Introduction to structural equation modelling - advanced modelling techniques

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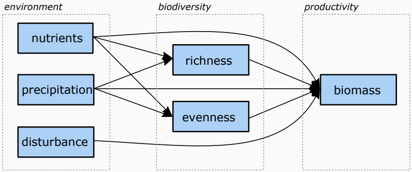
Overview

- Advanced SEM topics covered today:
    - Latent variables
    - Composite variables
    - Interactions
    - Complex survey designs

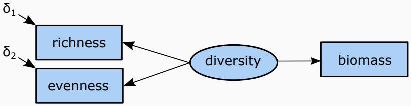
Revisiting the meta-model



- Meta-model are conceptual models that allow to link data with theory.
- So far, we have only worked with manifest (measured) variables.
- However, some aspects of a meta-model may be difficult to quantify and measure directly.
- This is because they represent an abstract, multifaceted concept (e.g., general intelligence).
- This is where latent and composite variables are needed.

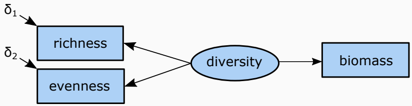
Latent variables

Latent variables



- Latent variables are unobserved, but their influence is captured by indicator variable(s).
- Graphically, latent variables are often represented by an oval node shapes (ellipses).
- Direction of causality reversed: from latent variables to the observed variables (reflective indicators).

Latent variables



- Indicator variables are emergent manifestation of the underlying phenomenon represented by the latent variable.
- All indicators should be positively correlated to the latent variable (i.e., driver).
- In contrast to indicators, latent variables are free of random or systematic measurement errors.

Latent variables

- Latents can be both endogenous and exogenous.
- *Measurement model* focuses solely on relating indicators to latent variables.
- *Structural model* is one with directed paths between latent variables.

Latent variables

Latents often fitted in two steps:

1) Confirmatory factor analysis

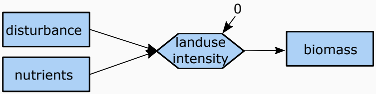
   - Multi-indicator latent variables test hypothesis that multiple indicator variables are generated by the same underlying process.
   - Precursor to evaluation of any structural models in which the latent variables appear.

2) Full model including latent variable

   - To estimate effect of latent variable on other variables.

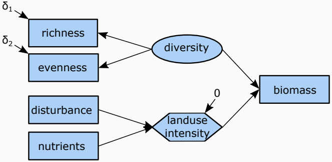
Composite variables

Composite variables



- Composite variables specify the influence of collections of variables (e.g., land use).
- In comparison to latent variables, composites arise from the indicators.
- They are visualized by arrows pointing from the indicators to the composite (formative or causal indicators).
- Values are determined by its causes (indicators), thus error variance is set to 0.
- Composites are shown as hexangular shapes.

Key differences between latent and composite variables



- Flow of causation in a latent variables is from the construct to its indicators, i.e., indicators are driven by an underlying, unmeasured process.
- As a latent variable represents an underlying, data-generating process, its indicators need to be correlated to each other.
- For composite variables, the flow of causation is reversed and the indicators are independent entities.
- In the case of a composite variable, there is no assumption about the relation between the indicators.

Key differences between latent and composite variables

How distinguish latent and composites:

- Rule of thumb 1: if the indicators are redundant, they likely belong to a latent variable.
- Rule of thumb 2: If the meaning of the construct changes after dropping one of the indicators, the construct likely is a composite.

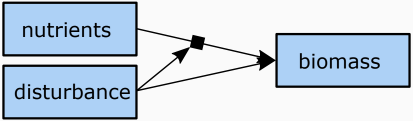
Exercise

Exercise:

- Revisit the meta-model you have drawn yesterday:
    - Which contructs could be modelled with a latent or composite variable?
    - Adapt your meta-model accordingly.

Interactions

Interactions



- In nature, things often are contingent on each other.
- For instance, the effect of nutrients on plant growth, may depend on how disturbed the environment is.
- Such a behaviour is called an interaction, which indicates that the effect of the two main effects are different when combined.
- Both positive and negative interactions are possible.
- In regression, the interaction is represented by a coefficient that estimates the effect of the product of the two predictors.

Interactions

Interactions can be modelled in different ways in lavaan:

1) Multiple groups
2) Composites

Interactions (multi group)

```
mod <- sem(model, group = "age_class", data = dd)
```

- Multigroup fitting allows coefficients to vary among groups.
- Lavaan offers the “group” argument to specify for which groups coefficients should be estimated.
- Importantly, groups have to be categorical (e.g., sex, age class).

Lavaan allows to introduce equality constraints on various aspects via the `group.equal` argument:

```
mod <- sem(model, group = "age_class", group.equal =
c("regressions"), data = dd)
```

Additional constraints could be:

```
group.equal=c(
"intercepts",
"means",
"regressions",
"residuals",
"residual.covariances")
```

Interactions (multi group)

- Even more control by having the same name for different parameters:

```
model <- '
y ~ c("b1", "b1") * x1 + c("b2", "b2") * x3
x2 ~ c("b3", "b4") * x1
x3 ~ c("b5", "b5") * x2
'
```

Same coefficients for all but the effect of x1 on x2.

Heywood cases: when things go wrong

Heywood cases : when things go wrong

- Improper solutions:
  - Negative variances
  - Correlations larger than 1
- Reasons for the warnings can be:
  1) Slightly negative error estimates (not really a problem)
  2) Indicators for latent variables need to be positively correlated
  3) Local non-identification
  4) General model misspecification

Complex sampling structure

Complex sampling structure

- Needed when data is nested, e.g.,
    - Within sites.
    - Within groups such as families, nests.
- Nesting violates the principle of independent and identically distributed observations.
- Necessary to account for this structure in the data in the model.

Complex sampling structure

```
library("lavaan.survey")
```

- The add-on package lavaan.survey allows the analysis of stratified, clustered or weighted data.
- Lavaan objects are processed with a specific data structure:
    1) Initialize the design
    2) Post-process the lavaan object and compute the adjusted results.
    3) Corrected lavaan object as result.

Complex sampling structure

```
design <- svydesign(ids = ~ plot, strata = ~ field,
nest = TRUE, data = dat)
summary(design)

fit.nested <- lavaan.survey(lavaan.fit = model,
survey.design = design)
```

- Needed to specify the study design
- Here we have plots (`ids`) nested in fields (`strata`)
- Next, we can refit the `simple` model from before with `lavaan.survey` using the specified study design as an argument.

Questions?

Live coding session

Your turn: working with the Seabloom dataset

Exercise 1

Start with the following model:

```
library("lavaan")

simple <-
"mass.above ~ nadd + disk + rich + even + precip.mm
rich ~ nadd + precip.mm
even ~ nadd + precip.mm

rich ~~ even"

fit.simple <- sem(simple, data = seabloom, estimator = "MLM")
summary(fit.simple)
```

- Construct latent variable diversity based on richness, evenness and ens.pie:
  - Run confirmatory factor analysis
  - What do you conclude?

Exercise 3

- Construct latent variable diversity only based on richness and evenness:
    - Run confirmatory factor analysis
    - Include latent variable into full model
    - What do you conclude?

Exercise 4

- Construct composite variable landuse based on nutrients and disturbance (disk):
    - What do you conclude?
    - Build composite manually.

Exercise 5

- Investigate possible interaction between disturbance and nutrient addition on AGB:
    - Construct composite variable to capture a possible interaction:
    - What do you conclude?
    - Incorporate composite into full model

Exercise 6

- Investigate possible interaction between disturbance and nutrient addition on AGB:
    - Use multi-group fitting to explore interaction.
    - What do you conclude?

Exercise 7

- Account for nested experimental design with the `lavaan.survey` package:
    - Add individual plots nested in fields.