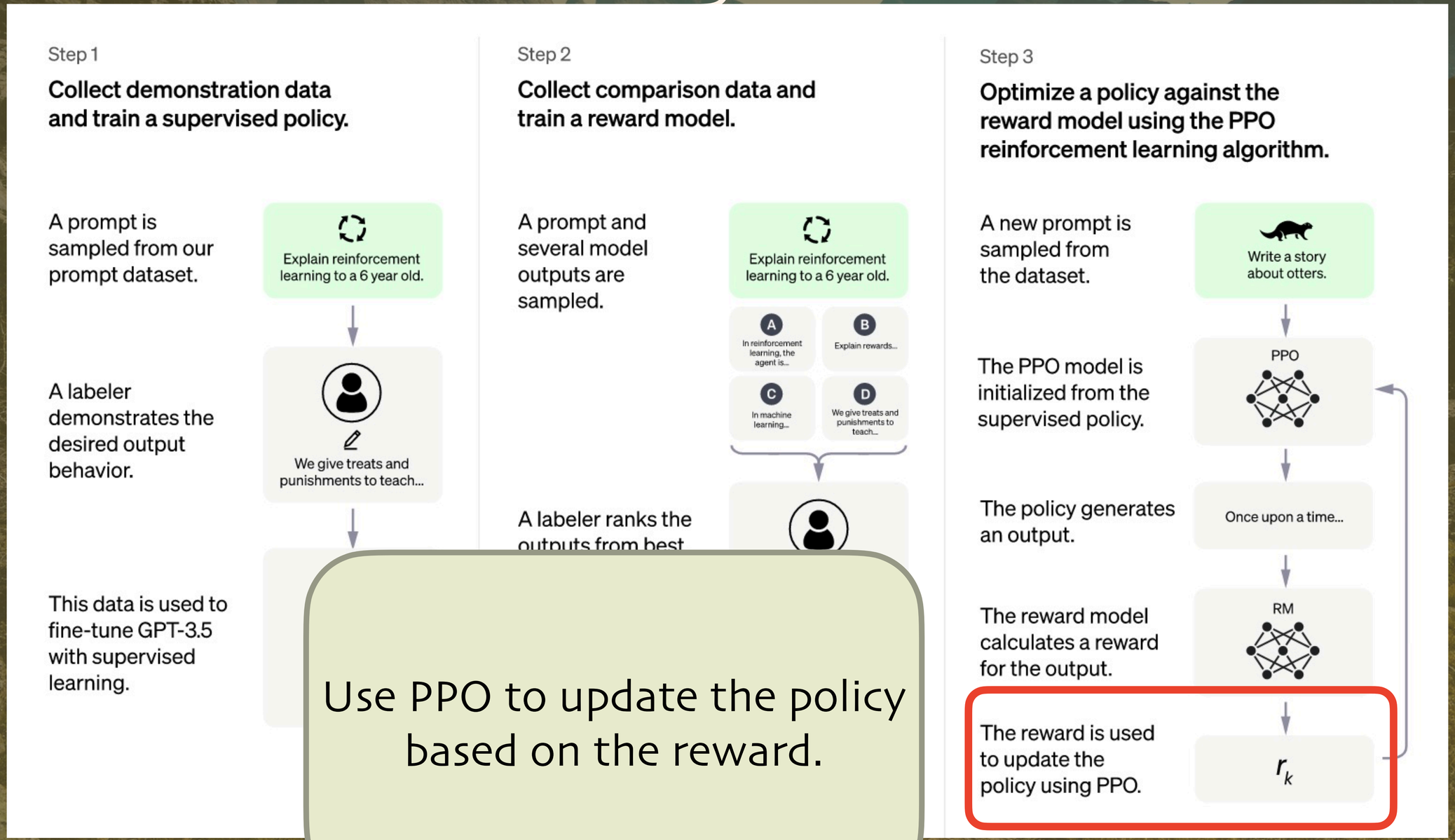
Reinforcement Learning from Human Feedback



… get the reward for this output from the reward model.

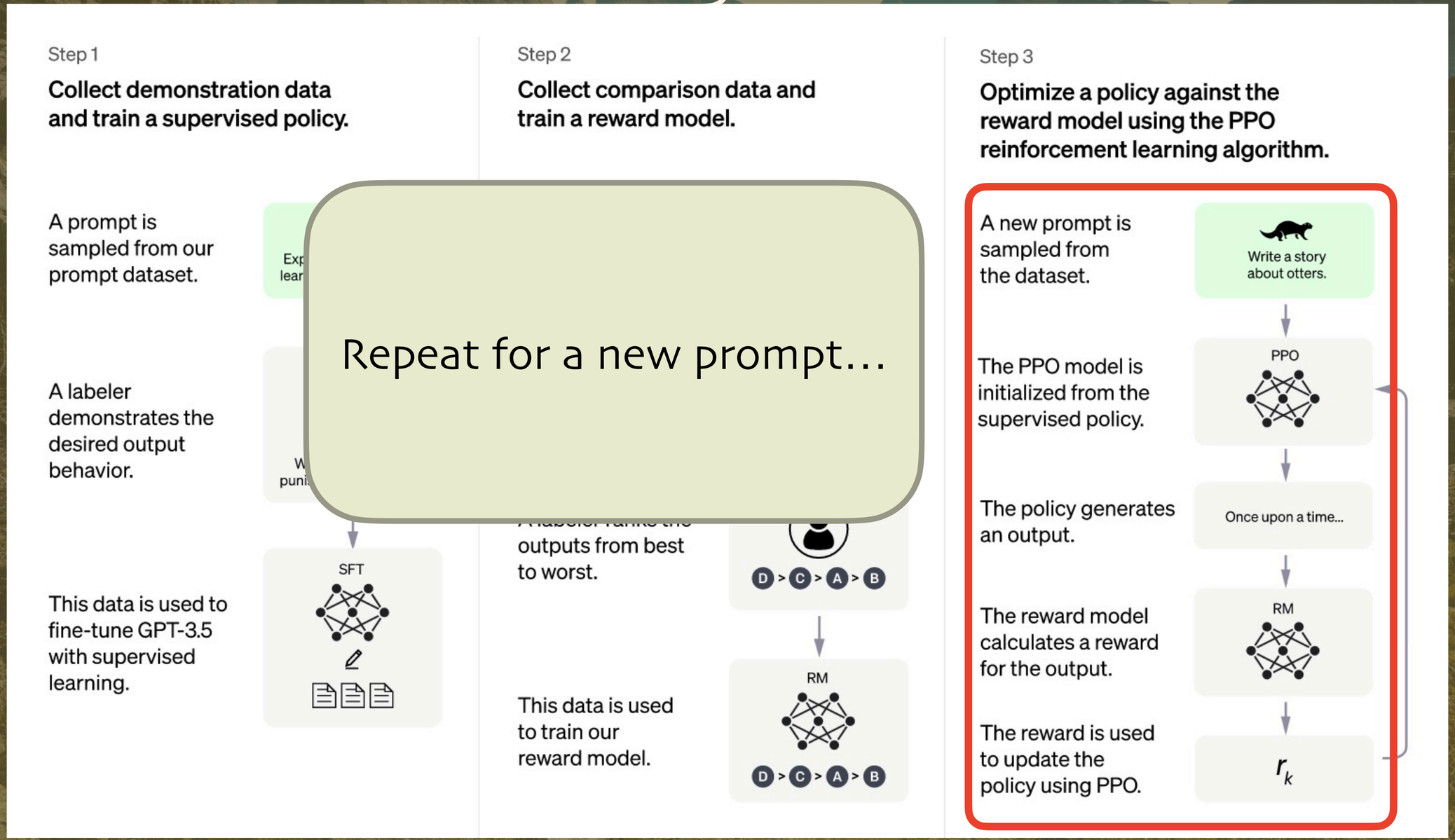
Credit: openai.com/blog/chatgpt

Reinforcement Learning from Human Feedback



Use PPO to update the policy based on the reward.

Reinforcement Learning from Human Feedback



Repeat for a new prompt…

Credit: openai.com/blog/chatgpt



Reinforcement Learning for Recommendations and Ad Placements

Preferences Change…



- You bought a toilet brush.
  - Do you want to keep seeing ads for toilet brushes?
- You've watched five action movies in a row.
  - Do you want to watch a sixth action movie or maybe watch something else for a change?

Preferences Change…

- How have your interests changed because of:
  - the weather
  - the economy
  - local, national, or world affairs
  - ???



RL for recommendations/ads helps with evolving preferences.

Considerations

- RL is less able to scale to large state spaces (e.g., all available movies catalog items).
- Traditional supervised learning methods are more scalable.



Real recommendation and ad systems must combine approaches; use RL once a subset of the state space is identified using a "classic" supervised learning approach.

Considerations

- A simulator is used to model real user behavior. (Training with real users doesn't scale well, etc.)



Or use offline RL with historical data about user behavior!

Considerations

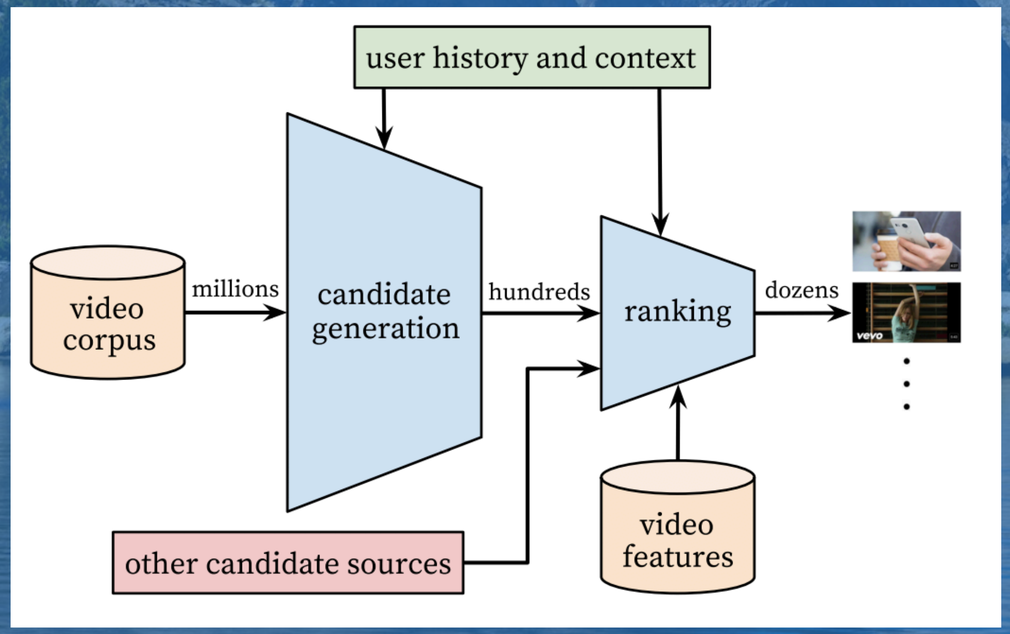
- What is the reward? Some combination of user happiness measures?
- Could be very specific to the sub-genre of entertainment or product category.



Reward calculation balances mixed preferences & tradeoffs as they evolve in response to use actions.

Considerations

- YouTube! Research:
  - research.google/pubs/pub45530/





See the Anyscale RL tutorial link at the end for a Recommendation example

goto;

Don't forget to
vote for this session
in the **GOTO Guide app**

To Learn More…

- rllib.io
- ray.io
- Anyscale RL & RLlib course:
  - https://applied-rl-course.netlify.app/en
- More resources in the extra slides!

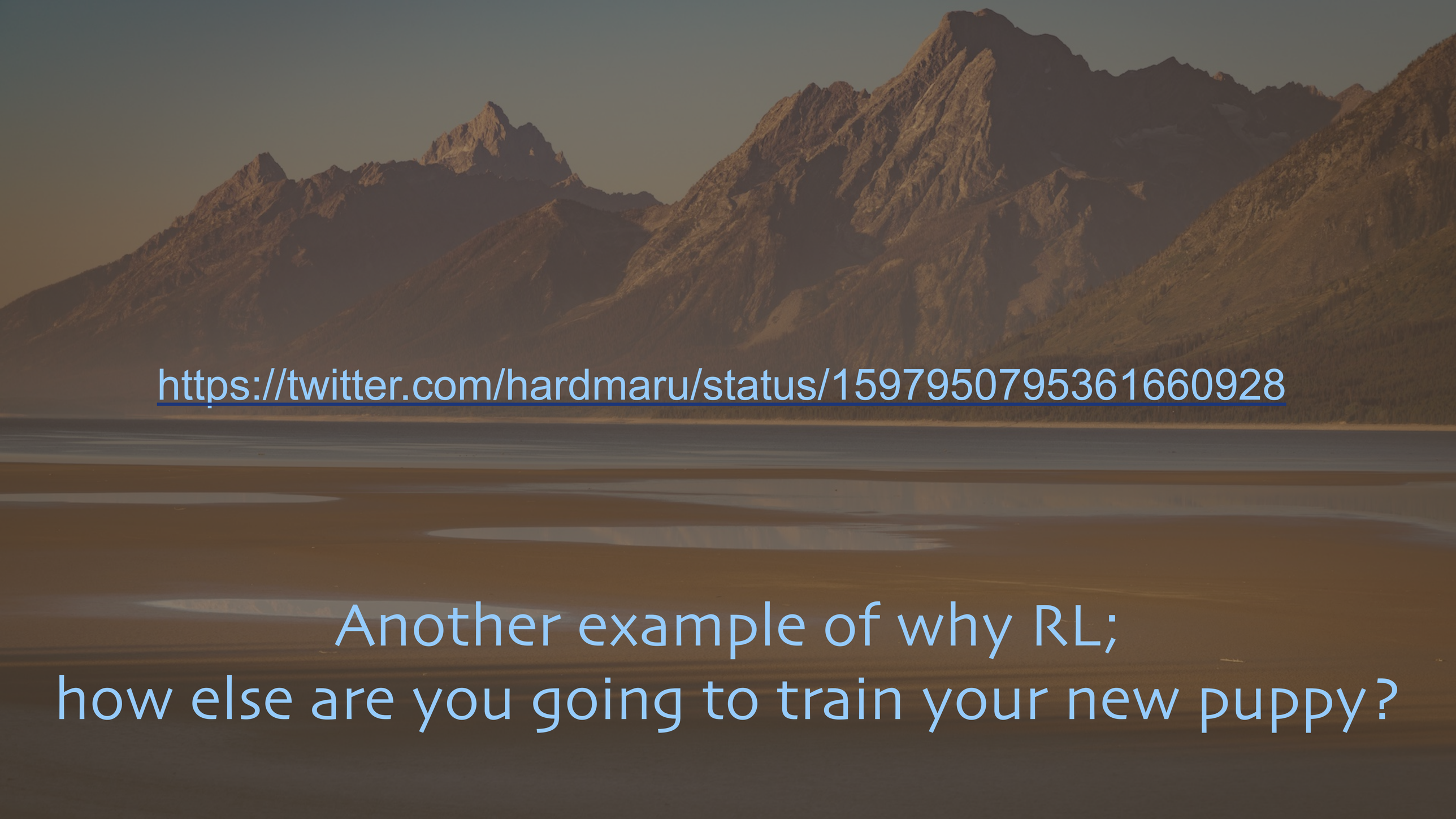
GOTO Chicago, May 23, 2023
dean@deanwampler.com
deanwampler.com/talks
IBM Research
@discuss.systems@deanwampler
@deanwampler

Extra Material



To Learn More…

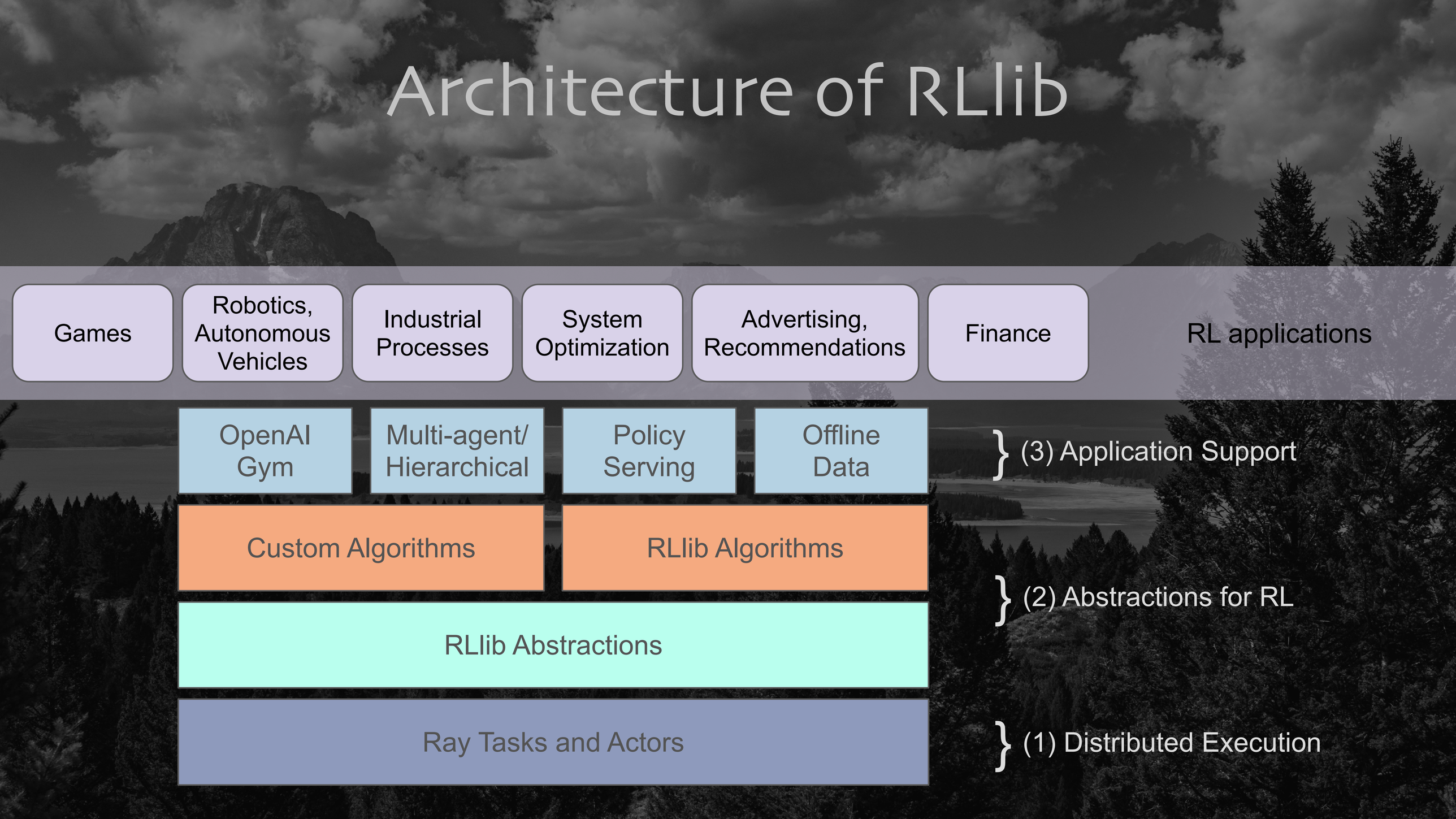
- Courses
  - Hugging Face RL course https://huggingface.co/deep-rl-course/
  - Delta Academy https://delta-academy.xyz/
  - Fast Deep RL https://courses.dibya.online/p/fastdeeprl
  - Coursera RL Specialization from U of A https://www.coursera.org/specializations/reinforcement-learning
  - Udacity RL coursehttps://www.udacity.com/course/reinforcement-learning--ud600
- Video lectures
  - David Silver's lectures https://www.davidsilver.uk/teaching/
  - Sergey Levine's lectures http://rail.eecs.berkeley.edu/deeprlcourse/
- Books
  - Sutton & Barto http://incompleteideas.net/book/the-book-2nd.html (considered the definitive RL book)
  - Deep RL Hands-On https://www.packtpub.com/product/deep-reinforcement-learning-hands-on-second-edition/9781838826994
- Other
  - Spinning Up https://spinningup.openai.com/en/latest/ (a well-known resource for RL)
  - Illustrated RL from Human Feedback: https://huggingface.co/blog/rlhf


https://twitter.com/hardmaru/status/1597950795361660928
Another example of why RL;
how else are you going to train your new puppy?



More about RLlib

Architecture of RLlib

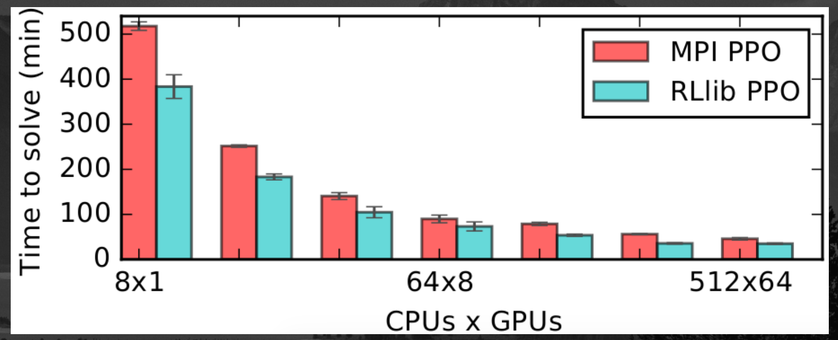


Some Algorithms in RLlib

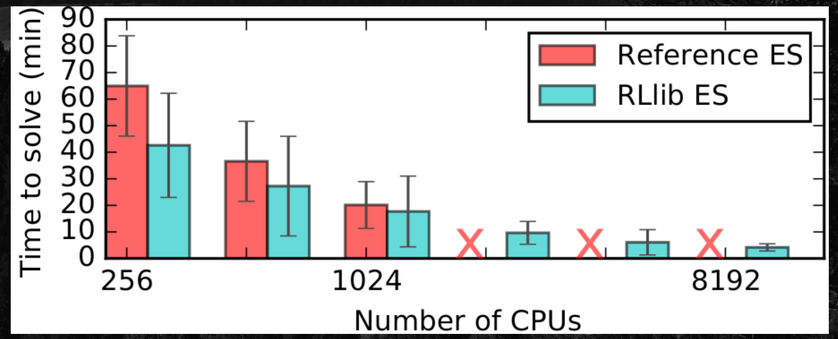
- High-throughput architectures
  - Distributed Prioritized Experience Replay (Ape-X)
  - Importance Weighted Actor-Learner Architecture (IMPALA)
  - Asynchronous Proximal Policy Optimization (APPO)
- Gradient-based
  - Soft Actor-Critic (SAC)
  - Advantage Actor-Critic (A2C, A3C)
  - Deep Deterministic Policy Gradients (DDPG, TD3)
  - Deep Q Networks (DQN, Rainbow, Parametric DQN)
  - Policy Gradients
  - Proximal Policy Optimization (PPO)
- gradient-free
  - Augmented Random Search (ARS)
  - Evolution Strategies
- Multi-agent specific
  - QMIX Monotonic Value Factorisation (QMIX, VDN, IQN)
- Offline
  - Advantage Re-Weighted Imitation Learning (MARWIL)

Excellent Performance vs. "Hand-tuned" Implementations

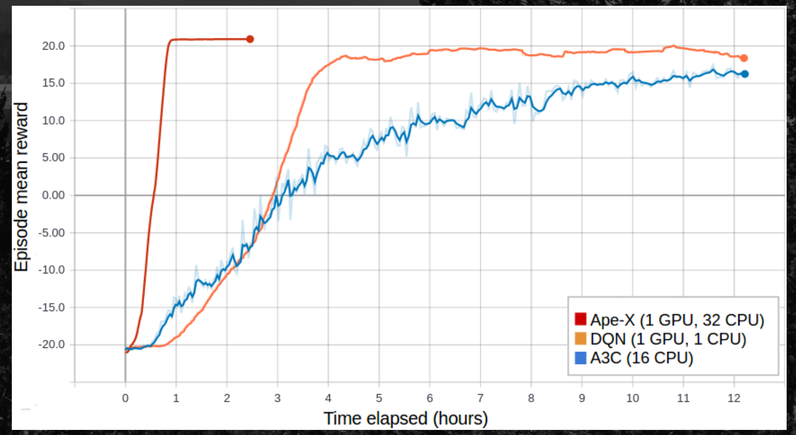
Distributed PPO



Evolution Strategies



Ape-X Distributed DQN, DDPG



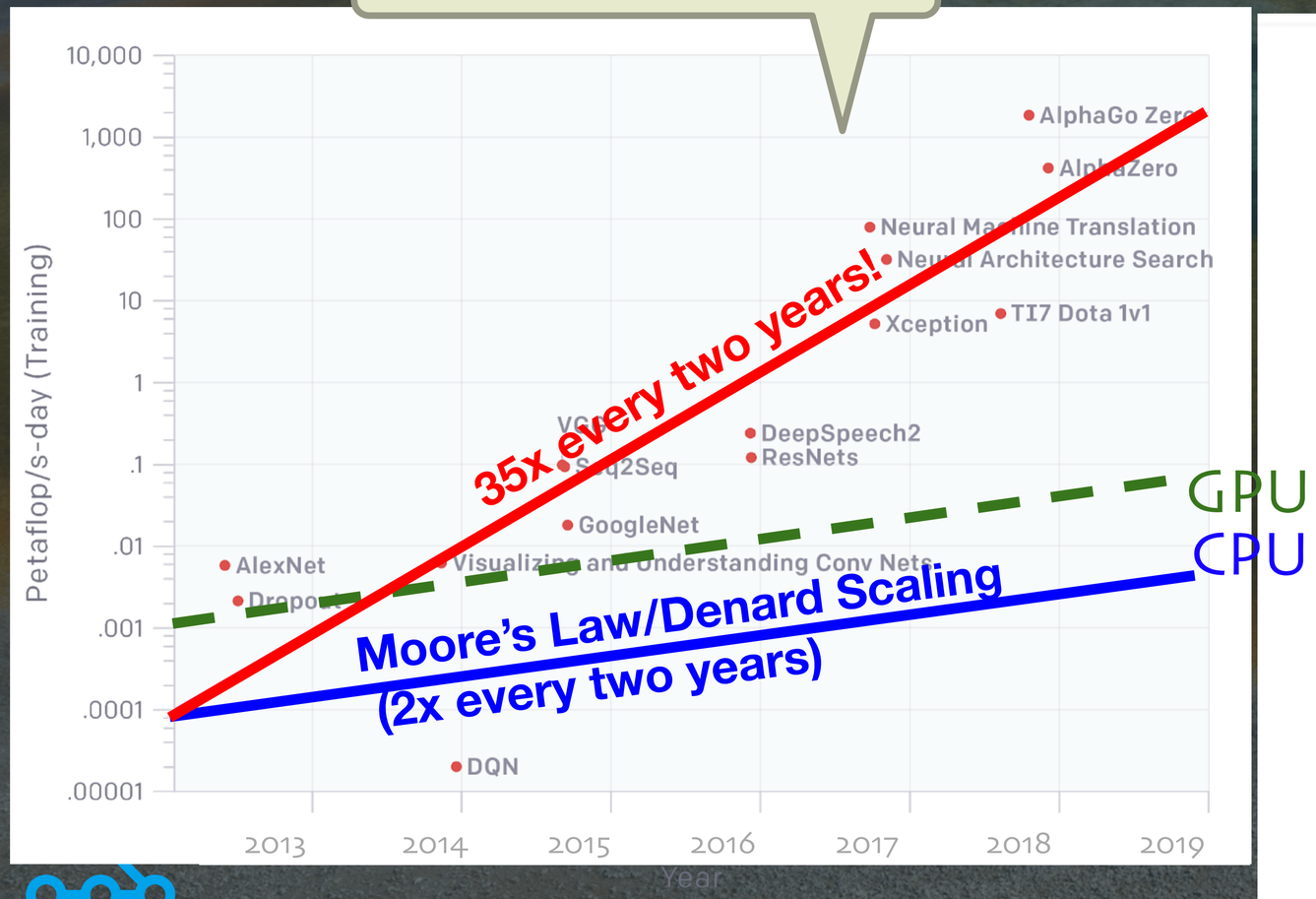

Why Ray??

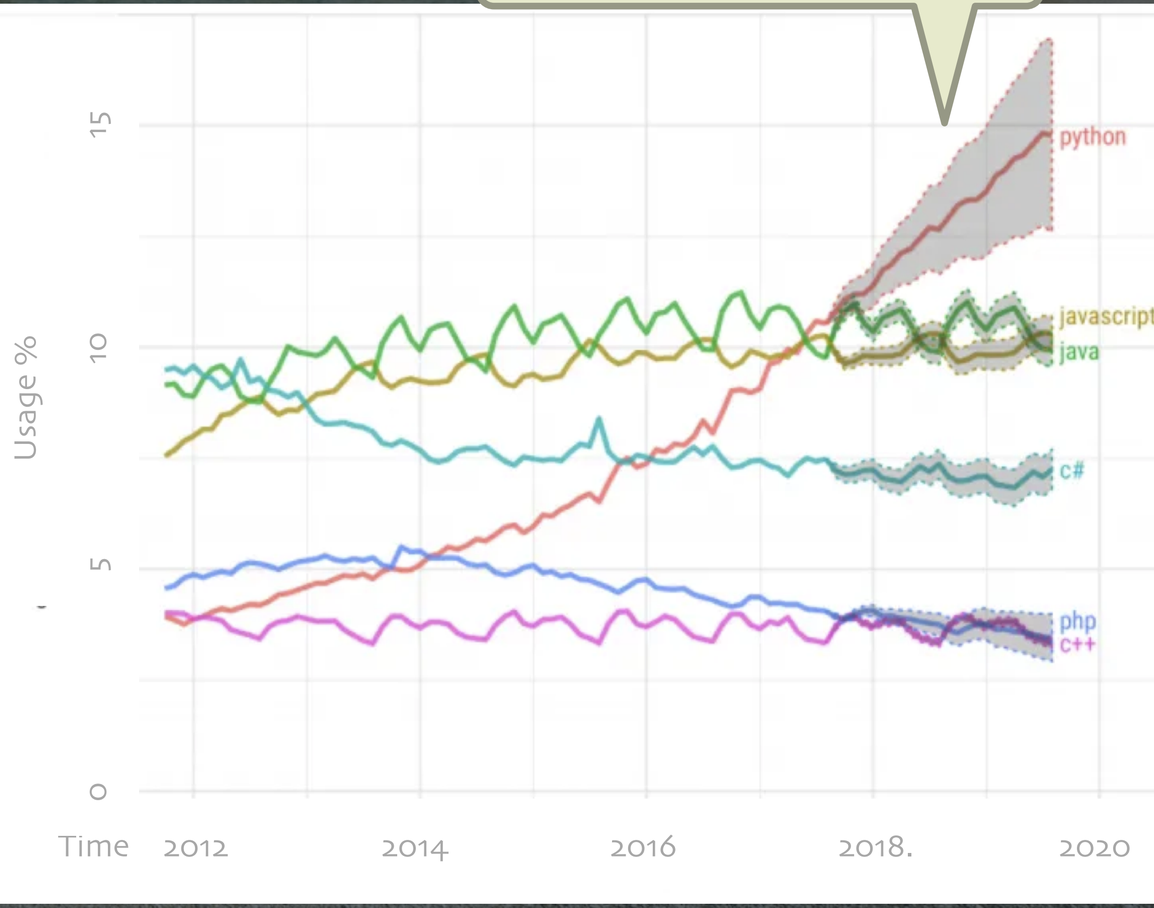
To Major Trends

Model sizes and therefore compute requirements outstripping Moore's Law

Hence, there is a pressing need for a robust, easy to use Python-centric distributed computing system

Python growth driven by ML/AI and other data science workloads





https://openai.com/blog/ai-and-compute/

The Data & ML Landscape Today

All require distributed implementations to scale

ETL	Streaming	HPO Tuning	Training	Simulation	Model Serving
Apache Spark	Apache Spark	SIGOPT	HOROVOD	MPI	Clipper
hadoop	Flink	talos AUTONOMY	PyTorch	akka	
	kafka		scikit learn	Orleans	



The Ray Vision: Sharing a Common Framework

Domain-specific libraries for each subsystem

Ray Data

Ray Tune

Ray Train

Ray RLlib

Ray Serve

ETL

Streaming

HPO Tuning

Training

Simulation

Model Serving

Framework for distributed Python (and other languages…)



RAY



Plus a growing list of 3rd-party libraries

Diverse Compute Requirements Motivated Creation of Ray!

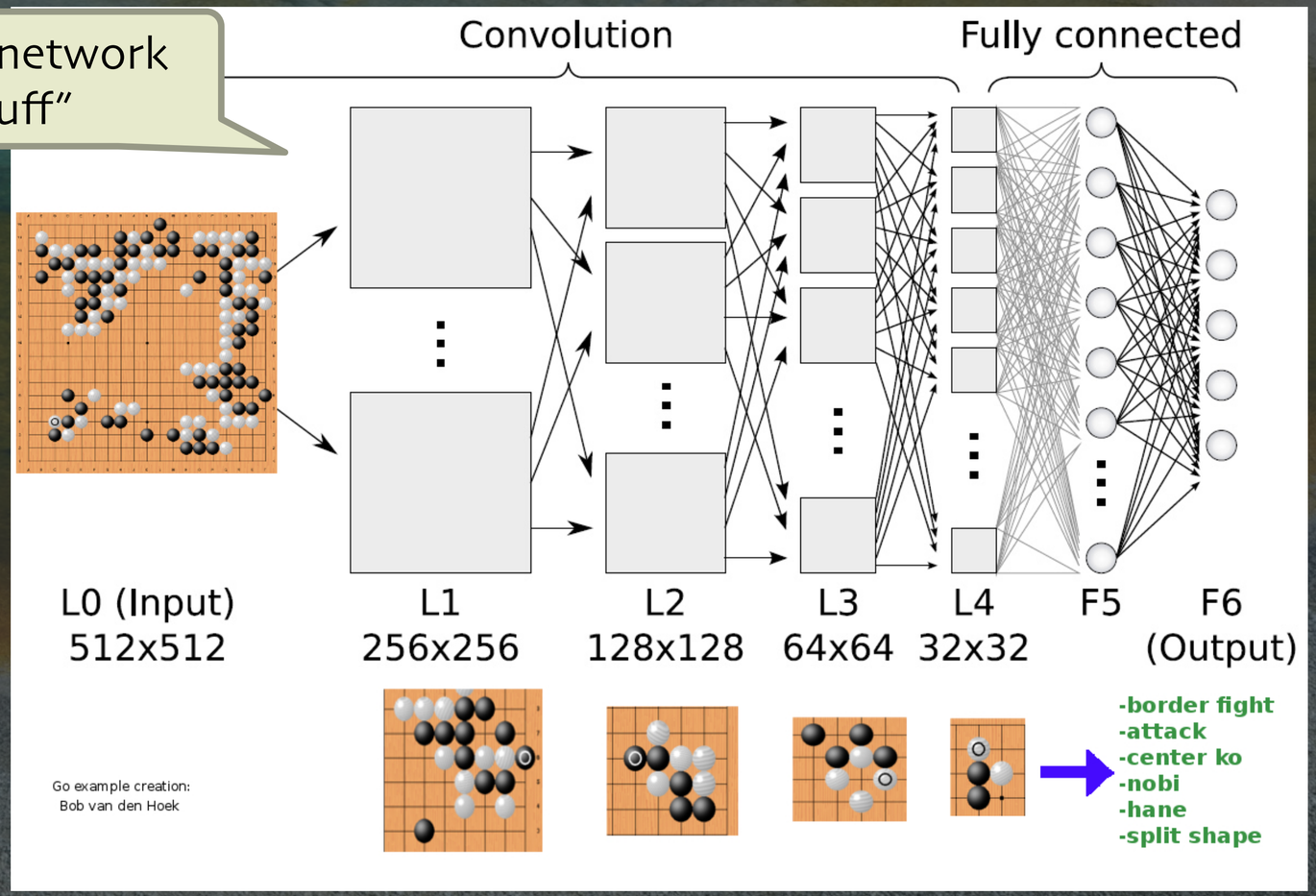
And repeated play, over and over again, to train for achieving the best reward

Neural network "stuff"

Simulator (game engine, robot sim, factory floor sim…)

Complex agent?







Quick Intro to the Ray API

API - Designed to Be Intuitive and Concise

Functions -> Tasks

```
def make_array(…):
    a = … # Construct a NumPy array
    return a


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

The Python you already know…



API - Designed to Be Intuitive and Concise

Functions -> Tasks

```
@ray.remote
def make_array(…):
    a = … # Construct a NumPy array
    return a

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

For completeness, add the initialization

```
import ray
import numpy as np
ray.init()
```

Now these functions are remote “tasks"



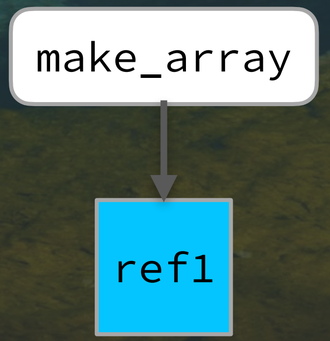
API - Designed to Be Intuitive and Concise

Functions -> Tasks

```
@ray.remote
def make_array(…):
    a = … # Construct a NumPy array
    return a

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

ref1 = make_array.remote(…)
```





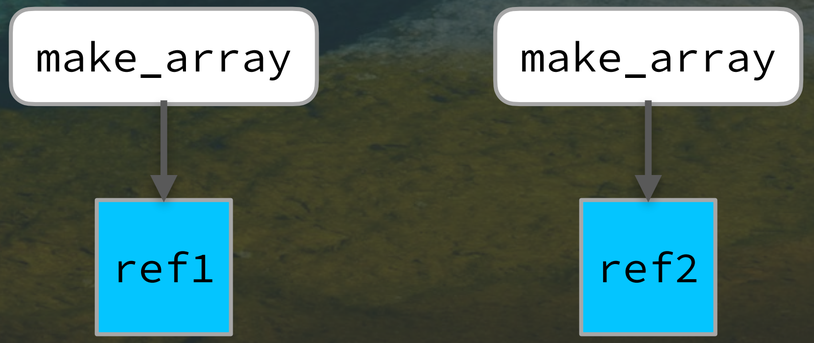
API - Designed to Be Intuitive and Concise

Functions -> Tasks

```
@ray.remote
def make_array(…):
    a = … # Construct a NumPy array
    return a

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

ref1 = make_array.remote(…)
ref2 = make_array.remote(…)
```





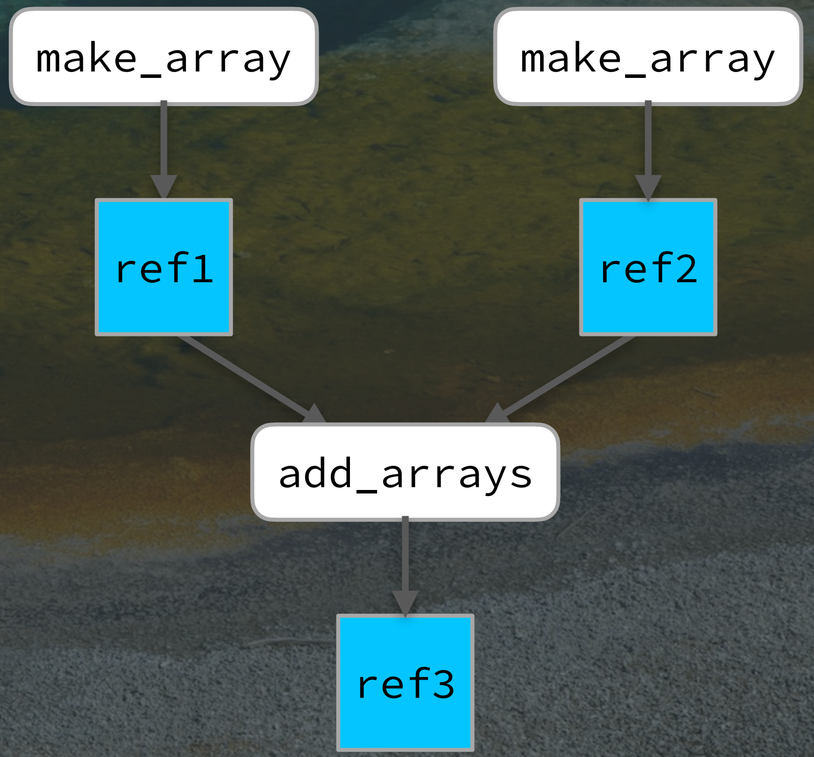
API - Designed to Be Intuitive and Concise

Functions -> Tasks

```
@ray.remote
def make_array(…):
    a = … # Construct a NumPy array
    return a

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

ref1 = make_array.remote(…)
ref2 = make_array.remote(…)
ref3 = add_arrays.remote(ref1, ref2)
```





API - Designed to Be Intuitive and Concise

Functions -> Tasks

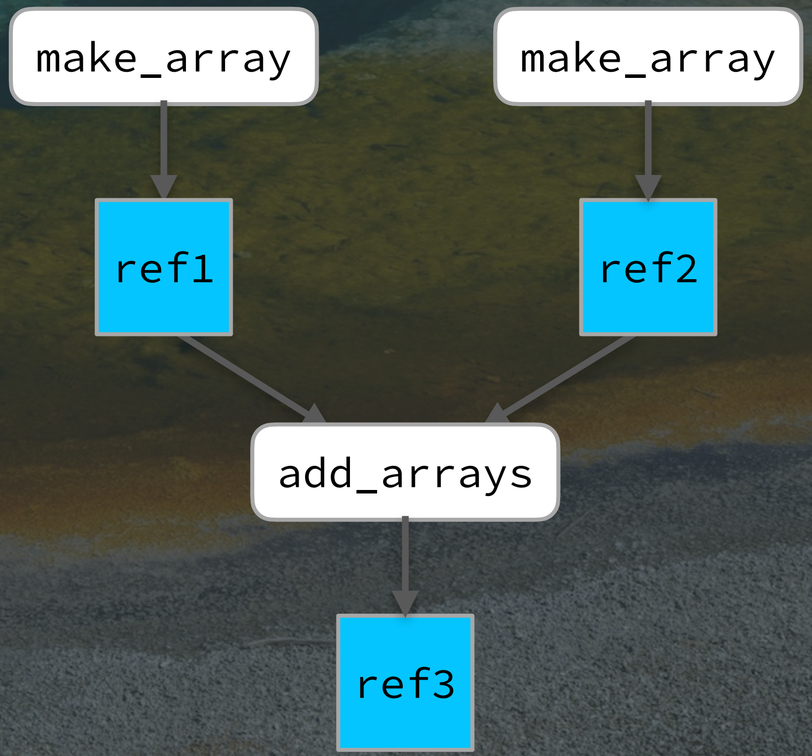
```
@ray.remote
def make_array(…):
    a = … # Construct a NumPy array
    return a

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

ref1 = make_array.remote(…)
ref2 = make_array.remote(…)
ref3 = add_arrays.remote(ref1, ref2)
ray.get(ref3)
```

Ray handles extracting the arrays from the object refs

Ray handles sequencing of async dependencies





API - Designed to Be Intuitive and Concise

What about distributed state?

Functions -> Tasks

```
@ray.remote
def make_array(…):
    a = … # Construct a NumPy array
    return a

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

ref1 = make_array.remote(…)
ref2 = make_array.remote(…)
ref3 = add_arrays.remote(ref1, ref2)
ray.get(ref3)
```



API - Designed to Be Intuitive and Concise

Functions -> Tasks

```
@ray.remote
def make_array(…):
    a = … # Construct a NumPy array
    return a

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

ref1 = make_array.remote(…)
ref2 = make_array.remote(…)
ref3 = add_arrays.remote(ref1, ref2)
ray.get(ref3)
```

Classes -> Actors

```
class Counter(object):
    def __init__(self):
        self.value = 0
    def increment(self):
        self.value += 1
        return self.value
```

The Python classes you love…



API - Designed to Be Intuitive and Concise

Functions -> Tasks

```
@ray.remote
def make_array(…):
    a = … # Construct a NumPy array
    return a

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

ref1 = make_array.remote(…)
ref2 = make_array.remote(…)
ref3 = add_arrays.remote(ref1, ref2)
ray.get(ref3)
```

Classes -> Actors

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

… now a remote "actor"

You need a "getter" method to read the state.



API - Designed to Be Intuitive and Concise

Functions -> Tasks

```
@ray.remote
def make_array(…):
    a = … # Construct a NumPy array
    return a

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

ref1 = make_array.remote(…)
ref2 = make_array.remote(…)
ref3 = add_arrays.remote(ref1, ref2)
ray.get(ref3)
```

Classes -> Actors

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

c = Counter.remote()
ref4 = c.increment.remote()
ref5 = c.increment.remote()
ray.get([ref4, ref5]) # [1, 2]
```



API - Designed to Be Intuitive and Concise

Functions -> Tasks

```
@ray.remote
def make_array(…):
    a = … # Construct a NumPy array
    return a

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

ref1 = make_array.remote(…)
ref2 = make_array.remote(…)
ref3 = add_arrays.remote(ref1, ref2)
ray.get(ref3)
```

Classes -> Actors

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

c = Counter.remote()
ref4 = c.increment.remote()
ref5 = c.increment.remote()
ray.get([ref4, ref5]) # [1, 2]
```

Optional configuration specifications



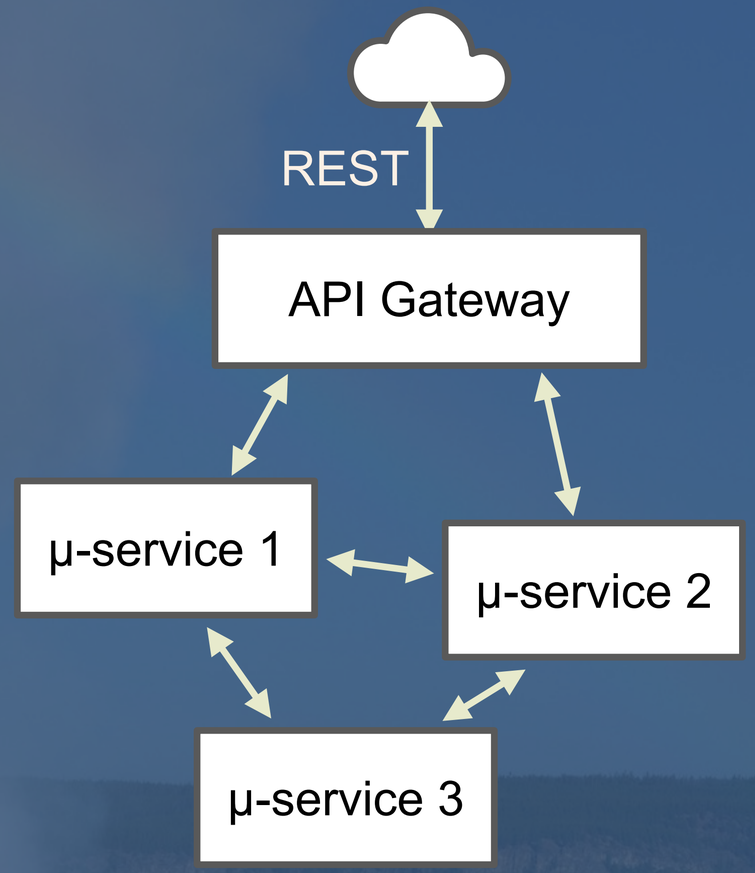
Other Uses of Ray: Microservices



© 2022 Dean Wampler

What Are Microservices?

- They partition the domain
  - Conway's Law - Embraced
  - Separate responsibilities
- Separate management



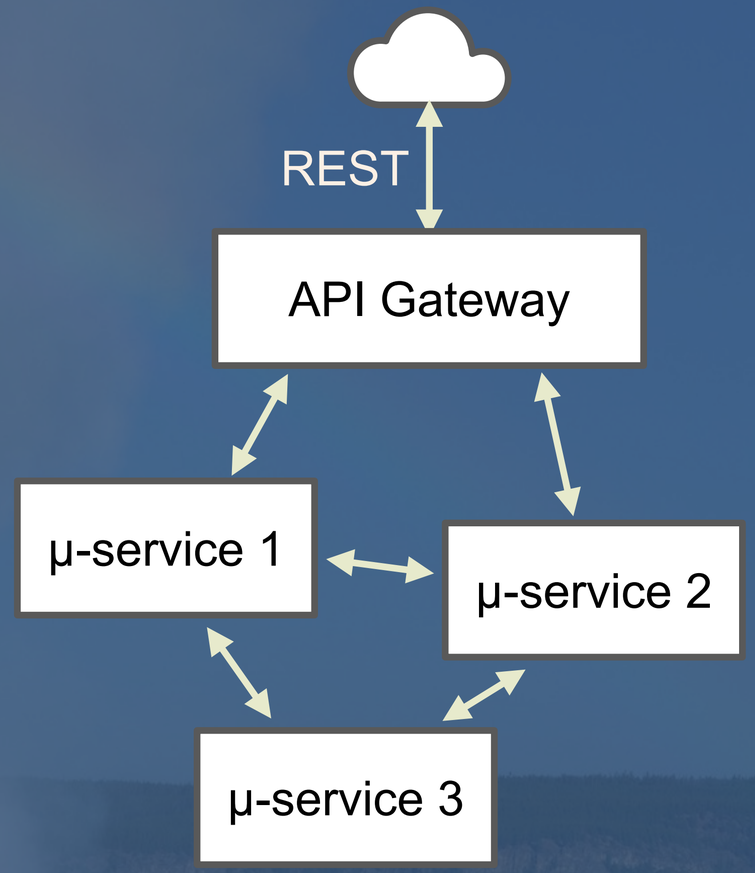


© 2022 Dean Wampler

What Are Microservices?

- They partition the domain
  - Conway's Law - Embraced
  - Separate responsibilities
- Separate management

What we mostly care about for today's talk, the "Ops in DevOps"

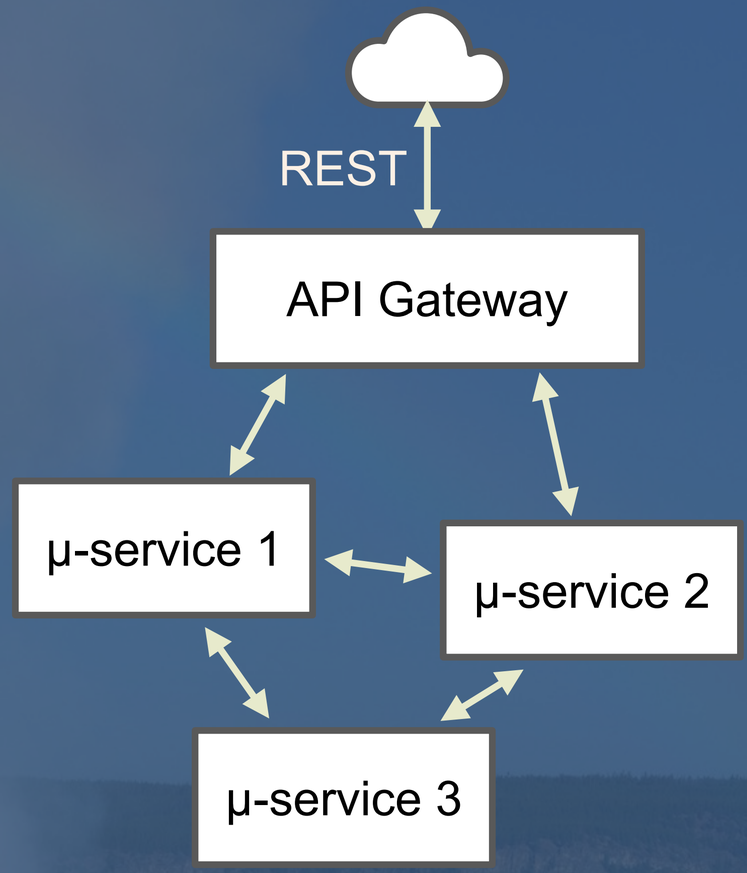




© 2022 Dean Wampler

Conway's Law - Embraced

- "Any organization that designs a system will produce a design whose structure is a copy of the organization's communication structure"
- Let each team own and manage the services for its part of the domain



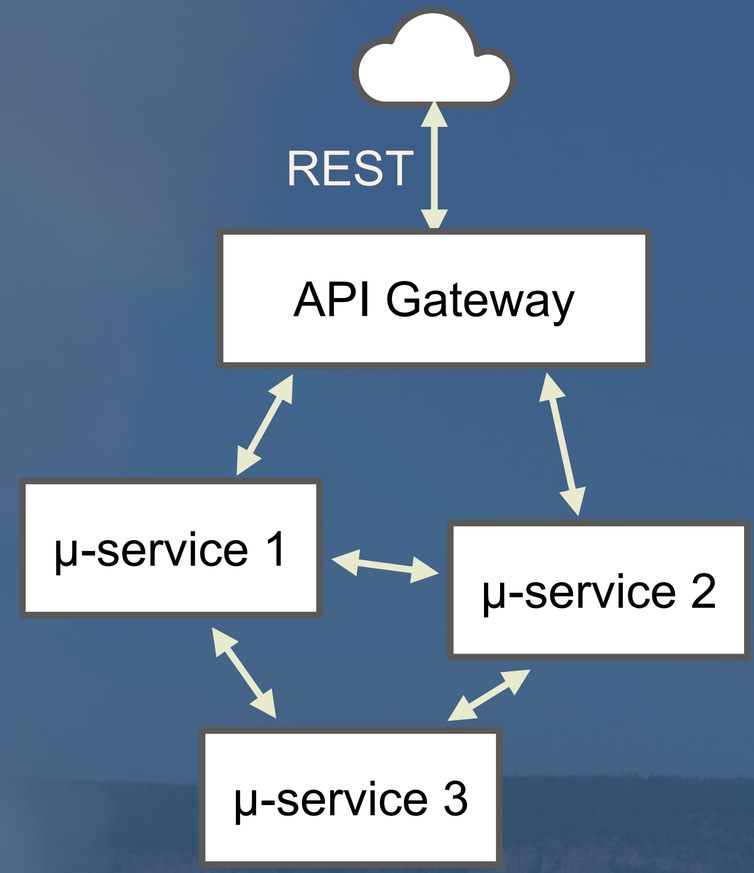


en.wikipedia.org/wiki/Conway's_law

© 2022 Dean Wampler

Separate Responsibilities

- Each microservice does "one thing", a single responsibility with minimal coupling to the other microservices
- (Like, hopefully, the teams are organized, too…)



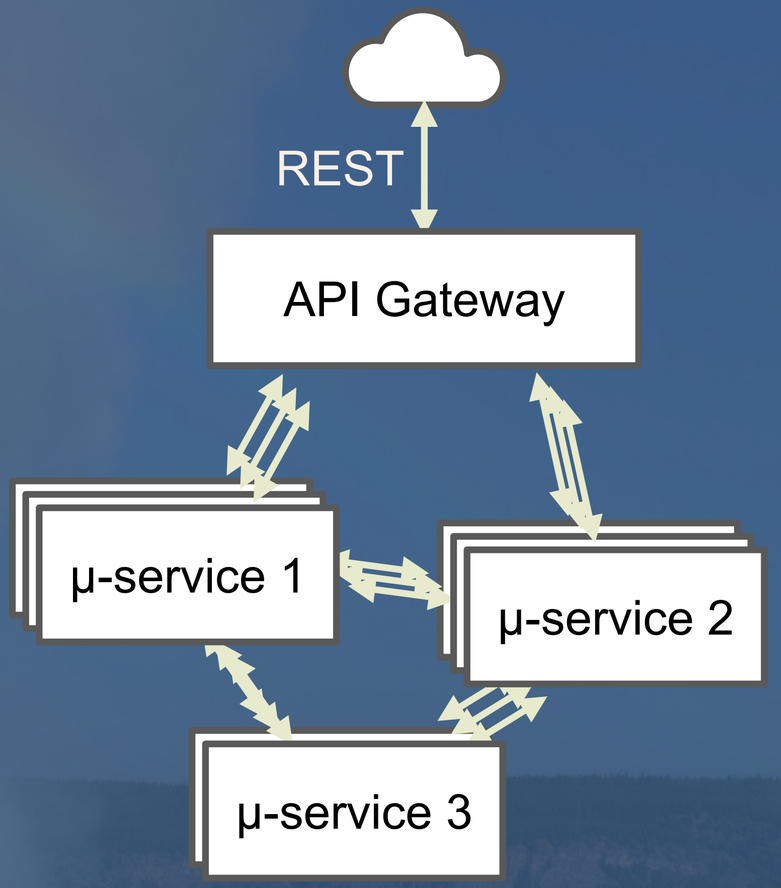


wikipedia.org/wiki/Single-responsibility_principle

© 2022 Dean Wampler

Separate Management

- Each team manages its own instances
- Each microservice has a different number of instances for scalability and resiliency
- But they have to be managed **explicitly**

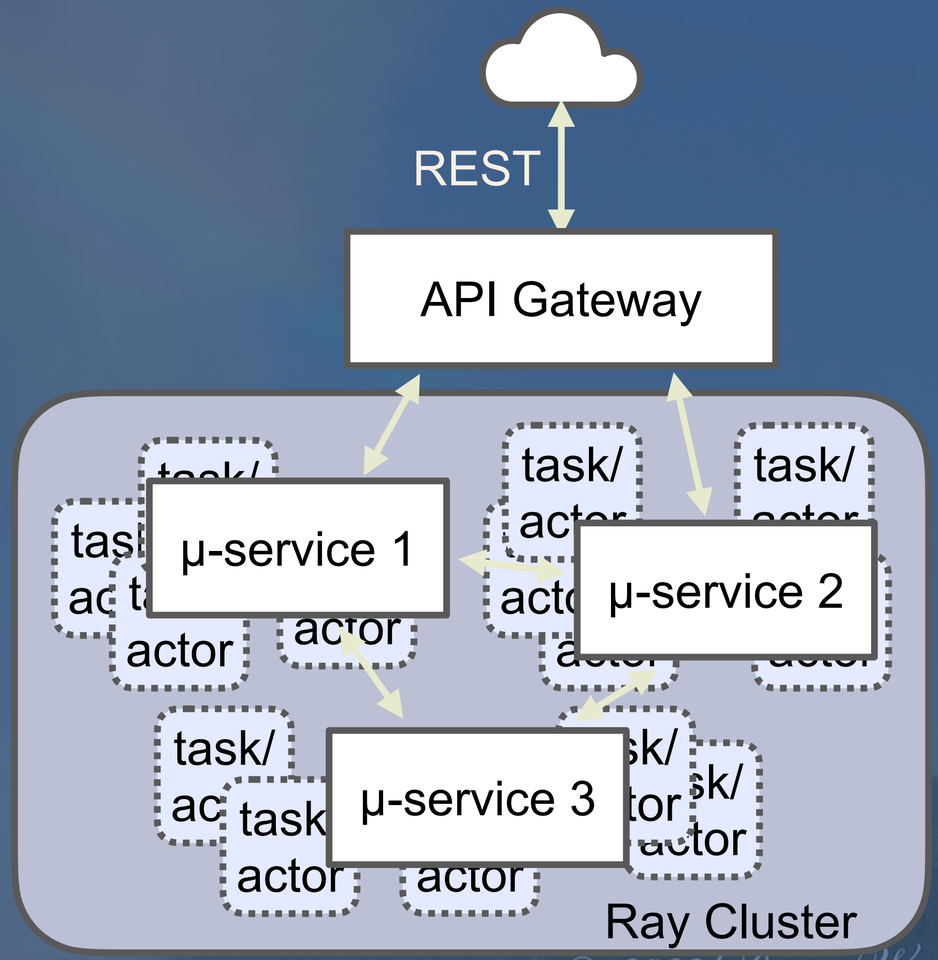




© 2022 Dean Wampler

Management - Simplified

- With Ray, you have one "logical" instance to manage and Ray does the cluster-wide scaling for you.

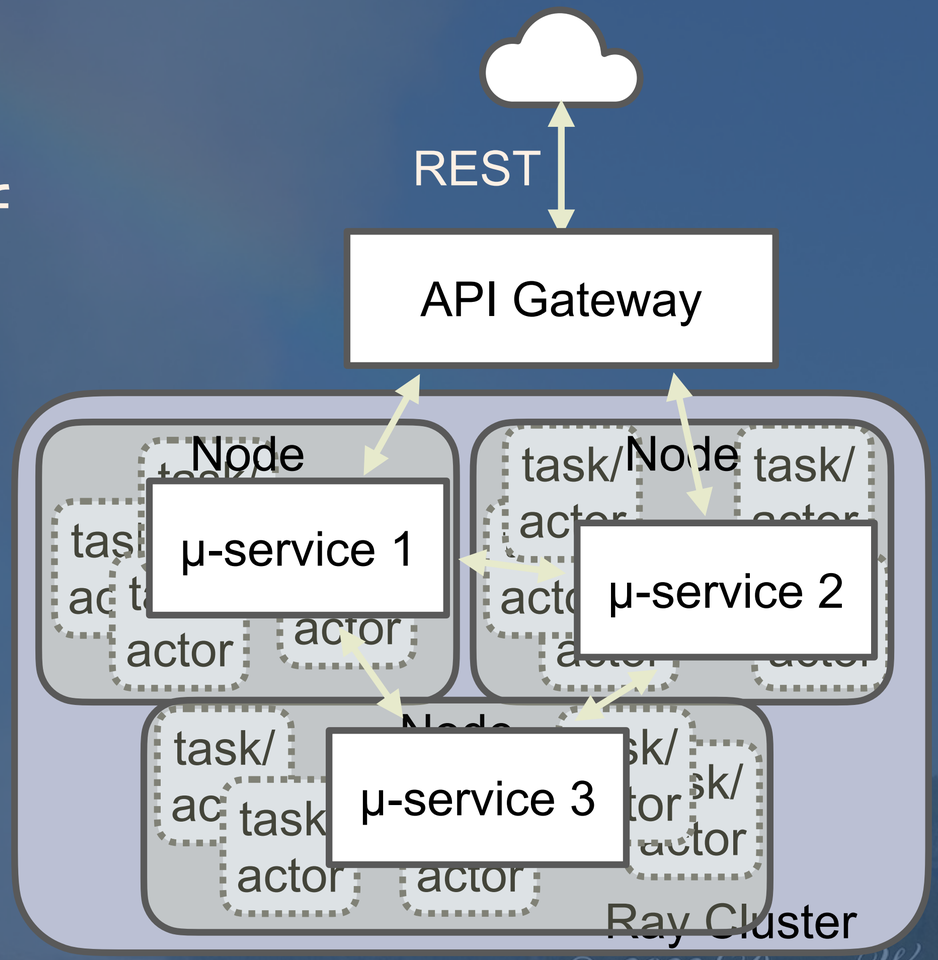




© 2022 Dean Wampler

What about Kubernetes (and others…)?

- Ray scaling is very fine grained.
- It operates within the "nodes" of coarse-grained managers
  - Containers, pods, VMs, or physical machines





© 2022 Dean Wampler

Hyper Parameter Tuning with Ray Tune



Hyper Parameter Tuning - Ray Tune

Domain-specific libraries for each subsystem

Ray Data

Ray Tune

Ray Train

Ray RLlib

Ray Serve

ETL

Streaming

HPO Tuning

Training

Simulation

Model Serving

Framework for distributed Python (and other languages…)



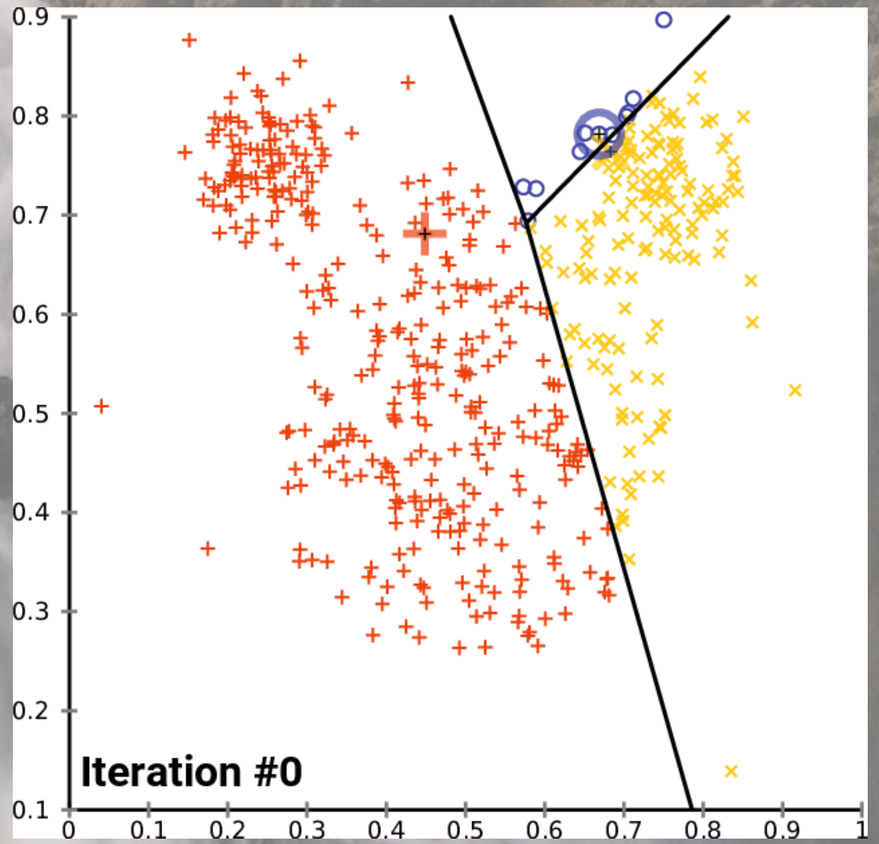
RAY



What Is Hyper Parameter Tuning (or Optimization - HPO)?

Trivial example:

- What's the best value for "k" in k-means??
  - k is a "hyperparameter"
    - The resulting clusters are defined by "parameters"

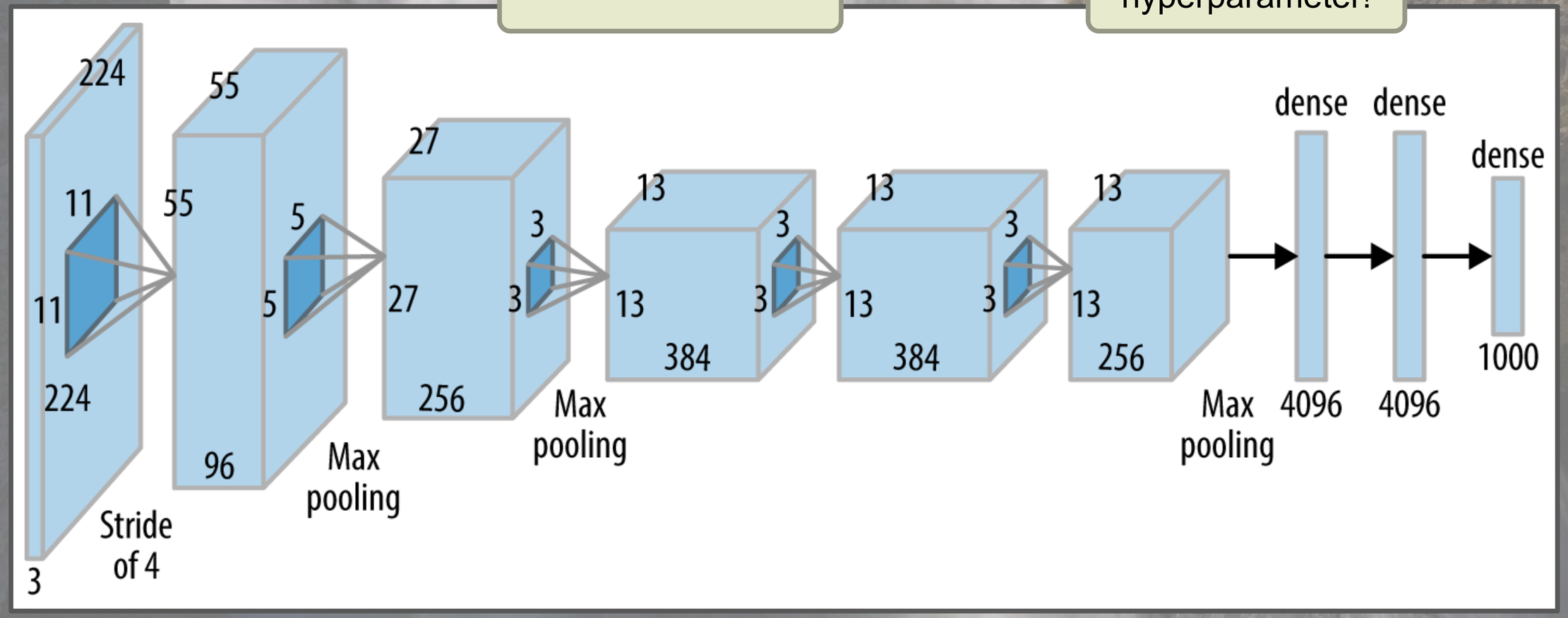


credit: https://commons.wikimedia.org/wiki/File:K-means_convergence.gif

Nontrivial Example - Neural Networks

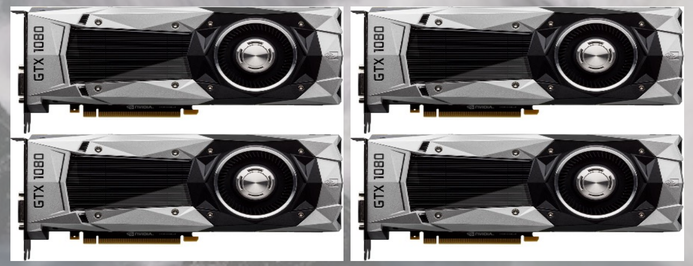
How many layers?
What kinds of layers?

Every number shown is a hyperparameter!

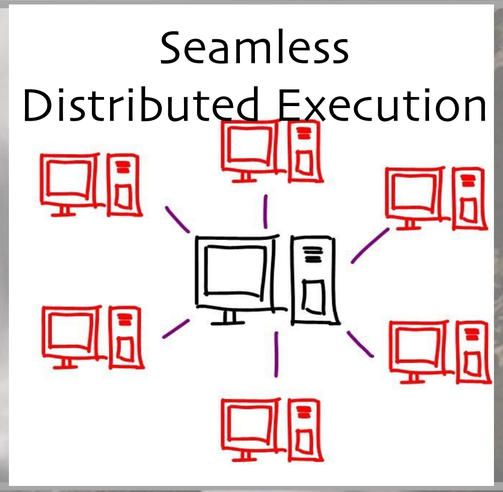


Tune is Built with Deep Learning as a Priority

Resource Aware Scheduling



Seamless Distributed Execution

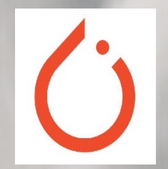


Simple API for new algorithms

```
class TrialScheduler:
    def on_result(self, trial, result): ...
    def choose_trial_to_run(self): ...
```

Framework Agnostic



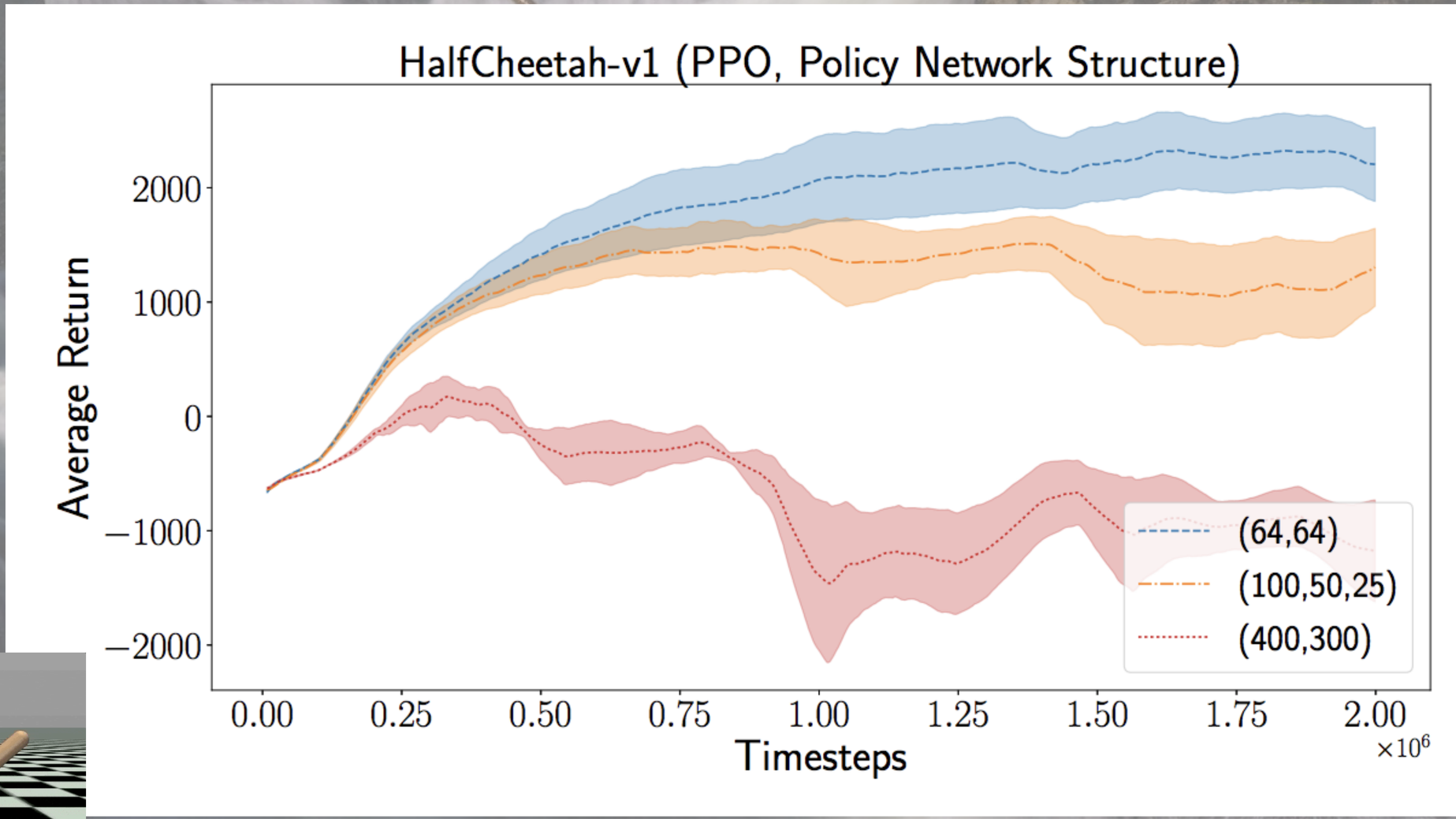


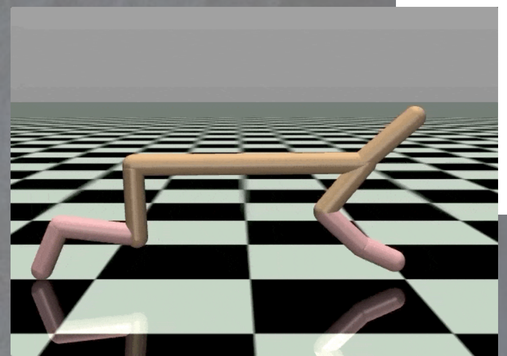




tune.io

Hyper Parameters Are Important for Performance





Why We Need a Framework for Tuning Hyper Parameters

We want the best model

Resources are expensive

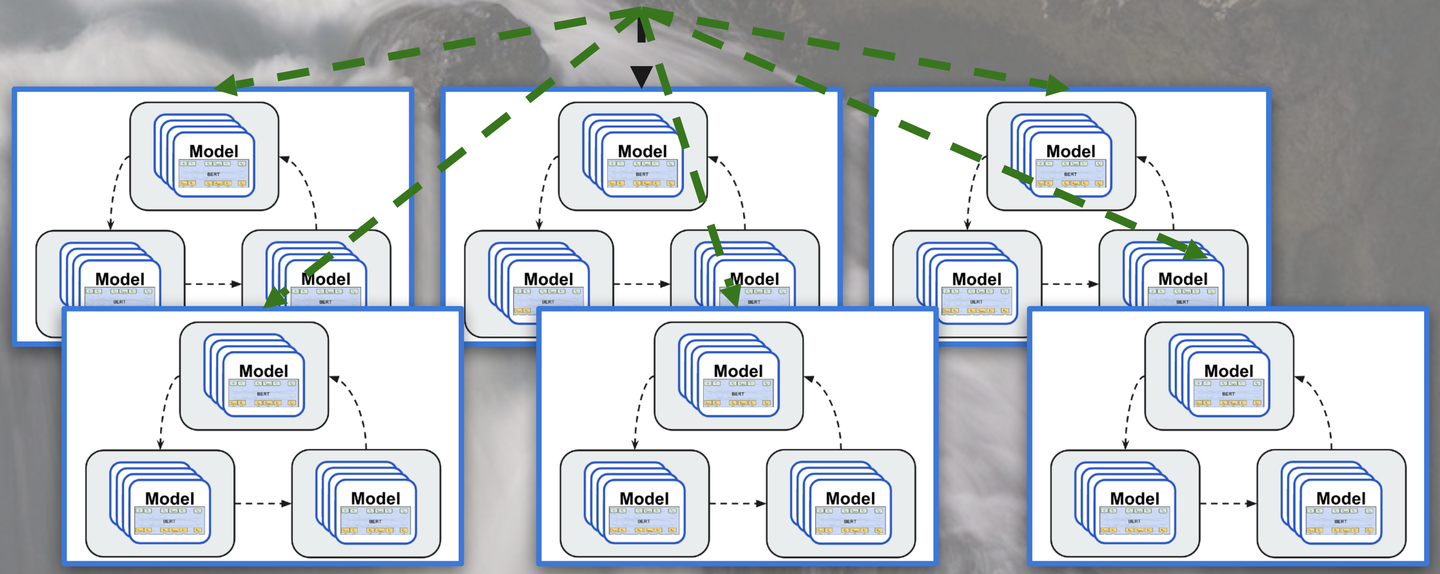
Model training is time-consuming



Tuning + Distributed Training

```
tune.run(PytorchTrainable,
        config={
            "model_creator": PretrainBERT,
            "data_creator": create_data_loader,
            "use_gpu": True,
            "num_replicas": 8,
            "lr": tune.uniform(0.001, 0.1)
        },
        num_samples=100,
        search_alg=BayesianOptimization()
)
```





Native Integration with TensorBoard HParams

