

# What Should We Grow Today so We Make Money Tomorrow?

## Reinforcement Learning for Small Farmers

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# Context

**Greenhouse-in-a-box:** an affordable, modular greenhouse that uses 90% less water, grows 7 times more food and gives farmers a steady dependable income.



# Challenge

Develop an optimization-driven **decision support system** for this low-resource sector, with a holistic eye towards real-world and multi-agent considerations.



# Decision support system

1. Plant **tomatoes** in December 2021
2. Plant **cucumbers** on April 24<sup>th</sup>, 2022
3. Plant **beetroot** on August 13<sup>th</sup>, 2022
4. Plant **cabbages** on November 11<sup>th</sup>, 2022

current state

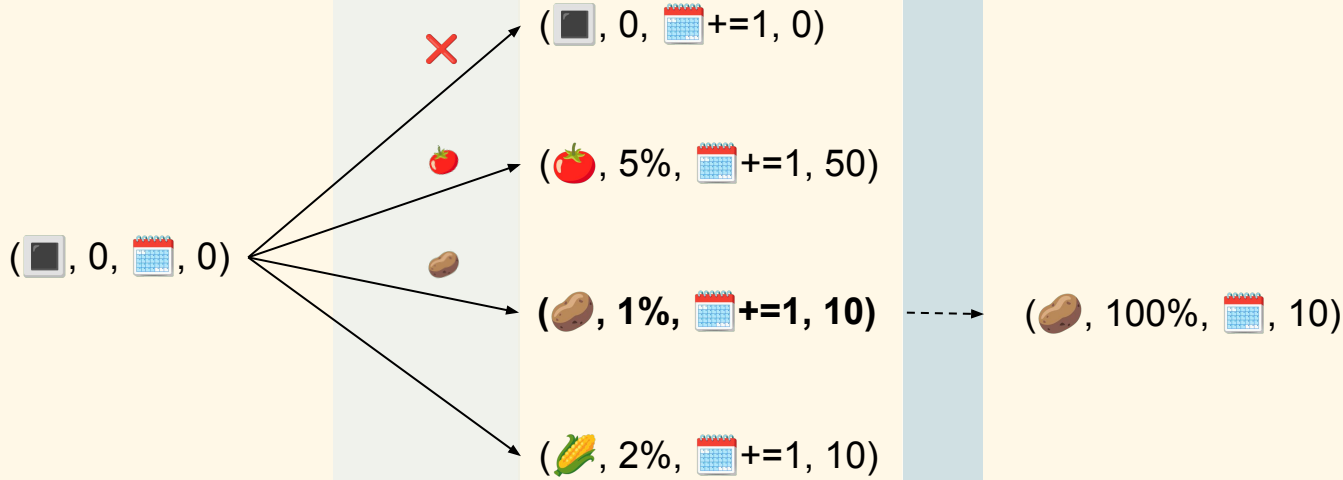
(crop, maturity, season, expected yield)

action

next state

...

next state



profit

₹ 0

₹ 0

current state  
(crop, maturity, season, expected yield)

action

next state

...

next state  
(crop, maturity, season, expected yield)

action

next state

(🌱, 0, 📅, 0)



(🌱, 0, 📅 +=1, 0)

(🍅, 5%, 📅 +=1, 50)

(🥔, 1%, 📅 +=1, 10)

(🌽, 2%, 📅 +=1, 10)

...

(🥔, 100%, 📅, 10)



(🌱, 0, 📅 +=1, 0)

Let's harvest.  
Tomorrow we will  
plant something new.

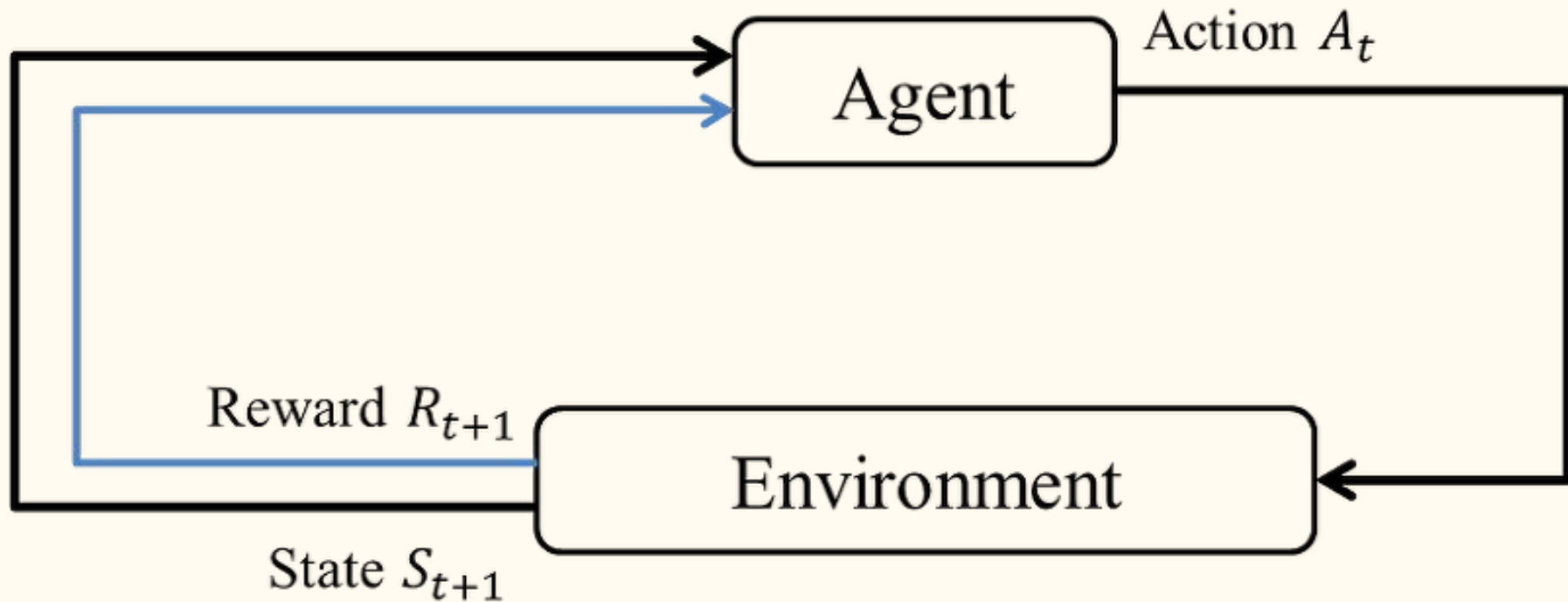
profit

₹ 0

₹ 0

₹ 1,000

# Markov Decision Process





# Markov Decision Process

**State Space** (*crop, maturity, expiry, date, flag*)

**Action Space** {*N/A, harvest, plant  $c_1$ , plant  $c_2$ , ...*}

**Transition function**  $P_a(s, s')$

**Reward function**

$$r(s, a, s') = \begin{cases} < 0 & \text{if } a \text{ yields a constraint violation} \\ y(\text{crop}) & \text{if } a \text{ is } \textit{harvest} \\ 0 & \text{otherwise} \end{cases}$$



Solve!

Goal: maximize expected total discounted reward  $\mathbb{E} \left[ \sum_{t=0}^{\infty} \gamma^t R_{a_t}(s_t, s_{t+1}) \right]$

$$V(s) := \sum_{s'} P_{\pi(s)}(s, s') (R_{\pi(s)}(s, s') + \gamma V(s'))$$

$$\pi(s) := \operatorname{argmax}_a \left\{ \sum_{s'} P_a(s, s') (R_a(s, s') + \gamma V(s')) \right\}$$

# Our planning algorithm produced this!

1. Plant **tomatoes** in December 2023  
Harvest a couple of times, but before they're fully harvested
2. Plant **cucumbers** on April 24<sup>th</sup>, 2024  
Harvest a couple of times, but before they're fully harvested
3. Plant **beetroot** on August 13<sup>th</sup>, 2024  
Rip them out of the ground in November so that you can plant
4. Plant **cabbages** on November 11<sup>th</sup>, 2024

Last summer, we improved:  
*learning* instead of *planning*

Adjusting the plan as we interact with the environment

# Reinforcement learning



# Solve!

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**Algorithm 1** Follow the Weighted Leader for MDP

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**Input:** Transition matrix  $P$ , parameter  $\theta \in [0, 1)$ , initial state  $s_0$

**Initialization:**  $\hat{R}_0$

1: **for**  $t = 1 : H$  **do**

2:     Update the weighted average of history rewards:

$$\hat{R}_t = (1 - \theta)\hat{R}_{t-1} + \theta R_{t-1}$$

Update estimates using observations

3:     Solve the MDP given reward matrix  $\hat{R}_t$  for the average optimal policy:

$$\pi_t \in \arg \max_{\pi} g_{\hat{R}_t}(\pi)$$

Recalculate the best action

4:     Execute  $\pi_t$ , Update current State  $s_t$

5:      $R_t \leftarrow$  true reward matrix(from market data)

Observe what happens

6: **end for**

**Output:**  $\pi_t$  at each time step  $t = 1, \dots, H$

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# Decision support system

Our algorithm produced this!

1. Plant **bottle brinjal** in December 2023  
Wait until bottle brinjal are fully grown, then harvest
2. Plant **cucumber** on March 12<sup>th</sup>, 2024  
Wait until cucumbers are fully grown, then harvest
3. Plant **beetroot** on July 16<sup>th</sup>, 2024  
Wait until beetroot are fully grown, then harvest
4. Plant **cucumber** on October 22<sup>nd</sup>, 2024  
Wait until cucumbers are fully grown, then harvest

Sounds like we have a working  
decision support system that  
recommends crops.

So what are we working on this summer?



# 1. We could do an even better job!

- a. Do we really need to reevaluate what action to take every day?
- b. The algorithm doesn't take into account future seasonality conditions.
- c. How would we explain the output to a farmer?

## 2. The **multiple** farmer universe

Is our recommendation still good if all of the farmers bring the same crops to market on the same day? **Probably not.**

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### Multi-agent reinforcement learning (MARL)

Each farmer is an agent motivated by their own rewards, and do actions to advance their own interests. In some MARL environments, these interests are opposed to the interests of other agents. We are in a unique position to provide small-scale coordination between agents.

Thank you

