Data-driven methods
Machine learning

INFO/STSCI/ILRST 3900: Causal Inference

16 Nov 2023

Learning goals for today

At the end of class, you will have intuition for how sample splitting makes it easier to

1. choose among many estimands
2. choose among many estimators
3. develop new data science approaches

Targeted treatments

Want to find the subgroup
with the **biggest** causal effect

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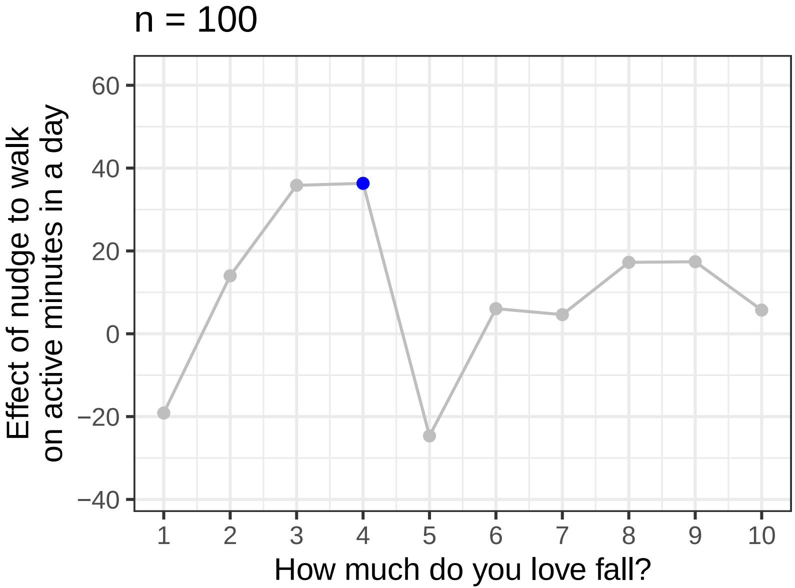
WATCH
fitbit
GARMIN



n = 100
Effect of nudge to walk
on active minutes in a day
60
40
20
0
−20
−40
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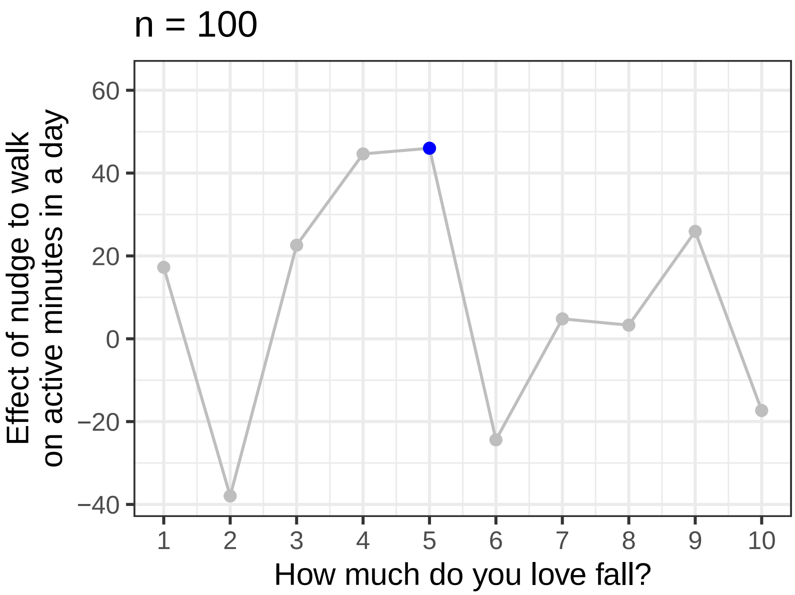
4
5
6
7
8
9
10
How much do you love fall?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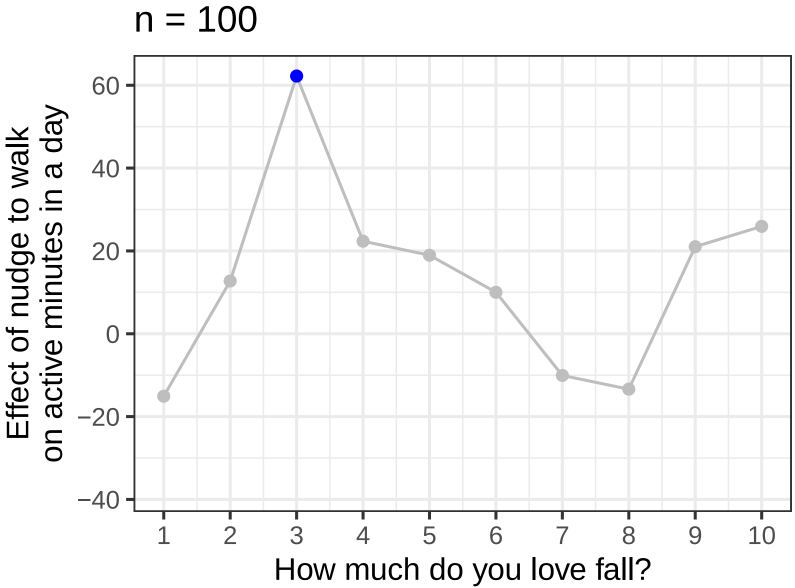
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When you pick the biggest effect,
you select high positive **noise**

$$\hat{\tau}_x = \underbrace{\tau_x}_{\substack{\textbf{signal} \\ \text{true} \\ \text{effect}}} + \underbrace{\epsilon_x}_{\substack{\textbf{noise} \\ \text{sampling} \\ \text{variability}}}$$

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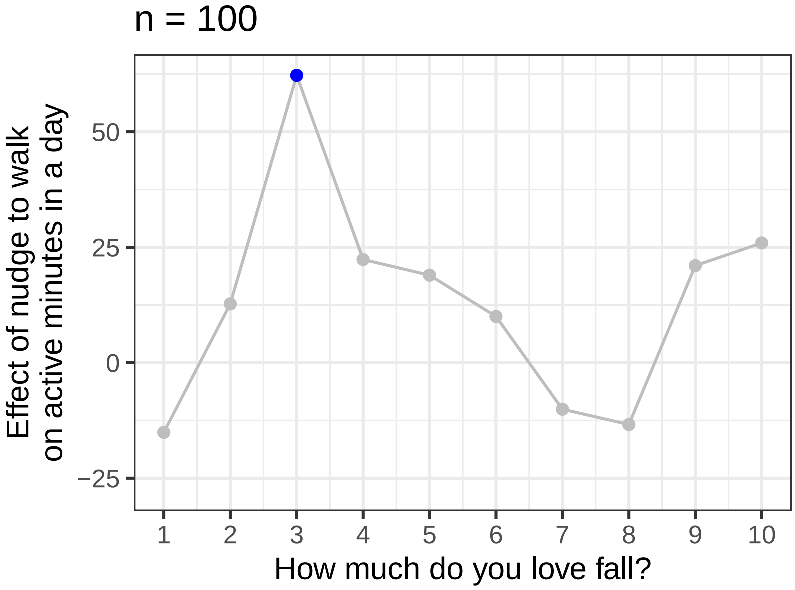
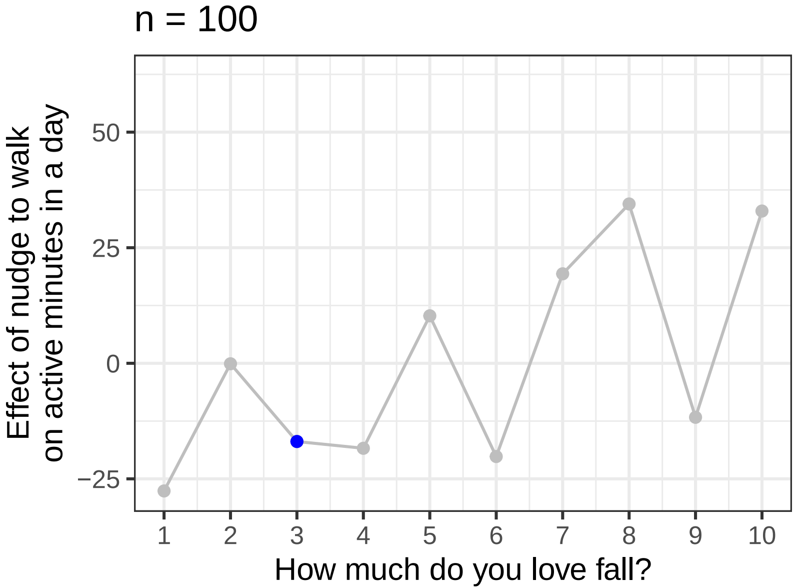
Solution: Two samples

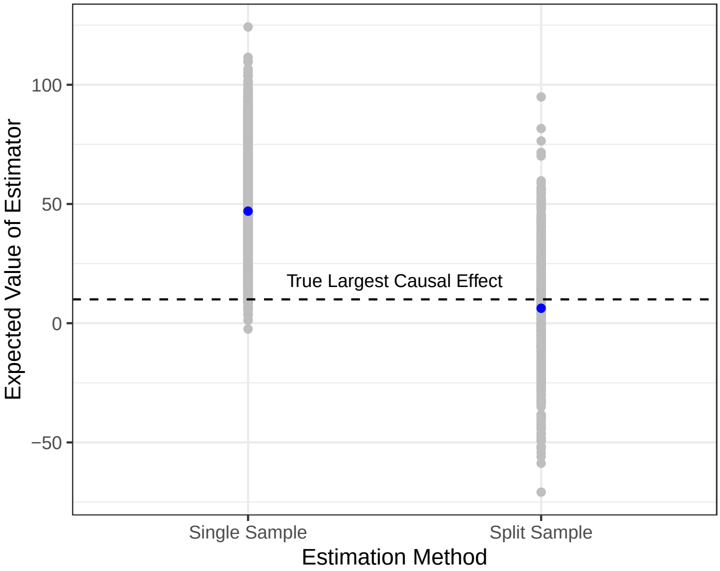
- select the X-value with the biggest effect
- estimate the effect in that subgroup

Selection sample

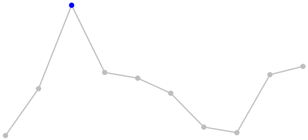


Estimation sample

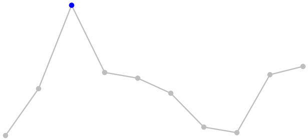




Expected Value of Estimator
100
50
0
−50
True Largest Causal Effect
Single Sample
Split Sample
Estimation Method



Where does the pick-the-largest estimator occur in practice?



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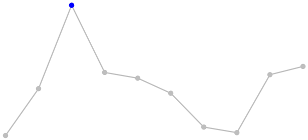

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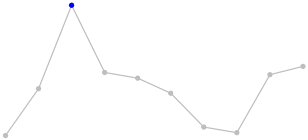
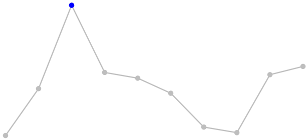


Where does the pick-the-largest estimator occur in practice?

- a data scientist searchers for effect heterogeneity
- they are excited about the biggest effect
- but it is really just noise



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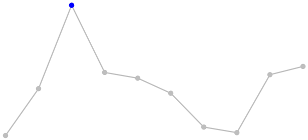

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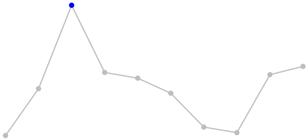

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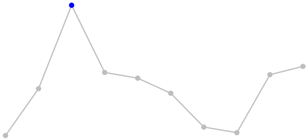

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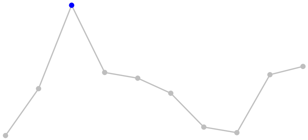

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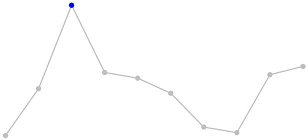

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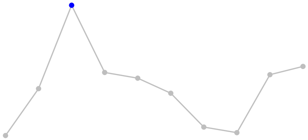

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- one researcher considers many estimators of one effect
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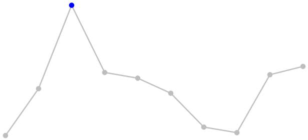

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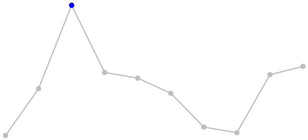
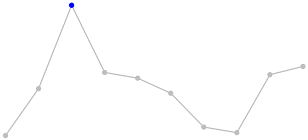


whenever you make many estimates
but report only one
you are at risk of this problem



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Sample splitting is an answer!

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At the end of class, you will have intuition for how sample splitting makes it easier to

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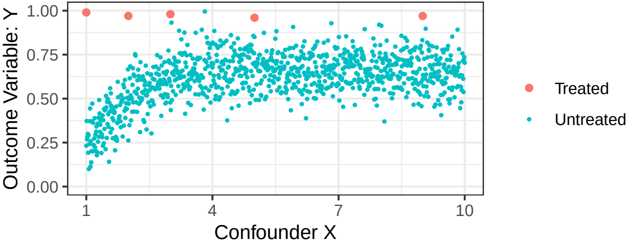
Sample splitting makes it easier to **choose among many estimators**



Estimand: Average Treatment Effect on the Treated

$$\mathrm{E}(Y^1 - Y^0 \mid A = 1) = \frac{1}{n_{A=1}} \sum_{i:A_i=1} \left(Y_i^1 - Y_i^0 \right)$$

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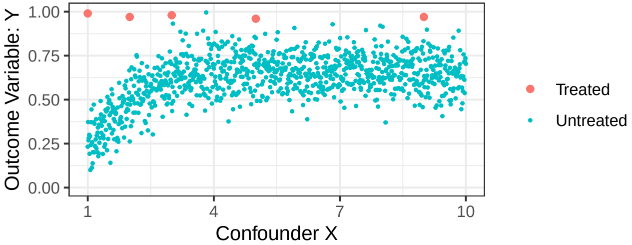

$$\begin{tikzcd} X \arrow[r] \arrow[rr, bend right] & A \arrow[r] & Y \end{tikzcd}$$

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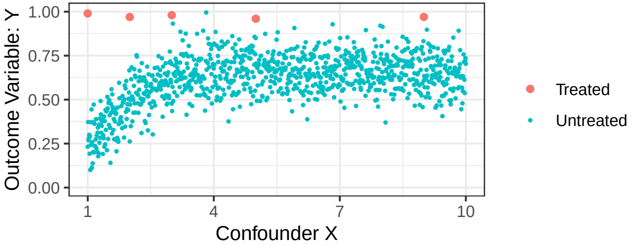

$$X \longrightarrow A \longrightarrow Y, \qquad X \longrightarrow Y$$

$$\mathrm{E}(Y^1 \mid A = 1) = \frac{1}{n_{A=1}} \sum_{i:A_i=1} Y_i$$

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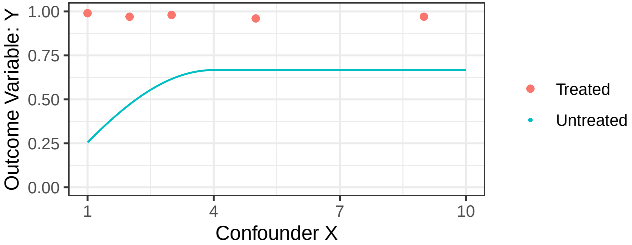

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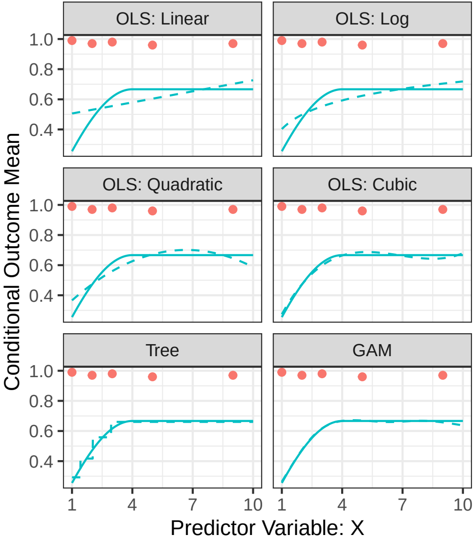
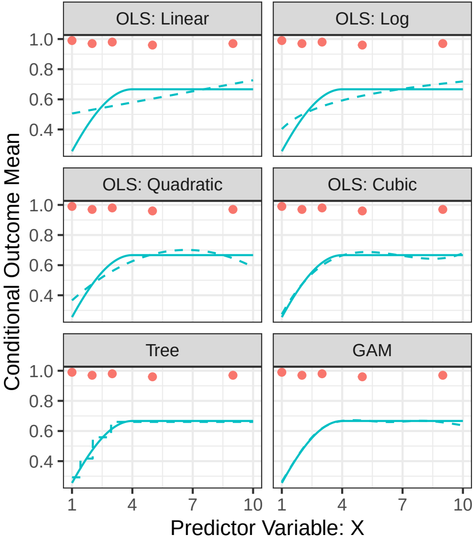
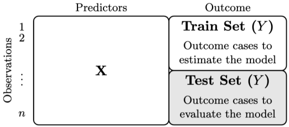


Example based on
[Lundberg, Brand, Jeon 2022](#)
Figure 5

Sample splitting makes it easier to **choose among many estimators**





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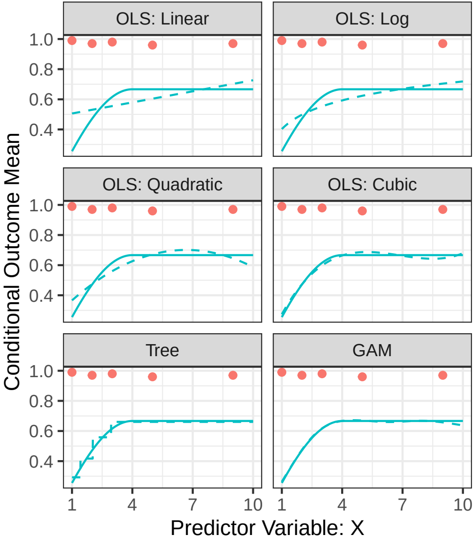

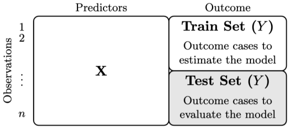

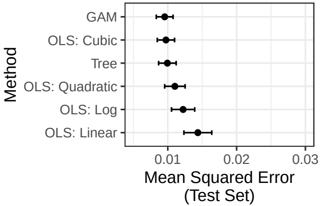

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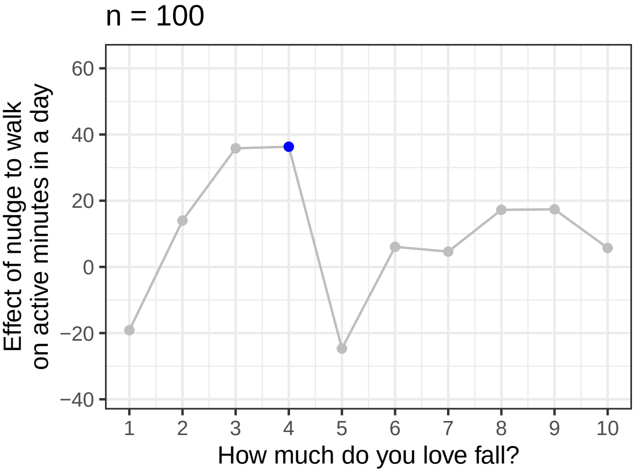

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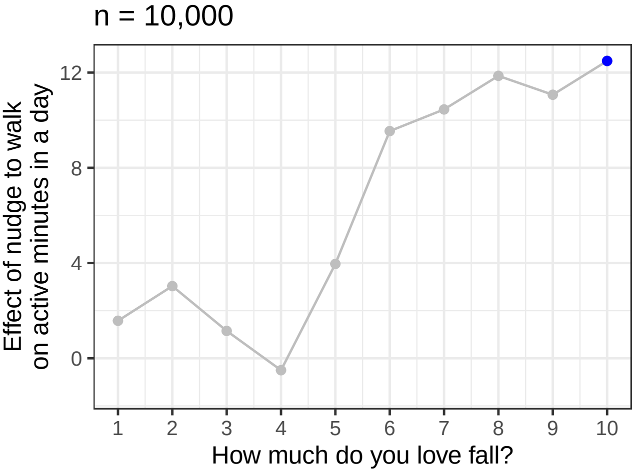

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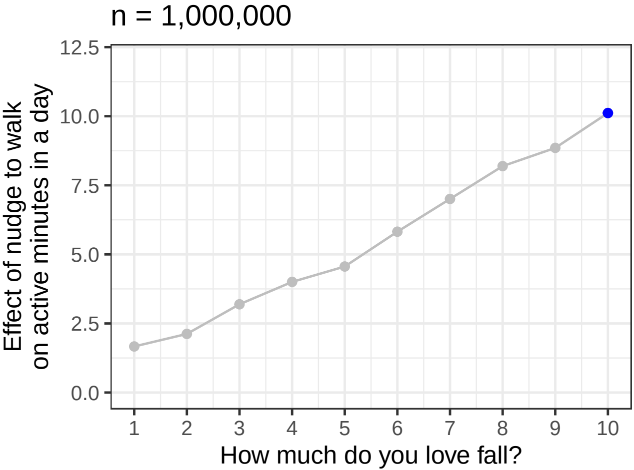

Sample splitting makes it easier to **develop new data science approaches**

How much do you love fall?

1 10

Sample splitting makes it easier to **develop new data science approaches**

How much do
you love fall?

repeatedly split into two halves
with highly heterogeneous
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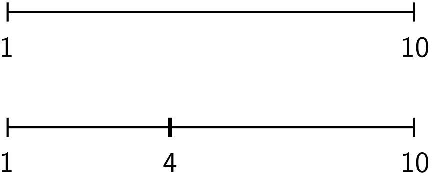

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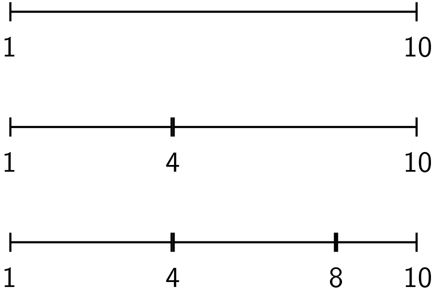

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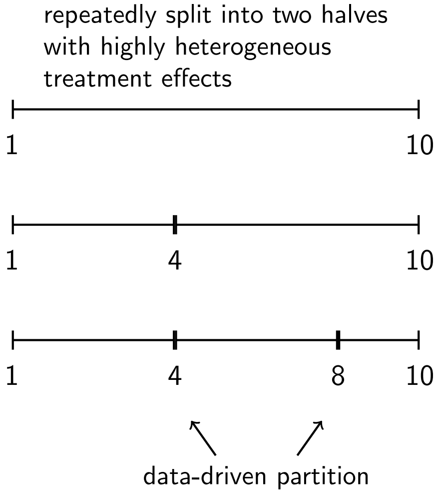

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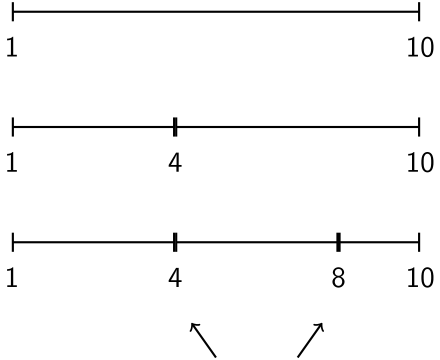
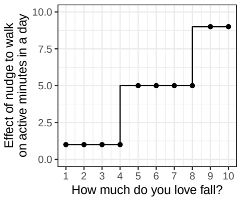


data-driven partition



Sample splitting makes it easier to **develop new data science approaches**

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In **Sample A**

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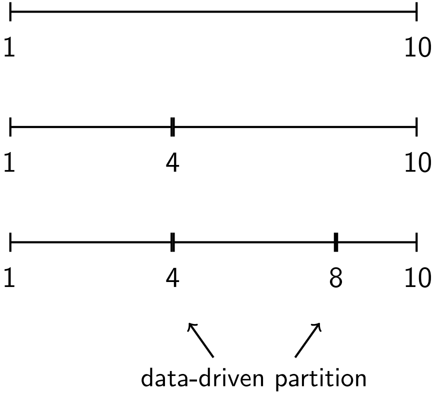
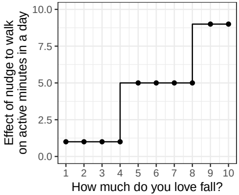


In **Sample B**
learn the response



Sample splitting makes it easier to **develop new data science approaches**

Athey, S., & Imbens, G. (2016).
Recursive partitioning for heterogeneous causal effects.
Proceedings of the National Academy of Sciences
113(27), 7353-7360.

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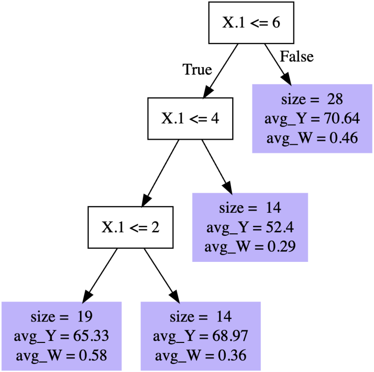

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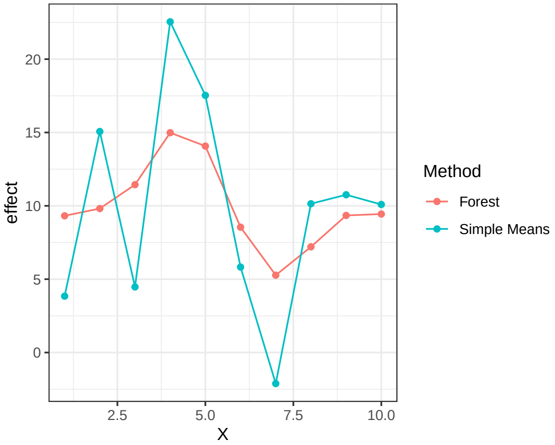

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