9.19(0): Computational Psycholinguistics, Pset 8 due 1 December 2021

22 November 2021

This pset is OPTIONAL. We will be dropping the lowest score of the 8 psets of the semester, and counting the highest 7 to the pset part of your class grade. So if you are happy with your pset grade so far, you don't need to do this pset – though if you complete it and turn it in we will gladly give feedback on your performance.
It is due on December 1 but we will not penalize you for turning it in up to a week late.

There's no Colab notebook for this pset. You can do it by pen, paper, and calculator (though you'll probably want to write a bit of code).

Noisy channel insertions and deletions

Gibson et al. (2013) presented participants with implausible sentences in five pairs of constructions, with one pair exemplified in (3) below:

(3) Transitive/intransitive alternation
  a. The tax law benefited from the businessman. (Intransitive)
  b. The businessman benefited the tax law. (Transitive)

For each sentence, the researchers asked participants a question that they were supposed to answer on the basis of the presented sentence, for example:

Did the tax law benefit from anything?

If the participant gave an answer consistent with the literal syntax of the sentence (a **yes** answer for this example question), that was considered a "literal" answer; if instead the participant answered in a way that would be consistent with a reassignment of the noun phrase roles to what would be more plausible given commonsense knowledge (for this example, a

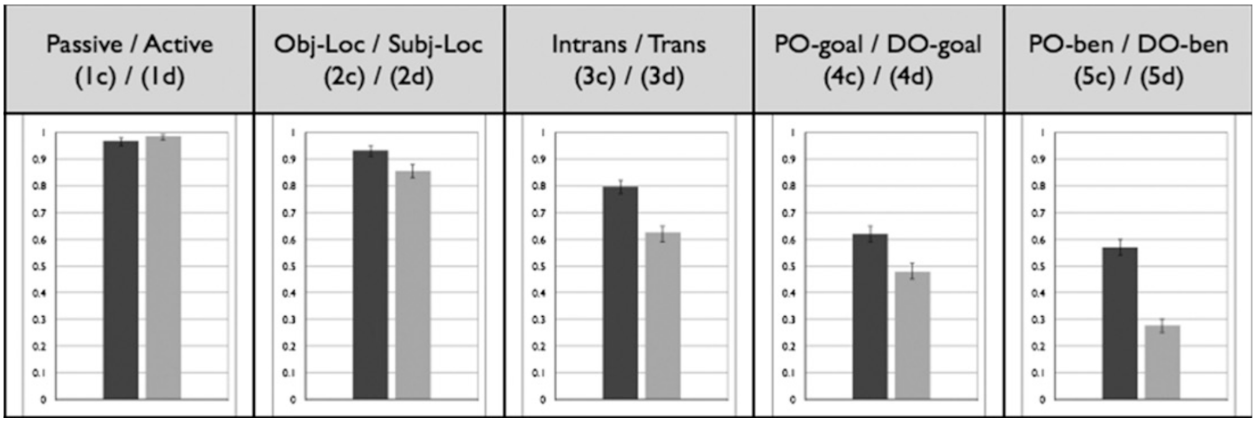

Figure 1: Rates of literal responses to questions in Gibson et al. (2013)

no answer, consistent with the daughter being the recipient and the candle the transferred entity of the giving event), that was considered a "non-literal" answer. Figure **??** shows the **literal-answer response rates** for Example (3) and for the additional construction pairs given below (except for **??**, for which there was a null result in the a/b comparison):

(1) Passive/active constructions
  a. The girl was kicked by the ball. (Passive)
  b. The ball kicked the girl. (Active)

(2) Uninverted/inverted locative constructions
  a. The table jumped onto a cat. (Uninverted locative; called "object-locative" in the paper)
  b. Onto the table jumped a cat. (Inverted locative; called "subject-locative" in the paper)

(4) Double object/Prepositional phrase object goal constructions
  a. The mother gave the daughter to the candle. (PO-goal)
  b. The mother gave the candle the daughter. (DO-goal)

(5) Double object/Prepositional phrase object benefactive constructions
  a. The cook baked Lucy for a cake. (PO-benefactive)
  b. The cook baked a cake Lucy. (DO-benefactive)

You will notice that the "b" version of each pair has a lower literal interpretation rate than the "a" version of the pair (setting aside the Passive/Active contrast, where the literal interpretation rates are nearly 100%). **Question:** within the noisy-channel theory of language comprehension, what is the explanation given for this pattern by Gibson et al.? (**Hint:** think about this in terms of prior and likelihood terms in Bayesian inference.)

Unsupervised Word Segmentation

The Goldwater et al. (2006, 2007, 2009) unigram model involves the following parameters (collectively termed θ):

h	The parameter defining the geometric probability distribution over utterance length $P(L)$ (so that $P(L) = (1-h)^{L-1}h)$[1]
α	The concentration parameter defining the probability of the next word being novel (see GGJ 2007, page 5)
$p_{\#}$	The parameter defining the geometric probability distribution over word length
V	The number of phonemes in the language

The utterance `ba.di.ba` has the likelihood

$$P(\texttt{ba.di.ba}|\theta) = \overbrace{(1-h)^2 h}^{\text{P(L=3)}} \overbrace{\frac{\alpha}{\alpha}\frac{\alpha}{1+\alpha}\frac{2}{2+\alpha}}^{P(\text{new,new,old}|\text{L})} \overbrace{(1-p_{\#})p_{\#}\frac{1}{V^2}}^{P(w_1|\text{new})} \overbrace{(1-p_{\#})p_{\#}\frac{1}{V^2}}^{P(w_2|\text{new})} \overbrace{\frac{1}{2}}^{P(w_3|\text{old})}$$

(Note that this ignores the possibility of having multiple distinct lexical entries with the same phonemic form `ba`—this oversimplification is OK for the purposes of this homework.)

1. Calculate the likelihood of the utterance `ba.diba` and use it to calculate the likelihood ratio

$$\frac{P(\texttt{ba.diba})}{P(\texttt{ba.di.ba})}$$

   (we did this in class). You can think of this likelihood ratio as a posterior belief ratio for two alternative lexicons—{`ba,di`} and {`ba,diba`}.

2. Imagine that the (unsegmented) utterance were extended to become `badibaba`. What are the likelihoods of the segmented utterances `ba.di.ba.ba` and `ba.diba.ba`? What is the effect of adding this additional `ba` on the likelihood ratio for the two lexicons described in problem **??**?

Rational Speech Acts model.

The Rational Speech Acts model (Goodman & Frank, 2016) has a number of variants, but here is the original version used in Frank and Goodman (2012), where r is a referent (or

[1] Actually, the GGJ model also puts a probability distribution over h, but we will ignore this detail here.

more generally a meaning) and u is an utterance:

$$
\begin{aligned}
L_0(r|u) &\propto \begin{cases} 1 & \text{if } r \text{ is compatible with the literal meaning of } u \\ 0 & \text{otherwise} \end{cases} \\
S_i(u|r) &\propto L_{i-1}(r|u) \\
L_i(r|u) &\propto S_i(u|r)P(r)
\end{aligned}
$$

where $P(r)$ is a prior distribution over referents (or more generally meanings). (In the supplementary information to Frank and Goodman (2012), L_0 is referred to as $\tilde{w}_C(o)$.) Sometimes you will see the speaker and listener "functions" applied to each other, e.g., $S_1 = S(L_0)$, $L_1 = L(S(L_0))$, and so forth, emphasizing the functional and recursive nature of this model of pragmatic inference as a special case of theory of mind.

1. For the context presented in Figure 1A of Frank and Goodman (2012), compute $S(L_0)$ and $L(S(L_0))$[2] for that paper's model (the *Rational Speech-Act theory*—RSA) under a uniform referent prior $P(r_S)$, assuming the set of alternative utterances is `blue`, `green`, `circle`, `square`.

2. Consider a variant of their model in which the referent prior is incorporated into the L_0 level. For this model, the literal listener L_0's distribution is determined by ruling out referents inconsistent with the literal meaning of w and renormalizing the prior over the remaining referents:

$$
L_0(r|u) \propto \begin{cases} P(r_S) & \text{if } r \text{ is compatible with the literal meaning of } u \\ 0 & \text{otherwise.} \end{cases}
$$

   Compute $S(L_0)$ and $L(S(L_0))$ for this revised listener under the referent prior $P(\square) = 0.2$, $P(\bigcirc) = P(\square) = 0.4$.

References

Frank, M. C., & Goodman, N. D. (2012). Predicting pragmatic reasoning in language games. *Science*, *336*(6084), 998.

Gibson, E., Bergen, L., & Piantadosi, S. T. (2013). Rational integration of noisy evidence and prior semantic expectations in sentence interpretation. *Proceedings of the National Academy of Sciences*, *110*(20), 8051–8056.

Goldwater, S., Griffiths, T. L., & Johnson, M. (2006). Contextual dependencies in unsupervised word segmentation, In *Proceedings of coling/acl*.

Goldwater, S., Griffiths, T. L., & Johnson, M. (2007). Distributional cues to word segmentation: Context is important, In *Proceedings of the 31st Boston University conference on language development*.

[2] i.e., for each of these functions produce an exhaustive list of values for all 12 logically possible referent/utterance pairs, preferably presented as a matrix.

Goldwater, S., Griffiths, T. L., & Johnson, M. (2009). A Bayesian framework for word segmentation: Exploring the effects of context. *Cognition*, *112*(1), 21–54.

Goodman, N. D., & Frank, M. C. (2016). Pragmatic language interpretation as probabilistic inference. *Trends in Cognitive Sciences*, *20*(11), 818–829.