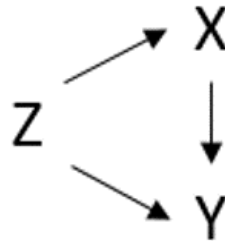


Advanced Artificial Intelligence Assignment Report

The solution to a) was derived from the Artificial Neural Networks, workshop 2's example of collecting probabilities from data.



X=0	Z=1	P(Y X,Z)	P(Y X,-Z)	No treatment		
T	T	0.81	0.19	Z	P(x0 Z)	
T	F	0.48	0.52	TRUE	0.61	0.39
F	T	0.83	0.17	FALSE	0.04	0.96
F	F	0.55	0.45			
P(X=1)	P(Z=1)	P(Y X,Z)	P(Y X,-Z)	Placebo		
T	T	0.76	0.24	Z	P(x1 Z)	
<u>I</u>	F	0.55	0.45	TRUE	0.49	0.51
<u>E</u>	T	0.87	0.13	FALSE	0.08	0.92
F	F	0.54	0.46			
P(X=2)	P(Z=1)	P(Y X,Z)	P(Y X,-Z)	Medicine		
<u>I</u>	T	0.91	0.09	Z	P(x2 Z)	P(x2/X -Z)
<u>I</u>	F	0.55	0.45	TRUE	0.09	0.91
<u>E</u>	T	0.77	0.23	FALSE	0.902	0.098
<u>E</u>	F	0.54	0.46			
Z	0.728	0.272		Y	0.746	0.254

This is possible for the values of X as well which give us a table of 12 elements.

For a given probability $P(y,x,z)$, the expansion of this gives us the following:

$P(Y|X,Z)$, $P(X,Z)$, $P(Z)$

To compute the intervention's probability for part b, I wrote a function that takes in the values of x,y and z and then computes the intervention for all given values of $X=0,1,2$ and $Z = 1,0$. This returned the probability of Y being true and not being true for the cases

```
def y_do_x(y_x_z, y_x_not_z, y_not_x_z, y_not_x_not_z, z):  
    y1_x1 = (y_x_z * z[t]) + (y_x_not_z * z[f])  
  
    y1_x0 = (y_not_x_z * z[t]) + (y_not_x_not_z * z[f])  
  
    return y1_x1, y1_x0  
    #Computes Y TRUE/FALSE given Z is TRUE  
    #AND Y TRUE/FALSE Given Z is false
```

```
y_do_x(p_y_x0_z1, p_y_x0_z0, p_y_x1_z1, p_y_x1_z0, Z)
```

```
(array([0.28259259, 0.71740741]), array([0.2998885, 0.7001115]))
```

```
y_do_x(p_y_x1_z1, p_y_x1_z0, p_y_x0_z1, p_y_x0_z0, Z)
```

```
(array([0.2998885, 0.7001115]), array([0.28259259, 0.71740741]))
```

```
y_do_x(p_y_x2_z1, p_y_x2_z0, p_y_x2_z1, p_y_x2_z0, Z)
```

```
(array([0.18778731, 0.81221269]), array([0.18778731, 0.81221269]))
```

For part C I based my solution on the workshop 3 example based on the condition that:

W in the full probability has no Parents and therefore the pre- and post-intervention are the same:

$$P(y|\text{do}(w)) = P(y|w)$$

$$P(Y|W) = \alpha P(Y, W)$$

$$= \alpha \sum_{z,x} P(Y, x, w, z)$$

$$= \alpha \sum_z \sum_x P(Y|x, z) * P(x|z) * P(z|w) * P(w)$$

$$= \alpha P(x|z) * \sum_z P(z|w) * \sum_x P(Y|x, z) * P(w)$$

$$P(Y|W) = \langle \neg(P(y|w), P(\neg y|w)) \rangle + \langle \neg P(y|\neg w), P(\neg y|\neg w) \rangle$$

```
#Y|do(x),w
def Y_W(y_x_z, y_not_x_z, y_not_x_not_z, y_x_not_z, x_z, x_not_z, z_w, w):
    y1_w1 = w[t]*(z_w[t,t]*(y_x_z[t]*x_z[t] + y_not_x_z*x_z[f])
              + z_w[f,t]*(y_x_not_z[t]*x_not_z[t] + y_not_x_not_z[t]*x_not_z[f]))

    y1_w0 = w[f]*(z_w[t,f]*(y_x_z[t]*x_z[t] + y_not_x_z*x_z[f])
                  + z_w[f,f]*(y_x_not_z[t]*x_not_z[t] + y_not_x_not_z[t]*x_not_z[f]))

    return y1_w1 - y1_w0
```

```
sum1 = Y_W(p_y_x1_z1, P_of_not_x1_given_z1, p_y_not_x1_z0, p_y_x1_z0, p_x1_z1, p_x1_z0, P_Z_W, P_W)#y/x1
sum0 = Y_W(p_y_x0_z1, P_of_not_x0_given_z1, p_y_not_x0_z0, p_y_x0_z0, p_x0_z1, p_x0_z0, P_Z_W, P_W)#y/x0
sum2 = Y_W(p_y_x2_z1, P_of_not_x2_given_z1, p_y_not_x2_z0, p_y_x2_z0, p_x2_z1, p_x2_z0, P_Z_W, P_W)#y/x2
```

```
Output = sum0+sum1+sum2
Output
```

0.7082547442053746

References

Nicola, B. (2021) Lecture 3 – Bayesian Networks, University of Lincoln, 25th October. Available from: https://blackboard.lincoln.ac.uk/webapps/blackboard/content/listContent.jsp?course_id= 166752_1&content_id= 5852525_1 [Accessed: 02/12/21]

Nicola, B. (2021) Lecture 6 – Casual Inference I, University of Lincoln, 15th November. Available from: https://blackboard.lincoln.ac.uk/ultra/courses/ 166752_1/cl/outline [Accessed: 02/12/21]