

Masked Generative Priors Improve World Models Sequence Modelling Capabilities

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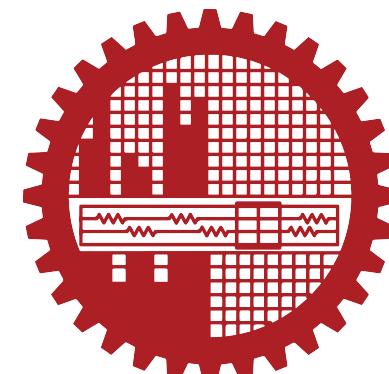
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Dianbo Liu

Anirudh Goyal

Justin Dauwels

Outstanding Paper Award!



World models

- Deep RL has achieved breakthrough performance in complex tasks.
- World models enable sample efficiency via “imagination”

Basic Training Formula...

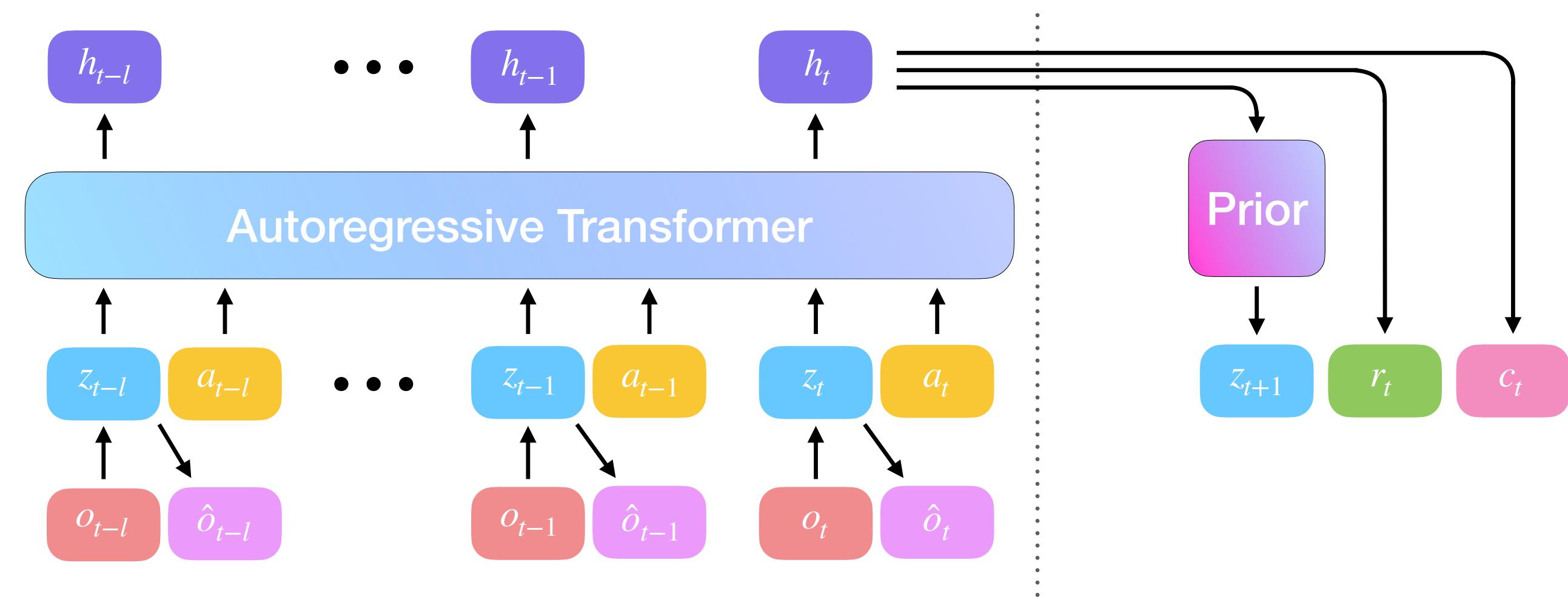
For visual observations

- Pixel space encoder
 - Turns observations to latent embeddings
- Sequence modeler
 - $f: \mathcal{S} \times \mathcal{A} \rightarrow \mathcal{S}$
- Learnt end-to-end through
 - Some reconstruction such as observation, latent, etc.

Autoregressive Transformer

As a sequence modeller

- Unidirectional generation process
 - Unable to fully capture global contexts
- e.g., STORM[1],
 - $h_t \rightarrow z_{t+1}$ is a MLP
 - Predicting categorical logits



What could go wrong?

- No global information
- Only *one* chance to predict z_t
 - What if $logit_1$ and $logit_2$ need to be distinct?
 - Result=Predicting **infeasible** states!

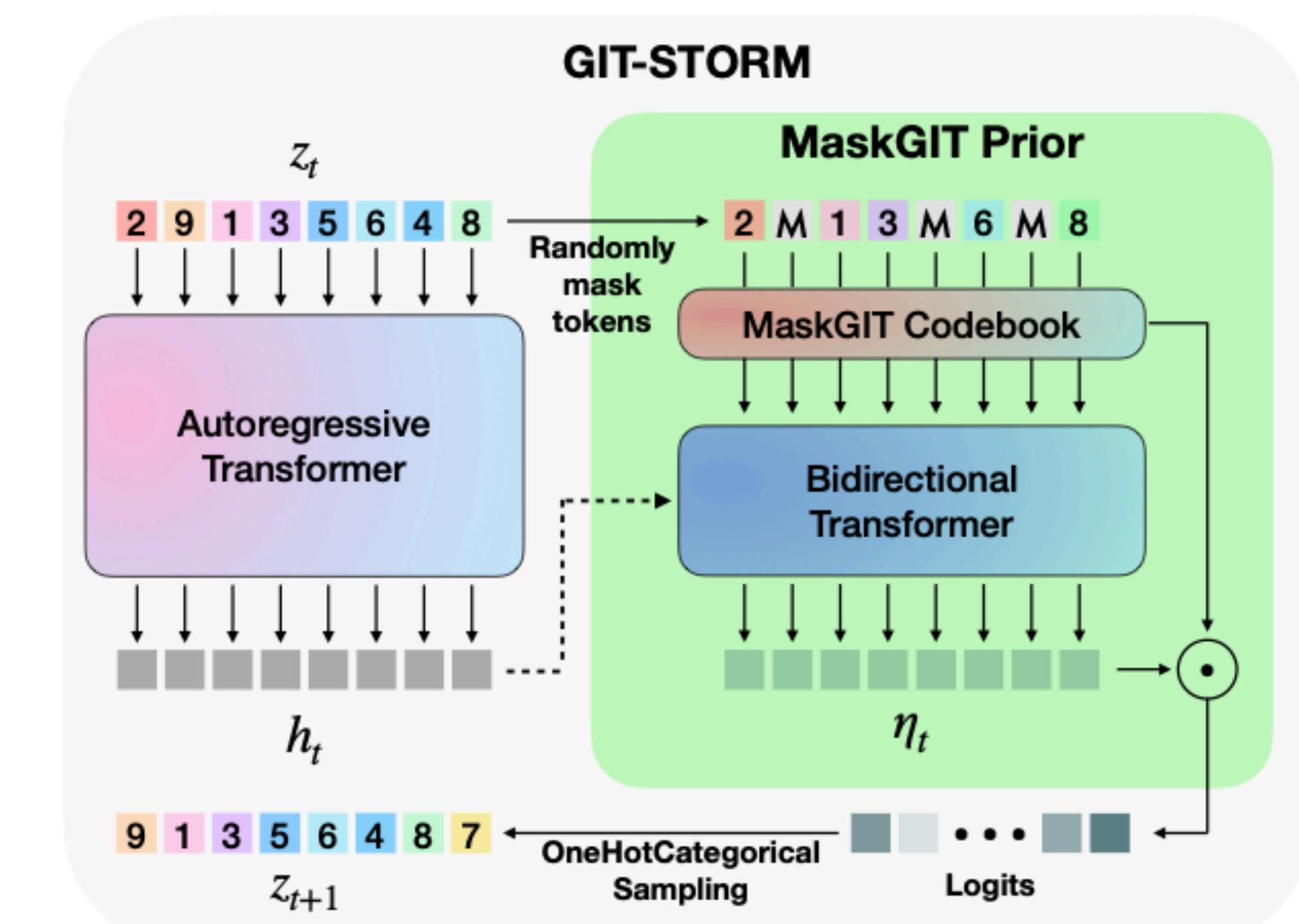
Masked Generative Modelling

- TECO [2] introduces MaskGIT[3] prior $p_\phi(z_{t+1} | h_t)$
 - draft-and-revise predicts the next discrete representations
- Uses global context
 - “Safer” approach to predict z_t
 - One step at a time (after looking at current global prediction)

World model w/ masked generative prior

tl;dr: we replace a MLP module with a MaskGIT module

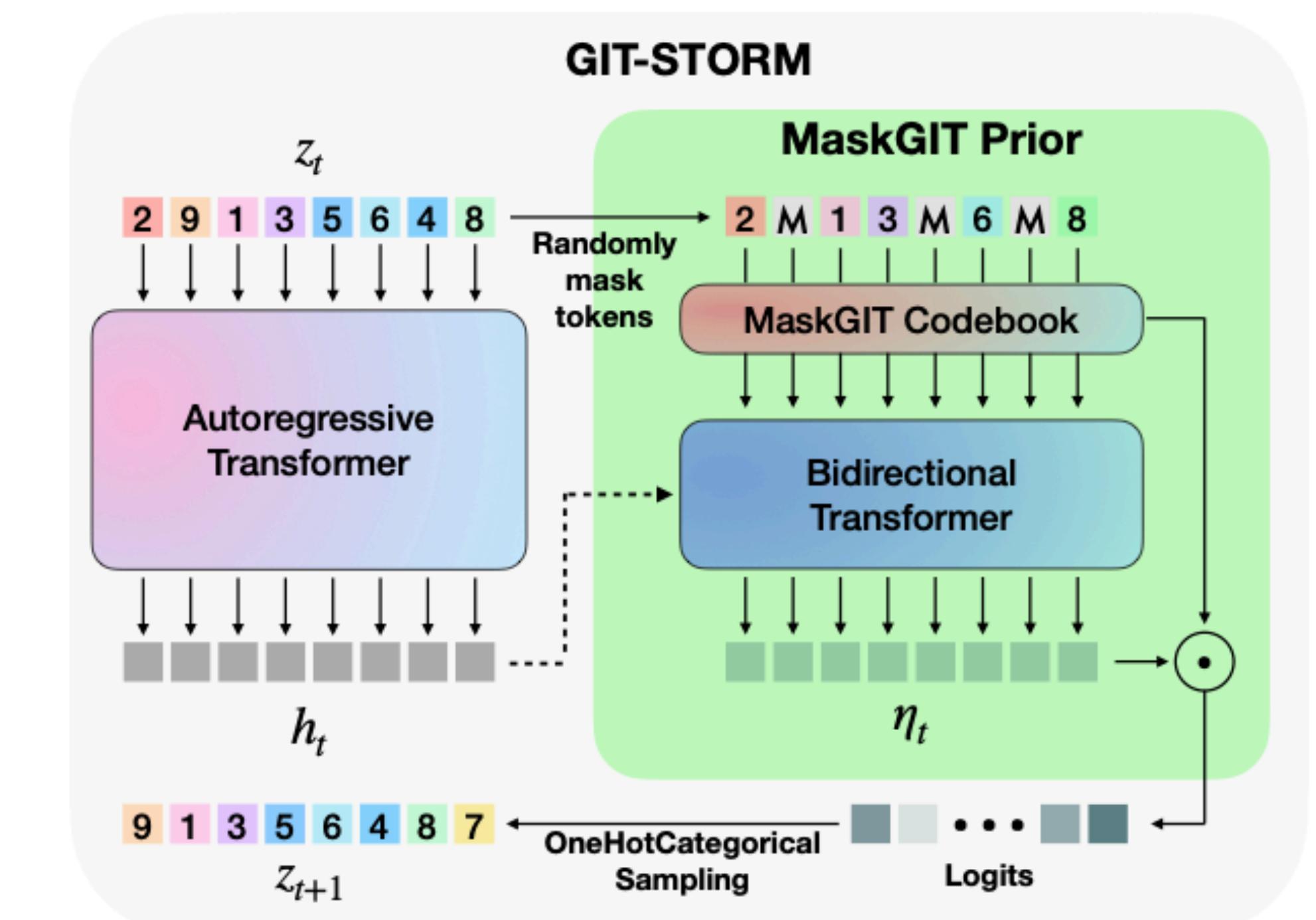
- Concatenate hidden state h_t with masked latent representation $m_t \cdot z_t$
 - Posterior latent prediction from masked latent z_t
- Minimize KL div. Between prior and post.
- Similar to previous methods



World model w/ masked generative prior

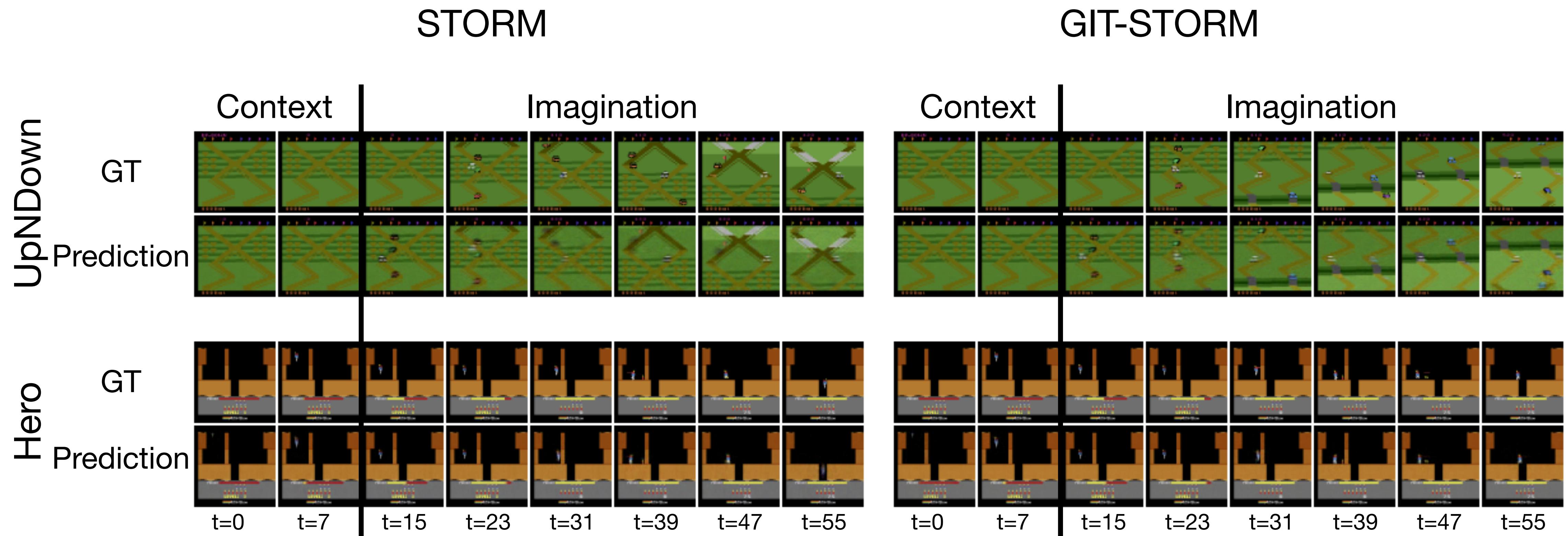
tl;dr: we replace a MLP module with a MaskGIT module

- During inference
 - perform draft-and-revise using masked decoding
- Don't generate everything at once
 - or do next-token-prediction
- Mask tokens, predict the next ones, and revise as needed



Results

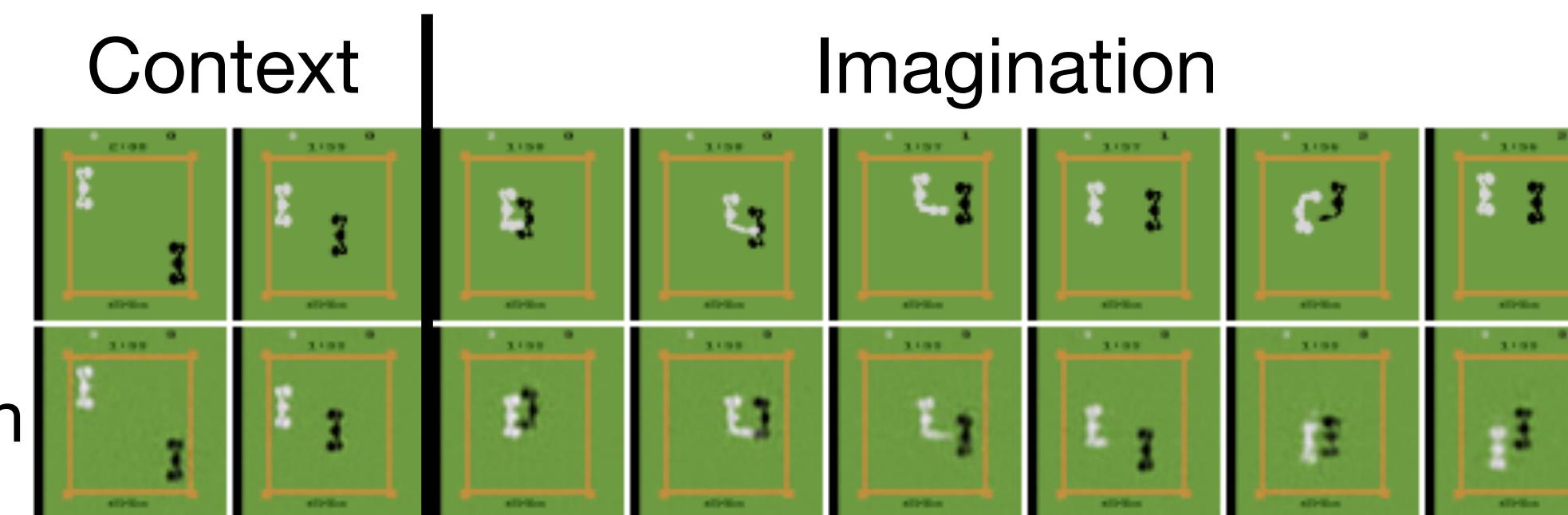
Better modeling capabilities!



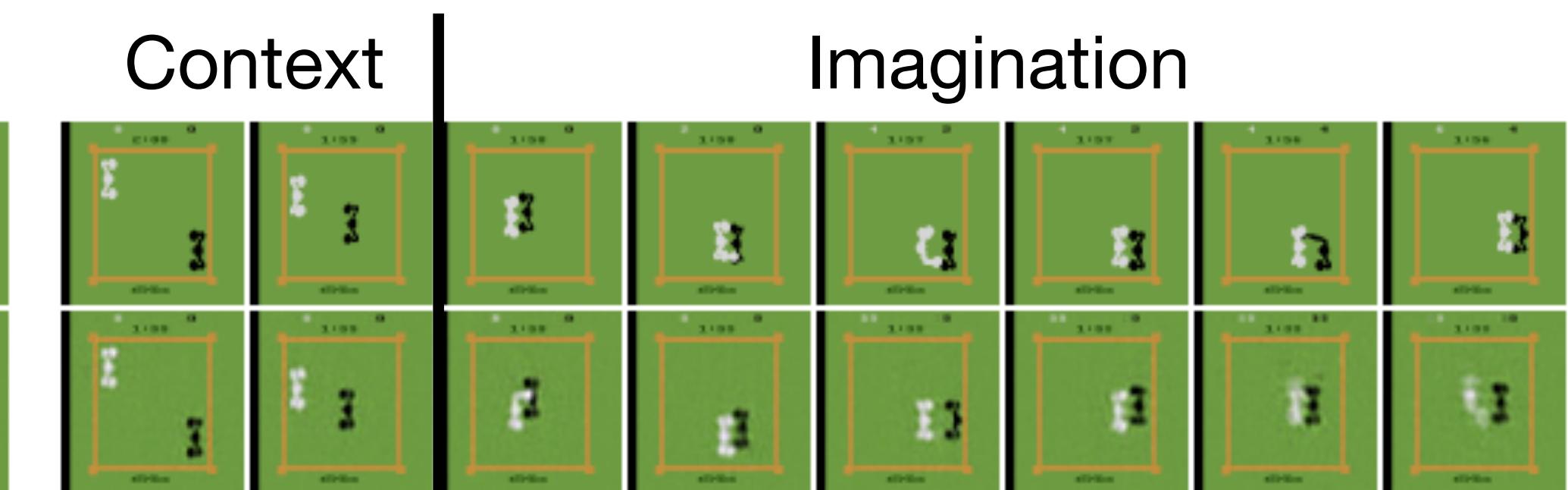
Results

Better modeling capabilities!

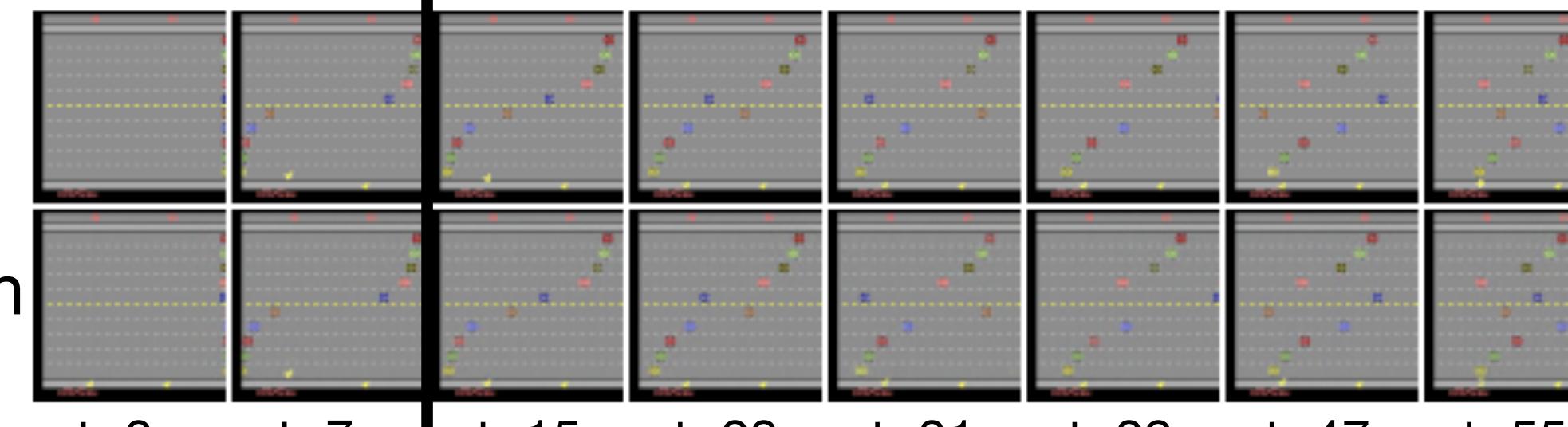
STORM



GIT-STORM



Freeway



Results

Better modeling capabilities!

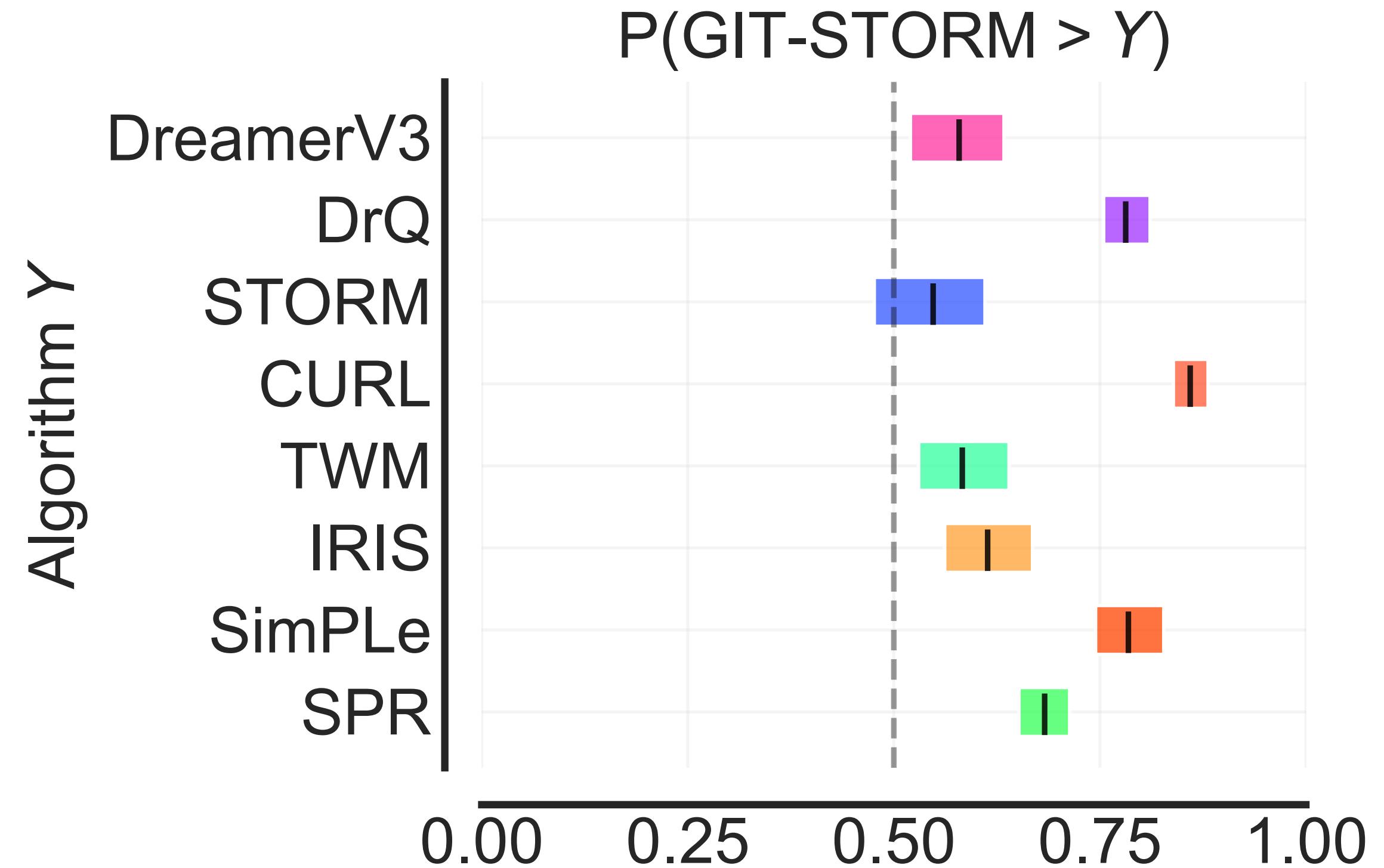
Game	FVD (↓)		Perplexity (↑)	
	STORM	GIT-STORM	STORM	GIT-STORM
Boxing	1458.32	1580.32	49.24	54.95
Hero	381.16	354.16	10.55	30.25
Freeway	105.45	80.33	33.15	67.92

Task	FVD (↓)		Perplexity (↑)	
	STORM	GIT-STORM	STORM	GIT-STORM
Cartpole Balance Sparse	2924.81	1892.44	1.00	3.76
Hopper Hop	4024.11	3458.19	3.39	22.59
Quadruped Run	3560.33	1000.91	1.00	2.61

Results

... Leading to better policy

- 19% higher human mean than STORM
- Over 20% improved IQM than STORM
- Over 50% probability of improvement to all baselines



Results

Works for continuous action environments too

- Transformer-based world models to continuous action spaces (DMC Suite) was unaddressed by IRIS, TECO or the original STORM
- GIT-STORM reports results on DMC benchmark
 - Over **50%** probability of improvement to STORM, PPO, and SAC

Limitations and Future Works

- Our method falls short on continuous action space benchmarks, compared to GRU based approaches
 - *Why does transformer based methods fails to capture continuous action space worlds?*
- We can use only one iteration for the Draft-and-Revise decoding scheme
 - *How to fully exploit the advantages of this decoding scheme?*

Summary

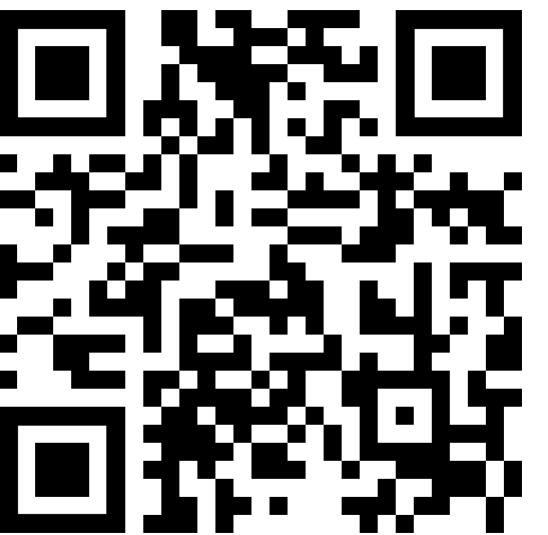
- World modeling approaches involve categorical distribution for latents
- Treat prior distributions as “2d grid”
 - Just like images
- Learn to uncover “mass” for the distributions using maskGIT
 - Refine prior distributions during inference

Thank You!



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Paper



Repository