Streaming Bayes GFlowNets

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I. Background: GFlowNets

GFlowNets are amortized algorithms for sampling from distributions over compositional objects, i.e., over objects that can be sequentially constructed from an initial state through the application of simple actions (e.g., graphs via edge-addition).

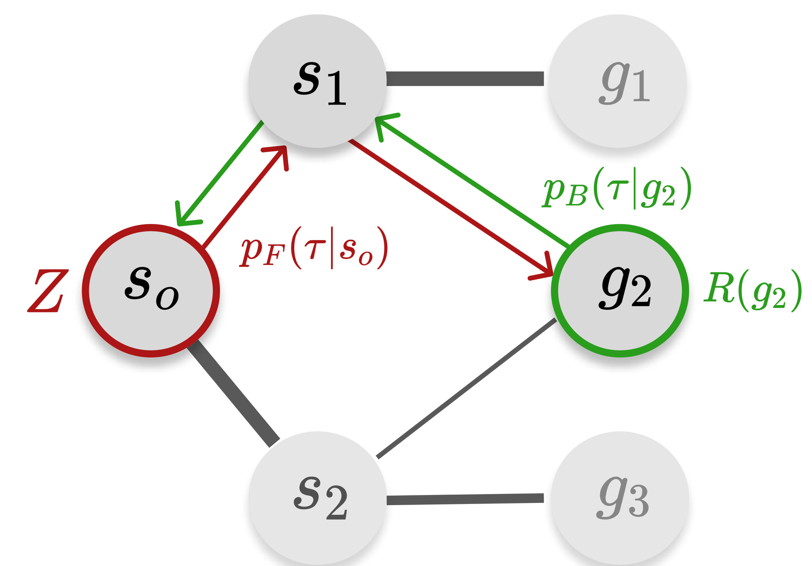

Figure 1: An illustration of the state graph as a DAG on $\mathcal{S}$.

To accomplish this, we learn a forward $p_F(\tau)$ and backward $p_B(\tau|x)$ policies on a state graph (illustrated above) such that

$$Zp_F(\tau) = p_B(\tau|x)R(x), \quad (1)$$

in which R is the unnormalized distribution of interest and Z is its partition function. If this condition is satisfied for each τ,

$$p_\top(x) = \sum_{\tau \rightsquigarrow x} p_F(\tau) \propto R(x), \quad (2)$$

ensuring that the correctness of the generative process.

II. Streaming Bayes GFlowNets

We introduce **Streaming Bayes GFlowNets** (SB-GFlowNets) as a general-purpose tool for streaming Bayesian inference over **discrete spaces**. Our model leverages a **GFlowNet** as a surrogate prior when updating the current posterior approximation based on new data, thereby **avoiding to repeatedly process old data** and **significantly accelerating** training convergence in a streaming setting.

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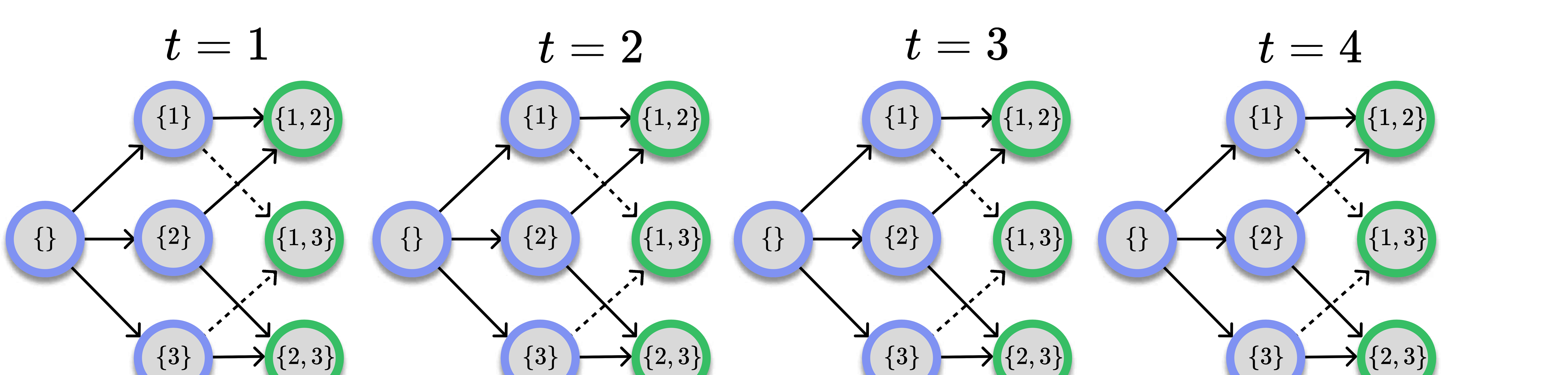

$\log R_1^{(\alpha)}(S) = \frac{1}{\alpha}\sum_{d \in S} f_1(d)$ $\quad p_\top^{(1)}(S) \propto R_1^{(\alpha)}(S)$

$\log R_2^{(\alpha)}(S) = \frac{1}{\alpha}\sum_{d \in S} f_2(d)$ $\quad p_\top^{(2)}(S) \propto R_1^{(\alpha)}(S)R_2^{(\alpha)}(S)$

$\log R_3^{(\alpha)}(S) = \frac{1}{\alpha}\sum_{d \in S} f_3(d)$ $\quad p_\top^{(3)}(S) \propto R_1^{(\alpha)}(S)R_2^{(\alpha)}(S)R_3^{(\alpha)}(S)$

$\log R_4^{(\alpha)}(S) = \frac{1}{\alpha}\sum_{d \in S} f_4(d)$ $\quad p_\top^{(4)}(S) \propto R_1^{(\alpha)}(S)R_2^{(\alpha)}(S)R_3^{(\alpha)}(S)R_4^{(\alpha)}(S)$

Figure 2: Streaming amortized inference with SB-GFlowNets.

Linear preference learning with integer-valued features.

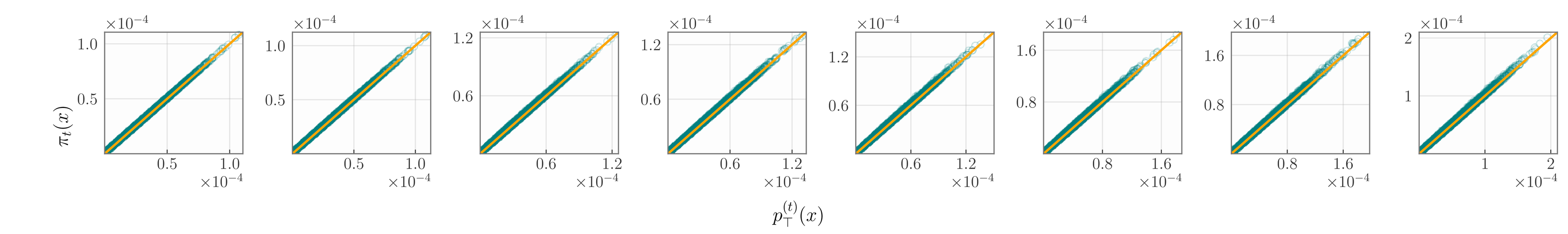

Figure 3: SB-GFlowNets accurately sample from the posterior distribution over the utility in integer-valued preference learning.

Streaming Bayesian structure learning with DAG-GFlowNets.

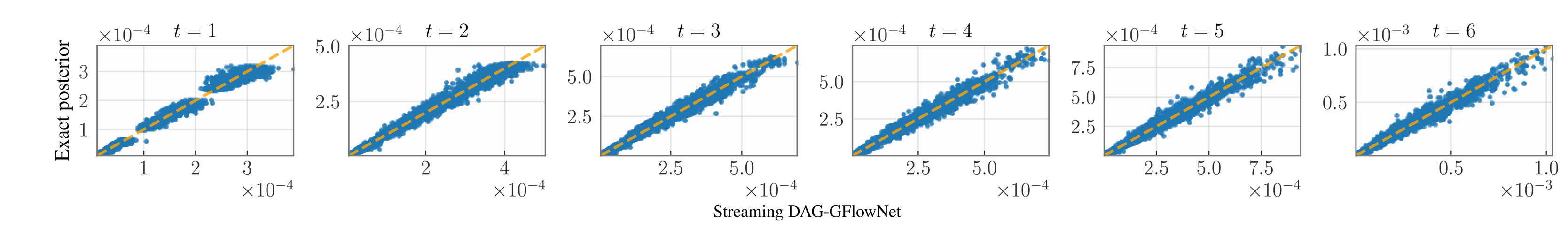

Figure 4: SB-GFlowNets accurately sample from an evolving belief distribution in a structure learning setting.

Online Bayesian phylogenetic inference.

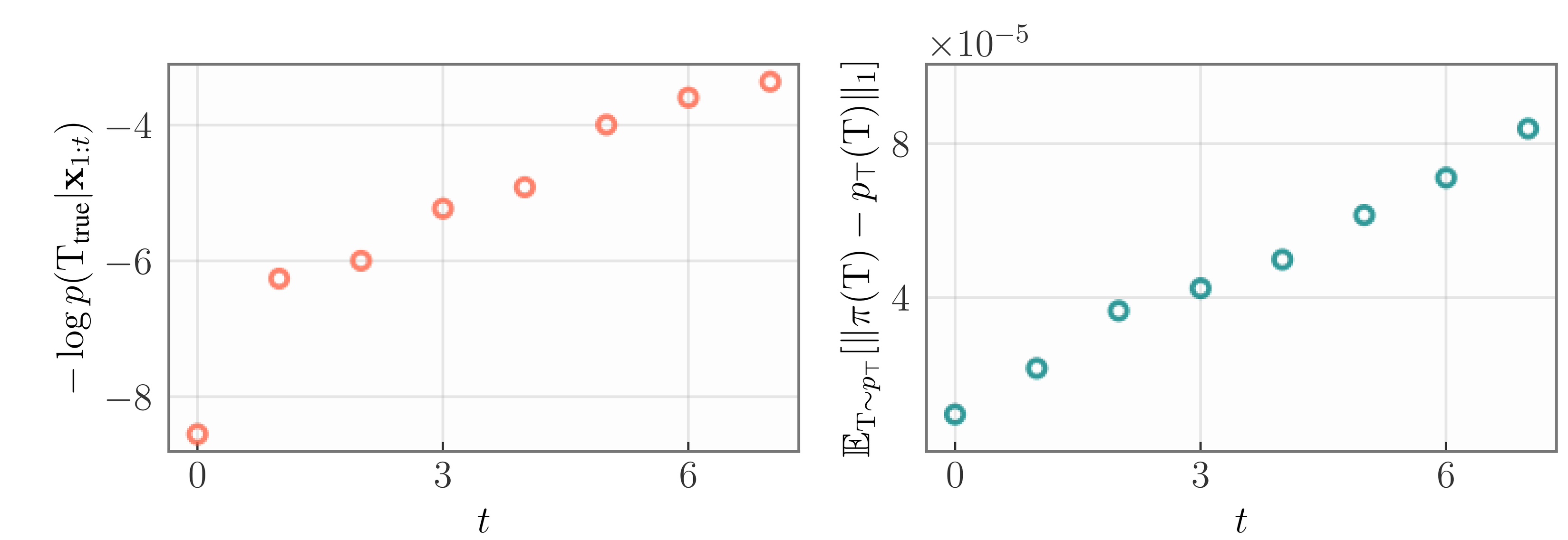

Figure 5: SB-GFlowNet's probability mass associated to the true phylogenetic tree increases as we observe more sequences.

	Model		
# of leaves	GFlowNet	SB-GFlowNet	% ↑
7	2846.88 s	**1279.68** s	0%
9	3779.11 s	**1714.49** s	−2%
11	4821.74 s	**2303.99** s	0%

SB-GFlowNets **achieve faster training convergence** than conventional GFlowNets in a streaming context — while **maintaining a comparable performance** in terms of the TV distance (right column).
(Results averaged across 3 runs.)

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