

# Multinomial Processing Tree with JAGS

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Joachim Vandekerckhove, Michael D. Lee

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# Multinomial Processing Trees

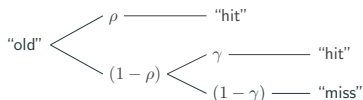
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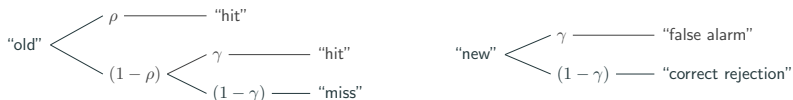
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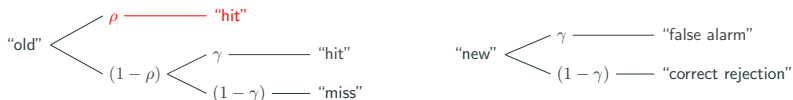
$$\begin{aligned}\theta^h &= \rho + (1 - \rho)\gamma \\ \theta^f &= \gamma\end{aligned}$$

See Matzke et al. (2018) for more like this!

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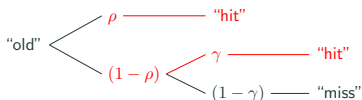
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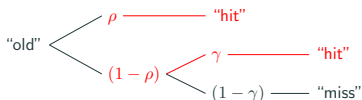
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# One-High Threshold Model

The remembering parameter  $\rho$  and the old-guessing parameter  $\gamma$  can both take any value with equal likelihood:

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Those rates tell us how often old items lead to hits (the data are  $k^h$  hits out of  $n_o$  old items) and how often new items lead to false alarms ( $k^f$  false alarms out of  $n_n$  new items):

$$k^h \sim \text{binomial}(\theta^h, n_o)$$

$$k^f \sim \text{binomial}(\theta^f, n_n)$$



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# One-High Threshold Model

|            |                                   | Amyloid Status | Hits | False Alarms |
|------------|-----------------------------------|----------------|------|--------------|
| $\rho$     | $\sim$ uniform $(0, 1)$           | negative       | 13   | 0            |
| $\gamma$   | $\sim$ uniform $(0, 1)$           | positive       | 8    | 4            |
| $\theta^h$ | $= \rho + (1 - \rho) \gamma$      | negative       | 12   | 1            |
| $\theta^f$ | $= \gamma$                        | negative       | 14   | 0            |
| $k^h$      | $\sim$ binomial $(\theta^h, n_o)$ | positive       | 9    | 4            |
| $k^f$      | $\sim$ binomial $(\theta^f, n_n)$ | ...            | ...  | ...          |

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| $\rho \sim \text{uniform}(0, 1)$          | negative       | 13   | 0            |
| $\gamma \sim \text{uniform}(0, 1)$        | positive       | 8    | 4            |
| $\theta^h = \rho + (1 - \rho) \gamma$     | negative       | 12   | 1            |
| $\theta^f = \gamma$                       | negative       | 14   | 0            |
| $k^h \sim \text{binomial}(\theta^h, n_o)$ | positive       | 9    | 4            |
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| $\theta^h = \rho + (1 - \rho) \gamma$     | positive       | 14   | 0            |
| $\theta^f = \gamma$                       | positive       | 14   | 1            |
| $k^h \sim \text{binomial}(\theta^h, n_o)$ | positive       | 13   | 2            |
| $k^f \sim \text{binomial}(\theta^f, n_n)$ | ...            | ...  | ...          |

# One-High Threshold Model

|   | AS | Hits | FA |  | AS | Hits | FA |
|---|----|------|----|--|----|------|----|
|   | +  | 8    | 4  |  | +  | 5    | 0  |
|   | +  | 9    | 4  |  | +  | 6    | 3  |
|   | +  | 14   | 0  |  | +  | 15   | 0  |
| $\rho \sim \text{uniform}(0, 1)$            | +  | 14   | 1  |  | +  | 11   | 0  |
| $\gamma \sim \text{uniform}(0, 1)$          | +  | 13   | 2  |  | +  | 14   | 1  |
| $\theta^h = \rho + (1 - \rho) \gamma$       | +  | 8    | 0  |  | +  | 12   | 2  |
|   | +  | 13   | 3  |  | +  | 12   | 1  |
| $\theta^f = \gamma$                         | +  | 12   | 1  |  | +  | 11   | 2  |
| $k^h \sim \text{binomial}(\theta^h, n_o)$   | +  | 11   | 3  |  | +  | 1    | 0  |
|   | +  | 4    | 0  |  | +  | 14   | 0  |
| $k^f \sim \text{binomial}(\theta^f, n_n)$   | +  | 8    | 0  |  | +  | 13   | 0  |
|   | +  | 13   | 1  |  | +  | 7    | 2  |
| There were 33 participants. Each saw 15 old | +  | 15   | 0  |  | +  | 11   | 1  |
| and 15 new stimuli.                         | +  | 12   | 0  |  | +  | 12   | 2  |
|   | +  | 11   | 0  |  | +  | 8    | 0  |
|   | +  | 9    | 0  |  | +  | 11   | 2  |
|   | +  | 5    | 1  |  |    |      |    |

# Amyloid Positive Inferences

Patients remember around 60-70% of the items, and guess “old” 5-10% of the time when they do not remember

| Parameter | Posterior |        |       | 95% Cred. Int. |       |
|-----------|-----------|--------|-------|----------------|-------|
|           | Mean      | Median | SD    | Lower          | Upper |
| gamma     | 0.075     | 0.074  | 0.012 | 0.053          | 0.100 |
| rho       | 0.665     | 0.665  | 0.023 | 0.619          | 0.709 |

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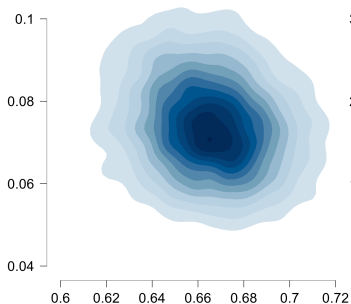
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*“Convergence of the MCMC procedure was good, with all  $\hat{R} < 1.01$ .”*

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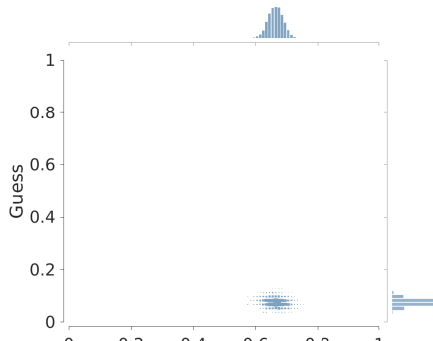
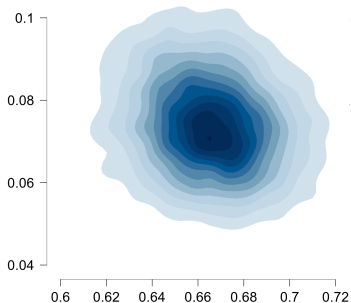
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## References

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Matzke, D., Boehm, U., & Vandekerckhove, J. (2018). Bayesian inference in psychology, part iii: Bayesian parameter estimation in nonstandard models. *Psychonomic Bulletin & Review*, 25, 77–101. doi: 10.3758/s13423-017-1394-5