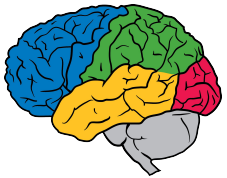
Rishabh Agarwal, Dale Schuurmans, Mohammad Norouzi

How I Learned To Stop Worrying And Love Offline RL

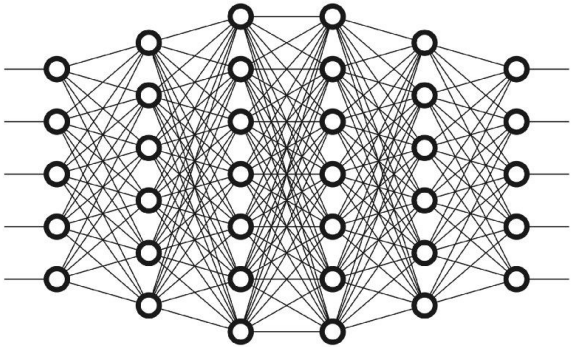
An Optimistic Perspective on Offline Reinforcement Learning



Google Research

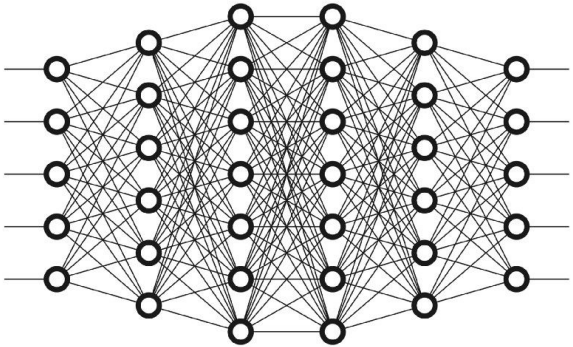
What makes Deep Learning Successful?

Expressive function approximators



What makes Deep Learning Successful?

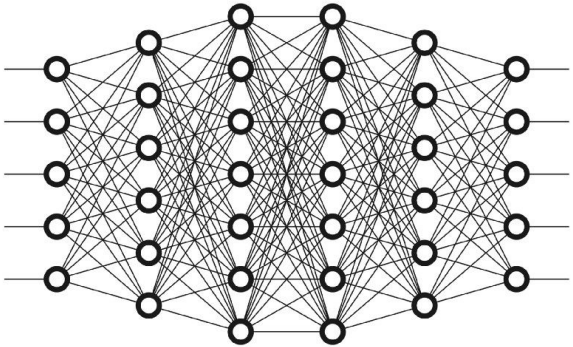
Expressive function approximators



Powerful learning algorithms

What makes Deep Learning Successful?

Expressive function approximators

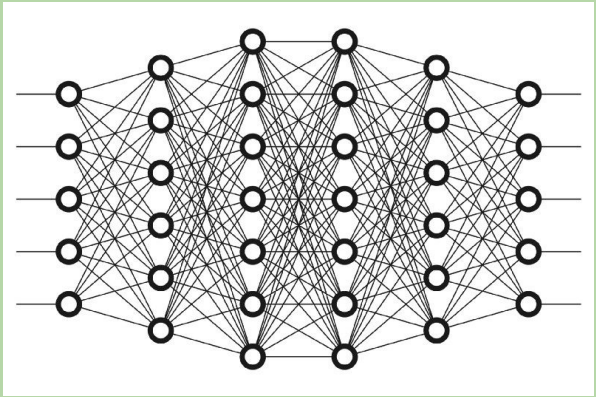


Powerful learning algorithms

Large and Diverse Datasets

How to make Deep RL similarly successful?

Expressive function approximators

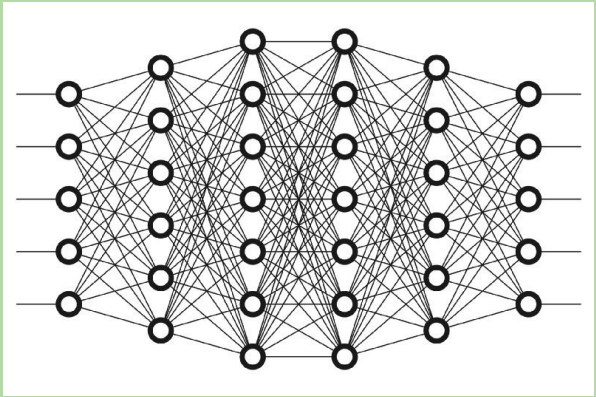


Good learning algorithms e.g., actor-critic, approx DP

Google Research

How to make Deep RL similarly successful?

Expressive function approximators

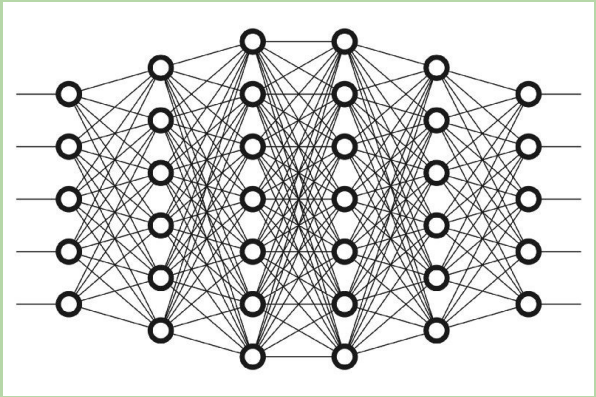


Good learning algorithms e.g., actor-critic, approx DP

Large and Diverse Datasets

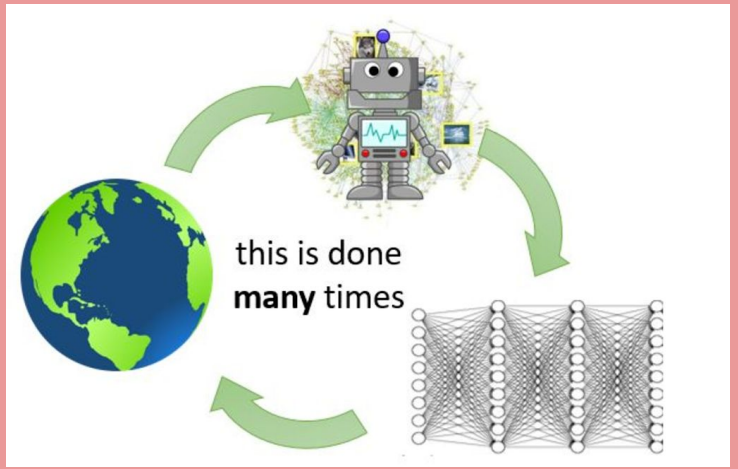
How to make Deep RL similarly successful?

Expressive function approximators



Good learning algorithms e.g., actor-critic, approx DP

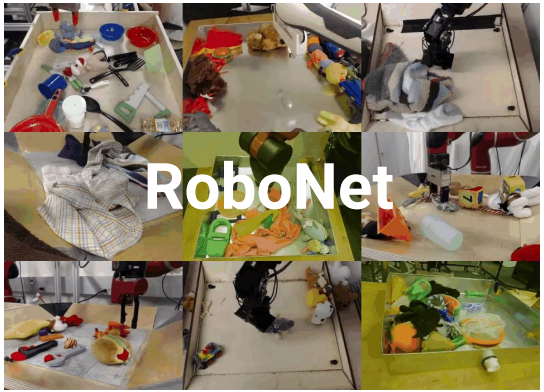
Interactive Environments



Active Data Collection

Google Research

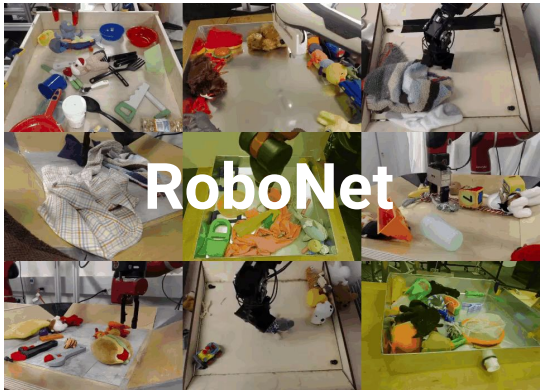
RL for Real-World: RL with Large Datasets



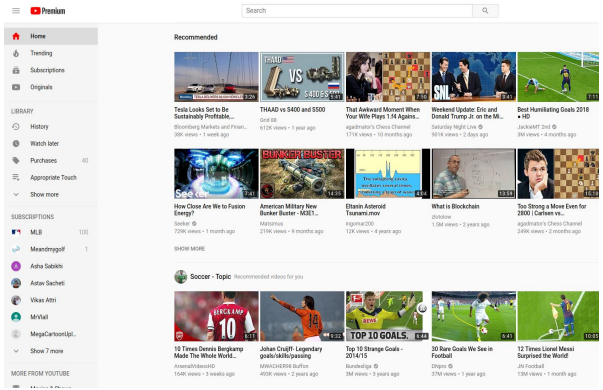
Robotics

[1] Dasari, Ebert, Tian, Nair, Bucher, Schmeckpeper, .. Finn. RoboNet: Large-Scale Multi-Robot Learning.
[2] Yu, Xian, Chen, Liu, Liao, Madhavan, Darrell. BDD100K: A Large-scale Diverse Driving Video Database.

RL for Real-World: RL with Large Datasets



Robotics

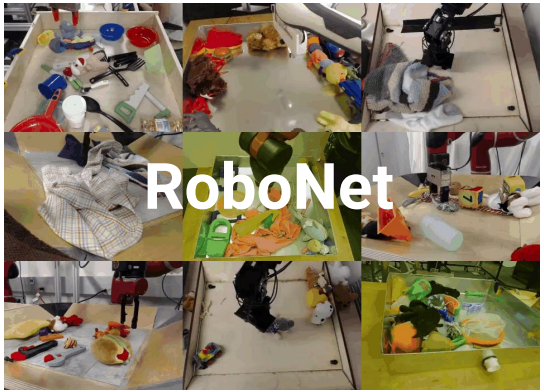


Recommender Systems

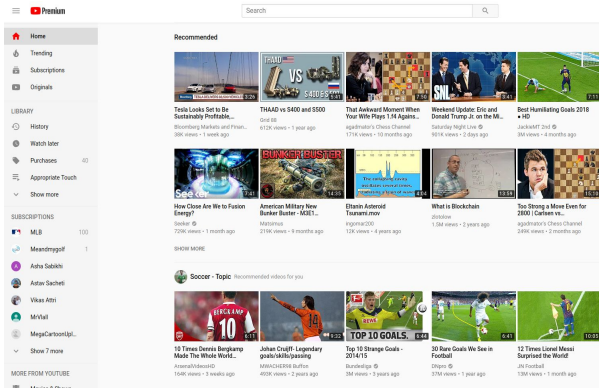
[1] Dasari, Ebert, Tian, Nair, Bucher, Schmeckpeper, .. Finn. RoboNet: Large-Scale Multi-Robot Learning.
[2] Yu, Xian, Chen, Liu, Liao, Madhavan, Darrell. BDD100K: A Large-scale Diverse Driving Video Database.

Google Research

RL for Real-World: RL with Large Datasets



Robotics



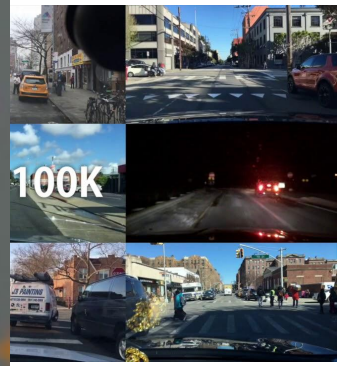
Recommender Systems

Self-Driving Cars

[1] Dasari, Ebert, Tian, Nair, Bucher, Schmeckpeper, .. Finn. RoboNet: Large-Scale Multi-Robot Learning.
[2] Yu, Xian, Chen, Liu, Liao, Madhavan, Darrell. BDD100K: A Large-scale Diverse Driving Video Database.

RL for Real-World: RL with Large Datasets

Roboti



ing Cars

[1] Dasari, Ebert, Tia ng.
[2] Yu, Xian, Chen, Liu, Liao, Madhavan, Darrell. BDD100K: A Large-scale Diverse Driving Video Database.

Offline RL: A Data-Driven RL Paradigm

Google Research

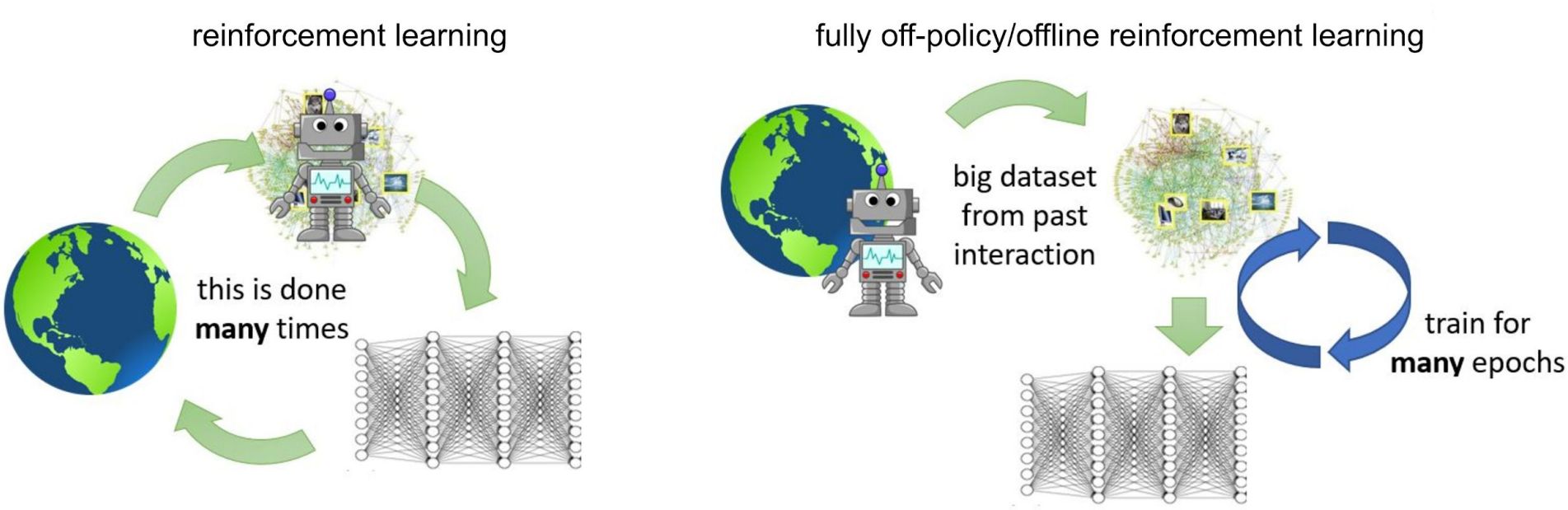


Image Source: Data-Driven Deep Reinforcement Learning, BAIR Blog. https://bair.berkeley.edu/blog/2019/12/05/bear/

Offline RL: A Data-Driven RL Paradigm

Offline RL can help:

- Pretrain agents on existing logged data.

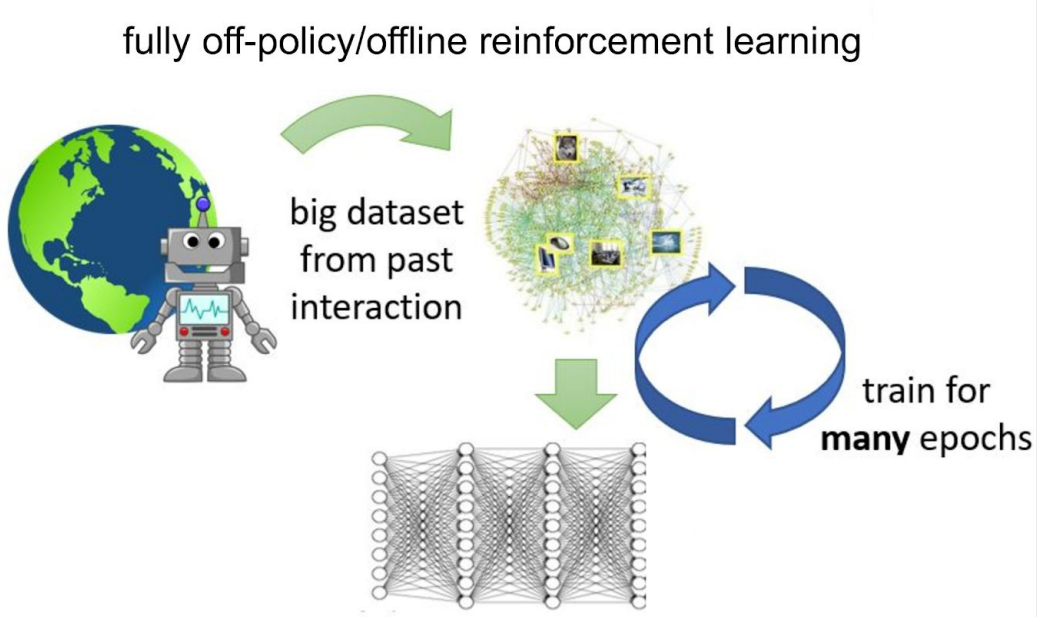


Image Source: Data-Driven Deep Reinforcement Learning, BAIR Blog. https://bair.berkeley.edu/blog/2019/12/05/bear/

Offline RL: A Data-Driven RL Paradigm

Offline RL can help:

- Pretrain agents on existing logged data.
- Evaluate RL algorithms on the basis of exploitation alone on common datasets.

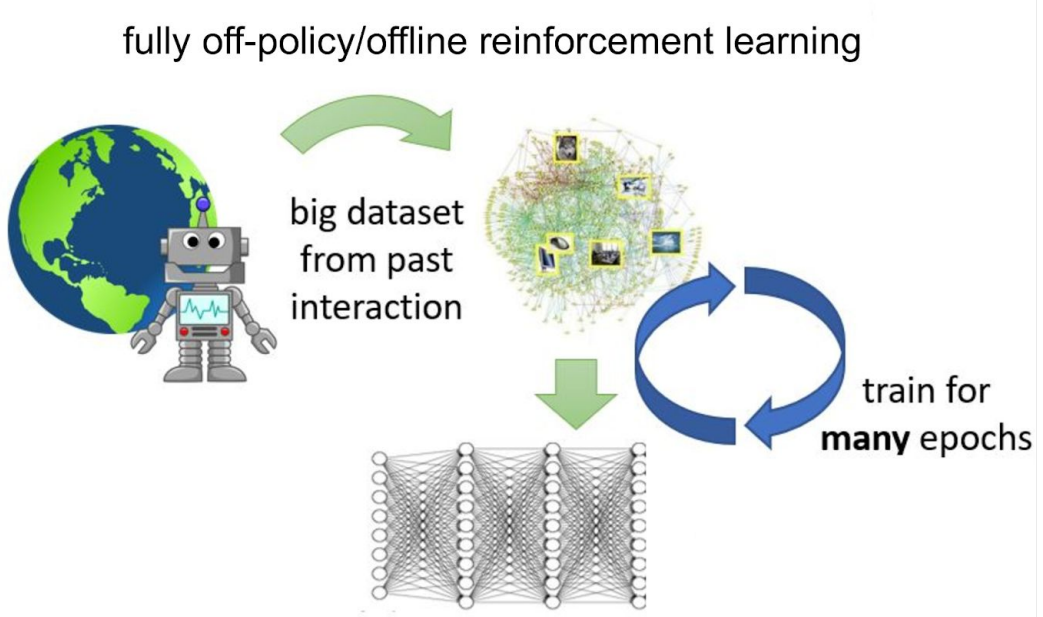


Image Source: Data-Driven Deep Reinforcement Learning, BAIR Blog. https://bair.berkeley.edu/blog/2019/12/05/bear/

Offline RL: A Data-Driven RL Paradigm

Offline RL can help:

- Pretrain the agents on existing logged data.
- Evaluate RL algorithms on the basis of exploitation alone on common datasets.
- Deliver real world impact.

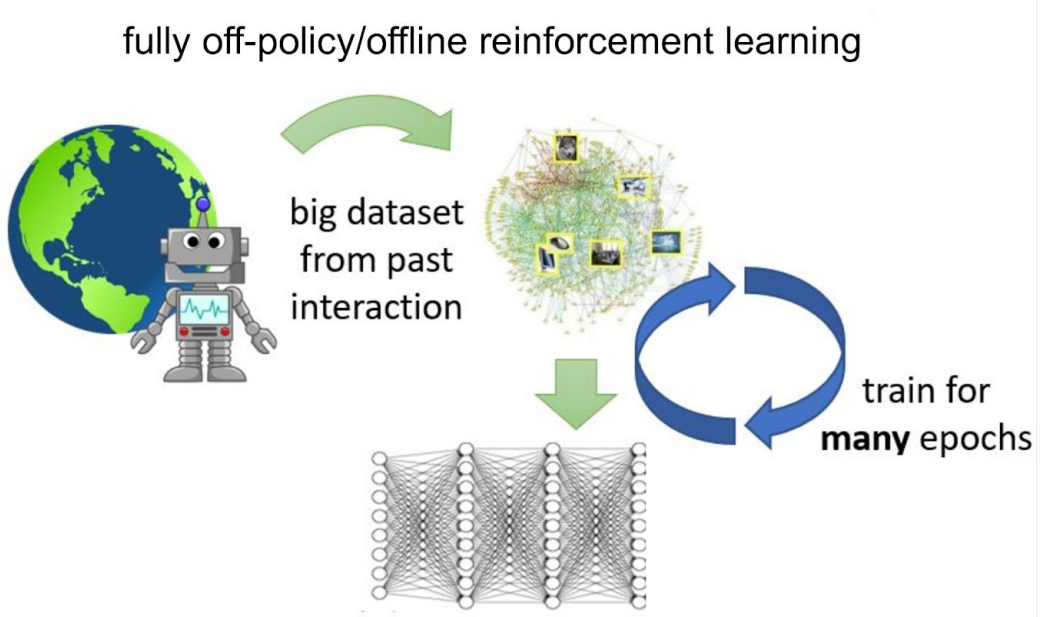


Image Source: Data-Driven Deep Reinforcement Learning, BAIR Blog. https://bair.berkeley.edu/blog/2019/12/05/bear/

But .. Offline RL is Hard!

NO new corrective feedback!

But .. Offline RL is Hard!

Requires Counterfactual Generalization

But .. Offline RL is Hard!

Fully Off-Policy

Bootstrapping
(Learning guess from a guess)

Function
Approximation

Google Research

Standard RL fails in Offline setting ..

Off-Policy Deep Reinforcement Learning without Exploration

Scott Fujimoto [1 2] **David Meger** [1 2] **Doina Precup** [1 2]

Abstract

Many practical applications of reinforcement learning constrain agents to learn from a fixed batch of data which has already been gathered, without offering further possibility for data collection. In this paper, we demonstrate that due to

require further interactions with the environment to compensate (Hester et al., 2017; Sun et al., 2018; Cheng et al., 2018). On the other hand, batch reinforcement learning offers a mechanism for learning from a fixed dataset without restrictions on the quality of the data.

Most modern off-policy deep reinforcement learning al-

Behavior Regularized Offline Reinforcement Learning

Yifan Wu* Carnegie Mellon University yw4@cs.cmu.edu

George Tucker Google Research gjt@google.com

Ofir Nachum Google Research ofirnachum@google.com

Abstract

In reinforcement learning (RL) research, it is common to assume access to direct *online* interactions with the environment. However in many real-world applications, access to the environment is limited to a fixed *offline* dataset of logged experience. In such settings, standard RL algorithms have been shown to diverge or otherwise yield poor performance. Accordingly, recent work has suggested a number of remedies to these issues. In this work, we introduce a general framework, *behavior regularized actor critic* (BRAC), to empirically evaluate recently proposed methods as well as a number of simple baselines across a variety of offline continuous control tasks. Surprisingly, we find that many of the technical complexities introduced in recent methods are unnecessary to achieve strong performance. Additional ablations provide insights into which design choices matter most in the offline RL setting.[1]

KEEP DOING WHAT WORKED: BEHAVIOR MODELLING PRIORS FOR OFFLINE REINFORCEMENT LEARNING

Noah Y. Siegel, Jost Tobias Springenberg, Felix Berkenkamp, Abbas Abdolmaleki, Michael Neunert, Thomas Lampe, Roland Hafner, Nicolas Heess, Martin Riedmiller

DeepMind
{siegeln}@google.com

ABSTRACT

Off-policy reinforcement learning algorithms promise to be applicable in settings where only a fixed data-set (batch) of environment interactions is available and no new experience can be acquired. This property makes these algorithms appealing

Stabilizing Off-Policy Q-Learning via Bootstrapping Error Reduction

Aviral Kumar* UC Berkeley aviralk@berkeley.edu

Justin Fu* UC Berkeley justinjfu@eecs.berkeley.edu

George Tucker Google Brain gjt@google.com

Sergey Levine UC Berkeley, Google Brain svlevine@eecs.berkeley.edu

Abstract

Off-policy reinforcement learning aims to leverage experience collected from prior policies for sample-efficient learning. However, in practice, commonly used off-policy approximate dynamic programming methods based on Q-learning and

Standard RL fails in Offline setting ..

Off-Policy Deep Reinforcement Learning without Exploration

Scott Fujimoto [1 2] David Meger [1 2] Doina Precup [1 2]

Abstract

Many practical applications of reinforcement learning constrain agents to learn from a fixed batch of data which has already been gathered, without offering further possibility for data collection. In this paper, we demonstrate that due to

require further interactions with the environment to compensate (Hester et al., 2017; Sun et al., 2018; Cheng et al., 2018). On the other hand, batch reinforcement learning offers a mechanism for learning from a fixed dataset without restrictions on the quality of the data.

Most modern off-policy deep reinforcement learning al-

Behavior Regularized Offline Reinforcement Learning

Yifan Wu*
Carnegie Mellon University
yw4@cs.cmu.edu

George Tucker
Google Research
gjt@google.com

Ofir Nachum
Google Research
ofirnachum@google.com

Abstract

In reinforcement learning (RL) research, it is common to assume access to direct *online* interactions with the environment. However in many real-world applications, access to the environment is limited to a fixed *offline* dataset of logged experience. In such settings, standard RL algorithms have been shown to diverge or otherwise yield poor performance. Accordingly, recent work has suggested a number of remedies to these issues. In this work, we introduce a general framework, *behavior regularized actor critic* (BRAC), to empirically evaluate recently proposed methods as well as a number of simple baselines across a variety of offline continuous control tasks. Surprisingly, we find that many of the technical complexities introduced in recent methods are unnecessary to achieve strong performance. Additional ablations provide insights into which design choices matter most in the offline RL setting.[1]

KEEP DOING WHAT WORKED: BEHAVIOR MODELLING PRIORS FOR OFFLINE REINFORCEMENT LEARNING

Noah Y. Siegel, Jost Tobias Springenberg, Felix Berkenkamp, Abbas Abdolmaleki, Michael Neunert, Thomas Lampe, Roland Hafner, Nicolas Heess, Martin Riedmiller

DeepMind
{siegeln}@google.com

ABSTRACT

Off-policy reinforcement learning algorithms promise to be applicable in settings where only a fixed data-set (batch) of environment interactions is available and no new experience can be acquired. This property makes these algorithms appealing

Stabilizing Off-Policy Q-Learning via Bootstrapping Error Reduction

Aviral Kumar*
UC Berkeley
aviralk@berkeley.edu

Justin Fu*
UC Berkeley
justinjfu@eecs.berkeley.edu

George Tucker
Google Brain
gjt@google.com

Sergey Levine
UC Berkeley, Google Brain
svlevine@eecs.berkeley.edu

Abstract

Off-policy reinforcement learning aims to leverage experience collected from prior policies for sample-efficient learning. However, in practice, commonly used off-policy approximate dynamic programming methods based on Q-learning and

Google Research

Standard RL fails in Offline setting ..

Off-Policy Deep Reinforcement Learning without Exploration

Scott Fujimoto [1 2] David Meger [1 2] Doina Precup [1 2]

Abstract

Many practical applications of reinforcement learning constrain agents to learn from a fixed batch of data which has already been gathered, without offering further possibility for data collection. In this paper, we demonstrate that due to

require further interactions with the environment to compensate (Hester et al., 2017; Sun et al., 2018; Cheng et al., 2018). On the other hand, batch reinforcement learning of

KEEP DOING WHAT WORKED:
BEHAVIOR MODELLING PRIORS FOR OFFLINE REINFORCEMENT LEARNING

Noah Y. Siegel, Jost Tobias Springenberg, Felix Berkenkamp, Abbas Abdolmaleki, Michael Neunert, Thomas Lampe, Roland Hafner, Nicolas Heess, Martin Riedmiller

DeepMind
{siegeln}@google.com

Behavior Regularized Offlin

Yifan Wu*
Carnegie Mellon University
yw4@cs.cmu.edu

George
Google
gjt@goo

Abstr

In reinforcement learning (RL) research *online* interactions with the environment. access to the environment is limited to a fix such settings, standard RL algorithms have poor performance. Accordingly, recent wor these issues. In this work, we introduce a ge *critic* (BRAC), to empirically evaluate recent simple baselines across a variety of offline co that many of the technical complexities introduced in recent methods are unnecessary to achieve strong performance. Additional ablations provide insights into which design choices matter most in the offline RL setting.[1]

A Deeper Look at Experience Replay

Shangtong Zhang, Richard S. Sutton
Dept. of Computing Science
University of Alberta
{shangtong.zhang, rsutton}@ualberta.ca

Abstract

Recently experience replay is widely used in various deep reinforcement learning (RL) algorithms, in this paper we rethink the utility of

et al. 2016), which is a desired property for many RL algorithms as they are often pretty hungry for data. Although algorithms in pre-deep-RL era do not need to care about how to stabilize a neural network, they do care data efficiency. If experience replay is a perfect idea,

n settings
ble and no
appealing

earning via Bootstrapping
eduction

Justin Fu*
UC Berkeley
justinjfu@eecs.berkeley.edu

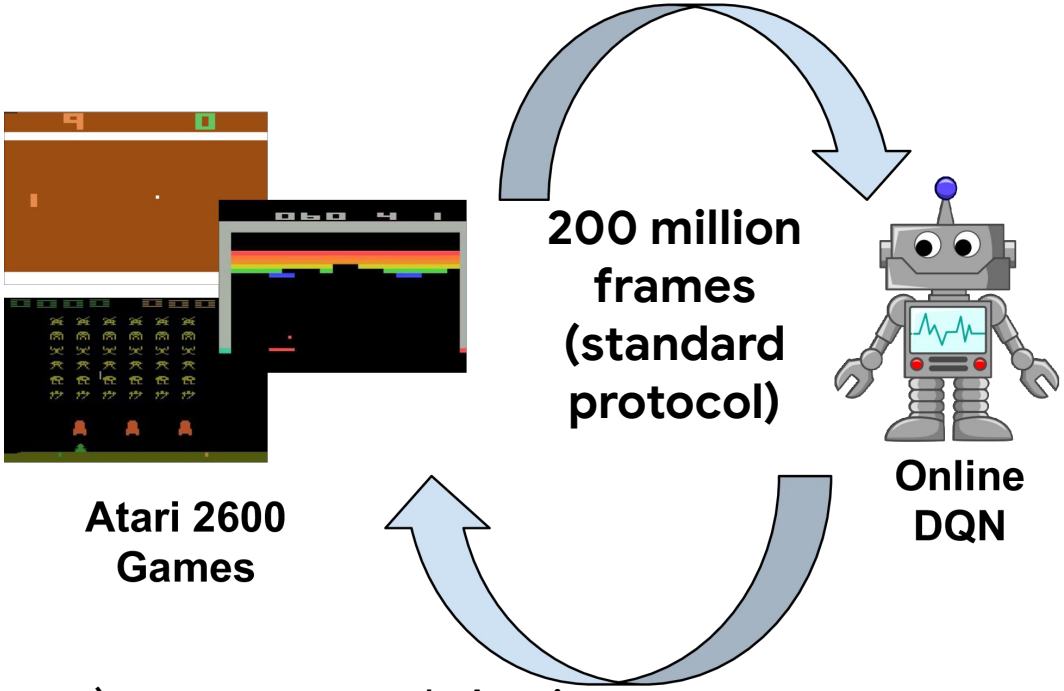
Sergey Levine
UC Berkeley, Google Brain
svlevine@eecs.berkeley.edu

tract

Off-policy reinforcement learning aims to leverage experience collected from prior policies for sample-efficient learning. However, in practice, commonly used off-policy approximate dynamic programming methods based on Q-learning and

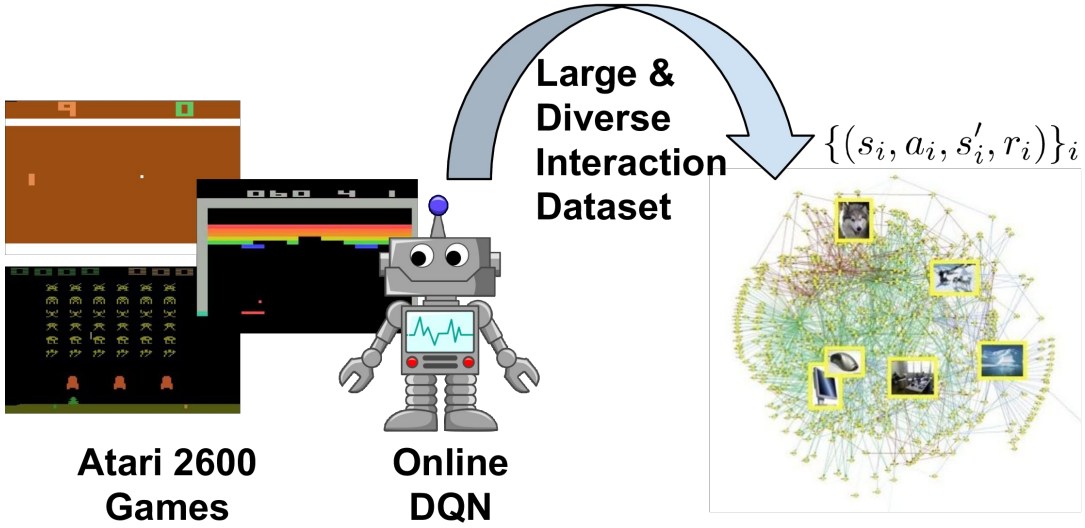
Can standard off-policy RL succeed in the offline Setting?

Offline RL on Atari 2600



Train 5 DQN (Nature) agents on each Atari game using sticky actions (stochasticity)

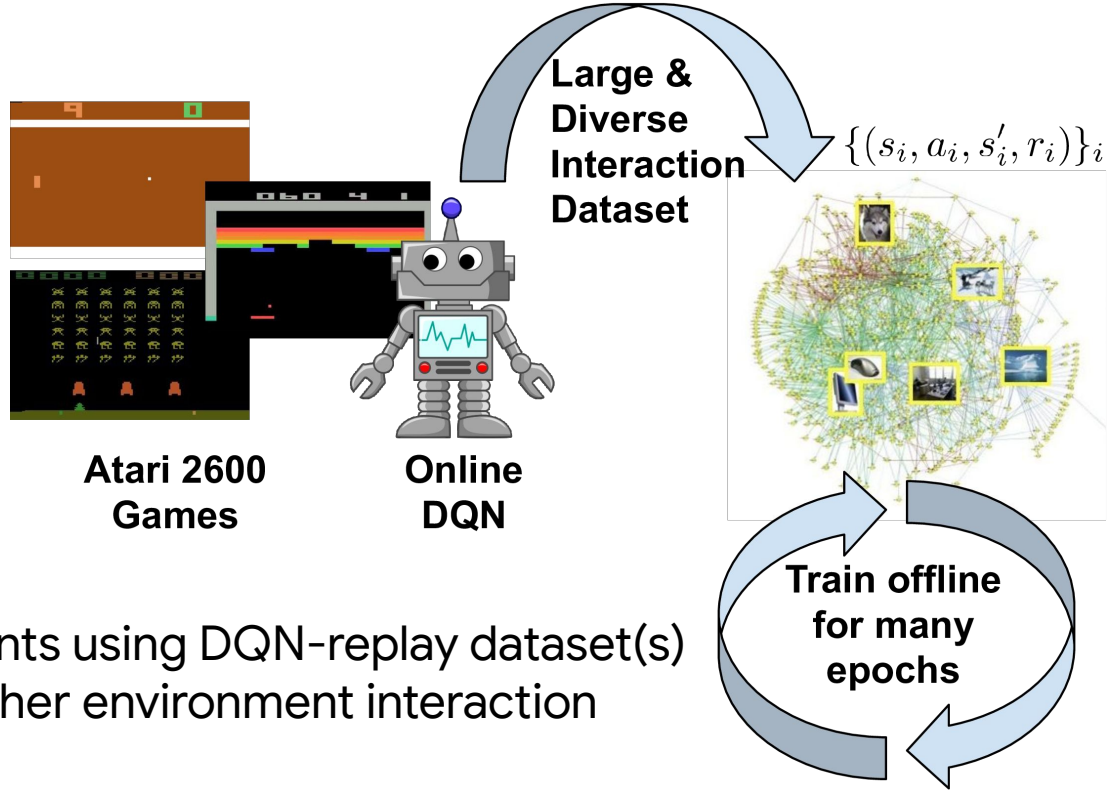
Offline RL on Atari 2600



Save all of the tuples of *(observation, action, next observation, reward)* encountered to DQN-replay dataset(s)

Google Research

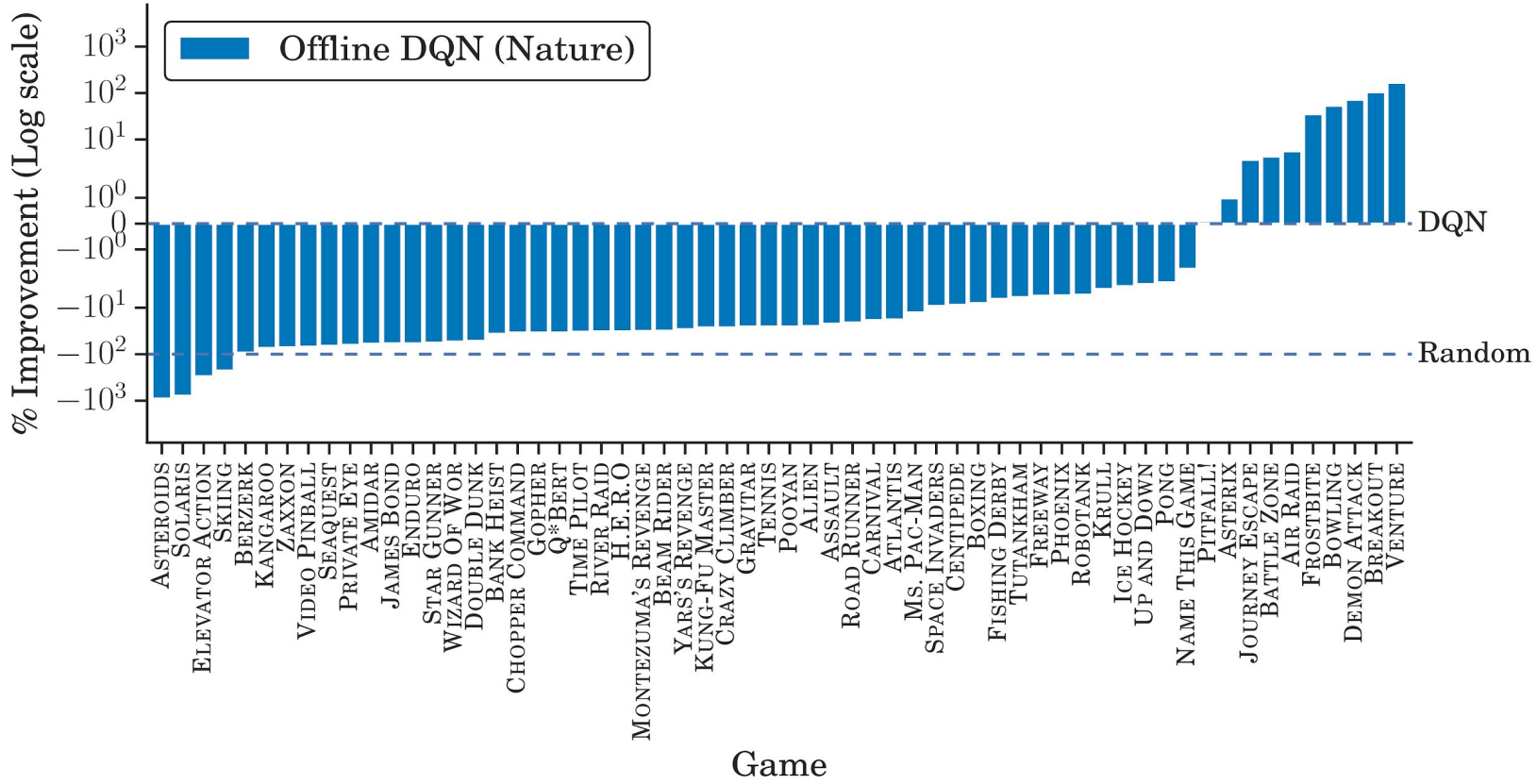
Offline RL on Atari 2600



Train off-policy agents using DQN-replay dataset(s) without any further environment interaction

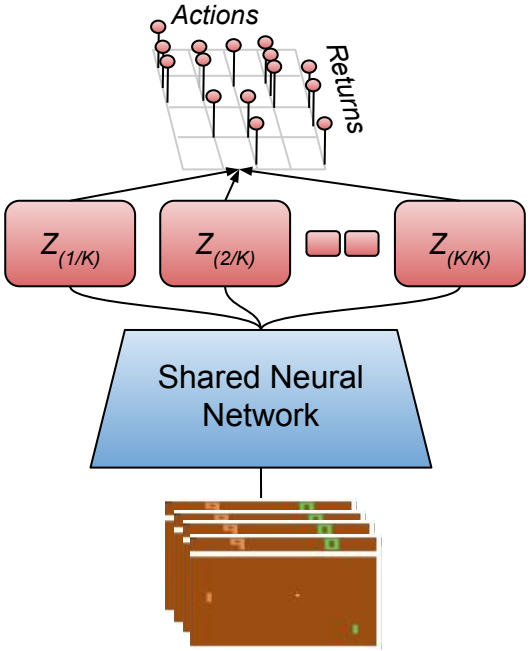
Google Research

Does Offline DQN work?



Let's try recent off-policy algorithms!

Google Research



QR-DQN

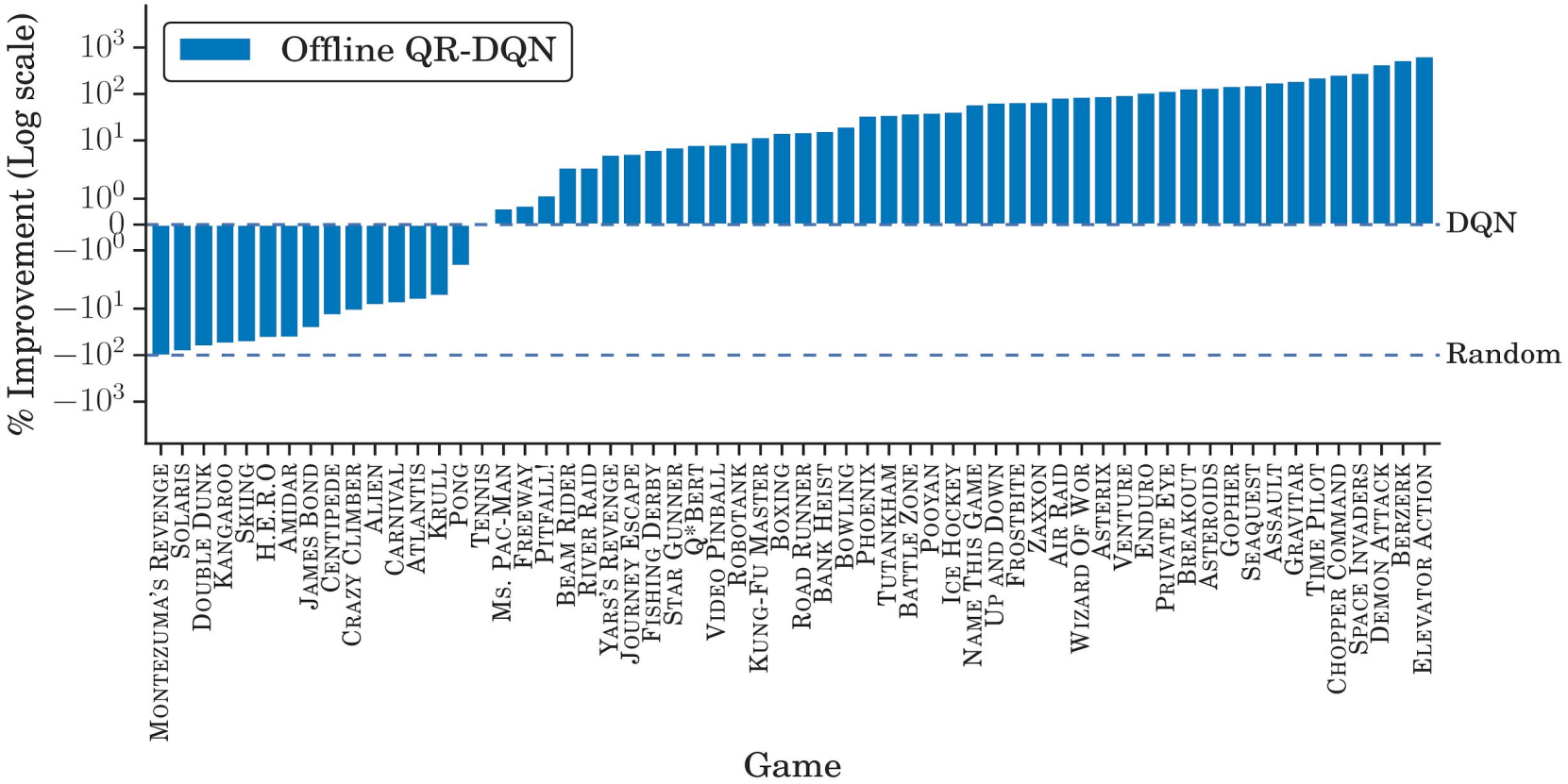
Distributional RL uses Z(s, a), a distribution over returns, instead of the Q-function.

$$Z(s,a;\theta) := \frac{1}{K}\sum_{i=1}^{K}\delta_{\theta_i(s,a)}$$

$$Q(s,a;\theta) := \mathbb{E}[Z] = \frac{1}{K}\sum_{i=1}^{K}\theta_i(s,a)$$

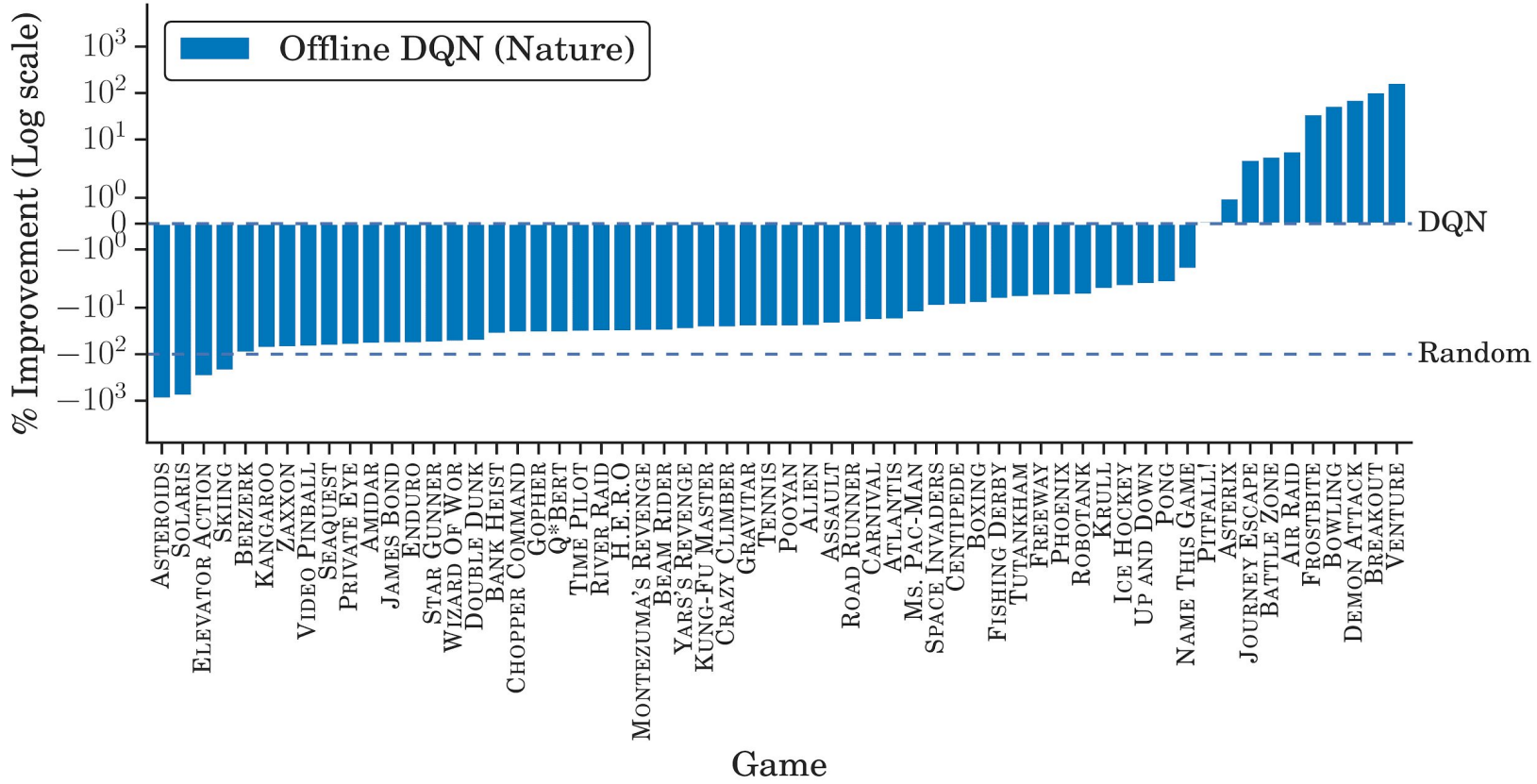
Google Research

Does Offline QR-DQN work?



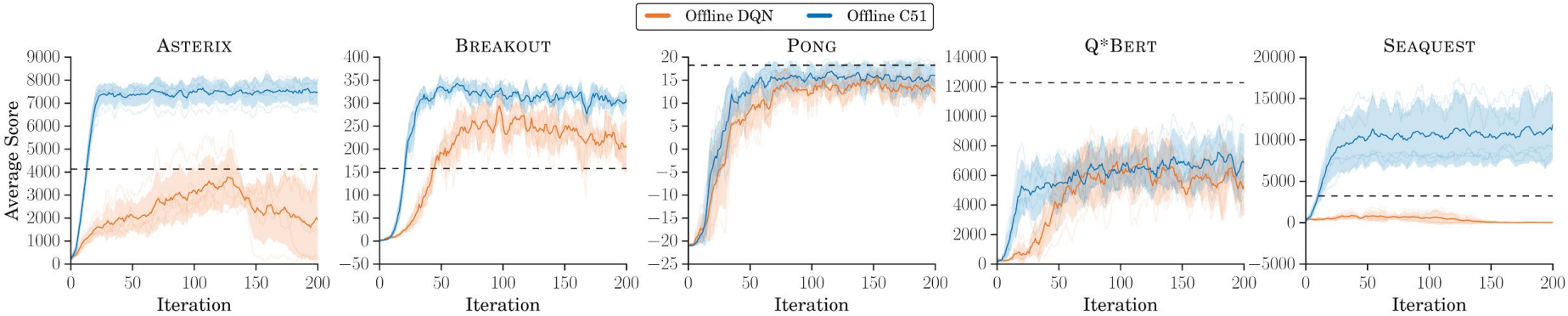
Google Research

Does Offline DQN work?



Offline DQN (Nature) vs Offline C51

Google Research



Average online scores of C51 and DQN (Nature) agents trained offline on DQN replay dataset for the same number of gradient steps as online DQN. The horizontal line shows the performance of fully-trained DQN.

Developing Robust Offline RL algorithms

Google Research

- Emphasis on Generalization
  - Given a fixed dataset, generalize to unseen states during evaluation.

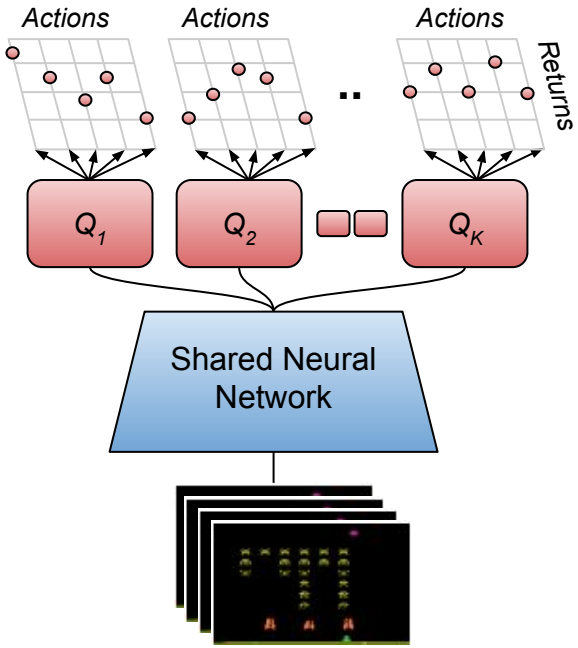
Developing Robust Offline RL algorithms

Google Research

- Emphasis on Generalization
  - Given a fixed dataset, generalize to unseen states during evaluation.
- Ensemble of Q-estimates:
  - Ensembling, Dropout widely used for improving generalization.

Google Research

Ensemble-DQN

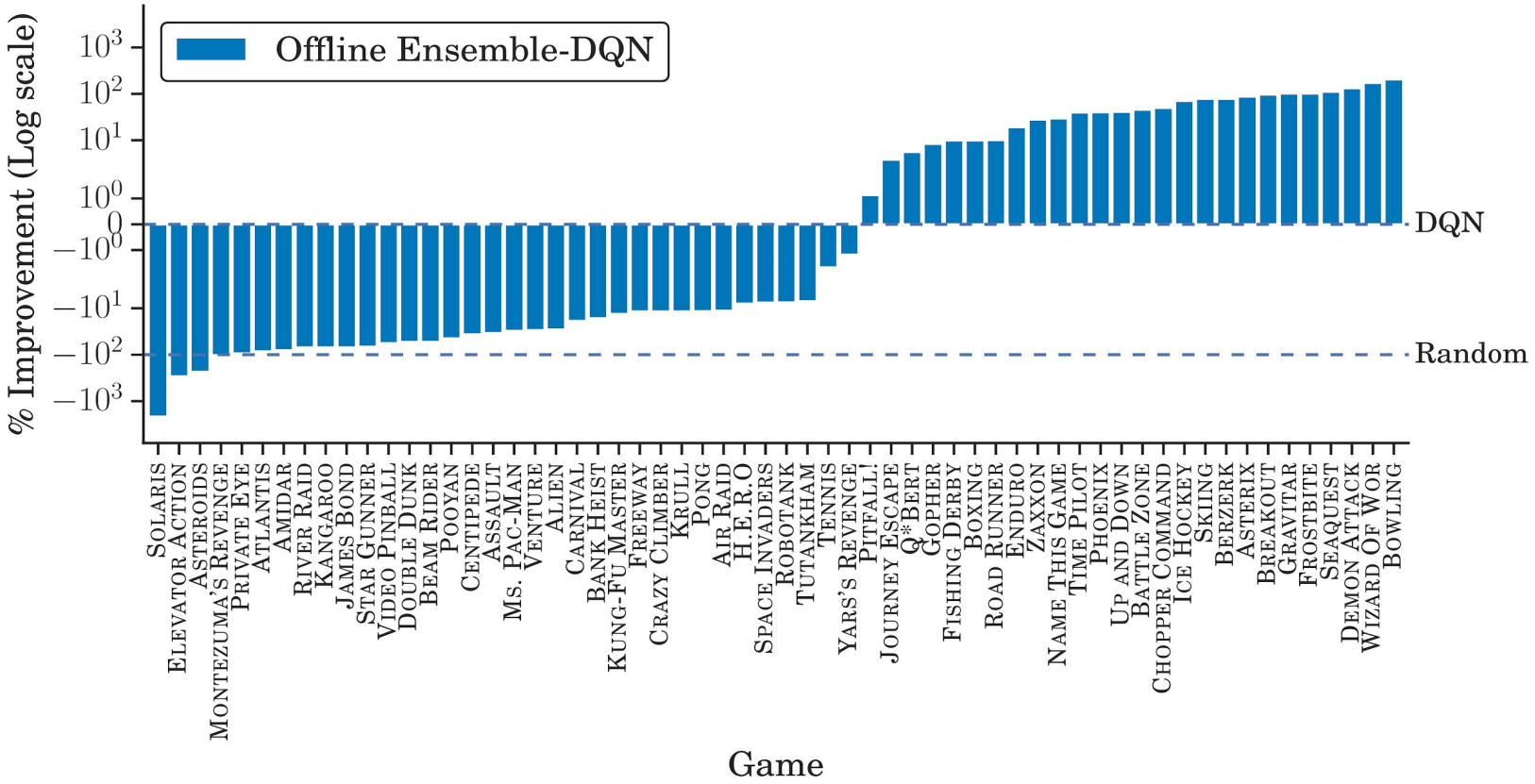


Ensemble-DQN

Train multiple (linear) Q-heads with different random initialization.

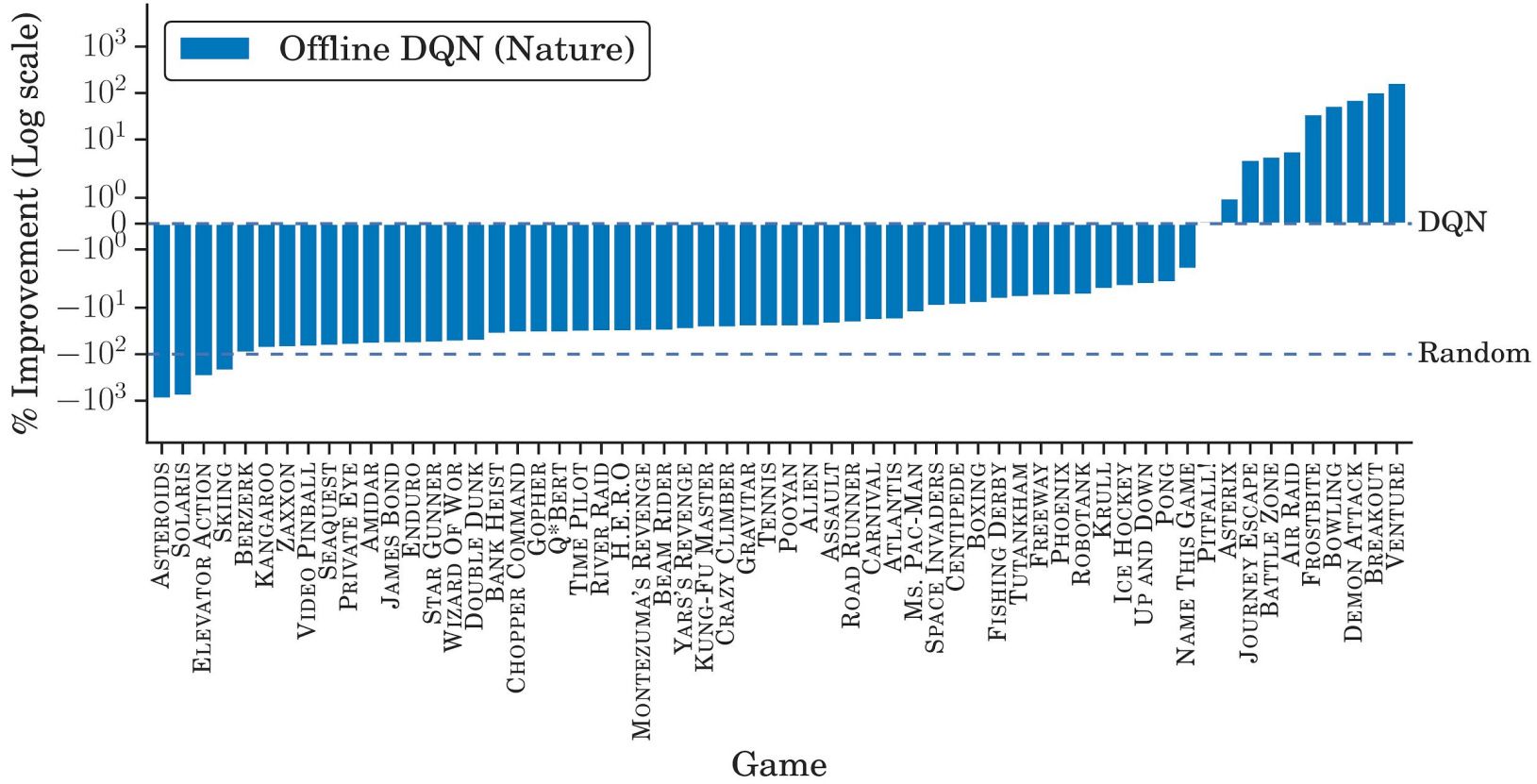
Google Research

Does Offline Ensemble-DQN work?



Google Research

Does Offline DQN work?

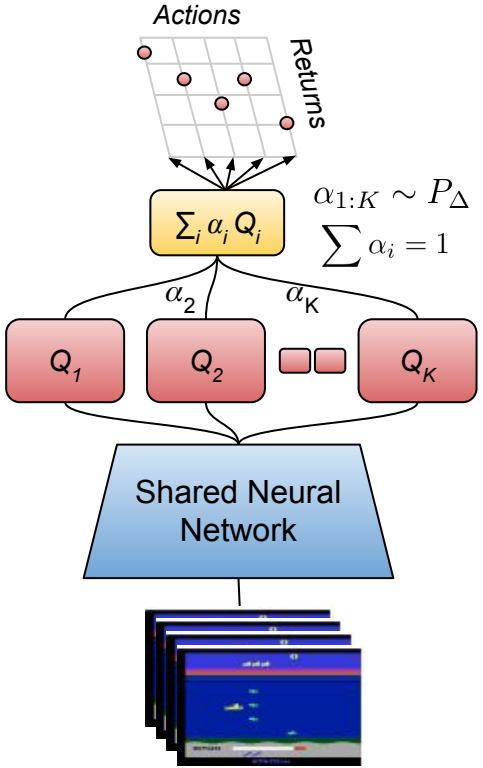


Developing Robust Offline RL algorithms

Google Research

- Emphasis on Generalization
  - Given a fixed dataset, generalize to unseen states during evaluation.
- Q-learning as constraint satisfaction:
  - $\forall\ (s, a, s', r):\ \ Q^*(s, a) = r\ + max_{a'}\ Q^*(s', a')$

Random Ensemble Mixture (REM)

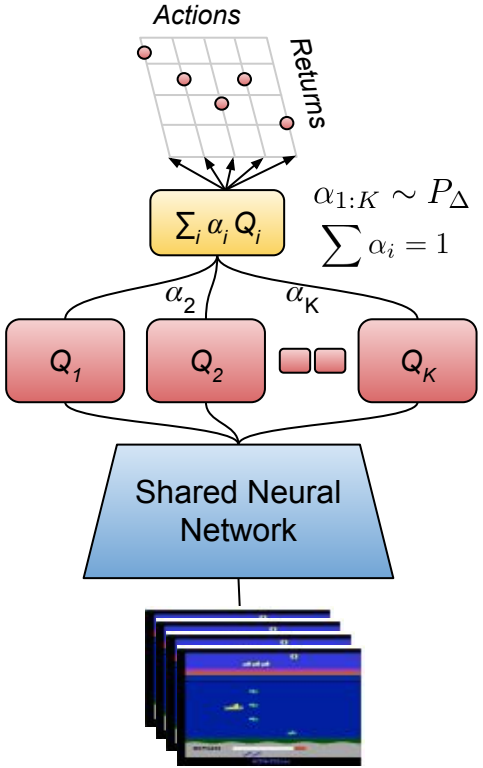


REM

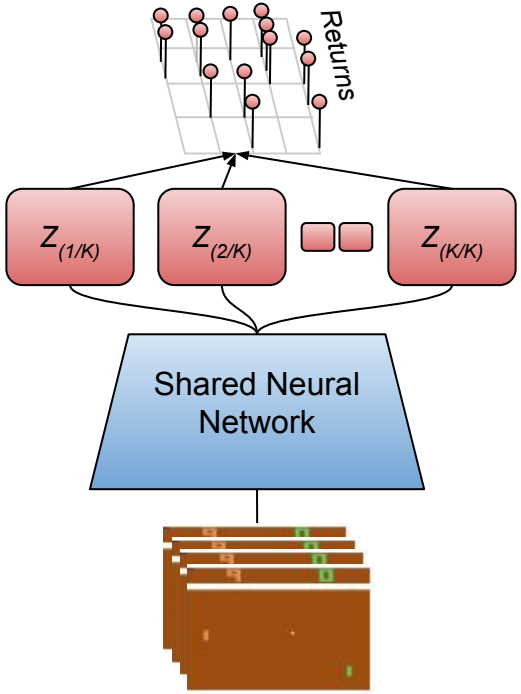
Minimize TD error on random (per minibatch) convex combination of multiple Q-estimates.

Google Research

REM vs QR-DQN



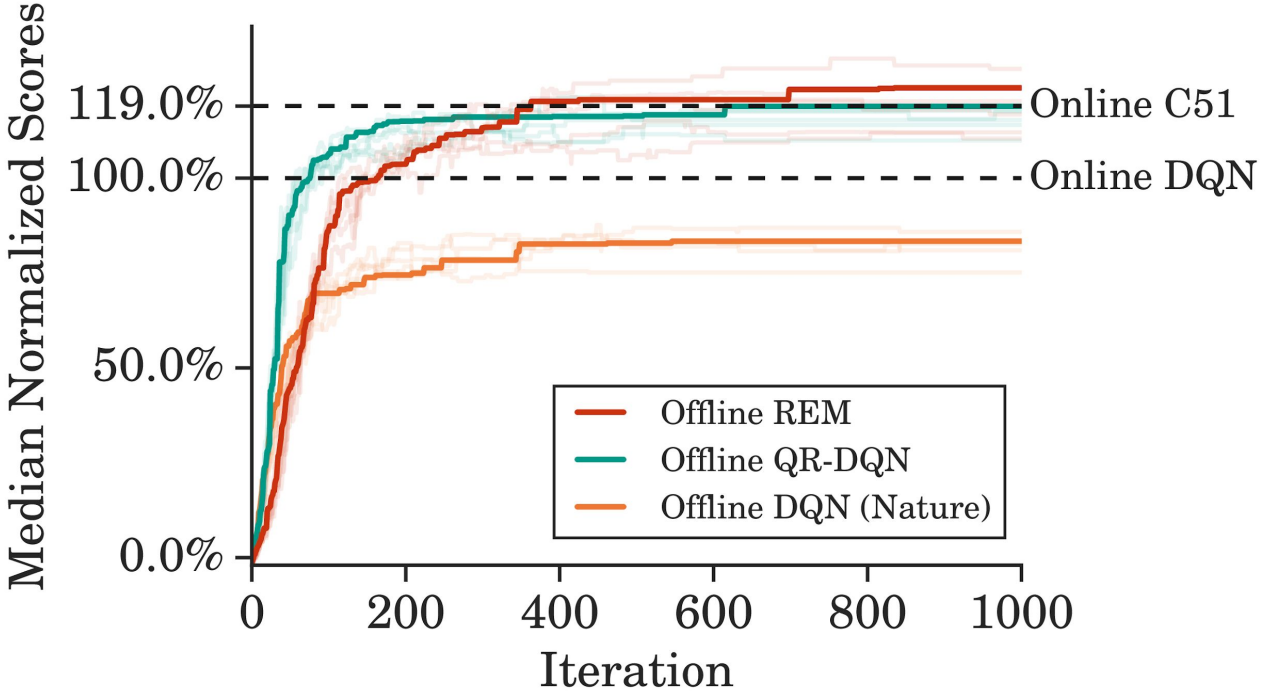
REM



QR-DQN

Google Research

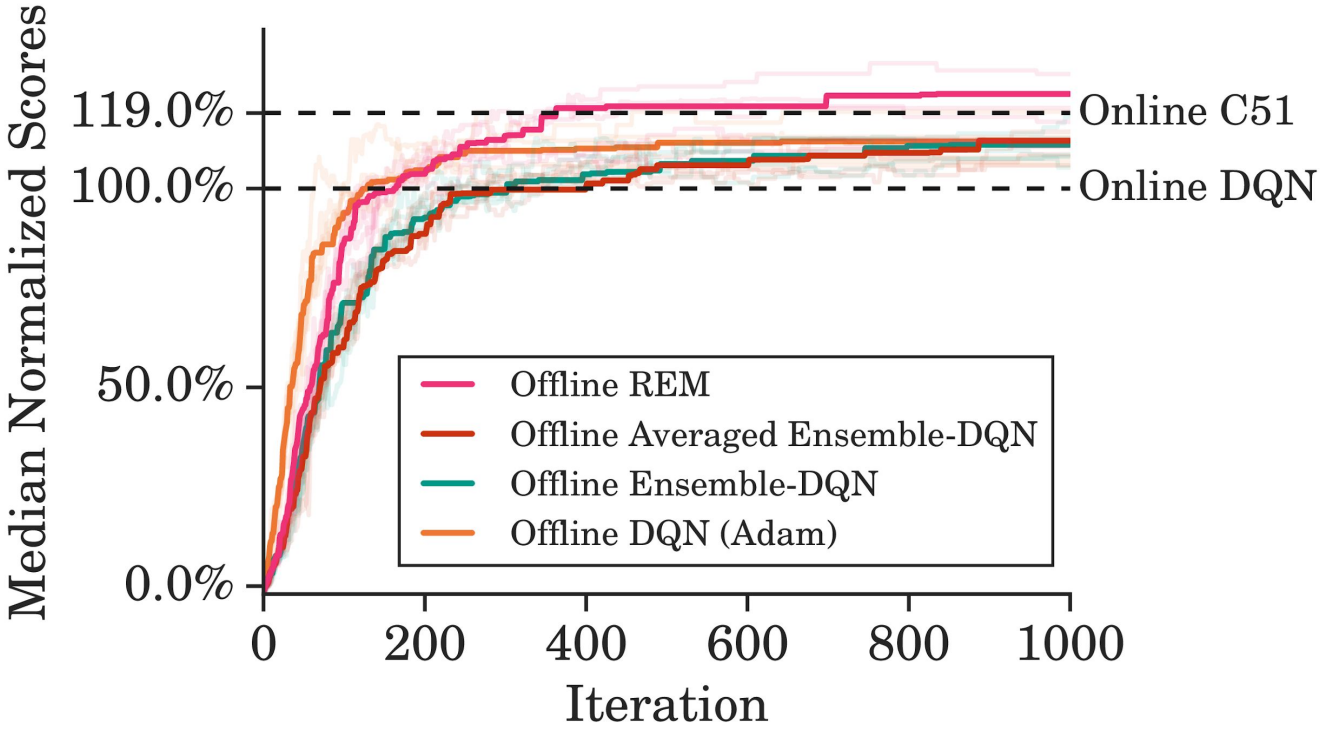
Offline Stochastic Atari Results



Scores averaged over 5 runs of offline agents trained using DQN replay data across 60 Atari games for 5X gradient steps. Offline REM surpasses gains from online C51 and offline QR-DQN.

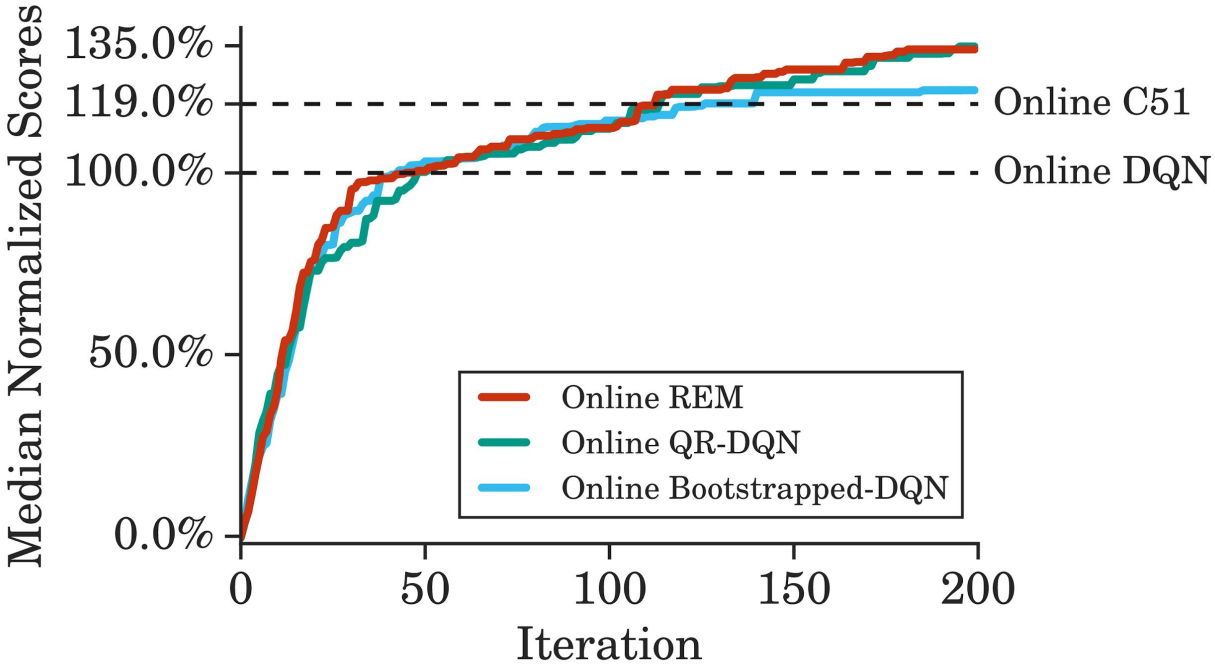
Google Research

Offline REM *vs.* Baselines



Reviewers asked: Does Online REM work?

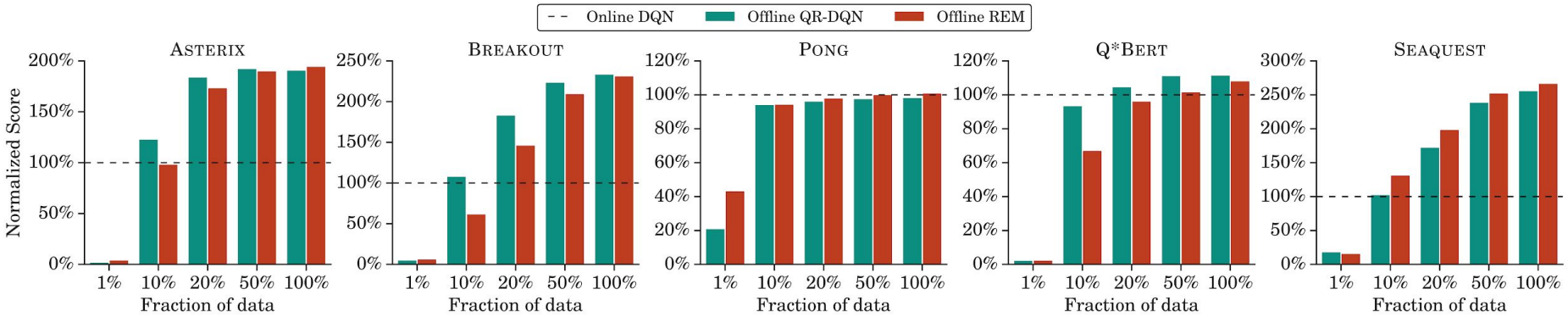
Google Research



Average normalized scores of online agents trained for 200 million game frames. Multi-network REM with 4 Q-functions performs comparably to QR-DQN.

Key Factor in Success: Offline Dataset Size

Google Research

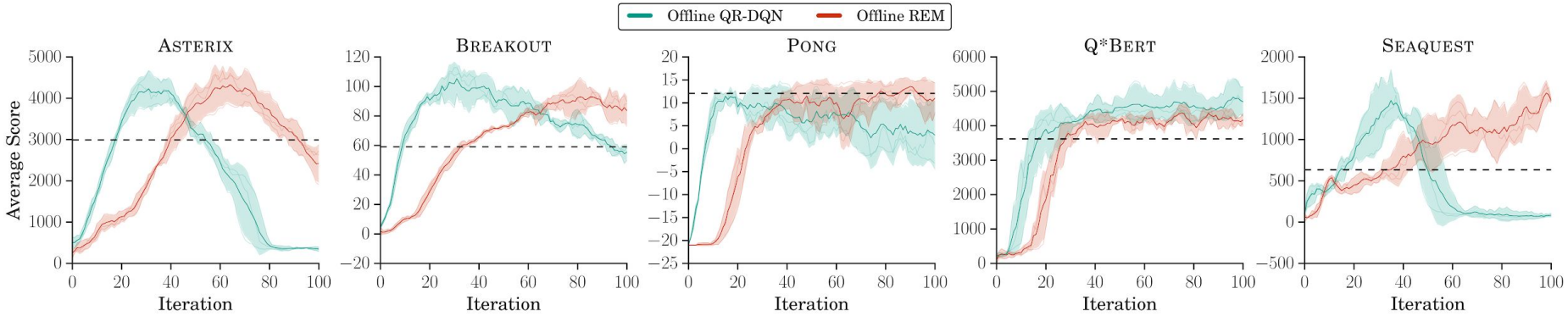


Randomly subsample N% of frames from 200 million frames for offline training.

Divergence with 1% of data for prolonged training!

Google Research

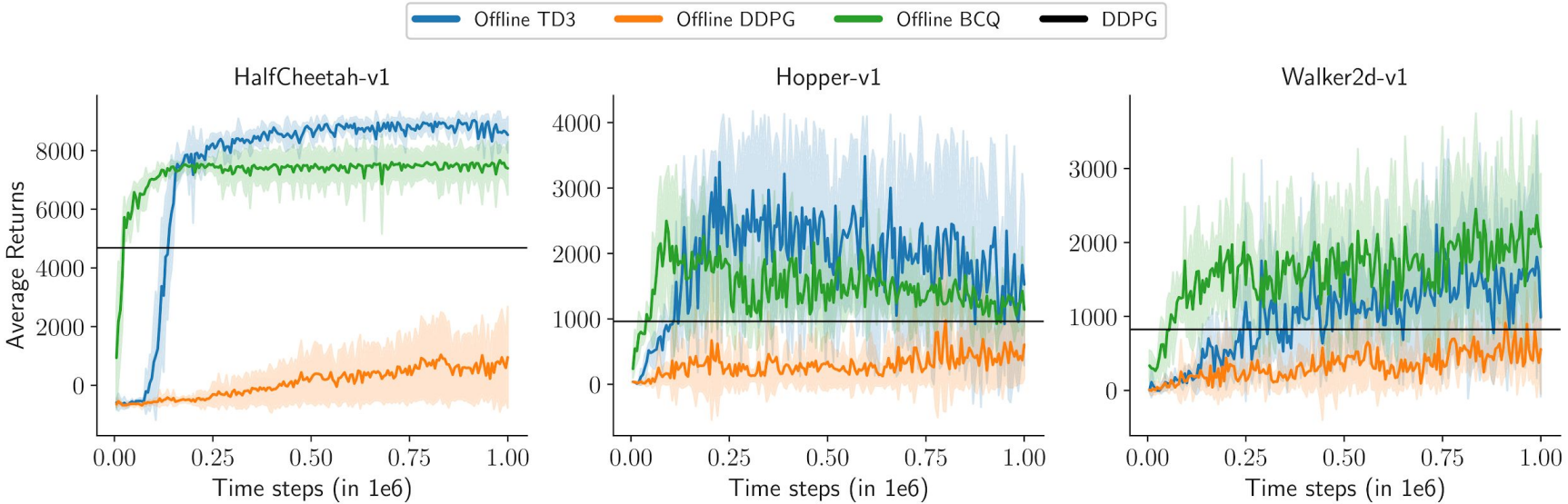
Key Factor in Success: Offline Dataset Composition



Subsample first 10% of total frames (20 million) for offline training -- much lower quality data.

Choice of Algorithm: Offline Continuous Control

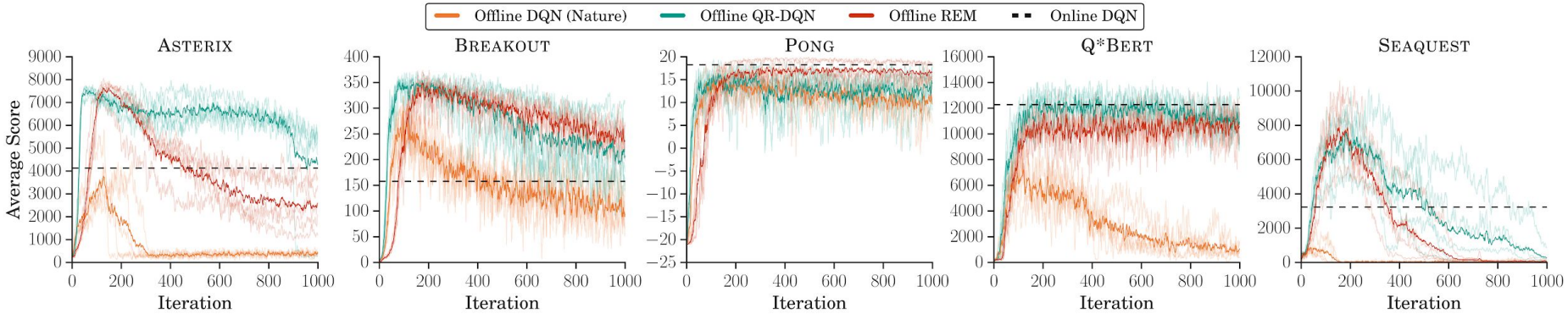
Google Research



Offline agents trained using full experience replay of DDPG on MuJoCo environments.

Google Research

Offline RL: Stability / Overfitting



Average online scores of offline agents trained on 5 games using logged DQN replay data for 5X gradient steps compared to online DQN.

More gradient updates eventually degrade performance :(

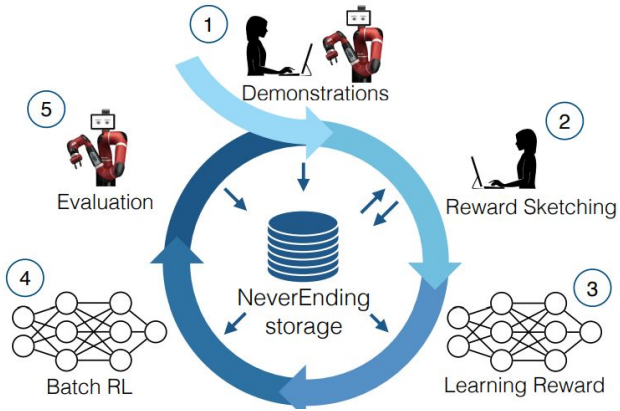
Offline RL for Robotics

Google Research

Scaling data-driven robotics with reward sketching and batch reinforcement learning

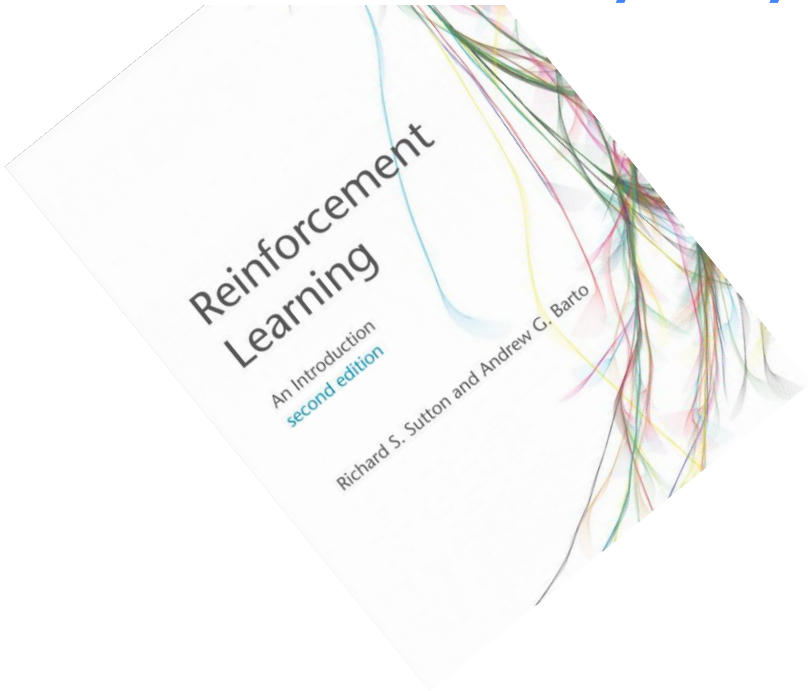
Serkan Cabi, Sergio Gómez Colmenarejo, Alexander Novikov, Ksenia Konyushkova, Scott Reed, Rae Jeong, Konrad Żołna, Yusuf Aytar, David Budden, Mel Vecerik, Oleg Sushkov, David Barker, Jonathan Scholz, Misha Denil, Nando de Freitas, Ziyu Wang

***Abstract*—By harnessing a growing dataset of robot experience, we learn control policies for a diverse and increasing set of related manipulation tasks. To make this possible, we introduce reward sketching: an effective way of eliciting human preferences to learn the reward function for a new task. This reward function is then used to retrospectively annotate all historical data, collected for different tasks, with predicted rewards for the new task. The resulting massive annotated dataset can then be used to learn manipulation policies with batch reinforcement learning (RL) from visual input in a completely off-line way, *i*.e. without interaction with the real robot. This approach makes it possible to scale up RL in robotics, as we no longer need to run the robot for each step of learning. We show that the trained batch RL agents, when deployed in real robots, can perform a variety of challenging tasks involving multiple interactions among**



Future Work

“The potential for off-policy learning remains tantalizing, the best way to achieve it still a mystery.” - Sutton & Barto



Google Research

Offline RL: Future Work

- Rigorous characterization of role of generalization in offline RL

Google Research

Offline RL: Future Work

- Rigorous characterization of role of generalization in offline RL
- **Benchmarking with various data collection strategies**
  - Subsampling DQN-replay datasets (*e.g.*, first / last *k* million frames)

Offline RL: Future Work

- Rigorous characterization of role of generalization in offline RL
- Benchmarking with various data collection strategies
  - Subsampling DQN-replay datasets (*e.g.,* first / last *k* million frames)
- **Offline Evaluation / Hyperparameter Tuning**
  - Currently, online evaluation used for early stopping. “True” offline RL requires offline policy evaluation.

Google Research

Offline RL: Future Work

- Rigorous characterization of role of generalization in offline RL
- Benchmarking with various data collection strategies
  - Subsampling DQN-replay datasets (*e.g.*, first / last *k* million frames)
- Offline Evaluation / Hyperparameter Tuning
  - Currently, online evaluation used for early stopping. “True” offline RL require offline policy evaluation.
- Model-based RL approaches

Google Research

TL;DR

- Robust RL algorithms (*e.g.* REM, QR-DQN), trained on sufficiently large and diverse datasets, perform quite well in the offline setting.

- Offline RL provides a standardized setup for:
  - Isolating *exploitation* from exploration
  - Developing *sample efficient* and *stable* *algorithms*
  - Pretrain RL agents on logged data

Thank you!

For code, DQN-replay dataset(s) and previous version of paper, refer to

offline-rl.github.io