Learning GFlowNets From Partial Episodes For Improved Convergence And Stability

Kanika Madan, Jarrid Rector-Brooks, Maksym Korablyov, Emmanuel Bengio, Moksh Jain, Andrei Cristian Nica, Tom Bosc, Yoshua Bengio, Nikolay Malkin

Generative Flow Networks (GFlowNets)

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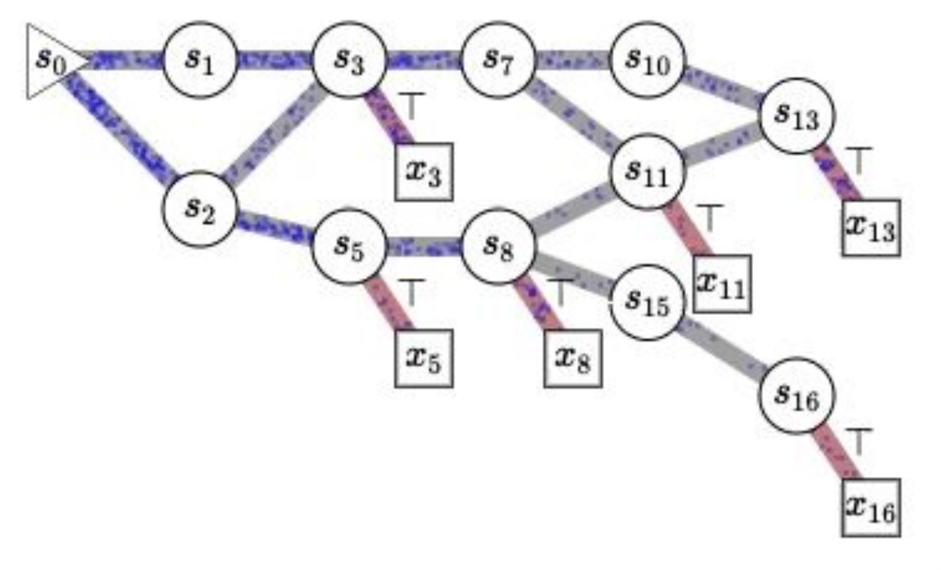
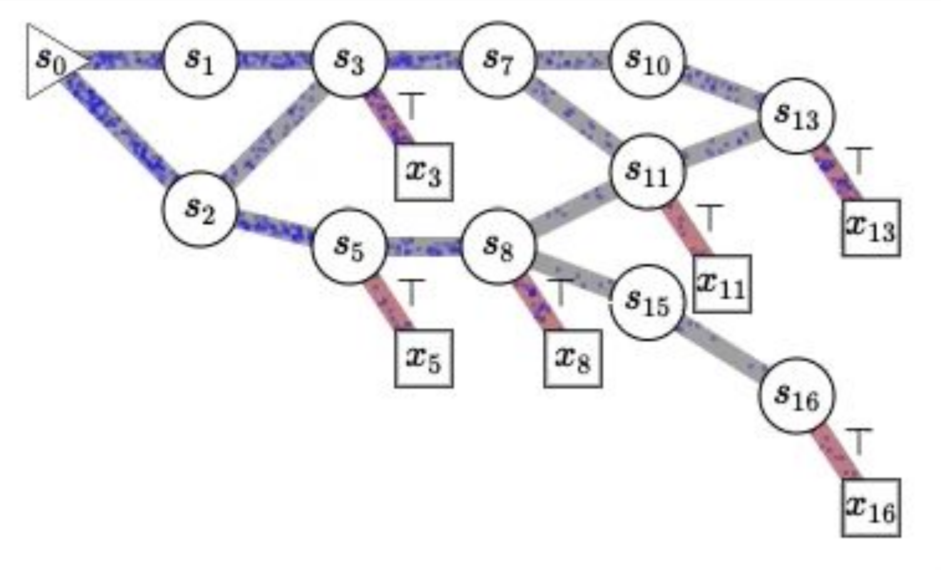
Flow of unnormalized probabilities



Generative Flow Networks (GFlowNets)

Flow of unnormalized probabilities

Flow Based Network



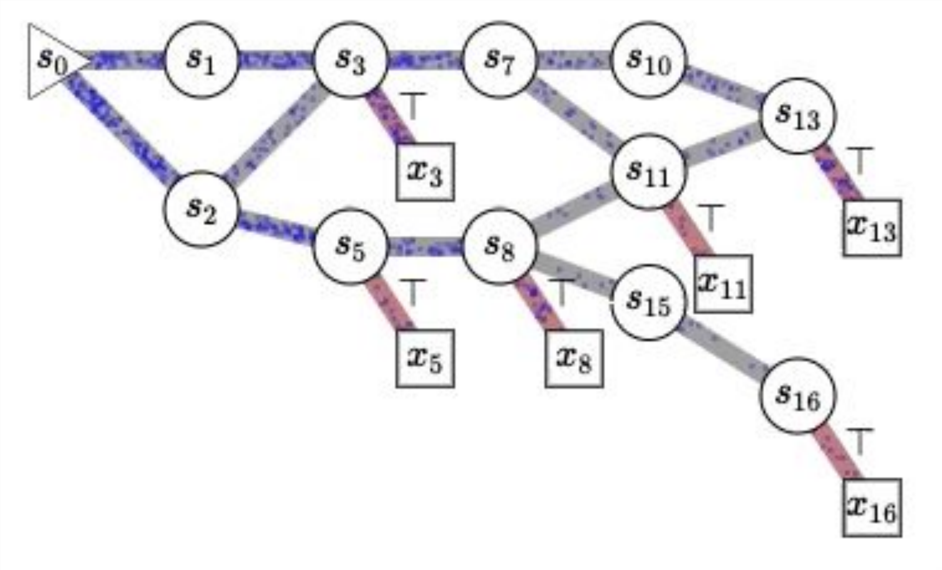
Generative Flow Networks (GFlowNets)

Flow of unnormalized probabilities

Flow Based Network

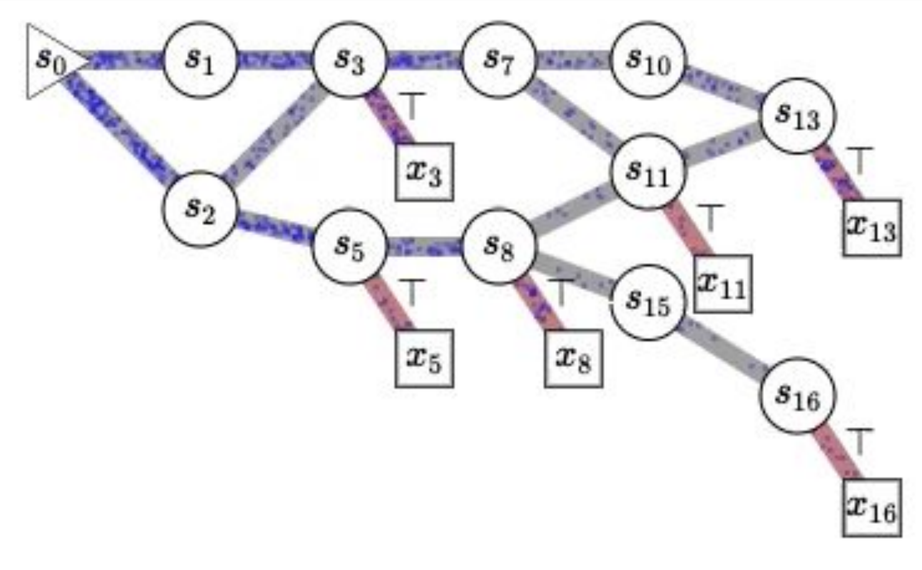
- Analogy:

  Water flowing from source to sink



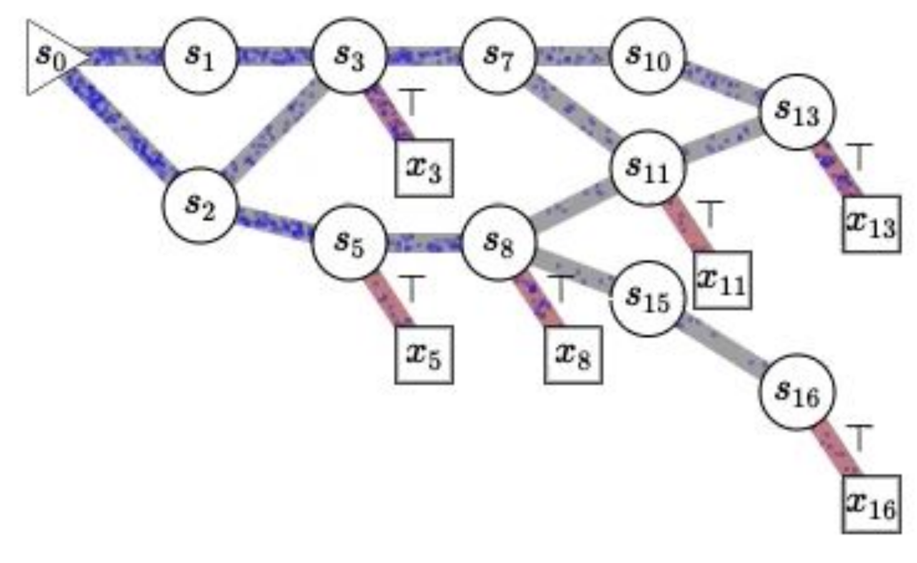
Generative Flow Networks (GFlowNets)

- Flow Based Network
- Generative Model



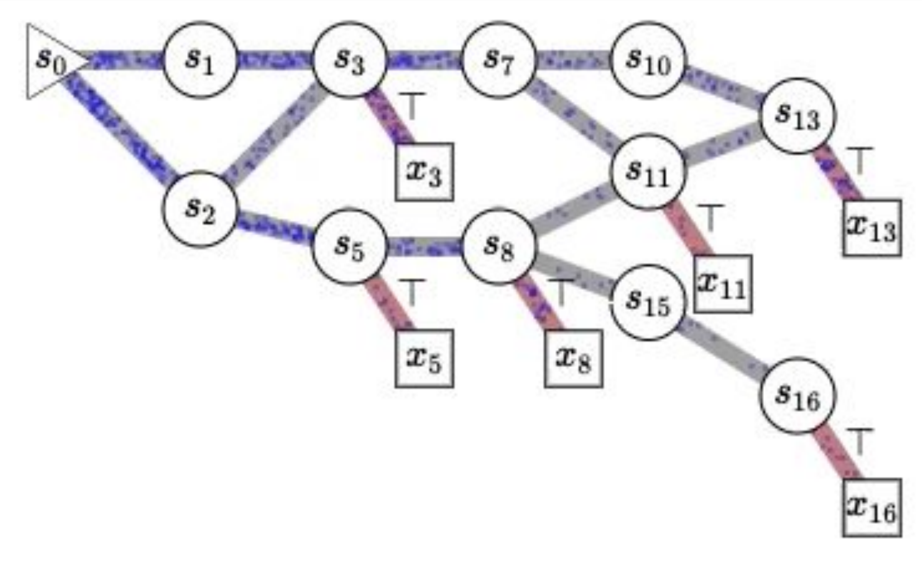
Generative Flow Networks (GFlowNets)

- Flow Based Network
- Generative Model
  - Stochastic Policy



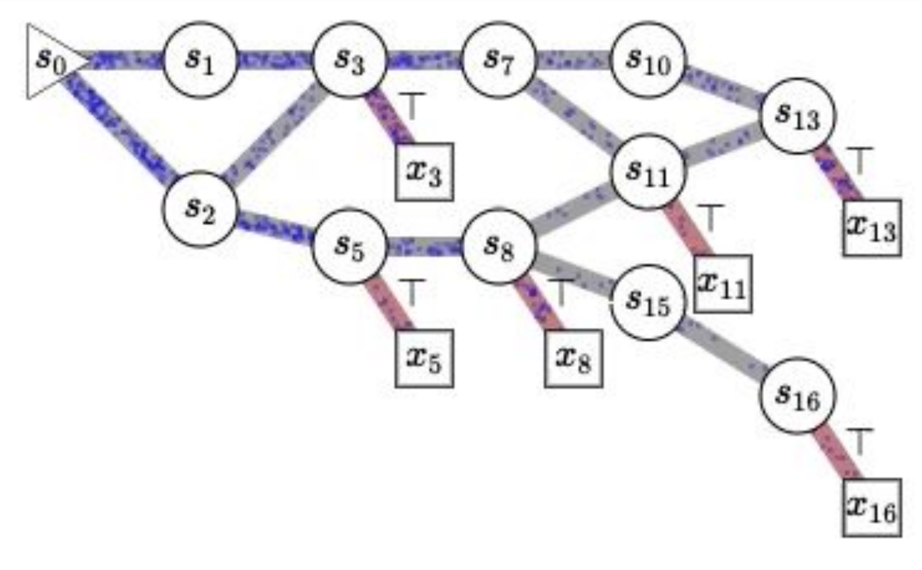
Generative Flow Networks (GFlowNets)

- Flow Based Network
- Generative Model
  - Stochastic Policy
- Generates objects sequentially



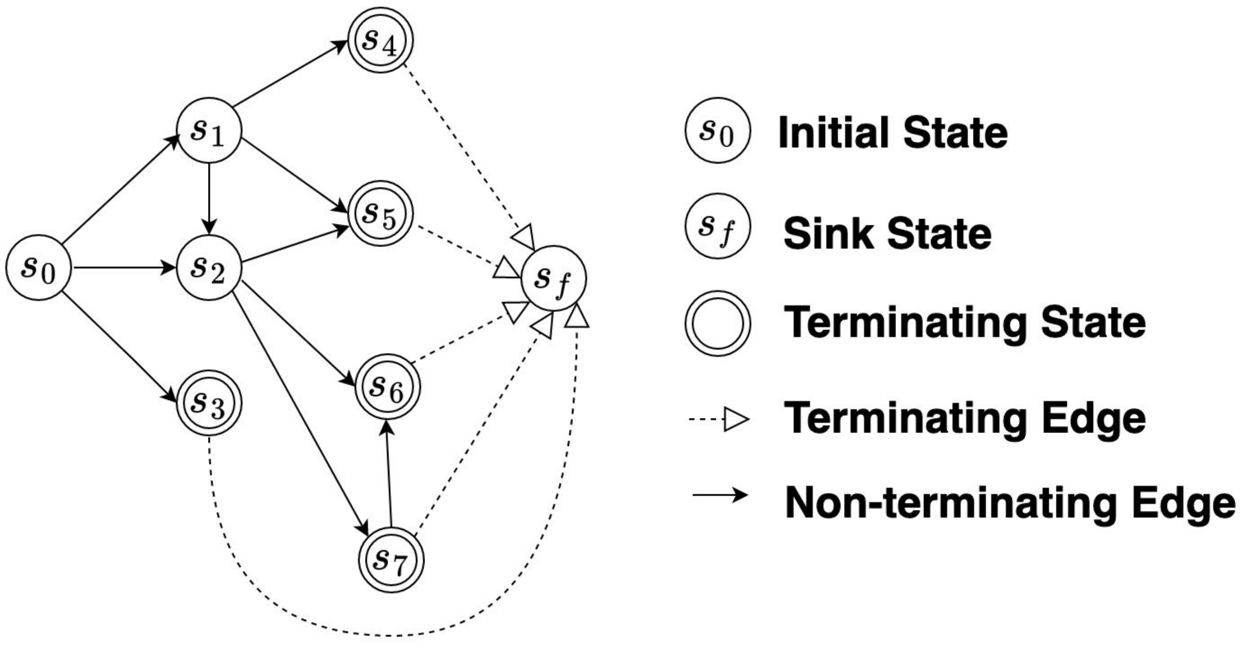
Generative Flow Networks (GFlowNets)

- Flow Based Network
- Generative Model
  - Stochastic Policy
- Generates objects sequentially
- Directed Acyclic Graph

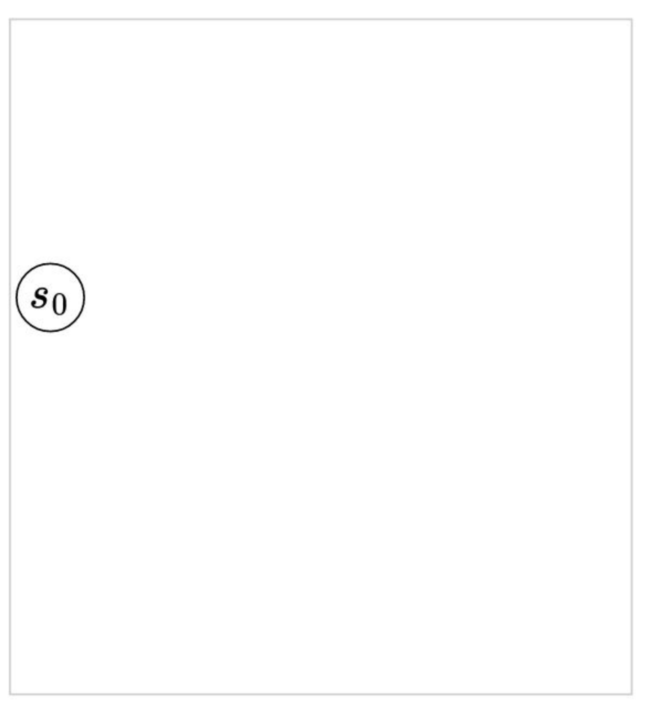


→ Generate Objects Sequentially

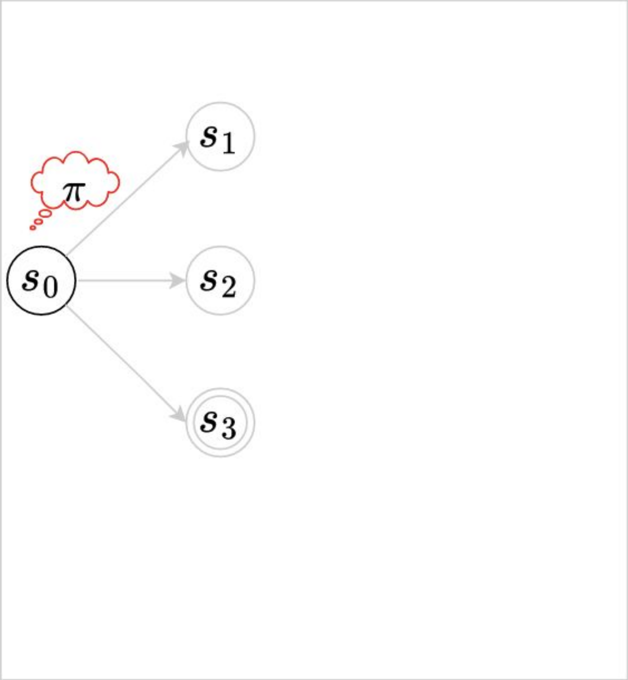
Generate Objects Sequentially



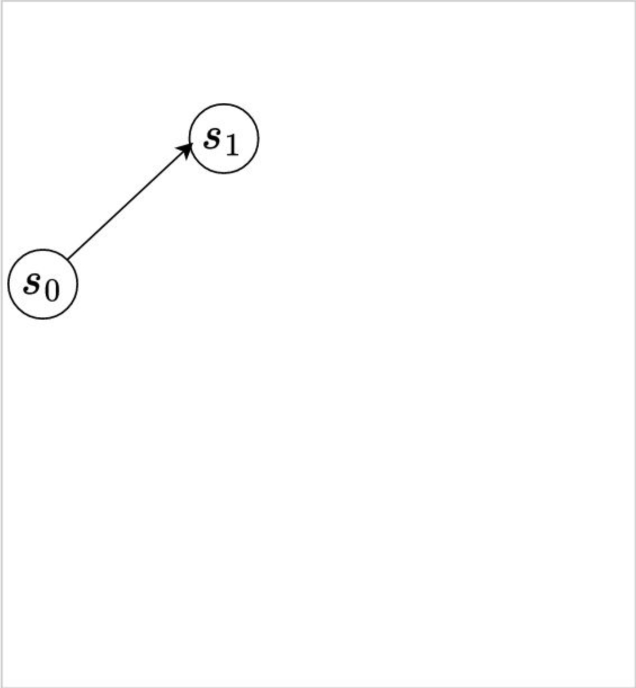
Generate Objects Sequentially - Trajectory 1



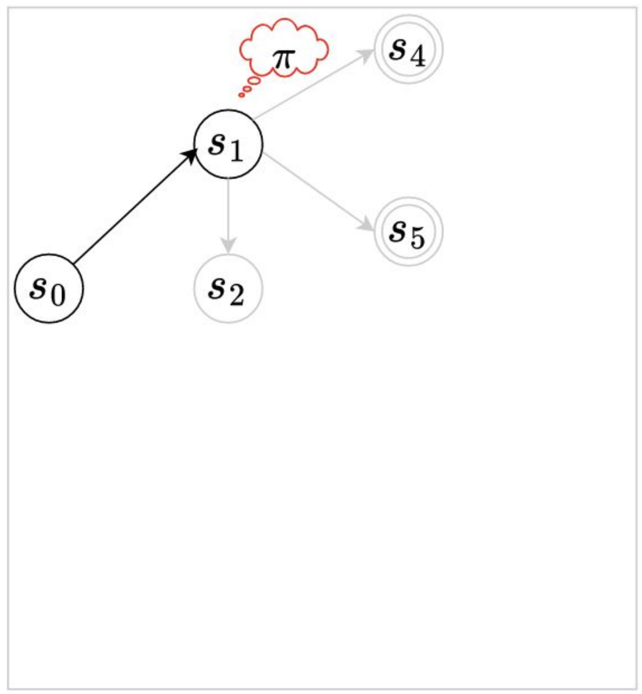
Generate Objects Sequentially - Trajectory 1



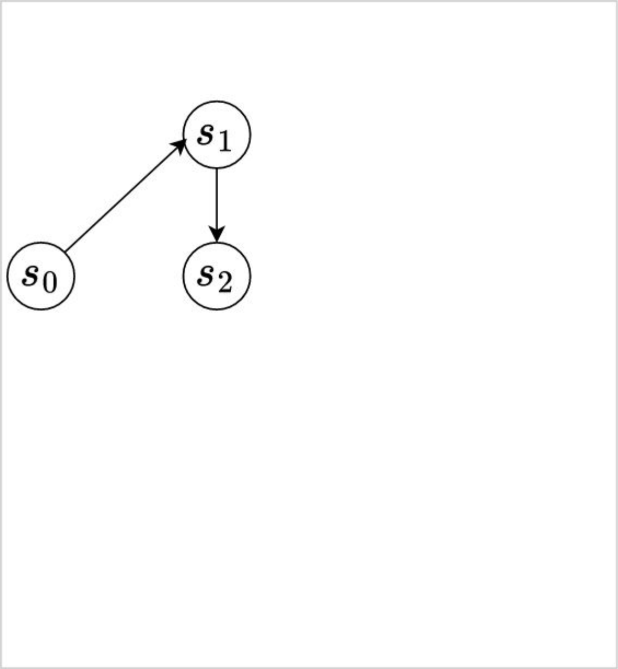
Generate Objects Sequentially - Trajectory 1



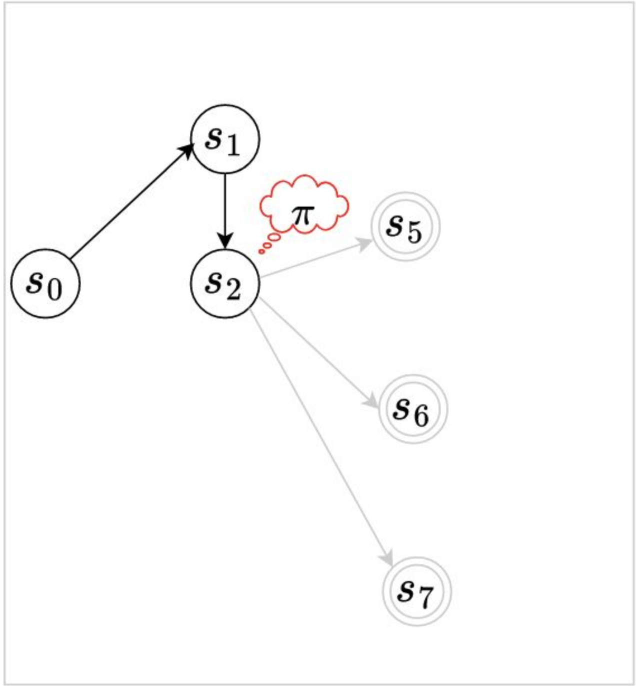
Generate Objects Sequentially - Trajectory 1



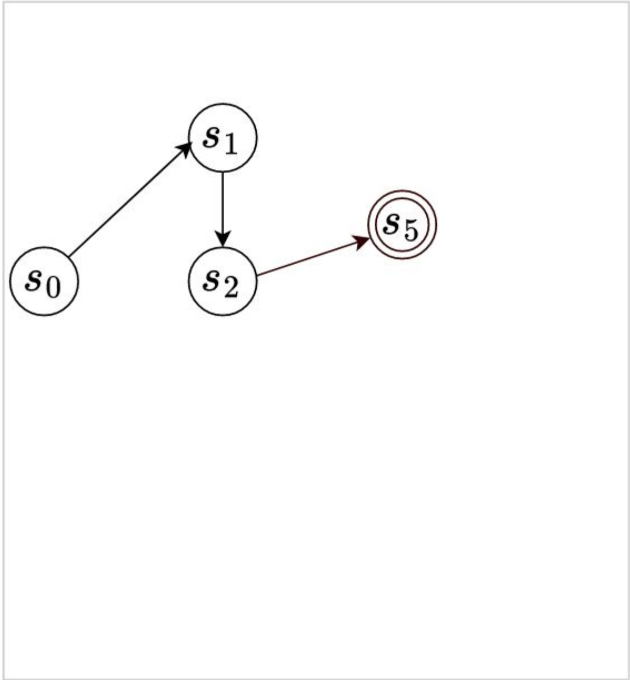
Generate Objects Sequentially - Trajectory 1



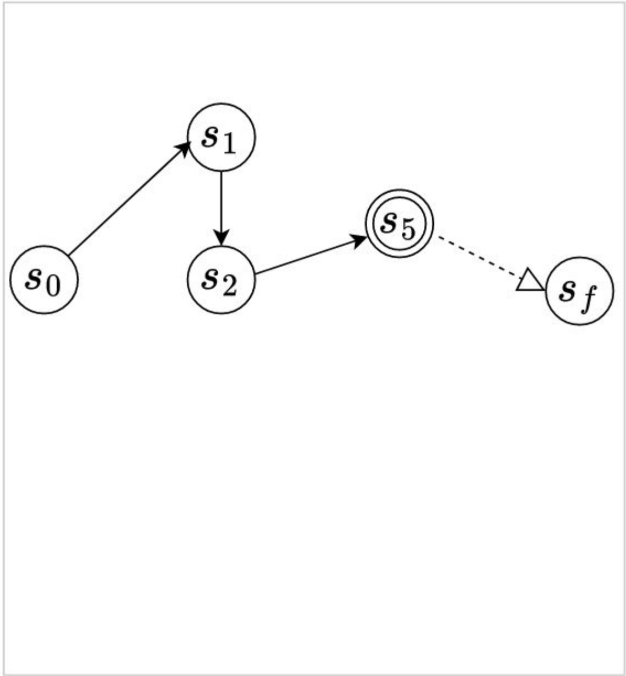
Generate Objects Sequentially - Trajectory 1



Generate Objects Sequentially - Trajectory 1



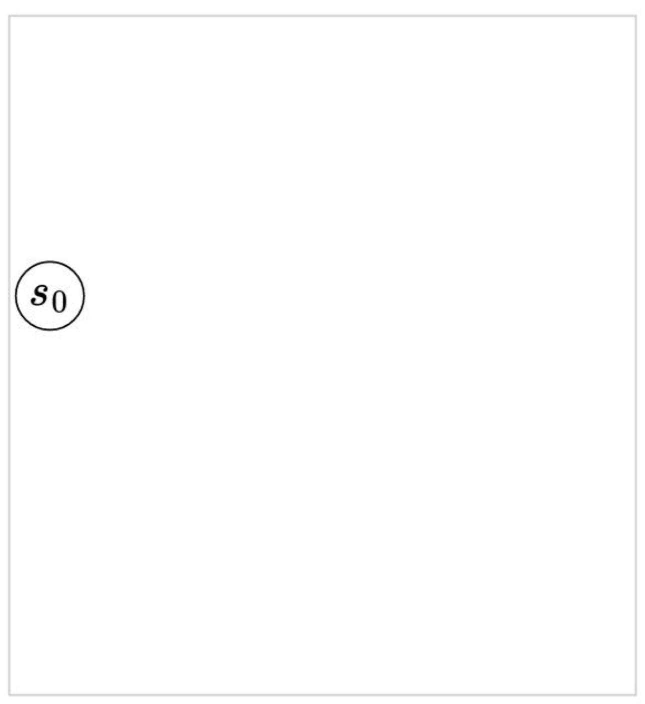
Generate Objects Sequentially - Trajectory 1



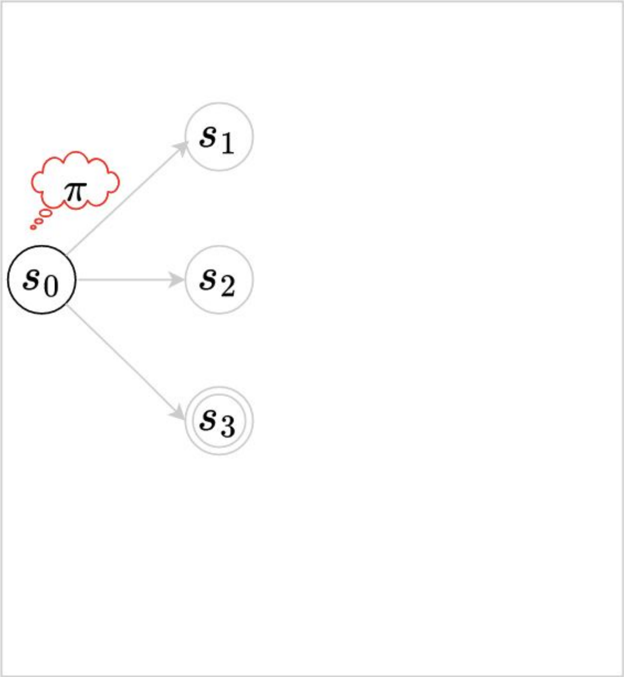
Generate Objects Sequentially

$\rightarrow$ Stochastic Policy

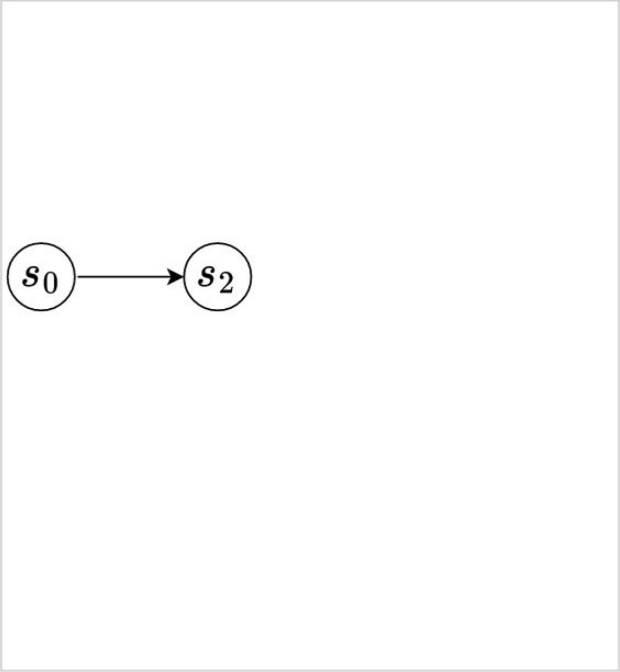
Generate Objects Sequentially - Trajectory 2



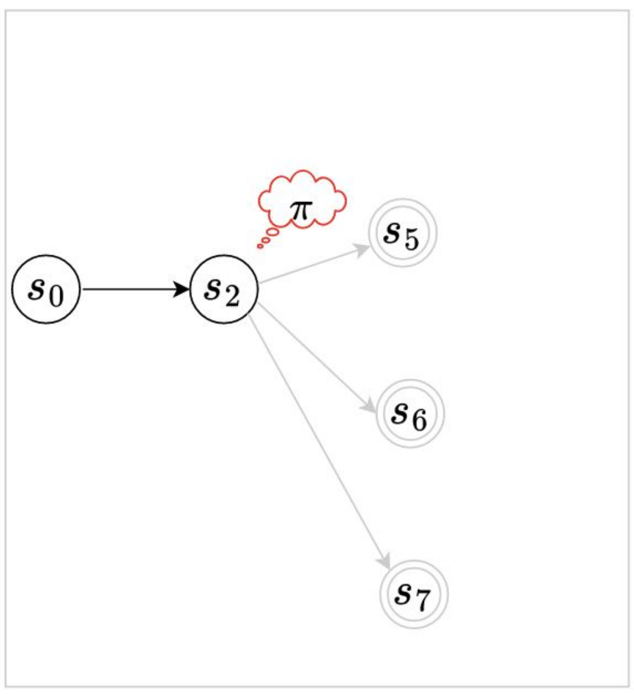
Generate Objects Sequentially - Trajectory 2



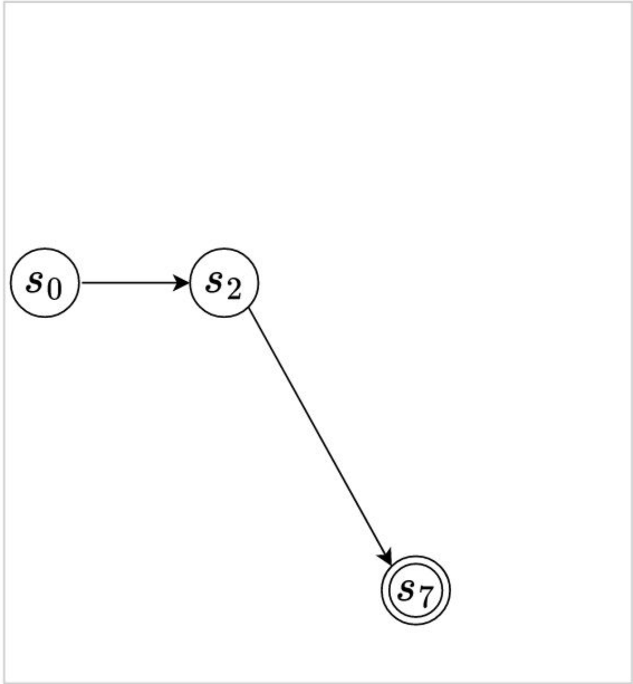
Generate Objects Sequentially - Trajectory 2



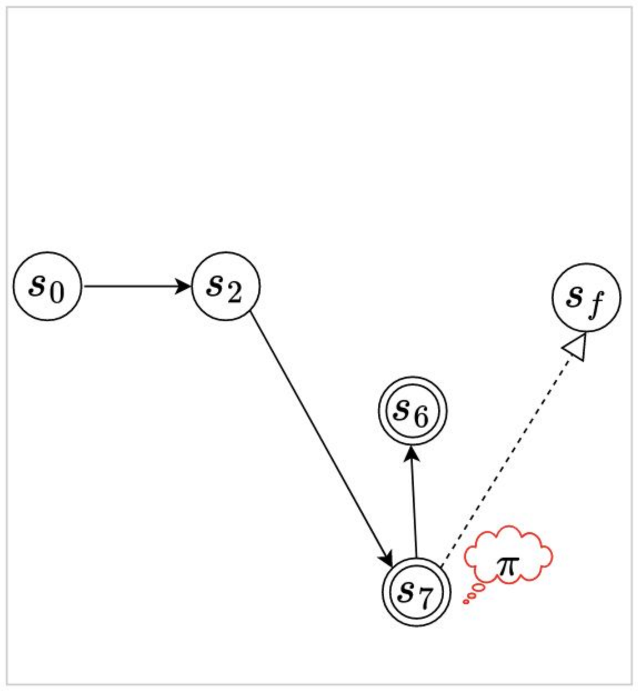
Generate Objects Sequentially - Trajectory 2



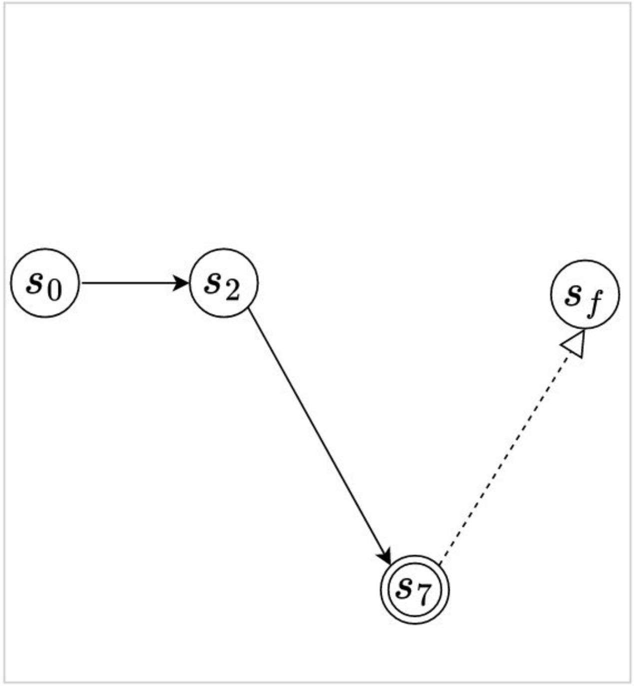
Generate Objects Sequentially - Trajectory 2



Generate Objects Sequentially - Trajectory 2



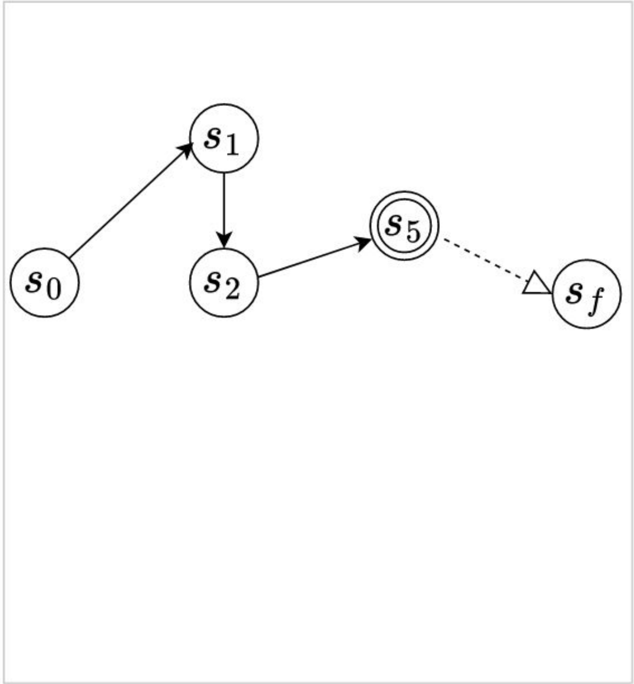
Generate Objects Sequentially - Trajectory 2

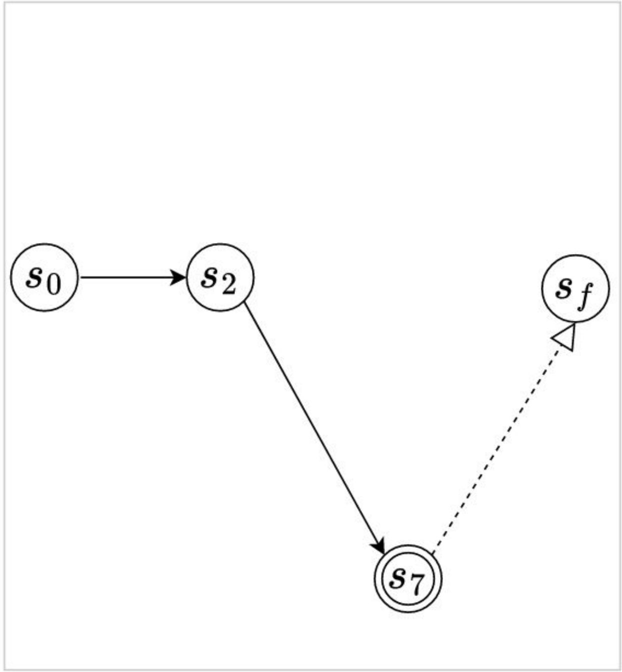


Generative Model

- Objects Generated Proportional to Reward

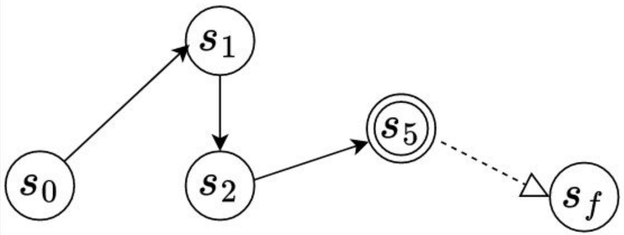
Generate Objects Sequentially - Trajectories





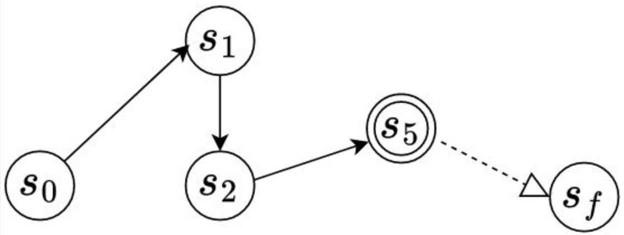
Generate Objects Sequentially - Trajectories

$$p(x_1) = p(s_0 s_1 s_2 s_5) \propto R(x_1)$$

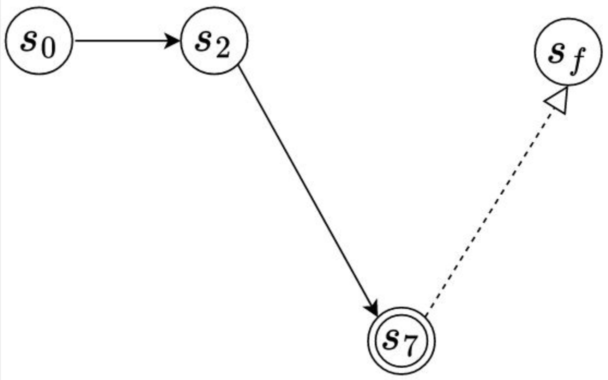


Generate Objects Sequentially - Trajectories

$$p(x_1) = p(s_0 s_1 s_2 s_5) \propto R(x_1)$$



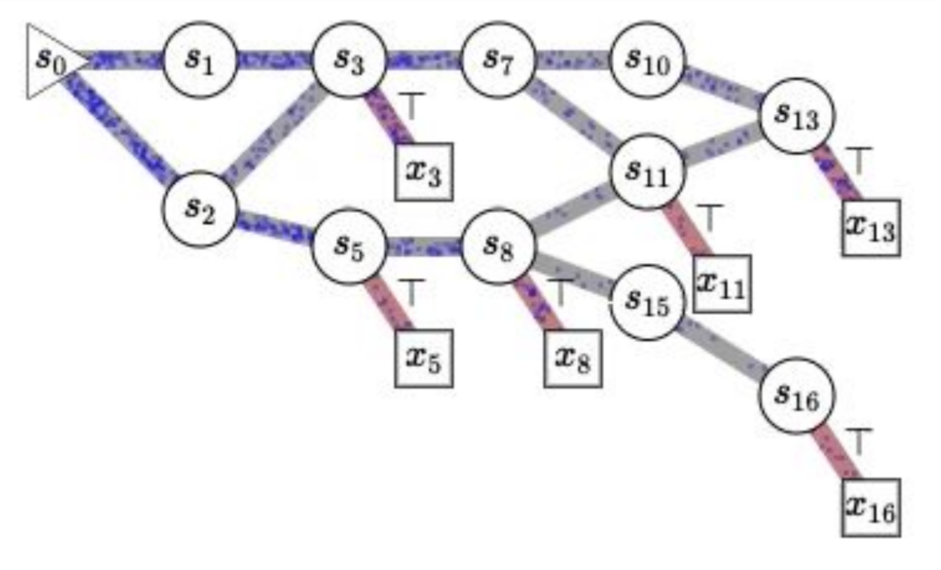
$$p(x_2) = p(s_0 s_2 s_7) \propto R(x_2)$$



Training GFlowNets

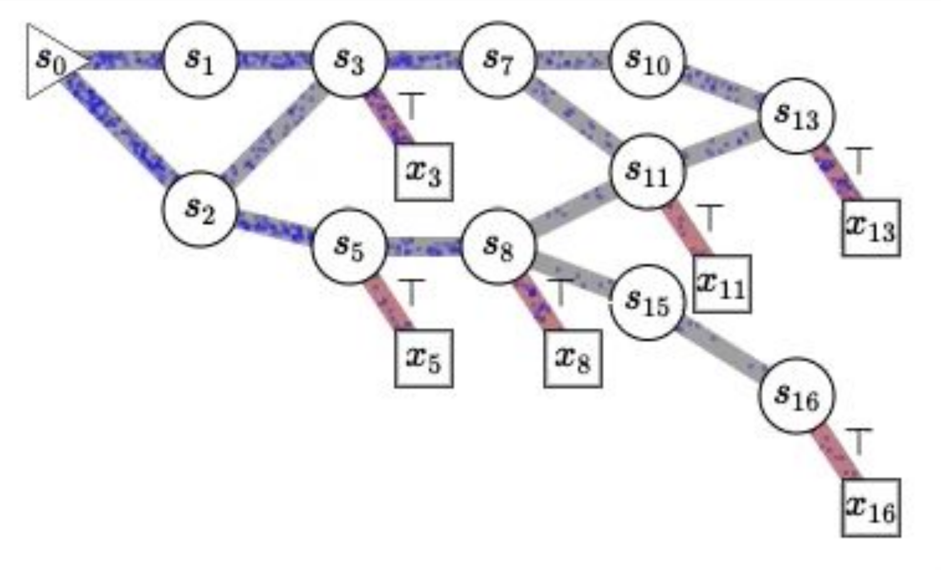
GFlowNets - Training

- Flow Consistency Equations



GFlowNets - Training

- Flow Consistency Equations
- Forward Flow = Backward Flow



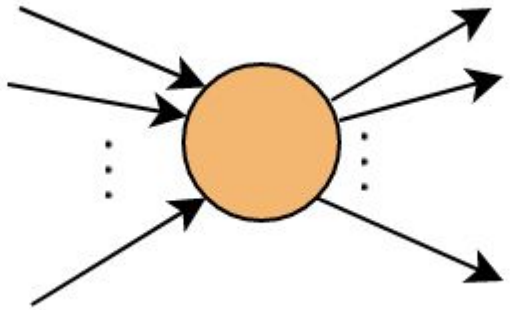
GFlowNets Training Objectives

Flow Matching Objective

- Flow Consistency Equations

- Flow Matching

$$\mathcal{L}_{\mathrm{FM}}(s) = \left(\log \frac{\sum_{s:(s \to t) \in \mathcal{A}} F(s \to t; \theta) + \epsilon}{\sum_{u:(t \to u) \in \mathcal{A}} F(t \to u; \theta) + \epsilon} \right)^2$$

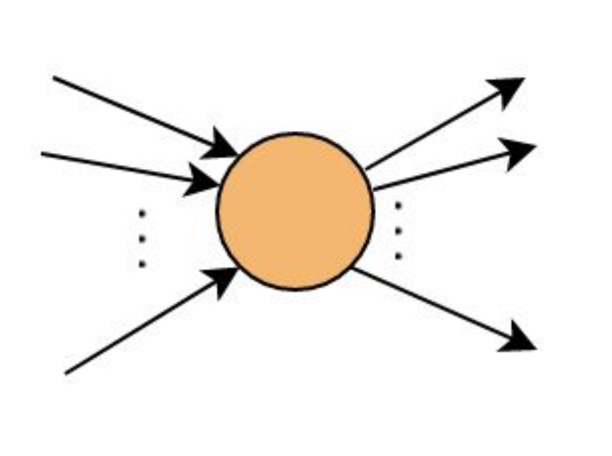


Flow Matching Objective

- Flow Consistency Equations

- Flow Matching
  - State level flow matching

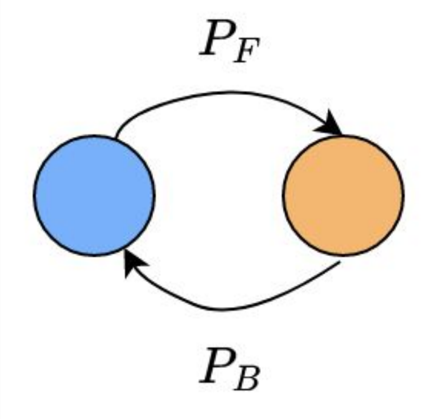
$$\mathcal{L}_{\mathrm{FM}}(s) = \left(\log \frac{\sum_{s:(s\rightarrow t)\in\mathcal{A}} F(s\rightarrow t;\theta) + \epsilon}{\sum_{u:(t\rightarrow u)\in\mathcal{A}} F(t\rightarrow u;\theta) + \epsilon}\right)^2$$



Detailed Balance Objective

- Flow Consistency Equations
- Detailed Balance:

$$\mathcal{L}_{\mathrm{DB}}(s, s') = \left(\log \frac{F_\theta(s) P_F(s' \mid s; \theta)}{F_\theta(s') P_B(s \mid s'; \theta)} \right)^2$$

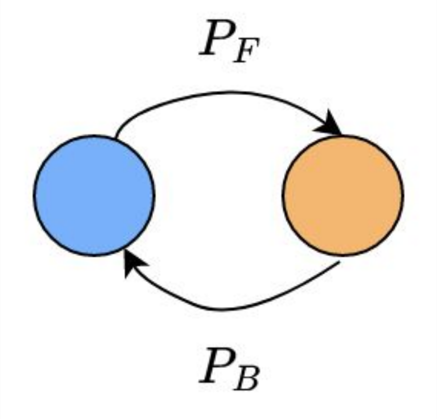


Detailed Balance Objective

- Flow Consistency Equations

- Detailed Balance:
  - Edge level flow matching

$$\mathcal{L}_{\mathrm{DB}}(s, s') = \left(\log \frac{F_\theta(s) P_F(s' \mid s; \theta)}{F_\theta(s') P_B(s \mid s'; \theta)} \right)^2$$

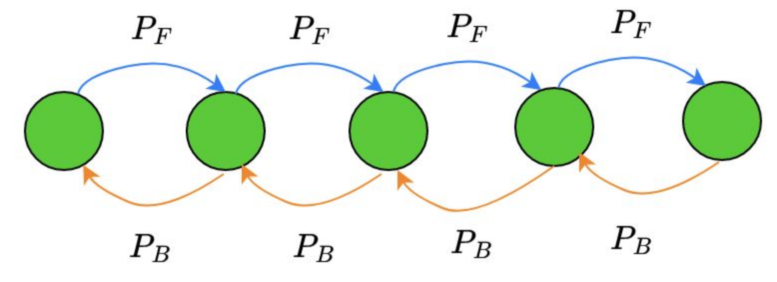


Trajectory Balance Objective

- Flow Consistency Equations

- Trajectory Balance:

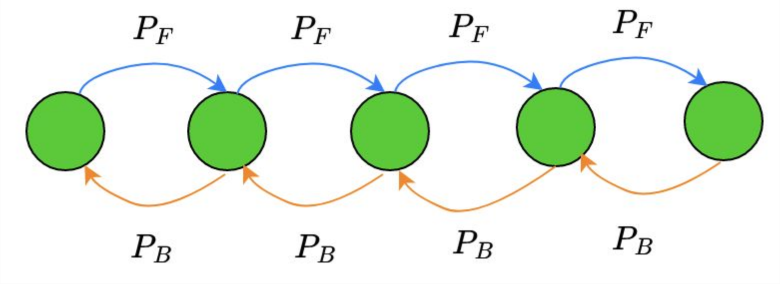
$$\mathcal{L}_{\mathrm{TB}}(\tau) = \left(\log \frac{Z_\theta P_F(\tau;\theta)}{R(x_\tau) P_B(\tau \mid x_\tau;\theta)}\right)^2$$



Trajectory Balance Objective

- Flow Consistency Equations
- Trajectory Balance:
  - Trajectory level flow matching

$$\mathcal{L}_{\mathrm{TB}}(\tau) = \left(\log \frac{Z_\theta P_F(\tau;\theta)}{R(x_\tau) P_B(\tau \mid x_\tau;\theta)}\right)^2$$



GFlowNets Training Objectives

Objective	Parametrization	Locality
FM	edge flow $F(s{\rightarrow}t;\theta)$	state s
DB	state flow $F(s;\theta)$, policies $P_F(-\|-;\theta)$, $P_B(-\|-;\theta)$	action $s{\rightarrow}t$
TB	initial state flow Z_θ, policies $P_F(-\|-;\theta)$, $P_B(-\|-;\theta)$	complete trajectory τ

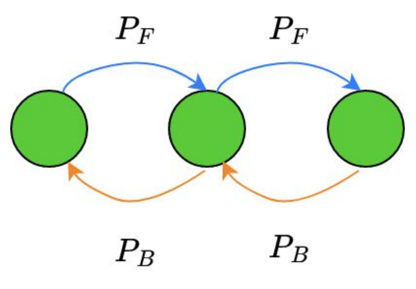
SubTrajectory Balance

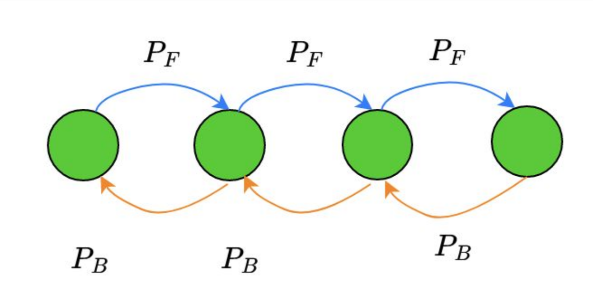
GFlowNets Training Objectives

Objective	**Parametrization**	**Locality**
FM	edge flow $F(s{\rightarrow}t;\theta)$	state s
DB	state flow $F(s;\theta)$, policies $P_F(-\|-;\theta)$, $P_B(-\|-;\theta)$	action $s{\rightarrow}t$
TB	initial state flow Z_θ, policies $P_F(-\|-;\theta)$, $P_B(-\|-;\theta)$	complete trajectory τ
SubTB(λ)	state flow $F(s;\theta)$, policies $P_F(-\|-;\theta)$, $P_B(-\|-;\theta)$	(partial) trajectory τ

SubTrajectory Balance

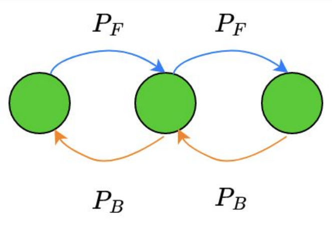
Subtrajectory balance	(partial) trajectory τ

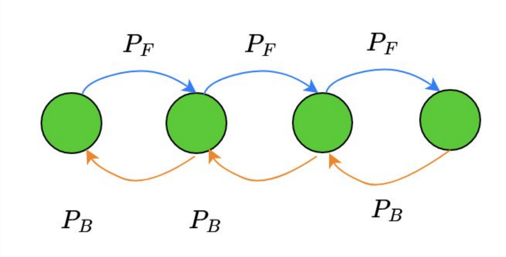


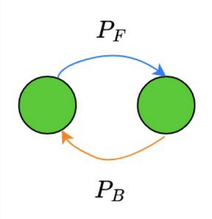


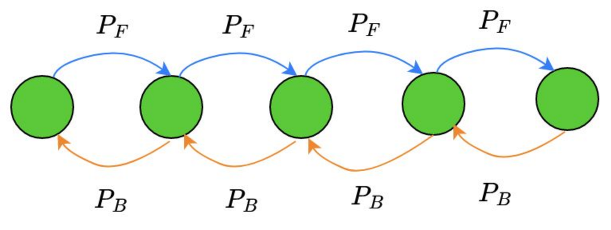
SubTrajectory Balance

Subtrajectory balance	(partial) trajectory τ



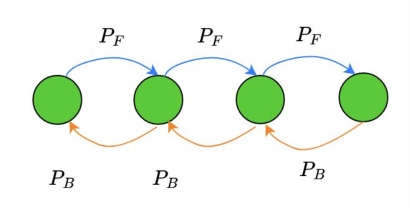


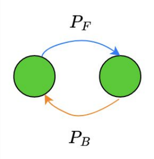


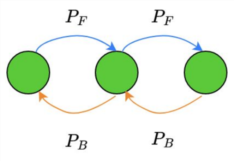


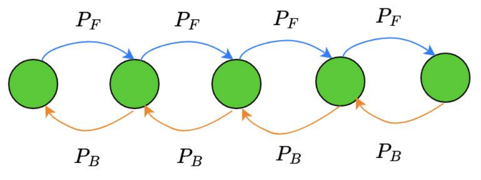
SubTrajectory Balance

$$F(s_m;\theta)\prod_{i=m}^{n-1} P_F(s_{i+1}|s_i;\theta) = F(s_n;\theta)\prod_{i=m}^{n-1} P_B(s_i|s_{i+1};\theta),$$



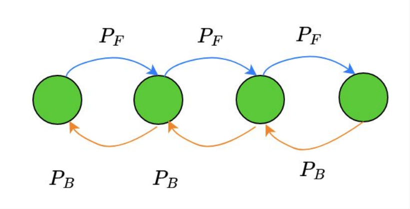


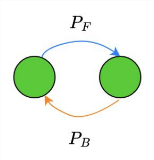


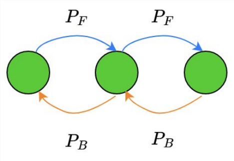


SubTrajectory Balance

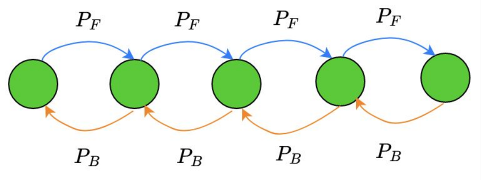
$$F(s_m;\theta)\prod_{i=m}^{n-1} P_F(s_{i+1}|s_i;\theta) = F(s_n;\theta)\prod_{i=m}^{n-1} P_B(s_i|s_{i+1};\theta),$$







$$\mathcal{L}_{\text{SubTB}}(\tau_{m:n}) = \left(\log \frac{F(s_m;\theta)\prod_{i=m}^{n-1} P_F(s_{i+1}|s_i;\theta)}{F(s_n;\theta)\prod_{i=m}^{n-1} P_B(s_i|s_{i+1};\theta)}\right)^2$$

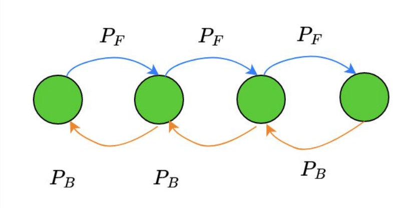


SubTrajectory(λ) or SubTB(λ):

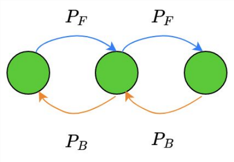
GFlowNet Objectives Unified

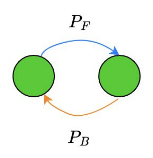
& Extended

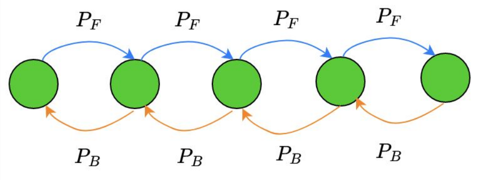
SubTrajectory (λ) or SubTB (λ)



$$\mathcal{L}_{\text{SubTB}(\lambda)}(\tau) = \frac{\sum_{0 \le m < n \le N} \lambda^{n-m} \mathcal{L}_{\text{SubTB}}(\tau_{m:n})}{\sum_{0 \le m < n \le N} \lambda^{n-m}}.$$







SubTrajectory (λ) or SubTB (λ)

- SubTrajectory (λ)

$$\mathcal{L}_{\mathrm{SubTB}(\lambda)}(\tau) = \frac{\sum_{0 \le m < n \le N} \lambda^{n-m} \mathcal{L}_{\mathrm{SubTB}}(\tau_{m:n})}{\sum_{0 \le m < n \le N} \lambda^{n-m}}.$$

- Unifies Detailed Balance and Trajectory Balance

SubTrajectory (λ) or SubTB (λ)

- SubTrajectory (λ)

$$\mathcal{L}_{\mathrm{SubTB}(\lambda)}(\tau) = \frac{\sum_{0 \le m < n \le N} \lambda^{n-m} \mathcal{L}_{\mathrm{SubTB}}(\tau_{m:n})}{\sum_{0 \le m < n \le N} \lambda^{n-m}}.$$

- Unifies Detailed Balance and Trajectory Balance

$$\lambda \to 0^+ : \sum_i \mathcal{L}_{\mathrm{DB}}(s_i, s_{i+1})$$

SubTrajectory (λ) or SubTB (λ)

- SubTrajectory (λ)

$$\mathcal{L}_{\mathrm{SubTB}(\lambda)}(\tau) = \frac{\sum_{0\le m<n\le N} \lambda^{n-m} \mathcal{L}_{\mathrm{SubTB}}(\tau_{m:n})}{\sum_{0\le m<n\le N} \lambda^{n-m}}.$$

- Unifies Detailed Balance and Trajectory Balance

$$\lambda \to 0^+ : \sum_i \mathcal{L}_{\mathrm{DB}}(s_i, s_{i+1})$$

$$\lambda \to +\infty : \mathcal{L}_{\mathrm{TB}}(\tau)$$

SubTrajectory (λ) or SubTB (λ)

- SubTrajectory (λ)

$$\mathcal{L}_{\mathrm{SubTB}(\lambda)}(\tau) = \frac{\sum_{0 \le m < n \le N} \lambda^{n-m} \mathcal{L}_{\mathrm{SubTB}}(\tau_{m:n})}{\sum_{0 \le m < n \le N} \lambda^{n-m}}.$$

- Unifies Previous Objectives
  - Detailed Balance: $\lambda \to 0^+$
  - Trajectory Balance: $\lambda \to +\infty$
- Lower gradient variance

SubTrajectory (λ) or SubTB (λ)

- SubTrajectory (λ)

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- Unifies Previous Objectives
  - Detailed Balance: $\lambda \to 0^{+}$
  - Trajectory Balance: $\lambda \to +\infty$
- Lower gradient variance
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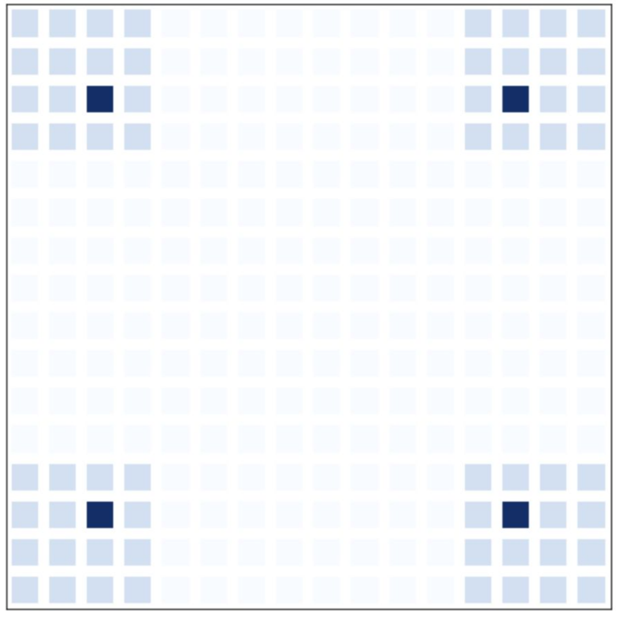
SubTB(λ): Experiments & Results

Experiments: SubTB (λ)

- 6 domains:

1. Hypergrid: Multi-dimensional grid
2. Small Molecule Synthesis: sequential generation of molecules from fixed graphs
3. Bit Sequence Generation: sequences of bits with fixed length
4. AMP: Antimicrobial Peptide sequence generation
5. GFP: Fluorescent Protein Generation - long sequences
6. Inverse protein folding: Non-autoregressive sequence generation

Experiments: Hypergrid



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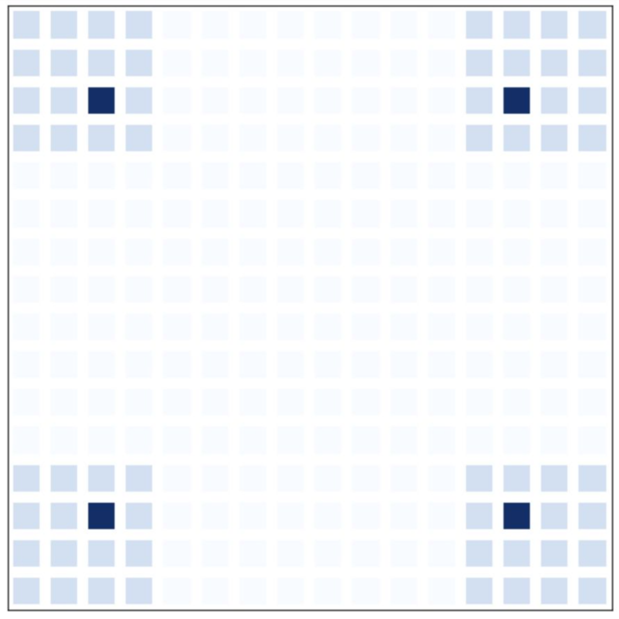

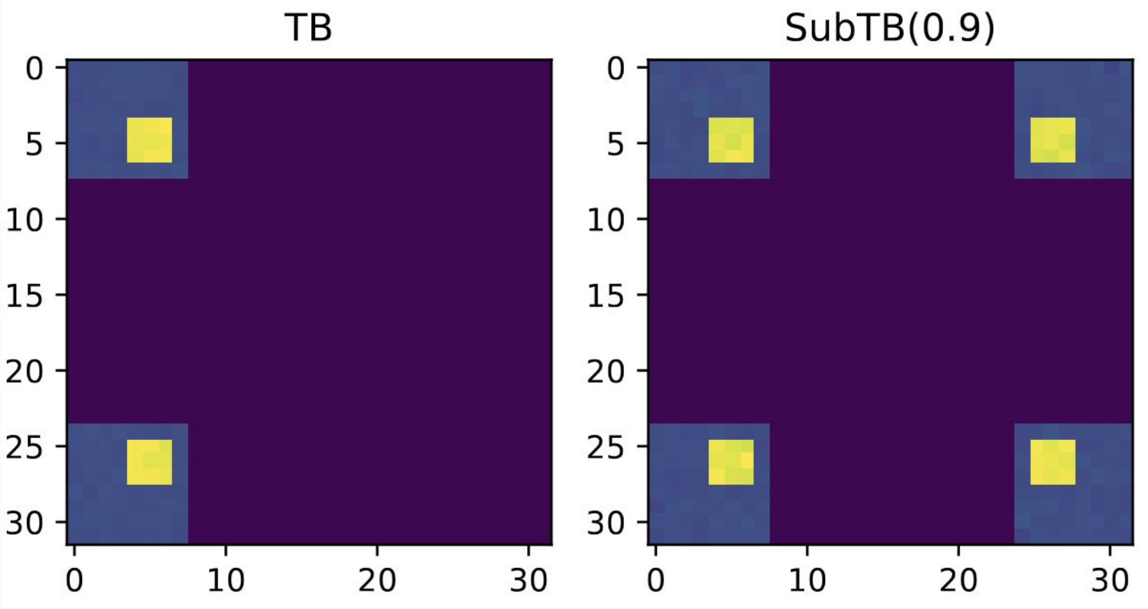

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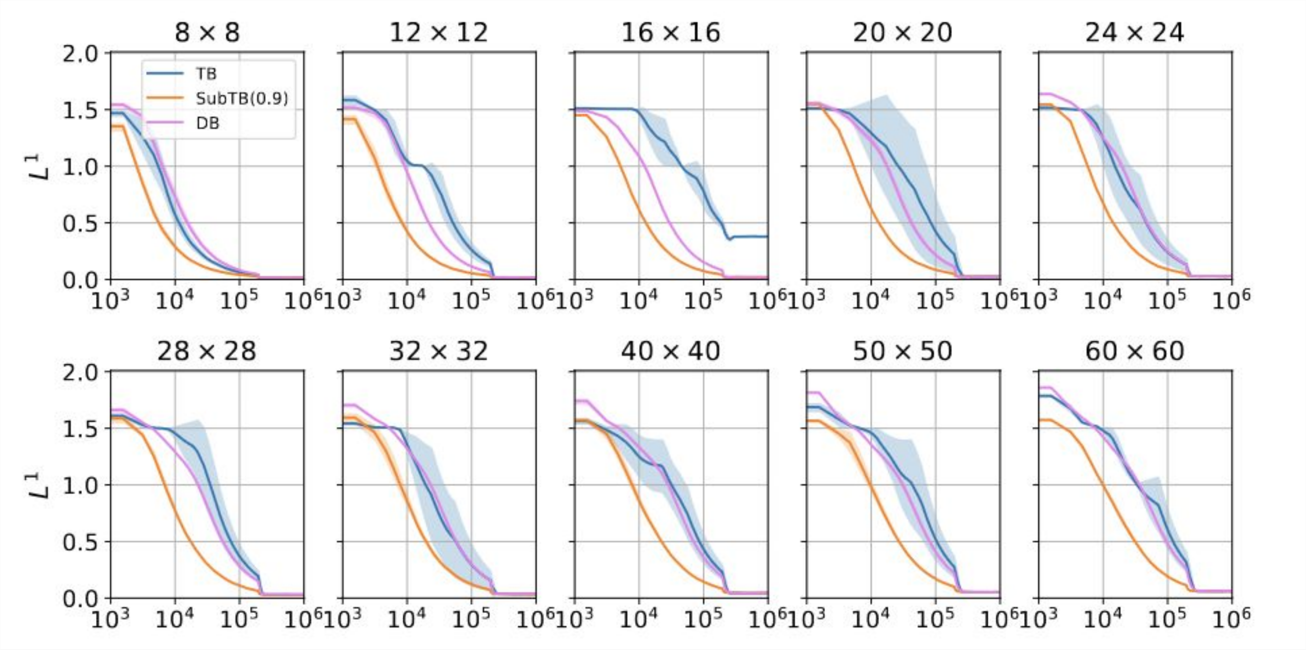

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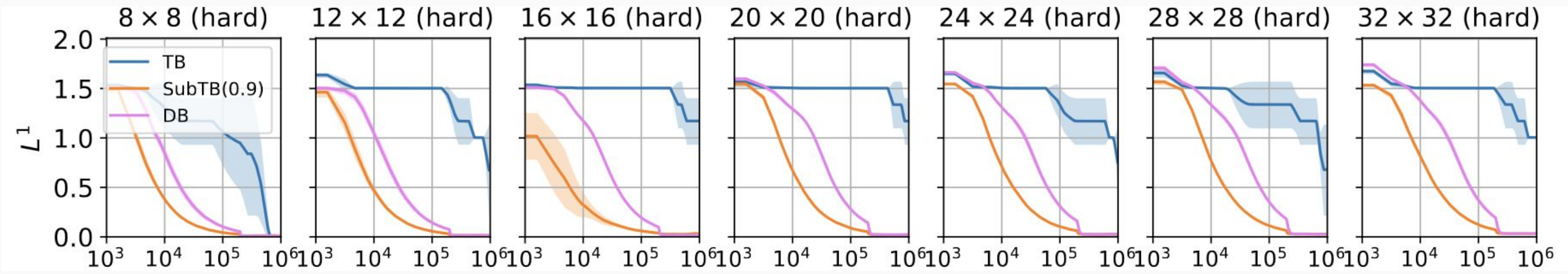
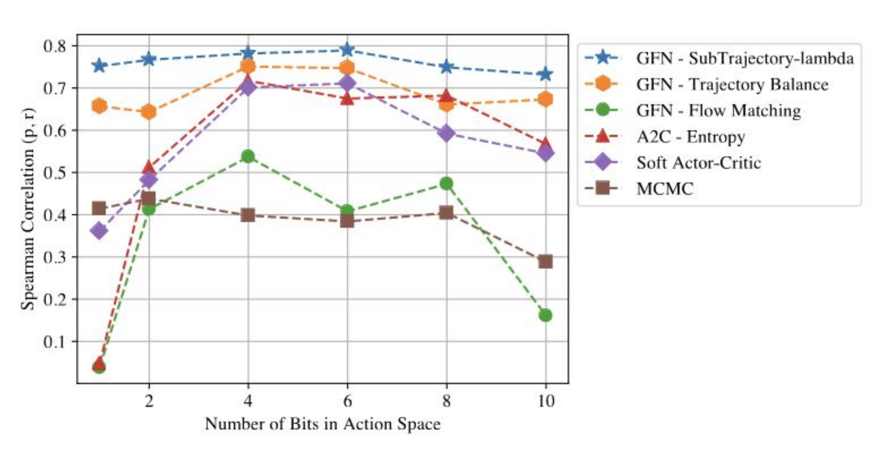
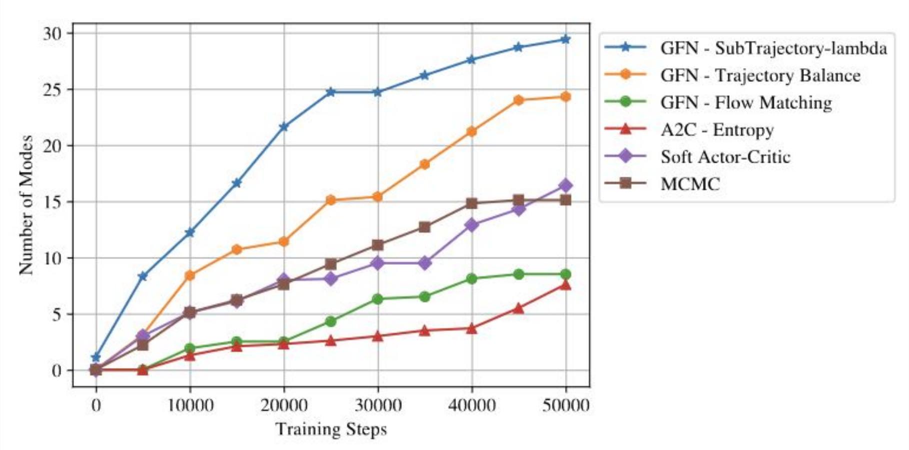
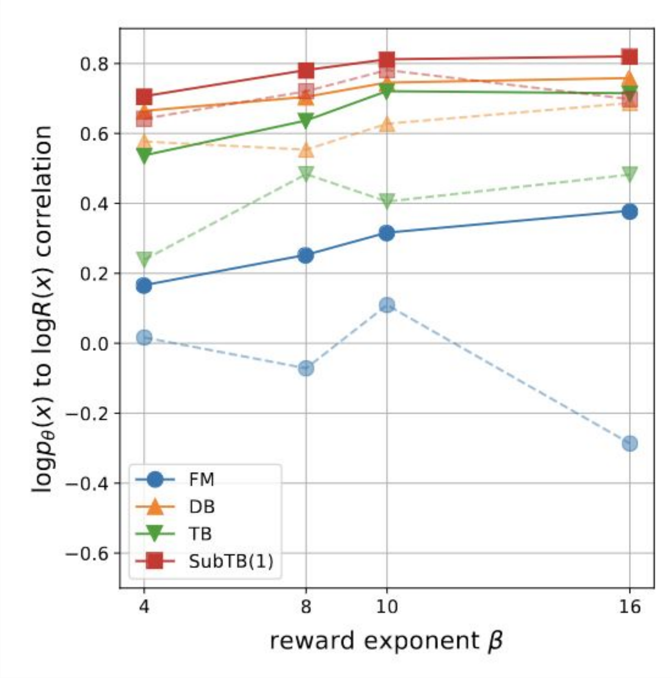


Experiments: Bit Sequence





Experiments: Small Molecule



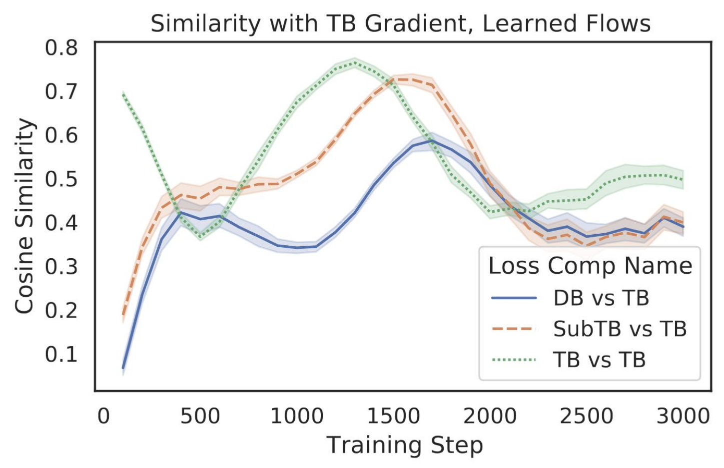
Experiments: AMP and GFP sequence

Algorithm	Top-100 Reward	Top-100 Diversity
GFN-$\mathcal{L}_{\text{SubTB}(\lambda)}$	0.96 ± 0.02	42.23 ± 3.4
GFN-$\mathcal{L}_{\text{TB}}$	0.90 ± 0.03	31.42 ± 2.9
GFN-$\mathcal{L}_{\text{FM}}/\mathcal{L}_{\text{DB}}$	0.78 ± 0.05	12.61 ± 1.32
SAC	0.80 ± 0.01	8.36 ± 1.44
AAC-ER	0.79 ± 0.02	7.32 ± 0.76
MCMC	0.75 ± 0.02	12.56 ± 1.45
GFN-$\mathcal{L}_{\text{SubTB}(\lambda)}$	1.18 ± 0.10	204.44 ± 0.45
GFN-$\mathcal{L}_{\text{TB}}$	0.76 ± 0.19	204.31 ± 0.44
GFN-$\mathcal{L}_{\text{FM}}/\mathcal{L}_{\text{DB}}$	0.30 ± 0.08	190.21 ± 6.78
SAC	0.23 ± 0.03	120.32 ± 15.57
AAC-ER	0.22 ± 0.02	113.65 ± 21.31
MCMC	0.28 ± 0.01	169.17 ± 12.44

SubTB(λ): Gradient Analysis

Gradient Analysis: SubTB(λ)

- **Small-batch** SubTB(λ) gradient is a good estimator of large-batch TB gradient.



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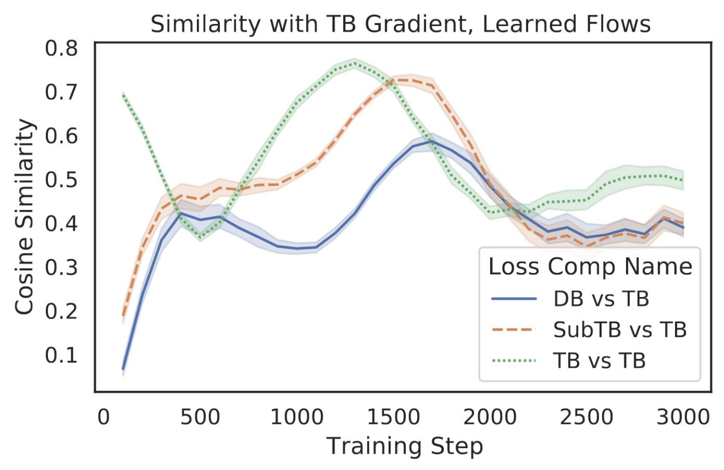

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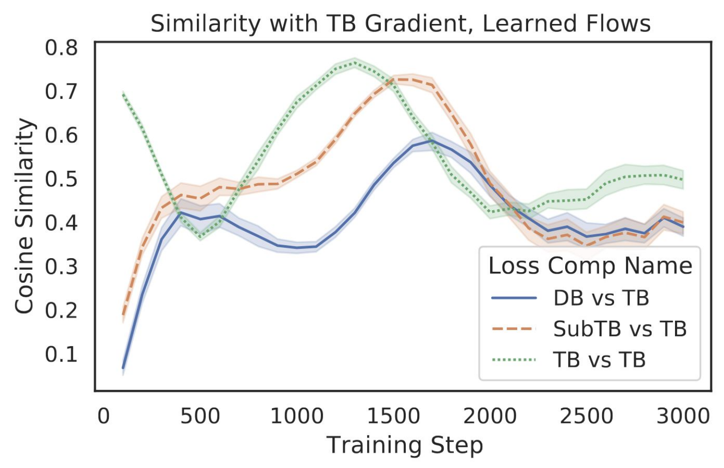
- SubTB(λ) interpolates between the unbiased gradient estimates of TB and the biased gradient estimates of DB.



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Thanks!

Poster -
26 Jul @ 2 p.m
Exhibit Hall 1 #535

Paper