Parsimonious Mixed Models

Reinhold Kliegl, ATTLIS 2016, University of Potsdam, 11-03-2016

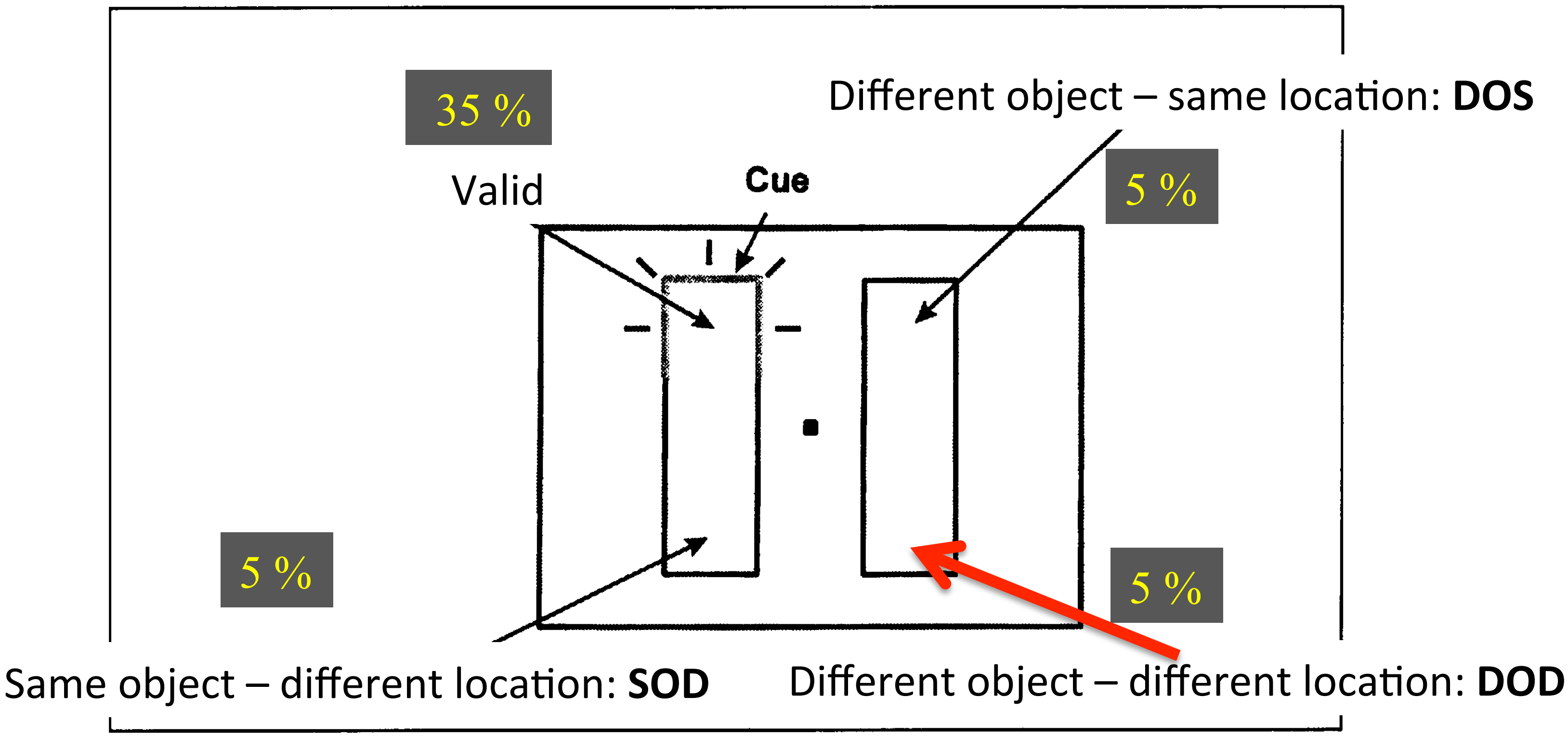
Part 1: Factorial-design experiments

- Fixed effects
- Variance components / correlation parameters ("random effects")
  - Alternative statistics (F1/F2, unbalanced data), …
  - … but what do they represent substantially?
- Parsimonious mixed model (vs. maximal models)
  - Not overparameterized (degenerate, singular)
  - Supported by available data (tradeoff w/ statistical assumptions)
- > library(RePsychLing); # KWDYZ, KKL vignettes

Part 2: Factorial-design exps + within-factor covariates

(Example: Rapid Automatized Naming; not in lecture)

Visual Attention



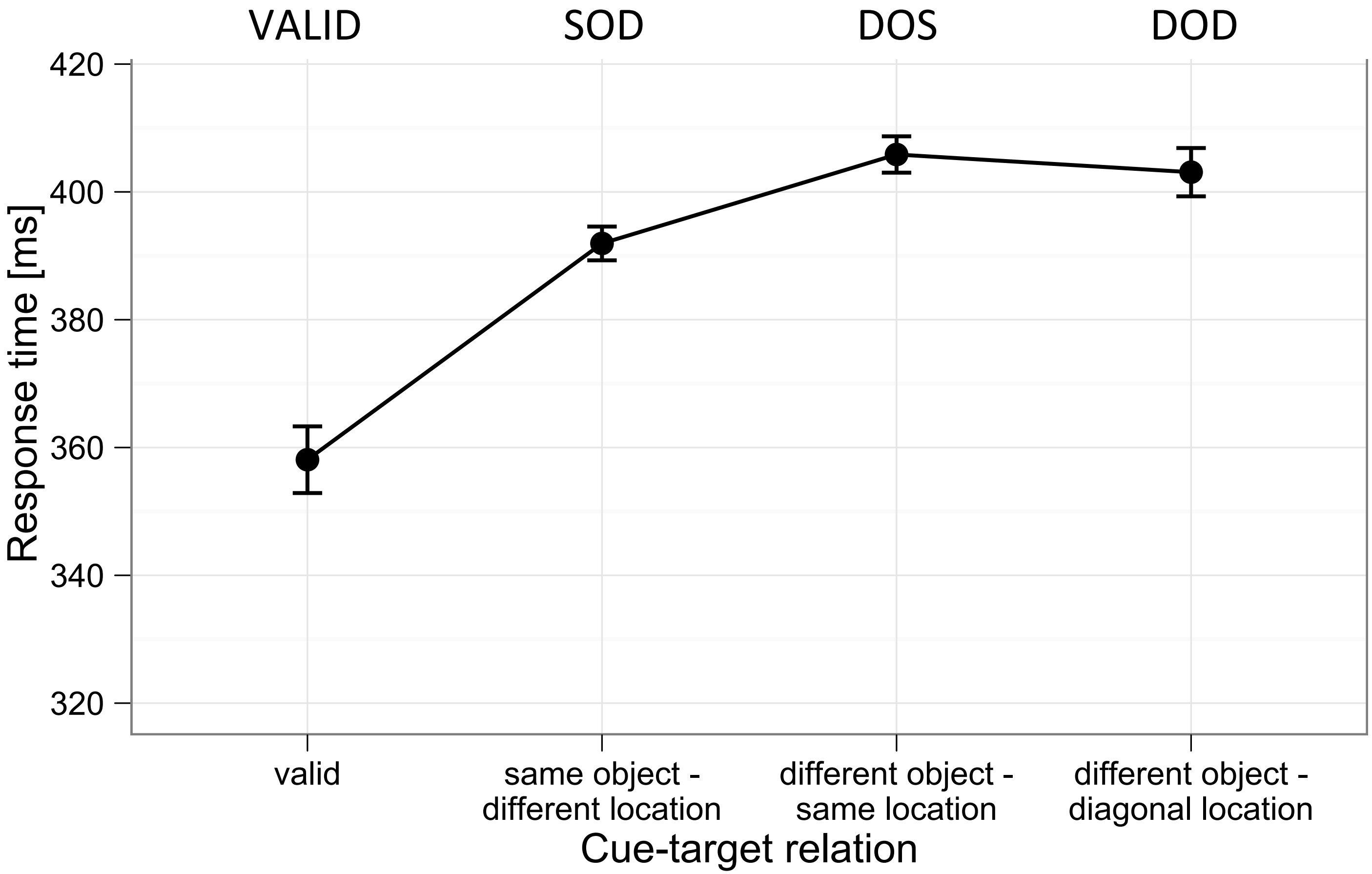
Other 50 % of trials with bars in horizontal direction

Fig. 1. Cartoon of the type of display and conditions that were used by Egly, Driver, and Rafal (1994) and in the present study (Experiment 1, no-occluder condition).

(Kliegl, Wei, Dambacher, Yan, & Zhou, 2011)

Visual Attention: The Power of Planned Comparisons

(1) Spatial effect = SOD − VALID
(2) Object effect = [DOS − VALID] − [SOD − VALID] = DOS − SOD
(3) Attraction effect = [DOS − VALID] − [DOD − VALID]) = DOS − DOD



(Kliegl, Wei, Dambacher, Yan, & Zhou, 2011)

Linear Mixed Model (maximal)

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: rt ~ 1 + c1 + c2 + c3 + (1 + c1 + c2 + c3 | subj)
   Data: KWDYZ

      AIC       BIC    logLik  deviance  df.resid
 325839.5  325963.5 -162904.8  325809.5     28695

Scaled residuals:
    Min      1Q  Median      3Q     Max
-4.4945 -0.5641 -0.0836  0.4617  5.6038

Random effects:
 Groups   Name        Variance Std.Dev. Corr
 subj     (Intercept) 3047.07  55.20
          c1           540.48  23.25     0.60
          c2           115.65  10.75    -0.13 -0.01
          c3            90.44   9.51    -0.25 -0.85  0.36
 Residual             4876.90  69.83
Number of obs: 28710, groups:  subj, 61

Fixed effects:
            Estimate Std. Error t value
(Intercept)  389.734      7.091   54.96
c1            33.782      3.287   10.28
c2            13.985      2.306    6.07
c3             2.747      2.214    1.24

Correlation of Fixed Effects:
   (Intr) c1     c2
c1  0.561
c2 -0.078 -0.229
c3 -0.136 -0.422  0.456
```

1. Fixed effects

Things to be clear about …

- **Fixed-effect coefficients in the LMM**
  - What does “(Intercept)” mean?
    Recommended: *Grand Mean* (i.e., estim. of mean of condition means)

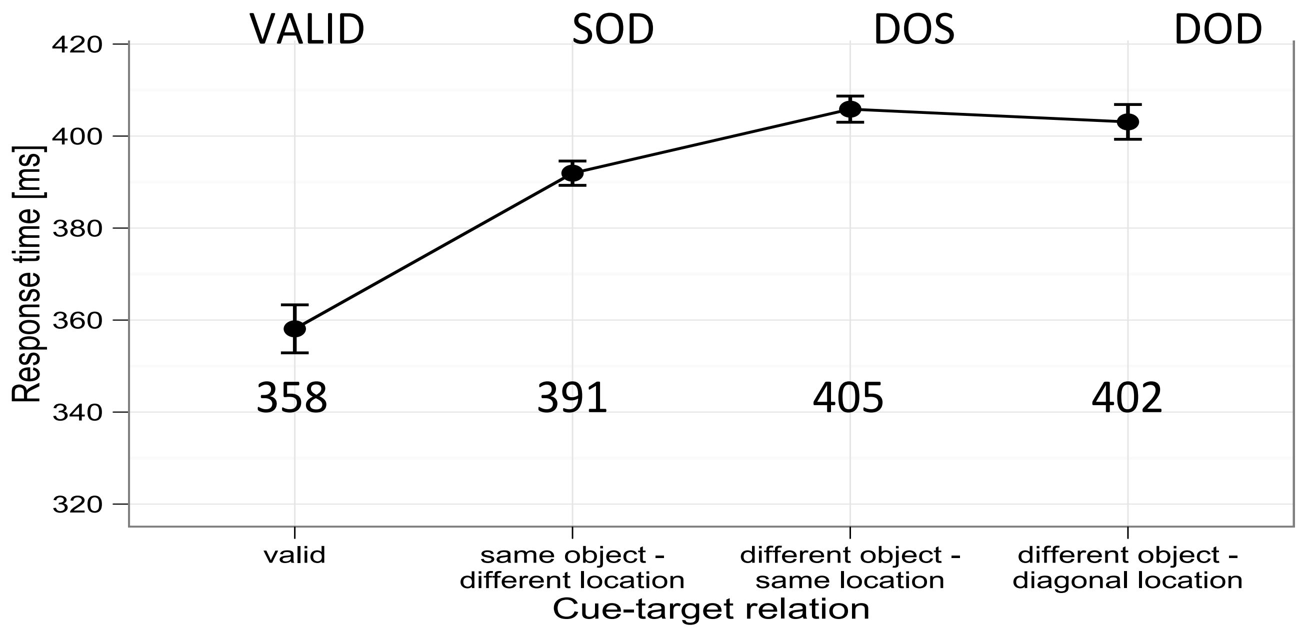
  - Which differences between condition means are estimated?
    Usually: main effects, interactions, or contrasts

  - Are these differences estimated between or within subjects (items)?

  - Choose contrasts in line with your hypothesis
```
> contrasts(KWDYZ$cue_target_relation) <- MASS:contr.sdif(4)
```

  - Convert contrasts to numeric covariates
```
> KWDYZ$c1 <- model.matrix( ~ cue_target_relation, data=KWDYZ)[ , 2]
> KWDYZ$c2 <- model.matrix( ~ cue_target_relation, data=KWDYZ)[ , 3]
> KWDYZ$c3 <- model.matrix( ~ cue_target_relation, data=KWDYZ)[ , 4]
```

Fixed Effects



Observed	M / Diff's	Kliegl et al. Fixed effects Estim	t	R-Default Fixed effects Estim	t
Grand Mean	389.2	389.7	55	358.1	58
Spatial: c1=Cond 2-1	33.2	33.8	10	33.8	10
Object: c2=Cond 3-2	13.9	14.0	6	47.8	13
Attract: c3=Cond 3-4	2.8	2.7	1	45.0	10

Linear Mixed Model (maximal)

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
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   Data: KWDYZ

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          c1           540.48  23.25     0.60
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Number of obs: 28710, groups:  subj, 61

Fixed effects:
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c3             2.747      2.214    1.24

Correlation of Fixed Effects:
   (Intr) c1     c2
c1  0.561
c2 -0.078 -0.229
c3 -0.136 -0.422  0.456
```
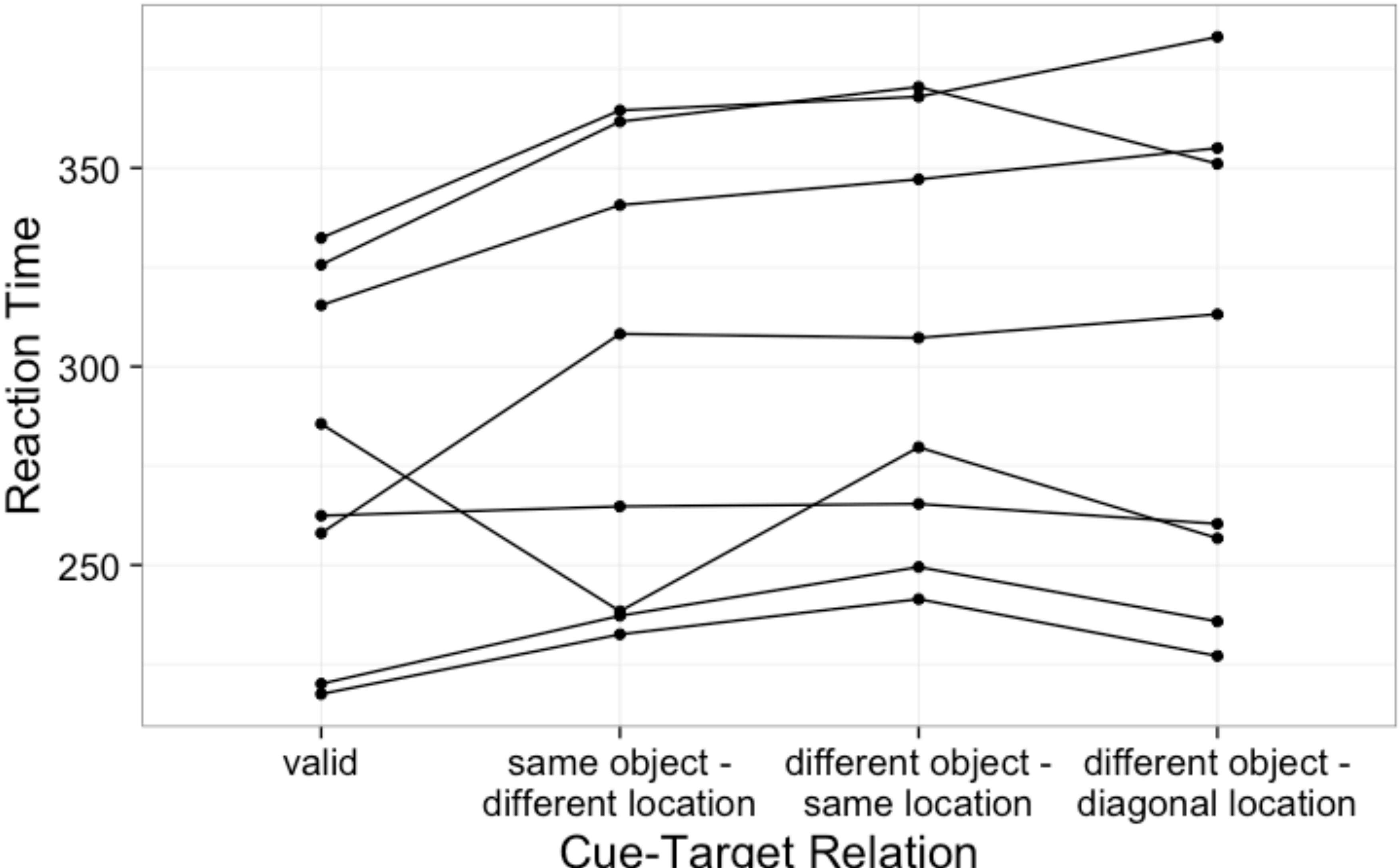

2. Variance components / Correlation parameters

Individual Differences in Grand Mean and Experimental Within-Subject Effects



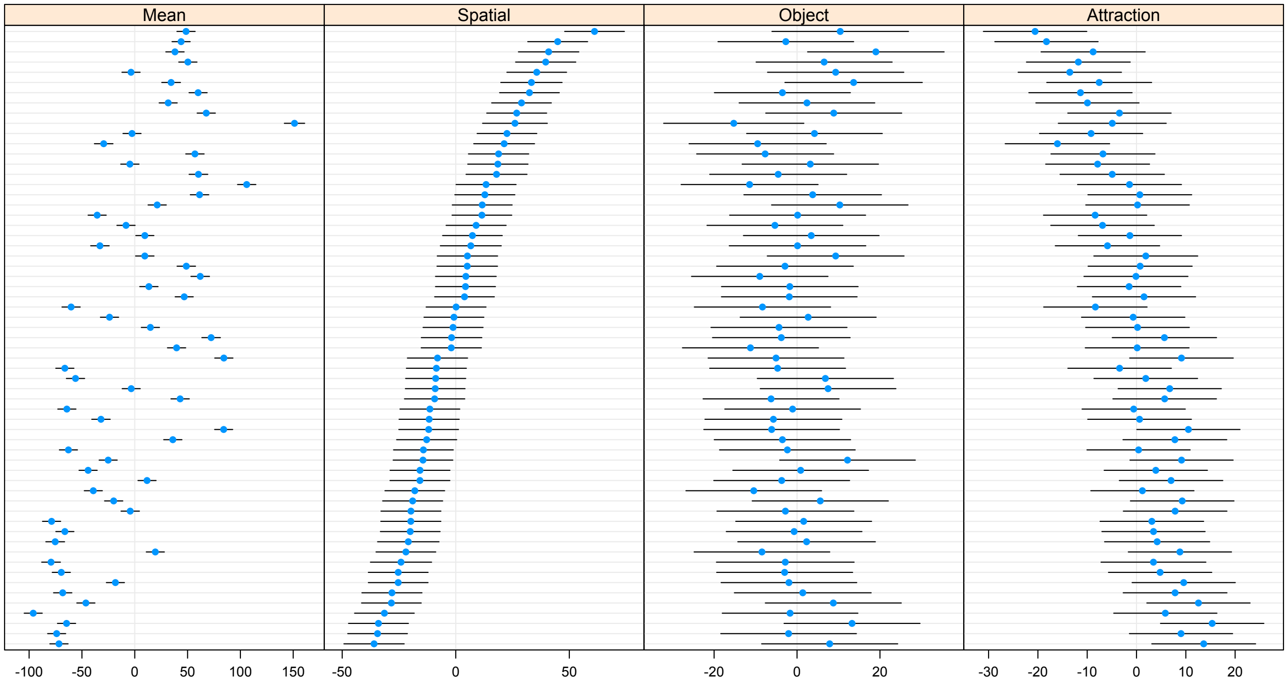
Things to be clear about …

- **Fixed-effect coefficients in the LMM**
    - What does "(Intercept)" mean?
      Recommended: *Grand Mean* (i.e., estim. of mean of condition means)
    - Which differences between condition means are estimated?
      Usually: main effects, interactions, or contrasts
    - Are these differences estimated between or within subjects (items)?

    - Choose contrasts in line with your hypothesis
    - Convert contrasts to numeric covariates

- **Variance components and correlation parameters**
  (determined by specification of fixed-effect coefficients)
    - Varying grand means (*random intercepts*):
      How much do intercepts differ between subjects (items)?
    - Varying slopes (*random slopes)*:
      How much do differences differ between subjects (items)?
    - Correlation parameters
      Are there any reliable correlations between intercepts and slopes

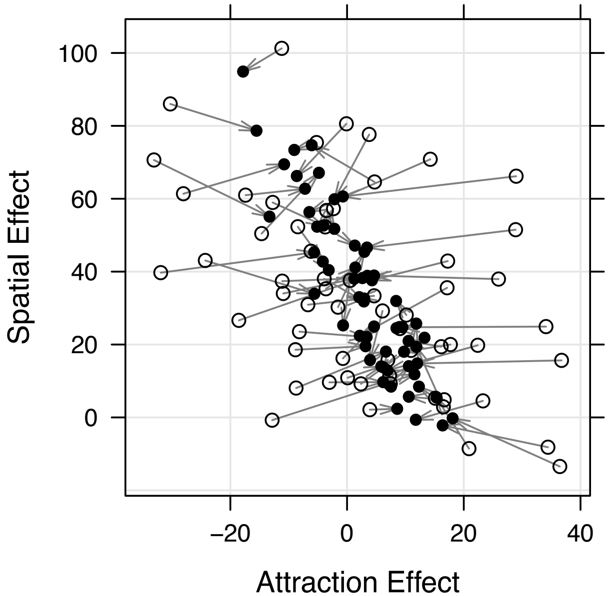
Conditional Modes (Predictions of Random Effects For Individual Subjects Using Model Parameters and Data)

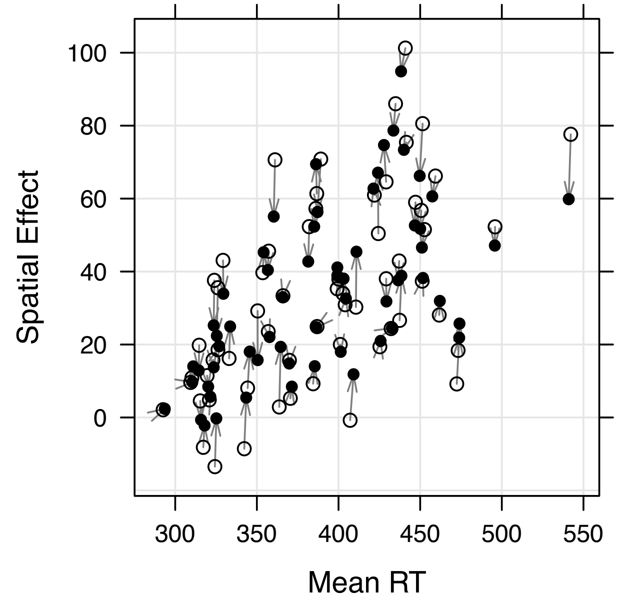



```
MODEL PARAMETERS:
 Groups   Name        Variance Std.Dev. Corr
 subj     (Intercept) 3047.07  55.20
          c1           540.48  23.25     0.60
          c2           115.65  10.75    -0.13 -0.01
          c3            90.44   9.51    -0.25 -0.85  0.36
 Residual             4876.90  69.83
```

(Kliegl et al, 2011)

Within-Subject Estimates (open) and Conditional Modes (filled):

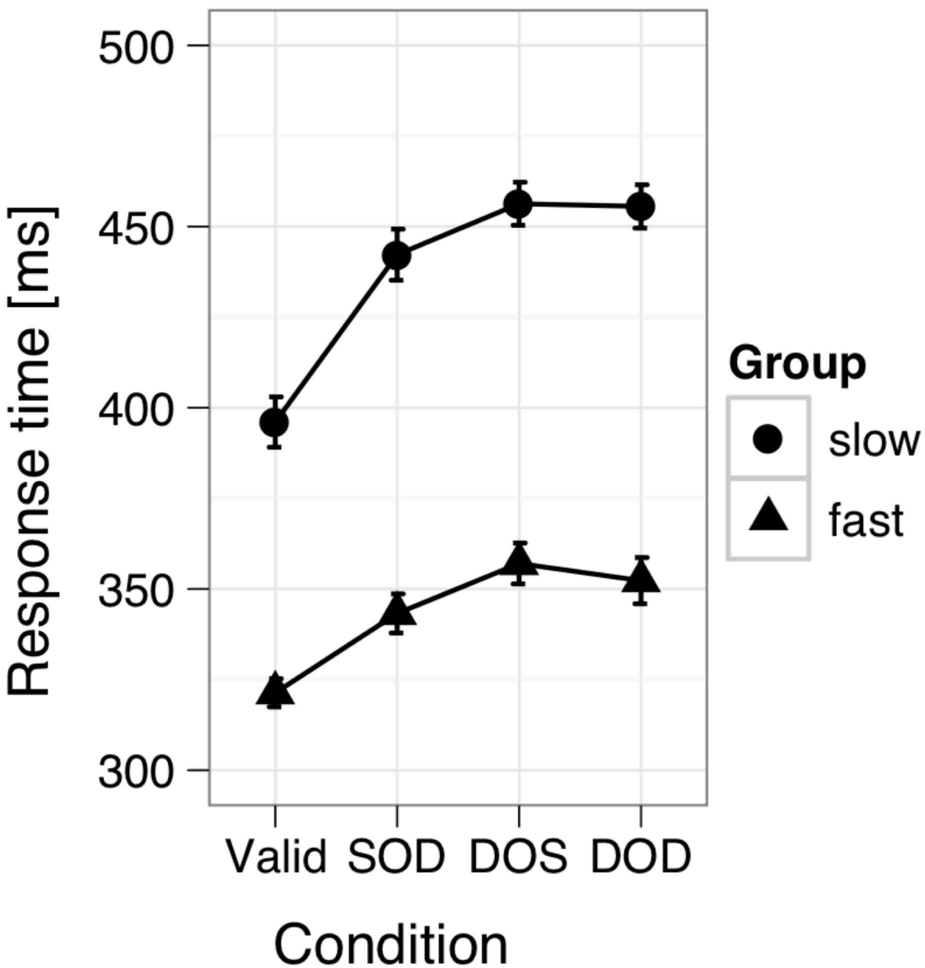


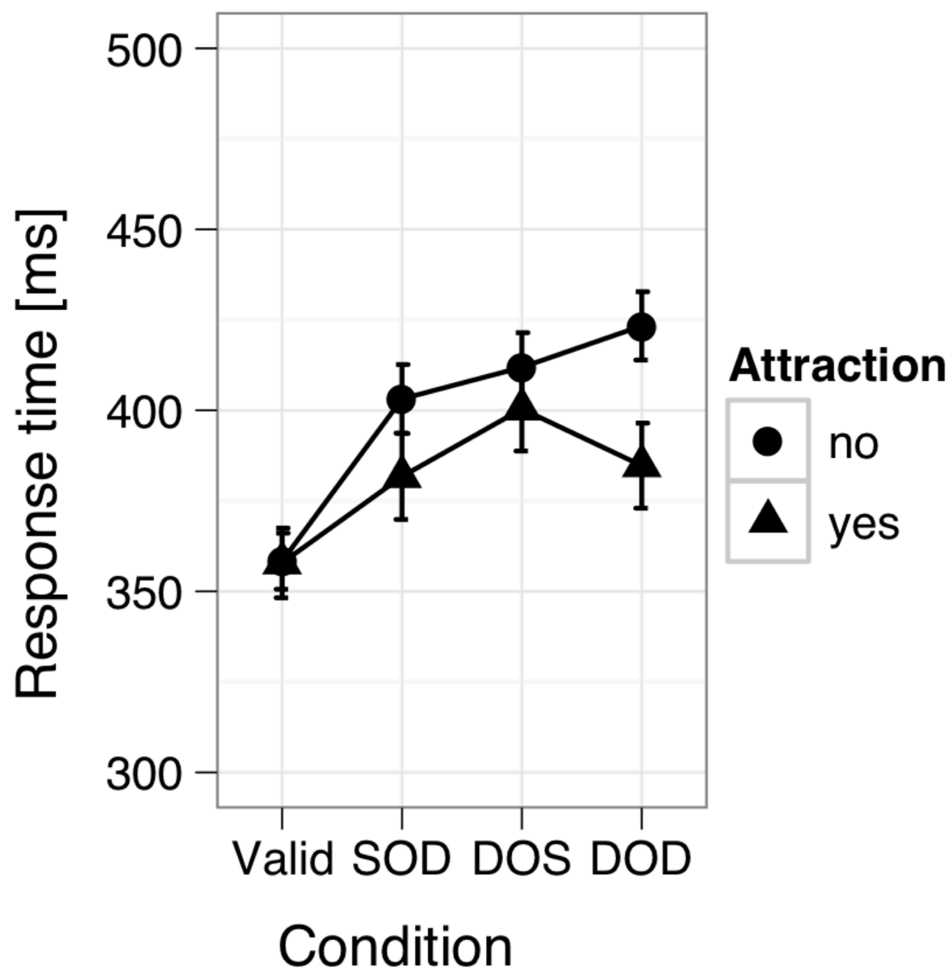


(1) Shrinkage „uncovers" correlations of random effects
(2) Mean RTs are not shrunken (arrows are vertical)

(Kliegl et al., 2011)

Correlation Parameters and Post-Hoc Group Effects





(Kliegl et al., 2011)

Linear Mixed Model (maximal, but degenerate!)

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: rt ~ 1 + c1 + c2 + c3 + (1 + c1 + c2 + c3 | subj)
   Data: KWDYZ

Random effects:
 Groups   Name        Variance Std.Dev. Corr
 subj     (Intercept) 3047.07  55.20
          c1           540.48  23.25     0.60
          c2           115.65  10.75    -0.13 -0.01
          c3            90.44   9.51    -0.25 -0.85  0.36
 Residual             4876.90  69.83
```

2. Variance components / Correlation parameters

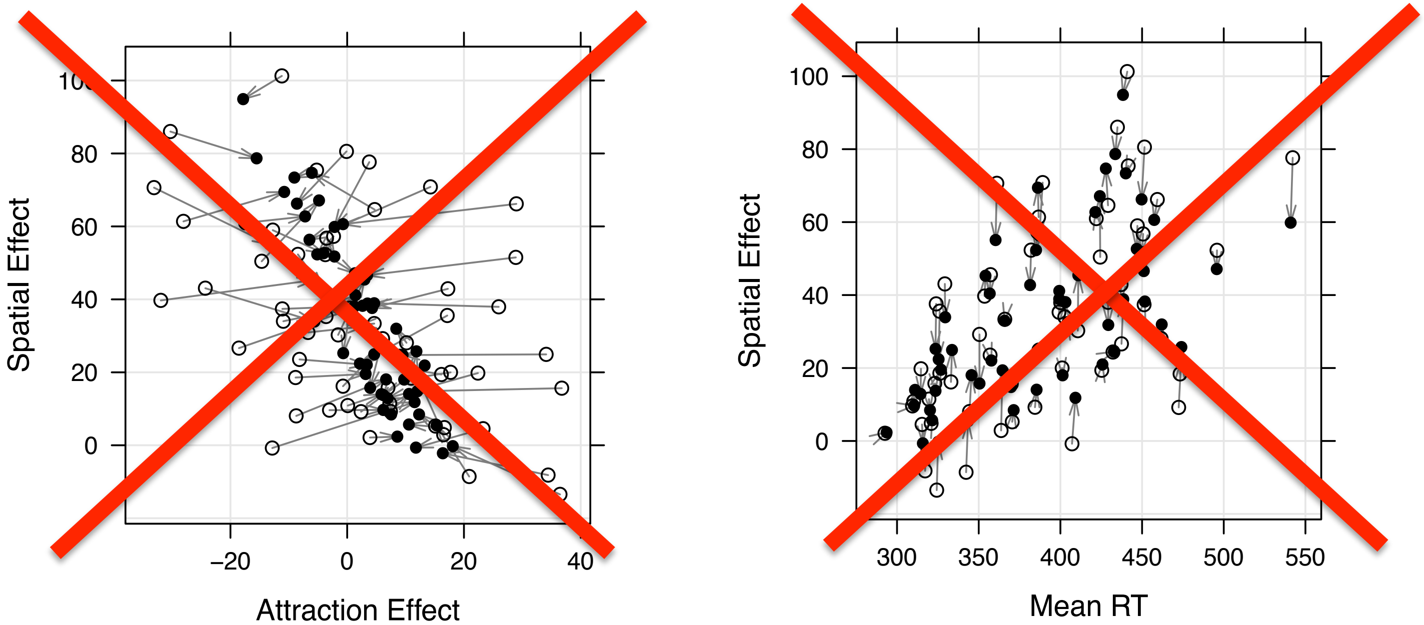
```
> library(RePsychLing)
> summary(rePCA(m0))
$subj
Importance of components:
                         [,1]   [,2]    [,3]      [,4]
Standard deviation     0.8200 0.2821 0.16110 4.309e-08
Proportion of Variance 0.8644 0.1023 0.03336 0.000e+00
Cumulative Proportion  0.8644 0.9666 1.00000 1.000e+00
```

Three principal components account for all the variance in the **four** variance components estimated. The data do not support a model of this complexity. You are asking too much. The model is overparameterized, is degenerate …

Parsimonious Linear Mixed Model (zero-correlation parameter)

```
>  m1 <- lmer(rt ~ 1+c1+c2+c3 + (1+c1+c2+c3 || subj), KWDYZ,
REML=FALSE)
> print(summary(m1), corr=FALSE)
...
Random effects:
 Groups   Name        Variance Std.Dev.
 subj     (Intercept) 2993.40  54.712
 subj.1   c1           574.61  23.971
 subj.2   c2           108.02  10.393
 subj.3   c3            74.11   8.609
 Residual             4877.42  69.838
...

> summary(rePCA(m1))
$subj
Importance of components:
                         [,1]   [,2]   [,3]    [,4]
Standard deviation     0.7834 0.3432 0.1488 0.12327
Proportion of Variance 0.7982 0.1532 0.0288 0.01976
Cumulative Proportion  0.7982 0.9514 0.9802 1.00000
```

Within-Subject Estimates (open) and Conditional Modes (filled)



~~(1) Shrinkage „uncovers" correlations of random effects~~

~~(2) Mean RTs are not shrunken (arrows are vertical)~~

MODEL NOT SUPPORTED BY THE DATA

(Kliegl et al., 2011)

Replication (and Extension)

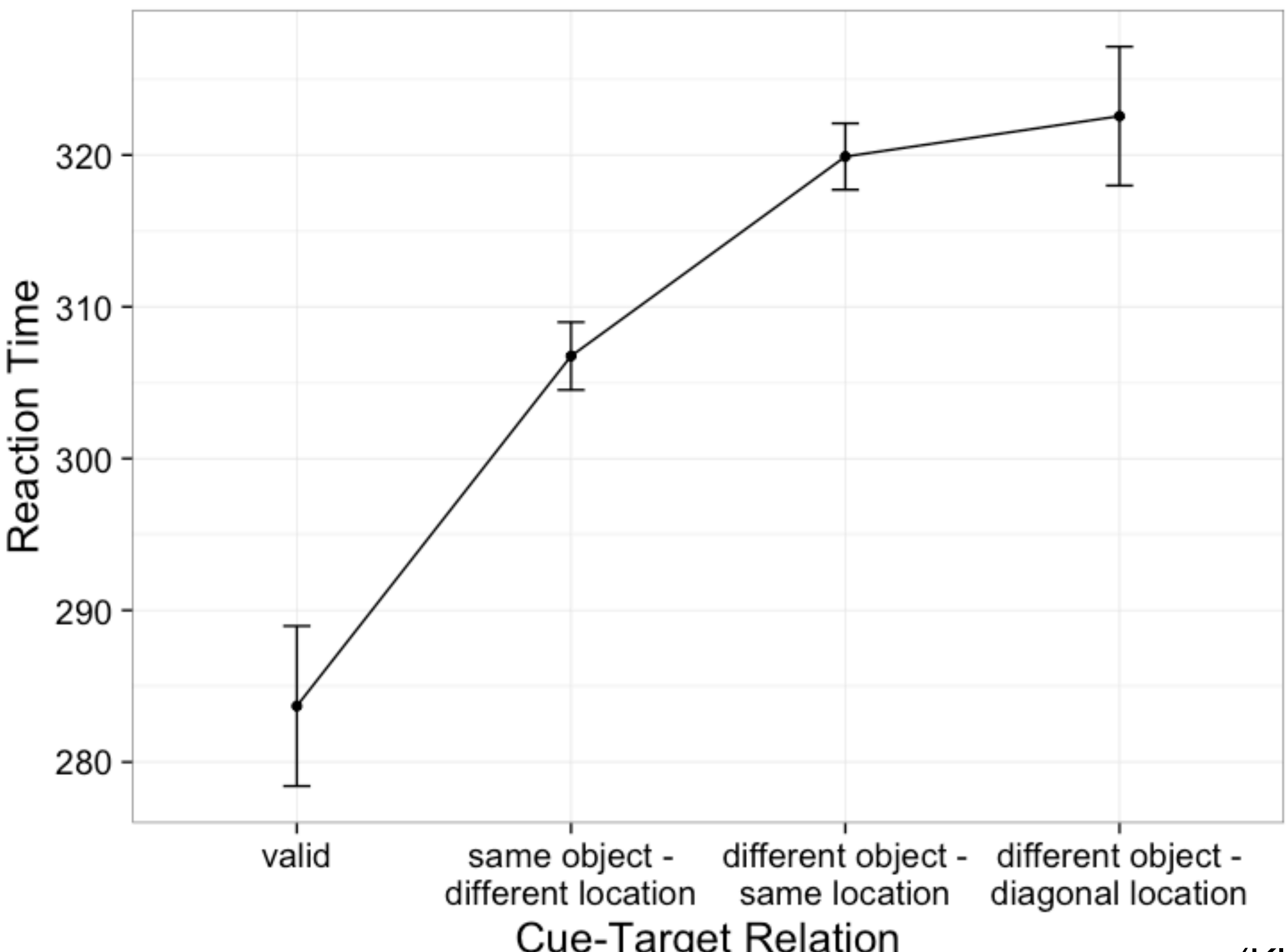
- Keep within-subject factor with four cue-target relations
- German/Potsdam, not Chinese/Beijing subjects
- Add one between-subject factor (size of target to be detected)
- Add one within-subject factor (orientation of bars (cardinal vs. diagnoal)
- Increase number of subjects from 61 to 86
- KKL vignette in package RePsychLing

(Kliegl, Kuschela, & Laubrock, 2014)

Replication of the Profile of Means

(1) Spatial effect = SOD − VALID
(2) Object effect = [DOS − VALID] − [SOD − VALID] = DOS − SOD
(3) Attraction effect = [DOS − VALID] − [DOD − VALID]) = DOS − DOD

VALID SOD DOS DOD



(Kliegl et al., 2014)

m0: Linear Mixed Model (maximal)

```
> print(summary(m0), corr=FALSE)
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: lrt ~ sze * (spt + obj + grv) * orn + (spt + obj + grv + orn + spt_orn + obj_orn + grv_orn | subj)

Random effects:
 Groups   Name        Variance  Std.Dev. Corr
 subj     (Intercept) 2.582e-02 0.160674
          spt         4.354e-03 0.065984  0.46
          obj         4.722e-04 0.021730  0.15 -0.08
          grv         1.100e-03 0.033166 -0.50 -0.59 -0.24
          orn         8.986e-03 0.094792  0.07 -0.03  0.02 -0.09
          spt_orn     9.294e-04 0.030485  0.24  0.05  0.17 -0.15  0.05
          obj_orn     3.331e-05 0.005772  0.16 -0.37  0.92 -0.13  0.11  0.04
          grv_orn     3.377e-04 0.018377 -0.35 -0.43 -0.07  0.81  0.00 -0.63  0.08
 Residual             3.619e-02
Number of obs: 53765, groups:  subj, 86

Fixed effects:
             Estimate Std. Error t value
(Intercept)  5.691049   0.017364   327.7
sze          0.184216   0.034729     5.3
spt          0.074412   0.007638     9.7
obj          0.040815   0.004355     9.4
grv         -0.001694   0.005134    -0.3
orn          0.040946   0.010479     3.9
sze:spt      0.048847   0.015276     3.2
sze:obj     -0.010655   0.008710    -1.2
sze:grv     -0.036301   0.010268    -3.5
sze:orn      0.016627   0.020958     0.8
spt:orn      0.020254   0.006454     3.1
obj:orn      0.009234   0.007368     1.3
grv:orn      0.010919   0.007629     1.4
sze:spt:orn -0.012727   0.012908    -1.0
sze:obj:orn -0.001961   0.014737    -0.1
sze:grv:orn -0.044308   0.015257    -2.9
convergence code: 0
maxfun < 10 * length(par)^2 is not recommended.
```

2. Variance components / Correlation parameters

1. Fixed effects

m0: Linear Mixed Model (maximal, but degenerate)

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: lrt ~ sze * (spt + obj + grv) * orn +
               (spt + obj + grv + orn + spt_orn + obj_orn +  grv_orn | subj)
   Data: KKL
```

2. Variance components / Correlation parameters

```
 Groups   Name        Variance  Std.Dev. Corr
 subj     (Intercept) 2.582e-02 0.160674
          spt         4.354e-03 0.065984  0.46
          obj         4.722e-04 0.021730  0.15 -0.08
          grv         1.100e-03 0.033166 -0.50 -0.59 -0.24
          orn         8.986e-03 0.094792  0.07 -0.03  0.02 -0.09
          spt_orn     9.294e-04 0.030485  0.24  0.05  0.17 -0.15  0.05
          obj_orn     3.331e-05 0.005772  0.16 -0.37  0.92 -0.13  0.11  0.04
          grv_orn     3.377e-04 0.018377 -0.35 -0.43 -0.07  0.81  0.00 -0.63  0.08
```

```
> library(RePsychLing)
> summary(rePCA(m0))
$subj
Importance of components:
                         [,1]   [,2]    [,3]    [,4]    [,5]    [,6]      [,7] [,8]
Standard deviation     0.8697 0.4978 0.31114 0.17399 0.13821 0.10443 8.175e-06    0
Proportion of Variance 0.6513 0.2134 0.08337 0.02607 0.01645 0.00939 0.000e+00    0
Cumulative Proportion  0.6513 0.8647 0.94809 0.97416 0.99061 1.00000 1.000e+00    1
```

Six principal components account for all the variance in the **eight** variance components estimated. The data do not support a model of this complexity. You are asking too much. The model is overparameterized, is degenerate …

m1: Parsimonious Linear Mixed Model (zero-correlation parameter)

```
Formula: lrt ~ sze * (spt + obj + grv) * orn +
               (spt + obj + grv + orn + spt_orn + obj_orn +  grv_orn || subj)
Data: KKL

Random effects:
 Groups   Name        Variance  Std.Dev.
 subj     (Intercept) 0.0255376 0.159805
 subj.1   spt         0.0044351 0.066596
 subj.2   obj         0.0005782 0.024045
 subj.3   grv         0.0012772 0.035738
 subj.4   orn         0.0089050 0.094366
 subj.5   spt_orn     0.0011806 0.034359
 subj.6   obj_orn     0.0000000 0.000000
 subj.7   grv_orn     0.0000482 0.006943
 Residual             0.0361966 0.190254

...
> summary(rePCA(m1))
$subj
Importance of components:
                         [,1]   [,2]   [,3]    [,4]    [,5]    [,6]    [,7] [,8]
Standard deviation     0.8400 0.4960 0.3500 0.18784 0.18060 0.12638 0.03649    0
Proportion of Variance 0.6086 0.2122 0.1057 0.03044 0.02813 0.01378 0.00115    0
Cumulative Proportion  0.6086 0.8208 0.9265 0.95694 0.98507 0.99885 1.00000    1
```

Problem is still there: **Six** principal components account for all the variance in the **eight** variance components estimated.

m2: Parsimonious Linear Mixed Model (reduced zero-correlation parameter)

```
Formula: lrt ~ sze * (spt + obj + grv) * orn +
               (spt + obj + grv + orn + spt_orn || subj)
Data: KKL

Random effects:
 Groups   Name        Variance  Std.Dev.
 subj     (Intercept) 0.0255373 0.15980
 subj.1   spt         0.0044350 0.06660
 subj.2   obj         0.0005782 0.02405
 subj.3   grv         0.0012771 0.03574
 subj.4   orn         0.0089052 0.09437
 subj.5   spt_orn     0.0011905 0.03450
 Residual             0.0361973 0.19026

...
> summary(rePCA(m2))
$subj
Importance of components:
                         [,1]   [,2]   [,3]    [,4]   [,5]    [,6]
Standard deviation     0.8399 0.4960 0.3500 0.18784 0.1814 0.12638
Proportion of Variance 0.6091 0.2124 0.1058 0.03046 0.0284 0.01379
Cumulative Proportion  0.6091 0.8216 0.9274 0.95781 0.9862 1.00000
```

Model looks ok.

m3: Parsimonious Linear Mixed Model (expanding the reduced model with corr param‘s)

```
Formula: lrt ~ sze * (spt + obj + grv) * orn +
               (spt + obj + grv + orn + spt_orn | subj)
Data: KKL

Random effects:
 Groups   Name        Variance  Std.Dev. Corr
 subj     (Intercept) 0.0258123 0.16066
          spt         0.0043509 0.06596   0.46
          obj         0.0004583 0.02141   0.16 -0.08
          grv         0.0010673 0.03267  -0.51 -0.60 -0.27
          orn         0.0089834 0.09478   0.07 -0.03  0.03 -0.09
          spt_orn     0.0012095 0.03478   0.29  0.08  0.27 -0.27  0.06
 Residual             0.0362029 0.19027
...
> summary(rePCA(m3))
$subj
Importance of components:
                         [,1]   [,2]    [,3]    [,4]    [,5]    [,6]
Standard deviation     0.8695 0.4976 0.30869 0.18225 0.12798 0.09133
Proportion of Variance 0.6535 0.2141 0.08237 0.02871 0.01416 0.00721
Cumulative Proportion  0.6535 0.8676 0.94992 0.97863 0.99279 1.00000
```

Model looks ok and fits better than the reduced zero-correlation parameter model

```
> anova (m2, m3)
 Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
m2 23 -24543 -24338  12294   -24589
m3 38 -24563 -24225  12319   -24639 50.043     15  1.185e-05
```

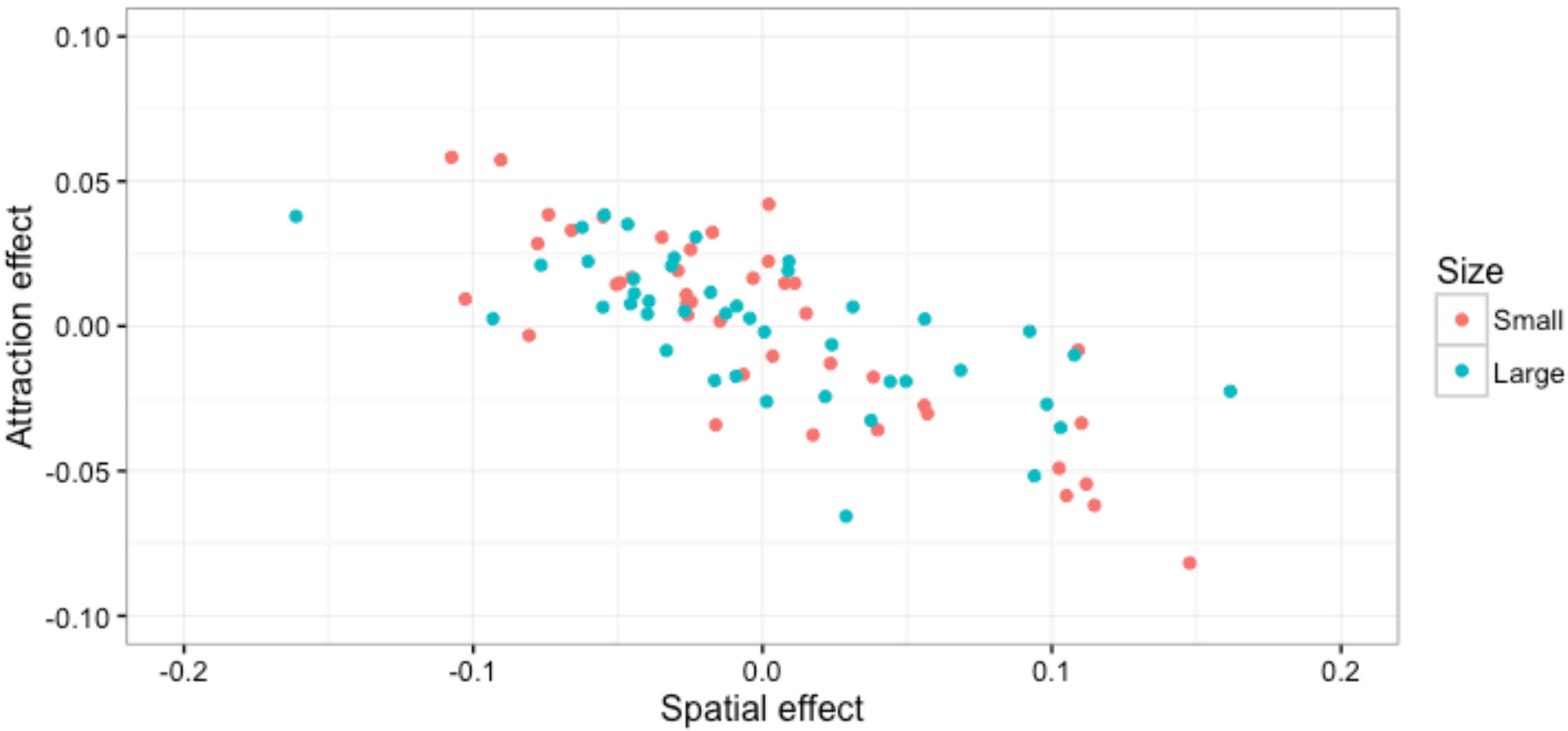
m4: Parsimonious Linear Mixed Model (pruning non-significant corr param's)

```
Formula: lrt ~ sze * (spt + obj + grv) * orn + (spt + grv | subj) +
               (0 + obj | subj) + (0 + orn | subj) + (0 + spt_orn | subj)
Data: KKL

Random effects:
 Groups   Name        Variance  Std.Dev. Corr
 subj     (Intercept) 0.0258259 0.16070
          spt         0.0042698 0.06534   0.49
          grv         0.0011978 0.03461  -0.51 -0.58
 subj.1   obj         0.0004758 0.02181
 subj.2   orn         0.0089109 0.09440
 subj.3   spt_orn     0.0011862 0.03444
 Residual             0.0362028 0.19027
...
> summary(rePCA(m4))
$subj
Importance of components:
                        [,1]   [,2]    [,3]    [,4]    [,5]    [,6]
Standard deviation     0.869 0.4961 0.30153 0.18101 0.13533 0.11465
Proportion of Variance 0.653 0.2128 0.07862 0.02833 0.01584 0.01137
Cumulative Proportion  0.653 0.8658 0.94447 0.97280 0.98863 1.00000
```

Model looks ok and fits as well as previous model

```
> anova (m4, m3)
 Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
m4 26 -24578 -24347  12315   -24630
m3 38 -24563 -24225  12319   -24639 8.3947     12     0.7536
```

Conditional Modes for Spatial and Attraction Effects



m4: Parsimonious Linear Mixed Model (profiling the model parameters)

```
> p_m4_1 <- profile(m4, which=1)   # increment 1 to 9
> confint(p_m4_1)
```

Name	Estimate	2.5%	975%
mean-SD	.16	.14	.19
spatial-SD	.07	.06	.08
gravitation-SD	.04	.03	.05
object-SD	.02	.01	.03
orientation-SD	.09	.08	.11
spat:orient-SD	.03	.02	.05
mean-spatial r	.49	.30	.64
mean-gravit r	-.51	-.73	-.25
spat-gravit r	-.58	-.88	-.30

What do I do with data from factorial experiments?

- DV
  - Use transformation that achieves normal distribution of residuals
  - (May require refitting model after **checking residuals** of final model)
- Independent variables (factors)
  - Specify contrasts for factor levels according to hypothesis
  - Convert contrasts to numeric covariates
- Estimate maximal model: Convergence: > summary (rePCA(model))
  - Model supported by data: Have a beer and then: REPLICATE EXPERIMENT!
  - Model not supported by data: See "**No convergence**"
- No convergence: Do the following until convergence and there is a model supported by data
  - Estimate zero-correlation parameter model: > summary (rePCA(model))
  - Or: Remove smallest variance component(s): > summary (rePCA(model))
- Model comparisons: Likelihood-ratio tests to zoom in on a model supported by the data: > anova(model1, model2)
- Profile parameters and **REPLICATE EXPERIMENT**

Stroup (2012, p. 185) on Maximal, Minimal and Parsimonious Models

"Neither the [maximal] nor the [minimal] linear mixed models are appropriate for most repeated measures analysis. Using the [maximal] model is generally wasteful and costly in terms of statistical power for testing hypotheses. On the other hand, the [minimal] model fails to account for nontrivial correlation among repeated measurements. This results in inflated [T]ype I error rates when non-negligible correlation does in fact exist. We can usually find middle ground, a covariance model that adequately accounts for correlation but is more parsimonious than the [maximal] model. Doing so allows us full control over [T]ype I error rates without needlessly sacrificing power."

Barr, D. J., Levy, R., Scheepers, C., & Tily, H. J. (2013). Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language, 68,* 255–278.

Stroup, W. W. (2012). *Generalized linear mixed models: Modern concepts, methods and applications.* CRC Press, Boca Raton.

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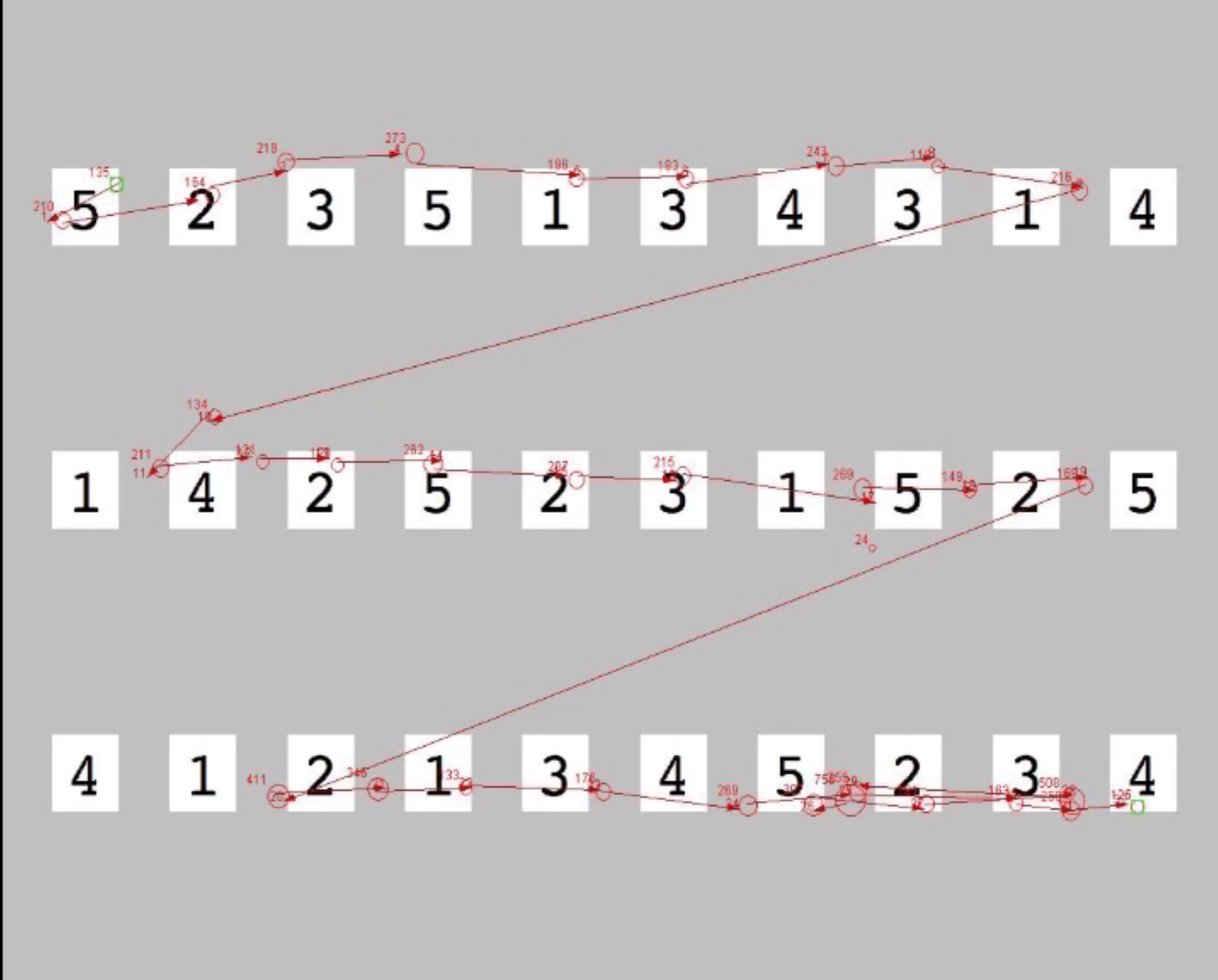
- Matuschek, H., Kliegl, R., Vasishth, S., Baayen, R.H., & Bates, D. (2015). Balancing type I error and power in linear mixed models. *arXiv:1511.0684*
- Baayen, R. H., Vasishth, S., Bates, D., & Kliegl, R. (2015). Out of the cage of shadows. *arXiv:1511.03120*

Part 2: Experimental Psychological Perspectives on Individual Differences (IDs)

- Two „sciences" of psychology (Cronbach)
- Differential-psychological perspective
  - **Repeated measures** yield latent constructs (**additive**)
  - Reliability of constructs==reliability of IDs
  - Multiple regression analysis (MRA), structural equation model (SEM), **hierarchical linear model (HLM)**, ...
- Experimental-psychological perspective
  - **Repeated measures** yield experimental effects
  - Experimental effects are difference scores (**subtractive, contrast**)
  - Individual difference scores are unreliable; aggregate subjects
  - Repeated-measures (rm) ANOVA, rm MRA, **linear mixed models (LMM)**, …
- Crossover is possible, but does not happen often; HLM and LMM make this more likely in the future.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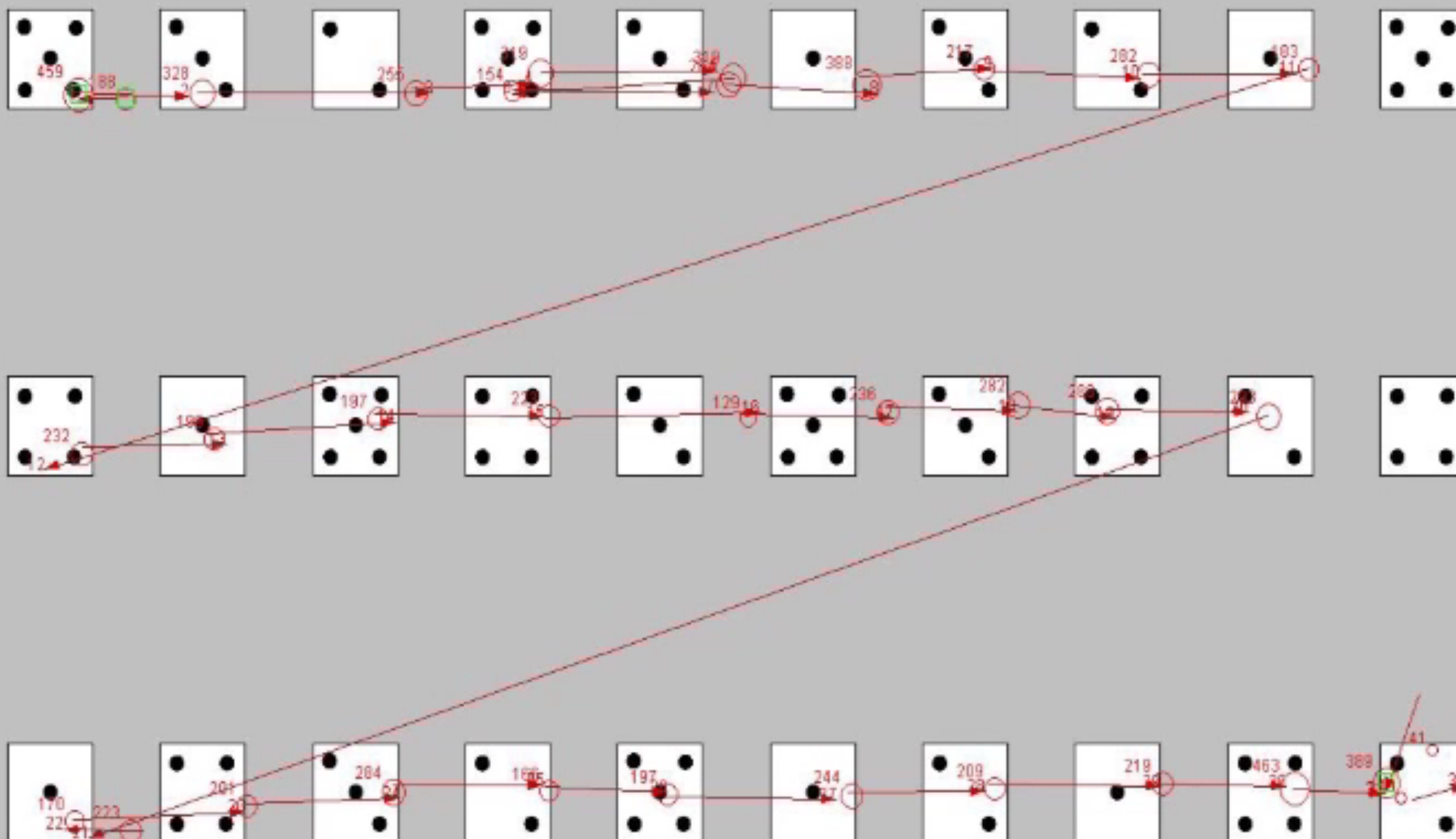
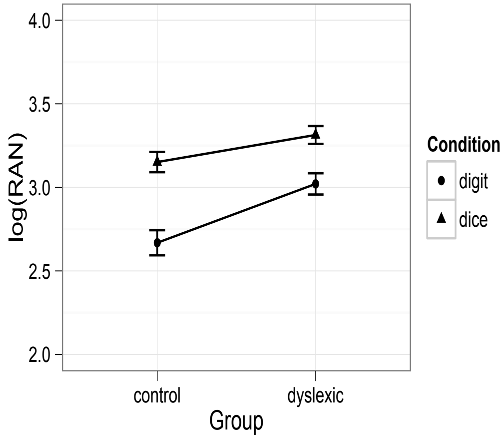
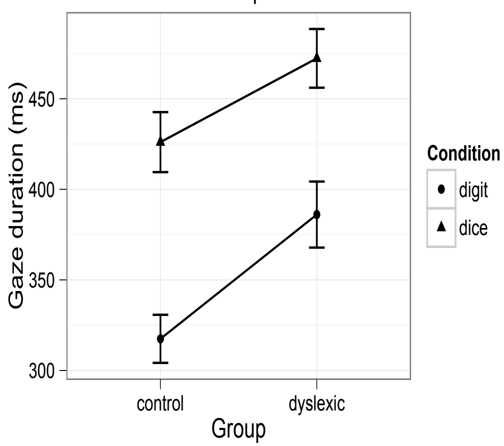


Digit-RAN vs. Dice-RAN: Phonology or Automaticity?

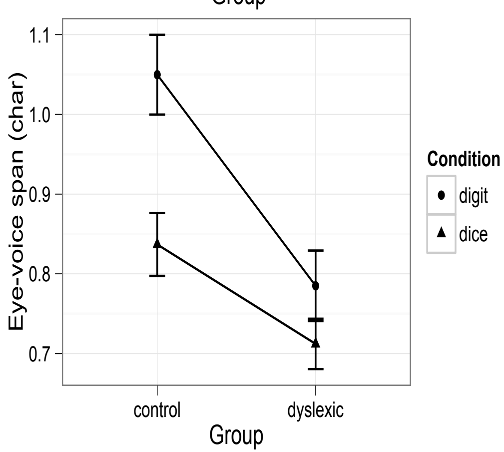
RAN



GAZE



EVS



Method

Subjects

- 26 control and
- 30 dyslexics Chinese first-grade children

Procedure

- Eye movements during two RAN tasks (digit, dice): Gaze and EVS
- Psychometric measures (reading, two RANs: digit, dice)

Results

Experimental perspective

Interactions RAN condition x reading ability

Individual-difference perspective

- *So far:* Use covariates to increase power
- *Now:* Two kinds of individual differences

(Pan, Yan, Laubrock, Shu, & Kliegl, 2012)

Two Kinds of Individual Differences in the RAN Tasks

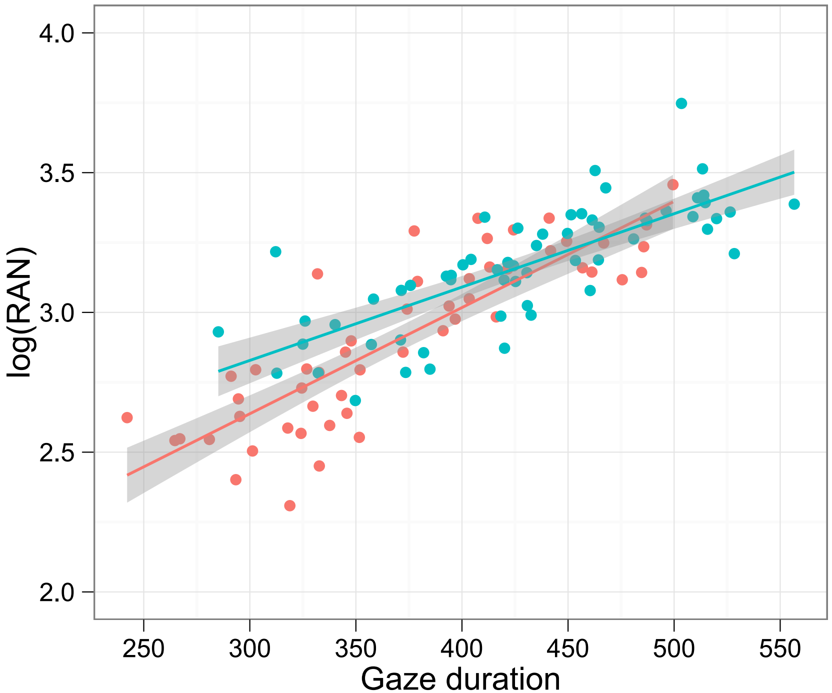
1. Dyslexic vs. control children: quasi-experimental variable
2. Individual differences (IDs) in RAN effect: digit-RAN - dice-RAN (psychometric version)
3. IDs in GAZE effect: digit-Gaze and dice-Gaze
4. IDs in EVS effect: digit-EVS and dice-EVS
5. …

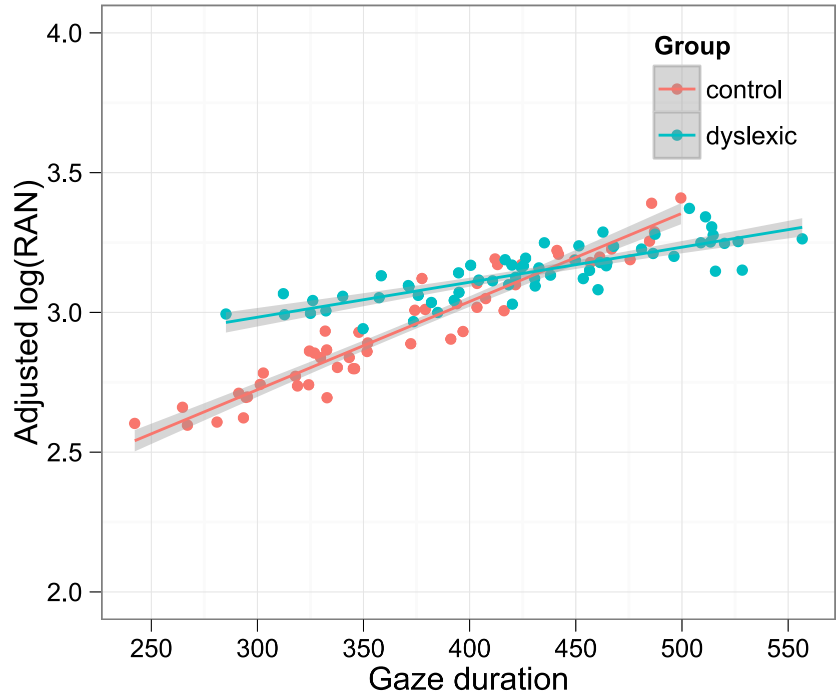
BUT

- RAN condition effect (digit-RAN – dice-RAN) is repeated measure
- MRA, not suitable; requires repeated-measures MRA or LMM
- Extension of “ANOVA logic” to individual differences

(Pan, Yan, Laubrock, Shu, & Kliegl, 2013)

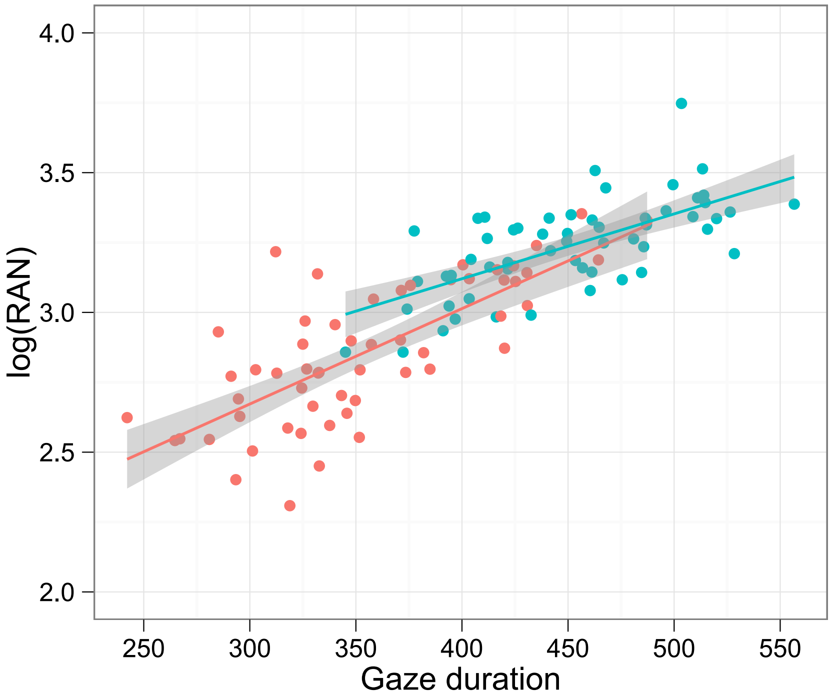
First Kind of Individual Differences in the RAN Tasks: Group (Control vs. Dyslexic) x Gaze Interaction

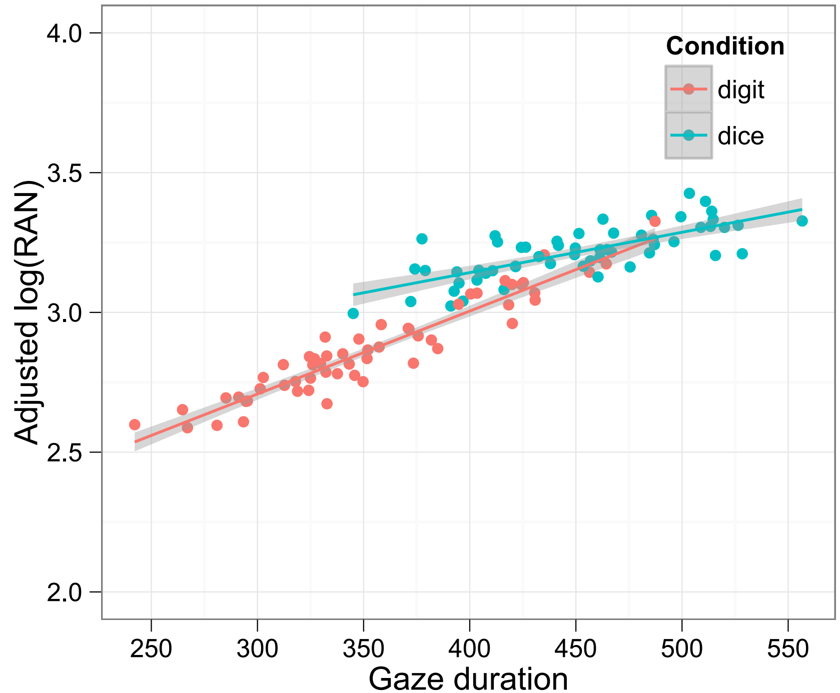




(Pan, Yan, Laubrock, Shu, & Kliegl, 2013)

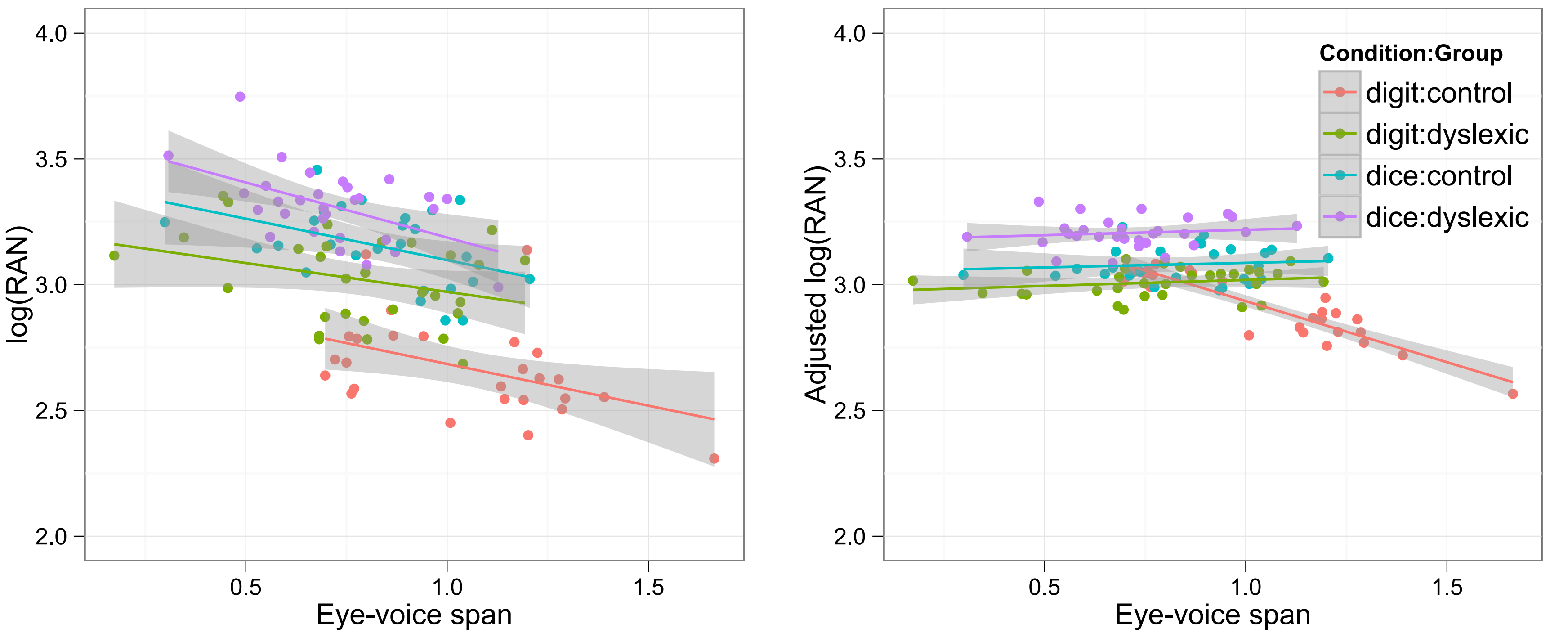
First Kind of Individual Differences in the RAN Tasks: Condition (Digit vs. Dice) x Gaze Interaction





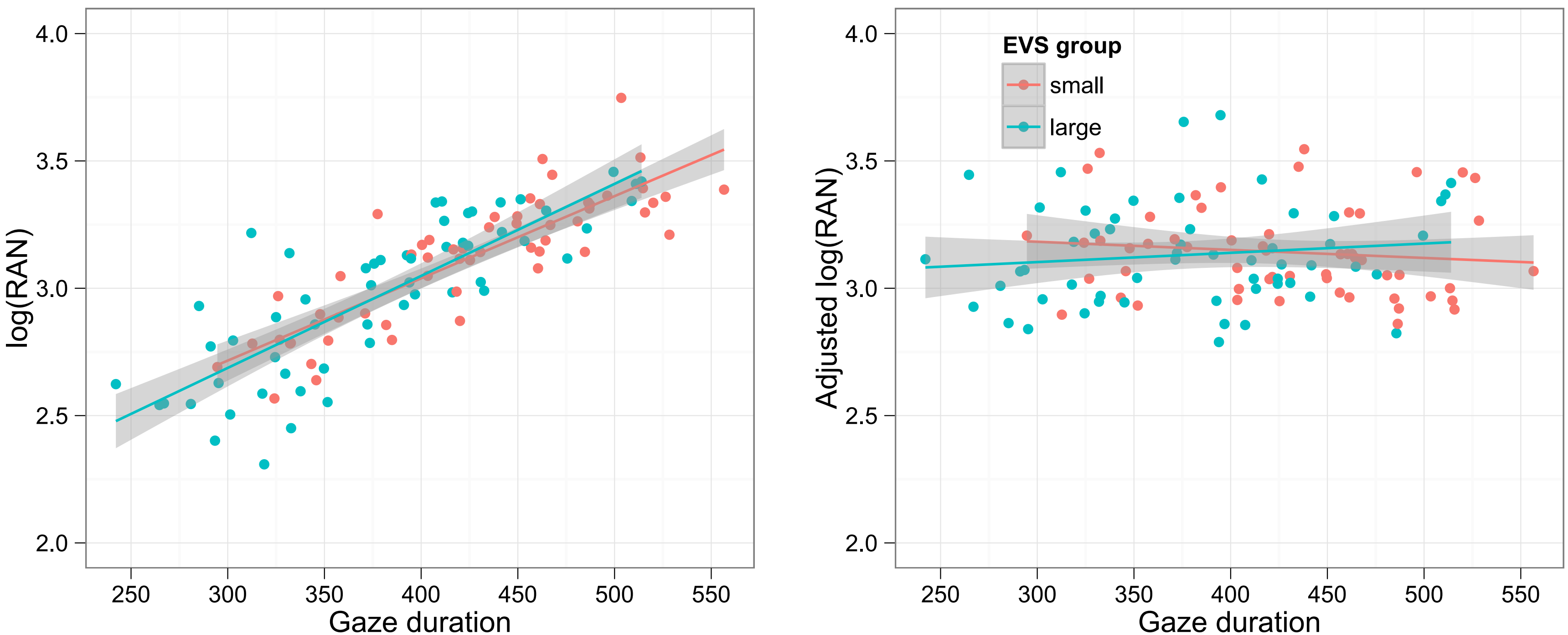
(Pan, Yan, Laubrock, Shu, & Kliegl, 2013)

First Kind of Individual Differences in the RAN Tasks: Group x Condition x Eye-Voice Span Interaction



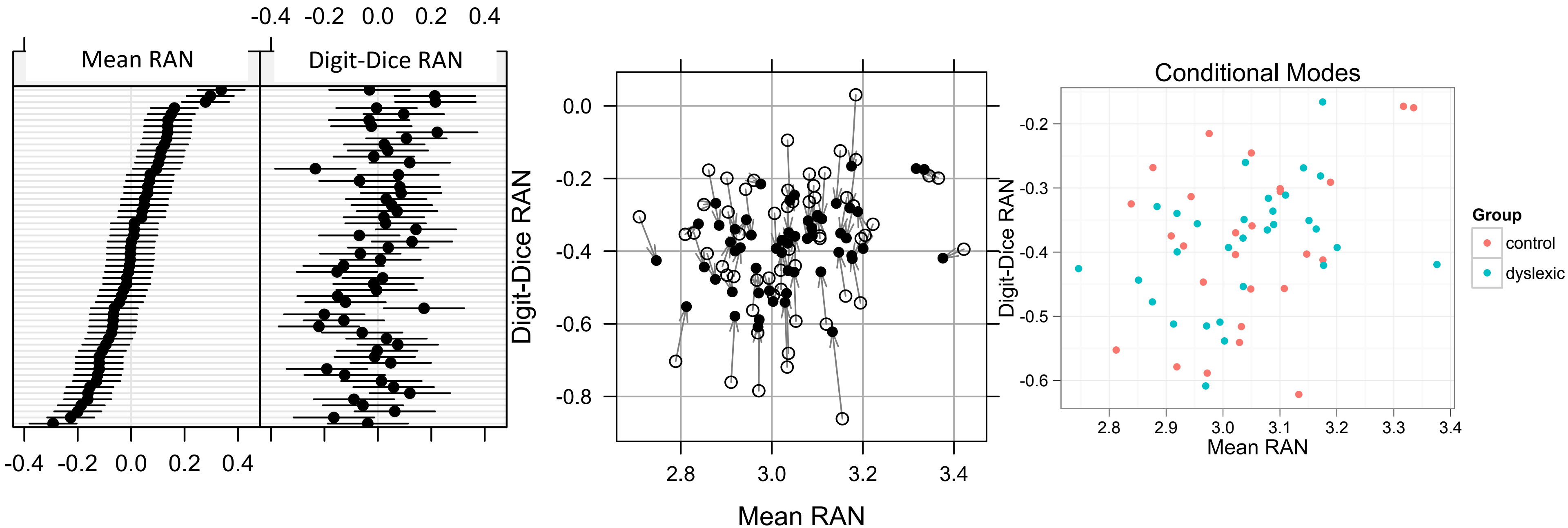
(Pan, Yan, Laubrock, Shu, & Kliegl, 2013)

First Kind of Individual Differences in the RAN Tasks: EVS (small, large) x Gaze Interaction



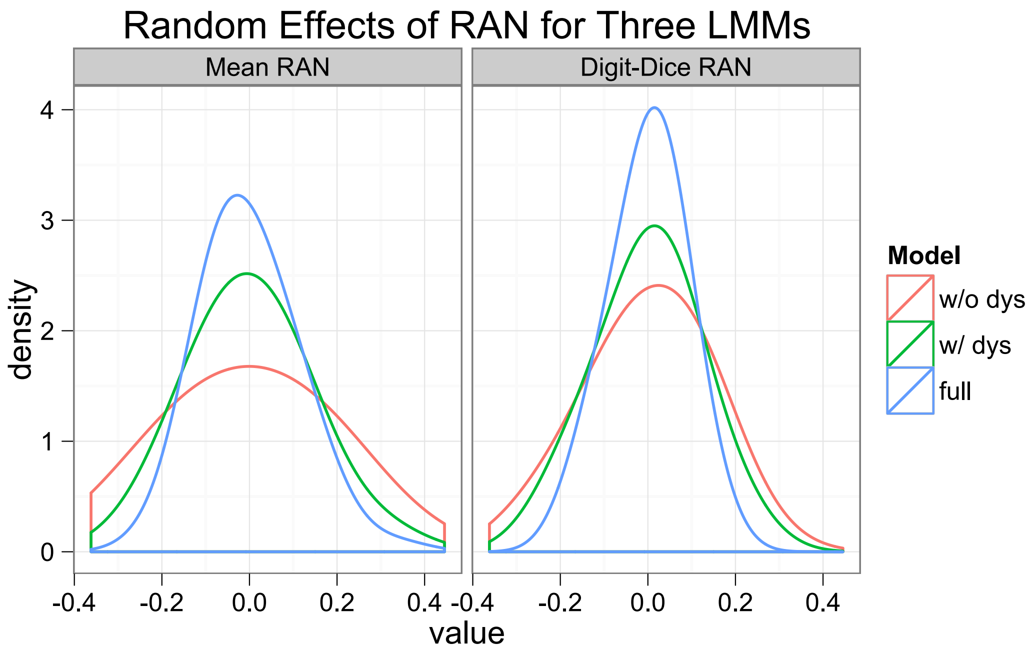
(Pan, Yan, Laubrock, Shu, & Kliegl, 2013)

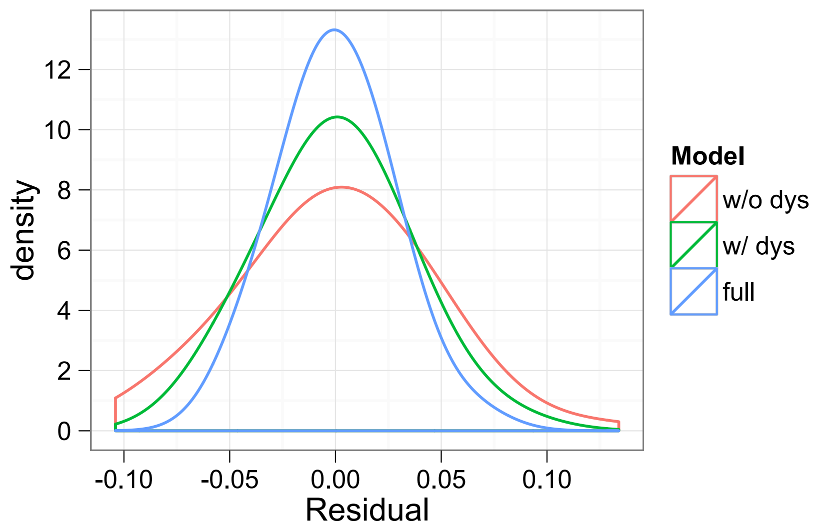
Second Kind of Individual Differences in the RAN Tasks:
- Reducing problem of unreliability of difference scores
- Heuristic for detecting unobserved group differences

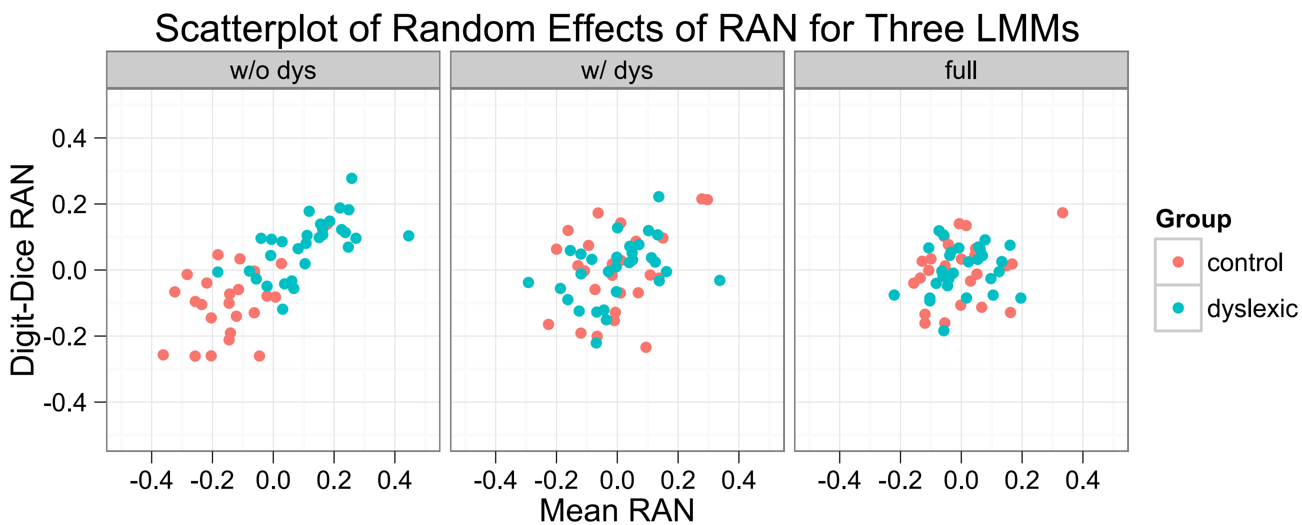


NOTE: An LMM with two variance-components (intercept and slope) requires more than two observations per subject for proper identification. Thus, the results shown here and on the following slide only illustrate the general point. Conceptually, everything is fine.

Individual Differences in the RAN Tasks: Systematic and Residual Variance Reductions







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Kliegl et al. (2011, FQPM). Experimental effects and individual differences in Linear Mixed Models: Estimating the relationship between spatial, object, and attraction effects in visual attention.

Sunday, 15 August 2010 21:56 Reinhold Kliegl

Kliegl, R., Wei, P., Dambacher, M., Yan, M., & Zhou, X. (2011). Experimental effects and individual differences in Linear Mixed Models: Estimating the relationship between spatial, object, and attraction effects in visual attention. *Frontiers in Quantitative Psychology and Measurement, 1.*

doi: 10.3389/fpsyg.2010.00238

Abstract. Linear mixed models (LMMs) provide a still underused methodological perspective on combining experimental and individual-differences research. Here we illustrate this approach with two-rectangle cueing in visual attention (Egly, Driver, & Rafal, 1994). We replicated previous experimental cue-validity effects relating to a spatial shift of attention within an object (spatial effect), to attention switch between objects (object effect), and to the attraction of attention towards the display centroid (attraction effect), taking also into account the design-inherent imbalance of valid and other trials. We simultaneously estimated variance/covariance components of subject-related random effects for these spatial, object, and attraction effects in addition to their mean RTs. The spatial effect showed a strong positive correlation with mean RT and a strong negative correlation with the attraction effect. The analysis of individual differences suggests that slow subjects engage attention more strongly at the cued location than fast subjects. We compare this joint LMM analysis of experimental effects and associated subject-related variances and correlations with two frequently used alternative statistical procedures.

Corrections. Titus von der Malsburg pointed out two errors in the publication relating to AIC and BIC values reported on page 7:

(1) The AIC-value for the model m2 was reported as 328540; the correct value is 325840. This was a transposition typo ("85" instead of "58").

(2) The BIC-value for model m1 (325941) is actually smaller than the BIC-value for model m2 (325964). Thus, for BIC, the fit of model m2 is not better than the one for model m1.

5 Jan 2011, R. Kliegl

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Add new comment

Advantages of LMM

- Useful when designs are unbalanced
(which they almost always are in psycholinguistic experiments)
  - Different number of subjects or trials (e.g., due to valid vs. invalid cues)
  - Errors in RT experiments
  - Missing observations (e.g., blinks in eye movements)
- Works with continuous independent variables (i.e., covariates), alternative for multiple regression, given repeated measures
- Handles grouped data (such as repeated measures); alternative for hierarchical linear models, allows also crossed random factors
- *lmer* allows easy specification of crossed random factors, alternative for F1- and F2-statistics in psycholinguistic research

... but most importantly for research driven by theory

- Focus on planned, theoretically motivated comparisons; "overall F"-test requires extra effort

- Use of systematic variance between subjects or items for theory-guided and heuristic purposes; traditionally lumped with error

- Integration of experimental and individual-difference perspectives

- Within R, it is available for free. Support *Open Science*!

That's it. Thank you and have fun!