

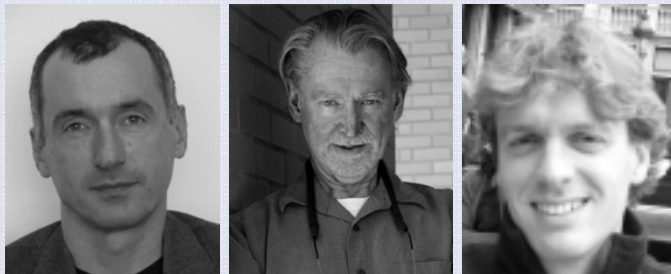
Bayesian Estimation of Multinomial Processing Tree Models with Heterogeneity in Participants and Items

Dora Matzke

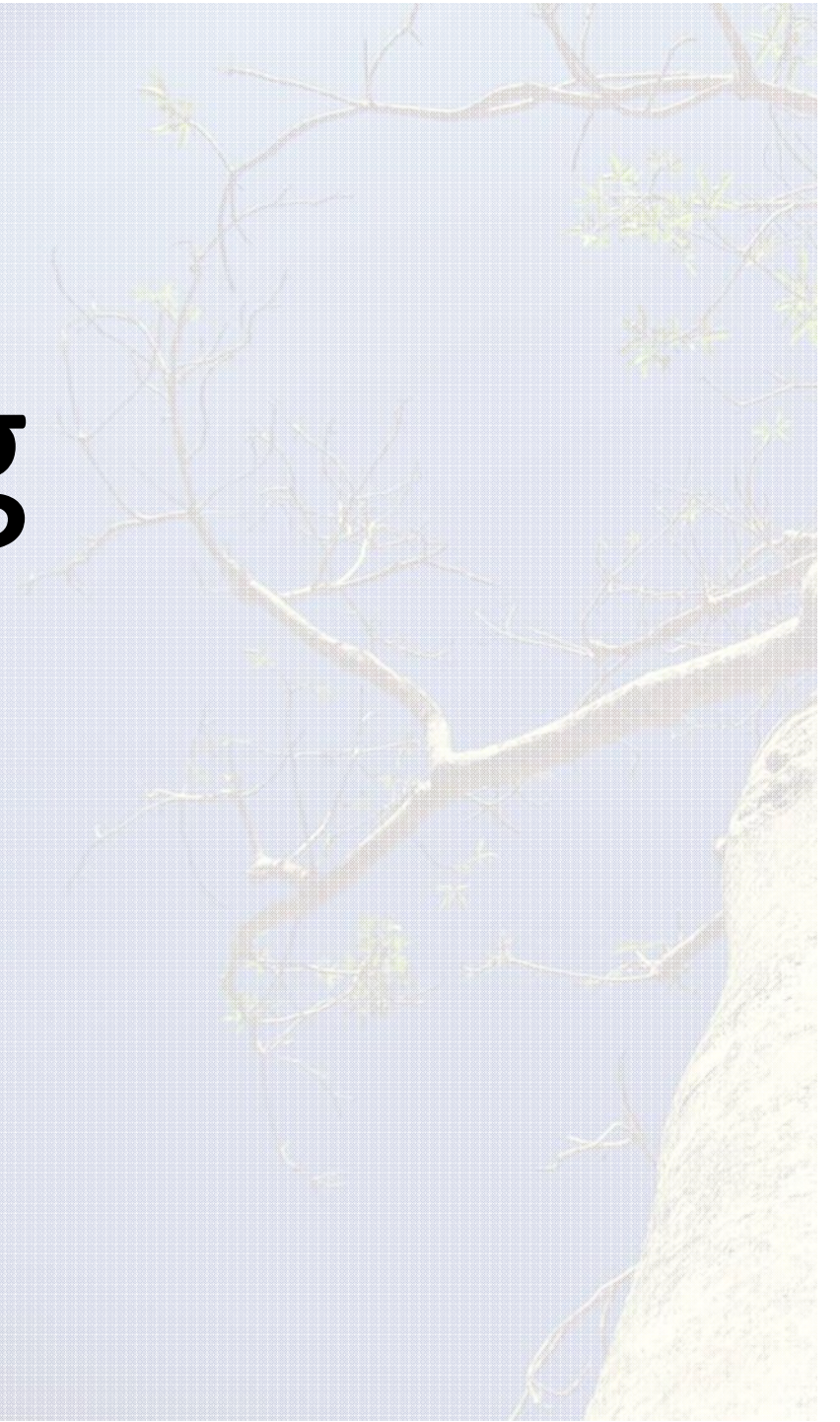
Conor Dolan

William Batchelder

EJ Wagenmakers



dog



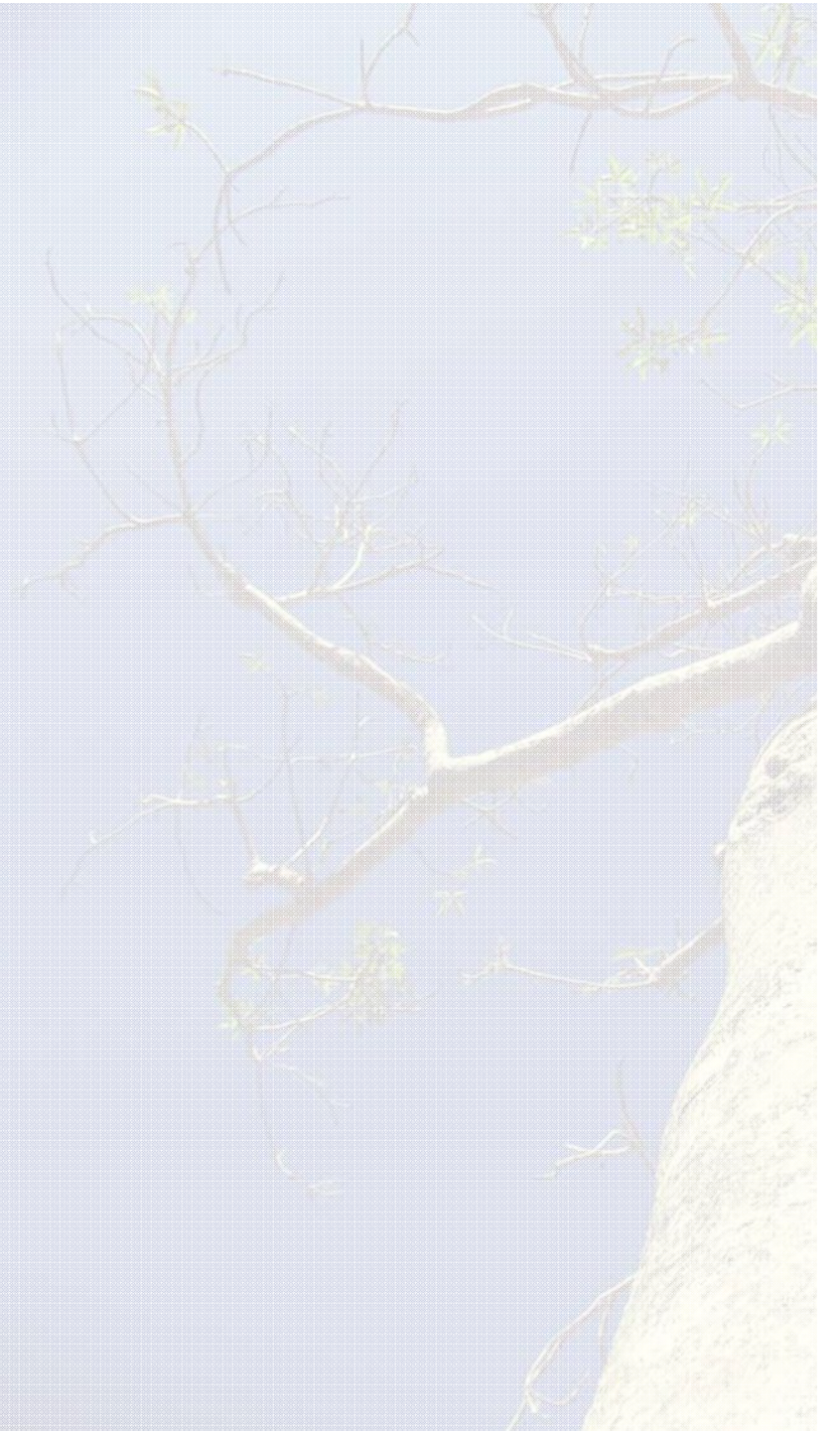
paper



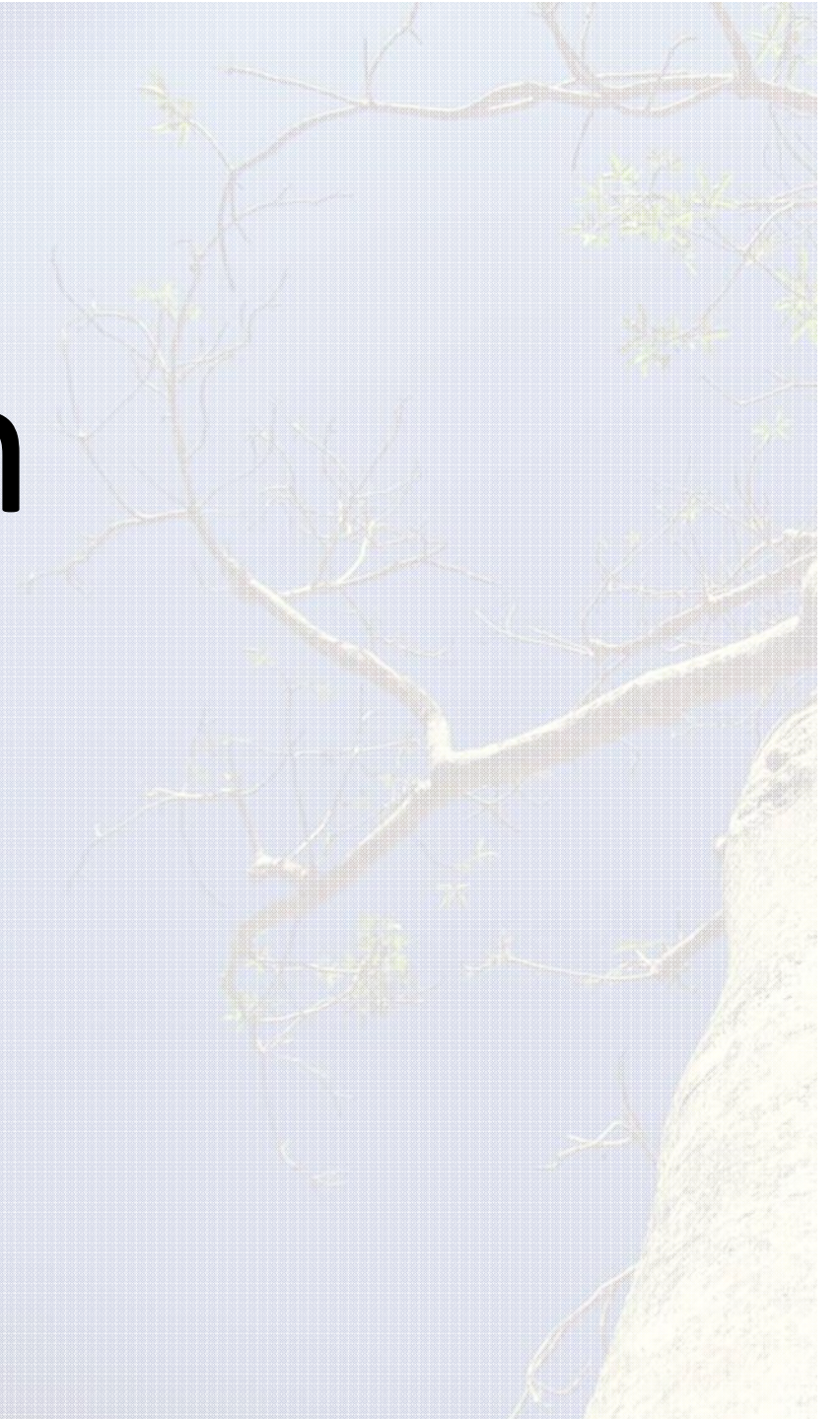
father



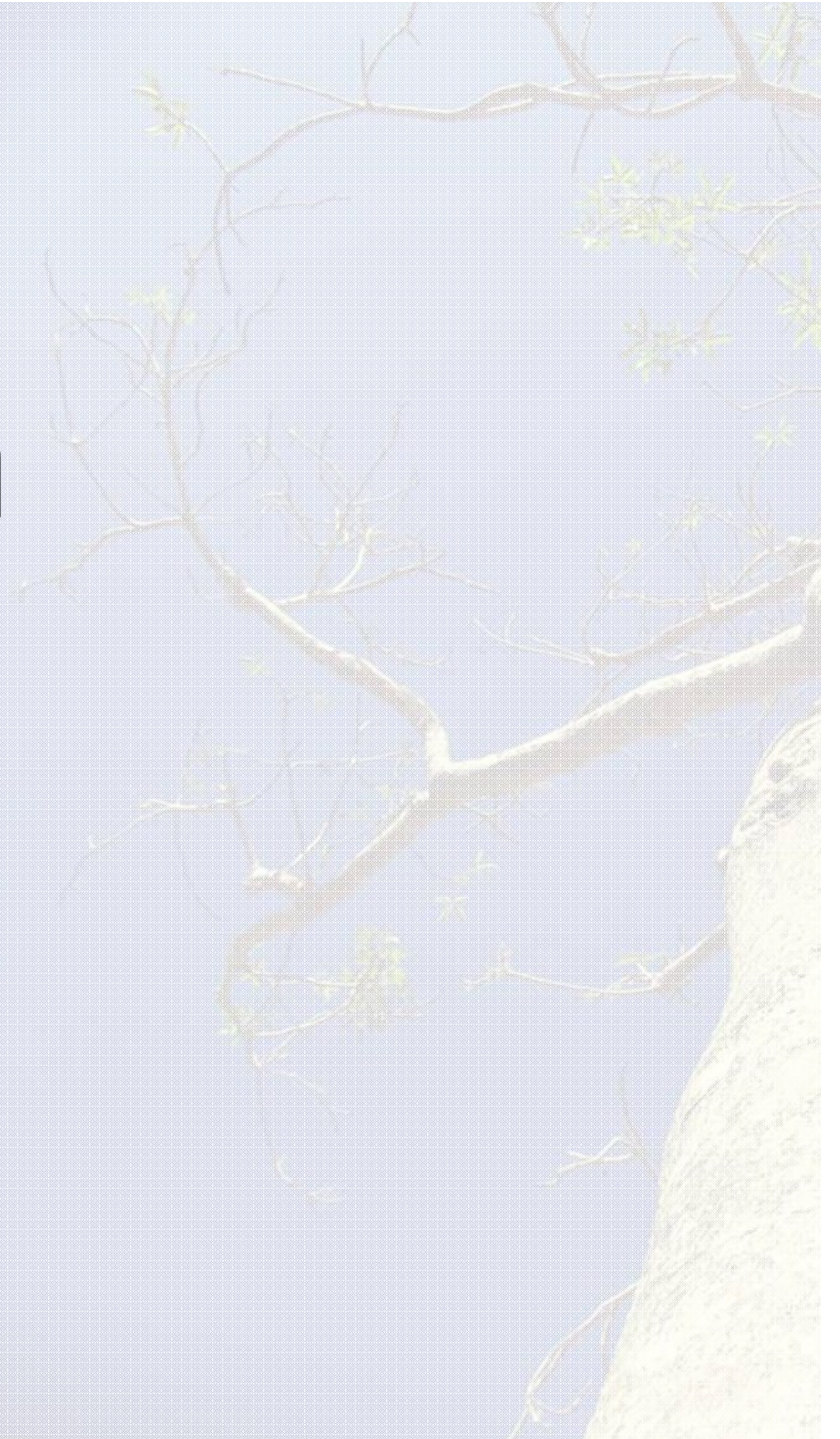
cat



pen



son



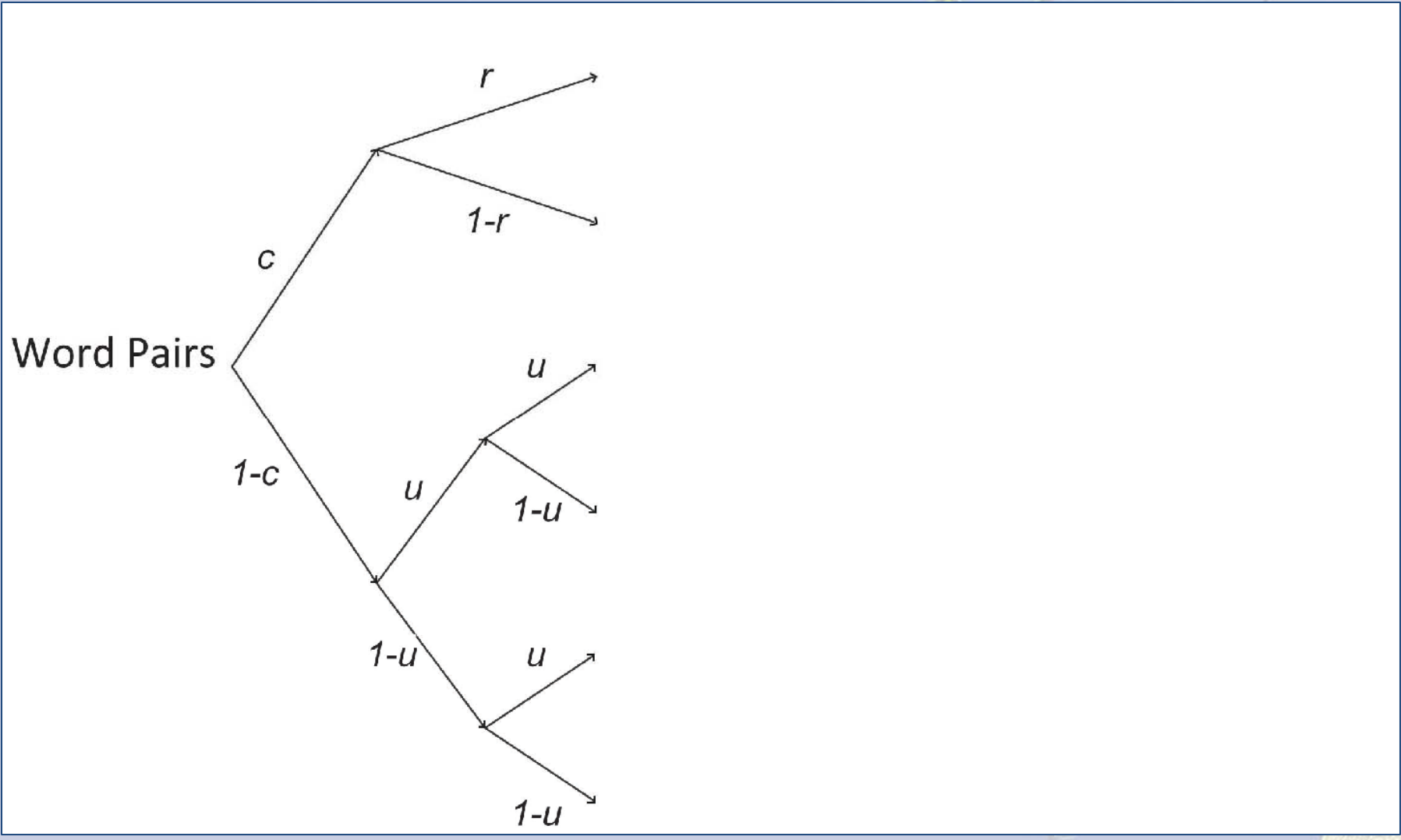
Pair-Clustering Paradigm

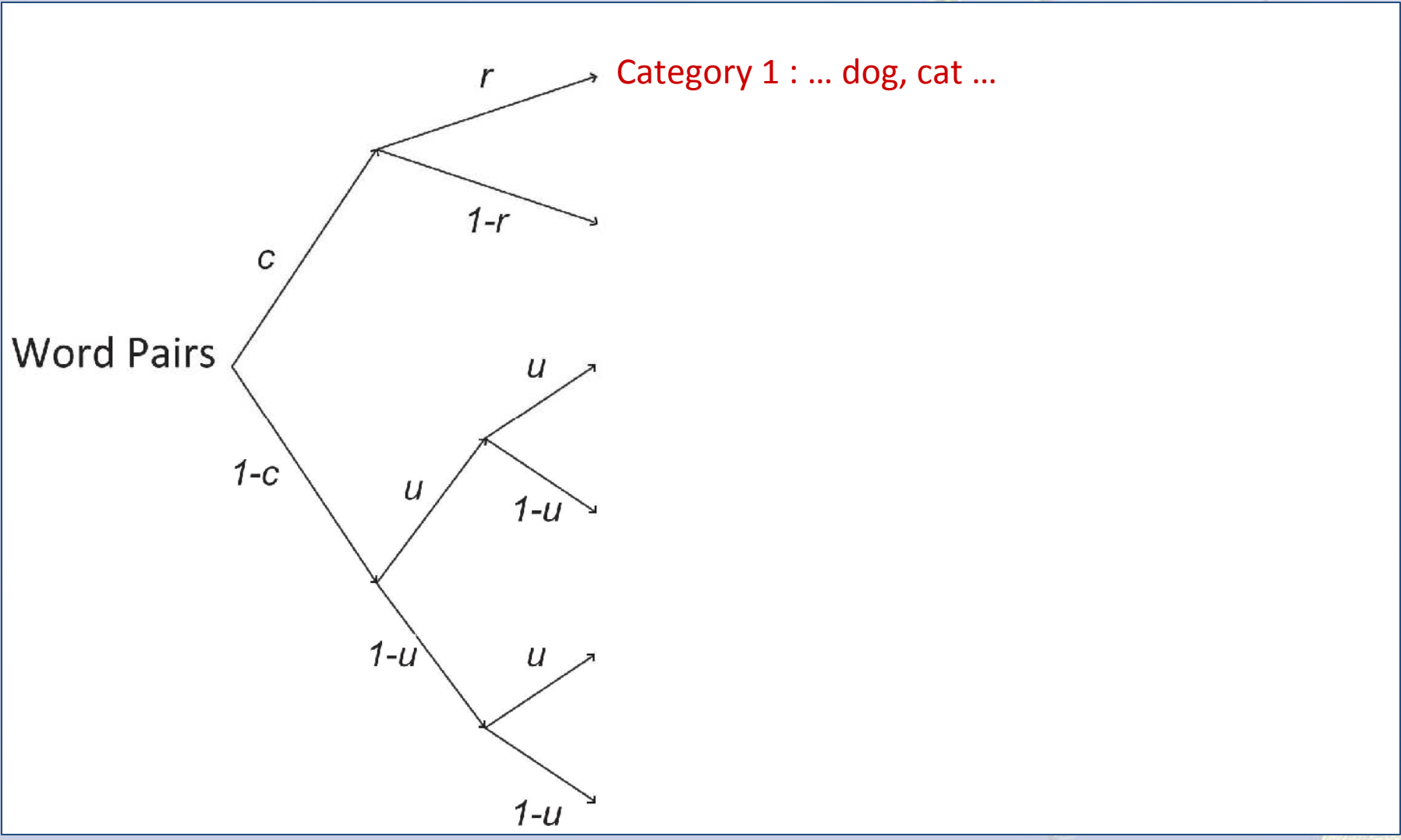
(Batchelder & Riefer, 1980, 1986)

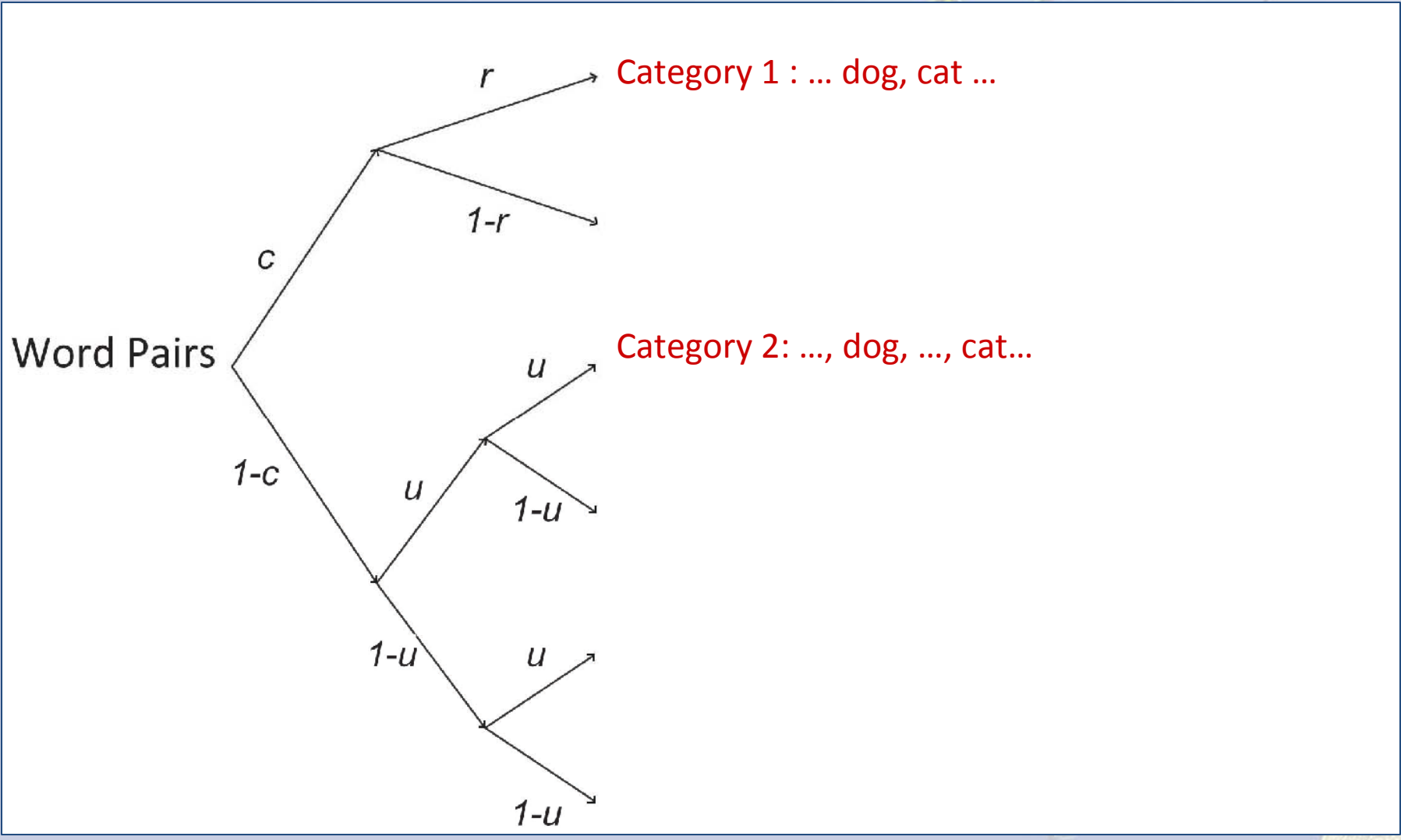
dog – cat

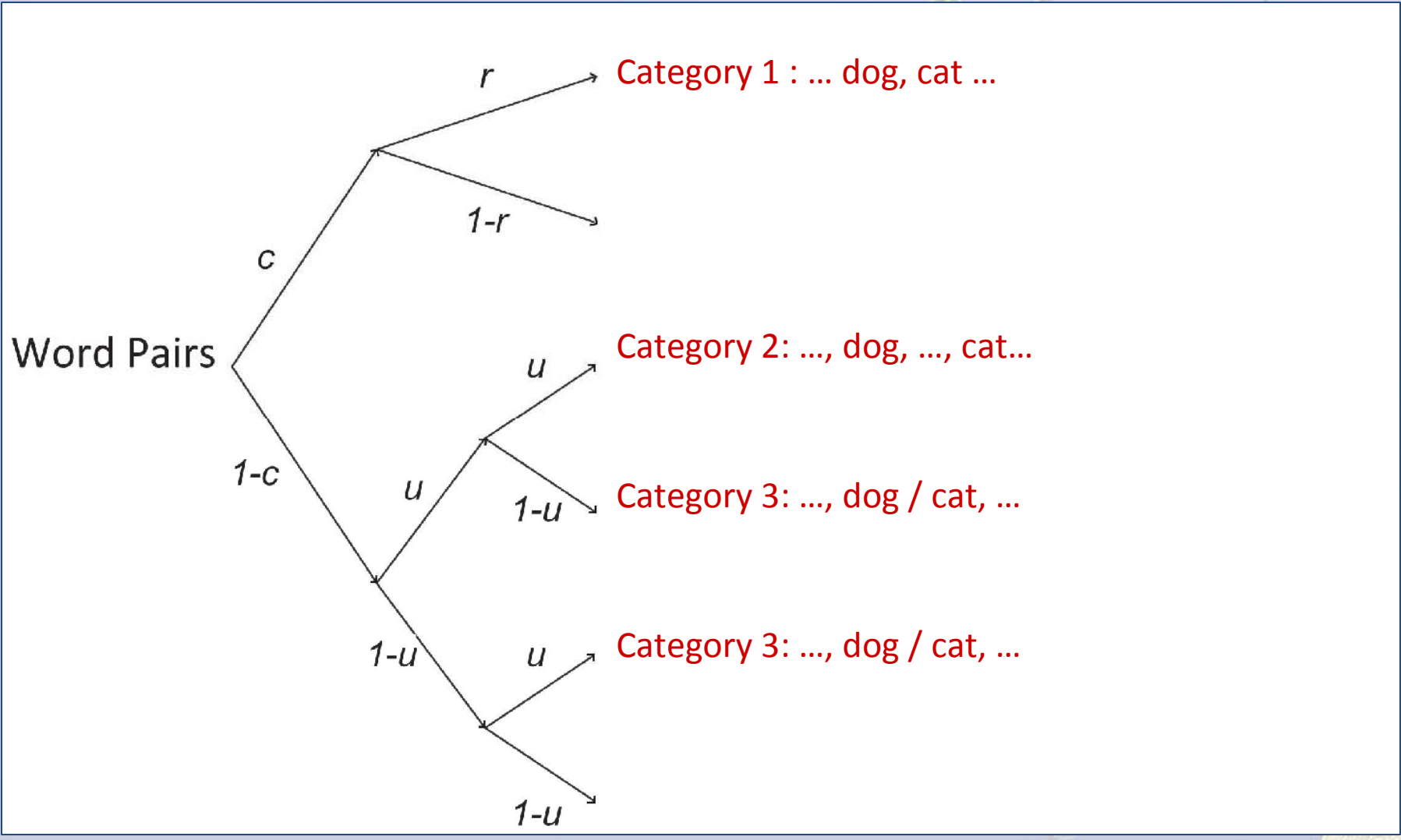
paper – pen

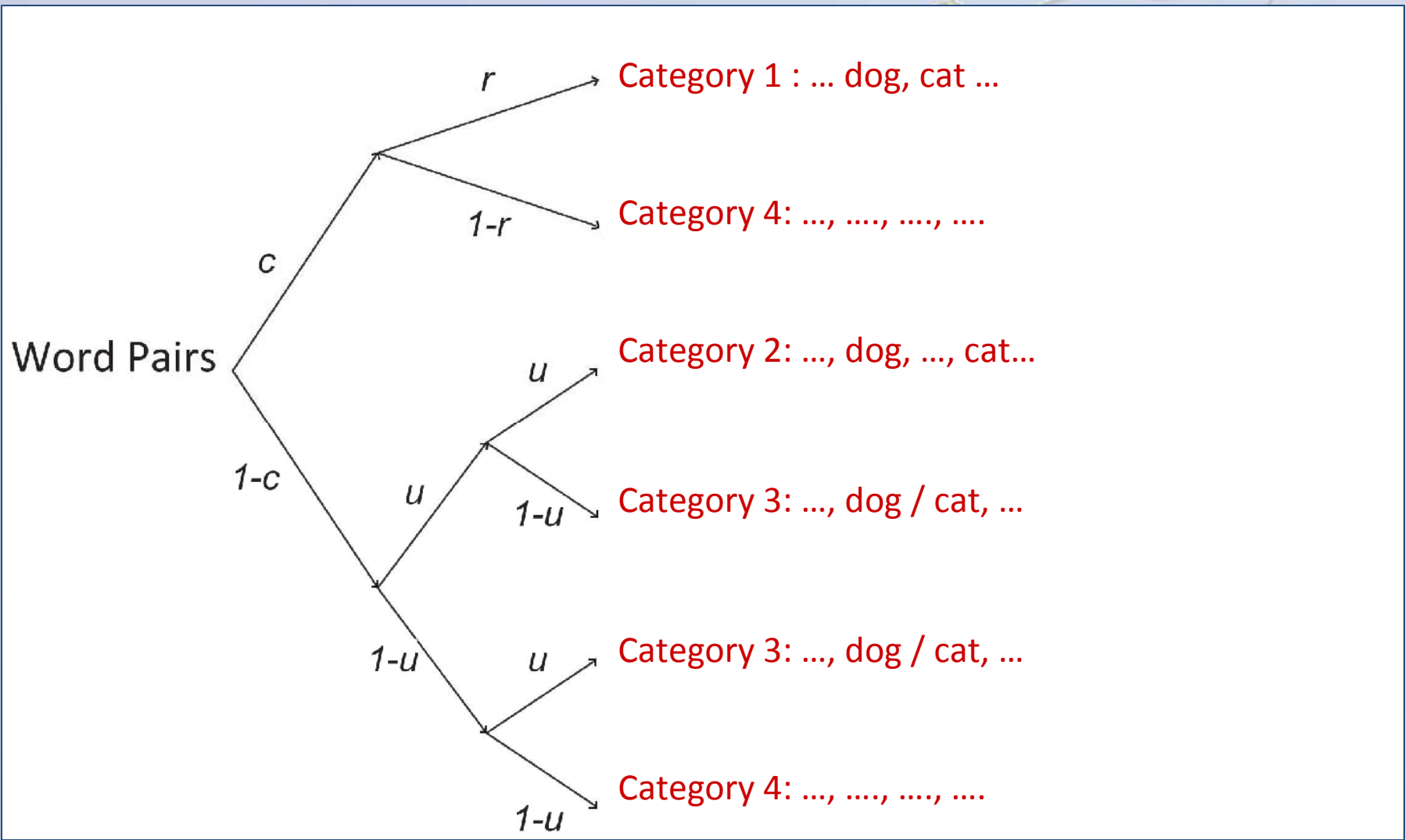
father – son

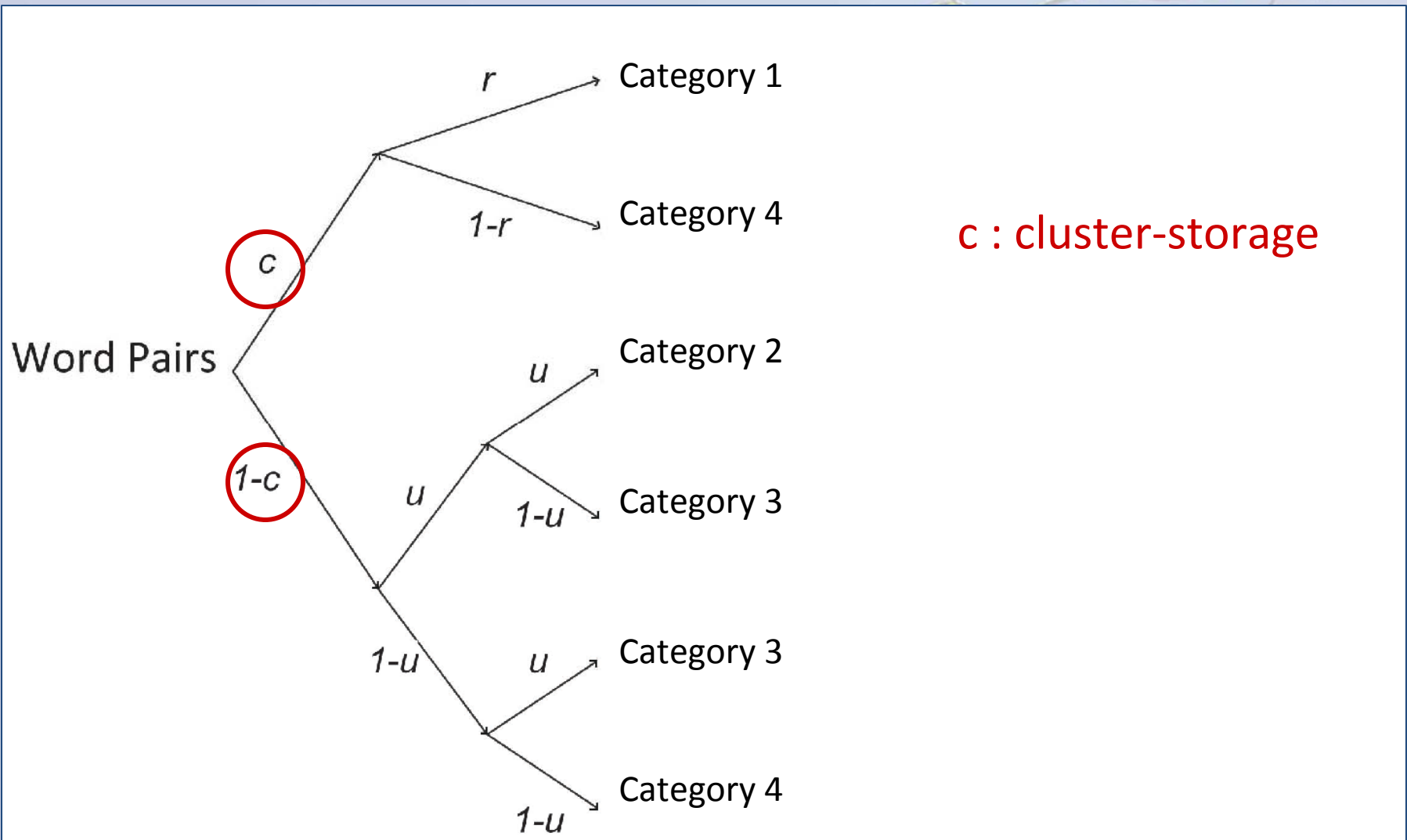


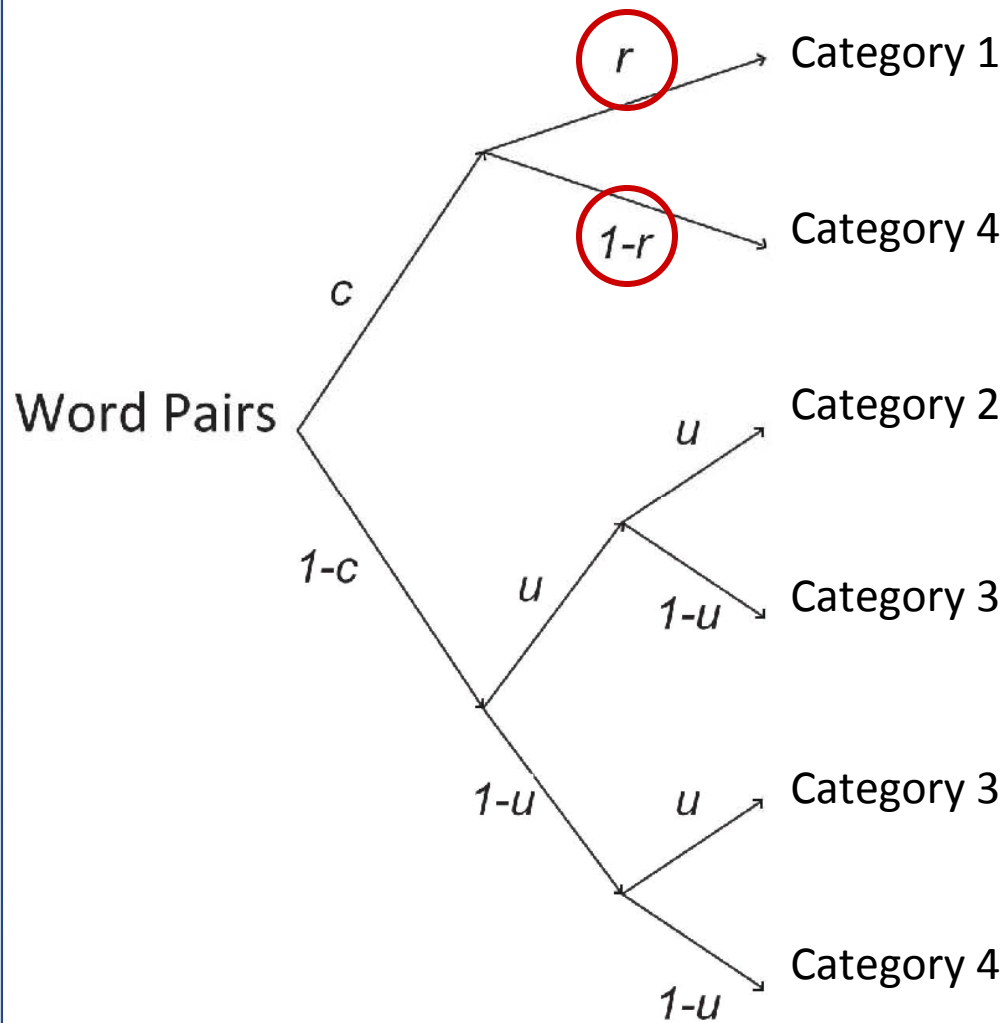






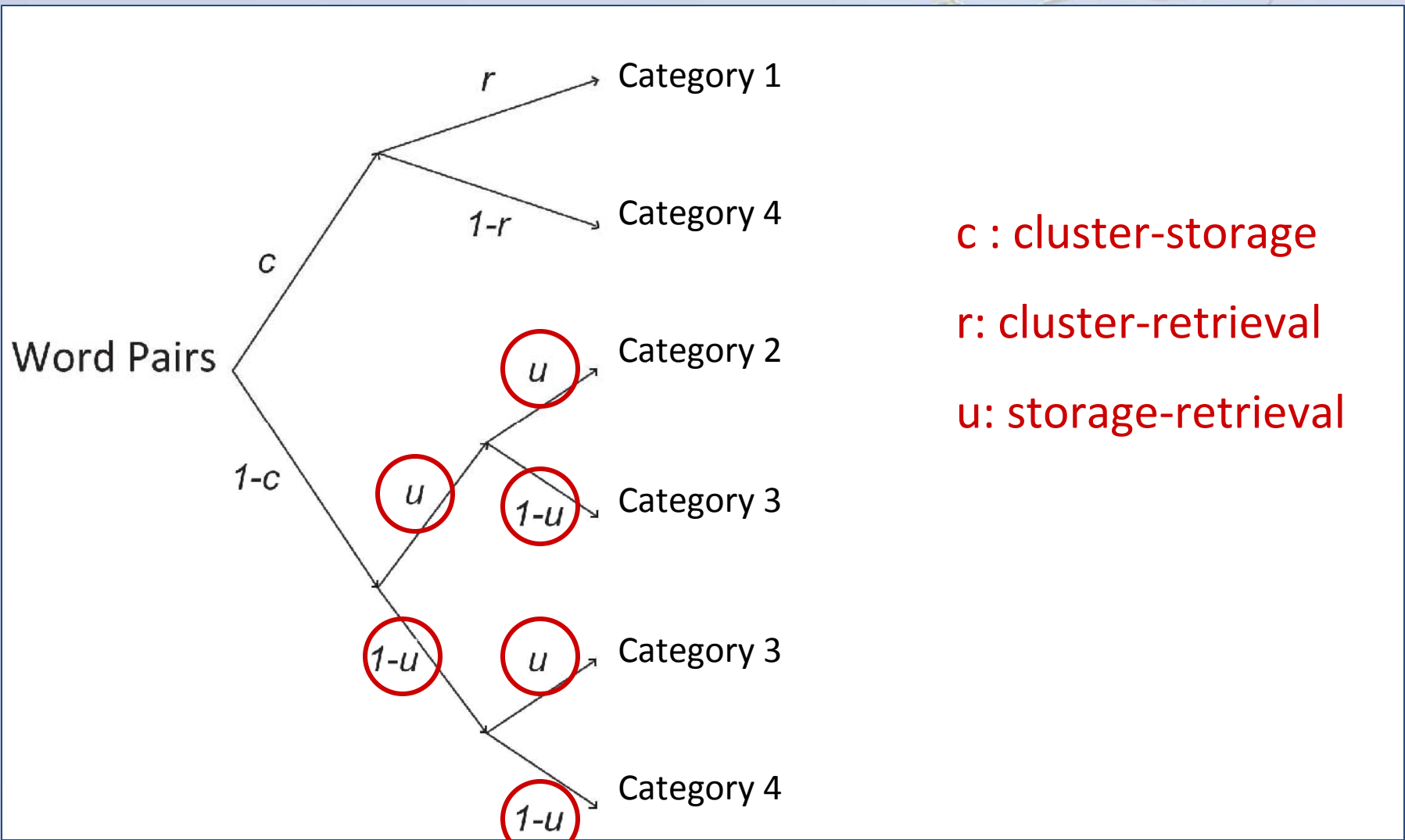






c : cluster-storage

r: cluster-retrieval



Parameter heterogeneity

- Traditional aggregate analysis biased if parameters are heterogeneous
- Incorporate participant heterogeneity in MPT models
 - Latent-trait approach (Klauer, 2010)
- Crossed-random effects extension
 - Participant and item heterogeneity

Outline

- Latent-trait approach (Klauer, 2010)
- Crossed-random effects extension
- Fitting experimental free recall data

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Latent-trait approach (Klauer, 2010)

- Parameter heterogeneity as a result of individual differences between participants
- Data aggregated only over word pairs
- (c_i, r_i, u_i) for $i=1, \dots, l$.

Latent-trait approach (Klauer, 2010)

- **Hierarchical Bayesian modeling** (e.g., Gelman & Hill, 2007)
- **Probit transformed individual parameters are multivariate normal distributed**
 - Between subject variability
 - Parameter correlations

Outline

- Latent-trait approach (Klauer, 2010)
- **Crossed-random effects extension**
- Fitting experimental free recall data

Crossed-random effects approach

- Parameter heterogeneity as a result of differences between participants and items
- Raw participant-by-item data
- $\Theta_{ik} = (c_{ik}, r_{ik}, u_{ik})$ for $i=1, \dots, I$, and $k=1, \dots, K$.

Crossed-random effects approach

- Reduce the number of parameters
- Participant effects + item effects (e.g, Rouder et al., 2007, 2008)

Data

for $i=1,\dots,l$, and $k=1,\dots,K$

- $\text{Data}_{ik} \sim \text{Multinomial}(\text{Pr}(C_1)_{ik}, \dots, \text{Pr}(C_4)_{ik})$

Data

for $i=1, \dots, l$, and $k=1, \dots, K$

- $\text{Data}_{ik} \sim \text{Multinomial}(\text{Pr}(C_1)_{ik}, \dots, \text{Pr}(C_4)_{ik})$
- $\text{Pr}(C_1)_{ik} = c_{ik} \times r_{ik}$
 $\text{Pr}(C_2)_{ik} = (1 - c_{ik}) \times u_{ik}^2$
 $\text{Pr}(C_3)_{ik} = (1 - c_{ik}) \times 2 \times u_{ik} \times (1 - u_{ik})$
 $\text{Pr}(C_4)_{ik} = c_{ik} \times (1 - r_{ik}) + (1 - c_{ik}) \times (1 - u_{ik})^2$

Probit transformation

for $i=1,\dots,l$, and $k=1,\dots,K$

- $c_{ij} = \Phi(c_{ij}^{\text{prb}})$
 $r_{ij} = \Phi(r_{ij}^{\text{prb}})$
 $u_{ij} = \Phi(u_{ij}^{\text{prb}})$

Additivity

for $i=1,\dots,l$, and $k=1,\dots,K$

- $c_{ik}^{\text{prb}} = \mu_c + \delta_{ci}^{\text{part}} + \delta_{ck}^{\text{item}}$
- $r_{ik}^{\text{prb}} = \mu_r + \delta_{ri}^{\text{part}} + \delta_{rk}^{\text{item}}$
- $u_{ik}^{\text{prb}} = \mu_u + \delta_{ui}^{\text{part}} + \delta_{uk}^{\text{item}}$

Prior distributions

$$\mu + \delta^{\text{part}} + \delta^{\text{item}}$$

- $\mu_c \sim \text{Normal}(0,1)$
- $\mu_r \sim \text{Normal}(0,1)$
- $\mu_u \sim \text{Normal}(0,1)$

Prior distributions

$$\mu + \delta_i^{\text{part}} + \delta_k^{\text{item}}$$

for $i=1, \dots, l$

- $(\delta_{ci}^{\text{part}}, \delta_{ri}^{\text{part}}, \delta_{ui}^{\text{part}}) \sim \text{MNormal}((0,0,0), S)$

Prior distributions

$$\mu + \delta_i^{\text{part}} + \delta_k^{\text{item}}$$

for $i=1, \dots, l$

- $(\delta_{c_i}^{\text{part}}, \delta_{r_i}^{\text{part}}, \delta_{u_i}^{\text{part}}) \sim \text{MNormal}((0,0,0), S)$
- $S \sim \text{Scaled - Inverse-Wishart}(l, \text{df} = 4, \xi^{\text{part}})$
 - $\xi_c^{\text{part}} \sim \text{Uniform}(0,100)$
 - $\xi_r^{\text{part}} \sim \text{Uniform}(0,100)$
 - $\xi_u^{\text{part}} \sim \text{Uniform}(0,100)$

Prior distributions

$$\mu + \delta_i^{\text{part}} + \delta_k^{\text{item}}$$

for $k=1, \dots, K$

- $\delta_{ck}^{\text{part}} \sim \text{Normal}(0, \sigma_c^2)$
- $\delta_{rk}^{\text{part}} \sim \text{Normal}(0, \sigma_r^2)$
- $\delta_{uk}^{\text{part}} \sim \text{Normal}(0, \sigma_u^2)$

Prior distributions

$$\mu + \delta_i^{\text{part}} + \delta_k^{\text{item}}$$

- $\sigma_c^2 \sim \text{Inverse - Gamma}(1, 1, \xi_c^{\text{item}})$
- $\sigma_r^2 \sim \text{Inverse - Gamma}(1, 1, \xi_r^{\text{item}})$
- $\sigma_u^2 \sim \text{Inverse - Gamma}(1, 1, \xi_u^{\text{item}})$
 - $\xi_c^{\text{item}} \sim \text{Uniform}(0, 100)$
 - $\xi_r^{\text{item}} \sim \text{Uniform}(0, 100)$
 - $\xi_u^{\text{item}} \sim \text{Uniform}(0, 100)$

Implementation

- MCMC sampling
- Implemented in WinBUGS
 - Easy-to-use

Outline

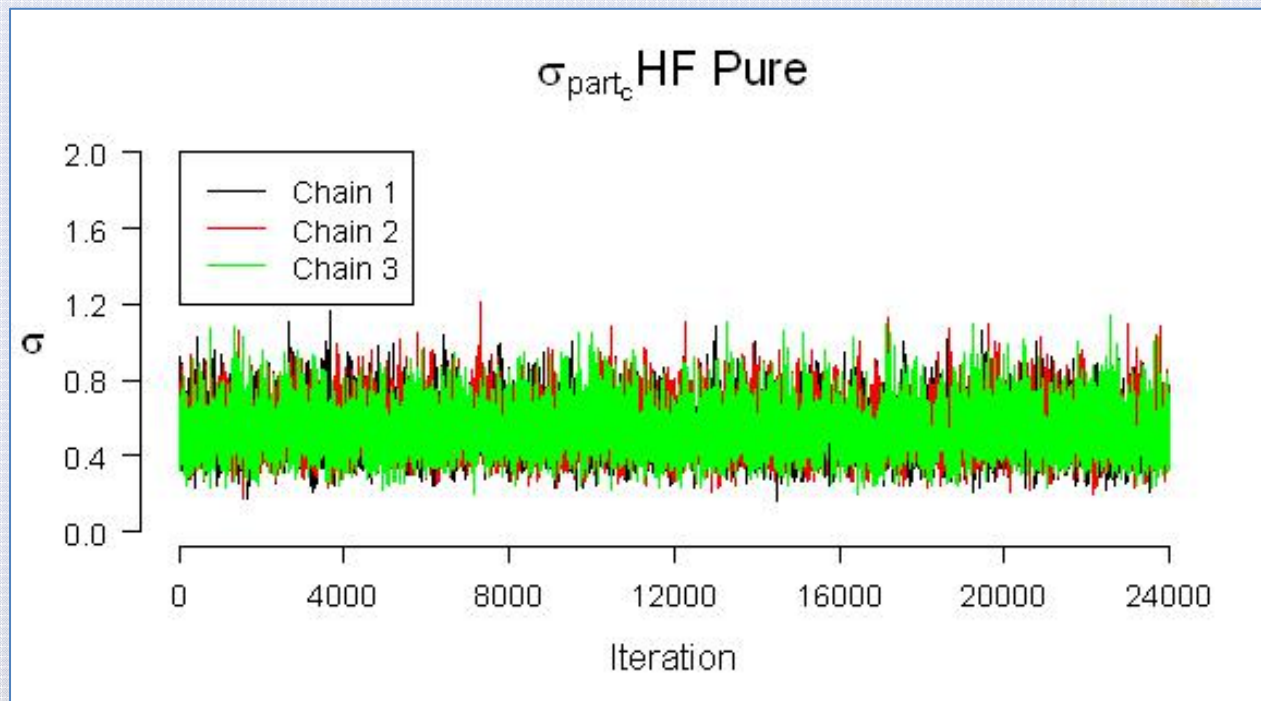
- Latent-trait approach (Klauer, 2010)
- Crossed-random effects extension
- **Fitting experimental free recall data**

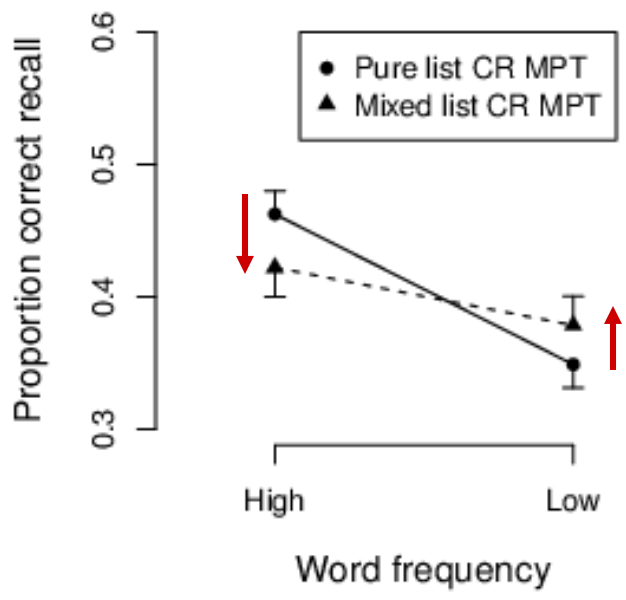
Fitting Real Data

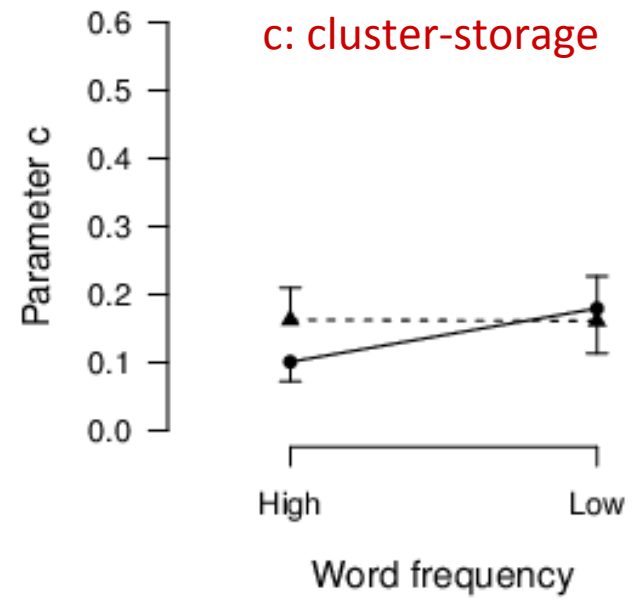
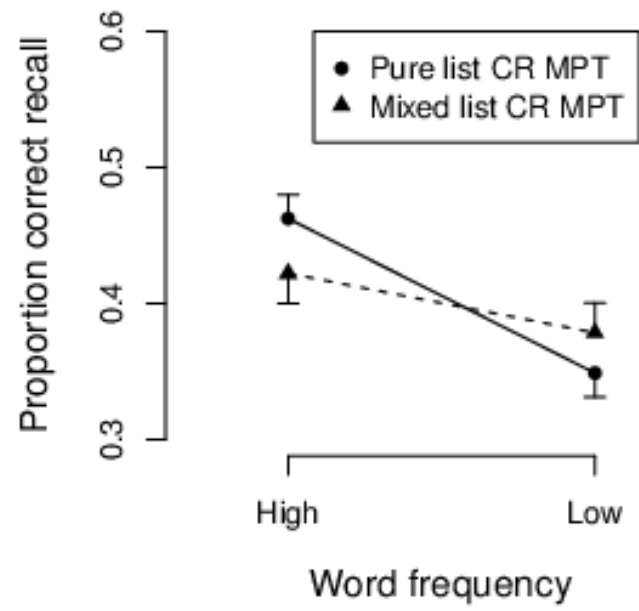
- Pure list vs. mixed list word frequency paradox
 - HF Pure $>$ LF Pure
 - HF Mixed \geq LF Mixed
- Orthographically related word pairs
- 65 participants and 4 list conditions
 - HF Pure
 - LF Pure
 - HF Mixed
 - LF Mixed

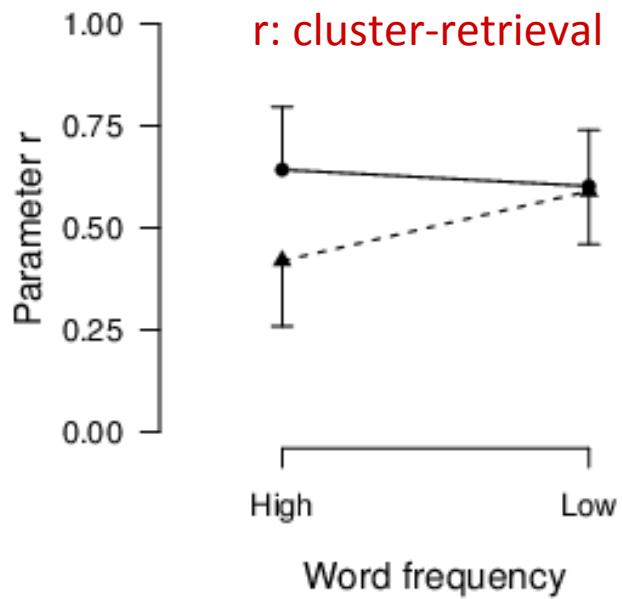
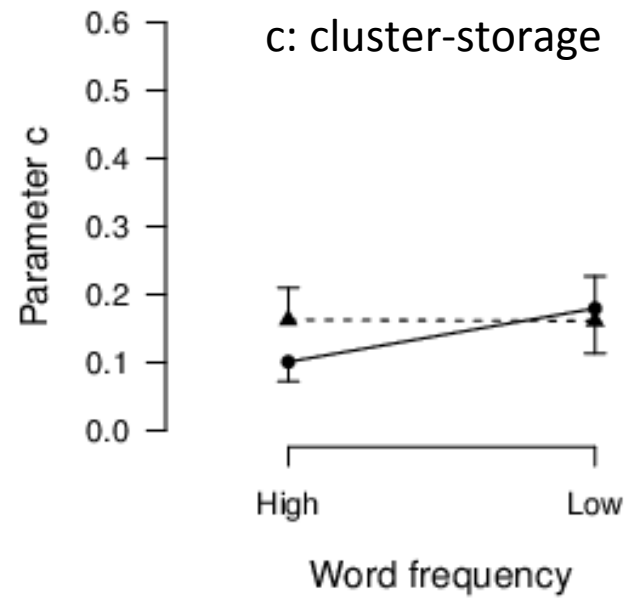
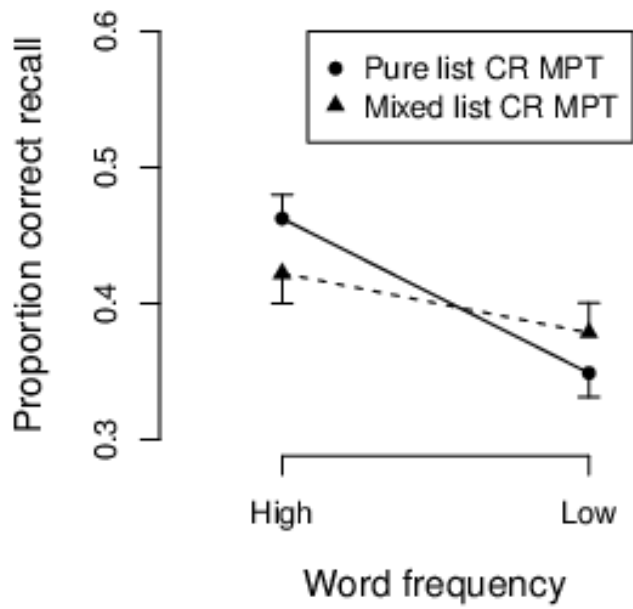
Fitting Real Data

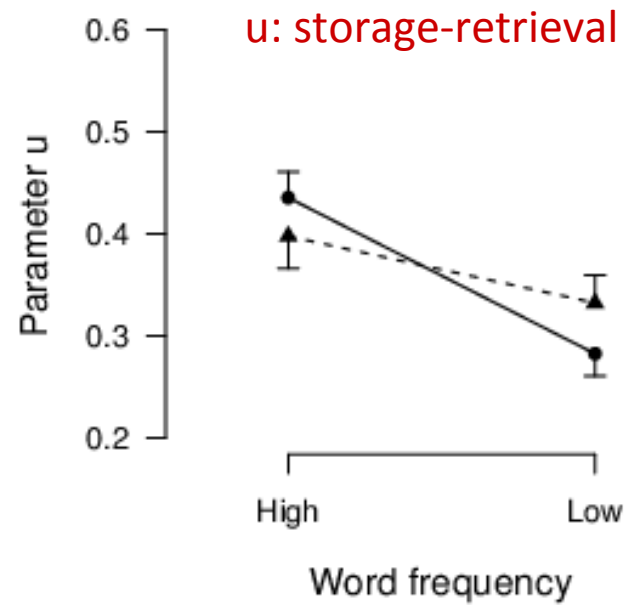
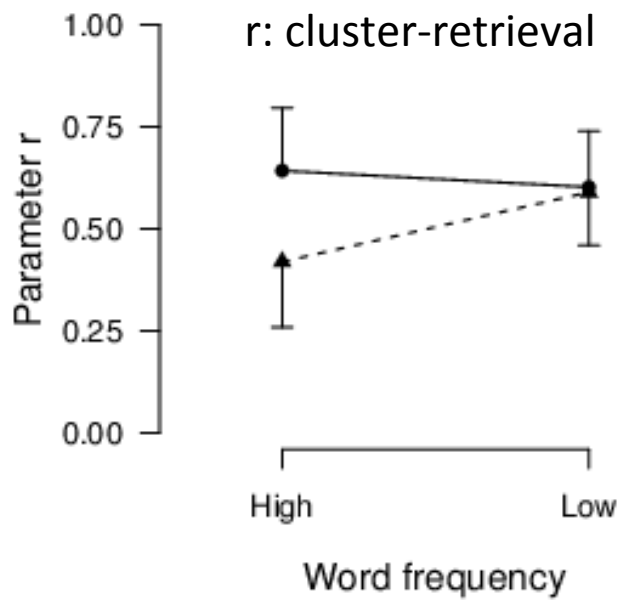
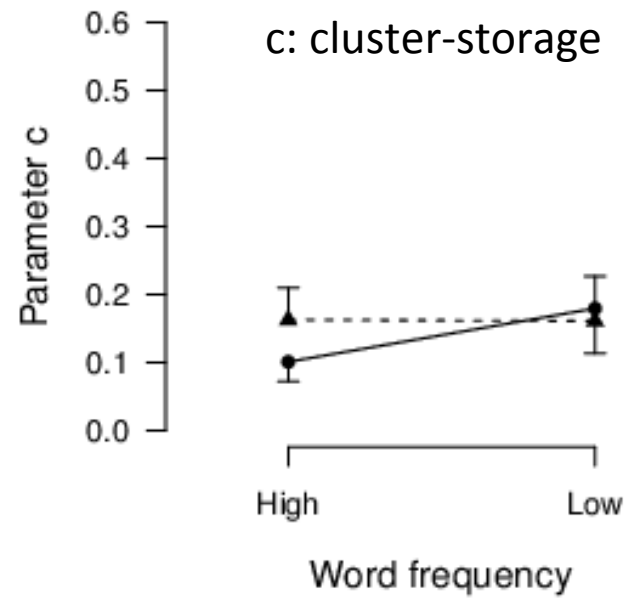
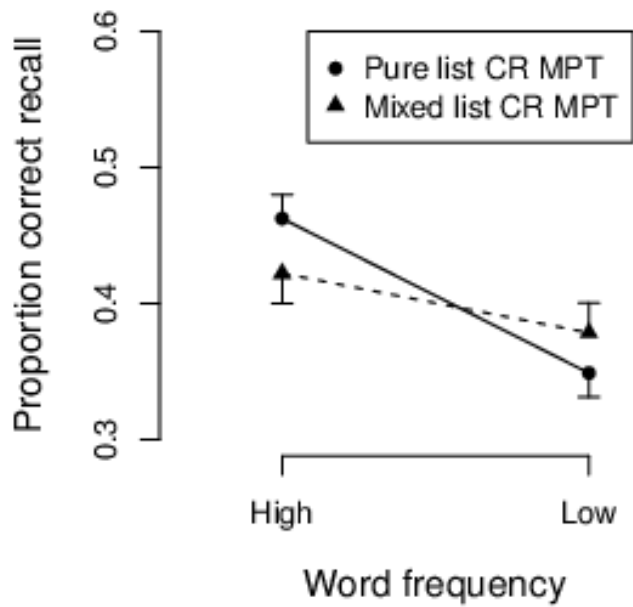
- Convergence: OK
- Posterior predictive model checks: OK

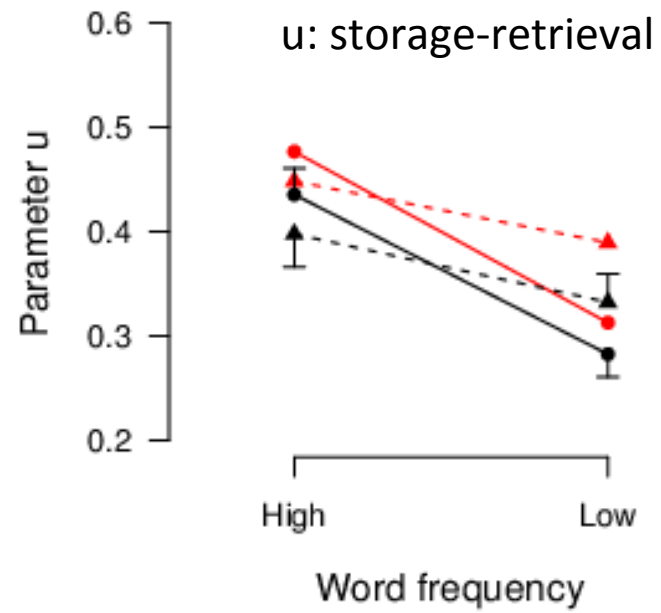
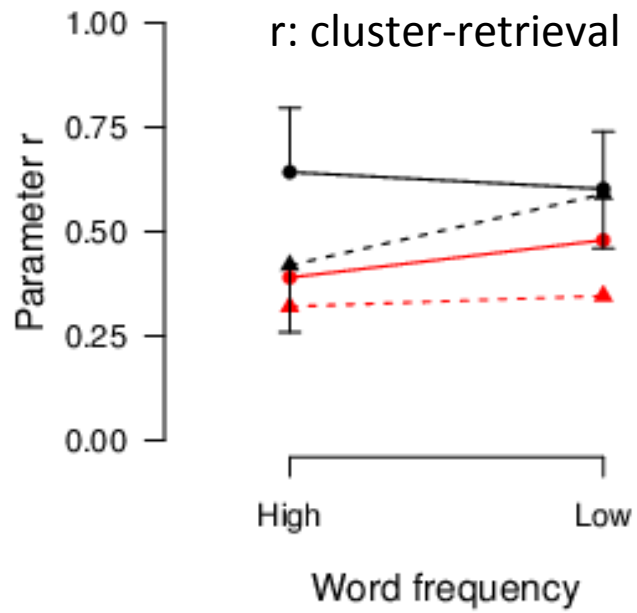
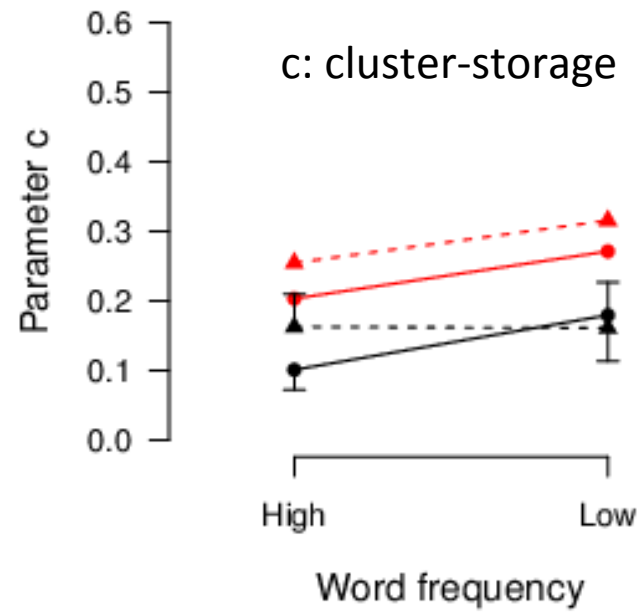
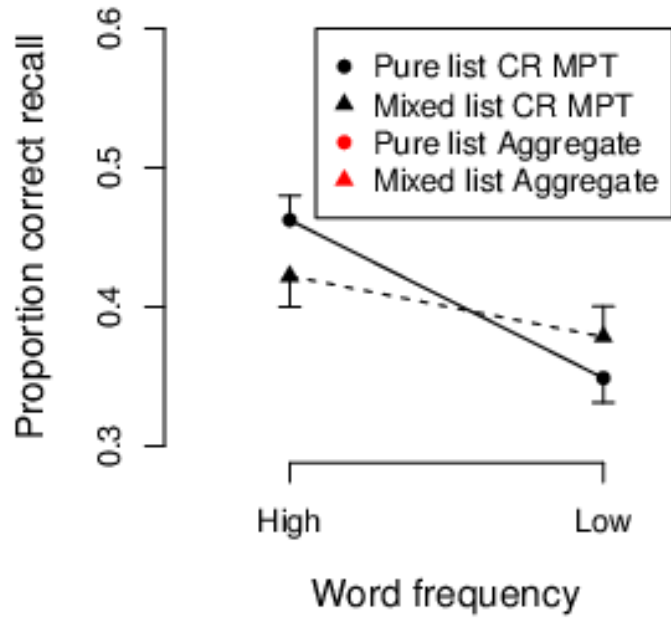








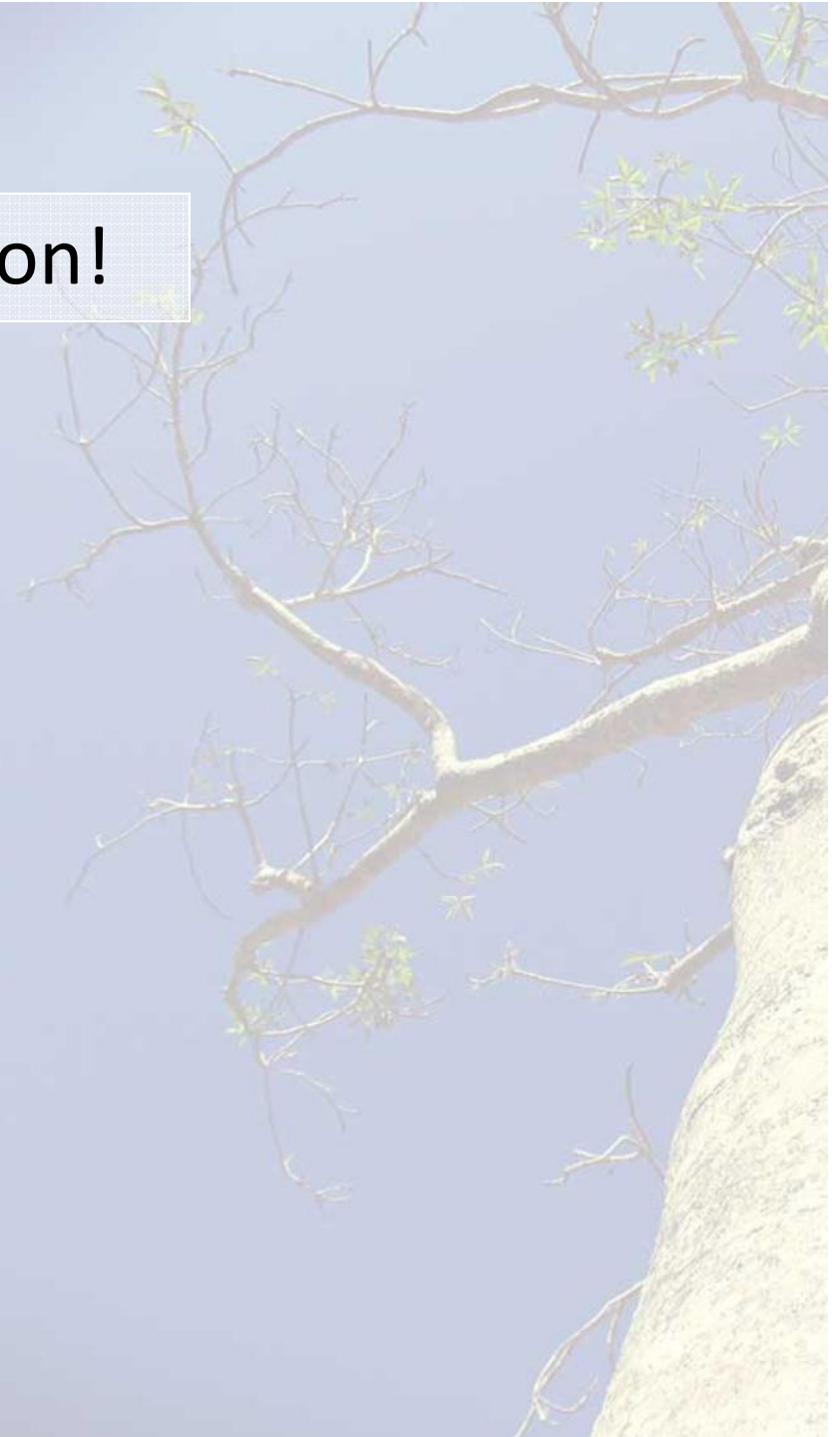




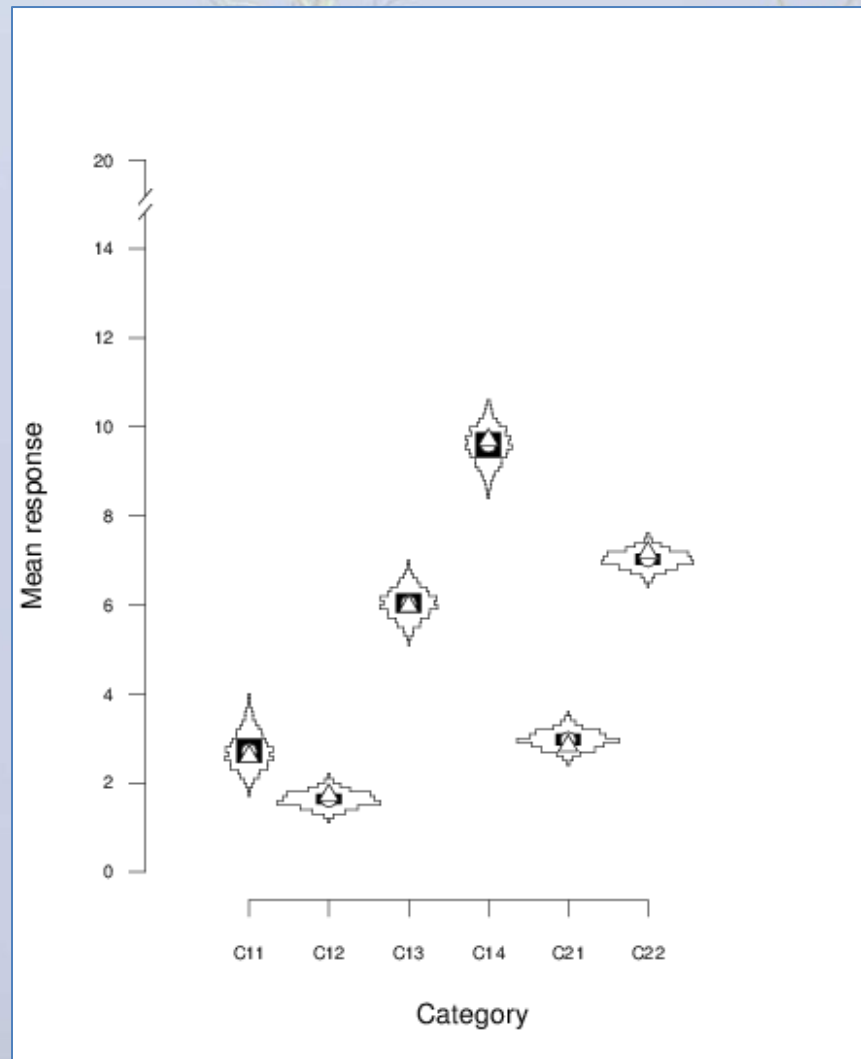
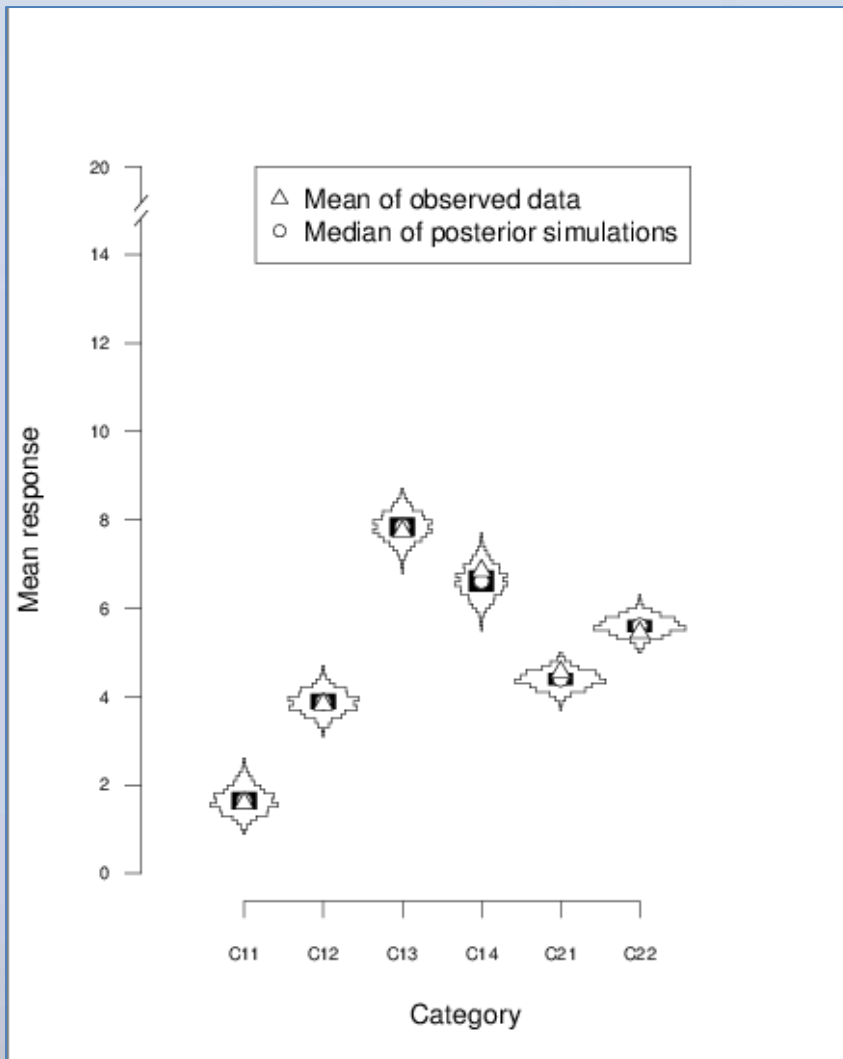
Summary

- WinBUGS implementations of a crossed–random effects MPT model
 - Conclusions about underlying cognitive processes
 - No need to aggregate
 - Flexible

Thank you for your attention!



Posterior Predictive Checks: Pure list



Posterior Predictive Checks: Mixed list

