Cultural Consensus Theory

Joachim Vandekerckhove

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- Traditional methods often rely on subjective assessments.
- Need: A formal, *quantitative* approach to shared cognition.

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- *Core assumptions of original CCT:*
  - There exists a "common truth"
  - Informants respond independently of one another
  - Items are homogeneous (equally difficult to a respondent with fixed competence)
- In other words, individuals will tend to agree more with each other and with the "truth" if they understand the domain.

Derivations from the model (Romney et al., 1986)

Derivations from the Model

We now turn to the task of deriving the cultural competence of the informants from the proportion of matches among them. The parameter D_i is informant i's cultural competence, namely, the probability that informant i "knows" the correct answer to any item ($0 \leq D_i \leq 1$). If the informant does not know the correct answer (with probability $[1-D_i]$), then they guess the answer with probability $1/L$ of a correct answer, where $(1-D_i)$ is the probability of not knowing the answer and L is the number of alternative answers to the question. For example, assume an informant's competence is .7 ($D_i = .7$) for a five-item multiple-choice questionnaire. In addition to expecting that the informant will get .7 of the questions correct we would also expect the informant to get some of the .3 $(1-D_i)$ questions correct by guessing. Namely, $1/L$ or $1/5$ of the remaining .3 of the questions or $(1-D_i)/L$, i.e., $.3 \times 1/5 = .06$ would be guessed correctly. We add this to the .7 giving a total expected correct of .76. More generally the probability of any question k being answered correctly by any informant i is given by

(3) $\Pr(Y_{ik} = 1) = D_i + (1-D_i)/L,$

and the probability of answering incorrectly is given by

$$\Pr(Y_{ik} = 0) = (1-D_i)\,(L-1)/L.$$

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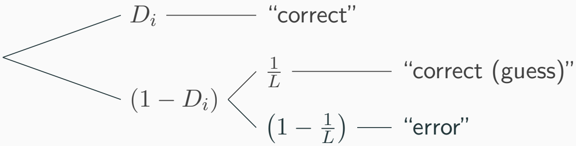

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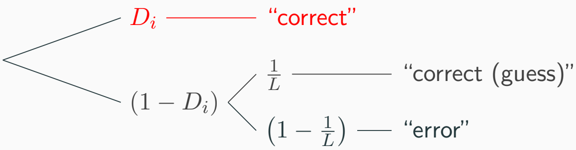

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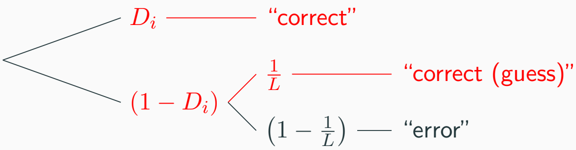

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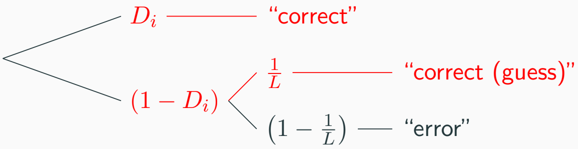

Of course we don't know which answers are "correct"!

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Let's instead think about the data Y_{ij} of participant i on item j, and let's focus on True/False questionnaires (so $L = 2$, and $T_j = 1$ if j is really true).

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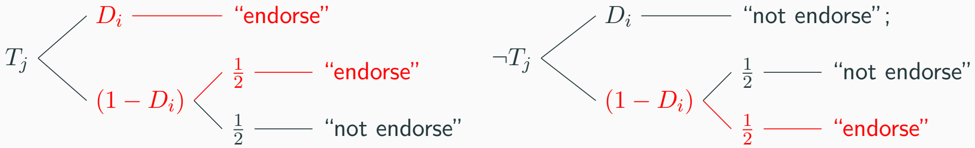

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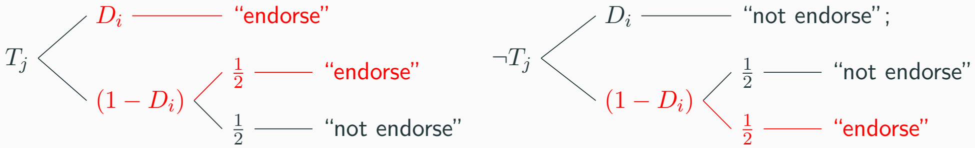

$$
\begin{aligned}
P\left(Y_{ij} = 1\right) &= T_j \left(D_i + \left(1 - D_i\right)\frac{1}{2}\right) + \left(1 - T_j\right)\left(1 - D_i\right)\frac{1}{2} \\
&= T_j D_i + \left(1 - D_i\right)\frac{1}{2}
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Guessing and acquiescence

$$P\left(Y_{ij}=1\right)=T_jD_i+\left(1-D_i\right)\frac{1}{2}$$

We made the simplifying assumption just now that $L=2$. Using the diagrams on the previous slide, convince yourself that this assumption was without loss of generality (WLOG) – that is, the same logic is true if $L>2$.

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We might even say that respondents have an individual bias g_i towards endorsing anything ("acquiescence bias"):

$$P\left(Y_{ij}=1\right)=T_j D_i+\left(1-D_i\right)g_i$$

Simplifying a little

Let's take out the guessing for now

$$T_j \begin{cases} D_i & \text{------ "endorse"} \\ (1 - D_i) & \text{--- "not endorse"} \end{cases} \qquad \neg T_j \begin{cases} D_i & \text{------ "not endorse"} \\ (1 - D_i) & \text{--- "endorse"} \end{cases}$$

Now, $P\left(Y_{ij} = 1\right) = T_j D_i + \left(1 - T_j\right)\left(1 - D_i\right)$

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  - Probability distribution for the correct answer to question j.
  - Reflects the estimated consensus or collective understanding.

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This makes the same predictions!

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  - Can estimate the probability of guessing vs. knowing/DK.

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- **Use:** Essential for effective public health interventions, understanding treatment seeking behavior, and communication strategies.

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- **Use:** Informs risk communication strategies, resource management plans, and community engagement efforts by tailoring messages to local knowledge.

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- What if the agreement patterns suggest multiple distinct viewpoints or subcultures?
- **Multiple Consensus Models:** Extensions that look for evidence of multiple latent factors in the agreement data.
- Bayesian frameworks are flexible and can be adapted to estimate parameters for multiple potential consensus models simultaneously.

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- The Bayesian approach provides a robust method that explicitly models uncertainty and can handle complexities like "Don't Know" responses.
- By analyzing agreement patterns, we can identify shared knowledge and the individuals who are most knowledgeable within that domain.
- It's a valuable but slightly underappreciated tool for researchers across social sciences and applied fields seeking to understand shared cognition.

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