Modeling Basketball Shooting Patterns Using Markov Chains: A Longitudinal Analysis of the Hot Hand Phenomenon

Dvir Ross

SCE and Shenkar Colleges

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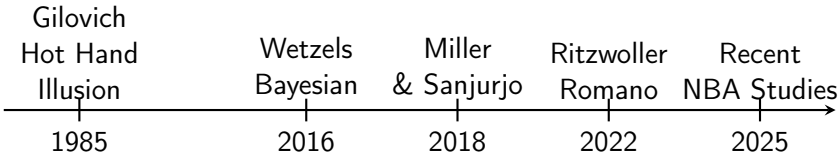
Motivation

- The **hot hand** hypothesis says that a player becomes more likely to score after recent successes.
- This is one of the most famous debates in sports analytics.
- The literature offers conflicting conclusions:
  - The hot hand is an illusion.
  - The hot hand is real but small.
  - The hot hand exists only for some players.
- We revisit the question using:
  - 20 NBA seasons.
  - First-order Markov chains.
  - Second-order Markov chains.

Hot Hand Literature



Our Contribution

We study 20 NBA seasons using first- and second-order Markov models.

Data

- NBA regular seasons from 2003–2004 through 2023–2024.
- All recorded field-goal attempts.
- Free throws are excluded.
- Variables:
  - Player.
  - Game.
  - Shot type: 2PT or 3PT.
  - Make or miss.
  - Time and period.

Goal: model each player's shot sequence.

State Encoding

$$\{\text{Make-2}, \text{Miss-2}, \text{Make-3}, \text{Miss-3}\}$$

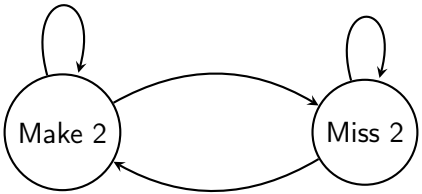
Additional state:

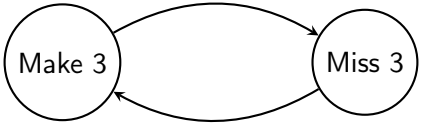
$$\text{Start}$$

A new sequence begins at:

- New game.
- Halftime.
- Long interruption.

Markov Chain Idea





Interpretation

First-Order Markov Model

$$P(X_t \mid X_{t-1}, X_{t-2}, \dots) = P(X_t \mid X_{t-1})$$

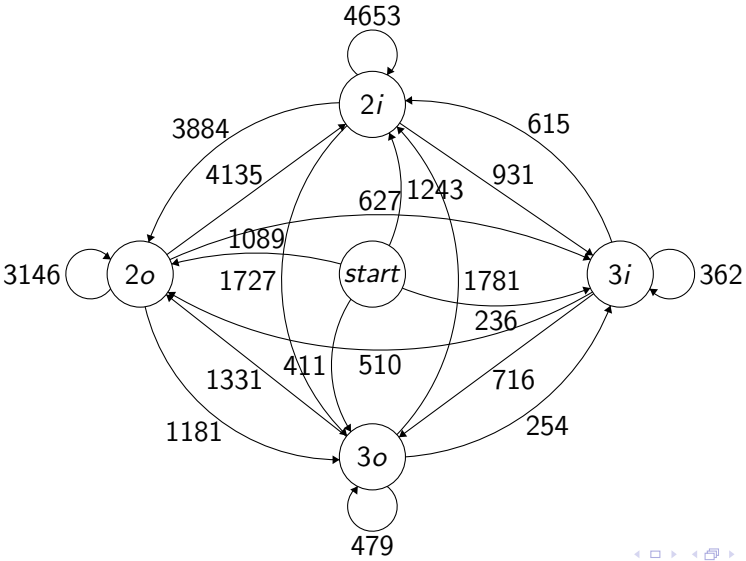
- The model depends only on the previous shot.
- It is estimated separately for each player.
- Inclusion criterion:

  $$N_{ij} \geq 30$$

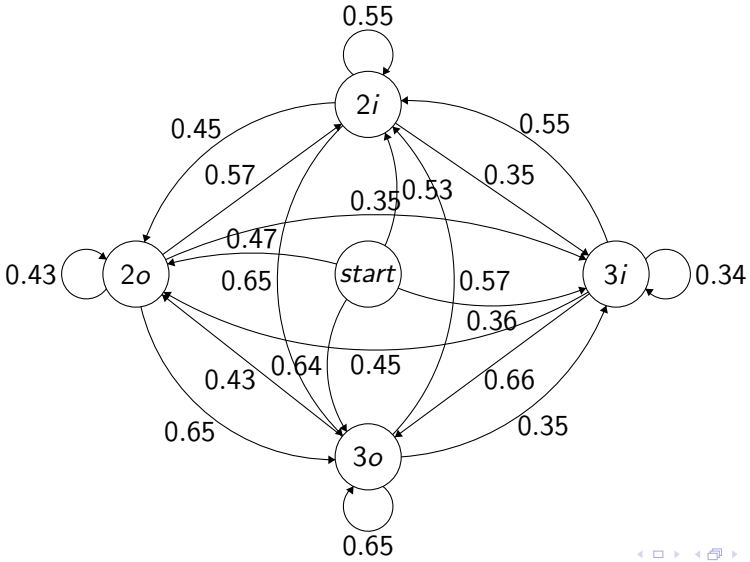
  for every state transition.

449 players qualified.

Example: LeBron James – Counts



Example: LeBron James – Probabilities



Testing Dependence

H_0 : Current shot outcome is independent of history

Pearson chi-square statistic:

$$\chi^2 = \sum \frac{(O - E)^2}{E}$$

We reject at:

$$\alpha = 0.05$$

LeBron James: Observed vs. Expected Transitions

	2PT transitions			3PT transitions		
State	Make_2	Miss_2	Total_2	Make_3	Miss_3	Total_3
Start	1243 (0.533)	1089 (0.467)	2332	236 (0.3648)	411 (0.6352)	647
Make_2	4653 (0.545)	3884 (0.455)	8537	931 (0.3503)	1727 (0.6497)	2658
Miss_2	4135 (0.5679)	3146 (0.4321)	7281	627 (0.3468)	1181 (0.6532)	1808
Make_3	615 (0.5467)	510 (0.4533)	1125	362 (0.3358)	716 (0.6642)	1078
Miss_3	1781 (0.5723)	1331 (0.4277)	3112	254 (0.3465)	479 (0.6535)	733
Total	12427 (0.5551)	9960 (0.4449)	22387	2410 (0.3481)	4514 (0.6519)	6924

Reading the table

The first number is the transition count, and the number in parentheses is the transition probability.

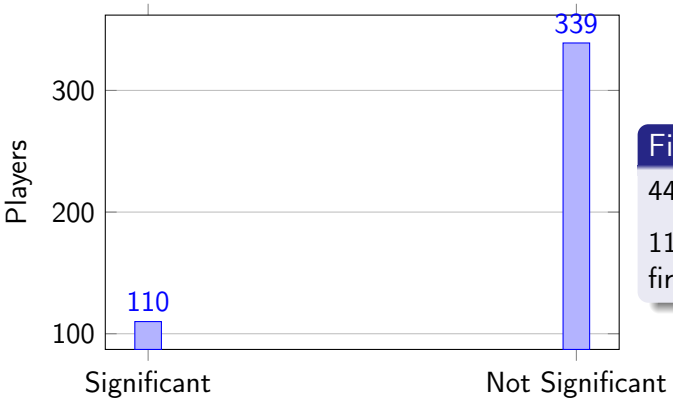
LeBron James: Observed Minus Expected

State	Make_2	Miss_2	Make_3	Miss_3
Start	1243-1294 = -51	1089-1038 = 51	236-225 = 11	411-422 = -11
Make_2	4653-4739 = -86	3884-3798 = 86	931-925 = 6	1727-1733 = -6
Miss_2	4135-4042 = 93	3146-3239 = -93	627-629 = -2	1181-1179 = 2
Make_3	615-624 = -9	510-501 = 9	362-375 = -13	716-703 = 13
Miss_3	1781-1727 = 54	1331-1385 = -54	254-255 = -1	479-478 = 1

Reading the table

Each cell shows Observed minus Expected, so positive values mean more transitions than expected under independence.

First-Order Results



Finding

449 players qualified.

110 players, or 24%, show significant first-order dependence.

Second-Order Markov Model

$$P(X_t \mid X_{t-1}, X_{t-2}, \dots) = P(X_t \mid X_{t-1}, X_{t-2})$$

The history consists of the previous two shots.

This creates a much larger state space.

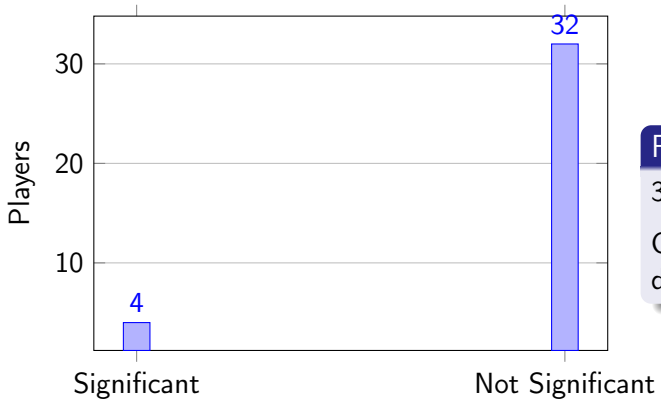
Inclusion criterion:

$$N_{ijk} \geq 30$$

for every transition triple.

Only 36 players qualified.

Second-Order Results

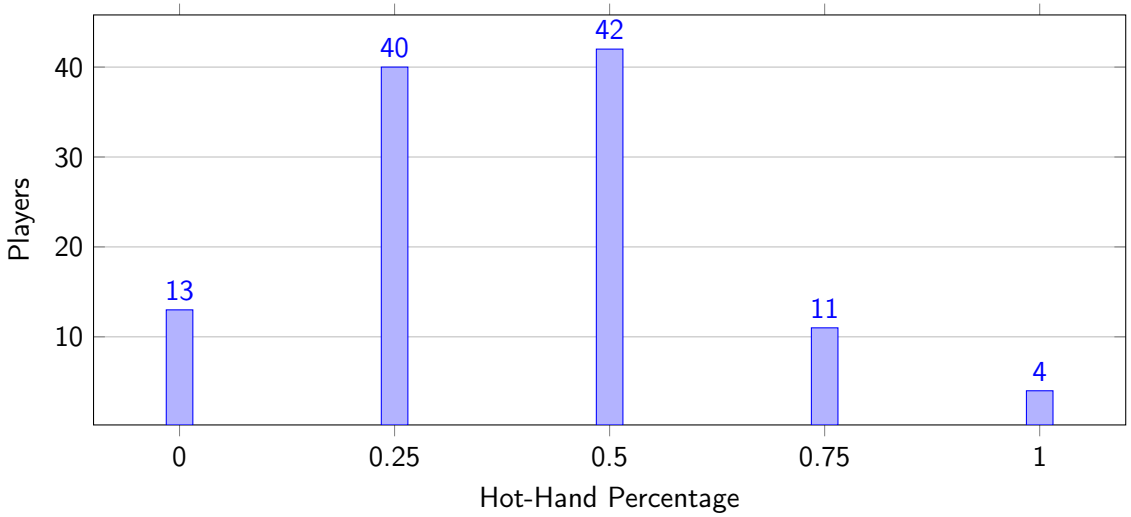


Finding

36 players qualified.

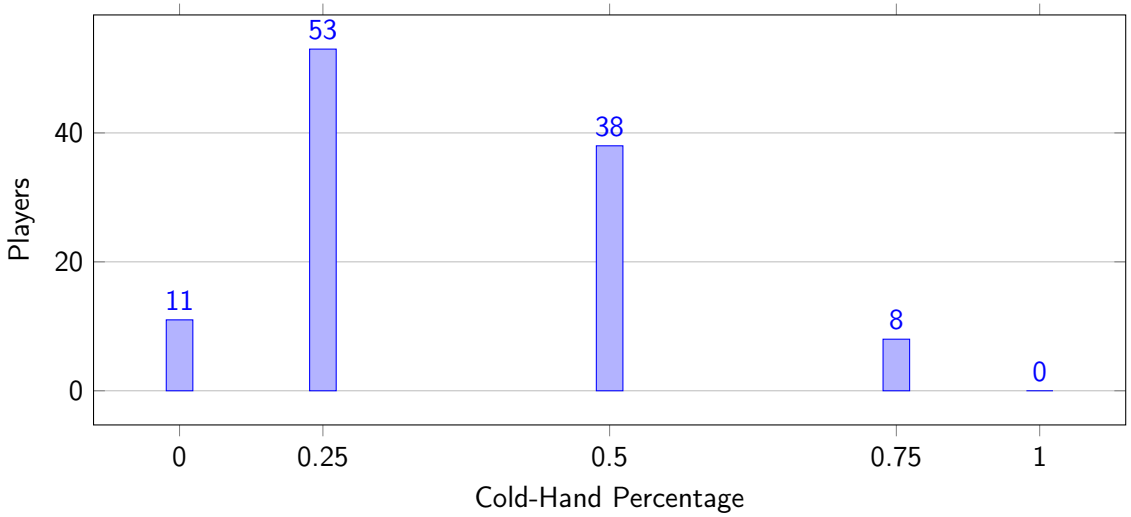
Only 4 players exhibit second-order dependence.

Hot-Hand Percentages



Most significant players show only moderate hot-hand effects

Cold-Hand Percentages



Most significant players exhibit only moderate cold-hand effects

Hot vs Cold Patterns

Metric	First Order	Second Order
Hot patterns	Present	Rare
Cold patterns	Present	Present
League-wide effect	No	No

Key Insight

Dependence does not necessarily imply a hot hand.