Psych 215L: Language Acquisition

Lecture 17 Poverty of the Stimulus IV: Anaphoric One

Domain-general & domain-specific

Language acquisition may not just one or the other.

Three components of a learning theory, any of which can be either domaingeneral or domain-specific:

Representations of the data co-occurrence probabilities of acoustic signal vs. phonemes, morphemes, syntactic trees Data learned from filters that exclude data beyond the first 10 seconds vs. filters that exclude data beyond the first clause

Updating process Bayesian updating vs. language-specific updating process

Case study: Anaphoric One

- Involves both a syntactic structural component (what structure does *one* refer to) and a semantic interpretation component (what does *one* refer to in the world).
- As adults, we have strong intuitions about the interpretation, which tells us what our unconscious intuitions are about the structure. Anaphoric *one* = a use of *one* that references some previous structure/string
- I followed the debate about acquisition but not the one about syntax. one interpretation = "debate"
- * I ran the car into the side of the road but not the one of the house. one interpretation should = "side", but the sentence doesn't sound right....why not?

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How linguists explain this:

 $\frac{One}{N} \text{ must refer to a structure that is larger than a simple noun (N^0).} \\ \text{Linguists sometimes call this larger structure N'.}$









More Adult Knowledge

"Jack likes this ball. Lily likes that one." one = ball

"Jack likes this red ball. Lily likes that one." one = red ball or ball? More Adult Knowledge

"Jack likes this ball. Lily likes that one." one = ball

"Jack likes this red ball. Lily likes that one." one = red ball

Linguists say: one should always refer to the same kind of structure. How are both of these strings the same (N')?



Question: How do children learn this?

- Should be able to use information about both the linguistic antecedent of one (the string one replaces) and the referent of one (what one refers to in the world) since both of these come into play when interpreting one.
- Classic response from linguists (Baker 1978, Hornstein & Lightfoot 1981, Crain 1991): Very little data available that clearly indicates *one* cannot be anaphoric to a N⁰ structure (that is, few data are unambiguous). Children must somehow know something about the structure of anaphoric *one* beforehand.
- Recent response from computational modelers (Regier & Gahl 2004): Actually, children can learn this from the available data if the hypothesis space is simply one refers to N⁰ vs. one refers to N¹. The key is to cleverly use data that are ambiguous between the two hypotheses, instead of only using unambiguous data for what one refers to N¹.







18-month-old behavior: Lidz, Waxman, & Freedman (2003)



Estimates of children's data (what 18-month-olds heard)

Unambiguous data 10 "Jack wants a red ball. Lily doesn't have one for him." Lily has a ball, but not a red ball. one = red ball, and one refers to N'

Type I Ambiguous data 183 "Jack wants a red ball. Lily has one for him." Lily has a red ball. one = ball OR one = red ball, one refers to N⁰ OR N¹

 $\label{eq:transformation} Type II Ambiguous Data 3805 $$ "Jack wants a ball. Lily has one for him." $$ Lily has a ball. $$ one = ball, one refers to N^0 OR N' $$ The second se$

Regier & Gahl (2004): A Model for how to learn the interpretation of *one*

Main idea: A Bayesian learner is a domain-general learning mechanism that would be able to use both Unambiguous and Type I Ambiguous data

Using Type I Ambiguous data:

"Jack wants a red ball, and Lily has one for him."

- All the relevant knowledge for anaphoric *one* can be derived from knowing whether the property red is important for the referent (the ball, in this case) to have. (If the ball is always red, *red* is important and part of the string *one* refers to and *red ball* is unequivocally N'.)
- Basic strategy: Keep track of how often the referent that *one* refers to has the property mentioned in the potential antecedent (e.g. How often is the ball red?)

Bayesian expectations: The referents of one entioned in the potential antecedent (e.g. red)

If the property mentioned in the potential antecedent (e.g. *red*) is not important, the set of objects (e.g. balls) that *one* refers to should look something like this.





Bayesian reasoning about referents

If the referents of *one* keep having the property mentioned in the potential antecedent (e.g. the balls keep being red when the phrase *red ball* is the potential antecedent), this is a conspicuous coincidence if the property isn't actually important. The Bayesian learner encodes this automatically and rewards the hypothesis that thinks the referent of *one* should be a red ball.

The reward is based on the relative size of the sets of potential referents (e.g., all balls vs. red balls).



Bayesian reasoning about referents

If instead red balls are a really large part of all the balls, it's not really that conspicuous that red balls keep being picked out. So, the Bayesian learner weakly rewards the hypothesis that the property red is actually important (i.e., that *red ball* is the antecedent). "…*red ball*…one…"



But what about the rest of the data?

One strength of Bayesian models are their ability to use all kinds of data, as long as the data are evenly mildly informative. So what about the Type II ambiguous data? Are these data informative? If so, it seems like a domain-general learner would use them as they make up the bulk of the data

But what about the rest of the data?

Type II ambiguous data are informative if we think about the hypothesis space of potential antecedent strings for anaphoric *one*.

Type II Ambiguous data example:

one = ball, one = Nº OR N'

Because of the layout of the hypothesis space (one hypothesis covers a subset of the strings the other covers), the Size Principle will favor the smaller hypothesis when the data are ambiguous.

Upshot: Type II Ambiguous data are informative about the syntactic category *one* refers to.



But maybe we wish they weren't...

Important Caveat: The smaller syntactic category hypothesis is that *one* refers to the category N⁰. (Oops!) This means that the Type II Ambiguous data favor the incorrect syntactic hypothesis. Semantic consequence: any property that might be mentioned in the potential antecedent (e.g. *red*) won't matter because that property would be part of the larger N' category, not the N⁰ category.

More pointedly, these data make up the bulk of the data to children - what would happen if a Bayesian learner used all the available informative data (Unambiguous, Ambiguous Type I, and Ambiguous Type II)?

An Equal-Opportunity Model

Generative model that learns by trying to construct the grammar that was used to generate the data ("analysis by synthesis").

Assumption: All data are generated by having *one* refer to an antecedent that is either an N⁰ or N' string (θ_N). If an N' string is chosen and a property is mentioned in a potential antecedent, *one* can refer either to the smaller/lower N' (without the property, e.g. *ball*) or the larger/upper N' (with the property, e.g. *red ball*) (θ_n).











Updating the Equal-Opportunity Learner

Unambiguous Data, from $\theta_N = \theta_U = 0.5$ 1 unambiguous data point, c = 5 (5 potential properties in the world) $\theta_N = \theta_U = 0.75$ Type I Ambiguous Data, from $\theta_N = \theta_U = 0.5$ 1 type I ambiguous data point, c = 5 (5 potential properties in the world) $\theta_N = 0.625, \ \theta_U = 0.666$ Type II Ambiguous Data, from $\theta_N = \theta_U = 0.5$ 1 type II ambiguous data point p(m = 1/2 (type string types, of which a

1 type II ambiguous data point, n/m = 1/2 (two string types, of which a simple noun string (*ball*) is 1)

 $\theta_{\rm N} = 0.417, \ \theta_{\rm U} = 0.5$

EO Model: Interpreting Anaphoric One

For a given utterance involving anaphoric *one* where there is more than one potential N' antecedent (e.g., *...red ball...one...*):

- Decide if the antecedent should be N⁰ or N', using θ_N.
 If the antecedent is N⁰, the referent is any object regardless of property (e.g., any ball)
 If the antecedent is N', decide if the antecedent is the smaller/lower or larger/upper N', using θ₀.
- Based on this decision, pick out the appropriate referent (e.g., lower = *ball*, so referent is any ball; upper = *red ball*, so referent is a red (4) ball)

Initial probability of adult interpretation (choose N', choose upper N'): $\theta_N^* \; \theta_U = 0.5 \; ^* \; 0.5 = 0.25.$

Good learning means this probability increases over time.

EO Model: Results with generous parameter value estimates



Probability of choosing *one* anaphoric to N' is low. But if the learner happens to do that, probability of choosing the correct N' is high. Making the parameter values less generous only exacerbates the problem. Upshot: Equal-Opportunity Learner has a problem.



Main point: Using some of the ambiguous data is better than ignoring it all (similar to what Regier & Gahl 2004 found). A data filter is useful for the learner...so how could a learner implement one sensibly?

About the data filter

Ignore some of the ambiguous data, but not all of it.

Domain-specific or domain-general?

Portain-specific of domain-general? Pearl & Lidz say: "Given that this filter requires the learner to single out a specific type of potentially informative data to ignore, and the property of this ignored data involves whether the potential linguistic antecedent has a modifier, we consider this filter to be specific to language learning. As such, it seems reasonable to consider it a domain-specific filter."

About a child implementing the data filter

Pearl & Lidz say: "It seems fairly obvious that the learner cannot (and probably should not) come equipped with a filter that says 'ignore type II ambiguous data' without some procedure for identifying this data. What we really want to know is whether there is a principled way to derive this filter. Specifically, we want the filter that ignores type II ambiguous data to be a consequence of some other principled learning strategy."

About a child implementing the data filter

A domain-general idea: Learn in cases of uncertainty.

- Type II Ambiguous data (...ball...one...) doesn't count as uncertain because in the local context (that is, for that one data point), the referent of one isn't uncertain - the antecedent is the simple noun (ball) and the referent is the object corresponding to that noun (ball). (However, at the global level (for deciding the syntactic category one is anaphoric with), this data point is uncertain.)
- Type I Ambiguous data (...red ball...one...), however, is uncertain in the local context because it is unclear which string one is anaphoric with (red ball, ball) and so unclear what the referent is.
- Upshot: "Learn in cases of local uncertainty" would cause the child to use Type I Ambiguous data and ignore Type II Ambiguous data...which then makes it possible to learn anaphoric one.

Pearl & Lidz conclusions

- "The case of anaphoric one demonstrates the interplay between domainspecificity and domain-generality in language learning. What we have seen is that a domain-general learning procedure can be successful in this case, but crucially only when paired with domain-specific filters on data intake. Moreover, we have suggested that the particular domainspecific filter that yields the best result can plausibly be derived from a domain-general learning strategy."
- "...emphasized the efficacy of data intake filtering on learners. Filtering the data is, in some sense, a counterintuitive approach to learning because it discards potentially informative data. Moreover, eliminating data can lead to a data sparseness problem. However, in order to find the correct generalizations in the data in our case, we found that eliminating some data was more effective than using it all. The right generalizations are hiding in the data, but paying attention to all of the data will make them harder to find."