

The Memoryless Magic Trick: Predicting the Future with Markov Chains

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Predicting the Future is Not Magic, it's Maths!

A Mall, an Offer, and a Mystery

Imagine you're assisting Ramesh, the owner of a bustling mall. He's planning to launch a new festive offer, but he wants to be strategic. He needs to choose the *right* place in the mall to maximize customer engagement and get the most bang for his buck.

The mall has four main areas:

- **Entrance (E):** Where customers first enter the mall.
- **Clothing Section (C):** Filled with trendy apparel.
- **Electronics Section (X):** Packed with the latest gadgets.
- **Food Court (F):** A place to relax and grab a bite.

Ramesh wonders, “*Where should I roll out this offer to get the most people excited about it?*

Some people suggest the Entrance, where everyone walks through. Others say the middle of the mall or the center, but that's very vague.

Which area do *you* think is best? Let's keep this question in mind as we explore Markov Chains. We'll revisit it later and see how we can use this powerful tool to help Ramesh make the best decision.

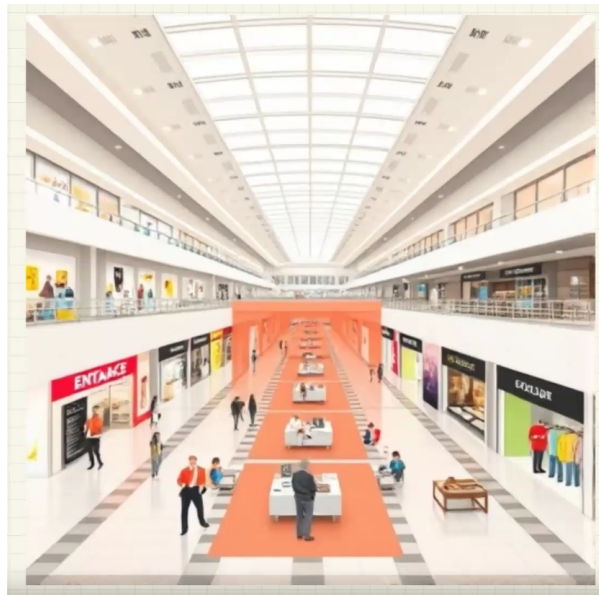


Figure 1: Shopping case Study!

Probability: The Foundation of Our Future

Before diving into Markov Chains, let's refresh our understanding of probability. Think about these simple scenarios:

- **Tossing a Fair Coin:** When you flip a fair coin, there's an equal chance of getting heads or tails. This means the probability of getting heads is $1/2$ (or 50%), and the probability of getting tails is also $1/2$ (or 50%).
- **Drawing Balls from a Bag:** Imagine a bag containing 5 red balls and 6 blue balls. What's the probability of picking a red ball?
 - There are a total of 11 balls (5 red + 6 blue).
 - The probability of picking a red ball is $5/11$.

Now, let's add a twist! Suppose you pick a red ball, but *don't* put it back in the bag. What's the probability of picking another red ball on your second try?

- Now there are only 10 balls left in the bag.
- And only 4 of them are red.
- So, the probability of picking another red ball is now $4/10$.

This brings us to an important concept:

- **Dependent Events:** Events where the outcome of one affects the probability of the other. In our ball example, the probability of picking a red ball the second time *depended* on whether we picked a red or blue ball the first time, and if we replaced it.
- **Independent Events:** In contrary, if we put the ball back into the bag after each draw, the outcome of each draw would not have affected the other and thus called independent events.

States and Transitions: A Tale of 1000 Students

Let's consider another scenario to introduce the core concepts of Markov Chains. Imagine we're observing 1000 students. At any given moment, a student can be in one of two states:

- **Studying**
- **Scrolling through Social Media**

Now, let's introduce some probabilities:

- **A student currently studying has a 60% (0.6) chance of continuing to study.** This also means they have a 40% (0.4) chance of switching to scrolling through social media.
- **A student currently scrolling through social media has an 80% (0.8) chance of continuing to scroll.** And only 20% (0.2) of these students start studying.

We can visualize this as a diagram with two circles (representing the states) and arrows showing the transitions between them, labeled with the corresponding probabilities.

Let's say that at time T_0 , there are 500 students studying and 500 students scrolling through social media. At time T_1 (the next moment), how many students will be studying?

- Out of the initial 500 studying, 60% will continue to study: $500 * 0.6 = 300$
- Out of the initial 500 scrolling, 20% will switch to studying: $500 * 0.2 = 100$

So, at time T_1 , we expect $300 + 100 = 400$ students to be studying. Similarly, we can calculate the number of students scrolling through social media.

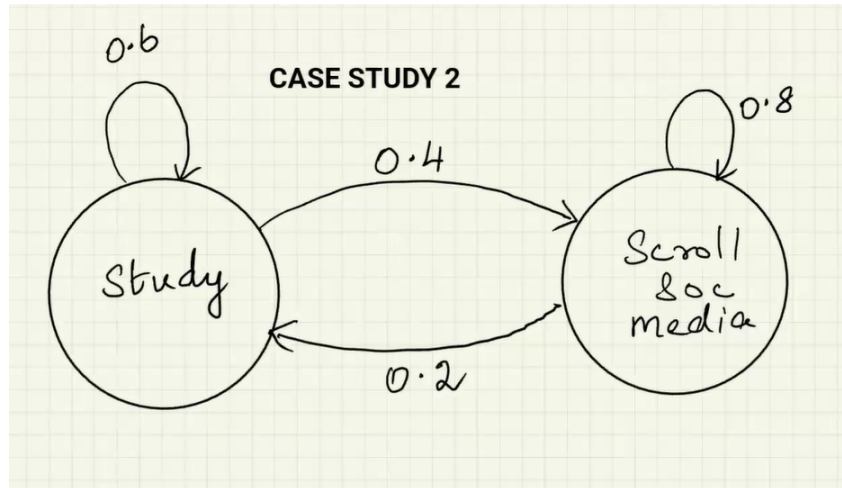


Figure 2: A state diagram showing the "Studying" and "Social Media" states, with arrows indicating transition probabilities (0.6, 0.4, 0.8, 0.2).

Predicting the Future with Excel

We can extend this concept to predict what happens in the future. Let's use a spreadsheet (like Google Sheets or Microsoft Excel) to simulate this process.

1. **Set up columns:** Create columns for Time (T0, T1, T2...), Number of Students Studying, and Number of Students Scrolling.
2. **Enter initial values:** In row T0, enter 500 for both "Studying" and "Scrolling."
3. **Write formulas:** In row T1, enter the formulas to calculate the number of students in each state based on the probabilities:
 - Studying (T1) = (Studying (T0) * 0.6) + (Scrolling (T0) * 0.2)
 - Scrolling (T1) = (Studying (T0) * 0.4) + (Scrolling (T0) * 0.8)
4. **Use the fill handle:** Select the cells with formulas and drag the fill handle down to automatically calculate the values for T2, T3, and so on.

What you'll notice is that over time, the number of students in each state will converge to a stable value. It doesn't matter what the initial numbers are, given large enough time. The student ratio will converge to roughly 33/67 due to probabilities.

The Transition Matrix: A Formal Representation

What we've been working with can be formally represented using a **transition matrix**. This is a square matrix that shows the probabilities of transitioning between different states.

For our student example, the transition matrix would be:

	Studying	Scrolling
Studying	0.6	0.4
Scrolling	0.2	0.8

Each row represents the current state, and each column represents the next state. For example, the value in the first row and second column (0.4) represents the probability of a student transitioning from the "Studying" state to the "Scrolling" state.

	A	B	C
1		Study	Scroll Soc. Media
2	T0	500	500
3	T1	400	600
4	T2	360	640
5	T3	344	656
6	T4	337.6	662.4
7	T5	335.04	664.96
8	T6	334.016	665.984
9	T7	333.6064	666.3936
10	T8	333.44256	666.55744
11	T9	333.377024	666.622976
12	T10	333.3508096	666.6491904

Figure 3: A screenshot of a spreadsheet showing the simulation of student transitions, with the numbers converging over time.

Back to the Mall: Using Markov Chains for Decision Making

Now, let's revisit Ramesh and his festive offer at the mall! To help him make the best decision, we need data about customer movement between the four areas: Entrance (E), Clothing (C), Electronics (X), and Food Court (F). Based on Ramesh's observation of customer flow, we've constructed the following transition matrix, visualized below, showing the probabilities of customers moving between areas:

	A	B	C	D	E	F	G	H	I	J	K
1		E	C	X	F		E	C	X	F	
2	From E	0.1	0.5	0.2	0.2		1000	0	0	0	
3	From C	0.3	0.4	0.2	0.1		100	500	200	200	1000
4	From X	0.2	0.3	0.4	0.1		220	330	260	190	1000
5	From F	0.1	0.1	0.3	0.5		192	339	271	198	1000
6							194.9	332.7	274	198.4	1000
7							193.94	332.57	274.64	198.85	1000
8							193.978	332.275	274.813	198.934	1000
9							193.9363	332.2363	274.856	198.9714	1000
10							193.93286	332.21661	274.86834	198.98219	1000

Figure 4: Mall Customer Transition Data and Simulation

The transition matrix is represented as:

	E	C	X	F
E	0.1	0.5	0.2	0.2
C	0.3	0.4	0.2	0.1
X	0.2	0.3	0.4	0.1
F	0.1	0.1	0.3	0.5

As evidenced by the simulation data, starting with 1000 customers entering the mall at the Entrance (E), the number of customers at each location over time settles into a relatively stable state. For example, this means if a customer is in the Clothing section now, there is 30% (0.3) chance that they move to Entrance, 40% (0.4) chance that they remain in Clothing section, 20% (0.2) chance that they move to Electronics, and 10% (0.1) chance that they move to Food court. The simulation (see Image) shows that

the Clothing (C) section consistently attracts a significant proportion of customers after a few iterations (time steps).

Therefore, based on this analysis, the Clothing section is the most strategic location to launch the Festive Offer for Ramesh to maximize customer engagement.

Markov Chains: Key Concepts

Here's a summary of the key concepts we've covered:

- **Markov Chain:** A mathematical model describing a system that transitions between states based on probabilities.
- **State:** A specific condition or situation of the system (e.g., "Studying," "Scrolling," "In the Entrance," "In the Clothing Section").
- **Transition Probability:** The probability of moving from one state to another.
- **Transition Matrix:** A matrix containing all the transition probabilities between the states.
- **Markov Property (Memoryless Property):** The future state depends only on the current state and not on the past history.
- **Convergence:** A state is reached where the proportion of individuals in each is balanced after a long time.

Real-World Applications

Markov Chains are used in many different areas, including:

- **Weather Forecasting:** Predicting the weather based on current conditions and transition probabilities between different weather states (sunny, rainy, cloudy).
- **Speech Recognition:** Recognizing spoken words by analyzing the sequence of sounds and their transition probabilities.
- **Finance:** Modeling stock prices and other financial data.
- **Recommendation Systems:** Predicting what products or movies a user might like based on their past behavior.
- **Reinforcement Learning:** This technique helps train AI agents by rewarding and penalizing specific actions.
- **Hidden Markov Models:** A model where the states are unknown, used for prediction of sequencing.

You've now taken your first steps into the world of Markov Chains! By understanding the basic concepts and applying them to practical examples, you can start using this powerful tool to model probabilistic systems and make better decisions. As you continue your AI journey, explore the various applications of Markov Chains and delve deeper into the mathematical foundations. Keep experimenting, keep learning, and you'll be amazed at what you can achieve!