

Analyzing scales

Examples of simulation

Steps in simulation

- Create pure, continuous, population model
- Sample from population model
- Distort sample with categorical items
- Distort sample with dichotomous item
- Distort sample with dichotomous items varying in difficulty

The pure model

```
> latent <- sim.congeneric(rep(.6,9),N=200,short=FALSE)
> latent
```

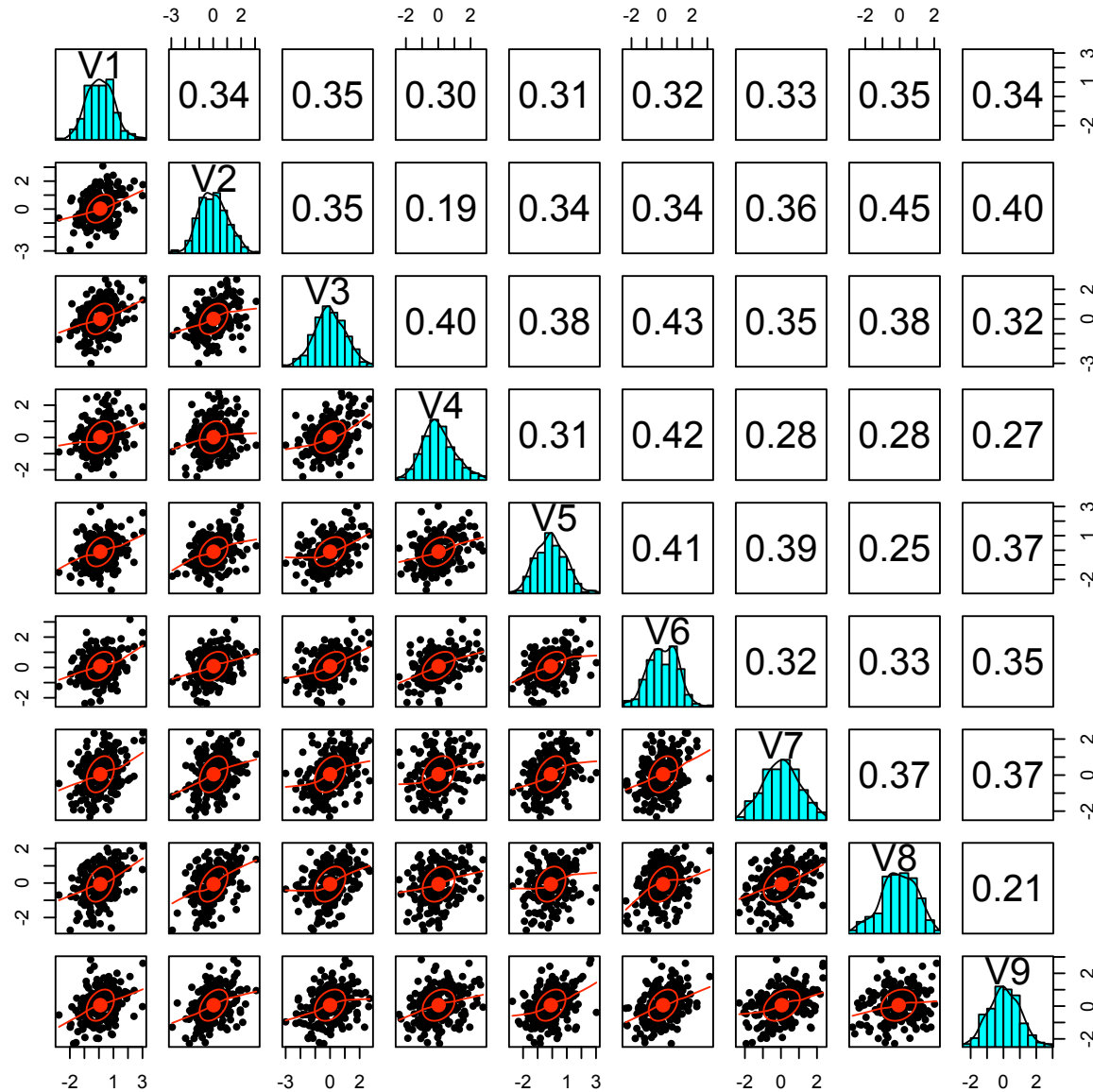
```
      $model (Population correlation matrix)
      V1    V2    V3    V4    V5    V6    V7    V8    V9
V1  1.00  0.36  0.36  0.36  0.36  0.36  0.36  0.36  0.36
V2  0.36  1.00  0.36  0.36  0.36  0.36  0.36  0.36  0.36
V3  0.36  0.36  1.00  0.36  0.36  0.36  0.36  0.36  0.36
V4  0.36  0.36  0.36  1.00  0.36  0.36  0.36  0.36  0.36
V5  0.36  0.36  0.36  0.36  1.00  0.36  0.36  0.36  0.36
V6  0.36  0.36  0.36  0.36  0.36  1.00  0.36  0.36  0.36
V7  0.36  0.36  0.36  0.36  0.36  0.36  1.00  0.36  0.36
V8  0.36  0.36  0.36  0.36  0.36  0.36  0.36  1.00  0.36
V9  0.36  0.36  0.36  0.36  0.36  0.36  0.36  0.36  1.00
```

Sample of model

```
$r (Sample correlation matrix for sample size = 200 )  
      V1      V2      V3      V4      V5      V6      V7      V8      V9  
V1 1.00 0.34 0.35 0.30 0.31 0.32 0.33 0.35 0.34  
V2 0.34 1.00 0.35 0.19 0.34 0.34 0.36 0.45 0.40  
V3 0.35 0.35 1.00 0.40 0.38 0.43 0.35 0.38 0.32  
V4 0.30 0.19 0.40 1.00 0.31 0.42 0.28 0.28 0.27  
V5 0.31 0.34 0.38 0.31 1.00 0.41 0.39 0.25 0.37  
V6 0.32 0.34 0.43 0.42 0.41 1.00 0.32 0.33 0.35  
V7 0.33 0.36 0.35 0.28 0.39 0.32 1.00 0.37 0.37  
V8 0.35 0.45 0.38 0.28 0.25 0.33 0.37 1.00 0.21  
V9 0.34 0.40 0.32 0.27 0.37 0.35 0.37 0.21 1.00
```

```
pairs.panels(latent$observed)
```

SPLOM



Number of factors?

```
> vss <- VSS(latent$r, SMC=FALSE, n.obs=200)
```

```
> vss
```

Very Simple Structure

VSS complexity 1 achieves a maximum of 0.77 with 1 factors

VSS complexity 2 achieves a maximum of 0.8 with 2 factors

The Velicer MAP criterion achieves a minimum of 1 with 1 factors

Velicer MAP

```
[1] 0.02 0.04 0.07 0.12 0.17 0.28 0.48 1.00
```

Very Simple Structure Complexity 1

```
[1] 0.77 0.48 0.45 0.44 0.43 0.44 0.44 0.48
```

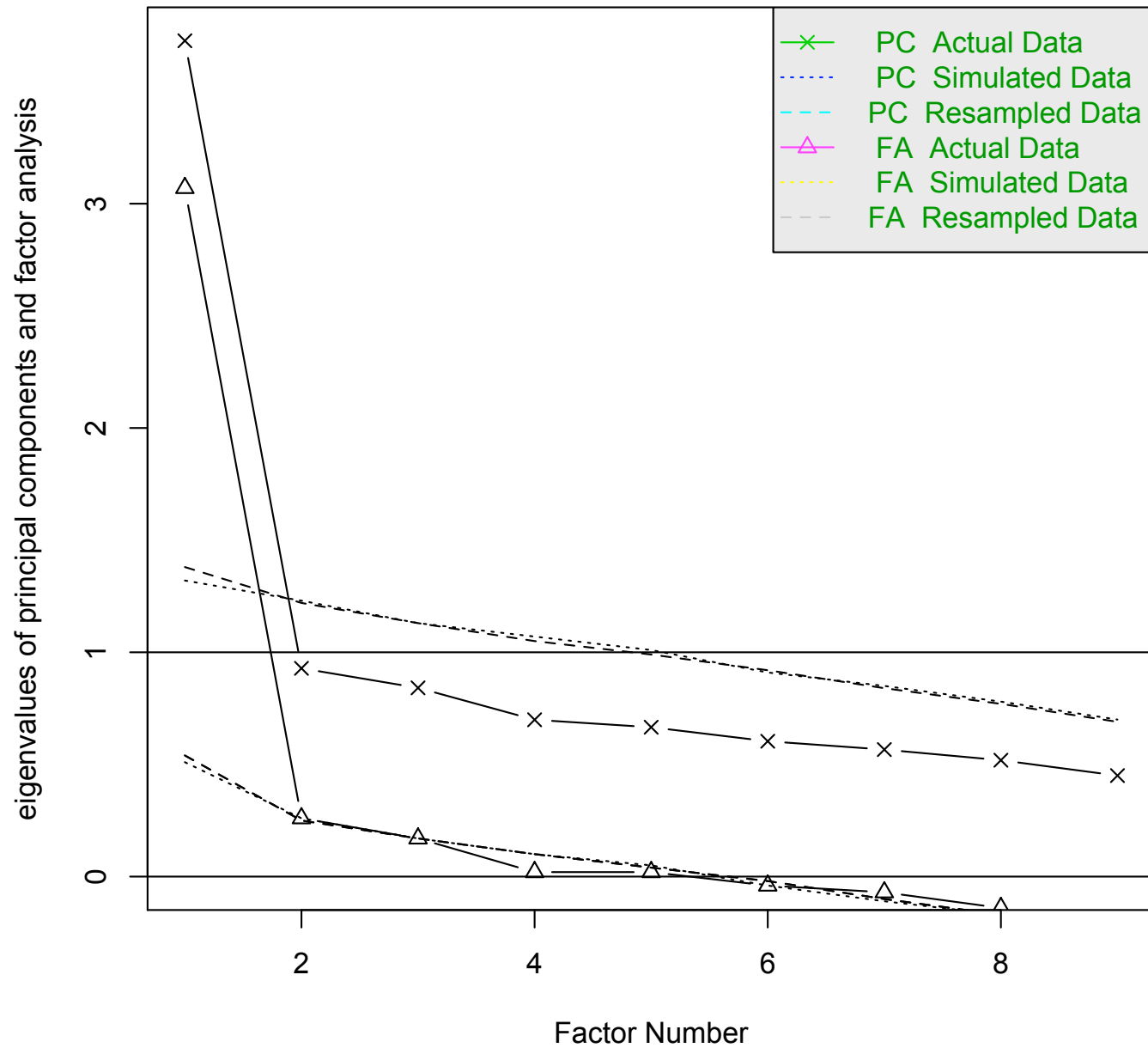
Very Simple Structure Complexity 2

```
[1] 0.00 0.80 0.75 0.74 0.69 0.67 0.65 0.66
```

Chi²

	dof	chisq		prob
1	27	3.757936e+01	0.08475115	
2	19	1.880069e+01	0.46968761	
3	12	4.713637e+00	0.96686629	
4	6	3.818237e+00	0.70125805	
5	1	6.672074e-01	0.41402694	
6	-3	2.398666e-01		NA
7	-6	6.638422e-02		NA
8	-8	1.026952e-04		NA

Parallel analysis of 200 sampled from continuous data



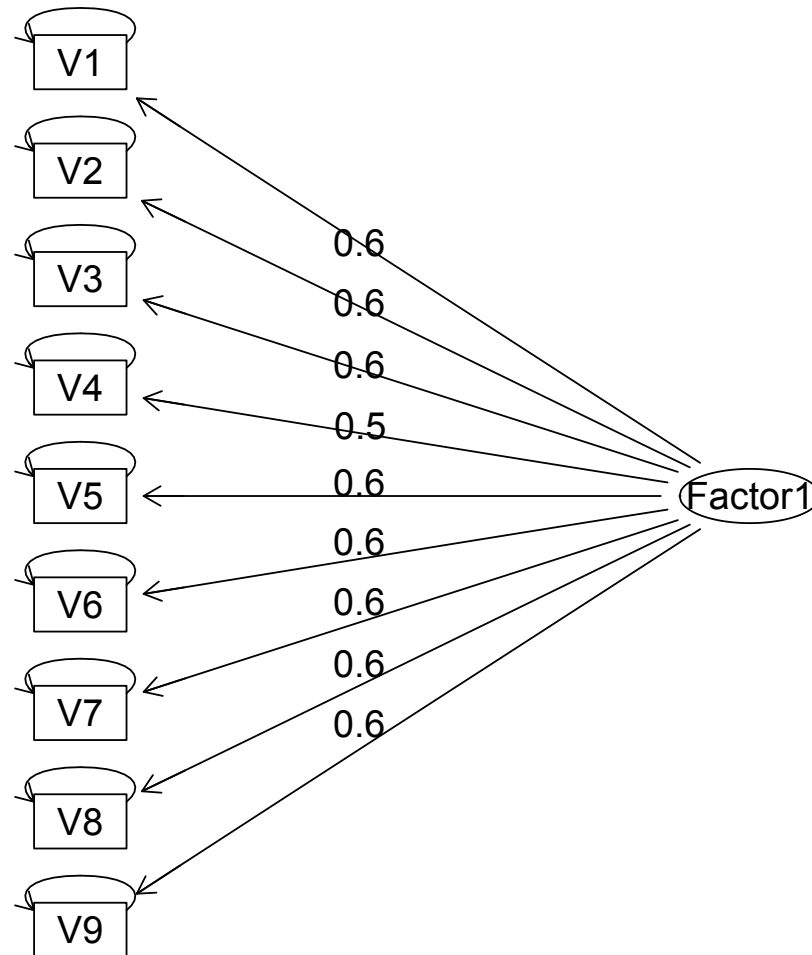
Factor analysis

```
> f1 <- factanal(latent$observed,1)
factanal(x = latent$observed, factors = 1)
Uniquenesses:
      V1      V2      V3      V4      V5      V6      V7      V8      V9
0.688 0.646 0.596 0.726 0.644 0.608 0.653 0.684 0.684
Loadings:
      Factor1
V1 0.559
V2 0.595
V3 0.635
V4 0.524
V5 0.597
V6 0.626
V7 0.589
V8 0.562
V9 0.563

      Factor1
SS loadings      3.072
Proportion Var   0.341
Test of the hypothesis that 1 factor is sufficient.
The chi square statistic is 37.57 on 27 degrees of freedom.
The p-value is 0.0849
```

Structural model

Structural model



```
mod.1 <- structure.graph(f1)    mod.1 <- structure.sem(f1)
```

```
> mod.1
```

	Path	Parameter	Value
[1,]	"Factor1->V1"	"v1"	NA
[2,]	"Factor1->V2"	"v2"	NA
[3,]	"Factor1->V3"	"v3"	NA
[4,]	"Factor1->V4"	"v4"	NA
[5,]	"Factor1->V5"	"v5"	NA
[6,]	"Factor1->V6"	"v6"	NA
[7,]	"Factor1->V7"	"v7"	NA
[8,]	"Factor1->V8"	"v8"	NA
[9,]	"Factor1->V9"	"v9"	NA
[10,]	"V1<->V1"	"x1e"	NA
[11,]	"V2<->V2"	"x2e"	NA
[12,]	"V3<->V3"	"x3e"	NA
[13,]	"V4<->V4"	"x4e"	NA
[14,]	"V5<->V5"	"x5e"	NA
[15,]	"V6<->V6"	"x6e"	NA
[16,]	"V7<->V7"	"x7e"	NA
[17,]	"V8<->V8"	"x8e"	NA
[18,]	"V9<->V9"	"x9e"	NA
[19,]	"Factor1<->Factor1"	NA	"1"

sem
model

sem summary

```
> summary(sem.1)
```

```
Model Chisquare = 38.441    Df = 27 Pr(>Chisq) = 0.071153  
Chisquare (null model) = 442.57    Df = 36  
Goodness-of-fit index = 0.95875  
Adjusted goodness-of-fit index = 0.93125  
RMSEA index = 0.046145    90% CI: (NA, 0.077156)  
Bentler-Bonnett NFI = 0.91314  
Tucker-Lewis NNFI = 0.96248  
Bentler CFI = 0.97186  
SRMR = 0.043651  
BIC = -104.61
```

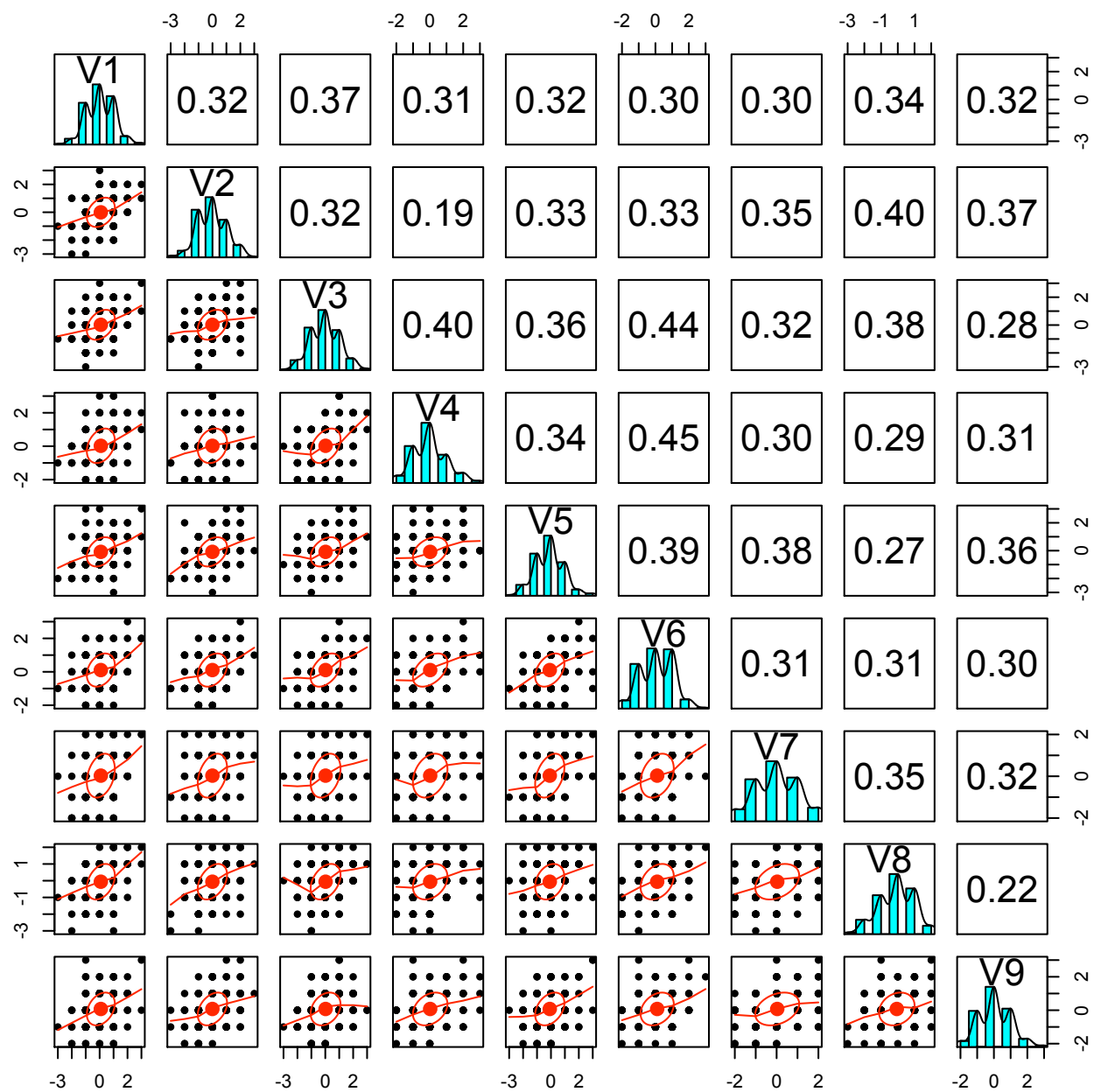
Parameters - 1 factor

Parameter Estimates

	Estimate	Std Error	z value	Pr(> z)	
V1	0.55887	0.071501	7.8162	5.5511e-15	V1 <--- Factor1
V2	0.59536	0.070960	8.3901	0.0000e+00	V2 <--- Factor1
V3	0.63541	0.069606	9.1286	0.0000e+00	V3 <--- Factor1
V4	0.52357	0.072652	7.2066	5.7376e-13	V4 <--- Factor1
V5	0.59670	0.070646	8.4463	0.0000e+00	V5 <--- Factor1
V6	0.62646	0.069951	8.9556	0.0000e+00	V6 <--- Factor1
V7	0.58882	0.070844	8.3115	0.0000e+00	V7 <--- Factor1
V8	0.56170	0.071800	7.8232	5.1070e-15	V8 <--- Factor1
V9	0.56253	0.071583	7.8584	3.9968e-15	V9 <--- Factor1
x1e	0.68767	0.076447	8.9954	0.0000e+00	V1 <--> V1
x2e	0.64554	0.073940	8.7307	0.0000e+00	V2 <--> V2
x3e	0.59625	0.070155	8.4991	0.0000e+00	V3 <--> V3
x4e	0.72588	0.079565	9.1231	0.0000e+00	V4 <--> V4
x5e	0.64395	0.073447	8.7675	0.0000e+00	V5 <--> V5
x6e	0.60755	0.071076	8.5479	0.0000e+00	V6 <--> V6
x7e	0.65329	0.074098	8.8166	0.0000e+00	V7 <--> V7
x8e	0.68449	0.076652	8.9299	0.0000e+00	V8 <--> V8
x9e	0.68356	0.076353	8.9527	0.0000e+00	V9 <--> V9

Distort by making categorical

```
> cate <- round(latent$observed)  
> pairs.panels(cate)
```



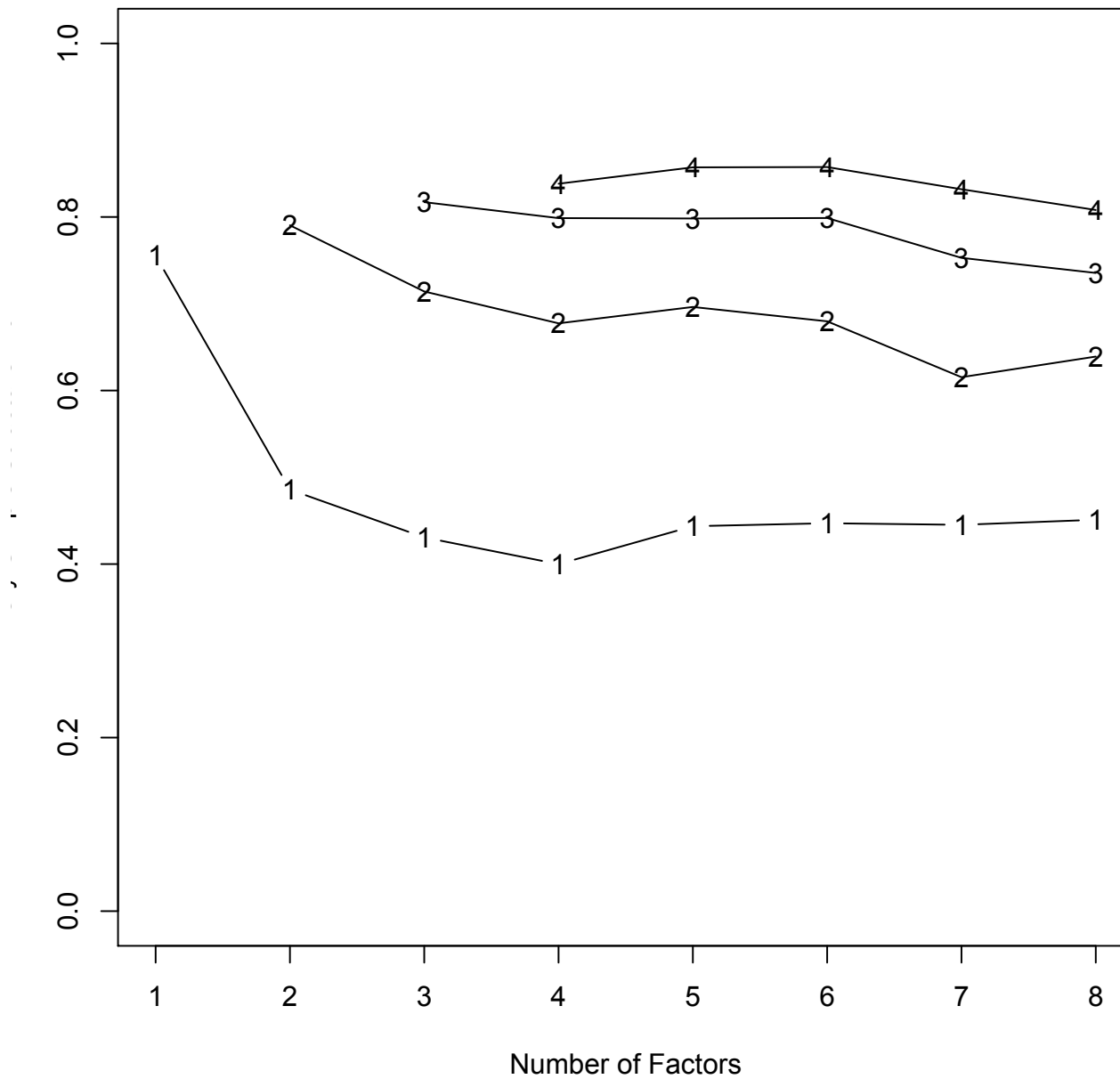
Differences in r by rounding

```
> round(cor(latent$observed) - cor(cate), 2)
```

	V1	V2	V3	V4	V5	V6	V7	V8	V9
V1	0.00	0.02	-0.02	-0.01	-0.01	0.01	0.03	0.01	0.02
V2	0.02	0.00	0.03	0.00	0.01	0.01	0.01	0.06	0.03
V3	-0.02	0.03	0.00	0.00	0.02	-0.01	0.03	0.00	0.04
V4	-0.01	0.00	0.00	0.00	-0.02	-0.03	-0.02	-0.01	-0.04
V5	-0.01	0.01	0.02	-0.02	0.00	0.02	0.01	-0.01	0.02
V6	0.01	0.01	-0.01	-0.03	0.02	0.00	0.00	0.02	0.05
V7	0.03	0.01	0.03	-0.02	0.01	0.00	0.00	0.02	0.05
V8	0.01	0.06	0.00	-0.01	-0.01	0.02	0.02	0.00	0.00
V9	0.02	0.03	0.04	-0.04	0.02	0.05	0.05	0.00	0.00

Very Simple Structure

VSS



```
> vss.c
```

```
Very Simple Structure
```

```
VSS complexity 1 achieves a maximum of 0.76 with 1  
factors
```

```
VSS complexity 2 achieves a maximum of 0.79 with 2  
factors
```

```
The Velicer MAP criterion achieves a minimum of 1 with 1  
factors
```

```
Velicer MAP
```

```
[1] 0.02 0.04 0.07 0.11 0.17 0.27 0.44 1.00
```

```
Very Simple Structure Complexity 1
```

```
[1] 0.76 0.49 0.43 0.40 0.44 0.45 0.45 0.45
```

```
Very Simple Structure Complexity 2
```

```
[1] 0.00 0.79 0.71 0.68 0.70 0.68 0.62 0.64
```

Chi²

```
> vss.c$vss.stats[,1:3]
```

	dof	chisq	prob
1	27	3.198998e+01	0.2324556
2	19	1.490603e+01	0.7285507
3	12	6.314856e+00	0.8993859
4	6	4.911160e+00	0.5552571
5	1	1.806164e+00	0.1789690
6	-3	1.377620e+00	NA
7	-6	8.126361e-03	NA
8	-8	2.158884e-04	NA

Call:

```
factanal(x = cate, factors = 1)
```

Uniquenesses:

V1	V2	V3	V4	V5	V6	V7	V8	V9
0.691	0.687	0.603	0.680	0.643	0.611	0.679	0.696	0.721

Loadings:

Factor1

V1 0.556

V2 0.559

V3 0.630

V4 0.565

V5 0.598

V6 0.623

V7 0.567

V8 0.551

V9 0.528

Factor1

SS loadings 2.989

Proportion Var 0.332

Test of the hypothesis that 1 factor is sufficient.

The chi square statistic is 31.97 on 27 degrees of freedom

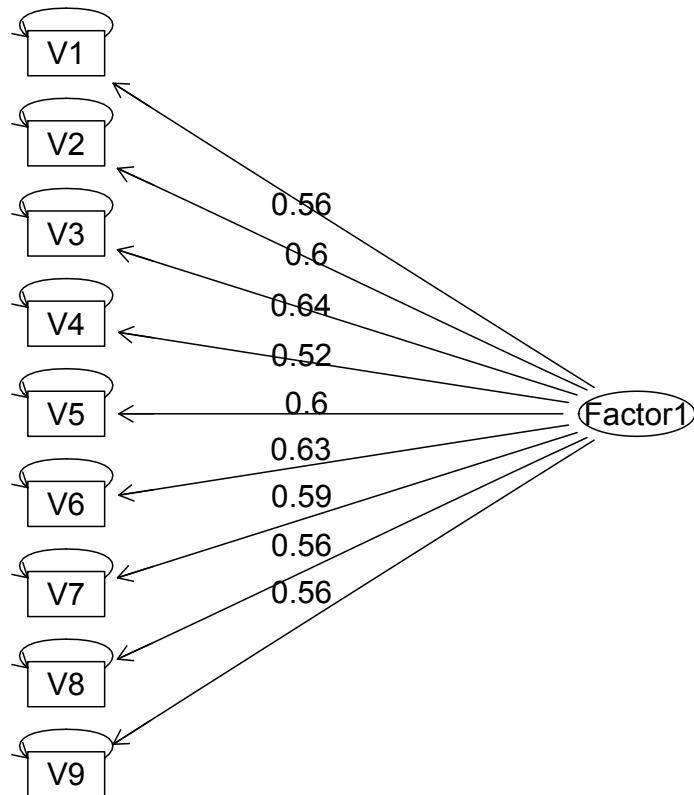
The p-value is 0.233

factanal

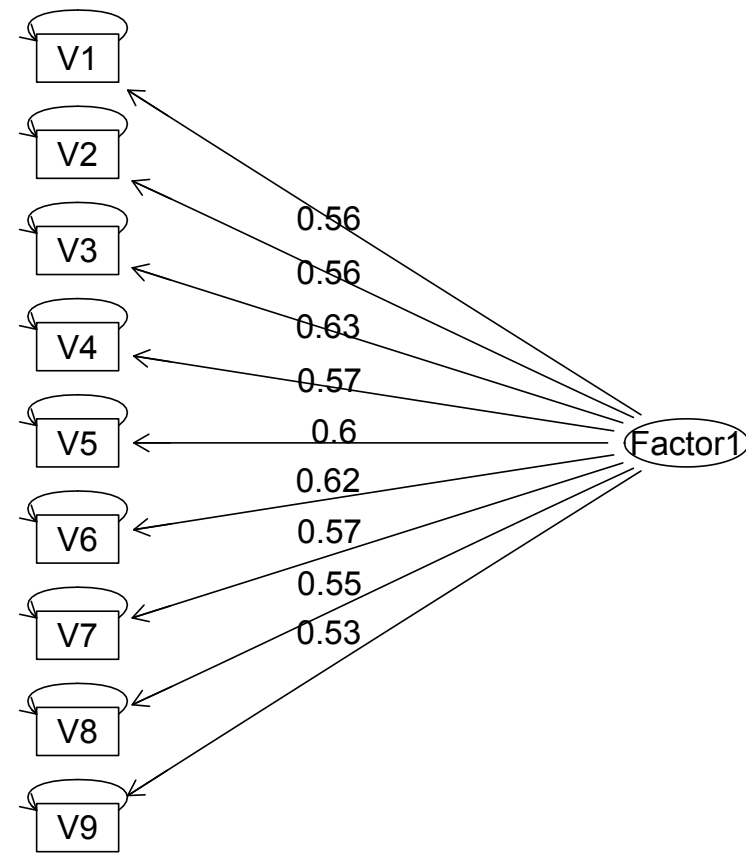
Compare the structures

```
> mod.f1 <- structure.graph(f1,digits=2)
```

Structural model



Structural model



```
mod.c1 <- structure.graph(c1,digits=2)
```

Sem of categorical data

```
> sem.c1 <- sem(mod.c1,cor(cate),200)
> summary(sem.c1)
```

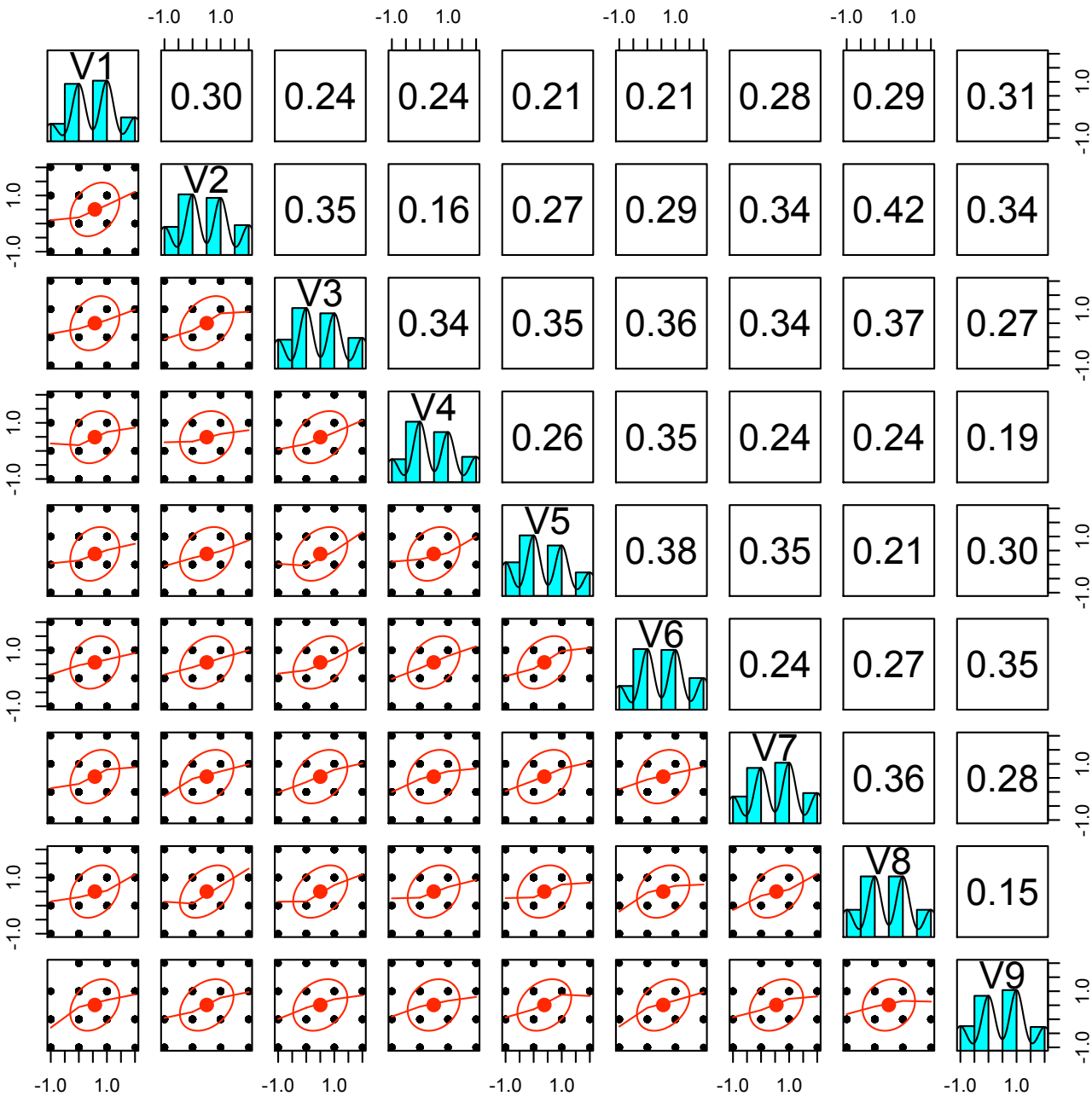
```
Model Chisquare = 32.711    Df = 27 Pr(>Chisq) = 0.20678
Chisquare (null model) = 418.48    Df = 36
Goodness-of-fit index = 0.9643
Adjusted goodness-of-fit index = 0.94049
RMSEA index = 0.032602    90% CI: (NA, 0.067294)
Bentler-Bonnett NFI = 0.92183
Tucker-Lewis NNFI = 0.9801
Bentler CFI = 0.98507
SRMR = 0.040899
BIC = -110.34
```

Make 4 categories

```
> cat4 <- latent$observed  
> cat4[cat4< -1 ] <- -1  
> cat4[(cat4<0)&cat4>-1] <- 0  
> cat4[cat4>1] <- 2  
> cat4[(cat4< 1 ) & (cat4>0)] <- 1
```

Figure 1 displays a 9x9 grid of plots showing the relationship between nine visual areas (V1-V9). The diagonal elements are histograms of the distribution of each visual area. The off-diagonal elements are scatter plots showing the relationship between pairs of visual areas, with a red ellipse indicating the correlation. The correlation values are displayed in the top right corner of each scatter plot. The axes for the scatter plots range from -1.0 to 1.0.

	V1	V2	V3	V4	V5	V6	V7	V8	V9
V1	Histogram	0.30	0.24	0.24	0.21	0.21	0.28	0.29	0.31
V2	0.35	Histogram	0.16	0.27	0.29	0.34	0.42	0.34	
V3	0.34	0.35	Histogram	0.36	0.34	0.37	0.27		
V4	0.26	0.35	0.24	Histogram	0.24	0.19			
V5	0.38	0.35	0.21	0.30	Histogram				
V6	0.24	0.27	0.35						
V7	0.36	0.28							
V8	0.15								
V9	Histogram								

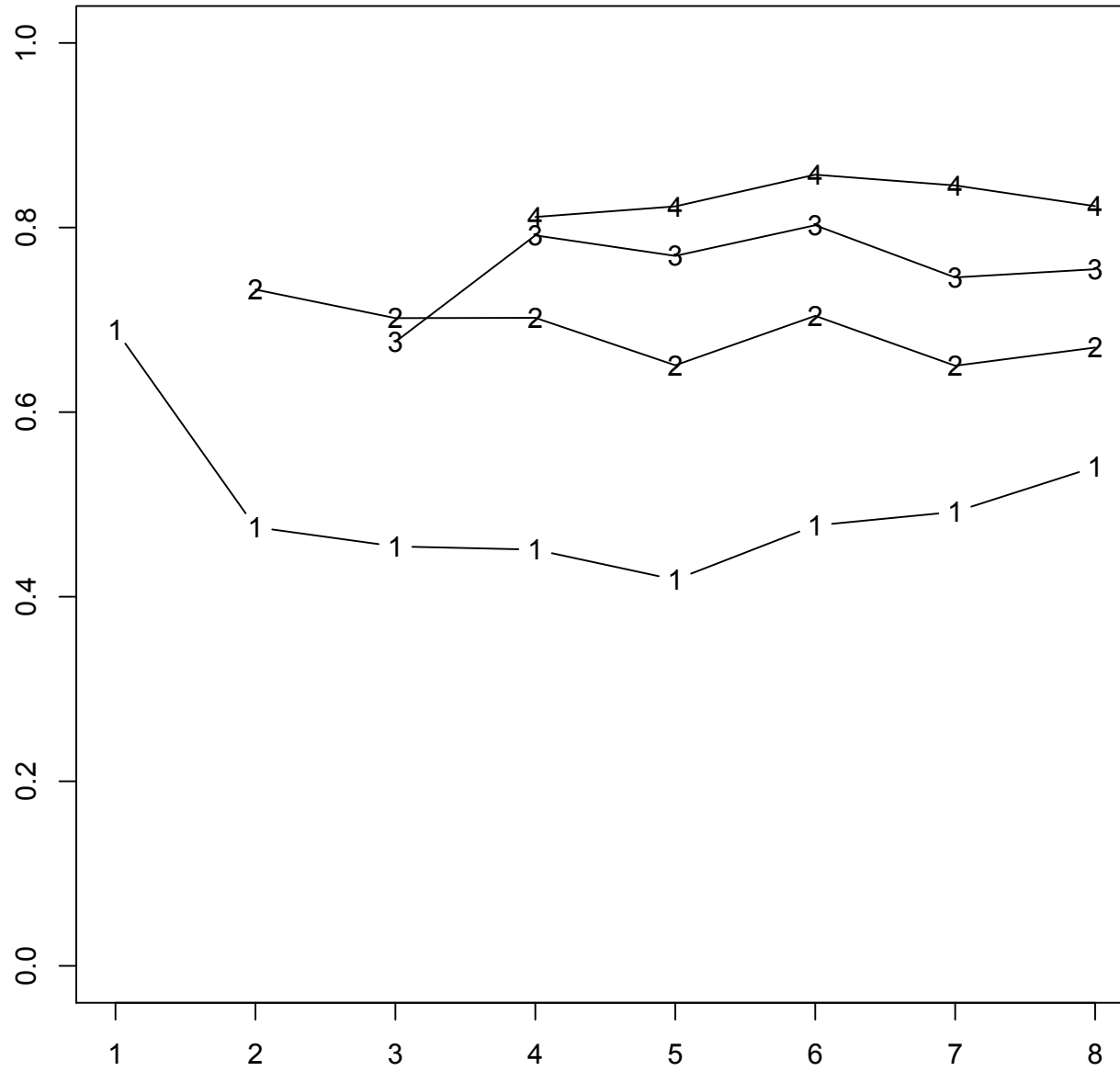


4 categories reduce r

```
> round(cor(latent$observed) - cor(cat4), 2)
```

	V1	V2	V3	V4	V5	V6	V7	V8	V9
V1	0.00	0.04	0.10	0.07	0.09	0.11	0.06	0.06	0.03
V2	0.04	0.00	0.00	0.03	0.07	0.05	0.02	0.04	0.06
V3	0.10	0.00	0.00	0.06	0.03	0.07	0.01	0.01	0.04
V4	0.07	0.03	0.06	0.00	0.06	0.07	0.04	0.04	0.08
V5	0.09	0.07	0.03	0.06	0.00	0.03	0.04	0.05	0.07
V6	0.11	0.05	0.07	0.07	0.03	0.00	0.08	0.06	0.00
V7	0.06	0.02	0.01	0.04	0.04	0.08	0.00	0.01	0.09
V8	0.06	0.04	0.01	0.04	0.05	0.06	0.01	0.00	0.06
V9	0.03	0.06	0.04	0.08	0.07	0.00	0.09	0.06	0.00

Very Simple Structure



VSS

```
> vss.4
```

```
Very Simple Structure
```

```
VSS complexity 1 achieves a maximum of 0.69 with 1  
factors
```

```
VSS complexity 2 achieves a maximum of 0.73 with 2  
factors
```

```
The Velicer MAP criterion achieves a minimum of 1 with 1  
factors
```

```
Velicer MAP
```

```
[1] 0.02 0.04 0.07 0.11 0.17 0.26 0.50 1.00
```

```
Very Simple Structure Complexity 1
```

```
[1] 0.69 0.48 0.45 0.45 0.42 0.48 0.49 0.54
```

```
Very Simple Structure Complexity 2
```

```
[1] 0.00 0.73 0.70 0.70 0.65 0.70 0.65 0.67
```

```
> vss$vss.stats[,1:3]
```

	dof	chisq	prob
1	27	3.757936e+01	0.08475115
2	19	1.880069e+01	0.46968761
3	12	4.713637e+00	0.96686629
4	6	3.818237e+00	0.70125805
5	1	6.672074e-01	0.41402694
6	-3	2.398666e-01	NA
7	-6	6.638422e-02	NA
8	-8	1.026952e-04	NA

```

> f4 <- factanal(cat4,1)
factanal(x = cat4, factors = 1)
Uniquenesses:
      V1      V2      V3      V4      V5      V6      V7      V8      V9
0.780 0.662 0.616 0.787 0.705 0.684 0.682 0.703 0.748
Loadings:
      Factor1
V1 0.469
V2 0.581
V3 0.619
V4 0.461
V5 0.543
V6 0.562
V7 0.564
V8 0.545
V9 0.502

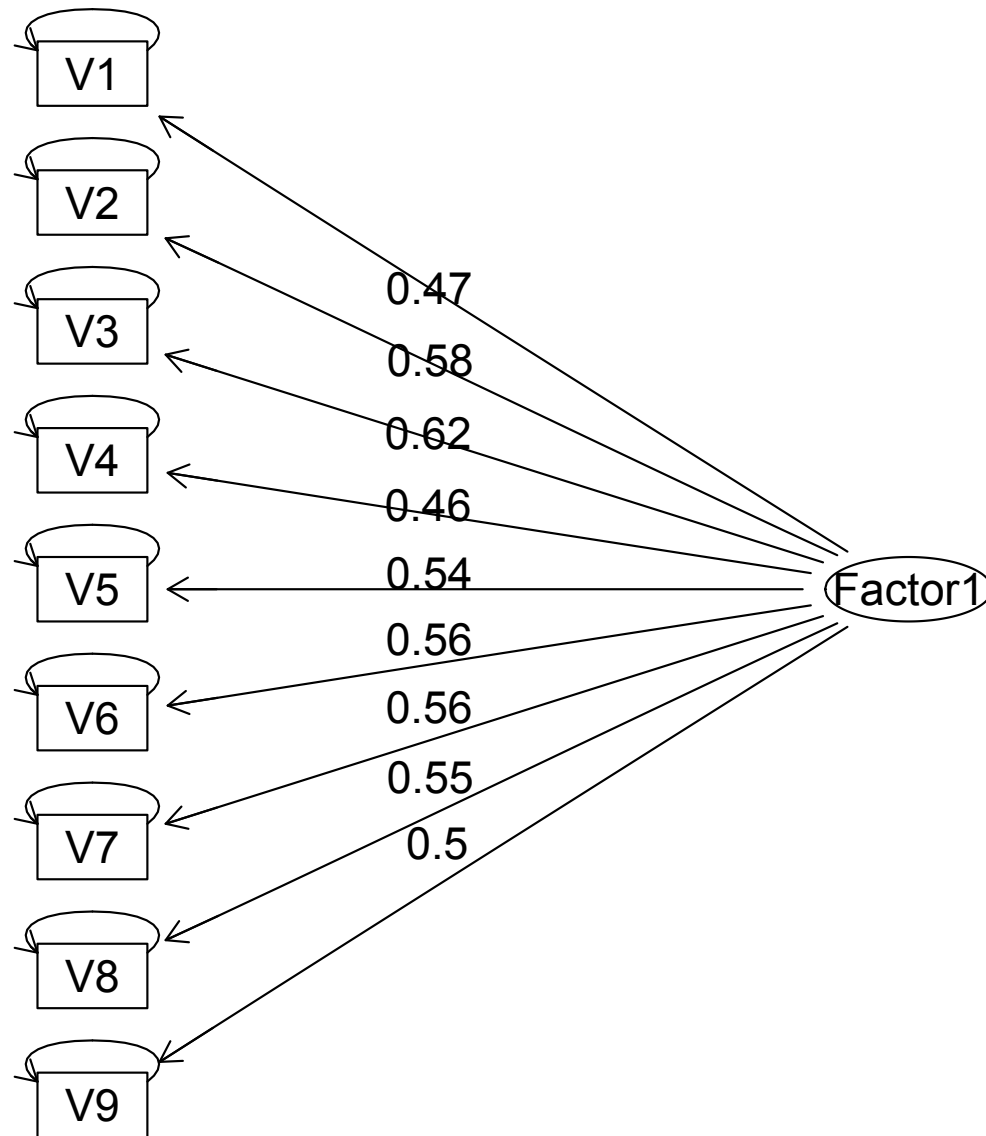
      Factor1
SS loadings      2.632
Proportion Var   0.292
Test of the hypothesis that 1 factor is sufficient.
The chi square statistic is 40.94 on 27 degrees of freedom.
The p-value is 0.0418

```

factanal

Structural model

loadings
are lower



sem fit

```
> sem.4 <- sem(mod.4,cor(cat4),200)
> summary(sem.4)
```

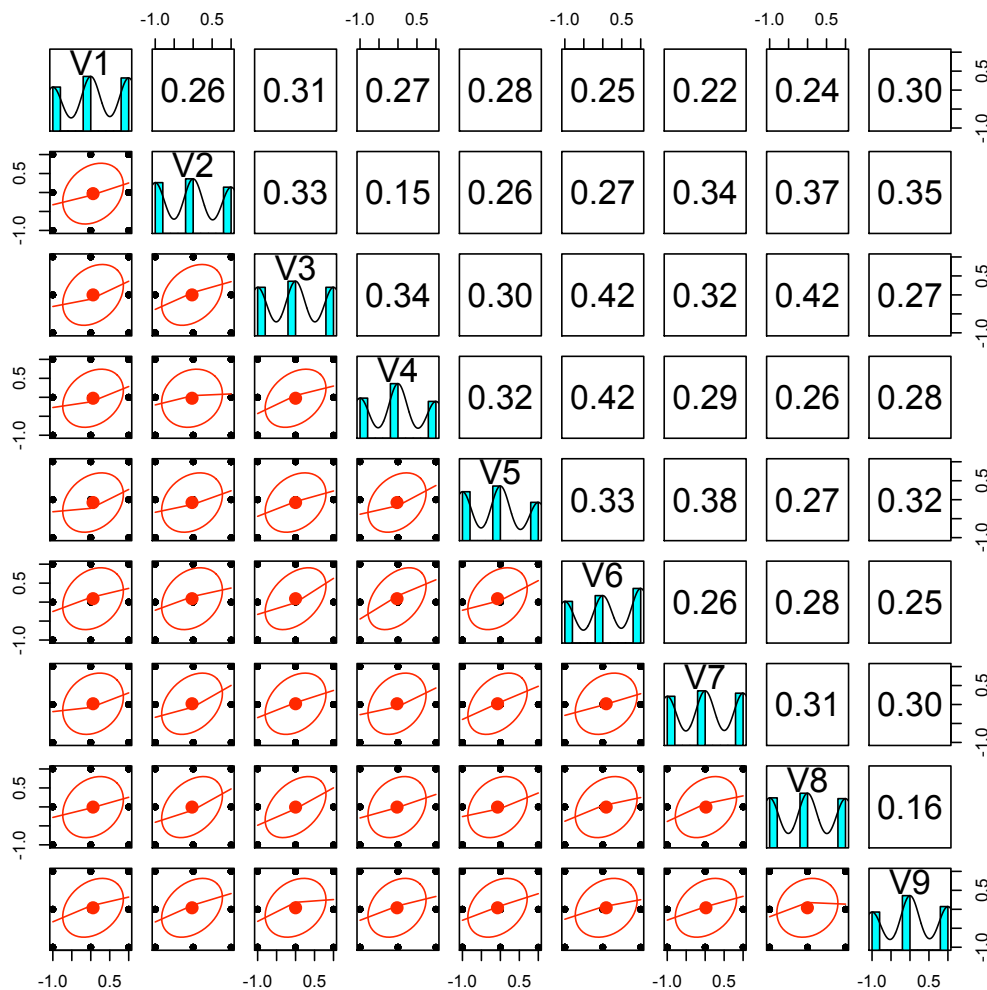
```
Model Chisquare = 41.884    Df = 27 Pr(>Chisq) = 0.033789
Chisquare (null model) = 354.65    Df = 36
Goodness-of-fit index = 0.95555
Adjusted goodness-of-fit index = 0.9259
RMSEA index = 0.052633    90% CI: (0.014957, 0.082409)
Bentler-Bonnett NFI = 0.8819
Tucker-Lewis NNFI = 0.93772
Bentler CFI = 0.95329
SRMR = 0.048461
BIC = -101.17
```

Normalized Residuals

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-1.65e+00	-5.12e-01	-1.13e-06	9.86e-04	4.06e-01	1.37e+00

3 level items

```
> cat3 <- latent$observed  
> cat3[cat3 < -.5] <- -1  
> cat3[cat3 > .5 ] <- 1  
> cat3[abs(cat3) < 1] <- 0  
> pairs.panels(cat3)
```



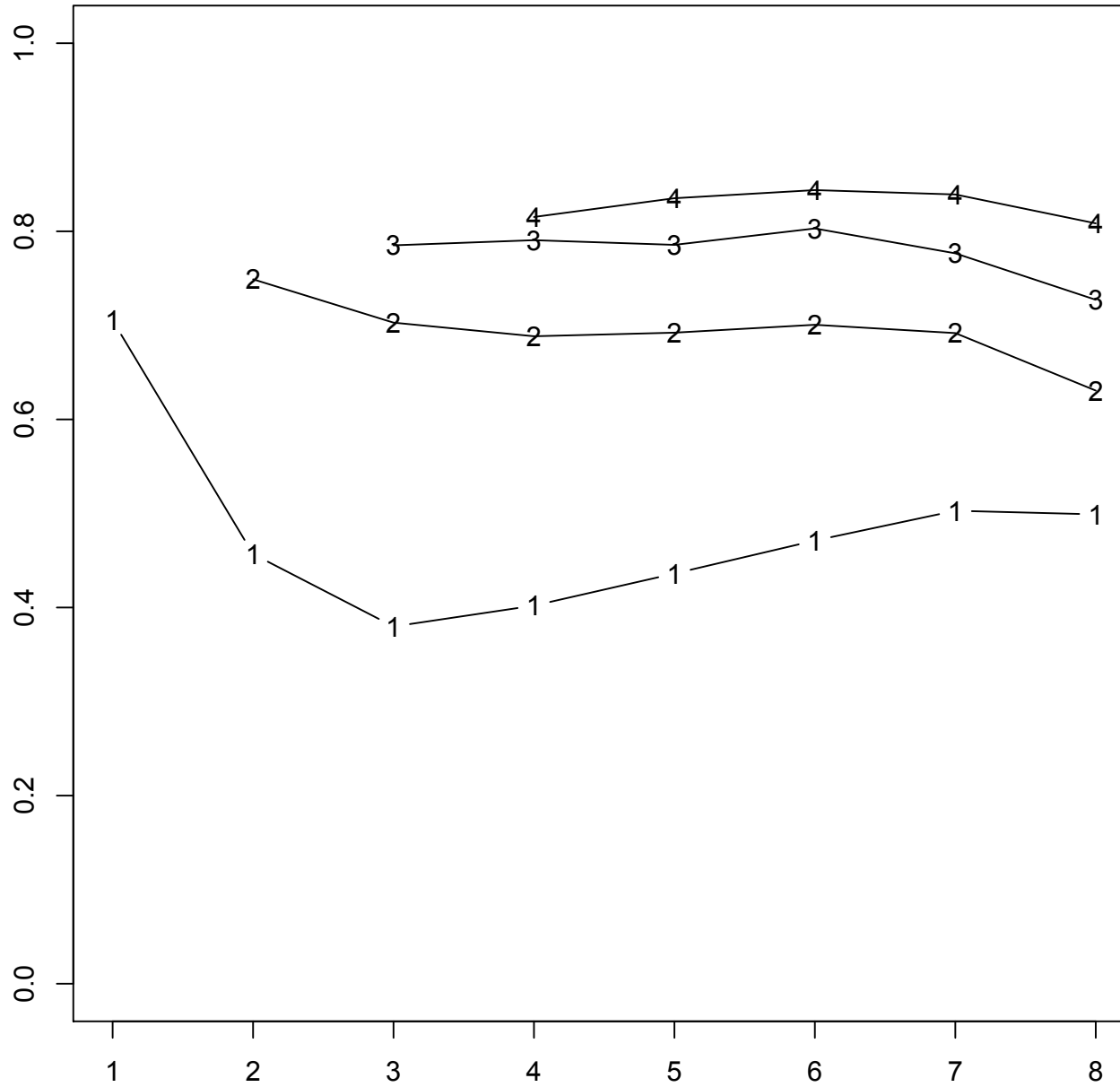
Correlations
are reduced

Most correlations are smaller

```
> round(cor(latent$observed) - cor(cat3),2)
```

	V1	V2	V3	V4	V5	V6	V7	V8	V9
V1	0.00	0.08	0.04	0.03	0.03	0.06	0.11	0.11	0.04
V2	0.08	0.00	0.02	0.04	0.08	0.07	0.02	0.08	0.05
V3	0.04	0.02	0.00	0.05	0.07	0.00	0.03	-0.04	0.04
V4	0.03	0.04	0.05	0.00	-0.01	0.00	-0.02	0.02	-0.01
V5	0.03	0.08	0.07	-0.01	0.00	0.08	0.01	-0.02	0.05
V6	0.06	0.07	0.00	0.00	0.08	0.00	0.05	0.04	0.10
V7	0.11	0.02	0.03	-0.02	0.01	0.05	0.00	0.06	0.07
V8	0.11	0.08	-0.04	0.02	-0.02	0.04	0.06	0.00	0.05
V9	0.04	0.05	0.04	-0.01	0.05	0.10	0.07	0.05	0.00

3 level items



VSS

VSS fits

```
> vss.3
```

```
Very Simple Structure of 3 level items
```

```
VSS complexity 1 achieves a maximum of 0.71 with 1  
factors
```

```
VSS complexity 2 achieves a maximum of 0.75 with 2  
factors
```

```
The Velicer MAP criterion achieves a minimum of 1 with 1  
factors
```

```
Velicer MAP
```

```
[1] 0.02 0.04 0.07 0.11 0.17 0.30 0.46 1.00
```

```
Very Simple Structure Complexity 1
```

```
[1] 0.71 0.46 0.38 0.40 0.44 0.47 0.50 0.50
```

```
Very Simple Structure Complexity 2
```

```
[1] 0.00 0.75 0.70 0.69 0.69 0.70 0.69 0.63
```

How many factors?

```
> vss.3$vss.stats[,1:3]
```

	dof	chisq	prob
1	27	4.011865e+01	0.04994193
2	19	2.175496e+01	0.29662056
3	12	8.841514e+00	0.71640433
4	6	7.578853e+00	0.27060879
5	1	3.089800e+00	0.07878449
6	-3	2.628320e+00	NA
7	-6	1.882974e-02	NA
8	-8	4.302505e-05	NA

```

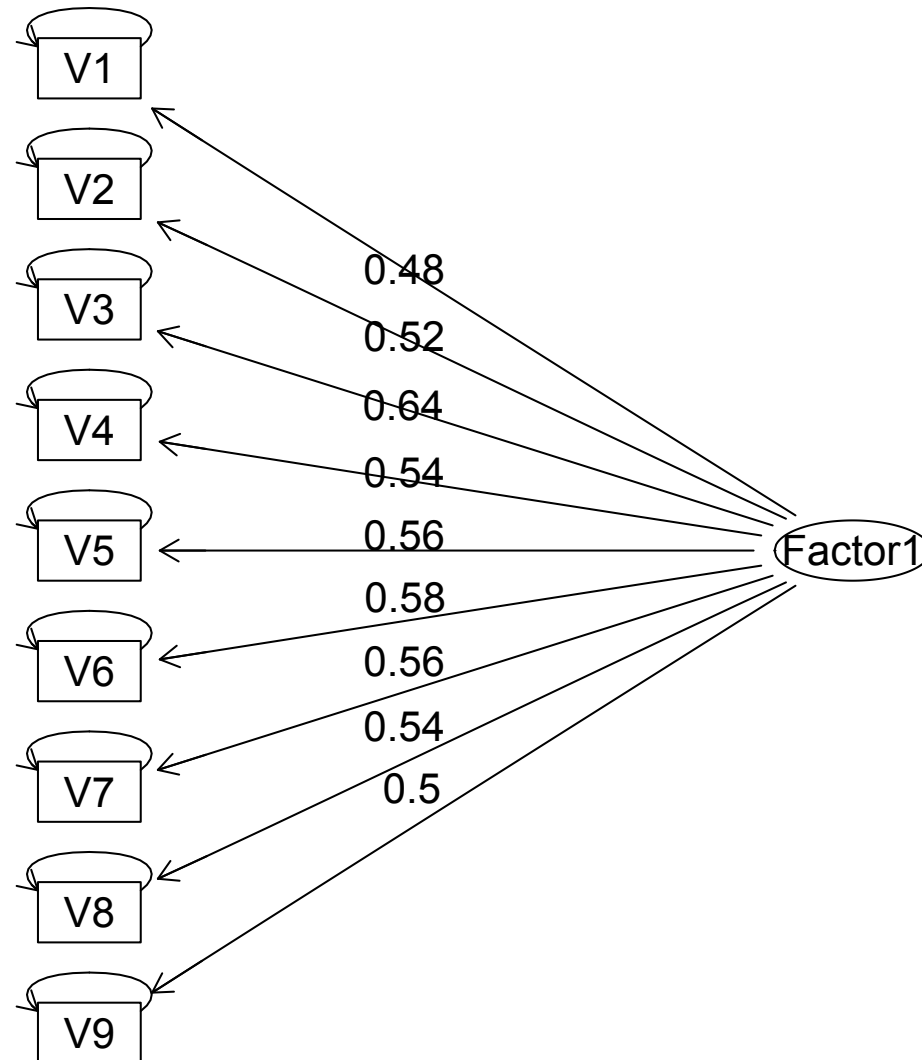
> f3 <- factanal(cat3,1)
factanal(x = cat3, factors = 1)
Uniquenesses:
      V1      V2      V3      V4      V5      V6      V7      V8      V9
0.770 0.725 0.595 0.709 0.682 0.661 0.692 0.710 0.751
Loadings:
      Factor1
V1 0.480
V2 0.525
V3 0.636
V4 0.540
V5 0.564
V6 0.582
V7 0.555
V8 0.538
V9 0.499

      Factor1
SS loadings      2.705
Proportion Var   0.301
Test of the hypothesis that 1 factor is sufficient.
The chi square statistic is 40.09 on 27 degrees of freedom.
The p-value is 0.0502

```

factanal

3 category items



```
> sem3 <- sem(mod3,cor(cat3),200)
> summary(sem3)
```

```
Model Chisquare = 41.018    Df = 27 Pr(>Chisq) = 0.041018
Chisquare (null model) = 368.11    Df = 36
Goodness-of-fit index = 0.95617
Adjusted goodness-of-fit index = 0.92695
RMSEA index = 0.051079    90% CI: (0.010671, 0.081127)
Bentler-Bonnett NFI = 0.88857
Tucker-Lewis NNFI = 0.94372
Bentler CFI = 0.95779
SRMR = 0.047473
BIC = -102.04
```

Normalized Residuals

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-1.86e+00	-4.43e-01	-7.19e-08	2.19e-03	2.64e-01	1.45e+00

3 category parameters

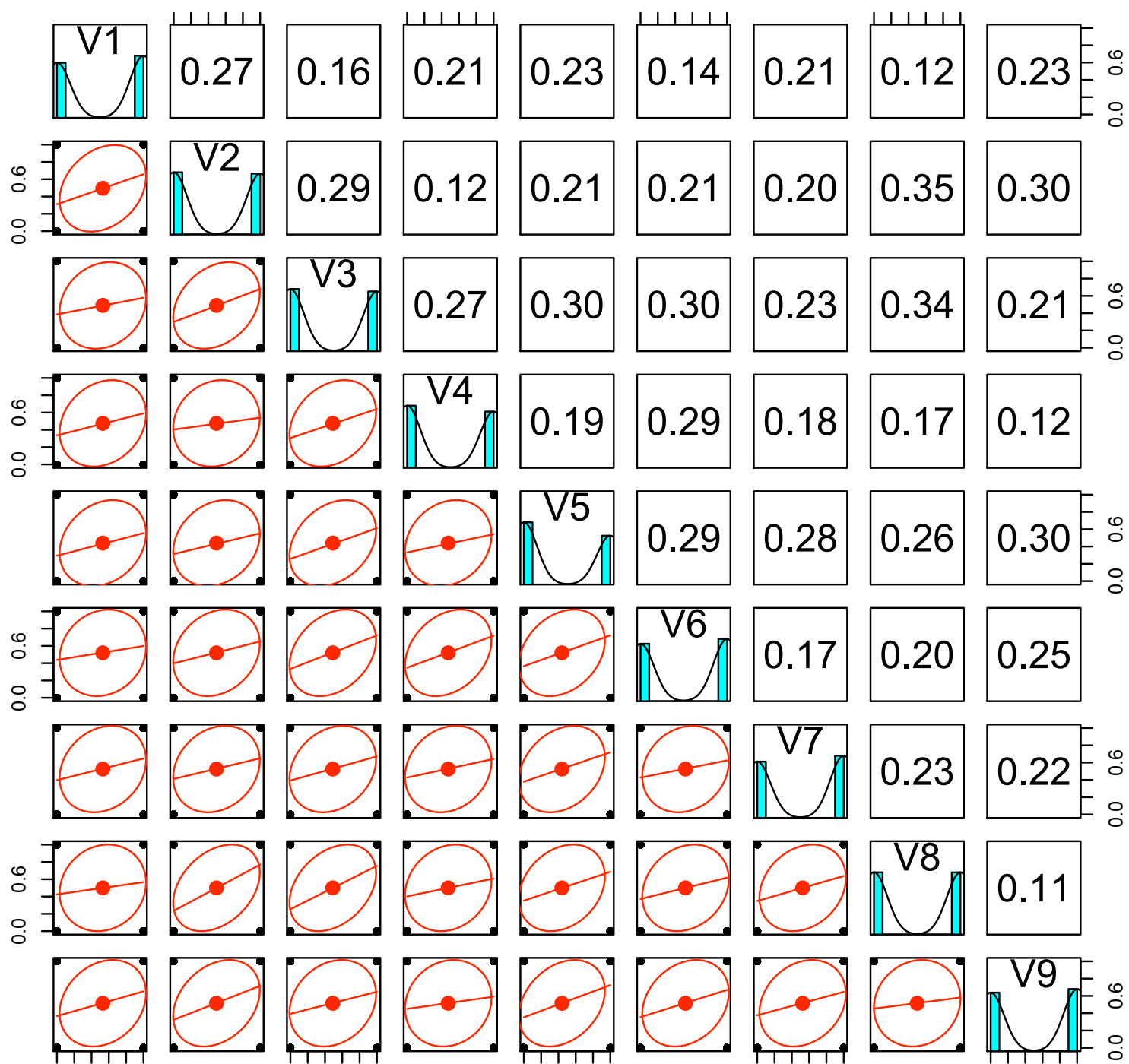
Parameter Estimates

	Estimate	Std Error	z value	Pr(> z)	
V1	0.47990	0.074676	6.4264	1.3063e-10	V1 <--- Factor1
V2	0.52484	0.074248	7.0687	1.5641e-12	V2 <--- Factor1
V3	0.63603	0.071347	8.9146	0.0000e+00	V3 <--- Factor1
V4	0.53957	0.073819	7.3093	2.6845e-13	V4 <--- Factor1
V5	0.56357	0.073055	7.7143	1.2212e-14	V5 <--- Factor1
V6	0.58192	0.072733	8.0007	1.3323e-15	V6 <--- Factor1
V7	0.55507	0.073273	7.5754	3.5749e-14	V7 <--- Factor1
V8	0.53832	0.073777	7.2966	2.9510e-13	V8 <--- Factor1
V9	0.49946	0.074634	6.6922	2.1983e-11	V9 <--- Factor1
x1e	0.76970	0.083653	9.2011	0.0000e+00	V1 <--> V1
x2e	0.72455	0.081107	8.9332	0.0000e+00	V2 <--> V2
x3e	0.59547	0.072907	8.1675	2.2204e-16	V3 <--> V3
x4e	0.70887	0.079989	8.8620	0.0000e+00	V4 <--> V4
x5e	0.68239	0.078053	8.7427	0.0000e+00	V5 <--> V5
x6e	0.66137	0.076873	8.6034	0.0000e+00	V6 <--> V6
x7e	0.69189	0.078684	8.7933	0.0000e+00	V7 <--> V7
x8e	0.71021	0.080001	8.8775	0.0000e+00	V8 <--> V8
x9e	0.75054	0.082664	9.0794	0.0000e+00	V9 <--> V9

Dichotomous items

```
> dichot <- (latent$observed>0)+0  
> pairs.panels(dichot)
```

But note that these are all of equal difficulty



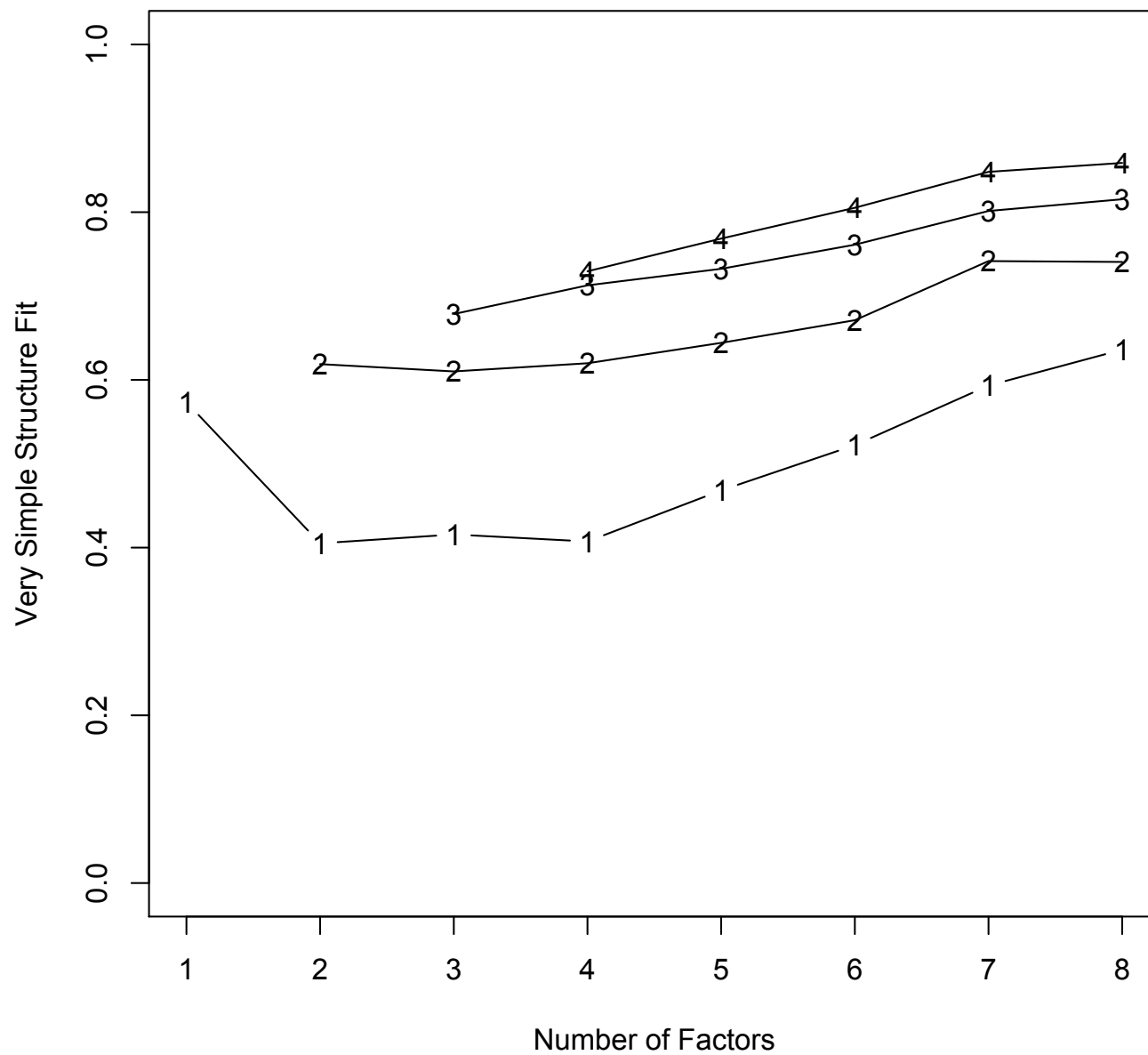
Most correlations are reduced

```
> round(cor(latent$observed) - cor(dichot),2)
```

	V1	V2	V3	V4	V5	V6	V7	V8	V9
V1	0.00	0.07	0.18	0.09	0.08	0.18	0.12	0.23	0.11
V2	0.07	0.00	0.06	0.07	0.13	0.13	0.16	0.10	0.10
V3	0.18	0.06	0.00	0.13	0.08	0.12	0.11	0.04	0.10
V4	0.09	0.07	0.13	0.00	0.13	0.13	0.09	0.11	0.15
V5	0.08	0.13	0.08	0.13	0.00	0.12	0.11	-0.01	0.08
V6	0.18	0.13	0.12	0.13	0.12	0.00	0.15	0.13	0.10
V7	0.12	0.16	0.11	0.09	0.11	0.15	0.00	0.14	0.15
V8	0.23	0.10	0.04	0.11	-0.01	0.13	0.14	0.00	0.10
V9	0.11	0.10	0.10	0.15	0.08	0.10	0.15	0.10	0.00

Dichotomous items

VSS



VSS stats

```
> vss.d
```

```
Very Simple Structure of Dichotomous items
```

```
VSS complexity 1 achieves a maximum of 0.64 with 8  
factors
```

```
VSS complexity 2 achieves a maximum of 0.74 with 7  
factors
```

```
The Velicer MAP criterion achieves a minimum of 1 with 1  
factors
```

```
Velicer MAP
```

```
[1] 0.02 0.04 0.07 0.11 0.17 0.29 0.47 1.00
```

```
Very Simple Structure Complexity 1
```

```
[1] 0.57 0.41 0.42 0.41 0.47 0.52 0.59 0.64
```

```
Very Simple Structure Complexity 2
```

```
[1] 0.00 0.62 0.61 0.62 0.64 0.67 0.74 0.74
```

VSS chi square uses factor.pa rather than mle

	dof	chisq	prob
1	27	3.310306e+01	0.1936903
2	19	2.273101e+01	0.2493977
3	12	1.038772e+01	0.5819866
4	6	4.544930e+00	0.6033534
5	1	2.419505e+00	0.1198328
6	-3	1.891661e-01	NA
7	-6	1.902598e-02	NA
8	-8	4.720899e-05	NA

```

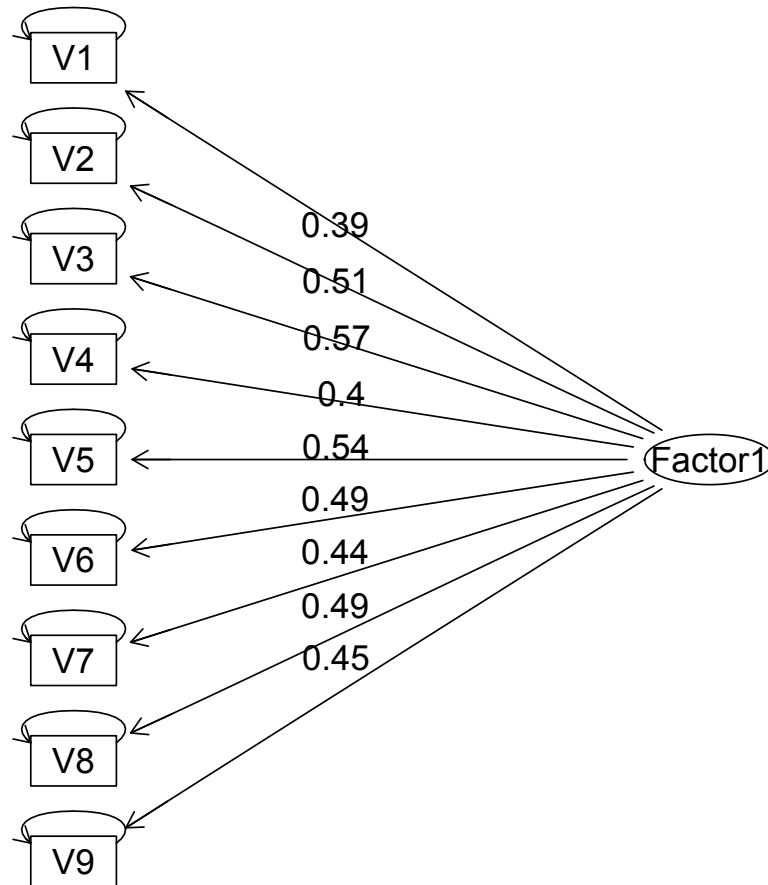
> fd <- factanal(dichot,1)
factanal(x = dichot, factors = 1)
Uniquenesses:
      V1      V2      V3      V4      V5      V6      V7      V8      V9
0.844 0.736 0.676 0.842 0.705 0.764 0.803 0.764 0.795
Loadings:
      Factor1
V1 0.394
V2 0.514
V3 0.569
V4 0.397
V5 0.543
V6 0.486
V7 0.444
V8 0.486
V9 0.453

      Factor1
SS loadings      2.071
Proportion Var   0.230
Test of the hypothesis that 1 factor is sufficient.
The chi square statistic is 33.08 on 27 degrees of freedom.
The p-value is 0.194

```

factanal

Dichotomous items



Once
again,
loadings
are lower

```
> summary(sem.d)
```

```
Model Chisquare = 33.85    Df = 27 Pr(>Chisq) = 0.17044  
Chisquare (null model) = 243.65    Df = 36  
Goodness-of-fit index = 0.9649  
Adjusted goodness-of-fit index = 0.9415  
RMSEA index = 0.035706    90% CI: (NA, 0.069392)  
Bentler-Bonnett NFI = 0.86107  
Tucker-Lewis NNFI = 0.95601  
Bentler CFI = 0.96701  
SRMR = 0.046655  
BIC = -109.20
```

```
Normalized Residuals
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-1.52e+00	-4.97e-01	-9.91e-06	2.16e-03	4.53e-01	1.38e+00

Manipulating dichotomous items

- Correlations of dichotomous items can be used to estimate continuous correlations using tetrachoric or polychoric correlations
- The hetcor function in the polychor package will do this

Using hetcor

- Items need to be in the form of `factors` rather than integers or reals
- Returned matrix is lower diagonal

```
> dichot.fact <- matrix(factor(dichot),ncol=9)
> head(dichot.fact)
      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9]
[1,] "1"  "1"  "1"  "1"  "0"  "1"  "0"  "1"  "0"
[2,] "1"  "1"  "1"  "1"  "1"  "1"  "1"  "1"  "1"
[3,] "0"  "1"  "1"  "0"  "1"  "1"  "1"  "1"  "1"
[4,] "1"  "0"  "1"  "0"  "1"  "0"  "0"  "1"  "0"
[5,] "0"  "0"  "1"  "0"  "0"  "0"  "1"  "0"  "0"
[6,] "1"  "1"  "0"  "0"  "1"  "0"  "0"  "0"  "0"
> poly.r <- hetcor(dichot.fact)
> poly.r
```

```
> poly.r
```

Two-Step Estimates

Correlations/Type of Correlation:										
	dichot.fact	X2	X3	X4	X5	X6	X7	X8	X9	
dichot.fact	1	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric
X2	0.4137	1	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric
X3	0.2513	0.4398	1	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric
X4	0.3302	0.187	0.4109	1	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric
X5	0.3551	0.3257	0.4555	0.2885	1	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric
X6	0.2152	0.325	0.456	0.4445	0.4389	1	Polychoric	Polychoric	Polychoric	Polychoric
X7	0.3207	0.3104	0.3559	0.284	0.4266	0.2615	1	Polychoric	Polychoric	Polychoric
X8	0.1879	0.5225	0.5092	0.2643	0.4017	0.3094	0.3542	1	Polychoric	Polychoric
X9	0.3519	0.4548	0.3252	0.1902	0.451	0.3815	0.3373	0.172	1	Polychoric

Standard Errors:

	dichot.fact	X2	X3	X4	X5	X6	X7	X8	X9
dichot.fact	0.09744								
X2	0.1062	0.09548							
X3	0.1026	0.1084	0.09759						
X4	0.1017	0.1031	0.09469	0.105					
X5	0.1076	0.1027	0.09433	0.09527	0.09608				
X6	0.1031	0.1035	0.1011	0.1049	0.097	0.1058			
X7	0.1084	0.08871	0.08991	0.1056	0.09856	0.1035	0.1012		
X8	0.1013	0.09438	0.1027	0.1083	0.09513	0.09949	0.1021	0.1088	
X9									

n = 200

How to get the correlations?

Examine the structure

```
> str(poly.r)
List of 7
 $ correlations: num [1:9, 1:9] 1 0.414 0.251 0.33 0.355 ...
  ..- attr(*, "dimnames")=List of 2
  .. ..$ : chr [1:9] "dichot.fact" "X2" "X3" "X4" ...
  .. ..$ : chr [1:9] "dichot.fact" "X2" "X3" "X4" ...
 $ type       : chr [1:9, 1:9] "" "Polychoric" "Polychoric"
"Polychoric" ...
 $ NA.method   : chr "complete.obs"
 $ ML          : logi FALSE
 $ std.errors  : num [1:9, 1:9] 0 0.0974 0.1062 0.1026 0.1017 ...
  ..- attr(*, "dimnames")=List of 2
  .. ..$ : chr [1:9] "dichot.fact" "X2" "X3" "X4" ...
  .. ..$ : chr [1:9] "dichot.fact" "X2" "X3" "X4" ...
 $ n           : int 200
 $ tests       : num [1:9, 1:9] 0 NA NA NA NA NA NA NA NA 0 ...
  ..- attr(*, "dimnames")=List of 2
  .. ..$ : chr [1:9] "dichot.fact" "X2" "X3" "X4" ...
  .. ..$ : chr [1:9] "dichot.fact" "X2" "X3" "X4" ...
- attr(*, "class")= chr "hetcor"
```

The polychoric correlations

```
> round(poly.r$correlation,2)
```

	dichot.fact	X2	X3	X4	X5	X6	X7	X8	X9
t.fact	1.00	0.41	0.25	0.33	0.36	0.22	0.32	0.19	0.35
	0.41	1.00	0.44	0.19	0.33	0.32	0.31	0.52	0.45
	0.25	0.44	1.00	0.41	0.46	0.46	0.36	0.51	0.33
	0.33	0.19	0.41	1.00	0.29	0.44	0.28	0.26	0.19
	0.36	0.33	0.46	0.29	1.00	0.44	0.43	0.40	0.45
	0.22	0.32	0.46	0.44	0.44	1.00	0.26	0.31	0.38
	0.32	0.31	0.36	0.28	0.43	0.26	1.00	0.35	0.34
	0.19	0.52	0.51	0.26	0.40	0.31	0.35	1.00	0.17
	0.35	0.45	0.33	0.19	0.45	0.38	0.34	0.17	1.00

Polychor recovers the correlations (somewhat)

```
> round(latent$r - poly.r$correlations,2)
```

	V1	V2	V3	V4	V5	V6	V7	V8	V9
V1	0.00	-0.07	0.09	-0.03	-0.05	0.10	0.01	0.16	-0.01
V2	-0.07	0.00	-0.09	0.00	0.01	0.01	0.05	-0.07	-0.06
V3	0.09	-0.09	0.00	-0.01	-0.08	-0.03	-0.01	-0.13	-0.01
V4	-0.03	0.00	-0.01	0.00	0.03	-0.02	-0.01	0.01	0.08
V5	-0.05	0.01	-0.08	0.03	0.00	-0.03	-0.03	-0.15	-0.08
V6	0.10	0.01	-0.03	-0.02	-0.03	0.00	0.05	0.02	-0.03
V7	0.01	0.05	-0.01	-0.01	-0.03	0.05	0.00	0.01	0.03
V8	0.16	-0.07	-0.13	0.01	-0.15	0.02	0.01	0.00	0.04
V9	-0.01	-0.06	-0.01	0.08	-0.08	-0.03	0.03	0.04	0.00

But, the fits are worse

```
> fpc <- factor.pa(poly.r$correlations,1,n.obs=200)
```

```
> fpc
```

	V	PA1
1	1	0.50
2	2	0.63
3	3	0.70
4	4	0.50
5	5	0.68
6	6	0.60
7	7	0.56
8	8	0.59
9	9	0.56

	PA1
SS loadings	3.18

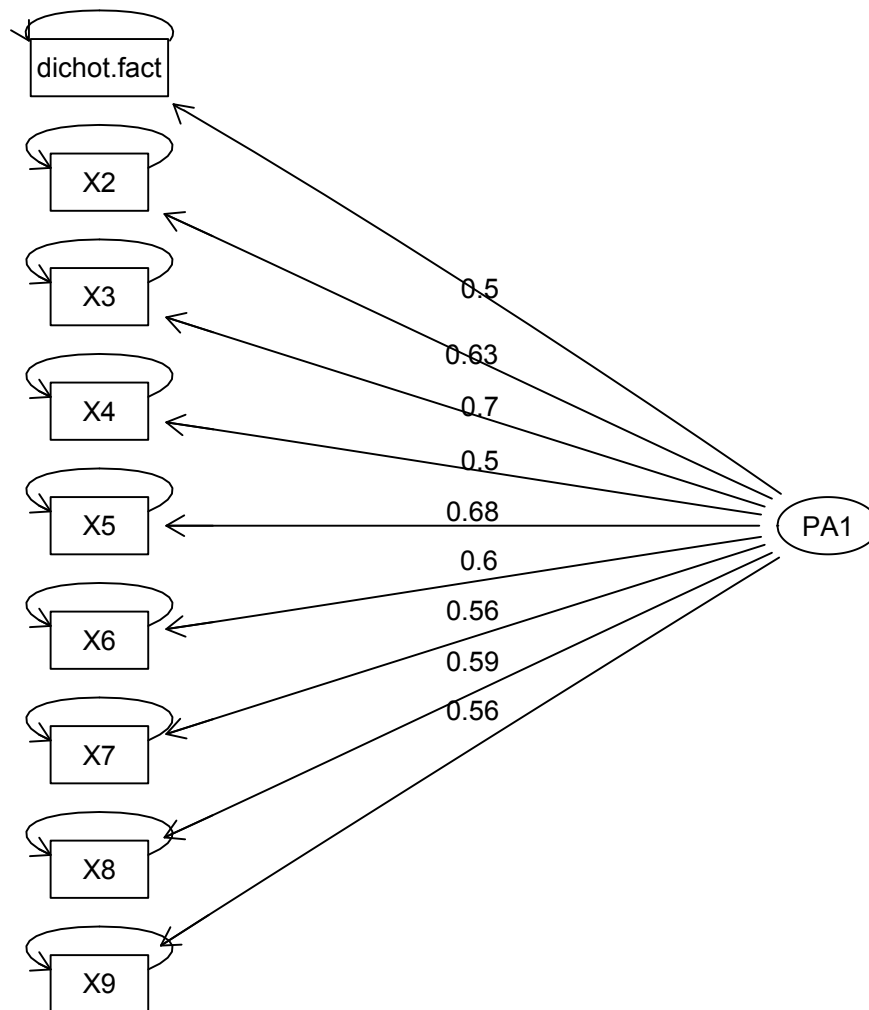
Proportion Var 0.35

Test of the hypothesis that 1 factor is sufficient.

The degrees of freedom for the model is 27 and the fit was 0.57

The number of observations was 200 with Chi Square = 111.24 with prob < 3.4e-12

principal factors of polychoric matrix



Structure of loadings

sem with polychorics

```
> sem.pc <- sem(mod.pc,poly.r$correlations,200)
> summary(sem.pc)
```

```
Model Chisquare = 113.67    Df = 27 Pr(>Chisq) =
1.3231e-12
Chisquare (null model) = 545.37    Df = 36
Goodness-of-fit index = 0.8996
Adjusted goodness-of-fit index = 0.83266
RMSEA index = 0.12701    90% CI: (0.10340, 0.15158)
Bentler-Bonnett NFI = 0.79157
Tucker-Lewis NNFI = 0.77313
Bentler CFI = 0.82985
SRMR = 0.068918
BIC = -29.384
Normalized Residuals
      Min.    1st Qu.    Median      Mean    3rd Qu.      Max.
-2.23e+00 -7.24e-01  9.55e-08  4.73e-03  6.85e-01  1.97e+00
```

Items differ in difficulty

```
> diff <- seq(-1,1,.25)
> diff
[1] -1.00 -0.75 -0.50 -0.25  0.00  0.25  0.50  0.75  1.00

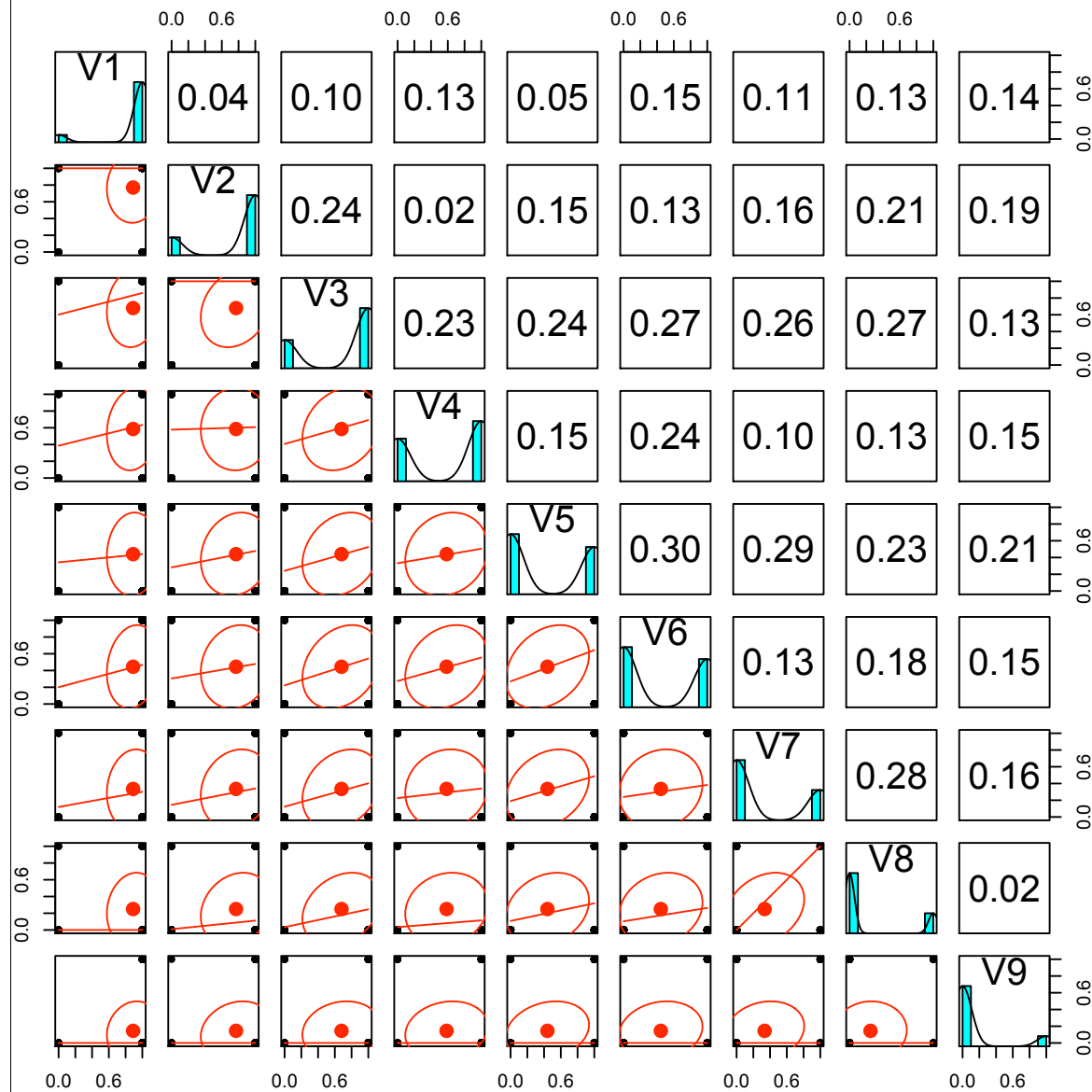
diff.dichot <- t((t(latent$observed)>diff) +0)

> describe(diff.dichot)
```

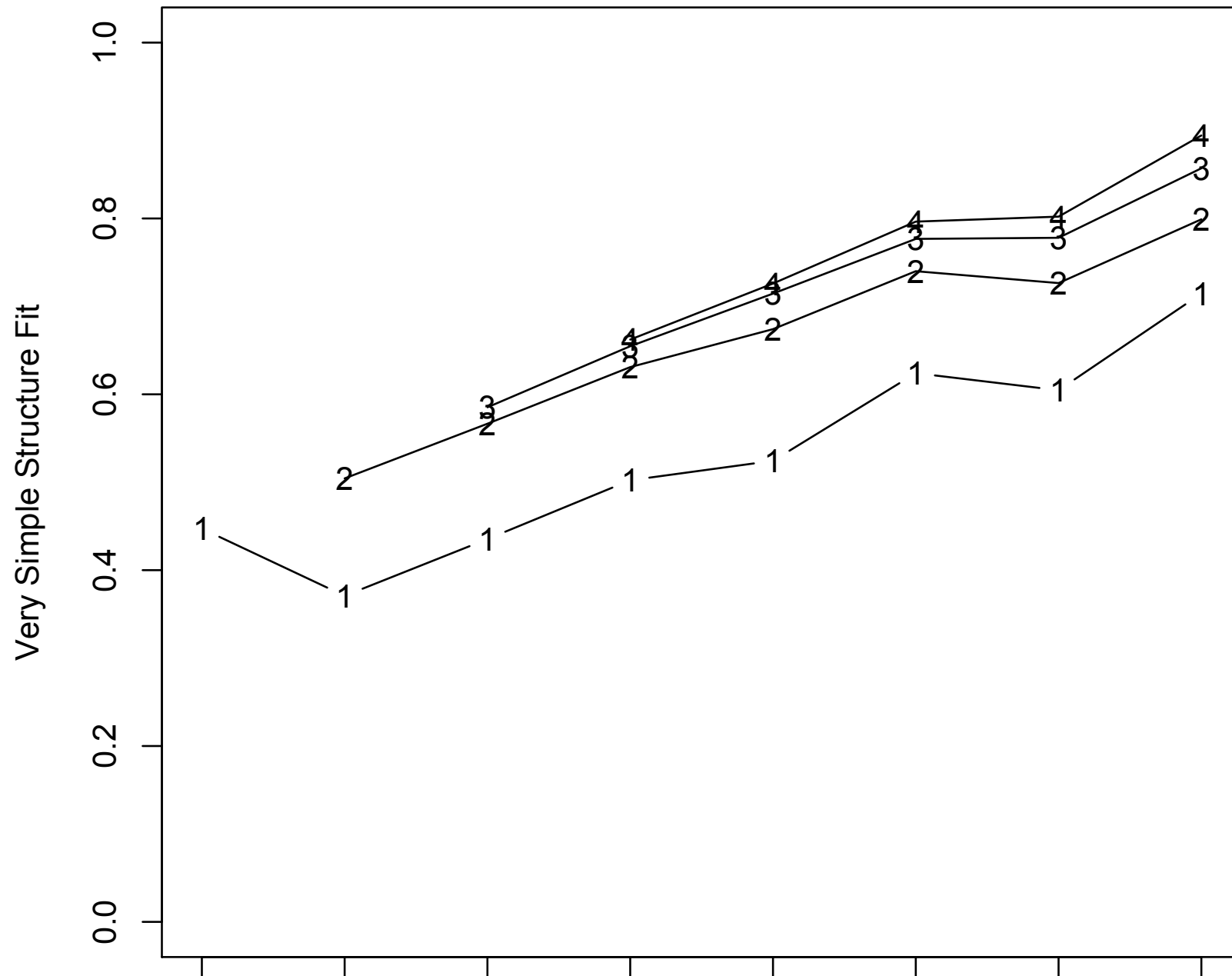
	var	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
V1	1	200	0.89	0.31	1	0.99	0	0	1	1	-2.47	4.14	0.02
V2	2	200	0.77	0.42	1	0.84	0	0	1	1	-1.27	-0.38	0.03
V3	3	200	0.68	0.47	1	0.72	0	0	1	1	-0.77	-1.42	0.03
V4	4	200	0.58	0.49	1	0.61	0	0	1	1	-0.34	-1.89	0.03
V5	5	200	0.44	0.50	0	0.42	0	0	1	1	0.24	-1.95	0.04
V6	6	200	0.44	0.50	0	0.43	0	0	1	1	0.22	-1.96	0.04
V7	7	200	0.34	0.47	0	0.29	0	0	1	1	0.69	-1.53	0.03
V8	8	200	0.25	0.43	0	0.19	0	0	1	1	1.15	-0.69	0.03
V9	9	200	0.14	0.35	0	0.06	0	0	1	1	2.00	2.02	0.02

```
>
```

The effect of difficulty on r



Very Simple Structure



MAP does a good job

```
> vss.dd
```

```
Very Simple Structure
```

```
VSS complexity 1 achieves a maximum of 0.71 with 8  
factors
```

```
VSS complexity 2 achieves a maximum of 0.8 with 8  
factors
```

```
The Velicer MAP criterion achieves a minimum of 1 with 1  
factors
```

```
Velicer MAP
```

```
[1] 0.02 0.04 0.07 0.12 0.18 0.26 0.45 1.00
```

```
Very Simple Structure Complexity 1
```

```
[1] 0.45 0.37 0.44 0.50 0.52 0.62 0.60 0.71
```

```
Very Simple Structure Complexity 2
```

```
[1] 0.00 0.50 0.57 0.63 0.67 0.74 0.73 0.80
```

Chi square

```
> vss.dd$vss.stats[,1:3]
dof          chisq          prob
1   27 2.716383e+01 0.4549829
2   19 1.808306e+01 0.5168968
3   12 9.767687e+00 0.6363331
4    6 7.077246e+00 0.3137626
5    1 2.690807e+00 0.1009287
6   -3 3.601937e-01      NA
7   -6 1.347089e-02      NA
8   -8 2.712477e-05      NA
```

```
factanal(x = diff.dichot, factors = 1)
```

```
Uniquenesses:
```

V1	V2	V3	V4	V5	V6	V7	V8	V9
0.946	0.880	0.698	0.882	0.730	0.776	0.782	0.790	0.902

```
Loadings:
```

	Factor1
V1	0.233
V2	0.347
V3	0.549
V4	0.344
V5	0.519
V6	0.473
V7	0.467
V8	0.458
V9	0.314

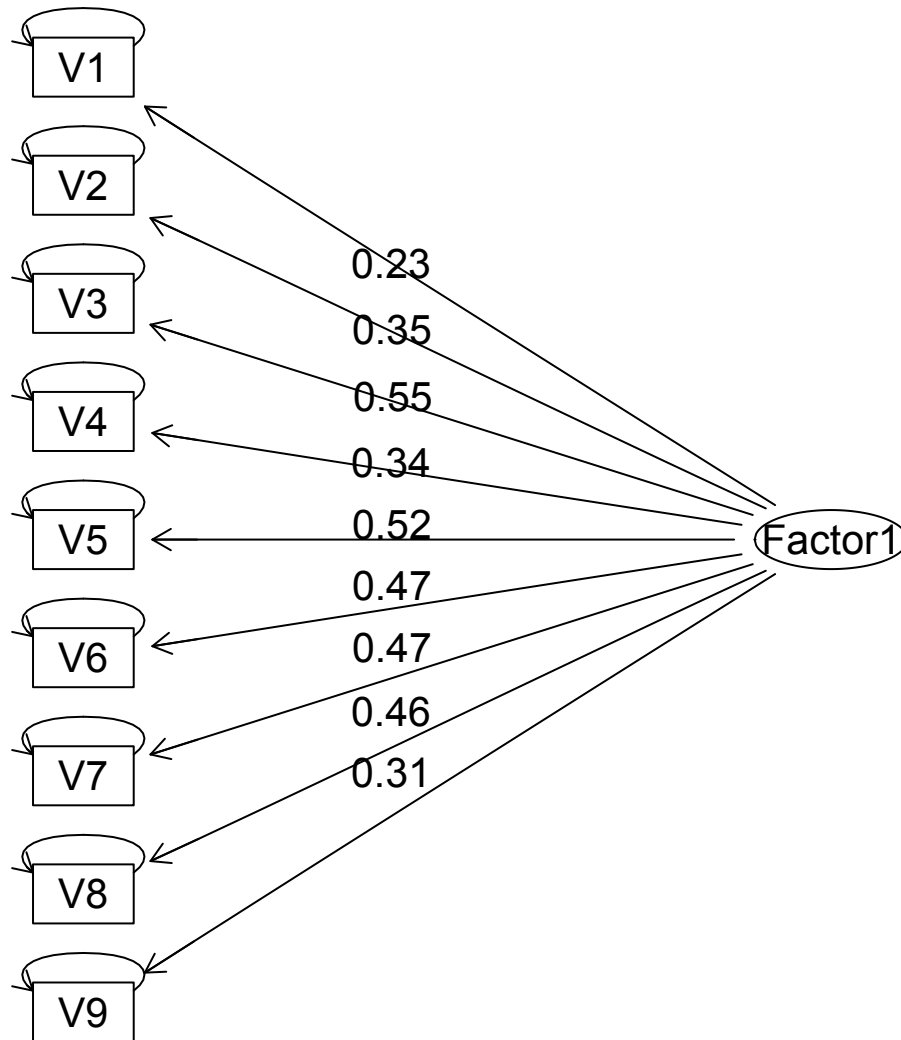
	Factor1
SS loadings	1.615
Proportion Var	0.179

Test of the hypothesis that 1 factor is sufficient.

The chi square statistic is 27.15 on 27 degrees of freedom.

The p-value is 0.456

dichotomous items differing in difficulty



The effect of difficulty

SEM of dichotomous items differing in difficulty

```
> summary(sem.dd)
```

```
Model Chisquare = 27.777    Df = 27 Pr(>Chisq) = 0.42255  
Chisquare (null model) = 167.01    Df = 36  
Goodness-of-fit index = 0.97115  
Adjusted goodness-of-fit index = 0.95192  
RMSEA index = 0.012024    90% CI: (NA, 0.057117)  
Bentler-Bonnett NFI = 0.83368  
Tucker-Lewis NNFI = 0.9921  
Bentler CFI = 0.99407  
SRMR = 0.045246  
BIC = -115.28
```

Try with polychorics

```
> dd.fact <- matrix(factor(diff.dichot),ncol=9)
> poly.dd <- hetcor(dd.fact)
```

Warning message:

```
In hetcor.data.frame(dframe, ML = ML, std.err = std.err, bins =
bins, :
```

the correlation matrix has been adjusted to make it positive-definite

```
> poly.dd
```

Two-Step Estimates

Correlations/Type of Correlation:										
	dd.fact	X2	X3	X4	X5	X6	X7	X8	X9	
dd.fact	1	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	
X2	0.1212	1	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	
X3	0.2133	0.3975	1	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	
X4	0.2657	0.04403	0.3618	1	Polychoric	Polychoric	Polychoric	Polychoric	Polychoric	
X5	0.1402	0.279	0.3955	0.2467	1	Polychoric	Polychoric	Polychoric	Polychoric	
X6	0.3228	0.2216	0.4363	0.3788	0.4518	1	Polychoric	Polychoric	Polychoric	
X7	0.2649	0.3024	0.4521	0.1696	0.4492	0.2124	1	Polychoric	Polychoric	
X8	0.3055	0.413	0.5225	0.2294	0.3699	0.3096	0.4474	1	Polychoric	
X9	0.8024	0.4893	0.2776	0.2835	0.3618	0.2926	0.2996	0.0982	1	

Some polychors are bad

```
> round(poly.dd$correlations,2)
```

	dd.fact	X2	X3	X4	X5	X6	X7	X8	X9
dd.fact	1.00	0.12	0.21	0.27	0.14	0.32	0.26	0.31	0.80
X2	0.12	1.00	0.40	0.04	0.28	0.22	0.30	0.41	0.49
X3	0.21	0.40	1.00	0.36	0.40	0.44	0.45	0.52	0.28
X4	0.27	0.04	0.36	1.00	0.25	0.38	0.17	0.23	0.28
X5	0.14	0.28	0.40	0.25	1.00	0.45	0.45	0.37	0.36
X6	0.32	0.22	0.44	0.38	0.45	1.00	0.21	0.31	0.29
X7	0.26	0.30	0.45	0.17	0.45	0.21	1.00	0.45	0.30
X8	0.31	0.41	0.52	0.23	0.37	0.31	0.45	1.00	0.10
X9	0.80	0.49	0.28	0.28	0.36	0.29	0.30	0.10	1.00

Compare to original sample

```
> round(latent$r-poly.dd$correlations,2)
```

	V1	V2	V3	V4	V5	V6	V7	V8	V9
V1	0.00	0.22	0.13	0.04	0.17	-0.01	0.07	0.05	-0.46
V2	0.22	0.00	-0.05	0.15	0.06	0.12	0.06	0.04	-0.09
V3	0.13	-0.05	0.00	0.04	-0.02	-0.01	-0.11	-0.15	0.04
V4	0.04	0.15	0.04	0.00	0.07	0.04	0.11	0.05	-0.01
V5	0.17	0.06	-0.02	0.07	0.00	-0.04	-0.06	-0.12	0.01
V6	-0.01	0.12	-0.01	0.04	-0.04	0.00	0.10	0.02	0.06
V7	0.07	0.06	-0.11	0.11	-0.06	0.10	0.00	-0.08	0.07
V8	0.05	0.04	-0.15	0.05	-0.12	0.02	-0.08	0.00	0.12
V9	-0.46	-0.09	0.04	-0.01	0.01	0.06	0.07	0.12	0.00

```

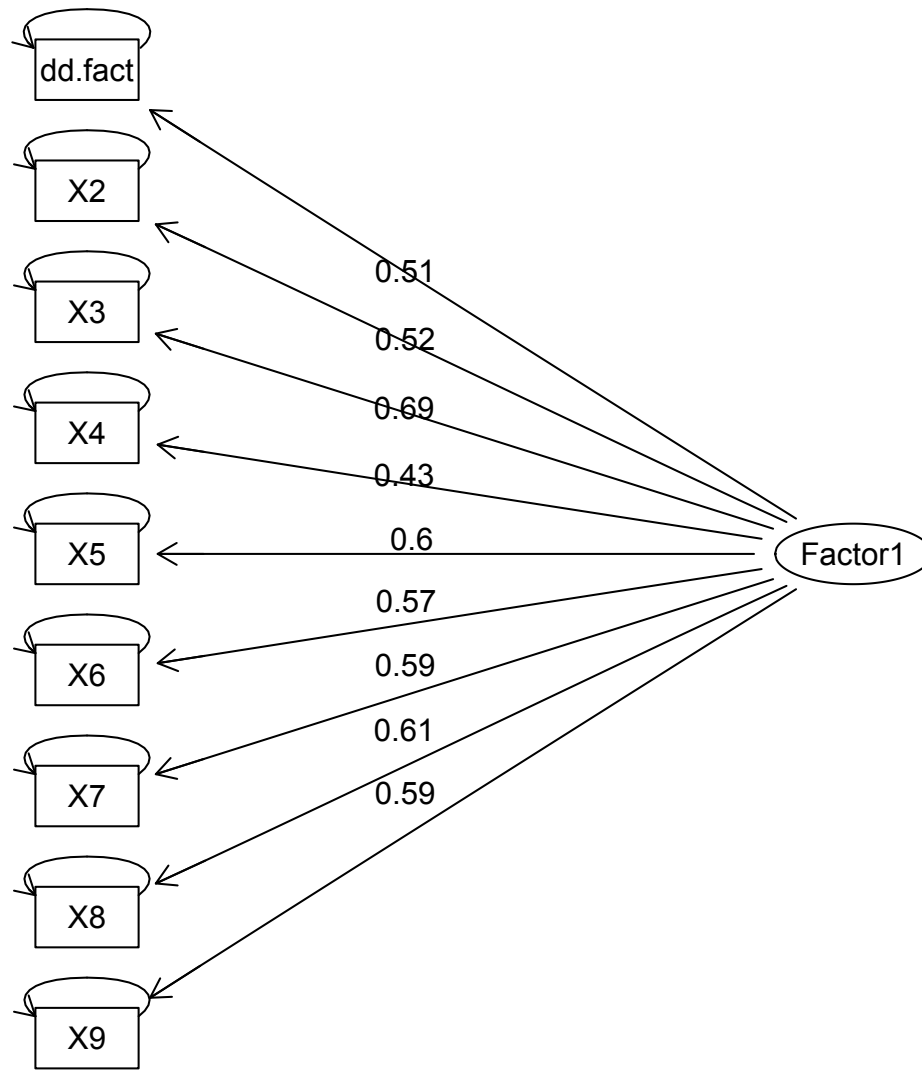
factanal(factors = 1, covmat = poly.dd$correlations, n.obs =
dd.fact      X2      X3      X4      X5      X6      X7
X9
    0.735    0.728    0.524    0.814    0.635    0.673    0.650    0.
0.653
Loadings:
      Factor1
dd.fact 0.514
X2      0.522
X3      0.690
X4      0.432
X5      0.604
X6      0.572
X7      0.592
X8      0.607
X9      0.589

      Factor1
SS loadings      2.958
Proportion Var   0.329
Test of the hypothesis that 1 factor is sufficient.
The chi square statistic is 3178.95 on 27 degrees of freedom
The p-value is 0

```

factanal

polychoric structure of items differing in difficulty



Factors
recover
structure

But fit is terrible!

```
Model Chisquare = 3252.5    Df = 27 Pr(>Chisq) = 0
Chisquare (null model) = 3635.7    Df = 36
Goodness-of-fit index = 0.7789
Adjusted goodness-of-fit index = 0.63149
RMSEA index = 0.7748    90% CI: (NA, NA)
Bentler-Bonnett NFI = 0.10539
Tucker-Lewis NNFI = -0.19474
Bentler CFI = 0.10395
SRMR = 0.11425
BIC = 3109.4
```

Parameters are fine!

Parameter Estimates

	Estimate	Std Error	z value	Pr(> z)	
dd.fact	0.51449	0.078937	6.5177	7.1372e-11	dd.fact <--- Factor1
X2	0.52201	0.073263	7.1251	1.0396e-12	X2 <--- Factor1
X3	0.68994	0.070252	9.8209	0.0000e+00	X3 <--- Factor1
X4	0.43166	0.074963	5.7584	8.4930e-09	X4 <--- Factor1
X5	0.60444	0.071100	8.5012	0.0000e+00	X5 <--- Factor1
X6	0.57186	0.071986	7.9441	1.9984e-15	X6 <--- Factor1
X7	0.59192	0.071588	8.2683	2.2204e-16	X7 <--- Factor1
X8	0.60726	0.072851	8.3356	0.0000e+00	X8 <--- Factor1
X9	0.58886	0.077977	7.5518	4.2855e-14	X9 <--- Factor1
x1e	0.73530	0.086127	8.5374	0.0000e+00	dd.fact <--> dd.fact
x2e	0.72751	0.080257	9.0647	0.0000e+00	X2 <--> X2
x3e	0.52398	0.069762	7.5109	5.8620e-14	X3 <--> X3
x4e	0.81367	0.086306	9.4277	0.0000e+00	X4 <--> X4
x5e	0.63465	0.073724	8.6085	0.0000e+00	X5 <--> X5
x6e	0.67297	0.076378	8.8111	0.0000e+00	X6 <--> X6
x7e	0.64963	0.074946	8.6681	0.0000e+00	X7 <--> X7
x8e	0.63123	0.076089	8.2960	0.0000e+00	X8 <--> X8
x9e	0.65324	0.083448	7.8281	4.8850e-15	X9 <--> X9

Conclusions about items

- No easy answers
- Need to examine factors, correlations, scatter plots, fits, residuals, etc.
- Consider different ways of analyzing the data