Causal inference is not just a statistics problem

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Lucy D'Agostino McGowan

Wake Forest University

Causal Inference is not a statistics problem

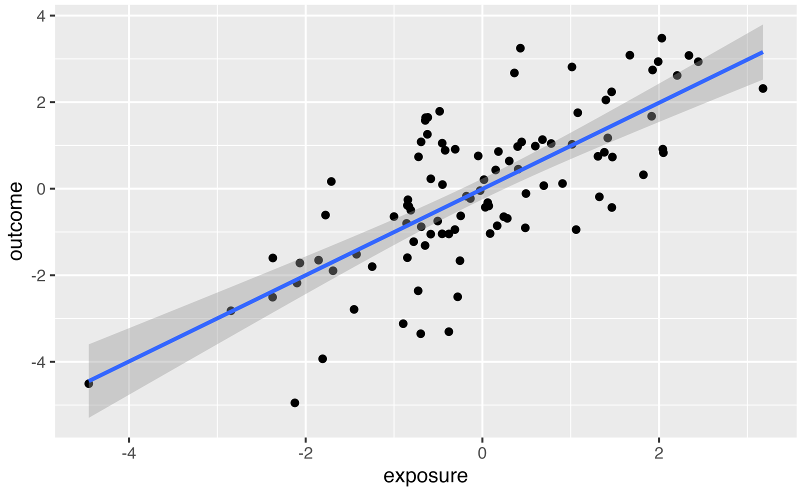
Causal Inference is not *just* a statistics problem

The problem

We have measured variables, what should we adjust for?

exposure	outcome	covariate
0.49	1.71	2.24
0.07	0.68	0.92
0.40	-1.60	-0.10
.	.	.
.	.	.
.	.	.
0.55	-1.73	-2.34

A bit more info




```r
cor(exposure, covariate)
```

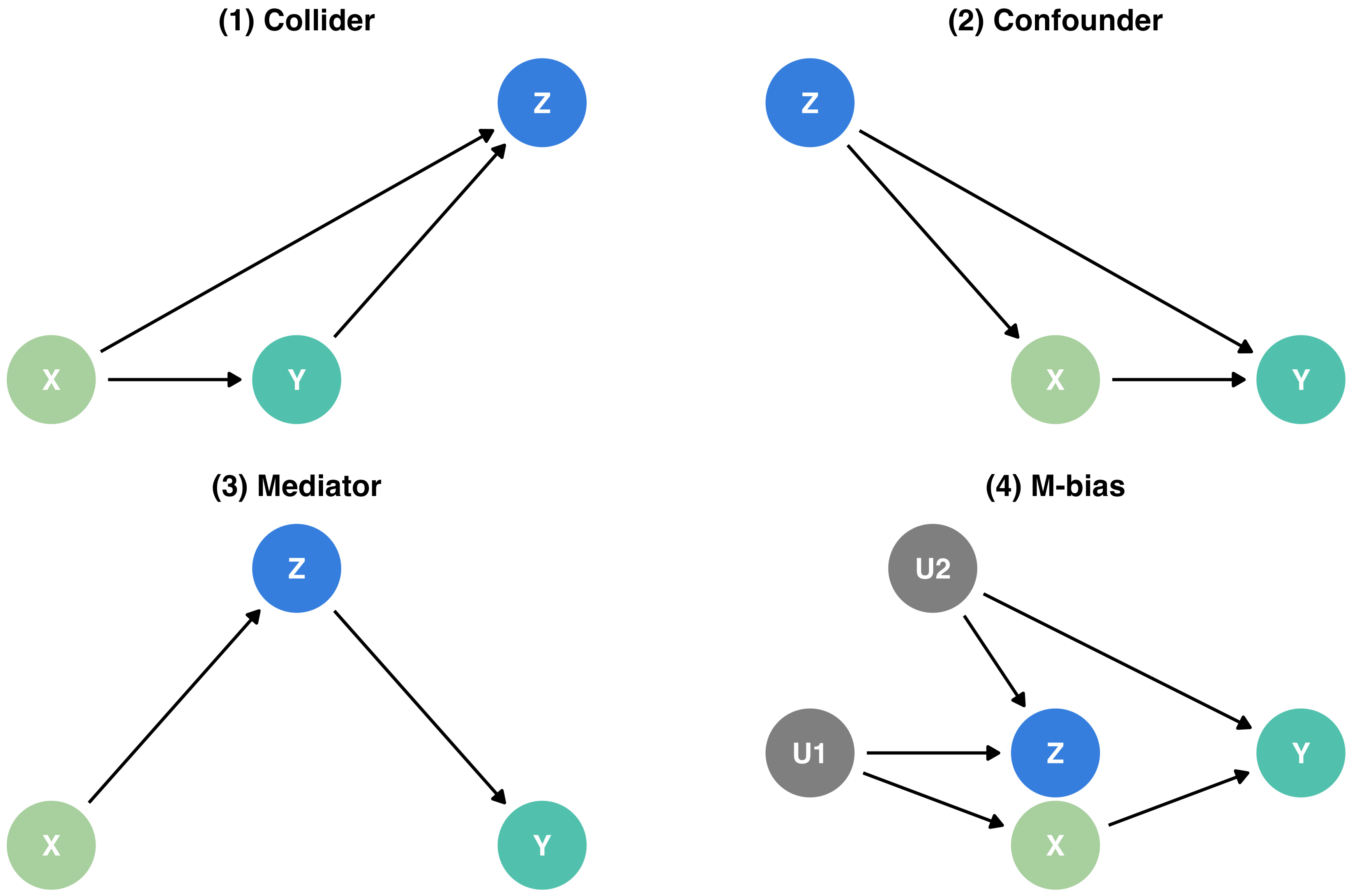
```
[1] 0.7
```

The exposure and measured factor are positively correlated

One unit increase in the exposure yields an average increase in the outcome of 1

To adjust or not adjust? That is the question.

Causal Quartet



quartets

Your turn 1

Load the `quartets` package

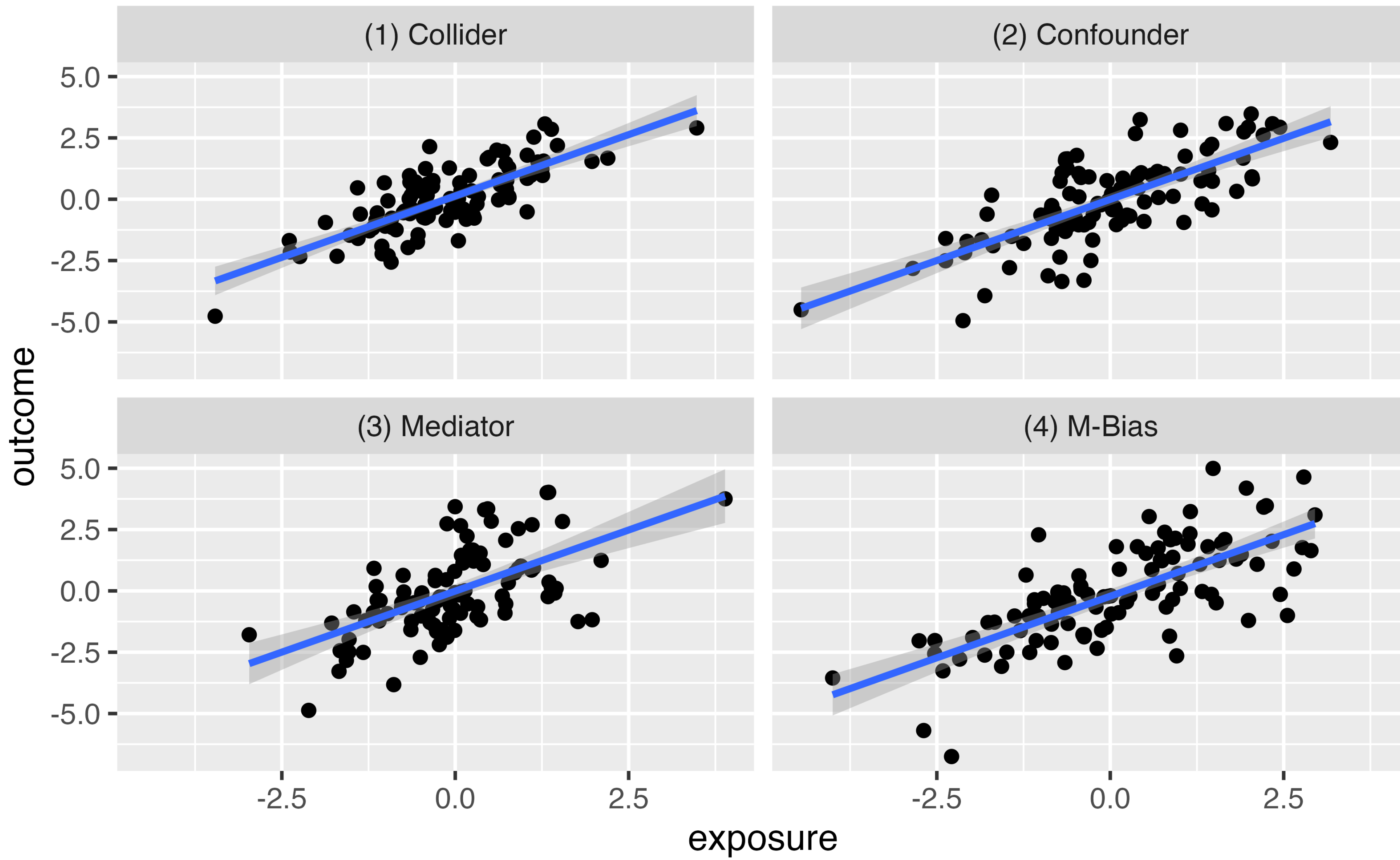
For each of the following 4 datasets, look at the correlation between `exposure` and `covariate`: `causal_collider`, `causal_confounding`, `causal_mediator`, `causal_m_bias`

For each of the above 4 datasets, create a scatterplot looking at the relationship between `exposure` and `outcome`

For each of the above 4 datasets, fit a linear model to examine the relationship between the `exposure` and the `outcome`

10:00

Relationship between exposure and outcome



Relationship between exposure and covariate

```
causal_quartet |>
  group_by(dataset) |>
  summarise(cor(exposure, covariate))
```

```
# A tibble: 4 × 2
  dataset          `cor(exposure, covariate)`
  <chr>                                 <dbl>
1 (1) Collider                          0.700
2 (2) Confounder                        0.696
3 (3) Mediator                          0.696
4 (4) M-Bias                            0.696
```

Correct effects

Data generating mechanism	Correct causal model	Correct causal effect
(1) Collider	Y ~ X	1.0
(2) Confounder	Y ~ X ; Z	0.5
(3) Mediator	Direct effect: Y ~ X ; Z Total Effect: Y ~ X	Direct effect: 0.0 Total effect: 1.0
(4) M-Bias	Y ~ X	1.0

D'Agostino McGowan L, Gerke T, Barrett M (2023). Causal inference is not a statistical problem. Preprint arXiv:2304.02683v1.

Observed effects

Data generating mechanism	ATE not adjusting for Z	ATE adjusting for Z	Correlation of X and Z
(1) Collider	1.00	0.55	0.70
(2) Confounder	1.00	0.50	0.70
(3) Mediator	1.00	0.00	0.70
(4) M-Bias	1.00	0.88	0.70

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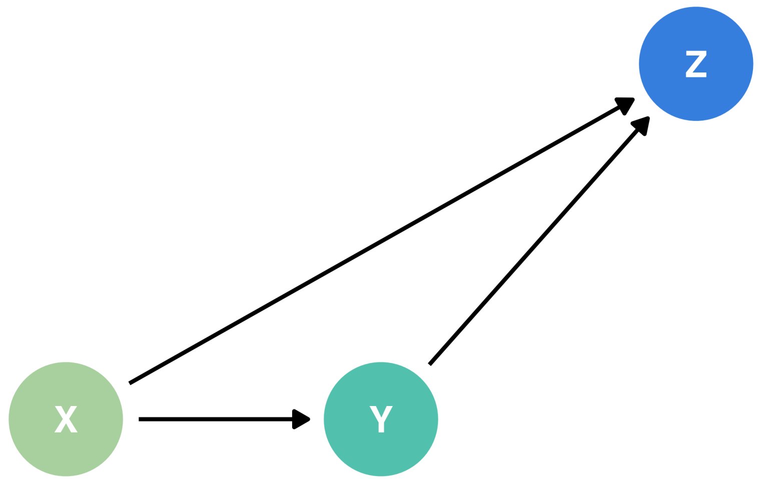
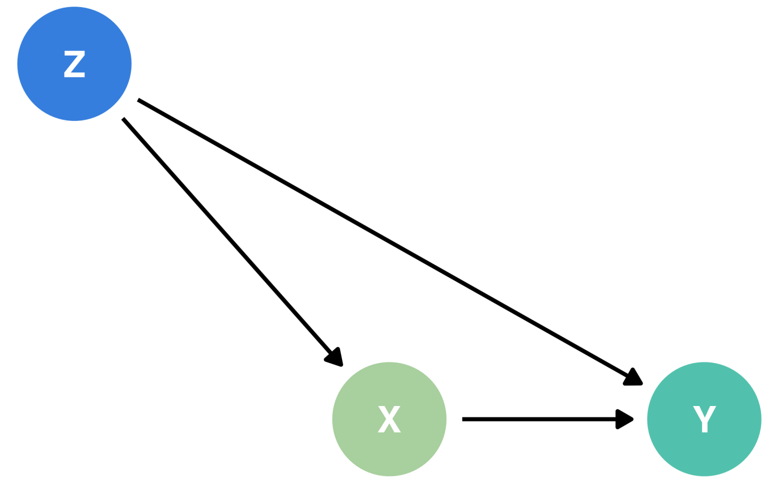
The solution

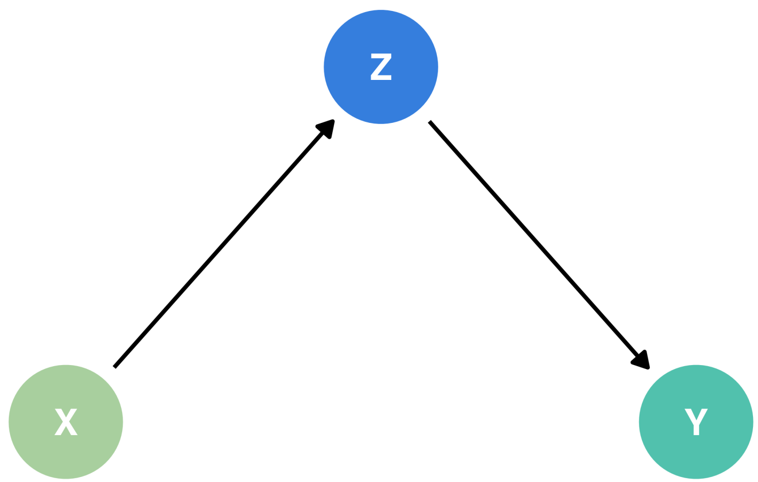
(1) Collider



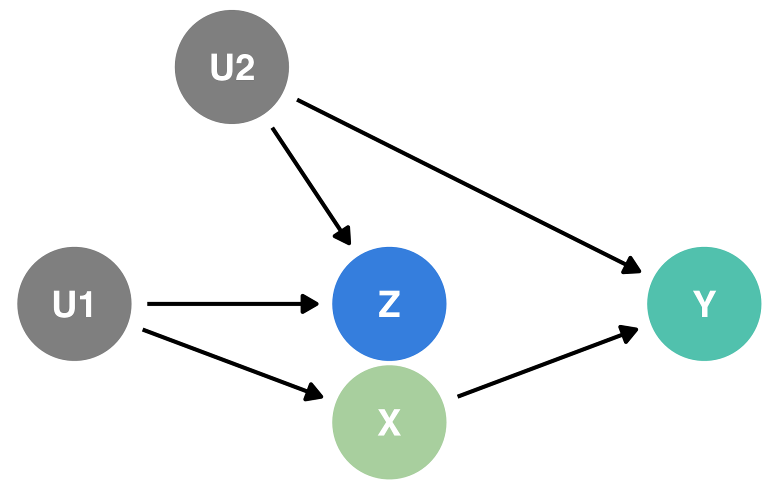
(2) Confounder



(3) Mediator



(4) M-bias



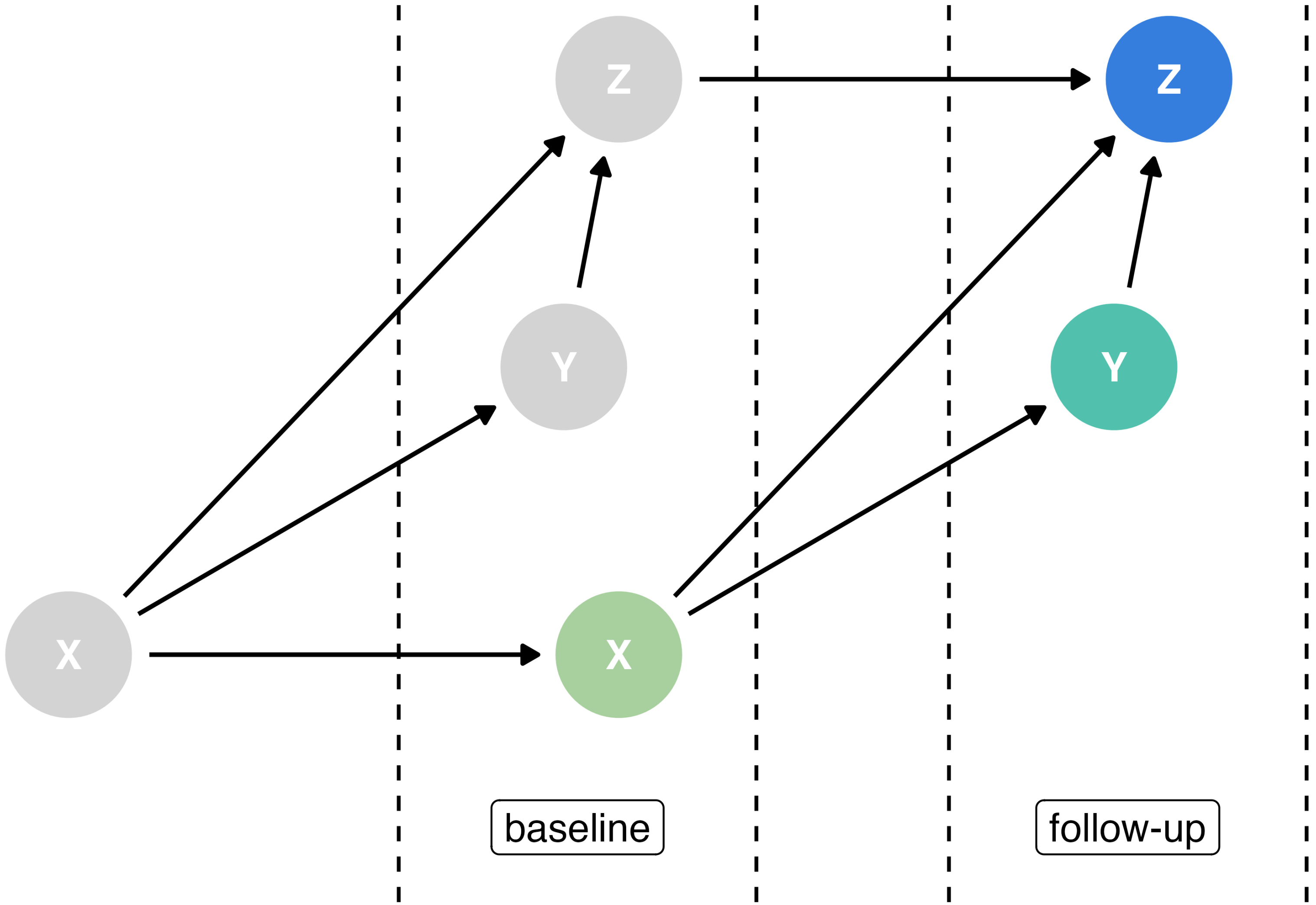
The *partial* solution

```r
causal_collider_time
```

```
# A tibble: 100 × 6
   exposure_baseline outcome_baseline covariate_baseline
               <dbl>            <dbl>              <dbl>
 1           -1.43              0.287            -0.0963
 2            0.0593           -0.978            -1.11
 3            0.370             0.348             0.647
 4            0.00471           0.851             0.755
 5            0.340             1.94              1.19
 6           -3.61             -0.235            -0.588
 7            1.44             -0.827            -1.13
 8            1.02             -0.0410            0.689
 9           -2.43             -2.10             -1.49
10           -1.26             -2.41             -2.78
# ℹ 90 more rows
# ℹ 3 more variables: exposure_followup <dbl>,
#   outcome_followup <dbl>, covariate_followup <dbl>
```

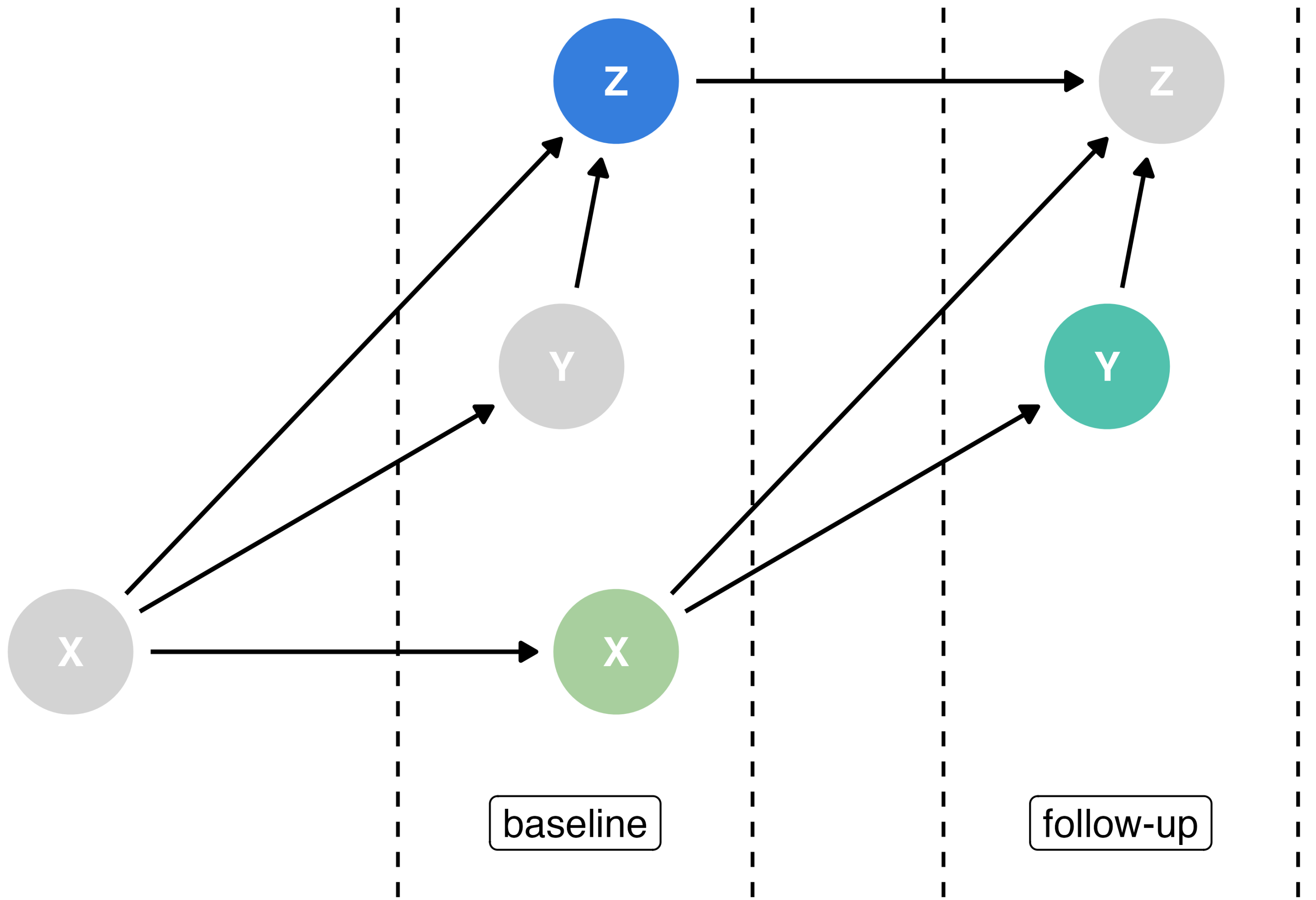
Time-varying data

Time-varying DAG



True causal effect: 1 Estimated causal effect: 0.55

Time-varying DAG



True causal effect: 1 Estimated causal effect: 1

```
outcome_followup ~ exposure_baseline + covariate_baseline
```

The *partial* solution

Data generating mechanism	ATE not adjusting for pre-exposure Z	ATE adjusting for pre-exposure Z	Correct causal effect
(1) Collider	1.00	1.00	1.00
(2) Confounder	1.00	0.50	0.50
(3) Mediator	1.00	1.00	1.00
(4) M-Bias	1.00	0.88	1.00

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On M-Bias

- The relationship between Z and the unmeasured confounders needs to be really large (Liu et al 2012)
- "To obsess about the possibility of [M-bias] generates bad practical advice in all but the most unusual circumstances" (Rubin 2009)
- There are (almost) no true zeros (Gelman 2011)
- Asymptotic theory shows that induction of M-bias is quite sensitive to various deviations from the exact M-Structure (Ding and Miratrix 2014)

Your turn 2

For each of the following 4 datasets, fit a linear linear model examining the relationship between `outcome_followup` and `exposure_baseline` adjusting for `covariate_baseline`:

`causal_collider_time`, `causal_confounding_time`, `causal_mediator_time`, `causal_m_bias_time`

10:00