Sign constraints on feature weights improve a joint model of word segmentation and phonology

Mark Johnson
Macquarie University

Joint work with Joe Pater, Robert Staubs and Emmanuel Dupoux

Summary

- Background on word segmentation and phonology
  - Liang et al and Berg-Kirkpatrick et al MaxEnt word segmentation models
  - Smolenksy's Harmony theory and Optimality theory of phonology
  - Goldwater et al MaxEnt phonology models
- A joint MaxEnt model of word segmentation and phonology
  - because Berg-Kirkpatrick's and Goldwater's models are MaxEnt models, and MaxEnt models can have arbitrary features, it is easy to combine them
  - Harmony theory and sign constraints on MaxEnt feature weights
- Experimental evaluation on Buckeye corpus
  - better results than Börschinger et al 2014 on a harder task
  - Harmony theory feature weight constraints improve model performance

Outline

Background

A joint model of word segmentation and phonology

Computational details

Experimental results

Conclusion

Word segmentation and phonological alternation

- Overall goal: model children's acquisition of words
- Input: phoneme sequences with *sentence boundaries* (Brent)
- Task: identify *word boundaries* in the data,
  and hence *words* of the language

j △ u ▲ w △ ɑ △ n △ t ▲ t △ u ▲ s △ i ▲ ð △ ə ▲ b △ ʊ △ k

ju wɑnt tu si ðə bʊk

"you want to see the book"

- But a word's pronunciation can vary, e.g, final /t/ in /wɑnt/ can delete
  - can we identify the *underlying forms* of words
  - can we learn how pronunciations alternate?

Prior work in word segmentation

- Brent et al 1996 proposed a Bayesian *unigram* segmentation model
- Goldwater et al 2006 proposed a Bayesian non-parametric *bigram* segmentation model that captures word-to-word dependencies
- Johnson et al 2008 proposed a hierarchical Bayesian non-parametric model that could learn and exploit phonotactic regularities (e.g., syllable structure constraints)
- Liang et al 2009 proposed a maximum likelihood unigram model with a *word-length penalty term*
- Berg-Kirkpatrick et al 2010 reformulated the Liang model as a MaxEnt model

The Berg-Kirkpatrick word segmentation model

- Input: sequence of utterances $D = (w_1, \ldots, w_n)$
  - each utterance $w_i = (s_{i,1}, \ldots, s_{i,m_i})$ is a sequence of (surface) phones
- The model is a *unigram model*, so probability of word sequence w is:

$$\mathrm{P}(w \mid \theta) = \sum_{\substack{s_1 \ldots s_\ell \\ \mathrm{s.t.} s_1 \ldots s_\ell = w}} \prod_{j=1}^{\ell} \mathrm{P}(s_j \mid \theta)$$

- The probability of a word $\mathrm{P}(s \mid \theta)$ is a MaxEnt model:

$$\begin{aligned} \mathrm{P}(s \mid \theta) &= \frac{1}{Z} \exp(\theta \cdot f(s)), \text{ where:} \\ Z &= \sum_{s' \in \mathcal{S}} \exp(\theta \cdot f(s')) \end{aligned}$$

- The set $\mathcal{S}$ of *possible surface forms* is the set of all substrings in D shorter than a length bound

Aside: the set $\mathcal{S}$ of possible word forms

$$\begin{aligned} \mathrm{P}(s \mid \theta) &= \frac{1}{Z} \exp(\theta \cdot f(s)), \text{ where:} \\ Z &= \sum_{s' \in \mathcal{S}} \exp(\theta \cdot f(s')) \end{aligned}$$

- Our estimators can be understood as adjusting the feature weights θ so the model doesn't "waste" probability on forms s that aren't useful for analysing the data
- In the generative non-parametric Bayesian models, $\mathcal{S}$ is the set of all possible strings
- In these MaxEnt models, $\mathcal{S}$ is the set of substrings that actually occur in the data
- How does the difference in $\mathcal{S}$ affect the estimate of θ?
- Could we use the *negative sampling* techniques of Mnih et al 2012 to estimate MaxEnt models with infinite $\mathcal{S}$?

The word length penalty term

- Easy to show that the MLE segmentation analyses each sentence as a single word
  - the MLE minimises the KL-divergence between the data distribution and the model's distribution

$\Rightarrow$ Liang and Berg-Kirkpatrick add a double-exponential *word length penalty*

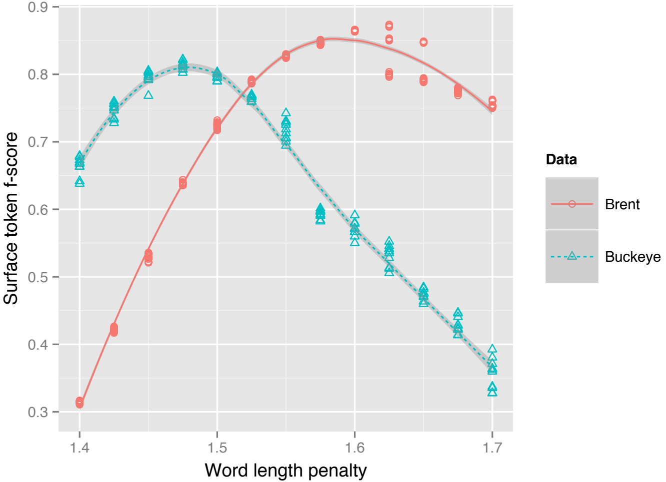
$$\mathrm{P}(w \mid \theta) \;=\; \sum_{\substack{s_1 \ldots s_\ell \\ \text{s.t.}\, s_1 \ldots s_\ell = w}} \prod_{j=1}^{\ell} \mathrm{P}(s_j \mid \theta) \exp(-|s_i|^d)$$

$\Rightarrow$ $\mathrm{P}(w \mid \theta)$ is *deficient* (i.e., $\sum_w \mathrm{P}(w \mid \theta) < 1$)
  - because we use a word length penalty in the same way, our models are deficient also

- The loss function they optimise is an L_2 regularised version of:

$$L_D(\theta) \;=\; \prod_{i=1}^{n} \mathrm{P}(w_i \mid \theta)$$

Sensitivity to word length penalty factor d



Phonological alternation

- Words are often pronounced in different ways depending on the context
- Segments may *change* or *delete*
  - here we model *word-final /d/ and /t/ deletion*
  - e.g., /w ɑ n t t u/ ⇒ [w ɑ n t u]
- These alternations can be modelled by:
  - assuming that each word has an *underlying form* which may differ from the observed *surface form*
  - there is a set of *phonological processes* mapping underlying forms into surface forms
  - these phonological processes can be *conditioned* on the context
    - e.g., /t/ and /d/ deletion is more common when the following segment is a consonant
  - these processes can also be *nondeterministic*
    - e.g., /t/ and /d/ deletion doesn't always occur even when the following segment is a consonant

Harmony theory and Optimality theory

- Harmony theory and Optimality theory are two models of linguistic phenomena (Smolensky 2005)
- There are two kinds of constraints:
  - *faithfulness constraints*, e.g., underlying /t/ should appear on surface
  - universal *markedness constraints*, e.g., $^{\star}tC$
- Languages differ in the importance they assign to these constraints:
  - in Harmony theory, violated constraints incur *real-valued costs*
  - in Optimality theory, constraints are *ranked*
- The grammatical analyses are those which are *optimal*
  - often not possible to simultaneously satisfy all constraints
  - in Harmony theory, the optimal analysis minimises the sum of the costs of the violated constraints
  - in Optimality theory, the optimal analysis violates the lowest-ranked constraint
    - Optimality theory can be viewed as a discrete approximation to Harmony theory

Harmony theory as Maximum Entropy models

- Harmony theory models can be viewed as Maximum Entropy a.k.a. log-linear a.k.a. exponential models

Harmony theory	**MaxEnt models**
underlying form u and surface form s	event $x = (s, u)$
Harmony constraints	MaxEnt features $\boldsymbol{f}(s, u)$
constraint costs	MaxEnt feature weights $\boldsymbol{\theta}$
Harmony	$-\boldsymbol{\theta} \cdot \boldsymbol{f}(s, u)$

$$\mathrm{P}(u, s) \quad = \quad \frac{1}{Z} \exp -\boldsymbol{\theta} \cdot \boldsymbol{f}(s, u)$$

Learning Harmonic grammar weights

- Goldwater et al 2003 learnt Harmonic grammar weights from (underlying,surface) word form pairs (i.e., supervised learning)
  - now widely used in phonology, e.g., Hayes and Wilson 2008
- Eisenstadt 2009 and Pater et al 2012 infer the underlying forms and learn Harmonic grammar weights from *surface paradigms* alone
- Linguistically, it makes sense to require the weights $-\theta$ to be negative since Harmony violations can only make a (s, u) pair less likely (Pater et al 2009)

Integrating word segmentation and phonology

- Prior work has used *generative models*
  - generate a sequence of underlying words from Goldwater's bigram model
  - map the underlying phoneme sequence into a sequence of surface phones
- Elsner et al 2012 learn a finite state transducer mapping underlying phonemes to surface phones
  - for computational reasons they only consider simple substitutions
- Börschinger et al 2013 only allows word-final /t/ to be deleted
- Because these are all generative models, they can't handle arbitrary feature dependencies (which a MaxEnt model can, and which are needed for Harmonic grammar)

Outline

Possible (underlying,surface) pairs

- Because Berg-Kirkpatrick's word segmentation model is a MaxEnt model, it is easier to integrate it with Harmonic Grammar/MaxEnt models of phonology
- $\mathrm{P}(x)$ is a distribution over surface form/underlying form pairs $x = (s, u)$ where:
  - $s \in \mathcal{S}$, where $\mathcal{S}$ is the set of length-bounded substrings of D, and
  - $s = u$ or $s \in p(u)$, where $p \in \mathcal{P}$ is a phonological alternation
    - our model has two alternations, word-final /t/ deletion and word-final /d/ deletion
  - we also require that $u \in \mathcal{S}$ (i.e., every underlying form must appear somewhere in D)
- Example: In Buckeye data, the candidate (s, u) pairs include ([l.ih.v], /l.ih.v/), ([l.ih.v], /l.ih.v.d/) and ([l.ih.v], /l.ih.v.t/)
  - these correspond to "live", "lived" and the non-word "livet"

Probabilistic model and optimisation objective

- The probability of word-final /t/ and /d/ deletion depends on the following word ⇒ distinguish the *contexts* $\mathcal{C} = \{\mathrm{C}, \mathrm{V}, \#\}$

$$\begin{aligned} \mathrm{P}(s, u \mid c, \theta) &= \frac{1}{Z_c} \exp(\theta \cdot f(s, u, c)), \text{ where:} \\ Z_c &= \sum_{(s,u) \in \mathcal{X}} \exp(\theta \cdot f(s, u, c)) \text{ for } c \in \mathcal{C} \end{aligned}$$

- We optimise an L_1 regularised log likelihood $Q_D(\theta)$, with the word length penalty applied to the underlying form u

$$\begin{aligned} Q(s \mid c, \theta) &= \sum_{u:(s,u) \in \mathcal{X}} \mathrm{P}(s, u \mid c, \theta) \exp(-|u|^d) \\ Q(w \mid \theta) &= \sum_{\substack{s_1 \ldots s_\ell \\ \text{s.t.} s_1 \ldots s_\ell = w}} \prod_{j=1}^{\ell} Q(s_j \mid c, \theta) \\ Q_D(\theta) &= \sum_{i=1}^{n} \log Q(w_i \mid \theta) - \lambda \, \|\theta\|_1 \end{aligned}$$

MaxEnt features

- Here are the features $f(s, u, c)$ where $s = [\text{l.ih.v}]$, $u = /\text{l.ih.v.t}/$ and $c = \text{C}$
  - *Underlying form lexical features:* A feature for each underlying form u. In our example, the feature is <U l ih v t>. These features enable the model to learn language-specific lexical entries.
    There are 4,803,734 underlying form lexical features (one for each possible substring in the training data).
  - *Surface markedness features:* The length of the surface string (<#L 3>), the number of vowels (<#V 1>), the surface prefix and suffix CV shape (<CVPrefix CV> and <CVSuffix VC>), and suffix+context CV shape (<CVContext _C> and <CVContext C _C>).
    There are 108 surface markedness features.
  - *Faithfulness features:* A feature for each divergence between underlying and surface forms (in this case, <*F t>).
    There are two faithfulness features.

L_1 regularisation and sign constraints

- We chose to use L_1 regularisation because it promotes *weight sparsity* (i.e., solutions where most weights are zero)
  - rather than assigning every possible lexical entry and constraint a non-zero weight (as L_2 would), we may identify the subset of lexical entries and constraints relevant to the language
  - in turns out that L_1 and L_2 regularisation produce similiar results
- The L_1 regularised log-likelihood is discontinuous at zero
  - gradient-based methods like LBFGS can't handle this discontinuity
  - $\Rightarrow$ the OWLQN extension of LBFGS stops the line minimisation whenever it crosses an *orthant boundary* (Andrew et al 2007)
  - easy to extend this to impose sign constraints on weights
- Sign constraints we explored:
  - Lexical entry weights must be positive (i.e., you learn what words are in the language)
  - Harmony faithfulness and markedness constraint weights must be negative

Outline

Determining the possible surface and underlying forms

- The set of possible surface forms $\mathcal{S}$ is the set of all substrings in the training data of length ≤ 15
- $\mathcal{X}$ contains *possible (surface,underlying) word pairs*. For each $s \in \mathcal{S}$, $(s, s) \in \mathcal{X}$, and $(s, s + /\mathrm{d}/) \in \mathcal{X}$ if $s + /\mathrm{d}/ \in \mathcal{S}$ (same for /t/)

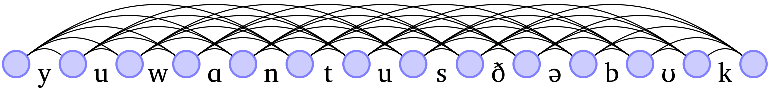
$$
\begin{aligned}
\mathrm{P}(s, u \mid c, \theta) &= \frac{1}{Z_c} \exp(\theta \cdot f(s, u, c)), \text{ where:} \\
Z_c &= \sum_{(s,u) \in \mathcal{X}} \exp(\theta \cdot f(s, u, c)) \text{ for } c \in \mathcal{C} \\
Q(s \mid c, \theta) &= \sum_{u:(s,u) \in \mathcal{X}} \mathrm{P}(s, u \mid c, \theta) \exp(-|u|^d) \\
\frac{\partial \log Q(s \mid c, \theta)}{\partial \theta} &= \mathrm{E}\left[f(s, u, c) \exp(-|u|^d) \mid s, c, \theta \right] - \mathrm{E}\left[f(s, u, c) \mid c, \theta \right]
\end{aligned}
$$

- The first expectation sums over underlying forms $u : (s, u) \in \mathcal{X}$, while the second expectation sums over all $(s, u) \in \mathcal{X}$

Dynamic programming for $\log Q(w \mid \theta)$

$$\begin{aligned} Q(w \mid \theta) &= \sum_{\substack{s_1 \ldots s_\ell \\ \text{s.t.} s_1 \ldots s_\ell = w}} \prod_{j=1}^{\ell} Q(s_j \mid c, \theta) \\ Q_D(\theta) &= \sum_{i=1}^{n} \log Q(w_i \mid \theta) - \lambda \|\theta\|_1 \end{aligned}$$

- We can sum/maximise over all $s_1 \ldots s_\ell$ such that $s_1 \ldots s_\ell = w$ by using *dynamic programming*



- A *forward-backward type calculation* calculates the expectations required to compute $\partial \log Q(w)/\partial\theta$

Outline

Data preparation procedure

- Data from *Buckeye corpus* of conversational speech (Pitt et al 2007)
  - provides an underlying and surface form for each word
- Data preparation as in Börschinger et al 2013
  - we use the Buckeye underlying form as our underlying form
  - we use the Buckeye underlying form as our surface form as well ...
  - except that if the Buckeye underlying form ends in a /d/ or /t/ and the surface form does not end in that segment our surface form is the Buckeye underlying form with that segment deleted
- Example: if Buckeye $u =$ /l.ih.v.d/ “lived”, $s =$ [l.ah.v]
  then our $u =$ /l.ih.v.d/, $s =$ [l.ih.v]
- Example: if Buckeye $u =$ /l.ih.v.d/ “lived”, $s =$ [l.ah.v.d]
  then our $u =$ /l.ih.v.d/, $s =$ [l.ih.v.d]

Data statistics

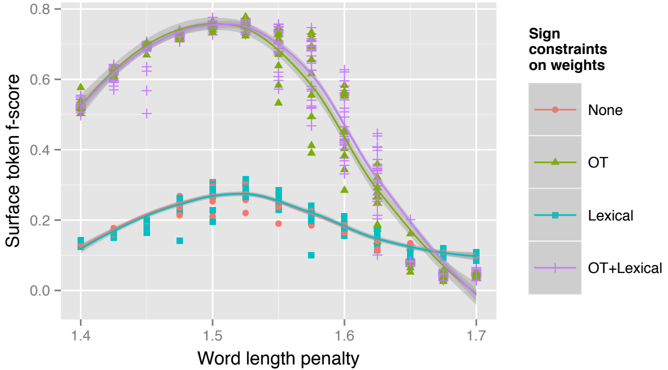
- The data contains 48,796 sentences and 890,597 segments.
- The longest sentence has 187 segments.
- The "gold" segmentation has 236,996 word boundaries, 285,792 word tokens, and 9,353 underlying word types.
- The longest word has 17 segments.
- Of the 41,186 /d/s and 73,392 /t/s in the underlying forms, 24,524 /d/s and 40,720 /t/s are word final, and of these 13,457 /d/s and 11,727 /t/s are deleted.
- All possible substrings of length 15 or less are possible surface forms $\mathcal{S}$
- There are 4,803,734 possible word types and 5,292,040 possible surface/underlying word type pairs.
- Taking the 3 contexts derived from the following word into account, there are 4,969,718 possible word+context types.
- When all possible surface/underlying pairs are considered in all possible contexts there are 15,876,120 possible surface/underlying/context triples.

Overall segmentation scores

	Börschinger et al. 2013	Our model
Surface token f-score	0.72	**0.76** (0.01)
Underlying type f-score	—	0.37 (0.02)
Deleted /t/ f-score	0.56	**0.58** (0.03)
Deleted /d/ f-score	—	0.62 (0.19)

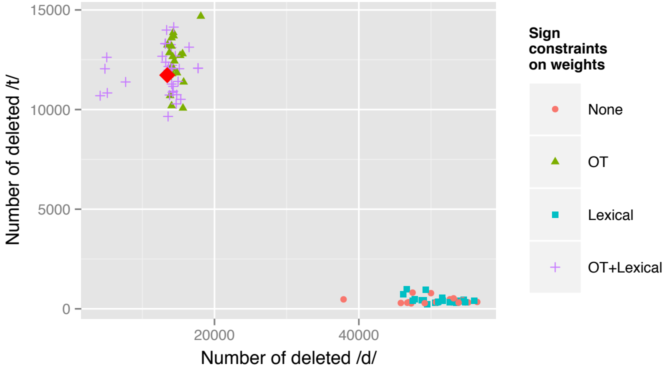
- Results summary for our model compared to Börschinger et al (2013)
  - their model only recovers word-final /t/ deletions and was run on data without word-final /d/ deletions, so it is solving a simpler problem
- Surface token f-score is the standard token f-score
- Underlying type or "lexicon" f-score measures the accuracy with which the underlying word types are recovered.
- Deleted /t/ and /d/ f-scores measure the accuracy with which the model recovers segments that don't appear in the surface.
- These results are averaged over 40 runs (standard deviations in parentheses) with the word length penalty $d = 1.525$ applied to underlying forms

The effect of feature weight constraints



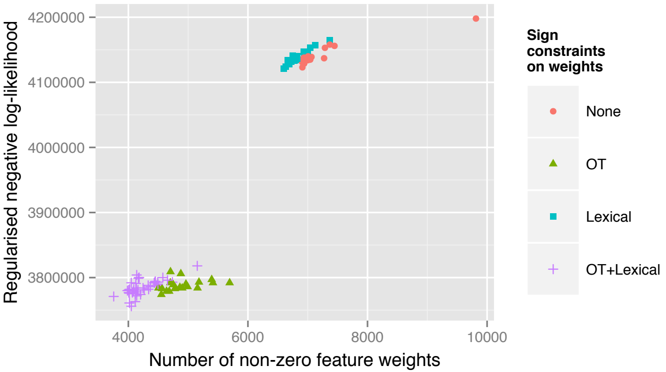
- The effect of constraints on feature weights on surface token f-score.
- "OT" indicates that the markedness and faithfulness features are required to be non-positive
- "Lexical" indicates that the underlying lexical features are required to be non-negative.

Number of underlying /d/ and /t/ posited



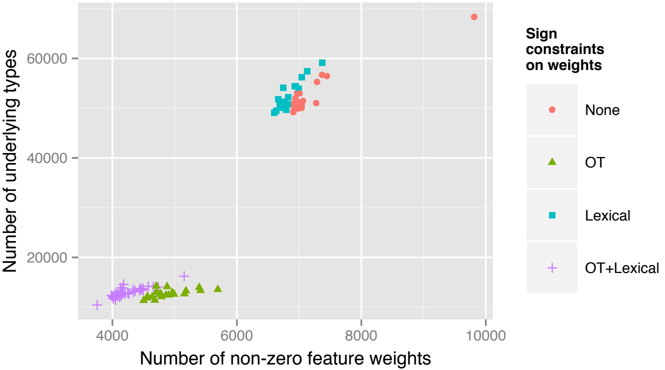
- The effect of feature weight constraints on the number of deleted underlying /d/ and /t/ segments posited by the model (d = 1.525).
- The red diamond indicates the 13,457 deleted underlying /d/ and 11,727 deleted underlying /t/ in the "gold" data.

Regularised log-likelihood



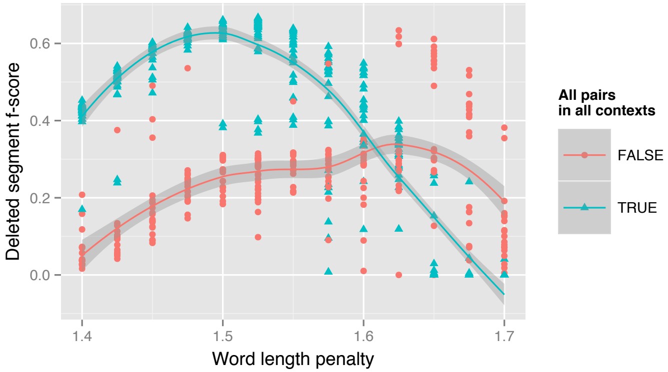
- The regularised log-likelihood as a function of the number of non-zero weights for different constraints on feature weights ($d = 1.525$).

The number of words posited by the model



- The number of underlying types proposed by the model as a function of the number of non-zero weights, for different constraints on feature weights ($d = 1.525$).
- There are 9,353 underlying types in the “gold” data.

Deleted segment f-score



- F-score for deleted /d/ and /t/ recovery as a function of word length penalty d and whether all surface/underlying pairs $\mathcal{X}$ are included in all contexts $\mathcal{C}$
- OT + Lexical weight constraints

Outline

Conclusion and future work

- Word segmentation and phonology can be integrated in a MaxEnt framework to produce state-of-the-art results
  - sensitivity to the *word length penalty* is a major drawback
  - can this be set in a principled way?
- Constraining the feature weights associated with Markedness and Faithfulness constraints improves the procedure's performance considerably
- Can we generalise the approach to cover a wider range of phonological processes?
- Can we generalise the approach to cover morpho-phonological processes, where a single form has several hierarchical structures?