

# Generalization in Large scale MDPs

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CS 6789: Foundations of Reinforcement Learning

# Recap on Bellman Error and Bellman Operator

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If  $BE(s, a) \neq 0$ , then  $f \neq Q^*$

# Notations

Probability of  $\pi$  visiting  $(s, a)$  at time step  $h$ :  $d_h^\pi(s, a)$

# Question for Today

We have seen tabular MDP and linear MDP, is there a **more general framework** that captures these two, and potentially many more, where efficient learning is possible?



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In other words, what structural conditions permit RL generalization, provably?

# Outline for Today

1. Bellman rank Definitions

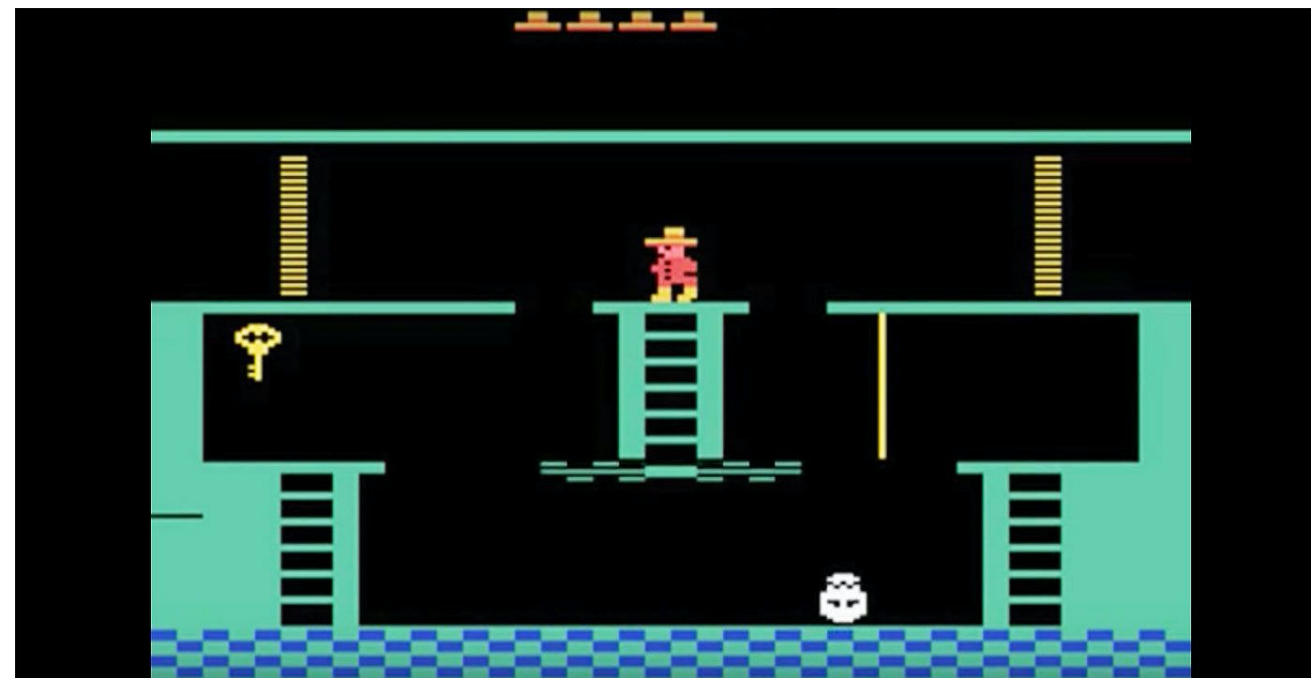
2. Examples that are captured by the Bellman rank framework

# Setting

Finite horizon episodic MDP  $\{ \{S_h\}_{h=0}^H, \{A_h\}_{h=0}^{H-1}, H, s_0, r, P \}$

State space  $S_h$  is extremely large:

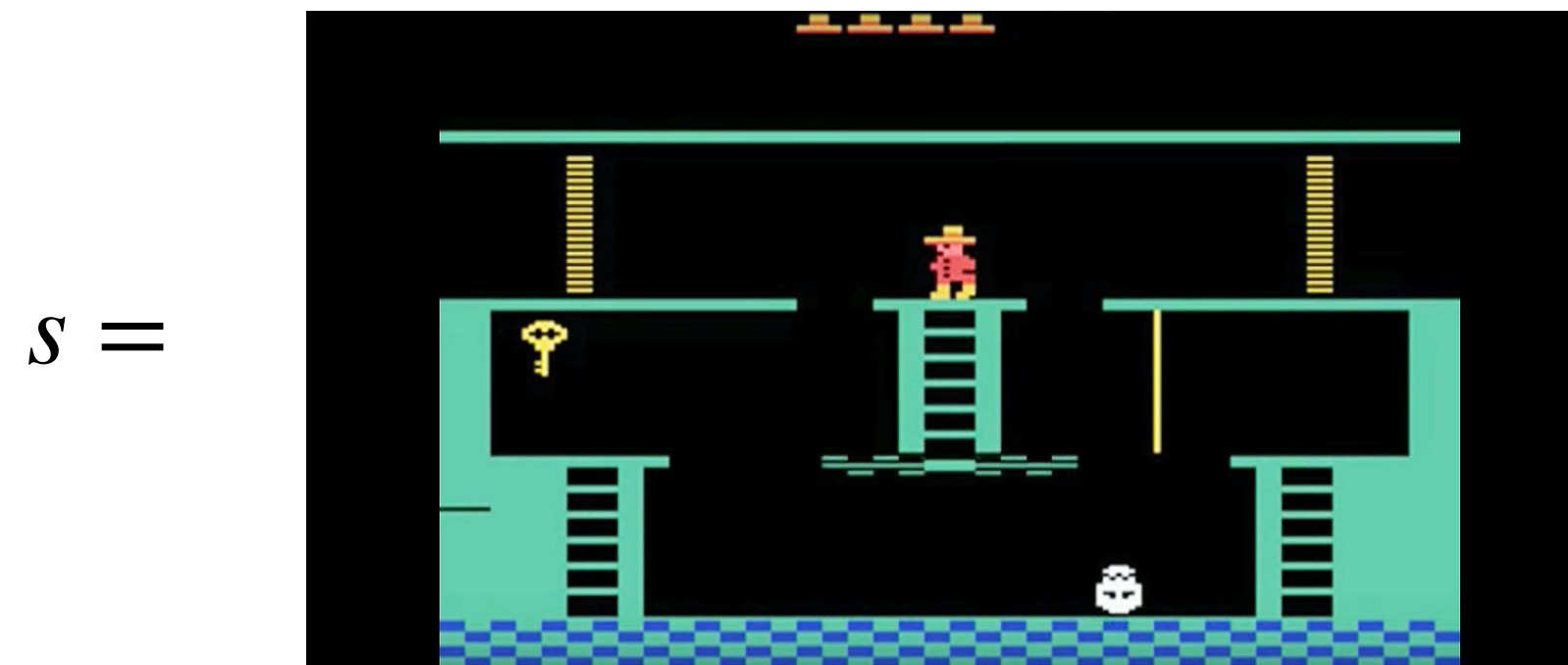
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Not acceptable:  $\text{poly}(|S|)$

Need to generalize via (nonlinear) function approximation

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We will consider **Q function class**

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Define **value function class**:  $\mathcal{V} = \{ V_f : V_f(s) = \max_a f(s, a) \mid f \in \mathcal{F} \}$



## **Learning Goal:**

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Given approximation error  $\epsilon$  and failure prob  $\delta$ ,  
can we learn  $\epsilon$  *near optimal policy* (i.e.,  $V^{\hat{\pi}} \geq V^* - \epsilon$ ) in # of samples scaling  
*poly* with all relevant parameters (*here, we need poly in  $\ln(|\mathcal{F}|)$* )

# How to check if a Q-approximator is good?

We define **average** Bellman error of a Q-estimate  $g$  below:

$$\mathcal{E}(g; f, h) = \mathbb{E}_{s_h, a_h \sim d_h^{\pi_f}} \left[ g(s_h, a_h) - r(s_h, a_h) - \mathbb{E}_{s_{h+1} \sim P(\cdot | s_h, a_h)} \left[ \max_{a \in \mathcal{A}} g(s_{h+1}, a) \right] \right]$$

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# The Q / V-Bellman rank

$$\forall h : \mathcal{E}_h \in \mathbb{R}^{|\mathcal{F}| \times |\mathcal{F}|}$$

	$g$	$f$			
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Rank of this Matrix is defined as Bellman Rank

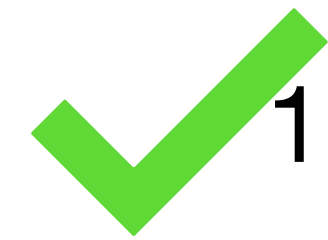
## The Q / V-Bellman rank

In other words, there are two mappings  $W_h : \mathcal{F} \mapsto \mathbb{R}^d$ ,  $X_h : \mathcal{F} \mapsto \mathbb{R}^d$  (d = Bellman-rank)

$$\forall f, g \in \mathcal{F} : \mathcal{E}(g; f, h) = \langle W_h(g), X_h(f) \rangle$$

Note, we just assume the existence of  $W, X$ , but they are unknown

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2. Examples that are captured by the Bellman rank framework

# The Linear Bellman Completion Model

Given feature  $\phi$ , take any linear function  $\theta^\top \phi(s, a)$ :

$$\forall h, \exists w \in \mathbb{R}^d, s.t., w^\top \phi(s, a) = r(s, a) + \mathbb{E}_{s' \sim P_h(s, a)} \max_{a'} \theta^\top \phi(s', a'), \forall s, a$$

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Note linear Bell-completion captures tabular / linear mdp already

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As we will see, linear  $Q^*$  &  $V^*$  is learnable, and recall linear  $Q^*$  is not...

# $Q^*$ - state abstraction

We have a small latent state space  $Z$ , and a **known** mapping  $\xi$  from state  $s$  to  $z$

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**Claim: this model has Q-Bellman rank  $|Z| |A| + |Z|$**

We can show that this model is captured by linear  $Q^*$  &  $V^*$

# Low-rank MDP

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Define representation class  $\Phi$ , with  $\phi^\star \in \Phi$

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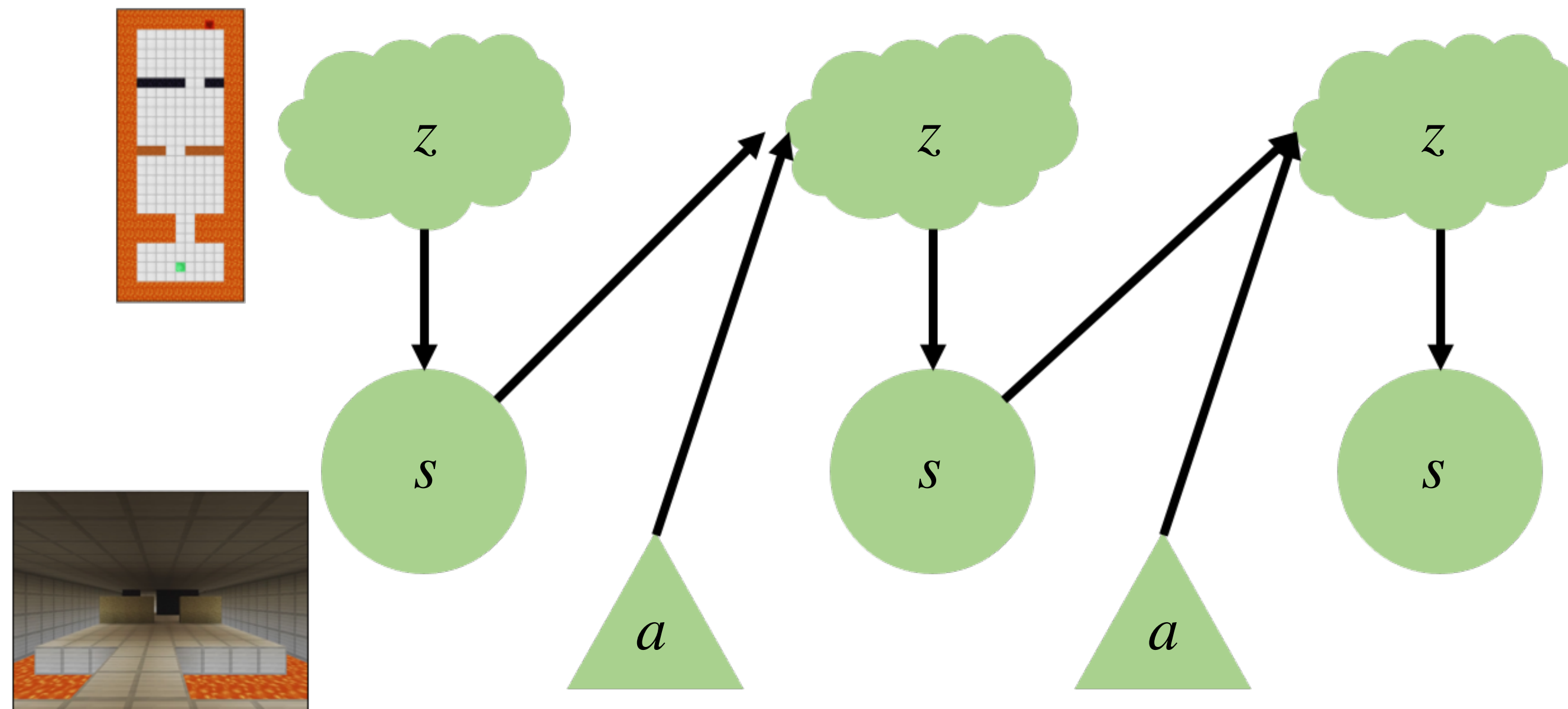
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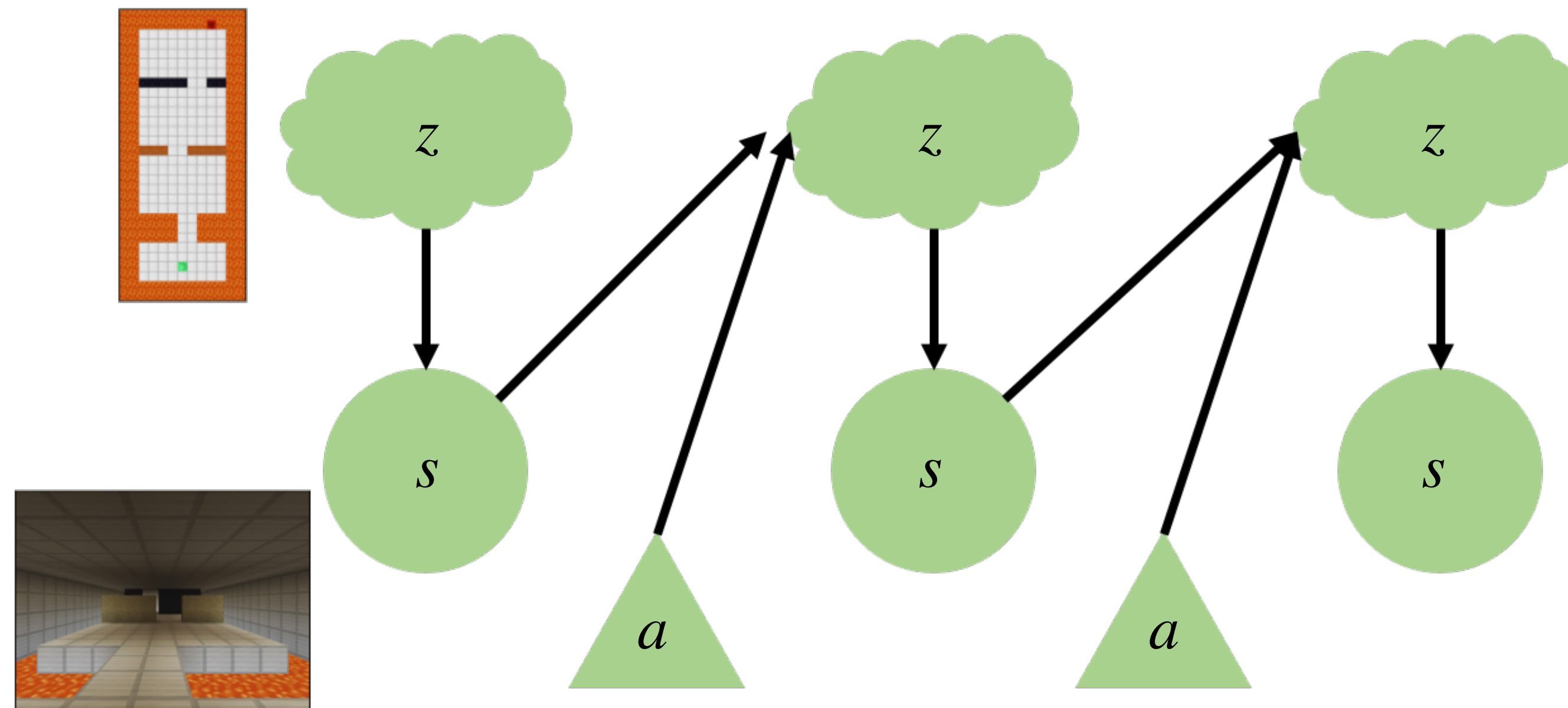
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Latent variable MDP is captured by low-rank MDP, so it has small V-Bellman rank...



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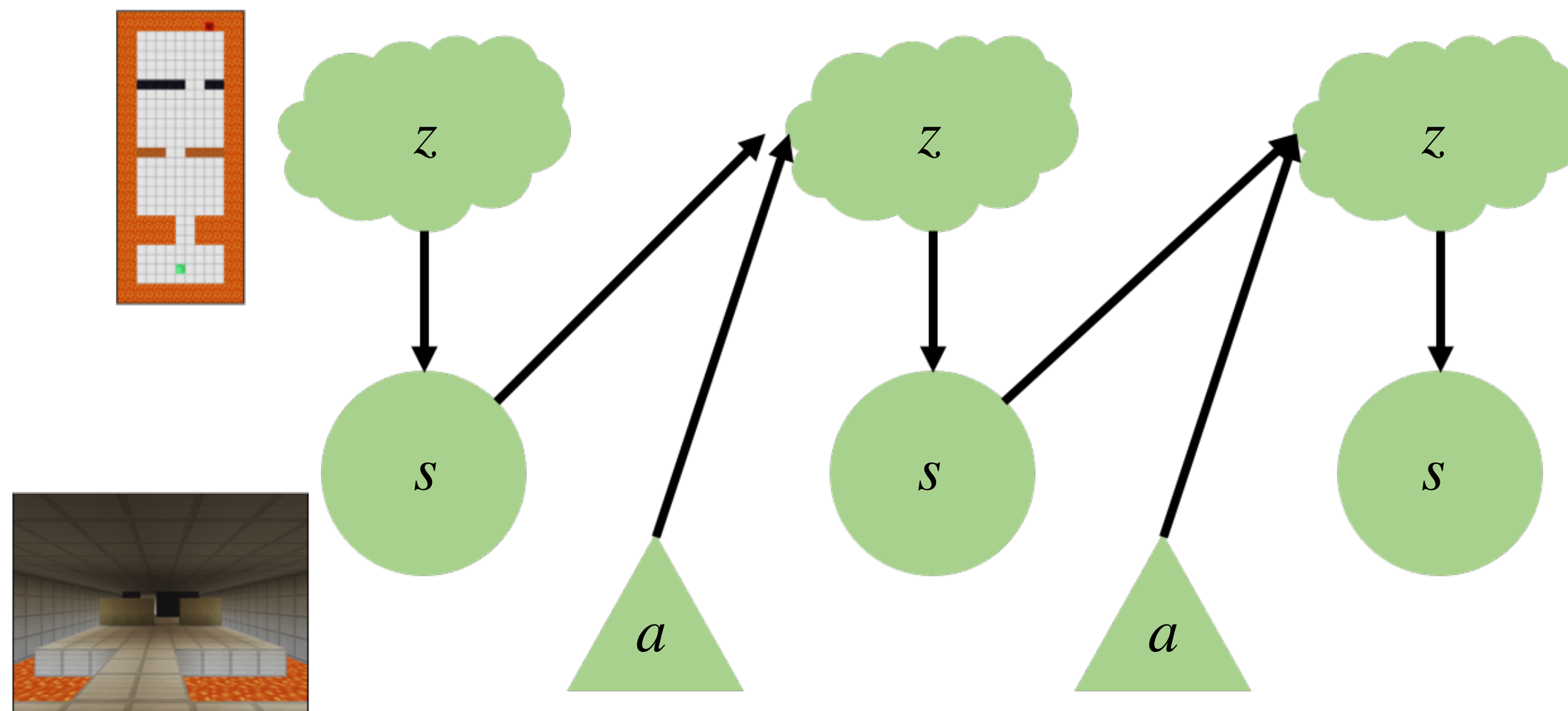
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Given  $s, a: z \sim \phi^*(s, a), s' \sim \nu^*(z)$

V-Bellman rank = Number of latent states



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4. Many models (more in the book chapter) indeed have low-Q or V Bellman rank

## Next week:

A general algorithm that can learn an  $\epsilon$  near optimal policy w/ # of samples

$\text{poly}(H, 1/\epsilon, \ln(|\mathcal{H}|), \text{b-rank})$