Causality and its applications in Machine Learning

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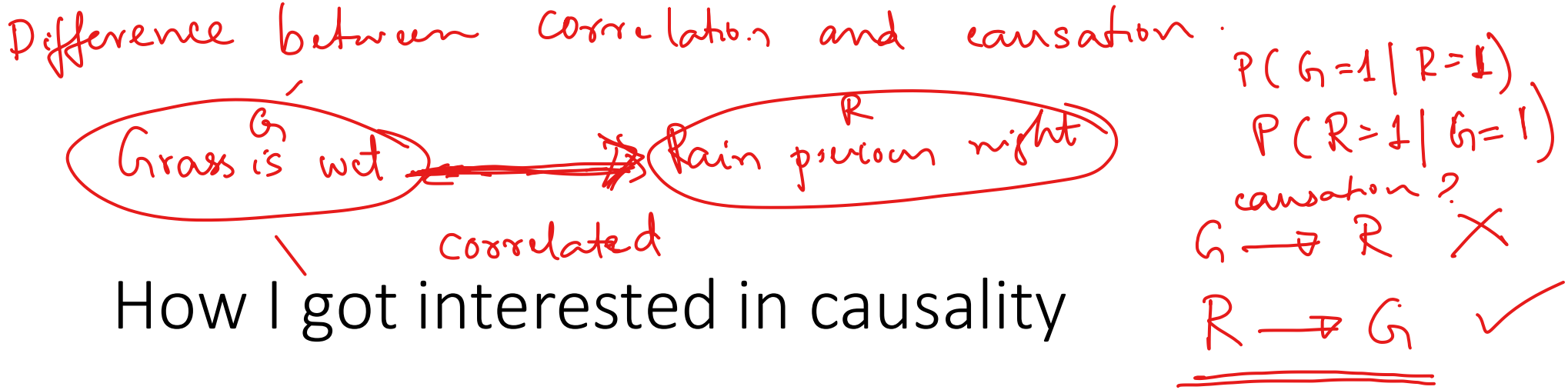
With annotations and augmentation by Sunita Sarawagi



How I got interested in causality

- 2012: Building a recommender system at LinkedIn
  - "Groups you may want to join"
- Use historical user activity as training data
  - Training is till month t, test is after month t
- Obtain accuracy numbers.
  - Suppose Algorithm A is better than B.
- Now deploy the recommendation algorithms A and B in a randomized experiment.
  - My manager: "You will be lucky if you find A performs better than B"
  - Why?

What is the **impact** of a recommender system on sales?

Can a recommender system **change** user's preferences?

Recommender System

How to **explain** why an item was recommended to a user?

What would happen if we **changed** the recommender algorithm?

What is the **impact** of a recommender system on sales?

Can a recommender system **change** user's preferences?

These are all questions about action and effect.
Need causality to answer them.

How to **explain** why an item was recommended to a user?

What would happen if we **changed** the recommender algorithm?

I. What is causality?

II. How can we reason about causality mathematically?

    From Bayesian Networks to Causal Bayesian Networks (causal DAGs)

III. Can we learn a causal DAG?

IV. Application 1: Estimating the effect of actions

V. Application 2: Building more generalizable prediction models

VI. Open questions

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The Three Layer Causal Hierarchy

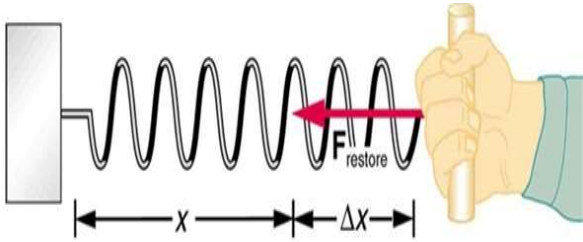
Pearl, Theoretical Impediments to Machine Learning with Seven Sparks from the Causal Revolution, arXiv:1801.04016v1. 11 Jan 2018

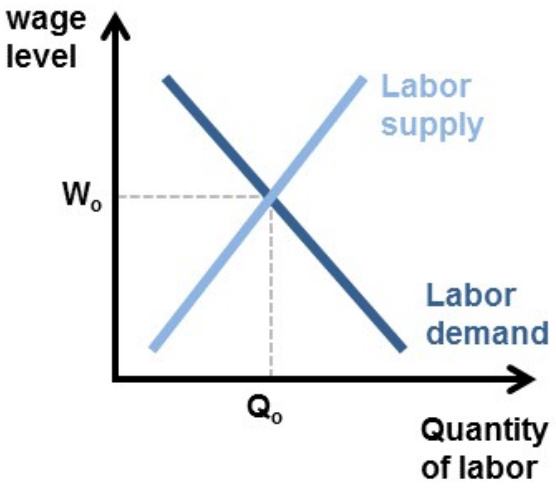
Level	Typical Activity	Typical Question	Examples
1. **Association** $P(y \mid x)$	*Seeing*	What is? How would seeing X change my belief in Y?	What does a symptom tell me about a disease? What does a survey tell us about the election results?
2. **Intervention** $P(y \mid do(x), z)$	*Doing, Intervening*	What if? What if I do X?	What if I take aspirin, will my headache be cured? What if we ban cigarettes?
3. **Counterfactuals** $P(y_x \mid x', y')$	*Imagining, Retrospection*	Why? Was it X that caused Y? What if I had acted differently?	Was it the aspirin that stopped my headache? What I had not been smoking the past 2 years?

Intervention and counterfactuals

- Questions of interventions and counterfactuals common in biomedical and social sciences
- Such questions form the basis of almost all scientific inquiry
  - Medicine: drug trials, effect of a drug
  - Social sciences: effect of a certain policy
  - Genetics: effect of genes on disease

- **So what is causality?**
- **What does it mean to *cause* something?**





Defining causality

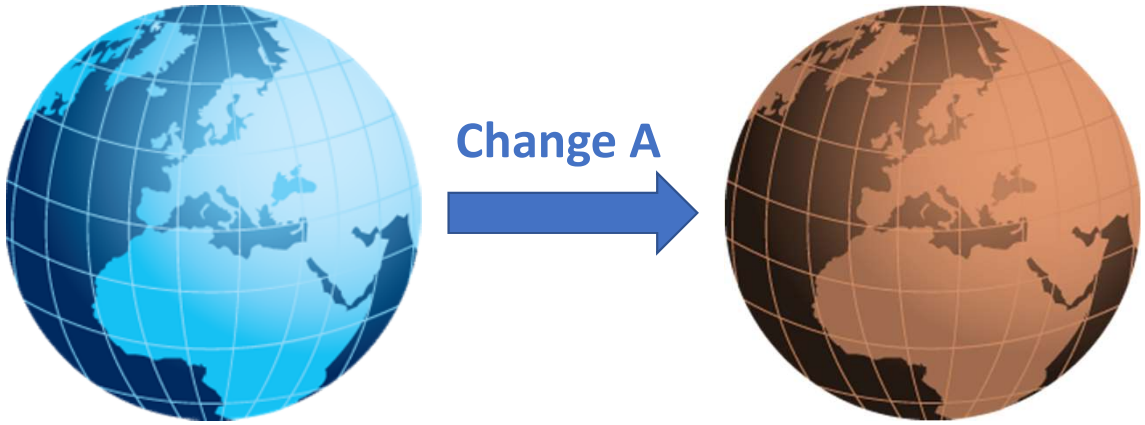
A longstanding philosophical debate.

"Interventionist" definition of causality:

A causes B if and only if

B would change if an appropriate manipulation on A were to be done.

A=a, B=b



A=a', B=b'

Causation and Manipulability (Stanford Encyclopedia of Philosophy)

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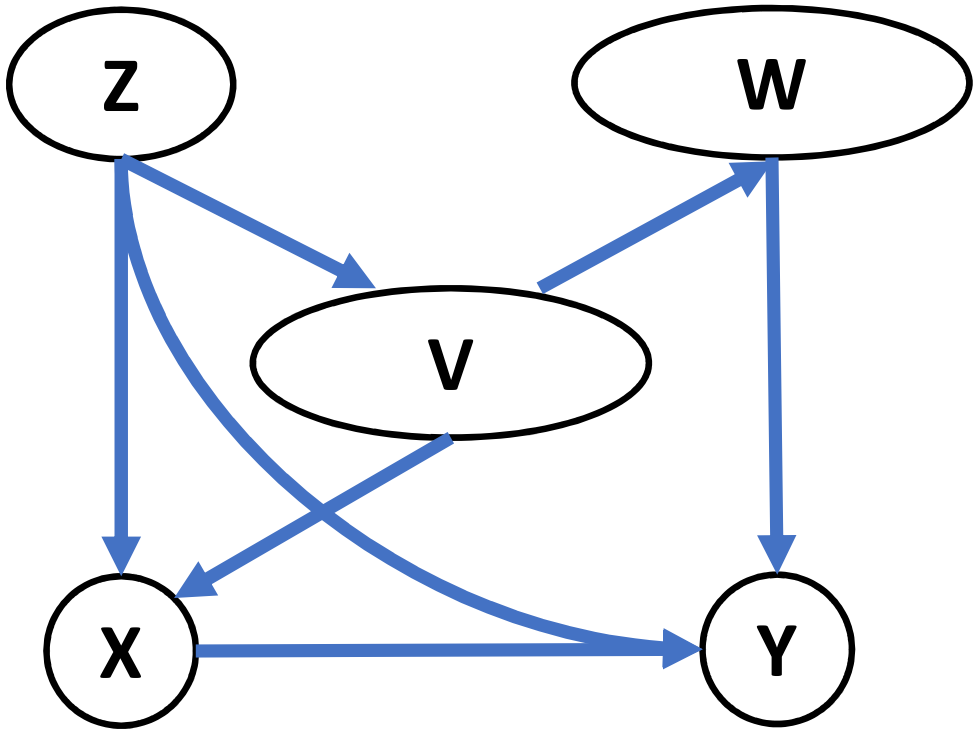
Recap: Bayesian Networks

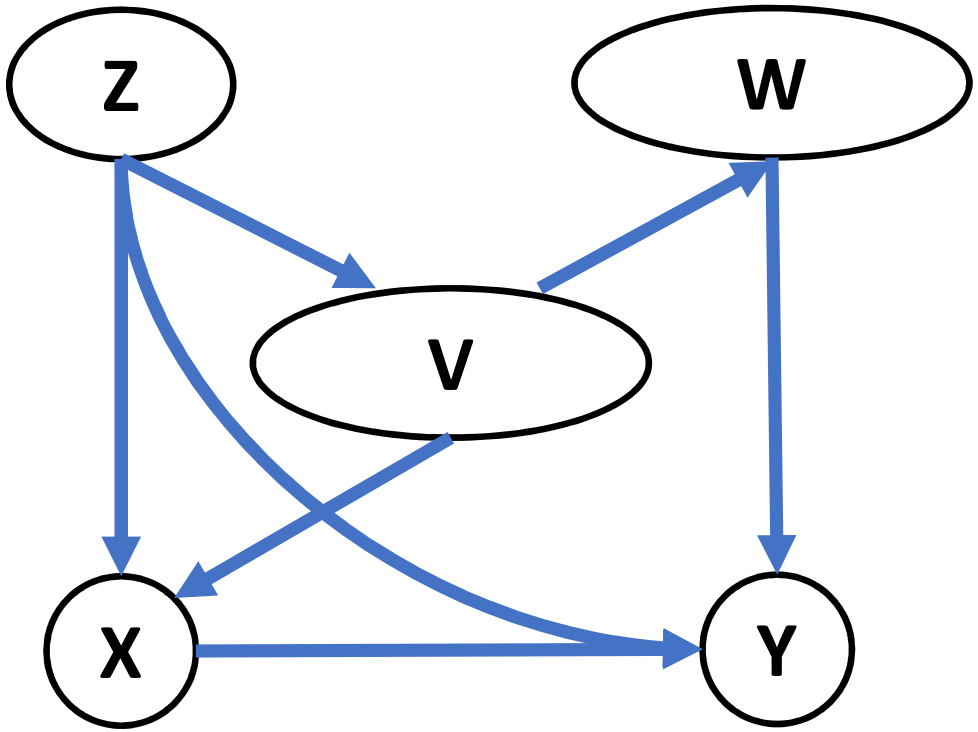


$$P(V, W, X, Y, Z) = P(Y|X, W, Z)\, P(X|V, Z)\, P(W|V)\, P(V|Z) P(Z)$$

Provides a factorization of the joint probability.

Each of the nodes' conditional probability can estimated independently.

Causal Bayesian Networks



Each directed edge corresponds to a causal relationship.

W causes Y.

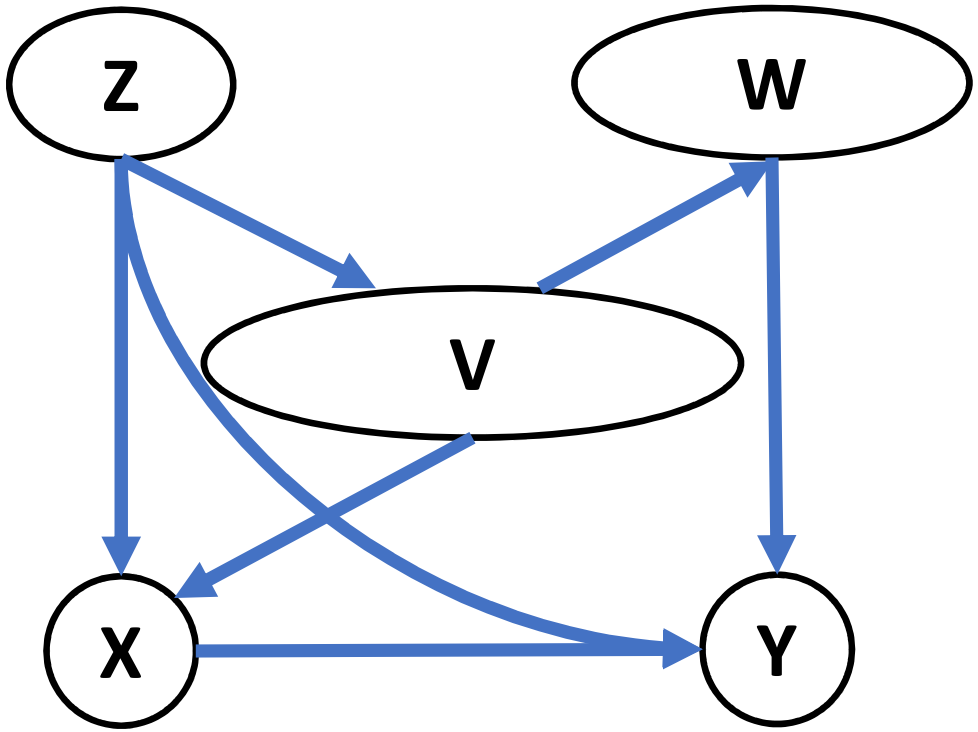
Z causes V, X, and Y.

Provides an explicit data-generation process.

Changing Y should not affect W.

Changing Z will affect V.

Important: Assumptions are the edges that are *missing*



Assumption 1: W does affect outcome Y.
Assumption 2: Z does not affect W.
Assumption 3: W does not affect V.
Assumption 4: X does not affect W.

..and so on.

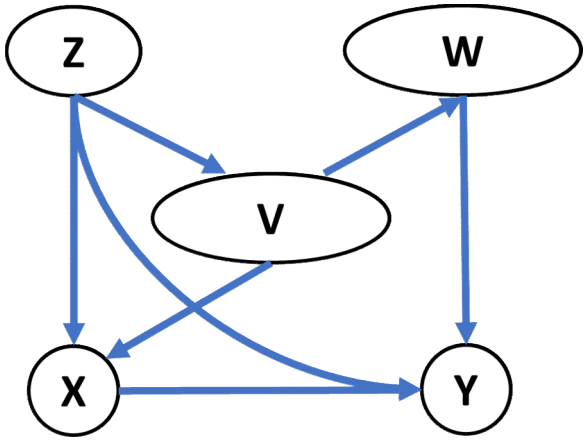
Conditional distribution

$P(x_i \mid Pa(x_i))$

Conditional probability Distributions

→ Tables (when discrete)

Structural Equations: An equivalent representation for causal Bayesian networks

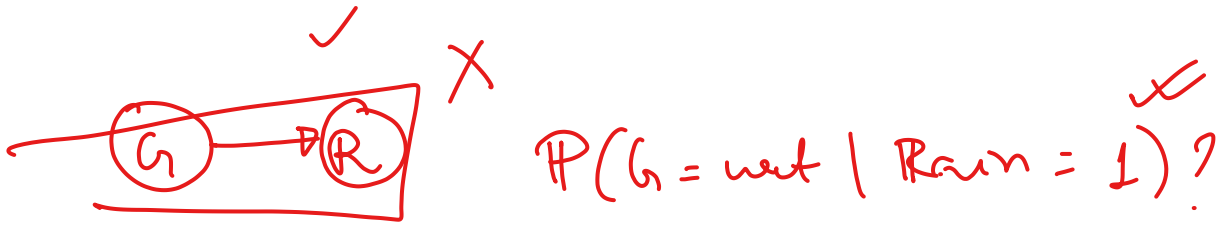


$$P(.) = P(Y|X,W,Z)\ P(X|V,Z)$$
$$P(W|V)\ P(V|Z)P(Z)$$

$$y := f(x, w, z, \epsilon_y)$$
$$x := g(v, z, \epsilon_x)$$
$$w := h(v, \epsilon_w)$$
$$v := i(z, \epsilon_v)$$

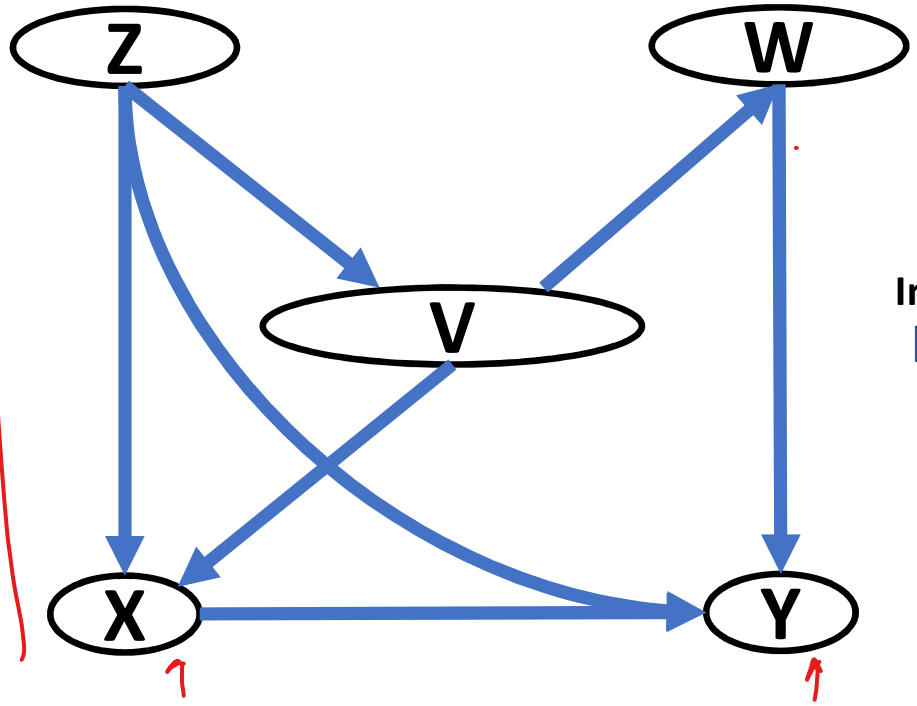
Independence of cause and mechanism (ICM) assumption
f, g, h and i are independent functions.

All ϵ error terms are mutually independent.

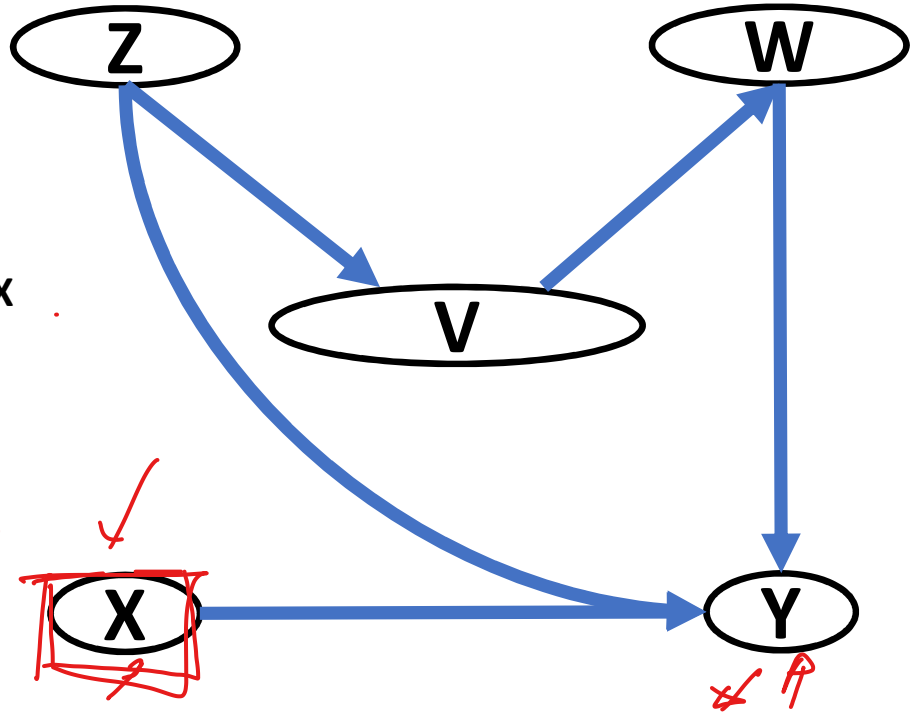


Now we are ready to define an intervention

An intervention on a variable changes its generating process.
Removes its existing relationship with its parents.



Intervene on X



$$P(.) = P(Y|X,W,Z)\,P(X|V,Z)\,P(W|V)\,P(V|Z)P(Z)$$

$$P^*(.) = P(Y|X,W,Z)\,P^*(X)\,P(W|V)\,P(V|Z)P(Z)$$

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An intervention on a variable changes its generating process.
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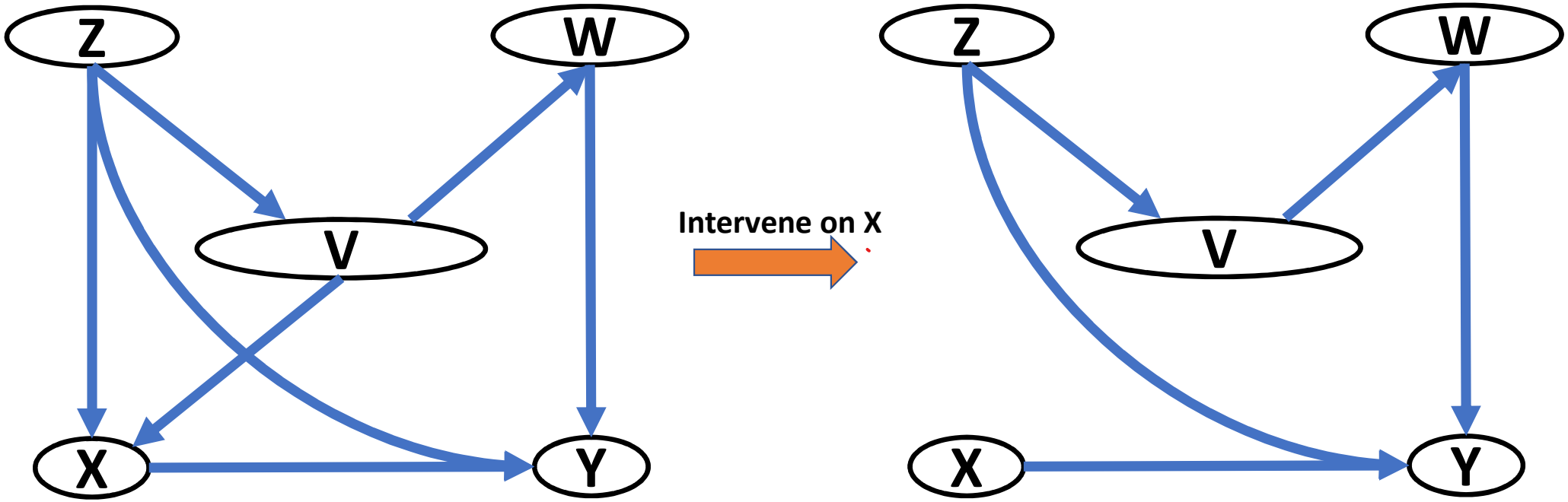
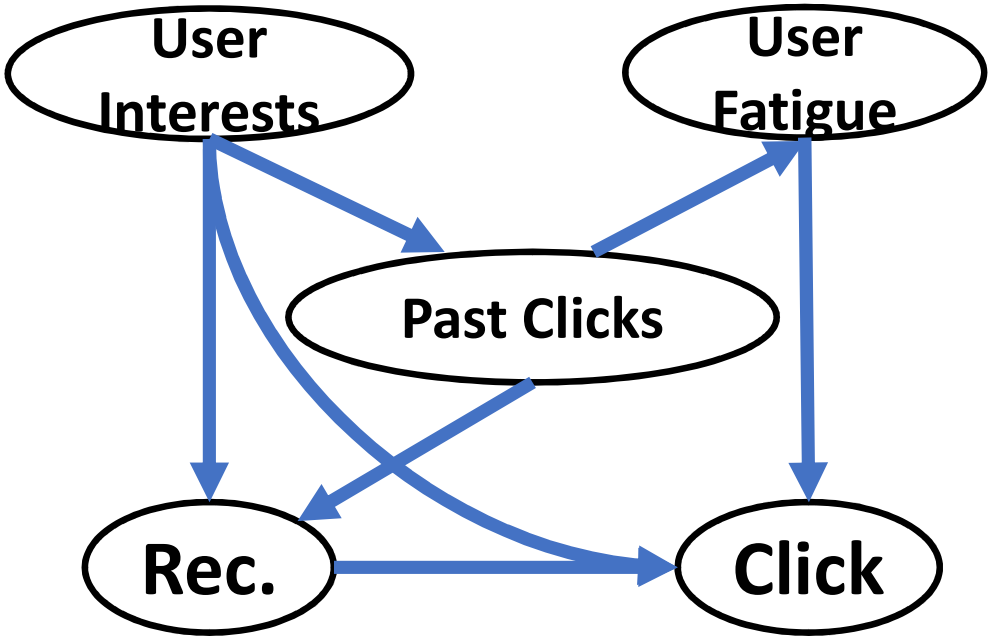


Causal Effect: $P(Y|do(X=x)) = P^*(Y|X=x) \neq P(Y|X=x)$

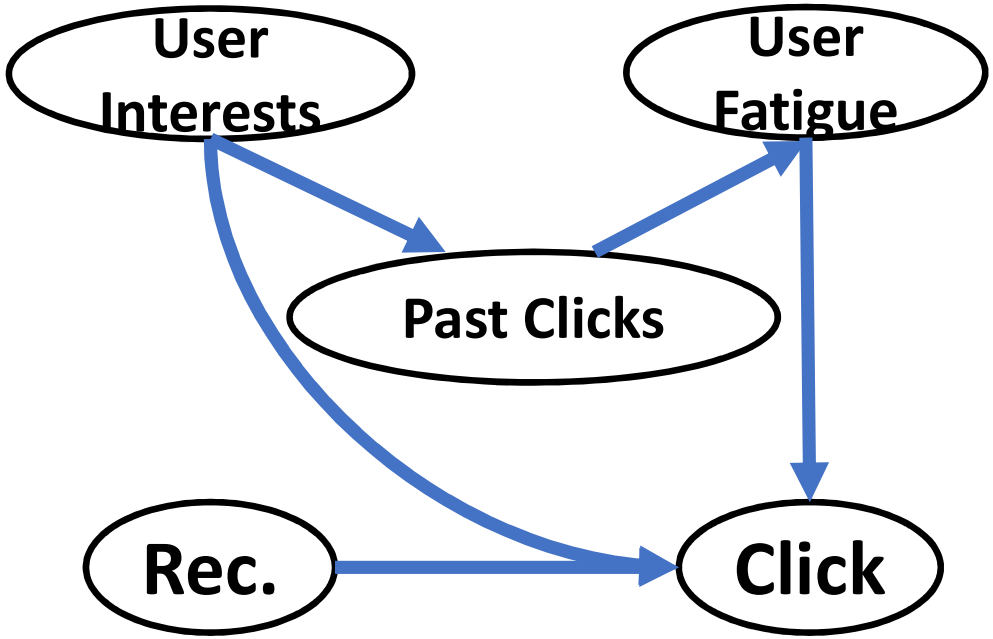
$P(R|do(G)=1)=0$

$P(R|G) = 0.2$

Example: How much does showing recommendations impact product discovery for users?



$\boldsymbol{P(Click|Rec.)}$ is confounded by the effect of User Interests.

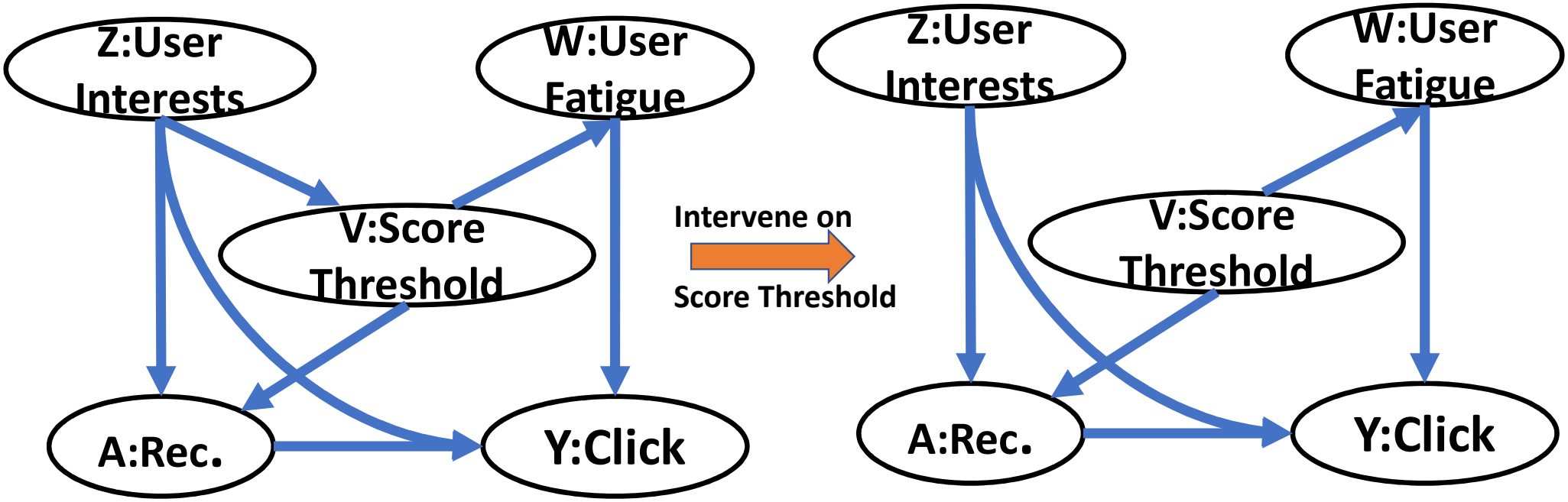


Instead, estimate $\boldsymbol{P(Click|do(Rec.)) = P^*(Click|Rec.)}$ where Rec. are generated independently of User Interests.

Power of causal Bayesian networks: Can estimate the result of interventions

Suppose V is a system parameter. Often is changed by systems team.

Build predictor for different interventions on V.



$$P(\phi) = P(Y|A,W,Z)\,P(A|V,Z)\,P(W|V)\,P(V|Z)P(Z)$$

$$P^*(\phi) = P(Y|A,W,Z)\,P(A|V,Z)\,P(W|V)P^*(V)P(Z)$$

$$\boldsymbol{P(\phi) = P(Y|X,W,Z)\, P(X|V,Z)\, P(W|V)\, P(V|Z)P(Z)}$$

$$\boldsymbol{P^*(\phi) = P(Y|A,W,Z)\, P(A|V,Z)\, P(W|V)P^*(V)P(Z)}$$

$$E_{P^*}[Y] = E_{\phi \sim P^*(\Phi)}[y]$$

$$= \int_{\phi} yP^*(\phi)$$

$$= \int_{\phi} y\frac{P(\phi)}{P(\phi)}P^*(\phi) = \int_{\phi} y\frac{P^*(\phi)}{P(\phi)}P(\phi)$$

$$= \int_{\phi} y\left[\frac{P^*(V)}{P(V|Z)}\right]P(\phi) \approx \frac{1}{n}\sum_{i=1:n} y\frac{P^*(V)}{P(V|Z)}$$

Can predict OOD outcome Y without any training data from the new distribution!

Importance Sampling. Adjusts to the new distribution. Estimate P(V|Z) using observed data. P*(V) could be a constant (V=0.5), a random variable ~$U(0,1)$ or any other arbitrary function.

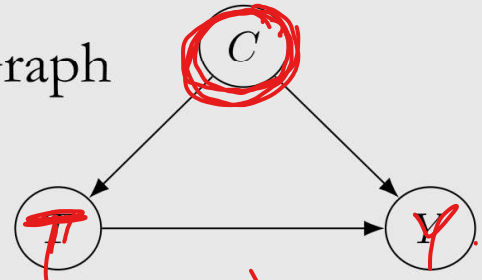
Examples of measuring effect of intervention

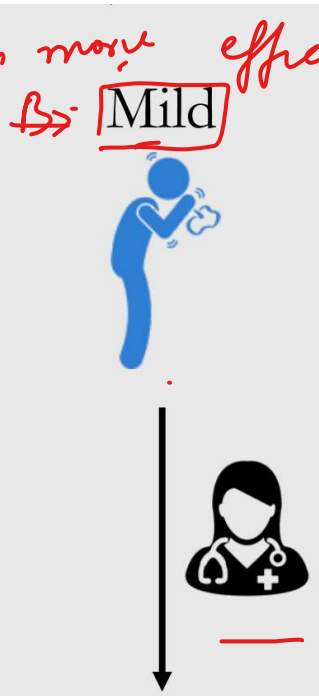
Treatment	Mild	Severe	Total
A	15% (210/1400)	30% (30/100)	**16%** (240/1500)
B	**10%** (5/50)	**20%** (100/500)	19% (105/550)

Condition

Simpson's paradox

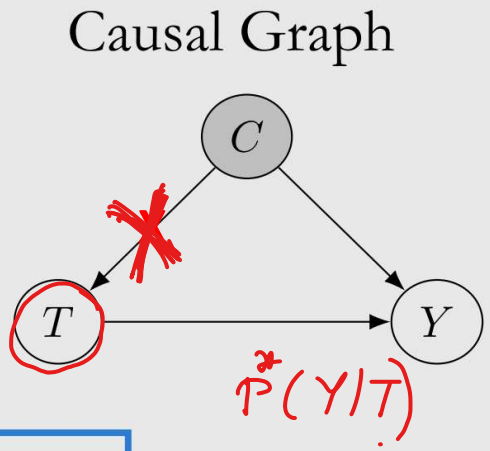
Causal Graph





Correct estimation of causal effect

$$\mathbb{E}[Y|\text{do}(T=t)] = \mathbb{E}_C\mathbb{E}[Y|t,C] = \sum_c \mathbb{E}[Y|t,c]P(c)$$



Treatment	Condition: Mild	Severe	Total	Causal
A	15% (210/1400)	30% (30/100)	**16%** (240/1500)	19.4%
B	**10%** (5/50)	**20%** (100/500)	19% (105/550)	**12.9%**
	$\mathbb{E}[Y\|t,C=0]$	$\mathbb{E}[Y\|t,C=1]$	$\mathbb{E}[Y\|t]$	$\mathbb{E}[Y\|\text{do}(t)]$

$$\frac{1450}{2050}(0.15) + \frac{600}{2050}(0.30) \approx 0.194$$

$$\frac{1450}{2050}(0.10) + \frac{600}{2050}(0.20) \approx 0.129$$

Can also define counterfactuals using causal Bayesian networks

- *E.g., We observe that a user was shown a recommendation and clicked on the product. What would have happened if he had not been shown the recommendation?*
- Interventions are about the effect of future actions.
- Counterfactuals are about hypothetical effects.
  - Advanced topic. Will skip.

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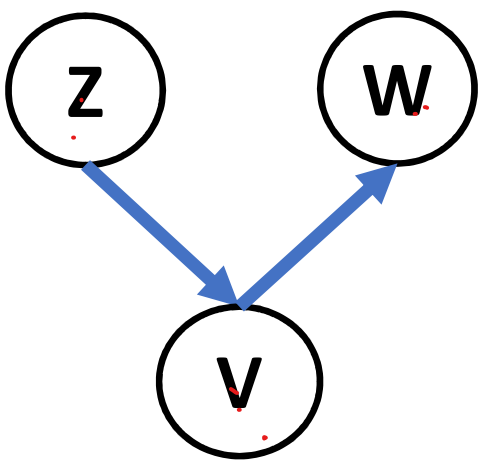
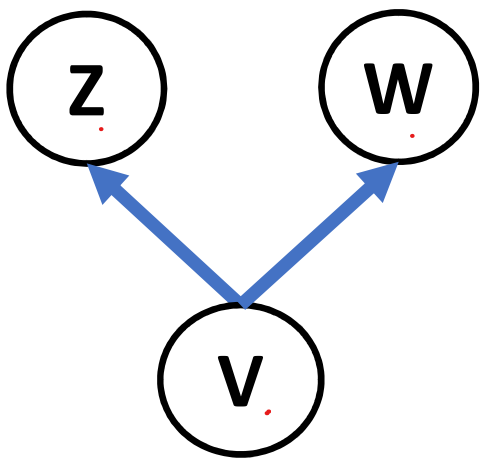
Like Bayesian networks, causal DAGs also imply conditional independencies



Chain

$Z \not\perp\!\!\!\perp W$

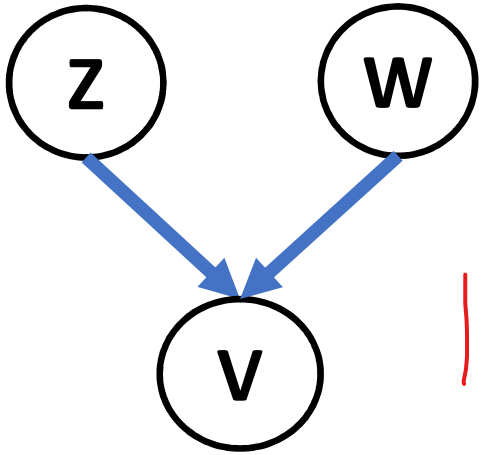
$Z \perp\!\!\!\perp W \mid V$



Fork

$Z \not\perp\!\!\!\perp W$

$Z \perp\!\!\!\perp W \mid V$



Collider

$Z \perp\!\!\!\perp W$

$Z \not\perp\!\!\!\perp W \mid V$

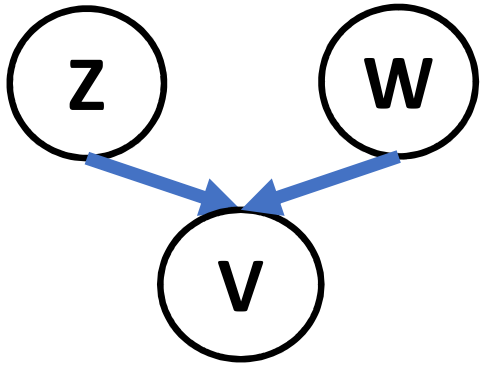
Two variables are **d-separated** if they are independent of each other.

Two variables are **conditionally d-separated** if they are independent conditional on some other variables.

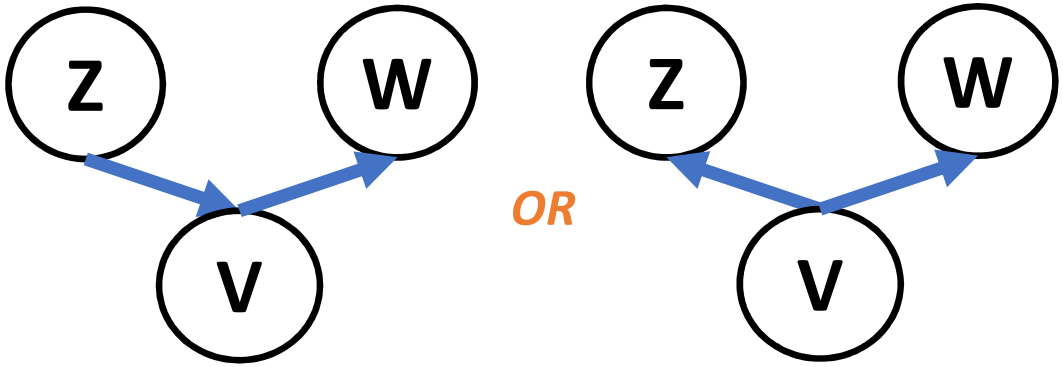
The conditional dependencies can be used to learn graph structure from data

Given a dataset (V, W, Z)

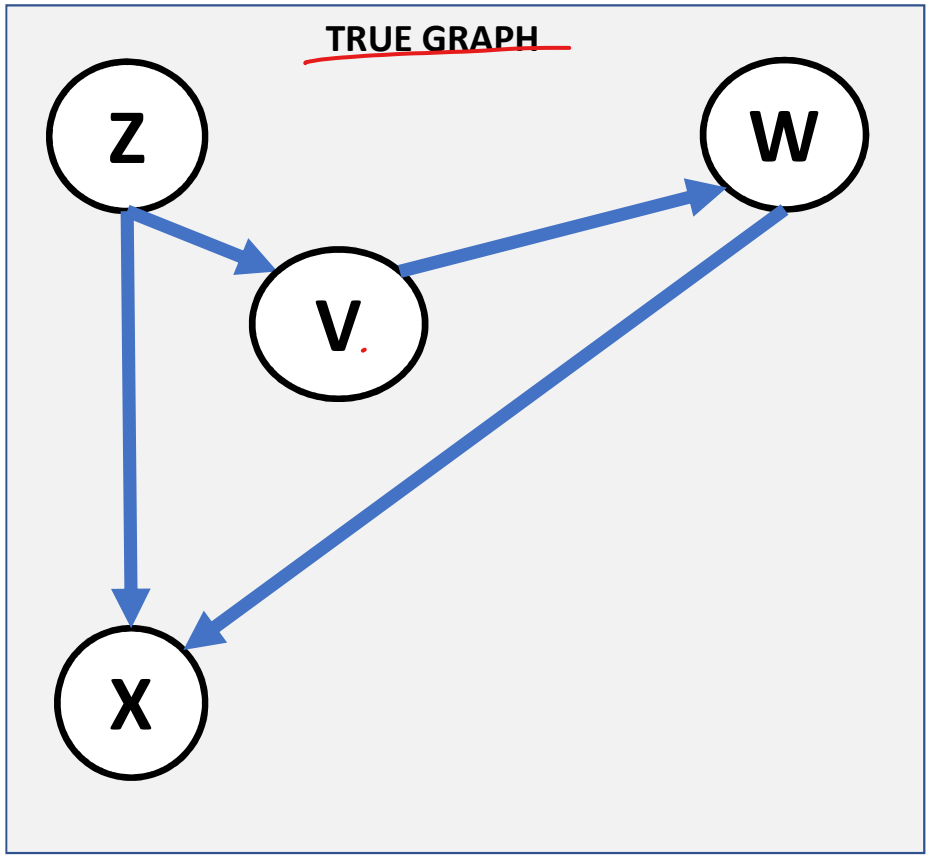
If $Z \perp\!\!\!\perp W$ and $Z \not\perp\!\!\!\perp W|V$

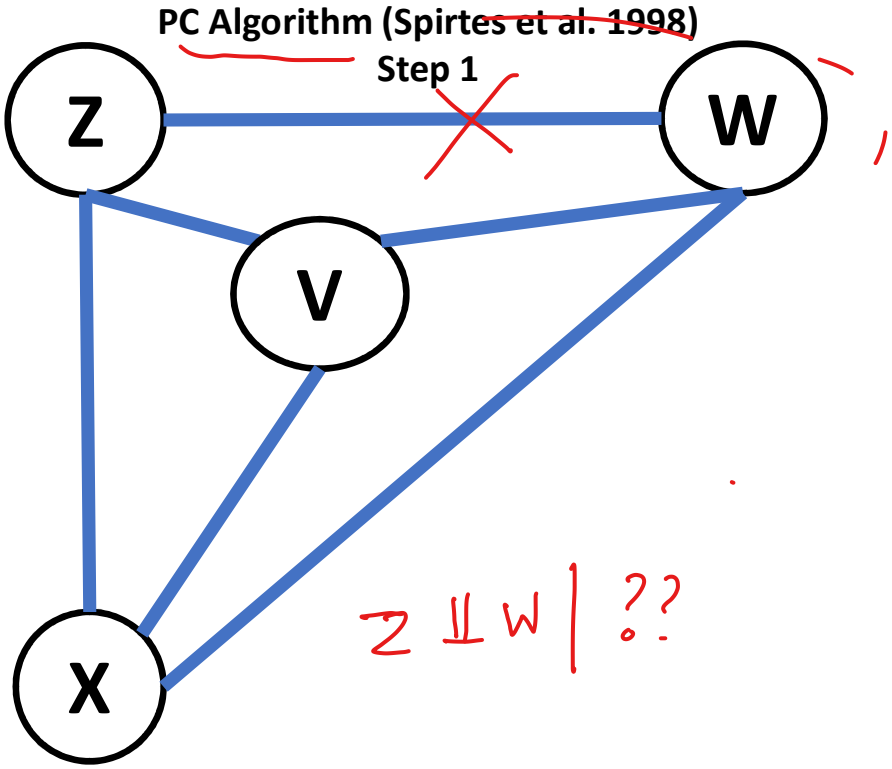


If $Z \not\perp\!\!\!\perp W$ and $Z \perp\!\!\!\perp W|V$



Causal DAGs can be learnt only upto Markov-equivalent graphs

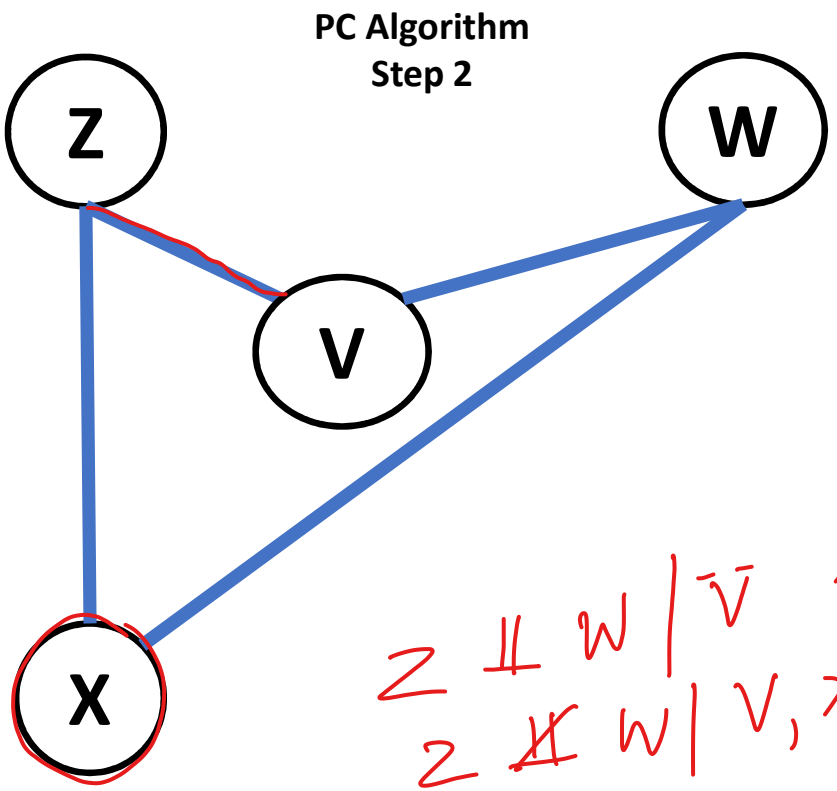




$Z \perp W|V \Rightarrow$ Z-W arrow can be removed.

$X \perp V|Z, W \Rightarrow$ X-V arrow can be removed.

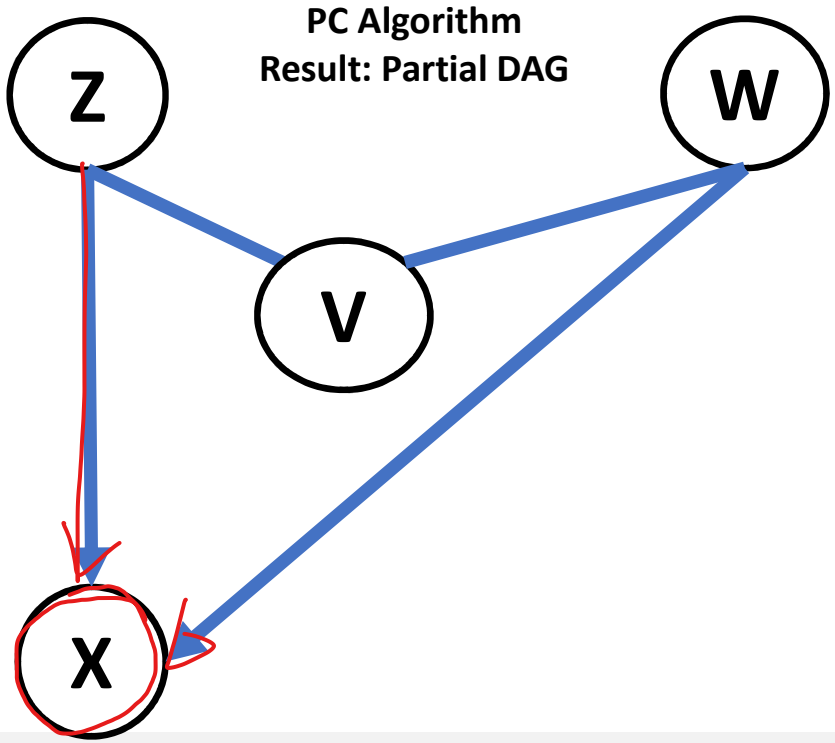
Causal DAGs can be learnt only upto Markov-equivalent graphs



$Z \not\perp W | X \Rightarrow$ orient edges as Z->X<-W

$Z \perp\!\!\!\perp W | \bar{V}$?

$Z \not\perp\!\!\!\perp W | V, X$ ✓



Partial DAG. Impossible to learn the direction of Z-V-W because both forks and chains imply the same observational distribution.

Overall algorithm

$x_1, x_2, \ldots x_n$: n- variables :

$G \leftarrow$ complete graph by connecting $x_i \sim x_j$ $\forall i, j$

for each $(i, j) \in G$.

if $\exists$ W s.t $X_i \perp\!\!\!\perp X_j \mid W$

$W \in Nbr(X_i) \cup Nbr(X_j)$

remove edge x_i, x_j

$Witness(X_i, X_j) \leftarrow W$.

/* Col the skeleton */

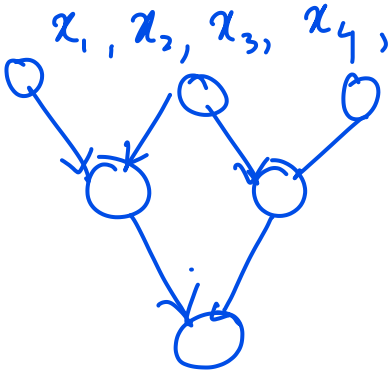
for each $(X_i - X_k - X_j) \in G$ { if $X_k \notin \overline{Witness(X_i, X_j)}$

add $X_i \rightarrow X_k \leftarrow X_j$ }.

More examples

- Consider a network whose true distribution is expressed as the graphical model below. Draw the best possible partial DAG

HW.



Apply PC algorithm to discover the DAGs.

Even when all variables are observed, the true graph cannot be learnt from a dataset

- Some exceptions under parametric assumptions (e.g., non-gaussian noise). But no general result.

- When some variables are unobserved, it is a harder problem.

- Active area of research. Recent work proposes a differentiable constraint to search for DAGs.
  - “No-tears” algorithm [NeurIPS 2018].
  - Connections to reinforcement learning and bandits

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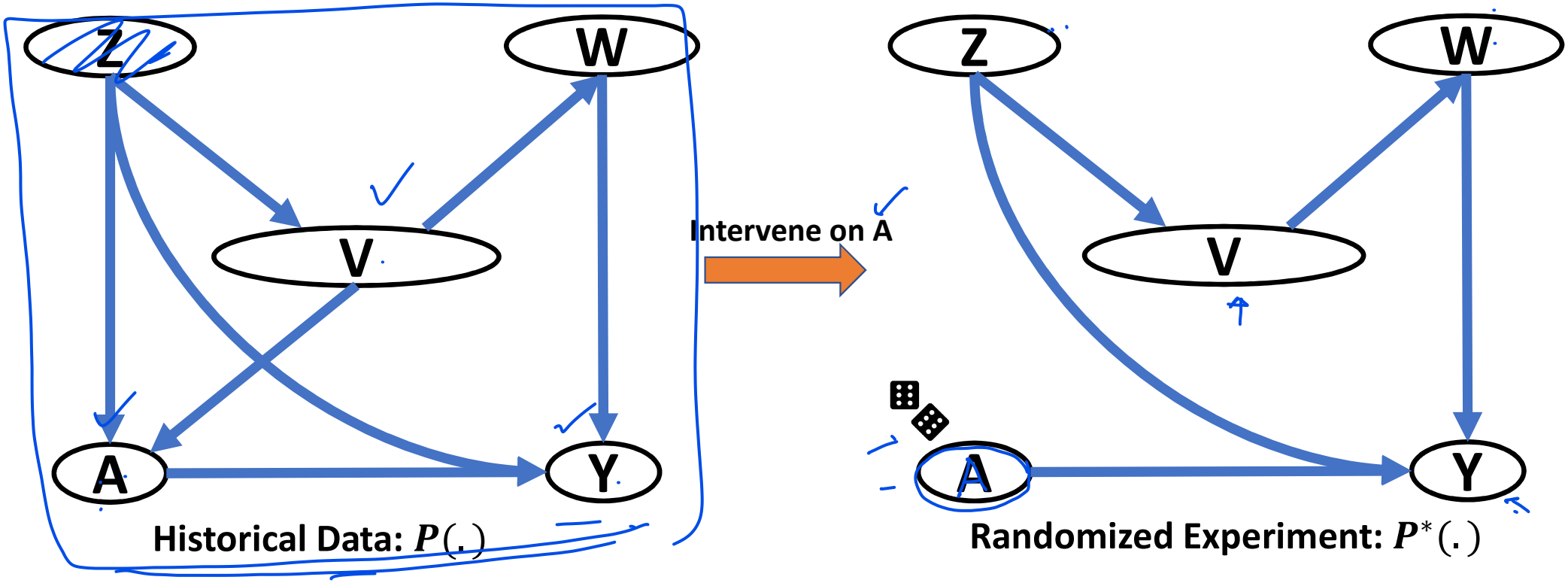
Estimating causal effect

- **Input:** Causal DAG, Action variable A, outcome variable Y
- **Output:** $P(Y|do(A))$, usually $E[Y|do(A)]$



Causal Effect: $\mathbf{E_P}[\boldsymbol{Y}|\boldsymbol{do}(\boldsymbol{A})] = \boldsymbol{E_{P^*}}(\boldsymbol{Y}|\boldsymbol{A} = \boldsymbol{a})$

$\mathrm{E_P}[Y|do(A=1)] - \mathrm{E_P}[Y|do(A=0)] = E_{P^*}(Y|A=1) - E_{P^*}(Y|A=0)$

But what if randomized P^* distribution is not available?

Identification problem:

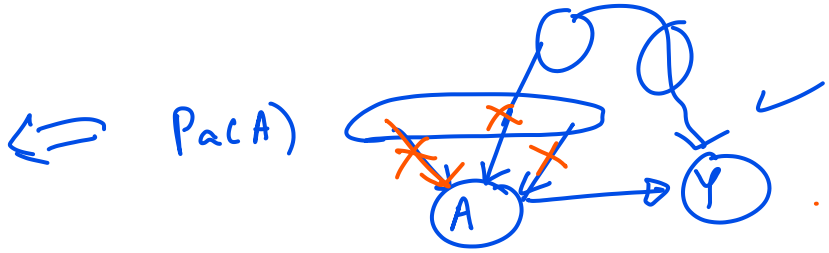
Can we $P(Y|do(A))$ purely as a probability expression computable over P?

Understanding **do-intervention** that leads to P^*:

The intervention makes A d-separated from Y after removing the A-> Y edge.

Q: Can we find how A can be d-separated from Y in the original distribution P?

Identifiability



- Conditions under which observations of P() can be used to estimate effect on interventions on a variable A, let us call this $P^{A*} = P*$ for short. The graphical models for P and P* differ only on the CPD attached to A.
- When all variables are observed (no hidden confounders) then we can always estimate P* from observations from P.

$$P(Y \mid do(A)) = P^*(Y \mid A) = \sum_{t \in Pa(A)} P(Y \mid A, Pa(A)=t)\, P(A \mid Pa(A))$$

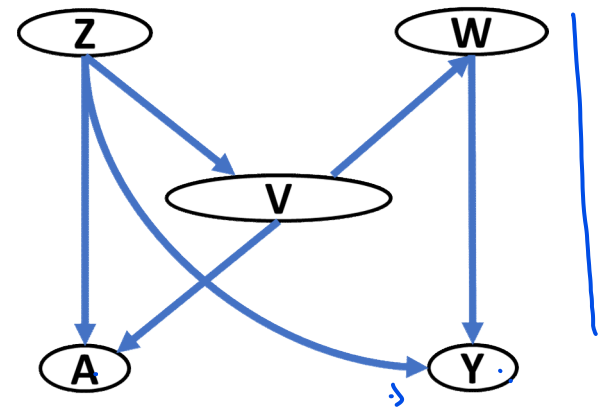
- Challenge is when subset of variables are not observed. Under what conditions can we still estimate $P^*(Y|A) = P(Y|do(A))$?

The backdoor criterion

1.Remove any edges going out from A.

2. Find the set of variables such that A is conditionally d-separated from Y.

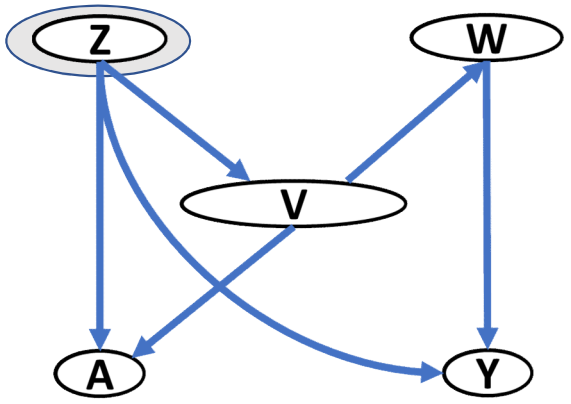
3. Condition on them.



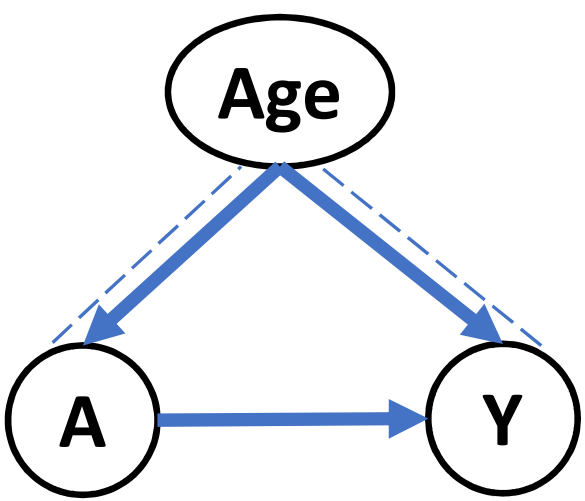
Backdoor set: $\{Z, W\}$ or $\{Z, V\}$

$$P(Y|do(A))$$

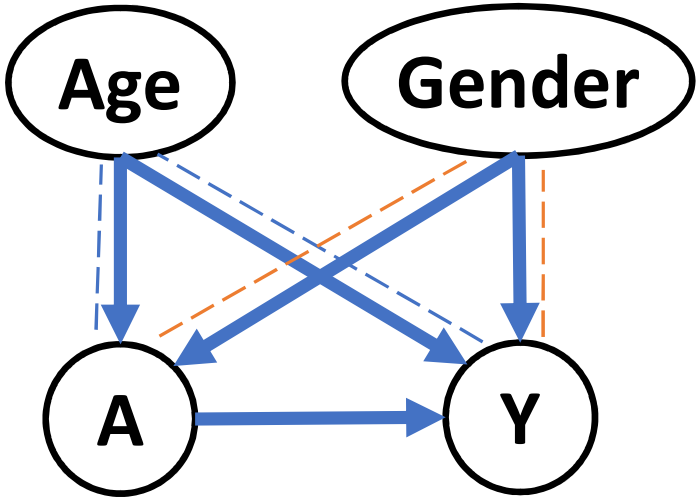
$$= \sum_{z,w} P(Y|A, Z = z, W = w)P(Z = z, W = w)$$



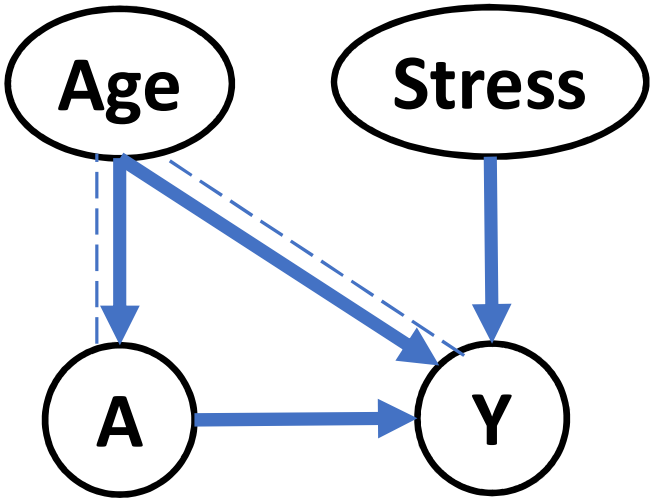
Find the backdoor set!



$\boldsymbol{B} = \{Age\}$

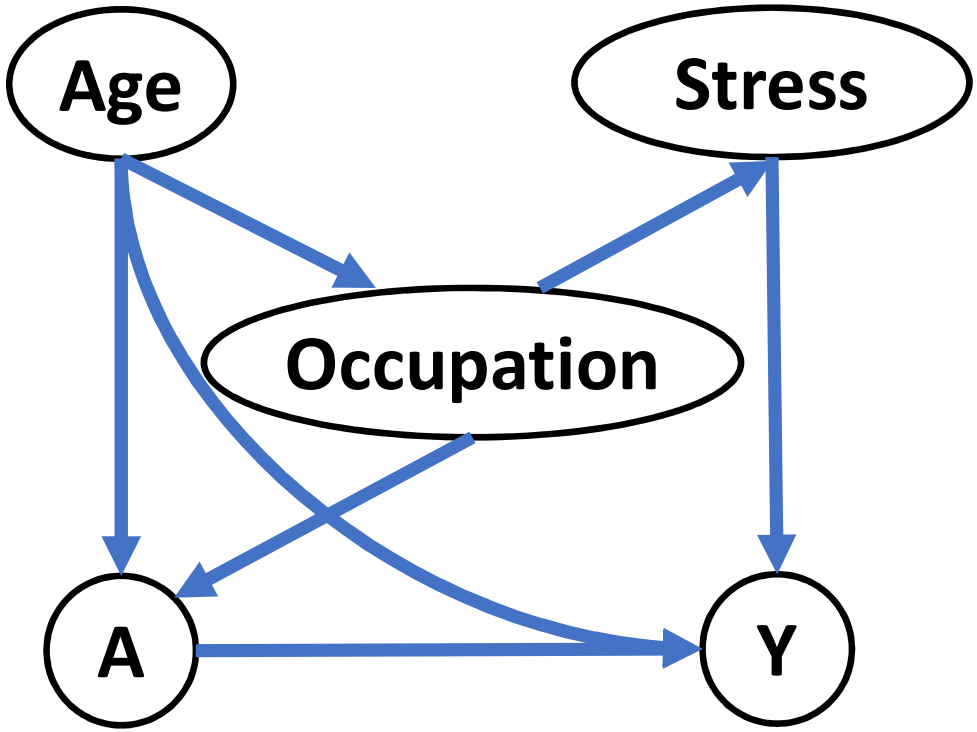


$\boldsymbol{B} = \{Age, Gender\}$



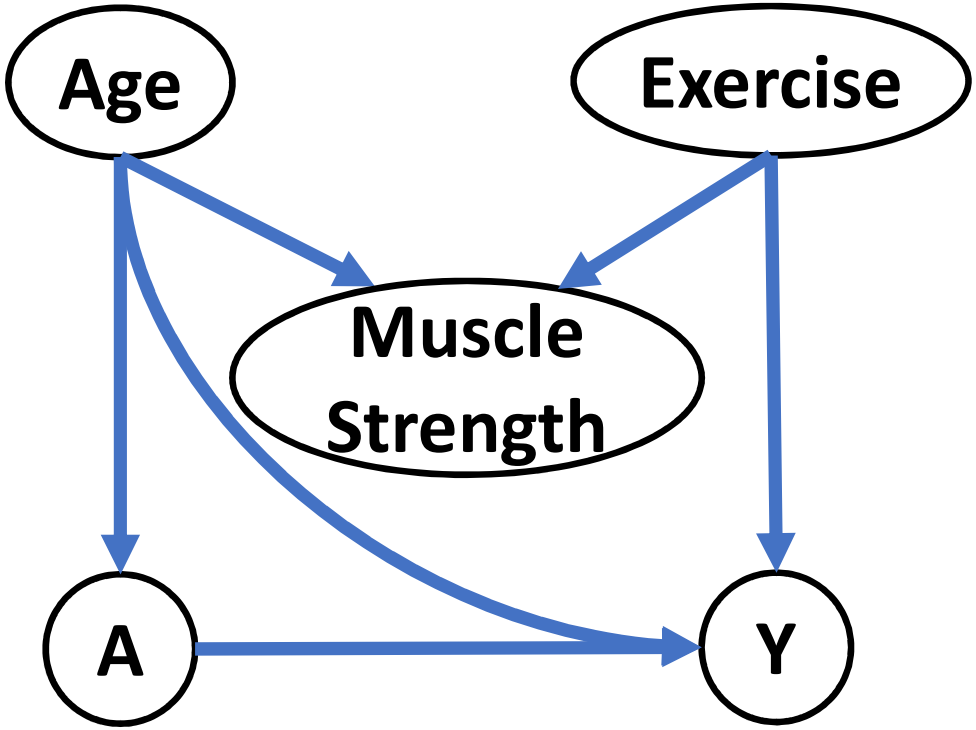
$\boldsymbol{B} = \{Age\}$

Find the backdoor set!



$\boldsymbol{B} = \{Age, Stress\}$

$\boldsymbol{B} = \{Age, Occupation\}$



$\boldsymbol{B} = \{Age, Exercise\}$ Correct?

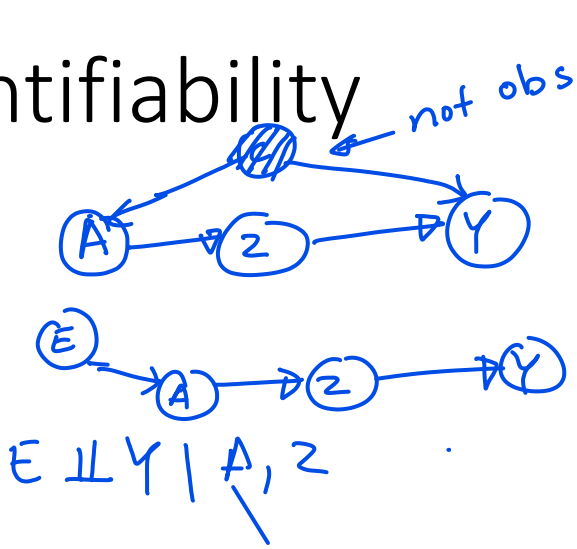
$\boldsymbol{B} \neq \{Age, MuscleStrength\}$

Backdoor is sufficient, but not a necessary criterion for identification

- There can be other ways to derive the do-expression (e.g., frontdoor criterion)
- Fortunately, there exists an algorithm that is both necessary and sufficient for an arbitrary causal DAG.
  - If it returns a probability expression, it is a valid identification.
  - If it fails to return an expression, then no valid non-parametric identification exists.
- Called ID algorithm [Shpitser and Pearl, 2006].
- Implemented in software libraries like DoWhy.

The frontdoor criteria for identifiability

- Remove all parents of A
- ~~Add an auxillary parent E to A~~
- If E is d-separated from Y given (W, A) then
  - $P(Y|do(A), W) = P(Y|W, A)$
- Additionally if we have some criteria (e.g. backdoor) to estimate P(W|do(A)), then
- $P(Y|do(A)) = \sum_w P(W = w|do(A))P(Y|w, A)$



More examples of identifiability

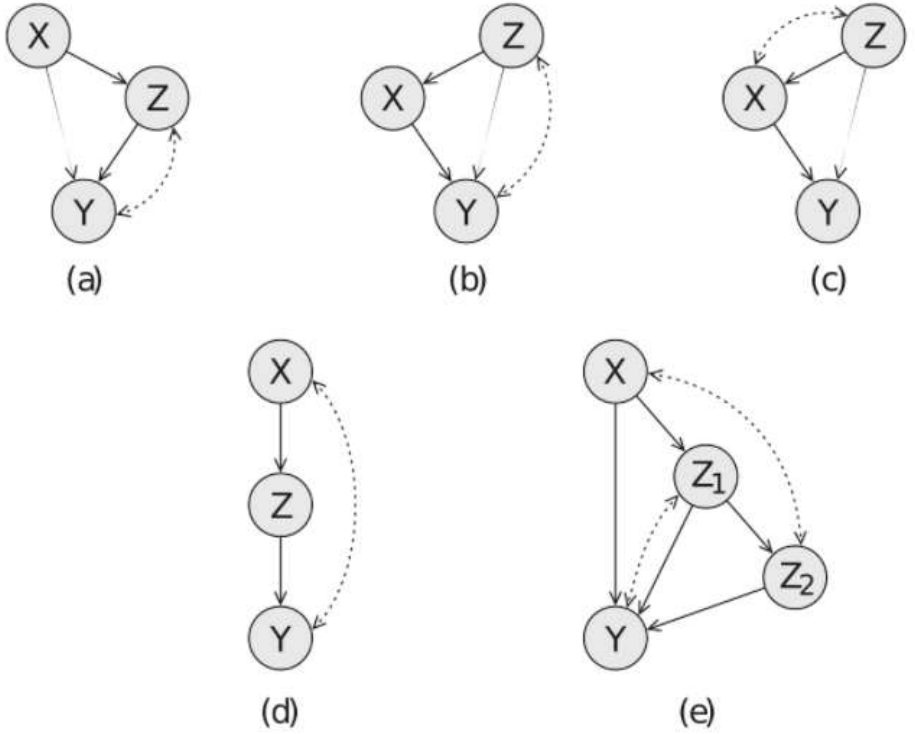


Figure 21.3 Examples of models where $P(Y \mid do(X))$ is identifiable. The bidirected dashed arrows denote cases where a latent variable affects both of the linked variables.

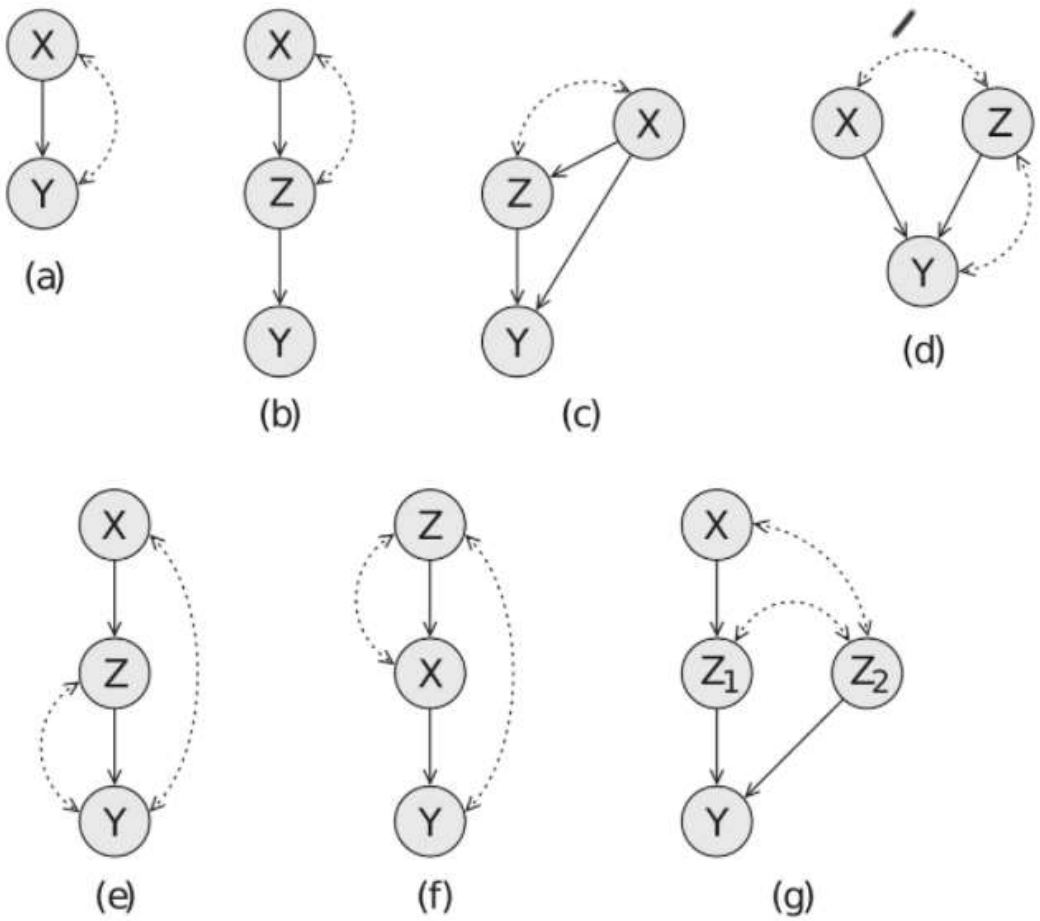


Figure 21.4 Examples of models where $P(Y \mid \boldsymbol{do}(X))$ is not identifiable. The bidirected dashed arrows denote cases where a latent variable affects both of the linked variables.

How to estimate the backdoor expression

$$P(Y|do(A)) = \sum_{z,w} P(Y|A, Z = z, W = w)P(Z = z, W = w)$$

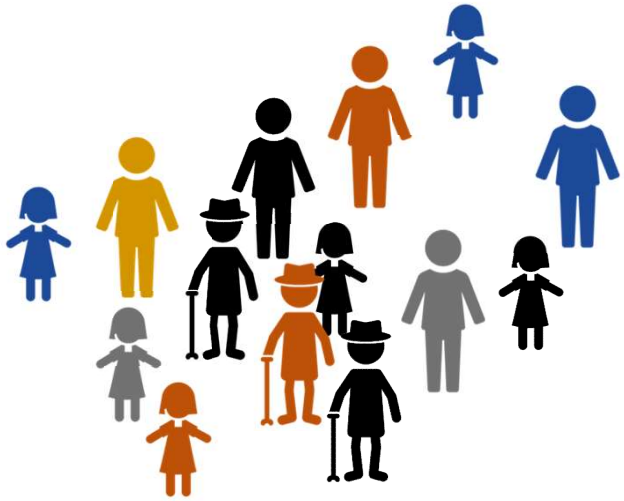
$$\mathrm{E}(Y|do(A)) = \sum_{z,w} E(Y|A, Z = z, W = w)P(Z = z, W = w)$$

- Conditional probability expression
  - Can apply any conditional expectation estimator (e.g., regression)
  - But certain methods have better bias-variance tradeoff

- Simple estimator for a binary action: Matching

Simple Matching: Match data points with the same backdoor variables and then compare their outcomes

Q. What is the effect of cycling on health outcomes?



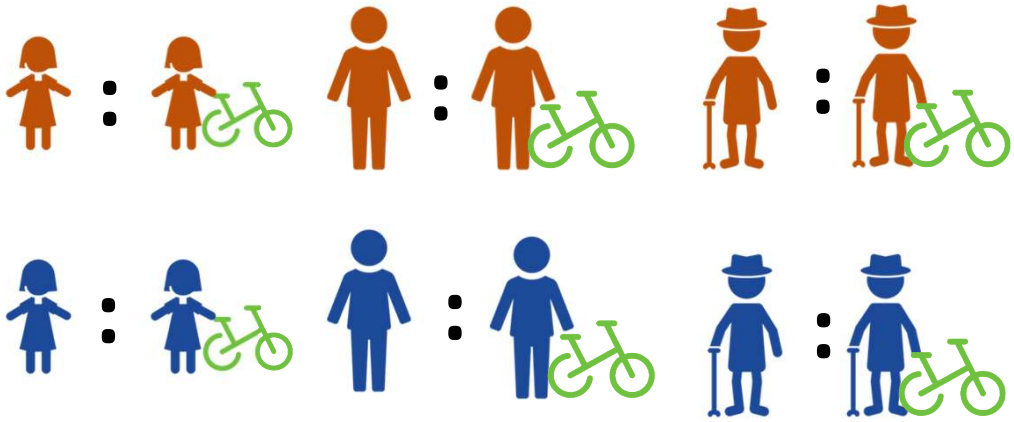
Control

Action(Cycling)

Simple Matching: Match data points with the same confounders and then compare their outcomes

Identify pairs of treated (j) and untreated individuals (k) who are similar or identical to each other.

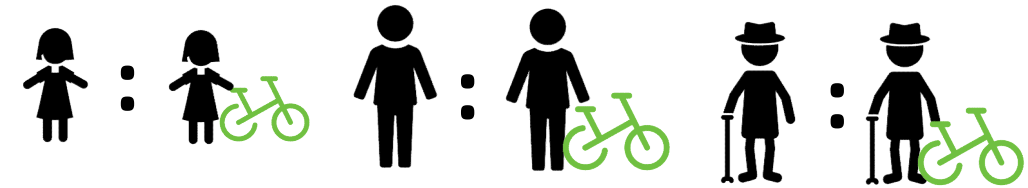
Match := $Distance(W_j, W_k) < \epsilon$

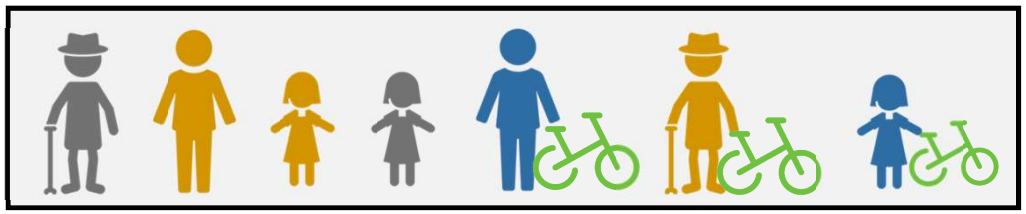


- Paired individuals have almost the same confounders.

  Causal Effect =

  $$\sum_{(j,k)\in Match}(y_j - y_k)$$





Challenges of building a good matching estimator

- **Variance:** If we have a stringent matching criterion, we may obtain very few matches and the estimate will be unreliable.
- **Bias:** If we relax the matching criterion, we obtain many more matches but now the estimate does not capture the target estimand.
- **Uneven treatment assignment:** If very few people have treatment, leads to both high bias and variance.

Advanced methods try to navigate the bias-variance tradeoff.

Important: There is no way to validate the estimate since there is no ground-truth causal effect available!

We never observe the ground-truth effect since action is either taken or not taken

Person	A	$Y_{A=1}$	$Y_{A=0}$
P1	1	0.4	0.3
P2	0	0.8	0.6
P3	1	0.3	0.2
P4	0	0.3	0.1
P5	1	0.5	0.5
P6	0	0.6	0.5
P7	0	0.3	0.1

Causal effect:

$$E[Y|do(A=1)] - E[Y|do(A=0)]$$
$$= E[Y_{A=1} - Y_{A=0}]$$

Fundamental problem of causal inference: For any person, observe only one: either $Y_{A=1}$ or $Y_{A=0}$

How to evaluate a causal effect estimate?

Gold Standard: Run a randomized experiment varying the action.

E.g., in recommender systems

Causal analysis can help identify the recommendation algorithms with highest expected causal effect.

Run an experiment using only those recommendations.

Other ways:

Sanity checks

Placebo Action. Replace action by a random variable=>effect goes to 0

Sensitivity analysis (what if the graph was missing a confounder)

Active area of research!

Summary: Causal effect inference has 4 steps

1. **Modeling:** Learn or build the causal graph.

2. **Identification:** Given the graph, derive $P(Y|do(A)$ in terms of observed data distribution only.

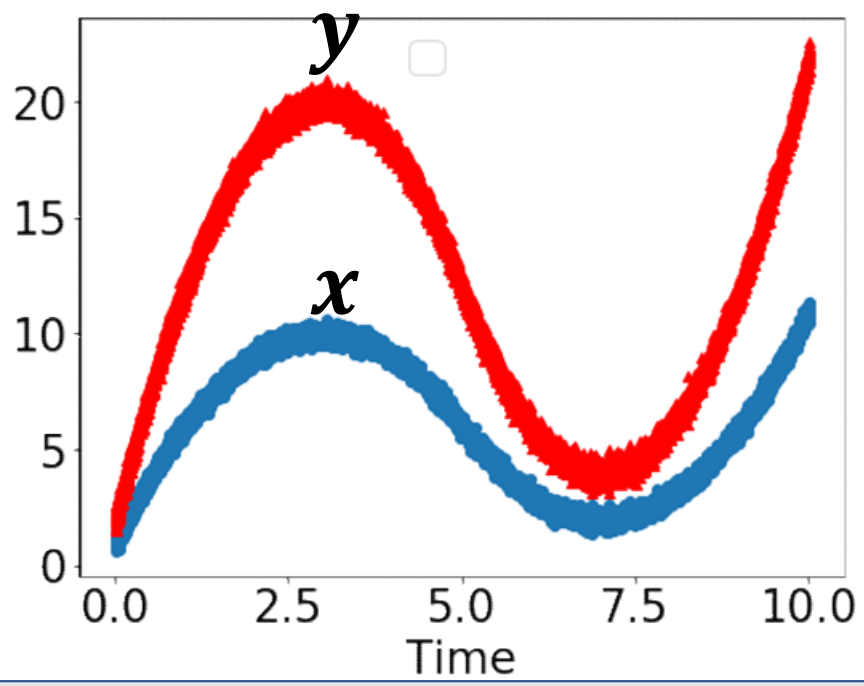
3. **Estimation:** Estimate the derived expression using a suitable method.

4. **Validation/Refutation:** Check whether the estimate is correct or not.

Example using DoWhy library: Search volume for two queries, x and y.

Does x's search volume have any effect on y?

https://github.com/microsoft/dowhy

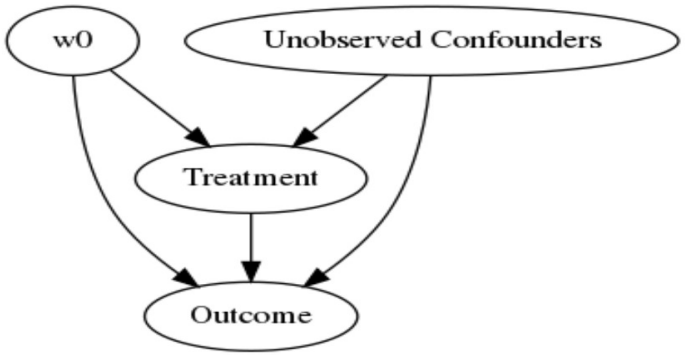


x	y	w
8.329680	16.546904	2.546634
2.083811	4.096492	-3.995819
6.138014	12.041800	0.041479
8.874336	17.833621	2.988497
5.282355	10.481077	-0.860686

You can **try out this example** on Github:
https://github.com/microsoft/dowhy/blob/master/docs/source/example_notebooks/dowhy_confounder_example.ipynb

1

```
model= CausalModel(
        data=df,
        treatment=data_dict["treatment_name"],
        outcome=data_dict["outcome_name"],
        common_causes=data_dict["common_causes_names"],
        instruments=data_dict["instrument_names"])
```



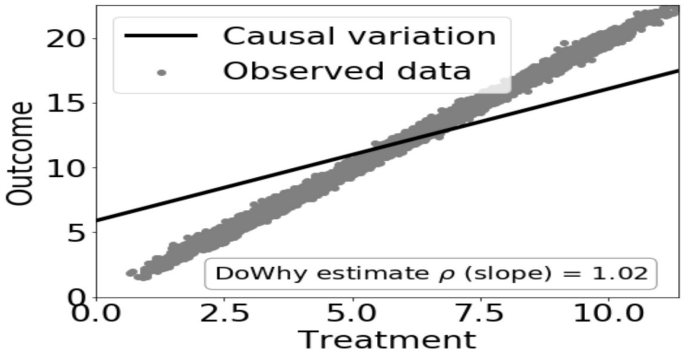
2

```
identified_estimand = model.identify_effect()
```

```
Estimand name: backdoor
Estimand expression:
     d
─────────────(Expectation(Outcome|w0))
d[Treatment]
```

3

```
estimate = model.estimate_effect(identified_estimand,
        method_name="backdoor.linear_regression")
```



4

```
res_placebo=model.refute_estimate(identified_estimand, estimate,
       method_name="placebo_treatment_refuter", placebo_type="permute")
```

```
Refute: Use a Placebo Treatment
Estimated effect:(1.0154712956668286,)
New effect:(-0.0012121433633147 66,)
```

I. What is causality?

II. How can we reason about causality mathematically?

    From Bayesian Networks to Causal Bayesian Networks (causal DAGs)

III. Can we learn a causal DAG?

IV. Application 1: Estimating the effect of actions

V. Application 2: Building more generalizable prediction models

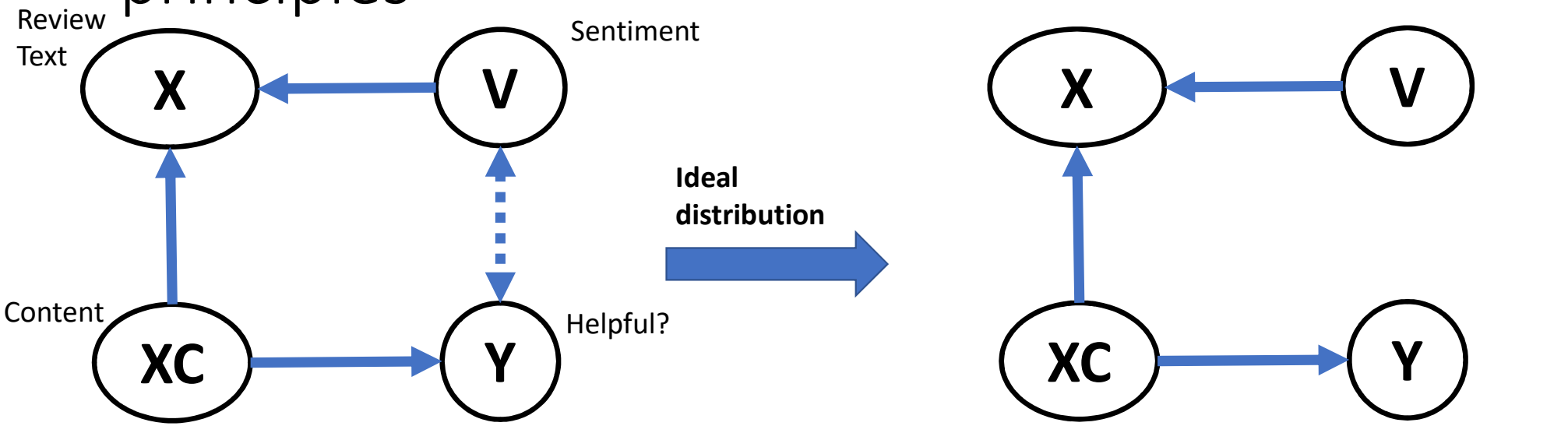
VI. Open questions

How can causal DAGs help in prediction?

- Causal DAGs represent the data-generating process that leads to the training dataset.
- Interventions on DAGs provide a formal way of expressing plausible distribution shifts.
- So using the same techniques, we can build predictors that are robust to those interventions.

IMPORTANT: Causal DAGs can help in formulating the right loss function or indicate which data to collect. But for training the model, we use standard ML techniques.

Building a generalizable predictor from first principles



$$P(.) = P(X|V, X_C)P(Y|X_C)P(V|Y)P(X_C)$$

$$P^*(.) = P(X|V, X_C)P(Y|X_C)P^*(V)P(X_C)$$

V is independent of Y. Any standard loss should work.

How to translate training dataset to ideal distribution?

$$P(.) = P(X|V, X_C)P(Y|X_C)P(V|Y)P(X_C)$$

$$P^*(.) = P(X|V, X_C)P(Y|X_C)P^*(V)P(X_C)$$

$$E_{P^*}[l(y, \hat{y})] = E_{\phi \sim P^*(\Phi)}[l(y, \hat{y})]$$

$$= \int_{\phi} l(y, \hat{y}) P^*(\phi)$$

$$= \int_{\phi} l(y, \hat{y}) \frac{P(\phi)}{P(\phi)} P^*(\phi) = \int_{\phi} l(y, \hat{y}) \frac{P^*(\phi)}{P(\phi)} P(\phi)$$

$$= \int_{\phi} l(y, \hat{y}) \left[\frac{P^*(V)}{P(V|Y)}\right] P(\phi) \quad \approx \frac{1}{n} \sum_{i=1:n} l(y, \hat{y}) \frac{P^*(V)}{P(V|Y)} = \frac{1}{n} \sum_{i=1:n} l(y, \hat{y}) \frac{1}{P(V|Y)}$$

Insight: Minimize weighted loss to obtain a predictor that does not depend on spurious feature V

Sometimes weighting can have high variance. So, use constraints from P^* on X_C

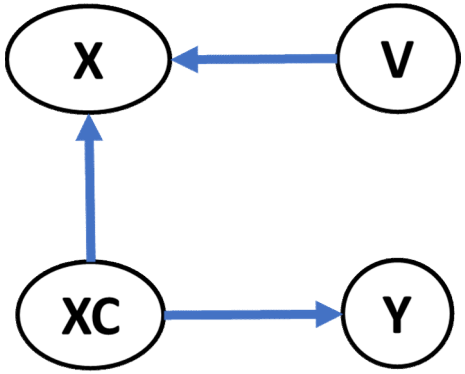
Going from P to P^*

$$Loss1: \frac{1}{n}\sum_{i=1:n} l(y,\hat{y}\,)\frac{1}{P(V_i|y)}$$

Going from P to P^*: $X_C \perp V$

Add a regularizer.

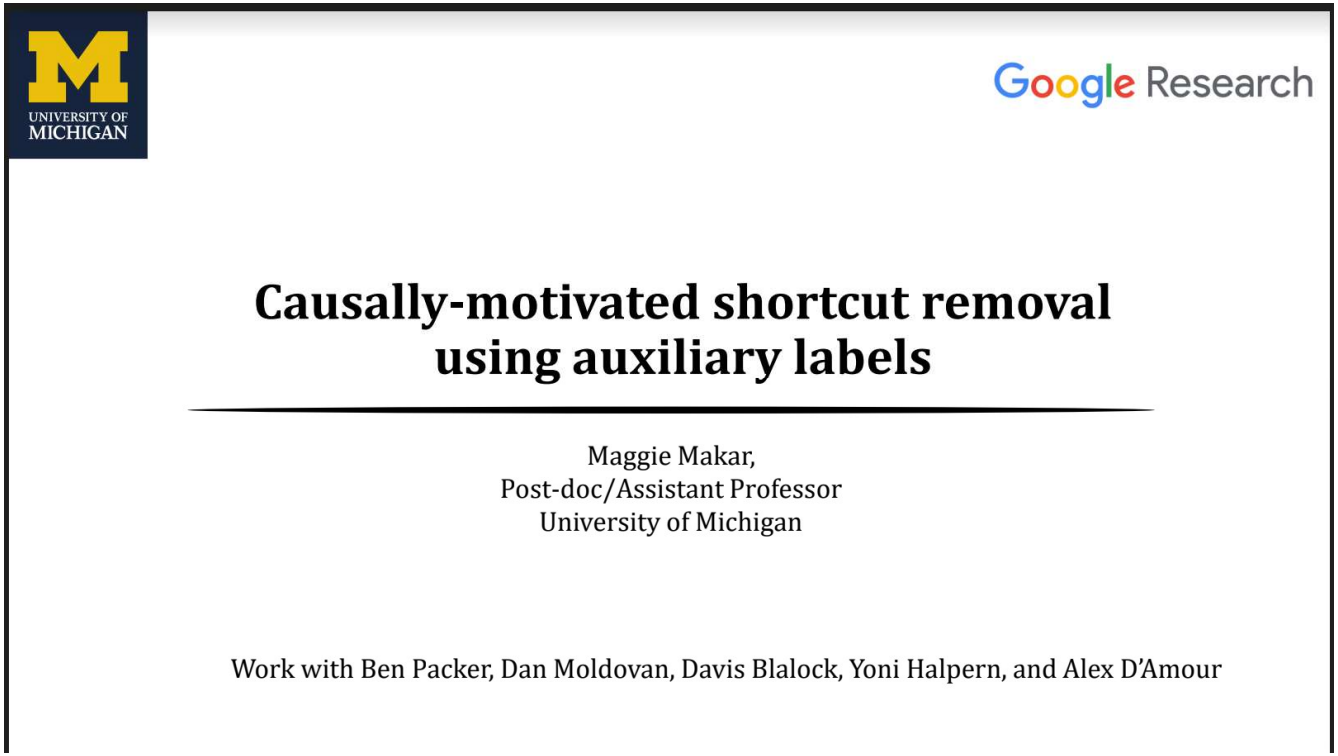
$$Loss2: \frac{1}{n}\sum_{i=1:n} l\big(y,\hat{y}\,\big) + Ind(\psi\big(x\ \ \big),V\ \ )$$



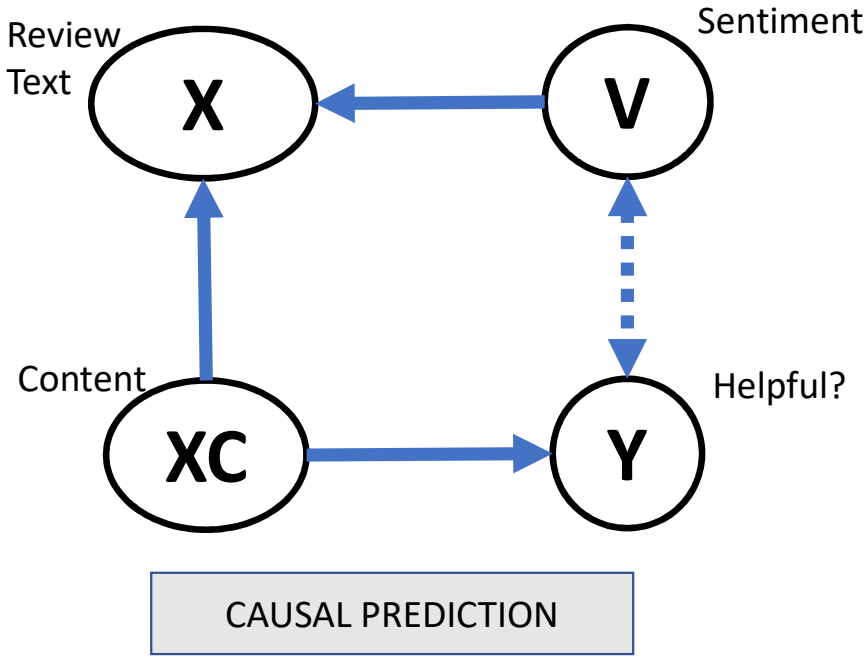
Can also combine both:

$Loss: \frac{1}{n}\sum_{i=1:n} l(y_i, h(\psi(x)\,)\frac{1}{P(V_i|Y_i)} + \lambda\, Ind(\psi(x),V)$

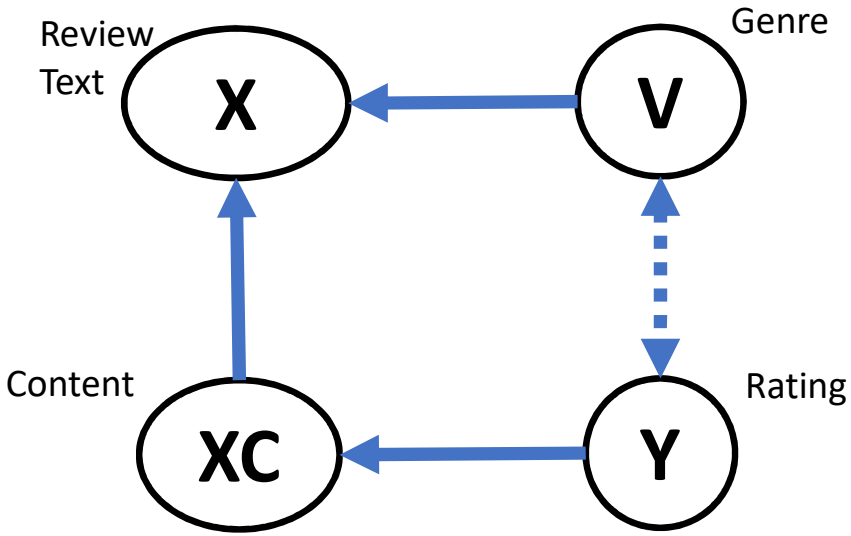
Case study


UNIVERSITY OF MICHIGAN
Google Research
Causally-motivated shortcut removal using auxiliary labels
Maggie Makar,
Post-doc/Assistant Professor
University of Michigan
Work with Ben Packer, Dan Moldovan, Davis Blalock, Yoni Halpern, and Alex D'Amour

So far, we discussed prediction from parents. But we can also predict from children.

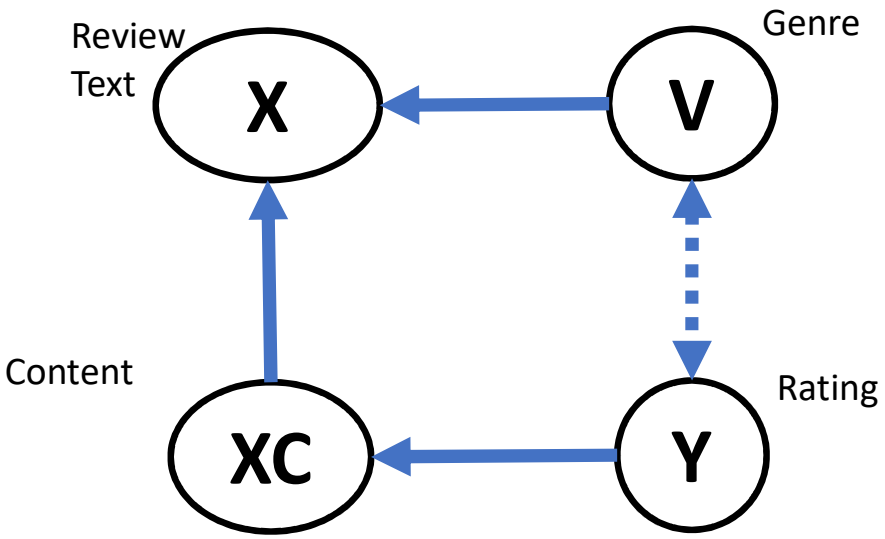


CAUSAL PREDICTION

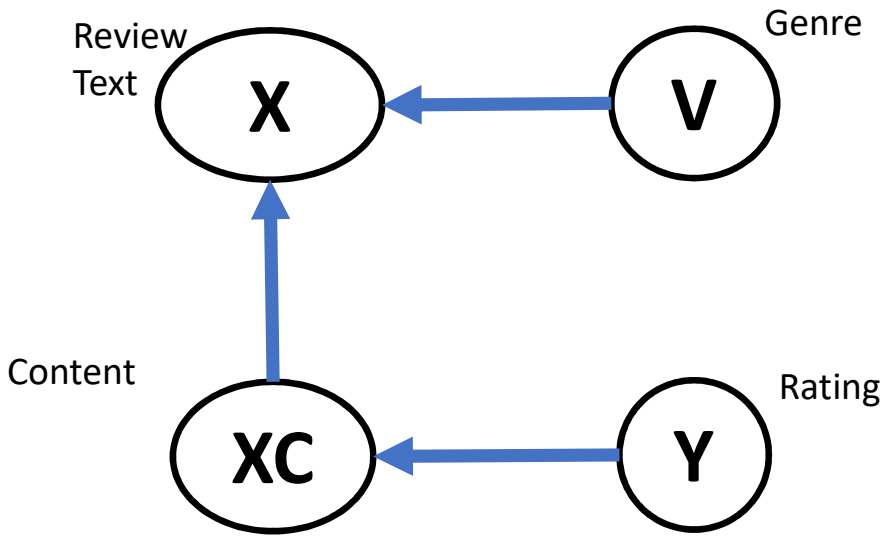


"ANTI-CAUSAL" PREDICTION

The same constraints won't work. Need to analyze afresh.



$$P(.) = P(X|V, X_C)P(X_C|Y)P(V|Y)\mathrm{P(Y)}$$

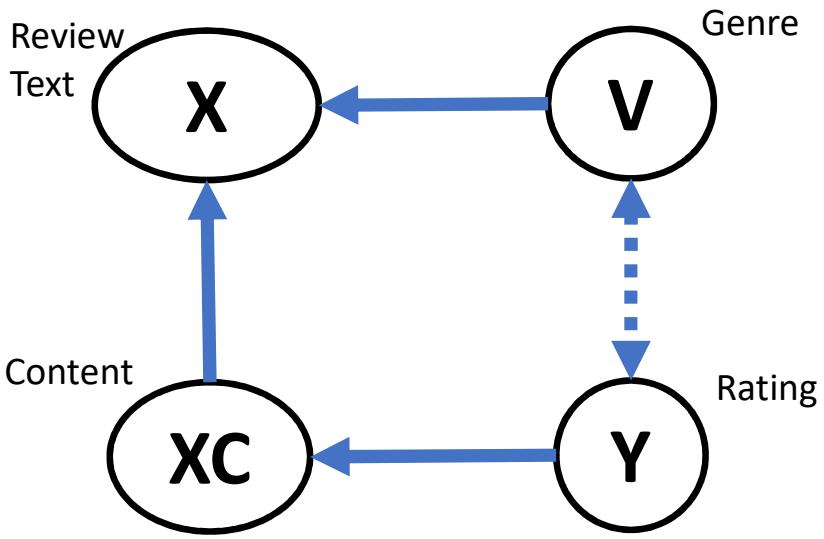


$$P^*(.) = P(X|V, X_C)P(X_C|Y)P^*(V)P(Y)$$

Weighting for the loss remains the same.

But Loss2 is not the correct constraint since $X_C \not\perp V$ under P.

✗ $Loss2: \frac{1}{n}\sum_{i=1:n} l(y, \hat{y}) + Ind(\psi(x\ ), V\ )$



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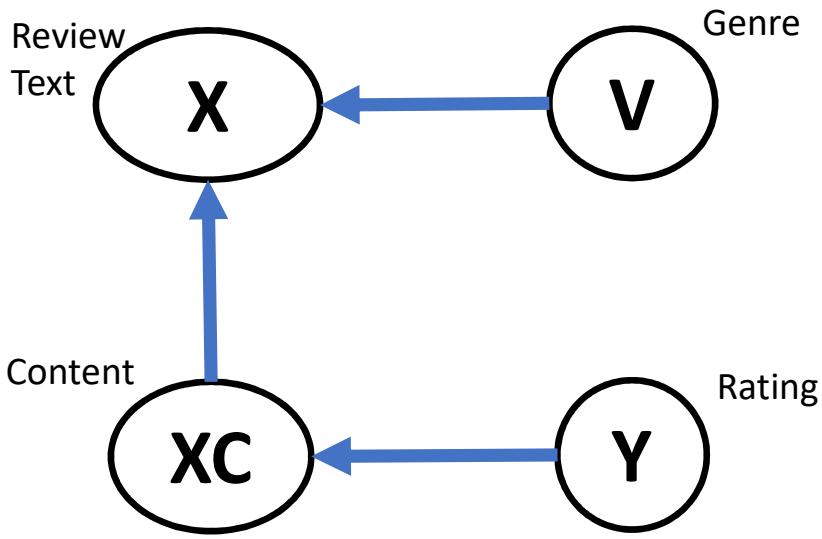


$$P^*(.) = P(X|V, X_C)P(X_C|Y)P^*(V)P(Y)$$

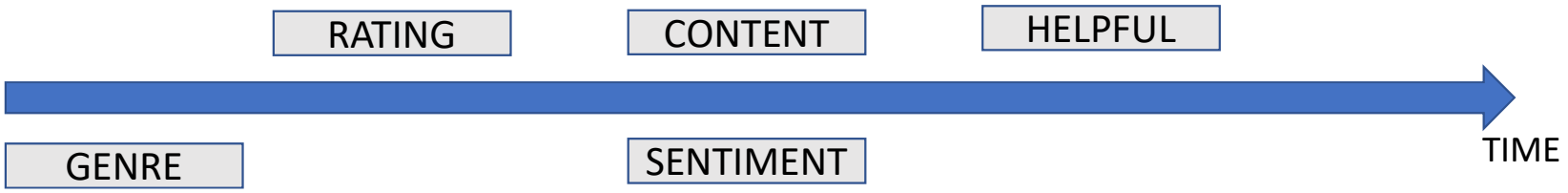
Correct Loss (conditional independence)

$$Loss2: \frac{1}{n}\sum_{i=1:n} l\left(y, \widehat{y}\right) + CondInd(\psi\left(x\right), V, Y)$$

Correct Loss (combine with weighting):

$$Loss: \frac{1}{n}\sum_{i=1:n} l(y_i, h(\psi(x)) \frac{1}{P(V_i|Y_i)} + \lambda\, Ind(\psi(x), V)$$

But wait, why does the regularization constraints depend on the graph?



Task: Predict helpfulness (causal direction)

- When content is written, there is no helpfulness label.
- So, content and sentiment are independently generated based on the rating and genre.

$\Rightarrow X_C \perp V$

Task: Predict rating (anti-causal direction)

- When content is written, it depends on the rating.
- So content, sentiment and genre-related words are generated based on the rating.

=> $X_C \perp V \mid Y$

Without causal analysis, regularizer will either *over-constraint* the loss or *under-constraint* it.

But wait, how do we know that the graph is correct?

- Can try multiple graphs and derive constraints from each
  - If constraints agree, that's a very good sign.
  - If they don't, try to justify which graph captures the data-generating process.

- In any case, can use cross-validation if labelled data is available from a new distribution.

Causal representation learning

- An extension of these ideas
- Often using data from multiple distributions
- How to generate the right constraints?

- Connections to domain adaptation, domain generalization, and OOD generalization literature.
  - Causal Representation learning. Scholkopf et al. 2021.
  - On causal and anti-causal learning. Schokopf et al. 2012.
  - Counterfactual invariance to spurious tests. Veitch et al. 2021
  - Causally Motivated Shortcut Removal Using Auxiliary Labels. Makar et al. 2022.

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Conclusion and open questions:

Causality is a natural concept to model, but still early days for causality in machine learning

1: Causal discovery using single training distribution is impossible.

How to do causal discovery with multiple train distributions?

2: Causal analysis still depends on the correct graph.

What are other ways of formally encoding domain knowledge?

3: Effect inference does not have ground-truth available.

What are good ways of evaluating causal effect estimates?

4: Causal analysis can provide regularizers for prediction.

Would causally motivated predictors have a significant impact in real-world applications?

Questions?

Amit Sharma

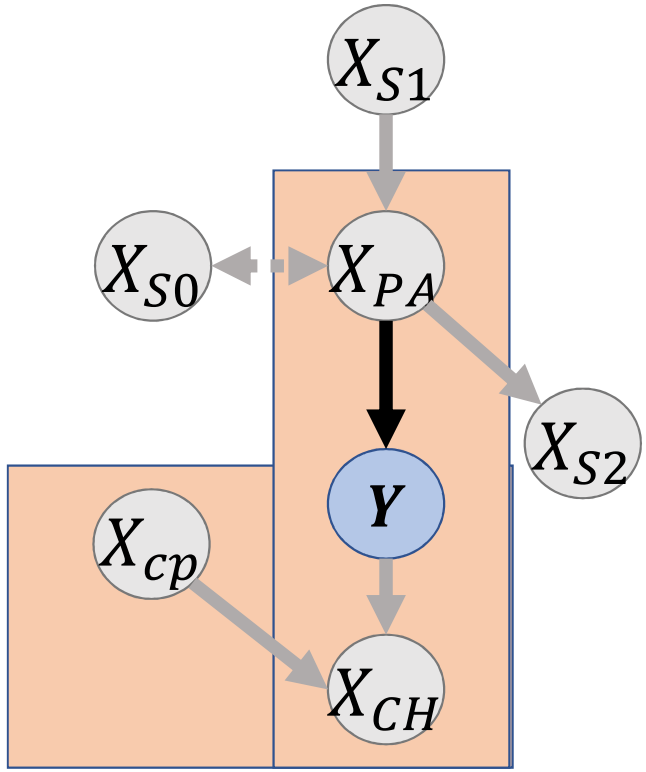
Building a predictor that generalizes to a new distribution

Markov Blanket:

Parents of Y
Children of Y
Parents of children of Y

Conditioned on the Markov Blanket, Y is independent of all other variables in the causal DAG.

So should we always use the Markov Blanket for predictive models that will be robust to distribution shifts?
Depends.

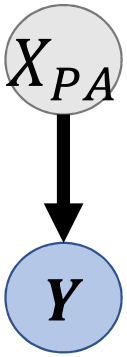


If you have unlabelled data from the new distribution, then it is okay to use children of Y.

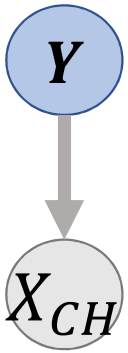
If not, then only use the parents.

Two kinds of prediction

CAUSAL



ANTI-CAUSAL



Markov factorization

$$P(Y, X_{PA}) = P(Y|X_{PA})P(X_{PA})$$

Thus, learnt function $P(Y|X_{PA})$ is independent of $P(X_{PA})$.

Unlabelled data $P^*(X_{PA})$ will not