Medical Statistics – Answers lab 8

Part 1: Building prediction models using backward elimination

Step 1: Fit the initial linear regression model

Create an initial model for hospital length of stay (`los`) using the following predictors: `age`, `gender`, `hr`, `sysbp`, `diasbp`, `bmi`, `cvd`, `sho`. Run/summarize the model to inspect coefficients and p-values.

```
Call:
lm(formula = los ~ age + gender + hr + sysbp + diasbp + bmi +
    cvd + sho, data = whas)

Residuals:
   Min     1Q Median     3Q    Max
-8.335 -2.653 -1.071  1.200 40.073

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   3.2648144  2.1394896   1.526 0.127659
age           0.0031994  0.0168850   0.189 0.849792
genderfemale  0.8575246  0.4489334   1.910 0.056698 .
hr            0.0190577  0.0090828   2.098 0.036396 *
sysbp        -0.0008358  0.0085656  -0.098 0.922304
diasbp        0.0141799  0.0128884   1.100 0.271780
bmi          -0.0304532  0.0427613  -0.712 0.476700
cvdyes        0.3903925  0.4981468   0.784 0.433600
shoyes        3.5265170  1.0329265   3.414 0.000693 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 4.632 on 491 degrees of freedom
Multiple R-squared:  0.04991,   Adjusted R-squared:  0.03443
F-statistic: 3.224 on 8 and 491 DF,  p-value: 0.001388
```

Step 2: Eliminate the least significant predictor

```
Anova Table (Type III tests)

Response: los
             Sum Sq  Df F value    Pr(>F)
(Intercept)    50.0   1  2.3286 0.1276592
age             0.8   1  0.0359 0.8497924
gender         78.3   1  3.6486 0.0566978 .
hr             94.5   1  4.4025 0.0363962 *
sysbp           0.2   1  0.0095 0.9223042
diasbp         26.0   1  1.2105 0.2717799
bmi            10.9   1  0.5072 0.4766997
cvd            13.2   1  0.6142 0.4336001
sho           250.1   1 11.6561 0.0006929 ***
Residuals   10535.8 491
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The ANOVA table shows that the predictor with the highest p-value is `sysbp` ($p = 0.92$). Systolic blood pressure is the least significant predictor and should be removed from the model.

Step 3: Repeat the steps

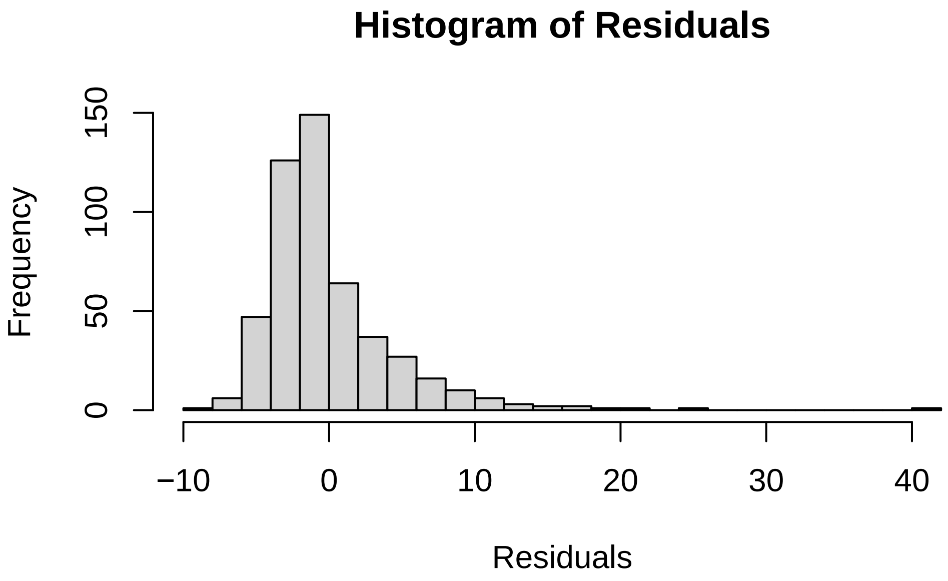
The following variables are sequentially removed from the model (after initially removing `sysbp`):

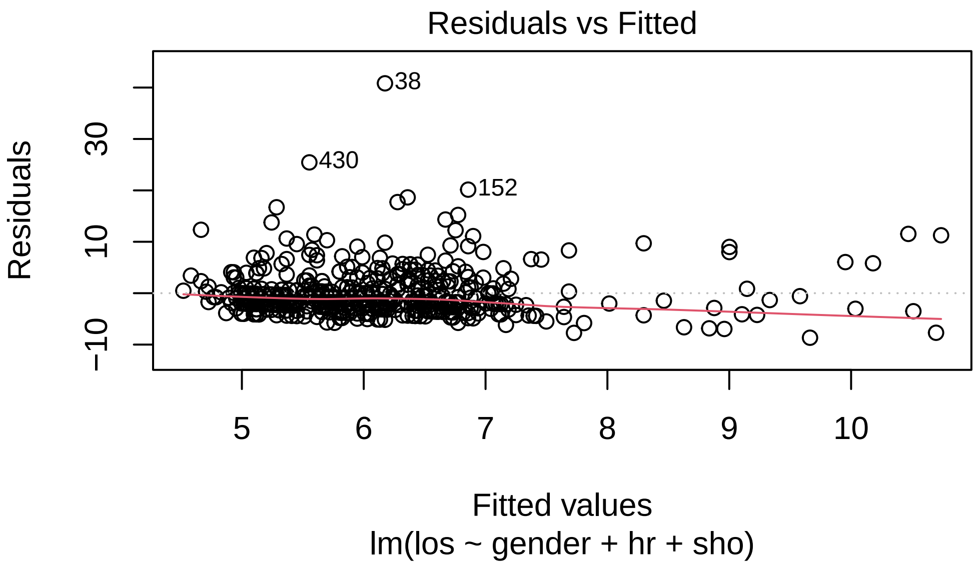
1. `age`: p-value = 0.86
2. `cvd`: p-value = 0.41
3. `bmi`: p-value = 0.44
4. `diasbp`: p-value = 0.22

Step 4: Final model

```
Call:
lm(formula = los ~ gender + hr + sho, data = whas)

Residuals:
   Min     1Q Median     3Q    Max 
-8.663 -2.661 -1.064  1.136 40.826 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.796075   0.799047   4.751 2.66e-06 ***
genderfemale 0.910388   0.424827   2.143 0.032602 *  
hr           0.020680   0.008843   2.339 0.019751 *  
shoyes       3.550448   1.009081   3.518 0.000474 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 

Residual standard error: 4.622 on 496 degrees of freedom
Multiple R-squared:  0.04443,   Adjusted R-squared:  0.03865 
F-statistic: 7.687 on 3 and 496 DF,  p-value: 4.976e-05 
```

Residual plots





The overall fit of the model appears reasonable, as the residuals are generally centered around zero with no major patterns suggesting severe violations of linearity. However, there are some outliers with very long lengths of stay (LOS) that are not adequately captured by the model. These outliers lead to a right skew in the residual distribution, as seen in the histogram, influencing model fit. While the current model seems to work reasonably well for most observations, further steps (e.g., transformations or robust regression techniques) could be considered to better account for these extreme cases.

Part 2: Automated procedures for building prediction models

Exercise: Automated procedures vs manual model

R

```
library(MASS)
fit <- lm(los ~ age + gender + hr + sysbp + diasbp + bmi + cvd + sho, data = whas)
step_model <- stepAIC(fit, direction = "backward")
```

```
Start:  AIC=1541.96
los ~ age + gender + hr + sysbp + diasbp + bmi + cvd + sho

         Df Sum of Sq   RSS    AIC
- sysbp   1     0.204 10536 1540.0
- age     1     0.770 10537 1540.0
- bmi     1    10.883 10547 1540.5
- cvd     1    13.179 10549 1540.6
- diasbp  1    25.974 10562 1541.2
<none>                10536 1542.0
- gender  1    78.292 10614 1543.7
- hr      1    94.469 10630 1544.4
- sho     1   250.115 10786 1551.7

Step:  AIC=1539.97
los ~ age + gender + hr + diasbp + bmi + cvd + sho

         Df Sum of Sq   RSS    AIC
- age     1     0.682 10537 1538.0
- bmi     1    11.109 10547 1538.5
- cvd     1    12.975 10549 1538.6
- diasbp  1    38.551 10575 1539.8
<none>                10536 1540.0
- gender  1    78.719 10615 1541.7
- hr      1    96.991 10633 1542.6
- sho     1   260.543 10797 1550.2
```

```
Step:  AIC=1538.01
los ~ gender + hr + diasbp + bmi + cvd + sho

         Df Sum of Sq   RSS    AIC
- cvd     1    14.624 10551 1536.7
- bmi     1    15.372 10552 1536.7
- diasbp  1    37.888 10575 1537.8
<none>                10537 1538.0
- gender  1    84.736 10621 1540.0
- hr      1   101.448 10638 1540.8
- sho     1   264.134 10801 1548.4

Step:  AIC=1536.7
los ~ gender + hr + diasbp + bmi + sho

         Df Sum of Sq   RSS    AIC
- bmi     1    12.883 10564 1535.3
- diasbp  1    38.599 10590 1536.5
<none>                10551 1536.7
- gender  1    97.518 10649 1539.3
- hr      1    99.732 10651 1539.4
- sho     1   266.183 10818 1547.2

Step:  AIC=1535.31
los ~ gender + hr + diasbp + sho

         Df Sum of Sq   RSS    AIC
- diasbp  1    32.352 10597 1534.8
<none>                10564 1535.3
- hr      1   104.369 10669 1538.2
- gender  1   108.564 10673 1538.4
- sho     1   273.160 10837 1546.1

Step:  AIC=1534.84
los ~ gender + hr + sho

         Df Sum of Sq   RSS    AIC
<none>                10597 1534.8
- gender  1     98.11 10695 1537.5
- hr      1    116.84 10713 1538.3
- sho     1    264.48 10861 1545.2
```

```r
summary(step_model)
```

```
Call:
lm(formula = los ~ gender + hr + sho, data = whas)

Residuals:
   Min     1Q Median     3Q    Max 
-8.663 -2.661 -1.064  1.136 40.826 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  3.796075   0.799047   4.751 2.66e-06 ***
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hr           0.020680   0.008843   2.339 0.019751 *  
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```
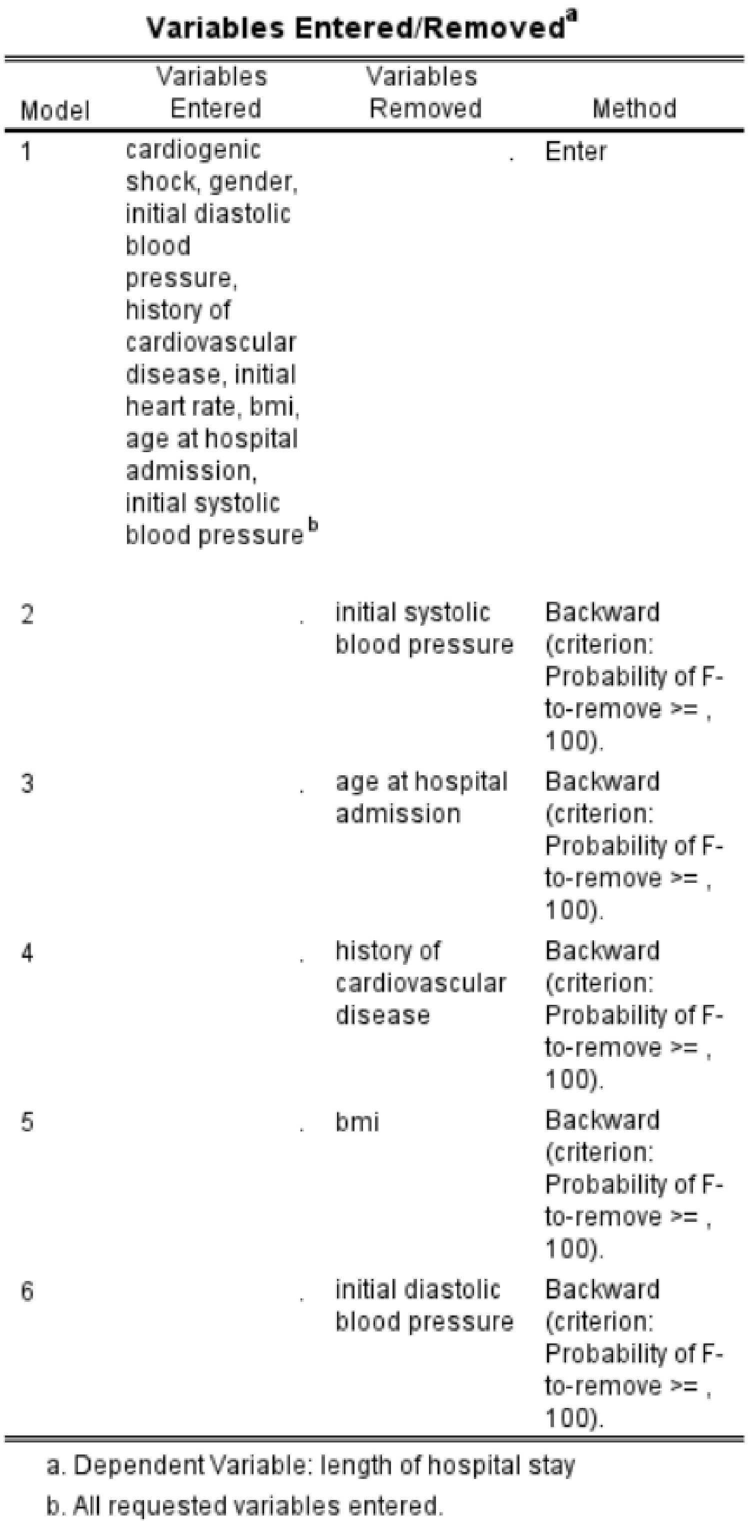

The final model obtained from the automated procedure is identical to the manually created model in Part 1.

SPSS



Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	cardiogenic shock, gender, initial diastolic blood pressure, history of cardiovascular disease, initial heart rate, bmi, age at hospital admission, initial systolic blood pressure[b]	.	Enter
2	.	initial systolic blood pressure	Backward (criterion: Probability of F-to-remove >= , 100).
3	.	age at hospital admission	Backward (criterion: Probability of F-to-remove >= , 100).
4	.	history of cardiovascular disease	Backward (criterion: Probability of F-to-remove >= , 100).
5	.	bmi	Backward (criterion: Probability of F-to-remove >= , 100).
6	.	initial diastolic blood pressure	Backward (criterion: Probability of F-to-remove >= , 100).

a. Dependent Variable: length of hospital stay

b. All requested variables entered.

Figure 1: SPSS results of the backward elimination procedure

The table above shows the variables eliminated at each step of the backward elimination procedure in SPSS. The final model obtained from the automated procedure is identical to the manually created model in Part 1.

Part 3: Causal diagrams

For each of the exercises below:

- Try solving the diagrams by hand by using the recipe from the lecture (see lecture slides on Brightspace)
- Check your answer using the DAGitty webtool

Exercise 1

In the graph depicted below, for which variables do you need to adjust to assess the unconfounded effect of E on O (there may be several possibilities)?

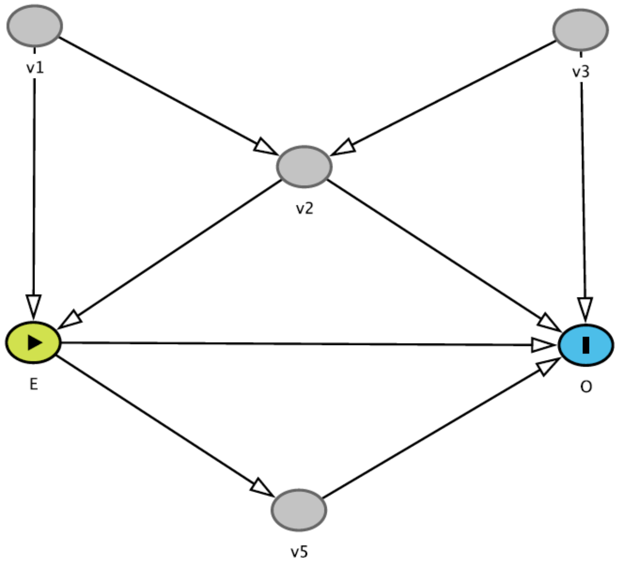


Figure 2: DAG exercise 1

Answer:
Following the recipe: after removing all arrows leaving E, there are several unblocked paths

leading from E to O. Just like in the lecture, adjusting for v2 opens a backdoor path (E – v1 – v3 – O) This newly opened backdoor path needs to be closed by also conditioning on v1 or v3, or both. Hence, there are 3 options: (v1, v2, v3) ; (v1, v2) ; and finally, (v2, v3).

Exercise 2

In the graph depicted below, what happens when you additionally adjust for **v5**?

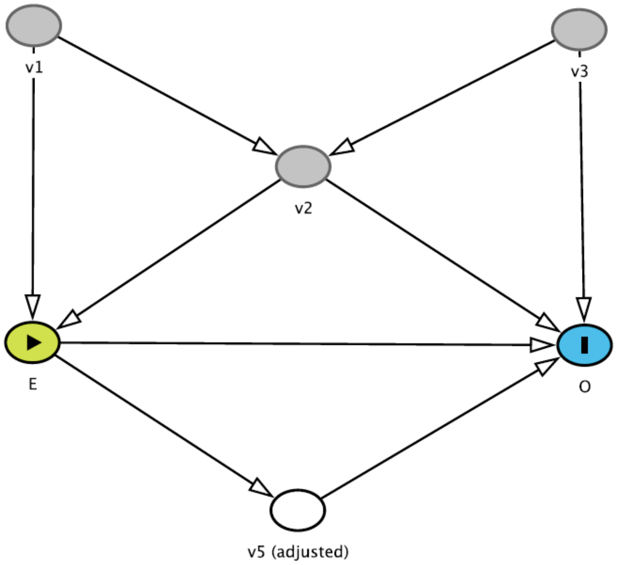


Figure 3: DAG exercise 2

Answer: When adjusting for v5, we are blocking the effect through this indirect path from E to O (v5 is a mediator between E and O). Instead of the total effect of E on O, we will be estimating the direct effect.

In DAGitty, when you set v5 to ‘adjusted’, the algorithm will say the following: “The total effect cannot be estimated due to adjustment for an intermediate or a descendant of an intermediate.”

Exercise 3

This diagram is slightly different: **v1** now is the exposure. For which variables do you need toadjust to assess the unconfounded effect of **v1** on **O**?

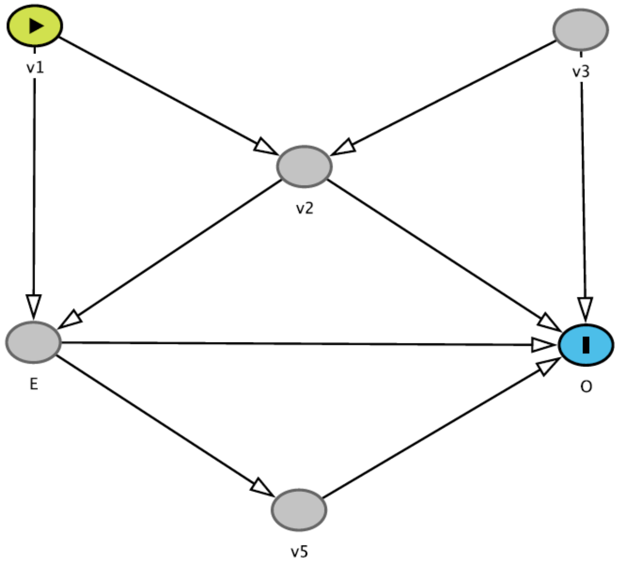


Figure 4: DAG exercise 3

Answer: No adjustment is needed: there are no backdoor paths (removing all arrows leaving v1 reveals no remaining unblocked path from v1 to O).

Exercise 4

Now, **v2** is the exposure. For which variables do you need to adjust to assess the total unconfounded effect of **v2** on **O**?

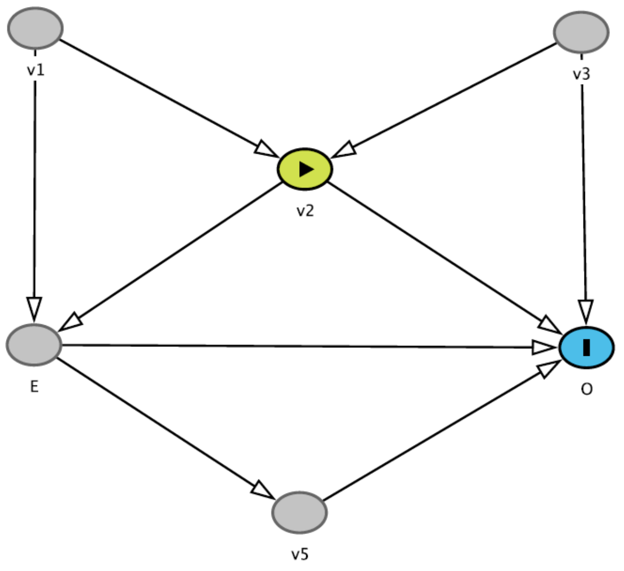


Figure 5: DAG exercise 4

Answer: Following the recipe, there are three unblocked paths left after removing the arrows leaving v2:

a) v2 – v3 – O and
b) v2 – v1 – E – O
c) v2 - v1 – E -v5 - O

Backdoor path a) can be closed by conditioning on v3.

Backdoor path b) can be closed by conditioning on v1 (but not by conditioning on E, as you would no longer be estimating the total effect by blocking the paths from v2 to O mediated by E).

In this case, you should therefore condition on v1 and v3.

Exercise 5

Back to the first DAG. However, **v2** is now unmeasured. Can we still obtain an unconfounded estimate of the effect of **E** on **O**?

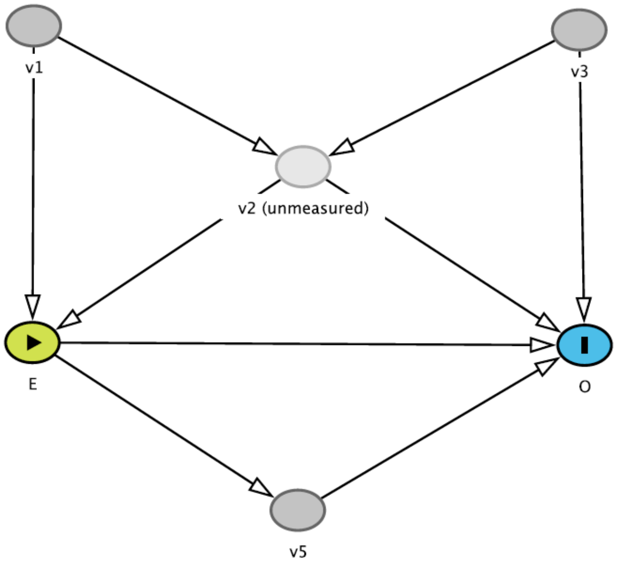


Figure 6: DAG exercise 5

Answer: No, we cannot close the backdoor path between E and O since v2 is unmeasured and cannot be corrected for.

Exercise 6

See the DAG below: you adjusted for **v5**. What would be the consequence of this action?

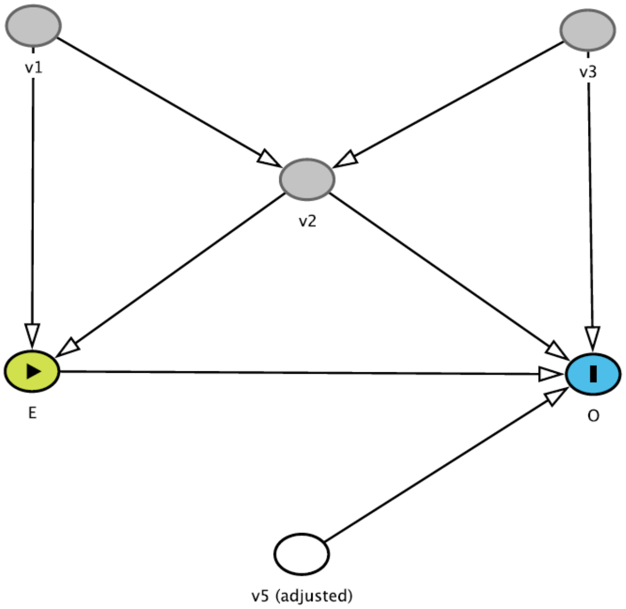


Figure 7: DAG exercise 6

Answer: There is no consequence: conditioning on v5 cannot alter any of the estimated effects in the DAG (it is neither a confounder, collider, nor a mediator in the E-O relationship).