

Bayesian Inference of Grammars

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March 2007

Outline

Introduction

Learning probabilistic context-free grammars

Morphological segmentation

Learning from types with Chinese restaurant processes

Adaptor grammars

Bigram dependencies in word segmentation

Conclusion

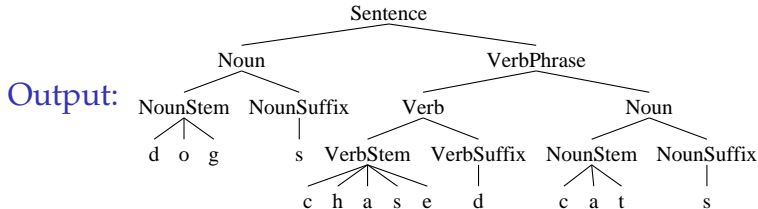
Research goal: language acquisition

- ▶ Goal of this research (as yet unachieved):

a grammar learning algorithm that trains from:

Input: “d o g s c h a s e d c a t s”
(actually broad phonemic transcription)

and produces:



Talk outline

- ▶ Maximum likelihood can be applied to grammar induction (expectation maximization) but generally produces poor results. Why?
- ▶ *Will new nonparametric Bayesian methods do better?*
 - ▶ Chinese restaurant processes and Dirichlet processes
- ▶ Strategy: develop methods that work for simple problems
 - ▶ morphological segmentation
 - ▶ word segmentation of unsegmented phonemic transcripts

Nonparametric Bayes: *a new lamppost*

Late one night, a drunk guy is crawling around under a lamppost. A cop comes up and asks him what he's doing.

"I'm looking for my keys," the drunk says. *"I lost them about three blocks away."*

"So why aren't you looking for them where you dropped them?" the cop asks.

The drunk looks at the cop, amazed that he'd ask so obvious a question. *"Because the light is better here."*

Probabilistic Context-Free Grammars

- ▶ PCFGs are perhaps the simplest models of hierarchical structure
- ▶ Probability of a tree is the *product of the probabilities of the rules* used to construct it

1.0 $S \rightarrow NP VP$

0.75 $NP \rightarrow \text{George}$

0.6 $VP \rightarrow \text{barks}$

0.25 $NP \rightarrow \text{Al}$

0.4 $VP \rightarrow \text{snores}$

$$P \left(\begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \\ | \quad | \\ \text{George} \quad \text{barks} \end{array} \right) = 0.45$$

$$P \left(\begin{array}{c} S \\ \swarrow \quad \searrow \\ NP \quad VP \\ | \quad | \\ \text{Al} \quad \text{snores} \end{array} \right) = 0.1$$

Learning the units of generalization

- ▶ Rules are units of generalization in PCFGs
- ▶ We can *estimate rule probabilities from data*
 - ▶ The Expectation Maximization algorithm finds rule probabilities that locally maximize likelihood of a set of strings
- ▶ Find rules using “generate and prune” approach:
 - ▶ generate a large number of possible rules
 - ▶ estimate the probability of each rule
 - ▶ prune low probability rules
- ▶ Unsupervised estimation of PCFGs generally produces *poor results*
- ▶ Nonparametric Bayesian techniques (CRPs, DPs)
 - ▶ integrate production search with parameter search
 - ▶ can construct more elaborate (realistic?) models

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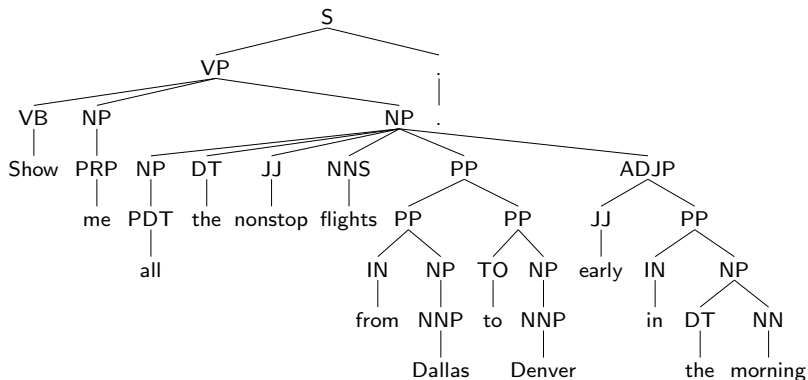
Adaptor grammars

Bigram dependencies in word segmentation

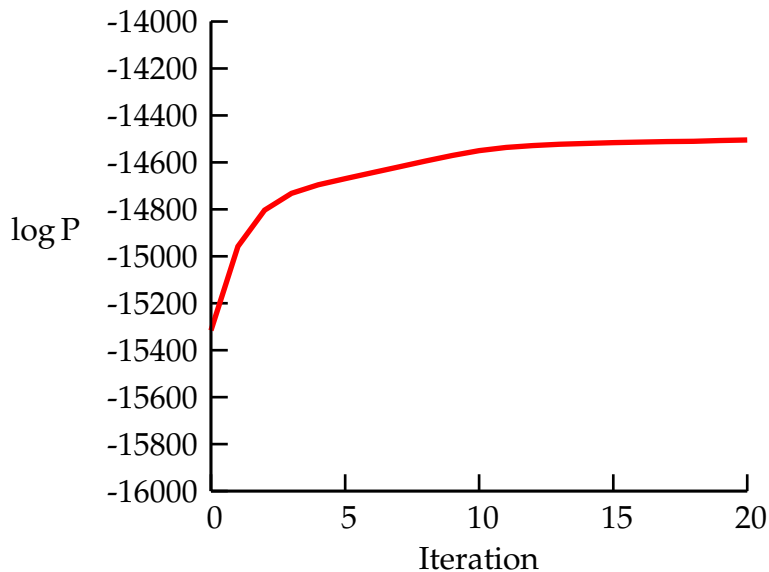
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Learning PCFGs using Expectation Maximization

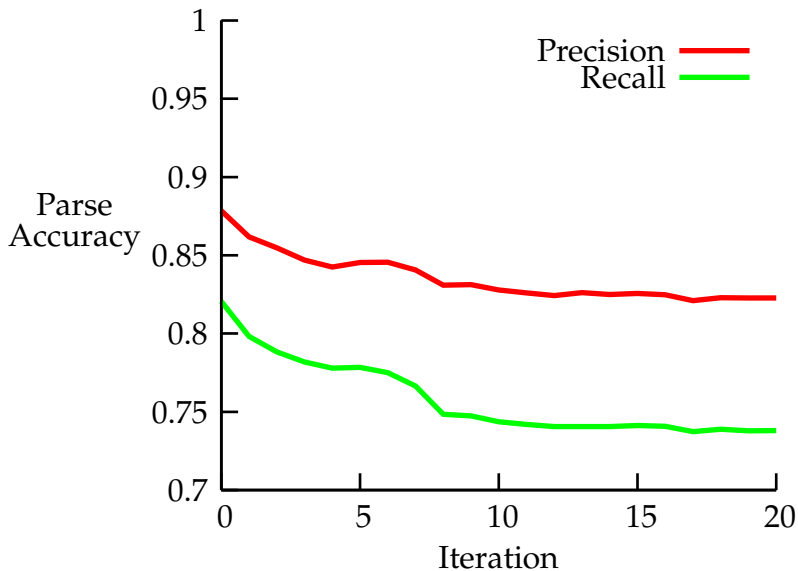
- ▶ ATIS treebank consists of 1,300 hand-constructed parse trees
- ▶ input consists of POS tags rather than words
- ▶ about 1,000 PCFG rules are needed to build these trees



Probability of training strings



Accuracy of parses



The PCFG model is wrong

- ▶ Parse accuracy drops as likelihood increases
 - ▶ higher likelihood \nrightarrow better parses
 - ▶ *the statistical model is wrong*
- ▶ *Initialized EM with correct parse trees*
 - ▶ started with true rules and their probabilities
 - \Rightarrow poor performance not due to search error
- ▶ Evaluated on training data
 - ▶ poor performance not due to over-learning

Why didn't it learn the right grammar?

- ▶ higher likelihood \nrightarrow parse accuracy
- \Rightarrow *probabilistic model and/or estimation procedure are wrong*
- ▶ Bayesian prior preferring smaller grammars doesn't help
- ▶ What could be wrong?
 - ▶ Wrong model of grammar (Klein and Manning)
 - ▶ Wrong estimation procedure (Smith and Eisner)
 - ▶ Wrong training data (Yang)
 - ▶ Predicting word strings is wrong objective
 - ▶ Grammar *ignores semantics* (Zettlemoyer and Collins)

de Marken (1995) "Lexical heads, phrase structure and the induction of grammar"

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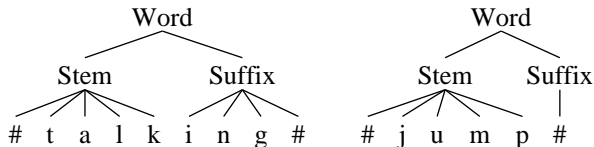
Conclusion

Learning English verbal morphology

Training data is a sequence of verbs, e.g.

$$\mathcal{D} = (\# \text{ t a l k i n g } \#, \# \text{ j u m p } \#, \dots)$$

Goal: infer trees such as:



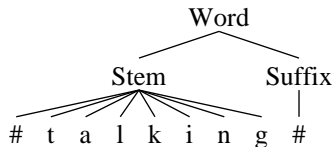
Word \rightarrow Stem Suffix

Stem \rightarrow *all possible stems*

Suffix \rightarrow *all possible suffixes*

Maximum likelihood always chooses no suffixes

- ▶ Maximum likelihood selects production probabilities that minimize KL-divergence between model and data distributions
 - ▶ *Saturated model* with $P(\text{Suffix} \rightarrow \#) = 1$ generates training data \mathcal{D} exactly
- ⇒ saturated model is maximum likelihood estimate



Bayesian estimation

- ▶ Bayesian estimates incorporate *prior* $P(\mathcal{H})$ over hypotheses \mathcal{H} (grammars) as well as *likelihood* $P(\mathcal{D}|\mathcal{H})$ of data \mathcal{D}

$$\underbrace{P(\mathcal{H}|\mathcal{D})}_{\text{Posterior}} \propto \underbrace{P(\mathcal{D}|\mathcal{H})}_{\text{Likelihood}} \underbrace{P(\mathcal{H})}_{\text{Prior}}$$

- ▶ Priors can be sensitive to linguistic structure (e.g., a word should contain a vowel)
- ▶ Priors can encode linguistic universals and markedness preferences (e.g., complex clusters appear at word onsets)
- ▶ Priors can prefer *sparse solutions*
- ▶ The choice of the prior is as much a linguistic issue as the design of the grammar!

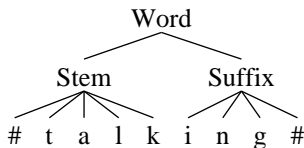
Morphological segmentation experiment

- ▶ Dirichlet prior prefers grammars with *fewer stems and suffixes*
 - ▶ grammars are sparser as Dirichlet parameter $\alpha \rightarrow 0$

Word \rightarrow Stem Suffix

Stem \rightarrow *all possible stems*

Suffix \rightarrow *all possible suffixes*

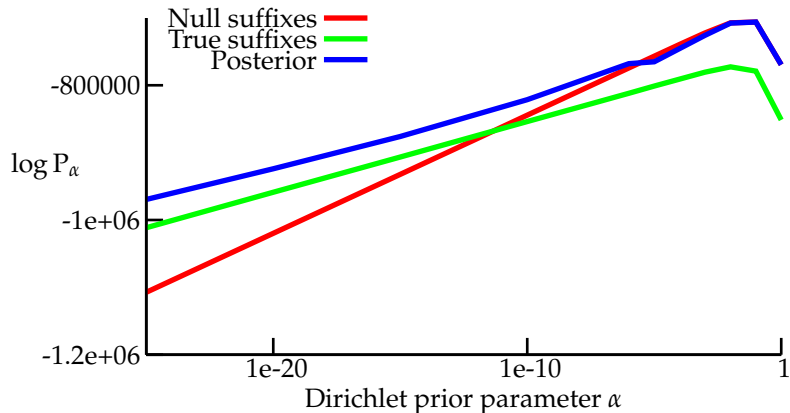


- ▶ Trained on orthographic verbs from PTB Wall Street Journal corpus
- ▶ Gibbs sampler samples from posterior distribution over parses
 - ▶ reanalyses each word using grammar estimated from parses of other words

Posterior samples from WSJ verb tokens

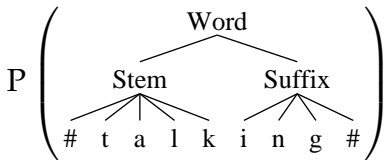
$\alpha = 0.1$	$\alpha = 10^{-5}$	$\alpha = 10^{-10}$	$\alpha = 10^{-15}$
expect	expect	expect	expect
expects	expects	expects	expects
expected	expected	expected	expected
expecting	expect ing	expect ing	expect ing
include	include	include	include
includes	includes	includ es	includ es
included	included	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
report	report	report	report

Log posterior of models on token data



- ▶ Correct solution is nowhere near as likely as posterior
- ⇒ model is wrong!

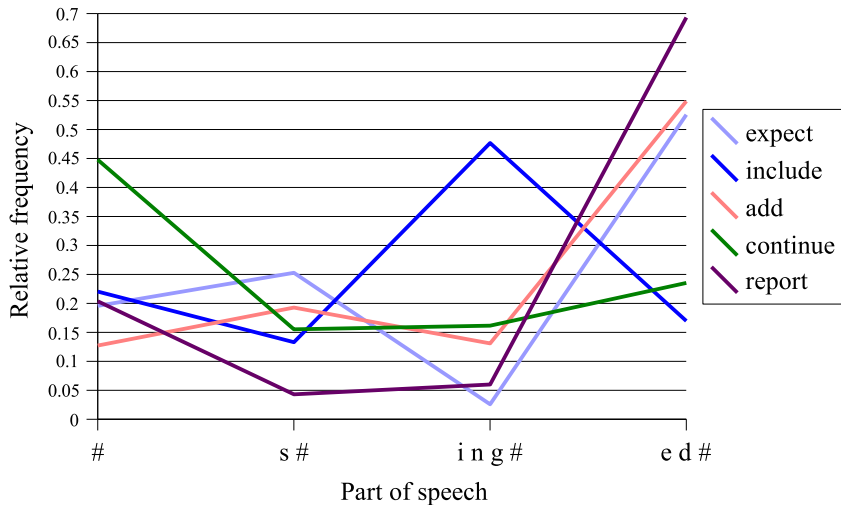
Independence assumption in PCFG model



$$= P(\text{Word} \rightarrow \text{Stem Suffix}) P(\text{Stem} \rightarrow \# t a l k) P(\text{Suffix} \rightarrow i n g \#)$$

- ▶ Model assumes relative frequency of each suffix *to be the same for all stems*
- ▶ This turns out not to be true

Relative frequencies of inflected verb forms



Types and tokens

- ▶ A word *type* is a distinct word shape
- ▶ A word *token* is an occurrence of a word

\mathcal{D} = “the cat chased the other cat”

Tokens(\mathcal{D}) = “the”, “cat”, “chased”, “the”, “other”, “cat”

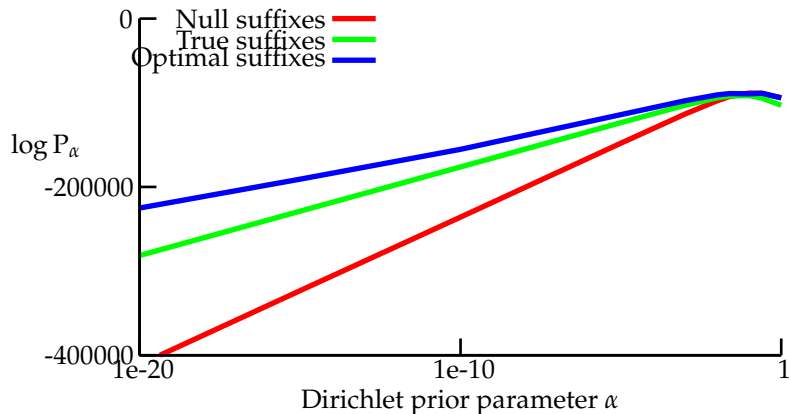
Types(\mathcal{D}) = “the”, “cat”, “chased”, “other”

- ▶ Estimating production probabilities from *word types* rather than word tokens eliminates (most) frequency variation
 - ▶ 4 common verb suffixes, so when estimating from verb types $P(\text{Suffix} \rightarrow \text{ing}\#) \approx 0.25$
- ▶ Some psycholinguistics claim that children learn morphology from types (Bybee, Pierrehumbert)

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
report	report	repo rt	rep ort

Log posterior of models on type data



- ▶ Correct solution is close to optimal at $\alpha = 10^{-3}$

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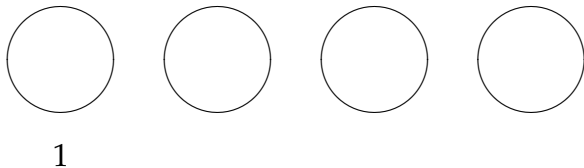
Bigram dependencies in word segmentation

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Generating tokens but learning from types

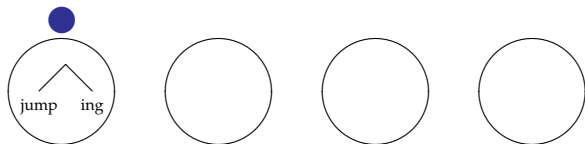
- ▶ Over-dispersion \Rightarrow estimate from types rather than tokens
- ▶ But in many cases the types are not available (e.g., speech does not come segmented into words (“s e e t h e d o g g i e”))
- ▶ Labeled Chinese restaurant process models
 - ▶ *Labeling distribution* P_G generates types
 - ▶ *Chinese restaurant process* replicates types to produce tokens
 - ▶ labeling distribution can be estimated from the CRP
- ▶ Adaptor grammars use CFGs to produce the labels for a hierarchy of CRPs

Chinese restaurant process (1st enters)



- ▶ Tokens \sim customers, types \sim tables, analyses \sim labels
- ▶ Outcomes are “tables” in an infinite Chinese restaurant
- ▶ Each “table” can seat an infinite number of “customers”
- ▶ Each “table” has a “dish” (label) shared by all “customers”
- ▶ Customer $n + 1$ walks into restaurant and tables $1, \dots, m$ are occupied,
 - ▶ sits at table $k \leq m$ with probability $n_k / (n + \alpha)$
 - ▶ sits at table $k = m + 1$ with probability $\alpha / (n + \alpha)$ and generates a new label y with probability $P_G(y)$

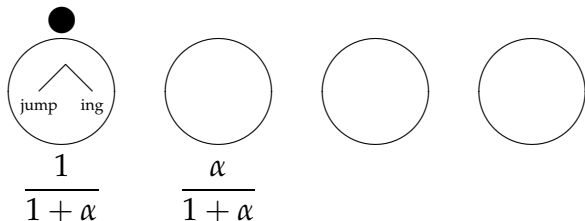
Chinese restaurant process (1st seated)



$$P_G(\text{jump} + \text{ing})$$

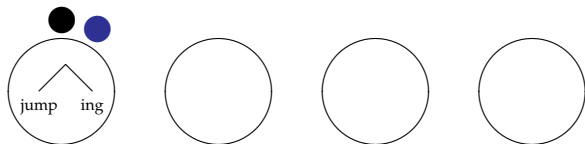
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Chinese restaurant process (2nd enters)



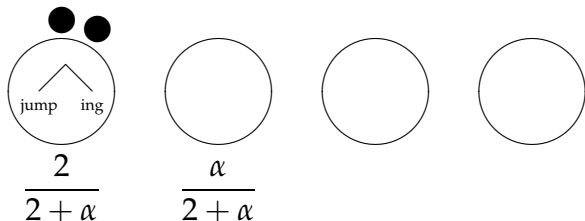
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Chinese restaurant process (2nd seated)



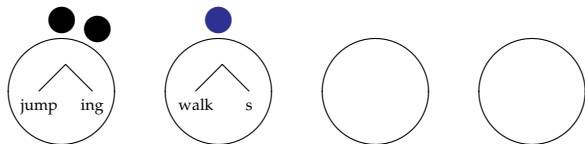
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- ▶ Outcomes are “tables” in an infinite Chinese restaurant
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 - ▶ sits at table $k = m + 1$ with probability $\alpha / (n + \alpha)$ and generates a new label y with probability $P_G(y)$

Chinese restaurant process (3rd enters)



- ▶ Tokens \sim customers, types \sim tables, analyses \sim labels
- ▶ Outcomes are “tables” in an infinite Chinese restaurant
- ▶ Each “table” can seat an infinite number of “customers”
- ▶ Each “table” has a “dish” (label) shared by all “customers”
- ▶ Customer $n + 1$ walks into restaurant and tables $1, \dots, m$ are occupied,
 - ▶ sits at table $k \leq m$ with probability $n_k / (n + \alpha)$
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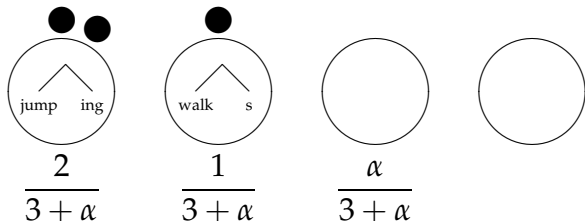
Chinese restaurant process (3rd seated)



$$P_G(\text{walk} + s)$$

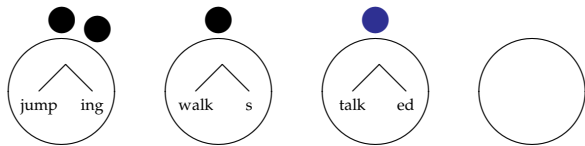
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Chinese restaurant process (4th enters)



- ▶ Tokens \sim customers, types \sim tables, analyses \sim labels
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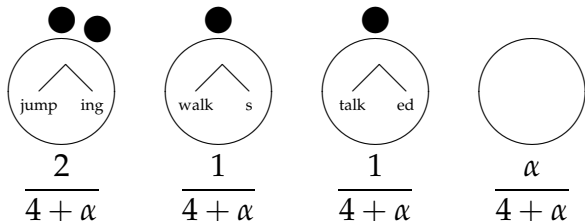
Chinese restaurant process (4th seated)



$$P_G(\text{talk} + \text{ed})$$

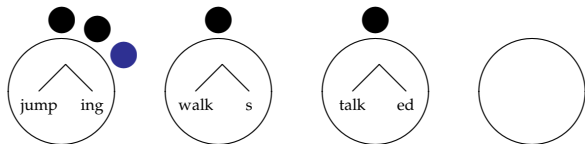
- ▶ Tokens \sim customers, types \sim tables, analyses \sim labels
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Chinese restaurant process (5th enters)



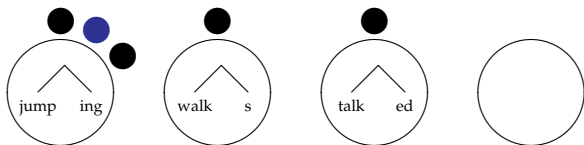
- ▶ Tokens \sim customers, types \sim tables, analyses \sim labels
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Chinese restaurant process (5th seated)



- ▶ Tokens \sim customers, types \sim tables, analyses \sim labels
- ▶ Outcomes are “tables” in an infinite Chinese restaurant
- ▶ Each “table” can seat an infinite number of “customers”
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Estimating CRP models via Gibbs sampling



- ▶ Gibbs sampling: resample the analysis of each word token given the analyses of other tokens
- ▶ Each word token is a customer: its table's label is its analysis
- ▶ Gibbs sampling step:
 - ▶ remove token from its current table (delete empty tables)
 - ▶ choose a table for the token (possibly creating new table)
- ▶ *Labeling distribution P_G estimated from labels on tables*
 - ▶ P_G is estimated from types (approximately)

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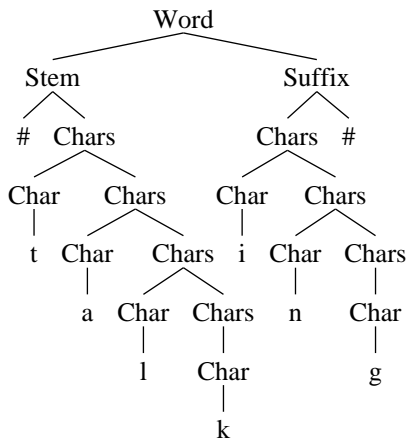
Bigram dependencies in word segmentation

Conclusion

From PCFGs to adaptor grammars

- ▶ An *adaptor grammar* is a PCFG together with a parameter α_A for each non-terminal A
- ▶ If $\alpha_A > 0$ then A is *adapted*
- ▶ Each adapted non-terminal A has its own CRP, labeled with trees generated by A
- ▶ Non-adapted non-terminals expand as in PCFG, i.e., pick production $A \rightarrow B_1 \dots B_n$ and recursively expand B_1, \dots, B_n
- ▶ An adapted non-terminal A expands by:
 - ▶ each expansion is a customer entering A 's restaurant
 - ▶ if customer sits at new table, generate tree to label new table as if A were not adapted
 - ▶ return the tree labeling the customer's table

Adaptor grammar morphology example

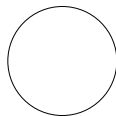
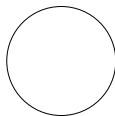
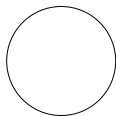
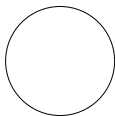


Word → Stem Suffix
Stem → # Chars
Suffix → #
Suffix → Chars #
Chars → Char
Chars → Char Chars
Char → a | ... | z

- ▶ CRPs for non-terminals Word, Stem and Suffix
 - ▶ Stem and Suffix CRPs generate all possible stems and suffixes

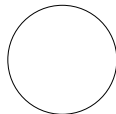
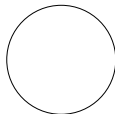
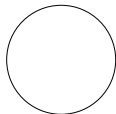
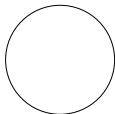
Morphology adaptor grammar (0)

Word restaurant
Word \rightarrow Stem Suffix



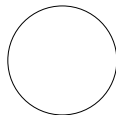
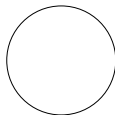
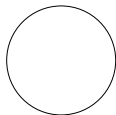
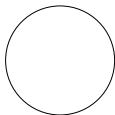
...

Stem restaurant
Stem \rightarrow #
Stem \rightarrow # Chars



...

Suffix restaurant
Suffix \rightarrow #
Suffix \rightarrow Chars #

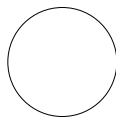
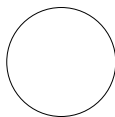
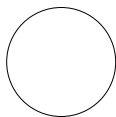
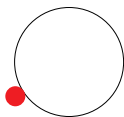


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Chars factory
Chars \rightarrow Char
Chars \rightarrow Char Chars
Char \rightarrow a . . . z

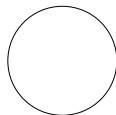
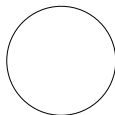
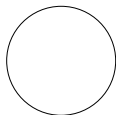
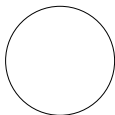
Morphology adaptor grammar (1a)

Word restaurant
Word \rightarrow Stem Suffix



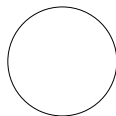
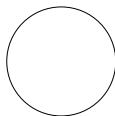
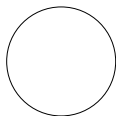
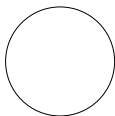
...

Stem restaurant
Stem \rightarrow #
Stem \rightarrow # Chars



...

Suffix restaurant
Suffix \rightarrow #
Suffix \rightarrow Chars #

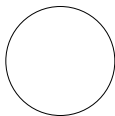
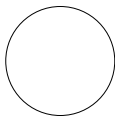
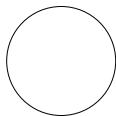
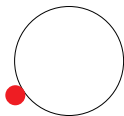


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Chars factory
Chars \rightarrow Char
Chars \rightarrow Char Chars
Char \rightarrow a...z

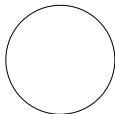
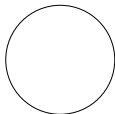
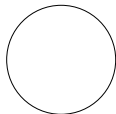
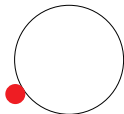
Morphology adaptor grammar (1b)

Word restaurant
Word \rightarrow Stem Suffix



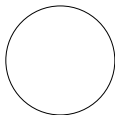
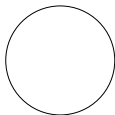
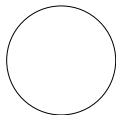
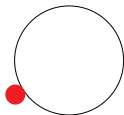
...

Stem restaurant
Stem \rightarrow #
Stem \rightarrow # Chars



...

Suffix restaurant
Suffix \rightarrow #
Suffix \rightarrow Chars #

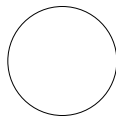
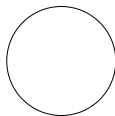
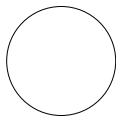
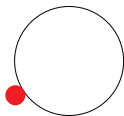


...

Chars factory
Chars \rightarrow Char
Chars \rightarrow Char Chars
Char \rightarrow a...z

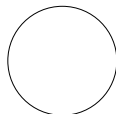
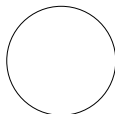
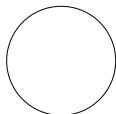
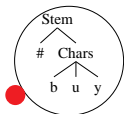
Morphology adaptor grammar (1c)

Word restaurant
Word \rightarrow Stem Suffix



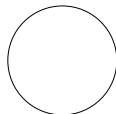
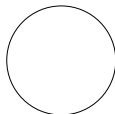
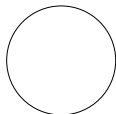
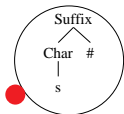
...

Stem restaurant
Stem \rightarrow #
Stem \rightarrow # Chars



...

Suffix restaurant
Suffix \rightarrow #
Suffix \rightarrow Chars #

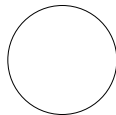
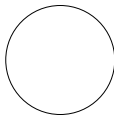
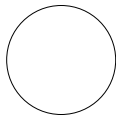
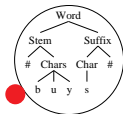


...

Chars factory
Chars \rightarrow Char
Chars \rightarrow Char Chars
Char \rightarrow a...z

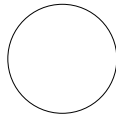
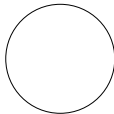
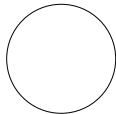
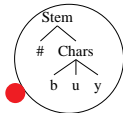
Morphology adaptor grammar (1d)

Word restaurant
Word \rightarrow Stem Suffix



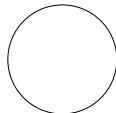
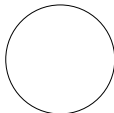
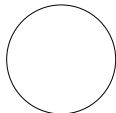
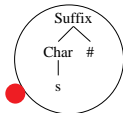
...

Stem restaurant
Stem \rightarrow #
Stem \rightarrow # Chars



...

Suffix restaurant
Suffix \rightarrow #
Suffix \rightarrow Chars #

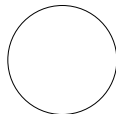
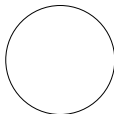
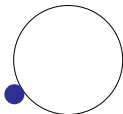
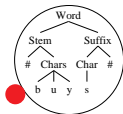


...

Chars factory
Chars \rightarrow Char
Chars \rightarrow Char Chars
Char \rightarrow a...z

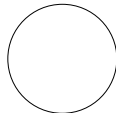
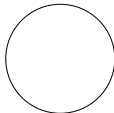
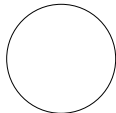
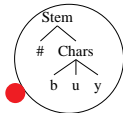
Morphology adaptor grammar (2a)

Word restaurant
Word \rightarrow Stem Suffix



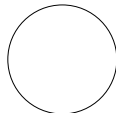
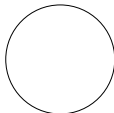
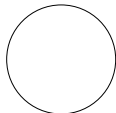
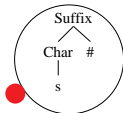
...

Stem restaurant
Stem \rightarrow #
Stem \rightarrow # Chars



...

Suffix restaurant
Suffix \rightarrow #
Suffix \rightarrow Chars #

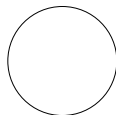
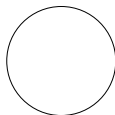
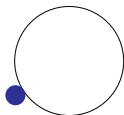
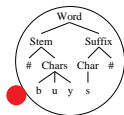


...

Chars factory
Chars \rightarrow Char
Chars \rightarrow Char Chars
Char \rightarrow a...z

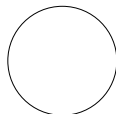
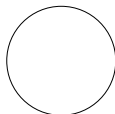
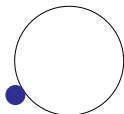
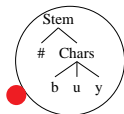
Morphology adaptor grammar (2b)

Word restaurant
Word \rightarrow Stem Suffix



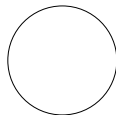
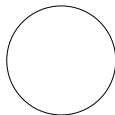
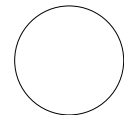
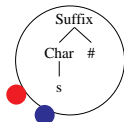
...

Stem restaurant
Stem \rightarrow #
Stem \rightarrow # Chars



...

Suffix restaurant
Suffix \rightarrow #
Suffix \rightarrow Chars #

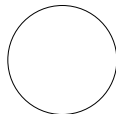
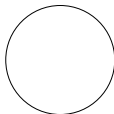
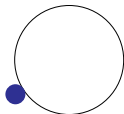
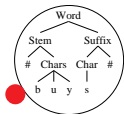


...

Chars factory
Chars \rightarrow Char
Chars \rightarrow Char Chars
Char \rightarrow a...z

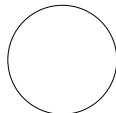
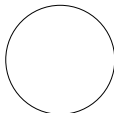
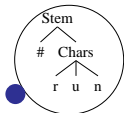
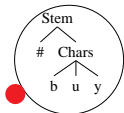
Morphology adaptor grammar (2c)

Word restaurant
Word \rightarrow Stem Suffix



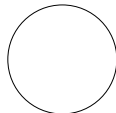
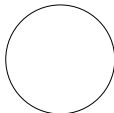
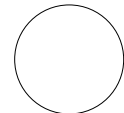
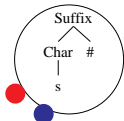
...

Stem restaurant
Stem \rightarrow #
Stem \rightarrow # Chars



...

Suffix restaurant
Suffix \rightarrow #
Suffix \rightarrow Chars #

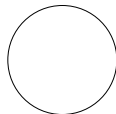
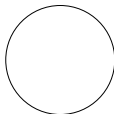
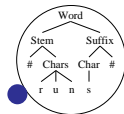
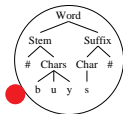


...

Chars factory
Chars \rightarrow Char
Chars \rightarrow Char Chars
Char \rightarrow a...z

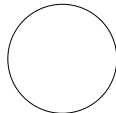
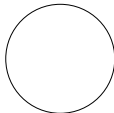
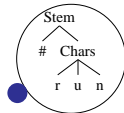
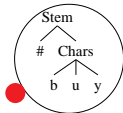
Morphology adaptor grammar (2d)

Word restaurant
Word \rightarrow Stem Suffix



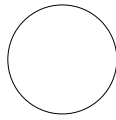
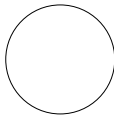
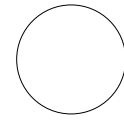
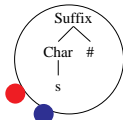
...

Stem restaurant
Stem \rightarrow #
Stem \rightarrow # Chars



...

Suffix restaurant
Suffix \rightarrow #
Suffix \rightarrow Chars #

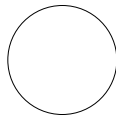
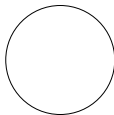
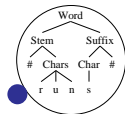
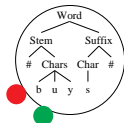


...

Chars factory
Chars \rightarrow Char
Chars \rightarrow Char Chars
Char \rightarrow a...z

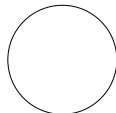
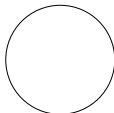
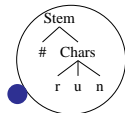
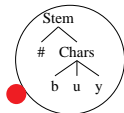
Morphology adaptor grammar (3)

Word restaurant
Word \rightarrow Stem Suffix



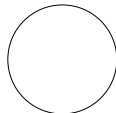
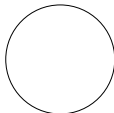
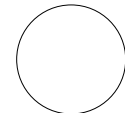
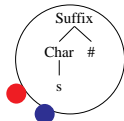
...

Stem restaurant
Stem \rightarrow #
Stem \rightarrow # Chars



...

Suffix restaurant
Suffix \rightarrow #
Suffix \rightarrow Chars #

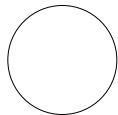
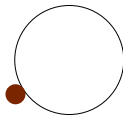
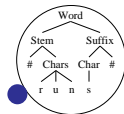
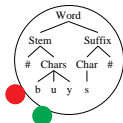


...

Chars factory
Chars \rightarrow Char
Chars \rightarrow Char Chars
Char \rightarrow a...z

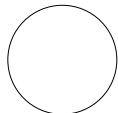
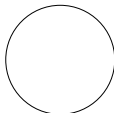
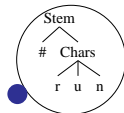
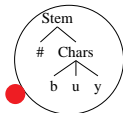
Morphology adaptor grammar (4a)

Word restaurant
Word \rightarrow Stem Suffix



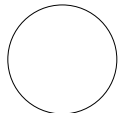
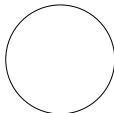
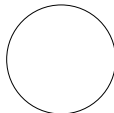
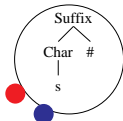
...

Stem restaurant
Stem \rightarrow #
Stem \rightarrow # Chars



...

Suffix restaurant
Suffix \rightarrow #
Suffix \rightarrow Chars #

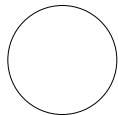
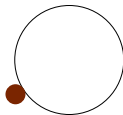
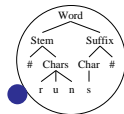
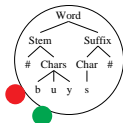


...

Chars factory
Chars \rightarrow Char
Chars \rightarrow Char Chars
Char \rightarrow a...z

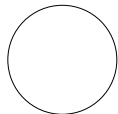
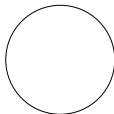
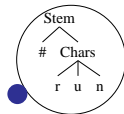
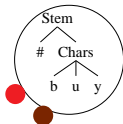
Morphology adaptor grammar (4b)

Word restaurant
Word \rightarrow Stem Suffix



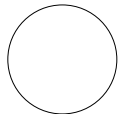
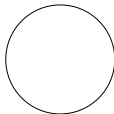
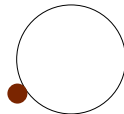
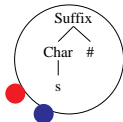
...

Stem restaurant
Stem \rightarrow #
Stem \rightarrow # Chars



...

Suffix restaurant
Suffix \rightarrow #
Suffix \rightarrow Chars #

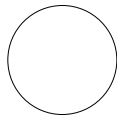
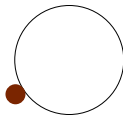
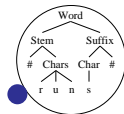
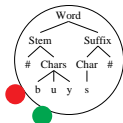


...

Chars factory
Chars \rightarrow Char
Chars \rightarrow Char Chars
Char \rightarrow a...z

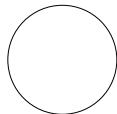
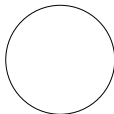
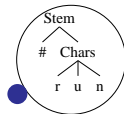
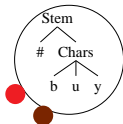
Morphology adaptor grammar (4c)

Word restaurant
Word \rightarrow Stem Suffix



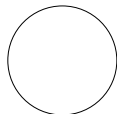
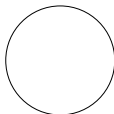
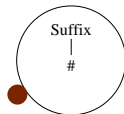
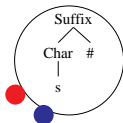
...

Stem restaurant
Stem \rightarrow #
Stem \rightarrow # Chars



...

Suffix restaurant
Suffix \rightarrow #
Suffix \rightarrow Chars #

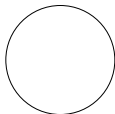
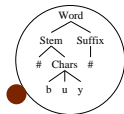
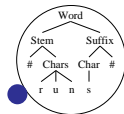
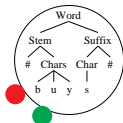


...

Chars factory
Chars \rightarrow Char
Chars \rightarrow Char Chars
Char \rightarrow a...z

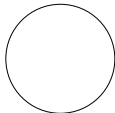
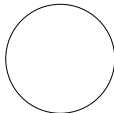
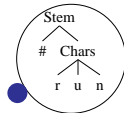
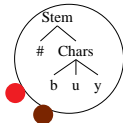
Morphology adaptor grammar (4d)

Word restaurant
Word \rightarrow Stem Suffix



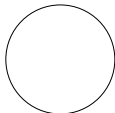
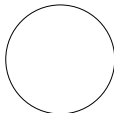
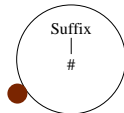
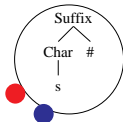
...

Stem restaurant
Stem \rightarrow #
Stem \rightarrow # Chars



...

Suffix restaurant
Suffix \rightarrow #
Suffix \rightarrow Chars #



...

Chars factory
Chars \rightarrow Char
Chars \rightarrow Char Chars
Char \rightarrow a...z

Estimating adaptor grammars

- ▶ Need to estimate:
 - ▶ table labels and customer count for each table
 - ▶ (optional) probabilities of productions labeling tables
- ▶ Component-wise Metropolis-Hastings sampler
 - ▶ i th component is the parse tree for input string i
 - ▶ re-parse input i using grammar estimated from parses for other inputs
- ▶ Sampling from conditional distribution of parses seems intractable
 - ▶ construct PCFG approximation on the fly
 - ▶ each table label corresponds to a production in PCFG approximation

Verbal morphology

Verb → Stem

Verb → Stem Suffix

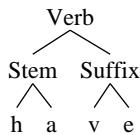
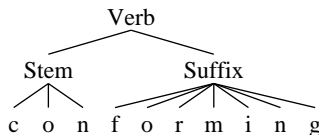
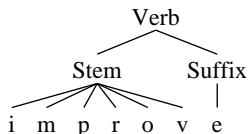
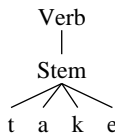
Stem → Chars

Suffix → Chars

Chars → Char

Chars → Char Chars

Char → a...z



- ▶ Restaurants for **Verb**, **Stem** and **Suffix**
- ▶ Given orthographic verb tokens from WSJ as input, 70% tokens, 66% types correctly segmented; many errors linguistically plausible
- ▶ Extends naturally to:
 - ▶ hidden word classes
 - ▶ agglutinative languages (with little phonology)

Unigram model of word segmentation

- ▶ Unigram model: each word is generated independently
- ▶ Input is *unsegmented broad phonemic transcription* (Brent)
Example: y u w a n t t u s i D 6 b u k
- ▶ CRP for **Word** non-terminal caches previously seen words

Words \rightarrow Word

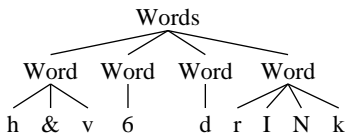
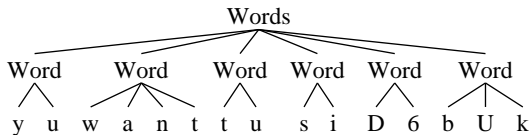
Words \rightarrow Word Words

Word \rightarrow Chars

Chars \rightarrow Char

Chars \rightarrow Char Chars

Char \rightarrow a | ... | z



- ▶ Unigram word segmentation on Brent corpus: 54% token f-score, 59% type f-score

Morphology and word segmentation

Words → Word

Words → Word Words

Word → Stem Suffix

Word → Stem

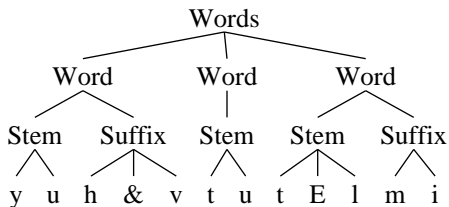
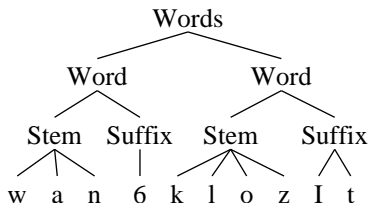
Stem → Chars

Suffix → Chars

Chars → Char

Chars → Char Chars

Char → a | ... | z



- ▶ CRPs for **Word**, **Stem** and **Suffix** terminals
- ▶ Doesn't do a good job of learning morphology

Outline

Introduction

Learning probabilistic context-free grammars

Morphological segmentation

Learning from types with Chinese restaurant processes

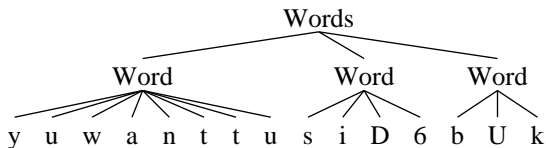
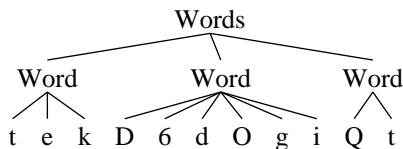
Adaptor grammars

Bigram dependencies in word segmentation

Conclusion

Unigram model often finds collocations

- ▶ Unigram word segmentation model assumes words are generated independently of context
- ▶ But there are strong inter-word dependencies (collocations) which the unigram model doesn't capture
- ▶ Unigram model tends to analyze collocations as words



Hierarchical CRP bigram word segmentation

- ▶ Bigram model: predict next word based on preceding word
- ▶ Each word w has a CRP BIGRAM_w to predict following word
 - ▶ Set of words is unknown, so CRPs constructed on the fly
- ▶ Each BIGRAM_w CRP shares same labeling distribution

UNIGRAM

- ▶ UNIGRAM is a CRP that generates a common vocabulary for all bigrams

$$\begin{array}{l|l} w_i & w_{i-1}, \text{BIGRAM}_{w_{i-1}} \\ \text{BIGRAM}_{w_{i-1}} & \alpha_2, \text{UNIGRAM} \\ \text{UNIGRAM} & \alpha_1, P_0 \end{array} \quad \begin{array}{l} \sim \text{BIGRAM}_{w_{i-1}} \\ \sim \text{DP}(\alpha_2, \text{UNIGRAM}) \\ \sim \text{DP}(\alpha_1, P_0) \end{array}$$

Bigram word segmentation model (0)

the book the book

UNIGRAM



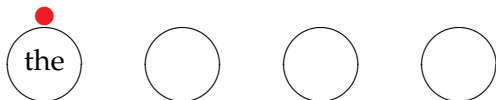
BIGRAM#



Bigram word segmentation model (1)

the book the book

UNIGRAM



BIGRAM_#

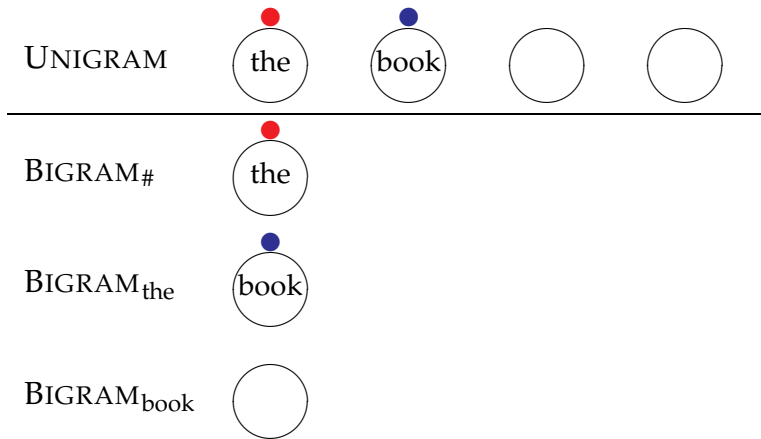


BIGRAM_{the}



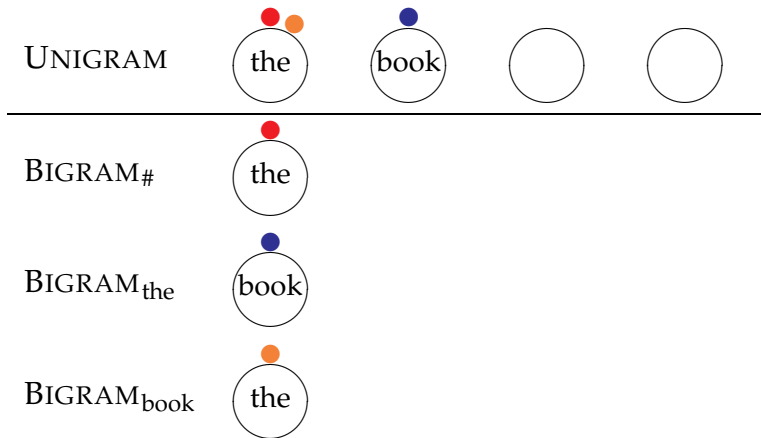
Bigram word segmentation model (2)

the **book** the book



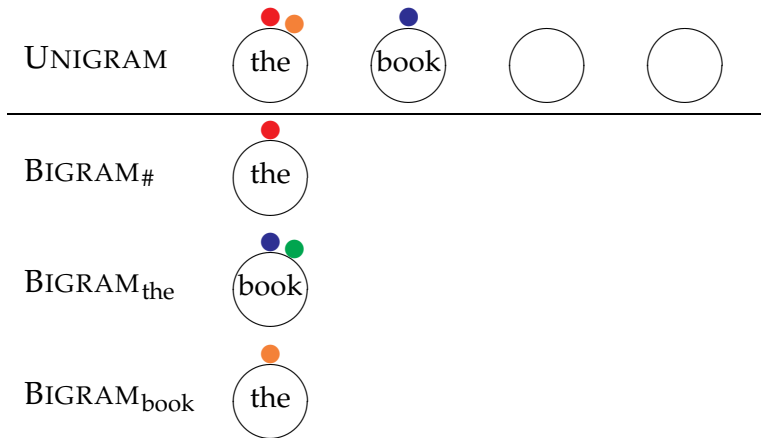
Bigram word segmentation model (3)

the book **the** book



Bigram word segmentation model (4)

the book the book



Bigram segmentation model

- ▶ Implemented using Gibbs sampling
 - ▶ i th component is “word boundary at position i ”
 - ▶ sampling amounts to possibly splitting a word at position i or joining the two words abutting at position i
 - ▶ Performs significantly better than unigram model
 - ▶ bigram: 77% token f-score, 63% type f-score
 - ▶ unigram: 54% token f-score, 59% type f-score
 - ▶ Number of CRPs is number of words, which is not known in advance
- ⇒ cannot be formulated as an adaptor grammar (which have a CRP per non-terminal)

Outline

Introduction

Learning probabilistic context-free grammars

Morphological segmentation

Learning from types with Chinese restaurant processes

Adaptor grammars

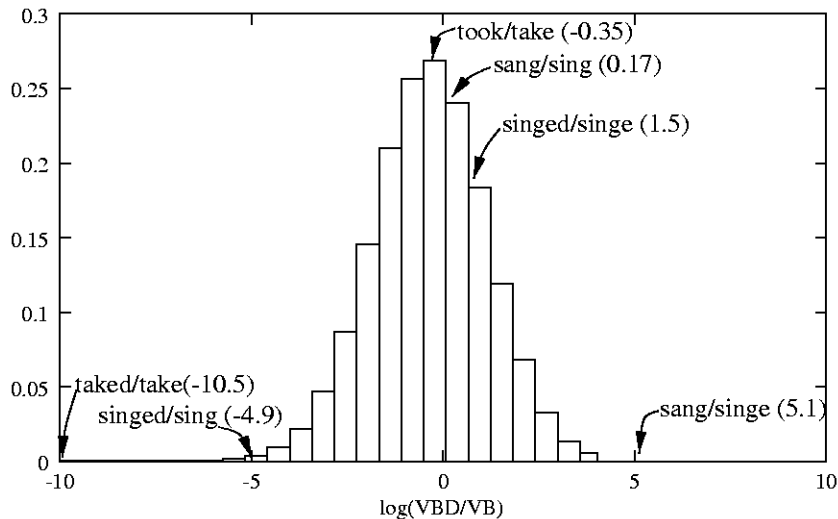
Bigram dependencies in word segmentation

Conclusion

Conclusion and future work

- ▶ Chinese restaurant process models can:
 - ▶ interpolate between types and tokens (morphology)
 - ▶ *learn the basic units of generalization* (morphology, word segmentation)
- ▶ Adaptor grammars can express many (but not all) hierarchical CRP models
 - ▶ General-purpose inference algorithm
 - ▶ Can model other tasks (e.g., hierarchical clustering)
- ▶ *Still a work in progress*
 - ▶ Is there a generalization of adaptor grammars that includes the bigram word segmentation model?
 - ▶ Difficult to select priors to get desired behavior
 - ▶ Gibbs sampler seems slow to converge with complex grammars and large data sets

Morpheme frequencies are useful



Yarowsky and Wicentowski (2000) "Minimally supervised Morphological Analysis by Multimodal Alignment"

From Chinese restaurants to Dirichlet processes

- ▶ Labeled Chinese restaurant processes take a base distribution P_G and return a stream of samples from a different distribution with the same support
- ▶ The Chinese restaurant process is a sequential process, generating the next item conditioned on the previous ones
- ▶ We can get a different distribution each time we run a CRP (placing customers on tables and labeling tables are random)
- ▶ Abstracting away from sequential generation, a CRP maps P_G to a *distribution over distributions* $DP(\alpha, P_G)$
- ▶ $DP(\alpha, P_G)$ is called a *Dirichlet process* with *concentration parameter* α and *base distribution* P_G
- ▶ Distributions in $DP(\alpha, P_G)$ are *discrete* (w.p. 1) even if the base distribution P_G is continuous

PCFGs as recursive mixtures

The distributions over strings induced by a PCFG in *Chomsky-normal form* (i.e., all productions are of the form $A \rightarrow BC$ or $A \rightarrow w$, where $A, B, C \in N$ and $w \in T$) is G_S where:

$$G_A = \sum_{A \rightarrow BC \in R_A} \theta_{A \rightarrow BC} G_B \bullet G_C + \sum_{A \rightarrow w \in R_A} \theta_{A \rightarrow w} \delta_w$$

$$(P \bullet Q)(z) = \sum_{xy=z} P(x)Q(y)$$

$$\delta_w(x) = 1 \text{ if } w = x \text{ and } 0 \text{ otherwise}$$

In fact, $G_A(x) = P(A \Rightarrow^* x | \theta)$, the sum of the probability of all trees with root node A and yield x

Adaptor grammars

An adaptor grammar (G, θ, α) is a PCFG (G, θ) together with a parameter vector α where for each $A \in N$, α_A is the parameter of the Dirichlet process associated with A .

$$G_A \sim \text{DP}(\alpha_A, H_A) \text{ if } \alpha_A > 0$$

$$= H_A \text{ if } \alpha_A = 0$$

$$H_A = \sum_{A \rightarrow BC \in R_A} \theta_{A \rightarrow BC} G_B \bullet G_C + \sum_{A \rightarrow w \in R_A} \theta_{A \rightarrow w} \delta_w$$

The probabilistic language defined by the grammar is G_S . There is one Dirichlet Process for each non-terminal A where $\alpha_A > 0$. Its base distribution H_A is a mixture of the language generated by the Dirichlet processes associated with other non-terminals.