Learning Dirichlet Priors for Affordance Aware Planning

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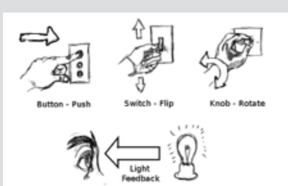
Goal

Previous Work: Provided an MDP with knowledge in order to solve extremely complex, previously unsolved tasks.

Proposal: Learn this knowledge to remove dependence on expert.

Background

Affordances: Direct agent toward relevant action possibilities.



"What [the environment] offers [an] animal, what [the environment] provides or furnishes, either for good or ill"

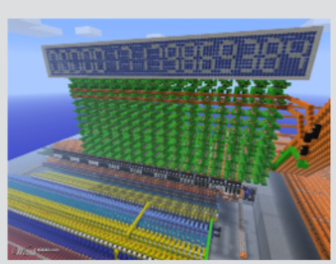
- J.J. Gibson, 1977

Formalism:

$$\Delta = \langle p, g \rangle \longmapsto \mathcal{A}'$$

p = predicate on states
g = lifted goal description
$\mathcal{A}'$ = subset of OO-MDP Actions

Domain: Minecraft



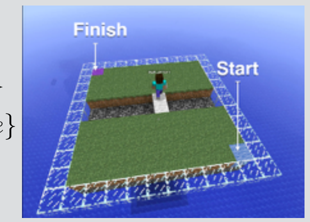
≈ Turing Complete Legos

Affordance Example

Solve the MDP using expert provided affordances

$\Delta_1 = \langle nearPlane, atLoc \rangle \longmapsto \{move\}$
$\Delta_2 = \langle nearTrench, atLoc \rangle \longmapsto \{place\}$

If Δ's predicate is true and Δ's goal type matches the current goal, use Δ's actions

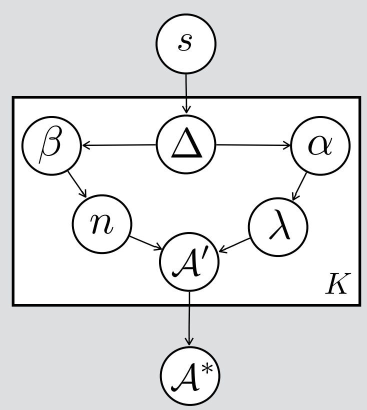


Learning

Goal: For a given state, for each affordance, learn which actions are most relevant:

$$\Pr(\mathcal{A}^* \mid s, \Delta_1 \ldots \Delta_K)$$

Graphical Model:

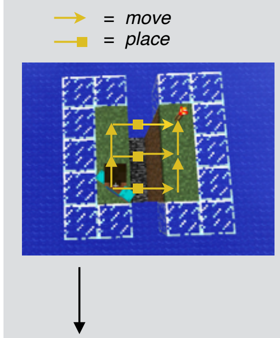


s = OO-MDP State
Δ = Affordance
α = Action Counts
β = Action Set Size Counts
λ = Distribution on Actions
n = Distribution on Action Set Size
$\mathcal{A}'$ = *One* Affordance's Action Set
$\mathcal{A}^* = \bigcup_{i=1}^{K} \mathcal{A}'_i$

Where:

$$\Pr(\lambda \mid \alpha) = DirMult(\alpha)$$
$$\Pr(n \mid \beta) = Dir(\beta)$$

Learning Example



1. Generate *W simple* worlds
2. Form policies (yellow) on each world
3. For each active affordance, count:

   $\alpha =$ number of worlds in which each action was used
   $\beta =$ number of unique actions used in each world

$\Delta_i.\alpha \leftarrow \{moveRight{+}{+}, moveForward{+}{+}, placeRight{+}{+}\}$
$\Delta_i.\beta \leftarrow \{3{+}{+}\}$

4. We have:

$\Delta_i.getActions(s)$:

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λ ← DirMult(Δ_i.α)
n ← Dir(Δ_i.β)
A' ←_n λ
return: A'
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5. When solving the MDP on a new state space, in each state *s*:

$$\mathcal{A}^* = \bigcup_{i=1}^{K} (\Delta_i.getActions(s))$$

Results

Avg. # Bellman Updates Per Converged Policy