Investment Decision Analysis Using Markov Decision Processes: A Case Study on Startups (New Application)

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1 Introduction

1.1 Motivation

The economic and venture capital landscape in India is characterized by conservative new angel investors. I want to get into venture capitalism and investment banking. This project explores applications of operations research and financial engineering by applying systematic approaches to assess risks and potential returns in startup investments. Using data from sources such as Preqin, this paper provides a practical use of Markov Decision Processes.

1.2 Goals

The primary goals of this project are to:

- Develop a Markov Decision Process (MDP) model for the problem.
- Maximize expected returns while minimizing associated risks (Expected Rewards).
- Provide investors/VC with an optimal policy they can leverage to make their investment decisions.

2 Problem Statement

2.1 Inputs

- 1. **Investment Amount:** VC specifies the amount of capital they intend to invest in USD.
- 2. Startup Stage: State/Stage identification of the potential startup VC wants to invest in.
- 3. **Investment Duration:** VC indicates the number of years they wish to lock their investment for
- 4. **Industry Preference:** VC specify the industry they are interested in investing in such as technology, healthcare, finance, etc.

2.2 Assumptions

- 1. **Rewards Proportional to Valuation Increase:** This assumption implies that we are focusing on the success rate of the startup as the primary driver of rewards. In the code, I have made valuation to be rewarding on a higher state by putting the state as an exponent on a number. I expand on the Valuation calculation in the next subsection.
- 2. **Transition Probabilities:** Transition probabilities are estimated using historical data on startup transitions.
- 3. **Holding Costs:** Holding costs are calculated as x% (Rate of Interest in a bank) of the invested amount per year. In the code, I used 5%.

2.3 Calculating Startup Valuation (Uncertainty)

Ways to calculate Valuation - Outside Scope of this class but interesting expansion of this project

- 1. Identify similar companies in the industry and average their performance metrics, then adjust based on the startup's unique value proposition. This method provides a benchmark for valuation while considering the uncertainty inherent in comparing startups to established companies.
- 2. Discount future cash flows to their present value using an appropriate discount rate to estimate the startup's valuation.
- 3. Utilizing ARIMA/exponential smoothing to forecast future revenues and profits.

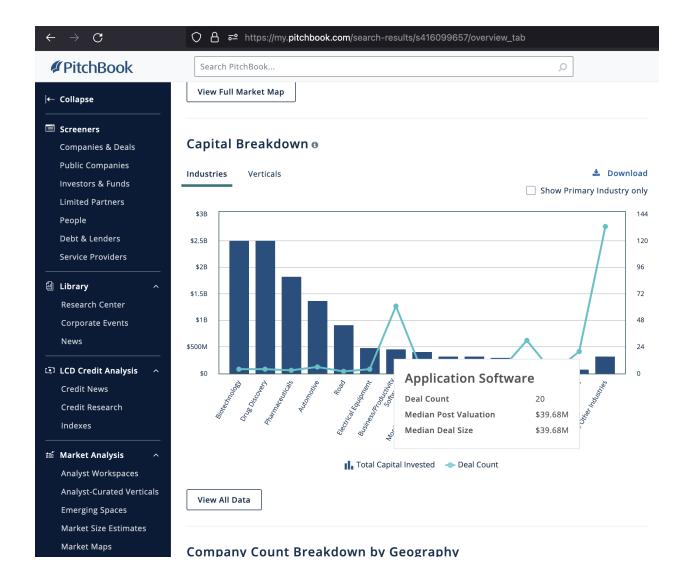


Figure 1: A way to estimate valuation. Source: https://www.pitchbook.com/

3 Implementation

3.1 Data Preparation

The historical data was found using the website Preqin. Information about data

- 1. Dartmouth Library \rightarrow Preqin \rightarrow Companies & deals \rightarrow Private Equity
- 2. This data is US based.
- 3. Data was exported and used for educational purposes.
- 4. Only essential columns including "DEAL.DATE", "TARGET.COMPANY.ID", "DEAL.TYPES", "PRIMARY.INDUSTRY", and "INVESTORS" were retained for analysis.

5. Only rows corresponding to startup investment rounds (e.g., Seed, Series A, etc.) were retained for further analysis.

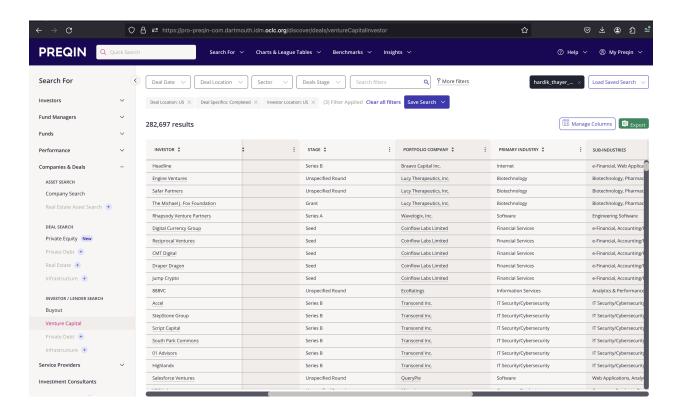


Figure 2: Source: https://www.preqin.com/

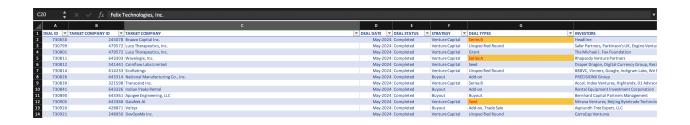


Figure 3: Data File

3.2 Markov Decision Process (MDP) Model

3.2.1 States

 $S = \{ \text{Seed}, \text{Series A}, \text{Series B}, \text{Series C}, \text{Series D}, \text{Series E}, \text{Series F}, \text{Series G}, \text{Series H}, \text{Series I}, \text{Series J}, \text{Series K}, \text{Series L}, \text{Pre-IPO}, \text{Venture Debt}, \text{Absorption/Exit} \}$

3.2.2 Actions

Let A be the set of actions available to the investor:

$$A = \{\text{Invest}, \text{Hold}, \text{Exit}\}$$

3.2.3 Transition Probabilities

Let $P(s' \mid s, a)$ be the transition probability of moving from state s to state s' under action a:

$$P: S \times A \times S \rightarrow [0,1]$$

such that:

$$\sum_{s' \in S} P(s' \mid s, a) = 1, \quad \forall s \in S, \forall a \in A$$

Calculation of transitional probabilities:

Algorithm 1 Calculate Transitional Probabilities for Startup Funding Stages

```
1: procedure ComputeTransitionProbabilities(Data, InitialStage, Stages)
        n \leftarrow \text{number of startups at InitialStage}
 3:
         for each s \in \text{Stages do}
             count_s \leftarrow \text{number of startups transitioning from InitialStage to } s
 4:
 5:
        count_{none} \leftarrow number of startups that did not transition anywhere
 6:
 7:
        total \leftarrow n
        for each s \in \text{Stages} \cup \{\text{none}\}\ \mathbf{do}
 8:
             P_s \leftarrow \frac{count_s}{total}
 9:
             Print P_s
10:
        end for
11:
12: end procedure
```

3.2.4 Rewards

Let R(s, a) be the reward function representing the immediate reward received after taking action a in the state s:

$$R: S \times A \to \mathbb{R}$$

The rewards are defined as follows:

• Investment Costs $C_{\text{invest}}(s)$: The negative reward (cost) for investing in a startup at state s:

$$C_{\text{invest}}(s) = -\cot(s)$$

• Holding Costs $C_{\text{hold}}(s)$: The negative reward (cost) for holding the investment at state s, calculated as 5% of the invested amount per year:

$$C_{\text{hold}}(s) = -0.05 \times \text{investment}(s)$$

• Exit Rewards $R_{\text{exit}}(s)$: The positive reward for exiting the investment at state s, proportional to the valuation of the startup at that stage:

$$R_{\text{exit}}(s) = \text{proportion of share} \times \text{valuation}(s)$$

3.2.5 Objective

The objective is to find the optimal policy π that maximizes the expected total reward over the lifecycle of the investment:

$$\pi^* = \arg\max_{\pi} \mathbb{E} \left[\sum_{t=0}^{T} R(s_t, \pi(s_t)) \mid s_0 \right]$$

where s_t is the state at time t, $\pi(s_t)$ is the action taken in state s_t , and T is the investment horizon.

3.3 Backward Induction

Backward induction was used to solve the MDP and determine the optimal policy. The value function and policy were recursively calculated, considering the discount factor for future rewards.

Algorithm 2 Recursive Backward Induction for Markov Decision Processes

```
1: function Recursive Backward Induction (P, r, rterm, \gamma, t, S, A, memo, policy)
 2:
         if t \in \text{memo then}
 3:
              return memo[t]
         end if
 4:
         V \leftarrow \operatorname{zeros}(S)
                                                                              ▶ Initialize value function for this stage
 5:
         if t = size(P, 3) - 1 then
                                                                                              ▷ Check if at the last stage
 6:
              for s = 1 to S do
 7:
                  Q \leftarrow \operatorname{zeros}(A)
                                                                                       ▶ Initialize action-value function
 8:
                  for a = 1 to A do
 9:
                       Q[a] \leftarrow r[s,t,a] + \gamma \sum_{sp=1}^{S} P[s,sp,t,a] \times rterm[sp]
10:
                  end for
11:
                  V[s] \leftarrow \max(Q)
12:
                  \operatorname{policy}[s,t] \leftarrow \arg \max(Q)
13:
              end for
14:
15:
         else
              for s = 1 to S do
16:
                  Q \leftarrow \operatorname{zeros}(A)
17:
                  for a = 1 to A do
18:
                       Q[a] \leftarrow r[s,t,a] + \gamma \sum_{sp=1}^{S} P[s,sp,t,a] \times \text{RecursiveBackwardInduction}(P,r,rterm,\gamma,t+1)
19:
     1, S, A, \text{memo, policy}[sp]
                  end for
20:
                  V[s] \leftarrow \max(Q)
21:
                  \operatorname{policy}[s,t] \leftarrow \arg \max(Q)
22:
              end for
23:
         end if
24:
         \text{memo}[t] \leftarrow V
25:
         return V
26:
27: end function
```

Algorithm 3 Backward Induction Recursive

- 1: **function** BackwardInductionRecursive $(P, r, rterm, \gamma)$
- 2: $S, T, A \leftarrow \text{dimensions of } P$
- 3: memo ←
- 4: $\operatorname{policy} \leftarrow \operatorname{zeros}(S, T, \operatorname{dtype=int})$
- 5: RECURSIVE BACKWARD INDUCTION $(P, r, rterm, \gamma, 0, S, A, memo, policy)$
- 6: **return** memo, policy
- 7: end function

4 Results

4.1 Transition Probabilities

The transition probabilities for the software industry were computed and normalized to reflect realistic scenarios. Below is a sample of the transition matrix for the 'Invest' action:

A snippet of the probabilities in a 30-year window:

2014-05-19 01:00:00	2024-05-16 01:00:00	Energy Storage & Batteries	Hold	14	12	0.0
2014-05-19 01:00:00	2024-05-16 01:00:00	Energy Storage & Batteries	Hold	14	13	0.0
2014-05-19 01:00:00	2024-05-16 01:00:00	Energy Storage & Batteries	Hold	14	14	0.0
2014-05-19 01:00:00	2024-05-16 01:00:00	Education/Training	Hold	0	0	0.5037593984962406
2014-05-19 01:00:00	2024-05-16 01:00:00	Education/Training	Hold	0	1	0.43609022556390975
2014-05-19 01:00:00	2024-05-16 01:00:00	Education/Training	Hold	0	2	0.06015037593984962

4.2 Optimal Policy

The optimal policy derived from the backward induction algorithm is summarized below. The policy indicates the best action (Invest, Hold, Exit) for each state over a 4-year horizon.

Input:

- **T**: 4
- Investment Amount: \$10,000
- Interest Rate: 3%
- Industry: Software

Output:

Γ	t1	t2	t3	t4
Seed	0	0	0	0
Series A	0	0	0	0
Series B	0	0	0	0
Series C	0	0	0	0
Series D	0	0	0	0
Series E	0	0	0	0
Series F	0	0	0	0
Series G	0	0	0	0
Series H	0	0	0	0
Series I	2	2	2	0
Series J	2	2	2	0
Series K	2	2	2	0
Series L	1	1	1	1
Pre-IPO	2	2	2	0
Venture Debt	0	0	0	0
Absorption/Exit	1	1	1	1

5 Conclusions

The MDP model developed in this project successfully identifies optimal investment strategies for startups in the given industry. Key findings include:

- Holding investments at early stages can be beneficial before making additional investments.
- The transition probabilities reflect realistic scenarios based on historical data.
- The reward function effectively balances the costs and benefits of different actions.

Potential extensions of this project could involve incorporating more sophisticated reward functions, considering additional industries, or analyzing the impact of external economic factors on investment decisions.

6 References

- 1. Dartmouth Libraries
- 2. Preqin.com
- 3. Series B, C Funding What It All Means And How It Works. Accessed: 2023-04-17. 2015. URL: https://www.investopedia.com/articles/personal-finance/102015/series-b-c-funding-what-it-all-means-and-how-it-works.asp
- 4. Vyara Kostadinova et al. "An application of Markov chains in stock price prediction and risk portfolio optimization". In: AIP Conference Proceedings. Vol. 2321. 1. University of Ruse Angel Kanchev. Feb. 2021, p. 030018. DOI: 10.1063/5.0041119. URL: https://www.researchgate.net/publication/349617762_An_application_of_Markov_chains_in_stock_price_prediction_and_risk_portfolio_optimization

- 5. Yijun Shou. "Venture Risk of Small- and Medium-Sized Sci-Tech Enterprises Based on Markov Model". In: Wireless Communications and Mobile Computing 2022 (2022). Ed. by Kalidoss Rajakani. Received 6 May 2022; Revised 17 May 2022; Accepted 27 May 2022; Published 13 June 2022, Article ID 2032771. DOI: 10.1155/2022/2032771. URL: https://www.hindawi.com/journals/wcmc/2022/2032771/
- 6. Use of CHAT GPT-4:Made the code for cleaning code and told my transitional probability logic. Ended up making a I \times S \times S \times A matrix, where I = Industry type
- 7. Use of my own HW3 code which I wrote for backward induction.