Modeling training performance in IMPRINT: Insights from MURI modeling

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Overview

- **MURI modeling goals**
  - Compare cognitive task models on 2 platforms (IMPRINT and ACT-R) *(IMPRINT not previously used for detailed cognitive modeling)*
  - Provide models that simulate and predict task performance

- **Additional benefit of modeling**
  - Behavioral and theoretical insights into modeled tasks

- **Today’s talk**
  - Brief description of 3 IMPRINT models developed
  - Example from each of what we learned through modeling
3 models of cognitive tasks

- **Digit data entry**
  - Simple number typing task

- **RADAR**
  - Visual search and detection of targets among distractors

- **Information integration**
  - Memory for serially presented targets used to make firing decision maximizing target damage
Digit data entry

- Modeled 2 experiments (Healy, Kole, Buck-Gengler, & Bourne, 2004)
  - Repeated (E1) and non-repeated (E2) 4-digit numbers
  - Contralateral training conditions (E2)
  - No typing feedback on screen
- Analysis of individual keystroke RTs indicated “number chunking”
  - RTs were longer on 3rd keystroke than on 2nd & 4th
Digit data entry

- Re-analysis of RT data for modeling details of subject behavior
  - Some subjects chunked, but some didn’t
  - Fairly consistent behavior across all items:

Keystroke 3 RT – Keystroke 2 RT

Chunker

Non-chunker
Digit data entry

- **Modeling chunking behavior**
  - About half the subjects chunked, half didn’t (both experiments)
  - Chunking was a *strategy choice*
  - Chunking strategy choice modeled probabilistically at subject level
  - Likelihood of chunking modeled probabilistically at item level
RADAR

- Modeled experimental data
  - (Young, Healy, Gonzalez, Dutt, & Bourne, in press, E1)

- Visual search of symbol targets on radar-like screen

- Trials varied by block in:
  - Mapping type - targets and distractors from different symbol sets (consistent mapping) or the same set (varied mapping)
  - Processing load - memory set and search field contained 1 symbol (low load) or 4 symbols (high load)

- Manipulated presence of simultaneous tone-counting task

- Secondary task crossed with session (training, test)
Experimental results showed effects on correct response time and hit rate:

- Simultaneous secondary task hurt performance
- More difficult trials (varied mapping and high processing load) had longer RTs and fewer hits
- Training with secondary task hurt test performance, regardless of test condition
- No improvement within or between sessions on either measure
• **Re-analysis of data for modeling of false alarms**

  • FAR showed improvement between blocks of same type
  • Improvement between blocks of same type was greatest when trials were most challenging:
    - First block of both sessions
    - More difficult varied mapping trials, especially high processing load trials
Modeling FAR improvements
  - First blocks of session
    - Initial positive responses high because of required task calibration
  - More difficult blocks
    - Improvement due to learning by subjects to inhibit positive responses
Information integration

- Modeled experimental data
  (Ketels, Healy, Wickens, Buck-Gengler, & Bourne, 2010, E3 serial recall condition)

- 7 target locations presented serially on a grid
  - order or items in series balanced across subjects

- Recall in serial order the 7 locations presented

- Choose firing location on grid to maximize target damage
Information integration

- **Experimental results**
  - Bow-shaped recall curve with primacy and a little recency
  - Firing location closer to initial items in list than final items in list
  - Firing closer to ends of list than middle of list
**Information integration**

- **Model development**
  - Theoretical question: Can firing location be predicted from item memory?
    - Assume start-end model (SEM) algorithms for serial recall (Henson, 1998)
  - Model allows us to use SEM algorithms to predict:
    - Serial recall accuracy
    - Explore extent to which firing decision depends on memory for items
Information integration

- **Model results**
  - Using SEM algorithms, model replicates serial recall results
Information integration

- **Model results**
  - Model predicts firing location relative to items by assuming that a given item contributes to the firing decision to the extent that it is remembered (as reflected in modeled recall accuracy of items)
Conclusions

- **Modeling effort designed to compare models on different platforms**

- **IMPRINT modeling also aided in**
  - Understanding details of human performance
  - Testing theoretical predictions
End