

Advanced Formal Tools

PRISM: Probabilistic Model Checking

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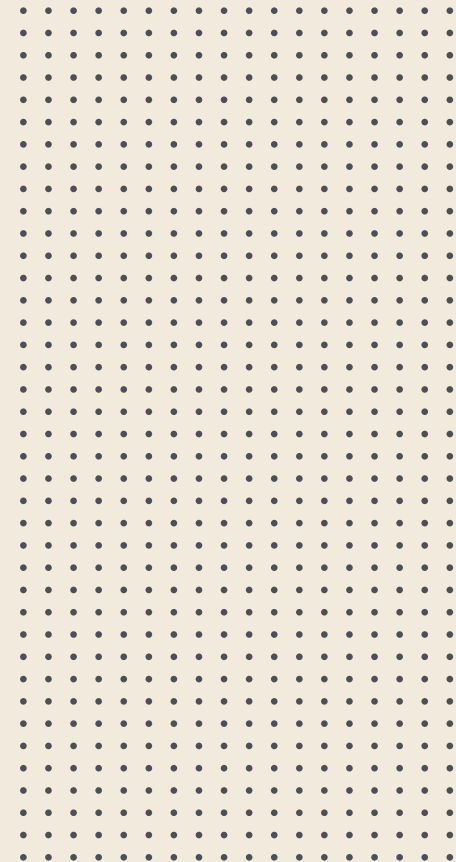
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Overview

1. Background and Theory
2. PRISM Usage and Limitations
3. Case Study
4. Future Work
5. Conclusion

Background and theory

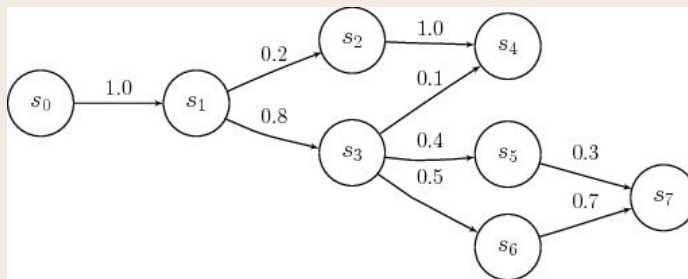
Probabilistic models

- Discrete Time Markov Chain
- Markov Decision Processes

Discrete Time Markov Chain

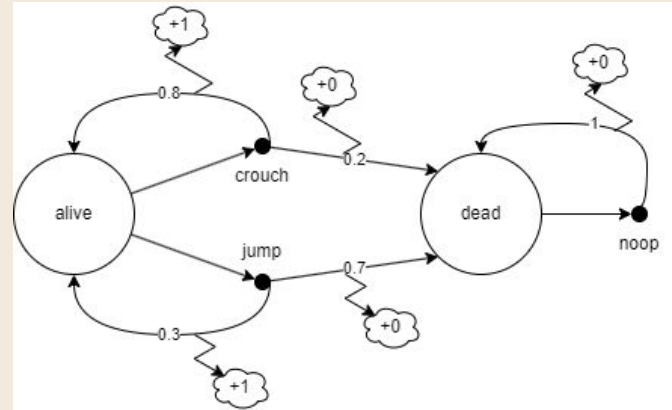
States: $\mathcal{S} = \{s_0, s_1, s_2, s_3, s_4, s_5, s_6, s_7\}$

Example transition: $s_0 \rightarrow s_1$, probability of 1, thus $p(s_1|s_0) = 1$



Markov Decision Process Model

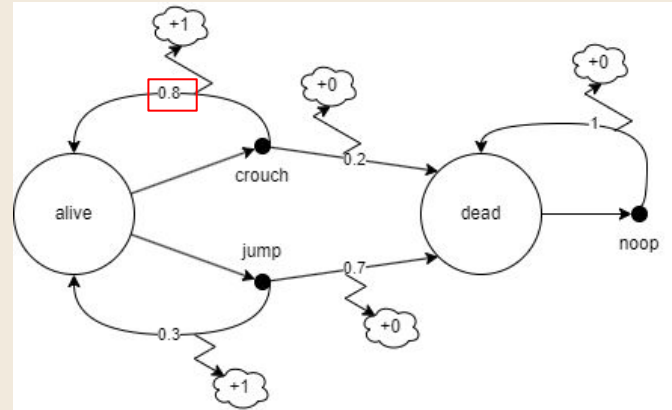
- **States:**
 - alive (init. state)
 - dead
- **Actions:**
 - crouch
 - jump



Non-deterministic, choose crouch or jump from alive ?

Markov Decision Process Model

- **States:**
 - alive (init. state)
 - dead
- **Actions:**
 - crouch
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Non-deterministic, choose crouch or jump from alive ?

- **Env. dynamics:**

$p(s', r | s, a)$

Ex: $P[S_{t+1} = \text{alive}, R_{t+1} = 1 | S_t = \text{alive}, A_t = \text{crouch}] = 0.8$

Markov Decision Process

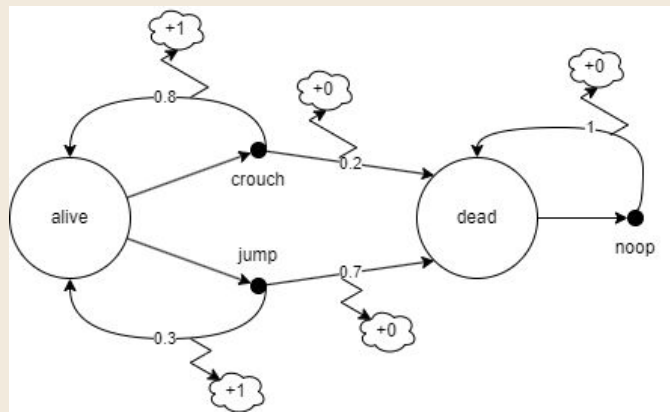
Policy & objective function

- **Policy/Strategy:**

$$\pi : \mathcal{S} \times \mathcal{A} \rightarrow [0, 1]$$

- **Expected cumulative reward:**

$$E(\pi) = \mathbb{E}_{\pi} \left[\sum_{i=1}^{\infty} R_i \middle| S_0 = s_0 \right]$$



Markov Decision Process

Policy & objective function

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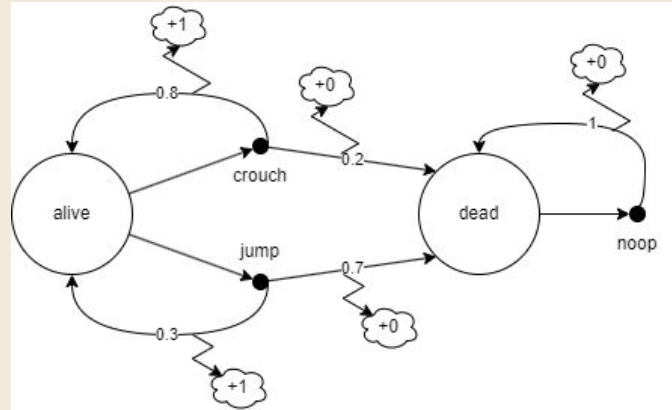
- Best policy:

$$\pi^* = \operatorname{argmax}_{\pi} E(\pi)$$

- Max. expected cumulative reward:

$$E(\pi^*)$$

Rmax=? [F "end"] in PRISM with "end" : s=0 (dead)



Markov Decision Process

Policy & objective function

- Policy/Strategy:

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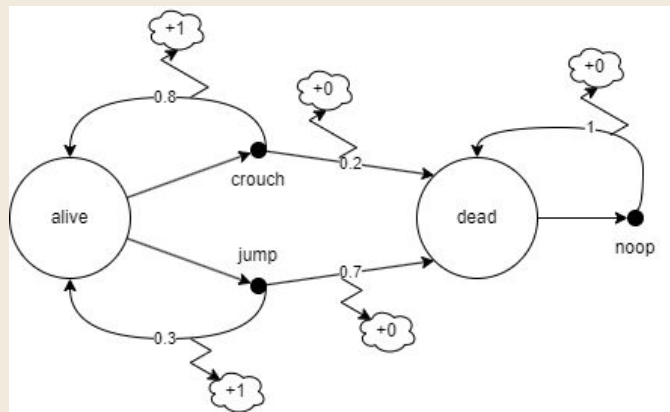
- Best** policy:

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- Max.** expected cumulative reward:

$$E(\pi^*)$$

Rmax=? [F "end"] in PRISM with "end" : s=0 (dead)



What about **worst** policy ?

Min. expected cumulative reward ?

Markov Decision Process

Reward structures

- Expected cumulative reward:

$$E(\pi) = \mathbb{E}_{\pi} \left[\sum_{i=1}^{\infty} R_i \middle| S_0 = s_0 \right]$$

- Best policy:

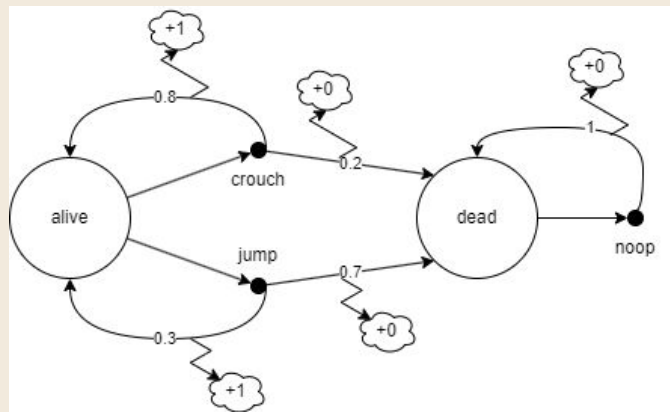
$$\pi^* = \operatorname{argmax}_{\pi} E(\pi)$$

- Max. expected cumulative reward:

$$E(\pi^*)$$

- Different reward distributions: reward structures**

- Enable verification of different props.
- Implicit verification of many MDPs.
- Ex: # of steps



Prism Usage and Limitations

Usage

- Coding
- Analysis

Limitations

PRISM Representation

mdp

module mdp_example

s : [0..1] init 1; // Alive initially

// non-deterministic choice from s =1

// jump vs crouch

[jump] (s=1) \rightarrow 0.3: (s'=1) + 0.7: (s'=0);

[crouch] (s=1) \rightarrow 0.8: (s'=1) + 0.2: (s'=0);

[noop] (s=0) \rightarrow (s'=0); // absorbing state

endmodule

rewards

(s=1) : 1; // reward for staying alive

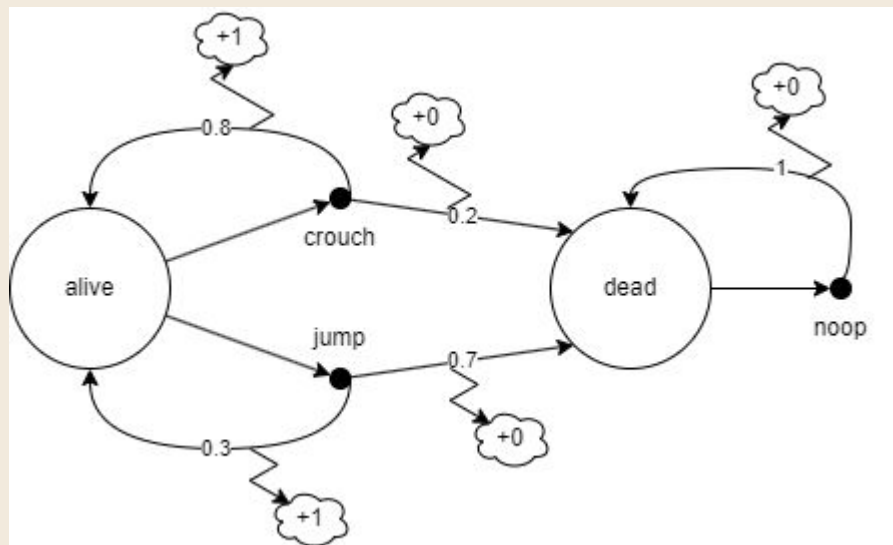
(s=0) : 0; // died

endrewards

rewards "steps"

true : 1;

endrewards



PRISM Model Analysis

Simulator

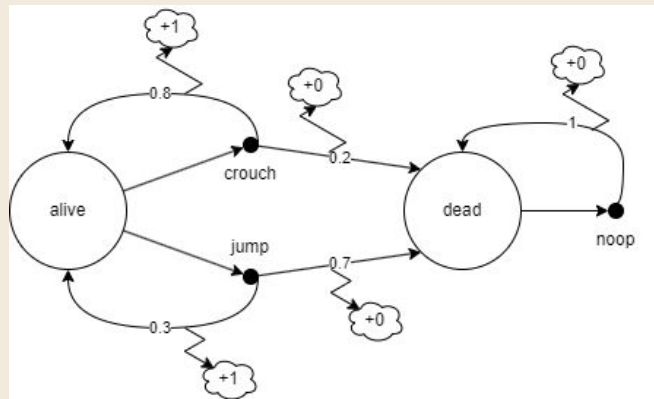
- Sample/simulate paths from probabilities
- Manually choose transitions

Properties

- PRISM's logics subsumes PCTL and others:
 - Extension with rewards
 - Extension with quantitative prop.

- Example of CTL vs PCTL for a given strategy:

CTL	$EG\ s=1$	Exist path where always alive
PCTL	$P > 0[G \leq 10\ s=1]$	Exist a path where alive for at least 10 steps
PRISM	$P = ?[G \leq 10\ s=1]$	PRISM can get the value (quant. prop.)





PRISM Limitations



DevOps

- No CTRL+F
- Missing standard graph tools, need to export data
- No for-loops

Modeling

- No negative rewards
- Can't assign probability distribution over rewards
- Simulation uses a uniform strategy to resolve non-determinism

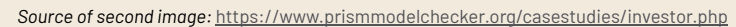
Case study: Market Bidding Investor

Description

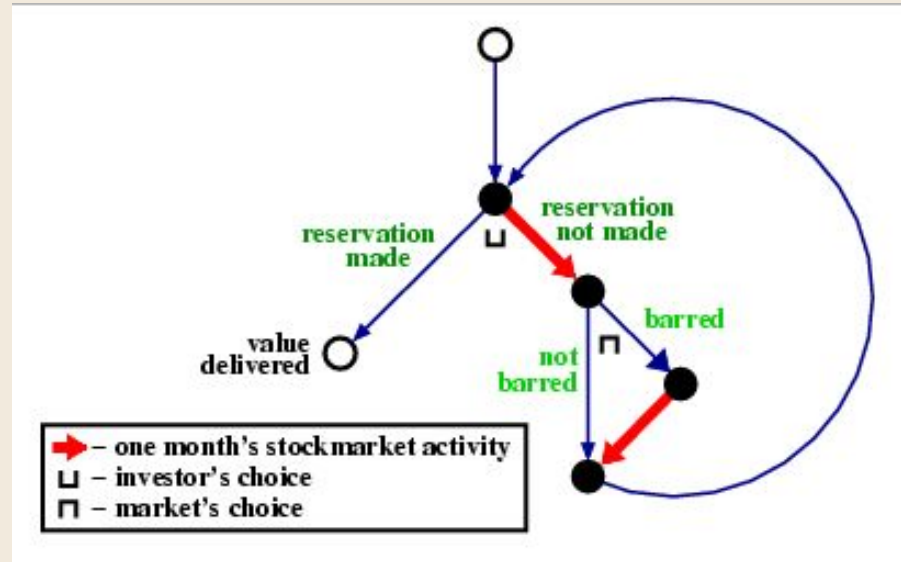
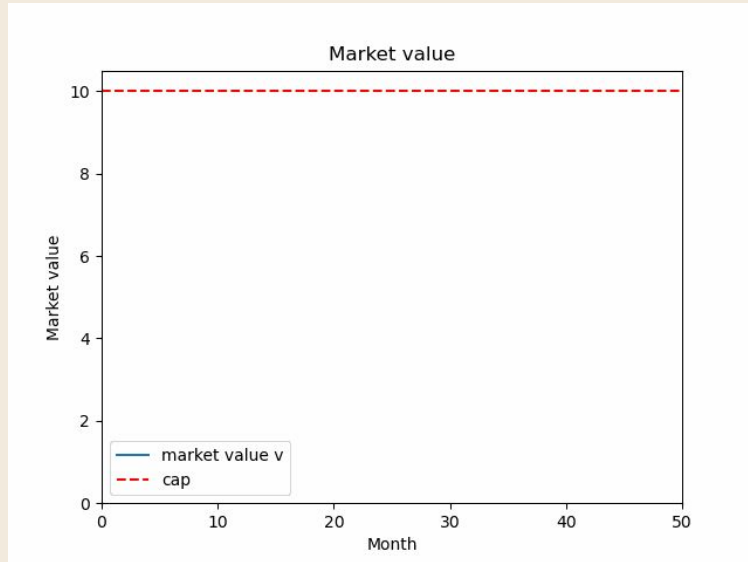
- Motivations
- Visual representation
- State transition

Analysis and Results

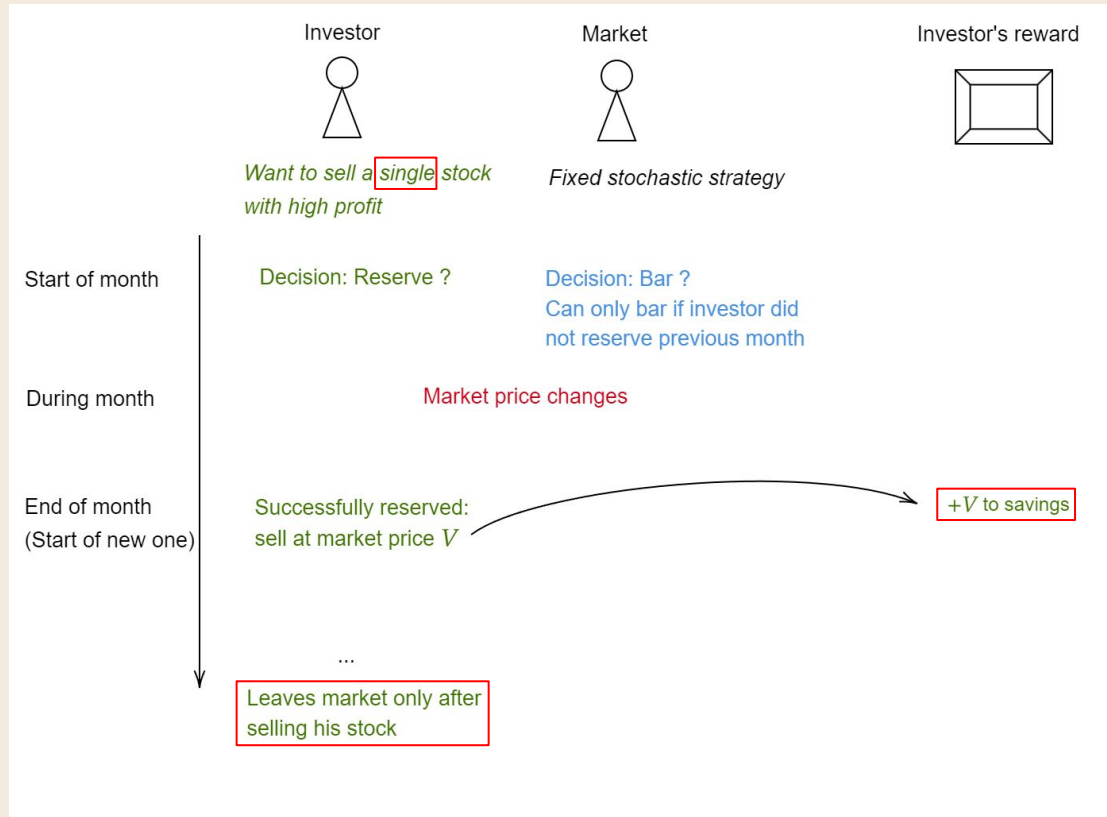
A 6x4 grid of dots, consisting of 6 rows and 4 columns of small black dots.



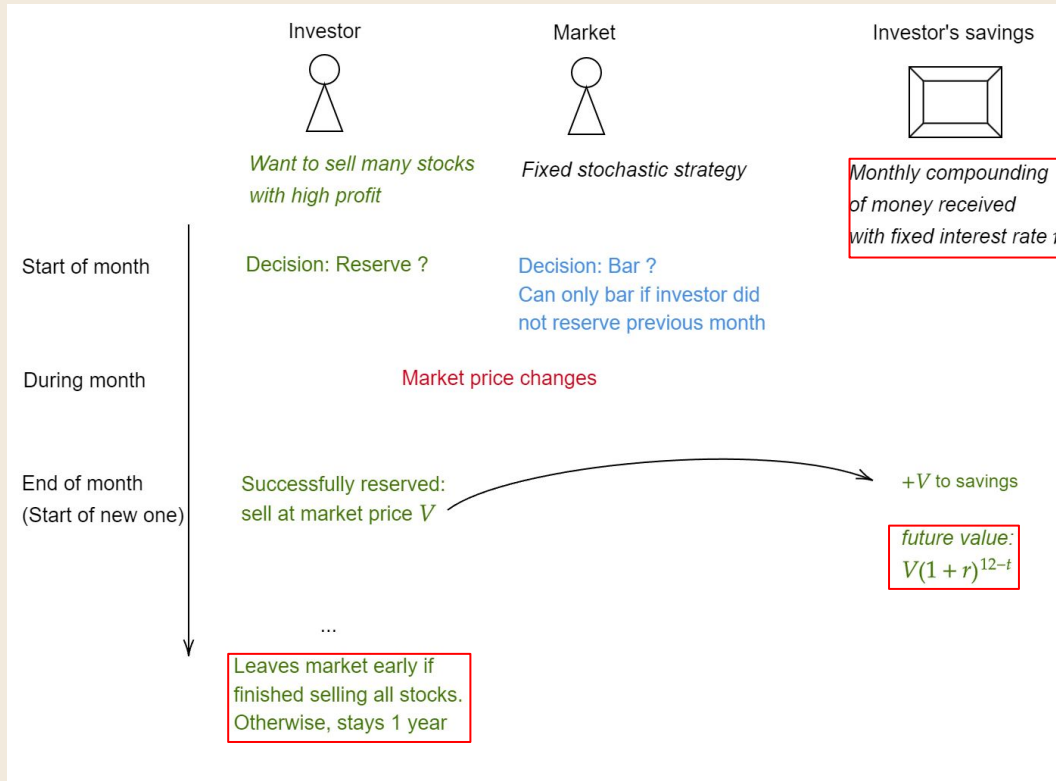
Original Case Study



Visual Representation

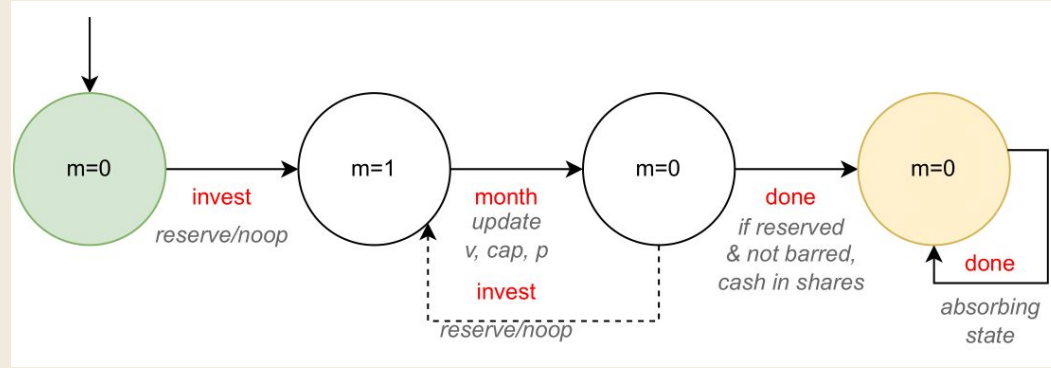


Extended Version

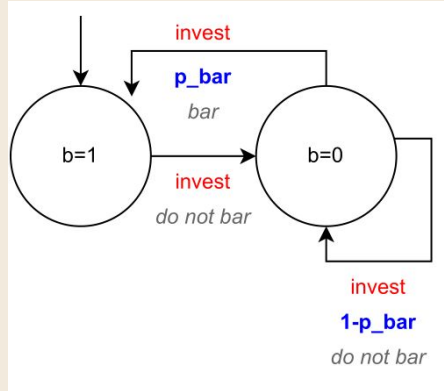


State transition Representation

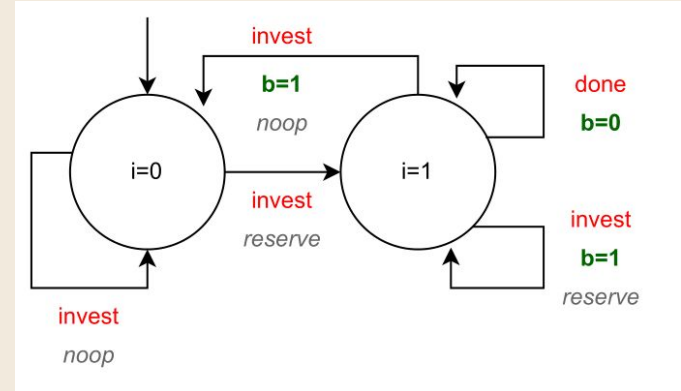
Month Module:



Market Module:

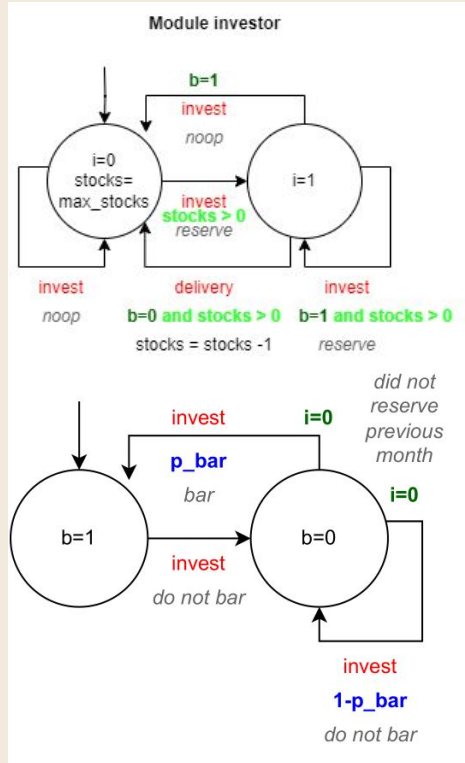


Investor Module:



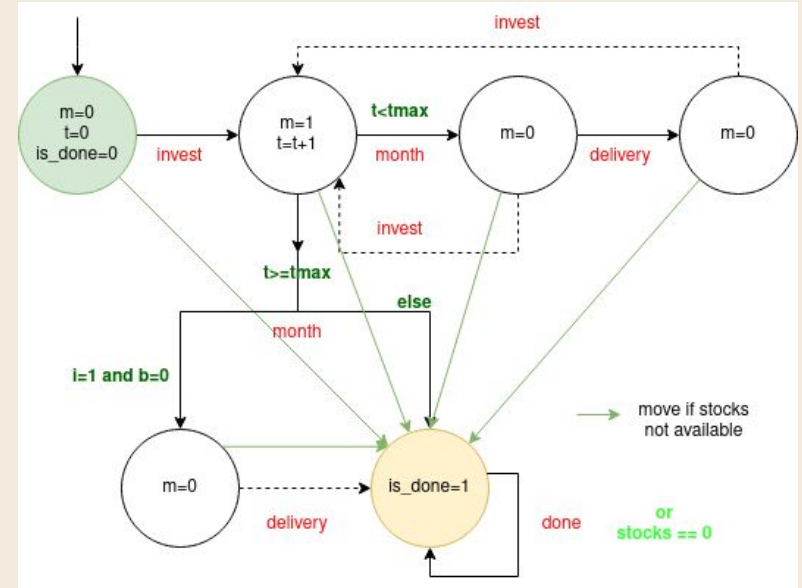
Representation with Changes

Investor Module:



Market Module:

Month Module:

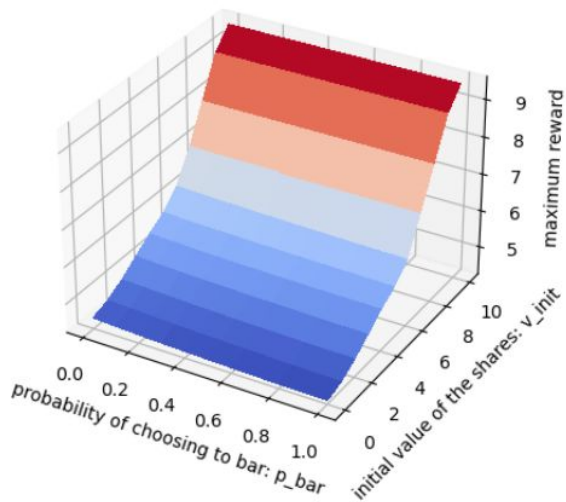




Results

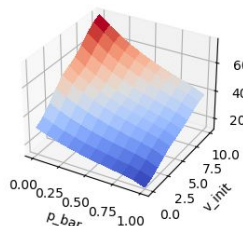
Zero interest rate

Non-zero interest rate

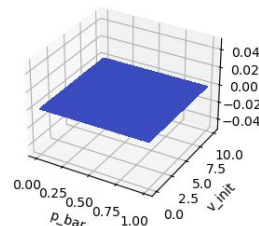


Some quantitative properties with:
 $p_{\text{bar}}=0:0.1:1$, interest=0,
 $v_{\text{init}}=0:1:10$, tmax=12 months

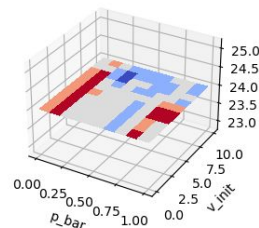
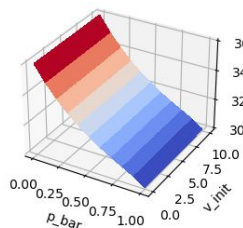
Rmax=? [F is_done=1]



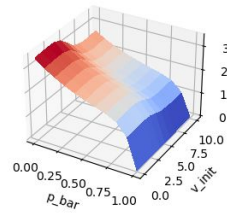
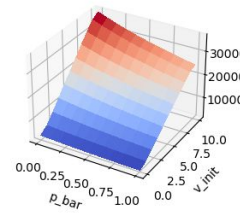
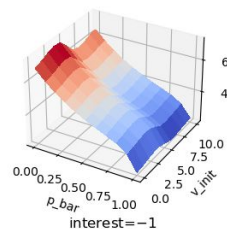
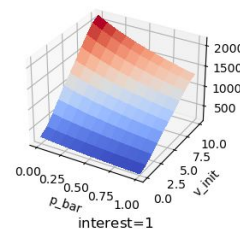
Rmin=? [F is_done=1]



R{"steps"}max=? [F is_done=1] R{"steps"}min=? [F is_done=1]



Rmax=? [F is_done=1] with:
 $p_{\text{bar}}=0:0.1:1$, interest $\in \{0.5, -0.5, 1, -1\}$,
 $v_{\text{init}}=0:1:10$, tmax=12 months, max_stocks=12
 interest=0.5 interest=-0.5



Original case study's results

Our case study's results



Future Work

- Analyze effect of interest together with max_stocks on number of steps
- Analyze effect of max_stocks on expected reward

PRISM-Games extension

- Analyze the case where market has no predefined strategy (stochastic multiplayer game)
- Introduce another investor, they take turns buying/selling to each other
- Implement a stock Future (both actors settle on a price now, for later)



Conclusion