Implications of Guessing Types in Multinomial Processing Tree Models

Conditional Reasoning as an Example

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**Conditionals: An Introductory Example**

- **If it rains, then the street is wet**
- **It rains**
- **The street is wet**

- Conditional reasoning investigates statements of the form “If A then C” (A → C) containing **antecedent A** and **consequent C**
- A form of **deductive reasoning**
- Research has shown that human reasoners do not follow classical logics
- Task is to model human performance in order to gain insight into cognitive processes
Conditional reasoning investigates statements of the form “If A then C” (A \rightarrow C) containing antecedent A and consequent C.

- A form of deductive reasoning
- Task is to model human performance in order to gain insight into cognitive processes
- Research has shown that human reasoners do not follow classical logics
Paired with a minor premise, inference mechanisms can be applied:

- Modus Ponens (MP): From $A \rightarrow C$, $A$ follows $C$
- Modus Tollens (MT): From $A \rightarrow C$, $\neg C$ follows $\neg A$
- Affirmation of Consequent (AC): From $A \rightarrow C$, $C$ follows $A$
- Denial of Antecedent (DA): From $A \rightarrow C$, $\neg A$ follows $\neg C$
Multinomial Processing Trees (MPTs)

- **Nodes** represent assumed latent processes (cognitive theory)
- **Parameters** denote success/failure probabilities
- **Leaves** indicate observable outcomes (i.e., inference patterns)
- Output probabilities correspond to path probabilities
- Fitted to experimental data via Maximum Likelihood Estimation

MPT Formalization of the Mental Models Theory (Oberauer, 2006).
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Problem: Missing responses

- Different theories may account for different sets of observable outcomes
- Standardized analysis is based on common data foundation
- **Problem:** How should responses not accounted for by the theory be handled?
- **Solution:** Add alternative response generation strategy, i.e. “guessing”
- **Question:** Does this kind of alteration affect the qualities of the model (performance/interpretation)?

![Diagram showing reasoning process with r and 1-r relationships]
• Extension of Oberauer’s (2006) investigation of cognitive theories for conditional reasoning

• Augment Oberauer’s MPT models using different guessing strategies

• Investigate the effects on model performance and interpretation
Guessing Strategies

<table>
<thead>
<tr>
<th>Guessing</th>
<th>Parameters</th>
<th>df</th>
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</thead>
<tbody>
<tr>
<td>Uniform</td>
<td>( g_1 = g_2 = g_3 = g_4 = \frac{1}{2} )</td>
<td>0</td>
</tr>
<tr>
<td>Bias(^1)</td>
<td>( g_1 = g_2 = g_3 = g_4 = g )</td>
<td>1</td>
</tr>
<tr>
<td>Independence(^2)</td>
<td>( g_1, g_2, g_3, g_4 )</td>
<td>4</td>
</tr>
</tbody>
</table>

\(^1\) Oberauer (2006)
\(^2\) Klauer et al. (2007)
• Set of 15 models (5 theories x 3 guessing strategies)
• Fitting to the data published by Oberauer (2006) using MPTinR
• Analysis of goodness of fit ($G^2$) and standard information criteria (AIC, BIC, FIA)

<table>
<thead>
<tr>
<th></th>
<th>MMT</th>
<th>MMT-Dir</th>
<th>Supp-Seq</th>
<th>Supp-Excl</th>
<th>DP</th>
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</thead>
<tbody>
<tr>
<td>Uniform</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Bias</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>7</td>
<td>8</td>
</tr>
<tr>
<td>Independence</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>10</td>
<td>11</td>
</tr>
</tbody>
</table>

Number of free parameters in the final models.
Fitting Results

- G^2
- AIC
- BIC
- F/A

- Uniform
- Bias
- Independence
Parameter Estimates

- MMT
- MMT with Dir.
- Supp.-Seq.
- Supp.-Excl.
- Dual Process
Summary of the Results

- Performance follows the number of free parameters in the models (Uniform > Bias > Independence)
- DP’s performance stands out (most flexible model, might be close to saturation)
- Best models across all guessing types are MMT-Dir. and DP
- Parameter values change for different guessing types
- Reasoning parameter values illustrate that complex guessing draws explanatory weight from the theoretical foundation
Conclusions

• Different guessing types are to be understood as attachments to the theoretical core
• As a result, fitting produces different parameter values
• Difficult to assess which guessing is correct
• Interpretation of the resulting model needs to be justified via psychological experimentation
• It might be a sensible idea for future work to invest time into finding a theory of guessing
Thank you for your attention.
