a glance at reinforcement learning

Adam Green

adam.green@adgefficiency.com

adgefficiency.com

one - background & terminology

two - introduction to reinforcement learning

three - value functions & DQN

four - improvements to DQN

five - policy gradients & Actor Critic

six - AlphaGo & AlphaZero

seven - practical concerns

eight - deep reinforcement learning doesn't work yet

About Me

Education

B.Eng Chemical Engineering

MSc Advanced Process Design for Energy

DSR Batch 9

Industry

Energy Engineer at ENGIE UK

Energy Data Scientist at Tempus Energy

Goals for the course

Introduction to **concepts, ideas and terminology**, and familiarity with important literature.

Course material

- slides
- detailed notes at `dsr-rl/notes`

These slides cover **model free reinforcement learning**.

Where to go next

Textbook Sutton & Barto - An Introduction to Reinforcement Learning (2nd Edition is in progress)

Video lectures David Silver's 10 lecture series on YouTube

Literature review Li (2017) Deep Reinforcement Learning: An Overview

one

nomenclature & statistics background

a few things about training neural networks

Nomenclature

Nomenclature in RL can be inconsistent

value function methods, action = a

policy gradient methods, action = u

Following Thomas & Okal (2016) A Notation for Markov Decision Processes

symbol	variable
s	state
s'	next state
a	action
r	reward
G_t	discounted return after time t
γ	discount factor [0, 1)
$a \sim \pi(s)$	sampling action from a stochastic policy
$a = \pi(s)$	determinstic policy
$\pi^\star$	optimal policy
$V_\pi(s)$	value function
$Q_\pi(s, a)$	value function
θ, ω	function parameters (weights)
$\mathbf{E}[f(x)]$	expectation of f(x)

Expectations

Weighted average of all possible values (the mean)

```
expected_value = probability * magnitude
```

$$\mathbf{E}[f(x)] = \sum p(x) \cdot f(x)$$

Expectations **allow us to approximate by sampling**

if we want to approximate the average time it takes us to get to work

we can measure how long it takes us for a week and get an approximation by averaging each of those days

Conditionals

Probability of one thing given another

probability of next state and reward given state & action

$$P(s'|s,a)$$

reward received from a state & action

$$R(r|s,a,s')$$

sampling an action from a stochastic policy conditioned on being in state s

$$a \sim \pi(s|a)$$

Variance & bias in supervised learning

Model generalization error = bias + variance + noise

Variance

error from sensitivity to noise in data set
seeing patterns that aren't there -> overfitting

Bias

error from assumptions in the learning algorithm
missing relevant patterns -> underfitting

Variance & bias in RL

Variance = deviation from expected value

how consistent is my model / sampling
can often be dealt with by sampling more
high variance = sample inefficient

Bias = expected deviation vs true value

how close to the truth is my model
approximations or bootstrapping tend to introduce bias
biased away from an optimal agent / policy

Bootstrapping

Doing something on your own

i.e. funding a startup with your own capital
using a function to improve / estimate itself

The Bellman Equation is bootstrapped equation

$$V(s) = r + \gamma V(s')$$

$$Q(s, a) = r + \gamma Q(s', a')$$

Bootstrapping often introduces bias

the agent has a chance to fool itself

Function approximation

Lookup tables

Two dimensions in the state variable

```
state = np.array([temperature, pressure])
```

state	temperature	pressure	estimate
0	high	high	unsafe
1	low	high	safe
2	high	low	safe
3	low	low	very safe

Lookup tables

Advantages

Stability

Each estimate is independent of every other estimate

Disadvantages

No sharing of knowledge between similar states/actions

Curse of dimensionality

High dimensional state/action spaces means lots of entries

Linear functions

$$V(s) = 3s_1 + 4s_2$$

Advantages

Less parameters than a table

Can generalize across states

Disadvantages

The real world is often non-linear

Non-linear functions

Most commonly neural networks

Advantages

Model complex dynamics

Convolution for vision

Recurrency for memory / temporal dependencies

Disadvantages

Instability

Difficult to train

IID

Fundamental assumption in statistical learning

Independent and identically distributed

In statistical learning one always assumes the training set is independently drawn from a fixed distribution

one

nomenclature & statistics background

a few things about training neural networks

A few things about training neural networks

Learning rate

Batch size

Scaling / preprocessing

Larger batch size

- larger learning rate
- decrease in generalization
- increase in batch normalization performance

Learning rate

Controls the strength of weight updates performed by the optimizer (SGD, RMSprop, ADAM etc)

$$\theta^{t+1} = \theta^t - \alpha \frac{\partial E(x, \theta^t)}{\partial \theta}$$

where $E(x, \theta^t)$ is the error backpropagated from sample x

Small learning rate

- slow training

High learning rate

- overshoot or divergence

Learning rate

Always intentionally set it

```
from keras.models import Sequential

#  don't do this!
model.compile(optimizer='rmsprop', loss='mse')

#  do this
from keras.optimizers import RMSprop
opt = RMSprop(lr=0.001)
model.compile(optimizer=opt, loss='mse')
```

Batch size

Modern reinforcement learning trains neural networks using batches of samples

Below we have a dataset with four samples, of shape (14, 2)

```
>>> import numpy as np
```

```
>>> data = np.arange(4*28).reshape(4, -1, 2)
```

```
>>> data.shape
```

```
(4, 14, 2)
```

The first dimension is the batch dimension - this is foundational in TensorFlow

```
tf.placeholder(shape=(None, 14, 2))
```

Passing in

Batch size

Smaller batches can fit onto smaller GPUs

- if a large sample dimension we can use less samples per batch

Batches allow us to learn faster

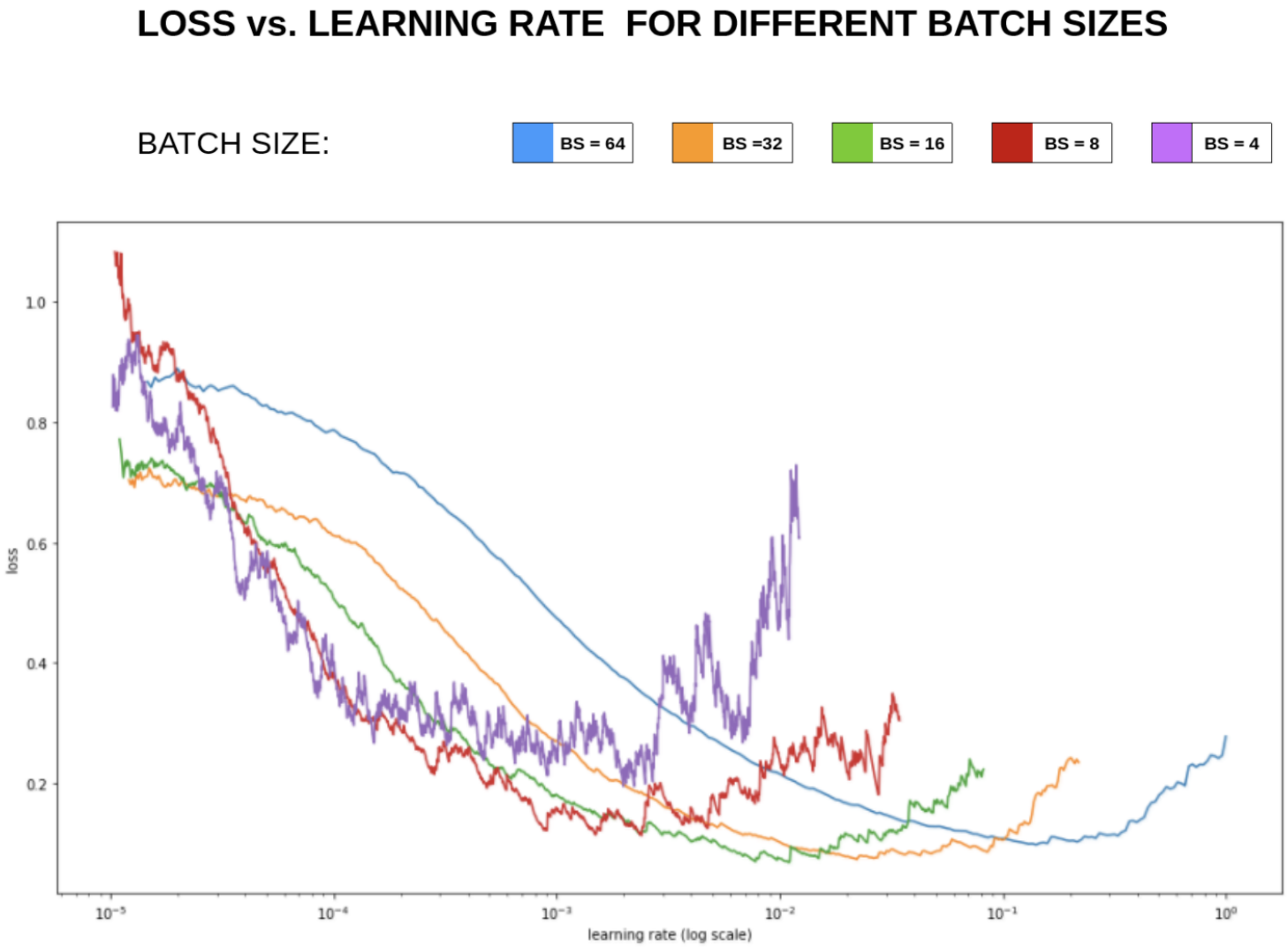
- weights are updated more often during each epoch

Batches give a less accurate estimate of the gradient

- this noise can be useful to escape local minima

Larger batch size -> larger learning rate

- more accurate estimation of the gradient (better distribution across batch)
- we can take larger steps



https://miguel-data-sc.github.io/2017-11-05-first/

Batch size

Observed that larger batch sizes decrease generalization performance

Poor generalization due to large batches converging to *sharp minimizers*

- areas with large positive eigenvalues $\nabla^2 f(x)$
- Hessian matrix (matrix of second derivatives) where all eigenvalues positive = positive definite = local minima

Batch size is a **hyperparameter that should be tuned**

Scaling aka pre-processing

Neural networks don't like numbers on different scales

- improperly scaled inputs or outputs can cause issues with gradients
- anything that touches a neural network needs to be within a reasonable range

We can estimate statistics like min/max/mean from the training set

- these statistics are as much a part of the ML model as weights
- in reinforcement learning we have no training set

Scaling aka pre-processing

Standardization = removing mean & scale by unit variance

$$\phi(x) = x - \frac{\mu(x)}{\sigma(x)}$$

Our data now has mean of 0, variance of 1

Normalization = min/max scaling

$$\phi(x) = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Our data is now between 0 and 1

Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift

Sergey Ioffe
Google Inc., *sioffe@google.com*

Christian Szegedy
Google Inc., *szegedy@google.com*

arXiv:1502.03167v3 [cs.LG] 2 Mar 2015

Batch Renormalization: Towards Reducing Minibatch Dependence in Batch-Normalized Models

Sergey Ioffe
Google Inc., *sioffe@google.com*

arXiv:1702.03275v2 [cs.LG] 30 Mar 2017

Batch normalization

Batch norm. is additional preprocessing of data as it moves between network layers

- used in very deep convolutional/residual nets

We use the mean and variance of the batch to normalize activations

- standardization is actually used!
- reduces sensitivty to weight & bias initialization
- allows higher learning rates
- originally applied before the activation - but this is a topic of debate

Batch normalization before or after relu - Reddit

Ian Goodfellow Lecture (3:20 onward)

Batch renormalization

Vanilla batch norm. struggles with small or non-iid batches

the estimated statistics are worse
vanilla batch norm. uses two different methods for normalization during training & testing
batch renormalization uses a single algorithm for both training & testing

two

introduction to reinforcement learning

four central challenges

Markov Decision Processes

Related methods

Evolutionary methods

- better able to deal with sparse error signals
- easily parallelizable
- tend to perform better that RL if state variable is hidden

Cross entropy method is often reccomended as an alternative

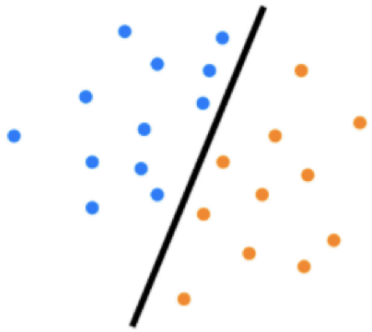
Constrained optimization such as **linear programming**

Any other **domain specific** algorithm for your problem

Machine learning

Supervised

learning
known
patterns

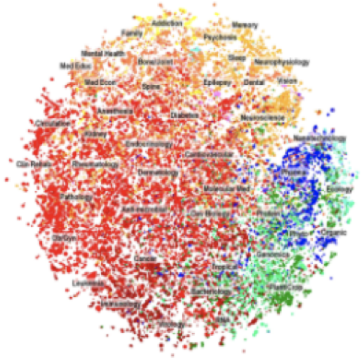


Random forests
Support vector machines

Feedforward neural net
Convolutional neural net
Recurrent neural net

Unsupervised

learning
unknown
patterns



Clustering algorithms

Generative adversarial nets
(GANS)

Reinforcement

taking actions
generating data
learning patterns

Value function methods

Policy gradients

Planning (i.e. model based)

Reinforcement learning is not

NOT an alternative method to use instead of a random forest, neural network etc

“I’ll try to solve this problem using a convolutional nn or RL” **this is nonsensical**

Neural networks (supervised techniques in general) are a tool that reinforcement learners can use to learn or approximate functions

classifier learns the function of image -> cat
regressor learns the function of market_data -> stock_price

Deep reinforcement learning

Deep learning

neural networks with multiple layers

Deep reinforcement learning

using multiple layer networks to approximate policies or value functions
feedforward
convolutional
recurrent

Model free reinforcment learning

Applications

RL is **decision making**

- Control physical systems: walk, fly, drive, swim, ...
- Interact with users: retain customers, personalise channel, optimise user experience, ...
- Solve logistical problems: scheduling, bandwidth allocation, elevator control, cognitive radio, power optimisation, ..
- Play games: chess, checkers, Go, Atari games, ...
- Learn sequential algorithms: attention, memory, conditional computation, activations, ...

David Silver – Deep Reinforcement Learning

Biological inspiration

Sutton & Barto - Reinforcment Learning: An Introduction

> *Of all the forms of machine learning, reinforcement learning is the closest to the kind of learning that humans and other animals do, and many of the core algorithms of reinforcement learning were originally inspired by biological learning systems*

Mnih et. al (2015) Human-level control through deep reinforcement learning

> *Neurobiological evidence that reward signals during perceptual learning may influence the characteristics of representations within the primate visual cortex*

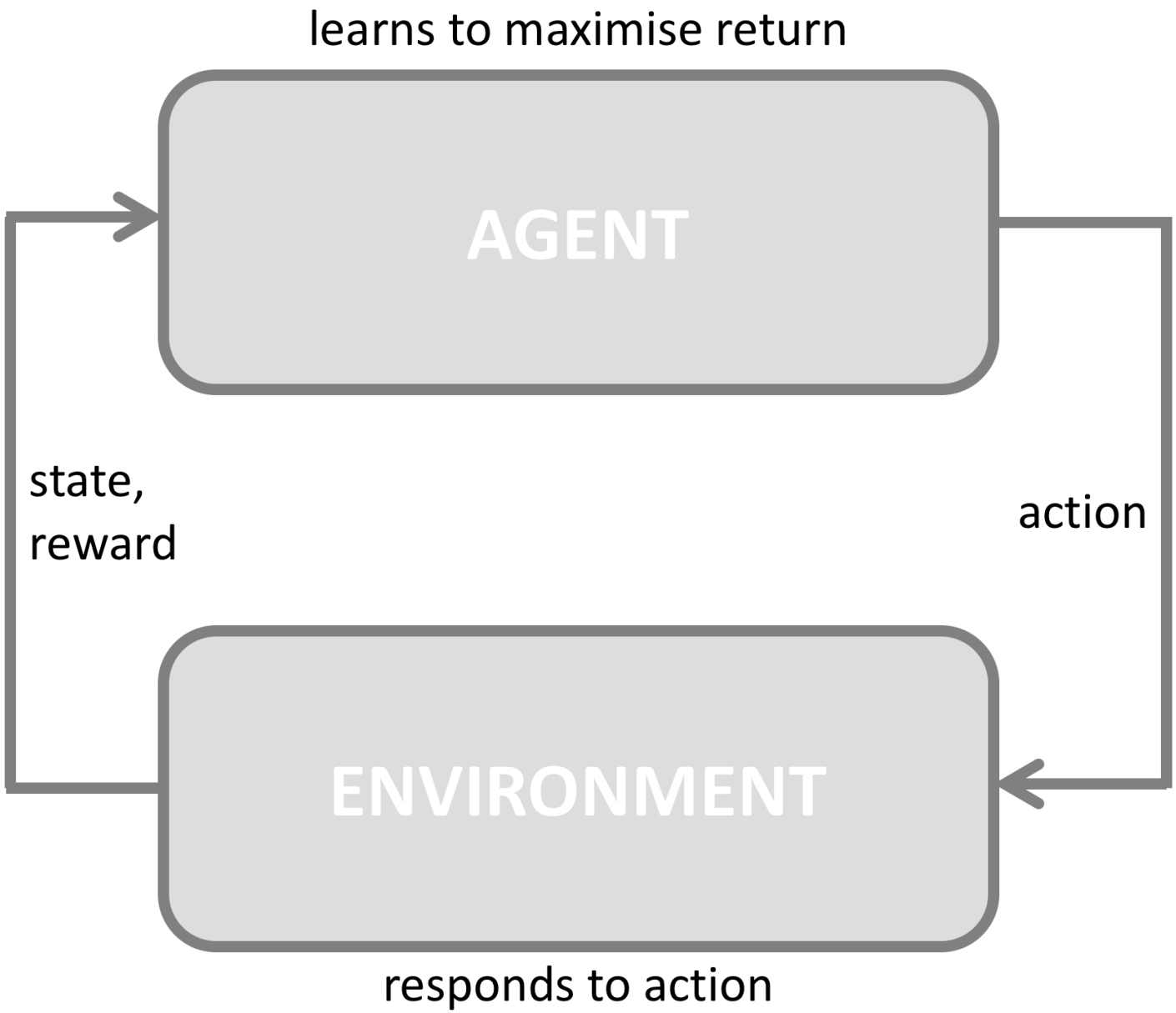
A new level of intelligence

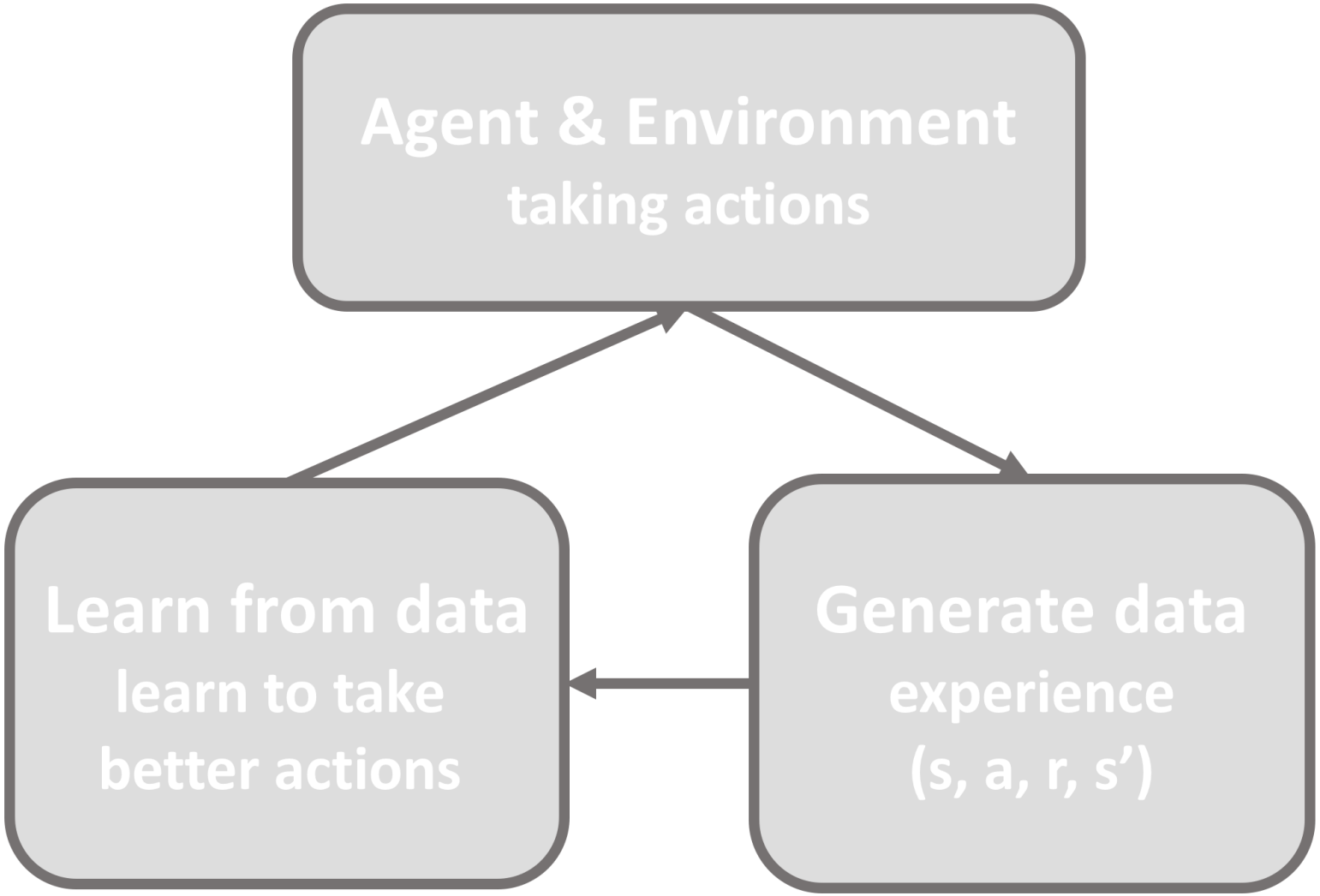
Founder & CEO of DeepMind Demis Hassabis on the brilliance of AlphaGo in it's 2015 series

Reinforcement Learning

is

learning through action


learns to maximise return
AGENT
state,
reward
action
ENVIRONMENT
responds to action


Agent & Environment
taking actions
Learn from data
learn to take
better actions
Generate data
experience
(s, a, r, s')

Contrast with supervised learning

Supervised learning

are given a dataset with labels
we are constrained by this dataset
test on unseen data

Reinforcement learning

are given no dataset and no labels
we can generate more data by acting
test using the same environment

Data in RL

the agent's experience (s, a, r, s')
it's not clear what we should do with this data
no implicit target

Reinforcement learning dataset

The dataset we generate is the agent's memory

$$[experience,$$
$$experience,$$
$$\dots$$
$$experience]$$

$$[(s_0, a_0, r_1, s_1),$$
$$(s_1, a_1, r_2, s_2),$$
$$\dots$$
$$(s_n, a_n, r_n, s_n)]$$

What should we do with this dataset?

two

introduction to reinforcement learning

four central challenges

Markov Decision Processes

Four central challenges

one - exploration vs exploitation

two - data quality

three - credit assignment

four - sample efficiency

Exploration vs exploitation

Do I go to the restaurant in Berlin I think is best – or do I try something new?

exploration = finding information
exploitation = using information

Agent needs to balance between the two

we don't want to waste time exploring poor quality states
we don't want to miss high quality states

Exploration vs exploitation

How stationary are the environment state transition and reward functions?

How stochastic is my policy?

Design of reward signal vs. exploration required

Time step matters

- too small = rewards are delayed = credit assignment harder
- too large = coarser control

Data quality

iid = independent sampling & identical distribution

RL breaks both in multiple ways

Independent sampling

all the samples collected on a given episode are correlated (along the state trajectory)
our agent will likely be following a policy that is biased (towards good states)

Identically distributed

learning changes the data distribution
exploration changes the data distribution
environment can be non-stationary

Reinforcement learning will **always** break supervised learning assumptions about data quality

Credit assignment

The reward we see now might not be because of the action we just took

Reward signal can be

delayed - benefit/penalty of action only seen much later
sparse - experience with reward = 0

Can design a more dense reward signal for a given environment

reward shaping
changing the reward signal can change behaviour

Sample efficiency

How quickly a learner learns

How often we reuse data

do we only learn once or can we learn from it again
can we learn off-policy

How much we squeeze out of data

i.e. learn a value function, learn a environment model

Requirement for sample efficiency depends on how expensive it is to generate data

cheap data -> less requirement for data efficiency
expensive / limited data -> squeeze more out of data

Four challenges

exploration vs exploitation

how good is my understanding of the range of options

data

biased sampling, non-stationary distribution

credit assignment

which action gave me this reward

sample efficiency

learning quickly, squeezing information from data

two

introduction to reinforcement learning

four central challenges

Markov Decision Processes

Markov Decision Processes

Mathematical framework for reinforcement learning

Markov property

Can be a requirement to gurantee convergence

Future is conditional only on the present

Can make prediction or decisions using only the current state

Any additional information about the history of the process will not improve our decision

$$P(s_{t+1}|s_t, a_t) = P(s_{t+1}|s_t, a_t \dots s_0, a_0)$$

Formal definition of a MDP

An MDP can be defined a tuple

$$(\mathcal{S}, \mathcal{A}, \mathcal{R}, P, R, d_0, \gamma)$$

Set of states $\mathcal{S}$

Set of actions $\mathcal{A}$

Set of rewards $\mathcal{R}$

State transition function $P(s'|s, a)$

Reward transition function $R(r|s, a, s')$

Distribution over initial states d_0

Discount factor γ

Object oriented definition of a MDP

Two objects - the agent and environment

Three signals - state, action & reward

```
class Agent

class Environment

state = env.reset()

action = agent.act(state)

reward, next_state = env.step(action)
```

Environment

Real or virtual

- modern RL uses virtual environments to generate lots of experience

Each environment has a state space and an action space

- these spaces can be discrete or continuous

Environments can be

- episodic (finite length, can be variable or fixed length)
- non-episodic (infinite length)

The MDP framework unites both in the same way by using the idea of a final absorbing state at the end of episodes

Discretiziation

Too coarse

- non-smooth control output

Too fine

- curse of dimensionality
- computational expense

Requires some prior knowledge

Lose the shape of the space

State

Infomation for the agent to **choose next action** and to **learn from**

State is a flexible concept - it's a n-d array

```
state = np.array([temperature, pressure])
```

```
state = np.array(pixels).reshape(height, width)
```

Observation

Many problems your agent won't be able to see everything that would help it learn - i.e. non-Markov

This then becomes a POMDP - partially observed MDP

```
state = np.array([temperature, pressure])

observation = np.array([temperature + noise])
```

Observation can be made more Markov by

concatenating state trajectories together
using function approximation with a memory element (LSTMs)

Agent

Our agent is the **learner and decision maker**

It's goal is to maximize total discounted reward

An agent always has a policy

Reward

Scalar

Delayed

Sparse

A well defined reward signal is a limit for applying RL

Reward hypothesis

Maximising expected return is making an assumption about the nature of our goals

Goals can be described by the maximization of expected cumulative reward

Do you agree with this?

- happiness
- status
- reputation

Think about the role of emotion in human decision making. Is there a place for this in RL?

Reward engineering

The Reward Engineering Principle: *As reinforcement-learning-based AI systems become more general and autonomous, the design of reward mechanisms that elicit desired behaviours becomes both more important and more difficult.*

Reinforcement Learning and the Reward Engineering Principle

Policy $\pi(s)$

$$\pi(s)$$

$$\pi(s, a|\theta)$$

$$\pi_\theta(s|a)$$

A policy is rules to select actions

act randomly
always pick a specific action
the optimal policy - the policy that maximizes future reward

Policy can be

parameterized directly (policy gradient methods)
generated from a value function (value function methods)

Deterministic or stochastic

Prediction versus control

Prediction / approximation

predicting return for given policy

Control

the optimal policy
the policy that maximizes expected future discounted reward

On versus off policy learning

On policy

learn about the policy we are using to make decisions

Off policy

evaluate or improve one policy while using another to make decisions

Control can be on or off policy

use general policy iteration to improve a policy using an on-policy approximation

Why would we want to learn off-policy?

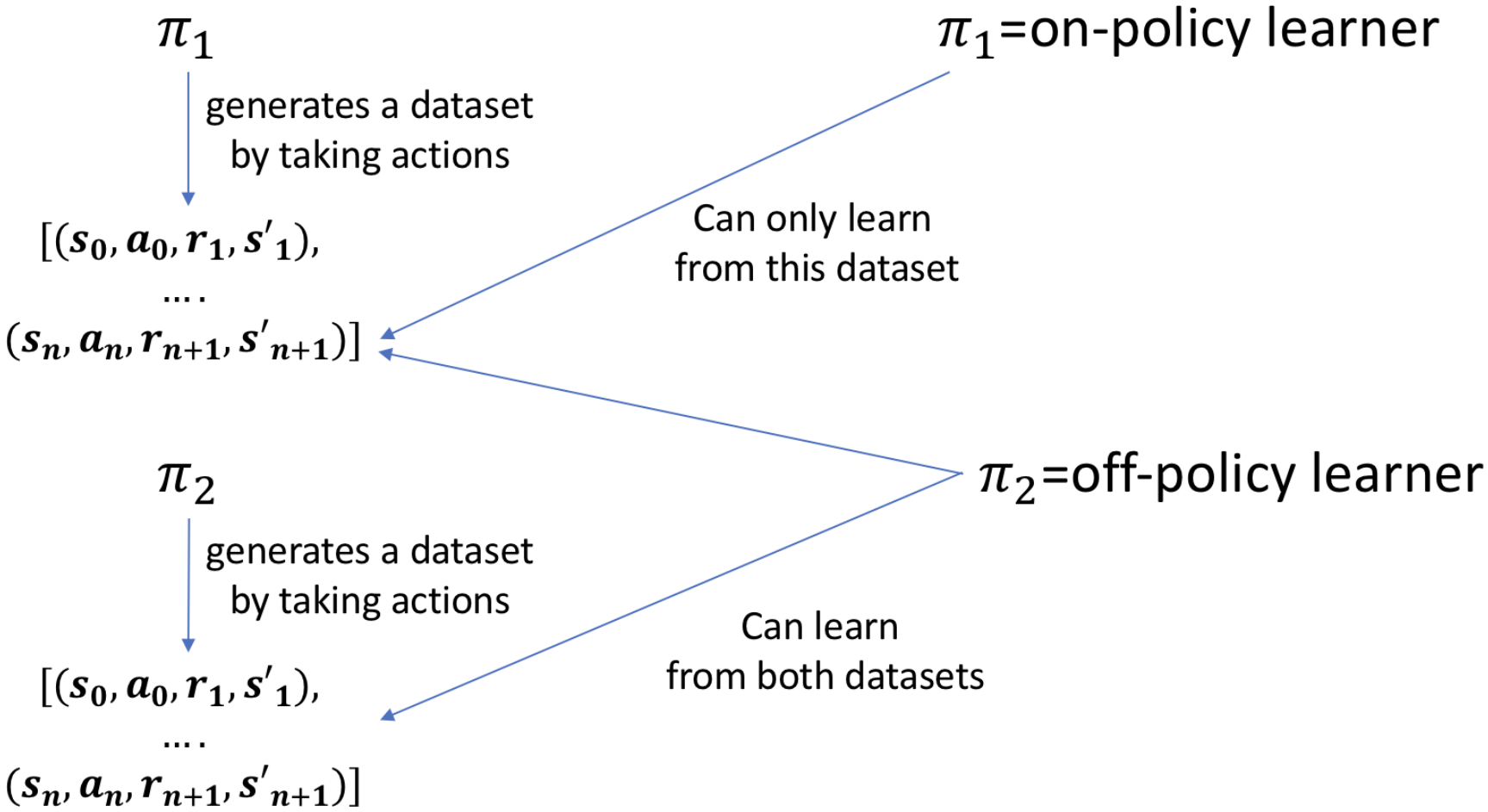
We can learn about policies that we don't have

learn the optimal policy from data generated by a random policy

We can reuse data

on-policy algorithms have to throw away experience after the policy is improved

Maybe the lesson we need to learn from deep learning is large capacity learners with large and diverse datasets - Sergey Levine


π_1
generates a dataset
by taking actions
$[(s_0, a_0, r_1, s'_1),$
$\ldots.$
$(s_n, a_n, r_{n+1}, s'_{n+1})]$
π_1=on-policy learner
Can only learn
from this dataset
π_2
generates a dataset
by taking actions
$[(s_0, a_0, r_1, s'_1),$
$\ldots.$
$(s_n, a_n, r_{n+1}, s'_{n+1})]$
π_2=off-policy learner
Can learn
from both datasets

Environment model

Our agent can learn an environment model

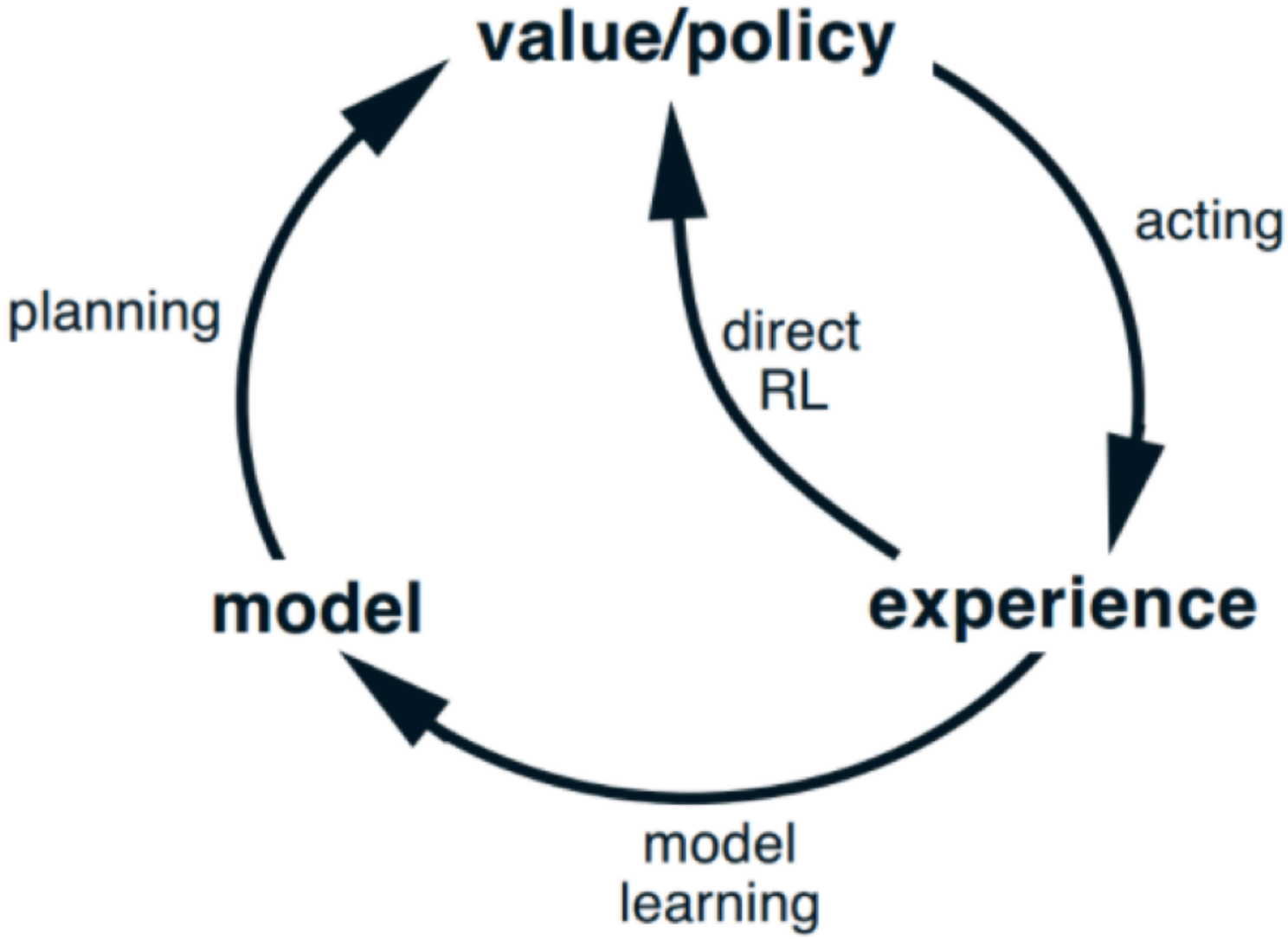
Predicts environment response to actions

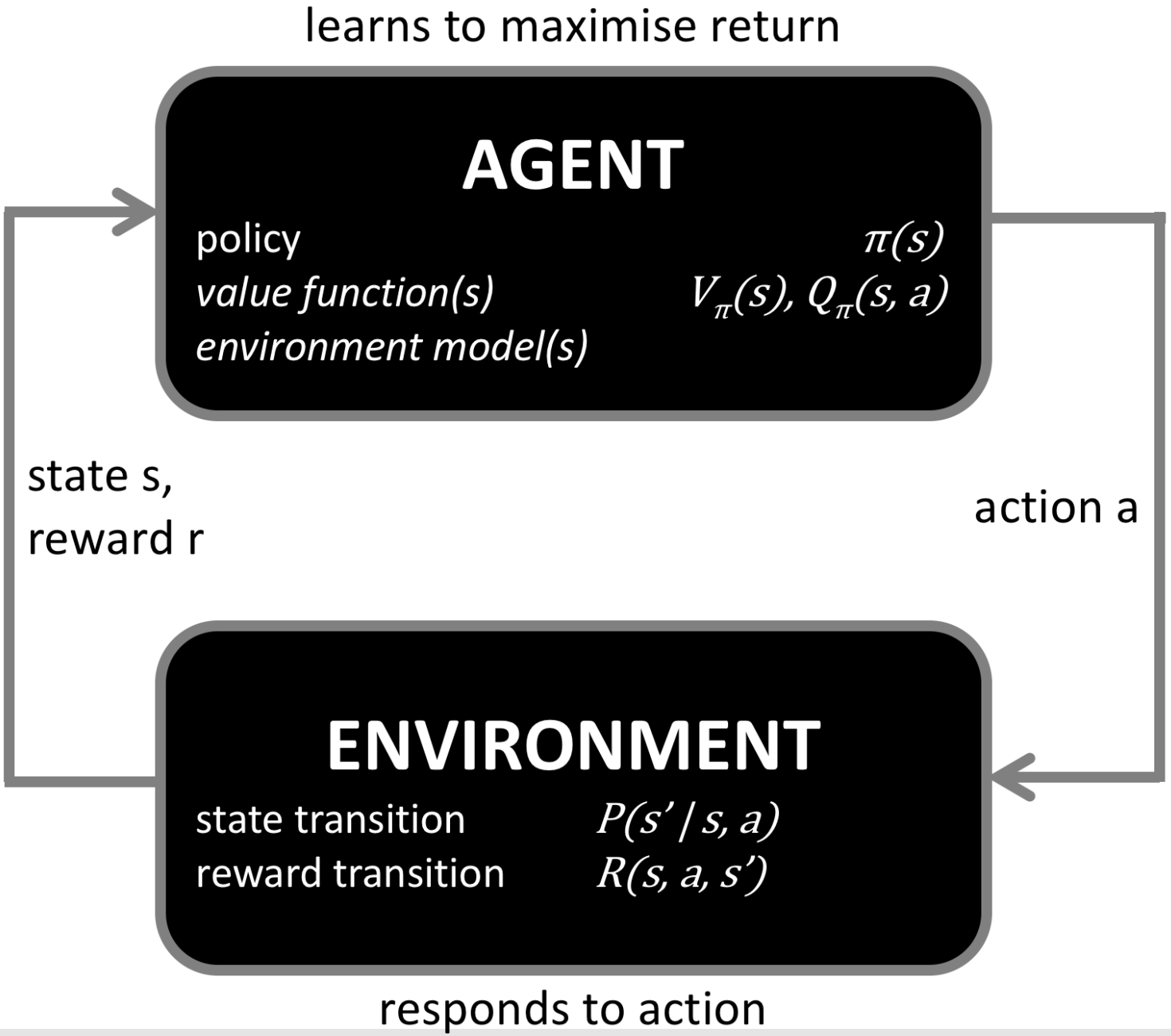
predicts s', r from s, a

```
def model(state, action):
    # do stuff
    return next_state, reward
```

Sample vs. distributional model

Model can be used to simulate trajectories for **planning**


value/policy
acting
direct
RL
planning
model
experience
model
learning


learns to maximise return
AGENT
policy
$\pi(s)$
value function(s)
$V_\pi(s)$, $Q_\pi(s, a)$
environment model(s)
state s,
reward r
action a
ENVIRONMENT
state transition
$P(s' \mid s, a)$
reward transition
$R(s, a, s')$
responds to action

Return

Goal of our agent is to maximize reward

Return (G_t) is the total discounted future reward

$$G_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \ldots = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$$

```
reward + discount * reward + discount^2 * reward ...
```

Why do we discount future rewards?

Discounting

Future is uncertain

- stochastic environment

Matches human thinking

- hyperbolic discounting

Finance

- time value of money

Makes the maths works

- return for infinite horizon problems finite
- discount rate is $[0, 1)$
- can make the sum of an infinite series finite
- geometric series

Discounting

Can use discount = 1 for

games with tree-like structures (without cycles)
when time to solve is irrelevant (i.e. a board game)

three

value functions

Bellman Equation

approximation methods

SARSA & Q-Learning

DQN

Value function

$$V_\pi(s)$$

how good is this state

Action-value function

$$Q_\pi(s, a)$$

how good is this action

Value function

$$V_\pi(s) = \mathbf{E}[G_t|s_t]$$

Expected return when in state s, following policy π

Action-value function

$$Q_\pi(s, a) = \mathbf{E}[G_t|s_t, a_t]$$

Expected return when in state s, taking action a, following policy π

Value functions are oracles

Prediction of the future

predict expected future discounted reward
always conditioned on a policy

We don’t know this function

agent must learn it
once we learn it – how will it help us to act?

Using a value function

given the optimal value function $Q_*(s, a)$

we are in state s

our set of actions $\mathcal{A} = a_1, a_2, a_3$

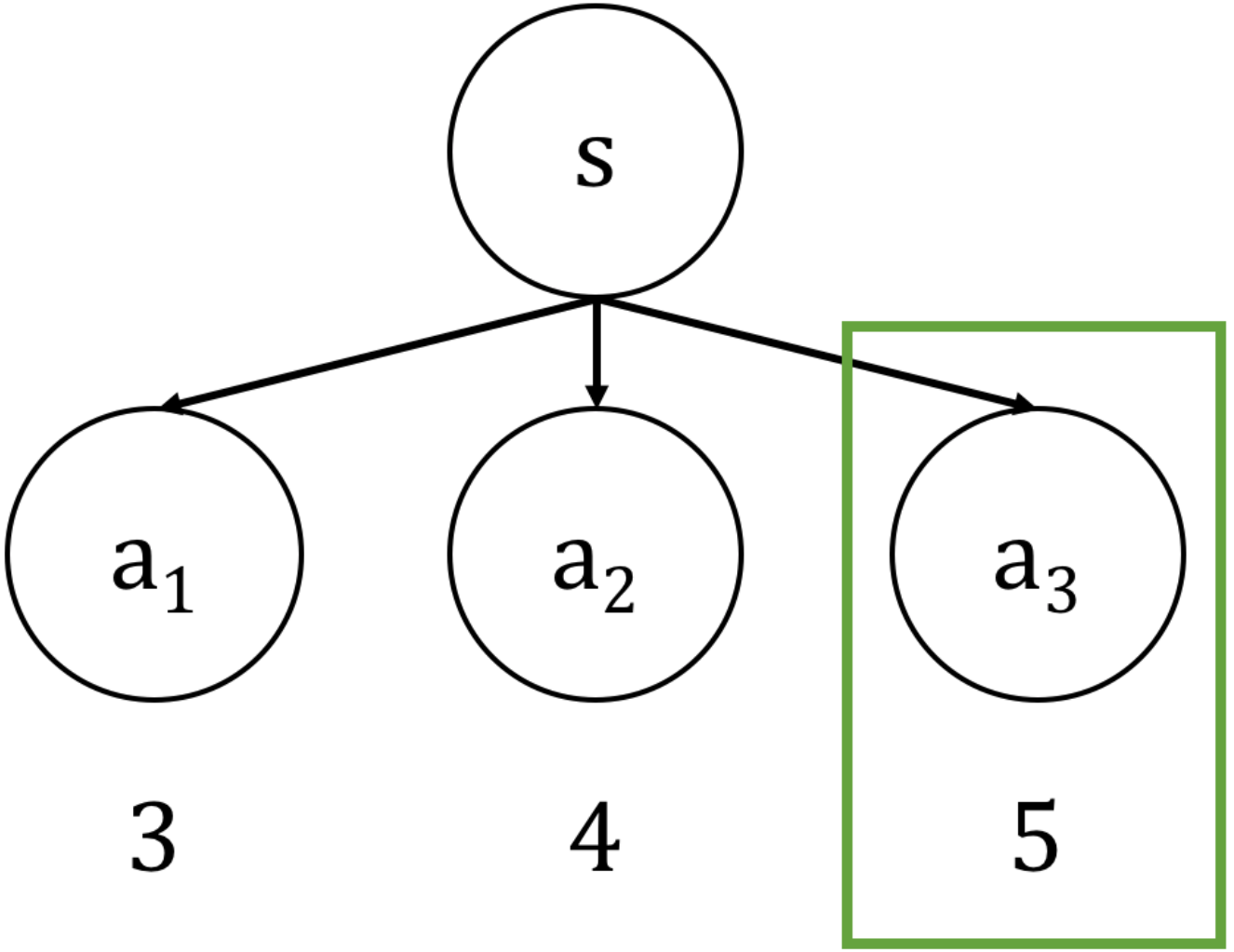
How can we act?

use the value function to determine which action has the highest expected return

select the action with the largest $Q(s, a)$ - ie take the $\arg\max_a Q(s, a)$

This is known as a *greedy policy*

Using a value function



```
def greedy_policy(state):

    #  get the Q values for each state_action pair
    q_values = value_function.predict(state)

    # select action with highest Q
    action = np.argmax(q_values)

    return action
```

Policy iteration

$$V_{k+1}(s) = \max_a \sum_{s',r} P(s', r|s, a)[r + \gamma V_k(s')]$$

These two steps are done sequentially in a process known as **policy iteration**

approximate our policy (i.e. $V_\pi(s)$)
act greedy wrt value function
approximate our (better) policy
act greedy
etc etc

Generalized policy iteration

Letting policy evaluation and improvement processes interact

Policy iteration

- sequence of approximating value function then making policy greedy wrt value function

Value iteration

- single iteration of policy evaluation done inbetween each policy improvement

Both of these can achieve the same result

The policy and value functions interact to move both towards their optimal values - this is one souce of non-stationary learning in RL

Policy iteration (using iterative policy evaluation)

1. Initialization
   $V(s) \in \mathbb{R}$ and $\pi(s) \in \mathcal{A}(s)$ arbitrarily for all $s \in \mathcal{S}$

2. Policy Evaluation
   Repeat
   $\Delta \leftarrow 0$
   For each $s \in \mathcal{S}$:
   $v \leftarrow V(s)$
   $V(s) \leftarrow \sum_{s',r} p(s', r \,|\, s, \pi(s)) \big[r + \gamma V(s')\big]$
   $\Delta \leftarrow \max(\Delta, |v - V(s)|)$
   until $\Delta < \theta$ (a small positive number)

3. Policy Improvement
   policy-stable $\leftarrow$ *true*
   For each $s \in \mathcal{S}$:
   old-action $\leftarrow \pi(s)$
   $\pi(s) \leftarrow \text{argmax}_a \sum_{s',r} p(s', r \,|\, s, a) \big[r + \gamma V(s')\big]$
   If *old-action* $\neq \pi(s)$, then *policy-stable* $\leftarrow$ *false*
   If *policy-stable*, then stop and return $V \approx v_*$ and $\pi \approx \pi_*$; else go to 2

Sutton & Barto

Value iteration

Initialize array V arbitrarily (e.g., $V(s) = 0$ for all $s \in \mathcal{S}^+$)

Repeat
  $\Delta \leftarrow 0$
  For each $s \in \mathcal{S}$:
    $v \leftarrow V(s)$
    $V(s) \leftarrow \max_a \sum_{s',r} p(s', r \mid s, a)\big[r + \gamma V(s')\big]$
    $\Delta \leftarrow \max(\Delta, |v - V(s)|)$
until $\Delta < \theta$ (a small positive number)

Output a deterministic policy, $\pi \approx \pi_*$, such that
  $\pi(s) = \arg\max_a \sum_{s',r} p(s', r \mid s, a)\big[r + \gamma V(s')\big]$

Value function approximation

To approximate a value function we can use one of the methods we looked at in the first section

- lookup table
- linear function
- non-linear function

Linear functions are appropriate with some agents or environments

Modern reinforcement learning is based on using neural networks

three

value functions

Bellman Equation

approximation methods

SARSA & Q-Learning

DQN

Richard Bellman

Invented dynamic programming in 1953.

Also introduced the curse of dimensionality

number of states $\mathcal{S}$ increases exponentially with number of dimensions in the state

On the naming of dynamic programming

> *I was interested in planning, in decision making, in thinking. But planning, is not a good word for various reasons. I decided therefore to use the word, 'programming.' I wanted to get across the idea that this was dynamic, this was multistage, this was time-varying...*

Bellman Equation

Bellman's contribution is remembered by the Bellman Equation

$$G_\pi(s) = r + \gamma G_\pi(s')$$

The Bellman equation relates the expected discounted return of the **current state** to the discounted value of the **next state**

The Bellman equation is a recursive definition - it is bootstrapped

We can apply it to value functions

$$V_\pi(s) = r + \gamma V_\pi(s')$$

$$Q_\pi(s, a) = r + \gamma Q_\pi(s', a')$$

How do we use the Bellman Equation?

Create **targets for learning**

train a neural network by minimizing the difference between the network output and the correct target

improve our approximation of a value function we need to create a targets for each sample of experience

minimize a loss function

$$loss = target - approximation$$

For an experience sample of (s, a, r, s')

$$loss = r + Q(s', a) - Q(s, a)$$

This is also known as the **temporal difference error**

three

value functions

Bellman Equation

approximation methods

SARSA & Q-Learning

DQN

Approximation methods

Look at three different methods for approximation

1. dynamic programming
2. Monte Carlo
3. temporal difference

We are **creating targets** to learn from

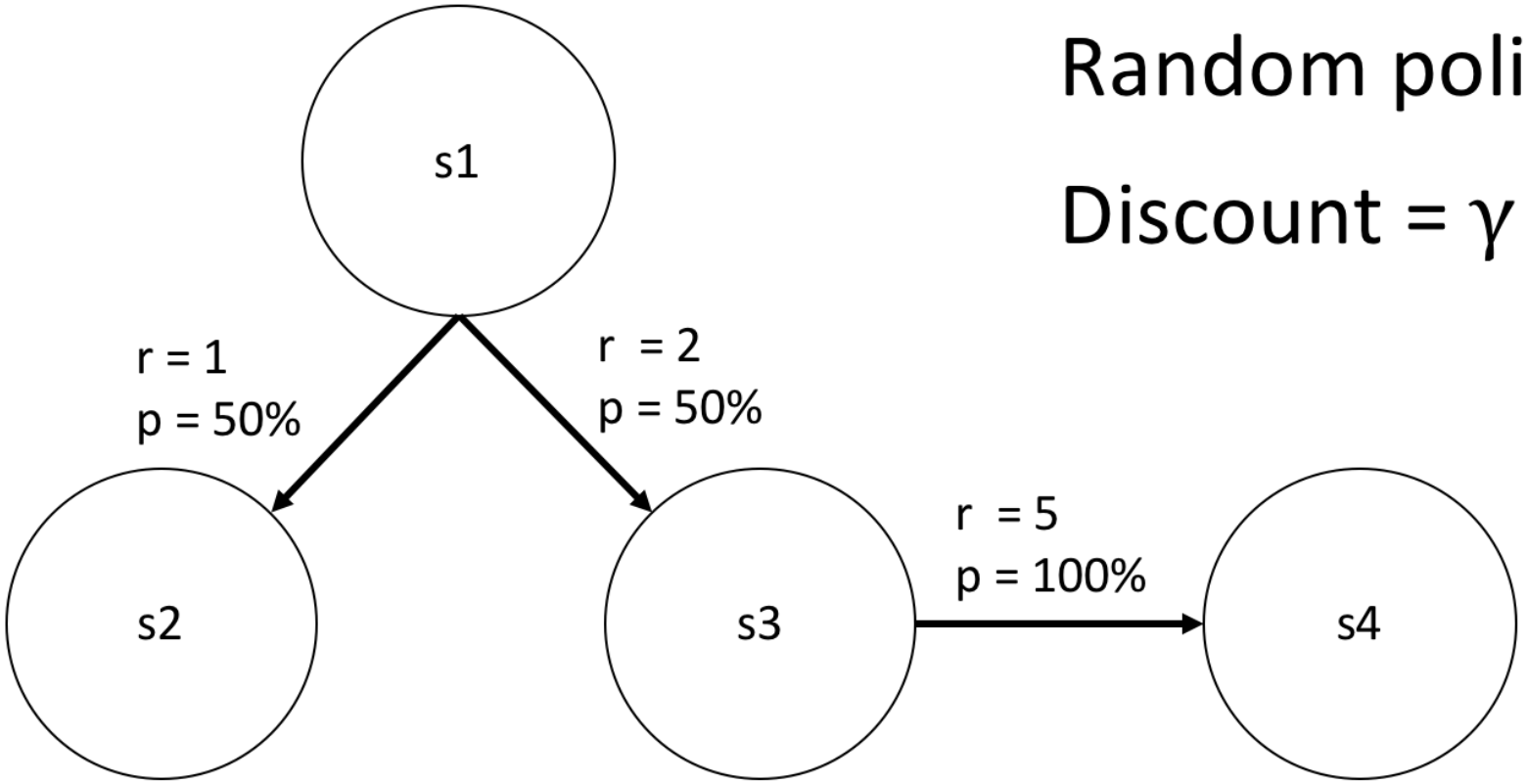
Policy improvement can be done by either policy iteration or value iteration for all of these different approximation methods

Dynamic programming

Imagine you had a perfect environment model

the state transition function $P(s'|s,a)$
the reward transition function $R(r|s,a,s')$

Can we use our perfect environment model for value function approximation?



Random policy

Discount = $\gamma = 0.9$

Note that the probabilities here depend both on the environment and the policy

Dynamic programming backup

We can perform iterative backups of the expected return for each state

The return for all terminal states is zero

$$V(s_2) = 0$$

$$V(s_4) = 0$$

We can then express the value functions for the remaining two states

$$V(s_3) = P_{34}[r_{34} + \gamma V(s_4)]$$

$$V(s_3) = 1 \cdot [5 + 0.9 \cdot 0] = 5$$

$$V(s_1) = P_{12}[r_{12} + \gamma V(s_2) + P_{13}[r_{13} + \gamma V(s_3)]$$

$$V(s_1) = 0.5 \cdot [1 + 0.9 \cdot 0] + 0.5 \cdot [2 + 0.9 \cdot 5] = 3.75$$

Dynamic programming

Our value function approximation depends on

- our policy (what actions we pick)
- the environment (where our actions take us and what rewards we get)
- our current estimate of $V(s')$

A dynamic programming update is expensive

- our new estimate $V(s)$ depends on the value of all other states (even if the probability is zero)

Asynchronous dynamic programming addresses this by updating states in an arbitrary order

Dynamic programming summary

Requries a **perfect environment model**

- we don't need to sample experience at all
  we don't ever actually take actions)

We make **full backups**

- the update to the value function is based on the probability distribution over all possible next states

Bootstrapped

- we use the recursive Bellman Equation to update our value function

Limited utility in practice but they provide an **essential foundation** for understanding reinforcement learning

- all RL can be thought of as attempts to achieve what DP can but without a model and with less computation

Monte Carlo

Monte Carlo methods = finding the expected value of a function of a random variable

No model

we learn from actual experience

We can also learn from **simulated experience**

we don't need to know the whole proability distribution
just be able to generate sample trajectories

No boostrapping

we take the average of the true discounted return

Episodic only

because we need to calcuate the true discounted return

Monte Carlo approximation

Estimate the value of a state by averaging the true discounted return observed after each visit to that state

As we run more episodes, our estimate should converge to the true expectation

Low bias & high variance - why?

Bias & variance of Monte Carlo

High variance

- we need to sample enough episodes for our averages to converge
- can be a lot for stochastic or path dependent environments

Low bias

- we are using actual experience

Monte Carlo algorithm

Algorithm for a lookup table based Monte Carlo approximation

Initialize:

$\pi \leftarrow$ policy to be evaluated **i.e. greedy policy**

$V \leftarrow$ an arbitrary state-value function

$Returns(s) \leftarrow$ an empty list, for all $s \in \mathcal{S}$

(lookup table)

Repeat forever:

(a) Generate an episode using π

(b) For each state s appearing in the episode:

$G \leftarrow$ return following the first occurrence of s

Append G to $Returns(s)$

$V(s) \leftarrow \text{average}(Returns(s))$

Interesting feature of Monte Carlo

Computational expense of estimating the value of state s is independent of the number of states $\mathcal{S}$

This is because we use experienced state transitions

Monte Carlo

Learn from **actual or simulated experience**

- no environment model

No bootstrapping

- use true discounted returns sampled from the environment

Episodic problems only

- no learning online

Ability to **focus** on interesting states and ignore others

High variance & low bias

Temporal difference

Learn from **actual experience**

- like Monte Carlo
- no environment model

Bootstrap

- like dynamic programming
- learn online

Episodic & non-episodic problems

Temporal difference

Use the Bellman Equation to approximate $V(s)$ using $V(s')$

Temporal difference error

$$actual = r + \gamma V(s')$$
$$predicted = V(s)$$

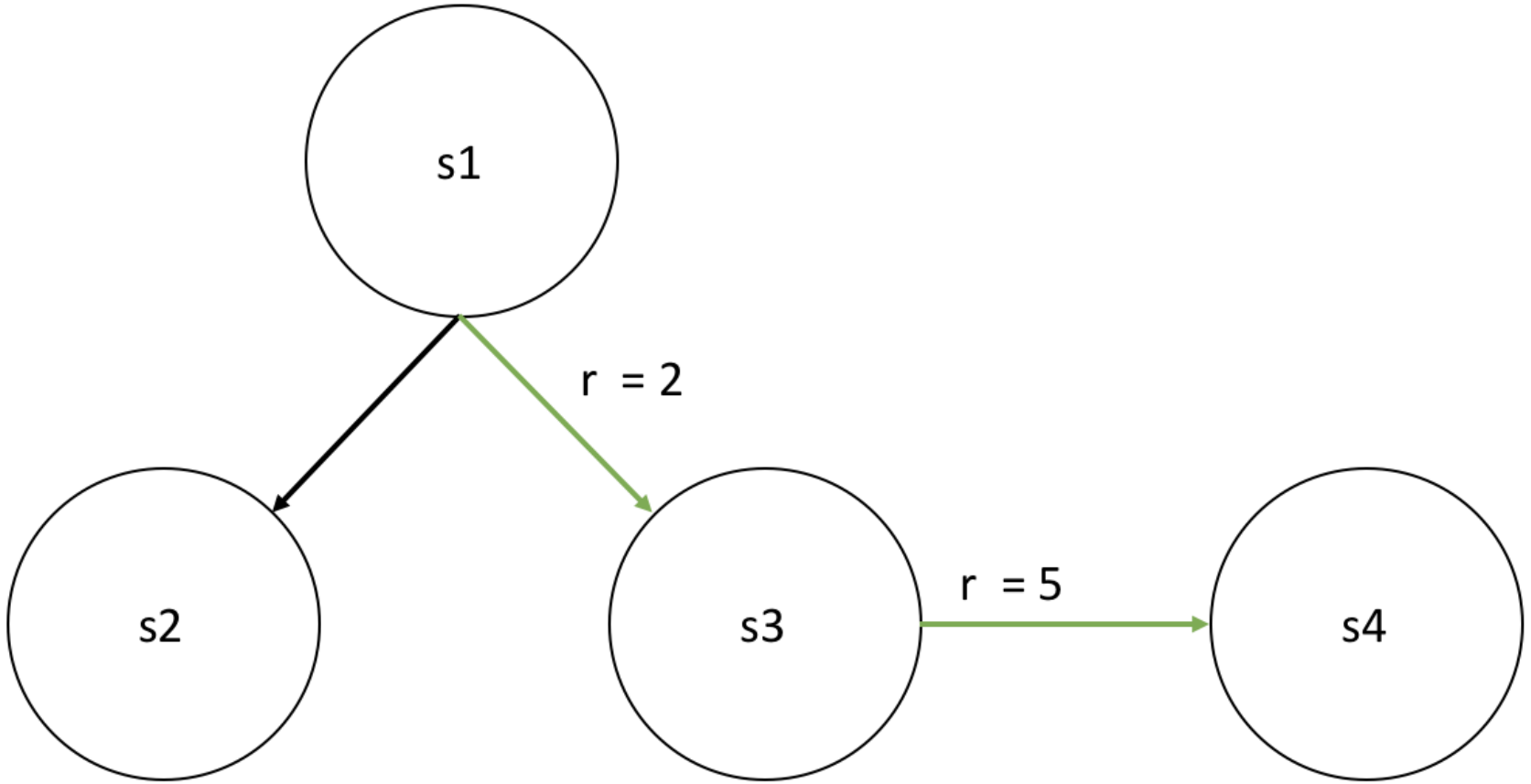
$$error = actual - predicted$$
$$error = r + \gamma V(s') - V(s)$$

Update rule for a table TD(0) approximation

$$V(S_t) \leftarrow V(S_t) + \alpha \Big[R_{t+1} + \gamma V(S_{t+1}) - V(S_t) \Big]$$

TD error

Temporal difference backup



$$V(s_1) \leftarrow V(s_1) + \alpha[r_{23} + \gamma V(s_3) - V(s_1)]$$

You are the predictor

Example 6.4 from Sutton & Barto

Imagine you observe the following episodes

format of (State Reward, State Reward)
i.e. A 0 B 0 = state A, reward 0, state B, reward 0

Episode	**Number times observed**
A 0, B 0	1
B 1	6
B 0	1

What are the optimal predictions for $V(A)$ and $V(B)$?

You are the predictor

We can estimate the expected return from state B by averaging the rewards

$$V(B) = 6/8 \cdot 1 + 2/6 \cdot 0 = 3/4$$

What about $V(A)$?

> We observed that every time we were in A we got 0 reward and ended up in B
> Therefore $V(A) = 0 + V(B) = 3/4$

or

> We observed a discounted return of 0 each time we saw A
> therefore $V(A) = 0$

Which is the Monte Carlo approach, which is the TD approach?

You are the predictor

Estimating $V(A) = 3/4$ is the answer given by TD(0)

Estimtating $V(A) = 0$ is the answer given by Monte Carlo

The MC method gives us the lowest error on fitting the data (i.e. minimizes MSE)

The TD method gives us the **maximum-likelihood estimate**

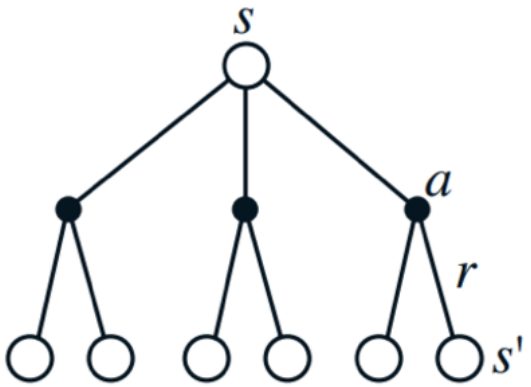
You are the predictor

The maximum likelihood estimate of a parameter is the parameter value whose probabilty of generating the data is greatest

We take into account the transition probabilities, which gives us the **certanitiy equivilance estimate** - which is the estimate we get when assuming we know the underlying model (rather than approximating it)

Recap

Dynamic Programming



Monte Carlo

Temporal Difference

Sutton & Barto

three

value functions

Bellman Equation

approximation methods

SARSA & Q-Learning

DQN

SARSA & Q-Learning

Approximation is a tool - **control** is what we really want

SARSA & Q-Learning are both based on the **action-value function** $Q(s, a)$

The practical today is based on DQN - the DeepMind implementation of Q-Learning

Why might we want to learn $Q(s, a)$ rather than $V(s)$?

$V(s)$ versus $Q(s, a)$

Imagine a simple MDP

$$\mathcal{S} = s_1, s_2, s_3$$

$$\mathcal{A} = a_1, a_2$$

Our agent finds itself in state s_2

We use our value function $V(s)$ to calculate

$$V(s_1) = 10$$
$$V(s_2) = 5$$
$$V(s_3) = 20$$

Which action should we take?

$V(s)$ versus $Q(s, a)$

Now imagine we had

$$Q(s_2, a_1) = 40$$

$$Q(s_2, a_2) = 20$$

It's now easy to pick the action that maximizes expected discounted return

$V(s)$ tells us how good a state is. We require the state transition probabilities for each action to use $V(s)$ for control

$Q(s, a)$ tells us how good an **action** is

SARSA

SARSA is an **on-policy** control method

we approximate the policy we are following
we improve the policy by being greedy wrt to our approximation

We use every element from our experience tuple (s, a, r, s')

and also a' - the next action selected by our agent

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma Q(s',a') - Q(s,a)]$$

Why is SARSA on-policy?

SARSA

SARSA is on-policy because we learn about the action a' that our agent choose to take

Our value function is always for the policy we are following

> the state transition probabilities depend on the policy

But we can improve it using general policy iteration (GPI)

> approximate $Q(s, a)$ for our current policy
> act greedily towards this approximation of $Q(s, a)$
> approximate $Q(s, a)$ for our new experience
> act greedily towards this new approximation
> repeat

Q-Learning

Q-Learning allows **off-policy control**

use every element from our experience tuple (s, a, r, s')

We take the **maximum over all possible next actions**

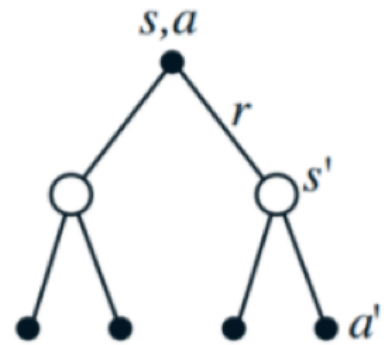
we don't need to know what action our agent took next (i.e. a')

This allows us to learn the optimal value function while following a sub-optimal policy

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_a Q(s', a') - Q(s,a)]$$

Don't learn Q_π - learn Q^* (the optimal policy)

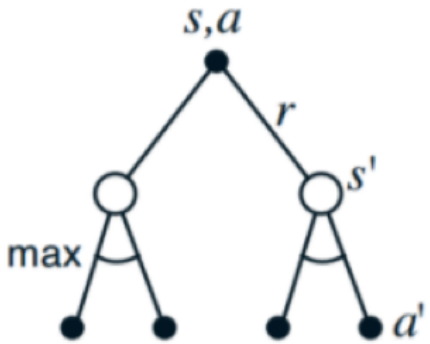
$q_\pi(a,s)$



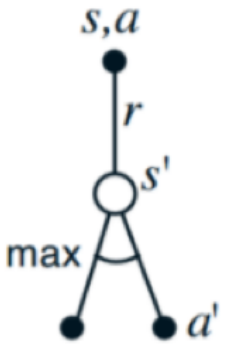
Q-policy evaluation

Sarsa

$q_*(a,s)$



Q-value iteration



Q-learning

Q-Learning

Selecting optimal actions in Q-Learning can be done by an $argmax$ across the action space

$$action = \underset{a}{argmax} Q(s, a)$$

The $argmax$ limits Q-Learning to **discrete action spaces only**

For a given approximation of $Q(s, a)$ acting greedy is deterministic

How then do we explore the environment?

ϵ-greedy exploration

A common exploration stragety is the **epsilon-greedy policy**

```
def epsilon_greedy_policy():
    if np.random.rand() < epsilon:
        #  act randomly
        action = np.random.uniform(action_space)

    else:
        #  act greedy
        action = np.argmax(Q_values)

    return action
```

ϵ is decayed during experiments to explore less as our agent learns (i.e. to exploit)

Exploration strageties

Boltzmann (a softmax)

temperature being annealed as learning progresses

Bayesian Neural Network

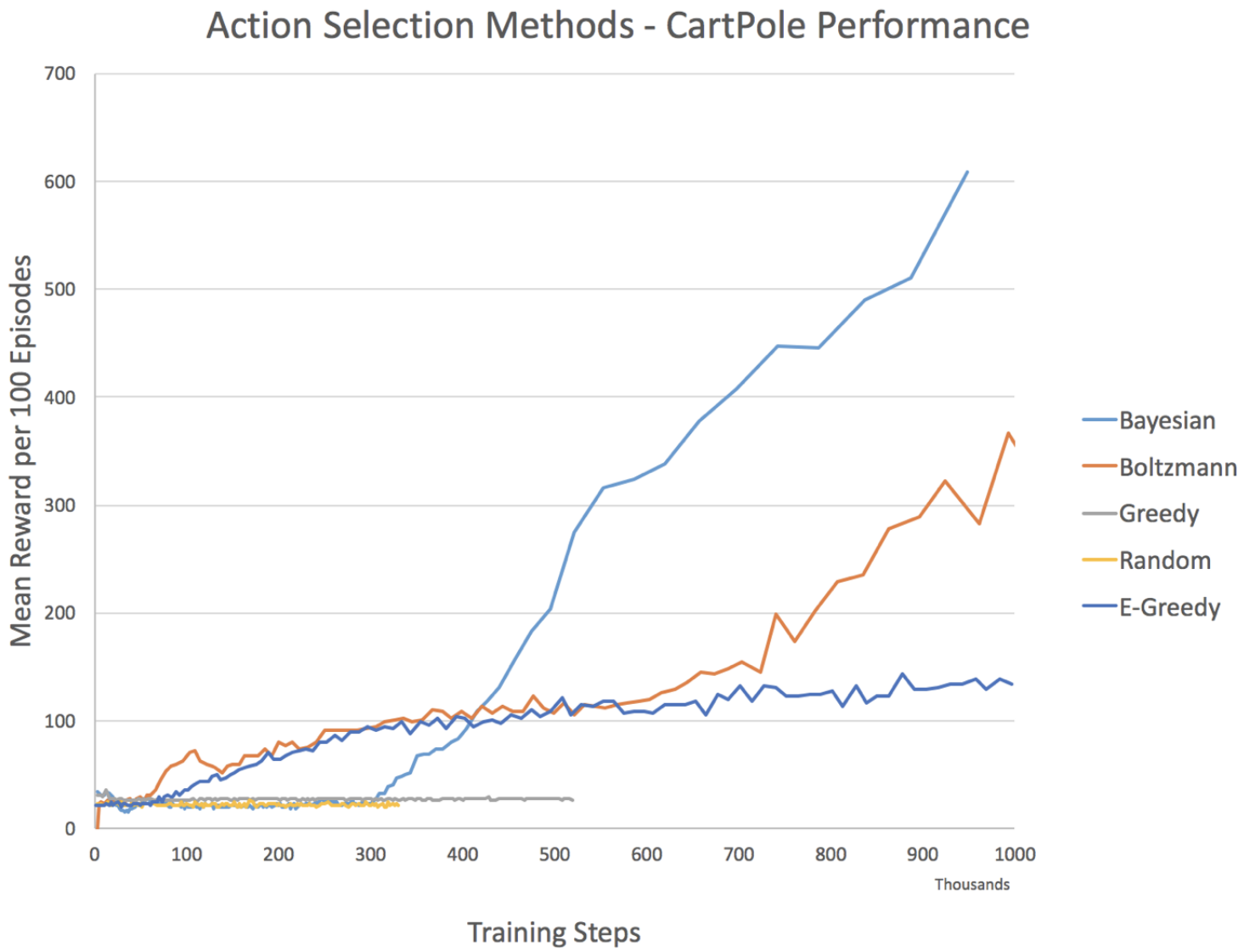
a network that maintains distributions over weights -> distribution over actions
this can also be performed using dropout to simulate a probabilistic network

Parameter noise

adding adaptive noise to weights of network

Action-Selection Strategies for Exploration

Plappert et al. (2018) Paramter Space Noise for Exploration


Action Selection Methods - CartPole Performance
Mean Reward per 100 Episodes
700
600
500
400
300
200
100
0
0
100
200
300
400
500
600
700
800
900
1000
Thousands
Training Steps
Bayesian
Boltzmann
Greedy
Random
E-Greedy

Problems with vanilla Q-Learning

Correlations in our dataset (the list of experience tuples)

combine this with bootstrapping and instability occurs

Small changes $Q(s, a)$ estimates can drastically change the policy

$$Q(s_1, a_1) = 10$$
$$Q(s_1, a_2) = 11$$

Then we do some learning and our estimates change

$$Q(s_1, a_1) = 12$$
$$Q(s_1, a_2) = 11$$

Now our policy is completely different!

Deadly triad

Sutton & Barto discuss the concept of the **deadly triad**

Three mechanisms that combine to produce instability and divergence

1. off-policy learning - to learn about the optimal policy while following an exploratory policy
2. function approximation - for scalability and generalization
3. bootstrapping - computational & sample efficiency

Deadly triad

It's not clear what causes instability

- dynamic programming can diverge with function approximation (so even on-policy learning can diverge)
- prediction can diverge
- linear functions can be unstable

Divergence is an emergent phenomenon

Up until 2013 the deadly triad caused instability when using Q-Learning with complex function approximators (i.e. neural networks)

Then came DeepMind & DQN

three

value functions

Bellman Equation

approximation methods

SARSA & Q-Learning

DQN

DQN

In 2013 a small London startup published a paper

- an agent based on Q-Learning
- superhuman level of performance in three Atari games

In 2014 Google purchased DeepMind for around £400M

This is for a company with

- no product
- no revenue
- no customers
- a few world class employees

Playing Atari with Deep Reinforcement Learning

Volodymyr Mnih **Koray Kavukcuoglu** **David Silver** **Alex Graves** **Ioannis Antonoglou**

Daan Wierstra **Martin Riedmiller**

DeepMind Technologies

{vlad,koray,david,alex.graves,ioannis,daan,martin.riedmiller} @ deepmind.com

19 Dec 2013

Significance

End to end deep reinforcement learning

- Q-Learning with neural networks was historically unstable

Learning from high dimensional input

- raw pixels

Ability to **generalize**

- same algorithm, network strucutre and hyperparameters

Reinforcement learning to play Atari

State

Last four screens concatenated together
Allows infomation about movement
Grey scale, cropped & normalized

Reward

Game score
Clipped to [-1, +1]

Actions

Joystick buttons (a discrete action space)

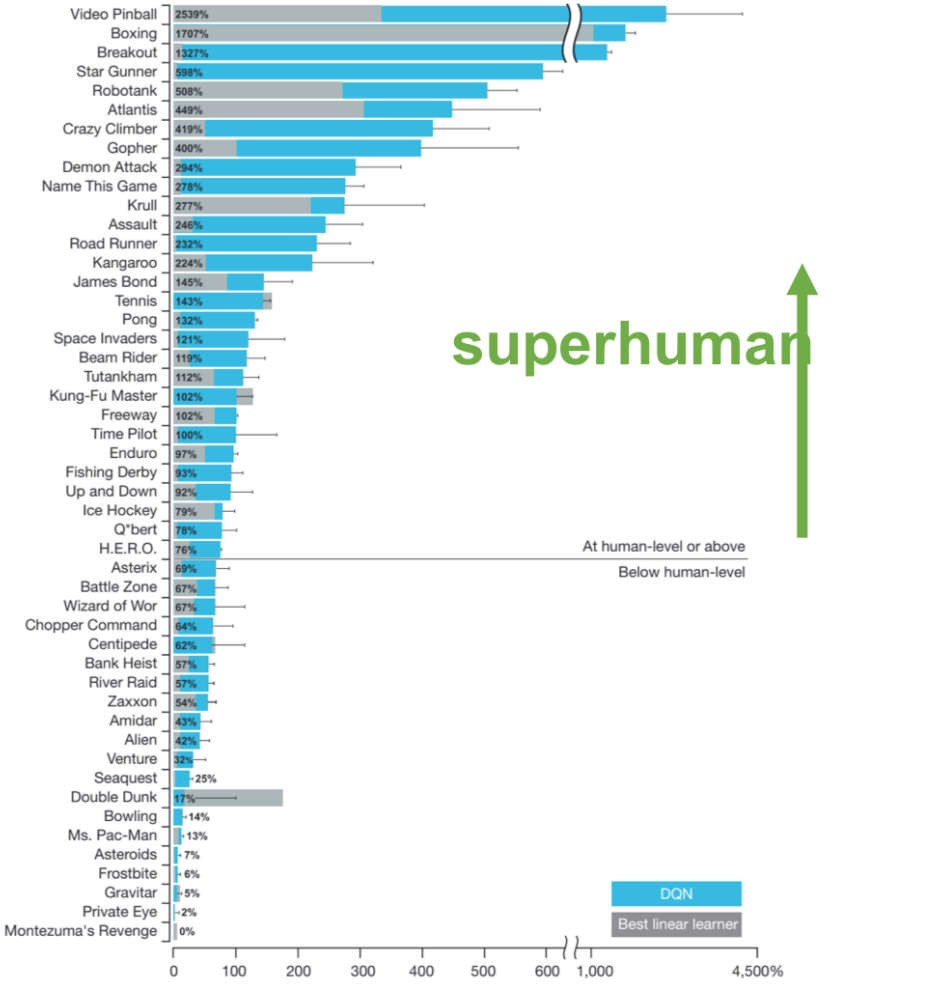
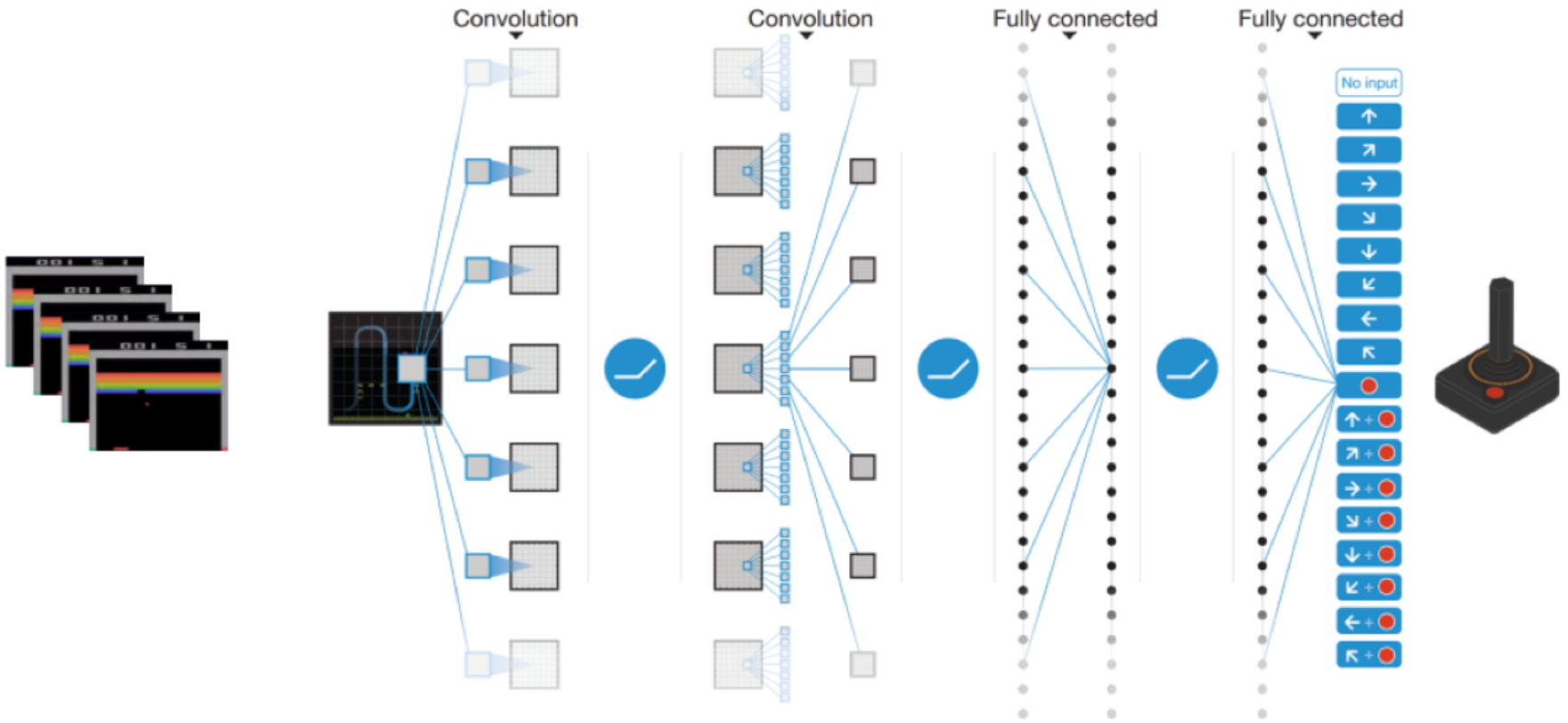


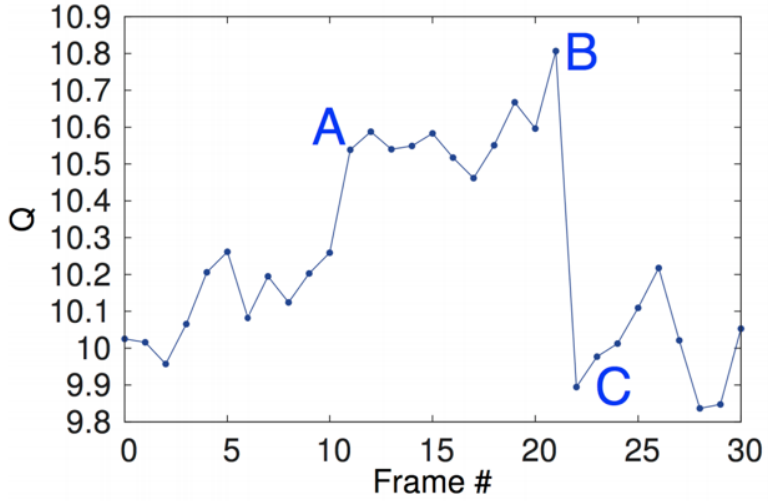
Figure 3 | Comparison of the DQN agent with the best reinforcement learning methods[15] in the literature. The performance of DQN is normalized with respect to a professional human games tester (that is, 100% level) and random play (that is, 0% level). Note that the normalized performance of DQN, expressed as a percentage, is calculated as: 100 × (DQN score − random play score)/(human score − random play score). It can be seen that DQN outperforms competing methods (also see Extended Data Table 2) in almost all the games, and performs at a level that is broadly comparable with or superior to a professional human games tester (that is, operationalized as a level of 75% or above) in the majority of games. Audio output was disabled for both human players and agents. Error bars indicate s.d. across the 30 evaluation episodes, starting with different initial conditions.



	Layer	Input	Filters	Filter size	Stride	Activation
1	Convolution	84x84x4	16 *(32)*	8×8	4	ReLU
2	Convolution	20x20x32	32 *(64)*	4×4	2	ReLU
3	*Convolution*	*64*	*64*	*3x3*	*1*	*ReLU*
4	Fully connected	256 *(512)*				Linear

2013 – Playing Atari with Deep Reinforcement learning

2015 – Human-level control through deep Reinforcement learning



Agent sees new enemy

Value function gets excited

Agent has fired torpedo

Value function is very excited

Reward received

Value function back to normal

A

B

C

Two key innovations in DQN

Experience replay

Target network

Both improve learning **stability**

Experience replay

Replay buffer

Sample uniform random

Training targets

$[(s_0, a_0, r_1, s'_1),$
$(s_1, a_1, r_2, s'_2),$
$(s_2, a_2, r_3, s'_3),$
$\ldots.$
$(s_n, a_n, r_{n+1}, s'_{n+1})]$

$[Q(s_0, a_0) = r_1 + \gamma \max_a Q(s_1, a),$
$\ldots,$
$Q(s_2, a_2) = r_3 + \gamma \max_a Q(s_3, a)]$

Memory of last 1 million frames

Trained using batches of 32-64 random samples

Experience replay

Experience replay helps to deal with our non-iid dataset

- randomizing the sampling of experience -> more independent
- brings the batch distribution closer to the true distribution -> more identical

Data efficiency

- we can learn from experience multiple times

Allows seeding of the memory with high quality experience

Biological basis for experience replay

Hippocampus may support an experience replay process in the brain

Time compressed reactivation of recently experienced trajectories during offline periods

Provides a mechanism where value functions can be efficiently updated through interactions with the basal ganglia

Mnih et. al (2015)

Target network

Second innovation behind DQN

Parameterize two separate neural networks (identical structure) - two sets of weights θ and θ^{-}

$$L_i(\theta_i) = \mathbb{E}_{(s,a,r,s')\sim U(D)}\left[r + \gamma \max_{a'} Q(s', a'; \boldsymbol{\theta_i^{-}}) - Q(s, a; \boldsymbol{\theta_i})^2\right]$$

target **approx.**

Original Atari work copied the online network weights to the target network every 10k - 100k steps

Can also use a small factor tau (τ) to smoothly update weights at each step

Target network

Changing value of one action changes value of all actions & similar states

- bigger networks less prone (less aliasing aka weight sharing)

Stable training

- no longer bootstrapping from the same function, but from an old & fixed version of $Q(s, a)$
  reduces correlation between the target created for the network and the network itself

Game	With replay, with target Q	With replay, without target Q	Without replay, with target Q	Without replay, without target Q
Breakout	316.8 **100x**	240.7	10.2	3.2
Enduro	1006.3 **1000x**	831.4	141.9	29.1
River Raid	7446.6 **5x**	4102.8	2867.7	1453.0
Seaquest	2894.4 **10x**	822.6	1003.0	275.8
Space Invaders	1088.9 **3x**	826.3	373.2	302.0

Algorithm 1: deep Q-learning with experience replay.

Initialize replay memory D to capacity N

Initialize action-value function Q with random weights θ

Initialize target action-value function $\hat{Q}$ with weights $\theta^{-} = \theta$

For episode $= 1, M$ **do**

Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$

For $t = 1$,T **do**

With probability ε select a random action a_t
otherwise select $a_t = \text{argmax}_a Q(\phi(s_t), a; \theta)$

ε-greedy action selection

Execute action a_t in emulator and observe reward r_t and image x_{t+1}

Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$

Store transition $\left(\phi_t, a_t, r_t, \phi_{t+1}\right)$ in D

Sample random minibatch of transitions $\left(\phi_j, a_j, r_j, \phi_{j+1}\right)$ from D

experience replay

Set $y_j = \begin{cases} r_j & \text{if episode terminates at step j+1} \\ r_j + \gamma \max_{a'} \hat{Q}\left(\phi_{j+1}, a'; \theta^{-}\right) & \text{otherwise} \end{cases}$

Perform a gradient descent step on $\left(y_j - Q\left(\phi_j, a_j; \theta\right)\right)^2$ with respect to the network parameters θ

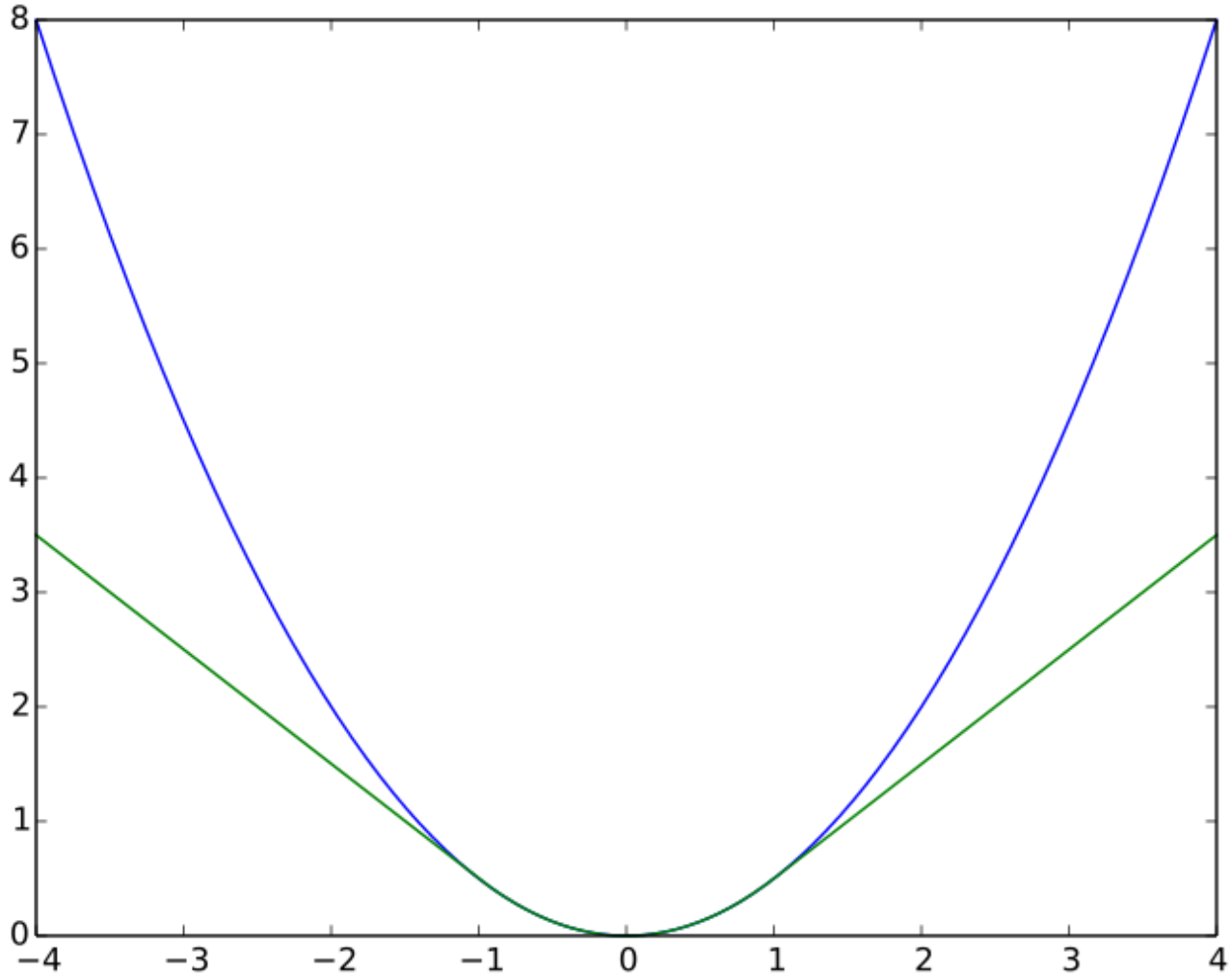
Every C steps reset $\hat{Q} = Q$

target network update

End For

End For

Huber loss



Timeline

1986 - Backprop by Rumelhart, Hinton & Williams in multi layer nets

1989 - Q-Learning (Watkins)

1992 - Experience replay (Lin)

2010 - Tabular Double Q-Learning

2010's - GPUs used for neural networks

2013 - DQN

2015 - Prioritized experience replay

2016 - Double DQN (DDQN)

2017 - Distributional Q-Learning

2018 - Rainbow

four

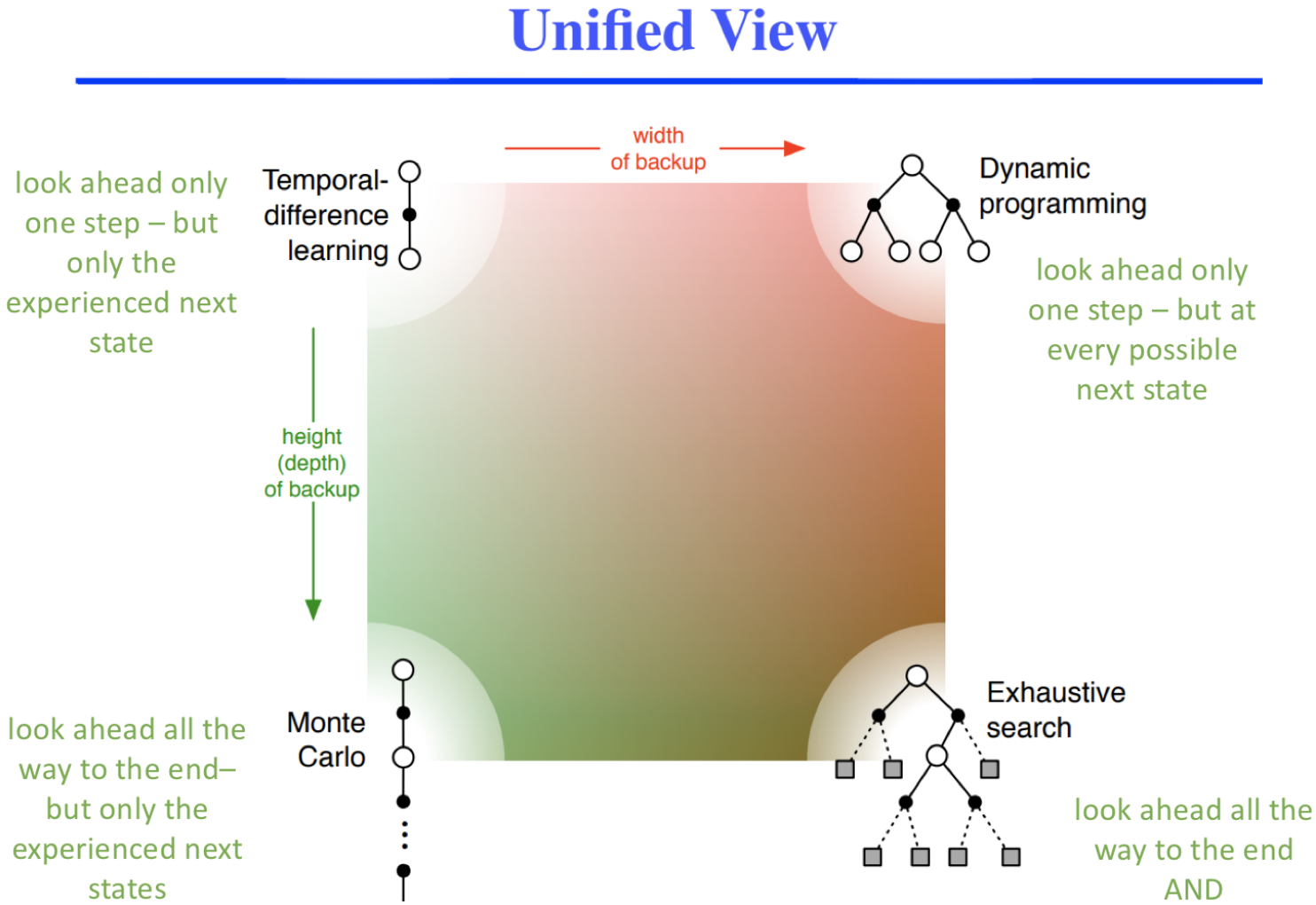
eligibility traces

prioritized experience replay

DDQN

Distributional Q-Learning

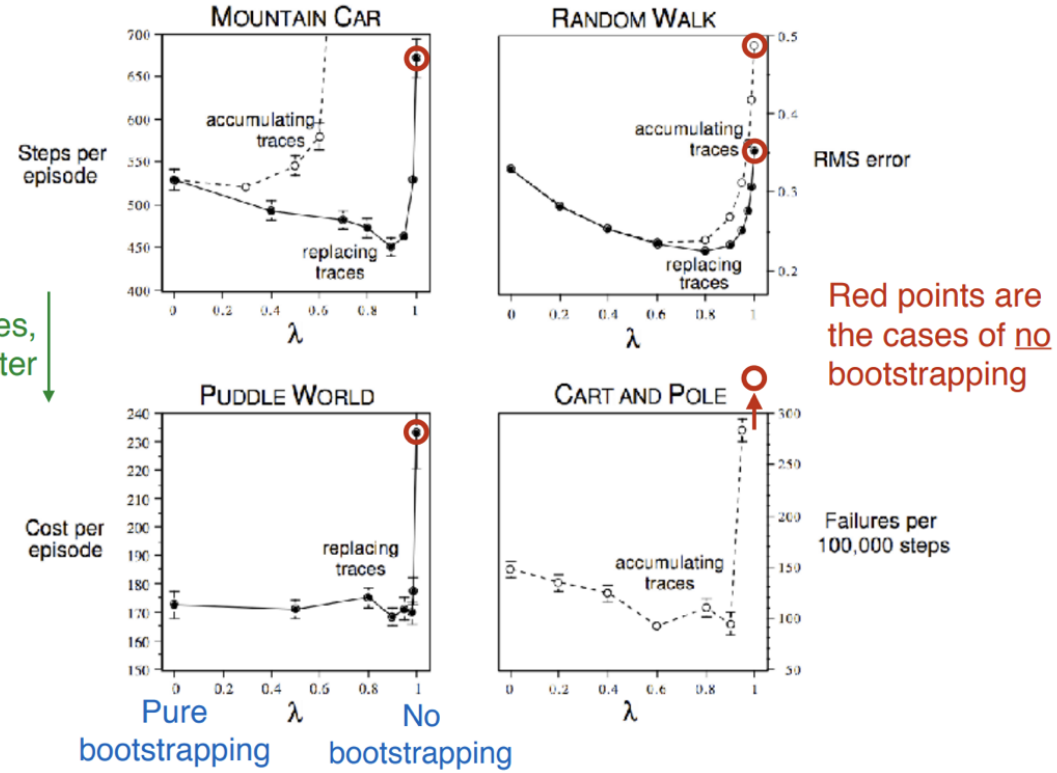
Rainbow



DeepMind's Richard Sutton - The Long-term of AI & Temporal-Difference Learning

4 examples of the effect of bootstrapping

suggest that λ=1 (no bootstrapping) is a very poor choice
(i.e., Monte Carlo has high variance)



λ = 0 = TD(0)

λ = 1 = full Monte Carlo

Conclusion – full Monte Carlo isn't very good!

DeepMind's Richard Sutton - The Long-term of AI & Temporal-Difference Learning

Eligibility traces

Family of methods between Temporal Difference & Monte Carlo

Eligibility traces allow us to **assign TD errors** to different states

- can be useful with delayed rewards or non-Markov environments
- requires more computation
- squeezes more out of data

Allow us to tradeoff between bias and variance

In between TD and MC exist a family of approximation methods known as **n-step returns**

Forward and backward view

We can look at eligibility traces from two perspectives

The **forward** view is helpful for understanding the theory

The **backward** view can be put into practice

The forward view

We can decompose return into **complex backups**

looking forward to future returns
can use a combination of experience based and model based backups

$$R_t = \frac{1}{2} R_t^2 + \frac{1}{2} R_t^4$$

$$R_t = \frac{1}{2} TD + \frac{1}{2} MC$$

The backward view

The backward view approximates the forward view

forward view is not practical (requires knowledge of the future)

It requires an additional variable in our agents memory

eligibility trace $e_t(s)$

At each step we decay the trace according to

$$e_t(s) = \gamma\lambda e_{t-1}(s)$$

Unless we visited that state, in which case we accumulate more eligibility

$$e_t(s) = \gamma\lambda e_{t-1}(s) + 1$$

The backward view

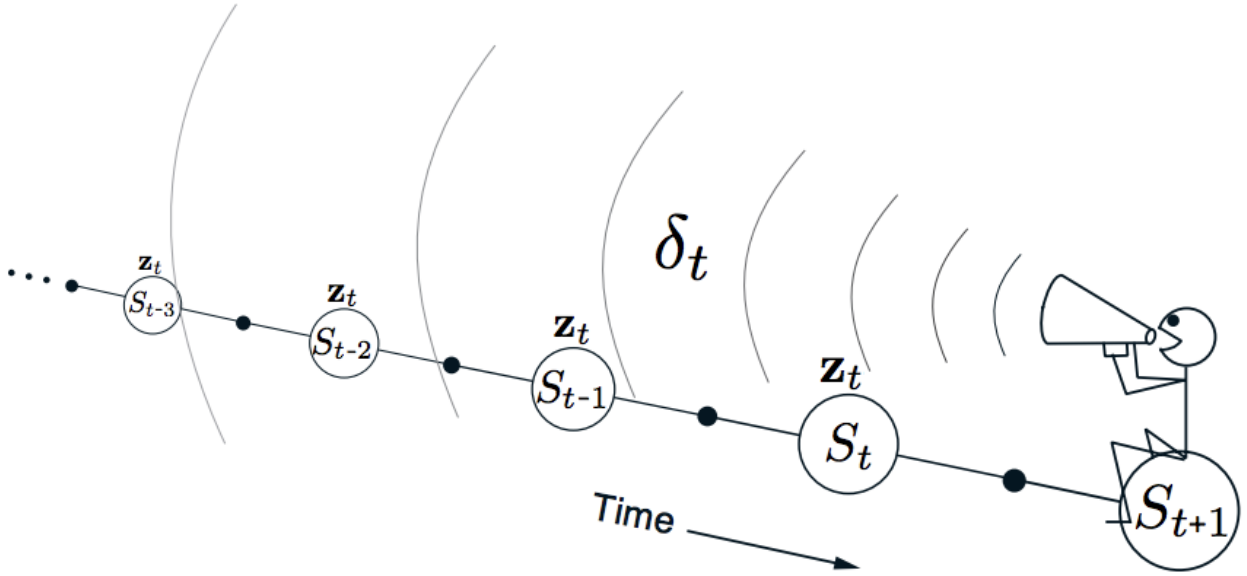
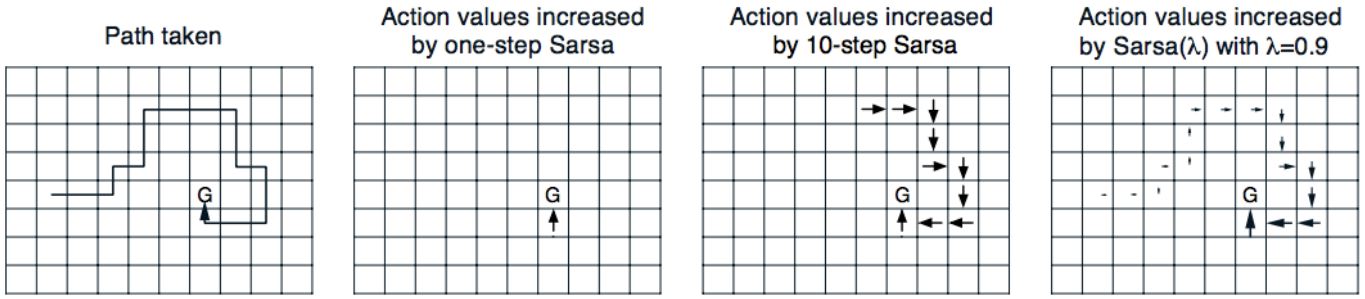


Figure 12.5: The backward or mechanistic view. Each update depends on the current TD error combined with the current eligibility traces of past events.

Traces in a grid world

Example 12.1: Traces in Gridworld The use of eligibility traces can substantially increase the efficiency of control algorithms over one-step methods and even over n-step methods. The reason for this is illustrated by the gridworld example below.



The first panel shows the path taken by an agent in a single episode. The initial estimated values were zero, and all rewards were zero except for a positive reward at the goal location marked by G. The arrows in the other panels show, for various algorithms, which action-values would be increased, and by how much, upon reaching the goal. A one-step method would increment only the last action value, whereas an n-step method would equally increment the last n action's values, and an eligibility trace method would update all the action values up to the beginning of the episode to different degrees, fading with recency. The fading strategy is often the best tradeoff, strongly learning how to reach the goal from the right, yet not as strongly learning the roundabout path to the goal from the left that was taken in this episode. ■

one step method would only update the last $Q(s, a)$

n-step method would update all $Q(s, a)$ equally

four

eligibility traces

prioritized experience replay

DDQN

Distributional Q-Learning

Rainbow

PRIORITIZED EXPERIENCE REPLAY

Tom Schaul, John Quan, Ioannis Antonoglou and David Silver
Google DeepMind
{schaul,johnquan,ioannisa,davidsilver}@google.com

Naive experience replay

Replay buffer

Sample uniform random

$[(s_0, a_0, r_1, s'_1),$
$(s_1, a_1, r_2, s'_2),$
$(s_2, a_2, r_3, s'_3),$
$\ldots.$
$(s_n, a_n, r_{n+1}, s'_{n+1})]$

Training targets

$[Q(s_0, a_0) = r_1 + \gamma \max_a Q(s_1, a),$
$\ldots,$
$Q(s_2, a_2) = r_3 + \gamma \max_a Q(s_3, a)]$

Memory of last 1 million frames

Trained using batches of 32-64 random samples

Prioritized Experience Replay

Naive experience replay randomly samples experience

learning occurs at the same frequency as experience

Some experience is more useful for learning than others

we can measure how useful experience is by the temporal difference error

$$error = r + \gamma Q(s', a) - Q(s, a)$$

TD error measures suprise

this transition gave a higher or lower reward than our value function expected

Prioritized Experience Replay

Non-random sampling introduces two problems

1. loss of diversity - we will only sample from high TD error experiences
2. introduce bias - non-independent sampling

Schaul et. al (2016) solves these problems by

1. loss of diversity -> make the prioritization stochastic
2. correct bias -> use importance sampling

four

eligibility traces

prioritized experience replay

DDQN

Distributional Q-Learing

Rainbow

Deep Reinforcement Learning with Double Q-learning

Hado van Hasselt and **Arthur Guez** and **David Silver**
Google DeepMind

arXiv:1509.06461v3 [cs.LG] 8 Dec 2015

DDQN

DDQN = Double Deep Q-Network

first introducued in a tabular setting in 2010
reintroduced in the content of DQN in 2016

DDQN aims to overcome the **maximization bias** of Q-Learning

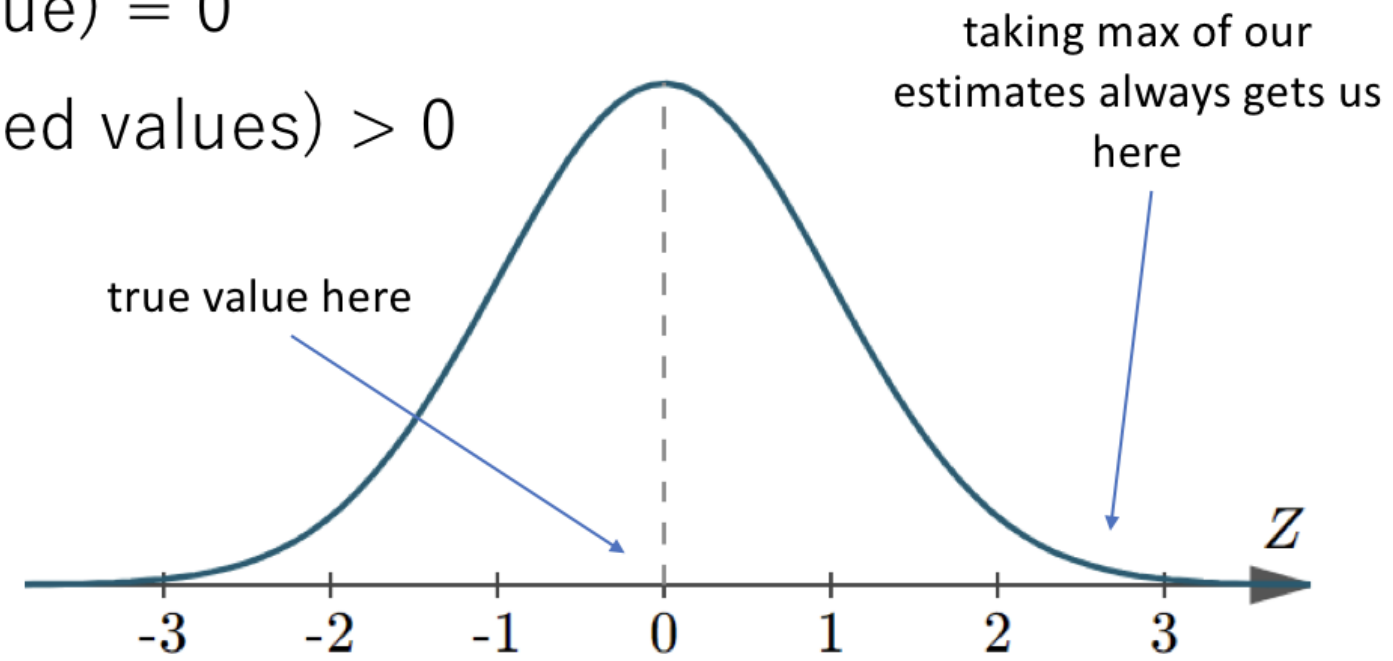
Maximization bias

Imagine a state where $Q(s, a) = 0$ for all a

Our estimates are normally distributed above and below 0

$$\max(\text{true value}) = 0$$

$$\max(\text{estimated values}) > 0$$



DDQN

The DDQN modification to DQN makes use of the target network as a different function to approximate Q(s,a)

Original DQN target

$$r + \gamma \max_a Q(s, a; \theta^-)$$

DDQN target

$$r + \gamma Q(s', argmax Q(s', a; \theta); \theta^-)$$
$$a$$

select the action according to the online network

quanitfy the value that action using the target network

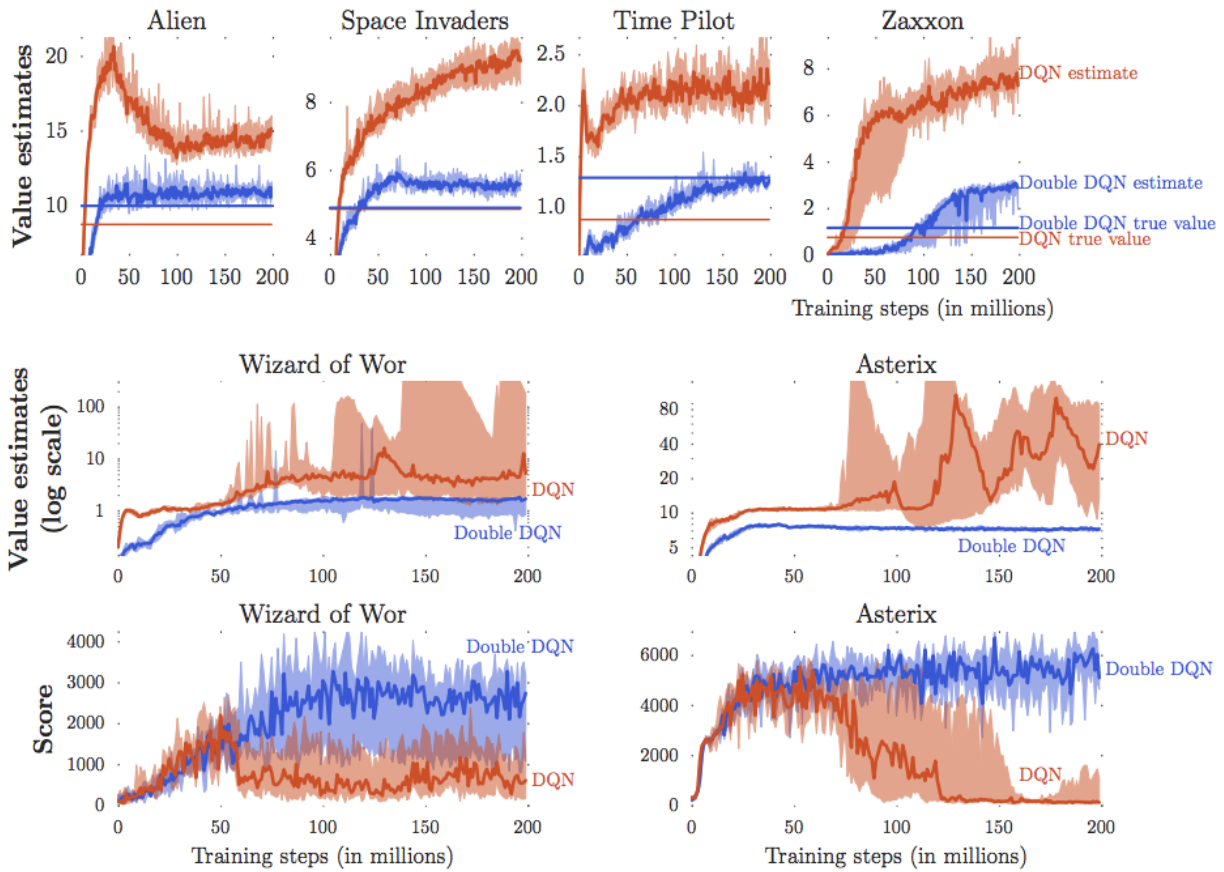


Figure 3: The **top** and **middle** rows show value estimates by DQN (orange) and Double DQN (blue) on six Atari games. The results are obtained by running DQN and Double DQN with 6 different random seeds with the hyper-parameters employed by Mnih et al. (2015). The darker line shows the median over seeds and we average the two extreme values to obtain the shaded area (i.e., 10% and 90% quantiles with linear interpolation). The straight horizontal orange (for DQN) and blue (for Double DQN) lines in the top row are computed by running the corresponding agents after learning concluded, and averaging the actual discounted return obtained from each visited state. These straight lines would match the learning curves at the right side of the plots if there is no bias. The **middle** row shows the value estimates (in log scale) for two games in which DQN's overoptimism is quite extreme. The **bottom** row shows the detrimental effect of this on the score achieved by the agent as it is evaluated during training: the scores drop when the overestimations begin. Learning with Double DQN is much more stable.

four

eligibility traces

prioritized experience replay

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Distributional Q-Learning

Rainbow

A Distributional Perspective on Reinforcement Learning

Marc G. Bellemare [*1] **Will Dabney** [*1] **Rémi Munos** [1]

21 Jul 2017

Beyond the expectation

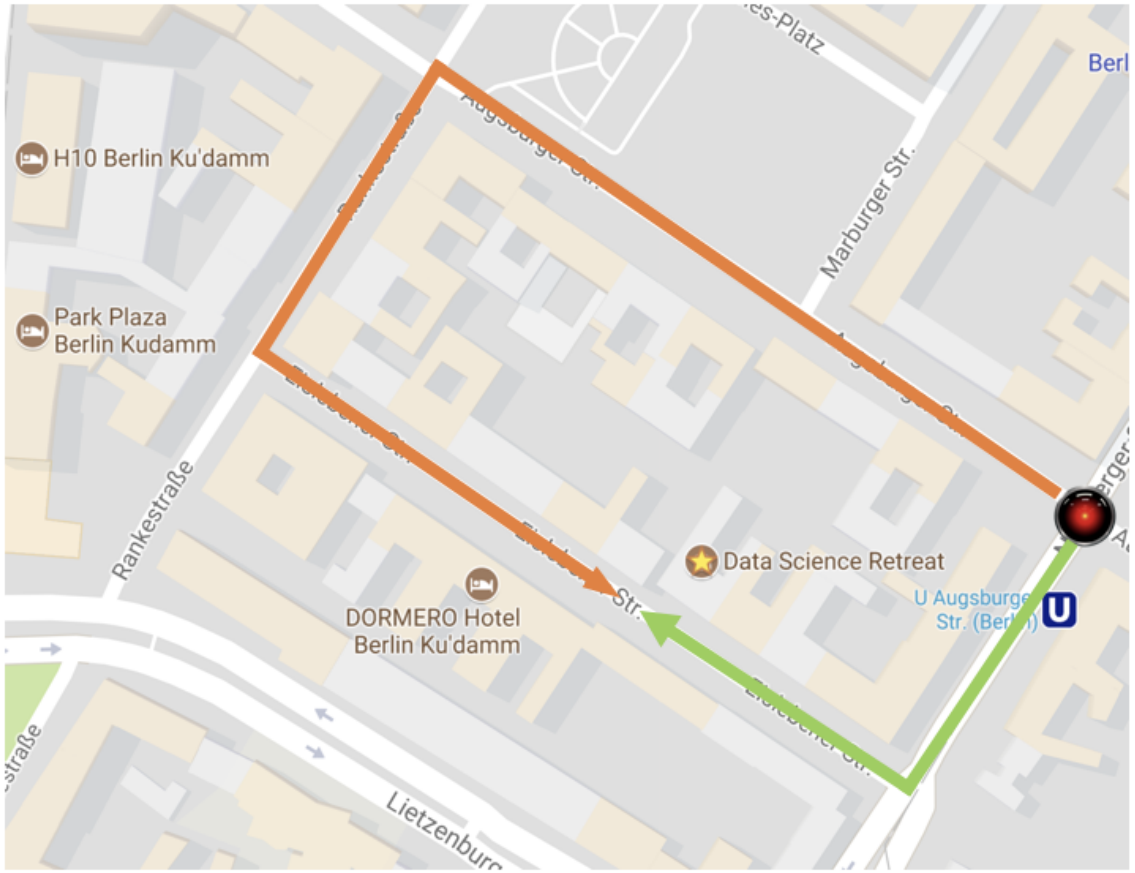
All the reinforcement learning we have seen focuses on the expectation (i.e. the mean)

$$Q(s,a) = \mathbf{E}[G_t] = \mathbf{E}[r + \gamma Q(s',a)]$$

In 2017 DeepMind introduced the idea of the value distribution

State of the art results on Atari (at the time - Rainbow is currently SOTA)

Beyond the expectation



$$Q(s, a_1) = 10 \text{ min}$$
$$Q(s, a_2) = 5 \text{ min}$$

Expectation for uniform random policy $= 7.5$ min!

The expectation of 7.5 min will never occur in reality!

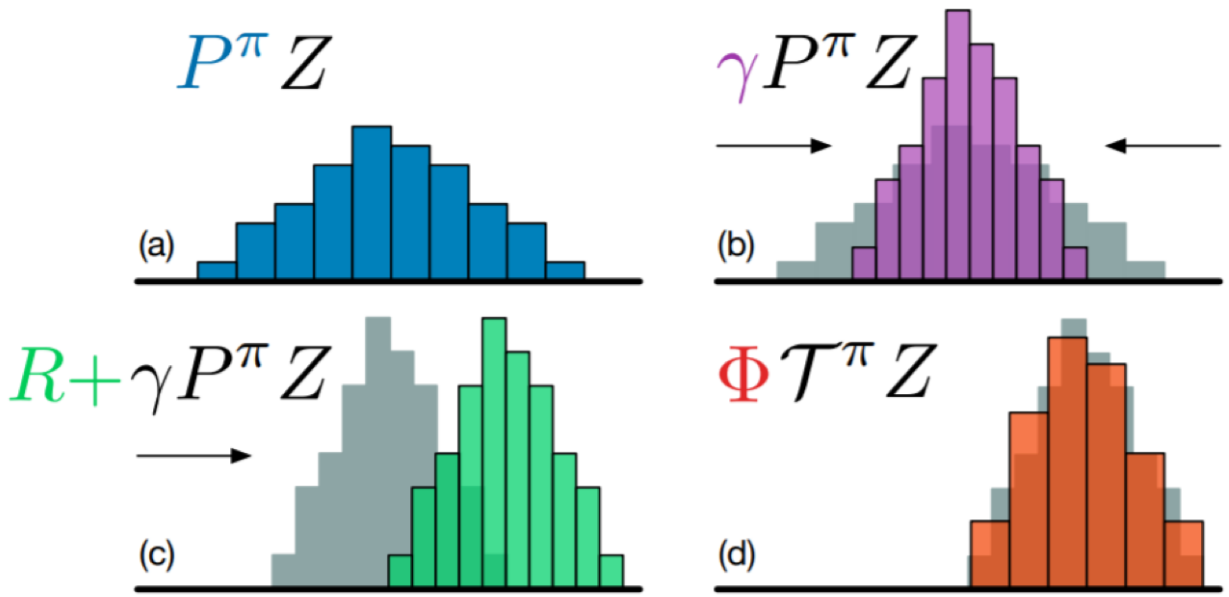


Figure 1. A distributional Bellman operator with a deterministic reward function: (a) Next state distribution under policy π, (b) Discounting shrinks the distribution towards 0, (c) The reward shifts it, and (d) Projection step (Section 4).

	Mean	Median	> H.B.	> DQN
DQN	228%	79%	24	0
DDQN	307%	118%	33	43
DUEL.	373%	151%	37	50
PRIOR.	434%	124%	39	48
PR. DUEL.	592%	172%	39	44
C51	**701%**	**178%**	**40**	**50**
UNREAL†	880%	250%	-	-

Figure 6. Mean and median scores across 57 Atari games, measured as percentages of human baseline (H.B., Nair et al., 2015).

† The UNREAL results are not altogether comparable, as they were generated in the asynchronous setting with per-game hyperparameter tuning (Jaderberg et al., 2017).

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Rainbow

Rainbow: Combining Improvements in Deep Reinforcement Learning

Matteo Hessel, Joseph Modayil, Hado van Hasselt, Tom Schaul, Georg Ostrovski, Will Dabney, Dan Horgan, Bilal Piot, Mohammad Azar, David Silver

(Submitted on 6 Oct 2017)

The deep reinforcement learning community has made several independent improvements to the DQN algorithm. However, it is unclear which of these extensions are complementary and can be fruitfully combined. This paper examines six extensions to the DQN algorithm and empirically studies their combination. Our experiments show that the combination provides state-of-the-art performance on the Atari 2600 benchmark, both in terms of data efficiency and final performance. We also provide results from a detailed ablation study that shows the contribution of each component to overall performance.

Rainbow

All the various improvements to DQN address different issues

- DDQN - overestimation bias
- prioritized experience replay - sample efficiency
- dueling - generalize across actions
- multi-step bootstrap targets - bias variance tradeoff
- distributional Q-learning - learn categorical distribution of $Q(s, a)$
- noisy DQN - stochastic layers for exploration

Rainbow combines these improvements

Evaluation Methodology. We evaluated all agents on 57 Atari 2600 games from the arcade learning environment (Bellemare et al. 2013). We follow the training and evaluation procedures of Mnih et al. (2015) and van Hasselt et al. (2016). The average scores of the agent are evaluated during training, every 1M steps in the environment, by suspending learning and evaluating the latest agent for 500K frames. Episodes are truncated at 108K frames (or 30 minutes of simulated play), as in van Hasselt et al. (2016).

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motivations for policy gradients

introduction

the score function

REINFORCE

Actor-Critic

Value functions

learn a value function

use value function to act

$V_\pi(s, \theta)$

$Q_\pi(s, a, \theta)$

Policy gradients

learn policy

use policy to act

$\pi(s, \theta)$

Actor-Critic

Parameterize both a value function & policy

$V_\pi(s, \theta)$

$Q_\pi(s, a, \theta)$

$\pi(s, \theta)$

Policy gradients

Previously we generated a policy from a value function

$$a = \underset{a}{argmax} Q(s, a)$$

In policy gradients we **parameterize a policy directly**

$$a \sim \pi(a_t | s_t; \theta)$$

John Schulan - Berkley, Open AI

Motivation - stochastic policies

A determinstic policy (i.e. always rock) is easily exploited

A stochastic policy means exploration is built into the policy

exploration can be controlled by the agent

Motivation - high dimensional action spaces

Q-Learning requires a discrete action space to argmax across

Lets imagine controlling a robot arm in three dimensions in the range [0, 90] degrees

This corresponds to approx. 750,000 actions a Q-Learner would need to argmax across

We also lose shape of the action space by discretization

Discretizing continuous action spaces

In [8]:
```
#  a robot arm operating in three dimensions with a 90 degree range
single_dimension = np.arange(91)
single_dimension
```

Out[8]:
```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
       17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
       34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50,
       51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67,
       68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84,
       85, 86, 87, 88, 89, 90])
```

In [32]:
```
#  we can use the combinations tool from the Python standard library
from itertools import product
all_dims = [single_dimension.tolist() for _ in range(3)]
all_actions = list(product(*all_dims))
print('num actions are {}'.format(len(all_actions)))
print('expected_num_actions are {}'.format(len(single_dimension)**3))

#  we can look at the first few combinations of actions
all_actions[0:10]
```

```
num actions are 753571
expected_num_actions are 753571
```

Out[32]:
```
[(0, 0, 0),
 (0, 0, 1),
 (0, 0, 2),
 (0, 0, 3),
 (0, 0, 4),
 (0, 0, 5),
 (0, 0, 6),
 (0, 0, 7),
 (0, 0, 8),
 (0, 0, 9)]
```

In [33]:
```
#  and the last few
all_actions[-10:]
```

Out[33]:
```
[(90, 90, 81),
 (90, 90, 82),
 (90, 90, 83),
 (90, 90, 84),
 (90, 90, 85),
 (90, 90, 86),
 (90, 90, 87),
 (90, 90, 88),
 (90, 90, 89),
 (90, 90, 90)]
```

Motivation - optimize return directly

When learning value functions our optimizer is working towards improving the predictive accuracy of the value function

- our gradients point in the direction of predicting return

This isn't what we really care about - we care about maximizing return

Policy methods optimize return directly

- changing weights according to the gradient that maximizes future reward
- aligning gradients with our objective (and hopefully a business objective)

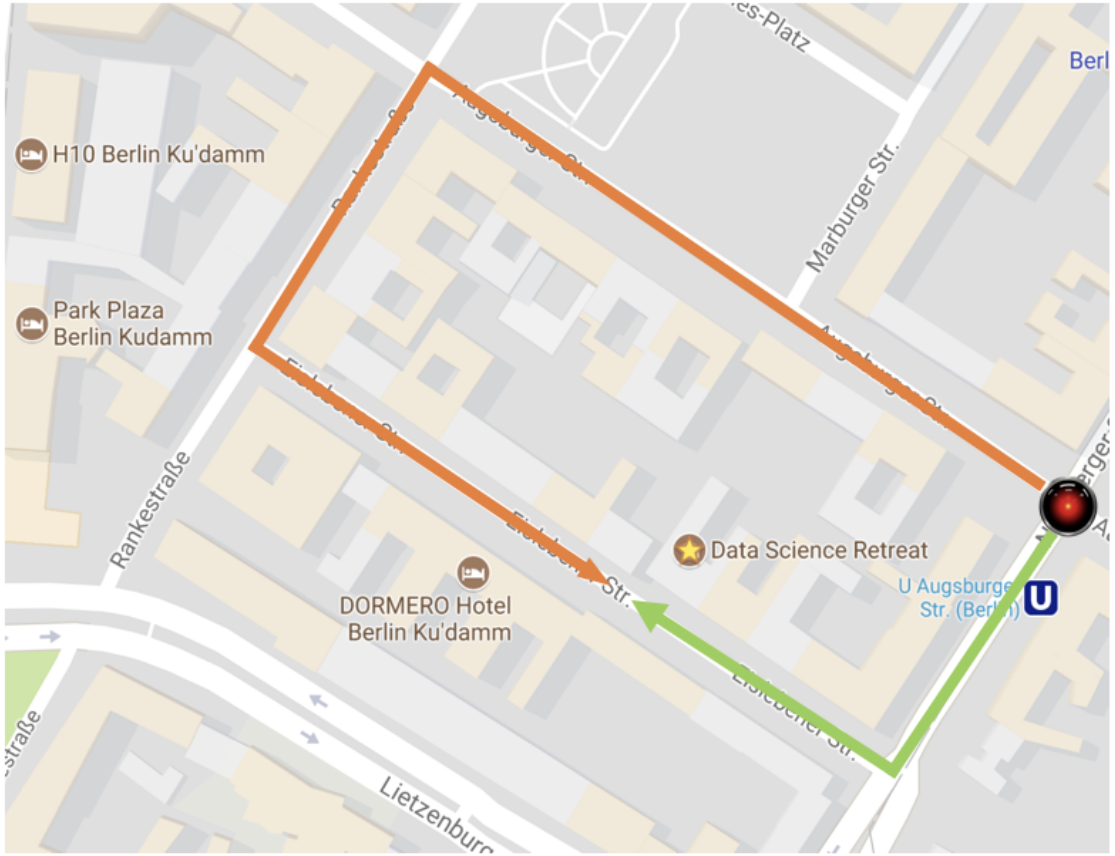
Motivation - simplicity

Sometimes it's eaiser to pick an action

rather than to quantify return for each action, then pick action

Policy gradients are more general and versatile

More compataible with recurrent neural networks



$$Q(s, a_1) = 10 \text{ min}$$
$$Q(s, a_2) = 5 \text{ min}$$

$$\underset{a}{\text{argmax}} \rightarrow a_2$$

vs

$$a_2 \sim \pi(s)$$

Policy gradients versus value functions

Policy gradients

optimize return directly
work in continuous and discrete action spaces
works better in high-dimensional action spaces

Value functions

optimize value function accuracy
off policy learning
exploration
better sample efficiency

five

motivations for policy gradients

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REINFORCE

Actor-Critic

≡ Deterministic Policy Gradient

Parameterizing policies

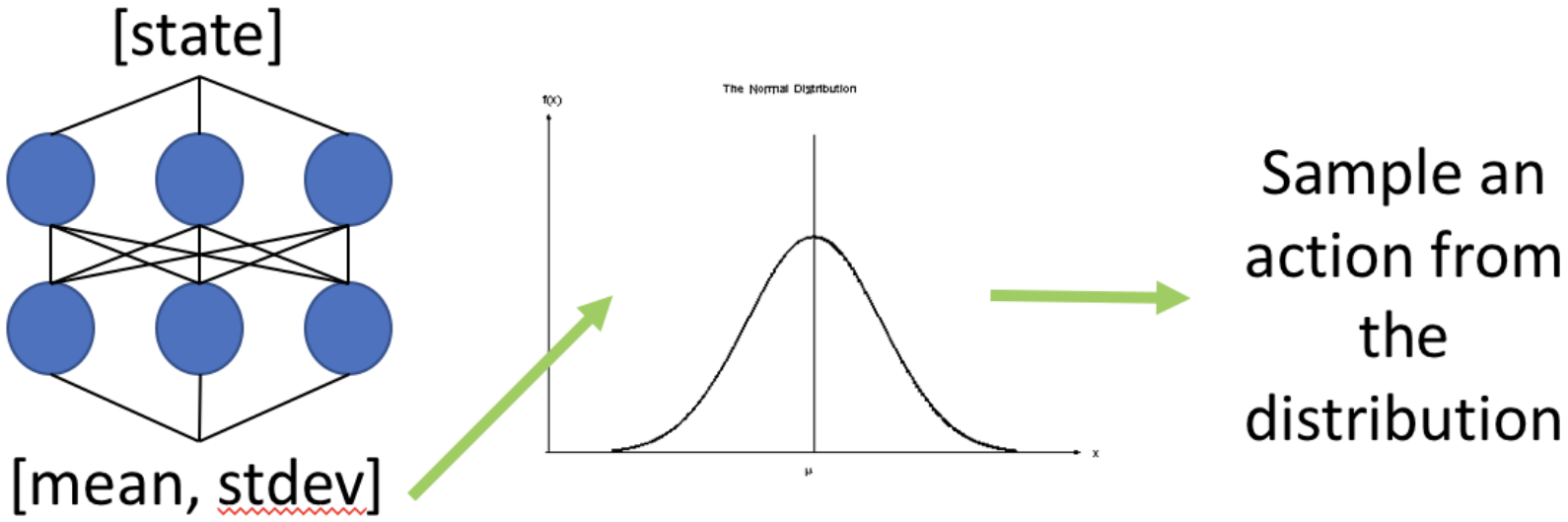
The type of policy you parameterize depends on the **action space**

Parameterizing policies

The type of policy you parameterize depends on the **action space**

continuous action space

output layer = mean & stdev



Policy gradients without equations

We have a parameterized policy

a neural network that outputs a distribution over actions

How do we improve it - how do we learn?

change parameters to take actions that get more reward
change parameters to favour probable actions

Reward function is not known

but we can calculate the *gradient the expected reward*

Policy gradients with a few equations

Our policy $\pi(a_t|s_t;\theta)$ is a **probability distribution over actions**

How do we improve it?

change parameters to take actions that get more reward
change parameters to favour probable actions

Reward function is not known

but we can calculate the *gradient of the expectation of reward*

$$\nabla_\theta \mathbf{E}[G_t] = \mathbf{E}[\nabla_\theta \log \pi(a|s) \cdot G_t]$$

We can figure out how to change our parameters without actually knowing the reward function itself

The score function in statistics

The **score function** comes from using the log-likelihood ratio trick

The score function allows us to get the gradient of a function by **taking an expectation**

Expectataions are averages

use sample based methods to approximate them

$$\nabla_\theta \mathbf{E}[f(x)] = \mathbf{E}[\nabla_\theta \log P(x) \cdot f(x)]$$

Deriving the score function

$$
\begin{aligned}
\nabla_\theta E_x[f(x)] &= \nabla_\theta \sum_x p(x) f(x) && \text{definition of expectation} \\
&= \sum_x \nabla_\theta p(x) f(x) && \text{swap sum and gradient} \\
&= \sum_x p(x) \frac{\nabla_\theta p(x)}{p(x)} f(x) && \text{both multiply and divide by } p(x) \\
&= \sum_x p(x) \nabla_\theta \log p(x) f(x) && \text{use the fact that } \nabla_\theta \log(z) = \frac{1}{z} \nabla_\theta z \\
&= E_x[f(x) \nabla_\theta \log p(x)] && \text{definition of expectation}
\end{aligned}
$$

http://karpathy.github.io/2016/05/31/rl/

The score function in reinforcement learning

$$\nabla_\theta \mathbf{E}[G_t] = \mathbf{E}[\nabla_\theta \log \pi(a|s) \cdot G_t]$$

```
gradient of return = expectation of the gradient of the
policy * return
```

The RHS is an expectation - we can estimate it by sampling

The expectation is made up of things we can sample from

- we can sample from our policy
- we can sample the return (from experience)

Training a policy

We use the score function to get the gradient, then follow the gradient

```
gradient = log(probability of action) * return
```

```
gradient = log(policy) * return
```

The score function limits us to on-policy learning

- we need to calculate the log probability of the action taken by the policy

Policy gradient intuition

$$\nabla_\theta \mathbf{E}[G_t] = \mathbf{E}[\nabla_\theta \log \pi(a|s) \cdot G_t]$$

$\log \pi(a_t|s_t;\theta)$

how probable was the action we picked
we want to reinforce actions we thought were good

G_t

how good was that action
we want to reinforce actions that were actually good

REINFORCE

Different methods to approximate the return G_t

We can use a Monte Carlo estimate - this is known as REINFORCE

Using a Monte Carlo approach comes with all the problems we saw earlier

- high variance
- no online learning
- requires episodic environment

How can we get some the advantages of Temporal Difference methods?

Baseline

We can introduce a baseline function

this reduces variance without introducing bias
a natural baseline is the value function (weights w).

$$\log \pi(a_t|s_t;\theta) \cdot (G_t - B(s_t;w))$$

This also gives rise to the concept of **advantage**

how much better this action is than the average action (policy & env dependent)

$$A_\pi(s_t, a_t) = Q_\pi(s_t, a_t) - V_\pi(s_t)$$

Value functions

Parameterize a value function

$V_\pi(s, \theta)$

$Q_\pi(s, a, \theta)$

Policy gradients

Parameterize a policy

$\pi(s, \theta)$

Actor-Critic

Parameterize both a value function & policy

$V_\pi(s, \theta)$

$Q_\pi(s, a, \theta)$

$\pi(s, \theta)$

Actor-Critic

Actor-Critic brings together value functions and policy gradients

We parameterize two functions

actor = policy
critic = value function

We update our actor (i.e. the behaviour policy) in the direction suggested by the critic

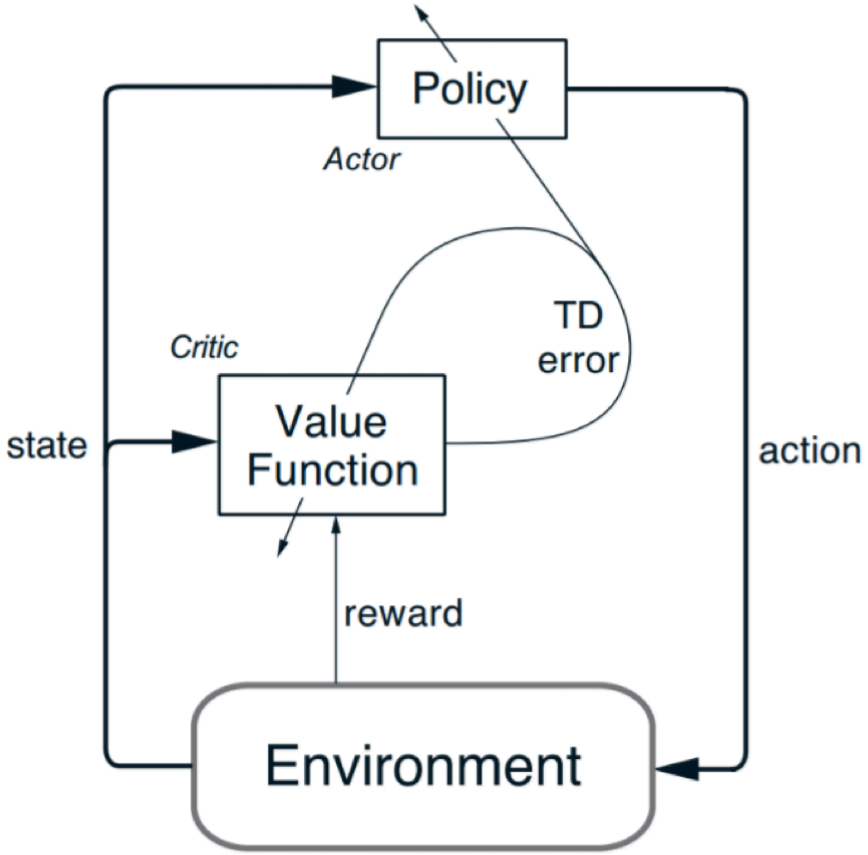


Figure 11.1: The actor–critic architecture.

Actor-Critic Algorithm

Input: policy $\pi(a|s, \boldsymbol{\theta})$, $\hat{v}(s, \boldsymbol{w})$
Parameters: step sizes, $\alpha > 0$, $\beta > 0$
Output: policy $\pi(a|s, \boldsymbol{\theta})$
initialize policy parameter $\boldsymbol{\theta}$ and state-value weights $\boldsymbol{w}$
for *true* **do**
  initialize s, the first state of the episode
  $I \leftarrow 1$
  for s *is not terminal* **do**
    $a \sim \pi(\cdot|s, \boldsymbol{\theta})$
    take action a, observe s', r
    $\delta \leftarrow r + \gamma \hat{v}(s', \boldsymbol{w}) - \hat{v}(s, \boldsymbol{w})$ (if s' is terminal, $\hat{v}(s', \boldsymbol{w}) \doteq 0$)
    $\boldsymbol{w} \leftarrow \boldsymbol{w} + \beta \delta \nabla_{\boldsymbol{w}} \hat{v}(s_t, \boldsymbol{w})$
    $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \alpha I \delta \nabla_{\boldsymbol{\theta}} log \pi(a_t|s_t, \boldsymbol{\theta})$
    $I \leftarrow \gamma I$
    $s \leftarrow s'$
  end
end

within episode updating

TD error

update value function (critic)

update policy (actor)

Algorithm 6: Actor-Critic (episodic), adapted from Sutton and Barto (2017)

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REINFORCE

Actor-Critic

Deterministic Policy Gradient

Deterministic Policy Gradient Algorithms

David Silver DAVID@DEEPMIND.COM
DeepMind Technologies, London, UK
Guy Lever GUY.LEVER@UCL.AC.UK
University College London, UK
Nicolas Heess, Thomas Degris, Daan Wierstra, Martin Riedmiller *@DEEPMIND.COM
DeepMind Technologies, London, UK

Proceedings of the 31st International Conference on Machine Learning, Beijing, China, 2014. JMLR: W&CP volume 32.

Deterministic Policy Gradient

Actor Critic

Determinstic policy

- more efficient than stochastic

Continuous action spaces

Off-policy learning

Uses experience replay

Uses target networks

Stochastic vs determinstic policies

Stochastic policy is a probability distribution over actions

Actions are selected by sampling from this distribution

$$\pi_\theta(a|s) = P[a|s;\theta]$$

$$a \sim \pi_\theta(a|s)$$

DPG parameterizes a determinstic policy

$$a = \mu_\theta(s)$$

DPG components

Actor

off policy
function that maps state to action
exploratory

Critic

on-policy
critic of the current policy
estimates $Q(s, a)$

Gradients

Updating policy weights

The gradient

$$\nabla_\theta J_\beta(\pi_\theta) = \mathbb{E}_{s\sim p^\beta}\ \nabla_\theta \mu_\theta(s)\, \nabla_a Q^\mu(s,a)\Big|_{a=\mu_\theta(s)}$$

The update function

$$\theta_{t+1} = \theta_t + \alpha\, \nabla_\theta \mu_\theta(s_t)\, \nabla_a Q^w(s_t,a_t)\Big|_{a=\mu_\theta(s)}$$

α learning rate

Q^w action value function parameterized by weights w

DPG results

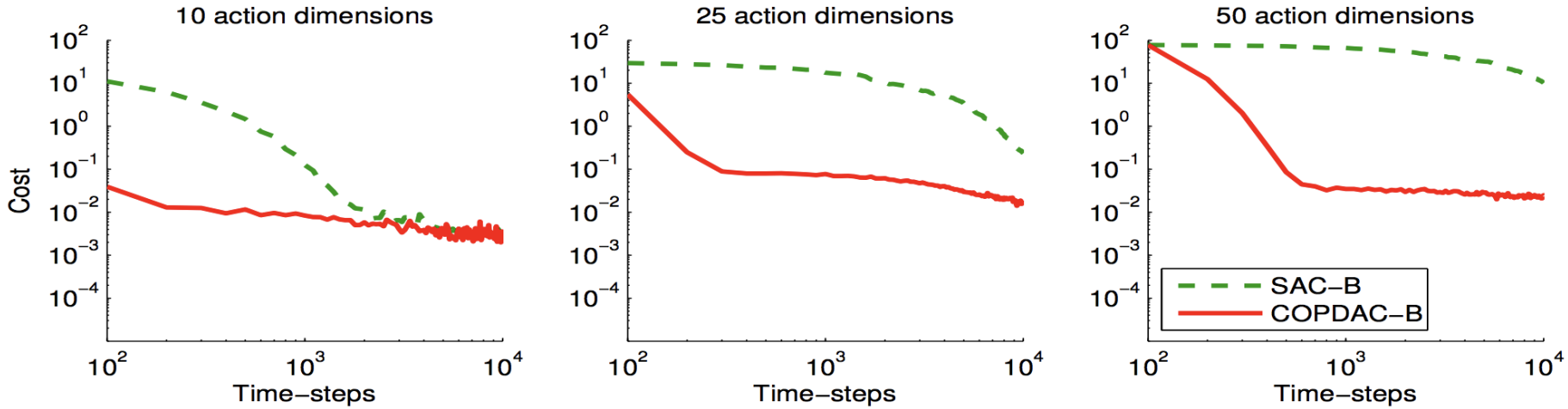
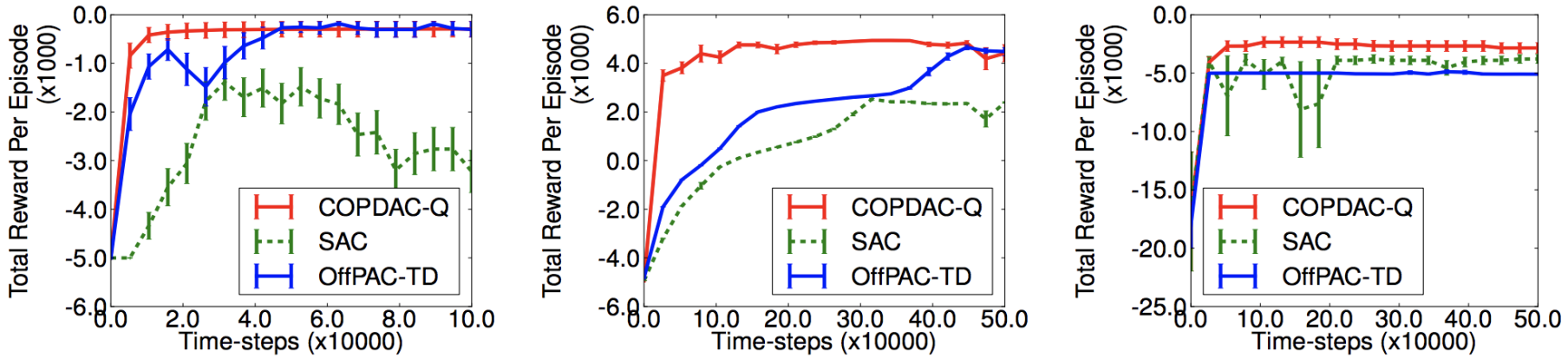


Figure 1. Comparison of stochastic actor-critic (SAC-B) and deterministic actor-critic (COPDAC-B) on the continuous bandit task.



(a) Mountain Car (b) Pendulum (c) 2D Puddle World

Figure 2. Comparison of stochastic on-policy actor-critic (SAC), stochastic off-policy actor-critic (OffPAC), and deterministic off-policy actor-critic (COPDAC) on continuous-action reinforcement learning. Each point is the average test performance of the mean policy.

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Actor-Critic

≡ Deterministic Policy Gradient

Asynchronous Methods for Deep Reinforcement Learning

Volodymyr Mnih[1] VMNIH@GOOGLE.COM
Adrià Puigdomènech Badia[1] ADRIAP@GOOGLE.COM
Mehdi Mirza[1,2] MIRZAMOM@IRO.UMONTREAL.CA
Alex Graves[1] GRAVESA@GOOGLE.COM
Tim Harley[1] THARLEY@GOOGLE.COM
Timothy P. Lillicrap[1] COUNTZERO@GOOGLE.COM
David Silver[1] DAVIDSILVER@GOOGLE.COM
Koray Kavukcuoglu [1] KORAYK@GOOGLE.COM

[1] Google DeepMind
[2] Montreal Institute for Learning Algorithms (MILA), University of Montreal

arXiv:1602.01783v2 [cs.LG] 16 Jun 2016

A3C

Asynchronous Advantage Actor-Critic

We saw earlier that experience replay is used to make learning more stable & decorrelate updates

but can only be used with off-policy learners

Asynchronous Advantage Actor-Critic

Asynchronous

multiple agents learning separately
experience of each agent is independent of other agents
learning in parallel stabilizes training
allows use of on-policy learners
runs on single multi-core CPU
learns faster than many GPU methods

Asynchronous **Advantage** Actor-Critic

Advantage = the advantage function

$$A_\pi(s_t, a_t) = Q_\pi(s_t, a_t) - V_\pi(s_t)$$

How much better an action is than the average action followed by the policy

Natural Policy Gradients, TRPO and PPO

All three of these papers build on the same idea - that we **want to constrain policy updates** to get more stable learning

Natural Policy Gradients uses an expensive second order derivative method

Trust Region Policy Optimization (TRPO) uses

Proximal Policy Optimization (PPO) uses the KL-divergence with an adaptive penatly

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AlphaGo

AlphaGo Zero

Residual networks

IBM Deep Blue

First defeat of a world chess champion by a machine in 1997

Deep Blue vs AlphaGo

Deep Blue was handcrafted by programmers & chess grandmasters

AlphaGo *learnt* from human moves & self play

AlphaGo evaluated fewer positions

width - policy network select states more intelligently
depth - value function evaluate states more precisely

Why Go?

Long held as the most challenging classic game for artificial intelligence

- massive search space
- more legal positions than atoms in universe
- difficult to evaluate positions & moves
- sparse & delayed reward

Components of the AlphaGo agent

Three policy networks $\pi(s)$

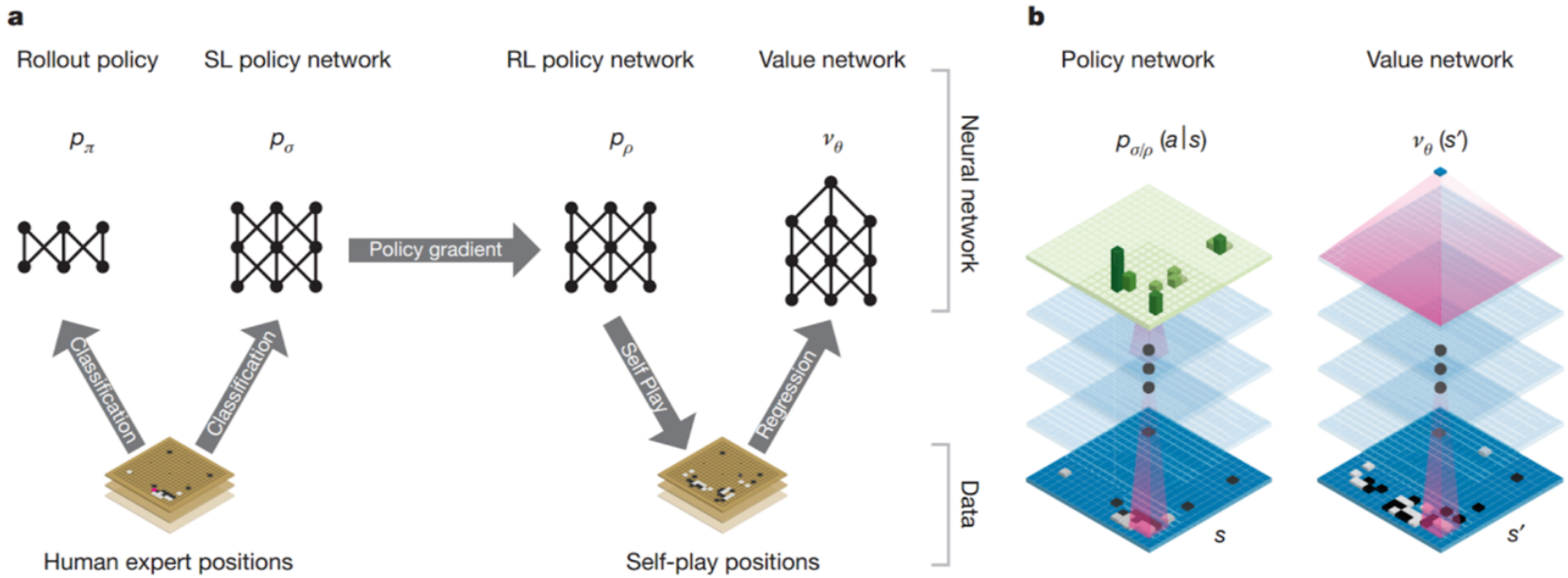
- fast rollout policy network – linear function
- supervised learning policy – 13 layer convolutional NN
- reinforcement learning policy – 13 layer convolutional NN

One value function $V(s)$

- convolutional neural network

Combined together using Monte Carlo tree search

Learning


a
Rollout policy
SL policy network
RL policy network
Value network
p_π
p_σ
p_ρ
v_θ
Policy gradient
Classification
Classification
Self Play
Regression
Human expert positions
Self-play positions
Neural network
Data
b
Policy network
Value network
$p_{\sigma/\rho}(a|s)$
$v_\theta(s')$
s
s'

Monte Carlo Tree Search

Value & policy networks combined using MCTS

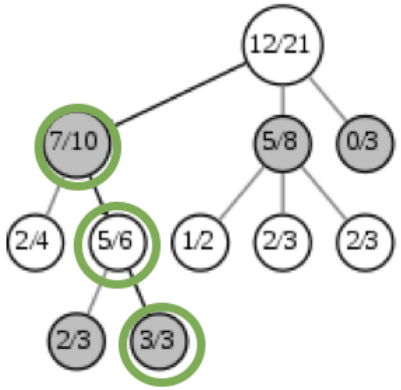
Basic idea = analyse most promising next moves

Planning algorithm

simulated (not actual experience)
roll out to end of game (a simulated Monte Carlo return)

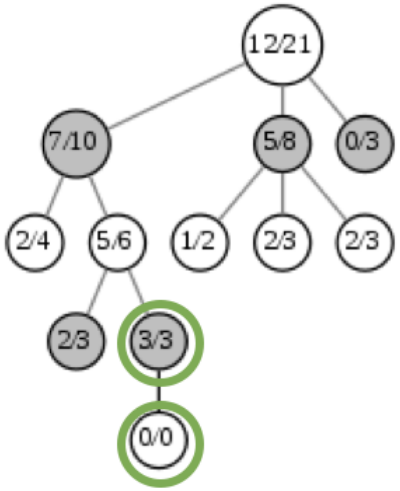
Monte Carlo Tree Search

Selection



Select nodes based on statistics collected so far

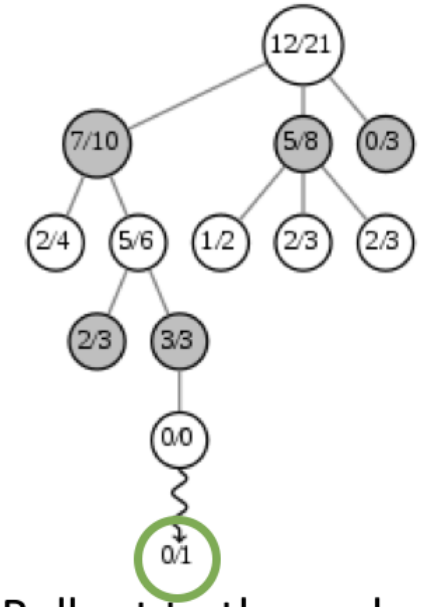
Expansion



If leaf node:

create & the select a new child node

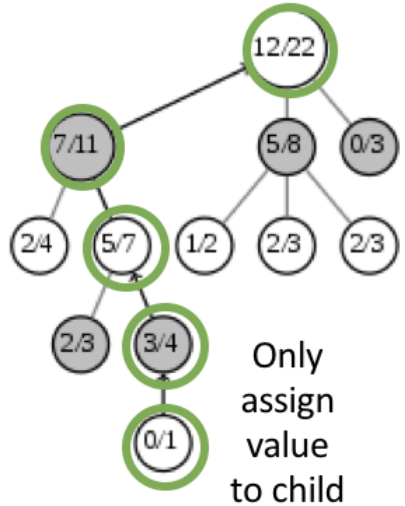
Simulation



Rollout to the end of the game

(simulated)

Backpropagation



Only assign value to child node

Backup the result through the tree to the root state

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

Monte Carlo Tree Search in AlphaGo

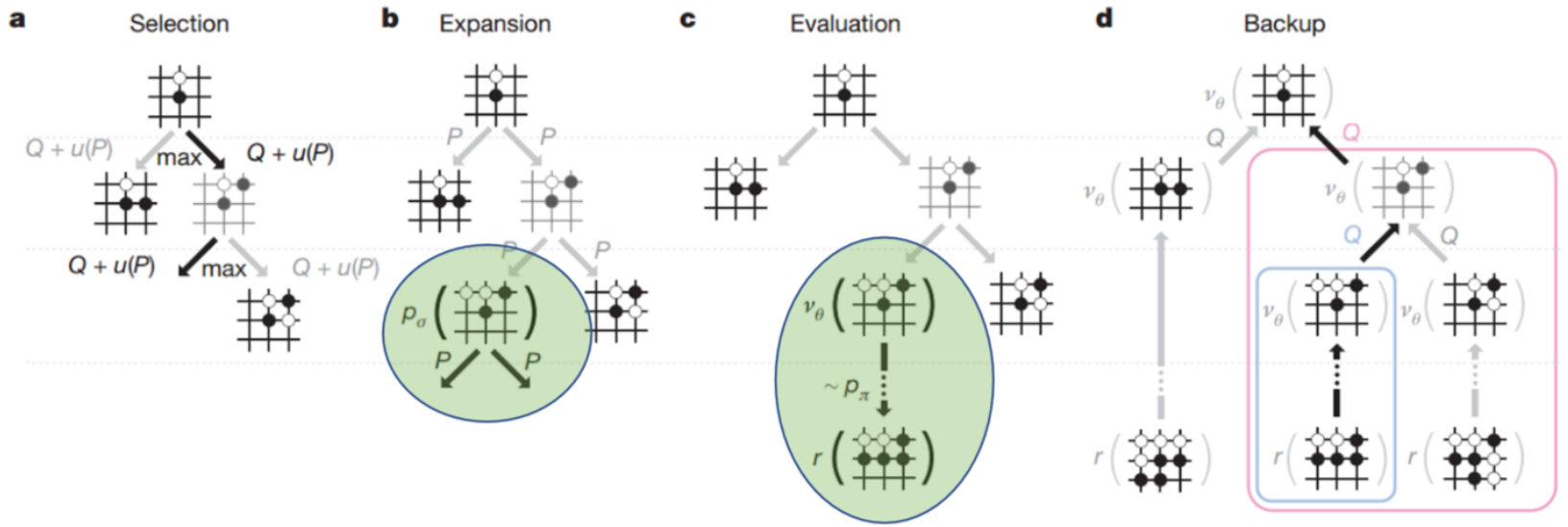
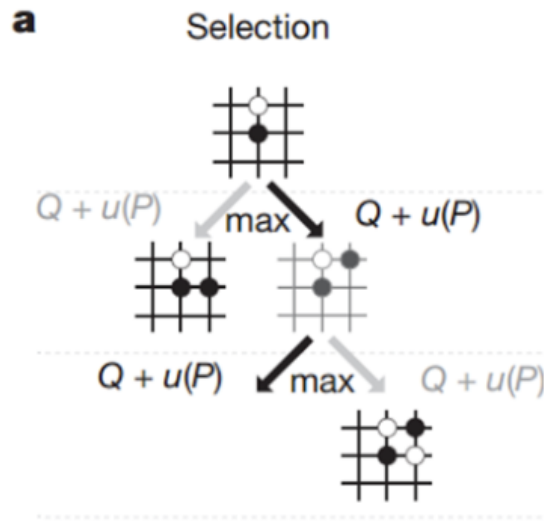


Figure 3 | Monte Carlo tree search in AlphaGo. a, Each simulation traverses the tree by selecting the edge with maximum action value Q, plus a bonus $u(P)$ that depends on a stored prior probability P for that edge. **b**, The leaf node may be expanded; the new node is processed once by the policy network p_σ and the output probabilities are stored as prior probabilities P for each action. **c**, At the end of a simulation, the leaf node is evaluated in two ways: using the value network v_θ; and by running a rollout to the end of the game with the fast rollout policy p_π, then computing the winner with function r. **d**, Action values Q are updated to track the mean value of all evaluations $r(\cdot)$ and $v_\theta(\cdot)$ in the subtree below that action.

Monte Carlo Tree Search in AlphaGo



Each edge (s, a) keeps track of statistics

action value	$Q(s, a)$
visit count	$N(s, a)$
prior probability	$P(s, a)$ SL policy network

Bonus $u(s, a)$ penalizes more visits to encourages exploration

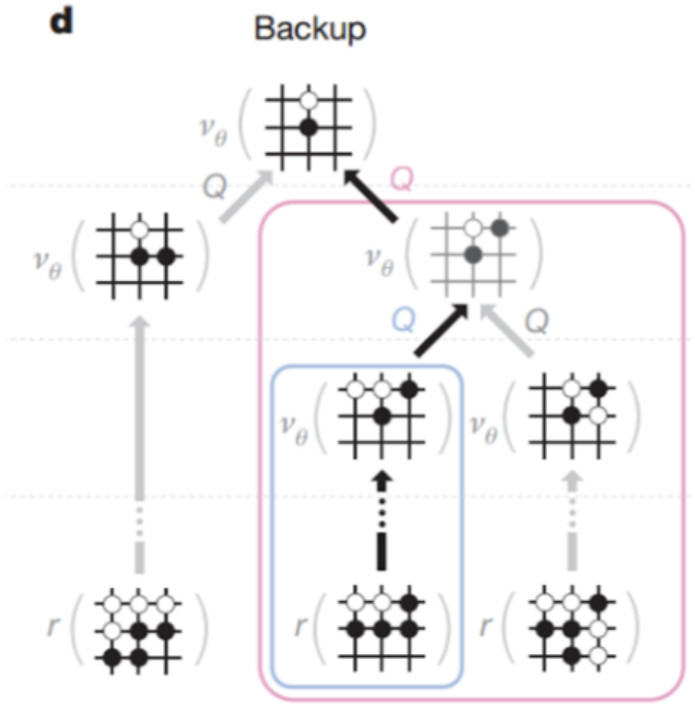
Action selected according too

$$a = \underset{a}{\text{argmax}}[Q(s, a) - u(s, a)]$$

where

$$u(s, a) \propto P(s, a)/[1 - N(s, a)]$$

Monte Carlo Tree Search in AlphaGo



After we finish our rollout – we calculate a state value for our leaf node s_L

$$V(s_L) = (1 - \lambda)v_\theta(s) + \lambda z$$

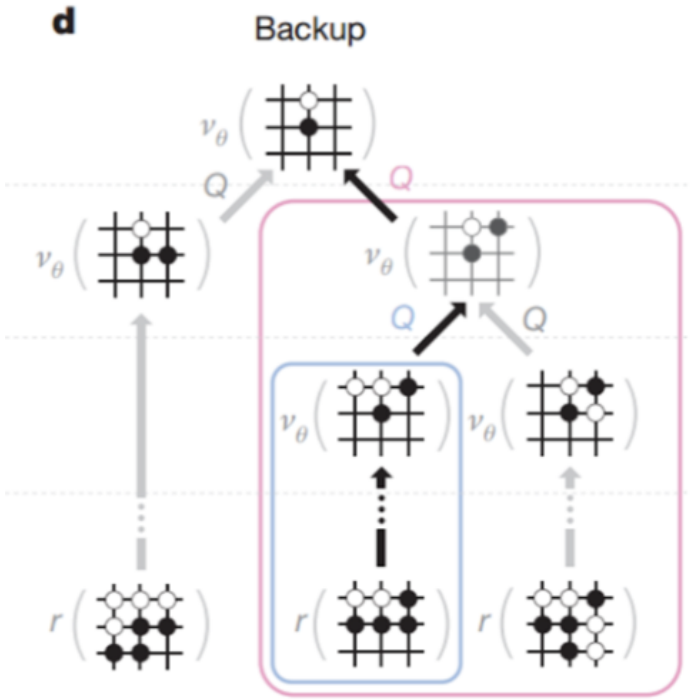
λ mixing parameter

v_θ value network estimate

z simulated result of rollout

We are combining the value network with the MCTS rollout

Monte Carlo Tree Search in AlphaGo



Then use our combined estimate $V(s_L)$ to update

action value $Q(s,a)$

visit count $N(s,a)$

$$Q(s,a) = \frac{1}{N(s,a)} \sum_{i=1}^{n} V(s_L^i)$$

We are averaging across all visits in the simulation

After all simulations finished - select the most visited action from the root state

AlphaGo, in context – Andrej Karpathy

Convenient properties of Go

fully deterministic
fully observed
discrete action space
access to perfect simulator
relatively short episodes
evaluation is clear
huge datasets of human play
energy consumption (human ≈ 50 W) 1080 ti = 250 W

https://medium.com/@karpathy/alphago-in-context-c47718cb95a5

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AlphaGo

AlphaGo Zero

Residual networks

Key ideas in AlphaGo Zero

Simpler

Search

Adversarial

Machine knowledge only

AlphaGo Zero Results

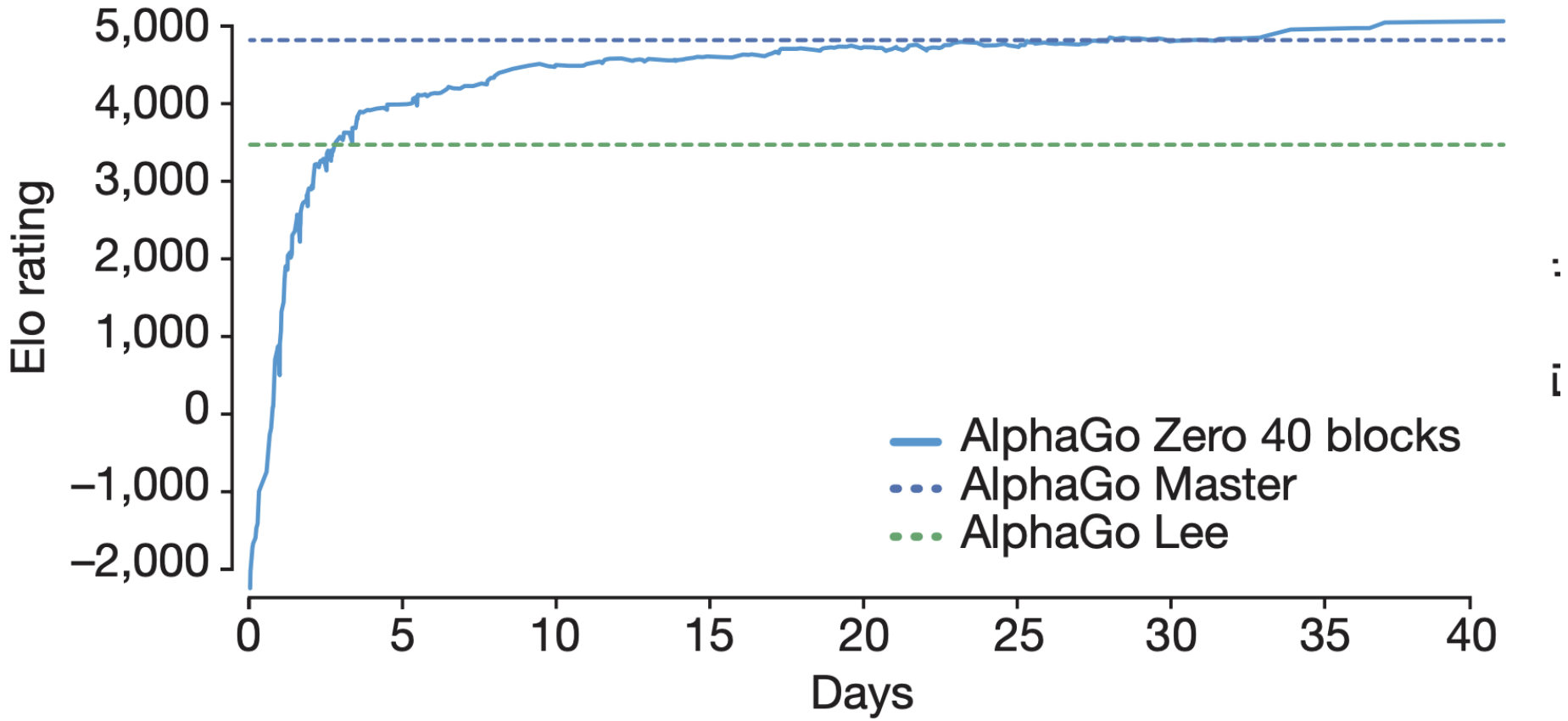
Training time & performance

AG Lee trained over several months
AG Zero beat AG Lee 100-0 after 72 hours of training

Computational efficiency

AG Lee = distributed w/ 48 TPU
AG Zero = single machine w/ 4 TPU

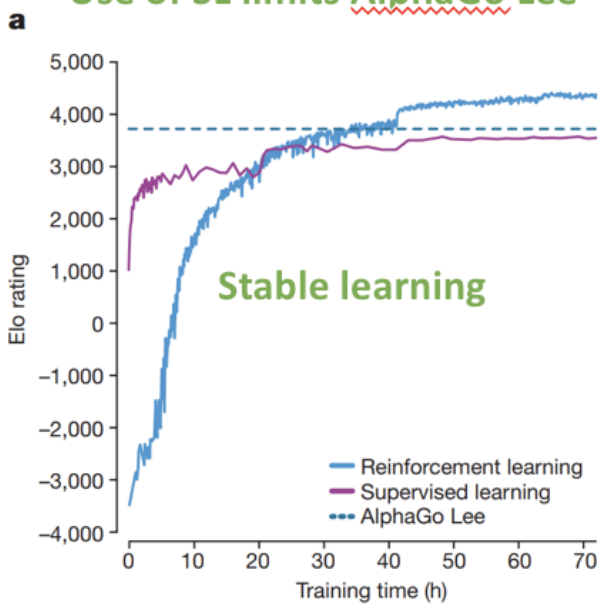
AlphaGo Zero learning curve



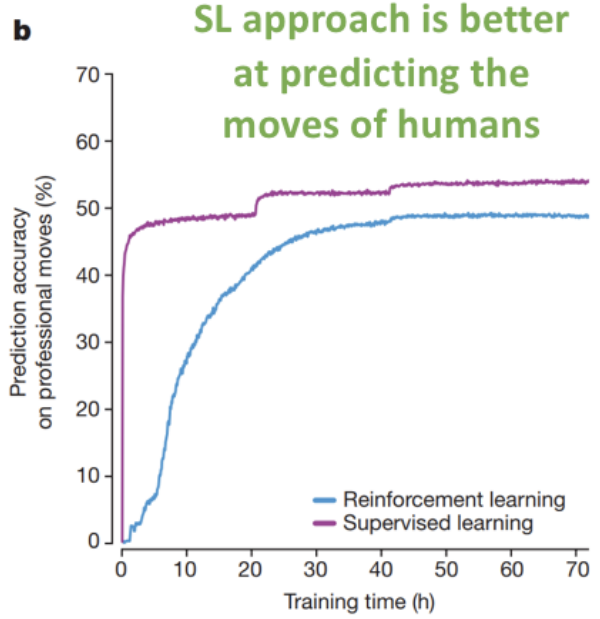
AlphaGo Zero learning curves

RL surpasses SL after around 1 day

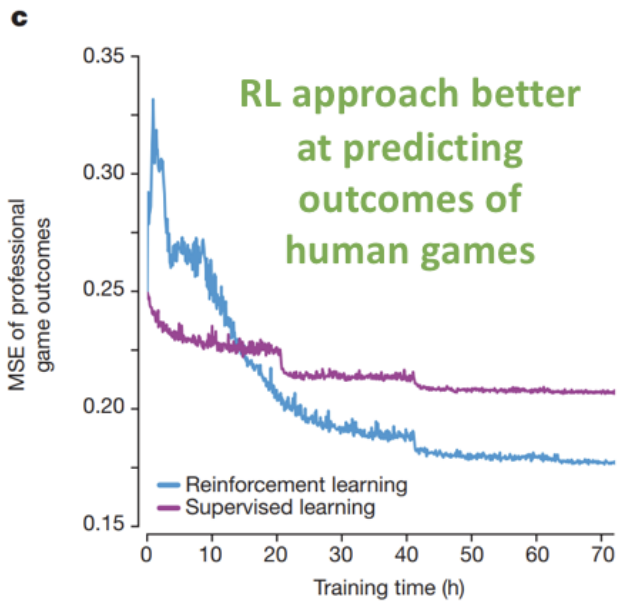
Use of SL limits AlphaGo Lee



SL approach is better at predicting the moves of humans



RL approach better at predicting outcomes of human games



AlphaGo Zero innovations

Learns using only self play

- no learning from human expert games
- no feature engineering
- learn purely from board positions

Single neural network

- combine the policy & value networks

MCTS only during acting (not during learning)

Use of residual networks

AlphaGo Zero acting & learning

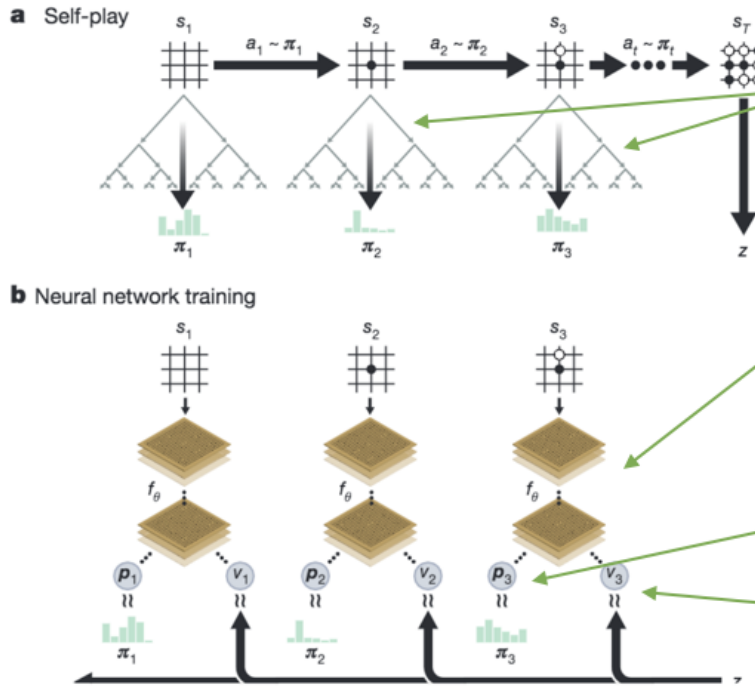


Figure 1 | Self-play reinforcement learning in AlphaGo Zero. a, The program plays a game $s_1, ..., s_T$ against itself. In each position s_t, an MCTS α_θ is executed (see Fig. 2) using the latest neural network f_θ. Moves are selected according to the search probabilities computed by the MCTS, $a_t \sim \pi_t$. The terminal position s_T is scored according to the rules of the game to compute the game winner z. **b**, Neural network training in AlphaGo Zero. The neural network takes the raw board position s_t as its input, passes it through many convolutional layers with parameters θ, and outputs both a vector $\boldsymbol{p}_t$, representing a probability distribution over moves, and a scalar value v_t, representing the probability of the current player winning in position s_t. The neural network parameters θ are updated to maximize the similarity of the policy vector $\boldsymbol{p}_t$ to the search probabilities π_t, and to minimize the error between the predicted winner v_t and the game winner z (see equation (1)). The new parameters are used in the next iteration of self-play as in **a**.

Use MCTS during acting

Single neural network

two outputs:

1 – probability dist. over actions

2 – the game outcome

Model is trained to predict the probabilities as generated by MCTS during acting

Search in AlphaGo Zero

Policy evaluation

Policy is evaluated through self play

This creates high quality training signals - the game result

Policy improvement

MCTS is used during acting to create the improved policy

The improved policy generated during acting becomes the target policy during training

Keynote David Silver NIPS 2017 Deep Reinforcement Learning Symposium AlphaZero

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AlphaGo

AlphaGo Zero

Residual networks

Residual networks

Deep Residual Learning for Image Recognition

Kaiming He Xiangyu Zhang Shaoqing Ren Jian Sun
Microsoft Research
{kahe, v-xiangz, v-shren, jiansun}@microsoft.com

arXiv:1512.03385v1 [cs.CV] 10 Dec 2015

Convolutional network with skip connections

Layers are reformulated as residuals of the input

Residual networks

Trying to learn $H(x)$

Instead of learning $F(x) = H(x)$

We learn the residual $F(x) = H(x) - x$

And can get $H(x) = F(x) + x$

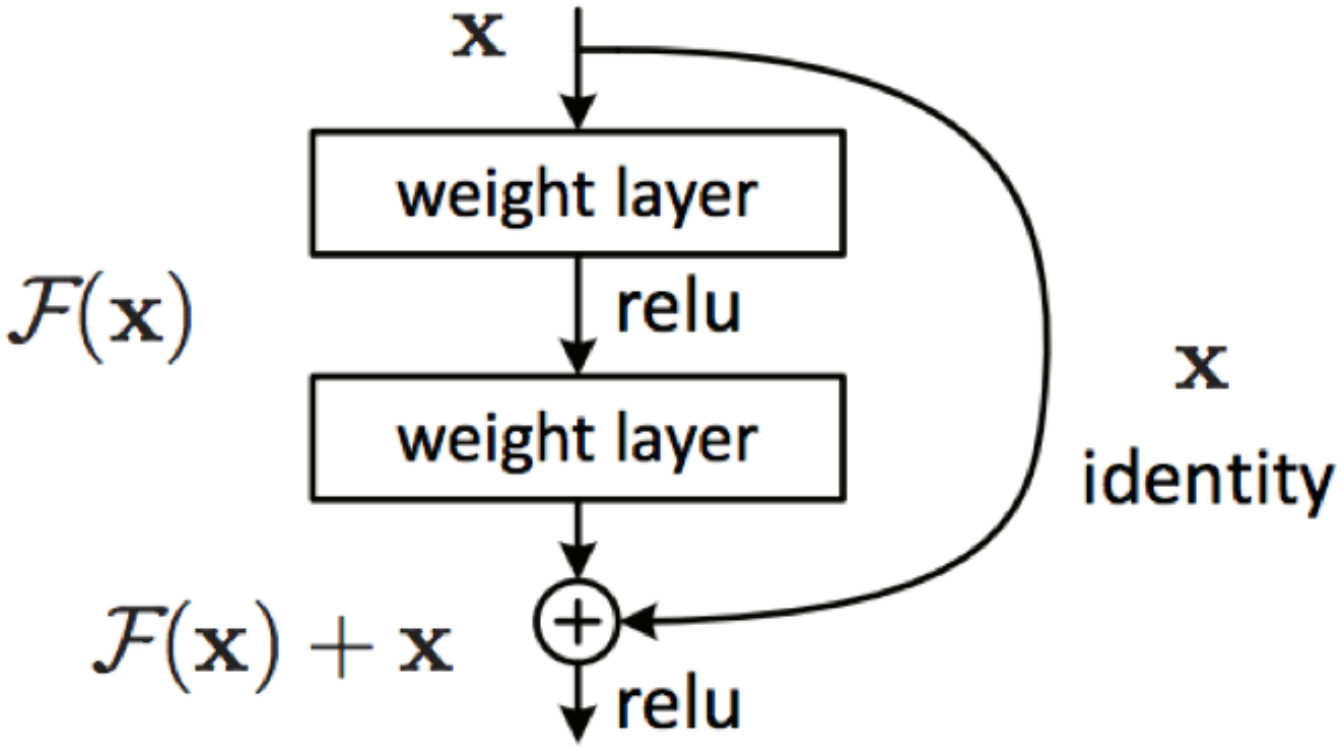

Figure 2. Residual learning: a building block.

DeepMind AlphaGo AMA

AMA: We are David Silver and Julian Schrittwieser from DeepMind's AlphaGo team. Ask us anything. (self.MachineLearning)

submitted 3 days ago * (last edited 1 day ago) by David_Silver

DeepMind - announcement

this post was submitted on 17 Oct 2017

245 points (97% upvoted)

shortlink: https://redd.it/76xjb5

DeepMind AlphaGo AMA

[–] David_Silver DeepMind [S] **9 points** 1 day ago

Creating a system that can learn entirely from self-play has been an open problem in reinforcement learning. Our initial attempts, as for many similar algorithms reported in the literature, were quite unstable. We tried many experiments - but ultimately the AlphaGo Zero algorithm was the most effective, and appears to have cracked this particular issue.

permalink source embed save save-RES parent report give gold reply hide child comments

[–] David_Silver DeepMind [S] **3 points** 1 day ago

In some sense, training from self-play is already somewhat adversarial: each iteration is attempting to find the "anti-strategy" against the previous version.

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[–] David_Silver DeepMind [S] **13 points** 1 day ago

Actually we never guided AlphaGo to address specific weaknesses - rather we always focused on principled machine learning algorithms that learned for themselves to correct their own weaknesses.

Of course it is infeasible to achieve optimal play - so there will always be weaknesses. In practice, it was important to use the right kind of exploration to ensure training did not get stuck in local optima - but we never used human nudges.

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seven

practical concerns

Should I use reinforcement learning for my problem?

What is the action space

- what can the agent choose to do
- does the action change the environment
- continuous or discrete

What is the reward function

- does it incentive behaviour

It is a complex problem

- classical optimization techniques such as linear programming or cross entropy may offer a simpler solution

Can I sample efficiently / cheaply

Reinforcement learning is hard

Debugging implementations is hard

- very easy to have subtle bugs that don't break your code

Tuning hyperparameters is hard

- tuning hyperparameters can also cover over bugs!

Results will succeed and fail over different random seeds (same hyperparameters!)

Machine learning is an empirical science, where the ability to do more experiments directly correlates with progress

Mistakes I've made so far

Normalizing targets - a high initial target that occurs due to the initial weights can skew the normalization for the entire experiment

Doing multiple epochs over a batch

Not keeping batch size the same for experience replay & training

Not setting
`next_observation = observation`

Not setting online & target network variables the same at the start of an experiment

Not gradient clipping

clip the norm of the gradient (I've seen between 1 - 5)

Mistakes DSR students have made in RL projects

Since I started teaching in Batch 10 we have had three RL projects

Saving agent brain

- not saving the optimizer state

Using too high a learning rate

- learning rate is always important!!!

Building both an agent and environment

Hyperparameters

Policy gradients

learning rate
clipping of distribution parameters (stochastic PG)
noise for exploration (deterministic PG)
network structure

Value function methods

learning rate
exploration (i.e. epsilon)
updating target network frequency
batch size
space discretization

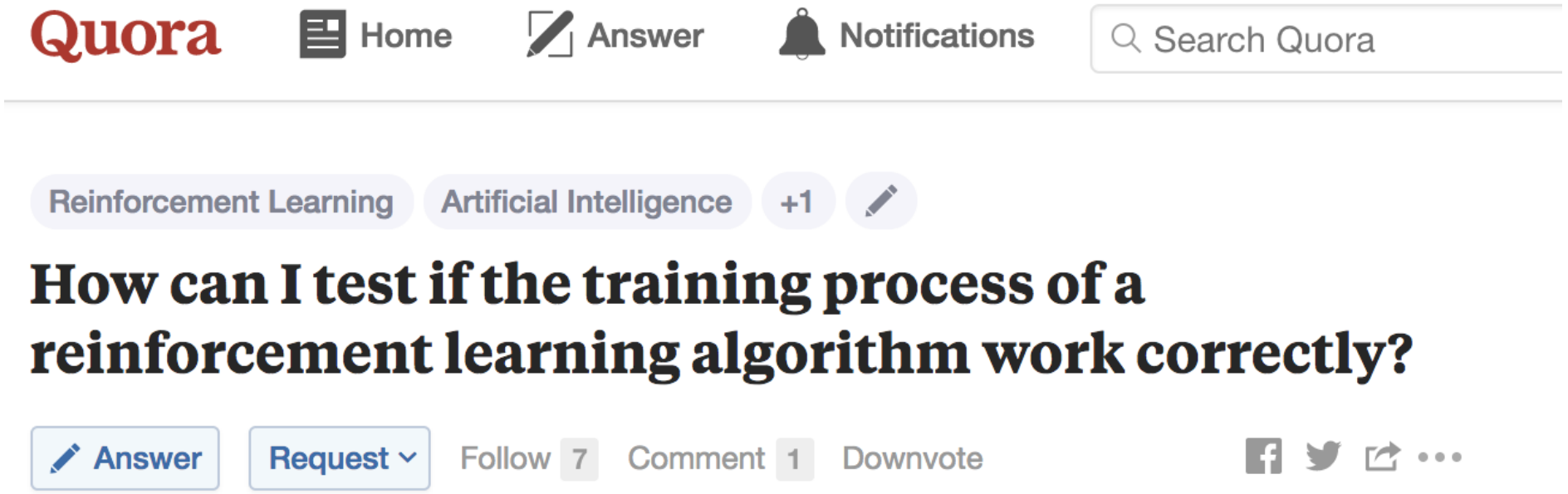
The Nuts and Bolts of Deep RL Research

John Schulman

OpenAI

August 26, 2017

John Schulman – Berkley Deep RL Bootcamp 2017



https://www.quora.com/How-can-I-test-if-the-training-process-of-a-reinforcement-learning-algorithm-work-correctly

Best practices

Quick experiments on small test problems

- CartPole for discrete action spaces
- Pendulum for continuous action spaces

Compare to baselines - a random agent is a good idea

Be careful not to overfit these simple problems

- use low capacity neural networks

Interpret & visualize learning process

- state visitation, value functions

Make it easier to get learning to happen (initially)

- input features, reward function design

Always use multiple random seeds

Best practices

In reinforcement learning we often don't know the true min/max/mean/standard deviation of observations/actions/rewards/returns

Standardize data

- if observations in unknown range, estimate running average mean & stdev
- use the min & max if known

Rescale rewards - but don’t shift mean

Standardize prediction targets (i.e. value functions) the same way

Batch size matters

Policy gradient methods – weight initialization matters determines initial state visitation (i.e. exploration)

Best practices

Compute useful statistics

explained variance (for seeing if your value functions are overfitting),
computing KL divergence of policy before and after update (a spike in KL usually means degradation of policy)
entropy of your policy

Visualize statistics

running min, mean, max of episode returns
KL of policy update
explained variance of value function fitting
network gradients

Gradient clipping is helpful - dropout & batchnorm not so much

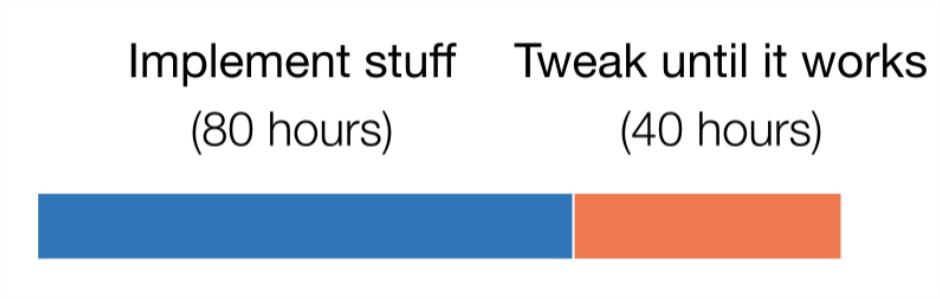
Amid Fish

Lessons Learned Reproducing a Deep Reinforcement Learning Paper

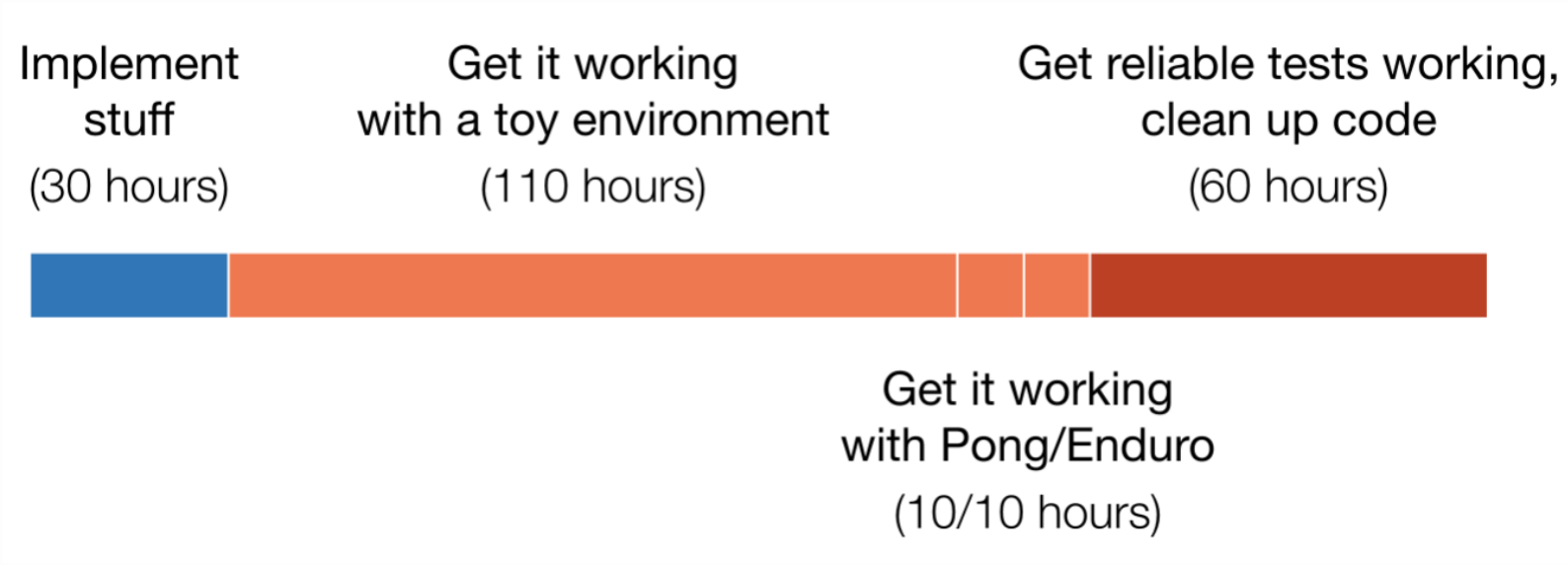
Apr 6, 2018

http://amid.fish/reproducing-deep-rl

The more interesting surprise was in how many hours each stage actually took. The main stages of my initial project plan were basically:



Here's how long each stage *actually* took.



In total, the project took:

- **150 hours of GPU time and 7,700 hours (wall time × cores) of CPU time** on Compute Engine,
- **292 hours of GPU time** on FloydHub,
- and **1,500 hours (wall time, 4 to 16 cores) of CPU time** on my university's cluster.

I was horrified to realise that in total, that added up to **about $850** ($200 on FloydHub, $650 on Compute Engine) over the 8 months of the project.

Reinforcement learning can be so unstable that you need to repeat every run multiple times with different seeds to be confident.

Matthew Rahtz of Amid Fish

It's not like my experience of programming in general so far where you get stuck but there's usually a clear trail to follow and you can get unstuck within a couple of days at most.

It's more like when you're trying to solve a puzzle, there are no clear inroads into the problem, and the only way to proceed is to try things until you find the key piece of evidence or get the key spark that lets you figure it out.

Debugging

Debugging in four steps

1. evidence about what the problem might be
2. form hypothesis about what the problem might be (evidence based)
3. choose most likely hypothesis, fix
4. repeat until problem goes away

Most programming involves rapid feedback

- you can see the effects of changes very quickly
- gathering evidence can be cheaper than forming hypotheses

In RL (and supervised learning with long run times) gathering evidence is expensive

- suggests spending more time on the hypothesis stage
- switch from experimenting a lot and thinking little to **experimenting a little and thinking a lot**
- reserve experiments for after you've really fleshed out the hypothesis space

Get more out of runs

Reccomends keeping a detailed work log

- what output am I working on now
- think out loud - what are the hypotheses, what to do next
- record of current runs with reminder about what each run is susposed to answer
- results of runs (i.e. TensorBoard)

Log all the metrics you can

- policy entropy for policy gradient methods

Matthew Rahtz of Amid Fish

RL specific

end to end tests of training
gym envs: -v0 environments mean 25% of the time action is ignored and previous action is repeated. Use -v4 to get rid of the randomness

General ML

for weight sharing, be careful with both dropout and batchnorm - you need to match additional variables
spikes in memory usages suggest validation batch size is too big
if you are struggling with the Adam optimizer, try an optimizer without momentum (i.e. RMSprop)

TensorFlow

`sess.run()`
can have a large overhead. Try to group session calls
use the

eight

deep reinforcement learning doesn't work yet

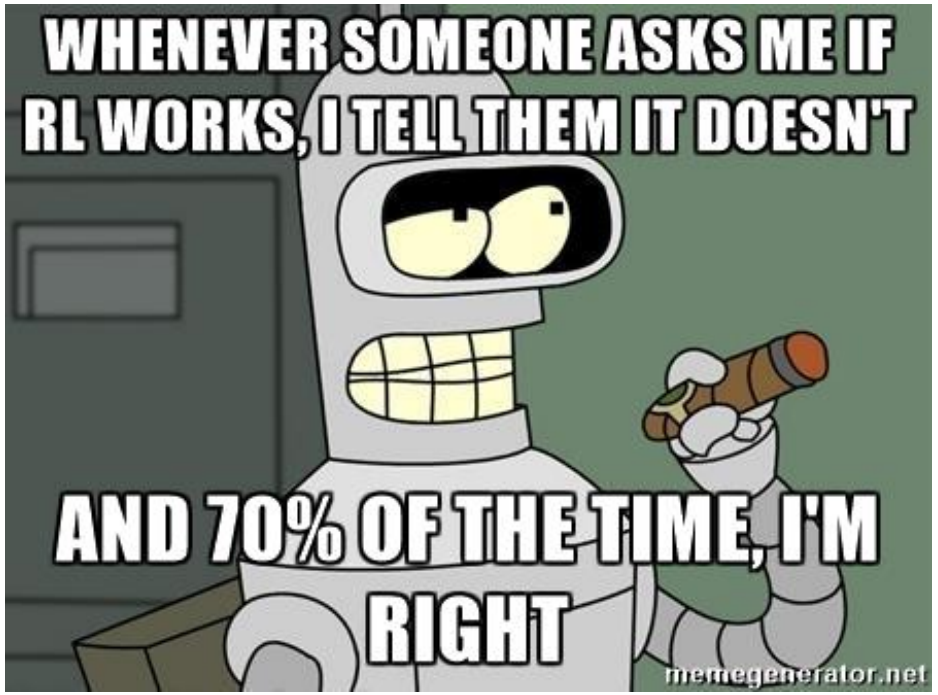
Sorta Insightful

Reviews Projects Archive Research About

In a world where everyone has opinions, one man...also has opinions

Deep Reinforcement Learning Doesn't Work Yet

Feb 14, 2018



Modern RL is sample inefficient

To pass the 100% median performance

Rainbow = 18 million frames = 83 hours of play
Distributional DQN = 70 million
DQN = never (even after 200 million frames!)

We can ignore sample efficiency if sampling is cheap

In the real world it can be hard or expensive to generate experience

It's not about learning time - it's about the ability to sample

Other methods often work better

Many problems are better solved by other methods

allowing the agent access to a ground truth model (i.e. simulator)
model based RL with a perfect model

Agent	*B.Rider*	*Breakout*	*Enduro*	*Pong*	*Q*bert*	*Seaquest*	*S.Invaders*
DQN	4092	168	470	20	1952	1705	581
-best	5184	225	661	21	4500	1740	1075
UCC	5342 (20)	175(5.63)	558(14)	19(0.3)	11574(44)	2273(23)	672(5.3)
-best	10514	351	942	21	29725	5100	1200
-greedy	5676	269	692	21	19890	2760	680
UCC-I	5388(4.6)	215(6.69)	601(11)	19(0.14)	13189(35.3)	2701(6.09)	670(4.24)
-best	10732	413	1026	21	29900	6100	910
-greedy	5702	380	741	21	20025	2995	692
UCR	2405(12)	143(6.7)	566(10.2)	19(0.3)	12755(40.7)	1024 (13.8)	441(8.1)

The generalizability of RL means that except in rare cases, domain specific algorithms work faster and better

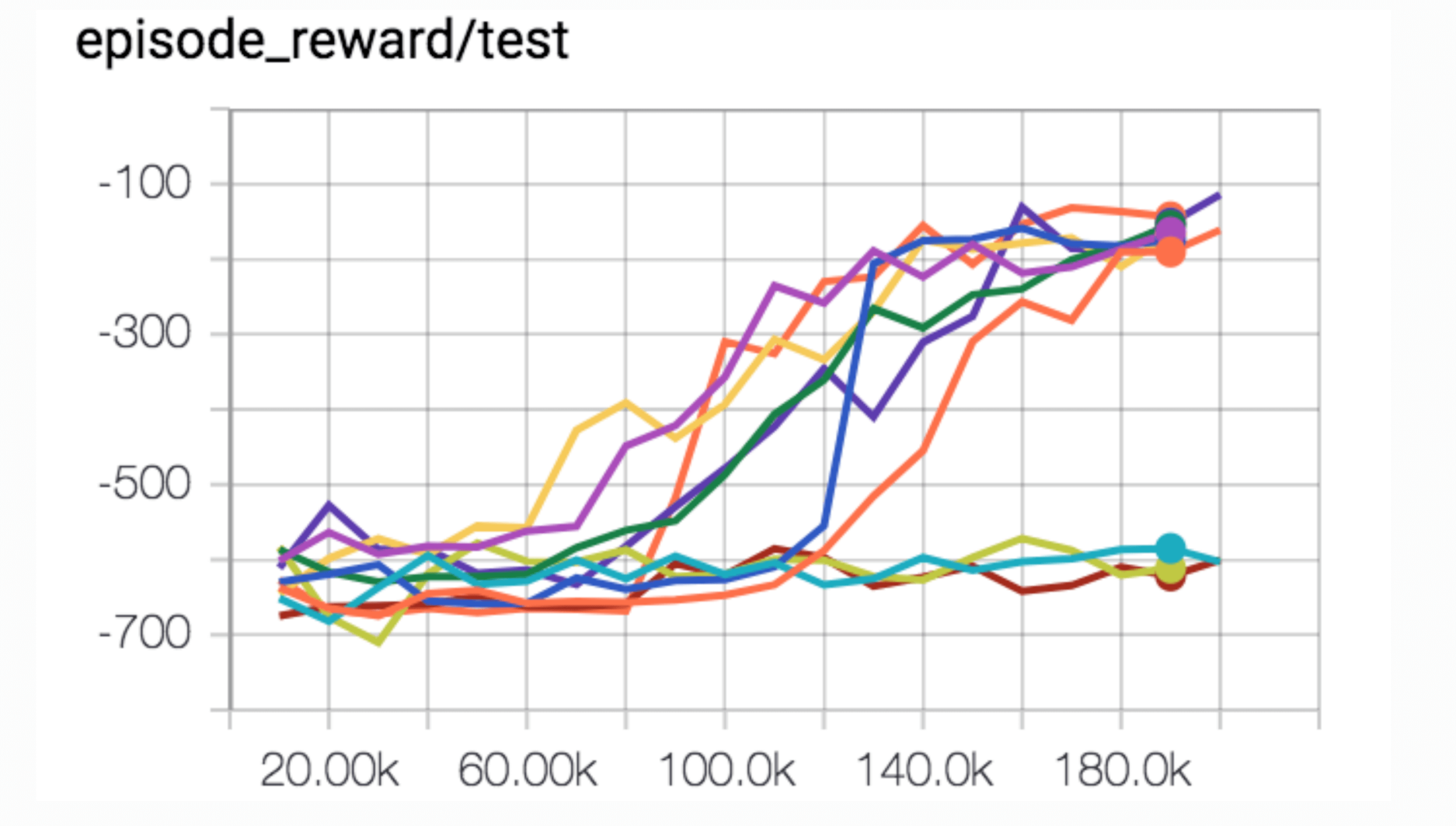
Requirement of a reward function

Reward function design is difficult

- need to encourage behaviour
- need to be learnable

Shaping rewards to help learning can change behaviour

Unstable and hard to reproduce results



Only difference is the random seed!

Machine learning adds more dimensions to your space of failure cases

RL adds an additional dimension - **random change**

A sample inefficient and unstable training algorithm heavily slows down your rate of productive research

> *[Supervised learning] wants to work. Even if you screw something up you'll usually get something non-random back. RL must be forced to work. If you screw something up or don't tune something well enough you're exceedingly likely to get a policy that is even worse than random. And even if it's all well tuned you'll get a bad policy 30% of the time, just because.*
>
> *Long story short your failure is more due to the difficulty of deep RL, and much less due to the difficulty of "designing neural networks".*
>
> Hacker News comment from Andrej Karpathy, back when he was at OpenAI

Going forward & the future

> The way I see it, either deep RL is still a research topic that isn't robust enough for widespread use, or it's usable and the people who've gotten it to work aren't publicizing it. I think the former is more likely.

Make learning eaiser

ability to generate near unbounded amounts of experience
problem is simplified into an eaiser form
you can introduce self-play into learning
learnable reward signal
any reward shaping should be rich

The future

local optima are good enough (is any human behaviour globally optimal)
improvements in hardware help with sample inefficiency
more learning signal - hallucinating rewards, auxillary tasks, model learning
model learning fixes a bunch of problems - difficulty is learning one

Closing thoughts

Exploration versus exploitation

Test your models on simple problems

Reinforcement learning is sample inefficient

Deep RL is hard

Reward engineering is key

Thank you

Adam Green

adgefficiency.com