Lexical Acquisition in the Presence of Noise and Homonymy

Jeffrey Mark Siskind*
Department of Computer Science
University of Toronto
Toronto Ontario M5S 1A4 CANADA
416/978–6114
internet: Qobi@CS.Toronto.EDU

Abstract

This paper conjectures a computational account of how children might learn the meanings of words in their native language. First, a simplified version of the lexical acquisition task faced by children is modeled by a precisely specified formal problem. Then, an implemented algorithm for solving this formal problem is presented. Key advances of this algorithm over previously proposed algorithms are its ability to learn homonymous word senses in the presence of noisy input and its ability to scale up to problems of the size faced by real children.

Introduction

When learning their native language, children must acquire a lexicon that maps the words in that language to their meanings. This paper explores one way that they might accomplish that task, adopting as few assumptions as possible. In particular, the techniques explored in this paper do not rely on children hearing single-word utterances in situations in which they can unambiguously determine their meaning from context. Consider, for instance, a child hearing a multi-word utterance such as *Mommy raised the ball*, in a context where she was uncertain as to whether that utterance as a whole meant that Mommy raised the ball, that Mommy was holding the ball, or that Mommy wanted the ball. In this situation, the child would have to determine both that 'Mommy raised the ball' was the correct meaning of the utterance as a whole, and that the words *Mommy*, *raised*, and *ball* meant 'Mommy,' 'raised,' and 'ball' respectively. In doing so, the child must somehow come to rule out many plausible but incorrect mappings—such as the mapping from *Mommy* to 'ball,' *raised* to 'Mommy,' and *ball* to 'raised'—despite the fact that such mappings would be consistent with the utterance just heard.

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This paper presents a computational study of this lexical acquisition task. It first attempts to characterize the task by defining a simplified formal approximation of the actual task faced by children. It then discusses a precise and implemented algorithm for solving this simplified formal task.

The proposed model of the task attempts to make as few assumptions as possible. First, it makes no assumption that utterances heard by the child refer to the immediate perceptual context. It requires only that the child be able to hypothesize from context a set of meanings for the complete utterance that usually, though not necessarily, includes the correct one. That utterance meaning need not refer to the here-and-now. Second, it makes no assumption that children can uniquely determine the meaning of each utterance from context. It allows for *referential uncertainty*: situations where the child is unsure of the meaning of an utterance. Referential uncertainty is modeled by allowing the child to hypothesize a *set* of potential meanings for each utterance heard. Third, it makes no assumption that the child is always successful in hypothesizing a set of potential meanings that contains the correct meaning of each utterance heard. It allows for *noisy input*: situations where the child unknowingly hypothesizes only incorrect meanings for an utterance. Fourth, it makes no assumption that each word has a single meaning. It allows words to be *homonymous*.

With high accuracy, the algorithm to be described learns a lexicon containing precisely the correct senses for each word heard. This ability to learn despite the presence of referential uncertainty, noise, and homonymy in the input are key capabilities which distinguish this algorithm from those proposed by Granger (1977), Salveter (1979), Berwick (1983), Pustejovsky (1988), Rayner et al. (1988), Pinker (1989), Gleitman (1990), Suppes et al. (1991), Regier (1992), and Fisher et al. (1994). Unlike some of these algorithms, the algorithm presented here has no prior access to any language-specific information. Furthermore, unlike some of these algorithms, the algorithm presented here can scale up to tasks of the size faced by children.

The Mapping Problem

The algorithm presented in this paper solves a precisely specified formal problem called *the mapping problem*. While this formal problem is simplified and abstract, it is likely that it accurately reflects the lexical acquisition task faced by children. In this problem, the learner is presented with a sequence of utterances, each being a sequence of words. Each utterance is paired with a set of expressions representing possible meanings for that *whole* utterance. This set of possible meaning expressions would be constructed by a general perceptual and conceptual apparatus that is independent of language. For example, the learner might hear the utterance *Mommy raised the ball*, look out into the world and see Mommy grasping and lifting the ball, and conjecture that CAUSE(**mother**, GO(**ball**, UP)) and GRASP(**mother**, **ball**) could be representations of potential meanings of that utterance. Not all utterances refer to observed events however. Perhaps the utterance meant that Mommy wanted the ball. Thus WANT(**mother**, **ball**) might be a representation of another potential meaning of that utterance. Since the learner might not be precisely sure of what some utterance means, the model allows her to conjecture a *set* of possible meanings. Such uncertainty on the part of the learner as to what each utterance means is termed *referential uncertainty*.

In theory, the set of referentially uncertain meanings could be infinite. This is the essence of the philosophical 'Gavagai' quandary discussed by Quine (1960). Thus the set of meaning representations paired with each utterance as input to the lexical acquisition algorithm is not intended to be the set of *all* true facts about the world in the situation where an utterance is heard. It is only the finite, possibly small, set of potential meanings that the learner conjectures based on some measure of salience. Sometimes this set will contain the correct meaning, while other times it will not. An utterance is considered to be *noisy* if it is paired with only incorrect meaning expressions. The only requirement for successful lexical acquisition is that utterances be non-noisy a sufficient fraction of the time.

This paper assumes that the learner brings to bear a language-independent theory of naive physics and naive psychology embodied in an elaborate perceptual and conceptual apparatus to hypothesize potential meanings for each utterance. However, issues such as the organization of this apparatus, and whether the knowledge it contains is innate or acquired, are orthogonal to questions about lexical acquisition. The essence of lexical acquisition is simply the process of learning the mapping between external words and internal conceptual representations.

We know very little about the conceptual representations used by the brain. Thus this paper makes as few assumptions as possible about such representations. It assumes only that conceptual representations take the form of expressions in some logic. It doesn't care about the particular inventory of constant, function, predicate, and logical connective symbols used to construct such expressions. The symbol $\perp$ is used to represent the meaning of words that fall outside the chosen representational calculus. The learning algorithm makes no use of the semantics or truth conditions of the meaning expressions themselves. As far as the lexical acquisition is concerned, these expressions are simply strings of uninterpreted symbols. The representations of Schank (1973), Jackendoff (1983), and Pinker (1989), for example, are all compatible with this minimal assumption.

In order to fully specify the mapping problem, one must specify the process by which the meanings of words combine to form the meanings of utterances containing those words. Here again, this paper makes as few assumptions as possible about this semantic interpretation process. It assumes that the lexicon L for a given language maps each word to a set of expressions denoting the meanings of different senses for that word, and that the meaning of an utterance u, consisting of an unordered multiset of words $\{w_1, \ldots, w_n\}$, is a member of the set computed by choosing some sense $t_i \in L(w_i)$ for each word w_i in the utterance, and applying the function INTERPRET to the unordered multiset of expressions $\{t_1, \ldots, t_n\}$. No claim that the actual human semantic interpretation process ignores word order is intended. This is simply a minimal assumption. If lexical acquisition can be successful under such an underspecified semantic interpretation rule, *a fortiori* it can be successful when stronger constraints are added.

The function INTERPRET is left unspecified except for the following condition. If $t \in$ INTERPRET$(\{t_1, \ldots, t_n\})$ then all symbols that appear in t must appear in at least one of $t_1, \ldots, t_n$, and all symbols that appear a total of k times in $t_1, \ldots, t_n$, except for variable symbols and the distinguished symbol $\perp$, must appear at least k times in t. This is simply the requirement that semantic interpretation be compositional and 'partially linear.' It shares with linearity the property that it cannot delete information from the meanings of words when producing the meaning of an utterance, and cannot add information to the meaning of an utterance that does not come from the meaning of some word in the utterance. It need not be truly linear since it can, however, copy information from a word or phrase so that it appears more than once in the resulting utterance meaning. Beyond this property, the lexical acquisition process uses INTERPRET as a 'black box' (with the exception of the RECONSTRUCT$(m, N(s))$ procedure to be described later).

The mapping problem can now be stated formally as follows. The learner is presented with a corpus of utterances u, each paired with a set M of hypothesized meaning expressions. A hidden lexicon L was used to generate the corpus. L maps each word in the corpus

to a set of senses, each represented as an expression. Some subset of the utterances in the corpus have the property that

$$(\exists t_1 \in L(w_1)) \cdots (\exists t_n \in L(w_n))$$
$$\textsc{Interpret}(\{t_1, \ldots, t_n\}) \cap M \neq \emptyset$$

where $u = \{w_1, \ldots, w_n\}$. The learner must find the lexicon L used to generate the corpus.

The Noise-Free Monosemous Case

Before presenting the full lexical acquisition algorithm, capable of dealing with noise and homonymy, I will first present a simplified algorithm that handles only noise-free input under the assumption that all words are monosemous. This algorithm receives as input a sequence of pairs $\langle u, M \rangle$ where each utterance u is an unordered multiset of words and M is the set of expressions representing referentially uncertain hypothesized meanings of u.

The algorithm is *on line* in the sense that it makes a single pass through the input corpus, processing each utterance in turn and discarding it before processing the next utterance. The algorithm retains only a small amount of inter-utterance information. This information takes the form of a number of maps from words to sets of senses, and from senses to sets of symbols and meaning expressions. The table $L(w)$ maps each word w to a set of senses. The table $N(s)$ maps each sense s to a set of symbols that have been determined to be *necessarily* part of the meaning of s. Likewise, the table $P(s)$ maps each sense s to a set of symbols that have been determined to be *possibly* part of the meaning of s. $N(s)$ initially maps each sense to the empty set $\emptyset$, while $P(s)$ initially maps each sense to the universal set $\top$. At all times, $N(s) \subseteq P(s)$ for all senses s. The algorithm monotonically adds elements to $N(s)$ and removes elements from $P(s)$ until $N(s) = P(s)$. When this happens, the algorithm is said to have *converged on the symbols* for the sense s, denoted $\textsc{ConvergedOnSymbols?}(s)$.

Having converged on the symbols for a given sense does not imply knowing its meaning. For example, knowing that some sense for the word *raise* contains precisely the set $\{\text{CAUSE}, \text{GO}, \text{UP}\}$ as its set of (non-variable) symbols does not specify whether the expression representing the meaning of that sense is $\text{CAUSE}(x, \text{GO}(y, \text{UP}))$, $\text{GO}(\text{CAUSE}, \text{UP})$, $\text{UP}(\text{CAUSE}(x), \text{GO}(x, y))$, and so forth. For this, the algorithm maintains a fourth table $D(s)$ that maps each sense s to a set of *possible* meaning expressions. $D(s)$ initially maps each sense s to the universal set $\top$. The algorithm monotonically removes elements from $D(s)$ until $D(s)$ is a singleton. When this happens, the algorithm is said to have *converged on the meaning* of the sense s, denoted $\textsc{ConvergedOnMeaning?}(s)$.

The algorithm maintains a fifth table $T(s)$ that maps each sense to a *temperature*, a non-negative integer. $T(s)$ initially maps each sense to zero. The temperature of a sense increases as the learner become more confident that she has not mistakingly hypothesized that sense to explain a noisy utterance. There are two integer constants, μ and $\mu_\perp$, denoting *freezing points*. A sense s is *frozen*, denoted $\textsc{Frozen?}(s)$, if it has converged on meaning and either $D(s) = \{\perp\}$ and $T(s) \geq \mu_\perp$, or $D(s) \neq \{\perp\}$ and $T(s) \geq \mu$. Senses are subject to a garbage collection process unless they are frozen.

Each sense passes through four stages, starting out unconverged, converging on symbols, then converging on meaning, and finally being frozen. Different senses can be in different stages at the same time. The processes that move senses through each of these stages are interleaved. They are implemented by the procedure $\textsc{Process}(S, M)$. The input to $\textsc{Process}(S, M)$ consists of an unordered multiset S of senses and a set M of expressions. In the noise-free monosemous case, the lexicon L maps each word w to a set containing a single sense. Each utterance $u = \{w_1, \ldots, w_n\}$, paired with a set M, is processed by letting s_i be the single element of $L(w_i)$, for each word w_i in the utterance, forming the unordered multiset $S = \{s_1, \ldots, s_n\}$, and calling $\textsc{Process}(S, M)$. In the following description, $F(m)$ denotes the set of all symbols that appear in the expression m, while $F_1(m)$ denotes the set of all symbols that appear only once in m.

Procedure $\textsc{Process}(S, M)$:

Step 1 Ignore those hypothesized utterance meanings that contain a symbol that is not possibly contributed by some word in the utterance or that are missing a symbol that is necessarily contributed by some word in the utterance.

$$M \leftarrow \{m \in M \mid \bigcup_{s \in S} N(s) \subseteq F(m) \wedge F(m) \subseteq \bigcup_{s \in S} P(s)\}$$

Step 2 For each word in the utterance, remove from the set of possible symbols for that word, any symbols that do not appear in some remaining hypothesized utterance meaning.

$$\textbf{for } s \in S \textbf{ do } P(s) \leftarrow P(s) \cap \bigcup_{m \in M} F(m) \textbf{ od}$$

Step 3 For each word in the utterance, add to the set of necessary symbols for that word, any symbols that appear in every remaining hypothesized utterance meaning but are missing from the set of possible symbols of all other words in the utterance.

$$\textbf{for } s \in S$$
$$\textbf{do } N(s) \leftarrow N(s) \cup \left[\left(\bigcap_{m \in M} F(m) \right) \setminus \bigcup_{s' \in S, s' \neq s} P(s') \right]$$
$$\textbf{od}$$

Step 4 For each word in the utterance, remove from the set of possible symbols for that word, any symbols that appear only once in every remaining hypothesized utterance meaning if they are necessarily contributed by some other word in the utterance.

for $s \in S$
do $P(s) \leftarrow P(s) \setminus \left[\left(\bigcap_{m \in M} F_1(m) \right) \cap \bigcup_{s' \in S, s' \neq s} N(s') \right]$
od

Step 5 For each word in the utterance that has converged on meaning, call the function RECONSTRUCT$(m, N(s))$ to compute the set of all fragments of the expression m that contain precisely the set of non-variable symbols $N(s)$, and remove from $D(s)$ any expressions not in that set.[1]

for $s \in S$
do if CONVERGEDONSYMBOLS?(s)
then $D(s) \leftarrow D(s) \cap \bigcup_{m \in M}$ RECONSTRUCT$(m, N(s))$
fi od

Step 6 If all words in the utterance have converged on symbols, for each word in the utterance, remove from the set of possible meaning expressions for that word, those meanings for which there do not exist possible meanings for the other words in the utterance that are compatible with one of the remaining hypothesized utterance meanings. This is a generalized form of arc consistency (Mackworth 1992).

if $(\forall s \in S)$CONVERGEDONSYMBOLS?(s)
then for $s \in S$
do if $(\forall s' \in S)[s' \neq s \rightarrow D(s') \neq \top]$
then $D(s) \leftarrow \{t \in D(s) |$
$\underbrace{(\exists t_1 \in D(s_1)) \cdots (\exists t_n \in D(s_n))}_{\{s, s_1, \ldots, s_n\} = S}$
$(\exists m \in M)$
$m \in$ INTERPRET$(\{t, t_1, \ldots, t_n\})\}$
fi od fi

Step 7 If all senses have converged on meaning, then increment the temperature of those senses that do mean $\perp$ if all senses that don't mean $\perp$ are frozen, and likewise increment the temperature of those senses that don't mean $\perp$ if all senses that do mean $\perp$ are frozen.

if $(\forall s \in S)$CONVERGEDONMEANING?(s)
then for $s \in S$
do if $[D(s) = \{\perp\} \wedge (\forall s \in S)(s \neq \{\perp\} \rightarrow$ FROZEN?$(s))] \vee [D(s) \neq \{\perp\} \wedge (\forall s \in S)(s = \{\perp\} \rightarrow$ FROZEN?$(s))]$
then $T(s) \leftarrow T(s) + 1$ **fi od fi** $\square$

[1] A future paper will describe the algorithm for computing RECONSTRUCT$(m, N(s))$ in greater detail.

While steps 1 through 4 always take a small amount of time, steps 5 and 6 can potentially take a large amount of time. Thus steps 5 and 6 are simply aborted if they take too long. This happens only a small fraction of the time in practice, usually for long utterances, and doesn't appear to significantly decrease the convergence rate of the algorithm.

The tables $N(s)$ and $P(s)$ are reminiscent of Mitchell's (1977) version-space algorithm. In the version-space algorithm, a *concept* is a set of *instances*. A concept is more *general* than its subsets and more *specific* than its supersets. When learning a concept, the version-space algorithm keeps two *sets* of concepts that bound the target concept from above and below. The target concept must be more general than each element of the lower bound and more specific than each element of the upper bound. Since the generality relation between concepts is transitive, each time a concept is added to the upper bound, any other concepts from the upper bound that are strictly more general are redundant and can be removed. Likewise, each time a concept is added to the lower bound, any other concepts from the lower bound that are strictly more specific are also redundant and can be removed. Because the addition of a new concept to either the upper or the lower bound will not always result in such a redundancy, the upper and lower bounds may grow to be sets of more than one element.

The algorithm presented here differs from the version-space algorithm in two important ways. First, the upper bound will always contain precisely two concepts. The sets $N(s)$ and $P(s)$ each denote a *single* concept, namely the set of expressions m such that $N(s) \subseteq F(m)$ or that $F(m) \subseteq P(s)$ respectively. Both of these concepts can be seen as members of the upper bound. The target concept must be more specific than each of these concepts. Each time a symbol is added to $N(s)$, a new concept results that is necessarily more specific than the prior $N(s)$ concept yet is neither more specific nor more general than the $P(s)$ concept. Thus adding a symbol to $N(s)$ replaces the prior $N(s)$ concept and leaves the $P(s)$ concept unchanged. Similarly, each time a symbol is removed from $P(s)$, a new concept results that is necessarily more specific than the prior $P(s)$ concept yet is neither more specific nor more general than the $N(s)$ concept. Thus removing a symbol from $P(s)$ replaces the prior $P(s)$ concept and leaves the $N(s)$ concept unchanged. Thus by induction, the upper bound will always contain precisely two concepts.

Second, the algorithm presented here has no analog to the version-space lower bound. Instead, the algorithm utilizes the domain specific fact that when $N(s) = P(s)$ the upper bound admits only two concepts, one a singleton and one empty. Since in this domain, all target concepts are singletons, the empty concept can be implicitly ruled out. Thus while in general, the version-space algorithm requires convergence

of the upper and lower bounds to uniquely identify target concepts, a special property of this domain allows target concepts to be identified using only upper bound reasoning. Thus the algorithm presented here is an important efficient special case of the version-space algorithm for the particular representation chosen for word meanings.

As normally viewed, the version-space algorithm generalizes the lower bound on the basis of observed positive instances of a concept and specializes the upper bound on the basis of observed negative instances. A common maxim in the linguistic community is that children rarely if ever receive negative evidence of any linguistic phenomena. In the particular case of learning word meanings, this means that children might be told or shown examples of what a word like *bicycle* means, but they are never told or shown examples of what *bicycle* does *not* mean. A naive interpretation of this fact would be that a learner could only apply half of the version-space algorithm to learn the lower bound, but could not learn the upper bound. This has prompted Berwick (1986) to propose the Subset Principle, the claim that learners are conservative, adopting only those concepts on the fringe of the lower bound.

This raises an apparent paradox. Since the algorithm presented here maintains only an upper bound and no lower bound, it would appear that it is learning *only* from negative evidence and not from positive evidence. Deeper inspection however reveals that the algorithm is taking advantage of two particular kinds of implicit negative evidence available when learning word meanings: inference between the same word heard in different non-linguistic contexts and inference between different words in the same sentence. The former is traditionally held by psychologists to be the basis of lexical acquisition in children (cf. Pinker 1989, Event Category Labeling). What is not traditionally acknowledged is that this is a form of implicit negative evidence. Hearing a word in multiple contexts and concluding that it must mean something shared by those contexts carries with it the implicit claim that a word cannot mean something that is not contained in the set of meanings hypothesized for an utterance containing that word. Use of the later form of implicit negative evidence, however, appears to be new. Given the particular semantic interpretation rule presented earlier, a learner hearing *John rode a bicycle* after having determined that *John* must mean **John** could infer that *bicycle* could *not* also mean **John**. Both of these forms of reasoning aid a learner in determining what words might *not* mean and allow the upper half of the version-space algorithm to apply. This has the important consequence that the Subset Principle is not strictly necessary, as had been previously thought, even if no explicit negative evidence is available.

Dealing with Noise and Homonymy

A sense s is termed *consistent* if $N(s) \subseteq P(s)$ and $D(s) \neq \emptyset$. The simplified algorithm will produce inconsistent senses if it is used to process a corpus that exhibits noise or homonymy. Nonetheless, the procedure PROCESS(S, M) can be used as a subroutine by an extended algorithm that can deal with noise and homonymy.

In the simplified algorithm, PROCESS(S, M) permanently updates the tables N, P, D, and T. The extended algorithm will additionally make use of a variant of this procedure, CONSISTENT?(S, M), that doesn't actually perform the updates but returns **true** if and only if every sense $s \in S$ would remain consistent if PROCESS(S, M) were called.

In the extended algorithm, L may map words to sets of senses, not just singleton senses. Initially, L maps each word to a unique singleton sense. The extended algorithm makes use of the following function.

$$\text{ALTERNATIVES}(u, M) \triangleq \{\{s_1, \ldots, s_n\} \mid \underbrace{s_1 \in L(w_1) \wedge \cdots \wedge s_n \in L(w_n)}_{\{w_1, \ldots, w_n\} = u} \wedge \text{CONSISTENT?}(\{s_1, \ldots, s_n\}, M)\}$$

The extended algorithm is presented below.

Procedure PROCESSUTTERANCE(u, M):

Step 1 If ALTERNATIVES$(u, M) \neq \emptyset$, choose the element $\{s_1, \ldots, s_n\} \in$ ALTERNATIVES(u, M) with the maximum value of $T(s_1) + \cdots + T(s_n)$, perform PROCESS$(\{s_1, \ldots, s_n\}, M)$, and return.

Step 2 Otherwise, find the smallest subset $u' \subseteq u$ such that if a new unique sense is added to $L(w)$ for each $w \in u'$, ALTERNATIVES$(u, M) \neq \emptyset$.

Step 3 Add a new unique sense to $L(w)$ for each $w \in u'$.

Step 4 Now ALTERNATIVES(u, M) must not be empty, so choose the element $\{s_1, \ldots, s_n\} \in$ ALTERNATIVES(u, M) with the maximum value of $T(s_1) + \cdots + T(s_n)$, call the procedure PROCESS$(\{s_1, \ldots, s_n\}, M)$, and return. □

Since either step 2 in the above algorithm, or the computation of ALTERNATIVES(u, M), may take a long time, an utterance is simply discarded if these computations exceed a certain time limit. The top-level procedure simply evaluates PROCESSUTTERANCE(u, M) for each input sample $\langle u, M \rangle$.

The intuitive idea behind this algorithm is as follows. The algorithm operates under the default assumption that each word has a single sense. Under this assumption, it tries to construct a lexicon that explains all of the utterances in the corpus, i.e. one that allows each utterance to take on as its meaning, one of the referentially uncertain expressions paired with that utterance. If the corpus does not exhibit noise or homonymy, it will succeed at this task. If however,

the corpus does exhibit noise or homonymy, some of the word senses will become inconsistent during the execution of the acquisition algorithm. This can happen for one of three reasons. Either (a) the current utterance contains a word used in a different sense than the current senses hypothesized for that word, (b) the current utterance is noise, or (c) some previous utterance was noise and processing that utterance polluted the hypothesized meanings of some words shared with the current utterance. The single mechanism of splitting word senses, embodied in steps 2 and 3 of PROCESSUTTERANCE(u, M), is used to cope with all three of these cases. If the current utterance does indeed contain words used in a different sense then previously hypothesized, it is likely that an attempt to merge the two senses into one will yield an inconsistency. Selecting the minimal set of senses to split to resolve such an inconsistency will likely correlate with the actual homonymous words encountered. Noisy utterances are also likely to yield an inconsistency. Paying attention to noisy utterances simply causes the creation of spurious new word senses to account for those utterances. These spurious senses are unlikely to be encountered more than once since they were created solely to account for a random noisy utterance. Thus these senses are unlikely to progress very far along the path to convergence on symbols, meaning, or being frozen. These senses are filtered out every so often by having the top-level procedure remove the non-frozen senses of each word if some sense for that word is frozen and the senses of each word that haven't converged on symbols if some sense for that word has converged on symbols.

Experiments

Since the algorithm presented learns from utterances paired with hypothesized utterance meanings, and there do not exist corpora of naturally occurring utterances paired with such meaning representations, it has been tested on synthetic corpora, generated randomly according to controllable distributional parameters. In one such experiment, a random lexicon mapping 1,000 words to 1,680 senses was generated. The 'words' in this lexicon were simply the symbols $w_1 \ldots w_{1000}$ while the 'senses' were randomly constructed S-expressions over a conceptual vocabulary of 250 conceptual symbols, denoted $s_1 \ldots s_{250}$. A uniform distribution was used to select the conceptual symbols when constructing the random S-expressions. Of these 1,680 senses, 800 were variable-free expressions. These had a maximal depth of 2 and a maximal branching factor of 3 and were intended to model noun-like word senses. Another 800 senses contained from 1 to 3 variables denoting open argument positions. These were intended to model verb-like word senses and had the same maximal depth and branching factor. A uniform distribution was used to control the choice of depth and branching factor used to generate each synthetic word sense. The final 80 word senses were taken to be $\perp$ to model function words. These 1,680 senses were uniformly distributed among the 1,000 words. Some words contained only a single sense while others contained several. A given word could have a mixture of noun-like, verb-like, and function-word-like senses.

Using this lexicon, a corpus of 246,439 random utterances containing 1,269,153 words was generated. A uniform distribution was used to select the words when generating the utterances. These utterances ranged in length from 2 to 27 words with an average of 5.15 words per utterance. The lexicon was used to parse each utterance and construct a semantic representation. 80% of the utterances were paired with their correct semantic representation along with the semantic representation of 9 other randomly generated utterances. 20% of the utterances were paired with 10 incorrect semantic representations corresponding to 10 other randomly generated utterances. Thus the corpus exhibited a degree of referential uncertainty of 10 representations per utterances and a noise rate of 20%. Finally, each utterance in the corpus was permuted randomly before being presented to the acquisition algorithm to guarantee that the algorithm did not make any use of word order.

This corpus was then presented to the lexical acquisition algorithm. During acquisition, of course, the algorithm had no access to the lexicon used to generate the corpus. After completion, the lexicon acquired by the algorithm was compared with the original lexicon used to generate the corpus. In a little over three days of CPU time on a Sun SPARCclassic,™ the algorithm succeeded in recovering at least one correct meaning for each of the 1,000 words in the lexicon. It failed to find 33 of the 1,680 word-to-meaning mappings and mistakingly conjectured 9 incorrect word-to-meaning mappings for a combined error rate of 2.5%. Due to computer resource limitations, for this experiment, the algorithm was set to terminate after it had acquired 98% of the word senses in the lexicon, thus accounting for the 33 false negatives. It appears likely that the algorithm would have succeeded in acquiring all 1,680 senses if it was left to run on a somewhat longer corpus.

It appears that the length of the corpus needed to learn a lexicon of a given size can depend significantly on the homonymy rate. Another experiment was conducted where the lexicon did not exhibit any homonymy but where all other corpus construction were kept parameters the same. In particular, the corpus still exhibited a degree of referential uncertainty of 10 and noise rate of 20%. For this experiment, the algorithm correctly acquired 1029 out of 1050 word-to-meaning mappings, making only a single mistake. Here again the algorithm was terminated before it could acquire the remaining 21 word-to-meaning mappings but would likely have done so with a somewhat longer corpus. The important difference is that this run re-

quired a corpus of only 12,840 utterances, less than one-twentieth the size of the first experiment. More work is necessary to determine whether this difference reflects a fundamental difficulty inherent in coping with homonymy or whether this is an artifact of the particular lexical acquisition algorithm presented here.

No claim is intended that these examples reflect all of the complexities faced by children learning their native language. First of all, it is unclear how to select appropriate values for corpus parameters such as noise rate, homonymy rate, and degree of referential uncertainty. In the above experiments, the noise rate of 20% and the value of 10 for the degree of referential uncertainty were chosen arbitrarily, purely to test the acquisition algorithm. Our current impoverished level of understanding of how conceptual representations are constructed from perceptual input, either by adults or by infants, makes it difficult to select a more motivated noise rate or degree of referential uncertainty. It is also difficult to accurately assess the homonymy rate in a given language as that depends on how one decides when two senses differ. The homonymy rate of 1.68 senses per word was chosen for the experiments presented here since the WordNet database (Beckwith et al. 1991) exhibits a homonymy rate of 1.68. No claim that children face similar noise and homonymy rates is intended.

Conclusion

A number of further questions must be answered before this algorithm can be proposed as a theory of how children learn word meanings. Currently, not much is known about the cognitive representations that children bring to the task of language learning, how wide the range of hypotheses that they construct is, how severe the noise problem is, or how much homonymy they face. But the present work shows that an algorithm that can cope with these problems exists and that despite quite pessimistic assumptions about the values of these parameters, the algorithm has reasonable running times and convergence rates. This research suggests that exploring the space of potential lexical acquisition procedures to find those that work will give insight into the lexical acquisition task, lead to a better understanding of how children might accomplish that task, and motivate experiments to determine how they actually do so.

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