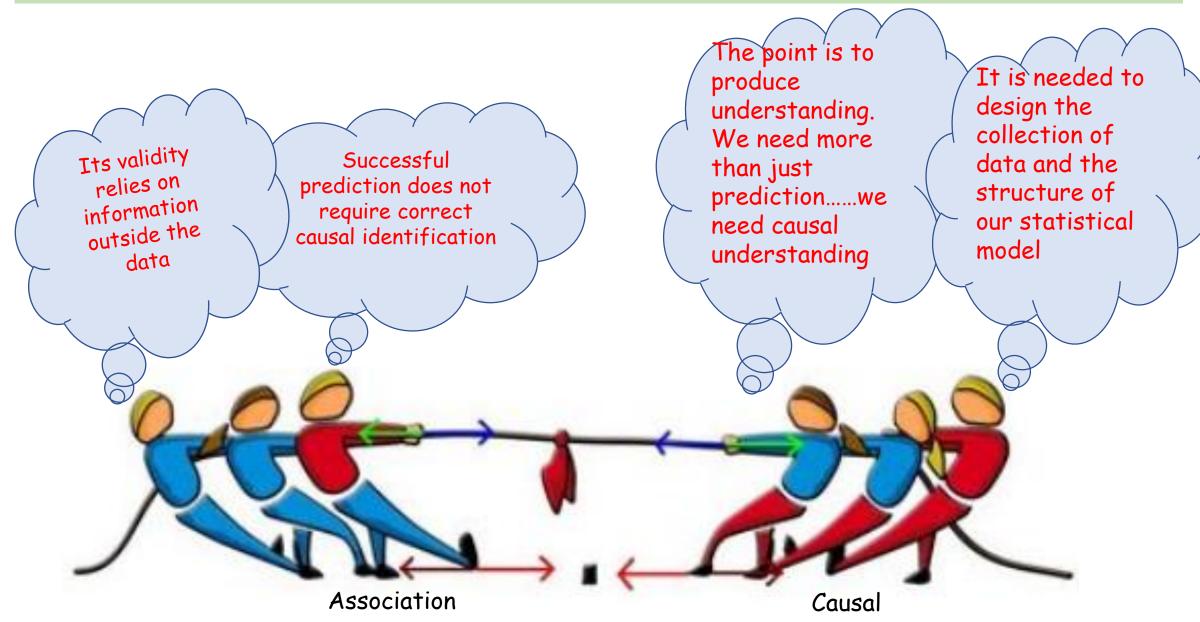
## Before a golem is born...



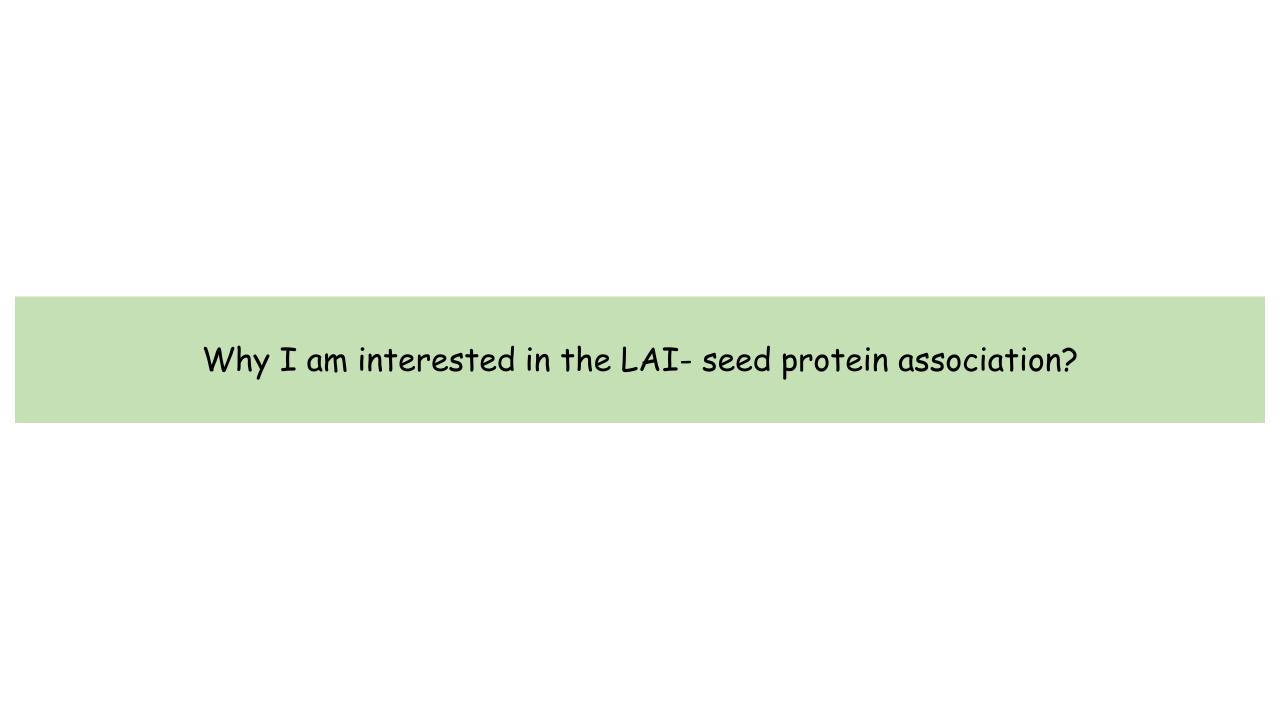
# Methods to distinguish between causal and association = Directed Acyclic Graph



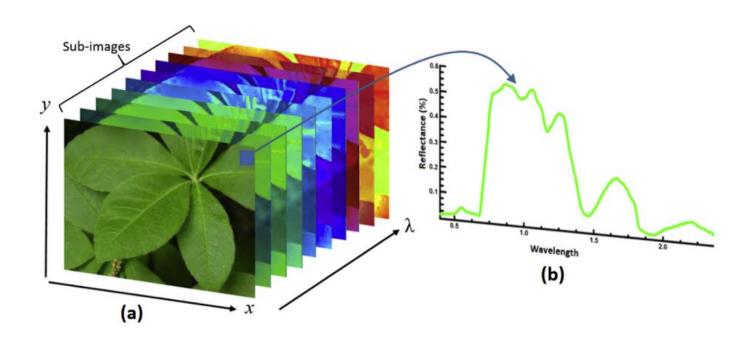
Can we use LAI for as a selection trait for soybean seed protein concentrations?

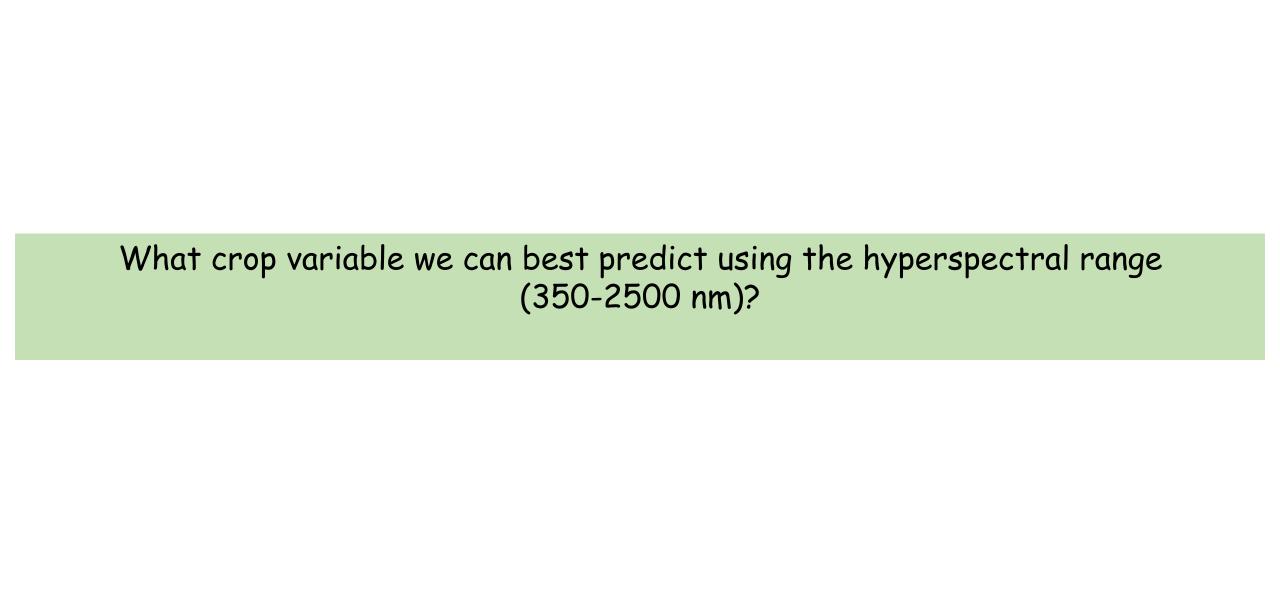
Is there a relationship between LAI and Protein Concentration?

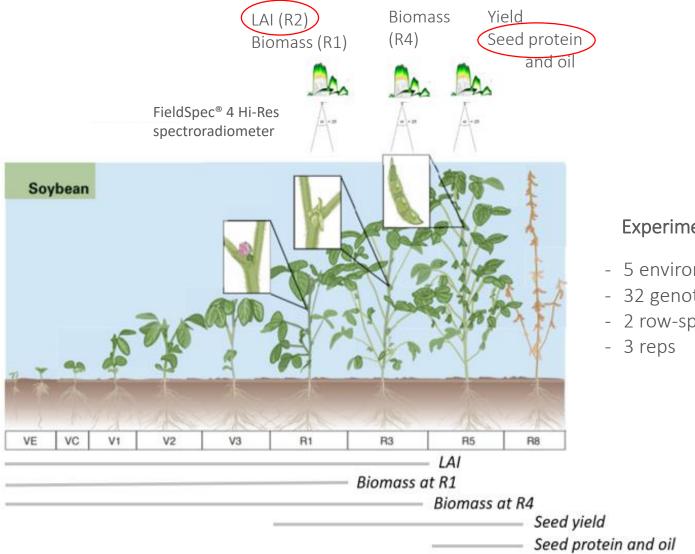
Is that relationship causal?



From a breeding perspective.......HI allows phenotyping in extensive areas in a faster, non-destructive, and more cost-effective manner compared to direct measurements.



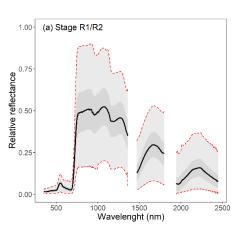


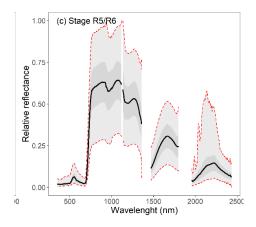


#### Experimental design

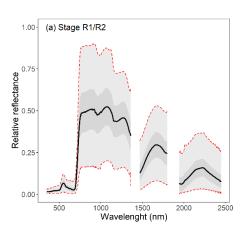
- 5 environments (yr./site)
- 32 genotypes
- 2 row-spacing (15 and 30 in)

#### Predictors

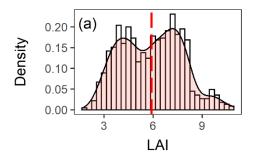


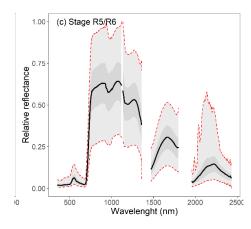


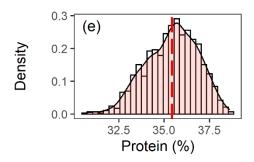
#### **Predictors**



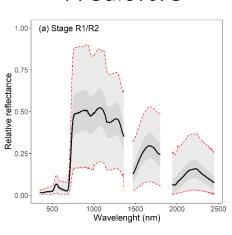
#### Observed variables



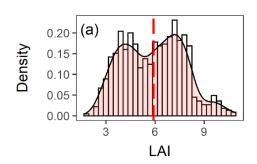


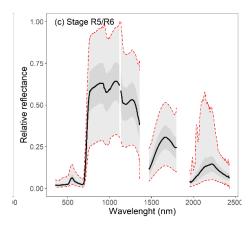


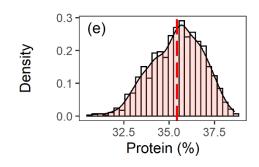
#### Predictors



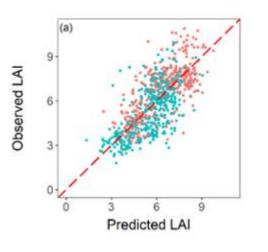
#### Observed variables



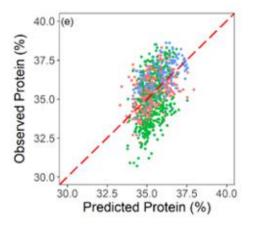




#### Predicted vs Observed values



ME= 0.5



ME= 0.2

Why I am interested in the LAI- seed protein association?

Because....LAI is the best variable we can extract from hyperspectral images and there is evidence of LAI and Protein % association

# Studying the total causal effect of the LAI on Protein concentration

A way of describing qualitative causal relations among variables:

DAGS = DIRECTED ACYCLIC GRAPH

DAGs in R.....

- dagitty: Graphical Analysis of Structural Causal Models
- ggdag: Analyze and Create Elegant Directed Acyclic Graphs is built on top of 'dagitty', makes it easy to tidy and plot 'dagitty' objects using 'ggplot2' and 'ggraph'

What variables to include or not include in the DAG......Here is the recipe:

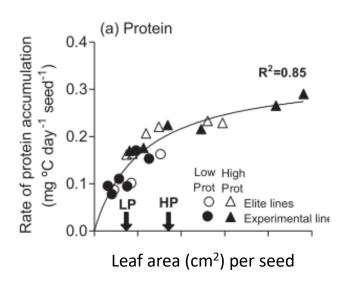
1. List all the paths connecting LAI (the potential cause of interest) and seed protein concentration (the outcome).

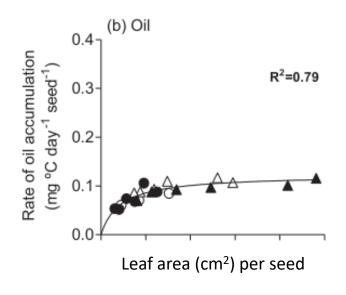
- 1. List all the paths connecting LAI (the potential cause of interest) and seed protein concentration (the outcome).
- 2. Classify each path by whether is open or close. A path is open unless it contains a collider.

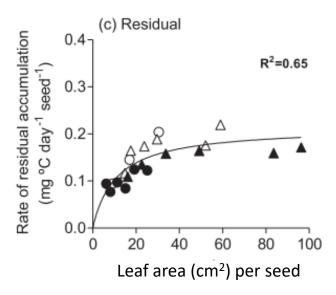
- 1. List all the paths connecting LAI (the potential cause of interest) and seed protein concentration (the outcome).
- 2. Classify each path by whether is open or close. A path is open unless it contains a collider.
- 3. Classify each path by whether it is a backdoor path. A backdoor path has an arrow entering LAI

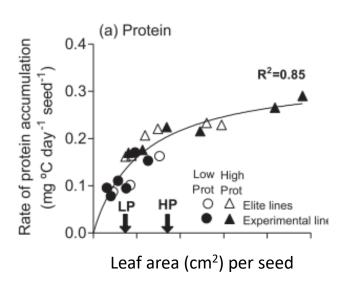
- 1. List all the paths connecting LAI (the potential cause of interest) and seed protein concentration (the outcome).
- 2. Classify each path by whether is open or close. A path is open unless it contains a collider.
- 3. Classify each path by whether it is a backdoor path. A backdoor path has an arrow entering LAI
- 4. If there are any open backdoor paths, decide which variable(s) to condition on to close it (if possible)

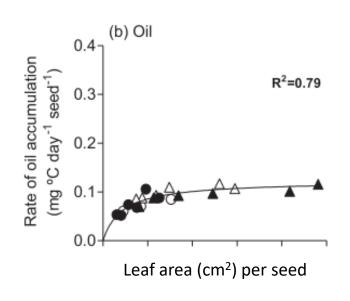
LAI per seed as a proxy for assimilates supply per seed.

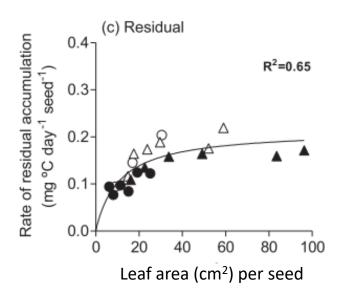






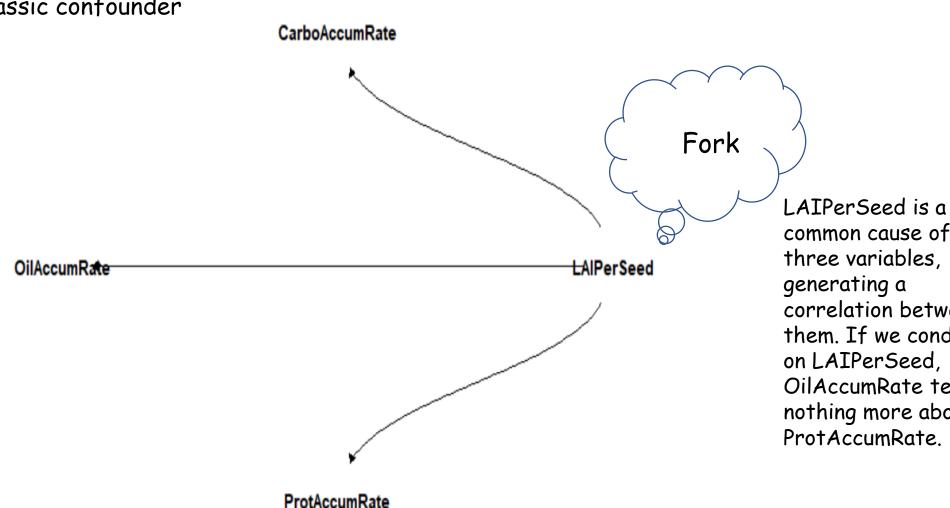






#### ggdag package

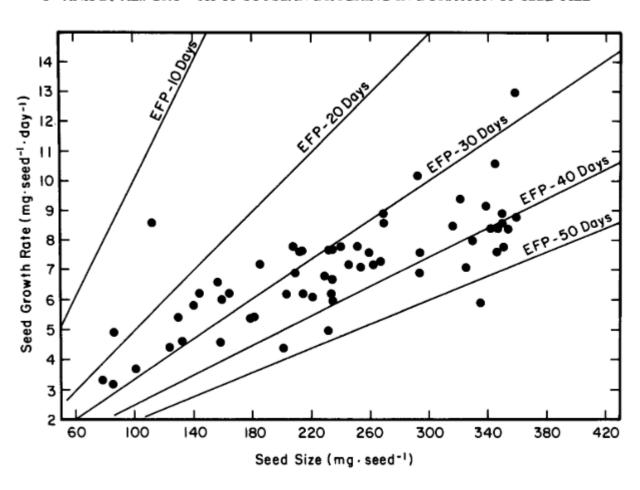
A fork is a classic confounder



common cause of three variables, generating a correlation between them. If we condition on LAIPerSeed, OilAccumRate tell us nothing more about ProtAccumRate.

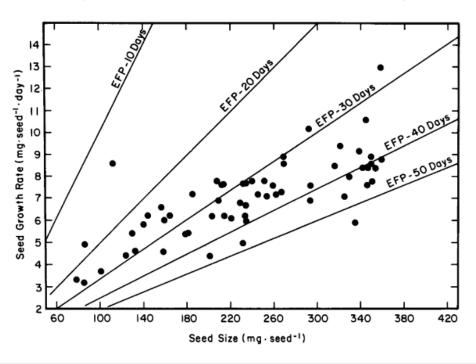
Content = rate x duration

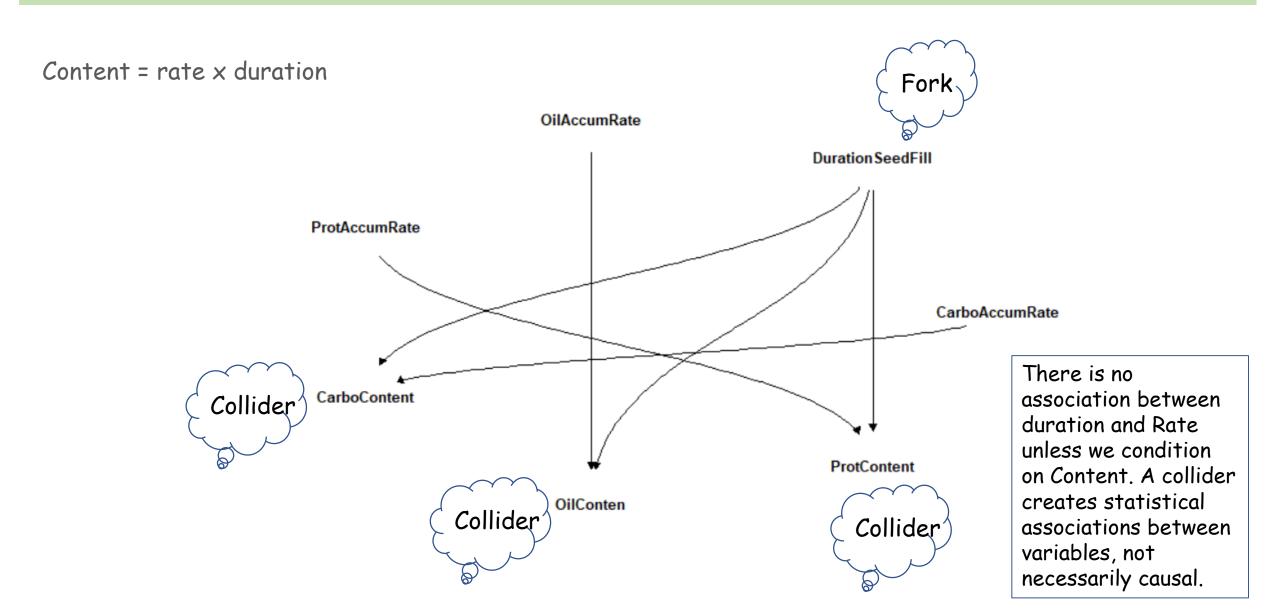
SWANK ET AL.: GROWTH OF SOYBEAN DIFFERING IN DURATION OF SEED FILL



SWANK ET AL.: GROWTH OF SOYBEAN DIFFERING IN DURATION OF SEED FILL







Concentration is a mathematical construct that relates the content of a particular component to the total weight of the seed (i.e. the sum of all components).

Protein Concentration (%) =

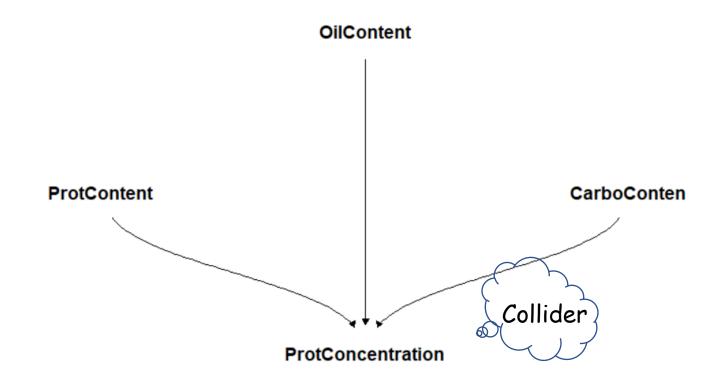
(mg protein/mg dry weight) \* 100

mg of Protein + Oil + Carbohydrates

```
small_dag3 <- dagify(ProtConcentration ~ CarboContent + ProtContent + OilContent,
exposure = "ProtContent",
outcome = "ProtConcentration")

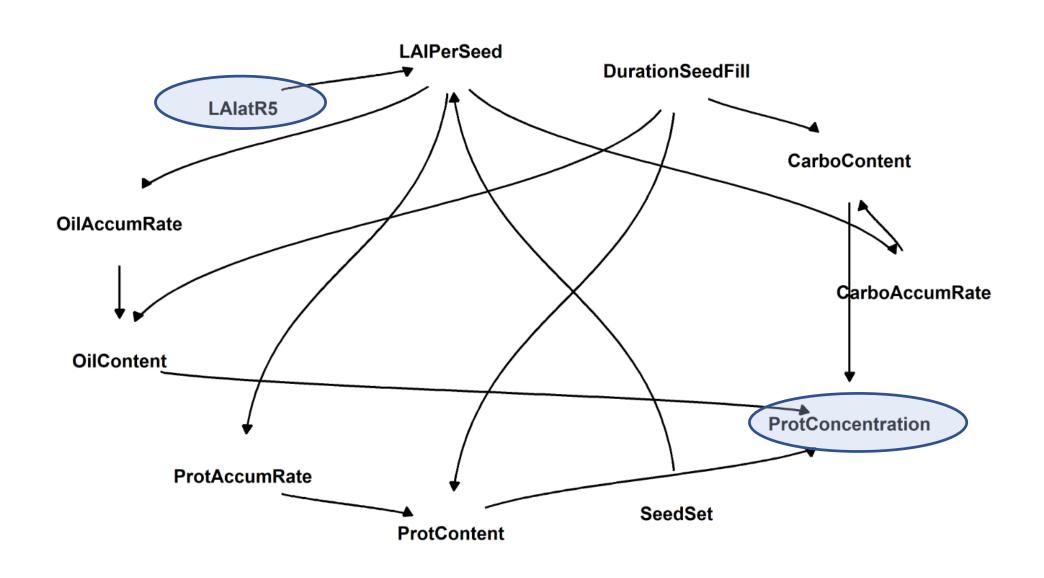
ggdag(small_dag3, layout = "circle", text_col = "black", node_size = 16, edge_type = "diagonal", node = FALSE, text_size
= 3.5)+
    theme_dag_blank()</pre>
```

Knowing protein concentration, then learning about Protein Content also give you information about Oil and Carbo Content. The same works in reverse

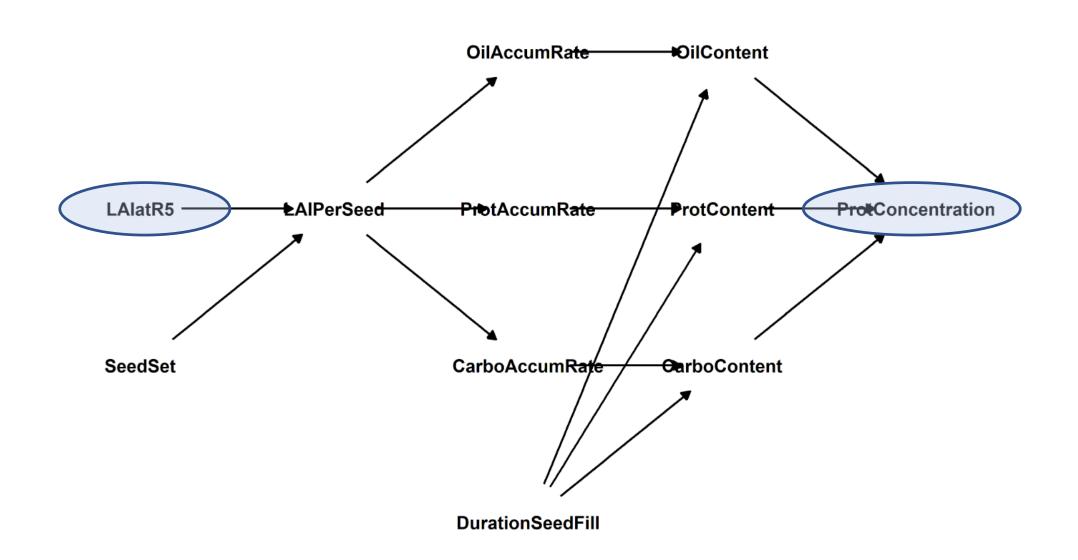


This is the reason for a negative association between ProtContent and OilContent

#### All paths together.....



```
# Modify the DAG format using coordinates
coords <- list(
  x = c(LAIatR5 = 1, SeedSet = 1, LAIPerSeed = 2, CarboAccumRate = 3, ProtAccumRate = 3, OilAccumRate = 3,
DurationSeedFill = 3, ProtContent = 4, OilContent = 4, CarboContent = 4, ProtConcentration = 5),
 y = c(SeedSet = -1, LAIatR5 = 0, LAIPerSeed = 0, ProtAccumRate = 0, OilAccumRate = 1, CarboAccumRate = -1, ProtContent
= 0, OilContent = 1, CarboContent = -1, DurationSeedFill = -2, ProtConcentration = 0)
coord df <- coords2df(coords)
coords2list(coord df)
bigger_dag2.2 <- dagify(ProtConcentration ~ CarboContent + ProtContent + OilContent,
                     CarboContent ~ CarboAccumRate + DurationSeedFill,
                     ProtContent ~ ProtAccumRate + DurationSeedFill,
                     OilContent ~ OilAccumRate + DurationSeedFill,
                     CarboAccumRate ~ LAIPerSeed.
                     ProtAccumRate ~ LAIPerSeed,
                     OilAccumRate ~ LAIPerSeed,
                     LAIPerSeed ~ LAIatR5 + SeedSet,
                     exposure = "LAIatR5",
                     outcome = "ProtConcentration")
coordinates(bigger_dag2.2) <- coords2list(coord_df)</pre>
ggdag(bigger_dag2.2, text_col = "black", text_size = 3.5, node = FALSE)+
 theme_dag_blank()+expand_plot()
ggsave("bigger_dag2.2.png", dpi = 500)
```



• Many potential predictor variables, why don't we add all of them?

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  - <u>Multicollinearity</u> = Strong association among predictor variables. None of the variables will be associated with the outcome. Ex = including both legs to predict height

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  - <u>Multicollinearity</u> = Strong association among predictor variables. None of the variables will be associated with the outcome. Ex = including both legs to predict height
  - <u>Post-treatment bias</u> = Included variables bias. Mistaken inference for including variables. Ex = including fungus and fungicide treatment to predict growth
  - <u>Collider bias</u> = When a variable is a common consequence of other variables. It generates statistical associations between the predictors. Ex = trustworthiness and newsworthiness influencing selection of proposals for funding.

Some variables are independent from others under certain conditions = Conditional Independencies

- Which variables should be associated (or not) with one another?
- Which variables become dis-associated when we condition on some other set of variables?

Some variables are independent from others under certain conditions = Conditional Independencies

- Which variables should be associated (or not) with one another.
- Which variables become dis-associated when we condition on some other set of variables.

Conditioning on a variable (Z) means learning its value and then asking if a variable X adds any additional information about Y.

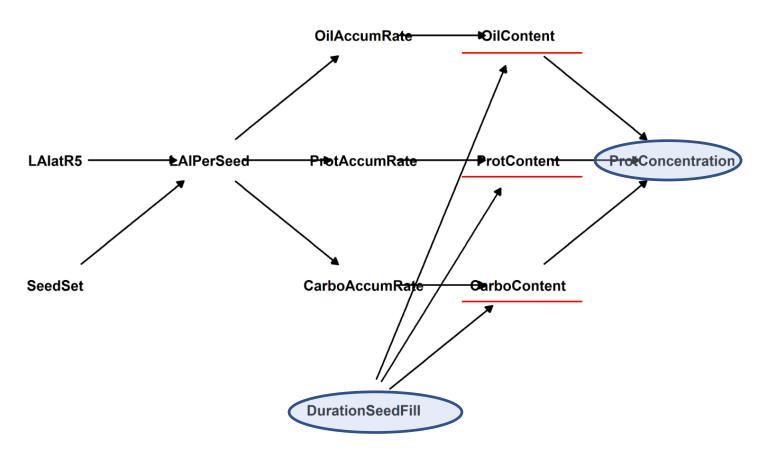
If I know the value of Z, should I include X in the model to know Y??



#### Examples.....

impliedConditionalIndependencies(bigger\_dag2)

 ${\tt DrSF} \ \_|\ |\_ \ {\tt PrtCnc} \ |\ {\tt CrbC}, \ {\tt OlCn}, \ {\tt PrtCnt}$ 



#### Examples.....

 $implied Conditional Independencies (bigger\_dag2)$ 

LAIR \_||\_ PrtCnc | CrAR, DrSF, OlCn, PrtCnt OilAccumRate **₩**ilContent LAlatR5 **Ł**AlPerSeed -PretAccumRate -ProtContent **Prot**Concentration CarboAccumRate OarboContent SeedSet

**DurationSeedFill** 

Shutting the backdoor: Blocking confounding paths between a predictor X and an outcome Y. We do not want spurious associations

Which path is open? All paths are open, unless they have a collider.

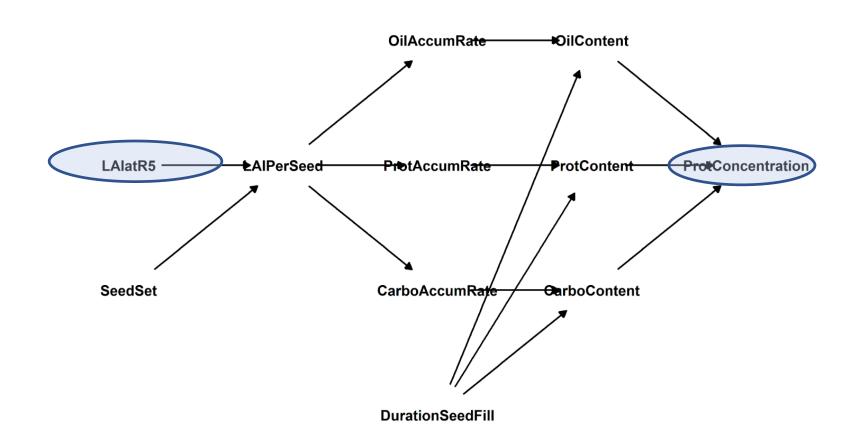
Analyze the graph and find the variables to control for in order to block the backdoor paths

```
adjustmentSets(bigger_dag2, exposure = "LAIatR5", outcome = "ProtConcentration")
```

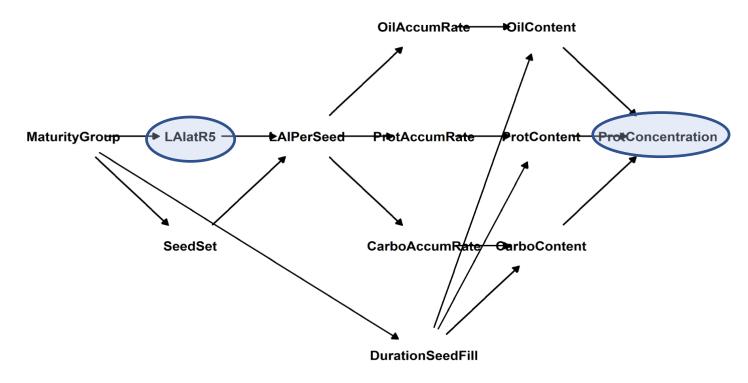
{}

No backdoor paths

- 1. List all the paths connecting LAI (the potential cause of interest) and seed protein concentration (the outcome).
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- 3. Classify each path by whether it is a backdoor path. A backdoor path has an arrow entering LAI



But, what if I include Maturity Group into the model......



adjustmentSets(bigger\_dag3)

```
{ DurationSeedFill, SeedSet } { MaturityGroup }
```