How to Make the Most out of Very Little

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Abstract

I review the problem of referential ambiguity that arises when children learn the meanings of words, along with a number of models that have been proposed to solve it. I then provide a formal analysis of why a resource-limited model that retains very few meaning hypotheses may be more effective than “big data” models that keep track of all word-meaning associations.

Word count: 4280
Pet ownership is at all time high. According to a 2006 Gallup survey, 44% of Americans owned a dog, 29% owned a cat, and 17% owned both. By 2012, the American Pet Products Association could reveal that these numbers had risen to 47% for dogs and 37% for cats. And multiple pet ownership had seen the most vigorous growth: a whopping 29% of Americans now own a dog as well as a cat.

For students of word learning, especially those under Lila Gleitman’s tutelage, this last statistic should set off alarm bells. In a cluttered family room where all members of the household congregate, how does the baby know that “dog” means DOG and “cat” means CAT, when both are likely to be present when either word is heard? This is not even to consider the interference from CHAIR, CRAYON, DESK, RUG, SHOE, SPOON, WINDOW, etc. that are also in the mix (Medina et al. 2011).

In this short note, I provide a preliminary analysis of how the child may overcome the ambiguity problem to find the meanings of words. Drawing from Lila and her colleagues’ research, I first review the severity of the problem in realistic word-learning environments (Section 1). Section 2 reviews some current approaches to the problem, including the Pursuit model which arose from a recent collaboration (Stevens et al. 2016). Surprisingly, resource-limited models that entertain a subset of available word-meaning pairings outperform “big data” models that attend the totality of learning experience. Section 3 sketches out a formal account of this paradoxical result. I suggest that the statistical distribution of language use, especially the sparsity of highly informative instances, in fact favors the restrictive models of word learning.

1 Gleitman’s Problem

As Lila and Henry Gleitman once memorably remarked (1992), a picture is worth a thousand words, and that’s the problem. Language is much more than here-and-now, and words do not present themselves in the environment to be readily picked up. When we say “let’s write a letter to grandma”, the “letter” is still imaginary and grandma may well be tending her garden in Canada. Indeed, the noisy pairing between words and their meanings, and more generally the creative aspect of language use, form a core argument in Chomsky’s critique of Skinner’s associationist program (1959). Yet children learn words rapidly, accurately, and in strikingly uniform ways (Carey and Bartlett 1978, Landau and Gleitman 1985, Miller 1991, Bloom 2000).

No one can seriously question the role of the experience in language acquisition: after all, New York

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1 I follow the Fodorian notation of using uppercase to denote the concept/referent (e.g., DOG) picked up by a phonological word (e.g., “dog”).
kids learn English ("dog") and Beijing kids learn Chinese ("gou"). The Human Simulation Paradigm (Gillette et al. 1999) has proved an effective tool to assess the ecological condition of language acquisition, and the environmental challenges children have to overcome to learn the meanings of words. In a typical study, adult participants watch silent videos of young children interacting with their mothers. They hear a beep when a target word is produced by the caretaker. Even though the participants are competent speakers who already have a full vocabulary, their performance is abysmal. On average, they could only identify nouns with 45% accuracy; for verbs, the accuracy drops to 15%. While modest improvement for nouns can be observed across multiple learning instances there is hardly any benefit for the verbs. The degree of referential ambiguity is very high: it is very difficult for a learner to correctly identify words solely from observation even though it’s quite not as bad as choosing one out of a thousand.

But there is hope. One of the consistent findings from the Human Simulation Paradigm is that while most words are hard to pick out from the environment, some are relatively easy. Conventionalized expressions ("Hi", "Bye-bye") and concrete nouns ("ball", "plane", "swing"), including those representing basic-level categories (Gentner 1982), are relatively easy to identify and may well serve as the foundation for vocabulary as well as grammatical acquisition (Pinker 1984, Gleitman et al. 2005). In the most recent and comprehensive study (Trueswell et al. 2016), the Human Simulation Paradigm was taken out of the laboratory to assess the potency of observational learning in the naturalistic situation of language acquisition. Using a video corpus of 351 vignettes of free play and focusing only on concrete nouns, Trueswell et al. 2016 find that, on average, only 18% of the guesses are correct but a good deal of variance is found within. In particular, there is a small but non-negligible subset of vignettes, about 15% in all, where participants guess the mystery noun correctly more than 70% of the time. The high informativity of these scenes appear to be the result of joint attention (Tomasello and Farrar 1986, Baldwin 1991, Woodward 2003) and clear visual signatures (Pereira et al. 2014) especially temporal cues indicative of causation (Scholl and Tremoulet 2000).

So Mother Nature may be parsimonious but she is not mean. For children, the smart move is to make maximum use of these highly informative learning instances. Such instances are identified by relying on heuristics and constraints to narrow down the range of word-meaning mappings. As just reviewed, these cues may be social, attentional, perceptual in nature and potentially domain general. They may also be structural and reflect domain-specific properties of human language (Markman 1990, Markman et al. 2003, de Marchena et al. 2011), especially in the study of syntactic bootstrapping (Gleitman 1990, Naigles 1990,
This paper tries to characterize word learning mechanisms that can make the most out of the rare but highly informative instances. For ease of exposition, I will focus on how to learn that “dog” means DOG. The problem is complicated by CAT, which is almost always present when the word “dog” is uttered. But every now and then the DOG goes out for a walk and the child comes along: Crucially, the CAT stays home and is therefore not in contention. Thus, the alone time with DOG is highly informative as it disambiguates DOG from CAT. While this somewhat silly example focuses on the learning of concrete nouns, it represents a wide range of word learning situations. Taking the DOG for a walk is equivalent to the occasional pointing or eye gaze direction that can guide children’s attention, thereby disambiguating CUP from PLATE on the kitchen table. Or it may represent a piece of structural information (“a seb” vs. “sebbing”) that settles the syntactic category of an unknown word (Brown 1957). DOG and CAT may also be stand-ins for CHASE and FLEE, PUSH and MOVE, etc., which are among Lila’s favorite verbs (Gleitman 1990, Fisher et al. 1994). While these twin verbs are often both compatible with the observation of an event — “I’m pushing the box” and “I’m moving the box” — walking the DOG is formally equivalent to the child hearing a critical disambiguating syntactic frame (Gleitman 1990, Naigles 1996): we can say “the box is moving” but not “the box is pushing”, “I’m pushing on the box” but not “I’m moving on the box”, which point to the vital syntactic and semantic differences between these verbs (Levin 1993).

The resolution of Gleitman’s Problem for word learning, then, must make good use of these rare but highly informative nuggets of information. With this in mind, let us review some word learning models on the market.

2 Two Worldviews and Three Learning Models

A picture may be worth a thousand words but what if each word is paired with a thousand pictures themselves, which allows the true meaning to emerge? For example, the word “dog” may, on average, be accompanied with more learning instances that contain DOG than those that contain CAT, and will thus come out as the winning candidate over time. The modern idea of cross-situational learning (Pinker 1994, Yu and Smith 2007) is an update of the associationist program for language (Quine 1960). In a formulation from that era, “whenever some stimulus other than the signifi cate [e.g., “dog”/DOG; CY] is contiguous with the signifi cate, it will acquire an increment of association with some portion of the total behavior
elicited by the signif_icate" (Osgood et al. 1957, p6). As long as the target meaning is associated sufficiently strongly — more strongly than its competitors — the learner may be able to tabulate and detect such statistical regularity. In the new age of empiricism fueled by Big Data and fast machines (Roy et al. 2006, Le 2013), this all seems plausible.

Unless children literally learn everything about a word in one shot, learning must make use of multiple learning instances. The key question concerns how such cross-situational information is used. It is instructive to distinguish two general approaches in the recent literature. A global approach (Siskind 1996, Yu and Smith 2007, Frank et al. 2009, Fazly et al. 2010, McMurray et al. 2012) resolves referential ambiguity by aggregating over word-meaning co-occurrences. The meaning of a word is the candidate with the strongest statistical correlation over all learning instances. By contrast, a local approach (Medina et al. 2011, Trueswell et al. 2013, Stevens et al. 2016, Aravind et al. 2018) attempts to resolve ambiguity in the moment. Specifically, it ignores all potential words meanings that do not serve to confirm or disconfirm a word’s hypothesized interpretation. In the limit, a local model resolves ambiguity by ignoring ambiguity: It only learn from unambiguous data, a powerful idea that has desirable formal properties (Angluin 1980, Berwick 1985) and has been proposed for other problems in language acquisition (Wexler and Culicover 1980, Fodor 1998).

To understand the differences between the local and global approaches to word learning, consider an illustrative example in Figure 1. The word is “mipen”, meaning ELEPHANT, and it is presented in five learning instances over time. Note that in learning instance (d), the target ELEPHANT is missing. This contrasts with almost all cross-situational learning experiments where the target meaning is always present, but is designed to better reflect language use in the real world, which is not bound by the here-and-now.

Consider the simplest global learner model, one which tabulates all word-object pairings and selects the winner in the end; the computational model of Fazly et al. (2010) is a faithful implementation of this idea. Figure 2(a) represents the internal state of the model during each learning instance, where each meaning candidate increases its score by one whenever “mipen” is heard. Despite the absence of ELEPHANT in learning instance (d), it still emerges the winning candidate at the conclusion of learning.

The Propose-but-Verify model (PbV; Medina et al. 2011, Trueswell et al. 2013) is the simplest local model and it operates in the tradition of hypothesis testing. The learner maintains a hypothesis for a word and checks it against each instance of the input data. The hypothesis is retained if confirmed (e.g.,
Figure 1: Mipen. Adapted from Stevens et al. 2016.

Figure 2: The dynamics of three word learning models. Adapted from Stevens et al. 2016.
the referent is observed); otherwise it is replaced by a new hypothesis (e.g., another referent from the environment). The dynamics of PbV is shown in Figure 2(b). For the sake of argument, suppose the learner initially guessed that “mipen” means, correctly, ELEPHANT. This hypothesis is subsequently confirmed for learning instance (b) and (c) and is thus retained. However, it is jettisoned due to absence of ELEPHANT in (d), and another hypothesis from the observation — say, CAT — is selected. The updated hypothesis is subsequently confirmed and the learner concludes, incorrectly, that “mipen” means CAT. It is important to note that a PbV learner never considers more than two hypotheses — the old hypothesis, and a new one if the old is rejected — and all other possible referents are completely ignored; hence the very narrow “window” of internal states in Figure 2(b). Note also that the PbV model is stochastic: because the model “guesses” the intended candidate meaning, it may produce different outcomes on multiple runs through the same input sequence. Thus Figure 2(b) is just one of the many paths available to the learner; they could have guessed CRAB initially but stumble on ELEPHANT in the final instance. In experimental studies, the PbV model is assessed by aggregating results from multiple subjects, which corresponds the expected probability of learning the target meaning in the formal analysis presented in Section 3.

The Pursuit model can be viewed as a probabilistic update of PbV. Here the hypotheses are stored in the memory with weights. Like PbV, this only applies to the hypotheses actively considered by the learner but not those that merely cooccur with the word: hence the slightly “wider” internal state in Figure 2(c) than PbV but much smaller than the cross-situational learner. Although there may be multiple hypotheses associated with a word, only one is tested against the input (again like PbV): its success or failure results in increment or decrement of the weights, following a simple scheme of reinforcement learning (Bush and Mosteller 1951, Rescorla and Wagner 1972, Sutton and Barto 1998, Dayan and Daw 2008) which has been effectively applied in other domains of language acquisition (Yang 2002, 2004). More specifically, Pursuit adopts a very aggressive “greedy” form of reinforcement learning. When multiple hypotheses are available for a word, the learner will singlemindedly pursue the best hypothesis, one which has the highest score. If confirmed, the rich will get richer. If it fails to be confirmed, its probability is decreased: the learner will

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2Most instantiations of reinforcement learning sample among the hypotheses according to their probabilities. It so implemented, the probabilistic model becomes formally equivalent to an online version of cross-situational learning and will inherit all the empirical problems (Stevens et al. 2016). The question is why a greedy scheme is used in word learning while human subjects are clearly capable of sampling over multiple hypotheses in probability matching (Herrnstein and Loveland 1975) and in the evaluation of grammatical hypotheses (Yang 2002). I speculate that the use of Pursuit in word learning may reflect the structure of the lexicon. Certain frequency effects (e.g., Swinney 1979) are consistent with a list-like representation of lexical entries ranked by frequency (Murray and Forster 2004, Lignos 2013, Yang 2016), which corresponds to the number of confirmations in the Pursuit model.
add a new candidate to the memory (again like PbV) but the just defeated candidate may still remain the best.

Consider how Pursuit learns “mipen”. Pursuit is also stochastic so its learning trajectory in Figure 2(c) is only one of the possible paths available to the learner. The score keeping of Pursuit is somewhat complex (see Stevens et al. 2016 for details) and we will use a simple counter here to illustrate the dynamics of learning. The initial (fortuitous) guess of ELEPHANT is rewarded continuously and reaches a score of 3 by scene (c). Note that since ELEPHANT has been confirmed, the learner does not register any other referents at all. At instance (d), however, the absence of ELEPHANT lowers its score 2. The learner adds another hypothesis, say CAT, to the list with a score of 1. In the final instance, the learner pursues the best hypothesis, which is still ELEPHANT despite the earlier mishap. It restores its score to 3 and will be selected as the winner in the end.

At least in this example, Pursuit captures the best of both worlds: the computational simplicity of PbV and the effect of cumulative evidence from cross-situational learning. Occasional failures such as learning instance (d) in the “mipen” example will not be catastrophic. Furthermore, if “mipen” indeed meant CAT, then the earlier misjudgment (ELEPHANT) presumably will be penalized in the future learning and eventually lose its lead. The memory component of Pursuit also accounts for the finding that hypotheses, if (and only if) entertained at some point during learning, leave behind a trace so that their probabilities of being selected in the end are greater than chance (Köhne et al. 2013).

Stevens et al. (2016) provide extensive computational analyses of the three models. The results include a surprisingly finding is that both local models provide at least as good, if not better, account of the behavioral results from Yu and Smith (2007), the paradigm study in support of global cross-situational learning. Experimental findings from other studies (e.g., Medina et al. 2011, Köhne et al. 2013, Trueswell et al. 2013) provide more direct and decisive support for the local models over global models.

Here I focus on another surprising result from our study, a quantitative evaluation of how these models fare “in the wild”. To maintain continuity with previous modeling efforts (Yu and Ballard 2007, Frank et al. 2009), we annotated two video clips from the CHILDES database (MacWhinney 2000). A learning instance is defined by a child-directed utterance; it consists of the set of words used and the set of perceptually salient referents — judged by the annotator — at the time of utterance. There are 34 unique words in all. We implemented the PvB model, the Pursuit model, as well as a cross-situational learning Fazly et al. (2010) that makes learning decisions on the overall tallies of word-meaning cooccurrences as described
in Figure 2(a). After the entire corpus is processed, the models’ output is compared against a gold standard lexicon. Three performance measures are reported: precision, recall, and F-score. Precision gives the percentage of the correct word-reference pairs learned by the model, recall measures the percentage of the target word-reference pairs in the gold standard lexicon that the model manages to learn, and F-score is a composite measure of the two. As is conventional in computational modeling research, the free parameters for all models are manually tuned so as to produce the best performance possible. Again, the cross-situational model is deterministic and was only run once, while both PbV and Pursuit are stochastic and their performance figures are averaged over 1,000 simulations. The results are summarized in Table 1.

<table>
<thead>
<tr>
<th>Model</th>
<th>Precision</th>
<th>Recall</th>
<th>F-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Propose-but-Verify</td>
<td>0.04</td>
<td>0.45</td>
<td>0.07</td>
</tr>
<tr>
<td>Cross-situational</td>
<td>0.39</td>
<td>0.21</td>
<td>0.27</td>
</tr>
<tr>
<td>Pursuit</td>
<td>0.45</td>
<td>0.37</td>
<td>0.41</td>
</tr>
</tbody>
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Table 1: Model performance on a small video corpus of child-directed English.

It must be said that the results in Table 1 are terrible: parents would be running to the family pediatrician if children were only able to learn more words incorrectly than correctly. At the same time, it is worth noting that the only information these learning models only capture one component of learning—the tracking and computation of word-meaning co-occurrences—and do not incorporate the linguistic as well as nonlinguistic constraints well documented in the empirical literature. The models’ abysmal performance only highlights the necessity of such constraints for successful language acquisition.

The most surprising finding here is the unreasonable effectiveness of Pursuit: a local, resource-limited, model that only considers a subset of word-referent pairings actually outperforms the cross-situational model that optimizes over the totality of the learning data. This will be the primary focus of our formal and quantitative analysis in Section 4 but a related, and intriguing, pattern emerged in the analysis of errors produced by these learning models, as shown in Figure 3.

The graphs in Figure 3 compare Pursuit and cross-situational learning for “easy” and “hard” words. Here the difficulty of a word is defined as its average ambiguity across all learning instances. For example, if a visual scene that accompanies the utterance of a word contains only one noticeable object (as judged by the human annotator), the word will have an ambiguity score of 1. If there are six objects, then the word will have an ambiguity score of 6. The distribution of ambiguity across learning instances is broadly consistent with the findings in Trueswell et al. (2016): most of times a word co-occurs with several objects
<table>
<thead>
<tr>
<th>Avg. Ambiguity</th>
<th>Model</th>
<th># Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 3</td>
<td>Cross-situational</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Pursuit</td>
<td>9</td>
</tr>
<tr>
<td>&gt;= 3</td>
<td>Cross-situational</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Pursuit</td>
<td>4</td>
</tr>
</tbody>
</table>

Figure 3: Performance of Pursuit and cross-situational models on high- and low-ambiguity words.

but occasionally the learning instance is highly salient (e.g., only one referent). Figure 3 shows that for words with an ambiguity score greater than or equal to 3 (“hard”), both models learn rather poorly, with the cross-situational model making only 3 correct mappings and the Pursuit model making 4 correct mappings. But when we look at those words that have an average ambiguity score less than 3 (“easy”), we see that while the cross-situational model doesn’t do much better on these words (4 correct mappings), Pursuit learns more than twice the number of words (9 correct mappings). Tellingly, there are 12 out of 34 words in the gold standard lexicon that have the average ambiguity less than 3; three quarters (9/12) of these are learned correctly by the Pursuit model, more than double the percentage of correct learning under the cross-situational model (4/12).

What makes a resource-limited model more effective than one that retains the totality of information? Why is it especially effective for low-ambiguity easy words? I now turn to investigate these puzzling results.
3 The Race between DOG and CAT

Let’s revisit DOG vs. CAT, a toy example that is nevertheless emblematic of ambiguity resolution in word learning. As reviewed in Section 1, word-meaning associations are generally highly ambiguous but there are rare instances of clarity. For the present analysis, it is not important what makes these instances informative (see Section 1): it is sufficient to assume that they exist albeit with low probabilities. This allows us to use the DOG and CAT example to study the dynamics of word learning: DOG and CAT are generally indistinguishable but the occasional walk DOG takes in the absence of the CAT constitutes the critical disambiguating evidence. In what follows, I will make some suggestions about how to make the most out such precious information, and why local models such as Pursuit are best positioned to do so. If correct, it also goes some way toward making sense of the simulation results that models with severe resource limitation outperform models with the totality of data at their disposal.

3.1 Formal Analysis

To begin, I will make some simplifying assumptions about the learning situation and the learning models. These will make a formal analysis tractable while still shedding light on the core task of referential ambiguity resolution. Specifically, let us assume that the input sequence starts with $N$ learning instances in which both DOG and CAT are present, followed by $U$ — which stands for unambiguous — instances in which the competitor CAT is not present (but DOG is). Furthermore, let’s assume that in each of the first $N$ instances, DOG and CAT have an equal probability of $p_N$ of being selected. In the $U$ instances that follow, DOG has a probability $p_U$ of being selected each time.

Here $p_N$ and $p_U$ can be flexibly defined. For instance, they may be inversely proportional to the number of potential meaning candidates in each instance, a frequent manipulation in the experimental study of word learning (Yu and Smith 2007, Medina et al. 2011, Köhne et al. 2013). For our purposes, we generally assume $p_N < p_U$; that is, the $N$ instances are not as helpful as the $U$ instances for learning DOG. In fact, the Human Simulation Paradigm research reviewed in Section 1 suggests that in general, $U \ll N$ and $p_U \gg p_N$. That is, most learning instances are highly ambiguous but the learner does occasionally receives highly informative cues.

It is clear that DOG and CAT will not be differentiated in the first $N$ learning instances. For the cross-situational learner, DOG and CAT will have the same numerical score. For Pursuit, which is stochastic,
DOG and CAT are expected to be in a tie. We are thus interested in quantifying the effectiveness of the $U$ instances as tie-breakers: the further that the $U$ instances pushes DOG ahead of CAT, the more likely will the learner succeed.

For a prototypical cross-situational learning (e.g., Fazly et al. 2010), the advantage of DOG over CAT is simply the proportion of the learning instances that contain DOG but not CAT. Let this term of advantage be $\Delta_X$ ($X$ for cross-situational):

$$\Delta_X = \frac{U}{N + U}$$

Note again that we are only considering the competition between DOG and CAT thereby completely ignoring other potential referents that the learning model may have picked up. In the current setup, if the learner were to choose between DOG and CAT after the $N$ instances, they would be at 50% under all learning models. The term advantage is a quantitative measure of the “above chance” boost conferred by the subsequent $U$ disambiguating instances.

Strictly speaking, a “true” cross-situational learner (Yu and Smith 2007, Frank et al. 2009, Fazly et al. 2010) will always select DOG with probability 1 because DOG will have a higher score than CAT. But the calculation of the cumulative advantage afforded by $U$ in Eq. 1, which is a ratio and thus a gradient measure, is both necessary and appropriate for at least two reasons. First, experiments (Smith and Yu 2008, Medina et al. 2011, Trueswell et al. 2013) clearly show that for word learning across multiple instances, the target meanings are only preferred rather than categorically selected; see Stevens et al. (2016) for discussion. This suggests that a cross-situational learning model must have a probabilistic/scalar component that encodes the learner’s confidence in DOG over other meaning candidates, such as the one described in Eq. 1. Second, in the computational evaluation of word learning models, it is necessary to introduce a threshold function, similar to those used in other learning and memory models (e.g., Anderson and Schooler 1991), that determines whether a meaning has been successfully acquired (e.g., Frank et al. 2009, Fazly et al. 2010, Stevens et al. 2016). These threshold functions operate on the relative strength of the candidates. If the advantage of DOG over CAT is weak, then the threshold must be set low in order for DOG to be acquired, but doing so will let in more false positives in the overall assessment of the learning model. Thus, it is only safe to set the association threshold to a relatively high value to attain the high accuracy necessary to model human word learning. This notion is again captured by $\Delta_X$: the higher it is, the more likely will
the cross-situational learner succeed to acquire DOG.

To be fair to the cross-situational approach, consider a more judicious learner. It still keeps track of all word-referent pairings but gives more credence to more informative learning instances. This reasonable assumption enables the learner to capitalize on low ambiguity instances: an observation with only one distractor is more useful than one with ten distractors. More concretely, let’s introduce a “bias” factor for the $U$ informative instances, and the resulting advantage for DOG over CAT for the *biased* cross-situational learner $\Delta_B$ is:

$$\Delta_B = \frac{UB}{UB + N} \text{, where } B = \frac{p_U}{p_N}$$

Consider now Pursuit. For the formal analysis to be tractable, I will use a modified model of Pursuit that only counts confirmations but does not penalize for disconfirmations. This simplification is justified because we are only comparing DOG and CAT and ignore other candidates the learner might have conjectured along the way. Because Pursuit always chooses the leader when learning stops, the problem becomes the calculation of the probability with which DOG is ahead of CAT after all $(N + U)$ learning instances. Since the first $N$ instances offer no opportunity for DOG to beat CAT on average, the decisive advantage can only be provided by the $U$ instances toward the end.

The race between DOG and CAT under Pursuit can be analyzed as a multinomial process which selects each with probability $p_N$ during the first $N$ instances, following a binomial process that selects DOG with probability $p_U$ in the subsequent $U$ instances. There are three possibilities after $N$:

- **DOG is already ahead of CAT:** $U$ will not provide any additional advantage.

- **CAT is at least $U$ steps ahead of DOG:** DOG cannot be salvaged by $U$.

- **CAT is $i$ (0 ≤ $i$ < $U$) steps ahead:** DOG can catch up if it is selected at least $(i + 1)$ times during $U$.

Since Pursuit is a stochastic process, the first two events are just luck that has nothing to do with $U$. The probability of the third event is the unique contribution of $U$ to push DOG ahead of CAT. Thus, the advantage for a Pursuit model ($\Delta_P$) afforded by $U$ is the product of two probabilities: that of CAT being ahead of DOG in $N$, and that of DOG catching up in $U$. 


\[ \Delta_P = \sum_{0 \leq i < U} \left[ \binom{N}{d, d+i} p_N^d p_N^{d+i} (1 - 2p_N)^{N-2d-i} \cdot \sum_{j=i+1}^U \binom{U}{j} p_U^j (1 - p_U)^{U-j} \right] \] (3)

The monstrosity in Eq. 3 is interpreted as follows. In the \( N \) instances, DOG has been chosen \( d \) times while CAT has been \( (d + i) \) times and is thus \( i \) steps ahead. The first term inside the square brackets expresses this multinomial probability. The second term is the probability of DOG being selected \( j \) times in the \( U \) learning instances, where \( j > i \) guarantees that DOG will surpass CAT in the end.

### 3.2 Numerical Results

The discussion so far has been abstract. The effectiveness of the models, which is measured by the advantage value \( \Delta \), are determined by the values of several parameters that specify the extent of referential ambiguity in word learning. We now explore these parameter values so as to understand the conditions under which the learning models are most effective – and whether such conditions correspond to realistic word learning situations. Here the results from the Human Simulation Paradigm studies (Trueswell et al. 2016) are critical, as they give us a realistic estimate of the ambiguity problem in word learning, thereby providing some baseline values for the parameters.

The first study focuses on how to make effective use of rare but highly informative learning instances. Following Trueswell et al. 2016 (briefly reviewed in Section 2), I will assume \( p_N = 0.2 \), which is roughly the average probability with which the subjects were able to identify the target referent, and \( p_U = 0.7 \), the probability of success on highly informative scenes. Figure 4 shows the relative advantage of DOG over CAT (\( \Delta \)) as a function of \( U \), the number of disambiguating learning instances, which take place after \( N = 100 \) ambiguous instances.

It is clear from Figure 4 that the advantage of DOG over CAT is significantly stronger under Pursuit than the cross-situational learning models, as long as the informative learning instances are relatively rare (the value of \( U \) being small). But the effectiveness of Pursuit is not absolute. For instance, when the value of \( U \) is large, i.e., when the informative instances are common, the biased cross-situational model begins to outperform the Pursuit model although the vanilla cross-situational model continues to struggle. In the present context, however, it is important that Pursuit excels precisely under the conditions that are most similar to actual word learning situations, namely, highly ambiguous input with relatively few informative instances for the purpose of disambiguation.
Figure 4: Pursuit makes better use of rare but informative learning instances.

Figure 5 fixes the value of $U$ at 15, again roughly following Trueswell et al. 2016, that approximately 15% of learning instances are highly informative. It explores the effect of the bias factor $B \left( \frac{P_U}{P_N} \right)$, which measures the informativeness of $U$ (over $N$). Again, we set $P_N = 0.2$ but values of $B$ will range from 0.25 to 4, corresponding to $P_U = 0.05$ where $U$ is actually less informative than $N$, and $P_U = 0.8$, where $U$ is much more informative than $N$.

The vanilla cross-situational model, which only tallies the number of word-reference occurrences, is not able to take advantage of the more informative learning instances. The effectiveness of Pursuit over the biased cross-situational learning model, however, is decisive. This is even so when $B < 1$, i.e., the $U$ instances, which are devoid of CAT, are more ambiguous than the $N$ instances. Nevertheless, DOG is able to receive a considerable advantage over CAT under the Pursuit model.

The formal analyses presented here can no doubt be enriched and refined but they already provide useful insight on the nature of word learning mechanisms. Both Figure 4 and Figure 5 suggest that a Pursuit-like model is better equipped than cross-situational models to capitalize on the rare but highly informative learning instances. Since the model can only select one hypothesis, the probability of selecting the target meaning, already higher in the informative instances, increases sharply. This can effectively build a decisive advantage over its competitors. By contrast, a cross-situational model, even one which
dynamically takes informativeness into account (Eq. 2), suffers from the problem of “dilution”: informative learning instances are diminished in the regression to the mean, which is dominated by the vast number of largely useless data. This, I believe, is the reason why the Pursuit model performs much better than cross-situational learning for the lower ambiguity words as shown in Figure 3: low-ambiguity words correspond to higher values of $B$ in Figure 5, where Pursuit holds a significant advantage.

4 Summary

This schematic paper seeks to identify word learning algorithms that can make the most out of very limited informative data in the environment, and to explain some puzzling results from the word learning literature. The Pursuit model, which only attends to a very limited subset of the learning data, may also have some interesting developmental implications. It has long been conjectured that children’s cognitive resource limitations may turn out to be a blessing in disguise, enabling them to focus on the critical aspects of the learning task at hand (Newport 1990, Elman 1993; see Yang 2016 for a learning-theoretic underpinning of this idea). Perhaps a young child — or even adults as in the many behavioral experiments that motivated the Pursuit model — do not have the cognitive capacity to entertain more than a couple of hypotheses for the meanings of words, and this turns out to just the right approach to Gleitman’s Problem
in the messy real world. The signal does exist but it is faint; the worst that can happen is for it to be drowned out by a “big data” model that tabulates and deliberates over everything. As Lila has taught us, word learning is hard; perhaps the best solution is to not try harder.

References


