To adjust or not adjust, that is the question

Brice Ozenne

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Setting

In a medical studies, we often want to relate:

- an outcome Y — e.g. fMRI
- to an exposure variable E — e.g. SAD, season

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What should we do with the covariates?

- nothing
- stratification
- interaction
- ...

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To have more precise estimates/increase the power of the test:

- the PET signal varies across age groups

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Parsimony principle

Including covariates, how to decide?

- solution 1:
- solution 2:
- solution 3:

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- solution 1: intuition
- solution 2:
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- solution 1: intuition
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- solution 3: ask Santa

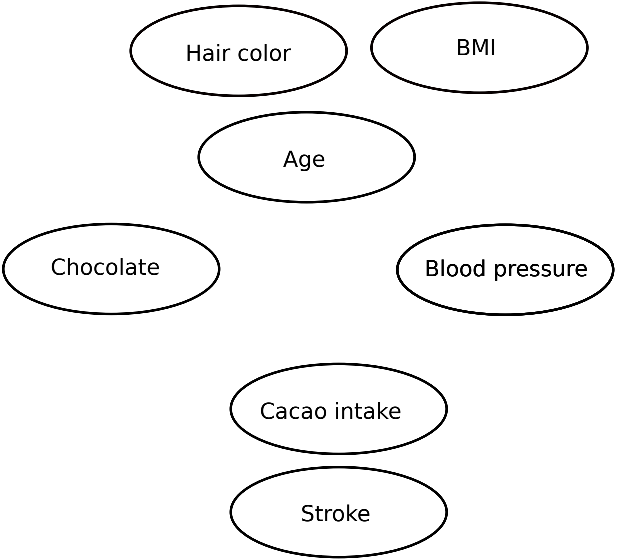
DAGs

Directed acyclic graphs (DAGs)

Graphical representation:

- of the variables that are being studied
- and their (causal) relationship
- in an ideal world where we could measure everything

Example of DAG with seven variables



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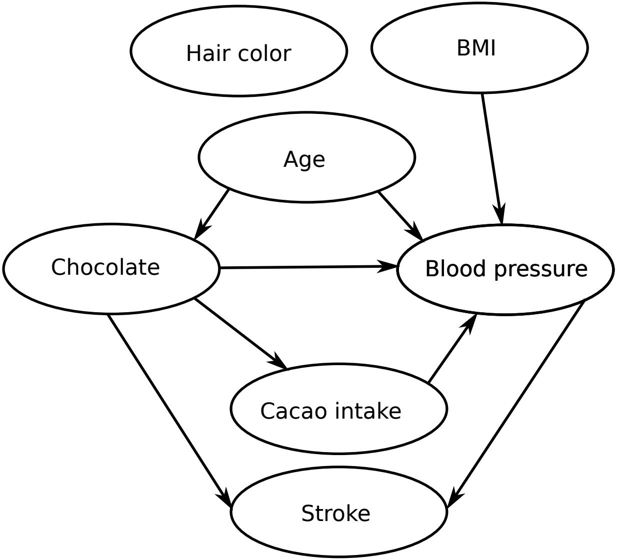
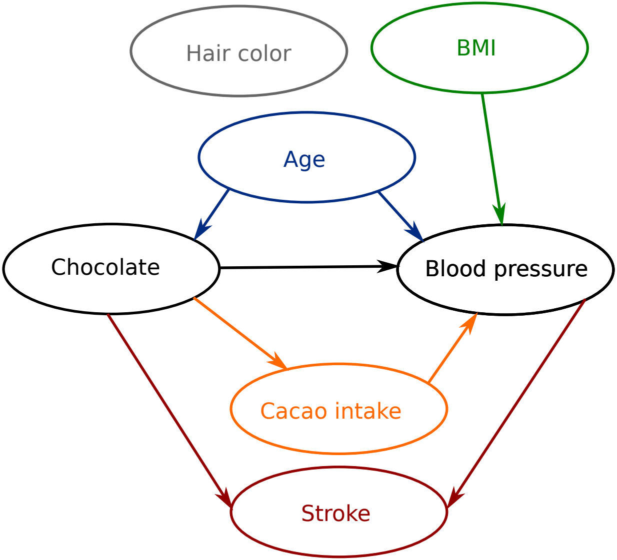


Causal DAGs

A causal DAG satisfies:

- lack of an arrow $\implies$ absence of direct causal effect
- any variable is a cause of its descendents
- all common causes (even unmeasured) are on the graph

Covariates as a structure in a DAG



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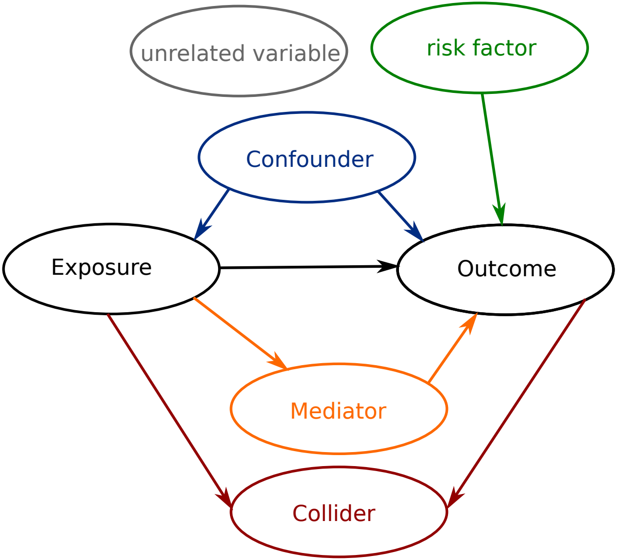


Including covariates, how to decide?

- unrelated variable: do not adjust (would decrease precision)
- risk factor: adjust (will increase precision)
- confounder: adjust (will reduce bias)
- mediator: it depends in what we are interested in
  (direct or total effect)
- collider: do not adjust (would increase bias)

A more general criteria (bias)

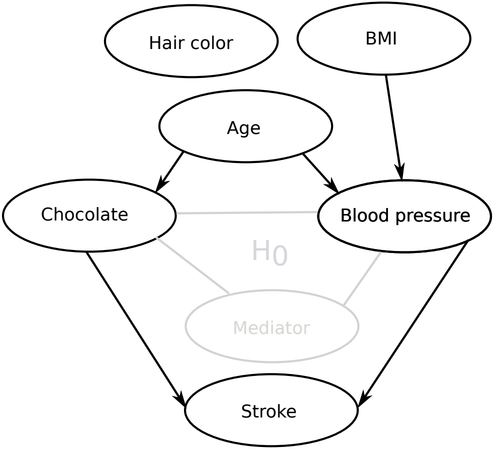
d-separation:

Two nodes Y and E are d-separated conditional on the node(s) X if every path between Y and E is blocked.

A path can be block if:

- it is a "colliding" path and does not intersect X
- it is not a "colliding" path and X it intersect X

Example - d-separation



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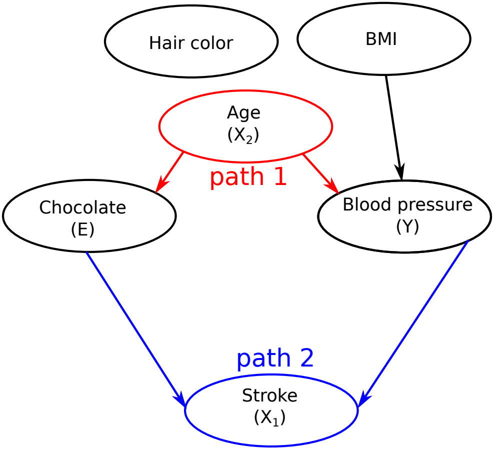

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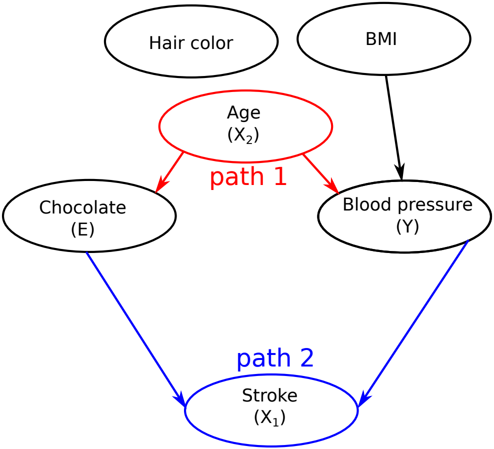

So we should adjust on Age and not on Stroke

Applications: Random assignment

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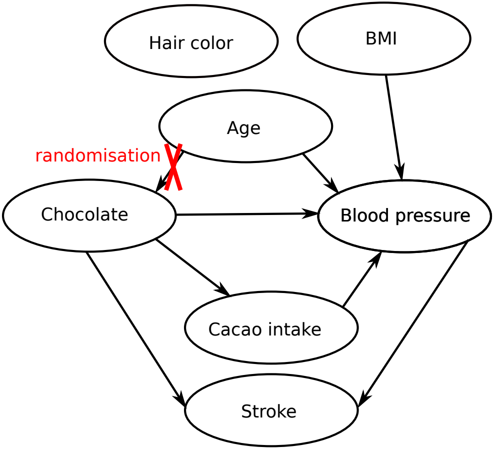
Remove the link with the parents of a node.

- no confounding possible
- unbiased if we don't condition on any variables



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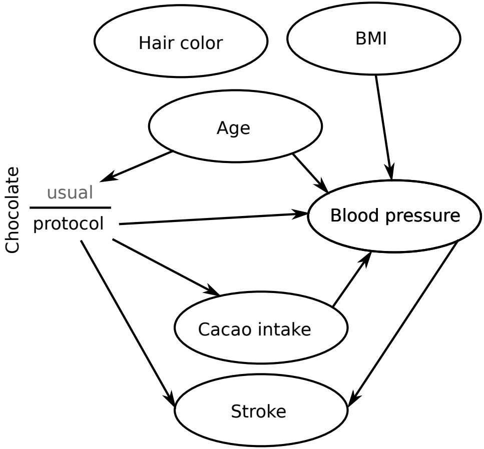

Applications: Selection bias

Study: relationship between coffee (E) and depression (Y)

- recrutement: volonteers

Fictitious world:

- being a researcher makes you drink more coffee an be more curious compared to other job (not the other way around)
- no relationship being researcher and depression
- your relatives influence your likelihood to be depressed and your interest in depression
- no relationship being coffee and depression
- main reasons for joining the study are curiosity and interested in depression

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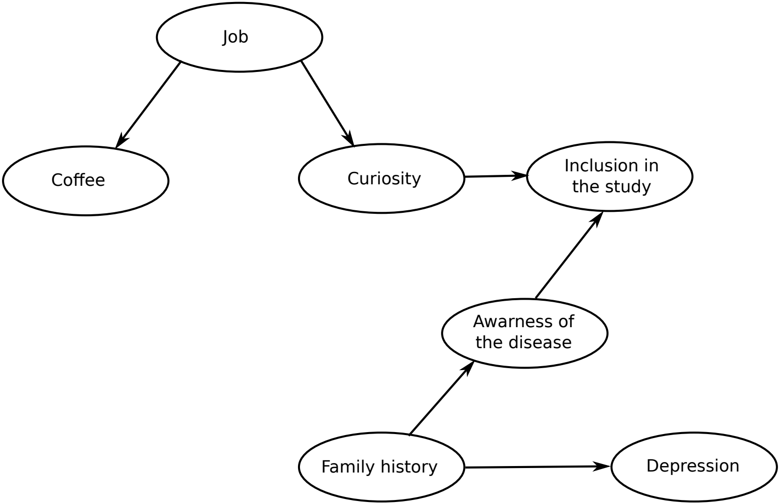

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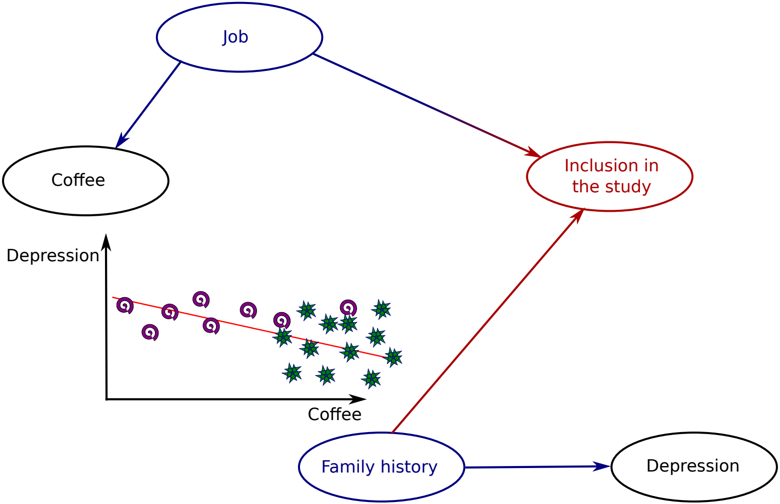

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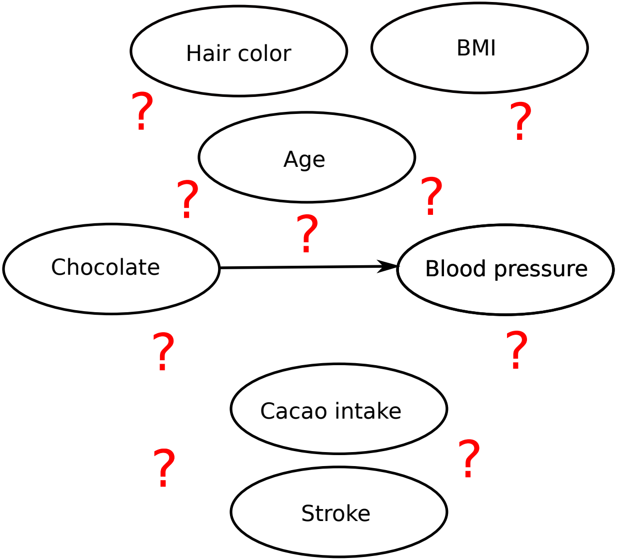
Limitations of DAGs:

- not well suited for displaying interactions
- difficult to do by hand when the number of variables is large
- require prior knowledge

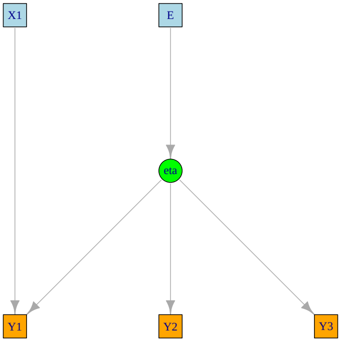
DAGs in practice (pessimistic view?)



DAGs and latent variable models

LVM as a DAGs

```
library(lava)
m <- lvm(c(Y1,Y2,Y3)~ eta, Y1 ~ X1, eta ~ E)
latent(m) <- ~eta
plot(m, plot.engine = "igraph")
```



Latent variable models

Latent variable models can be describe using path diagrams

- similar to DAGs, but can include covariance links

Can help you to decide on the presence/absence of an arrow

- but not on its direction
- and only if you enough power for the corresponding test

i.e. don't expect to identify the graph with n=10

Data-driven definition of the graph

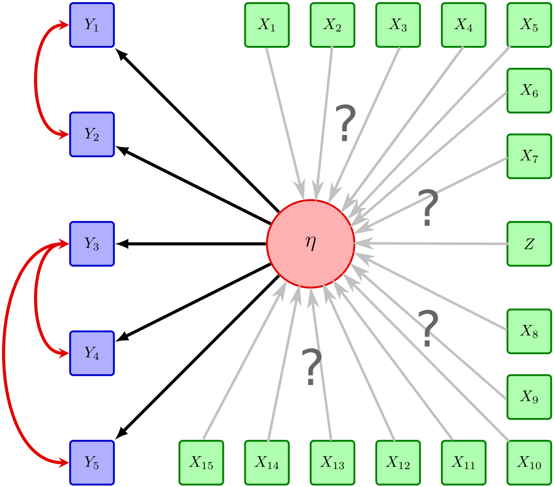
Functions `modelsearch` in lava under assumptions:

- linearity of the association
- Gaussian distribution

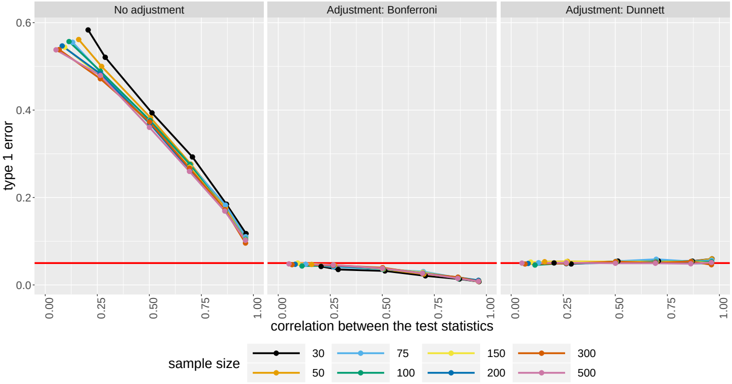
Testing several arrows requires ajustment for multiple comparisions:

- function `modelsearch2` in lava
- paper ready for submission!

(in short) Results: setting



(in short) Results: type 1 error



(in short) Results: power