Alternative Frameworks

Experimental Research

Prof. Yamil Velez (9/13/22)

Last class

- Defined the average treatment effect
  - Difference in average outcomes for treatment and control units
  - ATE depends on two crucial assumptions
    - Stable unit treatment value assumption (SUTVA)
    - Independence
      - Treatment status and potential outcomes are statistically independent
  - ATE = ATT + Selection Bias
  - Experiments recover causal effects because they eliminate selection bias

$$\mathbb{E}[Y_i(1) - Y_i(0) \mid T_i = 1] + (\mathbb{E}[Y_i(0) \mid T_i = 1] - \mathbb{E}[Y_i(0) \mid T_i = 0])$$

Potential outcome Under treatment

Potential outcome Under control

When assigned Treatment

Potential outcome Under control

When assigned Treatment

Potential outcome Under control

When assigned Control

Average treatment effect on the treated

Selection bias

$$\mathbb{E}[Y_i(1) - Y_i(0) \mid T_i = 1] + (\mathbb{E}[Y_i(0) \mid T_i = 1] - \mathbb{E}[Y_i(0) \mid T_i = 0])$$

Potential outcome Under treatment	Potential outcome Under control	When assigned Treatment	Potential outcome Under control	When assigned Treatment	Potential outcome Under control	When assigned Control

Average treatment effect on the treated

Selection bias

Population Avg. | given that… | Population Avg. | given that… | Population Avg. | given that…

$$\mathbb{E}[Y_i(1) - Y_i(0) \mid T_i = 1] + (\mathbb{E}[Y_i(0) \mid T_i = 1] - \mathbb{E}[Y_i(0) \mid T_i = 0])$$

Potential outcome Under treatment | Potential outcome Under control | When assigned Treatment | Potential outcome Under control | When assigned Treatment | Potential outcome Under control | When assigned Control

Average treatment effect on the treated

Selection bias

Average difference in potential outcomes for units assigned to treatment (T = 1)

Average control potential outcome for units assigned to treatment (T = 1)

Average control potential outcome for units assigned to control (T = 0)

$$Avg[Y_i(1) - Y_i(0) \mid T_i = 1] + (Avg[Y_i(0) \mid T_i = 1] - Avg[Y_i(0) \mid T_i = 0])$$

Potential outcome Under treatment

Potential outcome Under control

When assigned Treatment

Potential outcome Under control

When assigned Treatment

Potential outcome Under control

When assigned Control

Average treatment effect on the treated

Selection bias

Social Capital and Voter Turnout: Evidence from Saint's Day Fiestas in Mexico

Published online by Cambridge University Press: **28 November 2012**

Matthew D. Atkinson and Anthony Fowler

Article Figures Supplementary materials Metrics

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Abstract

Social capital and community activity are thought to increase voter turnout, but reverse causation and omitted variables may bias the results of previous studies. This article exploits saint's day fiestas in Mexico as a natural experiment to test this causal relationship. Saint's day fiestas provide temporary but large shocks to the connectedness and trust within a community, and the timing of these fiestas is quasi-random. For both cross-municipality and within-municipality estimates, saint's day fiestas occurring near an election decrease turnout by 2.5 to 3.5 percentage points. So community activities that generate social capital can inhibit political participation. These findings may give pause to scholars and policy makers who assume that such community activity and social capital will improve the performance of democracy.

Putting the Party Back into Politics: An Experiment Testing Whether Election Day Festivals Increase Voter Turnout

Published online by Cambridge University Press: **03 October 2007**

Elizabeth M. Addonizio, Donald P. Green and James M. Glaser

Show author details

	Festival $Y_i(1)$	~Festival $Y_i(0)$	T_i	τ_i
1	**1**	**0**	**1**	**1**
2	1	1	0	0
3	**0**	**0**	**1**	**0**
4	1	1	0	0

$$\mathbb{E}[Y_i(1) - Y_i(0) \mid T_i = 1] + (\mathbb{E}[Y_i(0) \mid T_i = 1] - \mathbb{E}[Y_i(0) \mid T_i = 0])$$

.5

	Festival $Y_i(1)$	~Festival $Y_i(0)$	T_i	τ_i
1	1	0	1	1
2	1	1	0	0
3	0	0	1	0
4	1	1	0	0

$$\mathbb{E}[Y_i(1) - Y_i(0) \mid T_i = 1] + (\mathbb{E}[Y_i(0) \mid T_i = 1] - \mathbb{E}[Y_i(0) \mid T_i = 0])$$

.5

0

	Festival $Y_i(1)$	~Festival $Y_i(0)$	T_i	τ_i
1	1	0	1	1
2	1	1	0	0
3	0	0	1	0
4	1	1	0	0

$$\mathbb{E}[Y_i(1) - Y_i(0) \mid T_i = 1] + (\mathbb{E}[Y_i(0) \mid T_i = 1] - \mathbb{E}[Y_i(0) \mid T_i = 0])$$

.5 **0** **1**

	Festival $Y_i(1)$	~Festival $Y_i(0)$	T_i	τ_i
1	1	0	1	1
2	1	1	0	0
3	0	0	1	0
4	1	1	0	0

$$\mathbb{E}[Y_i(1) - Y_i(0) \mid T_i = 1] + (\mathbb{E}[Y_i(0) \mid T_i = 1] - \mathbb{E}[Y_i(0) \mid T_i = 0])$$

ATT = .5 **Selection Bias = -1**

	Festival $Y_i(1)$	~Festival $Y_i(0)$	T_i	τ_i
1	1	0	1	1
2	1	1	0	0
3	0	0	1	0
4	1	1	0	0

$$\mathbb{E}[Y_i(1) - Y_i(0) \mid T_i = 1] + (\mathbb{E}[Y_i(0) \mid T_i = 1] - \mathbb{E}[Y_i(0) \mid T_i = 0])$$

ATT = .5 **Selection Bias = -1**

Average difference in potential outcomes for units assigned to treatment (T = 1)

Average control potential outcome for units assigned to treatment (T = 1)

Average control potential outcome for units assigned to control (T = 0)

$$Avg[Y_i(1) - Y_i(0) \mid T_i = 1] + (Avg[Y_i(0) \mid T_i = 1] - Avg[Y_i(0) \mid T_i = 0])$$

Potential outcome Under treatment

Potential outcome Under control

When assigned Treatment

Potential outcome Under control

When assigned Treatment

Potential outcome Under control

When assigned Control

Average treatment effect on the treated

Selection bias

$$(Avg[Y_i(0) \mid T_i = 1] = Avg[Y_i(0) \mid T_i = 0])$$

On average, untreated potential outcomes for those assigned to the treatment are identical to those who are assigned to the control.

	Treatment	Control
Age	22	22
Education	12	12
Income	40k	40k
Republican	0.33	0.33
Democrat	0.33	0.33
Independent	0.33	0.33
Treatment	**1**	**0**

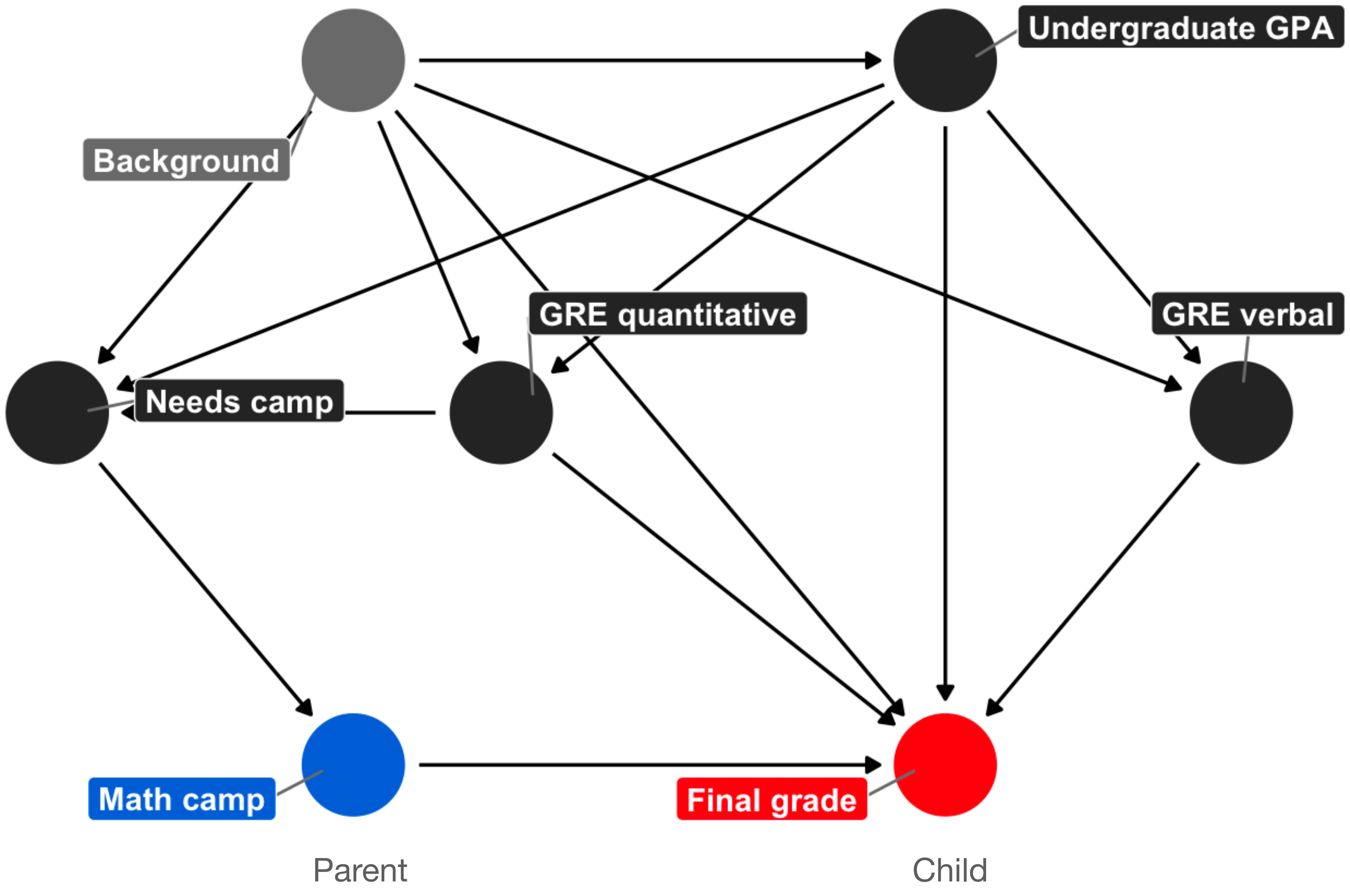
Statistical vs. experimental control

- Independence
  - Average treatment effect recovers a causal effect if treatment status and potential outcomes are independent
    - Experiments
    - But, you can also get there via conditional independence
      - $E[Y_i(1) \mid T_i = 1, X_i] = E[Y_i(1) \mid T_i = 0, X_i] = E[Y_i(1) \mid X_i]$
      - $E[Y_i(0) \mid T_i = 1, X_i] = E[Y_i(0) \mid T_i = 0, X_i] = E[Y_i(0) \mid X_i]$
      - This means that potential outcomes are independent of treatment assignment once you've controlled for the right variables

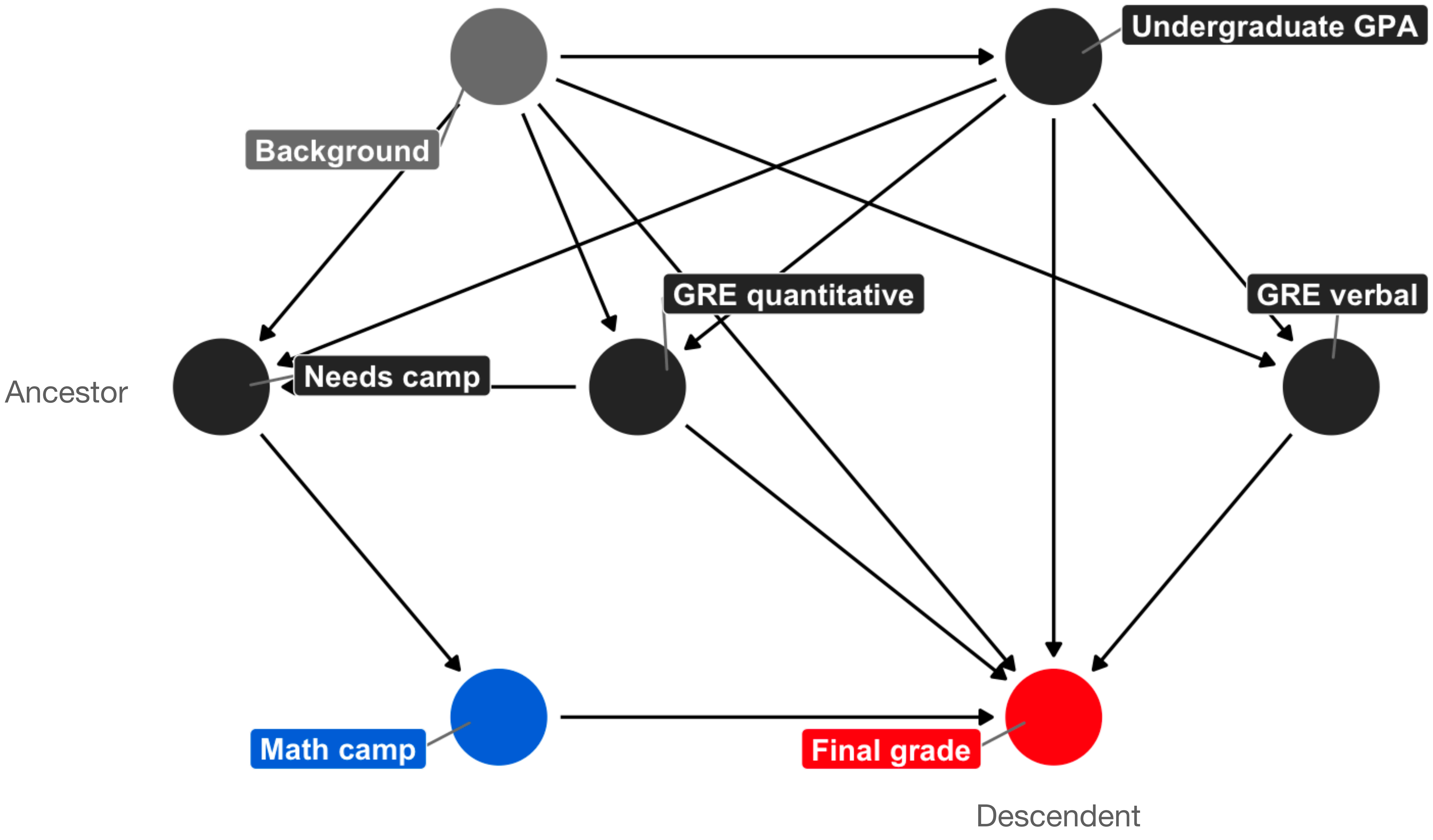
Directed acyclic graphs

- Directed acyclic graphs
    - Nodes (or vertices) that represent variables
    - Edges (directed arrows) that represent relationships
- Acyclic
    - No simultaneity
        - Causality only moves in one direction

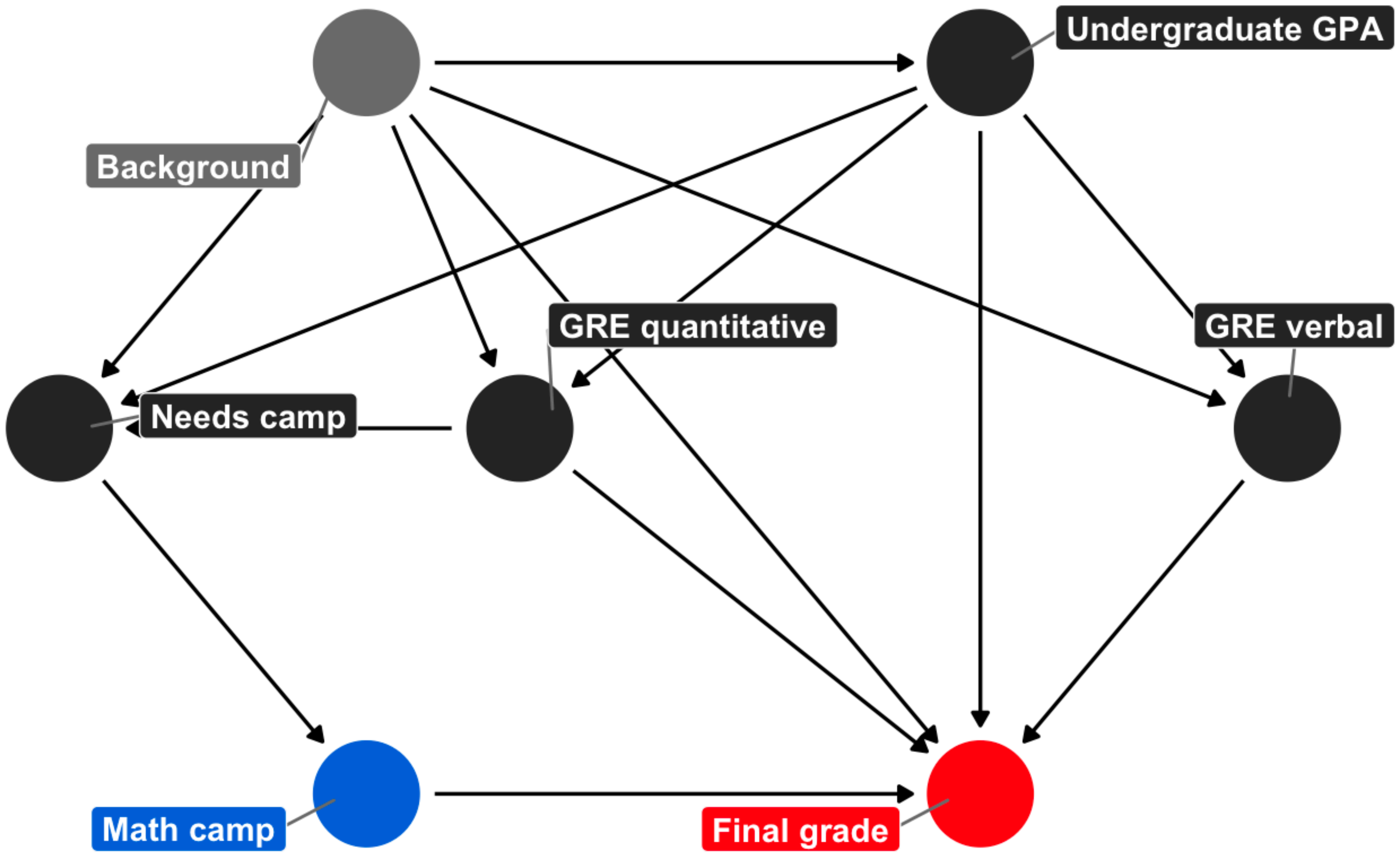
DAG Terminology



DAG Terminology



DAG Terminology



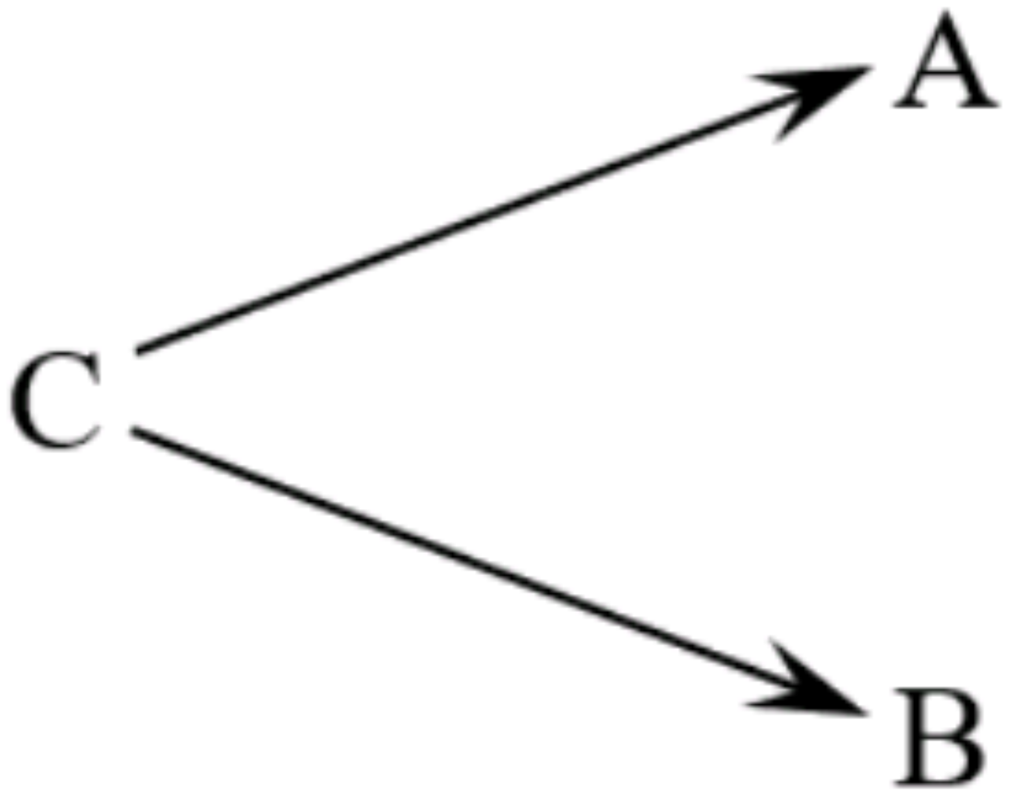
- Path
  - Sequence of adjacent nodes
- Collider
  - Node with two or more incoming arrows

DAG Terminology

- DAGs provide a visual depiction of causal structure
  - Nodes capture all of the variables that are relevant to a causal process of interest
  - Edges capture causal relationships between variables
    - Direct and indirect
- Illuminate what we should adjust for to obtain the appropriate causal quantities
  - Adjust for confounds, but not mediators, post-treatment outcomes, or colliders

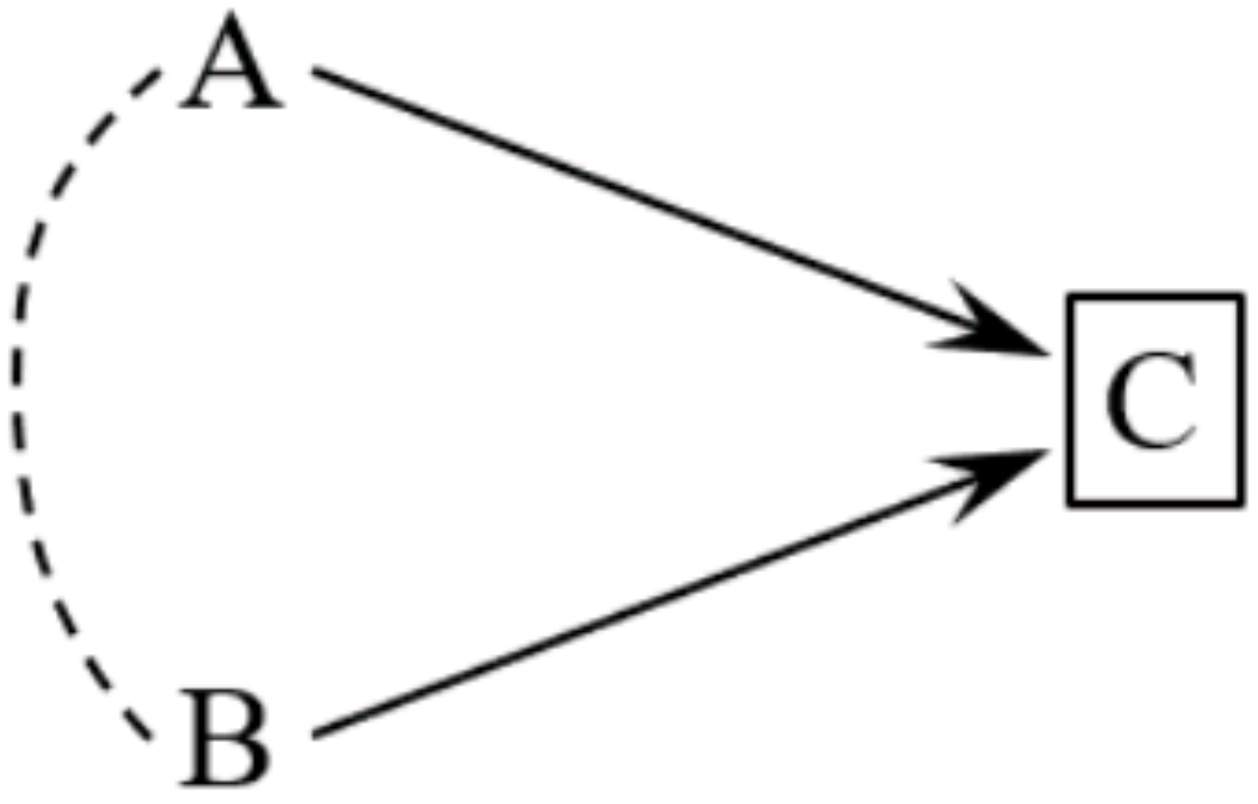
(1) Direct and indirect causation

$$A \not\perp B \text{ and } A \perp B|C$$



(2) Common cause confounding

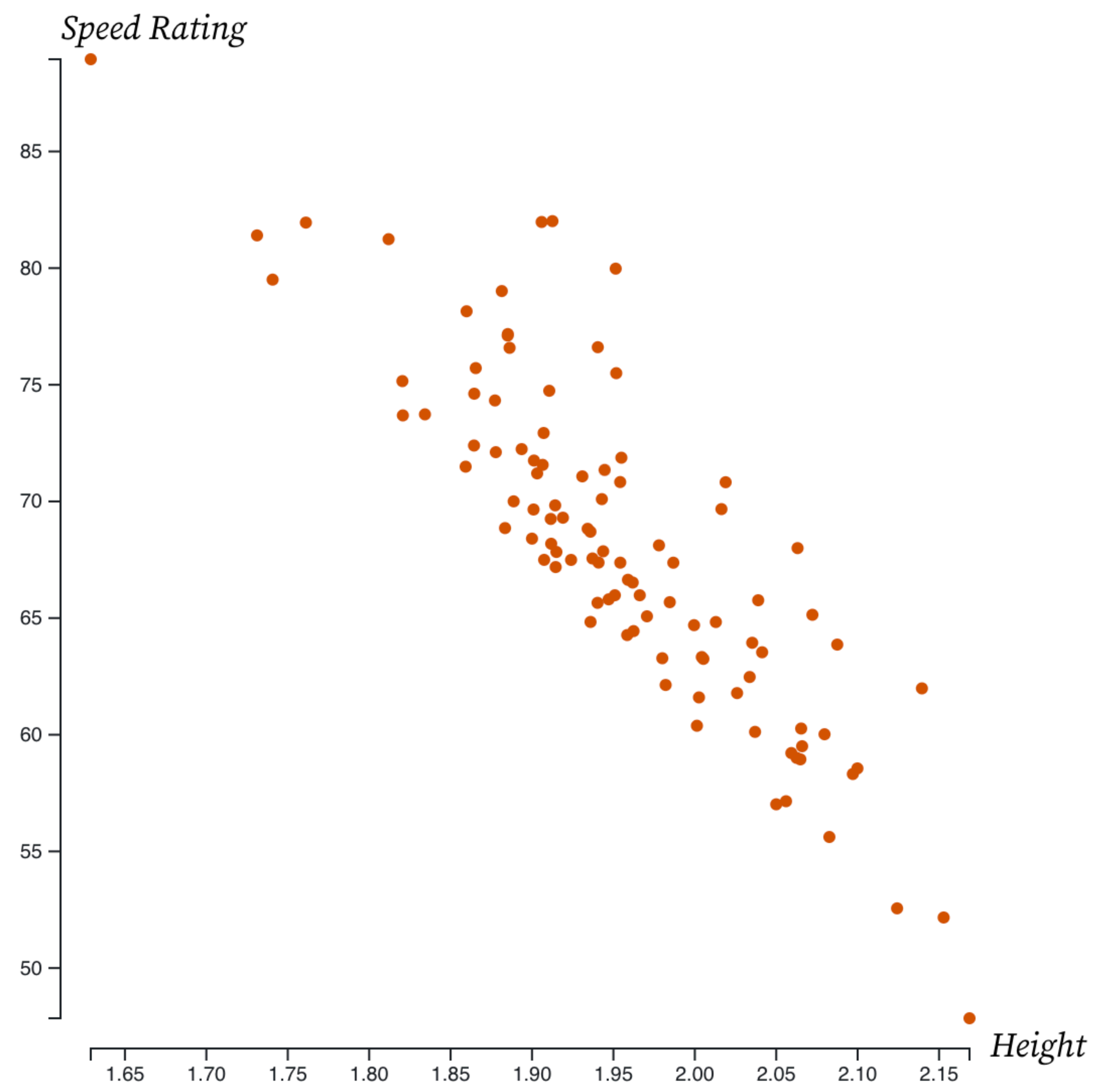
$$A \not\perp B \text{ and } A \perp B|C$$



(3) Conditioning on a common effect ("collider"): Selection

$$A \perp B \text{ and } A \not\perp B|C$$

Source: Elwert — Direct acyclic graphs



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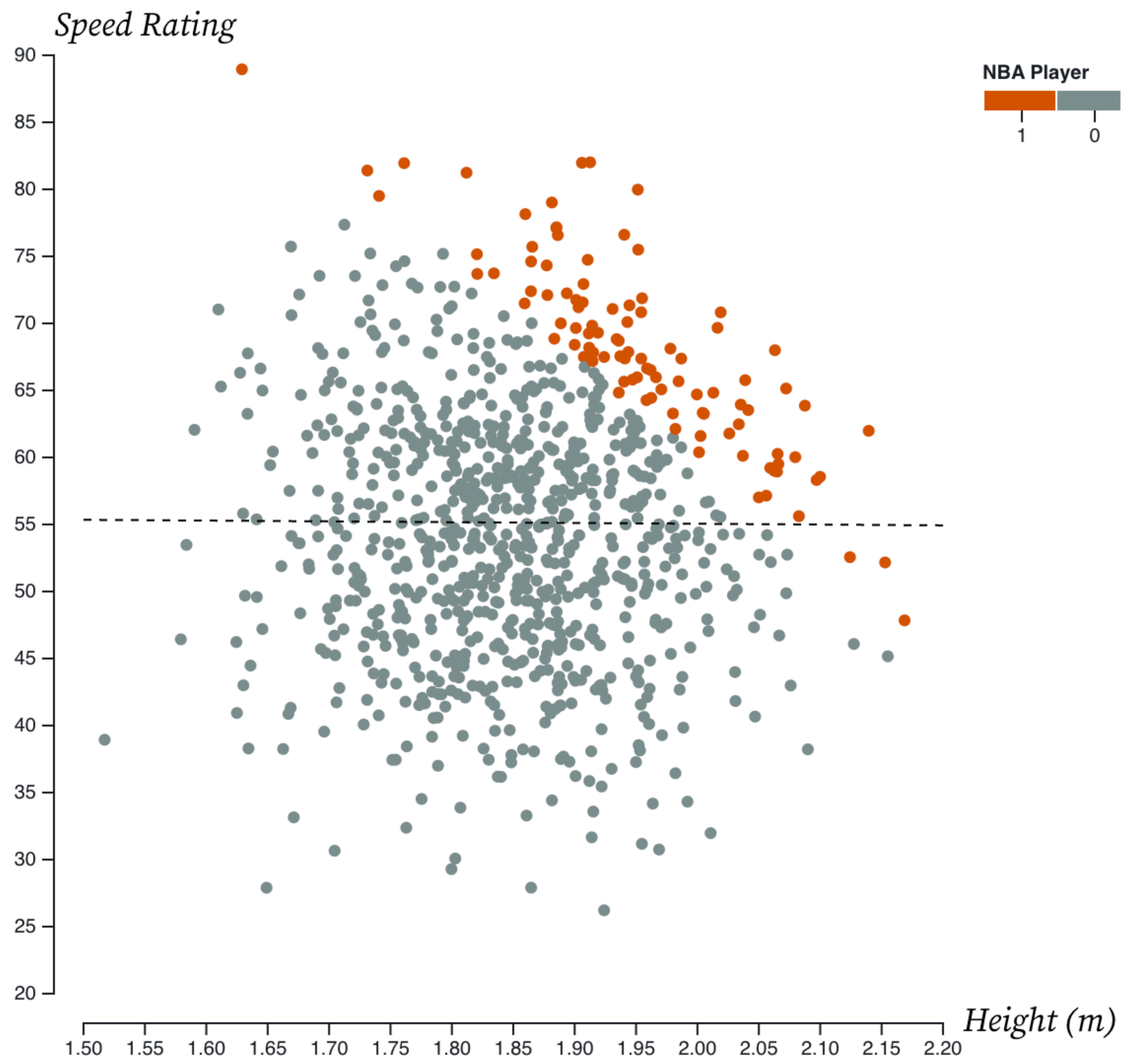
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