Operator Splitting Value Iteration

Anonymous Author(s)
Affiliation
Address
email

Abstract

We introduce new planning and reinforcement learning algorithms for discounted MDPs that utilize an approximate model of the environment to accelerate the convergence of the value function. Inspired by the splitting approach in numerical linear algebra, we introduce Operator Splitting Value Iteration (OS-VI) for both Policy Evaluation and Control problems. OS-VI achieves a much faster convergence rate when the model is accurate enough. We also introduce a sample-based version of the algorithm called OS-Dyna. Unlike the traditional Dyna architecture, OS-Dyna still converges to the correct value function in presence of model approximation error.

1 Introduction

Consider a planning problem for a discounted MDP with dynamics $\mathcal{P}$. Suppose that we have access to an approximate model $\hat{\mathcal{P}} \approx \mathcal{P}$ as well. For example, $\mathcal{P}$ might be a high-fidelity, but slow, simulator, and $\hat{\mathcal{P}}$ is a lower-fidelity, but fast, simulator. Or in a different, but relevant, context of model-based reinforcement learning (MBRL), $\mathcal{P}$ is the unknown dynamics of a real-world system, from which we can only acquire expensive samples, and $\hat{\mathcal{P}}$ is a learned model, from which samples can be cheaply acquired. Can we use this approximate model $\hat{\mathcal{P}}$ to *accelerate* the computation of the value function of a policy π (Policy Evaluation (PE) problem) or the optimal value function (Control problem)?

The Value Iteration (VI) algorithm, and its approximate variant, is a fundamental algorithm in Dynamic Programming that can find the value of a policy or the optimal value function. It is also a backbone of many reinforcement learning (RL) algorithms such as Temporal Difference Learning [Sutton, 1988], Fitted Value Iteration [Gordon, 1995, Ernst et al., 2005, Munos and Szepesvári, 2008], and Deep Q Network [Mnih et al., 2015]. This algorithm, however, can be slow when the discount factor is close to 1, as its convergence rate is $O(\gamma^k)$. Moreover, even though we could use VI using $\hat{\mathcal{P}}$ instead of $\mathcal{P}$, effectively avoiding any need for expensive queries to $\mathcal{P}$, the obtained value function would converge to a solution different from the value function of the original MDP.

This paper proposes an algorithm called Operator Splitting Value Iteration (OS-VI) that benefits from an approximate model $\hat{\mathcal{P}}$ to potentially accelerate the convergence of the value function sequence to the value function with respect to (w.r.t.) the true model $\mathcal{P}$ (Section 3). This algorithm is for both PE (Section 3.1) and Control (Section 3.2) problems. The acceleration is not uniform though, and depends on how close $\hat{\mathcal{P}}$ is to $\mathcal{P}$ (Section 4).

A key inspiration behind OS-VI is the (matrix) splitting approach in the numerical linear algebra, which is used for iterative solution of large linear systems of equations [Varga, 2000, Saad, 2003, Golub and Van Loan, 2013]. With a proper choice of splitting, one may change the convergence rate of linear system of equation solvers. We show that the conventional VI for PE can be seen as a particular choice of splitting. This observation suggests that one may choose other forms of splitting in order to change the convergence rate. It turns out that we can choose a splitting that benefits from

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having access to $\hat{\mathcal{P}}$ (Section 2). The new splitting leads to OS-VI for PE. For the Control problem, the connection between solving linear systems of equations and VI is not as straightforward anymore, as the former is linear, while the latter is not, but we can still get inspired from the splitting approach to design OS-VI for Control. The key step of such an algorithm is a new *policy improvement* step.

The form of the OS-VI algorithm opens up a connection to MBRL where the approximate model $\hat{\mathcal{P}}$ is learned using data. This leads to the OS-Dyna algorithm, inspired by a generic Dyna architecture [Sutton, 1990]. OS-Dyna is a hybrid of model-free and model-based algorithms. It uses the learned model in its inner planning loop, but uses samples from the true model $\mathcal{P}$ in order to correct the effect of errors in the model. Existing MBRL algorithms would converge to an incorrect solution if the approximate model $\hat{\mathcal{P}}$ does not converge to the true model $\mathcal{P}$. This would be the case whenever model approximation error exists. On the other hand, OS-Dyna can still converge to the correct value function even when $\hat{\mathcal{P}}$ does not converge to $\mathcal{P}$. As far as we know, this is the first model-based RL algorithm with such property.

2 From value iteration to splitting-based linear system of equations solvers and back

We briefly describe the VI algorithm and the splitting methods for solving linear systems of equations, and explain their connections. We consider a discounted Markov Decision Process (MDP) $(\mathcal{X}, \mathcal{A}, \mathcal{R}, \mathcal{P}, \gamma)$ [Bertsekas and Tsitsiklis, 1996, Szepesvári, 2010, Sutton and Barto, 2019]. We defer formal definitions to the supplementary material. We only mention that for a policy π, we denote by $\mathcal{P}^\pi$ its transition kernel, by $r^\pi : \mathcal{X} \to \mathbb{R}$ the expected value of its reward distribution, and by $V^\pi = V^\pi(\mathcal{R}, \mathcal{P})$ its state-value function. We also represent the optimal state-value function by $V^* = V^*(\mathcal{R}, \mathcal{P})$ and the optimal policy by $\pi^* = \pi^*(\mathcal{R}, \mathcal{P})$. The Bellman operator $T^\pi : \mathcal{B}(\mathcal{X}) \to \mathcal{B}(\mathcal{X})$ for policy π and the Bellman optimality operator $T^* : \mathcal{B}(\mathcal{X}) \to \mathcal{B}(\mathcal{X})$ are[1]

$$(T^\pi V)(x) \triangleq r^\pi(x) + \gamma \int \mathcal{P}^\pi(\mathrm{d}y|x) V(y); \quad (T^* V)(x) \triangleq \max_{a \in \mathcal{A}} \left\{ r(x,a) + \gamma \int \mathcal{P}(\mathrm{d}y|x,a) V(y) \right\}.$$

These operators can be written more compactly as $T^\pi : V \mapsto r^\pi + \gamma \mathcal{P}^\pi V$ and $T^* : V \mapsto \max_\pi \{ r^\pi + \gamma \mathcal{P}^\pi V \}$. The *greedy* policy at state $x \in \mathcal{X}$ is

$$\pi_g(x; V) \leftarrow \operatorname*{argmax}_{a \in \mathcal{A}} \left\{ r(x,a) + \gamma \int \mathcal{P}(\mathrm{d}y|x,a) V(y) \right\},$$

or more compactly, $\pi_g(V) \leftarrow \operatorname{argmax}_\pi T^\pi V$. We have $T^* V = T^{\pi_g(V)} V$, that is, the effect of the Bellman optimality operator T^* applied to a value function V is the same as applying the Bellman operator of the *greedy* policy w.r.t. V to V. Finally, we denote the m-step transition kernel of policy π by $\mathcal{P}^{\pi(m)}$ and define the discounted future-state distribution as

$$\eta^\pi(\cdot|x) = (1-\gamma) \sum_{m=0}^{\infty} \gamma^m \mathcal{P}^{\pi(m)}(\cdot|x). \tag{2.1}$$

2.1 Value Iteration

The value function V^π and the optimal value function V^* are the fixed points of the operators T^π and T^*, respectively, and satisfy the Bellman equation. For the PE problem, this means that

$$V^\pi = r^\pi + \gamma \mathcal{P}^\pi V^\pi \Rightarrow (\mathbf{I} - \gamma \mathcal{P}^\pi) V^\pi = r^\pi. \tag{2.2}$$

There are several ways to compute the value function of a policy π or the optimal value function V^*, including the iterative methods such as the Value Iteration (VI) and the Policy Iteration (PI) algorithms, or solving a linear systems of equations (for PE) or linear programming (for Control). We focus on the Value Iteration algorithm in this work. The VI algorithm repeatedly applies the Bellman operator to the most recent approximation of the value function: Given an initial value function V_0, it generates a sequence $(V_k)_{k \geq 0}$ as follows:

$$V_k \leftarrow \begin{cases} T^\pi V_{k-1}, & \text{(Policy Evaluation)} \\ T^* V_{k-1}. & \text{(Control)} \end{cases} \tag{2.3}$$

[1] For countable state and action spaces, the integrals are replaced by summations. We present OS-VI and its theoretical analysis for general state/action spaces, but limit our experiments to finite state/action problems.

VI for Control can be written in an equivalent form: At iteration k, we first compute the greedy policy $\pi_k \leftarrow \pi_g(V_{k-1})$ (policy improvement step), and then $V_k \leftarrow T^{\pi_k} V_{k-1}$. Therefore, the policy improvement step is obtained through finding a policy that is greedy w.r.t. the last value function V_{k-1}, that is, the best policy if we only look one step ahead. This form will be conductive for our later developments. As the Bellman operator is a γ-contraction w.r.t. the supremum norm, the convergence rate of V_k to V^π (or V^*) would be $O(\gamma^k)$. This rate can be slow when γ is very close to 1.

2.2 Matrix splitting for solving linear systems of equations

The VI for PE can be seen as a (matrix) splitting-based iterative method to solve the linear system of equations (2.2). Consider the linear systems of equations $Az = b$, with $A \in \mathbb{R}^{d\times d}$ and $z, b \in \mathbb{R}^d$. Suppose that A is decomposed to $A = M - N$ for some choices of $M, N \in \mathbb{R}^{d\times d}$ (more generally, A, M, and N can be linear operators). Therefore, z satisfies $Mz = Nz + b$. The splitting-based iterative approach defines the new approximation z_k given the current z_{k-1} by solving

$$Mz_k = Nz_{k-1} + b,$$

or equivalently

$$z_k = M^{-1}(Nz_{k-1} + b). \tag{2.4}$$

To analyze the convergence of this iterative method, consider the error $e_k \triangleq z_k - z$. As $Mz = Nz + b$, the dynamics of the error is

$$e_k = M^{-1}Ne_{k-1} = (M^{-1}N)^2 e_{k-2} = \cdots = (M^{-1}N)^k e_0. \tag{2.5}$$

Let $G \triangleq M^{-1}N$. The norm of the sequence $(e_k)_{k\geq 1}$ can be upper bounded as

$$\|e_k\| = \left\|G^k e_0\right\| \leq \left\|G^k\right\| \|e_0\| \leq \|G\|^k \|e_0\|. \tag{2.6}$$

The errors are (norm-) convergent if $\|G\| = \|M^{-1}N\| < 1$, for some choice of norm. More generally, the necessary and sufficient condition for convergence is that the spectral radius $\rho(G)$, the maximum of absolute values of eigenvalues of G, is smaller than one, see e.g., Theorem 4.1 of Saad [2003] or Theorem 11.2.1 of Golub and Van Loan [2013].[2] The convergence is faster if the spectral radius (or norm) is closer to zero.

The success of this iterative procedure depends on how we choose M and N such that the norm (or spectral radius) is as small as possible. Also we want to choose an M such that solving $Mz_k = Nz_{k-1} + b$ is not very expensive. For example, if M is an identity matrix $\mathbf{I}$, we get that $N = \mathbf{I} - A$, and the iteration becomes $z_k = (\mathbf{I} - A)z_{k-1} + b$. This iteration is convergent if $\rho(\mathbf{I} - A) < 1$. Other commonly used choices lead to the Jacobi and the Gauss-Seidel methods, which are described in the supplementary material.

We are now ready to make the connection between splitting-based iterative methods to the VI for PE. If we choose $A = \mathbf{I} - \gamma\mathcal{P}^\pi$, we see that the equation $AV^\pi = r^\pi$ is indeed the Bellman equation for policy π (2.2). The VI for PE, which is $V_k = \gamma\mathcal{P}^\pi V_{k-1} + r^\pi = (\mathbf{I} - A)V_{k-1} + r^\pi$, corresponds to the choice of $M = \mathbf{I}$ and $N = \gamma\mathcal{P}^\pi$. This brings up the question of whether it is possible to split A to other choices of M and N so that the resulting VI-like procedure has better improved convergence properties? We suggest a particular choice in the next section.

3 Operator splitting value iteration algorithm

This section introduces the Operator Splitting Value Iteration (OS-VI) algorithm. We start from the PE problem, and introduce the Control version based on that.

3.1 OS-VI for policy evaluation

Given a policy π, true model $\mathcal{P}$, and approximate model $\hat{\mathcal{P}}$, we split $\mathbf{I} - \gamma\mathcal{P}^\pi$ to M^π and N^π as

$$M^\pi = \mathbf{I} - \gamma\hat{\mathcal{P}}^\pi \qquad , \qquad N^\pi = \gamma(\mathcal{P}^\pi - \hat{\mathcal{P}}^\pi).$$

[2] For any matrix norm, we have $\rho(G) \leq \|G\|$, so the condition on the norm is sufficient, but not necessary. In this work, most of our analysis will be norm-based.

Following the recipe of (2.4), the OS-VI algorithm for PE would be

$$V_k \leftarrow (\mathbf{I} - \gamma\hat{\mathcal{P}}^\pi)^{-1}\Big[r^\pi + \gamma(\mathcal{P}^\pi - \hat{\mathcal{P}}^\pi)V_{k-1}\Big], \tag{3.1}$$

starting from an initial V_0.[3] To gain more intuition and prepare for further developments, we define a few notations. We define the *Varga operator* $S^\pi : \mathcal{B}(\mathcal{X}) \to \mathcal{B}(\mathcal{X})$, named after Richard S Varga (1928 – 2022) who has made significant contributions to matrix analysis, as the mapping between the space of all bounded functions over $\mathcal{X}$ to the same space as

$$S^\pi : V \mapsto (\mathbf{I} - \gamma\hat{\mathcal{P}}^\pi)^{-1}\Big[r^\pi + \gamma(\mathcal{P}^\pi - \hat{\mathcal{P}}^\pi)V\Big].$$

Observe that (3.1) can be compactly written as

$$V_k \leftarrow S^\pi V_{k-1}. \tag{3.2}$$

It is not difficult to see that $S^\pi V^\pi = V^\pi$, i.e., the value function of a policy π is a fixed-point of the Varga operator S^π. This and other properties of the Varga operator are in the supplementary material.

Given any value function V, define an auxiliary reward function $\bar{r}_V : \mathcal{X} \times \mathcal{A} \to \mathbb{R}$ as

$$\bar{r}_V(x,a) \triangleq r(x,a) + \gamma \int \Big(\mathcal{P}(\mathrm{d}y|x,a) - \hat{\mathcal{P}}(\mathrm{d}y|x,a)\Big)V(y). \tag{3.3}$$

Similar to the notation for r^π, we define $\bar{r}_V^\pi : \mathcal{X} \to \mathbb{R}$ as $\bar{r}_V^\pi(x) = \bar{r}_V(x, \pi(x))$ for a deterministic policy π (and similarly for a stochastic policy). With this notation,

$$S^\pi V = (\mathbf{I} - \gamma\hat{\mathcal{P}}^\pi)^{-1}\bar{r}_V^\pi.$$

This is the value function of following π in an MDP with the dynamics $\hat{\mathcal{P}}$ and the reward $\bar{r}_V$. Therefore, at each iteration of OS-VI (PE), we evaluate the policy π according to the approximate dynamics, and a reward function that consists of the original reward r and the correction term $\gamma(\mathcal{P} - \hat{\mathcal{P}})V_{k-1}$. The computation of this value function is a standard policy evaluation problem with the approximate model. For instance, we may use another VI (PE) with dynamics $\hat{\mathcal{P}}$ to solve it: We initialize $U_0 \leftarrow V$, and then for $i \geq 1$, we set $U_i \leftarrow \bar{r}_V^\pi + \gamma\hat{\mathcal{P}}^\pi U_{i-1}$. This converges to $S^\pi V = (\mathbf{I} - \gamma\hat{\mathcal{P}}^\pi)^{-1}\bar{r}_V^\pi$ with the usual rate of $O(\gamma^i)$. Note that aside the computation of $\bar{r}_V^\pi$, which requires querying $\mathcal{P}$ in order to compute the $\mathcal{P}^\pi V$ term, this iterative process only uses the approximate model $\hat{\mathcal{P}}$, which is assumed to be cheap to access.

What is the benefit of this OS-VI procedure? If the approximate model $\hat{\mathcal{P}}$ is close to the true dynamics $\mathcal{P}$, this leads to a faster convergence of V_k to V^π, as shall be quantified soon. The faster convergence is in terms of the number of queries to $\mathcal{P}$, which is assumed to be expensive. To see this, consider the hypothetical case that $\hat{\mathcal{P}}$ is exactly the same as $\mathcal{P}$, for example, if the cheap simulator happens to match the reality perfectly. Then, $S^\pi V = (\mathbf{I} - \gamma\mathcal{P}^\pi)^{-1}(r^\pi + 0V) = V^\pi$, and the value function for the original MDP is obtained in one iteration of OS-VI. Of course, we often can only hope for $\hat{\mathcal{P}} \approx \mathcal{P}$. In Section 4, we study the impact of error in $\hat{\mathcal{P}}$ on the convergence rate of OS-VI in more details, and show that the convergence of OS-VI can be much faster than classic algorithms even if $\hat{\mathcal{P}}$ is only a close approximation of $\mathcal{P}$.

3.2 OS-VI for control

The VI for Control can be seen as an iterative procedure that computes the greedy policy $\pi_k \leftarrow \pi_g(V_{k-1}) = \mathrm{argmax}_\pi T^\pi V_{k-1}$ in its policy improvement step, and uses one step of the Bellman operator w.r.t. the obtained policy π_k to compute the new estimate of the value function $V_k \leftarrow T^{\pi_k}V_{k-1}$, as described after (2.3). The OS-VI algorithm for Control follows a similar structure with the difference that (1) the improved policy is the optimizer of the Varga operator, and not the Bellman operator, and (2) the new value function is obtained by applying the Varga operator of the newly obtained policy. To be concrete, given a value function V, define the S-improved policy

$$\pi_V(V) \triangleq \operatorname*{argmax}_\pi S^\pi V [= (\mathbf{I} - \gamma\hat{\mathcal{P}}^\pi)^{-1}\bar{r}_V^\pi]. \tag{3.4}$$

[3] Although splitting is originally studied mostly in the context of linear algebra and matrices, we are applying the idea more generally. We are not assuming that the state space $\mathcal{X}$ is finite, and allow it to be more general, such as a subset of $\mathbb{R}^d$. Consequently, M^π, N^π, $\mathcal{P}^\pi$, etc. are operators rather than matrices.

This policy is the *optimal* policy for the auxiliary MDP $(\mathcal{X}, \mathcal{A}, \bar{r}_V, \hat{\mathcal{P}}, \gamma)$. We also define the *Varga optimal operator* $S^* : \mathcal{B}(\mathcal{X}) \to \mathcal{B}(\mathcal{X})$ as

$$S^* : V \mapsto \max_\pi S^\pi V [= \max_\pi (\mathbf{I} - \gamma \hat{\mathcal{P}}^\pi)^{-1} \bar{r}_V^\pi].$$

The function $S^* V$ is equal to $S^{\pi_V(V)} V$, i.e., the Varga operator of the S-improved policy w.r.t. V applied to a value function V (compare it with $T^* V = T^{\pi_g(V)} V$).

The OS-VI (Control) is then simply

$$V_k \leftarrow S^* V_{k-1}, \tag{3.5}$$

which in its expanded form, consists of the following two steps:

$$\pi_k \leftarrow \pi_V(V_{k-1}), \qquad \text{(policy improvement)}. \tag{3.6}$$

$$V_k \leftarrow S^{\pi_k} V_{k-1} \; [= (\mathbf{I} - \hat{\mathcal{P}}^{\pi_k})^{-1} (r^{\pi_k} + \gamma(\mathcal{P}^{\pi_k} - \hat{\mathcal{P}}^{\pi_k}) V_{k-1})], \text{(partial policy evaluation)}. \tag{3.7}$$

Comparing the S-improved policy (3.4) used in the policy improvement step (3.6) of OS-VI with the conventional greedy policy is insightful. The greedy policy is $\text{argmax}_\pi T^\pi V$. Expanding $T^\pi V$, we see that the greedy policy is the maximizer of $r^\pi + \gamma \mathcal{P}^\pi V$. The function $r^\pi + \gamma \mathcal{P}^\pi V$ is only a single-step bootstrapped estimate of the value of V^π, and its maximizer, the greedy policy, is in general different from the optimal policy, which maximizes V^π. On the other hand, the S-improved policy $\pi_V(V)$ solves a full MDP with an approximate model $\hat{\mathcal{P}}$ and the reward function that has both the original reward r and the correction term $\gamma(\mathcal{P} - \hat{\mathcal{P}})V$. In the special case that $\hat{\mathcal{P}} = \mathcal{P}$, the correction term is zero, and $\pi_V(V)$ would be the optimal policy π^* for the original MDP. As often $\hat{\mathcal{P}} \approx \mathcal{P}$, the value function of policy $\pi_V(V)$ is not exactly the optimal value. The partial policy evaluation step (3.7) updates the value function to a value that is closer to the optimal value function.

Remark. The use of matrix splitting-based ideas, either explicitly or implicitly, in the context of dynamic programming is not completely novel to this work. Kushner and Kleinman [1971] is one of the earliest paper that mention the Jacobi and Gauss-Seidel procedures for computing the value function. Porteus [1975] proposes several transformations to the reward and the probability transition matrix with the goal of improving the computational cost of solving the transformed MDP. One of the transformations, called *pre-inverse transform*, has some similarities with the operator splitting of this work. The end result, however, is different. Bacon and Precup [2016] provide a matrix splitting perspective on planning with options. The connection between multi-step models and matrix splitting is developed in Chapter 4 of Bacon [2018]. Refer to the supplementary material for more discussion.

4 Convergence analysis of operator splitting value iteration

In this section, we present the convergence analysis of OS-VI. Our results show that OS-VI has an $O(\gamma'^k)$ convergence rate for an effective discount factor γ' that depends on the error between $\hat{\mathcal{P}}$ and $\mathcal{P}$. For small enough error, $\gamma' < \gamma$ and OS-VI has a faster convergence rate compared to the classic VI, Policy Iteration (PI), and Modified Policy Iteration (MPI), which all have $O(\gamma^k)$ behaviour. We provide results for both the L_∞ and L_p norms.

4.1 Convergence of OS-VI for policy evaluation

We study convergence behaviour of OS-VI (PE) in presence of error in value updates. More specifically, we consider the setting that in each iteration k, the update (3.2) has an error, i.e.,

$$V_k = S^\pi V_{k-1} + \epsilon_k^{\text{value}} \tag{4.1}$$

The error $\epsilon_k^{\text{value}}$ encompasses various sources of errors that might occur in a practical application of OS-VI. This includes the function approximation error, caused by using a function approximator to represent V_k, and the estimation (i.e., statistical) error caused due to having a finite number of samples, instead of direct access to $\mathcal{P}$, in the RL setting, see [Györfi et al., 2002] for a general discussion of function approximation/estimation error in the supervised learning, and [Munos and Szepesvári, 2008, Antos et al., 2008, Farahmand et al., 2016, Chen and Jiang, 2019]. In this work, we do not analyze how the number of samples, the function approximator, etc. affect the errors

$\epsilon_k^{\text{value}}$. The result of this section provides an error propagation result similar to Munos [2007] (for approximate VI), Munos [2003] (for approximate PI), and Scherrer et al. [2015] (for approximate modified PI).

To study convergence behaviour of OS-VI (PE), let $G^\pi = (\mathbf{I} - \gamma\hat{\mathcal{P}}^\pi)^{-1}\gamma(\mathcal{P}^\pi - \hat{\mathcal{P}}^\pi)$. We use the fact that $S^\pi V^\pi = V^\pi$ and write

$$\begin{aligned}\|V^\pi - V_k\|_\infty &= \left\|S^\pi V^\pi - S^\pi V_{k-1} - \epsilon_k^{\text{value}}\right\|_\infty = \left\|G^\pi(V^\pi - V_{k-1}) - \epsilon_k^{\text{value}}\right\|_\infty \\ &\leq \|G^\pi\|_\infty \|V^\pi - V_{k-1}\|_\infty + \left\|\epsilon_k^{\text{value}}\right\|_\infty. \end{aligned} \tag{4.2}$$

Now, we have that

$$\|G^\pi\|_\infty = \left\|(\mathbf{I} - \gamma\hat{\mathcal{P}}^\pi)^{-1}\gamma(\mathcal{P}^\pi - \hat{\mathcal{P}}^\pi)\right\|_\infty \leq \frac{\gamma}{1-\gamma}\left\|\mathcal{P}^\pi - \hat{\mathcal{P}}^\pi\right\|_\infty, \tag{4.3}$$

where we used the fact that for any square matrix F with a matrix norm $\|F\|_p < 1$, it holds that $\|(\mathbf{I} - F)^{-1}\|_p \leq \frac{1}{1-\|F\|_p}$ (e.g., Lemma 2.3.3 of Golub and Van Loan 2013), and that the supremum norm of a stochastic matrix $\hat{\mathcal{P}}^\pi$ is 1. Assuming that $\|\epsilon_k^{\text{value}}\|_\infty \leq \epsilon^{\text{value}}$ for all $k \geq 1$ and defining effective discount factor $\gamma' = \frac{\gamma}{1-\gamma}\|\mathcal{P}^\pi - \hat{\mathcal{P}}^\pi\|_\infty$, the upper bounds (4.3) and (4.2) lead to $\|V^\pi - V_k\|_\infty \leq \gamma'^k \|V^\pi - V_0\|_\infty + \frac{1-\gamma'^k}{1-\gamma'}\epsilon^{\text{value}}$.

A few remarks are in order. First, whenever $\gamma' < \gamma$, this is guaranteed to be faster than the convergence rate of the conventional VI, which is $O(\gamma^k)$. This is the case if $\|\mathcal{P}^\pi - \hat{\mathcal{P}}^\pi\|_\infty < 1 - \gamma$. If the model is very accurate, we obtain much faster rate than VI's. Since each iteration k corresponds to a query to the true model $\mathcal{P}$, a faster rate entails that the algorithm requires fewer total number of queries to the expensive model to reach the same level of accuracy.

Second, although the model error $\|\mathcal{P}^\pi - \hat{\mathcal{P}}^\pi\|_\infty$ is a reasonable choice to measure the distances between distributions (it is the maximum of the Total Variation distance between $\mathcal{P}^\pi(\cdot|x)$ and $\hat{\mathcal{P}}^\pi(\cdot|x)$ over x, which itself can be upper bounded by their KL divergence; see the supplementary material), it is somewhat conservative as it takes the supremum over the state space. Likewise, requiring $\|\epsilon_k^{\text{value}}\|_\infty$ to be small is also conservative, as approximating $S^\pi V_{k-1}$ using a function approximator given samples (RL setting) often leads to an L_p-norm type of guarantee. We now provide a different analysis to address these issues.

To present the L_p norm result, we need to define some notations. First, we define the conditional discounted future-state distribution of policy π under $\hat{\mathcal{P}}$ as the following probability distribution: Given a measurable set B, we have $\hat{\eta}^\pi(B|x) = (1-\gamma)\sum_{t=0}^\infty \gamma^t \cdot \mathbb{P}\Big(X_t \in B | X_0 = x, \pi, \hat{\mathcal{P}}\Big)$, where the chain $(X_t)_{t\geq 0}$ starts from state x, and evolves by following policy π under $\hat{\mathcal{P}}$ transitions. This is the same as (2.1) with the change of $\mathcal{P}$ to $\hat{\mathcal{P}}$. For an arbitrary distribution ρ over the state space, we define the *discounted future-state distribution concentration coefficient* as

$$\hat{C}^\pi(\rho)^2 = \frac{1}{\gamma^2}\int \mathrm{d}\rho(x)\left\|\frac{\mathrm{d}\hat{\eta}^\pi(\cdot|x)}{\mathrm{d}\rho}\right\|_\infty^3. \tag{4.4}$$

Here $\frac{\mathrm{d}\hat{\eta}^\pi(\cdot|x)}{\mathrm{d}\rho}$ is the Radon–Nikodym derivative of the distribution $\hat{\eta}^\pi(\cdot|x)$ w.r.t. the distribution ρ, and it is assumed that for any $x \in \mathcal{X}$, $\hat{\eta}^\pi(\cdot|x) \ll \rho$, i.e., $\hat{\eta}^\pi(\cdot|x)$ is absolutely continuous w.r.t. ρ (otherwise, the coefficient would be set to infinity). This coefficient measures how concentrated the distribution $\hat{\eta}^\pi(\cdot|x)$ is compared to ρ. This is weighted according to the initial state distribution ρ. Similar concentrability coefficients, but not exactly this one, have appeared in the error propagation results [Kakade and Langford, 2002, Munos, 2003, 2007, Farahmand et al., 2010, Scherrer et al., 2015]. Finally, we define the weighted χ^2-divergence of $\hat{\mathcal{P}}^\pi$ and $\mathcal{P}^\pi$ as the following:

$$\chi^2_\rho(\mathcal{P}^\pi \,||\, \hat{\mathcal{P}}^\pi) \triangleq \int \mathrm{d}\rho(x)\chi^2\Big(\mathcal{P}^\pi(\cdot|x) \,||\, \hat{\mathcal{P}}^\pi(\cdot|x)\Big) = \int \mathrm{d}\rho(x)\int \frac{\left|\hat{\mathcal{P}}^\pi(\mathrm{d}y|x) - \mathcal{P}^\pi(\mathrm{d}y|x)\right|^2}{\hat{\mathcal{P}}^\pi(\mathrm{d}y|x)}.$$

This notion of model error is less strict in requiring accurate approximation $\mathcal{P}$ in all states. Usually only a subset of state space is important or even reachable in a problem. The above model error can only focus on specific areas of state space through the choice of distribution ρ.

We are now ready to to provide the main theorem for the approximate OS-VI (PE).

Theorem 1. *Consider the approximate OS-VI algorithm for PE (4.1). Let $\|\cdot\|_\star$ be either the supremum norm $\|\cdot\|_\infty$ ($\star = \infty$) or $\|\cdot\|_{4,\rho}$ for ρ being an arbitrary distribution over state space ($\star = 4, \rho$). Assume that $\|\epsilon_k^{value}\|_\star \leq \epsilon^{value}$ for all $k \geq 1$. Furthermore, define the effective discount factor as*

$$\gamma' = \frac{\gamma}{1-\gamma} \begin{cases} \left\|\mathcal{P}^\pi - \hat{\mathcal{P}}^\pi\right\|_\infty & (\star = \infty), \\ \sqrt{\hat{C}^\pi(\rho) \cdot \chi^2_\rho(\mathcal{P}^\pi \mid\mid \hat{\mathcal{P}}^\pi)} & (\star = 4, \rho). \end{cases}$$

For any $k \geq 0$, we have $\|V^\pi - V_k\|_\star \leq \gamma'^k \|V^\pi - V_0\|_\star + \frac{1-\gamma'^k}{1-\gamma'} \cdot \epsilon^{value}$.

4.2 Convergence of OS-VI for control

We turn to analyzing OS-VI for Control. Similar to the analysis of OS-VI for PE, we assume some error in each step of OS-VI. Each iteration of OS-VI for PE was solving the PE problem in the auxiliary MDP $(\mathcal{X}, \mathcal{A}, \bar{r}_V, \hat{\mathcal{P}}, \gamma)$. The error of this solution was the error of the calculated value function V_{k+1} w.r.t. the true value function in the MDP $S^\pi V_k$ leading to (4.1). In Control, each iteration is solving the control problem in the same auxiliary MDP. The difference is that we have two types of error. First, the error of value function w.r.t. true solution, i.e., $V_k - S^* V_{k-1}$. Second is the suboptimality of policy compared to the optimal policy of auxiliary MDP, i.e., $S^{\pi_k} V_{k-1} - S^* V_{k-1}$. More specifically

$$V_k = S^* V_{k-1} + \epsilon_k^{\text{value}}, \tag{4.5}$$

$$S^{\pi_k} V_{k-1} = S^* V_{k-1} + \epsilon_k^{\text{policy}}. \tag{4.6}$$

Theorem 2. *Consider the approximate OS-VI algorithm for control (4.5)-(4.6). Let $\|\cdot\|_\star$ be either the supremum norm $\|\cdot\|_\infty$ ($\star = \infty$) or $\|\cdot\|_{4,\rho}$ for ρ being an arbitrary distribution over state space ($\star = 4, \rho$). For any $k \geq 1$, let $\Pi_k = \{\pi^*, \pi_k\} \cup \{\pi_V(V_{i-1}) : 0 \leq i < k\}$. Assume that $\|\epsilon_k^{value}\|_\star \leq \epsilon^{value}$ for all $k \geq 1$. Furthermore, define the effective discount factor as*

$$\gamma' = \frac{\gamma}{1-\gamma} \begin{cases} \max_{\pi \in \Pi_k} \left\|\mathcal{P}^\pi - \hat{\mathcal{P}}^\pi\right\|_\infty & (\star = \infty), \\ \max_{\pi \in \Pi_k} \sqrt{\sqrt{2} \cdot \hat{C}^\pi(\rho) \cdot \chi^2_\rho(\mathcal{P}^\pi \mid\mid \hat{\mathcal{P}}^\pi)} & (\star = 4, \rho). \end{cases}$$

We then have

$$\|V^{\pi_k} - V^*\|_\star \leq \frac{2\gamma'^k}{1-\gamma'} \|V_0 - V^*\|_\star + \frac{2\gamma'(1-\gamma'^{k-1})}{(1-\gamma')^2} \cdot \epsilon^{value} + \frac{1}{1-\gamma'} \cdot \left\|\epsilon_k^{policy}\right\|_\star.$$

We can compare this result with the convergence result of VI. For VI with the supremum norm, following the proof of Equation (2.2) by Munos [2007], we can show that $\|V^* - V^{\pi_k}\|_\infty \leq \frac{2\gamma^k}{1-\gamma} \|V^* - V_0\|_\infty + \frac{2\gamma(1-\gamma^{k-1})\varepsilon}{(1-\gamma)^2}$, with $\|V_i - T^* V_{i-1}\|_\infty \leq \varepsilon$ for all $i < k$ (similar result for the L_p-norm also holds, see Theorem 5.2 of Munos 2007). For the approximate VI, the initial error $\|V^* - V_0\|_\infty$ decays with the rate of $O(\gamma^k)$. This should be compared with $O(\gamma'^k)$ rate of OS-VI. The effect of error at each step ϵ^{value} is also similar: approximate VI has $(1-\gamma)^{-2}$ dependence while approximate OS-VI has $(1-\gamma')^{-2}$. What is remarkable is that as opposed to γ, which is a fixed parameter of the problem and can be close to 1, γ' can be made arbitrary close to zero when the model is accurate. The additional information given by $\hat{\mathcal{P}}$ allows us to get much faster rate than VI. Of course, this requires the model to be accurate. An inaccurate model might be detrimental to the convergence rate, and may even lead to divergence.

5 Operator splitting Dyna

In this section, we generalize the operator splitting approach to an RL problem in which only samples from $\mathcal{P}$ are available. In this scenario, the approximate model $\hat{\mathcal{P}}$ may not be given, as assumed in previous sections. However, one can learn such an approximate model using samples from the environment as done in MBRL algorithms. Unlike MBRL approaches that solely rely on the model, our approach takes advantage of both the true environment and the model in its updates. Therefore, one can think of the operator splitting approach as a hybrid of MBRL and model-free RL.

Algorithm 1 OS-Dyna

Initialize $V, \bar{r} = 0$, and the approximate model $\hat{\mathcal{P}}$.
for $t = 1, 2, \ldots$ **do**
  Sample (X_t, A_t, R_t, X'_t) from environment.
  Update the model $\hat{\mathcal{P}}$ with (X_t, A_t, R_t, X'_t)
  $\bar{r}(X_t, A_t) \leftarrow \bar{r}(X_t, A_t) + \alpha_t \cdot \Big(R_t + \gamma V(X'_t) - \gamma \mathbb{E}_{X' \sim \hat{\mathcal{P}}(.|X_t, A_t)}[V(X')] - \bar{r}(X_t, A_t)\Big)$
  $V \leftarrow V^{\pi}(\bar{r}, \hat{\mathcal{P}})$ (For PE) or $V \leftarrow V^{*}(\bar{r}, \hat{\mathcal{P}})$, $\pi \leftarrow \pi^{*}(\bar{r}, \hat{\mathcal{P}})$ (For Control)
end for

Using a learned $\hat{\mathcal{P}}$, we can calculate V_k from the auxiliary reward function $\bar{r}_k \triangleq \bar{r}_{V_{k-1}}$ by solving PE or control problem in the auxiliary MDP $(\mathcal{X}, \mathcal{A}, \bar{r}_k, \hat{\mathcal{P}})$, as discussed in Section 3. A possible challenge of using a learned model is that in many cases, we can only take samples from it and do not have access to the full matrices in calculations. Fortunately, solving PE or control problems with such a model is a very common practice in RL and is also done in Dyna architecture. Therefore, we do not focus on this procedure.

The ability of calculating V_k from $\bar{r}_k$ lets us see the value function as a function of $\bar{r}_k$. Based on this view, we shift our attention to $\bar{r}_k$. Note that since there is a fixed connection between $\bar{r}_k$ and V_k as the solution of PE or control in $(\mathcal{X}, \mathcal{A}, \bar{r}_k, \hat{\mathcal{P}})$, the convergence of $\bar{r}_k$ and V_k are tied together. Therefore, focusing on updating $\bar{r}_k$ will have the same convergence properties. The following update rules can be written for $\bar{r}_k$ itself. For every (x, a),

$$\bar{r}_k(x, a) = r(x, a) + \gamma\Big(\mathcal{P}(\cdot|x, a) - \hat{\mathcal{P}}(\cdot|x, a)\Big) \cdot V^{\pi}(\bar{r}_{k-1}, \hat{\mathcal{P}}) \qquad \text{(Policy Evaluation)} \tag{5.1}$$

$$\bar{r}_k(x, a) = r(x, a) + \gamma\Big(\mathcal{P}(\cdot|x, a) - \hat{\mathcal{P}}(\cdot|x, a)\Big) \cdot V^{*}(\bar{r}_{k-1}, \hat{\mathcal{P}}) \qquad \text{(Control)} \tag{5.2}$$

In OS-Dyna, we maintain a vector (or a function approximation) for $\bar{r}$, and as we will show how, update it by samples. The value function is updated to $V^{\pi}(\bar{r}, \hat{\mathcal{P}})$ (for PE) or $V^{*}(\bar{r}, \hat{\mathcal{P}})$ (for control) with each update of $\bar{r}$. This way, we have the value functions in update rules (5.1) and (5.2). The only challenge is that the above update rules need access to distributions $\mathcal{P}(\cdot|x, a)$ and $\hat{\mathcal{P}}(\cdot|x, a)$ for every (x, a), while we only have samples from these distributions in some (x, a) pairs. Fortunately, this challenge has been tackled in developing sample-based algorithms based on classic value iteration:

$$\forall (x, a): \qquad Q_k(x, a) = r(x, a) + \gamma \mathcal{P}(\cdot|x, a) V_{k-1}, \tag{5.3}$$

where $V_{k-1} = Q_{k-1}(x, \pi(x))$ in PE and $V_{k-1} = \max_{a'} Q_{k-1}(x, a)$ in Control. There are multiple approaches to develop sample-based algorithms based on (5.3) such as Fitted Q-Iteration and Stochastic Approximation (SA). In this paper we use SA to develop OS-Dyna, but we point out that other algorithms and techniques can also be applied to develop other versions of OS-Dyna. The key step in SA is to use samples to find an unbiased estimate of the intended update value. For a step (X_t, A_t, R_t, X'_t) in the true environment, we can have the following estimate $Z = R_t + \gamma V(X'_t) - \gamma \mathbb{E}_{X' \sim \hat{\mathcal{P}}(\cdot|X_t, A_t)}[V(X')]$, where the expectation can also be estimated by samples from $\hat{\mathcal{P}}(\cdot|X_t, A_t)$. Finally, we make the following update to $\bar{r}$ with learning rate α_t

$$\bar{r}(X_t, A_t) \leftarrow \bar{r}(X_t, A_t) + \alpha_t \cdot (Z - \bar{r}(X_t, A_t)). \tag{5.4}$$

The final procedure of OS-Dyna is presented in Algorithm 1.

6 Experiments

We evaluate both OS-VI and OS-Dyna in a finite MDP, comparing our algorithms with existing methods. The MDP considered is a modified cliffwalk environment in a 6×6 grid with 4 actions (up, down, left and right). Full details of the environment is available in the supplementary material. Our convergence analysis shows that the convergence rates of our algorithms depend on the accuracy of $\hat{\mathcal{P}}$. To test OS-VI and OS-Dyna with models of different accuracies, we introduce the smoothed model $\hat{\mathcal{P}}$ of transitions $\mathcal{P}$ with smoothing parameter λ as

$$\hat{\mathcal{P}}(\cdot|x, a; \mathcal{P}, \lambda) = (1 - \lambda)\mathcal{P}(\cdot|x, a) + \lambda U\big(\{x'|\mathcal{P}(x'|x, a) > 0\}\big), \tag{6.1}$$

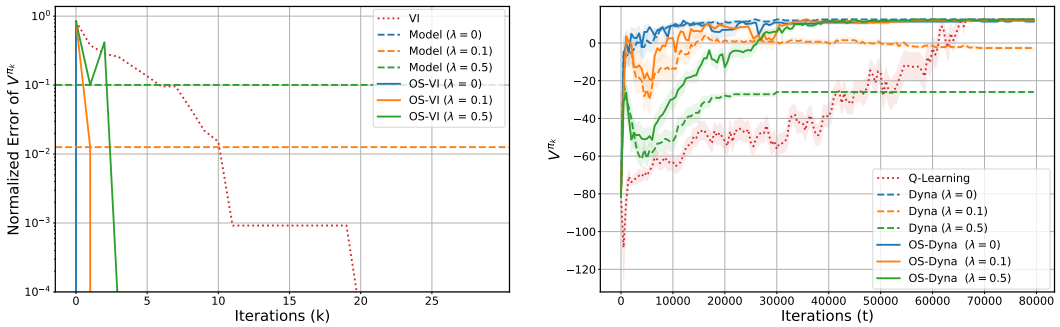

Figure 1: *(Left)* Normalized error comparisons of OS-VI, VI, and the optimal policy of model $\hat{\mathcal{P}}$. *(Right)* Comparison of OS-Dyna with Dyna and Q-Learning in the RL setting.

where $U(A)$ for some set A is the uniform distribution over A. Here, λ allows making adjustments to the amount of error introduced in $\hat{\mathcal{P}}$ w.r.t. $\mathcal{P}$. If $\lambda = 0$, $\hat{\mathcal{P}} = \mathcal{P}$ will be the accurate model, and if $\lambda = 1$, $\hat{\mathcal{P}}$ will be uniform over possible next states in $\mathcal{P}$.

We compare OS-VI and OS-Dyna for Control with other existing methods. The results for the PE problem are qualitatively similar and are provided in the supplementary material along with more experiments. The left plot in Figure 1 shows the convergence of OS-VI compared to VI and the solutions the model itself would lead to. The plot shows normalized error of V^{π_k} w.r.t V^*, i.e. $\|V^{\pi_k} - V^*\|_1 / \|V^*\|_1$. It can be seen that OS-VI has faster convergence with more accurate models and introduces acceleration compared to VI across different model errors. Note that the convergence of OS-VI has been achieved despite the error in the model. The dashed lines show how a fully model-based algorithm would obtain a suboptimal solution by only relying on the model.

We also compare OS-Dyna with with Dyna and Q-Learning in the RL setting. At each iteration t, the algorithms are given a sample (X_t, A_t, R_t, X'_t) where X_t, A_t are selected uniformly at random. For OS-Dyna and Dyna we use the smoothed Maximum-likelihood Estimation (MLE) model. If $\mathcal{P}_{\text{MLE}}$ is the current MLE estimation of the environment transitions, OS-Dyna and Dyna use $\hat{\mathcal{P}}(\mathcal{P}_{\text{MLE}}, \lambda)$ defined in (6.1) as their models. The learning rates are constant α for iterations $t \leq N$ and then decay in the form of $\alpha_t = \alpha/(t - N)$ afterwards. We have fine-tuned the learning rate schedule for *each* algorithm separately for the best results.

The right plot in Figure 1 shows the results for the RL setting. We evaluate the expected return of the policy at iteration t in the initial state of the environment, i.e. $V^{\pi_k}(0)$. Again, OS-Dyna has converged to the optimal policy much faster than Q-Learning for all model errors. Unlike OS-Dyna, classic Dyna has failed to find the optimal policy in presence of model error. The results show that OS-Dyna can effectively converge faster than Q-Learning without introducing bias to the final solution due to model error.

7 Conclusion

This paper introduced the Operator Splitting Value Iteration (OS-VI) algorithm, which can benefit from an approximate model $\hat{\mathcal{P}} \approx \mathcal{P}$ to accelerate the convergence of the approximate value to the true value function in terms of the number of queries to the true model $\mathcal{P}$. With a small model error, its convergence rate is exponentially faster compared to well-known dynamical programming algorithms such as Value Iteration and Policy Iteration. We also proposed OS-Dyna as a hybrid model-based/model-free algorithm that can bring in the benefits of a model-based RL algorithm without converging to a biased solution, as Dyna or any other purely model-based RL algorithm does. This paper opens up several future directions. Empirically studying the algorithms on problems with large state spaces, for which a function approximator such as a DNN is required, is an obvious one. This is postponed to a future work as our aim was to build the mathematical foundation and conducting experiments without worrying about challenges such as the optimization of a DNN. There are other algorithmic and theoretical directions to be pursued. One is exploring the space of splittings of $\mathbf{I} - \gamma \mathcal{P}^\pi$. The other is whether we can design Operator Splitting variants of other DP algorithms such as Policy Iteration and Modified Policy Iteration, and study their convergence behaviour.

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1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] In the end of Section 4 we show that the convergence and speed up need an accurate enough model.
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