

# Hierarchical Models

PSYC 573

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University of Southern California

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# Therapeutic Touch Example ( $N = 28$ )

# Data Points From One Person

*y*: whether the guess of  
which hand was hovered over  
was correct

Person S01

<b>y</b>	<b>s</b>
1	S01
0	S01
0	S01
0	S01
0	S01
0	S01
0	S01
0	S01
0	S01
0	S01

# Binomial Model

We can use a Bernoulli model:

$$y_i \sim \text{Bern}(\theta)$$

for  $i = 1, \dots, N$

Assuming exchangeability given  $\theta$ , more succinct to write

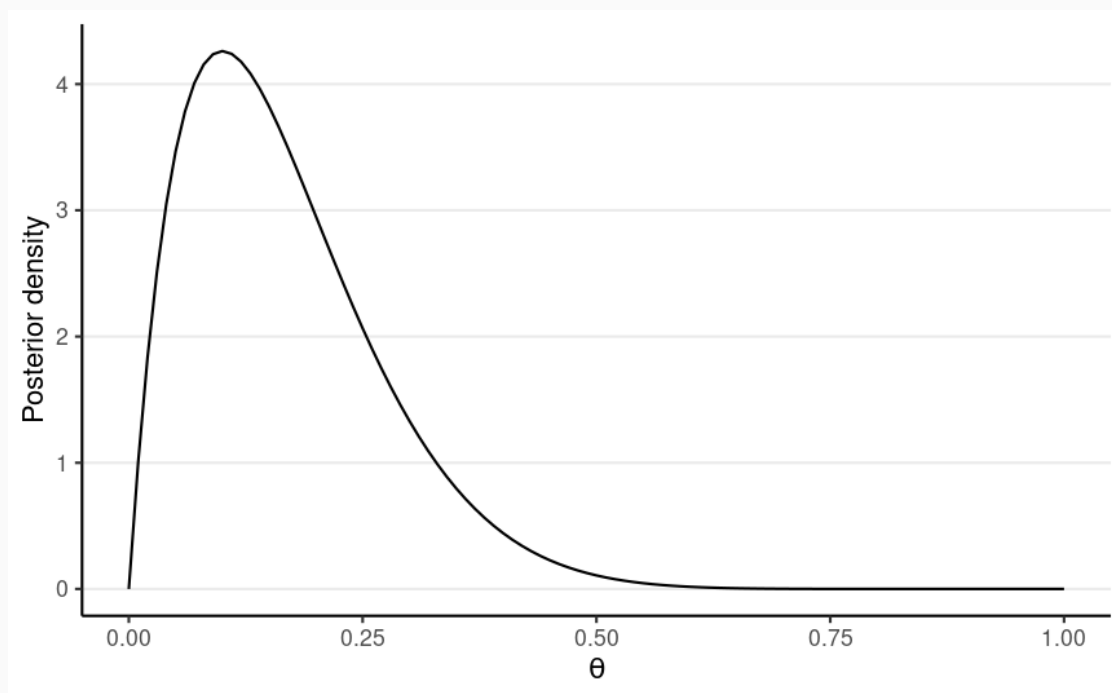
$$z \sim \text{Bin}(N, \theta)$$

for  $z = \sum_{i=1}^N y_i$

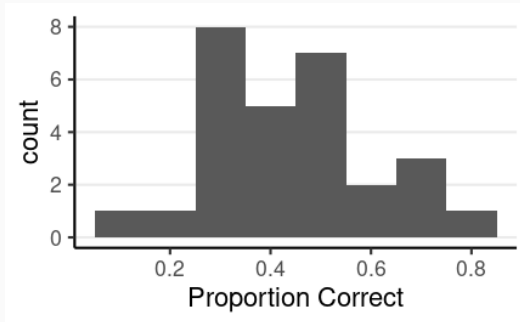
- Bernoulli: Individual trial
- Binomial: total count of "1"s

1 success, 9 failures

Posterior: Beta(2, 10)



# Multiple People



We could repeat the binomial model for each of the 28 participants, to obtain posteriors for  $\theta_1, \dots, \theta_{28}$

But . . .

Do we think our belief about  $\theta_1$  would inform our belief about  $\theta_2$ , etc?

After all, human beings share 99.9% of genetic makeup

# Three Positions of Pooling

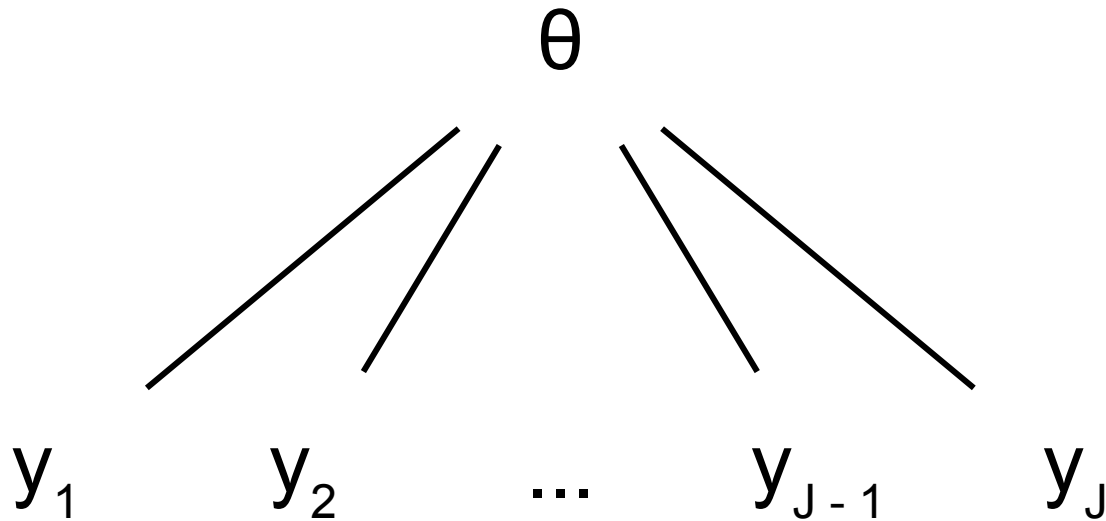
- No pooling: each individual is completely different; inference of  $\theta_1$  should be independent of  $\theta_2$ , etc
- Complete pooling: each individual is exactly the same; just one  $\theta$  instead of 28  $\theta_j$ 's
- **Partial pooling**: each individual has something in common but also is somewhat different

# No Pooling

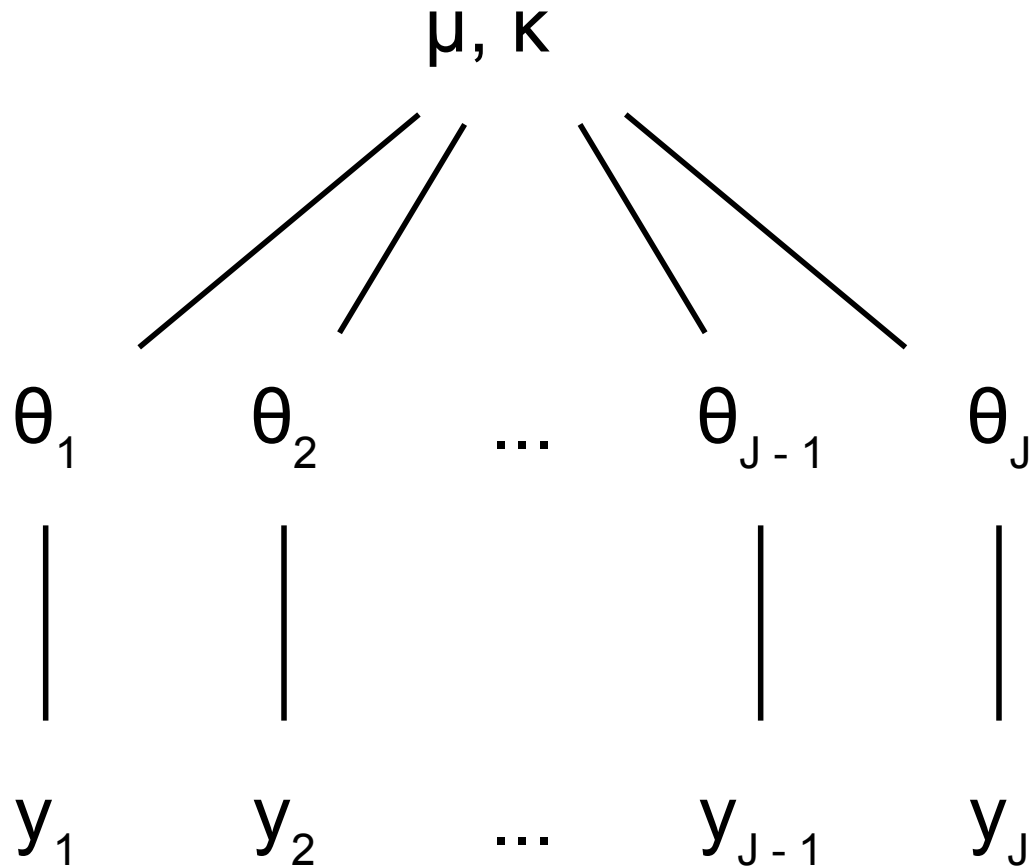
$$\begin{array}{ccccc} \theta_1 & \theta_2 & \dots & \theta_{J-1} & \theta_J \\ | & | & & | & | \\ y_1 & y_2 & \dots & y_{J-1} & y_J \end{array}$$



# Complete Pooling



# Partial Pooling



# Partial Pooling in Hierarchical Models

Hierarchical Priors:  $\theta_j \sim \text{Beta2}(\mu, \kappa)$

Beta2: *reparameterized* Beta distribution

- mean  $\mu = a / (a + b)$
- concentration  $\kappa = a + b$

Expresses the prior belief:

Individual  $\theta$ s follow a common Beta distribution with mean  $\mu$  and concentration  $\kappa$

# How to Choose $\kappa$

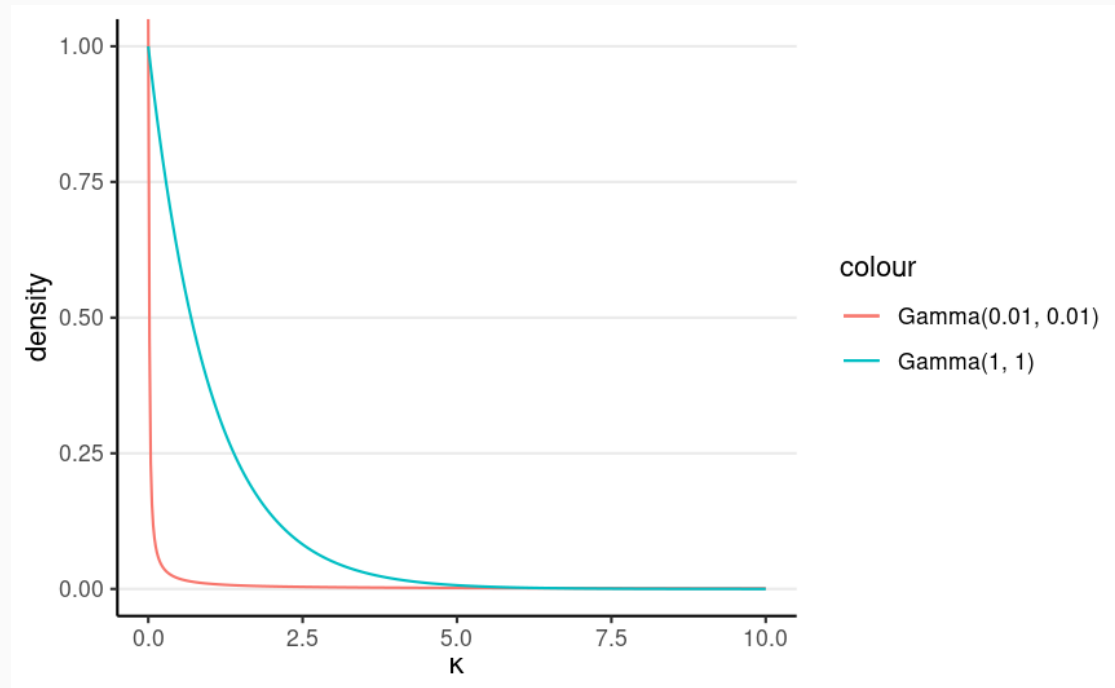
If  $\kappa \rightarrow \infty$ : everyone is the same; no individual differences (i.e., complete pooling)

If  $\kappa = 0$ : everybody is different; nothing is shared (i.e., no pooling)

We can fix a  $\kappa$  value based on our belief of how individuals are similar or different

A more Bayesian approach is to treat  $\kappa$  as an unknown, and use Bayesian inference to update our belief about  $\kappa$

Generic prior by Kruschke (2015):  $\kappa \sim \text{Gamma}(0.01, 0.01)$



Sometimes you may want a stronger prior like  $\text{Gamma}(1, 1)$ , if it is unrealistic to do no pooling

# Full Model

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Model	Stan code
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Model:

$$z_j \sim \text{Bin}(N_j, \theta_j)$$

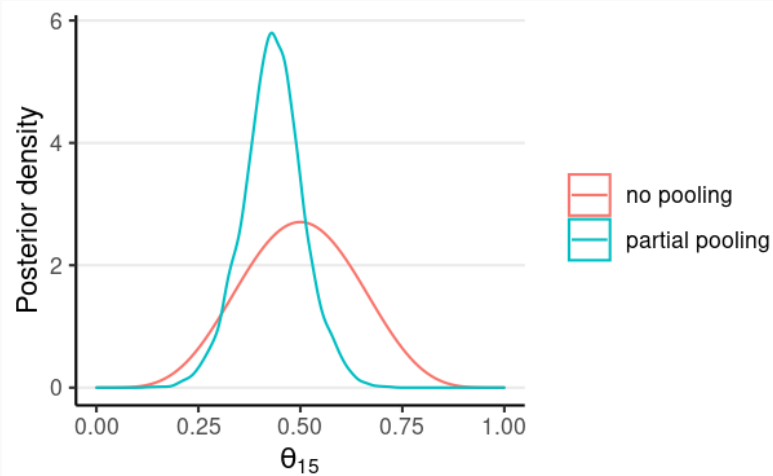
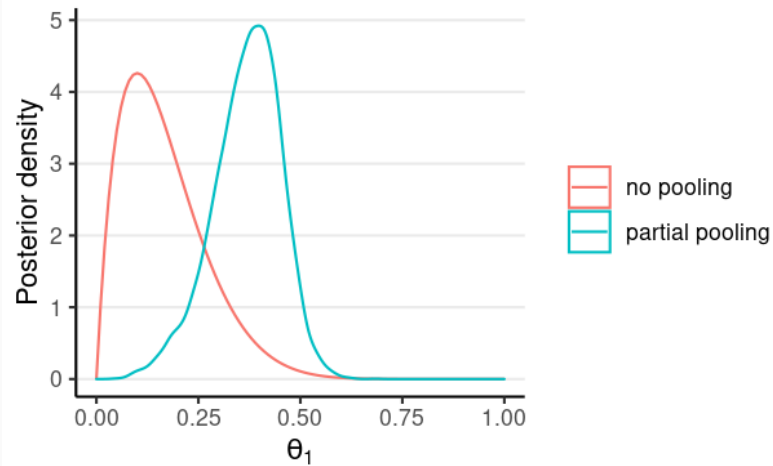
$$\theta_j \sim \text{Beta2}(\mu, \kappa)$$

Prior:

$$\mu \sim \text{Beta}(1.5, 1.5)$$

$$\kappa \sim \text{Gamma}(0.01, 0.01)$$

# Shrinkage



# Multiple Comparisons?

Frequentist: family-wise error rate depends on the number of intended contrasts

Bayesian: only one posterior; hierarchical priors already express the possibility that groups are the same

Thus, Bayesian hierarchical model "completely solves the multiple comparisons problem."<sup>1</sup>

[1]: see <https://statmodeling.stat.columbia.edu/2016/08/22/bayesian-inference-completely-solves-the-multiple-comparisons-problem/>

[2]: See more in ch 11.4 of Kruschke (2015)



# Hierarchical Normal Model

## Effect of coaching on SAT-V

School	Treatment Effect Estimate	Standard Error
A	28	15
B	8	10
C	-3	16
D	7	11
E	-1	9
F	1	11
G	18	10
H	12	18

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Model	Stan code
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Model:

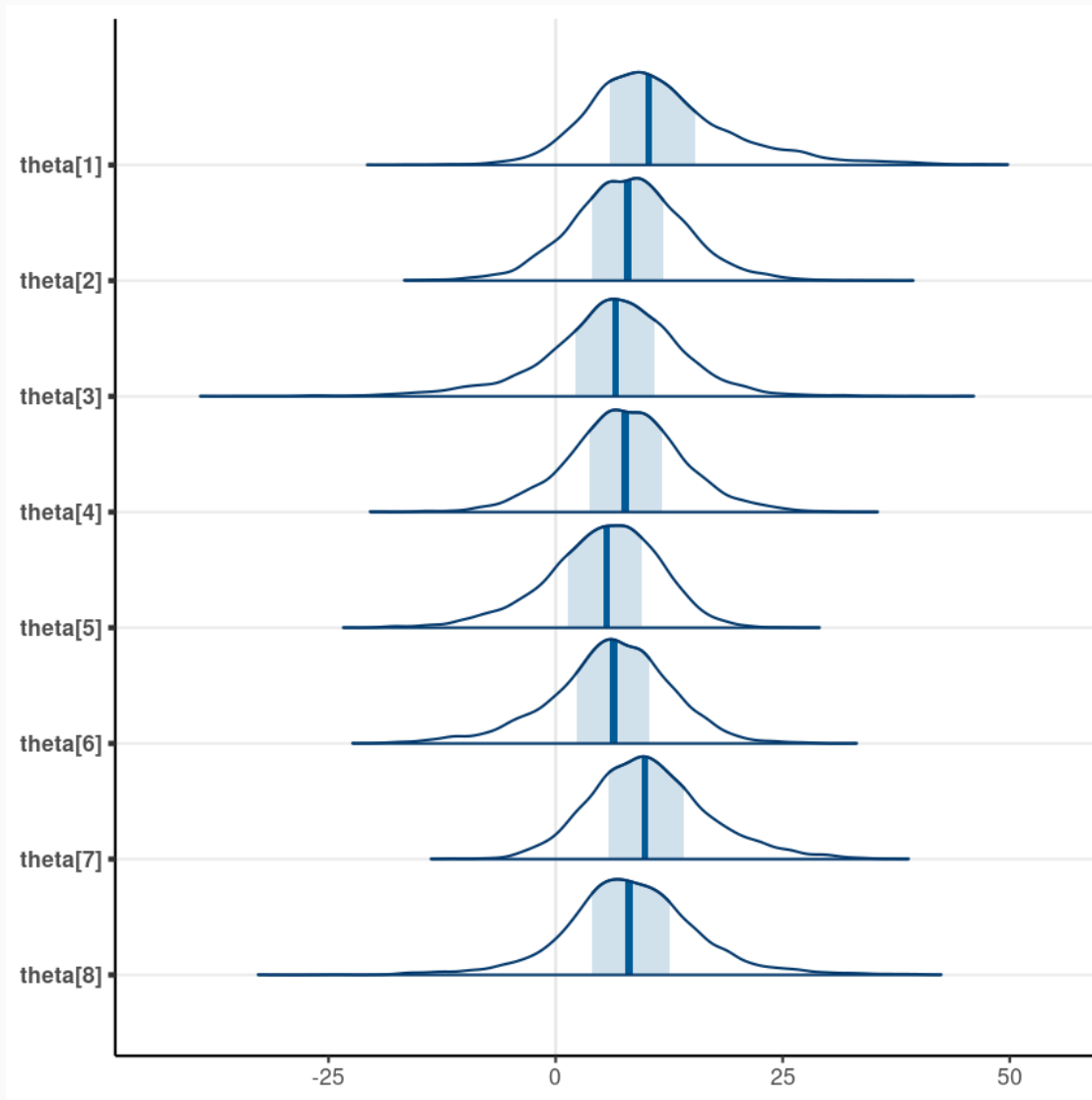
$$d_j \sim N(\theta_j, s_j)$$

$$\theta_j \sim N(\mu, \tau)$$

Prior:

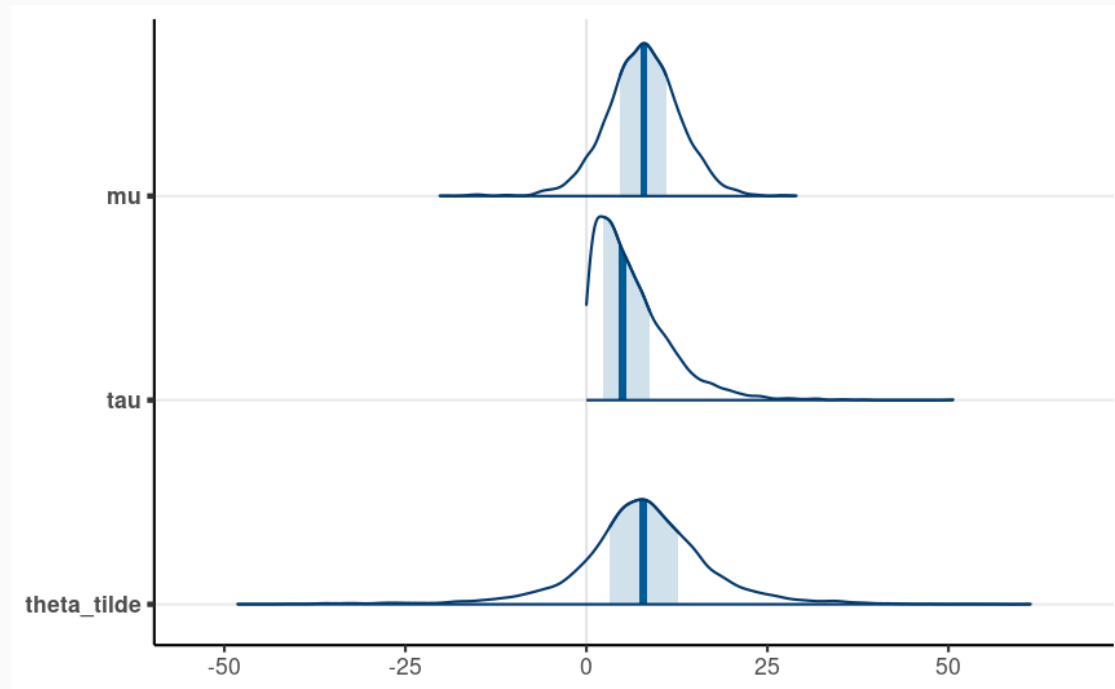
$$\mu \sim N(0, 100)$$

$$\tau \sim t_4^+(0, 100)$$



# Prediction Interval

Posterior distribution of the true effect size of a new study,  $\tilde{\theta}$



See <https://onlinelibrary.wiley.com/doi/abs/10.1002/jrsm.12> for an introductory paper on random-effect meta-analysis