Batch Stationary Distribution Estimation

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Abstract
We consider the problem of approximating the stationary distribution of an ergodic Markov chain given a set of sampled transitions. Classical simulation-based approaches assume access to the underlying process so that trajectories of sufficient length can be gathered to approximate stationary sampling. Instead, we consider an alternative setting where a fixed set of transitions has been collected beforehand, by a separate, possibly unknown procedure. The goal is still to estimate properties of the stationary distribution, but without additional access to the underlying system. We propose a consistent estimator that is based on recovering a correction ratio function over the given data. In particular, we develop a variational power method (VPM) that provides provably consistent estimates under general conditions. In addition to unifying a number of existing approaches from different subfields, we also find that VPM yields significantly better estimates across a range of problems, including queueing, stochastic differential equations, post-processing MCMC, and off-policy evaluation.

1. Introduction
Markov chains are a pervasive modeling tool in applied mathematics of particular importance in stochastic modeling and machine learning. A key property of an ergodic Markov chain is the existence of a unique stationary distribution, i.e., the long-run distribution of states that remains invariant under the transition kernel. In this paper, we consider a less well studied but still important version of the stationary distribution estimation problem, where one has access to a set of sampled transitions from a given Markov chain, but does not know the mechanism by which the probe points were chosen, nor is able to gather additional data from the underlying process. Nevertheless, one would still like to estimate target properties of the stationary distribution, such as the expected value of a random variable of interest.

This setting is inspired by many practical scenarios where sampling from the Markov process is costly or unavailable, but data has already been collected and available for analysis. A simple example is a queueing system consisting of a service desk that serves customers in a queue. Queue length changes stochastically as customers arrive or leave after being served. The long-term distribution of queue length (i.e., the stationary distribution of the underlying Markov chain) is the object of central interest for managing such a service (Haviv, 2009; Serfozo, 2009). In practice, however, queue lengths are physical quantities that can only be measured for moderate periods, perhaps on separate occasions, but rarely for sufficient time to ensure the (stochastic) queue length has reached the stationary distribution. Since the measurement process itself is expensive, it is essential to make reasonable inferences about the stationary distribution from the collected data alone.

We investigate methods for estimating properties of the stationary distribution solely from a batch of previously collected data. The key idea is to first estimate a correction ratio function over the given data, which can then be used to estimate expectations of interest with respect to the stationary distribution. To illustrate, consider an ergodic Markov chain with state space \( \mathcal{X} \), transition kernel \( T \), and a unique stationary distribution \( \mu \) that satisfies

\[
\mu(x') = \int T(x'|x) \mu(x) \, dx := (T \mu)(x').
\]

Assume we are given a fixed sample of state transitions, \( D = \{(x, x')\}_{i=1}^n \sim T(x'|x) \, p(x) \), such that each \( x \) has been sampled according to an unknown probe distribution \( p \), but each \( x' \) has been sampled according to the true underlying transition kernel, \( x'|x \sim T(x'|x) \). Below we investigate procedures for estimating the point-wise ratios, \( \hat{\tau}(x_i) \approx \frac{\hat{\mu}(x_i)}{p(x_i)} \), such that the weighted empirical distribution

\[
\hat{\mu}(x) := \left( \sum_{i=1}^n \hat{\tau}(x_i) \right)^{-1} \sum_{i=1}^n \hat{\tau}(x_i) \mathbb{1}[x = x_i]
\]

can be used to approximate \( \mu \) directly, or further used to estimate the expected value of some target function(s) of \( x \)
with respect to $\mu$. Crucially, the approach we propose does not require knowledge of the probe distribution $p$, nor does it require additional access to samples drawn from the transition kernel $T$, yet we will be able to establish consistency of the estimation strategy under general conditions.

In addition to developing the fundamental approach, we demonstrate its applicability and efficacy in a range of important scenarios beyond queueing, including:

- **Stochastic differential equations (SDEs)** SDEs are an essential modeling tool in many fields like statistical physics (Kadanoff, 2000), finance (Oksendal, 2013) and molecular dynamics (Liu, 2001). An autonomous SDE describes the instantaneous change of a random variable $X$ by
  \[
  dX = f(X) \, dt + \sigma(X) \, dW ,
  \]
  where $f(X)$ is a drift term, $\sigma(X)$ a diffusion term, and $W$ the Wiener process. Given data $D = \{(x, x')\}_{i=1}^n$ such that $x \sim p(x)$ is drawn from an unknown probe distribution and $x'$ is the next state after a small time step according to (2), we consider the problem of estimating quantities of the stationary distribution $\mu$ when one exists.

- **Off-policy evaluation (OPE)** Another important application is behavior-agnostic off-policy evaluation (Nachum et al., 2019) in reinforcement learning (RL). Consider a Markov decision process (MDP) specified by $M = (S, A, P, R)$, such that $S$ and $A$ are the state and action spaces, $P$ is the transition function, and $R$ is the reward function (Puterman, 2014). Given a policy $\pi$ that maps $s \in S$ to a distribution over $A$, a random trajectory can be generated starting from an initial state $s_0$: $(s_0, a_0, r_0, s_1, a_1, r_1, \ldots)$, where $a_t \sim \pi(\cdot|s_t)$, $s_{t+1} \sim P(\cdot|s_t, a_t)$ and $r_t \sim R(s_t, a_t)$. The value of a policy $\pi$ is defined to be its long-term average per-step reward:
  \[
  \rho(\pi) := \lim_{T \to \infty} \mathbb{E} \left[ \frac{1}{T} \sum_{t=0}^{T-1} r_t \right] = \mathbb{E}_{(s,a) \sim d_{\pi} \otimes \tau} [R(s, a)] ,
  \]
  where $d_{\pi}$ denotes the limiting distribution over states $S$ of the Markov process induced by $\pi$. In behavior-agnostic off-policy evaluation, one is given a target policy $\pi$ and a set of transitions $D = \{(s, a, r, s')\}_{i=1}^n \sim P(\cdot|s, a) p(s, a)$, potentially generated by multiple behavior policies. From such data, an estimate for $\rho(\pi)$ can be formed in terms of a stationary ratio estimator:
  \[
  \rho(\pi) = \mathbb{E}_{(s,a) \sim p} \left[ \frac{d_{\pi}(s,a)}{p(s,a)} \pi(\cdot|s) \right] \approx \frac{1}{n} \sum_{i=1}^{n} \frac{\pi(s_i, a_i)}{p(s_i, a_i)} r_i .
  \]
  We refer the interested readers to Section 5.4 and Appendix C for further discussion.

For the remainder of the paper, we will outline four main contributions. First, we generalize the classical power iteration method to obtain an algorithm, the **Variational Power Method** (VPM), that can work with arbitrary parametrizations in a functional space, allowing for a flexible yet practical approach. Second, we prove the consistency and convergence of VPM. Third, we illustrate how a diverse set of stationary distribution estimation problems, including those above, can be addressed by VPM in a unified manner. Finally, we demonstrate empirically that VPM significantly improves estimation quality in a range of applications, including queueing, sampling, SDEs and OPE.

## 2. Variational Power Method

To develop our approach, first recall the definition of $T$ and $\mu$ in (1). We make the following assumption about $T$ and $\mu$ throughout the paper.

**Assumption 1 (ergodicity)** The transition operator $T$ has a unique stationary distribution, denoted $\mu$.

Conditions under which this assumption holds are mild, and have been extensively discussed in standard textbooks (Meyn et al., 2009; Levin and Peres, 2017).

Next, to understand the role of the probe distribution $p$, note that we can always rewrite the stationary distribution as $\mu = p \circ \tau$ (i.e., $\mu(x) = p(x) \tau(x)$, hence $\tau(x) = \frac{\mu(x)}{p(x)}$), provided the following assumption holds.

**Assumption 2 (absolute continuity)** The stationary distribution $\mu$ is absolutely continuous w.r.t. $p$. That is, there exists $C < \infty$ such that $\|\tau\|_{\infty} \leq C$.

Assumption 2 follows previous work (Liu and Lee, 2017; Nachum et al., 2019), and is common in density ratio estimation (Sugiyama et al., 2008; Gretton et al., 2009) and off-policy evaluation (Wang et al., 2017; Xie et al., 2019).

Combining these two assumptions, definition (1) yields
\[
\mu(x') = \int T(x'|x) \mu(x) \, dx = \int T(x'|x) p(x) \frac{\mu(x)}{p(x)} \, dx
\]
\[
= \int T_p(x, x') \tau(x) \, dx ,
\]
which implies
\[
p(x') \tau(x') = \int T_p(x, x') \tau(x) \, dx := T_p \tau(x') .
\]

This development reveals how, under the two stated assumptions, there is sufficient information to determine the unique ratio function $\tau$ that ensures $p \circ \tau = \mu$ in principle. Given such a function $\tau$, we can then base inferences about $\mu$ solely on data sampled from $p$ and $\tau$.

### 2.1. Variational Power Iteration

To develop a practical algorithm for recovering $\tau$ from the constraint (4), in function space, we first consider the classical power method for recovering the $\mu$ that satisfies (1).
From (1) it can be seen that the stationary distribution \( \mu \) is an eigenfunction of \( T \). Moreover, it is the principal eigenfunction, corresponding to the largest eigenvalue \( \lambda_1 = 1 \). In the simpler case of finite \( \mathcal{X} \), the vector \( \mu \) is the principal (right) eigenvector of the transposed transition matrix. A standard approach to computing \( \mu \) is then the power method:

\[
\mu_{t+1} = T \mu_t,
\]

where the division is element-wise. Clearly the fixed point of (6) corresponds to the solution of (4) under the two assumptions stated above. Furthermore, just as for \( \mu_t \) in (5), \( \tau_t \) in (6) also converges to \( \tau \) at a linear rate for finite \( \mathcal{X} \). Unfortunately, the update (6) cannot be used directly in a practical algorithm for two important reasons. First, we do not have a point-wise evaluator for \( T_p \), but only samples from \( T_p \). Second, the operator \( T_p \) is applied to a function \( t \), which typically involves an intractable integral over \( \mathcal{X} \) in general. To overcome these issues, we propose a variational method that considers a series of reformulated problems whose optimal solutions correspond to the updates (6).

To begin to develop a practical variational approach, first note that (6) operates directly on the density ratio, which implies the density ratio estimation techniques of Nguyen et al. (2008) and Sugiyama et al. (2012) can be applied. Let \( \phi \) be a lower semicontinuous, convex function satisfying \( \phi(1) = 0 \), and consider the induced \( f \)-divergence,

\[
D_\phi(\tilde{p}\parallel \tilde{q}) = \int \tilde{p}(x) \phi \left( \frac{\tilde{q}(x)}{\tilde{p}(x)} \right) dx
\]

\[
= -\left( \min_\nu \mathbb{E}_p[\phi^+(\nu)] - \mathbb{E}_q[\nu] \right),
\]

where \( \phi^+(x) = \sup_{y \in \mathbb{R}} x^T y - \phi(y) \) is the conjugate function of \( \phi \). The key property of this formulation is that for any distributions \( \tilde{p} \) and \( \tilde{q} \), the inner optimum in \( \nu \) satisfies \( \partial \phi^+(\nu) = \tilde{q}/\tilde{p} \) (Nguyen et al., 2008); that is, the optimum in (7) can be used to directly recover the distribution ratio.

To apply this construction to our setting, first consider solving a problem of the following form in the dual space:

\[
\nu_{t+1} = \arg \min_\nu \mathbb{E}_p(x') \left[ \phi^+(\nu(x')) \right]
\]

\[
-\mathbb{E}_{T_p(x,x')} [\partial \phi^+(\nu_t(x)) \cdot \nu(x')]
\]

\[
= \arg \min_\nu \mathbb{E}_p(x') \left[ \phi^+(\nu(x')) \right]
\]

\[
-\mathbb{E}_{T_p(x,x')\tau_t(x)} [\nu(x')],
\]

where to achieve (9) we have applied the inductive assumption that \( \tau_t = \partial \phi^+(\nu_t) \). Then, by the optimality property of \( \nu_{t+1} \), we know that the solution \( \nu_{t+1} \) must satisfy

\[
\partial \phi^+(\nu_{t+1}) = \frac{T_p \tau_t}{p} = \tau_{t+1},
\]

hence the updated ratio \( \tau_{t+1} \) in (6) can be directly recovered from the dual solution \( \nu_{t+1} \), while also retaining the inductive property that \( \tau_{t+1} = \partial \phi^+(\nu_{t+1}) \) for the next iteration. These developments can be further simplified by considering the specific choice \( \phi(\tau) = (\tau - 1)^2 \), which leads to \( \phi^+(\nu) = \nu + \nu^2 - \frac{1}{4} \) and

\[
\tau_{t+1} = \arg \min_{\tau \geq 0} \mathbb{E}_p(x') \left[ T_p(x,x') \right] \mathbb{E}_{T_p(x,x')} [\nu_t(x) \tau(x')].
\]

(11)

Crucially, this variational update (11) determines the same update as (6), but overcomes the two aforementioned difficulties. First, it bypasses the direct evaluation of \( T_p \) and \( p \), and allows these to be replaced by unbiased estimates of expectations extracted from the data. Second, it similarly bypasses the intractability of the operator application \( T_p \tau_t \) in the functional space, replacing this with an expectation of \( \tau_t \circ \tau \) that can also be directly estimated from the data.

We now discuss some practical refinements of the approach.

### 2.2. Normalization

For \( \tau_t \) to be a proper ratio \( \frac{\mu_t}{\tau_t} \), it should be normalized w.r.t. \( p \), i.e. \( \mathbb{E}_p [\tau_t] = 1 \). To address this issue, we explicitly ensure normalization by considering a constrained optimization in place of (11):

\[
\min_{\tau \geq 0} \mathbb{E}_p(x') \left[ \tau^2(x') \right] - \mathbb{E}_{T_p(x,x')} [\tau_t(x) \tau(x')] \text{ s.t. } \mathbb{E}_p(x) [\tau(x)] = 1.
\]

(12)

We can tackle this by solving its Lagrangian. To avoid instability, we add a regularization term:

\[
\min_{\tau \geq 0} \max_{\nu \in \mathbb{R}} \frac{1}{2} \mathbb{E}_p(x') \left[ \tau^2(x') \right] - \mathbb{E}_{T_p(x,x')} [\tau_t(x) \tau(x')] + v (\mathbb{E}_p[\tau] - 1) - \frac{1}{2} v^2.
\]

where \( \lambda > 0 \) is a regularization parameter. Crucially, the dual variable \( v \) is a scalar, making this problem much simpler than dual embedding (Dai et al., 2017), where the dual variables form a parameterized function that introduces approximation error. The problem (13) is a straightforward convex-concave objective with respect to \( (\tau, v) \) that can be optimized by stochastic gradient descent.

The following theorem shows that under certain conditions, the normalization will be maintained for any \( \lambda > 0 \).

**Theorem 1 (Normalization of solution)** If \( \mathbb{E}_p [\tau_t] = 1 \), then for any \( \lambda > 0 \), the estimator (13) has the same solution as (12), hence \( \mathbb{E}_p [\tau_{t+1}] = 1 \).
A practical version of VPM is described in Algorithm 1. To control the error due to sampling, we introduce a damped version of the update (e.g., \(\tau_{t+1} = \frac{\tilde{T}_p}{\mu_t} \tau_t\)). The choice of stepsize \(\alpha_t\) and the optimization algorithm. There is a complex trade-off between these factors (Bottou and Bousquet, 2008), where more data, the statistical error is reduced, but on the other hand, with more data, the approximation error of the parametric family, \(\tau_{t+1} = \frac{\tilde{T}_p}{\mu_t} \tau_t\), and the optimization quality depends on the number of samples, \(B\). Hence, we can begin with any \(\tau_0\) satisfying \(\tau_0 \leq 1\). The argument easily extends to the ratio form (5) instead of the simpler form (11). We now demonstrate that the final algorithm obtains sufficient control over error accumulation to achieve consistency. For notation brevity, we discuss the result for the simpler form (5) instead of the ratio form (6). The argument easily extends to the ratio form.

### 3. Convergence Analysis

We now demonstrate that the final algorithm obtains sufficient control over error accumulation to achieve consistency. For notation brevity, we discuss the result for the simpler form (5) instead of the ratio form (6). The argument easily extends to the ratio form.

To control the error due to sampling, we introduce a damped version of the update (Ryu and Boyd, 2016), where instead of performing a stochastic update \(\tau_{t+1} = \frac{\tilde{T}_p}{\mu_t} \tau_t\), we instead perform a damped update given by

\[
\tau_{t+1} = (1 - \alpha_{t+1}) \cdot \tau_t + \alpha_{t+1} \cdot \frac{\tilde{T}_p}{\mu_t} \tau_t
\]

where \(\alpha_t \in (0, 1)\) is a stepsize parameter. Intuitively, the update error introduced by the stochasticity of \(\tilde{T}_p\) is now controlled by the stepsize \(\alpha_t\). The choice of stepsize and convergence of the algorithm is discussed in Section 3.

The damped iteration can be conveniently implemented with minor modifications to the previous objective. We only need to change the sample from \(\tilde{T}_p\) in (13) by a weighted sample:

\[
\min_{\tau \geq 0} \ max_{v \in \mathbb{R}} J(\tau, v) = \frac{1}{2} \mathbb{E}_{p(x')} \left[ \tau^2 (x') \right] - (1 - \alpha_{t+1}) \mathbb{E}_{p(x')} \left[ \tau_t(x') \tau(x') \right] - \alpha_{t+1} \mathbb{E}_{p(x,x')} \left[ \tau_t(x) \tau(x') \right] + v (\mathbb{E}_{p} \left[ \tau \right] - 1 - \frac{\lambda}{2} v^2).
\]

2.4. A Practical Algorithm

A practical version of VPM is described in Algorithm 1. It solves (15) using a parameterized \(\tau : \mathcal{X} \mapsto \mathbb{R}\) expressed as
the other hand, with a more flexible parametrization, such as neural networks, reduces the approximation error, but adds to the difficulty of optimization as the problem might no longer be convex. Alternatively, if the complexity of the parameterized family is increased, the consequences of statistical error also increases.

Representing $\tau$ in a reproducing kernel Hilbert space (RKHS) is a particularly interesting case, because the problem (13) becomes convex, hence the optimization error of the empirical surrogate is reduced to zero. Nguyen et al. (2008, Theorem 2) show that, under mild conditions, the statistical error can be bounded in rate $O \left( n^{-\frac{1}{2}} \right)$ in terms of Hellinger distance ($\beta$ denotes the exponent in the bracket entropy of the RKHS), while the approximation error will depend on the RKHS (Bach, 2014).

### 4. Related Work

The algorithm we have developed reduces distribution estimation to density ratio estimation, which has been extensively studied in numerous contexts. One example is learning under covariate shift (Shimodaira, 2000), where the ratio $\tau$ can be estimated by different techniques (Gretton et al., 2009; Nguyen et al., 2008; Sugiyama et al., 2008; Sugiyama and Kawanabe, 2012). These previous works differ from the current setting in that they require data to be sampled from both the target and proposal distributions. By contrast, we consider a substantially more challenging problem, where only data sampled from the proposal is available, and the target distribution is given only implicitly by (1) through the transition kernel $T$. A more relevant approach is Stein importance sampling (Liu and Lee, 2017), where the ratio is estimated by minimizing the kernelized Stein discrepancy (Liu et al., 2016). However, it requires additional gradient information about the target potential, whereas our method only requires sampled transitions. Moreover, the method of Liu and Lee (2017) is computationally expensive and does not extrapolate to new examples.

The algorithm we develop in this paper is inspired by the classic power method for finding principal eigenvectors. Many existing works have focused on the finite-dimension setting (Balasubramani et al., 2013; Hardt and Price, 2014; Yang et al., 2017), while Kim et al. (2005) and Xie et al. (2015) have extended the power method to the infinite-dimension case using RKHS. Not only do these algorithms require access to the transition kernel $T$, but they also require tractable operator multiplications. In contrast, our method avoids direct interaction with the operator $T$, and can use flexible parametrizations (such as neural networks) to learn the density ratio without per-step renormalization.

Another important class of methods for estimating or sampling from stationary distributions are based on simulations. A prominent example is Markov chain Monte Carlo (MCMC), which is widely used in many statistical inference scenarios (Andrieu et al., 2003; Koller and Friedman, 2009; Welling and Teh, 2011). Existing MCMC methods (e.g., Neal et al., 2011; Hoffman and Gelman, 2014) require repeated, and often many, interactions with the transition operator $T$ to acquire a single sample from the stationary distribution. Instead, VPM can be applied when only a fixed sample is available. Interestingly, this suggests that VPM can be used to “post-process” samples generated from typical MCMC methods to possibly make more effective use of the data. We demonstrated this possibility empirically in Section 5. Unlike VPM, other post-processing methods (Oates et al., 2017) require additional information about the target distribution (Robert and Casella, 2004). Recent advances have also shown that learning parametric samplers can be beneficial (Song et al., 2017; Li et al., 2019), but require the potential function. In contrast, VPM directly learns the stationary density ratio solely from transition data.

One important application of VPM is off-policy RL (Precup et al., 2001). In particular, in off-policy evaluation (OPE), one aims to evaluate a target policy’s performance, given data collected from a different behavior policy. This problem matches our proposed framework as the collected data naturally consists of transitions from a Markov chain, and one is interested in estimating quantities computed from the stationary distribution of a different policy. (See Appendix C for a detailed description of how the VPM algorithm can be applied to OPE, even when $\gamma = 1$.) Standard importance weighting is known to have high variance, and various techniques have been proposed to reduce variance (Precup et al., 2001; Jiang and Li, 2016; Rubinstein and Kroese, 2016; Thomas and Brunskill, 2016; Guo et al., 2017). However, these methods still exhibit exponential variance in the trajectory length (Li et al., 2015; Jiang and Li, 2016).

More related to the present paper is the recent work on off-policy RL that avoids the exponential blowup of variance. It is sufficient to adjust observed rewards according to the ratio between the target and behavior stationary distributions (Hallak and Mannor, 2017; Liu et al., 2018; Gelada and Bellemare, 2019). Unfortunately, these methods require knowledge of the behavior policy, $p(a|s)$, in addition to the transition data, which is not always available in practice. In this paper, we focus on the behavior-agnostic scenario where $p(a|s)$ is unknown. Although the recent work of Nachum et al. (2019) considers the same scenario, their approach is only applicable when the discount factor $\gamma < 1$, whereas the method in this paper can handle any $\gamma \in [0, 1]$.

### 5. Experimental Evaluation

In this section, we demonstrate the advantages of VPM in four representative applications. Due to space limit, experi-
We next apply VPM to solve a class of SDEs known as
where
The OUP has a closed-form solution, which converges to the
standard simulation-based method for solving SDEs. VPM
Euler-Maruyama (EM) method. The observed transition
is a uniform distribution over the states in
x = Unif([−6, 6]2), then transitioned through an
HMC operator (Neal et al., 2011). The transitioned pairs
are used as training set \( D \).

We compare VPM to a model-based method that explicitly
learns a transition model \( \widetilde{T}(x'|x) \), parametrized as a
neural network to produce Gaussian mean (with fixed stan-
dard deviation of 0.1). Then, we apply \( \widetilde{T} \) to a hold-out set
drawn from \( p(x) \) sufficiently many times, and use the final
instances as limiting samples (second column of Fig. 3). As
for VPM, since \( p \) is uniform, the estimated \( \hat{\theta} \) is propor-
tional to the true stationary distribution. To obtain limiting
samples (third column of Fig. 3), we resample from a hold-out
set drawn from \( p(x) \) with probability proportional to \( \hat{\theta} \).

The results are shown in Fig. 3. Note that the model-
based method quickly collapses all training data into high-
probability regions as stationary distributions, which is an in-
evitable tendency of restricted parametrized \( \widetilde{T} \). Our learned
ratio faithfully reconstructs the target density as shown in
the right-most column of Fig. 3. The resampled data of
VPM are much more accurate and diverse than that of the
model-based method. These experiments show that VPM
can indeed effectively use a fixed set of data to recover the
stationary distribution without additional information.

To compare the results quantitatively, Fig. 4 shows the MMD
of the estimated sample to a “true” sample. Since there is
no easy way to sample from the potential function, the “true”
sample consists of data after \( 2k \) HMC steps with rejection
sampler. After each MCMC step, VPM takes the transition

Figure 1. Log KL divergence between estimation and the truth.

5.1. Queueing

In this subsection, we use VPM to estimate the station-
ary distribution of queue length. Following the standard
Kendall’s notation in queueing theory (Haviv, 2009; Ser-
fozo, 2009), we analyze the discrete-time Geo/Geo/1 queue,
which is commonly used in the literature (Atencia and
Moreno, 2004; Li and Tian, 2008; Wang et al., 2014). Here
the customer inter-arrival time and service time are geo-
metrically distributed with one service desk. The probe
distribution \( p(x) \) is a uniform distribution over the states in
a predefined range \([0, B]\). The observed transition \((x, x')\)
is the length change in one time step. The queue has a closed-
form stationary distribution that we can compare to (Serfozo,
2009, Sec.1.11).

Fig. 1 provides the log KL divergence between the estimated
and true stationary distributions. We compare VPM to a
model-based approach, which estimates the transition matrix
\( \hat{T}(x'|x) \) from the same set of data, then simulates a long
trajectory using \( \hat{T} \). It can be seen that our method can
be more effective across different sample sizes and queue
configurations.

5.2. Solving SDEs

We next apply VPM to solve a class of SDEs known as
the Ornstein-Uhlenbeck process (OUP), which finds many
applications in biology (Butler and King, 2004), financial
mathematics and physical sciences (Oksendal, 2013). The
process is described by the equation:

\[
dX = \theta(m - X)dt + \sigma dW
\]

where \( m \) is the asymptotic mean, \( \sigma > 0 \) is the deviation,
\( \theta > 0 \) determines the strength, and \( W \) is the Wiener process.
The OUP has a closed-form solution, which converges to the
stationary distribution, a normal distribution \( N(m, \sigma^2/2\theta) \),
as \( t \to \infty \). This allows us to conveniently calculate the
Maximum Mean Discrepancy (MMD) between the adjusted
sample to a true sample. We compare our method with the
Euler-Maruyama (EM) method (Gardiner, 2009), which is a
standard simulation-based method for solving SDEs. VPM
uses samples from the EM steps to train the ratio network
and the learned ratio is used to compute weighted MMD.

The results are shown in Fig. 2, with different configurations
of parameters \((m, \sigma, \theta)\). It can be seen that VPM consistently
improves over the EM method in terms of the log MMD to a true sample from the normal distribution. The EM method
only uses the most recent data, which can be wasteful since the past data can carry additional information about the system dynamics.

In addition, we perform experiment on real-world phy-
logeny studies. OUP is widely used to model the evolution
of various organism traits. The results of two configura-
tions (Beaulieu et al., 2012; Santana et al., 2012, Tab.3&1
resp.) are shown in Fig. 2d. Notably VPM can improve over
the EM method by correcting the sample with learned ratio.

5.3. Post-processing MCMC

In this experiment, we demonstrate how VPM can post-
process MCMC to use transition data more effectively in
order to learn the target distributions. We use four com-
mon potential functions as shown in the first column of
Fig. 3 (Neal, 2003; Rezende and Mohamed, 2015; Li et al.,
2018). A point is sampled from the uniform distribution
\( p(x) = \text{Unif}([-6, 6]^2) \), then transitioned through an
HMC operator (Neal et al., 2011). The transitioned pairs
are used as training set \( D \).

We compare VPM to a model-based method that explicitly
learns a transition model \( \hat{T}(x'|x) \), parametrized as a
neural network to produce Gaussian mean (with fixed stan-
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The results are shown in Fig. 3. Note that the model-
based method quickly collapses all training data into high-
probability regions as stationary distributions, which is an in-
evitable tendency of restricted parametrized \( \hat{T} \). Our learned
ratio faithfully reconstructs the target density as shown in
the right-most column of Fig. 3. The resampled data of
VPM are much more accurate and diverse than that of the
model-based method. These experiments show that VPM
can indeed effectively use a fixed set of data to recover the
stationary distribution without additional information.

To compare the results quantitatively, Fig. 4 shows the MMD
of the estimated sample to a “true” sample. Since there is
no easy way to sample from the potential function, the “true”
sample consists of data after \( 2k \) HMC steps with rejection
sampler. After each MCMC step, VPM takes the transition

Figure 2. Comparison of (a) Number of samples and (b) Finish probability.
VPM is able to post-process the data and further reduce
pair denoting each transition in $D$'s behavior policy is
finally, we apply our method to behavior-agnostic off-

5.4. Off-Policy Evaluation

Finally, we apply our method to behavior-agnostic off-
policy evaluation outlined in Section 1, in which only
the transition data and the target policy are given, while
the behavior policy is unknown. Concretely, given a sample
$D = \{ (s, a, r, s')_{i=1}^n \}$ from the behavior policy, we
compose each transition in $D$ with a target action $a' \sim \pi (\cdot |s')$.
Denoting $x = (s, a)$, the data set can be expressed as
$D = \{ (x, x')_{i=1}^n \}$. Applying the proposed VPM with
$T(x'|x)$, we can estimate $\frac{\mu(x, a)}{p(x, a)}$, hence the average accumu-

Figure 2. Log MMD versus number of EM steps across different settings, default $(m, \sigma, \theta) = (2, 2, 2)$. (d) is based on the real-world phylogeny studies (Beaulieu et al., 2012; Santana et al., 2012) with $(m, \sigma, \theta) = (0.618, 1.584, 3.85)$, $(0.661, 0.710, 8.837)$ respectively.

Figure 3. The 2nd and 3rd columns are samples from the model-

base method and VPM respectively. Rows (from top to bottom) correspond to data sets: 2gauss, funnel, kidney, banana.

pairs as input and adjusts the sample importance according
to the learned ratio. As we can see, after each MCMC step,
VPM is able to post-process the data and further reduce
MMD by applying the ratio. The improvement is consistent
along different MCMC steps across different datasets.

We conduct experiments on the (discrete) Taxi environment
as in Liu et al. (2018), and the challenging (continuous)
environments including the Reacher, HalfCheetah and Ant.

Taxi is a gridworld environment in which the agent navigates
to pick up and drop off passengers in specific locations. The
target and behavior policies are set as in Liu et al. (2018). For
the continuous environments, the Reacher agent tries to
reach a specified location by swinging an robotic arm, while
the HalfCheetah/Ant agents are complex robots that try to
move forward as much as possible. The target policy is a
pre-trained PPO or A2C neural network, which produces a
Gaussian action distribution $\mathcal{N}(m_i, \Sigma_i)$. The behavior
policy is the same as target policy but using a larger action
variance $\Sigma_b = (1-\alpha)\Sigma_t + 2\alpha\Sigma_t$, $\alpha \in (0, 1]$. We collect $T$
trajectories of $n$ steps each, using the behavior policy.

We compare VPM to a model-based method that estimates
both the transition $T$ and reward $R$ functions. Using behav-
ior cloning, we also compare to the trajectory-wise and step-
wise weighted importance sampling (WIST,WISS) (Precup et al., 2001), as well as Liu et al. (2018) with their public code for the Taxi environment.

The results are shown in Fig. 5. The x-axes are different
configurations and the y-axes are the log Mean Square
VPM can work using different learning rates around the default Adam learning rate of 0.001. Even though large learning rate (e.g., 0.003) seems to converge faster, its final solution can be noisy. We can see that VPM can work using different learning rates around the default Adam learning rate of 0.001.

Regularization. Finally, we investigate the effect of the regularization parameter \( \lambda \). Intuitively, \( \lambda \) controls the capability of the dual variable \( v \) in Eq. (13). The results are shown in Fig. 6c. Although different \( \lambda \) values can have different convergence speeds, their final solutions can achieve low MMD given sufficient iterations, as suggested by Theorem 1.

5.5. Ablation Study

In this section, we conduct an ablation study to show that VPM is robust to different choices of the parameters. Fig. 6 shows the MMD curves for the MCMC funnel dataset in Section 5.3, using different learning rates, number of inner optimization steps and the regularization \( \lambda \). Other datasets show similar trends.

Learning rates. In all experiments, we use Adam optimizer (Kingma and Ba, 2014). Fig. 6a shows the convergent behaviour with different learning rates in \{0.0003, 0.0006, 0.001, 0.003\}. The algorithm can take a longer time to converge when using a small learning rate. Even though large learning rate (e.g., 0.003) seems to converge faster, its final solution can be noisy. We can see that VPM can work using different learning rates around the default Adam learning rate of 0.001.

Number of inner optimization steps. Recall that in each power iteration, VPM solves an inner optimization Eq. (15). Fig. 6b shows the the effect of different number of inner optimization steps \( M \). Larger \( M \) can produce more accurate power iteration and converge faster in terms of number of power iterations, but the time per iteration will also increase accordingly. If \( M \) is too small (e.g., 3), the learning can be unstable and the final ratio network can be inaccurate. Due to the damped update, the error in each power iteration can be controlled effectively and VPM can converge to the optimal ratio as long as \( M \) is reasonably large.

6. Conclusion

We have formally considered the problem of estimating stationary distribution of an ergodic Markov chain using a fixed set of transition data. We extended a classical power iteration approach to the batch setting, using an equivalent variational reformulation of the update rule to bypass the agnosticism of transition operator and the intractable operations in a functional space, yielding a new algorithm Variational...
Figure 6. Ablation study. MMD versus number of power iterations for the funnel dataset. Default \((lr, M, \lambda) = (0.001, 10, 0.5)\).

**Power Method (VPM).** We characterized the convergence of VPM theoretically, and demonstrated its empirical advantages for improving existing methods on several important problems such as queueing, solving SDEs, post-processing MCMC and behavior-agnostic off-policy evaluation.

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Appendix

A. Consistency of the Objectives

Theorem 1 (Normalization of solution) If $\mathbb{E}_p[\tau_t] = 1$, then for any $\lambda > 0$, the estimator (13) has the same solution as (12), hence $\mathbb{E}_p[\tau_{t+1}] = 1$.

Proof Taking derivative of the objective function in (12) and setting it to zero, we can see that the unconstrained solution is $\frac{T_{\pi_t}}{p}$. Moreover, it satisfies the constraint when $\mathbb{E}_p[\tau_t] = 1$: we can rewrite $\tau_t = \frac{\mu_t}{p}$ for some distribution $\mu_t$ and $\mathbb{E}_p \left[ \frac{T_{\pi_t}}{p} \right] = \int \mathcal{T}(x')(x) \mu_t(x) dx dx' = 1$.

We just need to show $\frac{T_{\pi_t}}{p}$ is also the solution to (13). First, note that for any primal $\tau$, the optimal dual $v$ can be attained at $v = \frac{1}{\lambda} (\mathbb{E}_p[\tau] - 1)$. Plugging it to (13), we have for any $\lambda > 0$

$$
\min_{\tau \geq 0} \frac{1}{2} \mathbb{E}_{p(x')}[\tau^2(x')] - \mathbb{E}_{T_p(x,x')}[\tau_t(x)\tau(x')] + \frac{1}{2\lambda}(\mathbb{E}_p[\tau] - 1)^2 \\
\geq \min_{\tau \geq 0} \frac{1}{2} \mathbb{E}_{p(x')}[\tau^2(x')] - \mathbb{E}_{T_p(x,x')}[\tau_t(x)\tau(x')] + \min_{\tau \geq 0} \frac{1}{2\lambda}(\mathbb{E}_p[\tau] - 1)^2 \\
= -\frac{1}{2\lambda}\mathbb{E}_p \left[ \left( \frac{T_{\pi_t}}{p} \right)^2 \right].
$$

This lower bound is attainable by plugging $\tau = \frac{T_{\pi_t}}{p}$ in (13). Finally, we conclude the proof by noticing that (13) is strictly convex so the optimal solution is unique.

B. Convergence Analysis

Let $(X, \Sigma, \nu)$ be a measure space. The $L^2(X)$ space consists of measurable functions $f : X \mapsto \mathbb{R}$ such that $\|f\| = (\int |f|^2 d\nu)^{1/2} < \infty$. Suppose the initial $\mu_0 \in L^2(X)$, we want to show the converging behavior of the following damped iteration:

$$
\mu_t = (1 - \alpha_t)\mu_{t-1} + \alpha_t \widehat{T}\mu_{t-1} \\
= (1 - \alpha_t)\mu_{t-1} + \alpha_t \widehat{T}\mu_{t-1} + \alpha_t \epsilon
$$

with suitable step-sizes $\alpha_t \in (0, 1)$, where $\epsilon \in L^2(X)$ is a random field due to stochaticity in $\widehat{T}$. To this end, we will use the following lemma.

Lemma 3 For $\alpha \in \mathbb{R}$, $f, g \in L^2(X)$

$$
\|(1 - \alpha)f + \alpha g\|^2 = (1 - \alpha)\|f\|^2 + \alpha \|g\|^2 - \alpha(1 - \alpha)\|f - g\|^2.
$$

This can be proved by expanding both sides. Now we state our main convergence result.

Theorem 2 Suppose $\mu_0 \in L^2(X)$, the step size is $\alpha_t = 1/\sqrt{t}$, $\epsilon \in L^2(X)$ is a random field and $\mathcal{T}$ has a unique stationary distribution $\mu$. After $t$ iterations, define the probability distribution over the iterations as

$$
\Pr(R = k) = \frac{\alpha_k(1 - \alpha_k)}{\sum_{k'=1}^{t} \alpha_{k'}(1 - \alpha_{k'})}
$$

Then there exist some constants $C_1, C_2 > 0$ such that

$$
\mathbb{E} \left[ \|\mu_R - \mathcal{T}\mu_R\|^2 \right] \leq \frac{C_1}{\sqrt{t}} \|\mu_0 - \mu\|^2 + \frac{C_2 \ln t}{\sqrt{t}} \|\epsilon\|^2.
$$
where the expectation is taken over $R$. Consequently, $\mu_R$ converges to $\mu$ for ergodic $T$.

**Proof** Using Lemma 3 and the fact that $T$ is non-expansive, we have
\[
\|\mu_t - \mu\|^2 = \|(1 - \alpha_t)(\mu_{t-1} - \mu) + \alpha_t(T\mu_{t-1} - \mu) + \alpha_t\epsilon\|^2 \\
\leq \|(1 - \alpha_t)(\mu_{t-1} - \mu) + \alpha_t(T\mu_{t-1} - \mu)\|^2 + \alpha_t^2\|\epsilon\|^2 \\
\leq (1 - \alpha_t)\|\mu_{t-1} - \mu\|^2 + \alpha_t\|T\mu_{t-1} - \mu\|^2 - \alpha_t(1 - \alpha_t)\|\mu_{t-1} - T\mu_{t-1}\|^2 + \alpha_t^2\|\epsilon\|^2 \\
\leq \|\mu_{t-1} - \mu\|^2 - \alpha_t(1 - \alpha_t)\|\mu_{t-1} - T\mu_{t-1}\|^2 + \alpha_t^2\|\epsilon\|^2.
\]

Then telescoping sum gives
\[
0 \leq \|\mu_t - \mu\|^2 \leq \|\mu_0 - \mu\|^2 + \sum_{k=1}^{t} \alpha_k(1 - \alpha_k)\|\mu_k - T\mu_k\|^2.
\]

So
\[
\sum_{k=1}^{t} \alpha_k(1 - \alpha_k)\|\mu_k - T\mu_k\|^2 \leq \|\mu_0 - \mu\|^2 + \sum_{k=1}^{t} \alpha_k^2\|\epsilon\|^2.
\]

Divide both sides by $\sum_{k=1}^{t} \alpha_k(1 - \alpha_k)$ (taking expectation over iterations) gives
\[
\mathbb{E}[\|\mu_R - T\mu_R\|^2] = \sum_{k=1}^{t} \frac{\alpha_k(1 - \alpha_k)}{\sum_{k'=1}^{t} \alpha_{k'}} \|\mu_k - T\mu_k\|^2 \leq \frac{\|\mu_0 - \mu\|^2 + \sum_{k=1}^{t} \alpha_k^2\|\epsilon\|^2}{\sum_{k=1}^{t} \alpha_k(1 - \alpha_k)}.
\]

When $\alpha_t = 1/\sqrt{t}$, we have
\[
\sum_{k=1}^{t} \alpha_k^2\|\epsilon\|^2 = \sum_{k=1}^{t} \frac{1}{k}\|\epsilon\|^2 \leq (\ln t + 1)\|\epsilon\|^2
\]
\[
\sum_{k=4}^{t} \alpha_k(1 - \alpha_k) = \sum_{k=4}^{t} \frac{1}{\sqrt{k}} - \frac{1}{k} \geq \int_{4}^{t} \left( \frac{1}{\sqrt{k+1}} - \frac{1}{k+1} \right) dk = \Omega \left( t^{1/2} \right).
\]

So for big enough $t$, there exists $C_0 > 0$ such that
\[
\mathbb{E} \left[ \|\mu_R - T\mu_R\|^2 \right] \leq \frac{\|\mu_0 - \mu\|^2 + (\ln t + 1)\|\epsilon\|^2}{C_0\sqrt{t}},
\]
which leads to the the bound in the theorem and $\mathbb{E} \left[ \|\mu_R - T\mu_R\|^2 \right] = \tilde{O} \left( t^{-1/2} \right)$. Additionally, since $T$ has a unique stationary distribution $\mu = T\mu$, we have $\mu_R$ converges to $\mu$.

### C. Application to Off-policy Stationary Ratio Estimation

We provide additional details describing how the variational power method we have developed in the main body of the paper can be applied to the behavior-agnostic off-policy estimation problem (OPE). The general framework has been introduced in Section 1 and the implementation for the undiscounted case ($\gamma = 1$) is demonstrated in Section 5.4. Specifically, given a sample $D = \{ (s, a, r, s') \}_{i=1}^{n}$ from the behavior policy, we compose each transition in $D$ with a target action $a' \sim \pi (\cdot | s')$. Denoting $x = (s, a)$, the data set can be expressed as $D = \{ (x, x') \}_{i=1}^{n}$. Applying the proposed VPM with $T(x'|x)$, we can estimate $\frac{\mu(x|a)}{\pi(x|a)}$. Here the $\mu(s, a) = d_x(s)\pi(a|s)$ consists of the stationary state occupancy $d_x$ and the target policy $\pi$, while $p(s, a)$ is the data-collecting distribution. Then the average accumulated reward can be obtained via (3).

Here we elaborate on how the discounted case (i.e., $\gamma \in (0, 1)$) can be handled by our method. We first introduce essential quantities similar to the undiscounted setting. For a trajectory generated stochastically using policy $\pi$ from an initial state $s_0$: $(s_0, a_0, r_0, s_1, a_1, r_1, \ldots)$, where $a_t \sim \pi (\cdot | s_t)$, $s_{t+1} \sim P (\cdot | s_t, a_t)$ and $r_t \sim R(s_t, a_t)$, the the policy value is
\[
\rho_\gamma (\pi) := (1 - \gamma) \mathbb{E}_{s_0 \sim \mu_0, a \sim \pi, s', P} \left[ \sum_{t=0}^{\infty} \gamma^t r_t \right],
\]
where $\mu_0$ is the initial-state distribution. Denote

$$d_t^\gamma (s, a) = P \left( s_t = s, a_t = a \left[ \begin{array}{l} s_0 \sim \mu_0, \forall i < t, \\ a_i \sim \pi (s_i), \\ s_{i+1} \sim P (s_{i+1} | s_i, a_i) \end{array} \right] \right).$$

The discounted occupancy distribution is

$$\mu_\gamma (s, a) := (1 - \gamma) \sum_{t=0}^{\infty} \gamma^t d_t^\gamma (s, a).$$

Then, we can re-express the discounted accumulated reward via $\mu_\gamma$ and the stationary density ratio,

$$\rho_\gamma (\pi) = E_{(s,a) \sim \mu_\gamma (s,a)} [r(s,a)] = E_{(s,a) \sim \rho (s,a)} \left[ \frac{\mu_\gamma (s,a)}{\rho (s,a)} r(s,a) \right].$$

The proposed VPM is applicable to estimating the density ratio in this discounted case. Denoting $x = (s, a), x' = (s', a')$ respectively for notational consistency, we expand $\mu_\gamma$ and use the definition of $d_t^\gamma$:

$$\mu_\gamma (s', a') = (1 - \gamma) \mu_0 (s') \pi (a' | s') + \gamma \int \pi (a' | s') P (s' | s, a) \mu_\gamma (s, a) ds \, da$$

$$\implies \rho (x') \tau^* (x') = (1 - \gamma) \mu_0 \pi (x') + \gamma \int T_p (x, x') \tau^* (x) \, dx,$$

where $\mu_0 \pi (x') = \mu_0 (s') \pi (a' | s')$ and $T_p (x, x') = \pi (a' | s') P (s' | s, a) \rho (s, a)$.

It has been shown that the RHS of (22) is contractive (Sutton and Barto, 1998; Mohri et al., 2012), therefore, the fix-point iteration,

$$\rho (x') \tau_{t+1} (x') = (1 - \gamma) \mu_0 \pi (x') + \gamma \int T_p (x, x') \tau_t (x) \, dx,$$

converges to the true $\tau$ as $t \to \infty$, provided the update above is carried out exactly. Compared to (6), we can see that the RHS of (23) is now a mixture of $\mu_0 \pi$ and $T_p$, with respective coefficients $(1 - \gamma)$ and $\gamma$.

Similarly, we construct the $(t+1)$-step variational update as

$$\tau_{t+1} = \arg \min_{\tau \geq 0} \frac{1}{2} E_{p(x')} \left[ \tau^2 (x') \right] - \gamma E_{T_p (x,x')} [\tau_t (x) \tau (x')] - (1 - \gamma) E_{\mu_0 p(x')} [\tau (x')] + \lambda (E_p [\tau] - 1)^2 .$$

Compared to (11), we see that the main difference is the third term of (24) involves the initial distribution. As $\gamma \to 1$, (24) reduces to (11).

D. Experiment Details

Here we provide additional details about the experiments. In all experiments, the regularization $\lambda = 0.5$ and the optimizer is Adam with $\beta_1 = 0.5$. The $\tau$ model is a neural network with 2 hidden layers of 64 units each with ReLU activation and softplus activation for the output.

D.1. Queueing

For Geo/Geo/1 queue, when the arrival and finish probabilities are $q_a, q_f \in (0, 1)$ respectively with $q_f > q_a$, the stationary distribution is $P (X = i) = (1 - \rho) \rho^i$ where $\rho = q_a (1 - q_f) / [q_f (1 - q_a)]$ (Serfozo, 2009, Sec.1.11). The defaults are $(n, q_a, q_f) = (100, 0.8, 0.9)$ for the figures. $\rho$ is called traffic intensity in the queueing literature and we set $B = \lfloor 40 \rho \rfloor$ in the experiment. The mean and standard error of the log KL divergence is computed based on 10 runs. We conduct closed-form update for 1000 steps. As for the model-based method, we simulate the transition chain for 200 steps to attain the estimated stationary distribution.
D.2. Solving SDEs

Using initial samples are uniformly spaced in $[0, 1]$, we run the Euler-Maruyama (EM) method and evaluate the MMD along the path. The $\tau$ model is a neural network with 2 hidden layers of 64 units each with ReLU and Softplus for the final layer. Numbers of outer and inner steps are $T = 50, M = 10$. The learning rate is 0.0005. At each evaluation time step $t$, we use the most recent 1% of evolution data to train our model $\tau$. The plots are reporting the mean and standard deviation over 10 runs. For the phylogeny studies, the number of particles is $1k$ and $dt = 0.0005$ for the EM simulation, while the rest settings using $dt = 0.001$.

D.3. Post-processing MCMC

The potential functions are collected from several open-source projects$^{1,2}$. 50$k examples are sampled from the uniform distribution $p(x) = \text{Unif}(x; [-6, 6]^2)$, then transition each $x$ through an HMC operator (one leapfrog step of size 0.5). The model-based $T$ has a similar structure as $\tau$ except the final layer has 2D output without activation to estimate the Gaussian mean. The mini-batch size is $B = 1k$, the maximum number of power iterations $T = 150$ and the number of inner optimization steps is $M = 10$. The model-based $T$ is given the same number of iterations ($MT = 1500$). The learning rate is 0.001 for $\tau$ and 0.0005 for $T$. To compute the model-based sample, we apply the estimated transition 100 time steps. The MMD plot is based on a “true sample” of size $2k$ from the stationary distribution (estimated by 2$k$ HMC transition steps). The numbers are mean and standard deviation over 10 runs. The MMD is computed by the Gaussian kernel with the median pairwise distance as kernel width.

The quality of the transition kernel and the generated data is critical. Since $x$ and $x'$ are supposed to be related, we use an HMC kernel with one leap-frog step. The initial $x$ is effectively forgotten if using too many leap-frog steps. The main point is to show that our method can utilize the intermediate samples from the chain other than the final point. Moreover, to conform with Assumption 2, the potential functions are numerically truncated.

To verify the convergent behavior of our method, Fig. 7 shows how the ratio network improves as we train the model. It can be seen that the our method quickly concentrates its mass to the region with high potentials.

D.4. Off-policy Evaluation

Taxi is a $5 \times 5$ gridworld in which the taxi agent navigates to pick up and drop off passengers in specific locations. It has a total of 2000 states and 6 actions. Each step incurs a $-1$ reward unless the agent picks up or drops off a passenger in the correct locations. The behavior policy is set to be the policy after 950 Q-learning iterations and the target policy is the policy after 1000 iterations. In the Taxi experiment, given a transition $(s, a, s')$, instead of sampling one single action from the target policy $\pi(a'|s')$, we use the whole distribution $\pi(\cdot|s')$ for estimation. We conduct closed-form update in the power method and the number of steps is $T = 100$.

Continuous experiments. The environments are using the open-source PyBullet engine. The state spaces are in $\mathbb{R}^9, \mathbb{R}^{26}, \mathbb{R}^{28}$ respectively and the action spaces are in $\mathbb{R}^2, \mathbb{R}^6, \mathbb{R}^8$ respectively. the $\tau$ model is the same as in the SDE

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$^1$https://github.com/kamenbliznashki/normalizing_flows
$^2$https://github.com/kevin-w-li/deep-kexpfam
experiment (except for input, which depends on the environment). $T = 200, M = 10, B = 1k$ and the learning rate is 0.0003. The model-based method has a similar neural network structure and is trained for $MT = 2k$ steps with a learning rate of 0.0005. The target policy for the Reacher agent is pretrained using PPO while the HalfCheetah and Ant agents are pretrained using A2C (all with two hidden layers of 64 units each).

The results in the plots are mean and standard deviation from 10 runs.