Markov Chains and Applications in Finance

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Transition Probability

Mouse in a Maze.



Figure 1: The Maze

The mouse can only go to adjacent rooms; its decisions are independent of any history and only depend on the current room the mouse is in; the mouse cannot stay in the same room forever.

Transition Probability



Figure 1: The Maze

- Let P_{ji} be the probability of going to room j when the mouse is in room i by one move.
- $P_{21} = \frac{1}{3}$ is the probability of moving to room 2 from room 1.
- $P_{11} = 0$ is the probability of staying at room 1 forever.

Matrix Representations

 To make it more computationally efficient: use matrix representations

To find the transition probability from state i to state j: look up P_{ji} in the matrix.

Transition Probability

- What is the probability of getting to room 5 after 1 step? The starting state matters.
- If we flip a coin to determine the starting point of the mouse: say, we put the mouse in room 1 if we get a head, and put the mouse in room 2 if we get a tail.
- P(starting from room 1) = P(starting from room 2) = $\frac{1}{2}$
- P(ending up in room 5) = $\frac{1}{2}P_{51} + \frac{1}{2}P_{52}$

Distributions of Transition Probabilities

Define every room as a state. What if the probabilities of initial states are different? Say, roll an unfair 5-sided dice to determine the starting room.



Combining the transition matrix and the distribution of probabilities

1. The distribution of transition probabilities on the states after 1 step starting from state s is the matrix-vector product $(Pq)_i = \sum_{j=1}^r P_{ij}q_j = P_{i1}q_1 + P_{i2}q_2 + ... + P_{ir}q_r$

2. The probability of ending up in state j after 2 steps starting from state j is:

$$(P^2)_{ji} = \sum_{k=1}^{\prime} P_{jk} P_{ki}$$

Markov Chains

- In English, [Next State] = [Matrix of Trans. Probabilities][Current State]
- ▶ The predicted value is based solely on the current value

Applications of Markov Chains

Predicting Stock Market Trends

A hypothetical market with trends shown as below:

То	Bull	Bear	Stagnant
From			
Bull	0.9	0.075	0.025
Bear	0.15	0.8	0.05
Stagnant	0.25	0.25	0.5
C			

For example, this means that the probability of going from the bull market to bear market is 0.075, but the probability of going from bear market to bull market s 0.15.

- In the previous example of mouse and maze, a state is defined as the room a mouse is in. In this problem a state is a time period. Assume in this problem a state is one week long.
- ▶ If we set the current week as bearish, then the vector of the initial state is $\begin{bmatrix} 0\\1\\ \end{bmatrix}$.

We can now calculate the probabilities of a bull, bear or a stagnant week from any number of weeks into the future.
1 week from now:

$$S_1 = \begin{bmatrix} 0.9 & 0.075 & 0.025 \\ 0.15 & 0.8 & 0.05 \\ 0.25 & 0.25 & 0.5 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.15 \\ 0.8 \\ 0.05 \end{bmatrix}$$

5 weeks from now:

$$\begin{bmatrix} 0.9 & 0.075 & 0.025 \\ 0.15 & 0.8 & 0.05 \\ 0.25 & 0.25 & 0.5 \end{bmatrix}^{5} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.48 \\ 0.45 \\ 0.07 \end{bmatrix}$$

52 weeks from now:

$$\begin{bmatrix} 0.9 & 0.075 & 0.025 \\ 0.15 & 0.8 & 0.05 \\ 0.25 & 0.25 & 0.5 \end{bmatrix}^{52} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.63 \\ 0.31 \\ 0.05 \end{bmatrix}$$

100 weeks from now:

 $\begin{bmatrix} 0.9 & 0.075 & 0.025 \\ 0.15 & 0.8 & 0.05 \\ 0.25 & 0.25 & 0.5 \end{bmatrix}^{100} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.63 \\ 0.31 \\ 0.05 \end{bmatrix}$ As the number of weeks go to infinity, the probabilities will converge to a steady state.

Hidden Markov Model (HMM)

Hidden Markov Model for Stock Trading (Nguyen, 2017)

- This is a simplified case because we know the matrix of transtion probabilities, But in many cases, we only know stock prices, but we dont know the how the market will change.
- Two stochastic processes involved: Observable: Stock Prices; Unobservable: 'State of the system'
- Basic elements of a hidden Markov model: Length of observation data T; Number of states N; Observation sequence O = {O_t, t = 1, 2...T}; Hidden state sequence Q = {q_t, t = 1, 2...T}; Possible values of each state {S_i, i = 1, 2...N}; Transition matrix A = (a_{ij}), a_{ij} = P(q_t = S_j | q_{t-1} = S_{j-1}); Vector of initial probability of being in state S_i at time t = 1: p = (p_i), p_i = P(q₁ = S_i); Observation matrix B.

Hidden Markov Model (HMM)

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Data:

SP 500 monthly prices from January 1950 to November 2016

Observable

Steps to predict stock prices using HMM:

1. Choose a fixed time period T, calibrate parameters A, B, p, decide the number of states N;

2. Move the given data (the given observation sequence) backward to get a new dataset $O^{new} = \{O_2, O_3...O_t - 1\}$; compute the vector $p = (p_i)$;

3. Keep moving backward until we find a new sequence O^* , where $p_i^* = P(O^*) \approx P(O)$;

4. Predict the price at time T + 1 using the formula $O_{T+1} = O_T + (O_{T^*+1} - O_{T^*}) \cdot (P(O \mid A, B) - P(O^* \mid A, B))$

Hidden Markov Model (HMM)

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Figure A1. S&P 500 's predicted prices using the four-state HMM for 40-month out-of-sample period (left) and 60-month out-of-sample period (right).



Figure A2 S&P 500 's predicted prices using the four-state HMM for 80-month out-of-sample period