Neural representations for nested tree structures

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microscale

Zuidema (2013), reanalyzing Gentner et al. 2006

Common problem
- Many alternative hypotheses that we need to control for
- E.g., to distinguish $A^p B^q$ sequences from $(AB)^p$ sequences it suffices to look for:
  1. the lagun $A^p$ (+)
  2. the lagun $B^q$ (+)
  3. the lagun $B^q$ (-)
  4. the start $A^p$ (+)
  5. the end $B^q$ (+)
  6. the start $AB^q$ (-)
  7. the end $AB^q$ (-)
  8. any sequence of $A$'s followed by $B$'s ($A^p B^q$)
  9. a mix of strategies 1-8
- Each of these alternative is plausible a priori, and none involves constraint-freeness (Zuidema, 2013, CogSci)

Figure 2: The $d'$ statistic calculated for the $A^p B^q$ vs. $(AB)^p$ distinction (left) and for various controls (right). Blue: Gentner et al. Red: CPG, Yellow: MIX.
This morning

- Increased sophistication of the hypotheses
  - UG -> merge -> dendrophilia -> Language of Thought w/ chunking;
  - Unique human ability to represent - > to learn - > to learn quickly;
  - Unique human ability for compositionality - > for symbols as reversible signs.

- Great innovations in experimental paradigms:
  - 1.1 Tesla imaging
  - Finger tracking
  - Brain response
  - Letting subjects produce rather than passively receive
  - Touch screen interface (Jiang et al., 2018)

A different route: representation learning

- Neural language models have become amazingly good at learning subtleties of human language structure, including syntactic structure
- Internal states of the Neural language models give us the best available predictions of activation in the human brain
  - Although not as accurate as often claimed!
Conclusions

• There's a long history to determining the uniquely human ingredient that has given us language
• Proven to be a very difficult challenge
• Theoretical and experimental innovations very welcome!
• Modern AI offers successful "representation learning" approaches that can be co-opted as hypothesis-generators on neural representations
• Modern LLMs are too big

And too data-hungry!