

Inference via Interpolation: Contrastive Representations Provably Enable Planning and Inference

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Code and paper!



https://github.com/vivekmyers/contrastive_planning

Q: Inference in high-dimensional time series?

Prediction/forecasting:



Planning/inpainting:



References

- [1] Srivastava, P., et al. (2016). Time-contrastive networks: Self-supervised learning from video. ICRA.
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- [3] Eysenbach, B. et al. (2022). Contrastive learning as goal-conditioned reinforcement learning. NeurIPS.
- [4] Ma, Z., Collins, M. (2018). Noise Contrastive Estimation and Negative Sampling for Conditional Models: Consistency and Statistical Efficiency. EMNLP.
- [5] Wang, T., Iqbal, P. (2020). Understanding contrastive representation learning through alignment and uniformity on the hypersphere. ICML.
- [6] Zheng, Changyi, et al. (2024). Stabilizing Contrastive RL: Techniques for Robotic Goal Reaching from Offline Data. ICLR.
- [7] He, Yecheng, Jason, et al. (2023). VIP: Towards Universal Visual Reward and Representation via Value-Implicit Pre-Training. ICLR.
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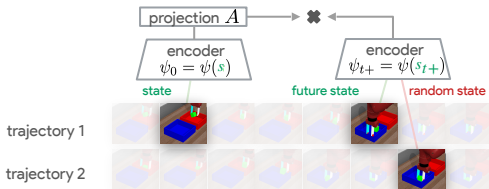
Open Questions

1. Applications to various time series datasets?
2. Can the assumptions always be satisfied?
3. How to extend this to large video/audio/text datasets?
4. Contrastive learning across multiple datasets (e.g., text ↔ videos ↔ audio)?
5. How does this relate to dynamic programming?
6. Might it inherit some TD-like properties (e.g., combinatorial generalization, shorter paths)?

Key Idea

- Key idea:** predict representations instead of observations.
- How should these representations be learned so they retain bits relevant to prediction and planning?
 - Avoid reconstruction methods (e.g., seq. VAE [Zhao '17]), which are computationally expensive.
- There's already exists a method in the literature that does this!

Temporal Contrastive Learning [1,2,3]



Setup and assumptions

Objective: (Symmetric) InfoNCE, with a quadratic energy function:

$$\min_{A, \psi(\cdot)} \mathbb{E}_{(x_0, x_T^{(1)}) \sim p(x_0, x_T), (x_T^{(i)}) \sim p(x_T)} \left[\log \frac{e^{-\|A\psi(x_0) - \psi(x_T^{(1)})\|_2^2}}{\sum_{i=1}^B e^{-\|A\psi(x_0) - \psi(x_T^{(i)})\|_2^2}} \right]$$

such that *expected* representation norm is small: $\frac{1}{k} \mathbb{E} p(x) [\|\psi(x)\|_2^2] \leq c$

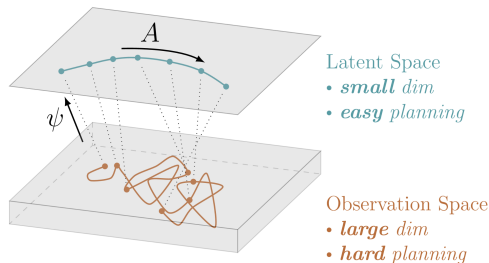
Assumption 1: (Bayes-optimal classifier) [4]

$$e^{-\frac{1}{2} \|A\psi(x_0) - \psi(x_T)\|_2^2} = \frac{p(x_T | x_0)}{p(x)C}$$

Assumption 2: (Pushforward measure is Gaussian) [5]

$$p(\psi) = \mathcal{N}(\psi; \mu = 0, \sigma = c \cdot I).$$

Theoretical Results



Theorem 1 (Prediction): Representation of a future state is Normally distributed, with mean that is a linear function of the current state representation.

$$p(\psi_{t+} | \psi_0) = \mathcal{N}\left(\mu = \frac{c}{c+1} A\psi_0, \Sigma = \frac{c}{c+1} I\right)$$

Theorem 2 (Planning): Representation of an intermediate state is Normally distributed, with mean that is a linear function of the current and final state representations.

$$p(\psi_w | \psi_0, \psi_{t+}) = \mathcal{N}\left(\psi_w; \mu = \Sigma^{-1}(A^T \psi_{t+} + A\psi_0), \Sigma = \frac{c}{c+1} A^T A + \frac{c+1}{c} I\right)$$

Theorem 3 (Multi-Step Planning): Joint distribution of representations is a Gaussian Markov chain, so intermediate representations are linear functions of initial and final representations.

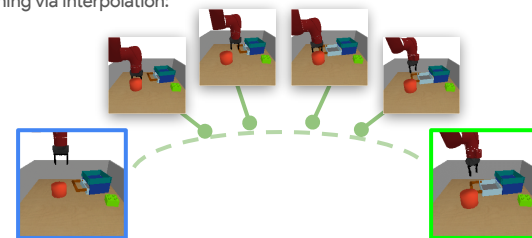
$$p(\psi_i | \psi_0, \psi_{t+}) = \mathcal{N}\left(\psi_i; \mu_i = (\Sigma\eta)^{(i)}, \Sigma_i = (\Lambda^{-1})^{(i,i)}\right)$$

(Σ and Λ are block matrices constructed from A .)

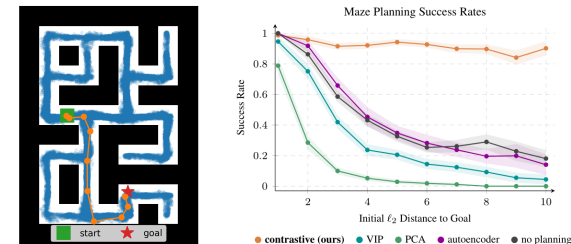
Corollary 3.1 (Special Case of Multi-Step Planning): If c is large and A is a rotation matrix, intermediate representations are a simple convex combination of initial and final representations.

Explains observation from prior work [6]

Planning via interpolation:



Application: Planning via (warped) interpolation



Visualizing the plans (TSNE)

