

# Factor analysis

## Vs. principal components

- ▶ 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 (get test of appropriateness)
  - ▶ In factor analysis, each variable modelled as: “common factor” (eg. verbal ability) and “specific factor” (left over).
  - ▶ Choose the common factors to “best” reproduce pattern seen in correlation matrix.
  - ▶ Iterative procedure, different answer from principal components.

# Packages

```
library(ggbiplot)
library(tidyverse)
library(conflicted)
conflict_prefer("mutate", "dplyr")
conflict_prefer("select", "dplyr")
conflict_prefer("filter", "dplyr")
conflict_prefer("arrange", "dplyr")
```

## 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 of scores on the tests:

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?

## To start: principal components

Using correlation matrix. Read that first:

```
my_url <- "http://ritsokiguess.site/datafiles/rex2.txt"
kids <- read_delim(my_url, " ")
kids
```

```
# A tibble: 5 x 6
```

	test	para	sent	word	add	dots
	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	para	1	0.722	0.714	0.203	0.095
2	sent	0.722	1	0.685	0.246	0.181
3	word	0.714	0.685	1	0.17	0.113
4	add	0.203	0.246	0.17	1	0.585
5	dots	0.095	0.181	0.113	0.585	1

# Principal components on correlation matrix

Turn into R matrix, using column test as column names:

```
kids %>%  
  column_to_rownames("test") %>%  
  as.matrix() -> m
```

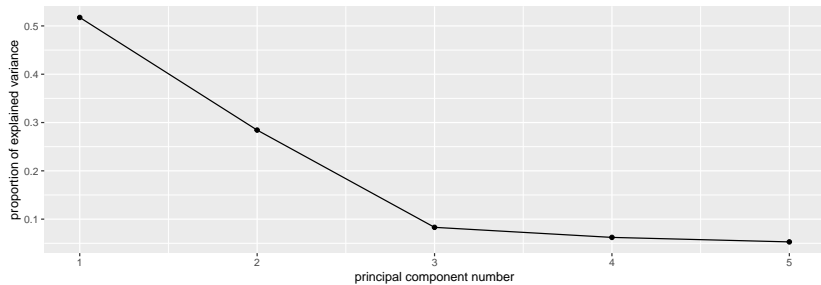
Principal components:

```
kids.0 <- princomp(covmat = m)
```

I used kids.0 here since I want kids.1 and kids.2 later.

# Scree plot

```
ggscreeplot(kids.0)
```



# Principal component results

► Need 2 components. Loadings:

```
kids.0$loadings
```

Loadings:

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5
para	0.534	0.245	0.114		0.795
sent	0.542	0.164		0.660	-0.489
word	0.523	0.247	-0.144	-0.738	-0.316
add	0.297	-0.627	0.707		
dots	0.241	-0.678	-0.680		0.143

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5
SS loadings	1.0	1.0	1.0	1.0	1.0
Proportion Var	0.2	0.2	0.2	0.2	0.2
Cumulative Var	0.2	0.4	0.6	0.8	1.0



## Comments

- ▶ First component has a bit of everything, though especially the first three tests.
- ▶ Second component rather more clearly add and dots.
- ▶ No scores, plots since no actual data.
- ▶ See how factor analysis compares on these data.

# Factor analysis

- ▶ Specify number of factors first, get solution with exactly that many factors.
- ▶ Includes hypothesis test, need to specify how many children wrote the tests.
- ▶ Works from correlation matrix via `covmat` or actual data, like `princomp`.
- ▶ Introduces extra feature, *rotation*, to make interpretation of loadings (factor-variable relation) easier.

## Factor analysis for the kids data

- ▶ Create “covariance list” to include number of children who wrote the tests.
- ▶ Feed this into `factanal`, specifying how many factors (2).
- ▶ Start with the matrix we made before.

`m`

```
      para  sent  word   add  dots
para 1.000 0.722 0.714 0.203 0.095
sent 0.722 1.000 0.685 0.246 0.181
word 0.714 0.685 1.000 0.170 0.113
add  0.203 0.246 0.170 1.000 0.585
dots 0.095 0.181 0.113 0.585 1.000
```

```
ml <- list(cov = m, n.obs = 145)
kids.2 <- factanal(factors = 2, covmat = ml)
```

# Uniquenesses

```
kids.2$uniquenesses
```

para	sent	word	add	dots
0.2424457	0.2997349	0.3272312	0.5743568	0.1554076

- ▶ Uniquenesses say how “unique” a variable is (size of specific factor). Small uniqueness means that the variable is summarized by a factor (good).
- ▶ Very large uniquenesses are bad; add’s uniqueness is largest but not large enough to be worried about.
- ▶ Also see “communality” for this idea, where *large* is good and *small* is bad.

# Loadings

```
kids.2$loadings
```

Loadings:

	Factor1	Factor2
para	0.867	
sent	0.820	0.166
word	0.816	
add	0.167	0.631
dots		0.918

	Factor1	Factor2
SS loadings	2.119	1.282
Proportion Var	0.424	0.256
Cumulative Var	0.424	0.680

- Loadings show how each factor depends on variables. Blanks indicate “small”, less than 0.1.

## Comments

- ▶ Factor 1 clearly the “linguistic” tasks, factor 2 clearly the “mathematical” ones.
- ▶ Two factors together explain 68% of variability (like regression R-squared).
- ▶ Which variables belong to which factor is *much* clearer than with principal components.

## Are 2 factors enough?

```
kids.2$STATISTIC
```

```
objective
```

```
0.5810578
```

```
kids.2$dof
```

```
[1] 1
```

```
kids.2$PVAL
```

```
objective
```

```
0.445898
```

P-value not small, so 2 factors OK.

## 1 factor

```
kids.1 <- factanal(factors = 1, covmat = ml)
kids.1$STATISTIC
```

```
objective
58.16534
```

```
kids.1$dof
```

```
[1] 5
```

```
kids.1$PVAL
```

```
objective
2.907856e-11
```

1 factor rejected (P-value small). Definitely need more than 1.



## Places rated, again

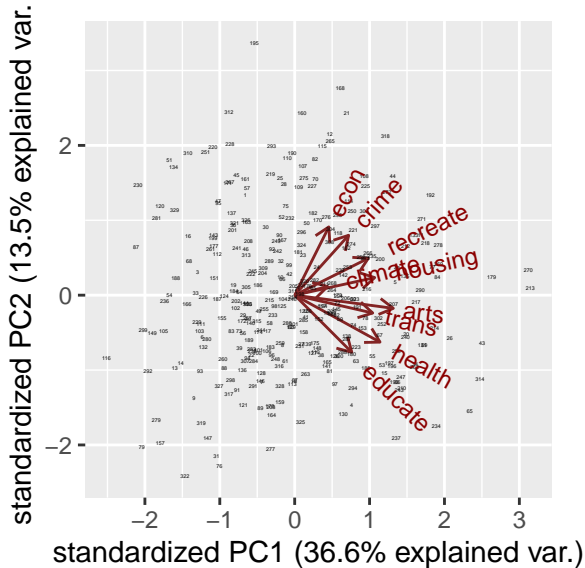
- Read data, transform, rerun principal components, get biplot:

```
my_url <- "http://ritsokiguess.site/datafiles/places.txt"
places0 <- read_table2(my_url)
places0 %>%
  mutate(across(-id, \(x) log(x))) -> places
places %>% select(-id) -> places_numeric
places.1 <- princomp(places_numeric, cor = TRUE)
g <- ggbiplot(places.1, labels = places$id,
              labels.size = 0.8)
```

- This is all exactly as for principal components (nothing new here).

# The biplot

09



# Comments

- ▶ Most of the criteria are part of components 1 *and* 2.
- ▶ If we can rotate the arrows counterclockwise:
  - ▶ economy and crime would point straight up
    - ▶ part of component 2 only
  - ▶ health and education would point to the right
    - ▶ part of component 1 only
- ▶ would be easier to see which variables belong to which component.
- ▶ Factor analysis includes a rotation to help with interpretation.

# Factor analysis

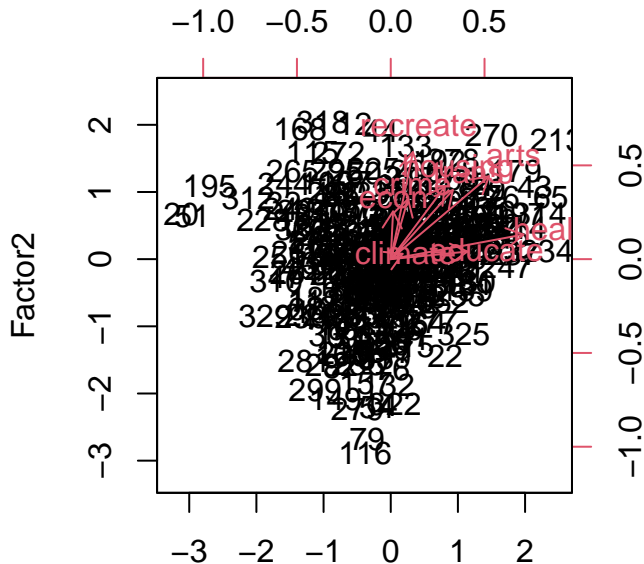
- ▶ Have to pick a number of factors *first*.
- ▶ Do this by running principal components and looking at scree plot.
- ▶ In this case, 3 factors seemed good (revisit later):

```
places.3 <- factanal(places_numeric, 3, scores = "r")
```

- ▶ There are different ways to get factor scores. These called “regression” scores.

## A bad biplot

```
biplot(places.3$scores, places.3$loadings,
       xlab = places$id)
```



## Comments

- ▶ I have to find a way to make a better biplot!
- ▶ Some of the variables now point straight up and some straight across (if you look carefully for the red arrows among the black points).
- ▶ This should make the factors more interpretable than the components were.

# Factor loadings

```
places.3$loadings
```

Loadings:

	Factor1	Factor2	Factor3
climate			0.994
housing	0.360	0.482	0.229
health	0.884	0.164	
crime	0.115	0.400	0.205
trans	0.414	0.460	
educate	0.511		
arts	0.655	0.552	0.102
recreate	0.148	0.714	
econ		0.318	-0.114

	Factor1	Factor2	Factor3
SS loadings	1.814	1.551	1.120
Proportion Var	0.202	0.172	0.124
Cumulative Var	0.202	0.374	0.498

## Comments on loadings

- ▶ These are at least somewhat clearer than for the principal components:
- ▶ Factor 1: health, education, arts: “well-being”
- ▶ Factor 2: housing, transportation, arts (again), recreation: “places to be”
- ▶ Factor 3: climate (only): “climate”
- ▶ In this analysis, economic factors don't seem to be important.



## Factor scores

- ▶ Make a dataframe with the city IDs and factor scores:

```
cbind(id = places$id, places[,3:scores]) %>%  
as_tibble() -> places_scores
```

- ▶ Make percentile ranks again (for checking):

```
places %>%  
mutate(across(-id, \(x) percent_rank(x))) -> places_pr
```

## Highest scores on factor 1, “well-being”:

► for the top 4 places:

```
places_scores %>%  
slice_max(Factor1, n = 4)
```

```
# A tibble: 4 x 4
```

	id	Factor1	Factor2	Factor3
	<dbl>	<dbl>	<dbl>	<dbl>
1	213	2.47	1.78	0.506
2	65	2.39	0.925	-0.287
3	234	2.32	0.122	0.524
4	314	2.22	0.671	0.521

## Check percentile ranks for factor 1

```
places_pr %>%  
select(id, health, educate, arts) %>%  
filter(id %in% c(213, 65, 234, 314))
```

```
# A tibble: 4 x 4
```

	id	health	educate	arts
	<dbl>	<dbl>	<dbl>	<dbl>
1	65	0.997	0.963	0.997
2	213	1	0.723	1
3	234	0.991	1	0.985
4	314	0.985	0.994	0.991

- ▶ These are definitely high on the well-being variables.
- ▶ City #213 is not so high on education, but is highest of all on the others.

## Highest scores on factor 2, “places to be”:

```
places_scores %>%  
  slice_max(Factor2, n = 4)
```

```
# A tibble: 4 x 4
```

	id	Factor1	Factor2	Factor3
	<dbl>	<dbl>	<dbl>	<dbl>
1	318	-1.01	2.05	-0.0957
2	12	-0.540	2.02	-3.80
3	168	-1.35	1.94	0.273
4	44	-0.149	1.92	-0.556

## Check percentile ranks for factor 2

```
places_pr %>%  
select(id, housing, trans, arts, recreate) %>%  
filter(id %in% c(318, 12, 168, 44))
```

# A tibble: 4 x 5

	id	housing	trans	arts	recreate
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	12	0.933	0.729	0.604	0.896
2	44	0.927	0.963	0.735	0.988
3	168	0.832	0.872	0.442	0.979
4	318	0.881	0.744	0.668	0.963

- ▶ These are definitely high on housing and recreation.
- ▶ Some are (very) high on transportation, but not so much on arts.
- ▶ Could look at more cities to see if #168 being low on arts is a fluke.

## Highest scores on factor 3, "climate":

```
places_scores %>%  
slice_max(Factor3, n = 4)
```

```
# A tibble: 4 x 4
```

	id	Factor1	Factor2	Factor3
	<dbl>	<dbl>	<dbl>	<dbl>
1	227	-0.184	0.385	2.04
2	218	0.881	0.897	2.02
3	269	0.932	1.19	1.98
4	270	1.50	1.84	1.94

## Check percentile ranks for factor 3

```
places_pr %>%  
select(id, climate) %>%  
filter(id %in% c(227, 218, 269, 270))
```

```
# A tibble: 4 x 2
```

	id	climate
	<dbl>	<dbl>
1	218	0.997
2	227	0.991
3	269	0.994
4	270	0.997

This is very clear.

# Uniquenesses

- ▶ We said earlier that the economy was not part of any of our factors:

```
places.3$uniquenesses
```

```
    climate    housing    health    crime    trans    educate  
0.0050000 0.5859175 0.1854084 0.7842407 0.6165449 0.7351921  
    econ  
0.8856382
```

- ▶ The higher the uniqueness, the less the variable concerned is part of any of our factors (and that maybe another factor is needed to accommodate it).
- ▶ This includes economy and maybe crime.



# Test of significance

We can test whether the three factors that we have is enough, or whether we need more to describe our data:

```
places.3$PVAL
```

```
objective
```

```
1.453217e-14
```

- ▶ 3 factors are not enough.
- ▶ What would 5 factors look like?

## Five factors

```
places.5 <- factanal(places_numeric, 5, scores = "r")  
places.5$loadings
```

Loadings:

	Factor1	Factor2	Factor3	Factor4	Factor5
climate				0.131	0.559
housing	0.286	0.505	0.289	-0.113	0.475
health	0.847	0.214			0.187
crime		0.196	0.143	0.948	0.181
trans	0.389	0.515		0.175	
educate	0.534				
arts	0.611	0.564		0.172	0.145
recreate		0.705		0.115	0.136
econ			0.978	0.135	

	Factor1	Factor2	Factor3	Factor4	Factor5
SS loadings	1.628	1.436	1.087	1.023	0.658
Proportion Var	0.181	0.160	0.121	0.114	0.073
Cumulative Var	0.181	0.340	0.461	0.575	0.648

## Comments 1/2

- ▶ On (new) 5 factors:
- ▶ Factor 1 is health, education, arts: same as factor 1 before.
- ▶ Factor 2 is housing, transportation, arts, recreation: as factor 2 before.
- ▶ Factor 3 is economy.
- ▶ Factor 4 is crime.
- ▶ Factor 5 is climate and housing: like factor 3 before.

## Comments 2/2

- ▶ The two added factors include the two “missing” variables.
- ▶ Is this now enough?

```
places.5$PVAL
```

objective

0.0009741394

- ▶ No. My guess is that the authors of Places Rated chose their 9 criteria to capture different aspects of what makes a city good or bad to live in, and so it was too much to hope that a small number of factors would come out of these.

## A bigger example: BEM sex role inventory

- ▶ 369 women asked to rate themselves on 60 traits, like “self-reliant” or “shy”.
- ▶ Rating 1 “never or almost never true of me” to 7 “always or almost always true of me”.
- ▶ 60 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

# Some of the data

```
my_url <- "http://ritsokiguess.site/datafiles/factor.txt"
bem <- read_tsv(my_url)
bem
```

```
# A tibble: 369 x 45
```

	subno	helpful	reliant	defbel	yielding	cheerful	indpt	athlet	shy	assert
	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	1	7	7	5	5	7	7	7	1	7
2	2	5	6	6	6	2	3	3	3	4
3	3	7	6	4	4	5	5	2	3	4
4	4	6	6	7	4	6	6	3	4	4
5	5	6	6	7	4	7	7	7	2	7
6	7	5	6	7	4	6	6	2	4	4
7	8	6	4	6	6	6	3	1	3	3
8	9	7	6	7	5	6	7	5	2	5
9	10	7	6	6	4	4	5	2	2	5
10	11	7	4	7	4	7	5	2	1	5

```
# i 359 more rows
```

```
# i 35 more variables: strpers <dbl>, forceful <dbl>, affect <dbl>,  
# flatter <dbl>, loyal <dbl>, analyt <dbl>, feminine <dbl>, sympathy <dbl>,  
# moody <dbl>, sensitiv <dbl>, undstand <dbl>, compass <dbl>, leaderab <dbl>,  
# soothe <dbl>, risk <dbl>, decide <dbl>, selfsuff <dbl>, conscien <dbl>,  
# dominant <dbl>, masculin <dbl>, stand <dbl>, happy <dbl>, softspok <dbl>,  
# warm <dbl>, truthful <dbl>, tender <dbl>, gullible <dbl>, ...
```

# Principal components first

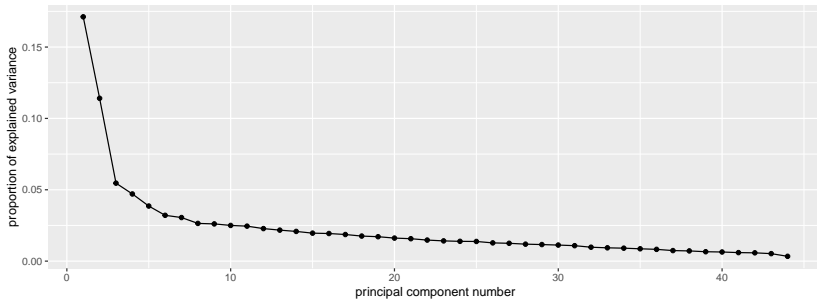
...to decide on number of factors:

```
bem.pc <- bem %>%  
select(-subno) %>%  
princomp(cor = T)
```



# The scree plot

```
(g <- ggscreeplot(bem.pc))
```

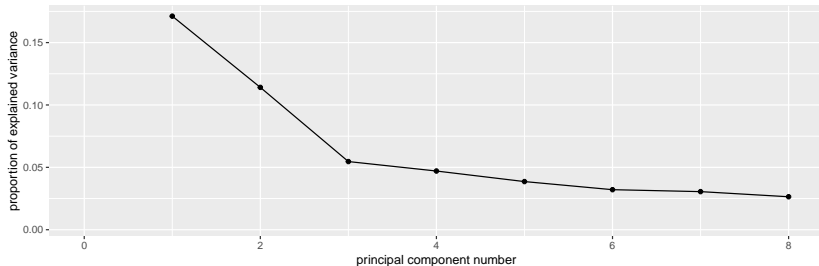


► No obvious elbow.

## Zoom in to search for elbow

Possible elbows at 3 (2 factors) and 6 (5):

```
g + scale_x_continuous(limits = c(0, 8))
```



but is 2 really good?

```
summary(bem.pc)
```

Importance of components:

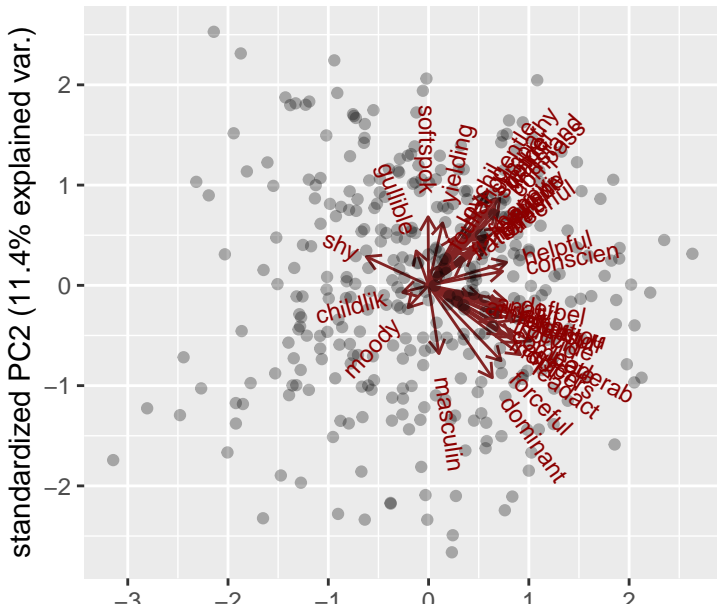
	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5
Standard deviation	2.7444993	2.2405789	1.55049106	1.43886350	1.30318840
Proportion of Variance	0.1711881	0.1140953	0.05463688	0.04705291	0.03859773
Cumulative Proportion	0.1711881	0.2852834	0.33992029	0.38697320	0.42557093
	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10
Standard deviation	1.18837867	1.15919129	1.07838912	1.07120568	1.04901318
Proportion of Variance	0.03209645	0.03053919	0.02643007	0.02607913	0.02500974
Cumulative Proportion	0.45766738	0.48820657	0.51463664	0.54071577	0.56572551
	Comp.11	Comp.12	Comp.13	Comp.14	Comp.15
Standard deviation	1.03848656	1.00152287	0.97753974	0.95697572	0.9287543
Proportion of Variance	0.02451033	0.02279655	0.02171782	0.02081369	0.0196042
Cumulative Proportion	0.59023584	0.61303238	0.63475020	0.65556390	0.6751681
	Comp.16	Comp.17	Comp.18	Comp.19	Comp.20
Standard deviation	0.92262649	0.90585705	0.8788668	0.86757525	0.84269120
Proportion of Variance	0.01934636	0.01864948	0.0175547	0.01710652	0.01613928
Cumulative Proportion	0.69451445	0.71316392	0.7307186	0.74782514	0.76396443
	Comp.21	Comp.22	Comp.23	Comp.24	Comp.25
Standard deviation	0.83124925	0.80564654	0.78975423	0.78100835	0.77852606
Proportion of Variance	0.01570398	0.01475151	0.01417527	0.01386305	0.01377506
Cumulative Proportion	0.77966841	0.79441992	0.80859519	0.82245823	0.83623330
	Comp.26	Comp.27	Comp.28	Comp.29	Comp.30
Standard deviation	0.74969868	0.74137885	0.72343693	0.71457305	0.70358645
Proportion of Variance	0.01277382	0.01249188	0.01189457	0.01160488	0.01125077
Cumulative Proportion	0.84244223	0.85691181	0.86840638	0.87991126	0.89116203

## Comments

- ▶ Want overall fraction of variance explained (“cumulative proportion’ ’) to be reasonably high.
- ▶ 2 factors, 28.5%. Terrible!
- ▶ Even 56% (10 factors) not that good!
- ▶ Have to live with that.

# Biplot

```
ggbiplot(bem.pc, alpha = 0.3)
```



## Comments

- ▶ Ignore individuals for now.
- ▶ Most variables point to 1 o'clock or 4 o'clock.
- ▶ Suggests factor analysis with rotation will get interpretable factors (rotate to 12 o'clock and 3 o'clock, for example).
- ▶ Try for 2-factor solution (rough interpretation, will be bad):

```
bem %>%  
select(-subno) %>%  
factanal(factors = 2) -> bem.2
```

- ▶ Show output in pieces (just print bem.2 to see all of it).

# Uniquenesses, sorted

```
sort(bem.2$uniquenesses)
```

leaderab	leadact	warm	tender	dominant	gentle
0.4091894	0.4166153	0.4764762	0.4928919	0.4942909	0.5064551
forceful	strpers	compass	stand	undstand	assert
0.5631857	0.5679398	0.5937073	0.6024001	0.6194392	0.6329347
soothe	affect	decide	selfsuff	sympathy	indpt
0.6596103	0.6616625	0.6938578	0.7210246	0.7231450	0.7282742
helpful	defbel	risk	reliant	individ	compete
0.7598223	0.7748448	0.7789761	0.7808058	0.7941998	0.7942910
conscien	happy	sensitiv	loyal	ambitiou	shy
0.7974820	0.8008966	0.8018851	0.8035264	0.8101599	0.8239496
softspok	cheerful	masculin	yielding	feminine	truthful
0.8339058	0.8394916	0.8453368	0.8688473	0.8829927	0.8889983
lovchil	analyt	athlet	flatter	gullible	moody
0.8924392	0.8968744	0.9229702	0.9409500	0.9583435	0.9730607
childlik	foullang				
0.9800360	0.9821662				

## Comments

- ▶ Mostly high or very high (bad).
- ▶ Some smaller, eg.: Leadership ability (0.409), Acts like leader (0.417), Warm (0.476), Tender (0.493).
- ▶ Smaller uniquenesses captured by one of our two factors.
- ▶ Larger uniquenesses are not: need more factors to capture them.



# Factor loadings some

```
bem.2$loadings
```

Loadings:

	Factor1	Factor2
helpful	0.314	0.376
reliant	0.453	0.117
defbel	0.434	0.193
yielding	-0.131	0.338
cheerful	0.152	0.371
indpt	0.521	
athlet	0.267	
shy	-0.414	
assert	0.605	
strpers	0.657	
forceful	0.649	-0.126
affect	0.178	0.554
flatter		0.223
loyal	0.151	0.417
analyt	0.295	0.127
feminine	0.113	0.323
sympathy		0.526
moody		-0.162
sensitiv	0.135	0.424
undstand		0.610
compass	0.114	0.627
helpful	0.525	

## Making a data frame

There are too many to read easily, so make a data frame. A bit tricky:

```
bem.2$loadings %>%  
unclass() %>%  
as_tibble() %>%  
mutate(trait = rownames(bem.2$loadings)) -> loadings  
loadings %>% slice(1:8)
```

```
# A tibble: 8 x 3  
  Factor1 Factor2 trait  
    <dbl>   <dbl> <chr>  
1  0.314  0.376  helpful  
2  0.453  0.117  reliant  
3  0.434  0.193  defbel  
4 -0.131  0.338  yielding  
5  0.152  0.371  cheerful  
6  0.521  0.00587 indpt  
7  0.267  0.0755  athlet  
8 -0.414 -0.0654  shy
```

## Pick out the big ones on factor 1

Arbitrarily defining  $> 0.4$  or  $< -0.4$  as “big”:

```
loadings %>% filter(abs(Factor1) > 0.4)
```

```
# A tibble: 17 x 3
```

	Factor1 <dbl>	Factor2 <dbl>	trait <chr>
1	0.453	0.117	reliant
2	0.434	0.193	defbel
3	0.521	0.00587	indpt
4	-0.414	-0.0654	shy
5	0.605	0.0330	assert
6	0.657	0.0208	strpers
7	0.649	-0.126	forceful
8	0.765	0.0695	leaderab
9	0.442	0.161	risk
10	0.542	0.113	decide
11	0.511	0.134	selfsuff
12	0.668	-0.245	dominant
13	0.607	0.172	stand
14	0.763	-0.0407	leadact
15	0.445	0.0891	individ
16	0.450	0.0532	compete
17	0.414	0.137	ambitiou

## Factor 2, the big ones

```
loadings %>% filter(abs(Factor2) > 0.4)
```

```
# A tibble: 11 x 3
```

	Factor1	Factor2	trait
	<dbl>	<dbl>	<chr>
1	0.178	0.554	affect
2	0.151	0.417	loyal
3	0.0230	0.526	sympathy
4	0.135	0.424	sensitiv
5	0.0911	0.610	undstand
6	0.114	0.627	compass
7	0.0606	0.580	soothe
8	0.119	0.430	happy
9	0.0796	0.719	warm
10	0.0511	0.710	tender
11	-0.0187	0.702	gentle

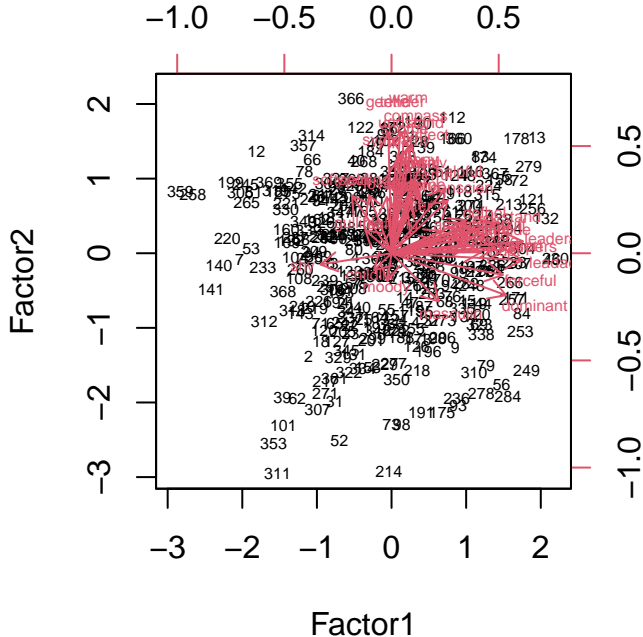
## Plotting the two factors

- ▶ A bi-plot, this time with the variables reduced in size. Looking for unusual individuals.
- ▶ Have to run `factanal` again to get factor scores for plotting.

```
bem %>% select(-subno) %>%  
factanal(factors = 2, scores = "r") -> bem.2a  
biplot(bem.2a$scores, bem.2a$loadings, cex = c(0.5, 0.5))
```

- ▶ Numbers on plot are row numbers of `bem` data frame.

## The (awful) biplot



## Comments

- ▶ Variables mostly up (“feminine”) and right (“masculine”), accomplished by rotation.
- ▶ Some unusual individuals: 311, 214 (low on factor 2), 366 (high on factor 2), 359, 258 (low on factor 1), 230 (high on factor 1).

## Individual 366

```
ben %>% slice(366) %>% glimpse()
```

```
Rows: 1
Columns: 45
$ subno      <dbl> 755
$ helpful    <dbl> 7
$ reliant    <dbl> 7
$ defbel     <dbl> 5
$ yielding   <dbl> 7
$ cheerful   <dbl> 7
$ indpt      <dbl> 7
$ athlet     <dbl> 7
$ shy        <dbl> 2
$ assert     <dbl> 1
$ strpers    <dbl> 3
$ forceful   <dbl> 1
$ affect     <dbl> 7
$ flatter    <dbl> 9
$ loyal      <dbl> 7
$ analyt     <dbl> 7
$ feminine   <dbl> 7
$ sympathy   <dbl> 7
$ moody      <dbl> 1
$ sensitiv   <dbl> 7
$ undstand   <dbl> 7
$ compass    <dbl> 6
$ leaderab   <dbl> 3
$ soothe     <dbl> 7
$ risk       <dbl> 7
$ decide     <dbl> 7
$ selfsuff   <dbl> 7
$ conscien   <dbl> 7
$ dominant   <dbl> 1
$ masculin   <dbl> 1
$ stand      <dbl> 7
$ happy      <dbl> 7
```



## Comments

- ▶ Individual 366 high on factor 2, but hard to see which traits should have high scores (unless we remember).
- ▶ Idea 1: use percentile ranks as before.
- ▶ Idea 2: Rating scale is easy to interpret. So *tidy* original data frame to make easier to look things up.

# Tidying original data

```
bem %>%  
ungroup() %>%  
mutate(row = row_number()) %>%  
pivot_longer(c(-subno, -row), names_to="trait",  
             values_to="score") -> bem_tidy  
bem_tidy
```

```
# A tibble: 16,236 x 4
```

	subno	row	trait	score
	<dbl>	<int>	<chr>	<dbl>
1	1	1	helpful	7
2	1	1	reliant	7
3	1	1	defbel	5
4	1	1	yielding	5
5	1	1	cheerful	7
6	1	1	indpt	7
7	1	1	athlet	7
8	1	1	shy	1
9	1	1	assert	7
10	1	1	strpers	7

```
# i 16,226 more rows
```

## Recall data frame of loadings

```
loadings %>% slice(1:10)
```

```
# A tibble: 10 x 3
  Factor1 Factor2 trait
  <dbl>    <dbl> <chr>
1  0.314  0.376  helpful
2  0.453  0.117  reliant
3  0.434  0.193  defbel
4 -0.131  0.338  yielding
5  0.152  0.371  cheerful
6  0.521  0.00587 indpt
7  0.267  0.0755  athlet
8 -0.414 -0.0654 shy
9  0.605  0.0330  assert
10 0.657  0.0208  strpers
```

Want to add the factor scores for each trait to our tidy data frame `bem_tidy`. This is a left-join (over), matching on the column `trait` that is in both data frames (thus, the default):

# Looking up loadings

```
bem_tidy %>% left_join(loadings) -> bem_tidy  
bem_tidy %>% sample_n(12)
```

# A tibble: 12 x 6

	subno	row	trait	score	Factor1	Factor2
	<dbl>	<int>	<chr>	<dbl>	<dbl>	<dbl>
1	509	294	gullible	4	-0.153	0.135
2	236	133	individ	6	0.445	0.0891
3	418	237	lovchil	7	-0.0271	0.327
4	4	4	masculin	2	0.276	-0.280
5	55	34	decide	4	0.542	0.113
6	424	240	assert	4	0.605	0.0330
7	318	186	leaderab	5	0.765	0.0695
8	229	127	yielding	5	-0.131	0.338
9	271	159	cheerful	6	0.152	0.371
10	498	285	warm	6	0.0796	0.719
11	159	106	athlet	7	0.267	0.0755
12	57	36	reliant	6	0.453	0.117

## Individual 366, high on Factor 2

So now pick out the rows of the tidy data frame that belong to individual 366 (row=366) and for which the Factor2 score exceeds 0.4 in absolute value (our “big” from before):

```
bem_tidy %>% filter(row == 366, abs(Factor2) > 0.4)
```

```
# A tibble: 11 x 6
```

	subno	row	trait	score	Factor1	Factor2
	<dbl>	<int>	<chr>	<dbl>	<dbl>	<dbl>
1	755	366	affect	7	0.178	0.554
2	755	366	loyal	7	0.151	0.417
3	755	366	sympathy	7	0.0230	0.526
4	755	366	sensitiv	7	0.135	0.424
5	755	366	undstand	7	0.0911	0.610
6	755	366	compass	6	0.114	0.627
7	755	366	soothe	7	0.0606	0.580
8	755	366	happy	7	0.119	0.430
9	755	366	warm	7	0.0796	0.719
10	755	366	tender	7	0.0511	0.710
11	755	366	gentle	7	-0.0187	0.702

As expected, high scorer on these.

## Several individuals

Rows 311 and 214 were *low* on Factor 2, so their scores should be low. Can we do them all at once?

```
bem_tidy %>% filter(  
  row %in% c(366, 311, 214),  
  abs(Factor2) > 0.4  
)
```

```
# A tibble: 33 x 6
```

	subno	row	trait	score	Factor1	Factor2
	<dbl>	<int>	<chr>	<dbl>	<dbl>	<dbl>
1	369	214	affect	1	0.178	0.554
2	369	214	loyal	7	0.151	0.417
3	369	214	sympathy	4	0.0230	0.526
4	369	214	sensitiv	7	0.135	0.424
5	369	214	undstand	5	0.0911	0.610
6	369	214	compass	5	0.114	0.627
7	369	214	soothe	3	0.0606	0.580
8	369	214	happy	4	0.119	0.430
9	369	214	warm	1	0.0796	0.719
10	369	214	tender	3	0.0511	0.710

```
# i 23 more rows
```

Can we display each individual in own column?

# Individual by column

Un-tidy, that is, pivot\_wider:

```
bem_tidy %>%  
filter(  
  row %in% c(366, 311, 214),  
  abs(Factor2) > 0.4  
) %>%  
select(-subno, -Factor1, -Factor2) %>%  
pivot_wider(names_from=row, values_from=score)
```

```
# A tibble: 11 x 4  
  trait    `214` `311` `366`  
  <chr>   <dbl> <dbl> <dbl>  
1 affect      1     5     7  
2 loyal       7     4     7  
3 sympathy    4     4     7  
4 sensitiv    7     4     7  
5 undstand    5     3     7  
6 compass     5     4     6  
7 soothe      3     4     7  
8 happy       4     3     7  
9 warm        1     3     7  
10 tender     3     4     7  
11 gentle     2     3     7
```

366 high, 311 middling, 214 (sometimes) low.

# Individuals 230, 258, 359

These were high, low, low on factor 1. Adapt code:

```
bem_tidy %>%  
filter(row %in% c(359, 258, 230), abs(Factor1) > 0.4) %>%  
select(-subno, -Factor1, -Factor2) %>%  
pivot_wider(names_from=row, values_from=score)
```

```
# A tibble: 17 x 4  
  trait      `230` `258` `359`  
  <chr>    <dbl> <dbl> <dbl>  
1 reliant      7     4     1  
2 defbel       7     1     1  
3 indpt        7     7     1  
4 shy          2     7     5  
5 assert       7     3     1  
6 strpers      7     1     3  
7 forceful     7     1     1  
8 leaderab     7     1     1  
9 risk         7     5     7  
10 decide      7     1     2  
11 selfsuff    7     4     1  
12 dominant    7     1     1  
13 stand       7     1     6  
14 leadact     7     1     1  
15 individ    7     3     3  
16 compete     6     2     1  
17 ambitiou    7     2     4
```



## Is 2 factors enough?

Suspect not:

```
bem.2$PVAL
```

objective

1.458183e-150

2 factors resoundingly rejected. Need more. Have to go all the way to 15 factors to not reject:

```
bem %>%
```

```
select(-subno) %>%
```

```
factanal(factors = 15) -> bem.15
```

```
bem.15$PVAL
```

objective

0.132617

Even then, only just over 50% of variability explained.

# What's important in 15 factors?

- ▶ Let's take a look at the important things in those 15 factors.
- ▶ Get 15-factor loadings into a data frame, as before:

```
bem.15$loadings %>%  
unclass() %>%  
as_tibble() %>%  
mutate(trait = rownames(bem.15$loadings)) -> loadings
```

- ▶ then show the highest few loadings on each factor.

## Factor 1 (of 15)

```
loadings %>%  
arrange(desc(abs(Factor1))) %>%  
select(Factor1, trait) %>%  
slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor1 trait  
    <dbl> <chr>  
1  0.813 compass  
2  0.676 undstand  
3  0.661 sympathy  
4  0.641 sensitiv  
5  0.597 soothe  
6  0.348 warm  
7  0.280 gentle  
8  0.279 tender  
9  0.250 helpful  
10 0.234 conscien
```

Compassionate, understanding, sympathetic, soothing: thoughtful of others.

## Factor 2

```
loadings %>%  
arrange(desc(abs(Factor2))) %>%  
select(Factor2, trait) %>%  
slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor2 trait  
    <dbl> <chr>  
1  0.762 strpers  
2  0.716 forceful  
3  0.698 assert  
4  0.504 dominant  
5  0.393 leaderab  
6  0.367 stand  
7  0.351 leadact  
8 -0.313 softspok  
9 -0.287 shy  
10 0.260 analyt
```

Strong personality, forceful, assertive, dominant: getting ahead.

## Factor 3

```
loadings %>%  
arrange(desc(abs(Factor3))) %>%  
select(Factor3, trait) %>%  
slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor3 trait  
    <dbl> <chr>  
1  0.670 reliant  
2  0.648 selfsuff  
3  0.620 indpt  
4  0.390 helpful  
5 -0.339 gullible  
6  0.333 individ  
7  0.332 decide  
8  0.329 conscien  
9  0.288 leaderab  
10 0.280 defbel
```

Self-reliant, self-sufficient, independent: going it alone.

## Factor 4

```
loadings %>%  
arrange(desc(abs(Factor4))) %>%  
select(Factor4, trait) %>%  
slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor4 trait  
    <dbl> <chr>  
1  0.696 gentle  
2  0.692 tender  
3  0.599 warm  
4  0.447 affect  
5  0.394 softspok  
6  0.278 lovchil  
7  0.244 undstand  
8  0.244 happy  
9  0.213 loyal  
10 0.202 soothe
```

Gentle, tender, warm (affectionate): caring for others.

## Factor 5

```
loadings %>%  
  arrange(desc(abs(Factor5))) %>%  
  select(Factor5, trait) %>%  
  slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor5 trait  
    <dbl> <chr>  
1  0.696 compete  
2  0.674 ambitiou  
3  0.345 risk  
4  0.342 individ  
5  0.281 athlet  
6  0.270 leaderab  
7  0.245 decide  
8  0.206 dominant  
9  0.193 leadact  
10 0.185 strpers
```

Ambitious, competitive (with a bit of risk-taking and individualism): Being the best.

## Factor 6

```
loadings %>%  
  arrange(desc(abs(Factor6))) %>%  
  select(Factor6, trait) %>%  
  slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor6 trait  
    <dbl> <chr>  
1  0.868 leadact  
2  0.608 leaderab  
3  0.338 dominant  
4  0.201 forceful  
5 -0.192 shy  
6  0.179 risk  
7  0.170 masculin  
8  0.164 decide  
9  0.159 compete  
10 0.147 athlet
```

Acts like a leader, leadership ability (with a bit of Dominant):  
Taking charge.



## Factor 7

```
loadings %>%  
arrange(desc(abs(Factor7))) %>%  
select(Factor7, trait) %>%  
slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor7 trait  
    <dbl> <chr>  
1  0.670 happy  
2  0.667 cheerful  
3 -0.522 moody  
4  0.219 athlet  
5  0.213 warm  
6  0.172 gentle  
7 -0.164 masculin  
8  0.160 reliant  
9  0.147 yielding  
10 0.141 lovchil
```

Happy and cheerful.

## Factor 8

```
loadings %>%  
arrange(desc(abs(Factor8))) %>%  
select(Factor8, trait) %>%  
slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor8 trait  
    <dbl> <chr>  
1  0.630 affect  
2  0.516 flatter  
3 -0.251 softspok  
4  0.221 warm  
5  0.188 tender  
6  0.185 strpers  
7 -0.180 shy  
8  0.180 compete  
9  0.166 loyal  
10 0.155 helpful
```

Affectionate, flattering: Making others feel good.

## Factor 9

```
loadings %>%  
arrange(desc(abs(Factor9))) %>%  
select(Factor9, trait) %>%  
slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor9 trait  
    <dbl> <chr>  
1  0.863 stand  
2  0.340 defbel  
3  0.245 individ  
4  0.194 risk  
5 -0.172 shy  
6  0.171 decide  
7  0.120 assert  
8  0.116 conscien  
9  0.112 analyt  
10 -0.112 gullible
```

Taking a stand.

# Factor 10

```
loadings %>%  
  arrange(desc(abs(Factor10))) %>%  
  select(Factor10, trait) %>%  
  slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor10 trait  
    <dbl> <chr>  
1    0.808 feminine  
2   -0.264 masculin  
3    0.245 softspok  
4    0.232 conscien  
5    0.202 selfsuff  
6    0.176 yielding  
7    0.141 gentle  
8    0.113 flatter  
9    0.109 decide  
10  -0.0941 lovchil
```

Feminine. (A little bit of not-masculine!)

# Factor 11

```
loadings %>%  
arrange(desc(abs(Factor11))) %>%  
select(Factor11, trait) %>%  
slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor11 trait  
    <dbl> <chr>  
1  0.916  loyal  
2  0.189  affect  
3  0.159  truthful  
4  0.125  helpful  
5  0.104  analyt  
6  0.101  tender  
7  0.0972 lovchil  
8  0.0964 gullible  
9  0.0935 cheerful  
10 0.0821 conscien
```

Loyal.

## Factor 12

```
loadings %>%  
arrange(desc(abs(Factor12))) %>%  
select(Factor12, trait) %>%  
slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor12 trait  
    <dbl> <chr>  
1    0.611 childlik  
2   -0.285 selfsuff  
3   -0.279 conscien  
4    0.259 moody  
5    0.201 shy  
6   -0.167 decide  
7    0.154 masculin  
8    0.146 dominant  
9    0.138 compass  
10   -0.130 leaderab
```

Childlike. (With a bit of moody, shy, not-self-sufficient, not-conscientious.)

## Factor 13

```
loadings %>%  
  arrange(desc(abs(Factor13))) %>%  
  select(Factor13, trait) %>%  
  slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor13 trait  
    <dbl> <chr>  
1    0.573 truthful  
2   -0.278 gullible  
3    0.263 happy  
4    0.189 warm  
5   -0.167 shy  
6    0.165 loyal  
7   -0.144 yielding  
8   -0.130 assert  
9    0.114 defbel  
10   -0.111 lovchil
```

Truthful. (With a bit of happy and not-gullible.)

## Factor 14

```
loadings %>%  
arrange(desc(abs(Factor14))) %>%  
select(Factor14, trait) %>%  
slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor14 trait  
    <dbl> <chr>  
1    0.443 decide  
2    0.237 selfsuff  
3    0.195 forceful  
4   -0.186 softspok  
5    0.160 risk  
6   -0.148 strpers  
7    0.146 dominant  
8    0.128 happy  
9    0.115 compass  
10   0.105 masculin
```

Decisive. (With a bit of self-sufficient and not-soft-spoken.)



## Factor 15

```
loadings %>%  
arrange(desc(abs(Factor15))) %>%  
select(Factor15, trait) %>%  
slice(1:10)
```

```
# A tibble: 10 x 2  
  Factor15 trait  
    <dbl> <chr>  
1  -0.324 compass  
2   0.247 athlet  
3   0.229 sensitiv  
4   0.199 risk  
5  -0.164 affect  
6   0.163 moody  
7  -0.112 individ  
8   0.110 warm  
9   0.105 cheerful  
10  0.101 reliant
```

Not-compassionate, athletic, sensitive: A mixed bag. (“Cares about self”?)

# Anything left out? Uniquenesses

```
enframe(bem.15$uniquenesses, name="quality", value="uniq") %>%  
  slice_max(uniq, n = 10)
```

```
# A tibble: 10 x 2
```

	quality	uniq
	<chr>	<dbl>
1	foullang	0.914
2	lovchil	0.824
3	analyt	0.812
4	yielding	0.791
5	masculin	0.723
6	athlet	0.722
7	shy	0.703
8	gullible	0.700
9	flatter	0.663
10	helpful	0.652

Uses foul language especially, also loves children and analytical. So could use even more factors.