A K-Fold Method for Baseline Estimation in Policy Gradient Algorithms

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Abstract

Baseline helps reduce variance in unbiased policy gradient algorithms such as REINFORCE, VPG and TRPO. However, baseline fitting itself suffers from

- *Underfitting*: When the policy changes drastically between iterations
- *Overfitting*: When the current data is used to fit the baseline

We propose a K-fold method for baseline estimation that can be used as a tuning parameter to adjust the bias-variance trade-off.

Policy Gradient Algorithm

Parameter update loop:

1. Sample M trajectories $\tau = (s_0, a_0, r_0, s_1, a_1, r_1, \ldots)$ using policy $\pi(a|s, \theta)$
2. Estimate the policy gradient $\mathbf{g}_\theta = \nabla_\theta \mathrm{E}_\tau[R(\tau) - b(\tau)]$ from sample data, where $R(\tau) = \sum_i \gamma^i r_i$ and $b(\tau)$ is a baseline function independent of θ.
3. Update the policy parameters using the policy gradients: $\theta \leftarrow \theta + \alpha \cdot \mathbf{g}_\theta$.

Baseline is used to **reduce variance** in gradient approximation step (2)

K-Fold Method

The K-fold method operates by breaking the data samples into K partitions. For each partition, a baseline is computed using data from all the other partitions.

- The fitting uses samples from the current policy, so we mitigate underfitting.
- We do not directly fit on the current partition's data samples, so we also mitigate overfitting.

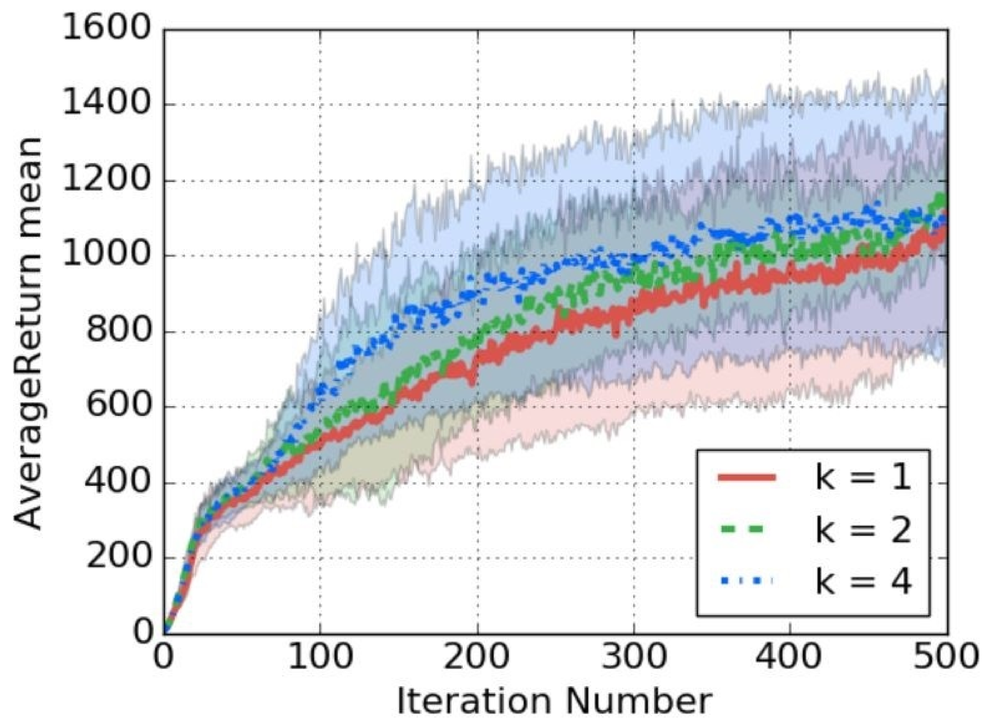
The K-Fold Algorithms

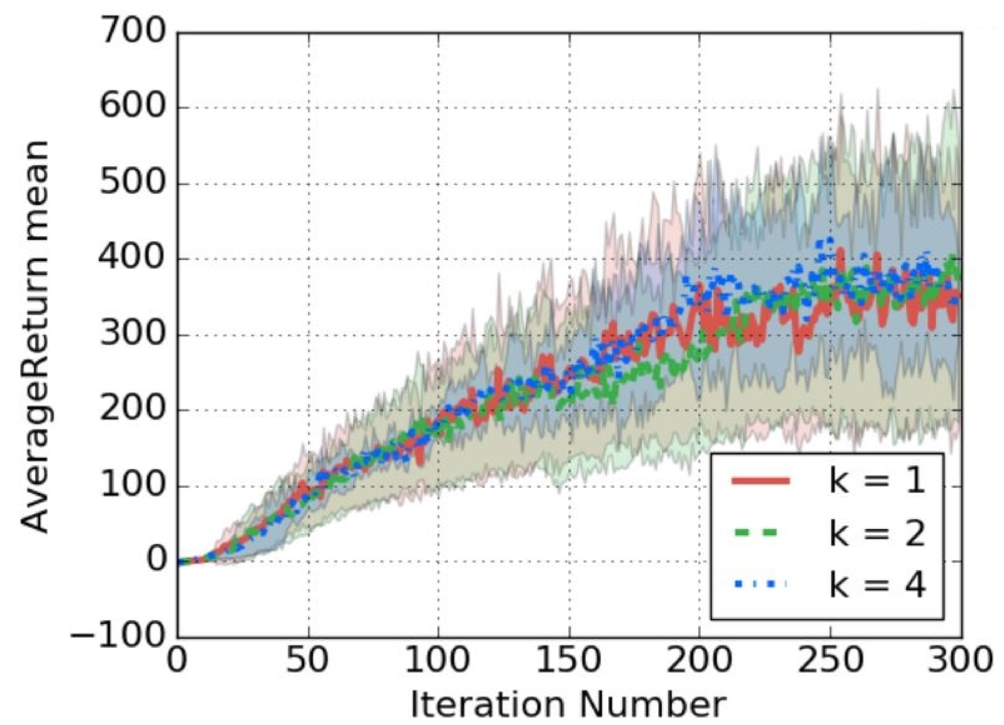
Method: We compute a baseline for each partition, use them to compute K different parameter updates and average all the parameters across the partitions.

Algorithm 1 Parameter-based K-Fold Baseline Estimation for Policy Optimization

Initialize: For iteration $i = 0$, initialize the policy parameter θ_0 randomly.
Iterate: Repeat for each iteration $i \in 1, 2, \ldots$ until convergence:

1: Sample N trajectories from policy $\pi(\cdot|\cdot, \theta_{i-1})$: $\tau_{j:1,\ldots,N}$.
2: Partition the N trajectories into $K < N$ disjoint subsets $S_1, \ldots, S_K$
3: **for** each subset S_k **do**
4: For each state $s_t \in \tau \in S_k$, compute discounted returns $R(\tau_{t:T}) = \sum_{t'=t}^{T} \gamma^{t'-t} r_{t'}$
5: Fit a baseline regression model $b_k^{(i-1)}(\cdot)$ for partition S_k using data from $\bigcup_{j \neq k} S_j$, i.e., with inputs $s_{t''} \in \tau' \in \bigcup_{j \neq k} S_j$ and outputs $R(\tau'_{t'':T})$.
6: Use policy optimization algorithm (such as the one to the left) with parameters θ_{i-1} and baseline $b_k^{(i-1)}(\cdot)$ to find optimized policy parameters θ_i^k.
7: **end for**
8: Update the policy parameters as the average of all the optimized policy parameters obtained, i.e. $\theta_i = \frac{1}{K} \sum_{k=1}^{K} \theta_i^k$.





(Left): Hopper with TRPO and a data size of 50000. (Right): Walker2D with TNPG and a data size of 5000.

Summary

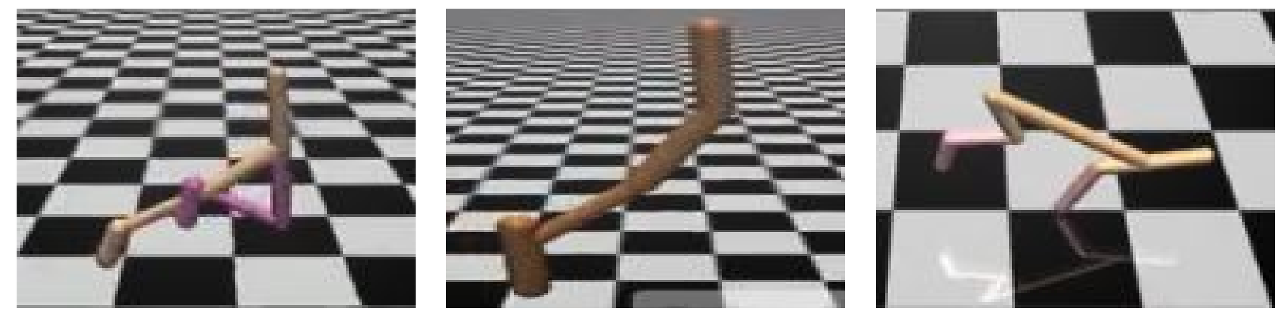
- The hyperparameter K is useful in achieving a good balance between overfitting and underfitting baseline.
- Future work will further this study for other environments, policy gradient algorithms, step sizes and batch sizes.

Experiment Setup

We use 5 random starting seeds and report the performance averaged over all the seeds.

- **Performance Metrics:** We define performance as the area under the average return curve.
- **Policy Network (Stochastic):** We use a feed-forward MLP network with 3 hidden layers of sizes 100, 50 and 25 with tanh nonlinearities after the first two hidden layers that maps states to the mean of a Gaussian distribution.
- **Baseline:** We use a Gaussian MLP for the baseline as well, with 2 hidden layers of size 32 each. The baseline is fitted using 10 ADAM steps.

Experimental Findings



Walker Hopper Half-Cheetah

Method 1 with TRPO and data size of 50,000.

Task	$K=1$	$K=2$	$K=4$
Walker	911.0 ± 681.0	$\mathbf{1015.7 \pm 327.3}$	938.7 ± 462.1
Hopper	727.7 ± 242.6	723.7 ± 190.5	$\mathbf{721.4 \pm 149.5}$
Cheetah	$\mathbf{1595.1 \pm 404.4}$	1528.5 ± 406.6	1383.8 ± 356.1

Method 2 with TRPO and data size of 50,000.

Task	$K=1$	$K=2$	$K=4$
Walker	911.0 ± 681.0	1035.0 ± 491.1	$\mathbf{1092.8 \pm 401.2}$
Hopper	727.7 ± 242.6	$\mathbf{786.0 \pm 171.1}$	847.7 ± 274.0
Cheetah	1595.1 ± 404.4	1664.1 ± 337.1	$\mathbf{1676.1 \pm 333.4}$

Method 2 with TNPG and data size of 5,000.

Task	$K=1$	$K=2$	$K=4$
Walker	299.4 ± 154.0	316.6 ± 164.6	$\mathbf{336.7 \pm 91.9}$
Hopper	331.4 ± 42.6	317.3 ± 29.5	$\mathbf{344.7 \pm 31.9}$
Cheetah	$\mathbf{609.5 \pm 215.3}$	445.9 ± 228.8	445.9 ± 181.9

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