Decoding Idiographic ACT-R Parameters from Brain Data

Andrea Stocco¹, Peiyun Zhou¹, Florian Sense², & Hedderik van Rijn² ¹University of Washington, Seattle ²University of Groningen, The Netherlands



Idiographic vs. Nomothetic











This talk

- > Pilot data presented at the 2018 ACT-R workshop
- > Newer and better results
- > Displays the power of this approach (and a peek to the future)











In-House Example

- Max likelihood to fit four parameters in a DM task
 PSS task
- > Plugged parameters in model of different task
 - Simon task
- Parameters predicted response times in incongruent trials



Data vs. Models

Task-Based Inference and Its limits

- > Optimize parameters that fit a set of task data
- > Depends on behavioral testing
 - can be long and complicated
 - Many many trials to get reliable measures
- > Requires reasonable models of a task
 - Garbage in, garbage out
- > Parameters should be the same across tasks
 - "Cognitive supermodels", à la Salvucci

A reductionist approach ~ Individual differences Individual differences = in biology different sets of parameters (B) (B) 0-0-0

What if we Could Bypass Behavior?

- > Parameters should reflect basic neural activity
- > Task-free neural measures exist
 - Anatomical MRI, DTI, SPECT/PET...
 - Most importantly, resting state functional connectivity



Resting-State Functional Connectivity

- > Participants rest for ~5 mins while brain activity is recorded
- > Spontaneous fluctuations in activity are highly organized
- > Identify networks of stably connected regions
- Connectivity measures predict individual variables (Age, IQ).



EEG: Emotiv EPOC Headsets

- > Reasonable price (< 1K)</p>
- > Decent characteristics
 - 14 channels @ 128 Hz
 - Frequently used for BCIs
- > Easy:
 - Portable, wireless systems
 - Saline-based electrodes
 - ~15 mins for correct application
 - Minimal training required
 - Great for individual difference studies





Decompose each epoch Into frequencies



Mean power of each frequency

Which Parameter? Long-Term Memory Decay

- > Perhaps the **cornerstone** of ACT-R
- > The most fundamental **learning** mechanism
- > Activation *A* is controlled by decay parameter *d*

$$A = \sum_{j} t_{j}^{-d}$$



> Used Pavlik & Anderson's (2005) equation $A = \sum_{j} t_{j}^{-d} \qquad d = ce^{A} + \alpha$

Consistent across very short and very long intervalsAccounts for spacing effects



How is α Measured?



W

Predict when the chunk is forgotten





If the chunk is remembered, reduce α





If the chunk was forgotten, increase α





Time

Reliability of estimates

- Hedderik and Florian have done massive work showing that *α* ...
 - Can be estimated fast (~ 12 mins, even when participants do not make mistakes)
 - Is consistent across materials (visual, verbal, complex facts)
 - Is highly stable and reliable over time (test-retest reliability between 0.5 and 0.8)
 - (Sense et al., 2016, *TopiCS*)
- > In essence, **α** is psychological "trait".

Can we decode α from Resting-State QEEG?

- > *N* = 50 UW undergraduates
- > All native English speakers
 - This is important!
- > Collected 5 minutes of resting state, eyes closed EEG
- > Learned 25 pairs of English-Swahili words
 - Same paradigm as Sense et al., 2016
- > Learned 25 pairs of USA City-Maps associations
 - Same paradigm as Sense et al., 2016

Correlations Between α and QEEG Power



Correlations (FDR-corrected)







- Many tests (14 channels x 7 bands), so FDR was applied.
- Nine channels (Eight in Maps) still showed significant correlations after FDR
- All correlations in Low and Upper Beta band (13-18 Hz)



0.4

8.0

0.2

0.3











- > Common and simple machine learning technique
- > Linear regression built-in penalty to reduce the number of explanatory variables/overfitting:

min($\|y - X\beta\|_2^2 + \lambda \|\beta\|_1$)

- > Can be seen as a GLM with constrain $\|\beta\|_1 < k (\propto 1/\lambda)$
- > The term trades off λ accuracy and simplicity





- > When multiple variables are actually grouped together, it makes sense to constrain them in groups
- In the case of EEG, groups are naturally formed by frequency bands.



Model fitting and validation



- > Used cross-validation
 - fit vs. generalizability
- > Used Leave-One-Out (LOOV)
- Guarantees ideal lambda is actually best estimate (minimum absolute loss)



Predicted vs. Observed

Cross-Validation: Predicted vs. Observed Rates of Forgetting





Predicted



Predicted vs. Observed

Cross-Validation: Predicted vs. Observed Rates of Forgetting





What does it look like?















What does it look like?















Why is this important?

- > Forgetting rate has many practical applications
 - Learning skills, scholastic achievement...
 - See work by Hedderik, & Florian, Kevin Gluck, Michael Collins
- > But it has implications for disorders that affect memory directly (Alzheimer's) or indirectly (PTSD)
- > Marieke will do a way better job talking about this!

Other research (aka: shout-out to my students)

- > **Yinan Xu** is applying this approach to fMRI data
- > Briana Smith is using this approach to predict hippocampal volume in PTSD
 - See her upcoming ICCM talk and paper
- > Patrick Rice is extending this approach to working memory
 - Mixture of parameters and strategy



Conclusion



Nomothetic Approach S Group averages Low predictive power ("one size fits all") Stale

Idiographic Approach Individual differences High predictive power Possibilities are endless











Peiyun Zhou

university of Y of WASHINGTON groningen

