CORL: RESEARCH-ORIENTED DEEP OFFLINE REINFORCEMENT LEARNING LIBRARY

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ABSTRACT

CORL[1] is an open-source library that provides single-file implementations of Deep Offline Reinforcement Learning algorithms. It emphasizes a simple developing experience with a straightforward codebase and a modern analysis tracking tool. In CORL, we isolate methods implementation into distinct single files, making performance-relevant details easier to recognise. Additionally, an experiment tracking feature is available to help log metrics, hyperparameters, dependencies, and more to the cloud. Finally, we have ensured the reliability of the implementations by benchmarking a commonly employed D4RL benchmark.

1 INTRODUCTION

Deep Offline Reinforcement Learning (Deep ORL) Levine et al. (2020) has been showing significant advancements in numerous domains such as robotics Smith et al. (2022); Kumar et al. (2021), autonomous driving Diehl et al. (2021) and recommender systems Chen et al. (2022). Due to such rapid development, many open-source ORL solutions[2] emerged to help RL practitioners understand and improve well-known ORL techniques in different fields. On the one hand, they introduce ORL algorithms standard interfaces and user-friendly APIs, simplifying ORL methods incorporation into *existing* projects. On the other hand, introduced abstractions may hinder the learning curve for newcomers and the ease of adoption for researchers interested in developing *new* algorithms. One needs to understand the modularity design (several files on average), which (1) can be comprised of thousands of lines of code or (2) can hardly fit for a novel method[3].

In this technical report, we take a different perspective on an ORL library. We propose CORL (Clean Offline Reinforcement Learning) – minimalistic and isolated single-file implementations of deep ORL algorithms, that are backed up by open-sourced D4RL benchmark results. The unadorned design allows practitioners to read and understand the implementations of the algorithms straightforwardly. Moreover, CORL supports optional integration with experiments tracking tool such as Weighs&Biases[4]. This provides practitioners with a convenient way to analyze the results and behavior of all algorithms, not merely relying on a final performance commonly reported in papers.

We hope that CORL library will help ORL newcomers to study implemented algorithms and aid the researchers in quickly modifying existing methods without a need to fight through different levels of abstraction. Finally, the obtained results may serve as a point of reference for D4RL benchmarks without a need to re-implement existing algorithms and tune hyperparameters.

2 RELATED WORK

Since the Atari breakthrough Mnih et al. (2015), numerous open-source RL frameworks and libraries have been developed over the last years: Dhariwal et al. (2017); Hill et al. (2018); Castro et al. (2018); Gauci et al. (2018); Keng & Graesser (2017); garage contributors (2019); Duan et al. (2016); Kolesnikov & Hrinchuk (2019); Fujita et al. (2021); Liang et al. (2018); Fujita et al. (2021);

[1] CORL Anonymized Repository: `https://anonymous.4open.science/r/CORL-E466`
[2] `https://github.com/hanjuku-kaso/awesome-offline-rl#oss`
[3] `https://github.com/takuseno/d3rlpy/issues/141`
[4] wandb.ai/

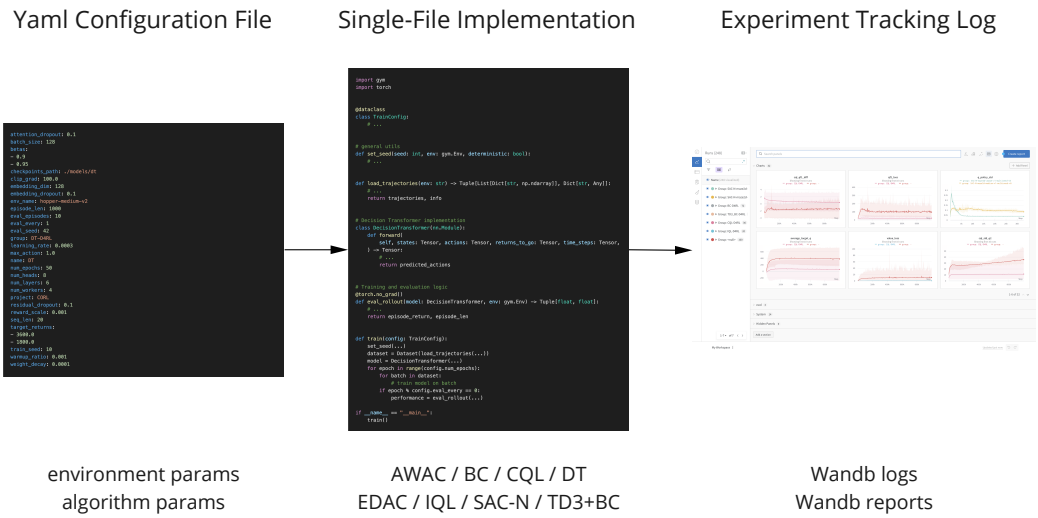

Figure 1: The illustration of the CORL library design. Single-file implementation takes a yaml configuration file with both environment and algorithm parameters to run the experiment, which logs all required statistics to wandb.

Liu et al. (2021); Huang et al. (2021); Weng et al. (2021); Stooke & Abbeel (2019), focusing on different perspectives of the RL. For example, stable-baselines (Hill et al. (2018)) provides many deep RL implementations that carefully reproduce results to back up RL practitioners with reliable baselines during methods comparison. On the other hand, Ray (Liang et al. (2018)) is focusing on implementations scalability and production-friendly usage. Finally, more nuanced solutions exist, such as Dopamine (Castro et al. (2018)), which emphasizes different DQN variants, or ReAgent (Gauci et al. (2018)), which applies RL for the RecSys domain.

At the same time, the ORL branch, which we are interested in this paper, is not yet covered as much: the only library that precisely focus on offline RL setting is d3rlpy Takuma Seno (2021). While CORL do also focus on ORL methods, similar to d3rlpy, it takes a different perspective on library design and provides *non-modular* independent algorithms implementations. More precisely, CORL does not introduce additional abstractions to make ORL more general but instead gives an ”easy-to-hack” starter kit for research needs.

Although CORL does not represent a first non-modular RL library, which is more likely the CleanRL Huang et al. (2021) case, it has two significant differences with its predecessor. First, CORL is focused on *offline* RL, while CleanRL implements *online* RL algorithms. Second, CORL intent to minimize the complexity of the requirements and external dependencies. To be more concrete, CORL does not have additional requirements with useful abstractions such as $stable\text{-}baselines$ or $envpool$ but instead implements everything from scratch in the codebase.

3 CORL Design

Single-File Implementations

It is known that implementation subtleties significantly impact agent performance in deep RL Henderson et al. (2018); Engstrom et al. (2020); Fujimoto & Gu (2021). Unfortunately, user-friendly abstractions and general interfaces, the core idea behind modular libraries, encapsulate and often hide these important nuances from the practitioners. For such a reason, CORL unwraps these de-

Table 1: Normalized performance of the last trained policy on D4RL averaged over 4 random seeds.

Task Name	**BC**	**BC-10%**	**TD3+BC**	**CQL**	**IQL**	**AWAC**	**SAC-N**	**EDAC**	**DT**
halfcheetah-medium-v2	42.40±0.21	42.29±0.40	48.10±0.21	46.64±0.24	48.31±0.11	49.90±0.43	68.20±1.48	67.70±1.20	41.44±0.39
halfcheetah-medium-expert-v2	55.95±8.49	91.45±2.57	90.78±6.98	87.10±11.41	94.55±0.21	95.51±0.95	98.96±10.74	104.76±0.74	84.39±4.27
halfcheetah-medium-replay-v2	35.66±2.68	29.65±2.11	44.84±0.68	44.67±0.28	43.53±0.43	44.72±0.84	60.70±1.17	62.06±1.27	27.50±5.49
hopper-medium-v2	53.51±2.03	51.16±12.98	60.37±4.03	56.88±4.46	62.75±6.02	69.32±8.99	40.82±11.44	101.70±0.32	48.41±6.11
hopper-medium-expert-v2	52.30±4.63	105.17±7.12	101.17±10.48	86.95±17.45	106.24±6.09	98.47±17.92	101.31±13.43	105.19±11.64	83.20±26.68
hopper-medium-replay-v2	29.81±2.39	23.89±11.61	64.42±24.84	84.21±18.27	84.57±13.49	98.83±3.11	100.33±0.90	99.66±0.94	42.83±22.92
walker2d-medium-v2	63.23±18.76	58.56±4.14	82.71±5.51	80.58±3.80	84.03±5.42	69.35±31.97	87.47±0.76	93.36±1.60	69.15±6.76
walker2d-medium-expert-v2	98.96±18.45	108.45±0.30	110.03±0.41	110.23±0.48	111.68±0.56	111.62±1.74	114.93±0.48	114.75±0.86	92.64±3.35
walker2d-medium-replay-v2	21.80±11.72	41.99±17.77	85.62±4.63	82.16±2.32	82.55±8.00	80.79±3.40	78.99±0.58	87.10±3.21	16.93±19.57
locomotion avg	50.40	61.40	76.45	75.49	79.80	79.84	83.52	92.92	56.28
maze2d-umaze-v1	0.36±10.03	-2.98±6.68	29.41±14.22	-6.97±17.41	37.69±1.99	65.72±22.99	128.56±18.65	97.89±12.84	-14.55±0.15
maze2d-medium-v1	0.79±3.76	2.04±3.52	59.45±41.86	2.77±7.24	35.45±0.98	85.36±41.42	88.42±21.25	56.74±3.38	-0.38±7.26
maze2d-large-v1	2.26±5.07	3.14±4.77	97.10±29.34	1.29±7.11	49.64±22.02	217.44±4.93	205.14±1.77	99.82±22.35	-0.45±1.51
maze2d avg	1.13	0.74	61.99	-0.97	40.92	122.84	140.71	84.82	-5.13
antmaze-umaze-v0	51.50±8.81	0.00±0.00	93.25±1.50	63.75±8.26	74.50±11.03	63.50±9.33	0.00±0.00	29.25±33.35	52.75±11.47
antmaze-medium-play-v0	0.00±0.00	0.00±0.00	0.00±0.00	0.00±0.00	71.50±12.56	0.00±0.00	0.00±0.00	0.00±0.00	0.00±0.00
antmaze-large-play-v0	0.00±0.00	0.00±0.00	0.00±0.00	0.00±0.00	40.75±12.69	0.00±0.00	0.00±0.00	0.00±0.00	0.00±0.00
antmaze avg	17.17	0.00	31.08	21.25	62.25	21.17	0.00	9.75	17.58
total avg	33.90	36.99	64.48	49.35	68.52	76.67	78.94	74.02	36.26

tails by adopting single-file implementations. To be more concrete, we put environment details, algorithms hyperparameters, and evaluation parameters into a single file [5]. For example, we have a

- $bc.py$ (397 LOC[6]) as a baseline algorithm for ORL methods comparison,
- $td3_bc.py$ (505 LOC) as a competitive minimalistic ORL algorithm Fujimoto & Gu (2021),
- $dt.py$ (512 LOC) as an example of the recently proposed trajectory optimization approach Chen et al. (2021)

Figure 1 depicts an overall library design. While such design produces code duplications among implementations, it has several essential benefits from the both educational and research perspective:

- **Smooth learning curve**. Having the entire code in one place makes understanding all its aspects more straightforward. In other words, one may find it easier to dive into 512 LOC of single-file Decision Transformer implementation rather than 10+ files of the original implementation.
- **Simple prototyping**. As we are not interested in code general applicability, we could make it implementation-specific. Such a design also removes the need for inheritance from general primitives or their refactoring, reducing abstraction overhead to zero. At the same time, this idea gives us complete freedom during code modification.
- **Faster debugging**. Without additional abstractions, implementation simplifies to a single for-loop with a global python name scope. Furthermore, such flat architecture makes it easier to access and inspect any created variable during the training process, which is crucial during modification and debugging.

CONFIGURATION FILES

Although it is a typical pattern to use a command line interface (CLI) for single-file experiments in the research community, CORL slightly improves it with predefined configuration files. Utilizing YAML parsing through CLI, for each experiment, we gather all environment and algorithm hyperparameters into such files so that you could use them as an initial setup. We found that such setup (1) simplifies experiments, eliminating the need to keep all algorithm-environment-specific parameters in mind, and (2) keeps it convenient with the familiar CLI approach.

EXPERIMENT TRACKING

ORL evaluation is another challenging aspect of the current ORL state Kurenkov & Kolesnikov (2022). To face this uncertainty, CORL supports integration with Wandb, a modern experiment

[5]We follow the PEP8 style guide with a maximum line length of 89, which increases LOC a bit.

[6]Lines Of Code

Table 2: Normalized performance of the best trained policy on D4RL averaged over 4 random seeds.

Task Name	**BC**	**BC-10%**	**TD3+BC**	**CQL**	**IQL**	**AWAC**	**SAC-N**	**EDAC**	**DT**
halfcheetah-medium-v2	43.60±0.16	43.74±0.18	48.93±0.13	47.26±0.23	48.77±0.06	50.85±0.23	72.21±0.35	69.72±1.06	42.63±0.09
halfcheetah-medium-expert-v2	79.69±3.58	93.98±0.18	96.59±1.01	95.82±0.31	95.83±0.38	96.85±0.29	111.73±0.55	110.62±1.20	87.34±0.65
halfcheetah-medium-replay-v2	40.52±0.22	41.45±0.10	45.84±0.30	45.97±0.32	45.06±0.16	46.52±0.29	67.29±0.39	66.55±1.21	32.20±2.50
hopper-medium-v2	69.04±3.35	66.91±2.30	70.44±1.37	69.09±0.85	80.74±1.27	99.00±0.59	101.79±0.23	103.26±0.16	61.95±4.63
hopper-medium-expert-v2	90.63±12.68	113.05±0.17	113.22±0.50	111.01±1.93	111.79±0.47	113.37±0.63	111.24±0.17	111.80±0.13	107.01±3.28
hopper-medium-replay-v2	68.88±11.93	53.82±8.10	98.12±1.34	102.10±0.41	102.33±0.44	101.66±0.43	103.83±0.61	103.28±0.57	59.65±13.50
walker2d-medium-v2	80.64±1.06	80.46±1.41	86.91±0.32	84.76±0.15	87.99±0.83	86.22±4.58	90.17±0.63	95.78±1.23	75.54±0.53
walker2d-medium-expert-v2	109.95±0.72	109.57±0.33	112.21±0.07	111.70±0.28	113.19±0.33	113.22±2.58	116.93±0.49	116.52±0.86	96.30±1.18
walker2d-medium-replay-v2	48.41±8.78	71.54±1.16	91.17±0.83	88.02±1.18	91.85±2.26	86.79±1.00	85.18±1.89	89.69±1.60	67.23±6.73
locomotion avg	70.15	74.95	84.83	83.97	86.40	88.28	95.60	96.36	69.98
maze2d-umaze-v1	16.09±1.00	16.85±0.60	99.33±18.66	18.82±0.63	44.04±3.02	137.07±13.88	151.75±8.65	143.23±3.65	-14.19±0.56
maze2d-medium-v1	19.16±1.44	24.81±4.09	150.93±4.50	17.96±5.24	92.25±40.74	154.12±21.80	89.36±21.25	153.63±2.41	45.13±6.25
maze2d-large-v1	20.75±7.69	35.66±6.40	197.64±6.07	12.27±5.34	138.70±44.70	227.66±1.88	207.07±1.17	179.84±3.61	3.94±2.24
maze2d avg	18.67	25.77	149.30	16.35	91.66	172.95	149.39	158.90	11.63
antmaze-umaze-v0	71.25±9.07	0.00±0.00	97.75±1.50	76.75±4.99	87.00±2.94	74.75±8.77	0.00±0.00	75.00±27.51	65.50±8.96
antmaze-medium-play-v0	4.75±2.22	0.00±0.00	6.00±2.00	1.75±0.96	86.00±2.16	14.00±11.80	0.00±0.00	0.00±0.00	1.00±2.00
antmaze-large-play-v0	0.75±0.50	0.00±0.00	0.50±0.58	0.00±0.00	53.00±6.83	0.00±0.00	0.00±0.00	0.00±0.00	0.00±0.00
antmaze avg	25.58	0.00	34.75	26.17	75.33	29.58	0.00	25.00	22.17
total avg	50.94	50.12	87.71	58.89	85.24	93.33	87.29	94.85	48.75

tracking tool. With each experiment, CORL automatically saves: (1) source code, (2) dependencies (requirements.txt), (3) hardware setup, (4) OS environment variables, (5) hyperparameters, (6) training and system metrics, (7) logs (stdout, stderr). See Appendix B for an example.

Although, Wandb is a proprietary solution, other alternatives such as Tensorboard or Aim could be used within a few lines of code change. It is also important to note that with Wandb tracking, one could straightforwardly use CORL with Wandb hyperparameter tuning or public reports.

We found full metrics tracking during the training process necessary for two reasons. First, it removes the possible bias of final or best performance commonly reported in papers. For example, one could evaluate ORL performance as max archived score, while another uses the average performance over N (last) evaluations Takuma Seno (2021). Second, it opens an opportunity for advanced performance analysis such as EOP Kurenkov & Kolesnikov (2022). In short, provided with all metrics logs, one can utilize any performance statistics, not merely relying on commonly used alternatives.

4 BENCHMARKS

In our library we implemented the following algorithms: $N\%$[7] Behavioral Cloning (BC), TD3 + BC Fujimoto & Gu (2021), CQL Kumar et al. (2020), IQL Kostrikov et al. (2021), AWAC Nair et al. (2020), SAC-N, EDAC An et al. (2021), and Decision Transformer (DT) Chen et al. (2021). We evaluated every algorithm on the D4RL benchmark Fu et al. (2020), focusing on Locomotion, Maze2D, and AntMaze tasks. Each algorithm was run for 1 million gradient steps[8] and evaluated every 5000 [8] steps using 10 and 100 episodes for locomotion and maze tasks, respectively. For our experiments, we used hyperparameters proposed in the original works (see Appendix C for details).

The final performance results are reported in Tables 1 and 2. The scores are normalized to the range between 0 and 100 Fu et al. (2020). Following recent works Takuma Seno (2021) we report both last (Table 1) and best (Table 2) obtained scores to illustrate potential performance and overfitting properties of each algorithm. See Appendix A for full training performance graphs.

According to the observed results, AWAC, SAC-N, and EDAC show the most competitive performance in both the last and best evaluation settings. At the same time, TD3 + BC performs well across all tasks without any hyperparameters tuning while other methods rely on it. Finally, simple yet effective BC-10% performs well on locomotion tasks when high-quality data is available and converges there almost instantly (see Appendix A).

[7] N is a percentage of best trajectories with the highest return used for training. We omit percentage when it is equal to 100.

[8] Except SAC-N, EDAC and DT due to their original hyperparameters. See Appendix C for details.

5 CONCLUSION

In this paper, we introduced CORL – a single-file implementation library for Offline Reinforcement Learning with configuration files and advanced metrics tracking support. All implemented algorithms were benchmarked on D4RL datasets, closely matching (sometimes overperforming) the original results. Focusing on implementation clarity and reproducibility, we hope that CORL will help RL practitioners in their research and applications.

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A ADDITIONAL BENCHMARK INFORMATION

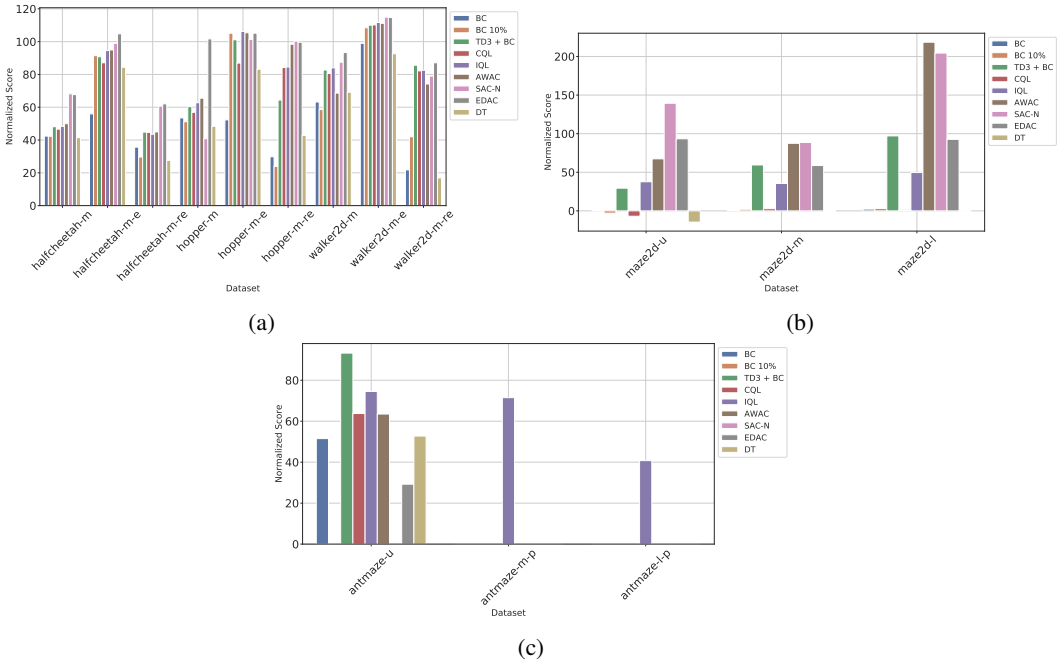


Figure 2: Graphical representation of the ormalized performance of the last trained policy on D4RL averaged over 4 random seeds. (a) Locomotion datasets. (b) Maze2d datasets (c) AntMaze datasets

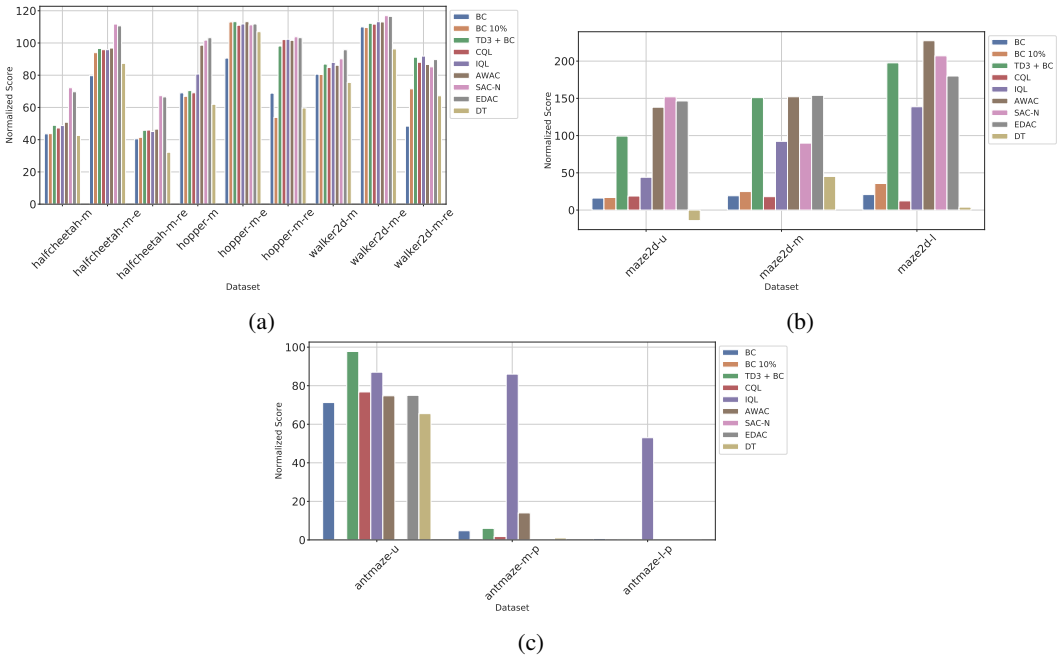
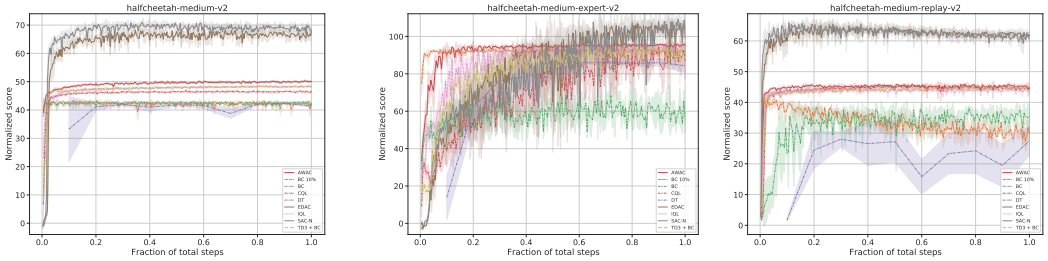
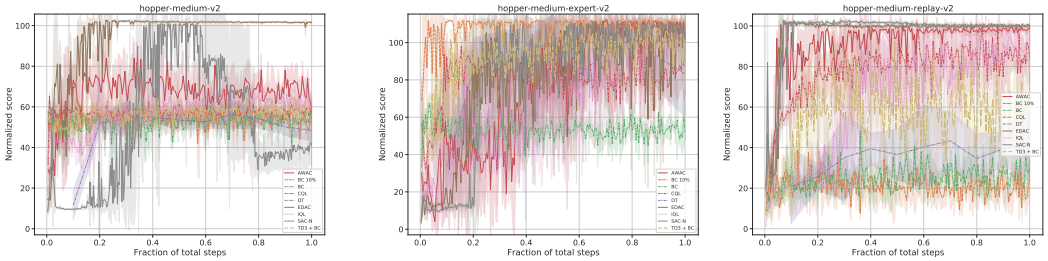


Figure 3: Graphical representation of the normalized performance of the best trained policy on D4RL averaged over 4 random seeds. (a) Locomotion datasets. (b) Maze2d datasets (c) AntMaze datasets



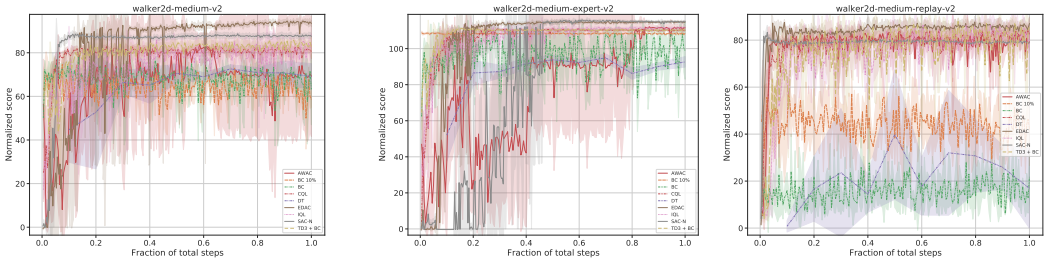
(a) (b) (c)

Figure 4: Training curves for HalfCheetah task.
(a) Medium dataset, (b) Medium-expert dataset, (c) Medium-replay dataset



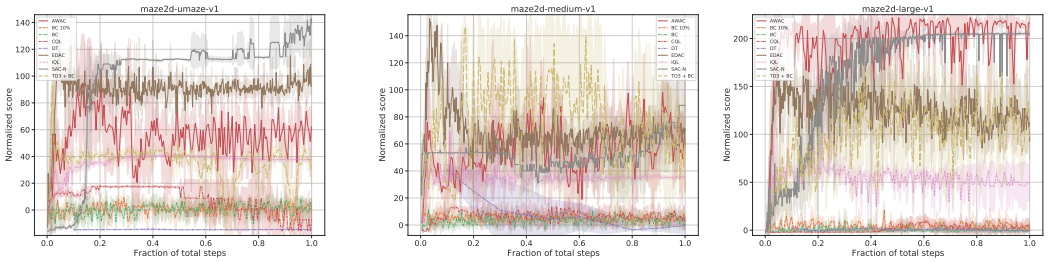
(a) (b) (c)

Figure 5: Training curves for Hopper task.
(a) Medium dataset, (b) Medium-expert dataset, (c) Medium-replay dataset



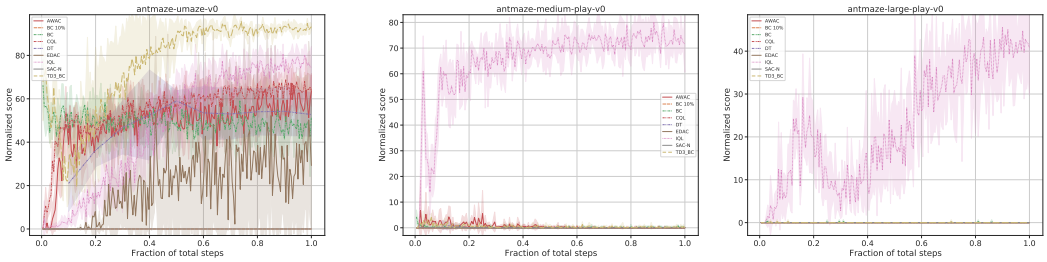
(a) (b) (c)

Figure 6: Training curves for Walker2d task.
(a) Medium dataset, (b) Medium-expert dataset, (c) Medium-replay dataset



(a) (b) (c)

Figure 7: Training curves for Maze2d task.
(a) Medium dataset, (b) Medium-expert dataset, (c) Medium-replay dataset



(a) (b) (c)

Figure 8: Training curves for AntMaze task.
(a) Umaze dataset, (b) Medium-play dataset, (c) Large-play dataset

B WANDB TRACKING

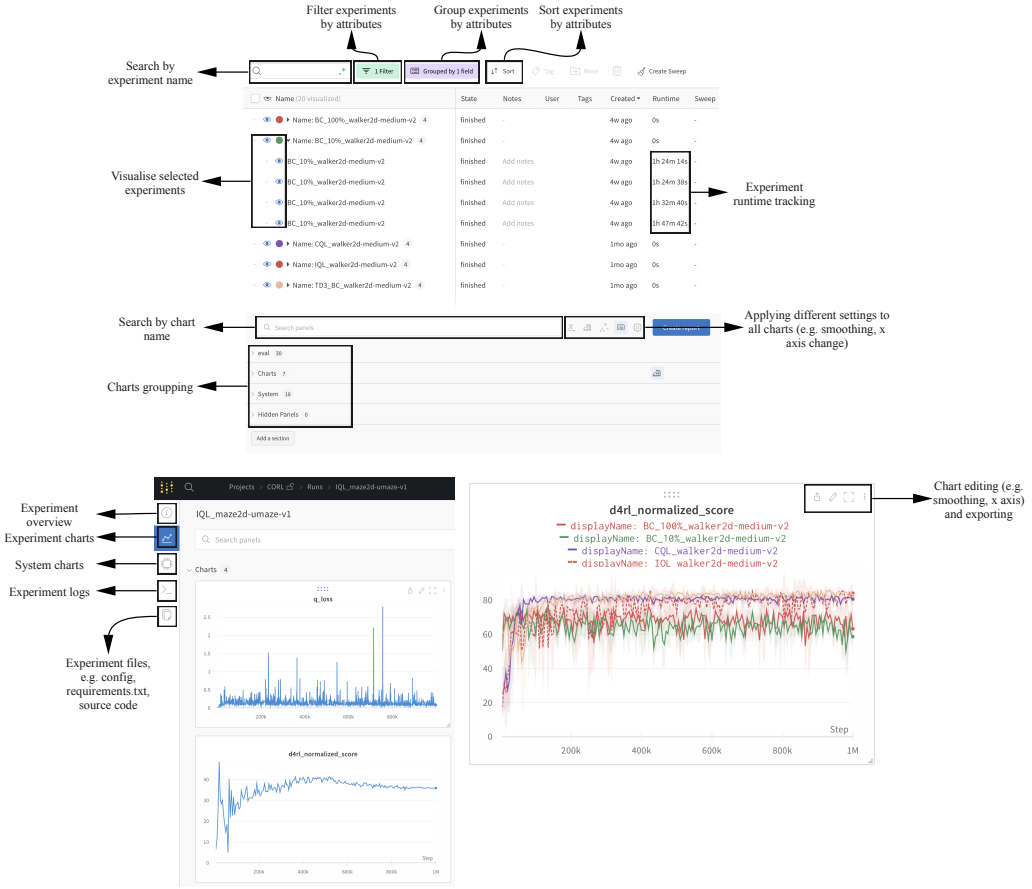


Figure 9: Screenshots of Wandb experiment tracking interface.

C EXPERIMENTAL DETAILS

We modify reward on AntMaze task by substructing 1 from reward as it is done in previous works.

We used original implementation of TD3 + BC[9], SAC-N[10] and EDAC[10] and custom implementations of IQL[11] and CQL[12] as the basis for ours. For most of the algorithms and datasets we use default hyperparameters if available. Configuration files for every algorithm and environment are presented in our GitHub repository.

C.1 NUMBER OF UPDATE STEPS AND EVALUATION RATE

Following original work SAC-N and EDAC are trained for 3 million steps (except AntMaze which is trained for 1 million steps) in order to obtain state-of-the-art performance and tested every 10000 steps. Decision Transformer (DT) training is splitted into datasets pass epochs, we train DT for 50 epochs on each dataset and evaluate every 5 epochs. All other algorithms are trained for 1 million steps and evaluated every 5000 steps. We evaluate every policy for 10 episodes on locomotion tasks and for 100 for Maze2d and AntMaze tasks.

C.2 HYPERPARAMETERS

	Hyperparameter	Value
BC Hyperparameters	Optimizer	Adam (Kingma & Ba, 2014)
	Learning Rate	3e-4
	Mini-batch size	256
Architecture	Policy hidden dim	256
	Policy hidden layers	2
	Policy activation function	ReLU
BC-$N\%$ Hyperparameters	Ratio of best trajectories used	0.1
	Discount factor†	0.99
	Max trajectory length†	1000

Table 3: BC and BC-$N\%$ hyperparameters. † used for the best trajectories choice.

[9] https://github.com/sfujim/TD3_BC
[10] https://github.com/snu-mllab/EDAC
[11] https://github.com/gwthomas/IQL-PyTorch
[12] https://github.com/young-geng/CQL

	Hyperparameter	Value
TD3 Hyperparameters	Optimizer	Adam (Kingma & Ba, 2014)
	Critic learning rate	3e-4
	Actor learning rate	3e-4
	Mini-batch size	256
	Discount factor	0.99
	Target update rate	5e-3
	Policy noise	0.2
	Policy noise clipping	(-0.5, 0.5)
	Policy update frequency	2
Architecture	Critic hidden dim	256
	Critic hidden layers	2
	Critic activation function	ReLU
	Actor hidden dim	256
	Actor hidden layers	2
	Actor activation function	ReLU
TD3+BC Hyperparameters	α	2.5

Table 4: TD3+BC Hyperparameters.

	Hyperparameter	Value
SAC Hyperparameters	Optimizer	Adam (Kingma & Ba, 2014)
	Critic learning rate	3e-4
	Actor learning rate	3e-5
	Mini-batch size	256
	Discount factor	0.99
	Target update rate	5e-3
	Target entropy	-1 $\cdot$ Action Dim
	Entropy in Q target	False
Architecture	Critic hidden dim	256
	Critic hidden layers	3
	Critic activation function	ReLU
	Actor hidden dim	256
	Actor hidden layers	3
	Actor activation function	ReLU
CQL Hyperparameters	Lagrange	False
	α	10
	Pre-training steps	0
	Num sampled actions (during eval)	10
	Num sampled actions (logsumexp)	10

Table 5: CQL Hyperparameters. Note: used hyperparameters are suboptimal for the implementation we provide.

	Hyperparameter	Value
IQL Hyperparameters	Optimizer	Adam (Kingma & Ba, 2014)
	Critic learning rate	3e-4
	Actor learning rate	3e-4
	Value learning rate	3e-4
	Mini-batch size	256
	Discount factor	0.99
	Target update rate	5e-3
	Learning rate decay	Cosine
	Deterministic policy	True Hopper Medium and Medium-replay False otherwise
	β	6.0 Hopper Medium-expert 10.0 AntMaze 3.0 otherwise
	τ	0.9 AntMaze 0.7 otherwise
Architecture	Critic hidden dim	256
	Critic hidden layers	2
	Critic activation function	ReLU
	Actor hidden dim	256
	Actor hidden layers	2
	Actor activation function	ReLU
	Value hidden dim	256
	Value hidden layers	2
	Value activation function	ReLU

Table 6: IQL hyperparameters.

	Hyperparameter	Value
AWAC Hyperparameters	Optimizer	Adam (Kingma & Ba, 2014)
	Critic learning rate	3e-4
	Actor learning rate	3e-4
	Mini-batch size	256
	Discount factor	0.99
	Target update rate	5e-3
	λ	0.1 Maze2d, AntMaze 0.3333 otherwise
Architecture	Critic hidden dim	256
	Critic hidden layers	2
	Critic activation function	ReLU
	Actor hidden dim	256
	Actor hidden layers	2
	Actor activation function	ReLU

Table 7: AWAC Hyperparameters.

	Hyperparameter	Value
SAC Hyperparameters	Optimizer	Adam (Kingma & Ba, 2014)
	Critic learning rate	3e-4
	Actor learning rate	3e-4
	α learning rate	3e-4
	Mini-batch size	256
	Discount factor	0.99
	Target update rate	5e-3
	Target entropy	-1 $\cdot$ Action Dim
Architecture	Critic hidden dim	256
	Critic hidden layers	3
	Critic activation function	ReLU
	Actor hidden dim	256
	Actor hidden layers	3
	Actor activation function	ReLU
SAC-N Hyperparameters	Number of critics	10 HalfCheetah 20 Walker2d 25 AntMaze 200 Hopper Medium-expert, Medium-replay 500 Hopper Medium
EDAC Hyperparameters	Number of critics	10 HalfCheetah 10 Walker2d, AntMaze 50
	μ	5.0 HalfCheetah Medium-expert, Walker2d Medium-expert 1.0 otherwise

Table 8: SAC-N and EDAC Hyperparameters.

	Hyperparameter	Value
DT Hyperparameters	Optimizer	AdamW (Loshchilov & Hutter, 2017)
	Batch size	128
	Return-to-go conditioning	(12000, 6000) HalfCheetah (3600, 1800) Hopper (5000, 2500) Walker2d (160, 80) Maze2d umaze (280, 140) Maze2d medium and large (1, 0.5) AntMaze
	Dropout	0.1
	Learning rate	0.0003
	Adam betas	(0.9, 0.95)
	Grad clip	100
	Weight decay	0.0003
	Learning rate decay	Lambda
	Warmup ratio	0.1
Architecture	Number of layers	6
	Number of attention heads	8
	Embedding dimension	128
	Activation function	GELU

Table 9: DT hyperparameters.