Computational Models of Hidden Structure Learning and Language Acquisition

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SCiL workshop
January 2019

September 19, 2020

Computational linguistics and natural language processing

- A brief history of natural language processing:
  - – 1985: symbolic parsing algorithms without explicit grammars
  - 1985 – 2000: symbolic parsing and generation algorithms with explicit grammar fragments
  - 2000 – 2015: broad-coverage statistical parsing models trained from large corpora
  - 2015 – : deep learning neural networks
- Most NLP and ML focuses on *supervised learning*, but language acquisition is an *unsupervised learning* problem
  - Unsupervised deep learning generally uses *supervised learning on proxy tasks*
- Unsupervised deep learning produces *distributed representations* that are *difficult to interpret*

How can computational models help us understand language acquistion?

- Unsupervised models of language acquisition generally don't have direct applications
  - Small amount of *labelled "seed" data* is extremely useful
- Demonstrate that learning is possible given specific inputs and assumptions
  - Which algorithms can learn which linguistic information from which inputs?
  - Identify the *crucial components* ⇒ ablation studies
- Identify surprising phenomena for experimentalists to study and predictions that experimentalists can test
  - E.g., the order in which words, morphemes, etc., are acquired
  - Reliable predictions are those from *multiple different models*

Things I think NLP does wrong

- "King of the Hill" focus on maximising evaluation score
  - No reason why highest-scoring model is most informative
  - Linguistics doesn't claim to explain language comprehension ("world knowledge")
  - Sample complexity ("learning trajectories") is perhaps more important
- Insisting on "realistic" data
  - Well-chosen "toy" examples should be informative (e.g. ideal gas laws)
  - No such thing as "the" distribution of English sentences
  - BUT: models often don't scale up (so what?)
- Separating training and test data for unsupervised learning
  - Formally, can always add training data to each test example
  - Humans are (probably) life-long learners
- Tuning language or corpus-specific parameters on development data when studying language acquisition
  - Children don't have development data

What I used to think matters ...

- Separating Marr's levels: Separate theory (model) and algorithm
- Ensuring that algorithm actually implements the theory
  - E.g., Metropolis-Hastings accept-reject correction steps
- Estimating the full Bayesian posterior
  - Important when solutions are sparse (?)
  - Point estimate (argmax) of Bayesian posterior now standard
- Summing over all possibilities to compute partition function
- Taking many samples to estimate a distribution
  - Poor samples are just ignored (perhaps?)

Outline

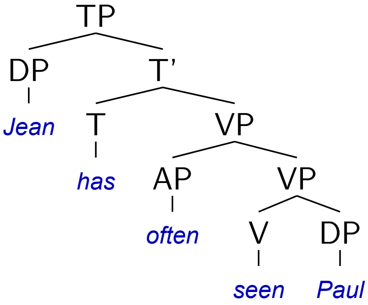
Learning Minimalist Grammar parameters

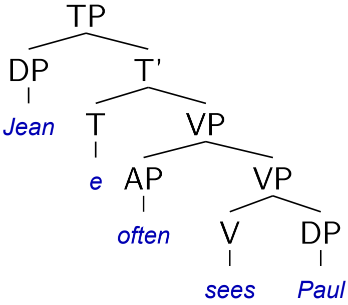
- Demonstrates that a toy Minimalist Grammar can be learnt from positive input (and a strong universal grammar)
- Input data: sentences (sequences of words)
- Universal grammar:
  - Formalisation of Minimalist Grammar (inspired by Stabler 2012)
  - Possible categories (e.g., V, N, D, C, etc.)
  - Possible parameters/empty categories (e.g., V>T, T>C, etc.)
- Output:
  - *Lexical entries* associating words with categories
  - Set of *parameter values*/empty categories for input data

A "toy" MG example

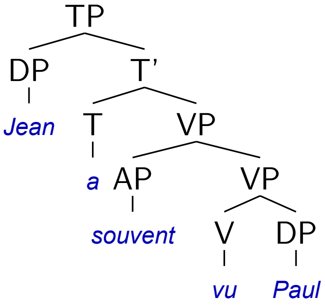
- 3 different sets of 25–40 input sentences involving XP movement, verb movement and inversion (Pollock 1989)
  - ("English") *Sam often sees Sasha, Q will Sam see Sasha, …*
  - ("French") *Sam sees often Sasha, Sam will often see Sasha, …*
  - ("German") *Sees Sam often Sasha, Often will Sam Sasha see, …*
- *Syntactic parameters*: V>T, T>C, T>Q, XP>SpecCP, V_{init}, V_{fin}
- *Lexical parameters* associating all words with all categories (e.g., *will*:I, *will*:Vi, *will*:Vt, *will*:D)
- Minimalist Grammar approximated by a *globally-normalised* (MaxEnt) *Context-Free Grammar with Features* (CFGF) in which *features are local* (Chiang 2004)
- Features correspond Minimalist Grammar parameters and possible lexical entries
- Recursive grammar ⇒ infinitely many derivations
- Sparse Gaussian prior prefers all features to have negative weight
- Optimisation using L-BFGS or SGD

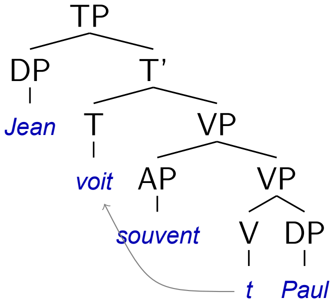
“English”: no V-to-T movement



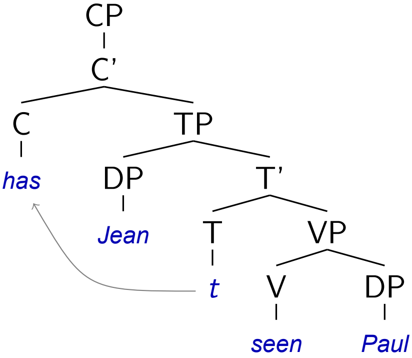


“French”: V-to-T movement

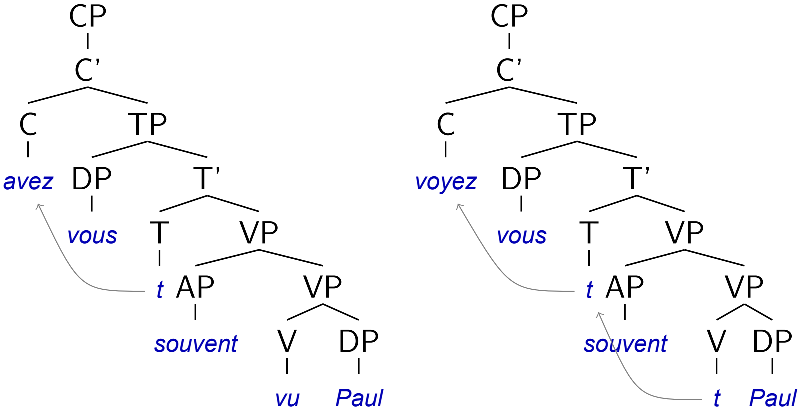




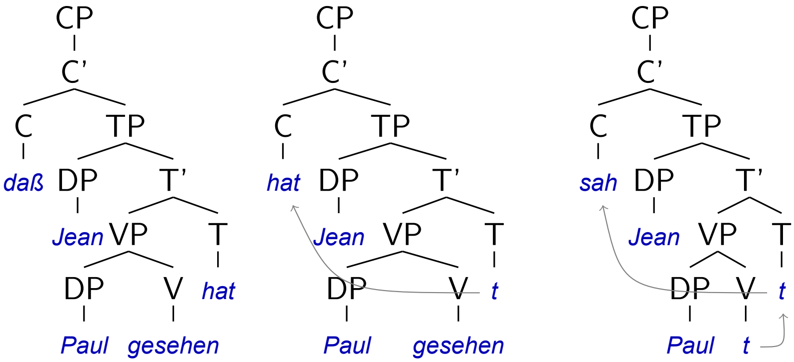
"English": T-to-C movement in questions



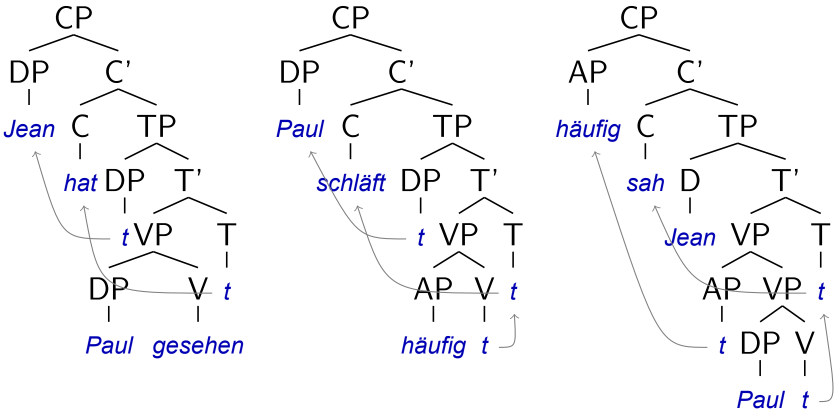
“French”: T-to-C movement in questions



“German”: V-to-T and T-to-C movement



“German”: V-to-T, T-to-C and XP-to-SpecCP movement



Context-free grammars with Features

- A *Context-Free Grammar with Features* (CFGF) is a globally-normalised "MaxEnt CFG" in which *features are local* (Chiang 2004), i.e.:
  - each rule r is assigned *feature values* $\boldsymbol{f}(r) = (f_1(r), \ldots, f_m(r))$
    - $f_i(r)$ is count of ith feature on r (normally 0 or 1)
  - features are associated with weights $\boldsymbol{w} = (w_1, \ldots, w_m)$
- The feature values of a tree t are the sum of the feature values of the rules $R(t) = (r_1, \ldots, r_\ell)$ that generate it:

$$\boldsymbol{f}(t) = \sum_{r \in R(t)} \boldsymbol{f}(r)$$

- A CFGF assigns probability $\mathrm{P}(t)$ to a tree t:

$$\mathrm{P}(t) \;=\; \frac{1}{Z} \exp(\boldsymbol{w} \cdot \boldsymbol{f}(t)), \text{ where: } Z \;=\; \sum_{t' \in \mathcal{T}} \exp(\boldsymbol{w} \cdot \boldsymbol{f}(t'))$$

  and $\mathcal{T}$ is the set of *all parses for all strings* generated by grammar

Log likelihood and its derivatives

- Minimise *negative log likelihood* plus a Gaussian regulariser
  - Gaussian mean $\mu = -1$, variance $\sigma^2 = 10$
- Derivative of log likelihood requires *derivative of log partition function* $\log Z$

$$\frac{\partial \log Z}{\partial w_j} = \mathrm{E}[f_j]$$

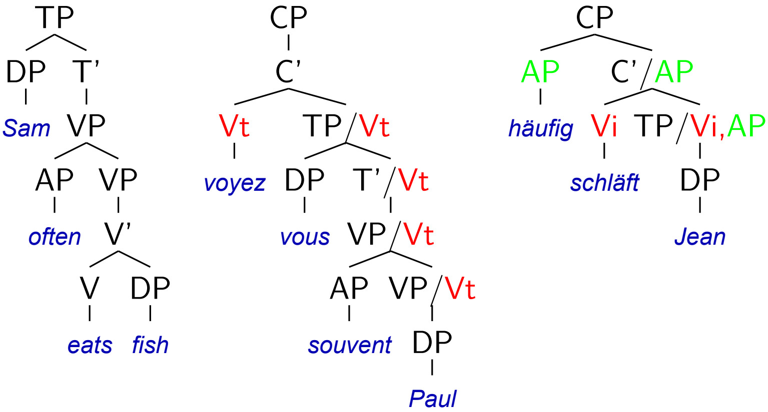
  where expectation is calculated over $\mathcal{T}$ (set of *all parses for all strings* generated by grammar)
- Novel (?) algorithm for calculating $\mathrm{E}[f_j]$ combining Inside-Outside algorithm (Lari and Young 1990) with a Nederhof and Satta (2009) algorithm for calculating Z (Chi 1999)

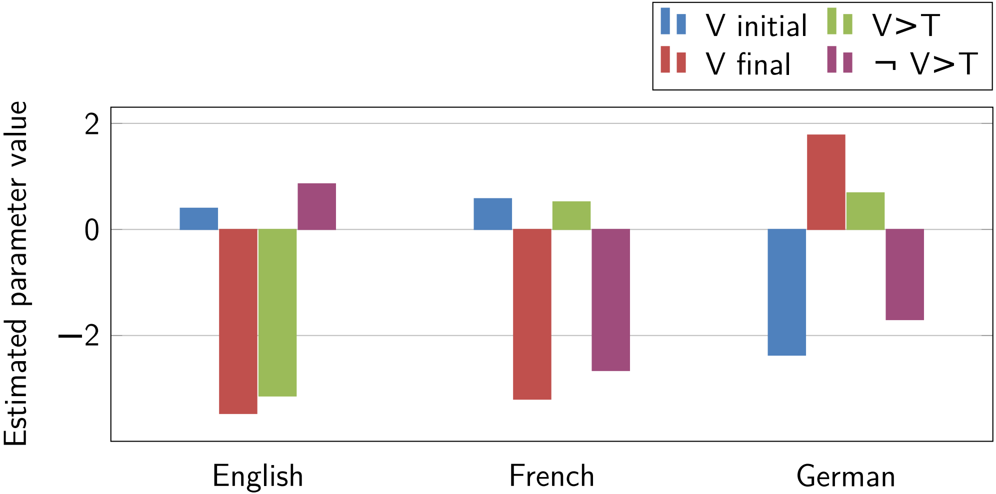
CFGF used here

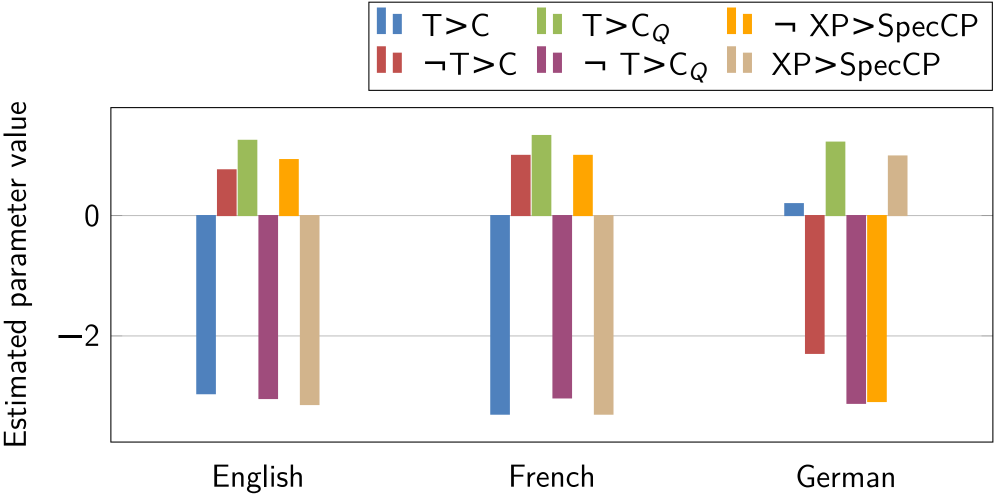
```
CP --> C'; ~Q ~XP>SpecCP
CP --> DP C'/DP; ~Q XP>SpecCP
C' --> TP; ~T>C
C'/DP --> TP/DP; ~T>C
C' --> T TP/T; T>C
C'/DP --> T TP/T,DP; T>C
C' --> Vi TP/Vi; V>T T>C
...
```

- Parser does not handle epsilon rules ⇒ manually "compiled out"
- 24-40 sentences, *44 features, 116 rules,* 40 nonterminals, 12 terminals
  - while every CFGF distribution can be generated by a PCFG with the same rules (Chi 1999), it is *differently parameterised* (Hunter and Dyer 2013)

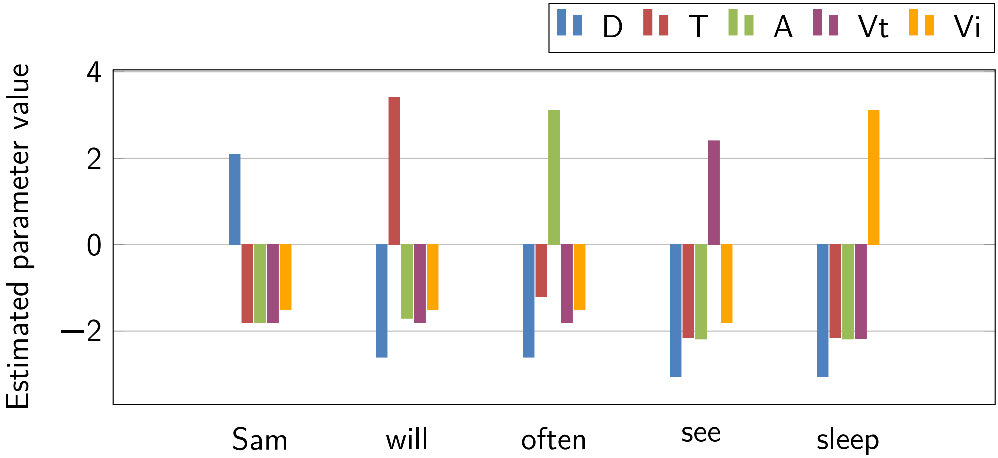
Sample trees generated by CFGF




V initial
V final
V>T
¬ V>T
Estimated parameter value
2
0
−2
English
French
German


T>C
¬T>C
$T>C_Q$
$\neg\ T>C_Q$
¬ XP>SpecCP
XP>SpecCP
Estimated parameter value
0
−2
English
French
German

Lexical parameters for English



Relation to other work

- Hunter and Dyer (2013) observe that the partition function Z for MGs can be *efficiently calculated* generalising the techniques of Nederhof and Satta (2008) if:
  - the parameters π are *functions of local subtrees of the derivation tree* τ, and
  - the possible MG derivations have a *context-free structure* (Stabler 2012)
- Inspired by Harmonic Grammar and Optimality Theory (Smolensky et al 1993)
- "Soft" version of Fodor et al (2000)'s super-parser
- Many other "toy" parameter-learning systems:
  - E.g., Yang (2002) describes an error-driven learner with templates triggering parameter value updates
  - we *jointly learn lexical categories and syntactic parameters*
- Error-driven learners like Yang's can be viewed as an approximation to the algorithm proposed here:
  - on-line error-driven parameter updates are a stochastic approximation to gradient-based hill-climbing
  - MG parsing is approximated with template matching

Conclusions

- Positive input strings alone are sufficient to learn both lexical entries and syntactic parameters
  - At least in a constrained "toy" setting
  - Statistical inference makes use of implicit negative evidence
- Computational models can make a point without realistic data or a competitive task

Outline

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Parameter setting for Minimalist Grammars

Segmentation models

- Stem-suffix morphology
- Word segmentation with Adaptor Grammars
- Synergies in language acquisition

Joint models of word segmentation and phonology

Neural networks and deep learning

Conclusions and future work

Segmenting verbs into stems and suffixes

- Data: orthographic forms of all verbs in the Penn Treebank
- Task: split verbs into stems and suffixes:
  - Example: *walk+ing*, *sleep+*
- Excellent toy problem for learning models!
- *Locally-normalised* Dirichlet-multinomial models
  - ⇒ Purely concatenative model that can't capture phonological context
  - ⇒ Gets irregular forms and phonological changes wrong
- Maximum likelihood solution analyses each word as stem+∅ suffix
  - ⇒ *sparse prior* that prefers fewer stems and fewer suffixes
- *Can we do this with a deep learning model?*
- Joint work with Sharon Goldwater and Tom Griffiths

Posterior samples from WSJ verb *tokens*

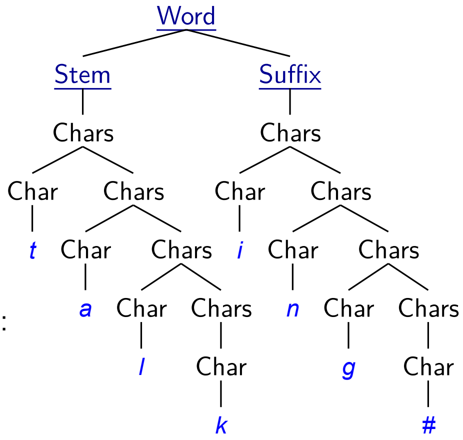
$\alpha = 0.1$	$\alpha = 10^{-5}$		$\alpha = 10^{-10}$		$\alpha = 10^{-15}$	
expect	expect		expect		expect	
expects	expects		expects		expects	
expected	expected		expected		expected	
expecting	expect	ing	expect	ing	expect	ing
include	include		include		include	
includes	includes		includ	es	includ	es
included	included		includ	ed	includ	ed
including	including		including		including	
add	add		add		add	
adds	adds		adds		add	s
added	added		add	ed	added	
adding	adding		add	ing	add	ing
continue	continue		continue		continue	
continues	continues		continue	s	continue	s
continued	continued		continu	ed	continu	ed
continuing	continuing		continu	ing	continu	ing

Posterior samples from WSJ verb *types*

$\alpha = 0.1$		$\alpha = 10^{-5}$		$\alpha = 10^{-10}$		$\alpha = 10^{-15}$	
expect		expect		expect		exp	ect
expects		expect	s	expect	s	exp	ects
expected		expect	ed	expect	ed	exp	ected
expect	ing	expect	ing	expect	ing	exp	ecting
include		includ	e	includ	e	includ	e
include	s	includ	es	includ	es	includ	es
included		includ	ed	includ	ed	includ	ed
including		includ	ing	includ	ing	includ	ing
add		add		add		add	
adds		add	s	add	s	add	s
add	ed	add	ed	add	ed	add	ed
adding		add	ing	add	ing	add	ing
continue		continu	e	continu	e	continu	e
continue	s	continu	es	continu	es	continu	es
continu	ed	continu	ed	continu	ed	continu	ed
continuing		continu	ing	continu	ing	continu	ing

Adaptor grammar for stem-suffix morphology

- Trees generated by an adaptor grammar are defined by CFG rules
- *Unadapted nonterminals* expand as in a PCFG
- *Adapted nonterminals* expand in two ways:
  - generate a previously generated string (with prob $\propto$ no. of times generated before), or
  - pick a rule and recursively expand its children (as in PCFG)
- To generate a new Word from Adaptor Grammar:
  - reuse an old Word, or
  - generate a Stem and a Suffix, by
    - reuse an old Stem (Suffix), or
    - generate a new Stem (Suffix) from PCFG
- *Lower in the tree $\Rightarrow$ higher in Bayesian hierarchy*



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Unsupervised word segmentation

- Input: phoneme sequences with *sentence boundaries* (Elman, Brent)
- Task: identify *word boundaries*, and hence *words*

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

ju wɑnt tu si ðə bʊk

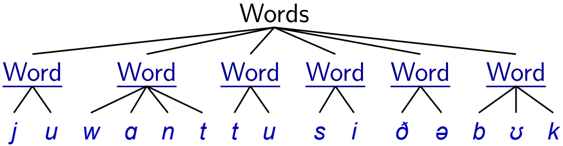
"you want to see the book"

- Ignoring phonology and morphology, this involves learning the pronunciation of each lexical items in the language
- This work often uses Bernstein-Ratner corpus of child-directed speech
  - ▶ Orthographic form looked up in pronouncing dictionary
  - ⇒ No phonetic variation or phonological alternations
- Joint work with Ben Börschinger, Katherine Demuth, Mike Frank, Sharon Goldwater, Tom Griffiths, and many others

Unigram word segmentation model as adaptor grammar

- Unigram "bag of words" model (Brent):
  - generate a *dictionary*, i.e., a set of words, where each word is a random sequence of phonemes
    - Bayesian prior prefers smaller dictionaries
  - generate each utterance by choosing each word at random from dictionary
- Brent's unigram model as an adaptor grammar:

$$\text{Words} \rightarrow \text{Word}^{+}$$
$$\underline{\text{Word}} \rightarrow \text{Phoneme}^{+}$$



- Word nonterminal is adapted, so to generate a Word:
  - regenerate previously generated Word string, with prob. $\propto$ number of times previously generated
  - generate fresh Phons expansion
- Segmentation accuracy: *56% token f-score* (same as Brent model)

Adaptor grammar learnt from Brent corpus

- **Initial grammar**

1	Words → Word Words	1	Words → Word
1	Word → Phon		
1	Phons → Phon Phons	1	Phons → Phon
1	Phon → *D*	1	Phon → *G*
1	Phon → *A*	1	Phon → *E*

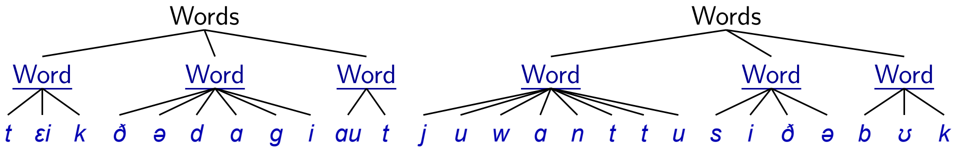
- **Grammar learnt from Brent corpus**

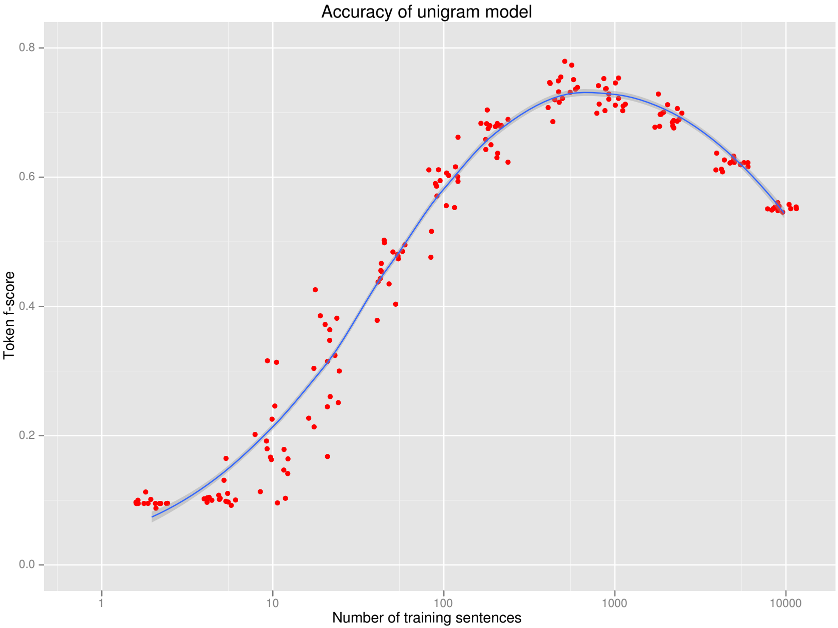
16625	Words → Word Words	9791	Words → Word
1575	Word → Phons		
4962	Phons → Phon Phons	1575	Phons → Phon
134	Phon → *D*	41	Phon → *G*
180	Phon → *A*	152	Phon → *E*
460	Word → (Phons (Phon *y*) (Phons (Phon *u*)))		
446	Word → (Phons (Phon *w*) (Phons (Phon *A*) (Phons (Phon *t*))))		
374	Word → (Phons (Phon *D*) (Phons (Phon *6*)))		
372	Word → (Phons (Phon *&*) (Phons (Phon *n*) (Phons (Phon *d*))))		

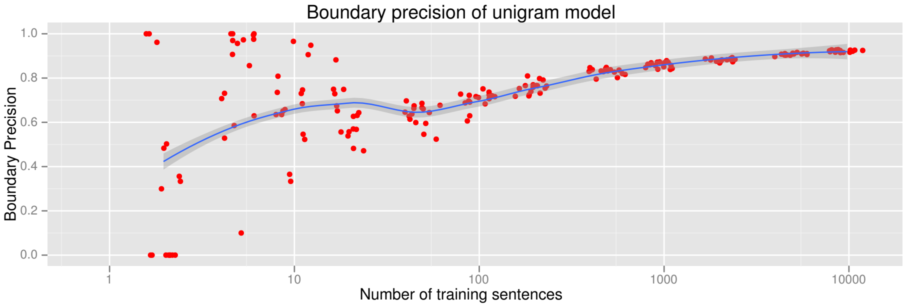
Undersegmentation errors with Unigram model

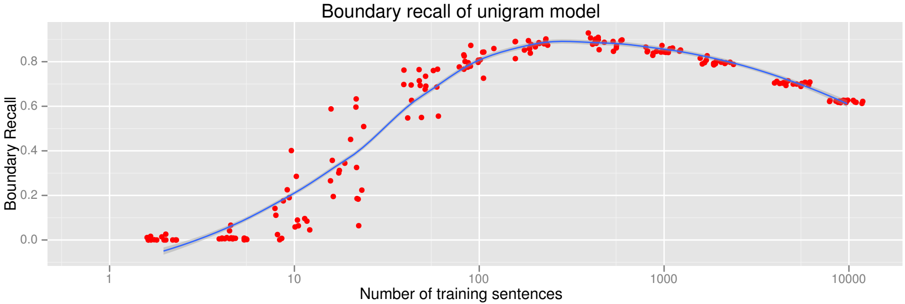
Words→<u>Word</u>$^+$ <u>Word</u>→Phon$^+$

- Unigram word segmentation model assumes each word is generated independently
- But there are strong inter-word dependencies (collocations)
- Unigram model can only capture such dependencies by analyzing collocations as words (Goldwater 2006)



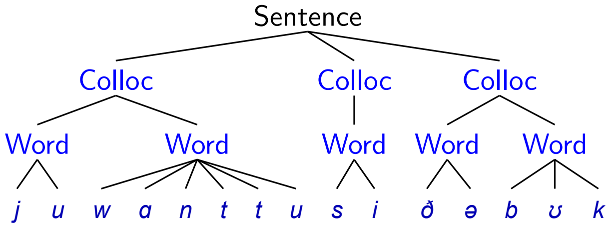

Accuracy of unigram model
Token f-score
0.0
0.2
0.4
0.6
0.8
1
10
100
1000
10000
Number of training sentences


Boundary precision of unigram model
Boundary Precision
1.0
0.8
0.6
0.4
0.2
0.0
1
10
100
1000
10000
Number of training sentences


Boundary recall of unigram model
Boundary Recall
0.8
0.6
0.4
0.2
0.0
1
10
100
1000
10000
Number of training sentences

Collocations ⇒ Words

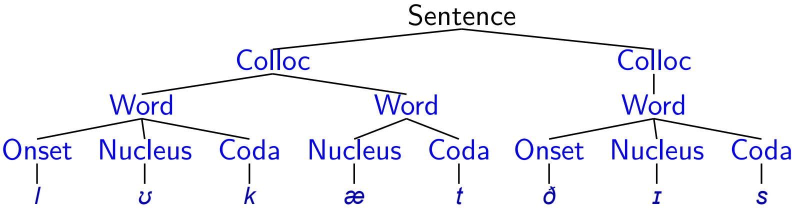
Sentence → Colloc$^+$
Colloc → Word$^+$
Word → Phon$^+$



- A Colloc(ation) consists of one or more words
- Both Words and Collocs are adapted (learnt)
- Significantly improves word segmentation accuracy over unigram model (76% f-score; ≈ Goldwater's bigram model)

Jointly learning words and syllables

Sentence$\rightarrow$Colloc$^+$	Colloc$\rightarrow$Word$^+$
Word$\rightarrow$Syllable$^{\{1:3\}}$	Syllable$\rightarrow$(Onset) Rhyme
Onset$\rightarrow$Consonant$^+$	Rhyme$\rightarrow$Nucleus (Coda)
Nucleus$\rightarrow$Vowel$^+$	Coda$\rightarrow$Consonant$^+$



- Rudimentary syllable model (improved model does better)
- With 2 Collocation levels, f-score = 84%
- Note: Because adaptor grammars only have one tree, can't simultaneously model syllable structure and morpology

Distinguishing internal onsets/codas helps

Sentence → Colloc$^+$

Word → SyllableIF

Word → SyllableI Syllable SyllableF

OnsetI → Consonant$^+$

Nucleus → Vowel$^+$

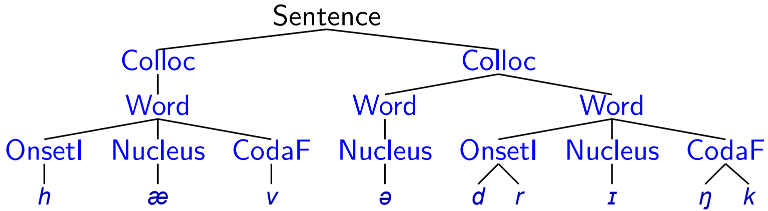
Colloc → Word$^+$

Word → SyllableI SyllableF

SyllableIF → (OnsetI) RhymeF

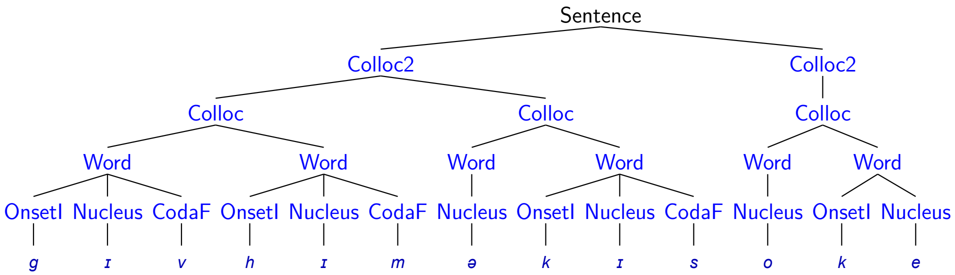
RhymeF → Nucleus (CodaF)

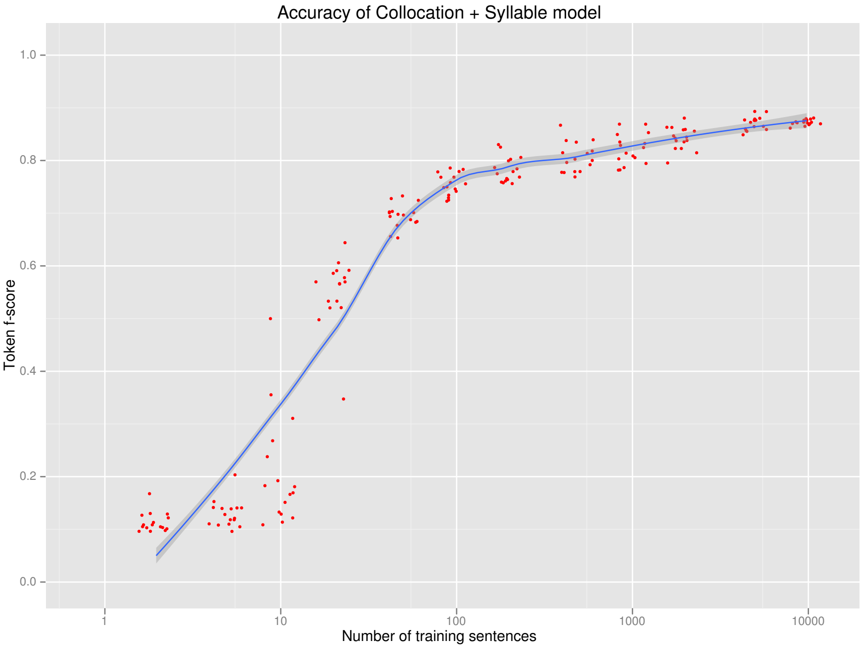
CodaF → Consonant$^+$

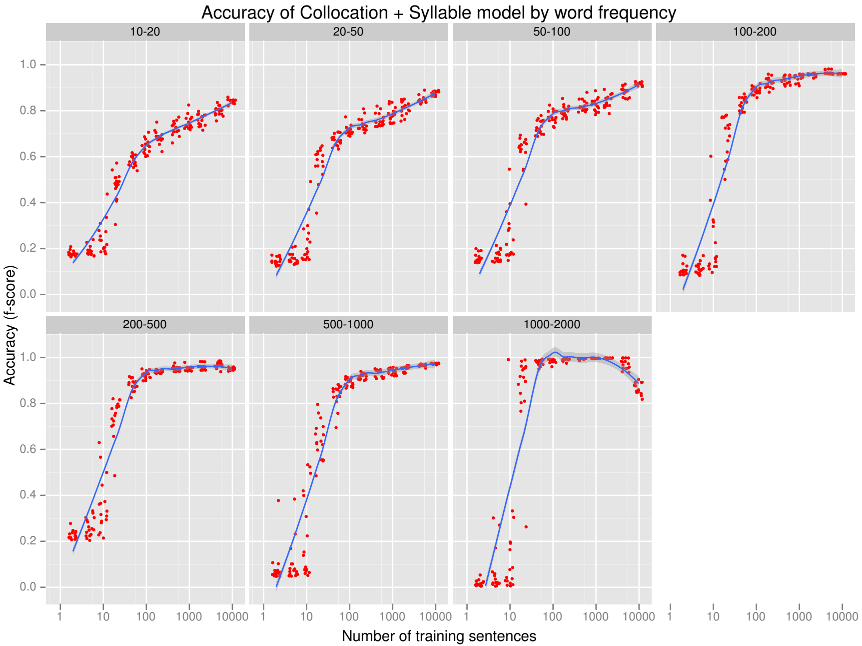


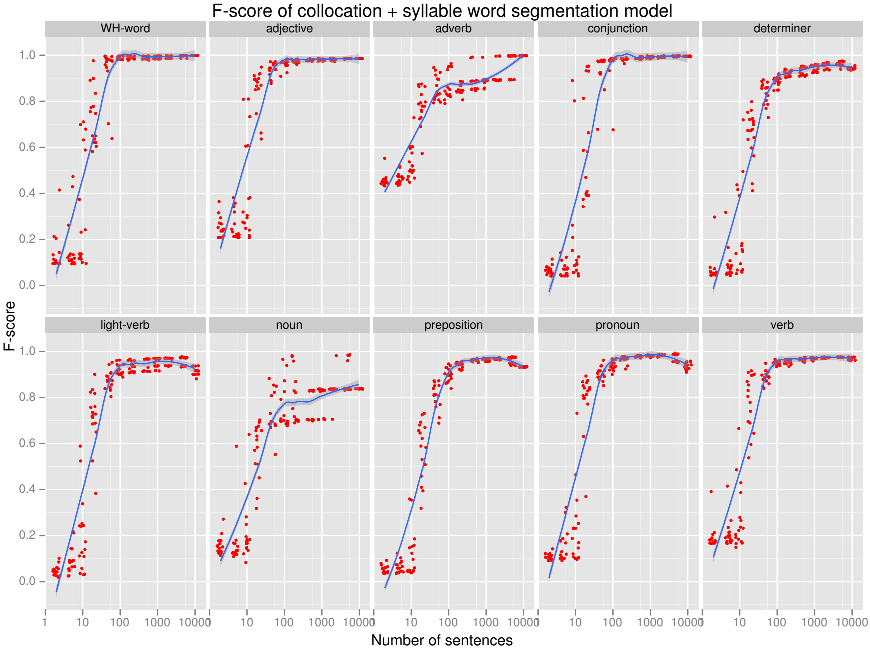
- With 2 Collocation levels, not distinguishing initial/final clusters, f-score = 84%
- With 3 Collocation levels, distinguishing initial/final clusters, f-score = 87%

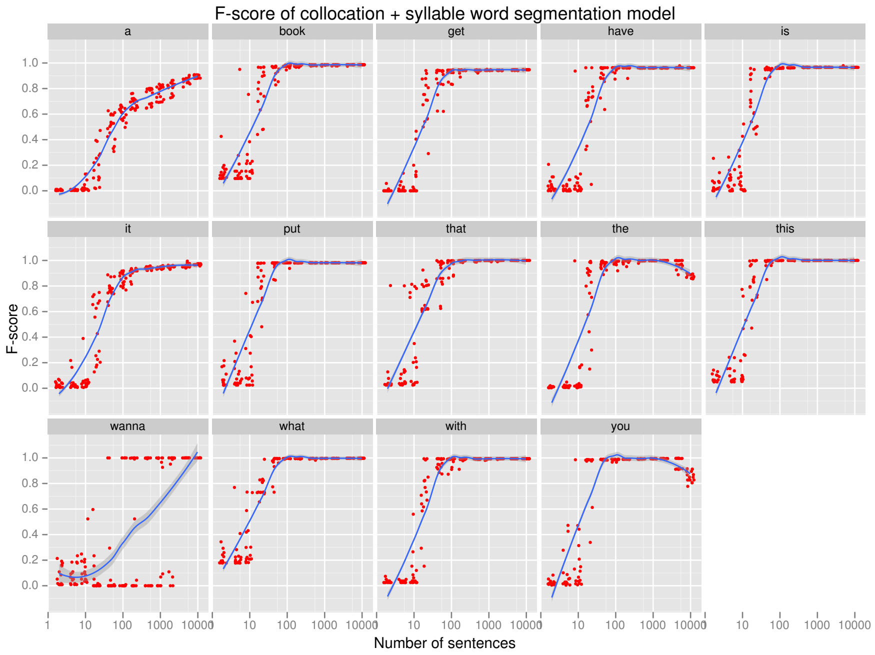
Collocations^2 ⇒ Words ⇒ Syllables



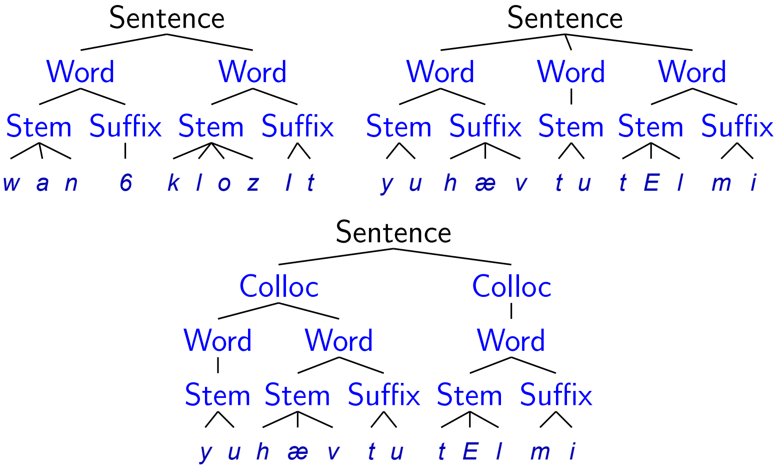

Accuracy of Collocation + Syllable model
Token f-score
1.0
0.8
0.6
0.4
0.2
0.0
1
10
100
1000
10000
Number of training sentences


Accuracy of Collocation + Syllable model by word frequency
10-20
20-50
50-100
100-200
200-500
500-1000
1000-2000
Accuracy (f-score)
0.0
0.2
0.4
0.6
0.8
1.0
1
10
100
1000
10000
Number of training sentences


F-score of collocation + syllable word segmentation model
WH-word
adjective
adverb
conjunction
determiner
light-verb
noun
preposition
pronoun
verb
F-score
1.0
0.8
0.6
0.4
0.2
0.0
1
10
100
1000
10000
Number of sentences


F-score of collocation + syllable word segmentation model
a
book
get
have
is
it
put
that
the
this
wanna
what
with
you
F-score
0.0
0.2
0.4
0.6
0.8
1.0
1
10
100
1000
10000
Number of sentences

Stem-suffix morphology and word segmentation



Summary of word segmentation models

- *Word segmentation accuracy depends on the kinds of generalisations learnt.*

Generalization	**Accuracy**
words as units (unigram)	56%
+ associations between words (collocations)	76%
+ syllable structure	84%
+ interaction between segmentation and syllable structure	87%

- *Synergies in learning words and syllable structure*
  - joint inference permits the learner to *explain away* potentially misleading generalizations
- We've also modelled word segmentation in *Mandarin* (and showed tone is a useful cue) and in *Sesotho* (where jointly modeling morphology improves accuracy)

Outline

Two hypotheses about language acquisition

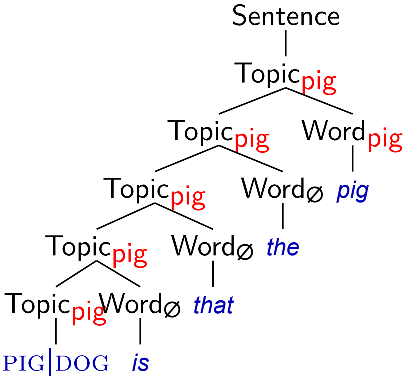
1. Pre-programmed *staged acquisition* of linguistic components
   - Conventional view of *lexical acquisition*, e.g., Kuhl (2004)
     - child first learns the phoneme inventory, which it then uses to learn
     - phonotactic cues for word segmentation, which are used to learn
     - phonological forms of words in the lexicon, …
2. *Interactive acquisition* of all linguistic components together
   - corresponds to *joint inference* for all components of language
   - can take advantage of *synergies* in acquisition
   - stages in language acquisition might be due to:
     - child's input may contain more information about some components
     - some components of language may be learnable with less data

Mapping words to referents

- Input to learner:
  - word sequence: *Is that the pig?*
  - objects in nonlinguistic context: DOG, PIG
- Learning objectives:
  - identify utterance topic: PIG
  - identify word-topic mapping: *pig* $\rightsquigarrow$ PIG

Frank et al (2009) "topic models" as PCFGs

- Prefix sentences with *possible topic marker*, e.g., PIG|DOG
- PCFG rules *choose a topic* from topic marker and *propagate it through sentence*
- Each word is either generated from sentence topic or null topic ∅



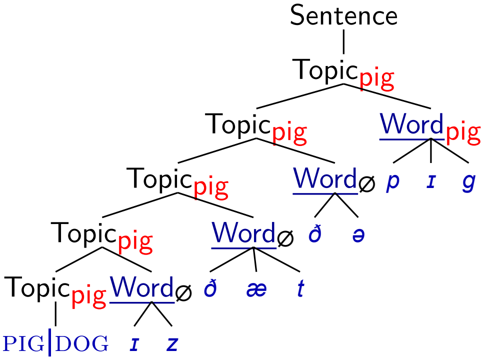
- Grammar can require *at most one topical word per sentence*
- Bayesian inference for PCFG rules and trees corresponds to Bayesian inference for word and sentence topics using topic model (Johnson 2010)

AGs for joint segmentation and referent-mapping

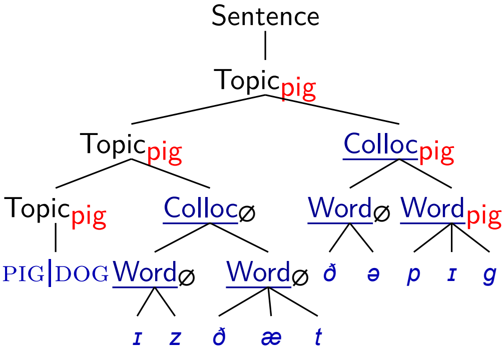
- Combine topic-model PCFG with word segmentation AGs
- Input consists of unsegmented phonemic forms prefixed with possible topics:

PIG|DOG *ɪ z ð æ t ð ə p ɪ g*

- E.g., combination of *Frank "topic model"* and *unigram segmentation model*
  - equivalent to Jones et al (2010)
- Easy to define *other combinations of topic models and segmentation models*



Collocation topic model AG



- Collocations are either "topical" or not
- Easy to modify this grammar so
  - at most one topical word per sentence, or
  - at most *one topical word per topical collocation*

Experimental set-up

- Input consists of unsegmented phonemic forms prefixed with possible topics:

$$\text{PIG}|\text{DOG}\ \textit{ɪ z ð æ t ð ə p ɪ g}$$

  - Child-directed speech corpus collected by Fernald et al (1993)
  - Objects in visual context annotated by Frank et al (2009)
- Bayesian inference for AGs using MCMC (Johnson et al 2009)
  - Uniform prior on PYP a parameter
  - "Sparse" Gamma$(100, 0.01)$ on PYP b parameter
- For each grammar we ran 8 MCMC chains for 5,000 iterations
  - collected word segmentation and topic assignments at every 10th iteration during last 2,500 iterations
    $\Rightarrow$ 2,000 sample analyses per sentence
  - computed and evaluated the modal (i.e., most frequent) sample analysis of each sentence

Does non-linguistic context help segmentation?

Model		word segmentation
segmentation	**topics**	**token f-score**
unigram	not used	0.533
unigram	any number	0.537
unigram	one per sentence	0.547
collocation	not used	0.695
collocation	any number	0.726
collocation	one per sentence	0.719
collocation	one per collocation	**0.750**

- Not much improvement with unigram model
  - consistent with results from Jones et al (2010)
- Larger improvement with collocation model
  - most gain with *one topical word per topical collocation*
    (this constraint cannot be imposed on unigram model)

Does better segmentation help topic identification?

- Task: identify object (if any) *this sentence* is about

Model		**sentence referent**	
segmentation	**topics**	**accuracy**	**f-score**
unigram	not used	0.709	0
unigram	any number	0.702	0.355
unigram	one per sentence	0.503	0.495
collocation	not used	0.709	0
collocation	any number	0.728	0.280
collocation	one per sentence	0.440	0.493
collocation	one per collocation	**0.839**	**0.747**

- The collocation grammar with *one topical word per topical collocation* is the only model clearly better than baseline

Does better segmentation help learning word-to-referent mappings?

- Task: identify *head nouns* of NPs referring to topical objects
  (e.g. *pɪg* ⇝ PIG in input PIG | DOG *ɪ z ð æ t ð ə p ɪ g*)

Model		topical word
segmentation	**topics**	**f-score**
unigram	not used	0
unigram	any number	0.149
unigram	one per sentence	0.147
collocation	not used	0
collocation	any number	0.220
collocation	one per sentence	0.321
collocation	one per collocation	**0.636**

- The collocation grammar with one topical word per topical collocation is best at identifying head nouns of referring NPs

Summary of grounded learning and word segmentation

- *Word to object mapping is learnt more accurately when words are segmented more accurately*
  - improving segmentation accuracy improves topic detection and acquisition of topical words
- *Word segmentation accuracy improves when exploiting non-linguistic context information*
  - incorporating word-topic mapping improves segmentation accuracy (at least with collocation grammars)

⇒ *There are synergies a learner can exploit when learning word segmentation and word-object mappings*

- Caveat: *Need to confirm results using different models*

Other topics investigated with Adaptor Grammars

- The role of *social cues* such as eye-gaze
  - Eye gaze (particularly from child) is strong topicality cue
  - Useful for identifying word referents
  - Not useful for word segmentation
- Stress and Phonotactics in English
  - Learns Unique Stress Constraint from unsegmented data (Yang 2004)
  - Additive interaction: model with both stress and phonotactics is better than with just one
- Monosyllabic "function words" are useful cues for word and phrase boundaries
  - Model inspired by Shi's experimental work
  - Increases word segmentation f-score from 0.87 to 0.92
  - After about 1,000 sentences, model overwhelming prefers to attach "function words" at left phrasal periphery
- Results should be confirmed with other kinds of models!

Outline

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/ $\Rightarrow$ [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 more common when following segment is consonantal
  - these processes can also be *nondeterministic*
    - e.g., /t/ and /d/ don't always delete even when followed by a consonant
- Joint work with Joe Pater, Robert Staubs and Emmanuel Dupoux

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)

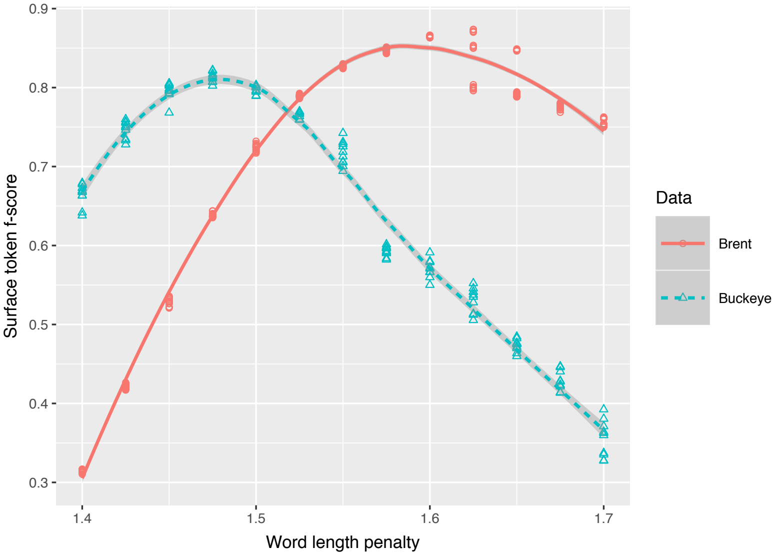
Liang/Berg-Kirkpatrick unigram segmentation model

- Liang/Berg-Kirkpatrick et al *MaxEnt unigram model with double exponential prior*:

$$\mathrm{P}(s \mid \boldsymbol{\theta}) \;=\; \frac{1}{Z}\exp(-\boldsymbol{\theta}\cdot\boldsymbol{f}(s))\,\underbrace{\exp(-|w|^d)}_{\text{length penalty}}$$

- Feature function $\boldsymbol{f}(s)$ includes word id, word prefix/suffix features, etc.
  - We extend s to be an surface/underlying pair $x = (s, u)$, and allow $\mathrm{P}(x)$ to condition on neigbouring surface segments
- Partition function Z
  - Doesn't normalise "length penalty" (so model is deficient)
  - Sums only over substrings in the training corpus (not all possible strings)
- "Length penalty" exponent d needs to be tuned somehow!
- Segmentation accuracy rivals adaptor grammar model with phonotactics and collocations
  - How can it do so well *without modelling supra-word context*?

Sensitivity to word length penalty factor d



A joint model of word segmentation and phonology

- Because Berg-Kirkpatrick's word segmentation model is a MaxEnt model, it is easy to integrate with Harmonic Grammar/MaxEnt 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 is either word-final /t/ or word-final /d/ deletion
- 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* $\mathcal{C} = \{\mathrm{C}, \mathrm{V}, \#\}$

$$\mathrm{P}(s, u \mid c, \boldsymbol{\theta}) \;\; \propto \;\; \frac{1}{Z_c} \exp(-\boldsymbol{\theta} \cdot f(s, u, c))$$

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

$$Q(s \mid c, \boldsymbol{\theta}) \;\; = \;\; \sum_{u:(s,u) \in \mathcal{X}} \mathrm{P}(s, u \mid c, \boldsymbol{\theta}) \exp(-|u|^d)$$

$$Q(w \mid \boldsymbol{\theta}) \;\; = \;\; \sum_{\substack{s_1 \ldots s_\ell \\ \text{s.t.}\, s_1 \ldots s_\ell = w}} \prod_{j=1}^{\ell} Q(s_j \mid c, \boldsymbol{\theta})$$

$$Q_D(\boldsymbol{\theta}) \;\; = \;\; \sum_{i=1}^{n} \log Q(w_i \mid \boldsymbol{\theta}) - \lambda \, \|\boldsymbol{\theta}\|_1$$

MaxEnt features

- Here are the features $f(s, u, c)$ where $s = [l.ih.v]$, $u = /l.ih.v.t/$ and $c = \mathrm{C}$
  - *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)
- 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

Experimental results: 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)

- 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

Conclusions from MaxEnt joint models of segmentation and phonology

- Globally-normalised MaxEnt model doesn't require a tree structure
  - ⇒ Can capture contextual dependency in phonological alternation
- No need to calculate partition function over all possible underlying/surface forms
- Liang/Berg-Kirkpatrick double-exponential word length penalty works extremely well
  - How do we set the d parameter?

Outline

Outline

Summary

- For toy examples, it's possible to learn abstract grammatical properties and lexical entries from positive evidence alone
- Bayesian segmentation models can solve word segmentation problems
  - Adaptor grammars can find complex hierachical structure
- Maximum entropy models can jointly learn word segmentation and (simple) phonology
- Neural networks don't need or produce explicit linguistic representations

Challenges for future work

- How are deep neural networks related to linguistic generalisations?
  - Deep networks can learn linguistic generalisations extremely well
  - But they can also learn apparently random patterns
  - Smolensky's Harmony Theory and Tensor Product Representations (?)
- Technology can get ahead of scientific understanding
  - The steam engine was developed centuries before statistical mechanics
  - Why can't a heat engine extract all the energy $\Rightarrow$ entropy