

# Assignment - 1 (CS6840 - Causal Inference)

Puneet Mangla - CSI7BTECH11029

Q.1

- (a)  $\{Y, W\}$   
 (b)  $\{Y, W, X\}$   
 (c)  $\{Y, Z\}$   
 (d)  $\{Y, Z, T\}$   
 (e)  $(X \rightarrow Y \rightarrow T), (X \rightarrow Y \rightarrow Z \rightarrow T), (X \rightarrow W \rightarrow Z \rightarrow T), (X \rightarrow W \rightarrow Y \rightarrow T),$   
 $(X \rightarrow W \rightarrow Y \rightarrow Z \rightarrow T), (X \rightarrow Y \rightarrow W \rightarrow Z \rightarrow T), (\cancel{X \rightarrow W \rightarrow Z \rightarrow T}), (\cancel{X \rightarrow W \rightarrow Y \rightarrow T})$   
 (f)  $(X \rightarrow Y \rightarrow T), (X \rightarrow W \rightarrow Y \rightarrow T), (X \rightarrow W \rightarrow Z \rightarrow T), (X \rightarrow Y \rightarrow Z \rightarrow T)$   
 $(\cancel{X \rightarrow W \rightarrow Y \rightarrow T}), (X \rightarrow W \rightarrow Y \rightarrow Z \rightarrow T)$   
 (g) No, as  $W$  is an ancestor of  $T$ , Both distributions are dependent.

(h)

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

- (i) No,  $W$  and  $T$  are not conditionally independent given  $Z$ , because there is a path from  $W \rightarrow Y \rightarrow T$ , hence, the path is unblocked by unobserved variable  $Y$ .

(j) Yes.

$$P(W, T|Z, Y) = \frac{P(W, T, Z, Y)}{P(Z, Y)} = \frac{\sum_X P(X, W, T, Z, Y)}{P(Z, Y)}$$

$$= \frac{\sum_X P(X) \cdot P(W|X) \cdot P(Y|X, W) \cdot P(Z|Y, W) \cdot P(T|Y, Z)}{P(Z, Y)}$$

$$= \sum_X \frac{P(W, X, Y) \cdot P(Y, W, Z) \cdot P(T|Y, Z)}{P(Y, W) \cdot P(Z, Y)}$$

$$= \sum_X P(X|W, Y) \cdot P(W|Z, Y) \cdot P(T|Z, Y)$$

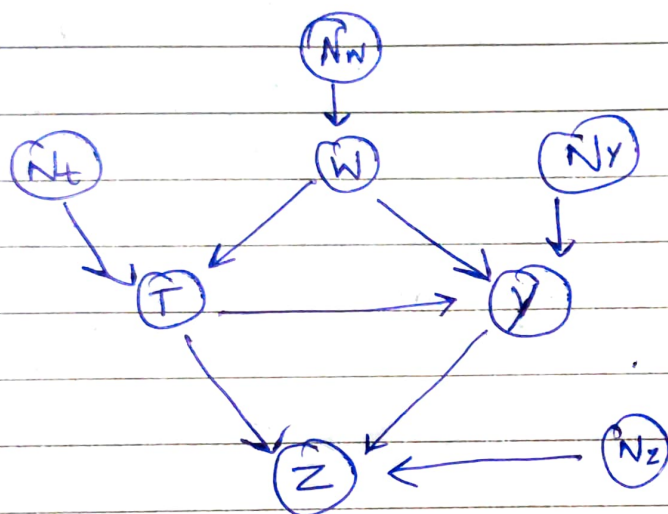
$$= P(W|Z, Y) \cdot P(T|Z, Y) \sum_X P(X|W, Y)$$

Q.2

k)  $Y, Z$  set or  $\{W, Y, Z\}$  is the only variable that d-separates  $X$  and  $T$ .

$X$  and  $T$  are conditionally independent if  $Y, Z$  are observed. or  $\{W, Y, Z\}$  are observed.

Q.3 a)



(b), (c), (d), (e) in Jupyter notebook attached.

0.2

a) For treatment unit 1

$$D(1,3) = 108.7$$

$$D(1,4) = 4$$

$$D(1,5) = 2.5$$

$$D(1,6) = 9$$

$$D(1,7) = 10$$

$$D(1,8) = 101.5$$

For treatment unit 2

$$D(2,3) = 40.2$$

$$D(2,4) = 112.5$$

$$D(2,5) = 106$$

$$D(2,6) = 100.5$$

$$D(2,7) = 118.5$$

$$D(2,8) = 7$$

Match is control  
unit 5

Match is control  
unit 3.

- b) Average Treatment Effect on treated is expected causal effect of the treatment for individuals in the treatment group. Mathematically,

$$\begin{aligned}ATE^T &= E[Y(1) - Y(0) | T=1] \\ &= E[Y(1) | T=1] - E[Y(0) | T=1]\end{aligned}$$

Let  $p$  be the percentage of population receiving treatment. then

$$\begin{aligned}ATE &= E[Y(1) - Y(0)] = p \cdot E[Y(1) - Y(0) | T=1] \\ &\quad + (1-p) E[Y(1) - Y(0) | T=0]\end{aligned}$$

$$\begin{aligned}&= \{ p E[Y(1) | T=1] + (1-p) E[Y(1) | T=0] \} \\ &\quad - \{ p E[Y(0) | T=1] + (1-p) E[Y(0) | T=0] \}\end{aligned}$$



when exchangeability holds (for eg. in RCTs)

$$E[Y(0)|T=0] = E[Y(0)|T=1] \quad \text{or}$$

$$E[Y(0)|T=0] = E[Y(0)|T=1]$$

$$\text{ie ATE} = E[Y(0)|T=1] - E[Y(1)|T=1] \\ = \text{ATT.}$$

$$c) \quad \text{AA} \approx \text{ATT} = E[Y(0) - Y(1)|T=1]$$

we know  $Y(0)$ , to  $Y(1)$  is counterfactual.  
So we will approximate it with  
closest match. in control group.

$$\begin{aligned} \text{ATT} &= E \left[ \frac{Y_1(0) - Y_1(1)}{2} + \frac{Y_2(0) - Y_2(1)}{2} \right] \\ &= \frac{Y_1(0) - Y_5(1)}{2} + \frac{Y_2(0) - Y_3(1)}{2} \\ &\quad \downarrow \qquad \qquad \downarrow \\ &\quad \{ \text{approximate with closest control unit} \} \\ &= \frac{30 - 19.5}{2} + \frac{12.5 - 17}{2} \end{aligned}$$

$$= 3$$

$$\text{So, ATT} = 3$$

Q.4

a) Mean independence assumption says that for a given random variable  $Y$  which mean independent of  $X$ , following is sufficient and necessary.

$$E[Y|X] = E[Y]$$

b) For  $\beta_1$  and  $\beta_0$  to be consistent and unbiased  $E[U|X]$  should be 0, also in general as

$$y = \beta_0 + \beta_1 x + u$$

$$u = y - \beta_0 - \beta_1 x \quad \text{or} \quad U = Y - \beta_0 - \beta_1 X$$

$$E[U|X] = E[Y|X] - E[\beta_0|X] - E[\beta_1 X|X]$$

$\downarrow$   
0

$$\Rightarrow E[Y|X] = E[\beta_0|X] + E[\beta_1 X|X]$$

$$= \beta_0 + \beta_1 X$$

hence if  $E[U|X] = 0$ ,  $\beta_0$  and  $\beta_1$  can be estimated consistently and unbiased

also  $E[U|X] = 0 = E[U] \Rightarrow U$  is mean independent of  $X$ .

c) Regression is conditional mean functions and not causal function. To use caus when exchangeability or conditional exchangeability holds, we can represent causal quantities as conditional quantities which allows us to use regression. If conditional exchangeability holds then the Average treatment effect will be conditional average treatment effect.

Q.5

$$P(Y=y | do(T=t)) = \sum_x P(y | t, x) P(x). \quad (1)$$

$$P(Y=y | T=t) = \sum_x P(y | t, x) P(x | t) \quad (2)$$

Now if distribution of  $x$  is same across treatment groups  $t$ .

$$\text{i.e. } P(x | t=0) = P(x | t=1)$$

$$\begin{aligned} p(x) &= P(t=0) p(x | t=0) + P(t=1) p(x | t=1) \\ &= [P(t=0) + P(t=1)] p(x | t=0) \\ &= \downarrow 1 \cdot p(x | t=0) \end{aligned}$$

$$\text{i.e. } P(x | t=0) = p(x) = P(x | t=1) \text{ or } P(x | t) = p(x)$$

now Eq-(2) becomes

$$P(Y=y | T=t) = \sum_x P(y | t, x) P(x | t)$$

$$= \sum_x P(y | t, x) p(x) = P(Y=y | do(T=t))$$