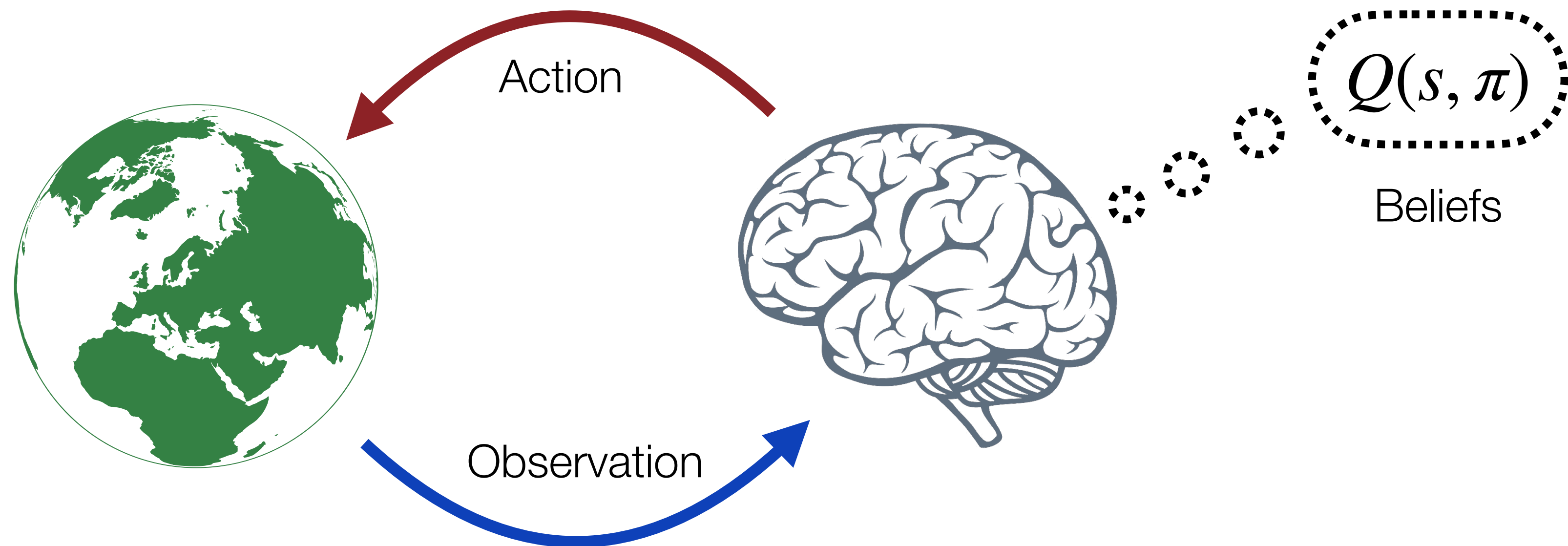


# Tutorial B: Part II

## Hands-on Active Inference with **pymdp**



Conor Heins and Daphne Demekas

# Tutorial B: Part II

When specifying a POMDP model for performing active inference, it's often useful to *factorize* the state-space of observations and hidden states

$$\mathbf{o}_t = \{o_t^1, o_t^2, \dots, o_t^M\}$$

Modalities

$$\mathbf{s}_t = \{s_t^1, s_t^2, \dots, s_t^F\}$$

Factors

When specifying a POMDP model for performing active inference, it's often useful to *factorize* the state-space of observations and hidden states



Several benefits to doing this:

- Computational efficiency (both memory-wise and CPU-wise)
- Generative model interpretability / transparency
- Neuronally-plausible? c.f. factorised (aka 'modular') representations

# Recall Grid-World

One hidden state factor

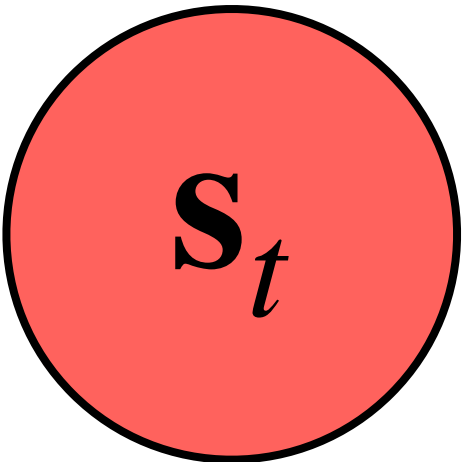
$$\mathbf{s}_t = \{s_t^{Loc}\} = \begin{array}{|c|c|c|c|c|c|c|c|c|} \hline 0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 \\ \hline \end{array}$$

9 levels

A “fully enumerated” state space

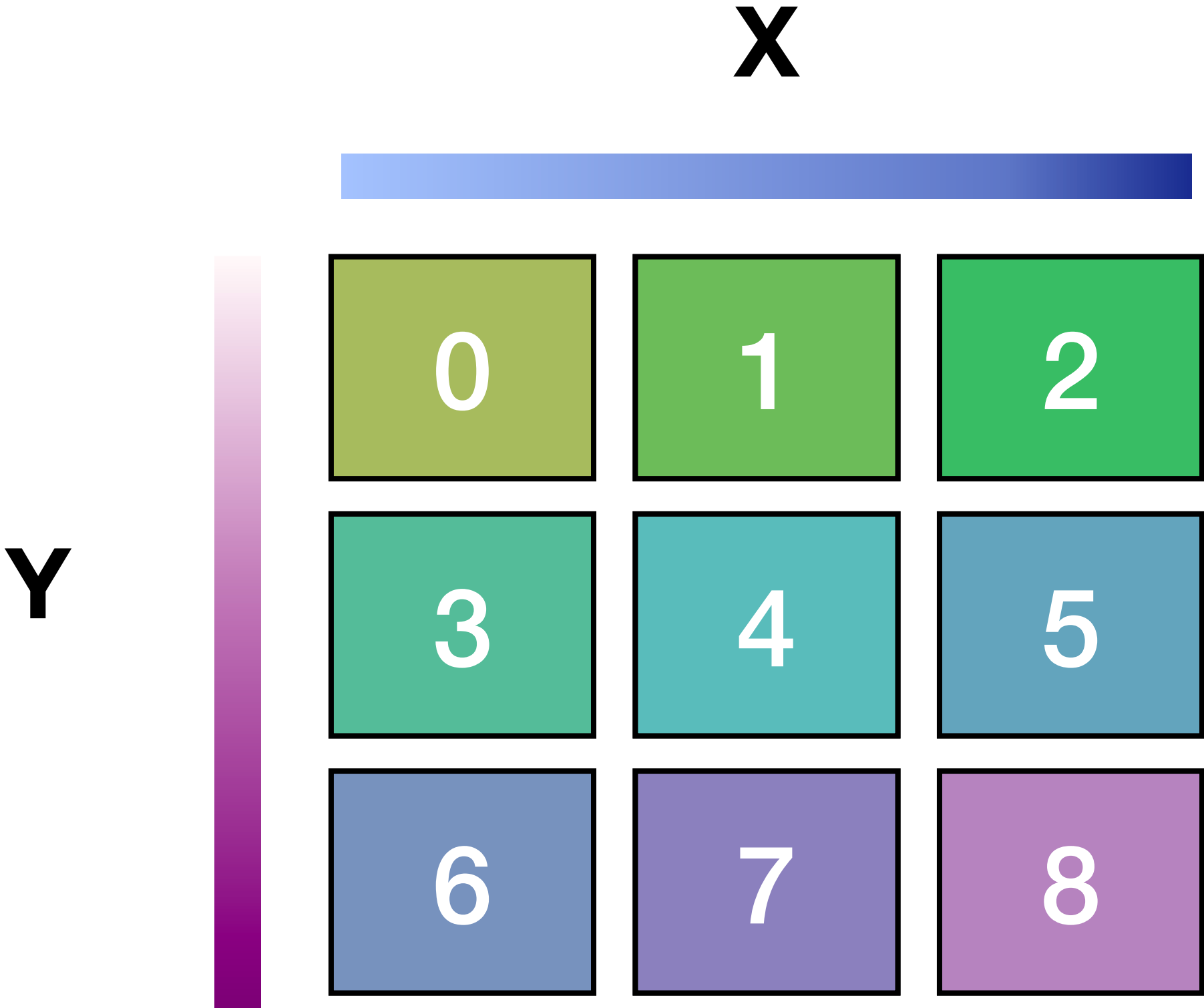
0	1	2
3	4	5
6	7	8

# Recall Grid-World



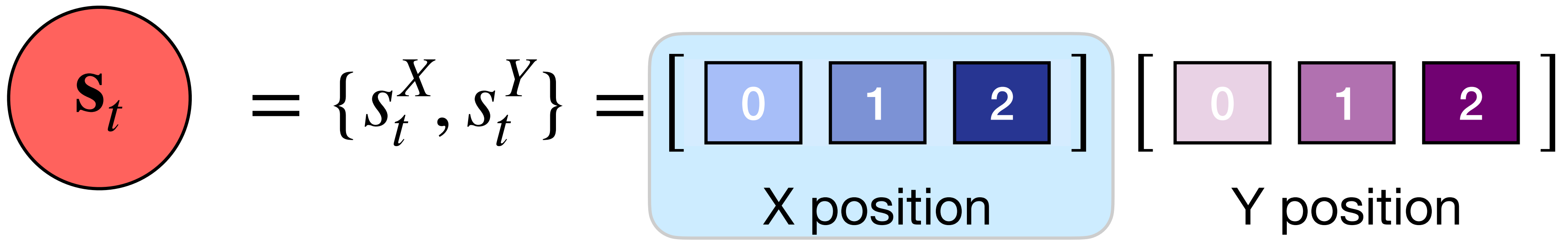
$$= \{s_t^X, s_t^Y\} = \left[ \begin{array}{|c|c|c|} \hline 0 & 1 & 2 \\ \hline \end{array} \right] \left[ \begin{array}{|c|c|c|} \hline 0 & 1 & 2 \\ \hline \end{array} \right]$$

X position                      Y position

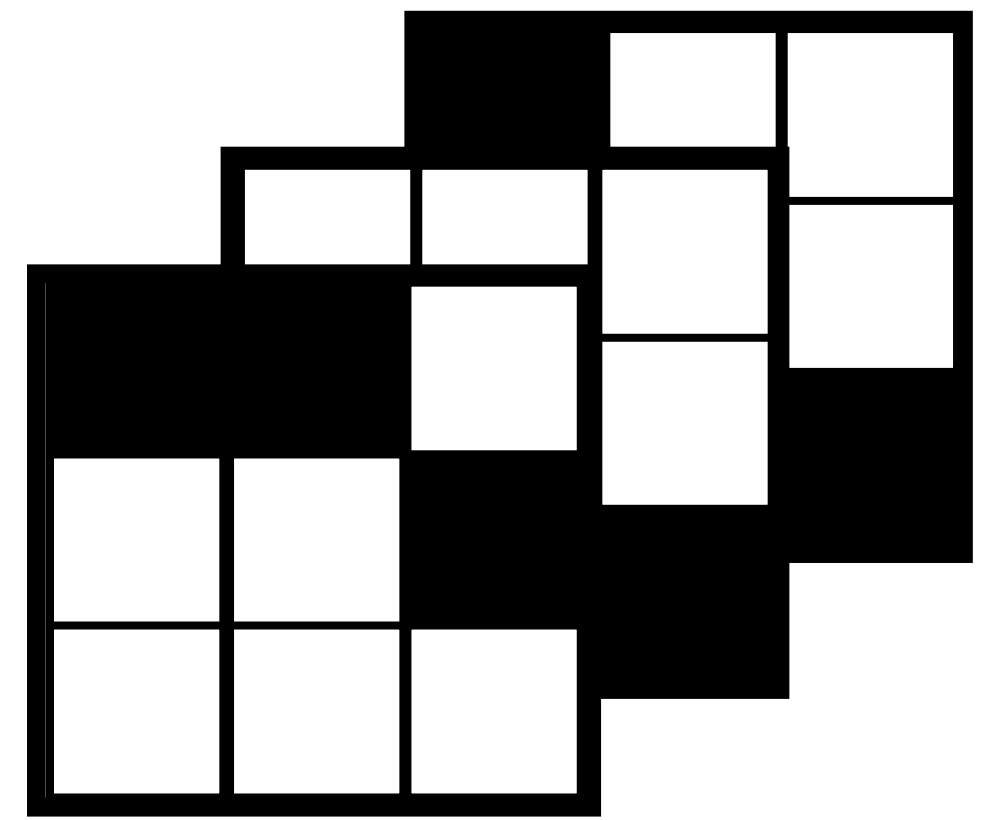


Each hidden state is now a pair of **two** hidden state factors

# How does this change the generative model representation?



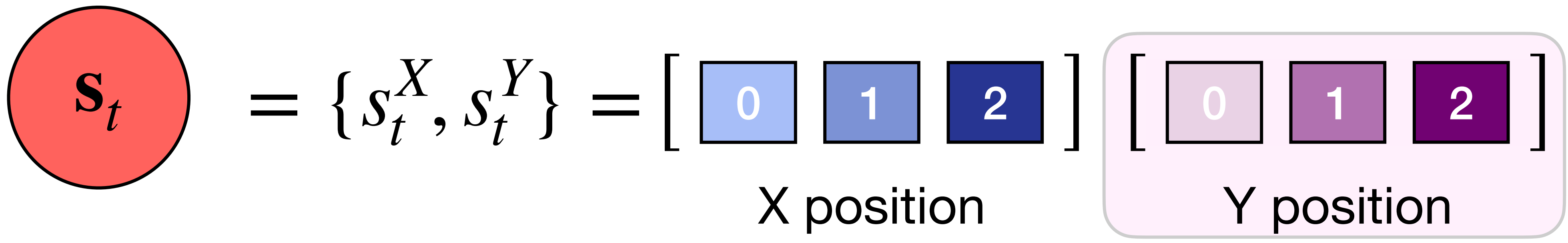
$$P(s_t^X | s_{t-1}^X, u_{t-1}^X)$$



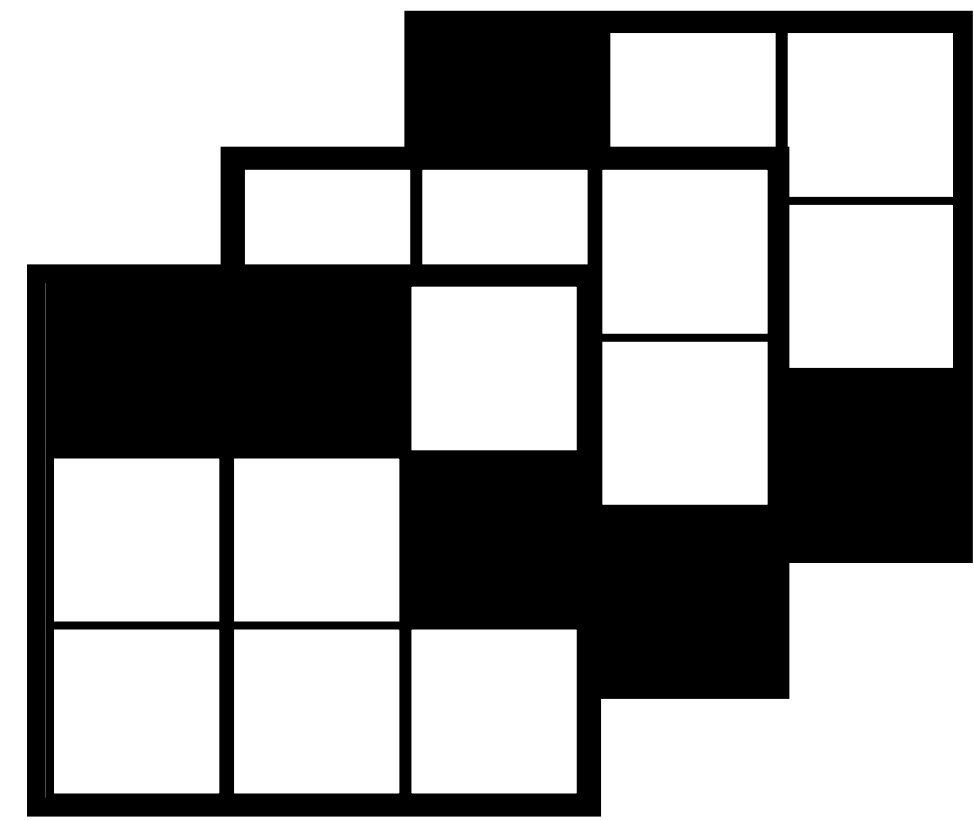
MOVE RIGHT

**B =**      B[0]

# How does this change the generative model representation?



$$P(s_t^Y | s_{t-1}^Y, u_{t-1}^Y)$$



MOVE DOWN

**B =**      B [ 1 ]

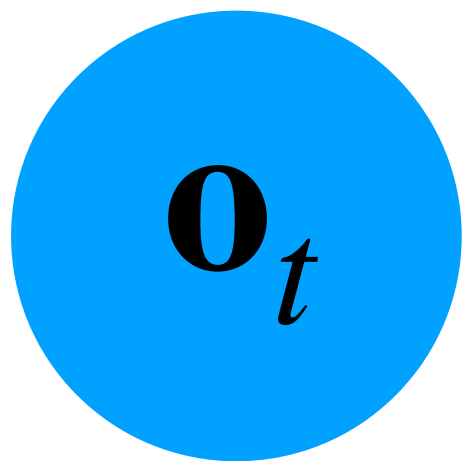


**How do we represent this in pymdp?**

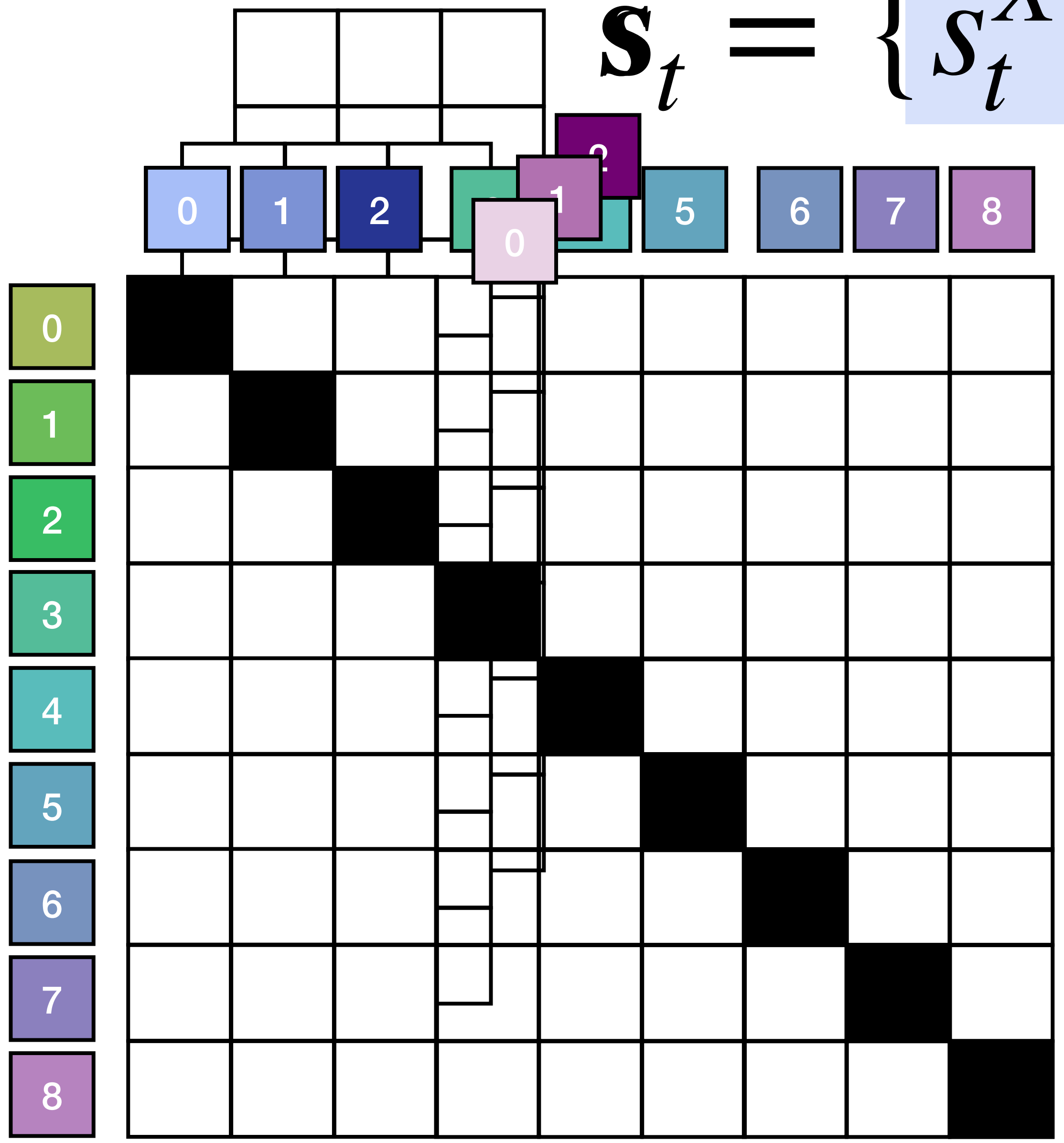
**(Go to Colab)**

Let's start with a single observation modality

$$\mathbf{s}_t = \{s_t^X, s_t^Y\}$$

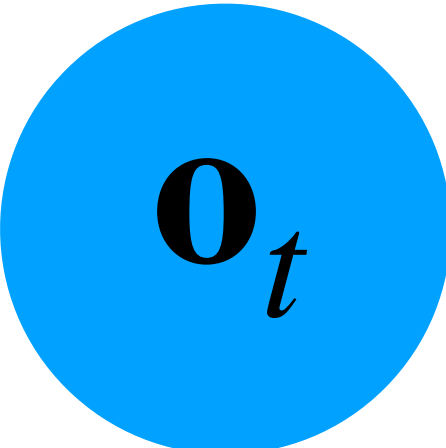
  $\mathbf{o}_t = \{o_t^{Loc}\}$

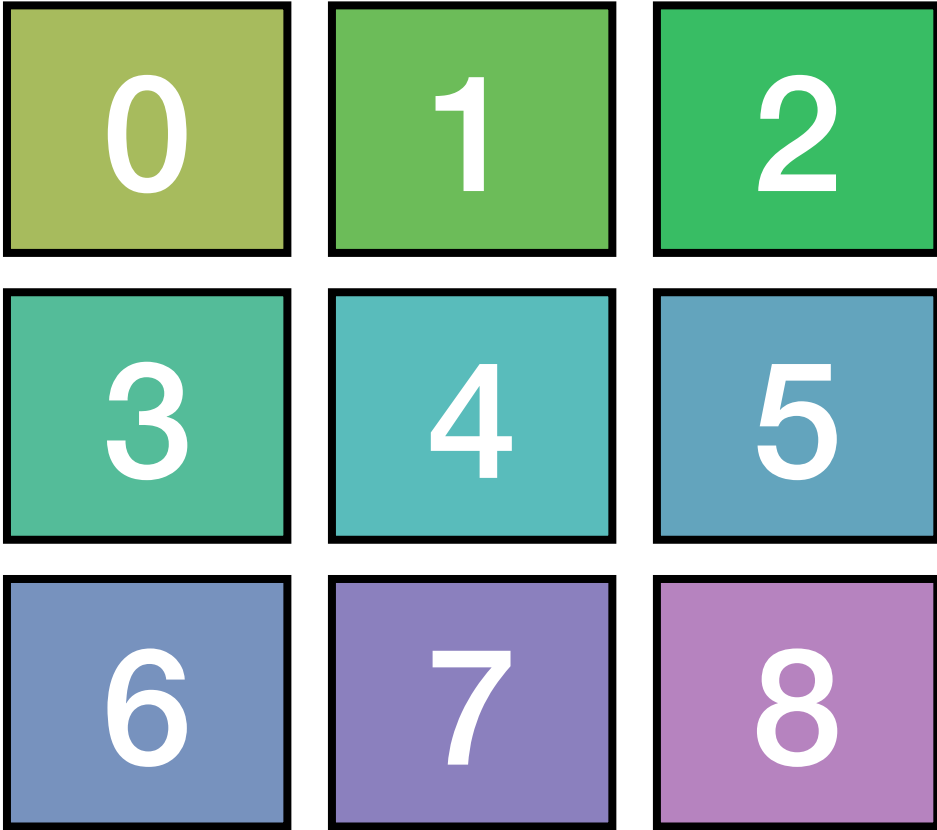
$O^{Loc}$



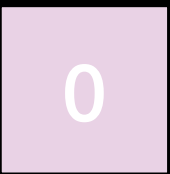
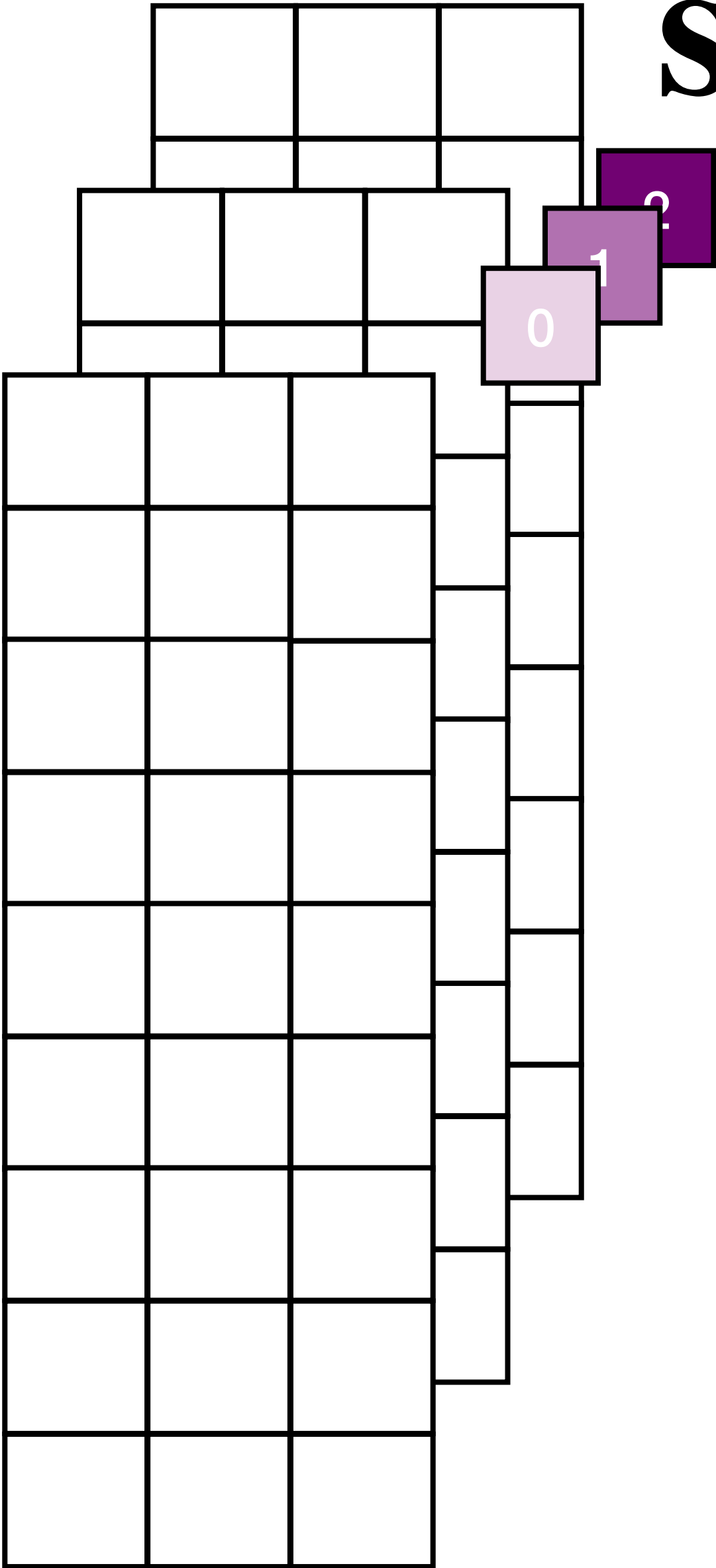
Let's start with a single observation modality

$$\mathbf{S}_t = \{s_t^X, s_t^Y\}$$

  $\mathbf{o}_t = \{o_t^{Loc}\}$




$o^{Loc}$



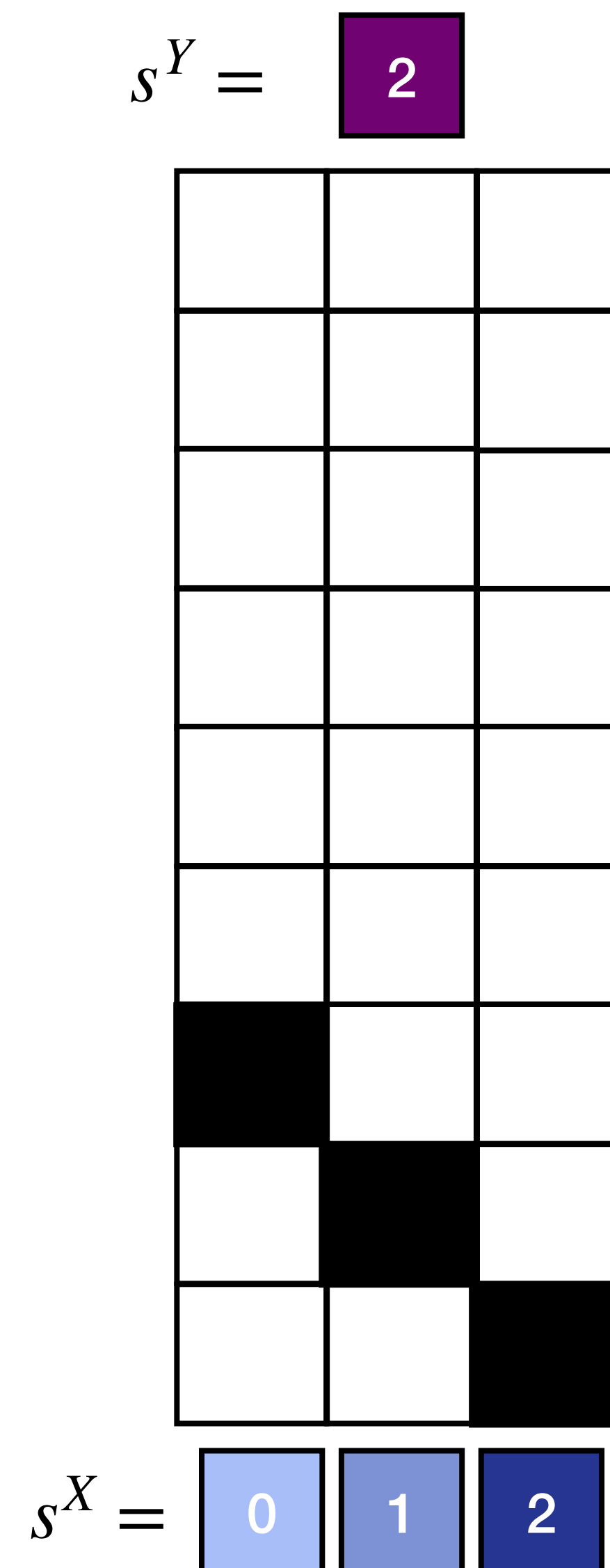
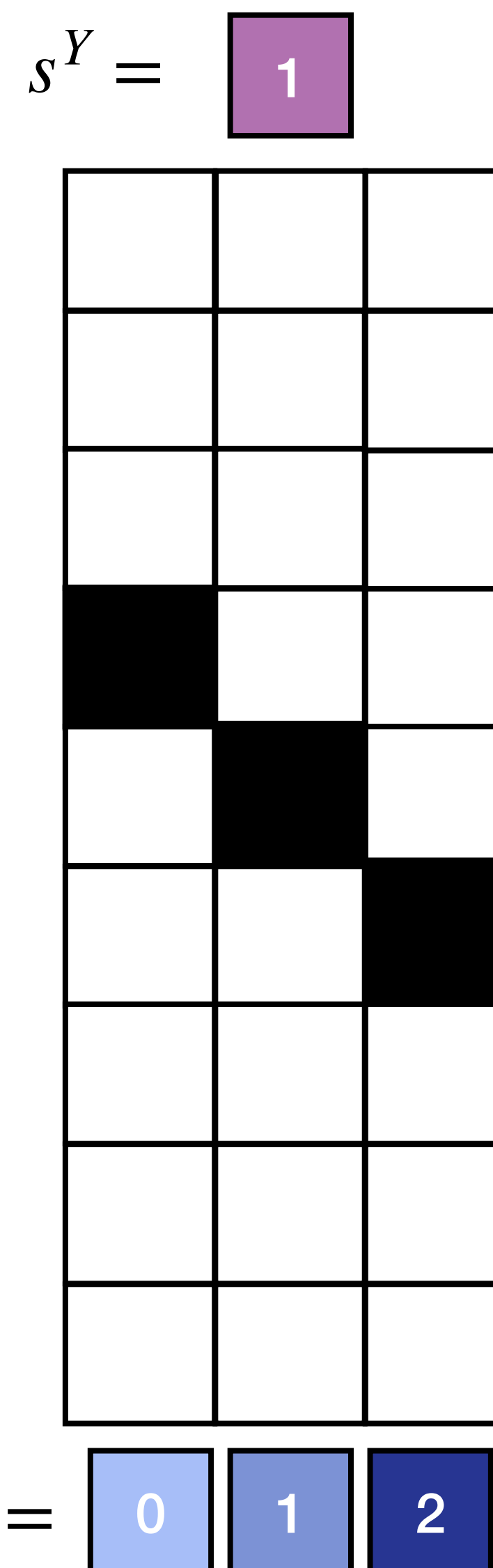
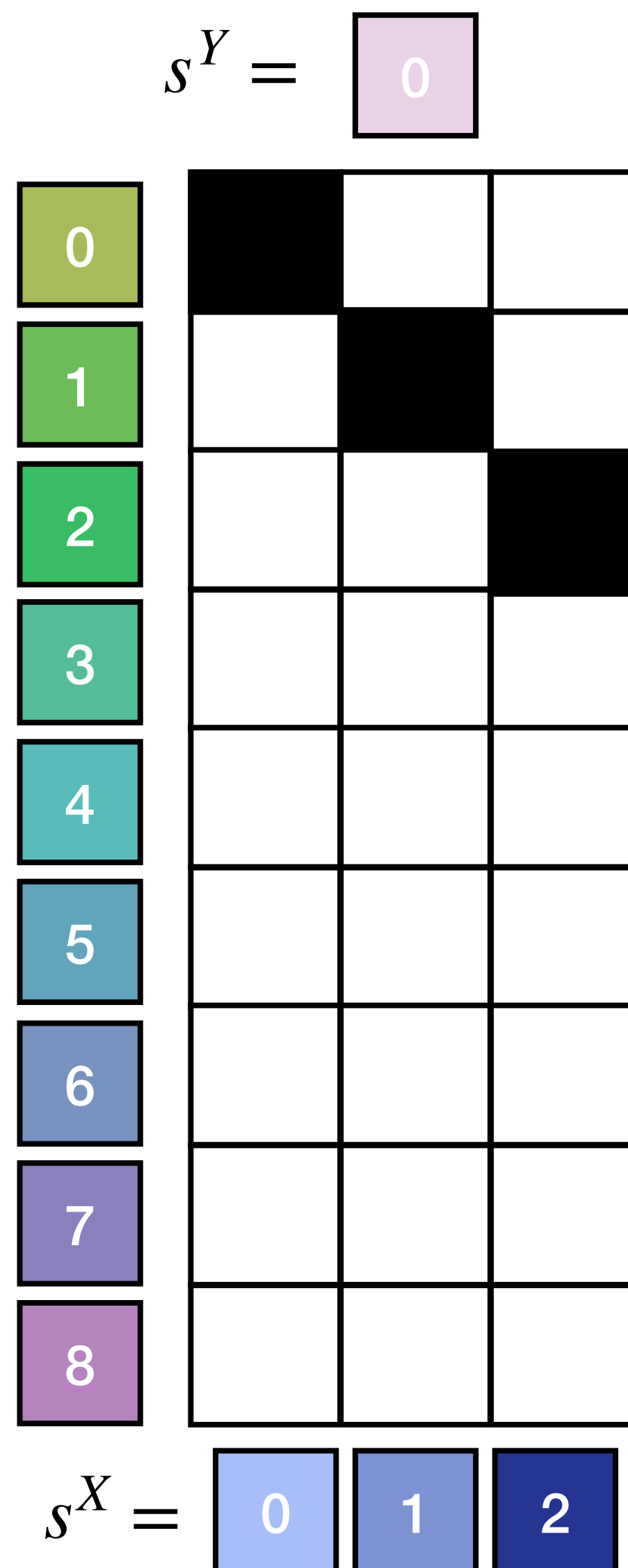
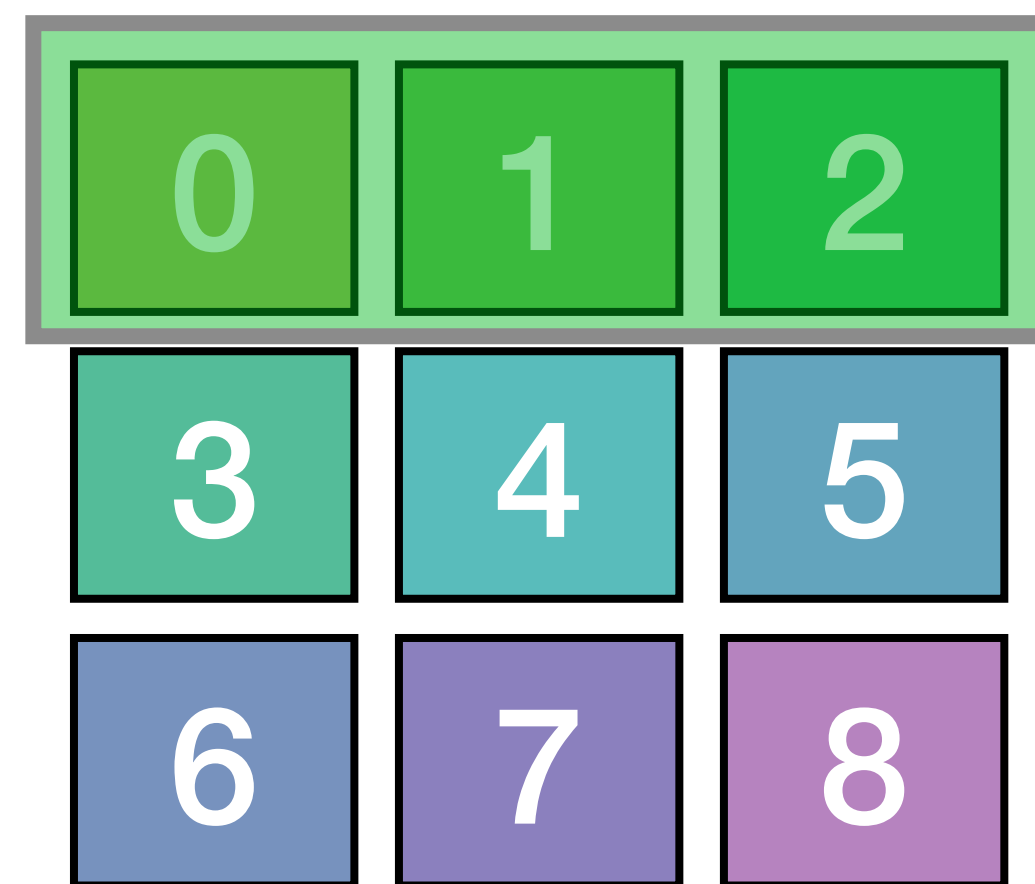
# Let's start with a single observation modality

```
A[0][0:3, :, 0] = np.eye(3)
```

$$\mathbf{s}_t = \{s_t^X, s_t^Y\}$$



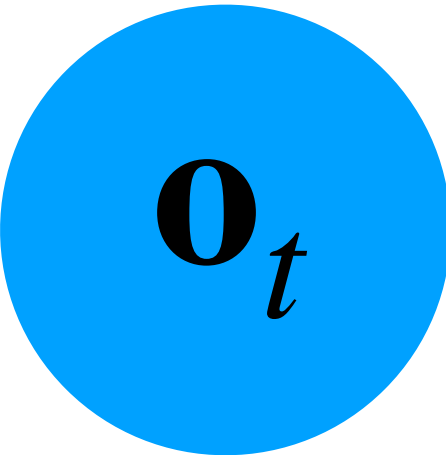
$$\mathbf{o}_t = \{o_t^{Loc}\}$$

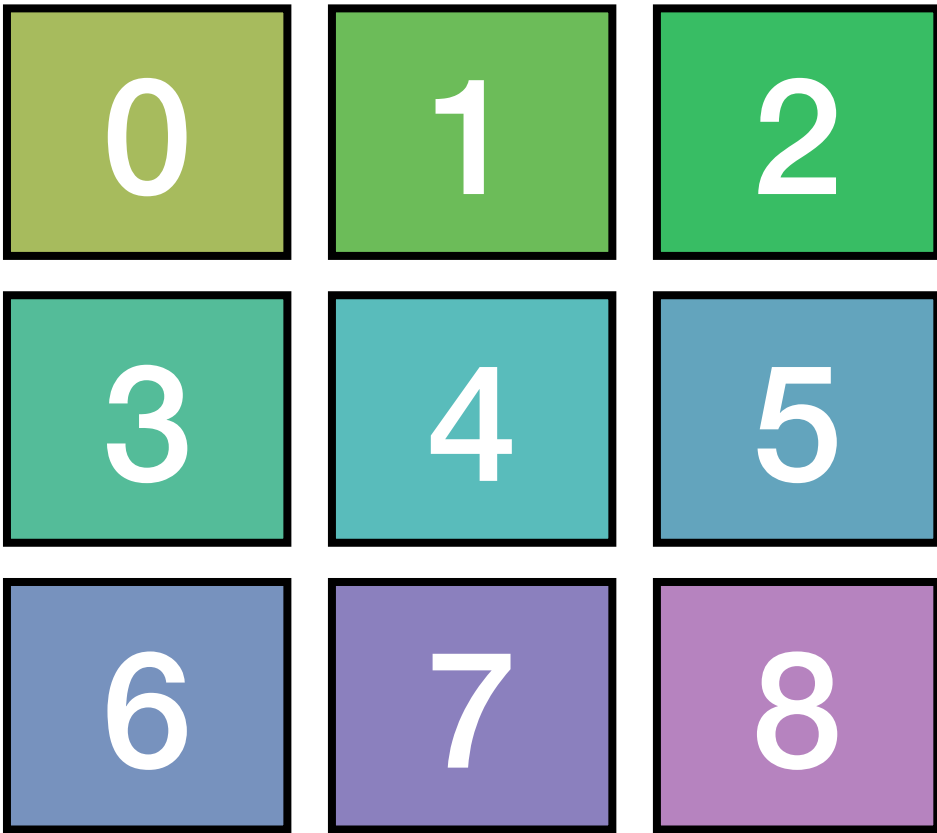


Let's start with a single observation modality

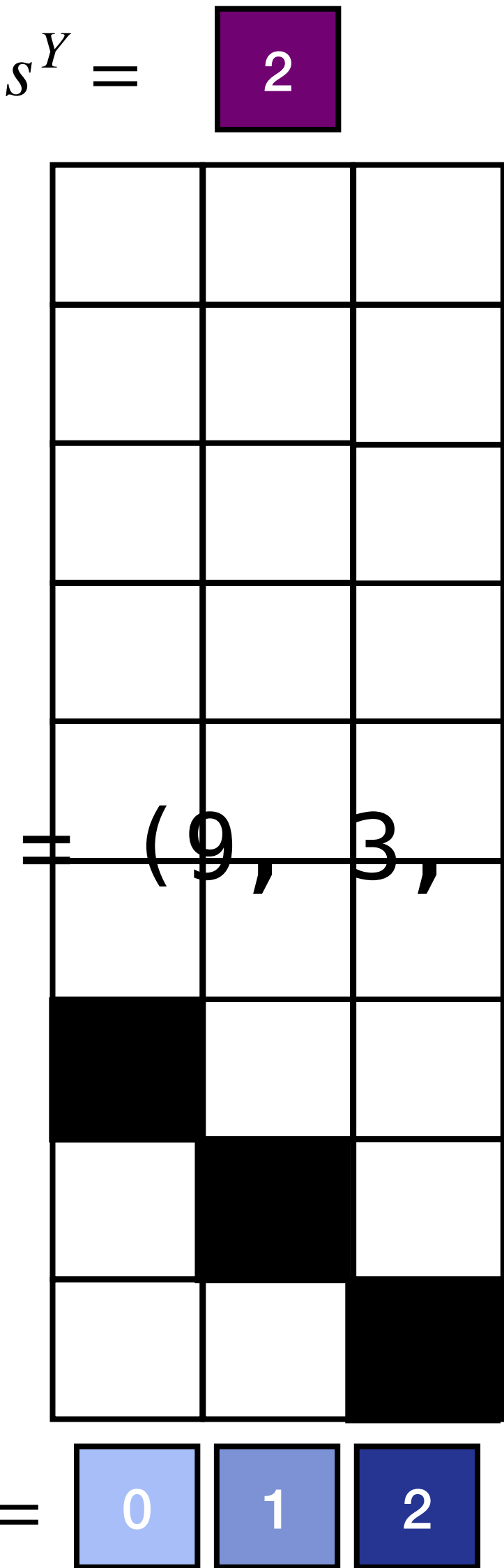
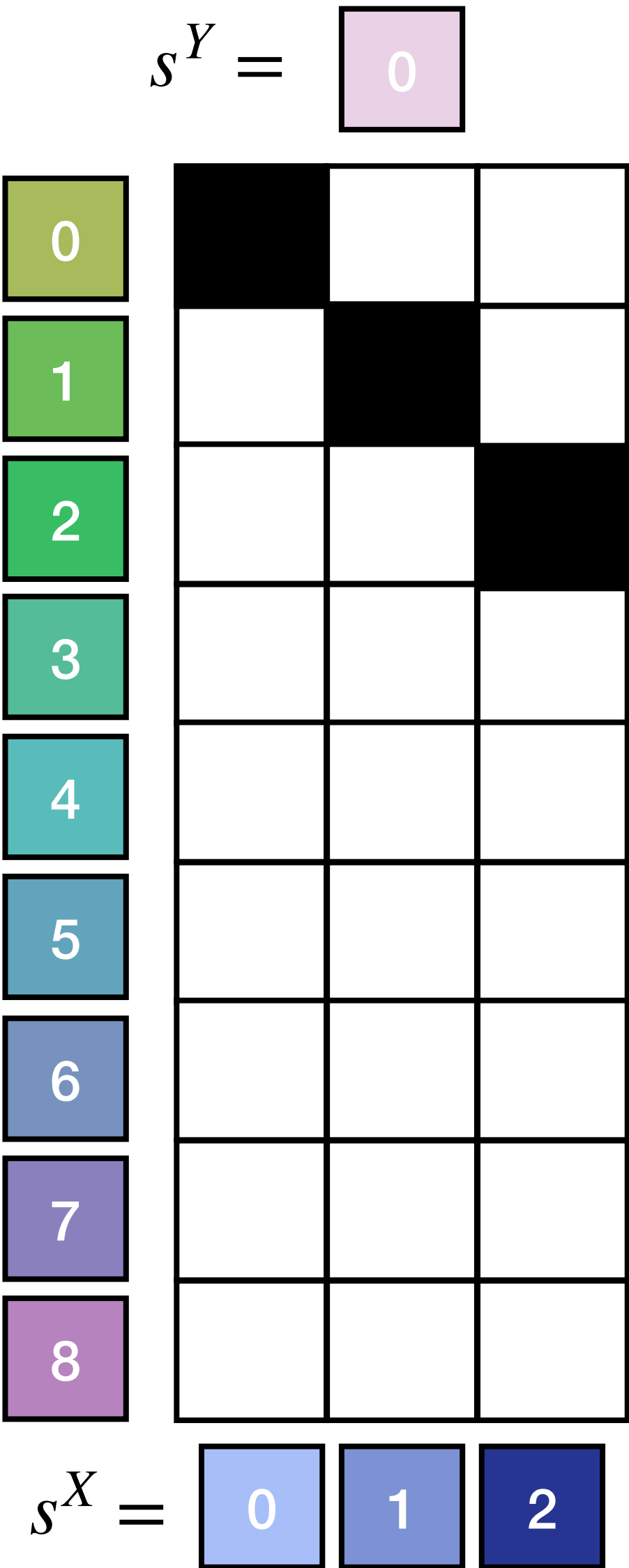
```
A[0][6:9,: ,2] = np.eye(3)
```

$$\mathbf{S}_t = \{s_t^X, s_t^Y\}$$

  $\mathbf{o}_t = \{o_t^{Loc}\}$



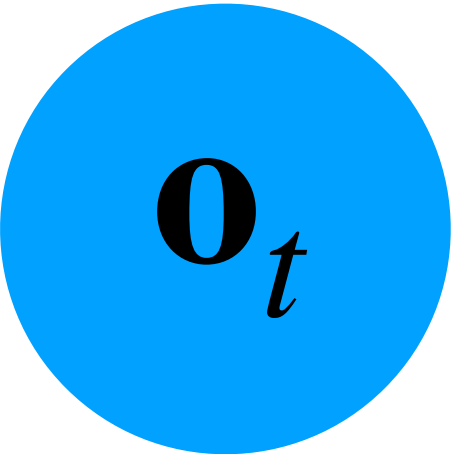
$o^{Loc}$

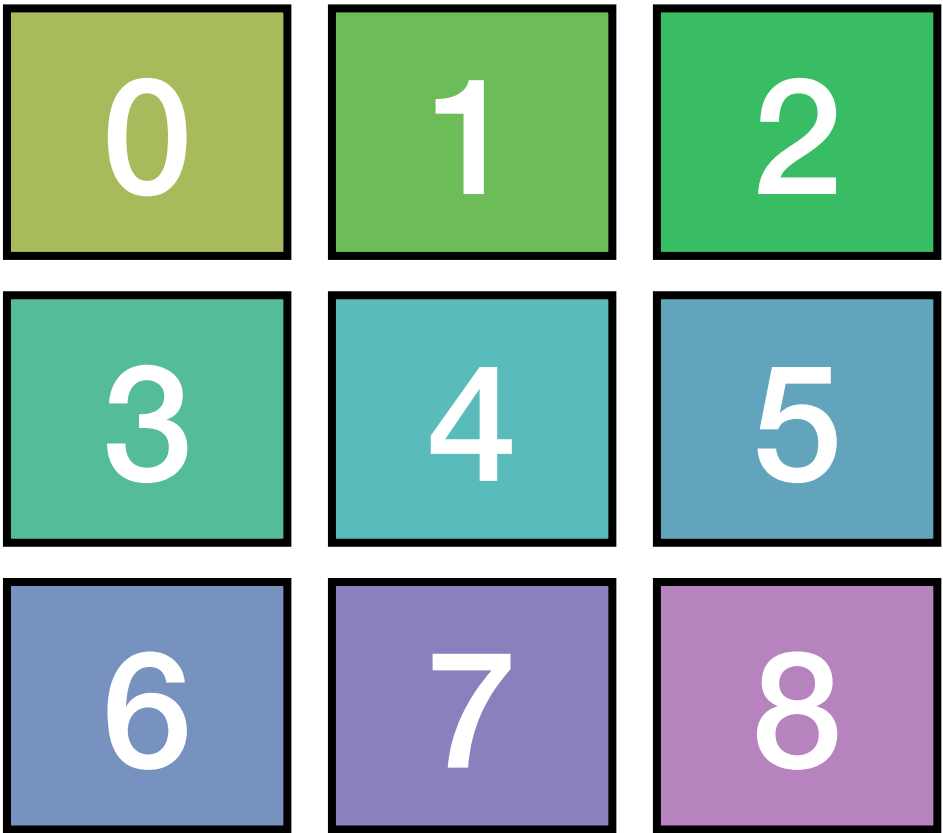


$A[0].shape = (9, 3, 3)$

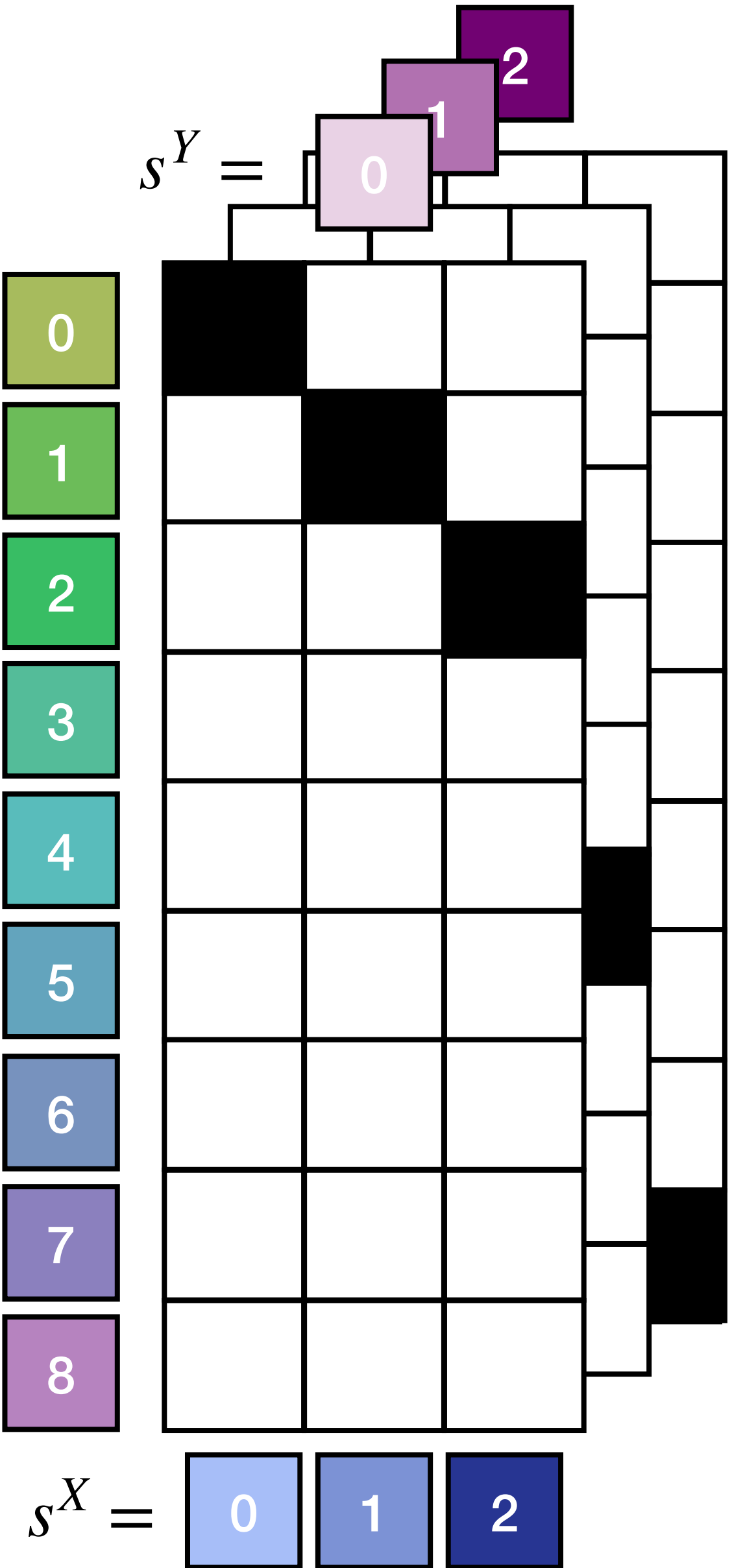
Let's start with a single observation modality

$$\mathbf{S}_t = \{s_t^X, s_t^Y\}$$

  $\mathbf{o}_t = \{o_t^{Loc}\}$

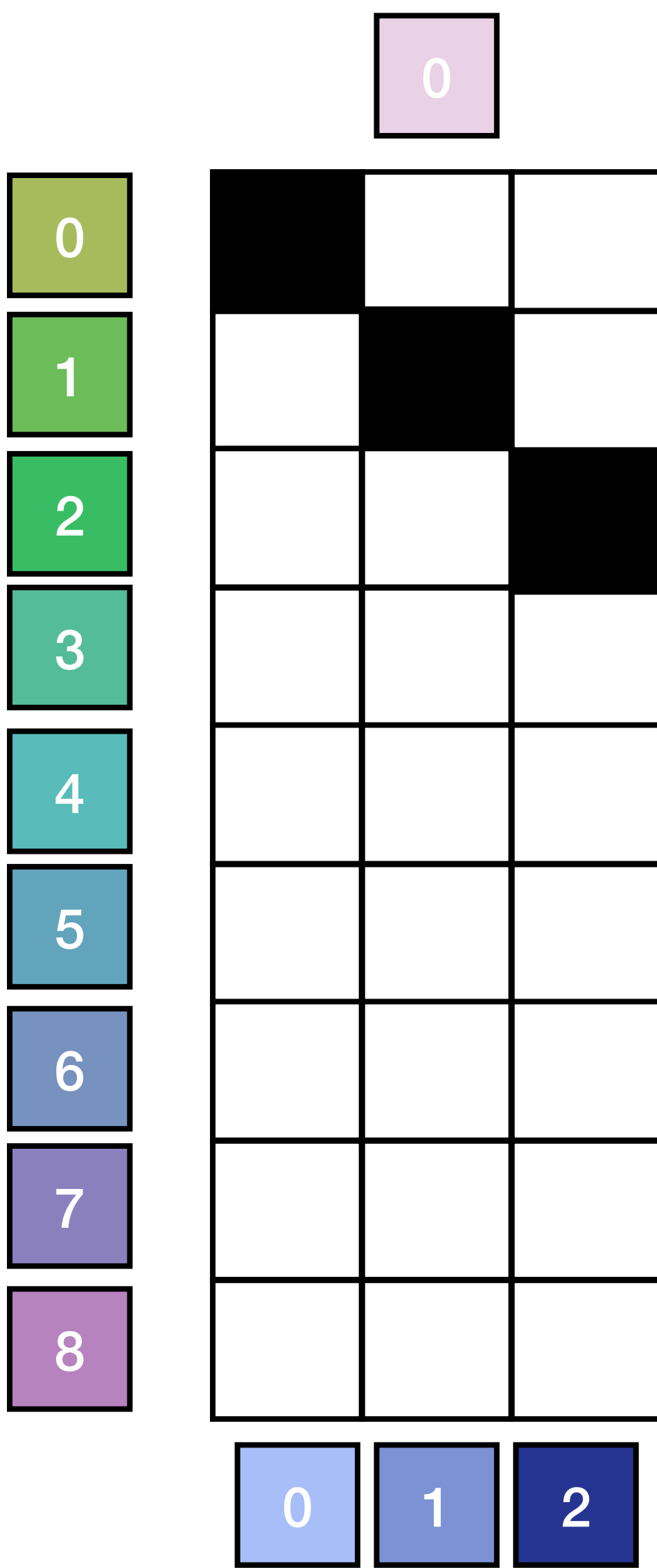


$o^{Loc}$

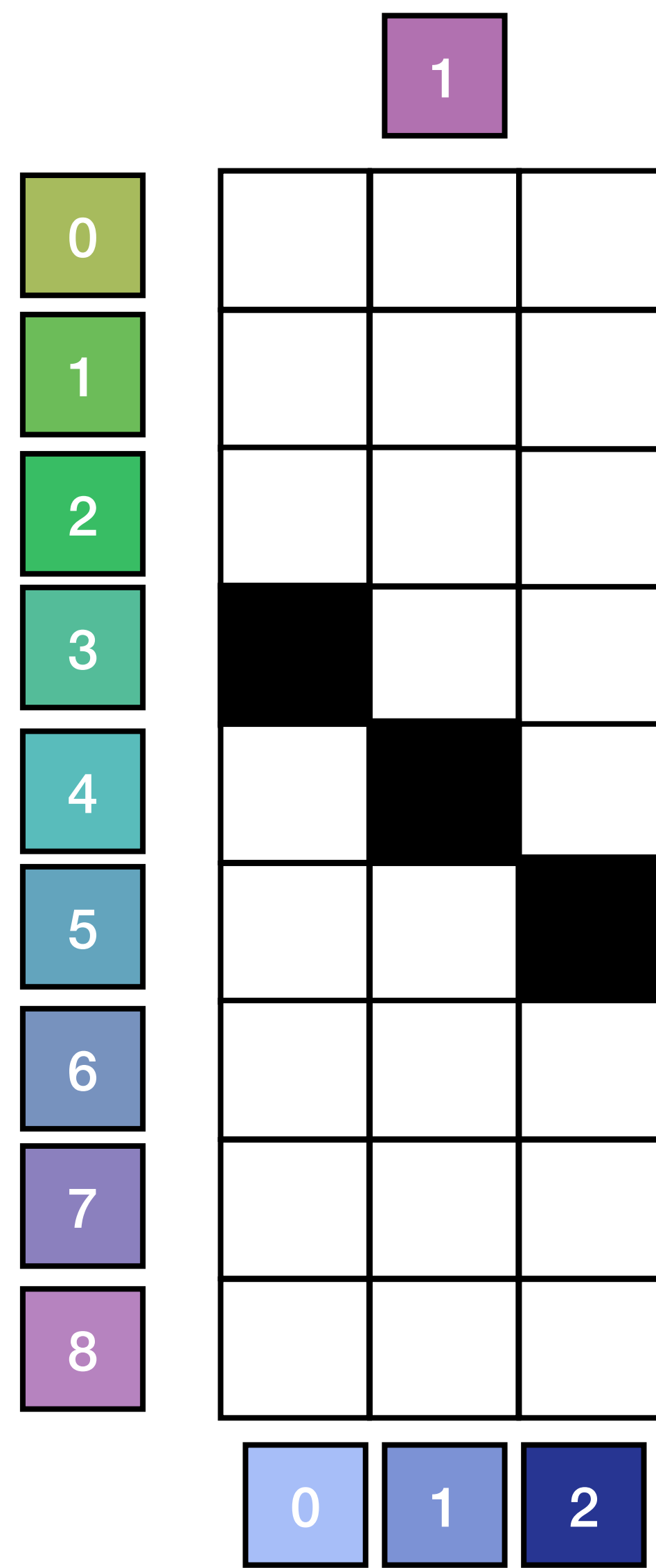


$$A[0][:, i, j] = P(o^{Loc} | s^X = i, s^Y = j)$$

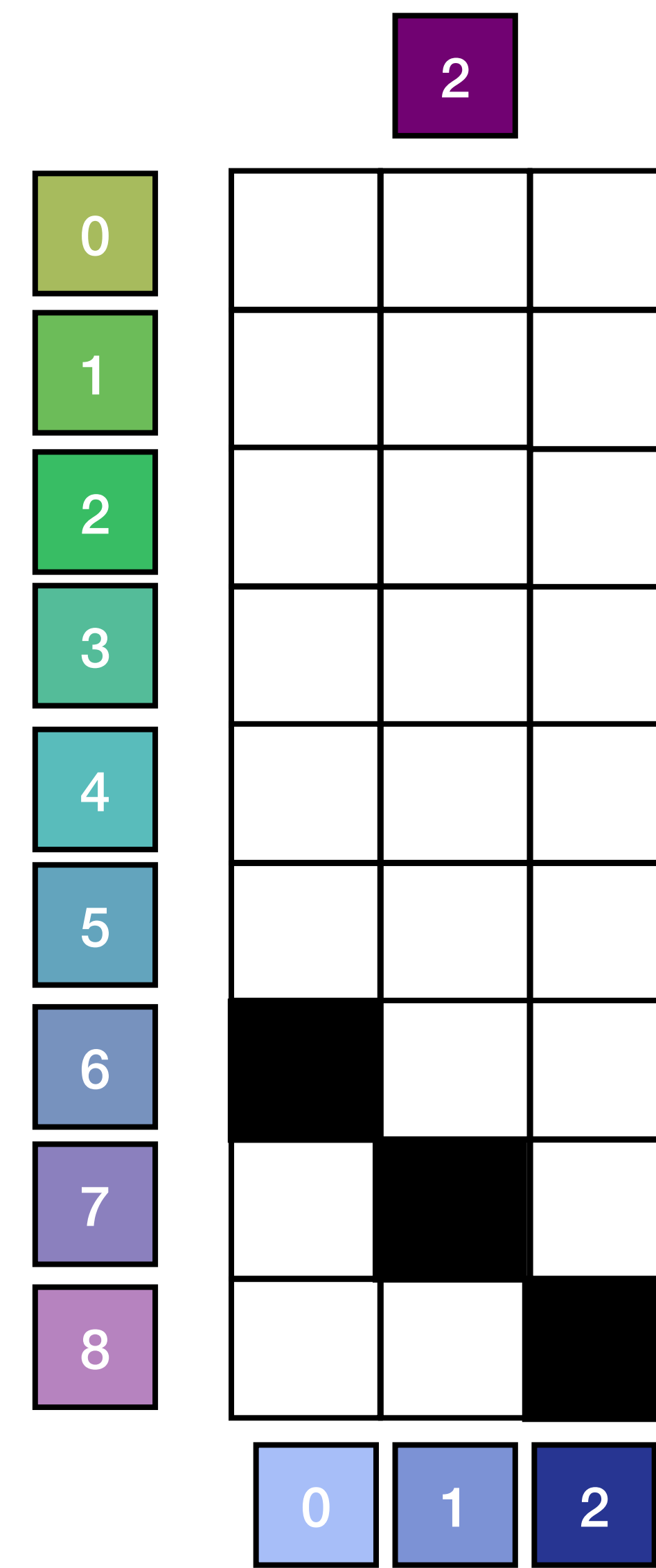
$O^{Loc}$



$A[0][:, :, 0]$



$A[0][:, :, 1]$



$A[0][:, :, 2]$

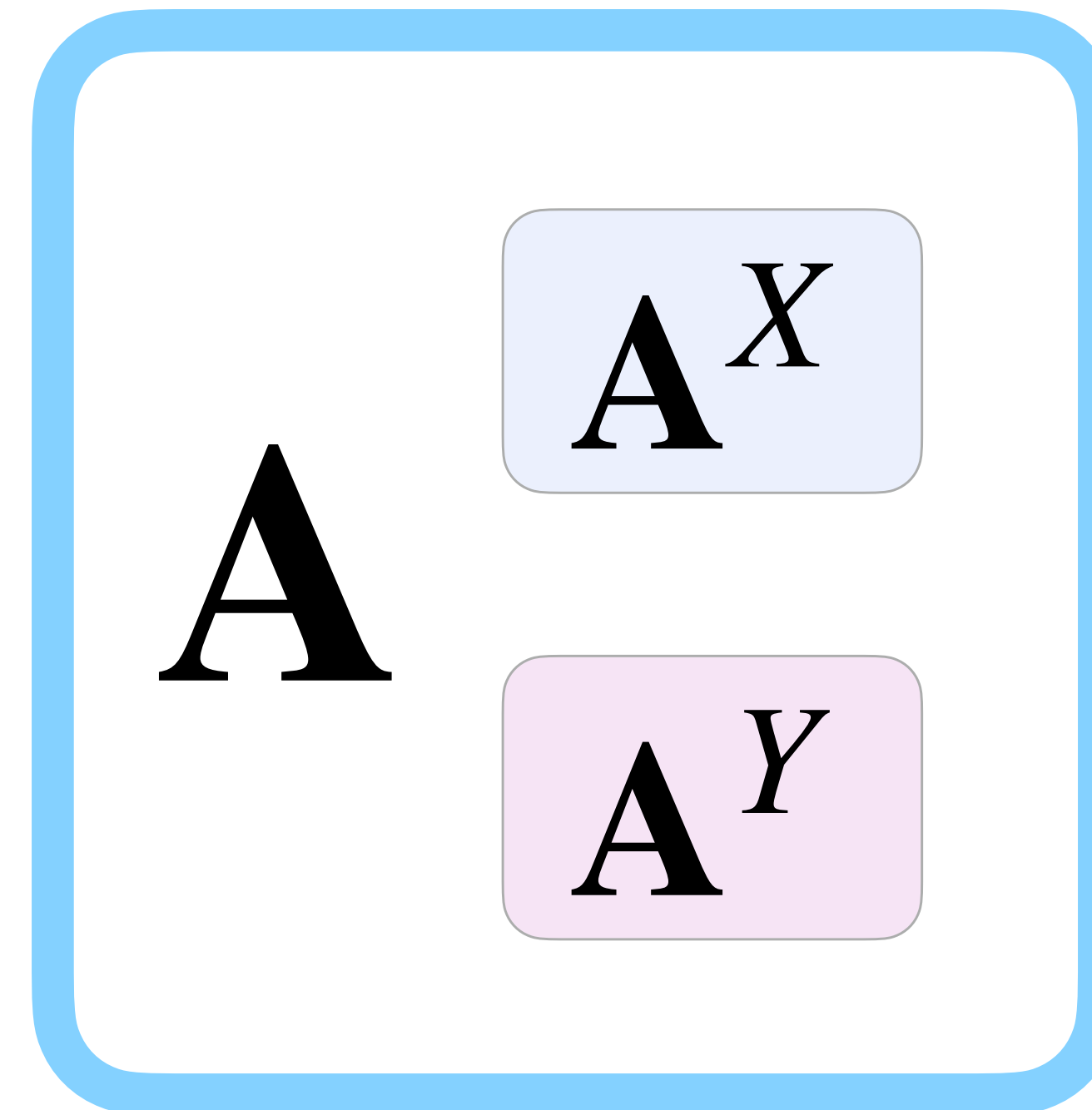
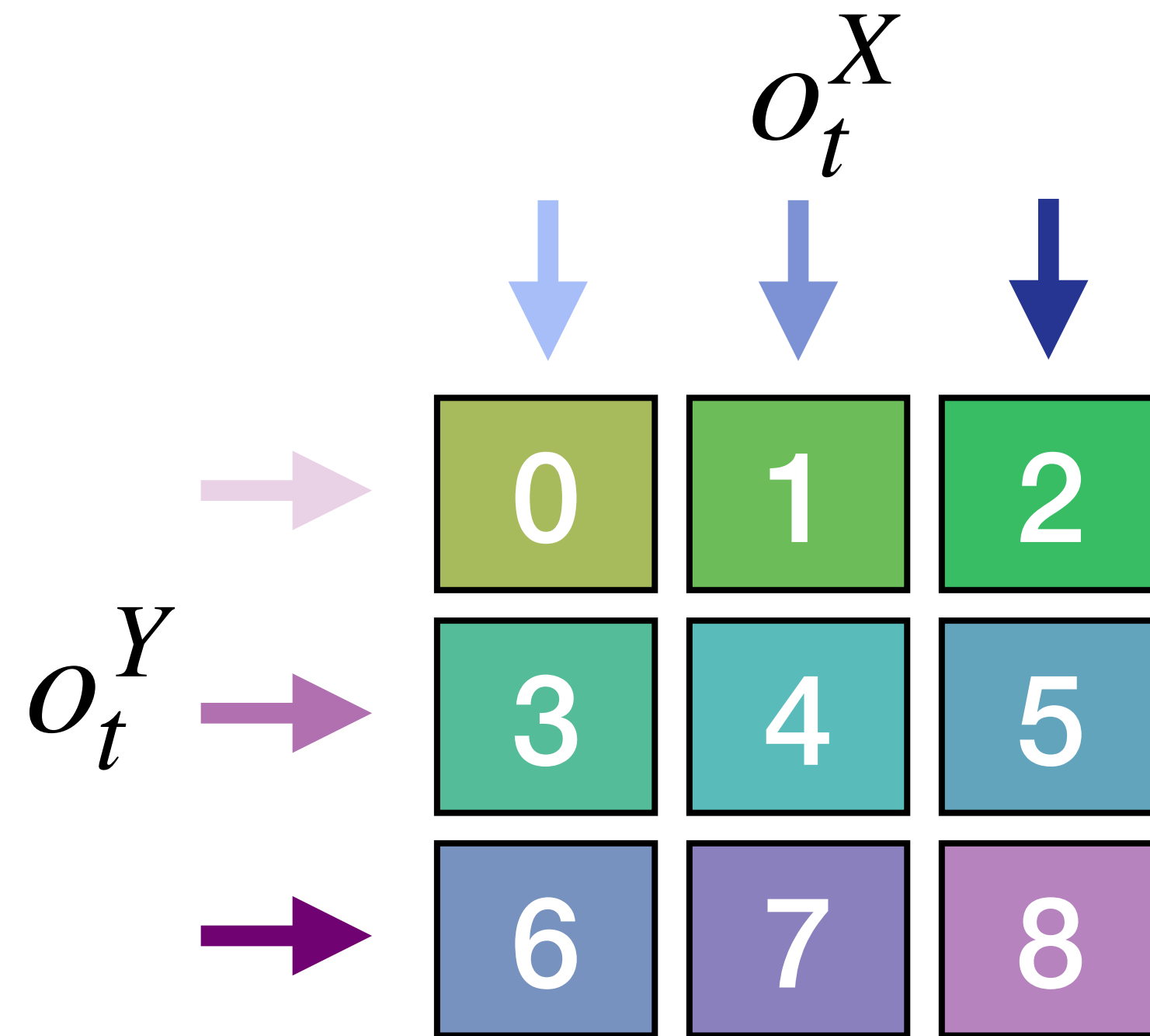
**Back to Colab...**



# Multiple observation modalities

$$\mathbf{o}_t = \{o_t^X, o_t^Y\}$$

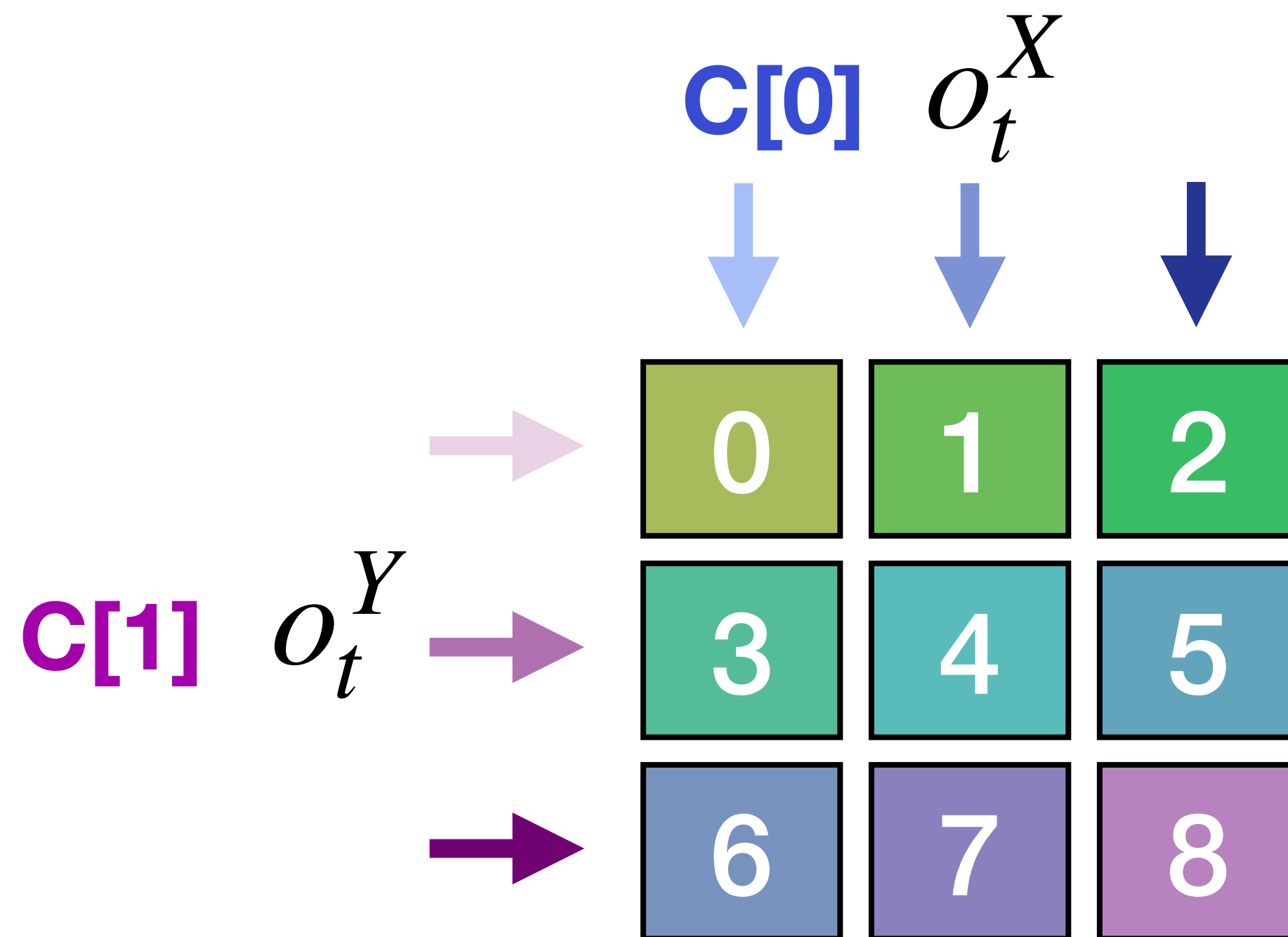
```
num_observations = [3, 3]
num_modalities = len(num_observations)
A = obj_array(num_modalities)
A[0] = ...
A[1] = ...
```



# Multiple observation modalities

$$\mathbf{o}_t = \{o_t^X, o_t^Y\}$$

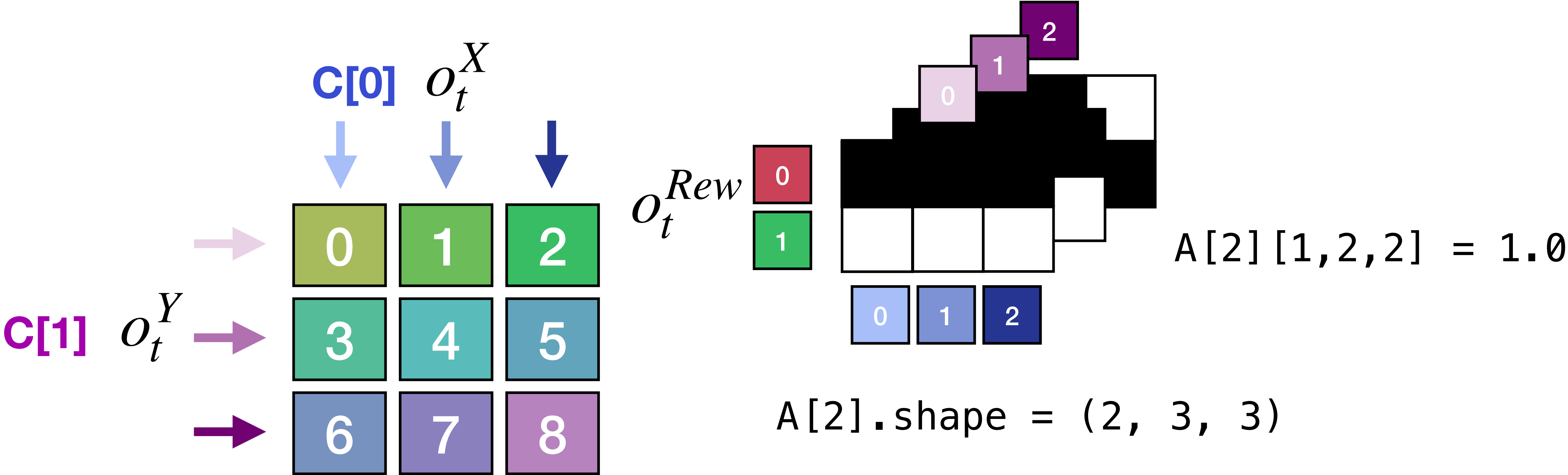
```
num_observations = [3, 3]
num_modalities = len(num_observations)
A = obj_array(num_modalities)
A[0] = ...
A[1] = ...
```



# Multiple observation modalities

$\mathbf{o}_t = \{o_t^X, o_t^Y, o_t^{Rew}\}$

```
num_observations = [3, 3, 2]  
num_modalities = len(num_observations)  
A = obj_array(num_modalities)  
A[0] = ...  
A[1] = ...  
A[2] = ...
```



**Questions ?**

**A new generative model: the epistemic two armed bandit**

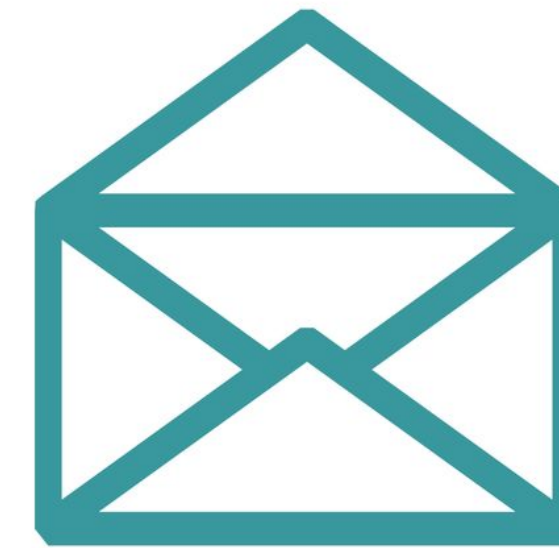
# A new generative model: the epistemic two armed bandit



VS.



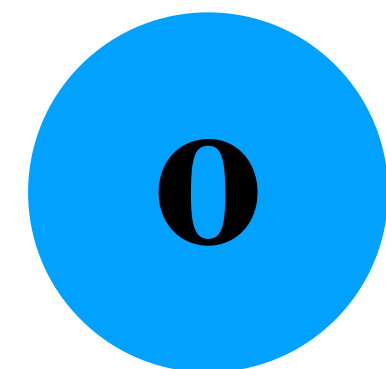
VS.



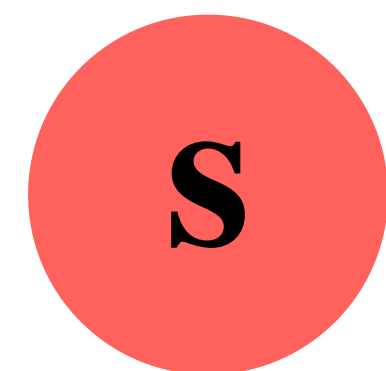
Left

Right

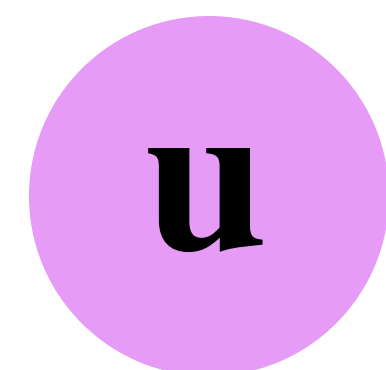
Hint



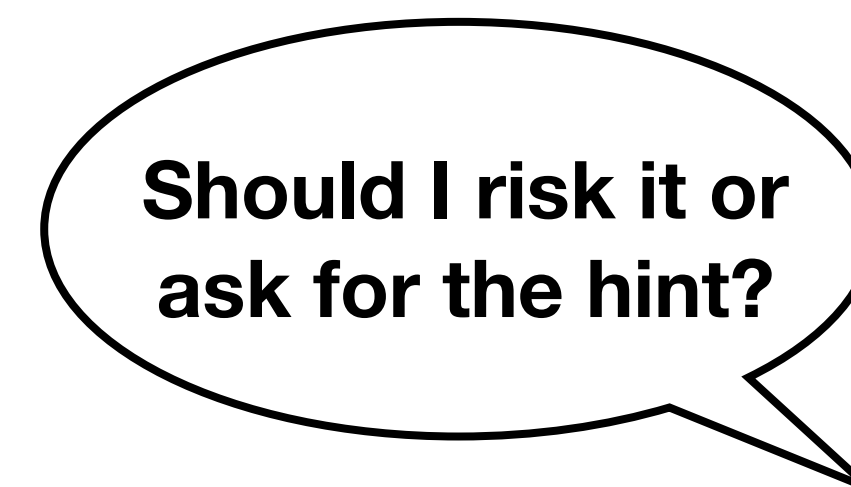
$$= \{o^{Hint}, o^{Reward}, o^{Choice}\}$$



$$= \{s^{Context}, s^{Choice}\}$$



$$= \{u^{Context}, u^{Choice}\}$$



# A new generative model: the epistemic two armed bandit

$$\mathbf{S} = \{s^{Context}, s^{Choice}\}$$

$$s^{Context} \in \{ \text{Left-Better}, \text{Right-Better} \}$$

$$s^{Choice} \in \{ \text{Start}, \text{Hint}, \text{Left}, \text{Right} \}$$

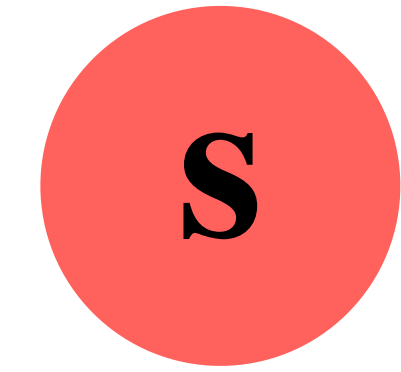
$$\mathbf{u} = \{u^{Context}, u^{Choice}\}$$

$$u^{Context} \in \{ \text{Do-nothing} \}$$

$$u^{Choice} \in \{ \text{Move-Start}, \text{Get-Hint}, \text{Play-Left}, \text{Play-Right} \}$$

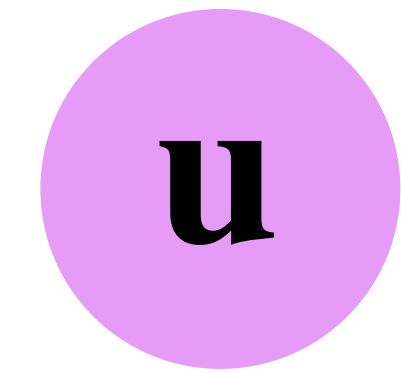
# A new generative model: the epistemic two armed bandit

$O^{Hint} \in \{ \text{Null, Hint-left, Hint-right} \}$



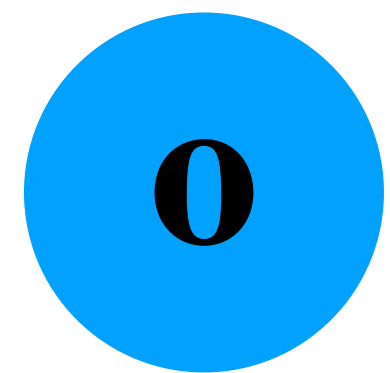
$= \{ s^{Context}, s^{Choice} \}$

$O^{Reward} \in \{ \text{Null, Loss, Reward} \}$



$= \{ u^{Context}, u^{Choice} \}$

$O^{Choice} \in \{ \text{Start, Hint, Left, Right} \}$



$= \{ O^{Hint}, O^{Reward}, O^{Choice} \}$



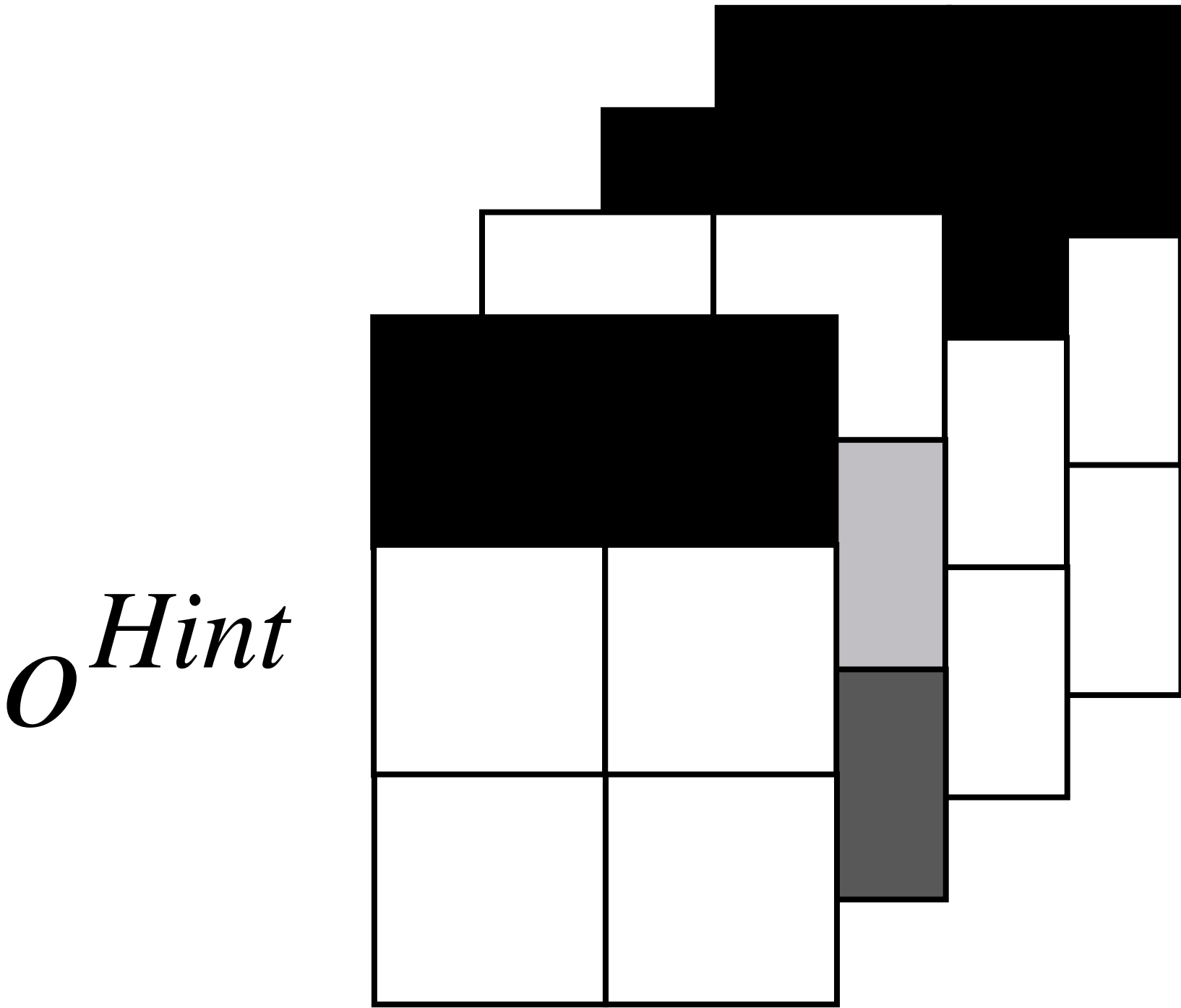
# The epistemic two armed bandit

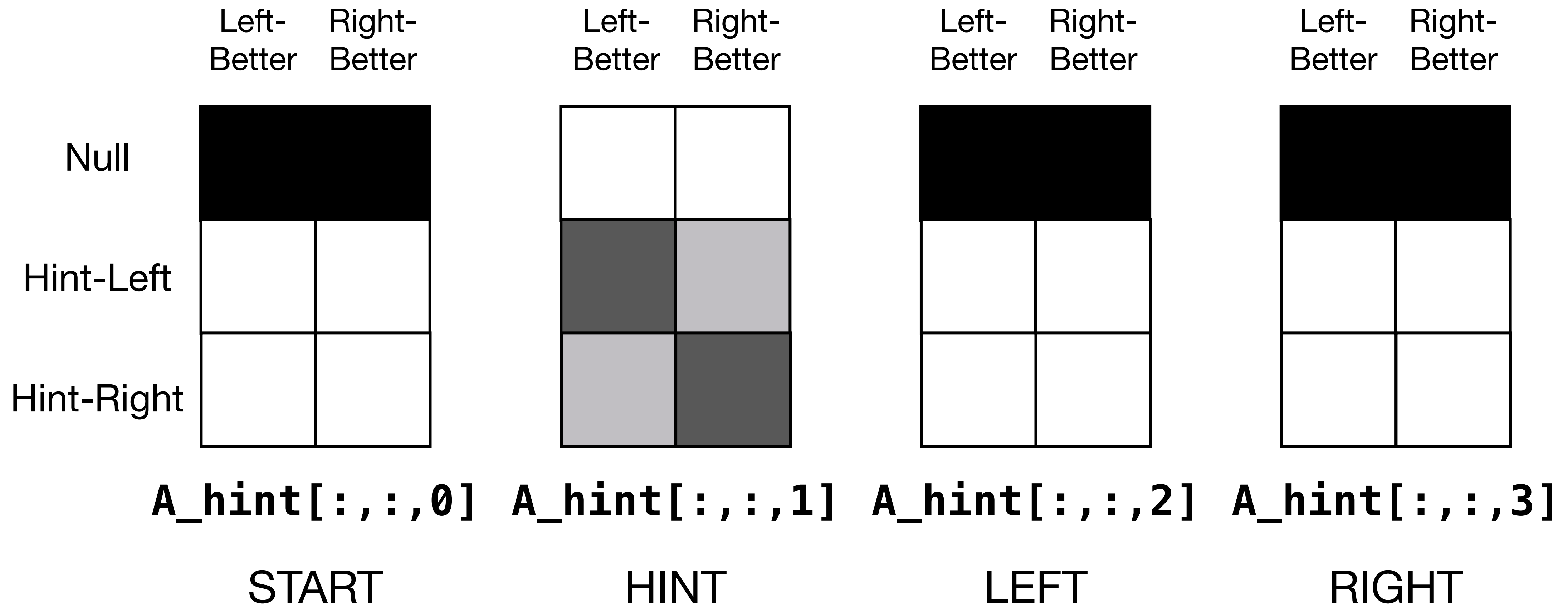
The **A** Matrix  
AKA  $P(o \mid s)$

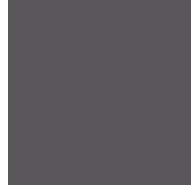
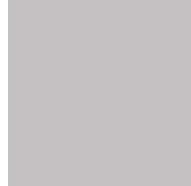
$$o^{Hint} \in \{ \text{Null}, \text{Hint-Left}, \text{Hint-Right} \}$$

	Left- Better	Right- Better
Null		
Hint-Left		
Hint-Right		

**SHIFT**





  **$p_{\text{hint}}$**   
  **$1.0 - p_{\text{hint}}$**

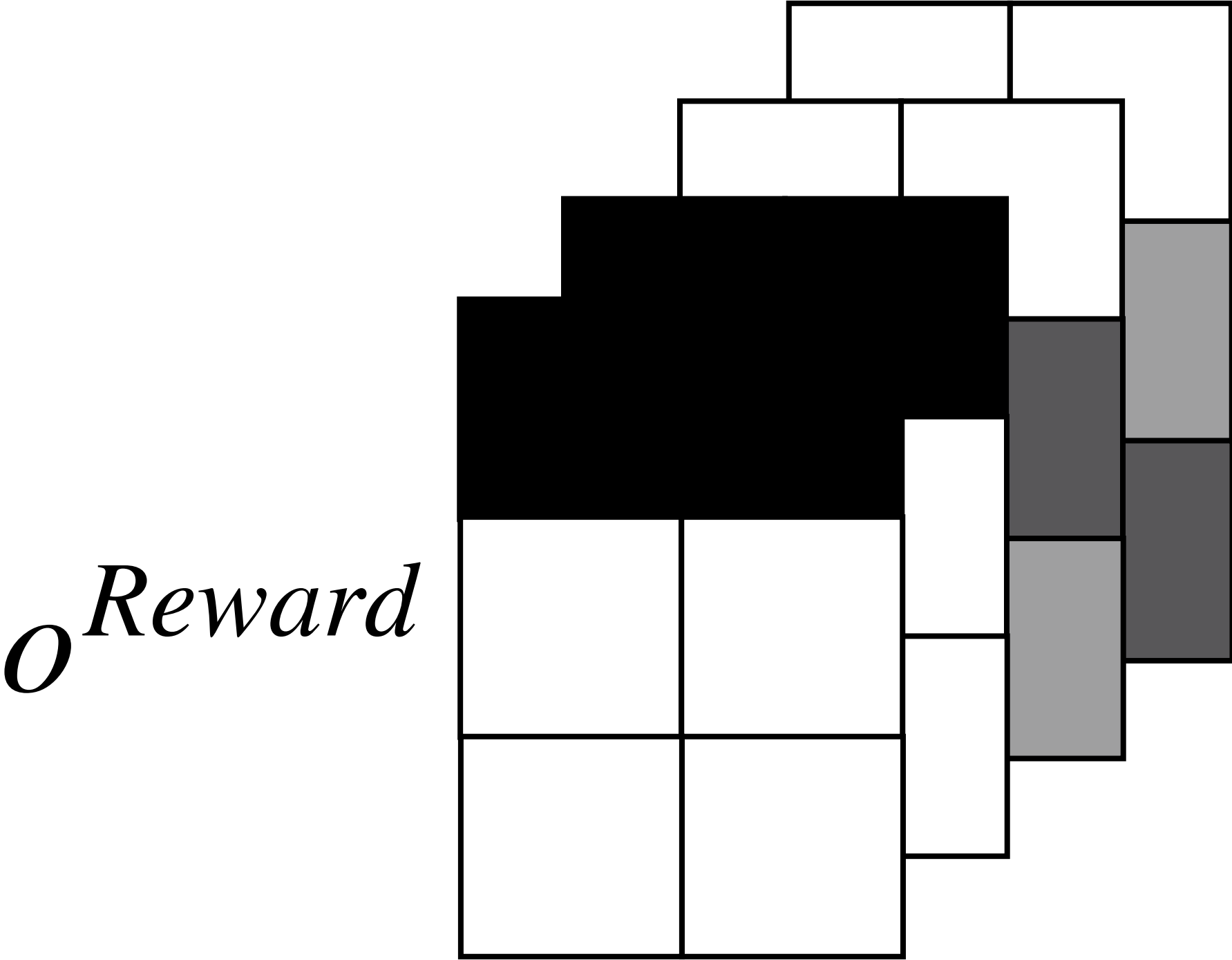
# The epistemic two armed bandit

The **A** Matrix

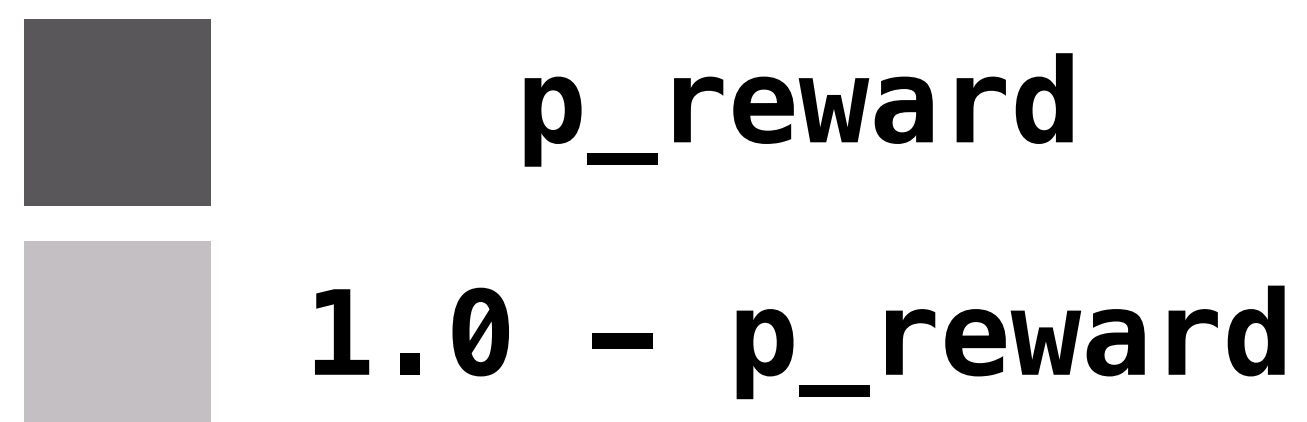
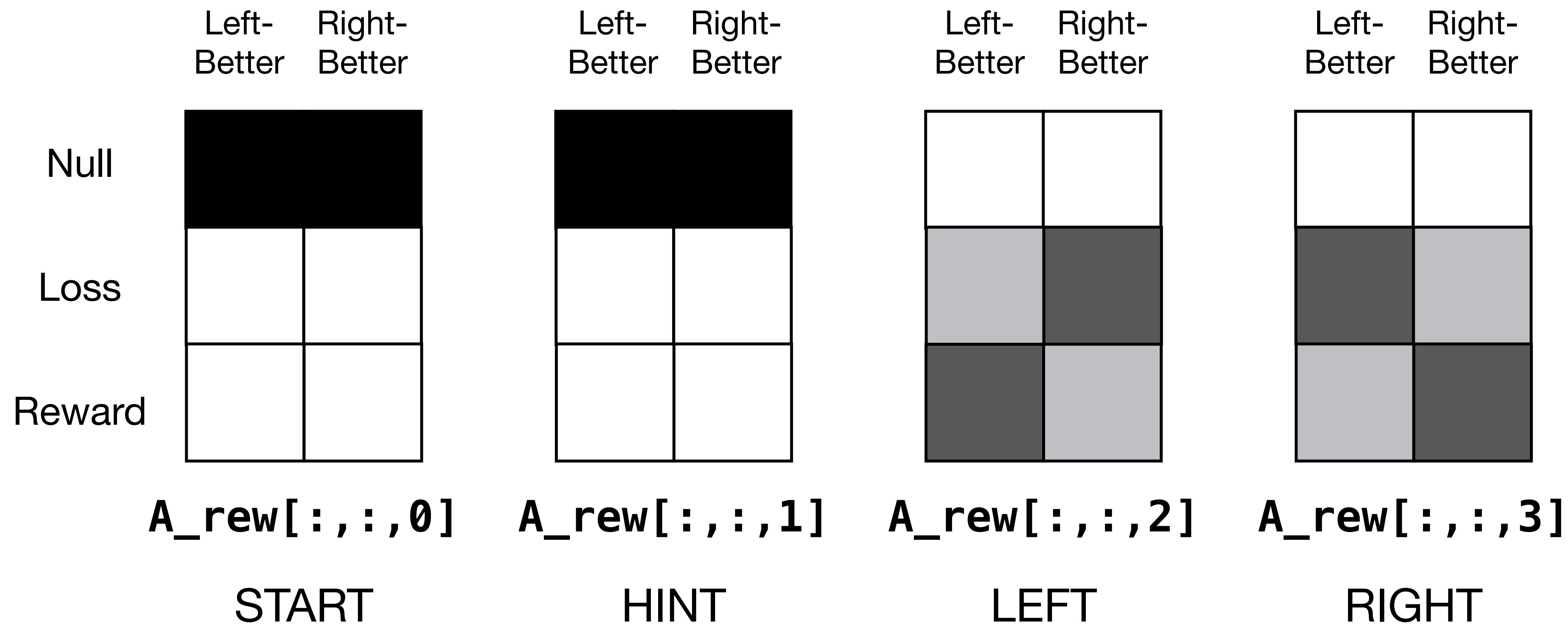
AKA  $P(o \mid s)$

$$o^{Reward} \in \{ \text{Null}, \text{Loss}, \text{Reward} \}$$

	Left- Better	Right- Better
Null		
Loss		
Reward		



**SHIFT**



# The epistemic two armed bandit

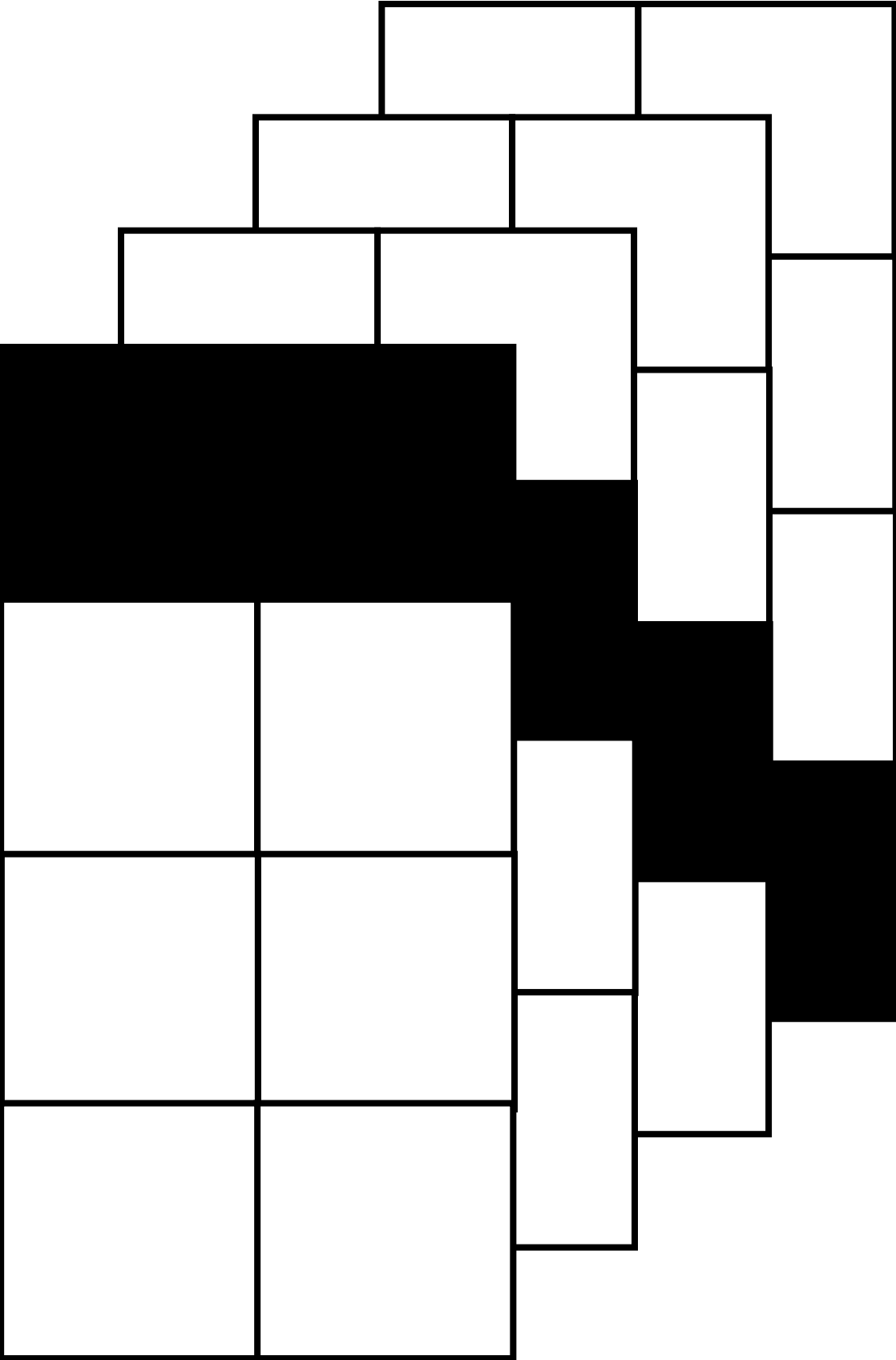
The **A** Matrix

AKA  $P(o \mid s)$

$$o^{Choice} \in \{ \text{Start, Hint, Left, Right} \}$$

	Left- Better	Right- Better
Start		
Hint		
Left		
Right		

$o^{Choice}$



Left-  
Better    Right-  
Better

START	
HINT	
LEFT	
RIGHT	

Left-  
Better    Right-  
Better

HINT	
LEFT	
RIGHT	

Left-  
Better    Right-  
Better

LEFT	
RIGHT	

Left-  
Better    Right-  
Better

RIGHT	

**A\_choice[:, :, 0]**

START

**A\_choice[:, :, 1]**

HINT

**A\_choice[:, :, 2]**

LEFT

**A\_choice[:, :, 3]**

RIGHT

**Back to Colab...**

# The epistemic two armed bandit

The **B** Matrix

AKA  $P(s_t \mid s_{t-1}, u_{t-1})$

	Left-Better	Right-Better
Left-Better		
Right-Better		

$B[0][:, :, 0]$



# The epistemic two armed bandit

The **B** Matrix

AKA  $P(s_t \mid s_{t-1}, u_{t-1})$

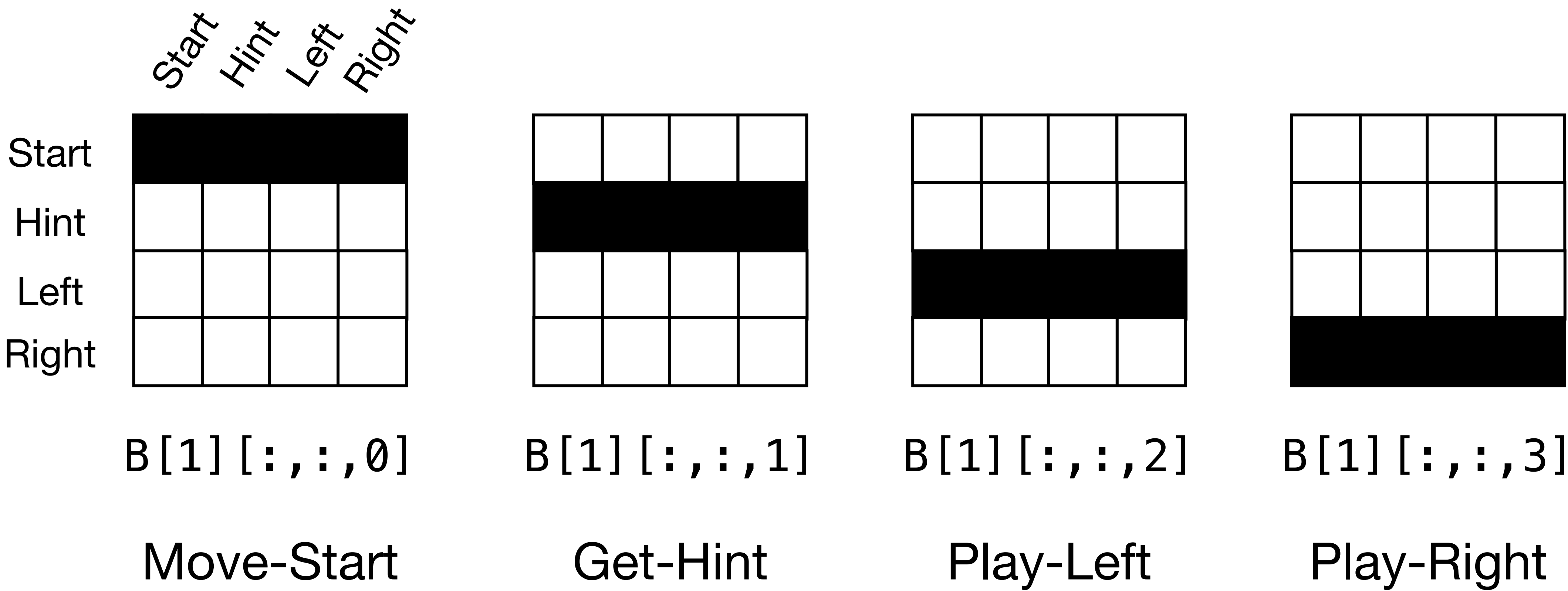
	Left- Better	Right- Better
Left- Better		
Right- Better		

`B_context[:, :, 0]`

# The epistemic two armed bandit

## The **B** Matrix

AKA  $P(s_t \mid s_{t-1}, u_{t-1})$



	Start	Hint	Left	Right
Start				
Hint				
Left				
Right				

B\_choice[:, :, 0]

Move-Start

	Start	Hint	Left	Right
Start				
Hint				
Left				
Right				

B\_choice[:, :, 1]

Get-Hint

	Start	Hint	Left	Right
Start				
Hint				
Left				
Right				

B\_choice[:, :, 2]

Play-Left

	Start	Hint	Left	Right
Start				
Hint				
Left				
Right				

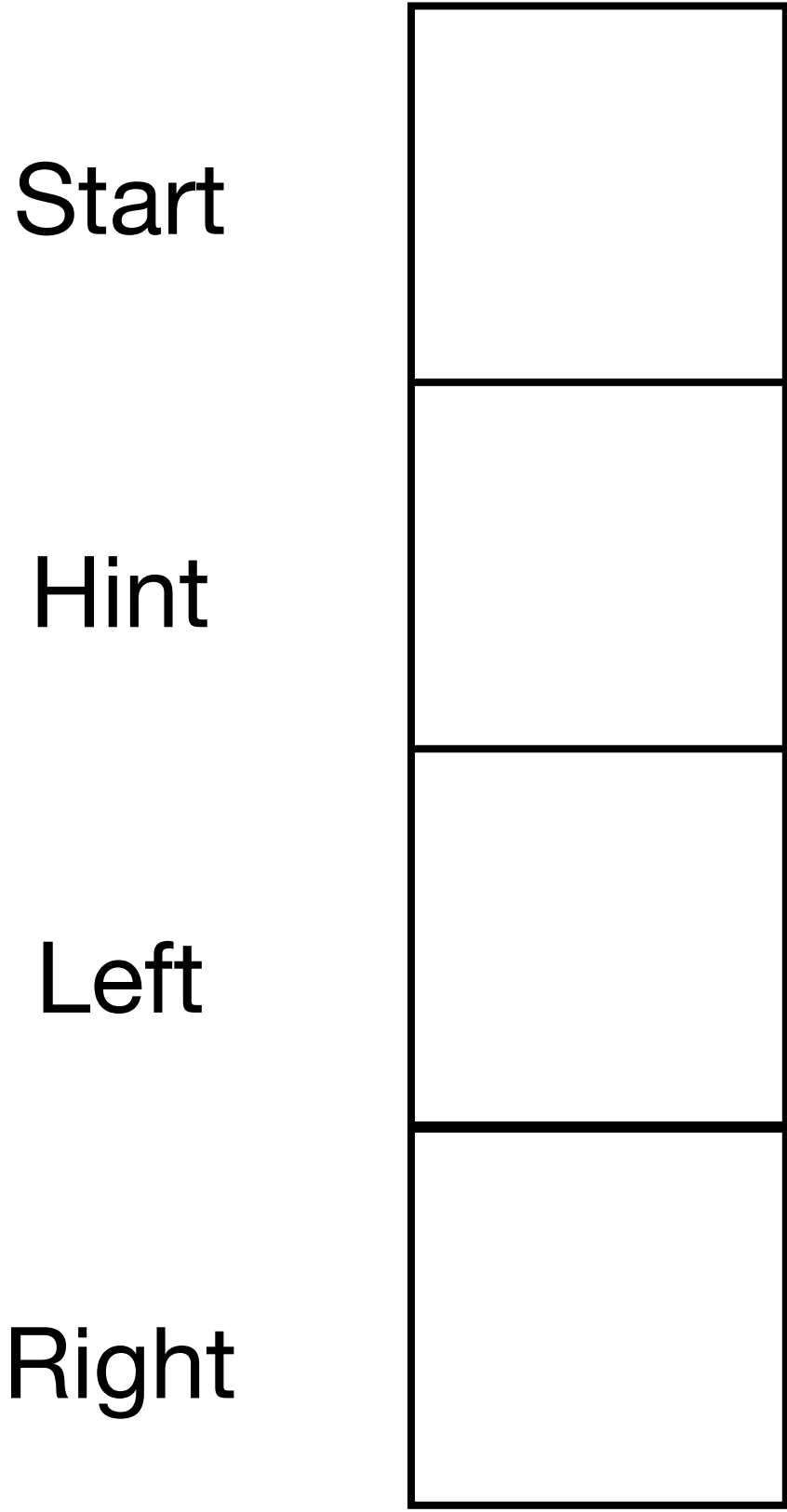
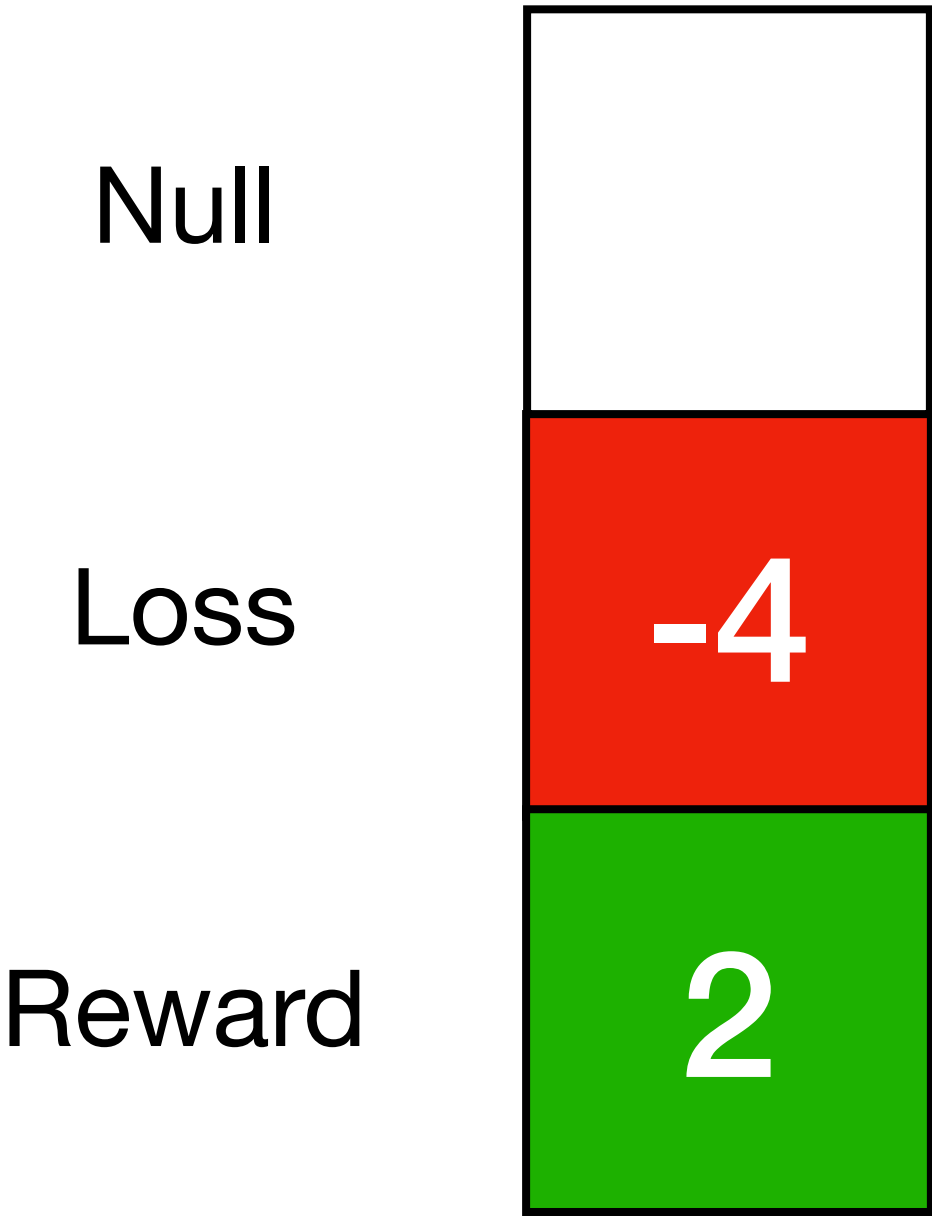
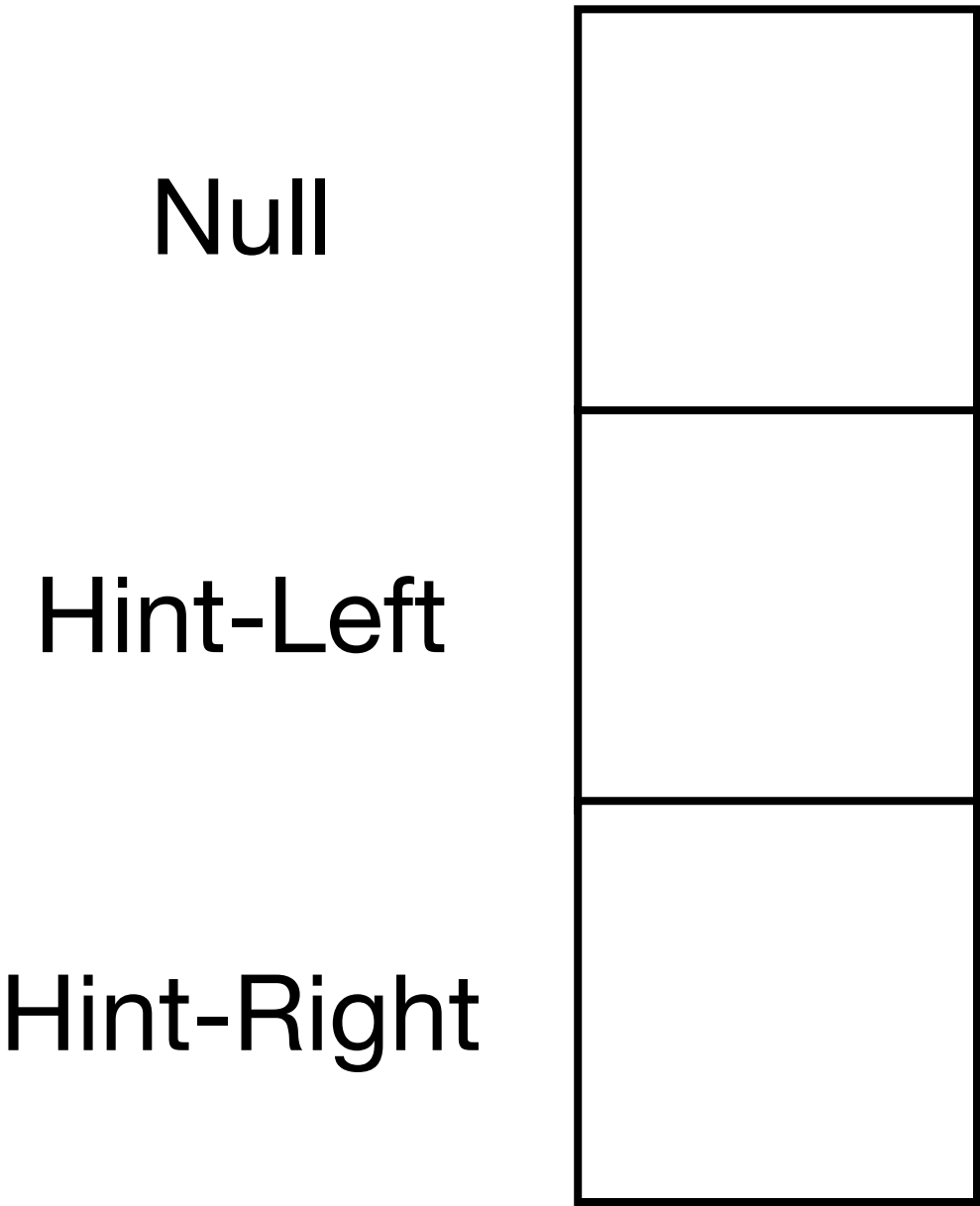
B\_choice[:, :, 3]

Play-Right

**Back to Colab...**

# The epistemic two armed bandit

## The **C** Vector



# The epistemic two armed bandit

## The **C** Vector

$$P(o | \mathbf{C}) = \sigma(\mathbf{C})$$

$$\sigma(C_i) = \frac{\exp(C_i)}{\sum_i \exp(C_i)}$$

Null	0.119
Loss	0.002
Reward	0.88

$$= \sigma \left( \begin{array}{c} \text{ } \\ -4 \\ 2 \end{array} \right)$$

# The **D** Vector

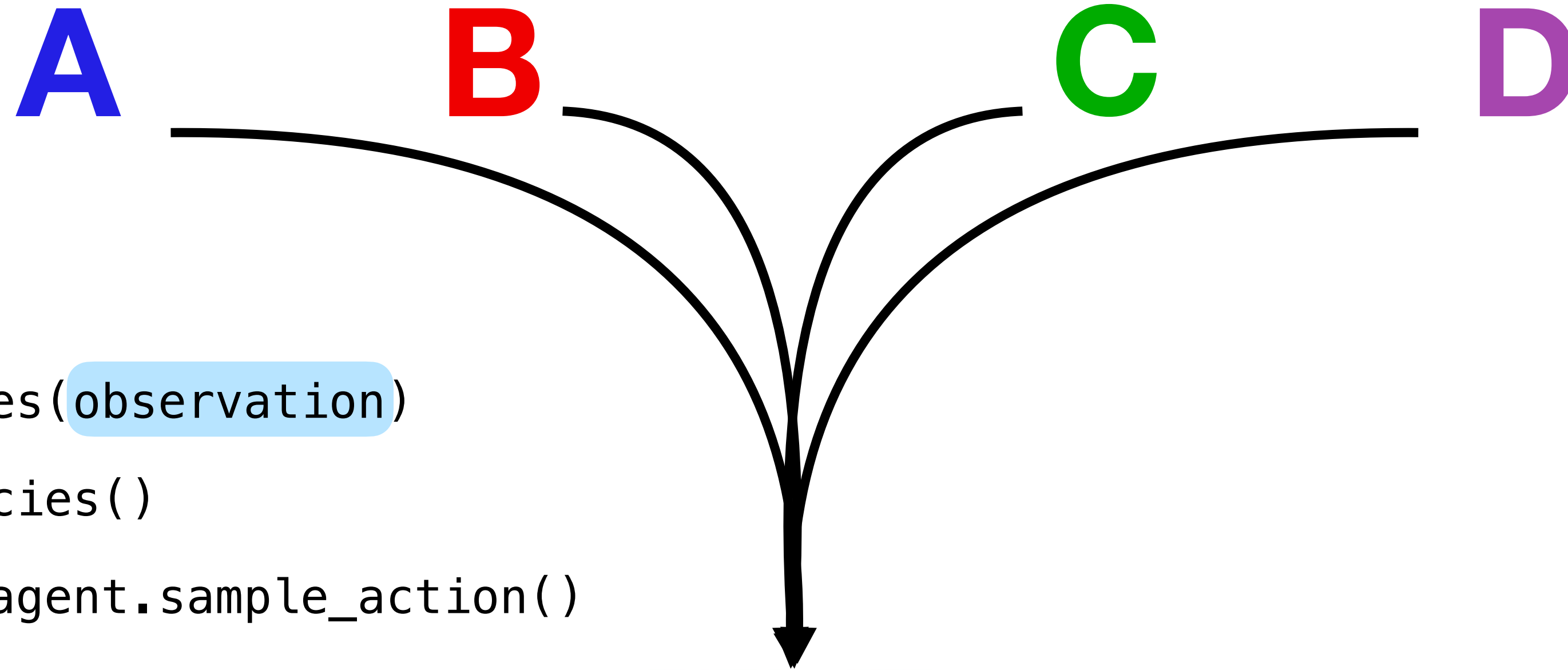
AKA  $P(s_0)$

Left-Better	0.5
Right-Better	0.5

Start	
Hint	
Left	
Right	

**Back to Colab...**





- `my_agent.infer_states(observation)`
- `my_agent.infer_policies()`
- `chosen_action = my_agent.sample_action()`

```
from pymdp.agent import Agent  
my_agent = Agent(A = A, B = B, C = C, D = D)
```

**Back to Colab...**

**Thank you for your attention!**

