We present a method for temporally-extended planning over high-dimensional state spaces by learning a state representation amenable to optimization and a goal-conditioned policy to abstract time.

**Introduction**

- Planning can solve temporally extended tasks
- Goals provide action and temporal abstraction
- Generally, states may live in unknown lower-dimensional manifold, making planning challenging

**Idea:** Learn dense state abstractions to make optimization feasible.

**Latent Embedding for Abstracted Planning (LEAP)**

Given the current state $s$ and goal $g$

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choose realistic latent vectors $z_1, \ldots, z_K$
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that minimize the norm of the feasibility vector

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\overline{\mathbf{V}}(s, g; 1:K, t_1; K+1, g) = \begin{bmatrix} V(s, g_1, t_1) \\ V(g_1, g_2, t_2) \\ V(g_2, g_3, t_3) \\ \vdots \\ V(g_{K-1}, g_K, t_K) \end{bmatrix}
```

where $g_k = \psi(z_k)$. Formally, solve

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z_{1:K}^* = \arg\min_{z_{1:K}} ||\overline{\mathbf{V}}(s, z_{1:K}, t_1; K+1, g)||_p - \lambda \sum_{k=1}^K \log p(z_k)
```

and go towards first goal $g_1 = \psi(z_1^*)$.

**Implementation details**

- Use cross-entropy method for optimization.
- Reuse encoder $\psi$ for RL networks.
- Use $\ell_\infty$-norm.
- Uniformly space $t_1 = t_2 = \cdots = t_K = \lfloor T_{max}/K \rfloor$

**References**
