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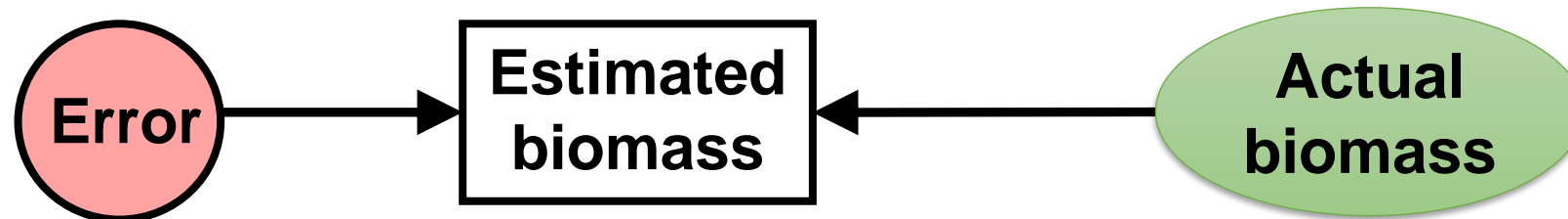
# Introduction to structural equation modeling and mixed models in

## **Day 5 – Part 2: SEM**

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- Latent Variables in SEM



## **Latent Variables in SEM**

- What are Latent Variables? Why to use them?
- Multi-indicator Latent Variables
- Fitting Latent Variables  
(Confirmatory Factor Analysis)

## **Latent Variables in SEM**

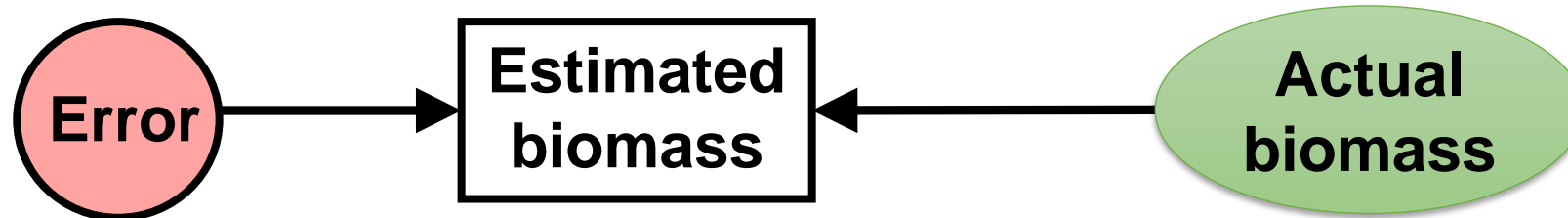
- **What are Latent Variables? Why to use them?**
- Multi-indicator Latent Variables
- Fitting Latent Variables  
(Confirmatory Factor Analysis)

# What is Latent Variable?

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**Latent** – hypothetical, hidden

- a variable that is **unmeasured**, but is **hypothesized to exist**
- scientific concept that is **not directly observed**, but is hypothetical **construct**
- can be **approximated using observable indicators**

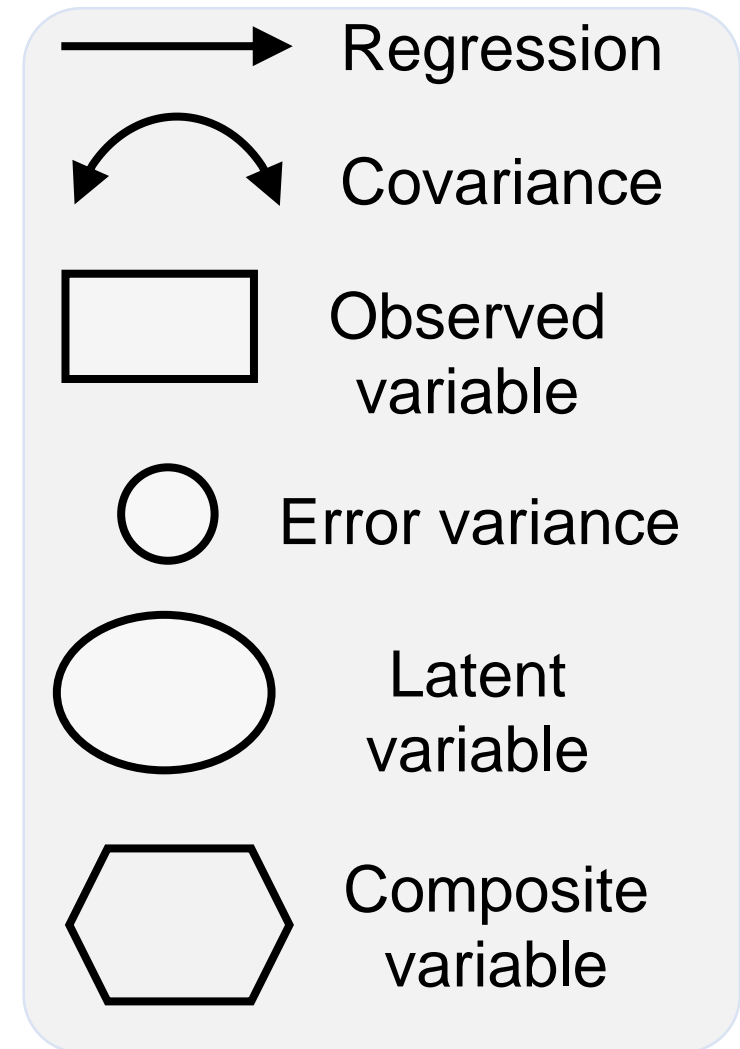


# What is Latent Variable?

## Specification operators in 'lavaan'

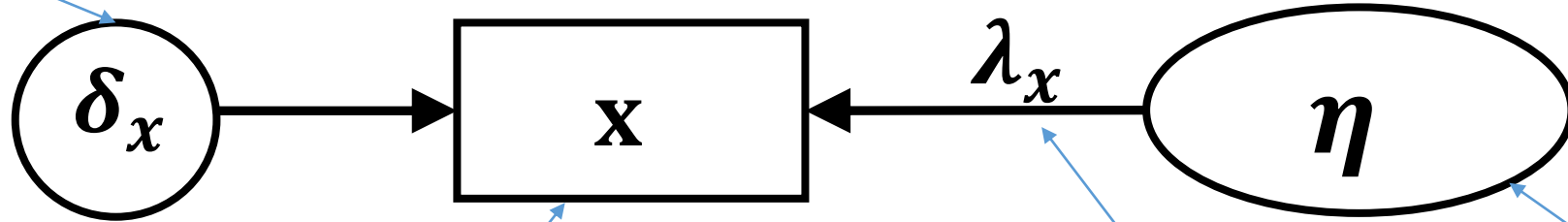
formula type	operator	meaning
Regression	~	"regressed on"
Correlation	~~	"correlated with"
Intercept	~ 1	"estimates intercept"
Latent variable	=~	"is measured by"
Composite	<~	"is caused by"

## Path Diagram Notations:



# What is Latent Variable?

The error in the measurement of  $x$  by  $\eta$



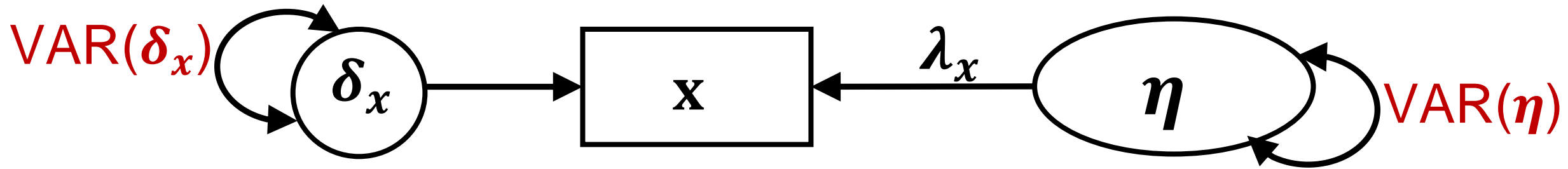
Observed variable  
“manifest indicator”

“factors” or “latent traits”

The relationship between a latent variable and its observed indicator

Latent variable

# What is Latent Variable?



$$\mathbf{x} = \lambda_x \eta + \delta_x$$

$$\eta \sim N(0, \text{SD}(\eta))$$

$$\delta \sim N(0, \text{SD}(\delta))$$

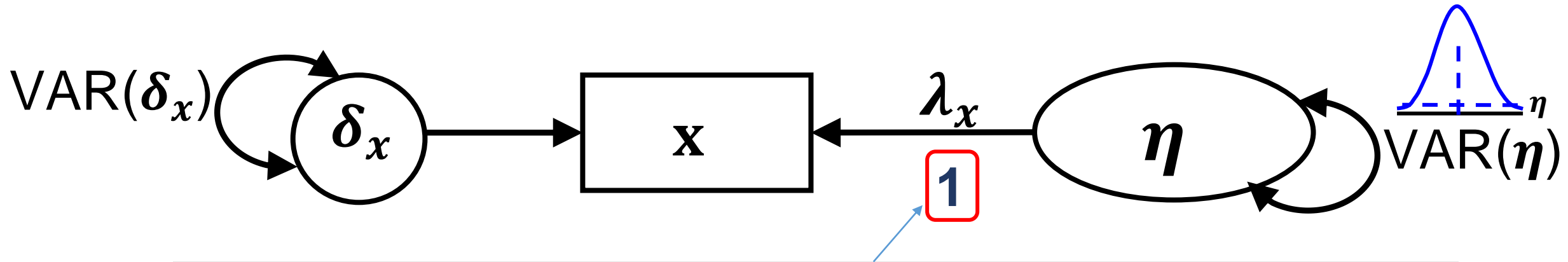
$$\text{VAR}(\mathbf{x}) = \lambda_x^2 \text{VAR}(\eta) + \text{VAR}(\delta)$$

How much variance does the LV explain?

$$\frac{\lambda_x^2 \text{VAR}(\eta)}{\lambda_x^2 \text{VAR}(\eta) + \text{VAR}(\delta)}$$



# What is Latent Variable?



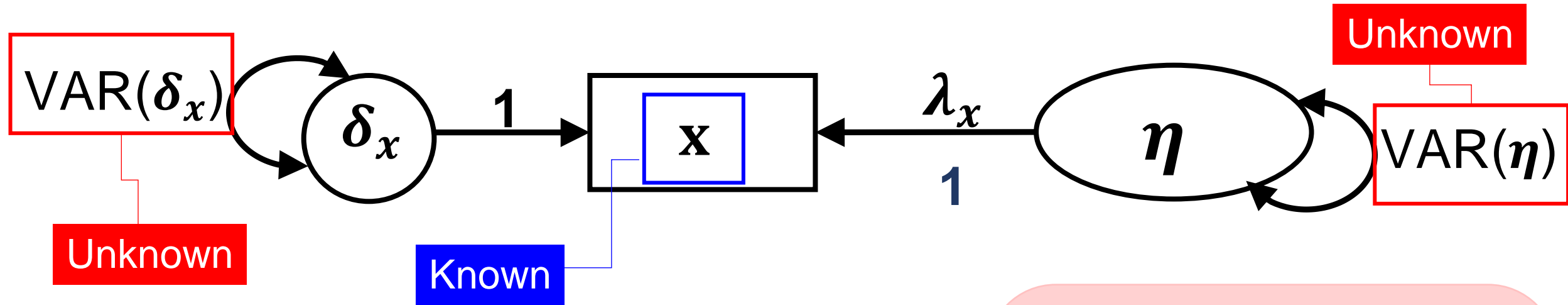
Raw scale coefficient: matches observed (co)variances to parameters  $\text{VAR}(\delta)$  and  $\text{VAR}(\eta)$

**We explain the data well if:**

$$\text{VAR}(\mathbf{x}) = \text{VAR}(\eta) + \text{VAR}(\delta)$$

- What is the scale/unit of our LV?  
It needs to be defined to get the regression weights.

# What is Latent Variable?



$$\text{DF} = t_{\max} - t = -1$$

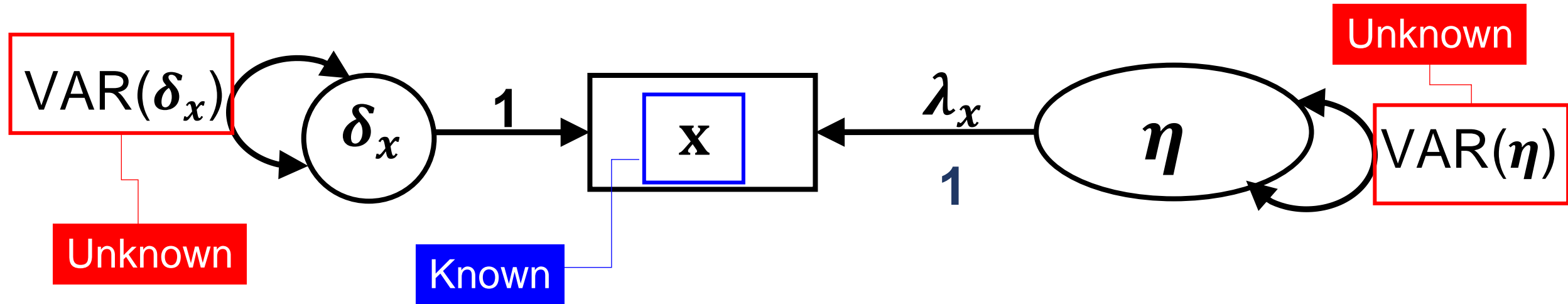
- Model is not identified

$$t \leq t_{\max}$$
$$t_{\max} = \frac{s(s+1)}{2} = 1$$

$s = 1$  known

$t = 2$  unknowns

# What is Latent Variable?



## Rules for LV models:

- Scaling of LV
- Non-negative DF

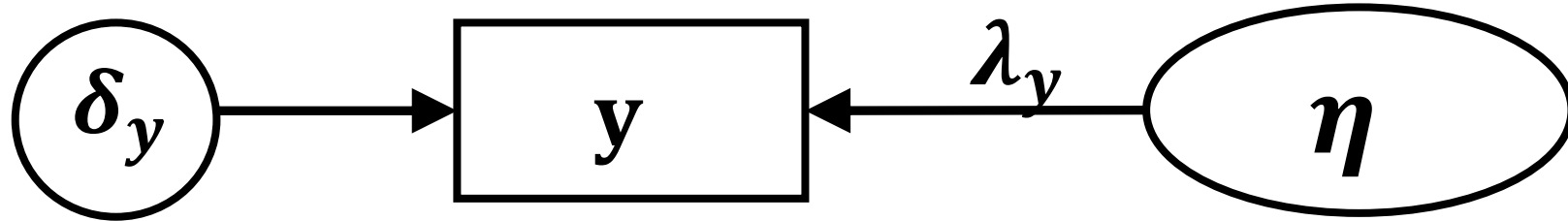


## We need at least:

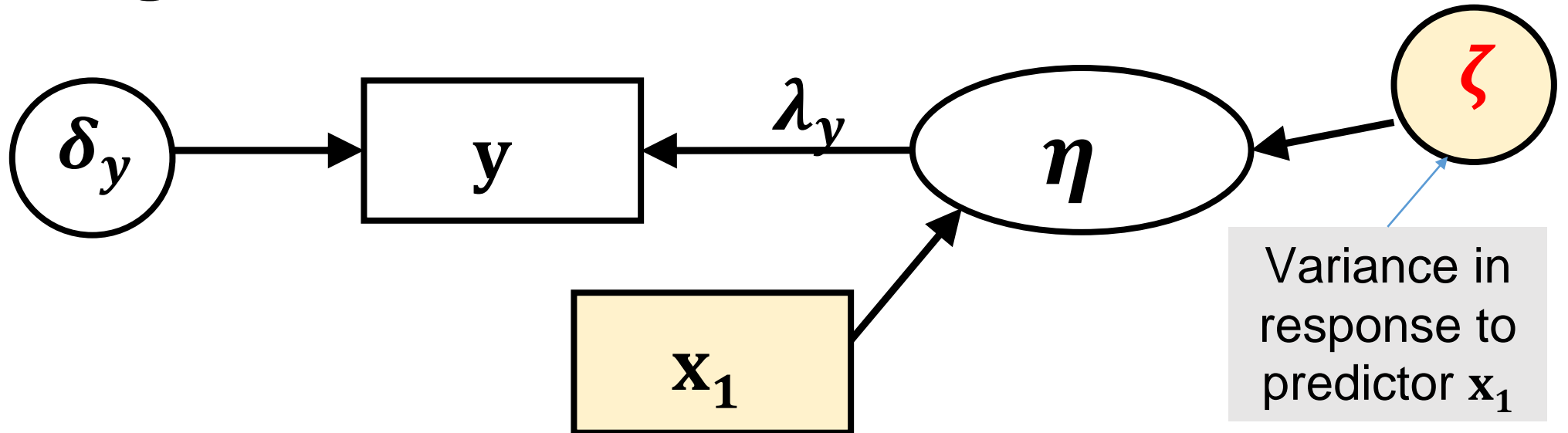
- 3 indicators for a single LV
- 2 indicators per LV for models with multiple (correlated) LVs

# What is Latent Variable?

## Latent **Exogenous** Variable



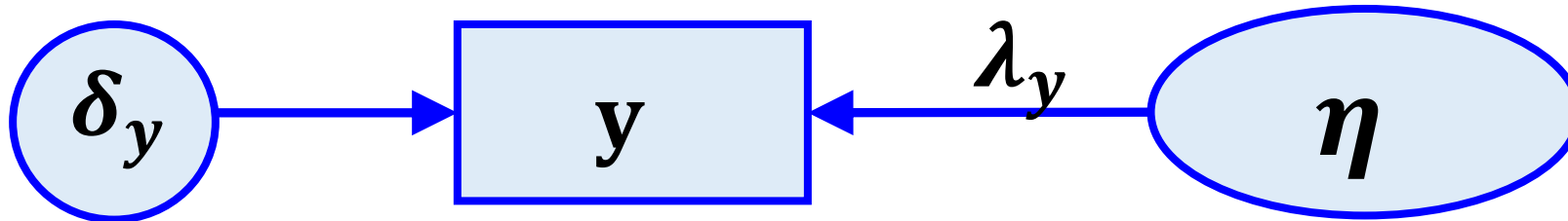
## Latent **Endogenous** Variable



# What is Latent Variable?

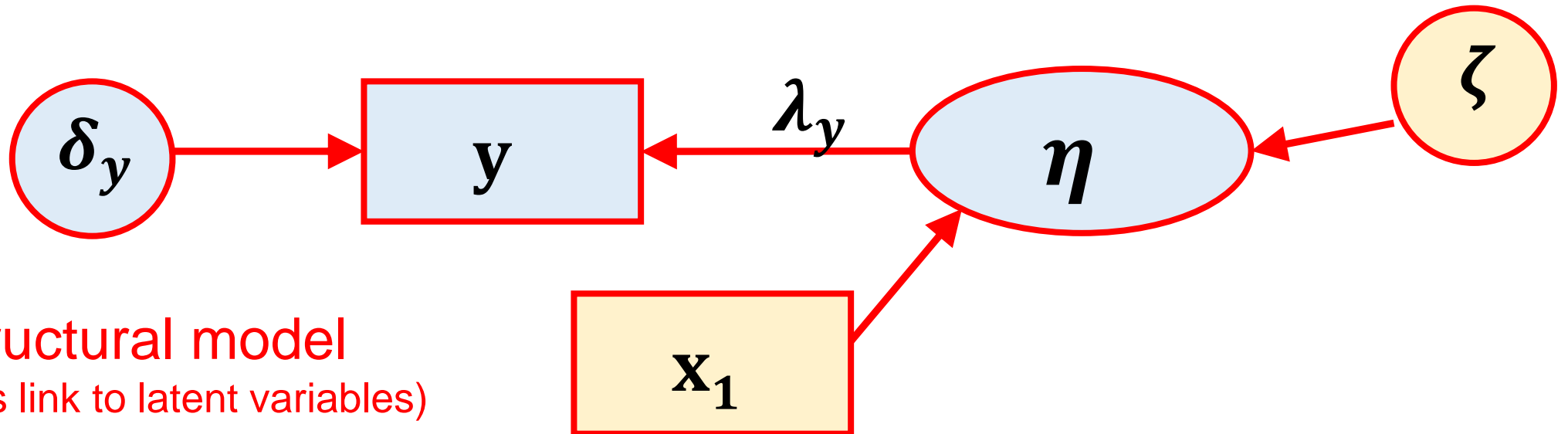
## Measurement model

(solely relates indicators to latent variables)

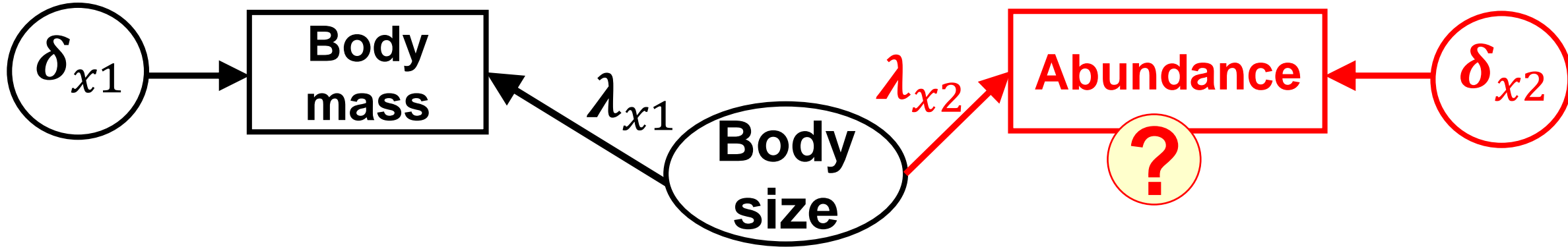


## Structural model

(has link to latent variables)



# Latent Variables



- Be sure that the latent variable reflects the actual properties captured by the indicator variables!

# Why use Latent Variables?

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- Allows estimating complex and **multifaceted concepts**
- **Reduces random error** in construct (latent variable)

random error in dependent variables  
→ less precisely measured estimates

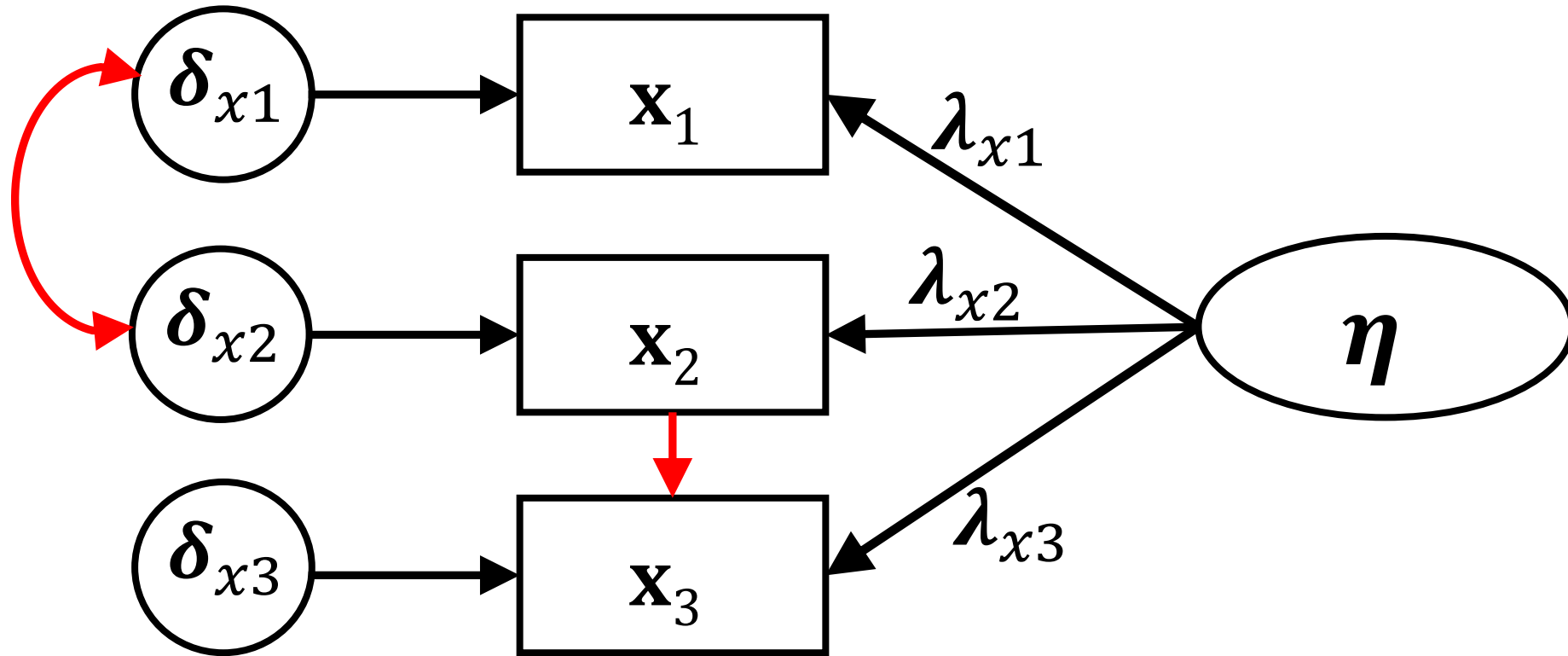
random error in independent variables  
→ underestimated regression coefficients

## **Latent Variables in SEM**

- What are Latent Variables? Why to use them?
- **Multi-indicator Latent Variables**
- Fitting Latent Variables  
(Confirmatory Factor Analysis)



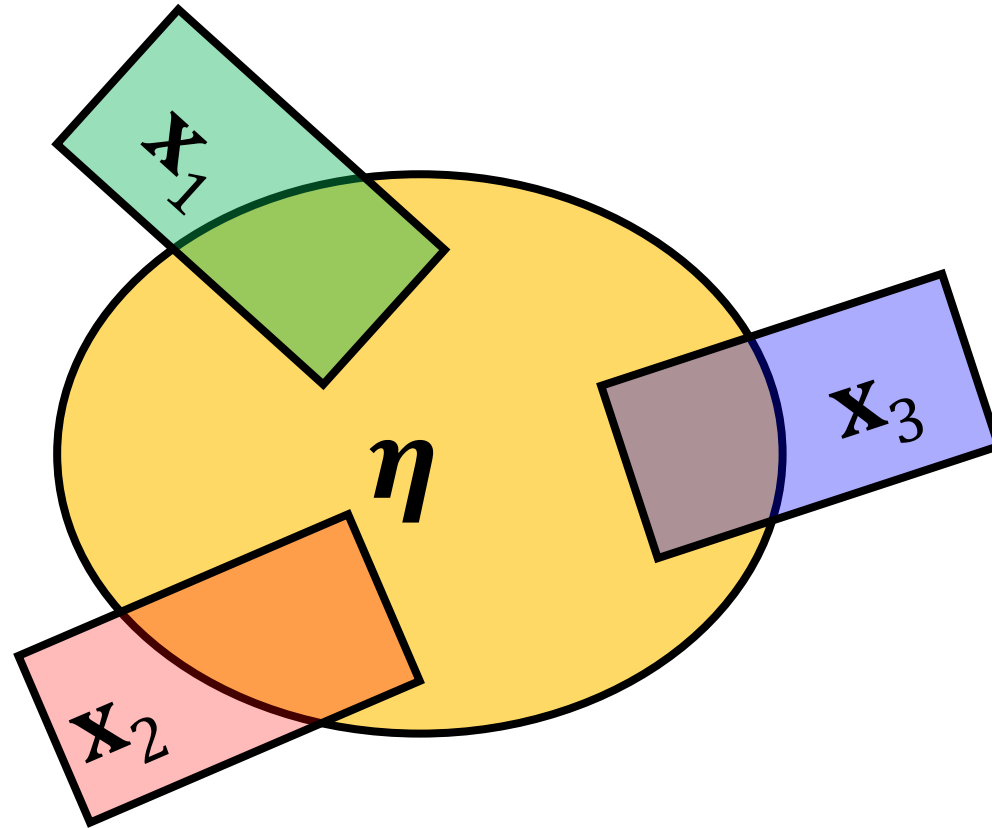
# Multi-indicator Latent Variables



- Indicators may have causal links
- Indicators may covary for other reasons

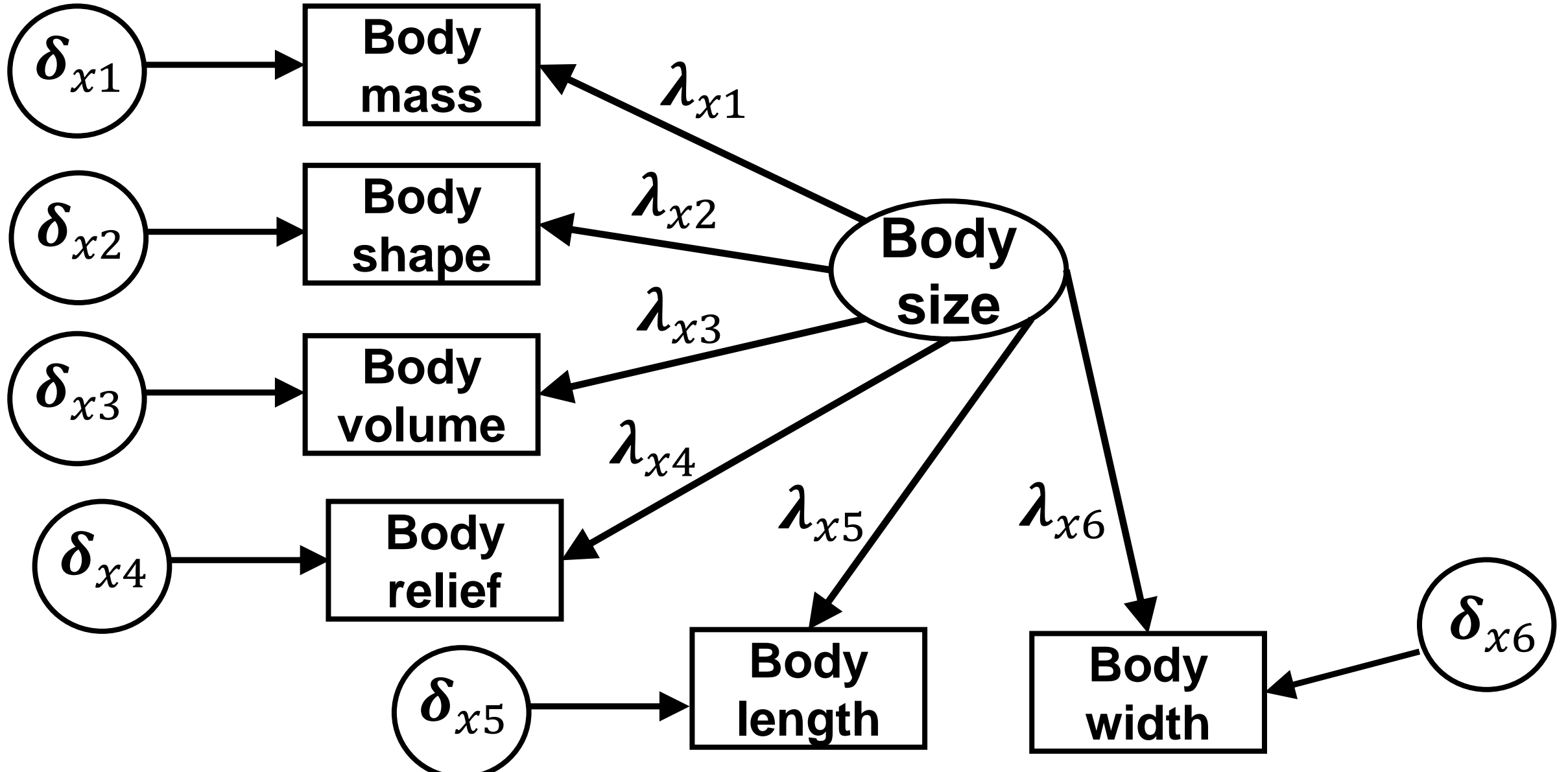
# Multi-indicator Latent Variables

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Latent variable  $\eta$  represents shared information of observed indicators  $\mathbf{x}$

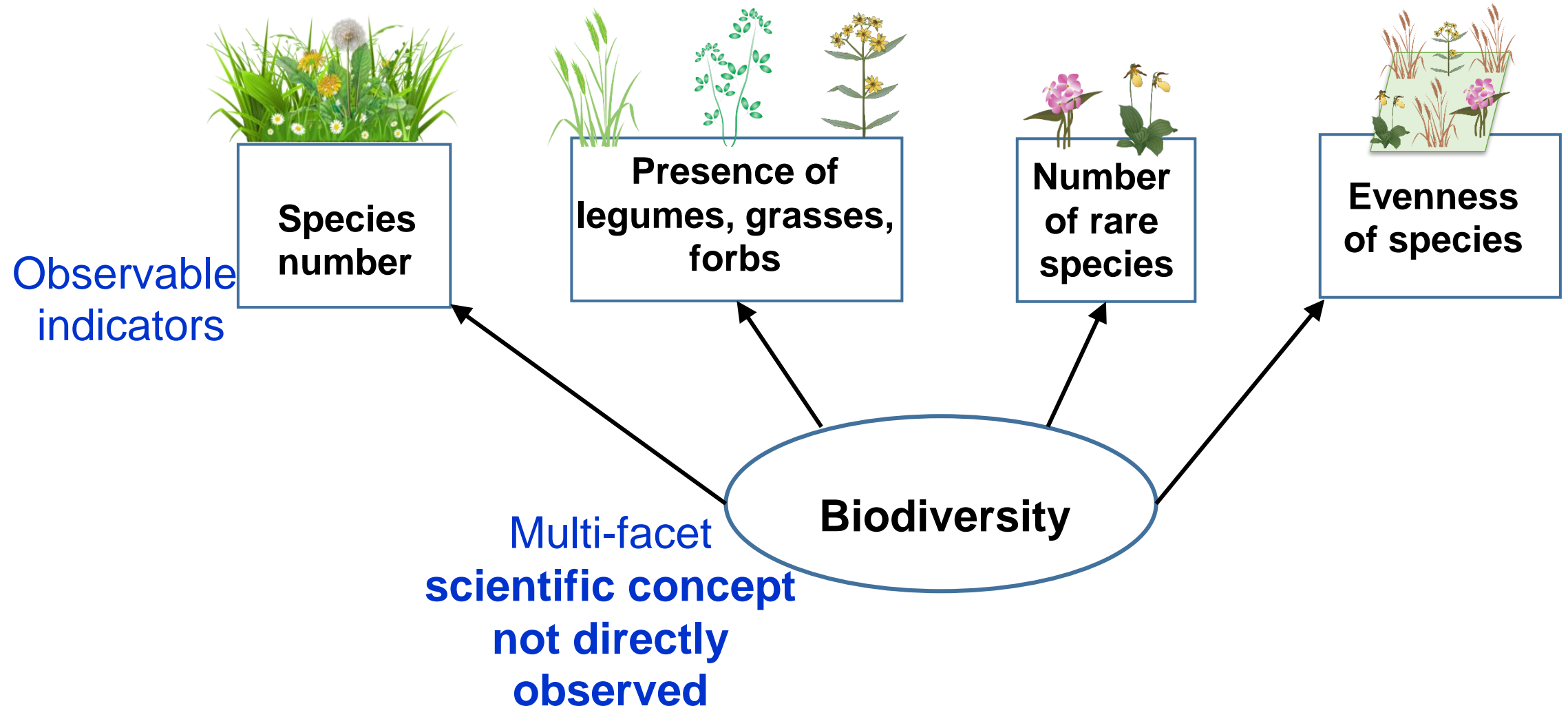
# Multi-indicator Latent Variables



# What is Latent Variable?

Example

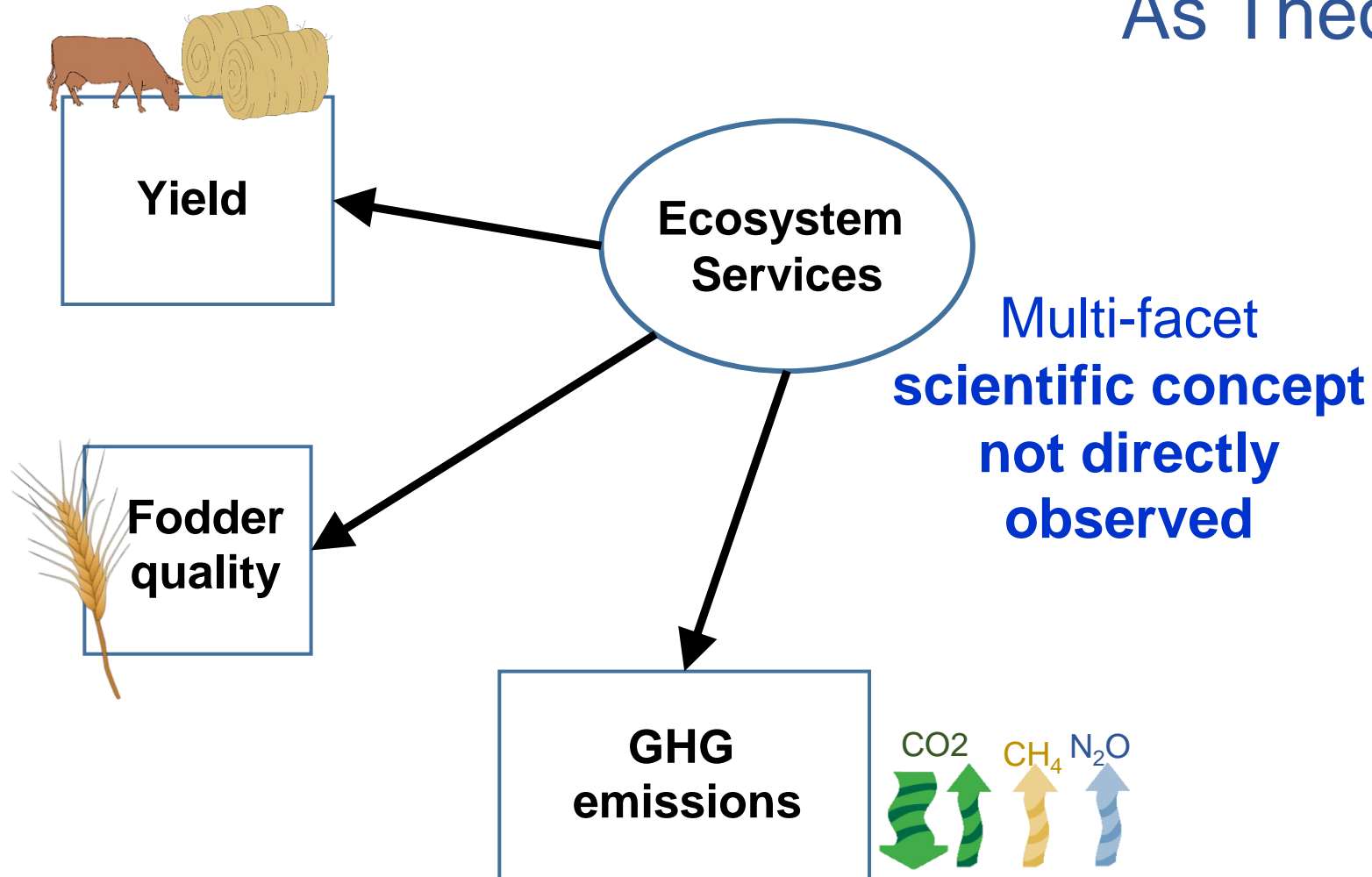
## As Theoretical Constructs



# What is Latent Variable?

Example

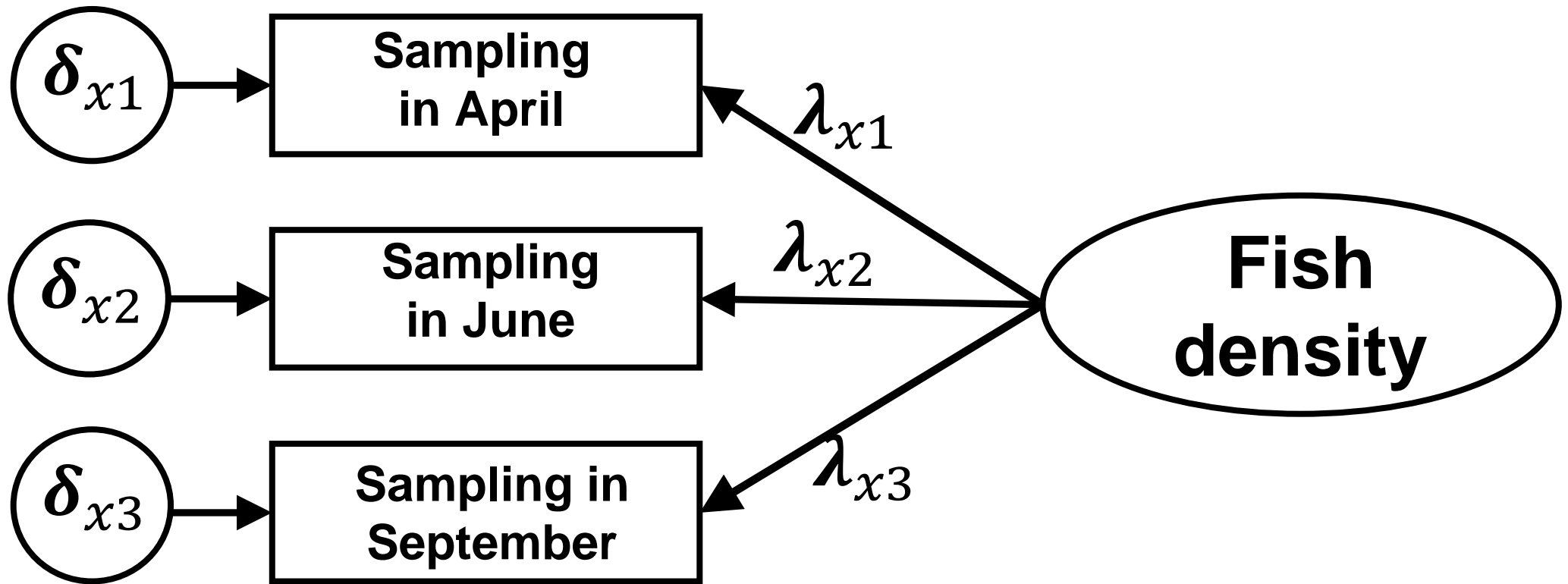
As Theoretical Constructs



# Multi-indicator Latent Variables

Example

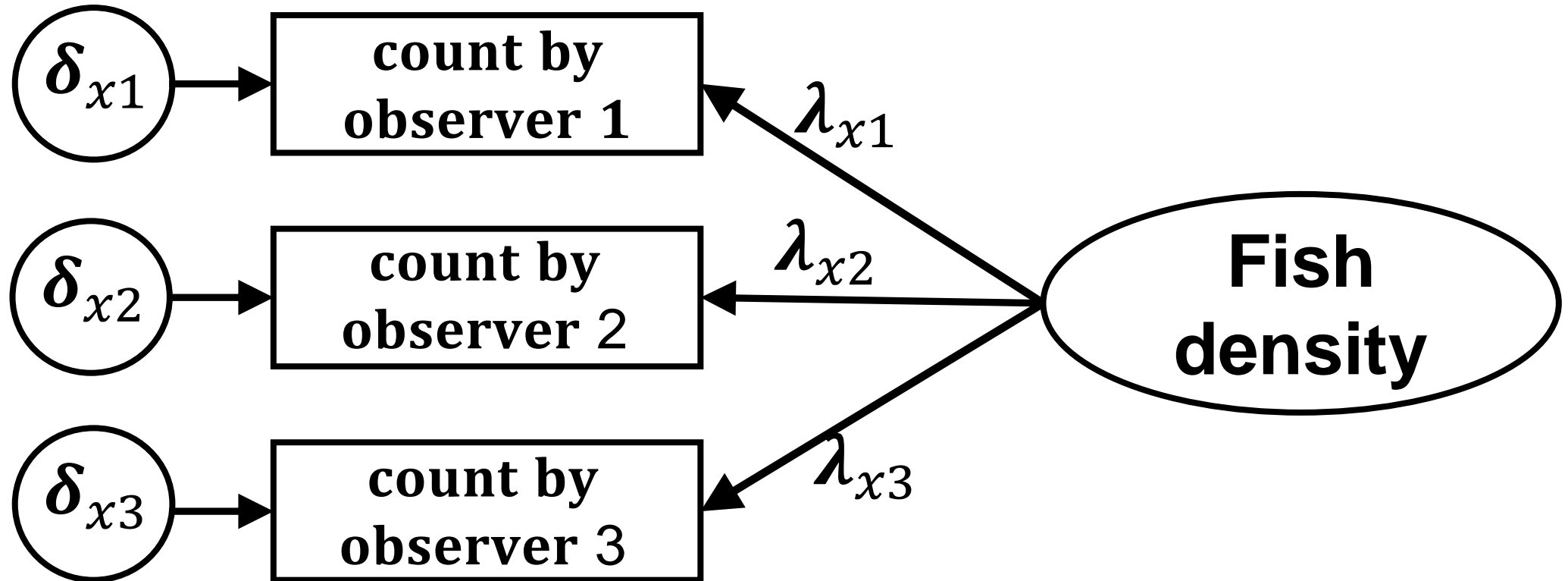
Repeated Measurements



# Multi-indicator Latent Variables

Example

Multi-sampling



# Why use Latent Variables with Multiple Indicators?

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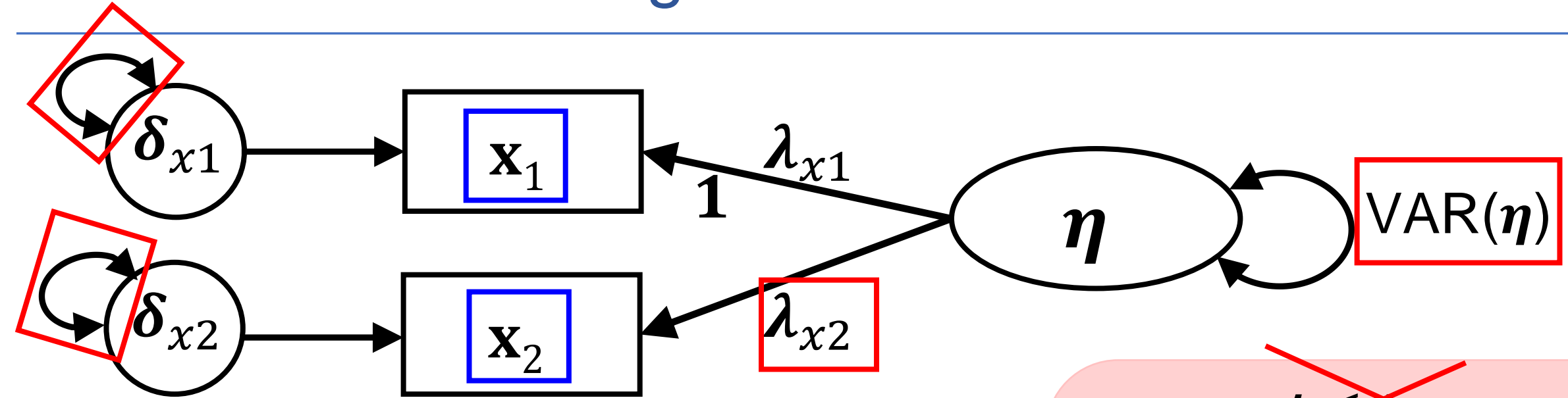
- Allows estimating complex and multifaceted concepts
- Reduces random error in construct (latent variable)
- Better accuracy in measurement of relationships due to shared variation between observed indicators.



## **Latent Variables in SEM**

- What are Latent Variables? Why to use them?
- Multi-indicator Latent Variables
- **Fitting Latent Variables**  
(Confirmatory Factor Analysis)

# Fitting Latent Variables



## Rules for LV models:

- Scaling of LV
- Non-negative DF

$$\text{DF} = -1$$

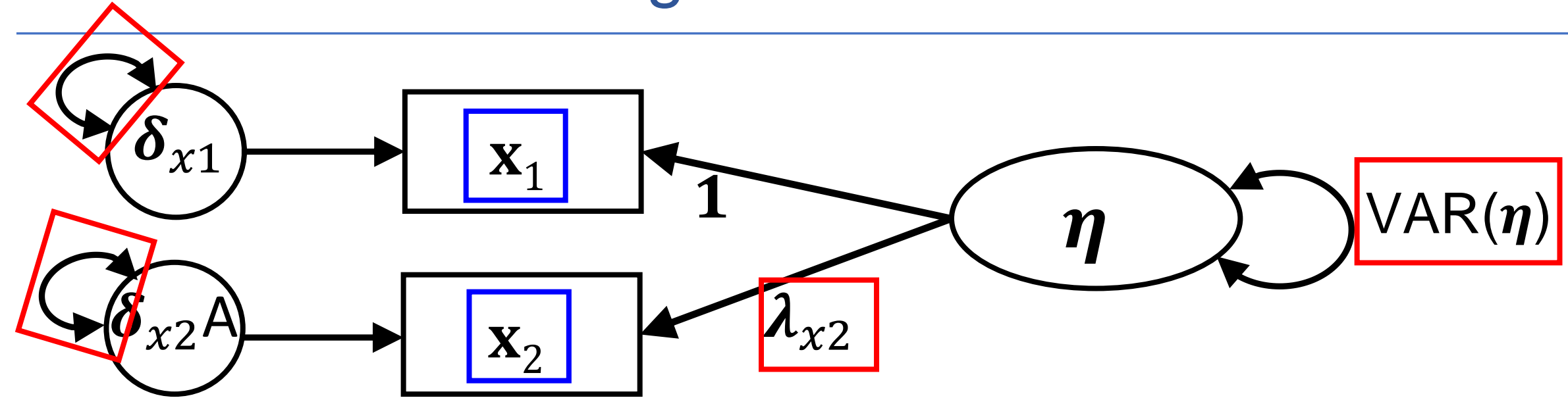
~~$t \leq t_{max}$~~

$$t_{max} = \frac{s(s+1)}{2} = 3$$

$s = 2$  knowns

$t = 4$  unknowns

# Fitting Latent Variables



## Rules for LV models:

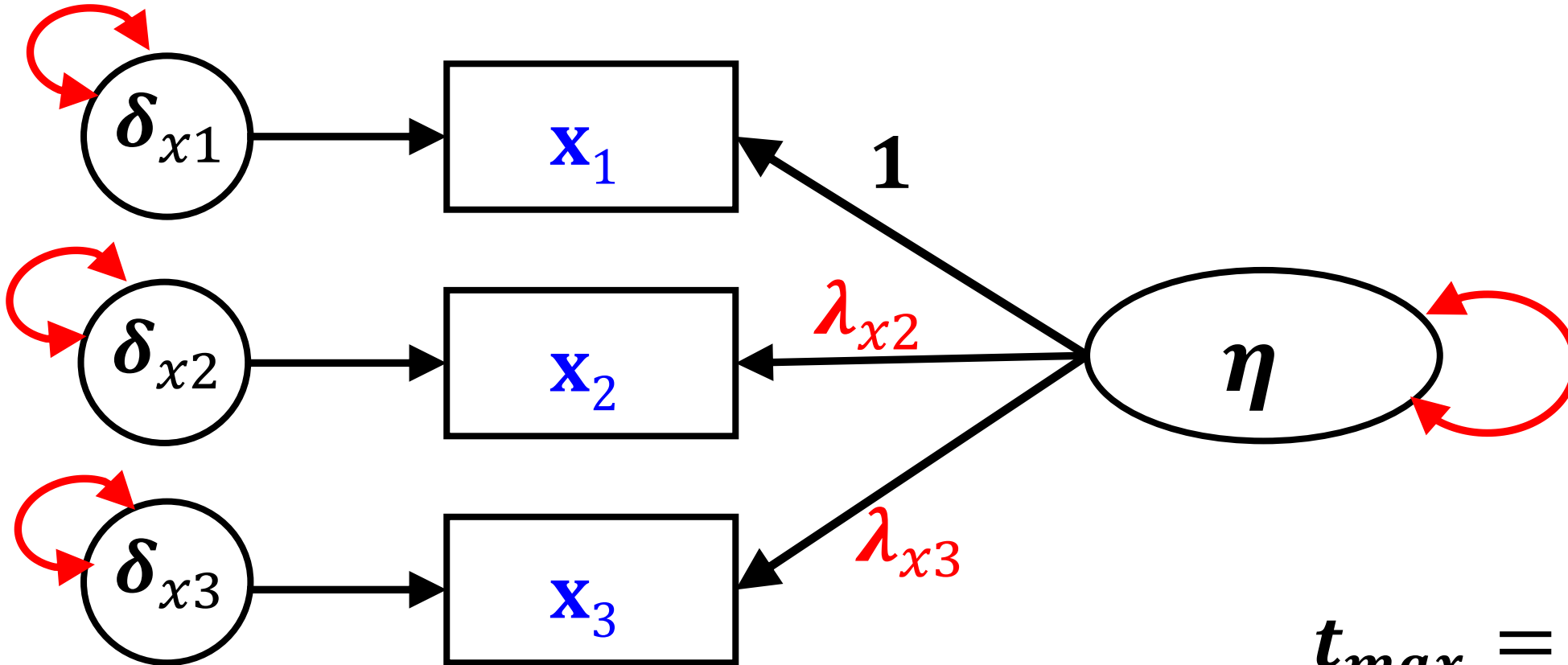
- Scaling of LV
- Non-negative DF



## We need at least:

- 3 indicators for a single LV
- 2 indicators per LV for models with multiple (correlated) LVs

# Fitting Latent Variables



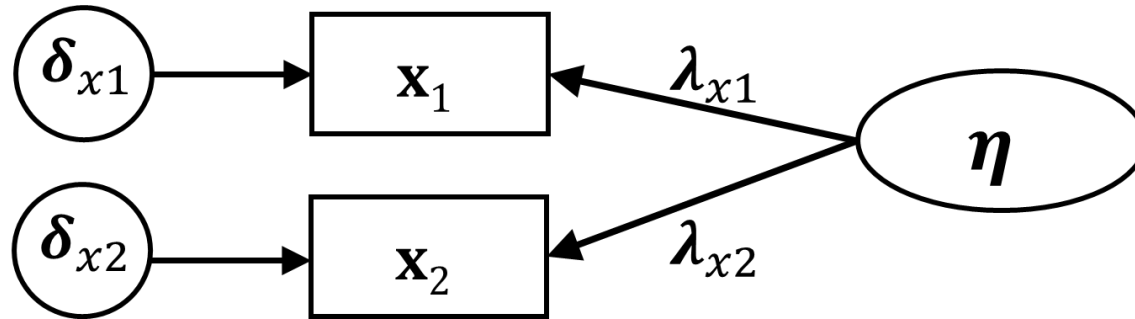
$$t_{max} = \frac{s(s+1)}{2} = 6$$

$s = 3$  knowns

$t = 6$  unknowns

$$\text{DF} = t_{max} - t = 0$$

# Fitting Latent Variables



## Two indicators of LV

Solution:

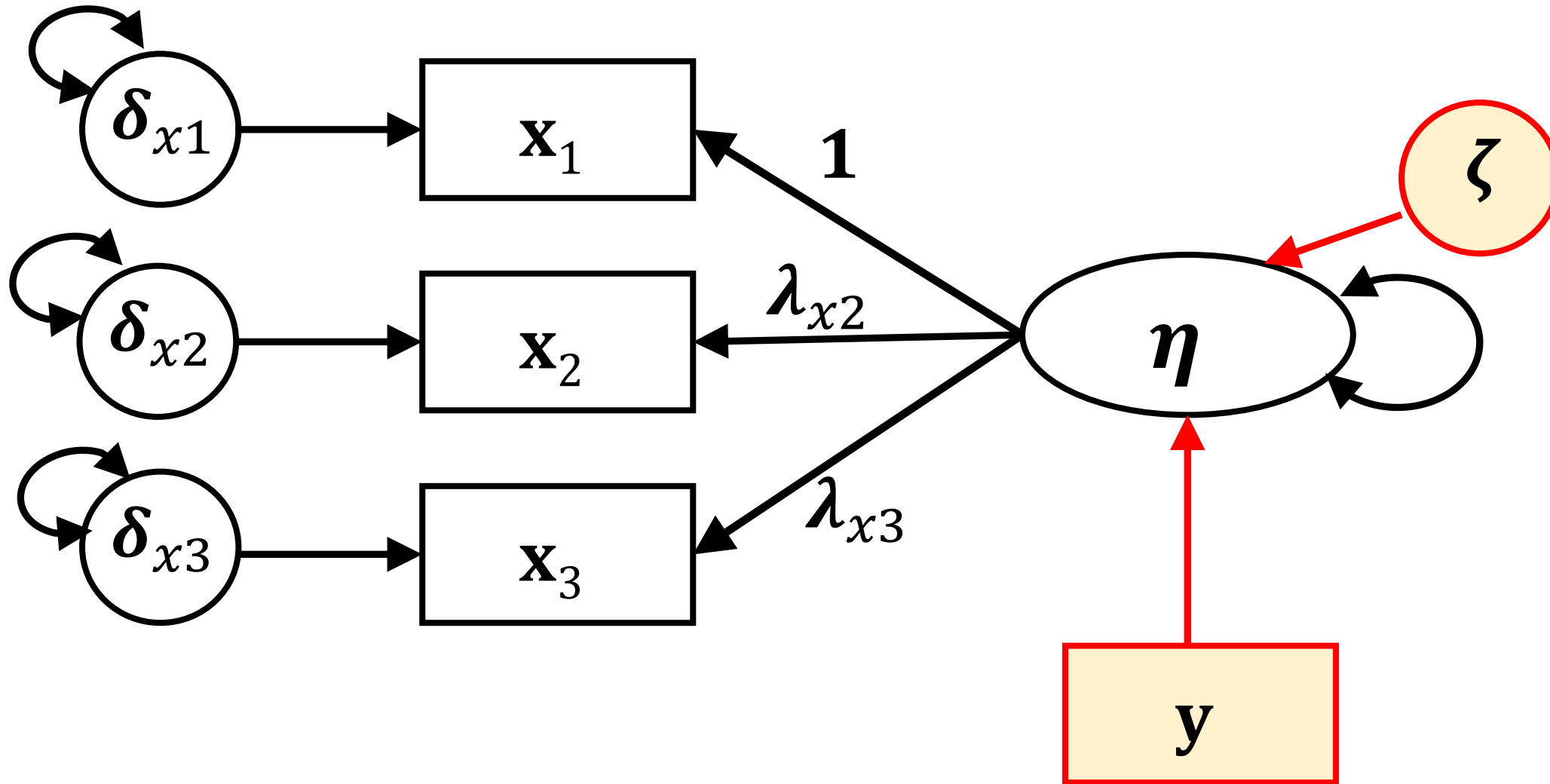
- 1) To set  $\lambda_{x1} = \lambda_{x2}$ , assuming that  $x_1$  and  $x_2$  have equal weight in the estimation of the LV
- 2) To measure errors experimentally.

```
# specify latent variable
Sem.mod <- '
    n =~ a1*x1 + a2*x2
    a1==a2 #  $\lambda_{x1} = \lambda_{x2}$ 
    x1 ~~ 0.213 * x1 # fix error variance
'
```

## Knowing your measurement error:

- Increases accuracy in estimating relationship between variables.
- Increases explanatory power of measured variables.

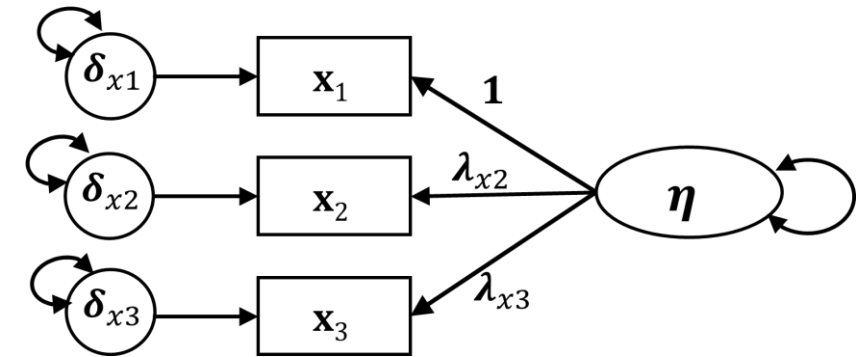
# Fitting Latent Variables



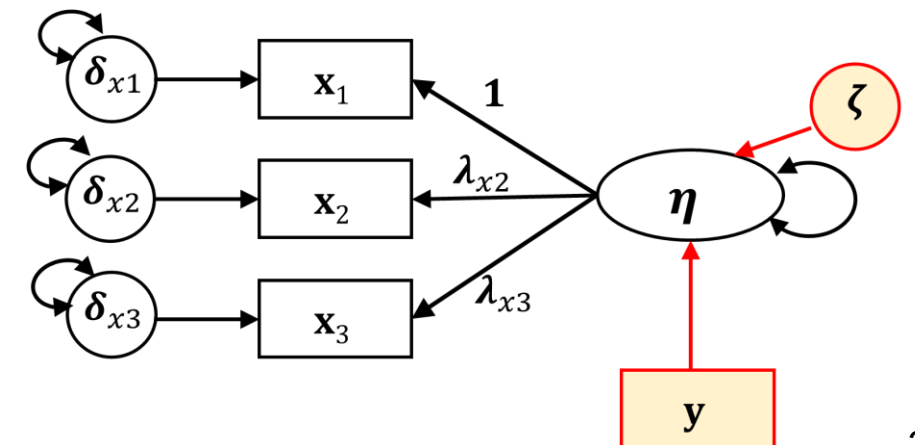
# Fitting Latent Variables

1) Evaluate the latent relationships among variables (**Confirmatory Factor Analysis**).

- Do our indicators make a Good Latent Variable?



2) Use Latent Variables as a Response or a Predictor



## Population-based ecological restoration

Aim: understand the performance of transplanted plants as a function of their dissimilarity to local conditions

Sabine National  
Wildlife  
Refuge, Louisiana,  
USA



```
# Read and check the data
```

```
travis <- read.csv(" Travis_data.csv")
```

Travis, S. E., & Grace, J. B. (2010). Predicting performance for ecological restoration: a case study using *Spartina alterniflora*. *Ecological Applications*, 20(1), 192-204.



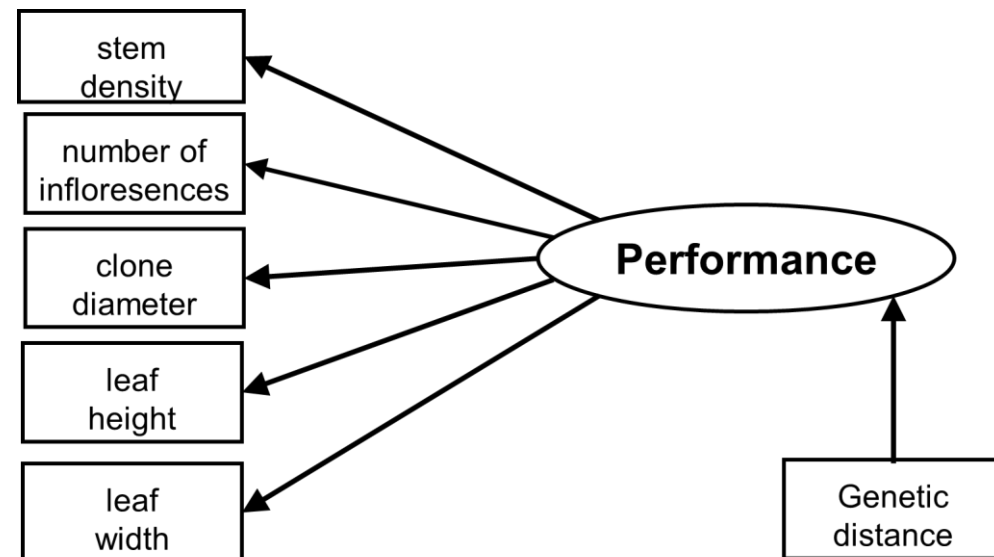
# Confirmatory Factor Analysis

## Exercise

Sabine National Wildlife  
Refuge, Louisiana, USA

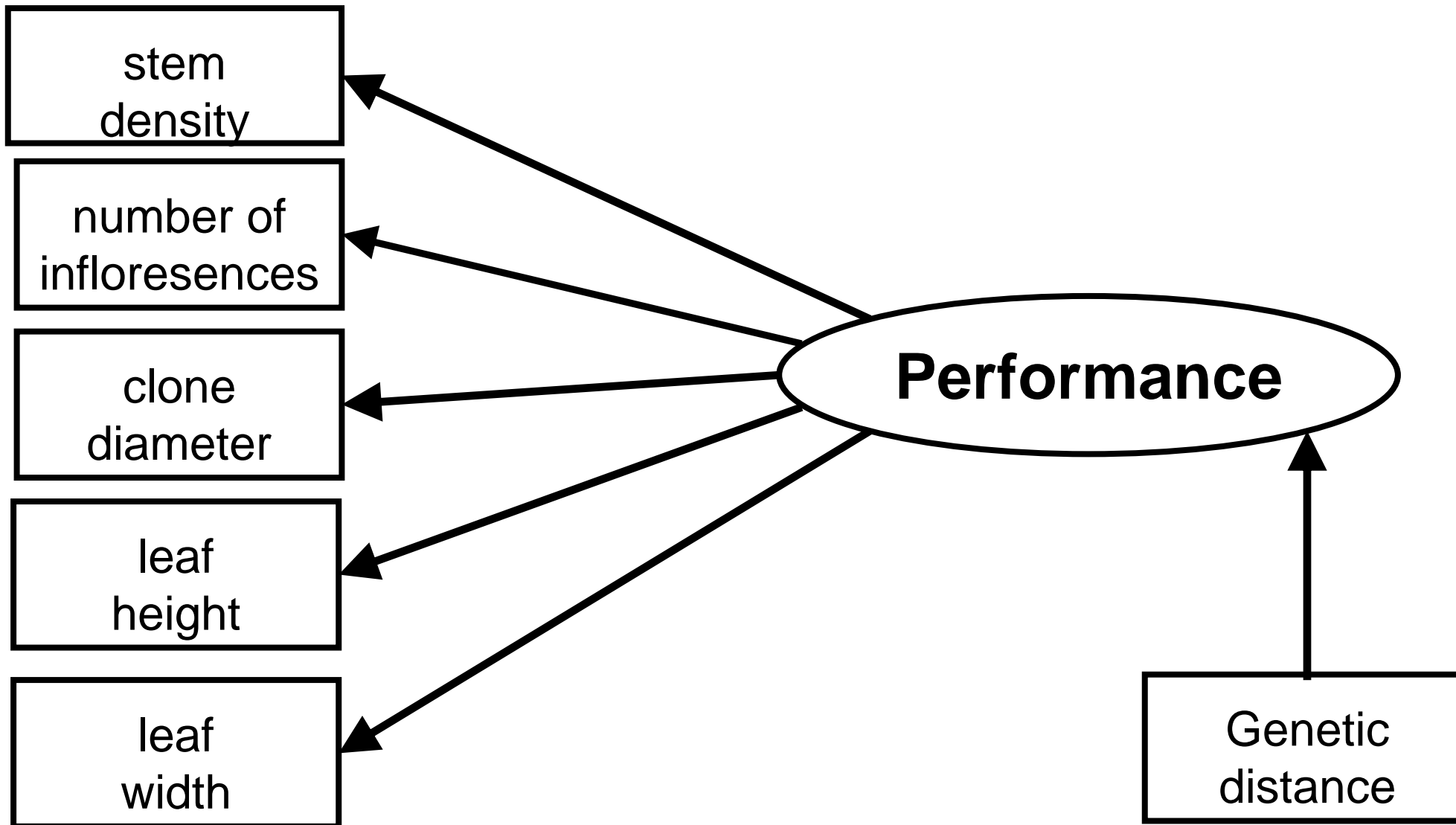


- Collected individuals of the salt marsh plant *Spartina alterniflora* eight clones each from 23 populations
- Transplanted individuals and measured their performance relative to local populations.
- Performance was approximated with stem density, the number of inflorescences, clone diameter, leaf height, and leaf width

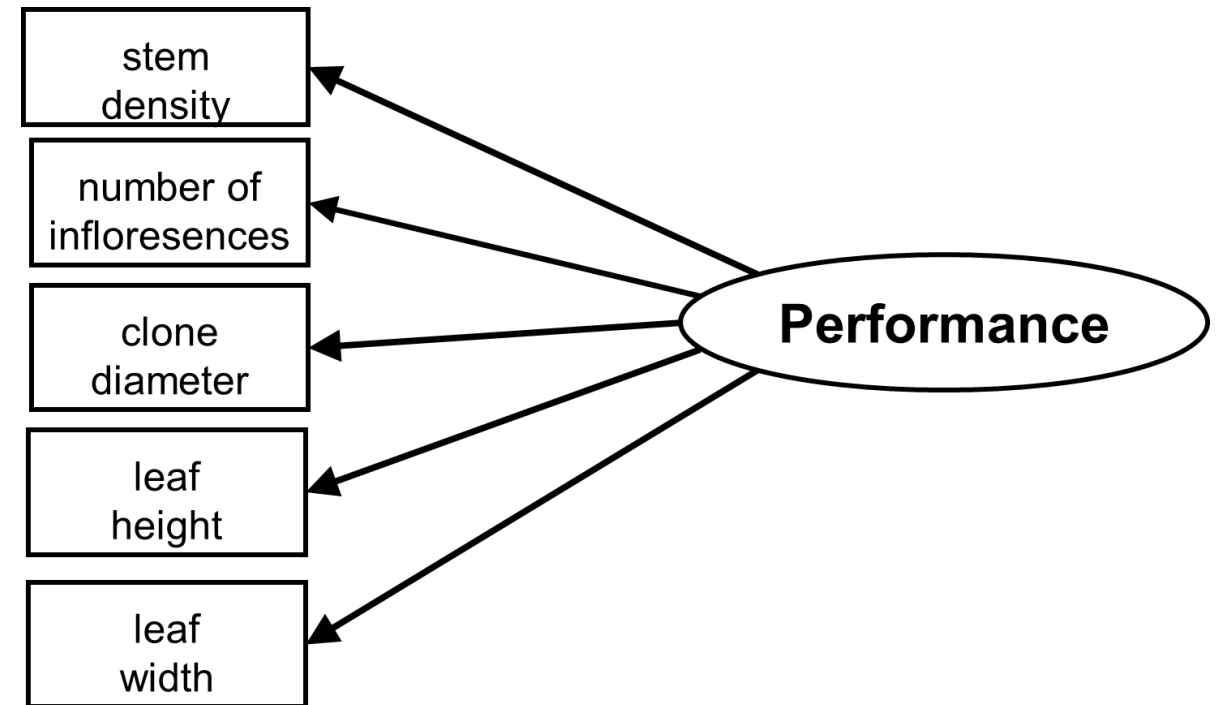


# Confirmatory Factor Analysis

Exercise



- 1) Evaluate the latent relationships among variables  
(**Confirmatory Factor Analysis**).
- Do our indicators make a Good Latent Variable?



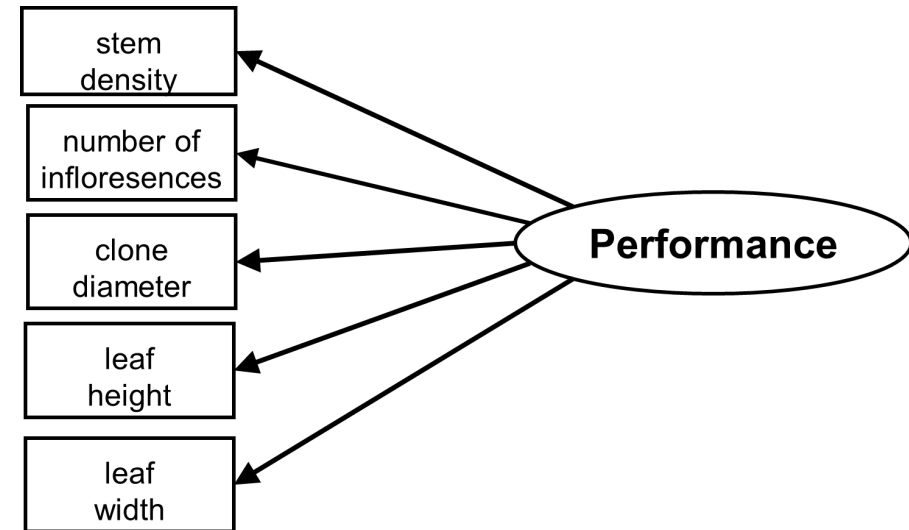
A first step is to analyze the “measurement model” using CFA.

# Confirmatory Factor Analysis

## Exercise

```
# Read and check the data
travis <- read.csv("Travis_data.csv")

str(travis)
# correlations
cor(travis[, 4:8])
```



```
> cor(travis[, 4:8])
```

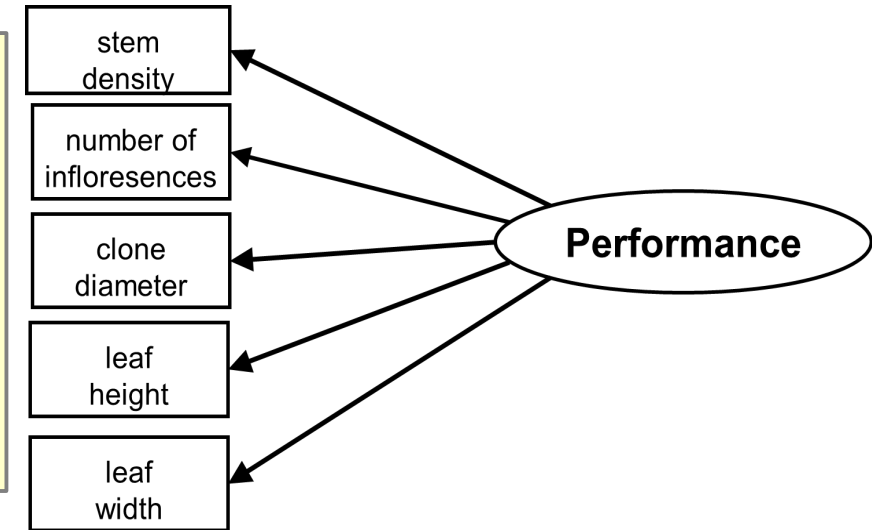
	stems	infls	clonediam	leafht	leafwidth
stems	1.0000000	0.8339227	0.9333150	0.7275625	0.6457378
infls	0.8339227	1.0000000	0.8126388	0.6925888	0.6026302
clonediam	0.9333150	0.8126388	1.0000000	0.7729843	0.7296621
leafht	0.7275625	0.6925888	0.7729843	1.0000000	0.9687725
leafwidth	0.6457378	0.6026302	0.7296621	0.9687725	1.0000000

# Confirmatory Factor Analysis

## Exercise

```
# specify the model
cfa_mod <- `
performance =~ stems + infls + clonediam + leafht + leafwidth
`

# fit the model
cfa_fit <- sem(cfa_mod, travis)
```



Warning message:

In lav\_object\_post\_check(object) :

lavaan WARNING: some estimated ov variances are negative

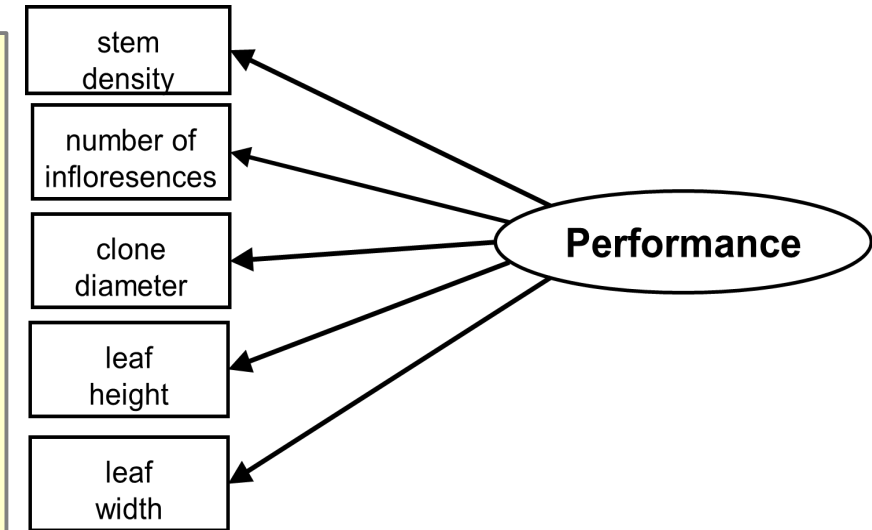
# Confirmatory Factor Analysis

## Exercise

```
> summary(cfa_fit)
```

```
lavaan 0.6-9 ended normally after 82 iterations
```

Estimator	ML
Optimization method	NLMINB
Number of model parameters	10
Number of observations	23
Model Test User Model:	
Test statistic	51.106
Degrees of freedom	5
P-value (Chi-square)	0.000



# Confirmatory Factor Analysis

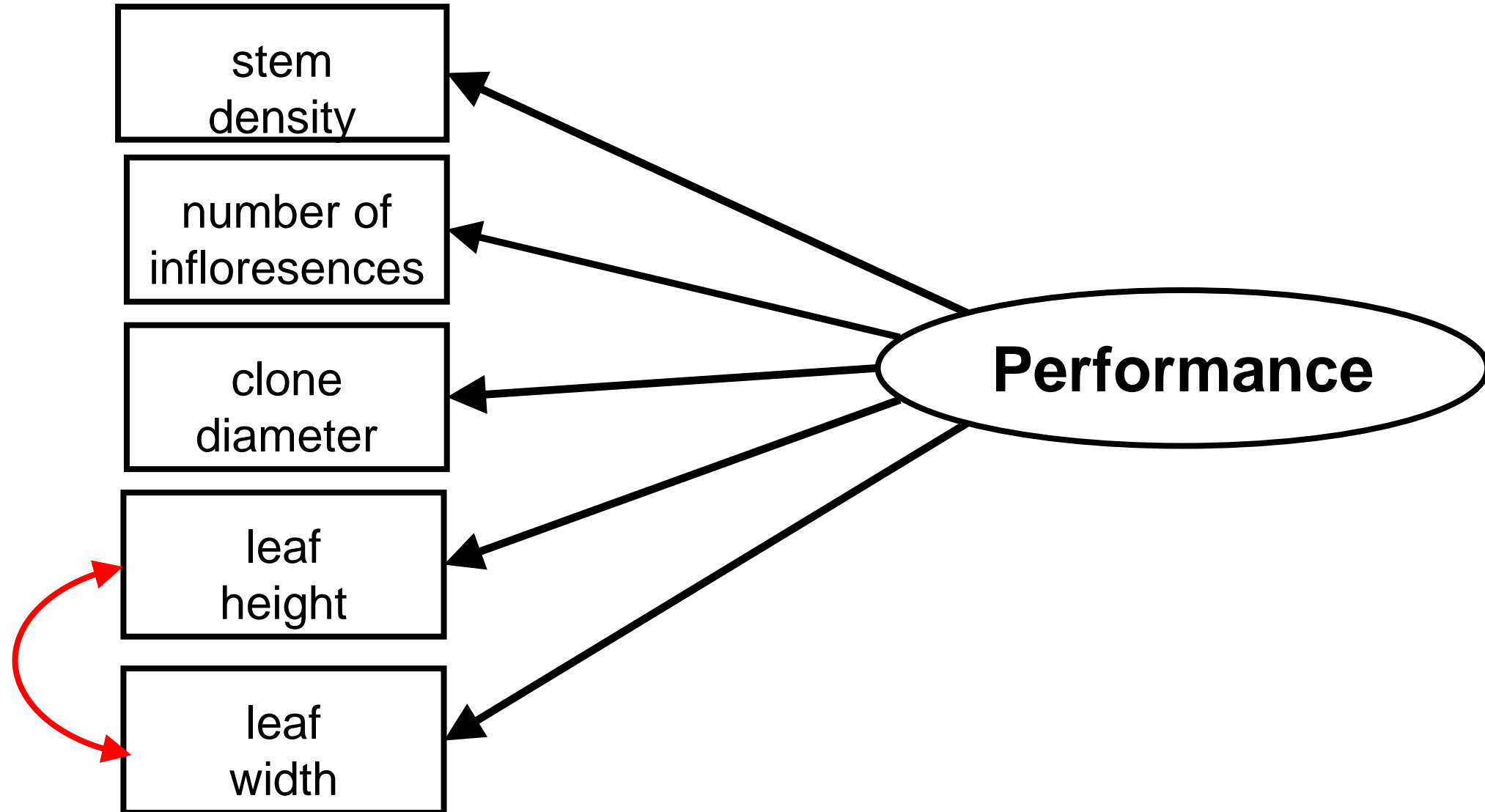
## Exercise

```
> modindices(cfa_fit)
```

	lhs	op	rhs	mi	epc	sepc.lv	sepc.all	sepc.nox
12	stems	~~	infls	10.470	11.784	11.784	0.677	0.677
13	stems	~~	clonediam	17.152	112.521	112.521	0.871	0.871
14	stems	~~	leafht	0.693	-7.889	-7.889	-0.517	-0.517
15	stems	~~	leafwidth	2.214	-1.836	-1.836	-0.346	-0.346
16	infls	~~	clonediam	8.773	11.092	11.092	0.621	0.621
17	infls	~~	leafht	0.062	-0.312	-0.312	-0.148	-0.148
18	infls	~~	leafwidth	2.906	-0.281	-0.281	-0.383	-0.383
19	clonediam	~~	leafht	4.028	-21.233	-21.233	-1.357	-1.357
20	clonediam	~~	leafwidth	0.037	-0.261	-0.261	-0.048	-0.048
21	leafht	~~	leafwidth	37.862	17.177	17.177	26.752	26.752

# Confirmatory Factor Analysis

Exercise

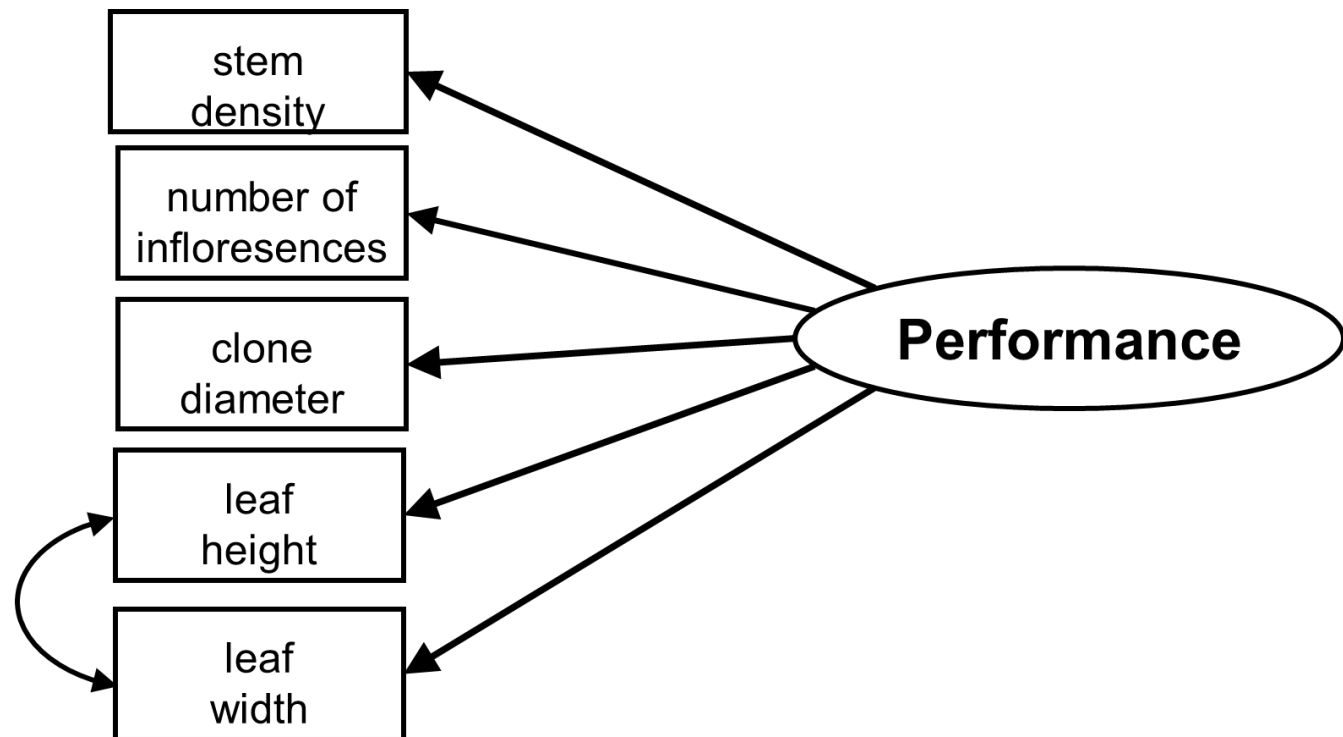




# Confirmatory Factor Analysis

## Exercise

```
cfa_mod2 <- '  
performance =~ stems + infls + clonediam + leafht + leafwidth  
leafht ~~ leafwidth  
'  
  
cfa_fit2 <- sem(cfa_mod2, travis)  
summary(cfa_fit2)
```



# Confirmatory Factor Analysis

## Exercise

Estimator	ML
Optimization method	NLMINB
Number of model parameters	11
Number of observations	23
Model Test User Model:	
Test statistic	7.410
Degrees of freedom	4
P-value (Chi-square)	0.116

# Confirmatory Factor Analysis

## Exercise

...

### Latent Variables:

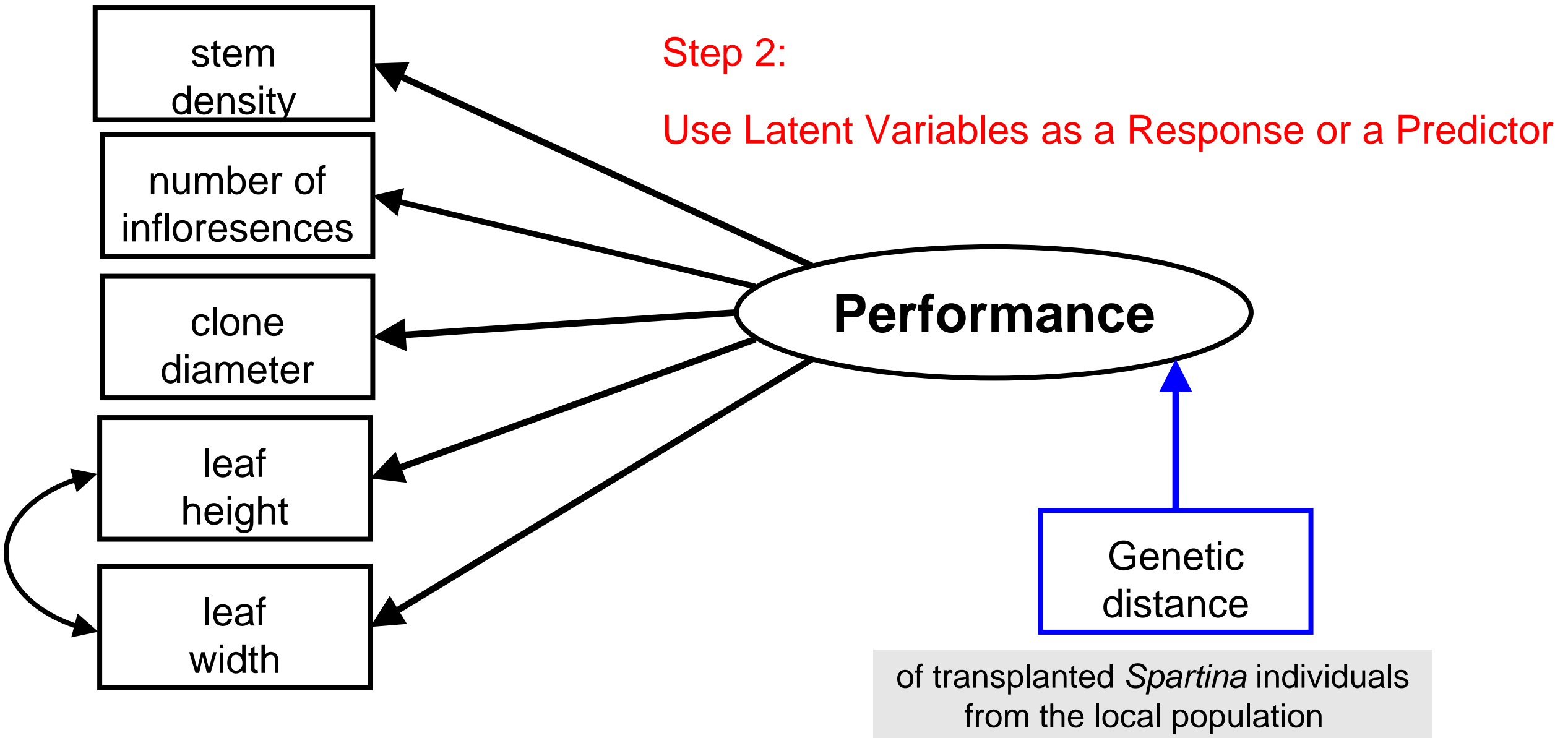
	Estimate	Std.Err	z-value	P(> z )
performance =~				
stems	1.000			
infls	0.117	0.016	7.173	0.000
clonediam	1.086	0.096	11.319	0.000
leafht	0.697	0.127	5.509	0.000
leafwidth	0.082	0.018	4.529	0.000

### Covariances:

	Estimate	Std.Err	z-value	P(> z )
.leafht ~~				
.leafwidth	10.831	3.432	3.156	0.002

# CFA as a part of structural model

Exercise



# CFA as a part of structural model

## Exercise

```
SEM_latent_mod <- `
  # latent
performance =~ stems + infls + clonedia + leafht + leafwdth

  # structural paths
performance ~ geneticdist

  # correlated errors
leafht ~~ leafwdth
`

SEM_latent_fit <- sem(SEM_latent_mod , travis)

summary(SEM_latent_fit, standardize = T, rsq = T, fit.measures=T)
```

# CFA as a part of structural model

## Exercise

Estimator

ML

Optimization method

NLMINB

Number of model parameters

12

Number of observations

23

Model Test User Model:

Test statistic

12.237

Degrees of freedom

8

P-value (Chi-square)

0.141

# CFA as a part of structural model

## Exercise

### Latent Variables:

	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
performance =~						
stems	1.000				15.555	0.962
infls	0.117	0.017	6.929	0.000	1.822	0.853
clonediam	1.106	0.096	11.508	0.000	17.199	0.969
leafht	0.711	0.127	5.601	0.000	11.066	0.785
leafwidth	0.084	0.018	4.650	0.000	1.308	0.718

### Regressions:

	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
performance ~						
geneticdist	-51.673	11.365	-4.547	0.000	-3.322	-0.708

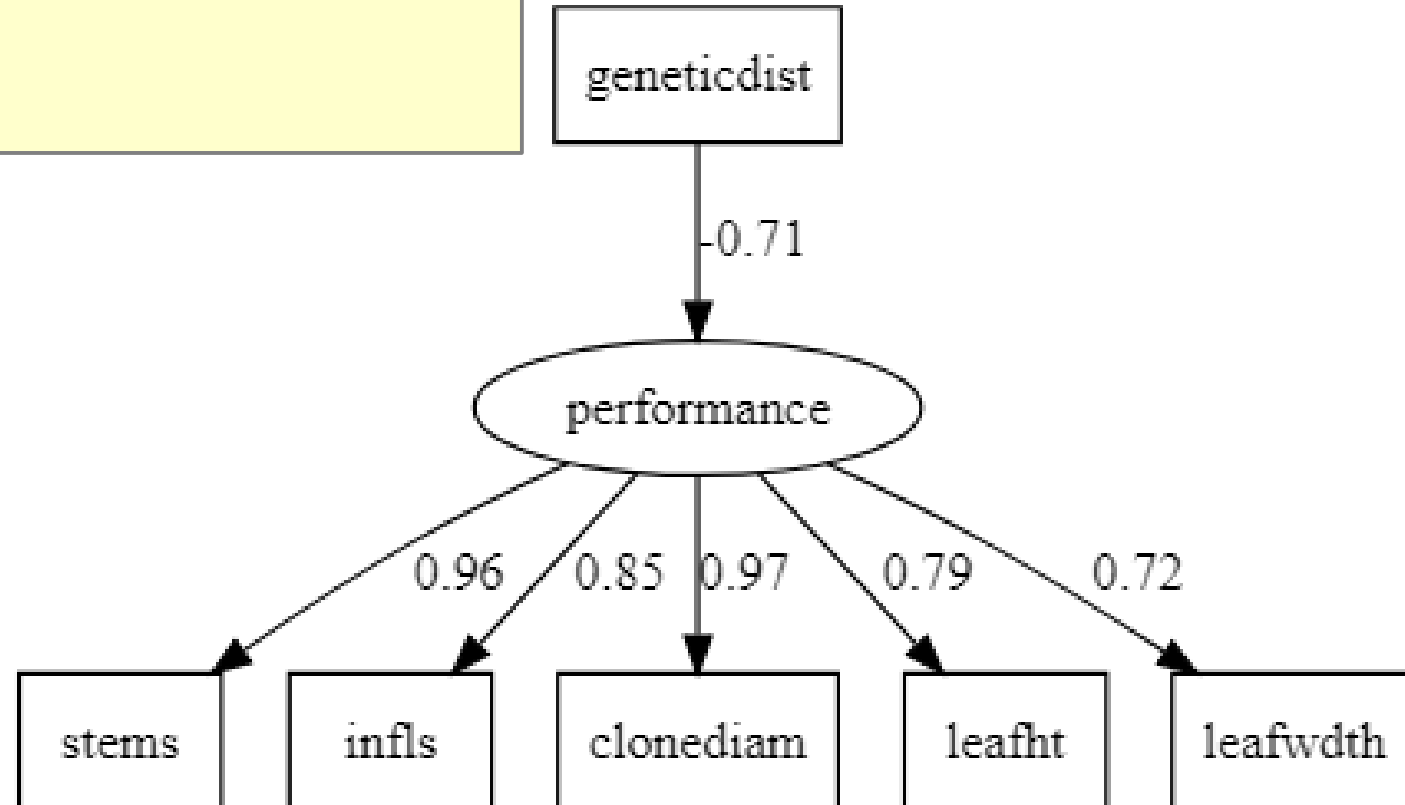
### Covariances:

	Estimate	Std.Err	z-value	P(> z )	Std.lv	Std.all
.leafht ~~						
.leafwidth	10.416	3.312	3.145	0.002	10.416	0.940

# CFA as a part of structural model

## Exercise

```
library(lavaanPlot)
lavaanPlot(model = SEM_latent_fit,
  coefs = TRUE, stand=TRUE,
  # graph_options = list(layout = "circo"),
  # stars = 'regress', # shows stars for regr coef
  digits = 2)
```



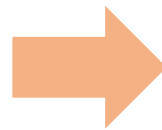


# Day 5 Task 2

## Human impact on macroinvertebrate body size in ponds



**Human  
Impact Intensity**



### Macroinvertebrate body size



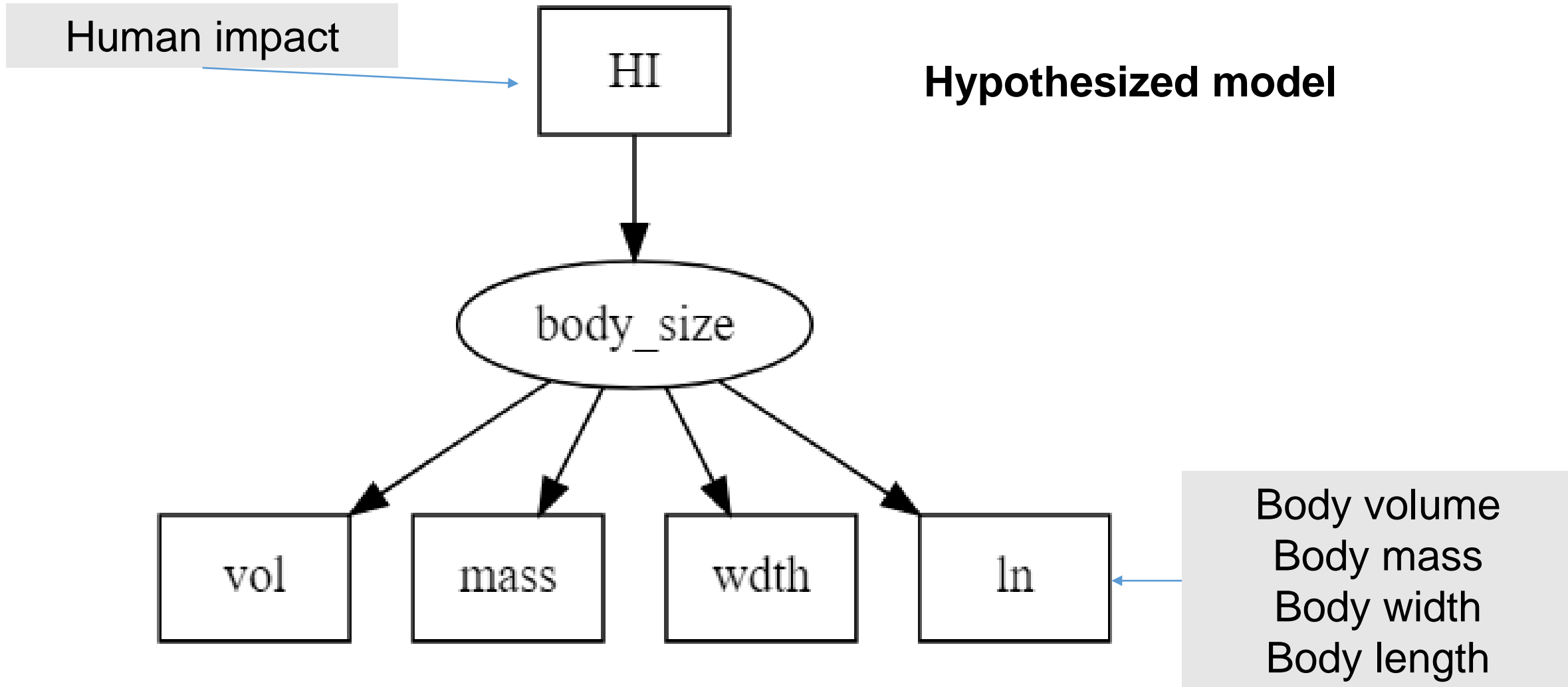
### Body size traits

Body mass  
Body volume  
Body length  
Body width

```
# Read and check the data  
read.csv(" Bodysize_data.csv")
```

# Day 5 Task 2

Human impact on  
macroinvertebrate body size in ponds



1. Perform the confirmatory factor analysis for the latent variable “body size”
2. Use the results from step 1 and perform the SEM by adding human impact variable
3. Fill in Standardized Coefficients and  $R^2$  for the model, add the fit indices
4. Think about how to interpret the results