



Probabilistic World Modeling with Asymmetric Distance Measure

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What is a good representation for planning?

• An *asymmetric* distance function reflecting the state transitions



Irreversible transitions

Asymmetric contrastive learning

• Applying contrastive learning to the Markov chain of world dynamics



Asymmetric contrastive learning



Two separate encoders: $cos(\psi(x), \phi(y)) \neq cos(\psi(y), \phi(x))$

C-step geometric abstraction



1-step transition graph

2-step transition graph

2-step reaching probability graph

$$P(X = x | Y = y) \approx \frac{1}{C} \sum_{t=1}^{C} (P^t)_{yx}$$

Reference state conditioned distance measure



Subgoal discovery

- Define *subgoals* as the states that reduce pairwise reaching probability, as perceived from the agent's current state.
- Identified using DBSCAN on the latent point density estimated according to $d_r(u, v)$.





probability density in the original state space

point density in the latent space

Experiments



Subgoals identified as gray states

The effect of step size C

The rooms and doorways are separated further apart in the representation space as C goes up.



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Summary

- Contrastive learning with two separate encoders gives rise of an **asymmetric similarity function** that encodes state reaching probability.
- Contrastive learning embeds a **geometric abstraction** of the original Markov transition graph.
- These two geometric properties together enable us to find perspective-conditioned subgoals easily.

paper

