

# DyMoDreamer: World Modeling with Dynamic Modulation

Advances in Neural Information Processing Systems (NeurIPS 2025)

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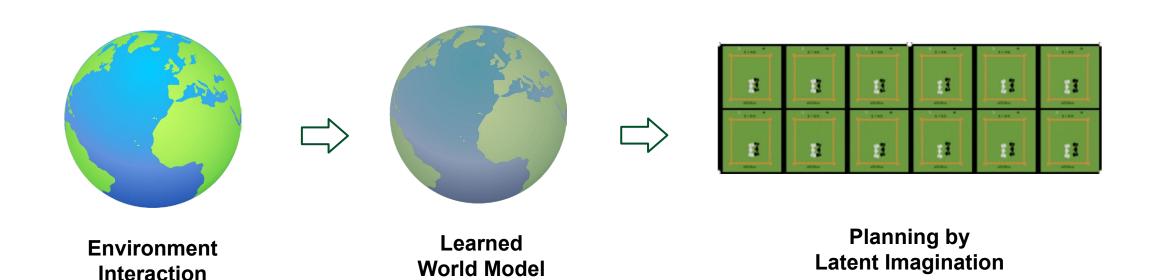
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# **Background**



#### World model-based reinforcement learning

- Learning latent dynamics for planning and decision-making;
- Generating "imagination trajectories" for agents to learn behaviors.



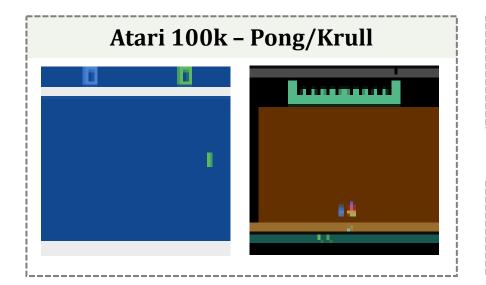


#### **Motivation**



### Cognitive Science

- Human infants naturally focus on dynamic object interactions to infer fundamental principles of their surroundings;
- Rewards are predominantly influenced by the dynamic parts.



 Conventional world models process observations holistically;



Designing a world model focus on the key dynamic features and temporal information.





### DyMoDreamer

- Prioritizing dynamic features through inter-frame differencing mask;
- Integrating a dynamic modulation mechanism into RSSM;
- All components are trained jointly without separate modulator training.

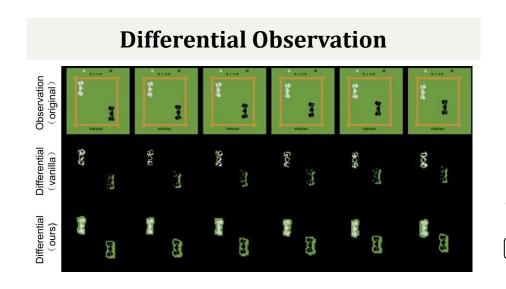
# Differential Observation (oncs) (vanilla) (vanilla) (oncibual) (original) (or

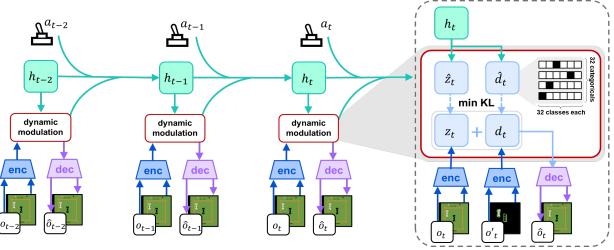




## DyMoDreamer

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# DyMoDreamer

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- All components are trained jointly without separate modulator training.

#### **Prediction Loss**

$$\mathcal{L}_{\text{pred}}(\phi) = \mathcal{L}_{\text{rec}}(\phi) + \mathcal{L}_{\text{rew}}(\phi) + \mathcal{L}_{\text{con}}(\phi)$$

$$\mathcal{L}_{rec}(\phi) = -\ln p_{\phi}(o_t|h_t, z_t, d_t)$$

$$\mathcal{L}_{\text{rew}}(\phi) = -\ln p_{\phi}(r_t|h_t, z_t, d_t)$$

$$\mathcal{L}_{con}(\phi) = -\ln p_{\phi}(c_t|h_t, z_t, d_t)$$

#### **Dynamic and Representation Loss**

$$\mathcal{L}_{\text{dyn}}(\phi) = \max \left( 1, \text{KL}[\text{sg}(q_{\phi}(z_t \mid h_t, o_t)) \parallel p_{\phi}(\hat{z}_t \mid h_t)] \right) + \underbrace{\max(1, \text{KL}[\text{sg}(q_{\phi}(d_t \mid h_t, o_t')) \parallel p_{\phi}(\hat{d}_t \mid h_t)])}_{\text{modulation's dynamic loss}}.$$

$$\mathcal{L}_{\text{rep}}(\phi) = \max \left( 1, \text{KL}[q_{\phi}(z_t \mid h_t, o_t) \parallel \text{sg}(p_{\phi}(\hat{z}_t \mid h_t))] \right) + \underbrace{\max(1, \text{KL}[q_{\phi}(d_t \mid h_t, o_t') \parallel \text{sg}(p_{\phi}(\hat{d}_t \mid h_t))])}_{}$$

modulation's representation loss

#### **Divergence Regularization**

$$\mathcal{L}_{\text{reg}}(\phi) = \frac{1}{B} \sum \text{KL}(\sigma(\Delta \hat{o}) \parallel \sigma(\Delta o)).$$

$$\sigma(\Delta \hat{o}_t) = \frac{\exp(\Delta \hat{o}_t/\tau)}{\sum_{h,w,c} \exp(\Delta \hat{o}_t/\tau)},$$

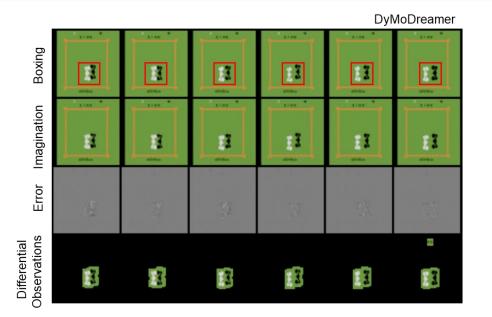
$$\sigma(\Delta o_t) = \frac{\exp(\Delta o_t/\tau)}{\sum_{h,w,c} \exp(\Delta o_t/\tau)}$$



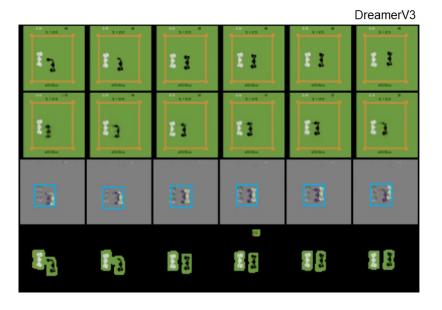


### > More Efficient Imagination

 DyMoDreamer highlights the dynamic features, exhibits less hallucinations during the imagination reconstruction than vanilla DreamerV3.









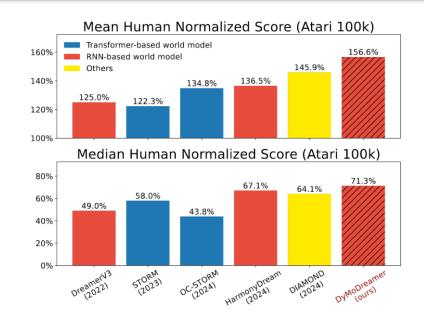
### **Results**



#### > Performance

 DyMoDreamer surpasses baselines on the Atari 100K, DeepMind Visual Control, and Crafter benchmark.

Atari 100k				
	OC-STORM	DIAMOND	DreamerV3	DyMoDreamer
	(2025)	(2024)	(2023)	(ours)
HNS Mean	134.8%	146%	125%	156.6%
HNS Median	43.8%	37%	49%	71.3%
	DeepMi	nd Visual Con	trol Suite	
	TD-MPC2	TWISTER	DreamerV3	DyMoDreamer
	(2023)	(2025)	(2023)	(ours)
Task Mean	720.9	801.8	786	832
Task Median	795.9	907.6	861	871
		Crafter		
	IRIS	Δ-IRIS	DreamerV3	DyMoDreamer
	(2023)	(2024)	(2023)	(ours)
Return @1M	5.5	7.7	9.4	10.3



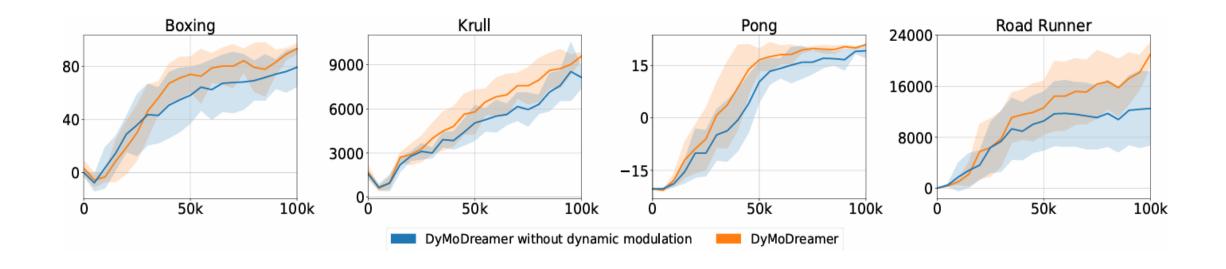


### **Ablation Studies**



### Removing Dynamic Modulation

 Simply appending differential observations fails to direct the world model's focus toward dynamic patterns.







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