

Set Size Does Not Matter. Entropy Drives Rule Induction in Non-Adjacent Dependency Learning

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From little evidence to abstract rules in language acquisition

- (1) statistical learning (Aslin & Newport, 2012)
- (2) algebra-like system (Marcus et al, 1999)

Entropy Model

Entropy (input complexity) \rightarrow Channel capacity (encoding power = entropy/time)

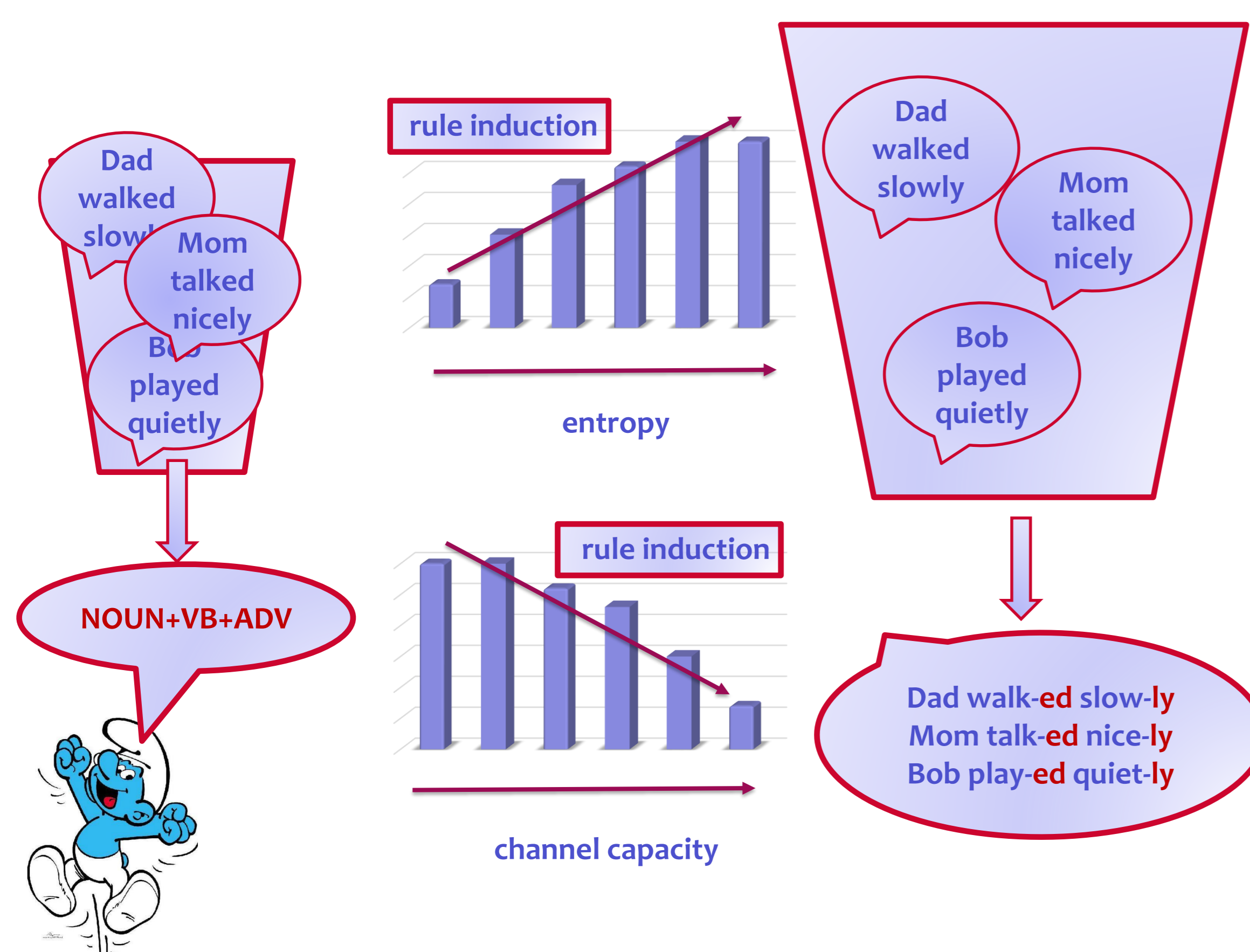
Entropy \rightarrow a function of the number of different items in the input and their probability of occurrence (frequency)
 \rightarrow a measure of input complexity (bits)

$$H(X) = -\sum_{i=1}^n p(x_i) \log p(x_i) \quad (\text{Shannon, 1948})$$

Rule Induction \rightarrow interaction of input complexity (entropy) and channel capacity

Entropy > channel capacity \rightarrow category-based generalizations

Entropy < channel capacity \rightarrow item-bound generalizations



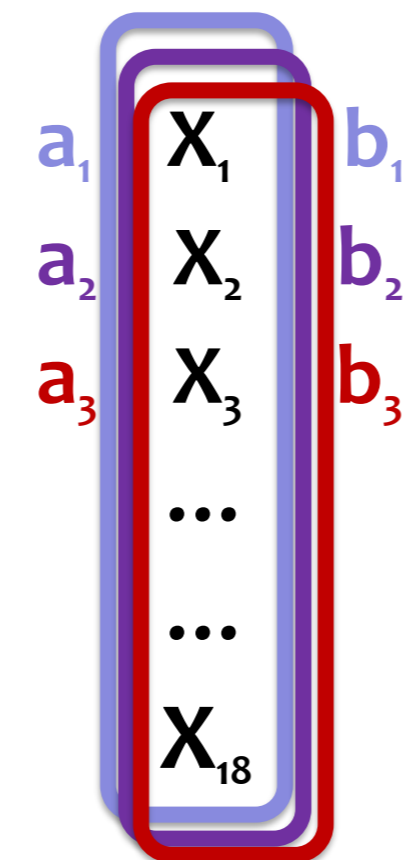
Predictions of Entropy Model for Non-Adjacent Dependency Learning

- Non-Adjacent Dependency Learning ($a X b$): captures the dynamics between item-bound generalizations (a_i predicts b_i) and category-based generalizations ($a_i b_i$ generalized over X)
- Low entropy drives item-bound generalizations (learning of $a_i b_i$ frames and their specific distributional patterns – by memorizing specific items and their combinations)
- High entropy drives category-based generalizations (generalizing over the intervening X category)

Experiment - Effect of Entropy on Rule Induction In Non-Adjacent Dependency Learning

High Entropy

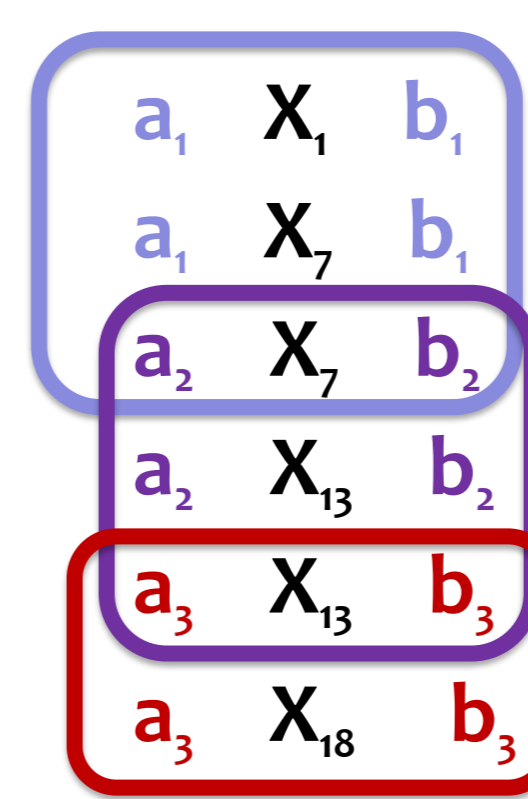
$$H_{\text{total}} = (H_{(\text{bigram})} + H_{(\text{trigram})}) / 2 = 4.7 \text{ bits}$$



$3 a_b / 18 Xs / 3 a_b * 18 Xs - 6 \text{ reps}$
20 participants

Medium Entropy

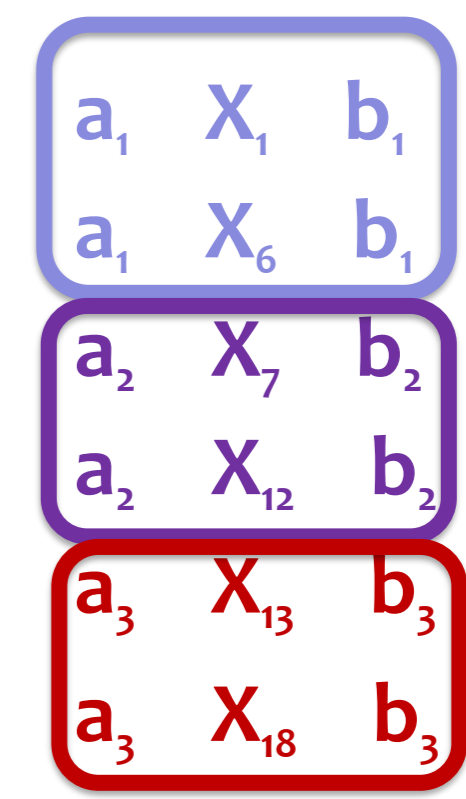
$$H_{\text{total}} = 4.27 \text{ bits}$$



$3 a_b / 18 Xs / 3 a_b * 12 Xs - 9 \text{ reps}$
27 participants

Low Entropy

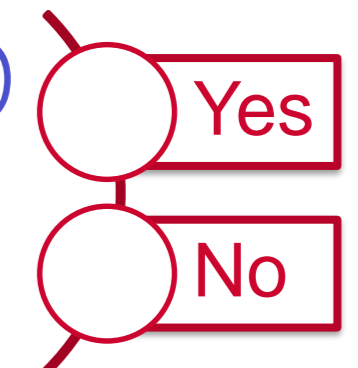
$$H_{\text{total}} = 3.52 \text{ bits}$$



$3 a_b / 18 Xs / 3 a_b * 6 Xs - 18 \text{ reps}$
29 participants

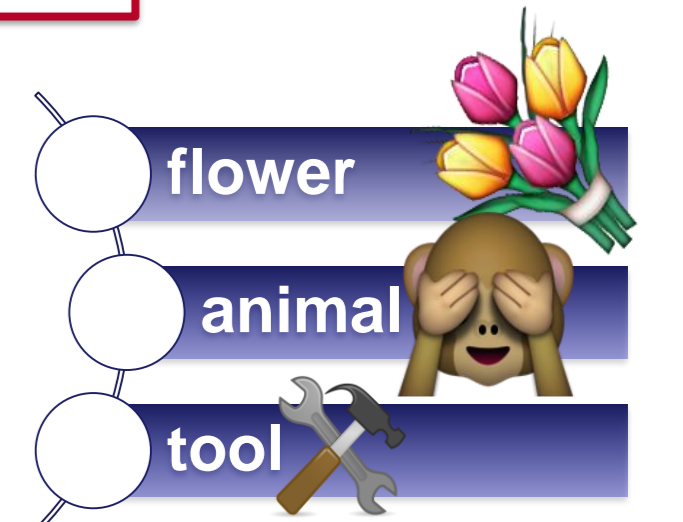
Test 1: NAD-Learning ("Is this string possible in the language that you heard?")

- Consistent: $a_1 Y_{1,2} b_1, a_2 Y_{1,2} b_2, a_3 Y_{1,2} b_3$
- Inconsistent: $a_1 Y_{1,2} b_2, a_2 Y_{1,2} b_3, a_3 Y_{1,2} b_1$



Test 2: Incidental Memorization ("Flower, animal or tool?")

- Familiarize participants with 30 pseudo-words they must classify
- Surprise test: 'Have you heard this word?' 15 targets + 15 foils
- [Memorization ~ Channel Capacity]



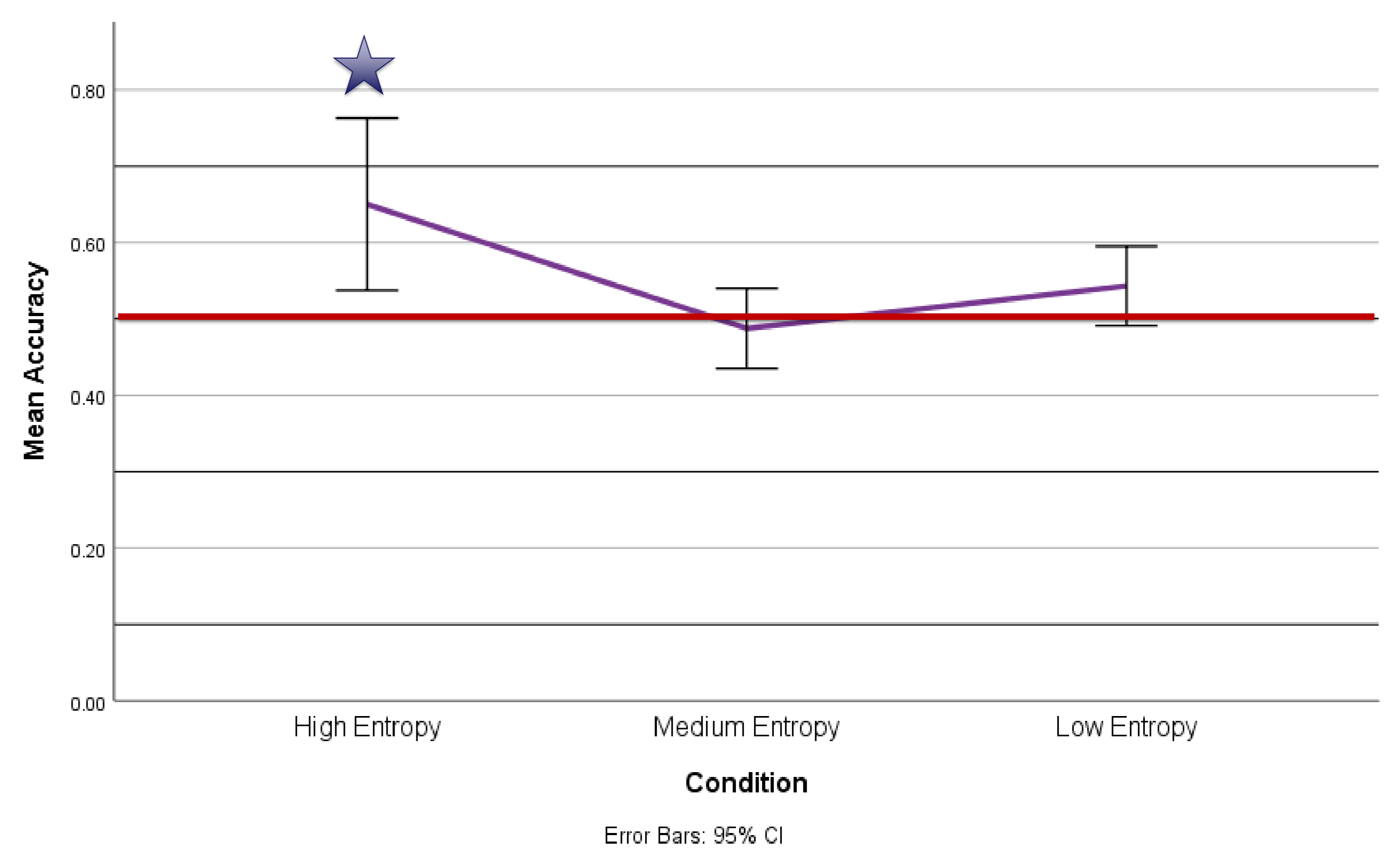
Test 3: Word Recall (Only Low Entropy) ("Did you hear this word in the first phase?")

- 28 items: 12 target a , X and b words and 16 foils
- [Does generalization of a_b rely on encoding a/b but not X ?]

Results

- Test 1: Generalized Linear Mixed Model (Accurate/Inaccurate response to each test item) - Significant effect of Condition ($F(2, 909) = 5.441, p = .004$)
- Post-hoc Comparisons: High Entropy > Medium ($p = .001$), High > Low ($p = .024$); Medium = Low ($p = .238$)
- High Entropy Condition – significantly above chance learning ($p = .019$)
- Test 2: No correlation with Incidental Memorization (item-specific encoding)
- Test 3 (Low Entropy): No correlation between Accuracy in Dependency-Learning and Accuracy in Word Recall (a/b , or X , or both)*

*Using d' instead of Accuracy as a dependent variable, a Linear Mixed Model found a/b Recall to be a significant positive predictor of Dependency-Learning ($p < .05$) and X Recall a near-significant negative predictor ($p = .095$)



Discussion

- High Entropy promotes better generalization of Non-Adjacent Dependencies even when X set size is kept constant
- Entropy does not linearly predict performance:
 - Is there a threshold of entropy that shifts the balance from item-specific learning to generalization?
 - Or a U-shape whereby Low Entropy facilitates the (item-specific) encoding of a_b frames?
- No correlation with item-specific encoding
- Future research: How can we measure the effect of Channel Capacity?

Conclusion

It is Entropy, and not mere set size, that drives Non-Adjacent Dependency-Learning!

Selected References

- Aslin, R.N., and Newport, E. (2012). Statistical learning: From acquiring specific items to forming general rules. *Current Directions in Psychological Science*, 21, 170–176.
- Gomez, R. L. (2002). Variability and detection of invariant structure. *Psychological Science*, 13(5), 431–436.
- Marcus, G. F., Vijayan, S., Rao, S. B., & Vishton, P. M. (1999). Rule learning by seven-month-old infants. *Science*, 283, 77–80.
- Shannon, C. E. (1948). *A mathematical theory of communication*. Bell System Technical Journal, 27, 379–423.

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