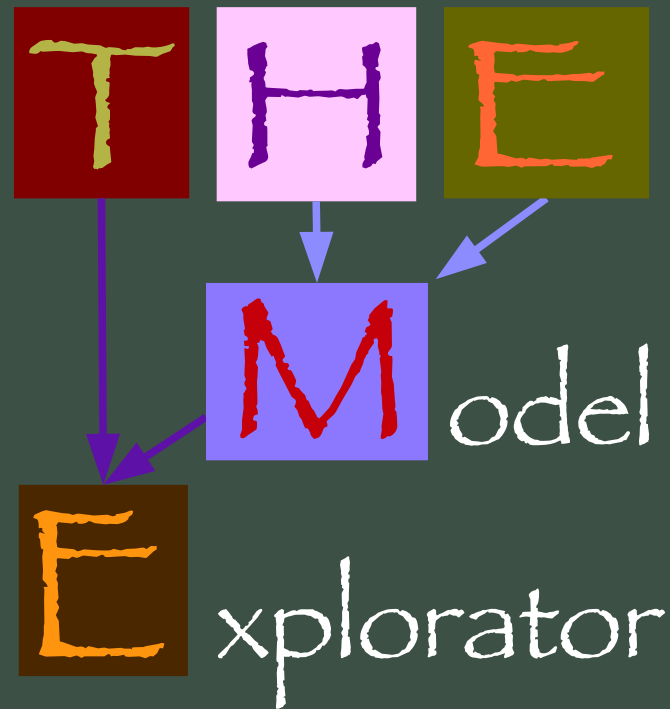


# A component-based Multidimensional Path Modelling R-package: **THEME**



*X. Bry*

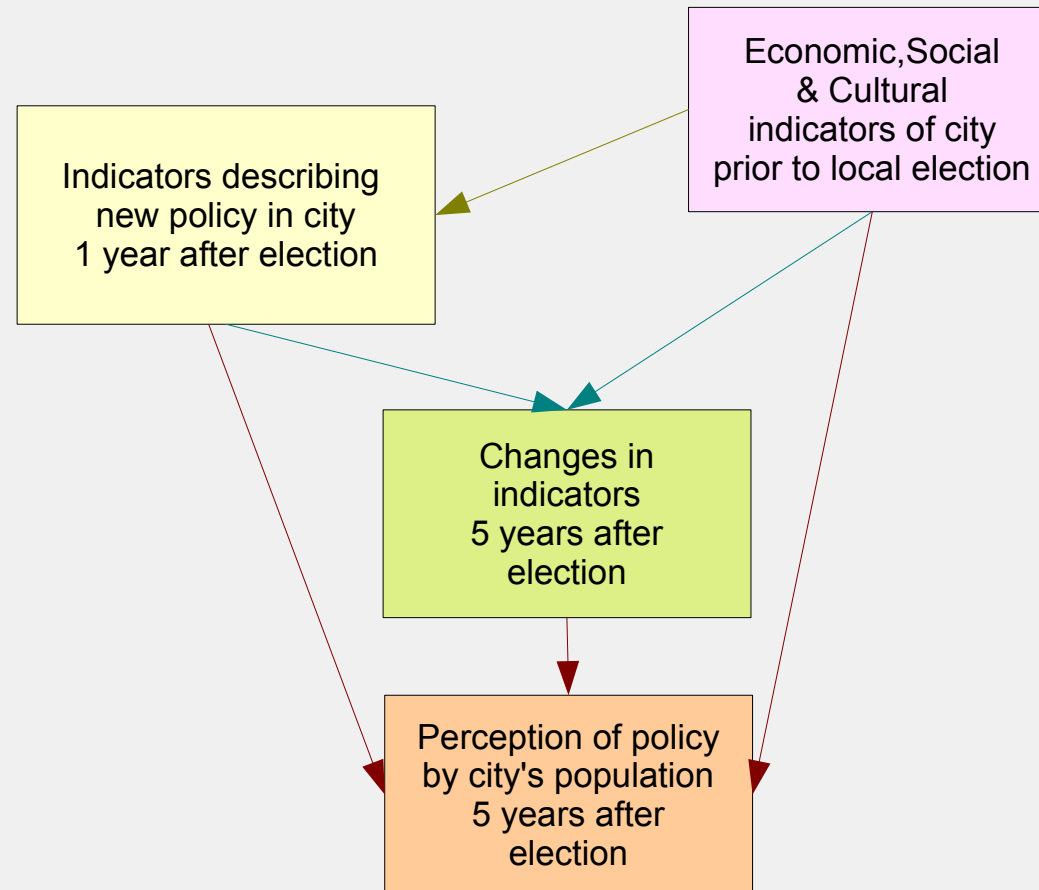
*T. Verron*

*I3M, Univ. Montpellier II*

*ITG - SEITA, Centre de recherche*

## Data and Problem:

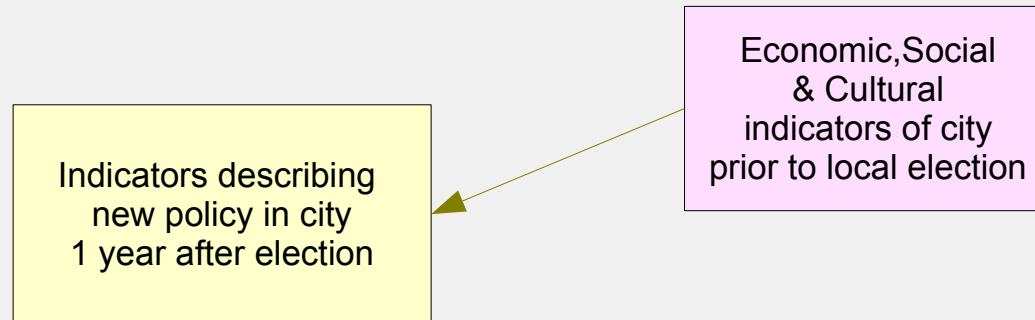
### *1. Conceptual model of a situation = Thematic Model*



## Data and Problem:

### *1. Conceptual model of a situation = Thematic Model*

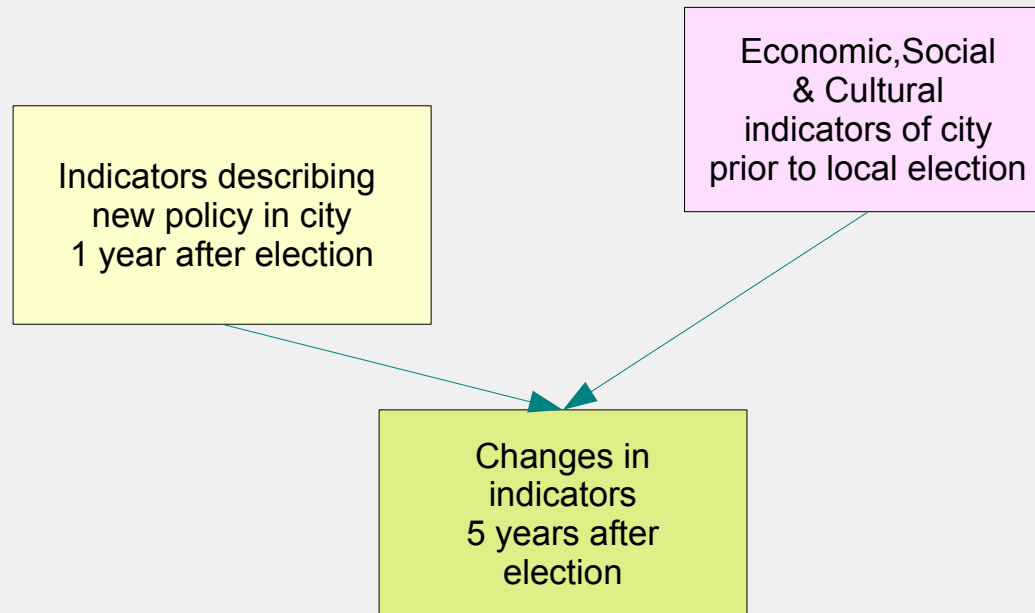
*Equation 1*



# Data and Problem:

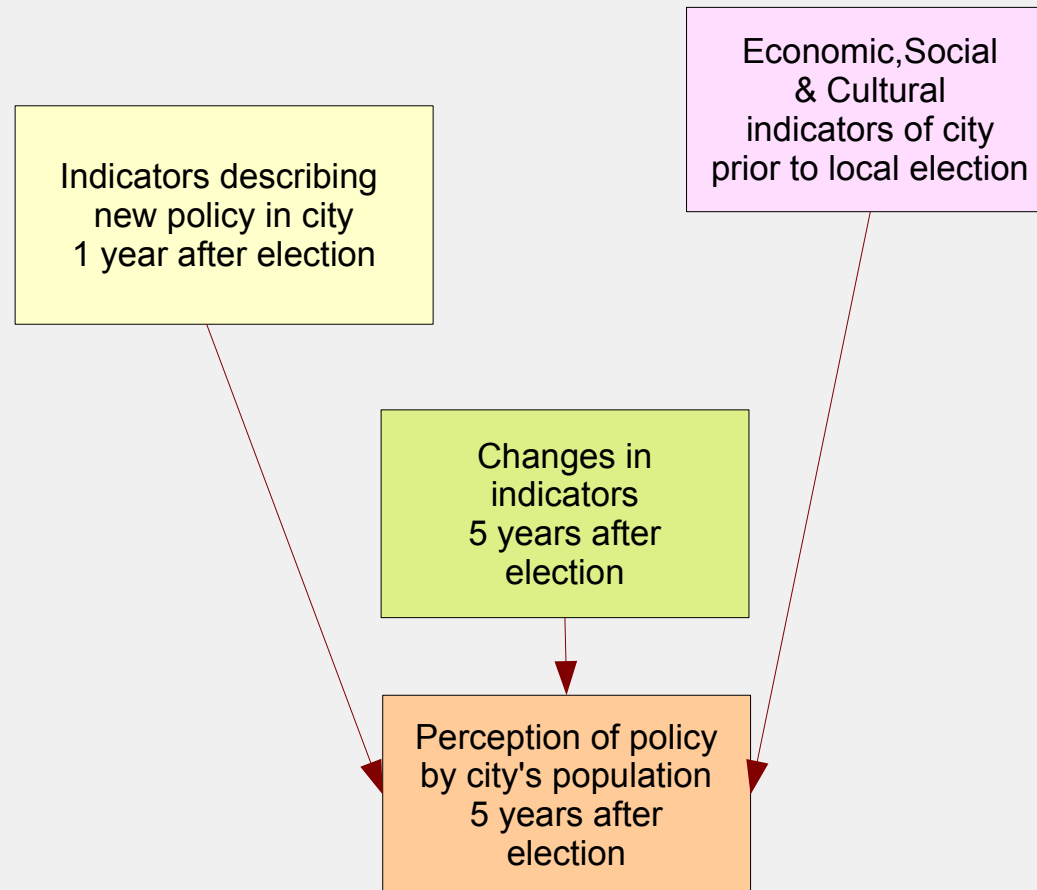
## 1. *Conceptual model of a situation = Thematic Model*

*Equation 2*



## Data and Problem:

### *1. Conceptual model of a situation = Thematic Model*

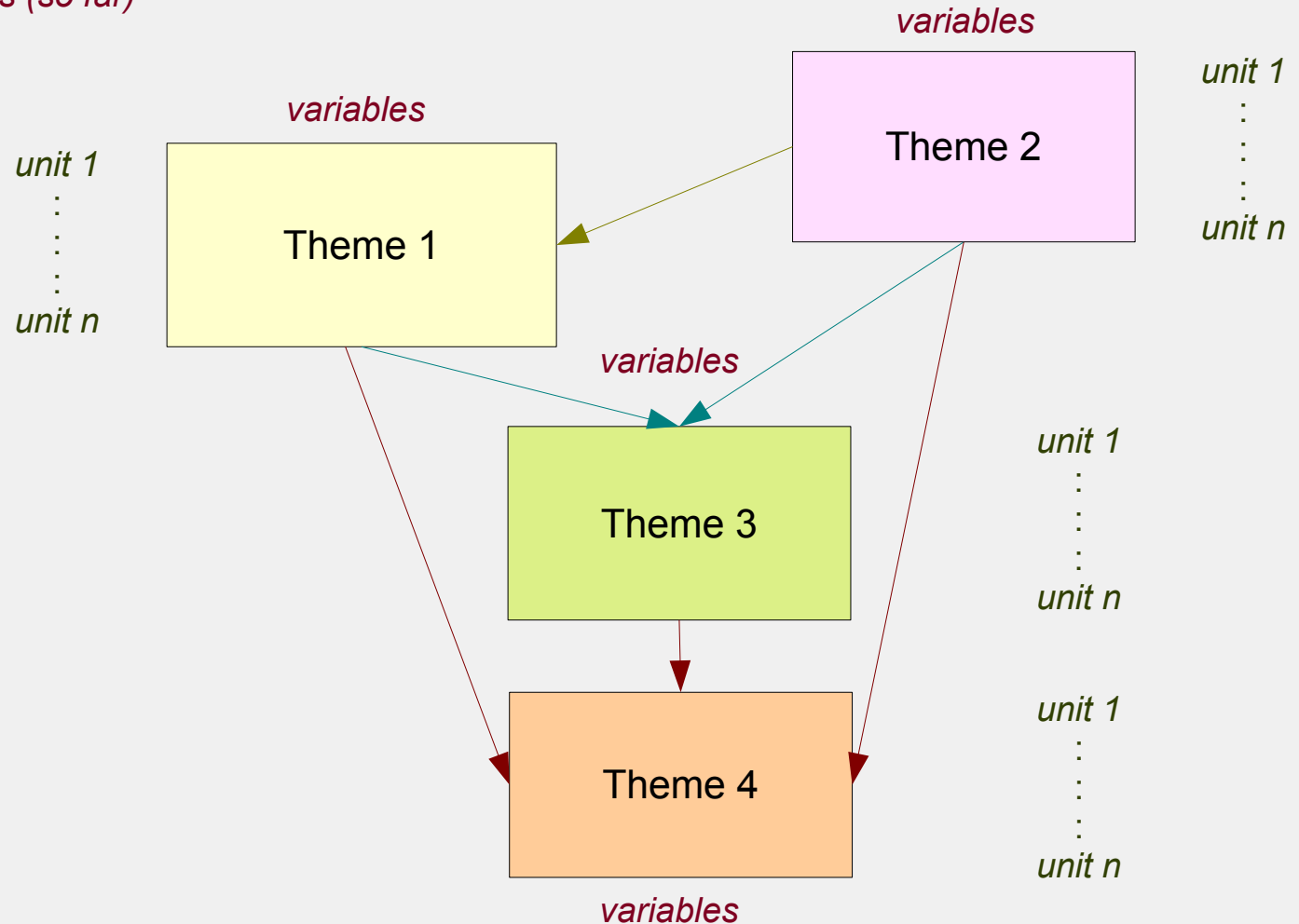


*Equation 3*

# Data and Problem:

## 1. *Conceptual model of a situation = Thematic Model*

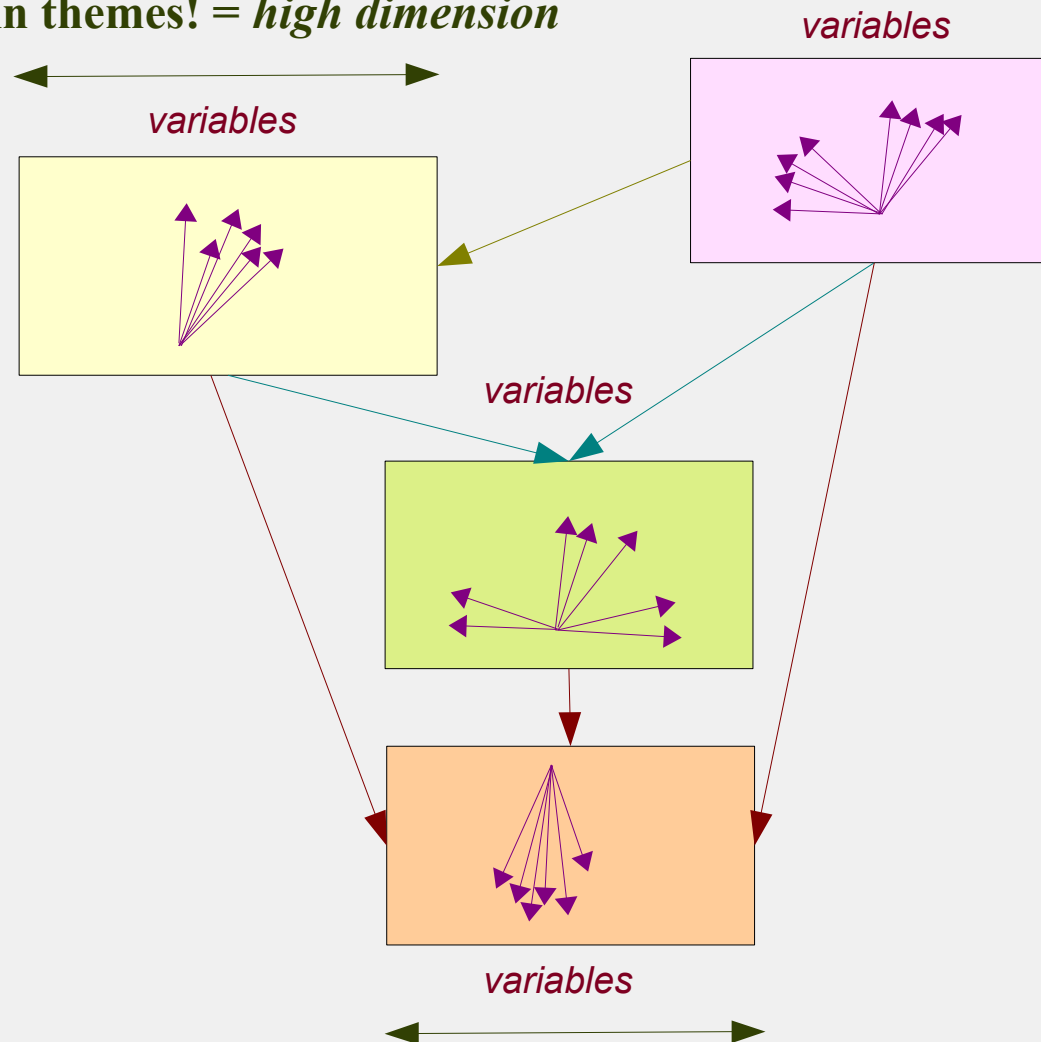
*Numeric variables (so far)*



# Data and Problem:

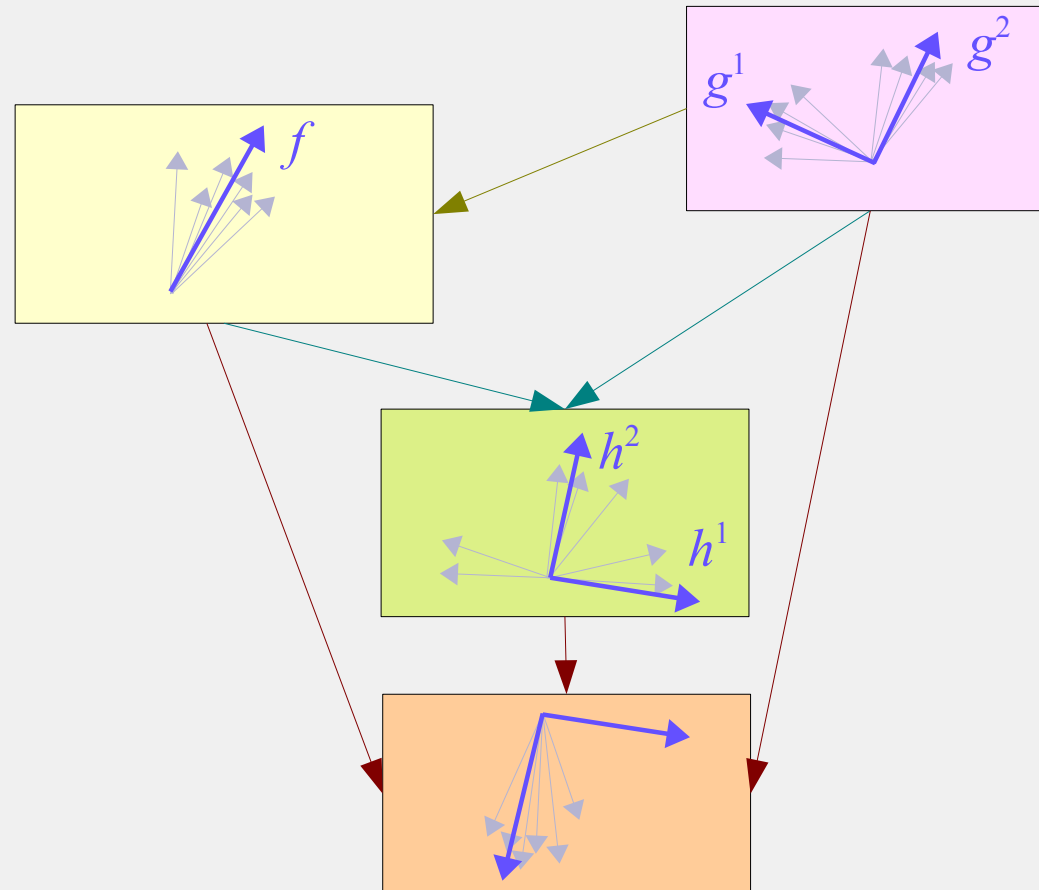
## 2. The Path-Modelling problem

- Too many variables in themes! = *high dimension*



# Data and Problem:

## 2. The Path-Modelling problem



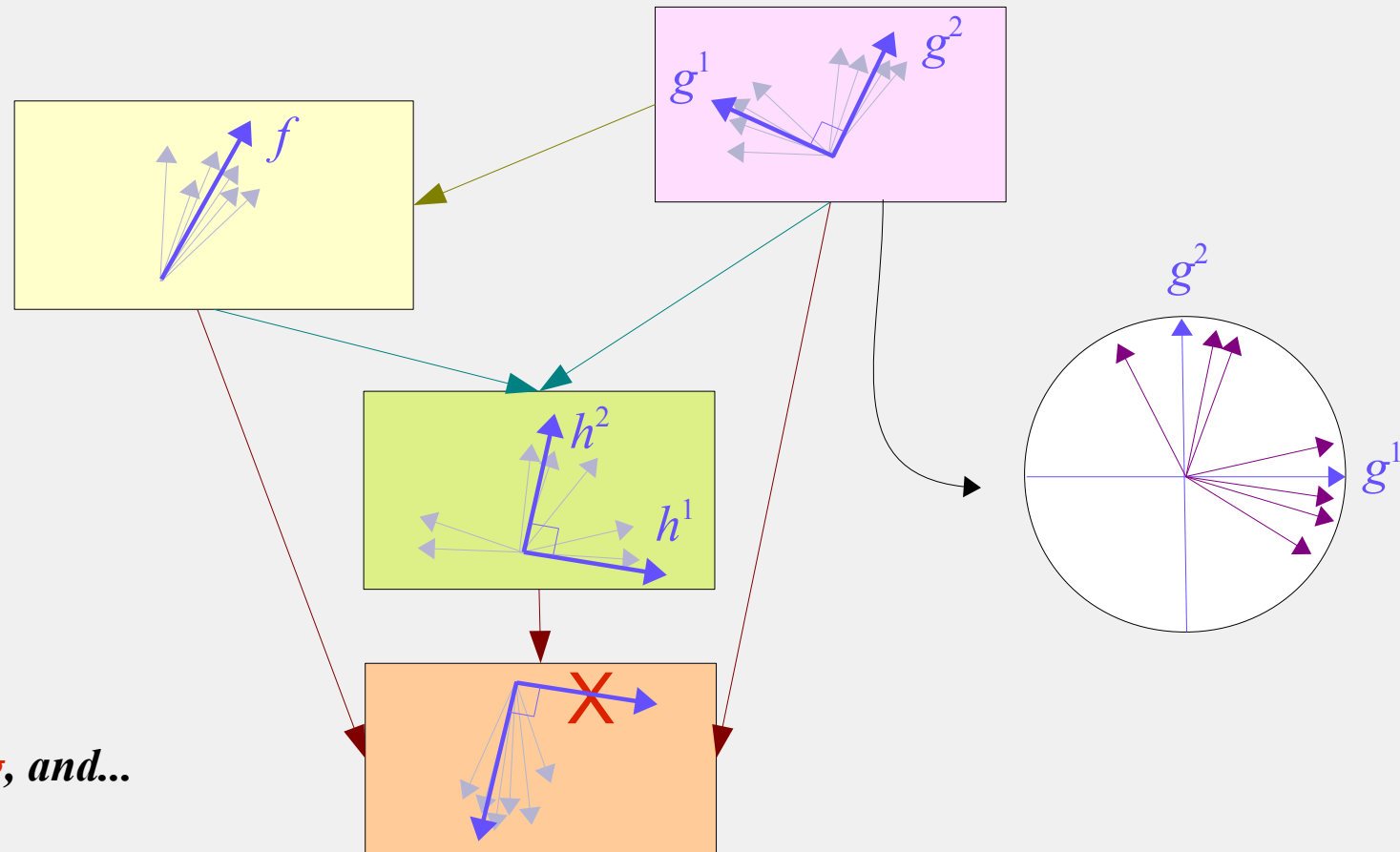
$\Rightarrow$  Reduce dimension  
in each theme ...

through a few  
*Thematic Components*



# Data and Problem:

## 2. The Path-Modelling problem



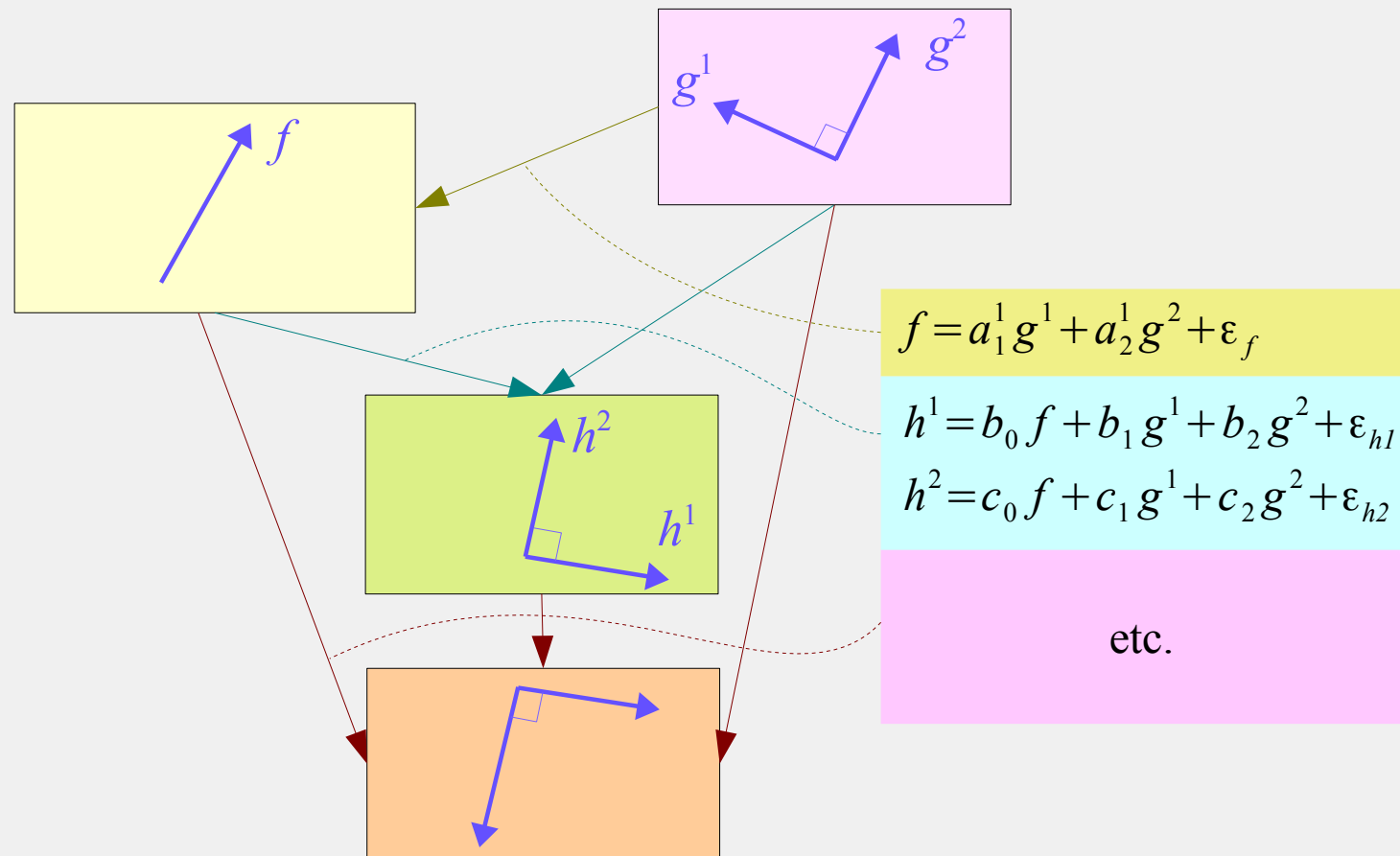
$\Rightarrow$  Reduce dimension  
in each theme ...

through a few  
*Thematic Components*

... *non-redundant, strong, and...*

## Data and Problem:

### 2. The Path-Modelling problem



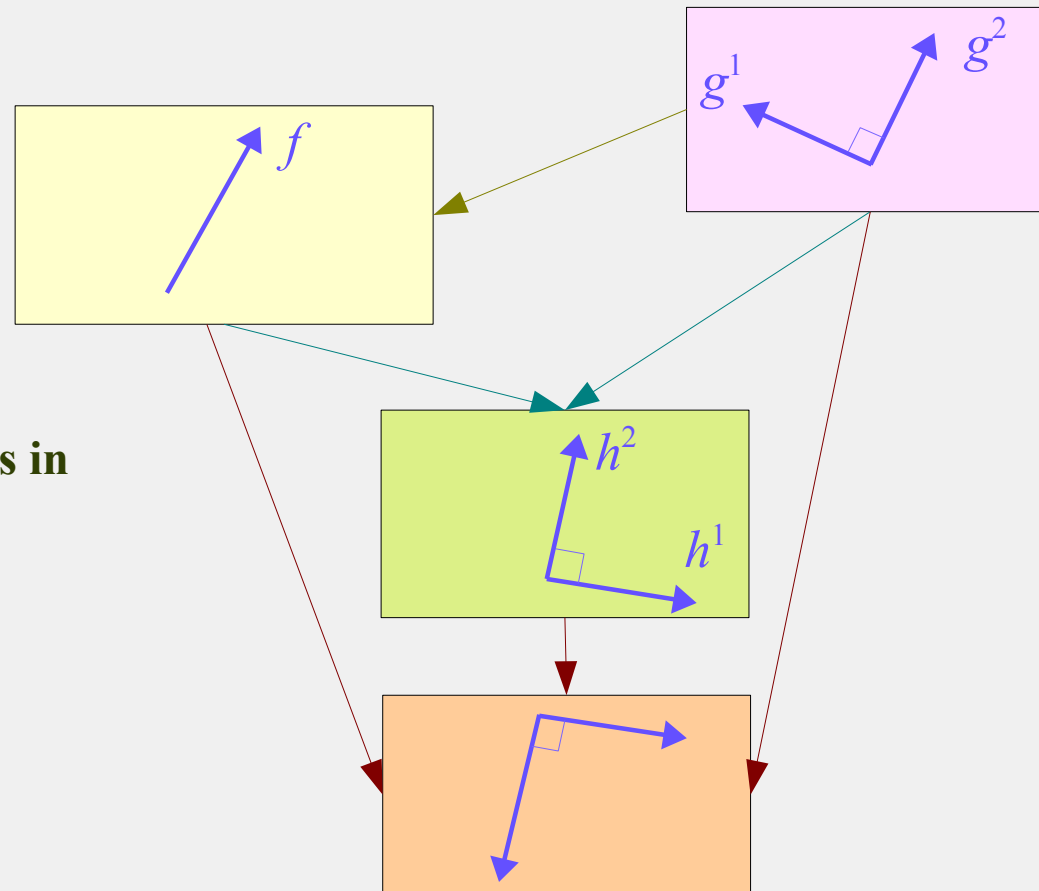
⇒ *Reduce dimension  
in each theme ...*

through a few  
*Thematic Components*

... *satisfying the model.*

# Data and Problem:

## 2. The Path-Modelling problem



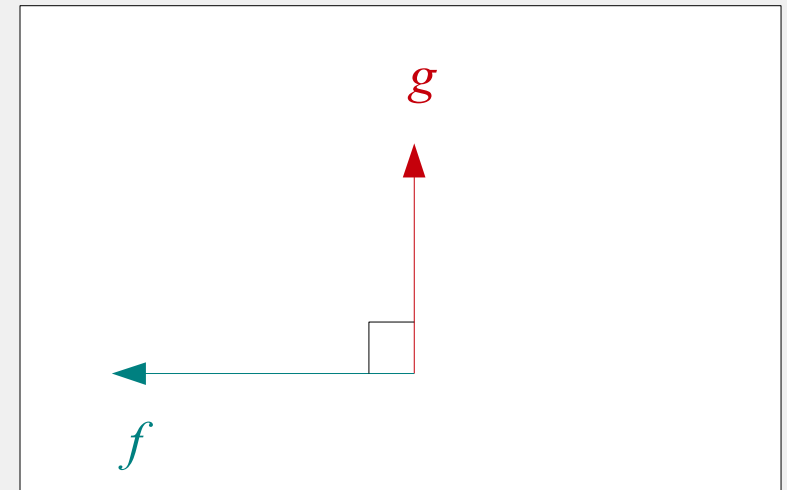
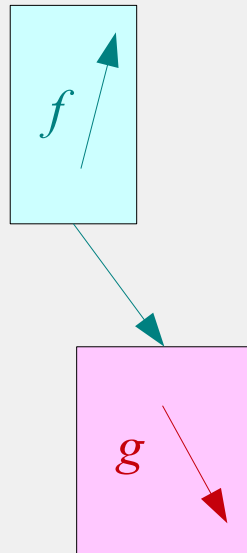
⇒ **How many** components in each theme?

... and **which**?

# How THEME works

## 2. The Path-Modelling problem

**Pb:** Every useful component partly depends on *all* others connected to it, directly or not...



$$r^2(g, f) = 0$$

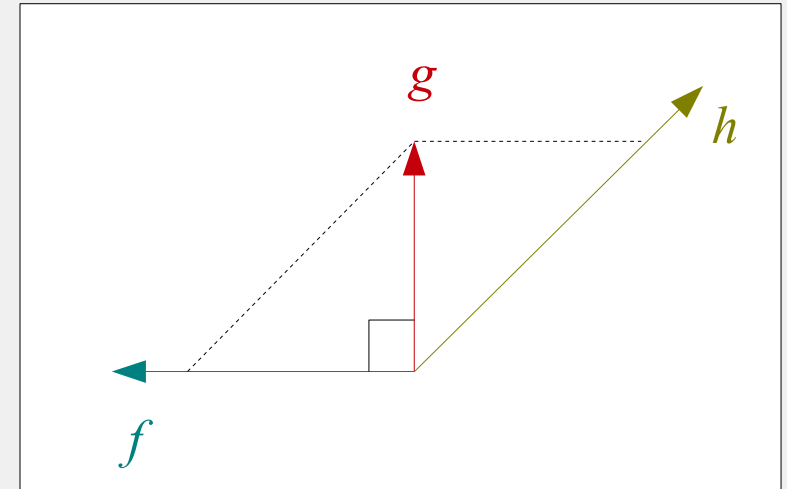
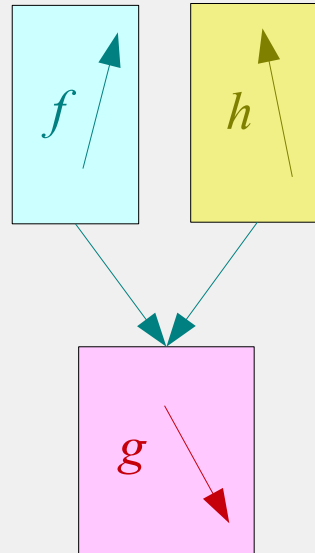
*No bivariate correlation  $r(f, g)$*



# How THEME works

## 1. Goodness of Fit of the Component Model

**Pb:** Every useful component partly depends on *all* others connected to it, directly or not...



$$R^2(g | f, h) = 1$$

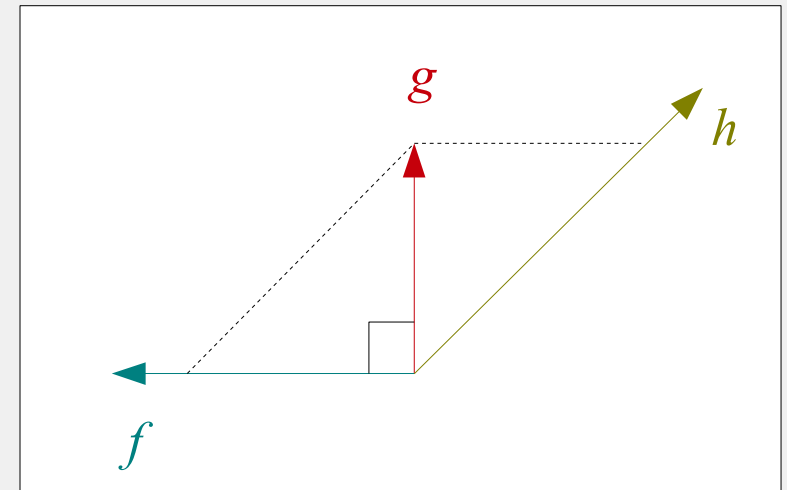
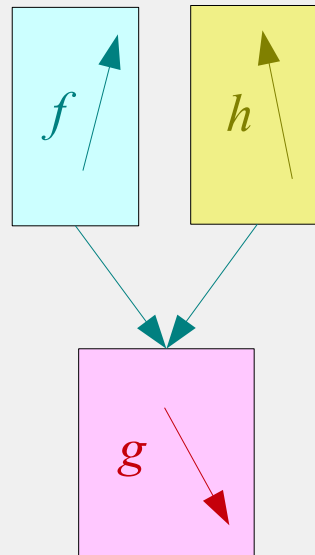
No bivariate correlation  $r(f, g)$   
 Important partial effect of  $f$  on  $g$ , conditional on  $h$



# How THEME works

## 1. Goodness of Fit of the Component Model

**Pb:** Every useful component partly depends on *all* others connected to it, directly or not...



$$R^2(g | f, h) = 1$$



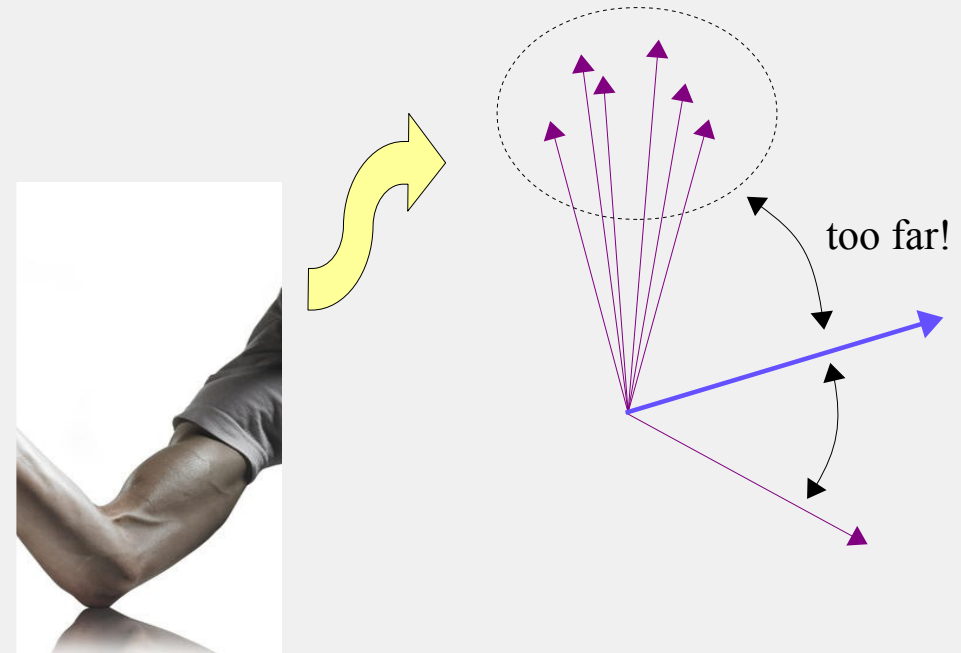
*Proper (partial) effects cannot be correctly captured through global bivariate indicators.*

⇒ **THEME** uses a Goodness-of-Fit criterion  $\psi$  capturing *multivariate* component-relationships

# How THEME works

## 2. Components must capture interpretable variable structures

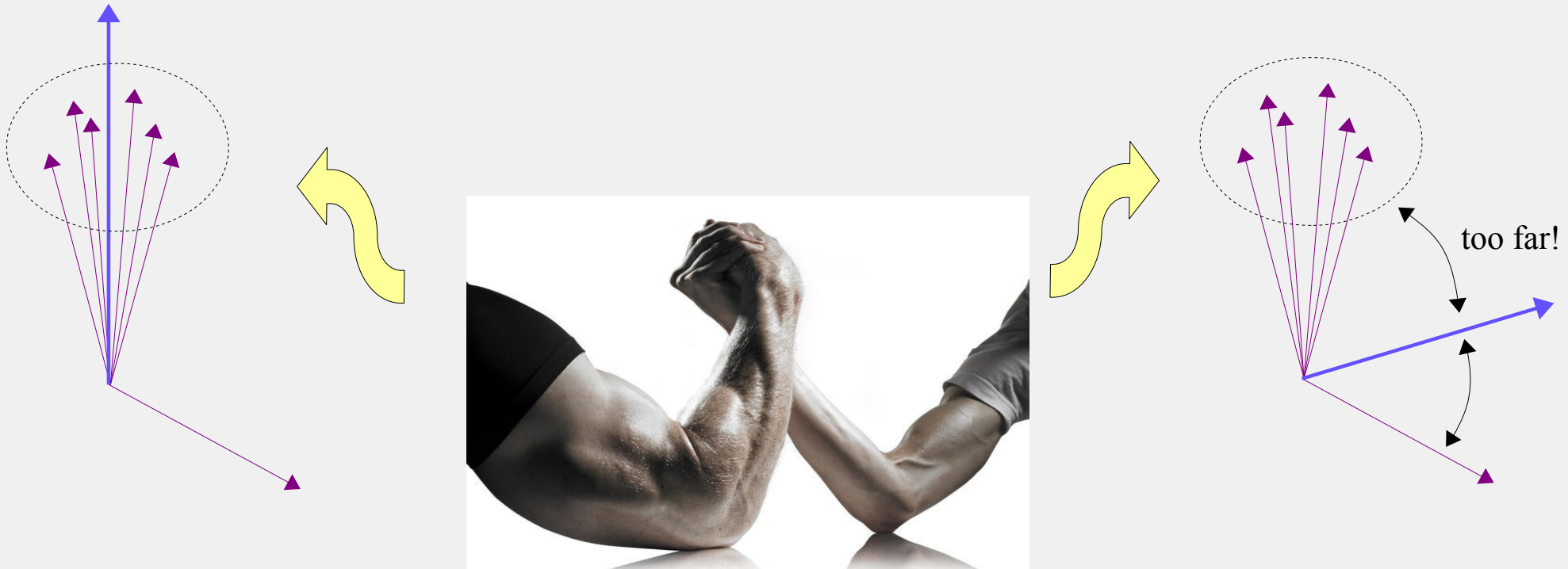
To be interpretable, components must be *structurally strong*,  
i.e. close to *observed variables bundles*



## How THEME works

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To be interpretable, components must be *structurally strong*,  
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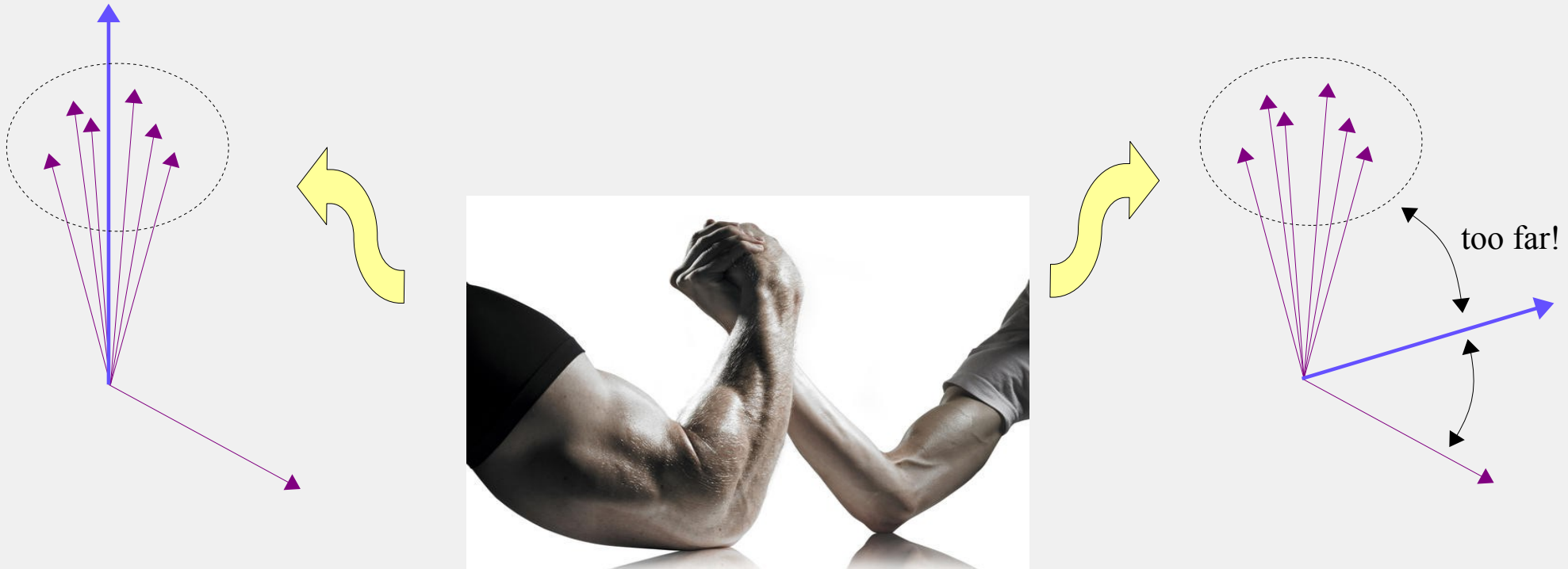




## How THEME works

### 2. Components must capture interpretable variable structures

To be interpretable, components must be *structurally strong*,  
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THEME uses an indicator of **structural strength**,  $\phi \simeq$  closeness to bundles.

## How THEME works

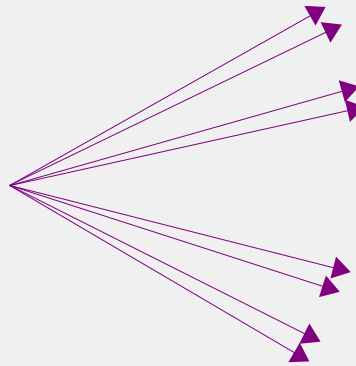
### 2. *Components must capture interpretable variable structures*

To be interpretable, components must be *structurally strong*,  
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*But What exactly is a bundle?*

The question arises of the “locality” of the bundles of directions to focus on.

We introduce a **parameter  $l$**  into  $\phi$ , to tune the **locality** considered. Example:



## How THEME works

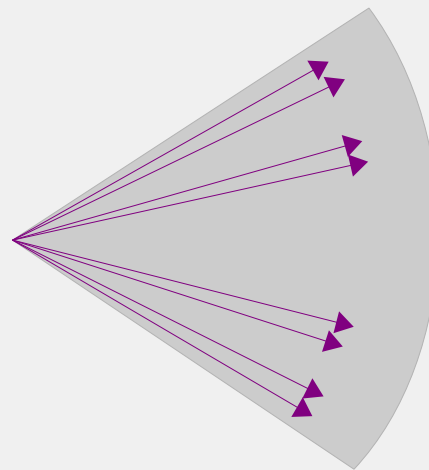
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... one bundle? ( $l \ll$ )

# How THEME works

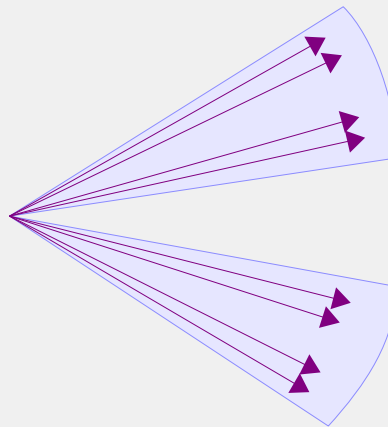
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... two bundles? ( $l \uparrow$ )

## How THEME works

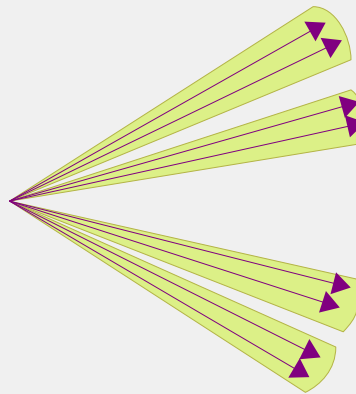
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*But What exactly is a bundle?*

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We introduce a **parameter  $l$**  into  $\phi$ , to tune the **locality** considered. Example:



... four bundles? ( $l \uparrow \uparrow$ )

## How THEME works

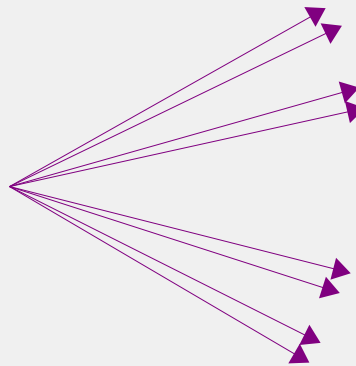
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We introduce a **parameter  $l$**  into  $\phi$ , to tune the **locality** considered. Example:



... eight bundles, each one being  
a single direction? ( $l \rightarrow \infty$ )

## How THEME works

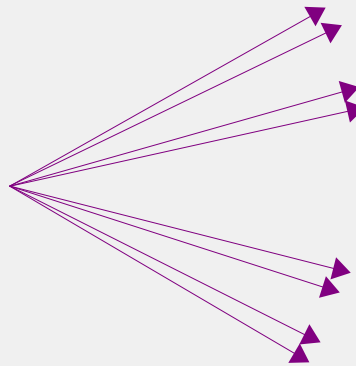
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We introduce a **parameter  $l$**  into  $\phi$ , to tune the **locality** considered. Example:



... eight bundles, each one being  
a single direction? ( $l \rightarrow \infty$ )

This ultimately depends on the data  
 $\beta$  Best  $l$  to be found through cross-validation.

## How THEME works

### 3. Combining goodness of fit $\psi$ and structural strength $\phi$

The criterion to be maximised by a component  $f$ , given *ALL* others:

$$\psi(f) \phi_l(f)^s$$

GoF  $\uparrow$   $\uparrow$  Str.  $\uparrow$  importance given to the SR relative to the GoF .

+1% on  $\phi$  is compensated by -s% on  $\psi$   
*Relative variations compensate at optimum*



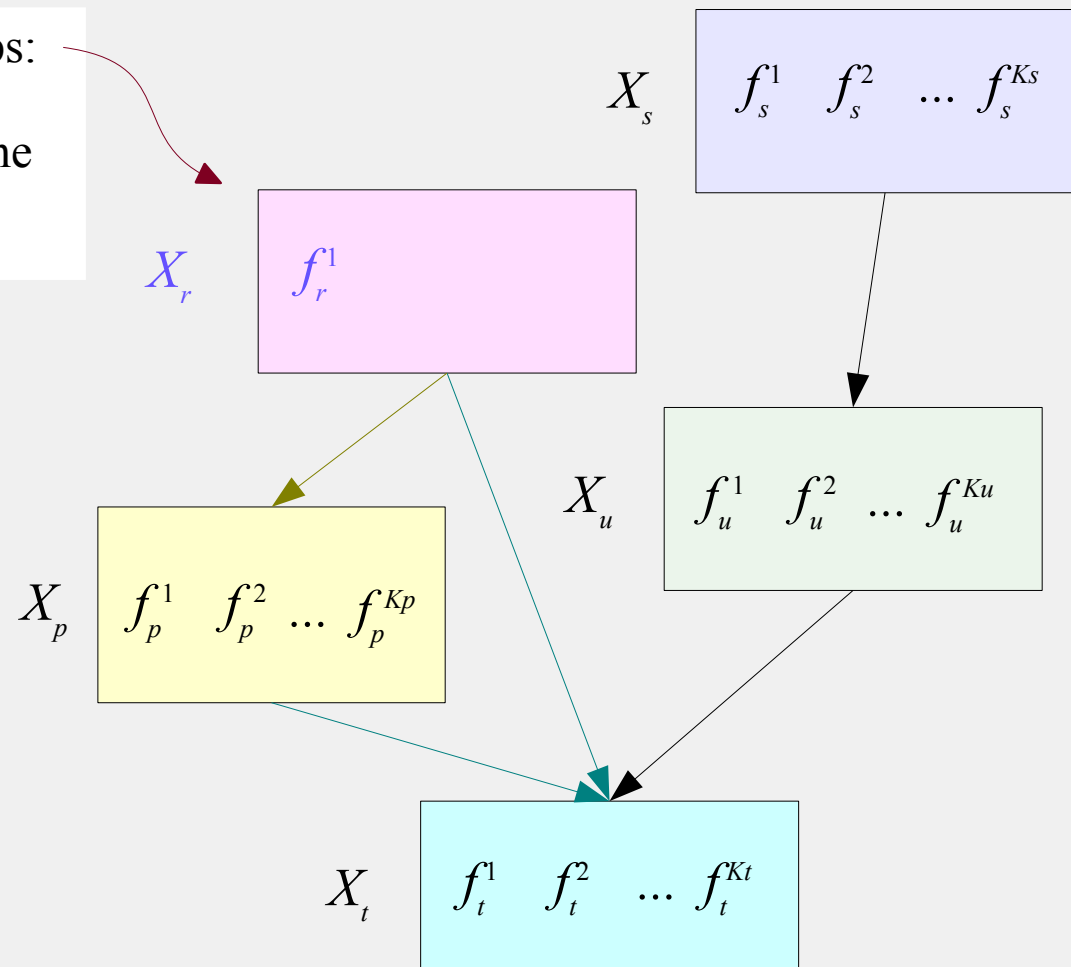
## How THEME works

### 4. Algorithm $\rightarrow$ component hierarchy

- The local-nesting (LocNes) principle:

In  $X_r$ , given all components in other groups:

$f_r^1$  is the best component with respect to the criterion;



## How THEME works

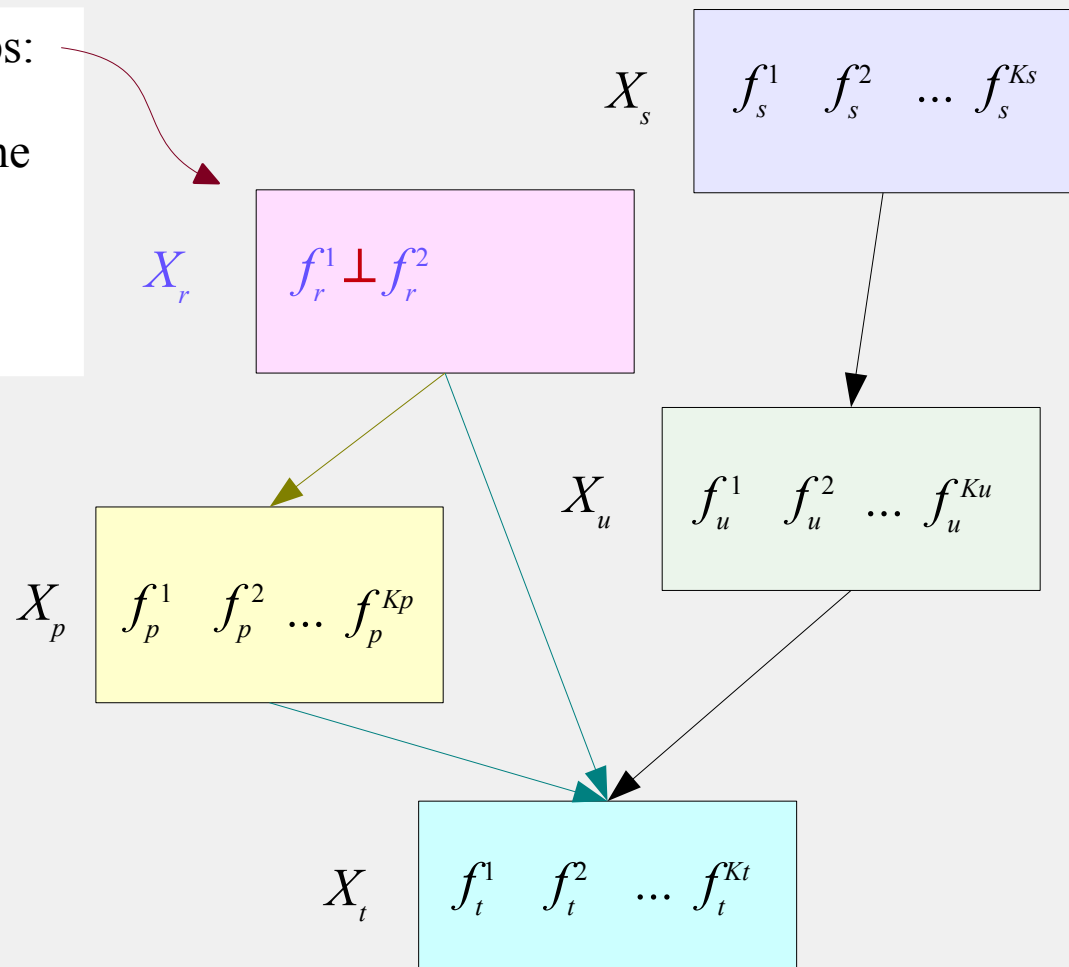
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## How THEME works

### 4. Algorithm $\rightarrow$ component hierarchy

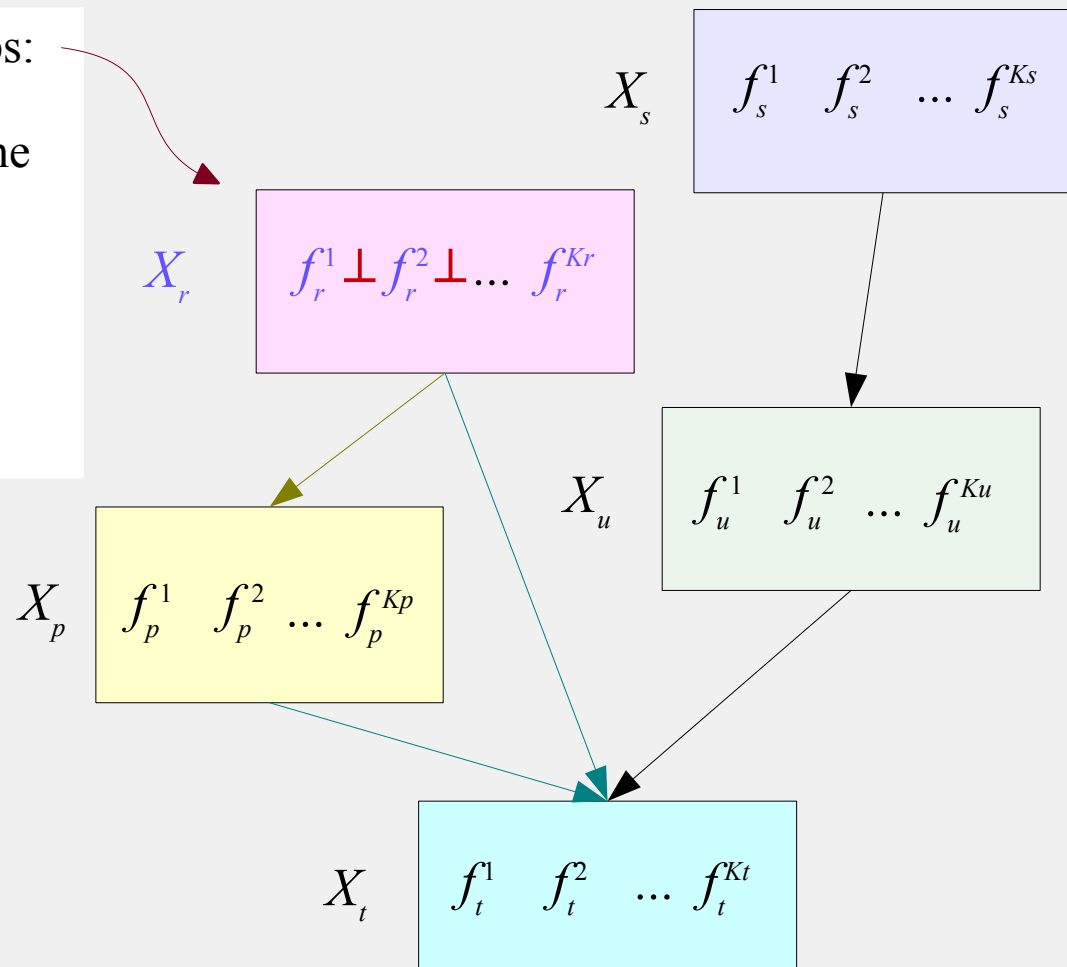
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... etc.



## How THEME works

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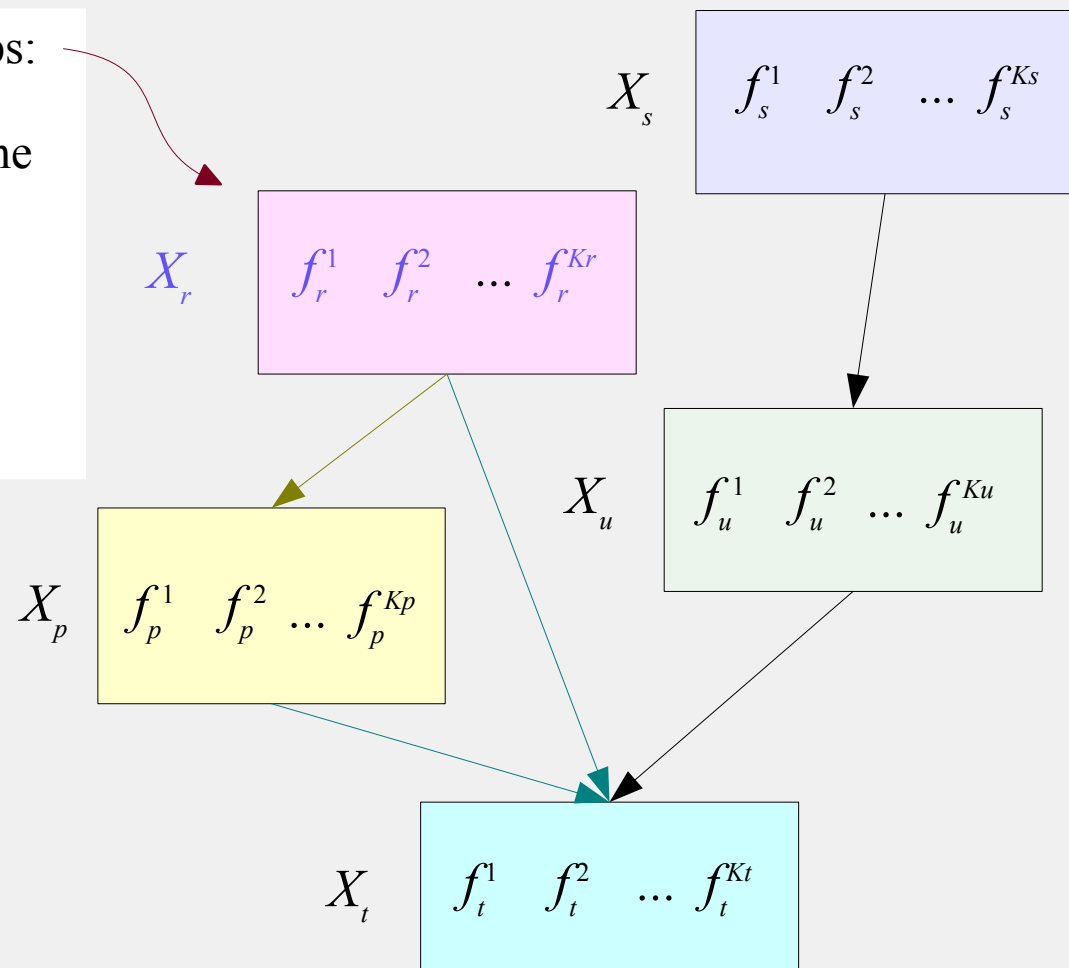
In  $X_r$ , given all components in other groups:

$f_r^1$  is the best component with respect to the criterion;

$f_r^2$  is its best orthogonal complement

... etc.

And the algorithm loops over groups  $X_r$  until convergence.

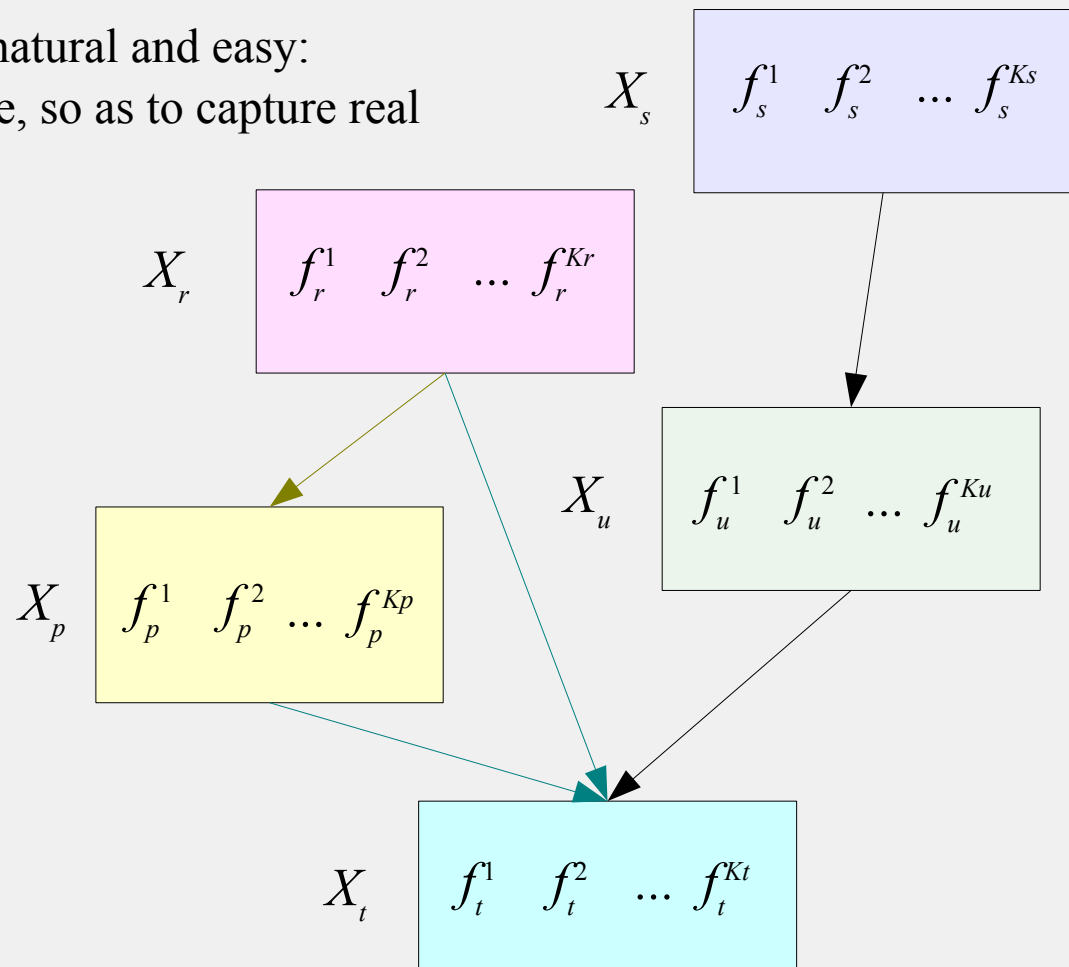


## How THEME works

### 5. *Backward component selection*

- How to select the suitable number of components in each group?

Local nesting makes *backward selection* natural and easy:  
Start with too many components per theme, so as to capture real partial effects.



# How THEME works

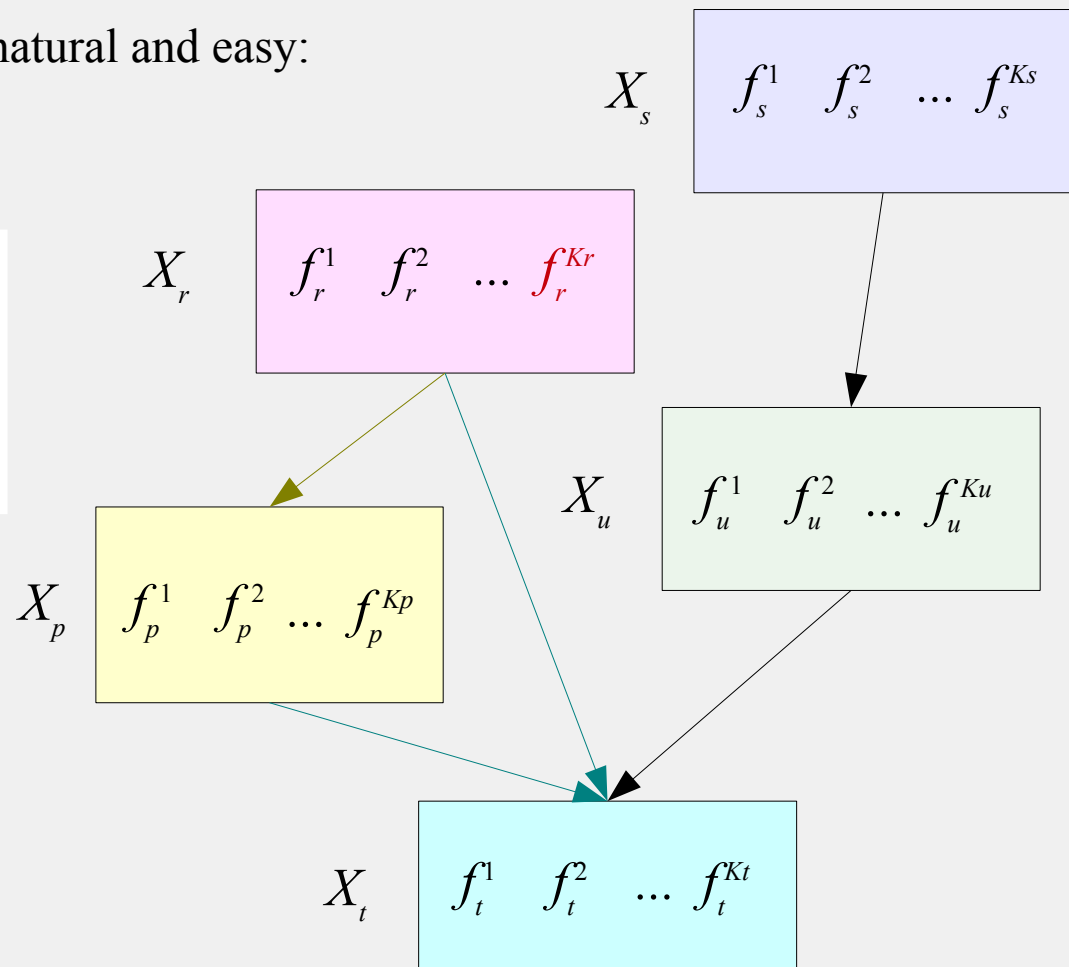
## 5. Backward component selection

- How to select the suitable number of components in each group?

Local nesting makes *backward selection* natural and easy:

The last component in each theme best complements *all* other components →

- measure the gain it brings;



## How THEME works

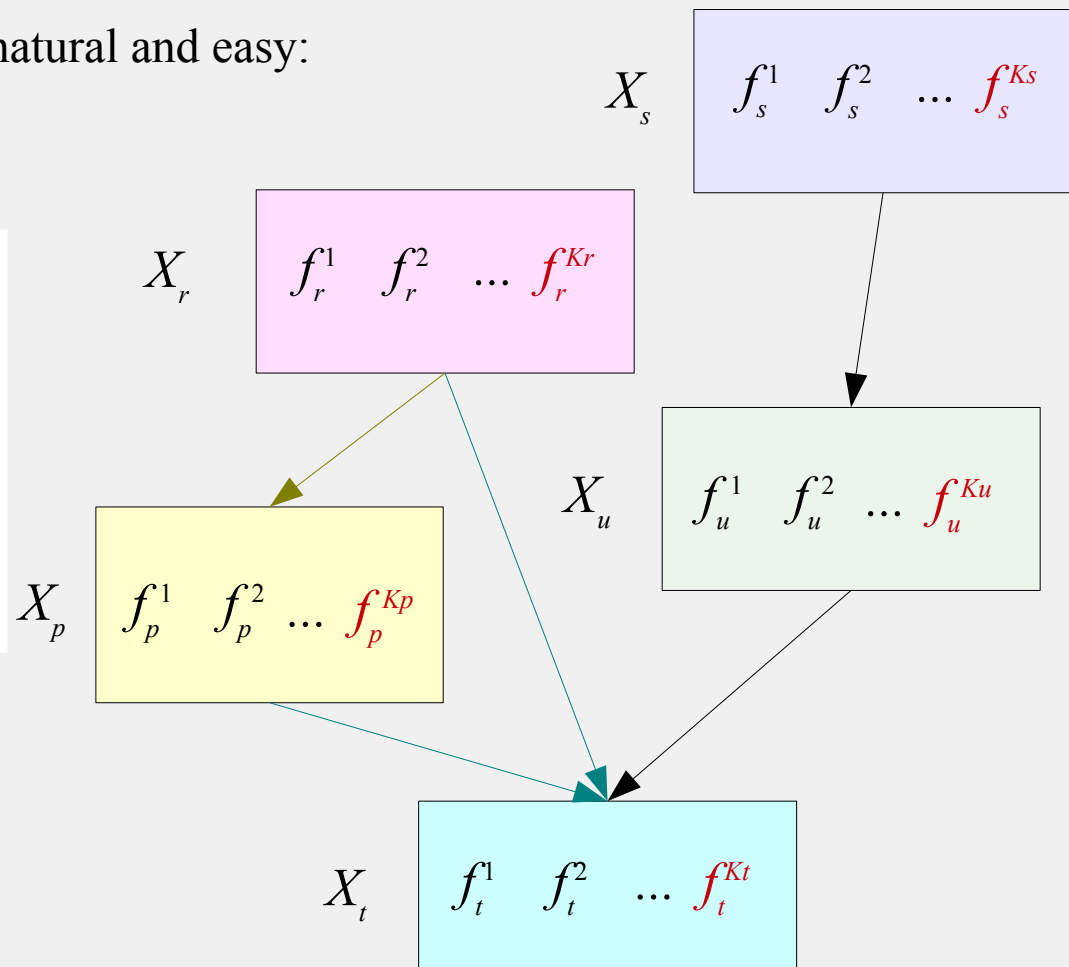
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- compare this gain to that of all last components;



## How THEME works

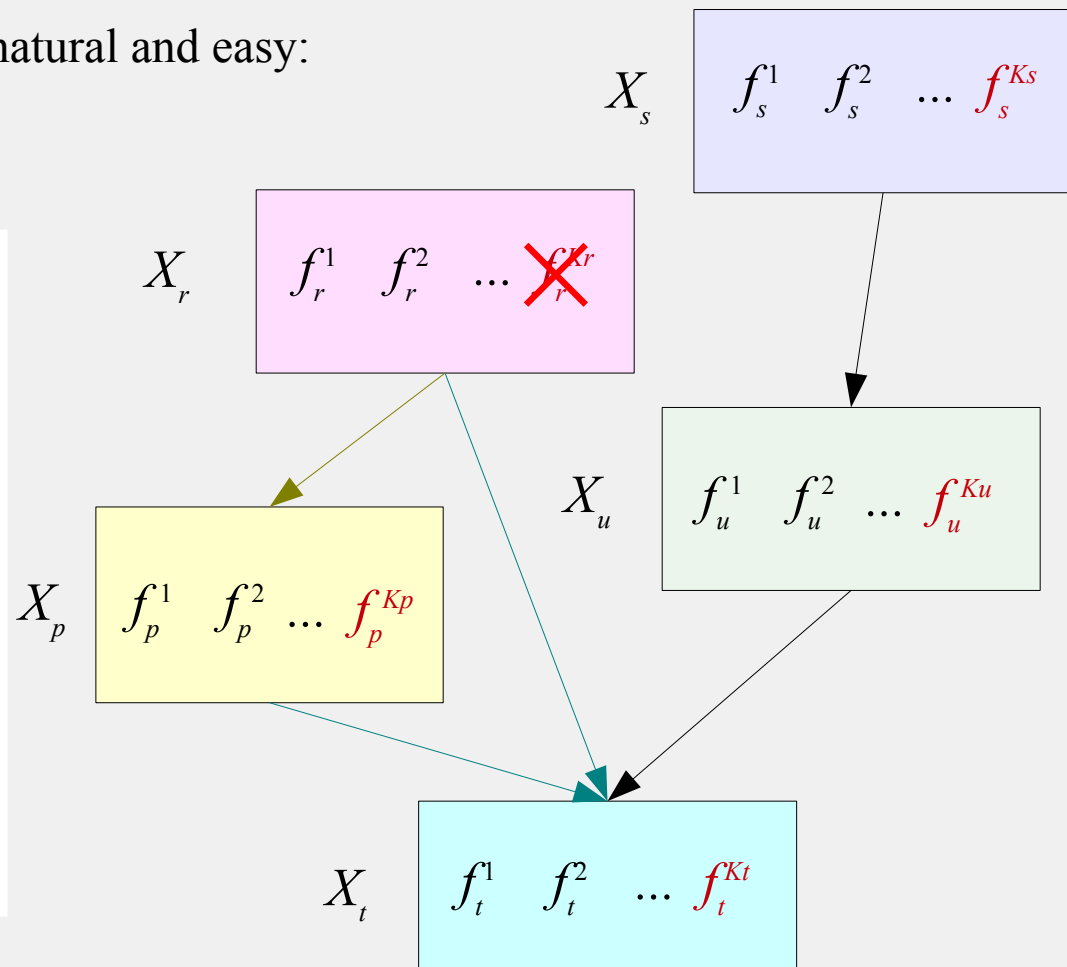
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- How to select the suitable number of components in each group?

Local nesting makes *backward selection* natural and easy:

The last component in each theme best complements *all* other components →

- measure the gain it brings;
- compare this gain to that of all last components;
- eliminate the component bringing the smallest gain;
- re-estimate the model, etc.





## How THEME works

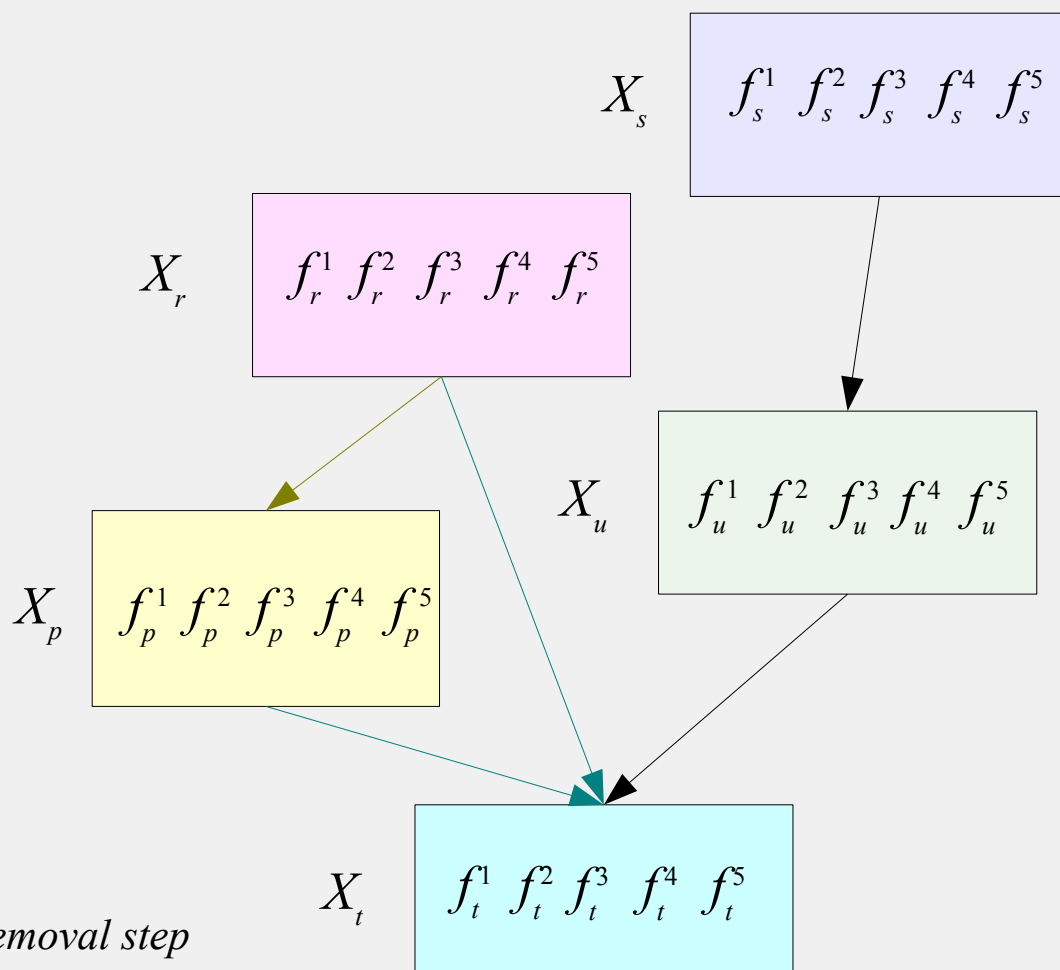
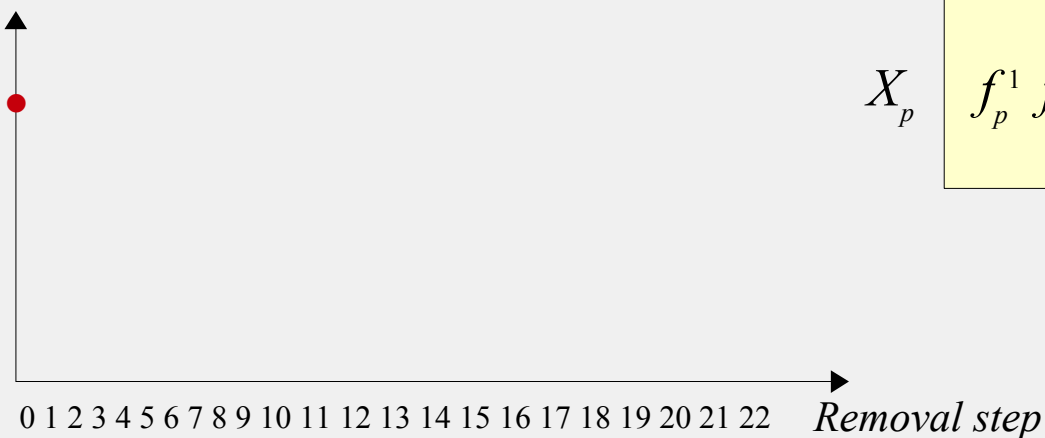
### 5. Backward component selection

- How to select the suitable number of components in each group?

Local nesting makes *backward selection* natural and easy:

#### Example:

Cross-validation  
prediction error rate



## How THEME works

### 5. Backward component selection

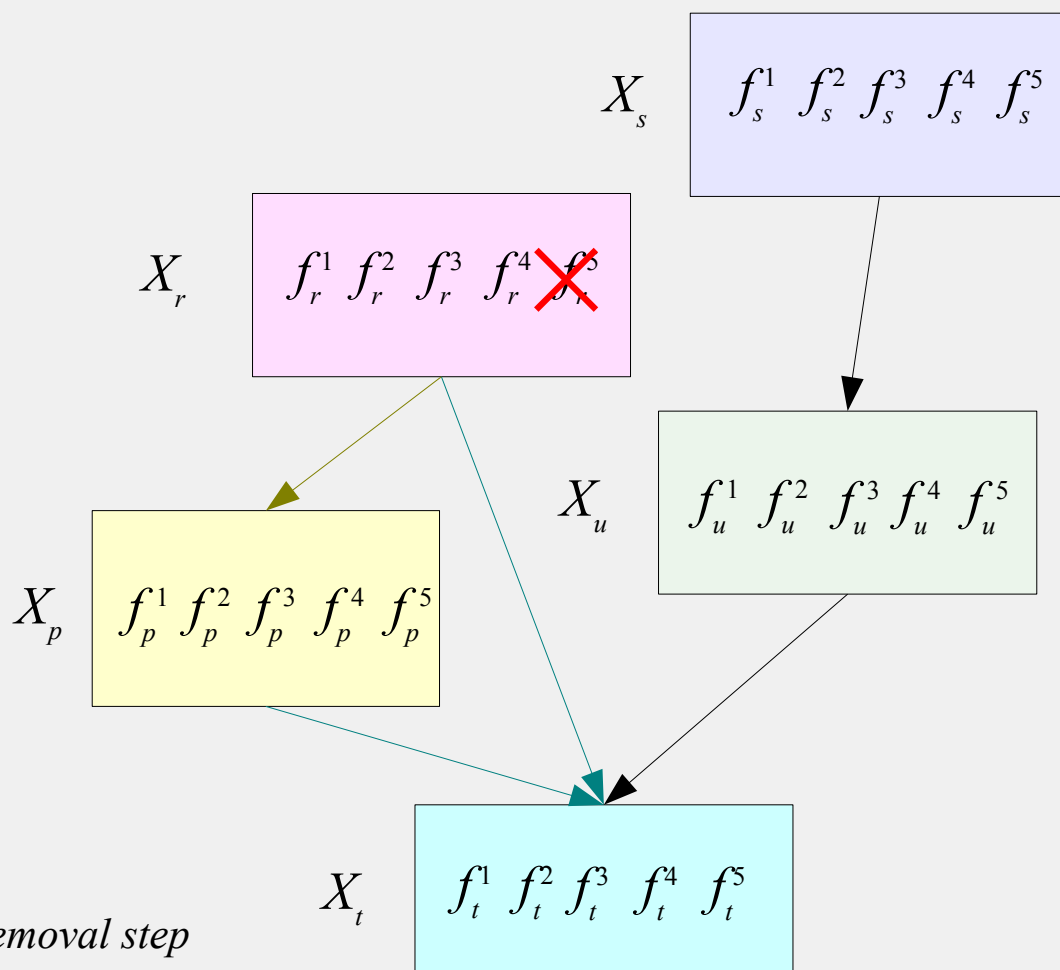
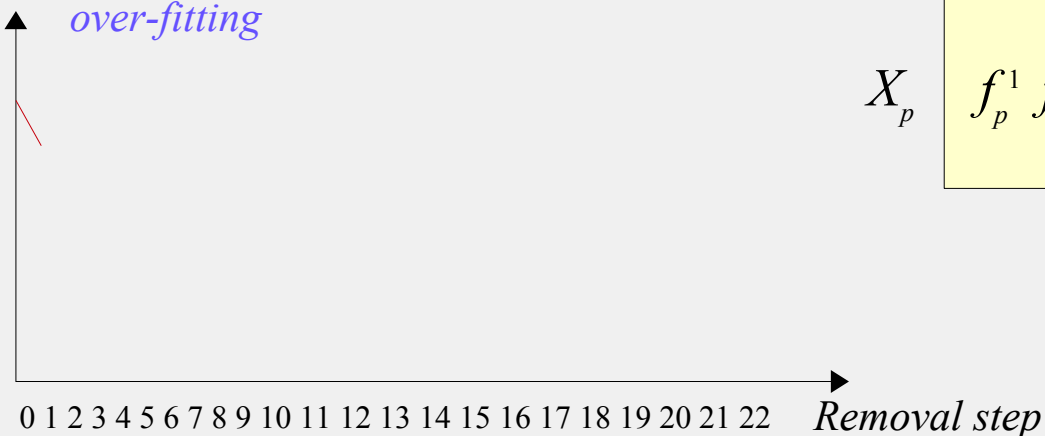
- How to select the suitable number of components in each group?

Local nesting makes *backward selection* natural and easy:

#### Example:

Cross-validation  
prediction error rate

over-fitting



## How THEME works

### 5. Backward component selection

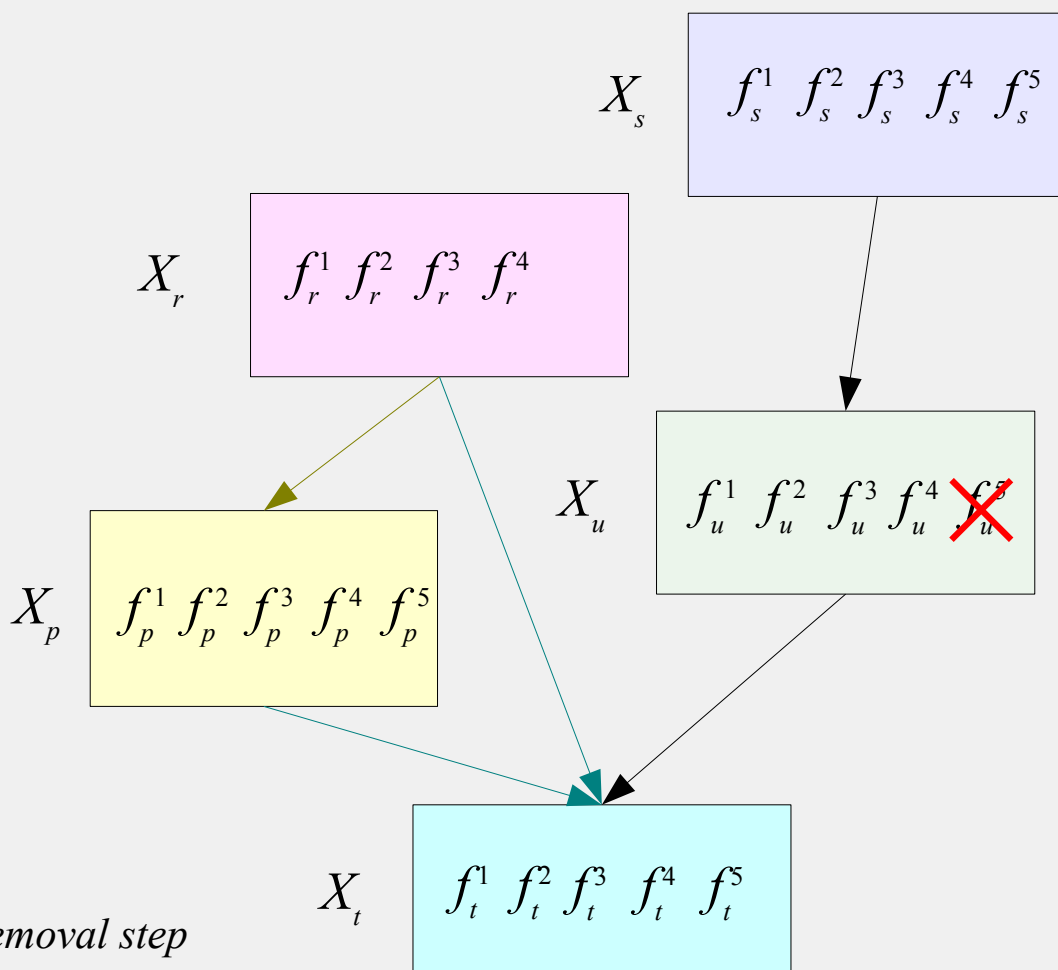
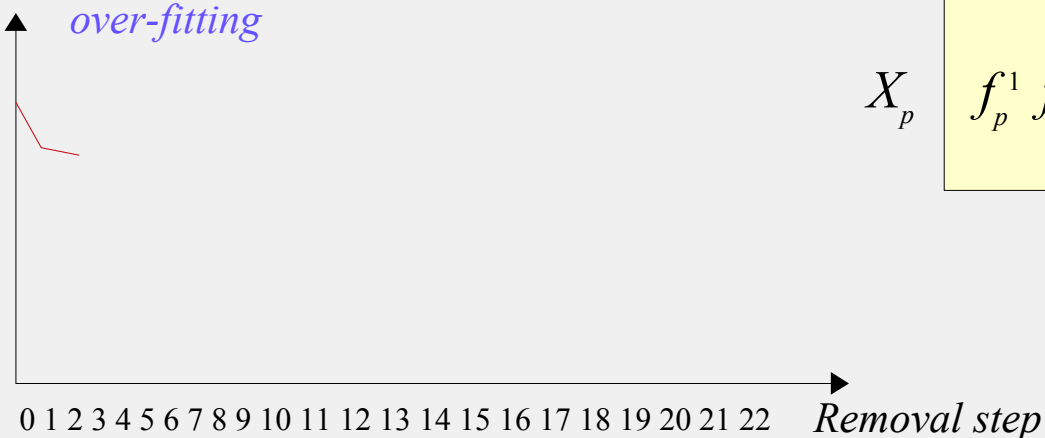
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## How THEME works

### 5. Backward component selection

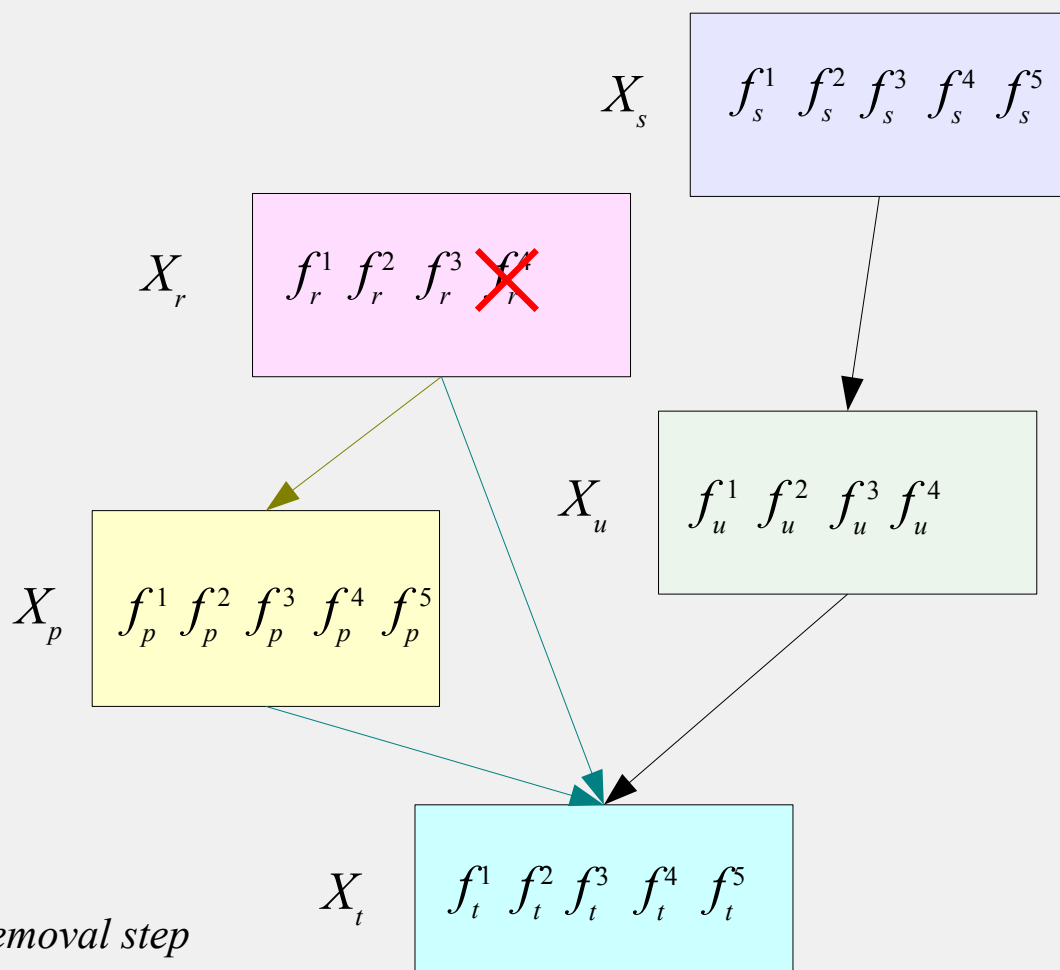
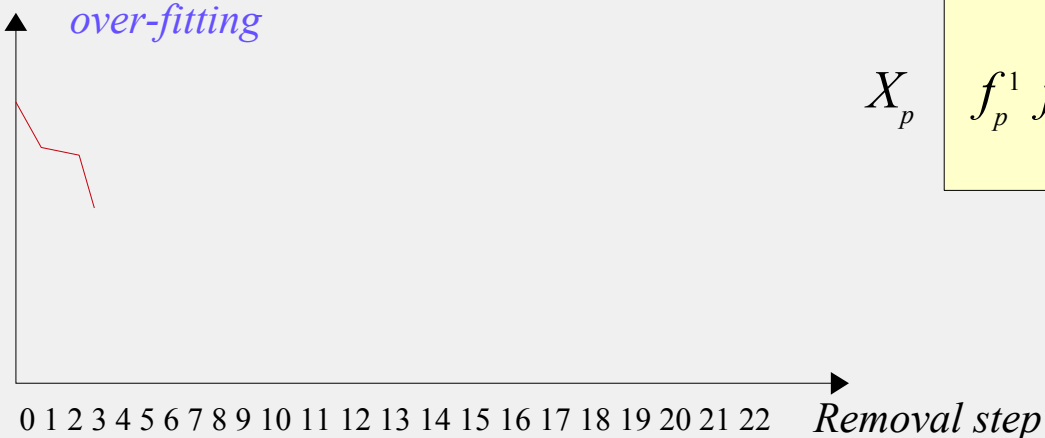
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# How THEME works

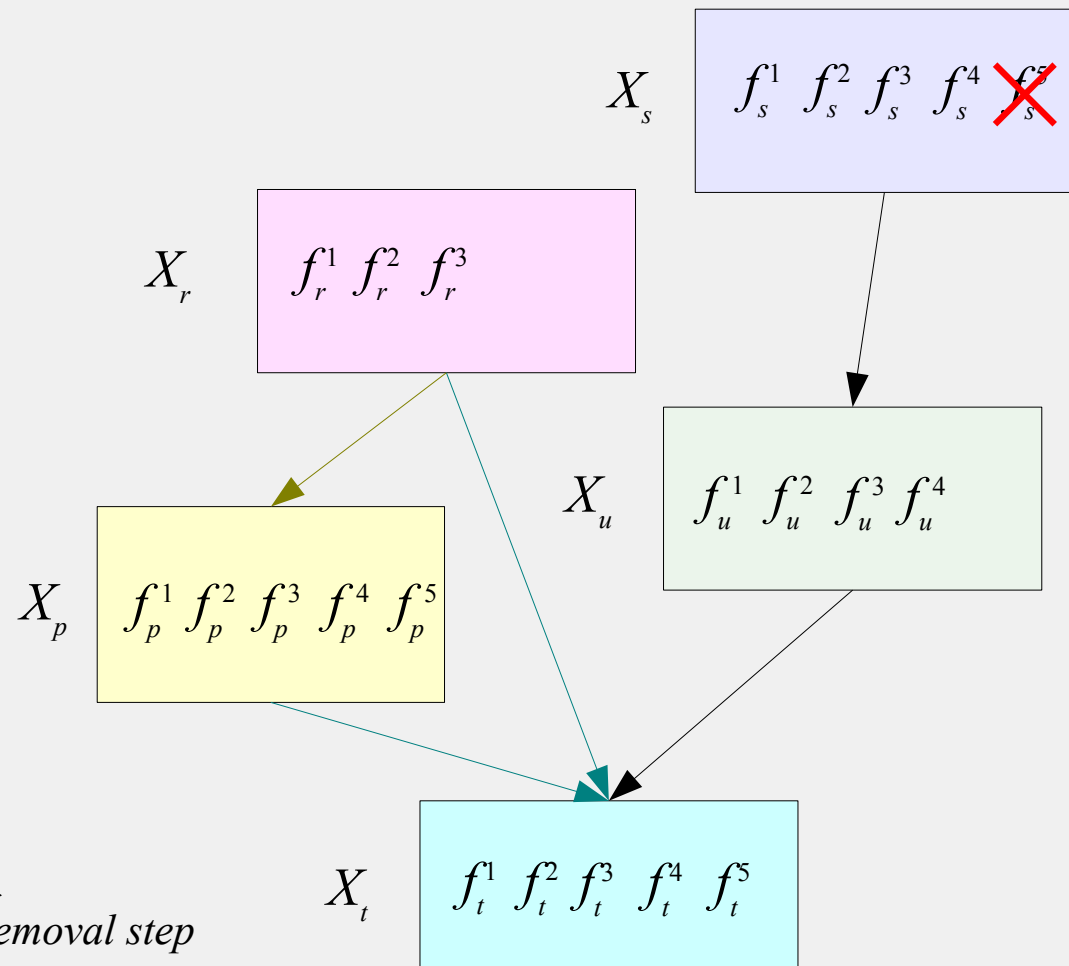
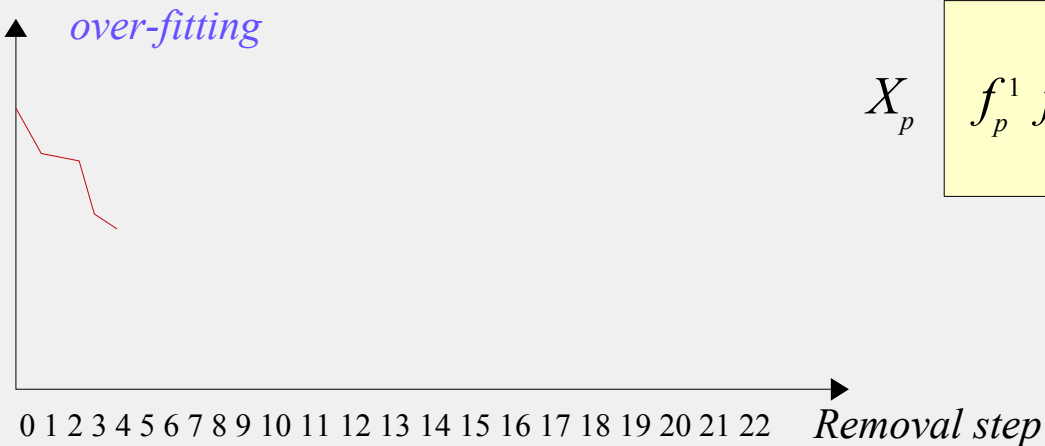
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## How THEME works

### 5. Backward component selection

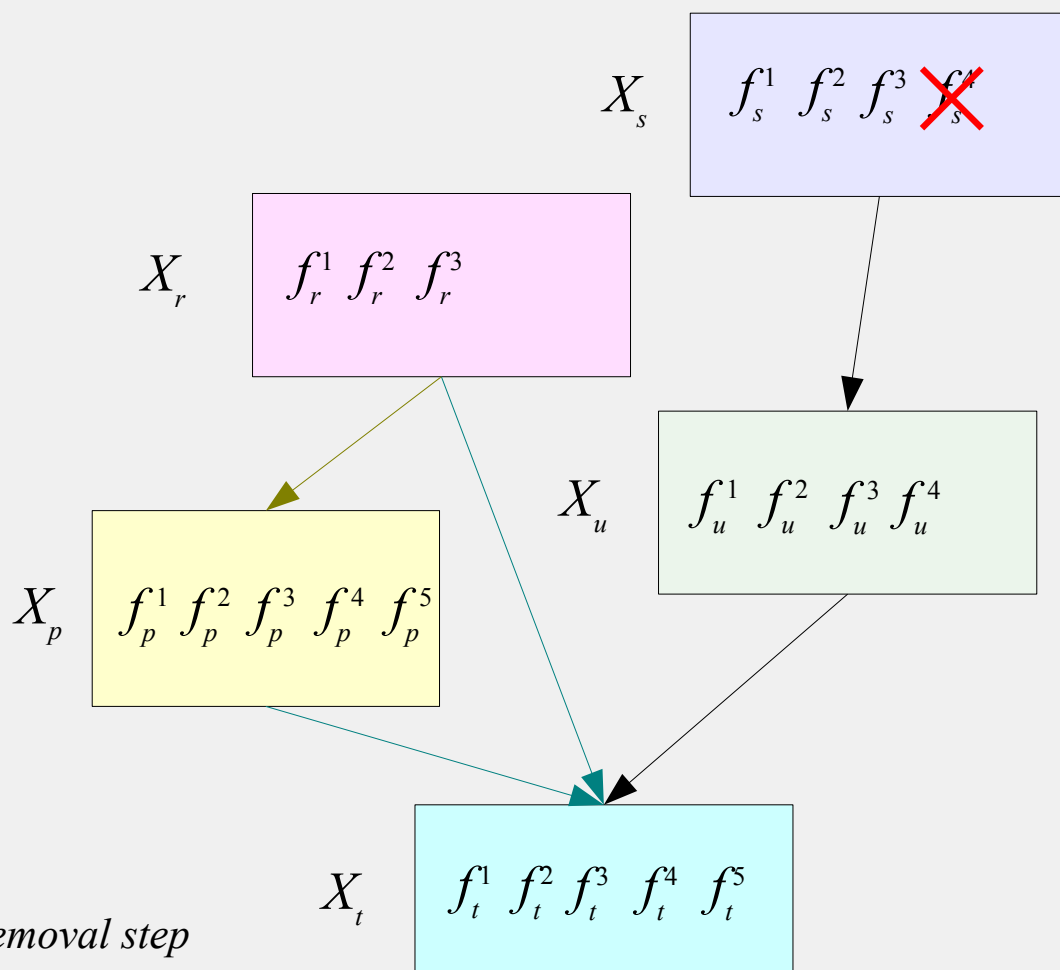
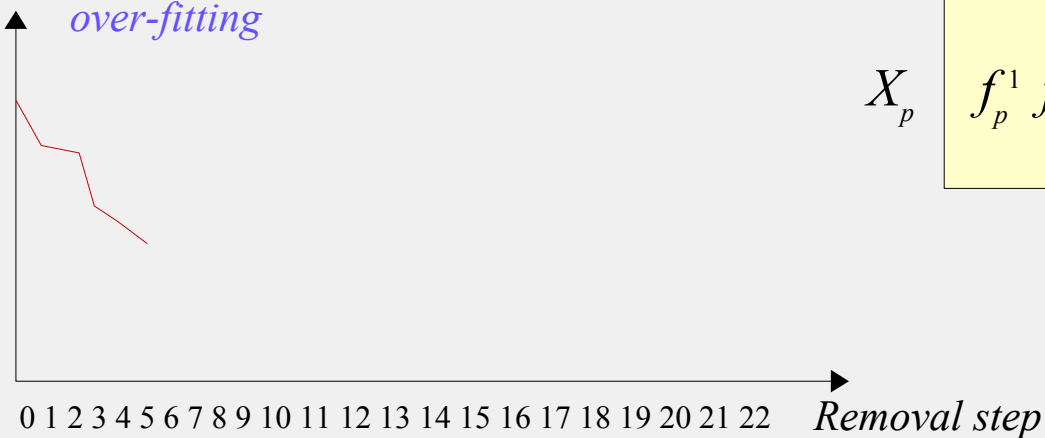
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## How THEME works

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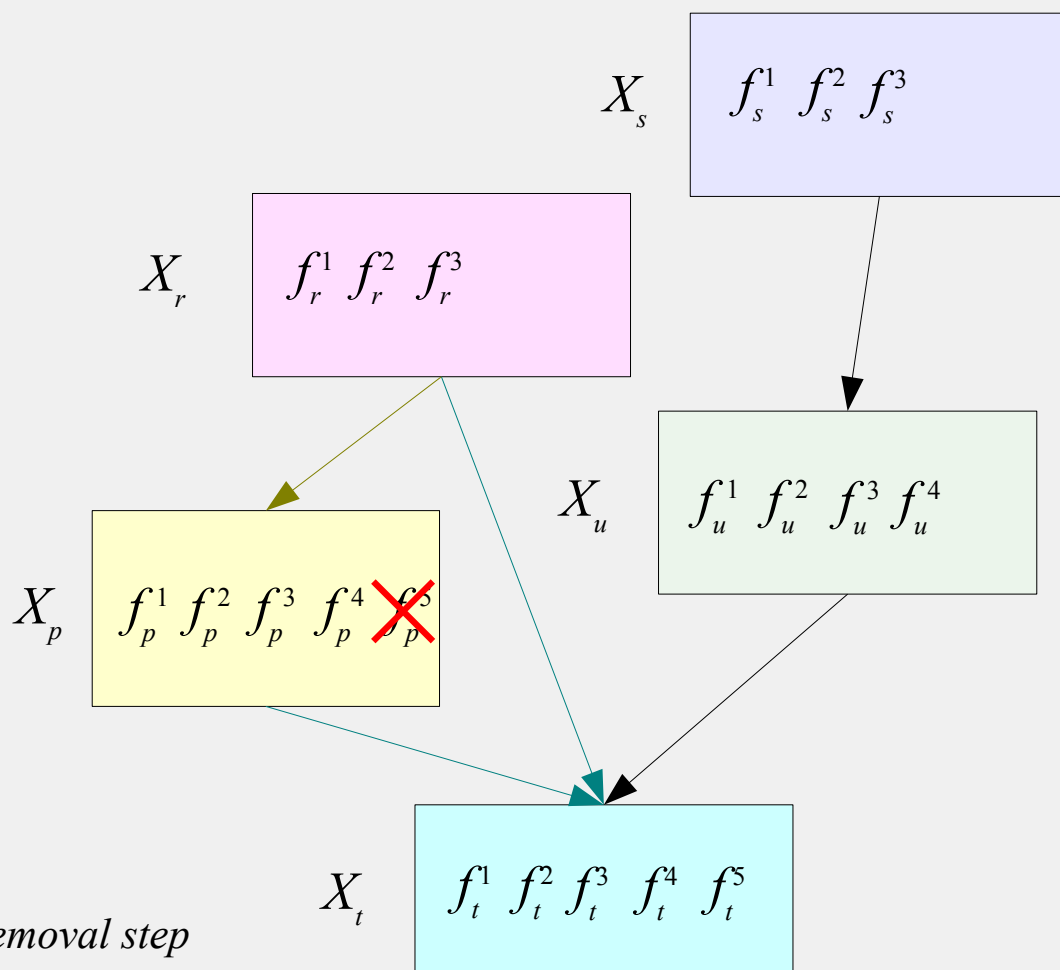
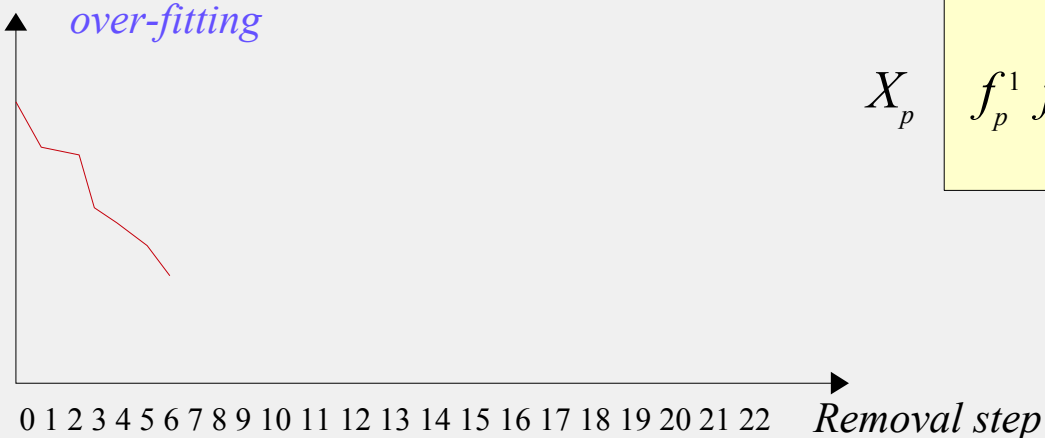
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Cross-validation prediction error rate

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## How THEME works

### 5. Backward component selection

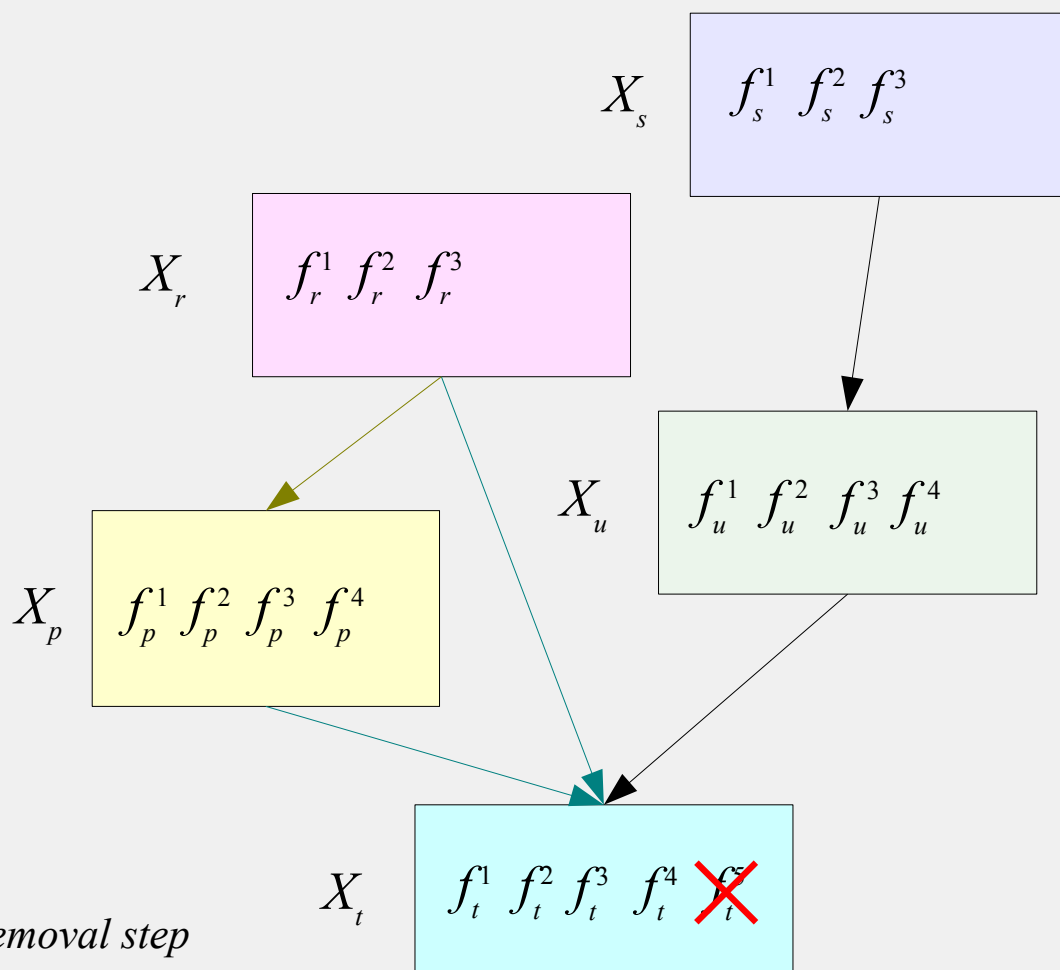
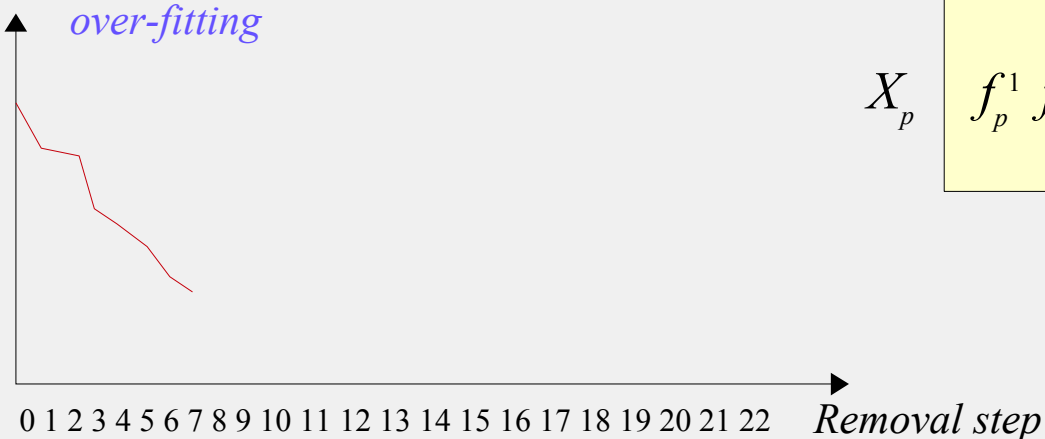
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#### Example:

Cross-validation  
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*over-fitting*





## How THEME works

### 5. Backward component selection

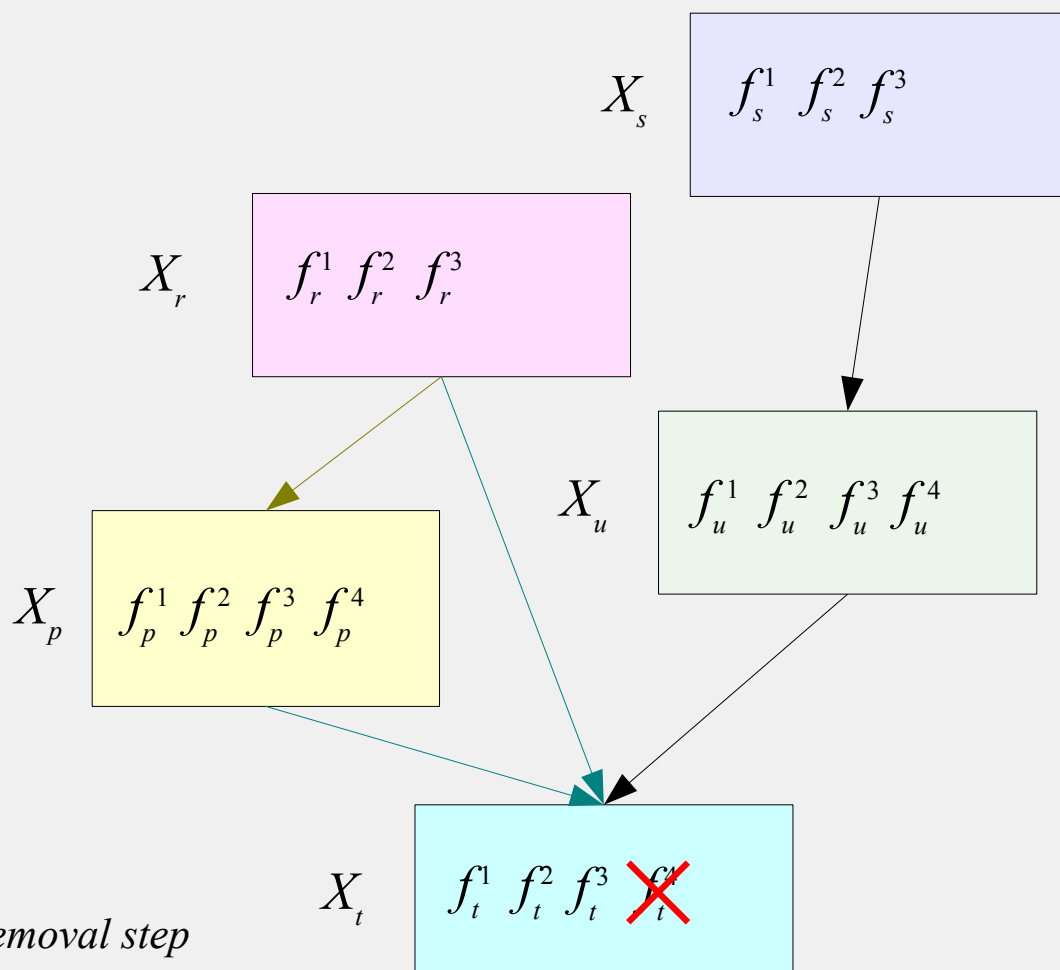
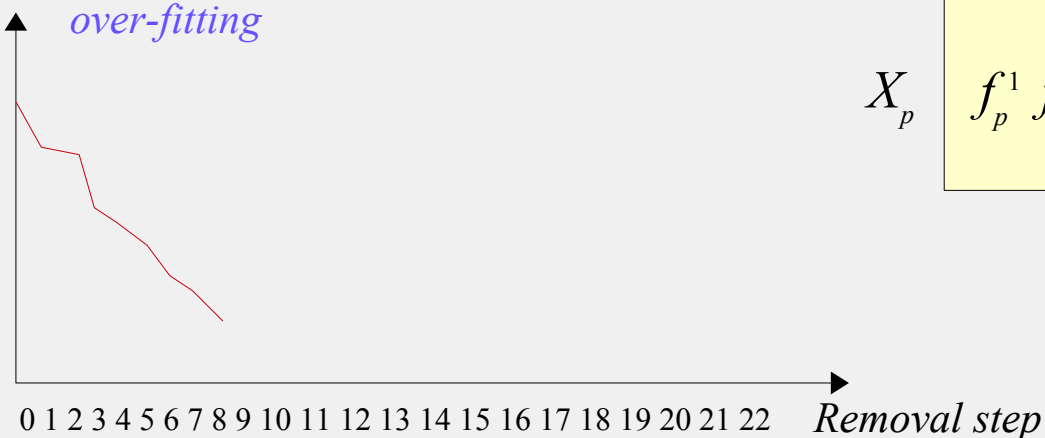
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Cross-validation prediction error rate

*over-fitting*



## How THEME works

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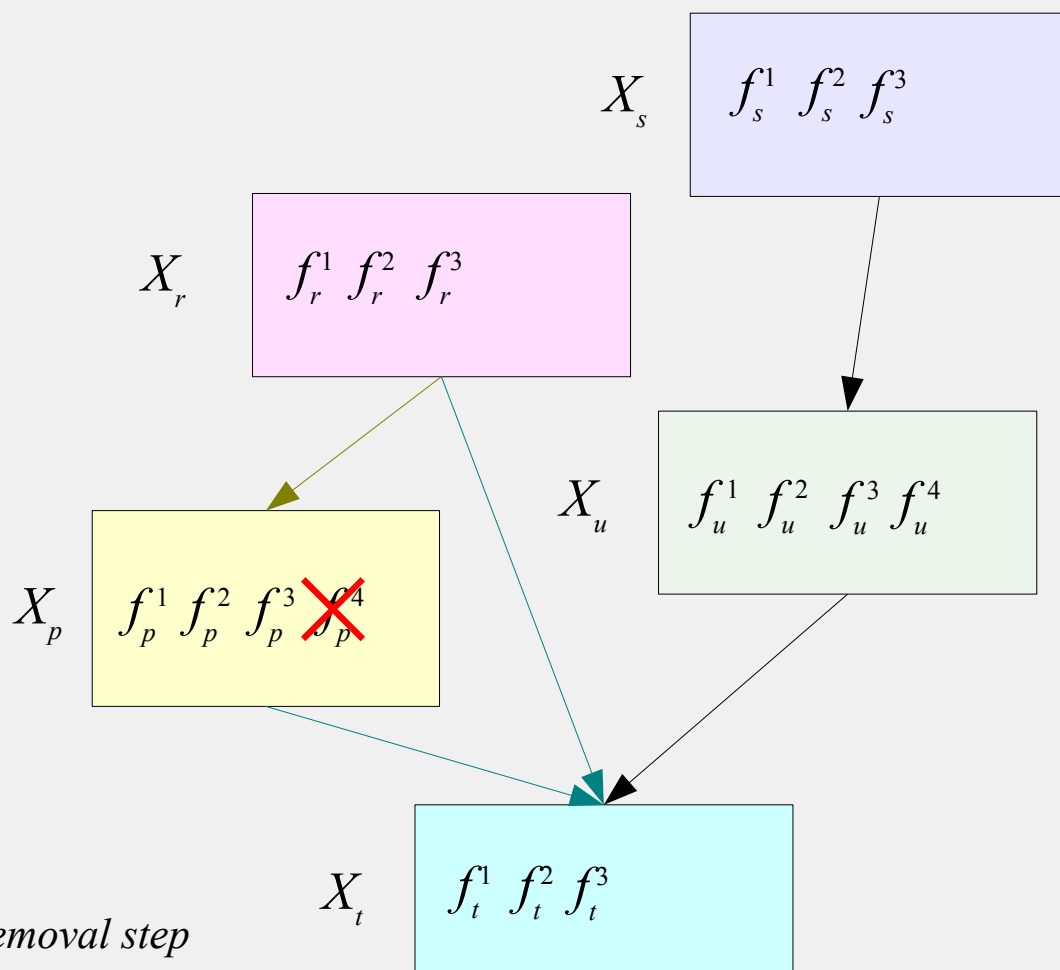
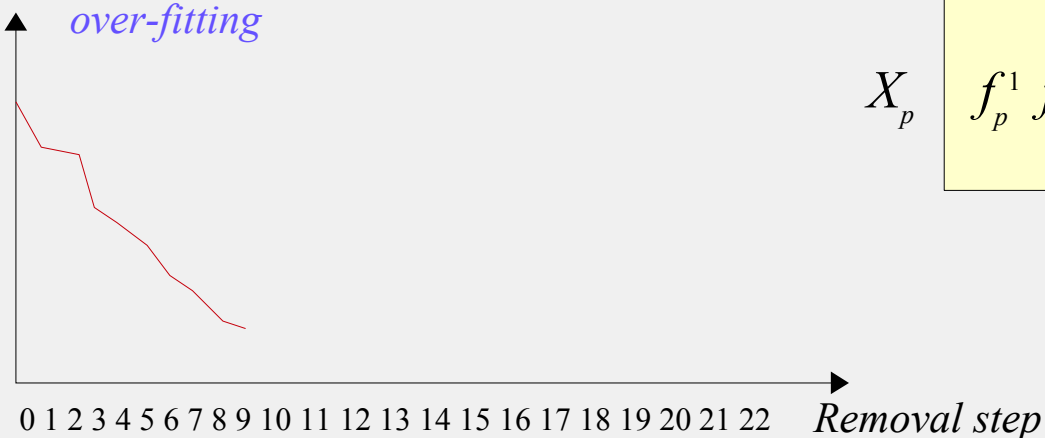
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Cross-validation prediction error rate

over-fitting



## How THEME works

### 5. Backward component selection

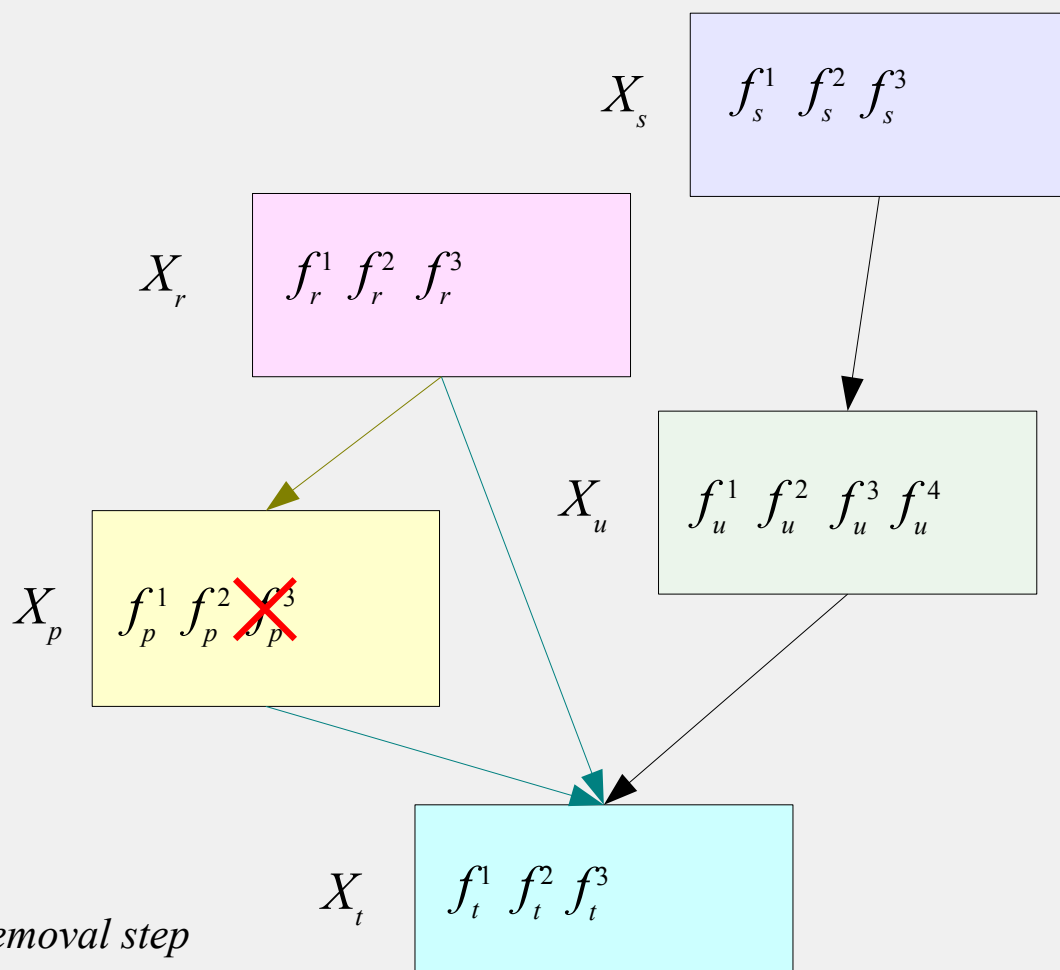
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Cross-validation  
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## How THEME works

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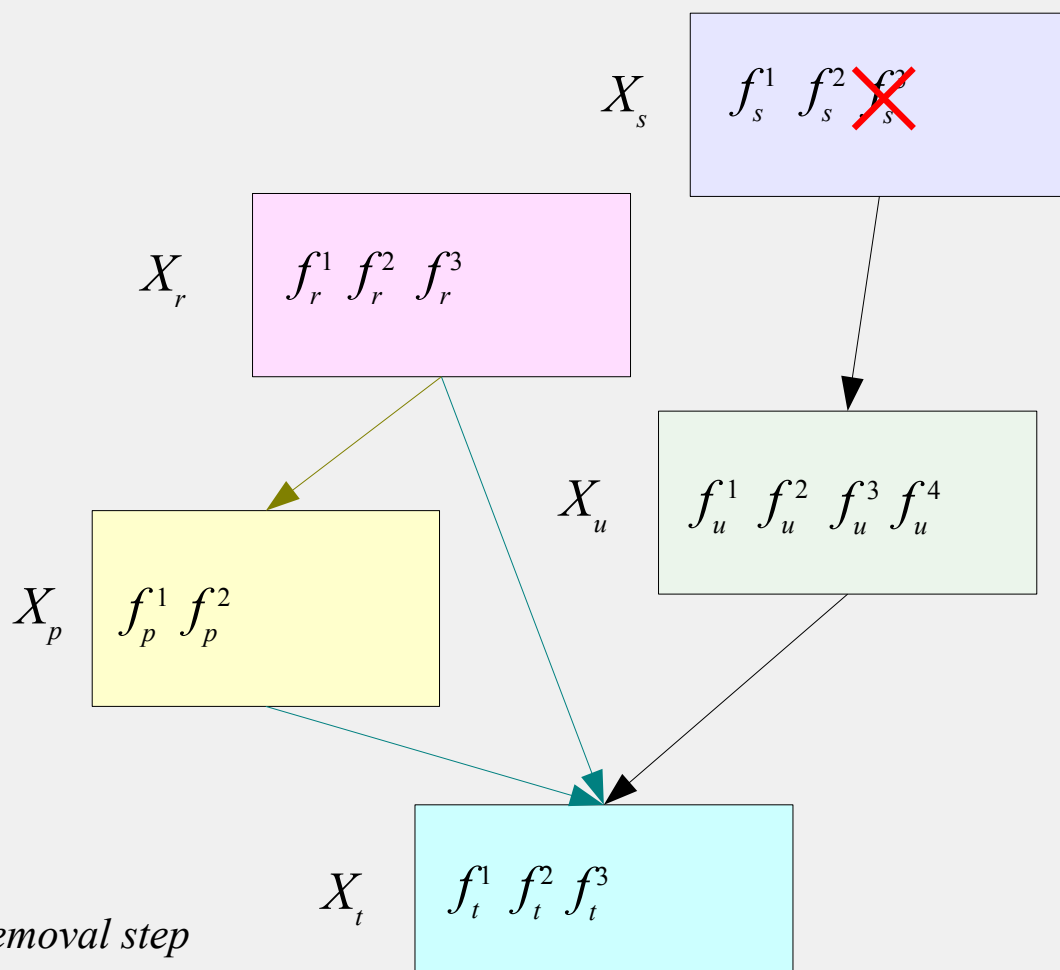
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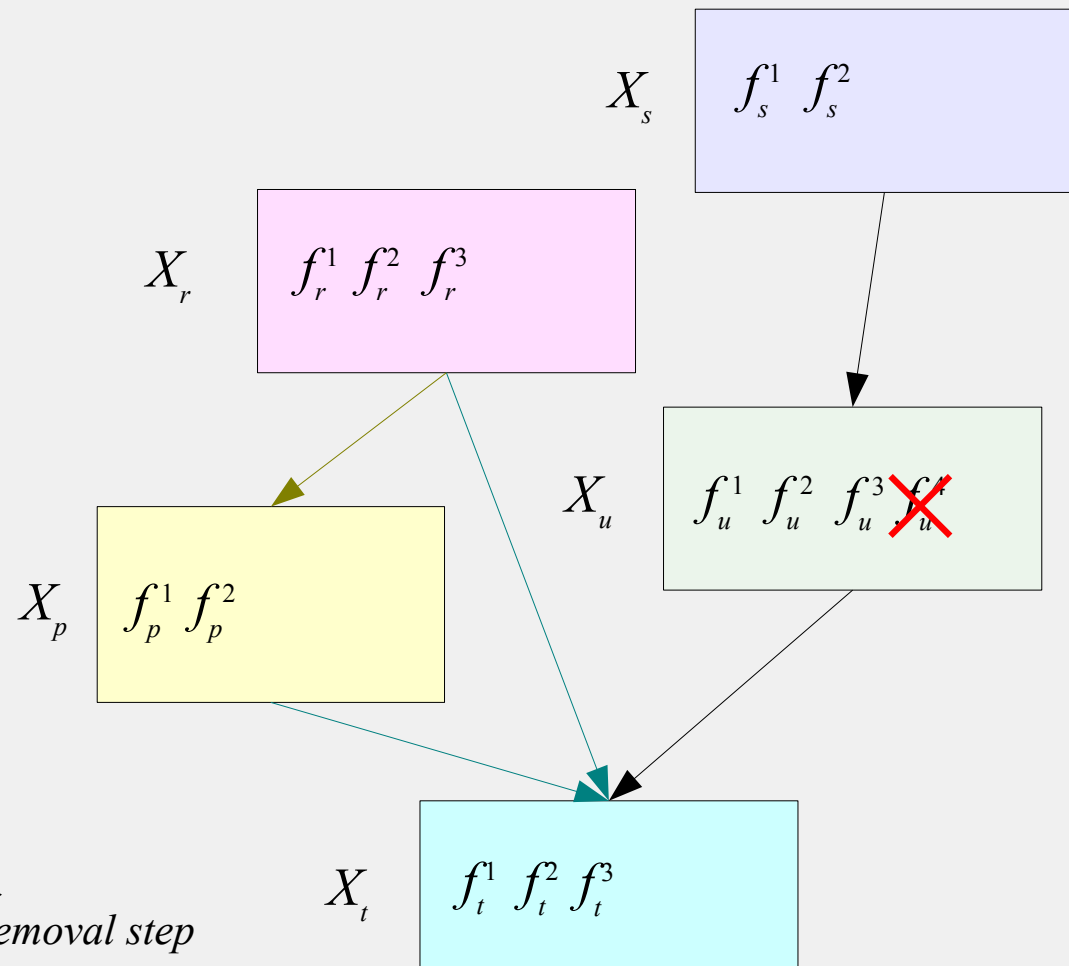
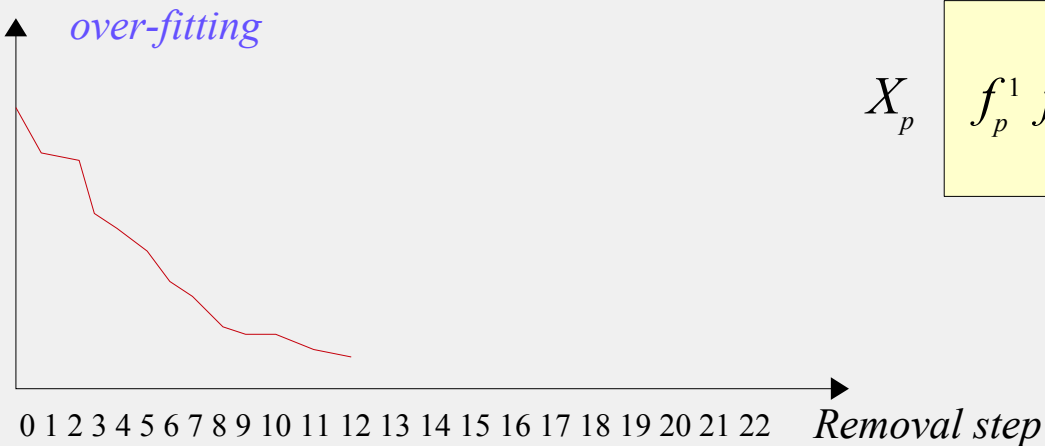
## 5. Backward component selection

- How to select the suitable number of components in each group?

Local nesting makes *backward selection* natural and easy:

### Example:

Cross-validation prediction error rate



## How THEME works

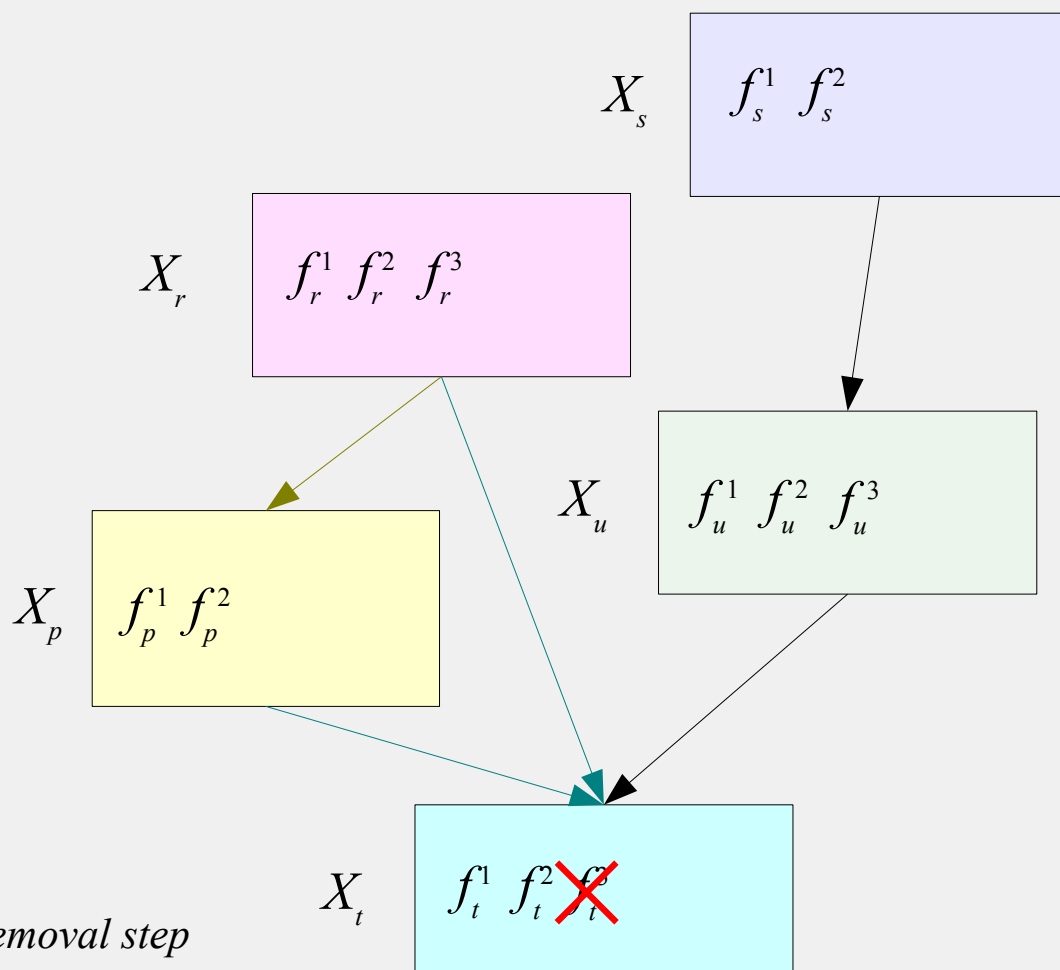
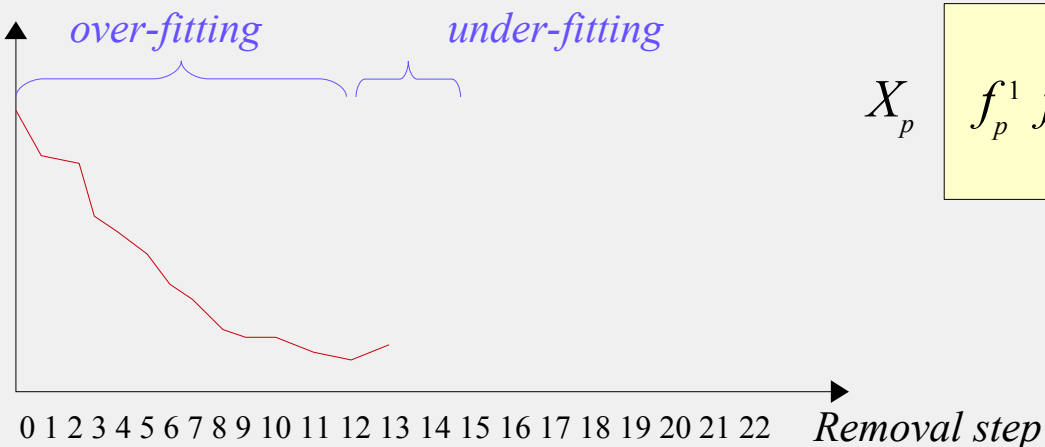
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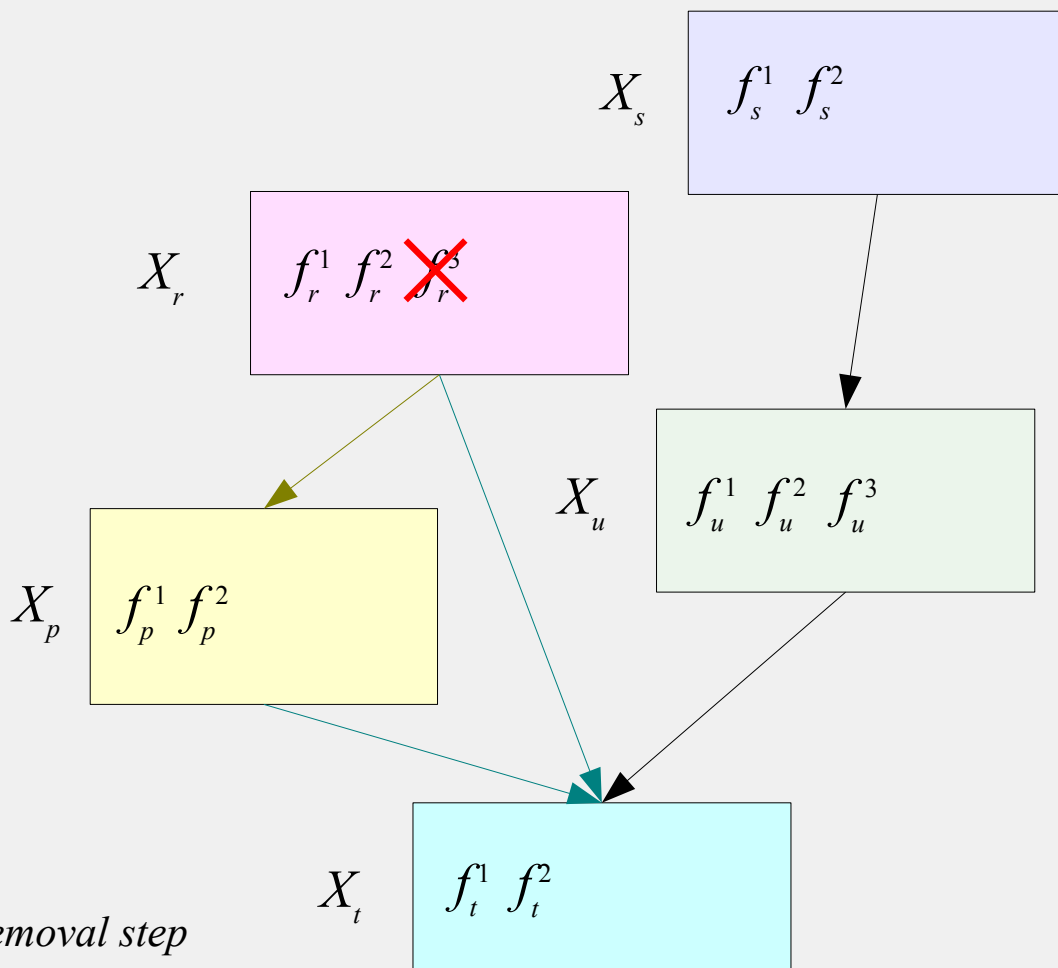
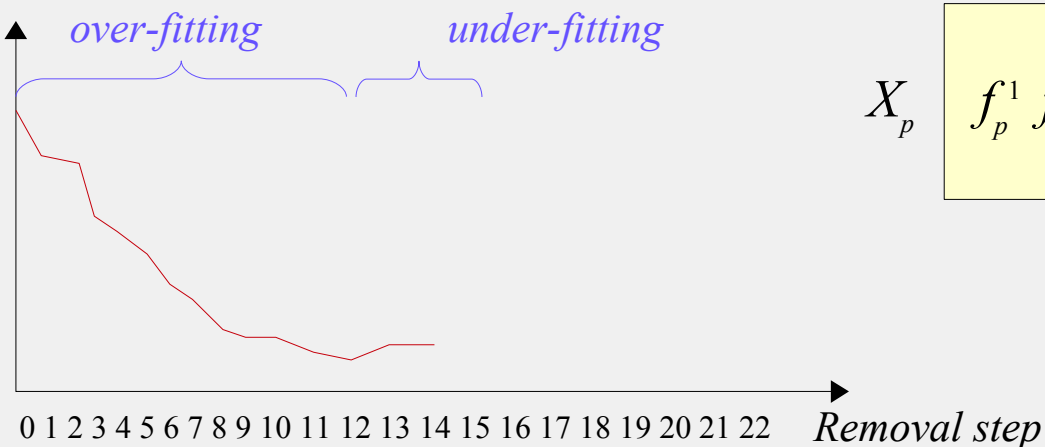
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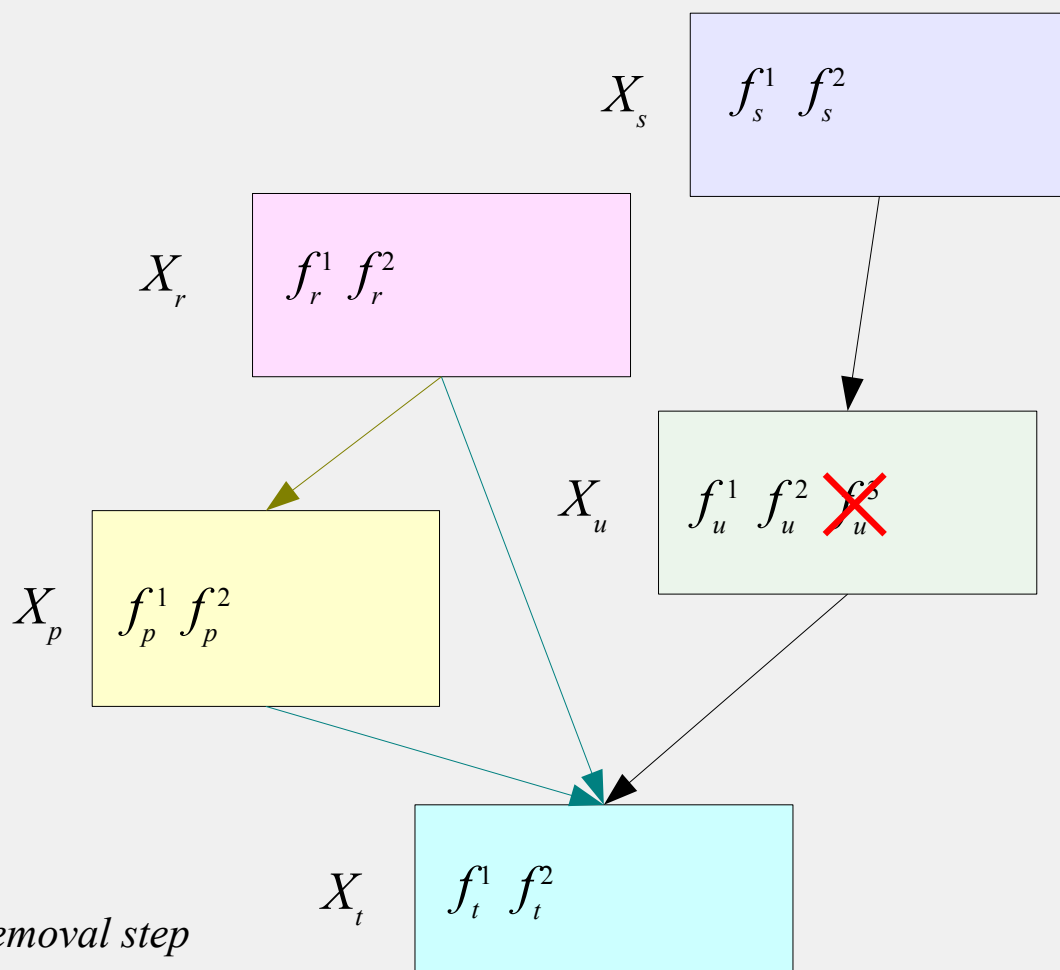
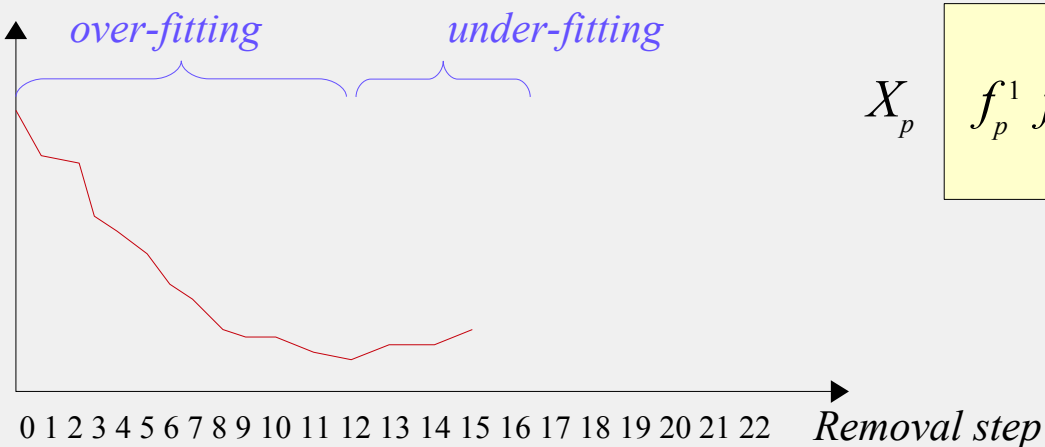
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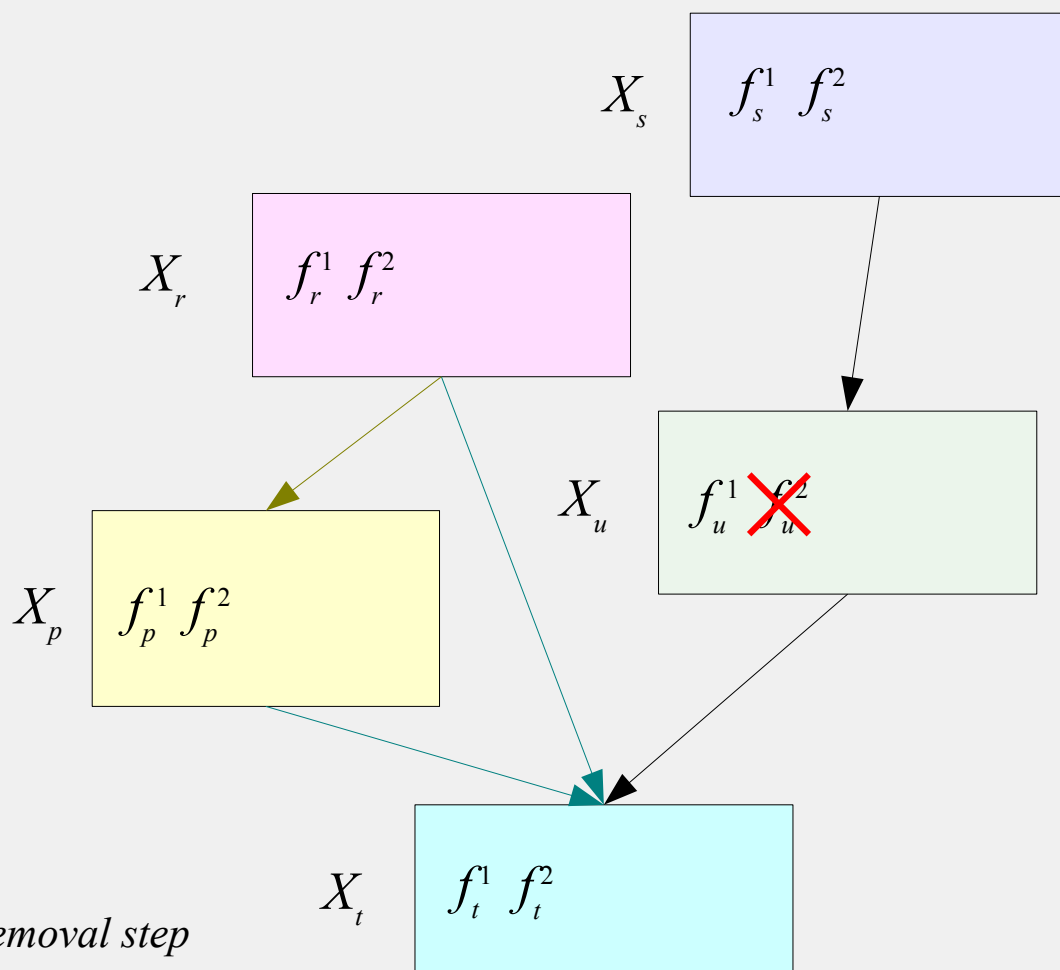
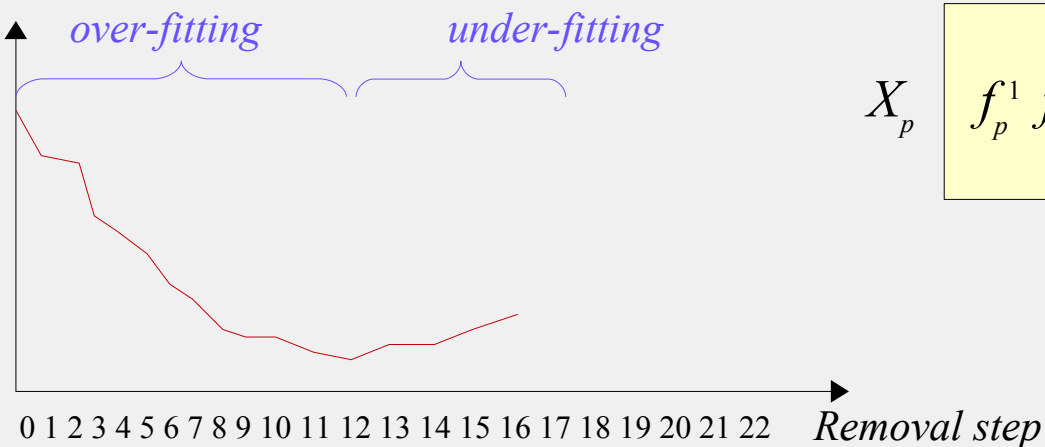
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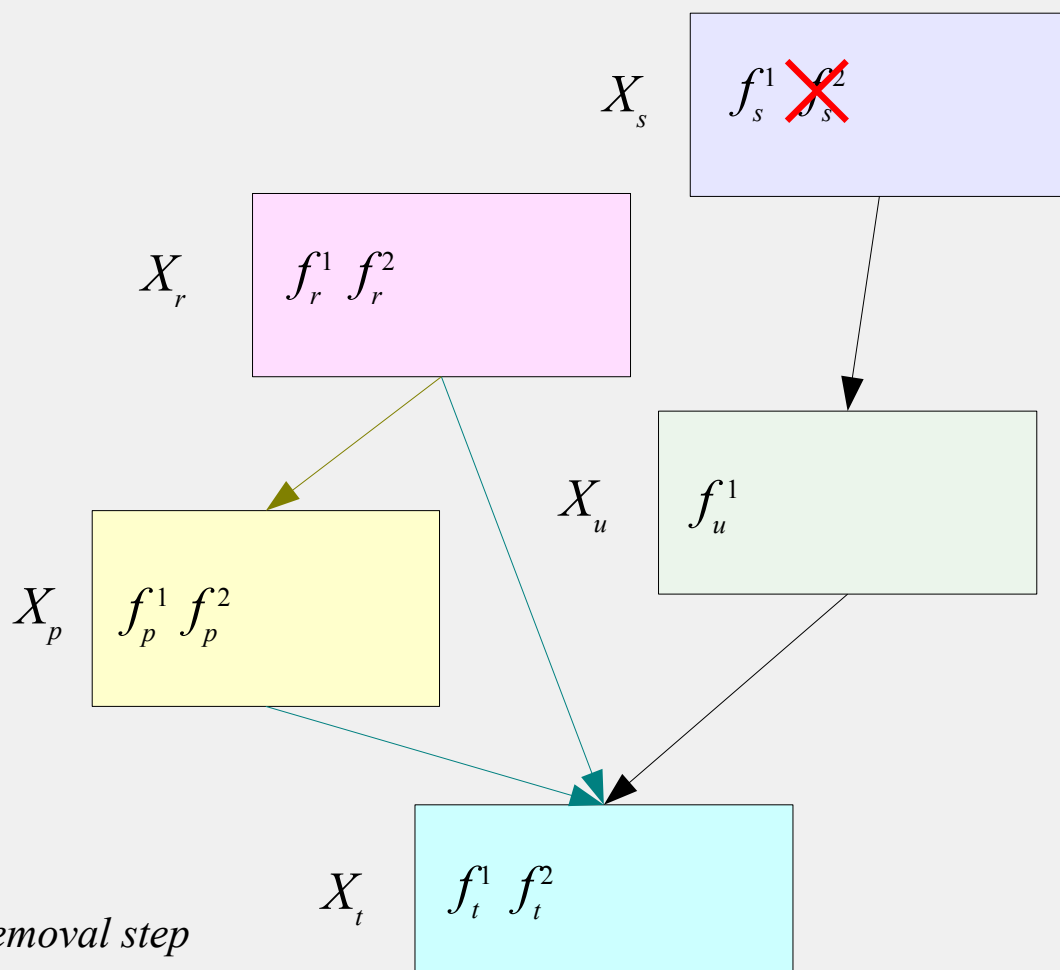
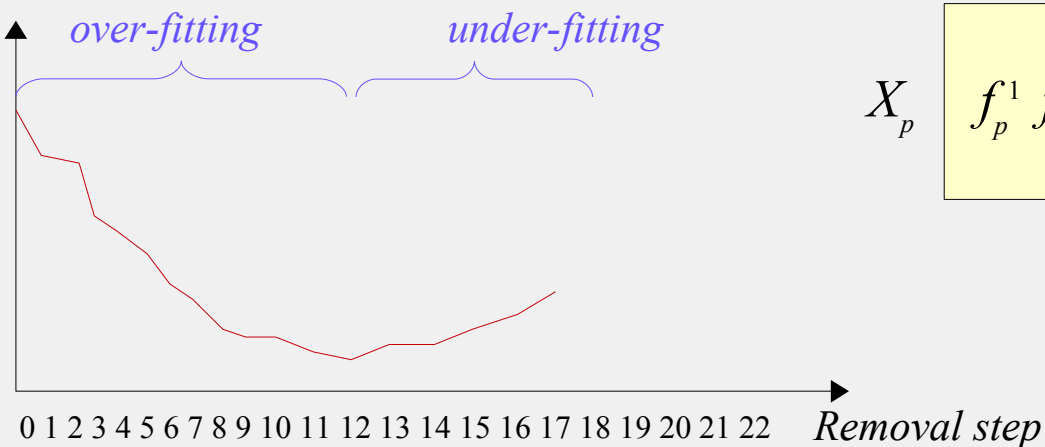
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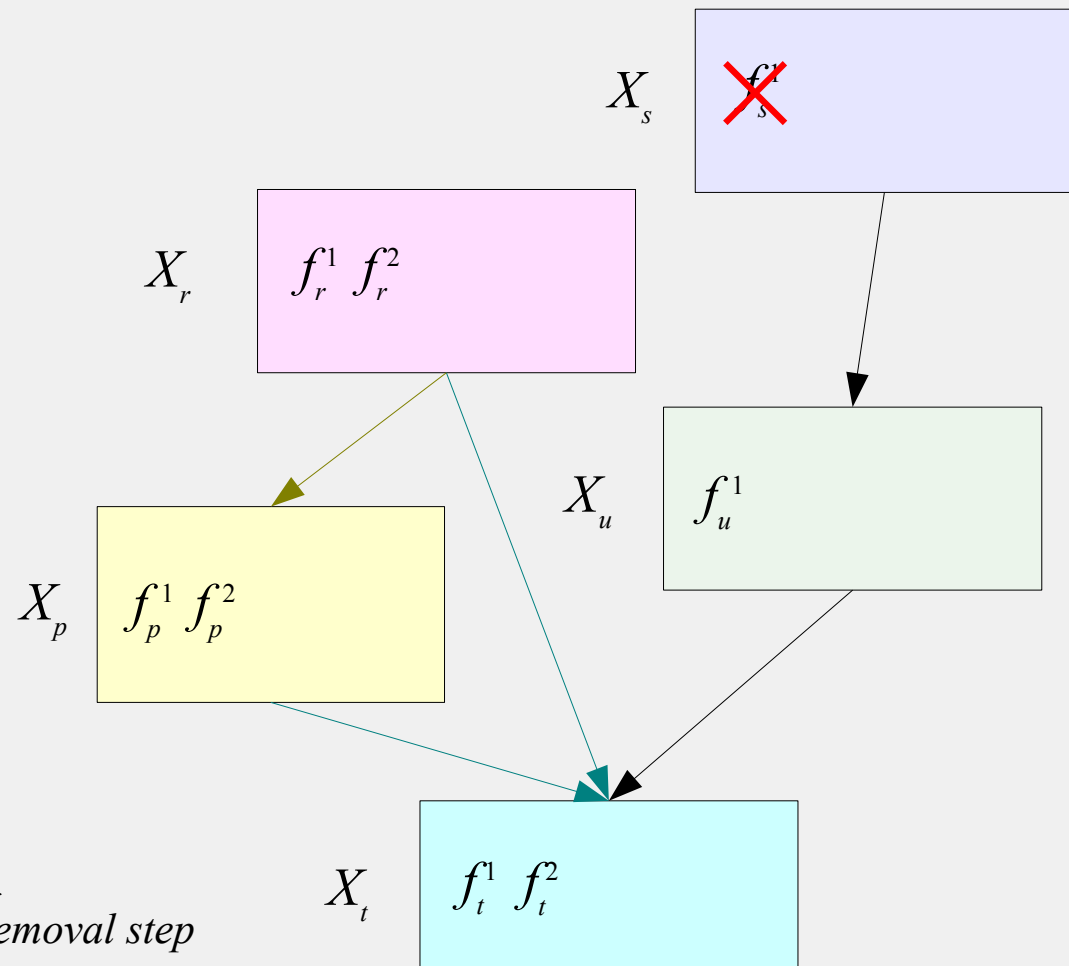
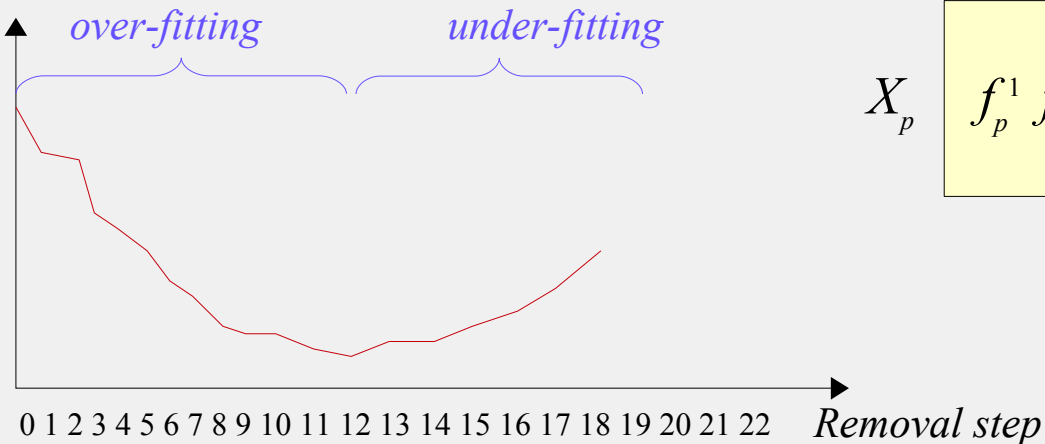
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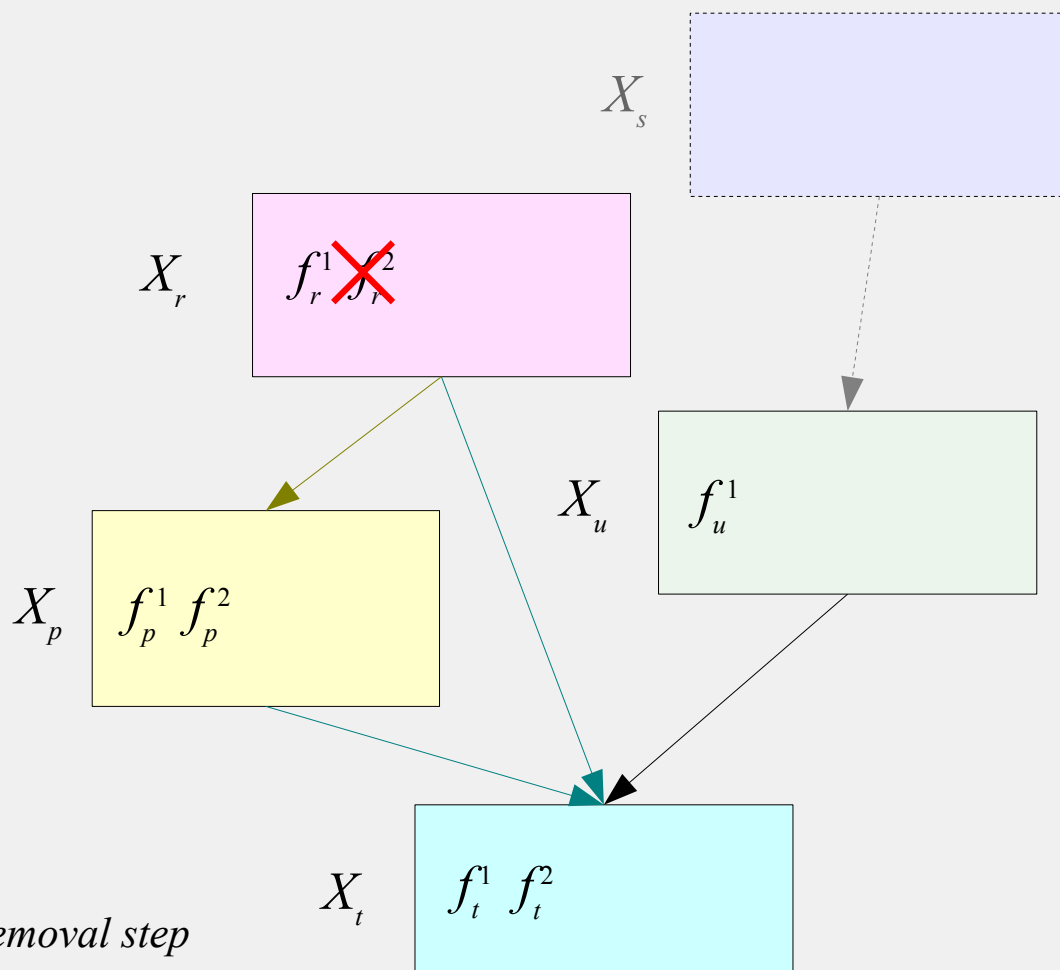
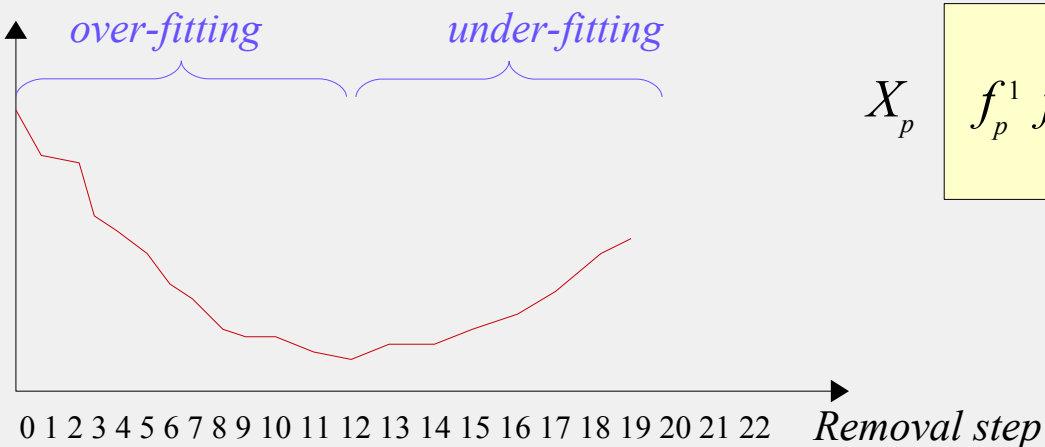
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prediction error rate



# How THEME works

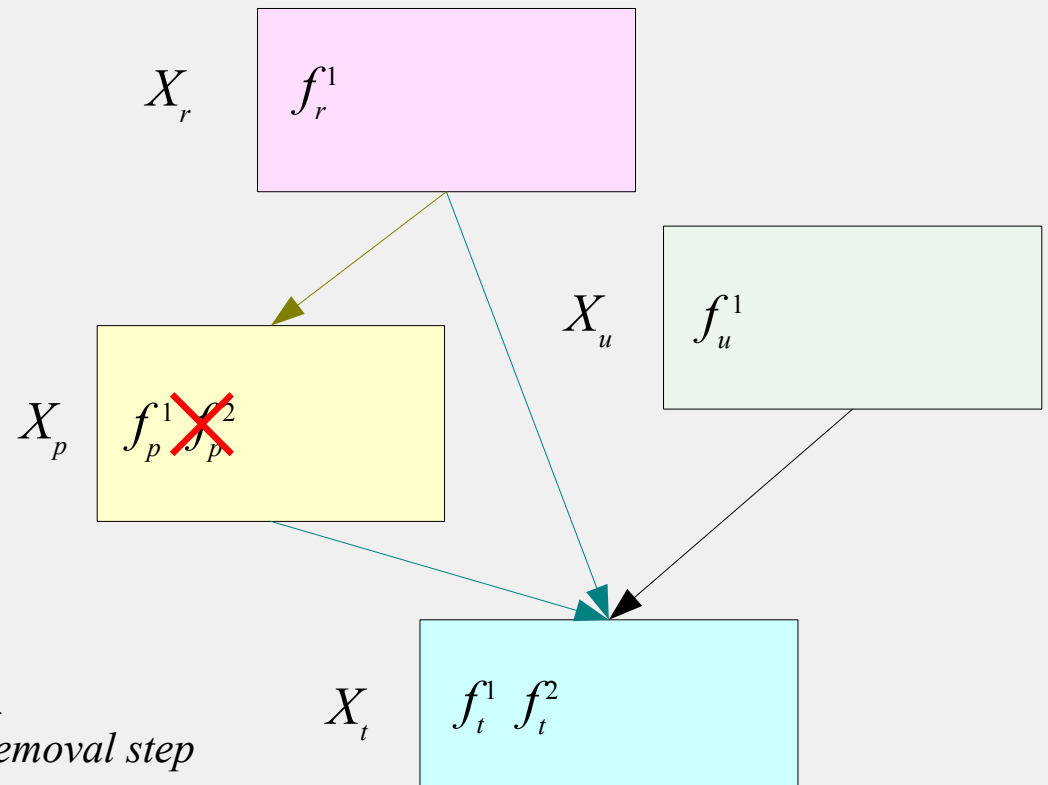
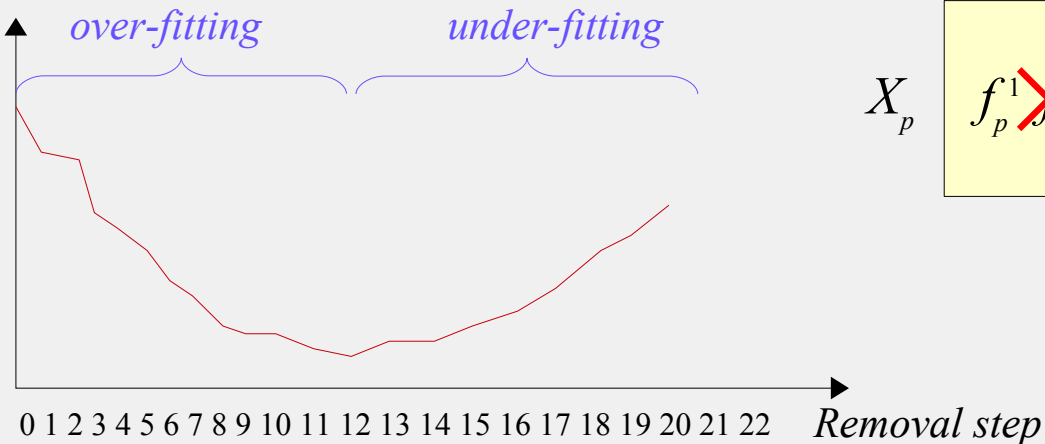
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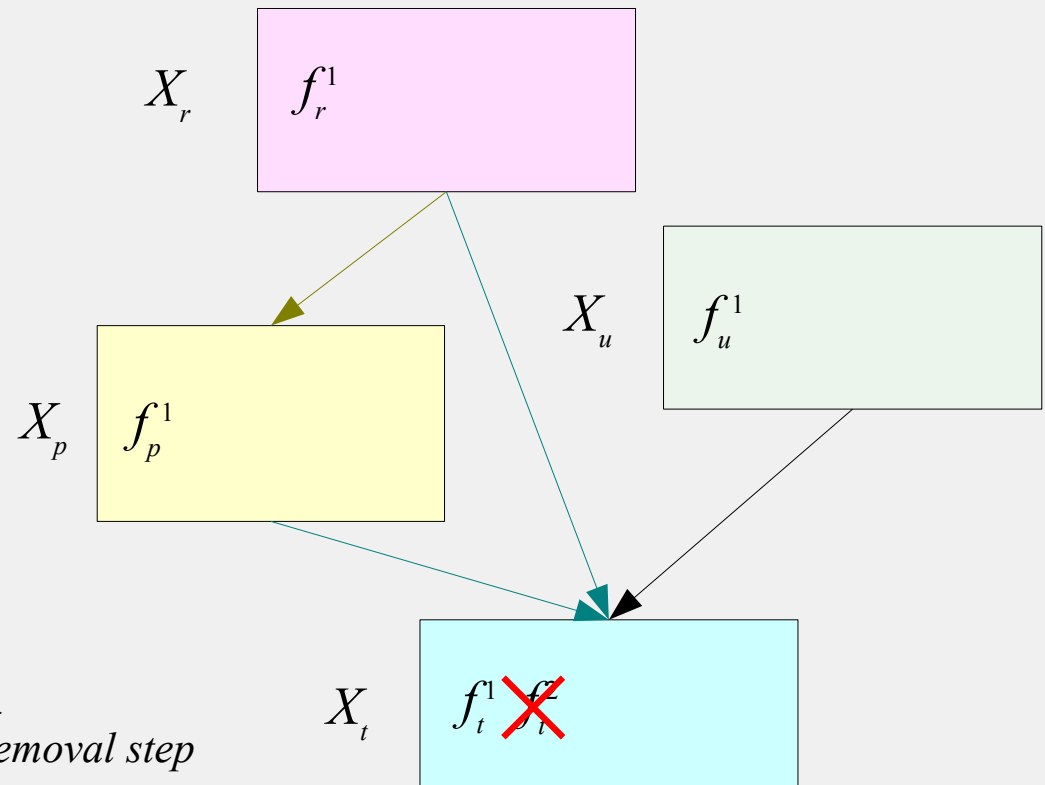
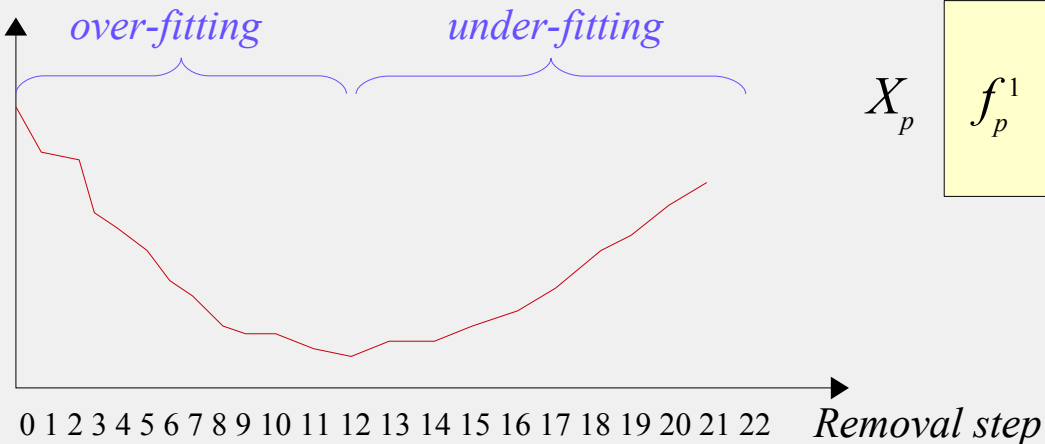
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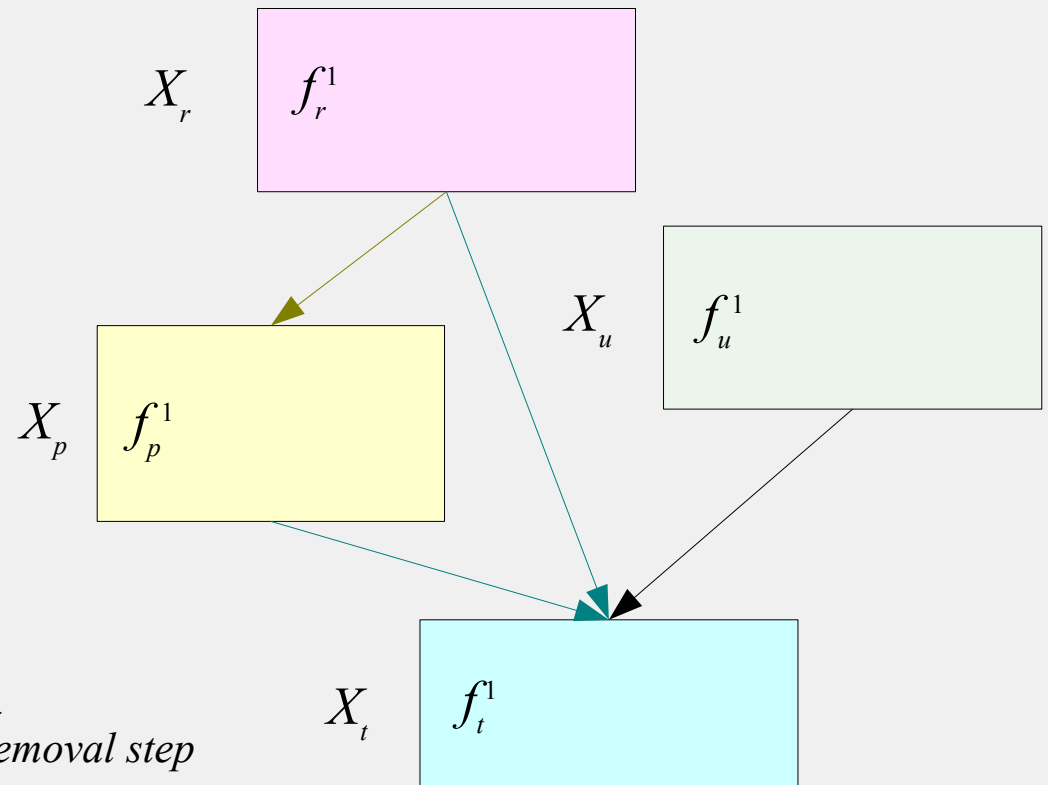
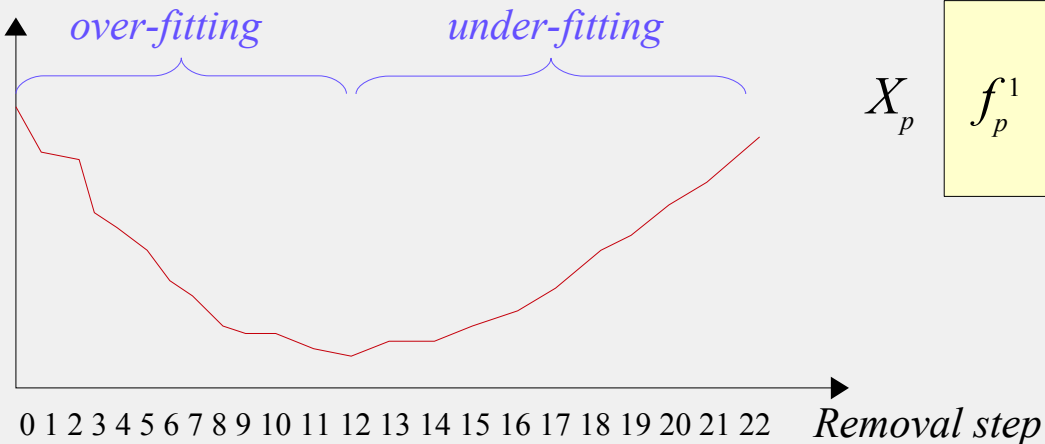
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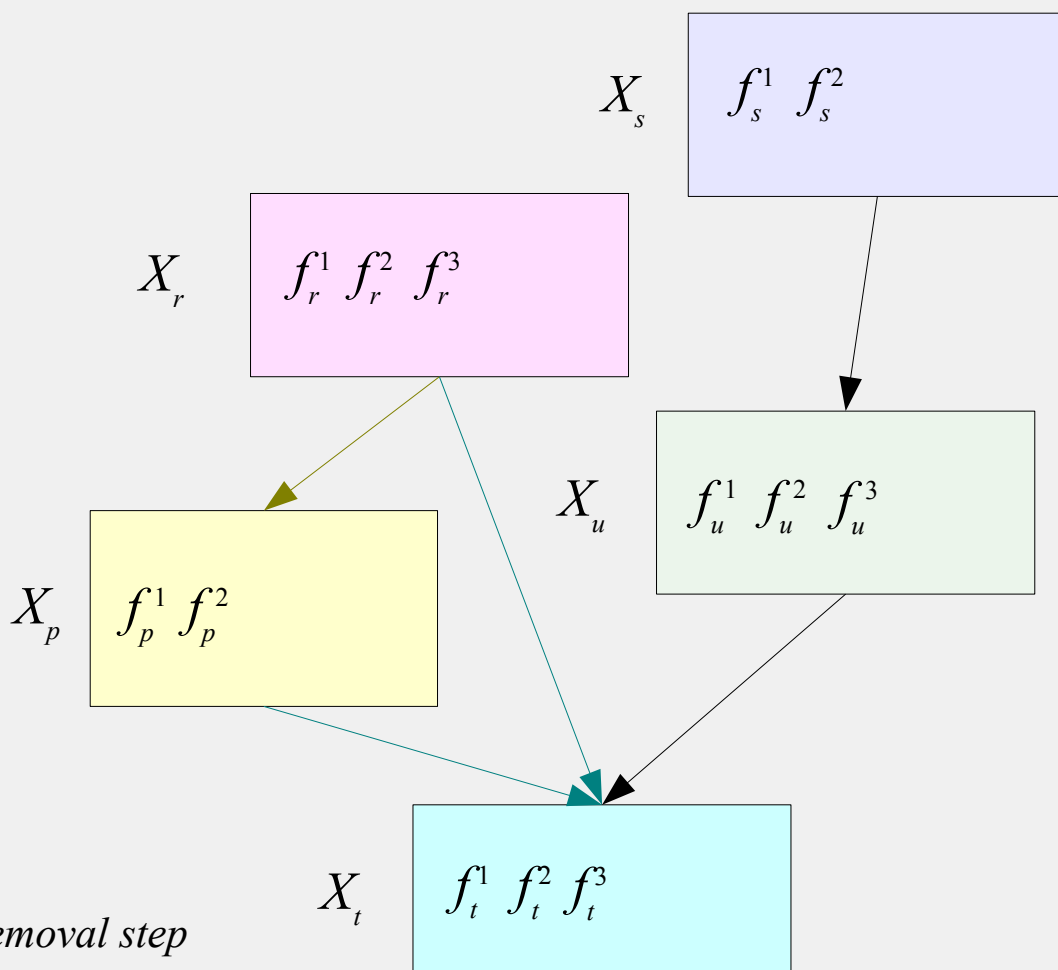
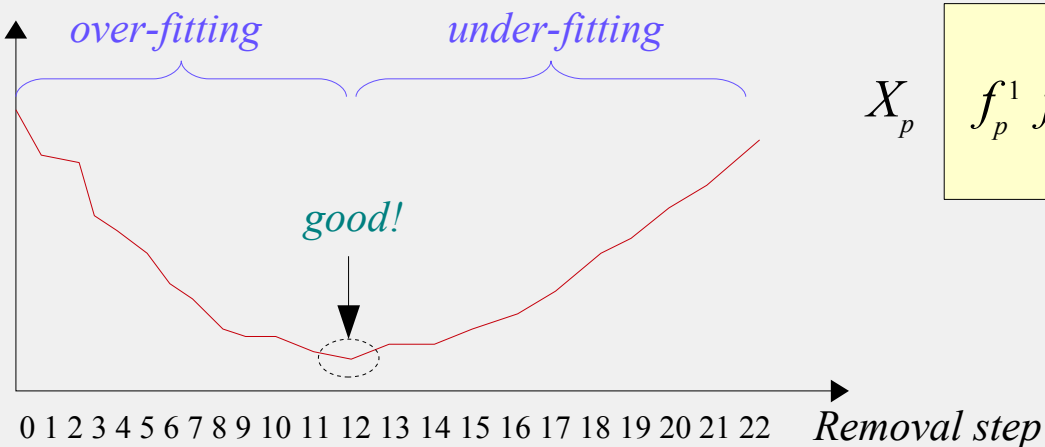
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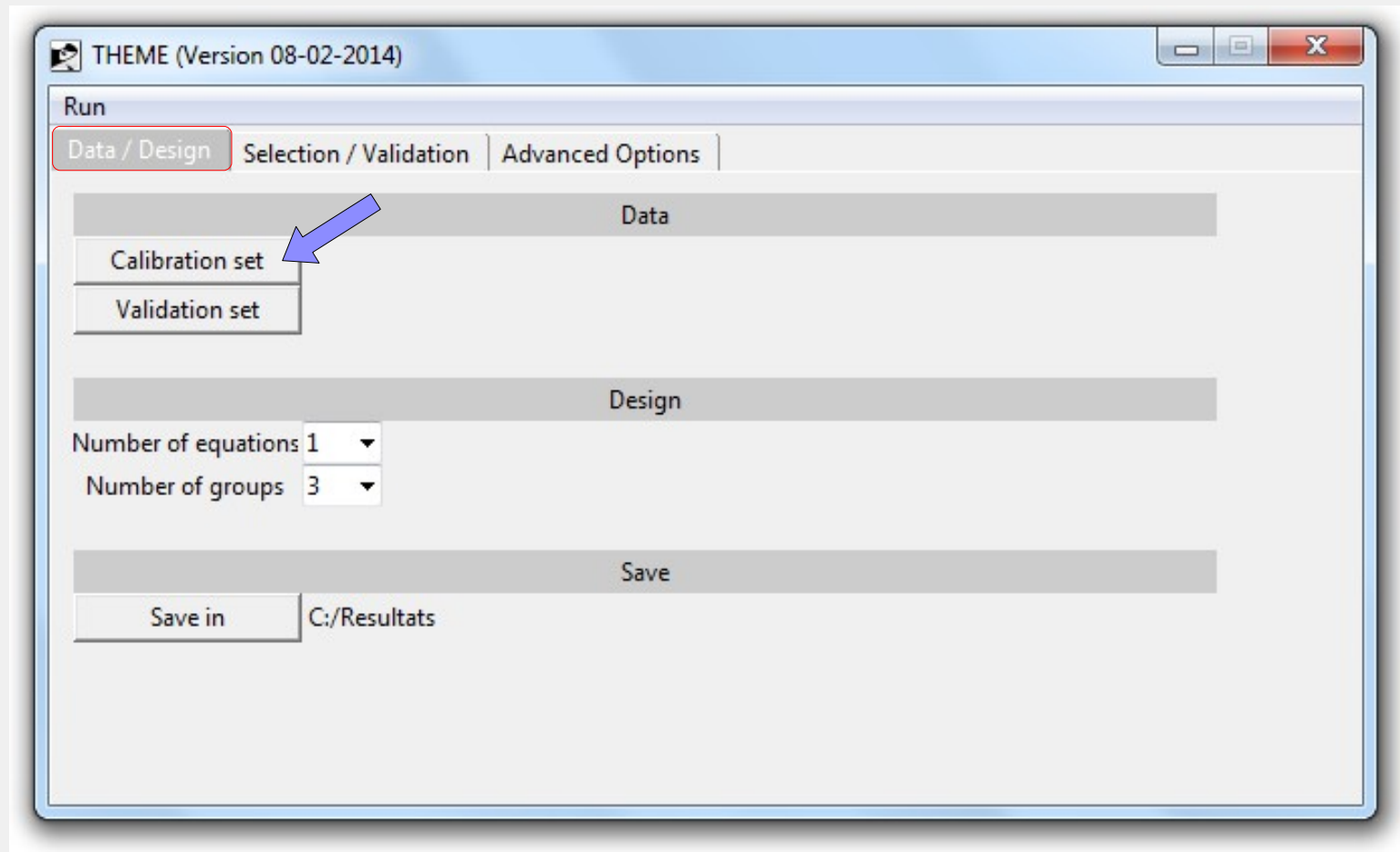


# How to operate the THEME R-software?

## 1. The main window

*Data Input*

*Output*



# How to operate the THEME R-software?

## 2. From raw data to Thematic Model

- *Data file* = ASCII-file with tab separator: `data_VDKM0_6groupes.txt`

Variables

Obs.

SAMPLE_NAME	code	Tchem_1	Tchem_2	Tchem_3	Tchem_4	Tchem_5	Tchem_6
cig1	6	1.54	0.67	1.85	42.38	3.56	89
cig2	2	0.4	0.92	1.95	42.18	2.31	66
cig3	1	0.56	0.75	1.8	43.23	2.74	123
cig4	5	0.97	0.96	1.83	41.27	2.79	96
cig5	5	0.66	0.85	1.47	41.37	2.29	119
cig6	1	0.89	0.77	2.03	42.2	2.88	142
...	...	...	...	...	...	...	...
cig29	4	0.87	0.77	1.89	40.72	2.75	177

# How to operate the THEME R-software?

## 2. From raw data to Thematic Model

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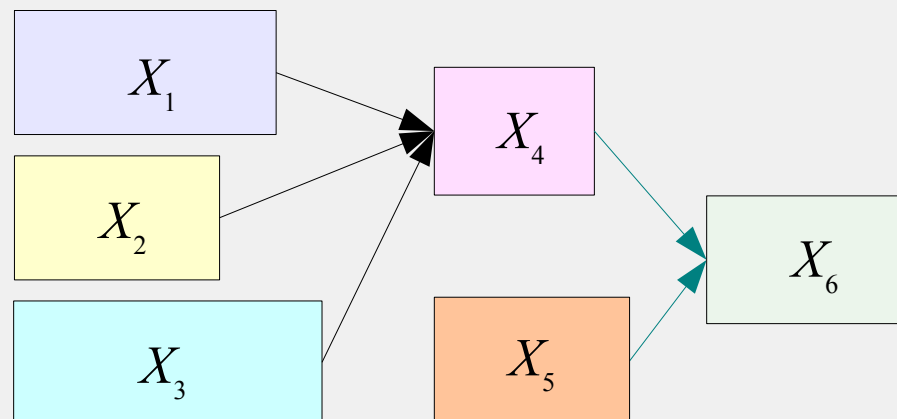
Variables

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...	...	...	...	...	...	...	...
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- *Design of the thematic model:*

6 themes  
2 equations



# How to operate the THEME R-software?

## 2. From raw data to Thematic Model

- *Data file* = ASCII-file with tab separator: `data_VDKM0_6groupes.txt`

Variables

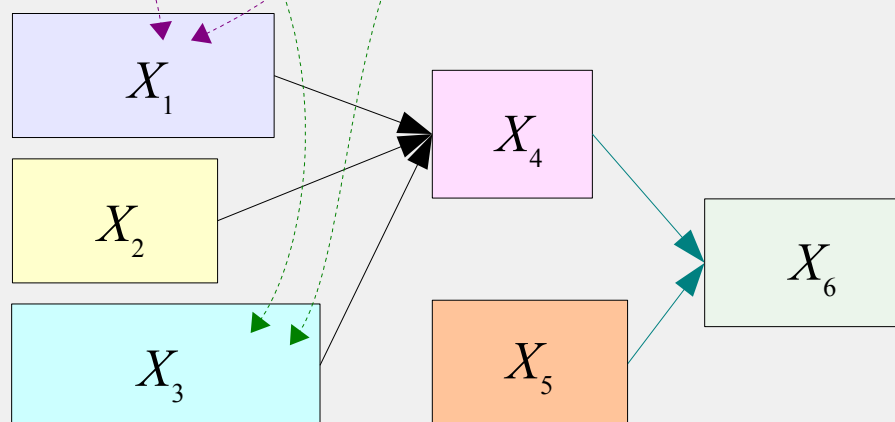
	SAMPLE_NAME	code	Tchem_1	Tchem_2	Tchem_3	Tchem_4	Tchem_5	Tchem_6
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	...	...	...	...	...	...	...	...
	cig29	4	0.87	0.77	1.89	40.72	2.75	177
	<b>TGC</b>	cci	1	3	1	3	1	1

Obs.

Thematic  
Group Coding  
(0 = variable not used)

- *Design of the thematic model:*

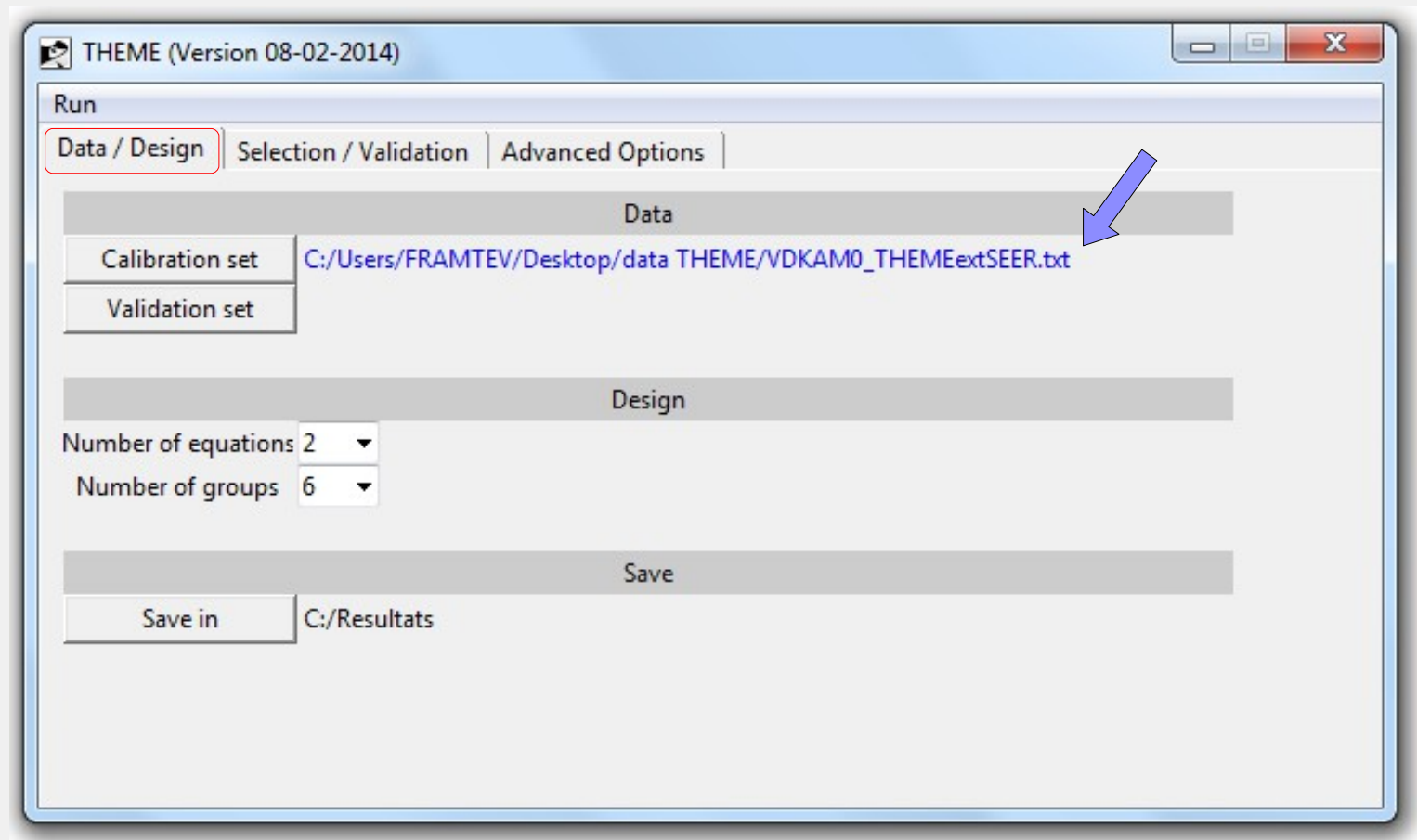
6 themes  
2 equations



# How to operate the THEME R-software?

## 2. From raw data to Thematic Model

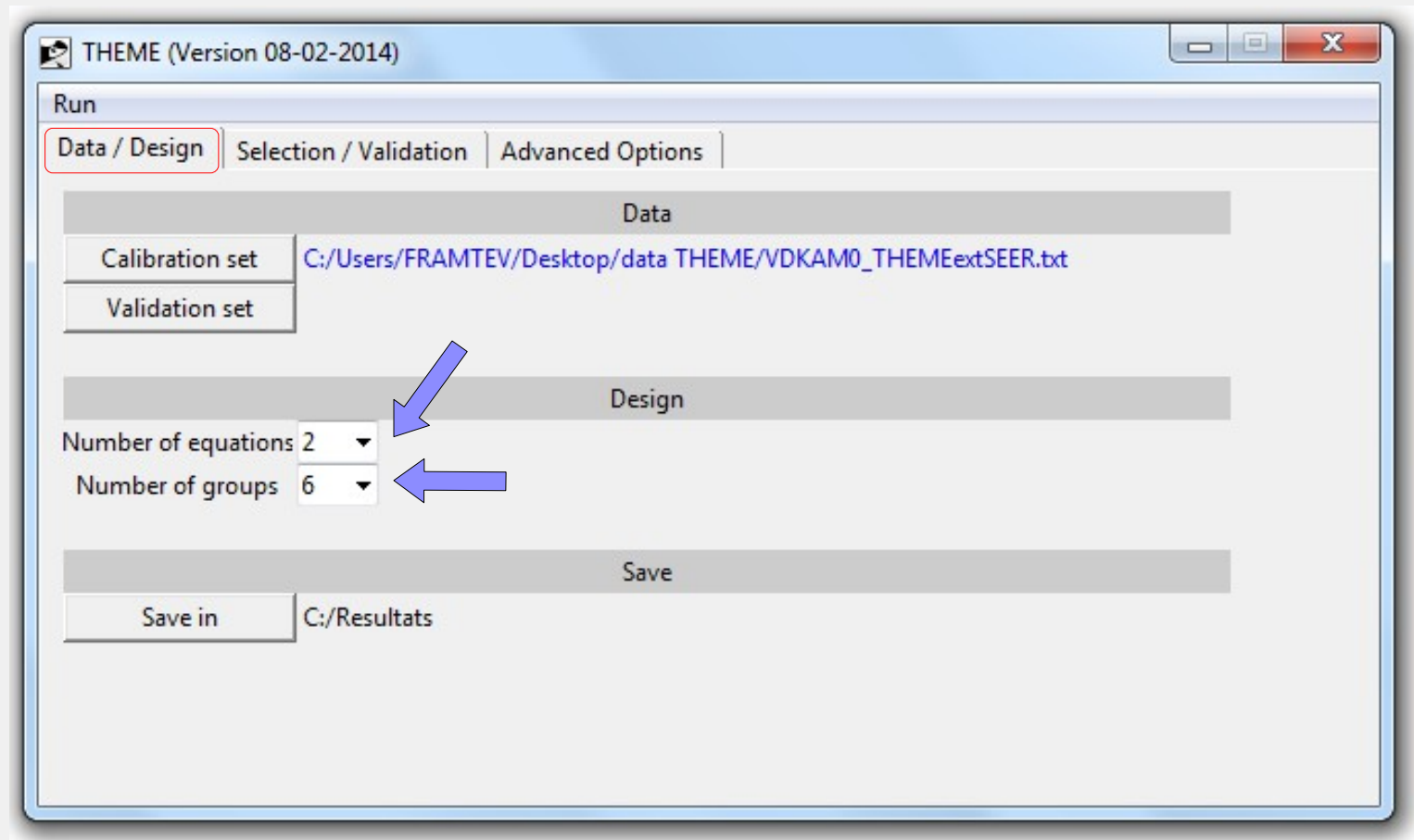
*Data Input*



# How to operate the THEME R-software?

## 2. From raw data to Thematic Model

*Model design*







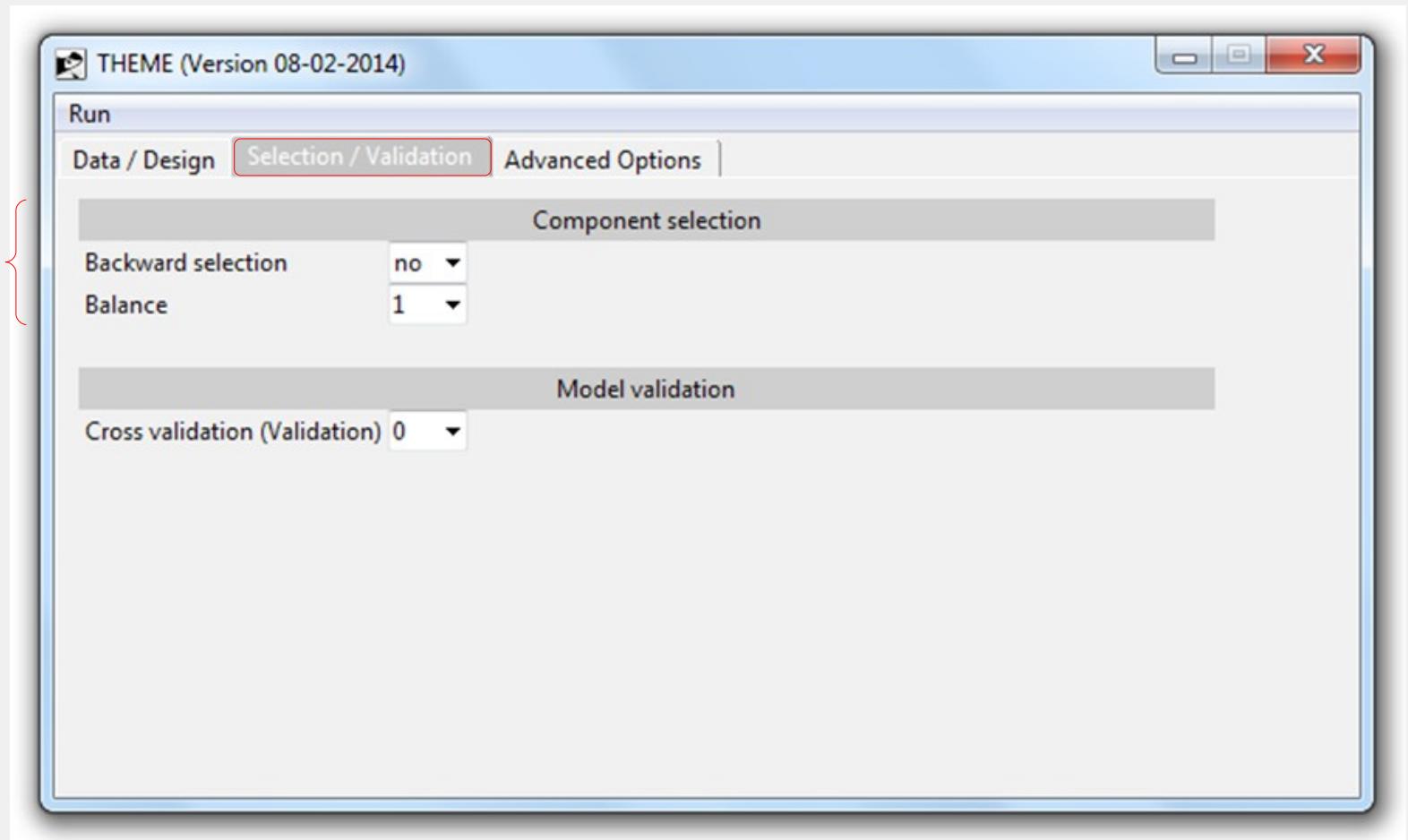




## How to operate the THEME R-software?

### 3. *Setting the selection & validation parameters*

*Component selection*

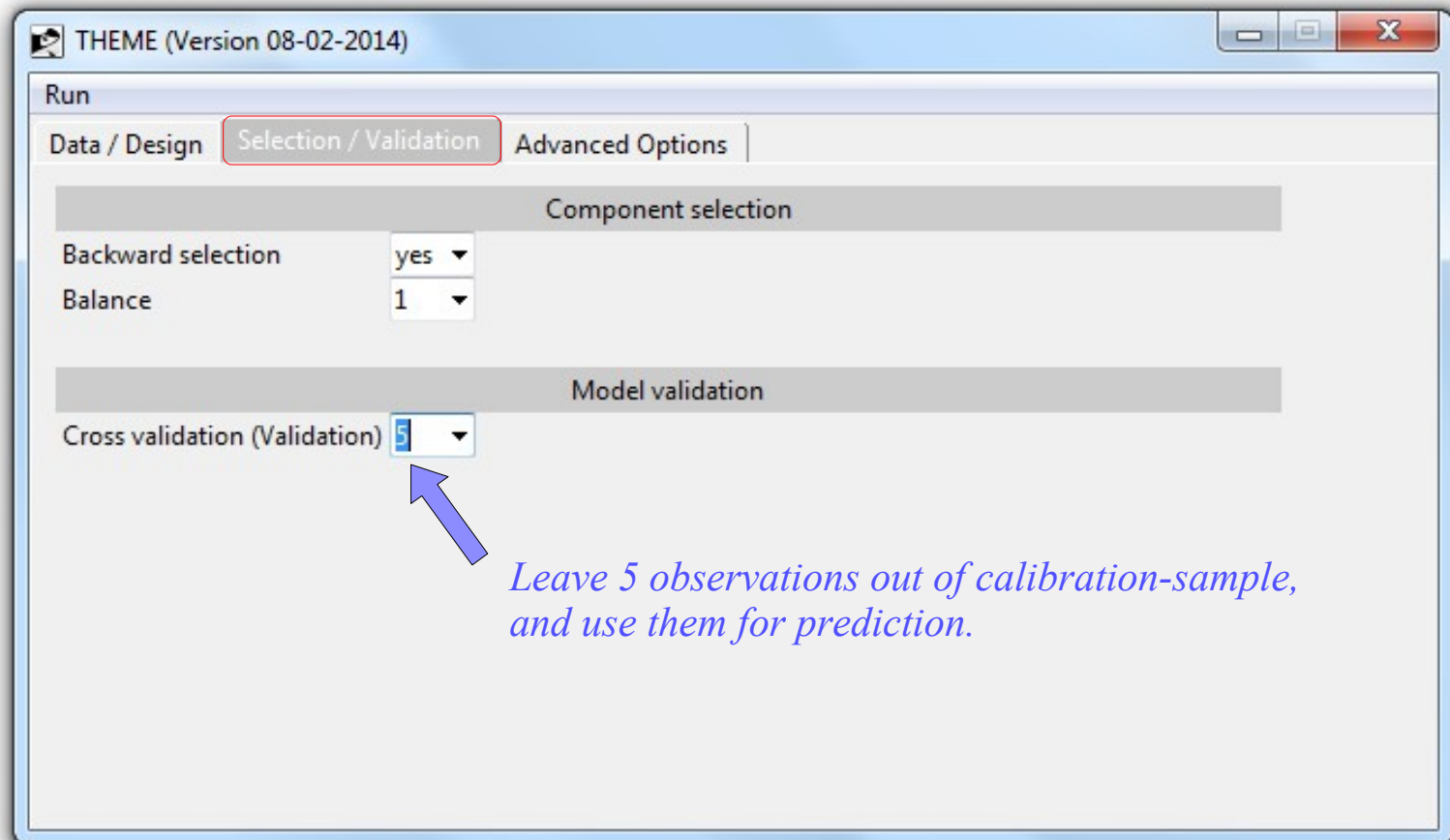


## How to operate the THEME R-software?

### 3. Setting the selection & validation parameters

*Component selection*

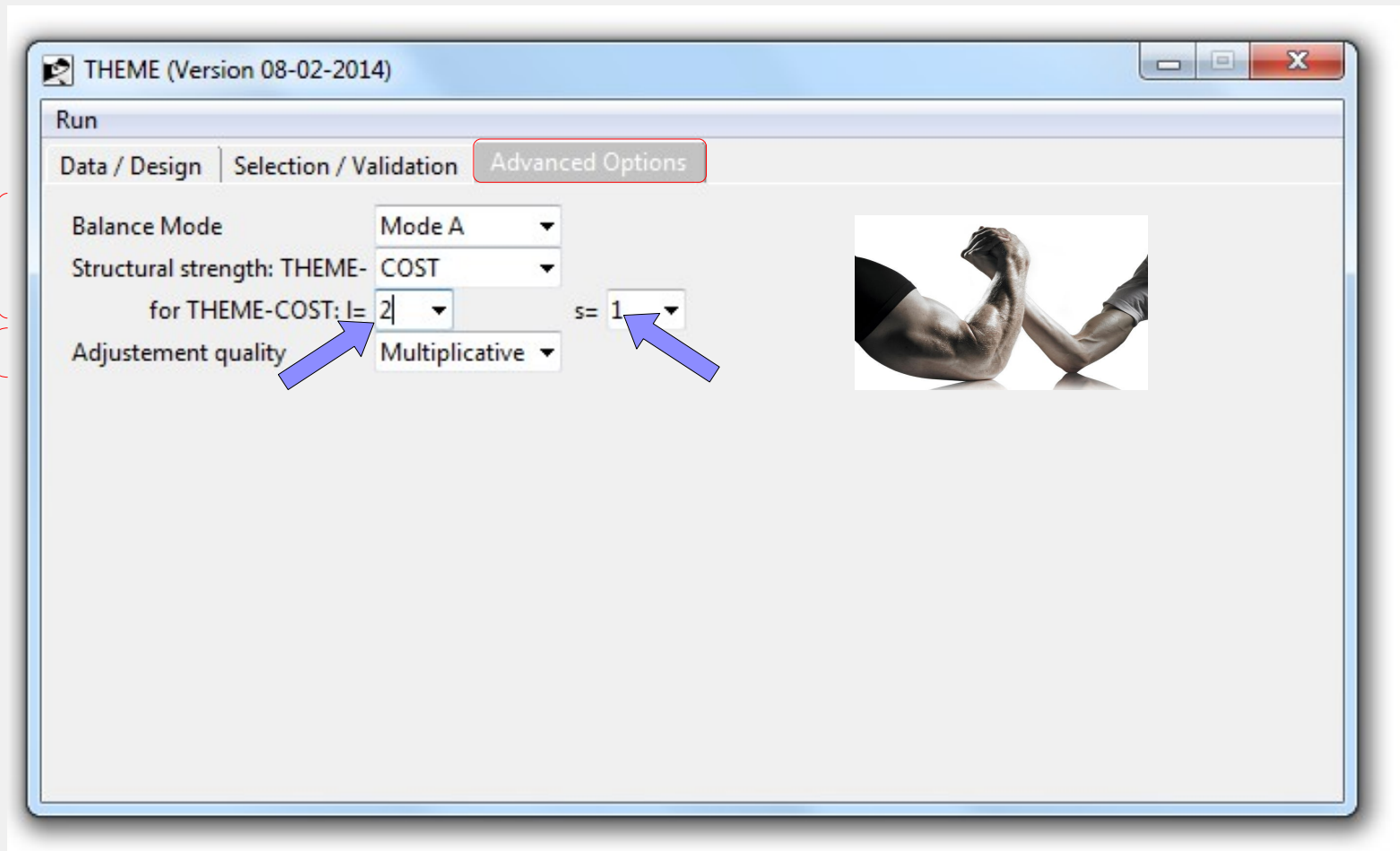
*Model cross-validation*



## How to operate the THEME R-software?

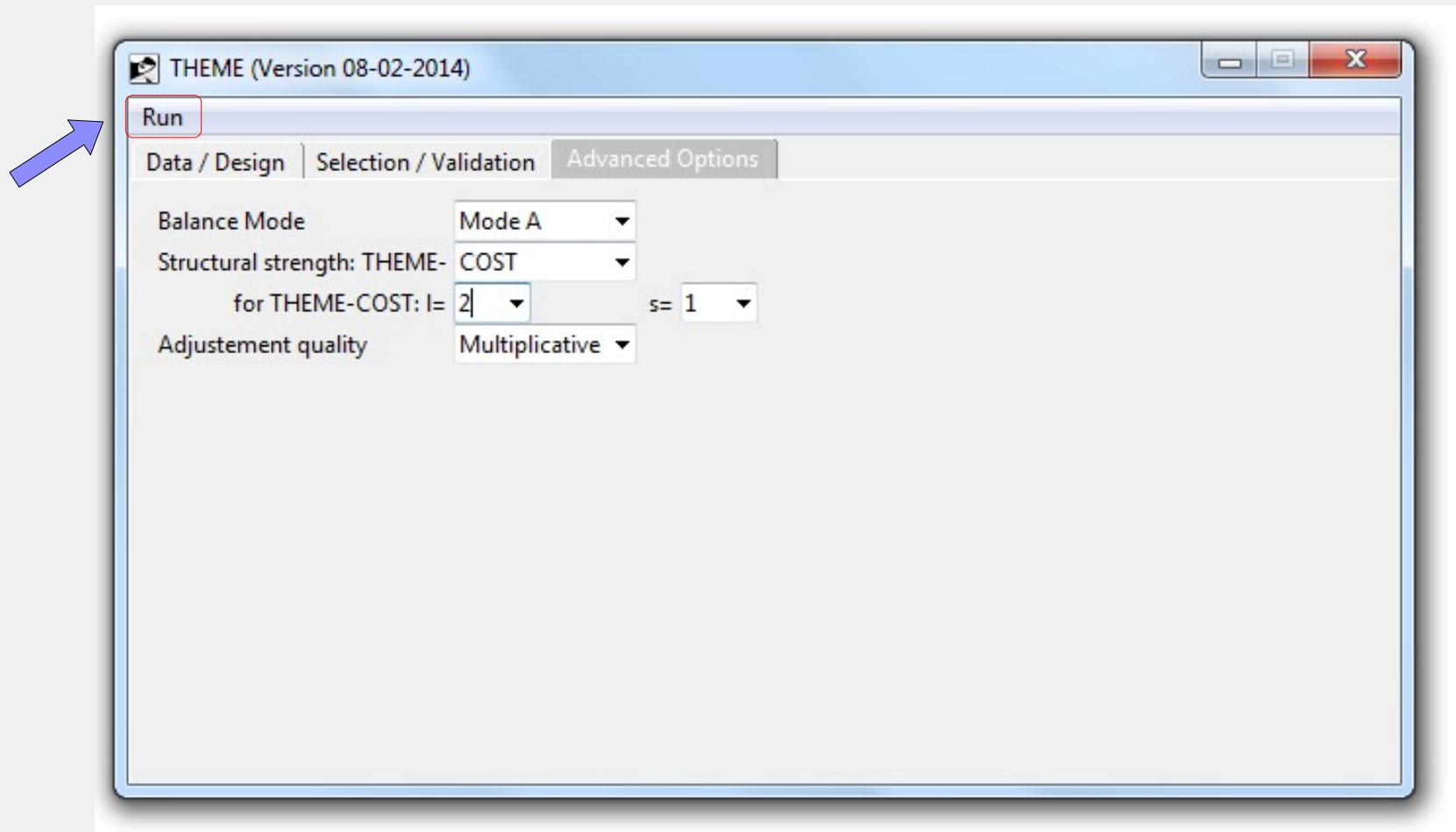
### 4. *Setting the structural strength and goodness of fit parameters*

*Structural strength parameters*  
*GoF*



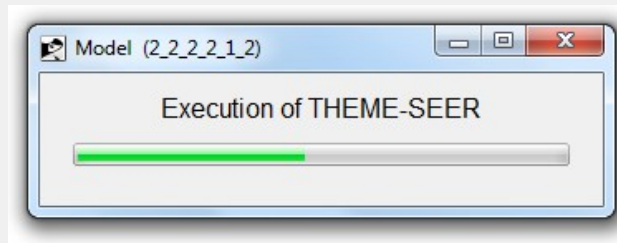
# How to operate the THEME R-software?

## 5. *Launching estimation*



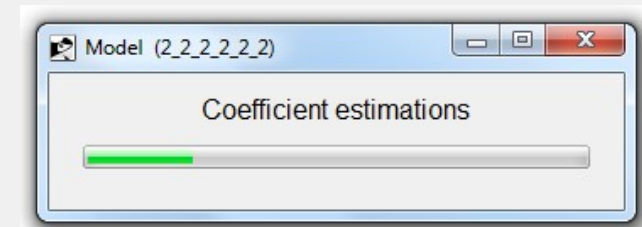
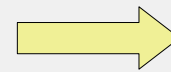
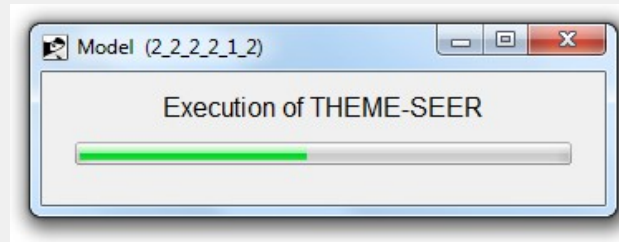
# How to operate the THEME R-software?

## 6. *Waiting for results*



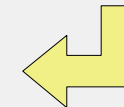
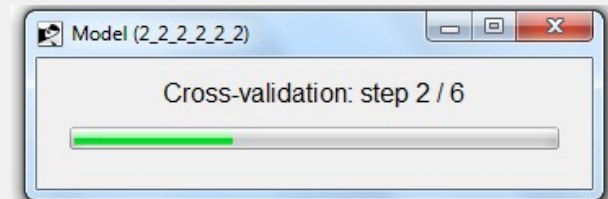
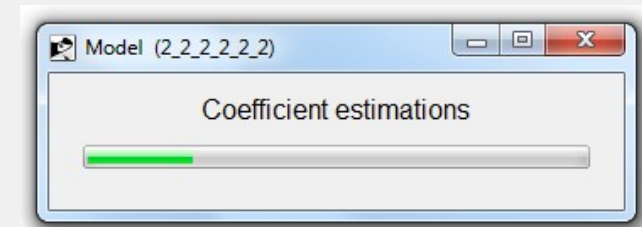
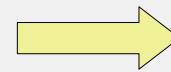
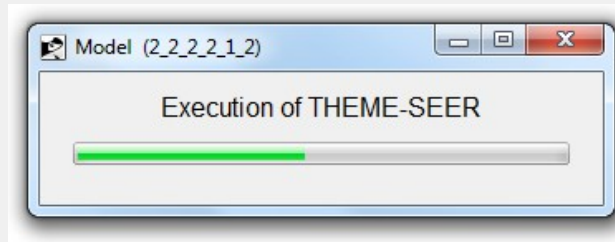
# How to operate the THEME R-software?

## 6. *Waiting for results*



# How to operate the THEME R-software?

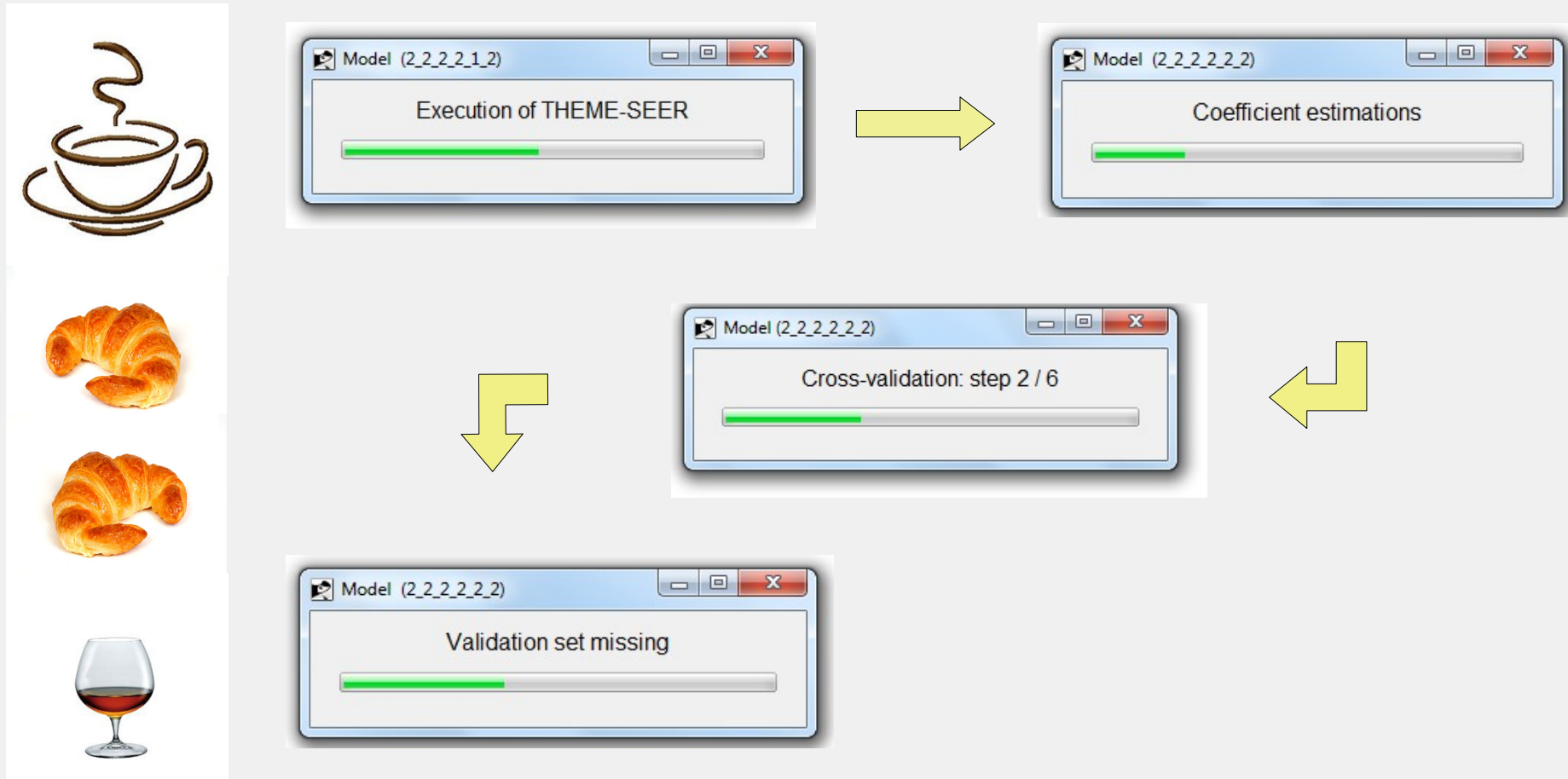
## 6. *Waiting for results*





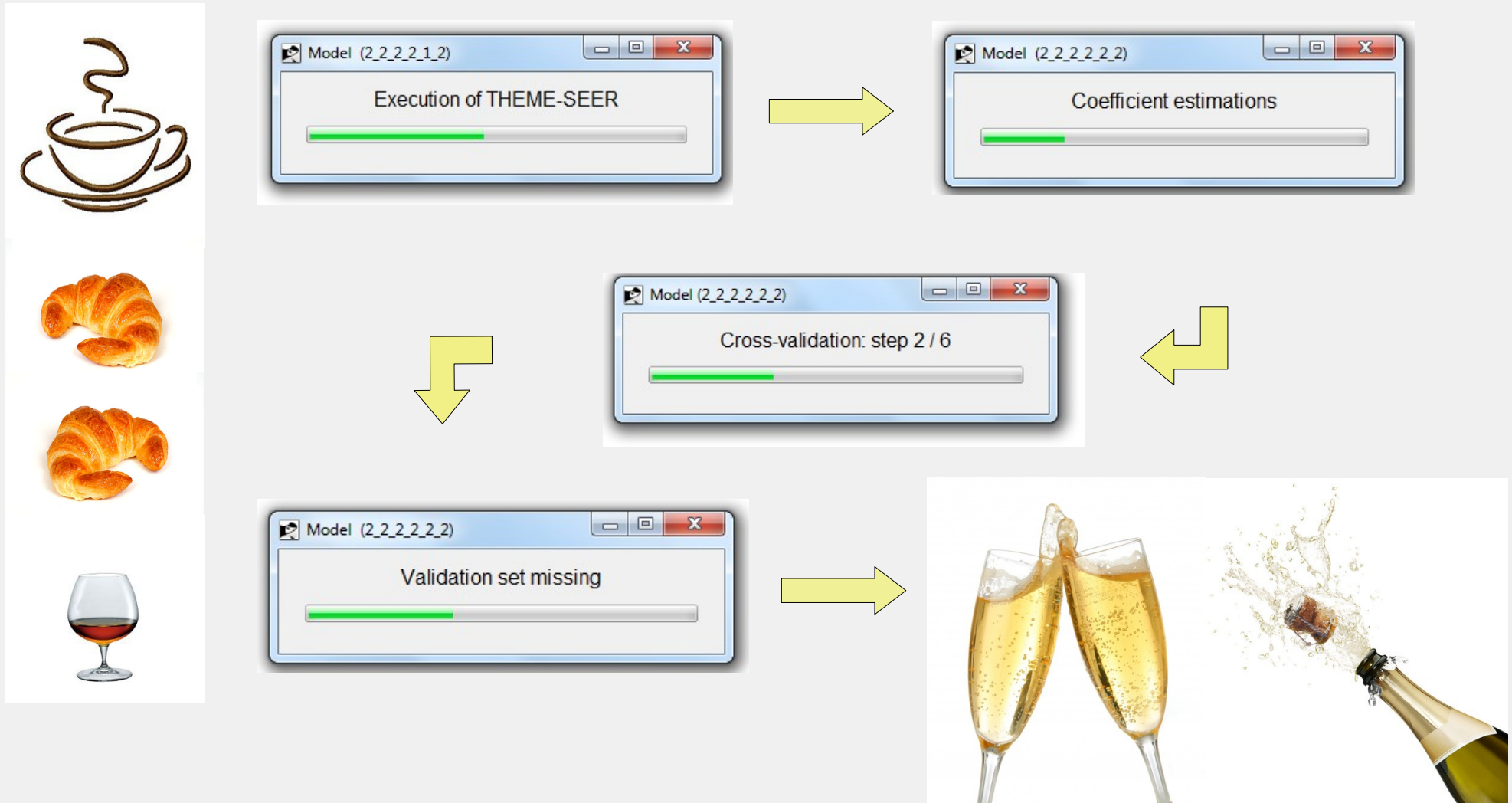
# How to operate the THEME R-software?

## 6. *Waiting for results*



# How to operate the THEME R-software?

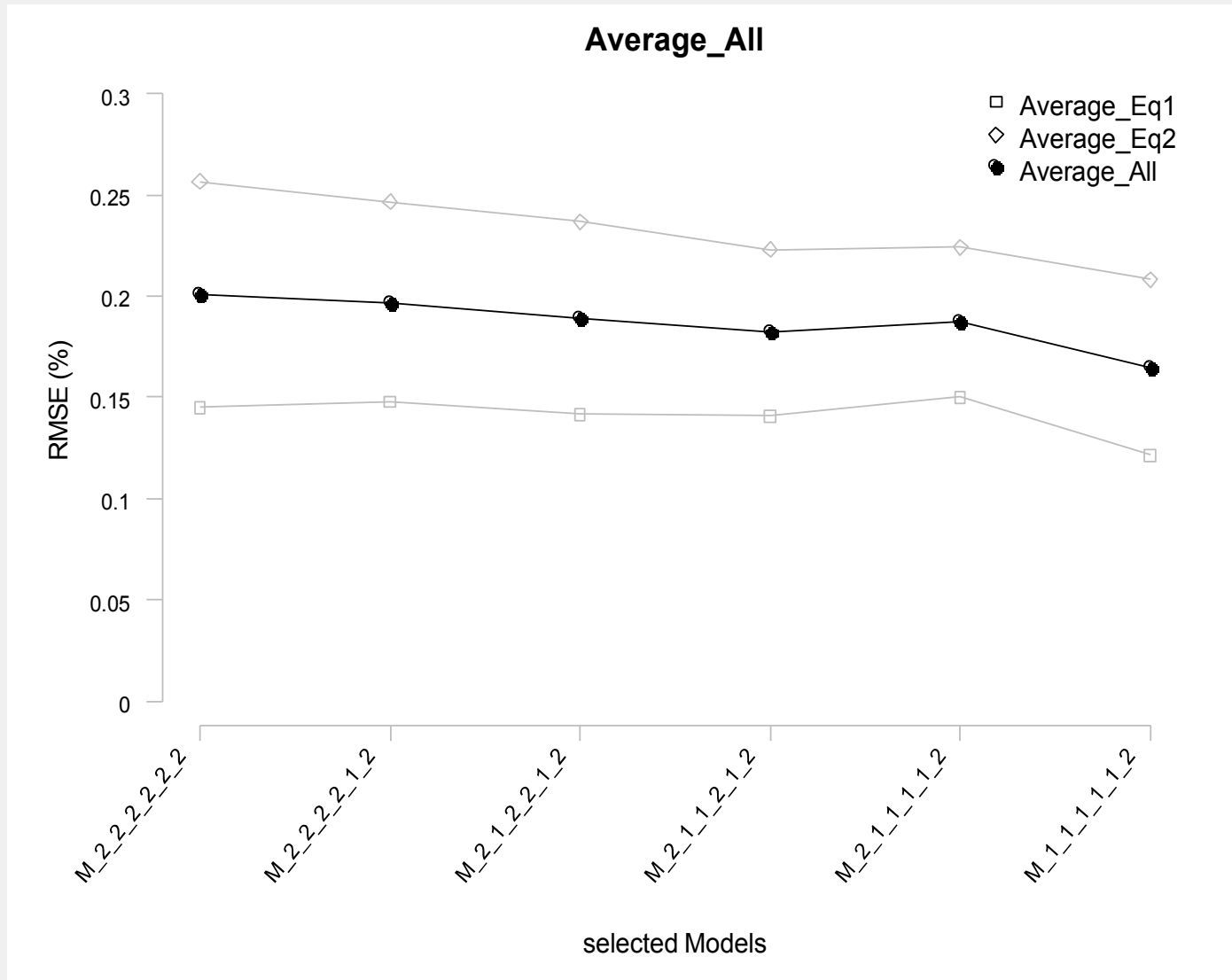
## 6. *Waiting for results*



# How to operate the THEME R-software?

## 7. Reaping results

### Model-selection



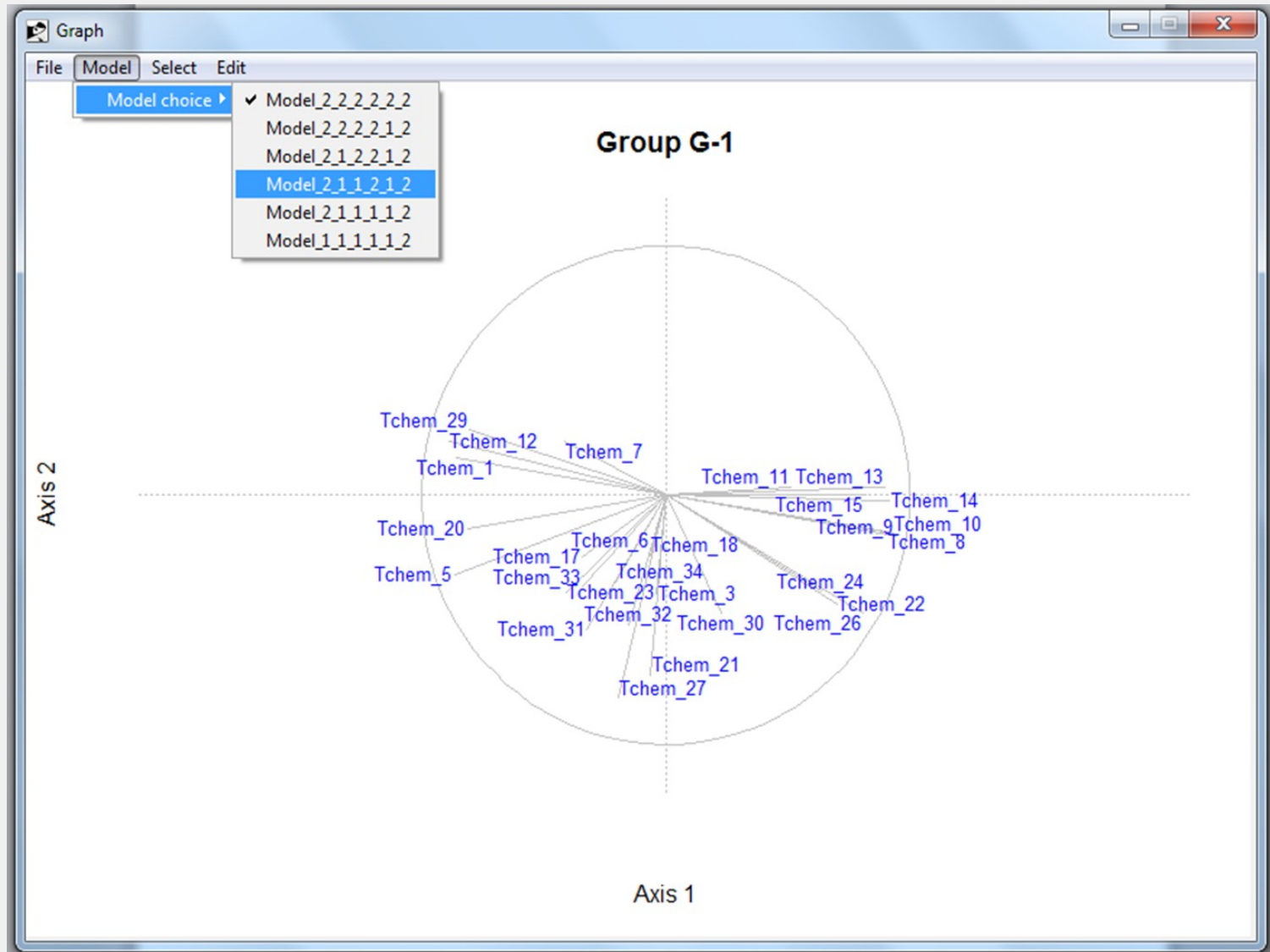
# How to operate the THEME R-software?

## 7. Reaping results

*Model-  
selection*

→

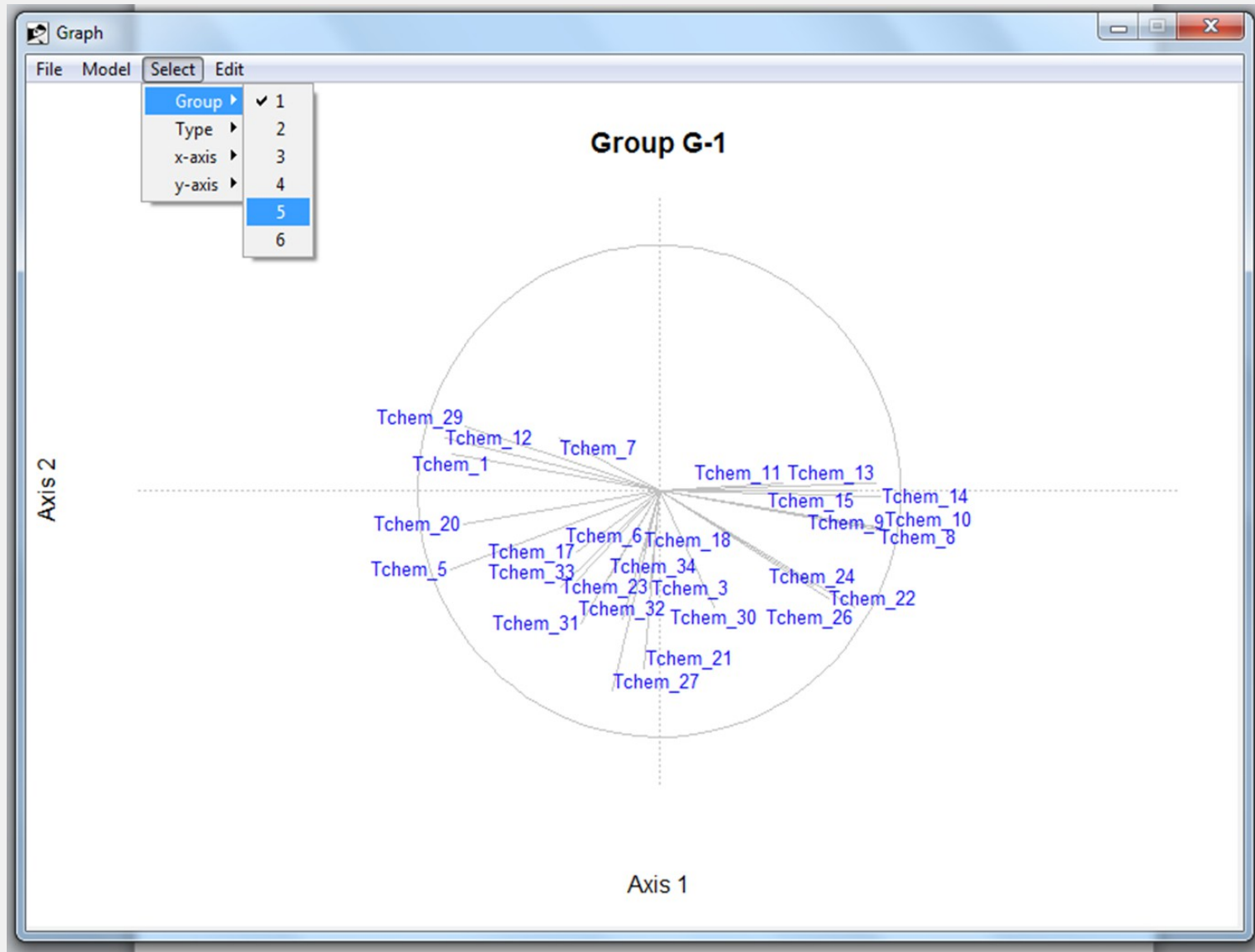
*Graphing  
variables*



# How to operate the THEME R-software?

## 7. Reaping results

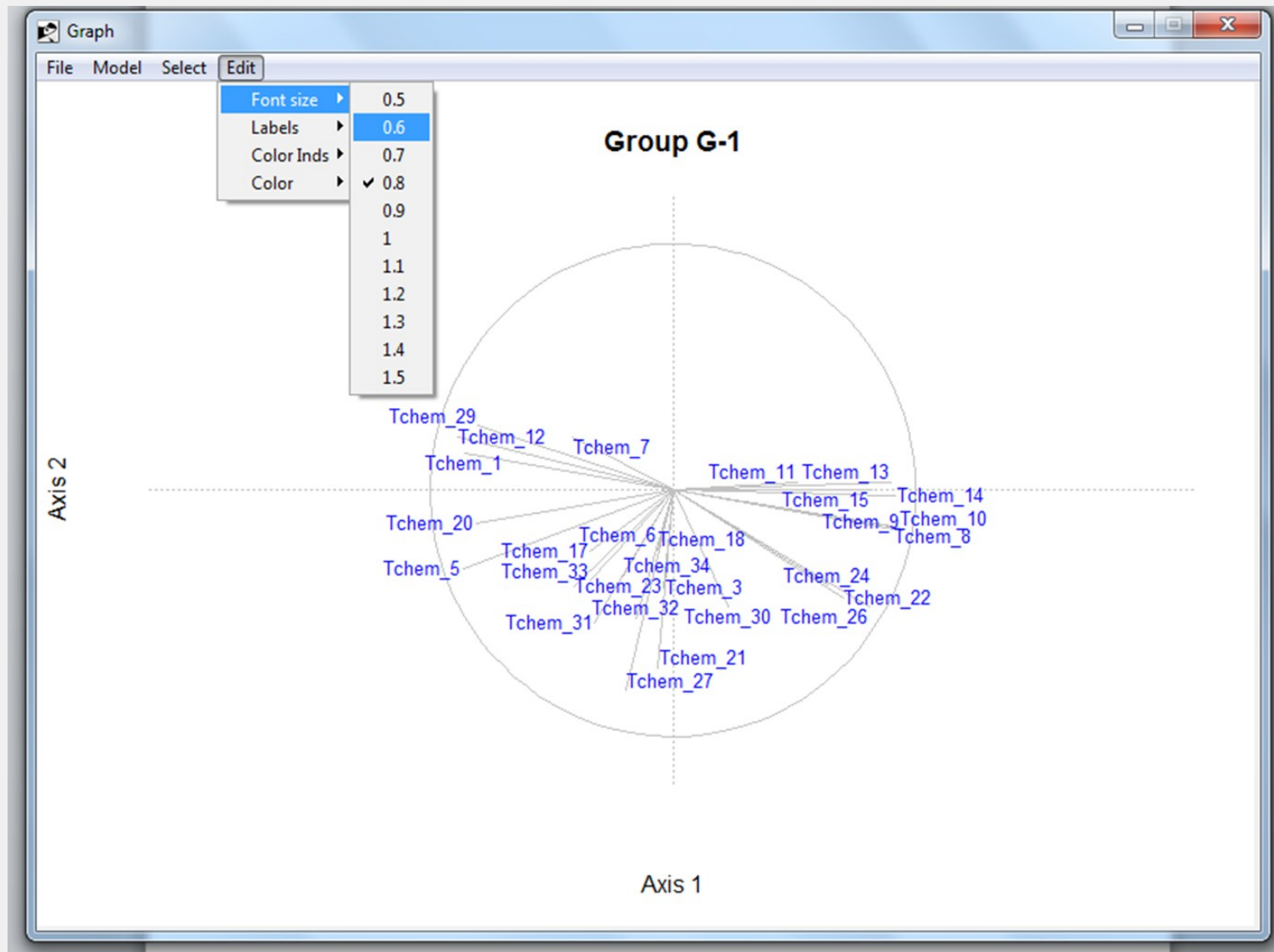
Graphing variables



# How to operate the THEME R-software?

## 7. Reaping results

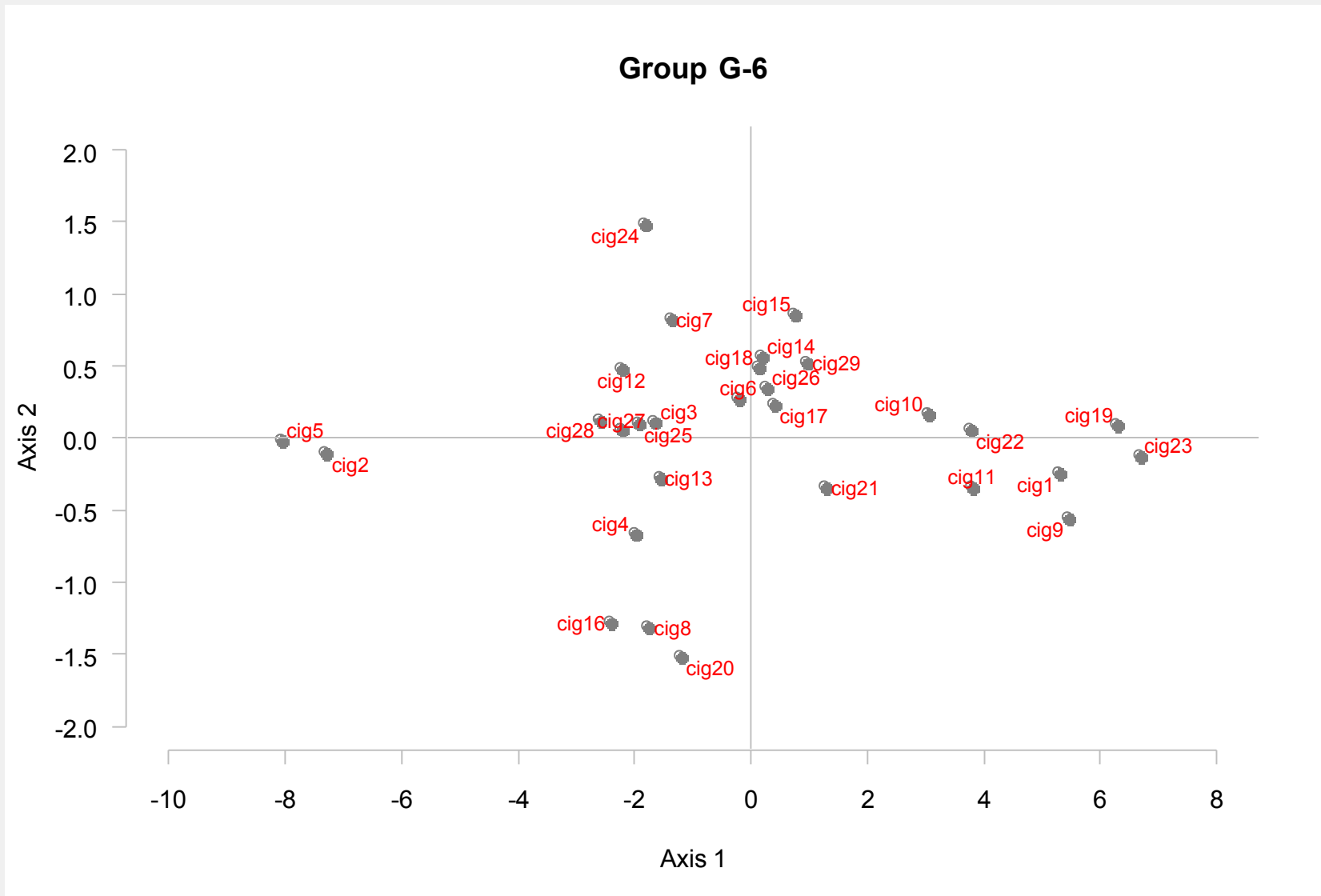
*Graphing variables*



# How to operate the THEME R-software?

## 7. Reaping results

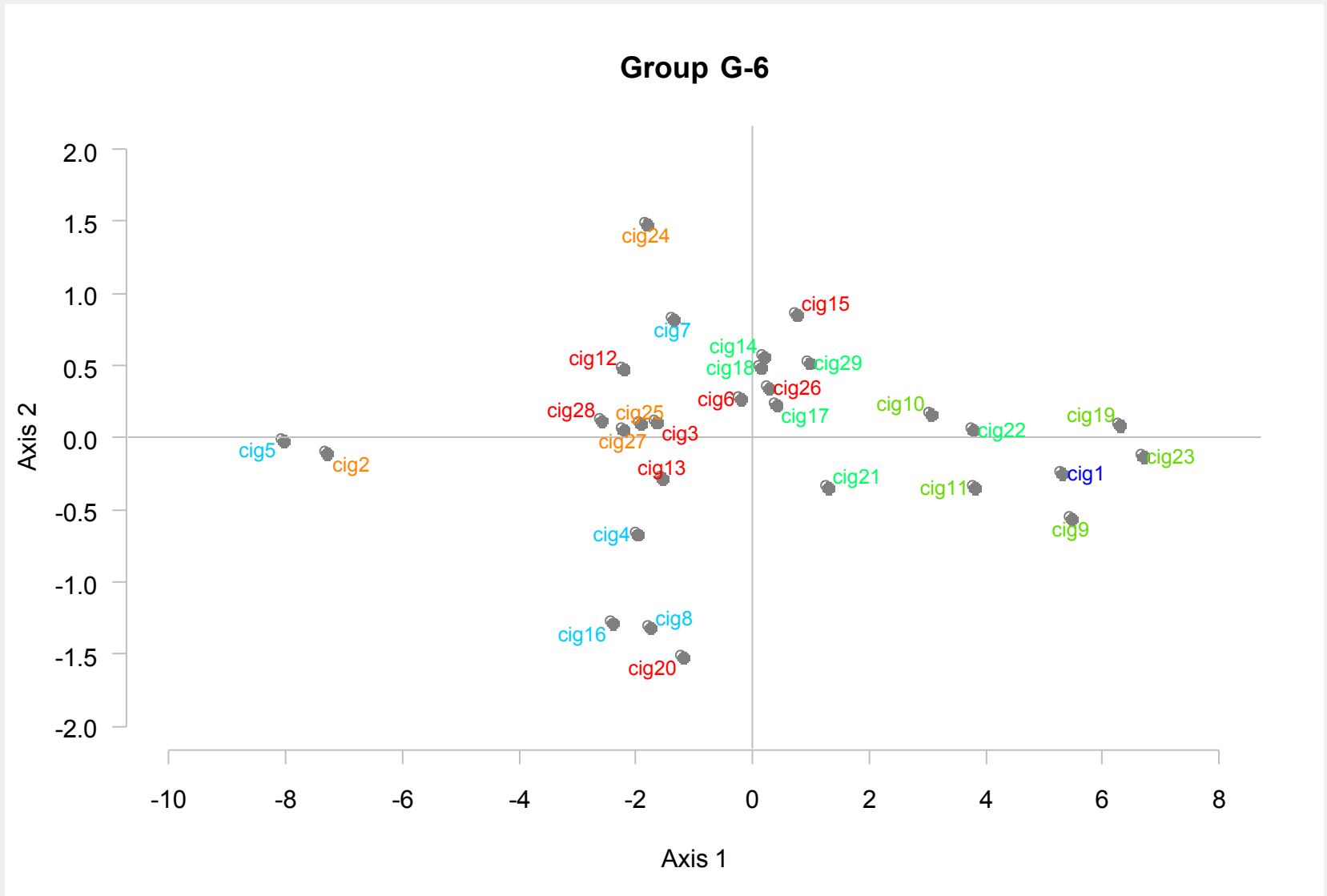
*Graphing observations*



# How to operate the THEME R-software?

## 7. Reaping results

*Graphing observations*

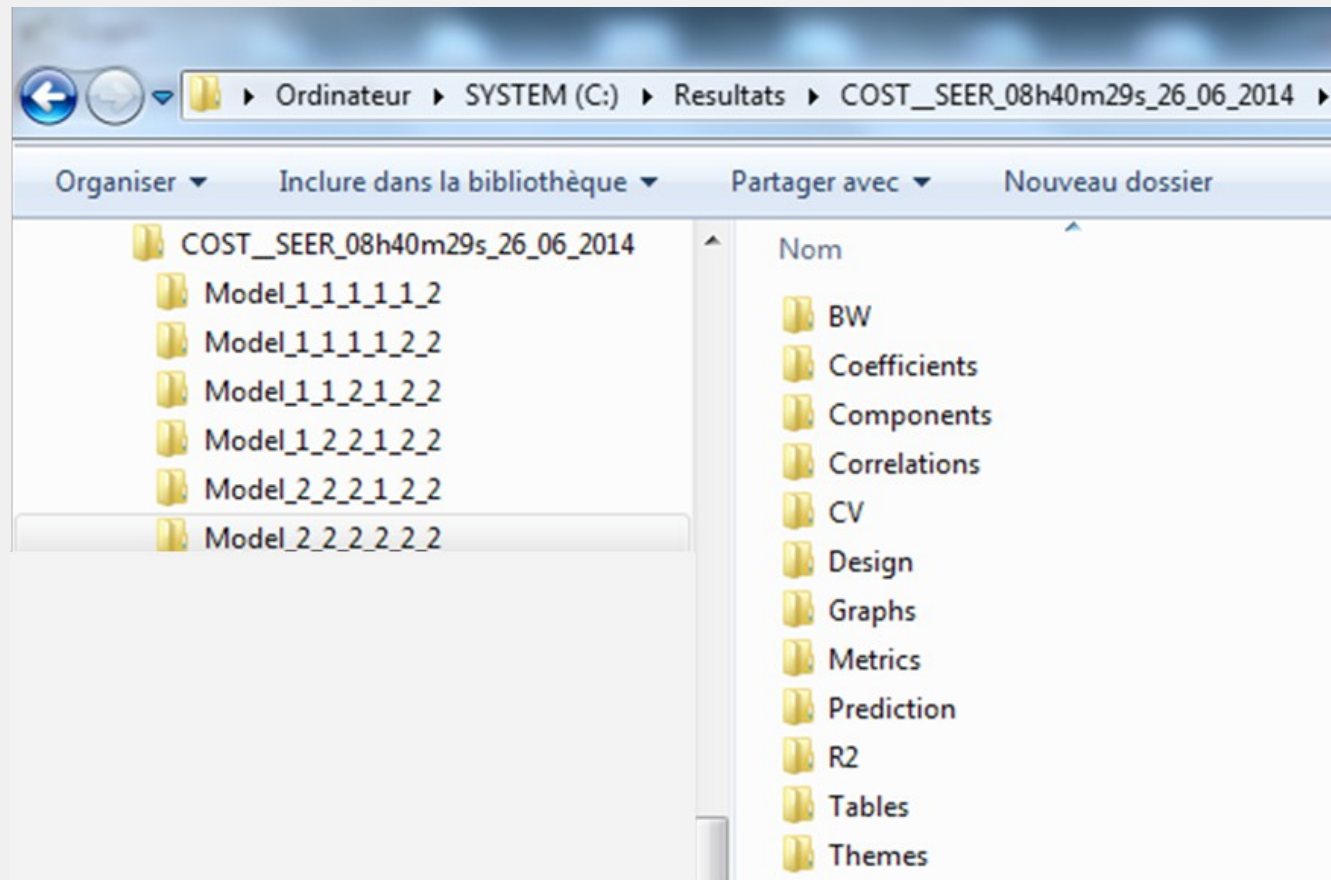




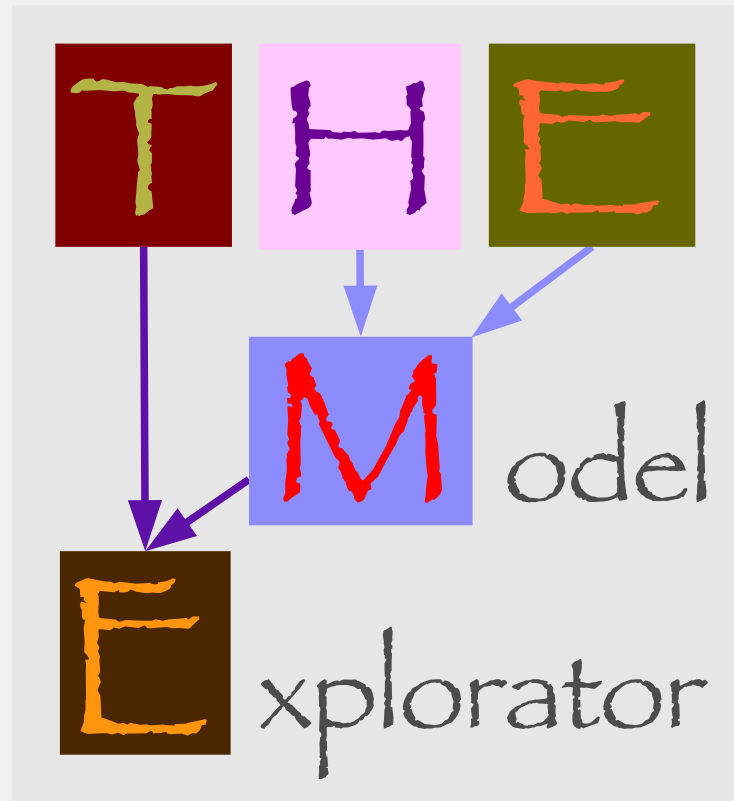
# How to operate the THEME R-software?

## 7. Reaping results

*Getting ALL  
the results  
as an object*



## How to get the THEME R-software?



*Help-files yet to be written...*

*Soon available on the CRAN*

THE END

*Thank you, all*

Bry X., Verron T., Redont P. (2010) : *Multidimensional Exploratory Analysis of a Structural Model using a class of generalized covariance criteria*, COMPSTAT 2010, Proceedings, Springer.

Bry X., Redont P., Verron T., Cazes P. (2012) : *THEME-SEER: a multidimensional exploratory technique to analyze a structural model using an extended covariance criterion*, Journal of chemometrics, 26, pp 158-169.