Advanced Statistical Methods for Observational Studies

LECTURE 06

different definitions of “similar”

matching on more than one metric

matching on more than one metric

- Intuition: matching on just propensity scores is like uniform randomization, whereas a Mahalanobis & pscores is more like a matched pairs randomization.

- We have a couple different definitions of “similar” floating around.

- Propensity is based on treatment assignment.
- Mahalanobis is based on “equal weighting.”
- Prognostic is based on covariates’ ability to predict variation in the outcome.

propensity score vs. prognostic score

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- Prognostic score is one way to address this:
  - Ben Hansen "The prognostic analog of the propensity score"

The Buffalo

- There are more ways to use information that is commonly considered.

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Dylan Greaves

The Buffalo

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Rocky Aikens

The Buffalo

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- What if, instead of using many controls to match to a treated, we use some of the controls to understand outcome variation.

Dylan Greaves

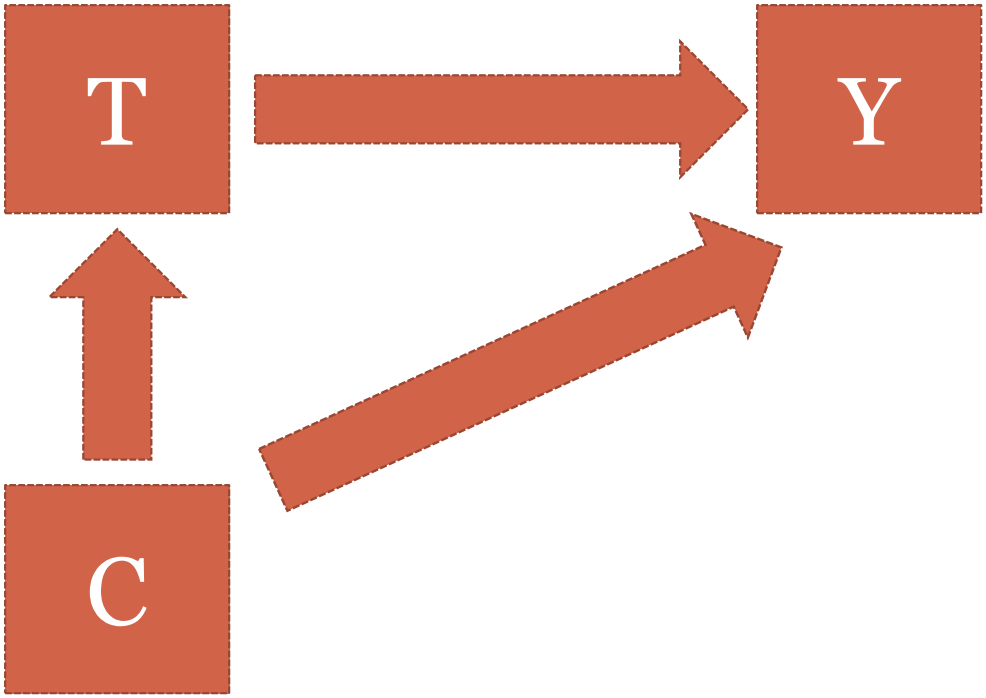
Rocky Aikens

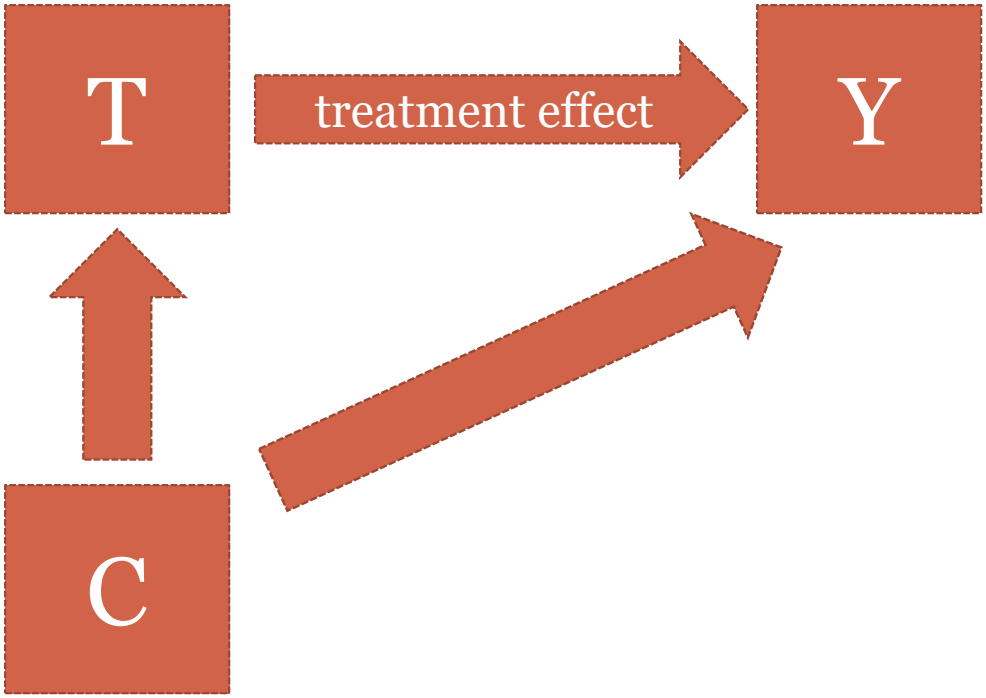
The Buffalo

- There are more ways to use information that is commonly considered.
- What if, instead of using many controls to match to a treated, we use some of the controls to understand outcome variation.
- Problematic because we are looking at the outcome for some observations, but maybe we can “burn” those and still benefit.

Dylan Greaves

Rocky Aikens


T
Y
C


T
treatment effect
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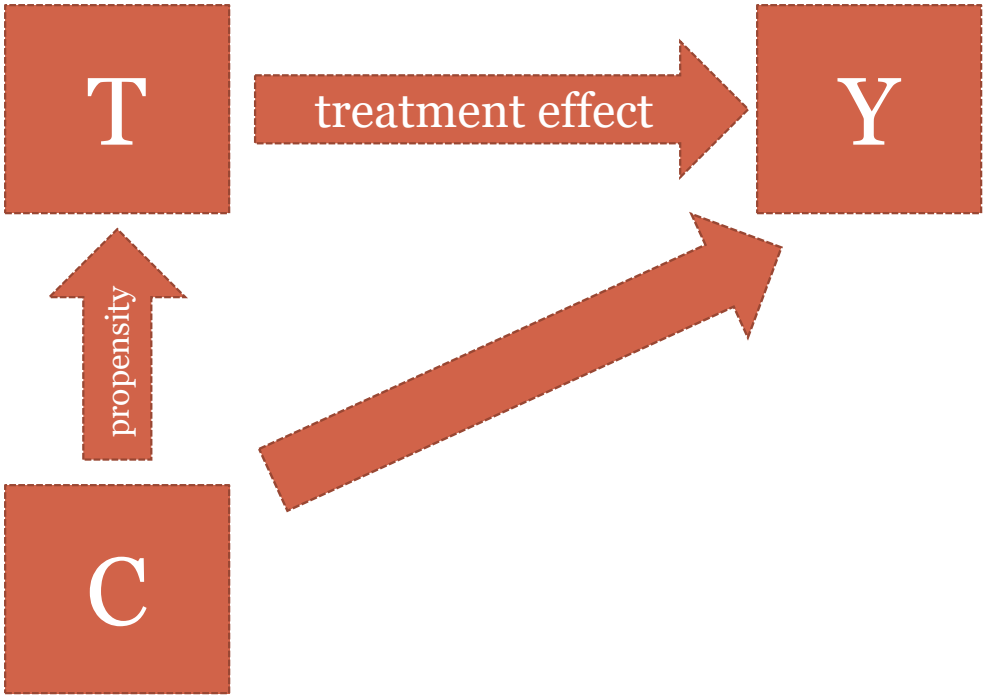
T
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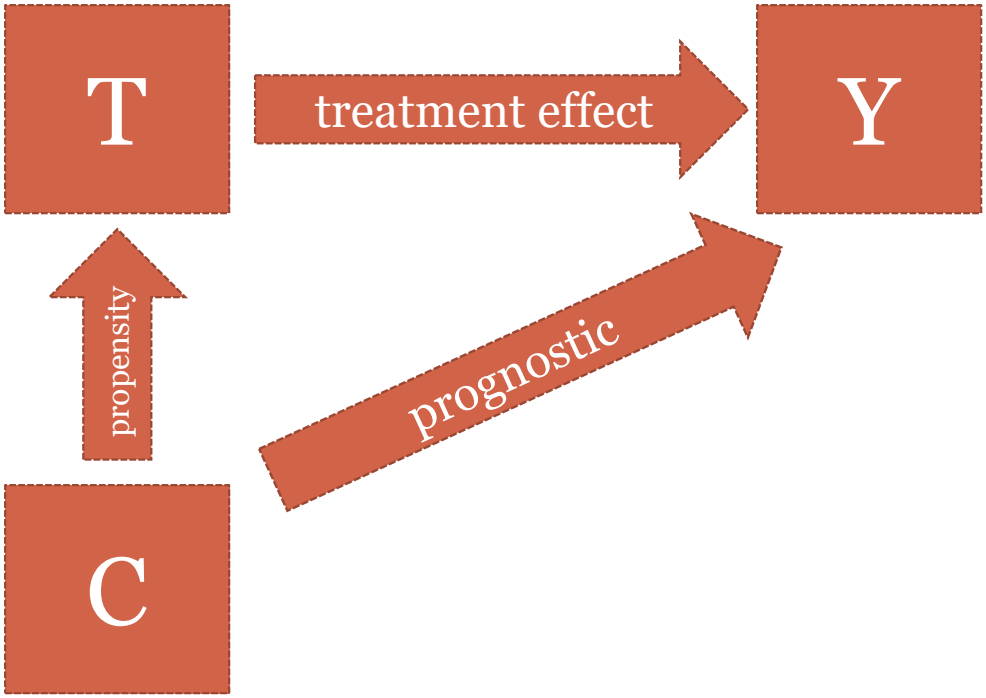
T
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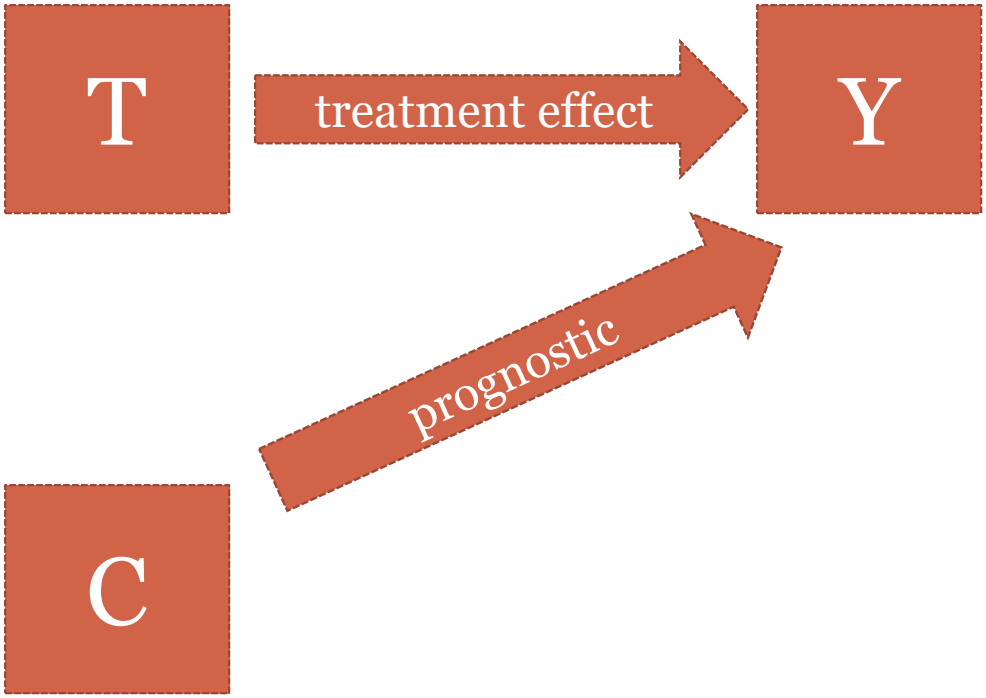
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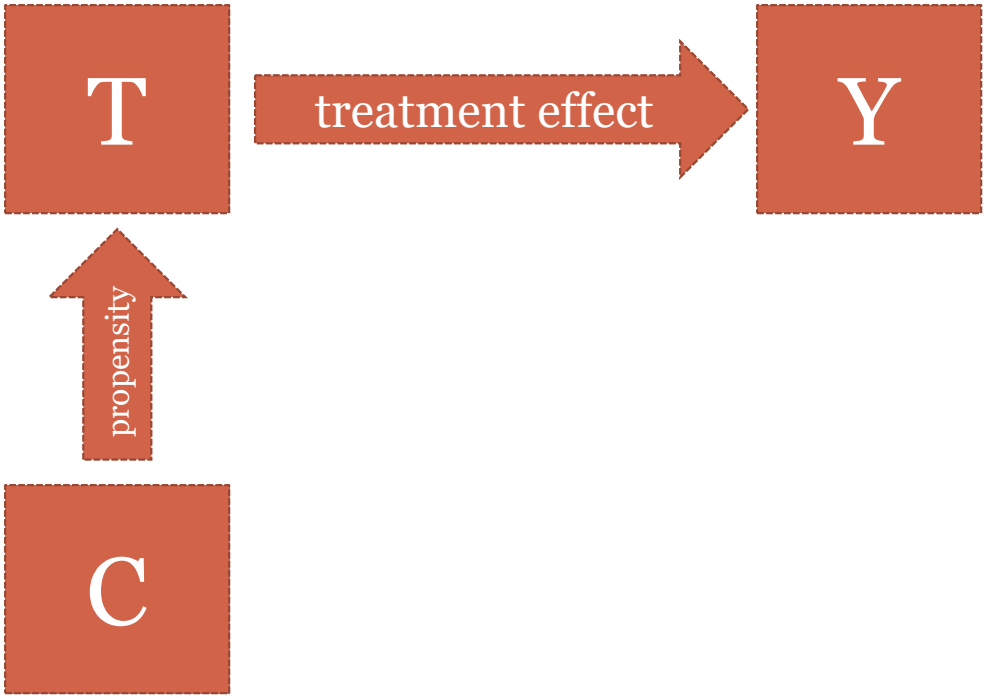
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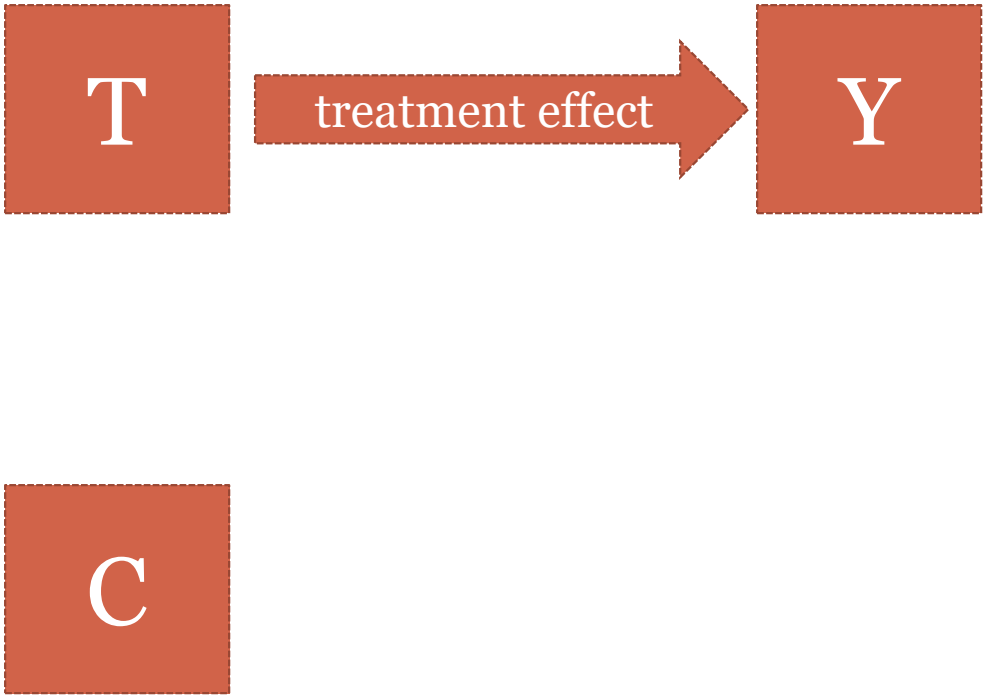
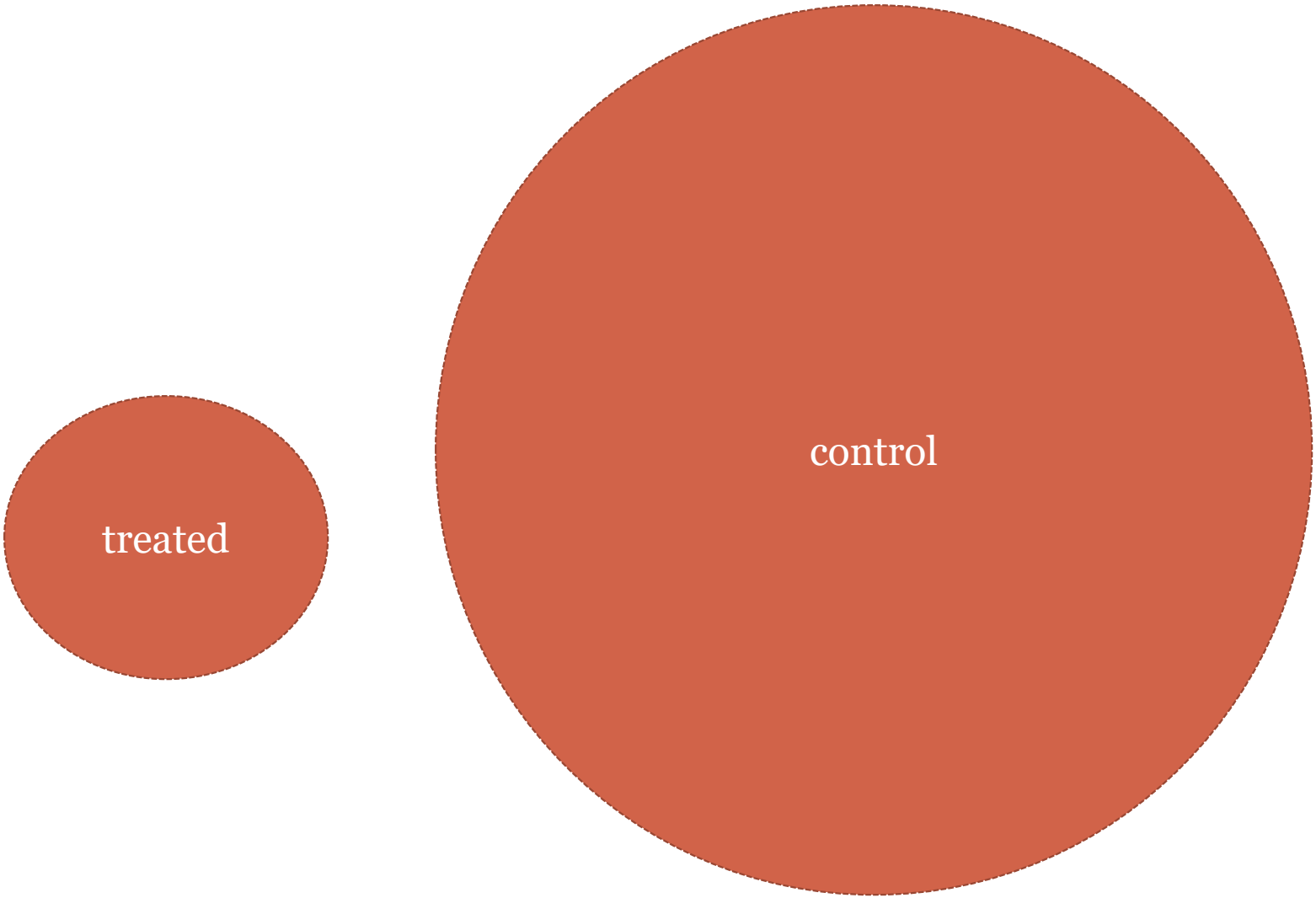
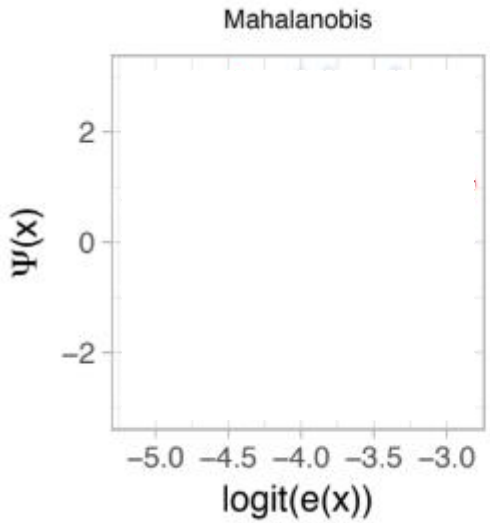
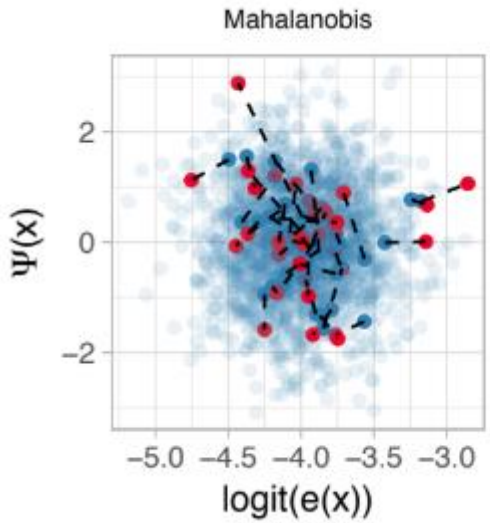

T
treatment effect
Y
C


treated


treated
control


Mahalanobis
2
0
−2
Ψ(x)
−5.0
−4.5
−4.0
−3.5
−3.0
logit(e(x))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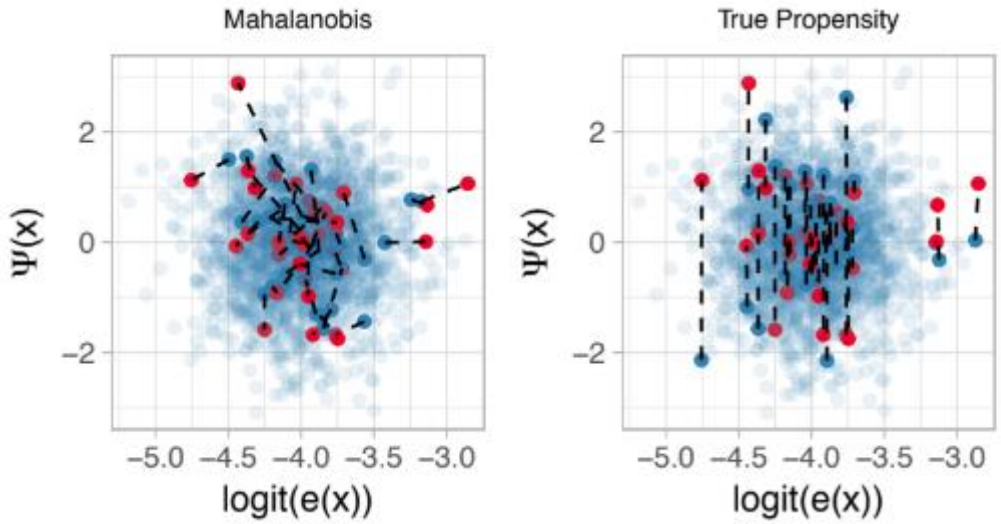
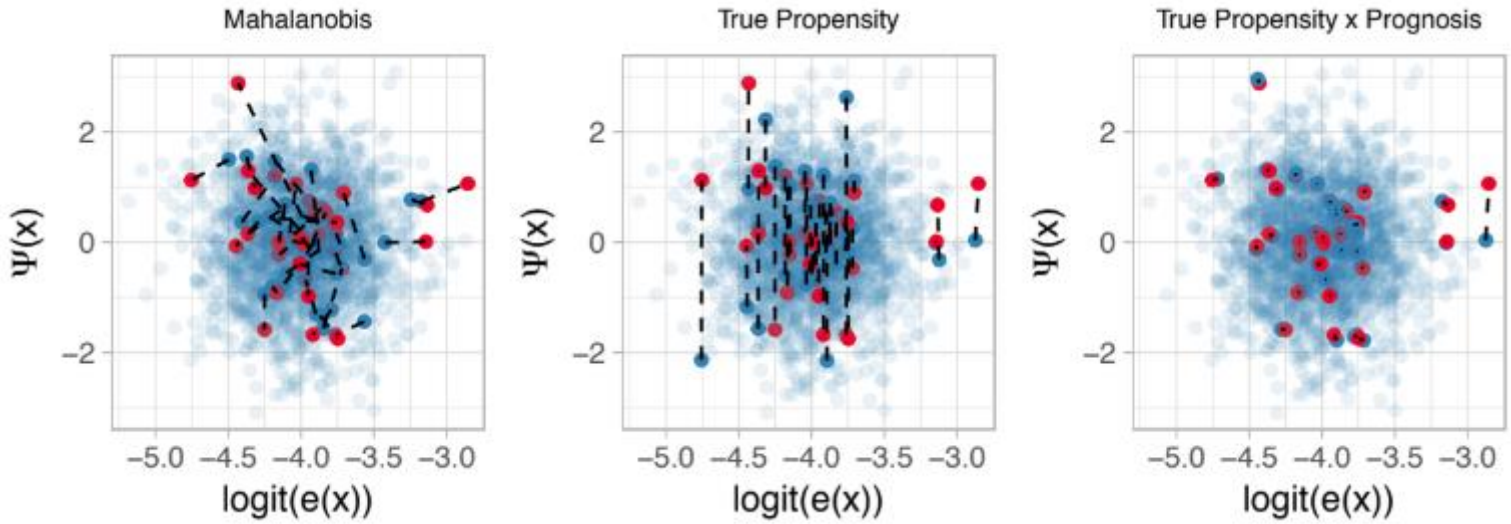
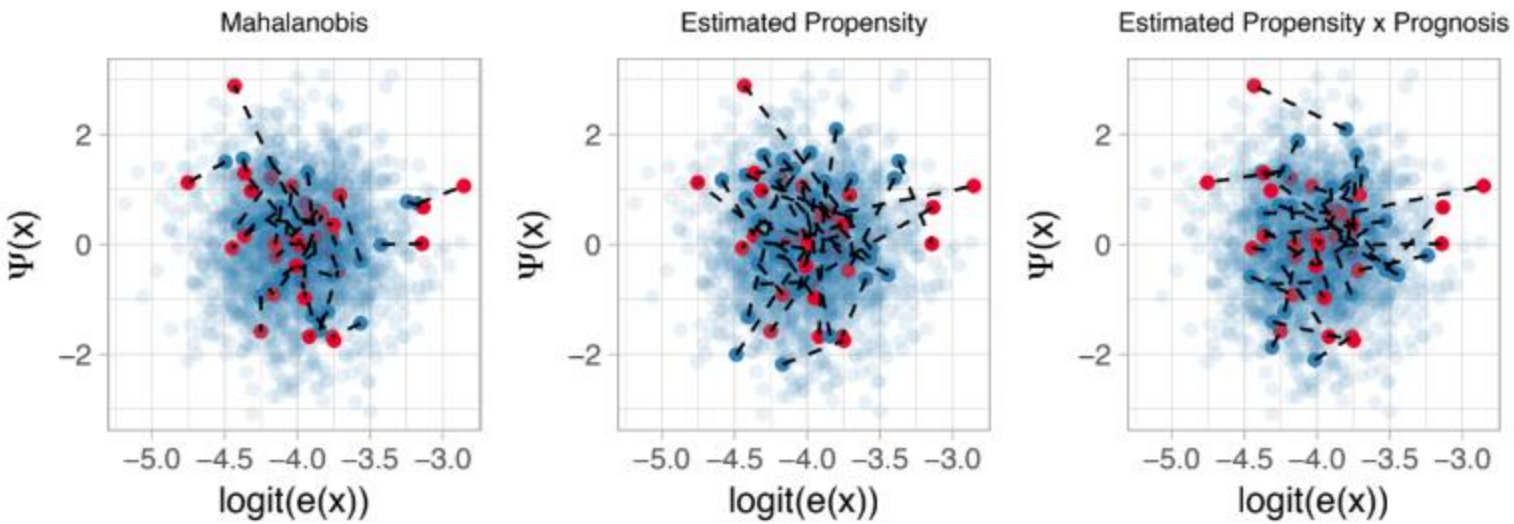

Mahalanobis
True Propensity
Ψ(x)
2
0
−2
−5.0 −4.5 −4.0 −3.5 −3.0
logit(e(x))


Mahalanobis
True Propensity
True Propensity x Prognosis
Ψ(x)
2
0
−2
−5.0 −4.5 −4.0 −3.5 −3.0
logit(e(x))


Mahalanobis
Estimated Propensity
Estimated Propensity x Prognosis
Ψ(x)
2
0
−2
−5.0 −4.5 −4.0 −3.5 −3.0
logit(e(x))

person id	x1	x2	...	x_p	treated
1	109	119		71	0
2	106	48		91	1
3	106	81		35	1
4	102	70		79	0
5	65	68		38	0
6	110	118		74	0
7	73	101		69	1
8	50	90		81	0
9	94	71		54	0
10	38	120		42	1
11	54	116		56	0
12	56	106		50	0
13	112	88		75	1

person id	x1	x2	...	x_p	treated	propensity
1	109	119		71	0	0.32
2	106	48		91	1	0.54
3	106	81		35	1	0.32
4	102	70		79	0	0.32
5	65	68		38	0	0.32
6	110	118		74	0	0.54
7	73	101		69	1	0.54
8	50	90		81	0	0.54
9	94	71		54	0	0.54
10	38	120		42	1	0.32
11	54	116		56	0	0.32
12	56	106		50	0	0.54
13	112	88		75	1	0.32

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4	102	70		79	0	0.32
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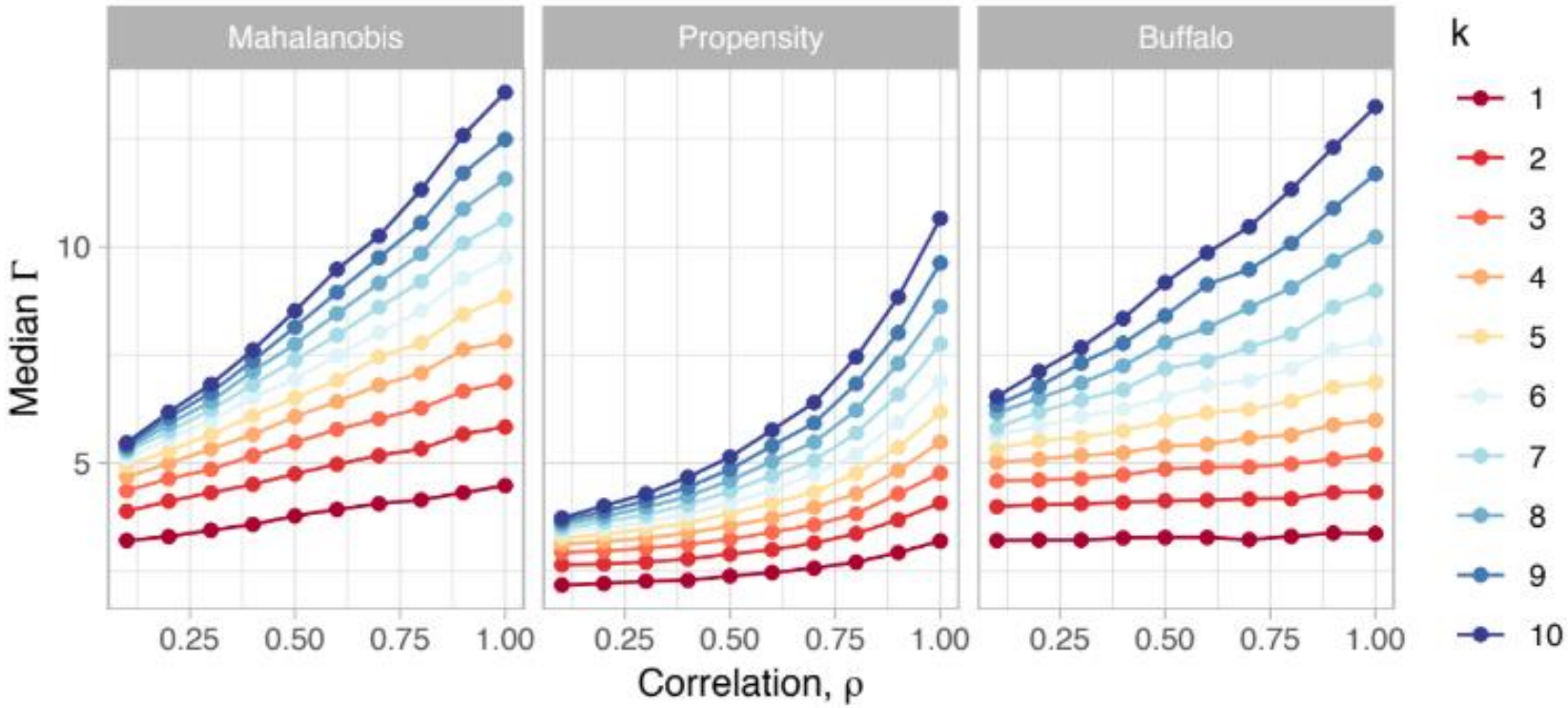
10	38	120		42	1	0.32
11	54	116		56	0	0.32
13	112	88		75	1	0.32
2	106	48		91	1	0.54
6	110	118		74	0	0.54
7	73	101		69	1	0.54
8	50	90		81	0	0.54
9	94	71		54	0	0.54
12	56	106		50	0	0.54

person id	x1	x2	…	x_p	treated	propensity	prognostic
1	109	119		71	0	0.32	10
3	106	81		35	1	0.32	16
4	102	70		79	0	0.32	6
5	65	68		38	0	0.32	13
10	38	120		42	1	0.32	18
11	54	116		56	0	0.32	18
13	112	88		75	1	0.32	5
2	106	48		91	1	0.54	18
6	110	118		74	0	0.54	13
7	73	101		69	1	0.54	7
8	50	90		81	0	0.54	18
9	94	71		54	0	0.54	16
12	56	106		50	0	0.54	5

person id	x1	x2	…	x_p	treated	propensity	prognostic
13	112	88		75	1	0.32	5
12	56	106		50	0	0.54	5
4	102	70		79	0	0.32	6
7	73	101		69	1	0.54	7
1	109	119		71	0	0.32	10
5	65	68		38	0	0.32	13
6	110	118		74	0	0.54	13
3	106	81		35	1	0.32	16
9	94	71		54	0	0.54	16
10	38	120		42	1	0.32	18
11	54	116		56	0	0.32	18
2	106	48		91	1	0.54	18
8	50	90		81	0	0.54	18

The Buffalo


Mahalanobis
Propensity
Buffalo
k
1
2
3
4
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6
7
8
9
10
Median Γ
10
5
0.25
0.50
0.75
1.00
Correlation, ρ

takeaway

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- This is OK – the theory of inference is predicated on randomization, not identical units going into the groups (Fisher)
- But it is better to start with similar groups (Mill)

a second outcome

Design of Observational Studies: chapter 5.2.3 and 5.2.4
Rosenbaum, "The Role of Known Effects in Observational Studies"

the structure of the argument: two outcomes

- If your theory is well developed then you might be able to locate multiple outcomes that will support your understanding of the mechanism of the intervention.

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  - The second outcome can be compatible (show violation)
  - The confirmation of a “null effect” can help rebuff claims of unobserved biases

the structure of the argument: two outcomes

- If your theory is well developed then you might be able to locate multiple outcomes that will support your understanding of the mechanism of the intervention.*
- Two ways this can happen:
  - The second outcome can be compatible (show violation)
  - The confirmation of a "null effect" can help rebuff claims of unobserved biases

*Keep this idea separate from "intermediate effects," not because there's a deep fundamental difference in these concepts but rather conflating them will tend to confuse discussions.

coherence

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- Claims of coherence or incoherence are arguable to the extent that the anticipated form of treatment effect is arguable.
- If you want to see the technical details of how to build a statistical argument around this then check out *Observational Studies*, section 17.2 (coherent signed rank statistic).

what does this look like?

an evolutionary process

an evolutionary process

Three distinct parts to developing gender based violence prevention programs.

an evolutionary process

Three distinct parts to developing gender based violence prevention programs.

- Advocacy

an evolutionary process

Three distinct parts to developing gender based violence prevention programs.

- Advocacy
- Theory

an evolutionary process

Three distinct parts to developing gender based violence prevention programs.

- Advocacy
- Theory
- Empirical assessment

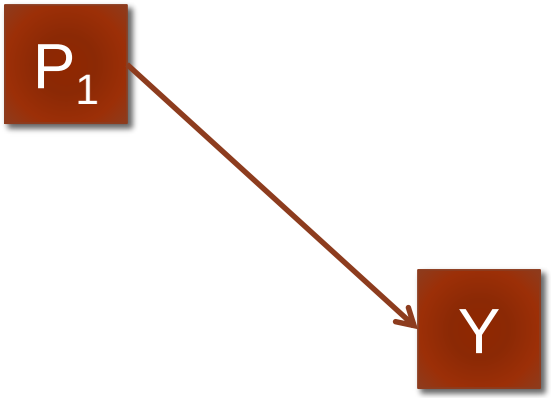
Y

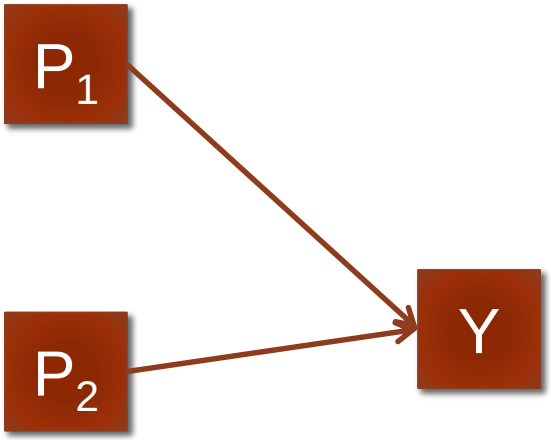
X

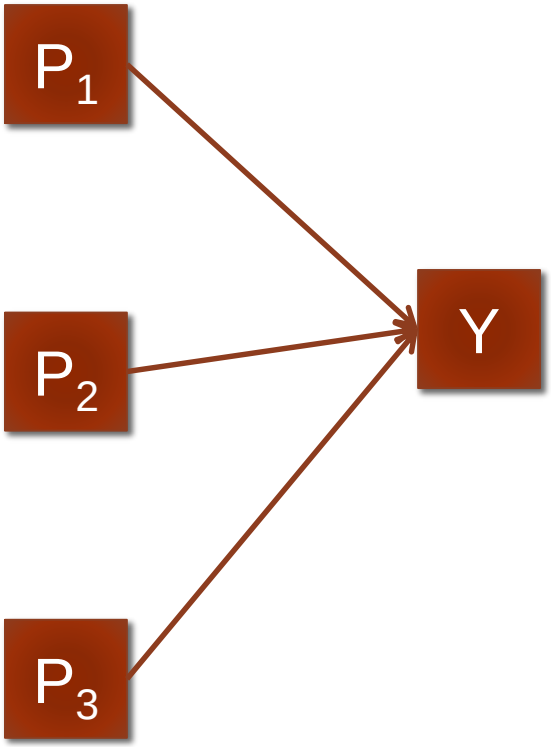
Y

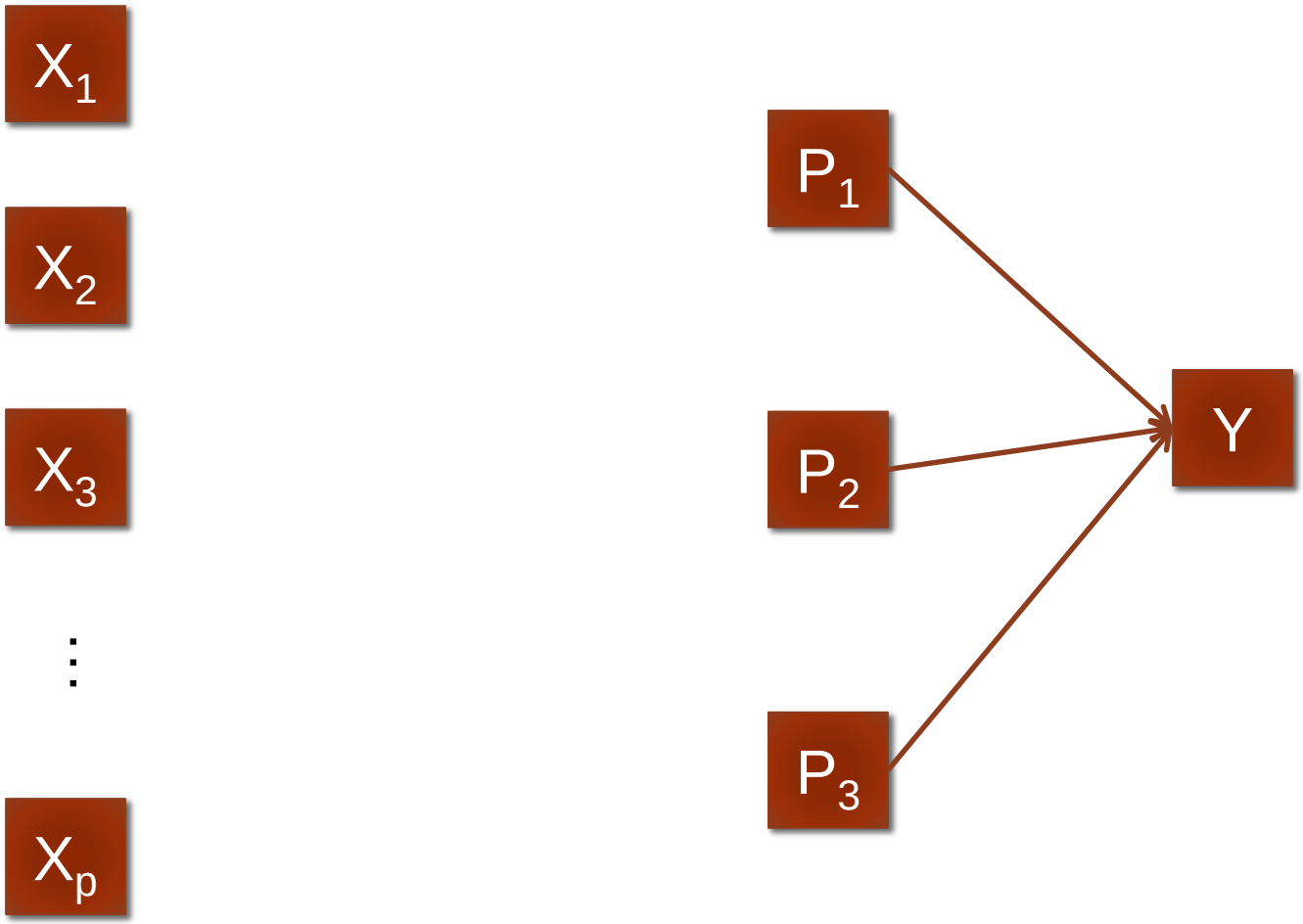

X
Y

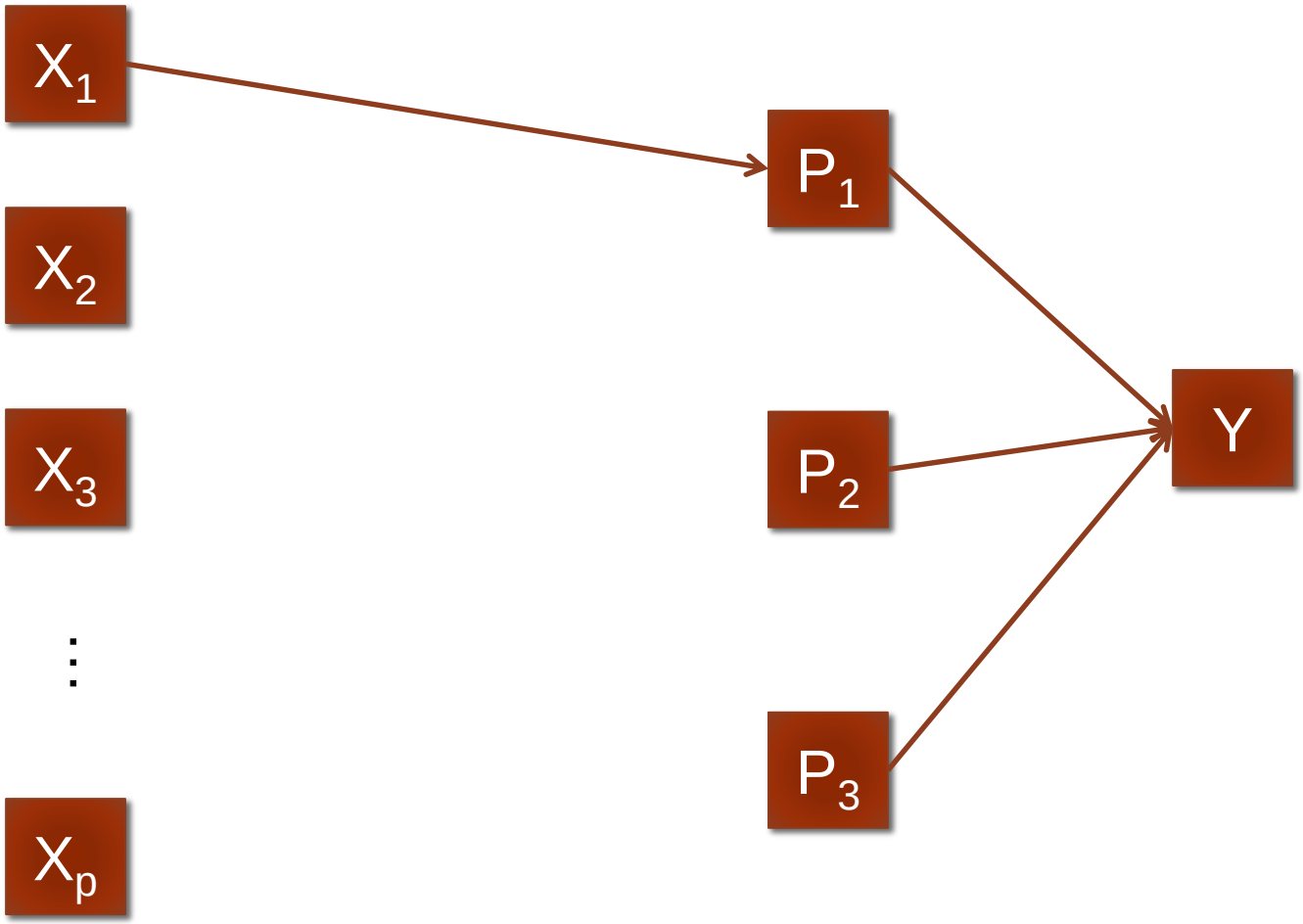
Y


P_1
Y


P_1
P_2
Y


P_1
P_2
P_3
Y


X_1
X_2
X_3
⋮
X_p
P_1
P_2
P_3
Y


X_1
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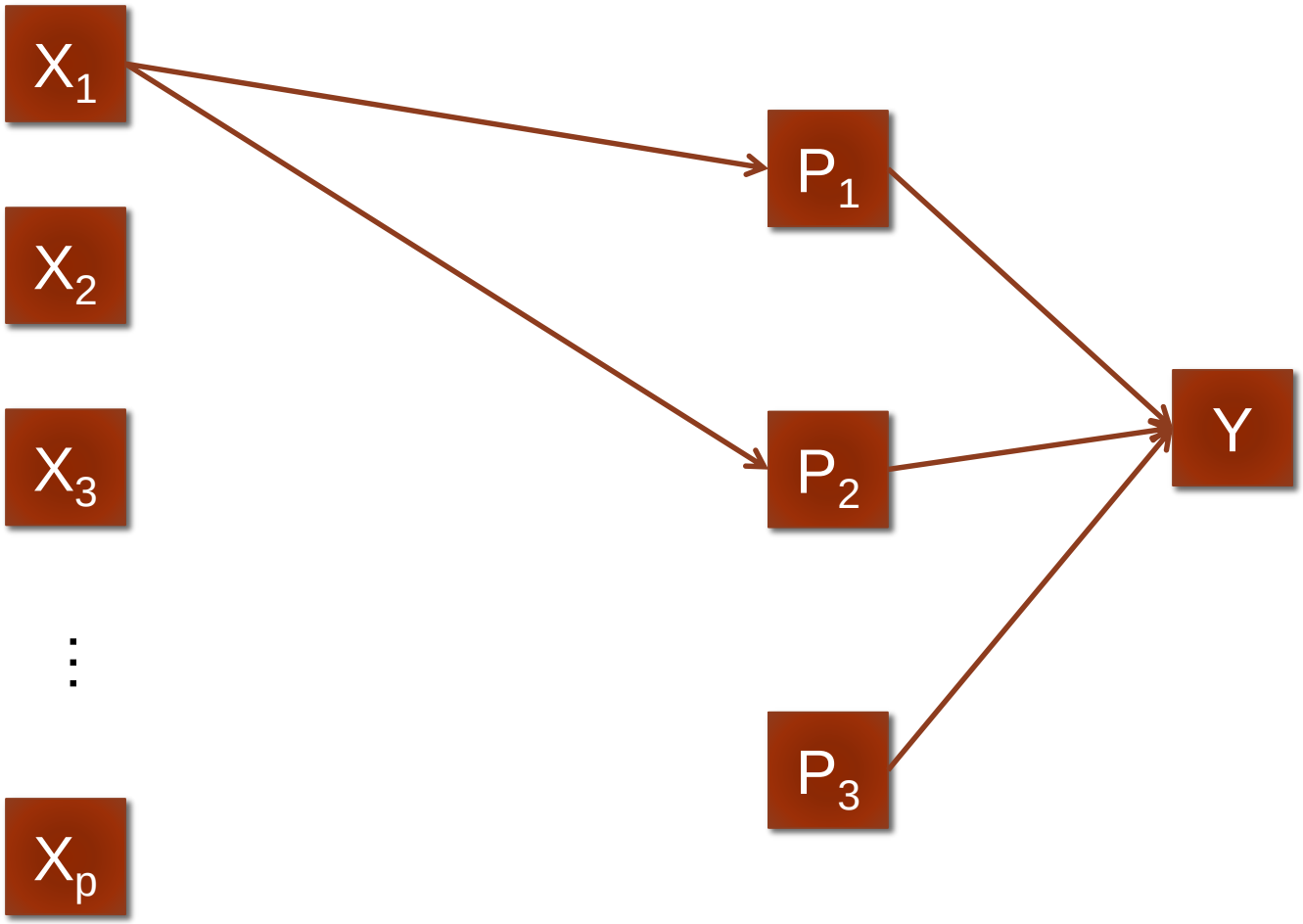
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X_p
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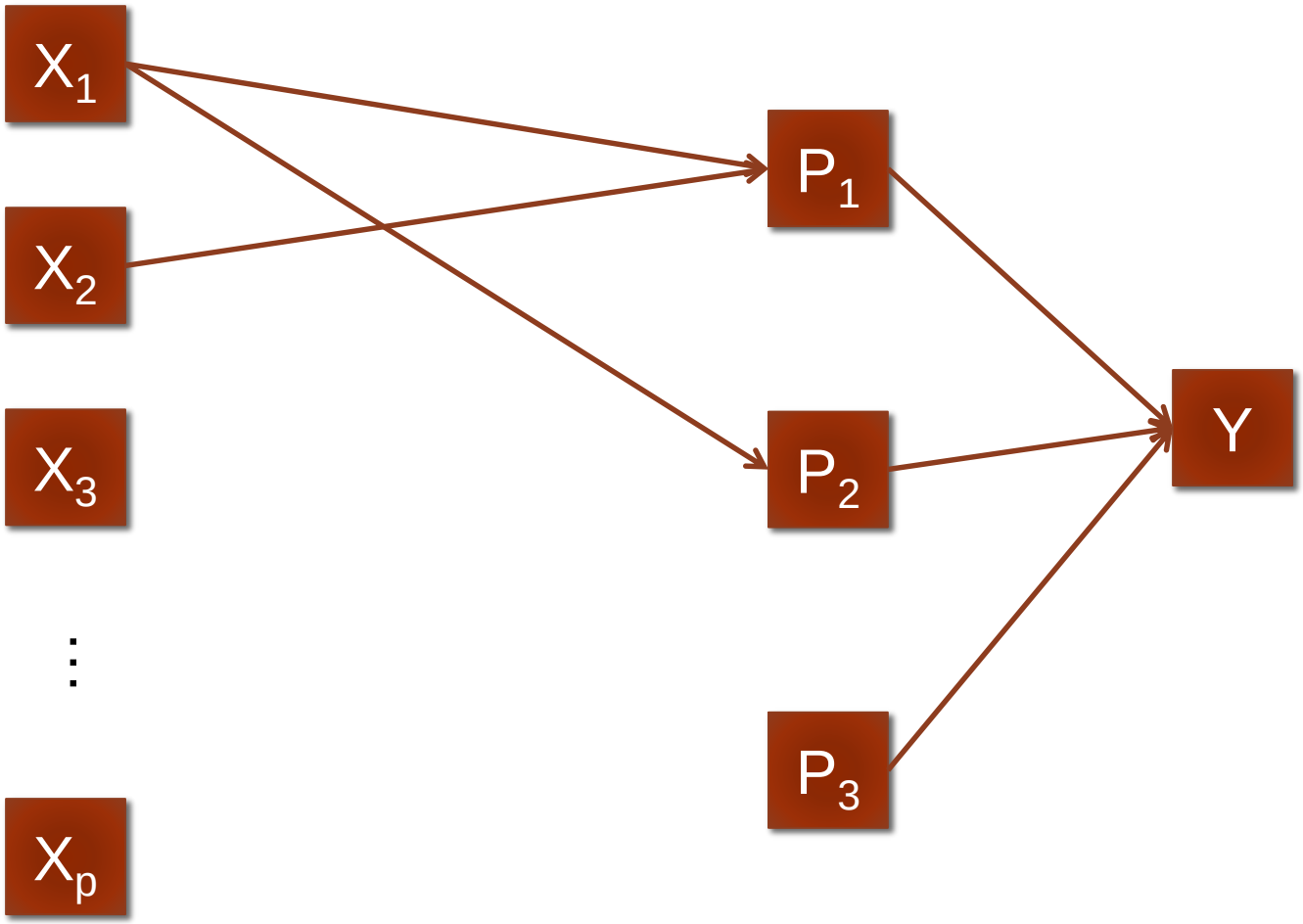
P_2
P_3
Y


X_1
X_2
X_3
⋮
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P_1
P_2
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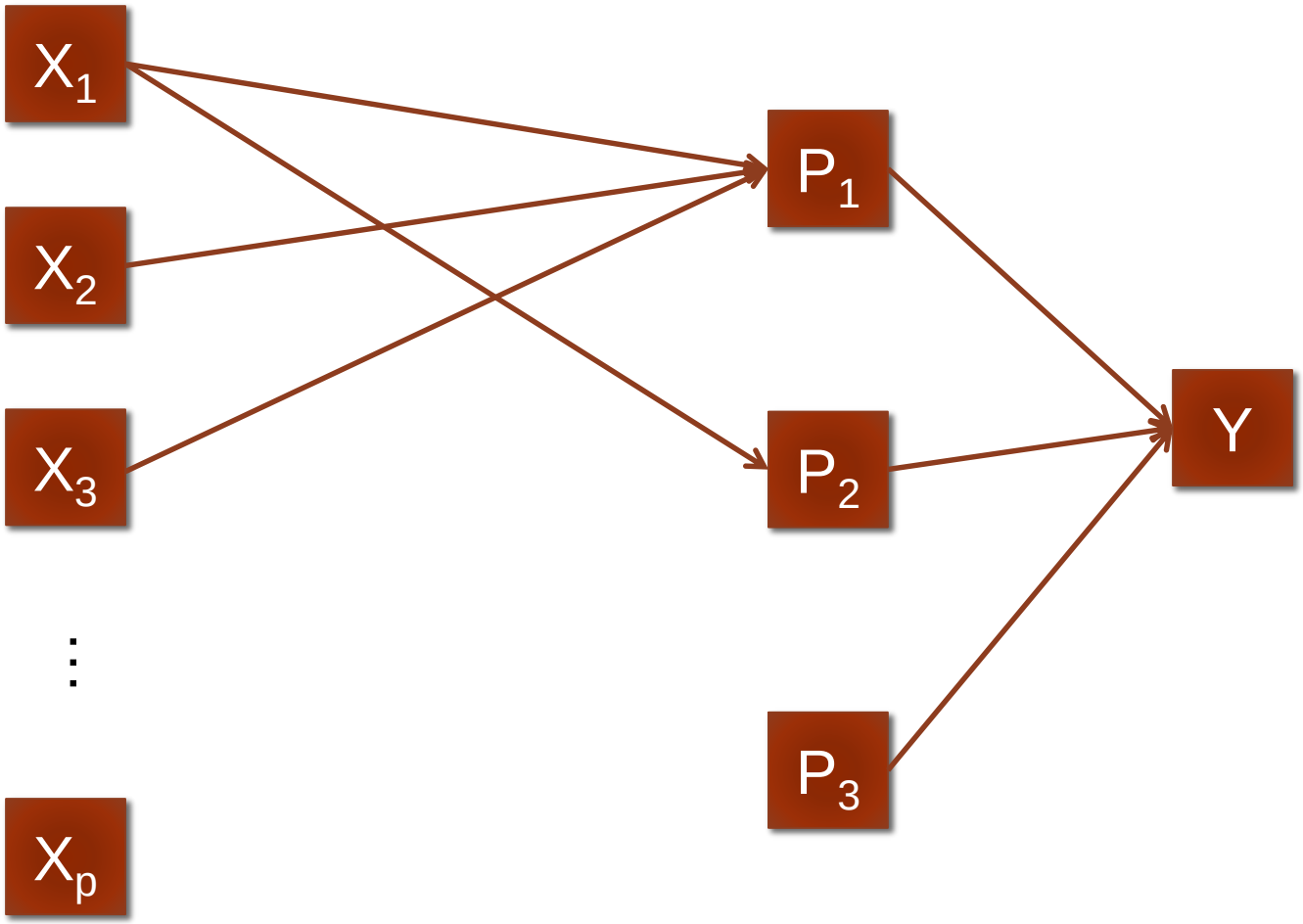
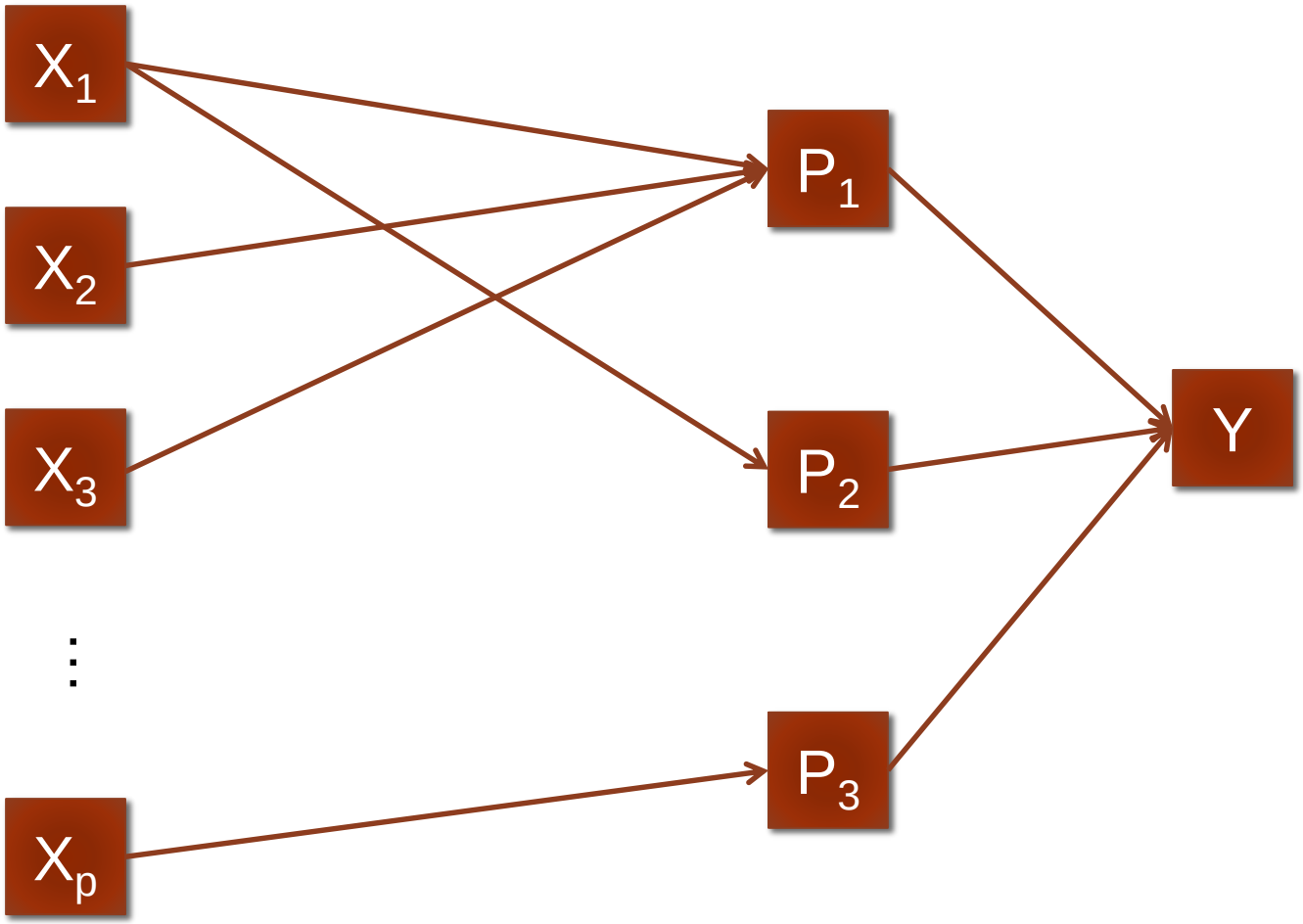
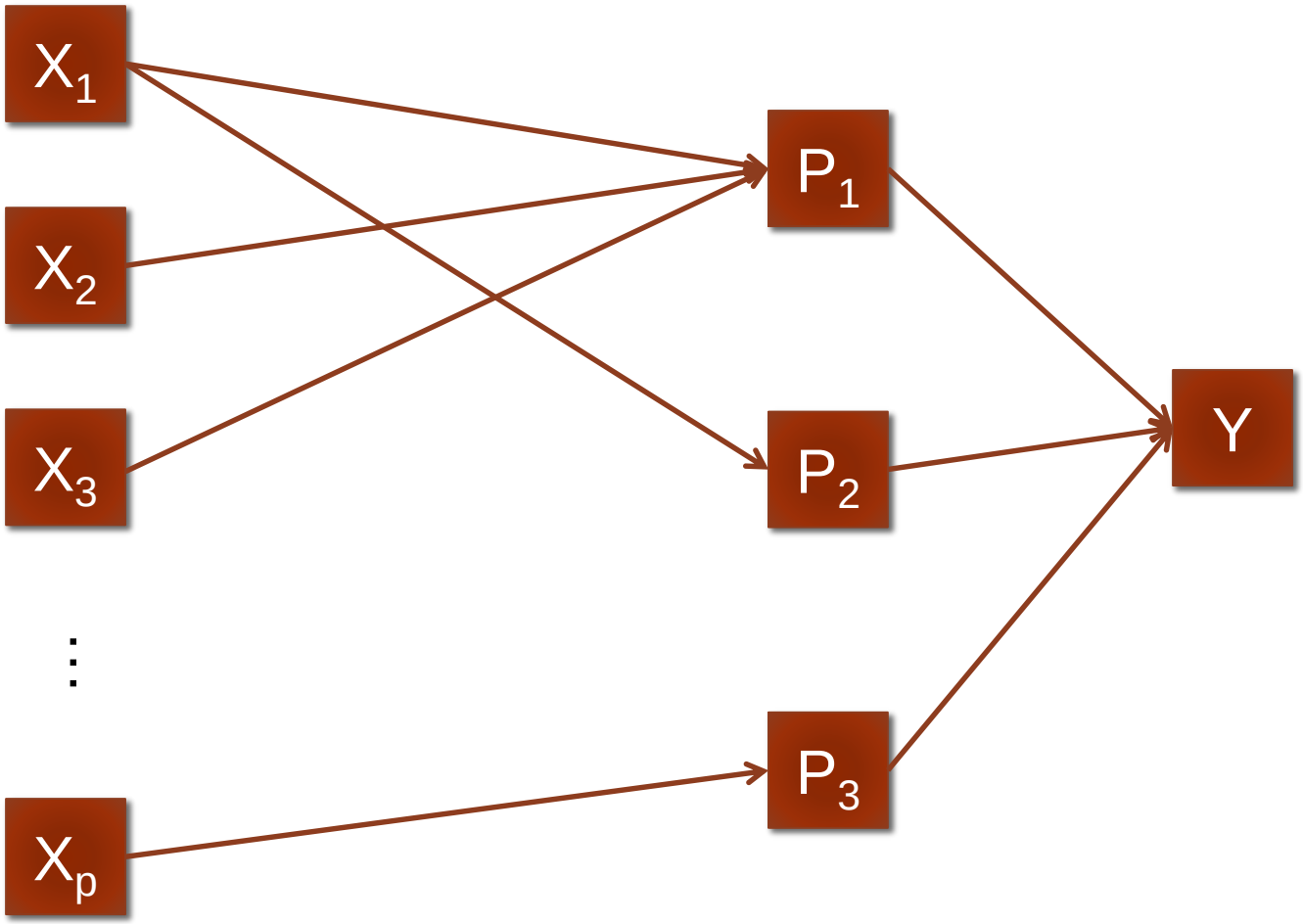
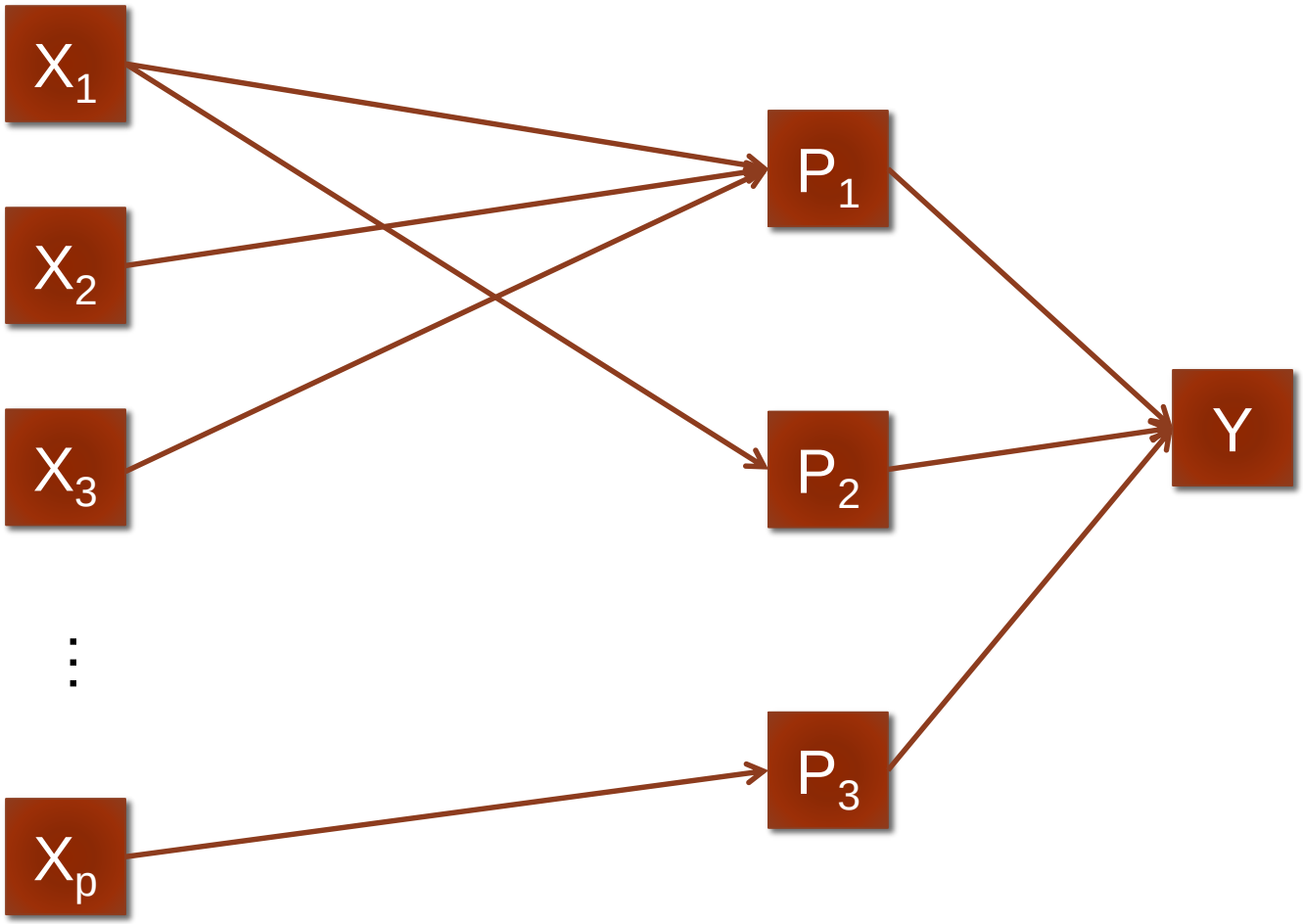

X_1
X_2
X_3
X_p
P_1
P_2
P_3
Y


X_1
X_2
X_3
X_p
P_1
P_2
P_3
Y

theory

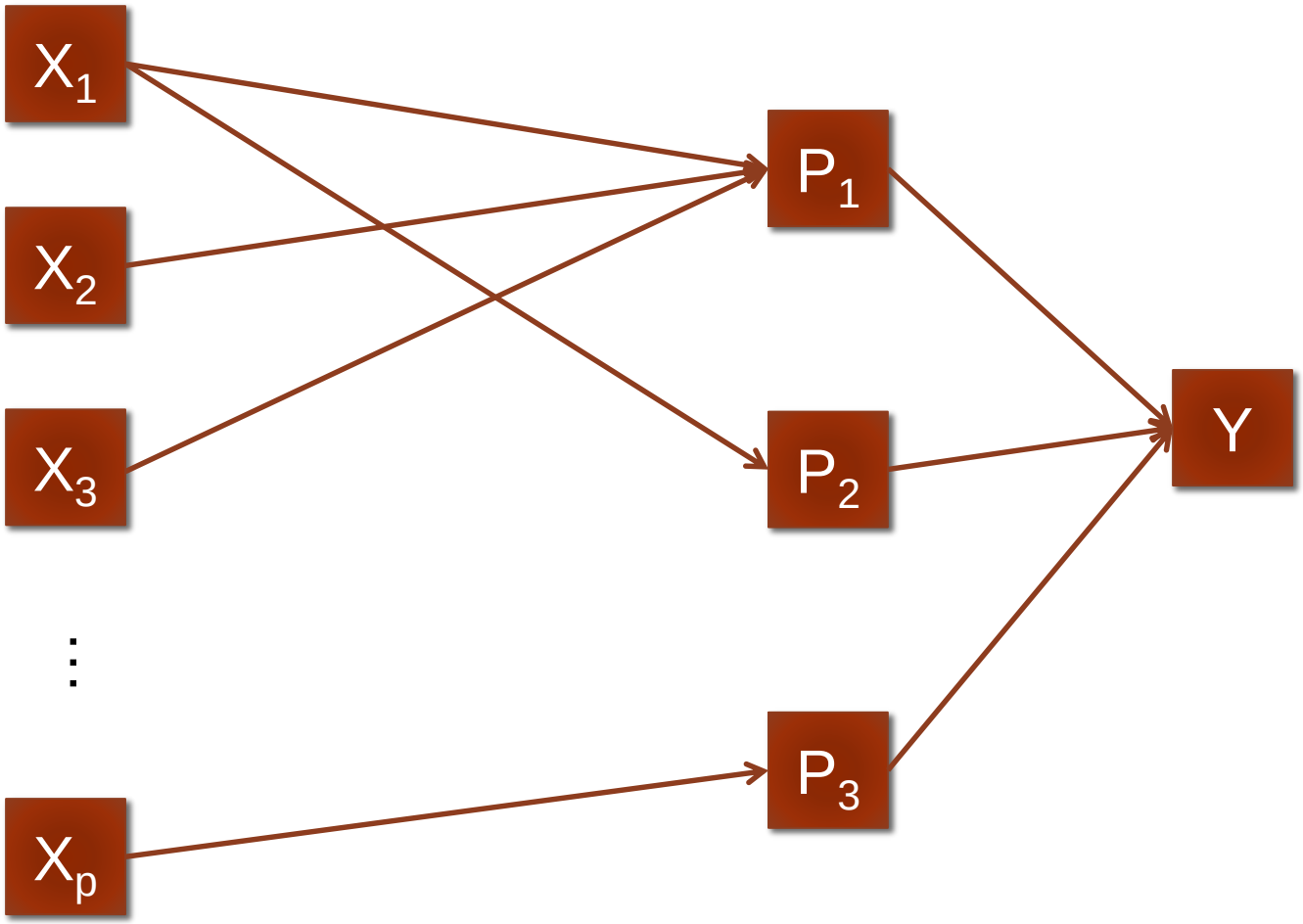


theory



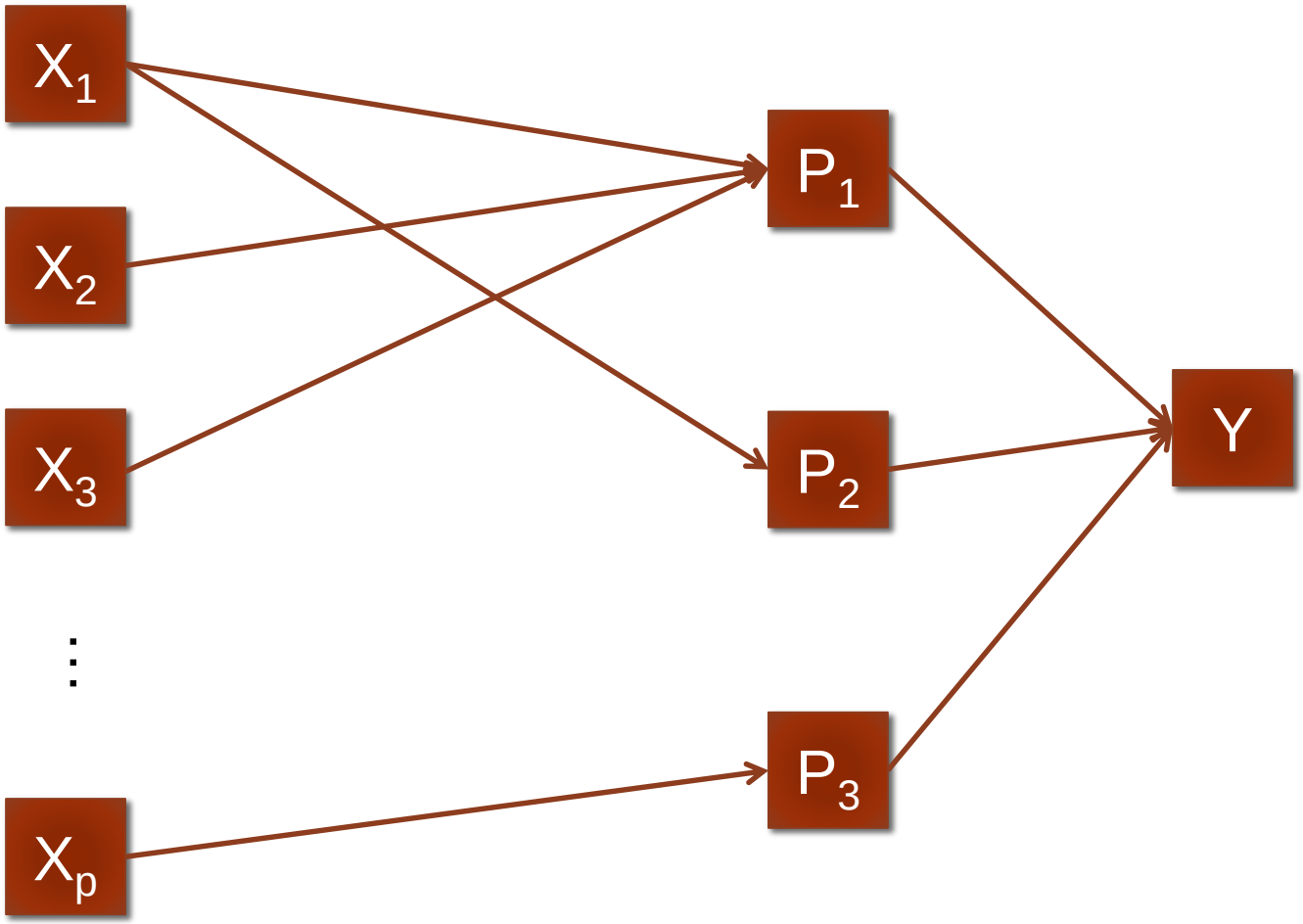
baseline

theory



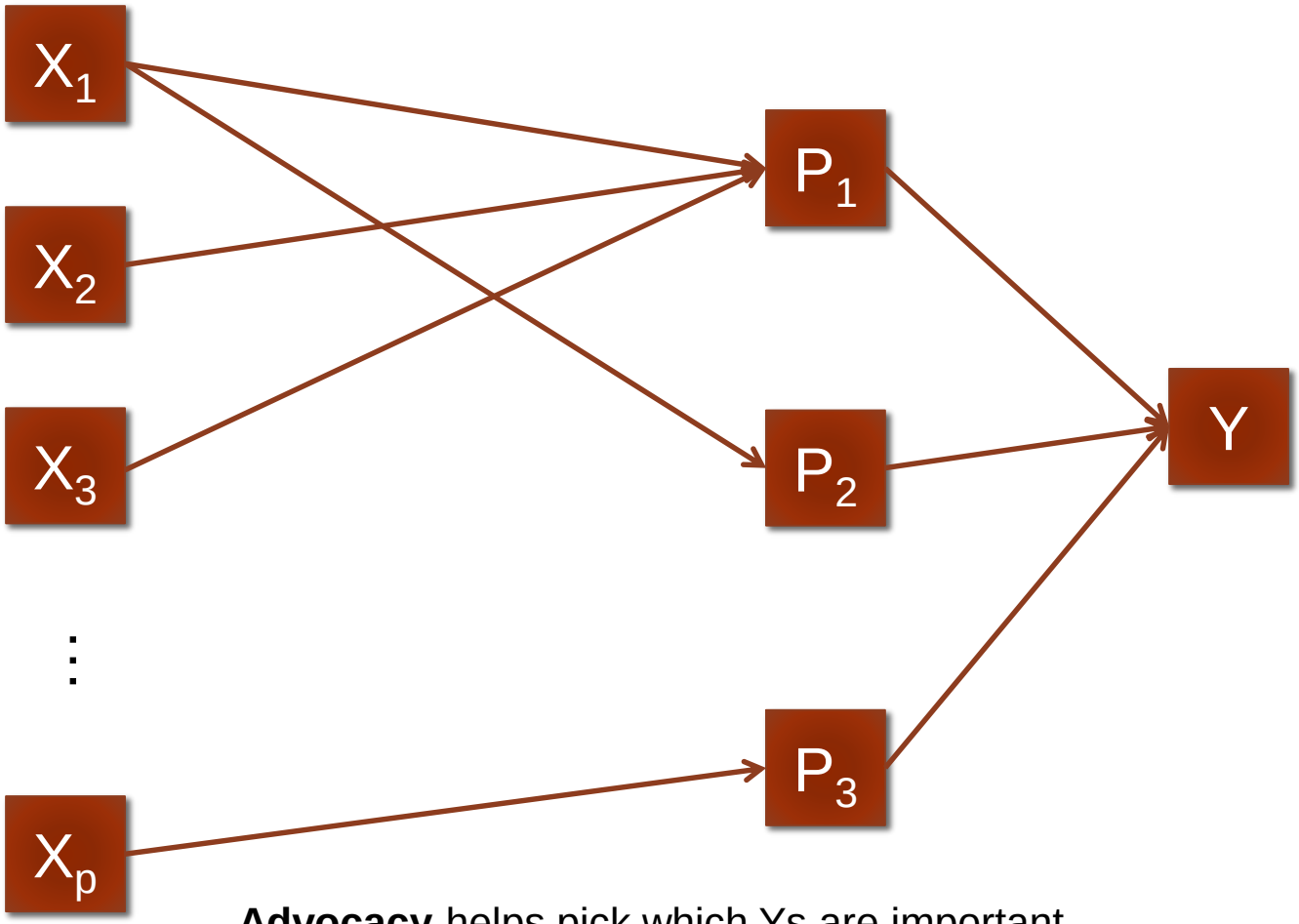
baseline pathway

theory



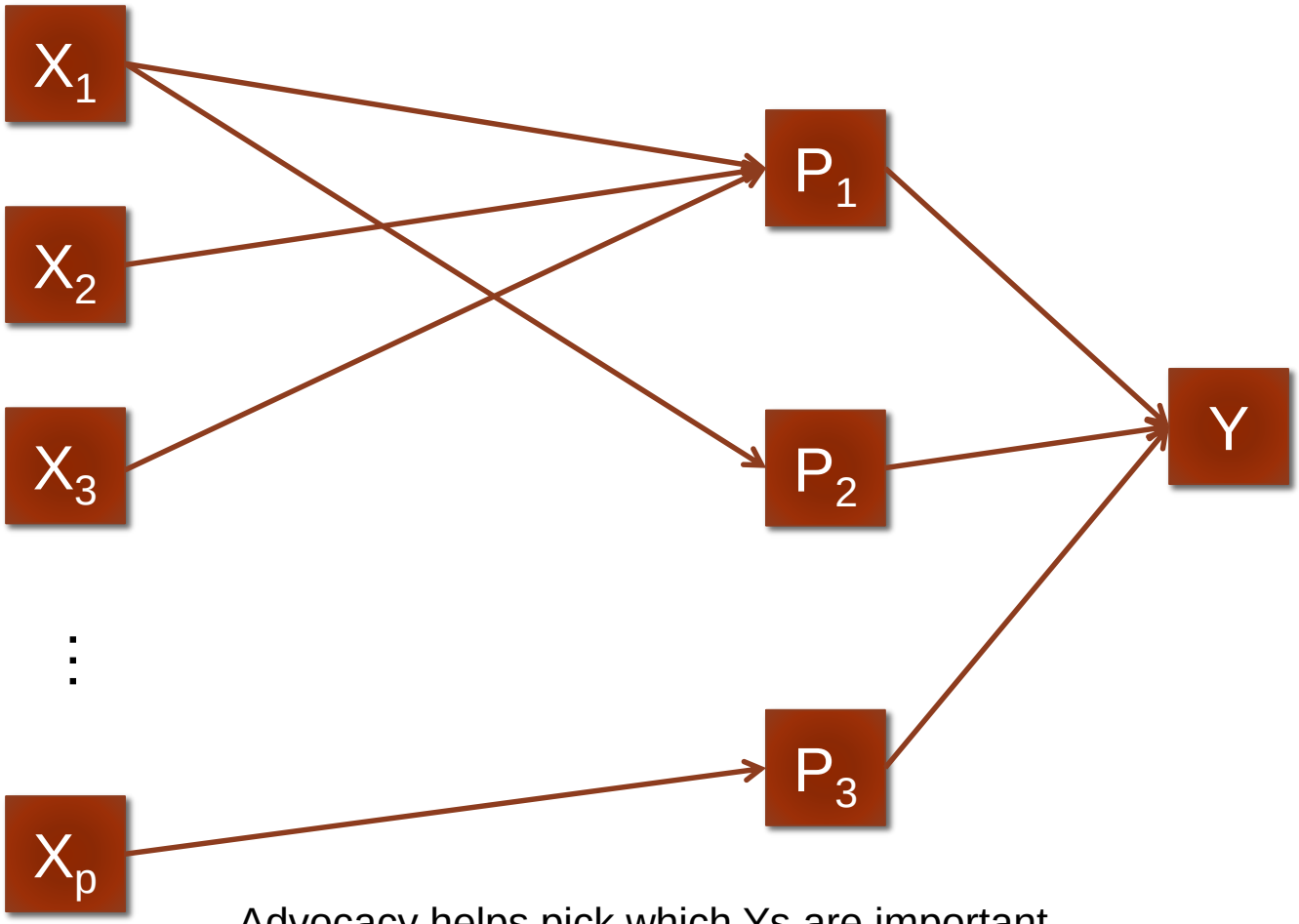
baseline pathway outcome

theory



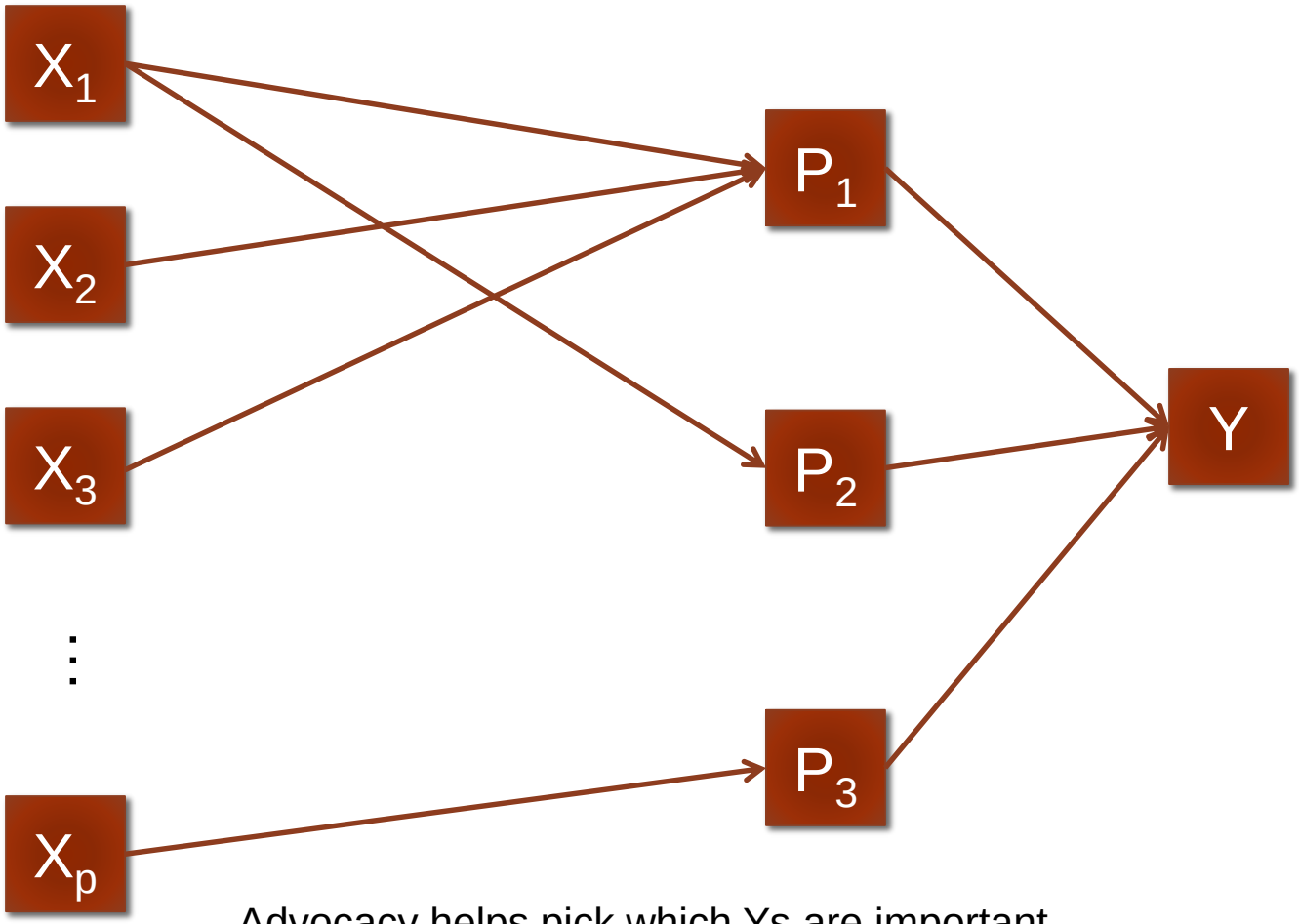
Advocacy helps pick which Ys are important.

theory



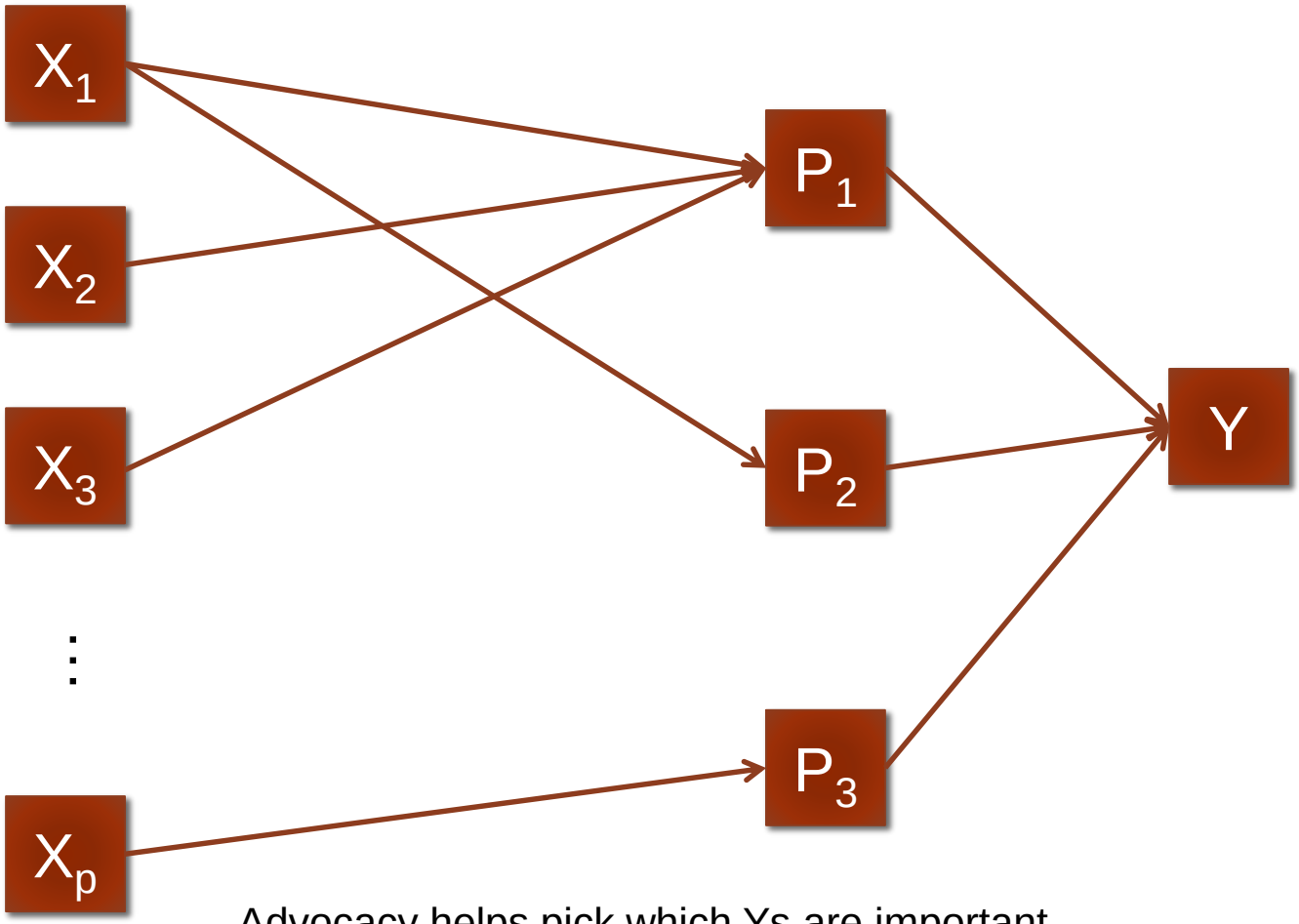
Advocacy helps pick which Ys are important.
Theory thinks carefully about which Ps flow into Y...

theory



Advocacy helps pick which Ys are important.
Theory thinks carefully about which Ps flow into Y and which Xs are involved.

theory



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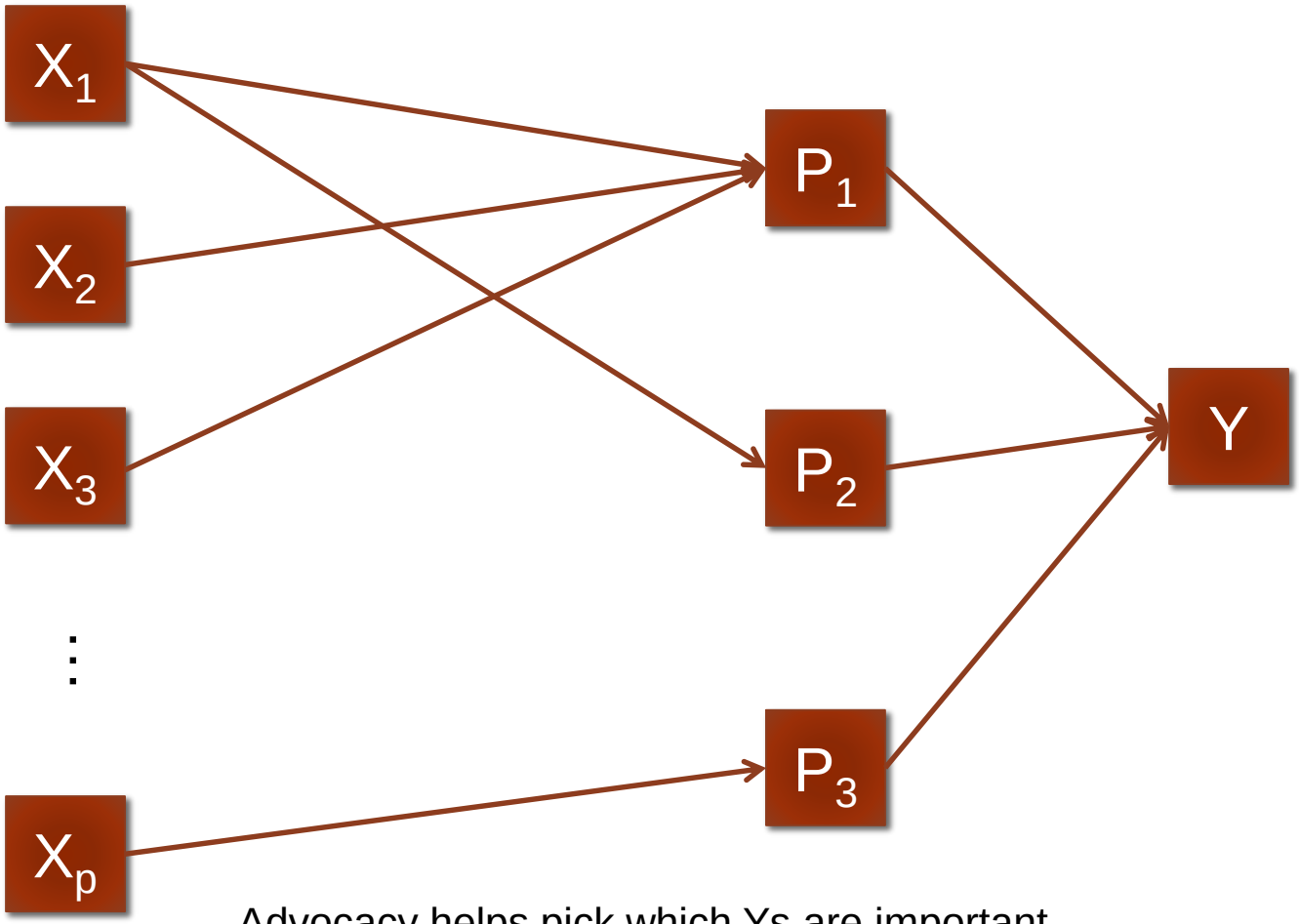
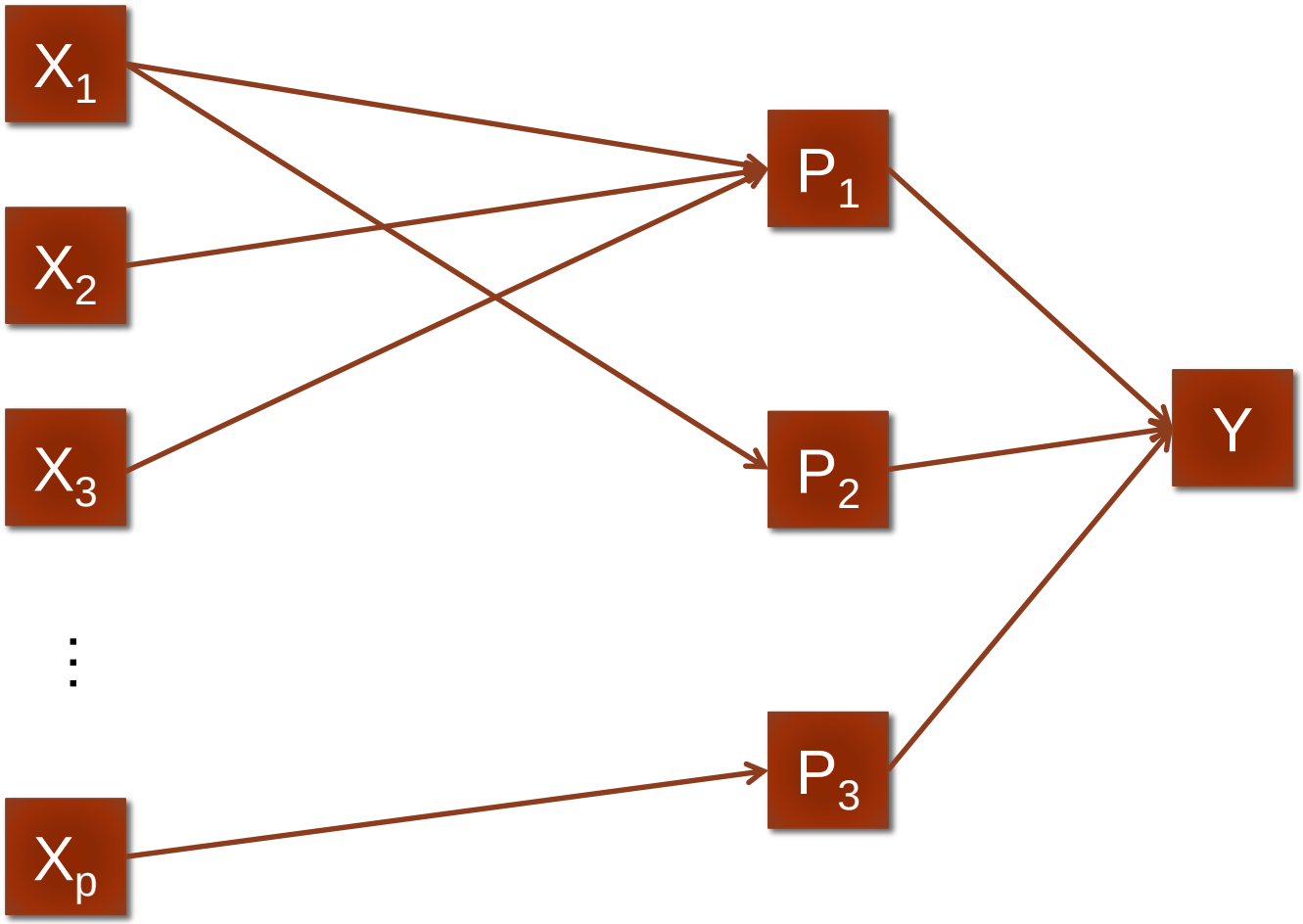
Theory thinks carefully about which Ps flow into Y and which Xs are involved.
Empirical assessment quantifies the arrows

theory

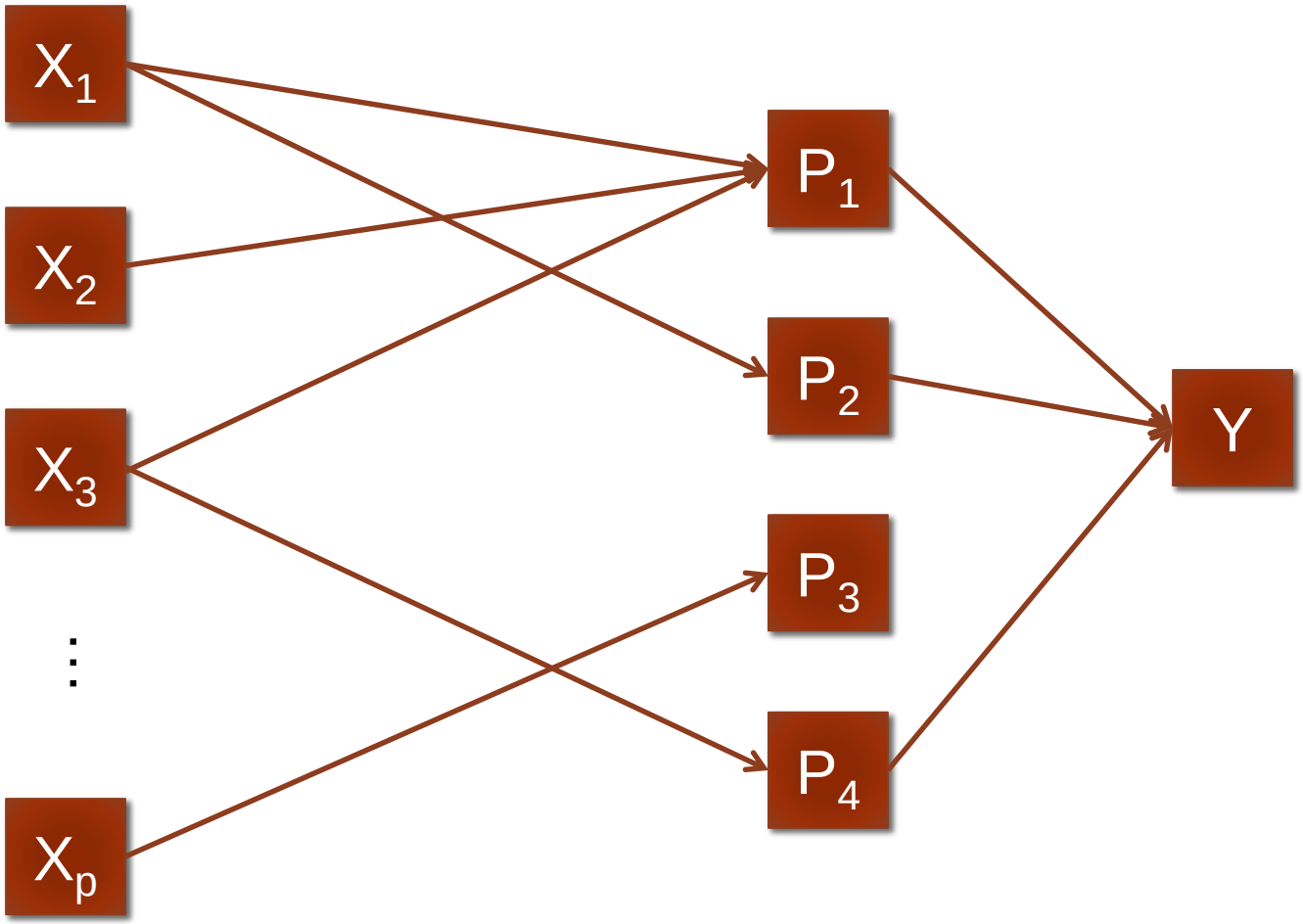


Advocacy helps pick which Ys are important.
Theory thinks carefully about which Ps flow into Y and which Xs are involved.
Empirical assessment quantifies the arrows (do they exist? are some stronger?)

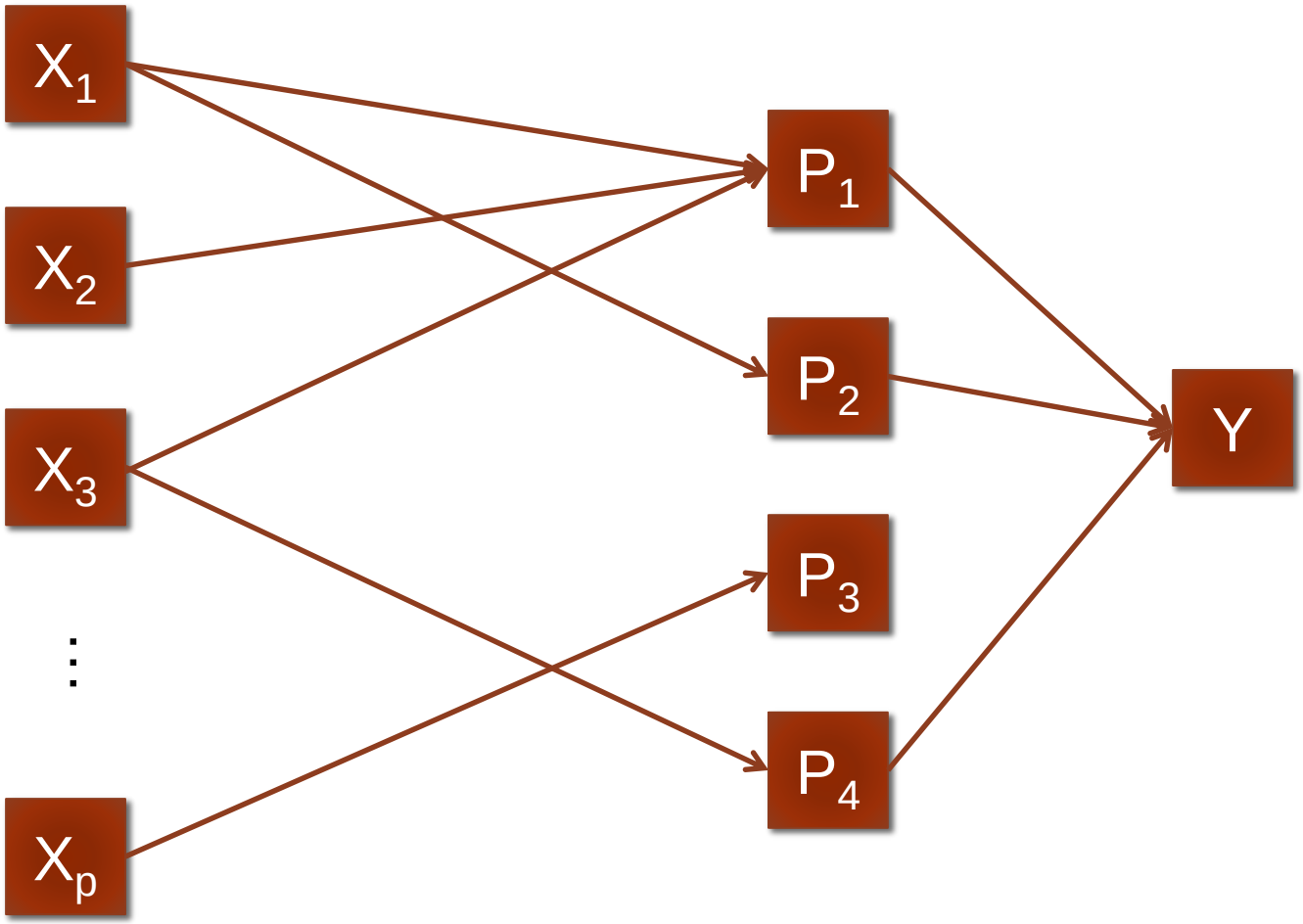
theory 1



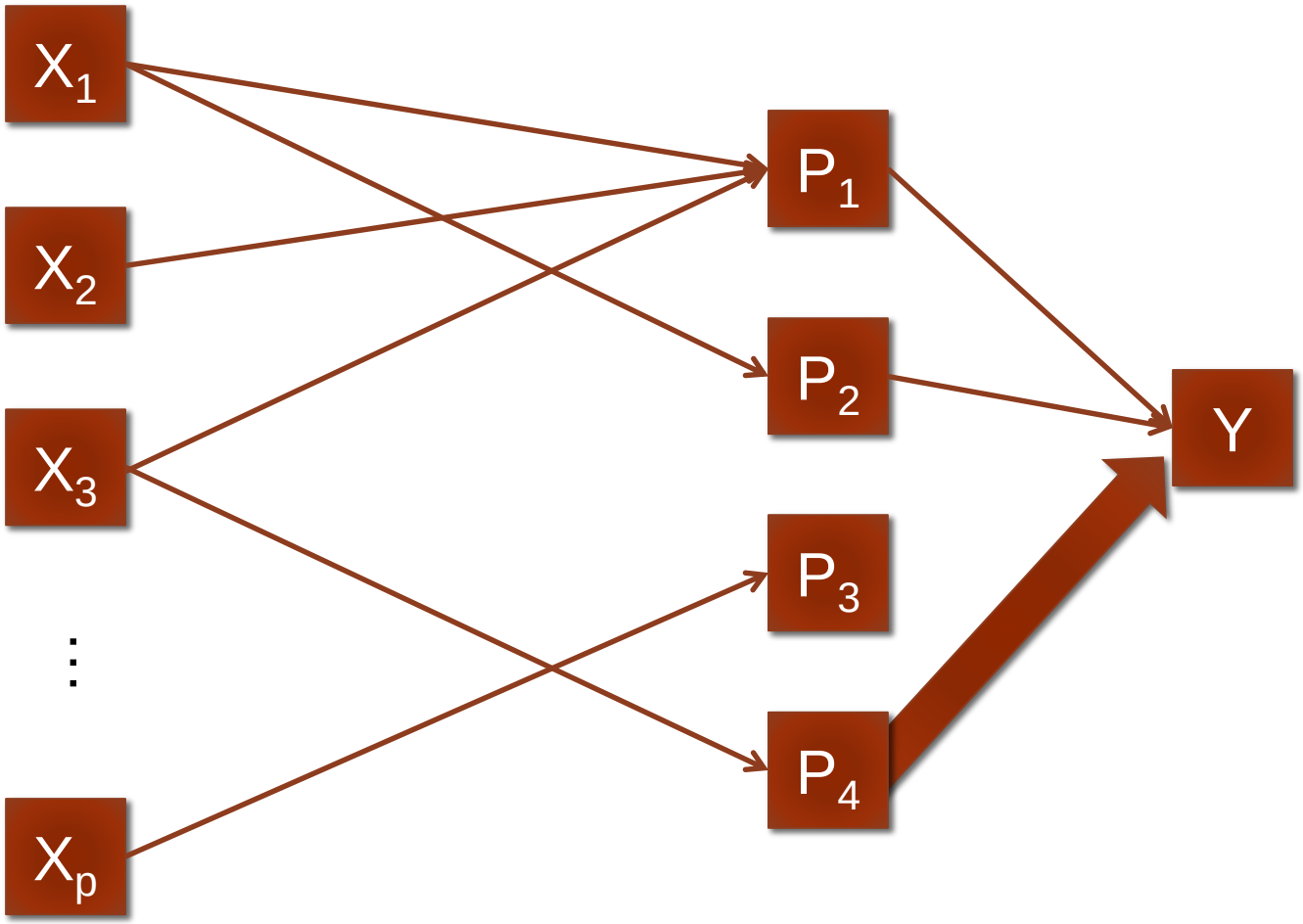
theory 2



empirical assessment



empirical assessment



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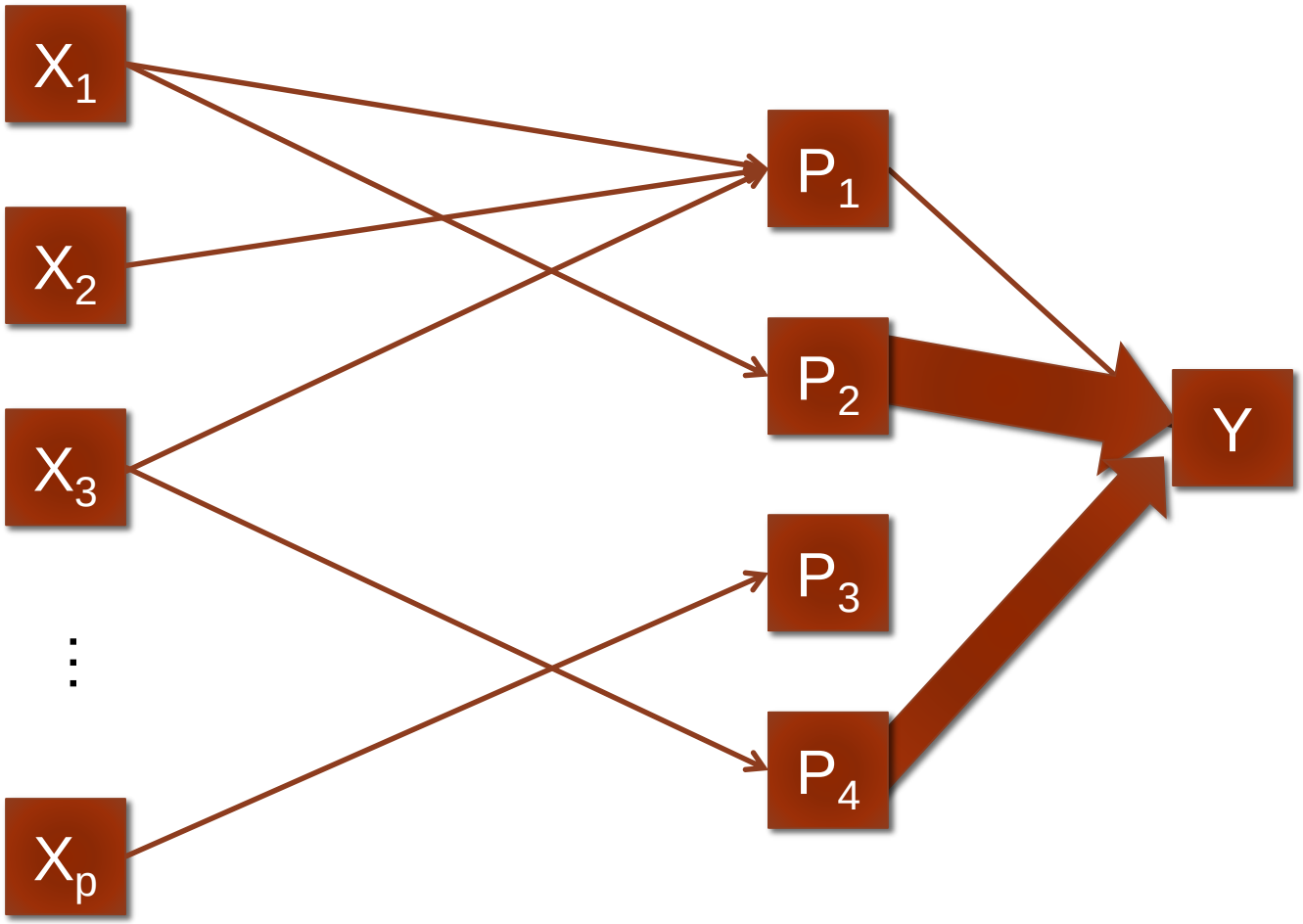

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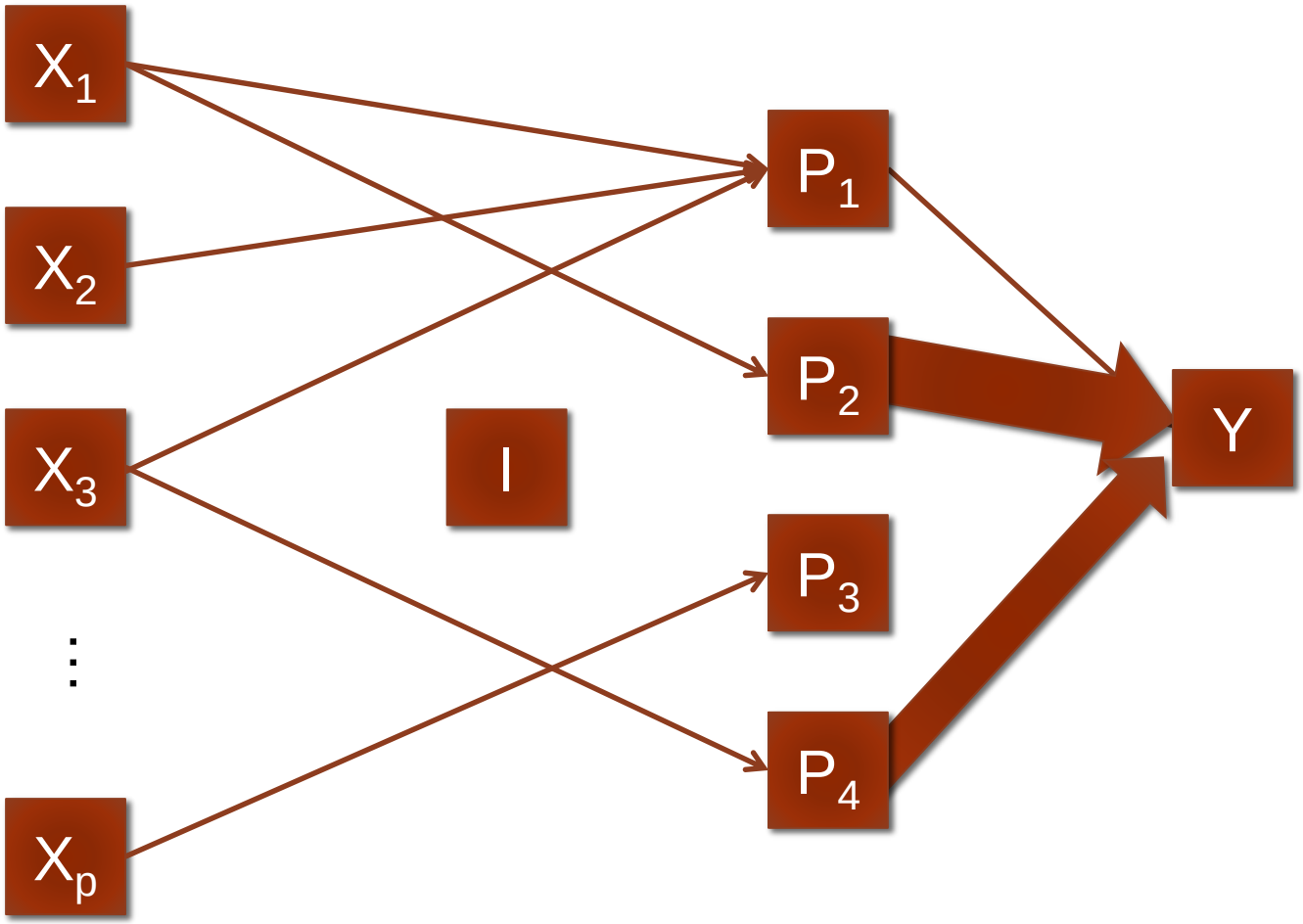

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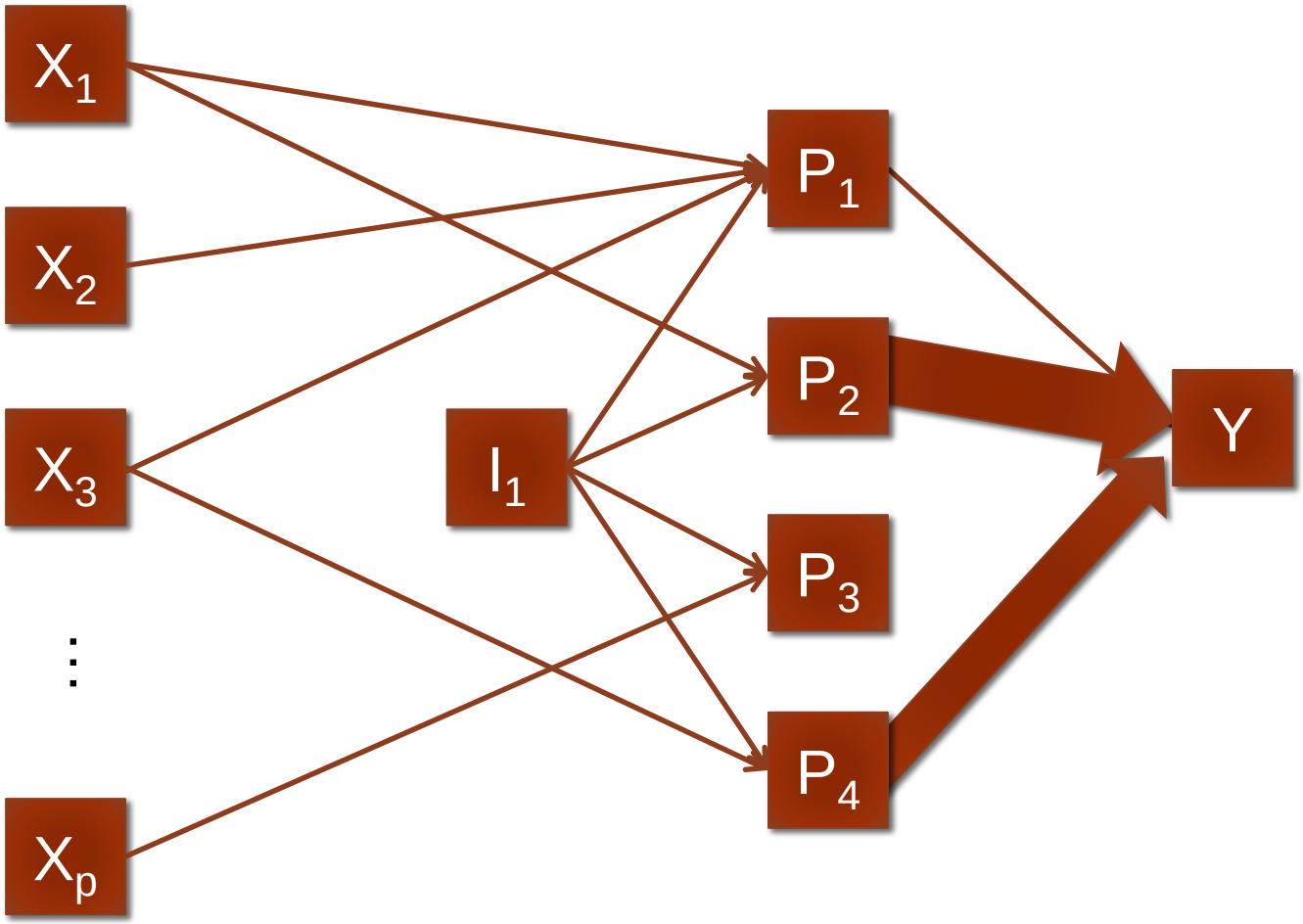

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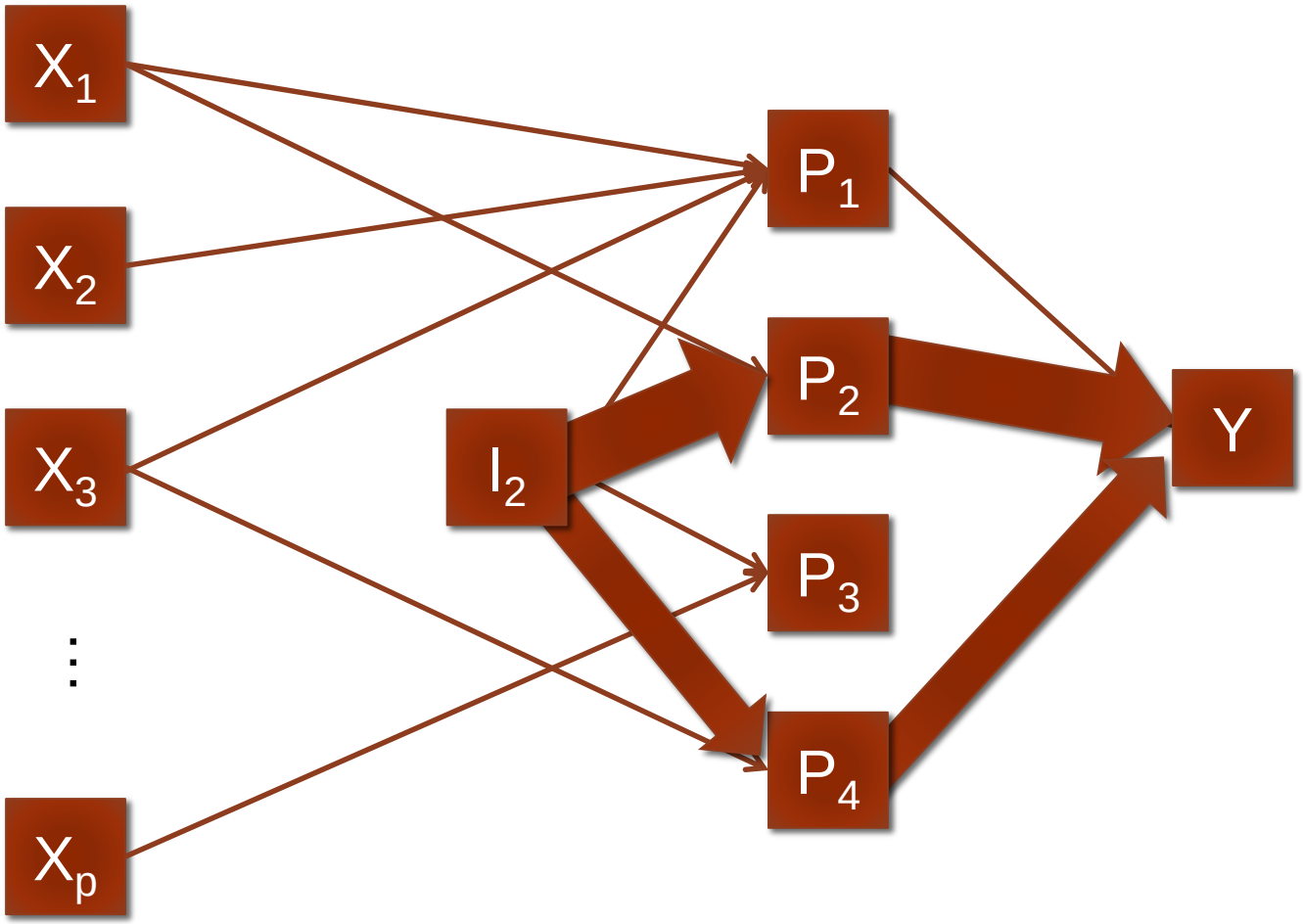

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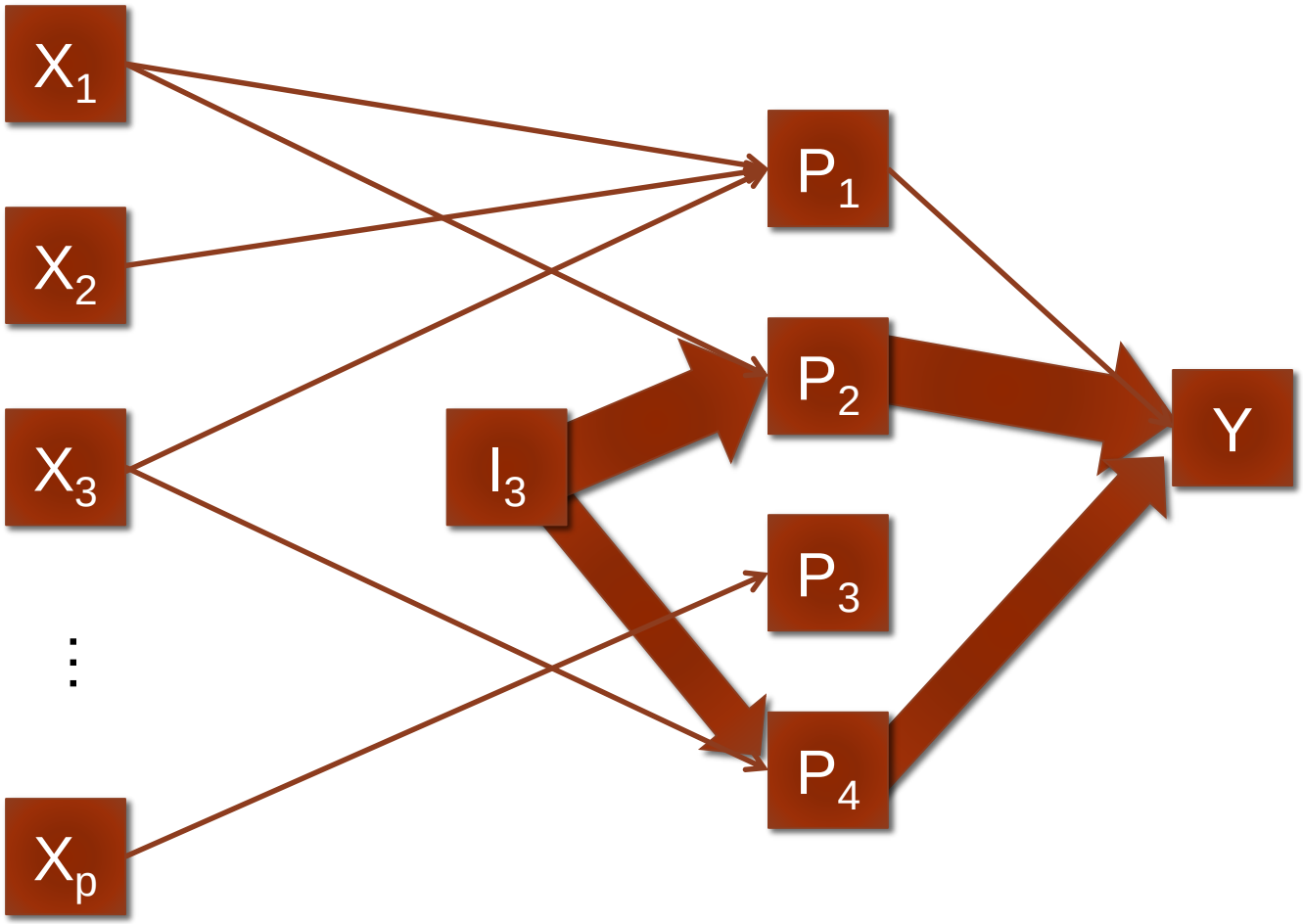

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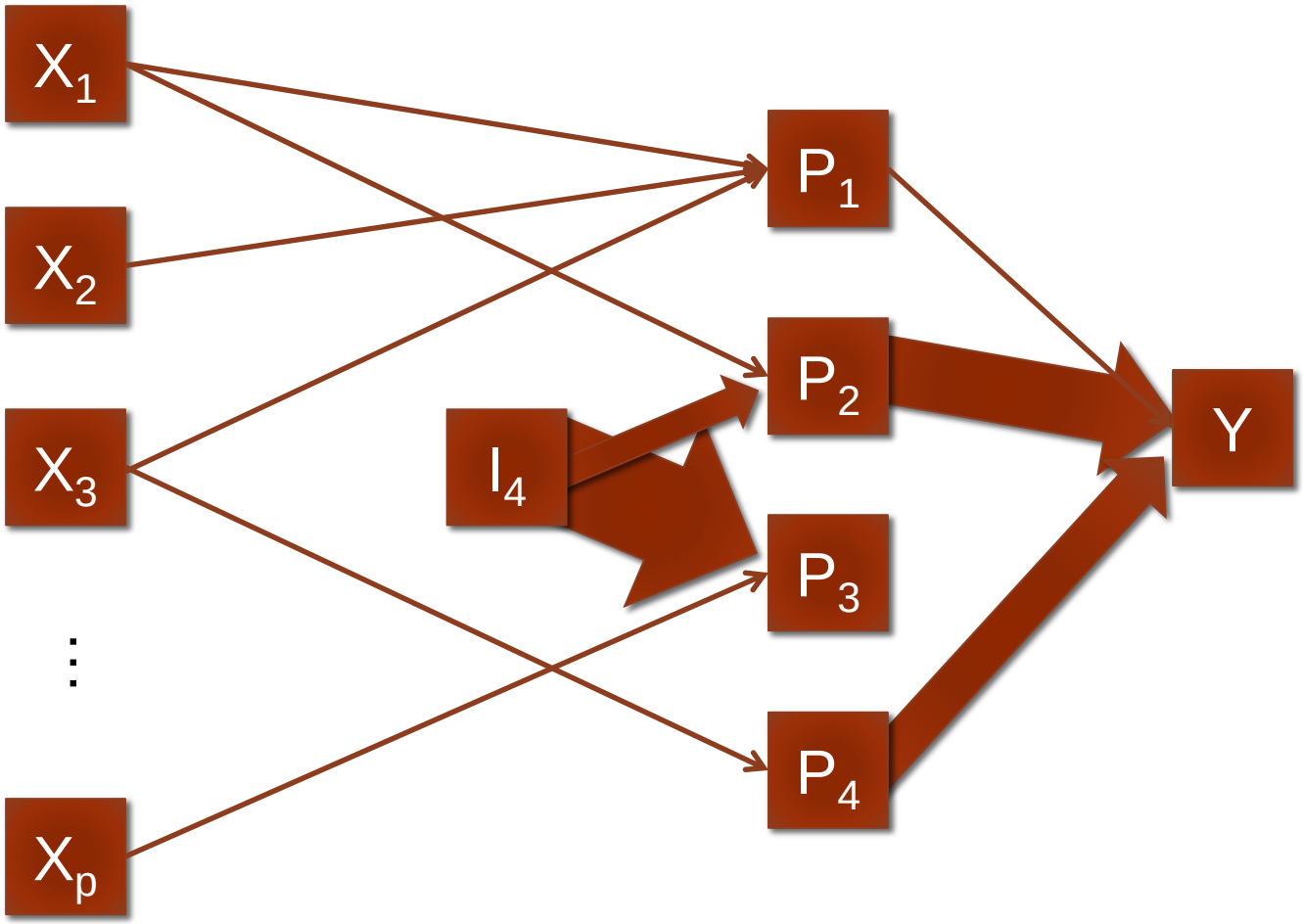
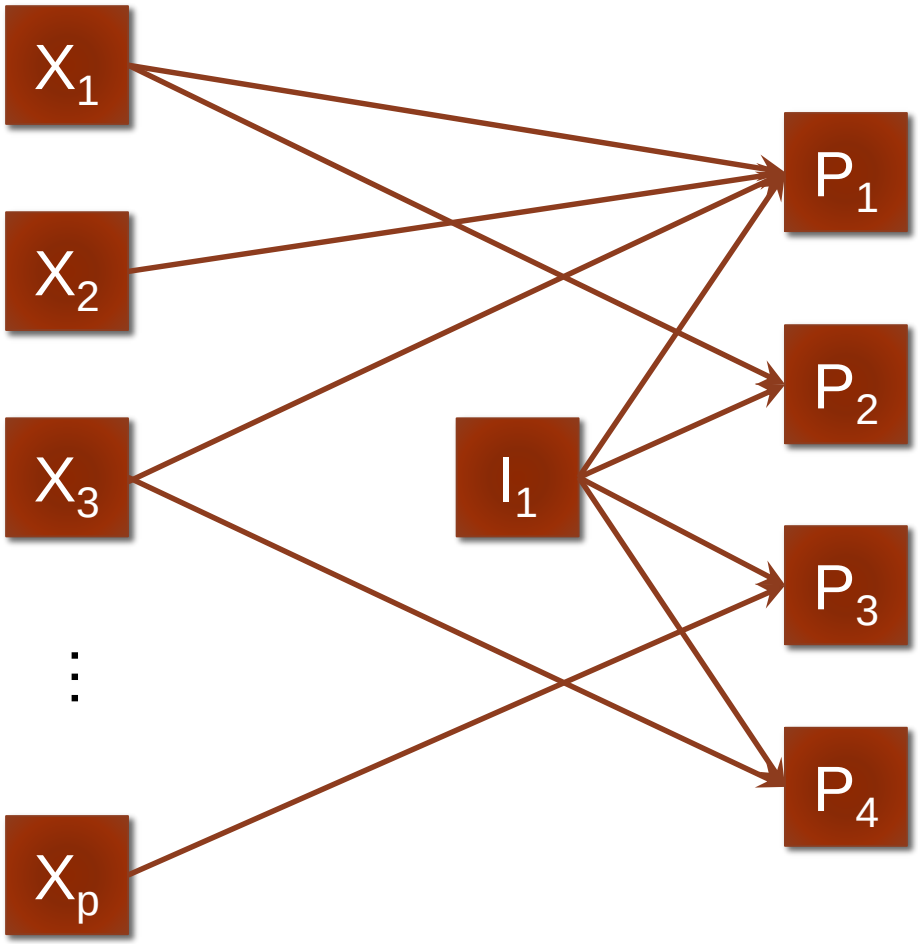


coherence



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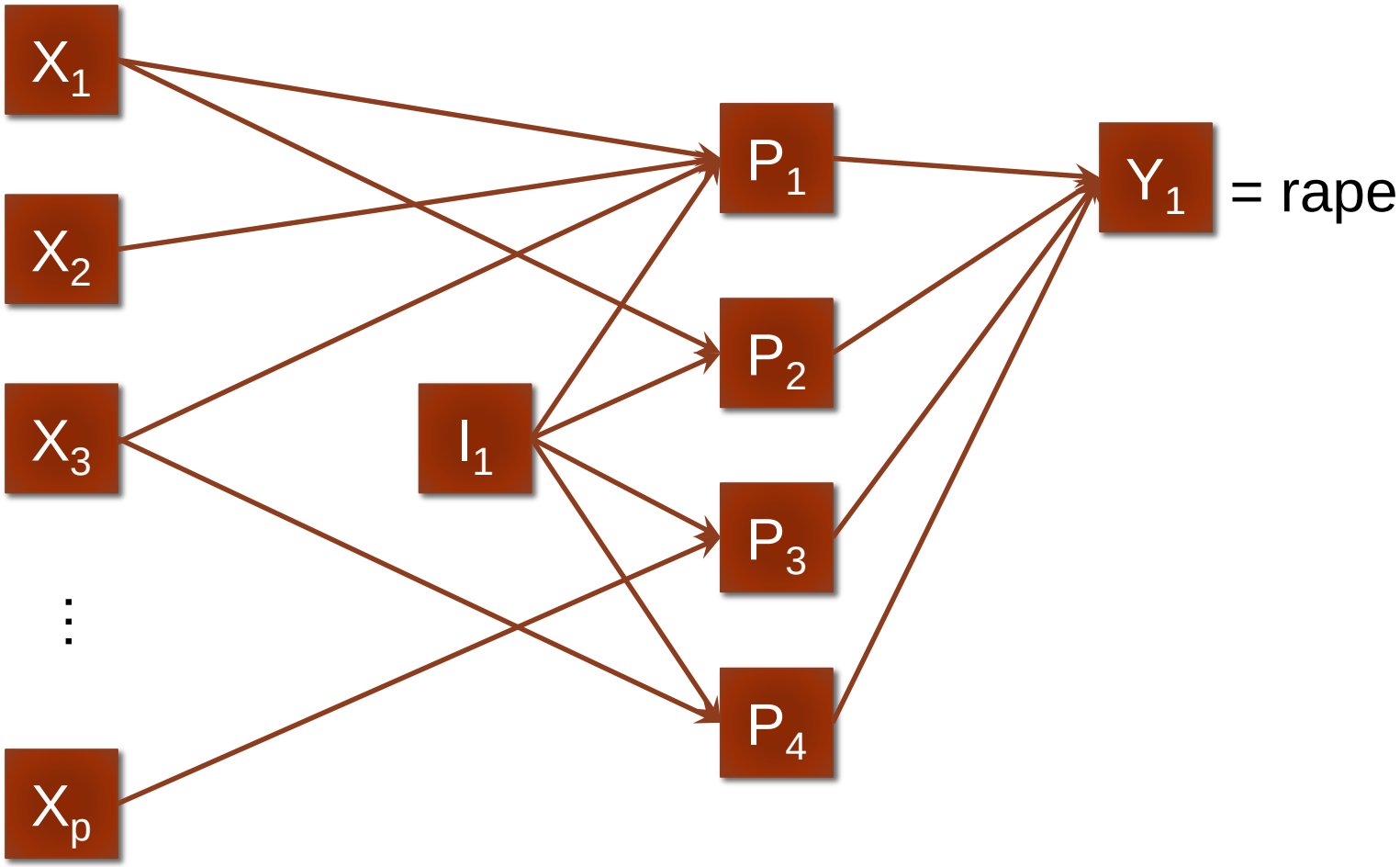

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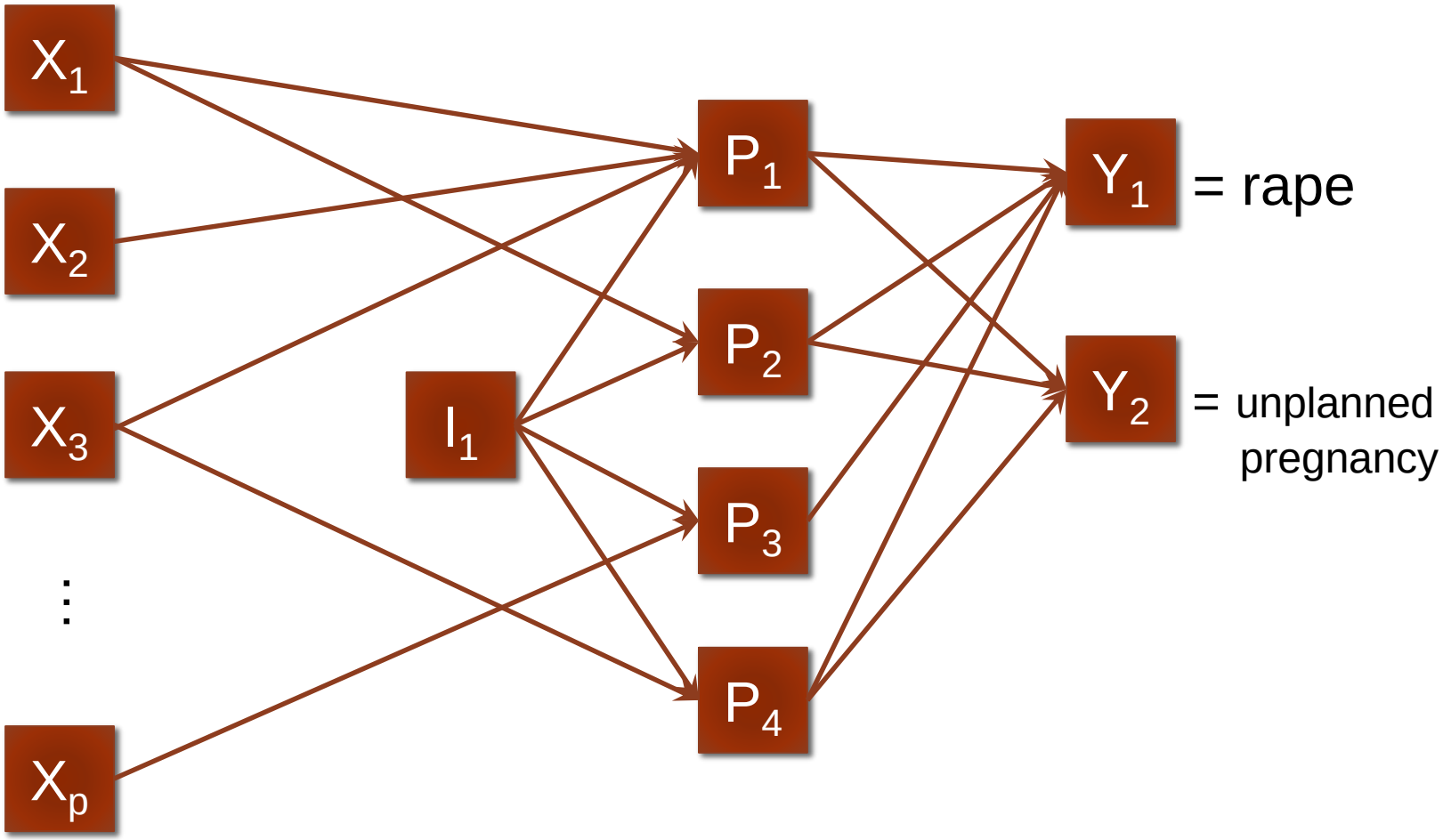

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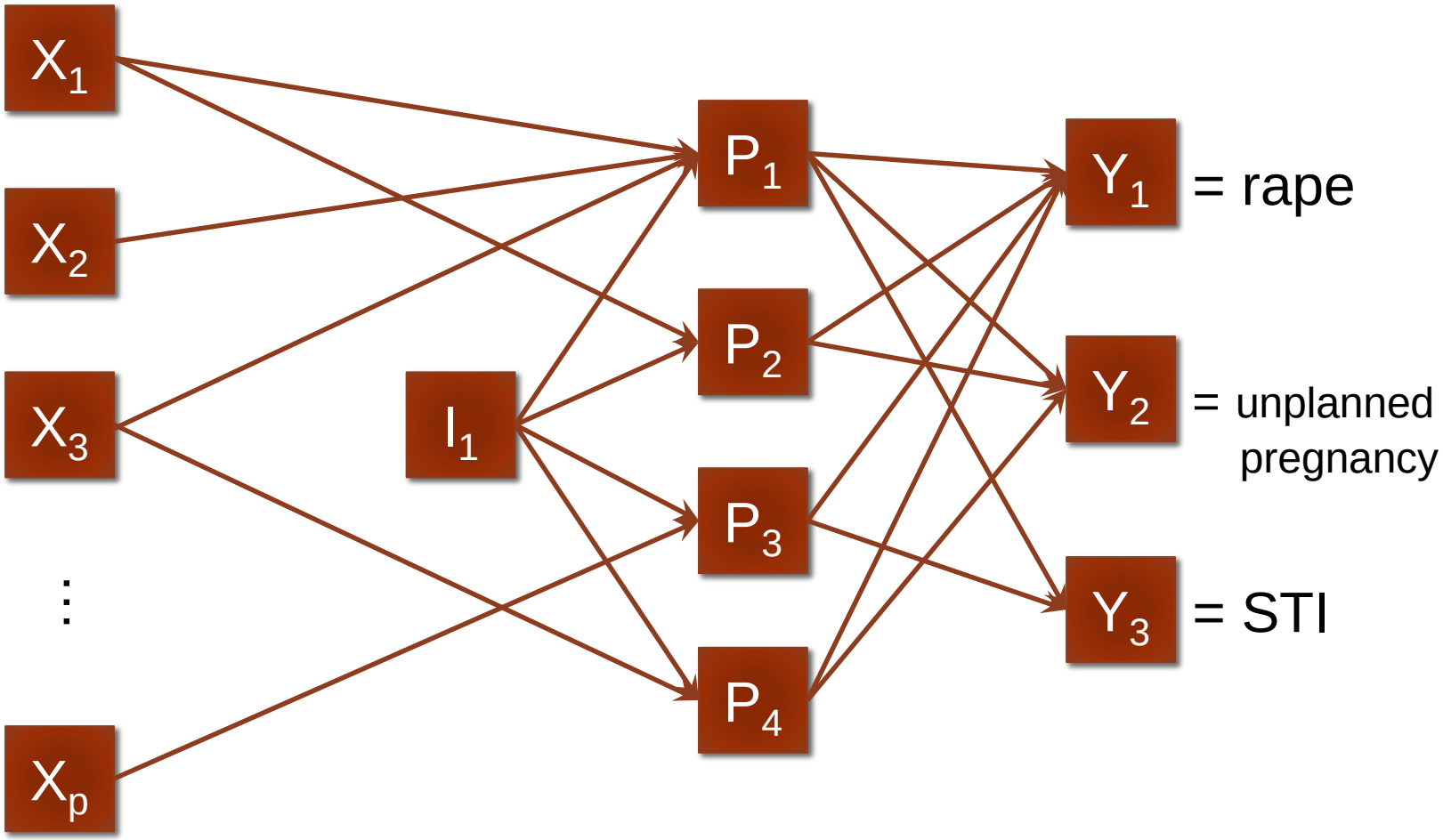

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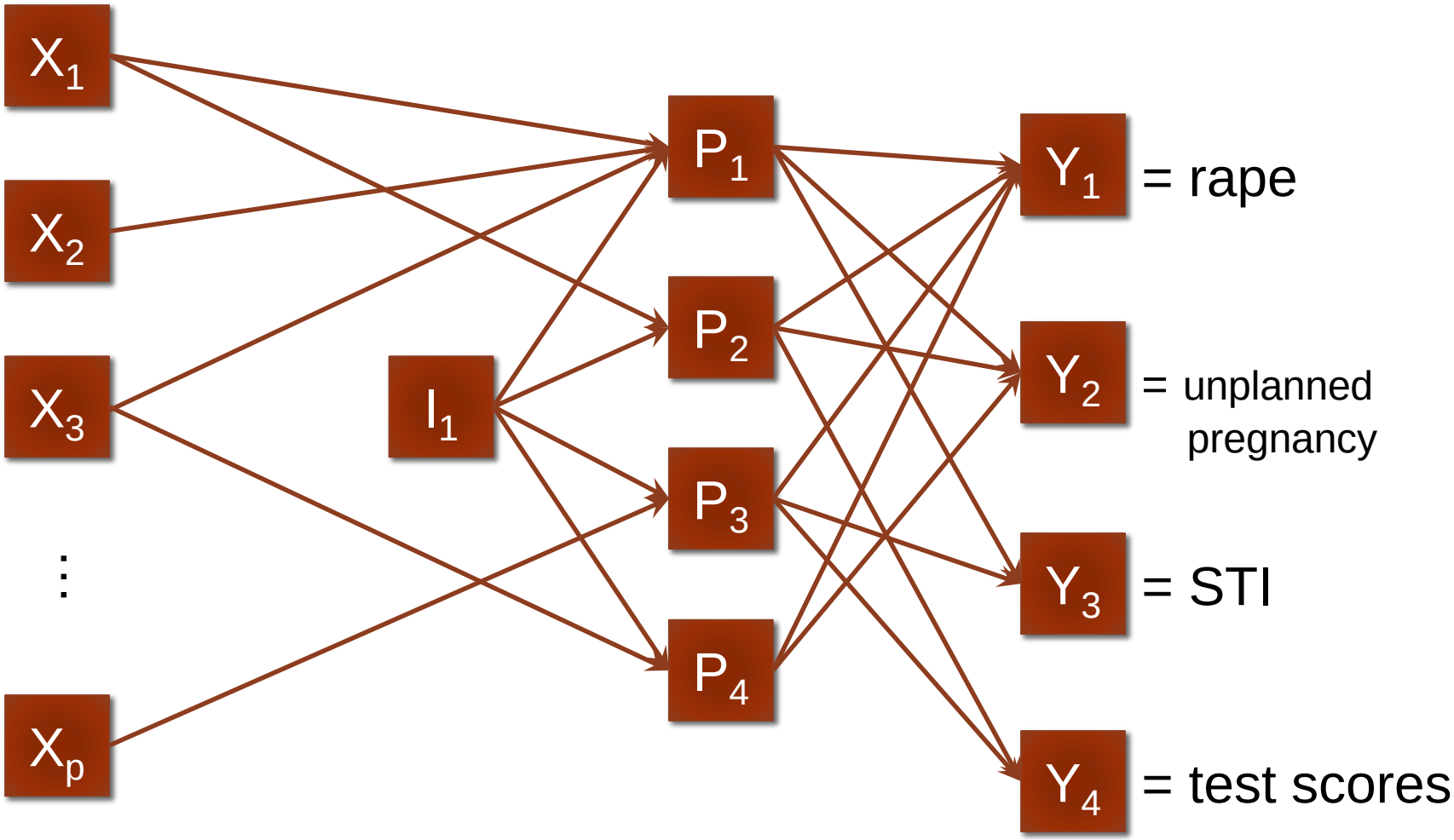
X_1
X_2
X_3
⋮
X_p
I_1
P_1
P_2
P_3
P_4
Y_1 = rape
Y_2 = unplanned pregnancy
Y_3 = STI
Y_4 = test scores

coherence

KNOWN NULL EFFECT

the structure of the argument: null effect outcomes

- Basic idea:

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- Basic idea: Suppose that a treatment is known to not change a particular outcome.

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- Basic idea: Suppose that a treatment is known to not change a particular outcome. Then if we see differences between the treatment and control groups on this particular outcome…

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- Basic idea: Suppose that a treatment is known to not change a particular outcome. Then if we see differences between the treatment and control groups on this particular outcome, this must mean that there are differences between the treatment and control group on unmeasured covariates and thus there is hidden bias.

example: methylmercury fish

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- Example: Skerfving (1974) studied whether eating fish contaminated with methylmercury causes chromosome damage.

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```
control.cu.cells <- c(2.7,.5,0,0,5,0,0,1.3,0,1.8,0,0,1,1.8,0,3.1)
exposed.cu.cells <- c(.7,1.7,0,4.6,0,9.5,5,2,2,2,1,3,2,3.5,0,4);
library(exactRankTests)
```

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exposed.cu.cells <- c(.7,1.7,0,4.6,0,9.5,5,2,2,2,1,3,2,3.5,0,4);
library(exactRankTests)

wilcox.exact(exposed.cu.cells,control.cu.cells,paired=TRUE)

        Exact Wilcoxon signed rank test

data:  exposed.cu.cells and control.cu.cells
V = 84, p-value = 0.04712

alternative hypothesis: true mu is not equal to 0
```

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- These can be considered outcomes since they describe the period when the exposed subjects were consuming contaminated fish.

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- Going further, *Skerfving* described other health conditions of these subjects including other diseases such as (i) hypertension, (ii) asthma, (iii) drugs taken regularly, (iv) diagnostic X-rays over the previous three years, (v) and viral diseases such as influenza.
- These can be considered outcomes since they describe the period when the exposed subjects were consuming contaminated fish.
- However, it is difficult to imagine that eating fish contaminated with methylmercury causes influenza or asthma, or prompts X-rays of the hip or lumbar spine.

example: methylmercury fish

- The data

example: methylmercury fish

- The data

```
control.other.health.conditions <- c(rep(0,8),2,rep(0,3),2,1,4,1)
exposed.other.health.conditions <- c(0,0,2,0,2,0,0,1,1,2,0,9,0,0,1,0)
```

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```

```
> wilcox.exact(control.other.health.conditions,exposed.other.health.conditions)

        Exact Wilcoxon rank sum test

data:  control.other.health.conditions and exposed.other.health.conditions
W = 112.5, p-value = 0.5257
alternative hypothesis: true mu is not equal to 0
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control.other.health.conditions <- c(rep(0,8),2,rep(0,3),2,1,4,1)
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- There is no evidence of hidden bias.
- But absence of evidence is not evidence of absence.

example: methylmercury fish

- Questions:

  (1) When does such a test have a reasonable prospect of detecting hidden bias?

  (2) If no evidence of hidden bias is found, does this imply reduced sensitivity to bias in the comparisons involving the outcomes of primary interest?

  (3) If evidence of bias is found, what can be said about its magnitude and its impact on the primary comparisons?

null effect outcomes

- Power of the test of hidden bias:

null effect outcomes

- <u>Power of the test of hidden bias</u>: Let $\boldsymbol{y}$ denote the outcome for which there is a known effect of zero. For a particular unobserved covariate $\boldsymbol{u}$, what unaffected outcome $\boldsymbol{y}$ would be useful in detecting hidden bias from $\boldsymbol{u}$?

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- Precise statement of results in:
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- Basic result:

null effect outcomes

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- Precise statement of results in:
  - "The Role of Known Effects in Observational Studies"
- Basic result: The power of the test of whether $\boldsymbol{y}$ is affected by the treatment increases with the strength of the relationship between $\boldsymbol{y}$ and $\boldsymbol{u}$. If one is concerned about a particular unobserved covariate $\boldsymbol{u}$, one should search for an unaffected outcome $\boldsymbol{y}$ that is strongly related to $\boldsymbol{u}$.

takeaway

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- Known null effects may help to address unobserved confounding

a second control group

TWO PROBLEMS
TWO CONTROLS

Design of Observational Studies: chapter 5.2.2
Rosenbaum, "The Role of a Second Control Group in an Observational Study"

structure of argument

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- The contrast of these two control groups with the treatment group may strengthen your analysis.

second control group: army toxicity

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- Complicating that comparison, though, is that the army sorted people into jobs which exposed them or to jobs which did not.
- The army used medical examinations – which were not well documented – to sort some individuals out of high-exposure jobs. This leaves the comparison between exposed and strictly unexposed potentially biased due to baseline conditions.

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- Each of these control groups is problematic: the first group is open to critiques of baseline differences in medical conditions; the second group has individuals who were potentially exposed to actively toxic chemical agents.
- But the first control group is unlikely to suffer from the bias encounter in the second control group, and vice versa.

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- Precise statements of how this argument works statistically, as well as a couple more examples from the literature, can be found in "The Role of a Second Control Group in an Observational Study"

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thick description

QUALIA HUNTING

pre-trial detention

pre-trial detention

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pre-trial detention

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- This is deeply insane

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- This incarceration has largely been at Riker's Island

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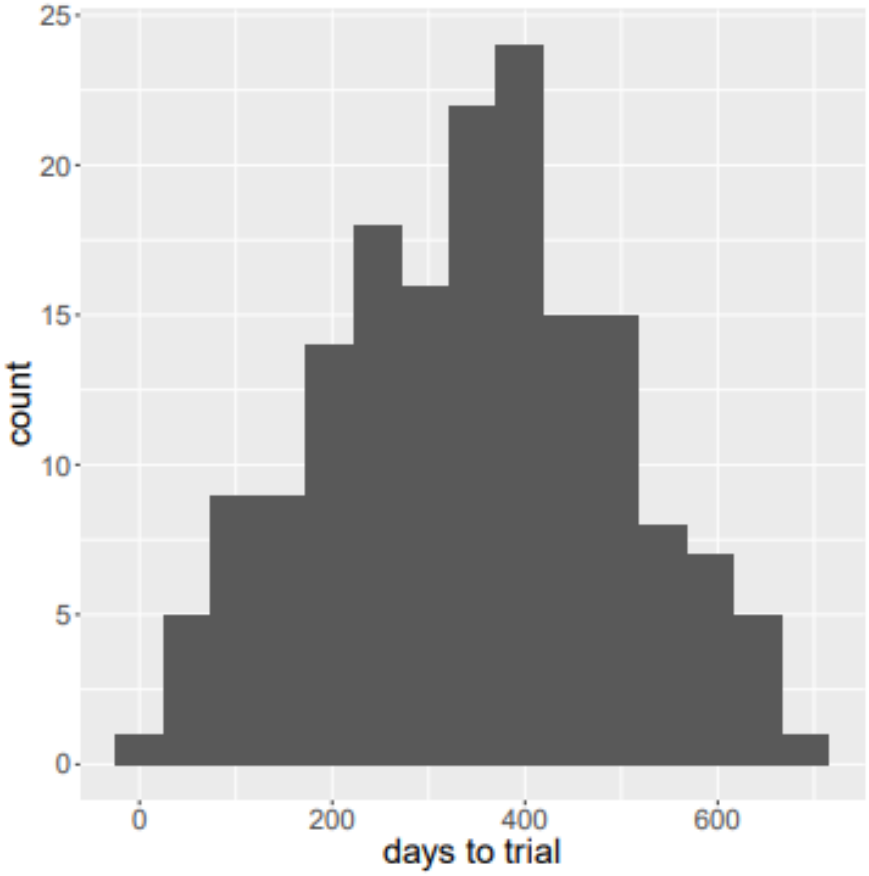

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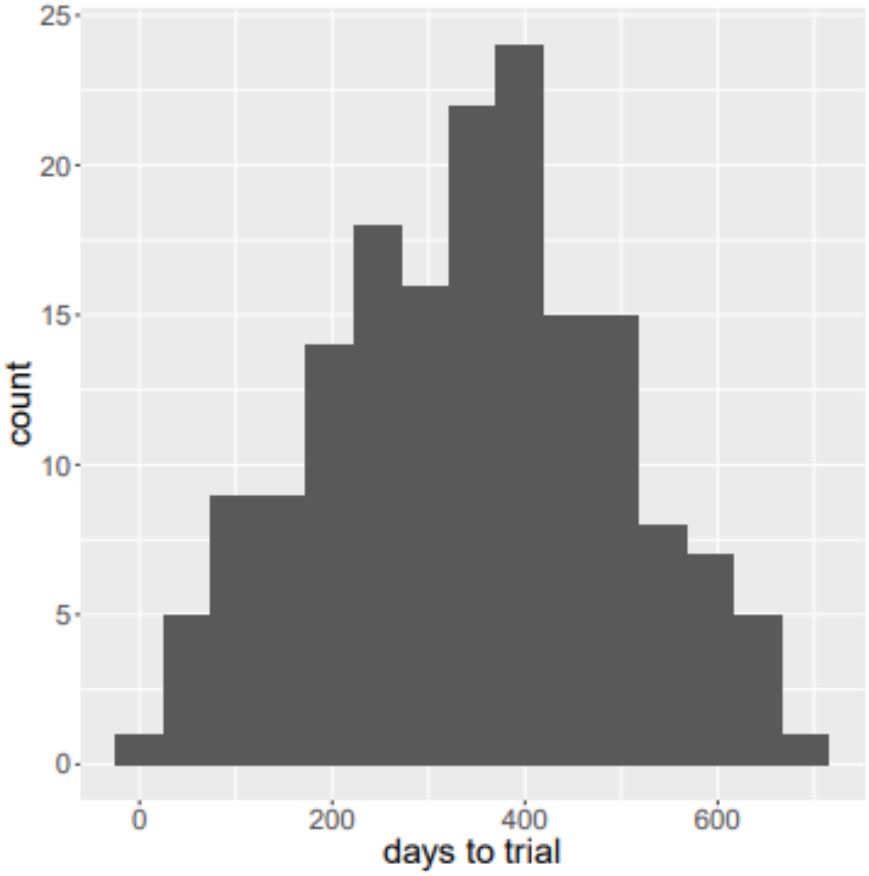

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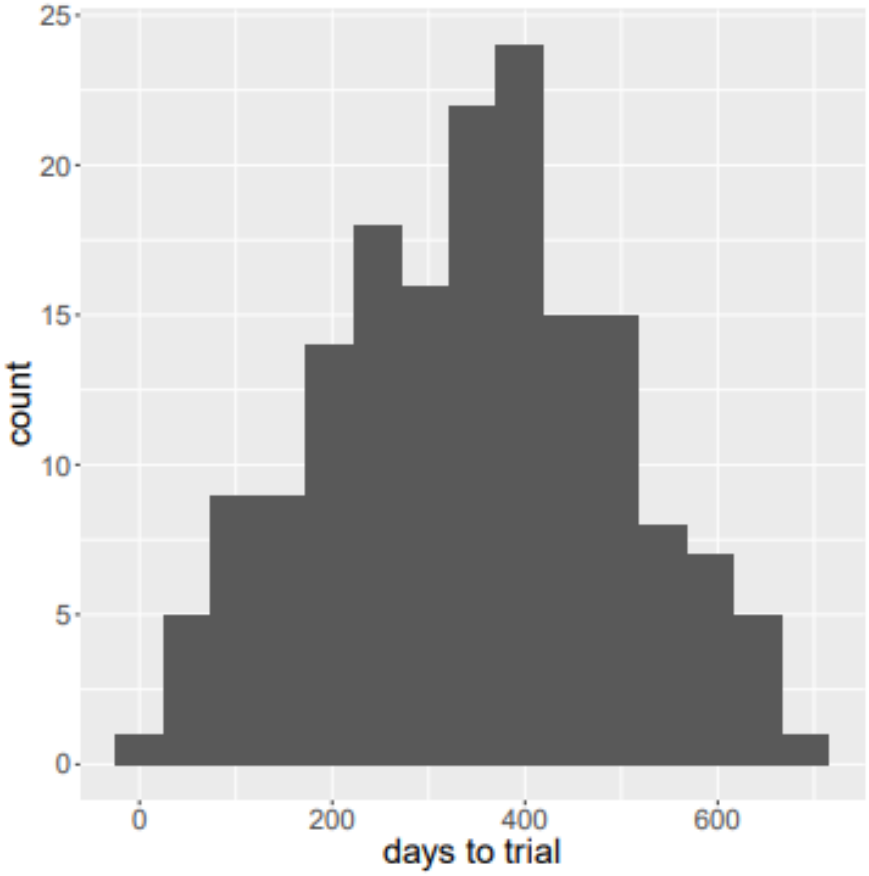

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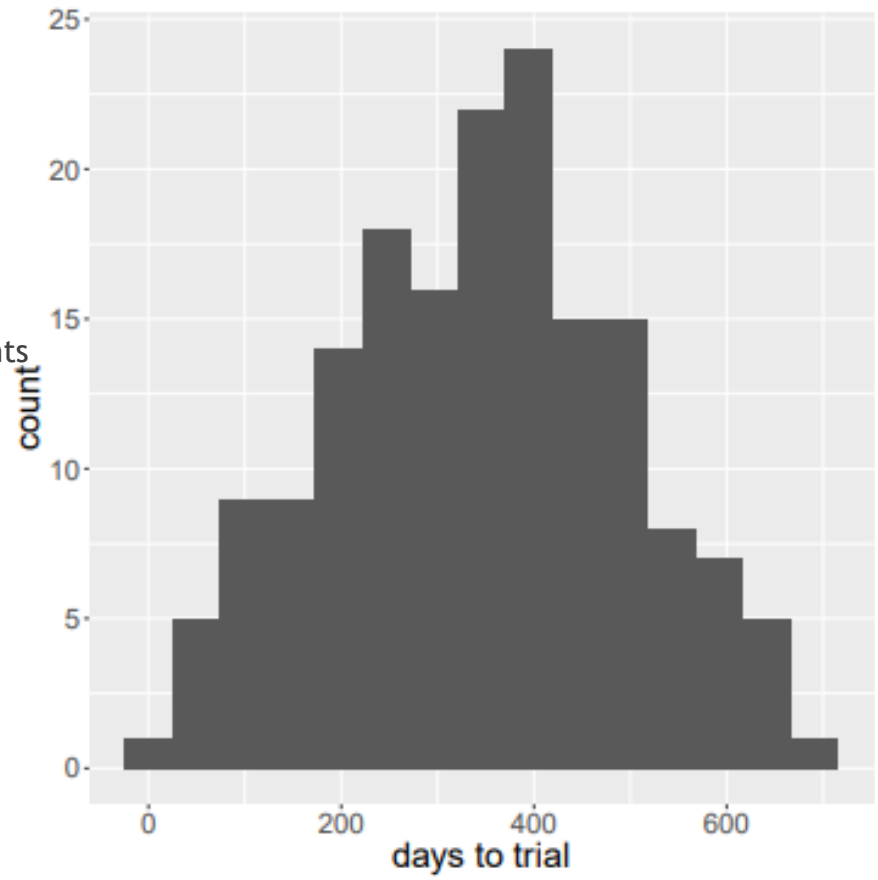

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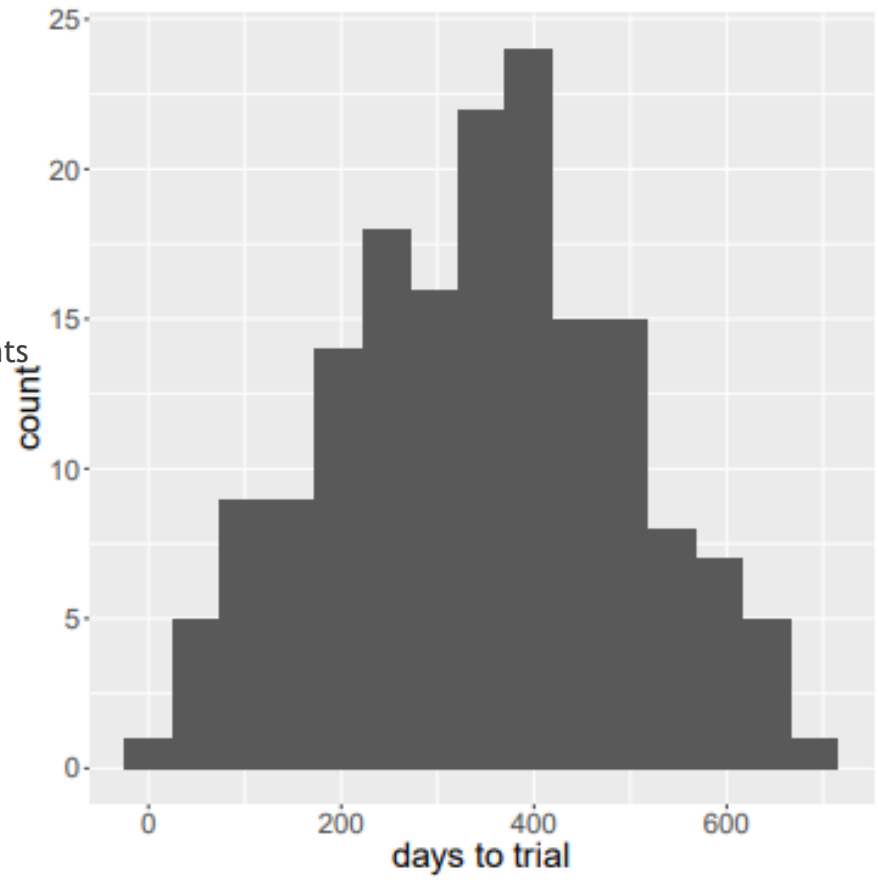

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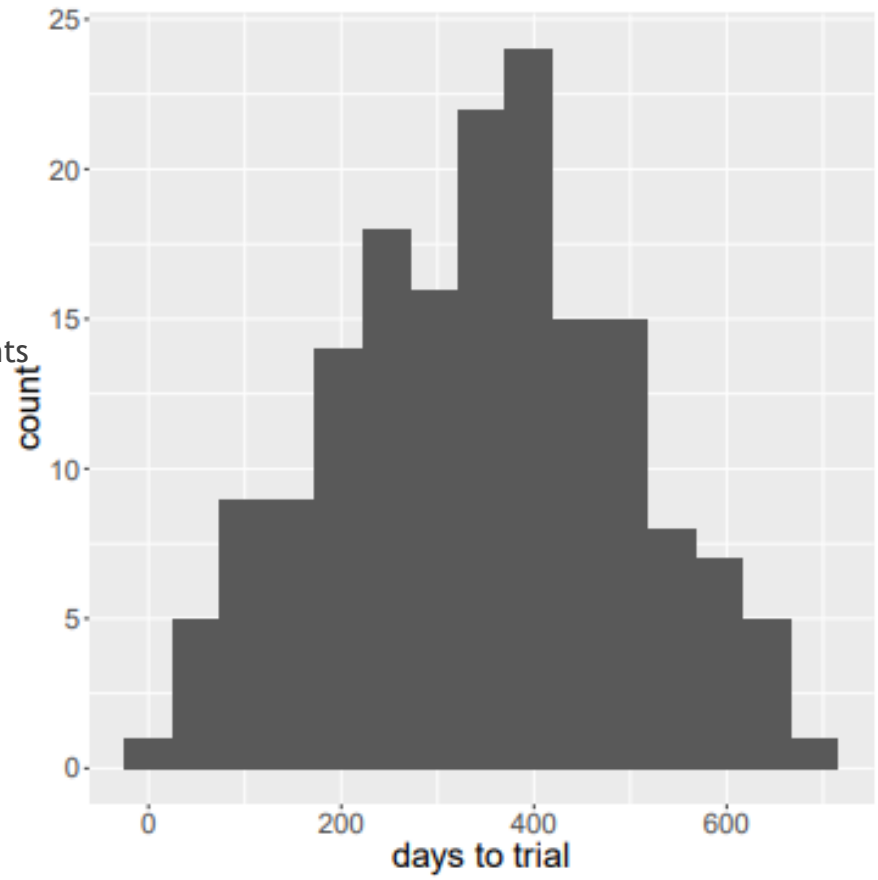

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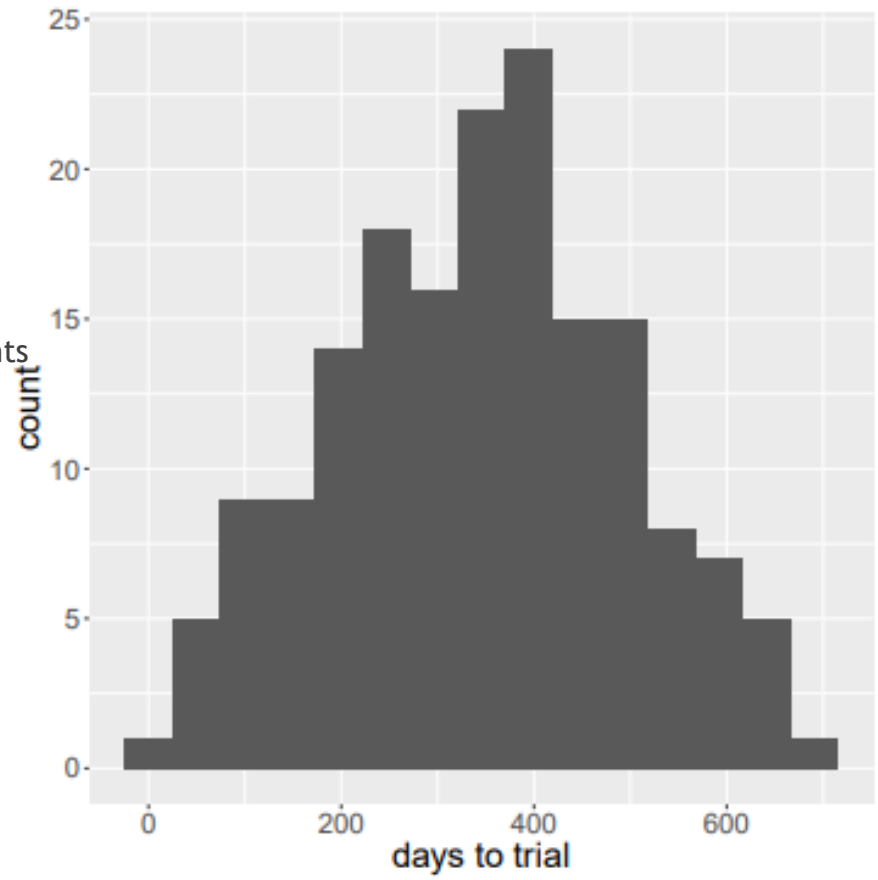

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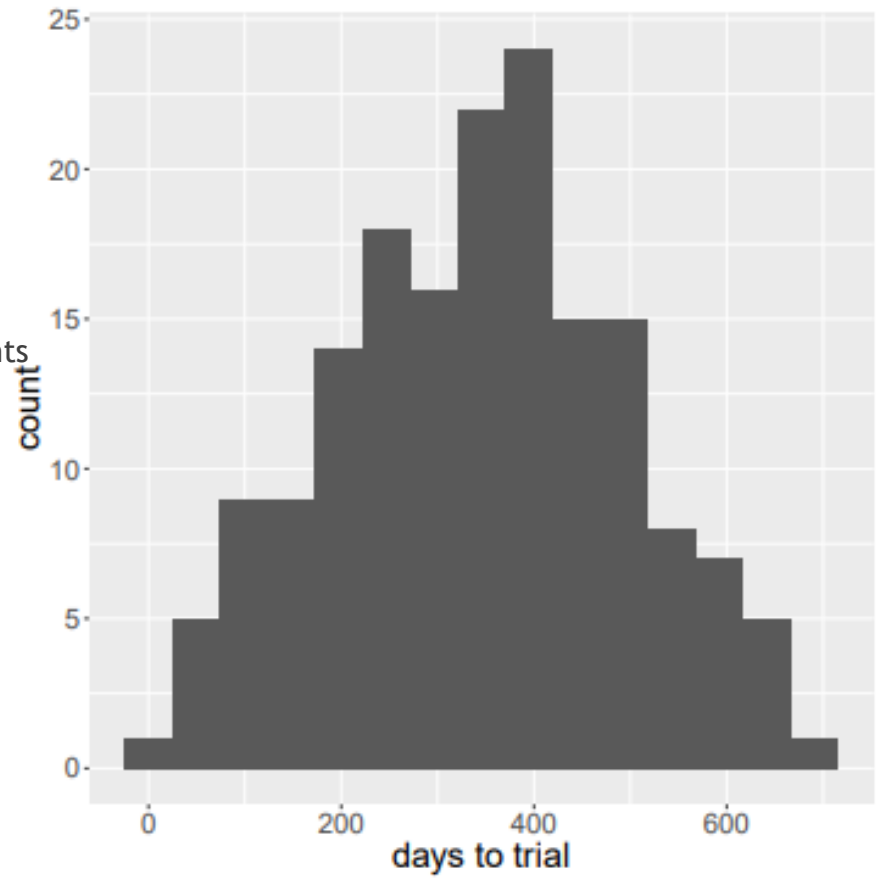

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- This is known as an “instrumental variable” study design

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Given the linear regression:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

where X_1 is an endogenous variable:

(1) Regress X_1 on Z_1, X_1, and X_3 to obtain $\hat{X}_1$

$$\hat{X}_1 = \gamma_0 + \gamma_1 Z_1 + \gamma_2 X_2 + \gamma_3 X_3 + v$$

where Z_1 is the instrumental variable

(2) Plug in the fitted values of $\hat{X}_1$ derived from equation (1) into the original linear regression equation:

$$Y = \beta_0 + \beta_1 \hat{X}_1 + \beta_2 X_2 + \beta_3 X_3 + v$$

where v is a composite error term that is uncorrelated with $\hat{X}_1, X_2$, and X_3

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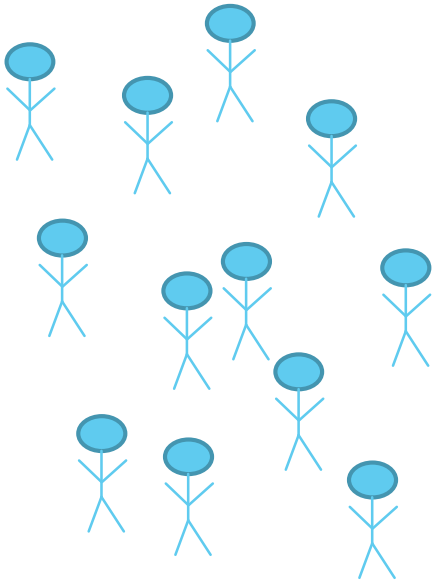

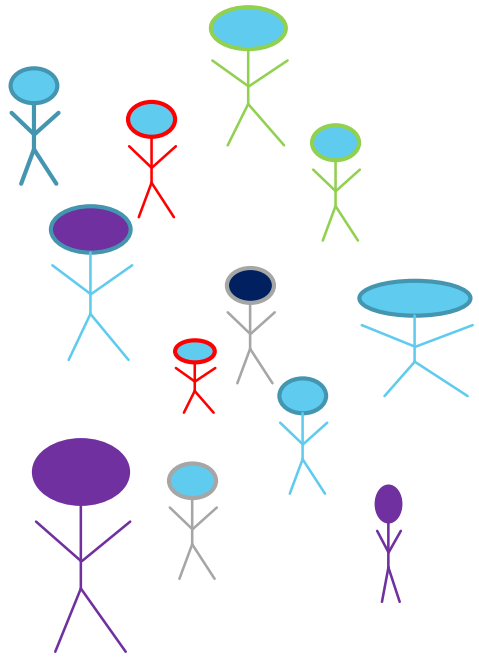

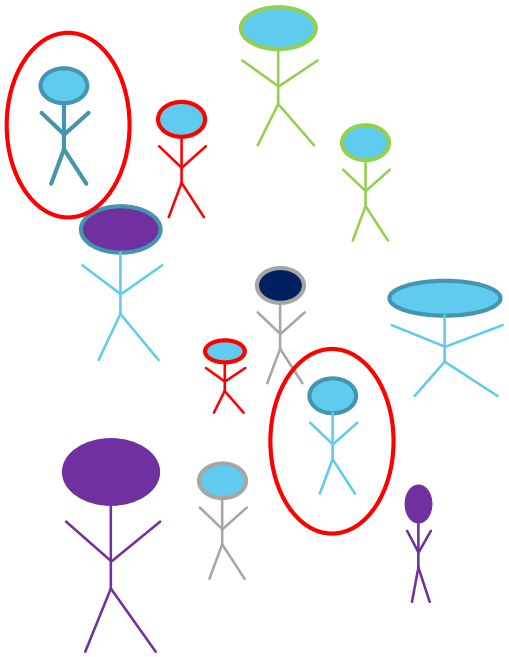

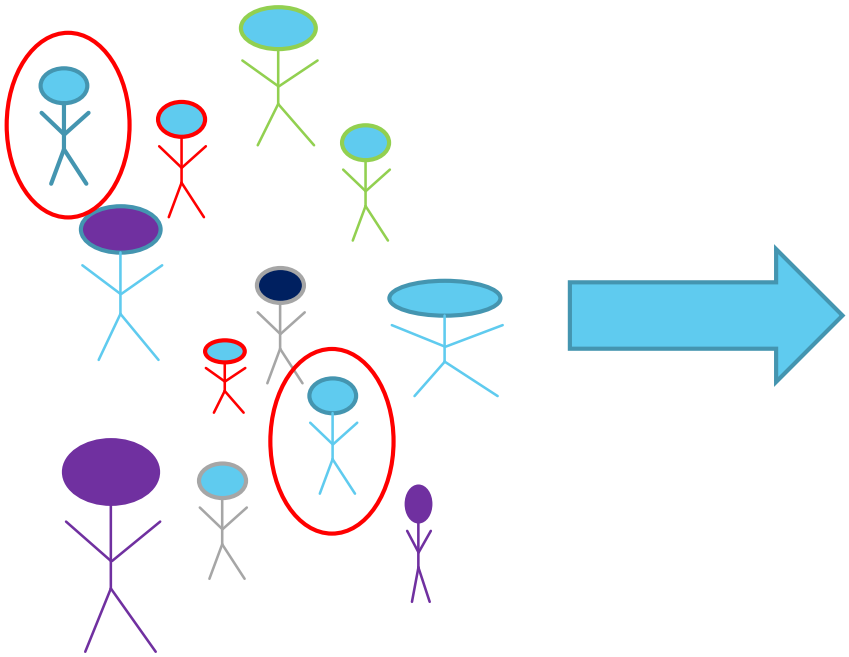

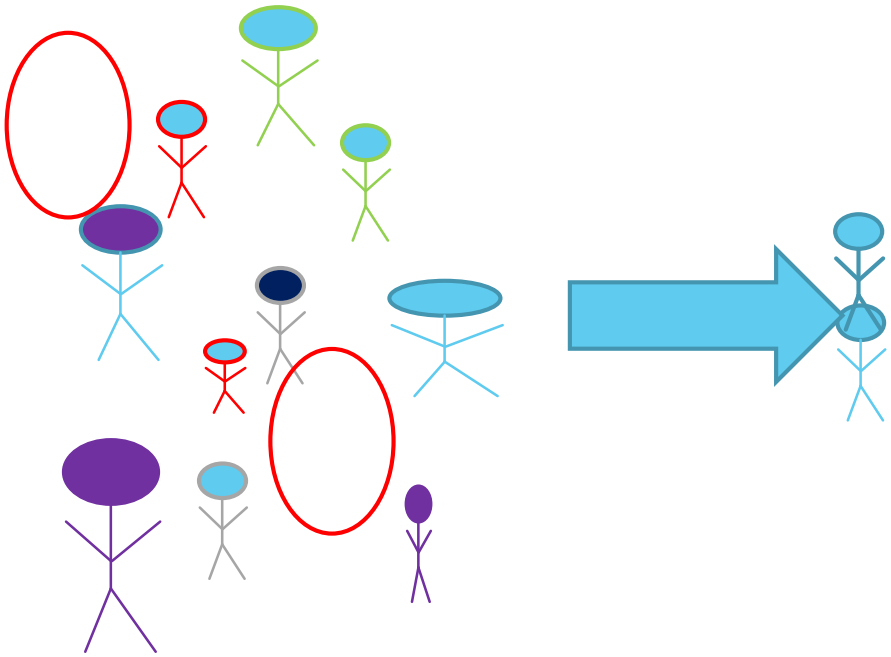

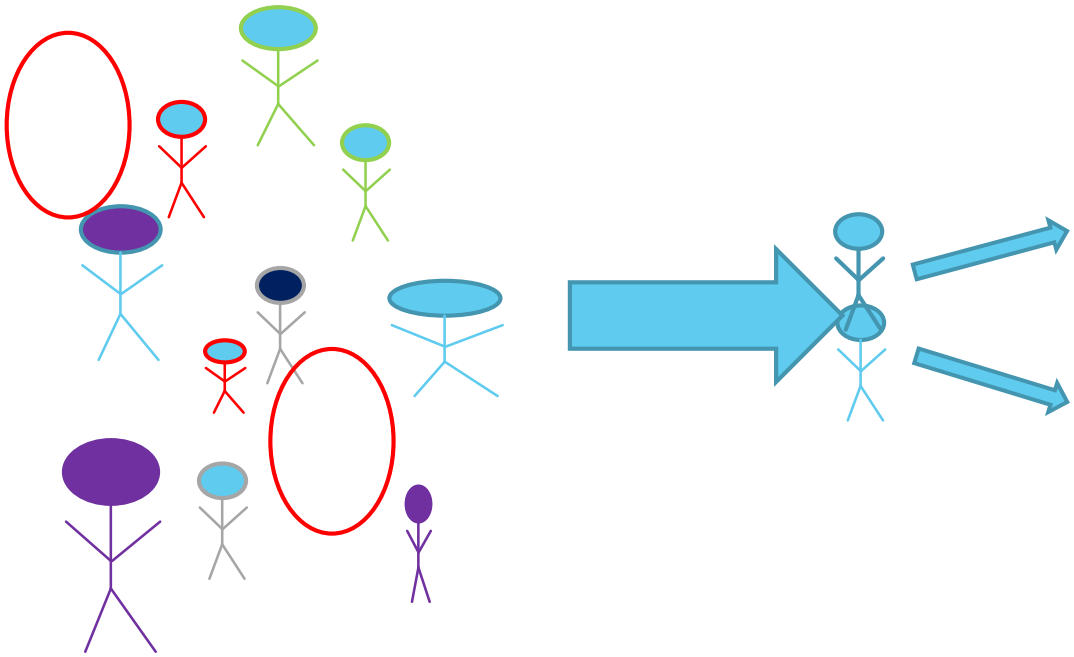

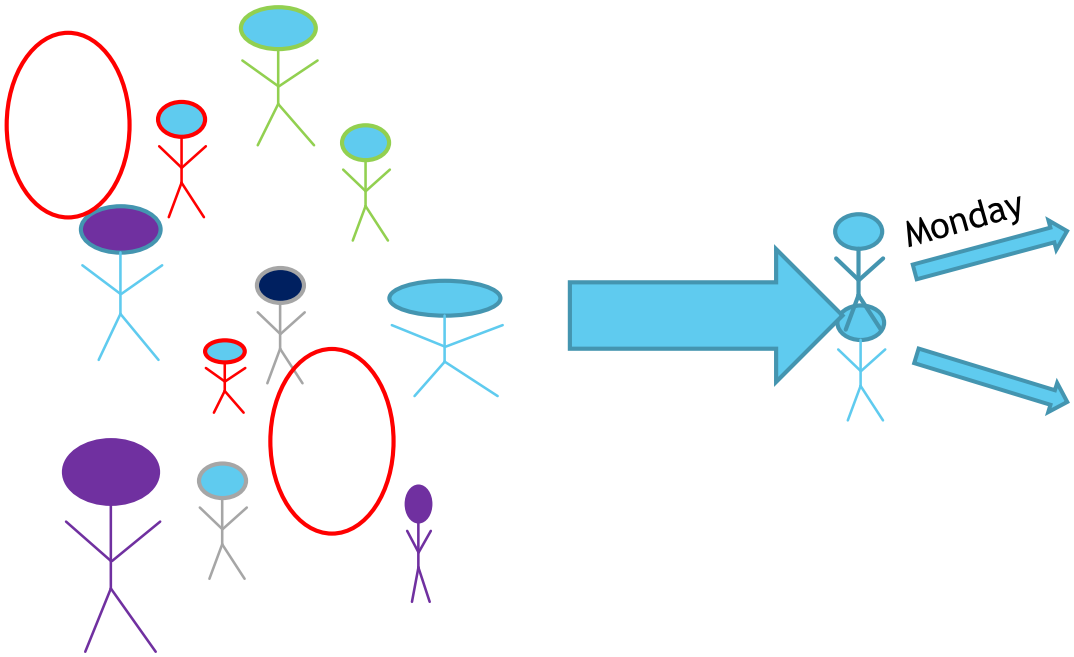
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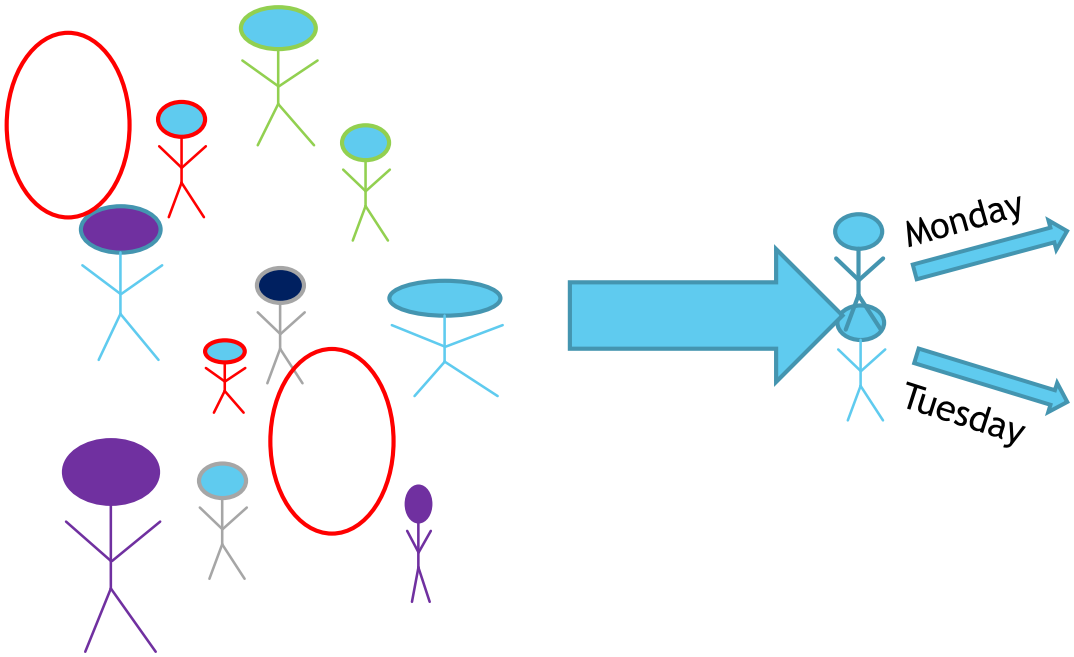
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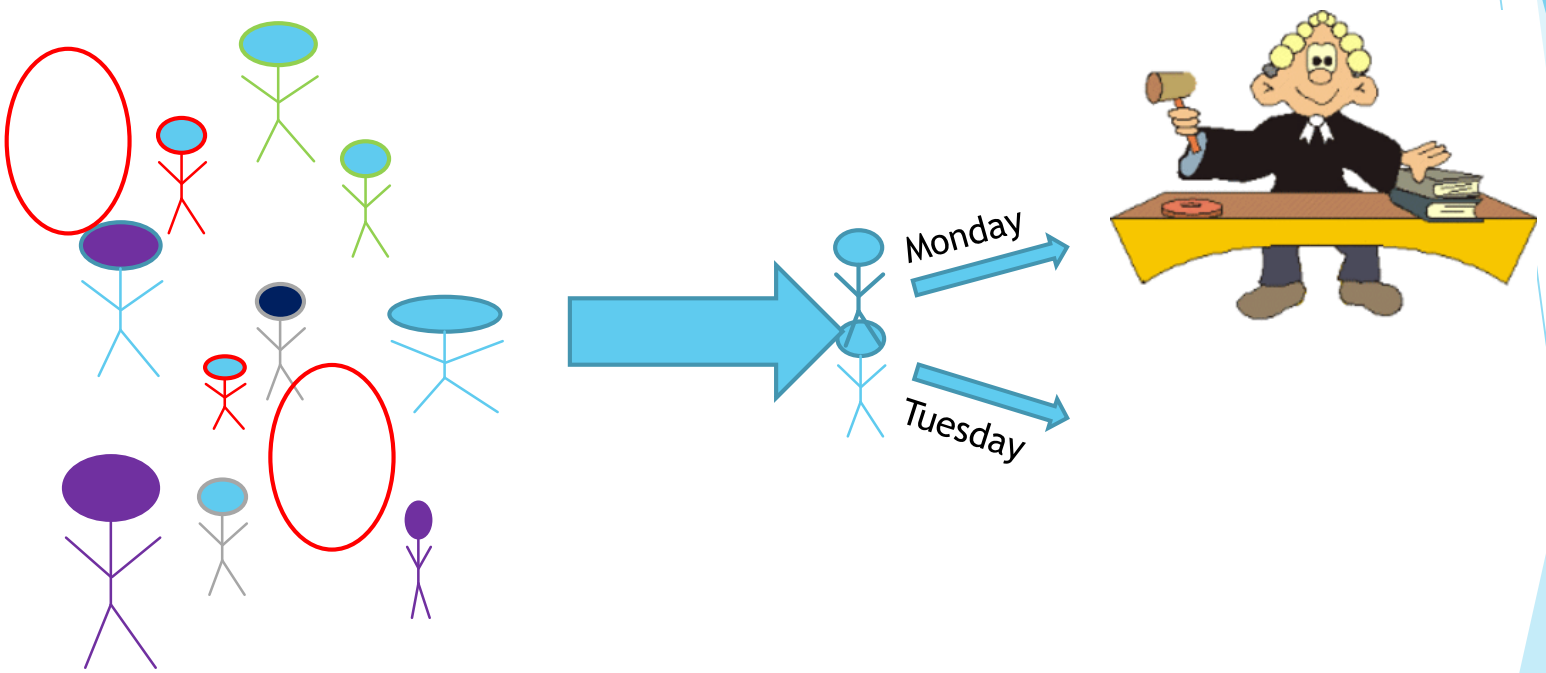
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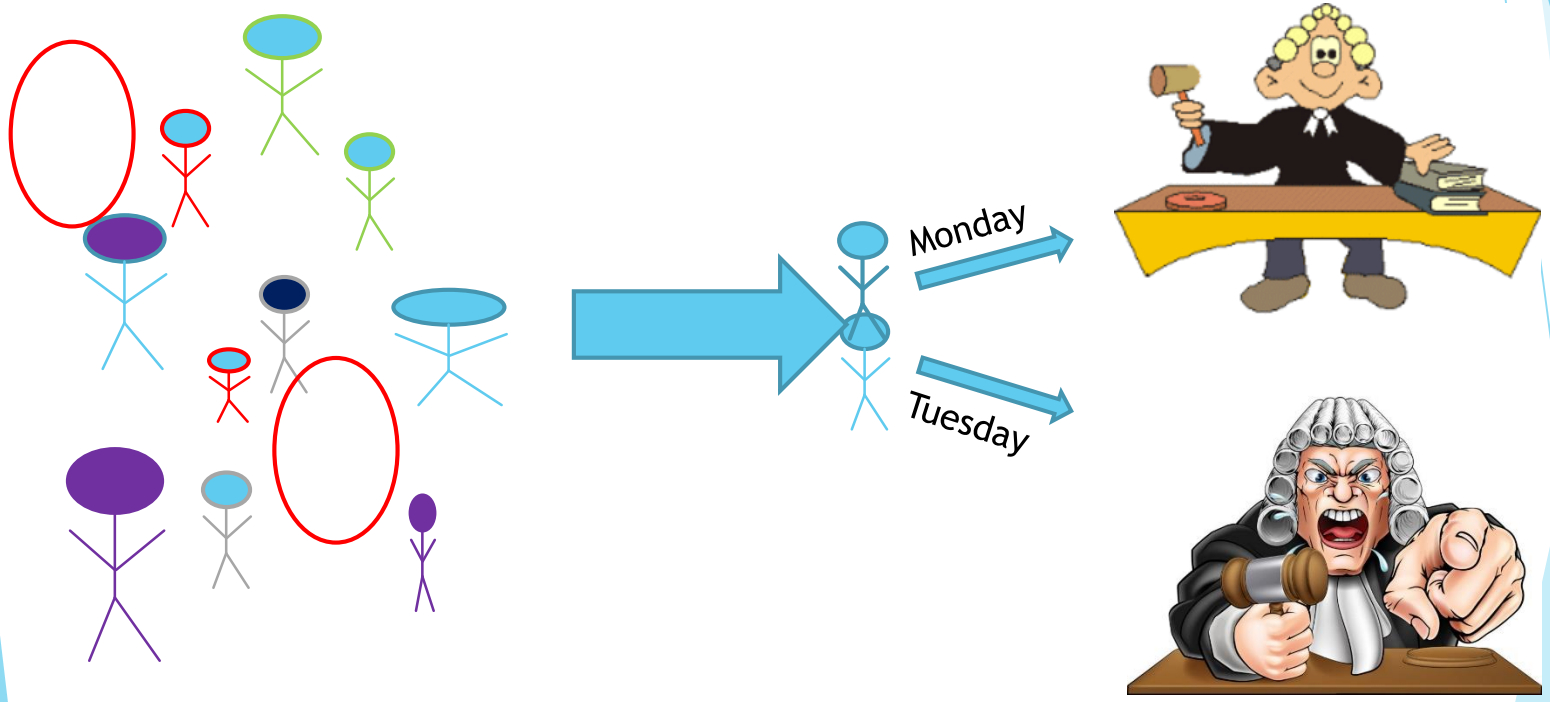
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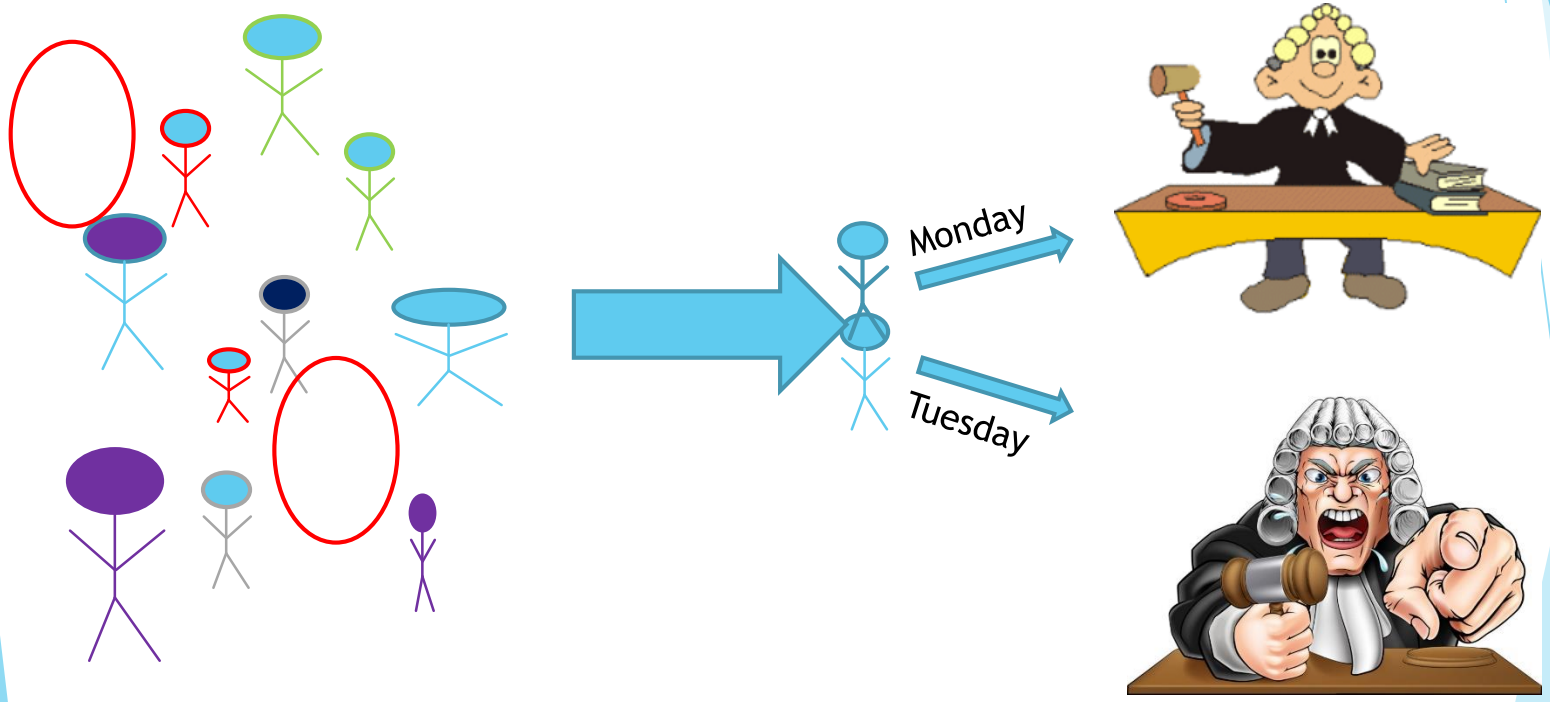

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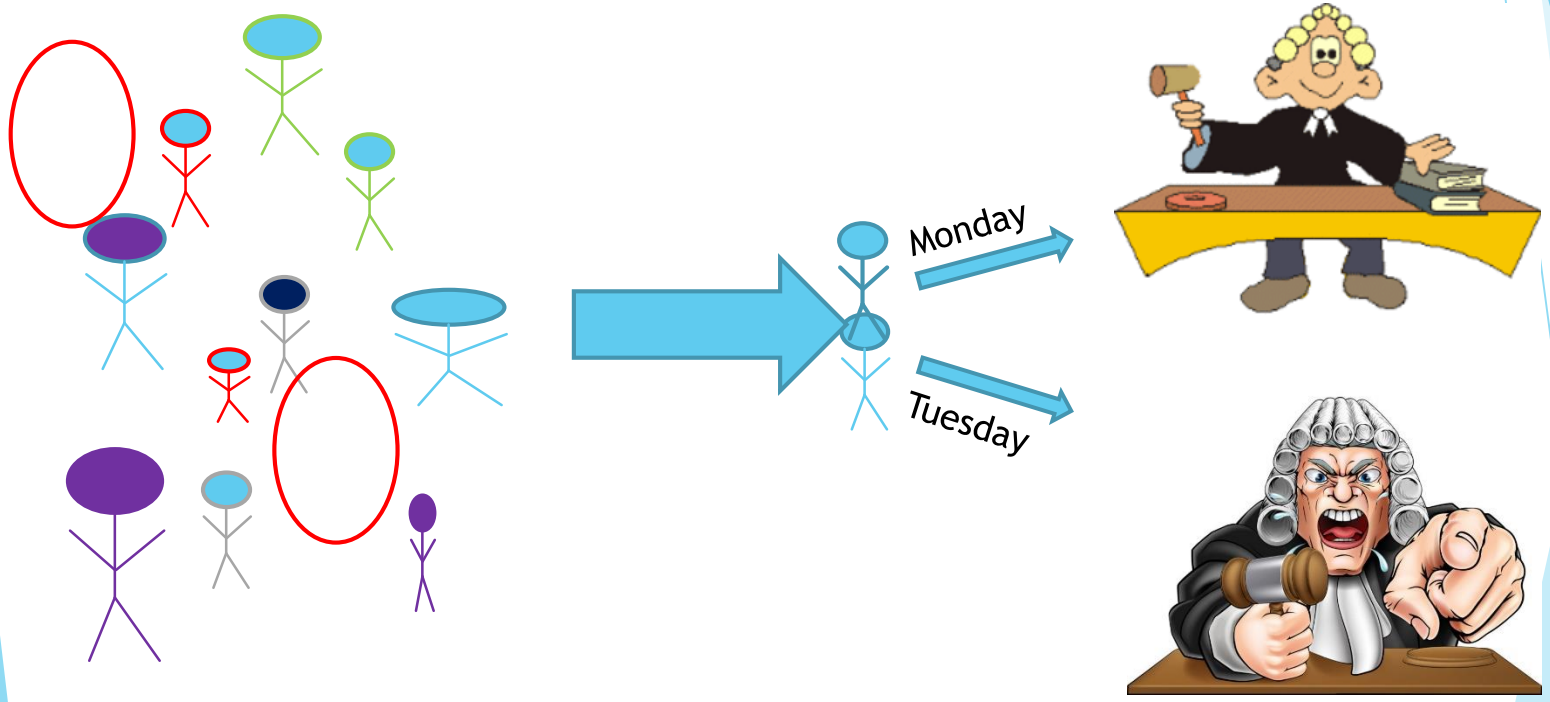

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- This is an improvement upon propensity score matching

enter:

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post matching

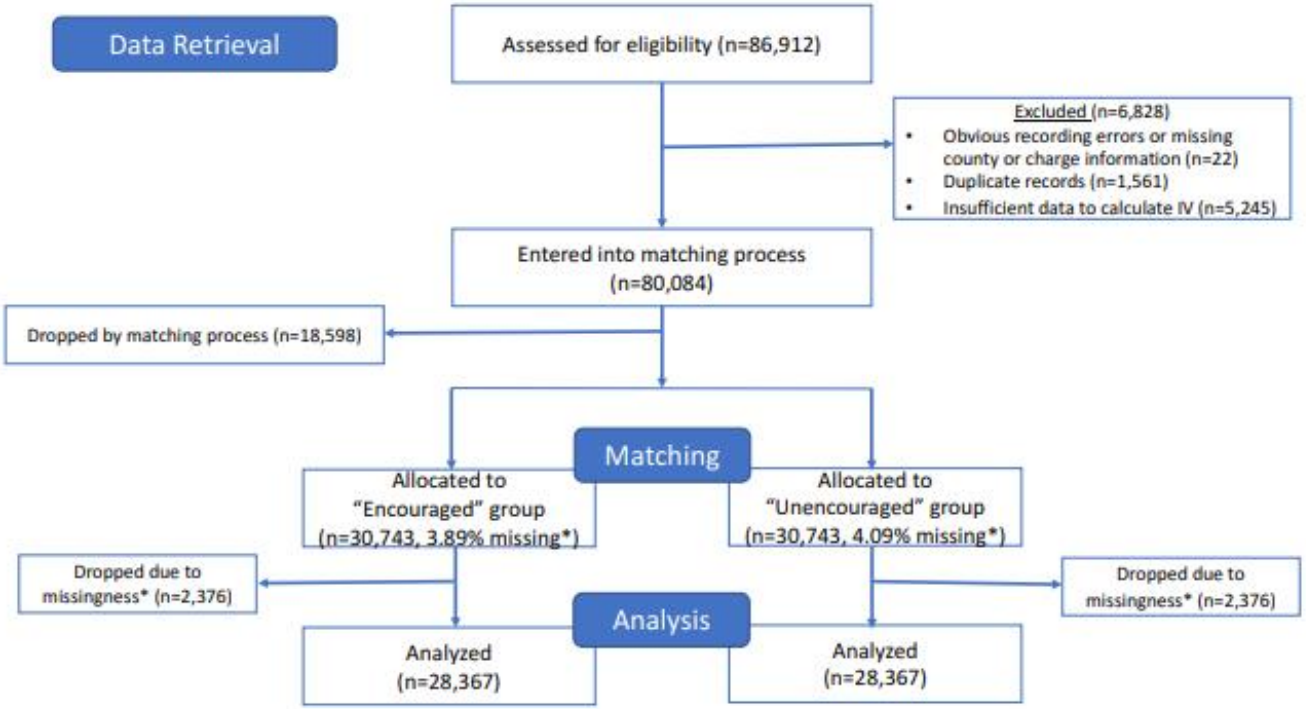

Figure 3: CONSORT flow diagram which shows the number of records dropped from the final analysis at each stage of the procedure.

pre-matching differences

	No Bail n=62826	Bail n=14057	Abs St Dif
Guilty	0.33	0.73	1.04
Bail Set	0.00	1.00	2.04
IV	0.01	-0.02	0.22
Age	31.93	35.94	0.32
White	0.29	0.28	0.02
Black	0.48	0.61	0.26
Non-Hispanic	0.63	0.66	0.08
Male	0.79	0.90	0.30
Prior Records 2014	0.38	1.36	0.70
Weekly Income	67.41	63.94	0.02
Any Income	0.15	0.14	0.02
Reported Employer	0.21	0.21	0.00
Reported Phone Number	0.18	0.19	0.04
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Table 3: Table of pre-match standardized differences.

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Table 3: Table of pre-match standardized differences.

post-matching

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	Strict n=28367	Lenient n=28367	Abs St Dif
Guilty	0.41	0.40	0.03
Bail Set	0.21	0.16	0.12
IV	-0.07	0.07	1.18
Age	32.69	32.71	0.00
White	0.28	0.28	0.00
Black	0.52	0.52	0.00
Non-Hispanic	0.65	0.65	0.00
Male	0.81	0.81	0.00
Prior Records 2014	0.54	0.53	0.00
Weekly Income	53.00	52.75	0.00
Any Income	0.12	0.12	0.00
Reported Employer	0.17	0.17	0.00
Reported Phone Number	0.15	0.15	0.00
Reported Address	0.91	0.91	0.00

Table 5: Table of post-match standardized differences. Summary of data analyzed.

a brief interlude

Kristian Lum decides to kick butt

Medium

Sign in

Kristian Lum Follow
Dec 13, 2017 · 7 min read

Statistics, we have a problem.

Recently, while browsing Twitter, I saw a few machine learning researchers post about an incident at one of their big conferences (NIPS) in which a band performing at the closing party made jokes about sexual assault. This is a band that is composed mostly of famous academics in machine learning and statistics. I was completely unsurprised to learn that a person involved in making the troubling comments is a well-respected academic who is widely known to behave inappropriately at conferences.

Google AI Researcher Accused of Sexual Harassment

By **Mark Bergen** and **Jeremy Kahn**
December 15, 2017, 4:03 PM PST

- Female statistician writes of harassment by two researchers
- Google is said to suspend Steven Scott after allegations

Sexual harassment accusations have hit another corner of the tech industry, with allegations involving prominent artificial intelligence researchers, including one at Google, a leader in the field.

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what happens next?

results and making a difference

results

results

Stratification	Stratum	Estimate	Lower	Upper	n	Signif
Aggregate	total	0.34	0.2	0.49	56734	*
County	New York	0.43	0.23	0.63	17010	*
	Kings	0.34	0.14	0.54	17936	*
	Bronx	-0.07	-0.52	0.33	7290	
	Queens	0.66	0.13	1.35	12174	*
	Richmond	0.88	0.11	2.89	2324	*
Crime Type	Felony	0.22	-0.12	0.58	8448	
	Misdemeanor	0.37	0.22	0.53	48286	*
Gender	Male	0.31	0.16	0.45	46118	*
	Female	0.65	0.12	1.27	10532	*

Table 6: Estimated causal impact of setting bail on judicial outcome

results

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Aggregate	total	0.34	0.2	0.49	56734	*
County	New York	0.43	0.23	0.63	17010	*
	Kings	0.34	0.14	0.54	17936	*
	Bronx	-0.07	-0.52	0.33	7290	
	Queens	0.66	0.13	1.35	12174	*
	Richmond	0.88	0.11	2.89	2324	*
Crime Type	Felony	0.22	-0.12	0.58	8448	
	Misdemeanor	0.37	0.22	0.53	48286	*
Gender	Male	0.31	0.16	0.45	46118	*
	Female	0.65	0.12	1.27	10532	*

Table 6: Estimated causal impact of setting bail on judicial outcome

If you had a 5% chance of “guilty” then bail would change that to 39%.

results

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- Marshall Project:

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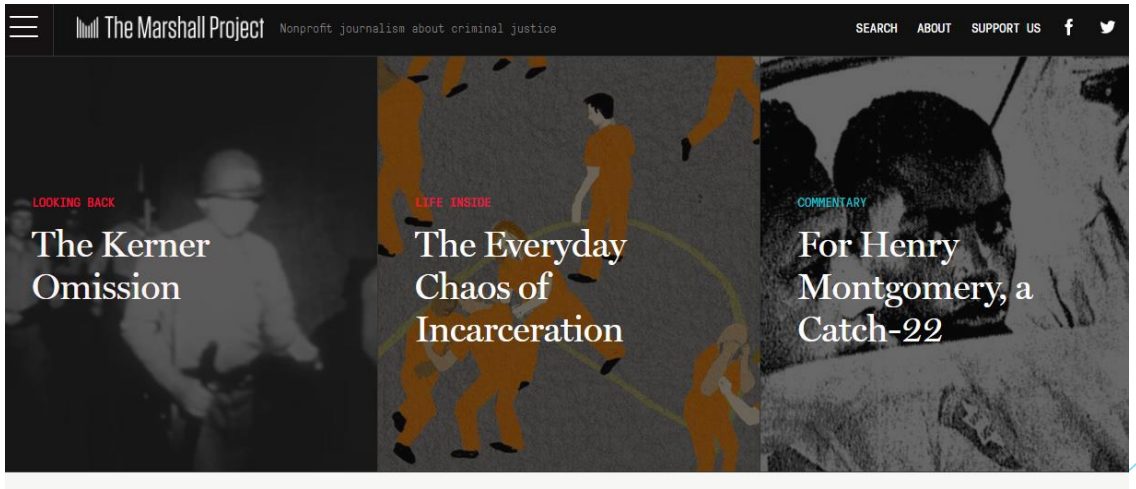

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- Because of our study design, we can look at individuals and compare them

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  - Finding out about their experiences in resolving the case

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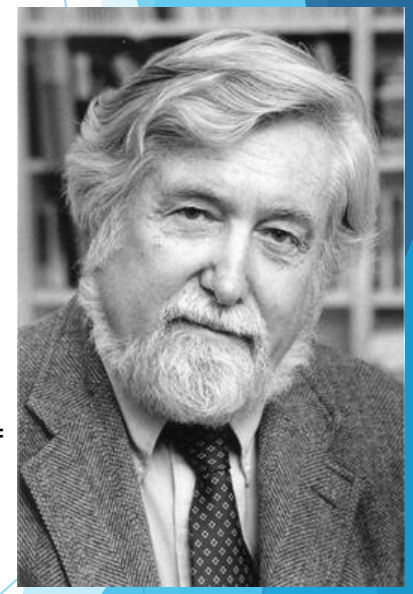
“thick description” =



Clifford Geertz

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  - Finding out about their experiences during pre-trial
  - Finding out about their experiences in resolving the case
- Marshall project will be putting out a special report

Did having bail set make you more likely to plead guilty?

Yes I believe so, because not being able to afford the bail money set, requires being remanded in county jail. Sitting in jail going back & forth to court with 2-3 months adjournments. After so many unjustified continuances time accumulating or frustrations wears out your resolve to fight for your freedom.

Did having bail set make you more likely to plead guilty?

At this point in my life No! Why? because this system has completed destroied my life, so really there's nothing left for them to take. We as a nation lock more people up for crime that have not even been committed and the blame is still on us.

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(212) 577-3509
jnorkin@legal-aid.org
www.legal-aid.org

MEMORANDUM OF SUPPORT

Comprehensive Bail Reform
A.09955 (Quart)

My bail was set at $25k, and I am a father of four, and only collect SSI disability. There is no way I could afford to take that money out of my kids mouth and still consider myself a decent man. - W.F., Legal Aid Client

Dear Legislator,

The Legal Aid Society supports A.09955 ("the Quart Bill"), and the New York State Assembly's efforts to reform our broken bail system. As you are well aware, Rikers Island and pretrial incarceration present an ongoing humanitarian crisis that requires urgent action.

In October 2017, Legal Aid released a ground-breaking report with the Human Rights Data Analysis Group and a Stanford University researcher on the impact that money bail has on our clients. The report definitively proved that New York's criminal justice system destroys the presumption of innocence. Specifically, the report found that "a strong causal relationship between setting bail and the outcome of a case for the [Legal Aid] clients. . . **setting bail results in a 34% increase in the chances that they will be found guilty.**" (Report found here: https://arxiv.org/pdf/1707.04666.pdf)

As part of this study, Legal Aid reached out to hundreds of our clients throughout New York to better understand how bail impacted their lives, their families, and their case. **Attached to this memorandum you will find 9 letters from Legal Aid clients detailing in vivid detail why the bail system must be reformed immediately.**

These stories are just one of many reasons why the Legal Aid Society strongly supports the Assembly's efforts to reform the system and the Quart Bill specifically. We remain opposed to the Governor's proposed bail legislation, which greatly expands the category of people eligible for remand, creates a presumption of detention, eliminates meaningful speedy trial release mechanisms, and permits courts to detain individuals for five days based on the mere request of the prosecutor—without any evidentiary showing or burden of proof.

Sincerely,

Justine Luongo
Attorney-in-Charge
Criminal Defense Practice
The Legal Aid Society

fin.