

PCA Part II

CLPS 2908

Lecture 11

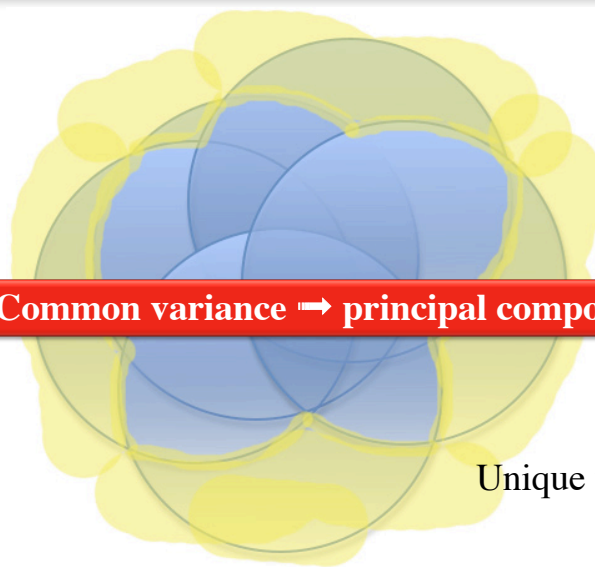
March 7, 2019

Communing Variables

Each circle
= 1 variable

Common variance → principal component

Unique variance



Communalities

- communality of each variable = h^2
 - ♦ = variance in given variable accounted for by selected components (non-uniqueness)

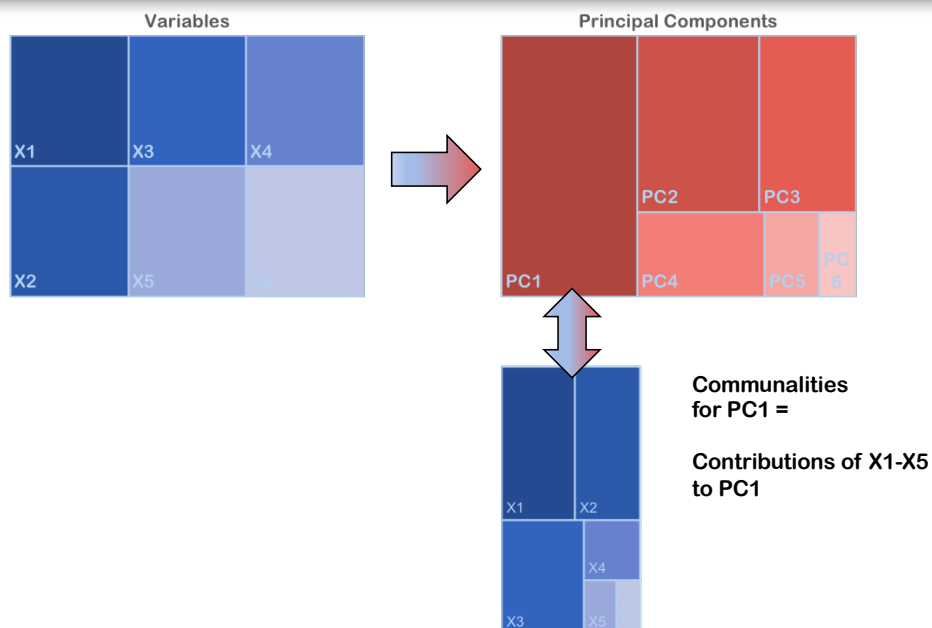
Communalities

	Initial	Extraction
X1	1.000	.625
x2	1.000	.718
x3	1.000	.769
x4	1.000	.792
x5	1.000	.532

(2 components extracted)

- ♦ If $r=p$, what's the sum of all the h_i^2 values?

Variance Rearrangement



Loading Matrix

Component Matrix (= Factor Loading Matrix)

Loading matrix A contains **correlations** between variables and components

	Factor 1	Factor 2
X1	.76362	-.20469
X2	.84590	.04739
X3	-.12137	.86847
X4	.04530	.88857
X5	.72907	.02616

Loading Matrix

Component Matrix (= Factor Loading Matrix)

Squared correlations = variance components.

Each X's summed variance components = its communality (what it contributes to PC)

	Factor 1	Factor 2	
X1	.76362	-.20469	$\rightarrow \hat{h}_1^2 = .625$
X2	.84590	.04739	
X3	-.12137	.86847	
X4	.04530	.88857	$\rightarrow \hat{h}_4^2 = .792$
X5	.72907	.02616	

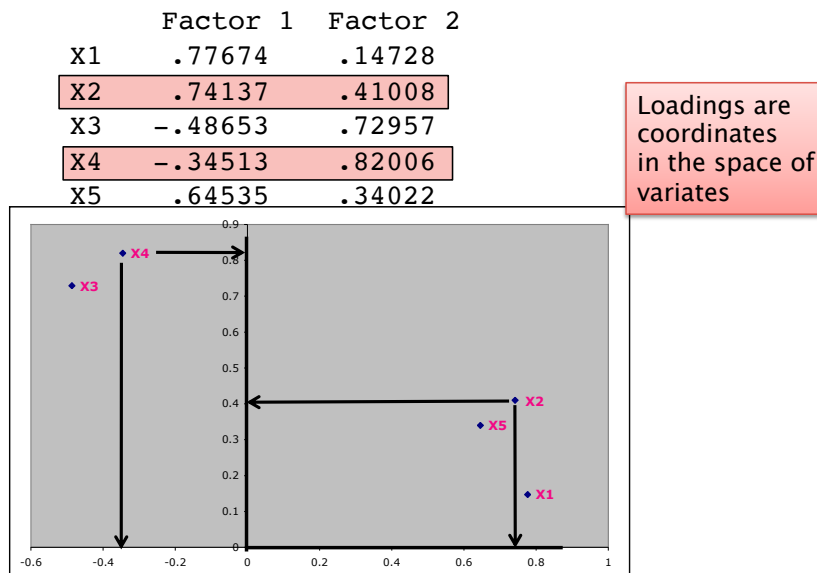
Loading Matrix

Component Matrix

PC 1' s summed variance components (squared loadings)
= its total variance, λ_1

	Factor 1	Factor 2	
X1	.76362	-.20469	$\rightarrow \hat{h}_1^2$
X2	.84590	.04739	
X3	-.12137	.86847	$\rightarrow \hat{h}_4^2$
X4	.04530	.88857	
X5	.72907	.02616	
	\downarrow	\downarrow	
	$\lambda_1 = 1.847$	$\lambda_2 = 1.589$	

Loadings = Coordinates



PCA So Far

- Spectral decomposition (original variables → linear combinations)

$$\mathbf{R} = \mathbf{V}\mathbf{\Lambda}\mathbf{V}'$$

- ♦ $\mathbf{\Lambda} \rightarrow$ eigenvalues λ_j (goal = maximal variance for linear combination)
- ♦ $\mathbf{V} \rightarrow$ eigenvectors v_j (weighting vector that produces linear combination)
- Extracting r components, whereby normally $r < p$
- Communalities h_i^2 (variable's variance contributing to / shared with / accounted for by components)
- Component ("Factor") Loadings a_{ij} $\sum_{j=1}^r a_{ij}^2 = h_i^2$
correlation with each component; if squared → shared variance)
- Rotation
- Component/Factor Scores

Rotation

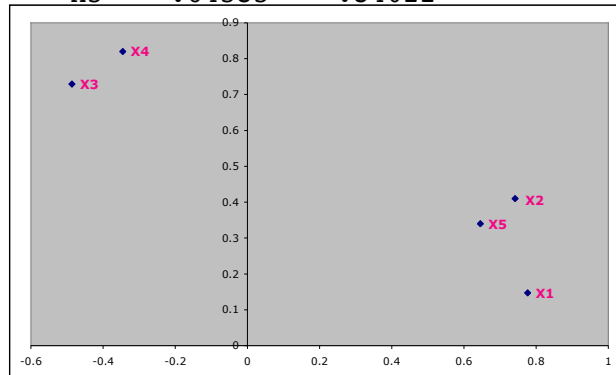
- Changes the reference axes to interpret the meaning of components
- Leaves the relative relationships of variables untouched
- Goal = rearrangement that yields **simple structure**
 - ♦ Ideally, each variable loads strongly on only one component.
 - ♦ Few components with large variance, each of which is defined by a few variables with large loadings (other variables have near-zero loading)

	C1	C2
X1	1	0
X2	1	0
X3	1	0
X4	0	1
X5	0	1
X6	0	1

Unrotated Loading Matrix

	Factor 1	Factor 2
X1	.77674	.14728
X2	.74137	.41008
X3	-.48653	.72957
X4	-.34513	.82006
X5	.64535	.34022

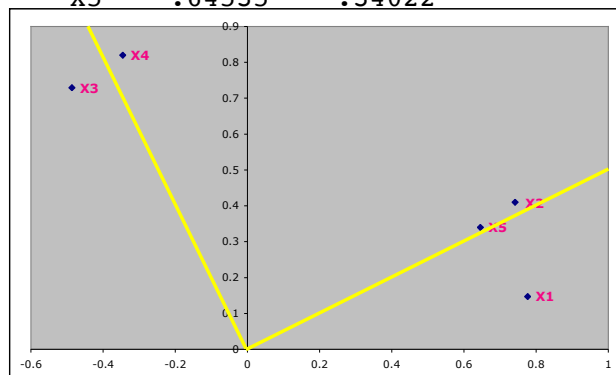
$A_{\text{unrotated}}$



Unrotated

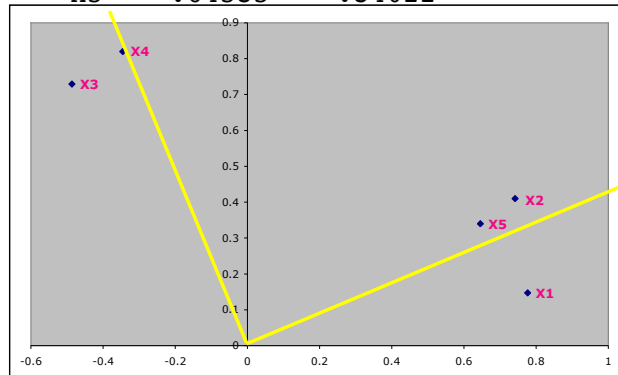
	Factor 1	Factor 2
X1	.77674	.14728
X2	.74137	.41008
X3	-.48653	.72957
X4	-.34513	.82006
X5	.64535	.34022

Search for
better fit
of axes
and
variables



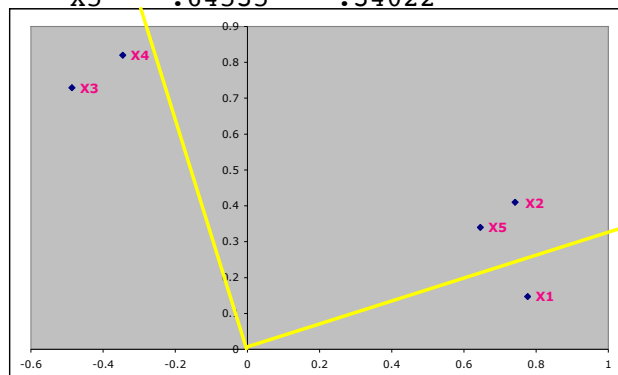
Unrotated

	Factor 1	Factor 2
X1	.77674	.14728
X2	.74137	.41008
X3	-.48653	.72957
X4	-.34513	.82006
X5	.64535	.34022



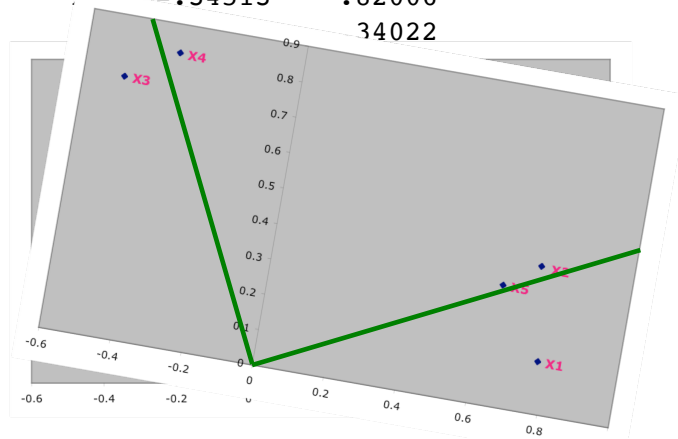
Unrotated

	Factor 1	Factor 2
X1	.77674	.14728
X2	.74137	.41008
X3	-.48653	.72957
X4	-.34513	.82006
X5	.64535	.34022



Unrotated

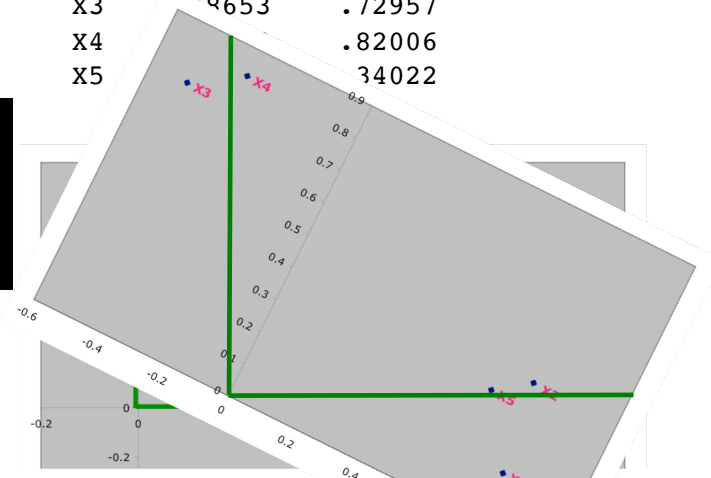
	Factor 1	Factor 2
X1	.77674	.14728
X2	.74137	.41008
X3	-.48653	.72957
X4	-.34513	.82006
X5		.34022



And Now Rotated...

	Factor 1	Factor 2
X1	.77674	.14728
X2	.74137	.41008
X3	-.48653	.72957
X4	-.34513	.82006
X5		.34022

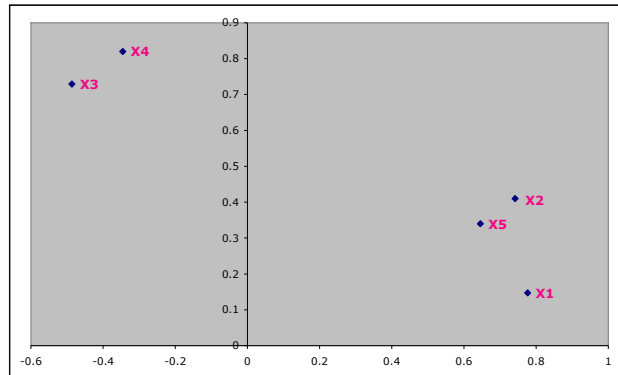
Actual axis
rotation:
Improved
"capture"



Amount of Rotation

Factor Transformation Matrix

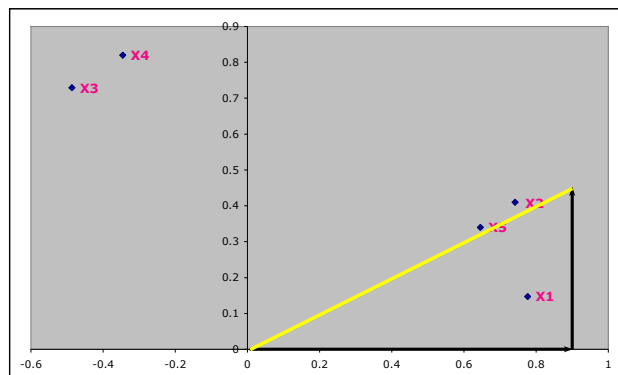
	Factor 1	Factor 2
Factor 1	.90076	-.43433
Factor 2	.43433	.90076



Amount of Rotation

Factor Transformation Matrix

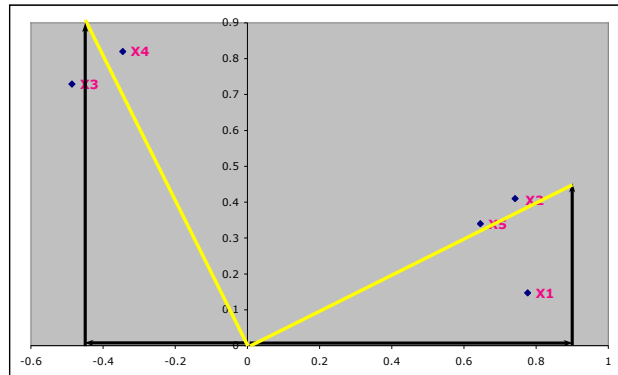
	Factor 1	Factor 2
Factor 1	.90076	-.43433
Factor 2	.43433	.90076



Amount of Rotation

Factor Transformation Matrix

	Factor 1	Factor 2
Factor 1	.90076	-.43433
Factor 2	.43433	.90076



Formal Operation

- Features of Rotation
 - ♦ Variables in multidimensional space stay put
 - ♦ Only reference axes change
 - ♦ Planets-in-space illustration
 - ♦ Formal proof of invariance:

$$\begin{aligned}
 R_{xx} &= A A' \\
 &= (AT) (AT)' \\
 &= AT T' A' \\
 &= A A'
 \end{aligned}$$

$$T T' = I$$

Component scores

Component scores = “Factor scores” :

- properties of individuals
- reflecting their standing on the r principal components C_j
- Resulting from a transformation of their standing on the original p variables X_i

$\mathbf{C} = \mathbf{X} \cdot \mathbf{W}$ Each person's linear combinations
 $n \times r$ $n \times p$ $p \times r$ of their own variable scores

$\mathbf{C} = \mathbf{Z} \cdot \mathbf{V}$ Each person's linear combinations
 $n \times r$ $n \times p$ $p \times r$ of their **standardized** scores

Output Example