Learning biases may prevent lexicalization of pragmatic inferences

A case study combining iterated (Bayesian) learning and functional selection

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The semantics-pragmatics distinction

Semantics

Literal meaning (truth-conditional)

Pragmatics

Information beyond literal meaning (e.g. defeasible inferences)

Scalar inferences

(1) $\langle$*few*, *some*, *many*, *most*, *all*$\rangle$

a. All students came to class
$\rightarrow$ Some students came to class

b. Some students came to class
$\rightsquigarrow$ Not all students came to class

(2) $\langle$*may*, *should*, *must*$\rangle$

(3) $\langle$*one*, *two*, *three*, ...$\rangle$

(4) ...

The use of a less informative expression when a more informative one could have been used* can license a defeasible inference that the stronger alternatives do not hold

*The hearer assumes the addressee to be knowledgeable and cooperative

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1. Why are (pragmatically inferred) upper-bounds of weak(er) alternatives not part of semantics?
2. What justifies semantic structure in light of pragmatic enrichment?

Today's talk:

- Propose a model to address (2) and analyze dynamics of linguistic pressures more broadly
- Use (1) as a case study for (2)

Model

Components I: Cultural transmission

Two competing pressures:

1. Communicative efficiency

   ... as replicator dynamics

2. Learnability

   ... iterated Bayesian learning as mutator dynamics

$\}$ Replicator-mutator dynamics

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Components II: Probabilistic (pragmatic) language users

- Varied lexica
- Varied production and comprehension behavior (here: parametrized *literal* or *pragmatic*)

A player's type

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Lexica

- s_1: Bill read all books
- s_2: Bill read some but not all books

$$L_a = \begin{array}{cc} & \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{array}{c} s_1 \\ s_2 \end{array} & \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix} \end{array}$$

$$L_b = \begin{array}{cc} & \begin{array}{cc} m_{\text{some}} & m_{\text{all}} \end{array} \\ \begin{array}{c} s_1 \\ s_2 \end{array} & \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \end{array}$$

Literal behavior

$$R_0(s|m;L) \propto P^*(s)L_{sm} \tag{1}$$

$$S_0(m|s;L) \propto \exp(\lambda L_{sm}) \tag{2}$$

Pragmatic behavior

$$R_1(s|m;L) \propto P^*(s)S_0(m|s;L) \tag{3}$$

$$S_1(m|s;L) \propto \exp(\lambda R_0(s|m;L)^\alpha) \tag{4}$$

A player type t_i is a combination of signaling behavior and a lexicon

Functional pressure

- Population of types x

  $x_i \propto$ players t_i in x

- Fitness of type i

  $f_i = \sum_j x_j U(x_i, x_j)$

- Average fitness in the population

  $\Phi = \sum_i x_i f_i$

Iterated learning

- $Q_{ji} \propto \sum_d P(d|t_j)P(t_i|d)$
- $d = \langle \langle s_h, m_n \rangle, ..., \langle s_l, m_o \rangle \rangle$ of length k
- $P(d|t_j)$ corresponds to the production probabilities of t_j
- $P(t_i|d) \propto [P(t_i)P(d|t_i)]^l$, $l \geq 1$
- The prior encodes the learning bias of players prior to data exposure

  $P(t_i) \propto n - c \cdot r$, where $n = |S|$ and r a count of semantically upper-bounded weak alternatives

Parametrized posterior $[P(t_i)P(d|t_i)]^l$

- $l = 1$ corresponds to posterior sampling
- $l \to \infty$ approaches maximum a posteriori estimate

N.B.: I will add a picture to exemplify how the mechanisms select hypotheses from the space of types

Analysis

Types & lexica considered

$$L_1 = \begin{pmatrix} 0 & 0 \\ 1 & 1 \end{pmatrix} \quad L_2 = \begin{pmatrix} 1 & 1 \\ 0 & 0 \end{pmatrix} \quad L_3 = \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$$

$$L_4 = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \quad L_5 = \begin{pmatrix} 0 & 1 \\ 1 & 1 \end{pmatrix} \quad L_6 = \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}$$

Results I

N.B.: Plots that exemplify results (effect of bias on dynamics)

Results II

N.B.: Plots that exemplify results with a focus on our competing lexica (semantic upper-bounds vs. pragmatically inferred)

Results III

N.B.: Plots that exemplify results (effect of parametrized learning)

Conclusion & Outlook

Concluding remarks

- Combination of functional pressure, iterated Bayesian learning, and probabilistic hearer & speaker models
- Learnability steers language towards simpler semantics
- Pragmatics compensates for potential loss in expressivity

References

References I