Analysis of sensory profiling data by taking account of the performance of the assessors

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Fixed vocabulary

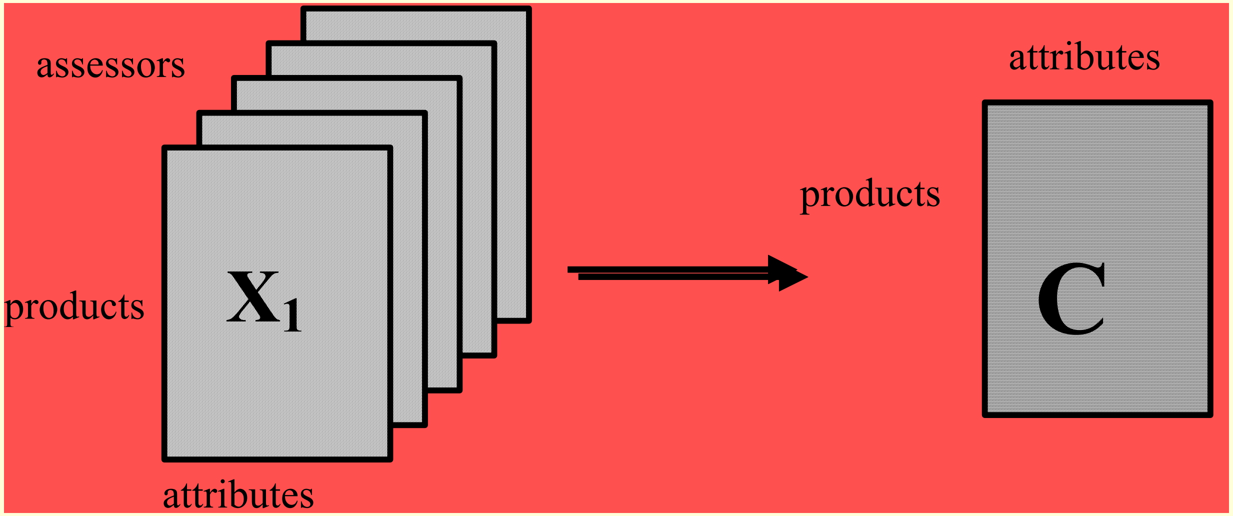
m : number of assessors

n : number de products

p : number of descriptors

X_i : data set (size n*p) associated with assessor *i*

Seeking a group average configuration



How to deal with the black sheep among your assessors?

First alternative

Hang them out to dry!

Second alternative

- Try to understand why?
- Train them again
- Compensate for their deficiencies (sources of variations) using appropriate statistical tools.
- Downweight

Pre-treatment

Removing some variations among assessors

- Center each data set:

  correct for the shift

- Isotropic pre-scaling in such a way that all assessors have the same total variance:

  correct for the variations in the range of scaling

Remark

In the following, the pre-treated data sets will also be denoted $\mathbf{X}_i$.

Shake the old habits!

The group average configuration is usually computed as solution to the minimization of :

$$\sum \left\| X_i - C \right\|^2 \quad \Longrightarrow \quad C = \frac{\sum_{i=1} X_i}{m}$$

You'd better seek a solution to the minimization of :

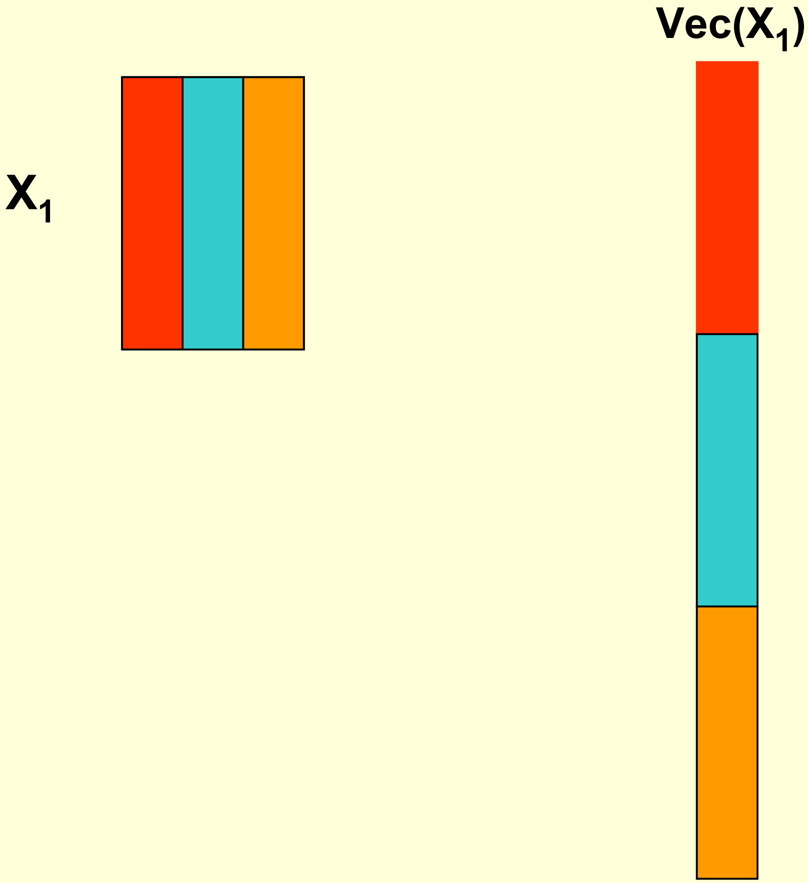
$$\sum \left\| \alpha_i X_i - C \right\|^2 . \quad \Longrightarrow \quad C = \frac{\sum_{i=1} \alpha_i X_i}{m}$$

Remark

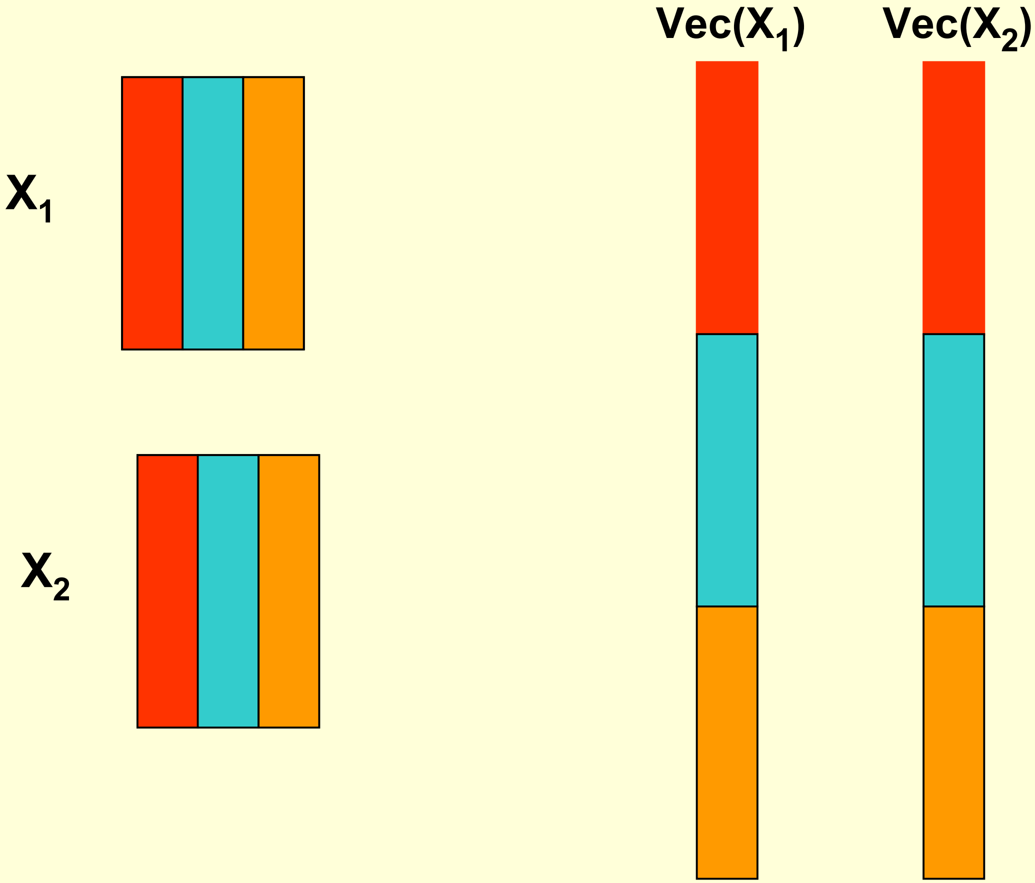
$$C = \frac{\sum_{i=1} \alpha_i X_i}{m}$$

These are not (isotropic) scaling factors but **<u>weights</u>**

Solution

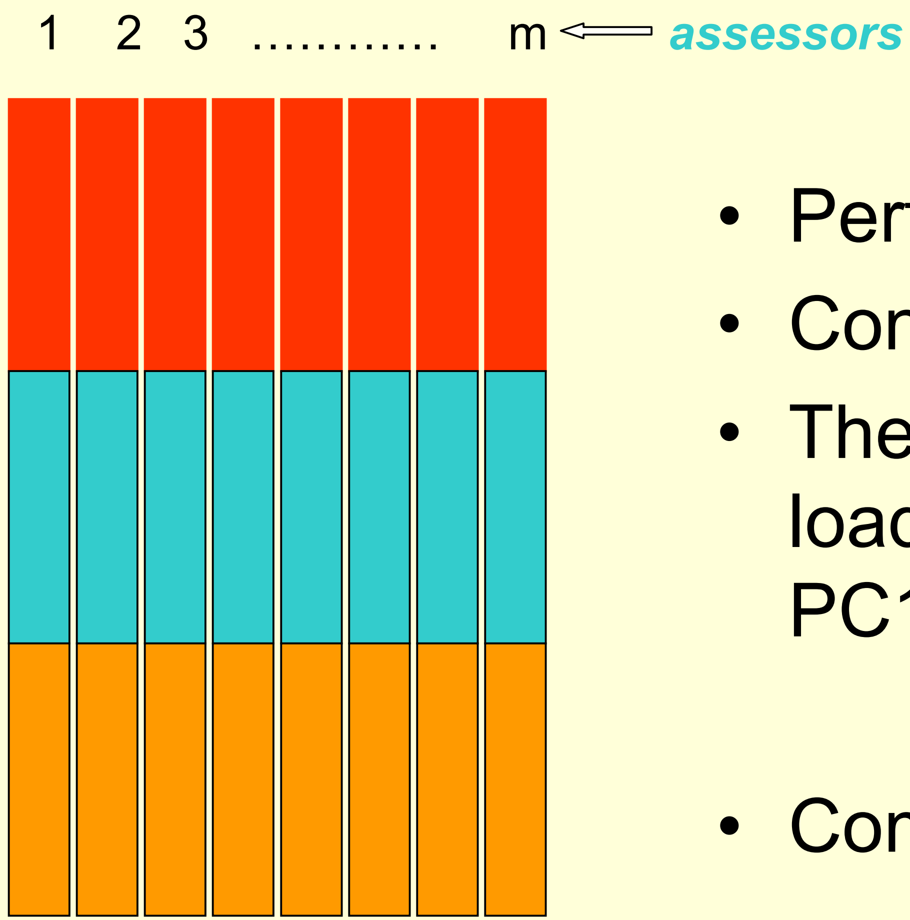


Solution



- And so on

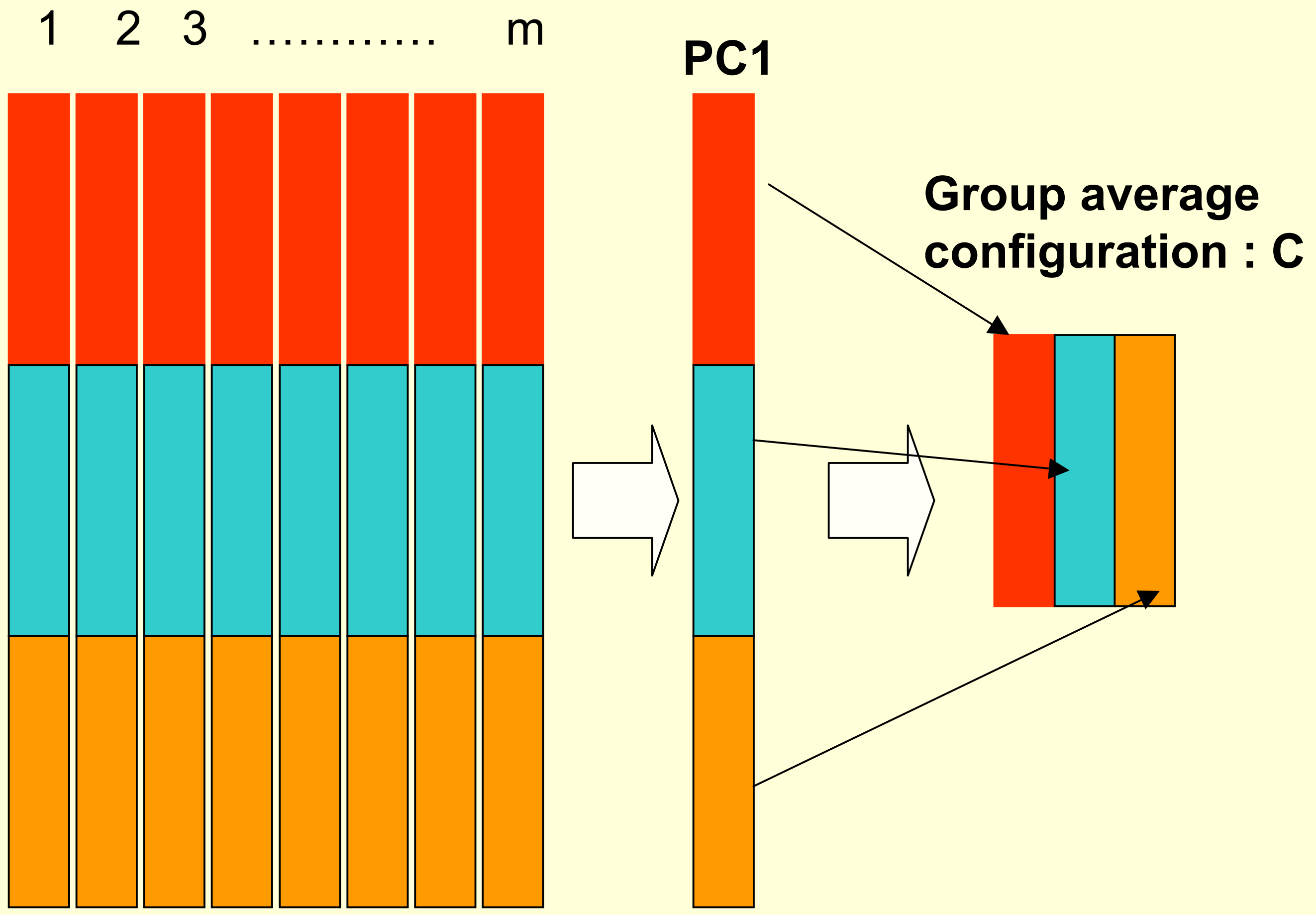
Solution



- Perform PCA.
- Consider the first PC : PC1
- The weights α_i are the loadings associated with PC1.
- Compute

$$C = \frac{\sum_{i=1} \alpha_i X_i}{m}$$

Solution



Remarks

Overall performance index of the panel :
percentage of variation explained by PC1

α_i stands as a performance index associated with assessor i, moreover : **α_i = correlation (X_i, C).**

What if an α_i is negative?
hang the associated assessor out to dry!

Illustration
Cider data

	First experiment
Assessors	α_i
Assessor 1	0.78
Assesor 2	0.79
Assessor 3	0.76
Assessor 4	0.79
Assessor 5	0.70
Assessor 6	0.78
Assessor 7	0.72
Panel	0.76

Illustration
Cider data

	First experiment	Second experiment
Assessors	α_i	α_i
Assessor 1	0.78	0.07
Assessor 2	0.79	0.77
Assessor 3	0.76	0.77
Assessor 4	0.79	0.78
Assessor 5	0.70	0.71
Assessor 6	0.78	0.77
Assessor 7	0.72	0.72
Panel	0.76	0.66

Hypothesis testing

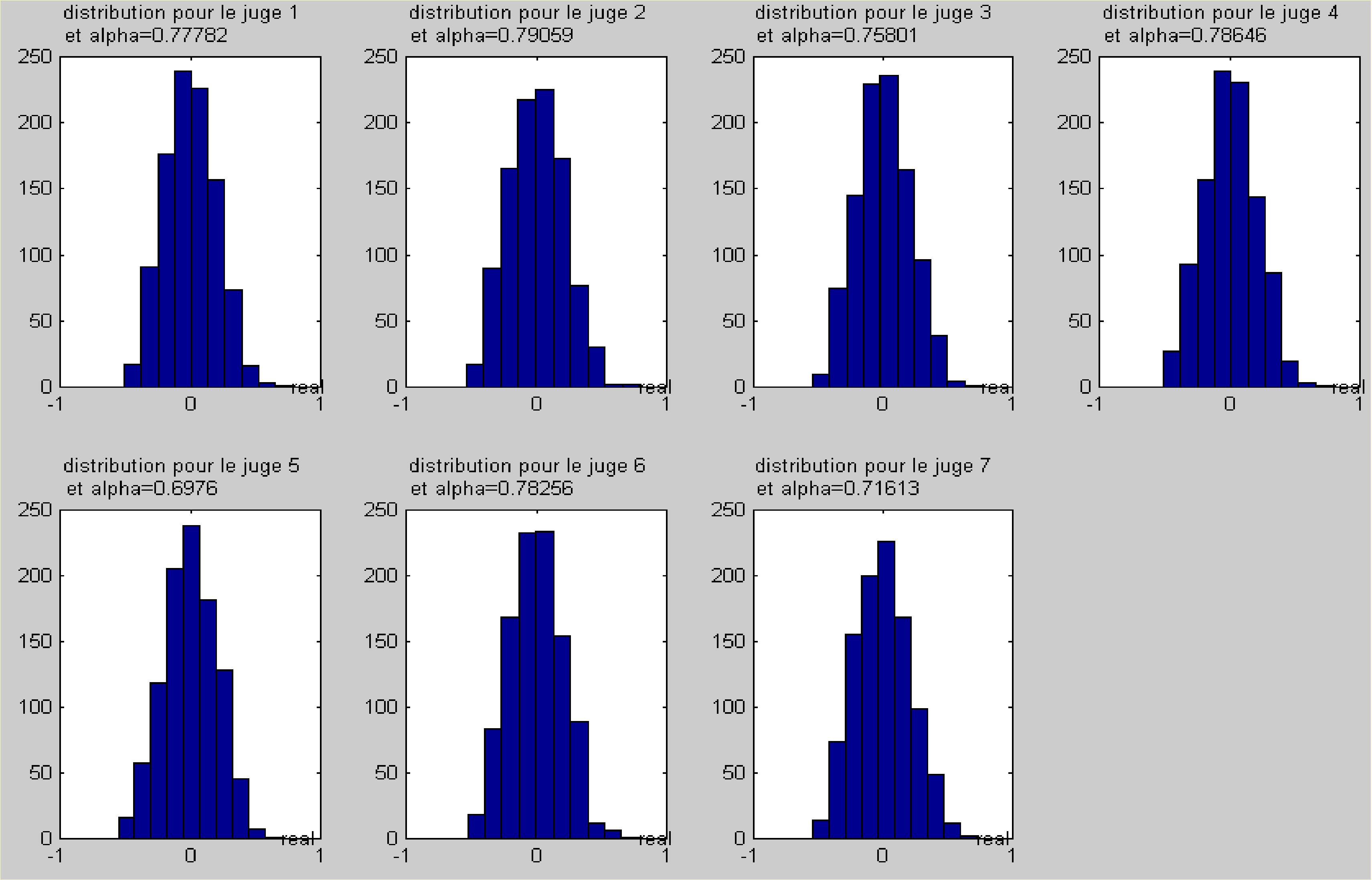
- $H_0 : \alpha_i = 0$ Against $H_1 : \alpha_i > 0$

***<u>Permutation test</u>* :**

α_i = correlation (vect(X_i), vect(C))

- Permute the rows of vect(Xi) → new_ vect(Xi)
- compute :
  new_ α_i = correlation (new_vect(X_i), vect(C))
- Repeat several times

Simulated distributions for the seven assessors



Results

	First experiment	Second experiment
Assessors	α_i	α_i
Assessor 1	0.78 (***)	0.07 (ns)
Assessor 2	0.79 (***)	0.77 (***)
Assessor 3	0.76 (***)	0.77 (***)
Assessor 4	0.79 (***)	0.78 (***)
Assessor 5	0.70 (***)	0.71 (***)
Assessor 6	0.78 (***)	0.77 (***)
Assessor 7	0.72 (***)	0.72 (***)
Panel	0.76 (***)	0.66 (***)

A weight for each attribute instead of an overall weight

- We seek a group configuration C and diagonal matrices Λ_i (i=1, …, m), where the diagonal elements are the weights associated with the various attributes, so as to minimize the quantity :

$$\sum \left\| X_i \Lambda_i - C \right\|^2 .$$

The solution will appeal to Garmt

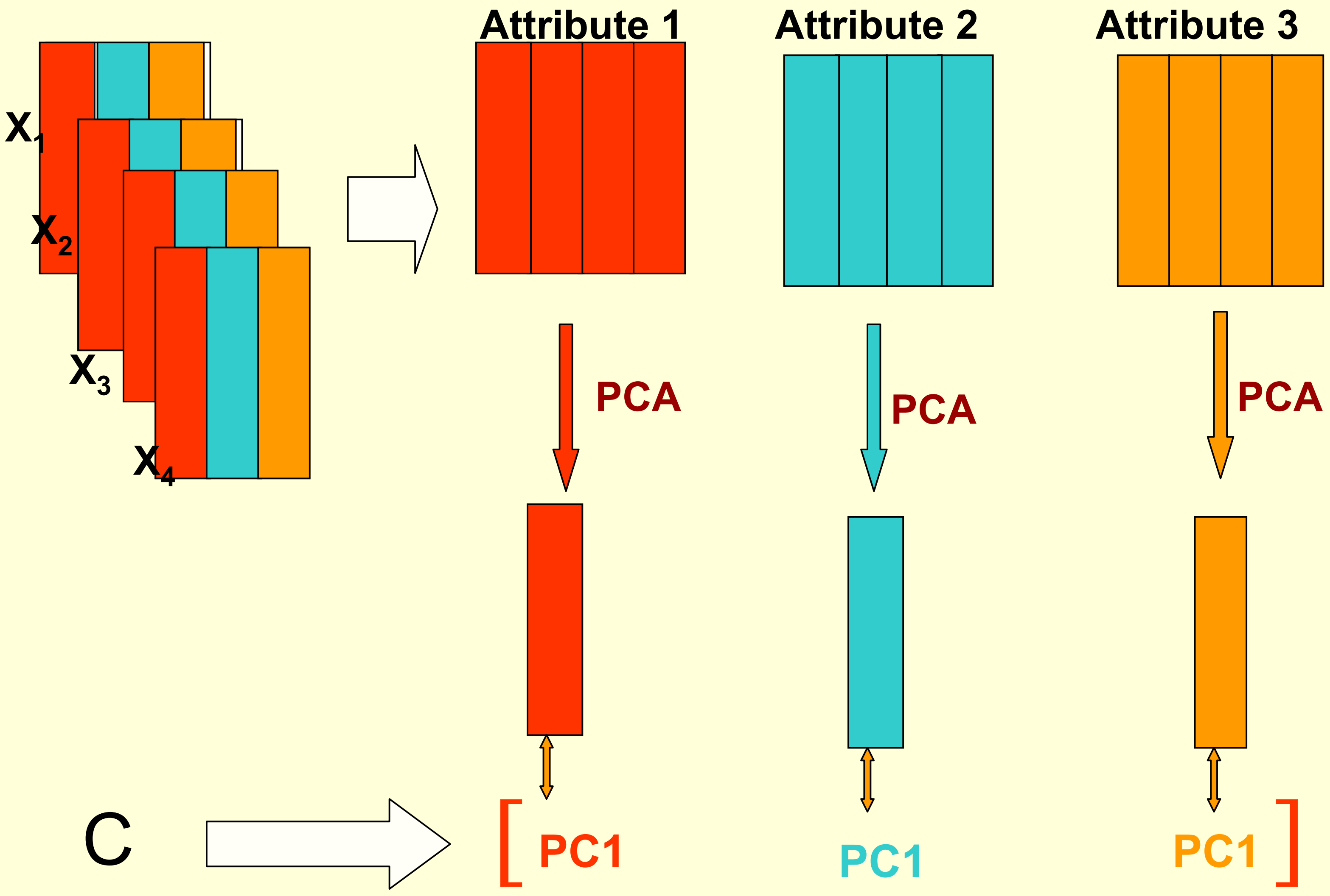


Illustration: Cider data

Overall performance per attribute

Attribute	alpha
INTENSITY ODOR	0.55
SWEETNESS	0.84
ACID	0.29
BITTER	0.54
ASTRINGENCY	0.38
SUFF	0.52
PIQU	0.33
ALCOHOL	0.62
PERFUM	0.78
FRUITNESS	0.85

Loadings : agreement among assessors for each attribute

	SWEET	ACID	BITTER	ASTR	ALCO	PERF	FRUI
Assessor1	0.38	0.46	0.47	0.05	0.42	0.39	0.38
Assessor2	0.40	-0.06	0.44	0.29	0.46	0.36	0.37
Assessor3	0.37	0.54	0.35	0.56	0.36	0.40	0.40
Assessor4	0.39	0.53	0.38	0.23	0.15	0.42	0.38
Assessor5	0.37	0.14	0.17	-0.47	0.40	0.35	0.36
Assessor6	0.36	0.28	0.24	-0.19	0.40	0.35	0.37
Assessor7	0.38	-0.32	0.48	0.54	0.38	0.37	0.38

Next level : allow for rotations and overall weights

Minimize $$\sum \left\| \alpha_i X_i H_i - C \right\|^2$$

$$C = \frac{\sum_{i=1} \alpha_i X_i H_i}{m}$$

These are not (isotropic) scaling factors but **weights**

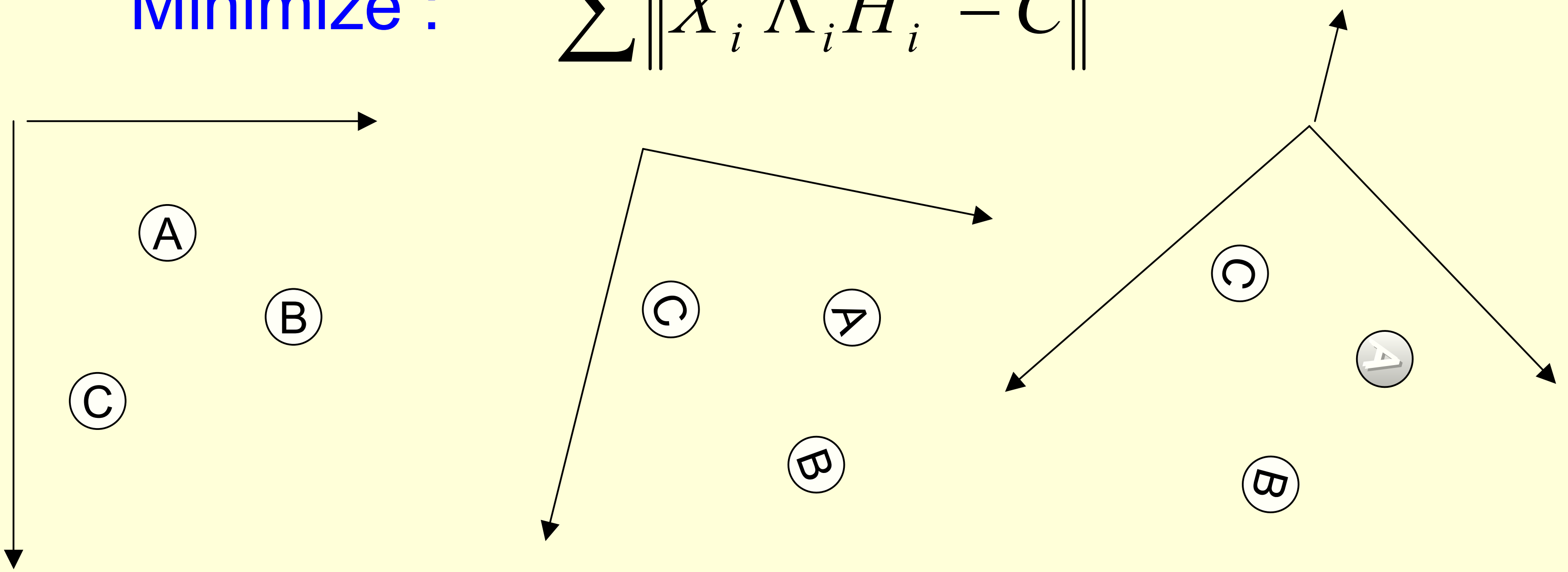
Solution : GPA

Comparison of methods

Criterion	Loss function
$\sum \left\| \alpha_i X_i - C \right\|^2$	46.31
$\sum \left\| \alpha_i X_i H_i - C \right\|^2$	16.86
$\sum \left\| X_i \Lambda_i - C \right\|^2.$	16.41

Next level : allow for rotations AND a weight for each attribute instead of an overall weight

Minimize : $$\sum \left\| X_i \Lambda_i H_i - C \right\|^2$$



Solution: forget it!

Comparison of methods

Criterion	Loss function
$\sum \left\| \alpha_i X_i - C \right\|^2$	46.31
$\sum \left\| \alpha_i X_i H_i - C \right\|^2$	16.86
$\sum \left\| X_i \Lambda_i - C \right\|^2.$	16.41
$\sum \left\| X_i \Lambda_i H_i - C \right\|^2$	9.26

Concluding remarks

- One should consider these methods as **tools** to assess the extent to which assessors are **behaving similarly** and, if not, what are the differences and to **which extent these differences are serious**.

- **Three main focuses** :

  * **Performance** (overall, per assessor, overall for each attribute, per attribute and per assessor).

  * **Hypothesis testing** framework.

  * **Weights** (robustness, …)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