today we will present a different perspective on exploration. And it's a bit unusual, but will get us thinking about what exploration really is. This lecture is more about the state-of-the-art research on exploration

# Exploration (Part 2)

# CS 285

Instructor: Sergey Levine
UC Berkeley

# Recap: what's the problem?

this is easy (mostly)


**Why?**

this is impossible

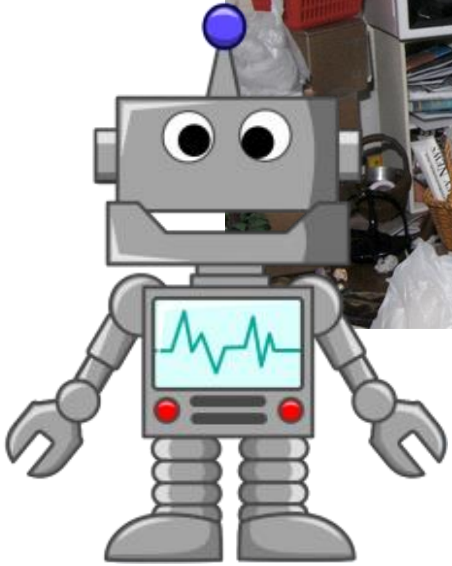
# Unsupervised learning of diverse behaviors

What if we want to recover diverse behavior **without any reward function at all**?

Why?

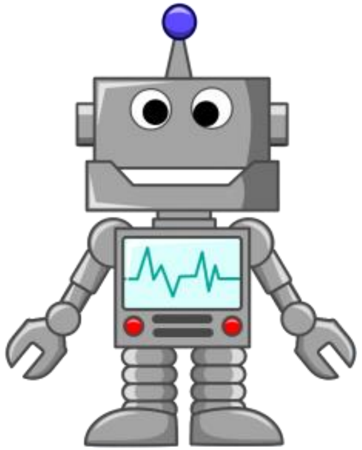
- *Learn skills without supervision, then use them to accomplish goals*
- *Learn sub-skills to use with hierarchical reinforcement learning*
- *Explore the space of possible behaviors*

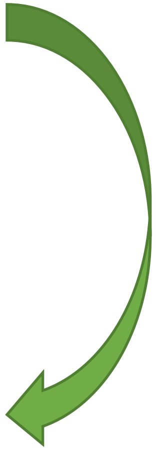
# An Example Scenario



How can you prepare for an **unknown** future goal?

training time: unsupervised





# In this lecture…

- ➢ Definitions & concepts from information theory
- ➢ Learning without a reward function by reaching goals
- ➢ A *state distribution-matching* formulation of reinforcement learning
- ➢ Is coverage of valid states a *good* exploration objective?
- ➢ Beyond state covering: covering the *space of skills*

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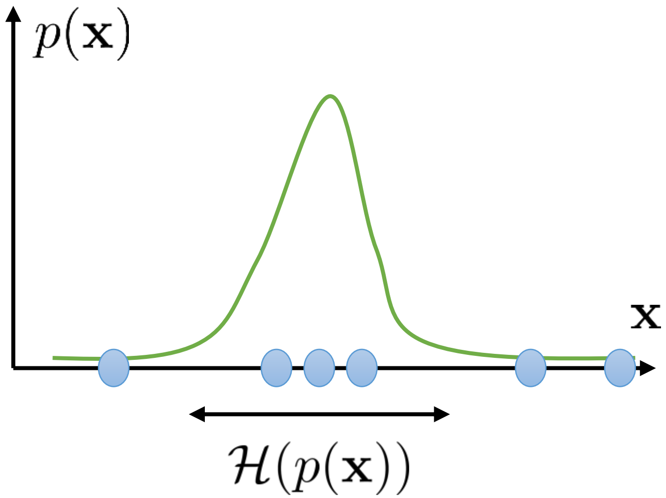
# Some useful identities

$p(\mathbf{x})$ distribution (e.g., over observations $\mathbf{x}$)

$$\mathcal{H}(p(\mathbf{x})) = -E_{\mathbf{x}\sim p(\mathbf{x})}[\log p(\mathbf{x})]$$

entropy – how "broad" $p(\mathbf{x})$ is



# Some useful identities

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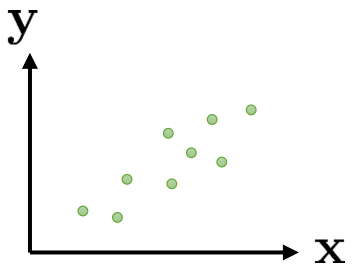
$$\mathcal{H}(p(\mathbf{x})) = -E_{\mathbf{x}\sim p(\mathbf{x})}[\log p(\mathbf{x})]$$

$$\mathcal{I}(\mathbf{x};\mathbf{y}) = D_{\mathrm{KL}}(p(\mathbf{x},\mathbf{y})\|p(\mathbf{x})p(\mathbf{y}))$$

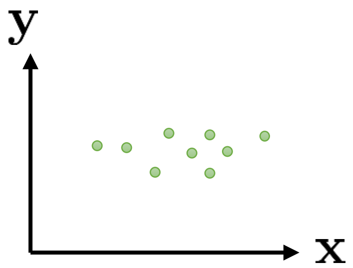
mutual information between x and y

$$= E_{(\mathbf{x},\mathbf{y})\sim p(\mathbf{x},\mathbf{y})}\left[\log \frac{p(\mathbf{x},\mathbf{y})}{p(\mathbf{x})p(\mathbf{y})}\right]$$

$$= \mathcal{H}(p(\mathbf{y})) - \mathcal{H}(p(\mathbf{y}|\mathbf{x}))$$




high MI: $\mathbf{x}$ and $\mathbf{y}$ are *dependent*




low MI: $\mathbf{x}$ and $\mathbf{y}$ are *independent*

mutual information is the reduction in entropy of y, given x. So it tells you how informative x is about y, and because it's symmetric it tells you how informative y is about x

# Information theoretic quantities in RL

$\pi(\mathbf{s})$ state *marginal* distribution of policy $\pi$

equivalent to p_theta(s) in other lectures

quantifies *coverage*

$\mathcal{H}(\pi(\mathbf{s}))$ state *marginal* entropy of policy $\pi$

example of mutual information: "empowerment" (Polani et al.)

$$\mathcal{I}(\mathbf{s}_{t+1};\mathbf{a}_t) = \mathcal{H}(\mathbf{s}_{t+1}) - \mathcal{H}(\mathbf{s}_{t+1}|\mathbf{a}_t)$$

can be viewed as quantifying "control authority" in an information-theoretic way

mutual information about the next state and current action

there's high entropy in the next state

theres low uncertainty of which state you'll end up in given a particular action

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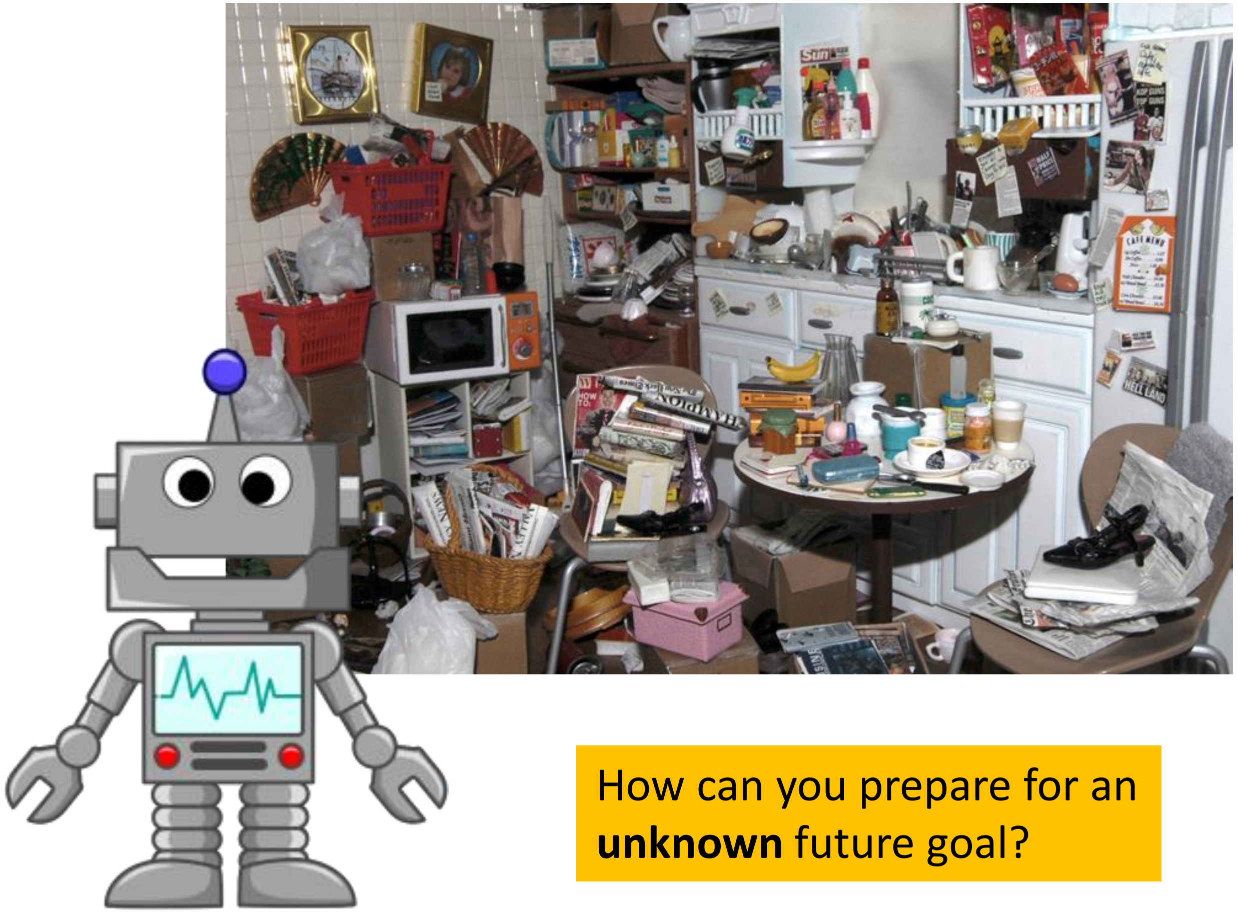
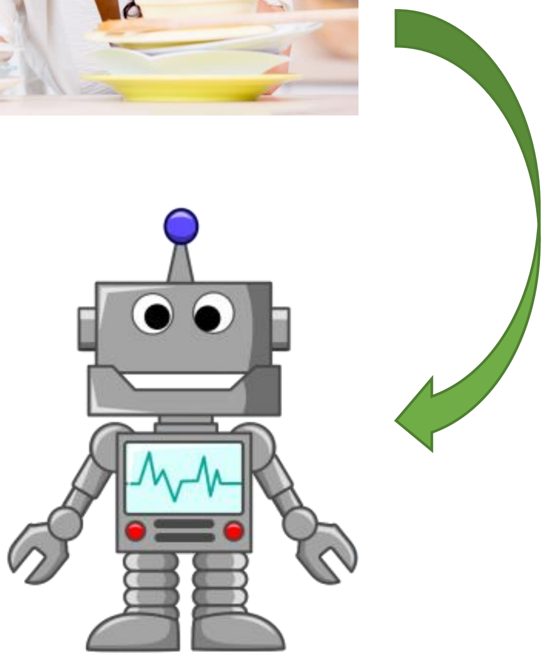
how do we learn without a reward function
by proposing and reaching goals

# An Example Scenario



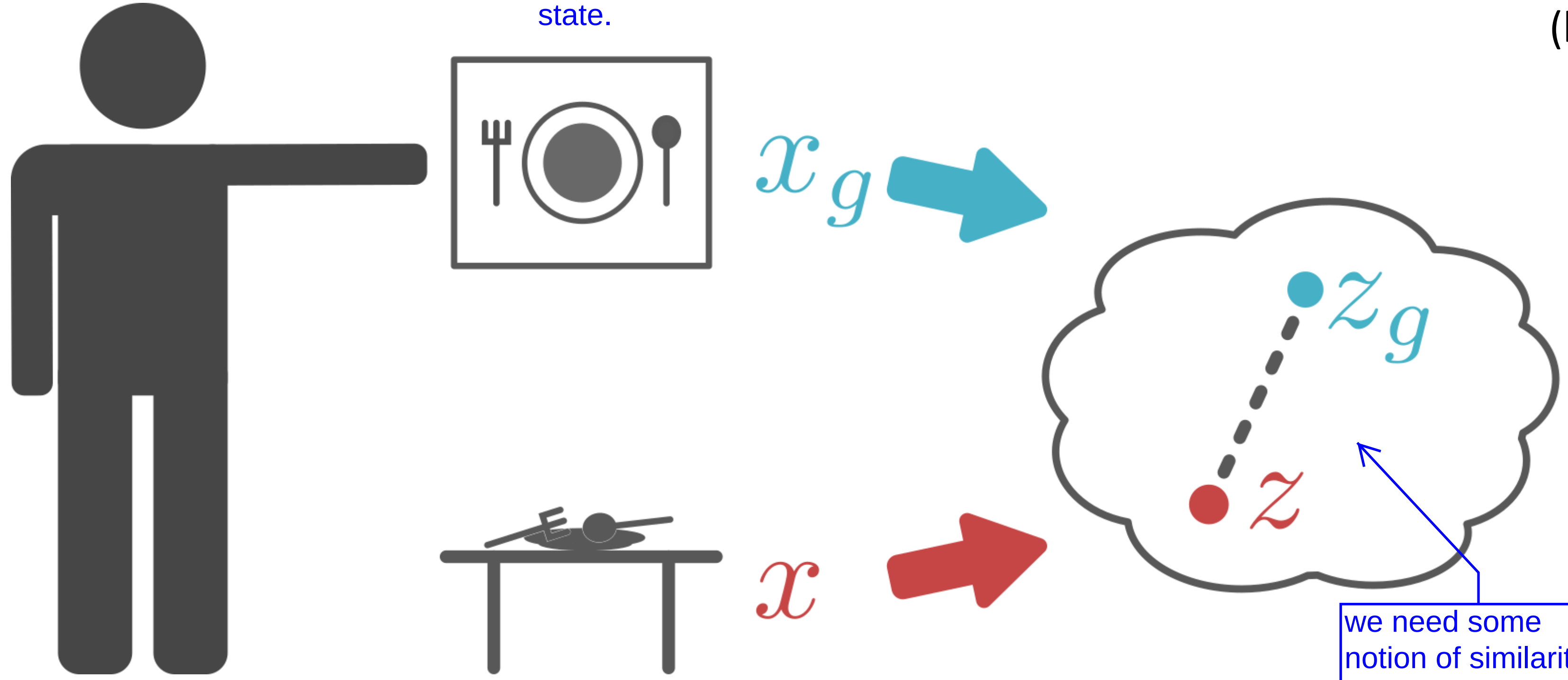
How can you prepare for an **unknown** future goal?

training time: unsupervised



# Learn without any rewards at all

give the agent the state that constitutes the goal for the task. Then the agent should figure out how to reach that state. In the unsupervised learning phase, a policy will get trained to reach that state.

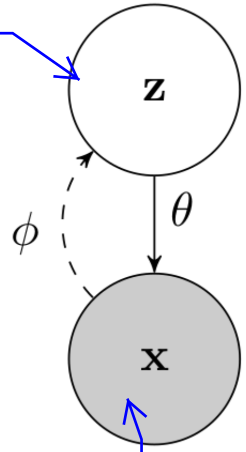



we need some notion of similarity between states. Because in high-dimensional env, every space is unique

VAE (Kingma & Welling '13)

(but there are many other choices)

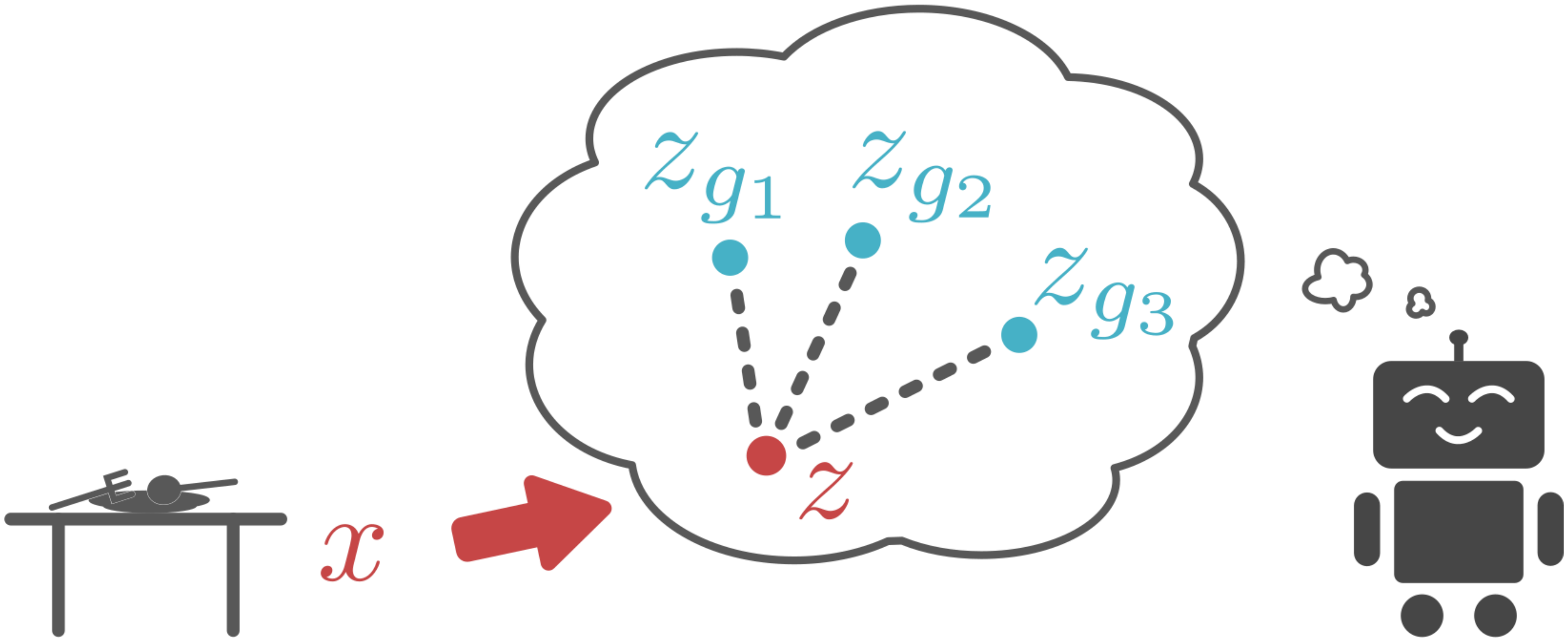
latent variable representation of the state. So z is a compact vector that describes the state




the state


Nair*, Pong*, Bahl, Dalal, Lin, L. **Visual Reinforcement Learning with Imagined Goals**. '18
Dalal*, Pong*, Lin*, Nair, Bahl, Levine. **Skew-Fit: State-Covering Self-Supervised Reinforcement Learning.** '19

# Learn without any rewards at all

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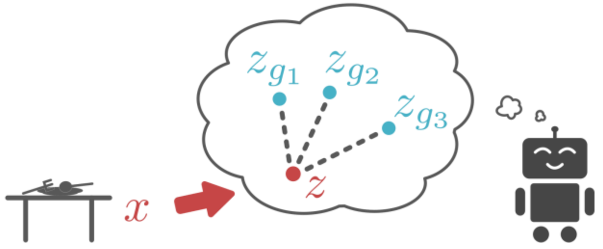
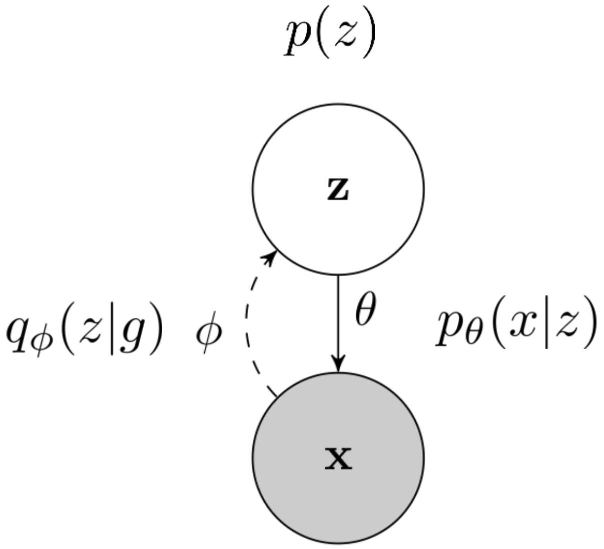
# Learn without any rewards at all

1. Propose goal: $z_g \sim p(z)$, $x_g \sim p_\theta(x_g|z_g)$
2. Attempt to reach goal using $\pi(a|x, x_g)$, reach $\bar{x}$
3. Use data to update $\pi$
4. Use data to update $p_\theta(x_g|z_g)$, $q_\phi(z_g|x_g)$

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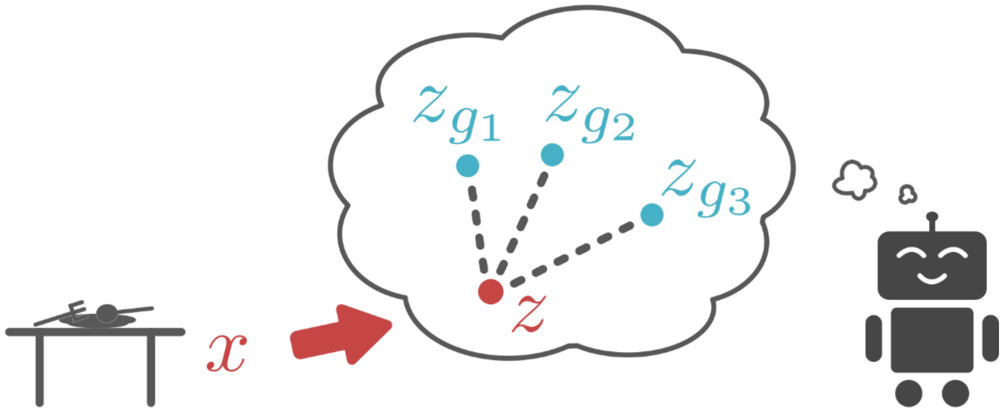
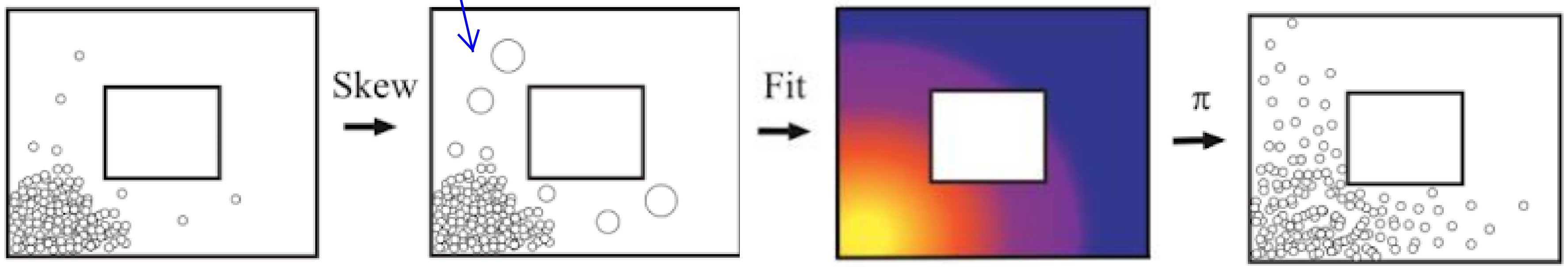
# How do we get diverse goals?




want to upweight
rare states

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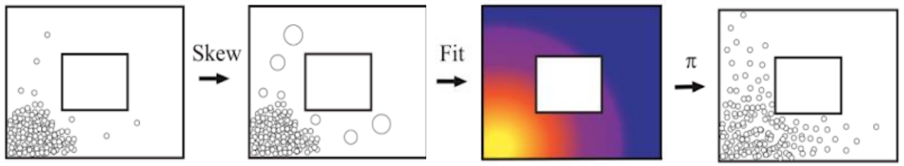
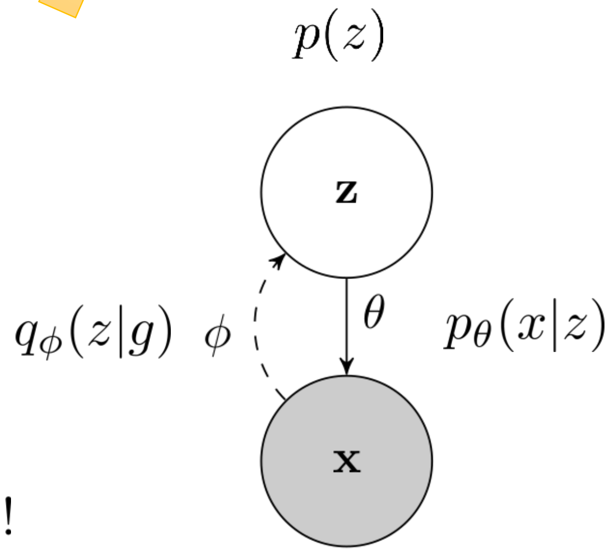
standard MLE: $\theta, \phi \leftarrow \arg\max_{\theta,\phi} E[\log p(\bar{x})]$

weighted MLE: $\theta, \phi \leftarrow \arg\max_{\theta,\phi} E[w(\bar{x}) \log p(\bar{x})]$

$w(\bar{x}) = p_\theta(\bar{x})^\alpha$

key result: for any $\alpha \in [-1, 0)$, entropy $\mathcal{H}(p_\theta(x))$ increases!





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# How do we get diverse goals?

what is the objective?

$$\max \mathcal{H}(p(G)) - \mathcal{H}(p(G|S))$$

goals get higher
entropy due to Skew-Fit

what does RL do?

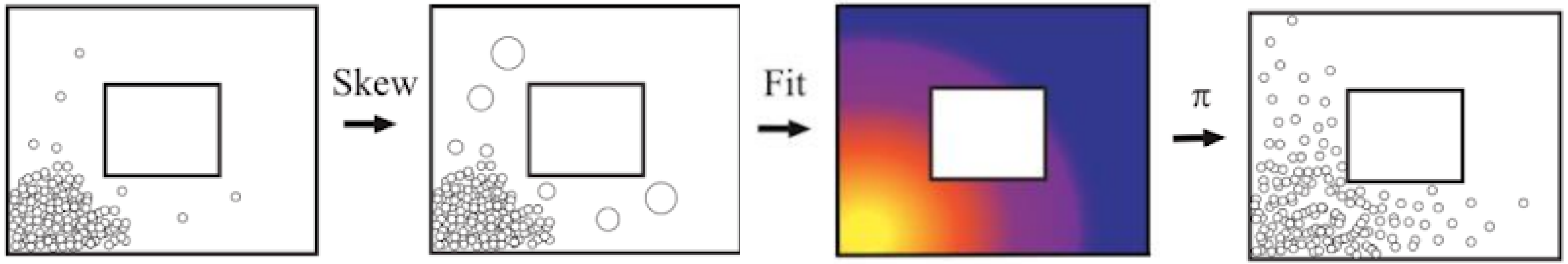
$\pi(a|S,G)$ trained to reach goal $G$

as $\pi$ gets better, final state $S$ gets close to $G$

that means $p(G|S)$ becomes more deterministic!

goal final state

$$w(\bar{x}) = p_\theta(\bar{x})^\alpha$$
$$\alpha \in [-1, 0)$$

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# How do we get diverse goals?

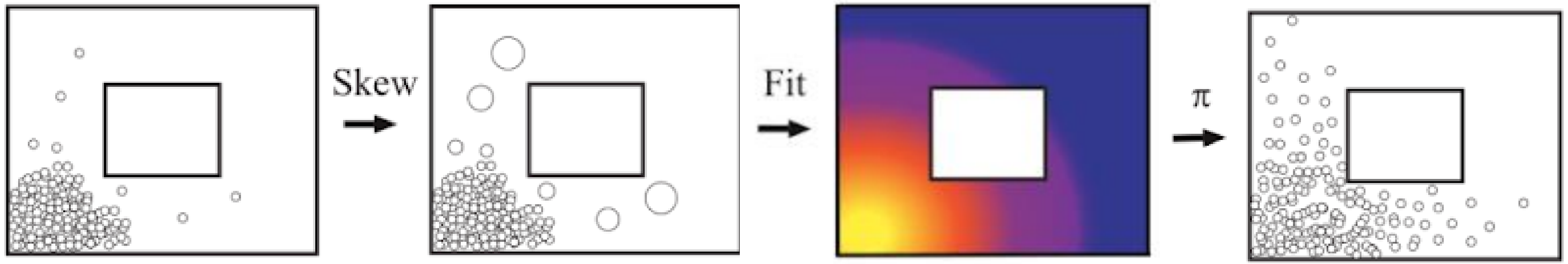
what is the objective?

$$\max \mathcal{H}(p(G)) - \mathcal{H}(p(G|S)) = \max \mathcal{I}(S;G)$$

maximizing mutual information between $S$ and $G$ leads to

good exploration (state coverage) – $\mathcal{H}(p(G))$

effective goal reaching – $\mathcal{H}(p(G|S))$

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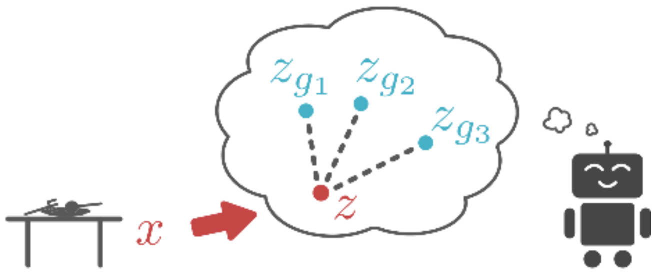
# Reinforcement learning with *imagined* goals





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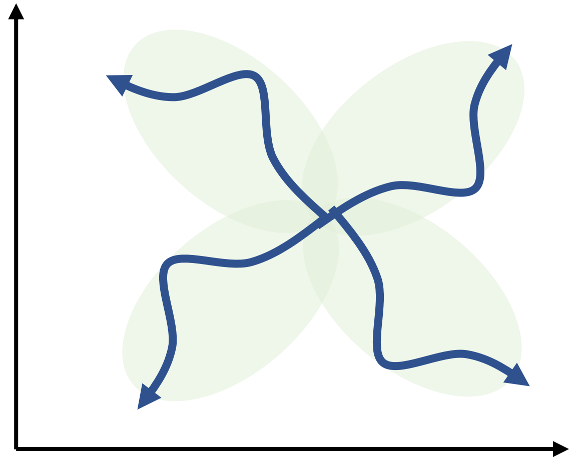
# Aside: exploration with intrinsic motivation



common method for exploration:

incentivize policy $\pi(\mathbf{a}|\mathbf{s})$ to explore diverse states

...before seeing any reward

reward visiting **novel** states

if a state is visited *often*, it is not *novel*

$\Rightarrow$ add an exploration bonus to reward: $\tilde{r}(\mathbf{s}) = r(\mathbf{s}) - \log p_\pi(\mathbf{s})$

state density under $\pi(\mathbf{a}|\mathbf{s})$

1. update $\pi(\mathbf{a}|\mathbf{s})$ to maximize $E_\pi[\tilde{r}(\mathbf{s})]$
2. update $p_\pi(\mathbf{s})$ to fit state marginal

# Can we use this for state marginal matching?

the state marginal matching problem: learn $\pi(\mathbf{a}|\mathbf{s})$ so as to minimze $D_{\mathrm{KL}}(p_\pi(\mathbf{s})\|p^\star(\mathbf{s}))$

target state density

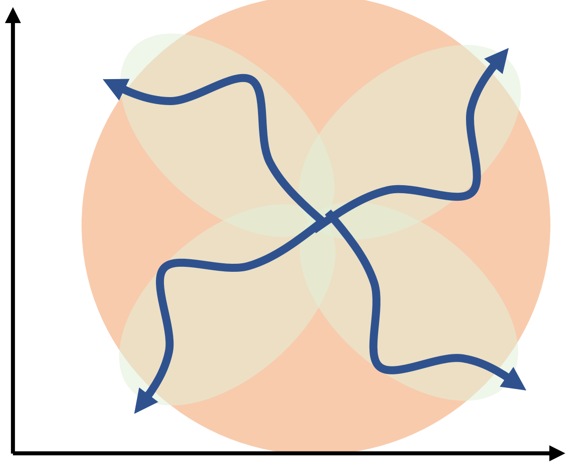
idea: can we use intrinsic motivation?

$\tilde{r}(\mathbf{s}) = \log p^\star(\mathbf{s}) - \log p_\pi(\mathbf{s})$

this does **not** perform marginal matching!

1. learn $\pi^k(\mathbf{a}|\mathbf{s})$ to maximize $E_\pi[\tilde{r}^k(\mathbf{s})]$
2. ~~update $p_{\pi^k}(\mathbf{s})$ to fit state marginal~~
2. update $p_{\pi^k}(\mathbf{s})$ to fit *all states seen so far*
3. return $\pi^\star(\mathbf{a}|\mathbf{s}) = \sum_k \pi^k(\mathbf{a}|\mathbf{s})$

this **does** perform marginal matching!



special case: $\log p^\star(\mathbf{s}) = C \Rightarrow$ *uniform* target

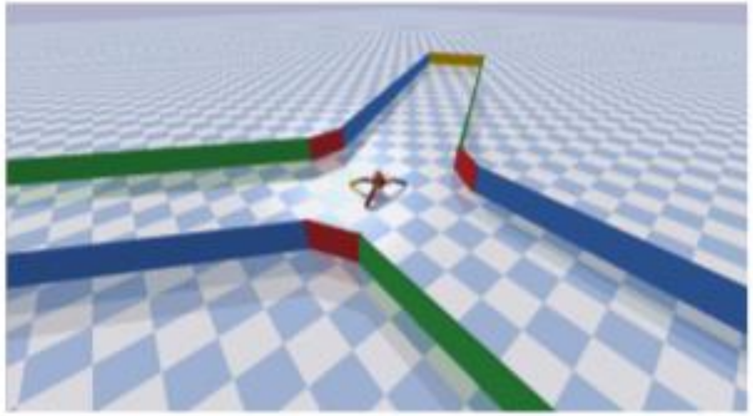
$D_{\mathrm{KL}}(p_\pi(\mathbf{s})\|U(\mathbf{s})) = \mathcal{H}(p_\pi(\mathbf{s}))$

$p_\pi(\mathbf{s}) = p^\star(\mathbf{s})$ is Nash equilibrium of two player game between $\pi^k$ and $p_{\pi^k}$

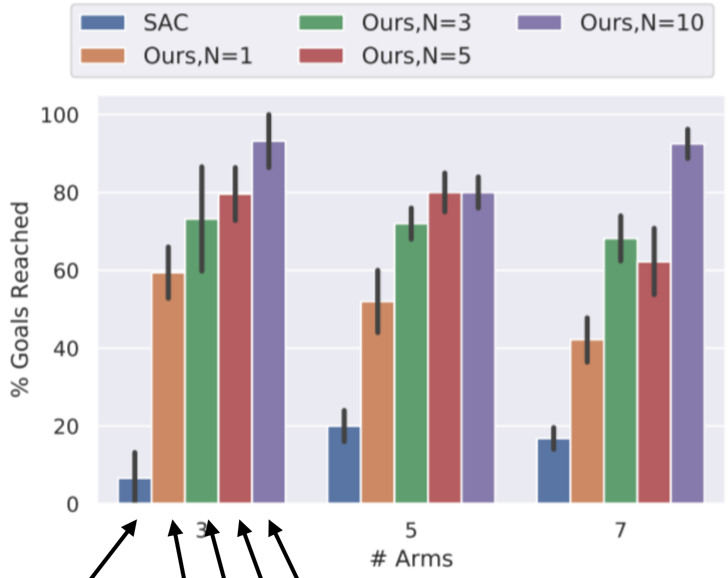
Lee*, Eysenbach*, Parisotto*, Xing, Levine, Salakhutdinov. **Efficient Exploration via State Marginal Matching**
See also: Hazan, Kakade, Singh, Van Soest. **Provably Efficient Maximum Entropy Exploration**

# State marginal matching for exploration

the state marginal matching problem: learn $\pi(\mathbf{a}|\mathbf{s})$ so as to minimze $D_{\mathrm{KL}}(p_\pi(\mathbf{s})||p^\star(\mathbf{s}))$




much better coverage!




MaxEnt on actions

variants of SMM

Lee*, Eysenbach*, Parisotto*, Xing, Levine, Salakhutdinov. **Efficient Exploration via State Marginal Matching**
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# Is state entropy *really* a good objective?

Skew-Fit: $\max \mathcal{H}(p(G)) - \mathcal{H}(p(G|S)) = \max \mathcal{I}(S; G)$

more or less the same thing

SMM (special case where $p^\star(\mathbf{s}) = C$): $\max \mathcal{H}(p_\pi(S))$

When is this a good idea?

"Eysenbach's Theorem" (not really what it's called)

(follows trivially from classic maximum entropy modeling)

at test time, an *adversary* will choose the *worst* goal $G$

which goal distribution should you use for *training*?

answer: choose $p(G) = \arg\max_p \mathcal{H}(p(G))$

See also: Hazan, Kakade, Singh, Van Soest. **Provably Efficient Maximum Entropy Exploration**



Gupta, Eysenbach, Finn, Levine. **Unsupervised Meta-Learning for Reinforcement Learning**

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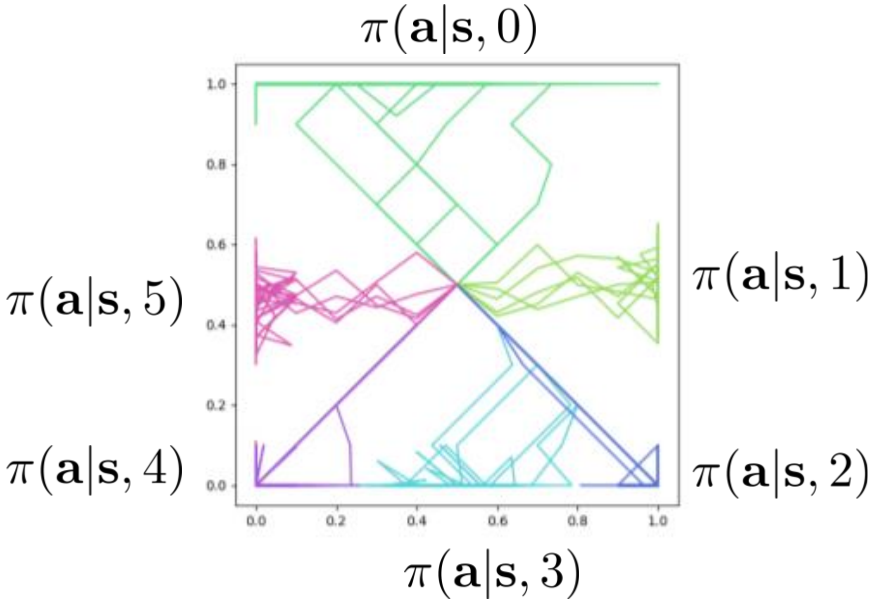
# Learning diverse skills

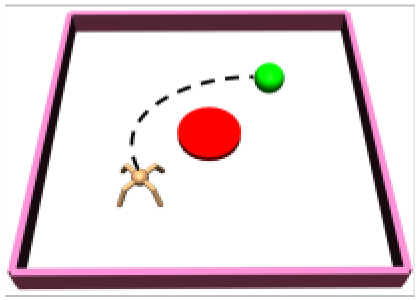
$$\pi(\mathbf{a}|\mathbf{s}, z)$$

task index




Reaching diverse **goals** is not the same as performing diverse **tasks**

not all behaviors can be captured by **goal-reaching**



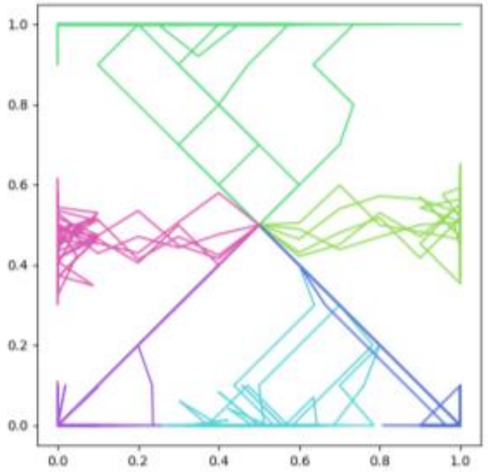
**Intuition:** different **skills** should visit different **state-space regions**

Eysenbach, Gupta, Ibarz, Levine. **Diversity is All You Need.**

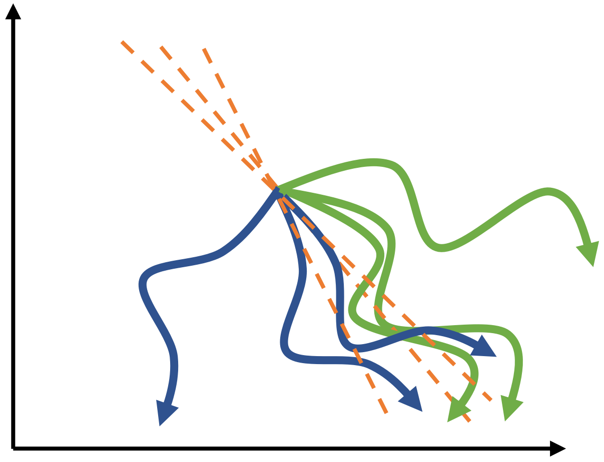
# Diversity-promoting reward function

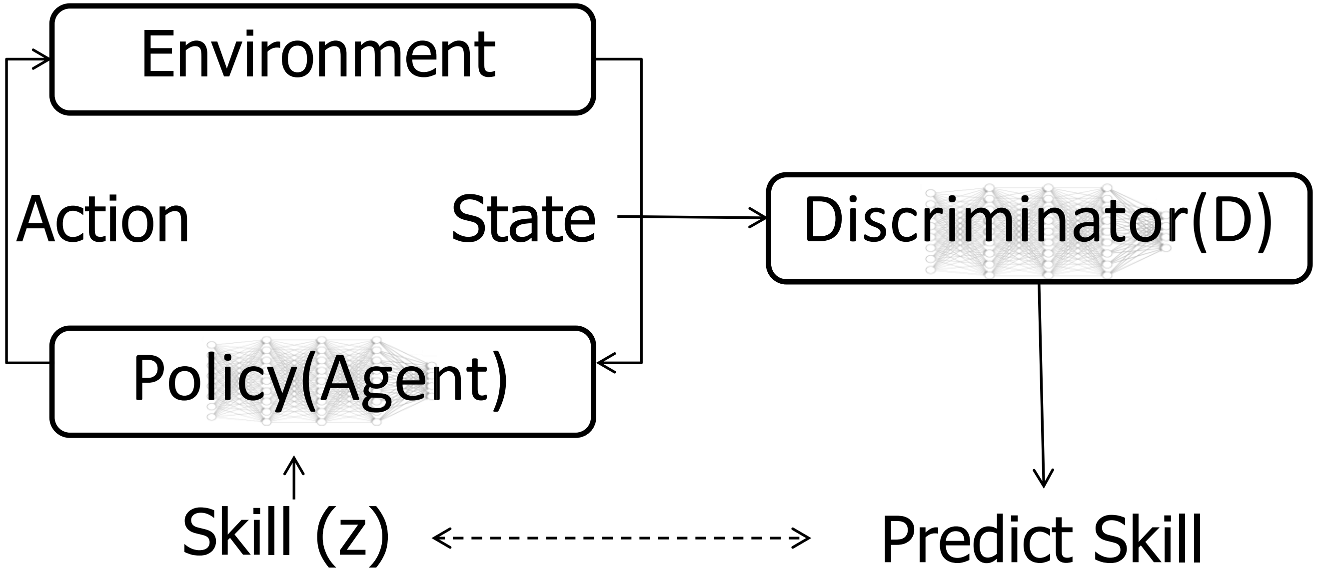
$$\pi(\mathbf{a}|\mathbf{s}, z) = \arg\max_{\pi} \sum_{z} E_{\mathbf{s}\sim\pi(\mathbf{s}|z)}[r(\mathbf{s}, z)]$$

reward states that are unlikely for other $z' \neq z$



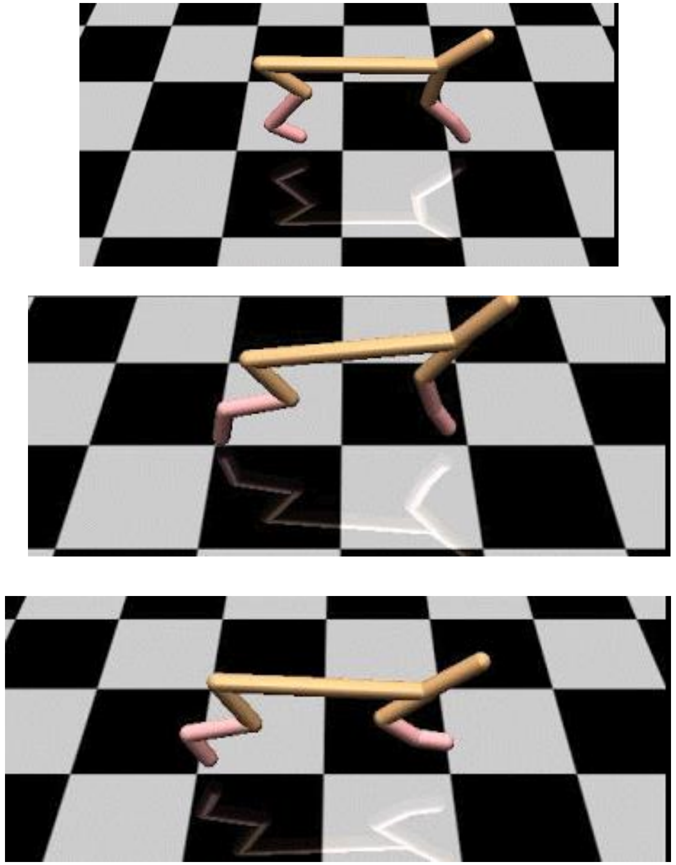

$$r(\mathbf{s}, z) = \log p(z|\mathbf{s})$$



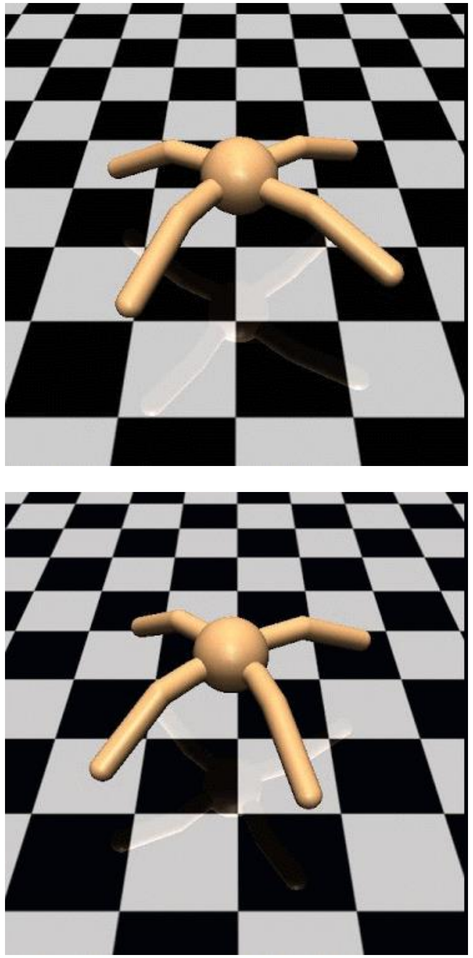



Eysenbach, Gupta, Ibarz, Levine. **Diversity is All You Need.**

# Examples of learned tasks



Cheetah



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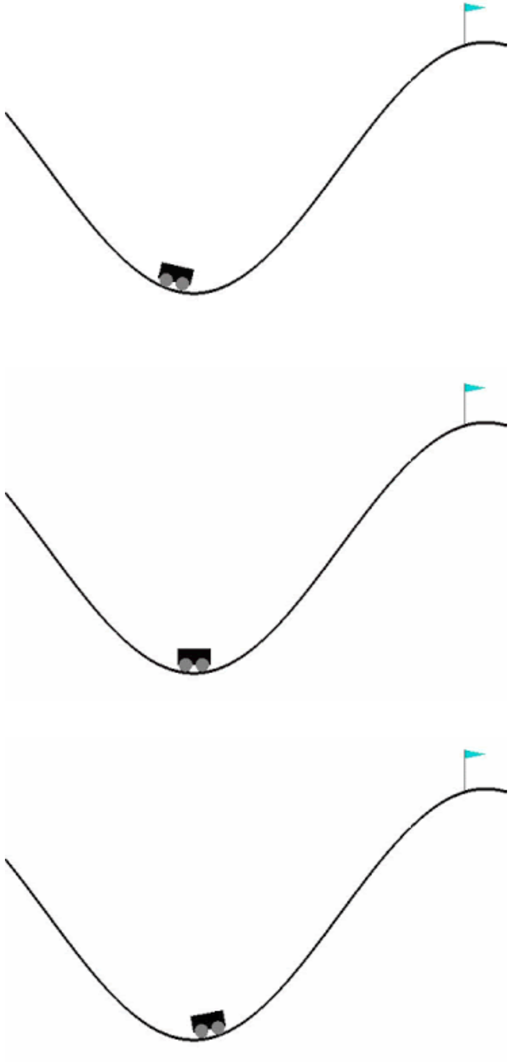

Mountain car

Eysenbach, Gupta, Ibarz, Levine. **Diversity is All You Need.**

# A connection to mutual information

$$\pi(\mathbf{a}|\mathbf{s}, z) = \arg\max_{\pi} \sum_{z} E_{\mathbf{s}\sim\pi(\mathbf{s}|z)}[r(\mathbf{s}, z)]$$

$$r(\mathbf{s}, z) = \log p(z|\mathbf{s})$$

$$I(z, \mathbf{s}) = H(z) - H(z|s)$$

maximized by using uniform prior $p(z)$

minimized by maximizing $\log p(z|\mathbf{s})$

Eysenbach, Gupta, Ibarz, Levine. **Diversity is All You Need.**

See also: Gregor et al. **Variational Intrinsic Control.** 2016