The Power of Objects in Morphology Learning

Constantine Lignos, Jana Beck
University of Pennsylvania

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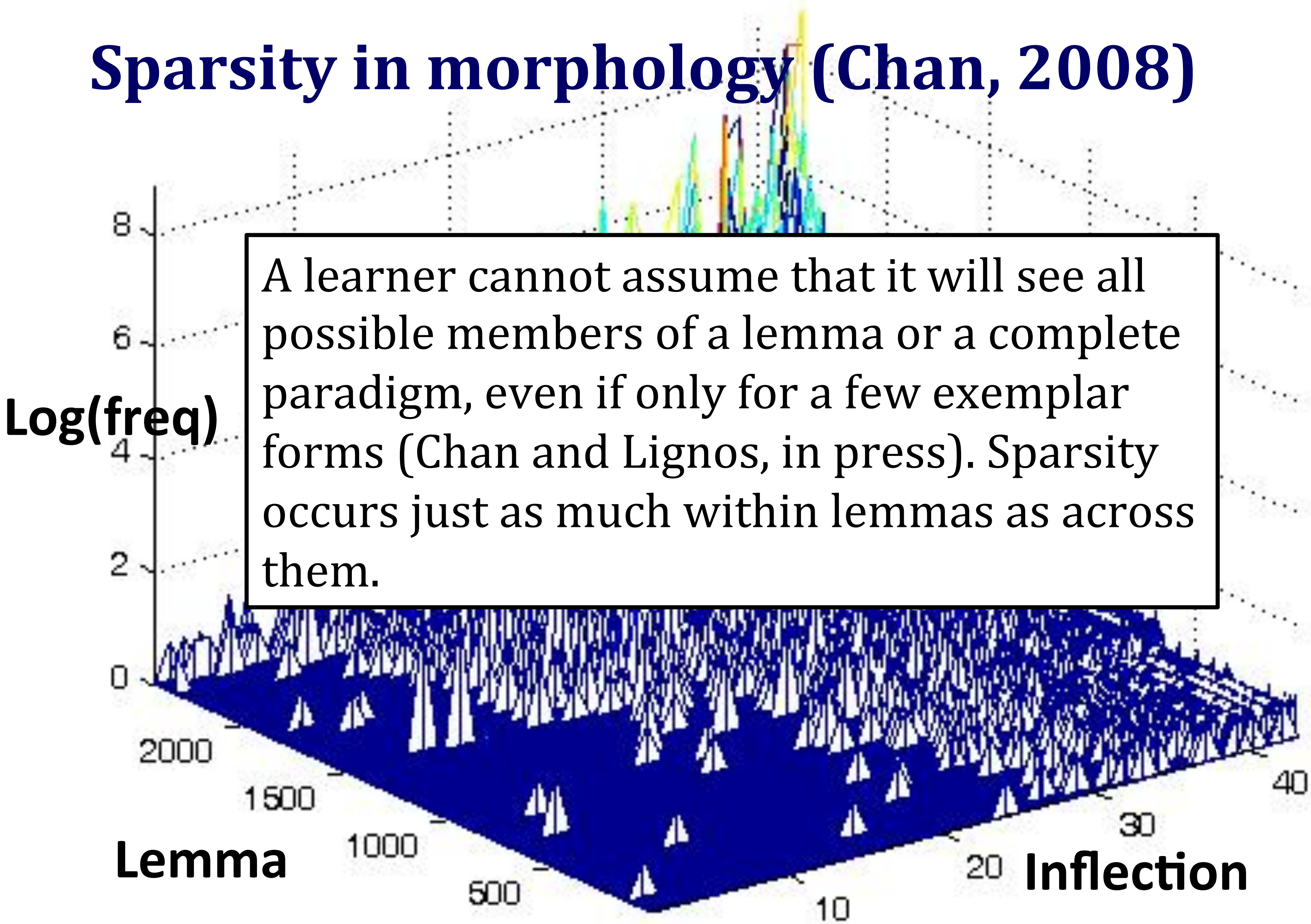
Overview

- **We'll talk about the intersection of three areas:**
  1. Sparsity within morphological forms
  2. Simulations of unsupervised morphology learning
  3. Representations of morphology
- **We'll discuss:**
  - How sparsity presents a problem for learning models
  - How selecting the right objects (representation) can help the learner tolerate sparsity better
- **We propose that continued research at this intersection can start to bring together work in learning models, morphological theory, and processing experiments**

Sparsity in morphology (Chan, 2008)



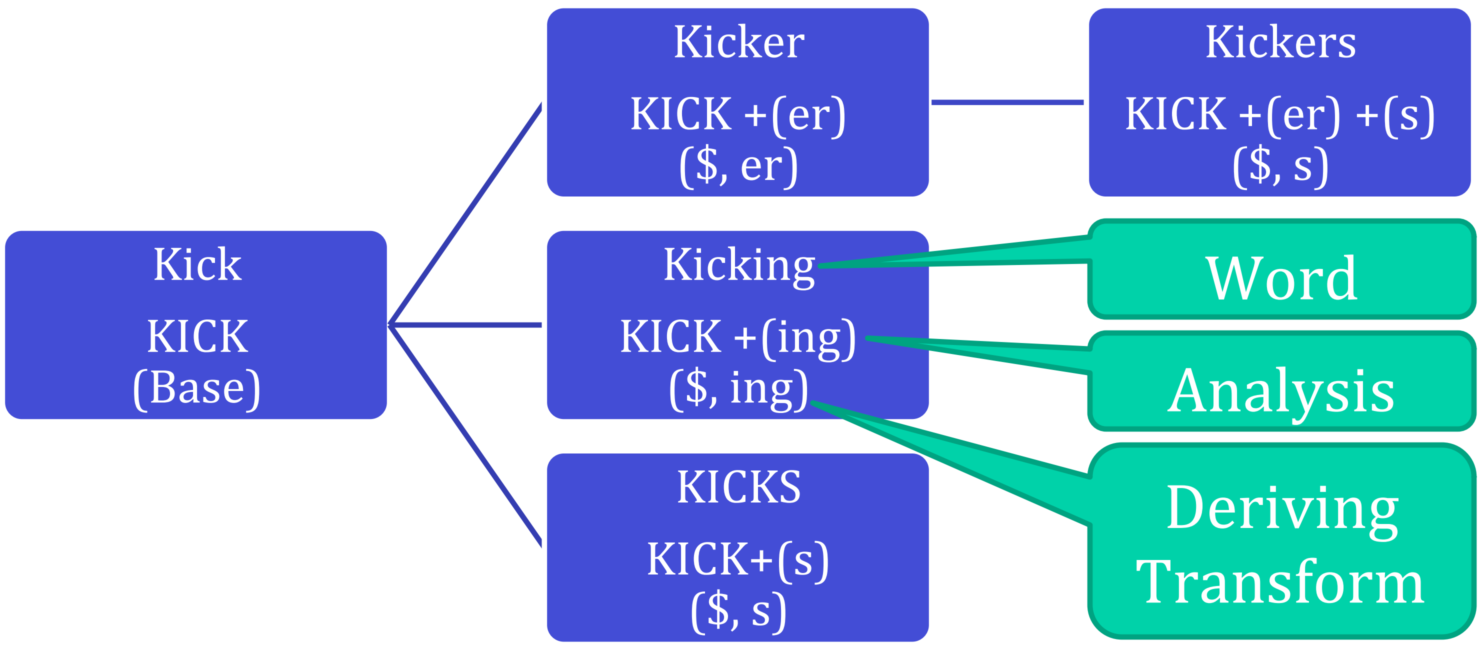
A learner cannot assume that it will see all possible members of a lemma or a complete paradigm, even if only for a few exemplar forms (Chan and Lignos, in press). Sparsity occurs just as much within lemmas as across them.

Spanish newswire verbs (2.5 M)

A simple, generative learning model

Base and Transforms Model (Chan, 2008)

- **The learner will learn a set of rules (transforms) and the word pairs they apply to (base-derived pairs)**



A rule learning algorithm (Chan, 2008)

- **Each iteration:**
  1. Count the most type-frequent final *n* characters in the existing bases and the unmodeled words
     - Ex: \$, -s, -d, -r, -er, -es, -g, -ng, -ing…
  2. Hypothesize transforms between the top affixes, and count how many word pairs each transform accounts for
     - Ex: (\$, s), (s, \$), (\$, ng), (ng, \$), (s, ng), (ng, s)…
  3. Choose the transform that accounts for the largest number of word pairs
     - Ex: (\$, s): dog/dogs, frog/frogs, run/runs…
  4. Mark the transform's base words as bases and the words it derives as modeled
     - Ex: dog + (\$, s) = dogs results in *dog* marked as a base, *dogs* marked as modeled

Structuring the lexicon

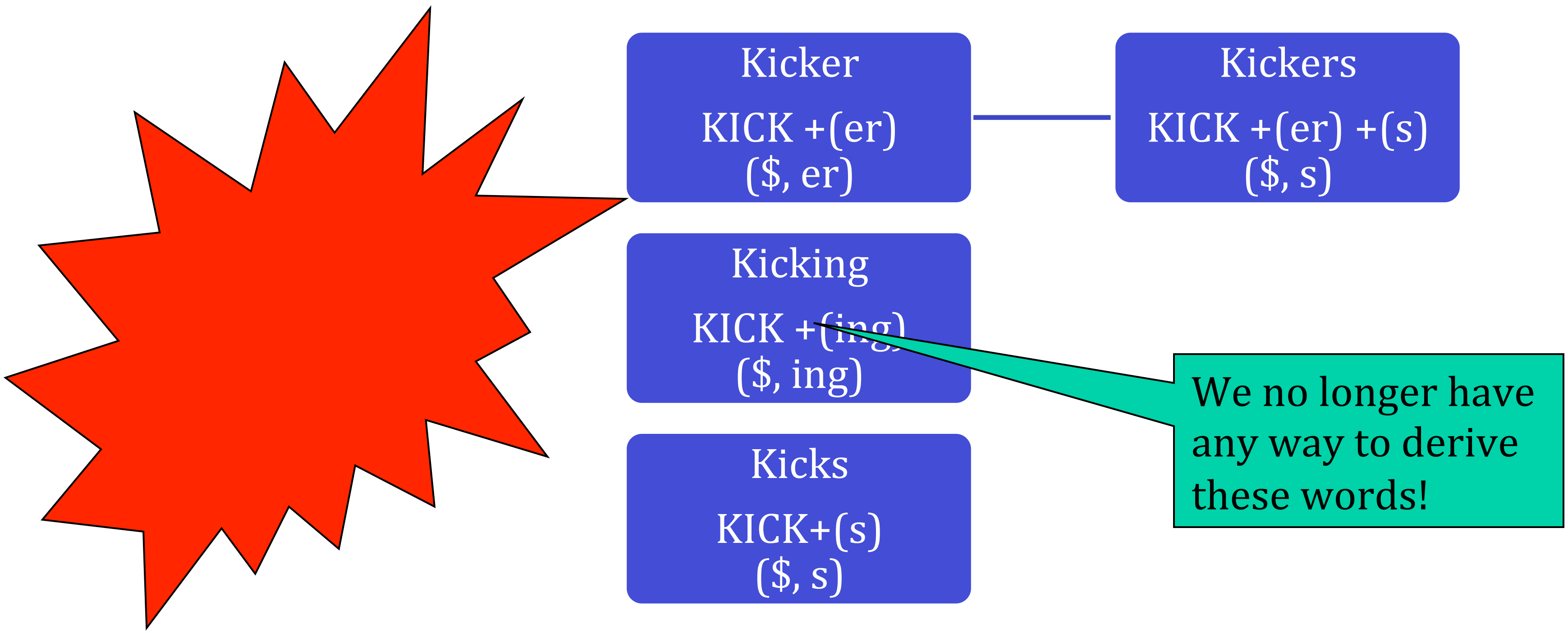
- **This model seeks structure in the lexicon through word relations similar to a number of approaches:**
  - Redundancy rules (Jackendoff, 1975)
  - Word Formation Rules (WFRs) (Aronoff, 1976, 1994; Anderson 1992)
- **Like most work concerned with morphological theory, those approaches did not develop an explicit learning model**
  - But did have a general goal of reducing the amount of information required in the lexicon

But where do bases come from? The answer isn't always trivial.

Let' s consider the case of an "accidental" (sparsity-induced) missing base.

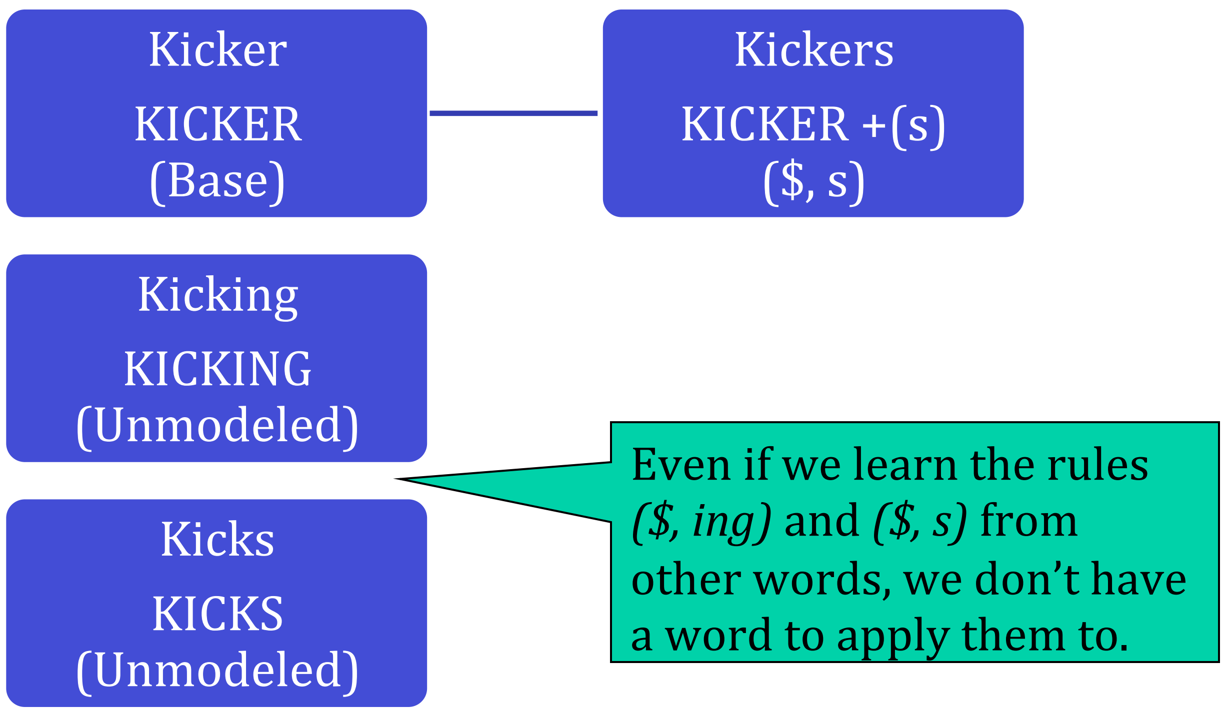
The perils of minimal pairs

- **What happens to the algorithm if *kick* isn't in the input?**



The new (uglier) picture

- **Without the right base for the derivation chain, even if the relevant rules are learned, the desired relationships are not**



It's not just a toy problem

- **While base forms are generally more frequent than forms derived from them (Wicentowski, 2002; Chan, 2008), they still are frequently unobserved**
  - Brown corpus: per CELEX analysis, 16.7% of derived words are missing their base
- **For rarer derivational forms, unobserved bases can prevent a rule from being learned at all**
- **The focus in the past has been on how to handle "intentional" gaps (**pot/potable*, **fiss/fission*) of this sort, but not accidental ones**

Working toward a solution

- **The answer in the generative tradition is to learn that words whose bases are missing still have the expected structure, but how do we reliably infer that structure?**
- **Naïve approach: if something could possibly be the result of applying a rule, just analyze it that way**
  - For example, we know the rule *($, ing)*, so just assume it applies to *kicking* because it ends in *–ing*
    - —For an algorithm applying this blindly is far from a good idea (*string, herring,* etc.*)*
- **Doing this analysis in a non-naïve way is the focus of most statistical morphology learning work, but that work provides little or no information about representation**

A modest solution: infer the bases you've never seen from a number of their likely derived forms.

Base Inference

- **To handle missing bases, infer them based on multiple words suggesting they should be there**
  - For example, in the Brown corpus *adjoins, adjoined,* and *adjoining* are in the corpus while *adjoin* is not
  - Allow these words to show us that *adjoin* should be in the lexicon, allowing us to *infer the missing base*
- **This inference happens as a part of the learning process, and not as a post-processing step, allowing it to feed later learning**
- **We leave aside the question of how the learner decides whether *adjoin* itself is an intentional or accidental gap**

—i.e., whether adjoin is [- Lexical Insertion] (Halle, 1973)

Base Inference

Base	Derived	Unmodeled	Transforms
		Plant Plants Planted Planting Adjoins Adjoined Adjoining	

Note *adjoin* is not in the corpus.

Base Inference

Base	Derived	Unmodeled	Transforms
Plant	Plants		($, s)
		Planted Planting Adjoins Adjoined Adjoining	

Now that we learned this rule, *adjoins* suggests that *adjoin* exists, but we don't take action yet.

Base Inference

Base	Derived	Unmodeled	Transforms
Plant	Plants Planted	Planting Adjoins Adjoined Adjoining	($, s) ($, ed)

Now both *adjoins* and *adjoined* suggest that *adjoin* exists. Let's pretend we saw *adjoin* and then reevaluate.

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Base Inference

Base	Derived	Unmodeled	Transforms
Plant	Plants Planted		($, s) ($, ed)
		Planting	
Adjoin	Adjoins Adjoined		
		Adjoining	

We infer the existence of *adjoin*, and treat it as if it was there all along.

Base Inference

Base	Derived	Unmodeled	Transforms
Plant	Plants Planted Planting		($, s) ($, ed) ($, ing)
Adjoin	Adjoins Adjoined Adjoining		

Now we can apply new rules to *adjoin* just like we can to *plant*, and *adjoin/adjoining* counts toward the score of *($, ing)*

Evaluating Base Inference

- **Does Base Inference infer the right forms?**
  - We evaluated the precision of relationships formed by Base Inference, such as *adjoins/adjoined*
  - As evaluated using CELEX on 1 million word corpora in each language, the relationships inferred are highly precise (English, 93.5%; German, 94.9%)

- **Some errors according to the gold standard:**

integration/integrity	unemployed/unemployment
unthinkable/unthinking	automatic/automation
tune/tunic	impassable/impasse
multiplication/multiplicity	unbelievable/unbelieving
complied/compliment	**rudder/ruddy**

What does this say about the objects in the system?

What does the learner's representation need to provide?

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Defining our objects

- **We can now consider the question of what we want to reify—what are the *objects* in the system and what can they do?**
- **We take an object to mean something the learner has an explicit representation of**
- **To perform Base Inference correctly, these objects need to support two operations:**
  - Identifying the presence of a morpheme in the output
    - —*-s, -ed, -ing,* etc. "trigger" the Base Inference mechanism
    - —In a more refined model this is more than a string match
  - Reversing/decomposing the process that generated that morpheme to create the missing base

Whither paradigms?

- **Note that while the learner benefited from having a set of rules, there are no paradigms in the representation**
  - A paradigm is not an *object* to the learner but rather an epiphenomenon of the learning *process*
- **A confluence of rules results in a viable alternative to the sparsity issues (Chan, 2008) encountered by paradigm learning approaches (Goldsmith, 2001, 2006; Monson 2008)**

Getting more from WFRs

- **Base Inference touches on a second role for WFRs, analysis for words that have no base such as *potable* (Jackendoff, 1975; Anderson, 1992)**
  - It is stated that WFRs/redundancy must have a parsing capability to cover intentional gaps (*potable)*
- **The prevalence of these missing forms suggests that this reversibility can play a crucial role to the learner outside of rarer intentional gaps—the more common case for this process is combating sparsity**
  - But we still need a more aggressive approach—only about 1 in 8 bases missing in the Brown corpus are recoverable by an ideal Base Inference process

Morphemes as objects

- **Piece-based approaches (Sciullo and Williams, 1987; Halle and Marantz, 1993) take the contrasting view that morphemes exist as more than rules that realize them**
- **The decompositional view taken by these approaches naturally integrates a process like Base Inference**
- **Building a new system from a piece-based approach we can explore the potential advantages of such a system**
  - And align with processing research on decomposition and recombination during processing (Caramazza et al., 1988; New et al., 2004; Taft, 2004; Lehtonen et al., 2006; Marslen-Wilson et al., 2008)

Closing thoughts

- **Sparsity within related forms is worse than you might think, even in English**
- **The best way to combat sparsity is to pick the right objects**
  - These objects need to be able to handle accidental gaps, which can be achieved by focusing on the reversal of rules or decomposition of morphemes
- **By building computational models that use these objects, we can compare the representations involved in morphological theories and address learning issues**

Thanks!

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