6.036/6.862: Introduction to Machine Learning

Lecture: starts Tuesdays 9:35am (Boston time zone)

Course website: introml.odl.mit.edu

Who's talking? Prof. Tamara Broderick

vote.mit.edu

Questions? discourse.odl.mit.edu ("Lecture 10" category)

Materials: Will all be available at course website

Last Time

I. Actions change the state of the world and gain reward: Markov decision processes (MDPs)

II. Choosing "best" actions

Today's Plan

I. Don't know reward function or transition function in advance

II. How to choose "best" actions

Recall

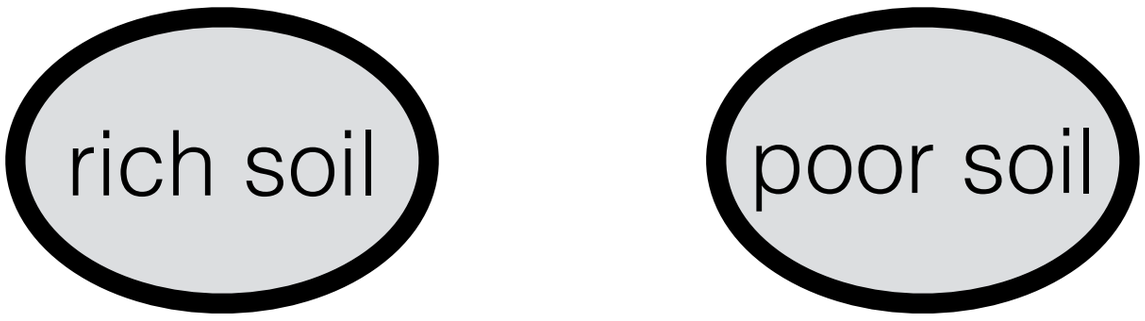
Recall

- Markov decision process

Recall

- Markov decision process: states $\mathcal{S}$

Recall



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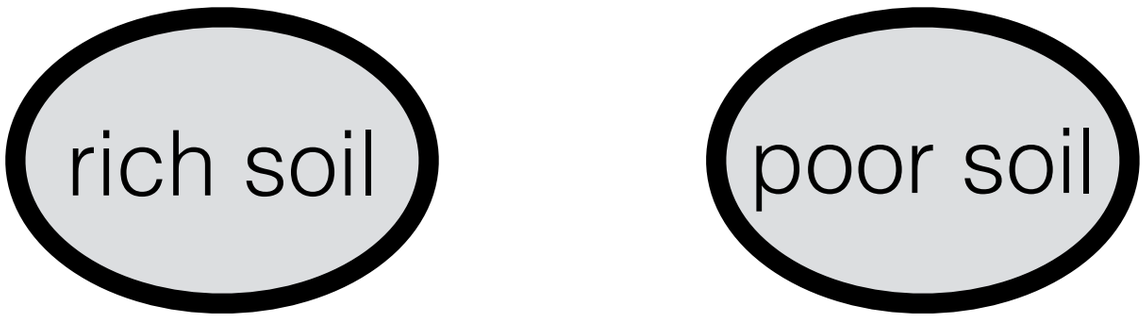

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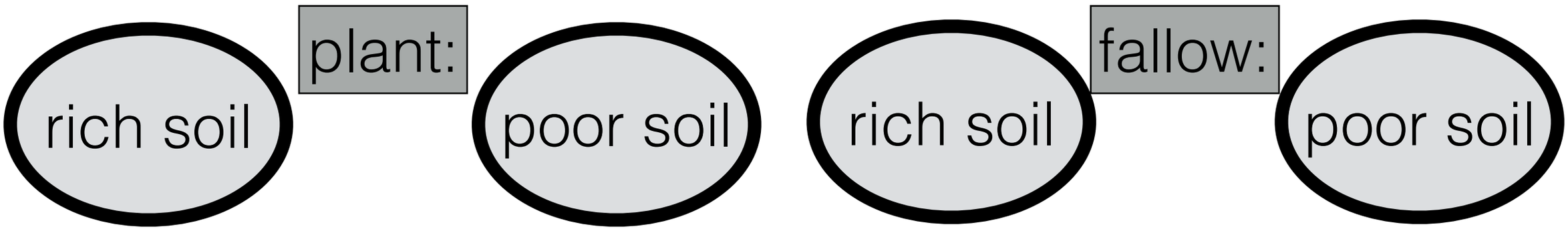

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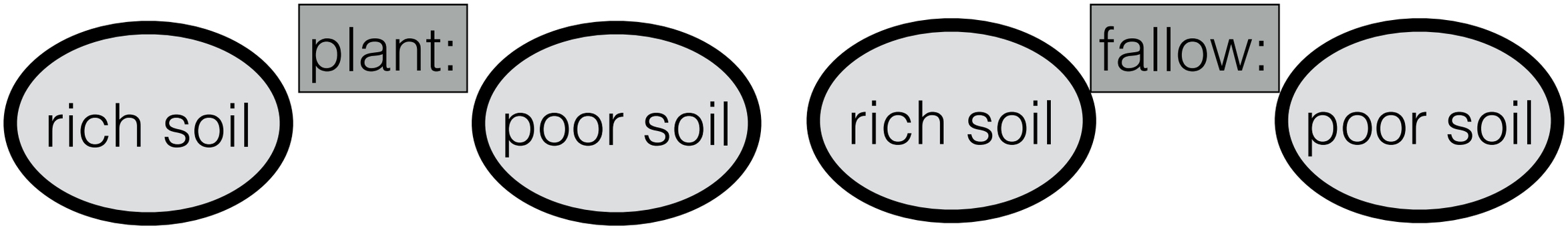

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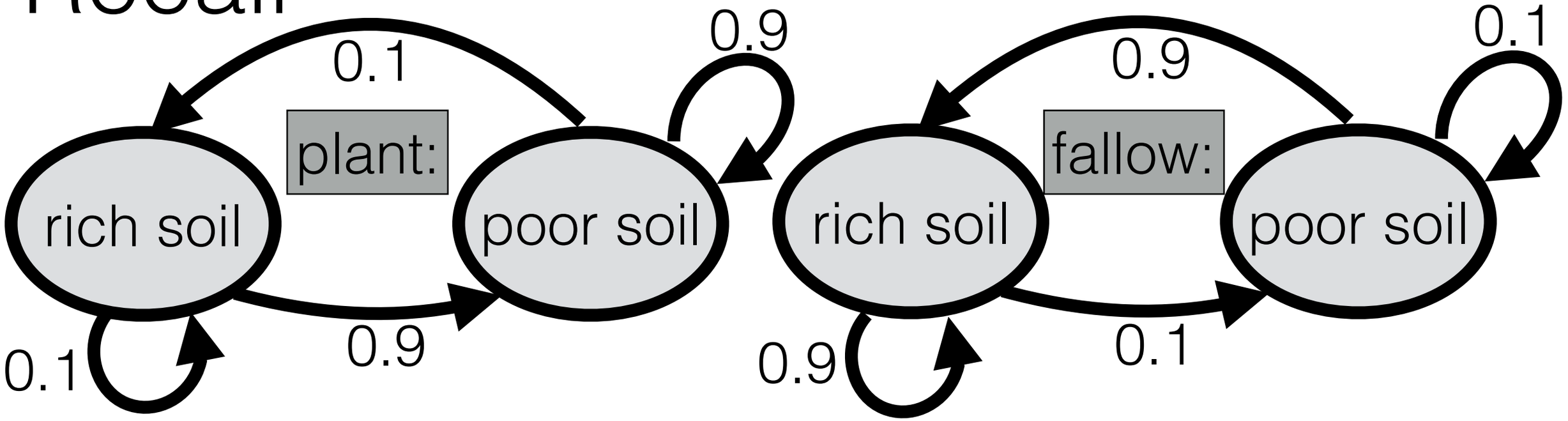

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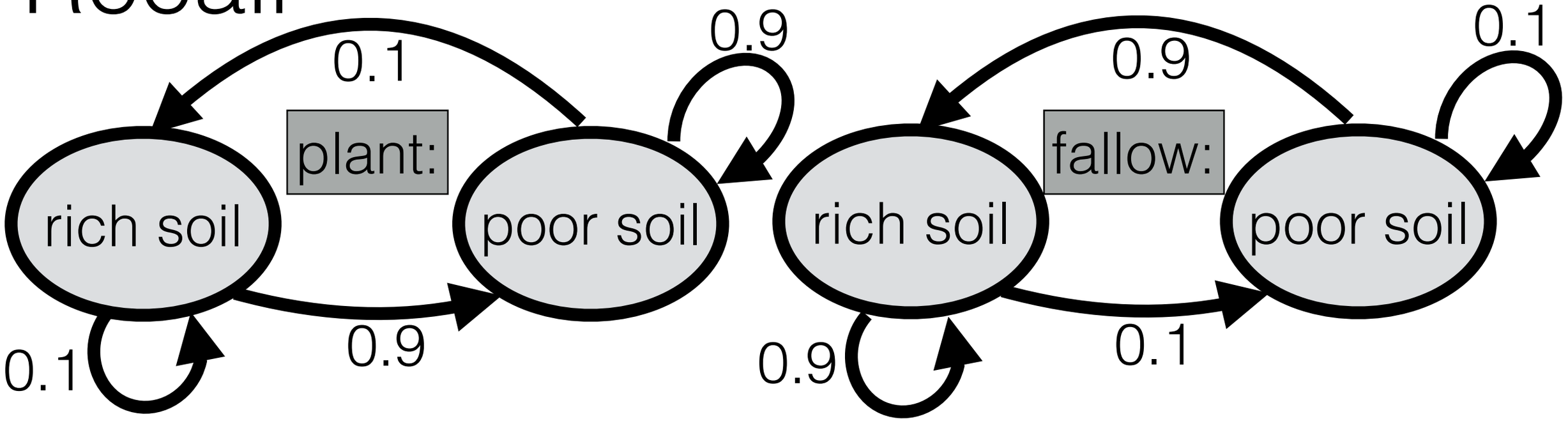

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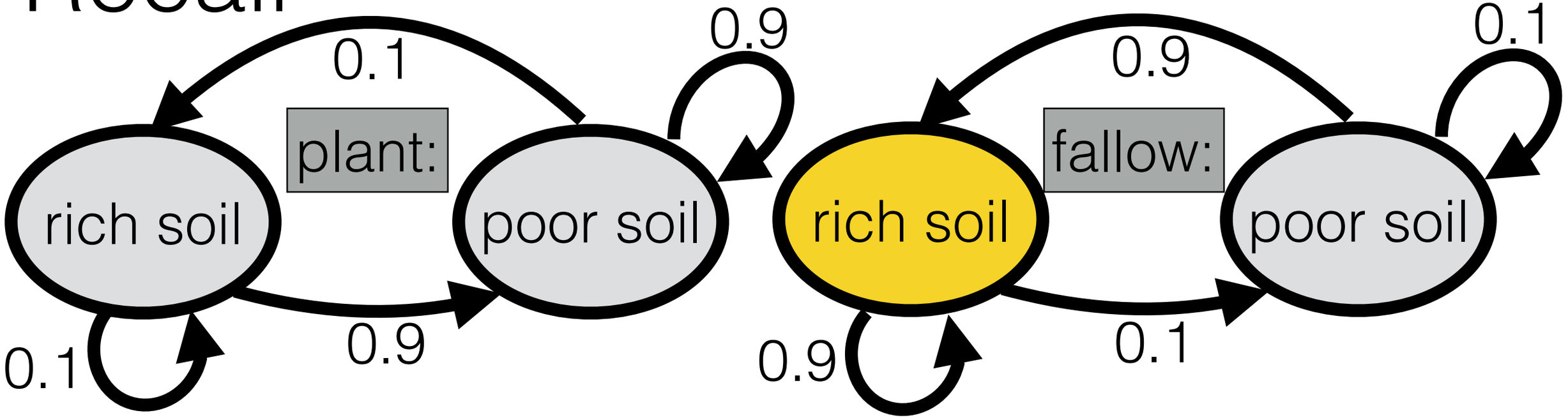

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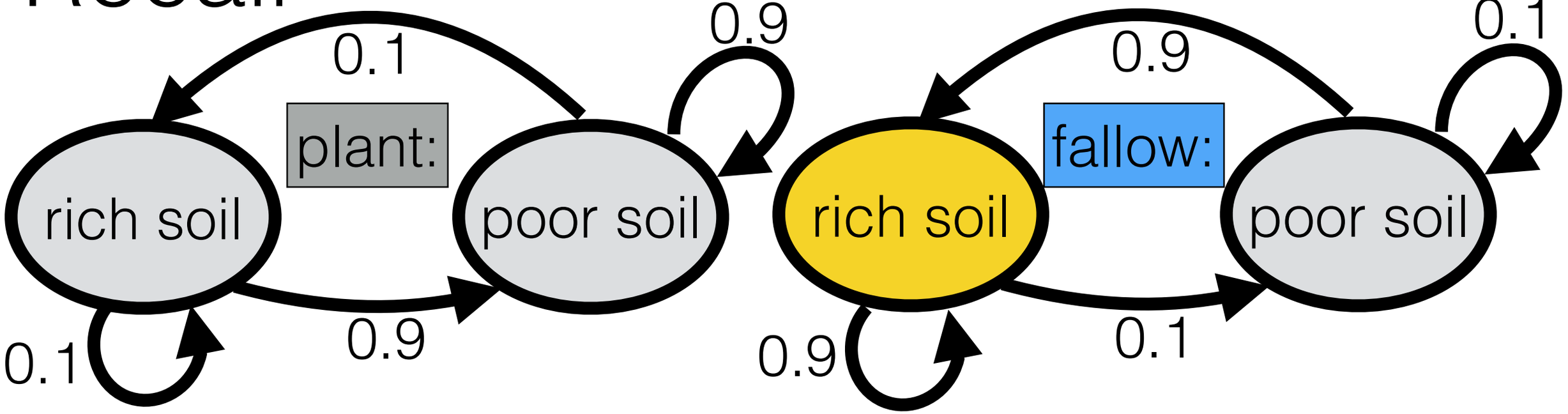

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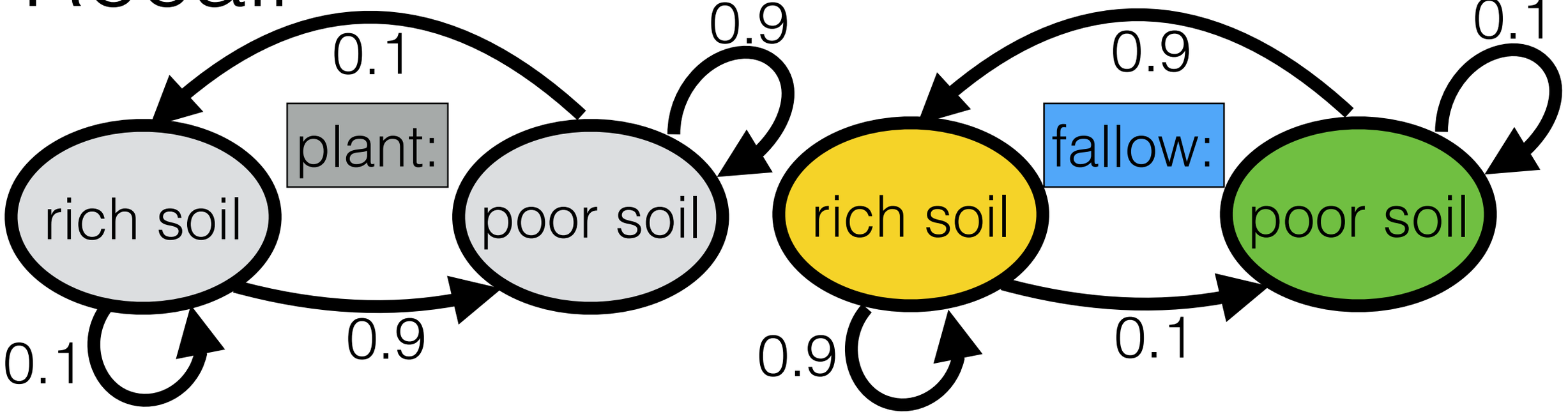

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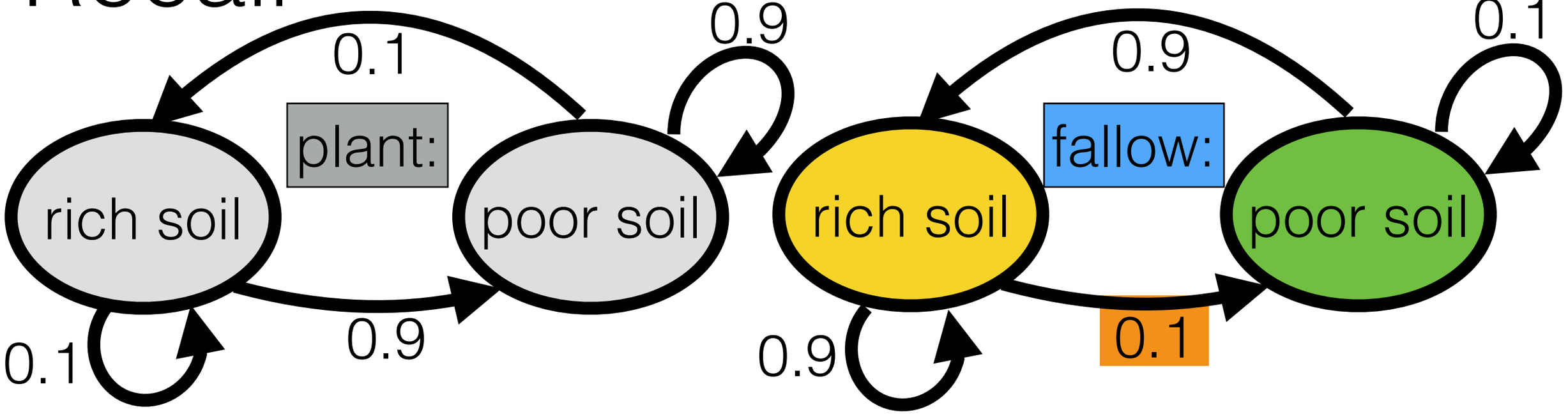

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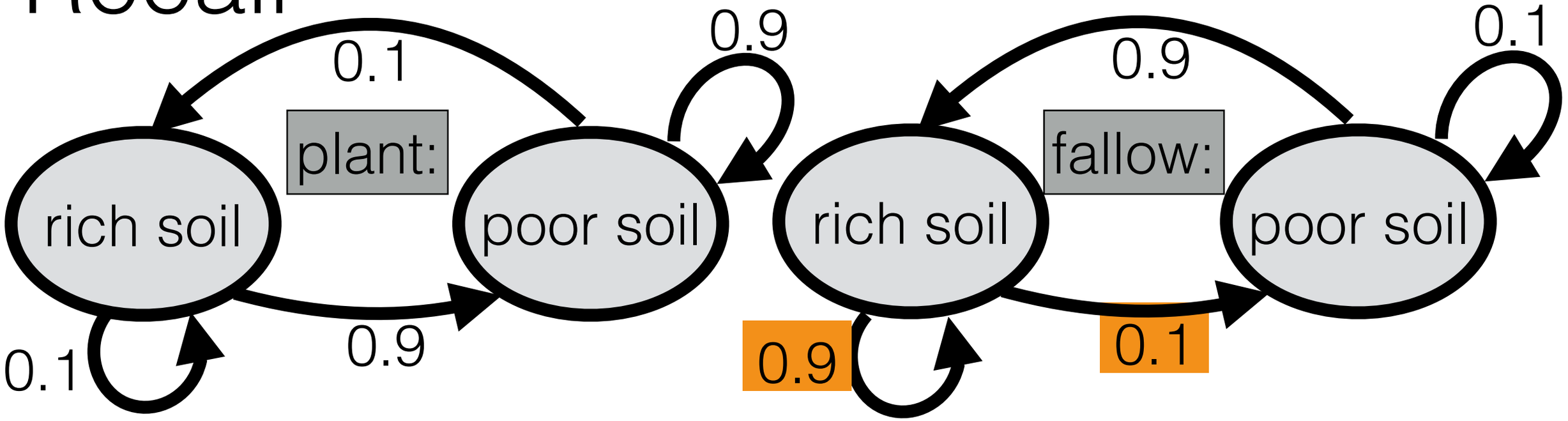

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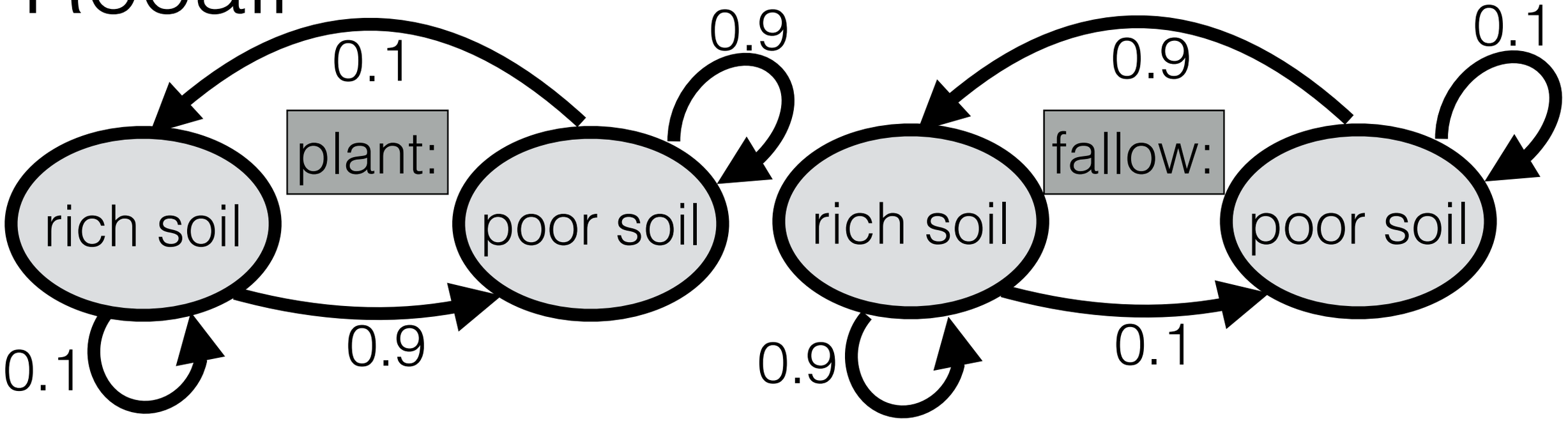

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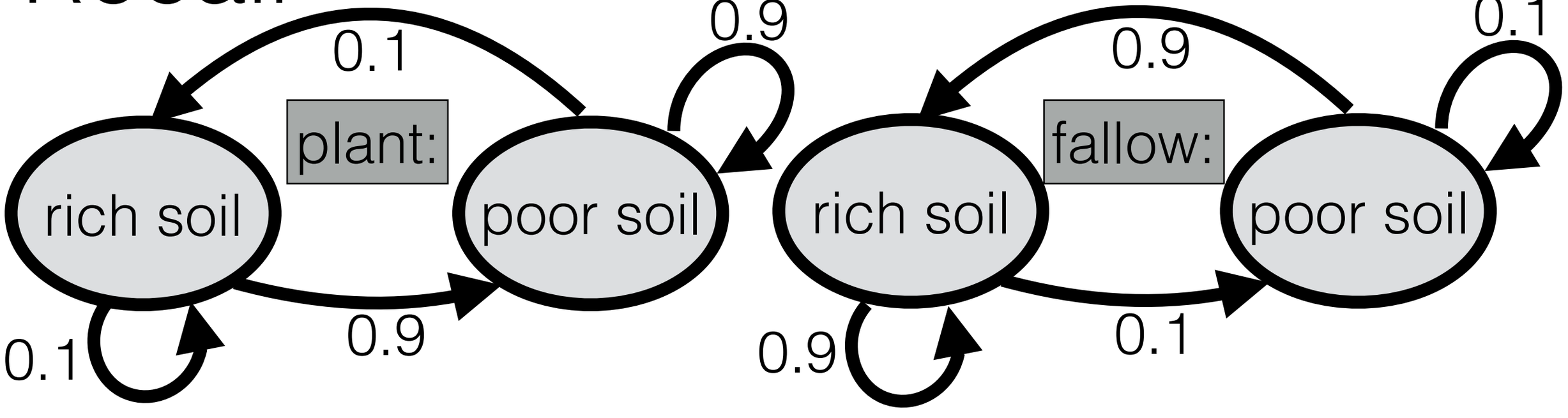

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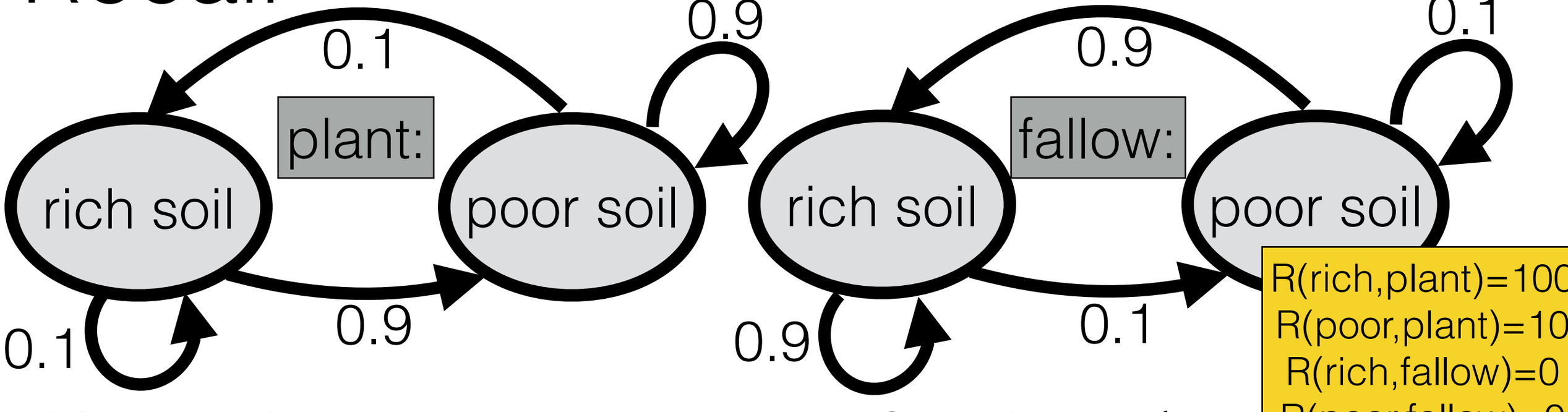

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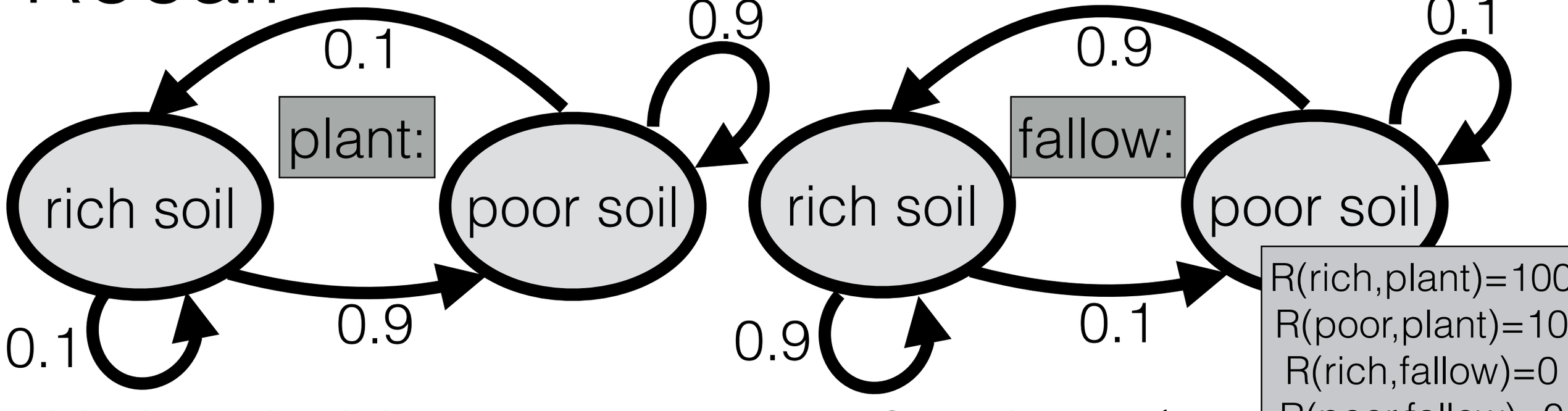

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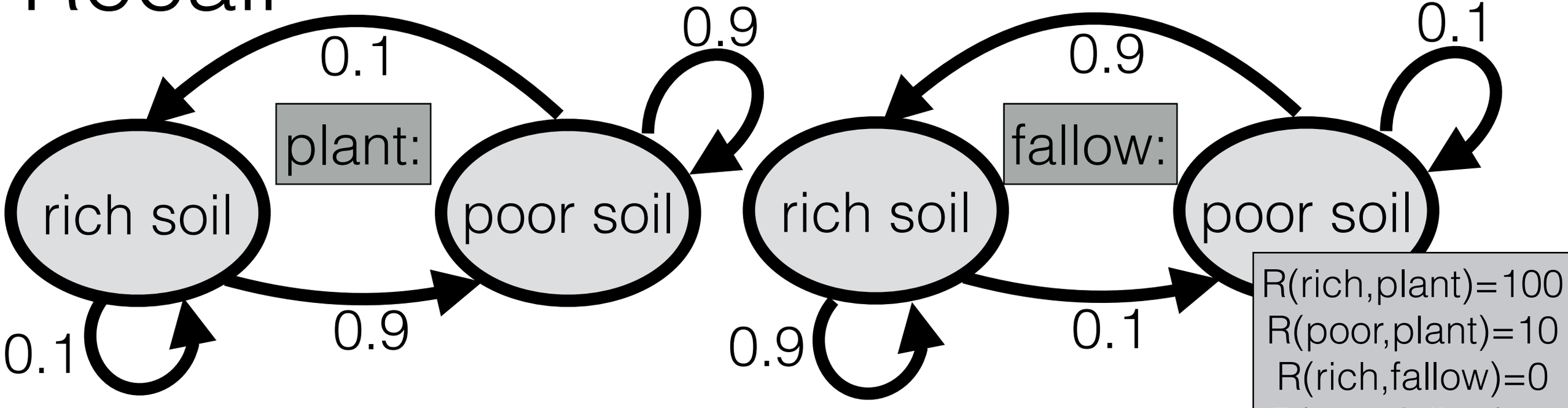

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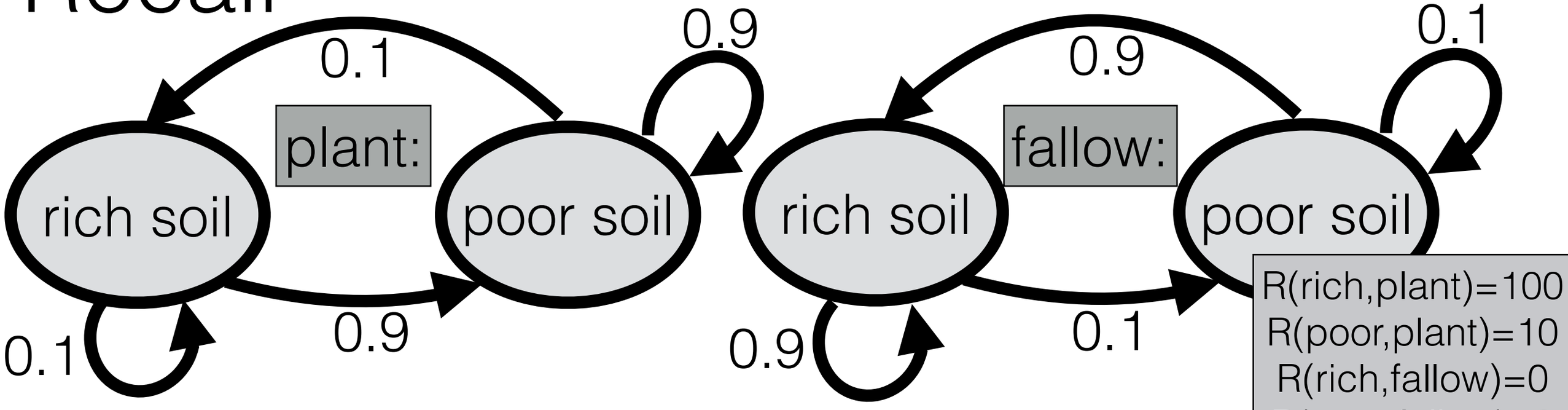

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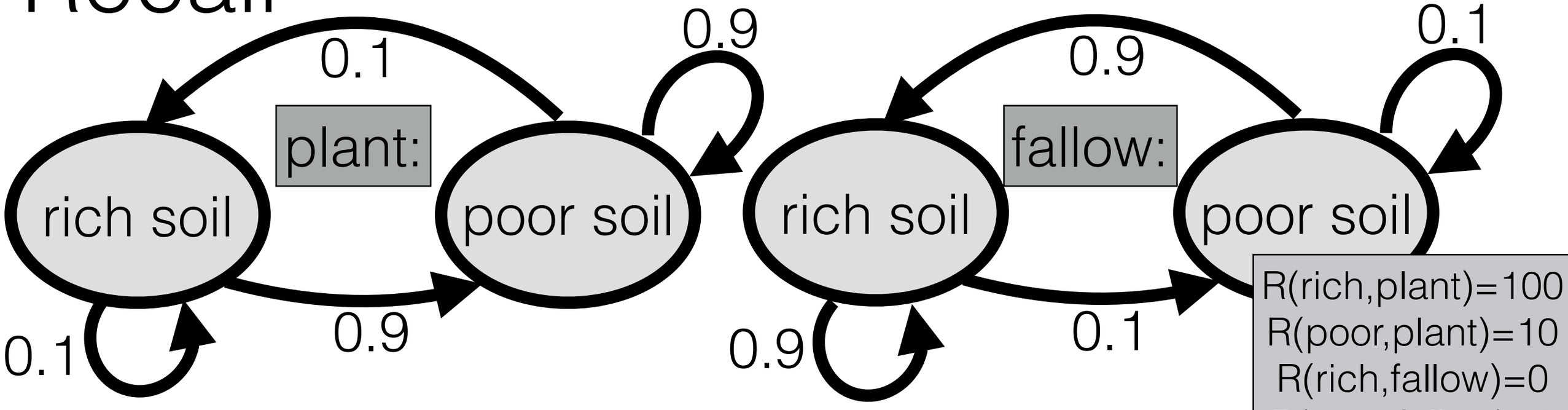

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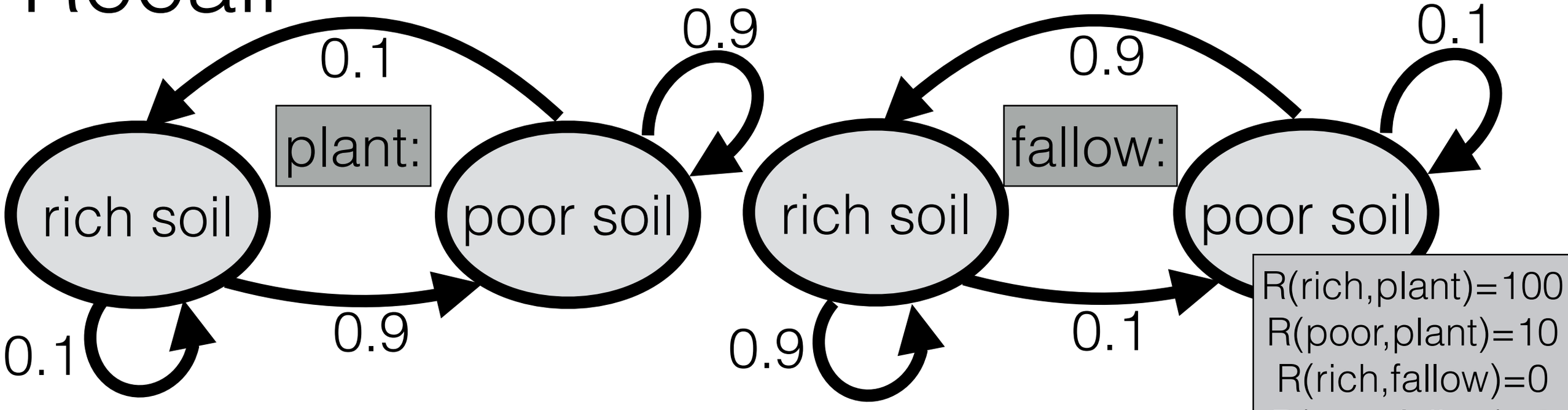

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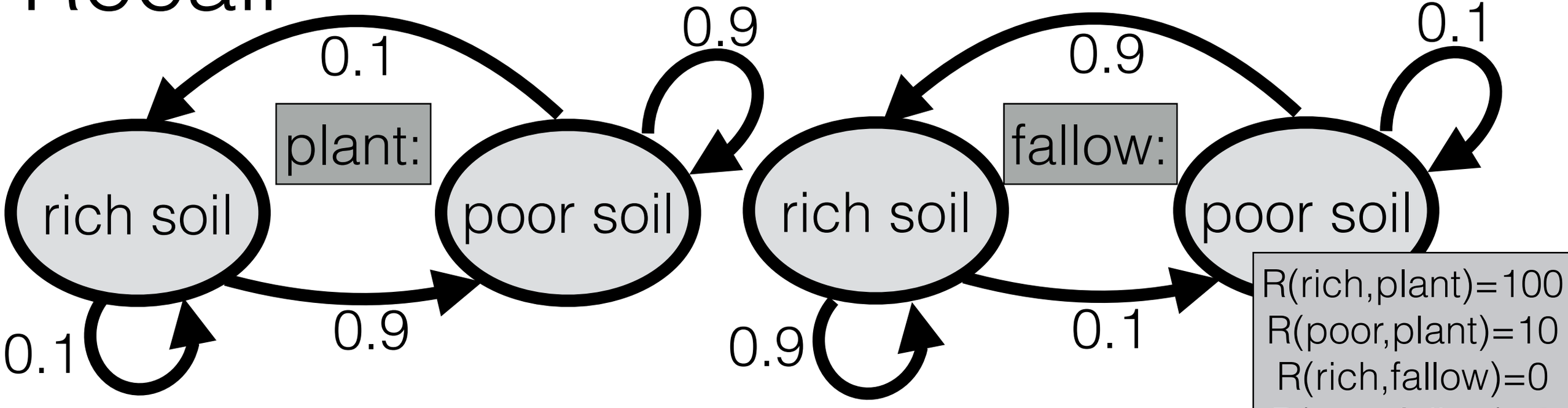

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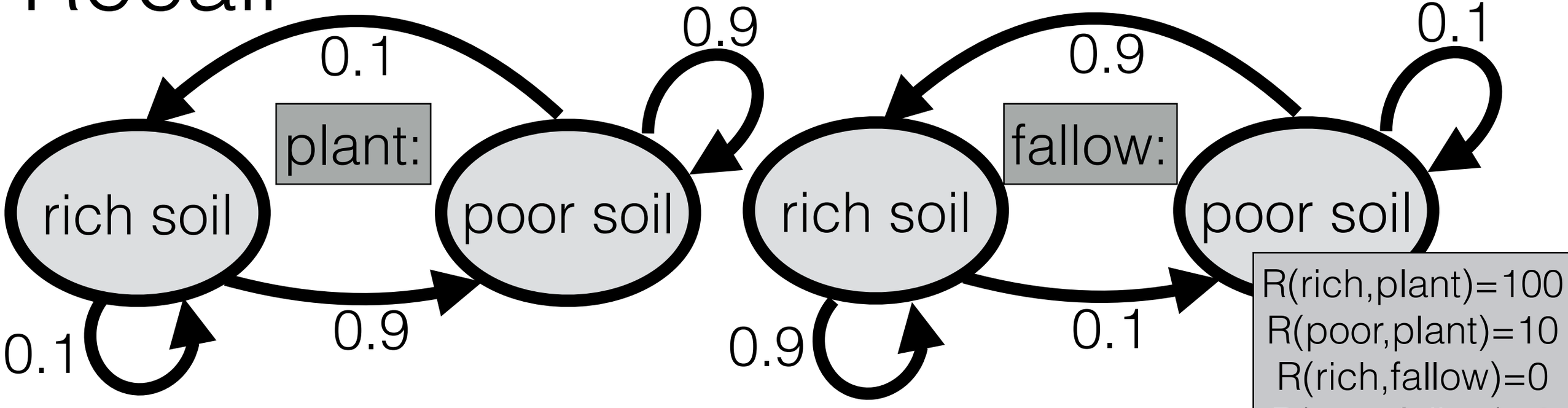

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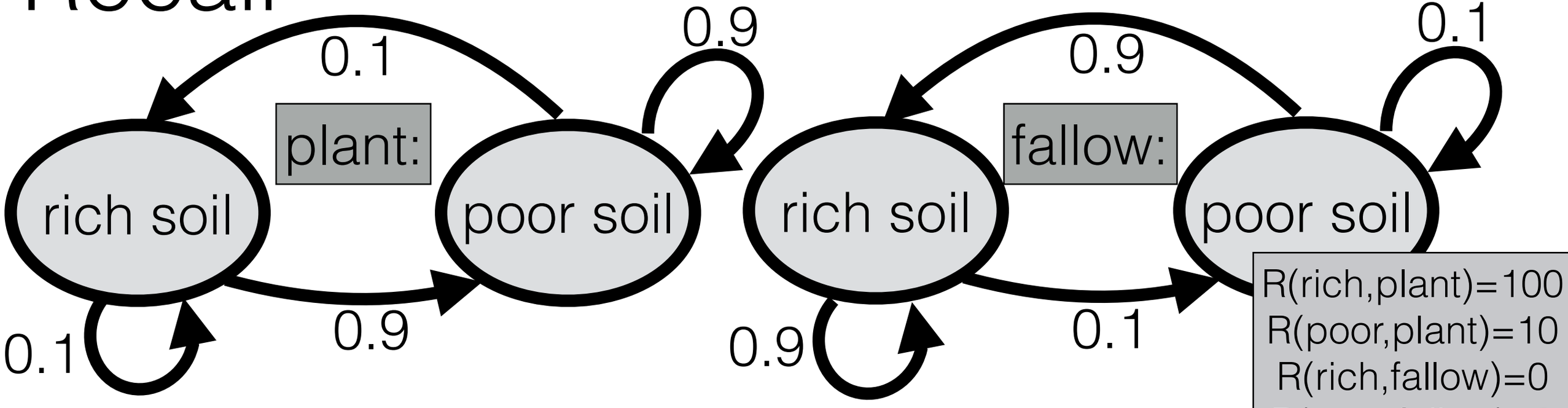

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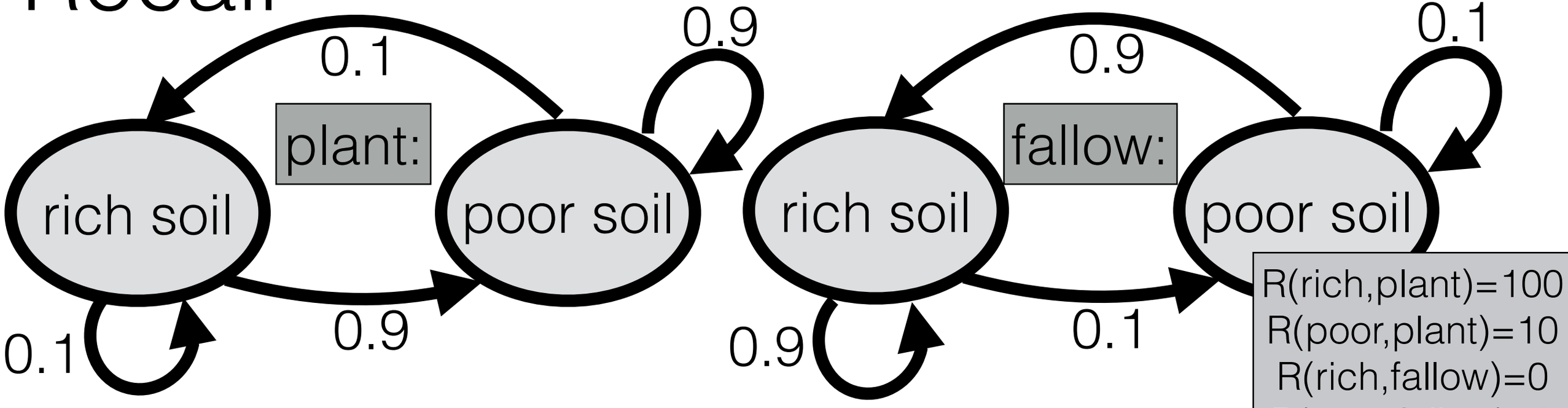

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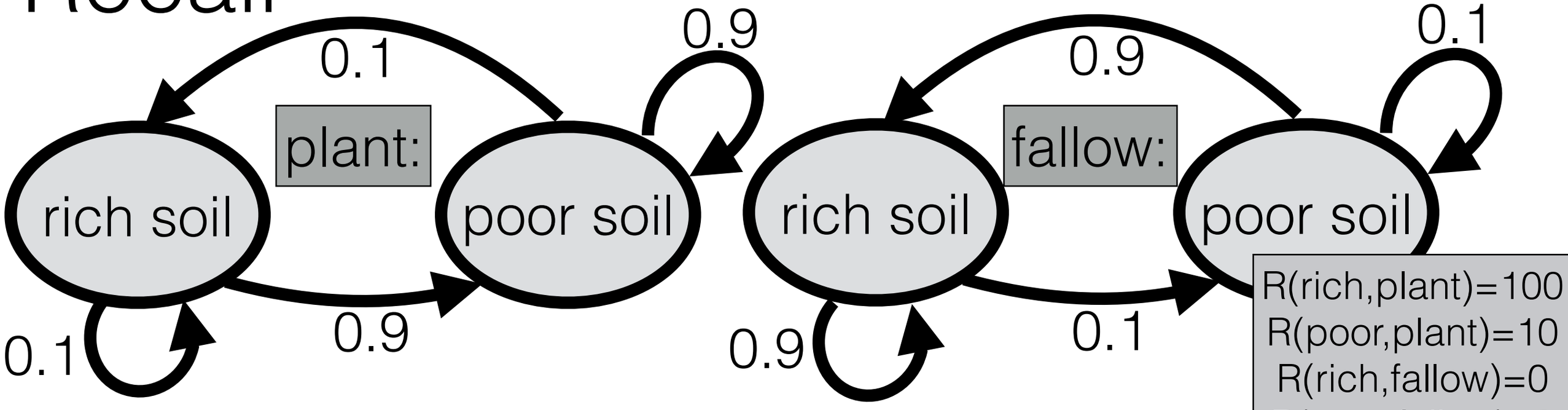

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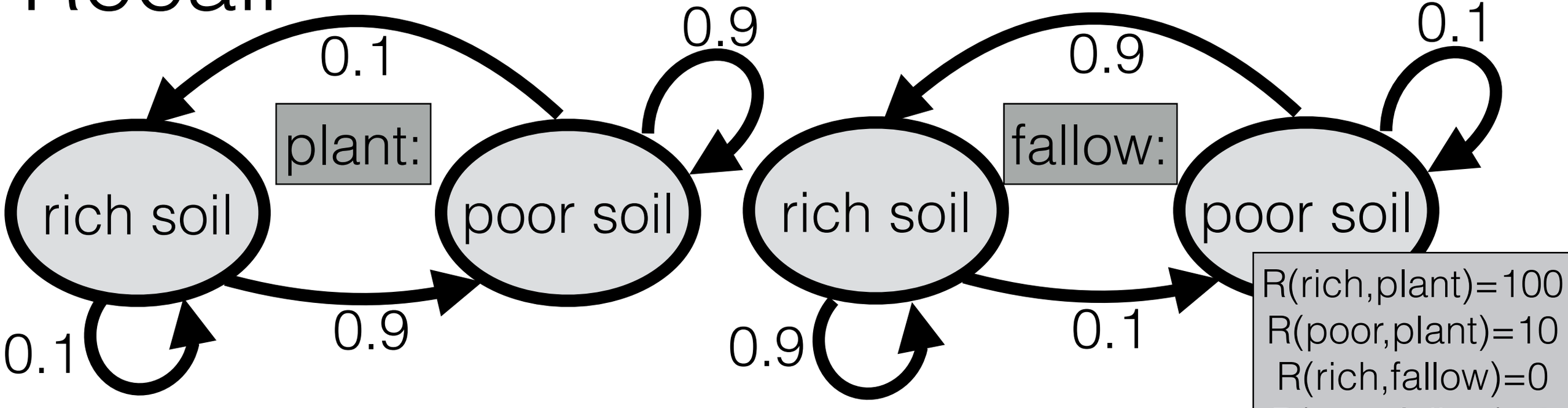

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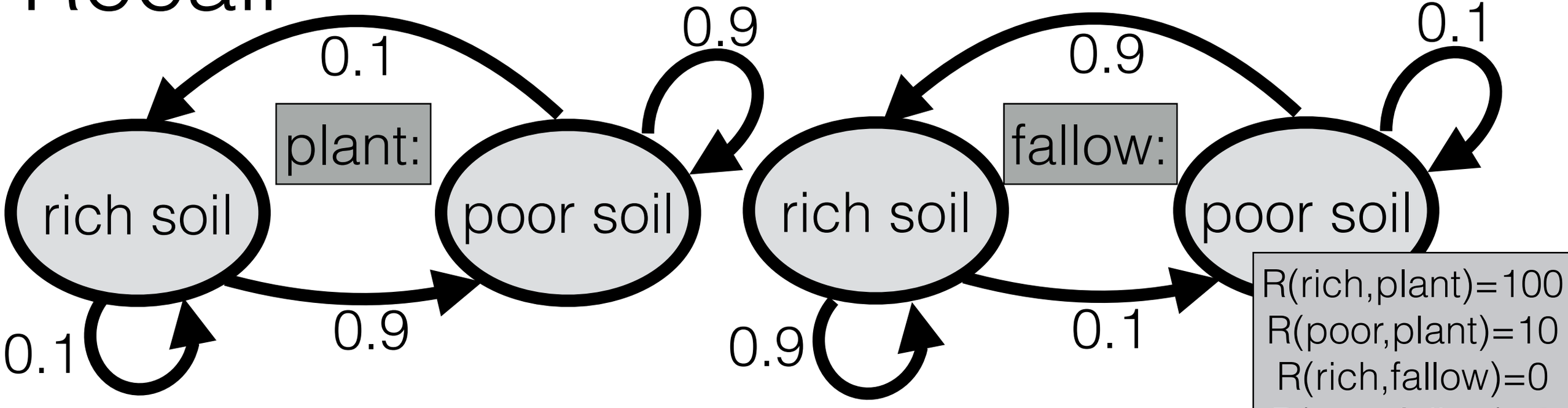

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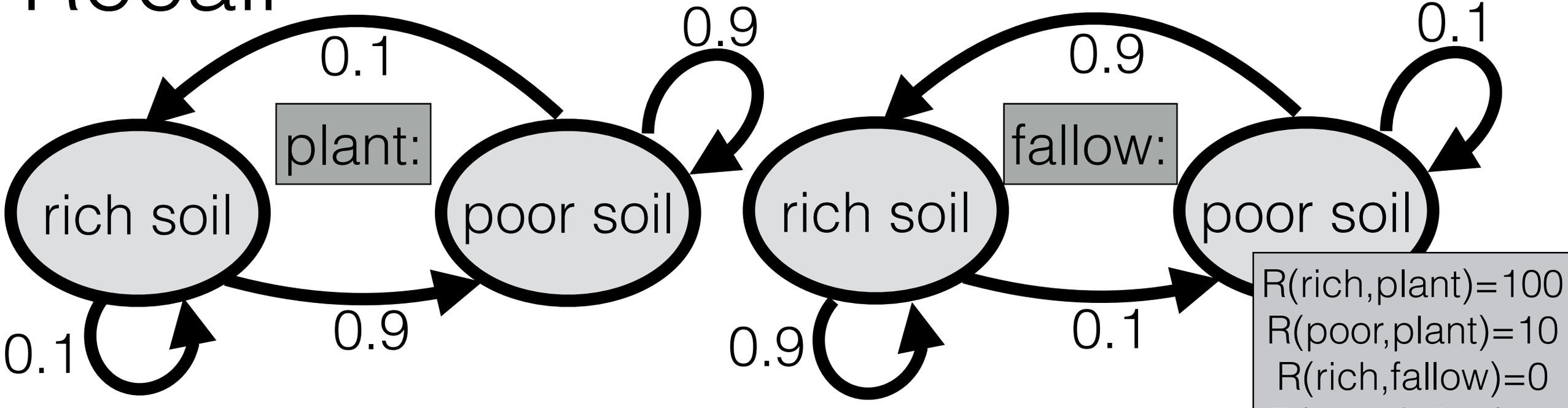

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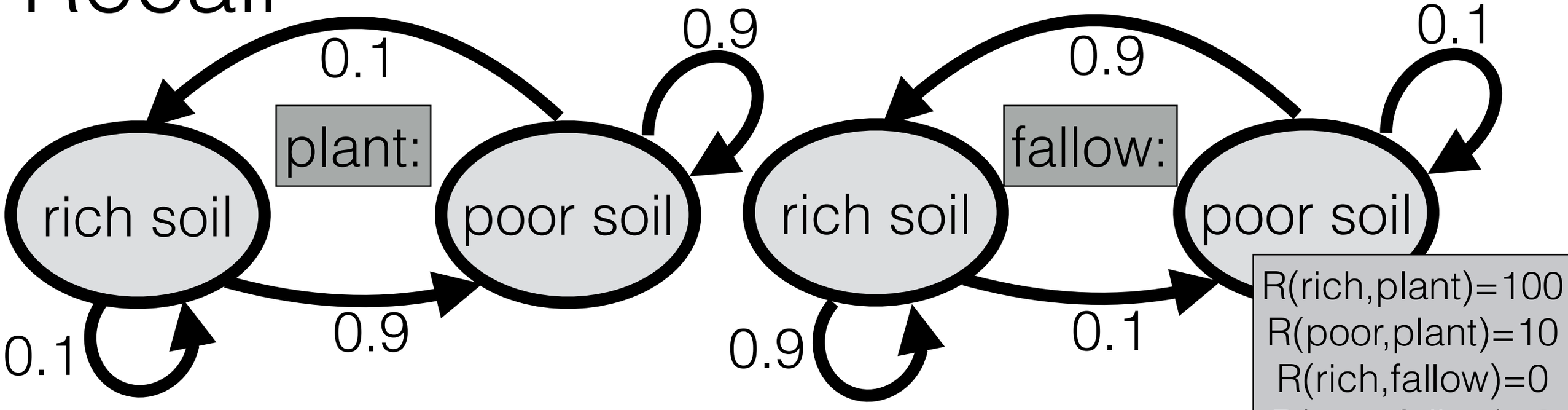

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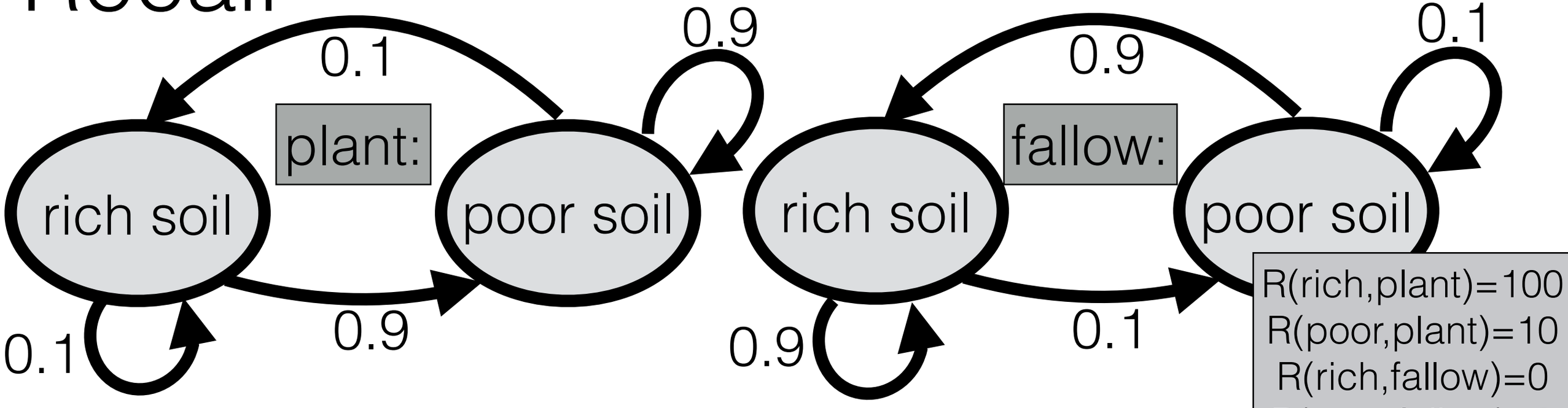

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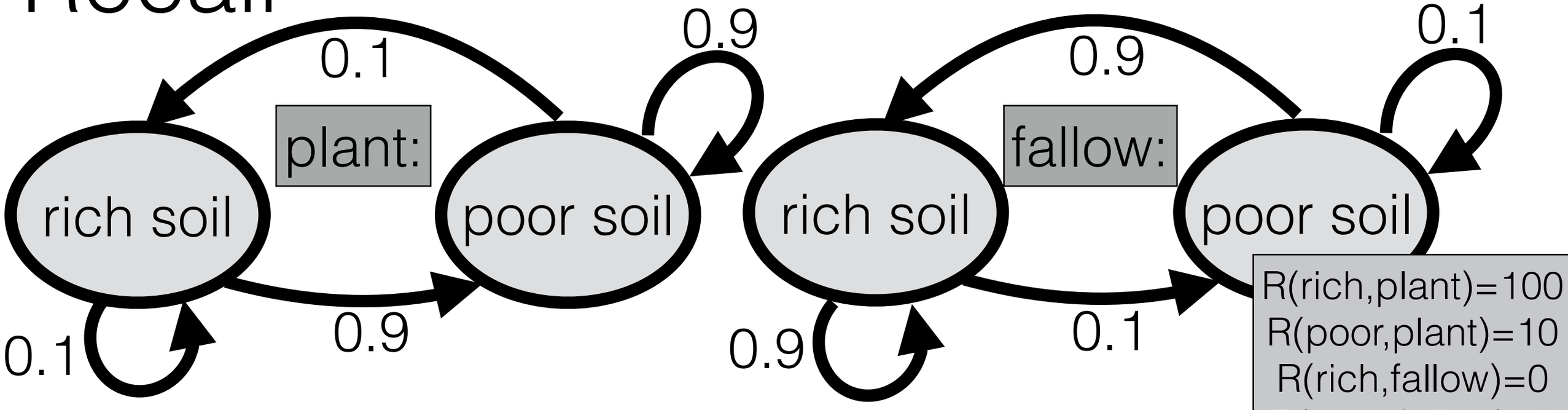

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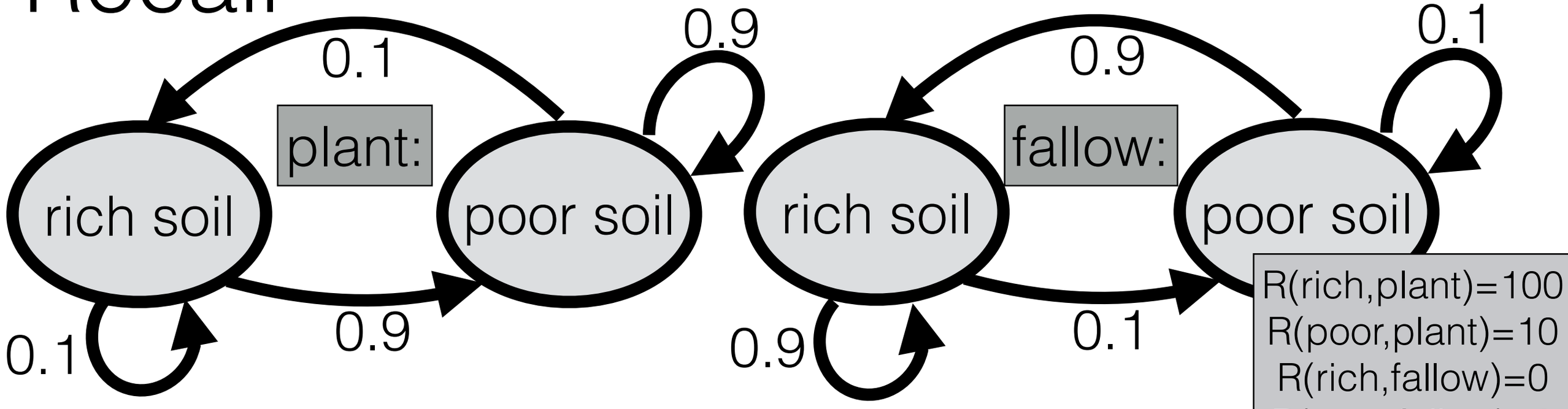

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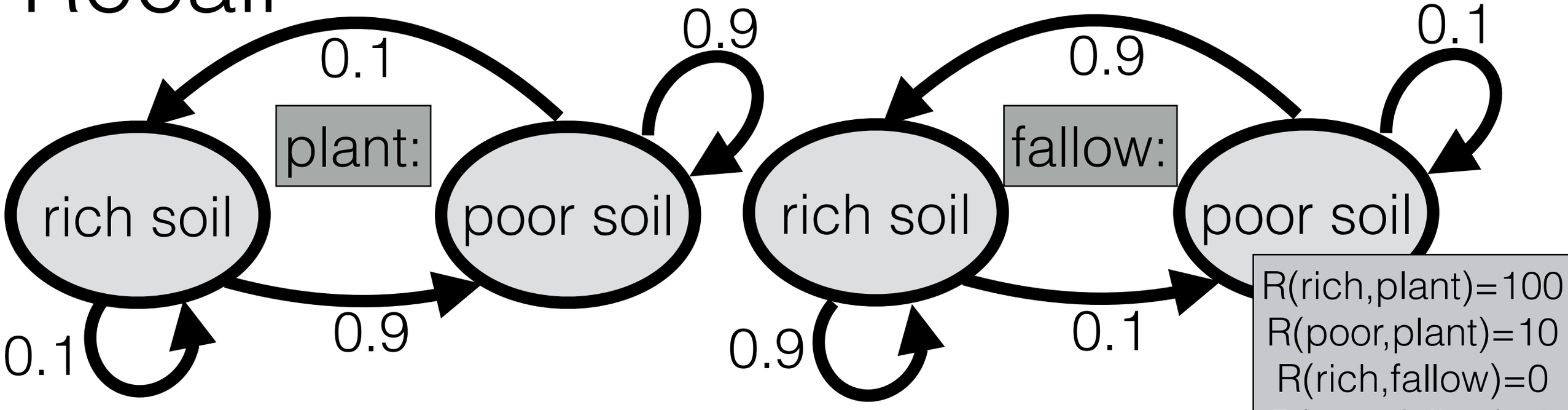

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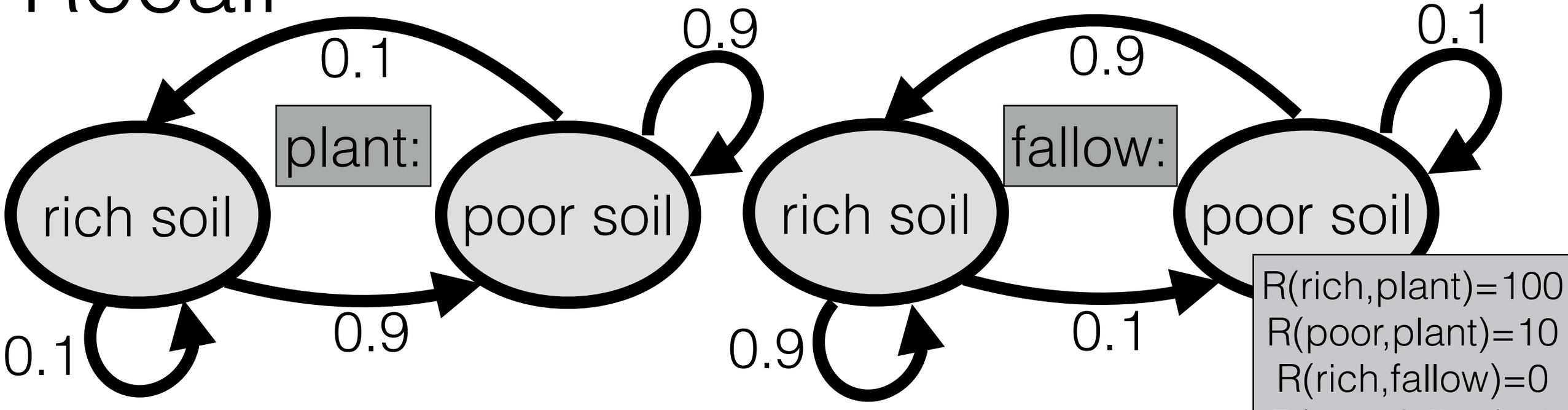

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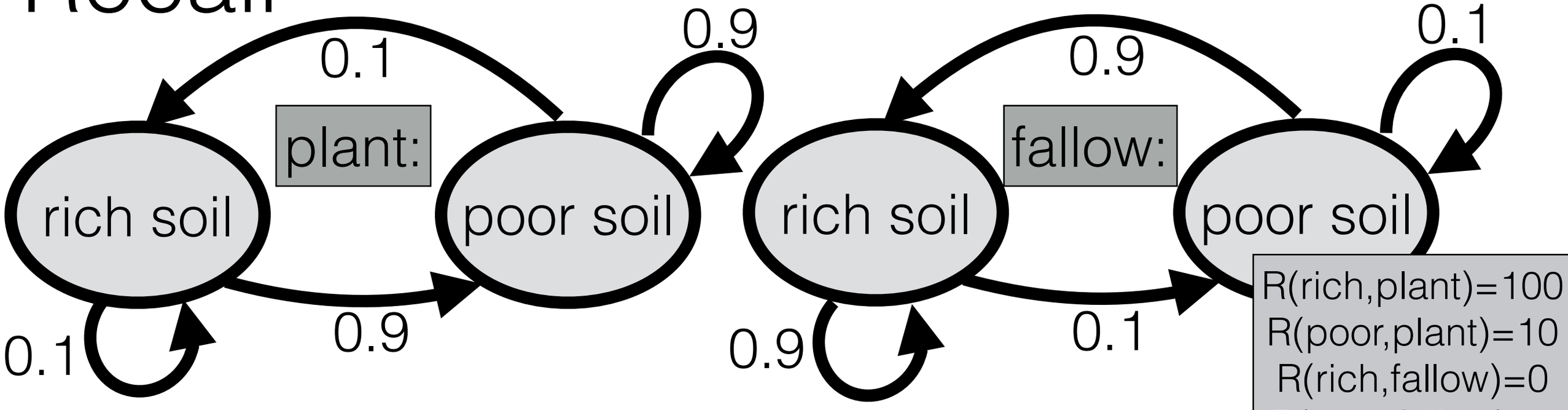

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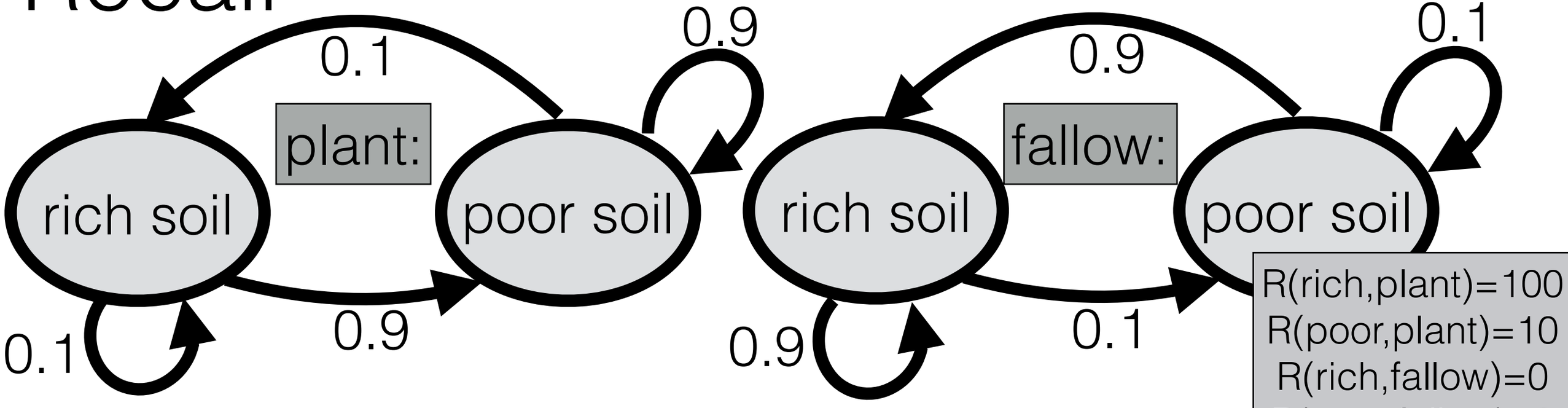

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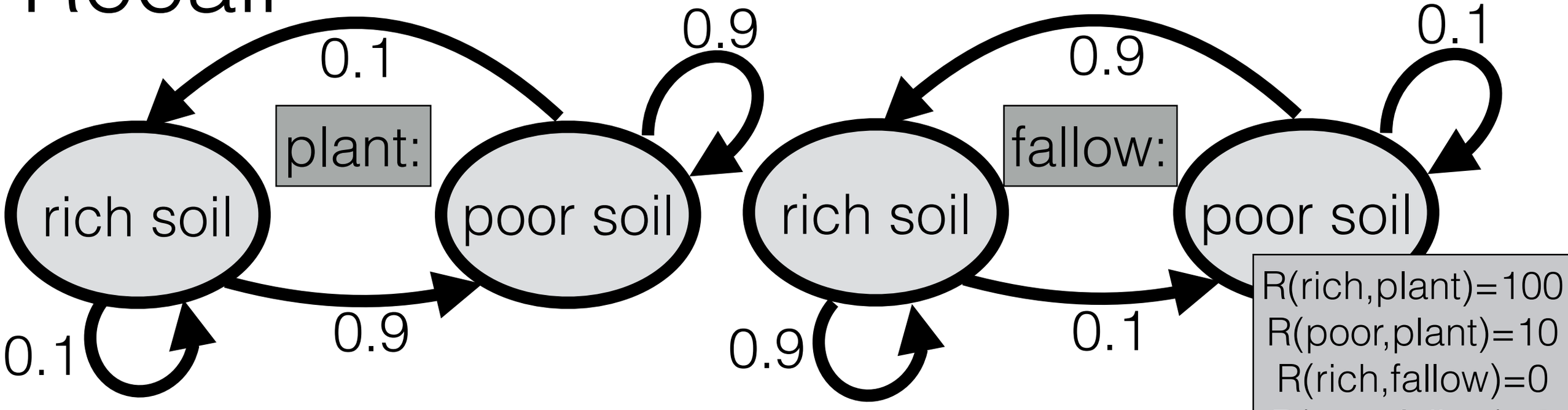

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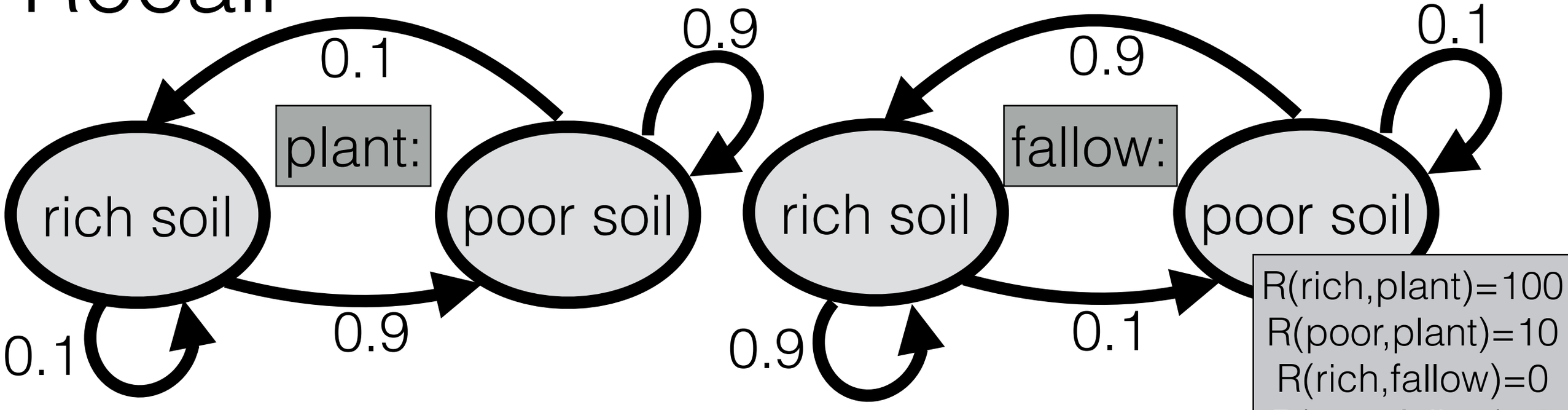

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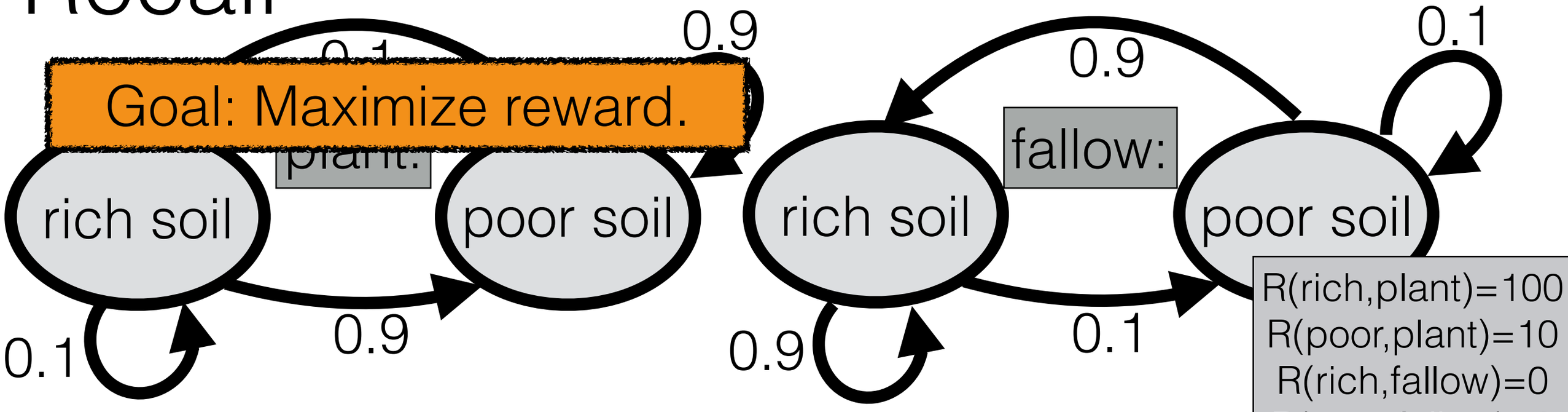

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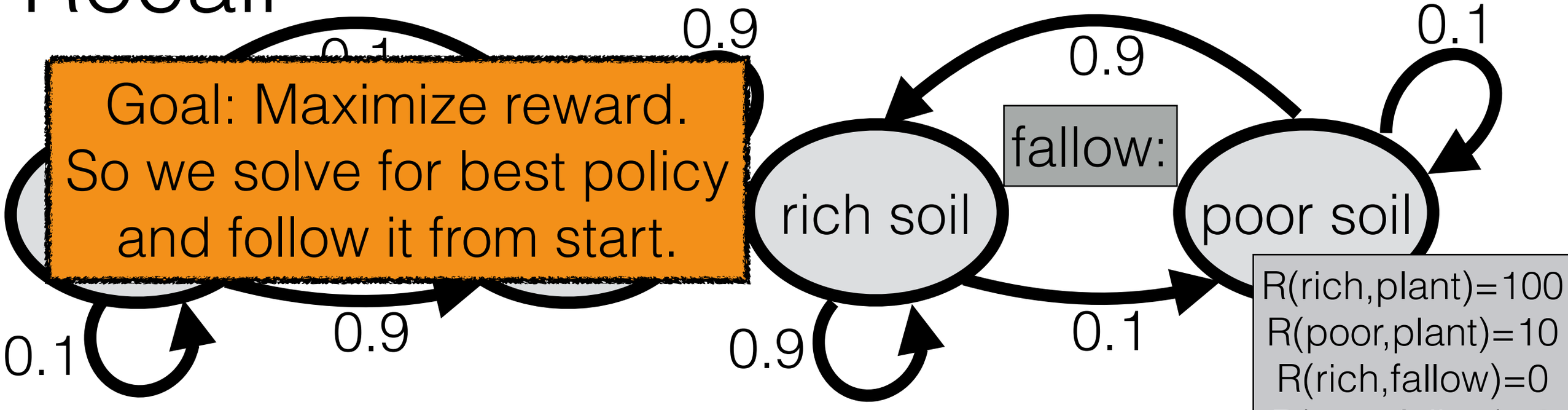

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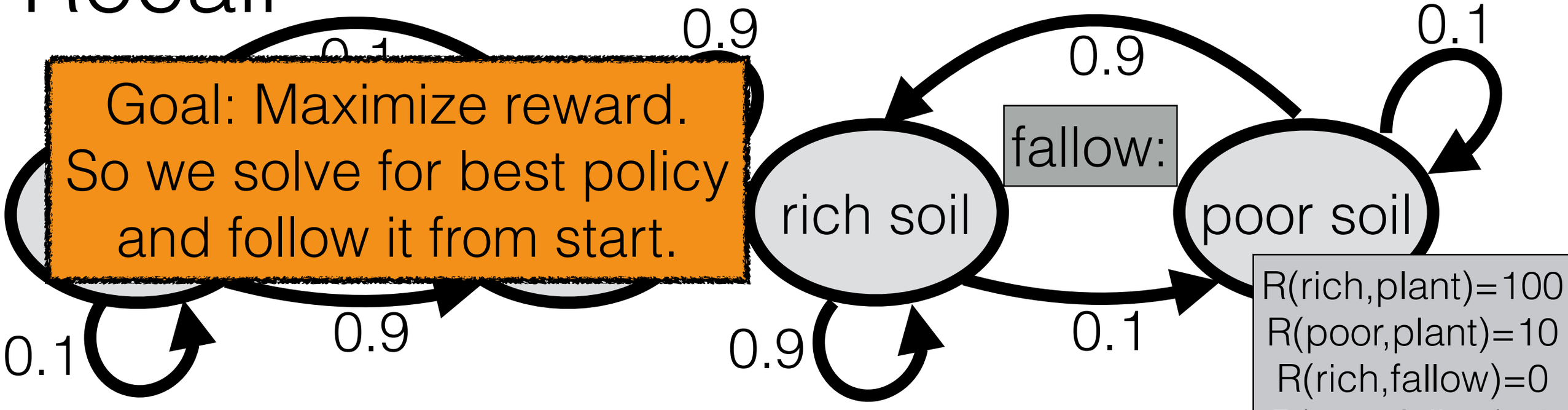

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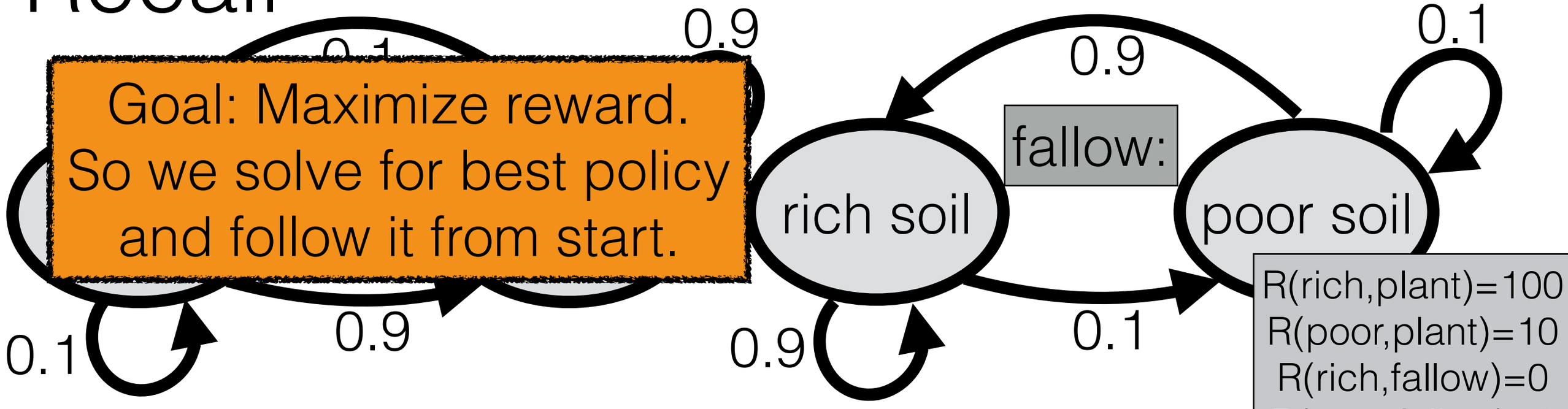

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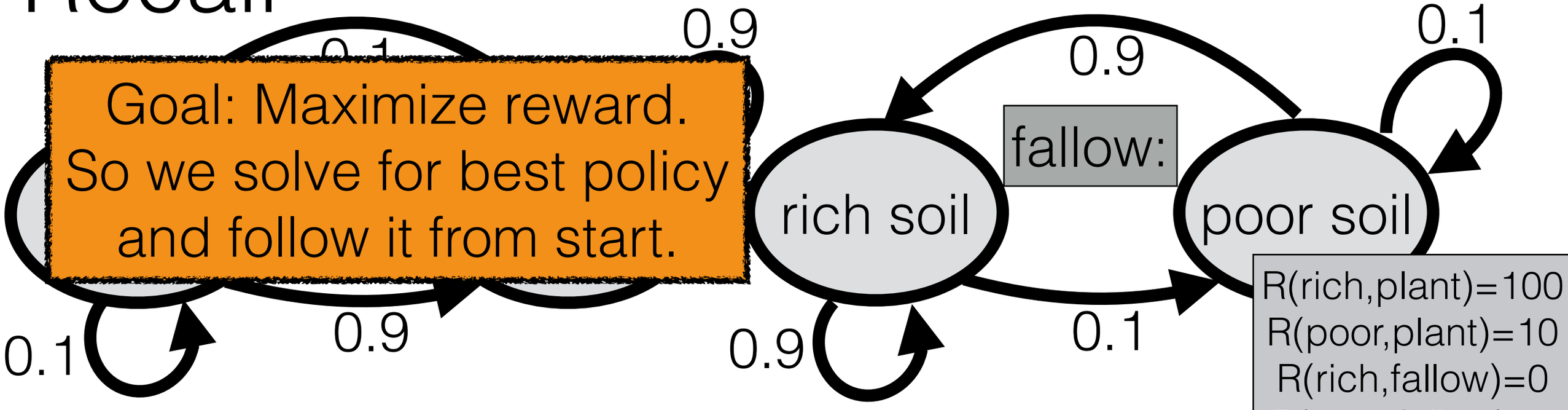

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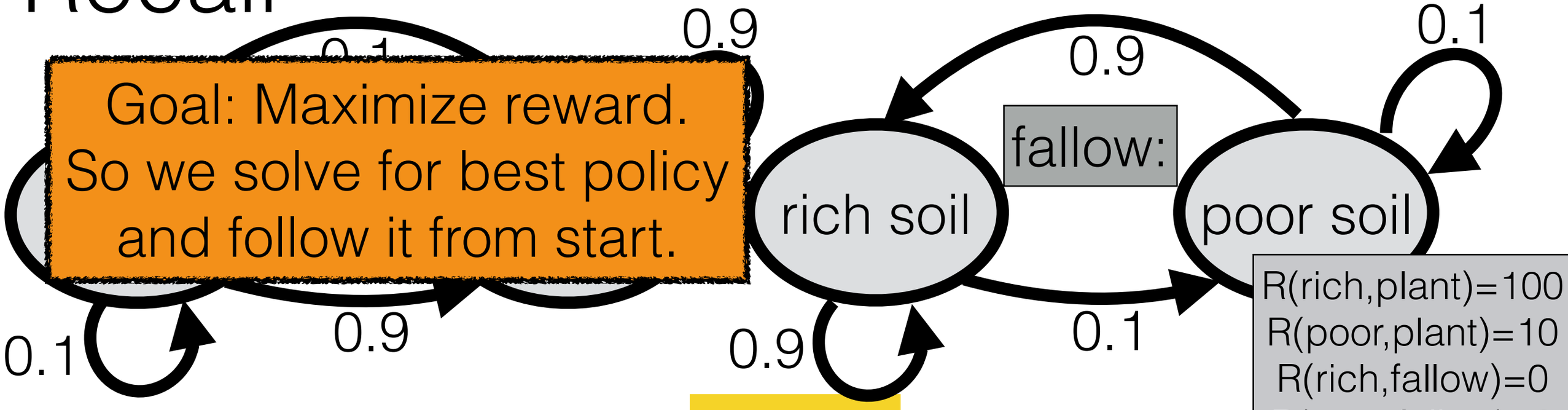

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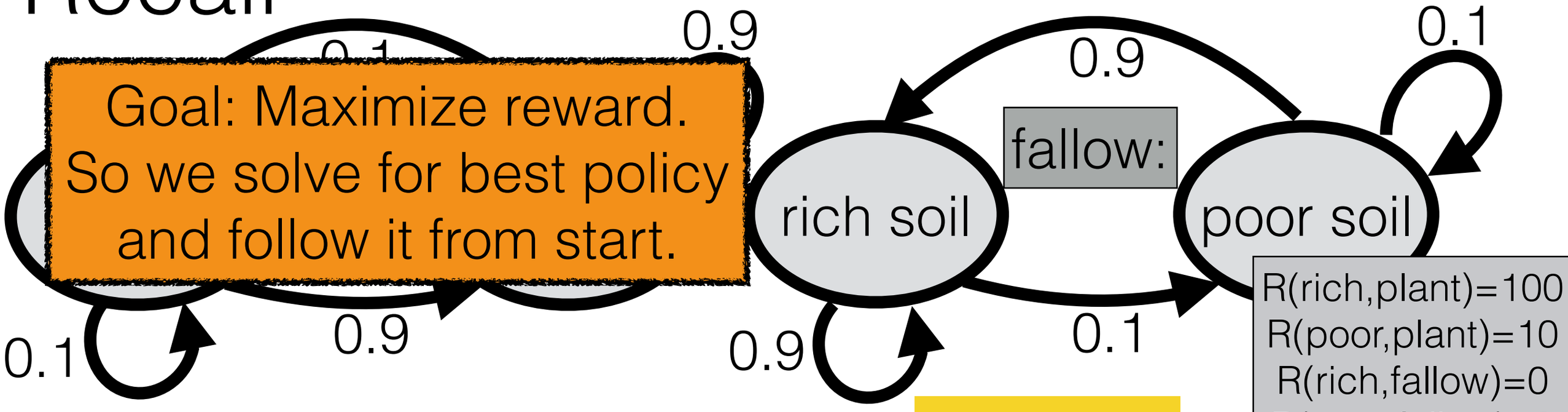

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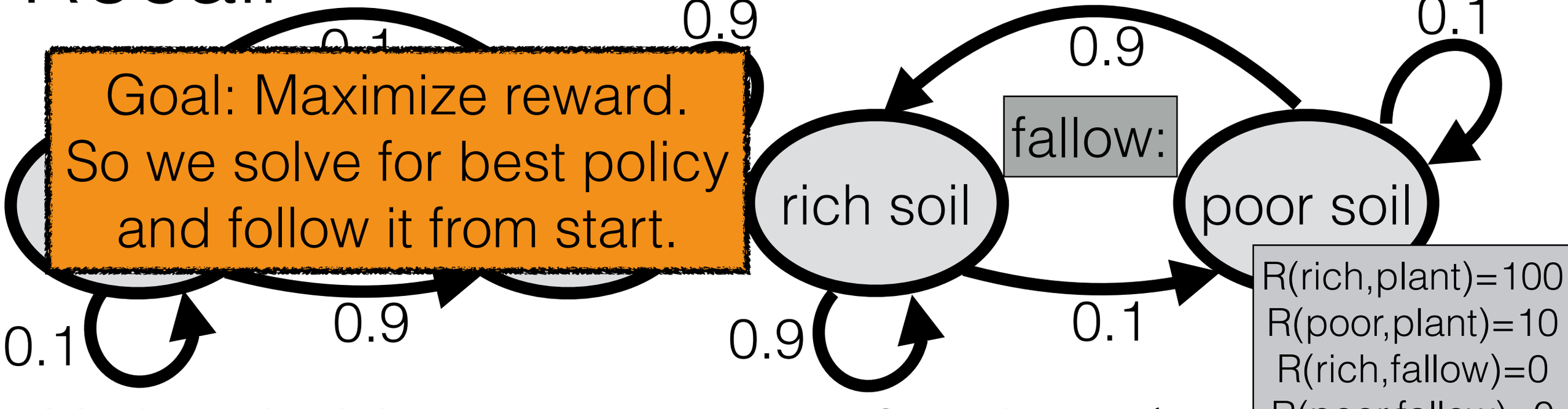

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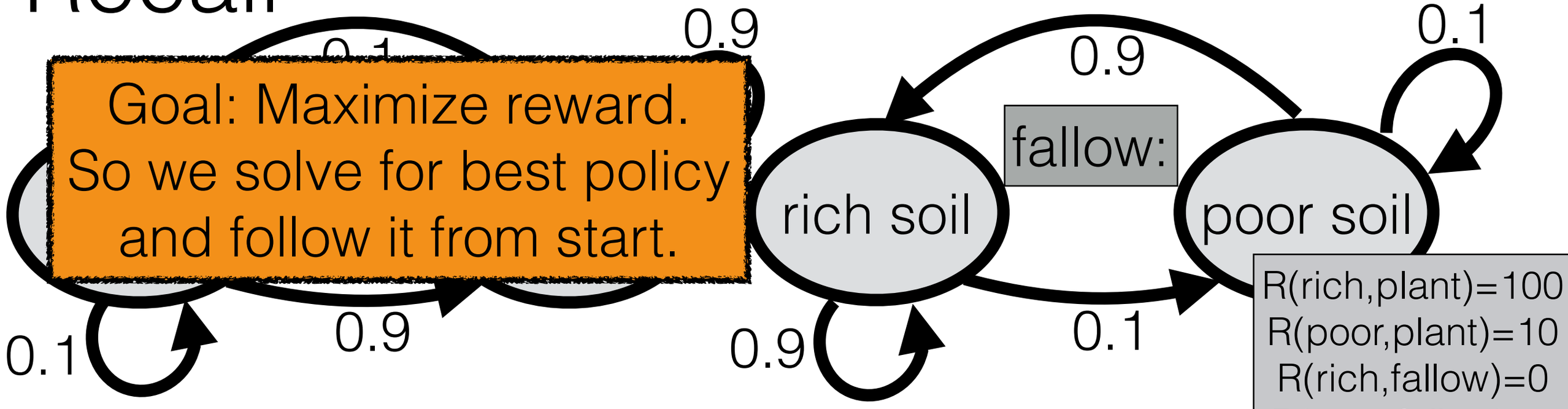

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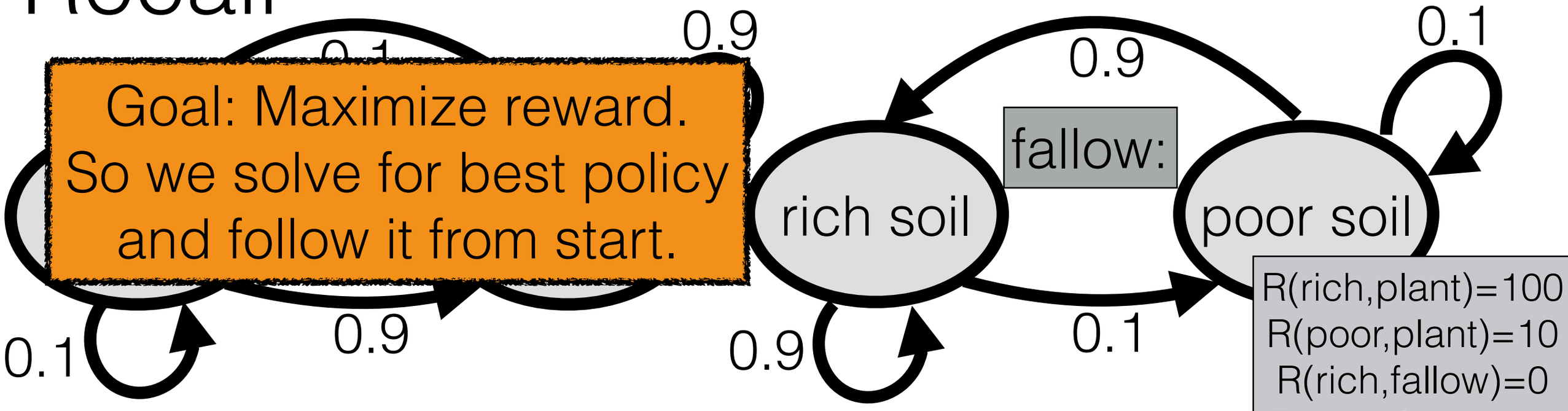

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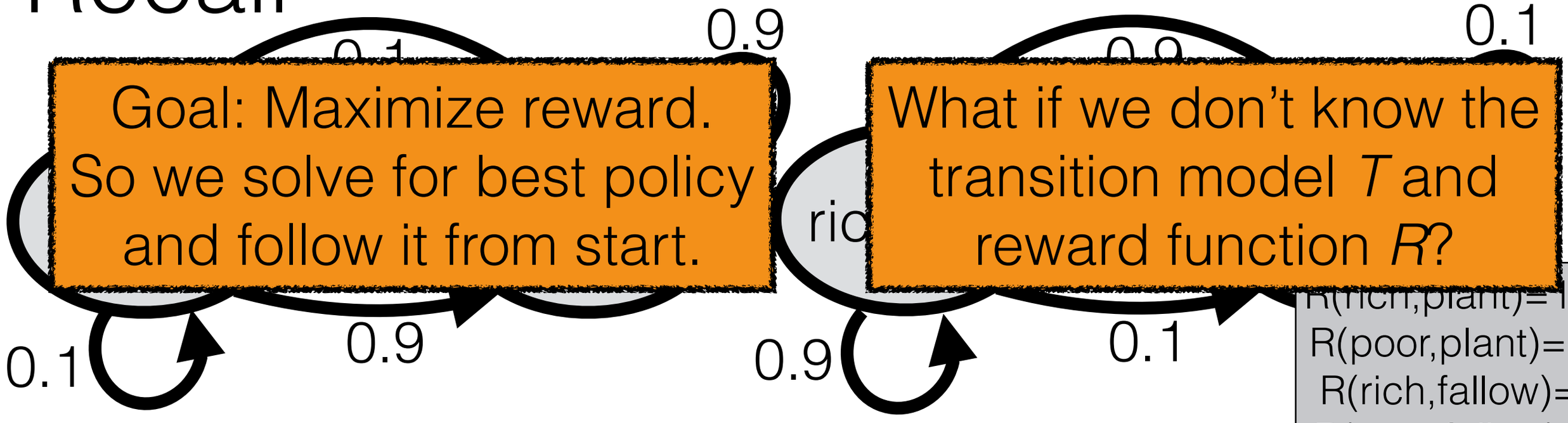

Goal: Maximize reward. So we solve for best policy and follow it from start.

What if we don't know the transition model *T* and reward function *R*?

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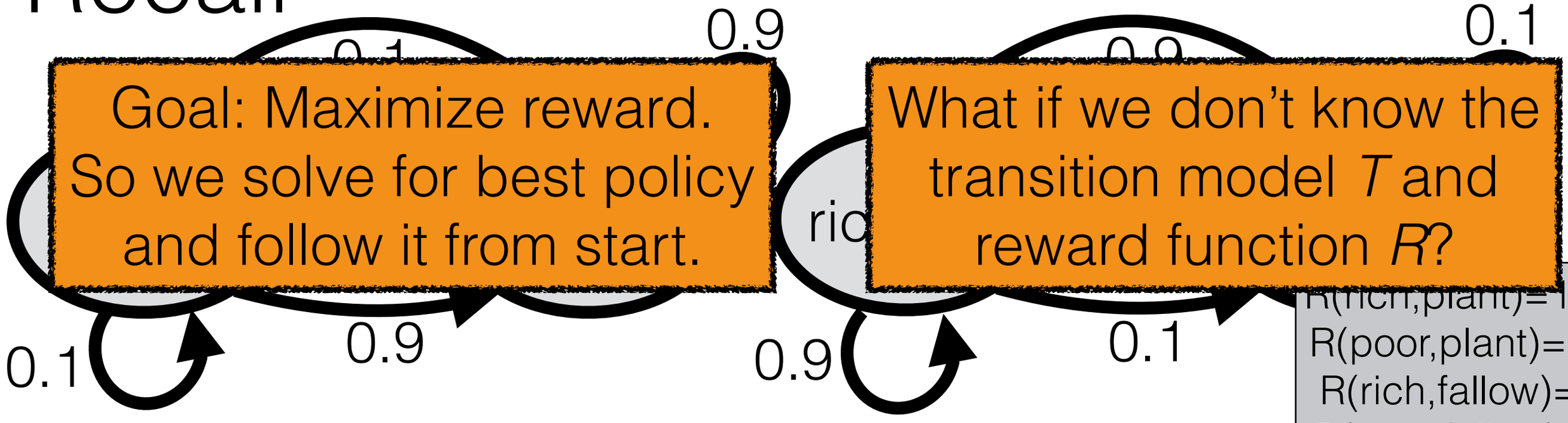

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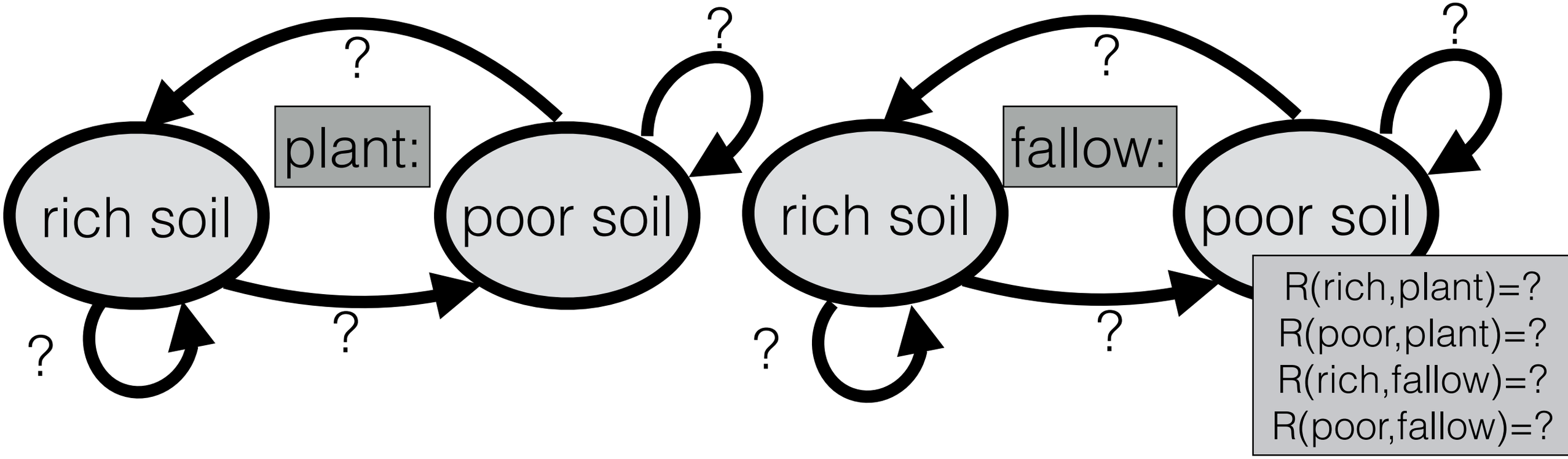
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?
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plant:
rich soil
poor soil
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fallow:
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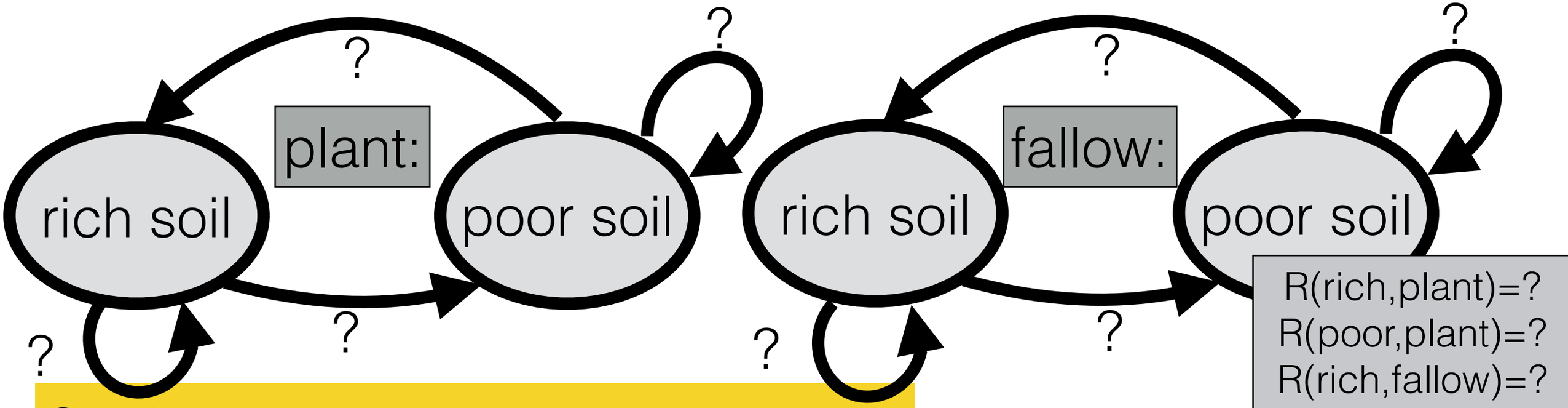
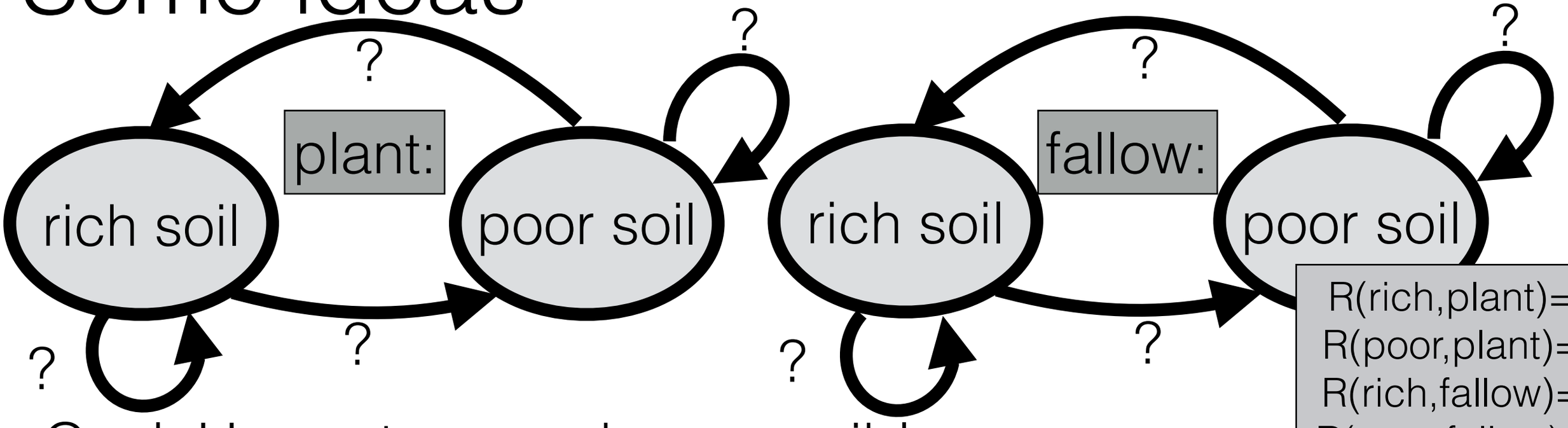


- Goal: Harvest as much as possible

Some ideas



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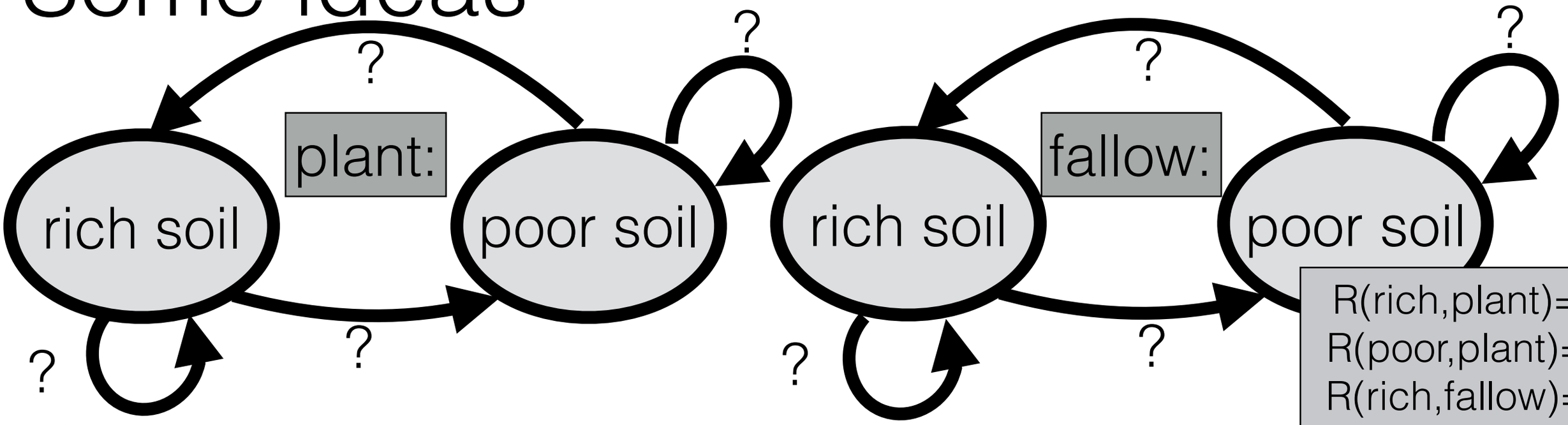

- Goal: Harvest as much as possible
- Strategy A

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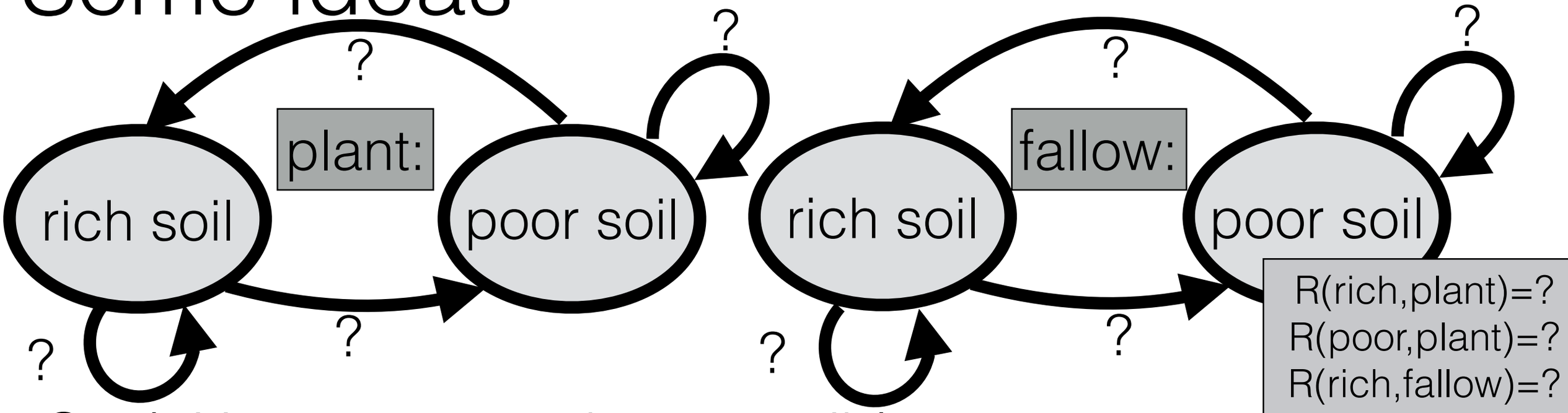

- Goal: Harvest as much as possible
- Strategy A: try a random action then do what seems best

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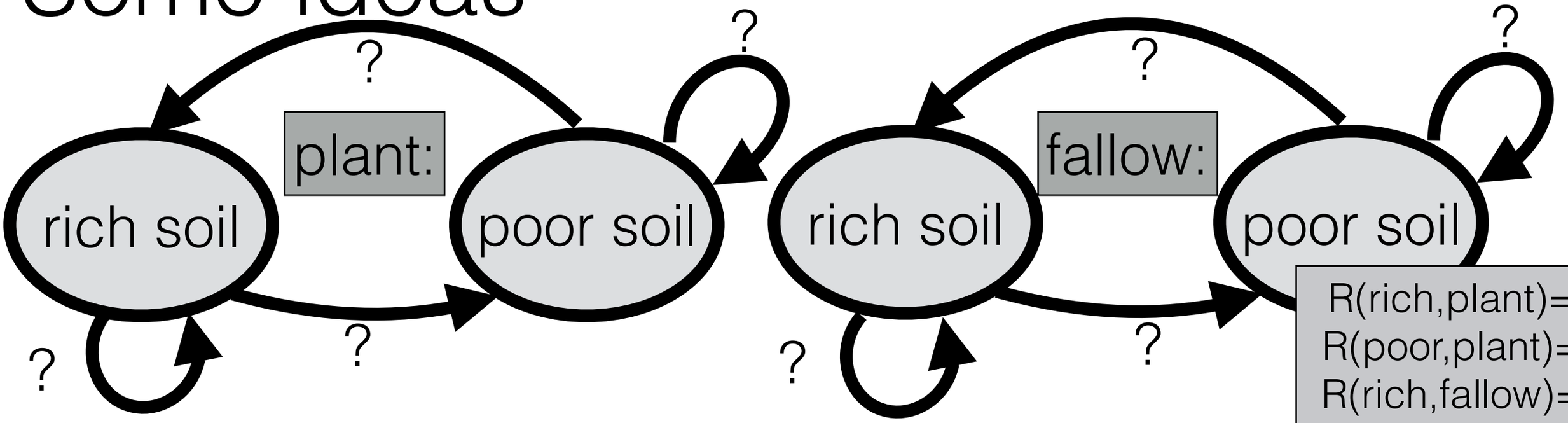

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- Example of this strategy in action:

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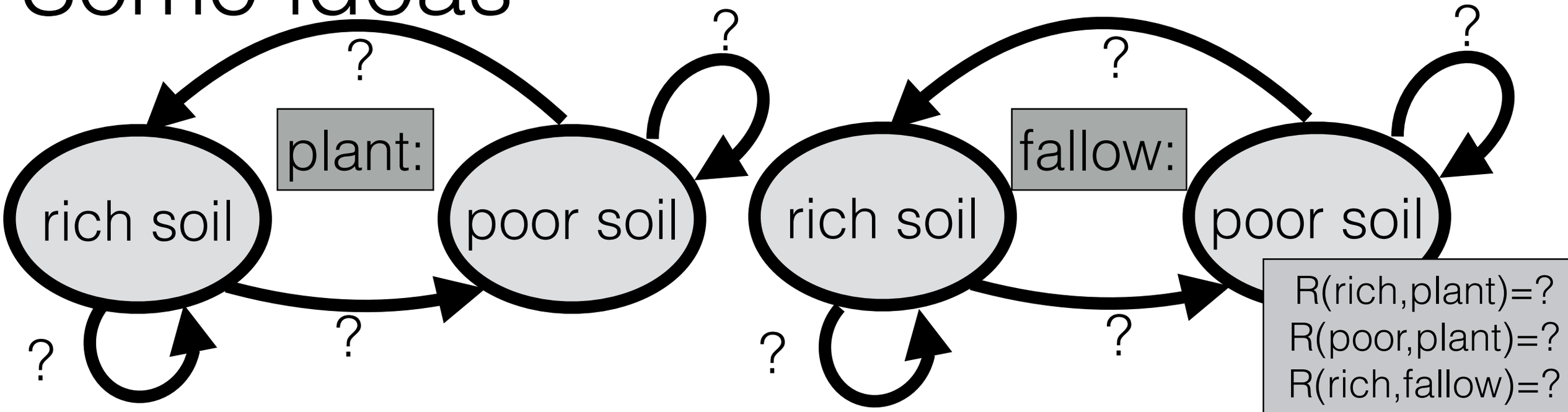

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$s^{(1)} = \text{rich}$

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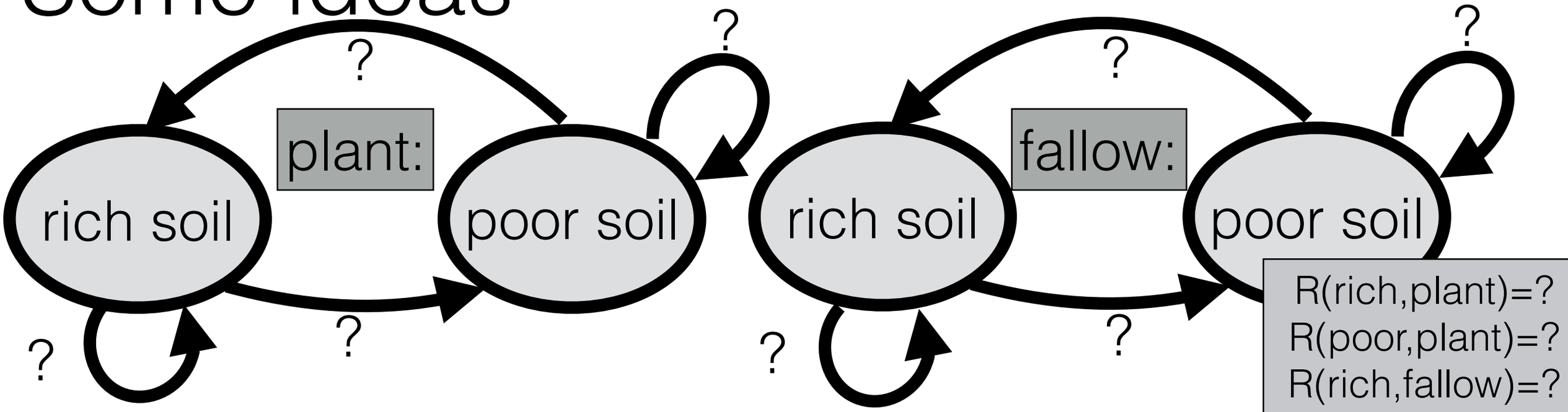

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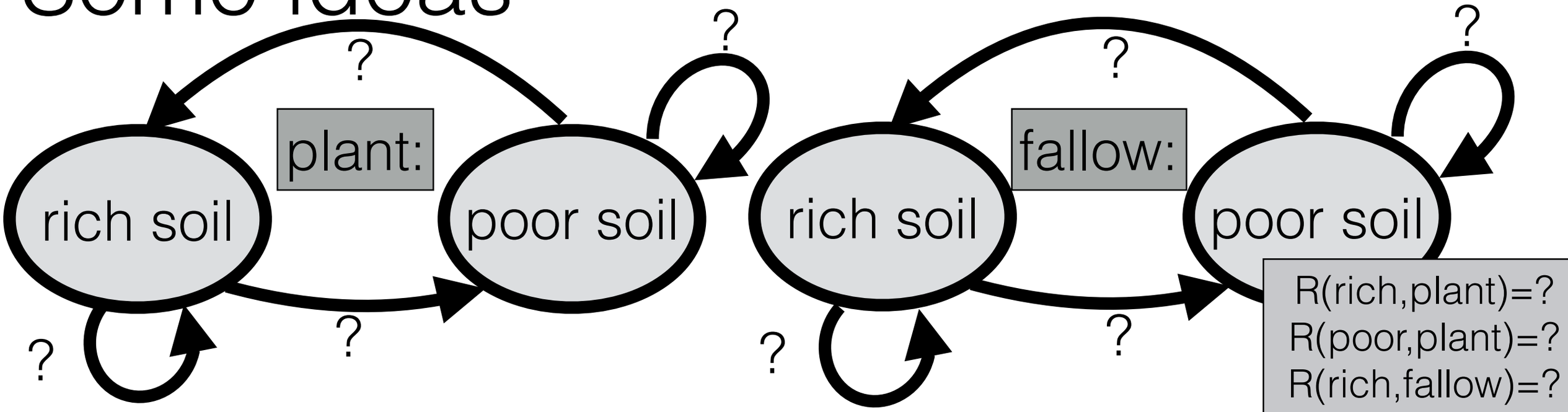
$a^{(1)} =$

Some ideas



- Goal: Harvest as much as possible
- Strategy A: try a random action then do what seems best
- Example of this strategy in action:

$s^{(1)} = \text{rich}$

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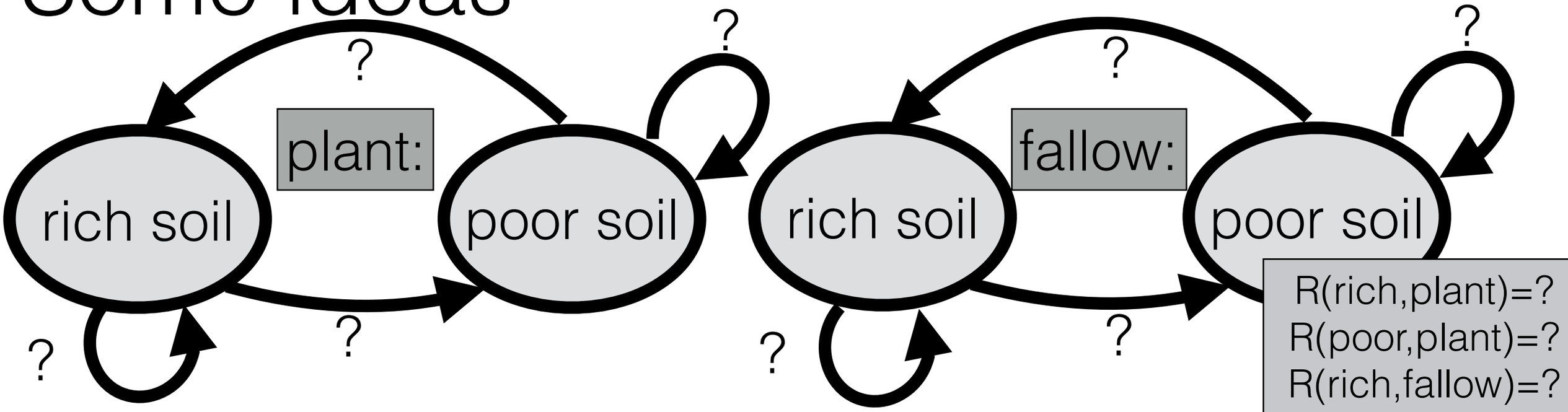
Some ideas



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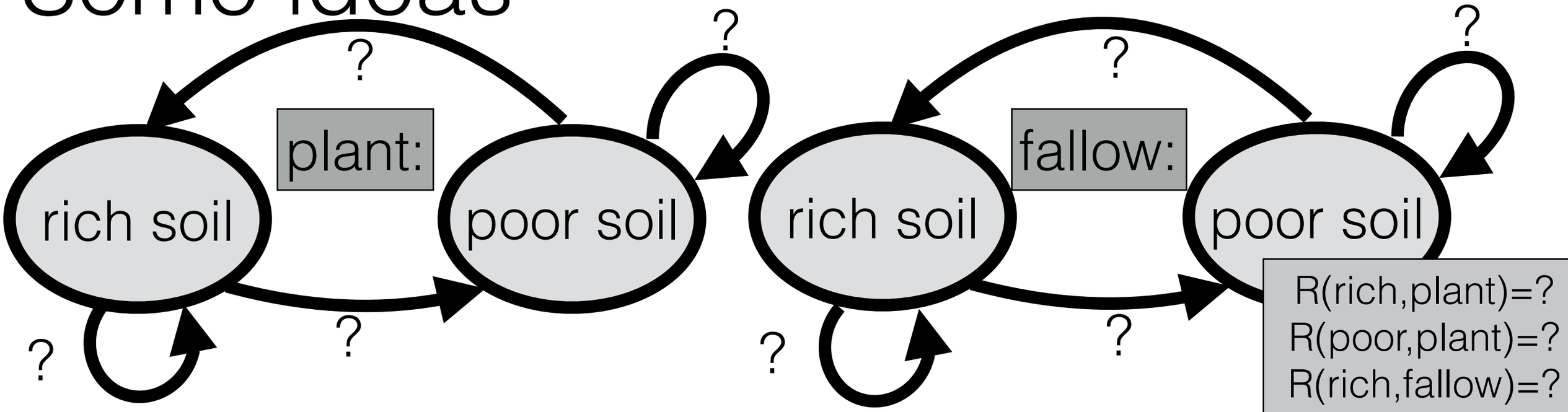
$a^{(1)} = \text{plant}; s^{(2)} =$

Some ideas



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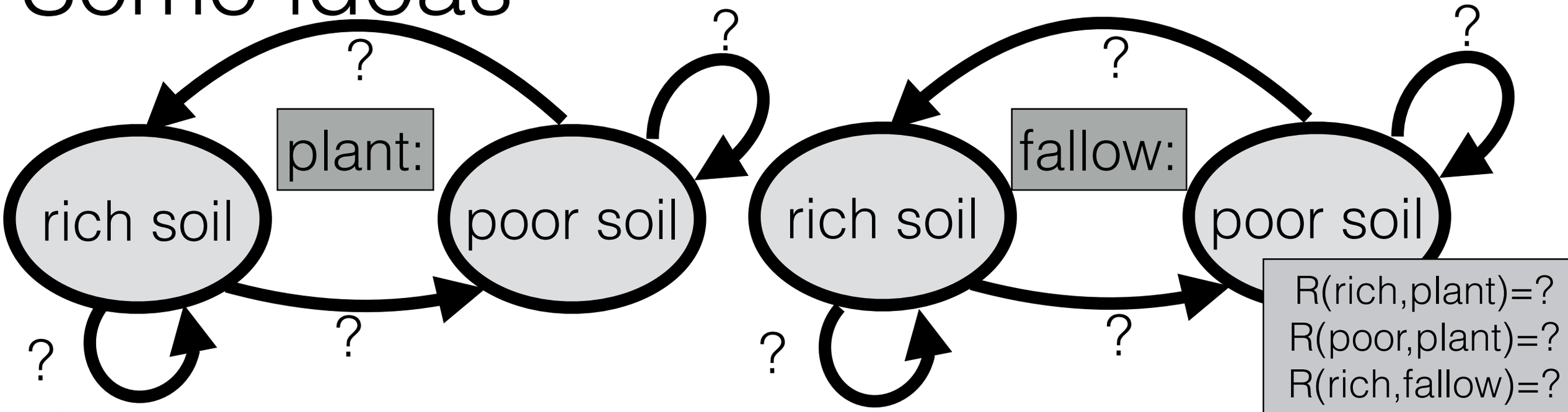

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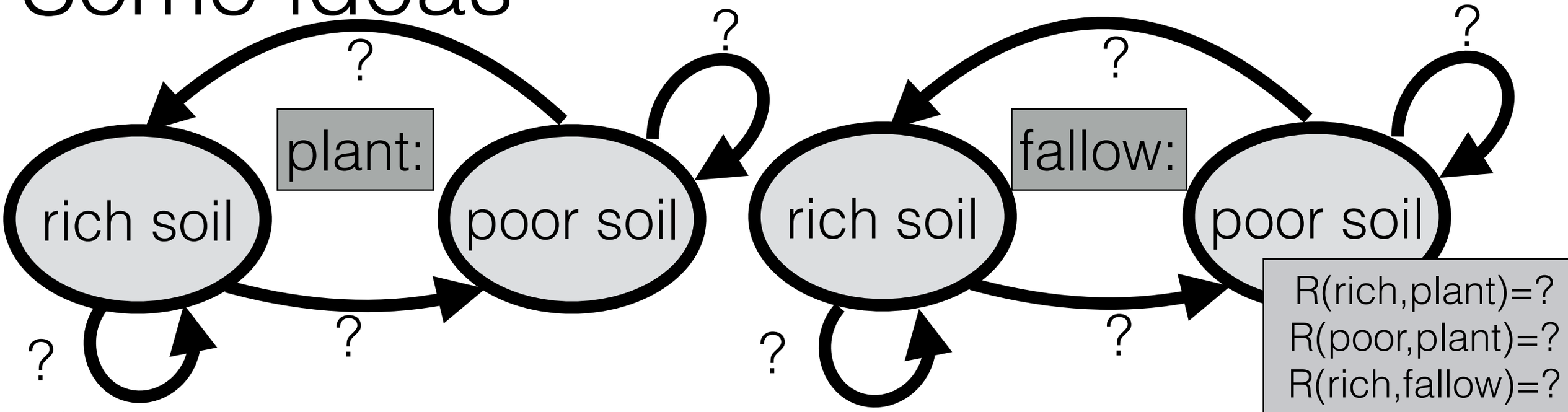
Some ideas



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$s^{(1)} = \text{rich}$

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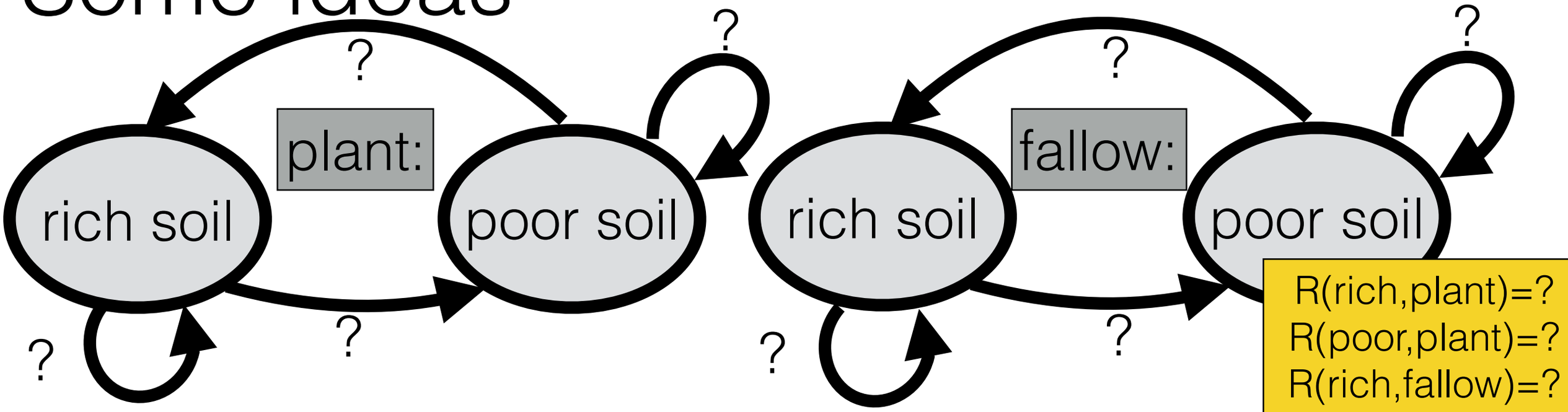
Some ideas



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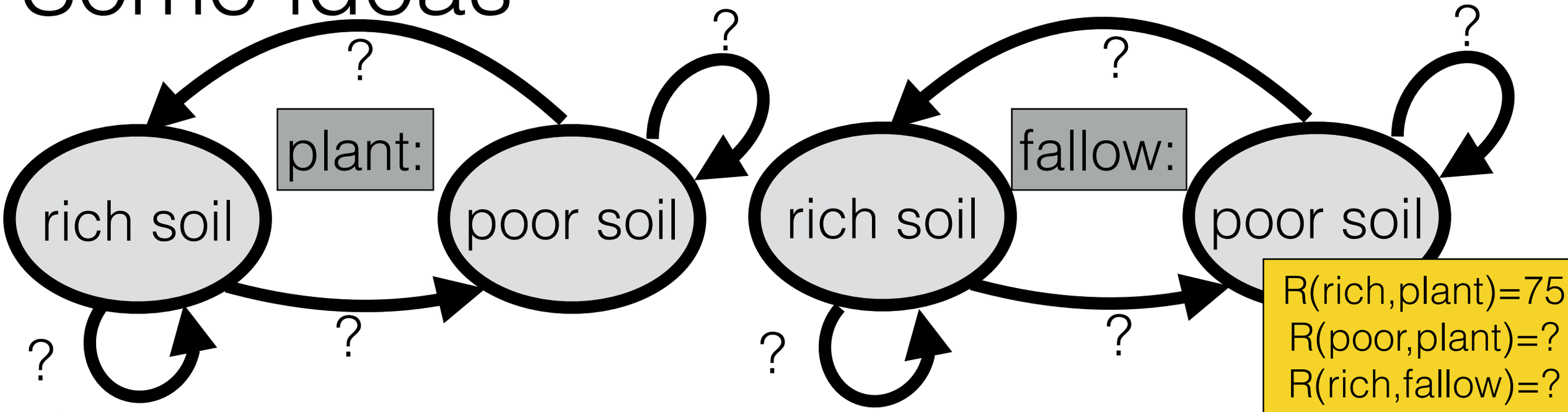

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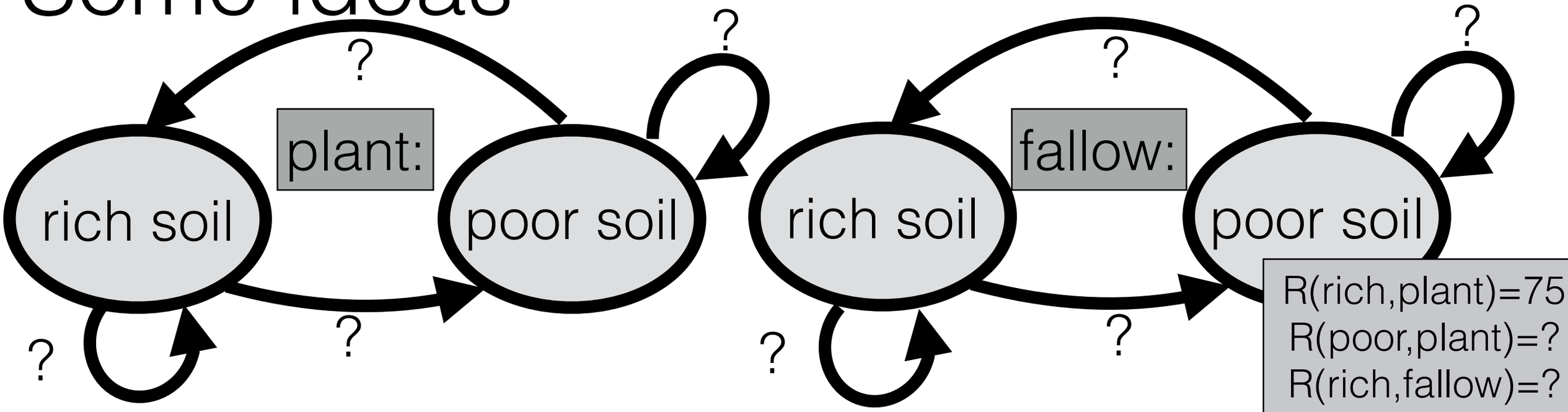

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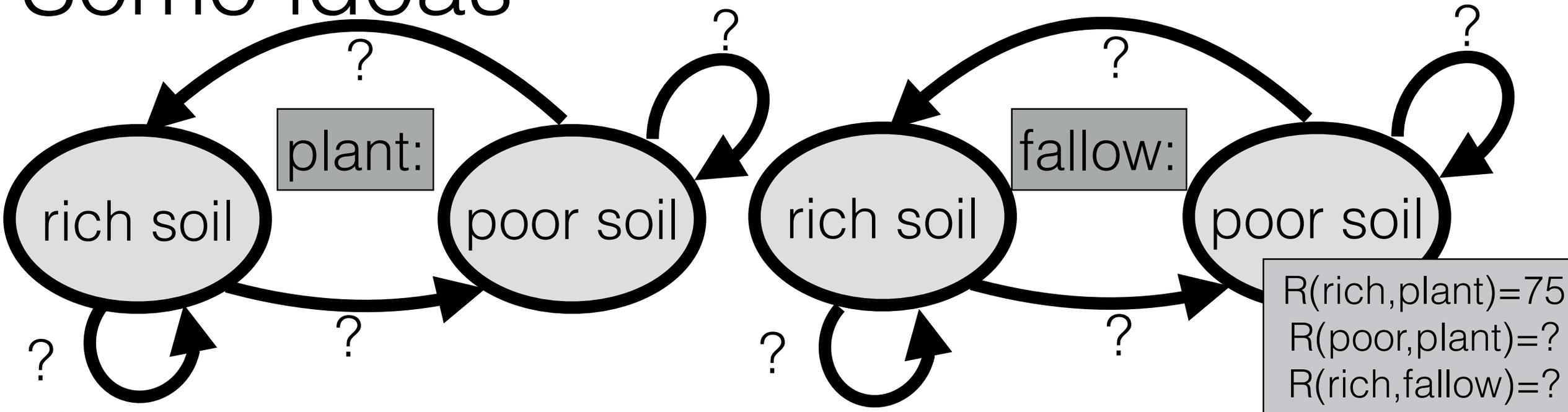

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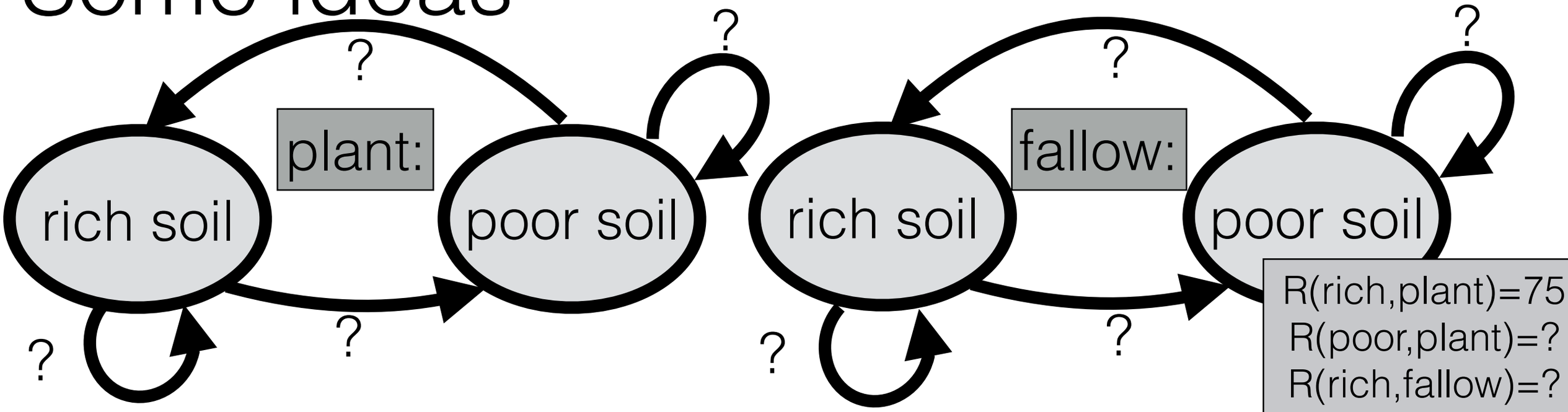
Is this a good strategy?

Some ideas



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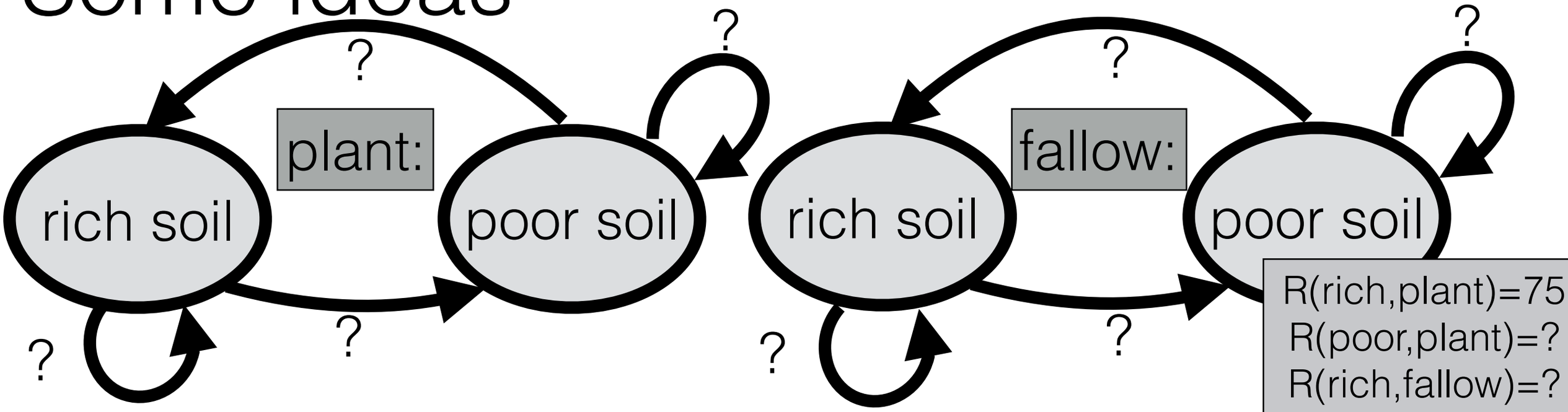
Could anything be improved about this strategy?

Some ideas



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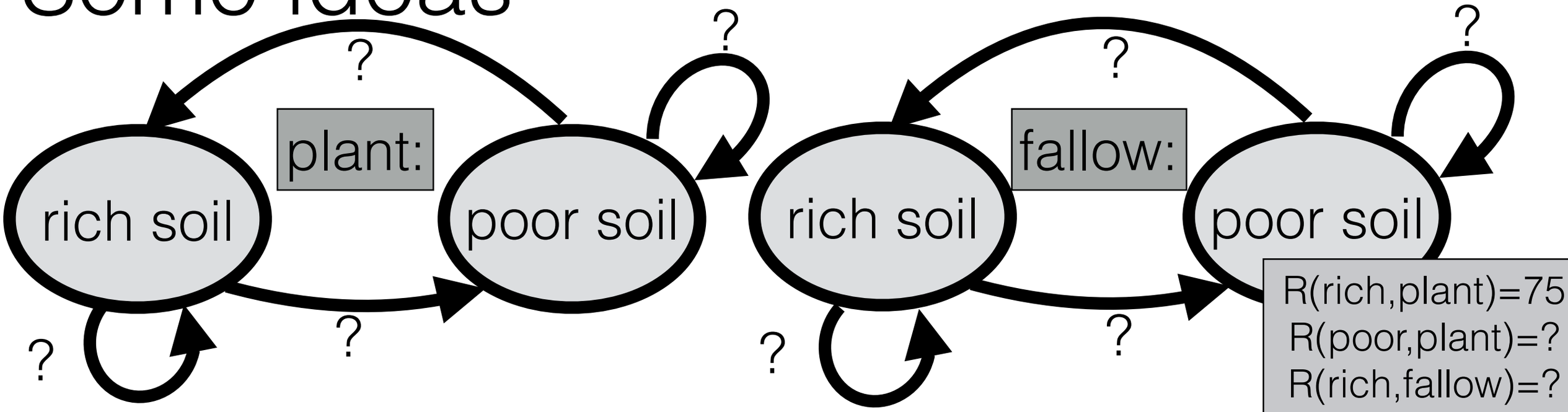
Some ideas



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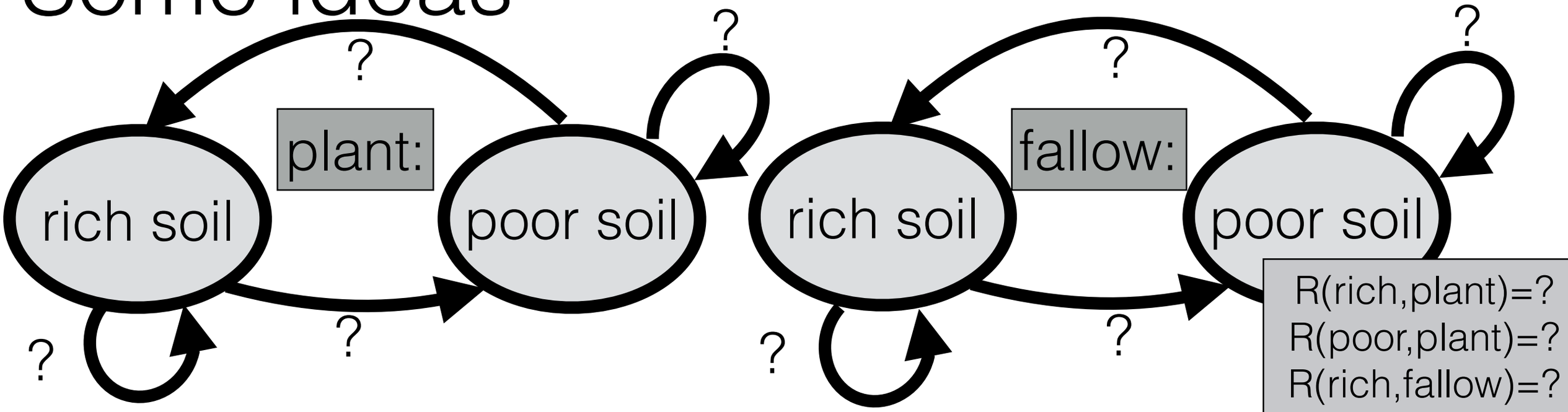

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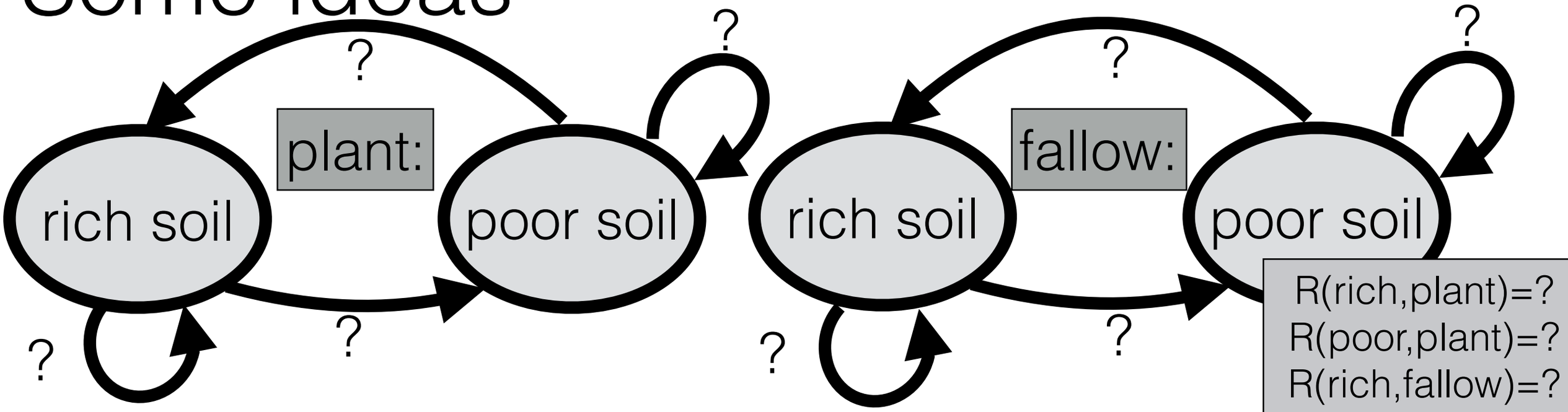

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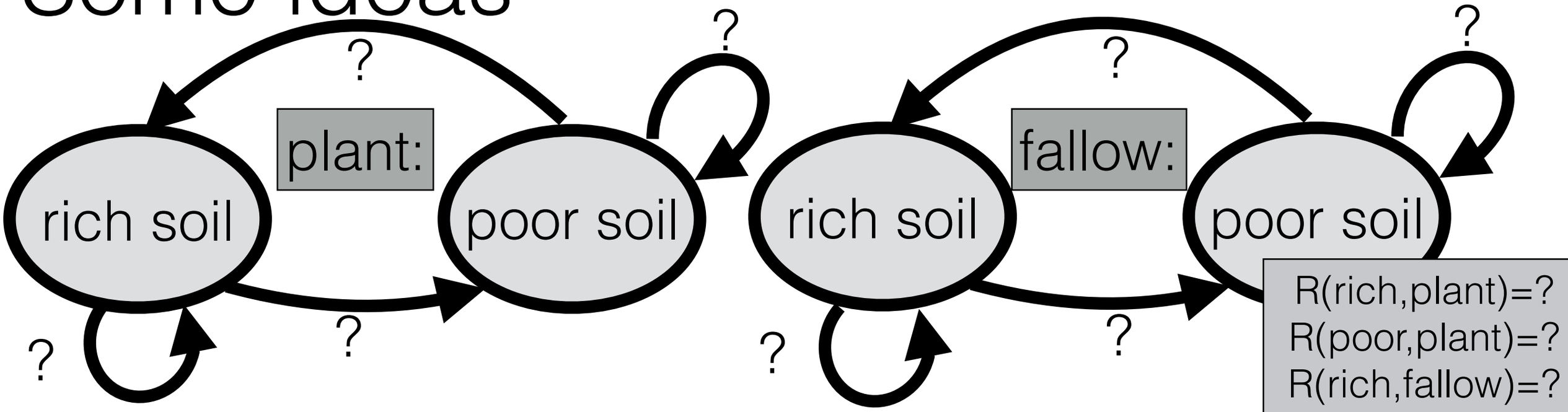
Some ideas



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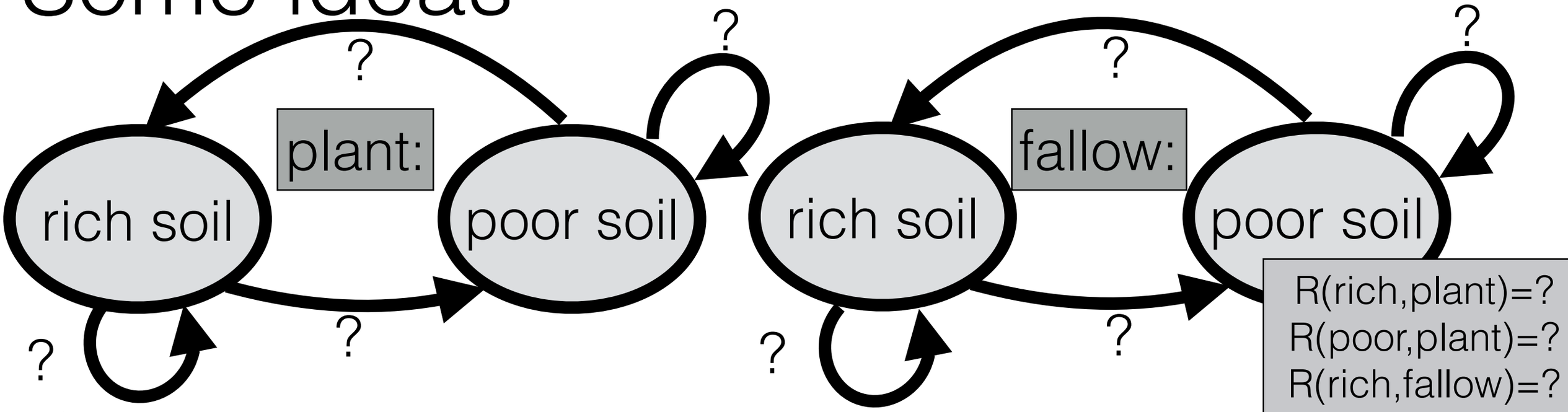
Some ideas



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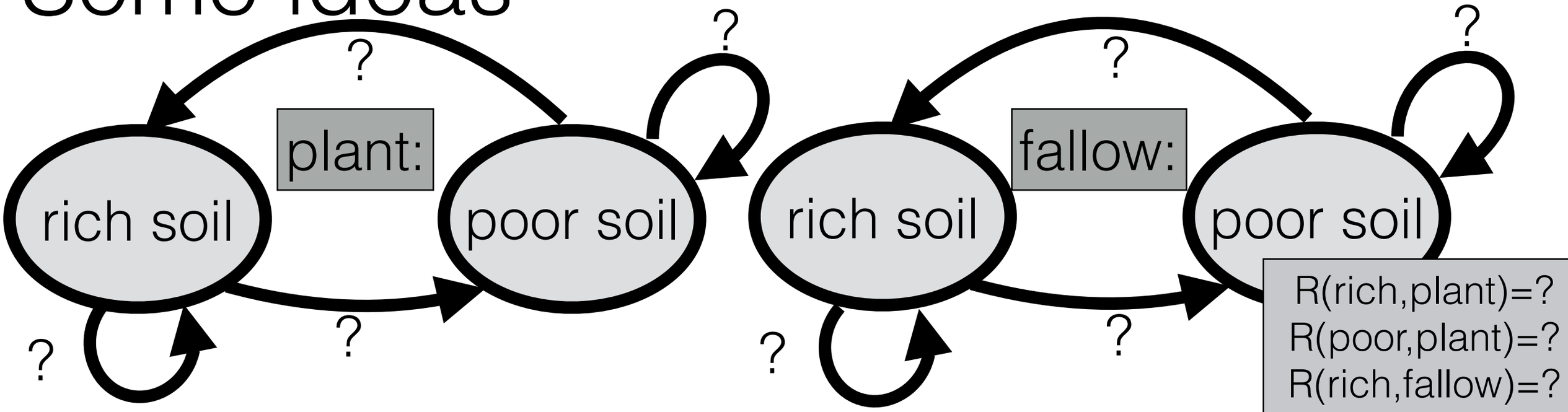

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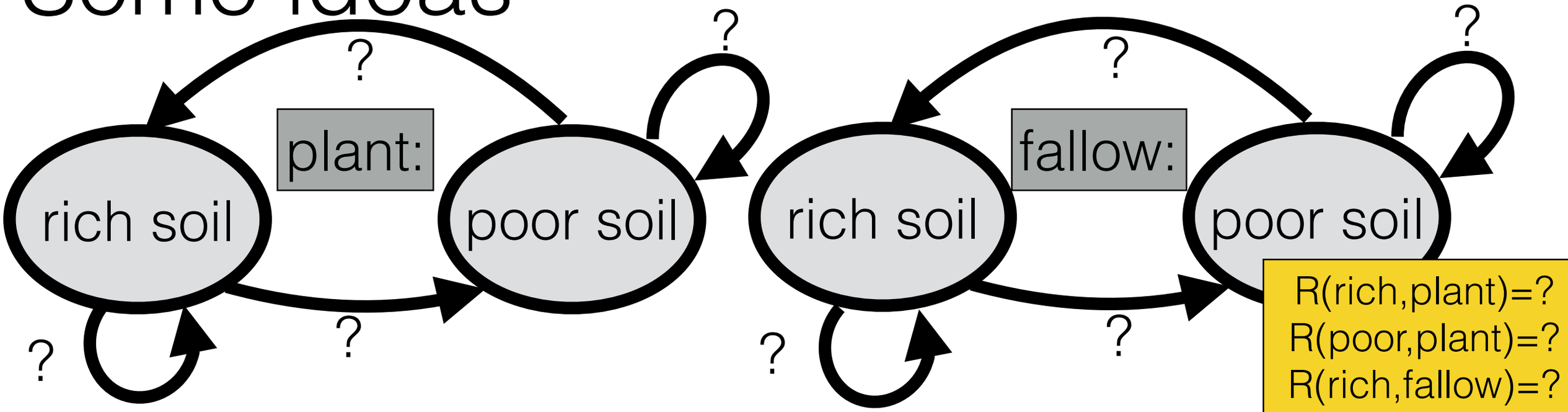

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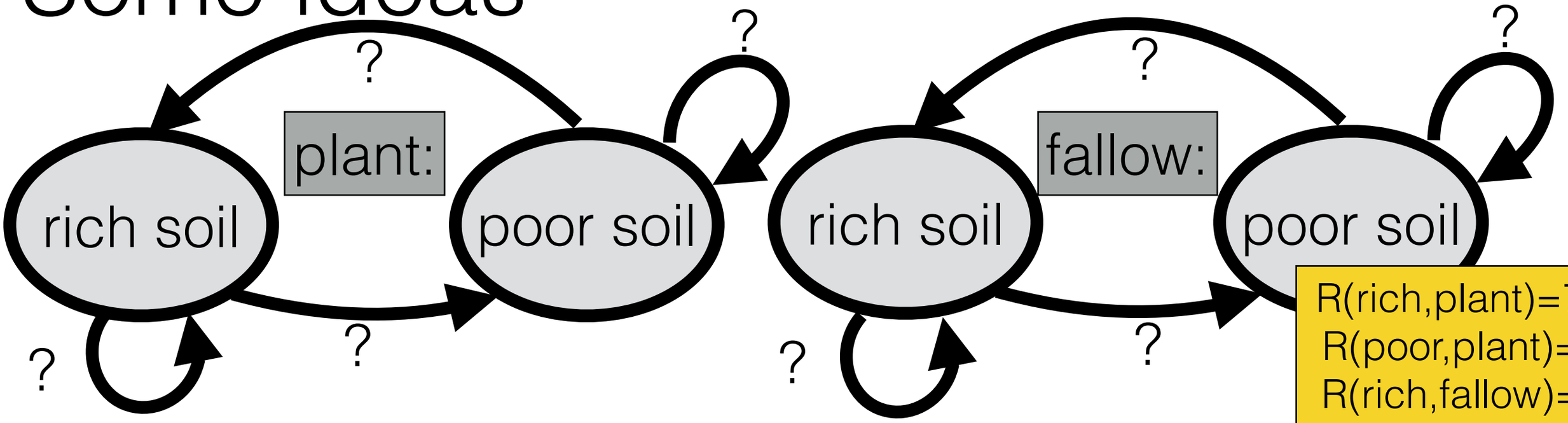

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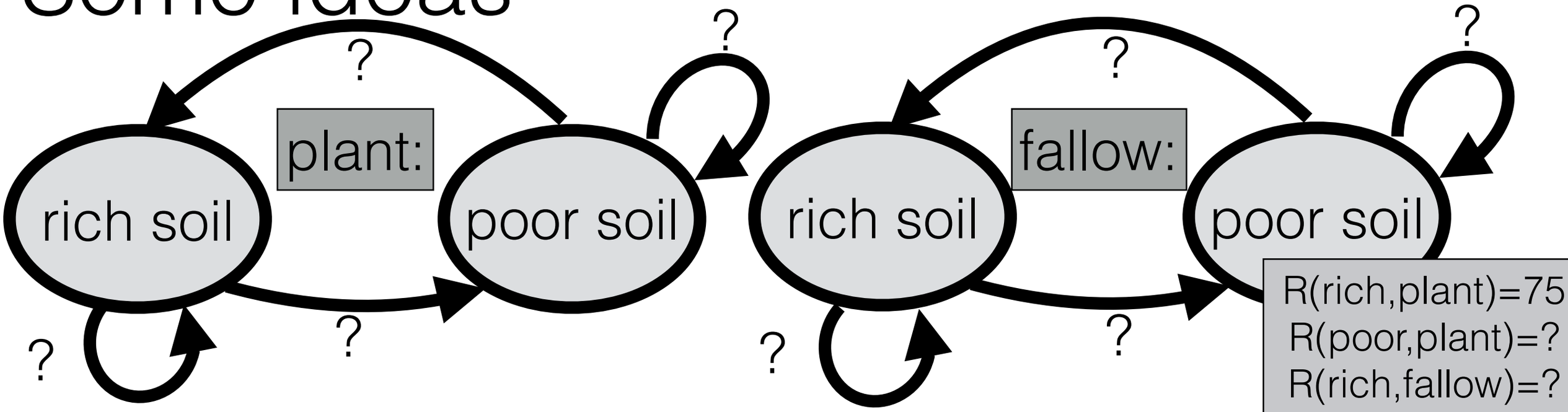

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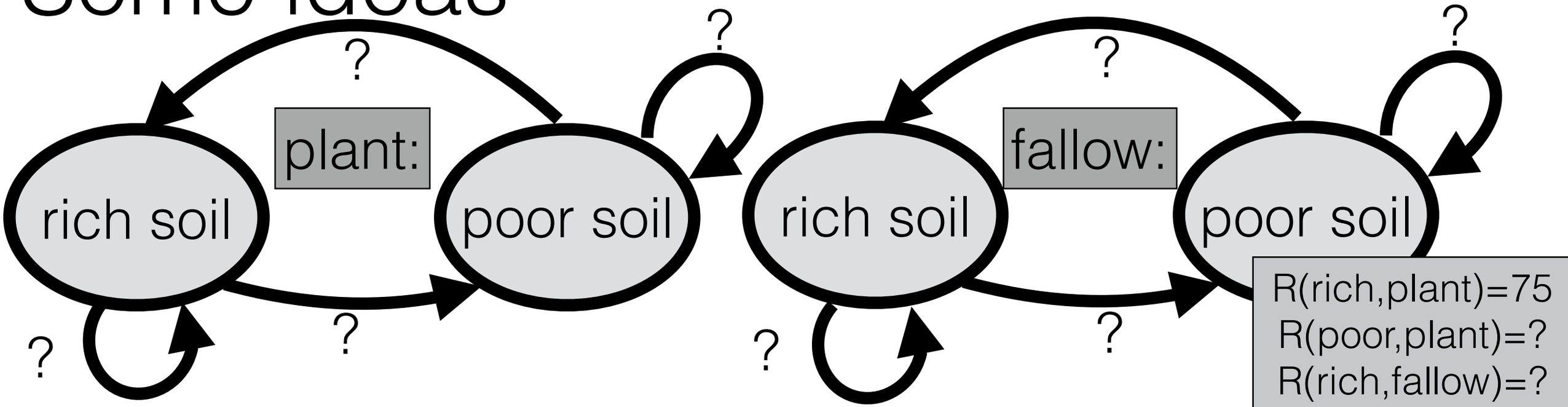
Some ideas



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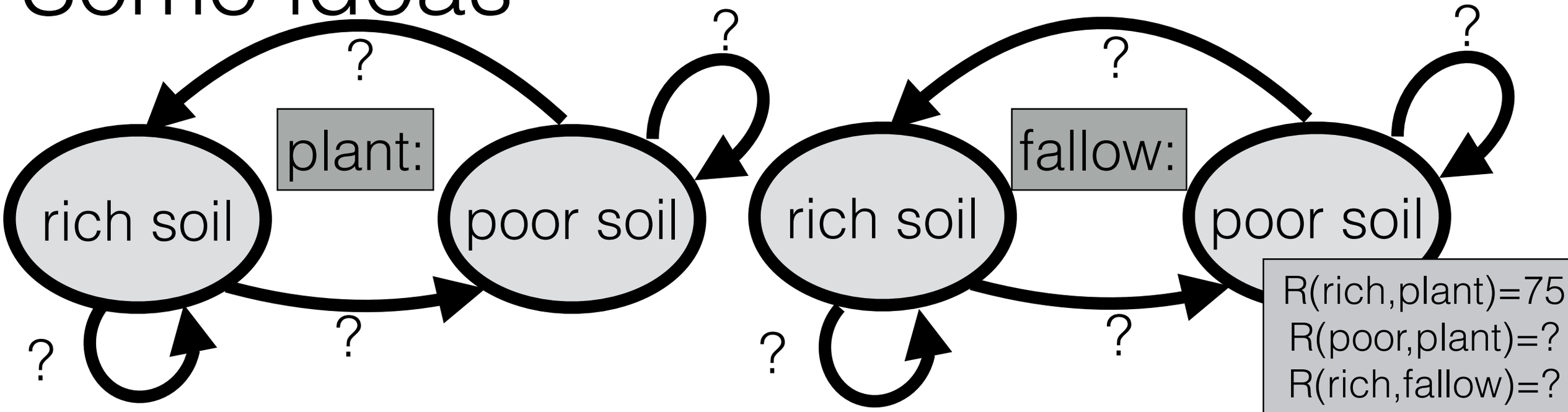
Some ideas



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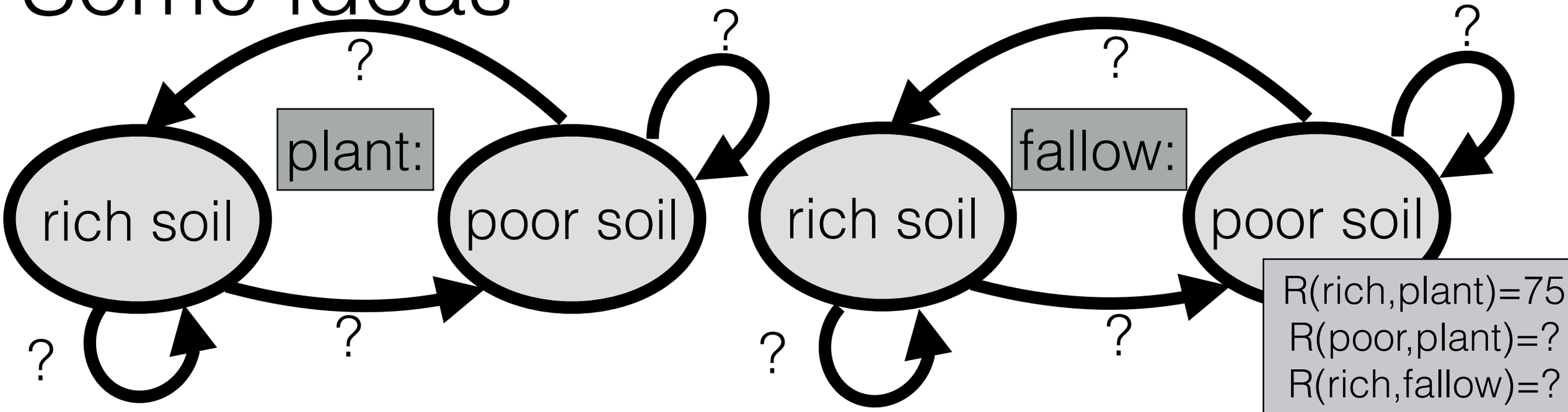

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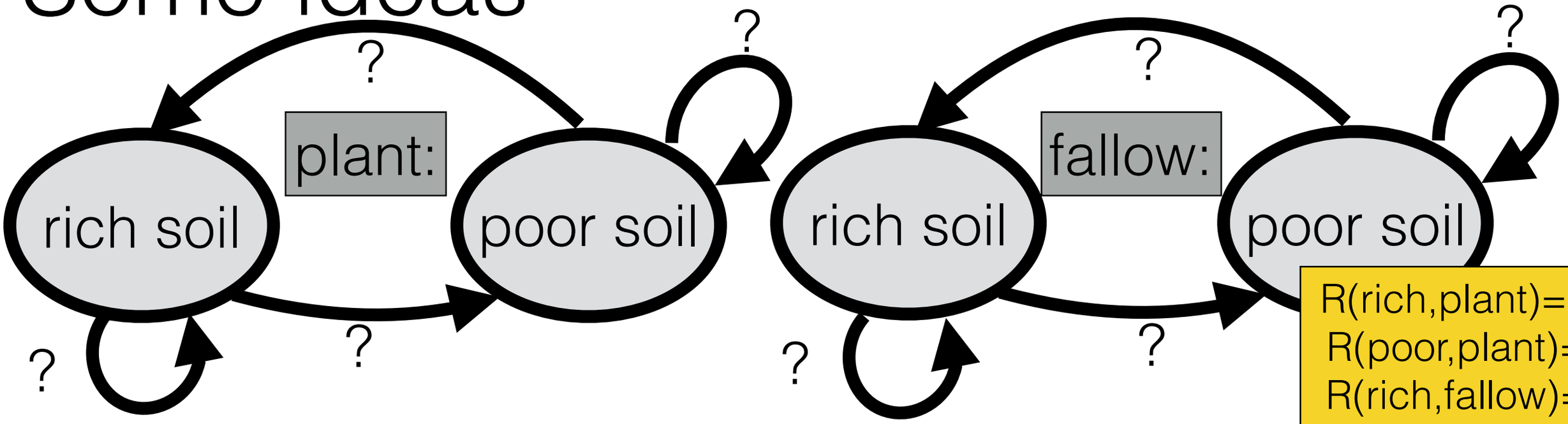

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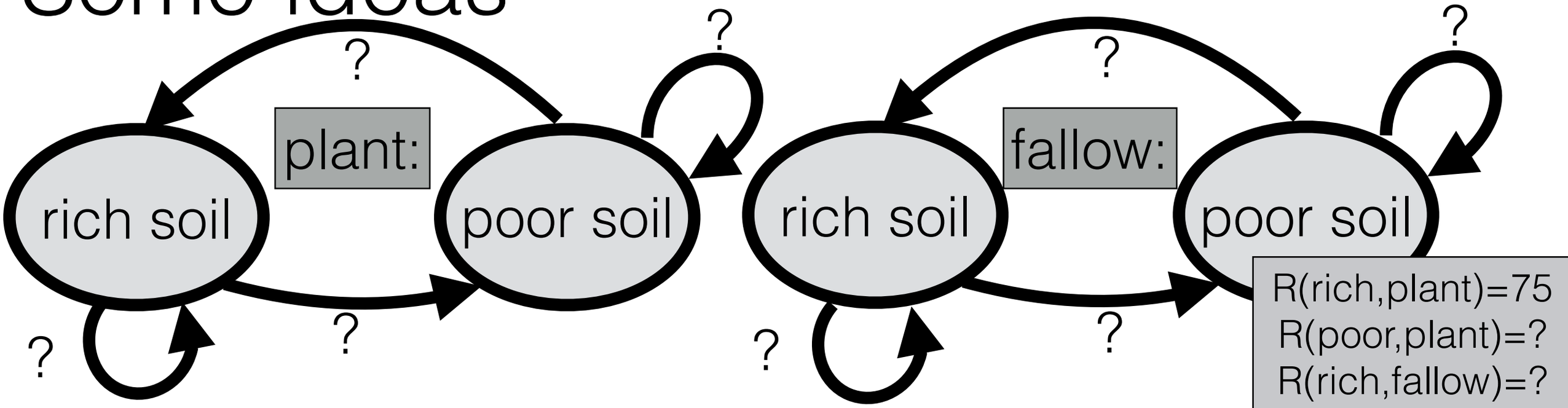

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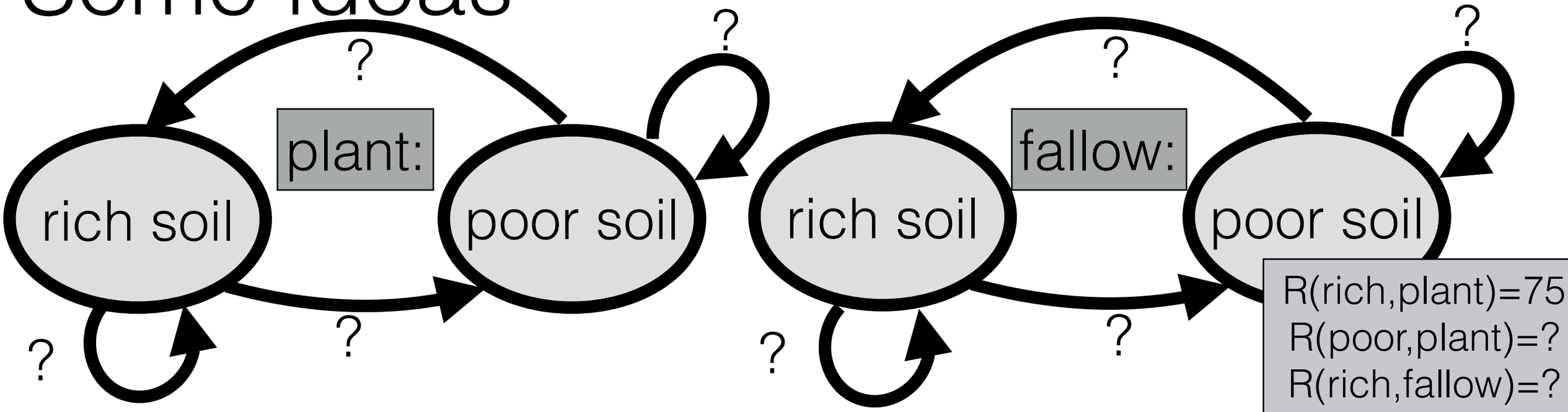

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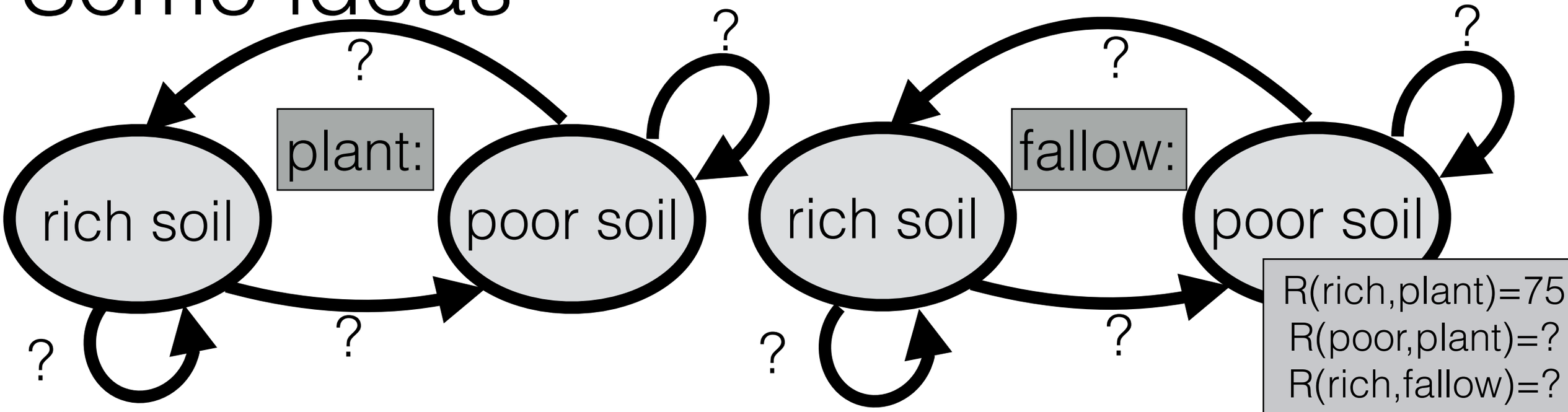
Some ideas



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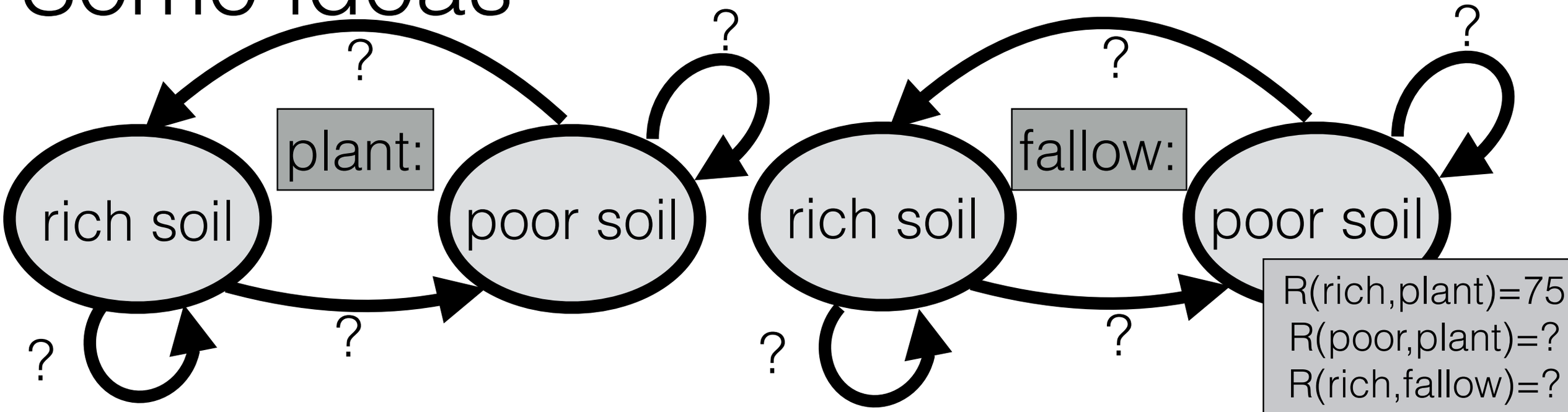
Some ideas



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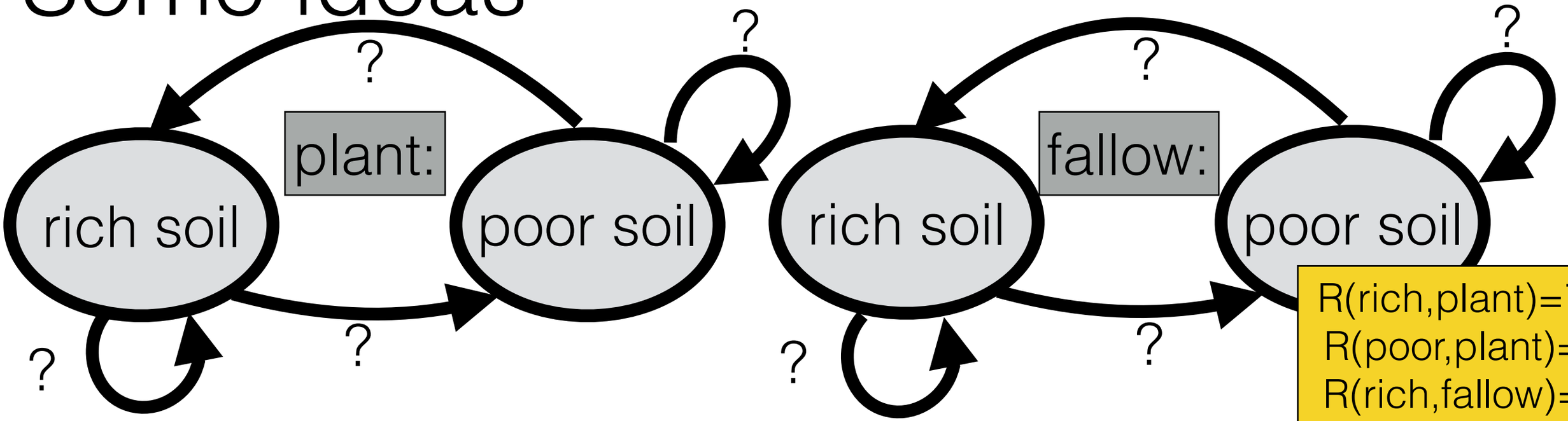
Some ideas



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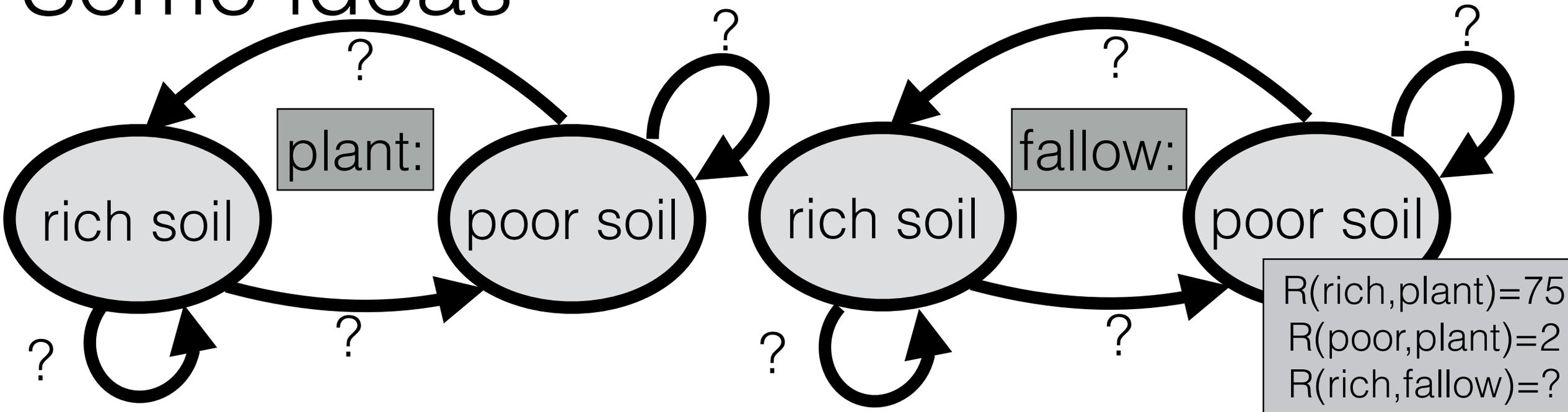
Some ideas



- Goal: Harvest as much as possible
- Strategy A: try a random action then do what seems best
  - Example of this strategy in action:

    $s^{(1)} = \text{rich}$

    $a^{(1)} = \text{plant}; s^{(2)} = \text{rich}; r^{(1)} = 75 \text{ bushels}$
    - Strategy from here: always plant!
- Strategy B: always try actions uniformly at random

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  $a^{(2)} = \text{plant}; s^{(3)} = \text{poor}; r^{(2)} = 75 \text{ bushels}$

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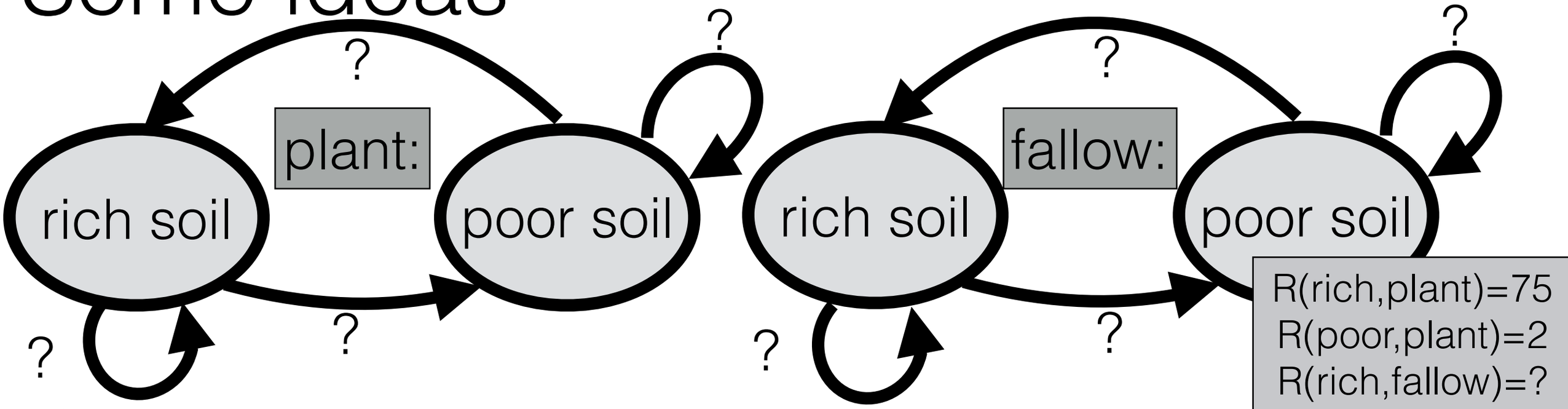
Is this a good strategy?

Some ideas



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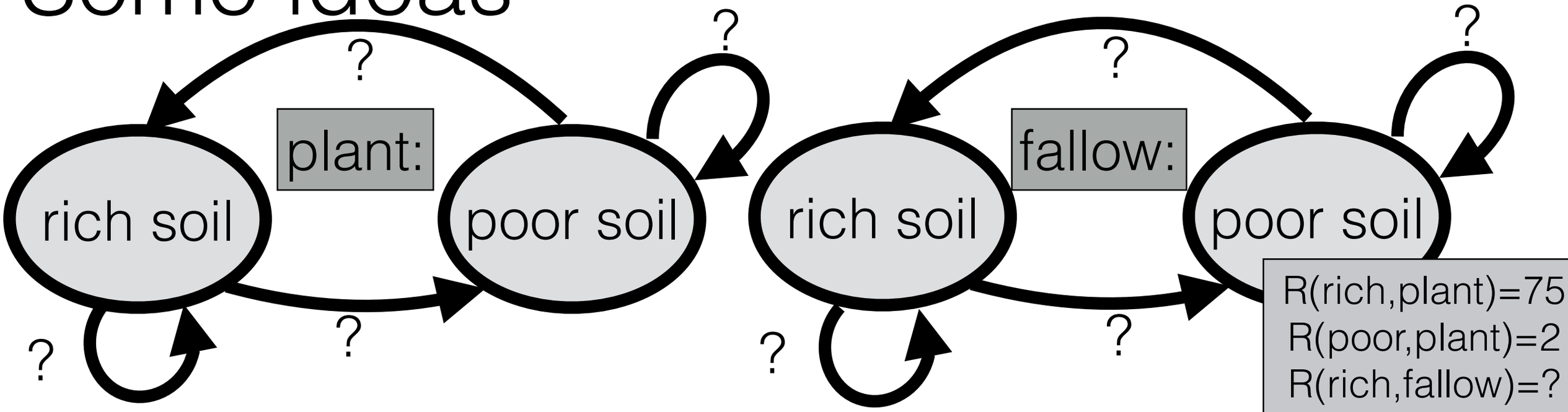
Some ideas



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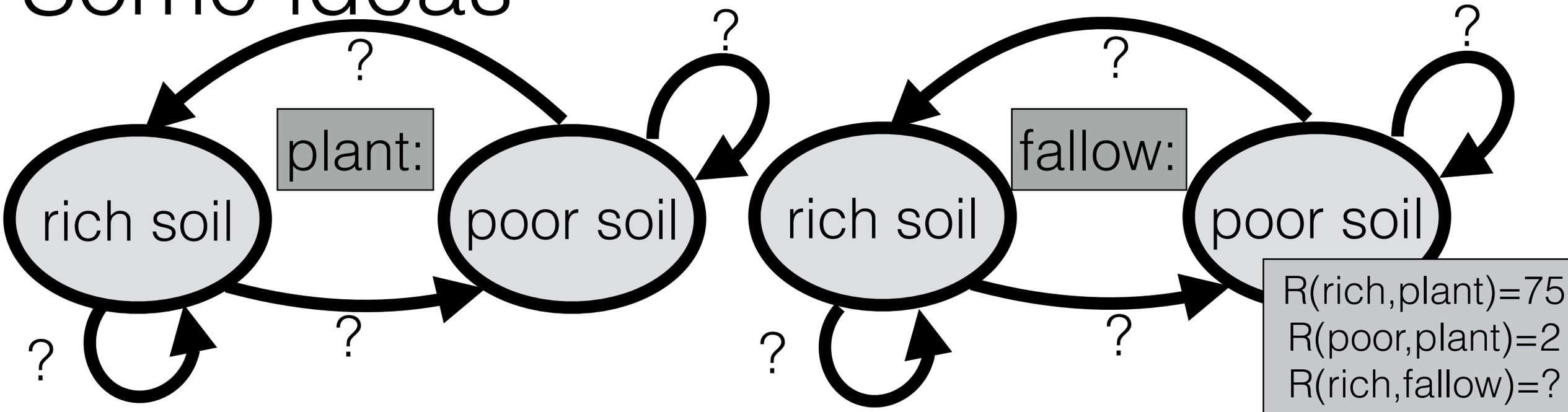
Focused on exploring

Some ideas



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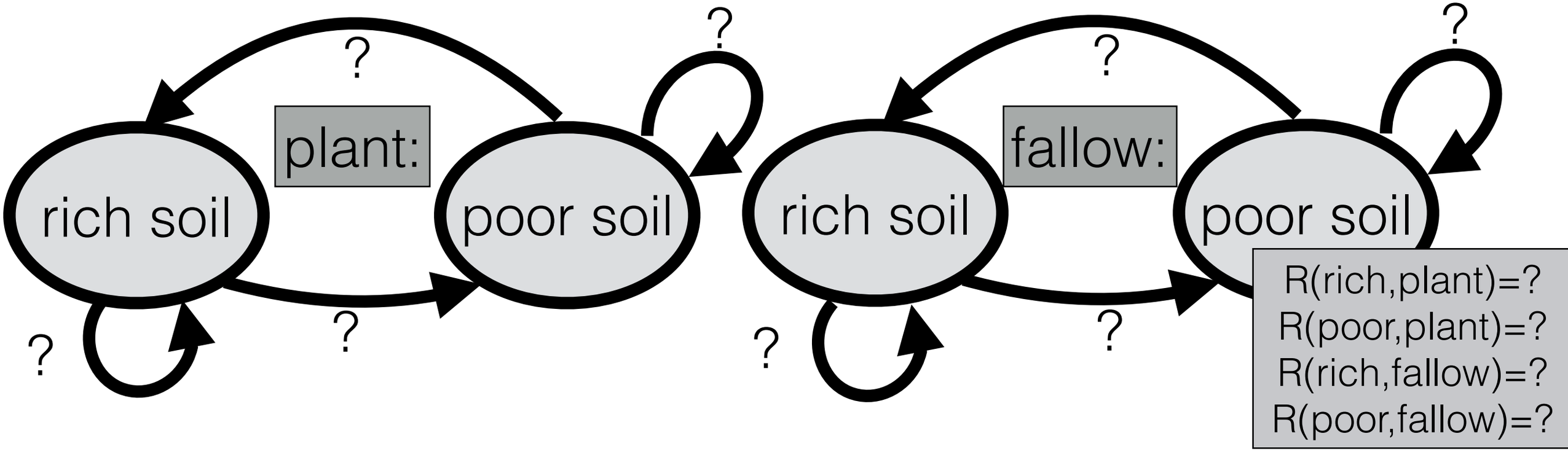
Focused on exploring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plant:
rich soil
poor soil
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fallow:
rich soil
poor soil
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R(rich,plant)=?
R(poor,plant)=?
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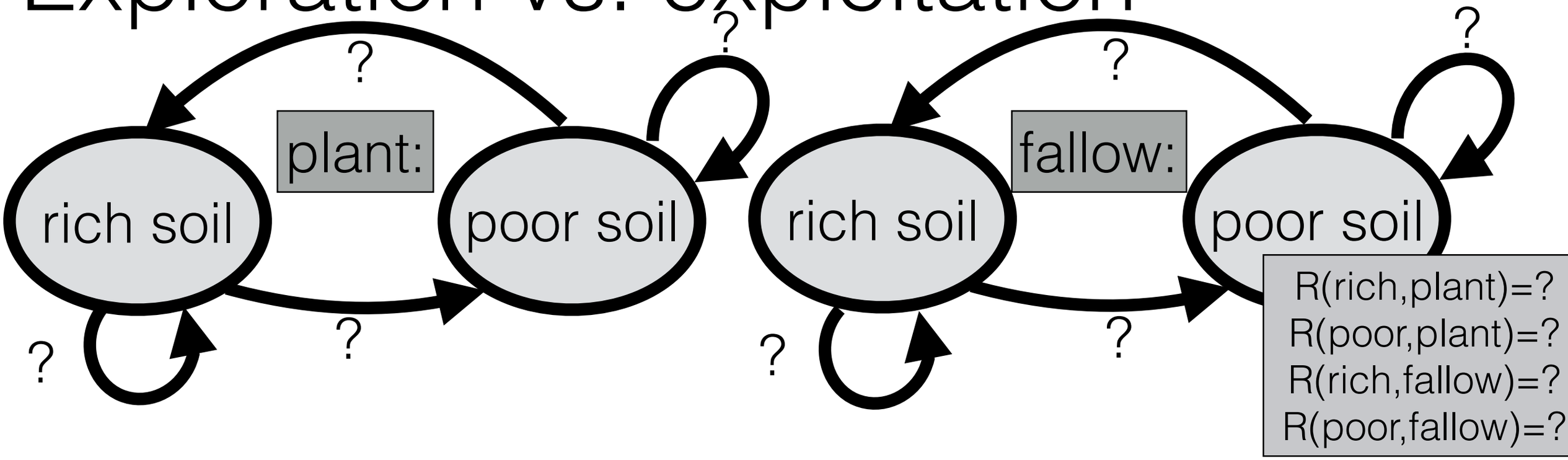
Exploration vs. exploitation



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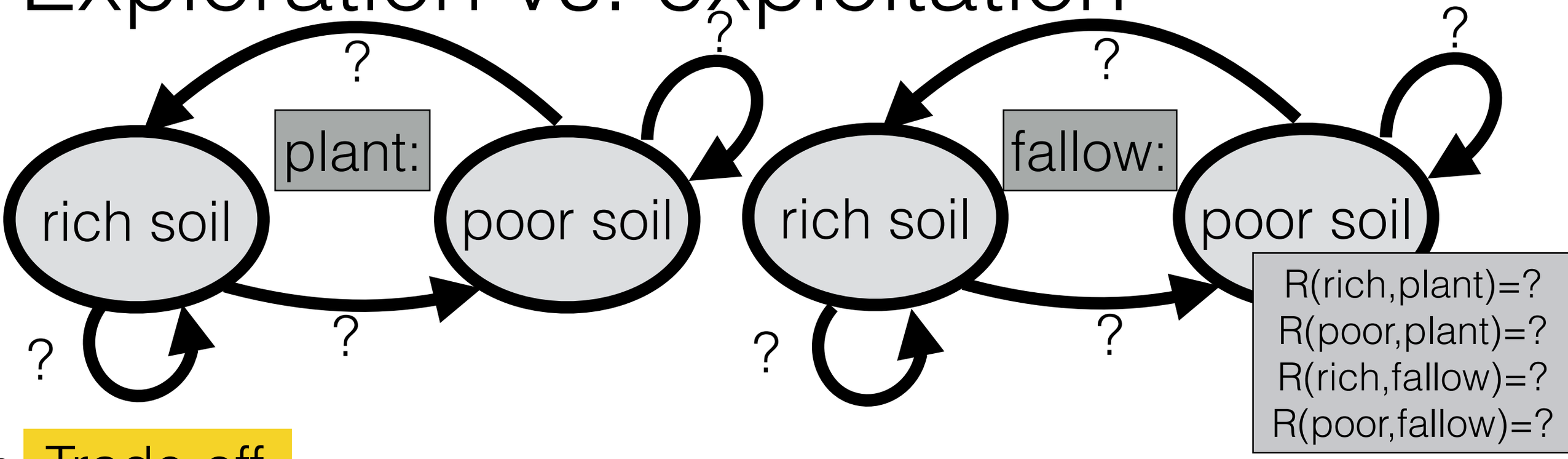

- Trade-off

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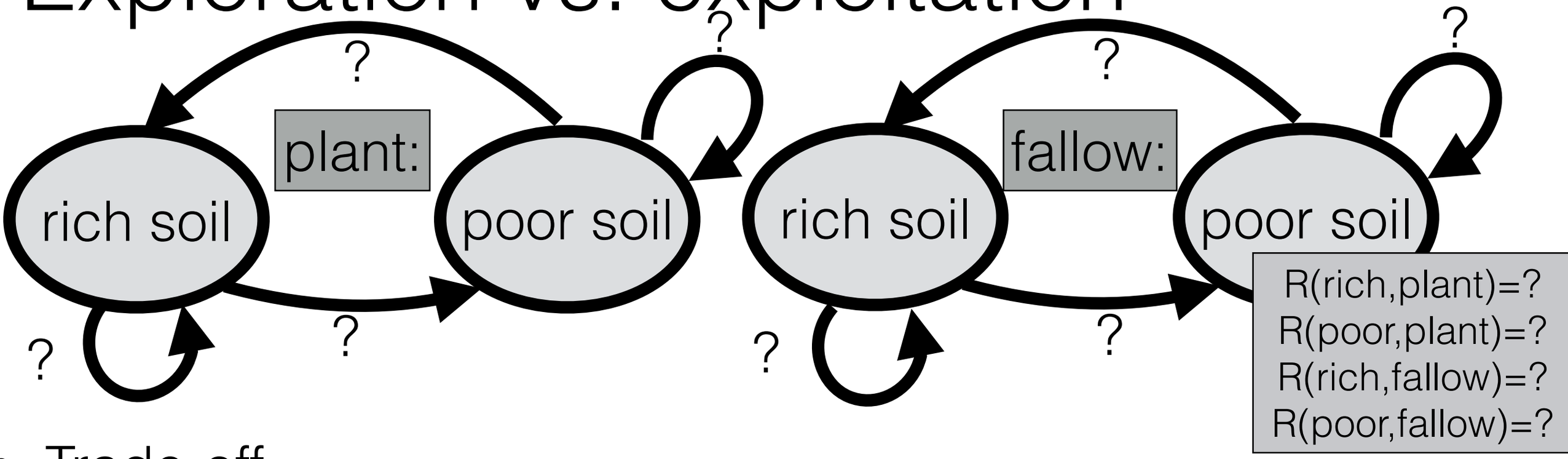
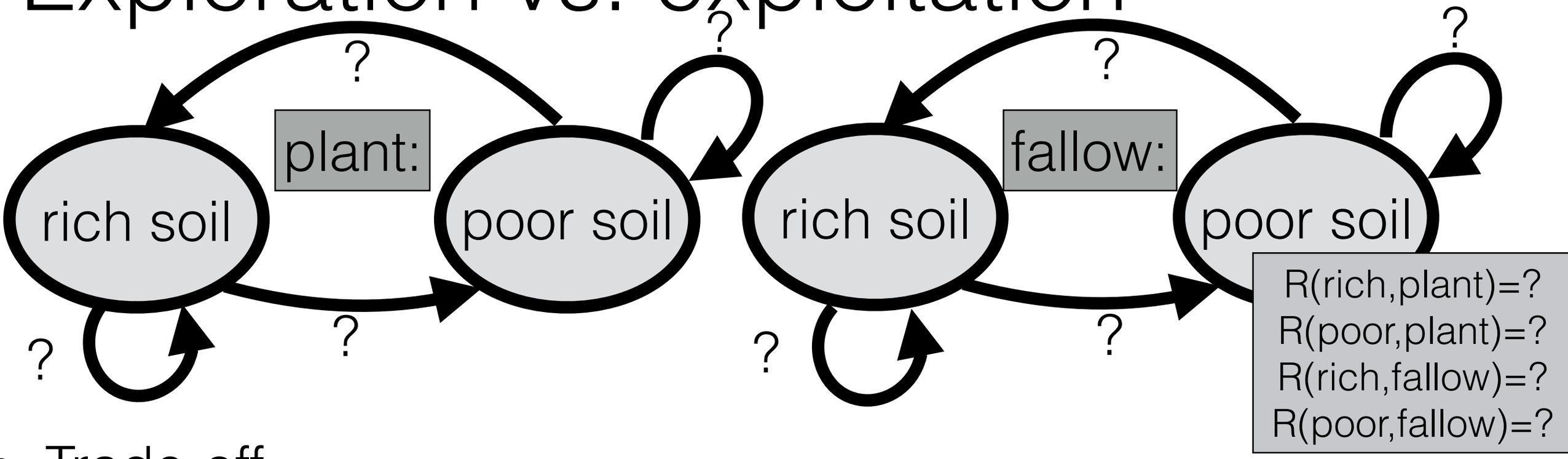


- Trade-off
- **Exploration**: the more we explore, the better we understand the world (e.g. *T* and *R*)

Exploration vs. exploitation



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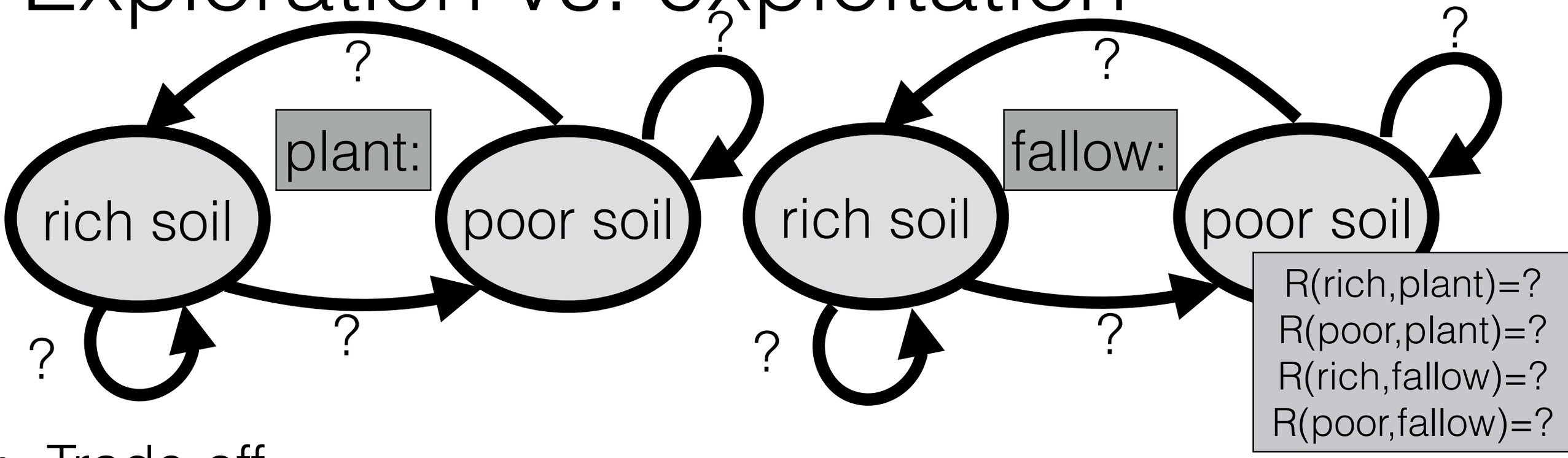

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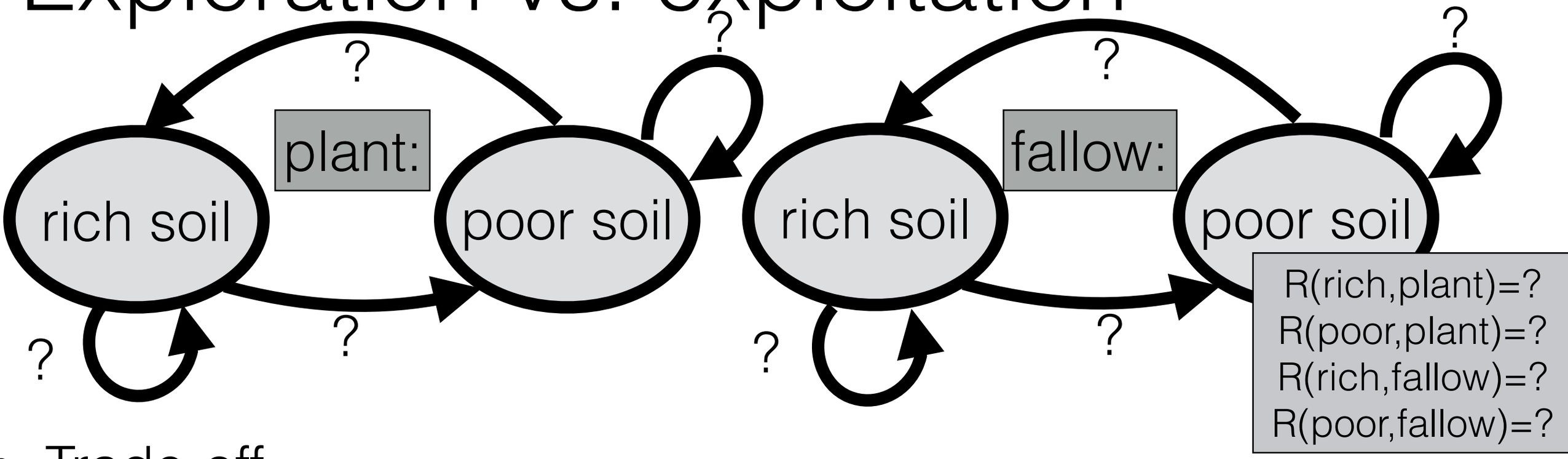

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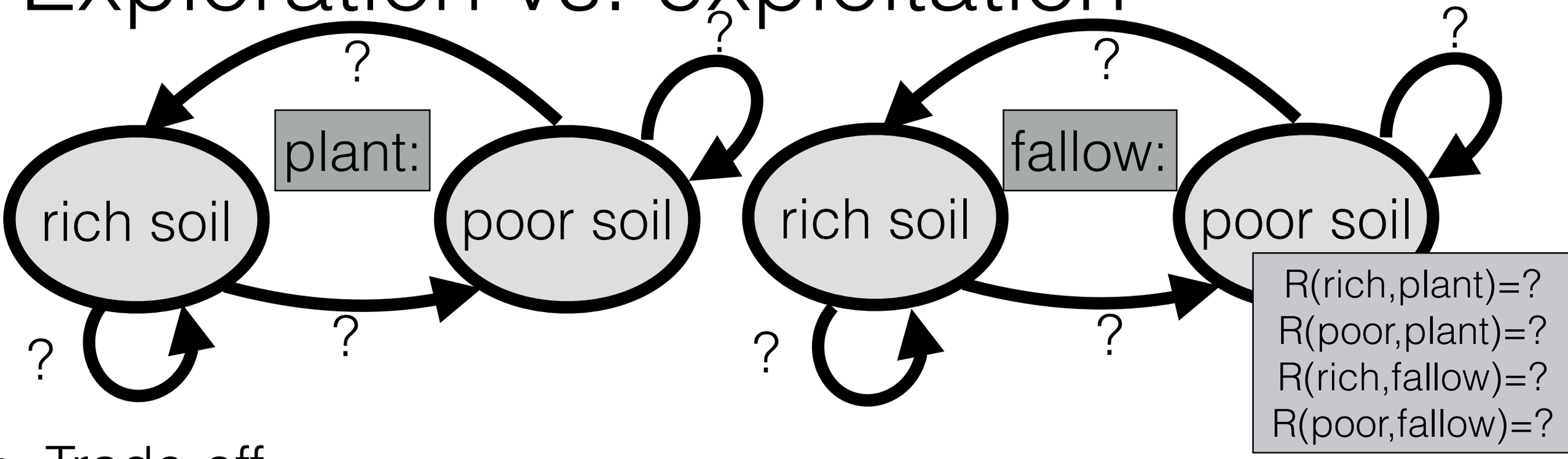
Exploration vs. exploitation



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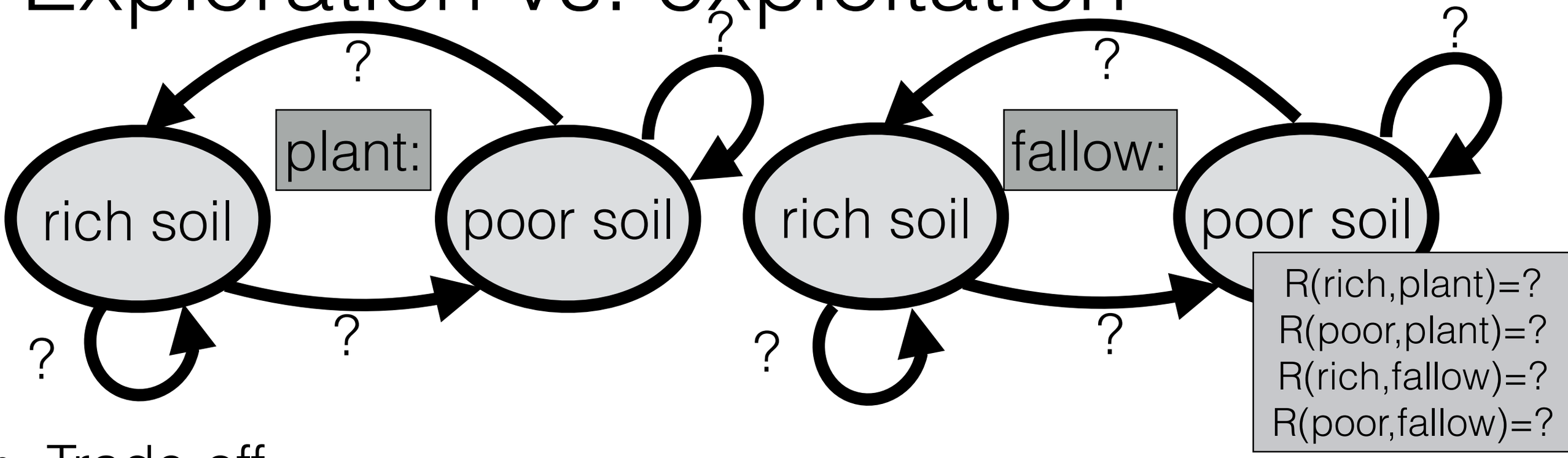

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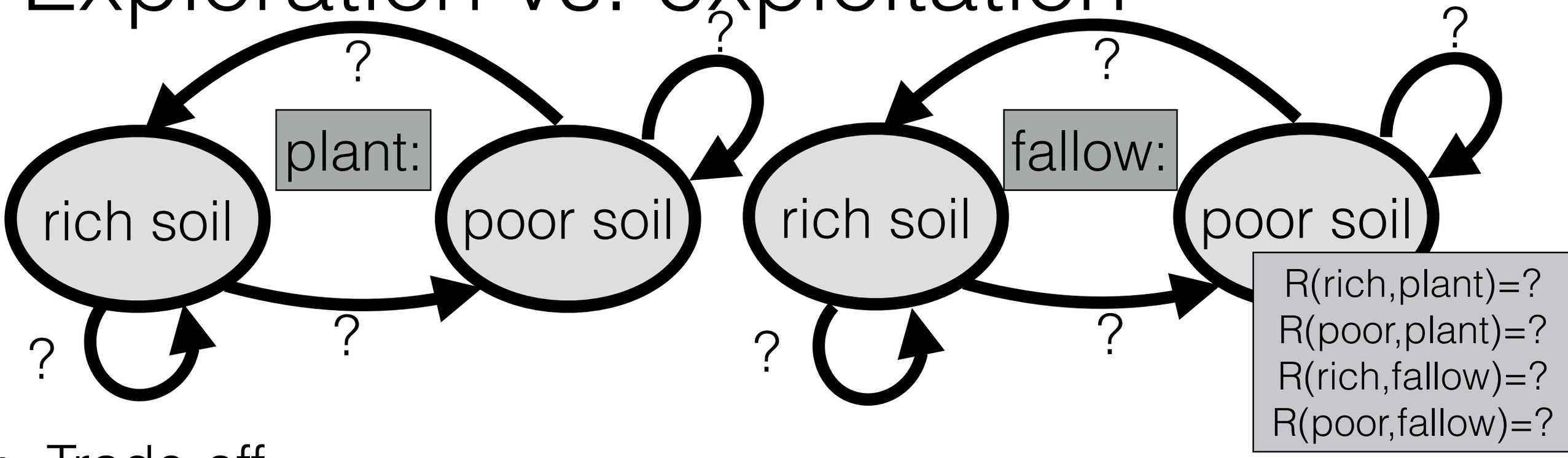

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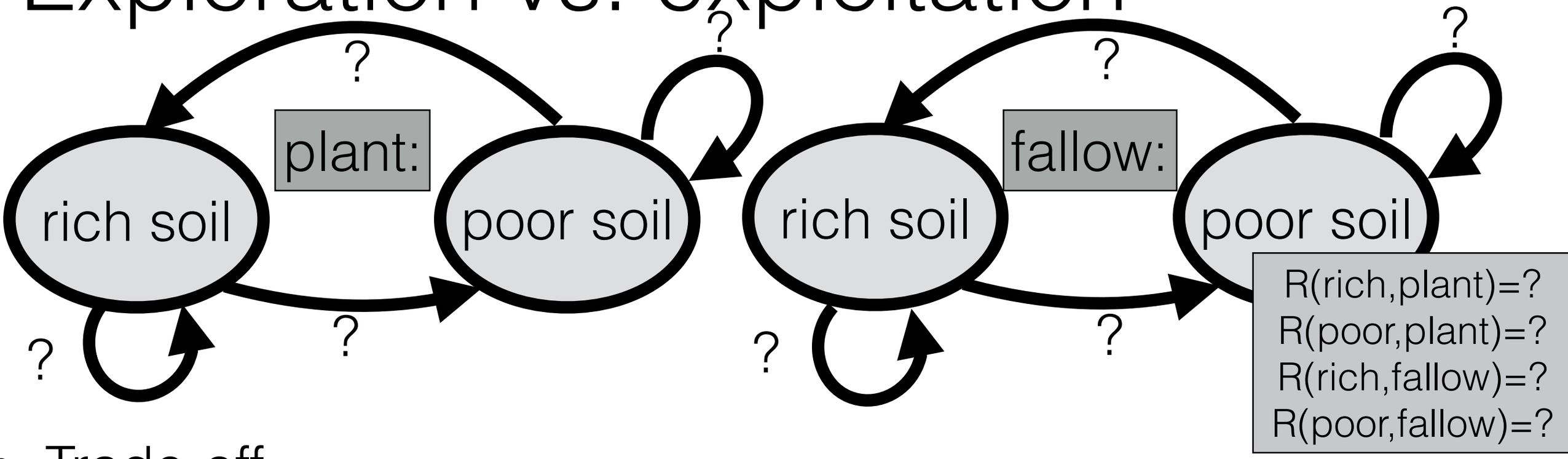

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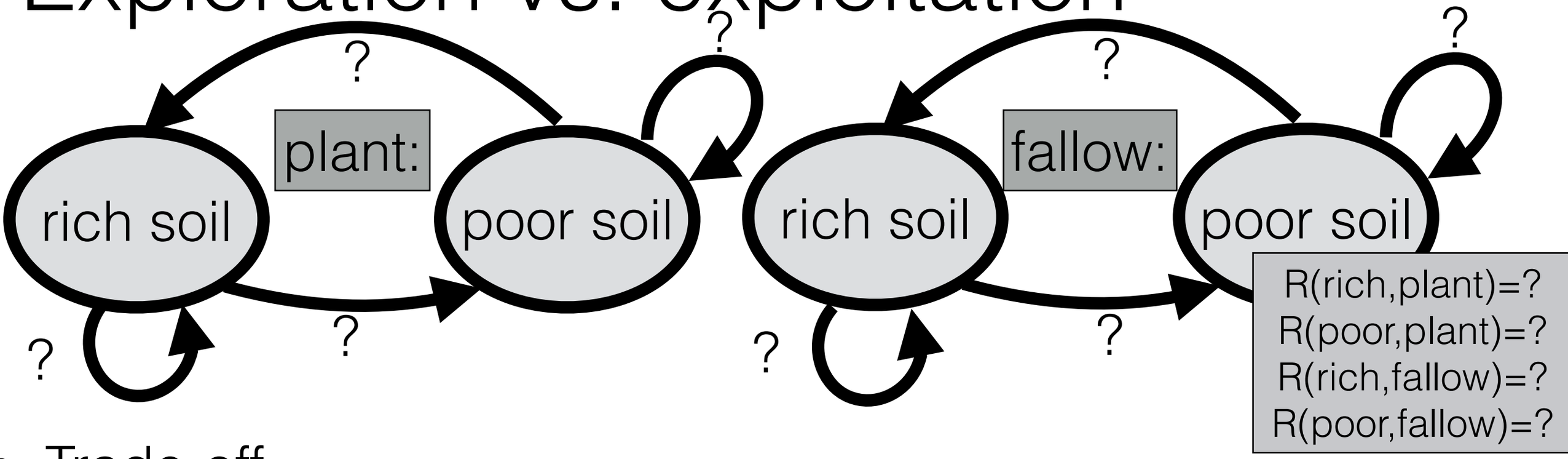

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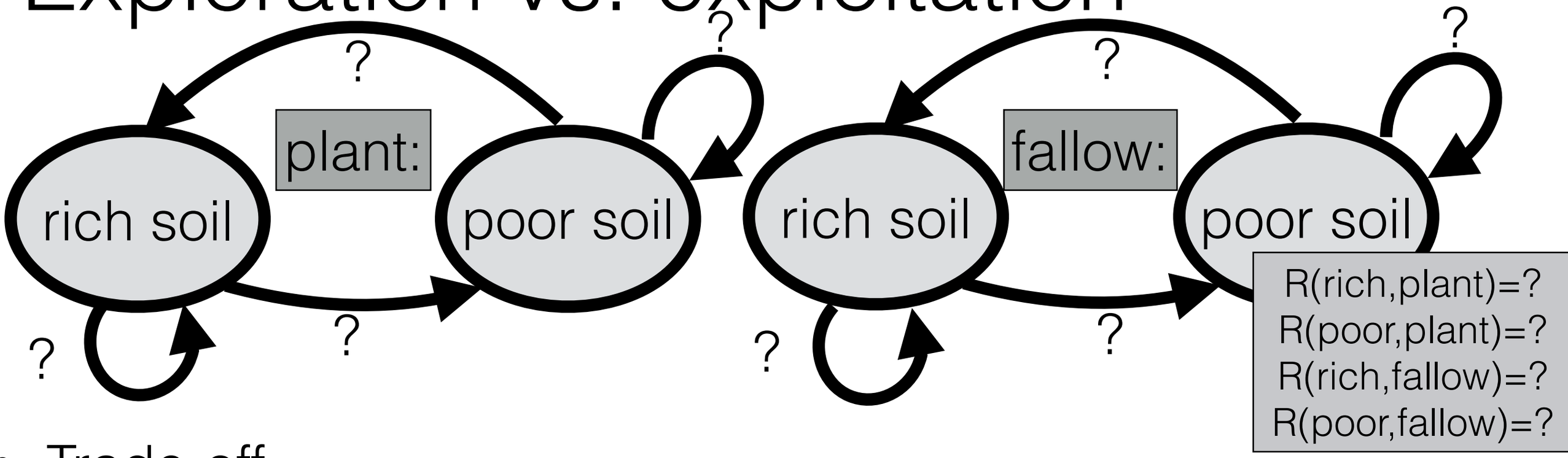

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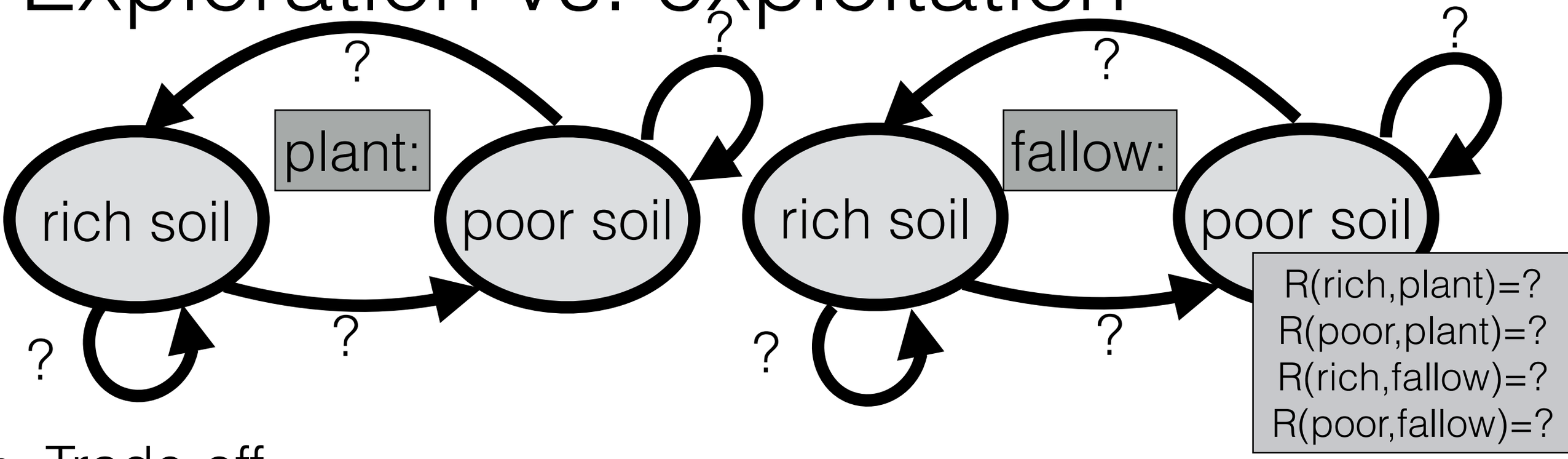

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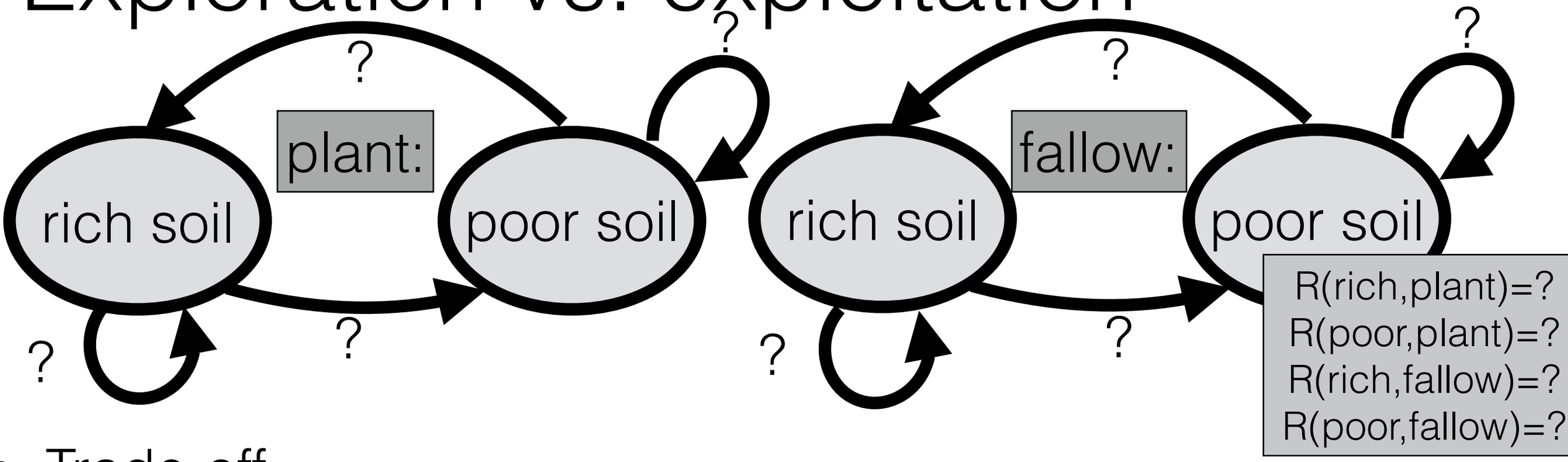

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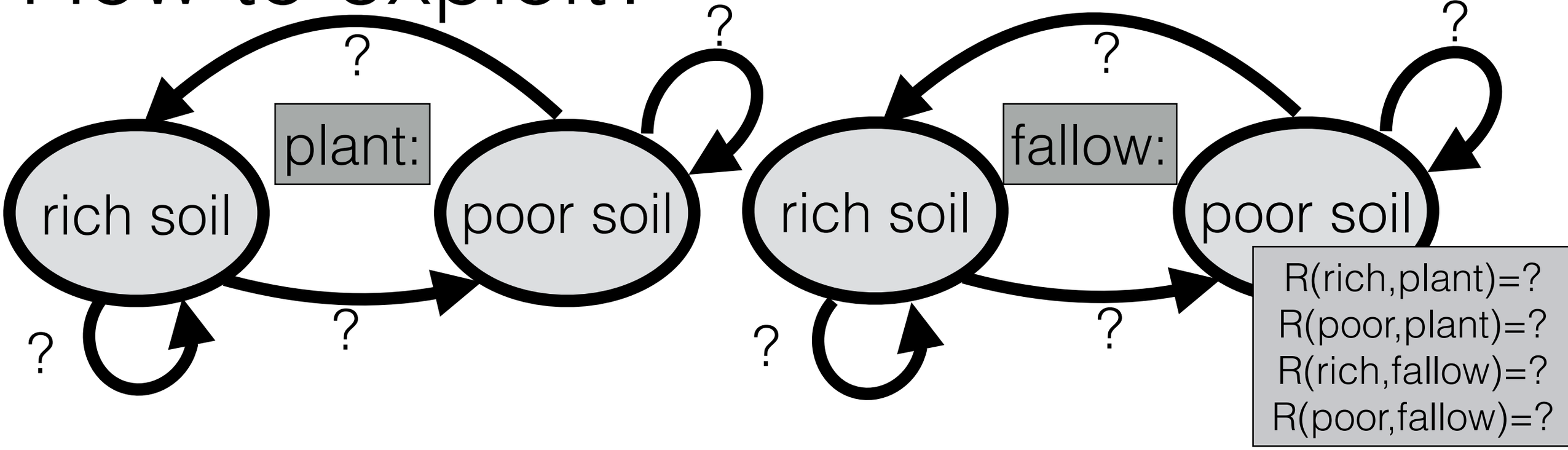
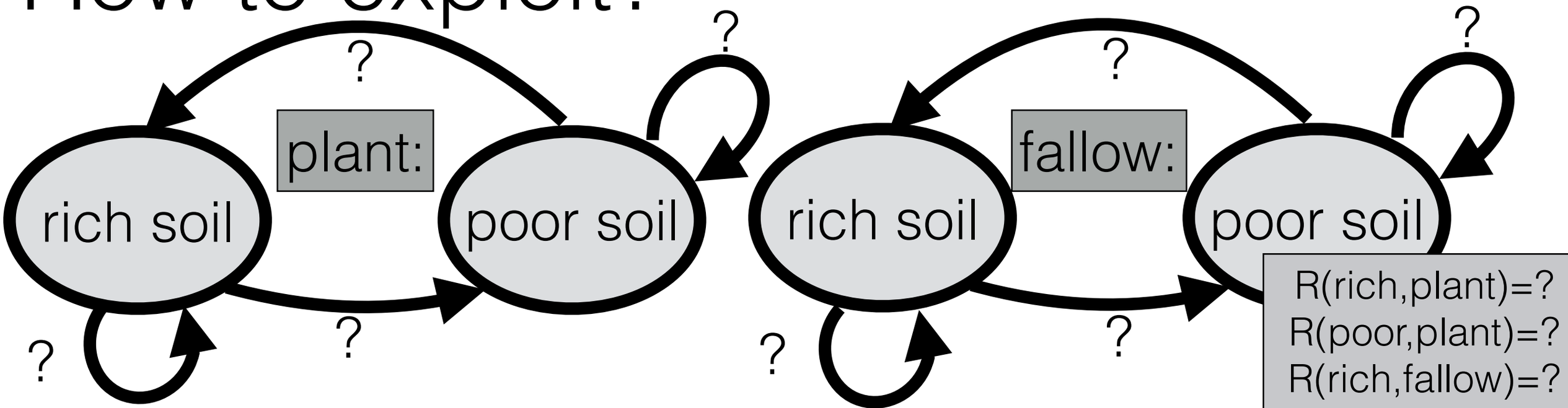
Need to specify how!

How to exploit?



How to exploit?



- If we knew *Q** ("value" of taking action *a* at state *s* if we make all the best actions after this step):

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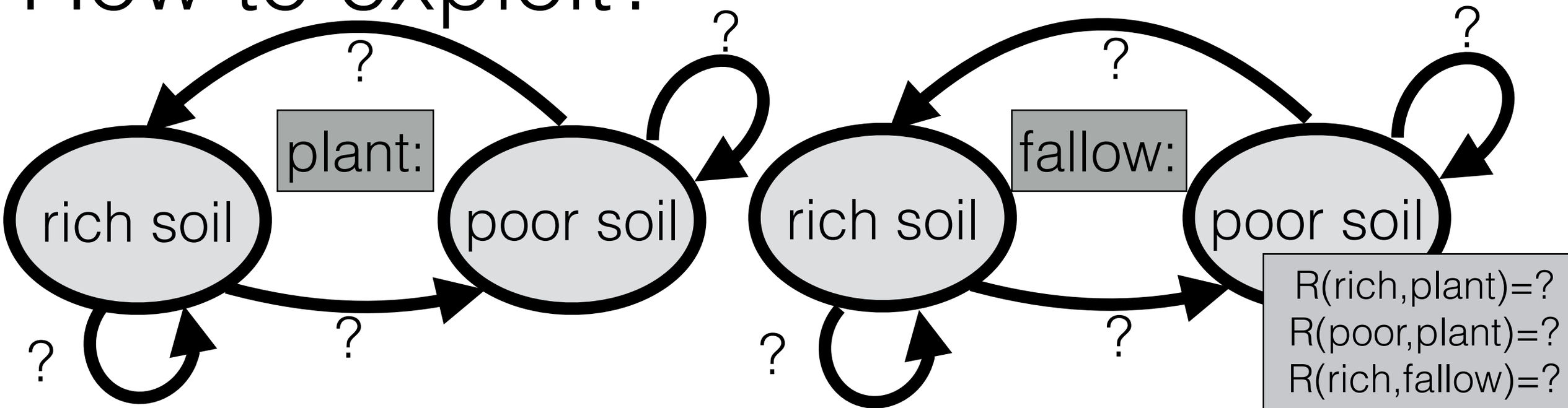

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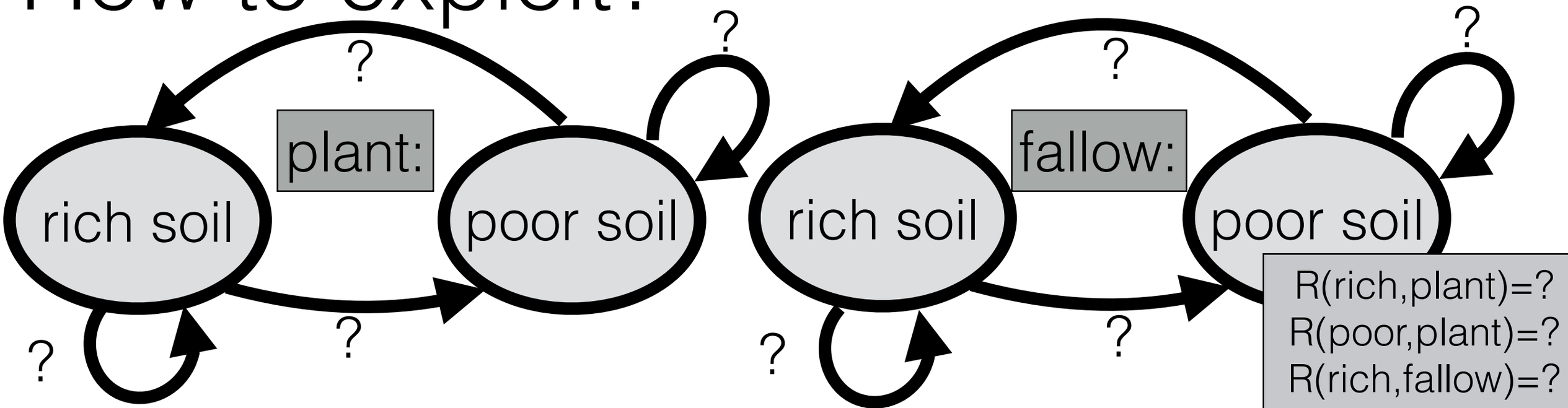

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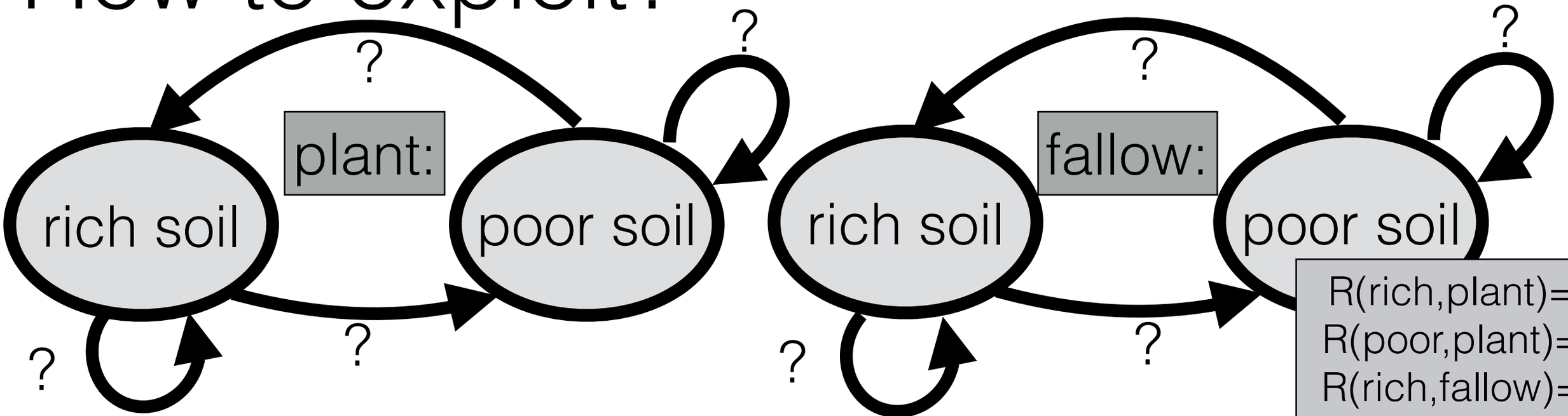

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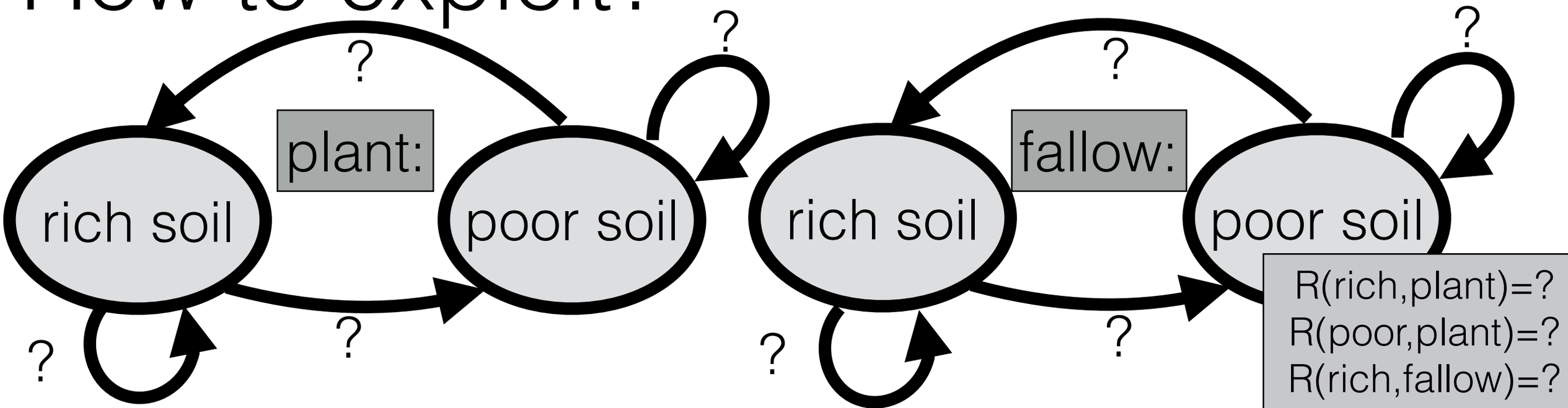

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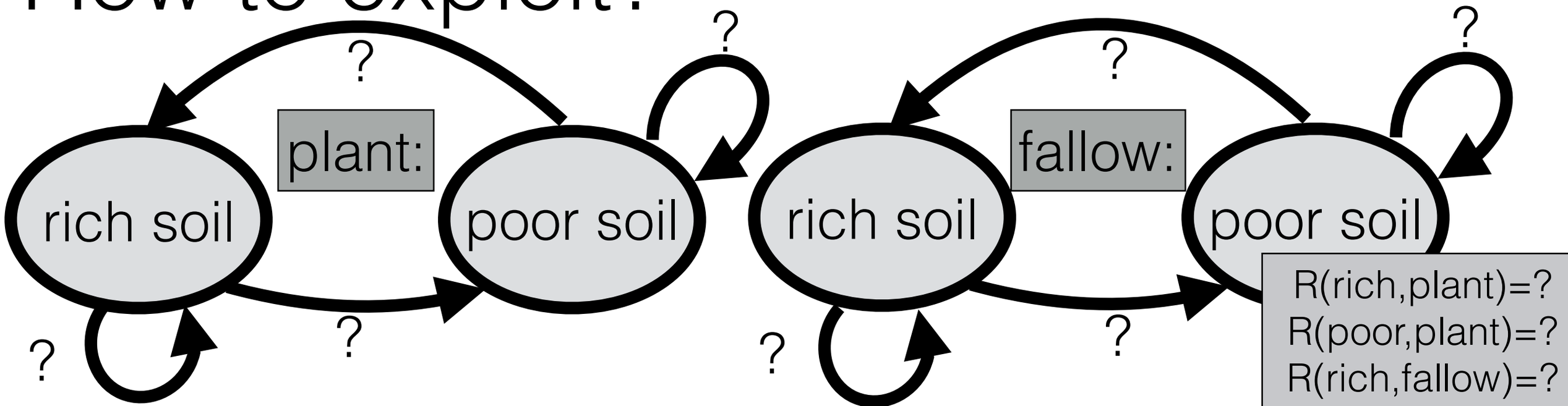
How to exploit?



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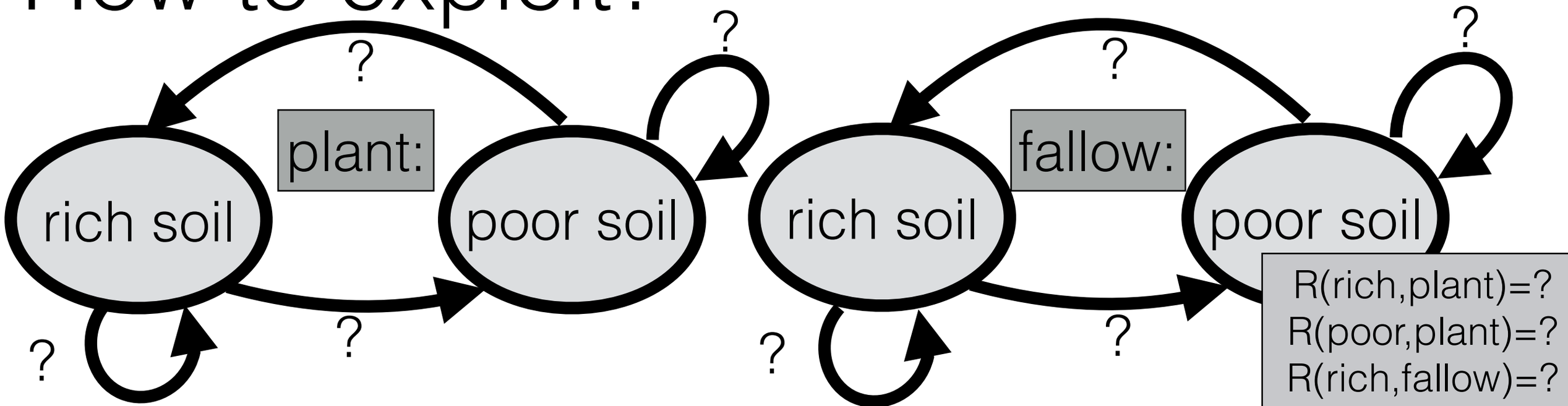
$$\pi_Q(s) = \arg\max_a Q(s,a)$$

- Question: how to get a good guess/estimate *Q* for *Q**?

How to exploit?



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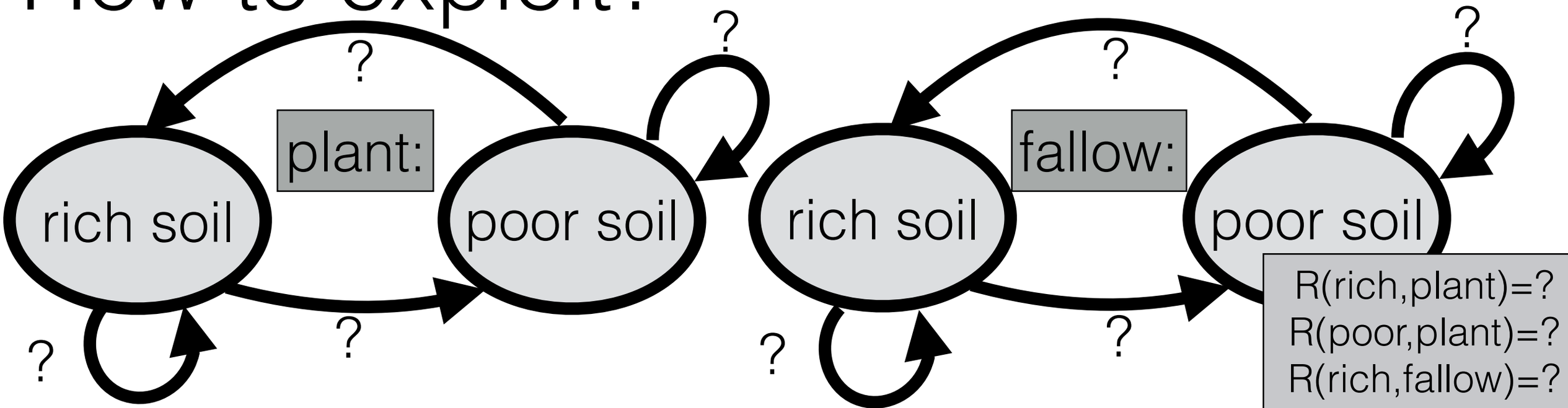
- Question: how to get a good guess/estimate *Q* for *Q**?
- Idea: Learn *Q* from the data we've seen so far

How to exploit?



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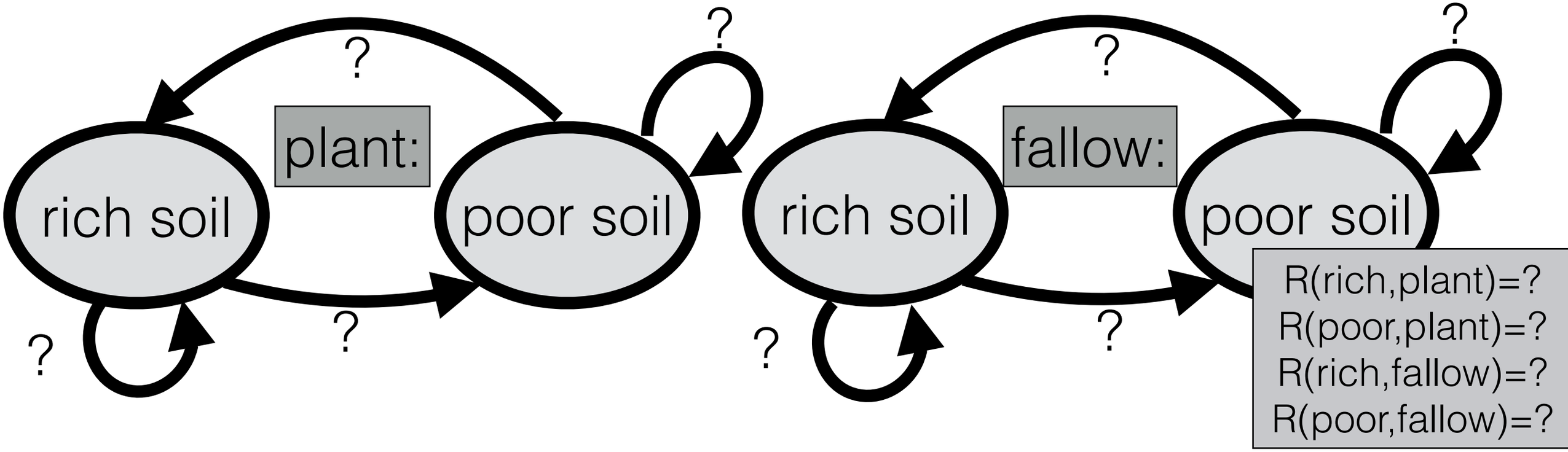
- Idea: Learn Q from the data we've seen so far

Data at step t: $s^{(t)}, a^{(t)}, r^{(t)}, s^{(t+1)}$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plant:
rich soil
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fallow:
rich soil
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R(rich,plant)=?
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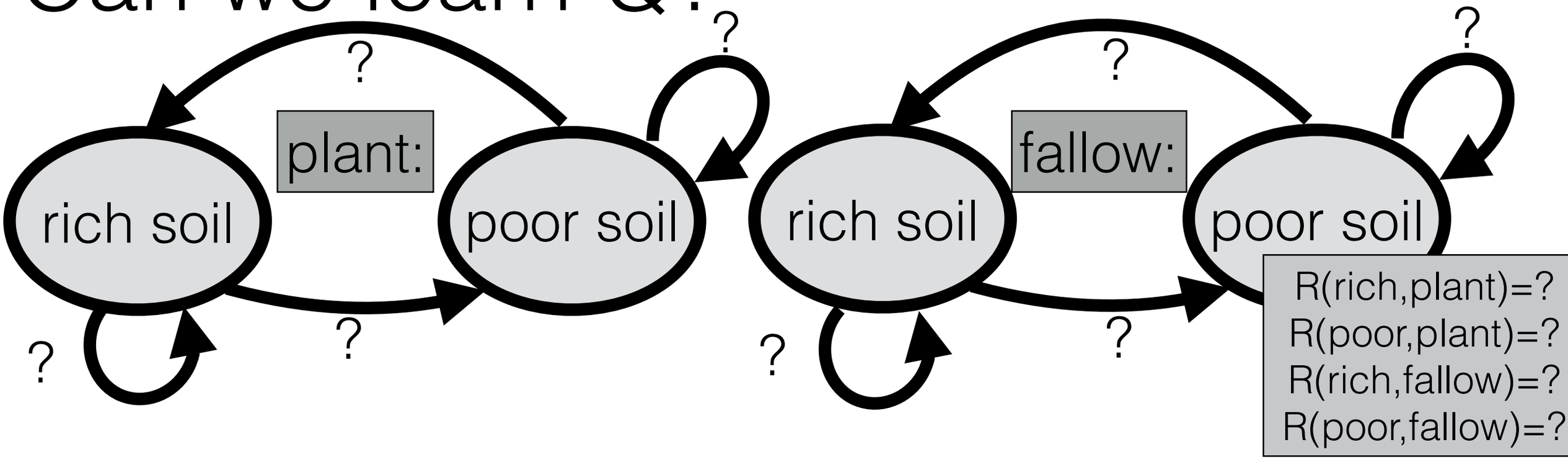
Can we learn *Q*?



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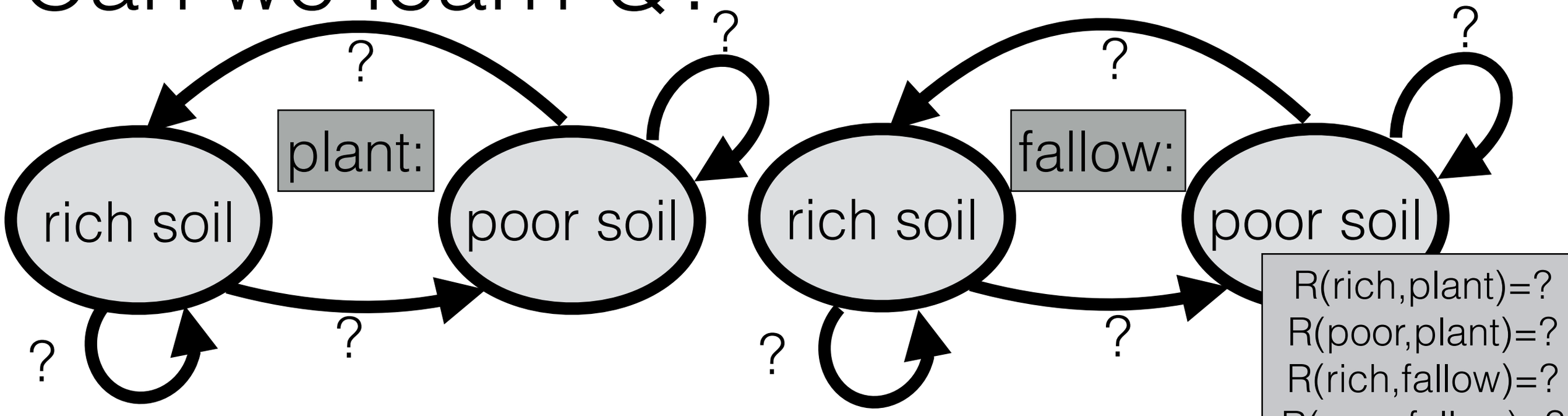

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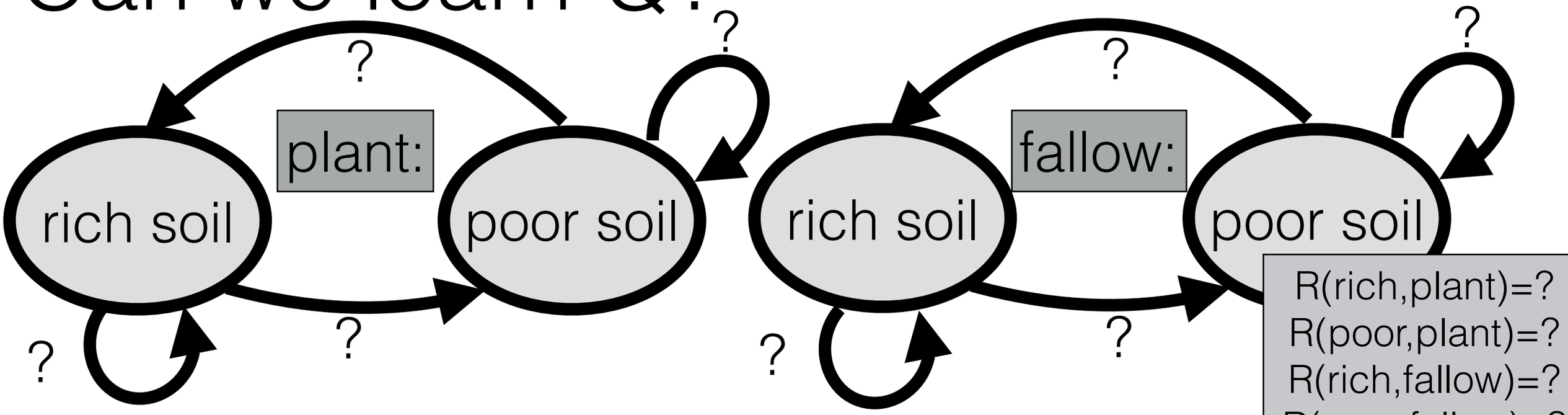
Can we learn *Q*?



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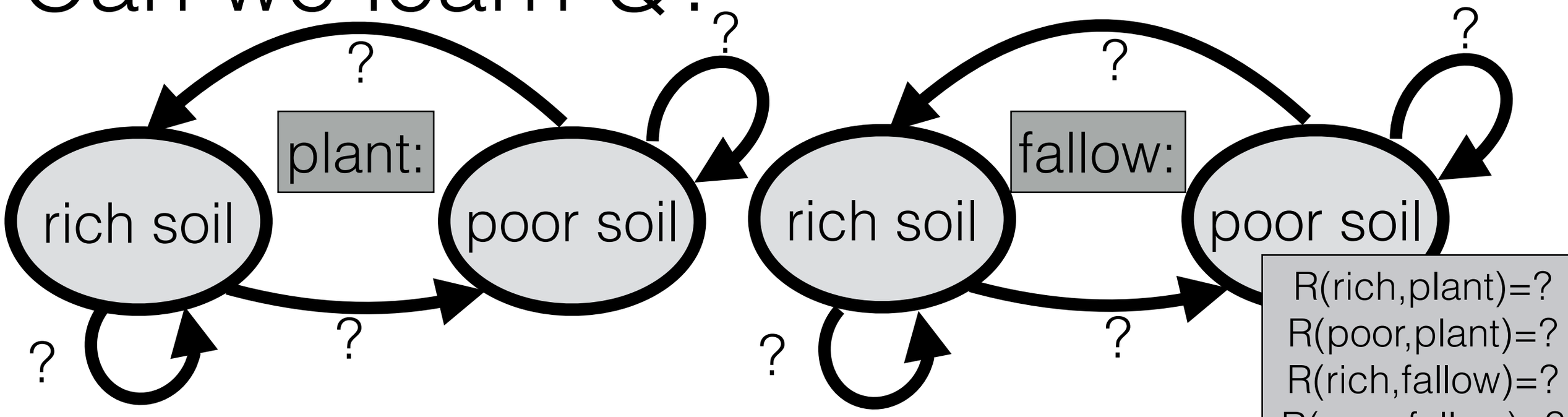
`Initialize` $s^{(1)} = s_0$

Can we learn *Q*?

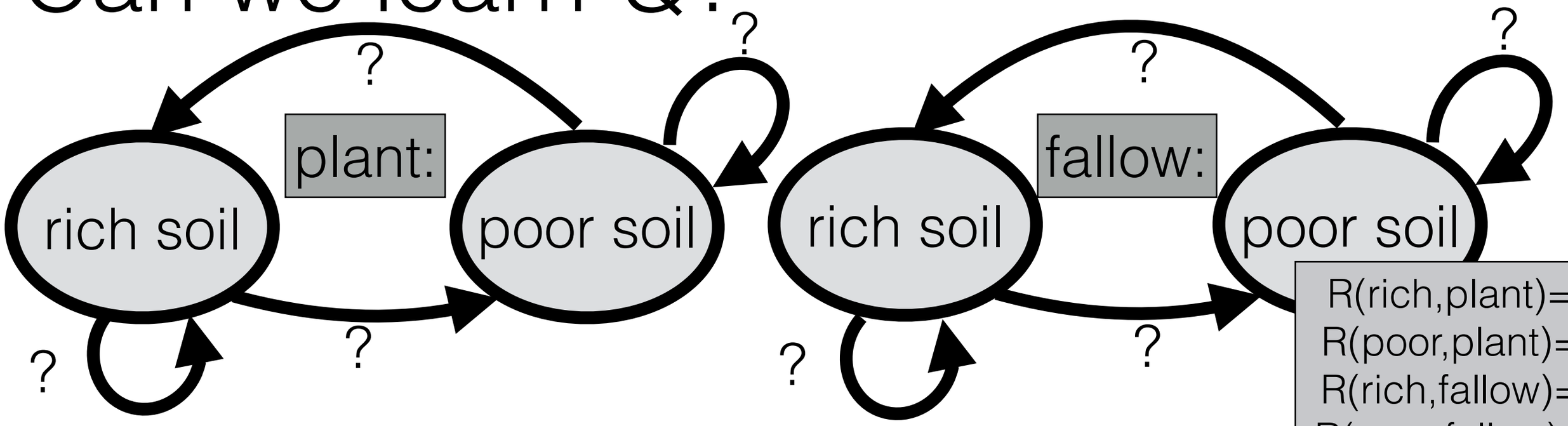


- Option 1: Estimate transition model *T* and reward function *R*

Initialize $s^{(1)} = s_0$

Initialize: any s, a, s': $\hat{T}(s,a,s') = \frac{1}{|\mathcal{S}|}; \hat{R}(s,a) = 0$

Can we learn *Q*?



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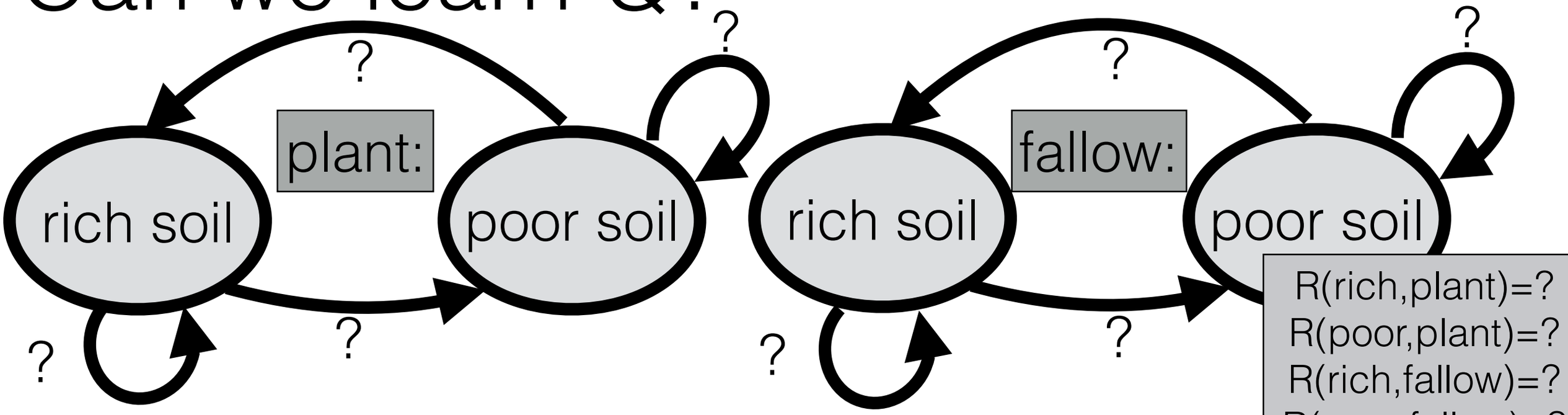

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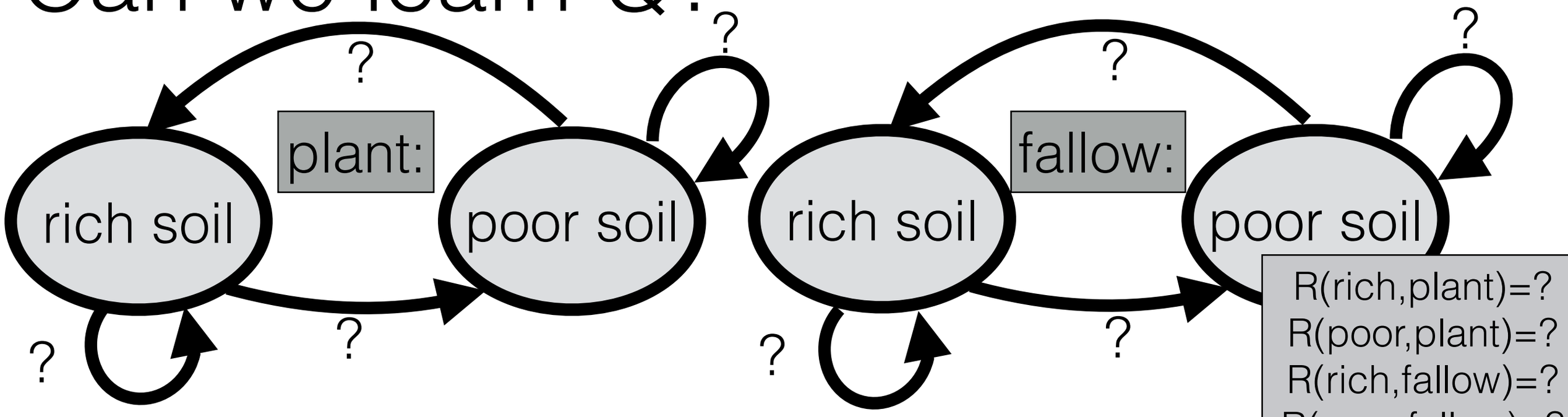
Initialize: any s, a, s': $\hat{T}(s,a,s') = \frac{1}{|S|}; \hat{R}(s,a) = 0; Q$

for t = 1, 2, 3, …

Can we learn *Q*?



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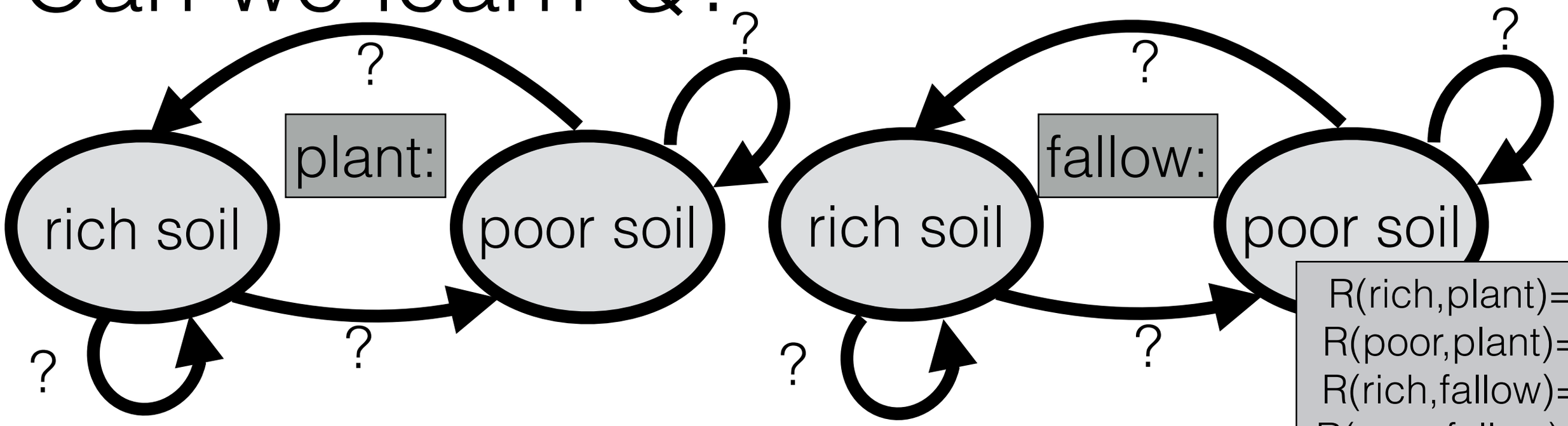

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E.g. ϵ**-greedy**

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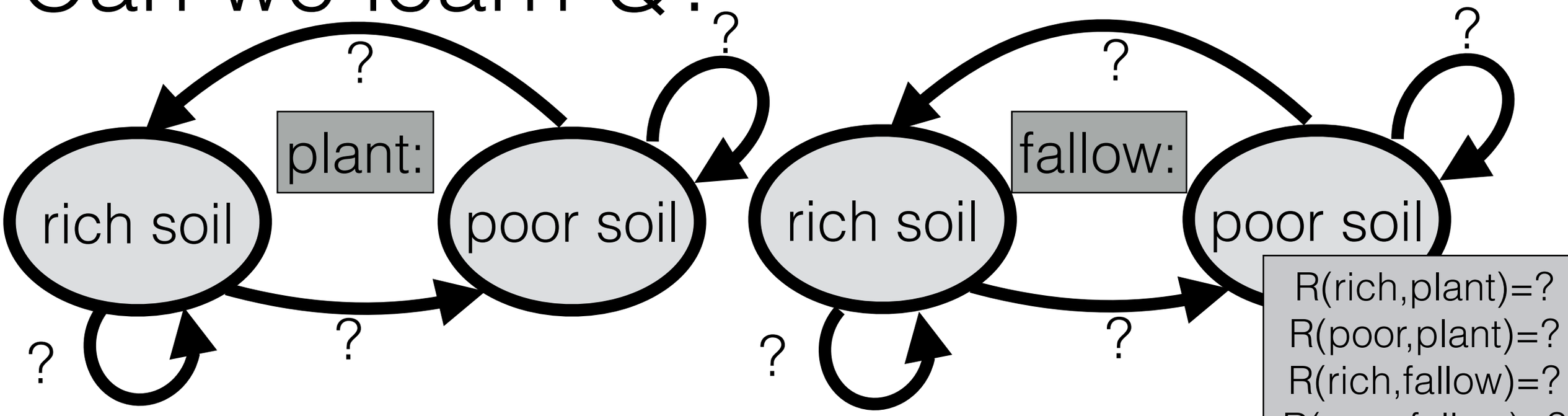

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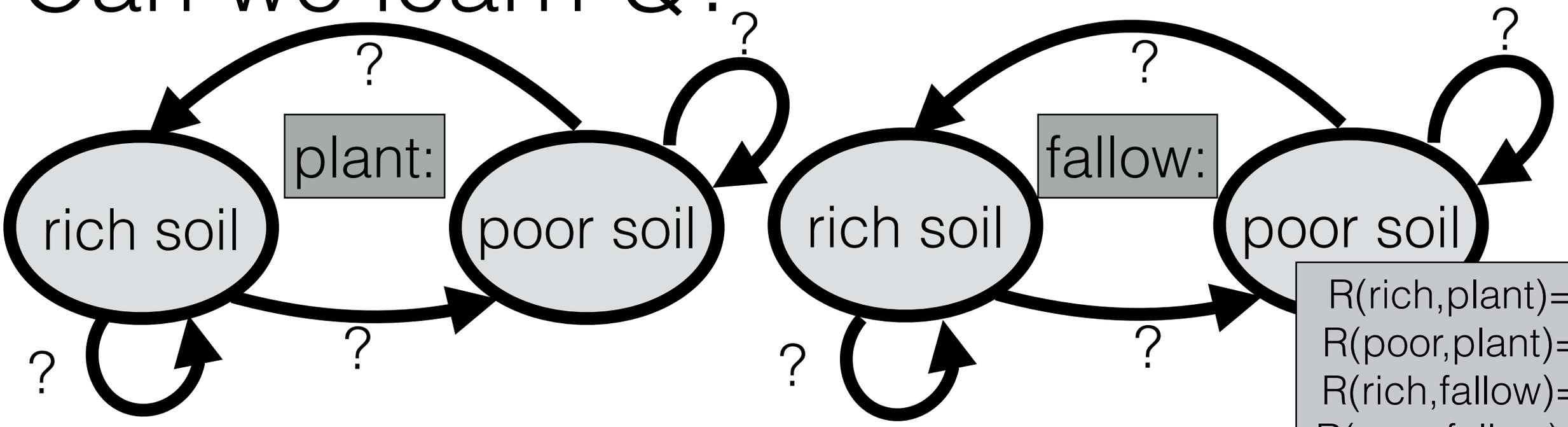

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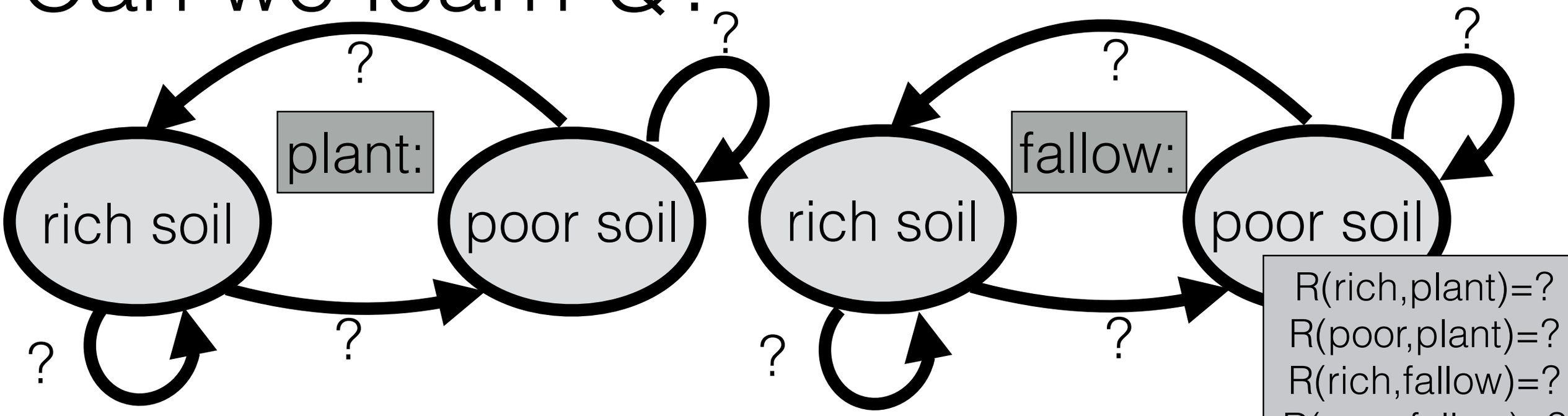

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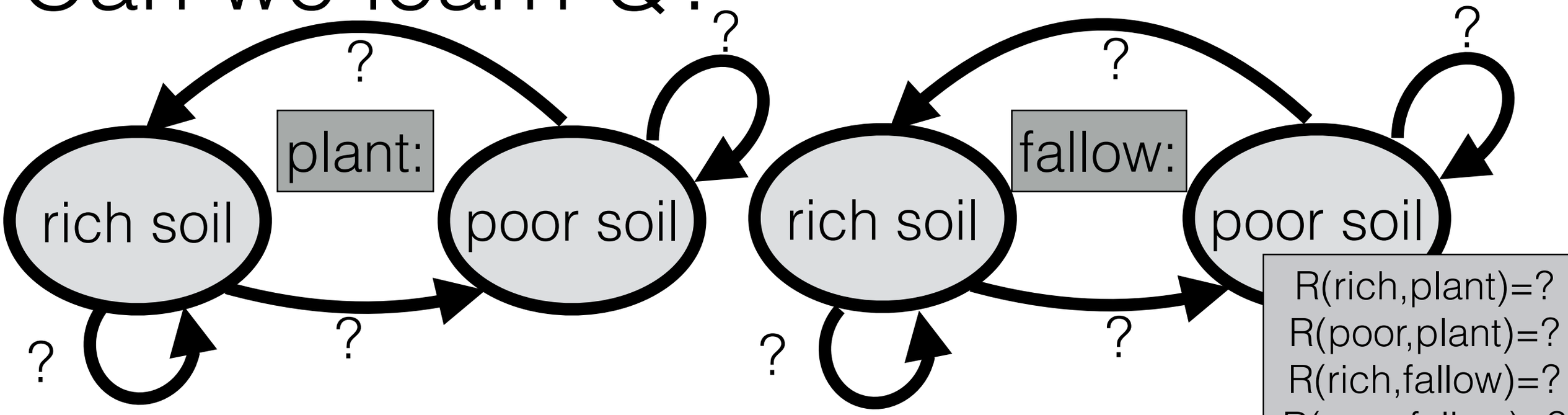

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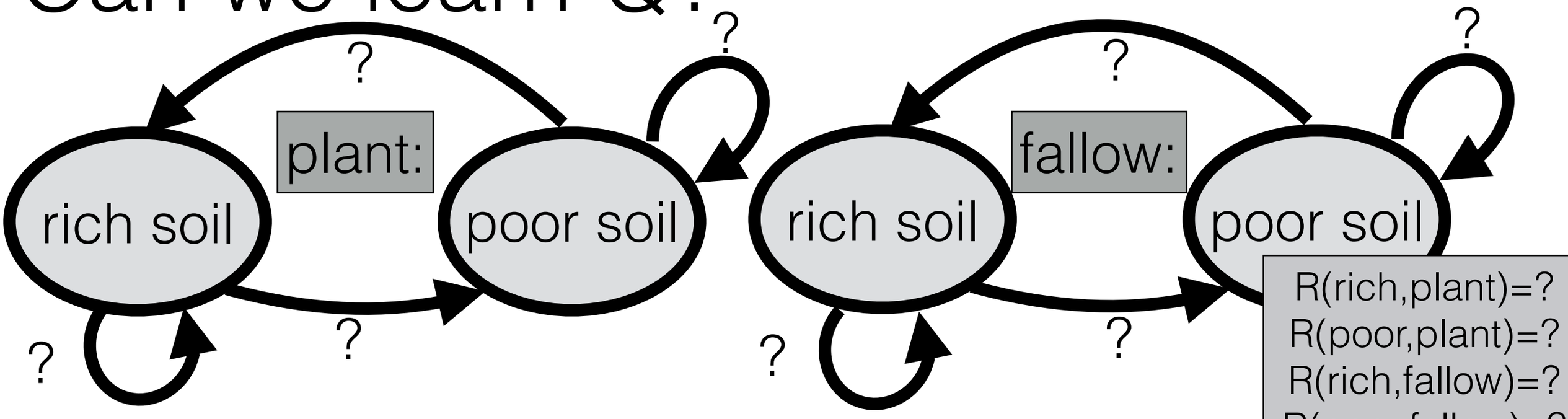

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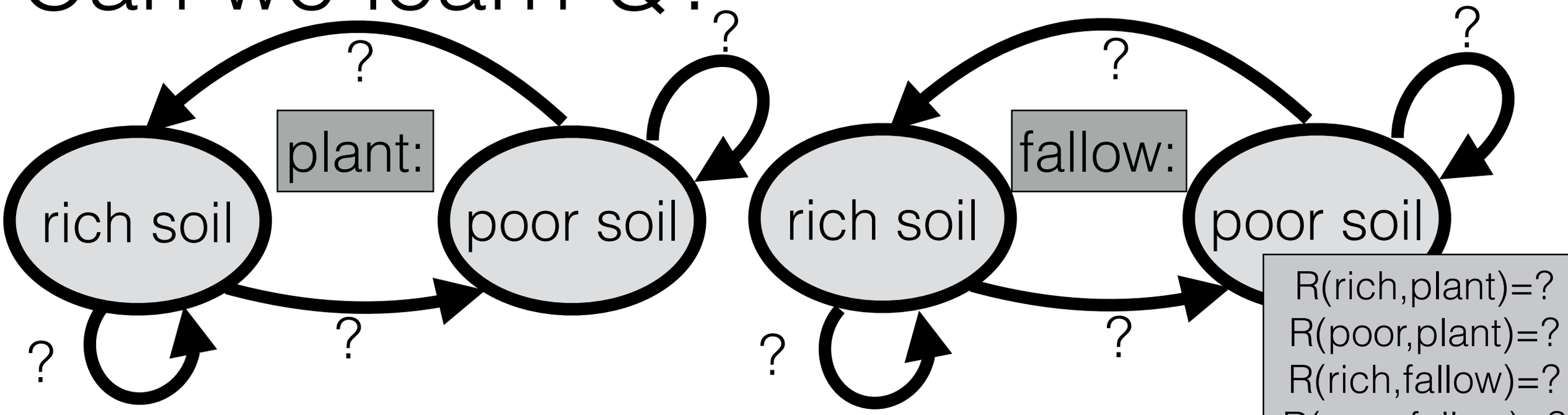

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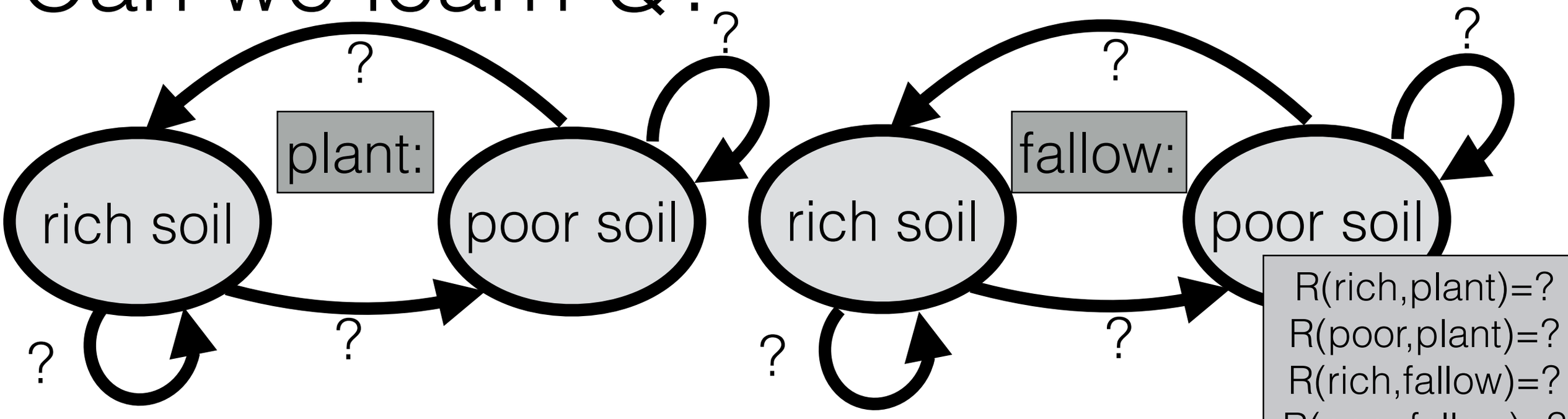

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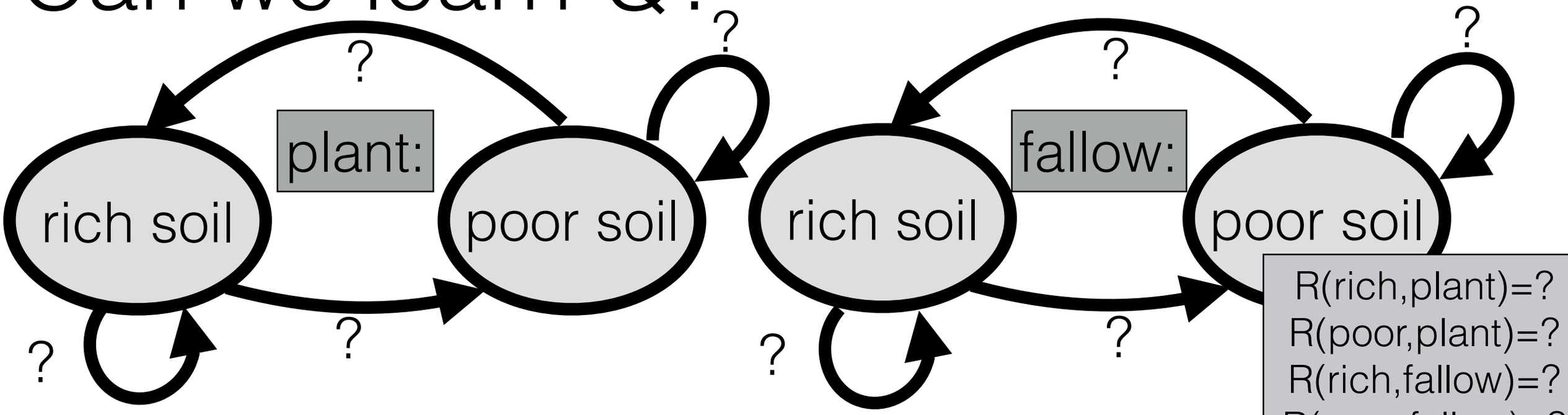

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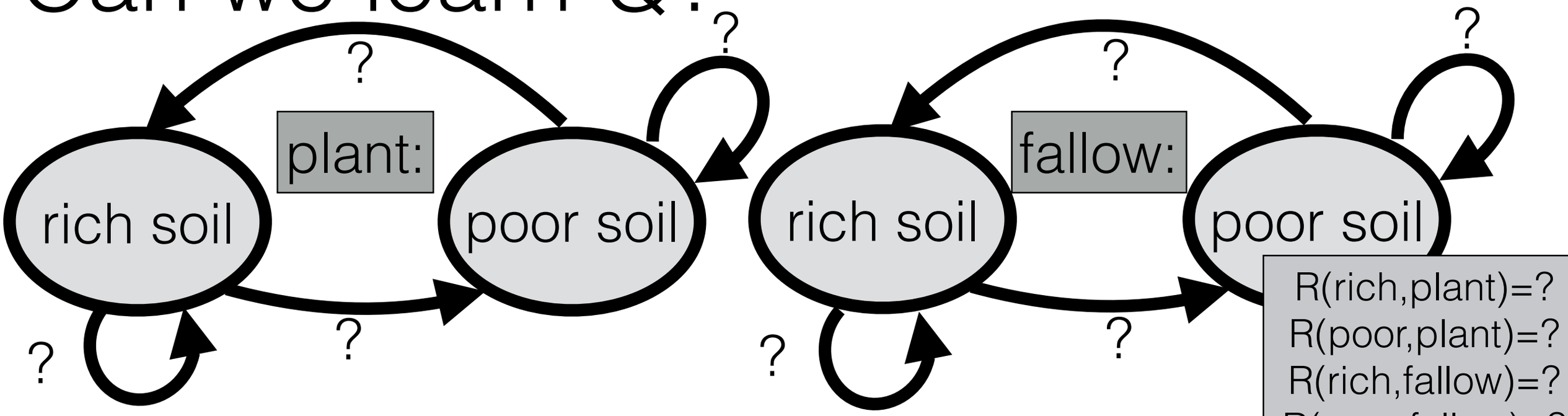

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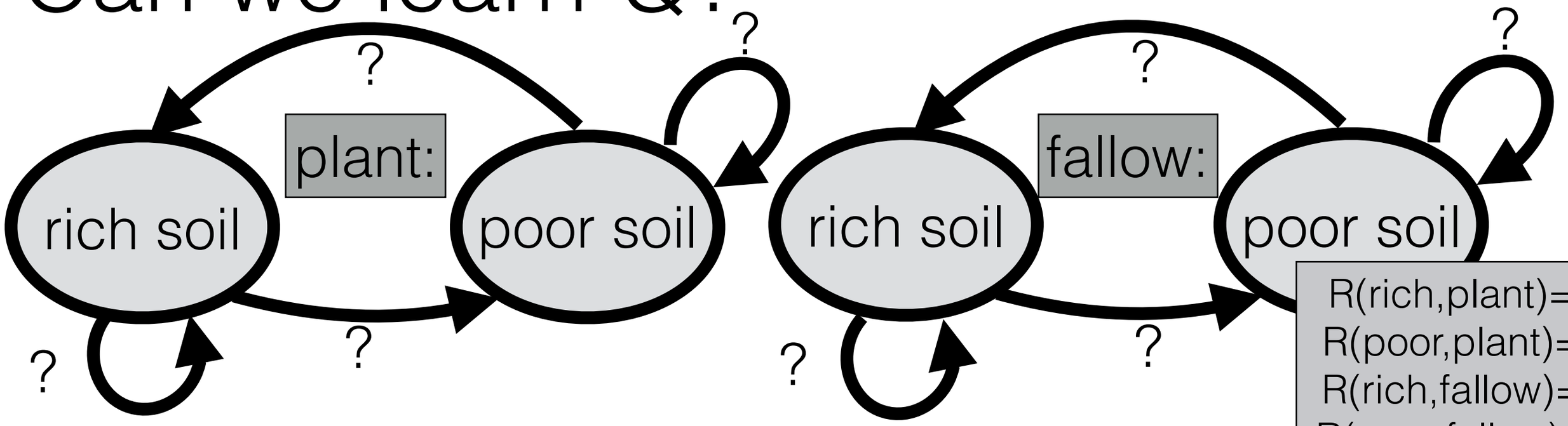

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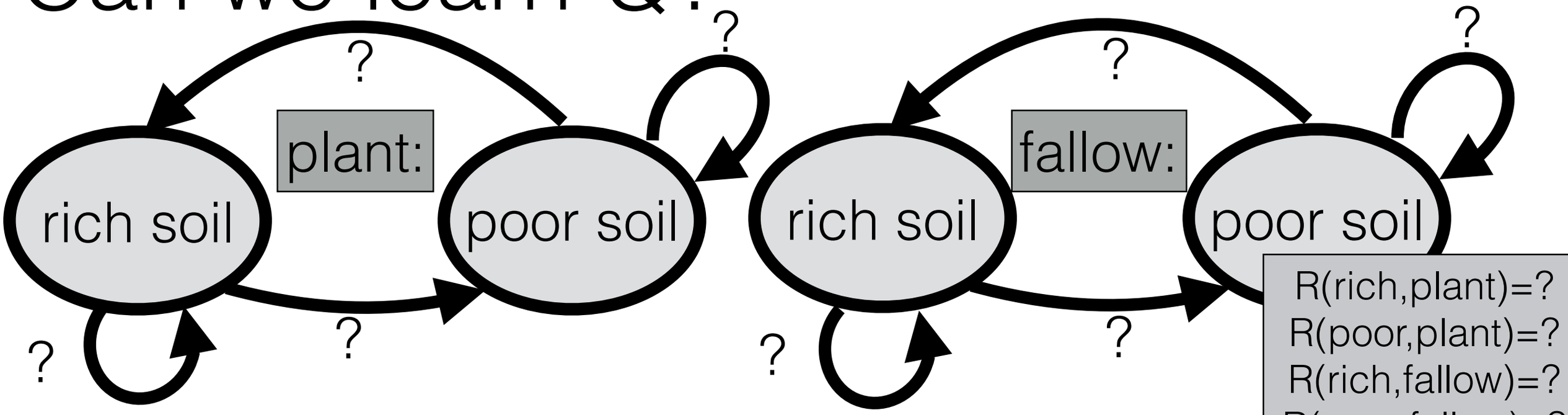

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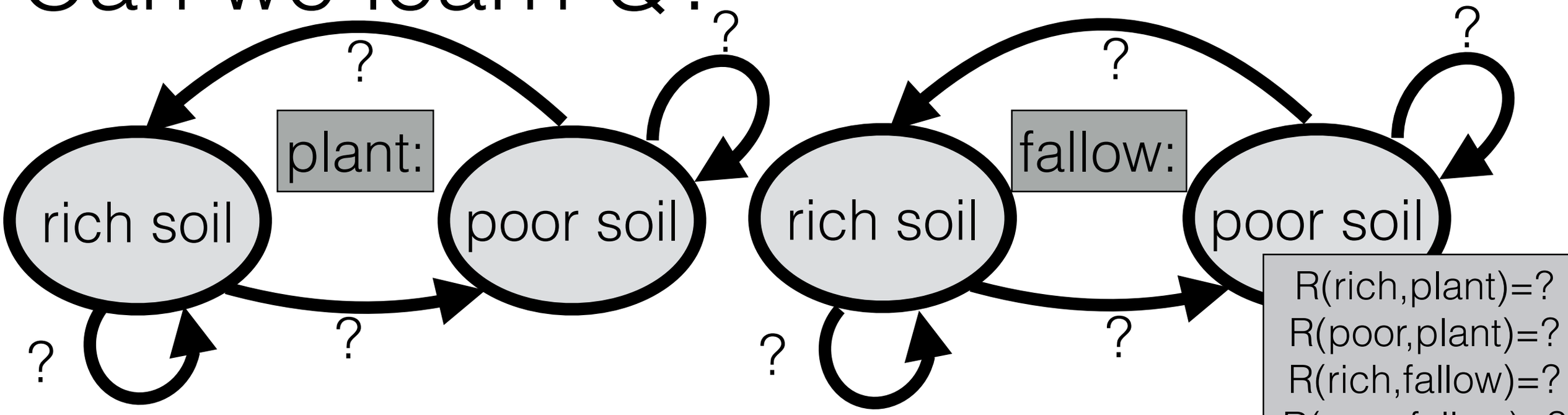

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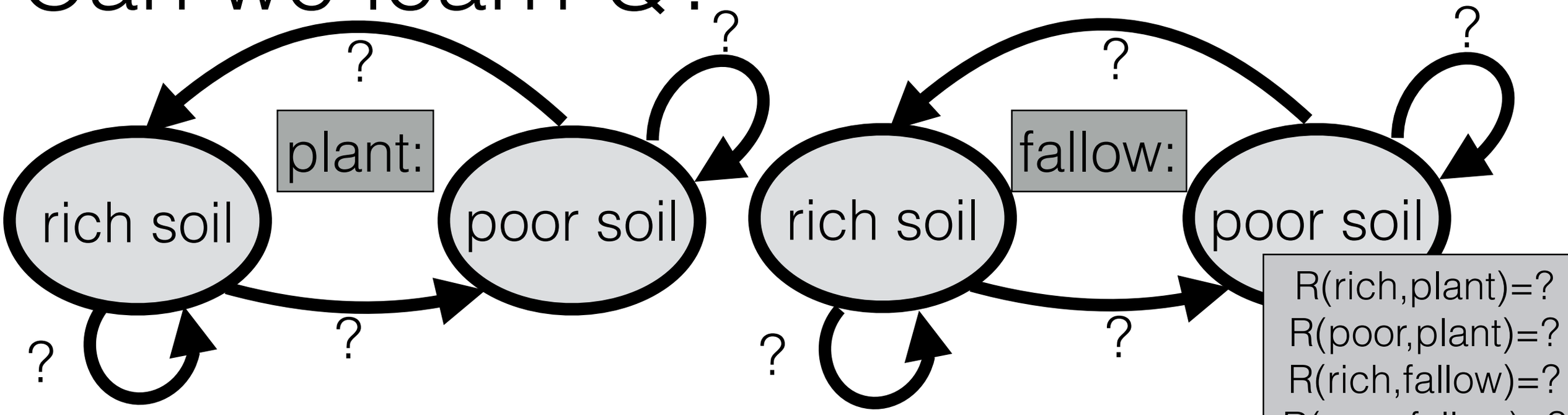

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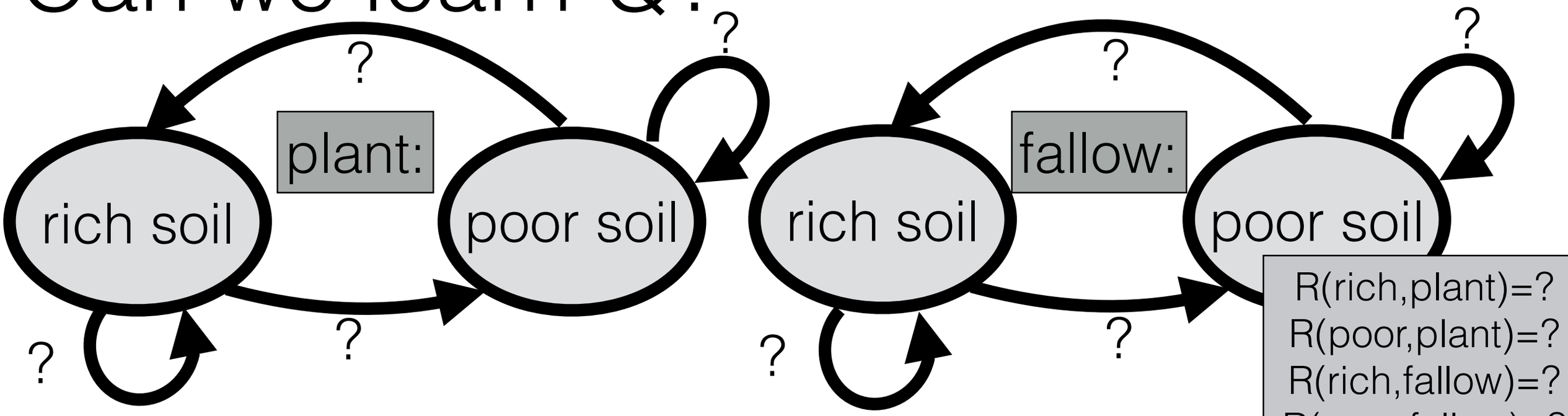

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    R̂(s^(t), a^(t)) = r^(t)
    Any s,a,s': T̂(s,a,s') = (1 + Σ_{i=1}^{t} 1{s^(i)=s, a^(i)=a, s^(i+1)=s'}) / (|S| + Σ_{i=1}^{t} 1{s^(i)=s, a^(i)=a})
    Q = infinite-horizon-value-iteration(R̂, T̂)
```

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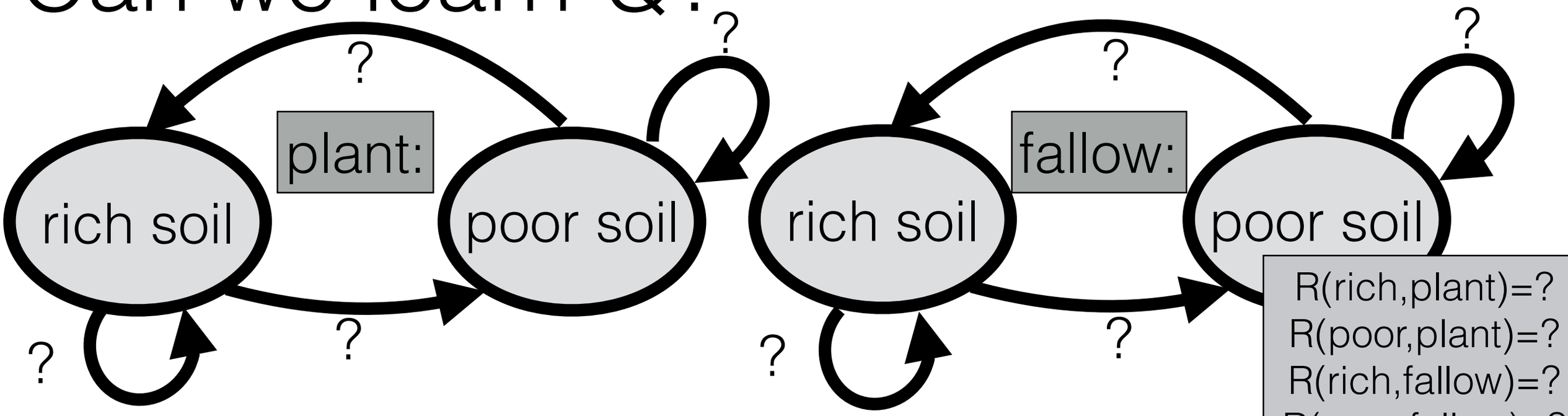

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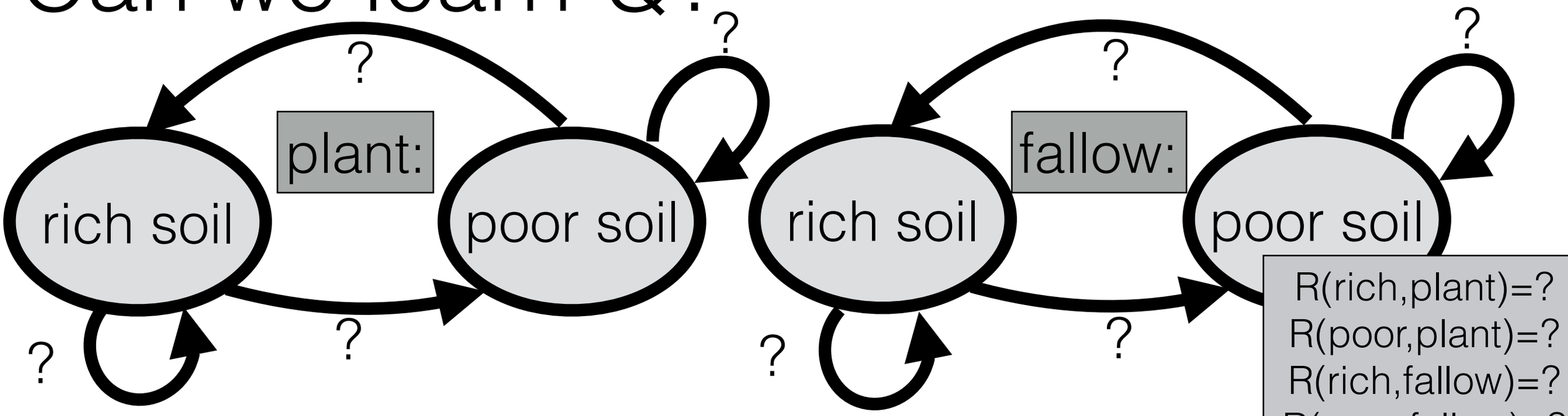

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Data Example: $\epsilon = 0.3$

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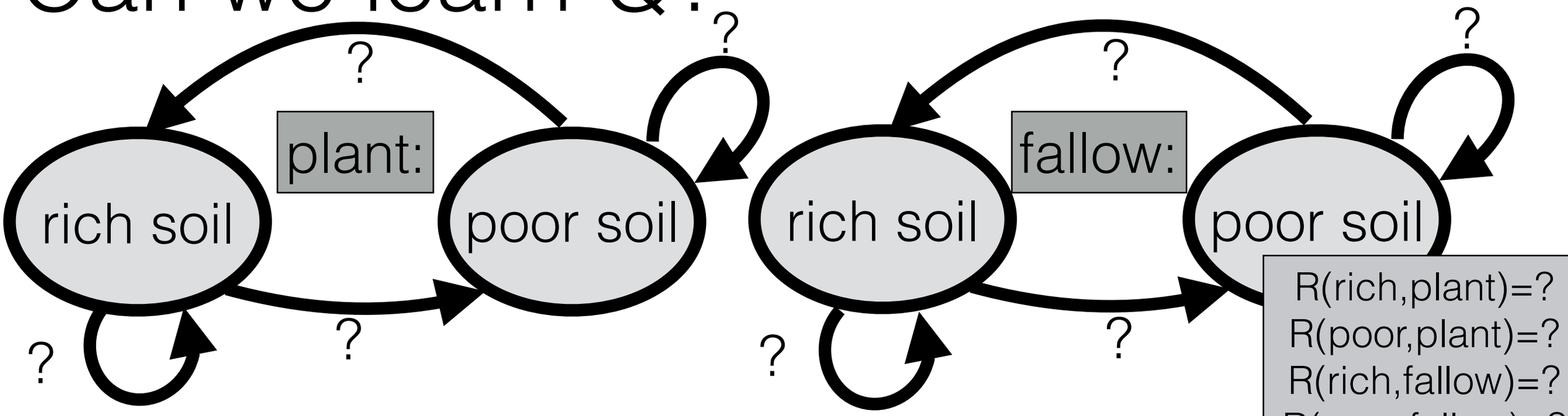

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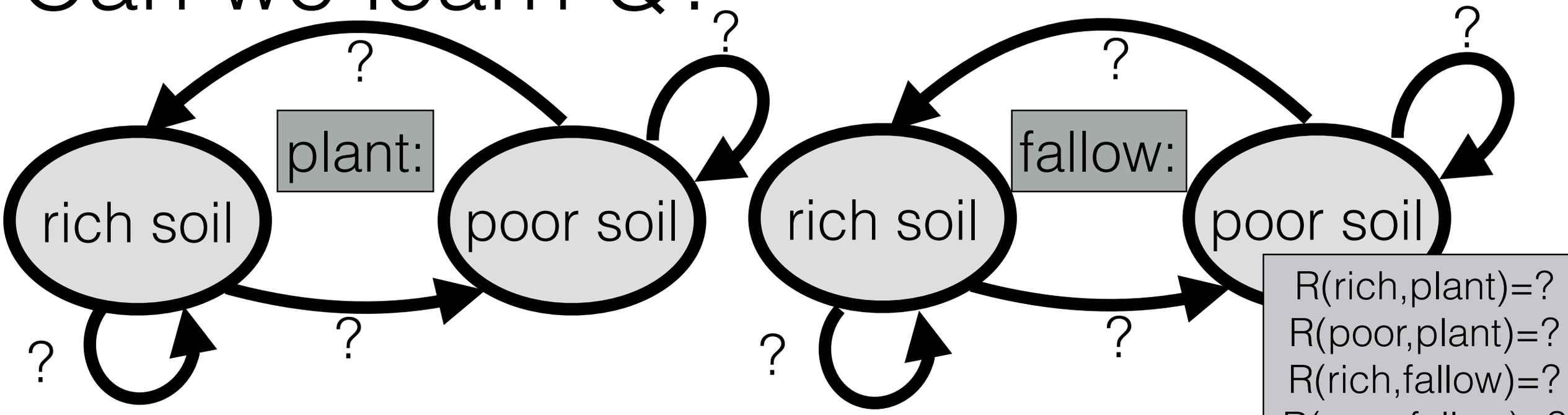

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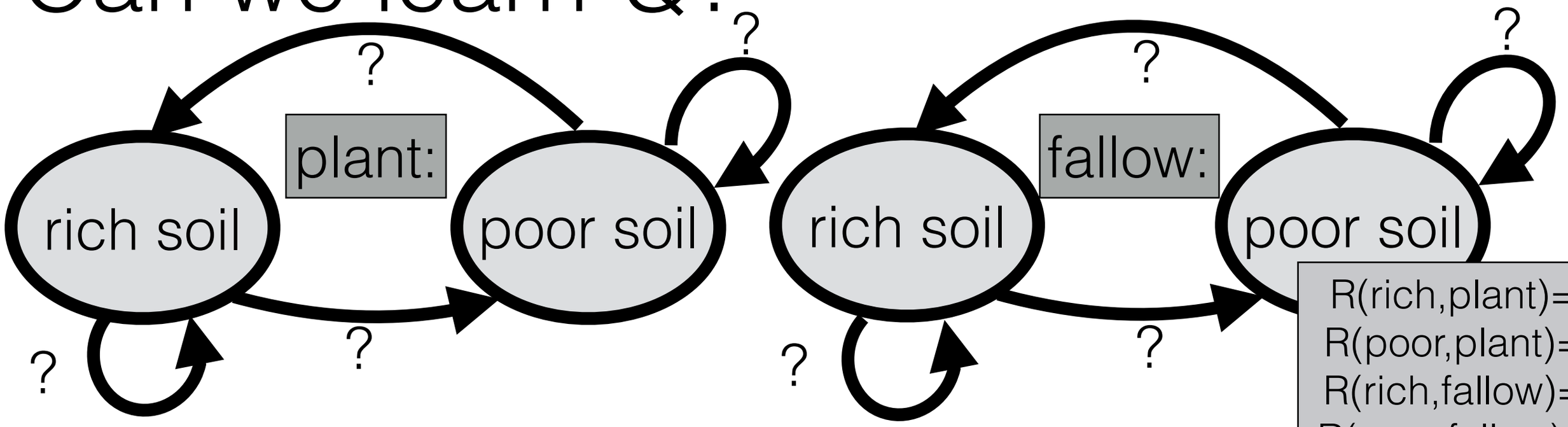

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Data

Example: $\epsilon = 0.3; \gamma = 0.99$
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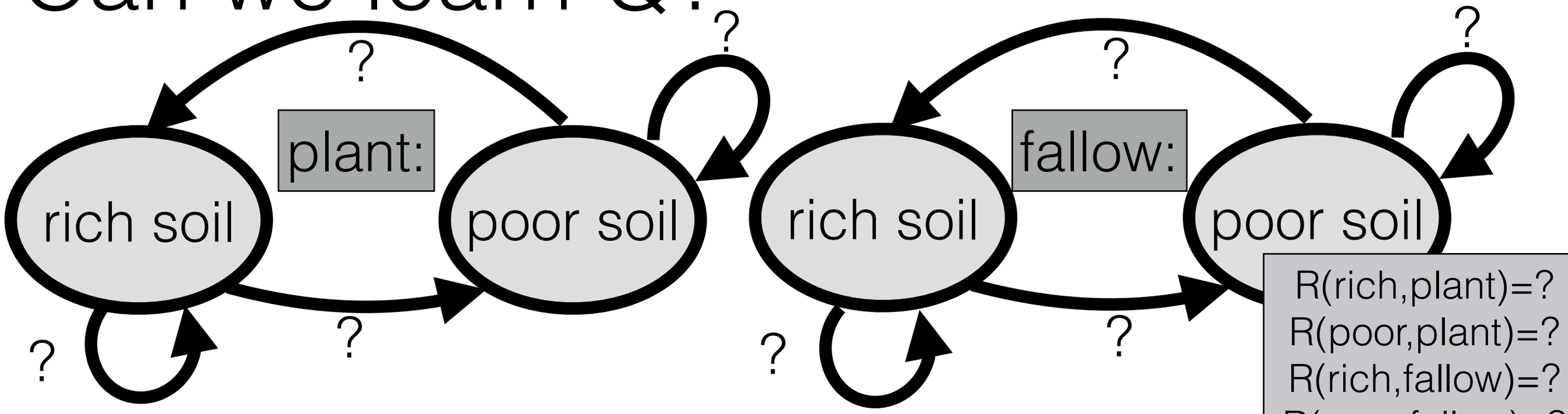
Q = infinite-horizon-value-iteration($\hat{R}, \hat{T}$)

E.g. **ϵ-greedy**

Can we learn *Q*?



- Option 1: Estimate transition model *T* and reward function *R*

Data

Example: $\epsilon = 0.3; \gamma = 0.99$
$s^{(1)} = \text{rich}$

Initialize $s^{(1)} = s_0$

Initialize: any s, a, s': $\hat{T}(s, a, s') = \frac{1}{|S|}; \hat{R}(s, a) = 0; Q$

for t = 1, 2, 3, …

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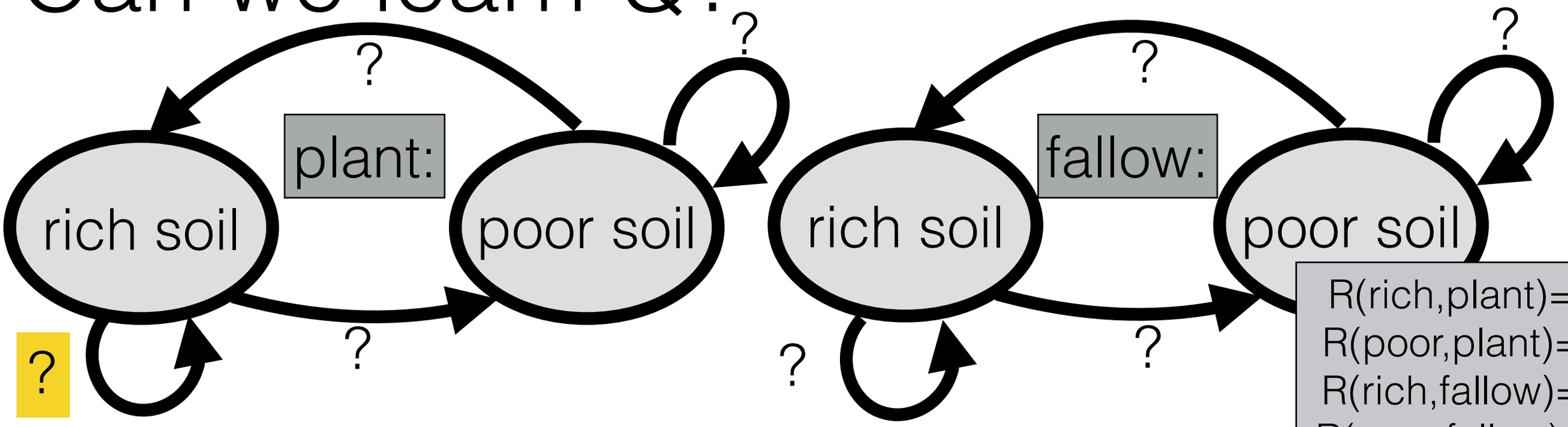

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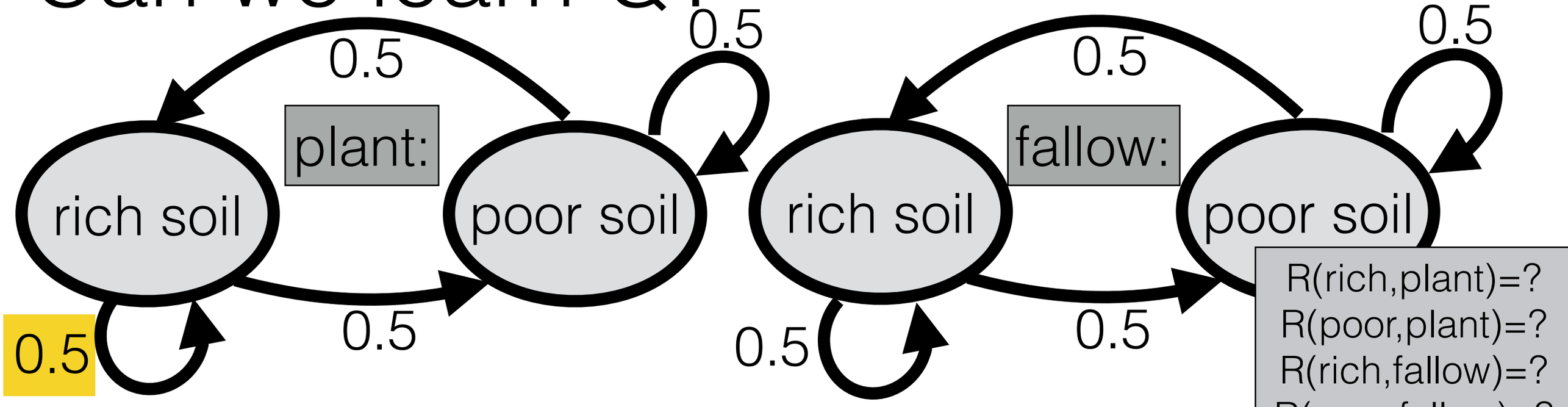

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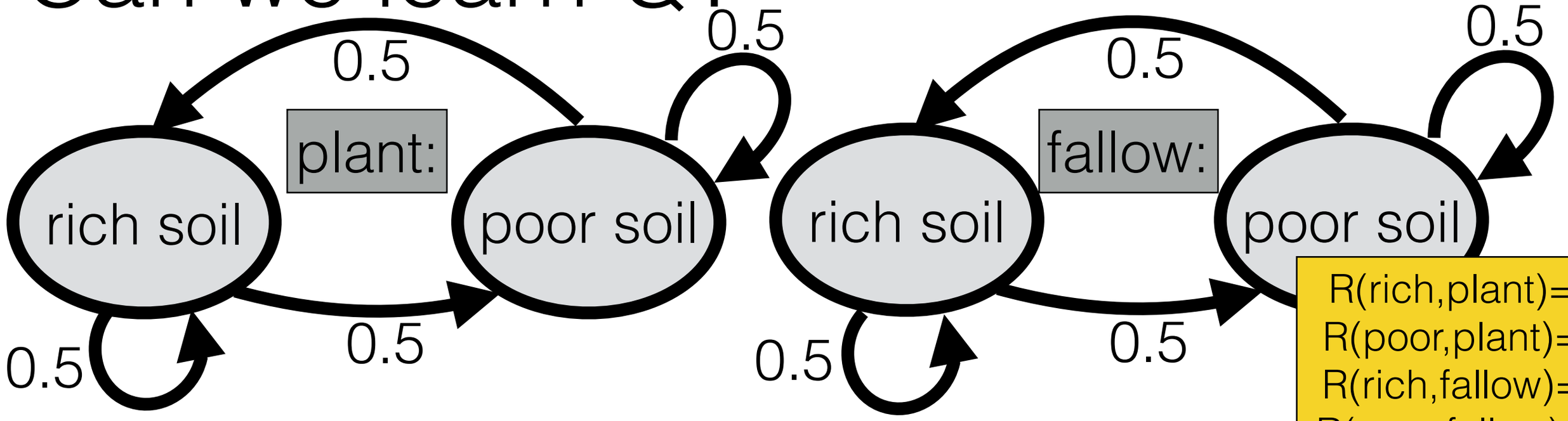

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Example: $\epsilon = 0.3; \gamma = 0.99$
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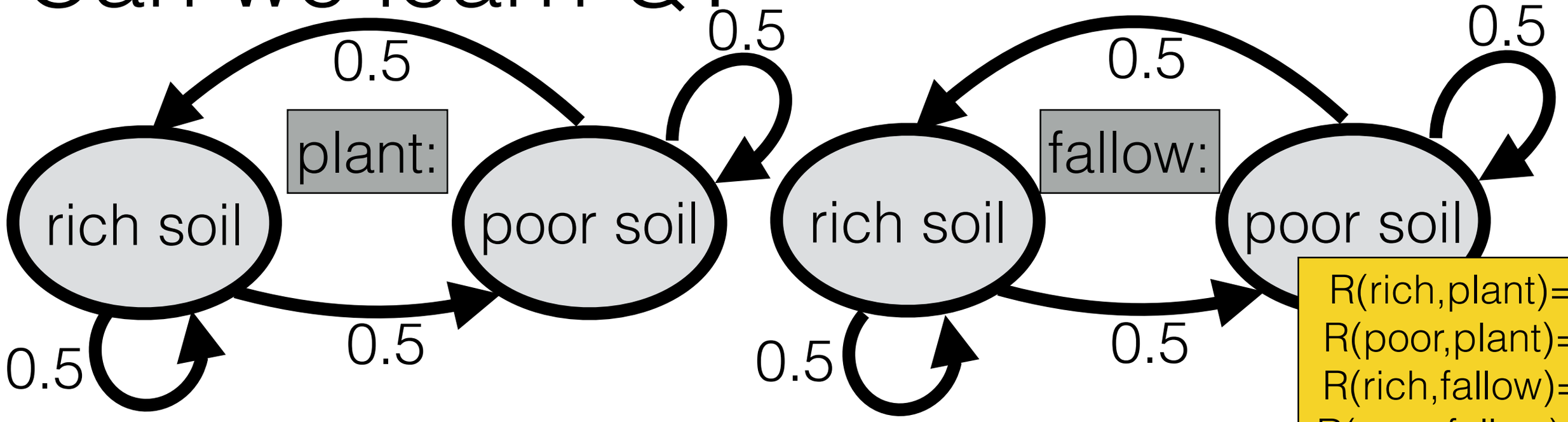

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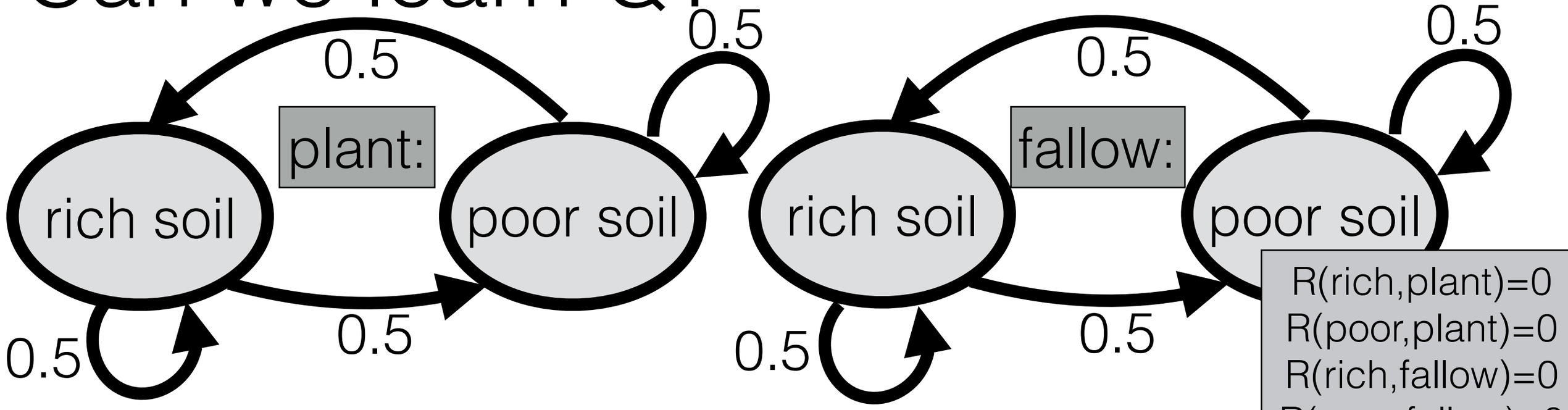

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Data

Example: $\epsilon = 0.3; \gamma = 0.99$
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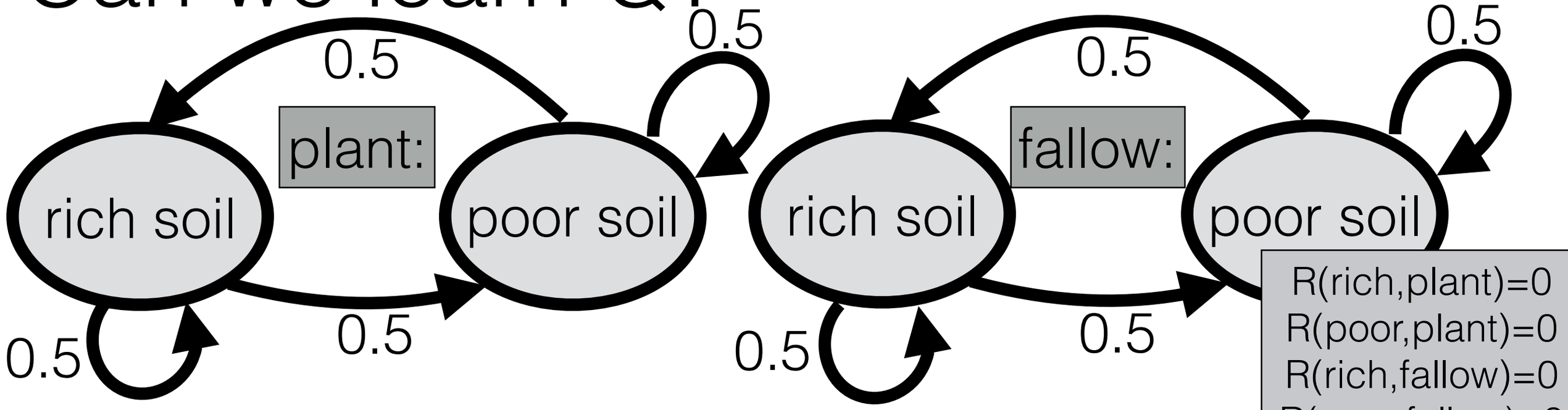

- Option 1: Estimate transition model *T* and reward function *R*

Data

Example: $\epsilon = 0.3; \gamma = 0.99$
$s^{(1)} = \text{rich; explore}$

Initialize $s^{(1)} = s_0$

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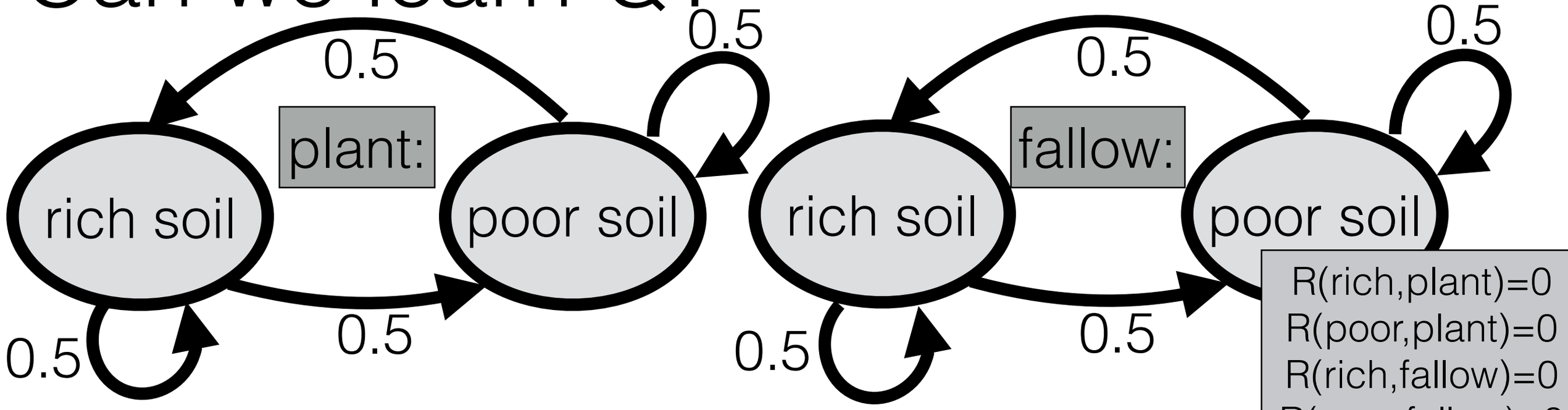

- Option 1: Estimate transition model *T* and reward function *R*

Data

Example: $\epsilon = 0.3; \gamma = 0.99$
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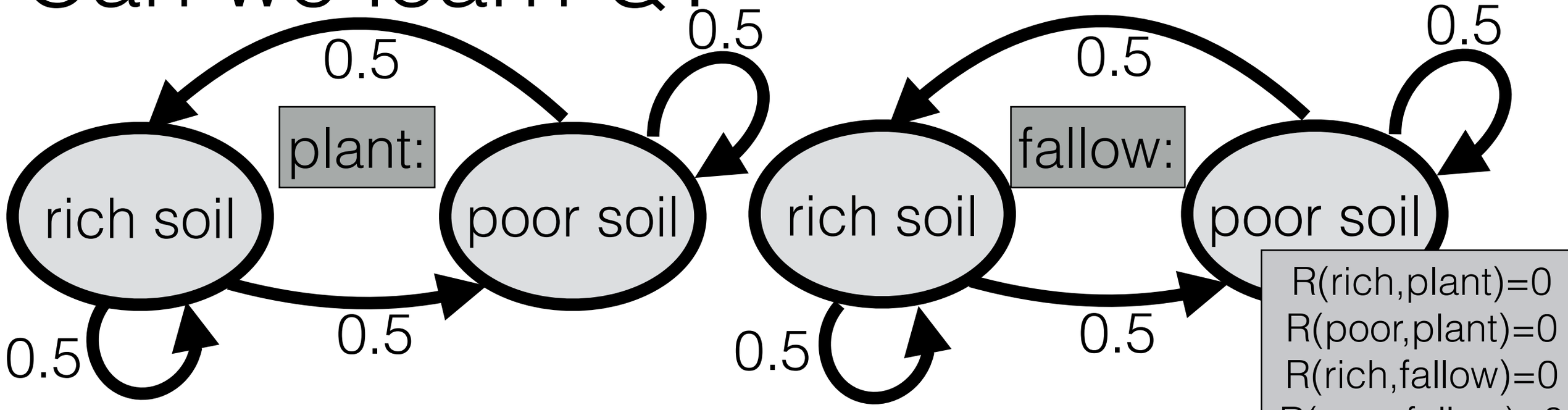

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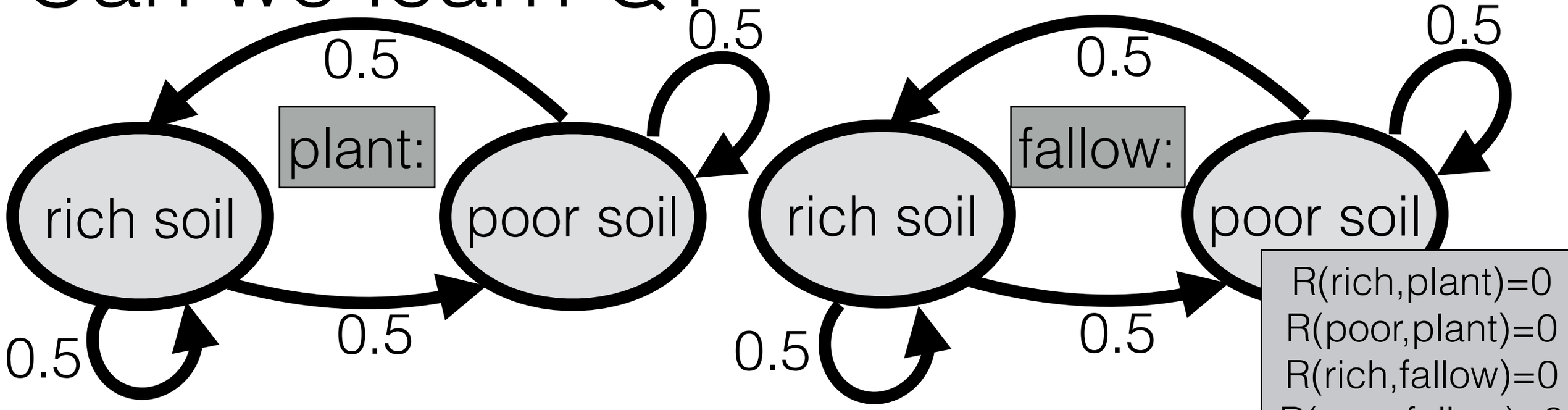

- Option 1: Estimate transition model *T* and reward function *R*

Data

Example: $\epsilon = 0.3; \gamma = 0.99$
$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$
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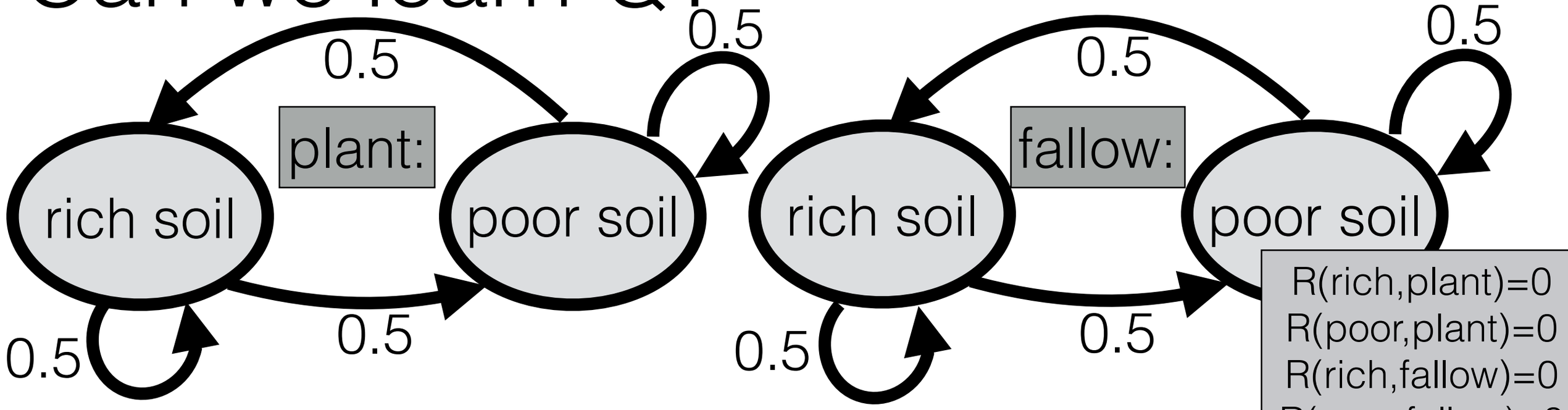

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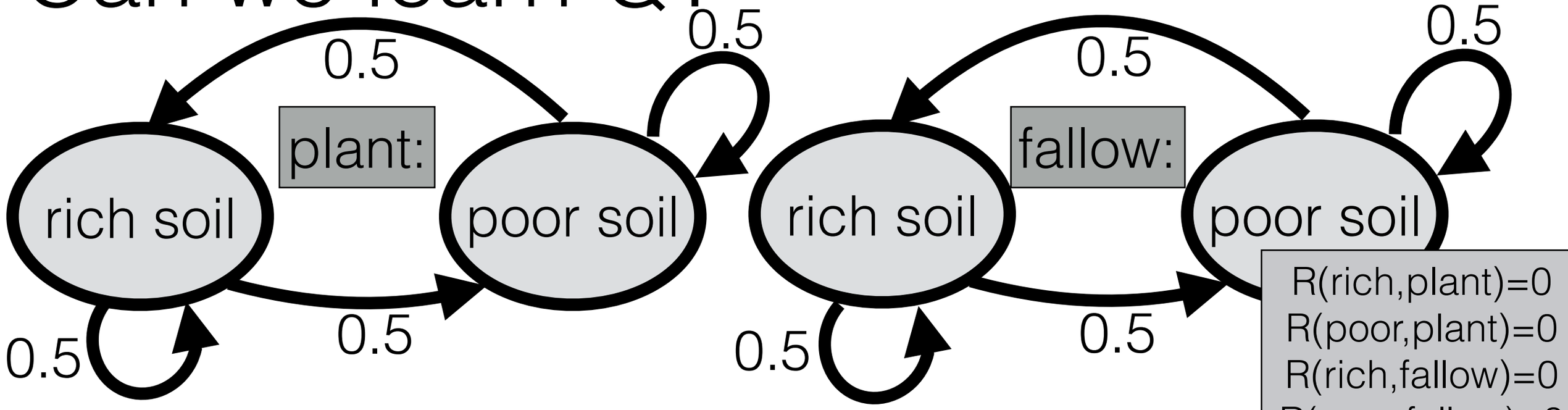

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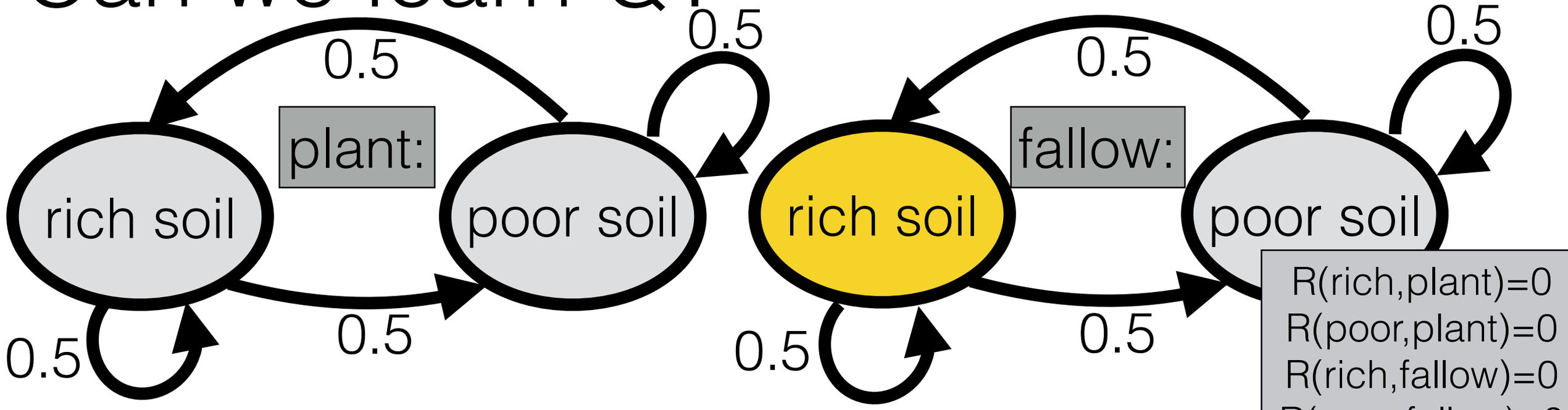

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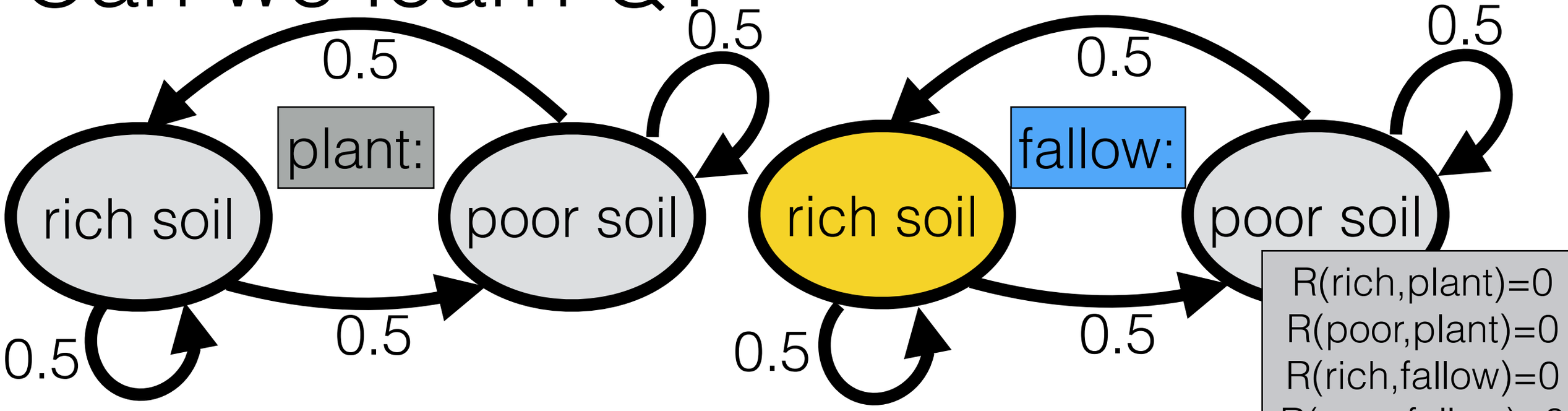

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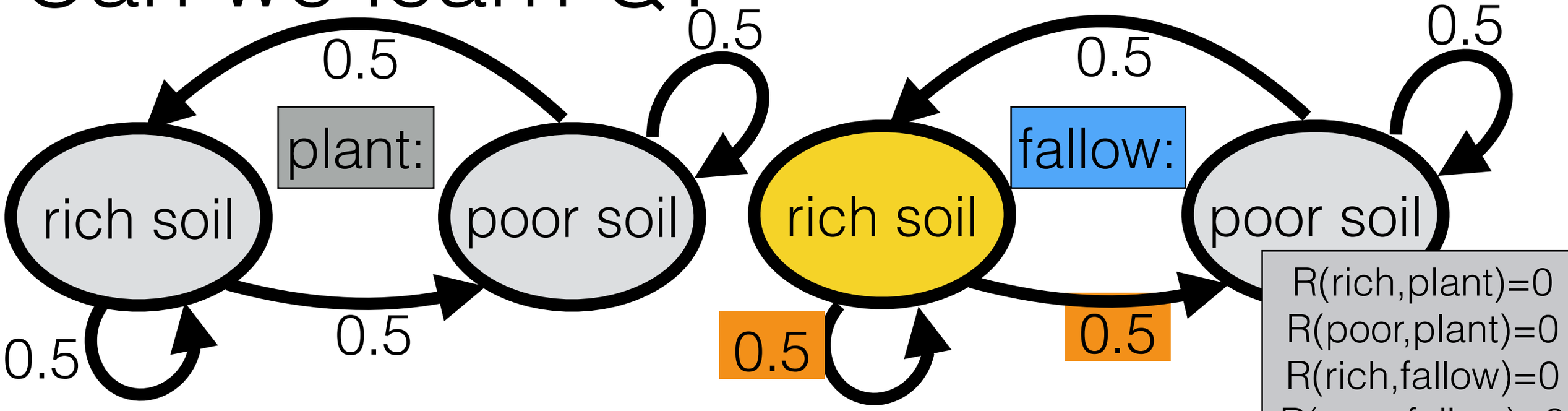

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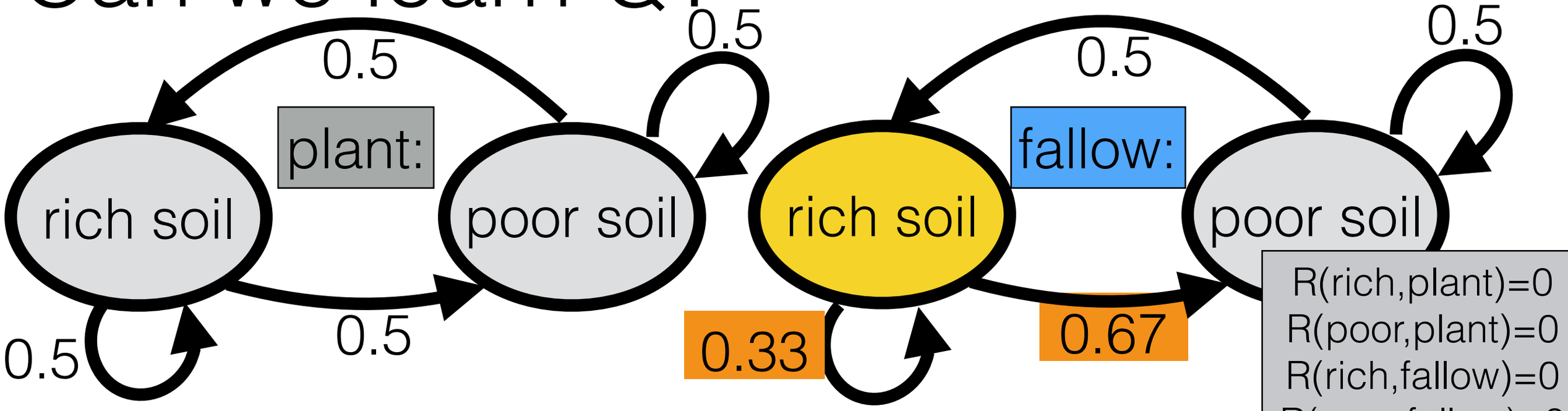

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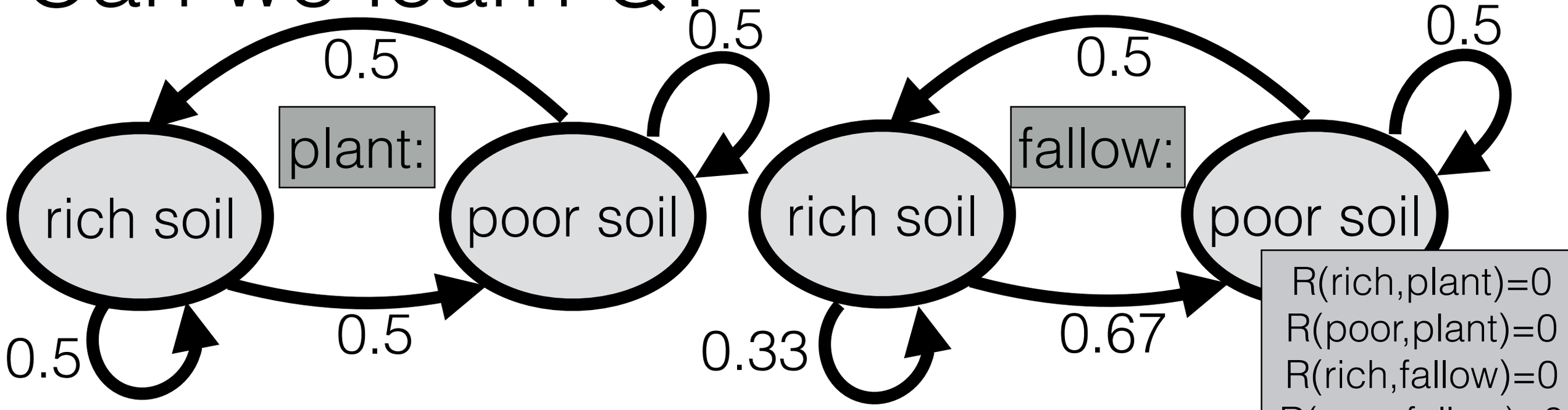

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for t = 1, 2, 3, …
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    r^(t), s^(t+1) = execute(a^(t))
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    Q = infinite-horizon-value-iteration(R̂, T̂)
```

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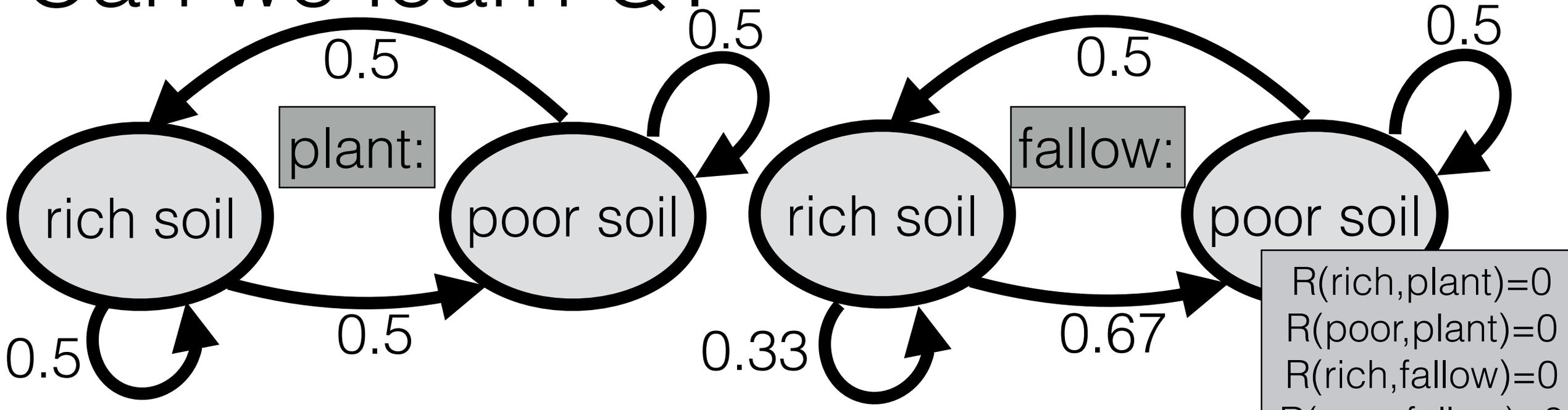

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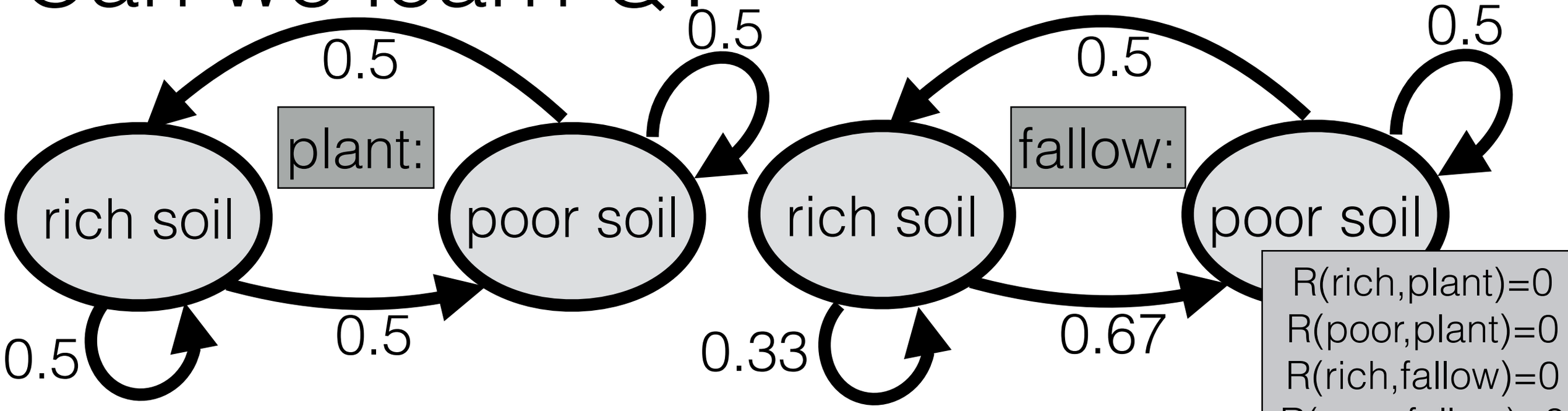
  r^(t), s^(t+1) = execute(a^(t))
  R̂(s^(t), a^(t)) = r^(t)
  Any s,a,s': T̂(s,a,s') = (1+Σ_{i=1}^{t} 1{s^(i)=s,a^(i)=a,s^(i+1)=s'}) / (|S|+Σ_{i=1}^{t} 1{s^(i)=s,a^(i)=a})
  Q = infinite-horizon-value-iteration(R̂, T̂)
```

Can we learn *Q*?



- Option 1: Estimate transition model *T* and reward function *R*

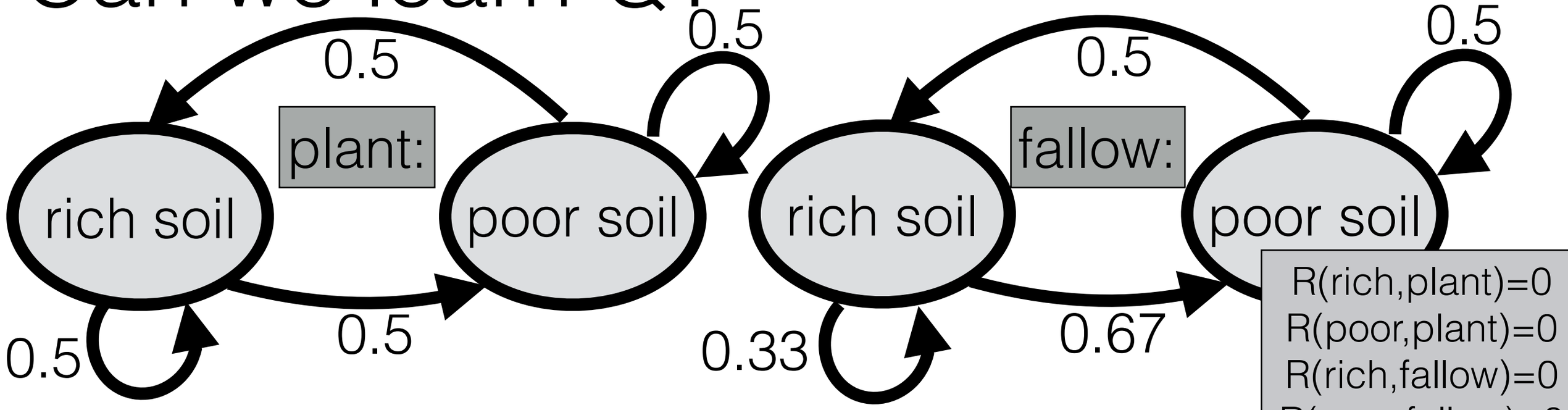
Data

Example: $\epsilon = 0.3; \gamma = 0.99$
$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$
$s^{(2)} = \text{poor}$

E.g. **ϵ-greedy**

```
Initialize s^(1) = s_0
Initialize: any s, a, s': T̂(
for t = 1, 2, 3, …
  a^(t) = select_action(s^(t), Q)
  r^(t), s^(t+1) = execute(a^(t))
  R̂(s^(t), a^(t)) = r^(t)
  Any s,a,s': T̂(s,a,s') = (1+Σ_{i=1}^{t} 1{s^(i)=s,a^(i)=a,s^(i+1)=s'}) / (|S|+Σ_{i=1}^{t} 1{s^(i)=s,a^(i)=a})
  Q = infinite-horizon-value-iteration(R̂, T̂)
```

Can we learn *Q*?



- Option 1: Estimate transition model *T* and reward function *R*

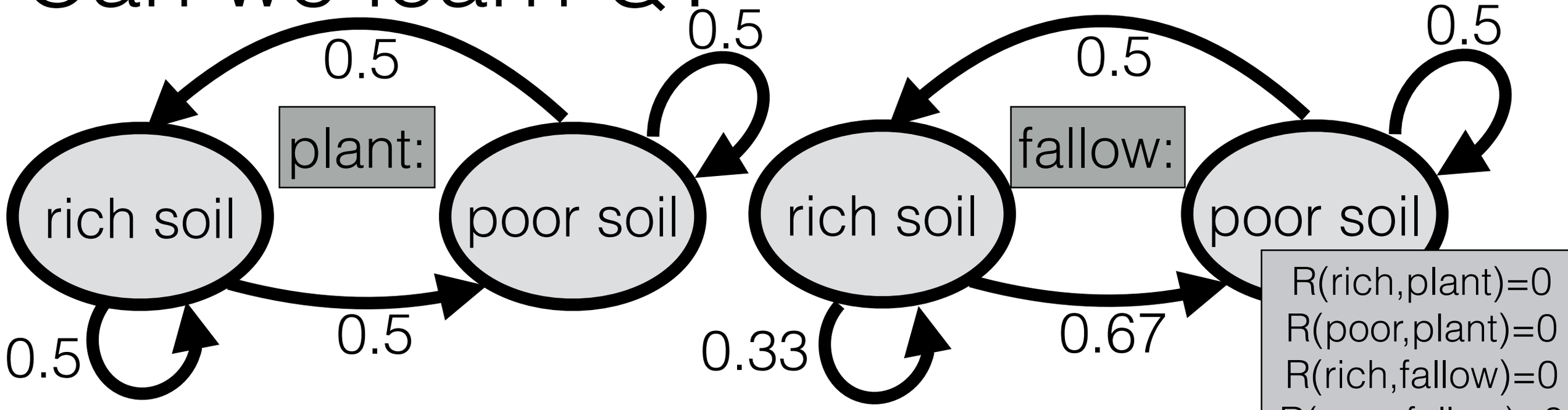
Data

Example: $\epsilon = 0.3; \gamma = 0.99$
$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$
$s^{(2)} = \text{poor}; \text{exploit}$

E.g. **ϵ-greedy**

```
Initialize s^(1) = s_0
Initialize: any s, a, s': T̂(
for t = 1, 2, 3, …
    a^(t) = select_action(s^(t), Q)
    r^(t), s^(t+1) = execute(a^(t))
    R̂(s^(t), a^(t)) = r^(t)
    Any s,a,s': T̂(s,a,s') = (1+Σ_{i=1}^{t} 1{s^(i)=s,a^(i)=a,s^(i+1)=s'}) / (|S|+Σ_{i=1}^{t} 1{s^(i)=s,a^(i)=a})
    Q = infinite-horizon-value-iteration(R̂, T̂)
```

Can we learn *Q*?



- Option 1: Estimate transition model *T* and reward function *R*

Data

Example: $\epsilon = 0.3; \gamma = 0.99$
$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$
$s^{(2)} = \text{poor}; \text{exploit}; a^{(2)} = \text{fallow}$

E.g. **ϵ-greedy**

```
Initialize s^(1) = s_0
Initialize: any s, a, s': T̂(
for t = 1, 2, 3, …
    a^(t) = select_action(s^(t), Q)
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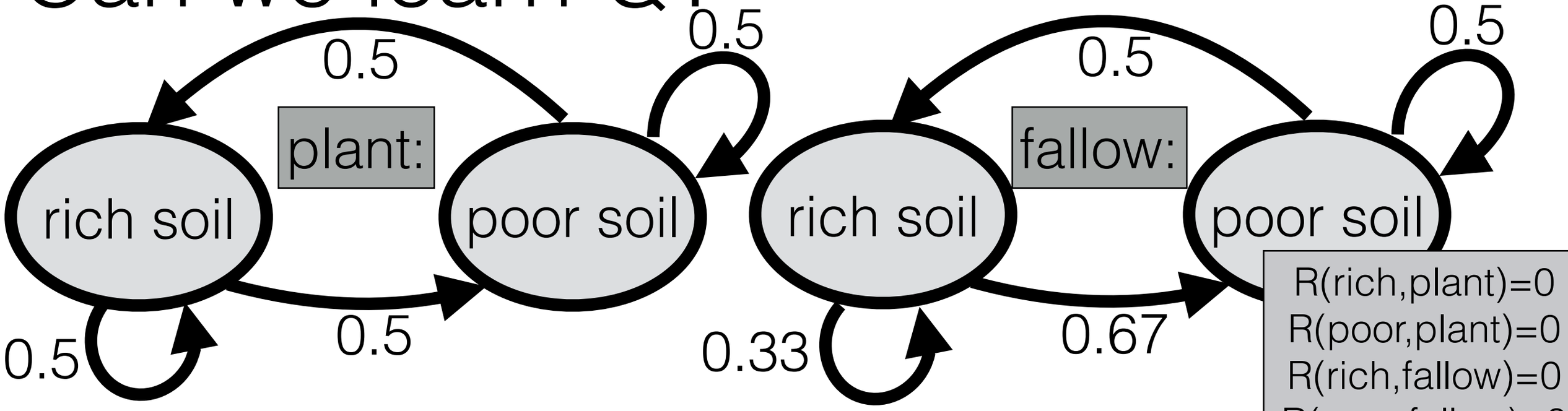
    R̂(s^(t), a^(t)) = r^(t)
    Any s,a,s': T̂(s, a, s') = (1 + Σ_{i=1}^{t} 1{s^(i)=s, a^(i)=a, s^(i+1)=s'}) / (|S| + Σ_{i=1}^{t} 1{s^(i)=s, a^(i)=a})
    Q = infinite-horizon-value-iteration(R̂, T̂)
```

Can we learn *Q*?



- Option 1: Estimate transition model *T* and reward function *R*

Initialize $s^{(1)} = s_0$

Initialize: any s, a, s': $\hat{T}($

for t = 1, 2, 3, …

$a^{(t)}$ = select_action($s^{(t)}, Q$)

$r^{(t)}, s^{(t+1)}$ = execute($a^{(t)}$)

$\hat{R}(s^{(t)}, a^{(t)}) = r^{(t)}$

Any s,a,s′: $\hat{T}(s, a, s') = \frac{1+\sum_{i=1}^{t} \mathbf{1}\{s^{(i)}=s, a^{(i)}=a, s^{(i+1)}=s'\}}{|\mathcal{S}|+\sum_{i=1}^{t} \mathbf{1}\{s^{(i)}=s, a^{(i)}=a\}}$

Q = infinite-horizon-value-iteration($\hat{R}, \hat{T}$)

Data

Example: $\epsilon = 0.3; \gamma = 0.99$

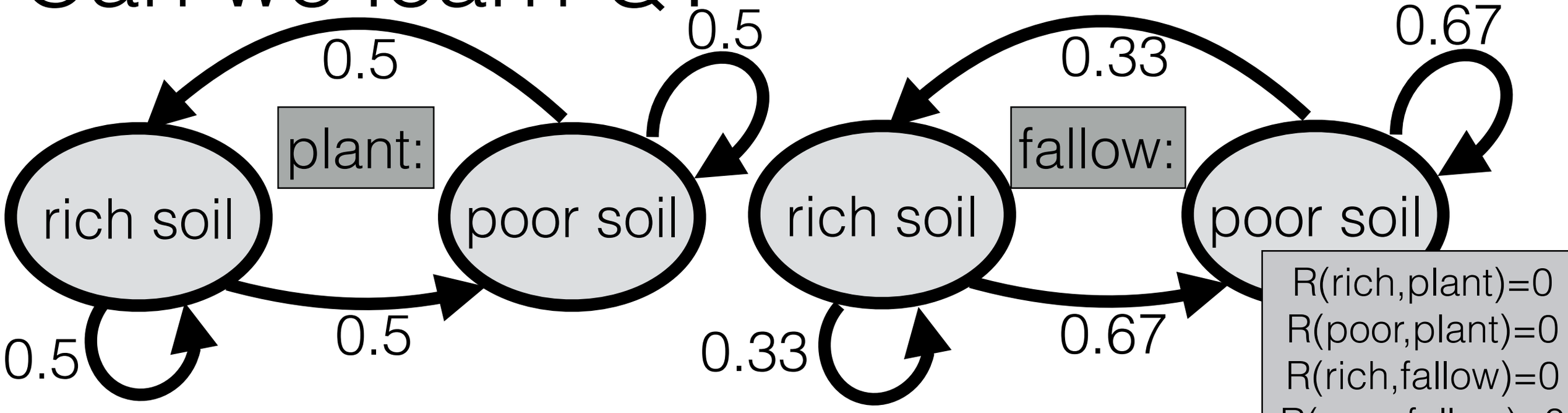
$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$

$s^{(2)} = \text{poor}; \text{exploit}; a^{(2)} = \text{fallow}$

$s^{(3)} = \text{poor}$

E.g. **ϵ-greedy**

Can we learn *Q*?



- Option 1: Estimate transition model *T* and reward function *R*

Initialize $s^{(1)} = s_0$

Initialize: any s, a, s': $\hat{T}($

for t = 1, 2, 3, …

$a^{(t)}$ = select_action($s^{(t)}, Q$)

$r^{(t)}, s^{(t+1)}$ = execute($a^{(t)}$)

$\hat{R}(s^{(t)}, a^{(t)}) = r^{(t)}$

Any s,a,s′: $\hat{T}(s, a, s') = \frac{1+\sum_{i=1}^{t} \mathbf{1}\{s^{(i)}=s, a^{(i)}=a, s^{(i+1)}=s'\}}{|\mathcal{S}|+\sum_{i=1}^{t} \mathbf{1}\{s^{(i)}=s, a^{(i)}=a\}}$

Q = infinite-horizon-value-iteration($\hat{R}, \hat{T}$)

Data

Example: $\epsilon = 0.3; \gamma = 0.99$

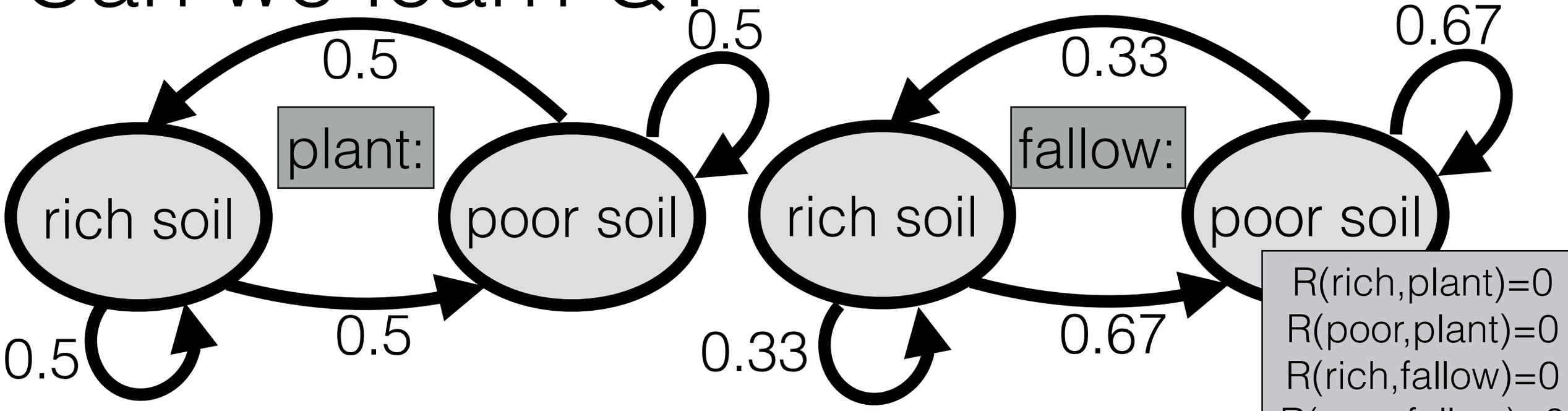
$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$

$s^{(2)} = \text{poor}; \text{exploit}; a^{(2)} = \text{fallow}$

$s^{(3)} = \text{poor}$

E.g. **ϵ-greedy**

Can we learn *Q*?



- Option 1: Estimate transition model *T* and reward function *R*

Data

Example: $\epsilon = 0.3; \gamma = 0.99$

$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$

$s^{(2)} = \text{poor}; \text{exploit}; a^{(2)} = \text{fallow}$

$s^{(3)} = \text{poor}; \text{exploit}; a^{(3)} = \text{fallow}$

E.g. **ϵ-greedy**

```
Initialize s^(1) = s_0
Initialize: any s, a, s': T̂(
for t = 1, 2, 3, …
    a^(t) = select_action(s^(t), Q)
    r^(t), s^(t+1) = execute(a^(t))
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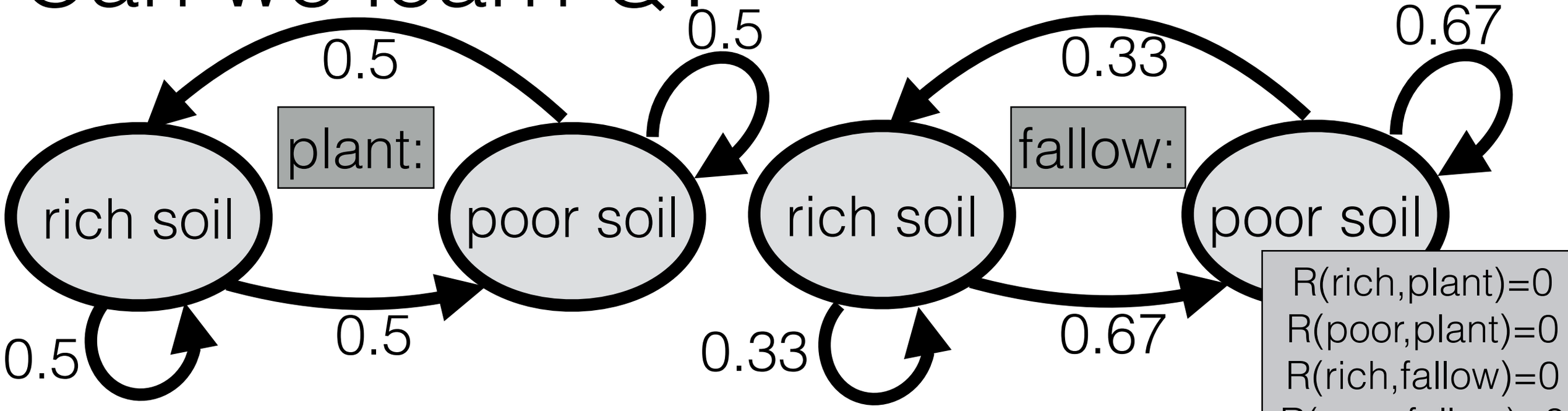
    Q = infinite-horizon-value-iteration(R̂, T̂)
```

Can we learn *Q*?



- Option 1: Estimate transition model *T* and reward function *R*

Initialize $s^{(1)} = s_0$

Initialize: any s, a, s': $\hat{T}($

for t = 1, 2, 3, …

$a^{(t)}$ = select_action($s^{(t)}$

$r^{(t)}, s^{(t+1)}$ = execute($a^{(t)}$)

$\hat{R}(s^{(t)}, a^{(t)}) = r^{(t)}$

Any s,a,s′: $\hat{T}(s, a, s') = \frac{1+\sum_{i=1}^{t} \mathbf{1}\{s^{(i)}=s, a^{(i)}=a, s^{(i+1)}=s'\}}{|\mathcal{S}|+\sum_{i=1}^{t} \mathbf{1}\{s^{(i)}=s, a^{(i)}=a\}}$

Q = infinite-horizon-value-iteration($\hat{R}, \hat{T}$)

Data

Example: $\epsilon = 0.3; \gamma = 0.99$

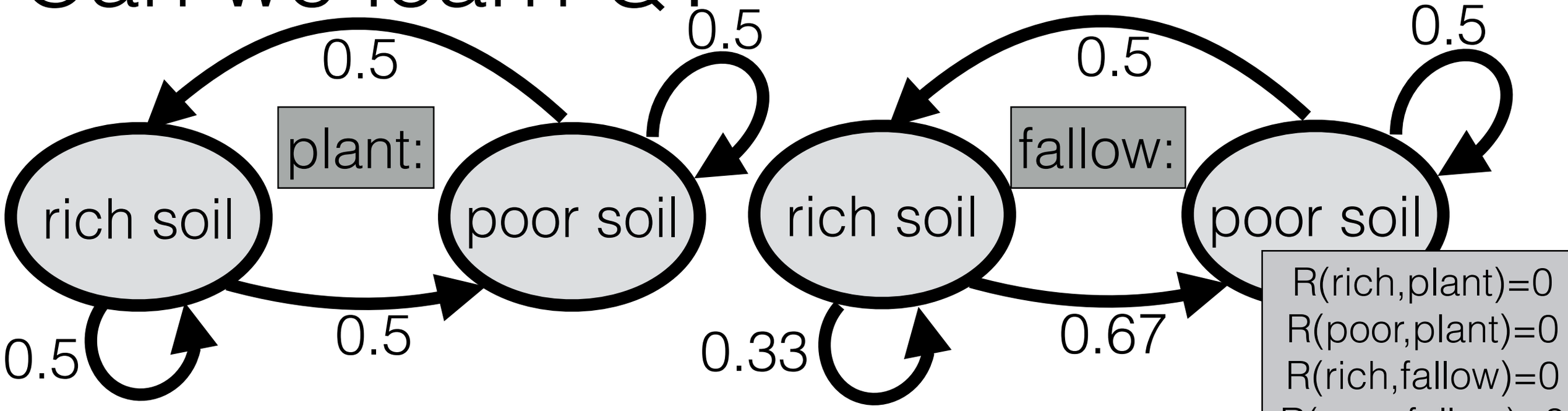
$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$

$s^{(2)} = \text{poor}; \text{exploit}; a^{(2)} = \text{fallow}$

$s^{(3)} = \text{poor}; \text{exploit}; a^{(3)} = \text{fallow}$

$s^{(4)} = \text{rich}$

Can we learn *Q*?



- Option 1: Estimate transition model *T* and reward function *R*

Initialize $s^{(1)} = s_0$

Initialize: any s, a, s': $\hat{T}($

for t = 1, 2, 3, …

$a^{(t)}$ = select_action($s^{(t)}$

$r^{(t)}, s^{(t+1)}$ = execute($a^{(t)}$)

$\hat{R}(s^{(t)}, a^{(t)}) = r^{(t)}$

Any s,a,s′: $\hat{T}(s, a, s') = \frac{1+\sum_{i=1}^{t} \mathbf{1}\{s^{(i)}=s, a^{(i)}=a, s^{(i+1)}=s'\}}{|\mathcal{S}|+\sum_{i=1}^{t} \mathbf{1}\{s^{(i)}=s, a^{(i)}=a\}}$

Q = infinite-horizon-value-iteration($\hat{R}, \hat{T}$)

Data

Example: $\epsilon = 0.3; \gamma = 0.99$

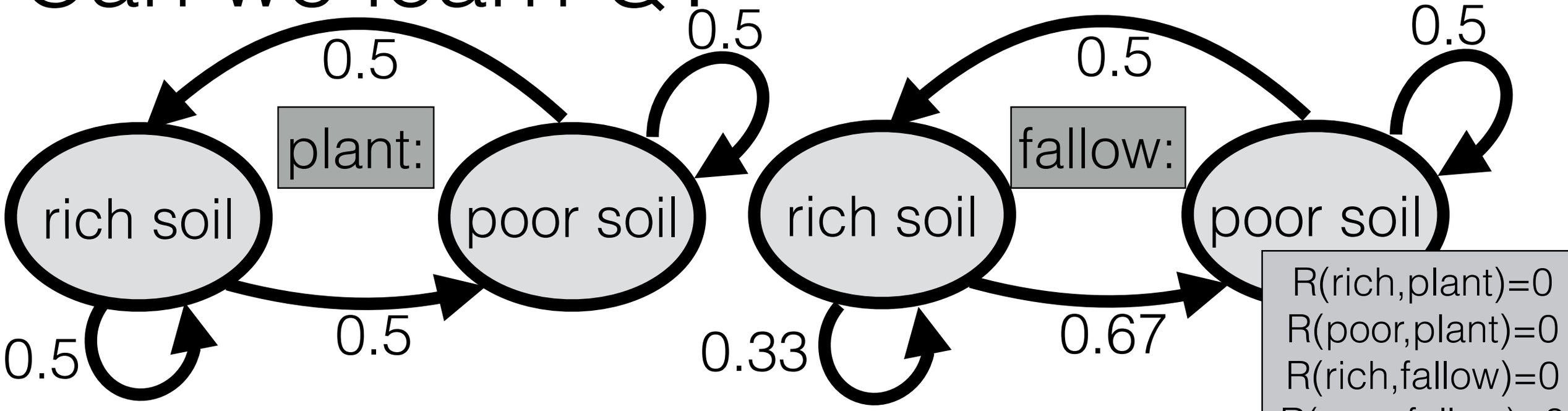
$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$

$s^{(2)} = \text{poor}; \text{exploit}; a^{(2)} = \text{fallow}$

$s^{(3)} = \text{poor}; \text{exploit}; a^{(3)} = \text{fallow}$

$s^{(4)} = \text{rich}$

Can we learn *Q*?



- Option 1: Estimate transition model *T* and reward function *R*

Data

Example: $\epsilon = 0.3; \gamma = 0.99$

$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$

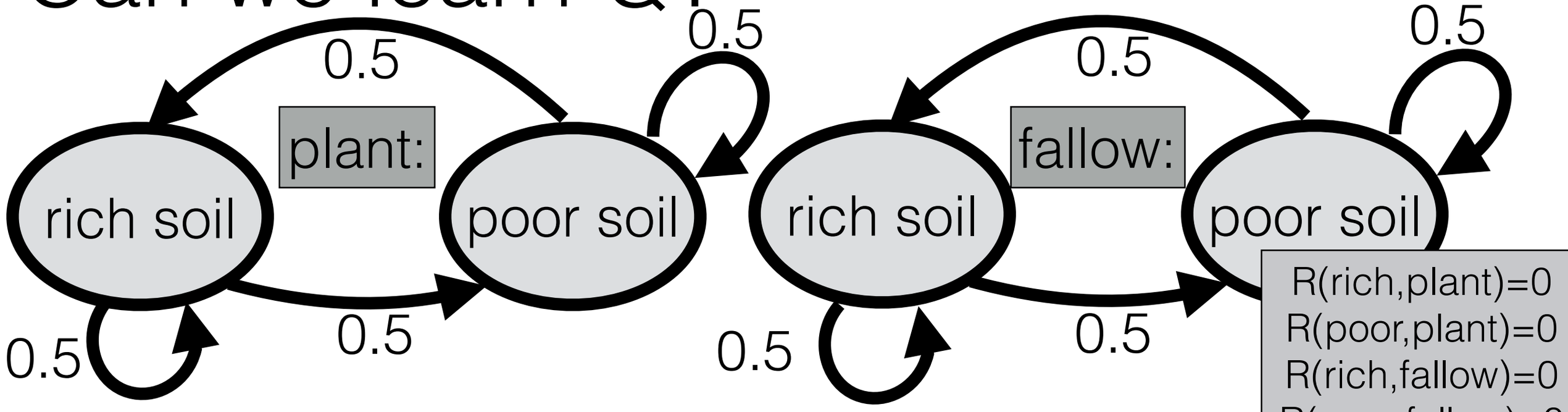
$s^{(2)} = \text{poor}; \text{exploit}; a^{(2)} = \text{fallow}$

$s^{(3)} = \text{poor}; \text{exploit}; a^{(3)} = \text{fallow}$

$s^{(4)} = \text{rich}; \text{exploit}; a^{(4)} = \text{fallow}$

```
Initialize s^(1) = s_0
Initialize: any s, a, s': T̂(
for t = 1, 2, 3, …
    a^(t) = select_action(s^(t)
    r^(t), s^(t+1) = execute(a^(t))
    R̂(s^(t), a^(t)) = r^(t)
    Any s,a,s': T̂(s,a,s') = (1+Σ_{i=1}^{t} 1{s^(i)=s,a^(i)=a,s^(i+1)=s'}) / (|S|+Σ_{i=1}^{t} 1{s^(i)=s,a^(i)=a})
    Q = infinite-horizon-value-iteration(R̂, T̂)
```

Can we learn *Q*?



- Option 1: Estimate transition model *T* and reward function *R*

Initialize $s^{(1)} = s_0$

Initialize: any s, a, s': $\hat{T}($

for t = 1, 2, 3, …

$a^{(t)}$ = select_action($s^{(t)}$

$r^{(t)}, s^{(t+1)}$ = execute($a^{(t)}$)

$\hat{R}(s^{(t)}, a^{(t)}) = r^{(t)}$

Any s,a,s′: $\hat{T}(s, a, s') = \frac{1+\sum_{i=1}^{t} \mathbf{1}\{s^{(i)}=s, a^{(i)}=a, s^{(i+1)}=s'\}}{|\mathcal{S}|+\sum_{i=1}^{t} \mathbf{1}\{s^{(i)}=s, a^{(i)}=a\}}$

Q = infinite-horizon-value-iteration($\hat{R}, \hat{T}$)

Data

Example: $\epsilon = 0.3; \gamma = 0.99$

$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$

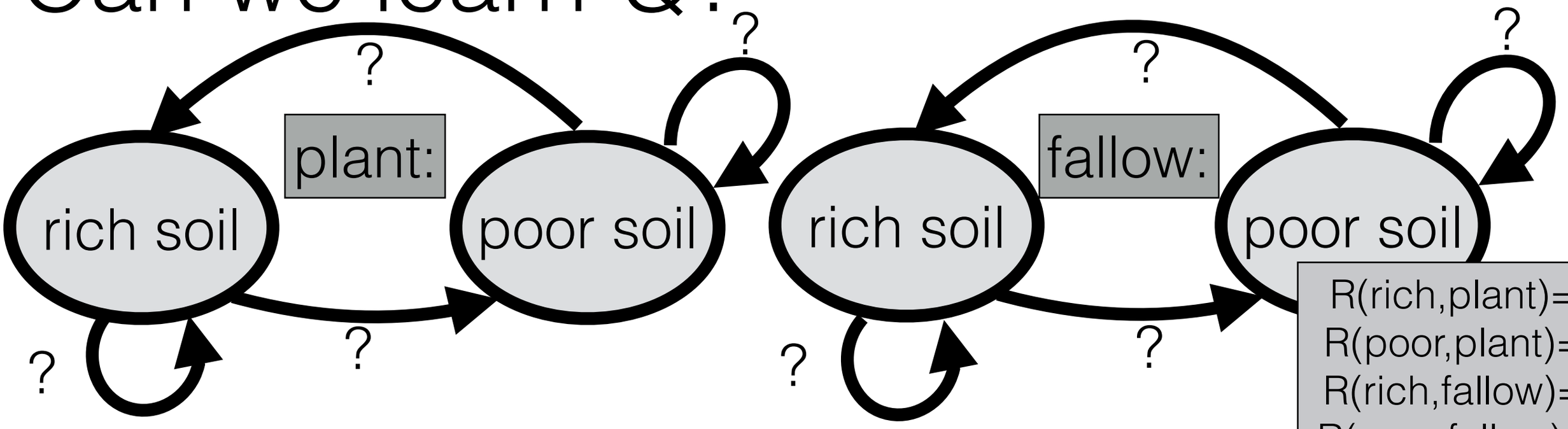
$s^{(2)} = \text{poor}; \text{exploit}; a^{(2)} = \text{fallow}$

$s^{(3)} = \text{poor}; \text{exploit}; a^{(3)} = \text{fallow}$

$s^{(4)} = \text{rich}; \text{exploit}; a^{(4)} = \text{fallow}$

$s^{(5)} = \text{rich}; \text{explore}; a^{(5)} = \text{plant}$

Can we learn *Q*?



- Option 1: Estimate transition model *T* and reward function *R*

Initialize $s^{(1)} = s_0$

Initialize: any s, a, s': $\hat{T}($

for t = 1, 2, 3, …

$a^{(t)}$ = select_action($s^{(t)}$,

$r^{(t)}, s^{(t+1)}$ = execute($a^{(t)}$)

$\hat{R}(s^{(t)}, a^{(t)}) = r^{(t)}$

Any s,a,s′: $\hat{T}(s, a, s') = \frac{1+\sum_{i=1}^{t} \mathbf{1}\{s^{(i)}=s, a^{(i)}=a, s^{(i+1)}=s'\}}{|\mathcal{S}|+\sum_{i=1}^{t} \mathbf{1}\{s^{(i)}=s, a^{(i)}=a\}}$

Q = infinite-horizon-value-iteration($\hat{R}, \hat{T}$)

Data

Example: $\epsilon = 0.3; \gamma = 0.99$

$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$

$s^{(2)} = \text{poor}; \text{exploit}; a^{(2)} = \text{fallow}$

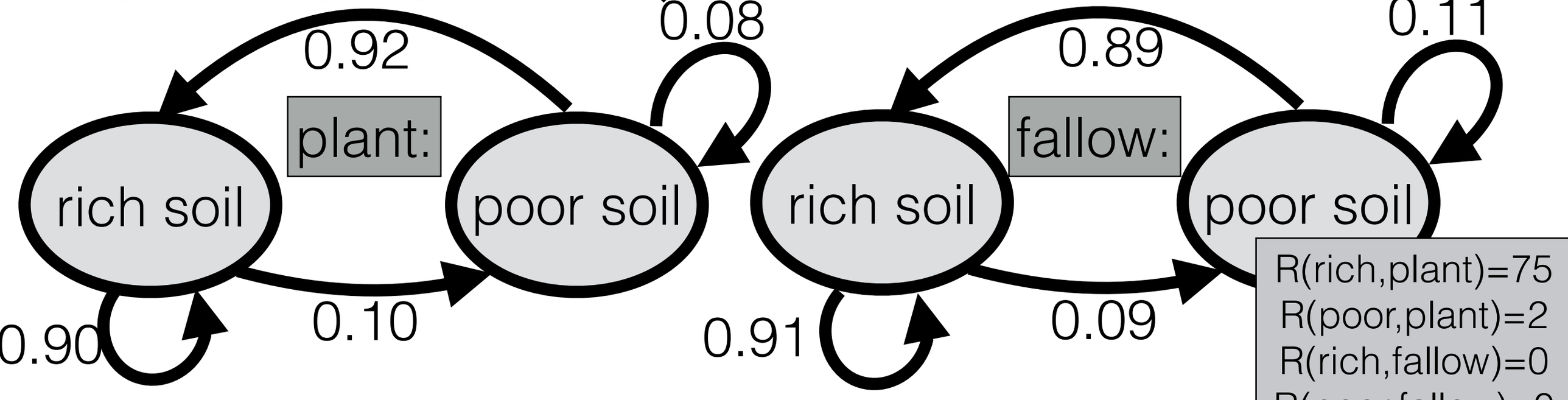
$s^{(3)} = \text{poor}; \text{exploit}; a^{(3)} = \text{fallow}$

$s^{(4)} = \text{rich}; \text{exploit}; a^{(4)} = \text{fallow}$

$s^{(5)} = \text{rich}; \text{explore}; a^{(5)} = \text{plant}$

…

Can we learn *Q*?



- Option 1: Estimate transition model *T* and reward function *R*

```
Initialize s^(1) = s_0
Initialize: any s, a, s': T̂(
for t = 1, 2, 3, …
  a^(t) = select_action(s^(t)
  r^(t), s^(t+1) = execute(a^(t))
  R̂(s^(t), a^(t)) = r^(t)
  Any s,a,s': T̂(s,a,s') = 1
  Q = infinite-horizon-value-iteration(R̂, T̂)
```

Data

Example: $\epsilon = 0.3; \gamma = 0.99$

$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$

$s^{(2)} = \text{poor}; \text{exploit}; a^{(2)} = \text{fallow}$

$s^{(3)} = \text{poor}; \text{exploit}; a^{(3)} = \text{fallow}$

$s^{(4)} = \text{rich}; \text{exploit}; a^{(4)} = \text{fallow}$

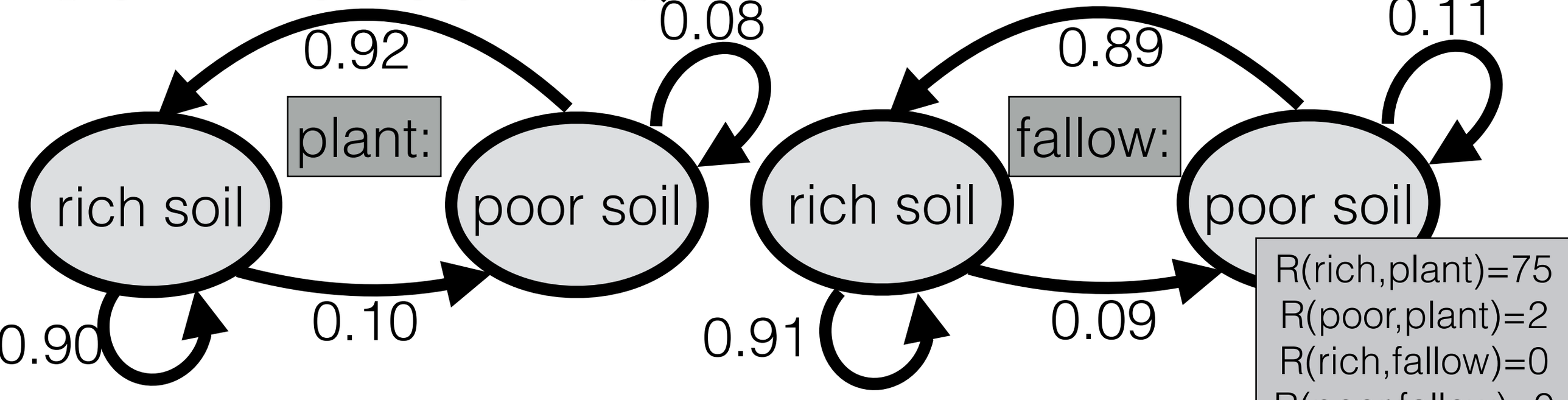
$s^{(5)} = \text{rich}; \text{explore}; a^{(5)} = \text{plant}$

…

$s^{(2718)} = \text{rich}; \text{exploit}; a^{(2718)} = \text{plant}$

$$\frac{|S| + \sum_{i=1}^{t} \mathbf{1}\{s^{(t)}=s, a^{(t)}=a\}}{}$$

Can we learn Q?



- Option 1: Estimate transition model T and reward function R

```
Initialize s^(1) = s_0
Initialize: any s, a, s': T̂(
for t = 1, 2, 3, …
  a^(t) = select_action(s^(t)
  r^(t), s^(t+1) = execute(a^(t))
  R̂(s^(t), a^(t)) = r^(t)
  Any s,a,s': T̂(s,a,s') = 1
  Q = infinite-horizon-value-iteration(R̂, T̂)
```

Data

Example: $\epsilon = 0.3; \gamma = 0.99$

$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$

$s^{(2)} = \text{poor}; \text{exploit}; a^{(2)} = \text{fallow}$

$s^{(3)} = \text{poor}; \text{exploit}; a^{(3)} = \text{fallow}$

$s^{(4)} = \text{rich}; \text{exploit}; a^{(4)} = \text{fallow}$

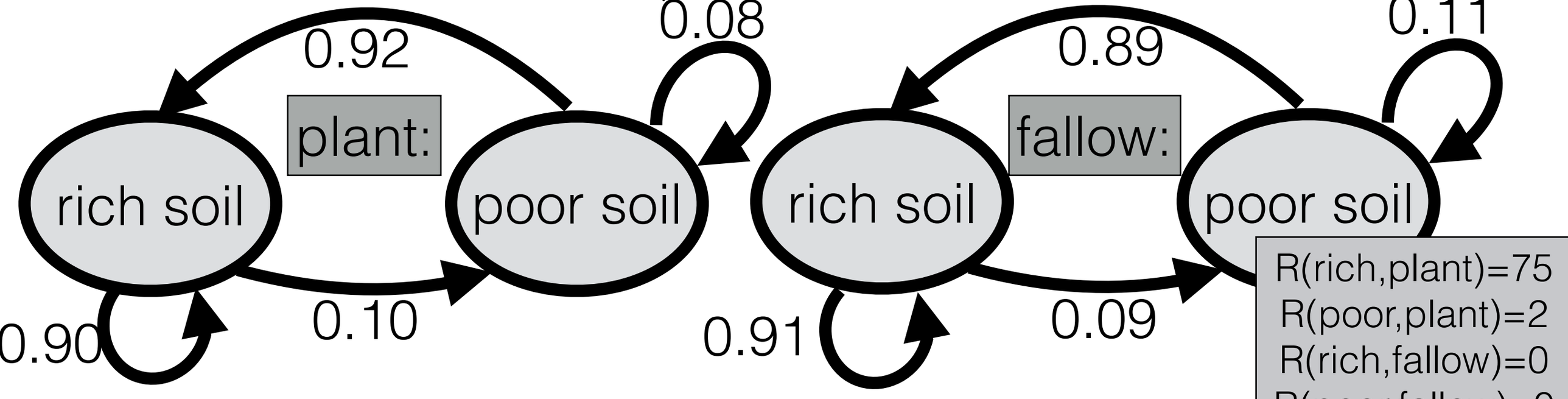
$s^{(5)} = \text{rich}; \text{explore}; a^{(5)} = \text{plant}$

…

$s^{(2718)} = \text{rich}; \text{exploit}; a^{(2718)} = \text{plant}$

$s^{(2719)} = \text{poor}; \text{exploit}; a^{(2719)} = \text{fallow}$

Can we learn *Q*?



- Option 1: Estimate transition model *T* and reward function *R*

```
Initialize s^(1) = s_0
Initialize: any s, a, s': T̂(
for t = 1, 2, 3, …
  a^(t) = select_action(s^(t)
  r^(t), s^(t+1) = execute(a^(t))
  R̂(s^(t), a^(t)) = r^(t)
  Any s,a,s': T̂(s, a, s') = 1
  Q = infinite-horizon-v
```

Data

Example: $\epsilon = 0.3; \gamma = 0.99$

$s^{(1)} = \text{rich}; \text{explore}; a^{(1)} = \text{fallow}$

$s^{(2)} = \text{poor}; \text{exploit}; a^{(2)} = \text{fallow}$

$s^{(3)} = \text{poor}; \text{exploit}; a^{(3)} = \text{fallow}$

$s^{(4)} = \text{rich}; \text{exploit}; a^{(4)} = \text{fallow}$

$s^{(5)} = \text{rich}; \text{explore}; a^{(5)} = \text{plant}$

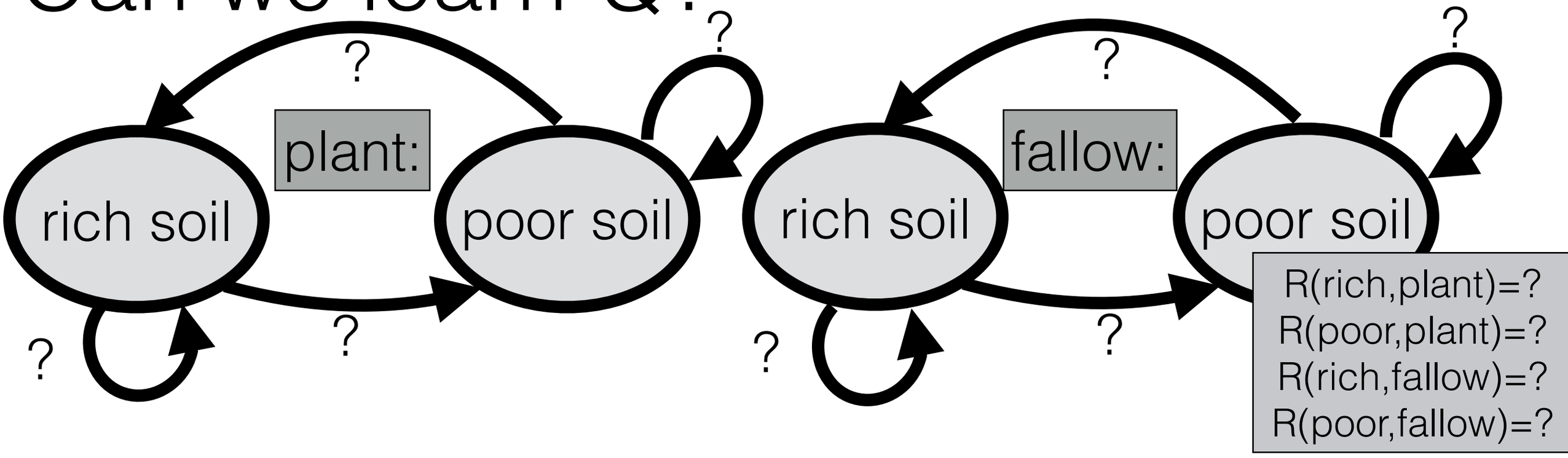
…

$s^{(2718)} = \text{rich}; \text{exploit}; a^{(2718)} = \text{plant}$

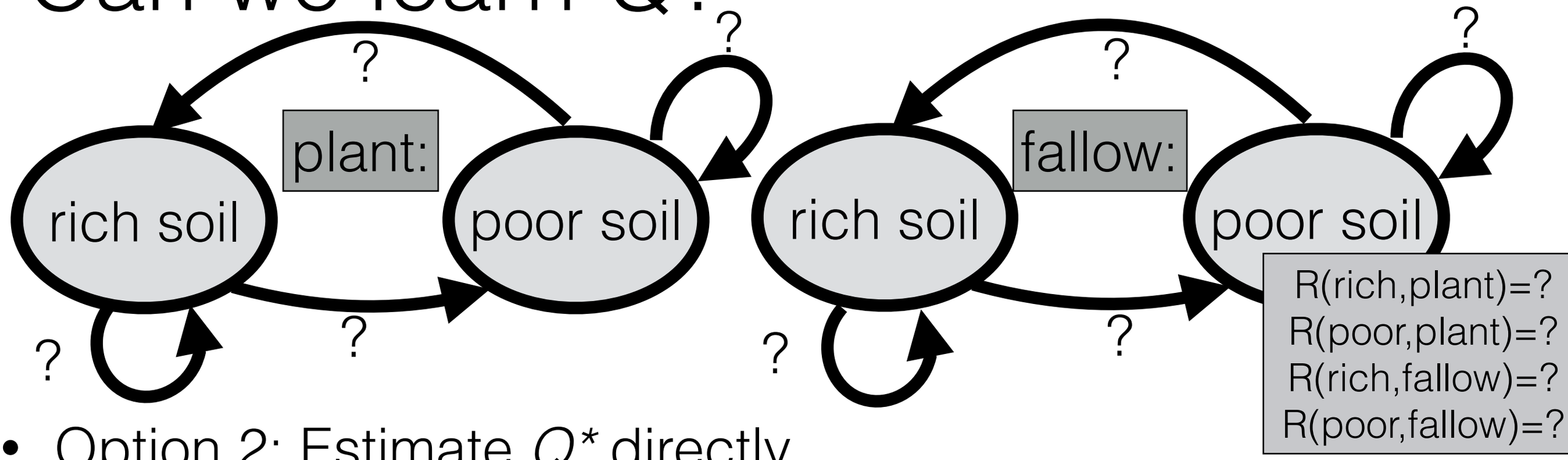
$s^{(2719)} = \text{poor}; \text{exploit}; a^{(2719)} = \text{fallow}$

$s^{(2720)} = \text{rich}; \text{explore}; a^{(2720)} = \text{fallow}$

Can we learn *Q*?

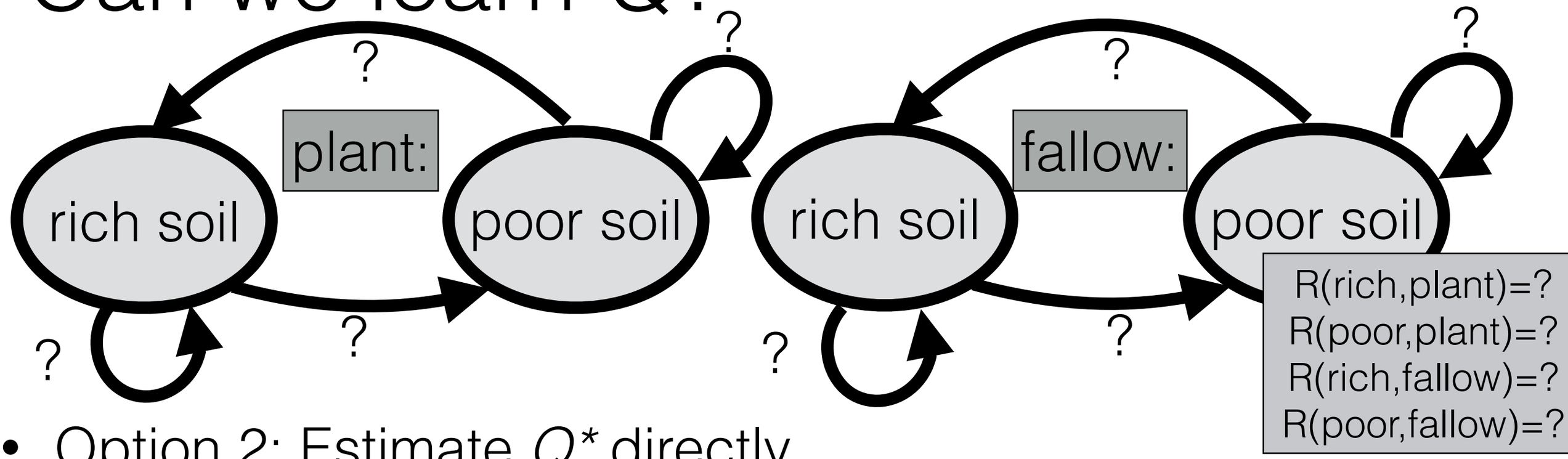


Can we learn *Q*?



- Option 2: Estimate *Q** directly

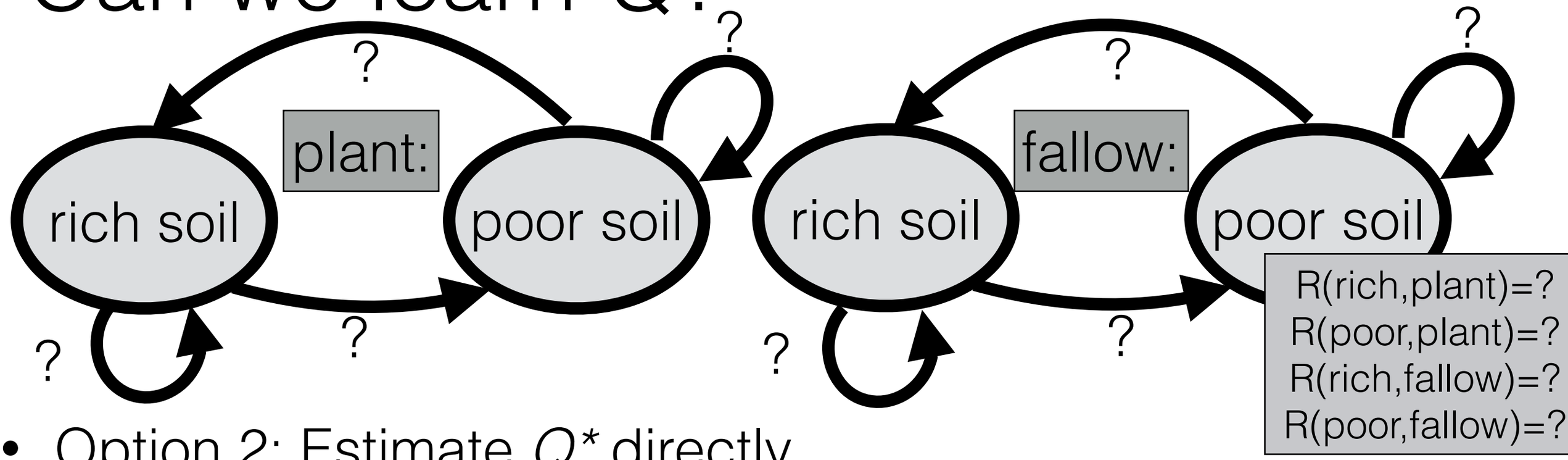
Can we learn *Q*?



- Option 2: Estimate *Q** directly
- Recall infinite horizon value iteration:

$$Q^*(s,a) = R(s,a) + \gamma \sum_{s'} T(s,a,s') \max_{a'} Q^*(s',a')$$

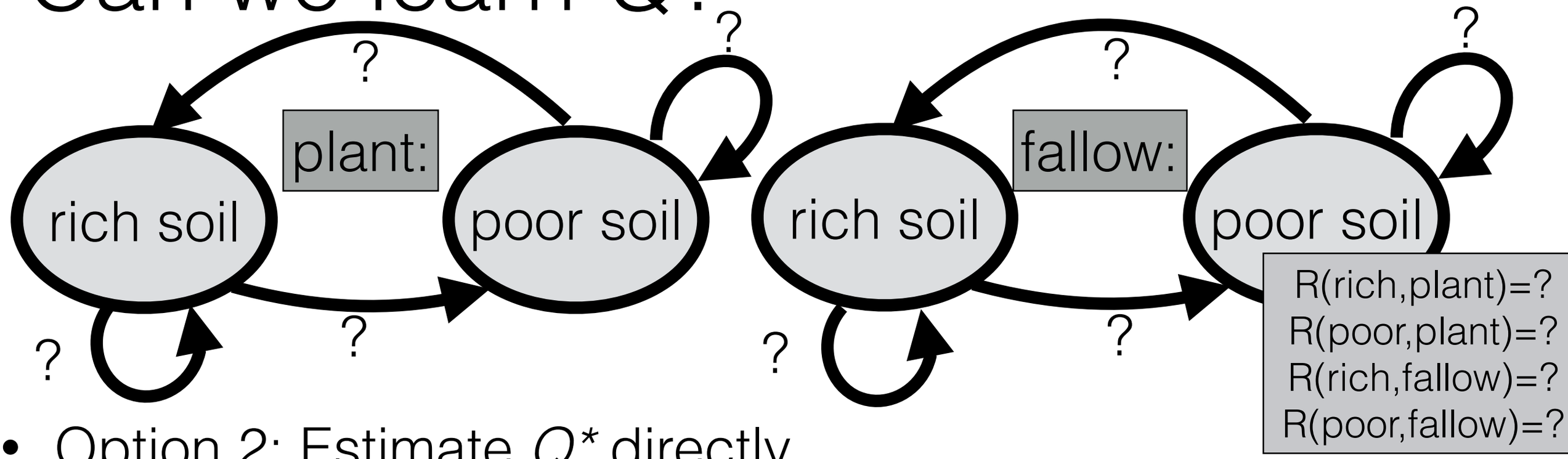
Can we learn *Q*?



- Option 2: Estimate *Q** directly
- Recall infinite horizon value iteration:

$$Q^*(s,a) = R(s,a) + \gamma \sum_{s'} T(s,a,s') \max_{a'} Q^*(s',a')$$

Can we learn *Q*?



- Option 2: Estimate Q^* directly
- Recall infinite horizon value iteration:

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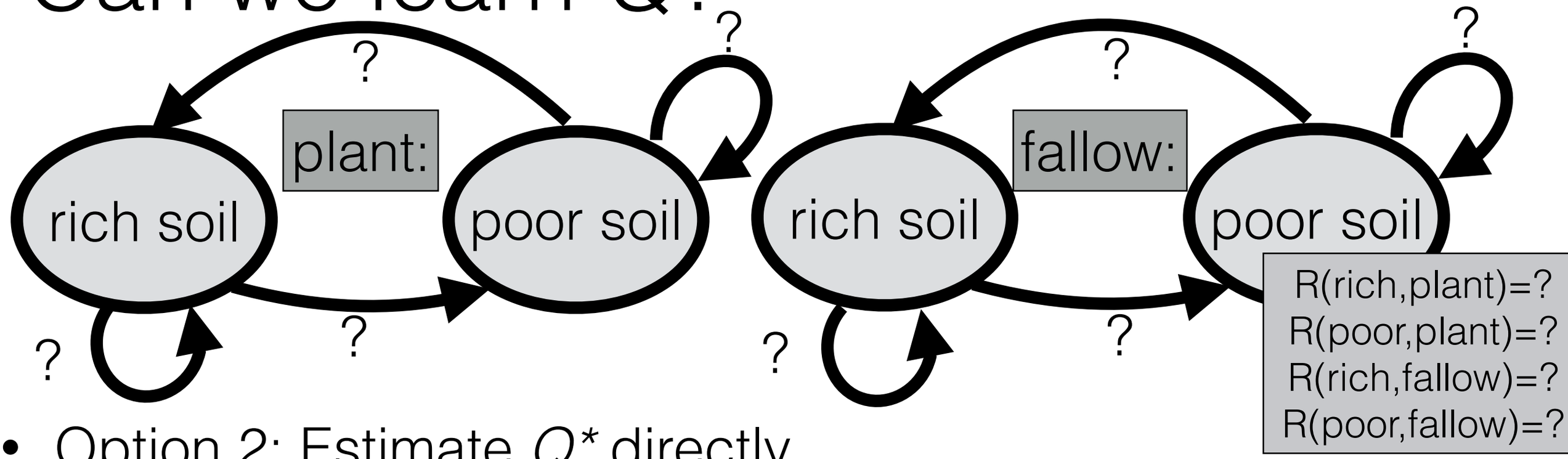

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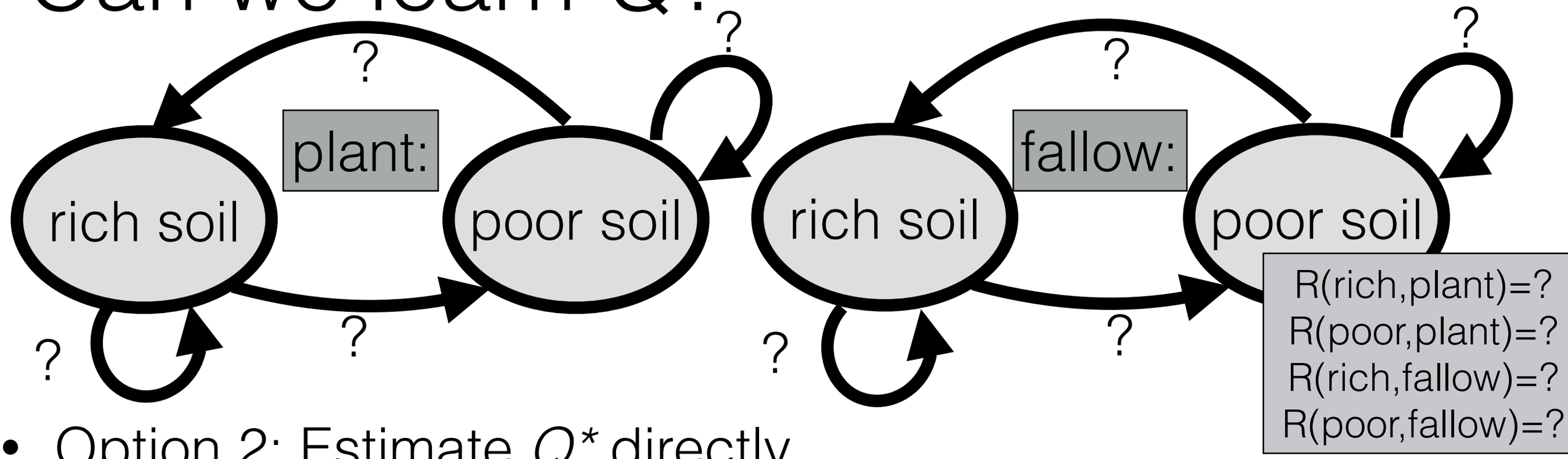

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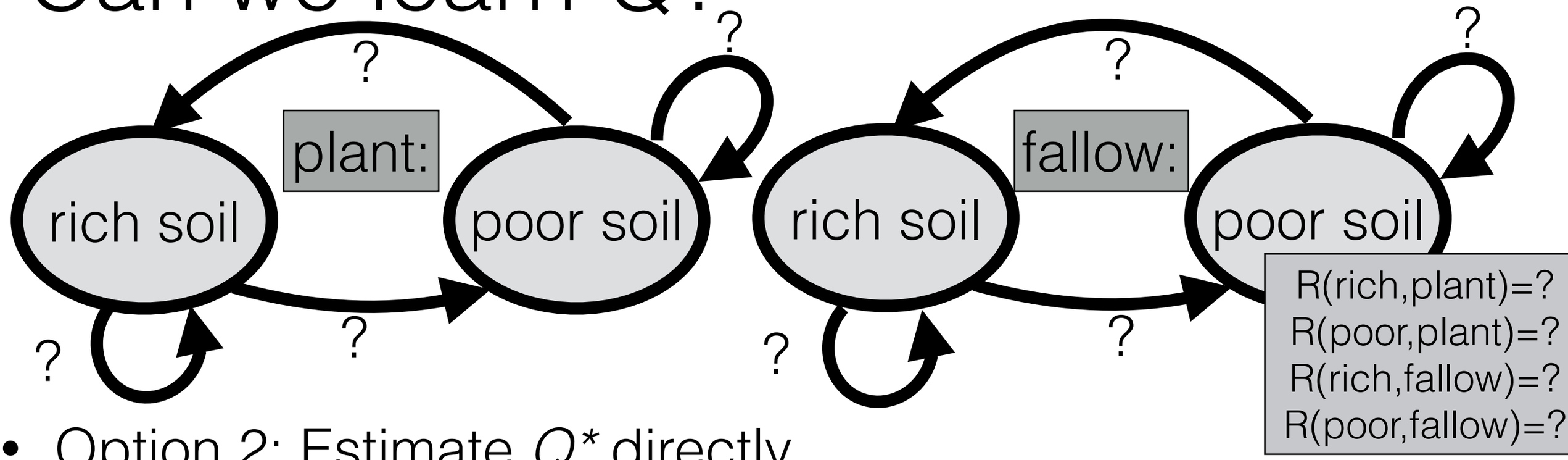

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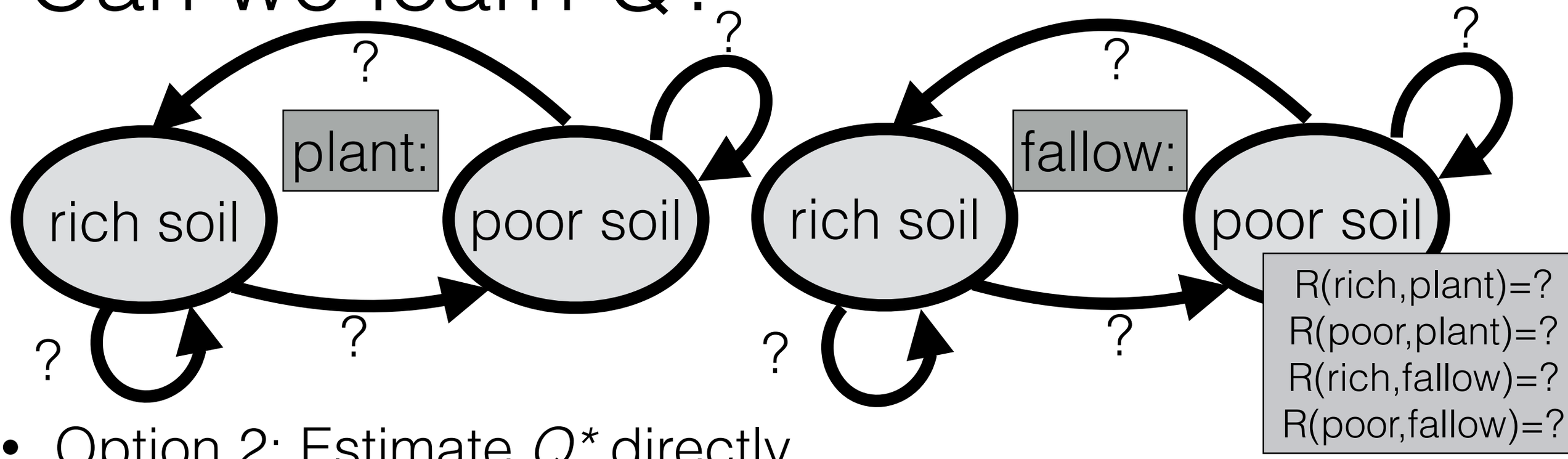

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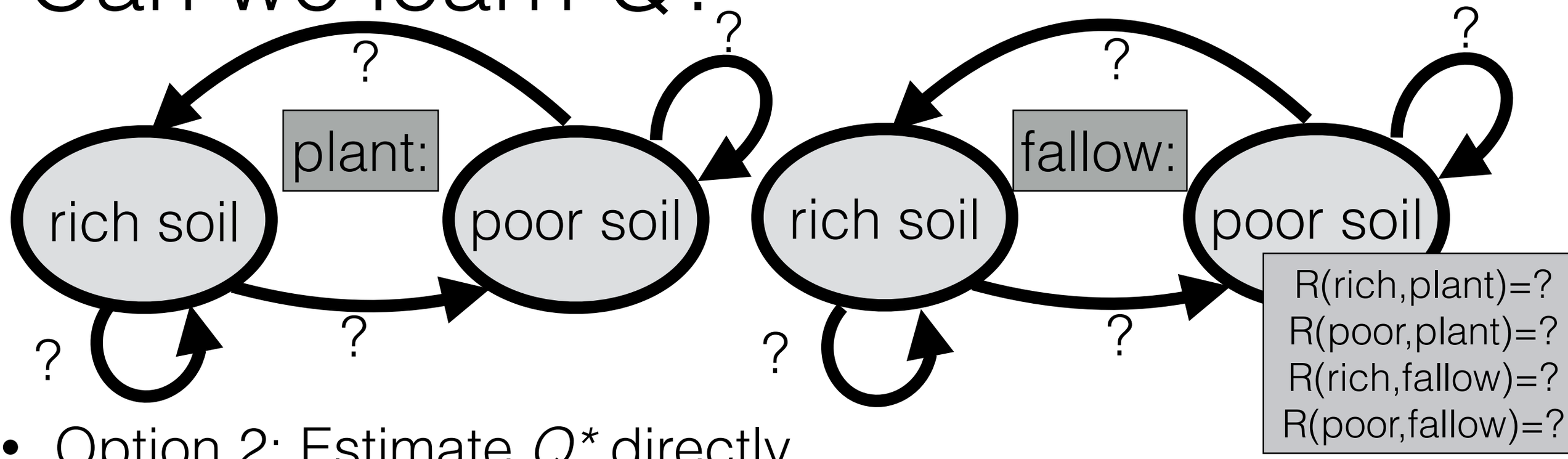

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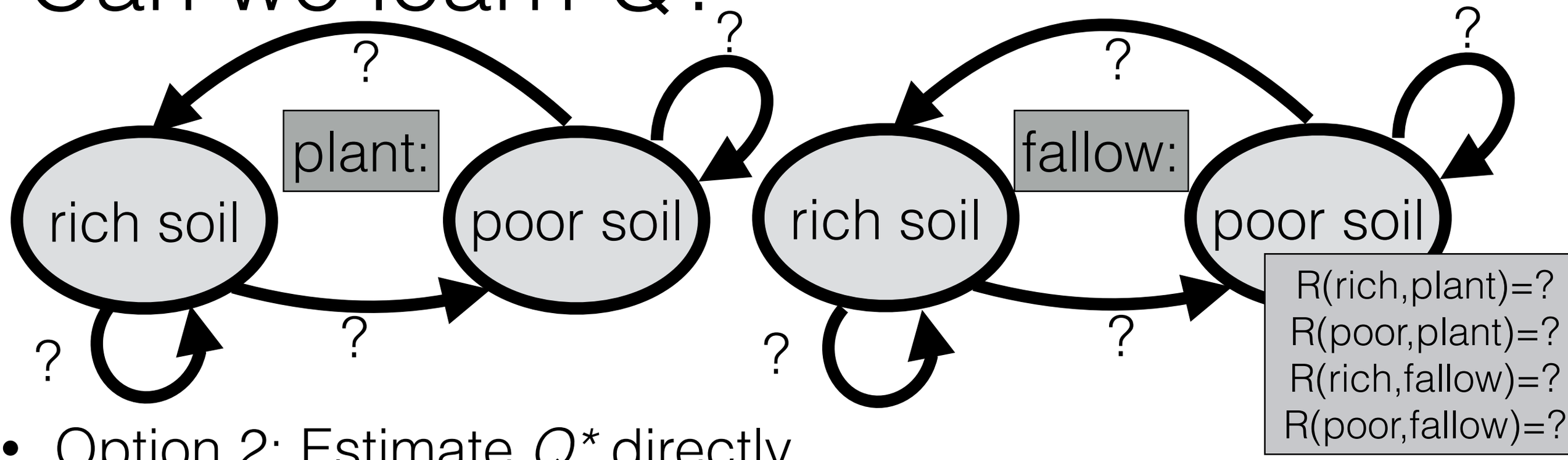

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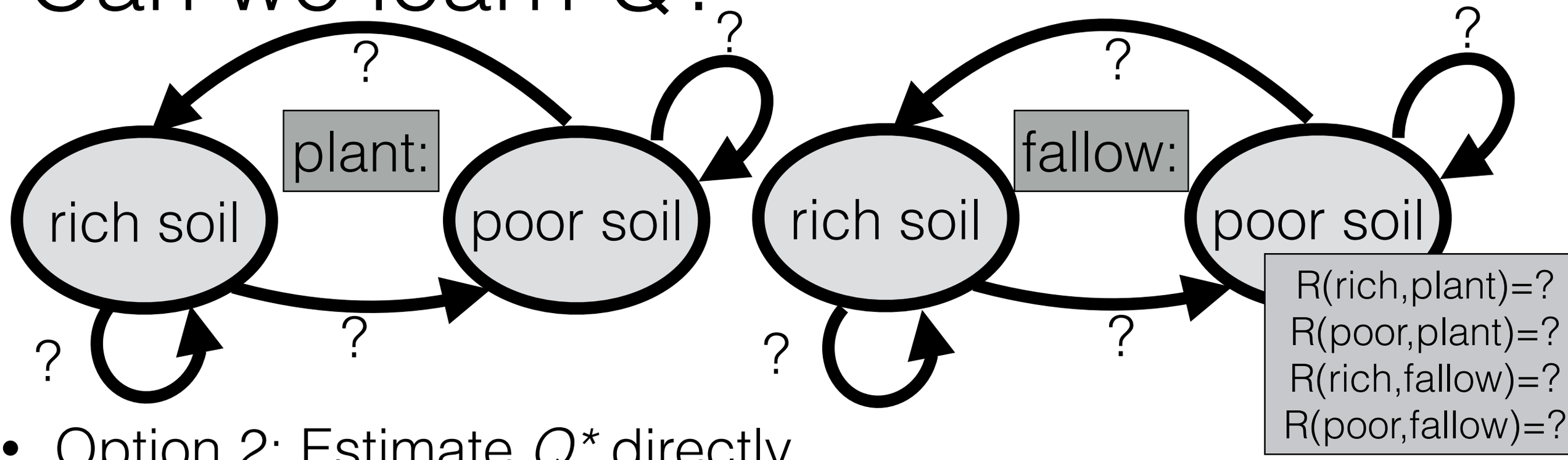

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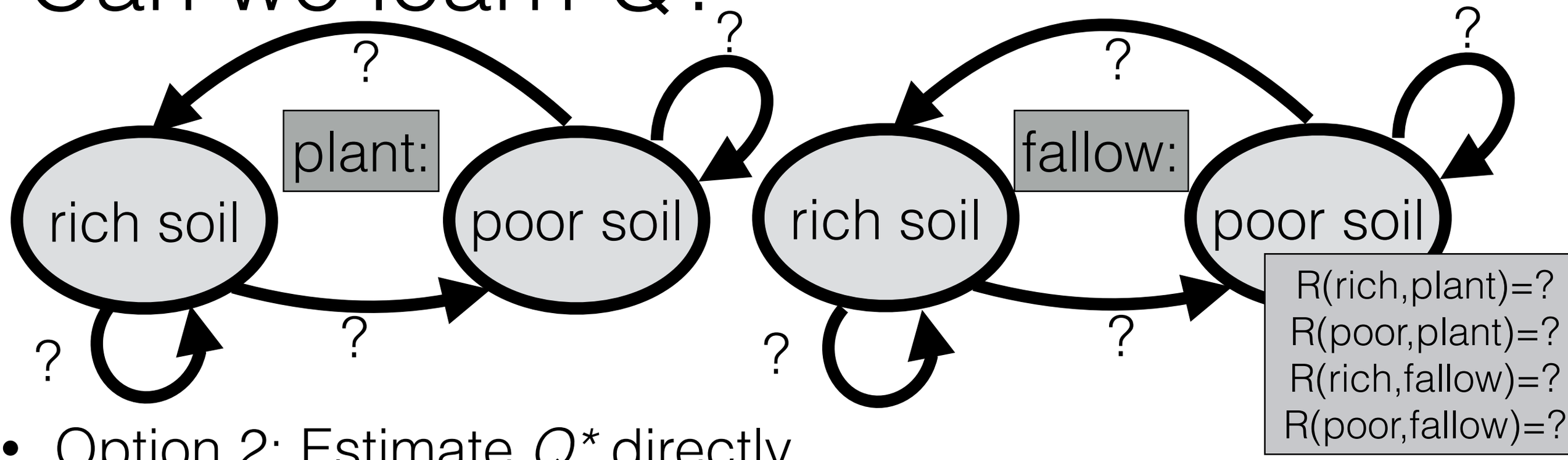

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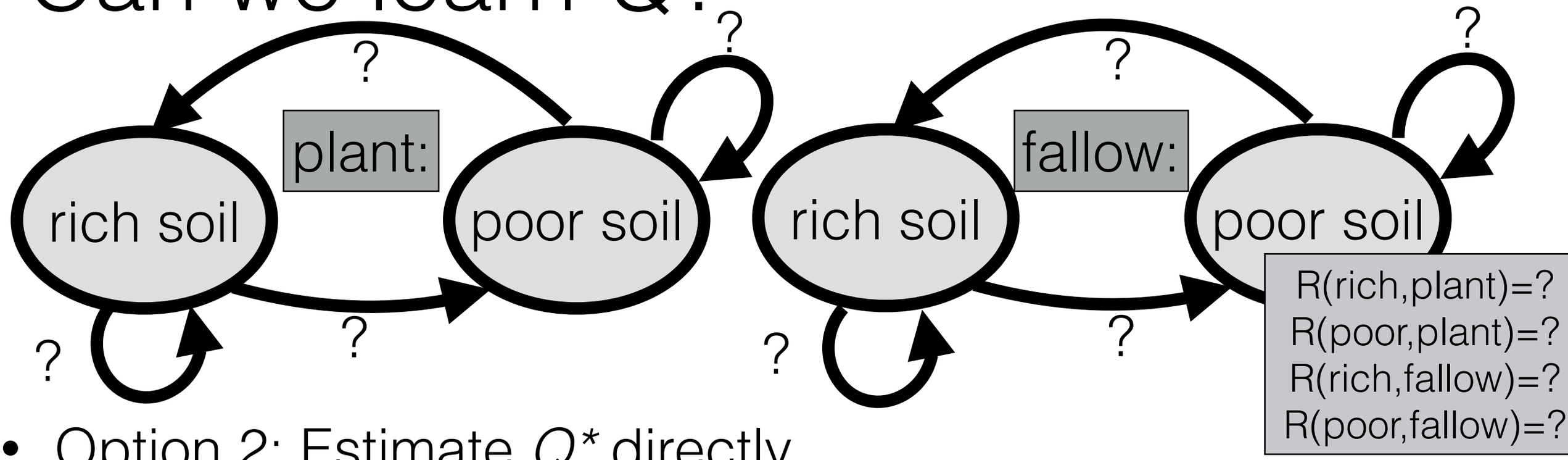

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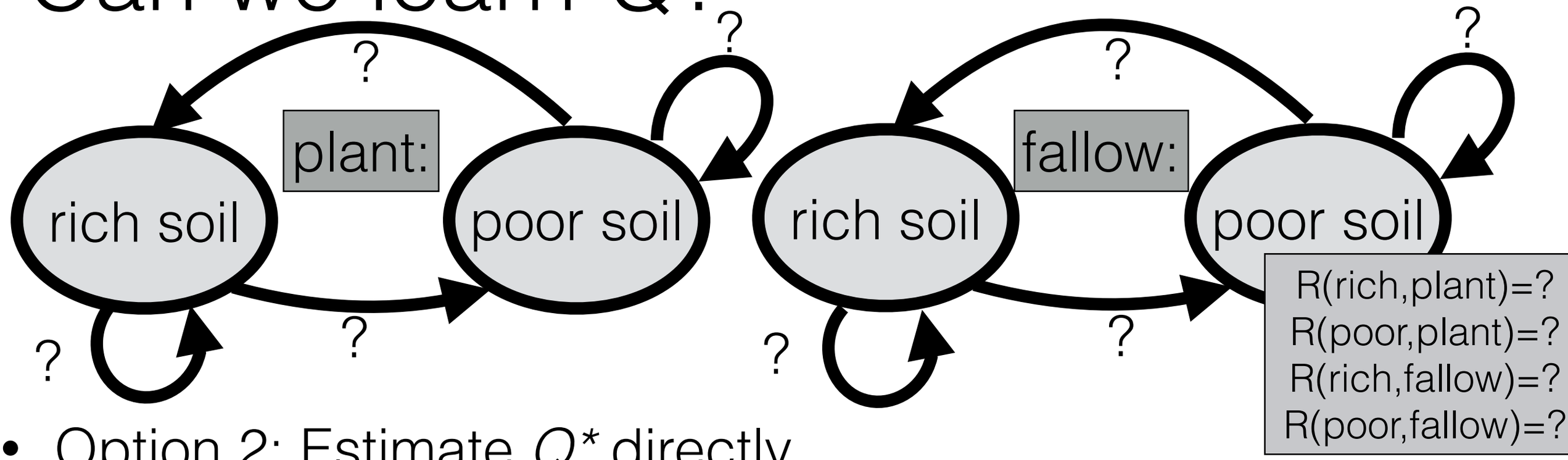

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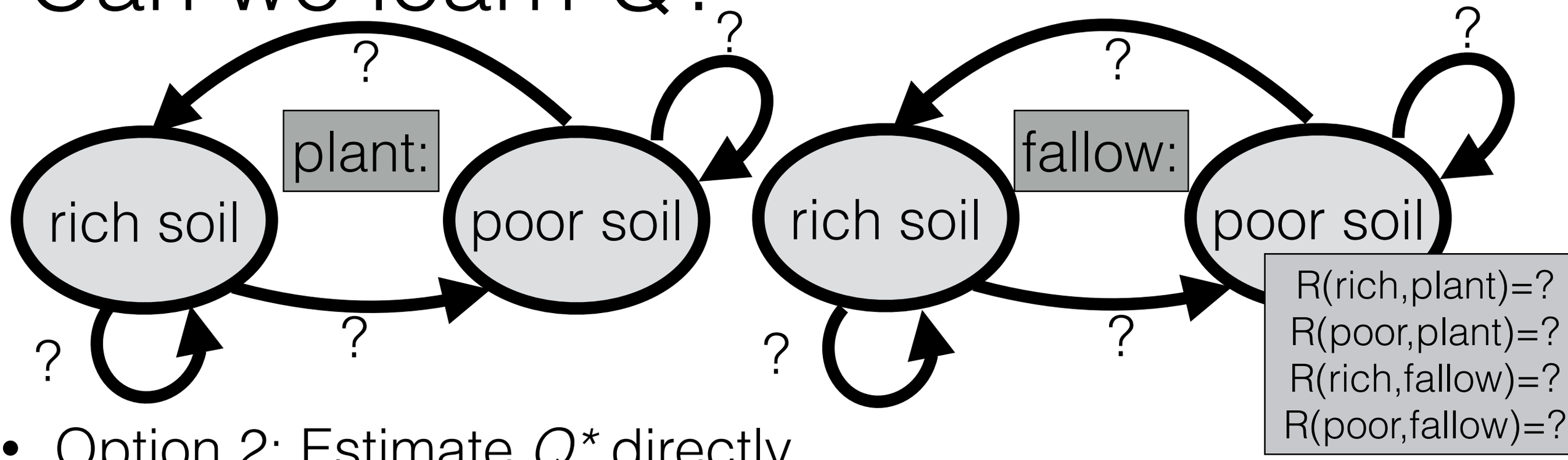

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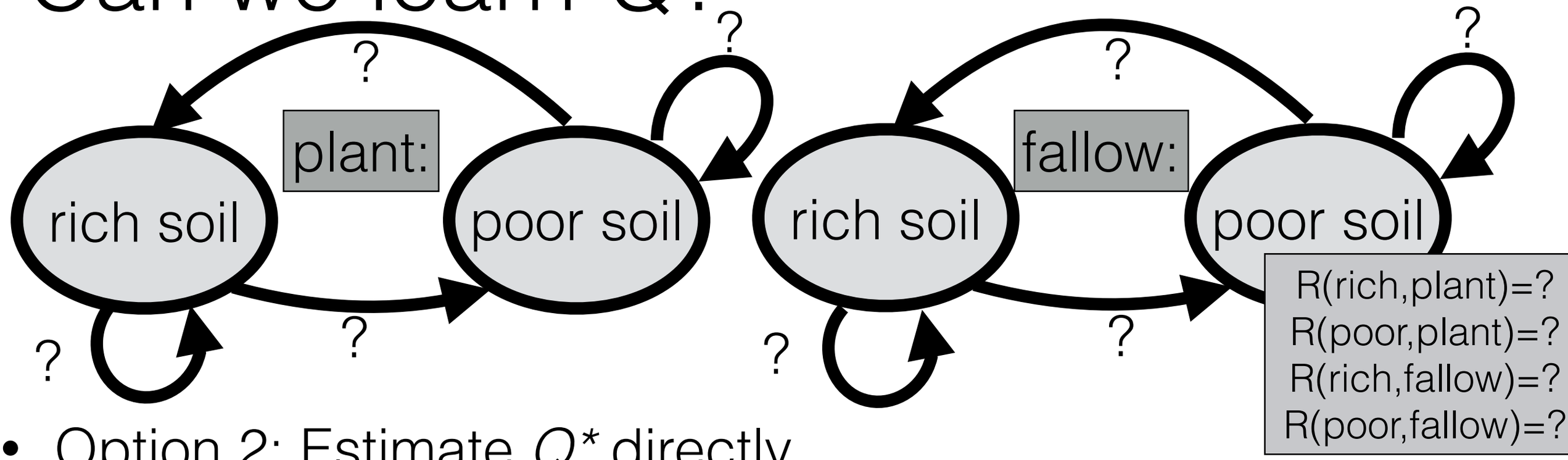

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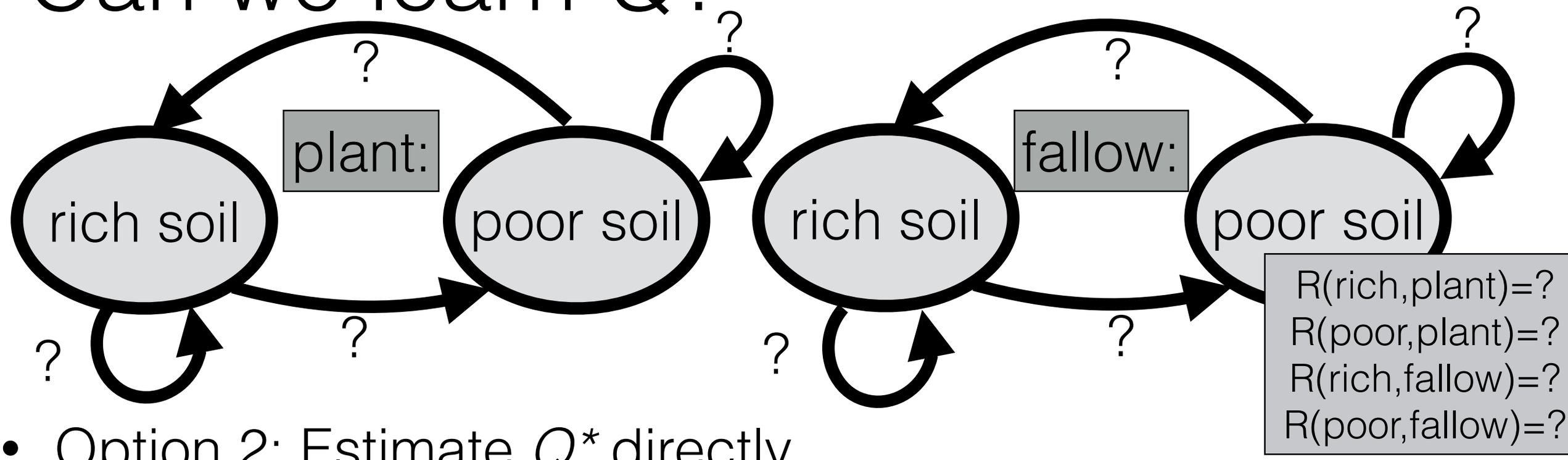

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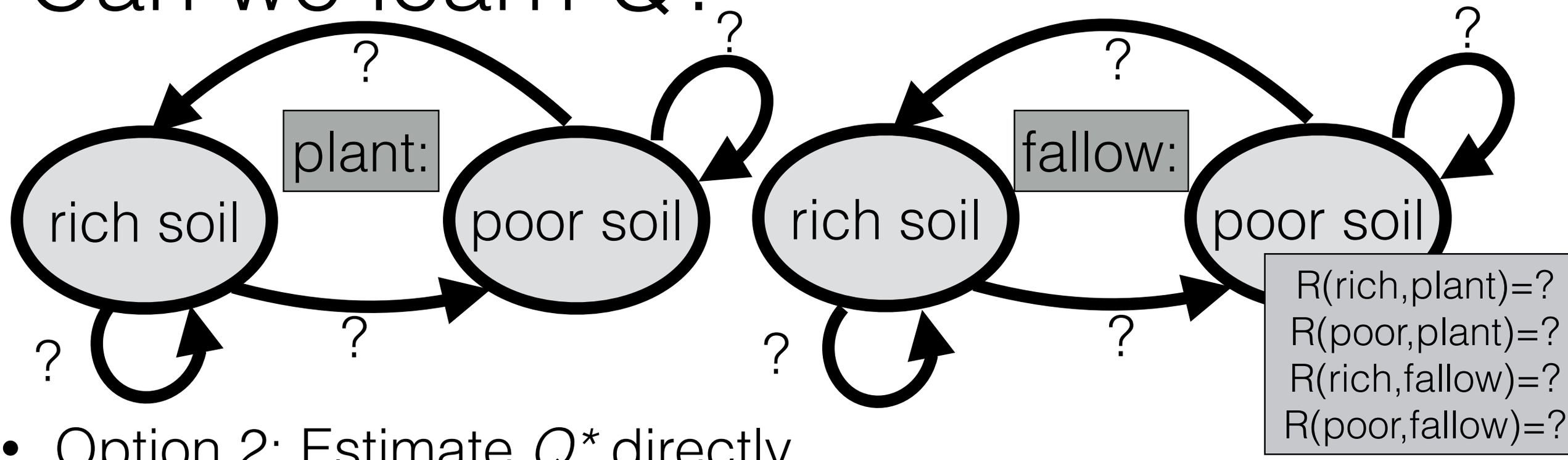

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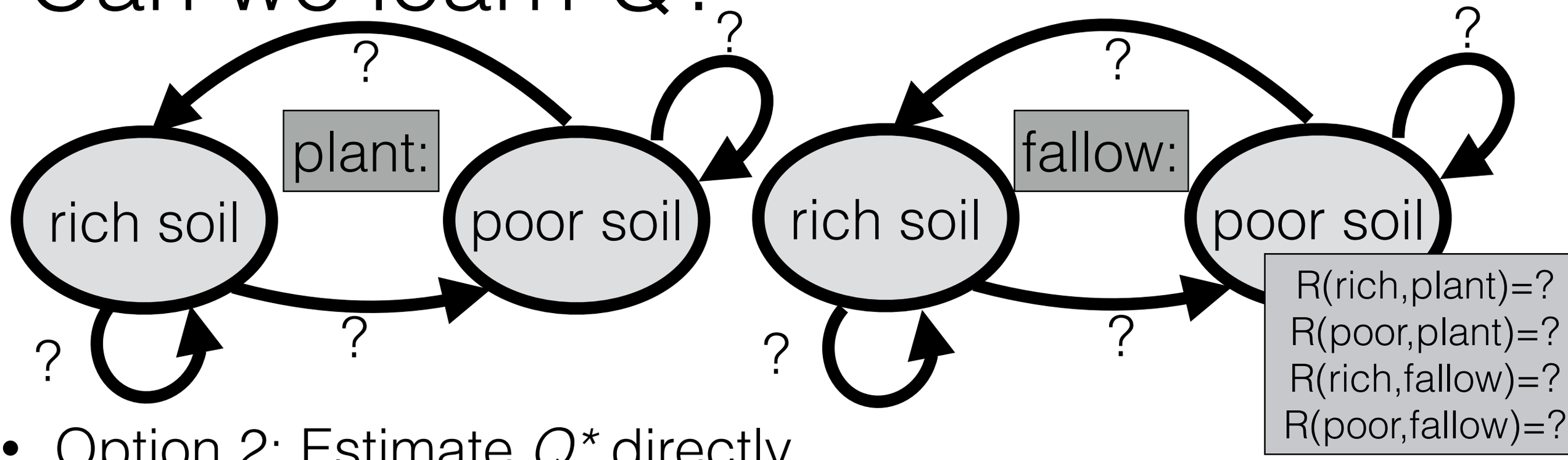

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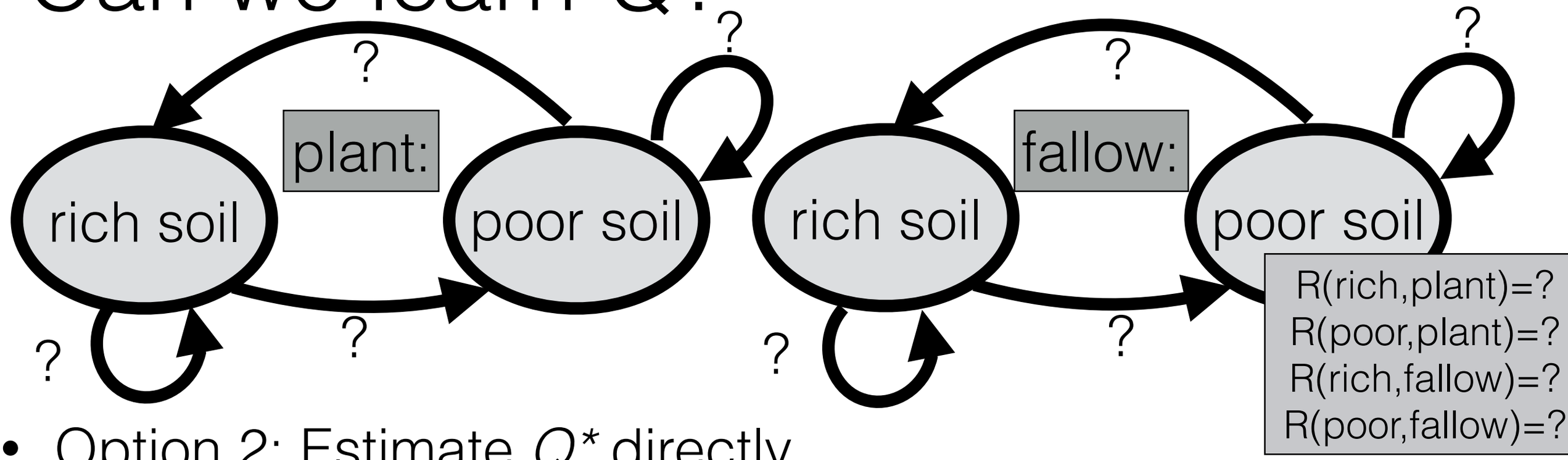

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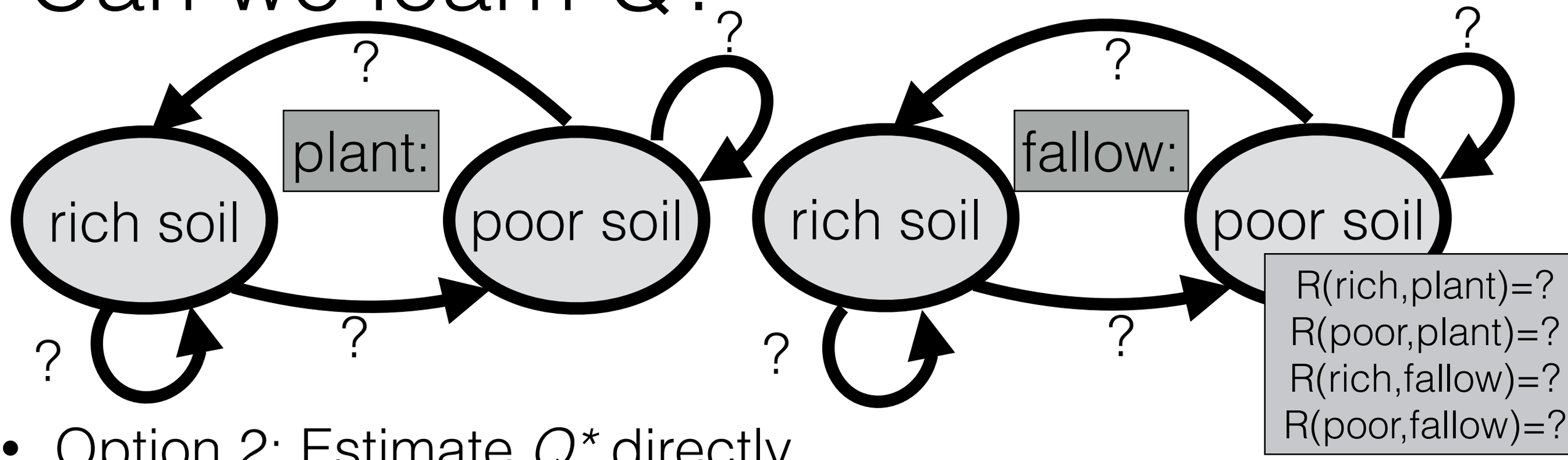

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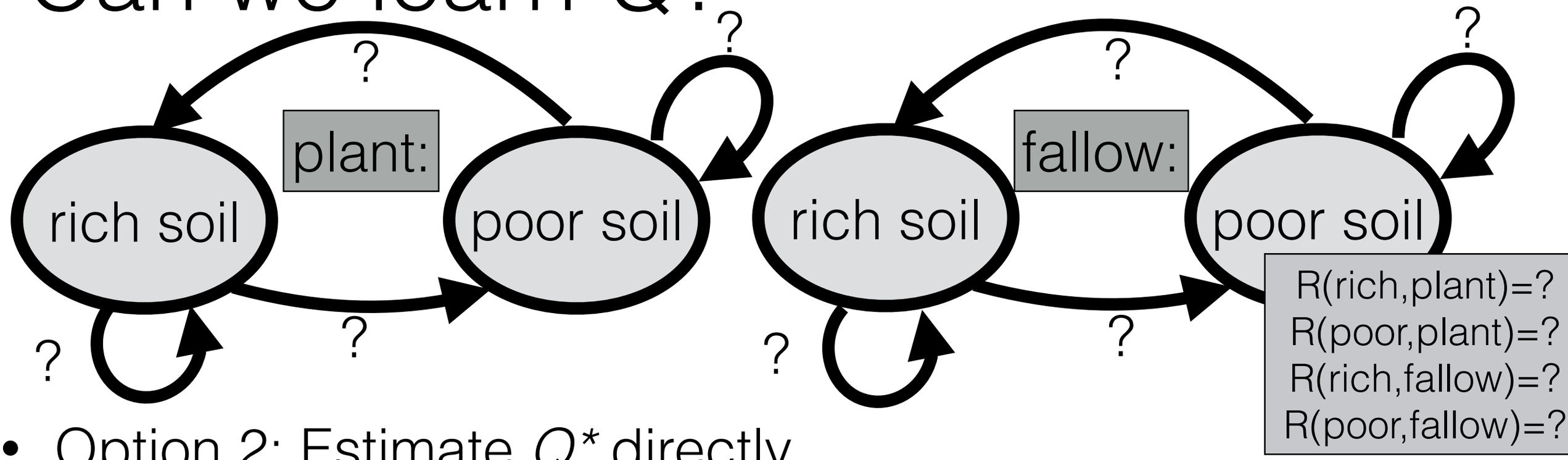

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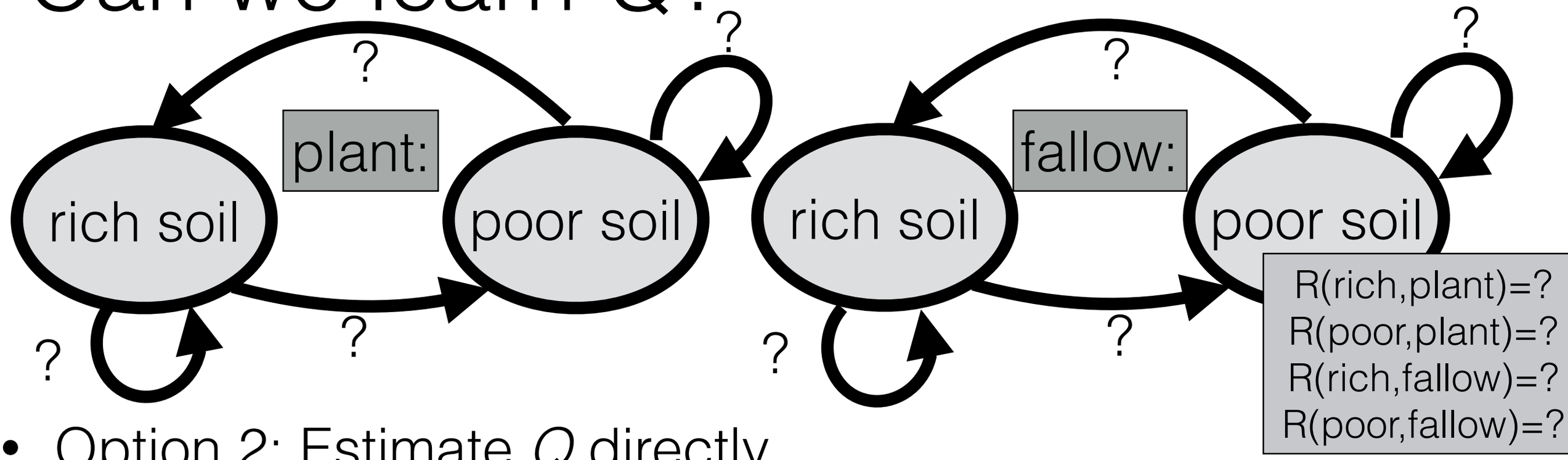
gives bigger weights to more recently observed values

Can we learn *Q*?



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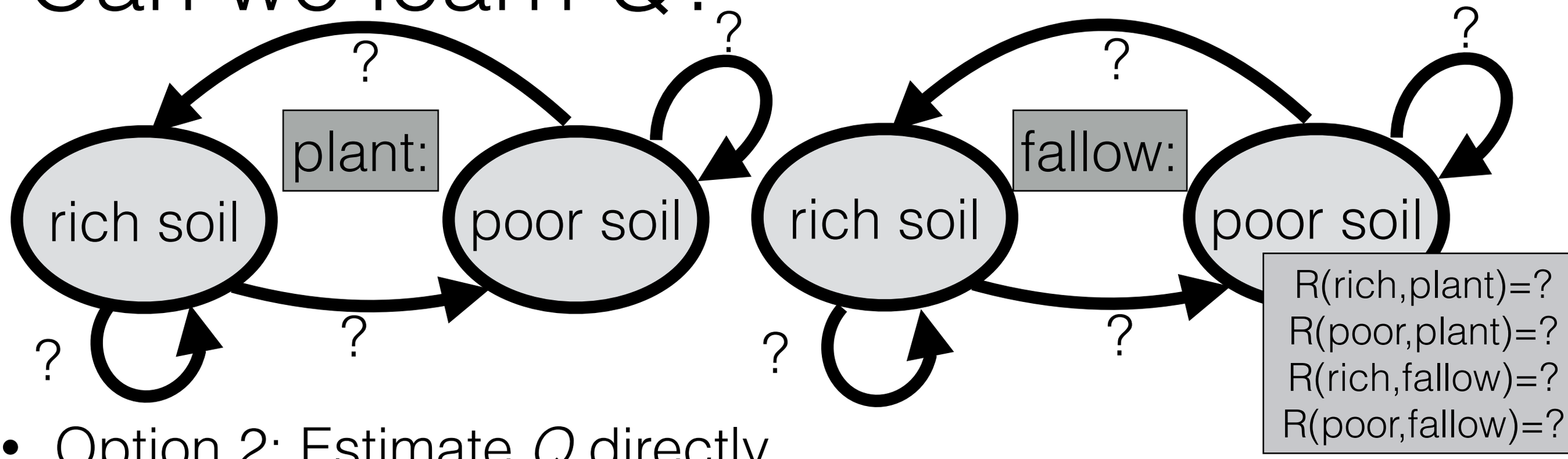

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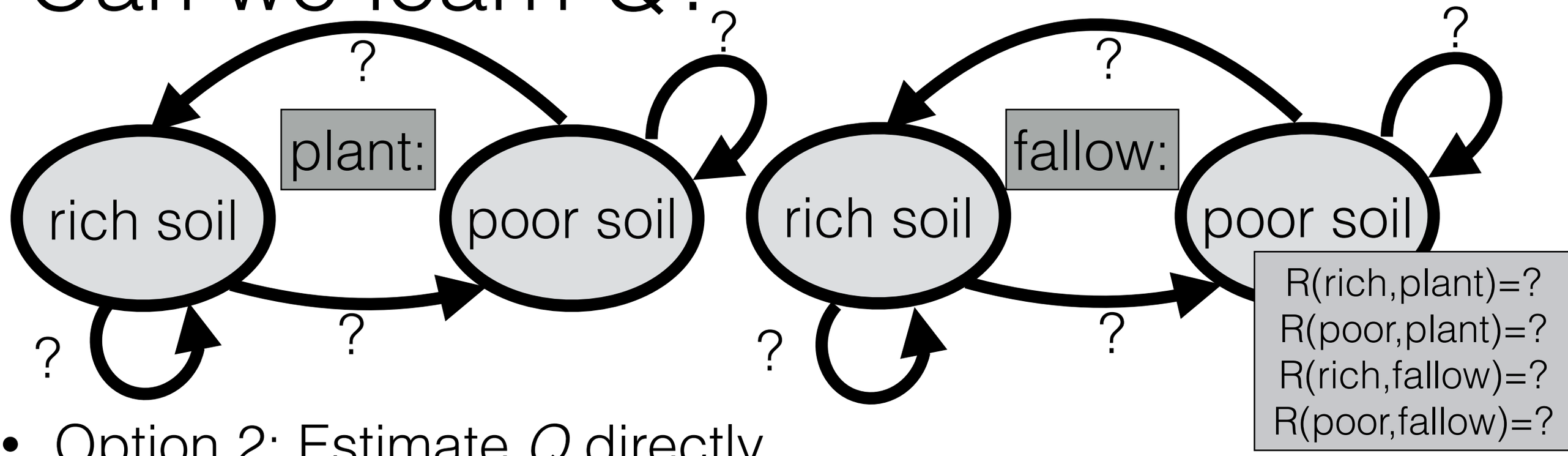

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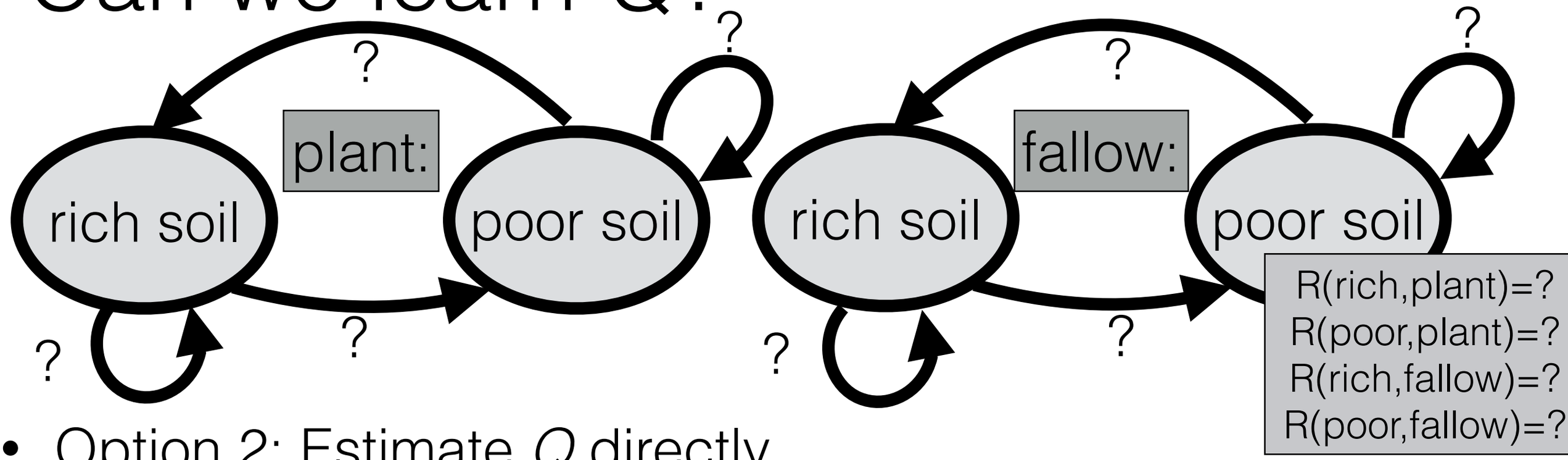

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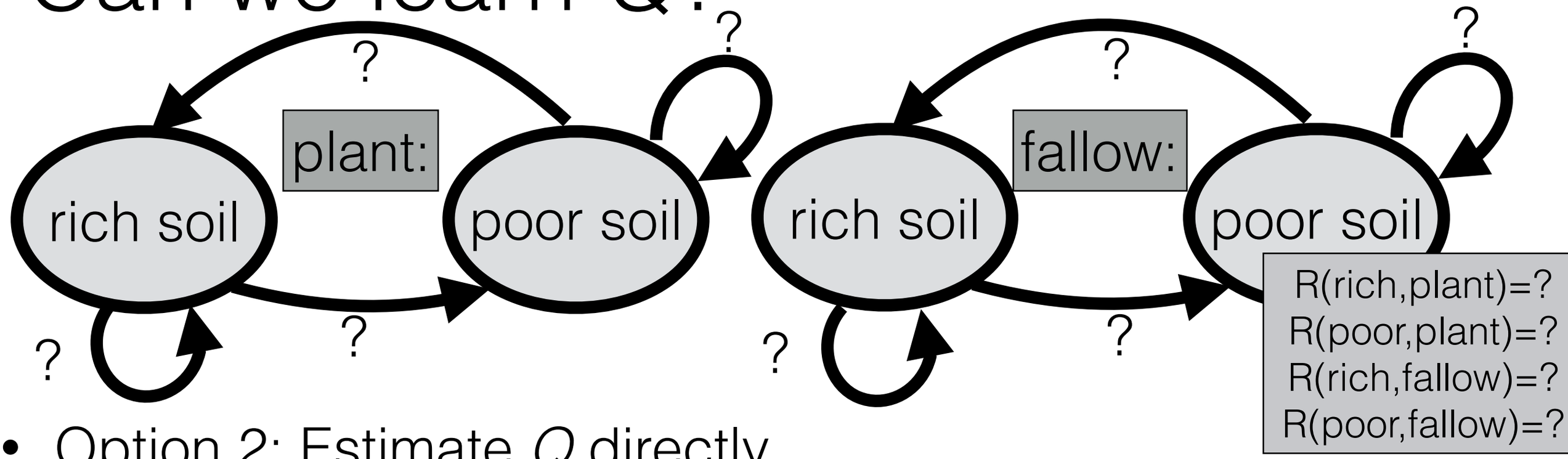

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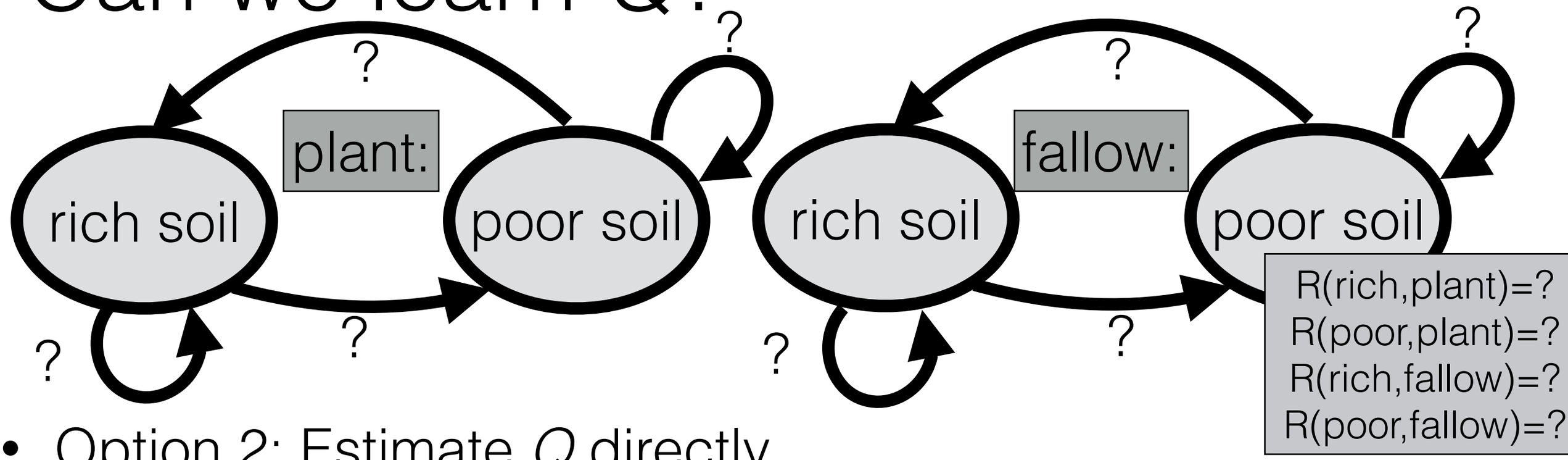

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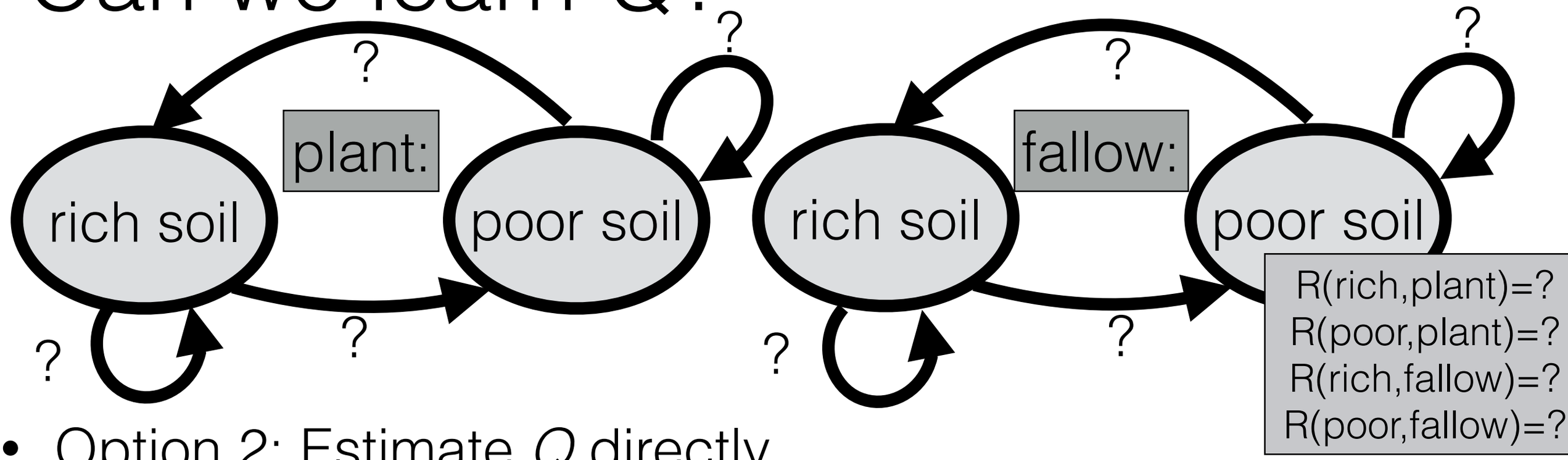

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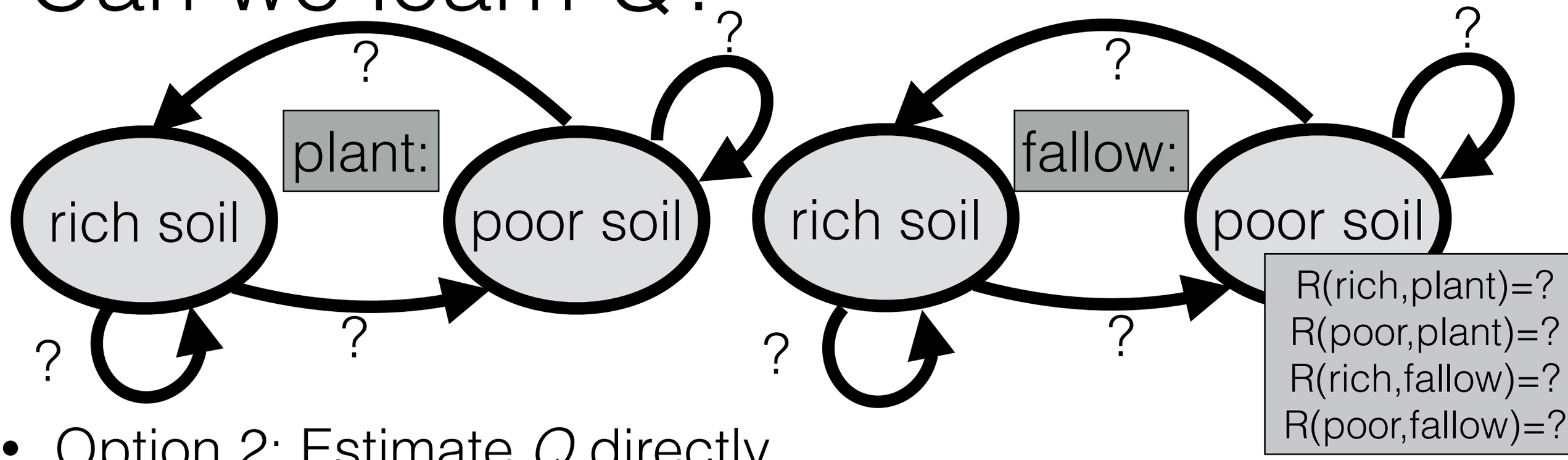

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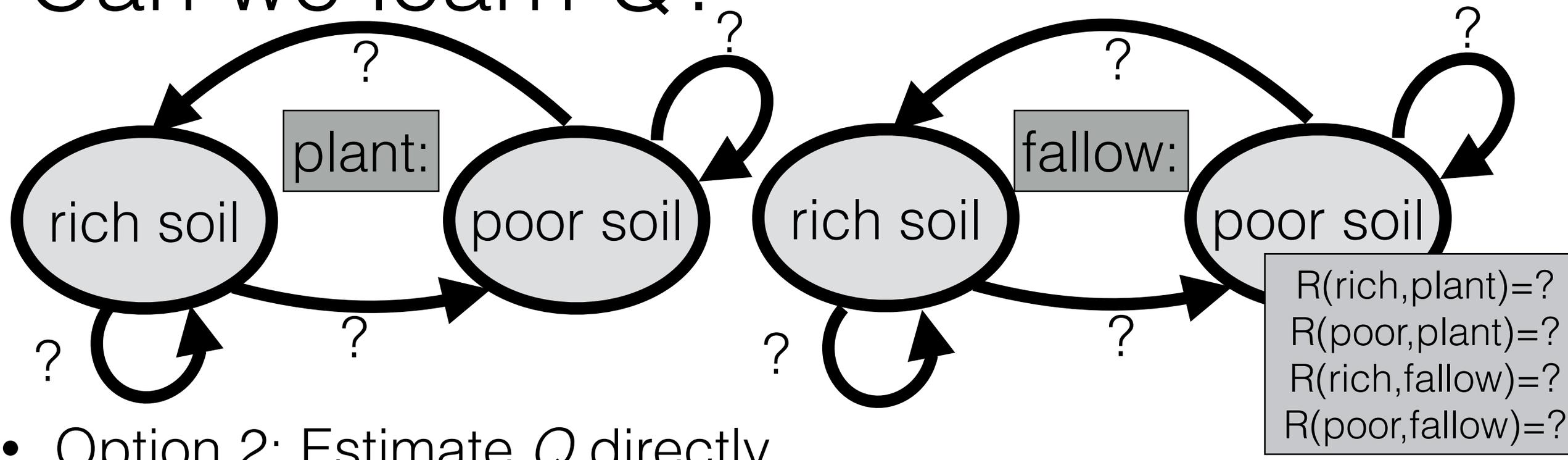

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- Update proposal: observe (*s*,*a*,*s*') & update estimate *Q*(*s*,*a*)

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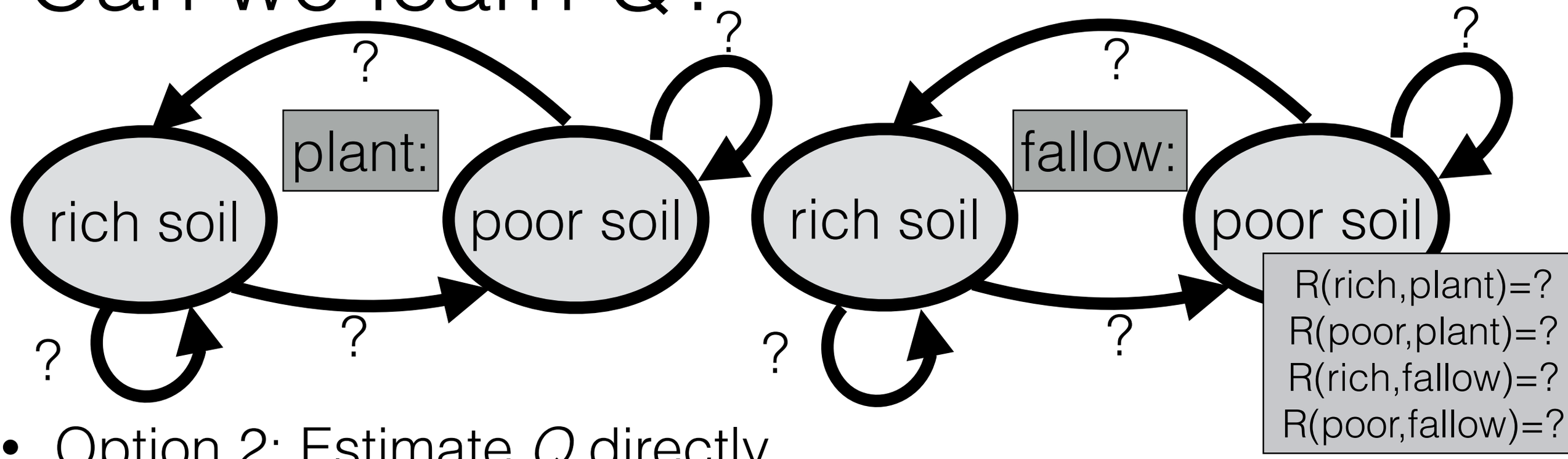
Can we learn *Q*?



- Option 2: Estimate *Q* directly
- Recall infinite horizon value iteration:

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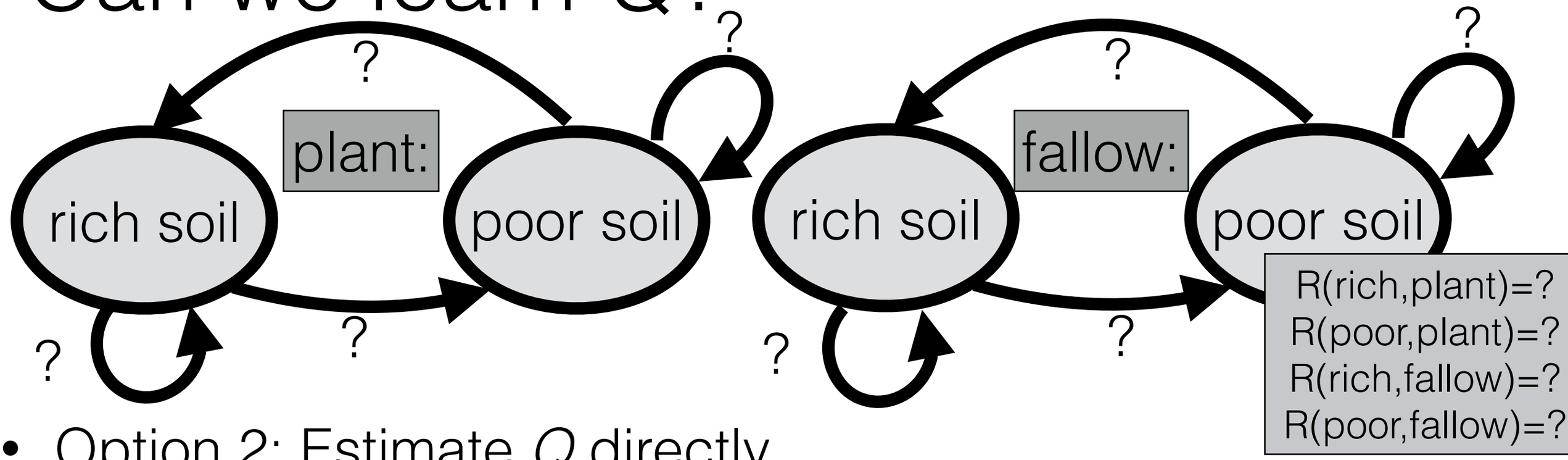

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`Q-learning`

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"temporal difference learning"

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Note: Algorithm never learns/stores *T* or *R;* just *Q*

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Note: This algorithm doesn't quite take actions according the policy we're learning

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"temporal difference learning"

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Some terminology

- *Reinforcement learning* (RL): learning (to maximize rewards) by interacting with the world
  - Contrast with *supervised learning*
- *Model-based RL*: uses explicit conception of next state and reward given current state and action
  - "Model" used many different ways in machine learning
  - Contrast with *Model-free RL*
- *Q-learning*
  - Contrast with the *Q** function (expected reward of starting at *s*, making action *a*, and then making the "best" action ever after)
  - Contrast with (any horizon) *value iteration*