Empowerment, Free Energy Principle and Maximum Occupancy Principle (MOP) Compared

MOP paper v1

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Motivation

Natural behavior, even stereotyped one, **is variable**. The reasons for this variability are unknown. We **propose** that the **goal of behavior is to produce guided variability**, i.e., generate all sorts of action-state paths compatible with the dynamics and constraints of the agent. We call this **Maximum Occupancy Principle (MOP)**. We compare MOP with other two reward-free approaches in Markov Decision Processes (MDP): Empowerment and Free Energy Principle

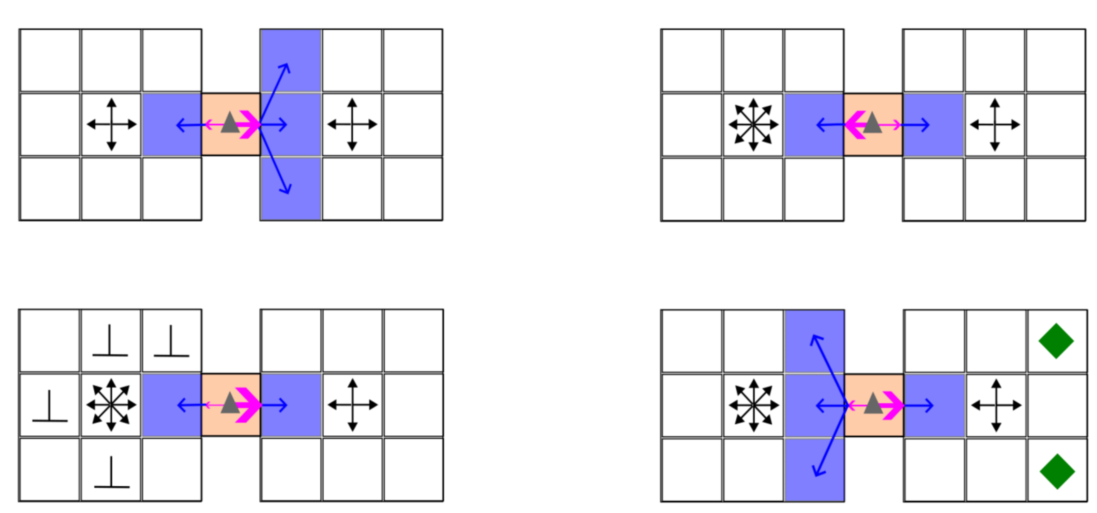
Maximum Occupancy Principle (MOP)

Goal: Maximize future cumulative action-state path entropy [1]
Bias: Agents prefer states that promise future action-state entropy (freedom & exploration) while avoiding absorbing states (survival instinct)
Recursive?: *Yes*, a Bellman equation can be written

$\pi(a_t|s_t)$ policy — $p(s_{t+1}|s_t,a_t)$ state transition prob. — $\tau \equiv (s_0,a_0,s_1,...,a_t,s_{t+1},...)$ action-state path (trajectory)

return
$$R(\tau) = -\sum_{t=0}^{\infty}\gamma^t \ln\left(\pi^\alpha(a_t|s_t)p^\beta(s_{t+1}|s_t,a_t)\right)$$

value
$$V_\pi(s) \equiv \mathbb{E}_{a_t\sim\pi(a_t|s_t),s_{t+1}\sim p(s_{t+1}|s_t,a_t)}[R(\tau)|s_0=s]$$
$$= \mathbb{E}_{a_t\sim\pi(a_t|s_t),s_{t+1}\sim p(s_{t+1}|s_t,a_t)}\left[\sum_{t=0}^{\infty}\gamma^t\left(\alpha\mathcal{H}(A|s_t)+\beta\mathcal{H}(S'|s_t,a_t)\right)\Big|s_0=s\right]$$



$$V^*(s) = \sum_{s',a}\pi^*(a|s)p(s'|s,a)\Big[\underbrace{-\ln\left(\pi^{*\alpha}(a|s)p^\beta(s'|s,a)\right)}_{\text{Immediate occupancy}} + \underbrace{\gamma V^*(s')}_{\text{Future occupancy}}\Big]$$

→ available actions in room ⊥ absorbing state ◆ food

Empowerment (MPOW)

Goal: Maximize mutual information between a sequence of actions and the resulting state [2]
Bias: Agents prefer empowered states, i.e., unstable fixed points of the dynamics
Recursive?: *No*, a Bellman equation cannot be written, because Mutual Info is not additive [1], but approximations exist [1,3]

$a_t^n = (a_t,a_{t+1},...,a_{t+n-1}) \in \mathcal{A}^n$ planned sequence of actions — $p(s_{t+n}|s_t,a_t^n) = \tau(a_t^n|s_t)\prod_{\tau=t}^{t+n-1}p(s_{\tau+1}|s_\tau,a_\tau)$ n-step transition probability

$$\mathcal{E}(s_t) = \max_{\tau(a_t^n|s_t)}\sum_{a_t^n,s_{t+1}}p(s_{t+n}|s_t,a_t^n)\tau(a_t^n|s_t)\log\left(\frac{p(s_{t+n}|s_t,a_t^n)}{\sum_{a_t^n}p(s_{t+n}|s_t,a_t^n)\tau(a_t^n|s_t)}\right)$$

state empowerment; transitions are greedy towards the accessible state with highest empowerment

Free Energy Principle (FEP / EFE)

Goal: Minimize KL divergence between actual and target distributions [4]
Bias: Agents prefer states where target distribution peaks (preferred states), and behavior tends to collapse to a deterministic policy around them
Recursive?: *Yes* in fully observable MDPs ('sophisticated inference')

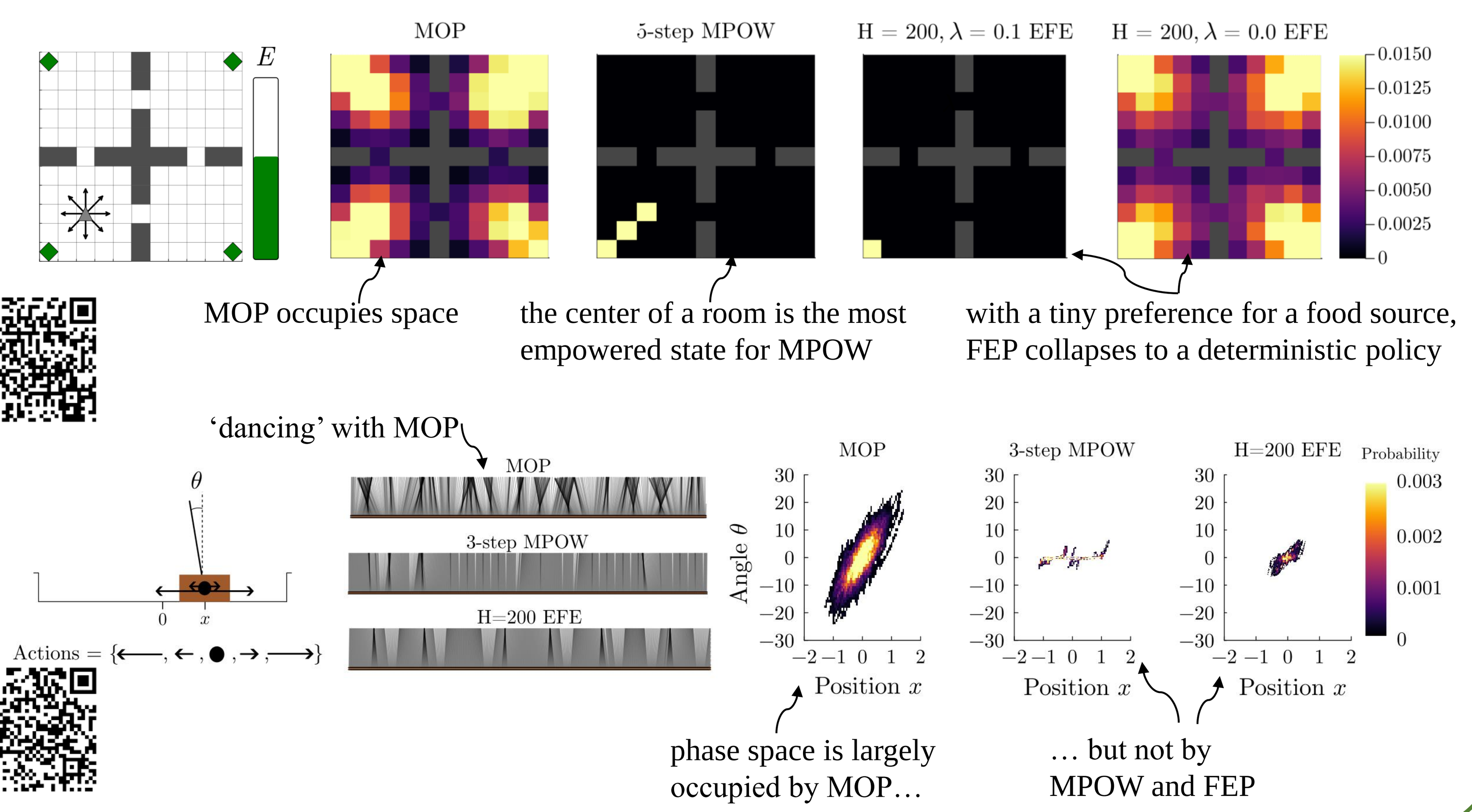
$a_t^{T-1} = (a_t,a_{t+1},...,a_{T-1})$ action path up to a horizon — $s_{t+1}^T = (s_{t+1},s_{t+2},...,s_T)$ state path up to a horizon — $q(s_{t+1}^T) = \prod_{\tau=t}^{T-1}q(s_{\tau+1})$ target distribution factorizes

cost
$$G_{\pi,t}(s_t) = \mathbb{E}_{a_t^{T-1}\sim\pi}\mathrm{KL}\left(p(s_{t+1}^T|a_t^{T-1},s_t)||q(s_{t+1}^T)\right)$$
$$= \sum_{s_{t+1}^T,a_t^{T-1}}p_\pi(s_{t+1}^T,a_t^{T-1}|s_t)\log\frac{p(s_{t+1}^T|a_t^{T-1},s_t)}{q(s_{t+1}^T)}$$

Bellman eq.
$$G_{\pi,t}(s_t) = \sum_{s_{t+1},a_t}\pi(a_t|s_t)p(s_{t+1}|s_t,a_t)\left[\log\frac{p(s_{t+1}|s_t,a_t)}{q(s_{t+1})}+G_{\pi,t+1}(s_{t+1})\right]$$

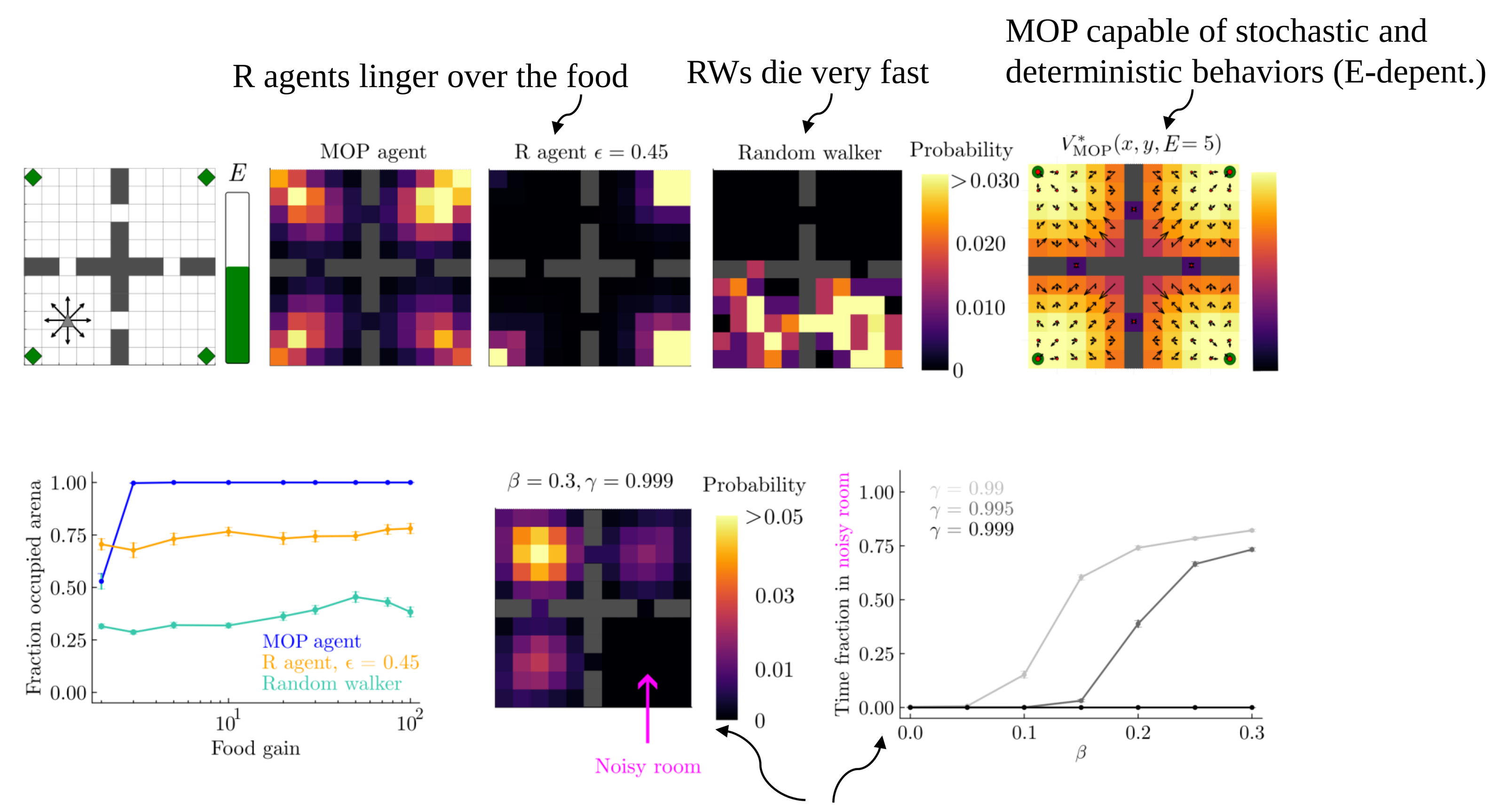
Main Result: MOP, MPOW & FEP compared

MOP produces action-state entropy non-stop, while MPOW favors unstable fix points and FEP collapses to deterministic behaviors in fully observable MDPs. This is observed in two very common environments, a grid-world and a cartpole: use QRs for compelling examples



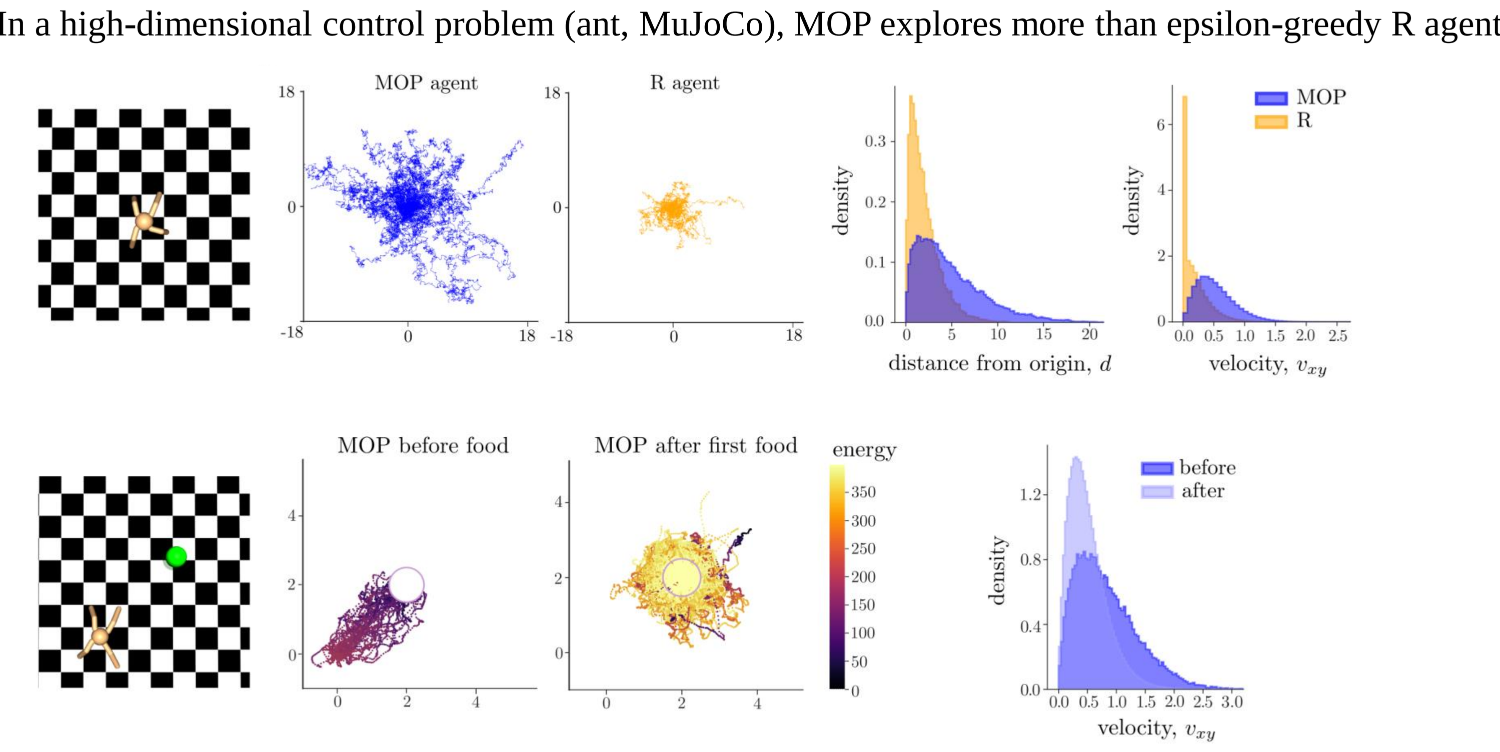
MOP vs Reward Maximization

MOP generates complex behavior in both a grid-world and ant environment.
In contrast, epsilon-greedy reward maximization matching survival times leads to less variable behaviors



MOP avoids a "noisy TV room" if gamma is large enough

In a high-dimensional control problem (ant, MuJoCo), MOP explores more than epsilon-greedy R agents



MOP develops both stochastic and deterministic state-dependent policies

References

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