Non-Standard Databases and Data Mining

Intervention

Dr. Özgür Özçep
Universität zu Lübeck
Institut für Informationssysteme

Presented by: Prof. Dr. Ralf Möller

Structural Causal Models

Slides prepared by Özgür Özçep

Part II: Intervention

Literature

- J.Pearl, M. Glymour, N. P. Jewell:
  Causal inference in statistics – A primer, Wiley, 2016.
  (Main Reference)
- J. Pearl: Causality, CUP, 2000.

Intervention

- Important aim of SCMs for given data: Where to intervene in order to achieve desired effects.

Examples

- Data on wildfires: How to intervene in order to decrease wildfires?
- Data on TV and aggression: How to intervene in order to lower aggression of children?

- How to model "intervention" and associated effects within SCMs and their graphs?

Randomized Controlled Experiment

- Randomized controlled experiment gold standard
  - Aim: Answer question whether a change in RV X has indeed an effect on some target RV Y
  - If outcome of experiment is yes, X is a RV to intervene upon
  - Test condition: all variables different from X are static (fixed) or vary fully randomly.
- Problem: Cannot always set up such an experiment
  - Example: cannot control weather in order to test variables influencing wildfire
- Instead: use observational data & causal model

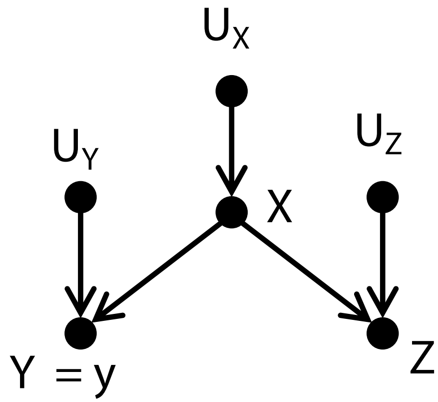
Intervention

Example (SCM 5; Intervention)

(X = Temperature, Y = Ice cream sale, Z = Crime)

- Would intervention on ice cream sales (Y) lead to decrease of crime (Z)?

- What does it mean to intervene on Y?
  - Fix value of Y in the sense of inhibiting the natural influences on Y according to SCM (here of U_Y and X)
  - Leads to change of the SCM



Intervention vs. Conditioning

- Intervention denoted by $do(Y = y)$

  $P(Z = z \mid do(Y = y)) =$

  probability of event $Z = z$ on intervening upon Y by setting $Y = y$

  Intervention changes the data generation mechanism

- In contrast

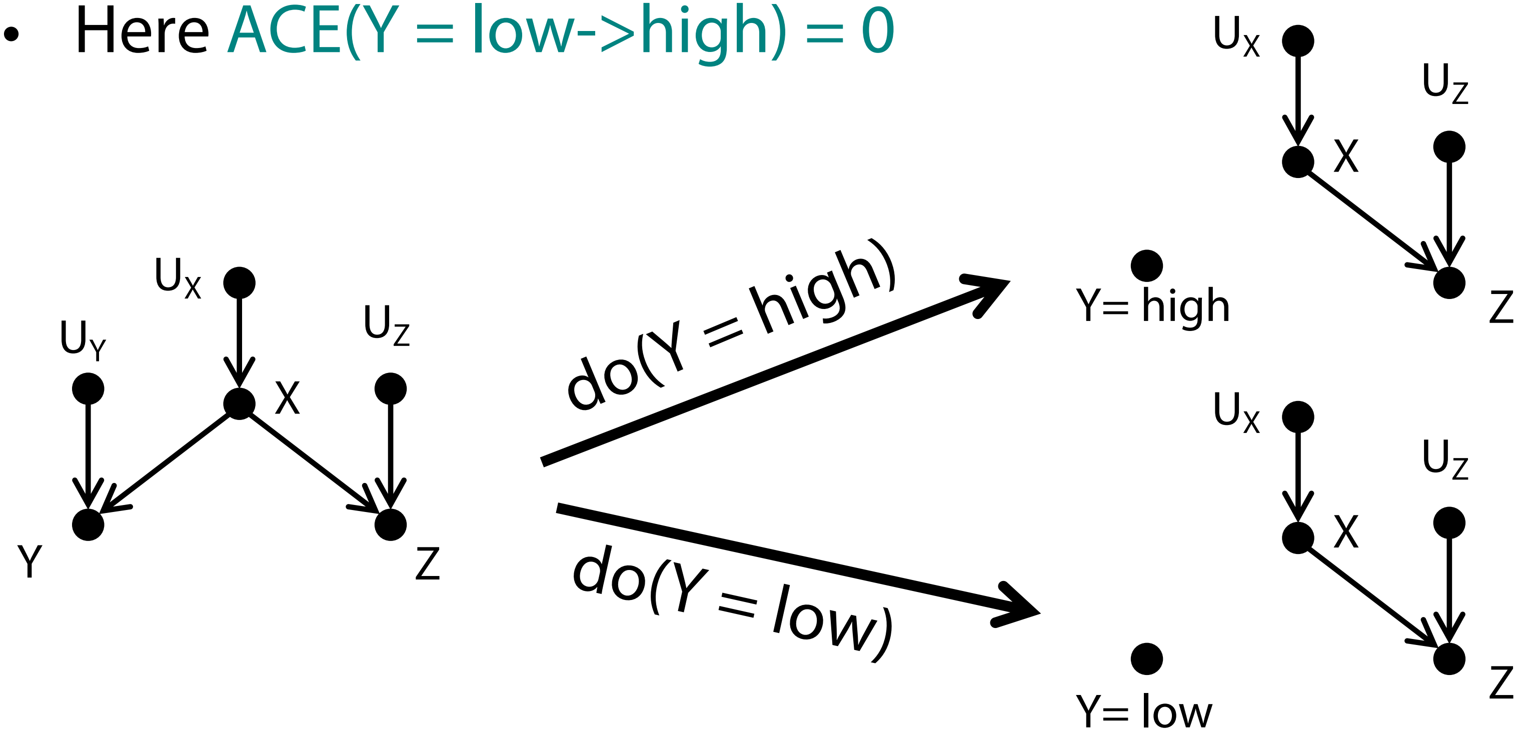
  $P(Z = z \mid Y = y) =$

  probability of event $Z = z$ when knowing that $Y = y$

  Conditioning only filters on the data

Average Causal Effect (ACE)

- Would an intervention on ice cream sales (Y) by increasing Y lead to a decrease of crime (Z)?
- Causal Effect Difference/Average Causal Effect (ACE)
  P(Z = low| do(Y = high)) – P(Z = low| do(Y = low))
- Here ACE(Y = low->high) = 0



General Causal Effect

- How effective is drug usage for recovery?
  ACE = $P(Y = 1 \mid do(X = 1)) - P(Y = 1 \mid do(X = 0))$
- Need to compute general causal effect

Definition

The general causal effect (GCE) of X on Y is given by

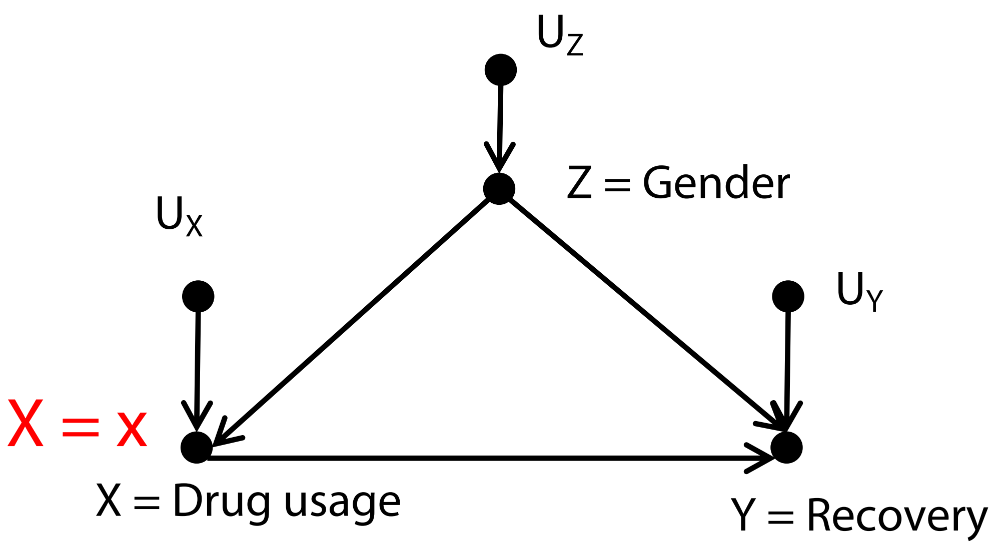
$$P(Y = y \mid do(X = x)) = P_m(Y = y \mid X = x)$$

= probability in **m**odified graph

General Causal Effect

Example (drug-recovery effect)

- How effective is drug usage for recovery?
  $ACE = P(Y=1 \mid do(X=1)) - P(Y=1 \mid do(X=0))$
- $P(Y=y \mid do(X=x)) = P_m(Y=y \mid X=x)$



Intervention (alternatively)

- There are different ways to define intervention (other than by manipulated graph)

- Model intervention do(X=x) with force variable F
  - F is parent of X,
  - Dom(F) = {do(X=x‘) | x in dom(X)} U {idle}
  - pa‘(X) = pa(X) U {F}
  - New ``CPT“ for X

$$P(X = x \mid pa'(X)) = \begin{cases} P(X=x \mid pa(X)) & \text{if } F = \text{idle} \\ 0 & \text{if } F = do(X=x') \text{ and } x \neq x' \\ 1 & \text{if } F = do(X=x') \text{ and } x = x' \end{cases}$$

Z value not effected by intervention on x: $f_Z: Z = f(U_Z)$

Example (drug-recovery effect)

- $P_m(Y = y \mid X = x) = ?$
- Need to reduce to probabilities w.r.t. original graph

1. $P_m(Z = z) = P(Z = z)$
2. $P_m(Y = y \mid Z = z, X = x) = P(Y = y \mid Z = z, X = x)$
3. Summing out

$P(Y = y \mid do(X = x)) = P_m(Y = y \mid X = x)$

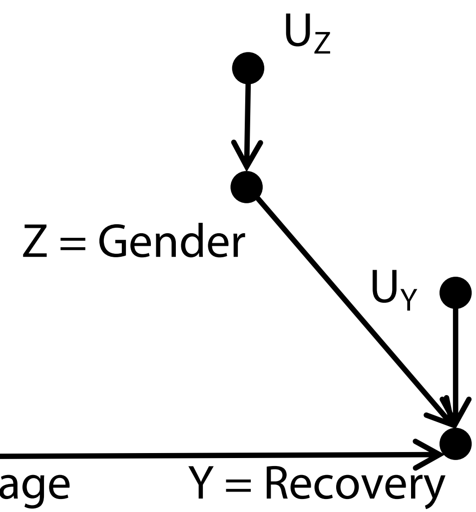
$= \sum_z P_m(Y = y \mid X = x, Z = z)\, P_m(Z = z \mid X = x)$

$= \sum_z P_m(Y = y \mid X = x, Z = z)\, P_m(Z = z)$

$= \sum_z P(Y = y \mid X = x, Z = z)\, P(Z = z)$

Y value not effected by intervention on x, $f_Y: Y = f(x,z,u_y)$

$X = x$



Digression

- Conditioning
  - $\mathbf{P}(\mathbf{Y}) = \sum_{\mathbf{z} \in \mathbf{Z}} \mathbf{P}(\mathbf{Y},\mathbf{z}) = \sum_{\mathbf{z} \in \mathbf{Z}} \mathbf{P}(\mathbf{Y}|\mathbf{z})P(\mathbf{z})$
  - $\mathbf{P}(\mathbf{Y}|\mathbf{X}) = \mathbf{P}(\mathbf{Y},\mathbf{X}) / \mathbf{P}(\mathbf{X})$

$$
\begin{aligned}
&= \textstyle\sum_{\mathbf{z} \in \mathbf{Z}} \mathbf{P}(\mathbf{Y},\mathbf{X},\mathbf{z}) / \mathbf{P}(\mathbf{X}) \\
&= \textstyle\sum_{\mathbf{z} \in \mathbf{Z}} \mathbf{P}(\mathbf{Y}|\mathbf{X},\mathbf{z})\, \mathbf{P}(\mathbf{X},\mathbf{z}) / \mathbf{P}(\mathbf{X}) \\
&= \textstyle\sum_{\mathbf{z} \in \mathbf{Z}} \mathbf{P}(\mathbf{Y}|\mathbf{X},\mathbf{z})\, \mathbf{P}(\mathbf{z},\mathbf{X}) / \mathbf{P}(\mathbf{X}) \\
&= \textstyle\sum_{\mathbf{z} \in \mathbf{Z}} \mathbf{P}(\mathbf{Y}|\mathbf{X},\mathbf{z})\, \mathbf{P}(\mathbf{z}|\mathbf{X})\, \mathbf{P}(\mathbf{X}) / \mathbf{P}(\mathbf{X}) \\
&= \textstyle\sum_{\mathbf{z} \in \mathbf{Z}} \mathbf{P}(\mathbf{Y}|\mathbf{X},\mathbf{z})\, \mathbf{P}(\mathbf{z}|\mathbf{X})
\end{aligned}
$$

Bayes rule is your friend

Adjustment

Definition

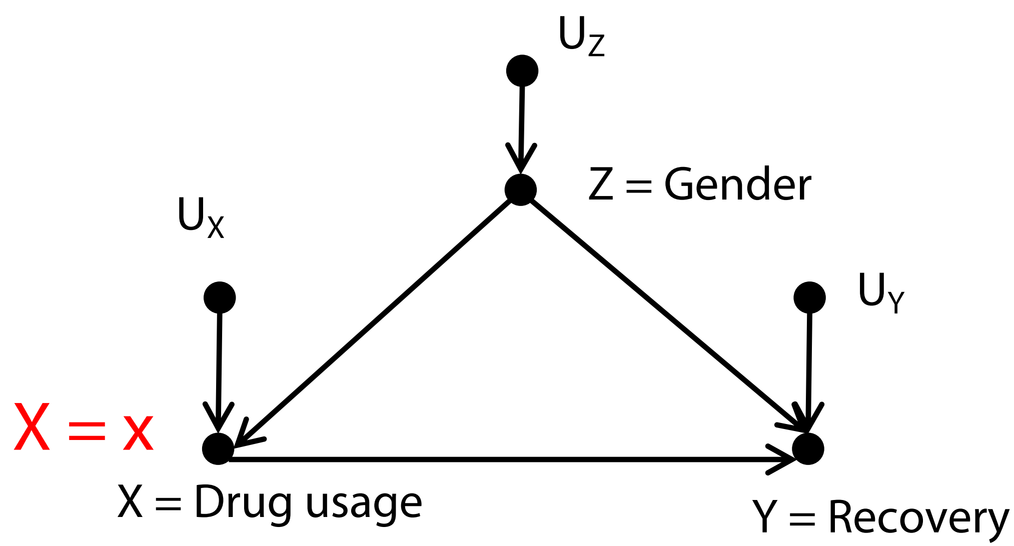
The adjustment formula (for single parent Z of X) for the calculation of the GCE is given by

$$P(Y = y \mid do(X = x)) \;=\; \sum_z P(Y = y \mid X = x, Z=z)\, P(Z = z)$$

Wording: „Adjusting for Z“ or „controlling Z“

Simpson's Paradox

- How effective is drug usage for recovery?
  ACE = $P(Y = 1 \mid do(X = 1)) - P(Y = 1 \mid do(X = 0))$
- $P(Y = y \mid do(X = x)) = P_m(Y = y \mid X = x)$



Recap: Simpson's Paradox

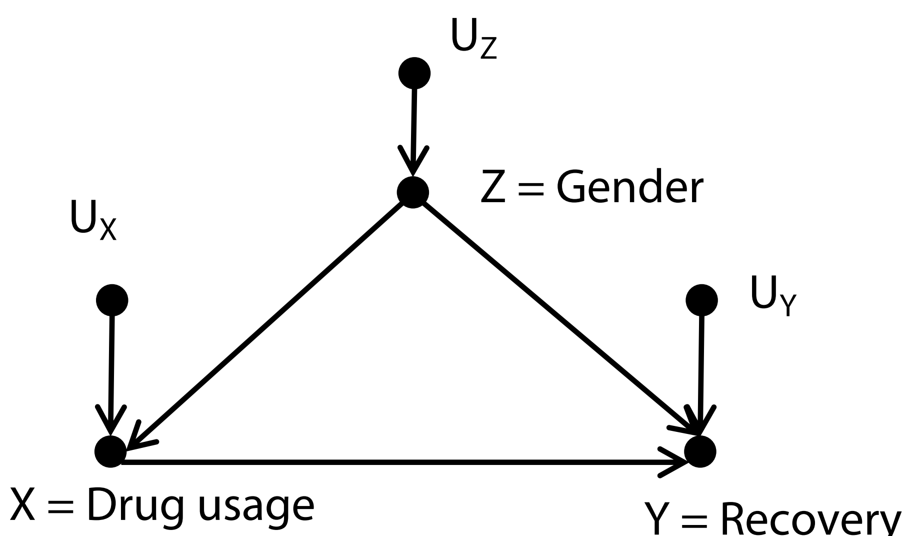
- Record recovery rates of 700 patients given access to a drug

	Recovery rate with drug	**Recovery rate without drug**
Men	81/87 (93%)	234/270 (87%)
Women	192/263 (73%)	55/80 (69%)
Combined	273/350 (78%)	289/350 (83%)

- Paradox:
  - For men, taking the drug has benefit
  - For women, taking the drug has benefit, too.
  - But: for all persons taking the drug seems to have no benefit

Resolving the Paradox (Formally)

- We have to understand the causal mechanisms that lead to the data in order to resolve the paradox
- Formally: What is the general causal effect of drug usage X on recovery Y?
  - $P(Y = y \mid do(X = x)) = ?$
  - $ACE = P(Y = 1 \mid do(X = 1)) - P(Y = 1 \mid do(X = 0)) = ?$



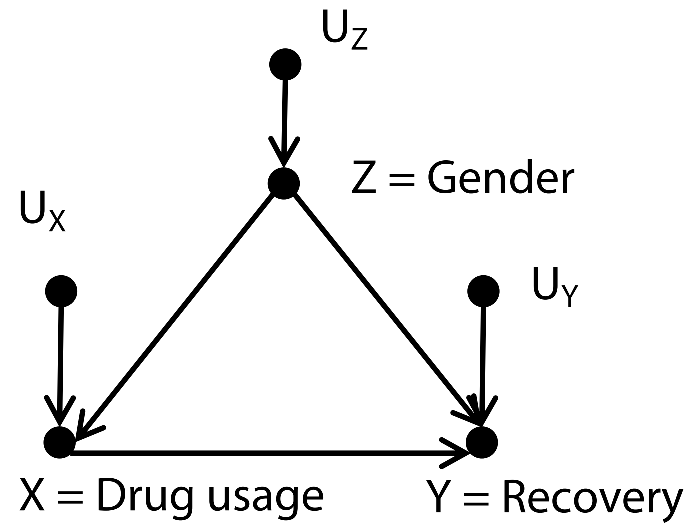
Resolving the Paradox (Formally)

- $P(Y=1 \mid do(X=1)) =$ (using adjustment formula)
- $= P(Y=1 \mid X=1, Z=1)P(Z=1) + P(Y=1 \mid X=1, Z=0)P(Z=0)$

$= 0.93(87 + 270)/700 + 0.73(263 + 80)/700 = 0.832$

- $P(Y=1 \mid do(X=0)) = 0.7818$
- $ACE = 0.832 - 0.7818 = 0.0502 > 0$
- One has to segregate the data w.r.t. Z (adjust for Z)

	Recovery rate with drug	**Recovery rate without drug**
Men	81/87 (93%)	234/270 (87%)
Women	192/263 (73%)	55/80 (69%)
Combined	273/350 (78%)	289/350 (83%)



Simpson Paradox (Again)

- Record recovery rates of 700 patients given access to a drug w.r.t. blood pressure (BP) segregation

	Recovery rate with drug	**Recovery rate without drug**
Low BP	234/270 (87%)	81/87 (93%)
High BP	55/80 (69%)	192/263 (73%)
Combined	289/350 (83%)	273/350 (78%)

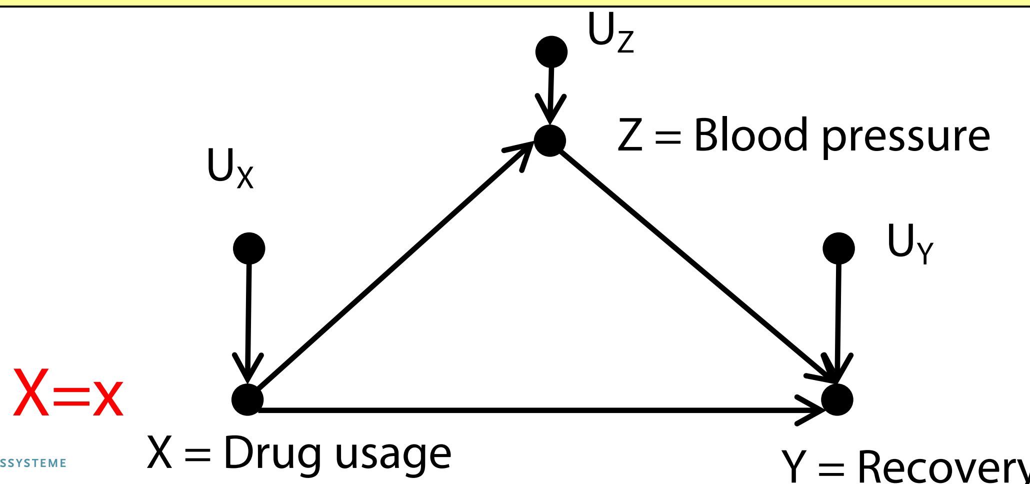
- BP recorded at end of experiment
- This time segregated data recommends not using drug whereas aggregated does

Resolving the Paradox (Formally)

- We have to understand the causal mechanisms that lead to the data in order to resolve the paradox
- Formally: What is the general causal effect of drug usage X on recovery Y?
  - $P(Y = y \mid do(X = x)) = ?$

    $= P_m(Y = y \mid X = x) = P(Y = y \mid X = x)$

So: Do not adjust for/segregate w.r.t. any variable



Causal Effect for Multiple Adjusted Variables

Rule (Calculation of causal effect)

$$P(Y = y \mid do(X = x)) = \sum_z P(Y = y \mid X = x, Pa(X) = z)\, P(Pa(X) = z)$$

- $Pa(X)$ = parents of X
- z = instantiation of all parent variables of X

Rule (Calculation of causal effect (alternative))

$$P(Y = y \mid do(X = x)) = \sum_z P(Y = y, X = x, Pa(X) = z) / P(X = x \mid Pa(X) = z)$$

Truncated Product Formula

- Handling of multiple interventions straightforward
- Joint prob. distribution on all other variables $X_1, \ldots, X_n$ after intervention on $Y_1,\ldots,Y_m$

That is, all variables are partitioned in X_is and Y_js

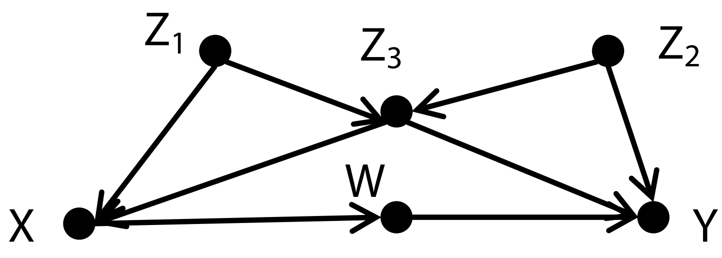
Definition (Truncated product formula (g-formula))

$$P(x_1, \ldots, x_n \mid do(Y_1=y_1, \ldots, Y_m=y_m)) = \prod_{1\leq j\leq n} P(x_i \mid pa(X_i))$$

$pa(X_i)$ = sub-vector of $(x_1, ..x_n, y_1, ...y_m)$ constrained to parents of X_i

Example 1

$P(z_1,z_2,w,y \mid do(X=x, Z_3=z_3))$
$= P(z_1)P(z_2)P(w|x)P(y|w,z_3,z_2)$



Truncated Product Formula

Definition (Truncated product formula (g-formula))

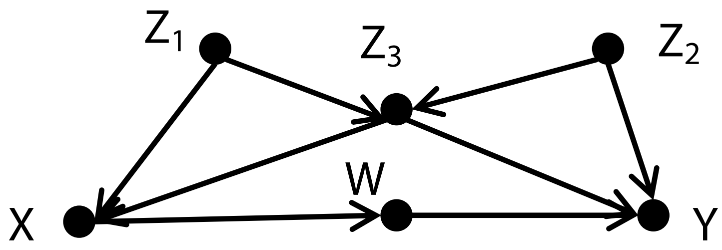
$P(x_1, \ldots, x_n \mid do(Y_1=y_1, \ldots, Y_m=y_m)) = \prod_{1 \le j \le n} P(x_i \mid pa(X_i))$

Example 2 (summing out)

$P(w,y \mid do(X=x, Z_3=z_3))$

$= \sum_{z1,z2} P(z_1)P(z_2)P(w|x)P(y|w,z_3,z_2)$

Can check that this formula is compatible with the adjustment formula



Backdoor Criterion (Motivation)

- Intervention on X requires adjusting parents of X
- But sometimes those variables are not measurable (though perhaps represented in graph)

- Need more general criterion to identify adjustment variables
  1. Block all spurious paths between X and Y
  2. Leave all directed paths from X to Y unperturbed
  3. Do not create new spurious paths

Backdoor Criterion (Formulation)

Definition

Set of variables Z satisfies backdoor criterion relative to a pair (X,Y) of variables iff

1. No node in Z is a descendant of X and
2. Z blocks every path between X and Y that contains an arrow into X

- Can adjust for Z satisfying backdoor criterion

$$P(Y = y \mid do(X = x)) = \sum_z P(Y = y \mid X = x, Z = z)P(Z=z)$$

Backdoor Criterion (Intuition)

Definition

Set of variables Z satisfies backdoor criterion relative to pair (X,Y) of variables iff

1. No node in Z is a descendant of X and
2. Z blocks every path between X and Y that contains an arrow into X

- Ad 1.: Descendants are effects of X, should not be conditioned on

  (compare drug usage X and blood pressure Z)

- Ad 2.: One is interested in effects of X on Y, not vice versa. Effects of Y on X should be blocked.

Backdoor Criterion Generalizes Adjustment

Definition

Set of variables Z satisfies backdoor criterion relative to pair (X,Y) of variables iff

1. No node in Z is a descendant of X and
2. Z blocks every path between X and Y that contains an arrow into X

- Z = Pa(X)
- For any W in Z both conditions fulfilled
  - W is not a descendant (as D**A**G)
  - Z blocks every path as every path into X must go trough a parent of X

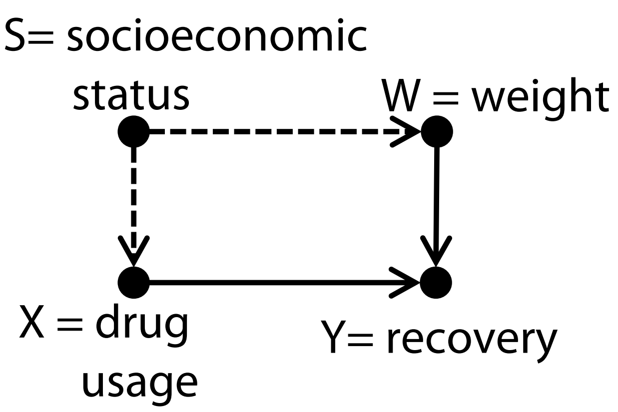
Backdoor Criterion (Example 1)

Definition

Set of variables Z satisfies backdoor criterion relative to pair (X,Y) of variables iff

1. No node in Z is a descendant of X and
2. Z blocks every path between X and Y that contains an arrow into X

- Causal effect of X on Y?
- S is not recorded in the data
- {W} for Z fulfills backdoor criterion
  - W not descendant of X
  - Blocks backdoor path



Backdoor Criterion (Example 1 (cont'd))

Definition

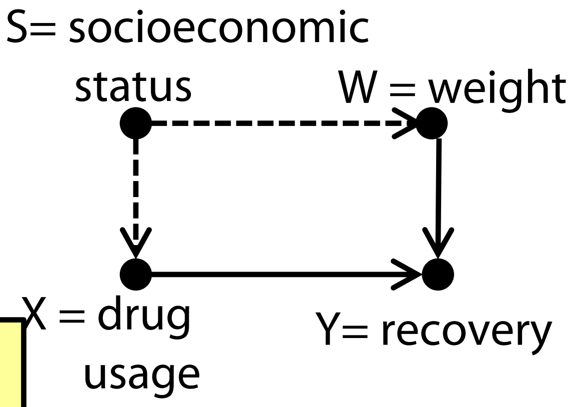
Set of variables Z satisfies backdoor criterion relative to pair (X,Y) of variables iff

1. No node in Z is a descendant of X and
2. Z blocks every path between X and Y that contains an arrow into X

- Causal effect of X on Y?

$P(y \mid do(x)) = \sum_w P(Y=y|X=x, W=w)P(W=w)$

$= \sum_s P(Y=y|X=x, S=s)P(S=s)$



Conditioning on different variables S vs. W with same effect calculation

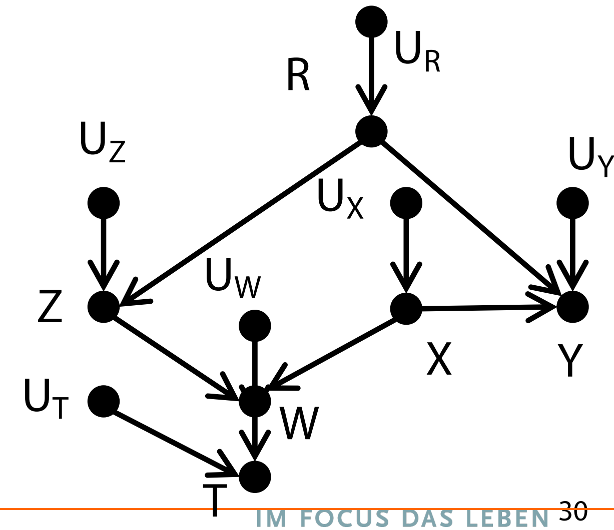
Backdoor Criterion (Example 2a)

Definition

Set of variables Z satisfies backdoor criterion relative to pair (X,Y) of variables iff

1. No node in Z is a descendant of X and
2. Z blocks every path between X and Y that contains an arrow into X

- Causal effect of X on Y?
- No backdoor paths
  - Can use Z = {}
  - $P(y \mid do(x)) = P(y \mid x)$



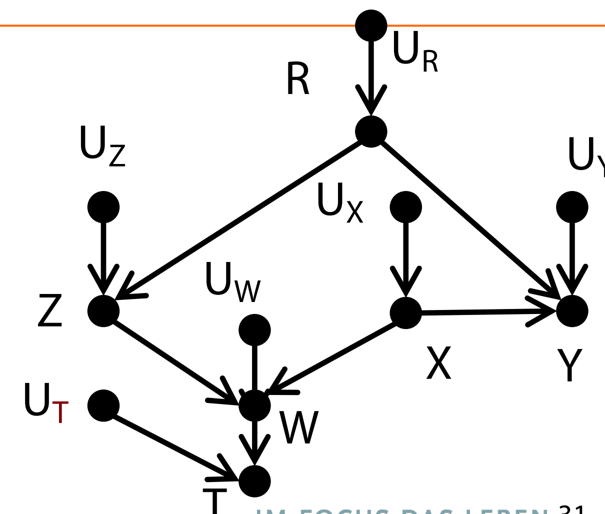
Backdoor Criterion (Example 2b)

Definition

Set of variables Z satisfies backdoor criterion relative to pair (X,Y) of variables iff

1. No node in Z is a descendant of X and
2. Z blocks every path between X and Y that contains an arrow into X

- Causal effect of X on Y?
- No backdoor paths
- Can one adjust for W?
  - No, then collider W not blocking spurious path



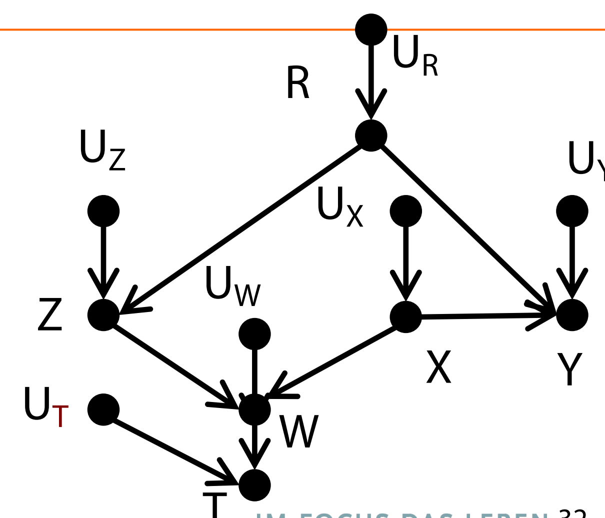
Backdoor Criterion (Example 2c)

Definition

Set of variables Z satisfies backdoor criterion relative to pair (X,Y) of variables iff

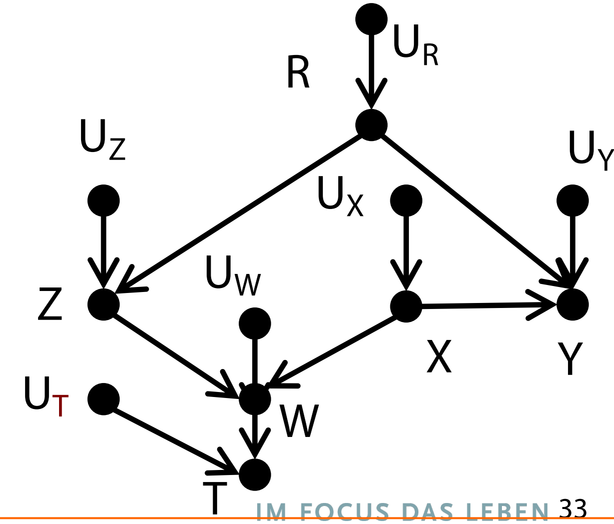
1. No node in Z is a descendant of X and
2. Z blocks every path between X and Y that contains an arrow into X

- From 2b we know: effect of X on Y not via conditioning on W.
- But how to calculate w-specific causal effect: $P(Y = y \mid do(X = x), W = w) = ?$



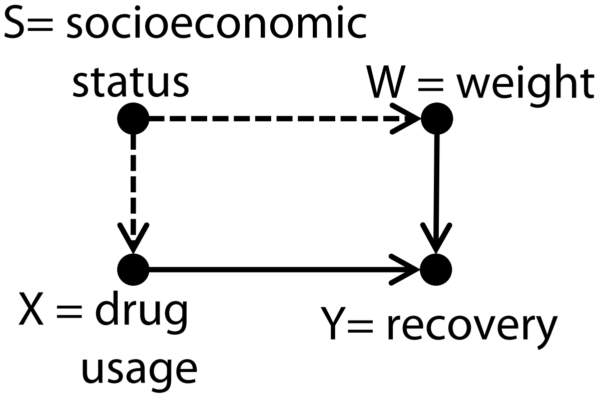
Backdoor Criterion (Example 2c (cont'd))

- W-specific causal effect $P(Y = y \mid do(X = x), W = w) = ?$
- Use fork R to condition on
  $P(Y = y \mid do(X = x), W = w) =$
  $$\sum_r P(Y=y|X=x,W=w,R=r)P(R=r|X=x,W=w)$$
- Degree to which causal effect of X on Y is modified by values of W is called effect modification or moderation



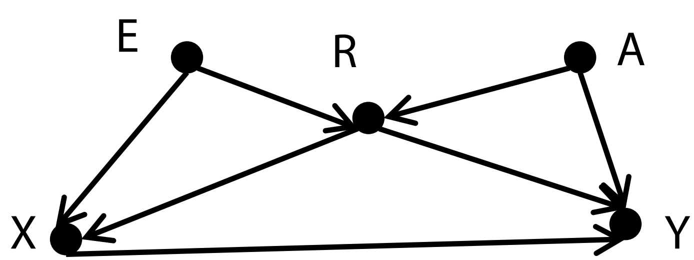
Backdoor Criterion (Example 3)

- What is effect modification for X on Y by W in drug example?
- Compare $P(Y = y \mid do(X = x), W = w)$ and $P(Y = y \mid do(X = x), W = w')$
- Here: As W blocks backdoor
  - $P(Y = y \mid do(X = x), W = w) = P(Y = y \mid X = x, W = w)$
  - $P(Y = y \mid do(X = x), W = w') = P(Y = y \mid X = x, W = w')$



Backdoor Criterion (Example 4)

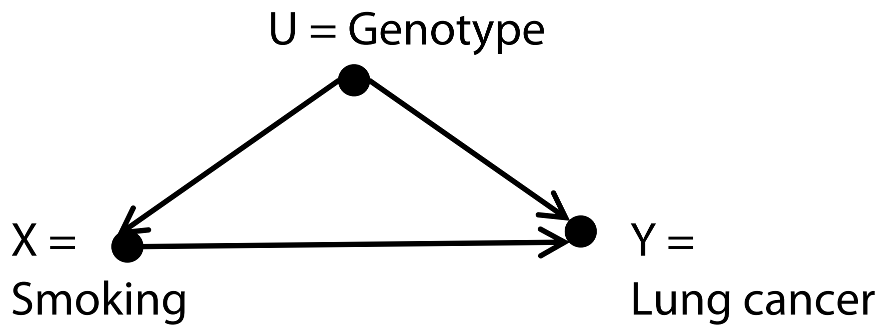
- Sometimes also need to condition on colliders
- There are four backdoor paths from X to Y
  1. $X \leftarrow E \rightarrow R \rightarrow Y$
  2. $X \leftarrow E \rightarrow R \leftarrow A \rightarrow Y$
  3. $X \leftarrow R \rightarrow Y$
  4. $X \leftarrow R \leftarrow A \rightarrow Y$
- R needed to block 3. path
- But R collider on 2. path, hence need further blocking variable
- Can use as blocking set Z
  {E,R}, {R,A} or {E,R,A}



Front-door Criterion (Motivating Example)

Example

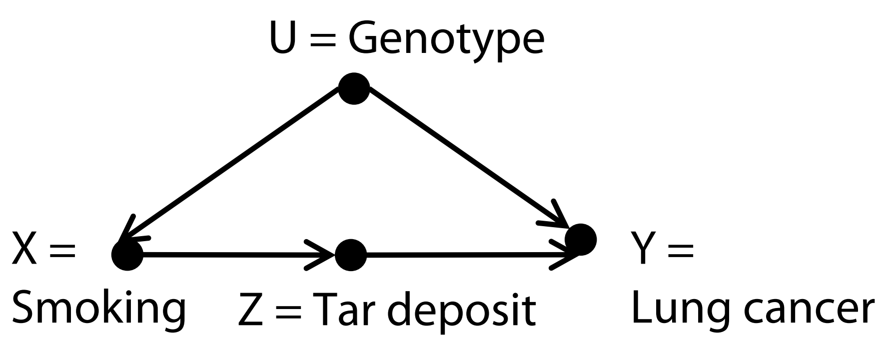
- Sometimes backdoor criterion not applicable
  - P(y | do(x)) = ?
  - Genotype U not observed in data
  - Hence conditioning on U does not help



Front-door Criterion (Motivating Example)

Example

- Sometimes backdoor criterion not applicable
  - $P(y \mid do(x)) = ?$
  - Genotype U not observed in data
  - Hence conditioning on U does not help
  - But sometimes a mediating variable helps



Front-door Criterion (Motivating Example)

	Tar (400)		No tar (400)		All subjects (800)	
	Smokers (380)	Nonsmokers (20)	Smokers (20)	Nonsmokers (380)	Smokers (400)	Nonsmokers (400)
No cancer	323 (85%)	1 (5%)	18 (90%)	38 (10%)	341 (85%)	39 (9.75%)
Cancer	57 (15%)	19 (95%)	2 (10%)	342 (90%)	59 (15%)	361 (92.25%)

Tobacco industry argues:

- 15% of smoker w/ cancer < 92.25% nonsmoker w/ cancer
- Tar: 15% smoker w/ cancer < 95% nonsmoker w/ cancer
- Non tar: 10% smoker w/ cancer < 90% nonsmoker w/ cancer

Front-door Criterion (Motivating Example)

	Smokers (400)		Nonsmokers (400)		All subjects (800)	
	Tar (380)	No tar (20)	Tar (20)	No tar (380)	Tar (400)	No tar (400)
No cancer	323 (85%)	18 (90%)	1 (5%)	38 (10%)	324 (81%)	56 (19%)
Cancer	57 (15%)	2 (10%)	19 (95%)	342 (90%)	76 (9%)	344 (81%)

Who is right?

Antismoking lobby argues:

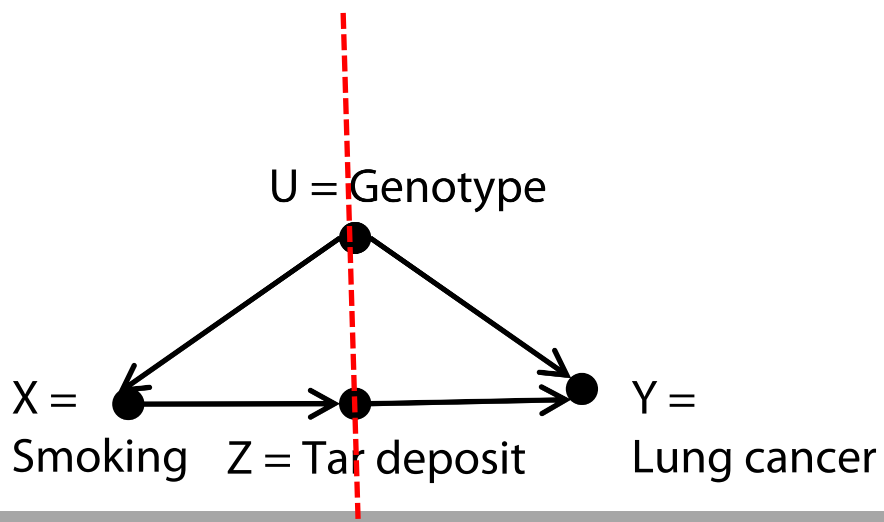
- Choosing to smoke increases chances of tar deposit (95% = 380/400)
- Effect of tar deposit: look separately at smokers vs. Non-smokers

  - Smokers: 10 % cancer $\xrightarrow{+\text{tar}}$ 15 % cancer
  - Nonsmokers: 90 % cancer $\xrightarrow{+\text{tar}}$ 95 % cancer

Front-door Criterion (Intuition)

- Separate effect of X on Y:

Effect of X on Y = effect of X on Z + effect of Z on Y



Front-door Criterion (Intuition)

- Effect of X on Z:

  $P(Z = z \mid do(X = x)) = P(Z= z \mid X = x)$

  (No unblocked X-Z backdoor path)

- Effect of Z on Y:

  $P(Y = y \mid do(Z = z)) = \sum_x P(Y = y \mid Z = z, X = x)P(X=x)$

  (X blocks Z-Y-backdoorpath)

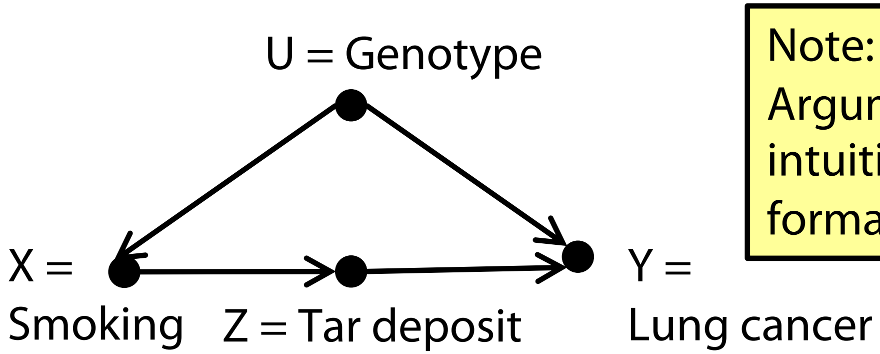
- Effect of X on Y:

  (Chaining and summing out)

  $P(Y = y \mid do(X=x))$

  $= \sum_z P(Y=y|do(Z=z))P(Z=z|do(X=x))$

  $= \sum_z \sum_{x'} P(Y=y|Z=z,X=x')P(X=x')P(Z=z|X=x')$



Note:
Argument in last step rather intuitive. See next slide for formal derivation

More detailed derivation

$P(y|do(X{=}x))$

$= \quad \sum_u P(Y{=}y|x,u)P(u)$ (adjustment on U)

$= \quad \sum_u \sum_z P(Y{=}y|z,x,u)P(z|x,u)P(u)$ (conditioning on Z)

$= \quad \sum_u \sum_z P(Y{=}y|z,x,u)P(z|x)P(u)$ (Z independent of U given X by (d-separation))

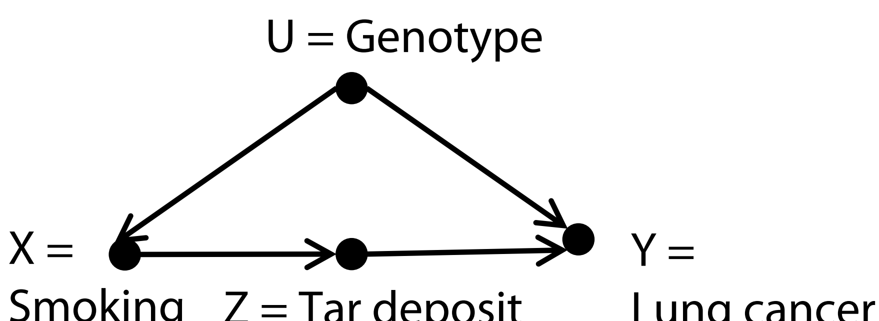
$= \quad \sum_z P(z|x) \sum_u P(Y{=}y|z,x,u)\, P(u)$ (factoring out)

$= \quad \sum_z P(z|x) \sum_u P(Y{=}y|z,u)\, P(u)$ (Y independent of X given Z,U)

$= \quad \sum_z P(z|x) P(Y|do(z))$ (definition of do())

$= \quad \sum_z P(z|x)\, \sum_{x'} P(Y|x',z)\, P(x')$ (adjustment via X)

$= \quad \sum_z \sum_{x'} P(z|x)\, P(Y|x',z)\, P(x')$



Front-door Criterion (Formulation & Theorem)

Definition

Set of variables Z satisfies front-door criterion w.r.t. pair of variables (X,Y) iff

1. Z intercepts all directed paths from X to Y
2. Every backdoor path from X to Z is blocked (by collider)
3. All Z-Y backdoor paths are blocked by X

Theorem (Front-door adjustment)

If Z fulfills front-door criterion w.r.t. (X,Y) and $P(x,z) > 0$

then $P(y|do(x)) = \sum_z P(z|x) \sum_{x'} P(y|z, x')P(x')$

Conditional Interventions (Example)

Example (conditioned drug administering)

- Administer drug ($X = 1$) if fever $Z > z$
- Formally:
  $P(Y = y \mid do(X = g(Z))$
  where $g(Z) = 1$ if $Z > z$ and $g(Z) = 0$ otherwise

- Can be reduced to calculating z-specific effect
  $P(Y = y \mid do(X = x), Z = z)$

Conditional Interventions (Rule)

Rule (z-specific effect)

If there is set S of variables s.t. $S \cup Z$ satisfies backdoor criterion

then the z-specific effect is given by

$$P(y \mid do(x), z) = \sum_s P(y \mid x,s,z)\, P(s \mid z)$$

Reduction of conditional intervention to z-specific effect:

$$P(Y = y \mid do(X = g(Z))) =$$

$$= \sum_z P(Y= y \mid do(X = g(Z), Z=z)\, P(Z=z \mid do(X = g(Z)))$$

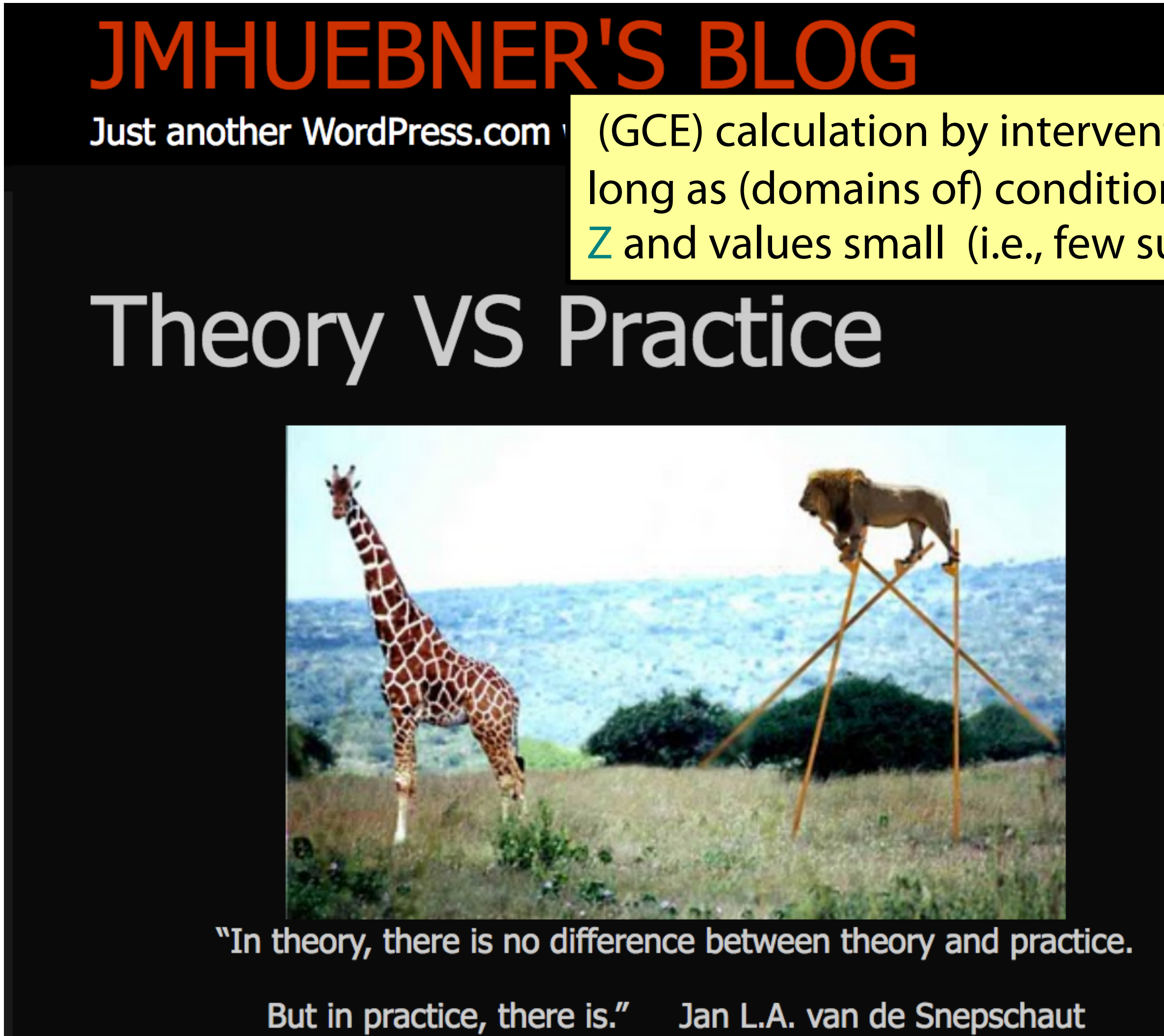
(conditioning on Z)

$$= \sum_z P(Y= y \mid do(X = g(Z), Z=z)\, P(Z=z)$$

(Z before X)

$$= \sum_z P(Y= y \mid do(X = x), z)_{|x=g(z)}\, P(Z=z)$$

Intervention Calculation in Practice?



(GCE) calculation by intervention useful as long as (domains of) conditioned variable set Z and values small (i.e., few summations)

Inverse Probability Weighting

- Inverse probability weighting gives estimation of GCE on small sample size $<< |z|$
- Estimation with propensity score $P(X=x|Z=z)$
  - Propensity score can be estimated similarly as in linear regression
  - Weight small sample set with propensity
  - Estimation of $P(y|do(x))$ by counting all events for y for each stratum $X = x$ (No summation over all instances of Z required)

Inverse Probability Weighting

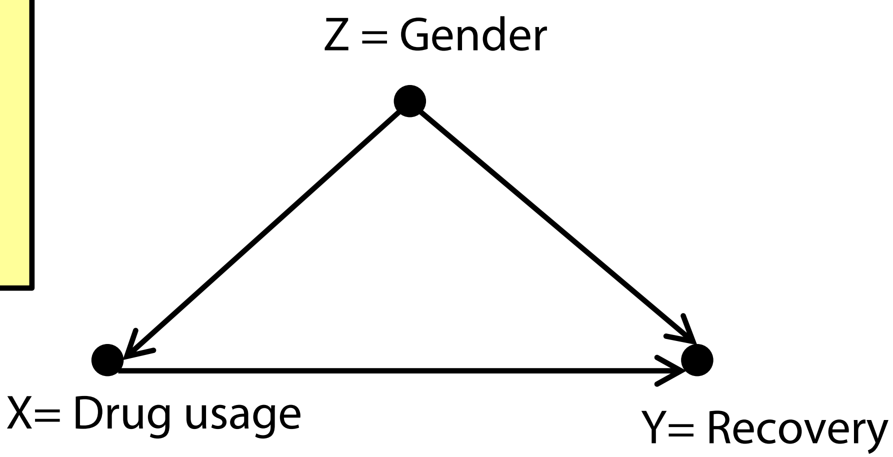
- Filtering-Case $P(Y=y,Z=z|X=x)$: Evidence leads to re-normalization of full joint probability
  - $P(Y=y,Z=z|X=x) = P(Y=y, Z=z, X=x)/P(X=x)$
  - Have to weight (Y,Z,X) samples by $1/P(X=x)$
- Intervention-Case $P(y|do(x))$: Weighting by propensity
  - $P(y\,|do(x))$
    $= \sum_z P(Y=y \mid X=x, Z=z)\, P(Z=z)$
    $= \sum_z P(Y=y \mid X=x, Z=z)\, P(Z=z)\, P(X=x|Z=z) \,/\, P(X=x|Z=z)$
    $= \sum_z P(X=x,Y=y, Z=z) \,/\, P(X=x|Z=z)$

Weighting joint distribution by inverse propensity

Inverse Probability Weighting (Example)

	Recovery rate with drug	**Recovery rate without drug**
Men	81/87 (93%)	234/270 (87%)
Women	192/263 (73%)	55/80 (69%)
Combined	273/350 (78%)	289/350 (83%)

- Rewrite table to get % of population for each (X,Y,Z) instance
- Example: %(yes, yes, male) = 81/700 = 0.116



Sample percentages

	Recovery rate **with** drug	Recovery rate **without** drug
Men	81/87 (93%)	234/270 (87%)
Women	192/263 (73%)	55/80 (69%)
Combined	273/350 (78%)	289/350 (83%)

X	Y	Z	% of population
yes	yes	male	0.116
yes	yes	female	0.274
yes	no	male	0.01
yes	no	female	0.101
no	yes	male	0.334
no	yes	female	0.079
no	no	male	0.051
no	no	female	0.036

Weighting when Filtering for X=yes

X	Y	Z	% of population
yes	yes	male	0.116
yes	yes	female	0.274
yes	no	male	0.01
yes	no	female	0.101
no	yes	male	0.334
no	yes	female	0.079
no	no	male	0.051
no	no	female	0.036

Consider X = yes & weight (X,Y,Z) with 1/P(X=yes) =1/(0.116+0.274+0.01+0.101)

X	Y	Z	% of population
yes	yes	male	0.232
yes	yes	female	0.547
yes	no	male	0.02
yes	no	female	0.202

Weighting when Intervening do(X=yes)

X	Y	Z	% of population
yes	yes	male	0.116
yes	yes	female	0.274
yes	no	male	0.01
yes	no	female	0.101
no	yes	male	0.334
no	yes	female	0.079
no	no	male	0.051
no	no	female	0.036

Consider X = yes & weight (X,Y,Z) with 1/P(X=yes|Z=z)
P(X=yes|Z=male) = (0.116 + 0.01)/(0.116+0.01 + 0.334 + 0.051)
P(X=yes|Z=female) = (0.274 + 0.101)/(0.274+0.101 + 0.079 + 0.036)

In this example no real savings!
These come into play when
dom(Z) >> sample size

X	Y	Z	% of population
yes	yes	male	0.476
yes	yes	female	0.357
yes	no	male	0.042
yes	no	female	0.132