

Countering Simpson's Paradox with Counterfactuals

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Introduction

- **Aggregation** is a powerful tool to show summary statistics in visualizations.
- However, it can also introduce additional **risks**, such as **Simpson's Paradox** — trends that appear at one level of aggregation may disappear or reverse when data is subdivided into lower levels of aggregation.

Simpson's Paradox

Stone Size	T_A	T_B
Small	93% (81/87)	87% (234/270)
Large	73% (192/263)	69% (55/80)
All	78% (273/350)	83% (289/350)

The above Kidney Stone study included patients with stones of variable size, classified as large or small.

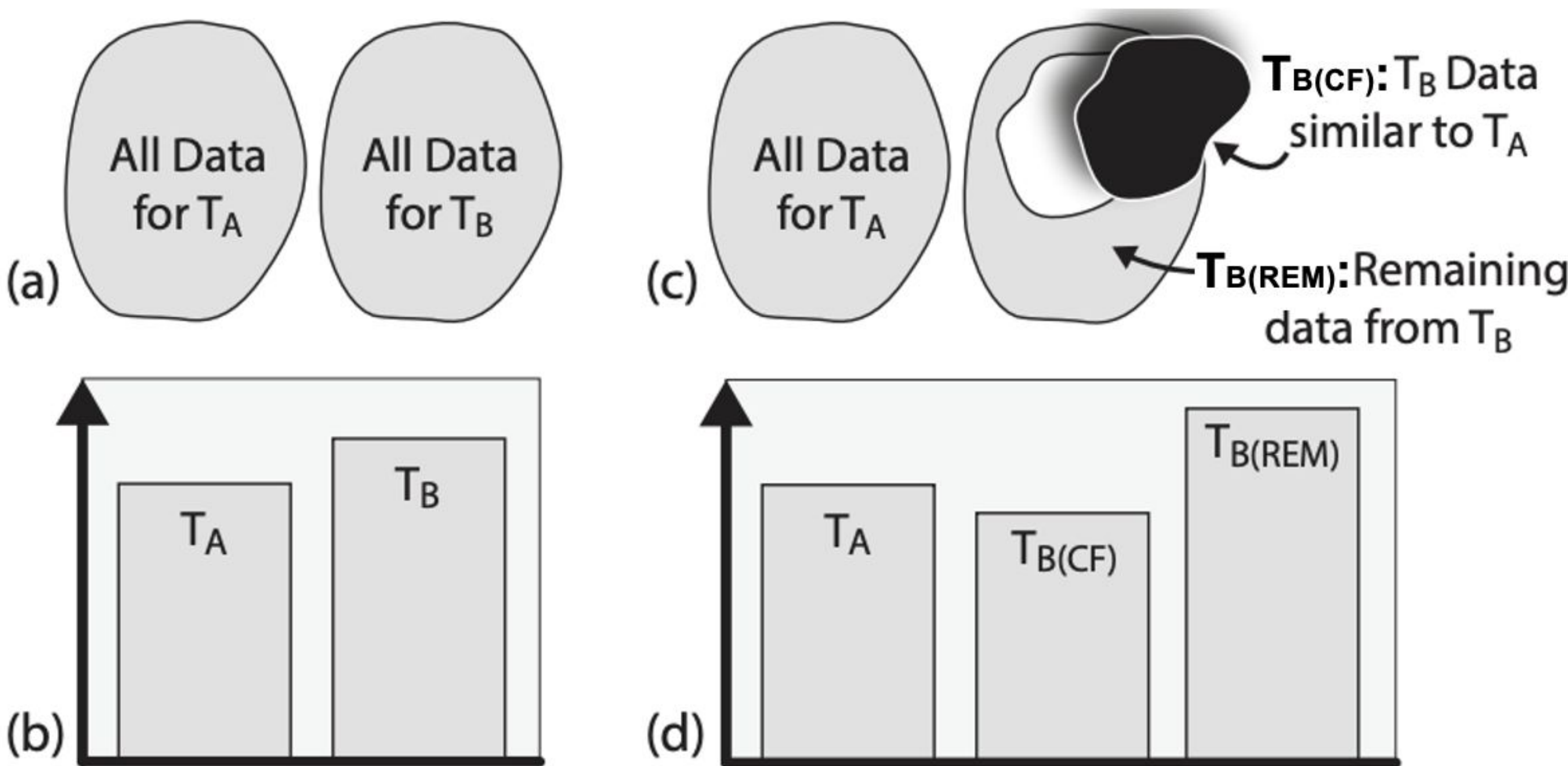
Compared to **Treatment B (T_B)**, **Treatment A (T_A)** performed best on small stones and best on large stones. However, counter-intuitively, **Treatment B** appeared to have a higher success rate overall, as a result of the **unequal distribution of patient groups**.

Visualization of Counterfactuals

Counterfactual reasoning, by constructing **hypothetical scenarios** ("what if things were the same except for this one fact?"), can be used to balance the distributions.

Counterfactuals can be simulated by sampling from the population receiving **T_B** a subset of patients similar to those patients receiving **T_A** , refer to **$T_{B(CF)}$** .

$T_{B(CF)}$ will comprise a group of patients with similar variable distributions to **T_A** . In the Kidney example, we sample a group of patients from **T_B** with the same ratio of *large:small* kidney stones as **T_A** to include in **$T_{B(CF)}$** . The reminder samples are noted as **$T_{B(REM)}$** .

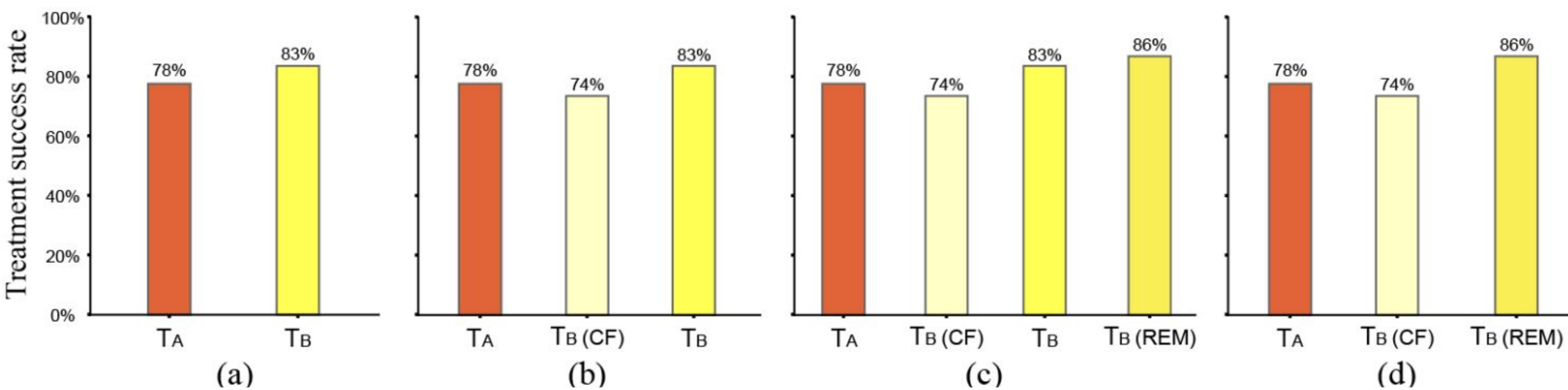


(a-b) are typical visualizations comparing **T_A** and **T_B** without considering counterfactuals.
(c) shows the construction of counterfactual subset **$T_{B(CF)}$** and reminder subset **$T_{B(REM)}$** .
(d) shows a visualization comparing **T_A** and **$T_{B(CF)}$** which can avoid Simpson's Paradox.

Countering Simpson's Paradox

Stone Size	T_A	T_B	$T_{B(CF)}$	$T_{B(REM)}$
Small	93% (81/87)	87% (234/270)	88% (23/26)	86% (211/244)
Large	73% (192/263)	69% (55/80)	69% (55/80)	N/A (0/0)
All	78% (273/350)	83% (289/350)	74% (78/106)	86% (211/244)

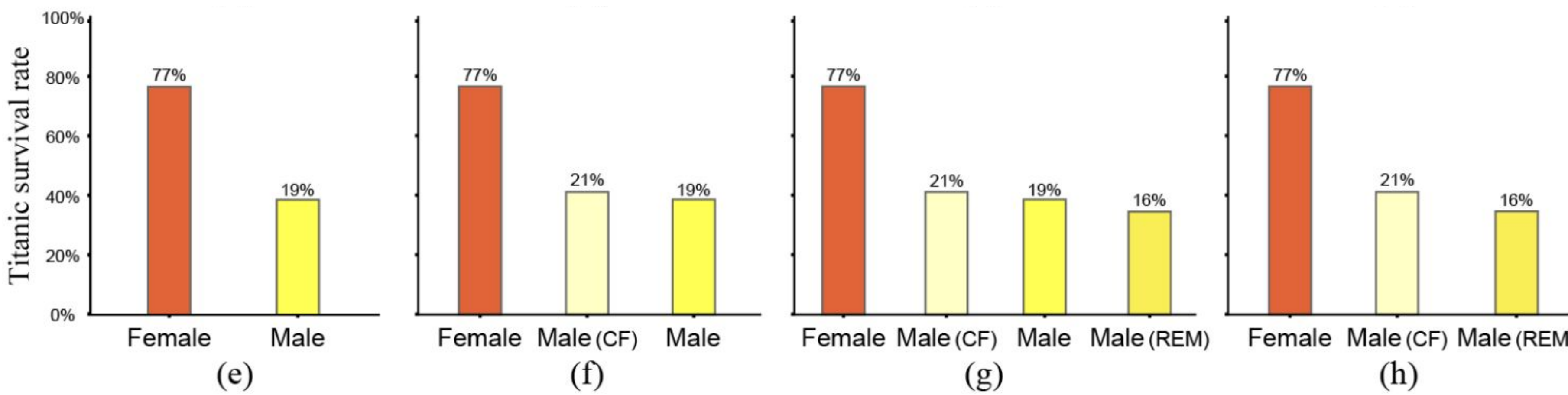
Constructed subsets of Kidney Stone dataset.
w/ Simpson's Paradox



Compared to (a) a traditional visualization of the two treatments, designs that incorporate counterfactuals (b-d) can more accurately communicate the desired comparison (**$T_{B(CF)}$** is worse than **T_A**) between treatments.

Cabin	Female	Male	$Male_{(CF)}$	$Male_{(REM)}$
Class 1	97% (91/94)	37% (45/122)	37% (35/94)	36% (10/28)
Class 2	92% (70/76)	16% (17/108)	16% (12/76)	16% (5/32)
Class 3	56% (81/144)	14% (47/347)	14% (20/144)	13% (27/203)
All	77% (242/314)	19% (109/577)	21% (67/314)	16% (42/263)

Constructed subsets of Titanic Survival dataset.
w/o Simpson's Paradox



When Simpson's Paradox is not present, a traditional visualization (e) and designs that incorporate counterfactuals (f-h) can both accurately communicate the desired comparison (**$Male_{(CF)}$** is lower than **$Female$**).