Three Stats Pitfalls Facing the New Data Scientist

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Do I Know You?

- Apache Spark committer, PMC
- "Advanced Analytics with Spark"
- Recently: Director, Data Science @ Cloudera

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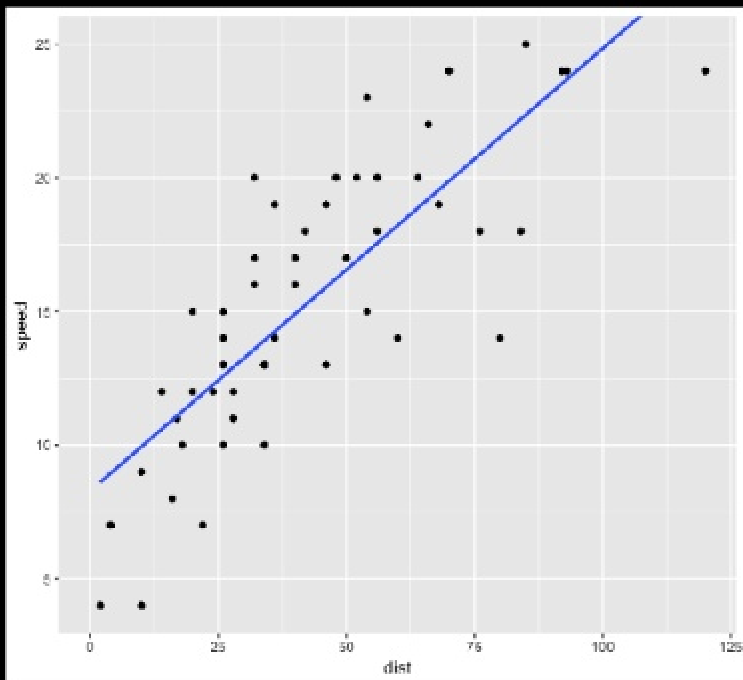
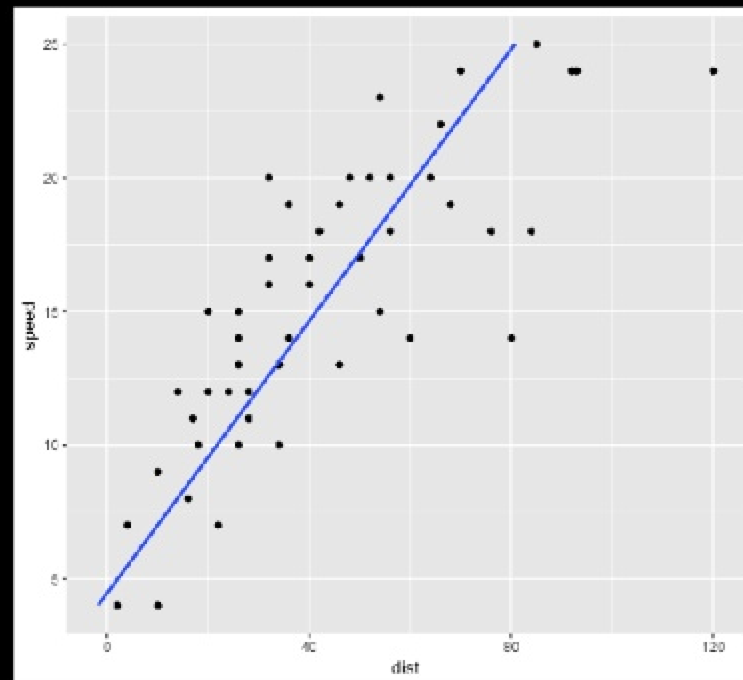
Correlation is not causation.
But then, what is causation?

Which Best-Fit Line Is Best?



`lm(speed ~ dist, cars)`



`lm(dist ~ speed, cars)`

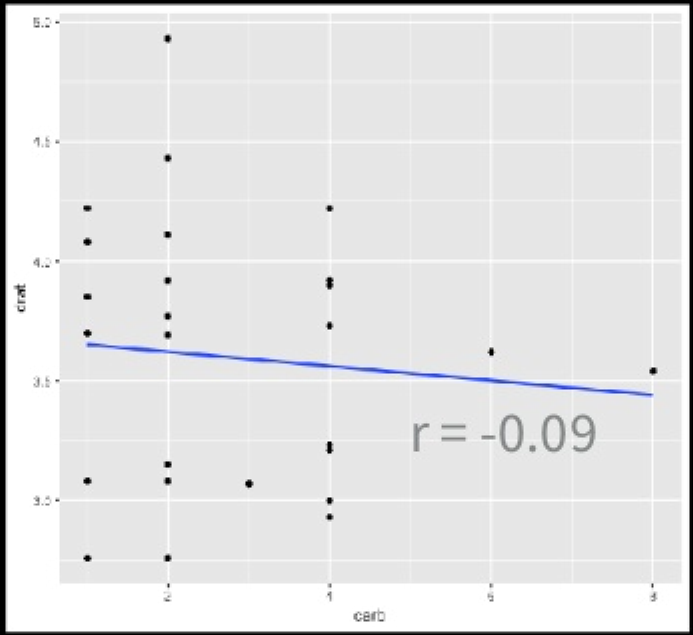
Which Treatment is Better?

	Treatment A	Treatment B
Small Stones	**93% (81/87)**	87% (234/270)
Large Stones	**73% (192/263)**	69% (55/80)
	78% (273/350)	**83% (289/350)**

Now, Which Treatment is Better?

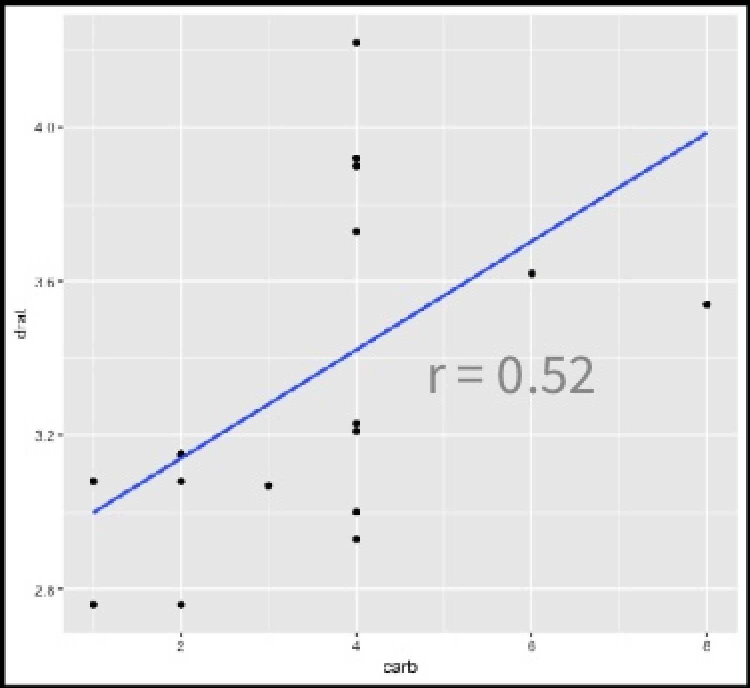
	Treatment A	Treatment B
Low Blood pH	**93% (81/87)**	87% (234/270)
High Blood pH	**73% (192/263)**	69% (55/80)
	78% (273/350)	**83% (289/350)**

Carburetors and Axle Ratio Uncorrelated

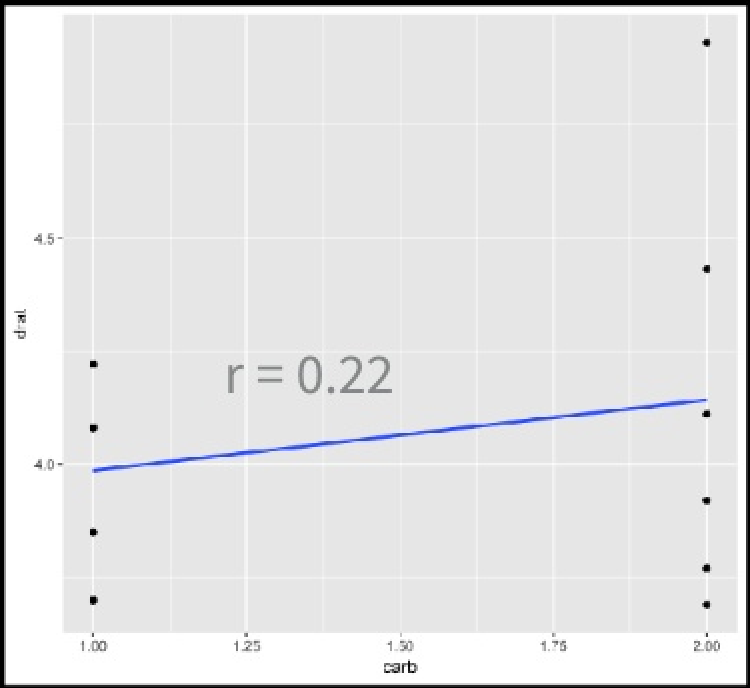



```
lm(drat ~ carb, mtcars)
```

… Except in Both Halves of the Data?




```
lm(drat ~ carb, mtcars[
  which(mtcars$cyl >= 6),])
```



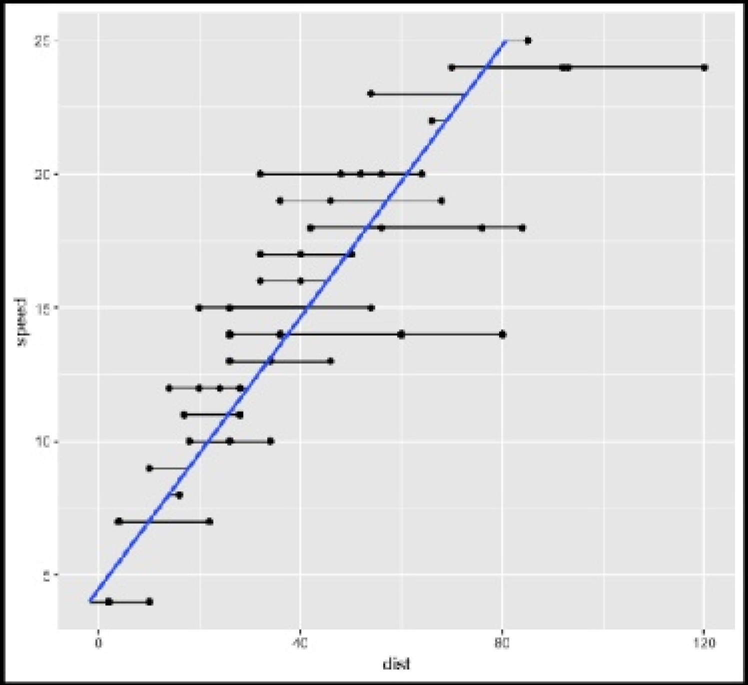

```
lm(drat ~ carb, mtcars[
  which(mtcars$cyl < 6),])
```

3 Answers

Resolution: Causation

- Humans reason causally
- Data doesn't contain causal information
- Data correlations consistent with multiple causal models
- Correct inference requires adding causal model

One Consistent with Causal Knowledge

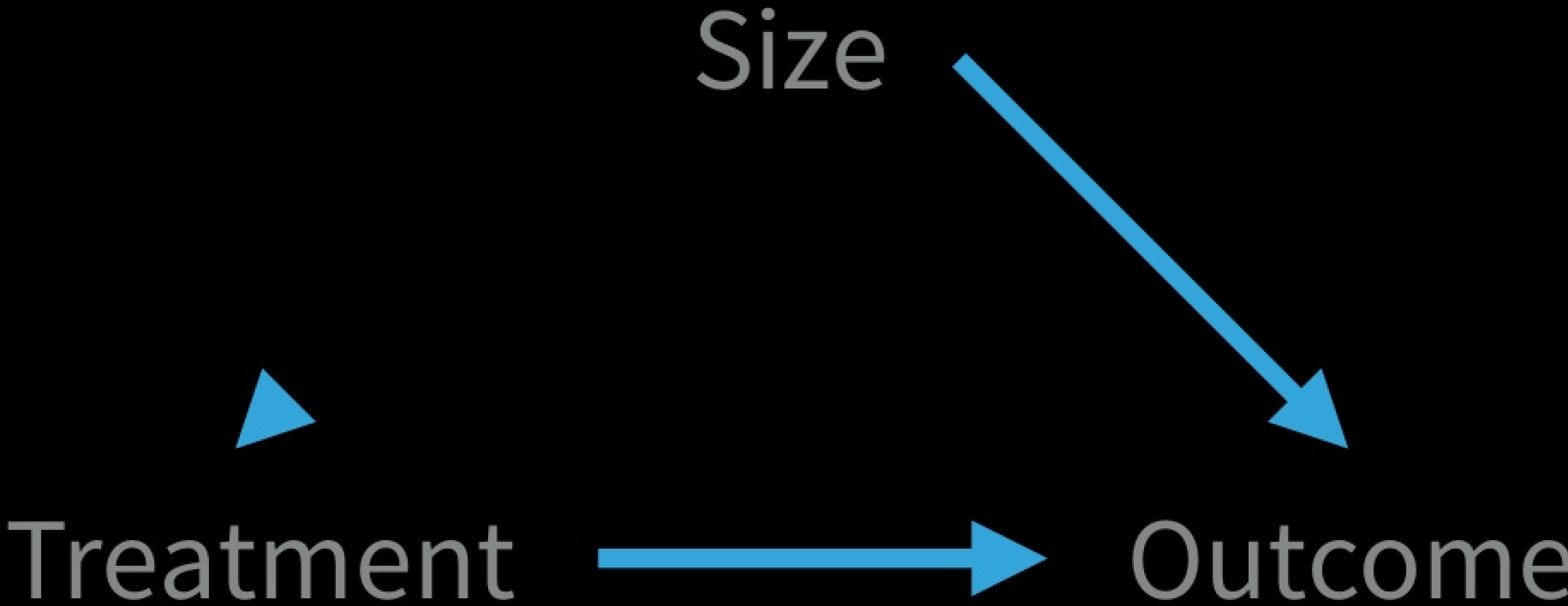


$$dist_i = \beta_0 + \beta_1 speed_i + \epsilon_i$$

Speed → Distance

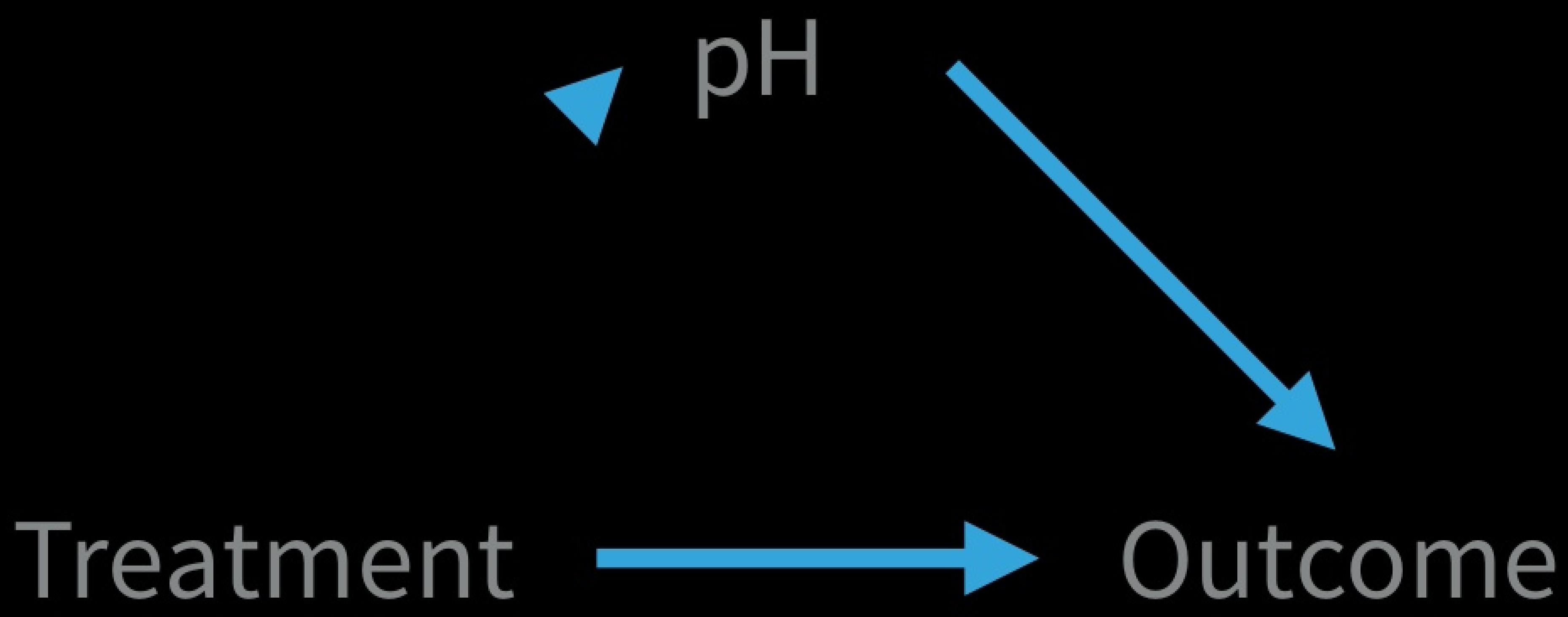
Controlling Confounders is Right

	Treatment A	Treatment B
Small Stones	**93% (81/87)**	87% (234/270)
Large Stones	**73% (192/263)**	69% (55/80)
	78% (273/350)	**83% (289/350)**

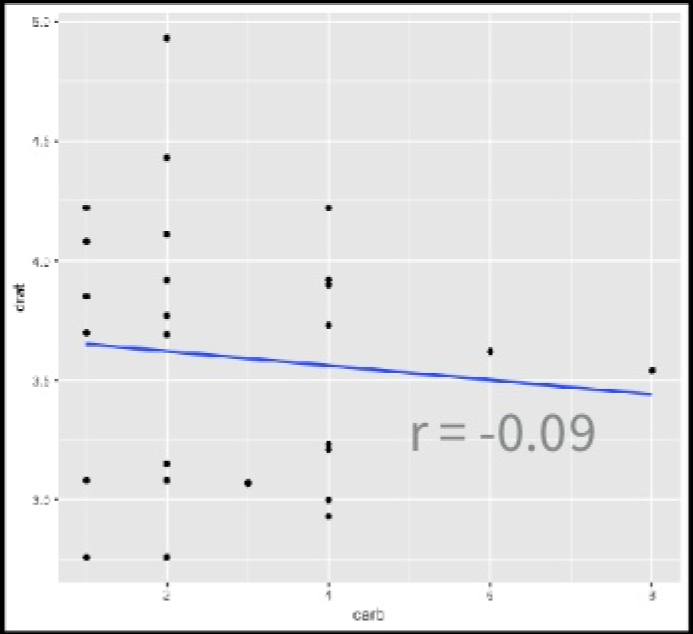

Size
Treatment
Outcome

Controlling Mediators is Wrong

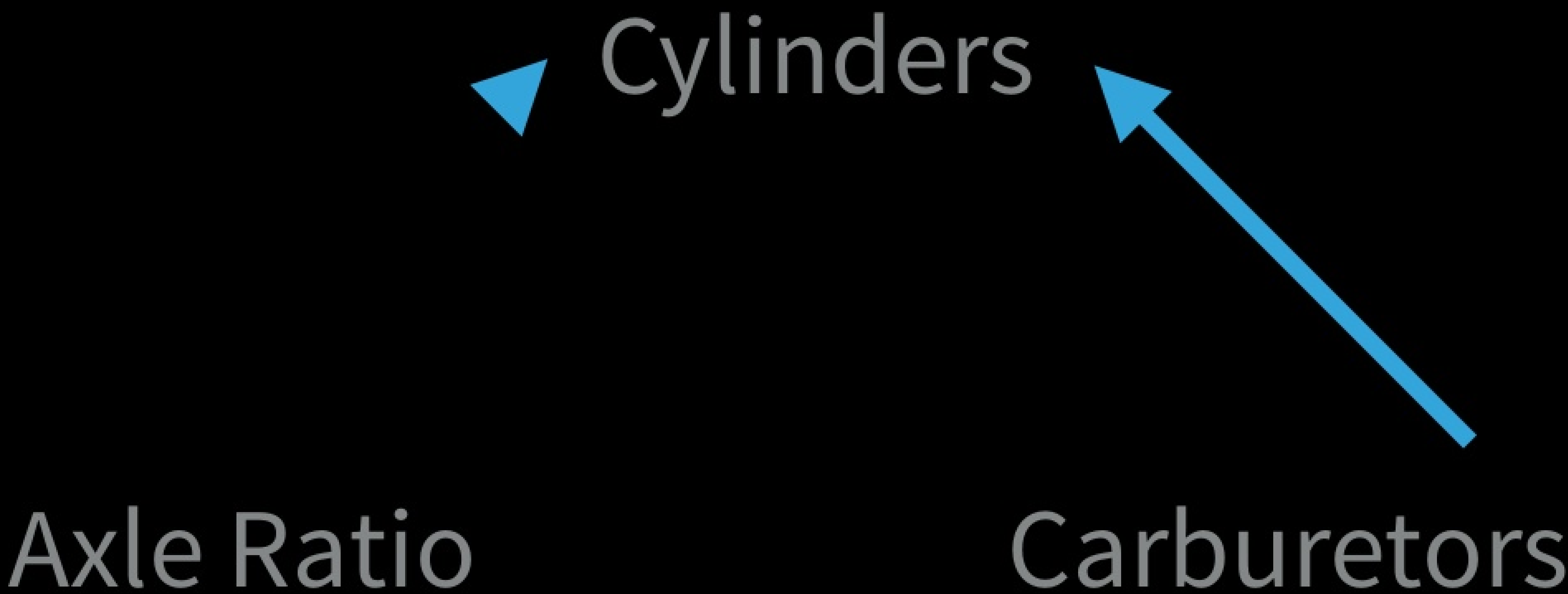
	Treatment A	Treatment B
Low Blood pH	**93% (81/87)**	87% (234/270)
High Blood pH	**73% (192/263)**	69% (55/80)
	78% (273/350)	**83% (289/350)**


pH
Treatment
Outcome

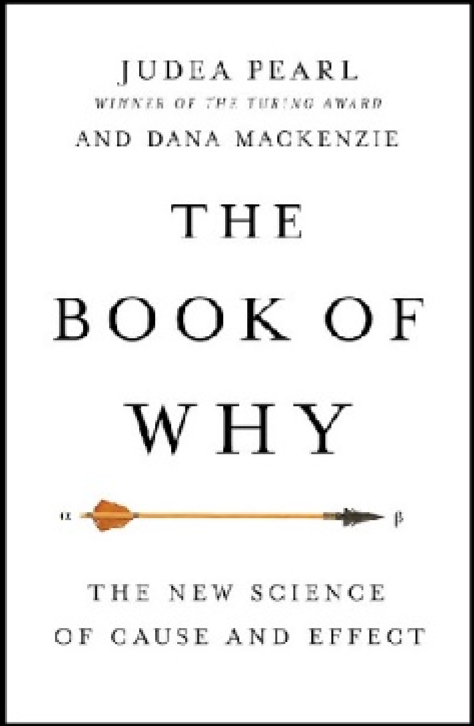
Colliders Create Correlation



`lm(drat ~ carb, mtcars)`


Cylinders
Axle Ratio
Carburetors

Causation and do-Calculus

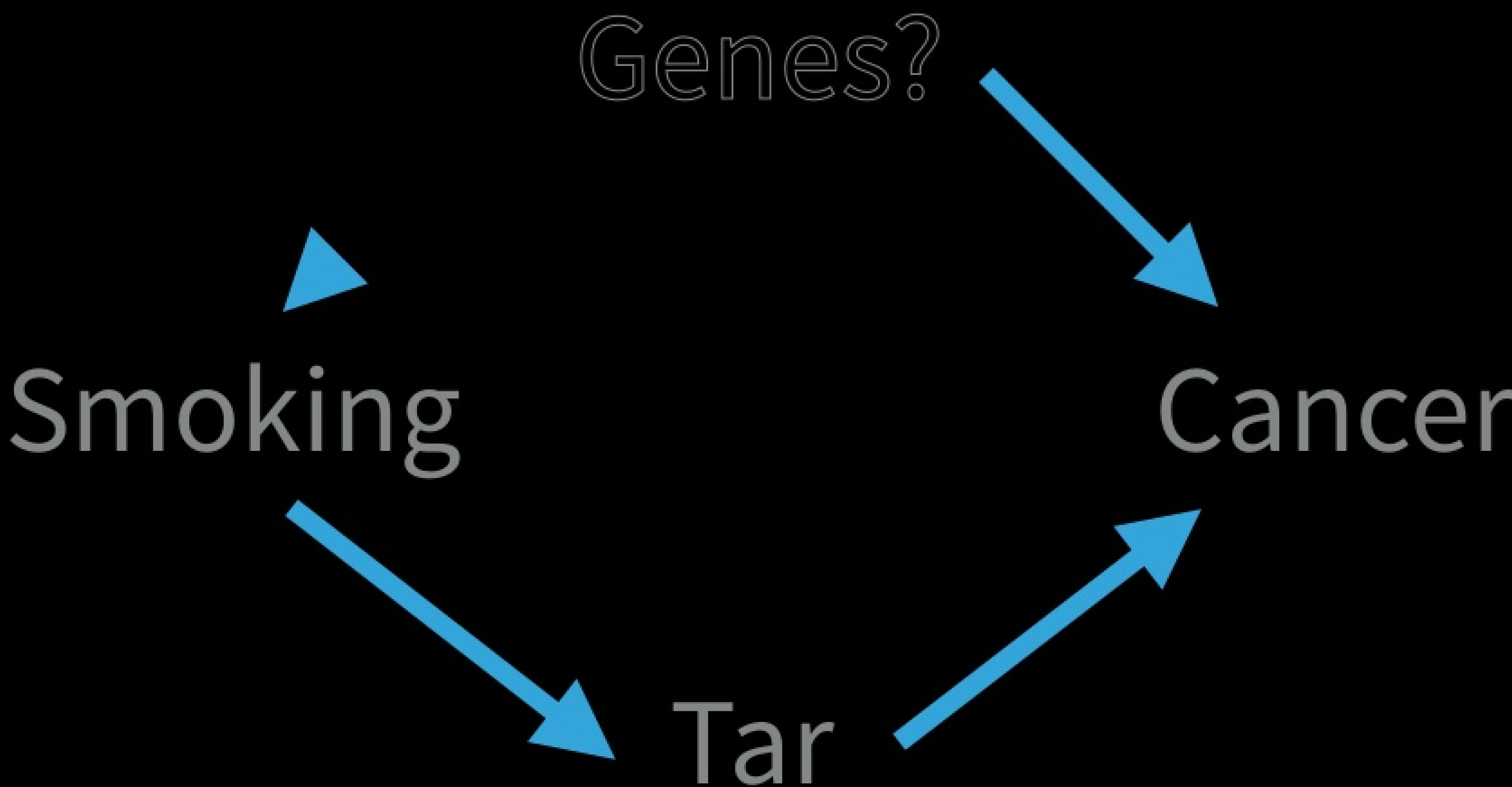


do-Calculus

$$P(Y|X) \neq P(Y|do(X))$$

Just because it's more often raining when you walk outside with an umbrella …

… doesn't mean that you carrying an umbrella makes it more likely to be raining.



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$$
\begin{aligned}
P(C \mid do(S)) &= \sum_t P(C \mid do(S), t) P(t \mid do(S)) \\
&= \sum_t P(C \mid do(S), do(t)) P(t \mid do(S)) \\
&= \sum_t P(C \mid do(S), do(t)) P(t \mid S) \\
&= \sum_t P(C \mid do(t)) P(t \mid S) \\
&= \sum_{s'} \sum_t P(C \mid do(t), s') P(s' \mid do(t)) P(t \mid S) \\
&= \sum_{s'} \sum_t P(C \mid t, s') P(s' \mid do(t)) P(t \mid S) \\
&= \sum_{s'} \sum_t P(C \mid t, s') P(s') P(t \mid S)
\end{aligned}
$$

Conclusion

- Must bring causal info to data for proper interpretation
- Know common causal pitfalls!
- PGMs help reason about causal effects
- Do-calculus can clarify reasoning about intervention

Thank You

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