Advanced Statistical Methods for Observational Studies

LECTURE 07

class management

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- Questions?

regression discontinuity

RD designs

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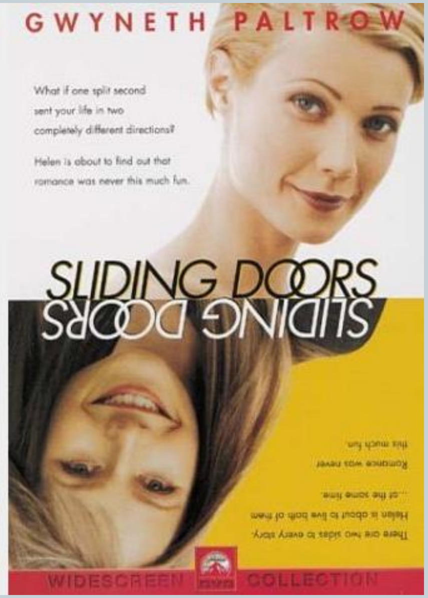

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- Research question: How much benefit does the student receive from being given support for college?
- The naïve comparison is horrid: Those who work to get the NMS are outstanding and those who don't get it are a mixed bag.
- But there are millions of students who take the PSAT every year, maybe we can find a subgroup.

RD design: National Merit Scholarship

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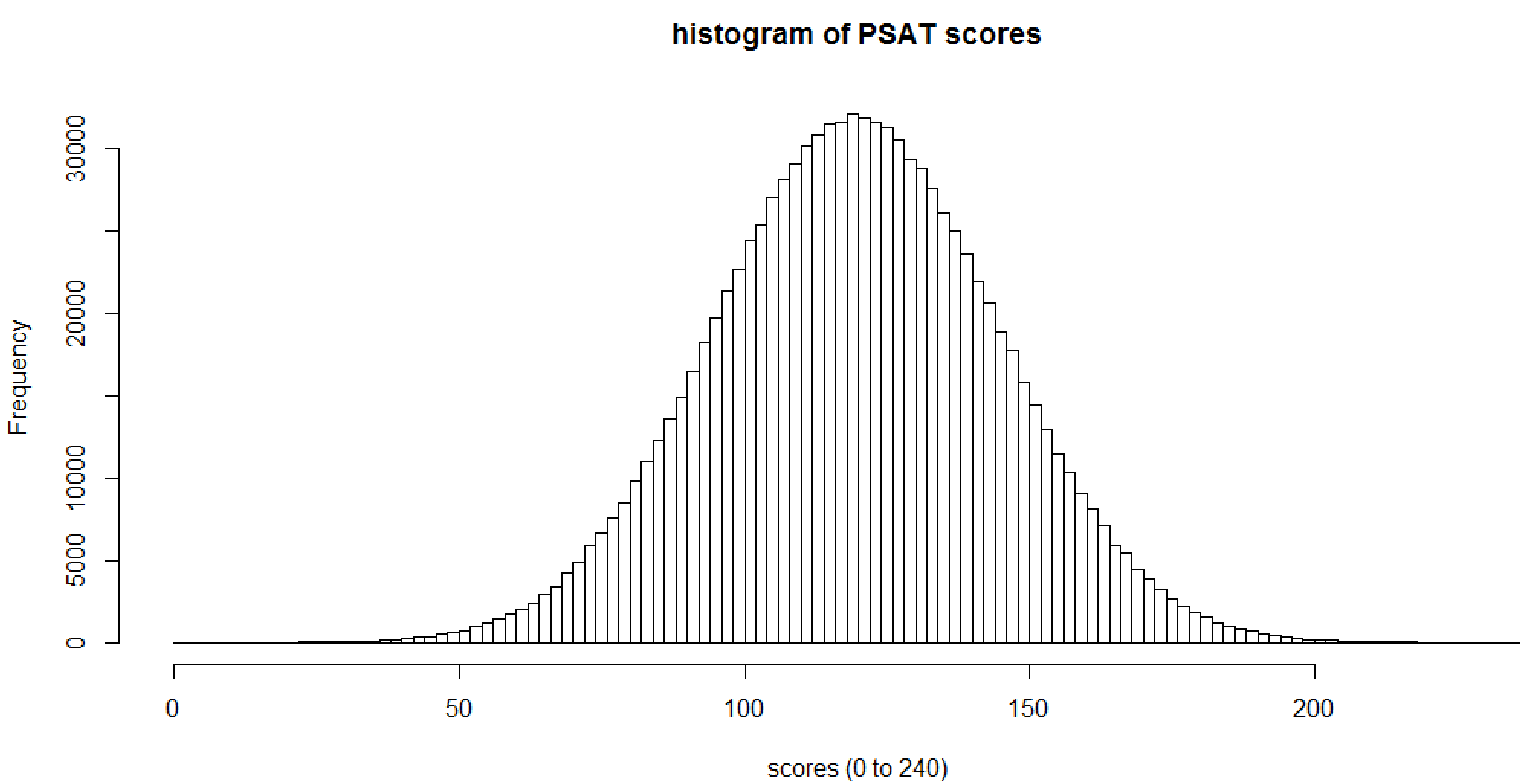

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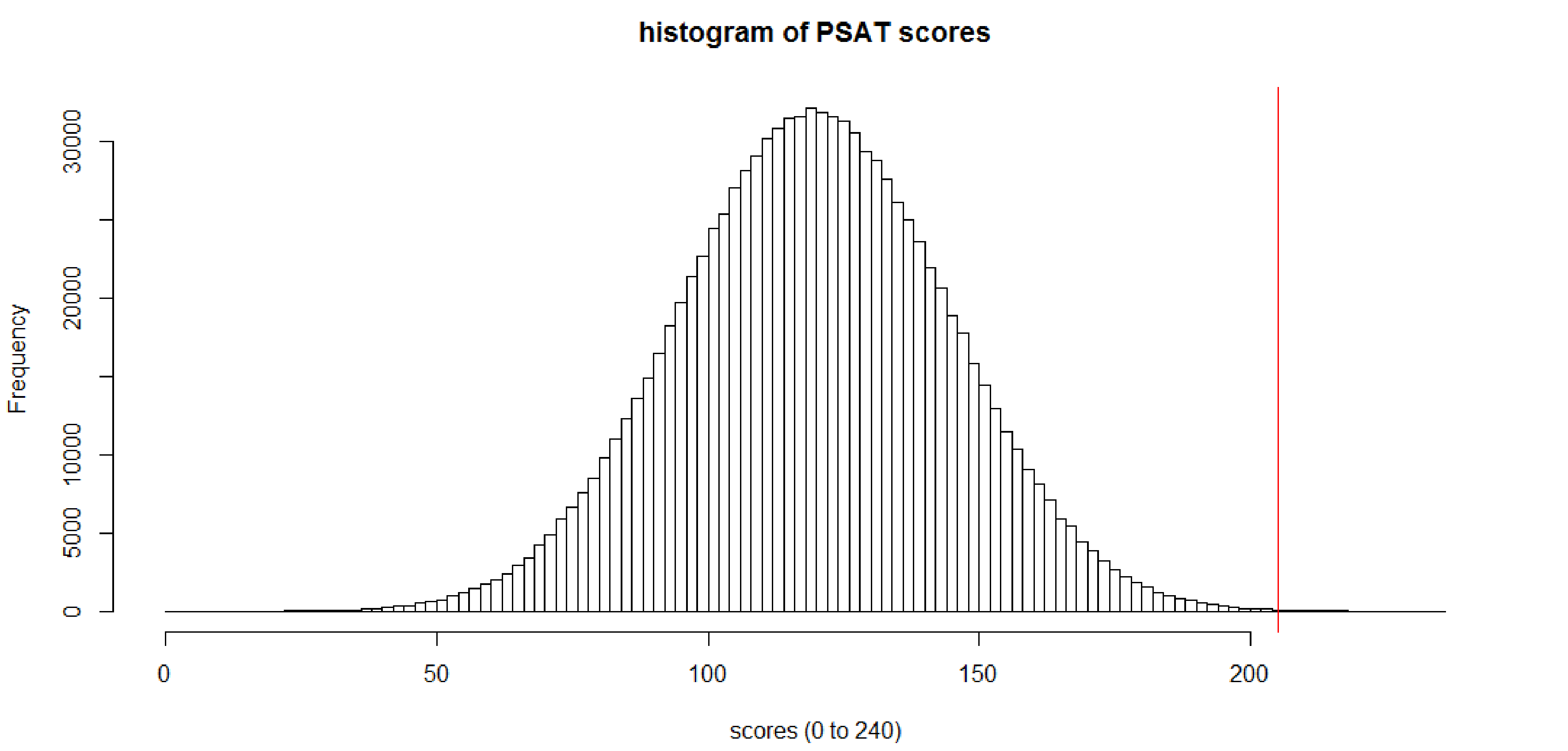

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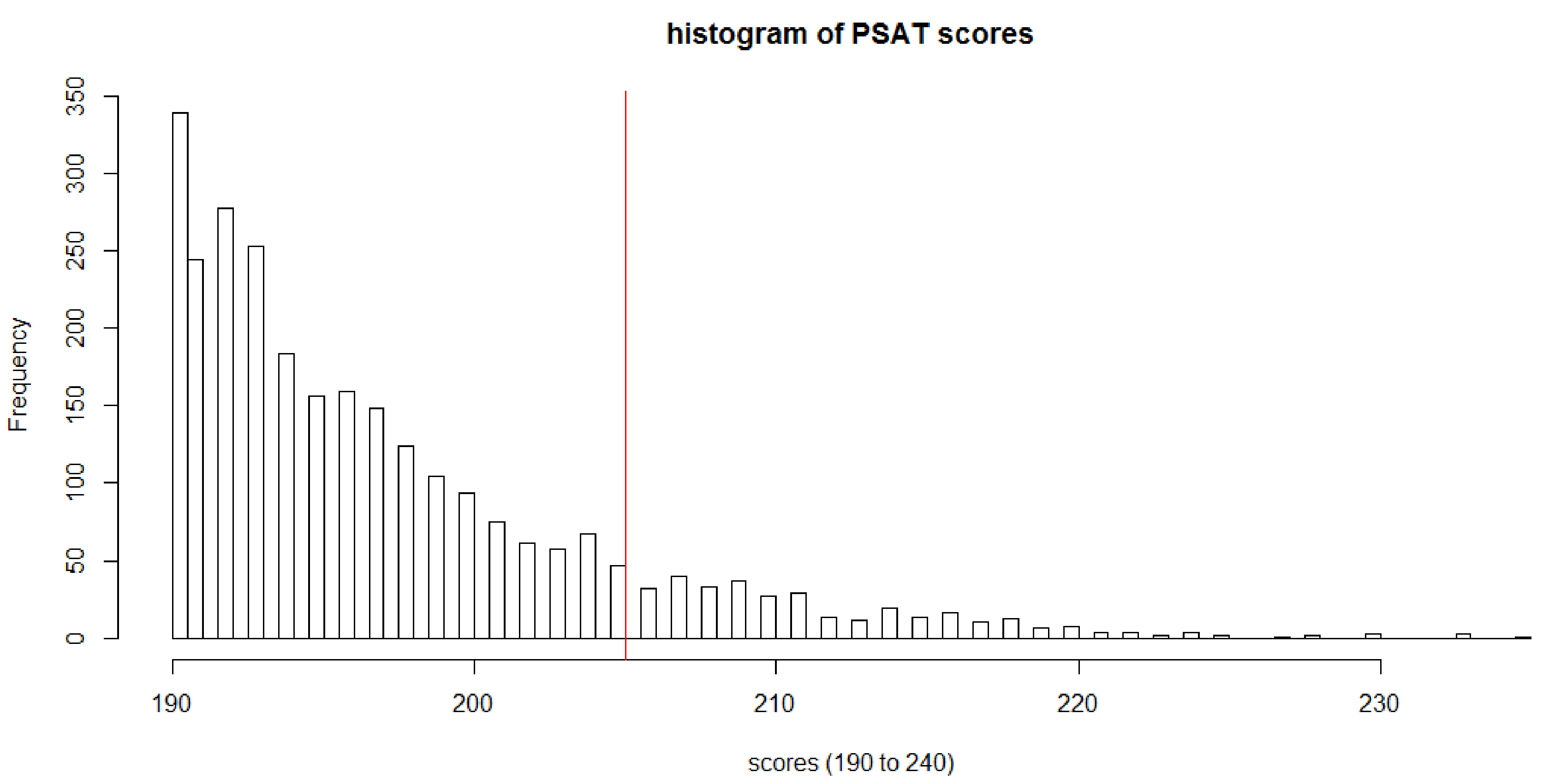

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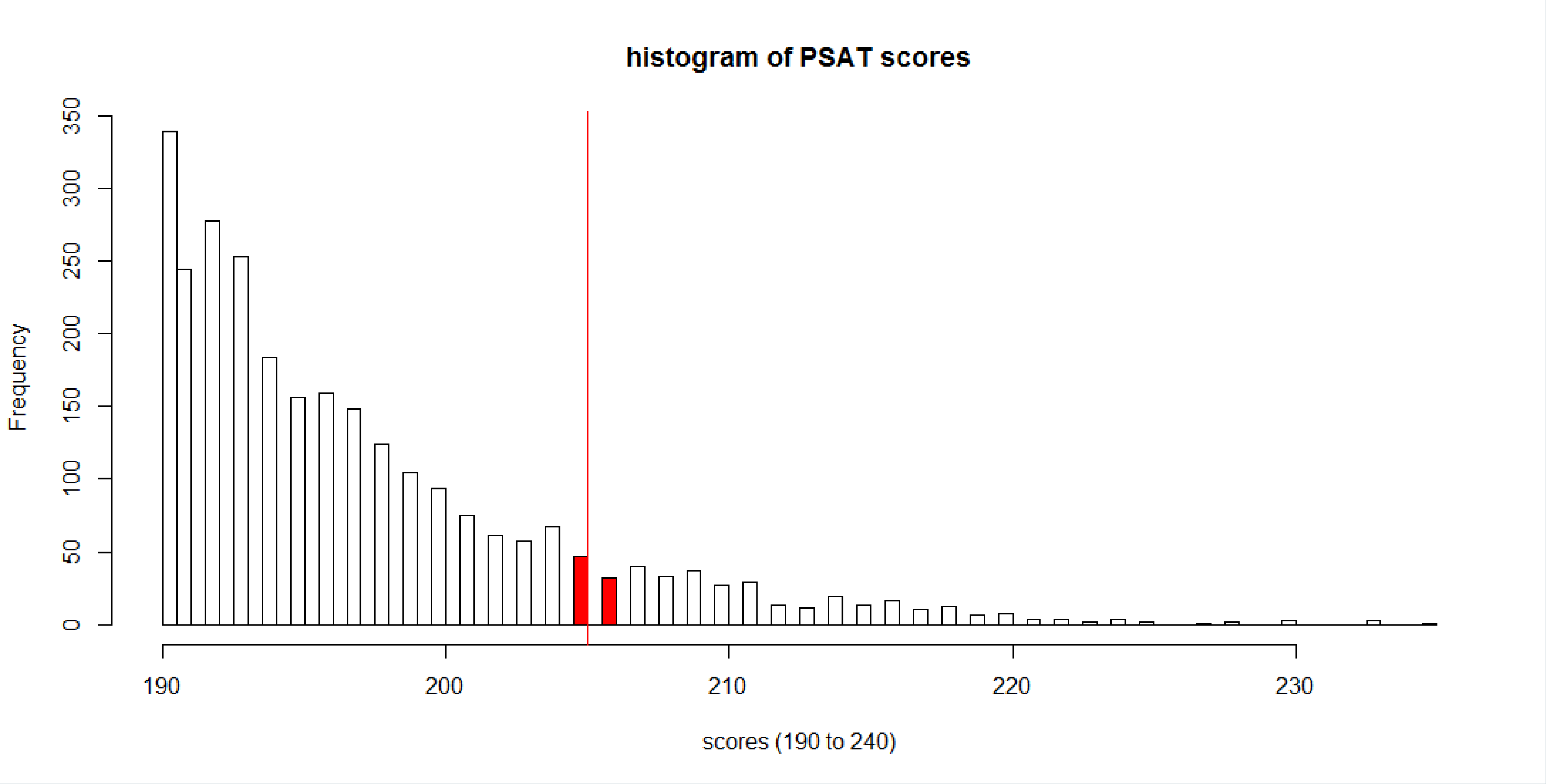

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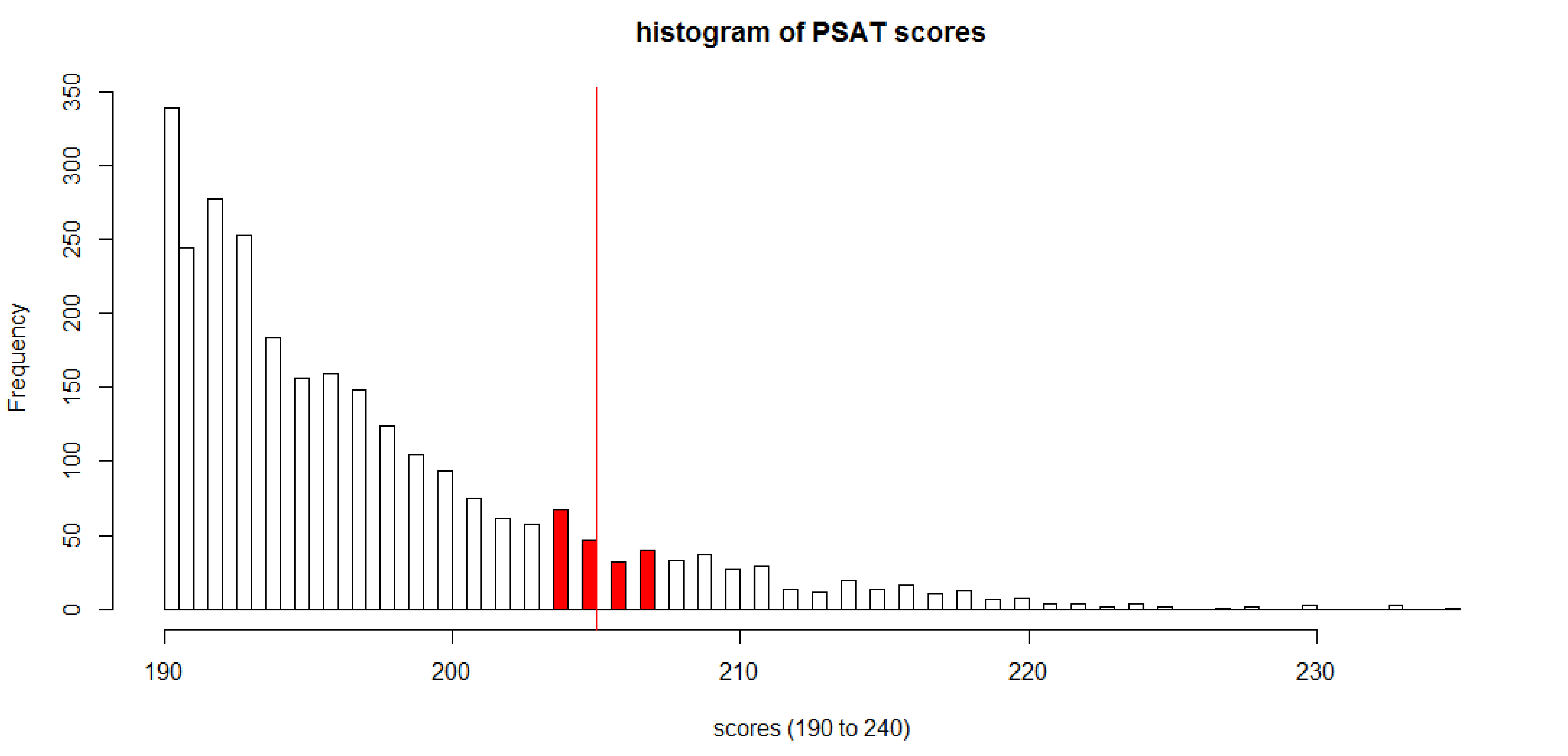

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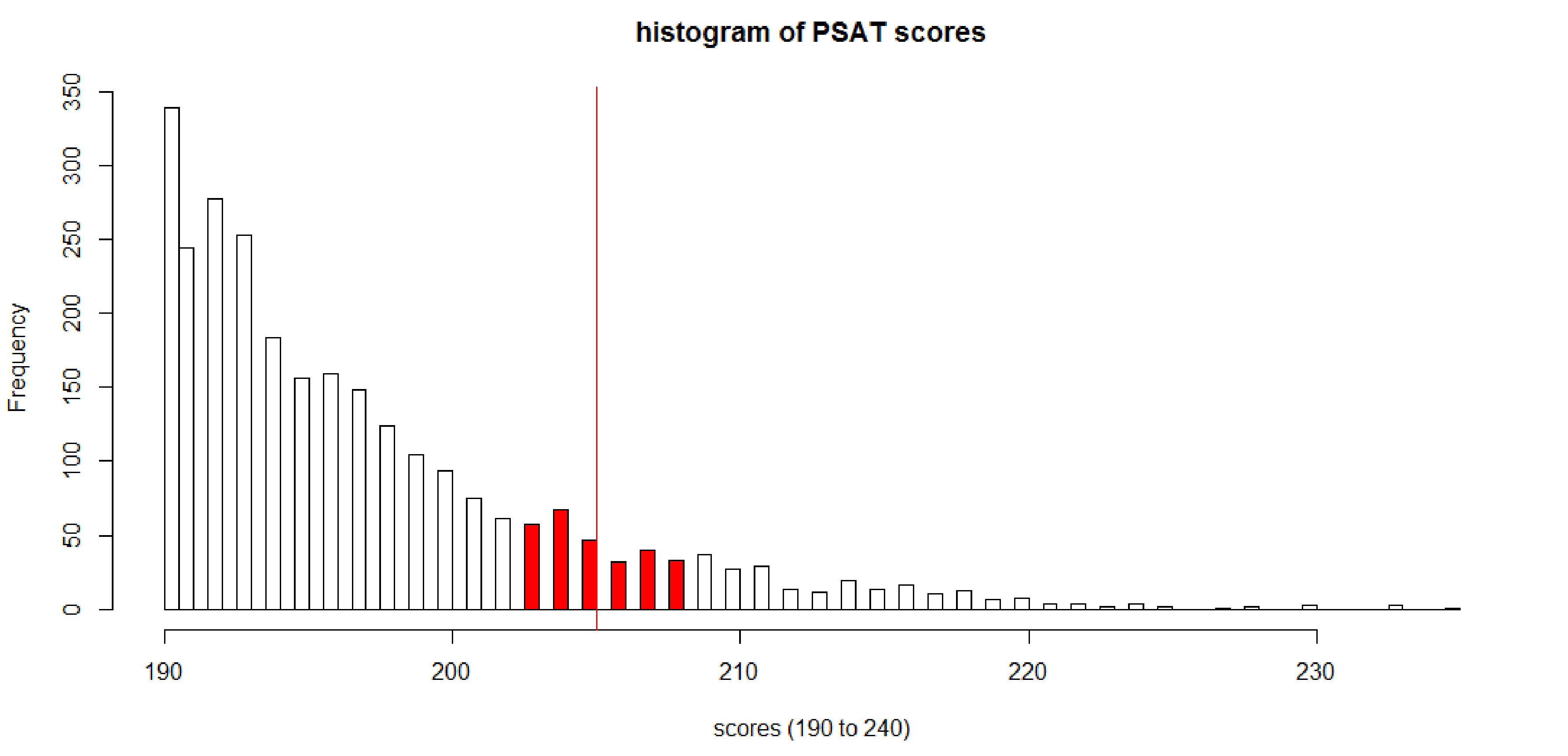

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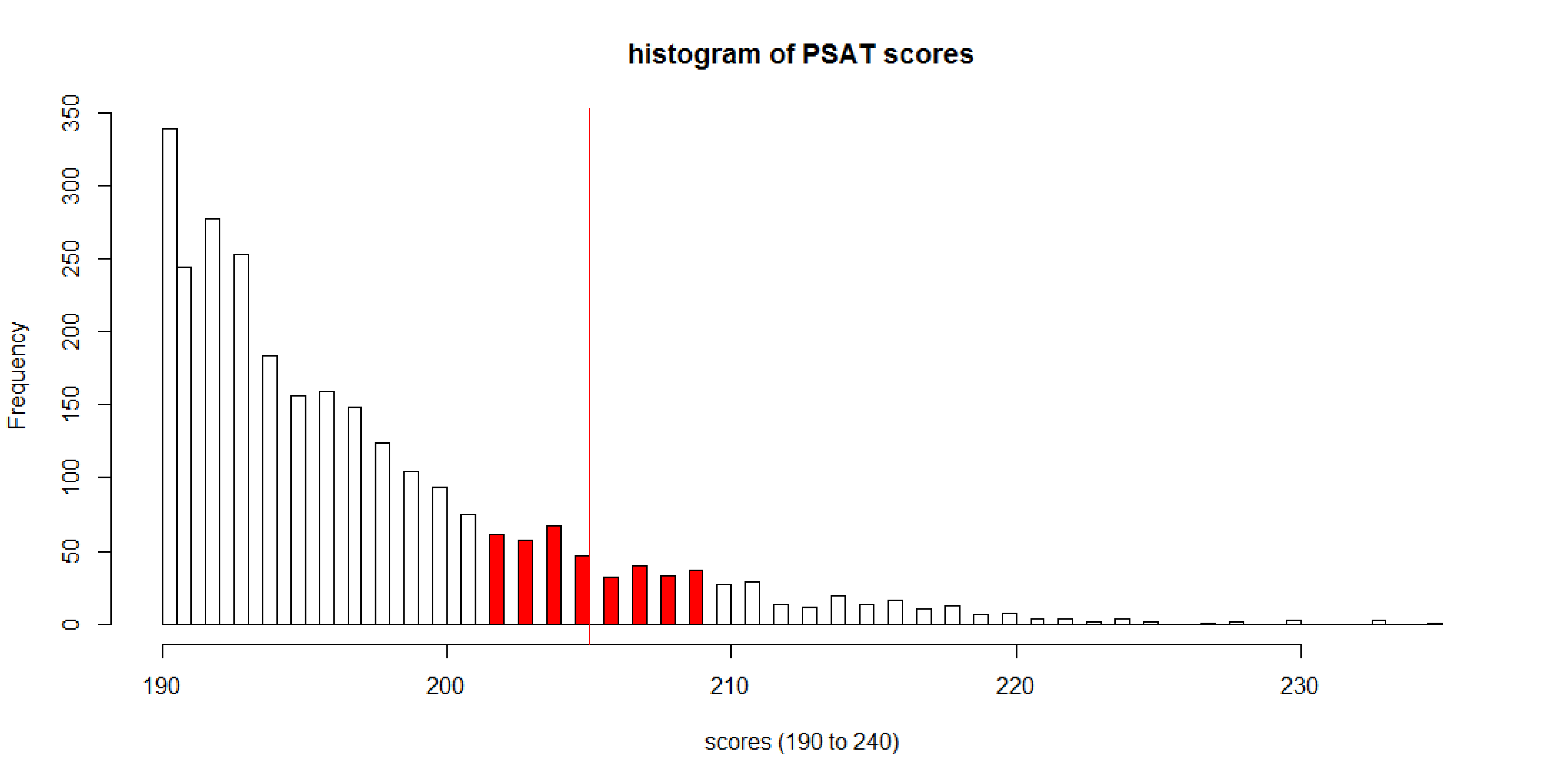

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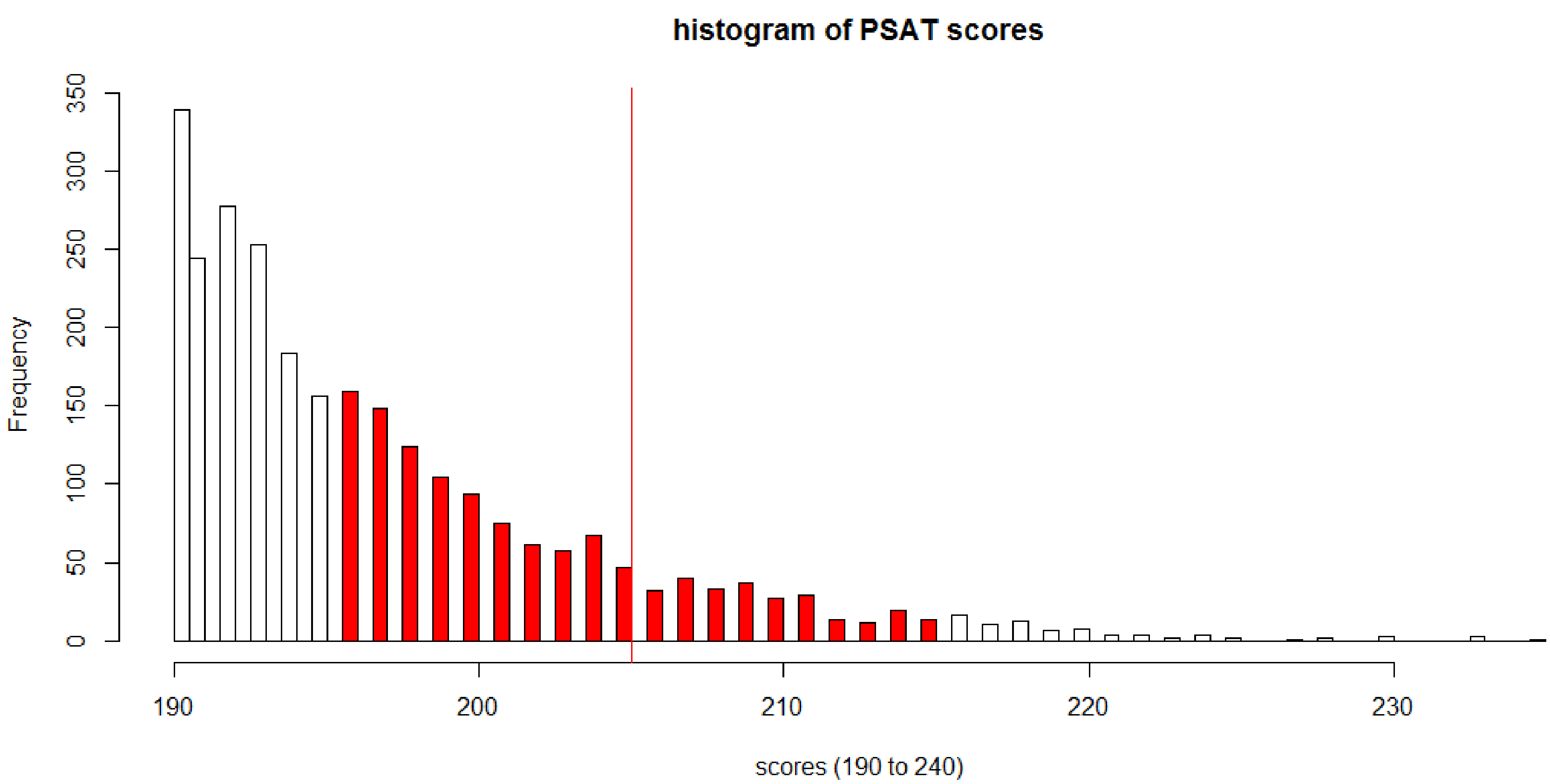

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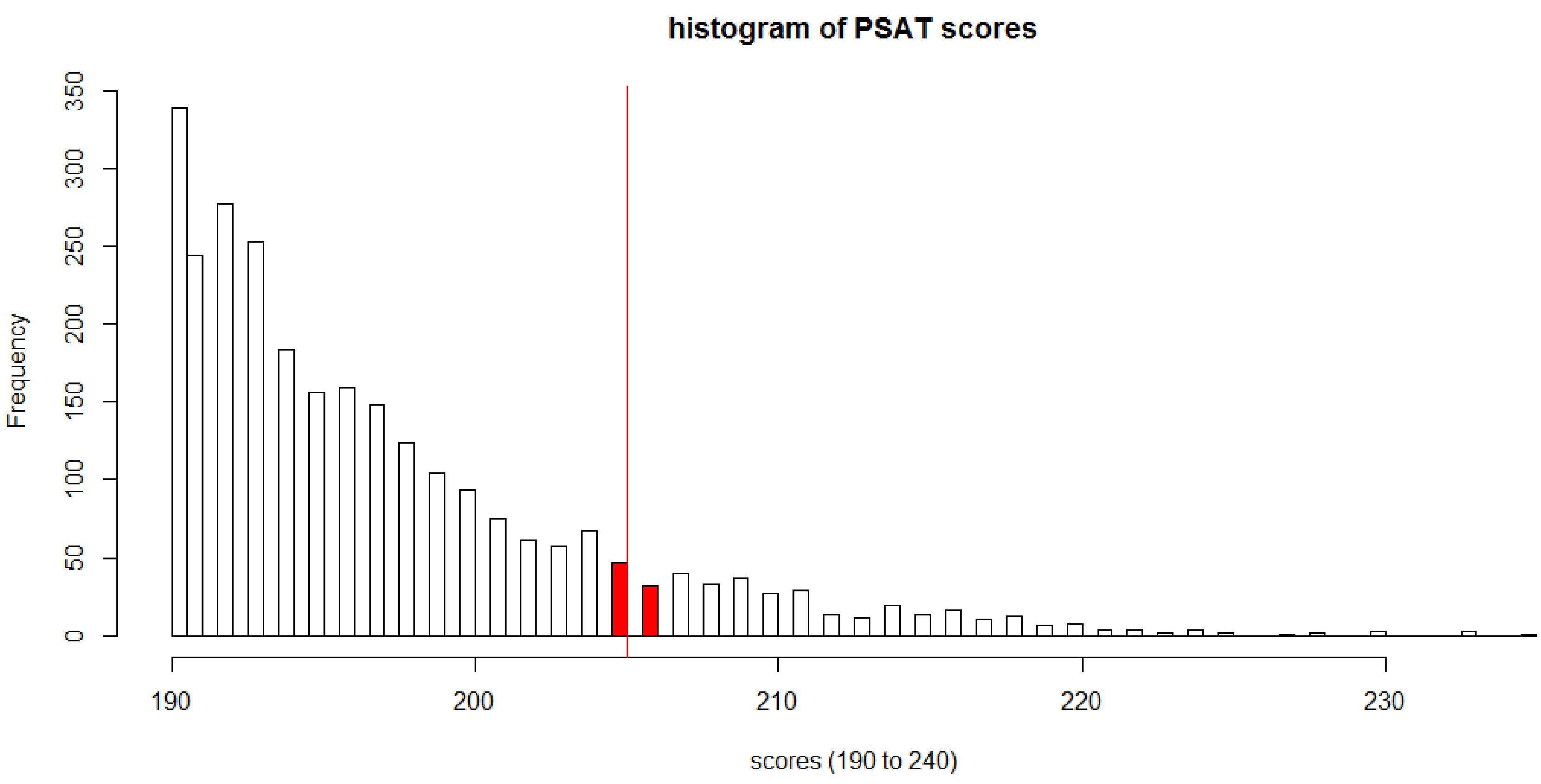

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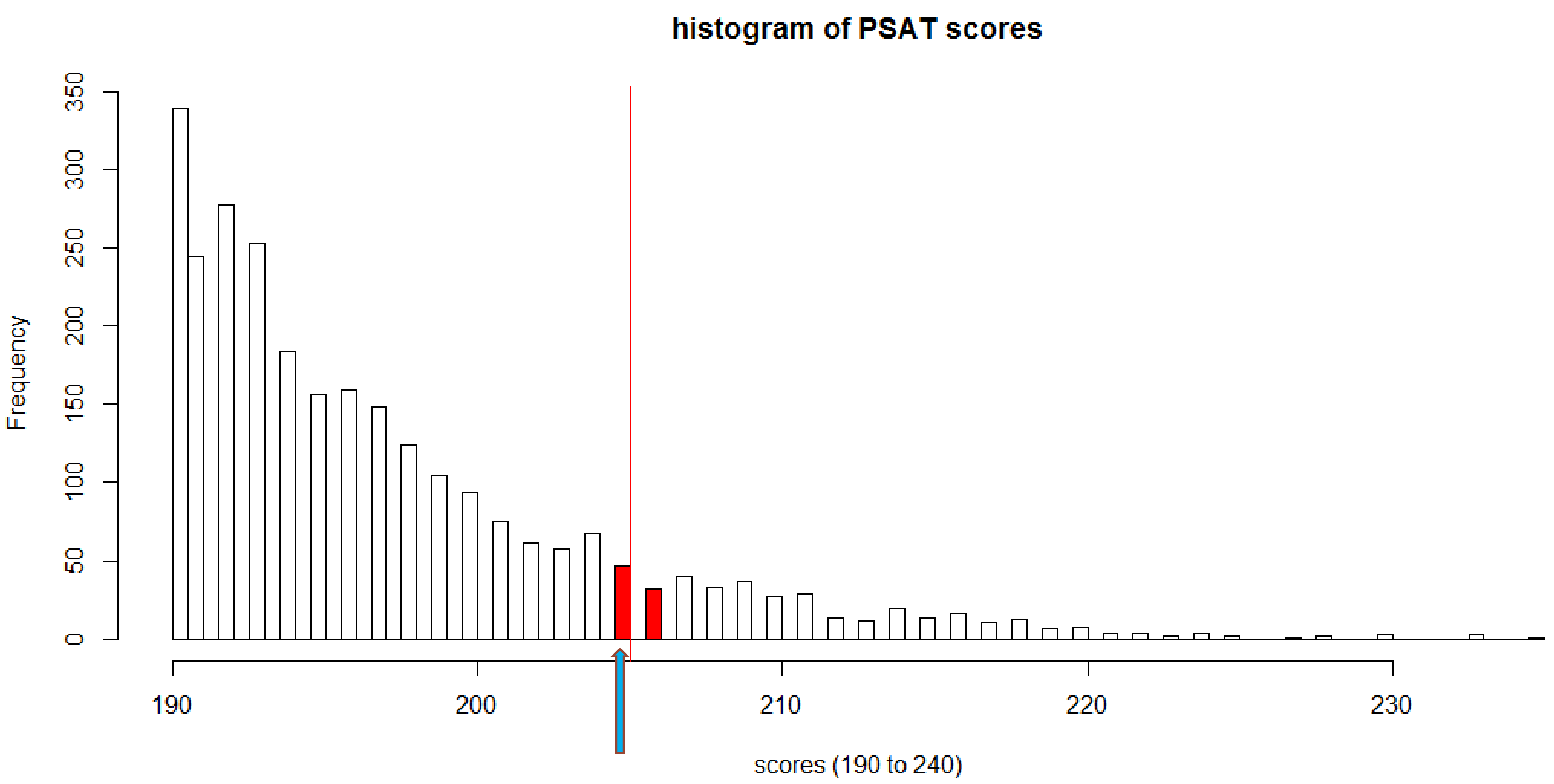

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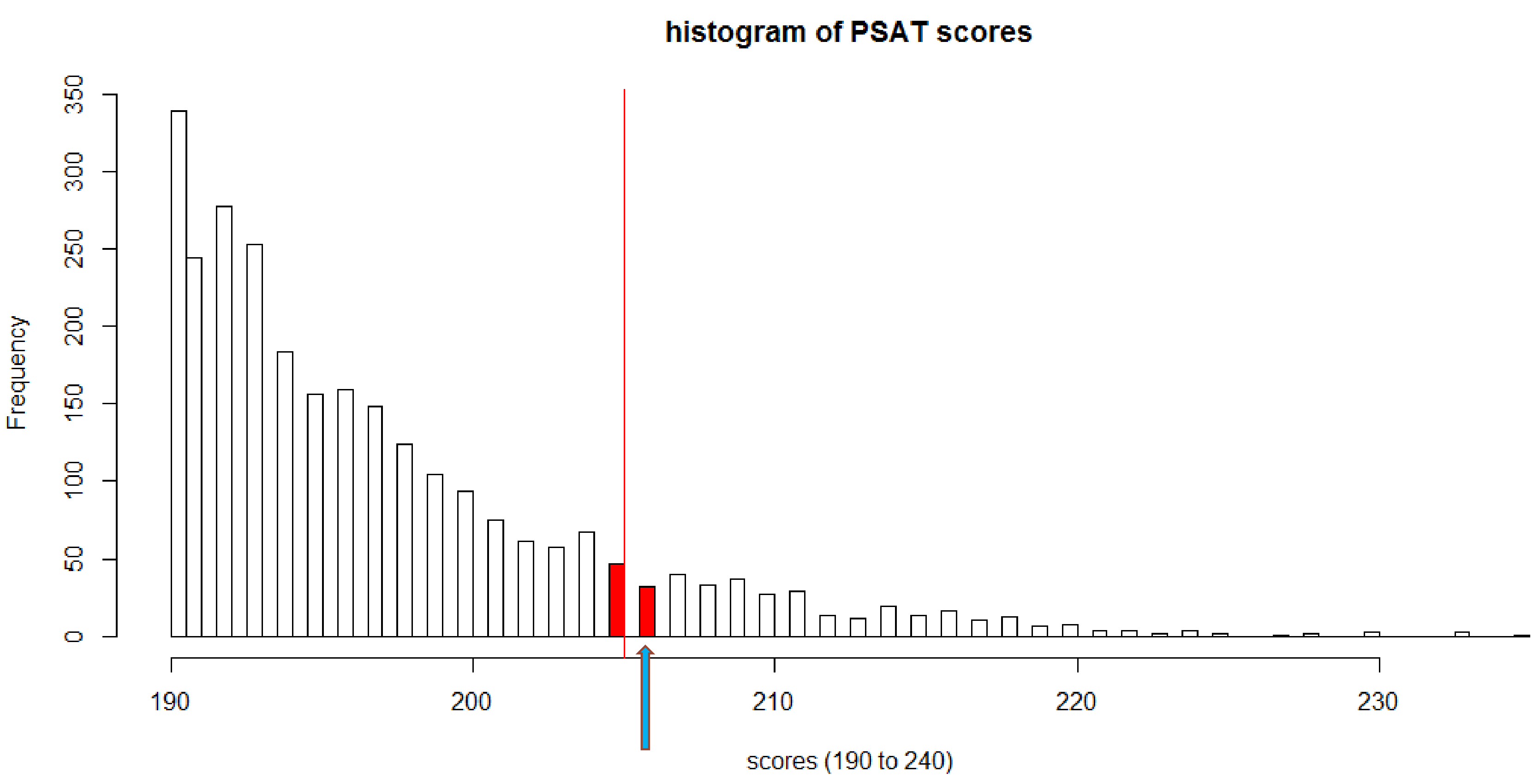

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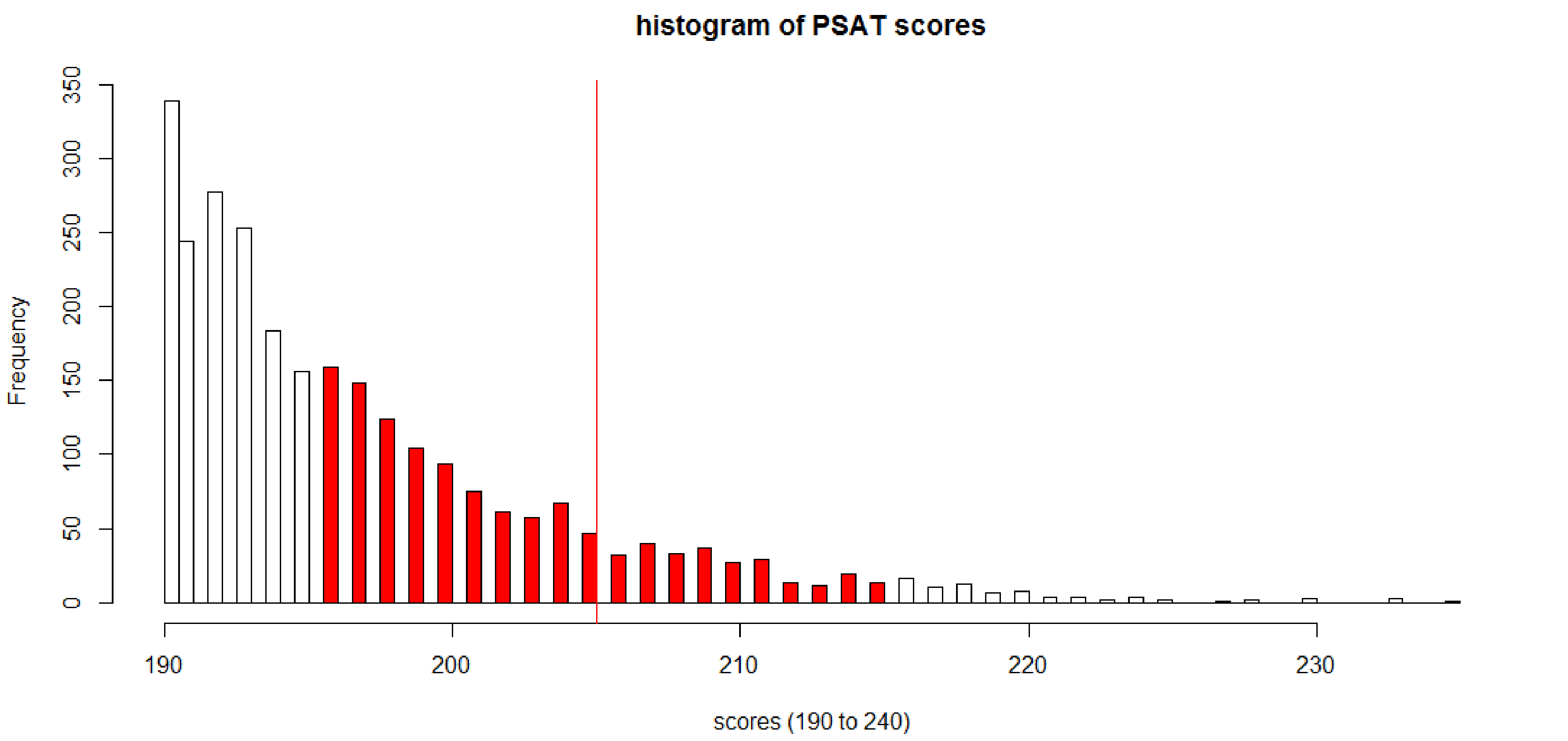

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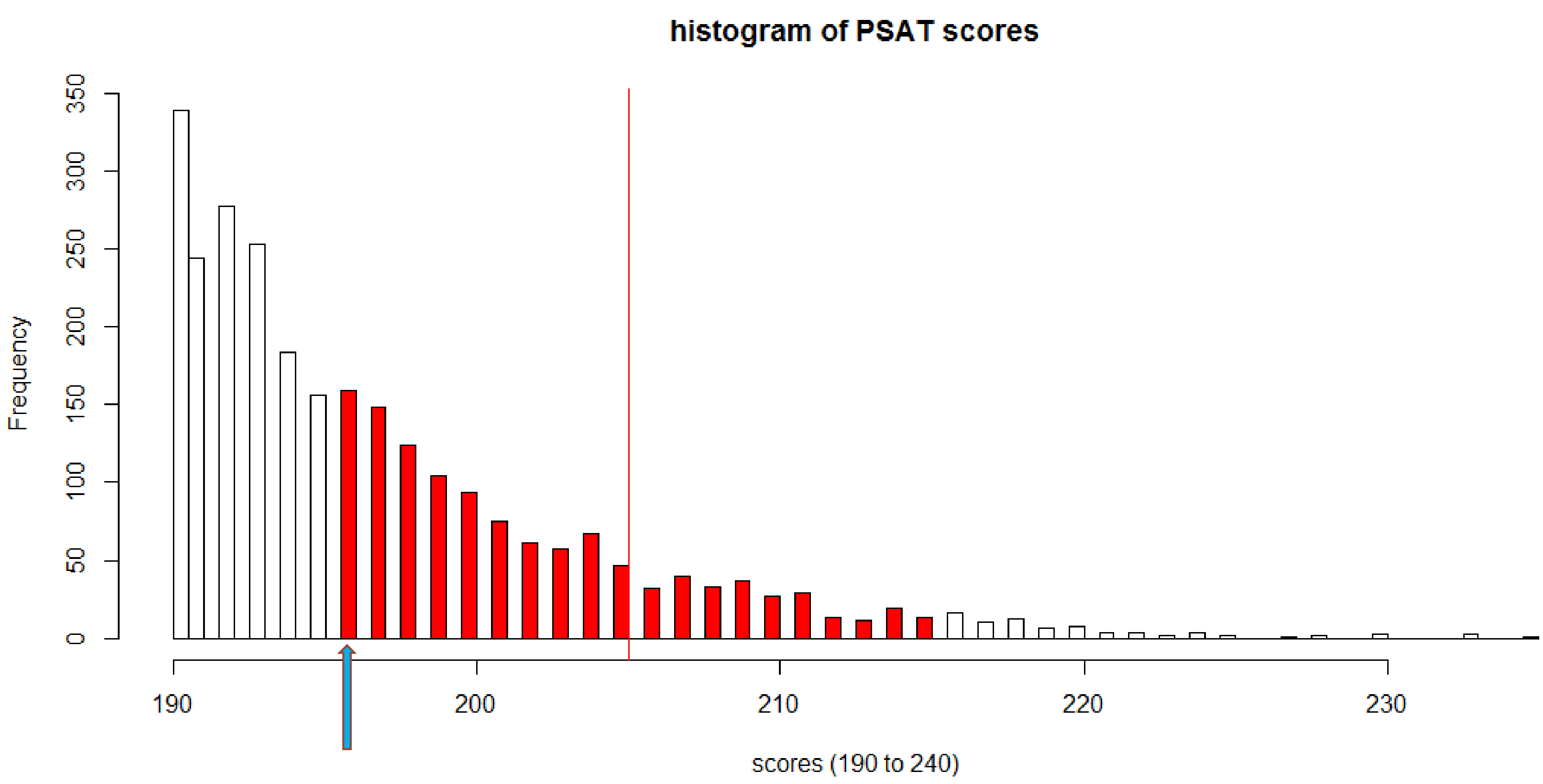

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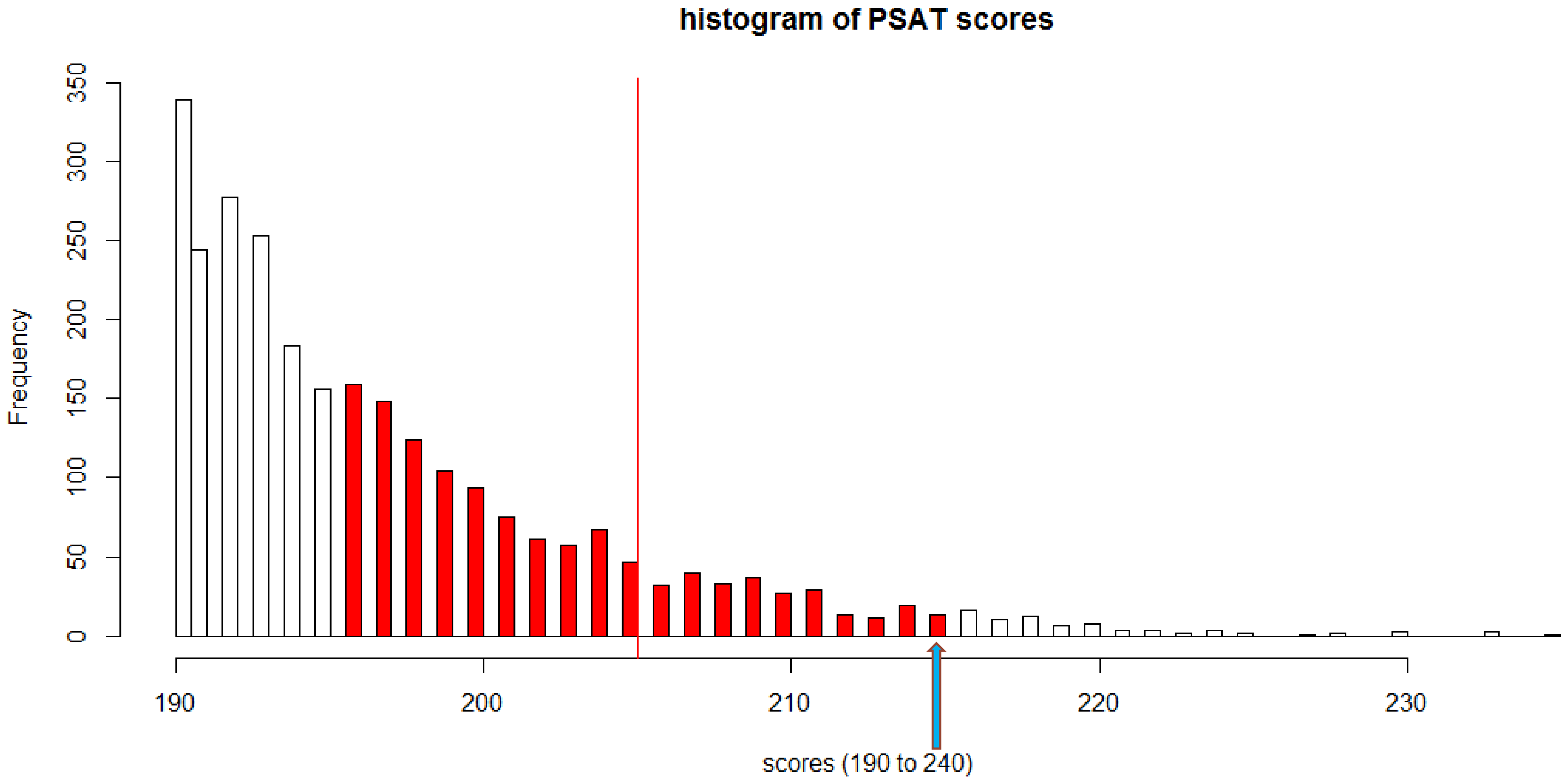

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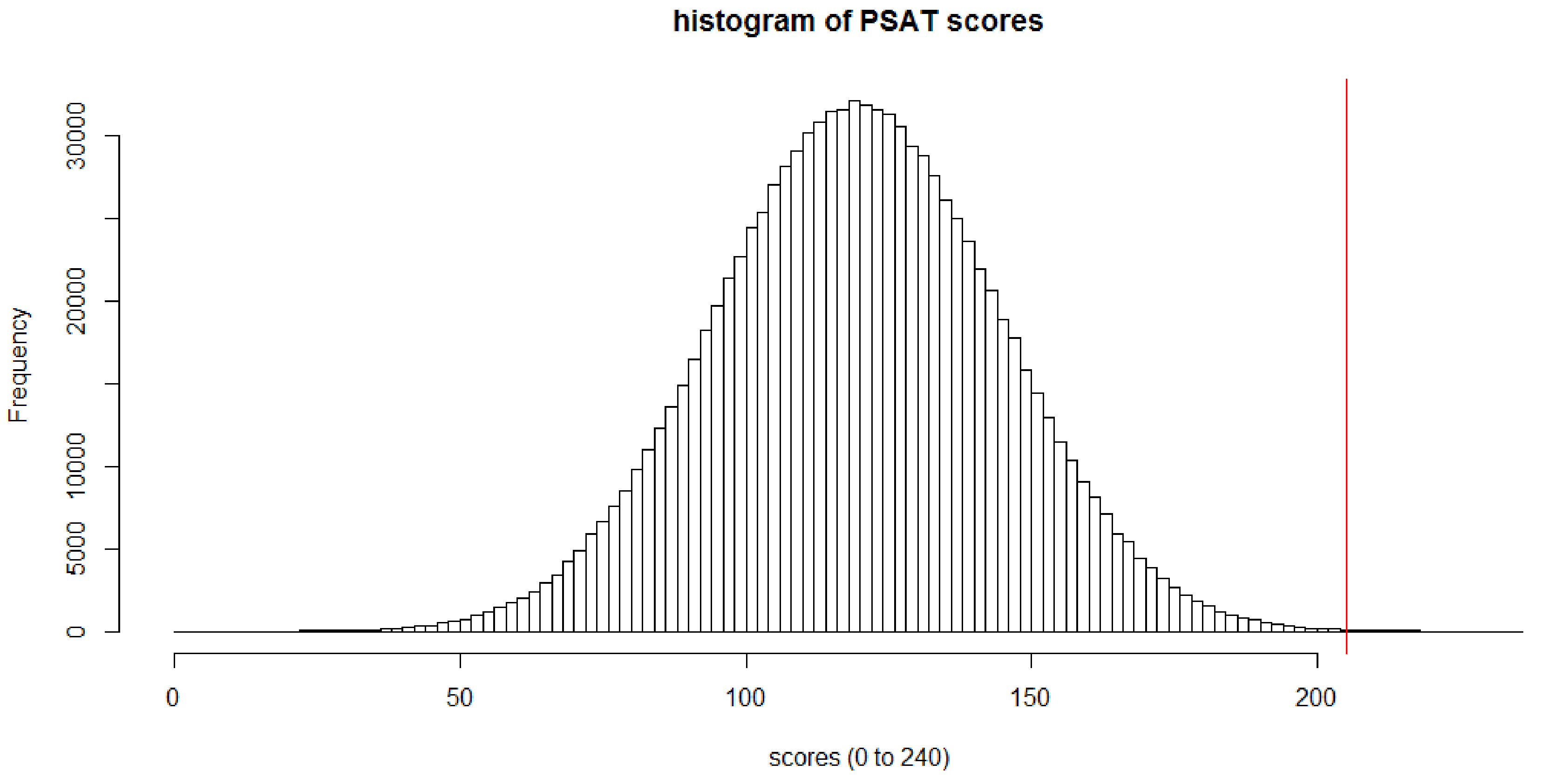

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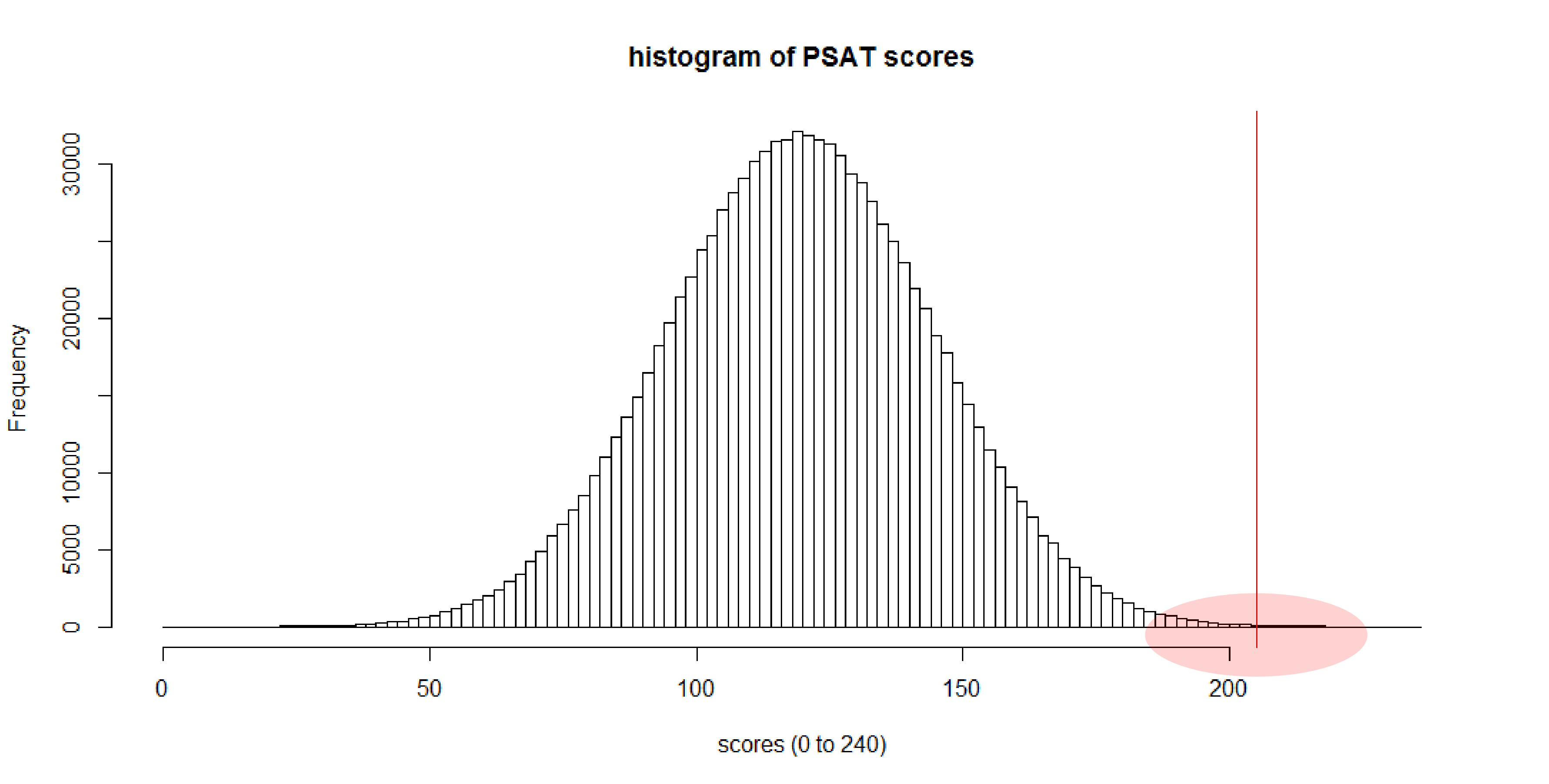

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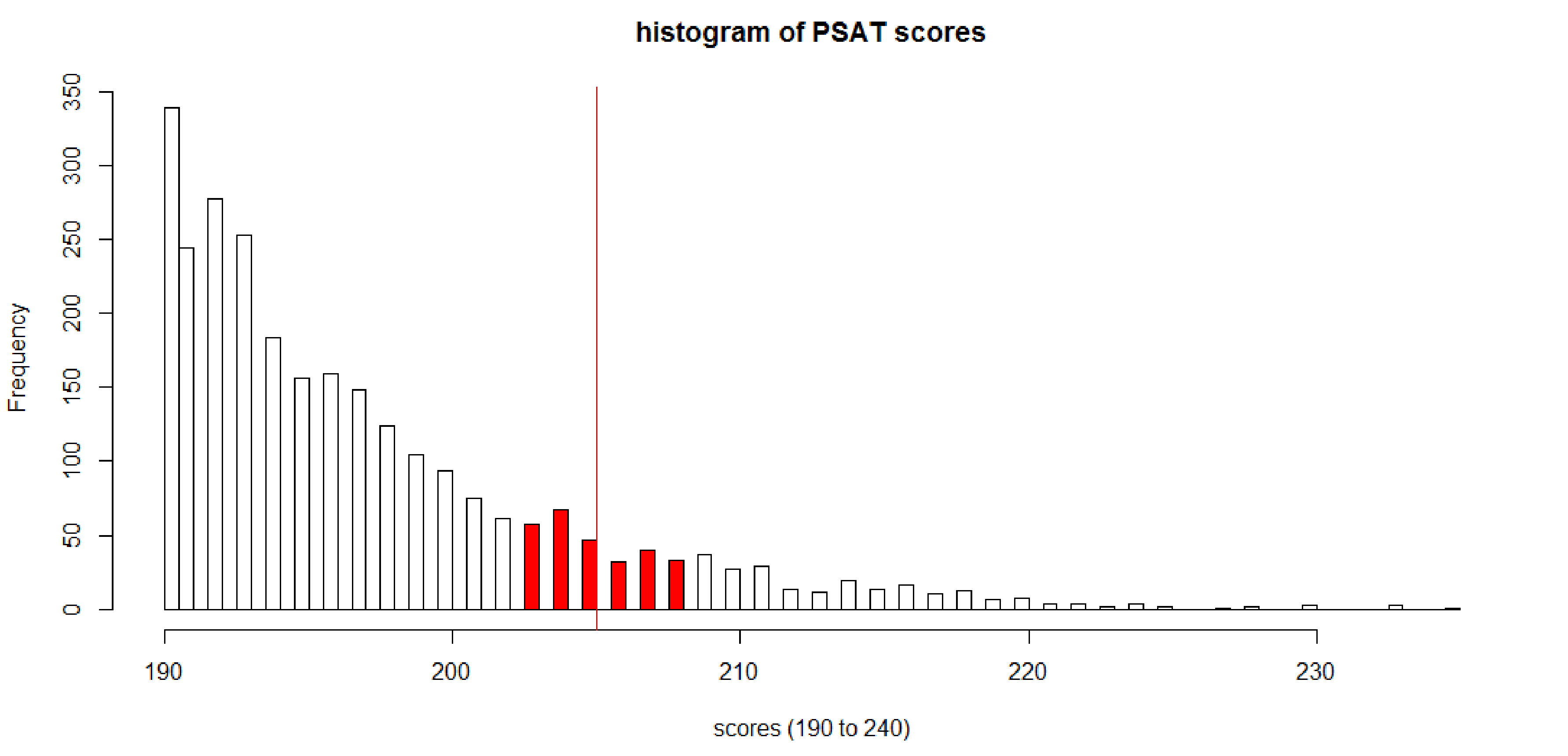

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- Many economists will use some kind of SEM:

$$y_{i,j} = \theta_i + \beta * d_j + \varepsilon_{i,j}$$

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P(scholarship)

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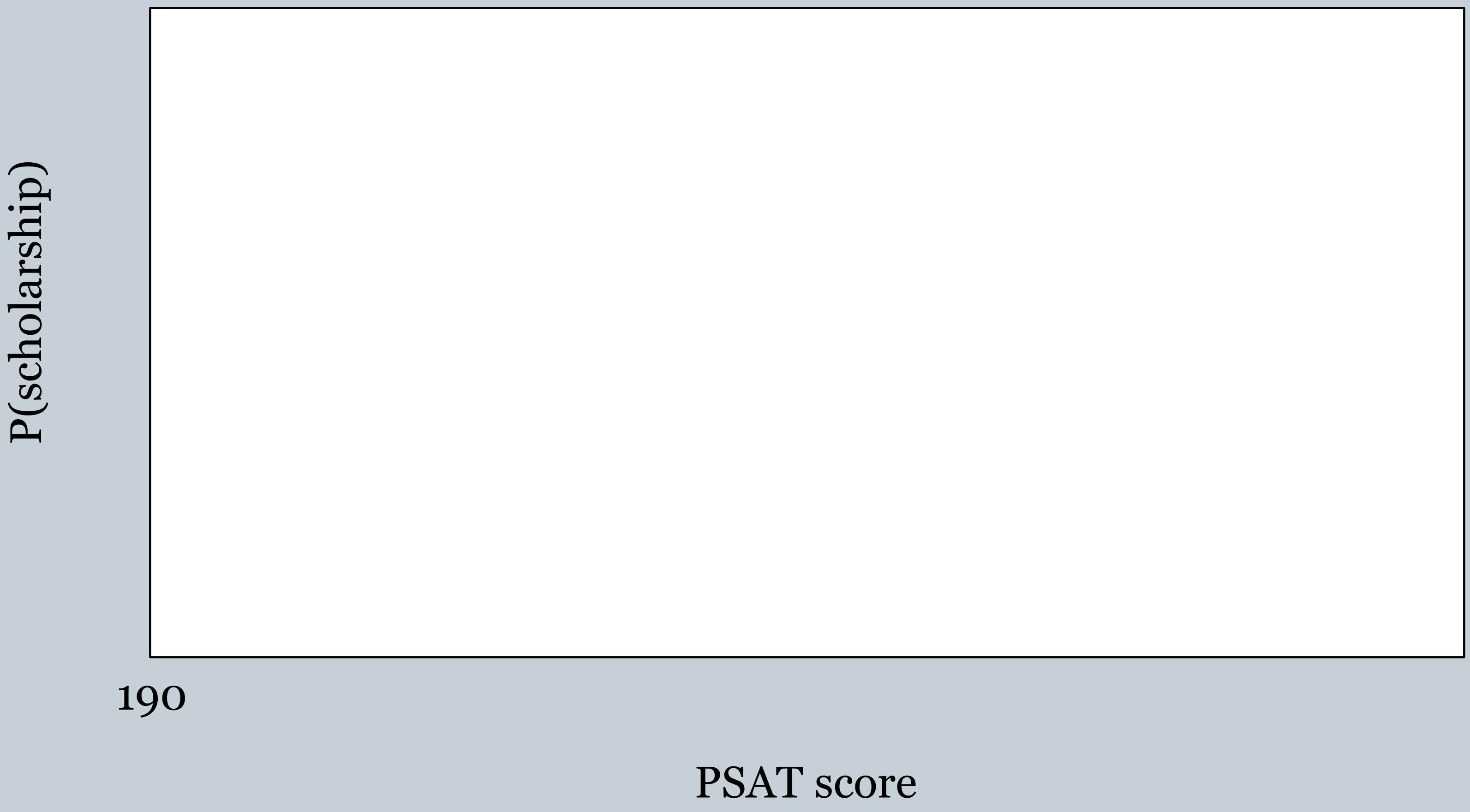
P(scholarship)

PSAT score

RD designs



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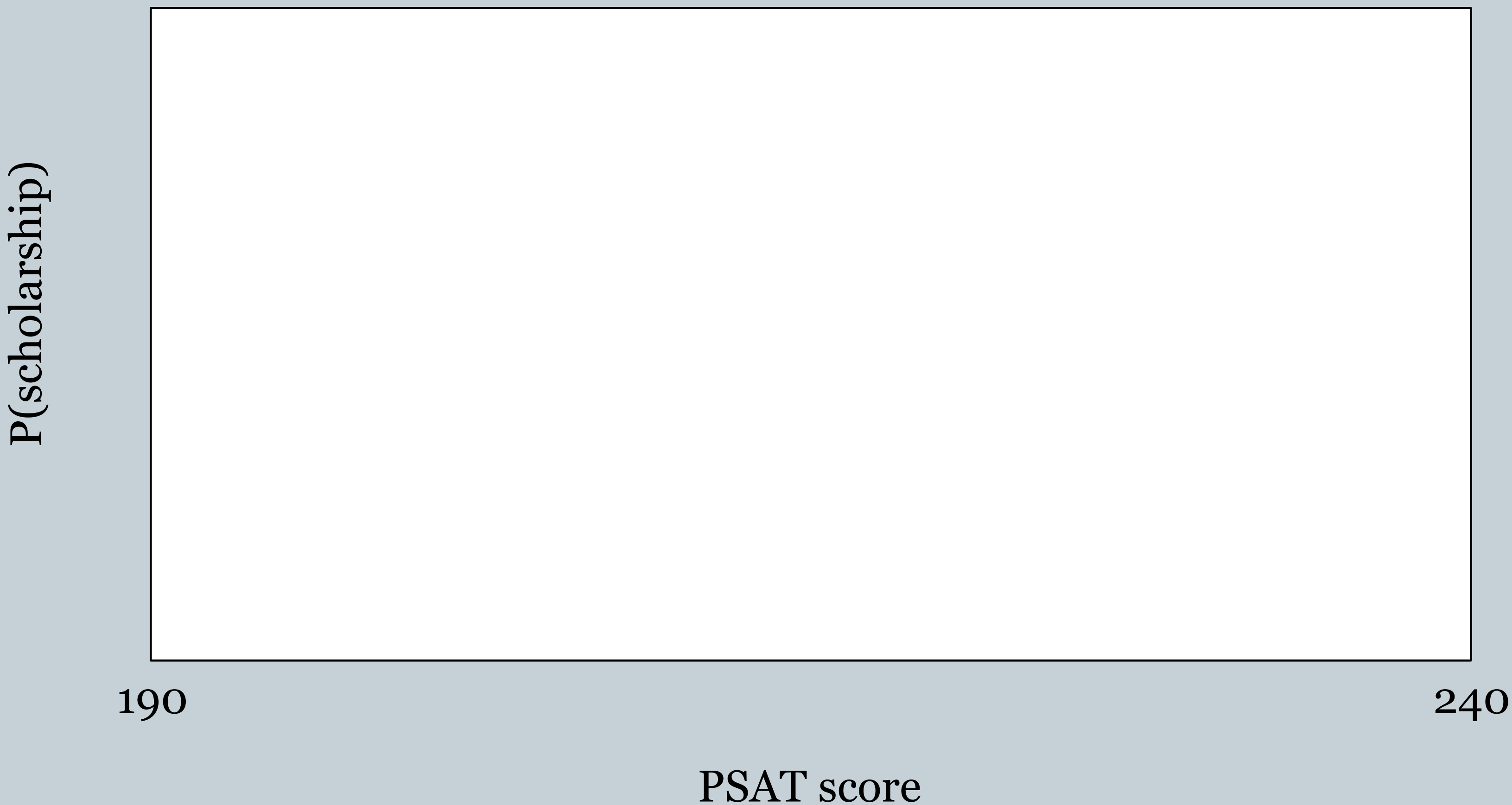

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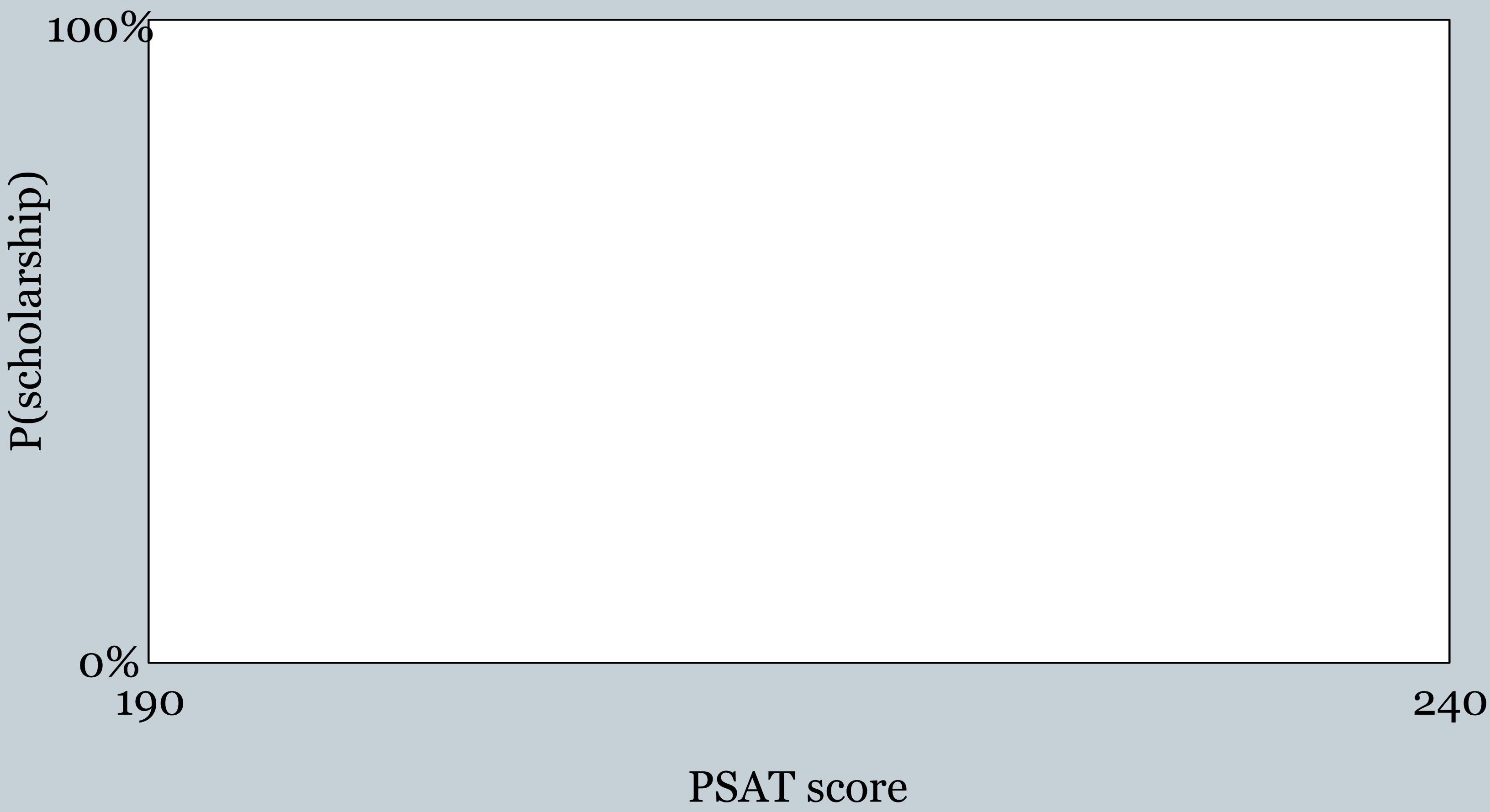

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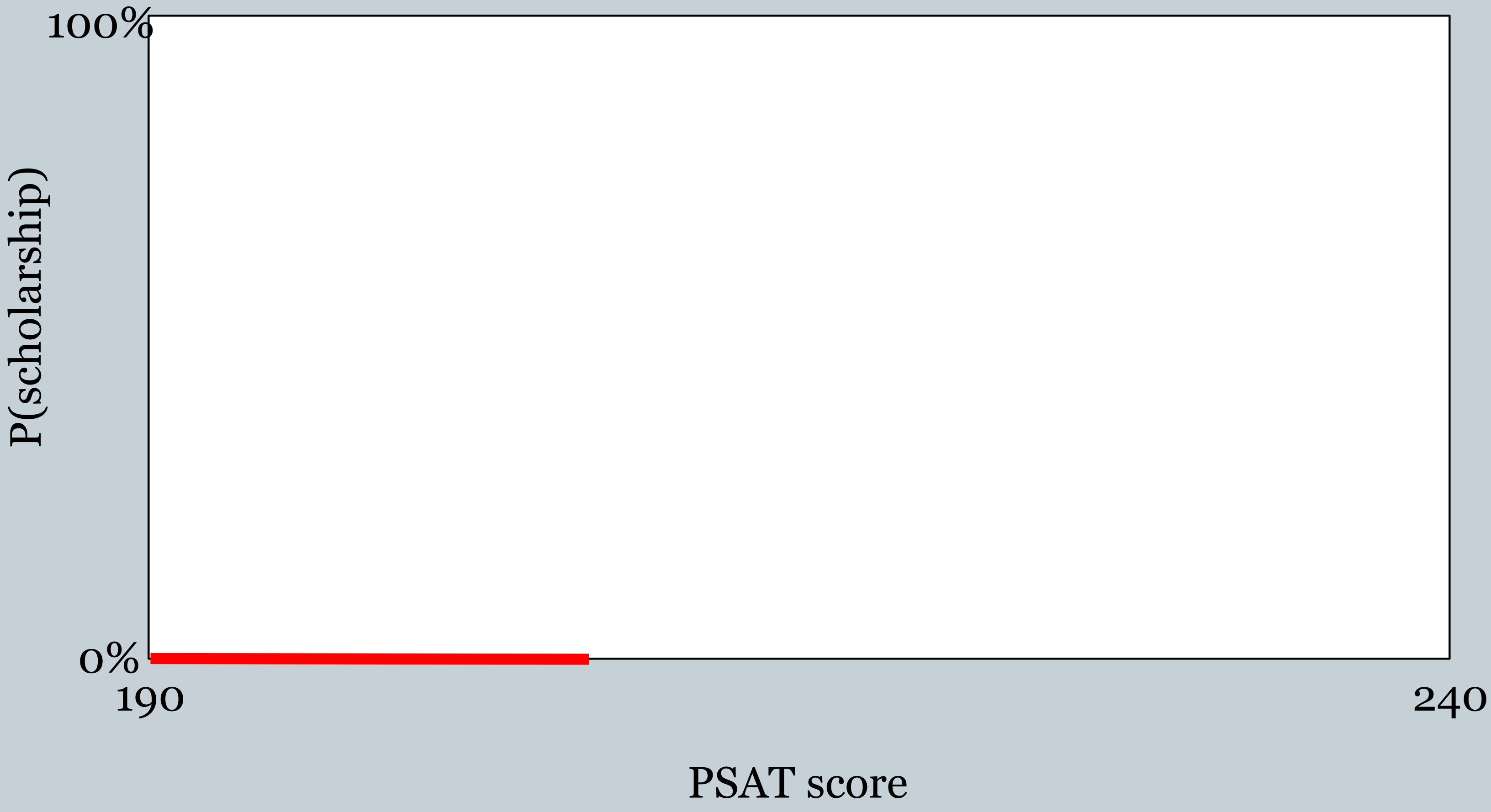

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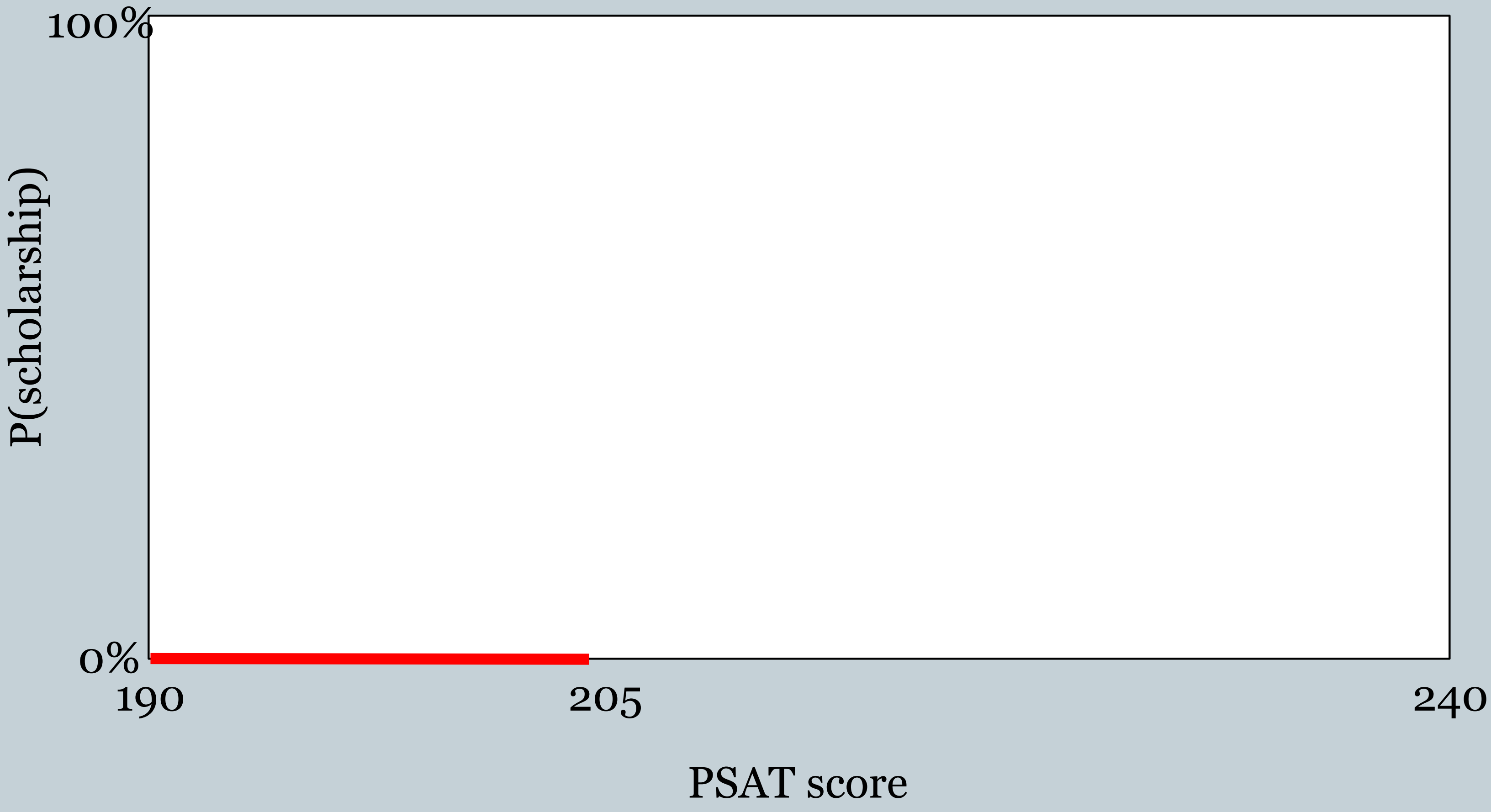

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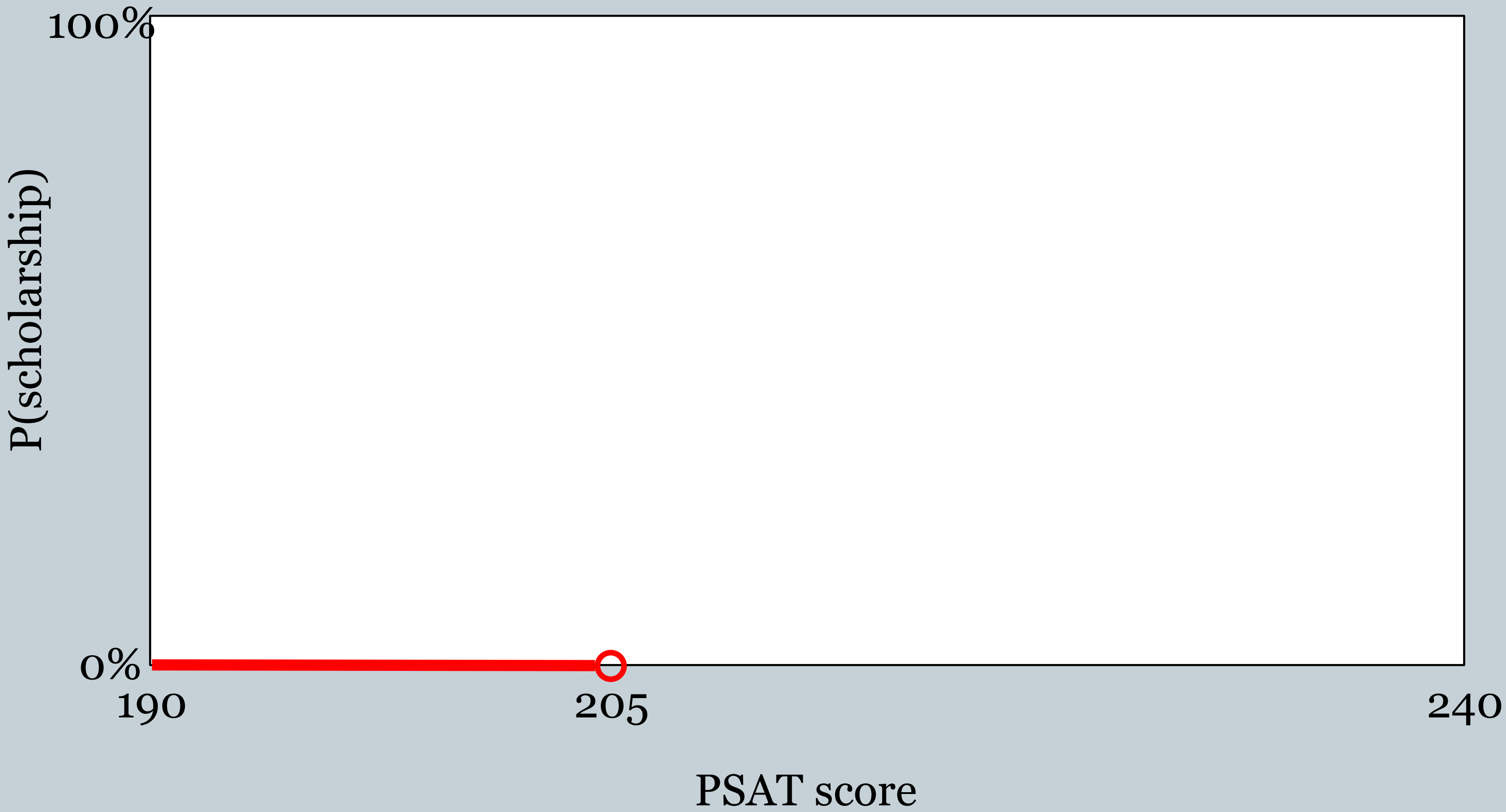

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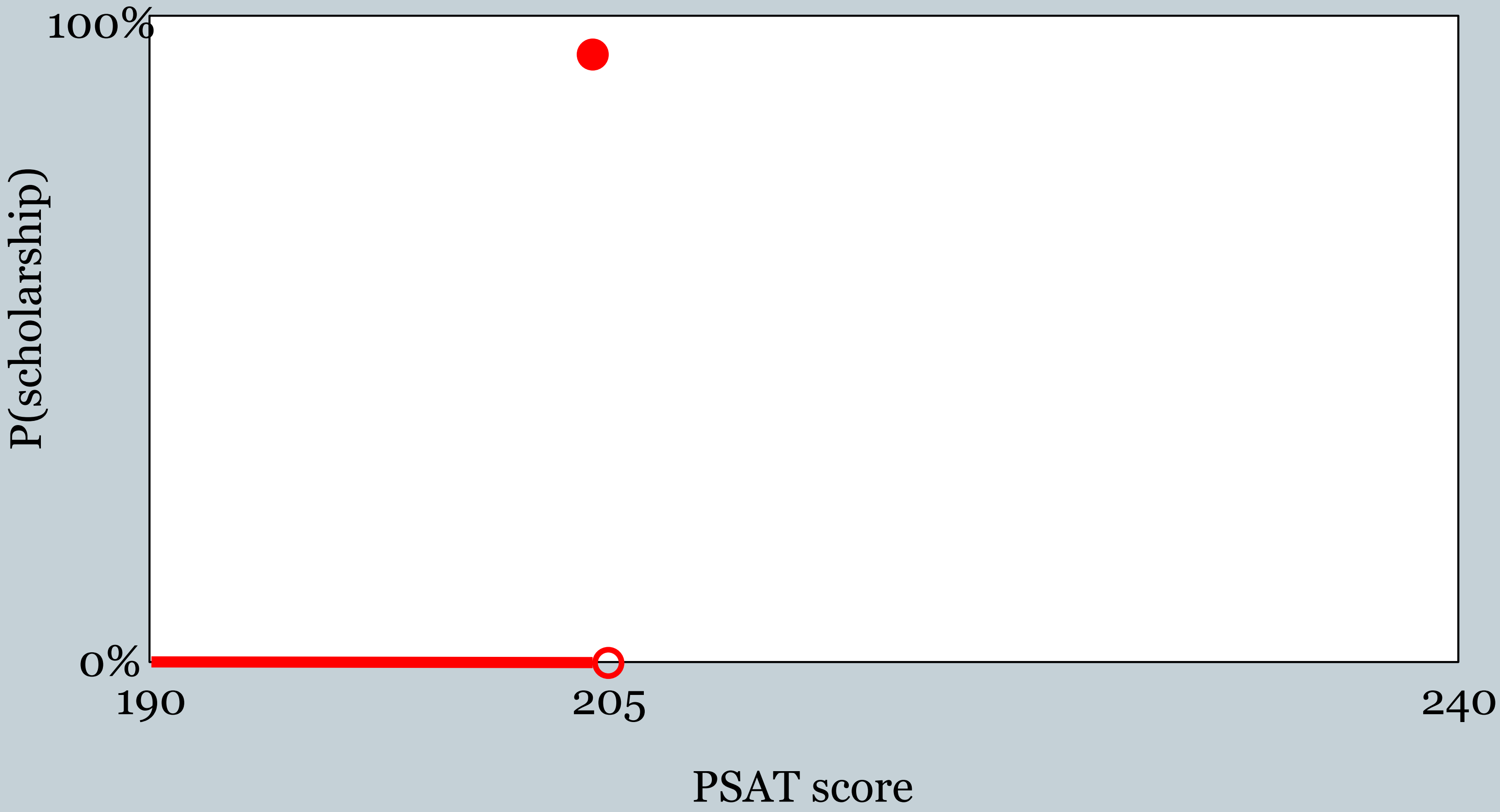

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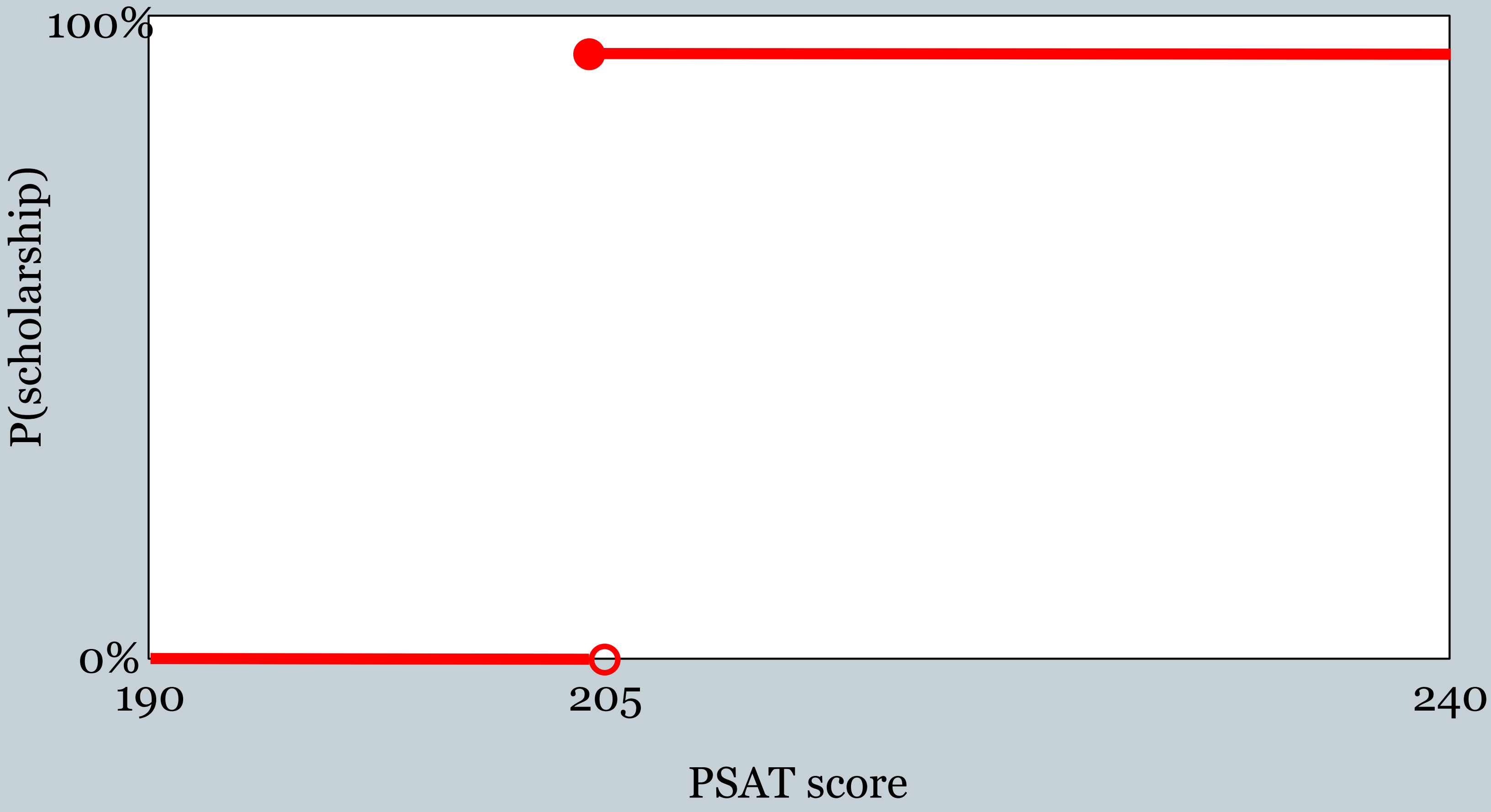

fuzzy

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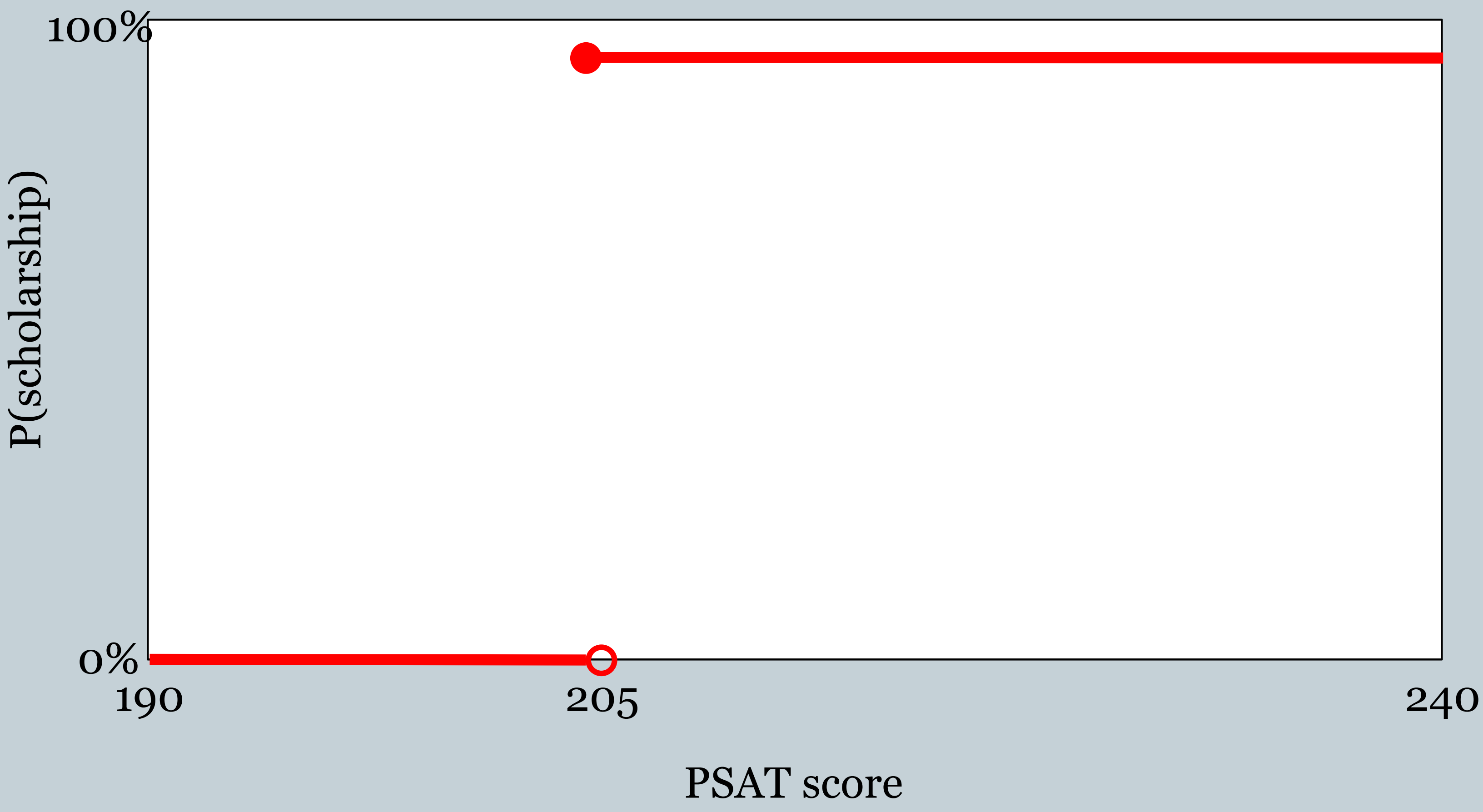

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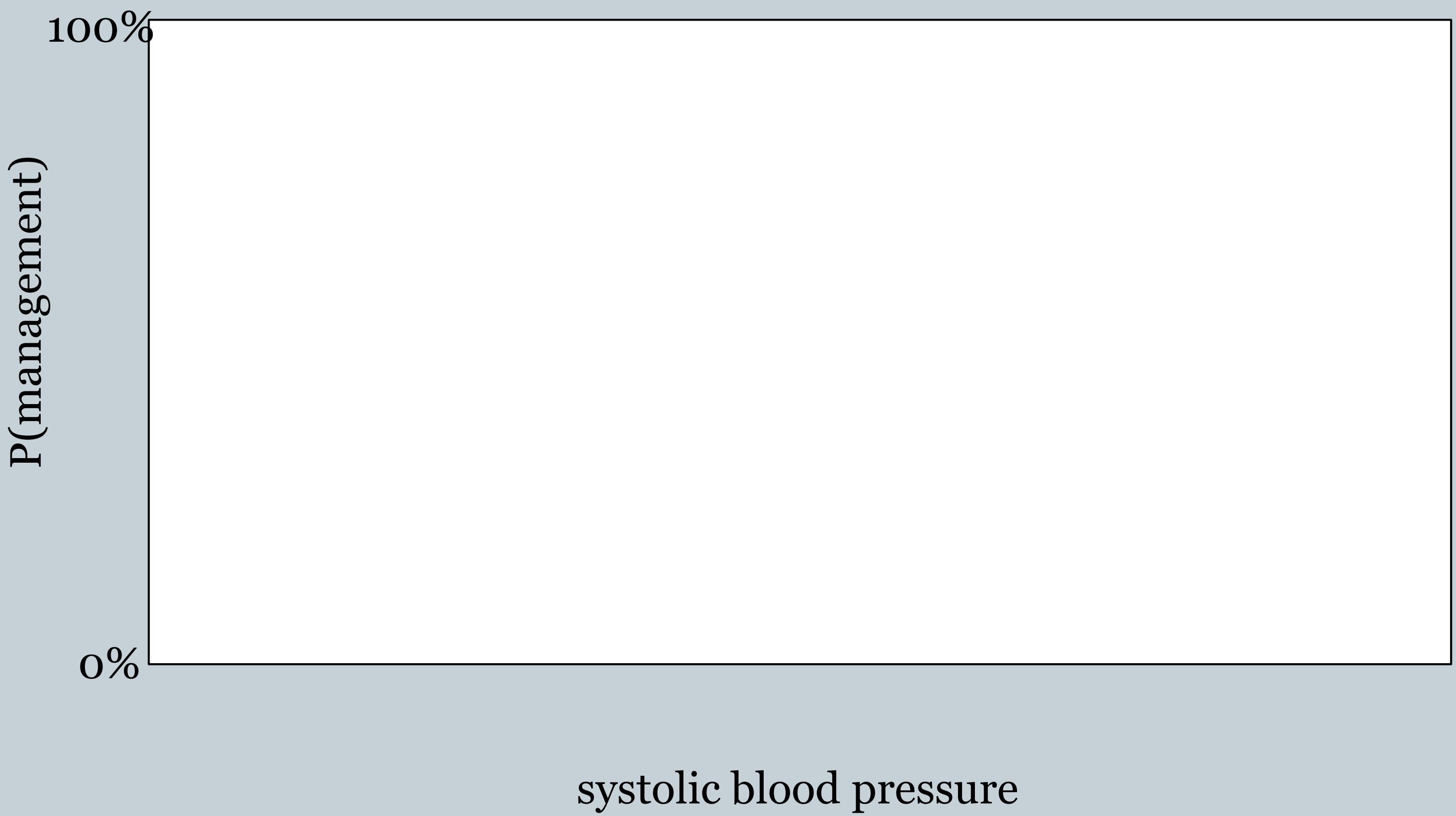

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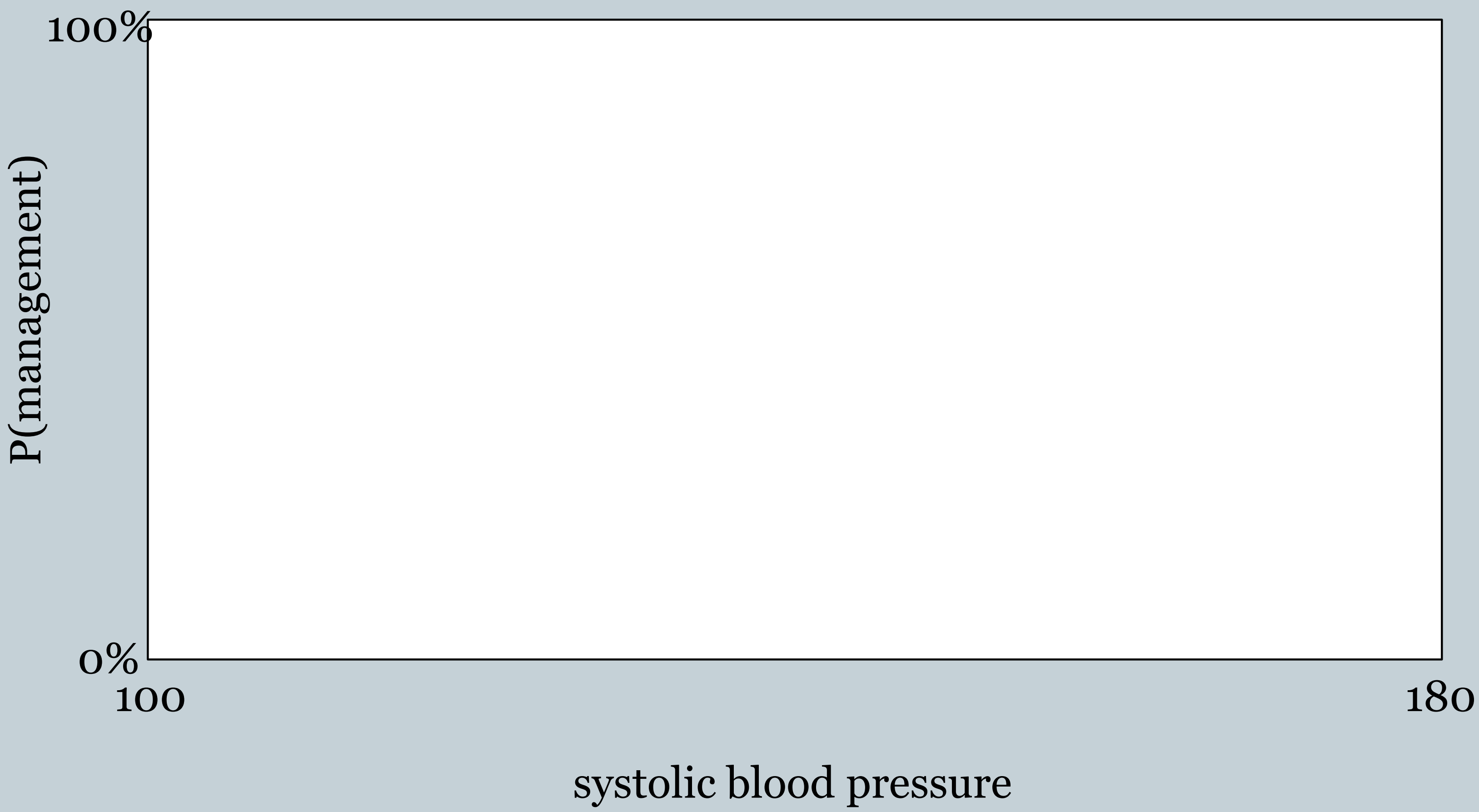

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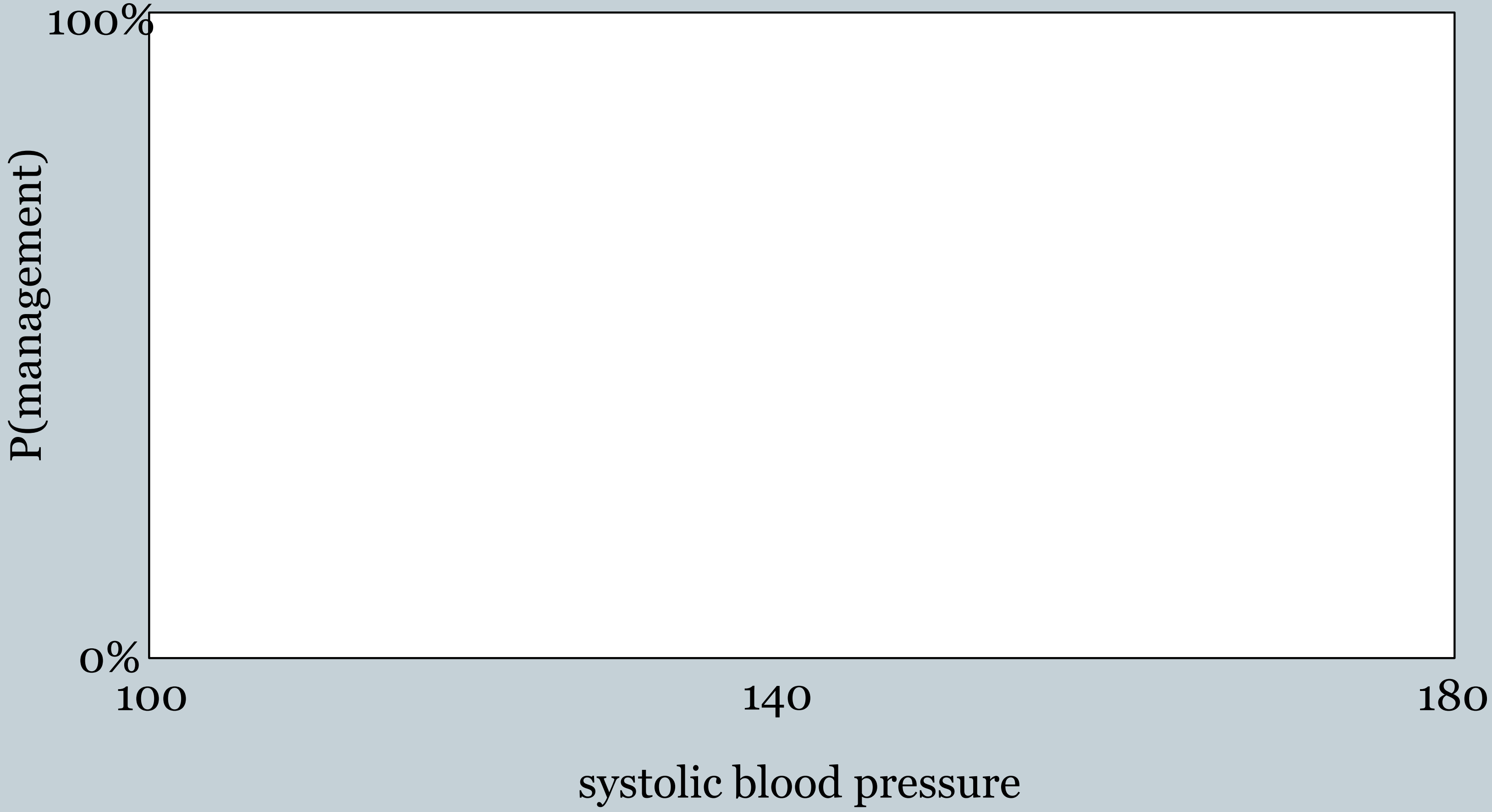

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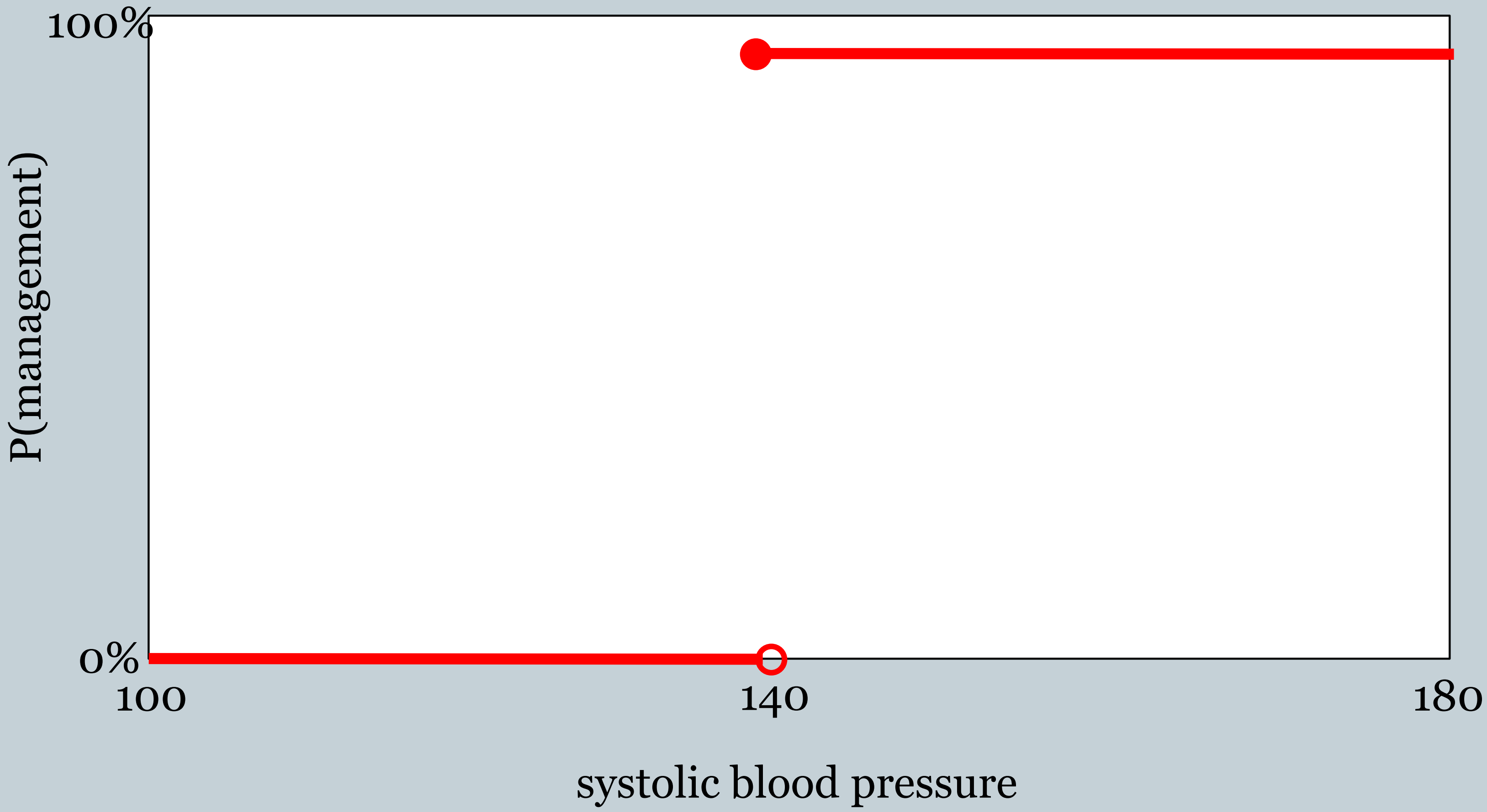

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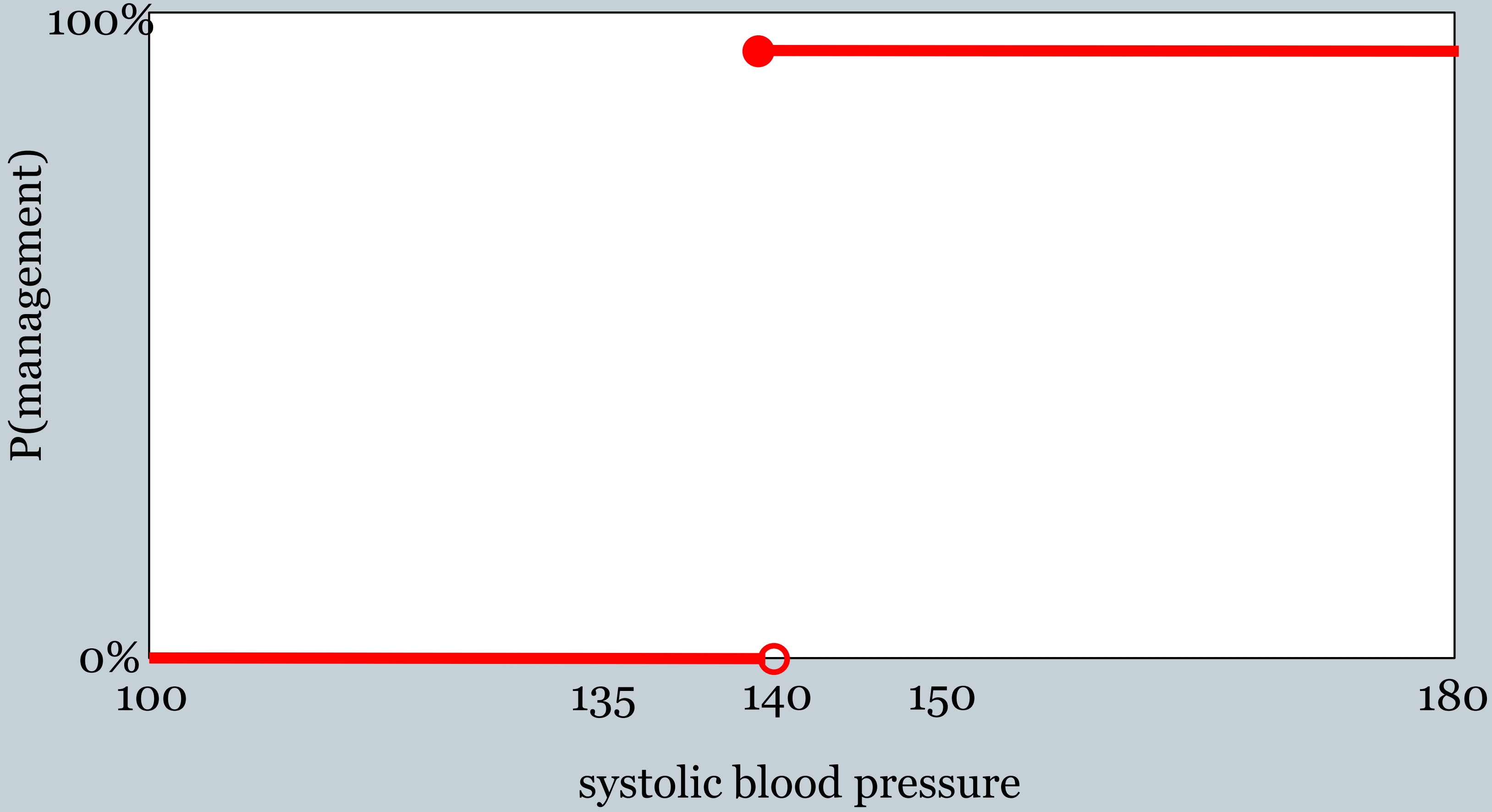

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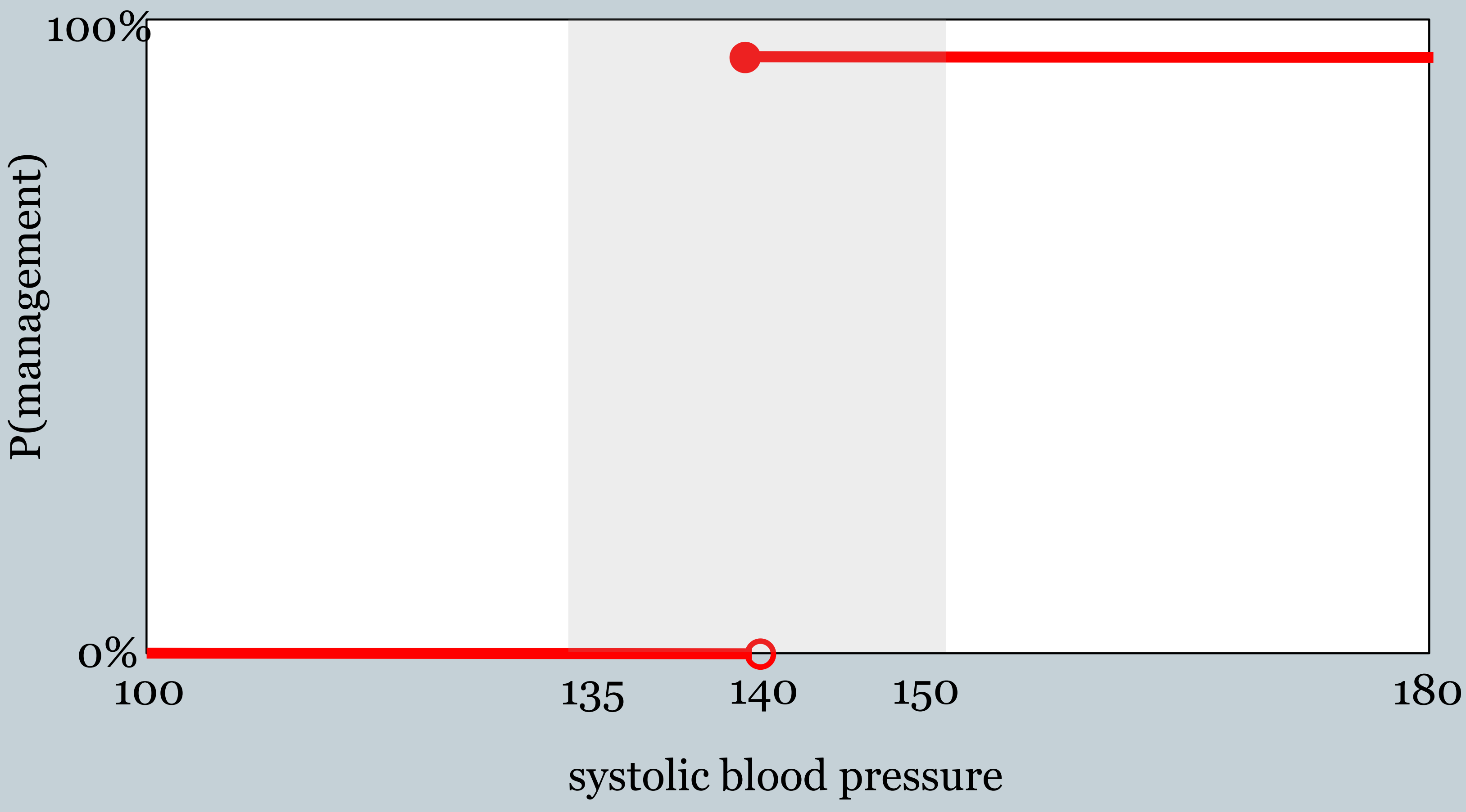

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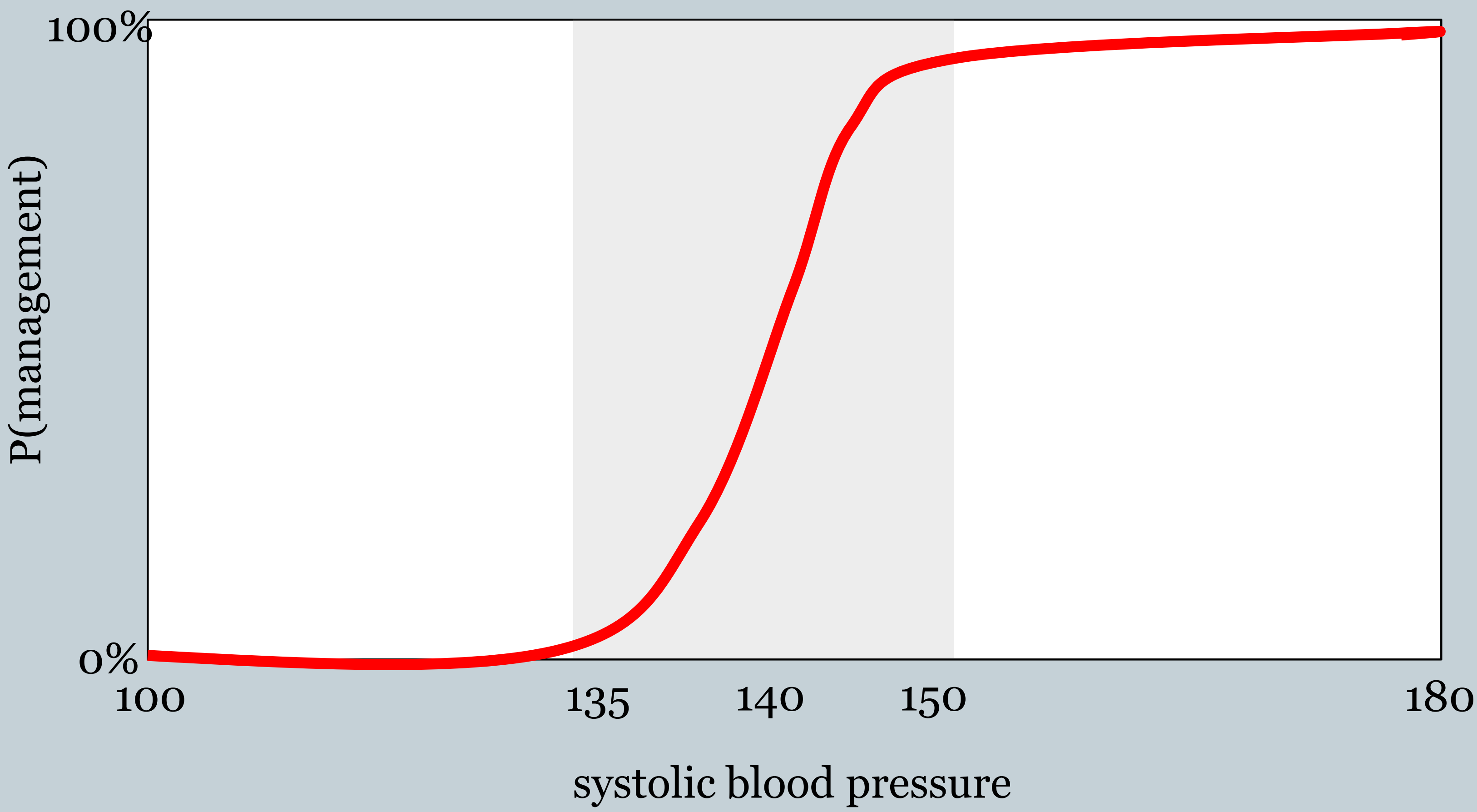
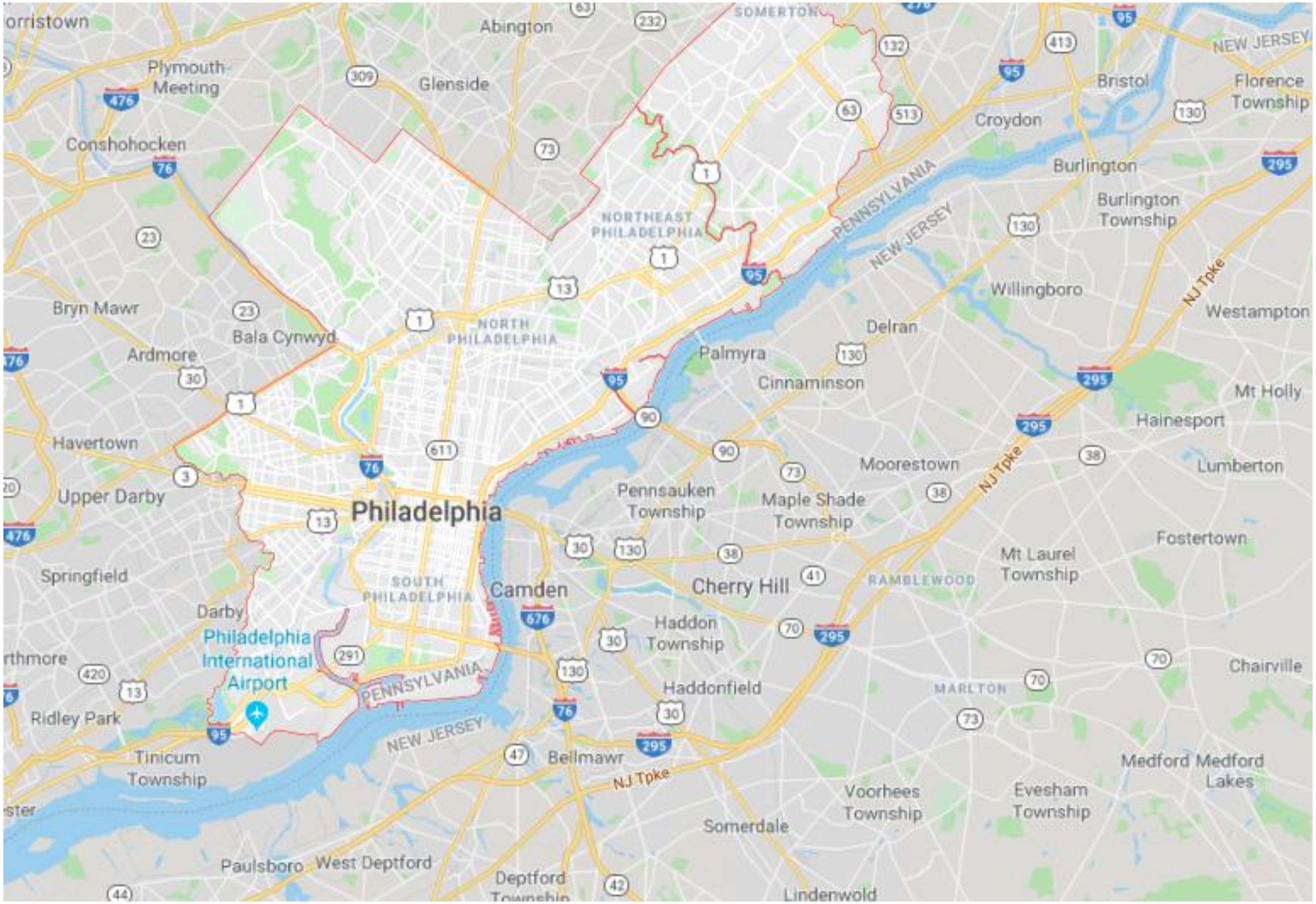
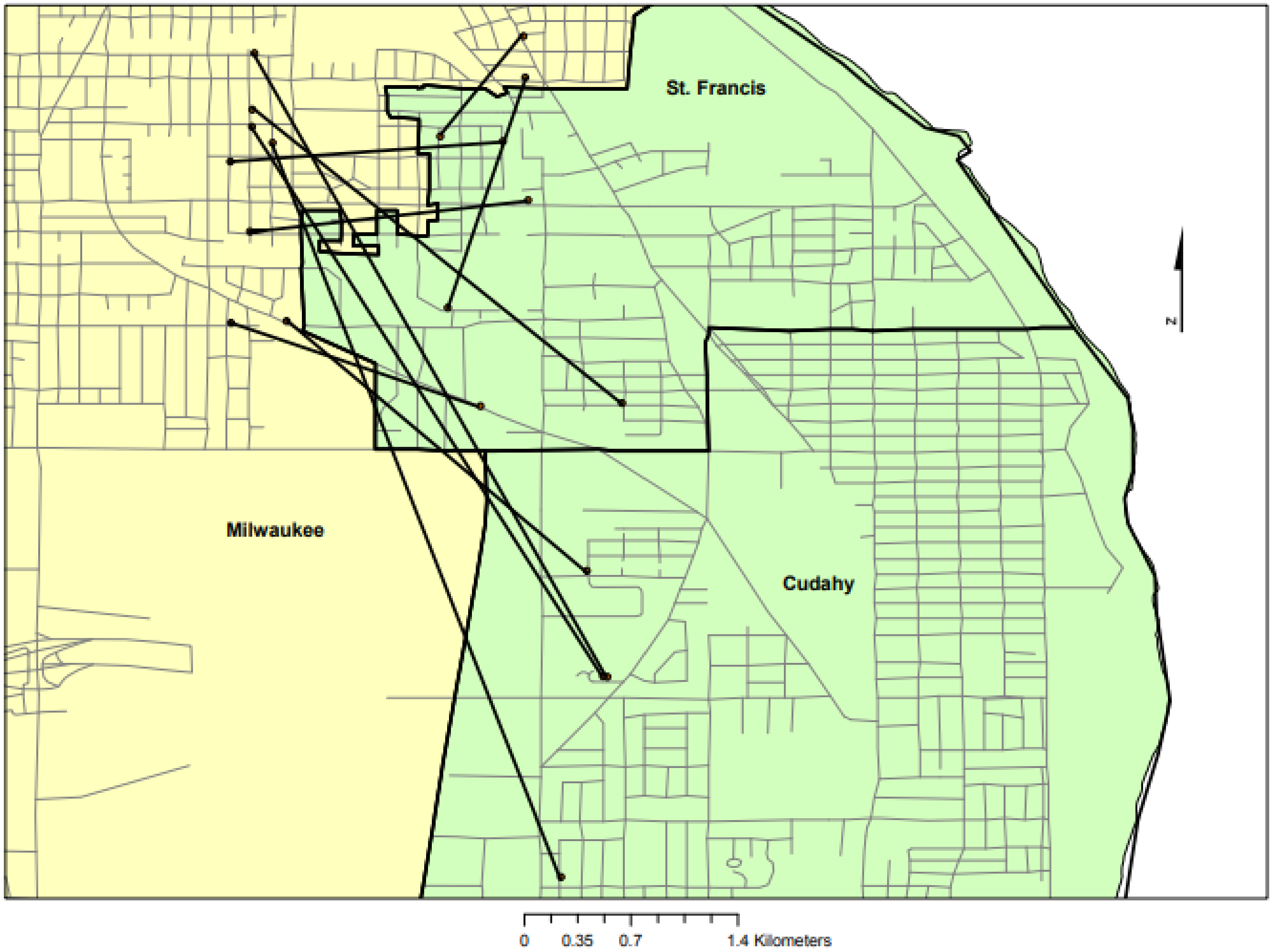


Card and Krueger: minimum wages

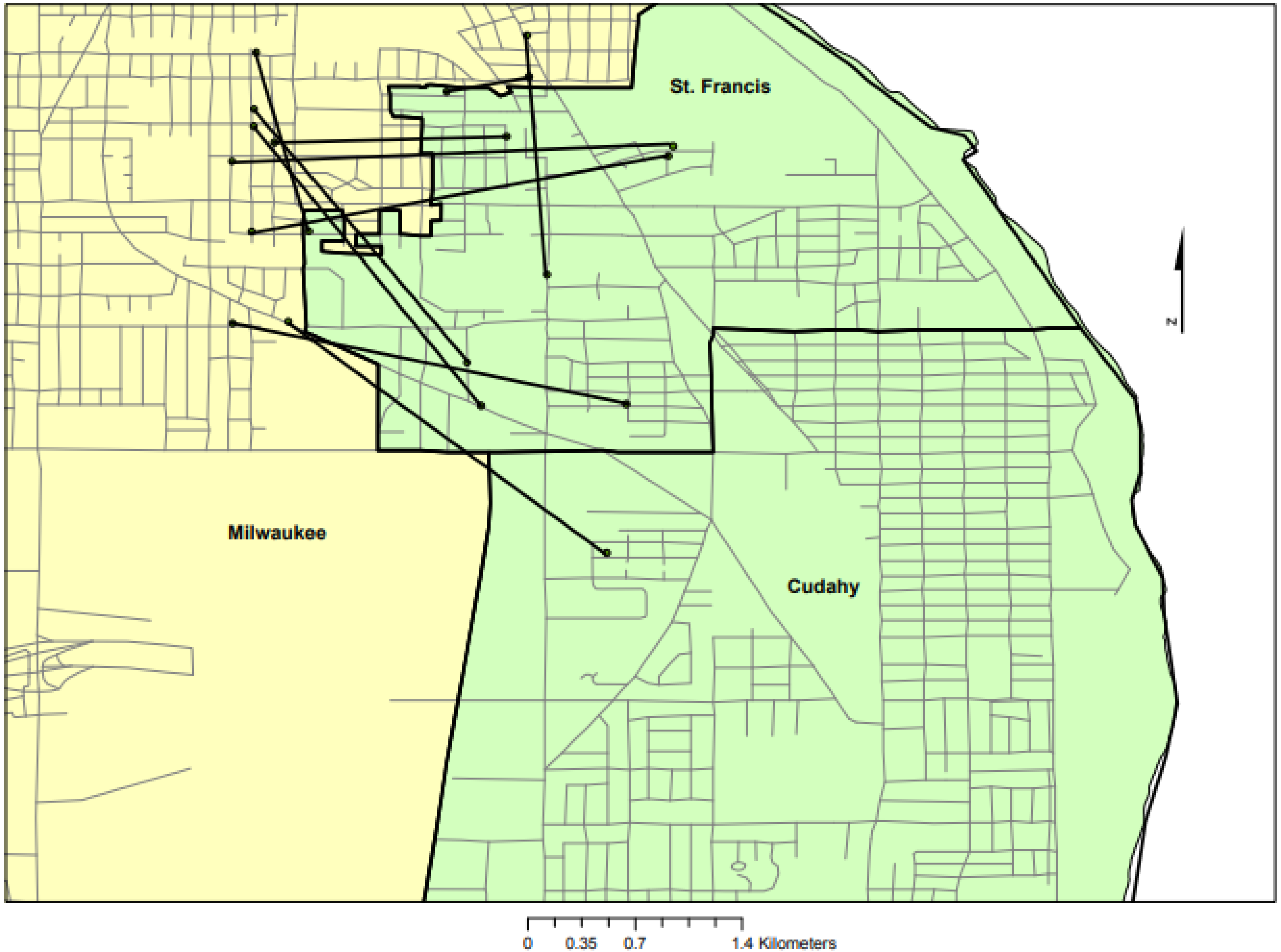


https://www.nber.org/papers/w4509.pdf

Keele et al: getting the vote out

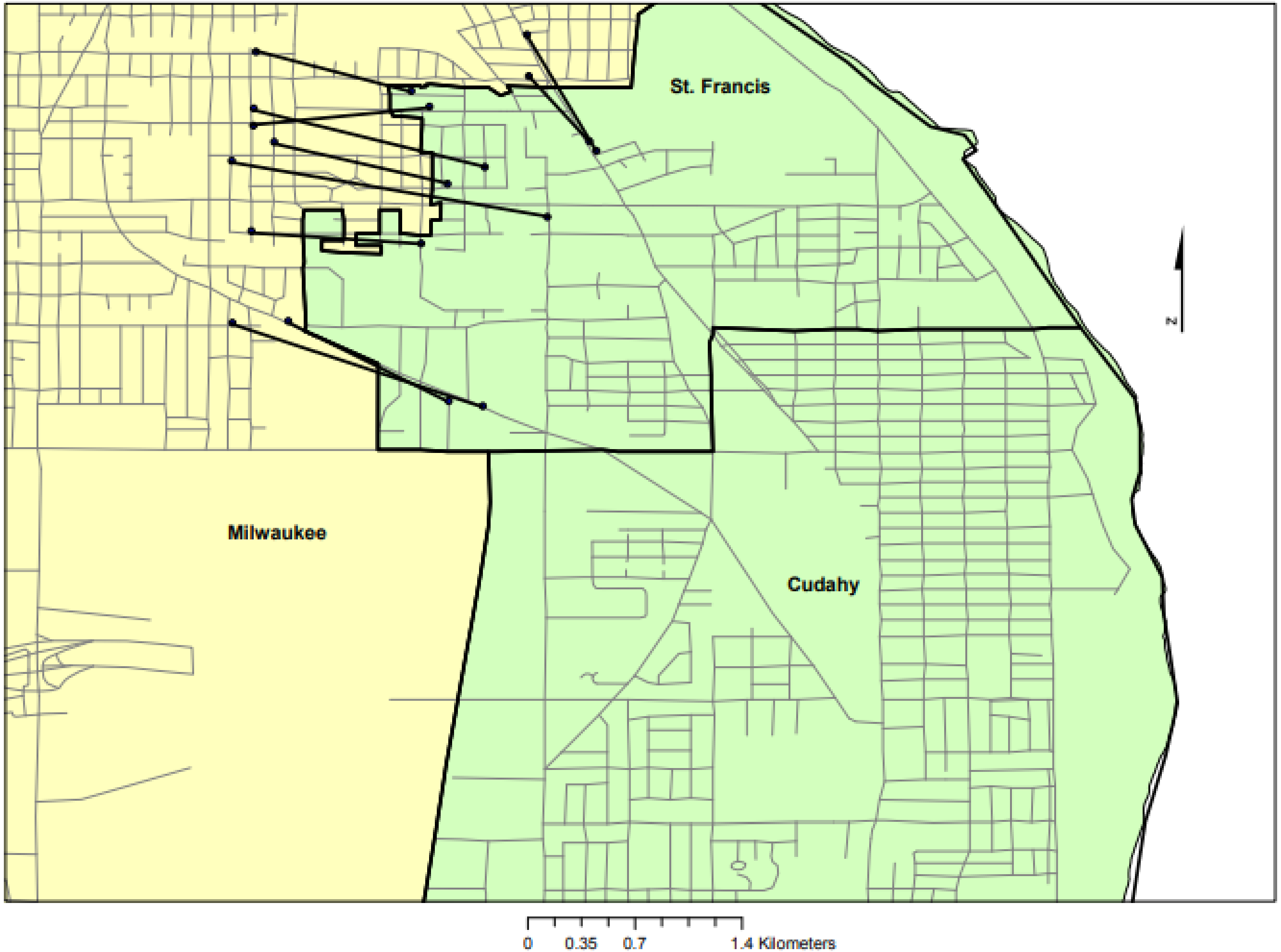


(a) Design 1 - Covariates Only Match



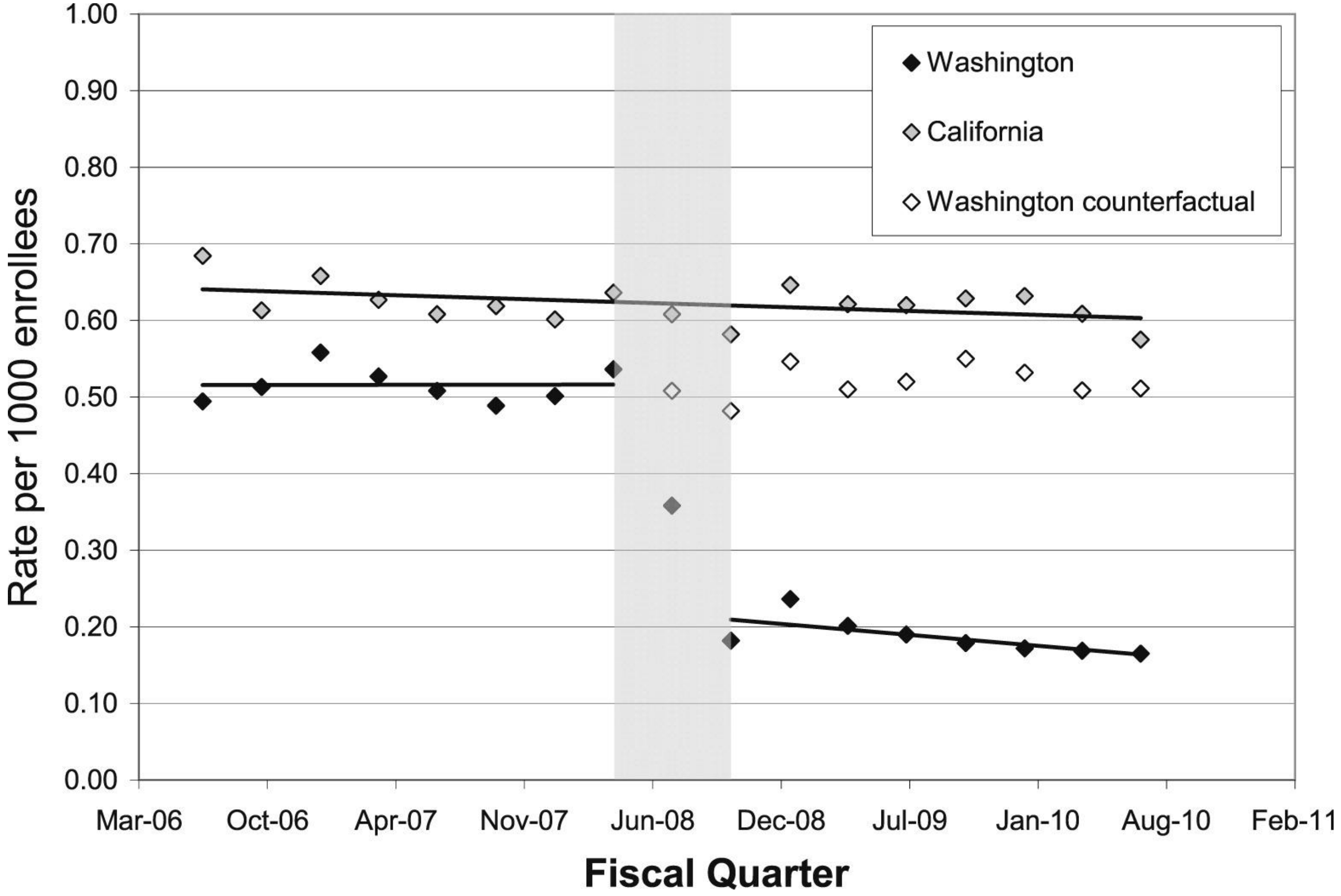
(b) Design 2 - Distance Only Match

https://www0.gsb.columbia.edu/mygsb/faculty/research/pubfiles/6137/GeoMatch.pdf



(c) Design 3 - Covariates and Distance Match

Hilt et al.: policy to reduce ADHD meds



https://www.sciencedirect.com/science/article/pii/S1876285913002106

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- Inference can be done like the pscore set up (sharp RD).

“case-control” studies

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- Out-of-favor in modern causal inference
- If you’re being intellectually lazy then these studies feel a bit similar to what we’ve been doing.

case-noncase

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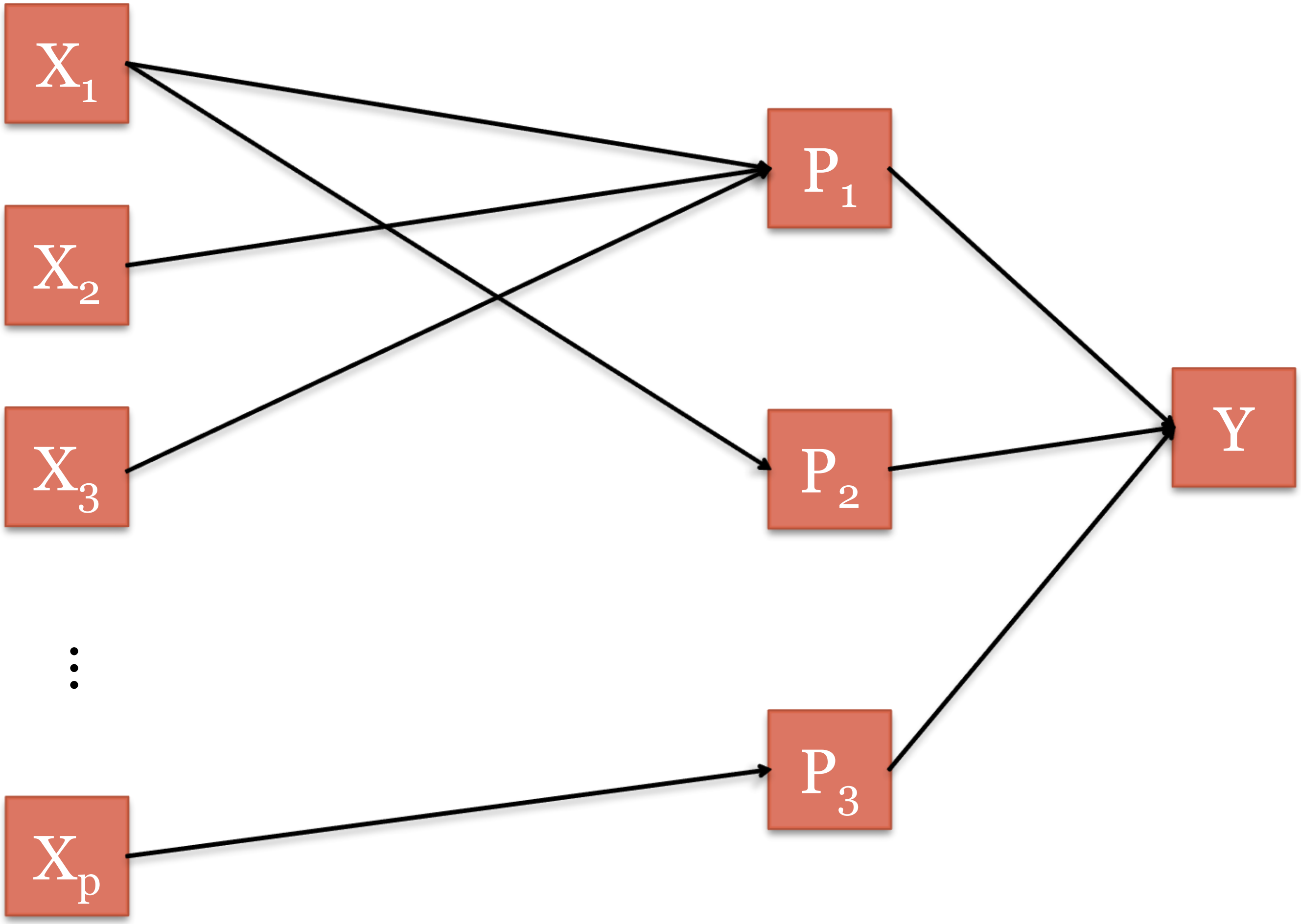
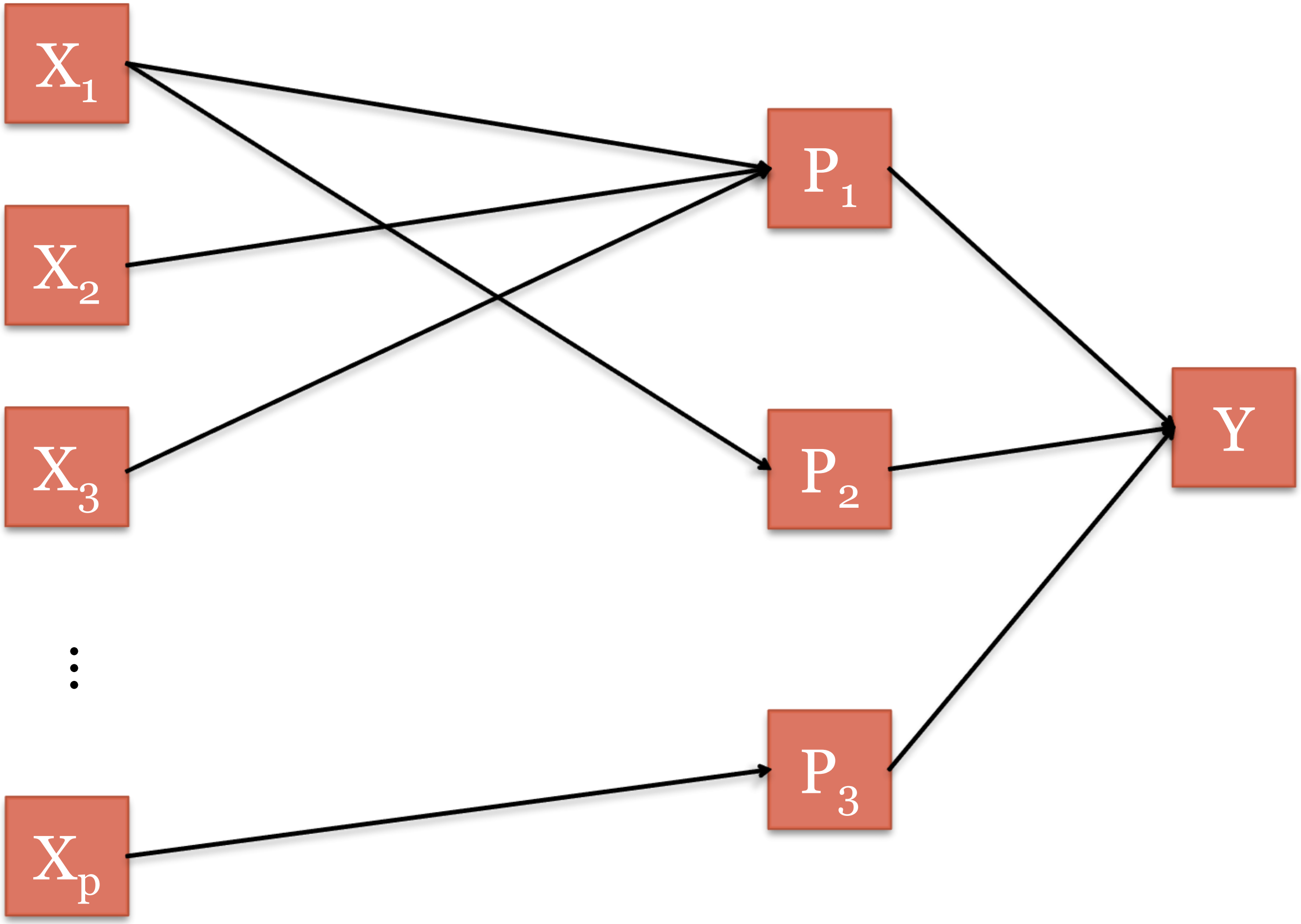
- Staple of epi
- Out-of-favor in modern causal inference
- If you’re being intellectually lazy then these studies feel a bit similar to what we’ve been doing.
- The structure of argument is much weaker than what we’ve been doing.

case-noncase

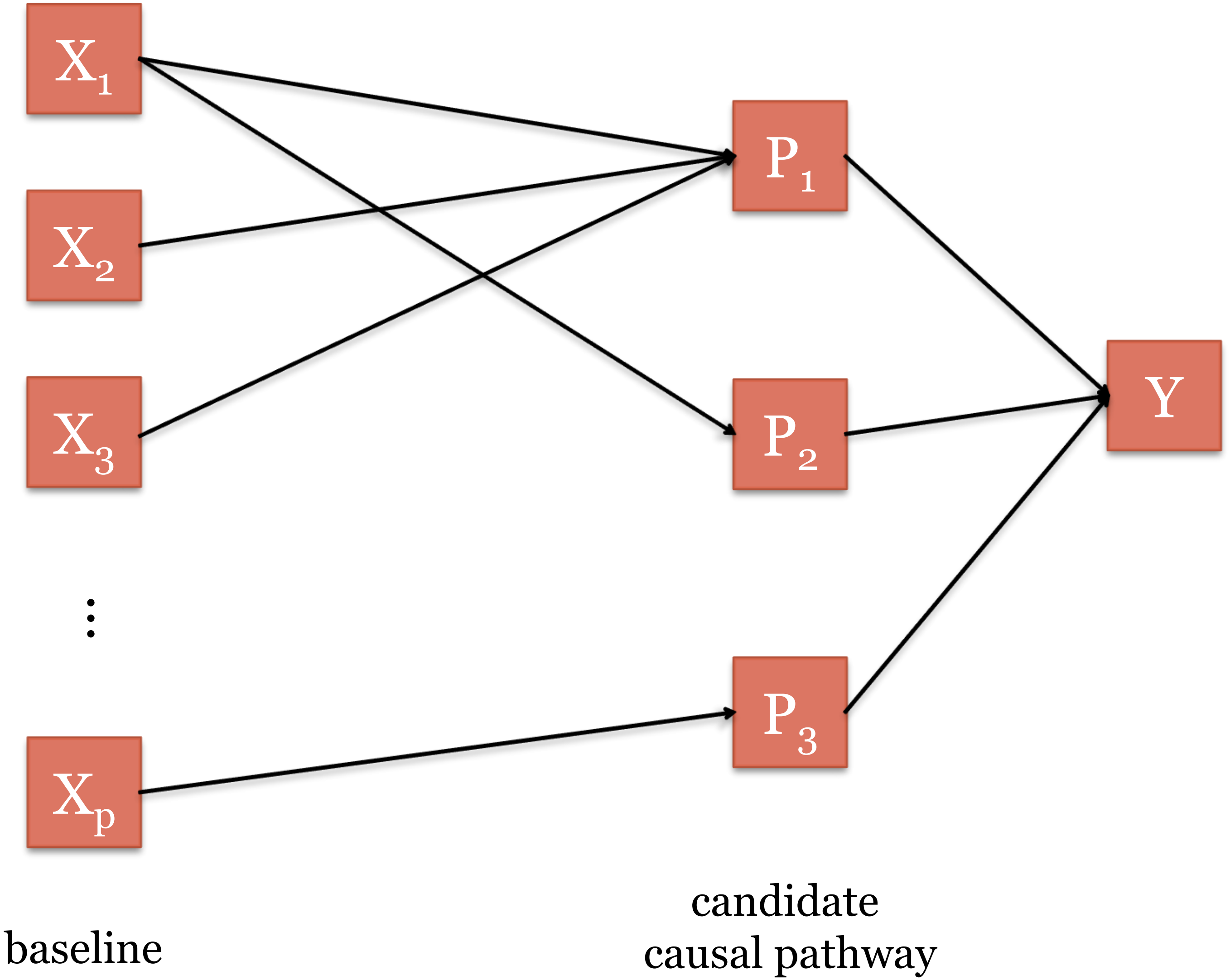
- Diagram of what we've been doing (start with cause and look at an outcome) – swap structure and go backward from outcome to candidate causes.

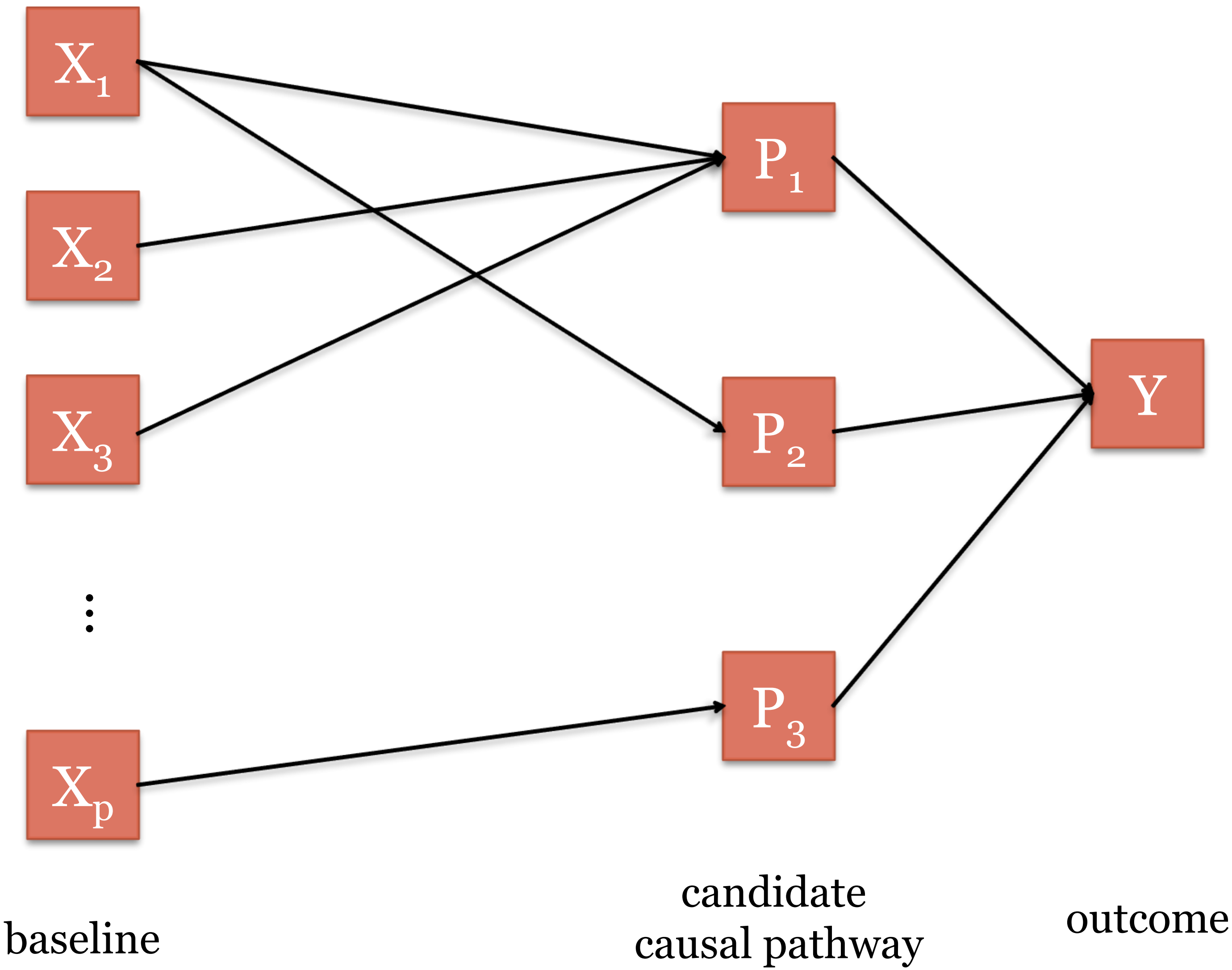


X1
X2
X3
⋮
Xp
P1
P2
P3
Y



baseline


X_1
X_2
X_3
⋮
X_p
P_1
P_2
P_3
Y
baseline
candidate
causal pathway



X_1
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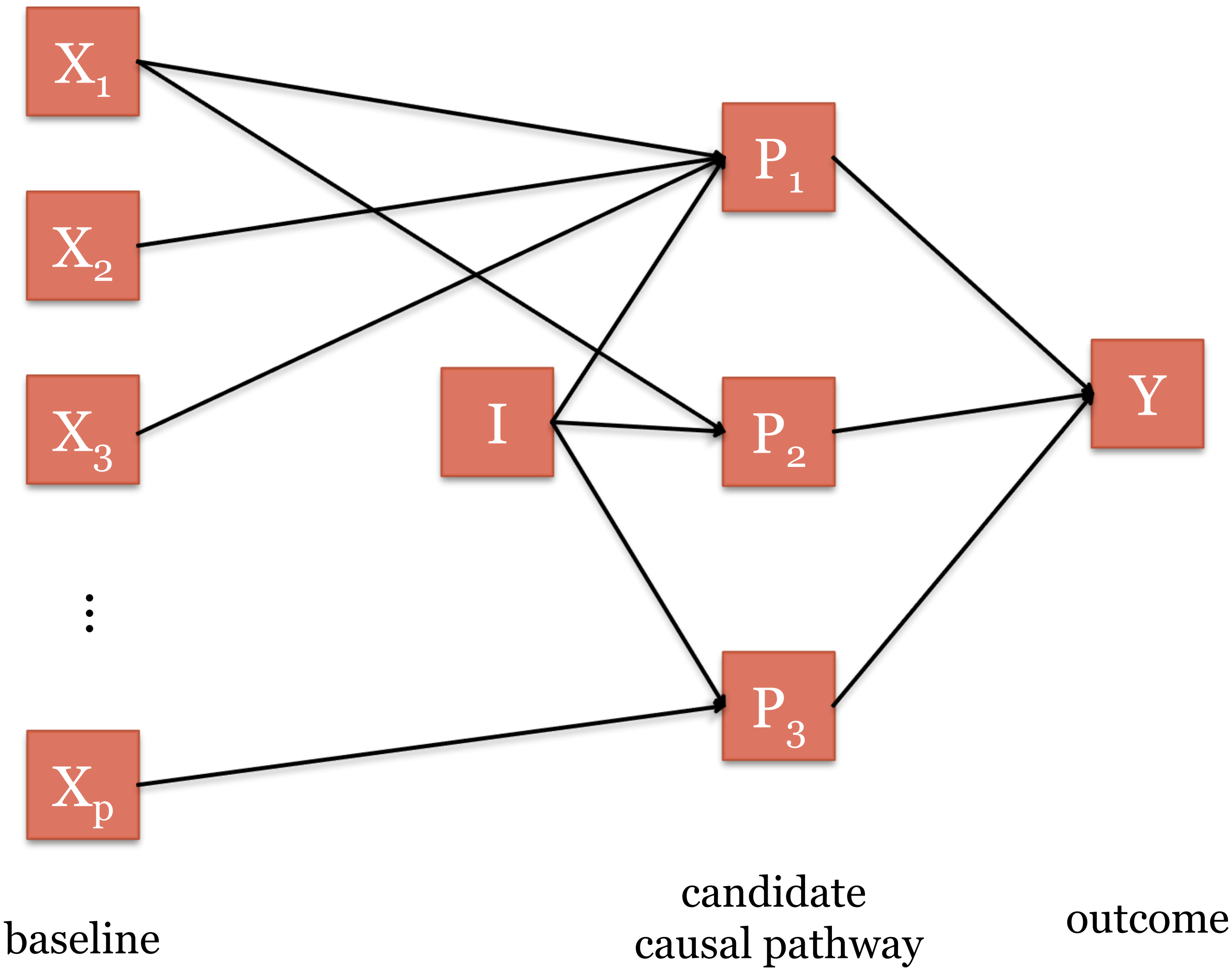
P_3
Y
baseline
candidate
causal pathway
outcome


X_1
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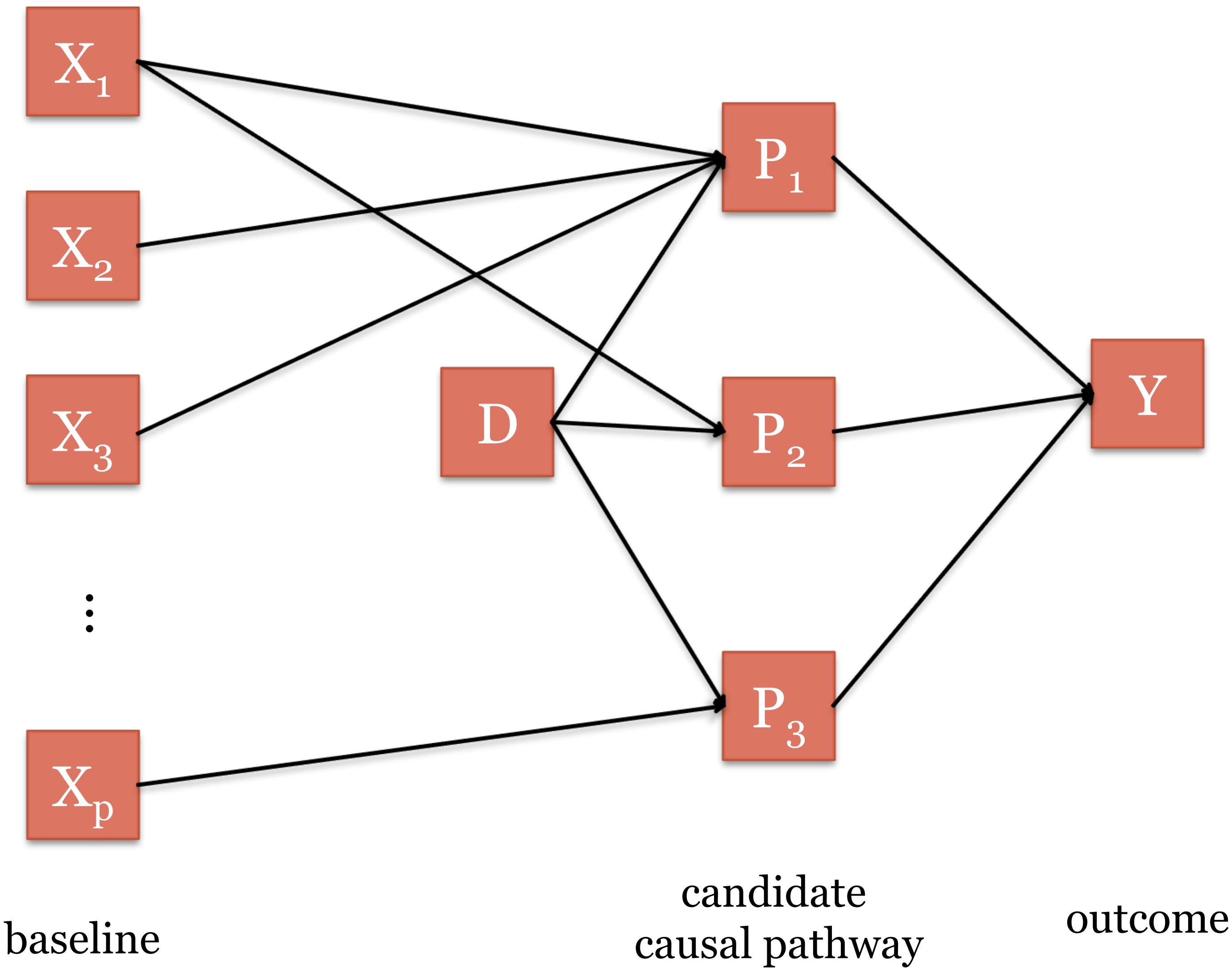
X1
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D
P1
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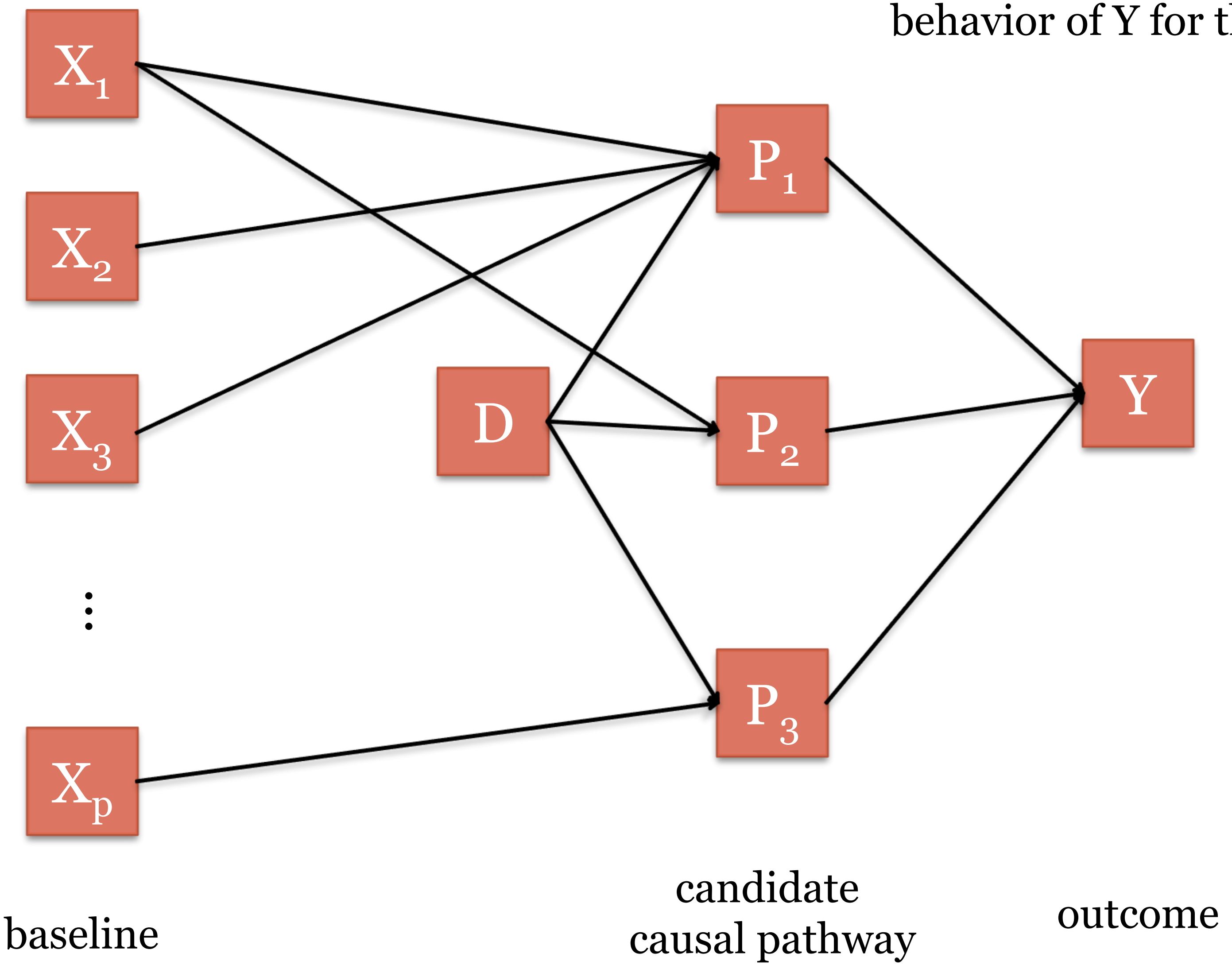
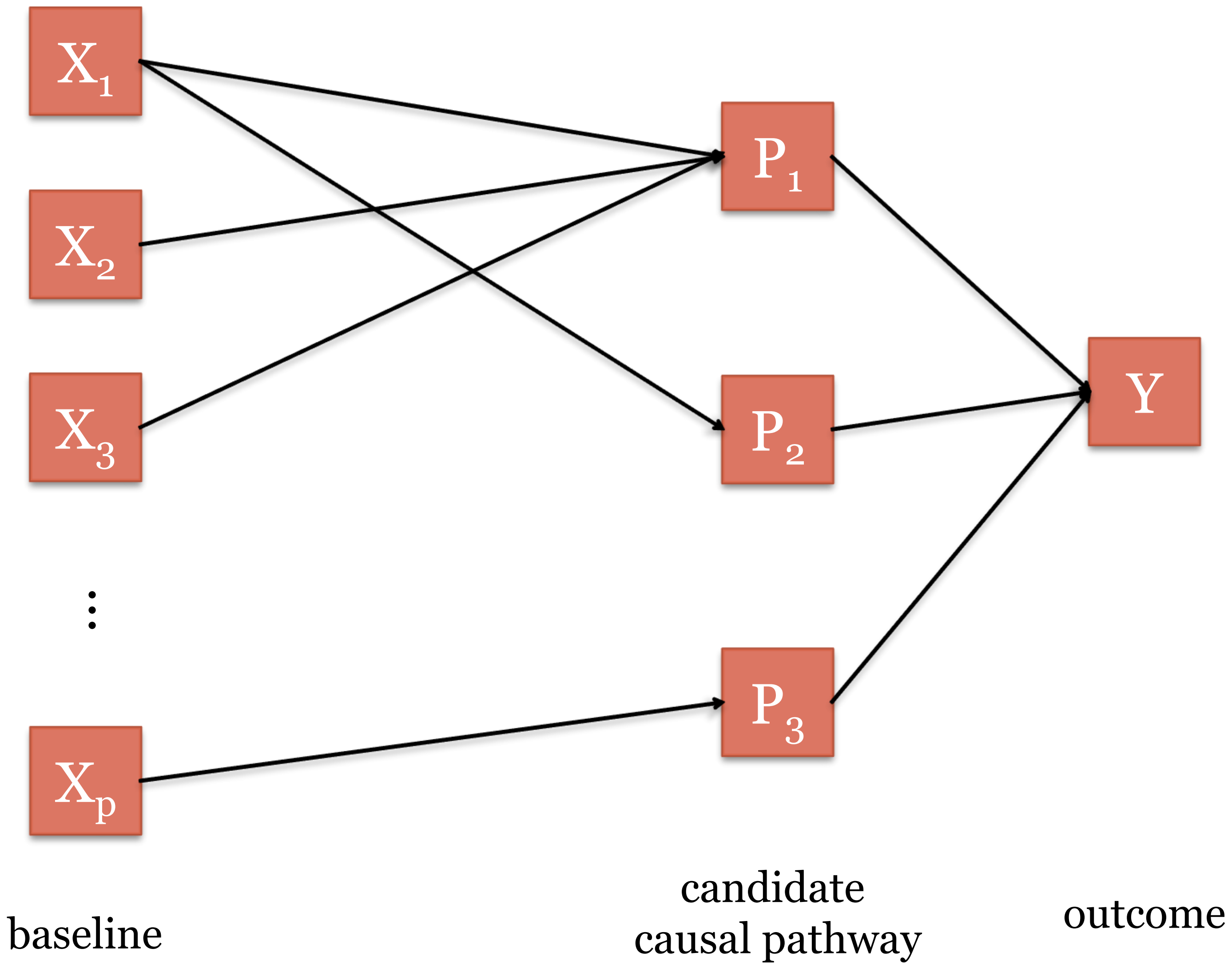
baseline
candidate
causal pathway
outcome

Contrast $d_i = 1, d_j = 0$. Then compare behavior of Y for the two groups.





X1
X2
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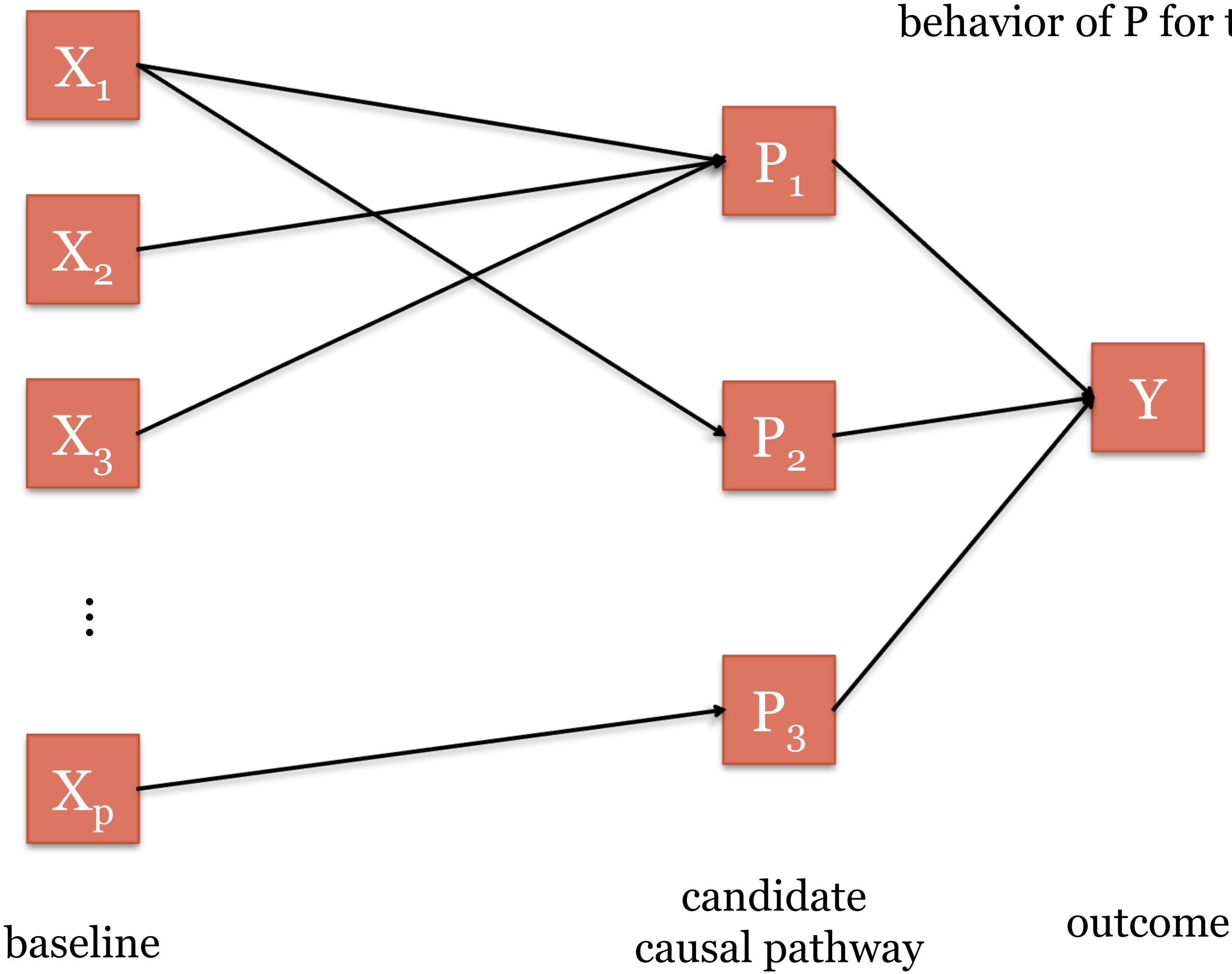
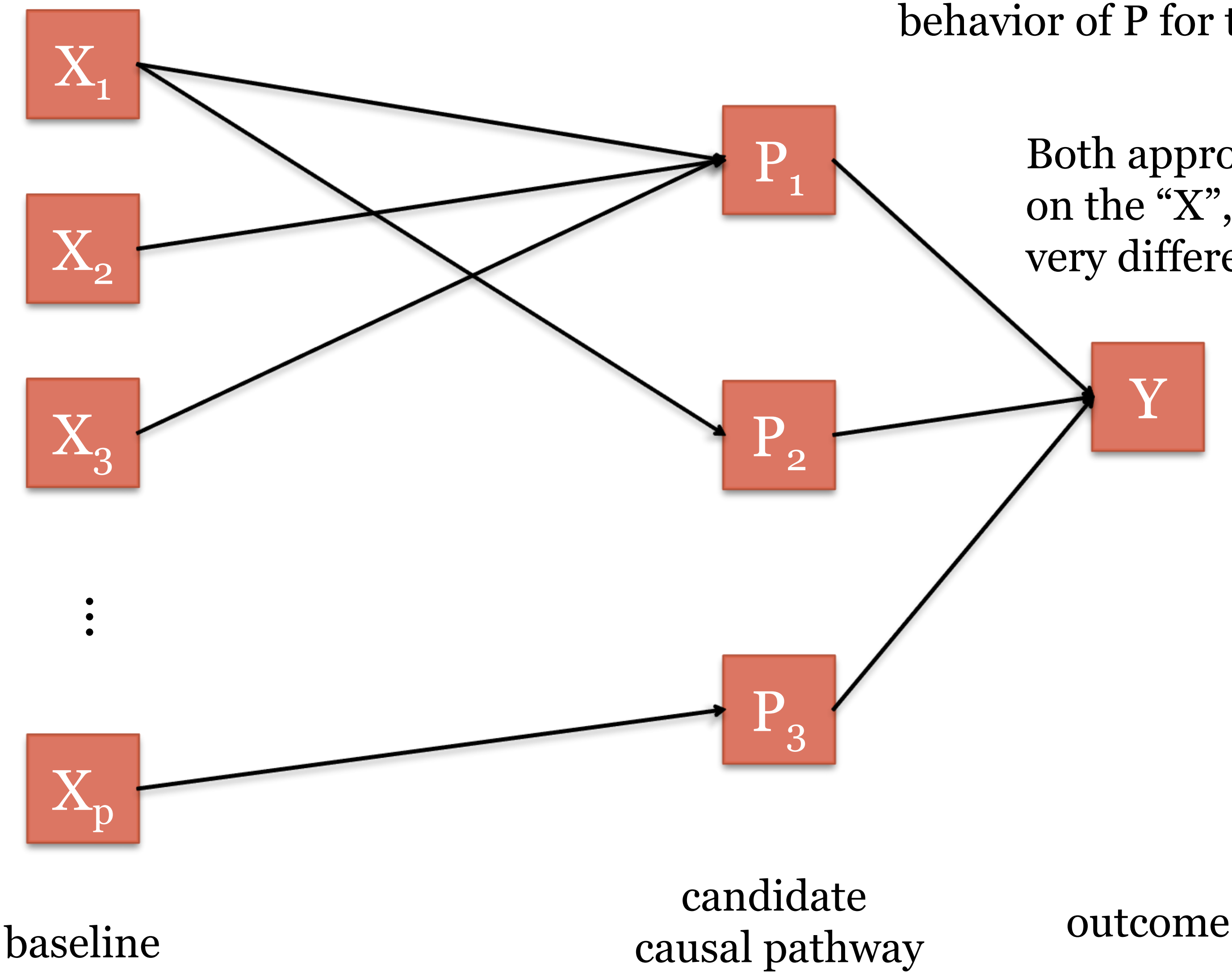
baseline
candidate
causal pathway
outcome

Contrast $y_i = 1, y_j = 0$. Then compare behavior of P for the two groups.

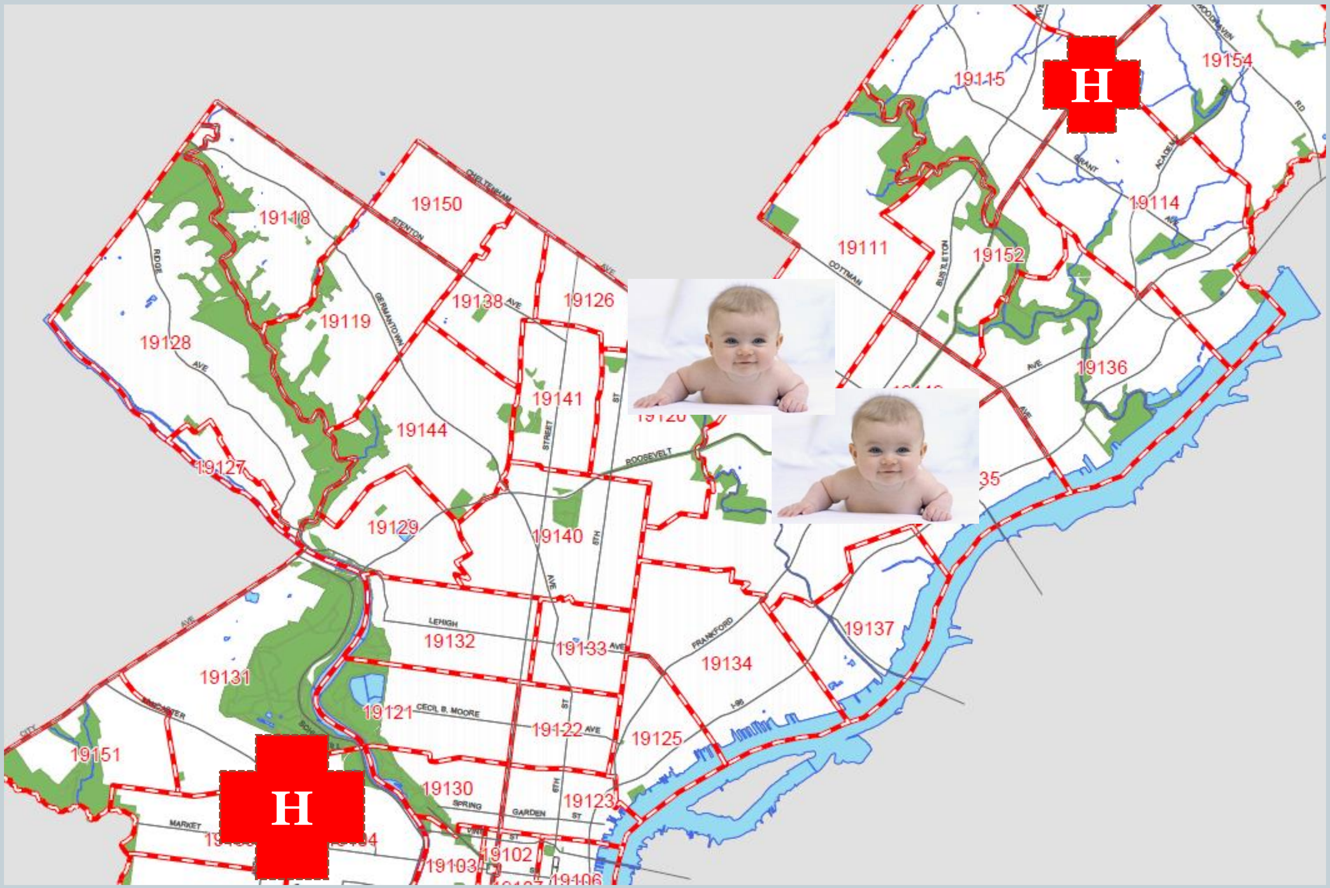


Contrast $y_i = 1, y_j = 0$. Then compare behavior of P for the two groups.

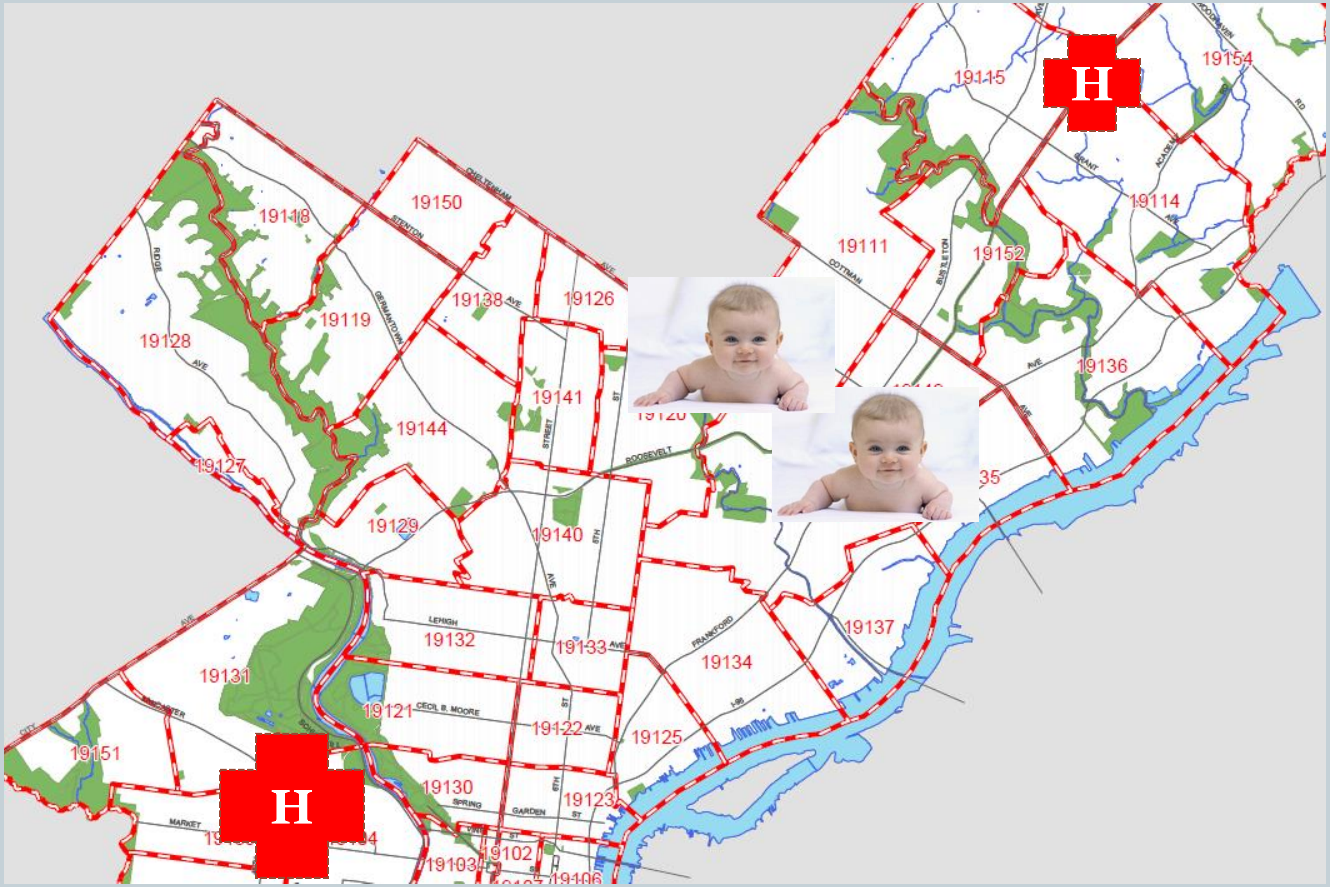
Both approaches condition on the “X”, but match between very different types of groups.



pscore matching

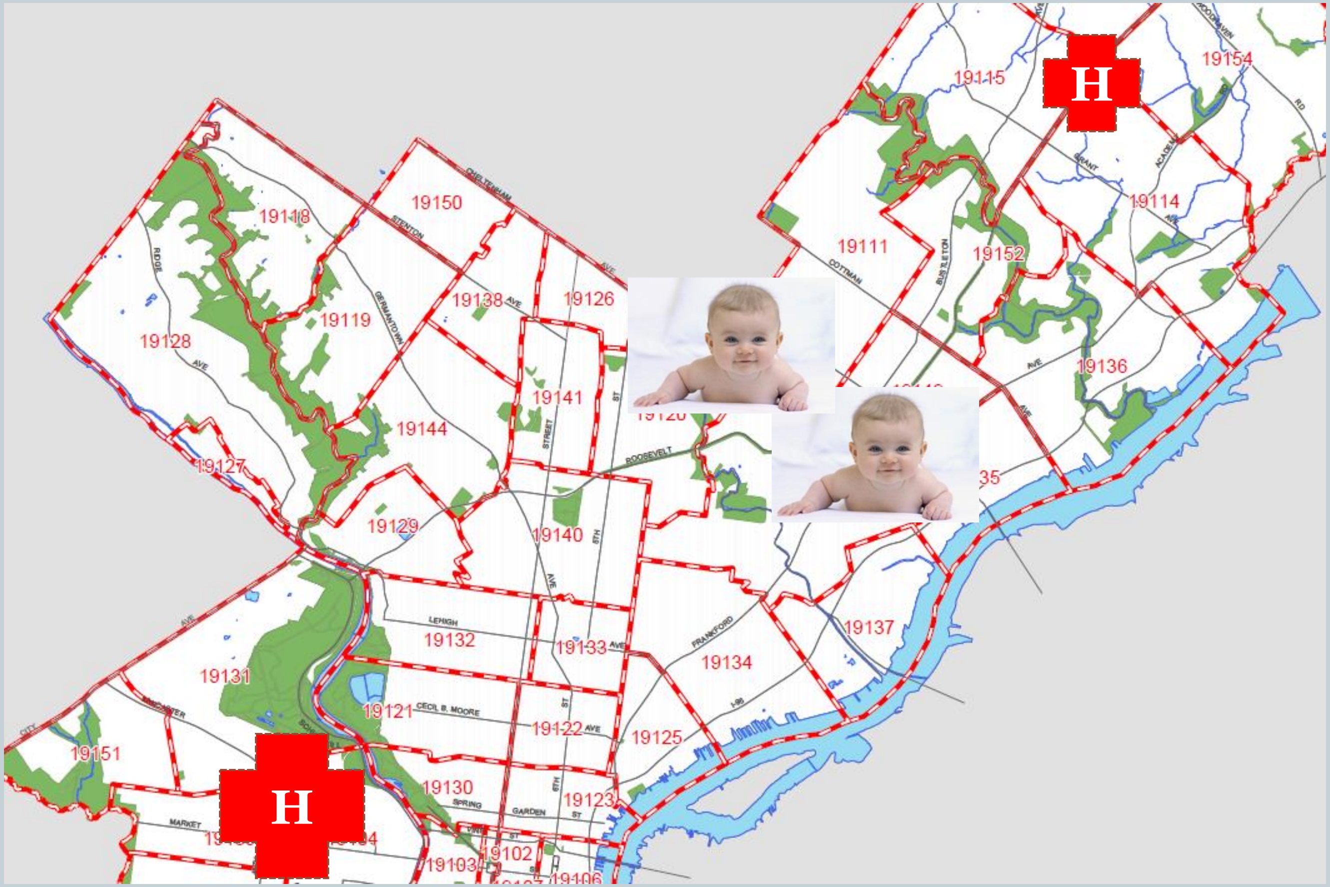


pscore matching



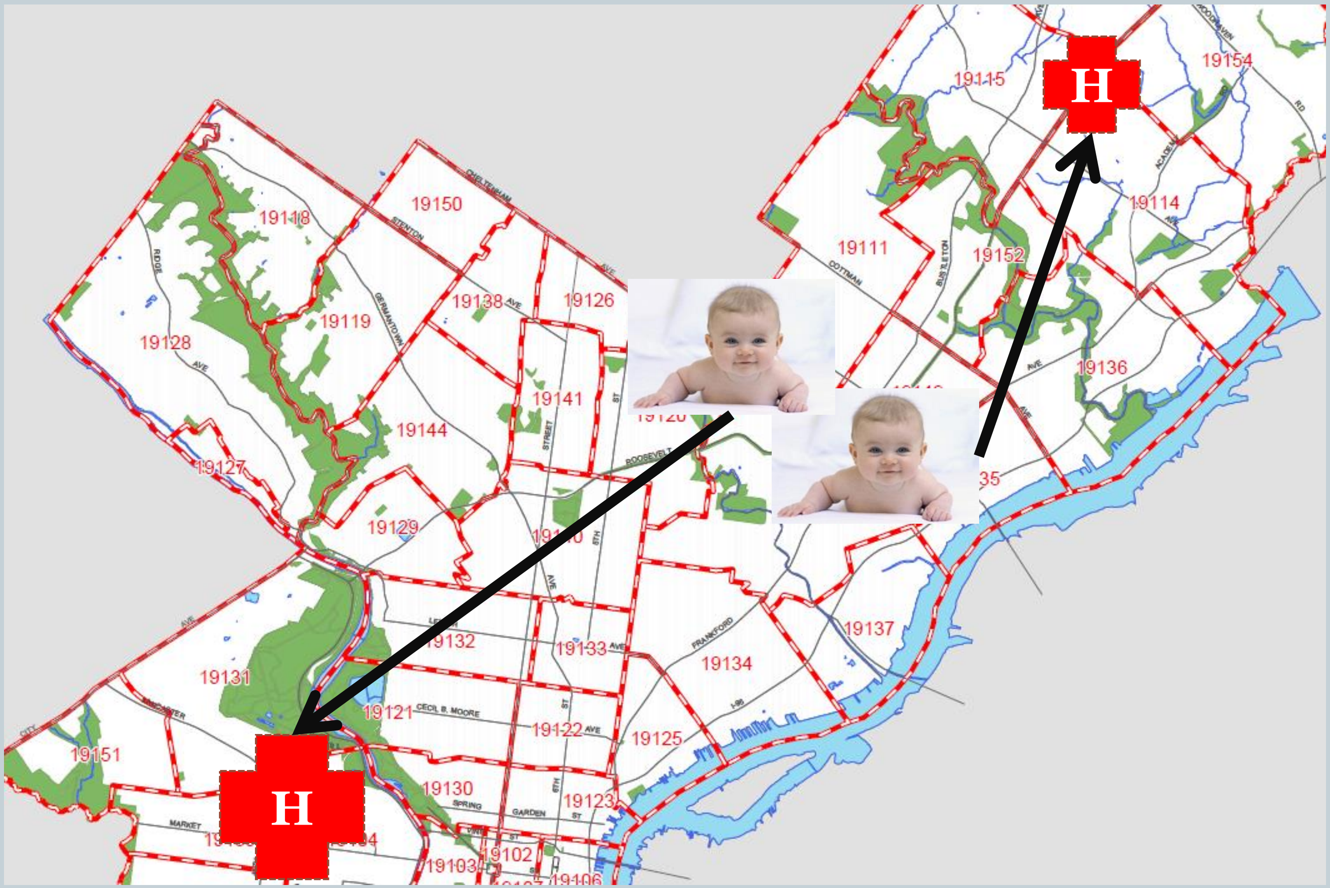
Use pre-intervention covariates to fit a pscore.

pscore matching



Use pre-intervention covariates to fit a pscore. Match on pscore between observations that used t=1 vs t=0.

pscore matching



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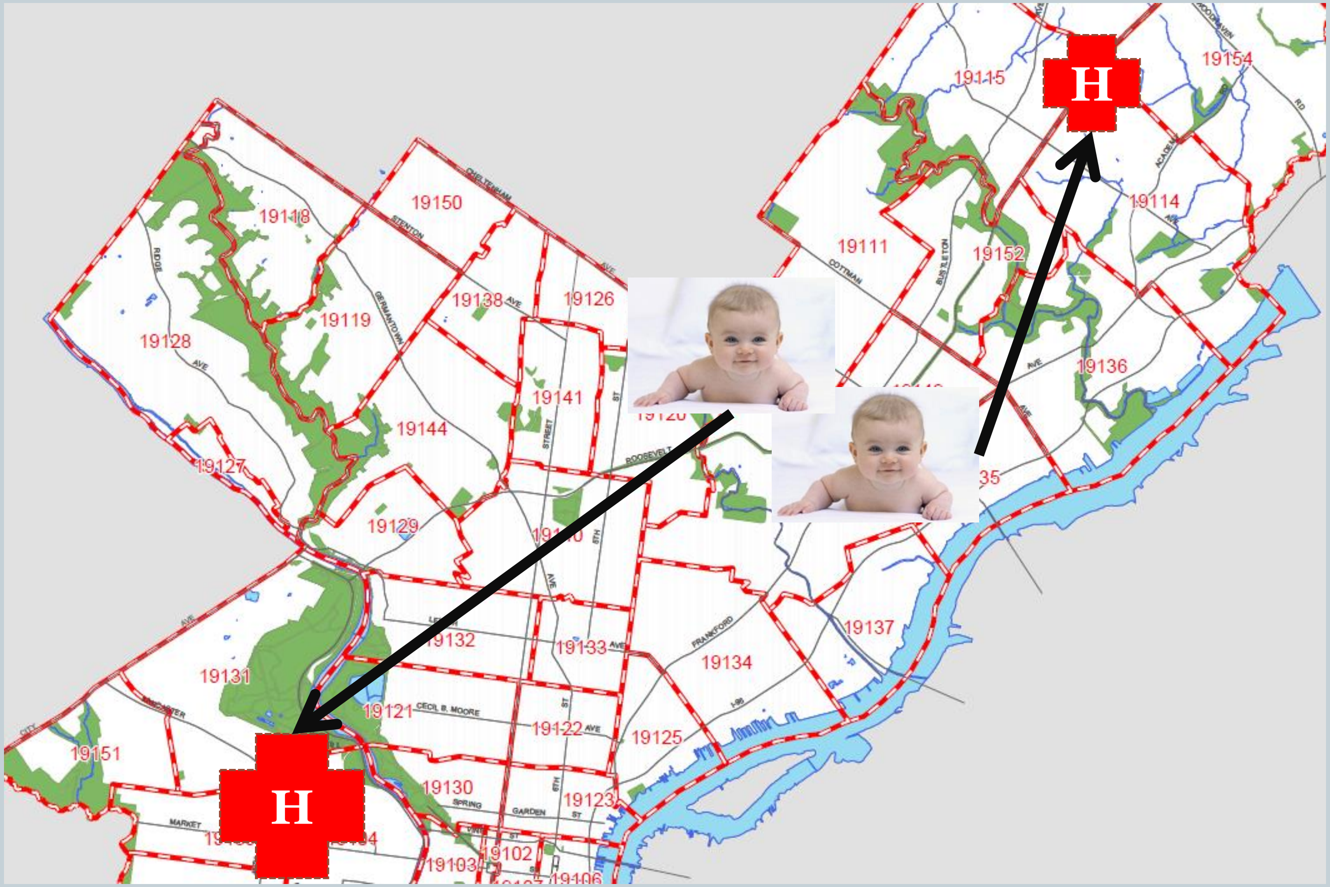
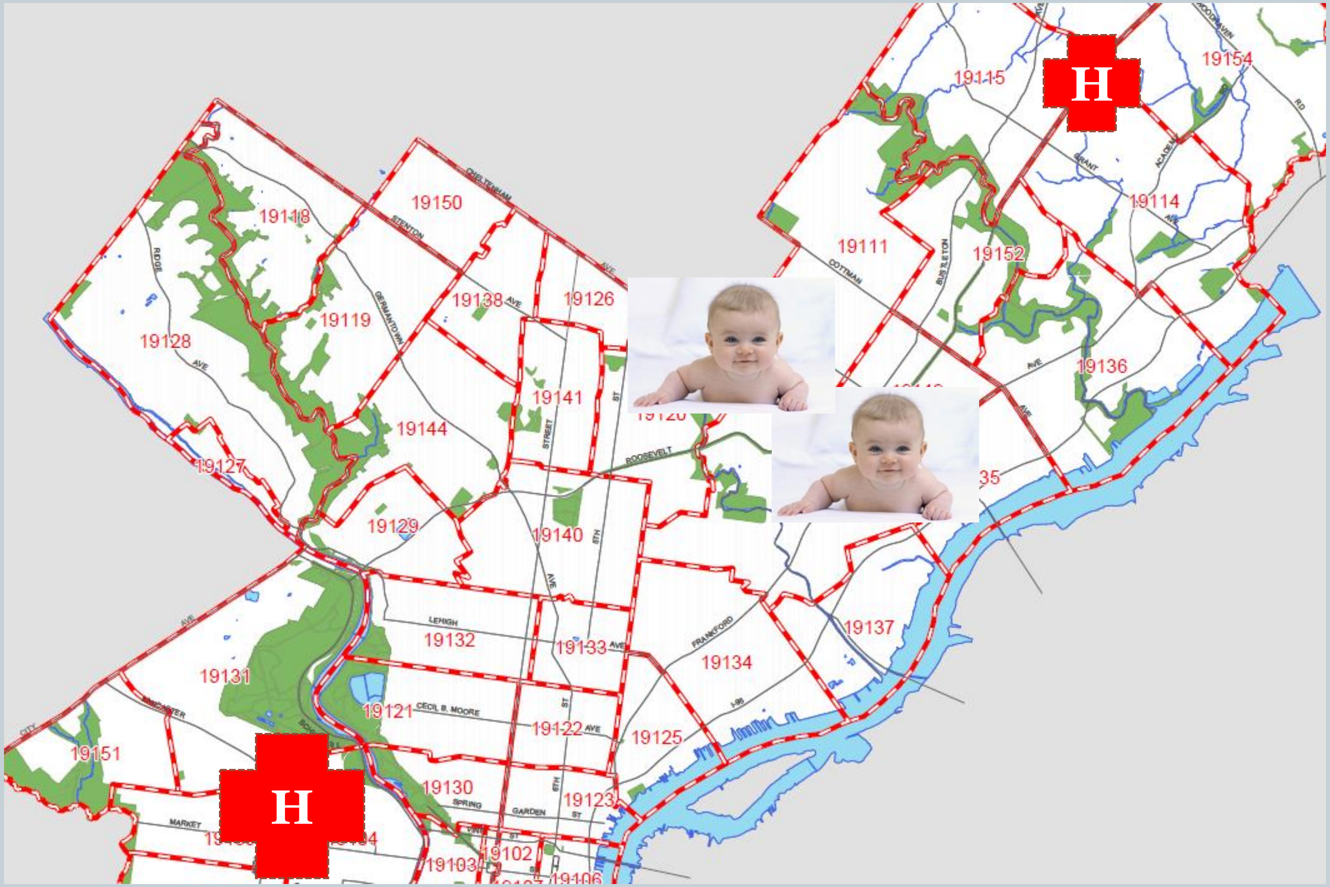
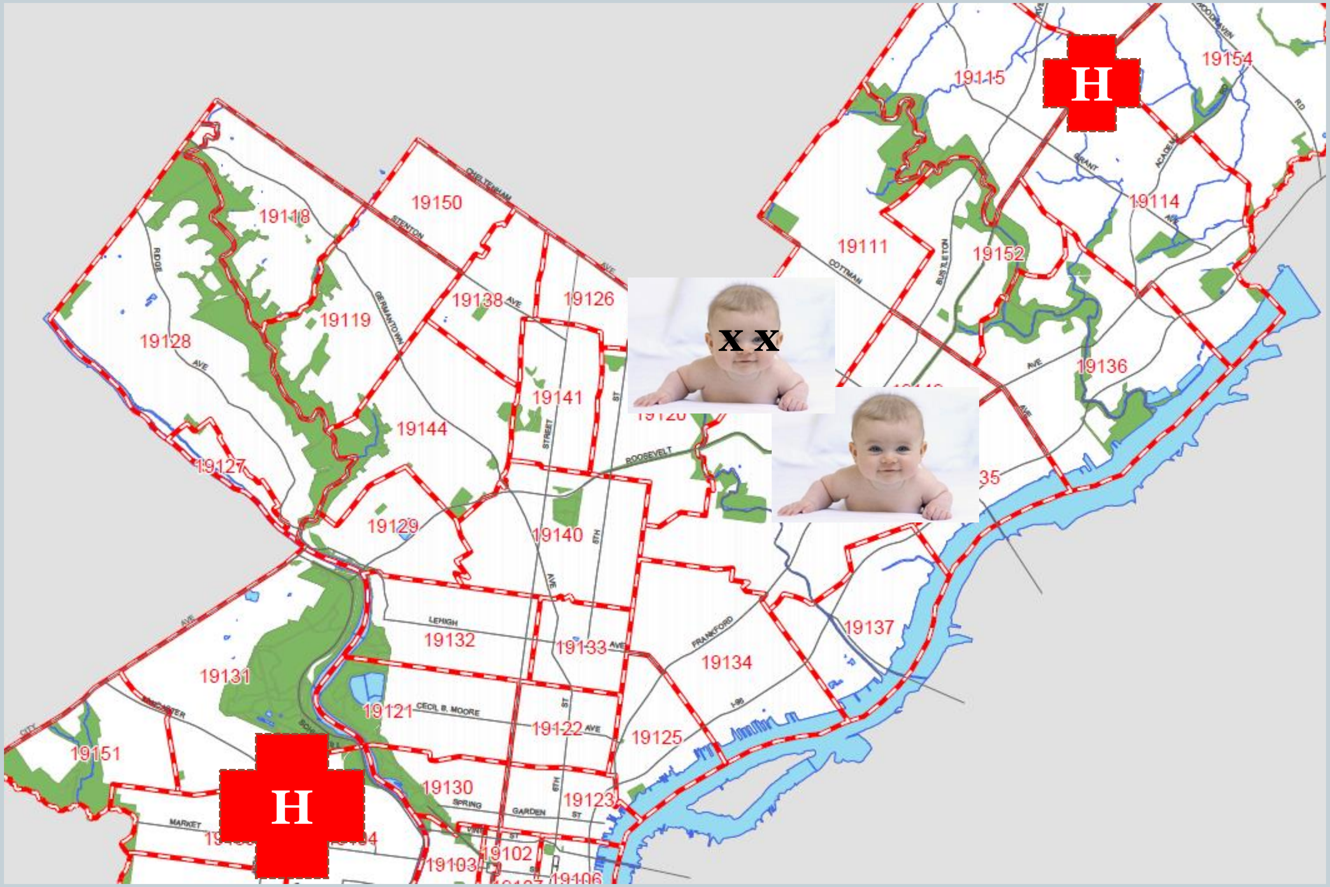


Use pre-intervention covariates to fit a pscore. Match on pscore between observations that used t=1 vs t=0. Examine distributions of outcomes between the two groups.

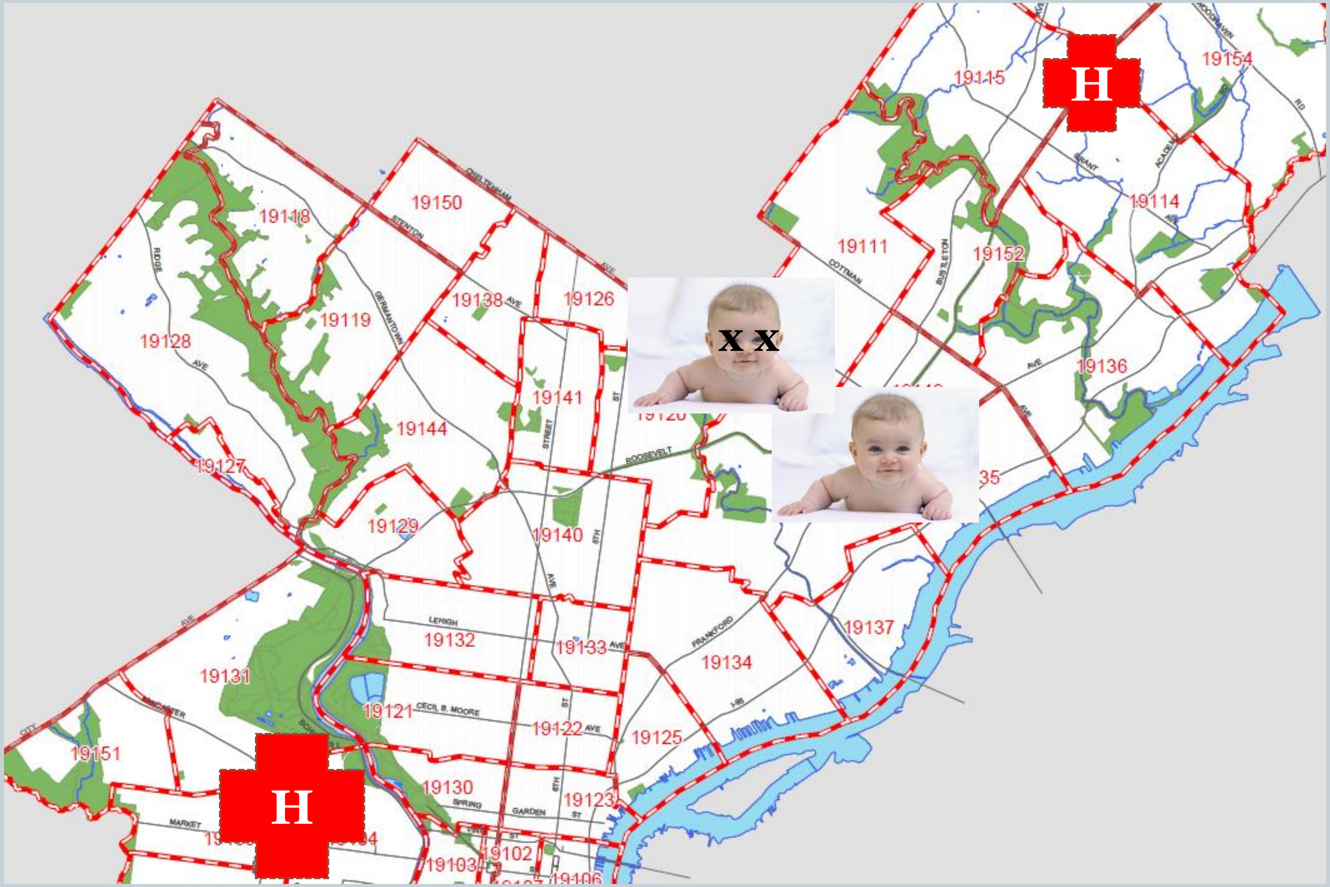
case-control matching



case-control matching

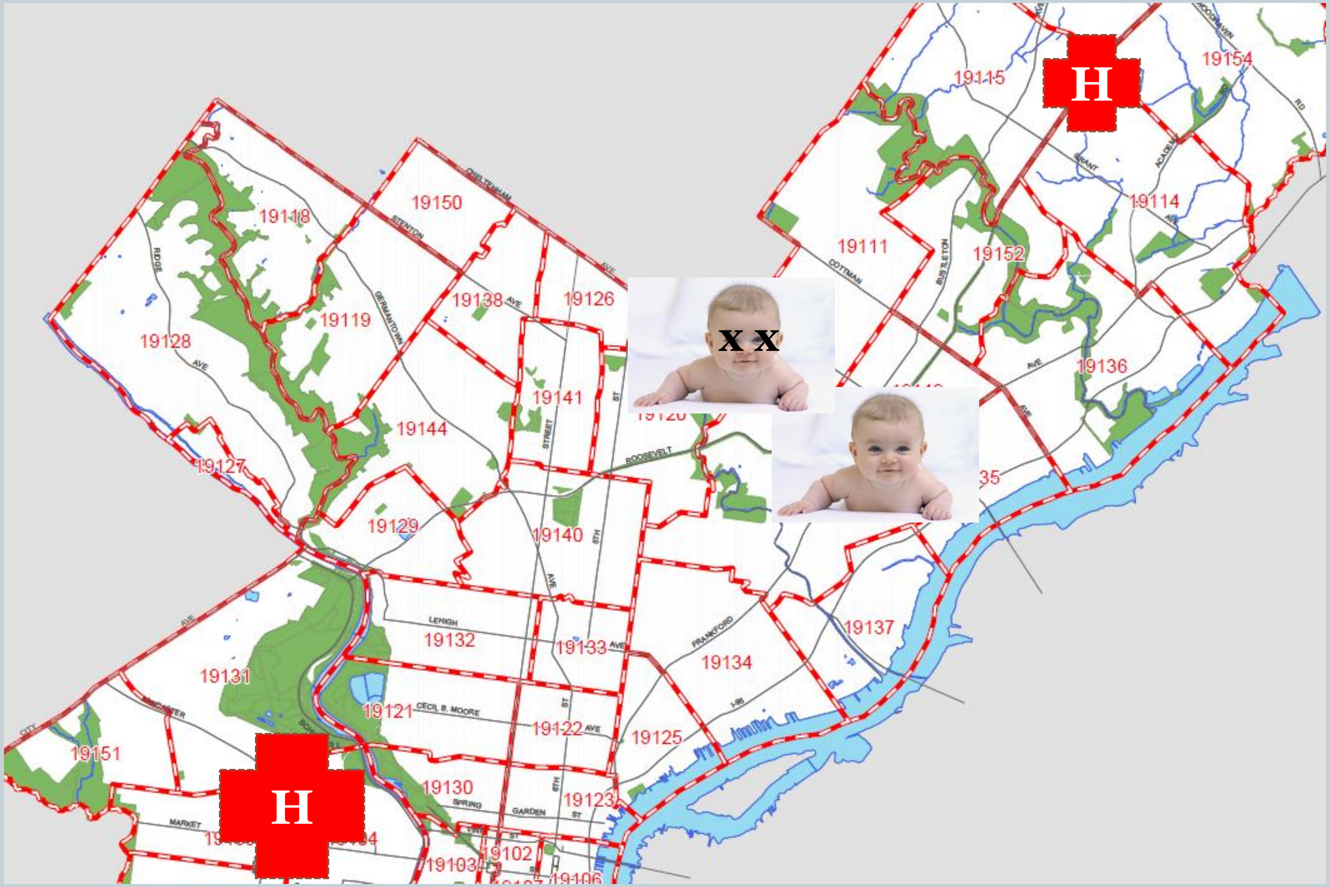


case-control matching



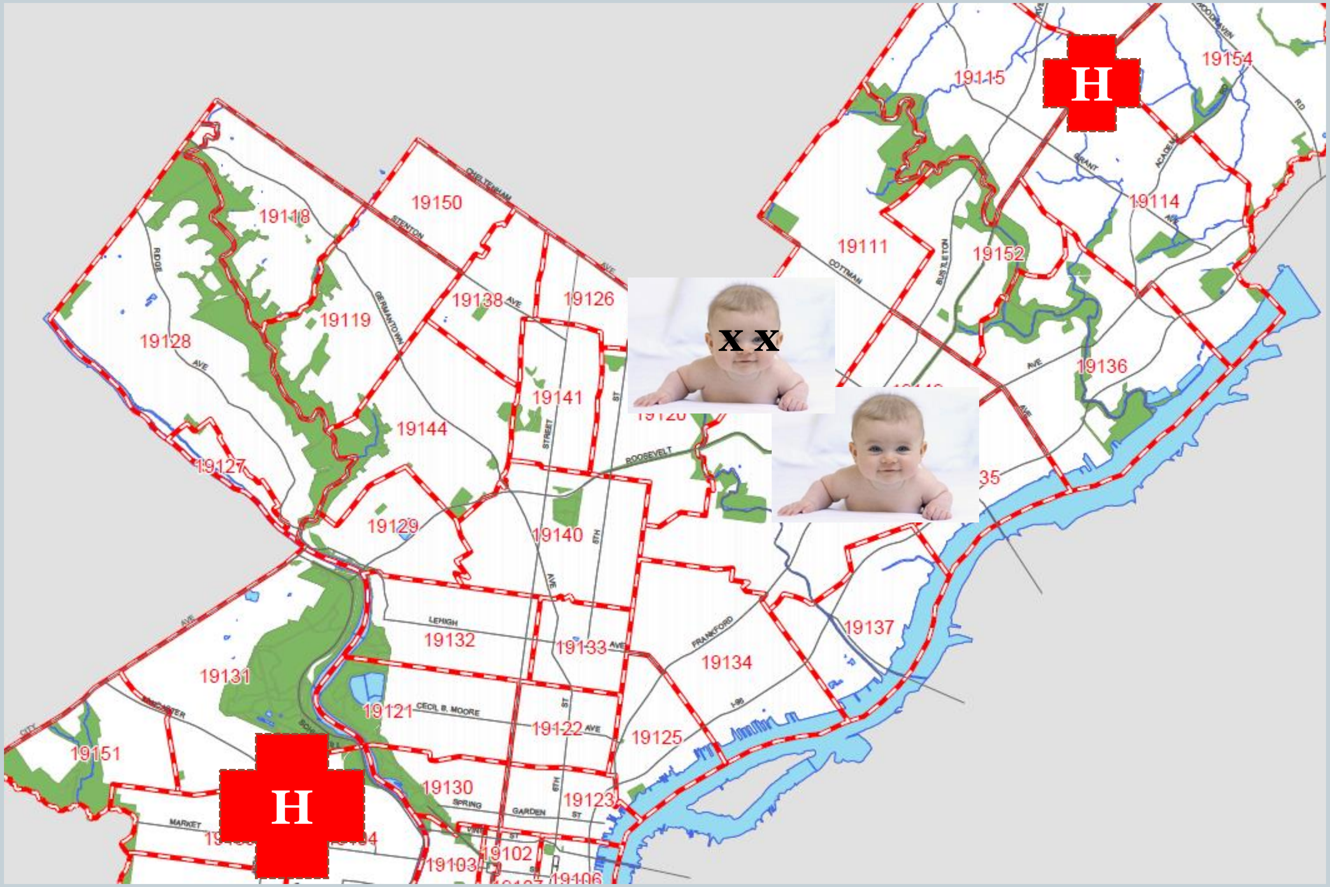
Use pre-intervention covariates to match.

case-control matching



Use pre-intervention covariates to match. Match between observations y=1 vs y=0.

case-control matching



Use pre-intervention covariates to match. Match between observations y=1 vs y=0. Examine distributions of candidate causes between the two groups.

case-noncase

case-noncase

- Match from Y=1 to Y=0 on all baseline characteristics…

case-noncase

- Match from Y=1 to Y=0 on all baseline characteristics, POSSIBLY some intermediate variables…

case-noncase

- Match from Y=1 to Y=0 on all baseline characteristics, POSSIBLY some intermediate variables, but NOT the candidate causal covariates of interest.

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  - For the matching we've discussed in this class we've got all we need: (d, y). It's not clear that we have all the d that cause variation in y.

case-noncase

You know the difference in logical reasoning here.

case-noncase

You know the difference in logical reasoning here.

Canonical archetypes:

case-noncase

You know the difference in logical reasoning here.

Canonical archetypes:

scientist

case-noncase

You know the difference in logical reasoning here.

Canonical archetypes:

scientist

detective

isolation

isolation by design

- Natural experiments:

https://projecteuclid.org/download/pdfview_1/euclid.aoas/1419001736

isolation by design

- Natural experiments:
  - Natural experiments are a type of observational study, that is, a study of the effects caused by treatments when random assignment is infeasible or unethical.

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isolation by design

- Natural experiments:
  - Natural experiments are a type of observational study, that is, a study of the effects caused by treatments when random assignment is infeasible or unethical.
  - What distinguishes a natural experiment from other observational studies is the emphasis placed upon finding unusual circumstances in which treatment assignment, though not randomized, seems to resemble randomized assignment in that it is haphazard, not the result of deliberation or considered judgement, not confounded by the typical attributes that determine treatment assignment in a particular empirical field.

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regionalizing care for acute type A aortic dissections

Andrew B. Goldstone, MD,PhD, Peter Chiu, MD, Michael Baiocchi, PhD,
Bharathi Lingala, PhD, Michael P. Fischbein, MD, PhD, Joseph Woo, MD

Stanford University

acute aortic dissection

acute aortic dissection

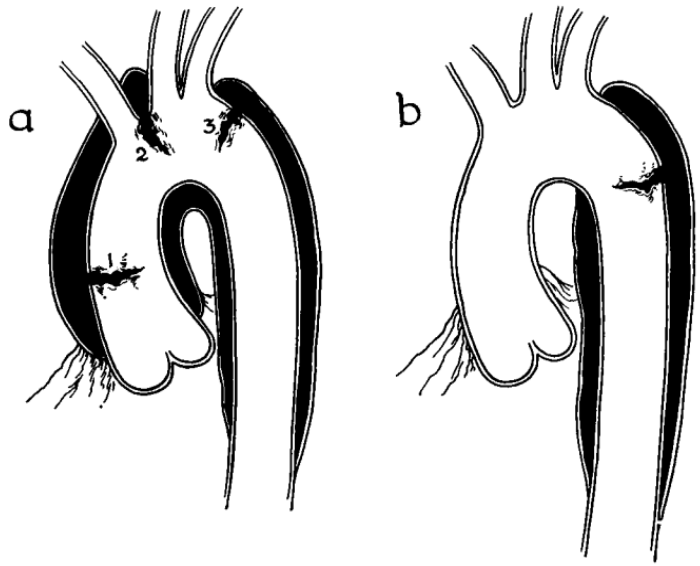


FIG. 3. Classification of aortic dissections. In type A the ascending aorta is dissected (a). *The intimal tear has always been at position* 1, *but it can occur at positions* 2 *or* 3 *(see text). In type B dissection the dissection is limited to the descending aorta* (b), *and the intimal tear is usually within 2 to 5 cm. of the left subclavian artery.*

Daily et al., *Ann Thorac Surg,* 1970

acute aortic dissection

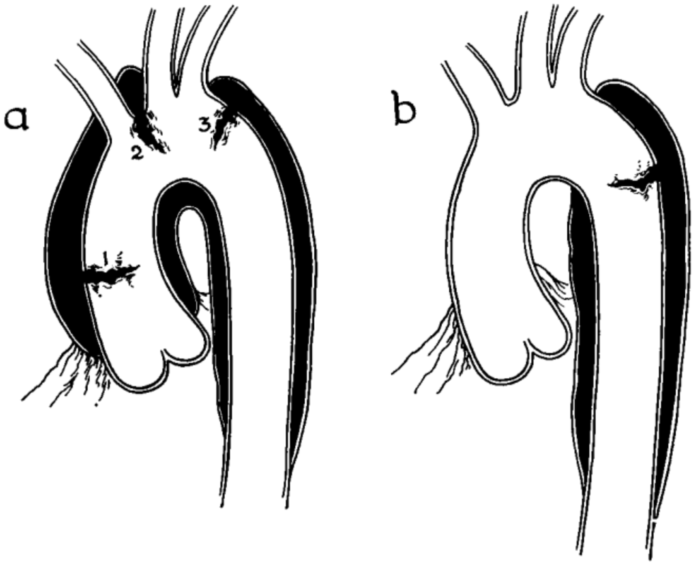
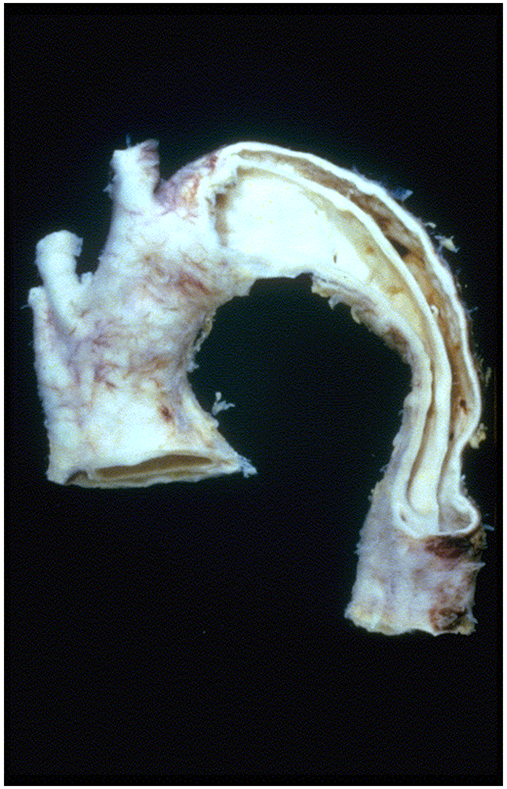


FIG. 3. Classification of aortic dissections. In type A the ascending aorta is dissected (a). *The intimal tear has always been at position* 1, *but it can occur at positions* 2 *or* 3 *(see text). In type B dissection the dissection is limited to the descending aorta* (b), *and the intimal tear is usually within 2 to 5 cm. of the left subclavian artery.*



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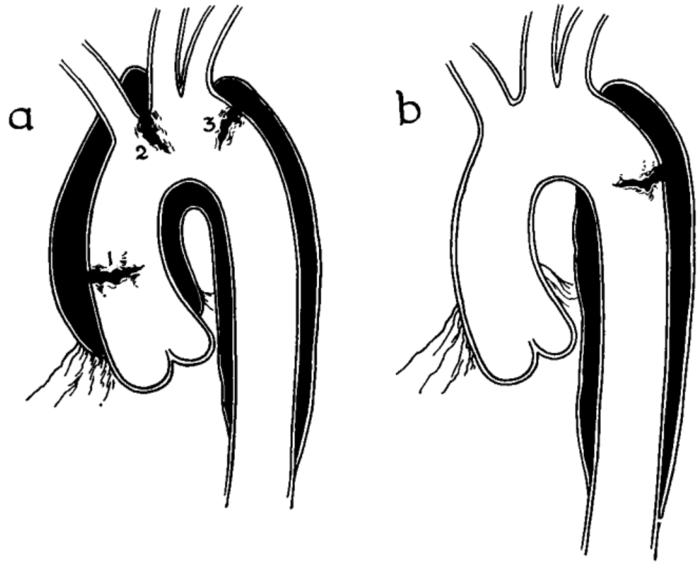
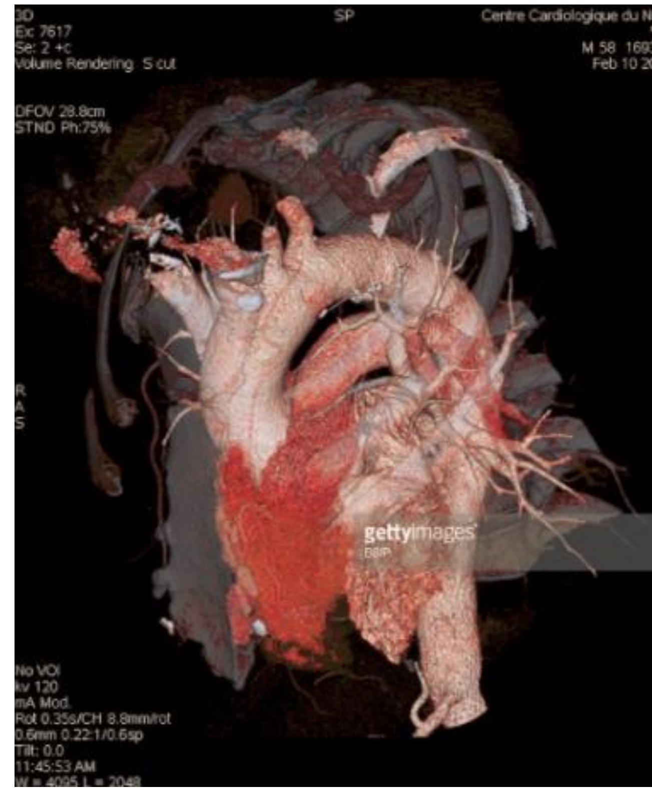


FIG. 3. Classification of aortic dissections. In type A the ascending aorta is dissected (a). *The intimal tear has always been at position* 1, *but it can occur at positions* 2 *or* 3 *(see text). In type B dissection the dissection is limited to the descending aorta* (b), *and the intimal tear is usually within 2 to 5 cm. of the left subclavian artery.*



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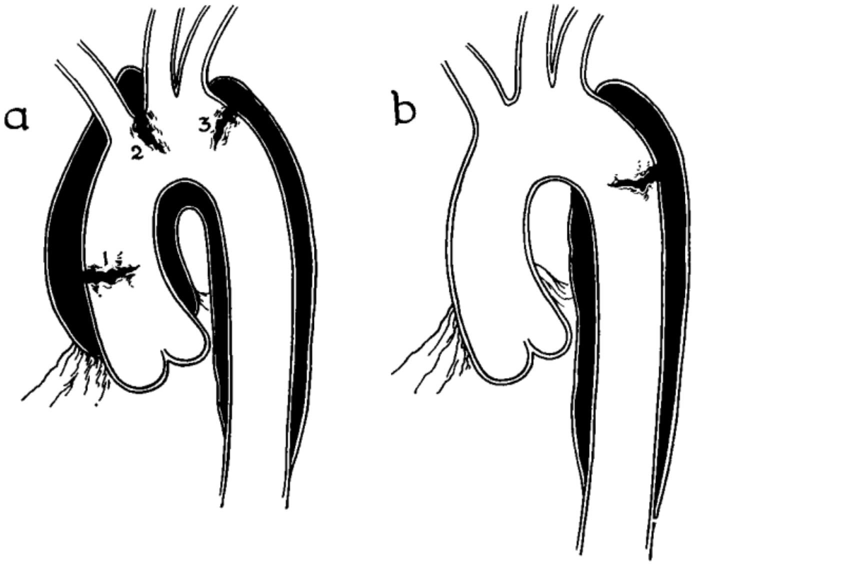
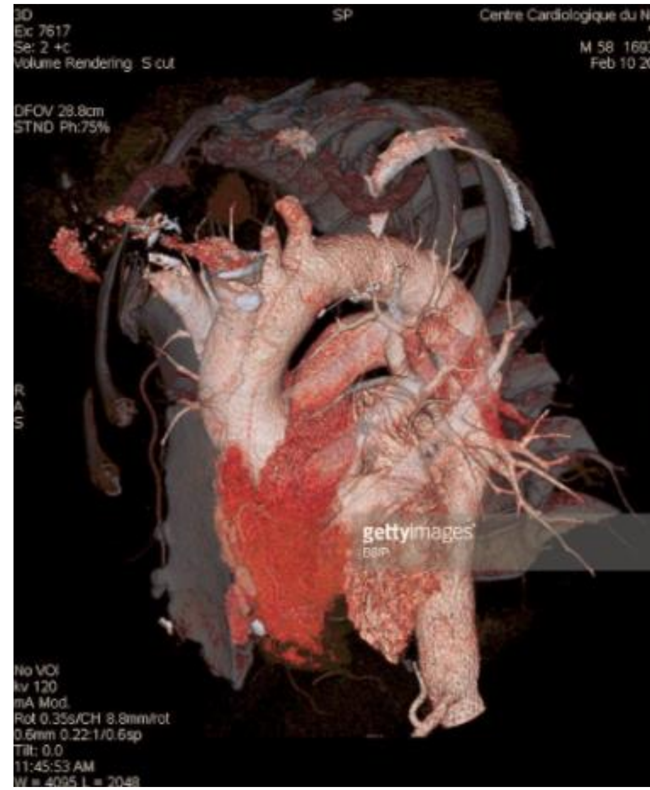


FIG. 3. Classification of aortic dissections. In type A the ascending aorta is dissected (a). *The intimal tear has always been at position* 1, *but it can occur at positions* 2 *or* 3 *(see text). In type B dissection the dissection is limited to the descending aorta* (b), *and the intimal tear is usually within 2 to 5 cm. of the left subclavian artery.*



(that's a Norm MacDonald joke)

Daily et al., *Ann Thorac Surg,* 1970

aortic dissection

aortic dissection

It’s a particularly scary situation:

aortic dissection

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- Incidence is 4-7 per 100,000

aortic dissection

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- Mortality for untreated acute type A
  - First 24hrs =
  - First 48hrs =

aortic dissection

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  - First 48hrs = 40%

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- Upon diagnosis patients are rushed to operating room.

aortic dissection

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aortic dissection

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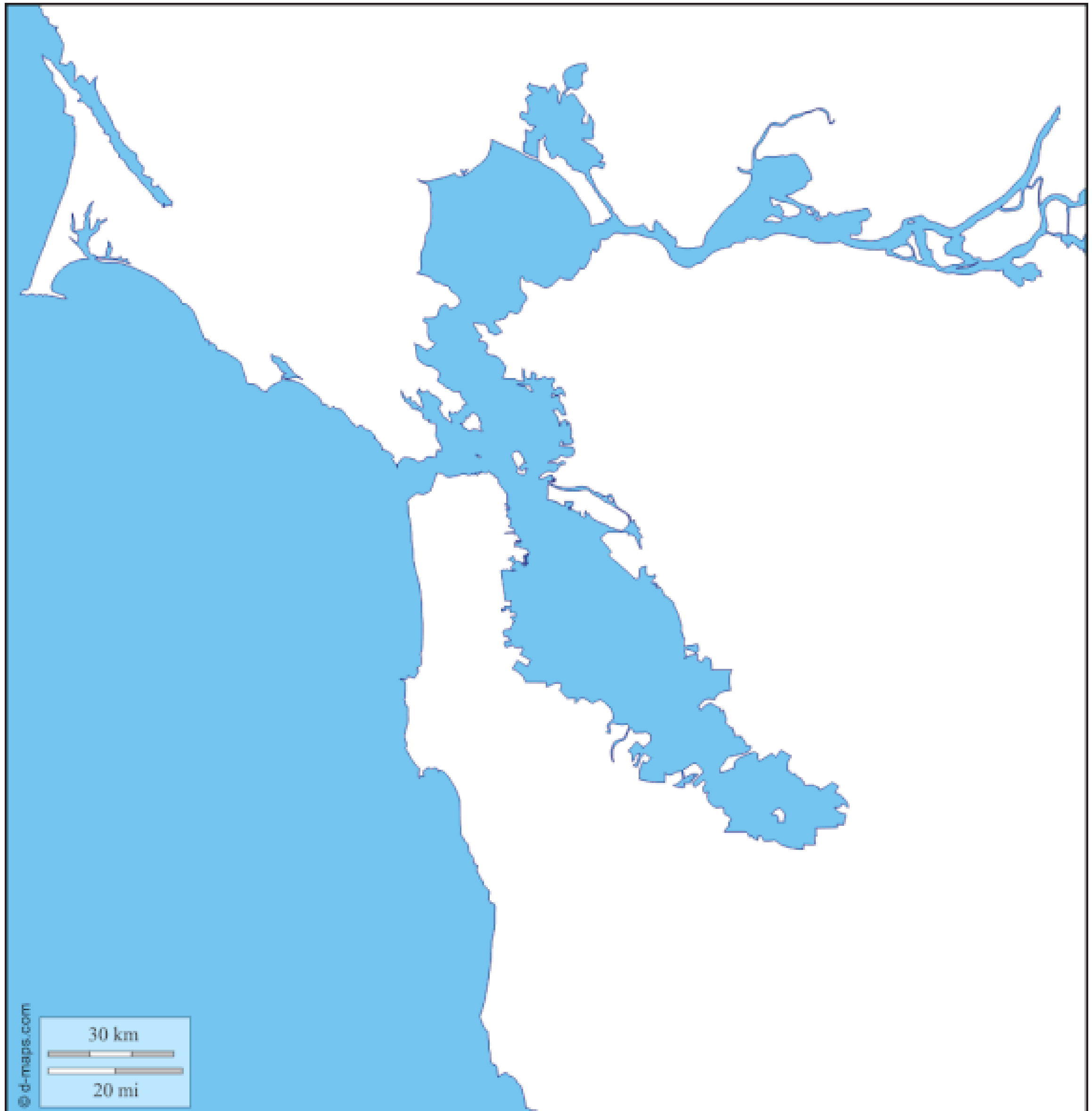
- Upon diagnosis patients are rushed to operating room.
- Operative mortality in the range of 19-28%
- Interfacility transfer = ?


30 km
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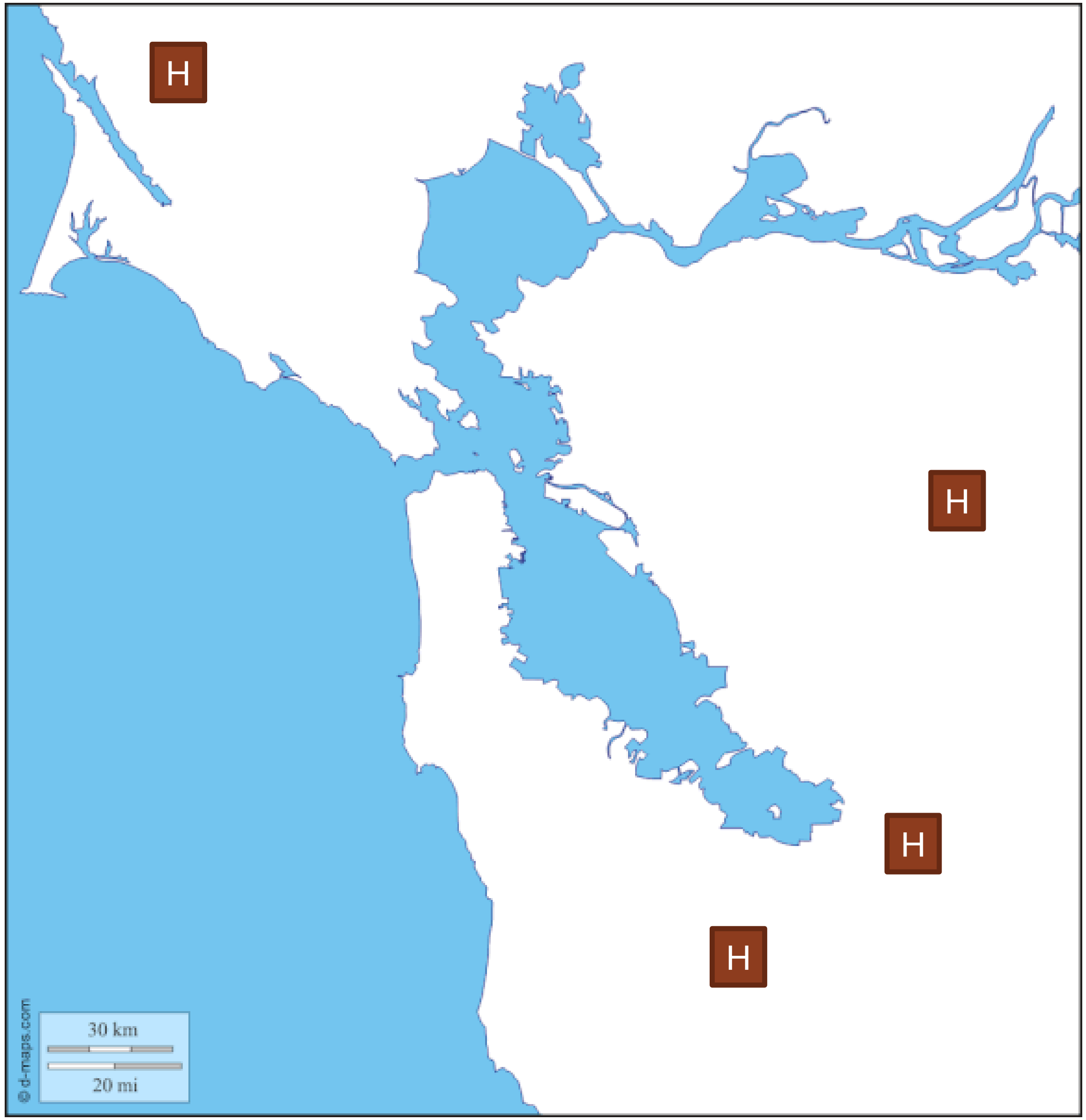
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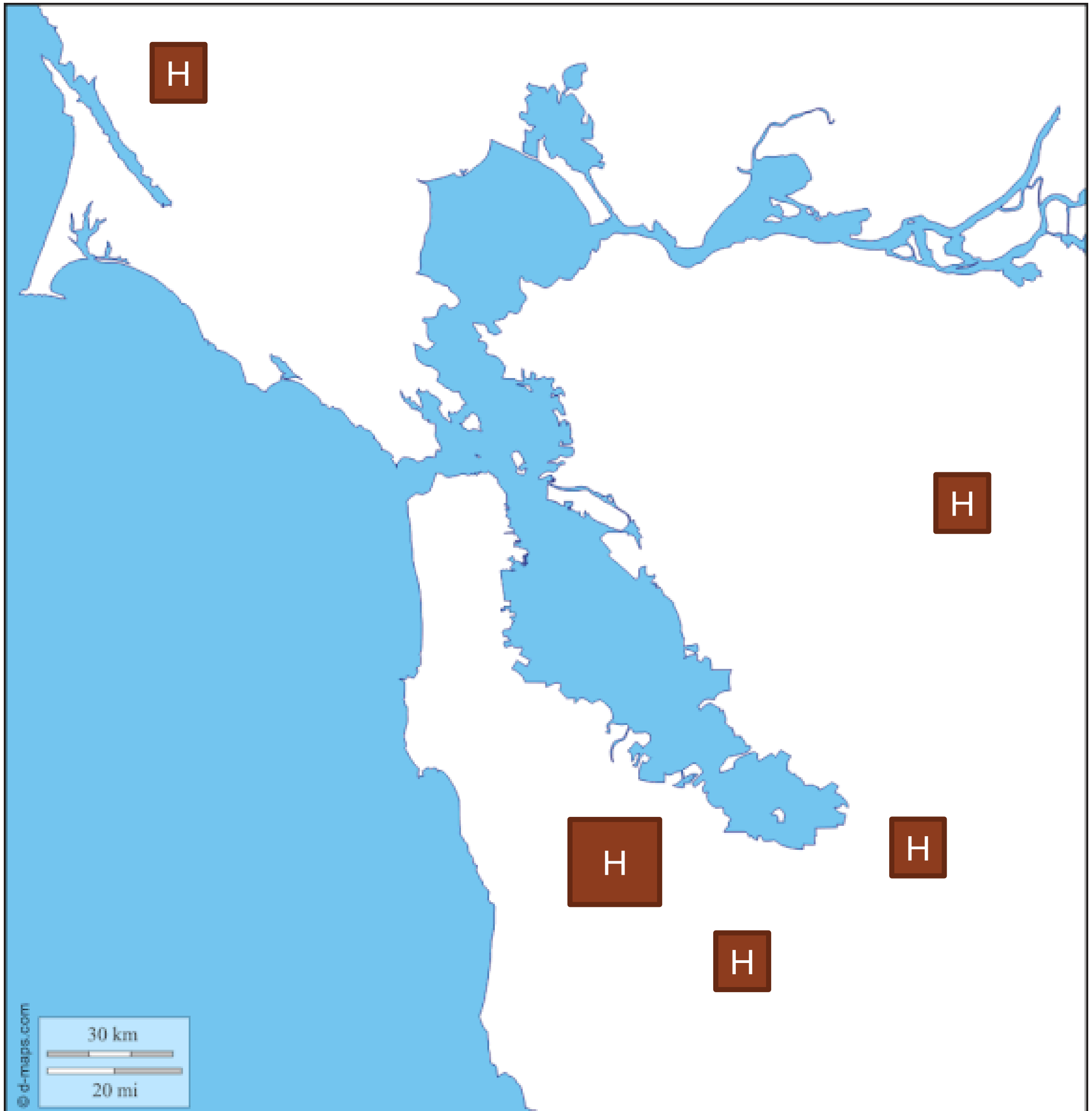
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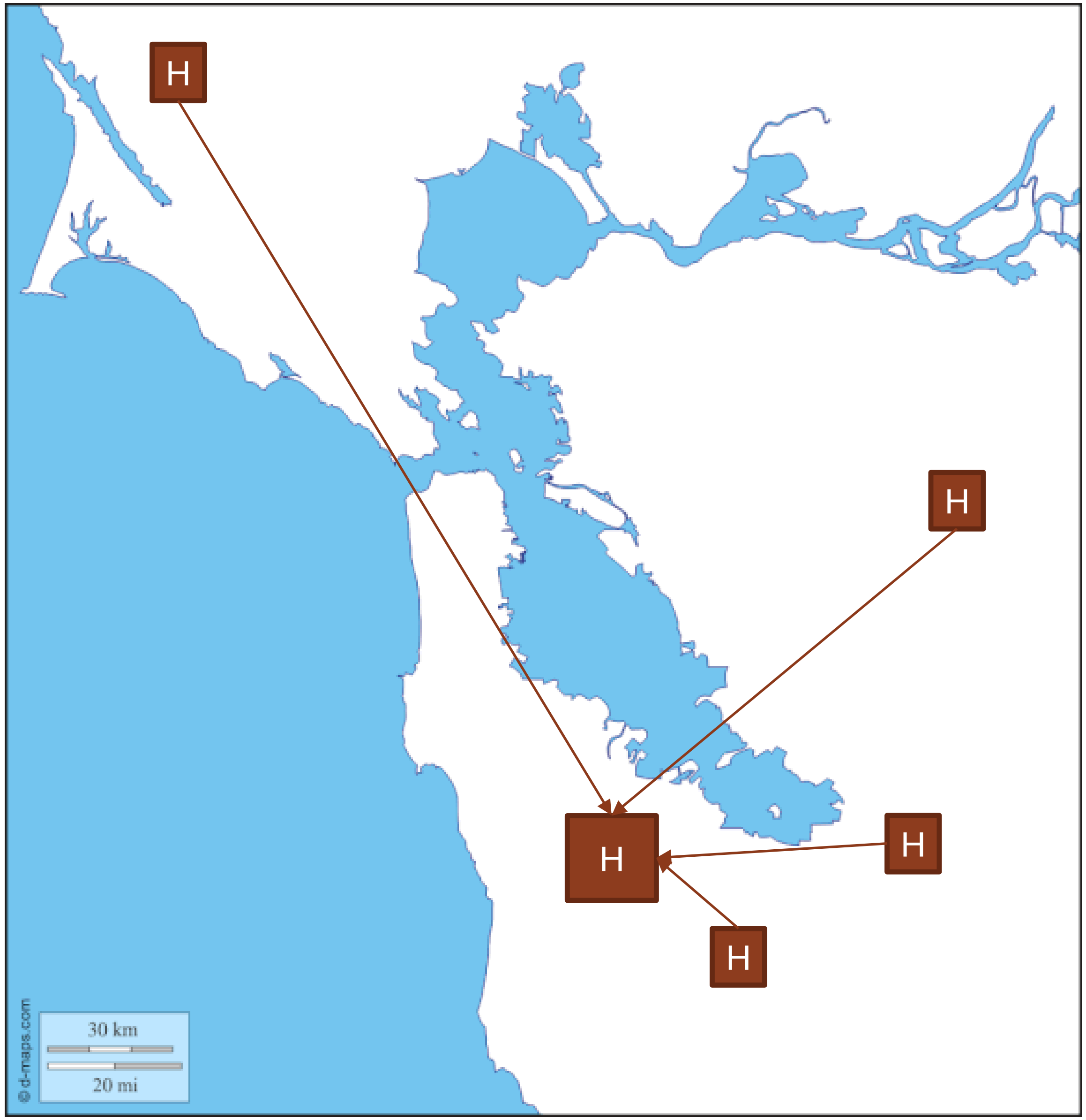
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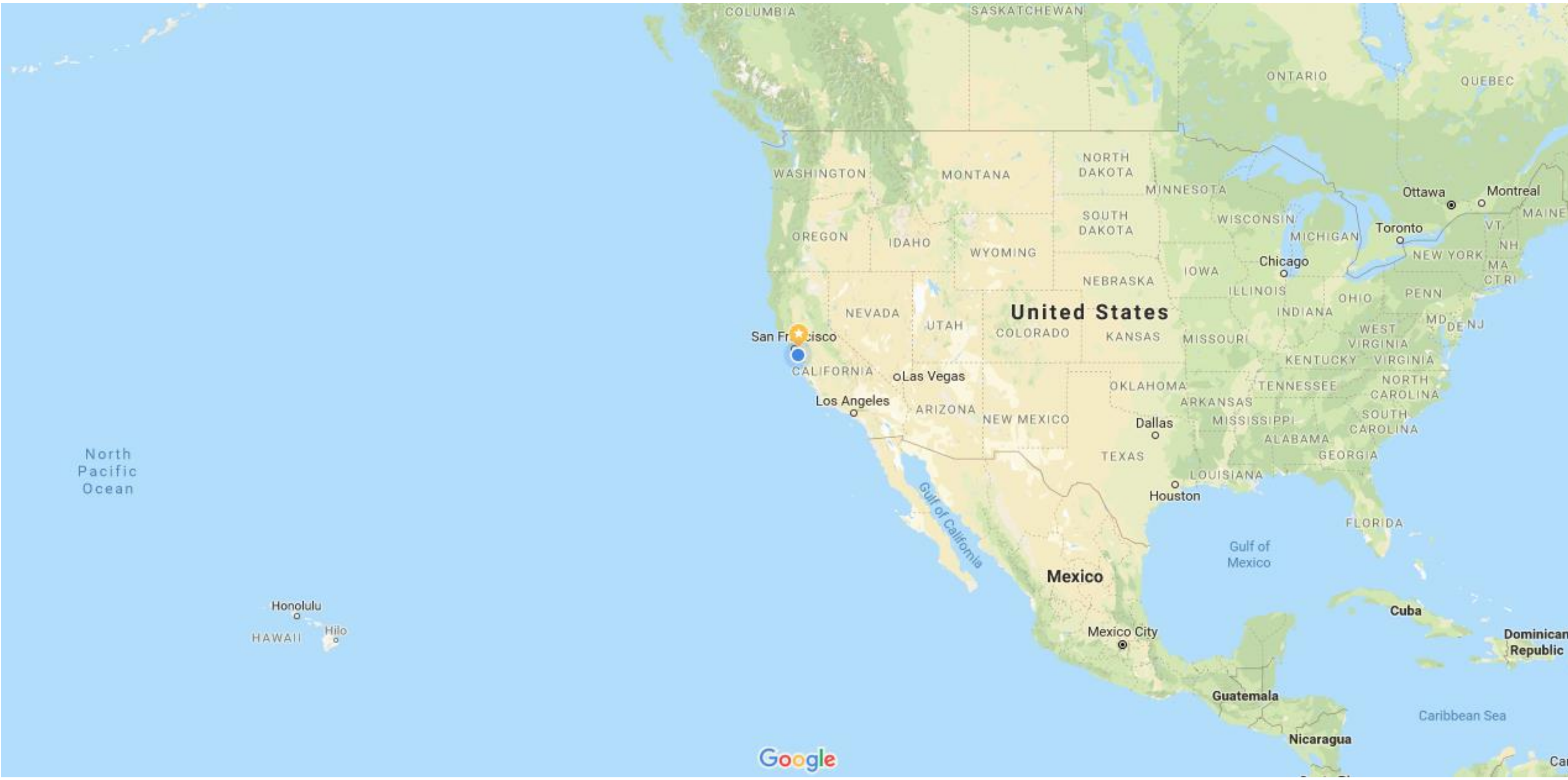
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IDAHO
WYOMING
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CT RI
IOWA
Chicago
NEBRASKA
ILLINOIS
OHIO
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TENNESSEE
NORTH CAROLINA
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NEW MEXICO
ARKANSAS
Dallas
MISSISSIPPI
SOUTH CAROLINA
ALABAMA
GEORGIA
TEXAS
LOUISIANA
Houston
FLORIDA
Gulf of California
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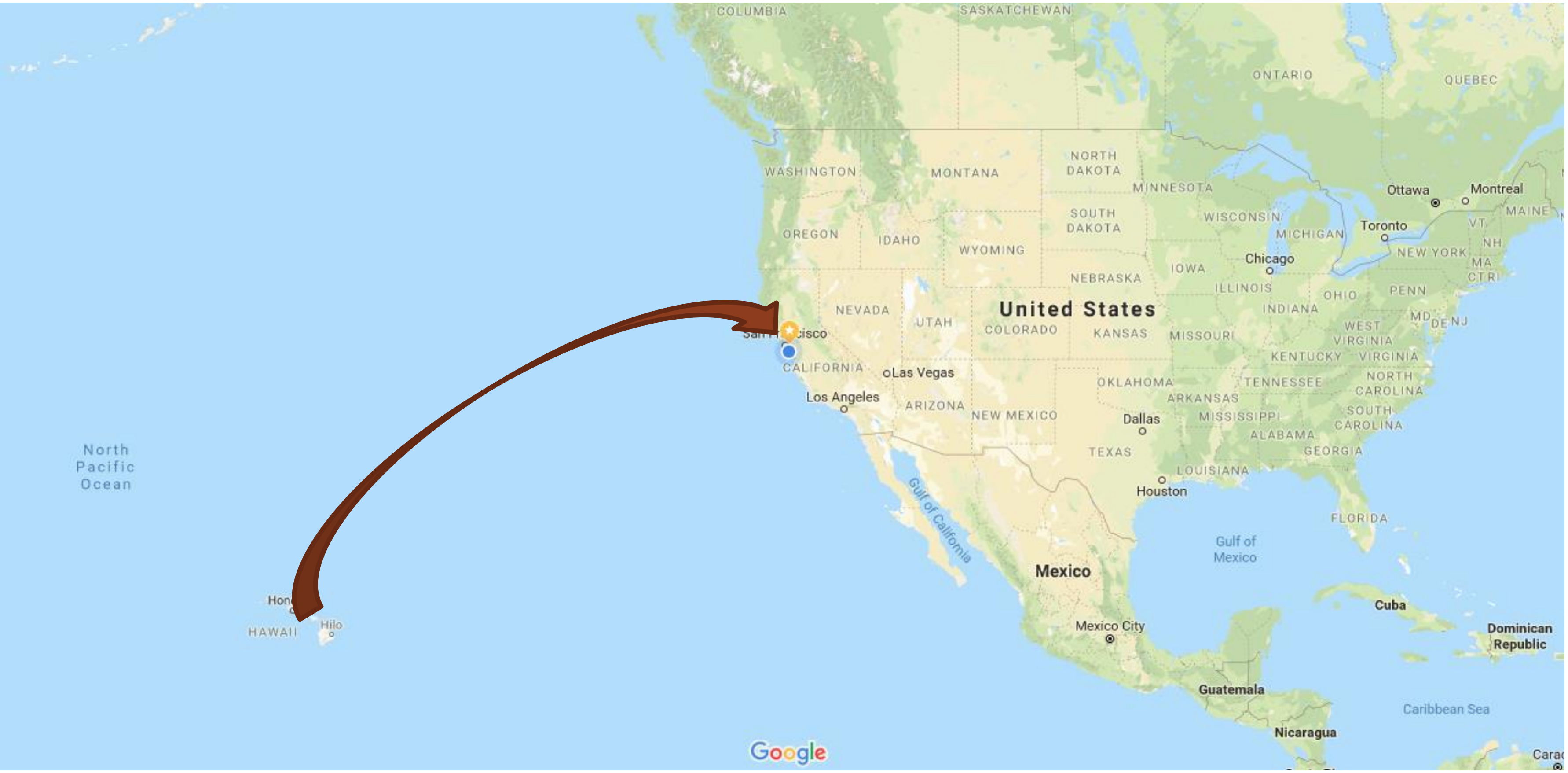
Mexico City
Guatemala
Caribbean Sea
Nicaragua
Google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Dallas
Houston
Chicago
Toronto
Ottawa
Montreal
Mexico
Mexico City
Gulf of California
Gulf of Mexico
Cuba
Dominican Republic
Guatemala
Nicaragua
Caribbean Sea
Google

policy question

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But there might an exception here because of the time-sensitivity and fragility of these cases.

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Q: What would happen if we regionalized care to high-volume centers?

answering this question

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Ideally:

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Ideally:

Logistically:

answering this question

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Ideally: individually randomize patients to receive care at high-volume vs low-volume.

Logistically:

answering this question

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Ideally: individually randomize patients to receive care at high-volume vs low-volume.

Logistically: (i) can’t identify patients until they’re at the facility, (ii) likely unable to get consent because these patients are so compromised.

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Perhaps we could move up to a higher level of randomization:

answering this question

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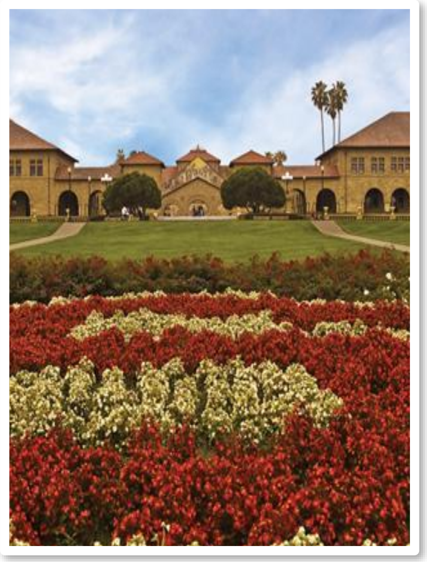
Ideally: individually randomize patients to receive care at high-volume vs low-volume.

Logistically: (i) can’t identify patients until they’re at the facility, (ii) likely unable to get consent because these patients are so compromised.

Perhaps we could move up to a higher level of randomization: could work with some hospitals to have them implement regionalization, others not.

study design

isolating a natural experiment



control for what you know

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Found about 12,500 type A patients.

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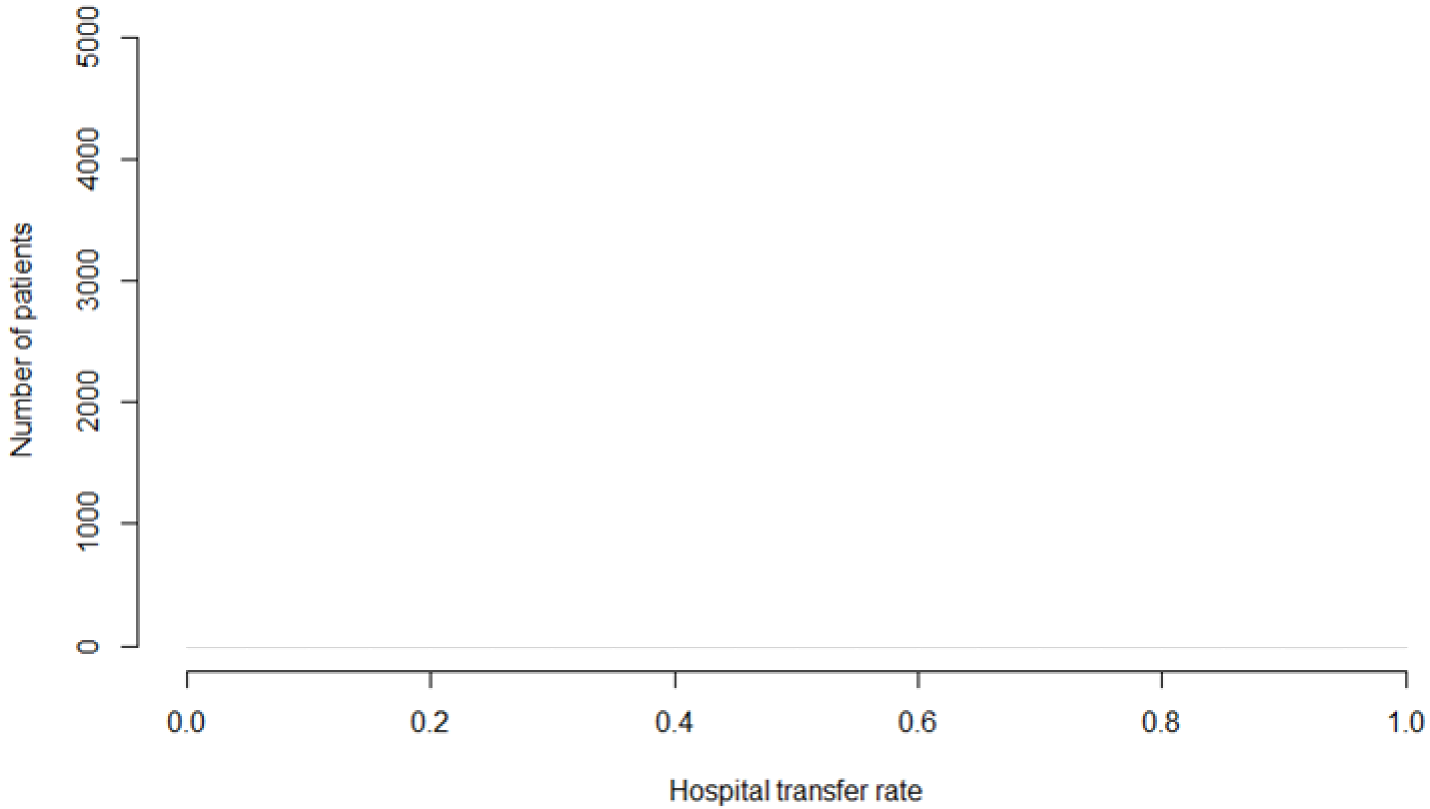
- Have 30ish baseline covariates on each patient.

Table 1. Baseline and Operative Characteristics of the Study Population and the Population for the Analysis of Regional

Characteristic	Overall Study Population (N=16,886)	Before Matching: Not Rerouted (N=7910)	Before Matching: Rerouted (N=4520)	SMD
Age – yr	72.44 (9.50)	72.29 (9.46)	72.46 (9.41)	0.017
Age <65 yrs – n (%)	1935 (11.5)	946 (12.0)	510 (11.3)	0.021
Year of surgery – yr	2006.78 (4.57)	2006.71 (4.57)	2006.86 (4.59)	0.033
Male sex – n (%)	9397 (55.6)	4412 (55.8)	2513 (55.6)	0.004
Race – n (%)				
White	14 335 (84.9)	6717 (84.9)	3830 (84.7)	0.005
Black	1787 (10.6)	748 (9.5)	534 (11.8)	0.077
Asian	268 (1.6)	177 (2.2)	48 (1.1)	0.092
Hispanic	191 (1.1)	98 (1.2)	34 (0.8)	0.049
Other	305 (1.8)	170 (2.1)	74 (1.6)	0.038
Prior myocardial infarction – n (%)	574 (3.4)	279 (3.5)	151 (3.3)	0.01
Alzheimer's dementia – n (%)	806 (4.8)	369 (4.7)	230 (5.1)	0.02
Atrial fibrillation – n (%)	2735 (16.2)	1204 (15.2)	675 (14.9)	0.008
Chronic kidney disease – n (%)	2555 (15.1)	1166 (14.7)	704 (15.6)	0.023
COPD – n (%)	3848 (22.8)	1752 (22.1)	1114 (24.6)	0.059
Congestive heart failure – n (%)	4230 (25.1)	1863 (23.6)	1118 (24.7)	0.028
Diabetes mellitus – n (%)	3049 (18.1)	1364 (17.2)	841 (18.6)	0.036
Hip facture – n (%)	250 (1.5)	107 (1.4)	82 (1.8)	0.037
Ischemic heart disease – n (%)	7842 (46.4)	3503 (44.3)	2049 (45.3)	0.021
Arthritis – n (%)	2222 (13.2)	1020 (12.9)	571 (12.6)	0.008
Stroke – n (%)	1825 (10.8)	832 (10.5)	502 (11.1)	0.019
Cancer – n (%)	2039 (12.1)	929 (11.7)	557 (12.3)	0.018
Anemia – n (%)	6524 (38.6)	2908 (36.8)	1758 (38.9)	0.044
Hyperlipidemia – n (%)	9249 (54.8)	4247 (53.7)	2490 (55.1)	0.028
Hypertension – n (%)	12 225 (72.4)	5618 (71.0)	3326 (73.6)	0.057
Hypothyroidism – n (%)	2329 (13.8)	1099 (13.9)	602 (13.3)	0.017
Region				
New England – n (%)	947 (5.6)	273 (3.5)	364 (8.1)	0.199
Mideast – n (%)	3035 (18.0)	839 (10.6)	1121 (24.8)	0.378
Great Lakes – n (%)	3061 (18.1)	1302 (16.5)	910 (20.1)	0.095
Plains – n (%)	1 267 (7.5)	689 (8.7)	263 (5.8)	0.112
Southeast – n (%)	4669 (27.7)	2223 (28.1)	1215 (26.9)	0.027
Southwest – n (%)	1 504 (8.9)	875 (11.1)	300 (6.6)	0.156
Rocky Mountain – n (%)	460 (2.7)	365 (4.6)	41 (0.9)	0.228
Prior Procedures				
Aortic valve surgery – n (%)	375 (2.2)	163 (2.1)	108 (2.4)	0.022
Thoracic aortic replacement – n (%)	36 (0.2)	10 (0.1)	16 (0.4)	0.046
Thoracoabdominal aortic replacement – n (%)	19 (0.1)	4 (0.1)	9 (0.2)	0.042
TEVAR – n (%)	22 (0.1)	9 (0.1)	7 (0.2)	0.011
EVAR – n (%)	53 (0.3)	25 (0.3)	11 (0.2)	0.014
Abdominal aortic replacement – n (%)	199 (1.2)	84 (1.1)	62 (1.4)	0.028
Mitral valve surgery – n (%)	155 (0.9)	68 (0.9)	41 (0.9)	0.005
Tricuspid valve surgery – n (%)	15 (0.1)	5 (0.1)	6 (0.1)	0.022
CABG – n (%)	988 (5.9)	440 (5.6)	278 (6.2)	0.025
VAD/ECMO – n (%)	14 (0.1)	4 (0.1)	7 (0.2)	0.033
Other cardiac surgery – n (%)	82 (0.5)	33 (0.4)	28 (0.6)	0.028
Index Surgical Procedures				
Aortic valve surgery – n (%)	2428 (14.4)	1056 (13.4)	587 (13.0)	0.011
Aortic root replacement – n (%)	4816 (28.5)	2280 (28.8)	1193 (26.4)	0.054
Ascending aortic replacement – n (%)	12 228 (72.4)	5700 (72.1)	3362 (74.4)	0.052
Aortic arch replacement – n (%)	3044 (18.0)	799 (10.1)	1214 (26.9)	0.442
Descending thoracic aortic replacement – n (%)	195 (1.2)	73 (0.9)	62 (1.4)	0.042
Thoracoabdominal aortic replacement – n (%)	25 (0.1)	13 (0.2)	5 (0.1)	0.015
TEVAR – n (%)	154 (0.9)	37 (0.5)	62 (1.4)	0.095
EVAR – n (%)	19 (0.1)	8 (0.1)	6 (0.1)	0.009
Abdominal aortic replacement – n (%)	39 (0.2)	23 (0.3)	7 (0.2)	0.029
CABG – n (%)	4181 (24.8)	2029 (25.7)	866 (19.2)	0.156
Other valve surgery – n (%)	8 (0.0)	5 (0.1)	0 (0.0)	0.036
Other cardiac surgery – n (%)	340 (2.0)	133 (1.7)	79 (1.7)	0.005
Transferred – n (%)	6836 (40.5)	2316 (29.3)	4520 (100.0)	2.198
Surgery at high-volume center – n (%)	8976 (53.2)	0 (0.0)	4520 (100.0)	-
Rerouted – n (%)	4520 (26.4)	0 (0.0)	4520 (100.0)	-

*Plus-minus values are means +/- standard deviation. Variables excluded from table though well-balanced (SMD <0.1):

B Distribution of patients presenting to hospitals with varying transfer rates for acute type A aortic dissection



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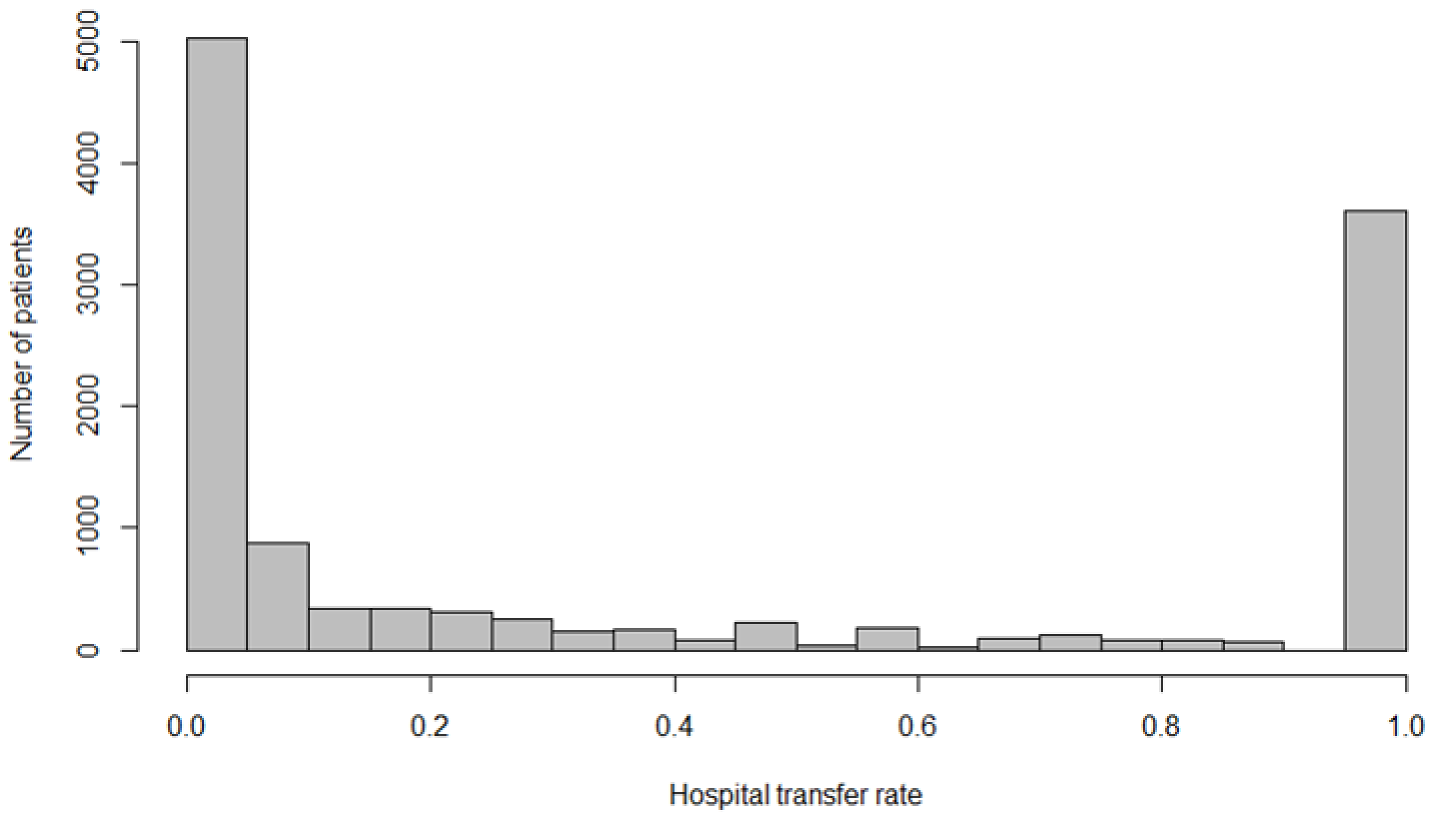
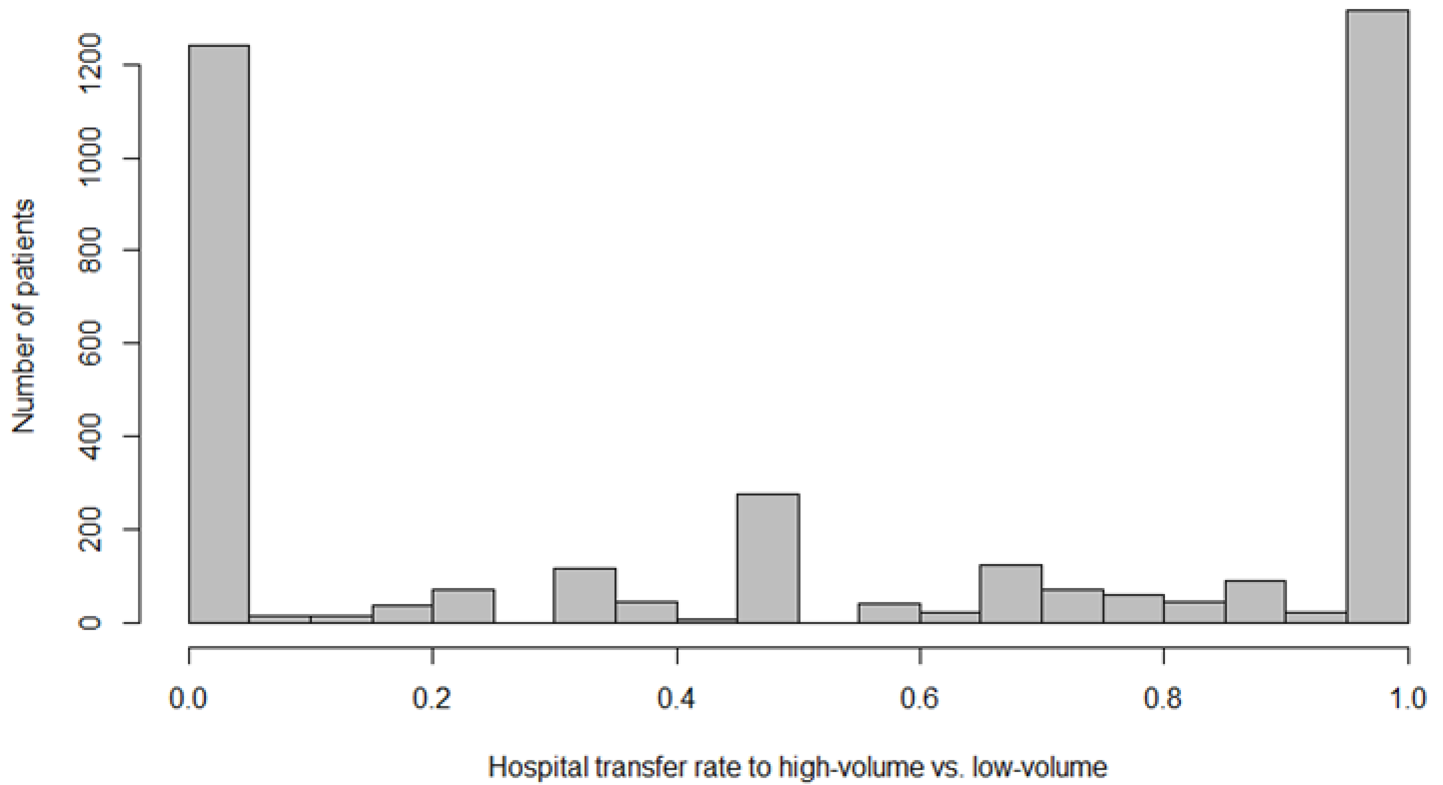


D Distribution of patients presenting to hospitals with varying transfer rates to high-volume centers among hospitals that always transferred patients with acute type A aortic dissection

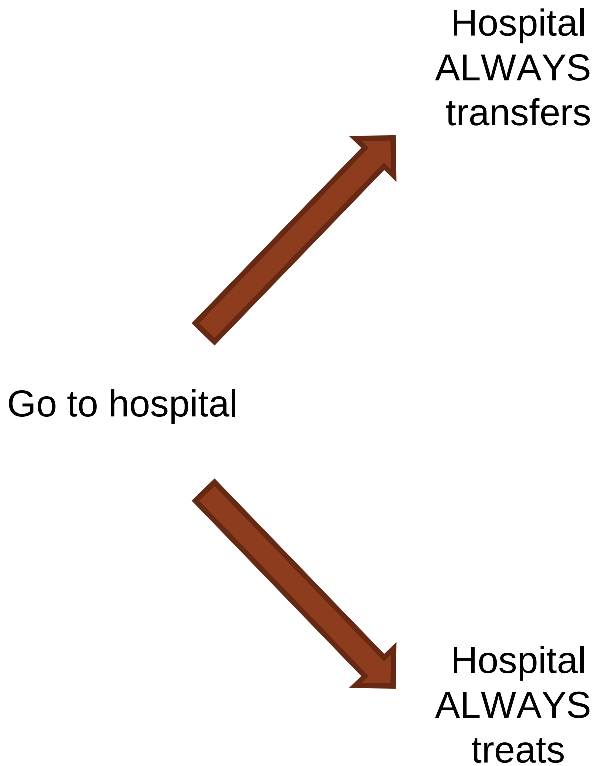


Go to hospital

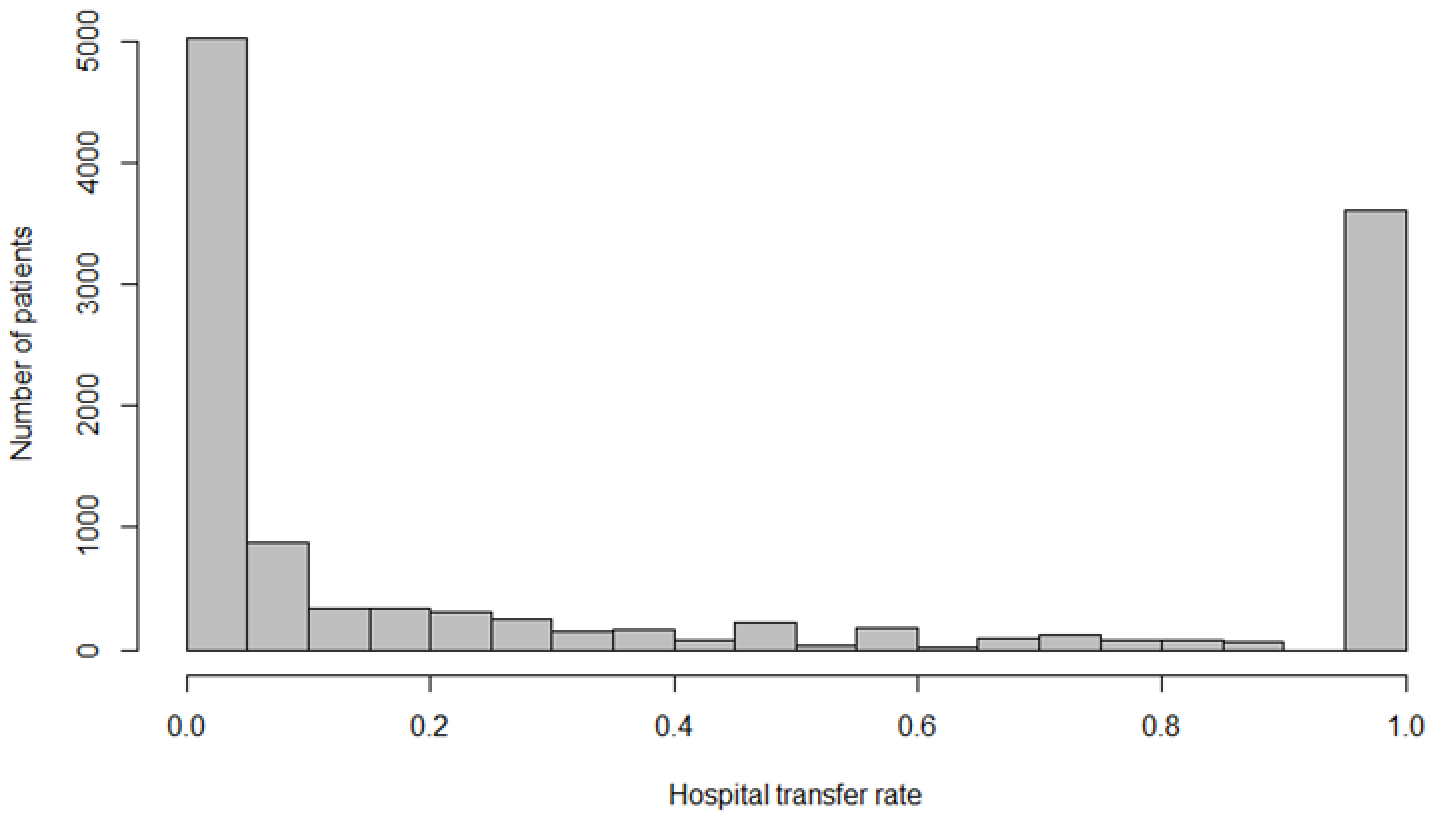
Go to hospital

Hospital ALWAYS transfers

Go to hospital


Hospital ALWAYS transfers
Go to hospital
Hospital ALWAYS treats

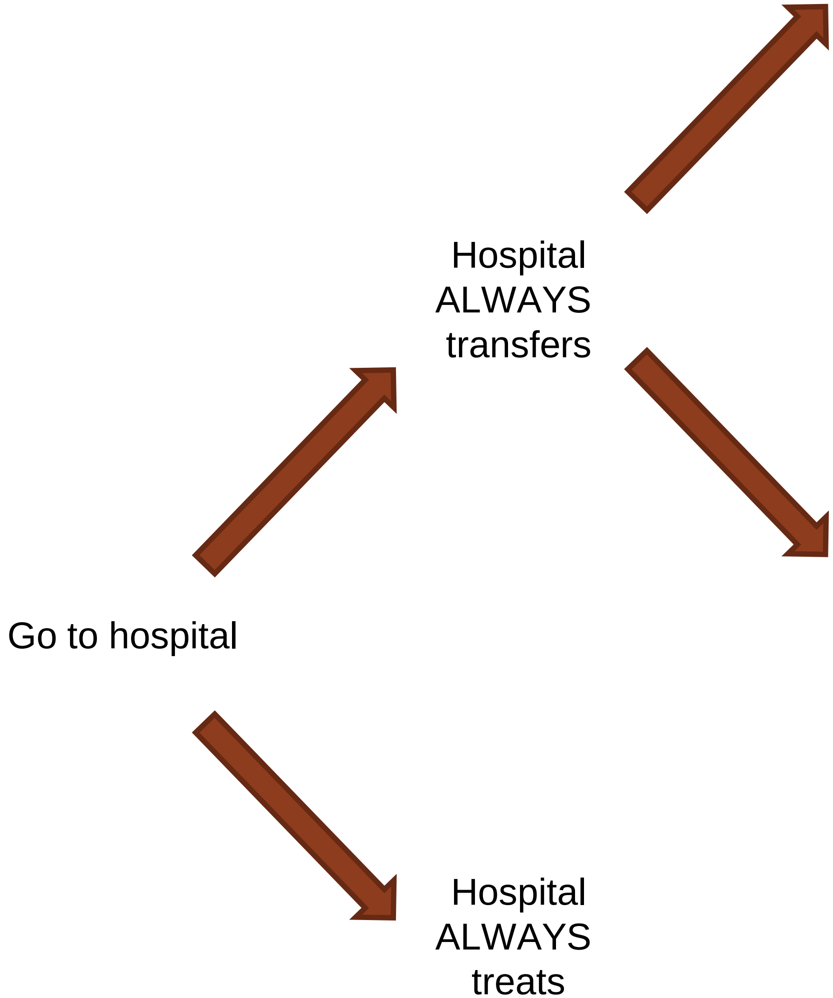
B Distribution of patients presenting to hospitals with varying transfer rates for acute type A aortic dissection

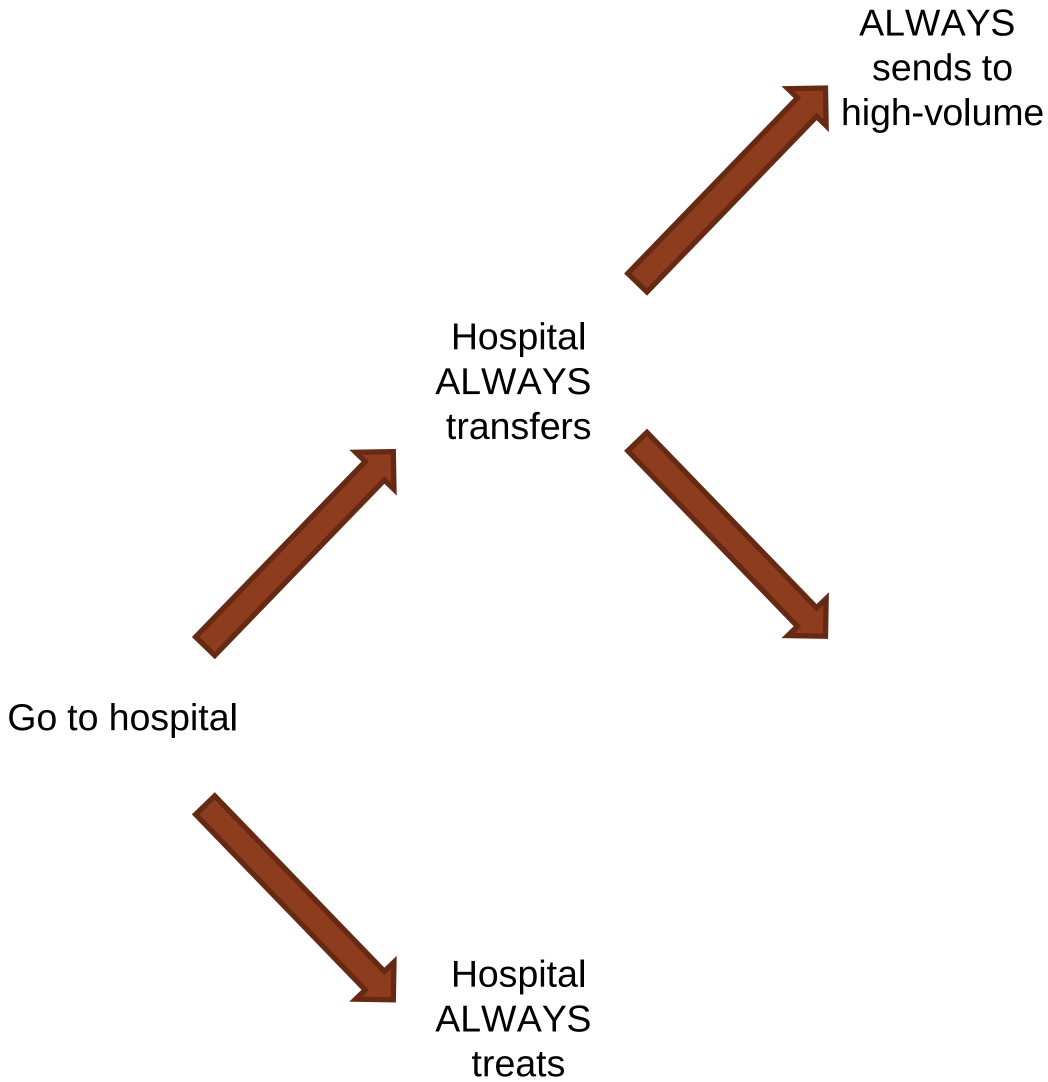


Hospital ALWAYS transfers

Go to hospital

Hospital ALWAYS treats


Hospital ALWAYS transfers
Go to hospital
Hospital ALWAYS treats


ALWAYS
sends to
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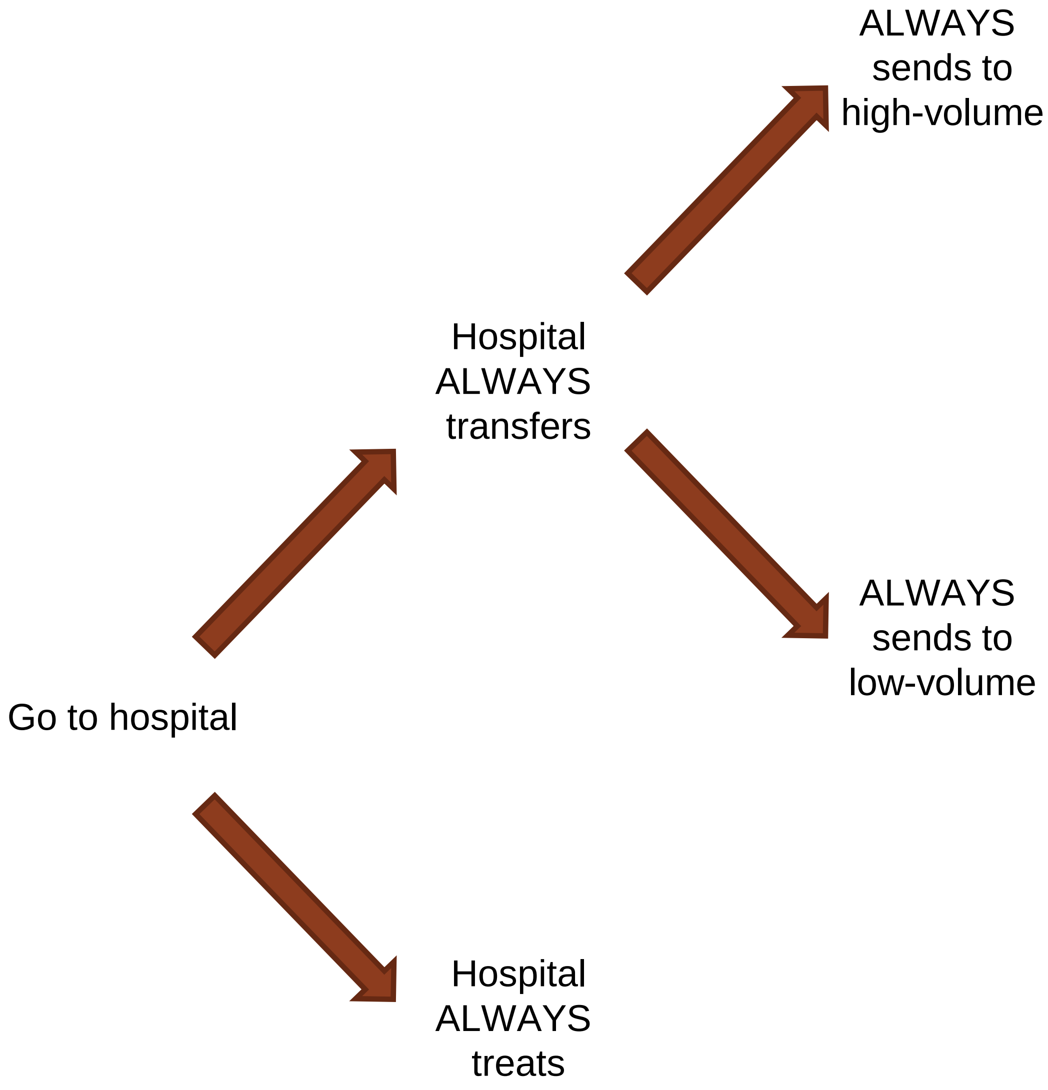
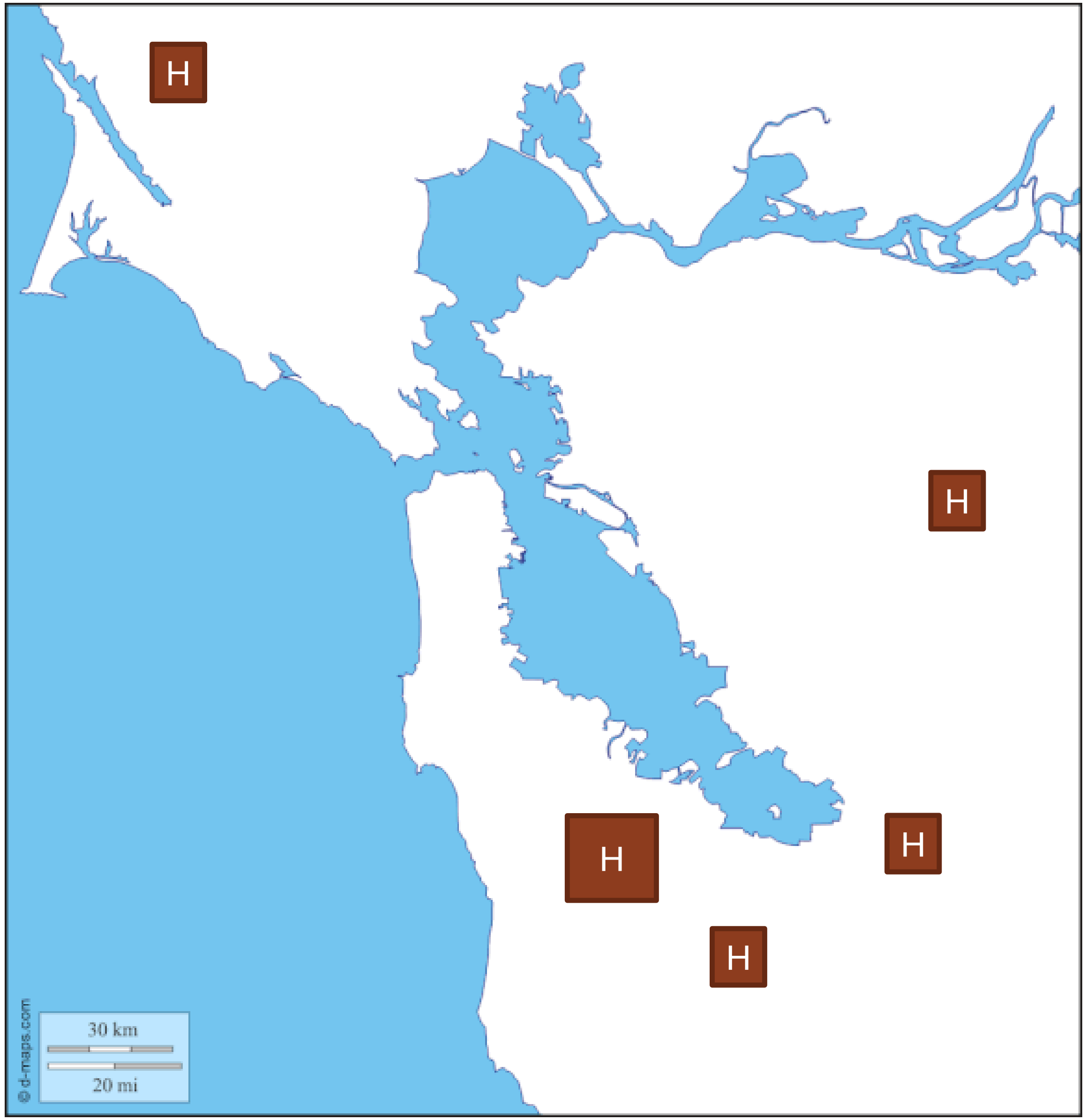

ALWAYS sends to high-volume
Hospital ALWAYS transfers
ALWAYS sends to low-volume
Go to hospital
Hospital ALWAYS treats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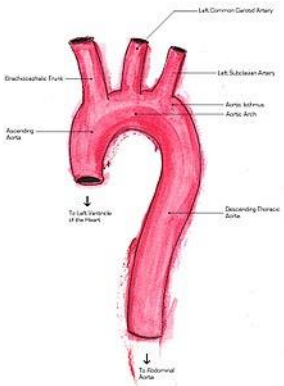

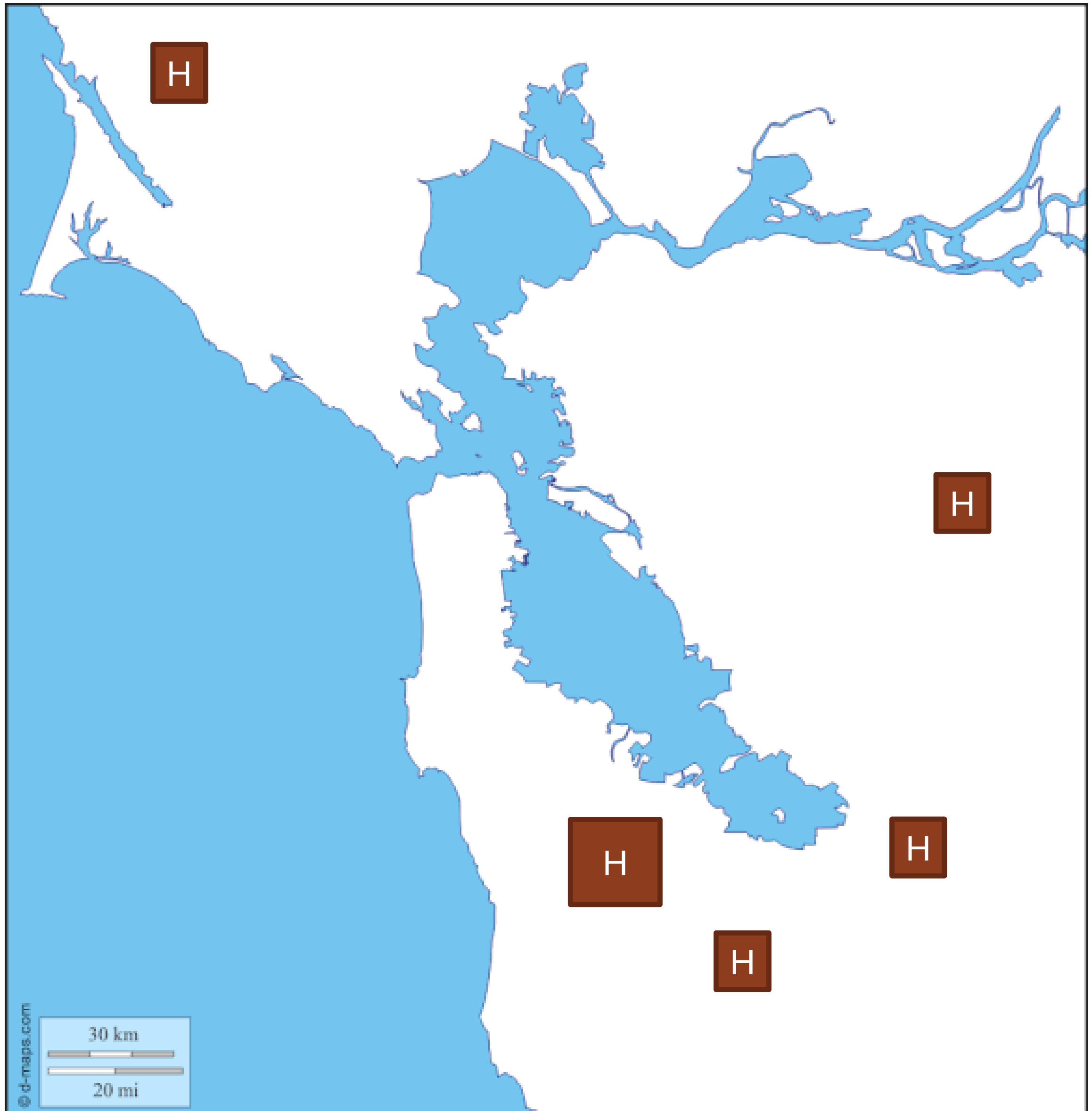

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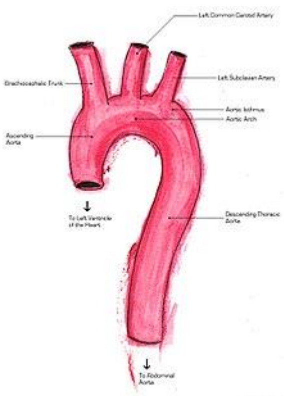
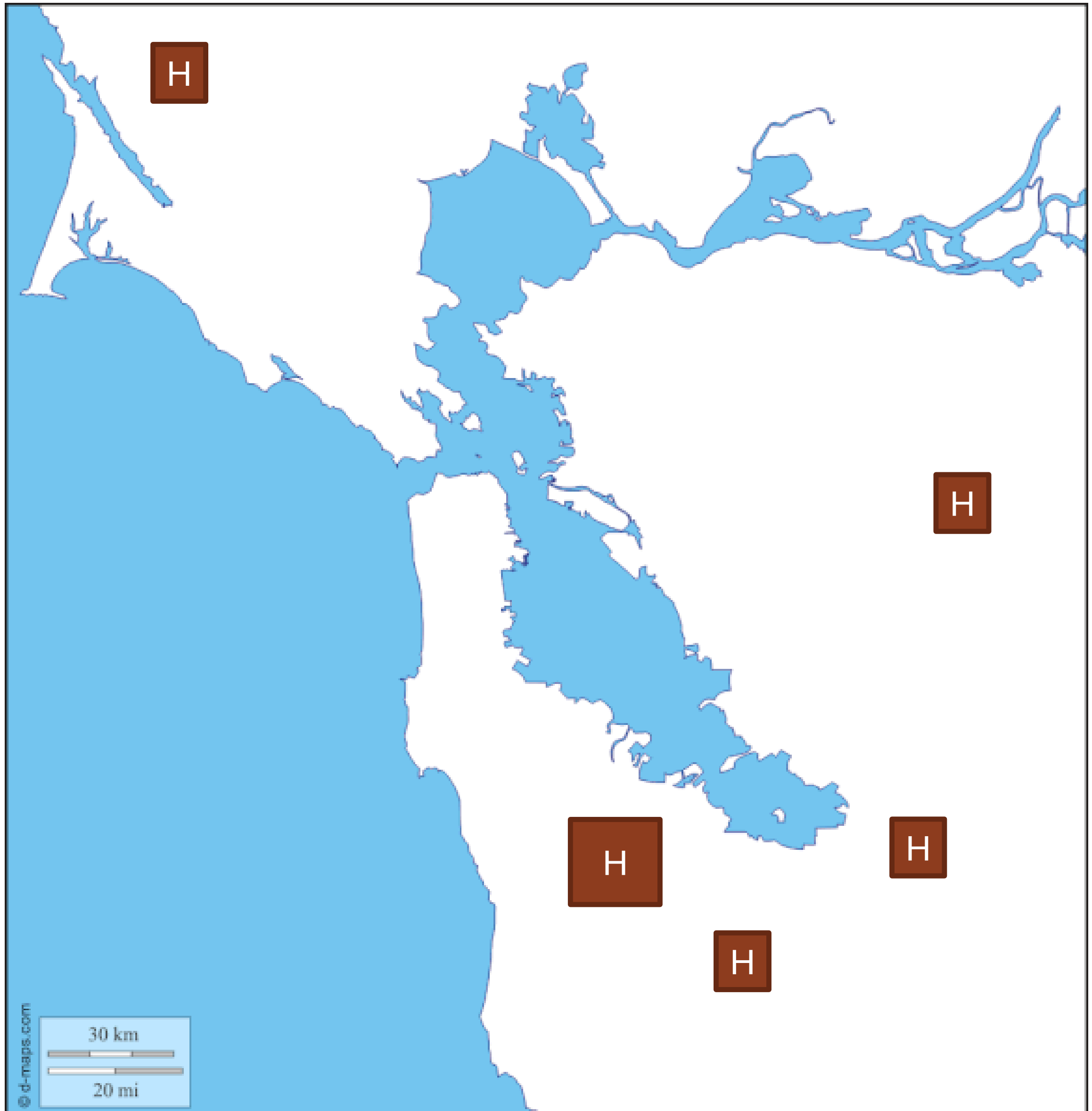

Left Common Carotid Artery
Brachiocephalic Trunk
Left Subclavian Artery
Aortic Isthmus
Aortic Arch
Ascending Aorta
To Left Ventricle of the Heart
Descending Thoracic Aorta
To Abdominal Aorta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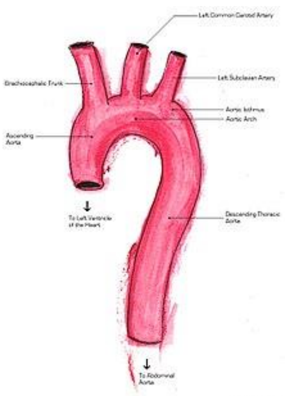
< 10/year = low

> 10/year = high



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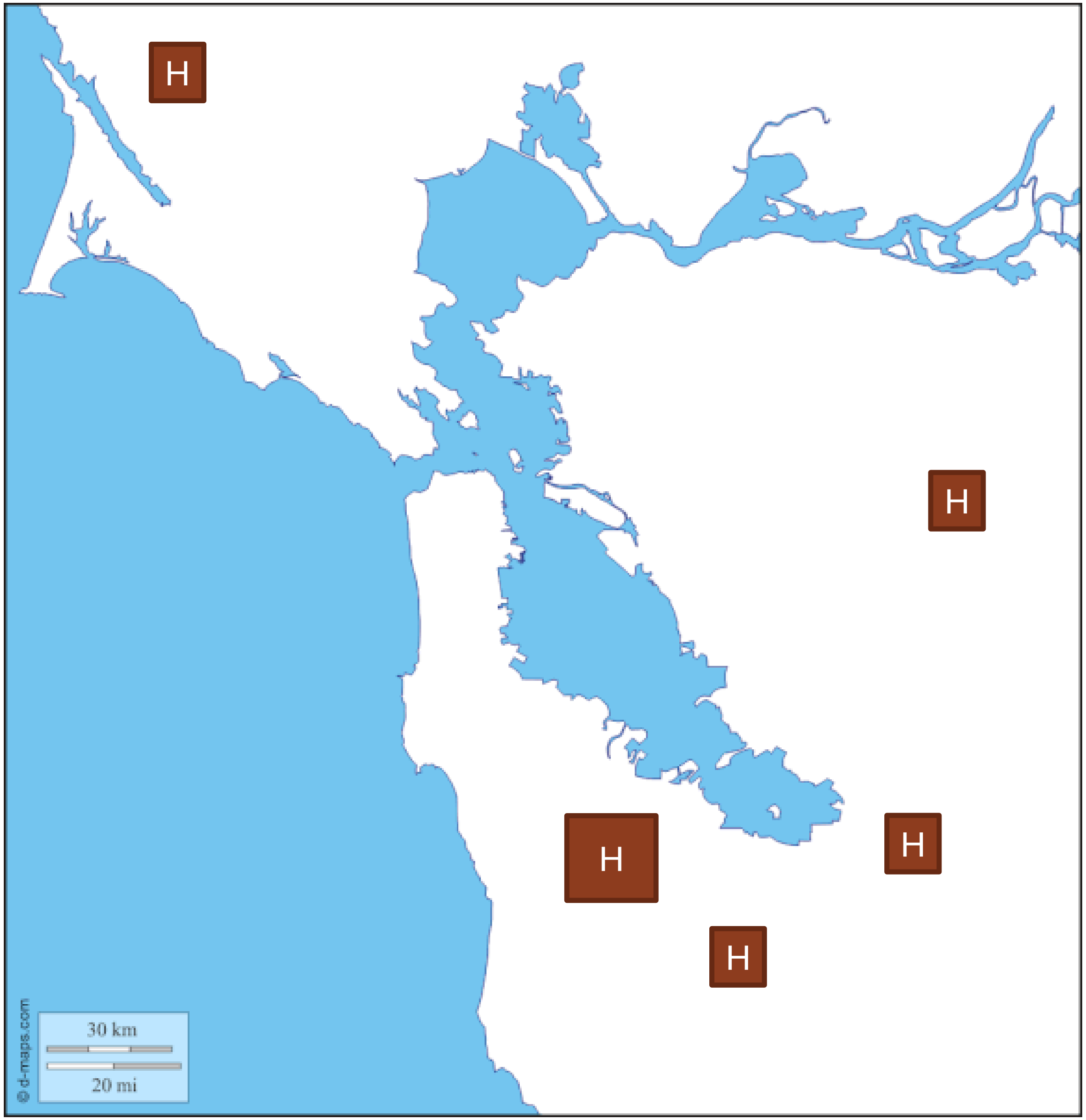

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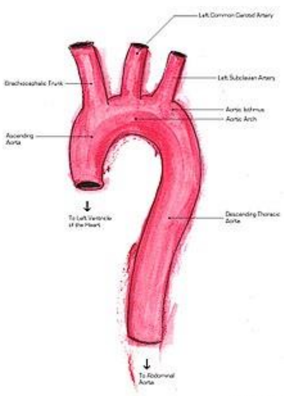
> 10/year = high



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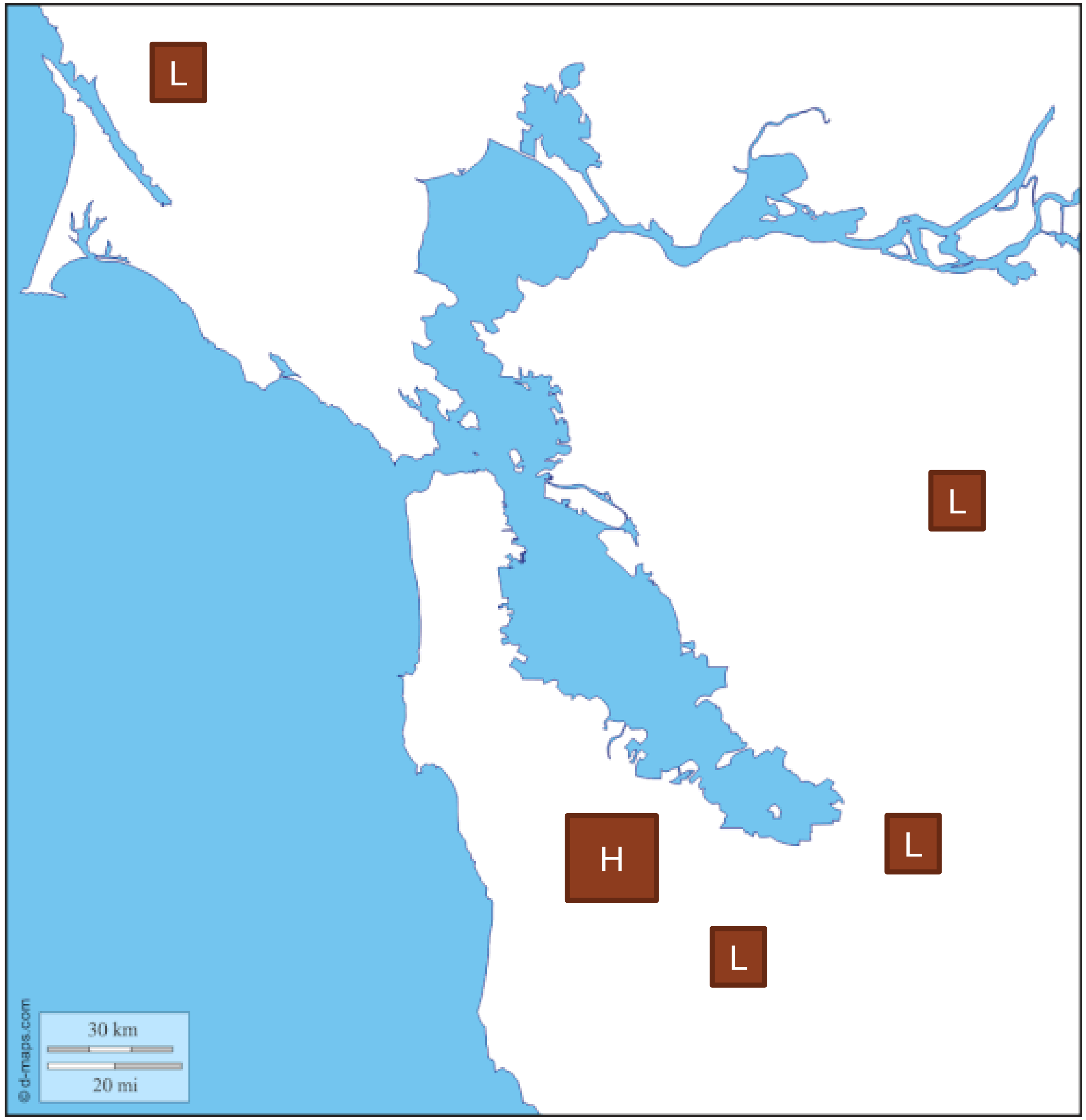

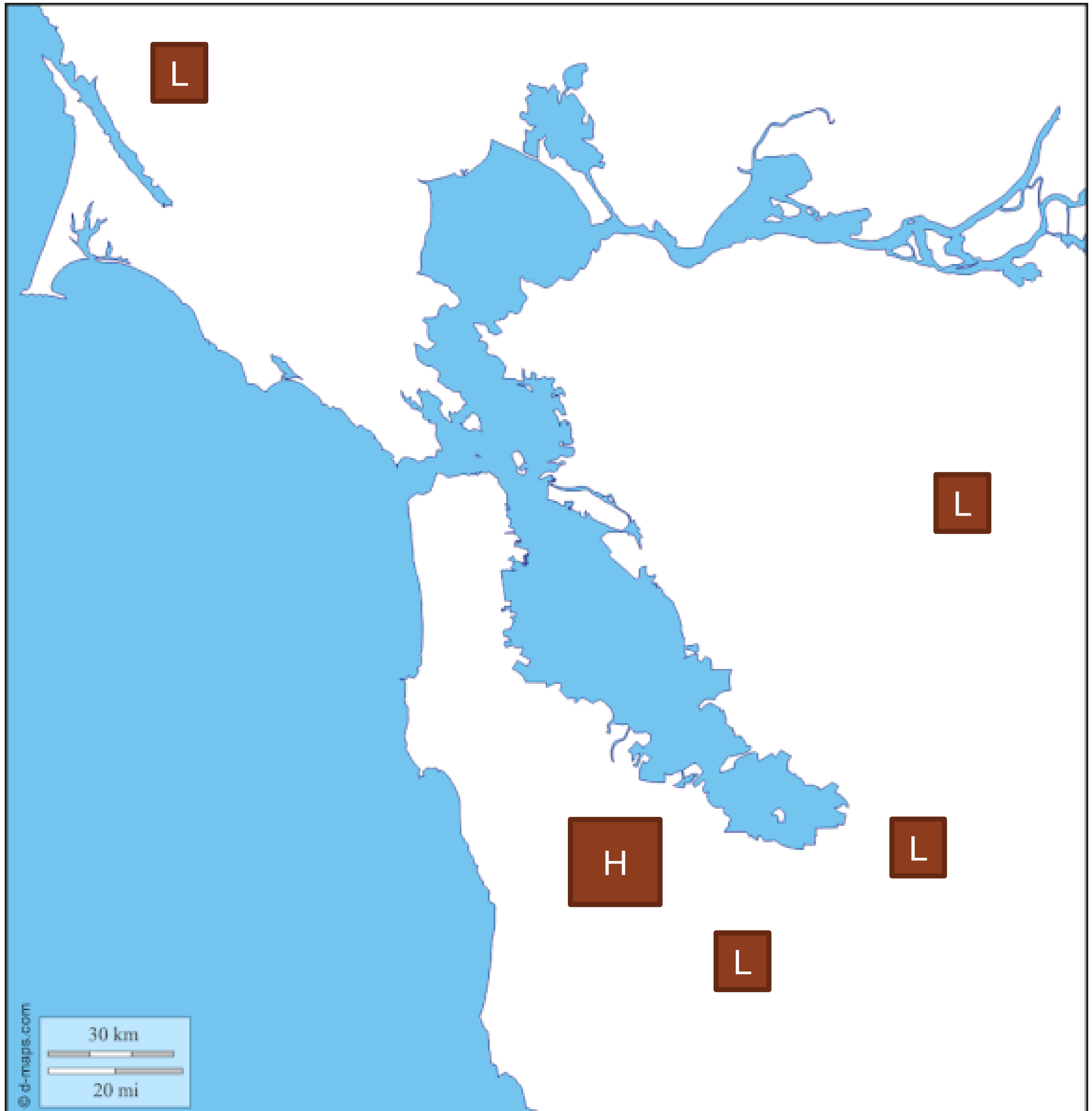

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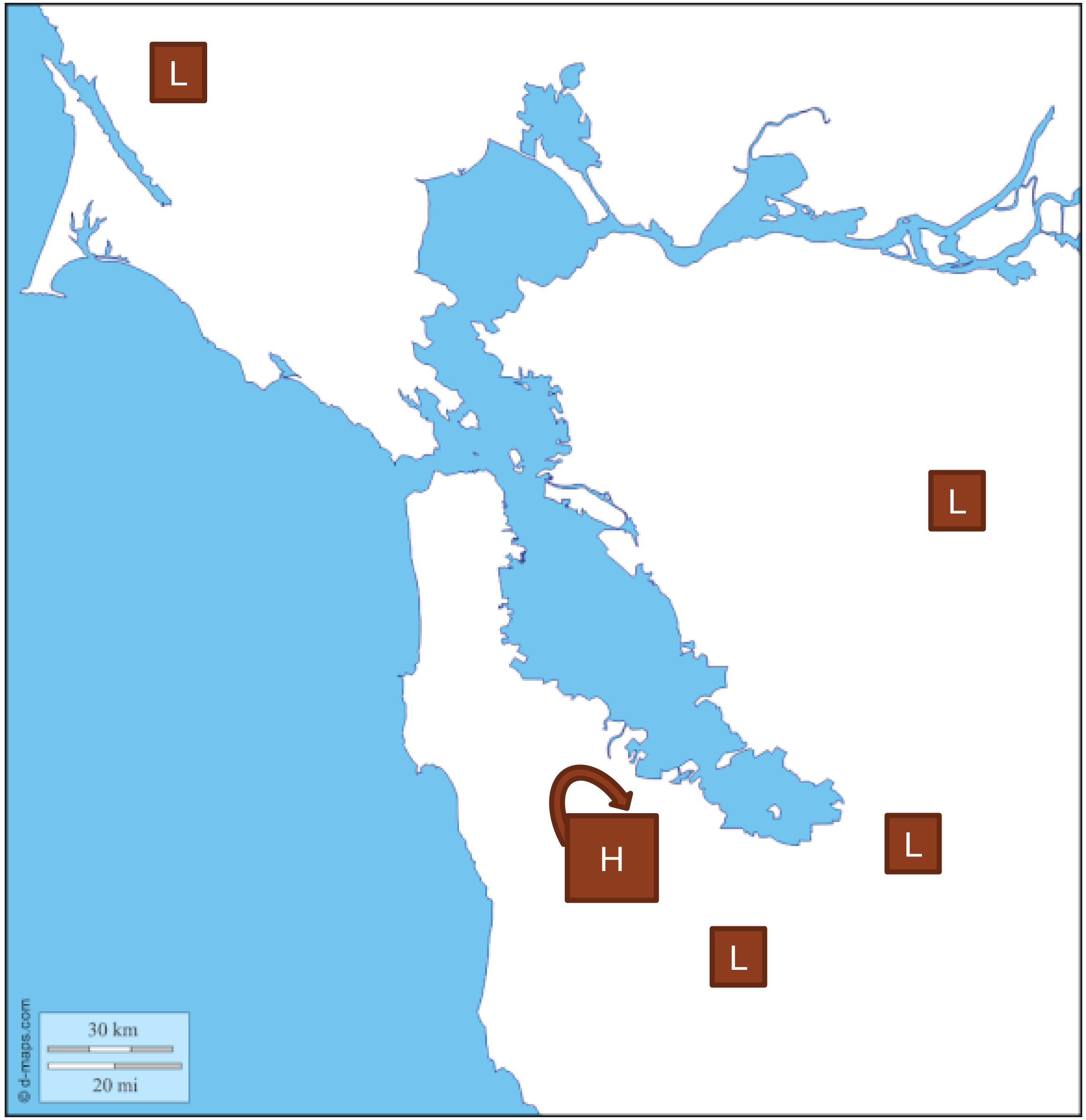
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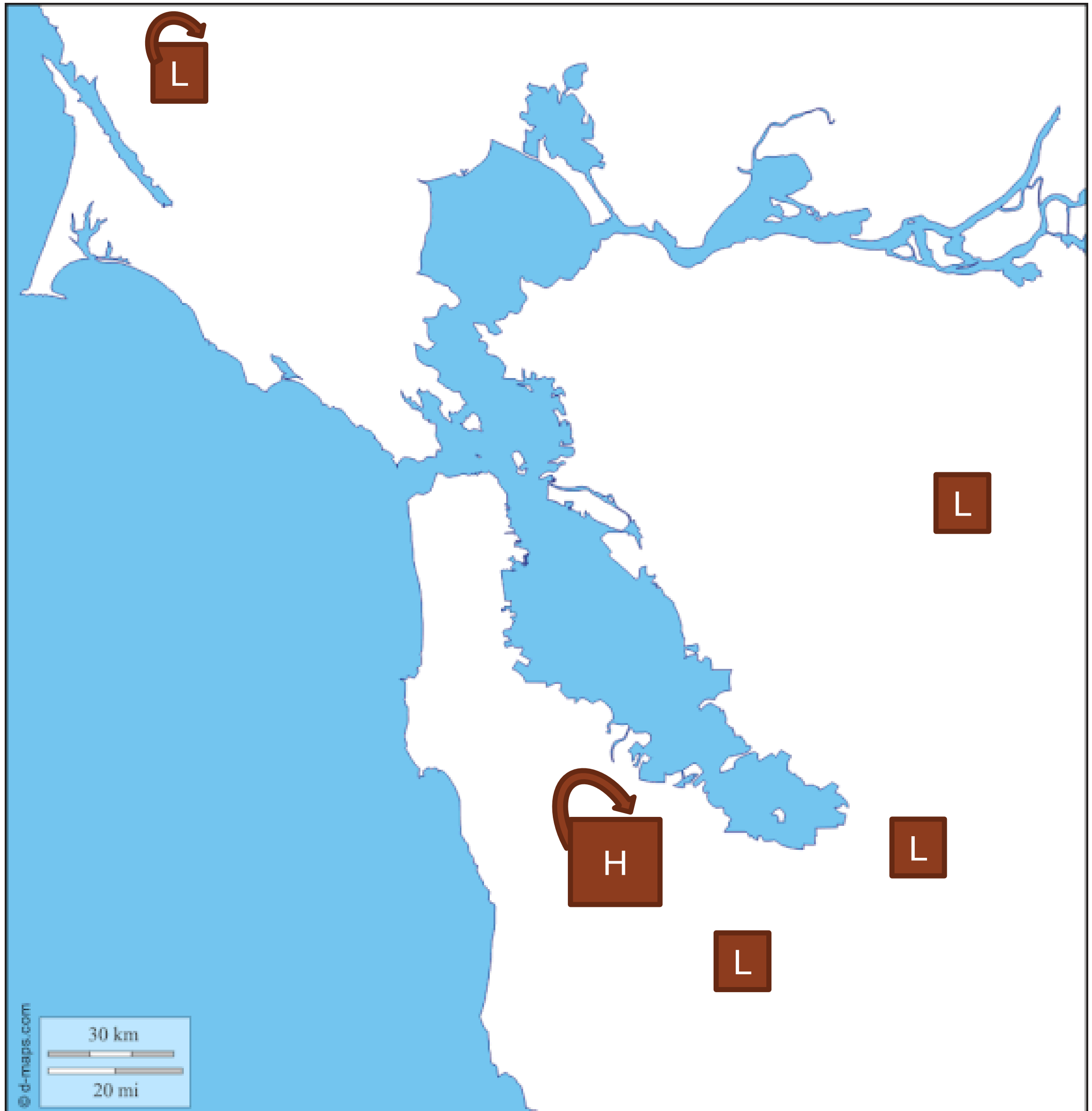
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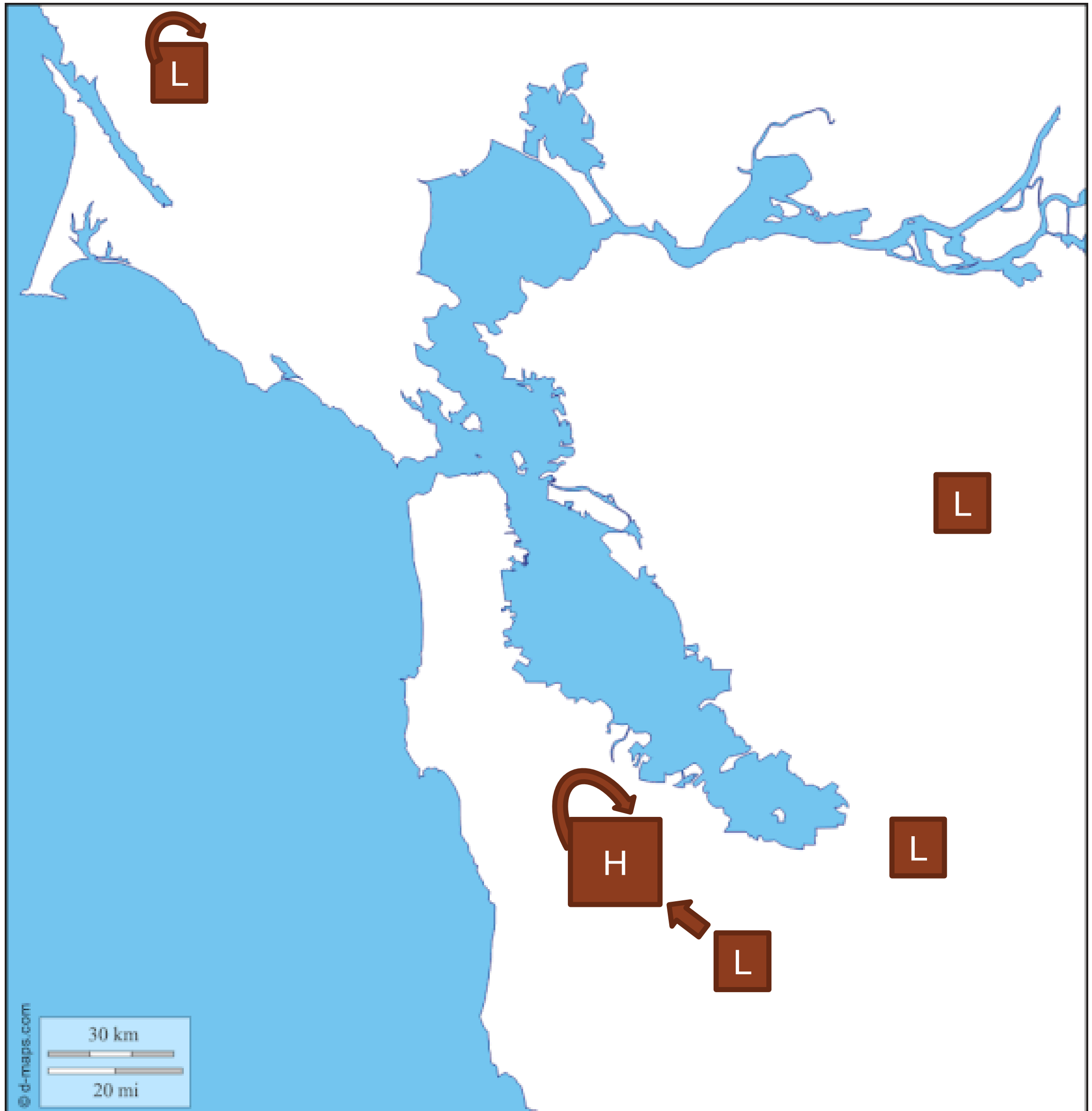
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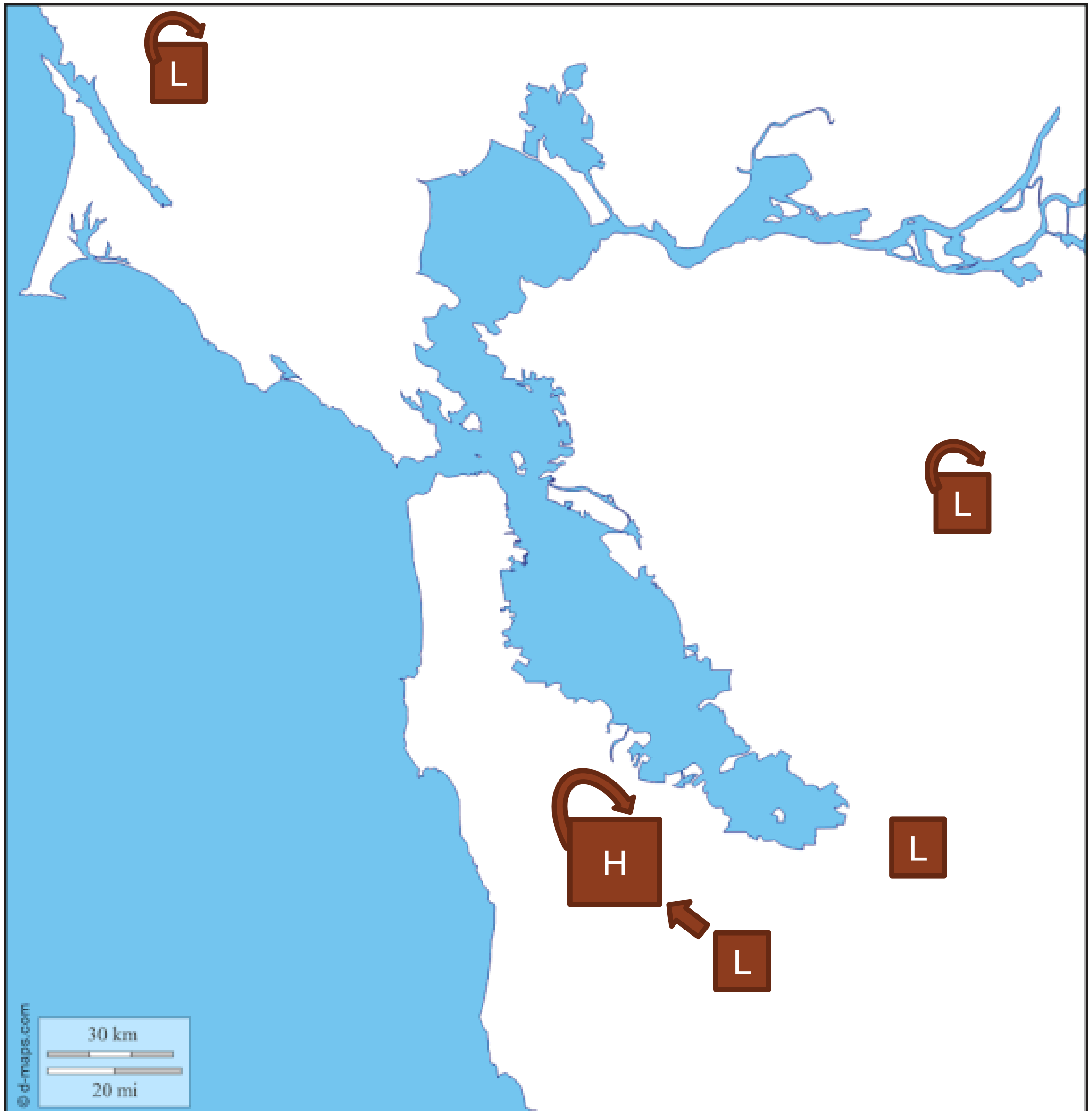
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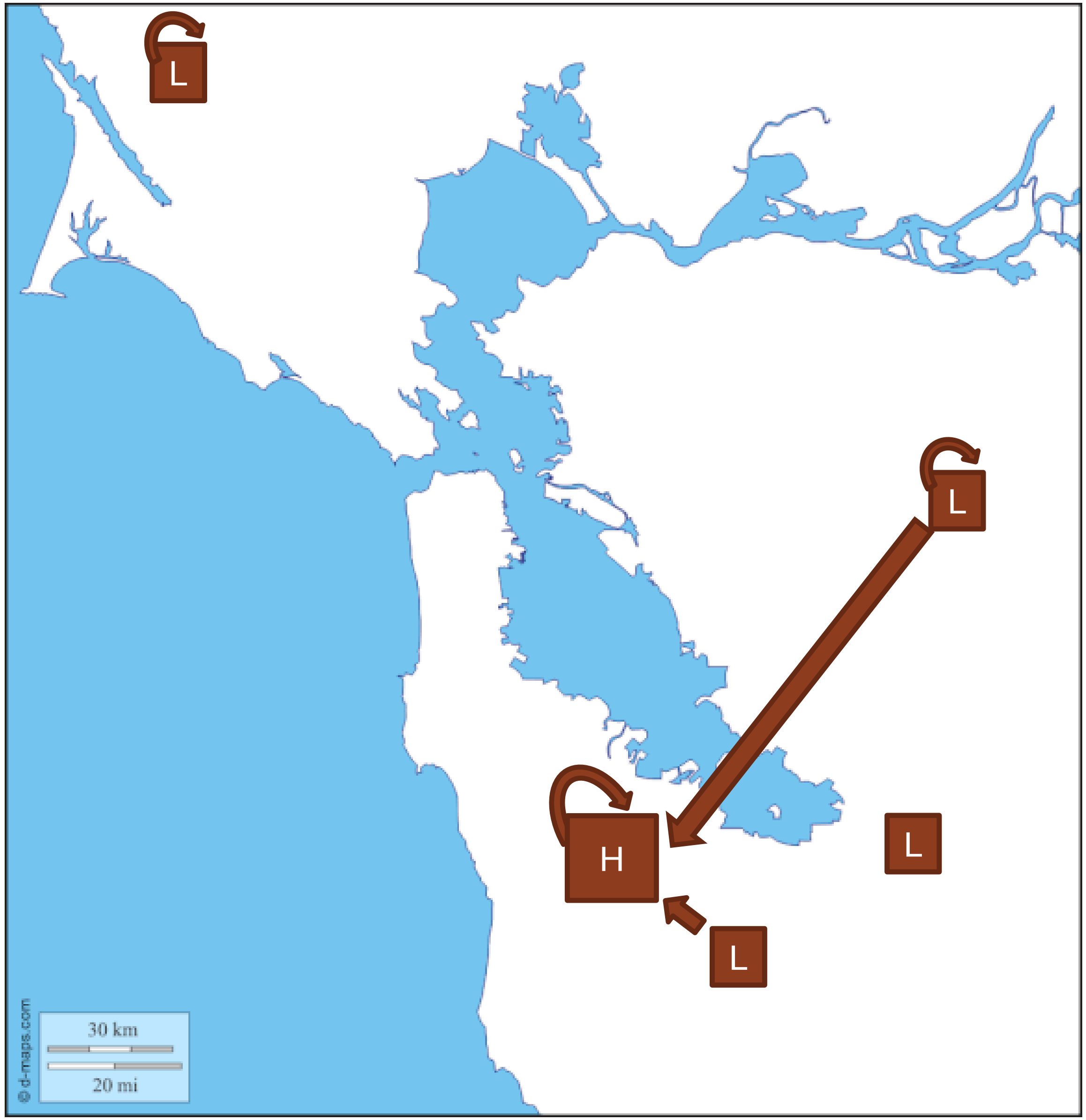

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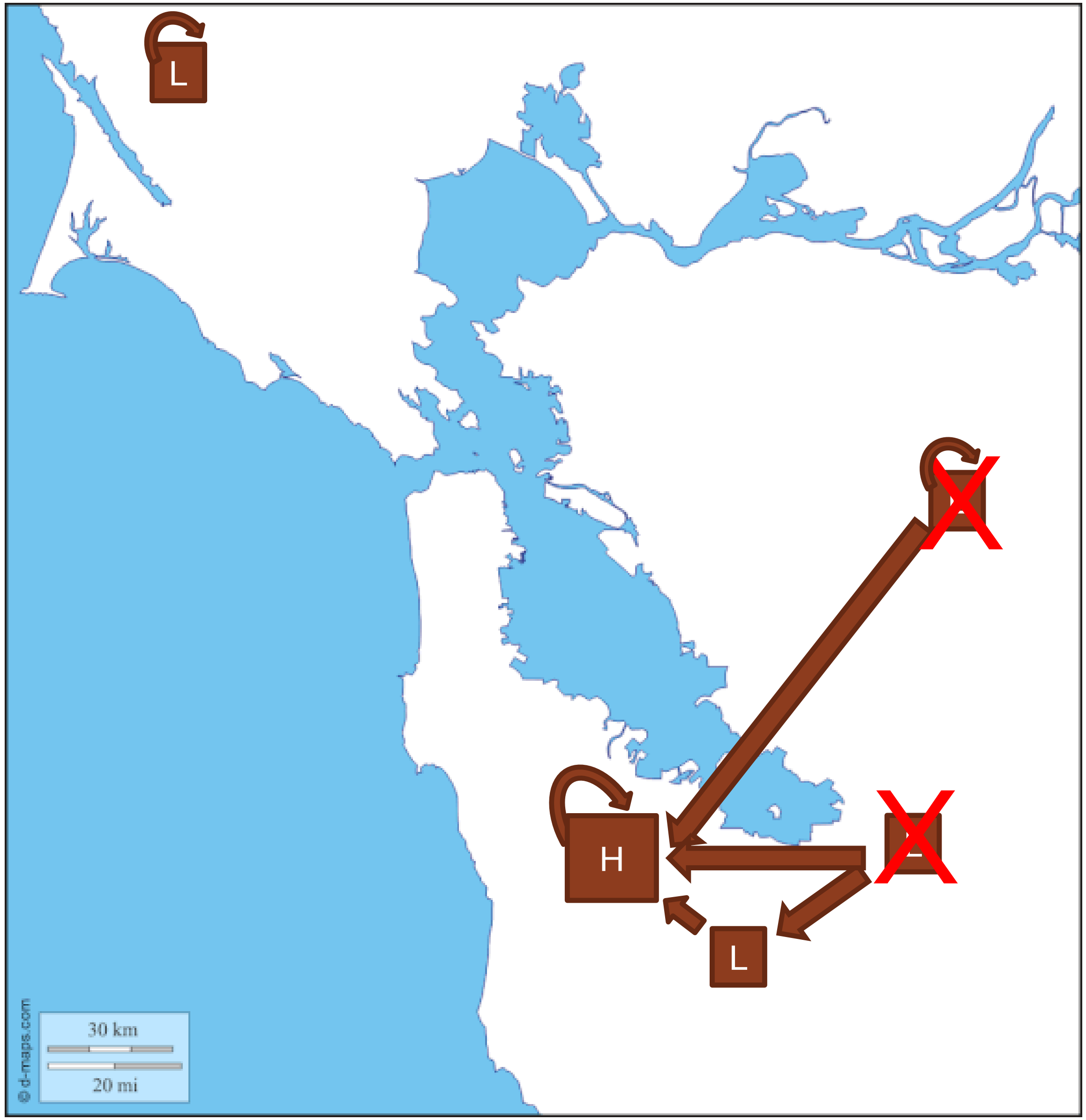
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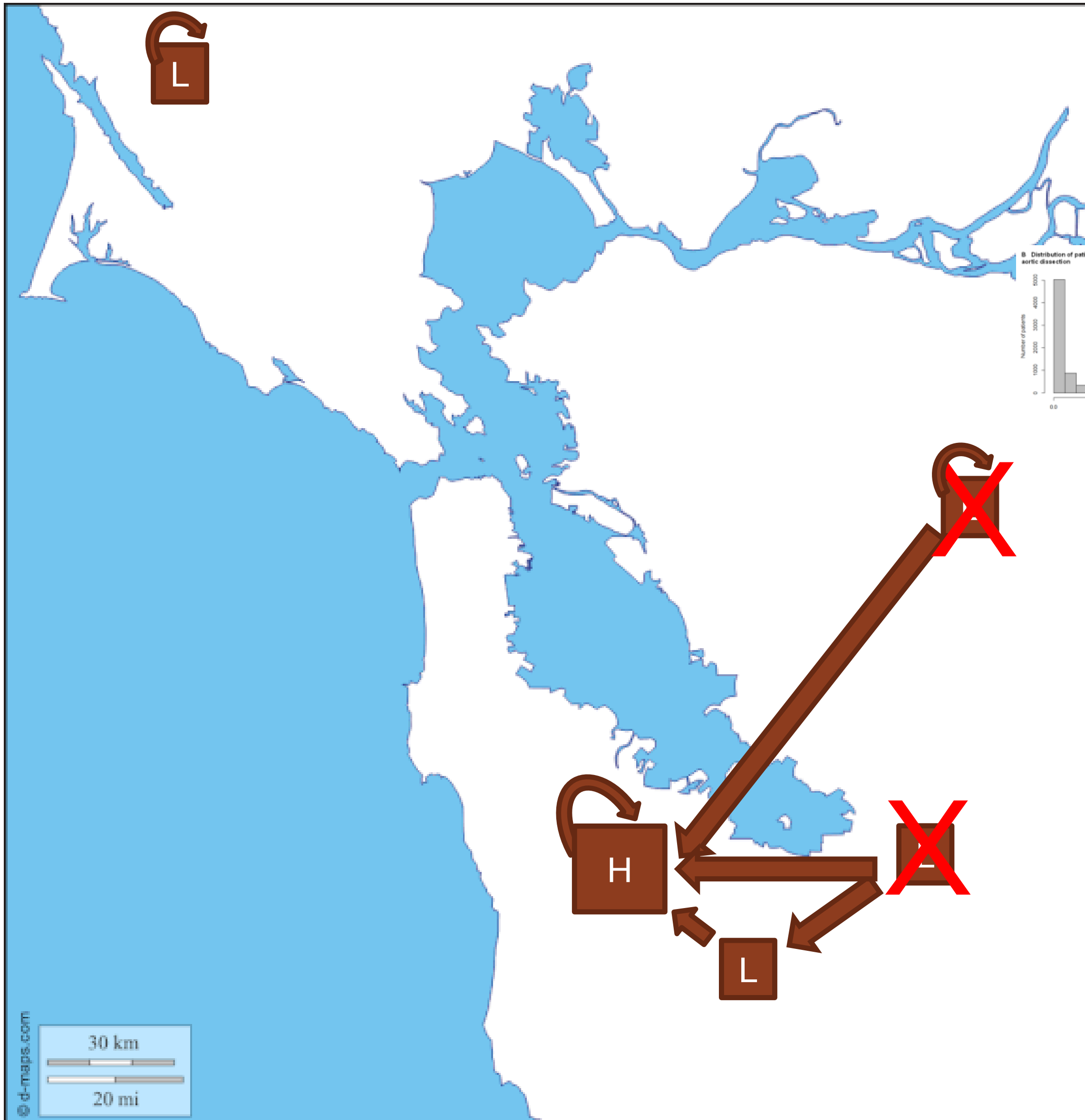

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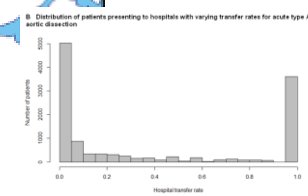

B Distribution of patients presenting to hospitals with varying transfer rates for acute type A aortic dissection
Number of patients
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5000
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0.2
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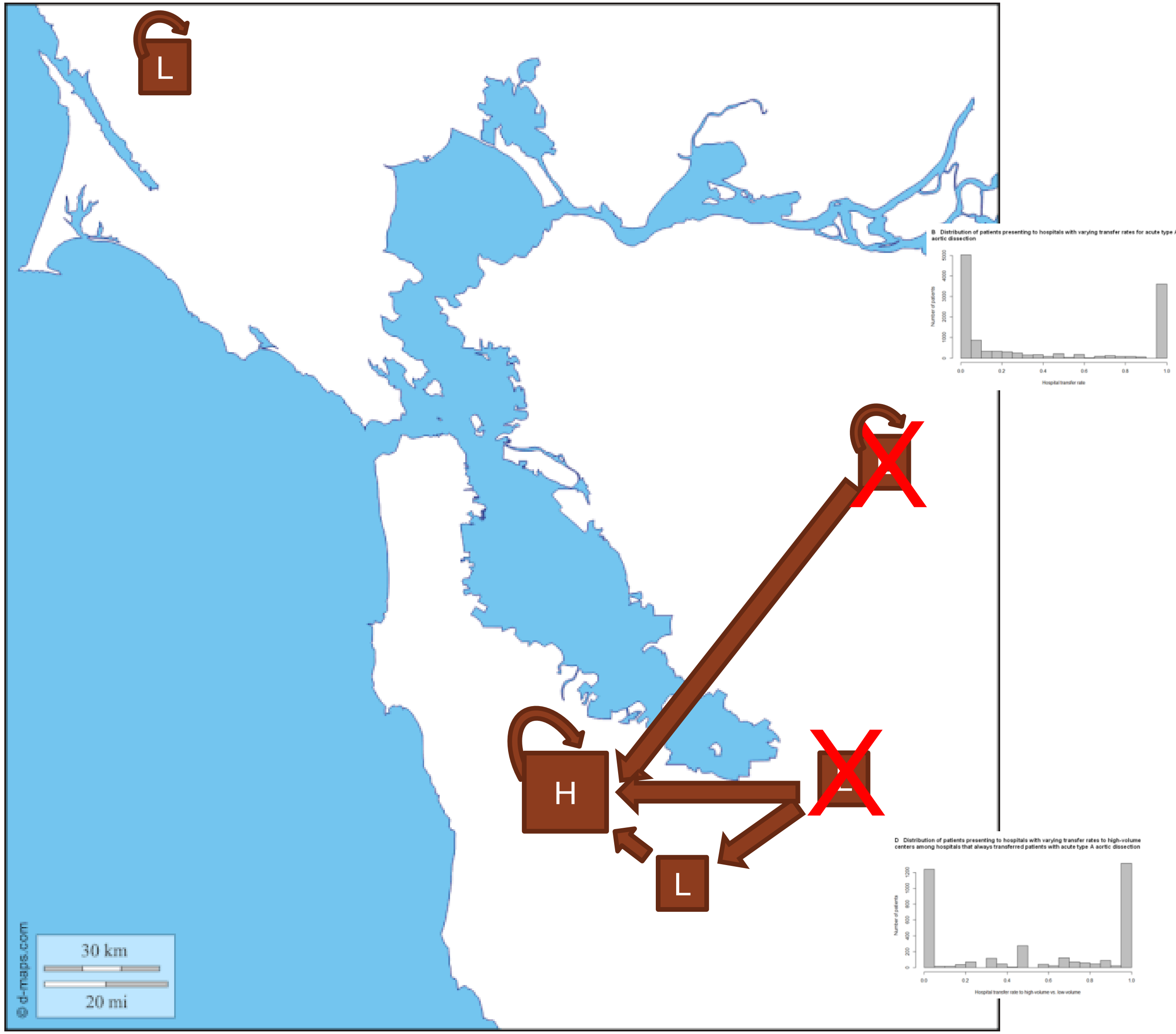
1.0
Hospital transfer rate



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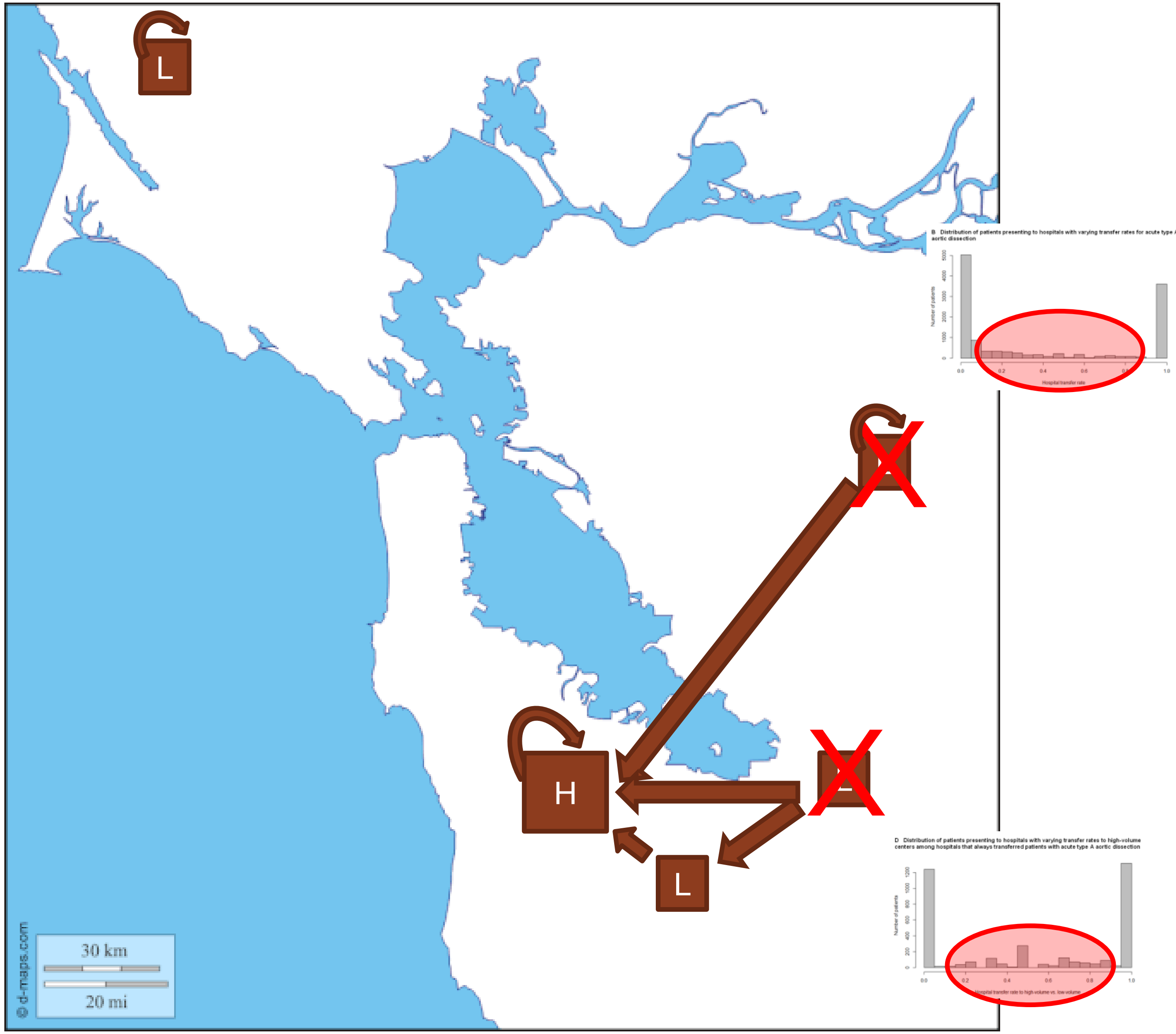

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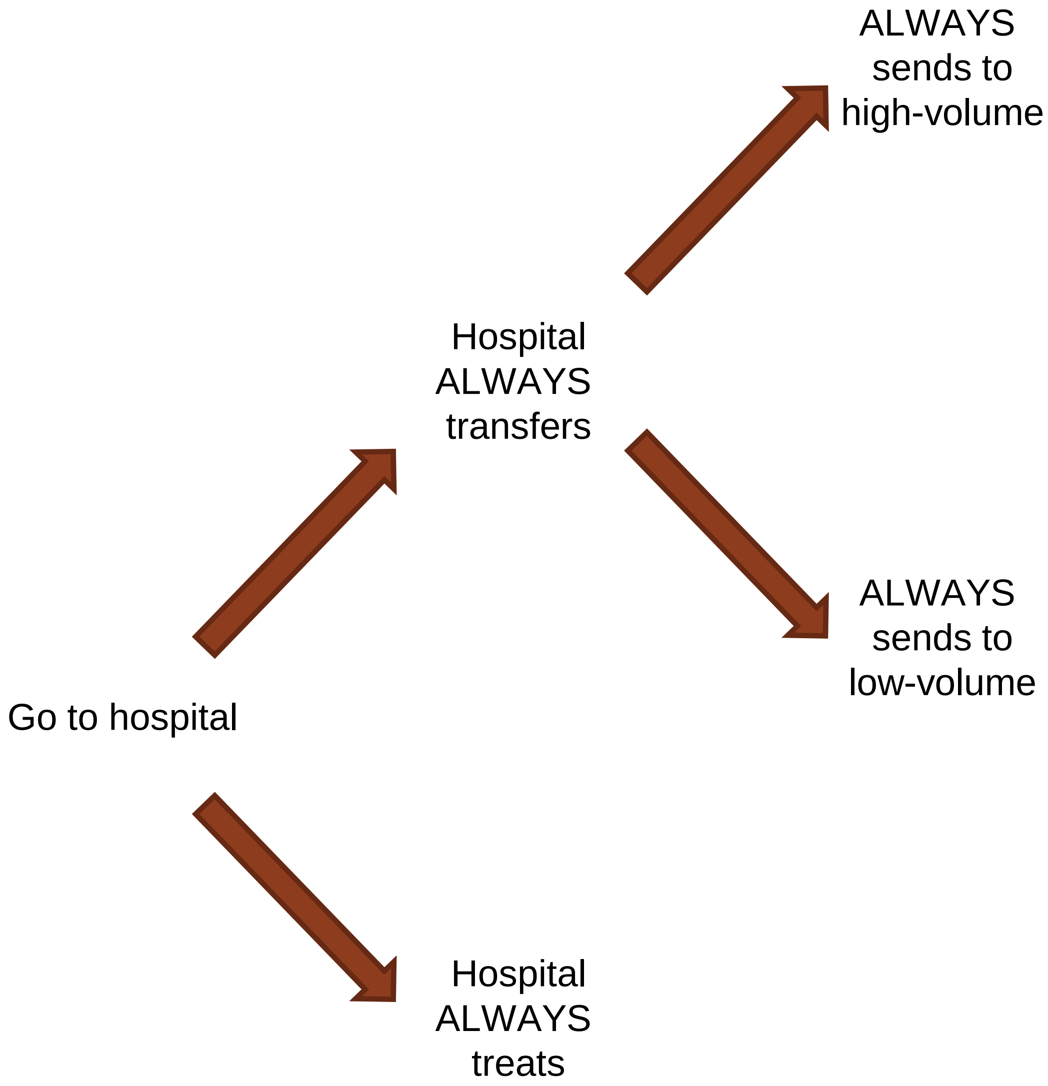
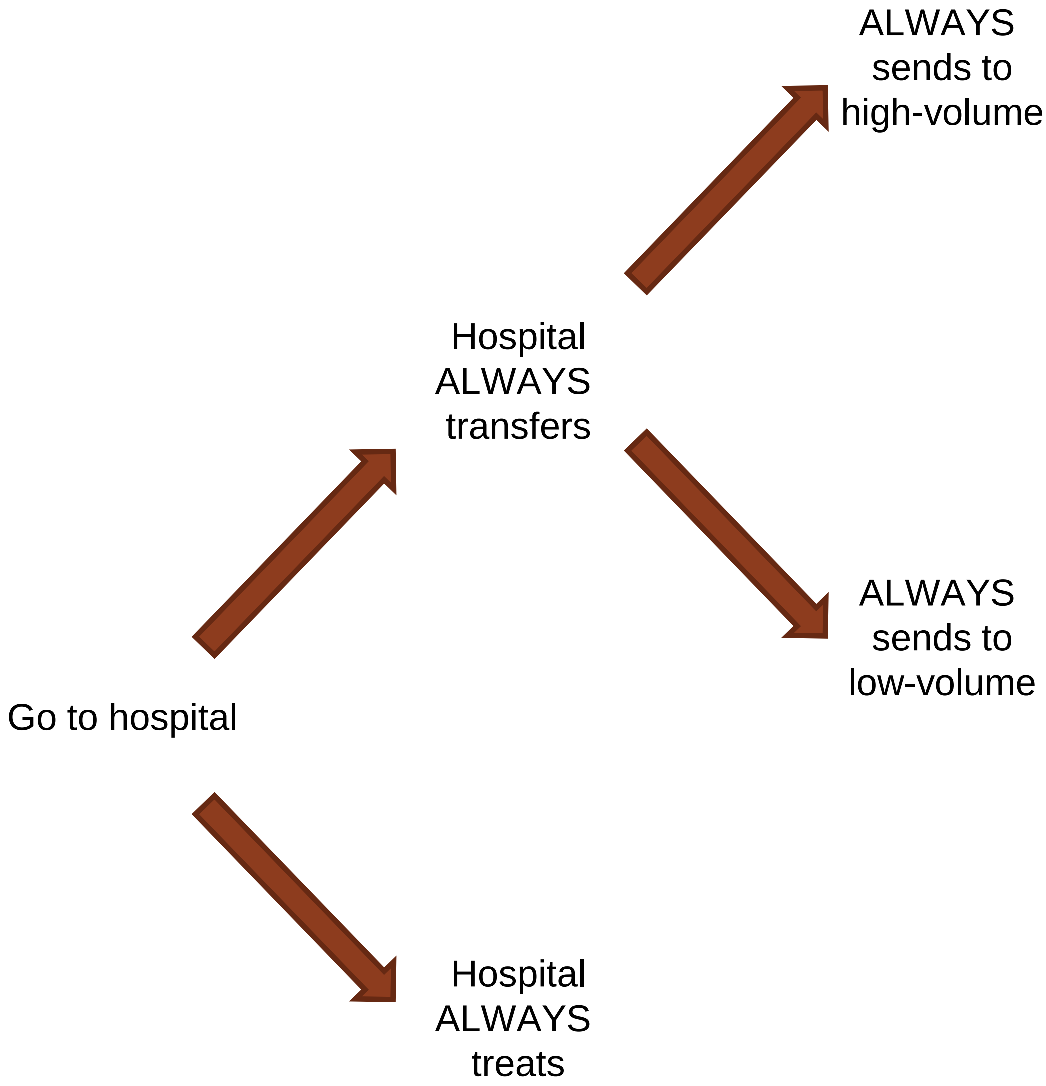
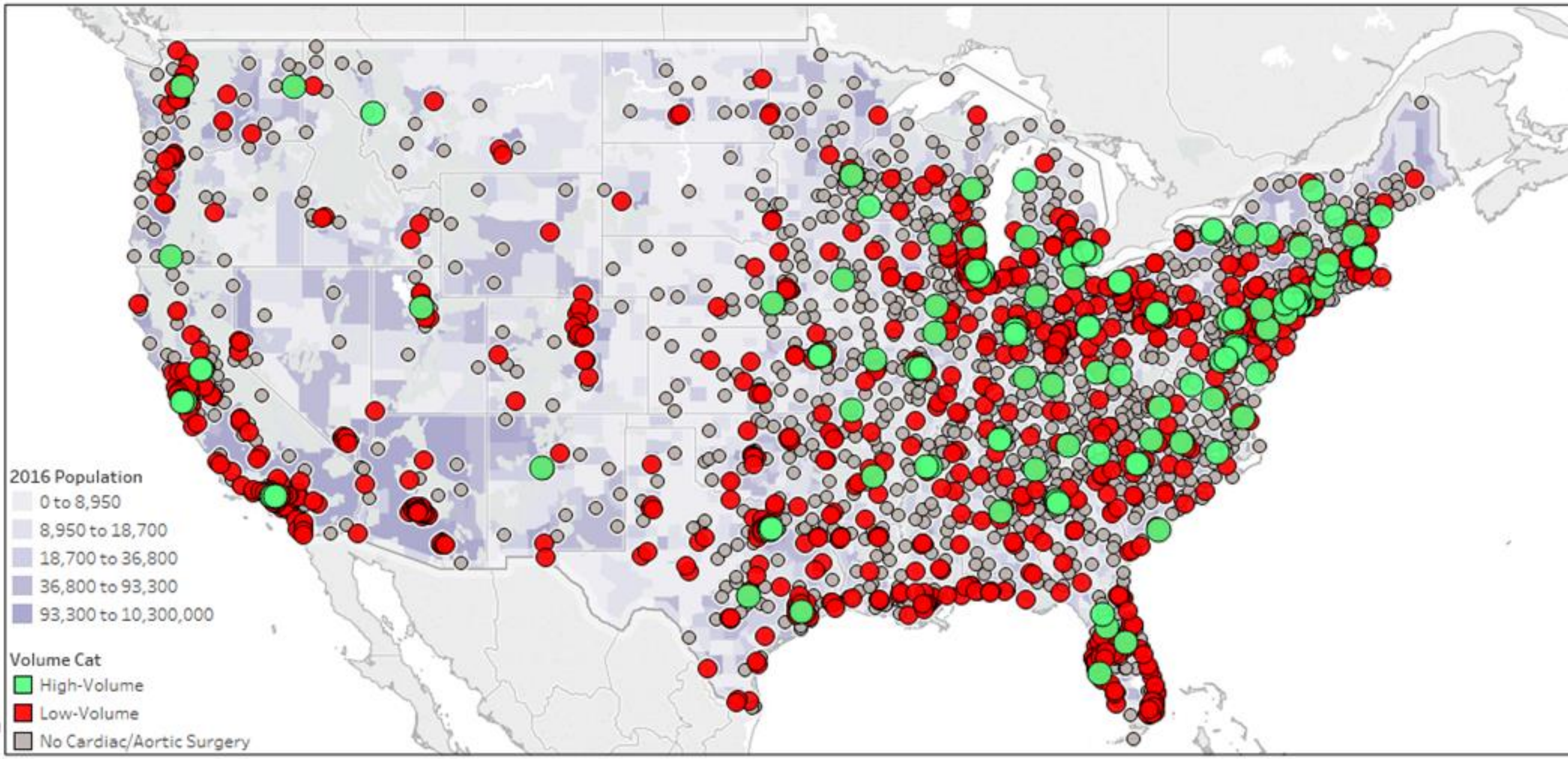
B Distribution of patients presenting to hospitals with varying transfer rates for acute type A aortic dissection
Number of patients
Hospital transfer rate
D Distribution of patients presenting to hospitals with varying transfer rates to high-volume centers among hospitals that always transferred patients with acute type A aortic dissection
Number of patients
Hospital transfer rate to high-volume vs. low-volume


ALWAYS sends to high-volume
Hospital ALWAYS transfers
ALWAYS sends to low-volume
Go to hospital
Hospital ALWAYS treats



	high	low
transfer		
stay		

A Distribution of United States Hospitals Categorized by Proximal Aortic Surgery Volume, 1999-2010



is our sorting process "orthogonal"?

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We have to think about the decision making process that goes into these decisions.

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Why are hospitals always sending? Always keeping?

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Why are hospitals always sending to one type?

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We can punt (a little bit) on the above two questions because we can merely observe that this is, in fact, the case.

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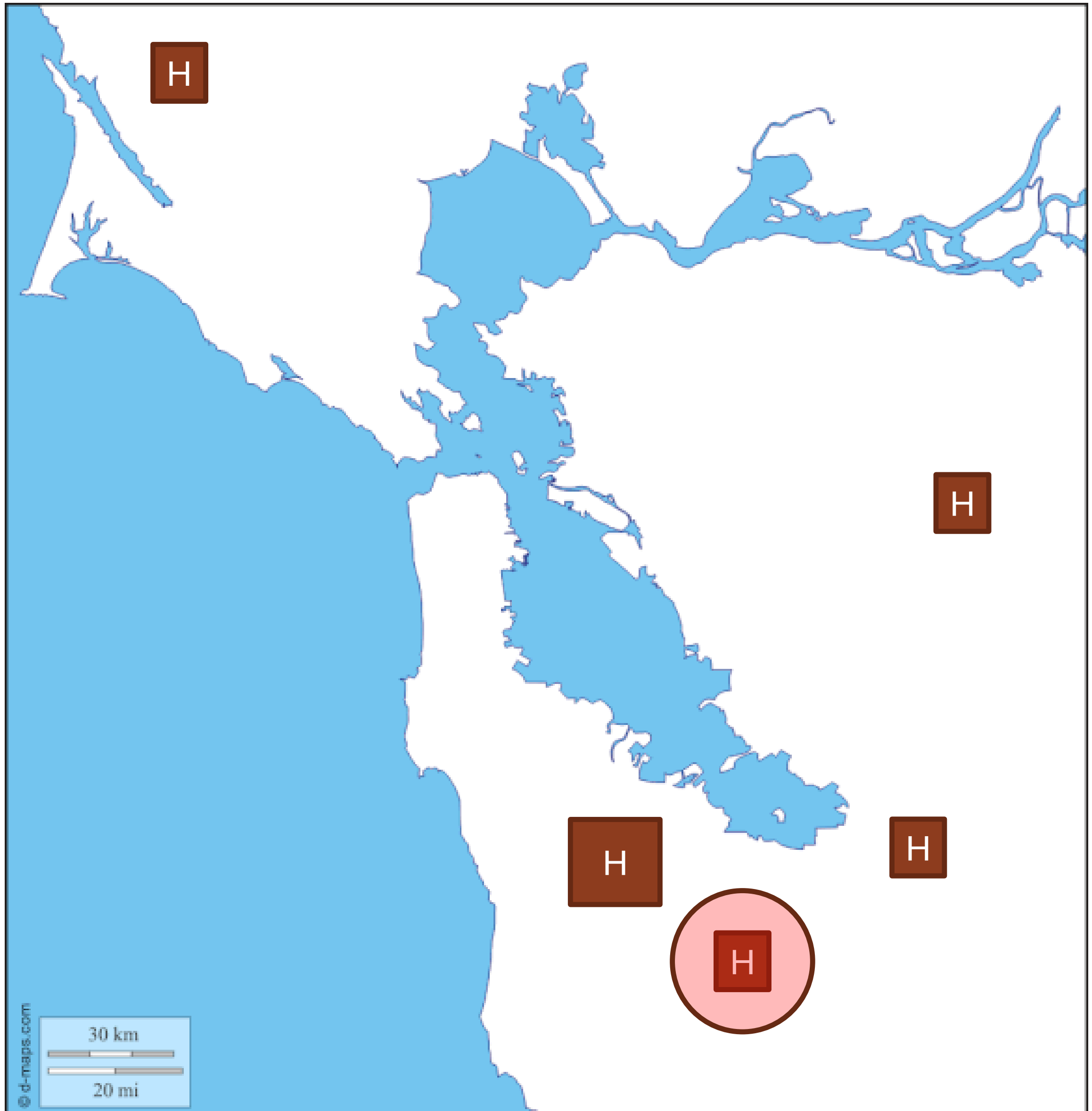
Why are hospitals always sending? Always keeping?

Why are hospitals always sending to one type?

We can punt (a little bit) on the above two questions because we can merely observe that this is, in fact, the case.

How did patients end up at the original hospital?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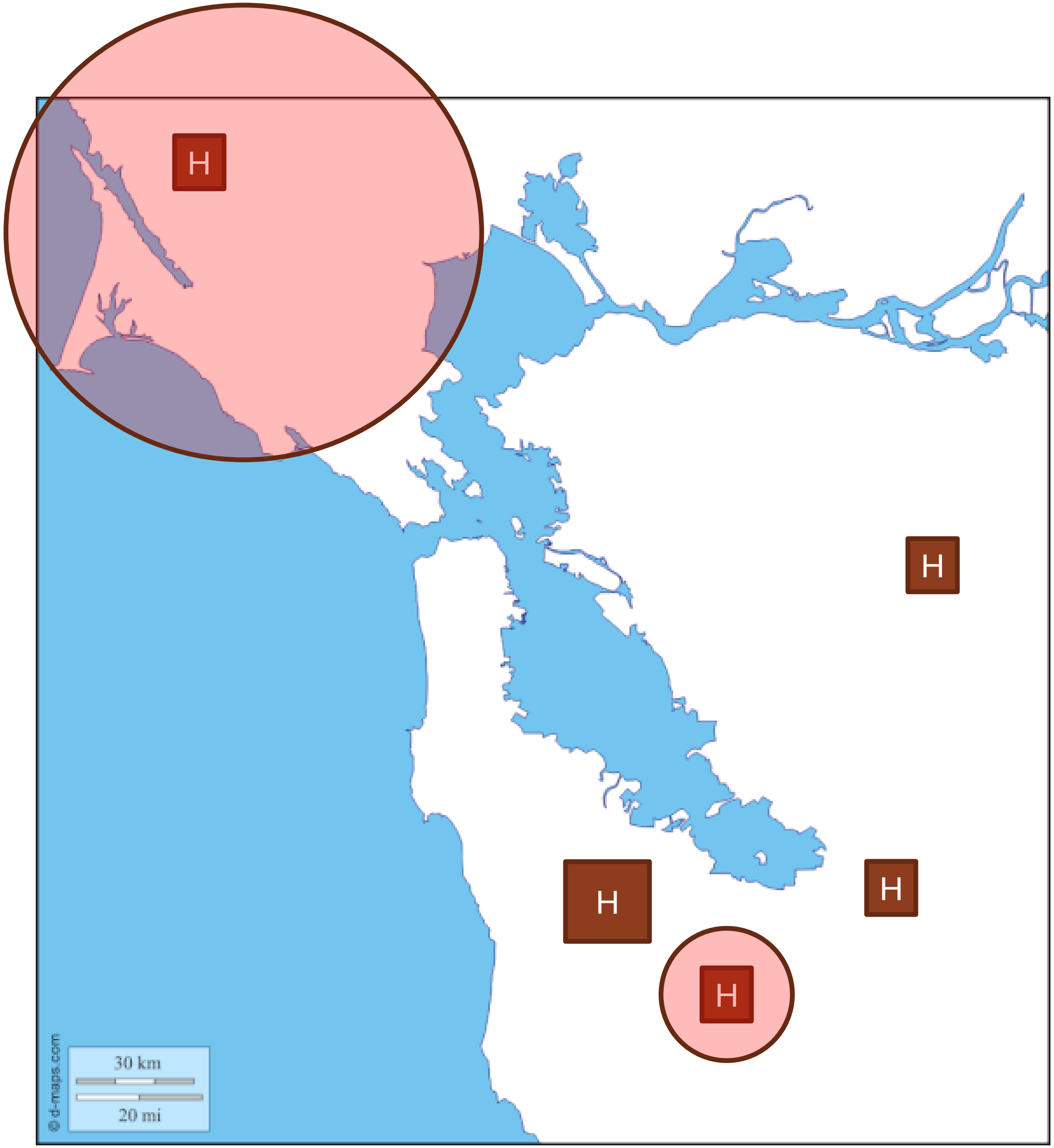
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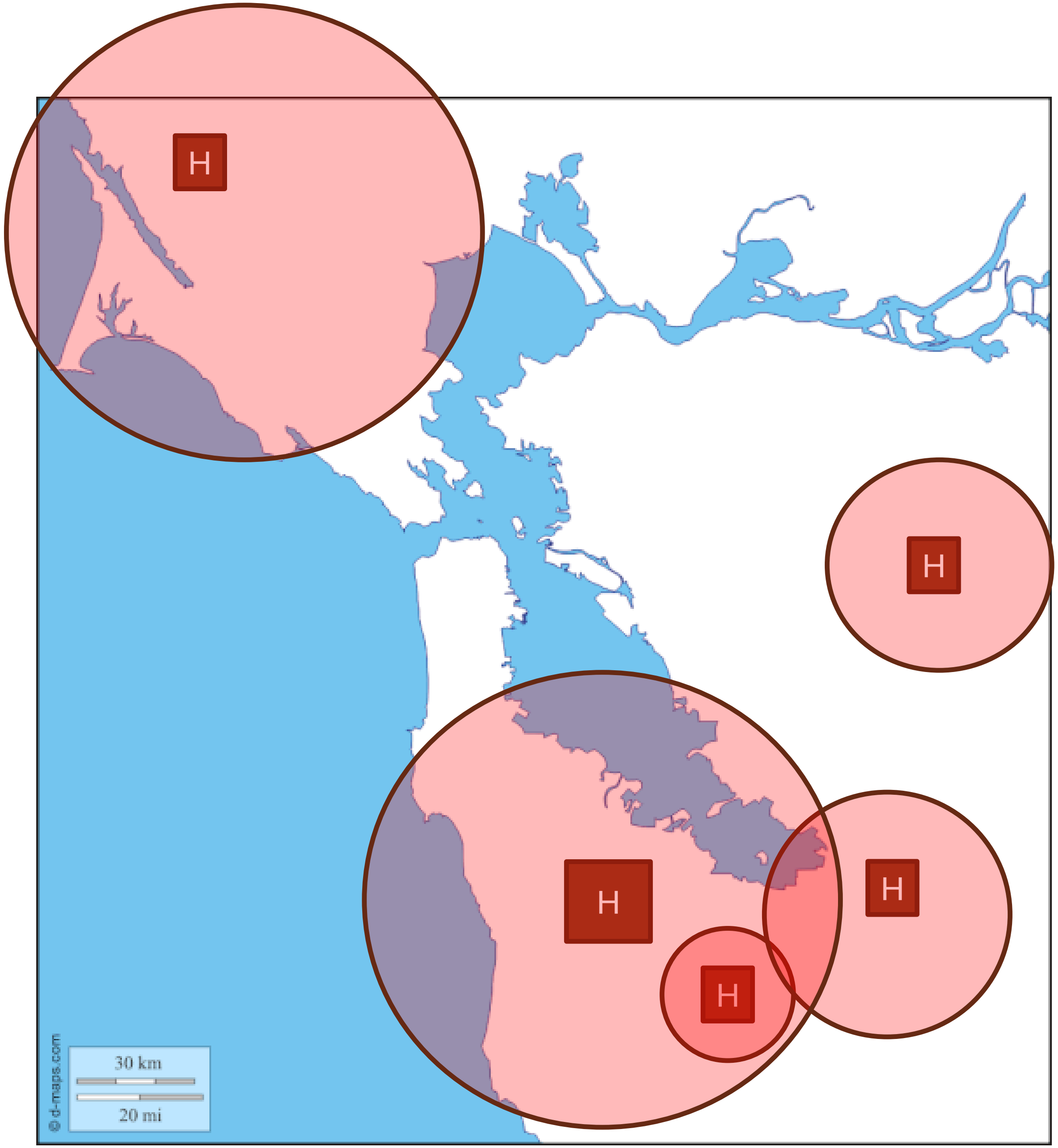

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let’s go find out.

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An undergrad in STATS 60 approached me after class and expressed interest in statistics

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Pulled county-level transport protocols for all of California and summarized their guidelines.

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NEMSIS data base:

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let's go out into the real world and find out.

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let's go out into the real world and find out.

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NEMSIS data base: (nearly) all EMS transport records in the USA. 50% patient/family decision

out into the real world and let's go find out.

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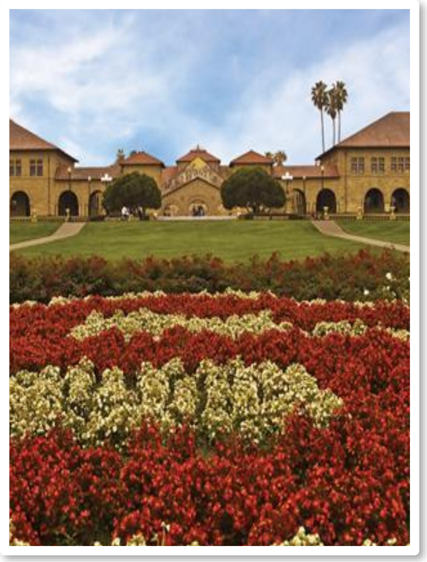
Pulled county-level transport protocols for all of California and summarized their guidelines.

NEMSIS data base: (nearly) all EMS transport records in the USA. 50% patient/family decision, 40% proximity

results



would regionalizing improve survival?

would regionalizing improve survival?

Table 2. Between-Group Differences in Operative Mortality and Overall Survival for Comparison of Transfer and Regionalization

Operative Mortality	**Transferred vs. Stayed (reference)**			**Rerouted vs. Not Rerouted (reference)***		
Group Contrast Measure	Estimate	95% CI	P Value	Estimate	95% CI	P Value
Absolute Risk Difference (%)	-0.62	-2.6 - 1.34	0.57	-7.5	-10.6 - -4.4	<0.001
Odds Ratio	0.97	0.87 - 1.08	0.55	0.68	0.57 - 0.80	<0.001
Number Needed to Treat (no.)	-	-	-	14	9 - 23	-

Overall Survival	**Transferred vs. Stayed (reference)**			**Rerouted vs. Not Rerouted (reference)**		
Group Contrast Measure	Estimate	95% CI	P Value	Estimate	95% CI	P Value
Hazard Ratio (PH model)	1.02	0.94 - 1.11	0.64	0.8	0.74 - 0.86	<0.001
Restricted Mean Survival Time		15 years			15 years	
Difference (days)	-44.9	-141.2 - 51.5	0.36	232.2	105.2 - 359.1	<0.001
Ratio	0.98	0.94 - 1.02	0.36	1.12	1.05 - 1.18	<0.001
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Group Contrast Measure	Estimate	95% CI	P Value	Estimate	95% CI	P Value
Absolute Risk Difference (%)	-0.62	-2.6 - 1.34	0.57	-7.5	-10.6 - -4.4	<0.001
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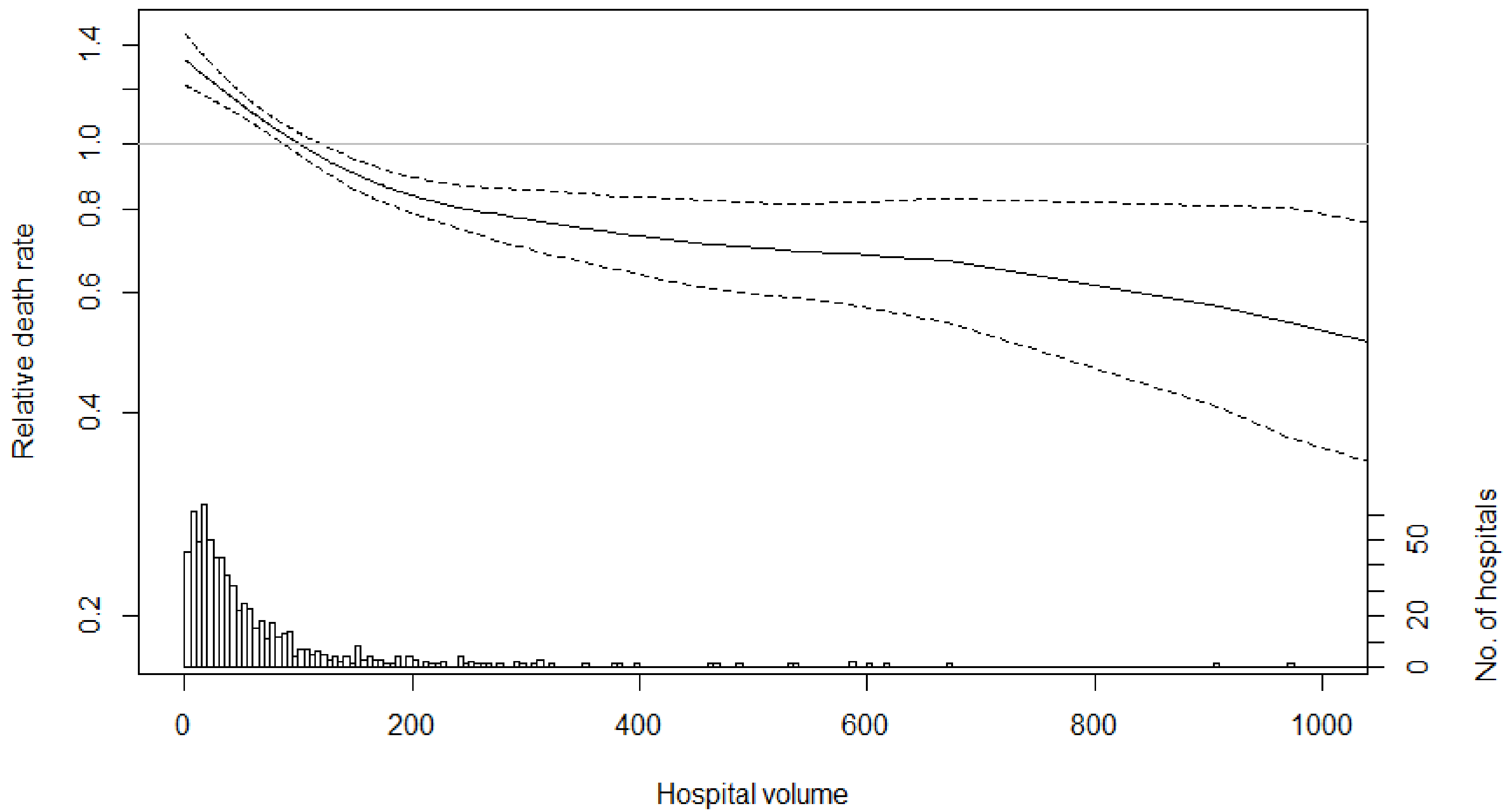

careful reasoning: the effect of transfer

careful reasoning: the effect of transfer

What if we didn't use our study design?

(a)

(b)

(c)

careful reasoning: the effect of transfer

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would regionalizing improve survival?

would regionalizing improve survival?

Using “all of the data.”

would regionalizing improve survival?

Table S7. Propensity Score Analsyis - Between-Group Differences in Operative Mortality and Overall Survival for Comparison of Transfer and Regionalization

Operative Mortality	**Transferred vs. Stayed (reference)**			**High-Volume vs. Low-Volume (reference)***			**Rerouted vs. Not Rerouted (reference)****		
Group Contrast Measure	Estimate	95% CI	P Value	Estimate	95% CI	P Value	Estimate	95% CI	P Value
Absolute Risk Difference (%)	-1.7	-3.2 - -0.001	0.03	-6.1	-7.7 - -4.5	<0.001	-9.6	-11.4 - -7.8	<0.001
Odds Ratio	0.9	0.82 - 0.99	0.03	0.73	0.67 - 0.79	<0.001	0.6	0.54 - 0.67	<0.001
Number Needed to Treat (no.)	-	-	-	17	13 - 23	-	11	9 - 13	-
Overall Survival	**Transferred vs. Stayed (reference)**			**High-Volume vs. Low-Volume (reference)***			**Rerouted vs. Not Rerouted (reference)****		
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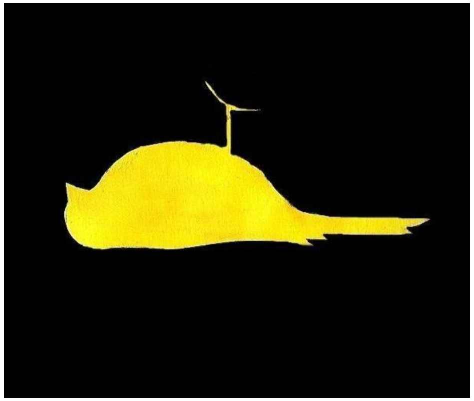

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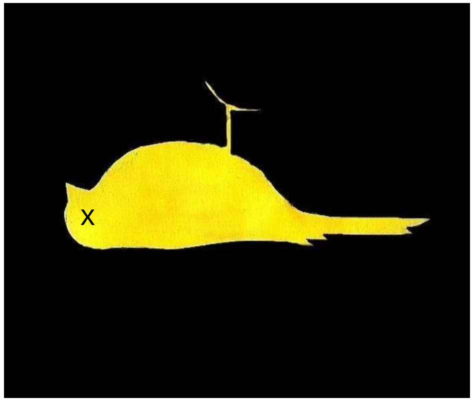

fin.

difference-in-differences

diff-in-diff

- Intuition:

diff-in-diff

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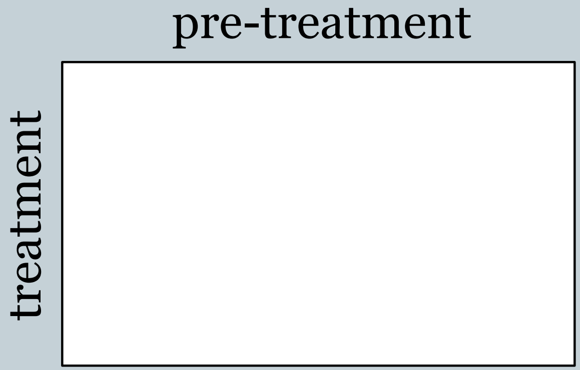
diff-in-diff



diff-in-diff

	pre-treatment	post-treatment
treatment		

diff-in-diff

	pre-treatment	post-treatment
treatment		
control		

diff-in-diff

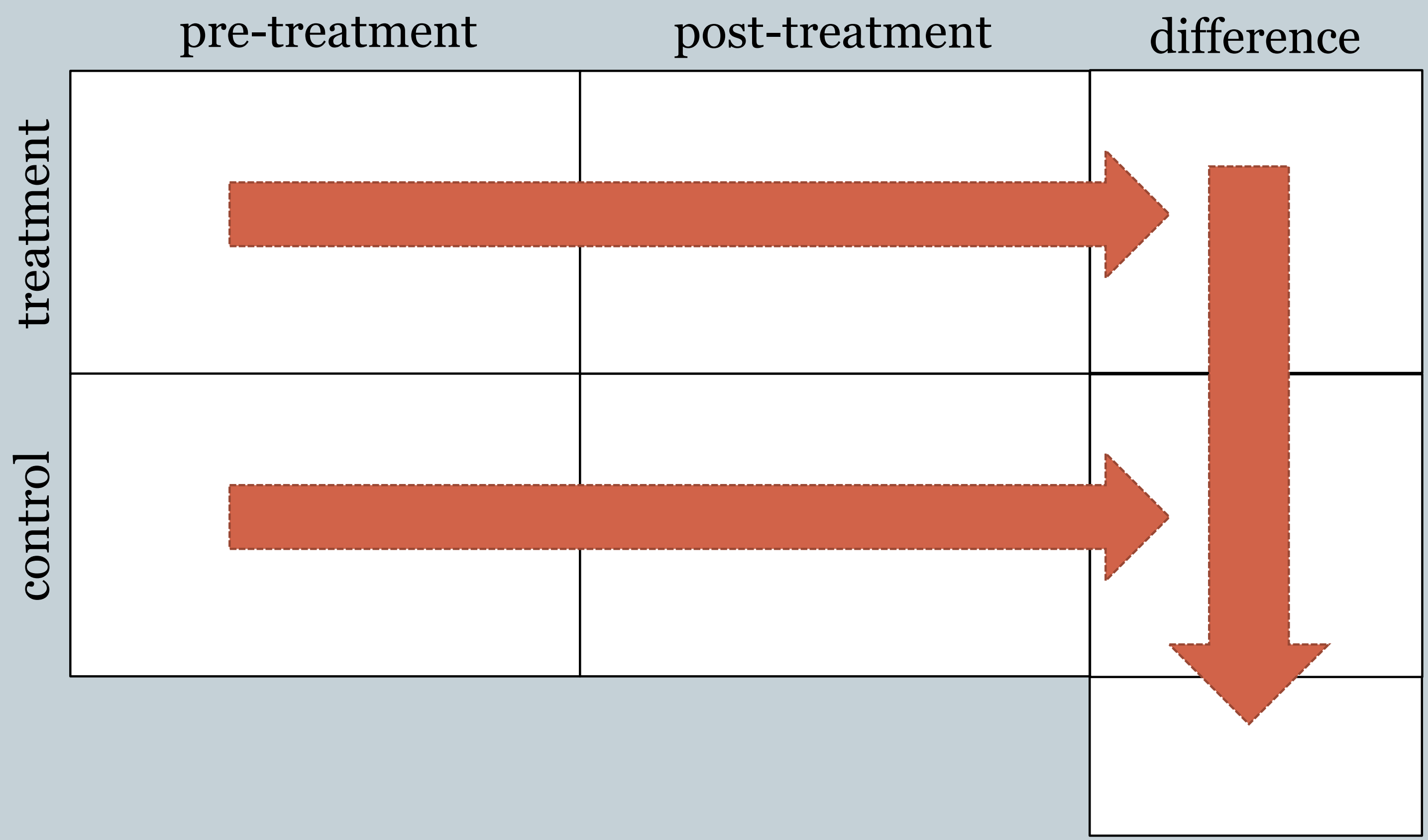
diff-in-diff

	pre-treatment	post-treatment	difference
treatment			
control			

diff-in-diff


pre-treatment
post-treatment
difference
treatment
control

diff-in-diff


pre-treatment
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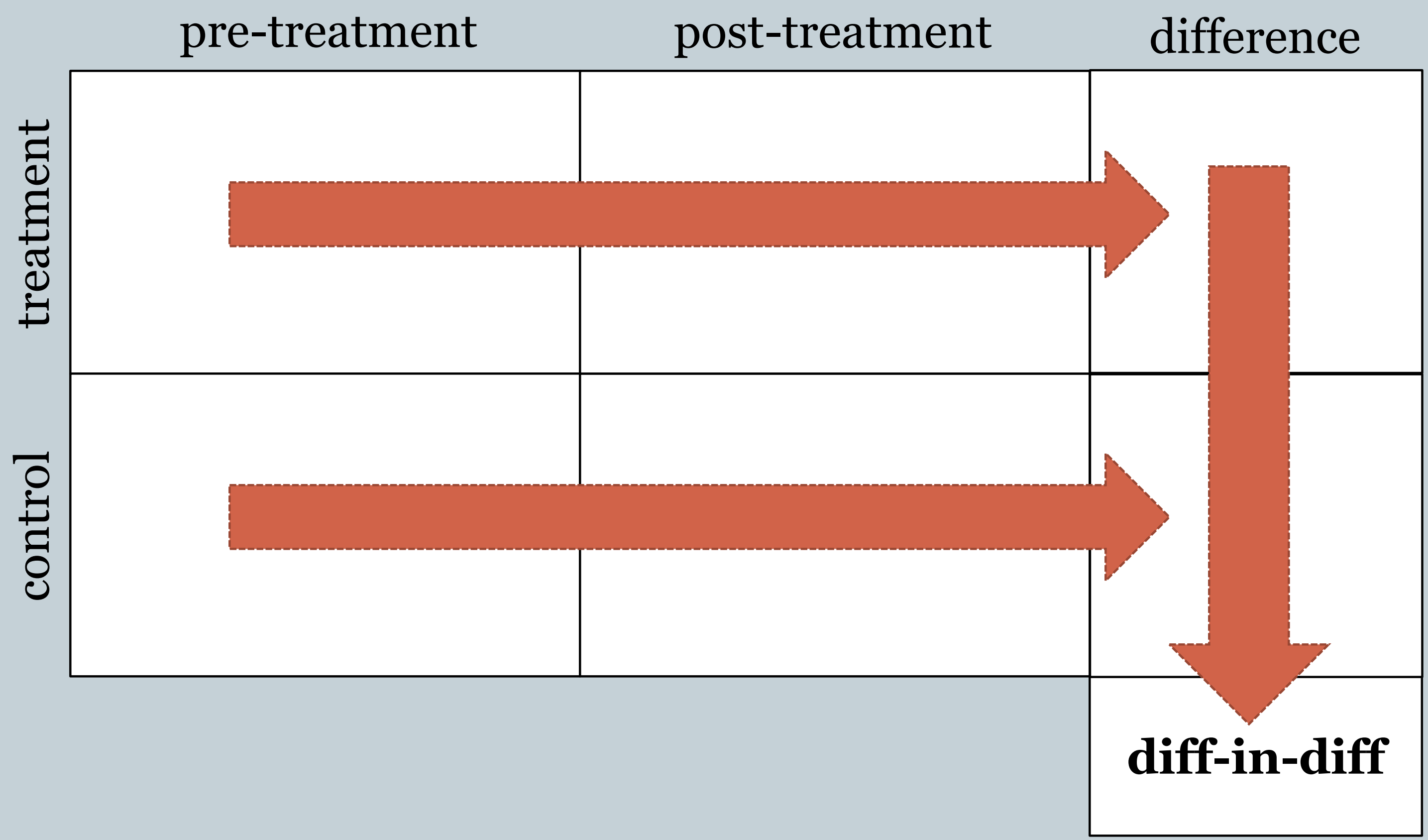
diff-in-diff


pre-treatment
post-treatment
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diff-in-diff

diff-in-diff: inference

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diff-in-diff: inference

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  - Researchers end up using matching a lot in diff-in-diff designs.

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$$y_{i,t} = \beta_0 + \beta_t * t_i + \beta_d * d_i + \beta_{t*d} t_i * d_i + \varepsilon_{i,t}$$

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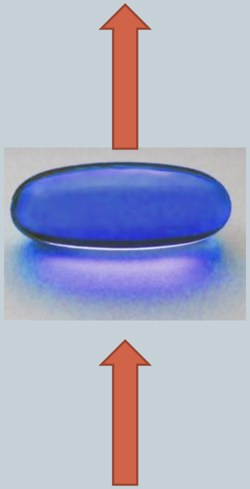
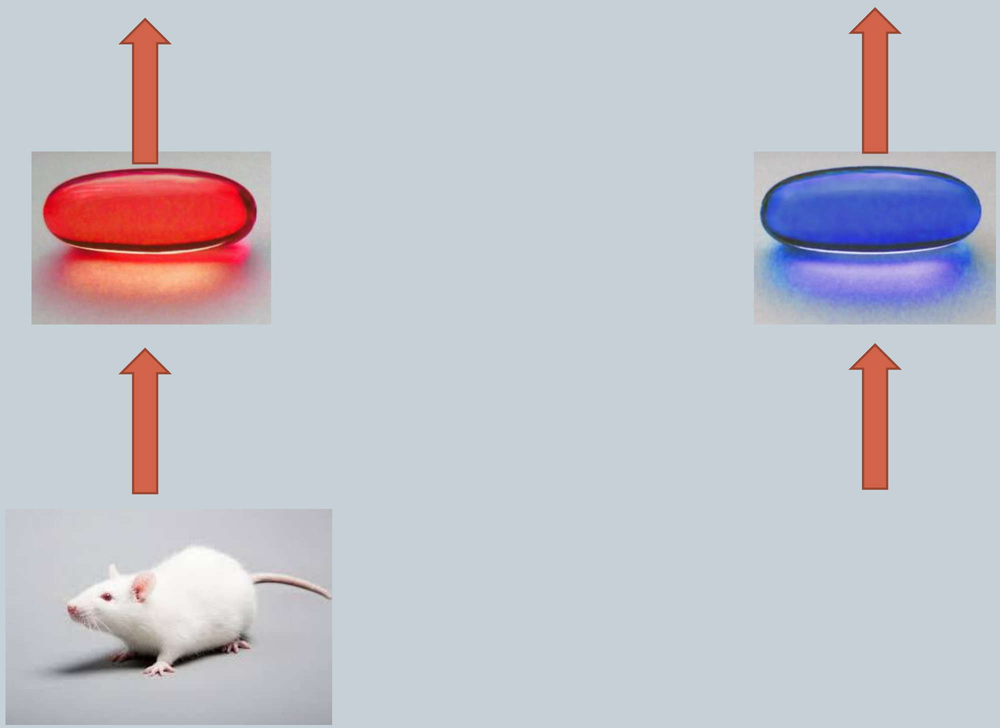
method of difference



method of difference



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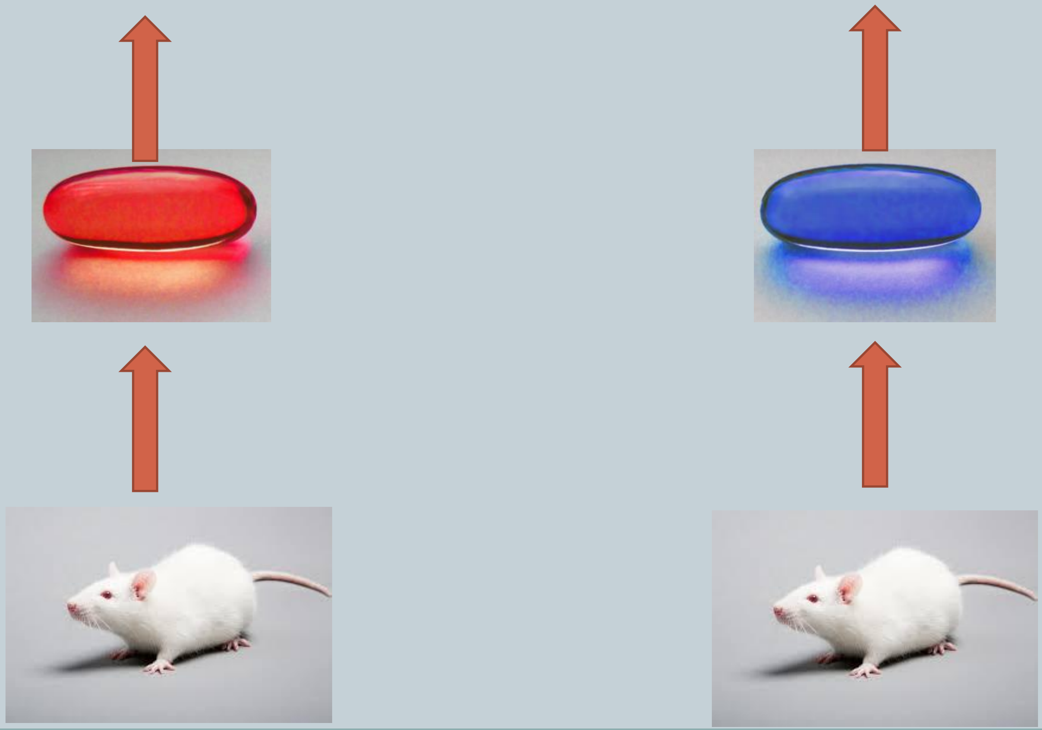

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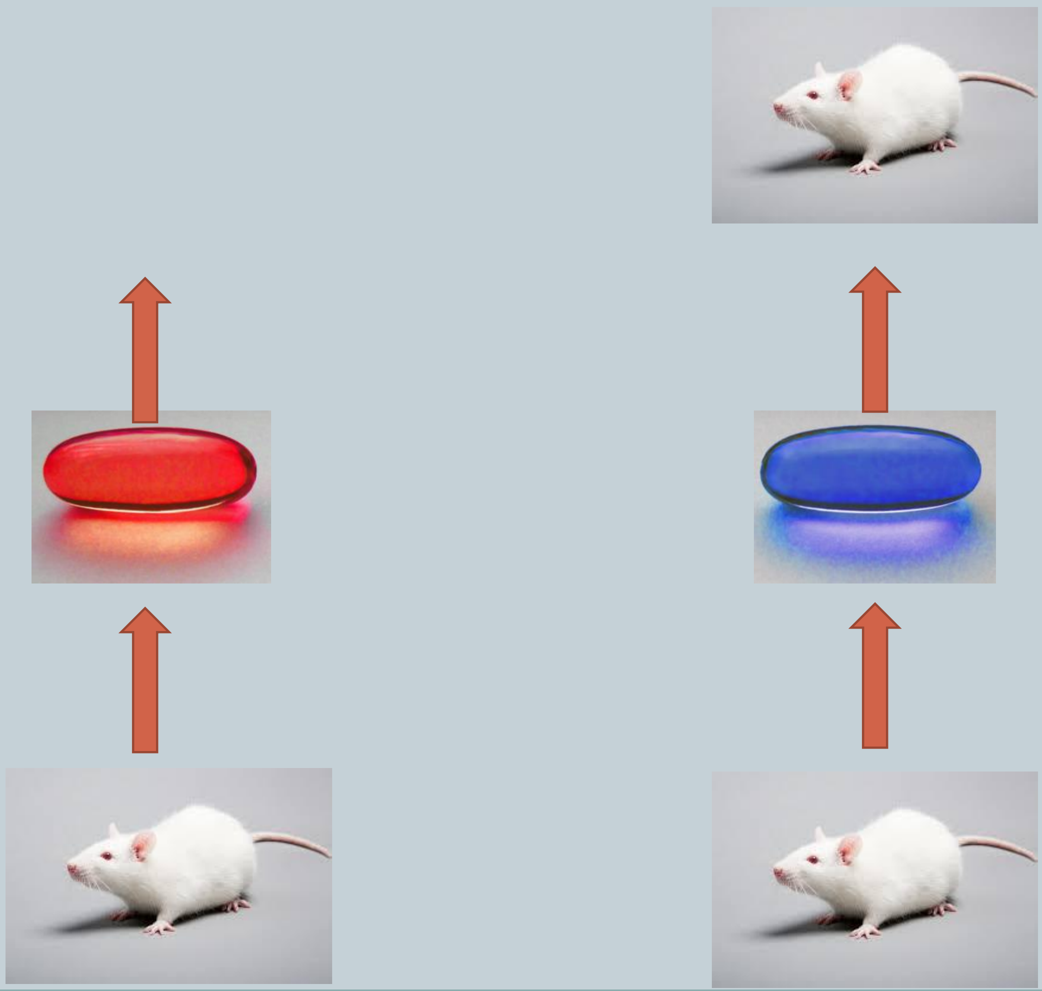

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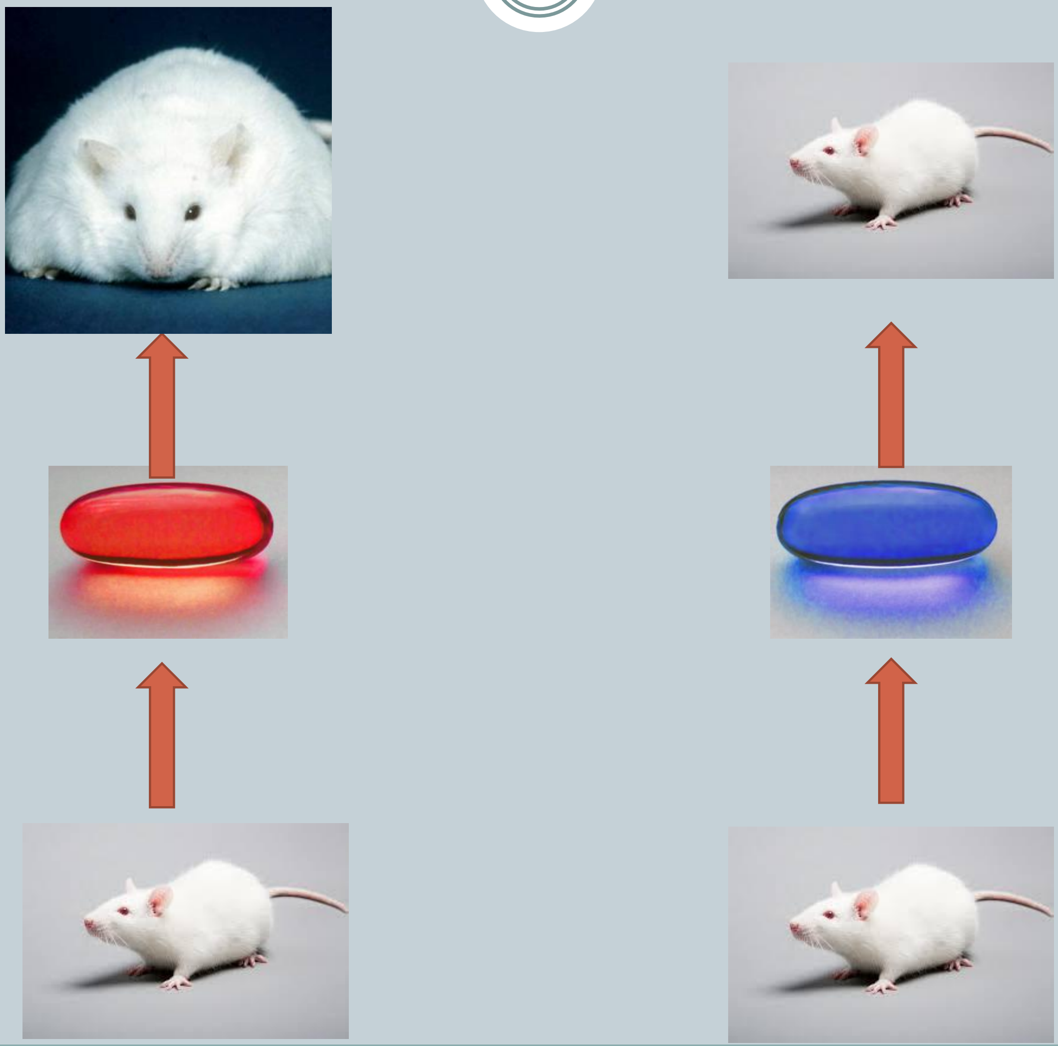
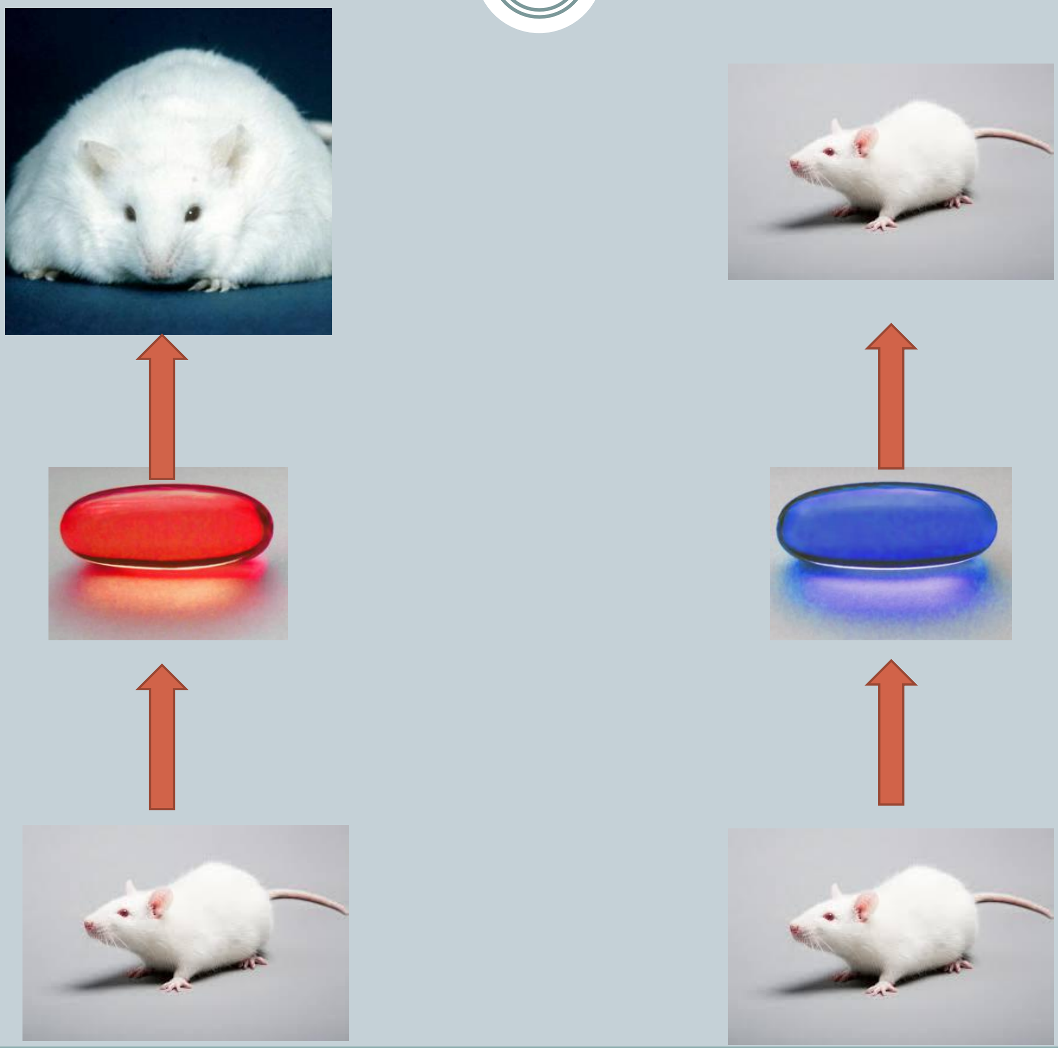
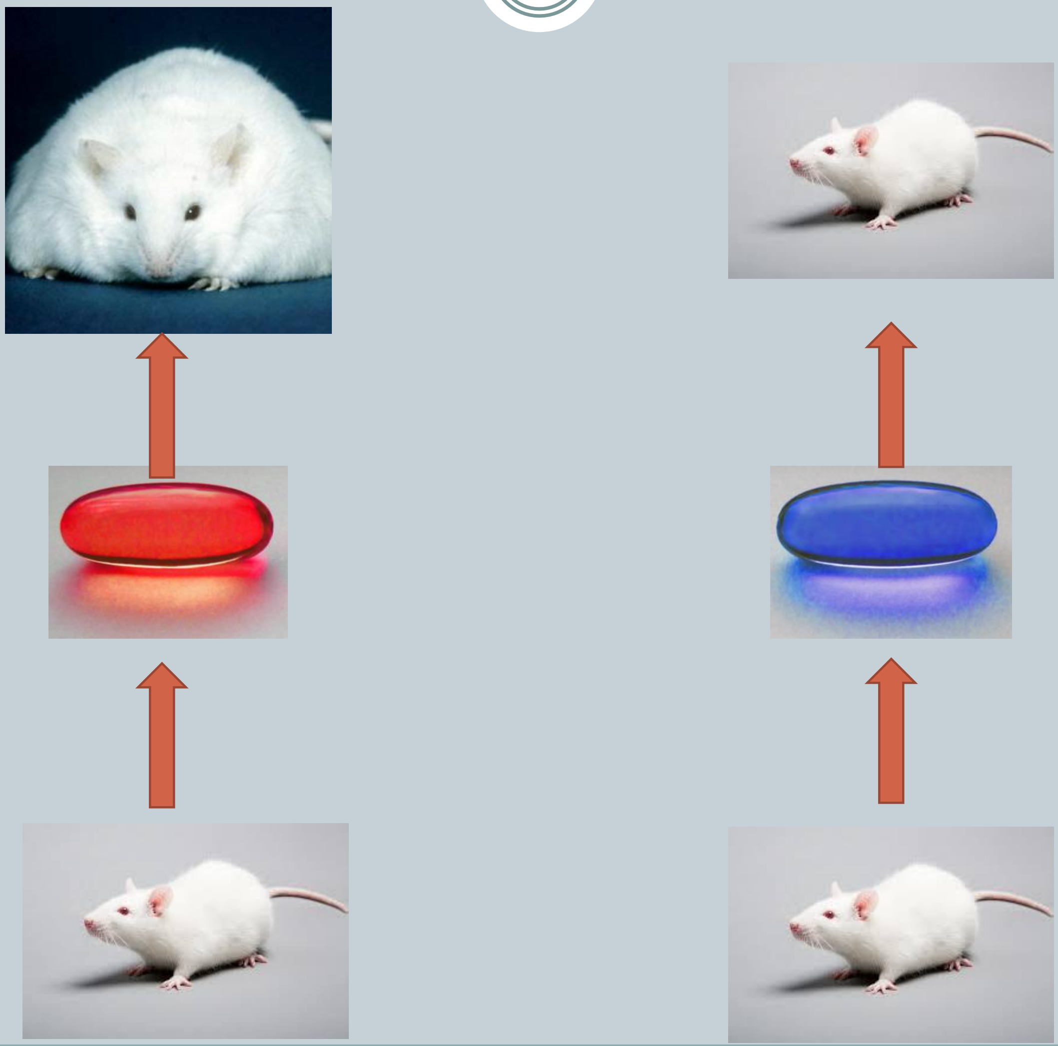
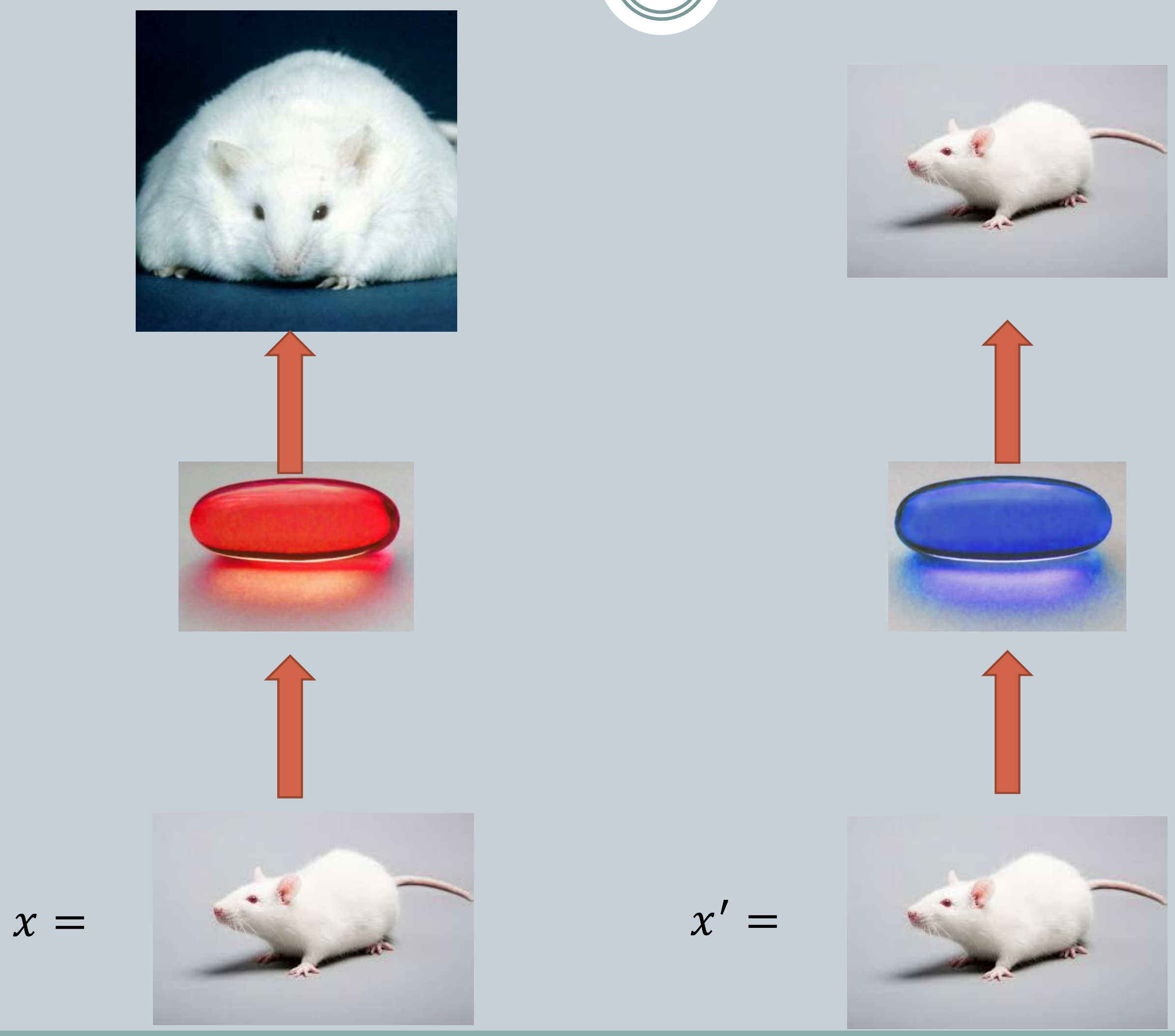




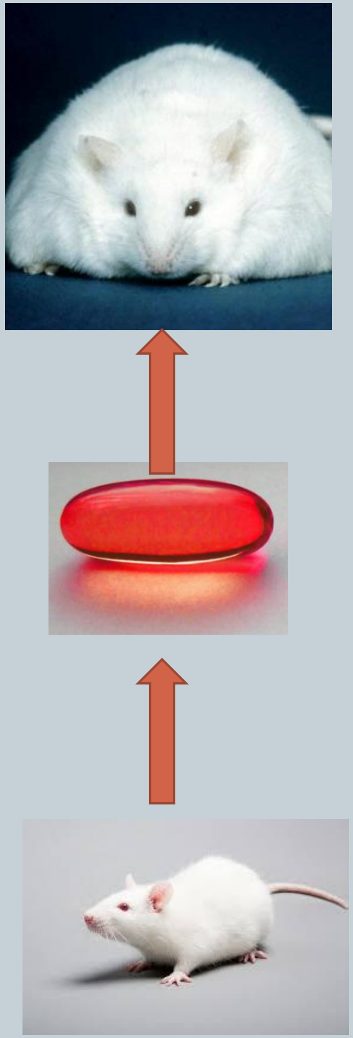
$x =$





$x =$
$x' =$

$r_T = f(d = 1, X = x)$ $r_C = f(d = 0, X = x')$



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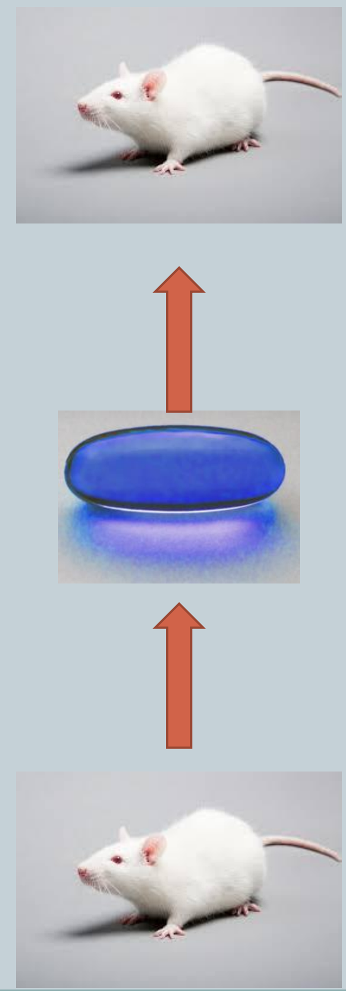

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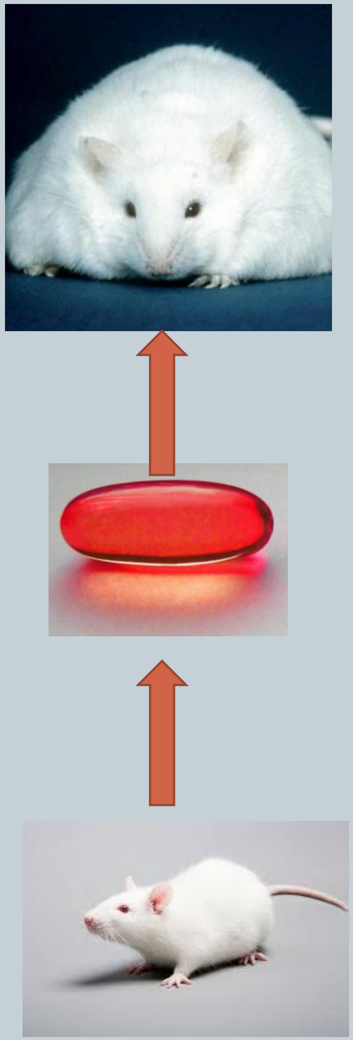
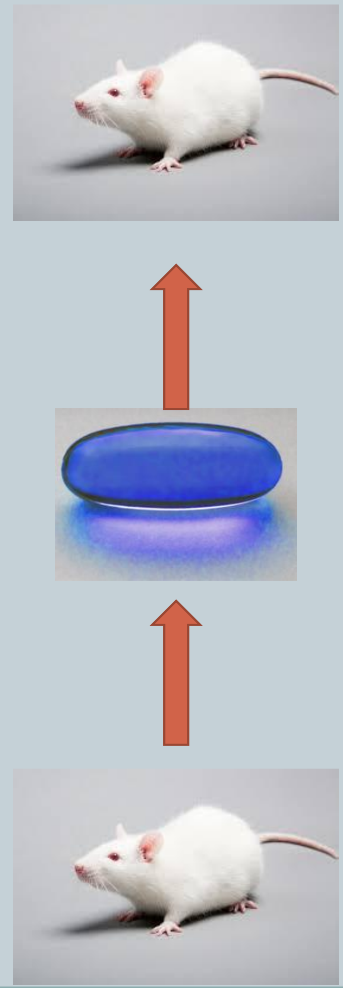


$x =$



$\boldsymbol{x} =$

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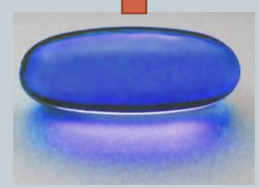

$x =$

$\boldsymbol{x} =$

The only difference

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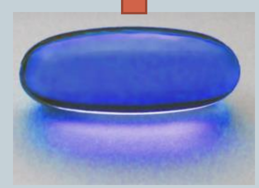
$r_C = f(d = 0, X = \boldsymbol{x})$

$\boldsymbol{x} =$



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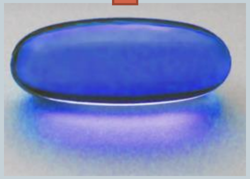

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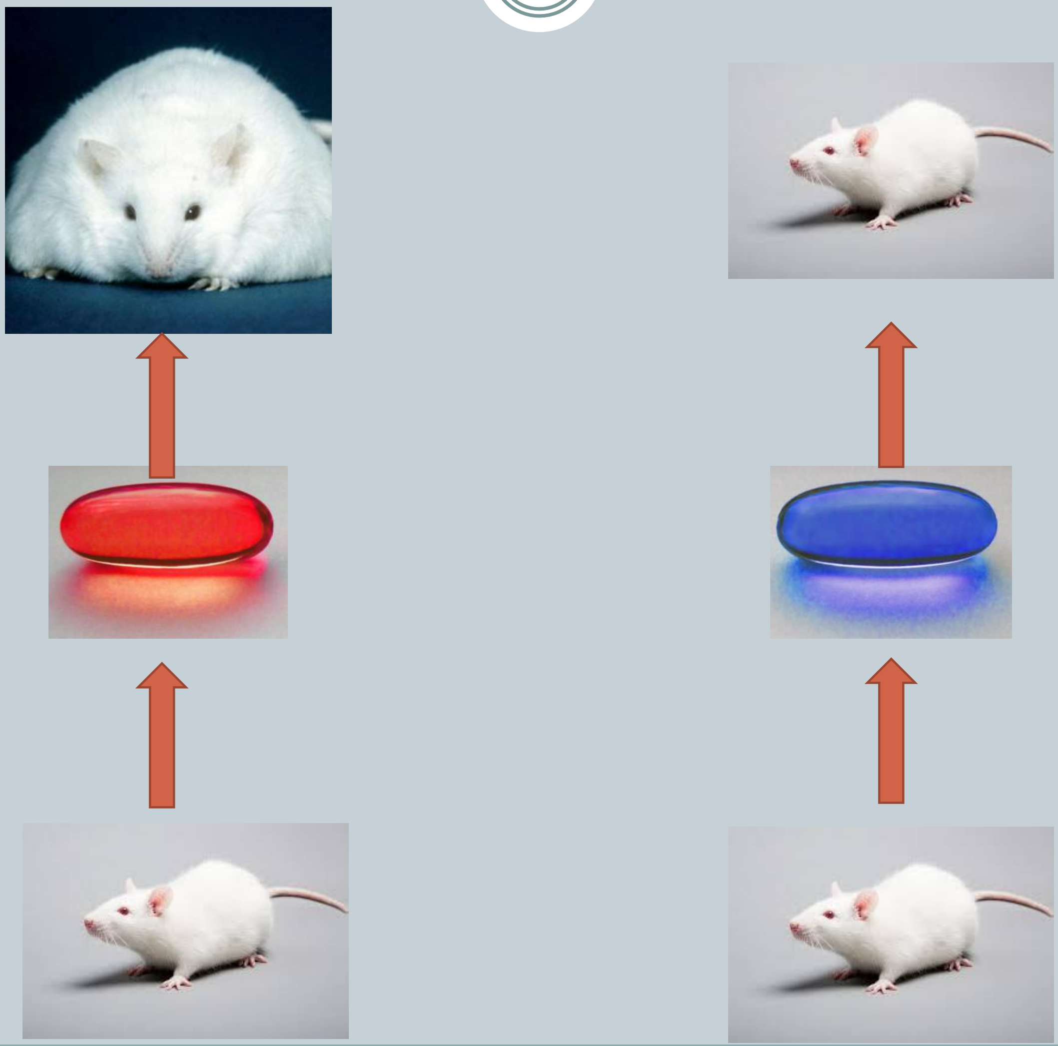
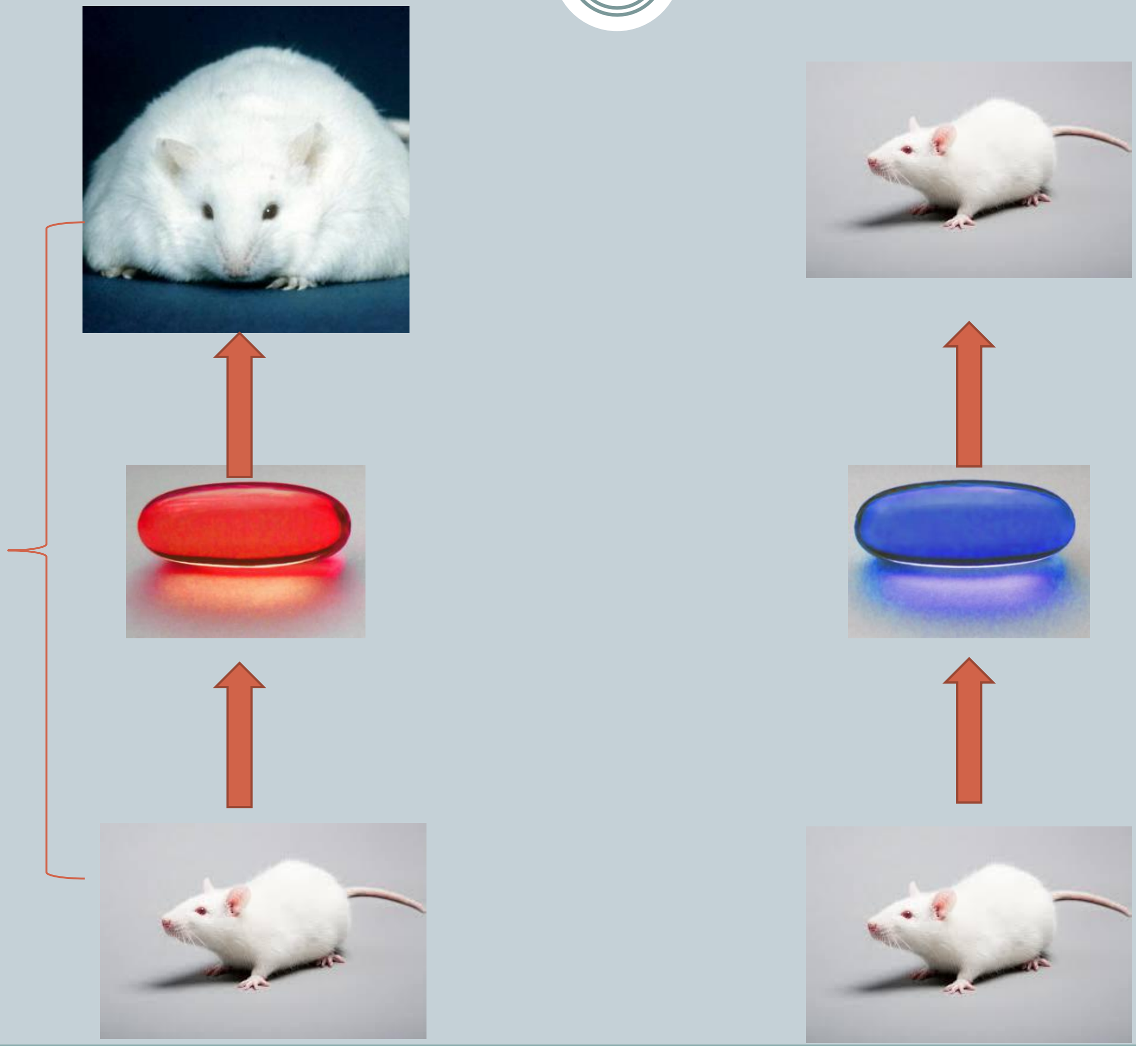
diff-in-diff

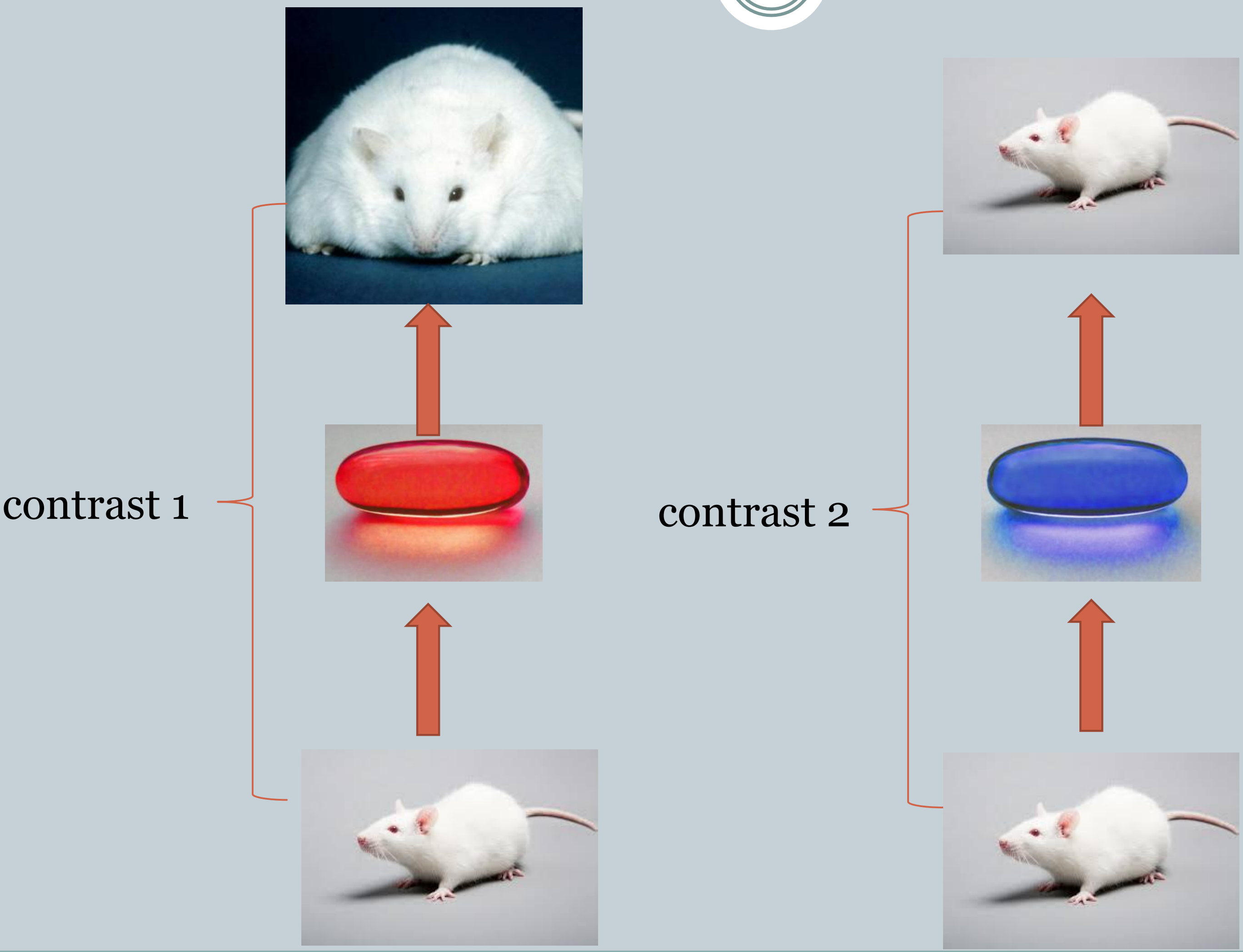


diff-in-diff

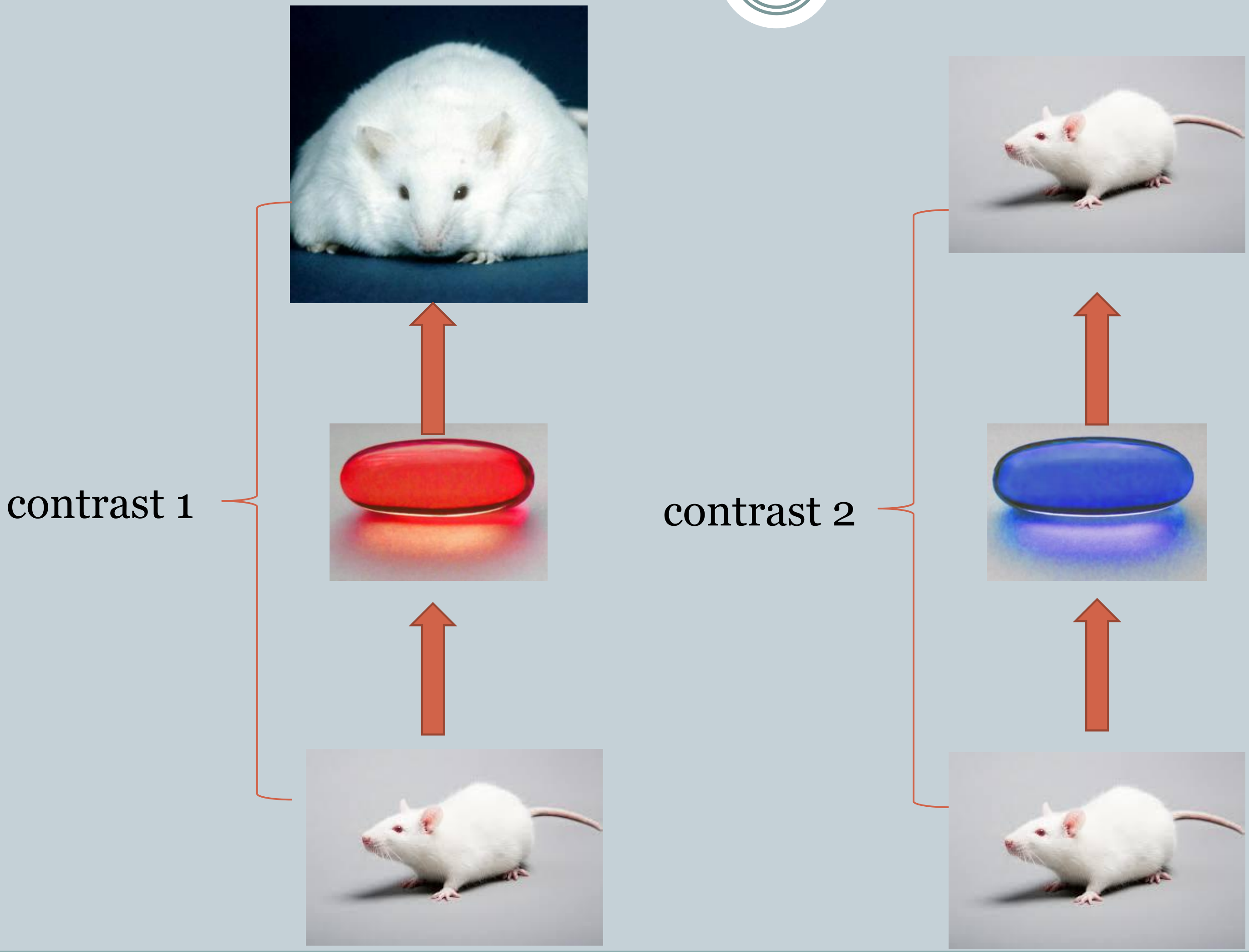


contrast 1

diff-in-diff



(contrast 1) – (contrast 2) = difference-in-differences



diff-in-diff

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