
Collapsed amortized variational inference for switching nonlinear dynamical systems

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Abstract

We propose an efficient inference method for switching nonlinear dynamical systems. The key idea is to learn an inference network which can be used as a proposal distribution for the continuous latent variables, while performing exact marginalization of the discrete latent variables. This allows us to use the reparameterization trick, and apply end-to-end training with stochastic gradient descent. We show that the proposed method can successfully segment time series data, including videos and 3D human pose, into meaningful “regimes” by using the piece-wise nonlinear dynamics.

1. Introduction

Consider looking down on an airplane flying across country or a car driving through a field. The vehicle’s motion is composed of straight, linear dynamics and curving, nonlinear dynamics. An example is illustrated in fig. 1(a). In this paper, we propose a new inference algorithm for fitting switching nonlinear dynamical systems (SNLDS), which can be used to segment time series of high-dimensional signals, such as videos, or lower dimensional signals, such as (x,y) locations, into meaningful discrete temporal “modes” or “regimes”. The transitions between these modes may correspond to the changes in internal goals of the agent (e.g., a mouse switching from running to resting, as in Johnson et al. (2016)) or may be caused by external factors (e.g., changes in the road curvature). Discovering such discrete modes is useful for scientific applications (c.f., Wiltchko et al. (2015); Linderman et al. (2019); Sharma et al. (2018)) as well as for planning in the context of hierarchical reinforcement learning (c.f., Kipf et al. (2019)).

Extensive previous work, some of which we review in Sec-

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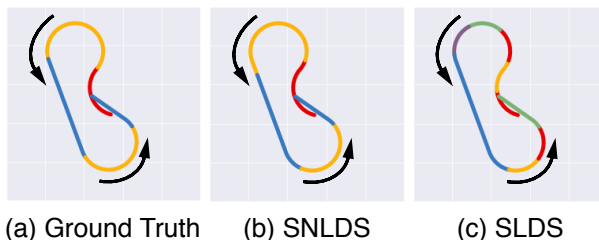


Figure 1. (a): Trajectory and ground truth segmentation of a particle. The direction of motion is indicated by the arrows. Blue is moving straight, yellow is turning counter-clockwise, red is turning clockwise. (c) Segmentation learned by our SNLDS model. (d) Segmentation learned by a SLDS model. Note that to model the nonlinear dynamics, the SLDS model needs to use more segments.

tion 3, explores modeling temporal data using various forms of state space models (SSM). We are interested in the class of SSM which has both discrete and continuous latent variables, which we denote by s_t and \mathbf{z}_t , where t is the discrete time index. The discrete state, $s_t \in \{1, 2, \dots, K\}$, represents the mode of the system at time t , and the continuous state, $\mathbf{z}_t \in \mathbb{R}^H$, represents other factors of variation, such as location and velocity. The observed data is denoted by $\mathbf{x}_t \in \mathbb{R}^D$, and can either be a low dimensional projection of \mathbf{z}_t , such as the current location, or a high dimensional signal that is informative about \mathbf{z}_t , such as an image. We may optionally have observed input or control signals $\mathbf{u}_t \in \mathbb{R}^U$, which drive the system in addition to unobserved stochastic noise. We are interested in learning a generative model of the form $p_{\theta}(s_{1:T}, \mathbf{z}_{1:T}, \mathbf{x}_{1:T} | \mathbf{u}_{1:T})$ from partial observations, namely $(\mathbf{x}_{1:T}, \mathbf{u}_{1:T})$. This requires inferring the posterior over the latent states, $p_{\theta}(s_{1:T}, \mathbf{z}_{1:T} | \mathbf{v}_{1:T})$, where $\mathbf{v}_t = (\mathbf{x}_t, \mathbf{u}_t)$ contains all the visible variables at time t . For training purposes, we usually assume that we have multiple such trajectories, possibly of different lengths, but we omit the sequence indices from our notations for simplicity. This problem is very challenging, because the model contains both discrete and continuous latent variables (a so-called “hybrid system”) and has nonlinear transition and observation models.

The main contribution of our paper is a new way to perform efficient approximate inference in this class of SNLDS

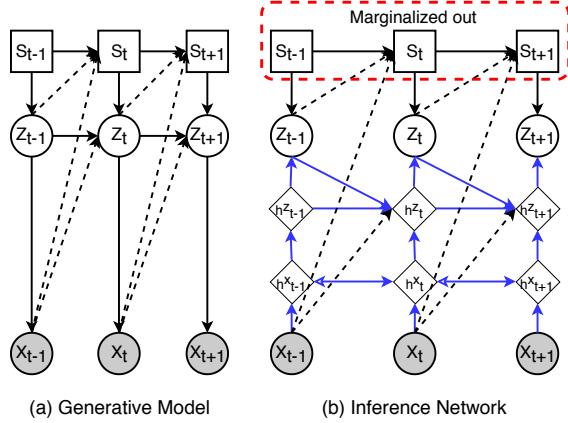


Figure 2. **Left:** Illustration of the generative model. Dashed arrows indicate optional connections. **Right:** Illustration of the inference network. Solid black arrows share parameters θ with the generative model, solid blue arrows have parameters ϕ that are unique to q . The diamonds represent deterministic nodes computed with RNNs: h_t^x is a bidirectional RNN applied to $\mathbf{x}_{1:T}$, and h_t^z is a unidirectional RNN applied to \mathbf{h}_{t-1}^x and \mathbf{z}_{t-1} .

models. The key observation is that, conditioned on knowing $\mathbf{z}_{1:T}$ as well as $\mathbf{v}_{1:T}$, we can marginalize out $s_{1:T}$ in linear time using the forward-backward algorithm. In particular, we can efficiently compute the gradient of the log marginal likelihood, $\nabla \sum_{s_{1:T}} \log p(s_{1:T} | \tilde{\mathbf{z}}_{1:T}, \mathbf{v}_{1:T})$, where $\tilde{\mathbf{z}}_{1:T}$ is a posterior sample that we need for model fitting. To efficiently compute posterior samples $\tilde{\mathbf{z}}_{1:T}$, we learn an amortized inference network $q_\phi(\mathbf{z}_{1:T} | \mathbf{v}_{1:T})$ for the “collapsed” NLDS model $p(\mathbf{z}_{1:T}, \mathbf{v}_{1:T})$. Collapsing removes the discrete variables, and allows us to use reparameterization for the continuous state \mathbf{z} . These tricks let us use stochastic gradient descent (SGD) to learn p and q jointly, as explained in Section 4. We can then use q as a proposal distribution inside a Rao-Blackwellised particle filter (Doucet et al., 2000), although in this paper, we just use a single posterior sample, as is common with Variational AutoEncoders (VAEs, Kingma & Welling (2014); Rezende et al. (2014)).

Although the above “trick” allows us efficiently perform inference and learning, we find that in challenging problems (e.g., when the dynamical model $p(\mathbf{z}_t | \mathbf{z}_{t-1}, \mathbf{v}_t)$ is very flexible), the model uses only a single discrete latent variable and does not perform mode switching. This is a form of “posterior collapse”, similar to VAEs, where powerful decoders can cause the latent variables to be ignored, as explained in Alemi et al. (2018). Our second contribution is a new form of posterior regularization, which prevents the aforementioned problem and results in a significantly improved segmentation.

We apply our method, as well as various existing methods, to two previously proposed low-dimensional time series

segmentation problems, namely a 1d bouncing ball, and a 2d moving arm. In the 1d case, the dynamics are piecewise linear, and all methods perform perfectly. In the 2d case, the dynamics are piecewise nonlinear, and we show that our method infers much better segmentation than previous approaches for comparable computational cost. We also apply our method to a simple new video dataset (see fig. 1 for an example) and sequences of human poses, and find that it performs well, provided we use our proposed regularization method.

In summary, our main contributions are

- Learning switching nonlinear dynamical systems parameterized with neural networks by marginalizing out discrete variables.
- Using entropy regularization and annealing to encourage discrete state transitions.
- Demonstrating that the discrete states of nonlinear models are more interpretable.

2. Model Formulation

We consider the following state space model:

$$p_\theta(\mathbf{x}, \mathbf{z}, \mathbf{s}) = p(\mathbf{x}_1 | \mathbf{z}_1) p(\mathbf{z}_1 | s_1) \prod_{t=2}^T p(\mathbf{x}_t | \mathbf{z}_t) p(\mathbf{z}_t | \mathbf{z}_{t-1}, s_t) p(s_t | s_{t-1}, \mathbf{x}_{t-1}), \quad (1)$$

where $s_t \in \{1, \dots, K\}$ is the discrete hidden state, $\mathbf{z}_t \in \mathbb{R}^H$ is the continuous hidden state, and $\mathbf{x}_t \in \mathbb{R}^D$ is the observed output, as in fig. 2(a). For notational simplicity, we ignore any observed inputs or control signals \mathbf{u}_t , but these can be trivially added to our model.

Note that the discrete state influences the latent dynamics \mathbf{z}_t , but we could trivially make it influence the observations \mathbf{x}_t as well. More interesting are which edges we choose to add as parents of the discrete state s_t . We consider the case where s_t depends on the previous discrete state, s_{t-1} , as in a hidden Markov model (HMM), but also depends on the previous observation, \mathbf{x}_{t-1} . This means that state changes do not have to happen “open loop”, but instead may be triggered by signals from the environment. We can trivially depend on multiple previous observations; we assume first-order Markov for simplicity. We can also condition \mathbf{z}_t on \mathbf{x}_{t-1} , and s_t on \mathbf{z}_{t-1} . It is straightforward to handle such additional dependencies (shown by dashed lines in fig. 2(a)) in our inference method, which is not true for some of the other methods we discuss below.

The functional form of the conditional probability distributions also need to be specified. Common forms in the

literature are

$$p(\mathbf{x}_t|\mathbf{z}_t) = \mathcal{N}(\mathbf{x}_t|f_x(\mathbf{z}_t), \mathbf{R}), \quad (2)$$

$$p(\mathbf{z}_t|\mathbf{z}_{t-1}, s_t = k) = \mathcal{N}(\mathbf{z}_t|f_z(\mathbf{z}_{t-1}, k), \mathbf{Q}), \quad (3)$$

$$p(s_t|s_{t-1} = j, \mathbf{x}_{t-1}) = \text{Cat}(s_t|\mathcal{S}(f_s(\mathbf{x}_{t-1}, j))), \quad (4)$$

where $\mathcal{N}(\cdot, \cdot)$ is a multivariate Gaussian distribution, $\text{Cat}(\cdot)$ is a categorical distribution, and $\mathcal{S}(\cdot)$ is a softmax function. $\mathbf{R} \in \mathbb{R}^{D \times D}$ and $\mathbf{Q} \in \mathbb{R}^{H \times H}$ are learned covariance matrices for the Gaussian emission and transition noise. Typical assumptions are that f_x is linear or non-linear, and $f_{z,s}$ are linear, e.g., Linderman et al. (2017); Linderman & Johnson (2017); Johnson et al. (2016); Chow & Zhang (2013), as discussed in Section 3. In contrast, our method may use linear or non-linear functions for f_z and may use any reparameterizable distribution for $p(\mathbf{z}_t|\mathbf{z}_{t-1}, s_t = k)$.

3. Related Work

3.1. State space models

As introduced in Section 2, if f_x and f_z are both linear, and $p(s_t|s_{t-1})$ is first-order Markov without dependence on \mathbf{z}_{t-1} , the model is called a switching linear dynamical system (SLDS). If we allow s_t to depend on \mathbf{z}_{t-1} , the model is called a recurrent SLDS (Linderman et al., 2017; Linderman & Johnson, 2017). We will compare to rSLDS in our experiments.

If f_z is linear, but f_x is nonlinear, the model is sometimes called a “structured variational autoencoder” (SVAE) (Johnson et al., 2016), although that term is ambiguous, since there are many forms of structure. We will compare to SVAEs in our experiments.

If f_z is a linear function, the model may need to use many discrete states in order to approximate the nonlinear dynamics, as illustrated in fig. 1(d). We therefore allow f_z (and f_x) to be nonlinear. The resulting model is called a switching nonlinear dynamical system (SNLDS), or Nonlinear Regime-Switching State-Space Model (RSSSM) (Chow & Zhang, 2013). Prior work typically assumes f_z is a simple nonlinear model, such as polynomial regression. If we let f_z be a very flexible neural network, there is a risk that the model will not need to use the discrete states at all. We discuss a solution to this in Section 4.3.

The discrete dynamics can be modeled as a semi-Markov process, where states have explicit durations (see e.g., Duong et al. (2005); Chiappa (2014)). One recurrent, variational version is the recurrent hidden semi-Markov model (rHSMM, Dai et al. (2017)). Rather than having a stochastic continuous variable at every timestep, rHSMM instead stochastically switches between states with deterministic dynamics. The semi-Markovian structures in this work have an explicit maximum duration, which makes

them less flexible. A revised method, (Kipf et al., 2019), is able to better handle unknown durations, but produces a potentially infinite number of distinct states, each with deterministic dynamics. The deterministic dynamics of these works may limit their ability to handle noise.

3.2. Variational inference and learning

A common approach to learning latent variable models is to maximize the evidence lower bound (ELBO) on the log marginal likelihood (see e.g., Blei et al. (2016)). This is given by $\log p(\mathbf{x}) \leq \mathcal{L}(\mathbf{x}; \theta, \phi) = \mathbb{E}_{q_\phi(\mathbf{z}, \mathbf{s}|\mathbf{x})} [\log p_\theta(\mathbf{x}, \mathbf{z}, \mathbf{s}) - \log q_\phi(\mathbf{z}, \mathbf{s}|\mathbf{x})]$, where $q_\phi(\mathbf{z}, \mathbf{s}|\mathbf{x})$ is an approximate posterior.¹ Rather than computing q using optimization for each \mathbf{x} , we can train an inference network, $f_\phi(\mathbf{x})$, which emits the parameters of q . This is known as “amortized inference” (see e.g., Kingma & Welling (2014)).

If the posterior distribution $q_\phi(\mathbf{z}, \mathbf{s}|\mathbf{x})$ is reparameterizable, then we can make the noise independent of ϕ , and hence apply the standard SGD to optimize θ, ϕ . Unfortunately, the discrete distribution $p(\mathbf{s}|\mathbf{x})$ is not reparameterizable. In such cases, we can either resort to higher variance methods for estimating the gradient, such as REINFORCE, or we can use continuous relaxations of the discrete variables, such as Gumbel Softmax (Jang et al., 2017) / Concrete (Maddison et al., 2017b), or combining both, such as REBAR (Tucker et al., 2017). We will compare against a Gumbel-Softmax version of SNLDS in our experiments. The continuous relaxation approach was applied to SLDS models in (Becker-Ehmck et al., 2019) and HSMM models in (Liu et al., 2018a; Kipf et al., 2019). However, the relaxation can lose many of the benefits of having discrete variables (Le et al., 2019). Relaxing the distribution to a soft mixture of dynamics results in the Kalman VAE (KVAE) model of Fraccaro et al. (2017). We will compare to KVAE in our experiments. A concern is that soft models may use a mixture of dynamics for distinct ground truth states rather than assigning a distinct mode of dynamics at each step as a discrete model must do. In Section 4, we propose a new method to avoid these issues, in which we collapse out \mathbf{s} so that the entire model is differentiable.

The SVAE model of Johnson et al. (2016) also uses the forward-backward algorithm to compute $q(\mathbf{s}|\mathbf{v})$; however, they assume the dynamics of \mathbf{z} are linear Gaussian, so they can apply the Kalman smoother to compute $q(\mathbf{z}|\mathbf{v})$. Assuming linear dynamics can result in over-segmentation, as we have discussed. A forward-backward algorithm is applied once to the discrete states and once to the continuous states to compute a structured mean field posterior $q(\mathbf{z})q(\mathbf{s})$. In

¹In the case of sequential models, we can create tighter lower bounds using methods such as FIVO (Maddison et al., 2017a), although this is orthogonal to our work.

contrast, we perform approximate inference for \mathbf{z} using one forward-backward pass of a non-linear network and then exact inference for \mathbf{s} using a second pass, as we explain in Section 4.

3.3. Monte Carlo inference

There is a large literature on using sequential Monte Carlo methods for inference in state space models as particle filters (see e.g., Doucet & Johansen (2011)). When the model is nonlinear (as in our case), we may need many particles to get a good approximation, which can be expensive. We can often get better (lower variance) approximations by analytically marginalizing out some of the latent variables; the resulting method is called a ‘‘Rao Blackwellised particle filter’’ (RBPF).

Prior work (e.g., Doucet et al. (2001)) has applied RBPF to SLDS models, leveraging the fact that it is possible to marginalize out $p(\mathbf{z}|\mathbf{s}, \mathbf{v})$ using the Kalman filter. It is also possible to compute the optimal proposal distribution for sampling from $p(\mathbf{s}_t|\mathbf{s}_{t-1}, \mathbf{v})$ in this case. However, this relies on the model being conditionally linear Gaussian. In contrast, we marginalize out $p(\mathbf{s}|\mathbf{z}, \mathbf{v})$, so we can handle nonlinear models. In this case, it is hard to compute the optimal proposal distribution for sampling from $p(\mathbf{z}_t|\mathbf{z}_{t-1}, \mathbf{v})$, so instead we use variational inference to learn to approximate this.

4. Method

4.1. Inference

We use the following variational posterior: $q_{\phi, \theta}(\mathbf{z}, \mathbf{s}|\mathbf{x}) = q_{\phi}(\mathbf{z}|\mathbf{x})p_{\theta}(\mathbf{s}|\mathbf{z}, \mathbf{x})$, where $p_{\theta}(\mathbf{s}|\mathbf{z}, \mathbf{x})$ is the exact posterior (under the generative model) computed using the forward-backward algorithm, and $q_{\phi}(\mathbf{z}|\mathbf{x})$ is defined below. To compute $q_{\phi}(\mathbf{z}|\mathbf{x})$, we first process $\mathbf{x}_{1:T}$ through a bidirectional RNN, whose state at time t is denoted by \mathbf{h}_t^x . We then use a forward (causal) RNN, whose state denoted by \mathbf{h}_t^z , to compute the parameters of $q(\mathbf{z}_t|\mathbf{z}_{1:t-1}, \mathbf{x}_{1:T})$, where the hidden state is computed based on \mathbf{h}_{t-1}^z and \mathbf{h}_t^x . This gives the following approximate posterior: $q_{\phi}(\mathbf{z}_{1:T}|\mathbf{x}_{1:T}) = \prod_t q(\mathbf{z}_t|\mathbf{z}_{1:t-1}, \mathbf{x}_{1:T}) = \prod_t q(\mathbf{z}_t|\mathbf{h}_t^z)$. See fig. 2(b) for an illustration.

We can draw a sample $\mathbf{z}_{1:T} \sim q_{\phi}(\mathbf{z}|\mathbf{x})$ sequentially, and then treat this as ‘‘soft evidence’’ for the HMM model. We can use a forward-backward algorithm to integrate out the discrete variables and compute gradients as Eqn. 9. This approach offers a great amount of modeling flexibility. The only constraints are that $q(\mathbf{z}|\mathbf{x})$ is differentiable and that the discrete variables can be integrated out of $p(\mathbf{x}, \mathbf{z})$ to also make it differentiable. The continuous transition dynamics can be linear, a simple non-linear kernel function, or a complicated function parameterized as an artificial neural

network or RNN. The discrete transitions can depend on observed data, control signals, or the soft evidence samples, $\mathbf{z}_{1:T}$. The flexibility of this formulation allows it to cover the model families of multiple prior works (Johnson et al., 2016; Linderman et al., 2017; Chow & Zhang, 2013; Doucet et al., 2000) with a single core algorithm.

4.2. Learning

The evidence lower bound (ELBO) for a single sequence \mathbf{x} is given by

$$\begin{aligned} \mathcal{L}_{\text{ELBO}} &= \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x})p_{\theta}(\mathbf{s}|\mathbf{z}, \mathbf{x})} [\log p_{\theta}(\mathbf{x}, \mathbf{z})p_{\theta}(\mathbf{s}|\mathbf{x}, \mathbf{z}) \\ &\quad - \log q_{\phi}(\mathbf{z}|\mathbf{x})p_{\theta}(\mathbf{s}|\mathbf{z}, \mathbf{x})] \end{aligned} \quad (5)$$

$$= \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x})} [\log p_{\theta}(\mathbf{x}, \mathbf{z}) - \log q_{\phi}(\mathbf{z}|\mathbf{x})] \quad (6)$$

Because $q_{\phi}(\mathbf{z})$ is reparameterizable, we can approximate the gradient as follows:

$$\nabla_{\theta, \phi} \mathcal{L}(\theta, \phi) \approx \nabla_{\theta, \phi} \log p_{\theta}(\mathbf{x}, \tilde{\mathbf{z}}) - \nabla_{\phi} \log q_{\phi}(\tilde{\mathbf{z}}|\mathbf{x}) \quad (7)$$

where $\tilde{\mathbf{z}}$ is a sample from the variational proposal $\tilde{\mathbf{z}} \sim q_{\phi}(\tilde{\mathbf{z}}_1|\mathbf{x}_{1:T}) \prod_{t=2}^T q_{\phi}(\tilde{\mathbf{z}}_t|\tilde{\mathbf{z}}_{t-1}, \mathbf{x}_{1:T})$. The second term can be computed by applying backpropagation through time to the inference RNN. The first term can be estimated by applying auto-differentiation on the following term

$$\begin{aligned} &\sum_{t=2}^T \sum_{j,k} \gamma_t^2(j, k) [\log B_t(k)A_t(j, k)] \\ &\quad + \sum_k \gamma_1^1(k) [\log B_1(k)\pi(k)] \end{aligned} \quad (8)$$

where

$$\begin{aligned} A_t(j, k) &= p(s_t = j | s_{t-1} = k, \mathbf{x}_{t-1}) \\ B_t(k) &= p(\mathbf{x}_t | \mathbf{z}_t) p(\mathbf{z}_t | \mathbf{z}_{t-1}, s_t = k) \quad (t > 1) \\ B_1(k) &= p(\mathbf{x}_1 | \mathbf{z}_1) p(\mathbf{z}_1 | s_1 = k) \\ \gamma_t^2(j, k) &= p(s_t = k, s_{t-1} = j | \mathbf{x}_{1:T}, \mathbf{z}_{1:T}) \\ \gamma_t^1(k) &= p(s_t = k | \mathbf{x}_{1:T}, \mathbf{z}_{1:T}) \end{aligned}$$

In the appendix, we show that auto-differentiation of the first term is equivalent to

$$\begin{aligned} \nabla_{\theta, \phi} \log p_{\theta}(\mathbf{x}, \tilde{\mathbf{z}}) &= \\ &\sum_{t=2}^T \sum_{j,k} \gamma_t^2(j, k) \nabla [\log B_t(k)A_t(j, k)] \\ &\quad + \sum_k \gamma_1^1(k) \nabla [\log B_1(k)\pi(k)] \end{aligned} \quad (9)$$

4.3. Entropy regularization and temperature annealing

When using expressive nonlinear functions (e.g. an RNN or MLP) to model $p(\mathbf{z}_t|\mathbf{z}_{t-1}, s_t)$, we sometimes found that

the model only used a single discrete state, analogous to posterior collapse in VAEs (see e.g., Alemi et al. (2018)). The forward-backward algorithm causes this behavior because low-probability states are never receive gradients and never improved. Prior work, such as (Linderman et al., 2017), solves this problem by multi-step pretraining to ensure the model is well initialized. To encourage the model to utilize multiple states, we add an additional regularizing term to the ELBO that penalizes the KL divergence between the state posterior at each time step and a uniform prior $p_{\text{prior}}(s_t = k) = 1/K$ (Burke et al., 2019). We call this a cross-entropy regularizer:

$$\mathcal{L}_{\text{CE}} = \sum_{t=1}^T \text{KL}(p_{\text{prior}}(s_t) || p(s_t | \mathbf{z}_{1:T}, \mathbf{x}_{1:T})). \quad (10)$$

Our overall objective now becomes

$$\mathcal{L}(\theta, \phi) = \mathcal{L}_{\text{ELBO}}(\theta, \phi) - \beta \mathcal{L}_{\text{CE}}(\theta, \phi), \quad (11)$$

where $\beta > 0$ is a scaling factor.

To further smooth the optimization problem, we apply temperature annealing to the discrete state transitions, as follows: $p(s_t = k | s_{t-1} = j, \mathbf{x}_{t-1}) = \mathcal{S}(\frac{p(s_t=k | s_{t-1}=j, \mathbf{x}_{t-1})}{\tau})$, where τ is the temperature.

At the beginning stage of training, β , τ are set to large values. Doing so ensures that all states are visited, and can explain the data well. Over time, we reduce the regularizers to 0 and temperature to 1, according to a fixed annealing schedule. Initially, the regularization induces correlated dynamics because each state needs to be used, but annealing allows the dynamics to decorrelate (See Appendix A.6 and c.f., Rose (1998)). The result is similar to multi-step pretraining but our approach works in a continuous end-to-end fashion.

5. Experiments

In this section, we compare our method to various other methods that have been recently proposed for time series segmentation using latent variable models. Since it is hard to evaluate segmentation without labels, we use three synthetic datasets where we know the ground truth for quantitative evaluation but we also qualitatively evaluate the segmentation on a real world dataset.

In each case, we fit the model to the data, and then estimate the most likely discrete hidden state at each time step, $\hat{s}_t = \text{argmax}_k q(s_t | \mathbf{x}_{1:T})$. Since the model is unidentifiable, the state labels have no meaning, so we post-process

Code and additional information: <https://sites.google.com/view/cavi-snlDs>.

them by selecting the permutation over labels that maximizes the F_1 score across frames. The F_1 score is the harmonic mean of precision and recall, $2 \times \text{precision} \times \text{recall} / (\text{precision} + \text{recall})$, where **precision** is the percentage of the predictions that match the ground truth states, and **recall** is the percentage of the ground truth states that match the predictions. We also compute the switching-point F_1 by only considering the frames where the ground truth state changes. This measure compliments the frame-wise F_1 , because it measures temporal specificity.

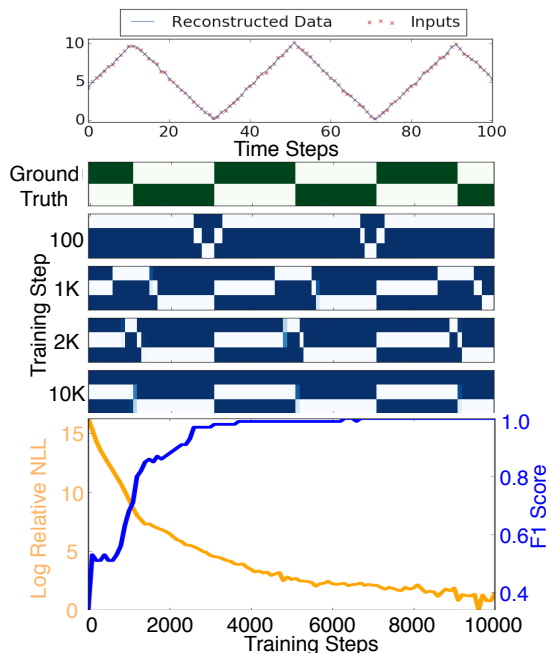


Figure 3. SNLDS Segmentation on bouncing ball task with an RNN continuous transition function. **Top**: illustration of input sequence and reconstruction. **Center (green)**: ground truth of the latent discrete states that correspond to the two directions of motion. **Center (blue)**: the posterior marginals of $p(s_t = k | \mathbf{x}_{1:T}, \mathbf{z}_{1:T})$ of SNLDS at 100, 1000, 2000 and 10000 training steps, where lighter colors represent higher likelihood. **Bottom**: Training progress of the log relative negative log-likelihood (Orange) and frame-wise F1 score (Blue) for SNLDS. Log relative negative log-likelihood is calculated as $\ln(\text{nll} - \min(\text{nll}) + 1)$, where **nll** is negative log-likelihood. The scale emphasizes that the loss still improves even late during training.

5.1. 1d bouncing ball

In this section, we use a simple dataset from Johnson et al. (2016). The data encodes the location of a ball bouncing between two walls in a one dimensional space. The initial position and velocity are random, but the wall locations are constant.

We apply our SNLDS model to this data, where f_x and f_z

Table 1. Quantitative comparisons (in % $\pm \sigma$) for segmentation on bouncing ball and reacher task. We report the F_1 scores in percentage with mean and standard deviation over 5 runs. (S.P. for switching point, F.W. for frame-wise, the best mean is in bold.) The F_1 score for CompILE is adapted from Kipf et al. (2019), where only switching point F_1 score is provided. The F_1 score for KVAE is computed based on taking ‘argmax’ on the ‘dynamics parameter network’ as described in Fraccaro et al. (2017).

DATASET	Bouncing Ball		Reacher Task	
	F_1 (S.P.)	F_1 (F.W.)	F_1 (S.P.)	F_1 (F.W.)
SLDS (Ours)	100.	100.	59.6 \pm 3.2	81.0 \pm 3.4
rSLDS	100.	100.	47.2 \pm 3.2	69.8 \pm 3.5
SVAE	100.	100.	35.3 \pm 2.6	62.3 \pm 4.9
KVAE	100.	100.	21.5 \pm 8.0	33.7 \pm 7.5
SNLDS (Ours)	100.	100.	78.1 \pm 4.2	89.0 \pm 2.0
Gumbel-Softmax SNLDS	97.6 \pm 1.8	93.8 \pm 4.0	5.0 \pm 8.7	14.2 \pm 9.3
CompILE	-	-	74.3 \pm 3.3	-

Table 2. Quantitative comparisons (in %) for S(N)LDS on Dubins path. For SLDS, F_1 scores with both greedy 1-to-1 matching (*Greedy*) and optimal merging (*Merging*) are provided. The switching point F_1 scores are estimated with both precise matching (*Tol 0*) or allowing at most 5-step displacement (*Tol 5*).

METRIC	SLDS (Greedy)	SLDS (Merging)	SNLDS
F_1 (Switching point, Tol 0)	3.5 \pm 1.0	4.4 \pm 3.1	11.3 \pm 5.7
F_1 (Switching point, Tol 5)	33.7 \pm 2.5	67.0 \pm 3.4	82.5 \pm 1.9
F_1 (Frame-wise)	29.4 \pm 3.6	61.5 \pm 8.0	84.3 \pm 7.2

are both MLPs. We found that regularization was not necessary in this experiment. We also consider the case where f_x and f_z are linear (i.e. an SLDS model), the rSLDS model of Linderman et al. (2017), the SVAE model of Johnson et al. (2016), the Kalman VAE (KVAE) model of Fraccaro et al. (2017) and a Gumbel-Softmax version of SNLDS as described in Appendix A.2. We use the implementations of rSLDS, SVAE, and KVAE provided by the authors.

All models we tested learn a perfect segmentation, as shown in Figure 4(a) and Table 1. This serves as a “sanity check” that we are able to use and implement the rSLDS, SVAE, KVAE and Gumbel-Softmax SNLDS code correctly. (See also Appendix A.3 for further analysis.)

Note that the “true” number of discrete states is just 2, encoding whether the ball is moving up or down. We find that our method can learn to ignore irrelevant discrete states if they are not needed. This is presumably because we are maximizing the marginal likelihood since we sum over all hidden states, and this is known to encourage model simplicity due to the “Bayesian Occam’s razor” effect (Murray & Ghahramani, 2005). By contrast, we had to be more careful in setting K when using the other methods.

An example of training a SNLDS model on the Bouncing Ball task is provided as Figure 3. Early in training, the discrete states do not align well to the ground truth transitions.

The three states transition rapidly near one of the walls and the frame-wise F_1 score is near chance values. However, by ten thousand iterations, the model has learned to ignore one state and switches between the two states corresponding to the ball bouncing from the wall. Notably the negative log-likelihood changes by over 10 orders of magnitude before the model learns accurate segmentation of even this simple problem. We hypothesize that the likelihood is dominated by errors in continuous dynamics rather than in the discrete segmentation until very late in training.

5.2. 2d reacher task

In this section, we consider a dataset proposed in the CompILE paper (Kipf et al., 2019). The observations are sequences of 36 dimensional vectors, derived from the 2d locations of various static objects, and the 2d joint locations of a moving arm (see Appendix A.4 for details and a visualization). The ground truth discrete state for this task is the identity of the target that the arm is currently reaching for (i.e., its “goal”).

We fit the same 6 models as above to this dataset. It is a much harder problem that requires more expressive dynamics, and we found that we needed to add regularization to our model to encourage it to switch states. Figure 4(b) visualizes the resulting segmentation (after label permutation) for a single

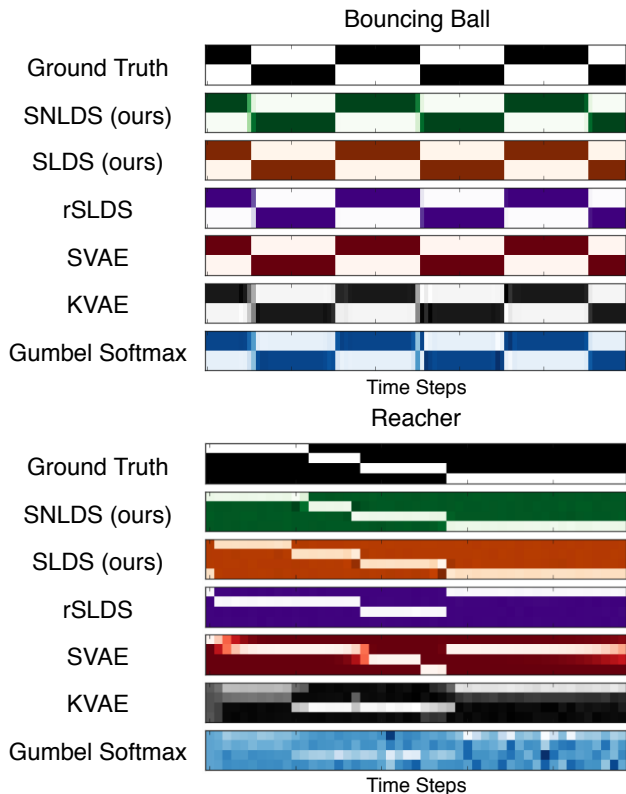


Figure 4. Segmentation on bouncing ball (top) and reacher task (bottom). From top to bottom: ground truth of latent discrete states, then the posterior marginals, $p(s_t = k | \mathbf{x}_{1:T}, \mathbf{z}_{1:T})$, of the SNLDS, SLDS, rSLDS, SVAE, KVAE, and Gumbel-Softmax SNLDS models respectively, where lighter color represents higher probability. CompILE is not included because it represents a different model family that directly predicts the segment boundary without calculating posterior marginals at each time step.

example. We see that our SNLDS model matches the ground truth more closely than our SLDS model, as well as the rSLDS, SVAE, KVAE, and Gumbel-Softmax baselines.

To compare performance quantitatively, we evaluate the models from 5 different training runs on the same held-out dataset of size 32, and compute the F_1 scores. We also report the F_1 number from CompILE. The CompILE paper uses an iterative segmentation scheme that can detect state changes, but it does not infer what the current latent state is, so we cannot include it in Figure 4(b). In Table 1, we find that our SNLDS method is significantly better than the other approaches.

5.3. Dubins path

In this section, we apply our method to a new dataset that is created by rendering a point moving in the 2d plane.

The motion follows the Dubins model², a simple model for piece-wise nonlinear (but smooth) motion that is commonly used in the fields of robotics and control theory because it corresponds to the shortest path between two points that can be traversed by wheeled robots, airplanes, etc. In the Dubins model, the change in direction is determined by an external control signal u_t . We replace this with three latent discrete control states: go straight, turn left, and turn right. These correspond to fixed, but unobserved, input signals u_t (see Appendix A.5 for details). After generating the motion, we create a series of images, where we render the location of the moving object as a small circle on a white background. Our goal in generating this dataset was to assess how well we can recover latent dynamics from image data in a very simple, yet somewhat realistic, setting.

The publicly released code for rSLDS and SVAE does not support high dimensional inputs like images (even though the SVAE has been applied to an image dataset in Johnson et al. (2016)), and there is no public code for CompILE. Therefore we could not compare to these methods for this experiment. As we already showed in Section 5.2 that our method is much better than these other approaches, as well as Kalman VAE and Gumbel-Softmax version of SNLDS, on other tasks, we expect the same conclusion to hold on the harder task of segmenting videos.

Instead we focus on comparing inferred SNLDS states with SLDS states to determine the advantage of allowing each regime to be represented by a nonlinear model. The results of segmenting one sequence with these models using 5 states are shown in Figure 1. We see that the SLDS model has to approximate the left and right turns with multiple discrete states, whereas the non-linear model learns a more interpretable representation.

We again compare the models in Table 2 using F_1 scores. Since matching the exact time of the switching point is very hard in the unsupervised setting with noisy observations, we also report an F1 computed with a tolerance of detecting a change within 5 frames. Because the SLDS model used too many states, we calculated two versions of the metrics. The first was a greedy approach that optimally assigned the best single state to match each ground truth state. The second used an oracle to optimally merge states to match the ground truth. The SNLDS model significantly outperforms the SLDS in both scenarios.

5.4. Salsa Dancing from CMU MoCap

In this section, we demonstrate the capacity of SNLDS on segmenting 3D human pose dynamics on CMU MoCap

²https://en.wikipedia.org/wiki/Dubins_path

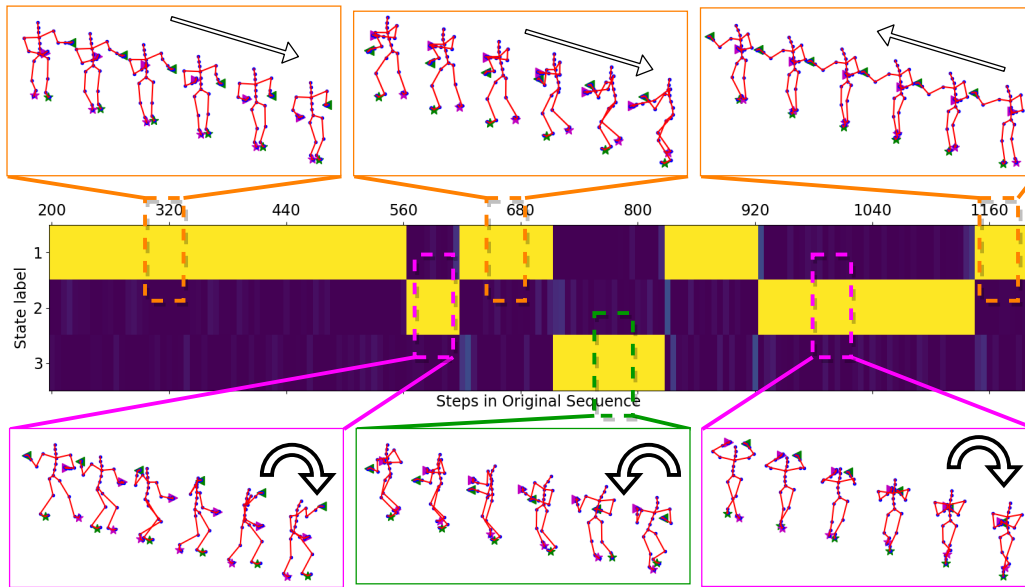


Figure 5. SNLDS segmentation result for Salsa dancing trial in CMU MoCap dataset. The model segment the motion into three different dynamical modes: moving forward and backward (orange colored), clockwise turning (magenta) and counter-clockwise turning (green). The center depicts the posterior marginal for each state and the boxes show samples of motion from each state.

data³. There are 30 trials of Salsa dancing sequences in the dataset. We use 29 of them as the training data, and hold out the other for evaluation. The training sequences are generated by down-sampling the original sequences using every 6 frames. The input to the model consists of 3D coordinates of 31 joints. Using MLP to describe the nonlinear transition of continuous hidden states, SNLDS can segment sequences into 3 modes of primitive motions, which could be interpreted as: turning clockwise, turning counter-clockwise, and translational motion. Without ground truth segmentation, we only evaluate the segmentation qualitatively, as shown in the Figure 5.

5.5. Analysis of the annealing schedule

Many latent variable models are trained in multiple stages to avoid getting stuck in bad local optima. For example, to fit the rSLDS model, Linderman et al. (2017) first pretrain an AR-HMM and SLDS model, and then merge them; similarly, to fit the SVAE model, Johnson et al. (2016) first train with a single latent state and then increase K .

We found a similar strategy was necessary for the Reacher, Dubins, and Salsa tasks, but we do this in a smooth way using annealed regularization. Early in training, we train with large temperature τ and entropy coefficient β . This encourages the model to use all states equally, so that the dynamics, inference, and emission sub-networks stabilized before beginning to learn specialized behavior. We then

³<http://mocap.cs.cmu.edu/>

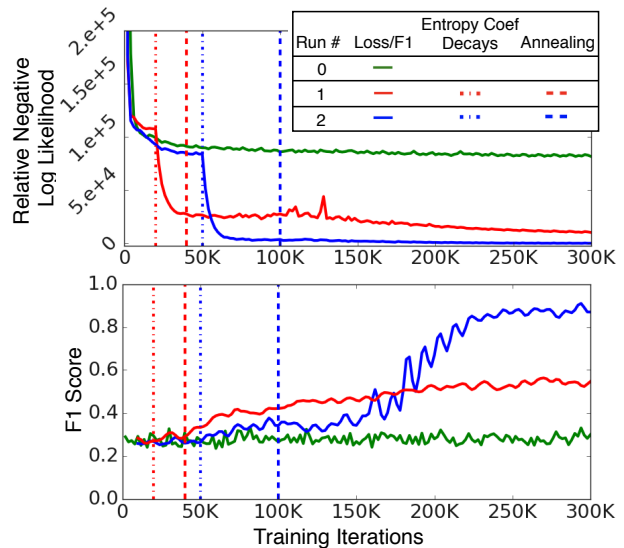


Figure 6. Comparing the relative negative log-likelihood (top) and the frame-wise F_1 scores (bottom) on Dubins paths with 3 different annealing schedules. In the first run (green), the regularization coefficient and temperature start to decay at the very beginning of training. In the second run (red), the cross entropy regularization coefficient starts to decay at step 20,000, while temperature annealing starts at step 40,000. In the third run (blue), the coefficient decay starts at step 50,000, while temperature annealing starts at step 100,000.

anneal the entropy coefficient to 0, and the temperature to 1 over time. We found it best to first decay the entropy

coefficient β and then decay the temperature τ .

Figure 6 demonstrates the effect of 3 different annealing schedules on the relative log likelihood (defined as $L_t - L_{\min}$, where $L_{\min} = \min_t L_{t;1,2,3}$ across all three runs, and L_t is the negative log-likelihood.), and the F_1 score. We find that the final negative log-likelihood and F_1 scores improve when we delay the annealing schedule to $50k$ steps on the Dubins task. Surprisingly, the F_1 score does not improve significantly until an additional $50k$ steps after the temperature begins annealing. On real problems, where we have no ground truth, we cannot use the F_1 score as a metric to determine the best annealing schedule. However, it seems that the schedules that improve F_1 the most also improve likelihood the most.

6. Conclusion

We have demonstrated that our proposed method can effectively learn to segment high dimensional sequences into meaningful discrete regimes. Future work includes applying this to harder image sequences and to hierarchical reinforcement learning.

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