

Principal components and factor analysis

- Principal components:
 - ◆ Purely mathematical.
 - ◆ Find eigenvalues, eigenvectors of correlation matrix.
 - ◆ No testing whether observed components reproducible, or even probability model behind it.
- Factor analysis:
 - ◆ some way towards fixing this (confirmatory factor analysis, later, a long way).
 - ◆ In factor analysis, each variable modelled as: “common factor” (eg. verbal ability) and “specific factor” (left over).
 - ◆ SAS: choose the common factors to “best” reproduce pattern seen in correlation matrix.
 - ◆ Iterative procedure, different answer from principal components.

Example

- 145 children given 5 tests, called PARA, SENT, WORD, ADD and DOTS. 3 linguistic tasks (paragraph comprehension, sentence completion and word meaning), 2 mathematical ones (addition and counting dots).

- Correlation matrix:

```
para 1      0.722  0.714  0.203  0.095
sent 0.722  1      0.685  0.246  0.181
word 0.714  0.685  1      0.170  0.113
add  0.203  0.246  0.170  1      0.585
dots 0.095  0.181  0.113  0.585  1
```

- Is there small number of underlying “constructs” (unobservable) that explains this pattern of correlations?
- First item on each line is name of variable: use SAS special variable `_name_` to read these in.
- First task: figure out number of factors:
 - ◆ again can count eigenvalues > 1
 - ◆ draw *scree plot* and look for “elbow”.

```
data rmat(type=corr);  
  infile "rex2.dat";  
  input _name_ $ para sent word add dots;  
  
proc factor scree method=prinit;
```

- Names on INPUT line same as names of variables in file.
- On PROC FACTOR line, specify method of extracting factors (there are others) and ask for scree plot.
- As in principal components, can ask for output data set containing factor scores, but:
 - ◆ only if have actual data rather than correlations
 - ◆ only goal for this run of PROC FACTOR is to determine a good number of factors.

Start with eigenvalues:

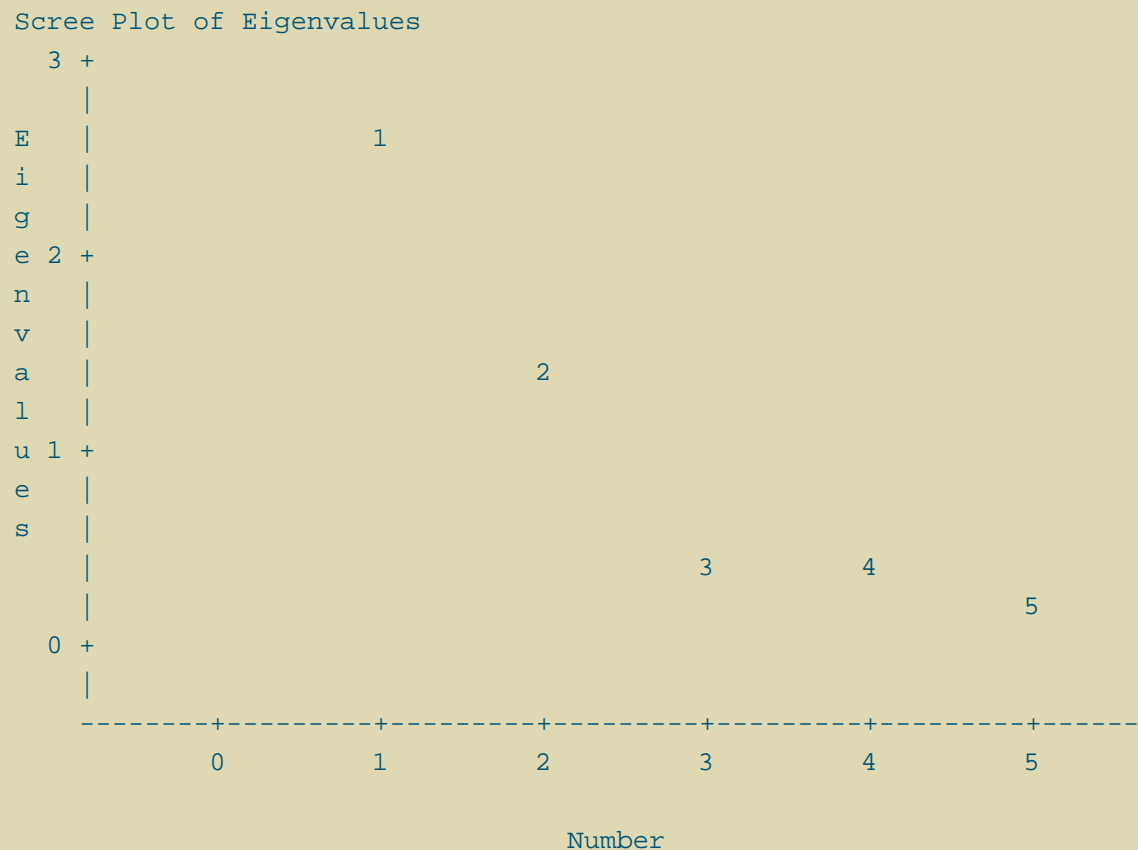
Preliminary Eigenvalues: Total = 5 Average = 1

	Eigenvalue	Difference	Proportion	Cumulative
1	2.58746987	1.16575215	0.5175	0.5175
2	1.42171772	1.00652661	0.2843	0.8018
3	0.41519110	0.10409071	0.0830	0.8849
4	0.31110040	0.04657948	0.0622	0.9471
5	0.26452092		0.0529	1.0000

2 factors will be retained by the MINEIGEN criterion.

2 eigenvalues bigger than 1, so SAS keeps 2 factors. 80% of variability explained by these, not bad.

Scree plot



Looking for where plot “turns corner” or “has elbow”: at 3rd eigenvalue, so keep $3 - 1 = 2$ factors.

Eigenvalues of reduced correlation matrix

After SAS has finished iterating, the eigenvalues are different:

Eigenvalues of the Reduced Correlation Matrix:

Total = 3.31477718 Average = 0.66295544

	Eigenvalue	Difference	Proportion	Cumulative
1	2.28220070	1.25031114	0.6885	0.6885
2	1.03188956	1.00687378	0.3113	0.9998
3	0.02501578	0.02604204	0.0075	1.0073
4	-.00102626	0.02227632	-0.0003	1.0070
5	-.02330258		-0.0070	1.0000

Sometimes they are slightly negative, but this is nothing to worry about.

SAS chose 2 factors, so other eigenvalues very close to 0.

Factor pattern and communality estimates

Factor Pattern

	Factor1	Factor2
para	0.83498	-0.24200
sent	0.82533	-0.13946
word	0.78992	-0.22671
add	0.40982	0.63174
dots	0.33454	0.70949

Factor 1 mostly “words” and factor 2 mostly “numbers”, but could be clearer. Called “factor loadings”, easier to interpret if close to 0 or ± 1 .

Final Communality Estimates: Total = 3.314090

para	sent	word	add	dots
0.75574929	0.70062380	0.67537332	0.56705315	0.61529069

Show how each variable related to the factors (jointly): a low communality means the variable concerned not related to any of the factors. Here, though, all communalities reasonably high. (Actually R-squareds from regression of variable on factor.)

What to do next

- 2 factors appears to be good. No longer worry about scree plot or getting SAS to choose: we specify.
- *Factor rotation*:
 - ◆ So far, choose 1st factor to maximize spread, and 2nd factor ditto, while unrelated to 1st factor.
 - ◆ Now know we'll have 2 factors, so choose them to jointly maximize spread.
 - ◆ Introduces extra “degree of freedom”, can use to get “interpretable” factors by idea of *factor rotation*.
 - ◆ *Varimax* rotation tries to drive *columns* of factor pattern close to 0 or ± 1 .
 - ◆ *Quartimax* rotation tries to arrange that each variable only appears in *one* factor.

More code

Replace previous PROC FACTOR call with following:

```
proc factor n=2 method=prinit rotate=varimax;
```

We decide on 2 factors, ask for varimax rotation.

Produces output from before plus following:

Rotated factors

Rotated Factor Pattern

	Factor1	Factor2
para	0.86556	0.08098
sent	0.81899	0.17284
word	0.81804	0.07868
add	0.14966	0.73801
dots	0.05112	0.78274

Now rather clearer that factor 1 is verbal ability and factor 2 mathematical.

Final Communality Estimates: Total = 3.314090

para	sent	word	add	dots
0.75574929	0.70062380	0.67537332	0.56705315	0.61529069

Communalities unaffected by rotation.

A bigger example: BEM sex role inventory

- 369 women asked to rate themselves on 44 traits, like “self-reliant” or “shy”.
- Rating 1 “never or almost never true of me” to 7 “always or almost always true of me”.
- 44 personality traits is a lot. Can we find a smaller number of factors that capture aspects of personality?
- The whole BEM sex role inventory on next page.

The whole inventory

1. self reliant
2. yielding
3. helpful
4. defends own beliefs
5. cheerful
6. moody
7. independent
8. shy
9. conscientious
10. athletic
11. affectionate
12. theatrical
13. assertive
14. flatterable
15. happy
16. strong personality
17. loyal
18. unpredictable
19. forceful
20. feminine

21. reliable
22. analytical
23. sympathetic
24. jealous
25. leadership ability
26. sensitive to other's needs
27. truthful
28. willing to take risks
29. understanding
30. secretive
31. makes decisions easily
32. compassionate
33. sincere
34. self-sufficient
35. eager to soothe hurt feelings
36. conceited
37. dominant
38. soft spoken
39. likable
40. masculine

41. warm
42. solemn
43. willing to take a stand
44. tender
45. friendly
46. aggressive
47. gullible
48. inefficient
49. acts as a leader
50. childlike
51. adaptable
52. individualistic
53. does not use harsh language
54. unsystematic
55. competitive
56. loves children
57. tactful
58. ambitious
59. gentle
60. conventional

Reading a SAS data set

- Data come to us as a SAS data set (somebody else has read the numbers in from a file and created a SAS data set, which they saved).
- First step is to specify the `libname`, where the data set file is, which is usually in same folder as code. This can be given any name, like `fred`, resulting in
`libname fred '.';`
- Then data step only needs to contain one line (no `infile`, `input` etc):
`data x;`
 `set fred.datasetname;`
links our SAS data set `x` to SAS data set file `datasetname` in current directory (folder).

More; number of factors

- In our case, data in file `factor.sas7bdat`, so code as below. Also, data step can contain other things like defining new variables. In our case, data file contains variable `subno`, which we don't want:

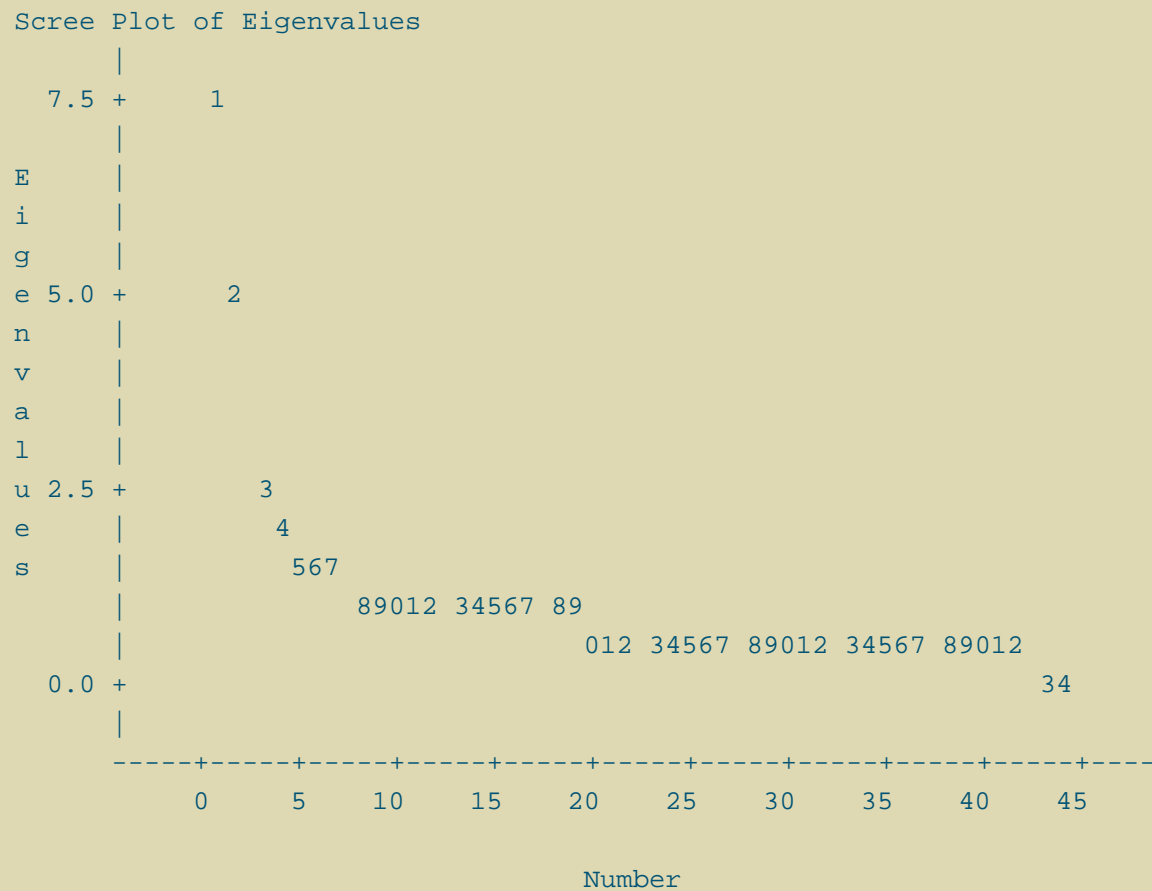
```
libname sasdata '.';
```

```
data bem;  
  set sasdata.factor;  
  drop subno;
```

- Run PROC FACTOR with scree plot, look at eigenvalues.
- No rotation yet, since interpretation later.

```
proc factor scree method=prinit;
```

Scree plot



Scale makes it hard to tell, but might be an elbow at 5, favouring 4 factors.

The eigenvalues

Preliminary Eigenvalues: Total = 44 Average = 1

	Eigenvalue	Difference	Proportion	Cumulative
1	7.53227628	2.51208242	0.1712	0.1712
2	5.02019387	2.61617135	0.1141	0.2853
3	2.40402251	0.33369433	0.0546	0.3399
4	2.07032818	0.37202817	0.0471	0.3870
5	1.69830001	0.28605615	0.0386	0.4256
6	1.41224387	0.06851943	0.0321	0.4577
7	1.34372444	0.18080134	0.0305	0.4882
8	1.16292310	0.01544149	0.0264	0.5146
9	1.14748161	0.04705296	0.0261	0.5407
10	1.10042865	0.02197431	0.0250	0.5657
11	1.07845434	0.07540628	0.0245	0.5902
12	1.00304806	0.04746411	0.0228	0.6130
13	0.95558395	0.03978141	0.0217	0.6348
14	0.91580253	0.05321790	0.0208	0.6556
15	0.86258464	0.01134500	0.0196	0.6752
16	0.85123963	0.03066264	0.0193	0.6945
...				
43	0.23079710	0.08266928	0.0052	0.9966
44	0.14812782		0.0034	1.0000

Interpreting eigenvalues

- No “obvious” gaps – maybe first 2 eigenvalues bigger than others (but then only 28.5% of variability explained).
- Scree plot said 4 eigenvalues before “elbow”.
- 12 eigenvalues > 1 , even then only 61.3% of variability explained.
- Personality is complicated, multidimensional thing.

Extract 4 factors for interpretation

- Specify to extract 4 factors.
- Aim for interpretation of them: rotation (varimax).
- Plot factor scores for first 2.
- Code:

```
proc factor method=prinit n=4 rotate=varimax out=fred;  
  
proc plot data=fred;  
    plot Factor2*Factor1;
```

Rotated factor pattern

	Factor1	Factor2	Factor3	Factor4
HELPFUL	0.26184	0.26300	0.27923	0.20967
RELIANT	0.36213	0.07112	0.11709	0.43997
DEFBEL	0.42138	0.01991	0.27629	0.07063
YIELDING	-0.14990	0.31860	0.15308	0.04241
CHEERFUL	0.14162	0.50944	0.02272	0.11443
INDPT	0.44735	0.00272	0.01255	0.43723
ATHLET	0.30056	0.22166	-0.10326	-0.03315
SHY	-0.40567	-0.07819	-0.04059	-0.05705
ASSERT	0.63003	-0.04904	0.12778	-0.02520
STRPERS	0.70736	0.00870	0.05617	-0.07512
FORCEFUL	0.67282	-0.18610	0.04465	-0.03587
AFFECT	0.25423	0.47711	0.32397	-0.30032
FLATTER	0.18401	0.26908	0.06747	-0.30375
LOYAL	0.17038	0.31797	0.27964	-0.07210
ANALYT	0.28690	-0.00555	0.19432	0.05692

More

FEMININE	0.06328	0.27971	0.18228	0.15442
SYMPATHY	-0.02104	0.13347	0.65757	-0.00735
MOODY	0.05025	-0.32997	0.11292	-0.34756
SENSITIV	0.08165	0.04258	0.59779	0.06167
UNDSTAND	0.01071	0.22379	0.68323	0.14200
COMPASS	0.05335	0.18929	0.75108	0.04977
LEADERAB	0.70626	0.04234	0.08985	0.20489
SOOTHE	0.03670	0.31150	0.53622	-0.05341
RISK	0.45177	0.14371	0.09032	0.02003
DECIDE	0.47222	0.10438	0.06711	0.35742
SELSUFF	0.39617	0.10659	0.08957	0.63085
CONSCIEN	0.21155	0.16877	0.28705	0.43193
DOMINANT	0.67958	-0.26115	-0.05550	0.02484
MASCULIN	0.30166	-0.29009	-0.09734	-0.06293
STAND	0.58910	0.03865	0.22935	0.14560
HAPPY	0.11130	0.62439	-0.00707	0.12417

More

SOFTSPOK	-0.30162	0.30583	0.13379	0.22252
WARM	0.09721	0.61767	0.39400	-0.12470
TRUTHFUL	0.08921	0.20685	0.23252	0.07630
TENDER	0.07217	0.60209	0.37809	-0.10875
GULLIBLE	-0.07654	0.14233	0.04295	-0.36485
LEADACT	0.71462	0.00697	-0.02843	0.17498
CHILDLIK	0.00468	-0.07610	-0.07340	-0.40445
INDIV	0.43371	0.10224	0.03320	0.18009
FOULLANG	-0.00735	0.16780	0.01744	0.03762
LOVECHIL	0.00090	0.30809	0.13968	-0.09332
COMPETE	0.50472	0.19757	-0.11419	-0.06369
AMBITIOU	0.41041	0.18988	0.00370	0.11983
GENTLE	-0.02111	0.61269	0.35327	-0.03461

Interpretation

- I used 0.40 (or close) as cutoff.
- Factor 1: defends own beliefs, independent, not-shy, assertive, strong personality, forceful, has leadership ability, takes risks, is decisive, self-sufficient, dominant, willing to take a stand.
- Factor 2: cheerful, affectionate, happy, warm, tender, gentle.
- Factor 3: sympathetic, sensitive, understanding, compassionate, soothes hurt feelings, warm.
- Factor 4: self-reliant, independent, self-sufficient, conscientious, not-childlike.
- Decide for yourself what traits in each factor have in common!
- Some traits appear in more than one factor, some in none.

Communalities

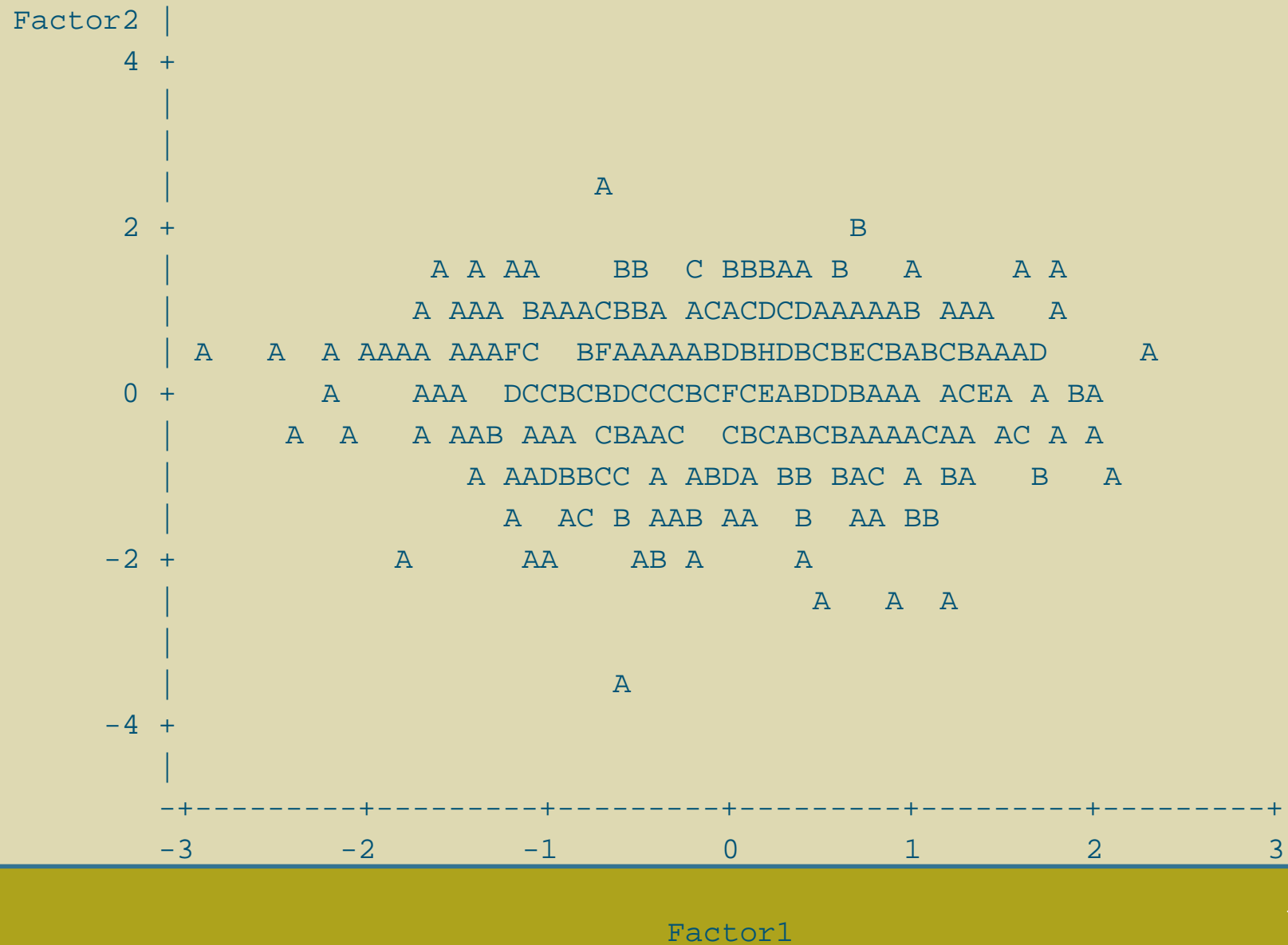
HELPFUL	RELIANT	DEFBEL	YIELDING	CHEERFUL	INDPT
0.25966592	0.34347676	0.25927866	0.14921084	0.29319613	0.39145262
ATHLET	SHY	ASSERT	STRPERS	FORCEFUL	AFFECT
0.15123194	0.17558566	0.41630723	0.50923469	0.49059572	0.48740930
FLATTER	LOYAL	ANALYT	FEMININE	SYMPATHY	MOODY
0.20308368	0.21353167	0.12334064	0.13931465	0.45071468	0.24495805
SENSITIV	UNDSTAND	COMPASS	LEADERAB	SOOTHE	RISK
0.36963797	0.53717166	0.60527481	0.55064036	0.38876534	0.23331239
DECIDE	SELSUFF	CONSCIEN	DOMINANT	MASCULIN	STAND
0.36614500	0.57430213	0.34219775	0.53373041	0.18858344	0.42233319
HAPPY	SOFTSPOK	WARM	TRUTHFUL	TENDER	GULLIBLE
0.41771222	0.25191883	0.56174959	0.11063193	0.52249779	0.16107602
LEADACT	CHILDLIK	INDIV	FOULLANG	LOVECHIL	COMPETE
0.54215483	0.17477789	0.23208669	0.02992972	0.12313782	0.31086844
		AMBITION		GENTLE	
		0.21885749		0.50182441	

Interpreting communalities

- Low communality means variable not related to any factor.
- Eg. yielding, athletic, shy, feminine, masculine, truthful, gullible, childlike, uses foul language (very low), loves children.
- Large number of low communalities means that more factors necessary to describe data well.

Factor scores plot

Plot of Factor2*Factor1. Legend: A = 1 obs, B = 2 obs, etc.



Unusual individuals

- With factor 1 score near -3 (left)
- with factor 2 score less than -3 (bottom)
- Find in data set by printing out factor scores for everyone, then printing out variable values for everyone. Note syntax for selecting a lot of variables.

```
proc print;  
  var Factor1 Factor2;
```

```
proc print;  
  var helpful--gentle;
```

Obs	Factor1	Factor2
214	-0.64023	-3.32687
258	-2.87195	0.47781

Then find these individuals in second PROC PRINT output.

The unusual individuals

Obs				Y	C						F						F	S				S	U			L			
	H	R		I	H						S	O				F	E	Y				E	N	C	E				
	E	E	D	E	E	A			A	T	R	A	L	A		M	M				N	D	O	A					
	L	L	E	L	E	I	T			S	R	C	F	A	L	N	I	P	M	S	S	M	D						
	P	I	F	D	R	N	H			S	P	E	F	T	O	A	N	A	O	I	T	P	E						
	F	A	B	I	F	D	L	S	E	E	F	E	T	Y	L	I	T	O	T	A	A	R							
Obs	U	N	E	N	U	P	E	H	R	R	U	C	E	A	Y	N	H	D	I	N	S	A							
	L	T	L	G	L	T	T	Y	T	S	L	T	R	L	T	E	Y	Y	V	D	S	B							
	214	7	5	3	1	3	6	1	3	5	4	2	1	1	7	7	3	4	4	7	5	5	6						
	258	6	4	1	7	5	7	7	7	3	1	1	4	1	7	4	4	7	3	7	7	6	1						
				S	C	D	M						S			T			G			C			F	L			A
				E	O	O	A						O			R			U	L			H			O	O	C	M
Obs	S			D	L	N	M	S						F			U	T	L	E	I			U	V	O	B	G	
	O			E	F	S	I	C	S	H	T			T	E	L	A	L	I	L	E	M	I	E					
	O	R	C	S	C	N	U	T	A	S	W	H	N	I	D	D	N	L	C	P	T	N							
	T	I	I	U	I	A	L	A	P	P	A	F	D	B	A	L	D	A	H	E	I	T							
	H	S	D	F	E	N	I	N	P	O	R	U	E	L	C	I	I	N	I	T	O	L							
	E	K	E	F	N	T	N	D	Y	K	M	L	R	E	T	K	V	G	L	E	U	E							
214	3	1	7	6	7	4	4	5	4	7	1	6	3	4	5	1	5	5	7	2	4	2							
258	7	5	1	4	7	1	1	1	6	6	6	5	6	7	1	1	3	4	7	2	2	7							

What makes them unusual

- #214 scores mostly low on cheerful (3), affectionate (1), happy (4), warm (1), tender (3), gentle (2).
- #258 scores mostly low on defends own beliefs (1), independent (7?), high on shy (7), low on assertive (3), strong personality (1), forceful (1), leadership ability (1), takes risks (5), decisive (1), self-sufficient (4), dominant (1), take stand (1).

12 factors

Just for fun, I tried 12 factors (the number of eigenvalues > 1).

High loadings (bigger than 0.5) are now:

1. assertive, strong personality, forceful, dominant
2. sympathetic, sensitive, understanding, compassionate, soothes hurt feelings
3. affectionate, loyal, warm, tender, gentle (0.48)
4. self-reliant, independent, self-sufficient
5. competitive, ambitious, athletic (0.33), takes risks (0.36)
6. cheerful, not-moody, happy
7. leadership ability, acts like a leader, dominant (0.34)
8. feminine, not-masculine (0.38)
9. soft-spoken, gentle (0.48)
10. willing to take a stand (0.47), truthful (0.43), defends own beliefs (0.35), not-gullible (0.30)
11. childlike, not-self-sufficient (0.30)
12. decisive, takes risks (0.34), willing to take a stand (0.30)

Confirmatory factor analysis

- Exploratory: what do data suggest as hidden underlying factors (in terms of variables observed)?
- Confirmatory: have *theory* about how underlying factors depend on observed variables; test whether theory supported by data:
 - ◆ does theory provide *some* explanation (better than nothing)
 - ◆ can we do better?
- Also can compare two theories about factors: is more complicated one significantly better than simpler one?

Children and tests again

- Previously had this data (based on 145 children):

```
para 1      0.722  0.714  0.203  0.095
sent 0.722  1      0.685  0.246  0.181
word 0.714  0.685  1      0.170  0.113
add  0.203  0.246  0.170  1      0.585
dots 0.095  0.181  0.113  0.585  1
```

- SAS: use `type=corr`. Special variable `_NAME_` for reading in variable names; numbers read as correlations by default.
- Now have to specify sample size. Now have to use special variable `_TYPE_` which is CORR for correlation, N for sample size.
- Only one sample size, but need to be 5 values: others can be missing.

New data file and code

Note that sample size has no variable name (all variables have $n = 145$):

```
n . 145 . . . .  
corr para 1 0.722 0.714 0.203 0.095  
corr sent 0.722 1 0.685 0.246 0.181  
corr word 0.714 0.685 1 0.170 0.113  
corr add 0.203 0.246 0.170 1 0.585  
corr dots 0.095 0.181 0.113 0.585 1
```

Read it in with

```
data rex(type=corr);  
  infile "rex3.dat";  
  input _type_ $ _name_ $ para sent word add dots;
```


How to specify theories

- SAS uses PROC CALIS for confirmatory factor analysis (and many other things besides).
- Specify relationship between variables and factors (looks like regression analysis with “error”).
- Two competing theories:
 - ◆ One-factor “general intelligence” model: all the test scores are high or low together for a child.
 - ◆ Two-factor “verbal and mathematical intelligence” model: a child might be good at the verbal tests, or good at the mathematical tests (or both or neither). These are 2 factors we found before.

Code for the 1-factor model

Specify how each variable related to the factor(s) hypothesized.
I use symbol f for common factor(s) and e for specific factors.

```
proc calis method=lsml;  
  lineqs  
    para=x1 f1 + e1,  
    sent=x2 f1 + e2,  
    word=x3 f1 + e3,  
    add =x4 f1 + e4,  
    dots=x5 f1 + e5;  
  std  
    f1=1,  
    e1-e5=eps1-eps5;  
  bounds  
    eps1-eps5>0;
```

Note punctuation in `lineqs` section (and other sections):
commas at end of each line, except semicolon at end of last.

Output (heavily edited)

To start:

```
                                The 5 Endogenous Variables
Manifest      para  sent  word  add  dots
Latent
```

```
                                The 6 Exogenous Variables
Manifest
Latent      f1
Error      e1  e2  e3  e4  e5
```

- “Endogenous” means “going in”.
- “Manifest” means “observed”.
- “Latent” means “not able to be observed”.
- “Exogenous” means “coming out”.
- Original variables are endogenous and manifest.
- Factors are exogenous and latent (or “error”, for specific factors).

Did it converge?

Look for “maximum likelihood estimation”:

				Objective		Max Abs	Ratio	
				Function	Change	Gradient	Between	
				Function	Change	Element	Actual	and
Iter	Restarts	Function Calls	Active Constraints	Function	Change	Element	Predicted	Change
1	0	2	0	0.41335	0.0104	0.0256	0	1.206
2	0	3	0	0.41302	0.000329	0.00349	0	1.174
3	0	4	0	0.41301	9.497E-6	0.000603	0	1.171
4	0	5	0	0.41301	2.771E-7	0.000099	0	1.171
5	0	6	0	0.41301	8.072E-9	0.000017	0	1.171
6	0	7	0	0.41301	2.35E-10	2.905E-6	0	1.171

Optimization Results

Iterations	6	Function Calls	8
Jacobian Calls	7	Active Constraints	0
Objective Function	0.4130083436	Max Abs Gradient Element	2.9047445E-6
Lambda	0	Actual Over Pred Change	1.1706449333
Radius	0.0000463356		

GCONV convergence criterion satisfied.

Answer: yes. Objective function stopped changing, and the largest gradient element very close to 0. Also, see last line.

Assessing and testing the fit

There follows a long list of things, of which we need only these:

Goodness of Fit Index (GFI)	0.8764
GFI Adjusted for Degrees of Freedom (AGFI)	0.6291
Chi-Square	59.4732
Chi-Square DF	5
Pr > Chi-Square	<.0001
Independence Model Chi-Square	298.65
Independence Model Chi-Square DF	10

- GFI and AGFI like R-squared and adjusted R-squared in regression.
- AGFI quite a bit smaller here because we estimated a lot of things.
- Model that fits perfectly has 0 DF.
- 1st chi-square and P-value says “are we significantly worse than perfect”, ie. “can we do better”? Answer here “yes”.

Are we better than nothing?

Chi-Square	59.4732
Chi-Square DF	5
Pr > Chi-Square	<.0001

Independence Model Chi-Square	298.65
Independence Model Chi-Square DF	10

- Independence model has no common factors (only specific factors), so by comparing our model chisquare and DF with it, we answer “are we better than nothing?”. Take difference of chi-squares, $298.65 - 59.47 = 239.18$, difference of DF, $10 - 5 = 5$ to get very small P-value.
- 1-factor model doing better than nothing, but can do better.

Improving the model

Obvious way to improve things: original idea of 2 common factors, one verbal (para, sent, words), one mathematical (add, dots). Code for that:

```
proc calis method=lsml;  
  lineqs  
    para=x1 f1 + e1,  
    sent=x2 f1 + e2,  
    word=x3 f1 + e3,  
    add =x4 f2 + e4,  
    dots=x5 f2 + e5;  
  std  
    f1=1,  
    f2=1,  
    e1-e5=eps1-eps5;  
  bounds  
    eps1-eps5>0;  
  cov  
    f1 f2 = rho;
```

Allow 2 factors to be correlated, and estimate correlation.

Endogenous and exogenous variables

The 5 Endogenous Variables

Manifest	para	sent	word	add	dots
Latent					

The 7 Exogenous Variables

Manifest					
Latent	f1	f2			
Error	e1	e2	e3	e4	e5

Now 2 exogenous latent variables (common factors).

Convergence

All good:

				Max Abs			Actual	
				Gradient			Over	
				Element			Pred	
Iter	Rest arts	Func Calls	Act Con	Objective Function	Obj Fun Change	Gradient Element	Lambda	Change
1	0	2	0	0.02038	0.00325	0.00679	0	1.019
2	0	3	0	0.02035	0.000026	0.000721	0	1.028
3	0	4	0	0.02035	2.16E-7	0.000043	0	1.058
4	0	5	0	0.02035	1.61E-9	5.325E-6	0	1.081

Optimization Results

Iterations	4	Function Calls	6
Jacobian Calls	5	Active Constraints	0
Objective Function	0.0203513722	Max Abs Gradient Element	5.3251548E-6
Lambda	0	Actual Over Pred Change	1.0814713689
Radius	0.0008266204		

ABSGCONV convergence criterion satisfied.



Quality of fit

Goodness of Fit Index (GFI)	0.9919
GFI Adjusted for Degrees of Freedom (AGFI)	0.9697

GFI and (especially) AGFI much better than 0.88 and 0.63 from before. Near-perfect fit.

Chi-Square	2.9306
Chi-Square DF	4
Pr > Chi-Square	0.5695

No longer significantly worse than perfect fit: no point trying to do better.



Better than nothing?

Predictably yes:

Chi-Square	2.9306
Chi-Square DF	4
Pr > Chi-Square	0.5695
Independence Model Chi-Square	298.65
Independence Model Chi-Square DF	10

Chi-square $298.65 - 2.93 = 295.72$ with $10 - 4 = 6$ DF. P-value extremely small.

Communalities and estimated correlation

Squared Multiple Correlations

	Variable	Error Variance	Total Variance	R-Square
1	para	0.25049	1.00000	0.7495
2	sent	0.30038	1.00000	0.6996
3	word	0.32651	1.00000	0.6735
4	add	0.04949	1.00000	0.9505
5	dots	0.63996	1.00000	0.3600

Correlations Among Exogenous Variables

Var1	Var2	Parameter	Estimate
f1	f2	rho	0.25197

Communalities (in R-squared column) nice and high (possibly excepting DOTS). Correlation between factors estimated at 0.25.

Using SAS to figure out those P-values

To save hauling out your calculator and tables to figure out the comparison between 298.65 with 10 DF and 2.9306 with 4 DF, make a file `stat.dat` with this in it:

```
298.65 10 2.9306 4
```

and a file `stat.sas` with this in it:

```
data xx;
  infile "stat.dat";
  input c1 df1 c2 df2;
  mystat=c1-c2;
  mydf=df1-df2;
  pval=1-probchi(mystat,mydf);

proc print;
```

This works out the P-value in `pval`; printing out the whole “data set” shows it to you.



The P-value

Obs	c1	df1	c2	df2	mystat	mydf	pval
1	298.65	10	2.9306	4	295.719	6	0

...is close to 0.

Can also compare the 1- and 2-factor models to see if the 2-factor one fits significantly better. The chi square statistics are 59.4732 with 5 DF and 2.93 with 4 DF, so change `stat.dat` to read 59.4372 5 2.93 4 and re-run to get:

Obs	c1	df1	c2	df2	mystat	mydf	pval
1	59.4372	5	2.9306	4	56.5066	1	5.5955E-14

P-value is the merest smidgen bigger than 0. The 2-factor model is a significantly better description of the data than the 1-factor.