

## More on reliability

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## Outline

### 1 Types of reliability

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### 2 Calculating reliabilities

- Congeneric measures
- Hierarchical structures

### 3 $2 \neq 1$

- Multiple dimensions - falsely labeled as one
- Using score.items to find reliabilities of multiple scales

### 4 Intraclass correlations

- ICC of judges

### 5 Kappa

- Cohen's kappa
- Weighted kappa



# Types of reliability

- Internal consistency
    - $\alpha$
    - $\omega_{hierarchical}$
    - $\omega_{total}$
    - $\beta$
  - Intraclass
  - Agreement
  - Test-retest, alternate form
  - Generalizability
- 
- Internal consistency
    - alpha,
    - score.items
    - omega
    - iclust
  - icc
  - wkappa,  
cohen.kappa
  - cor
  - aov



## Alpha and its alternatives

## Alpha and its alternatives

- Reliability =  $\frac{\sigma_t^2}{\sigma_x^2} = 1 - \frac{\sigma_e^2}{\sigma_x^2}$
- If there is another test, then  $\sigma_t = \sigma_{t_1 t_2}$  (covariance of test  $X_1$  with test  $X_2 = C_{xx}$ )
- But, if there is only one test, we can estimate  $\sigma_t^2$  based upon the observed covariances within test 1
- How do we find  $\sigma_e^2$  ?
- The worst case, (Guttman case 1) all of an item's variance is error and thus the error variance of a test X with variance-covariance  $C_x$ 
  - $C_x = \sigma_e^2 = \text{diag}(C_x)$
  - $\lambda_1 = \frac{C_x - \text{diag}(C_x)}{C_x}$
- A better case (Guttman case 3,  $\alpha$ ) is that the average covariance between the items on the test is the same as the average true score variance for each item.
  - $C_x = \sigma_e^2 = \text{diag}(C_x)$
  - $\lambda_3 = \alpha = \lambda_1 * \frac{n}{n-1} = \frac{(C_x - \text{diag}(C_x)) * n / (n-1)}{C_x}$



## Guttman 6: estimating using the Squared Multiple Correlation

- Reliability =  $\frac{\sigma_t^2}{\sigma_x^2} = 1 - \frac{\sigma_e^2}{\sigma_x^2}$
- Estimate true item variance as squared multiple correlation with other items
- $\lambda_6 = \frac{(C_x - \text{diag}(C_x) + \Sigma(\text{smc}_i))}{C_x}$ 
  - This takes observed covariance, subtracts the diagonal, and replaces with the squared multiple correlation
  - Similar to  $\alpha$  which replaces with average inter-item covariance
- Squared Multiple Correlation is found by smc and is just  $\text{smc}_i = 1 - 1/R_{ii}^{-1}$



## Congeneric measures

## Alpha and its alternatives: Case 1: congeneric measures

First, create some simulated data with a known structure

```
> set.seed(42)
> v4 <- sim.congeneric(N=200,short=FALSE)
> str(v4) #show the structure of the resulting object
List of 6
$ model   : num [1:4, 1:4] 1 0.56 0.48 0.4 0.56 1 0.42 0.35 0.48 0.42 ...
..- attr(*, "dimnames")=List of 2
... $ : chr [1:4] "V1" "V2" "V3" "V4"
... $ : chr [1:4] "V1" "V2" "V3" "V4"
$ pattern : num [1:4, 1:5] 0.8 0.7 0.6 0.5 0.6 ...
..- attr(*, "dimnames")=List of 2
... $ : chr [1:4] "V1" "V2" "V3" "V4"
... $ : chr [1:5] "theta" "e1" "e2" "e3" ...
$ r       : num [1:4, 1:4] 1 0.546 0.466 0.341 0.546 ...
..- attr(*, "dimnames")=List of 2
... $ : chr [1:4] "V1" "V2" "V3" "V4"
... $ : chr [1:4] "V1" "V2" "V3" "V4"
$ latent  : num [1:200, 1:5] 1.371 -0.565 0.363 0.633 0.404 ...
..- attr(*, "dimnames")=List of 2
... $ : NULL
... $ : chr [1:5] "theta" "e1" "e2" "e3" ...
$ observed: num [1:200, 1:4] -0.104 -0.251 0.993 1.742 -0.503 ...
..- attr(*, "dimnames")=List of 2
... $ : NULL
... $ : chr [1:4] "V1" "V2" "V3" "V4"
$ N       : num 200
- attr(*, "class")= chr [1:2] "psych" "sim"
```

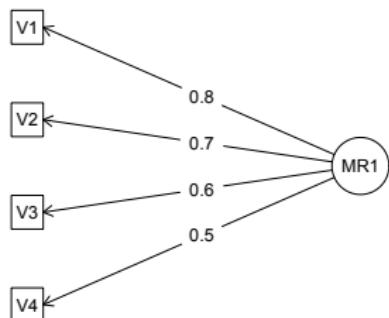


## Congeneric measures

## A congeneric model

```
> f1 <- fa(v4$model)
> fa.diagram(f1)
```

Factor Analysis



&gt; v4\$model

	V1	V2	V3	V4
V1	1.00	0.56	0.48	0.40
V2	0.56	1.00	0.42	0.35
V3	0.48	0.42	1.00	0.30
V4	0.40	0.35	0.30	1.00

&gt; round(cor(v4\$observed), 2)

	V1	V2	V3	V4
V1	1.00	0.55	0.47	0.34
V2	0.55	1.00	0.38	0.30
V3	0.47	0.38	1.00	0.31
V4	0.34	0.30	0.31	1.00



## Congeneric measures

Find  $\alpha$  and related stats for the simulated data

```
> alpha(v4$observed)
```

Reliability analysis

```
Call: alpha(x = v4$observed)
```

	raw_alpha	std.alpha	G6(smc)	average_r	mean	sd
	0.71	0.72	0.67	0.39	-0.036	0.72

Reliability if an item is dropped:

	raw_alpha	std.alpha	G6(smc)	average_r
V1	0.59	0.60	0.50	0.33
V2	0.63	0.64	0.55	0.37
V3	0.65	0.66	0.59	0.40
V4	0.72	0.72	0.64	0.46

Item statistics

	n	r	r.cor	r.drop	mean	sd
V1	200	0.80	0.72	0.60	-0.015	0.93
V2	200	0.76	0.64	0.53	-0.060	0.98
V3	200	0.73	0.59	0.50	-0.119	0.92
V4	200	0.66	0.46	0.40	0.049	1.09

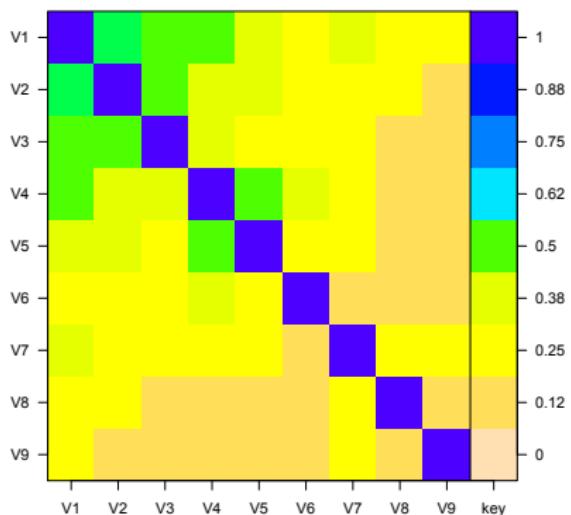


## Hierarchical structures

## A hierarchical structure

cor.plot(r9)

Correlation plot



```
> set.seed(42)
> r9 <- sim.hierarchical()
> round(r9,2)
```

	V1	V2	V3	V4	V5	V6	V7	V8	V9
V1	1.00	0.56	0.48	0.40	0.35	0.29	0.30	0.25	0.20
V2	0.56	1.00	0.42	0.35	0.30	0.25	0.26	0.22	0.18
V3	0.48	0.42	1.00	0.30	0.26	0.22	0.23	0.19	0.15
V4	0.40	0.35	0.30	1.00	0.42	0.35	0.24	0.20	0.16
V5	0.35	0.30	0.26	0.42	1.00	0.30	0.20	0.17	0.13
V6	0.29	0.25	0.22	0.35	0.30	1.00	0.17	0.14	0.11
V7	0.30	0.26	0.23	0.24	0.20	0.17	1.00	0.30	0.24
V8	0.25	0.22	0.19	0.20	0.17	0.14	0.30	1.00	0.20
V9	0.20	0.18	0.15	0.16	0.13	0.11	0.24	0.20	1.00



## Hierarchical structures

 $\alpha$  of the 9 hierarchical variables

```
> alpha(r9)
```

Reliability analysis

Call: alpha(x = r9)

	raw_alpha	std.alpha	G6(smc)	average_r
	0.76	0.76	0.76	0.26

Reliability if an item is dropped:

	raw_alpha	std.alpha	G6(smc)	average_r
V1	0.71	0.71	0.70	0.24
V2	0.72	0.72	0.71	0.25
V3	0.74	0.74	0.73	0.26
V4	0.73	0.73	0.72	0.25
V5	0.74	0.74	0.73	0.26
V6	0.75	0.75	0.74	0.27
V7	0.75	0.75	0.74	0.27
V8	0.76	0.76	0.75	0.28
V9	0.77	0.77	0.76	0.29

Item statistics

r r.cor

V1 0.72 0.71

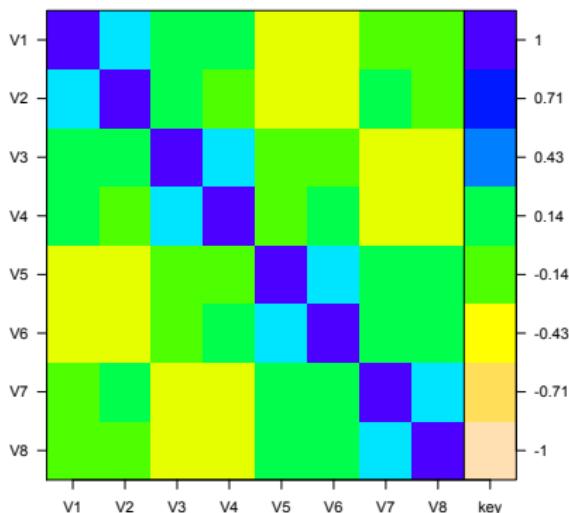
V2 0.67 0.68



Multiple dimensions - falsely labeled as one

## An example of two different scales confused as one

Correlation plot



```
> set.seed(17)
> two.f <- sim.item(8)
> round(cor(two.f),2)
```

	V1	V2	V3	V4	V5	V6	V7	V8
V1	1.00	0.29	0.05	0.03	-0.38	-0.38	-0.06	-0.08
V2	0.29	1.00	0.03	-0.02	-0.35	-0.33	0.02	-0.04
V3	0.05	0.03	1.00	0.34	-0.02	-0.10	-0.40	-0.39
V4	0.03	-0.02	0.34	1.00	-0.01	0.06	-0.36	-0.37
V5	-0.38	-0.35	-0.02	-0.01	1.00	0.33	0.03	0.05
V6	-0.38	-0.33	-0.10	0.06	0.33	1.00	0.04	0.03
V7	-0.06	0.02	-0.40	-0.36	0.03	0.04	1.00	0.37
V8	-0.08	-0.04	-0.39	-0.37	0.05	0.03	0.37	1.00

```
> cor.plot(cor(two.f),zlim=c(-1,1),colors=TRUE)
```



Multiple dimensions - falsely labeled as one

## α of two scales confused as one

Note the use of the keys parameter to specify how some items should be reversed.

```
> alpha(two.f,keys=c(rep(1,4),rep(-1,4)))
```

Reliability analysis

```
Call: alpha(x = two.f, keys = c(rep(1, 4), rep(-1, 4)))
```

	raw_alpha	std.alpha	G6(smc)	average_r	mean	sd
	0.62	0.62	0.65	0.17	-0.0051	0.27

Reliability if an item is dropped:

	raw_alpha	std.alpha	G6(smc)	average_r
V1	0.59	0.58	0.61	0.17
V2	0.61	0.60	0.63	0.18
V3	0.58	0.58	0.60	0.16
V4	0.60	0.60	0.62	0.18
V5	0.59	0.59	0.61	0.17
V6	0.59	0.59	0.61	0.17
V7	0.58	0.58	0.61	0.17
V8	0.58	0.58	0.60	0.16

Item statistics

	n	r	r.cor	r.drop	mean	sd
V1	500	0.54	0.44	0.33	0.063	1.01
V2	500	0.48	0.35	0.26	0.070	0.95
V3	500	0.56	0.47	0.36	-0.030	1.01
V4	500	0.48	0.37	0.28	-0.130	0.97
V5	500	0.52	0.42	0.31	-0.073	0.97
V6	500	0.52	0.41	0.31	-0.071	0.95
V7	500	0.53	0.44	0.34	0.035	1.00
V8	500	0.56	0.47	0.36	0.097	1.02



Using score.items to find reliabilities of multiple scales

## Score as two different scales

First, make up a keys matrix to specify which items should be scored, and in which way

```
> keys <- make.keys(nvars=8,keys.list=list(one=c(1,2,-5,-6),two=c(3,4,-7,-8)))  
> keys
```

	one	two
[1,]	1	0
[2,]	1	0
[3,]	0	1
[4,]	0	1
[5,]	-1	0
[6,]	-1	0
[7,]	0	-1
[8,]	0	-1



Using score.items to find reliabilities of multiple scales

## Now score the two scales and find $\alpha$ and other reliability estimates

```
> score.items(keys,two.f)
Call: score.items(keys = keys, items = two.f)
(Unstandardized) Alpha:
  one two
alpha 0.68 0.7
Average item correlation:
  one two
average.r 0.34 0.37
Guttman 6* reliability:
  one two
Lambda.6 0.62 0.64
Scale intercorrelations corrected for attenuation
  raw correlations below the diagonal, alpha on the diagonal
  corrected correlations above the diagonal:
  one two
one 0.68 0.08
two 0.06 0.70
Item by scale correlations:
  corrected for item overlap and scale reliability
  one two
V1  0.57  0.09
V2  0.52  0.01
V3  0.09  0.59
V4 -0.02  0.56
V5 -0.58 -0.05
V6 -0.57 -0.05
V7 -0.05 -0.58
V8 -0.09 -0.59
```



## Reliability of judges

- When raters (judges) rate targets, there are multiple sources of variance
  - Between targets
  - Between judges
  - Interaction of judges and targets
- The intraclass correlation is an analysis of variance decomposition of these components
- Different ICC's depending upon what is important to consider
  - Absolute scores: each target gets just one judge, and judges differ
  - Relative scores: each judge rates multiple targets, and the mean for the judge is removed
  - Each judge rates multiple targets, judge and target effects removed



ICC of judges

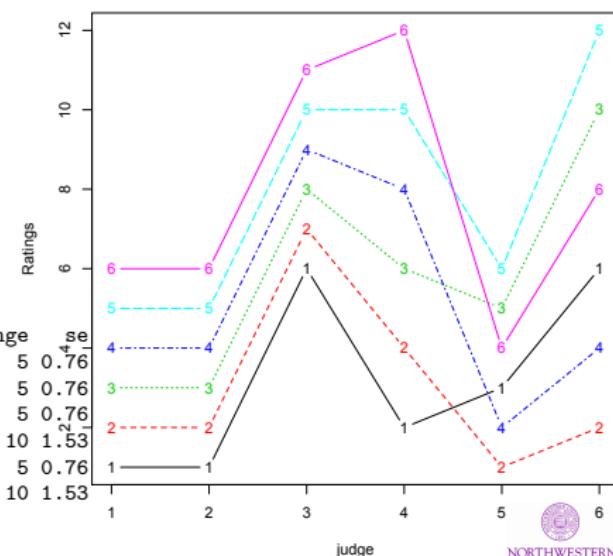
## Ratings of judges

What is the reliability of ratings of different judges across ratees?  
 It depends. Depends upon the pairing of judges, depends upon the targets. ICC does an Anova decomposition.

```
> Ratings
  J1 J2 J3 J4 J5 J6
1  1  1  6  2  3  6
2  2  2  7  4  1  2
3  3  3  8  6  5 10
4  4  4  9  8  2  4
5  5  5 10 10  6 12
6  6  6 11 12  4  8
```

```
> describe(Ratings, skew=FALSE)
```

	n	mean	sd	median	trimmed	mad	min	max	range	se
J1	1	6	3.5	1.87	3.5	3.5	2.22	1	6	5 0.76
J2	2	6	3.5	1.87	3.5	3.5	2.22	1	6	5 0.76
J3	3	6	8.5	1.87	8.5	8.5	2.22	6	11	5 0.76
J4	4	6	7.0	3.74	7.0	7.0	4.45	2	12	10 1.53
J5	5	6	3.5	1.87	3.5	3.5	2.22	1	6	5 0.76
J6	6	6	7.0	3.74	7.0	7.0	4.45	2	12	10 1.53

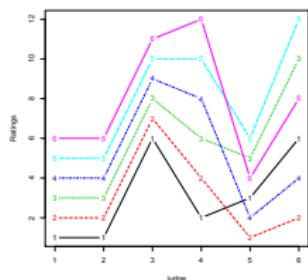


ICC of judges

## Sources of variances and the Intraclass Correlation Coefficient

Table: Sources of variances and the Intraclass Correlation Coefficient.

	(J1, J2)	(J3, J4)	(J5, J6)	(J1, J3)	(J1, J5)	(J1 ... J3)	(J1 ... J4)	(J1 ... J6)
Variance estimates								
$MS_b$	7	15.75	15.75	7.0	5.2	10.50	21.88	21.88
$MS_w$	0	2.58	7.58	12.5	1.5	8.33	7.12	7.12
$MS_j$	0	6.75	36.75	75.0	0.0	50.00	38.38	38.38
$MS_e$	0	1.75	1.75	0.0	1.8	0.00	.88	.88
Intraclass correlations								
ICC(1,1)	1.00	.72	.35	-.28	.55	.08	.34	.34
ICC(2,1)	1.00	.73	.48	.22	.53	.30	.42	.42
ICC(3,1)	1.00	.80	.80	1.00	.49	1.00	.86	.86
ICC(1,k)	1.00	.84	.52	-.79	.71	.21	.67	.67
ICC(2,k)	1.00	.85	.65	.36	.69	.56	.75	.75
ICC(3,k)	1.00	.89	.89	1.00	.65	1.00	.96	.96



ICC of judges

# ICC is done by calling anova

```
aov.x <- aov(values ~ subs + ind, data = x.df)
s.aov <- summary(aov.x)
stats <- matrix(unlist(s.aov), ncol = 3, byrow = TRUE)
MSB <- stats[3, 1]
MSW <- (stats[2, 2] + stats[2, 3])/(stats[1, 2] + stats[1,
3])
MSJ <- stats[3, 2]
MSE <- stats[3, 3]
ICC1 <- (MSB - MSW)/(MSB + (nj - 1) * MSW)
ICC2 <- (MSB - MSE)/(MSB + (nj - 1) * MSE + nj * (MSJ - MSE)/n.obs)
ICC3 <- (MSB - MSE)/(MSB + (nj - 1) * MSE)
ICC12 <- (MSB - MSW)/(MSB)
ICC22 <- (MSB - MSE)/(MSB + (MSJ - MSE)/n.obs)
ICC32 <- (MSB - MSE)/MSB
```



ICC of judges

# Intraclass Correlations using the ICC function

```
> print(ICC(Ratings),all=TRUE)    #get more output than normal
$results
      type   ICC     F df1 df2     p lower bound upper bound
Single_raters_absolute  ICC1 0.32  3.84    5 30 0.01      0.04      0.79
Single_random_raters    ICC2 0.37 10.37    5 25 0.00      0.09      0.80
Single_fixed_raters     ICC3 0.61 10.37    5 25 0.00      0.28      0.91
Average_raters_absolute ICC1k 0.74  3.84    5 30 0.01      0.21      0.96
Average_random_raters  ICC2k 0.78 10.37    5 25 0.00      0.38      0.96
Average_fixed_raters   ICC3k 0.90 10.37    5 25 0.00      0.70      0.98

$summary
        Df  Sum Sq Mean Sq F value    Pr(>F)
subs      5 141.667 28.3333 10.366 1.801e-05 ***
ind       5 153.000 30.6000 11.195 9.644e-06 ***
Residuals 25  68.333  2.7333
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1  . 1

$stats
      [,1]      [,2]      [,3]
[1,] 5.000000e+00 5.000000e+00 25.000000
[2,] 1.416667e+02 1.530000e+02 68.333333
[3,] 2.833333e+01 3.060000e+01  2.733333
[4,] 1.036585e+01 1.119512e+01      NA
[5,] 1.800581e-05 9.644359e-06      NA

$MSW
[1] 7.377778

$Call
ICC(x = Ratings)
```



## Cohen's kappa

## Cohen's kappa and weighted kappa

- When considering agreement in diagnostic categories, without numerical values, it is useful to consider the kappa coefficient.
  - Emphasizes matches of ratings
  - Doesn't consider how far off disagreements are.
- Weighted kappa weights the off diagonal distance.
- Diagnostic categories: normal, neurotic, psychotic



Weighted kappa

## Cohen kappa and weighted kappa

```
> cohen
     [,1] [,2] [,3]
[1,] 0.44 0.07 0.09
[2,] 0.05 0.20 0.05
[3,] 0.01 0.03 0.06
> cohen.weights
     [,1] [,2] [,3]
[1,]    0    1    3
[2,]    1    0    6
[3,]    3    6    0
> cohen.kappa(cohen,cohen.weights)
Call: cohen.kappa1(x = x, w = w, n.obs = n.obs, alpha = alpha)
```

Cohen Kappa and Weighted Kappa correlation coefficients and confidence boundaries

	lower	estimate	upper
unweighted kappa	-0.92	0.49	1.9
weighted kappa	-10.04	0.35	10.7

see the other examples in ?cohen.kappa

