Méthodes psychométriques en qualité de vie

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30 ANS

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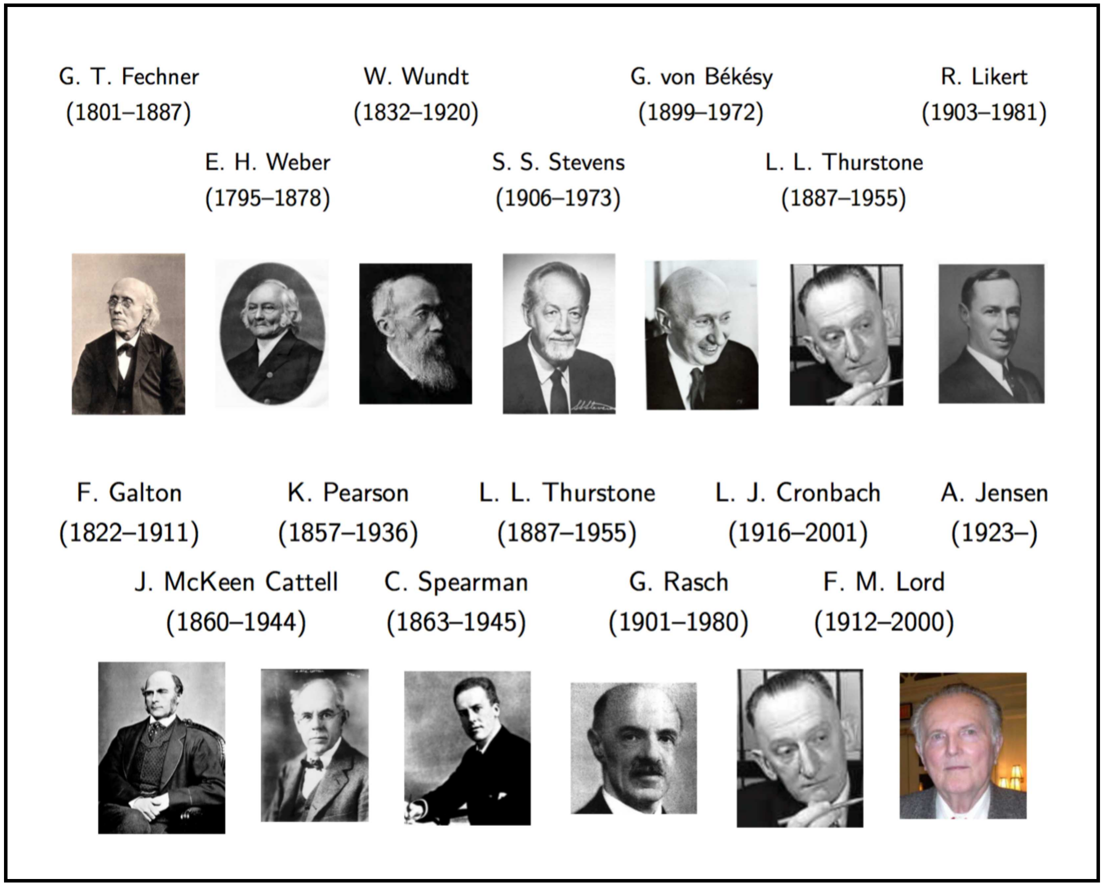
Analyses factorielles

- Analyse en composantes principales et analyse factorielle
- Analyse factorielle exploratoire
- Analyse factorielle confirmatoire

It is rather surprising that systematic studies of human abilities were not undertaken until the second half of the last century. . . An accurate method was available for measuring the circumference of the earth 2,000 years before the first systematic measures of human ability were developed. [1]

1. J Nunnally et I Bernstein. *Psychometric Theory*. 3rd. McGraw-Hill, 1994.

Avant Jan de Leeuw & Bengt Muthén



Multivariate Behavioral Research, 1987, 22, 267–305

A Brief History of the Philosophical Foundations of Exploratory Factor Analysis

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Exploratory factor analysis derives its key ideas from many sources. From the Greek rationalists and atomists comes the idea that appearance is to be explained by something not observed. From Aristotle comes the idea of induction and seeking common features of things as explanations of them. From Francis Bacon comes the idea of an automatic algorithm for inductively discovering common causes. From Descartes come the ideas of analysis and synthesis that underlie the emphasis on analysis of variables into orthogonal or linearly independent factors and focus on reproducing (synthesizing) the correlation matrix from the factors. From empiricist statisticians like Pearson and Yule comes the idea of exploratory, descriptive statistics. Also from the empiricist heritage comes the false expectation some have that factor analysis yields unique and unambiguous knowledge without prior assumptions—the inductivist fallacy. This expectation founders on the indeterminacy of factors, even after their loadings are defined by rotation. Indeterminacy is unavoidable in the interpretation of common factors because the process of interpretation is inductive and inductive inferences are not uniquely determined by the data on which they are based. But from Kant we learn not to discard inductive inferences but to treat them as hypotheses that must be tested against additional data to establish their objectivity. And so the conclusions of exploratory factor analyses are never complete without a subsequent confirmatory analysis with additional variables and new data.

ACP et AF

▷ 01a-scores.pdf

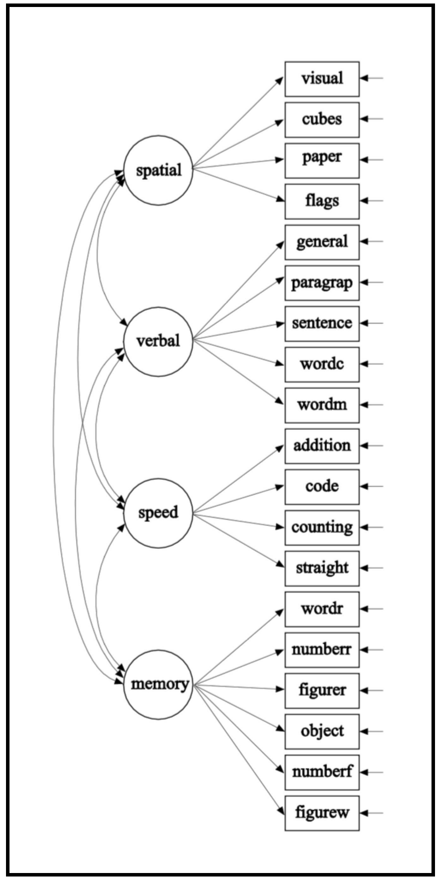
Les composantes C_i $(i = 1, \ldots, p)$ de l'analyse en composantes principales (ACP) sont construites comme de simples combinaisons linéaires des p variables d'origine : $C_i = \sum_{j=1}^{p} w_{ij} x_j$.

Dans le cadre de l'analyse factorielle, on considère au contraire des combinaisons linéaires de facteurs[2] :

$$x_i \approx \sum_{j=1}^{k} w_{ij} F_j.$$

2. W Revelle. *An introduction to psychometric theory with applications in R*. http ://www.personality-project.org/r/book/. 2016, chap. 6.

Modèle de Holzinger & Swineford



Comparaison ACP *versus* AF

```
library(psych)
principal(HS[,c("visual","cubes", paper")], nfactors = 3,
          rotate = "none")
```

```
Standardized loadings (pattern matrix) based upon correlation matrix
        PC1   PC2   PC3 h2       u2 com
visual 0.77 -0.41  0.48  1  0.0e+00 2.3
cubes  0.70  0.71  0.10  1 -4.4e-16 2.0 ❶
paper  0.80 -0.22 -0.56  1 -6.7e-16 2.0

                      PC1  PC2  PC3
SS loadings          1.72 0.72 0.56
Proportion Var       0.57 0.24 0.19
```

```
fa(HS[,c("visual", "cubes", "paper")], nfactors = 1)
```

```
Standardized loadings (pattern matrix) based upon correlation matrix
        MR1   h2   u2 com
visual 0.62 0.39 0.61   1
cubes  0.48 0.23 0.77   1 ❶
paper  0.71 0.50 0.50   1

                MR1
SS loadings    1.12
Proportion Var 0.37
```

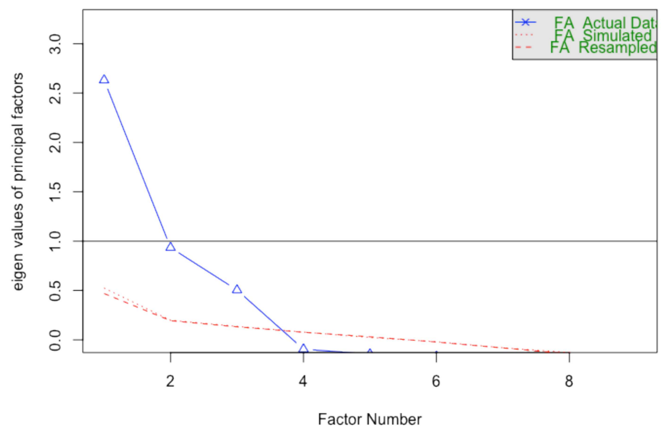
Sélection de modèle

— Sélection des variables à inclure : analyse d'items ou hypothèses *a priori*
— Sélection du nombre de facteurs : méthode exploratoire, hypothèses *a priori*, analyse parallèle
— Type de rotation : en fonction des hypothèses théoriques
— Méthode d'estimation (OLS, ML, WLS et PA)
— Matrice de corrélation (Pearson, tétra- ou polychorique)
— Nombre de sujets nécessaires [3]

3. Rouquette A et Falissard B. « Sample size requirements for the internal validation of psychiatric scales ». In : *International Journal of Methods in Psychiatric Research* 20.4 (2011), p. 235–249.

Analyse parallèle

```
d <- HS[,7:15]
describe(d))
fa.parallel(d, fm = "pa", fa = "fa", main = "")
```



Solution factorielle à 1 facteur

	PA1	PA2	PA3	*h2*	*u2*
visual	0,559			0,313	0,687
cubes	0,301			0,090	0,910
paper	0,365			0,133	0,867
paragrap	0,761			0,580	0,420
sentence	0,724			0,525	0,475
wordm	0,768			0,590	0,410
addition	0,259			0,067	0,933
counting	0,339			0,115	0,885
straight	0,468			0,219	0,781

```
m1 <- fa(d, nfactors = 1, fm ="pa")
m2 <- fa(d, nfactors = 2, fm ="pa")
m3 <- fa(d, nfactors = 3, fm ="pa")
```

Solution factorielle à 2 facteurs

	PA1	PA2	PA3	*h2*	*u2*
visual	0,275	0,430		0,341	0,659
cubes	0,134	0,244		0,100	0,900
paper	0,060	0,449		0,223	0,777
paragrap	0,851	0,005		0,727	0,273
sentence	0,854	-0,038		0,709	0,291
wordm	0,828	0,033		0,705	0,295
addition	-0,034	0,434		0,180	0,820
counting	-0,083	0,642		0,383	0,617
straight	0,007	0,734		0,542	0,458

```
m1 <- fa(d, nfactors = 1, fm ="pa")
m2 <- fa(d, nfactors = 2, fm ="pa")
m3 <- fa(d, nfactors = 3, fm ="pa")
```


Solution factorielle à 3 facteurs

	PA1	PA2	PA3	*h2*	*u2*
visual	0,196	0,591	0,032	0,477	0,523
cubes	0,043	0,510	-0,121	0,256	0,744
paper	-0,062	0,685	0,020	0,453	0,547
paragrap	0,846	0,016	0,007	0,728	0,272
sentence	0,885	-0,065	0,007	0,753	0,247
wordm	0,805	0,080	-0,013	0,692	0,308
addition	0,045	-0,154	0,732	0,512	0,488
counting	-0,034	0,121	0,691	0,524	0,476
straight	0,032	0,380	0,458	0,461	0,539

```
m1 <- fa(d, nfactors = 1, fm ="pa")
m2 <- fa(d, nfactors = 2, fm ="pa")
m3 <- fa(d, nfactors = 3, fm ="pa")
```

Modèles de mesure en analyse factorielle

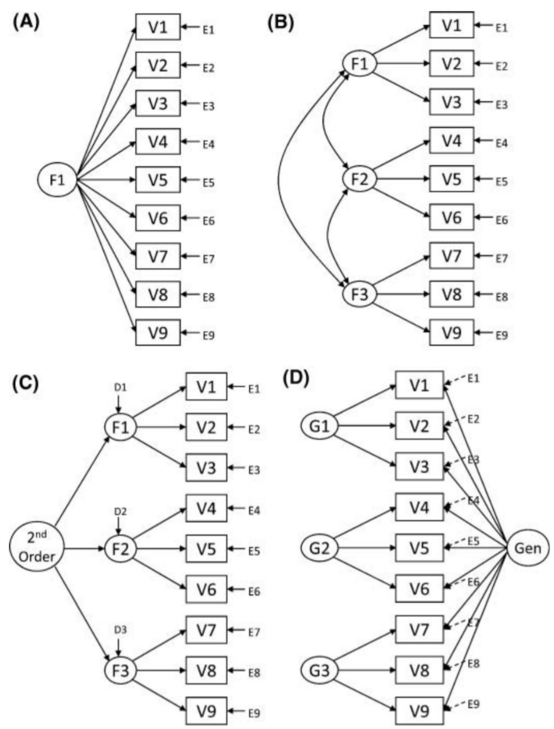


FIGURE 1.—Model A, a unidimensional model; Model B, a correlated traits model; Model C, a second-order model; and Model D, a bifactor model. F = factor; E = error; D = disturbance; V = measured variable.

Fichier de données et scripts R disponibles à l'adresse suivante :
`https://bitbucket.org/chlalanne/eespe11`

– Typeset with FoilTEX (version 2), Revision 337c8db