

Was Courtney Lee Better Than Stephen Curry?

Simpson's paradox

Probability and Statistics for Data Science

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These slides are based on the book [Probability and Statistics for Data Science](#) by Carlos Fernandez-Granda, available for purchase [here](#). A free preprint, videos, code, slides and solutions to exercises are available at <https://www.ps4ds.net>

Data

NBA games from the 2014/2015 season

3-point shot percentage

Stephen Curry: 41.7%

Courtney Lee: **43.9%**

Was Lee the better shooter?

A closer look at the data

	Stephen Curry	Courtney Lee
Short threes (≤ 24 feet)	$45/90 = \mathbf{50.0\%}$	$56/116 = 48.3\%$
Long threes (> 24 feet)	$145/366 = \mathbf{39.6\%}$	$19/55 = 34.5\%$
Total	$190/456 = 41.7\%$	$75/171 = \mathbf{43.9\%}$

Simpson's paradox

Causal inference perspective

3-point shot \tilde{y} : If shot goes in $\tilde{y} = 1$, if not $\tilde{y} = 0$

Treatment \tilde{t} : Player who shoots

From observed data

$$P(\tilde{y} = 1 \mid \tilde{t} = \text{Curry}) = 0.417$$

$$P(\tilde{y} = 1 \mid \tilde{t} = \text{Lee}) = 0.439$$

What this means

$$P(\tilde{y} = 1 \mid \tilde{t} = \text{Curry}) = 0.417$$

$$P(\tilde{y} = 1 \mid \tilde{t} = \text{Lee}) = 0.439$$

Curry makes 41.7% of his 3-point shots

Lee makes 43.9% of his 3-point shots

What this does not mean

$$P(\tilde{y} = 1 \mid \tilde{t} = \text{Curry}) = 0.417$$

$$P(\tilde{y} = 1 \mid \tilde{t} = \text{Lee}) = 0.439$$

If Lee had taken Curry's shots, he would have made 43.9% instead of 41.7%

Potential outcomes

$\widetilde{\text{po}}_{\text{Curry}}$: Outcome if Curry shoots

$\widetilde{\text{po}}_{\text{Curry}} = 1$ shot made, $\widetilde{\text{po}}_{\text{Curry}} = 0$ shot missed

$\widetilde{\text{po}}_{\text{Lee}}$: Outcome if Lee shoots

$\widetilde{\text{po}}_{\text{Lee}} = 1$ shot made, $\widetilde{\text{po}}_{\text{Lee}} = 0$ shot missed

What we actually observe:











$$\tilde{y} := \begin{cases} \widetilde{\text{po}}_{\text{Curry}} & \text{if } \tilde{t} = \text{Curry} \\ \widetilde{\text{po}}_{\text{Lee}} & \text{if } \tilde{t} = \text{Lee} \end{cases}$$

Was Lee the better shooter?

$$P(\widetilde{\text{po}}_{\text{Lee}} = 1) > P(\widetilde{\text{po}}_{\text{Curry}} = 1)?$$

Challenge: We cannot observe them simultaneously!

Observed data

Treatment \tilde{t}	Observed outcome \tilde{y}	Outcome if Curry $\widetilde{po}_{\text{Curry}}$	Outcome if Lee $\widetilde{po}_{\text{Lee}}$
Curry			?
Curry			?
Lee		?	
Lee		?	
Lee		?	

? are counterfactuals

Can we trust the data?

$$P(\widetilde{\text{po}}_{\text{Curry}} = 1) \stackrel{=?}{=} P(\tilde{y} = 1 \mid \tilde{t} = \text{Curry}) = P(\widetilde{\text{po}}_{\text{Curry}} = 1 \mid \tilde{t} = \text{Curry})$$

$$P(\widetilde{\text{po}}_{\text{Lee}} = 1) \stackrel{=?}{=} P(\tilde{y} = 1 \mid \tilde{t} = \text{Lee}) = P(\widetilde{\text{po}}_{\text{Lee}} = 1 \mid \tilde{t} = \text{Lee})$$

True if \tilde{t} and $\widetilde{\text{po}}_{\text{Curry}} / \widetilde{\text{po}}_{\text{Lee}}$ are independent

Are they independent?

Shot distance \tilde{d}

	Stephen Curry	Courtney Lee
Short threes (≤ 24 feet)	45/90 = 50.0%	56/116 = 48.3%
Long threes (> 24 feet)	145/366 = 39.6%	19/55 = 34.5%

$$P(\tilde{d} = \text{short} \mid \tilde{t} = \text{Curry}) = 0.197$$

$$P(\tilde{d} = \text{short} \mid \tilde{t} = \text{Lee}) = 0.678$$

$$P(\tilde{y} = 1 \mid \tilde{d} = \text{short}, \tilde{t} = \text{Curry}) = 0.5$$

$$P(\tilde{y} = 1 \mid \tilde{d} = \text{short}, \tilde{t} = \text{Lee}) = 0.483$$

$$P(\tilde{y} = 1 \mid \tilde{d} = \text{long}, \tilde{t} = \text{Curry}) = 0.396$$

$$P(\tilde{y} = 1 \mid \tilde{d} = \text{long}, \tilde{t} = \text{Lee}) = 0.345$$

Confounding factor

$\widetilde{\text{po}}_{\text{Curry}} / \widetilde{\text{po}}_{\text{Lee}}$ depend on distance \tilde{d}

Distance \tilde{d} depends on \tilde{t}

$\widetilde{\text{po}}_{\text{Curry}} / \widetilde{\text{po}}_{\text{Lee}}$ and \tilde{t} are not independent

$$P(\widetilde{\text{po}}_{\text{Curry}} = 1) \neq P(\tilde{y} = 1 \mid \tilde{t} = \text{Curry}) = P(\widetilde{\text{po}}_{\text{Curry}} = 1 \mid \tilde{t} = \text{Curry})$$

$$P(\widetilde{\text{po}}_{\text{Lee}} = 1) \neq P(\tilde{y} = 1 \mid \tilde{t} = \text{Lee}) = P(\widetilde{\text{po}}_{\text{Lee}} = 1 \mid \tilde{t} = \text{Lee})$$

Confounding factor

$$\begin{aligned} &P(\tilde{y} = 1 \mid \tilde{t} = \text{Lee}) \\ &= P(\tilde{y} = 1, \tilde{d} = \text{short} \mid \tilde{t} = \text{Lee}) + P(\tilde{y} = 1, \tilde{d} = \text{long} \mid \tilde{t} = \text{Lee}) \\ &= P(\tilde{d} = \text{short} \mid \tilde{t} = \text{Lee})P(\tilde{y} = 1 \mid \tilde{d} = \text{short}, \tilde{t} = \text{Lee}) \\ &\quad + P(\tilde{d} = \text{long} \mid \tilde{t} = \text{Lee})P(\tilde{y} = 1 \mid \tilde{d} = \text{long}, \tilde{t} = \text{Lee}) \\ &= 0.678 \cdot 0.483 + 0.322 \cdot 0.345 = 0.439 \end{aligned}$$

Confounding factor

$$\begin{aligned} &P(\tilde{y} = 1 \mid \tilde{t} = \text{Lee}) \\ &= 0.678 \cdot 0.483 + 0.322 \cdot 0.345 = 0.439 \end{aligned}$$

$$\begin{aligned} &P(\tilde{y} = 1 \mid \tilde{t} = \text{Curry}) \\ &= P(\tilde{y} = 1, \tilde{d} = \text{short} \mid \tilde{t} = \text{Curry}) \\ &\quad + P(\tilde{y} = 1, \tilde{d} = \text{long} \mid \tilde{t} = \text{Curry}) \\ &= P(\tilde{d} = \text{short} \mid \tilde{t} = \text{Curry})P(\tilde{y} = 1 \mid \tilde{d} = \text{short}, \tilde{t} = \text{Curry}) \\ &\quad + P(\tilde{d} = \text{long} \mid \tilde{t} = \text{Curry})P(\tilde{y} = 1 \mid \tilde{d} = \text{long}, \tilde{t} = \text{Curry}) \\ &= 0.197 \cdot 0.500 + 0.803 \cdot 0.396 = 0.416 \end{aligned}$$

Adjusting for the confounding factor

$$p_{\widetilde{\text{po}}_{\text{Curry}}}(1) = \sum_{d \in \{\text{short}, \text{long}\}} p_{\tilde{d}}(d) p_{\widetilde{\text{po}}_{\text{Curry}} | \tilde{d}}(1 | d)$$

Do we know $p_{\tilde{d}}$?

Do we know $p_{\widetilde{\text{po}}_{\text{Curry}} | \tilde{d}}$?

$$p_{\widetilde{\text{po}}_{\text{Curry}} | \tilde{d}}$$

Assumption: $\widetilde{\text{po}}_{\text{Curry}}$ and \tilde{t} are conditionally independent given \tilde{d}

$$\begin{aligned} P(\tilde{y} = 1 | \tilde{d} = \text{short}, \tilde{t} = \text{Curry}) &= P(\widetilde{\text{po}}_{\text{Curry}} = 1 | \tilde{d} = \text{short}, \tilde{t} = \text{Curry}) \\ &= P(\widetilde{\text{po}}_{\text{Curry}} = 1 | \tilde{d} = \text{short}) = 0.5 \end{aligned}$$

$$\begin{aligned} P(\tilde{y} = 1 | \tilde{d} = \text{long}, \tilde{t} = \text{Curry}) &= P(\widetilde{\text{po}}_{\text{Curry}} = 1 | \tilde{d} = \text{long}, \tilde{t} = \text{Curry}) \\ &= P(\widetilde{\text{po}}_{\text{Curry}} = 1 | \tilde{d} = \text{long}) = 0.396 \end{aligned}$$

$$p_{\widetilde{\text{po}}_{\text{Lee}} | \tilde{d}}$$

Assumption: $\widetilde{\text{po}}_{\text{Lee}}$ and \tilde{t} are conditionally independent given \tilde{d}

$$\begin{aligned} P(\tilde{y} = 1 | \tilde{d} = \text{short}, \tilde{t} = \text{Lee}) &= P(\widetilde{\text{po}}_{\text{Lee}} = 1 | \tilde{d} = \text{short}, \tilde{t} = \text{Lee}) \\ &= P(\widetilde{\text{po}}_{\text{Lee}} = 1 | \tilde{d} = \text{short}) = 0.483 \end{aligned}$$

$$\begin{aligned} P(\tilde{y} = 1 | \tilde{d} = \text{long}, \tilde{t} = \text{Lee}) &= P(\widetilde{\text{po}}_{\text{Lee}} = 1 | \tilde{d} = \text{long}, \tilde{t} = \text{Lee}) \\ &= P(\widetilde{\text{po}}_{\text{Lee}} = 1 | \tilde{d} = \text{long}) = 0.345 \end{aligned}$$

Adjusting for the confounding factor

$$\begin{aligned} p_{\widetilde{\text{po}}_{\text{Curry}}}(1) &= \sum_{d \in \{\text{short}, \text{long}\}} p_{\tilde{d}}(d) p_{\tilde{y} | \tilde{d}, \tilde{t}}(1 | d, \text{Curry}) \\ &= 0.329 \cdot 0.5 + 0.671 \cdot 0.396 = \mathbf{0.430} \quad (\neq 0.417) \end{aligned}$$

$$\begin{aligned} p_{\widetilde{\text{po}}_{\text{Lee}}}(1) &= \sum_{d \in \{\text{short}, \text{long}\}} p_{\tilde{d}}(d) p_{\tilde{y} | \tilde{d}, \tilde{t}}(1 | d, \text{Lee}) \\ &= 0.329 \cdot 0.483 + 0.671 \cdot 0.345 = \mathbf{0.390} \quad (\neq 0.439) \end{aligned}$$

Are our assumptions correct? **No**

Is this a better measure of shooting ability? **Yes**

What have we learned?

Causal inference from observational data is very challenging

Confounders can severely distort conditional probabilities (Simpson's paradox)

We can adjust for known confounders