Probabilistic estimation of probabilistic syntactic models

Joan Andreu Sánchez

Departamento Sistemas Informáticos y Computación
Instituto Tecnológico de Informática
Universidad Politécnica Valencia

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URL: http://www.dsic.upv.es/∼jandreu
e-mail: jandreu@dsic.upv.es

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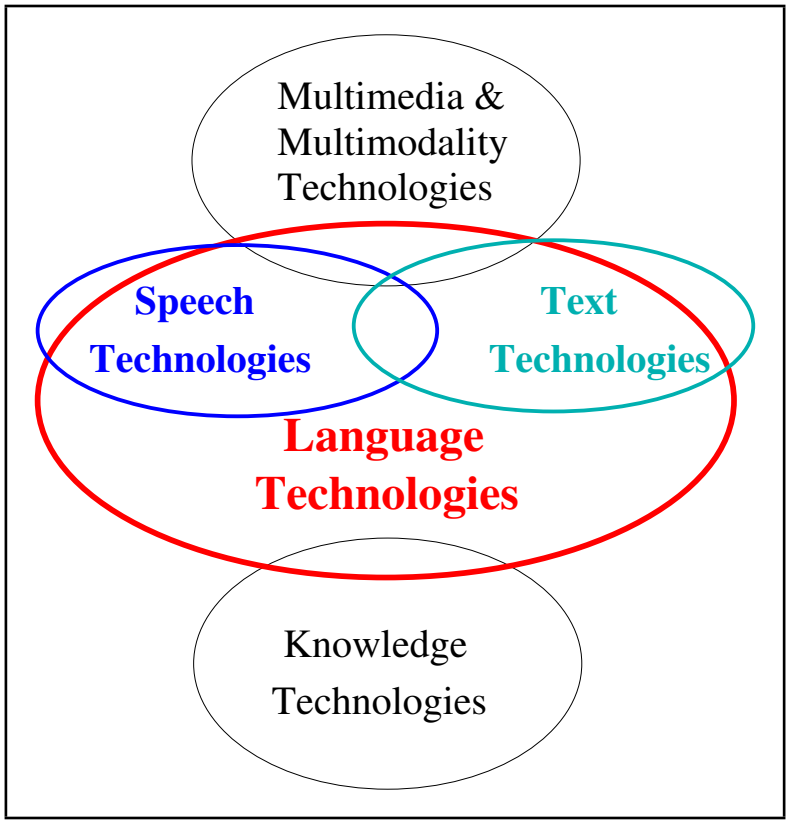
"Computational Linguistics" deals with the most difficult communication process: **Natural Language**



Goal:

To develop systems that are able to process, to understand and, to produce Natural Language

Motivation:

- Natural Language is the main way to represent and to transfer human knowledge
- There exist lots of information and knowledge in Natural Language
- There exist a lot of potential users that need to communicate with computers in Natural Language

Example:

`Dave Bowman:` Open the pod bay doors, HAL.

`HAL:` I'm sorry Dave. I'm afraid I can't do that.

Stanley Kubrick and Arthur C. Clarke, *2001: A Space Odyssey.*

Applications

- Systems for information extraction from text and speech

  Examples:

  information retrieval, information extraction, text categorization, ...

- Systems for speech/text to speech/text:

  Examples:

  machine translation, speech translation, speech recognition, ...

- Systems for communication with humans:

  Examples:

  dialog systems, query systems, ...

Probabilistic approach

- Interpretation by using the probabilistic decision rule

  `[ to generate a desired interpretation (output) ]`

- Modeling the human perception with Statistical Decision techniques and Formal Language theory

  `[ to define the statistical dependence between observations (input) and interpretation (output) ]`

- Learning knowledge from examples

  `[ to learn the model parameters from training examples ]`

Main goals of the course

- **To solve difficult problems related to Natural Language with syntactic approaches**

- To study fundamentals related to Computational Linguistics

- To learn basic techniques that are necessary to develop robust systems that are able to understand text data

Applications

- Automatic Speech Recognition
- Machine Translation
- Dialog Systems
- Automatic Summarization
- Text Classification
- Information Retrieval
- . . .

Abstract tasks

- *Language Modeling*
- Part of Speech Tagging
- *Parsing*
- Lexical Disambiguation
- Semantic Analysis
- Discourse Analysis
- . . .

Knowledge levels in Natural Language:

- Morphology: word structure
- Syntax:

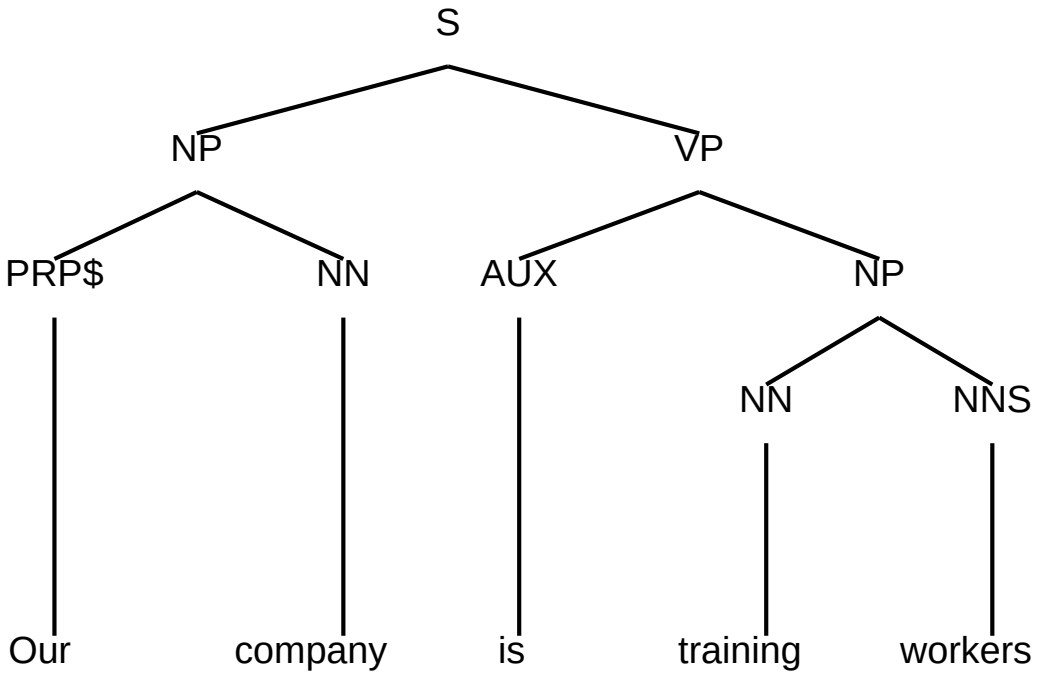
word category	–	Part of Speech tagging
sentence structure	–	*Parsing*

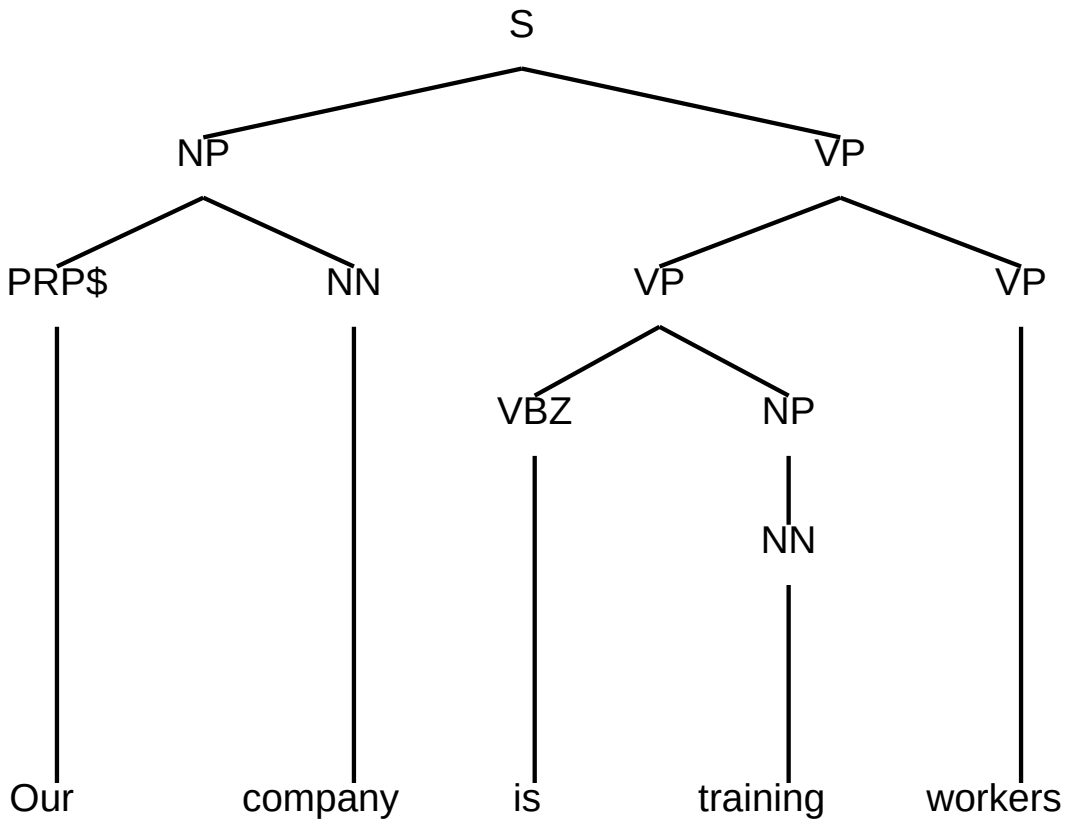
- Semantics:

word semantics
sentence semantics

- Pragmatics: use of the language, cultural issues, environment
- Discourse: dialog structure

Difficulties in Parsing: Ambiguity





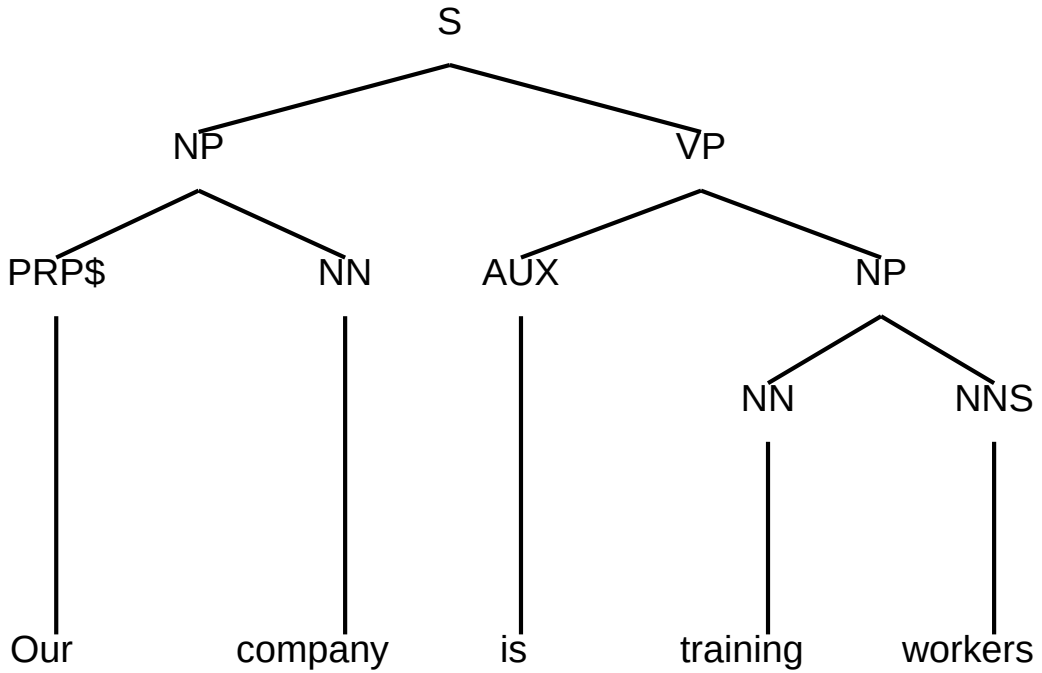
Parsing with syntactic models: (Formal) grammar

S	→	NP VP	PRP$	→	Our
NP	→	PRP$ NN	NN	→	company
NP	→	NN NNS	AUX	→	is
NP	→	NN	NN	→	training
VP	→	AUX NP	NNS	→	workers
VP	→	VP VP			
VP	→	VBZ NP			

Parsing with syntactic models: (Formal) grammar

1.0	S	→	NP VP
0.4	NP	→	PRP$ NN
0.3	NP	→	NN NNS
0.3	NP	→	NN
0.5	VP	→	AUX NP
0.3	VP	→	VP VP
0.2	VP	→	VBZ NP

1.0	PRP$	→	Our
0.6	NN	→	company
1.0	AUX	→	is
0.4	NN	→	training
1.0	NNS	→	workers

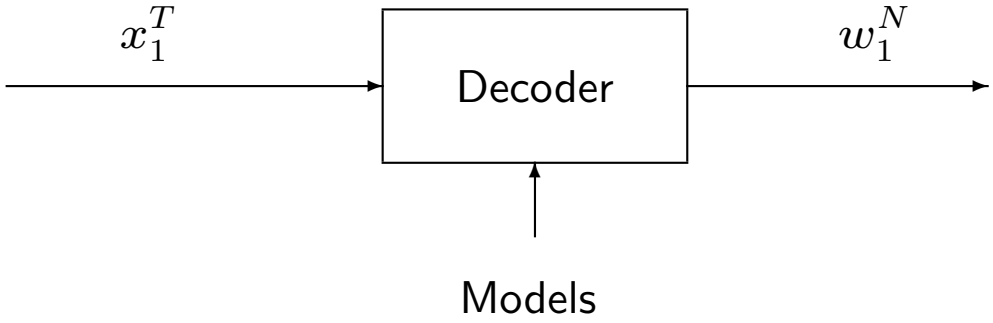


Recognition with noisy channel

$$\widehat{I} = \arg\max_{I} \Pr(I|O) = \arg\max_{I} \Pr(O|I)\Pr(I)$$

$\Pr(I)$: language model probability
$\Pr(O|I)$: channel probability

Automatic Speech Recognition



$$\widehat{w_1^N} = \arg\max_{w_1^N} \Pr(w_1^N|x_1^T) = \arg\max_{w_1^N} \Pr(x_1^T|w_1^N)\Pr(w_1^N)$$

Language Model

$$\Pr(w_1^N) = \Pr(w_1)\prod_{n=2}^{N}\Pr(w_n|w_1^{n-1})$$

➢ **N-Gram models:** Restriction on the history length w_1^{n-1}

$$\Pr(w_1^N) = \Pr(w_1) \prod_{n=2}^{N} \Pr(w_n | w_{n-k+1}^{n-1})$$

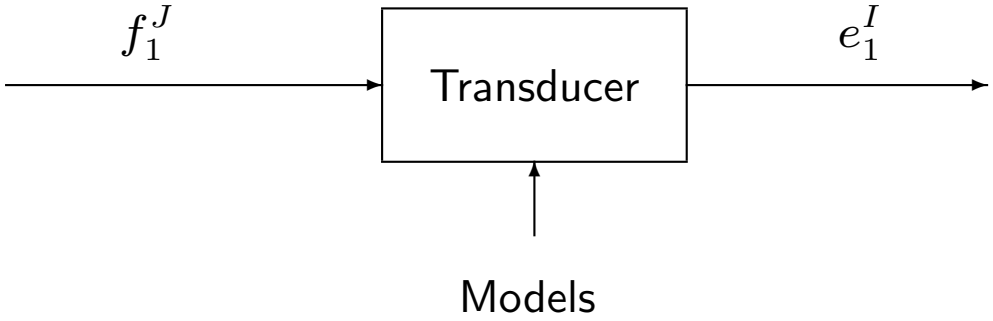
- ✗ don't capture long-term dependencies
- ✔ efficient to compute
- ✔ efficient methods to estimate the model parameters

➢ **Grammatical models:** No restriction on the history length w_1^{n-1}

$$\Pr(w_1^N) = \Pr(w_1) \prod_{n=2}^{N} \Pr(w_n | w_1^{n-1})$$

- ✔ capture long-term dependencies
- ✗ expensive to compute
- ✗ efficient methods to estimate the model parameters, but expensive

Machine Translation



- Inverse approach (noisy channel)

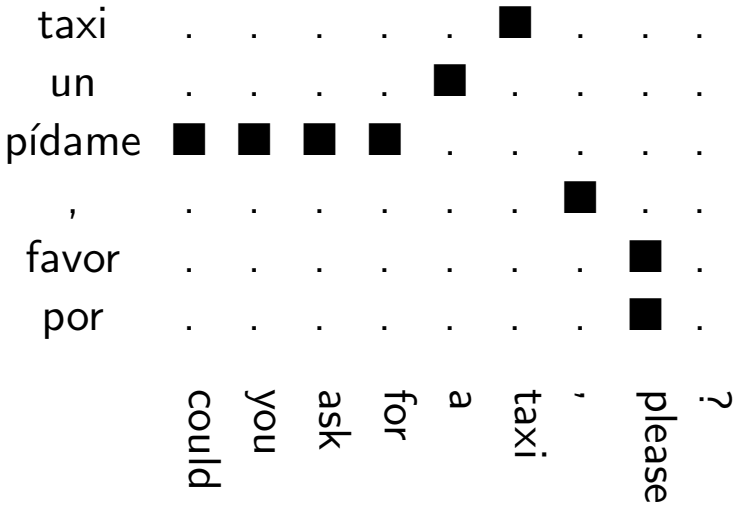
$$\widehat{e_1^I} = \arg\max_{e_1^I} \Pr(e_1^I|f_1^J) = \arg\max_{e_1^I} \Pr(f_1^J|e_1^I)\Pr(e_1^I)$$

- Direct approach

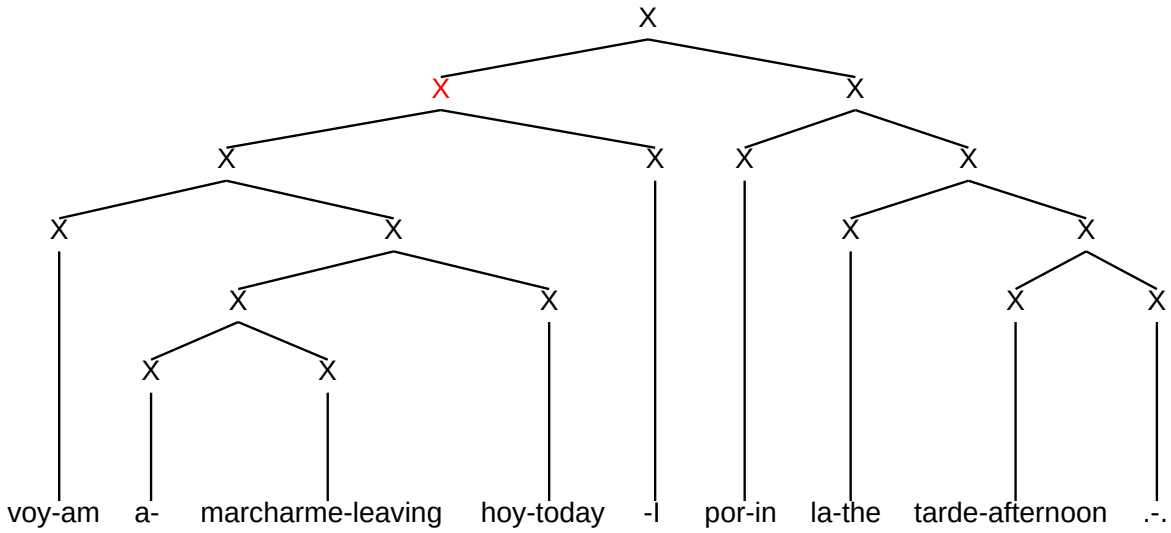
$$\widehat{e_1^I} = \arg\max_{e_1^I} \Pr(e_1^I|f_1^J)$$

Statistical approaches to MT:

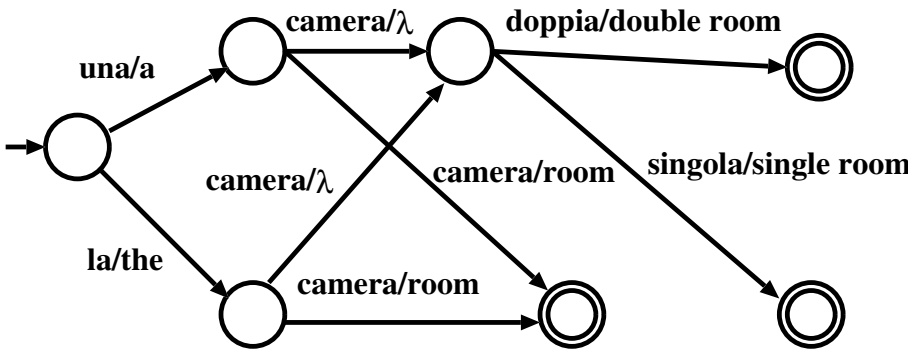
➔ Word-alignment approaches



➔ Syntactic approaches



➔ Finite-state approaches



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Context-free grammar: [Aho,72]

- Simple and compact models for parsing
- Formal framework well understood
- Natural Language is no regular (but almost)
- Adequate representation of long-term syntactic structures
- Adequate modeling of ambiguity

Example

- Primitives: alphabet

  words, punctuation symbols, . . .

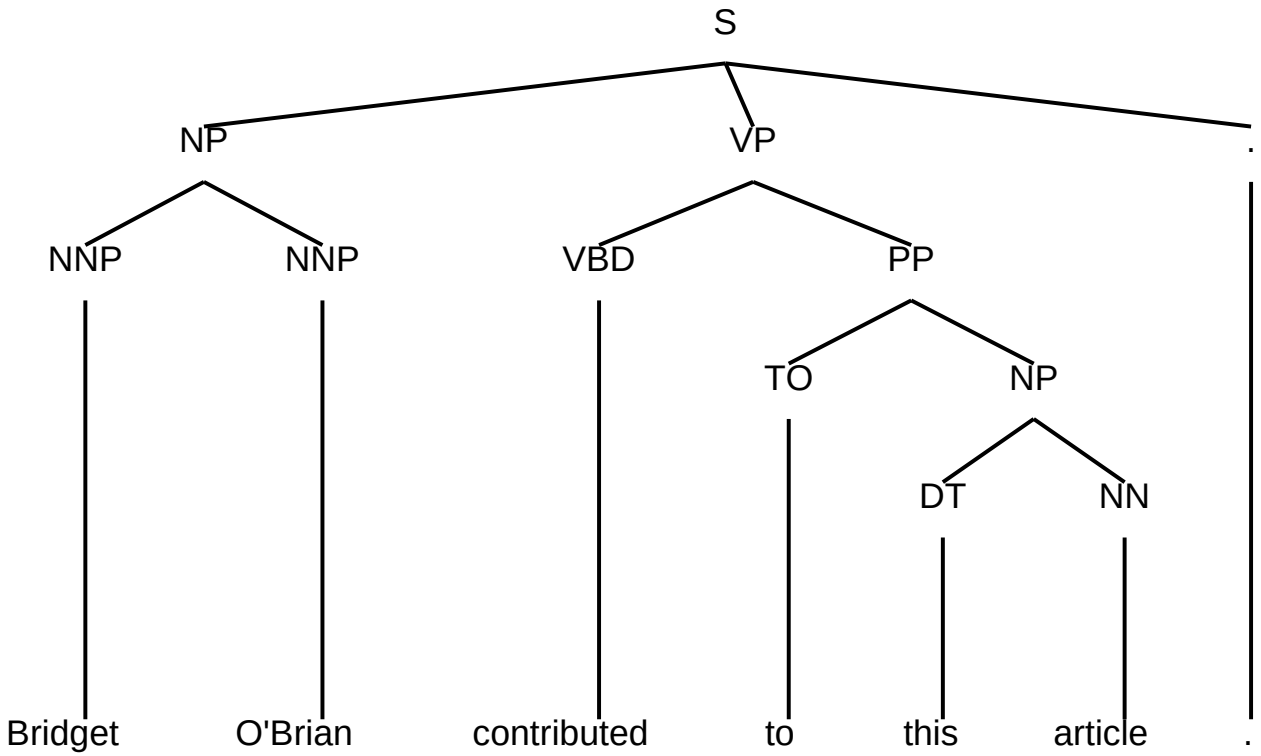
- Object representation: written sentences

  "Bridget O'Brian contributed to this article"

- Pattern set

  sentences

- Interpretation: syntactic analysis



- An **alphabet** T is a finite set of symbols.
- A **string** $x = a_1 \cdots a_n \ \ (a_i \in T; i : 1 \ldots n)$, is a finite sequence of symbols of T. The length of the string is noted by $|x|$. Let x and y be two strings, $x, y \in T^*$, then the **concatenation** of x and y is the string xy. $|xy| = |x| + |y|$.
- The **empty string** ϵ, is the string with length equal to zero. For any string x, $x \in T^*$: $\epsilon x = x\epsilon = x$.
- The **closure** T^* is the infinite and countable set of all strings with finite length composed with symbols of T, ϵ included. The **positive closure** T^+ is defined as: $T^+ = T^* - \{\epsilon\}$.
- A **language** L is a set of strings composed with symbols of T $(L \subseteq T^*)$.

- **Grammar:** $G = (N, T, P, S)$

  $V = N \cup T;\ N \cap T = \emptyset;\ S \in N;\quad (A \to \beta) \in P;\qquad A \in N; \beta \in V^*$

- **Derivation**:

  $$\mu A \delta \Longrightarrow \mu \beta \delta \text{ iff } \exists (A \to \beta) \in P; \qquad \mu, \delta \in V^*$$

- **Sentential Form**:

  $$\alpha \in V^* \text{ is a } \textit{sentential form} \text{ of } G \text{ if } S \overset{*}{\Longrightarrow} \alpha$$

- **Language generated by** G:

  $$L(G) = \{x \in T^* \mid S \overset{*}{\Longrightarrow} x\}$$

- **Grammar classification**:

  - **Type 2**: *context free grammars*

    $A \to \beta \qquad A \in N; \beta \in V^*$

  - **Type 3**: *regular grammars*

    $A \to aB, \quad A \to a \qquad A, B \in N; a \in T$

Approaches

- Top-Down parsing
- Down-Top parsing

Depending on time complexity

- Backtracking methods — `Exponential complexity`
- Deterministic methods — `Linear complexity`

  Grammars: LL(1), SLR(1), LALR(1), LR(1), ...

- Tabular methods — `Cubic complexity`

  CKY algorithm
  Earley algorithm [Aho 72, Stolcke 95]

ALGORITHM: Cocke-Kasami-Younger

Input $G = (N, T, P, S)$ in CNF and **x** $= x_1 \dots x_n \in T^*$

Output Parsing table $t[i, l] \quad (1 \leq i, l \leq n)$

$A \in t[i, l]$ if $A \overset{*}{\Longrightarrow} x_{i+1} \dots x_l$

METHOD

for all $i : \ 0 \dots n-1$ **do**

$$t[i, i+1] := t[i, i+1] \ \cup \ \{A \mid (A \to b) \in P; \ \ b = x_{i+1}\}$$

for all $j : \ 2 \dots n$ **do**

for all $i : \ 0 \dots n-j$ **do**

for all $k : \ 1 \dots j-1$ **do**

$$t[i, i+j] := t[i, i+j] \ \cup \ \{A \mid (A \to BC) \in P;$$

$$B \in t[i, i+k]; \ \ C \in t[i+k, i+j]\}$$

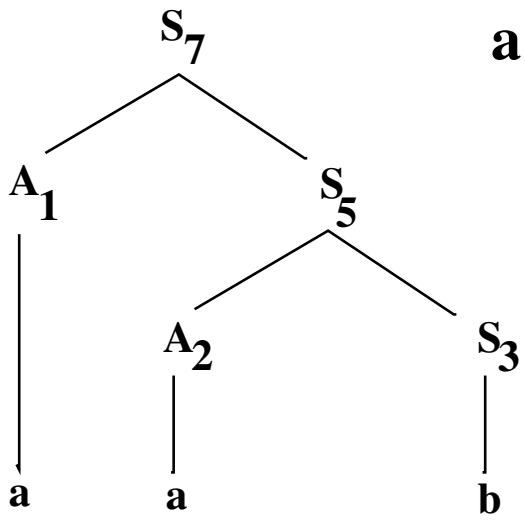
if $S \in t[0, n]$ **then** $x \in L(G)$ **else** $x \notin L(G)$

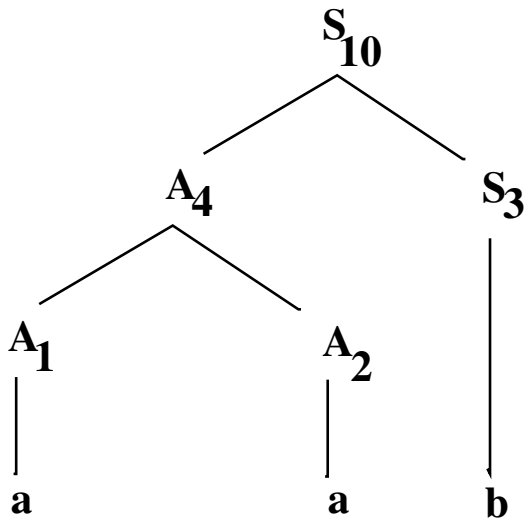
END

S --> A S
S --> b
A --> A S
A --> A A
A --> a

	l = 1	l = 2	l = 3	
i = 0	1: (A, 0, 0)	4: (A, 1, 2)	7: (S, 1, 5) 8: (A, 1, 5) 9: (A, 1, 6) 10: (S, 4, 3) 11: (A, 4, 3)	
i = 1		2: (A, 0, 0)	5: (S, 2, 3) 6: (A, 2, 3)	
i = 2			3: (S, 0, 0)	

a a b





Let $x \in T^*$ and a stochastic model M characterized by a parameter vector θ, we are interested in computing: $p_\theta(x)$

Stochastic language (L, ϕ) over T [Wetherell 80]:

- $L \subseteq T^*$ characteristic language
- $\phi : T^* \longrightarrow [0, 1]$ computable stochastic function:

i) $x \notin L \Longrightarrow \phi(x) = 0 \qquad \forall x \in T^*$
ii) $x \in L \Longrightarrow 0 < \phi(x) \leq 1 \qquad \forall x \in T^*$
iii) $\sum_{x \in L} \phi(x) = 1$

Example [Booth 73]

Given the alphabet $T = \{a, b\}$, the following language is defined: $L = \{a^n b^n \mid n \geq 0\}$, where $\phi(x) = 0$, $\forall x \notin L$ and $\phi(a^n b^n) = \frac{1}{en!}$

$$\sum_{x \in L} \phi(x) = \sum_{0 \leq n \leq \infty} \frac{1}{en!} = \frac{1}{e} \sum_{0 \leq n \leq \infty} \frac{1}{n!} = \frac{1}{e} e = 1$$

Probabilistic context-free grammar: $G_s = (G, p)$

- $G = (N, T, P, S)$ characteristic grammar
- $p : P \rightarrow]0, 1]$ probability of the rules. $\forall A_i \in N$:

$$\sum_{1 \leq j \leq n_i} p(A_i \rightarrow \alpha_j) = 1,$$

where n_i is the number of rules with A_i in the left side of the rules.

Stochastic derivation for PCFG

Given a sequence of stochastic events:

$$S = \alpha_0 \overset{r_1}{\Rightarrow} \alpha_1 \overset{r_2}{\Rightarrow} \alpha_2 \cdots \alpha_{m-1} \overset{r_m}{\Rightarrow} \alpha_m = x$$

the probability of x being generated by $G_s = (G, p)$ from the rule sequence $d_x = r_1, \ldots, r_m$, is:

$$\Pr_{G_s}(x, d_x) = p(r_1)p(r_2 \mid r_1) \cdots p(r_m \mid r_1 \cdots r_{m-1})$$

- **problem**: computation of the probabilities

- **restriction**: $p(r_j \mid r_1 \cdots r_{j-1}) = p(r_j)$

$$\Pr_{G_s}(x, d_x) = \prod_{j=1 \cdots m} p(r_j)$$

Probability of a derivation $d_x = r_1, \ldots, r_m$

$$\Pr_{G_s}(x, d_x) = \prod_{j=1 \cdots m} p(r_j) = \prod_{\forall (A \to \alpha) \in P} p(A \to \alpha)^{\mathrm{N}(A \to \alpha, d_x)}$$

Probability of a string

$$\Pr_{G_s}(x) = \sum_{d_x \in D_x} \Pr_{G_s}(x, d_x)$$

Probability of the best derivation

$$\widehat{\Pr}_{G_s}(x) = \max_{d_x \in D_x} \Pr_{G_s}(x, d_x)$$

Probability of a string with a subset of derivations $\Delta_x \subseteq D_x$

$$\Pr_{G_s}(x, \Delta_x) = \sum_{d_x \in \Delta_x} \Pr_{G_s}(x, d_x)$$

Language generated by a PCFG

$$L(G_s) = \{x \in L(G) \mid \Pr_{G_s}(x) > 0\}$$

Consistent grammar

A PCFG $G_s = (G, p)$ is consistent iff:

$$\sum_{x \in L(G)} \Pr_{G_s}(x) = 1$$

Theorem [Booth 73]

There exist stochastic languages (L, ϕ) that can not be generated by a stochastic grammar $G_s = (G, p)$

Dem. outline Let $L = \{a^n b^n \mid n \geq 0\}$ be a stochastic language:

$$\phi(a^n b^n) = \frac{1}{en!}$$

There is not any G_s such that $\phi(x) = \Pr_{G_s}(x) \quad \forall x \in L$

Inside algorithm for PCFG [Lari 90]

- Given $x = x_1 \dots x_n \in T^*$ and $A \in N$

$$e(A < i, l >) = \Pr_{G_s}(A \stackrel{*}{\Rightarrow} x_i \dots x_l)$$

- Compute $\forall A \in N$:

$$e(A < i, i >) = p(A \to b)\ \delta(b, x_i) \qquad 1 \leq i \leq n$$

$$e(A < i, j >) = \sum_{B,C \in N} p(A \to BC) \sum_{k=i}^{j-1} e(B < i, k >)\ e(C < k+1, j >)$$

$$1 \leq i < j \leq n$$

- $\Pr_{G_s}(x) = e(S < 1, n >)$
- Time complexity: $O(|x|^3 |P|)$

Inside algorithm for PCFG (bracketed version [Pereira 92])

- Bracketed sentence:

  (((Pierre Vinken) , ((61 years) old) ,) (will (join (the board) (as (a nonexecutive director)) (Nov. 29.))) .)

$$c(i,j) = \begin{cases} 1 & \text{if } (i,j) \text{ does not overlap any span in the sentence,} \\ 0 & \text{otherwise.} \end{cases}$$

- Compute $\forall A \in N$:

$$e(A < i, i >) = p(A \rightarrow b)\ \delta(b, x_i) \qquad 1 \leq i \leq n$$

$$e(A < i, j >) = c(i,j) \sum_{B,C \in N} p(A \rightarrow BC) \sum_{k=i}^{j-1} e(B < i, k >)\ e(C < k+1, j >)$$

$$1 \leq i < j \leq n$$

- Linear if full bracketing

Viterbi algorithm for PCFG [Ney 91]

- Given $x = x_1 \dots x_n \in T^*$ and $A \in N$

$$\widehat{e}(A < i, l >) = \widehat{\Pr}_{G_s}(A \stackrel{*}{\Rightarrow} x_i \dots x_l)$$

- Compute $\forall A \in N$:

$$\begin{aligned} \widehat{e}(A < i, i >) &= p(A \to b)\ \delta(b, x_i) && 0 \leq i \leq n \\ \widehat{e}(A < i, j >) &= \max_{B,C \in N} p(A \to BC) \max_{k=i,\dots,j-1} \widehat{e}(B < i, k >)\widehat{e}(C < k+1, j >) \\ & && 1 \leq i < j \leq n \end{aligned}$$

- $\widehat{\Pr}_{G_s}(x) = \widehat{e}(S < 1, n >)$
- Time complexity: $O(|x|^3|P|)$ (Bracketed version: linear if full bracketing)

Outside algorithm for PCFG

- Given $x = x_1 \dots x_n \in T^*$ and $A \in N$

$$f(A < i, l >) = \Pr_{G_s}(S \overset{*}{\Rightarrow} x_1 \dots x_{i-1}\ A\ x_{l+1} \dots x_n)$$

- Compute $\forall A \in N$:

$$\begin{aligned} f(A < 1, n >) &= \delta(A, S) \\ f(A < i, j >) &= \sum_{B,C \in N} p(B \to CA) \sum_{k=1}^{i-1} f(B < k, j >)\ e(C < k, i-1 >) \\ &+ \sum_{B,C \in N} p(B \to AC) \sum_{k=j+1}^{n} f(B < i, k >)\ e(C < j+1, k >) \end{aligned}$$

$$1 \le i \le j \le n$$

- $\Pr_{G_s}(x) = \sum_{A \in N} f(A < i, i >)\ p(A \to x_i),$ $1 \le i \le n$
- Time complexity: $O(|x|^3 |P|)$ (Bracketed version: linear if full bracketing)

Probability of an initial substring: LRI algorithm

$$T(A \Rightarrow B) = \sum_{\alpha} \Pr_{G_s}(A \overset{*}{\Rightarrow} B\alpha)$$

$$T(A \Rightarrow BC) = p(A \rightarrow BC) + \sum_{D} T(A \Rightarrow D)p(D \rightarrow BC)$$

- Given $x = x_1 \dots x_n \in T^*$ and $A \in N$

$$e(A \ll i, l) = \Pr_{G_s}(A \overset{*}{\Rightarrow} x_i \dots x_l \dots)$$

- Compute $\forall A \in N$:

$$e(A \ll i, i) = p(A \rightarrow x_i) + \sum_{D} T(A \Rightarrow D)\, p(D \rightarrow x_i) \qquad 1 \leq i \leq n$$

$$e(A \ll i, j) = \sum_{B,C \in N} T(A \Rightarrow BC) \sum_{k=i}^{j-1} e(B < i, k >)\, e(C \ll k+1, j) \qquad 1 \leq i < j$$

- $\Pr_{G_e}(x_1 \dots x_k \dots) = e(S \ll 1, k)$
- Time complexity: $O(|x|^3|P|)$

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➢ Supervised methods

- ➢ Maximum likelihood estimation

$$\widehat{\Pr}(A \to \alpha) = \frac{C(A \to \alpha)}{C(A)}$$

- ➢ Annotated data is needed ("treebank")

➢ Non-supervised methods

- ➢ EM algorithms
- ➢ Problem: local optimum

Let G_s a PCFG with parameters θ and a sample $\Omega = \{x_1, x_2, \ldots, x_n\}$.

$$\hat{\theta} = \arg\max_{\theta} F_\theta(\Omega)$$

- Optimization method
  - Growth transformations
- Optimization function
  - **Maximum likelihood**
  - Corrective training
  - Maximum mutual information

Theorem [Baum 72]

Let $P(\Theta)$ be a homogeneous polynomial with non-negative coefficients. Let $\theta = \{\theta_{ij}\}$ be a point in the domain $D = \{\theta_{ij} \mid \theta_{ij} \geq 0; \sum_{j=1}^{q_i} \theta_{ij} = 1,\ i = 1, \ldots, p; \quad j = 1, \ldots, q_i\}$, and let $Q(\theta)$ be a close transformation in D, that is defined as:

$$Q(\theta)_{ij} = \frac{\theta_{ij}(\partial P/\partial \Theta_{ij})_\theta}{\sum_{k=1}^{q_i} \theta_{ik}(\partial P/\partial \Theta_{ik})_\theta}$$

with the denominator different from zero. Then, $P(Q(\theta)) > P(\theta)$ except if $Q(\theta) = \theta$.

input $P(\Theta)$
$\theta =$ initial values
repeat
    compute $Q(\theta)$ using $P(\Theta)$
    $\theta = Q(\theta)$
until convergence
output θ

Let a PCFG G_s, a sample Ω and a set of derivations Δ_x for each $x \in \Omega$

$$\Pr_{G_s}(\Omega, \Delta_\Omega) = \prod_{x \in \Omega} \Pr_{G_s}(x, \Delta_x)$$

$\forall (A \rightarrow \alpha) \in P$ (See demonstration [Benedí 05])

$$\overline{p}(A \rightarrow \alpha) = \frac{\sum_{x \in \Omega} \frac{1}{\Pr_{G_s}(x, \Delta_x)} \sum_{\forall d_x \in \Delta_x} \mathrm{N}(A \rightarrow \alpha, d_x) \Pr_{G_s}(x, d_x)}{\sum_{x \in \Omega} \frac{1}{\Pr_{G_s}(x, \Delta_x)} \sum_{\forall d_x \in \Delta_x} \mathrm{N}(A, d_x) \Pr_{G_s}(x, d_x)}$$

Optimization function ($\Delta_x = D_x$)

$$\Pr_{G_s}(\Omega) = \prod_{x \in \Omega} \Pr_{G_s}(x)$$

➢ $\forall (A \rightarrow BC) \in P$; y $\forall (A \rightarrow b) \in P$ (See demonstration)

$$\overline{p}(A \rightarrow BC) = \frac{\sum_{x \in \Omega} \frac{p(A \rightarrow BC)}{\Pr_{G_s}(x)} \sum_{i=0}^{n-j} \sum_{j=2}^{n} \sum_{k=1}^{j-1} f(A < i, i+j >) e(B < i, i+k >) e(C < i+k, i+j >)}{\sum_{x \in \Omega} \frac{1}{\Pr_{G_s}(x)} \sum_{i=0}^{n-j} \sum_{j=1}^{n} f(A < i, i+j >) e(A < i, i+j >)}$$

$$\overline{p}(A \rightarrow b) = \frac{\sum_{x \in \Omega} \frac{1}{\Pr_{G_s}(x)} \sum_{i=0,\ b=x_i}^{n-1} f(A < i, i >) p(A \rightarrow b)}{\sum_{x \in \Omega} \frac{1}{\Pr_{G_s}(x)} \sum_{i=0}^{n-j} \sum_{j=1}^{n} f(A < i, i+j >) e(A < i, i+j >)}$$

➢ Time complexity: $O(|LT|^3 |P|)$

Optimization function ($\Delta_x = \widehat{d}_x$) [Benedí 05]

$$\Pr_{G_s}(\widehat{\Omega}) = \prod_{x \in \Omega} \Pr_{G_s}(x, \widehat{d}_x)$$

- $\forall (A \to \alpha) \in P$

$$\overline{p}(A \to \alpha) = \frac{\sum_{x \in \Omega} \mathrm{N}(A \to \alpha, \widehat{d}_x)}{\sum_{x \in \Omega} \mathrm{N}(A, \widehat{d}_x)}.$$

- Time complexity: $O(|LT|^3 |P|)$

1. Carrying out the maximazitaion $G_s^{(i)}$:

$$\widehat{D}_x^{(i)} = \{\widehat{d}_x^{(i)} : \widehat{d}_x^{(i)} = \arg \max_{d_x \in D_x} \Pr_{G_s^{(i)}}(x, d_x)\}$$

2. Aplying the transformation: $G_s^{(i+1)}$.

The function to be optimized is defined after step 1. This function is continous and differentiable:

$$\prod_{x \in \Omega} \Pr_{G_s^{(i)}}(x, \widehat{d}_x^{(i)}) \leq \prod_{x \in \Omega} \Pr_{G_s^{(i+1)}}(x, \widehat{d}_x^{(i)})$$

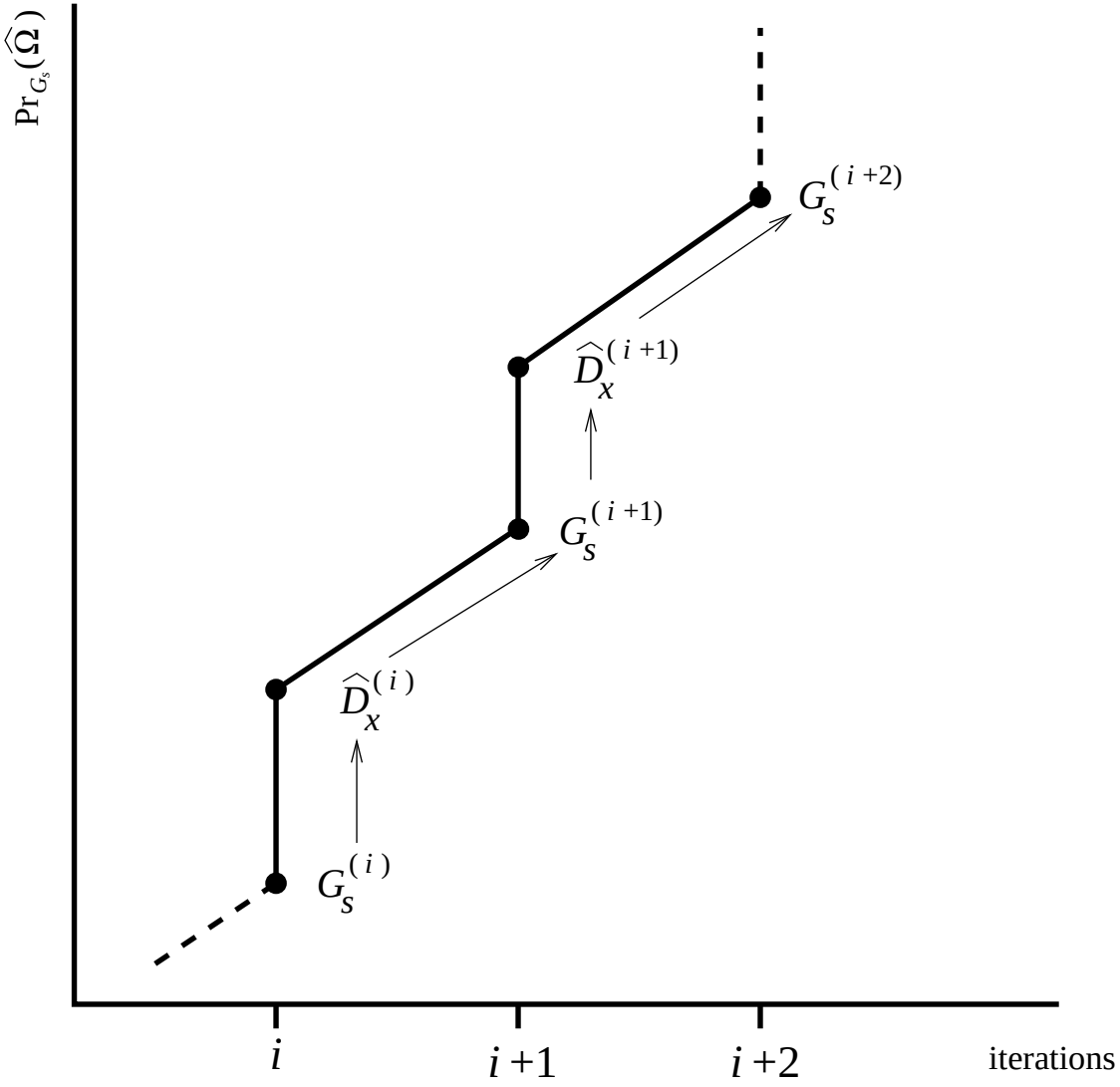
In the next step $i+1$, the most probable tree $\widehat{D}_x^{(i+1)}$ is computed for each string x with $G_s^{(i+1)}$, and therefore:

$$\Pr_{G_s^{(i+1)}}(x, \widehat{d}_x^{(i)}) \leq \Pr_{G_s^{(i+1)}}(x, \widehat{d}_x^{(i+1)}) \quad \forall x \in \Omega,$$

and hence

$$\prod_{x \in \Omega} \Pr_{G_s^{(i+1)}}(x, \widehat{d}_x^{(i)}) \leq \prod_{x \in \Omega} \Pr_{G_s^{(i+1)}}(x, \widehat{d}_x^{(i+1)})$$

3.3 Viterbi algorithm



Theorem [Booth 73] A PCFG is consistent if $\rho(E) < 1$, where $\rho(E)$ is the spectral radius (absolute value of the largest eigenvalue) of matrix E.

Probabilistic expectation matrix: $E = (e_{ij})$, expected number of times that the non-terminal A_j is derived directly from A_i:

$$e_{ij} = \sum_{(A_i \to \alpha)} p(A_i \to \alpha) \mathrm{N}(A_j, \alpha) \qquad 1 \leq i, j \leq |N|$$

Expectation matrix

$Q = \sum_{i=0}^{\infty} E^i$. If G_s is consistent, then the sum converges to: $Q = (I - E)^{-1}$

Theorem [Sánchez 97] Let $G_s = (G, p)$ be a PCFG and let Ω be a sample from $L(G)$. If $\overline{G}_s = (G, \overline{p})$ is a PCFG obtained from G_s when applying the previous growth transformation, the $\overline{G}_s$ is consistent.

Palindrome language

$$\{\, ww^R \mid w \in \{a,b\}^+;\ R = \text{ reverse string}\}$$

- Original model

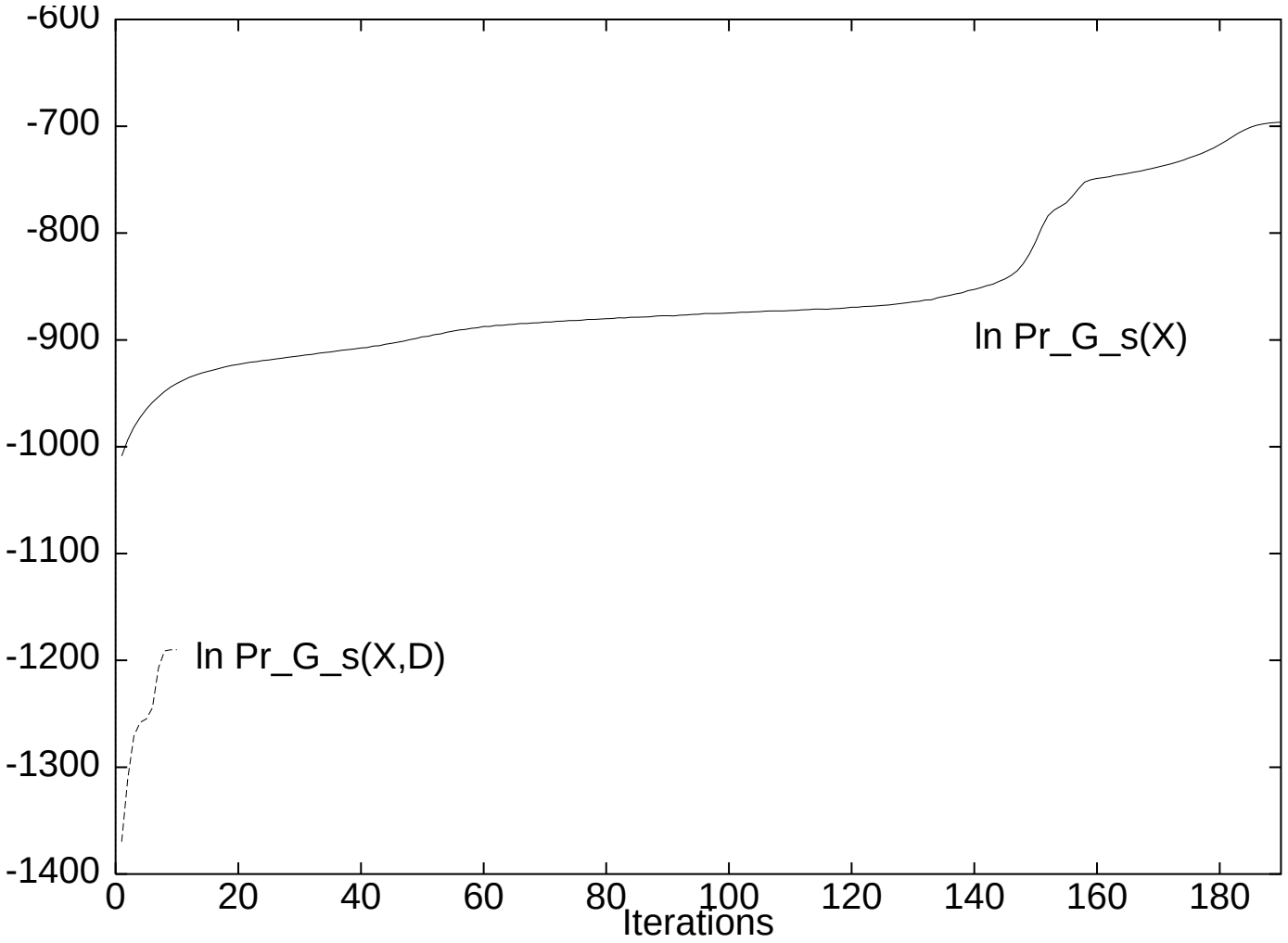
$S \to AC\ 0.4$	$S \to BB\ 0.1$	$C \to SA\ 1.0$	$A \to a\ 1.0$
$S \to BD\ 0.4$	$S \to AA\ 0.1$	$D \to SB\ 1.0$	$B \to b\ 1.0$

- Training set: 1000 strings

- Initial model to be estimated
  - 5 non-terminals and 2 terminals $\Rightarrow 130$ rules
  - Random probabilities attached to the rules

Algorithm	kld	Palindromes (%)	Non palindromes (%)
VS	6.00	1.9	98.1
IO	1.88	76.0	24.0

Functions optimized by IO algorithm and Viterbi algorithm

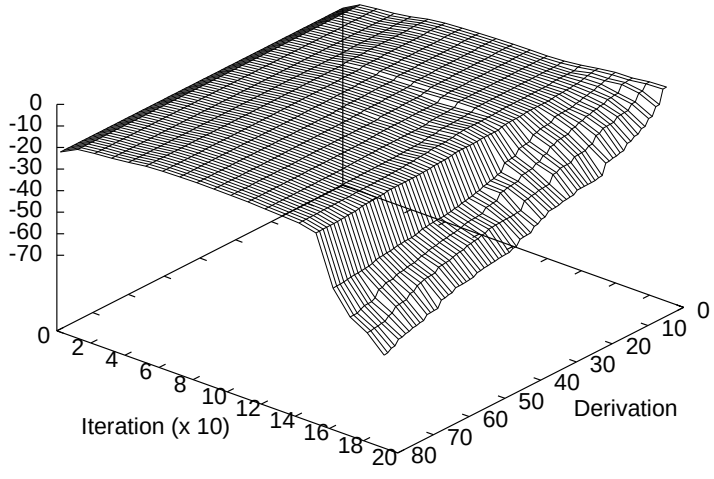


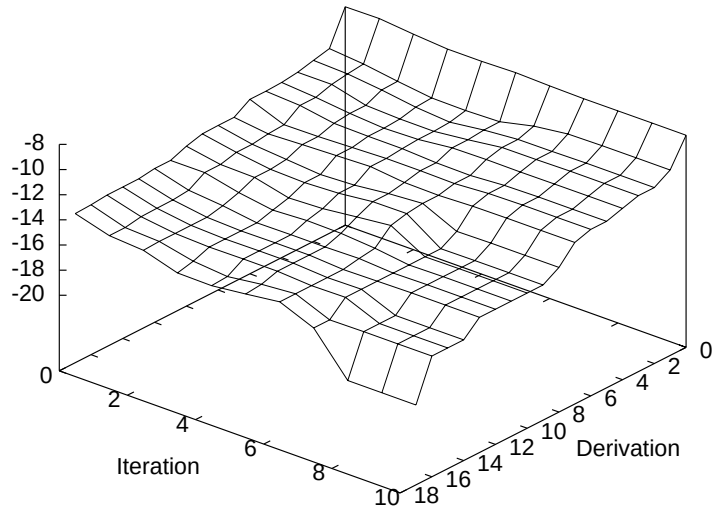
Accumulated probability mass

	IO	
iteration	apm	5bd
0	0.002	50.0%
340	0.724	97.4%

	VS	
iteration	apm	5bd
0	0.002	50.0%
10	0.024	95.7%

Evolution of the probability of a string





Combination of N-Grams and PCFG for LM [Benedi 05]

$$\Pr(w) = \Pr(w_1 \dots w_n) = \prod_{k=1}^{n} \Pr(w_k | w_1 \dots w_{k-1})$$

$$\Pr(w) = \prod_{k=1}^{n} \Pr(w_k | w_{k-n+1} \dots w_{k-1})$$

$$\boxed{\Pr(w_k | w_1 \dots w_{k-1}) = \alpha \Pr_N(w_k | w_{k-n+1} \dots w_{k-1}) + (1-\alpha) \Pr_{M_s}(w_k | w_1 \dots w_{k-1})}$$

- M_s: a PCFG G_c of categories (PoS tags) and a word-category distribution C_w

$$\Pr_{G_c, C_w}(w_k | w_1 \dots w_{k-1})$$

Model estimation

- Word N-Gram
- word-category distribution: C_w

$$C_w = \Pr(w|c) = \frac{\mathrm{N}(w,c)}{\sum_{w'} \mathrm{N}(w',c)}$$

- PCFG of categories: G_c
  - (partially) unsupervised models: **IOb** and **VSb**
  - supervised models: **"tree-bank grammars"**

Probability of the following word

$$Pr_{G_c,C_w}(w_k|w_1 \dots w_{k-1}) = \frac{\Pr_{G_c,C_w}(w_1 \dots w_k \dots)}{\Pr_{G_c,C_w}(w_1 \dots w_{k-1} \dots)}$$

- Prefix probability from G_c, C_w

$$\Pr_{G_c,C_w}(w_1 \dots w_k \dots)$$

3.5 Use of PCFG for LM

- Definition:

$$e(A \ll i, l)) = \Pr_{G_c, C_w}(A \stackrel{*}{\Rightarrow} w_{i+1} \dots w_l \dots)$$

- Recursion:

$$e(A \ll i, i+j) = \sum_{B,C \in N} T(A \Rightarrow BC) \sum_{k=1}^{j-1} e(B < i, i+k >) e(C \ll i+k, i+j)$$

- Base:

$$e(A \ll i, i+1) = \sum_{\mathbf{c}} [\, p(A \to c) \Pr(\mathbf{w_{i+1}} | \mathbf{c}) + \sum_{D} T(A \Rightarrow D) p(D \to c) \Pr(\mathbf{w_i} | \mathbf{c})]$$

- Result: $\Pr_{G_c, C_w}(w_1 \dots w_k \dots) = e(S \ll 0, k).$

3.5 Use of PCFG for LM

- Definition:

$$e(A < i, l >) = \Pr_{G_c, C_w}(A \stackrel{*}{\Rightarrow} w_{i+1} \dots w_l)$$

- Recursion:

$$e(A < i, i+j >) = \sum_{B,C \in N} p(A \to BC) \sum_{k=1}^{j-1} e(B < i, i+k >) e(C < i+k, i+j >)$$

- Base:

$$e(A < i, i+1 >) = \sum_{\mathbf{c}} p(A \to c) \Pr(\mathbf{w_{i+1}} | \mathbf{c})$$

- Result: $\Pr_{G_c, C_w}(w_1 \dots w_n) = e(S < 0, n >)$

WSJ Experiments

➢ WSJ characteristics:

Data set	Directories	No. of senten.	No. of words
Training (full)	00-20	42,075	1,004,073
Training (≤ 50)	00-20	41,315 (98,2%)	959,390 (95,6%)
Tuning	21-22	3,371	80,156
Test	23-24	3,762	89,537

➢ Vocabulary (Training) $10,000$ more frequent words

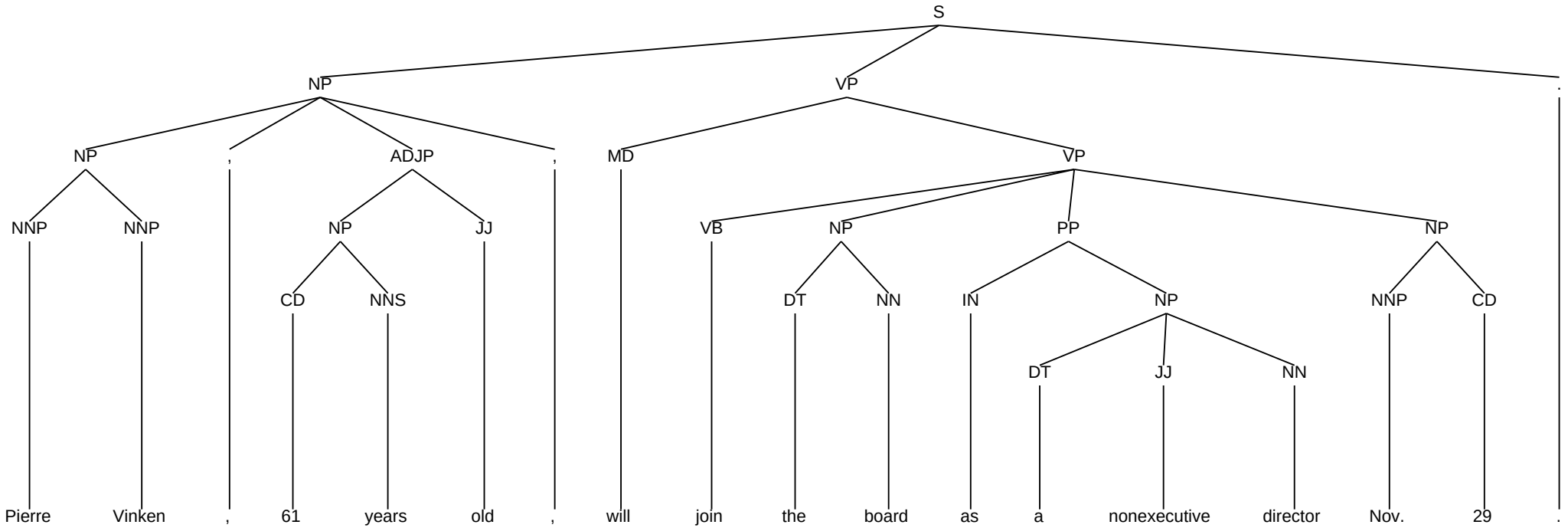
➢ 3-Gram model: (*linear discounting*)

- *Tuning set perplexity*: 160.3;
- *Test set perplexity*: 167.3;

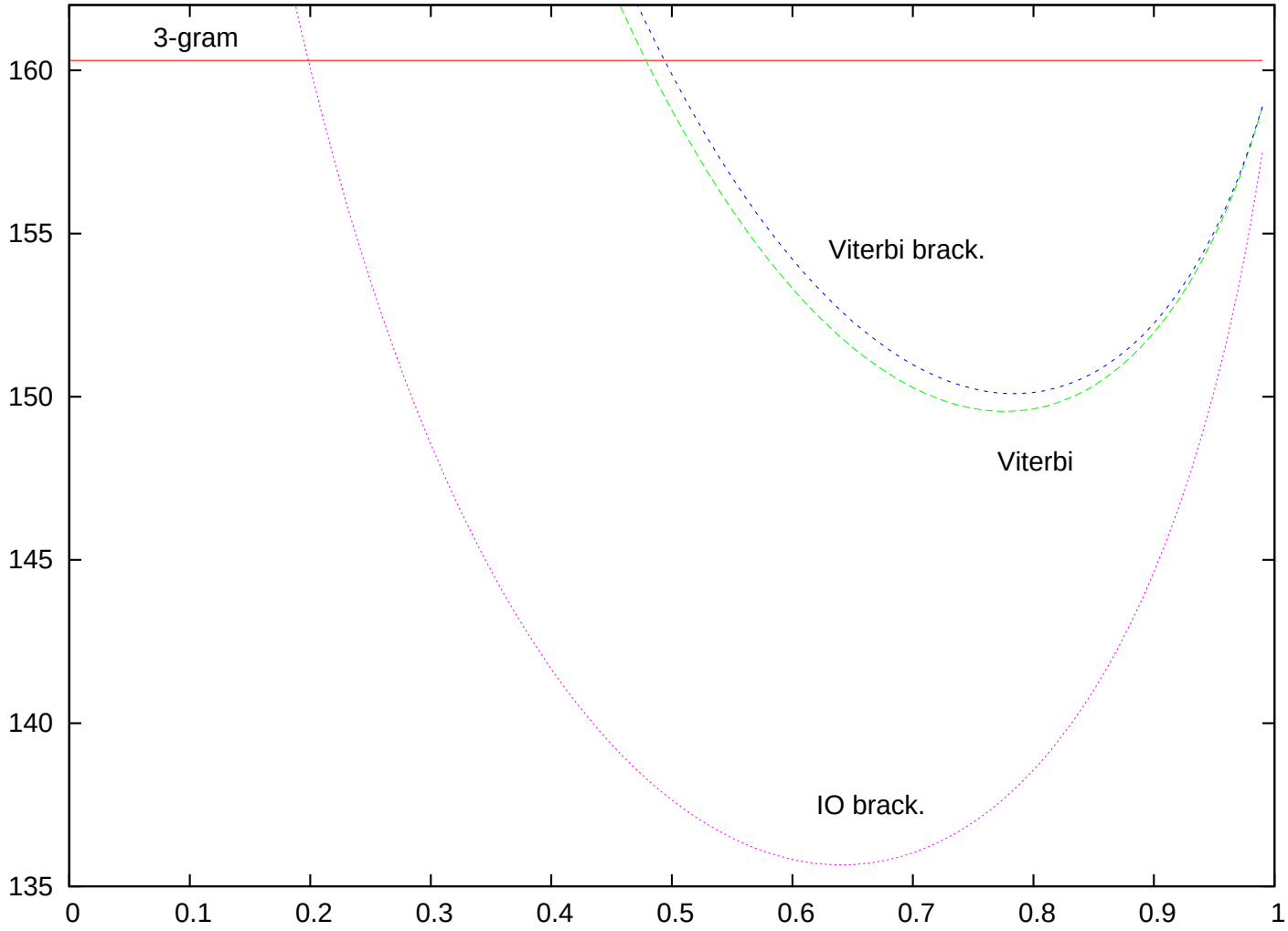
3.5 Use of PCFG for LM

Example: *"Pierre Vinken, 61 years old, will join the board as a nonexecutive director Nov. 29."*

((S (NP-SBJ (NP (NNP Pierre) (NNP Vinken)) (,,) (ADJP (NP (CD 61) (NNS years)) (JJ old)) (,,)) (VP (MD will) (VP (VB join) (NP (DT the) (NN board)) (PP-CLR (IN as) (NP (DT a) (JJ nonexecutive) (NN director))) (NP-TMP (NNP Nov.) (CD 29)))) (..)))



Tuning set perplexity



Test set perplexity

Model	Perplexity		% improvement
	Trigram	Interpolated	
[Chelba 00]	167.1	148.9	10.9
[Roark 01]	167.0	137.3	17.8
IOb	167.3	142.3	14.9

WER

Model	Training Size	Vocabulary Size	LM Weight	WER
[Chelba 00]	20M	20K	16	13.0
[Roark 01]	1M	10K	15	15.1
Treebank trigram	1M	10K	5	16.6
No language model			0	16.8
Current model	1M	10K	6	16.0

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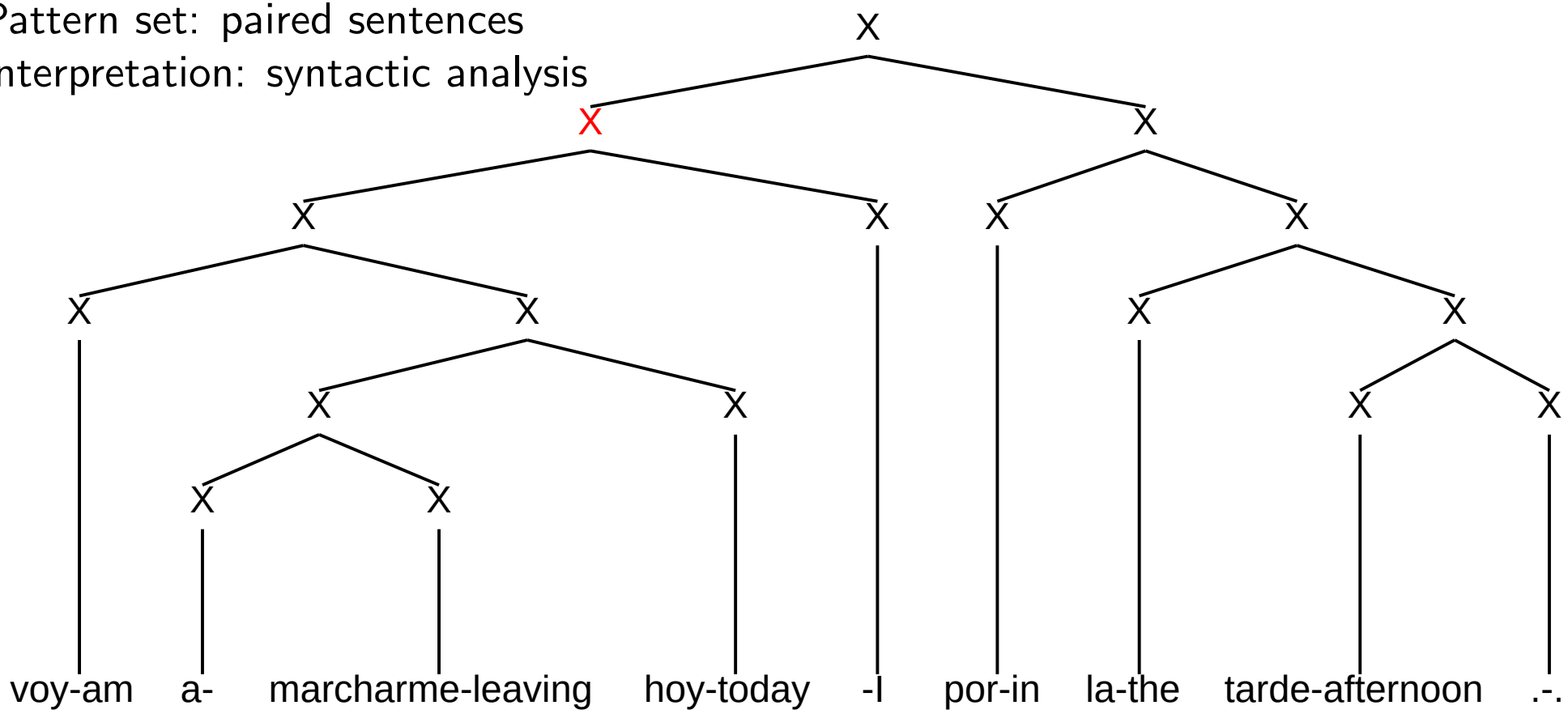
Stochastic inversion transduction grammars [Wu 97, Maryanski 79]

- Primitives: two alphabets (words, punctuation symbols, . . .)
- Object representation: two paired written sentences

"voy a marcharme hoy por la tarde" $\Longleftrightarrow$ "I am leaving today in the afternoon"

- Pattern set: paired sentences
- Interpretation: syntactic analysis



- ITG: $G = (N, W_1, W_2, R, S)$

  R is a finite set of straight orientation rules $A \rightarrow [a_1 a_2 \dots a_r]$ and inverted orientation rules $A \rightarrow \langle a_1 a_2 \dots a_r \rangle$, $a_i \in N \cup X$ and $X = (W_1 \cup \{\epsilon\}) \times (W_2 \cup \{\epsilon\})$

  Theorem. For any ITG G, there exists an equivalent ITG G' in which every production takes one of the following forms:

$$\begin{array}{lll} S \rightarrow \epsilon/\epsilon & A \rightarrow x/\epsilon & A \rightarrow [BC] \\ S \rightarrow x/y & A \rightarrow \epsilon/y & A \rightarrow \langle BC \rangle \end{array}$$

- SITG: $G_s = (G, p)$ where:
  - G is an ITG
  - p is a function that attaches a probability to each rule:
    $p : R \rightarrow]0, 1]$

$$\sum_{1 \leq j \leq n_i} p(A_i \rightarrow \alpha_j) = 1, \qquad \forall A_i \in N$$

Stochastic derivation for SITG

Given a sequence of stochastic events:

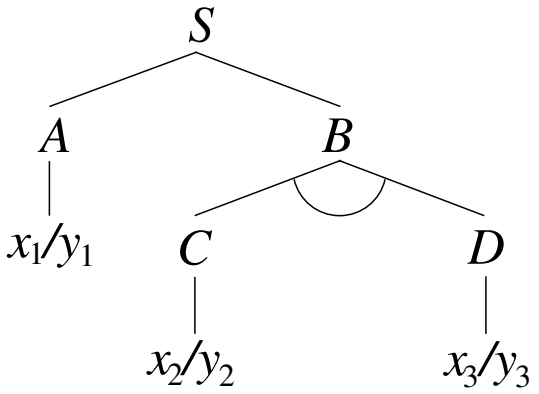
$$(S,S) = (\alpha_0,\beta_0) \overset{r_1}{\Rightarrow} (\alpha_1,\beta_1) \overset{r_2}{\Rightarrow} (\alpha_2,\beta_2) \cdots (\alpha_{m-1},\beta_{m-1}) \overset{r_m}{\Rightarrow} (\alpha_m,\beta_m) = (x,y)$$

Probability of (x,y) being generated by $G_s = (G,p)$ from the rule sequence $d_x = (r_1,\ldots,r_m)$, is:

$$P_{G_s}((x,y),d_x) = \prod_{j=1\cdots m} p(r_j)$$

Example

$$\begin{array}{lcl} S & \rightarrow & [AB] \\ A & \rightarrow & x_1/y_1 \\ B & \rightarrow & \langle CD \rangle \\ C & \rightarrow & x_2/y_2 \\ D & \rightarrow & x_3/y_3 \end{array}$$



$$(S,S) \Rightarrow (AB,AB) \Rightarrow (x_1B,y_1B) \Rightarrow (x_1CD,y_1DC) \Rightarrow (x_1x_2D,y_1Dy_2) \Rightarrow (x_1x_2x_3,y_1y_3y_2)$$

Probability of a string pair

$$\Pr_{G_s}(x, y) = \sum_{d_x \in D_x} \Pr_{G_s}((x, y), d_x)$$

Probability of the best derivation

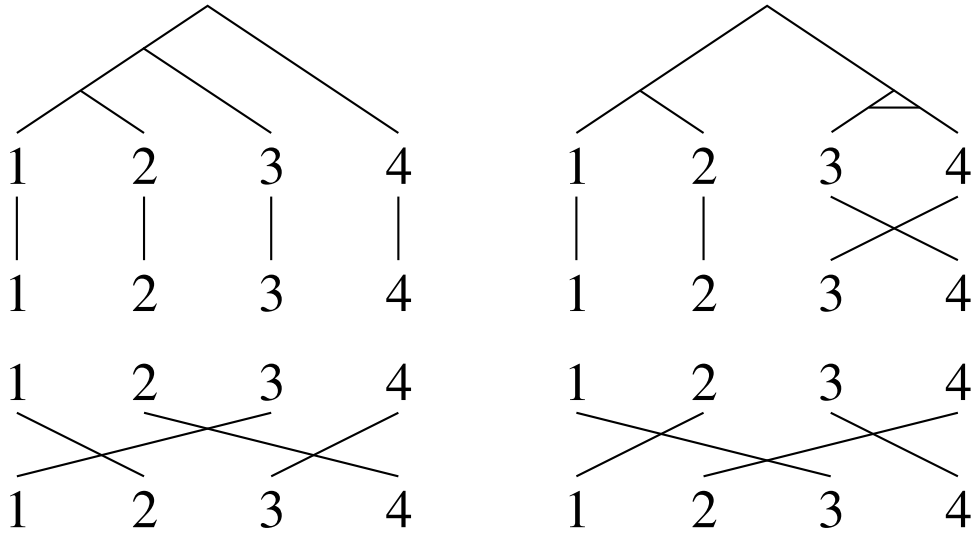
$$\widehat{\Pr}_{G_s}(x, y) = \max_{d_x \in D_x} \Pr_{G_s}((x, y), d_x)$$

Language generated by a SITG

$$L(G_s) = \{(x, y) \mid \Pr_{G_s}(x, y) > 0\}$$

Expressiveness of ITGs

YES



NO

r	ITG	all matchings	ratio
1	1	1	1.000
2	2	2	1.000
3	6	6	1.000
4	22	24	0.917
5	90	120	0.750

r	ITG	all matchings	ratio
6	394	720	0.547
7	1,806	5,040	0.358
8	8,558	40,320	0.212
9	41,586	362,880	0.115
10	206,098	3,628,800	0.057

4.2 Parsing with SITG

- Parsing:
  - Inside algorithm
  - Viterbi algorithm
- Learning:
  - Structure learning
  - Probabilistic estimation: Inside-outside estimation
    Viterbi-based estimation
- Translation:
  - Adapted Cooke-Kasami-Younger parser algorithm

Viterbi algorithm [Wu 97, Gascó 10b]

- Given $(x, y) \in (W_1^*, W_2^*)$ and $A \in N$

$$\delta_{i,j,k,l}(A) = \widehat{\Pr}(A \overset{*}{\Rightarrow} x_{i+1} \cdots x_j / y_{k+1} \cdots y_l)$$

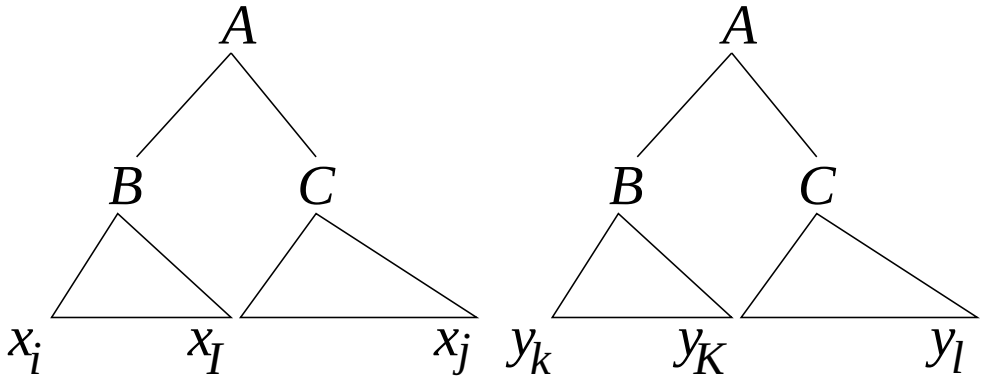
- Initialization

$$\begin{aligned}
\delta_{i-1,i,k-1,k}(A) &= p(A \to x_i/y_k) && 1 \leq i \leq |x|, 1 \leq k \leq |y| \\
\delta_{i-1,i,k,k}(A) &= p(A \to x_i/\epsilon) && 1 \leq i \leq |x|, 0 \leq k \leq |y| \\
\delta_{i,i,k-1,k}(A) &= p(A \to \epsilon/y_k) && 0 \leq i \leq |x|, 1 \leq k \leq |y|
\end{aligned}$$

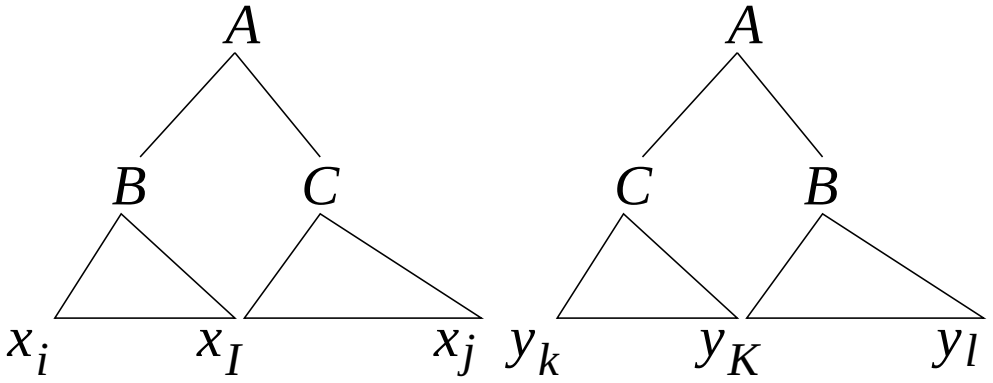
- Recursion. For all $A \in N$, and i, j, k, l such that $0 \leq i < j \leq |x|$, $0 \leq k < l \leq |y|$ and $j - i + l - k \geq 2$:

$$\delta_{ijkl}(A) = \max(\delta^{[]}_{ijkl}(A), \delta^{\langle\rangle}_{ijkl}(A))$$

$$\delta^{[]}_{ijkl}(A) = \max_{\substack{B,C \in N \\ i \leq I \leq j, k \leq K \leq l \\ ((j-I)+(l-K)) \times ((l-i)+(K-k) \neq 0}} p(A \rightarrow [BC]) \delta_{iIkK}(B) \delta_{IjKl}(C)$$



$$\delta^{\langle\rangle}_{ijkl}(A) = \max_{\substack{B,C \in N \\ i \leq I \leq j, k \leq K \leq l \\ ((j-I)+(K-k)) \times ((I-i)+(I-K)) \neq 0}} p(A \rightarrow \langle BC \rangle) \delta_{iIKl}(B) \delta_{IjkK}(C)$$



Inside algorithm [Gascó 10c]

- Given $(x, y) \in (W_1^*, W_2^*)$ and $A \in N$

$$\mathcal{E}_{i,i+j,k,k+l}[A] = \Pr(A \stackrel{*}{\Rightarrow} x_{i+1} \cdots x_{i+j} / y_{k+1} \cdots y_{k+l})$$

  Substitute $\max$ by $\sum$ in Viterbi algorithm

- **Theorem**. If the *inside* algorithm is applied to the substring pair $(x_{i+1} \ldots x_{i+j}, y_{k+1} \ldots y_{k+j})$ with a SITG $\mathcal{G}$, then the probabilistic parse matrix $\mathcal{E}$ collects correctly the probability of this substring pair.

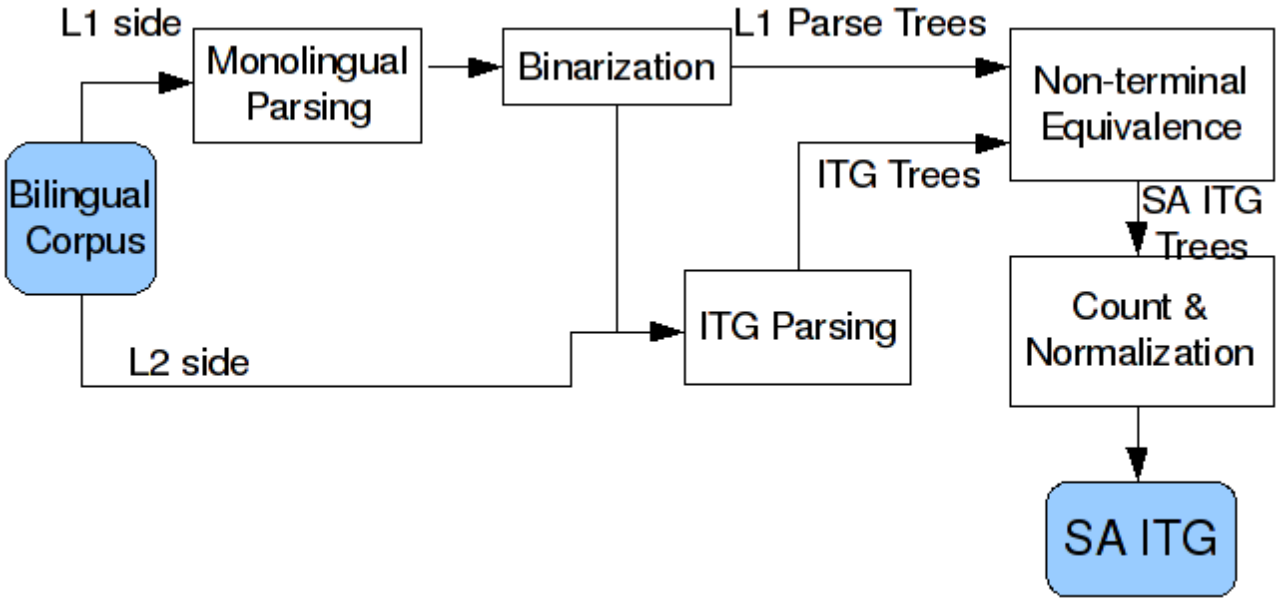
- **Corollary**. The probability of the pair string $(x_1 \ldots x_{|x|}, y_1 \ldots y_{|y|})$ can be computed by means of the probabilistic parse matrix $\mathcal{E}$ as:

$$\Pr(S \stackrel{+}{\Rightarrow} x_1 \ldots x_{|x|} / y_1 \ldots y_{|y|}) = \mathcal{E}_{0,|x|,0,|y|}[S]$$

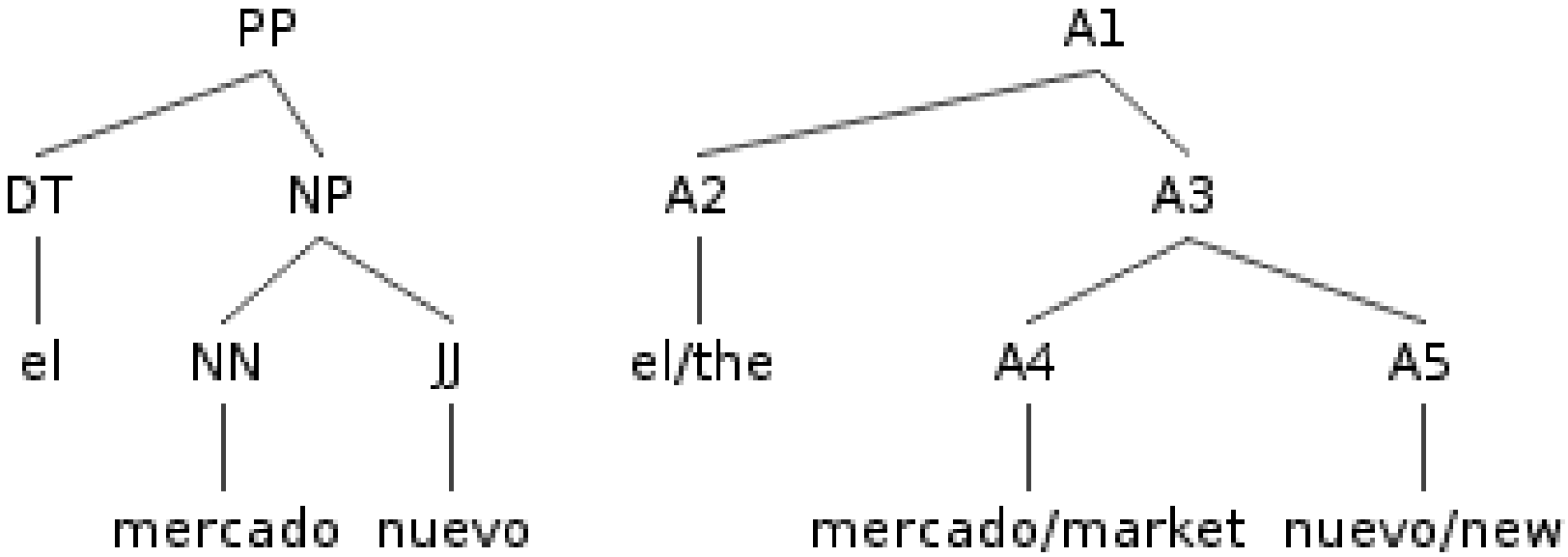
4.3 Use of SITG for MT

[Gascó 10a]

1. To create an initial SITG
2. To estimate the probabilities
3. To attach linguistic information to the non-terminal symbols



4.3 Use of SITG for MT



4.3 Use of SITG for MT

- IWSLT 2008 (Chinese-English BTEC)
- Standard tools: GIZA++, ZMERT
- Stanford parser for Chinese
- Baseline: Moses, 5-gram

Corpus Set	Statistic	Chinese	English
Training	Sentences	42,655	
	Words	330,163	380,431
	Voc. Size	8,773	8,387
DevSet	Sentences	489	
	Words	3,169	3,861
	OOV Words	111	115
Test	Sentences	507	
	Words	3,357	-
	OOV Words	97	-

System	%BLEU
Baseline PBT	41.1
Initial ITG	41.2
Re-estimated ITG	41.8
Source SAITG	42.9
Target SAITG	43.0

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Problem definition [Liang 09]:

- Probabilistic model: $p(\mathbf{x}, \mathbf{z}; \theta)$

  Input: $\mathbf{x}$ (a sentence)
  Hidden output: $\mathbf{z}$ (a parse tree)
  Parameters: θ (rule probabilities)

- Given a set of unlabeled example $\mathbf{x}^{(1)}, \ldots, \mathbf{x}^{(n)}$, maxime the marginal log-likelihood:

$$l(\theta) = \sum_{i=1}^{n} \log p(\mathbf{x}^{(i)}; \theta)$$

- Evaluation of the trained model $\widehat{\theta}$: accuracy

$$\text{true output } \mathbf{z}^{(i)} \leftrightarrow \arg\max_{\mathbf{z}} p(\mathbf{z}|\mathbf{x}^{(i)}; \theta)$$

- Training algorithm: EM algorithm [Dempster 77, Neal 98, Cappé 09]

EM algorithm [Liang 09]:

Batch EM

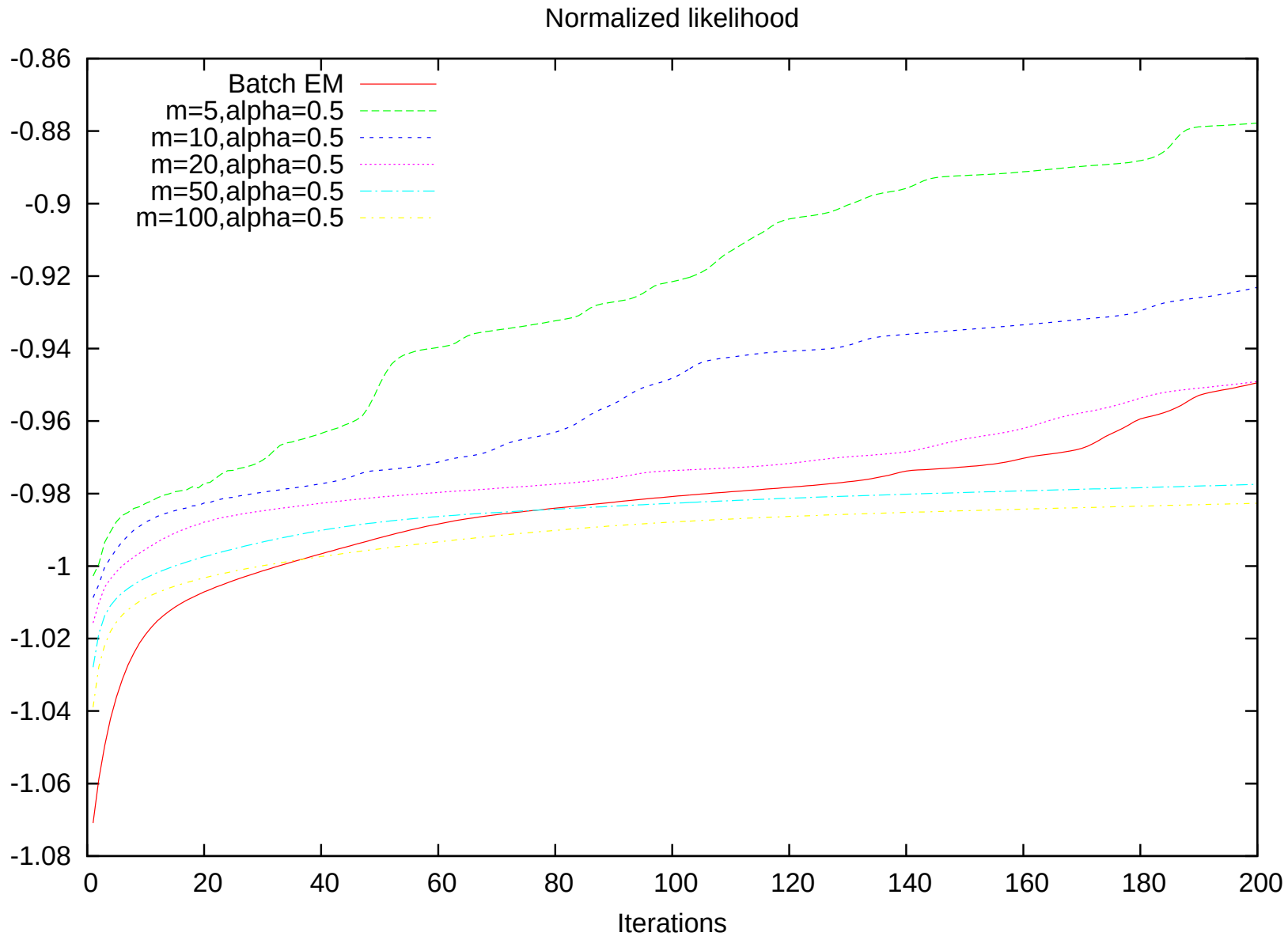
$\mu \leftarrow$ initialization
for each iteration $t = 1, \ldots, T$:
  $\mu' \leftarrow 0$
  for each example $i = 1, \ldots, n$:
    $s'_i \leftarrow \sum_{\mathbf{z}} p(\mathbf{z}|\mathbf{x}^{(i)}; \theta(\mu))\ \phi(\mathbf{x}^{(i)}, \mathbf{z})$
    $\mu' \leftarrow \mu' + s'_i$
$\mu \leftarrow \mu'$

Stepwise EM

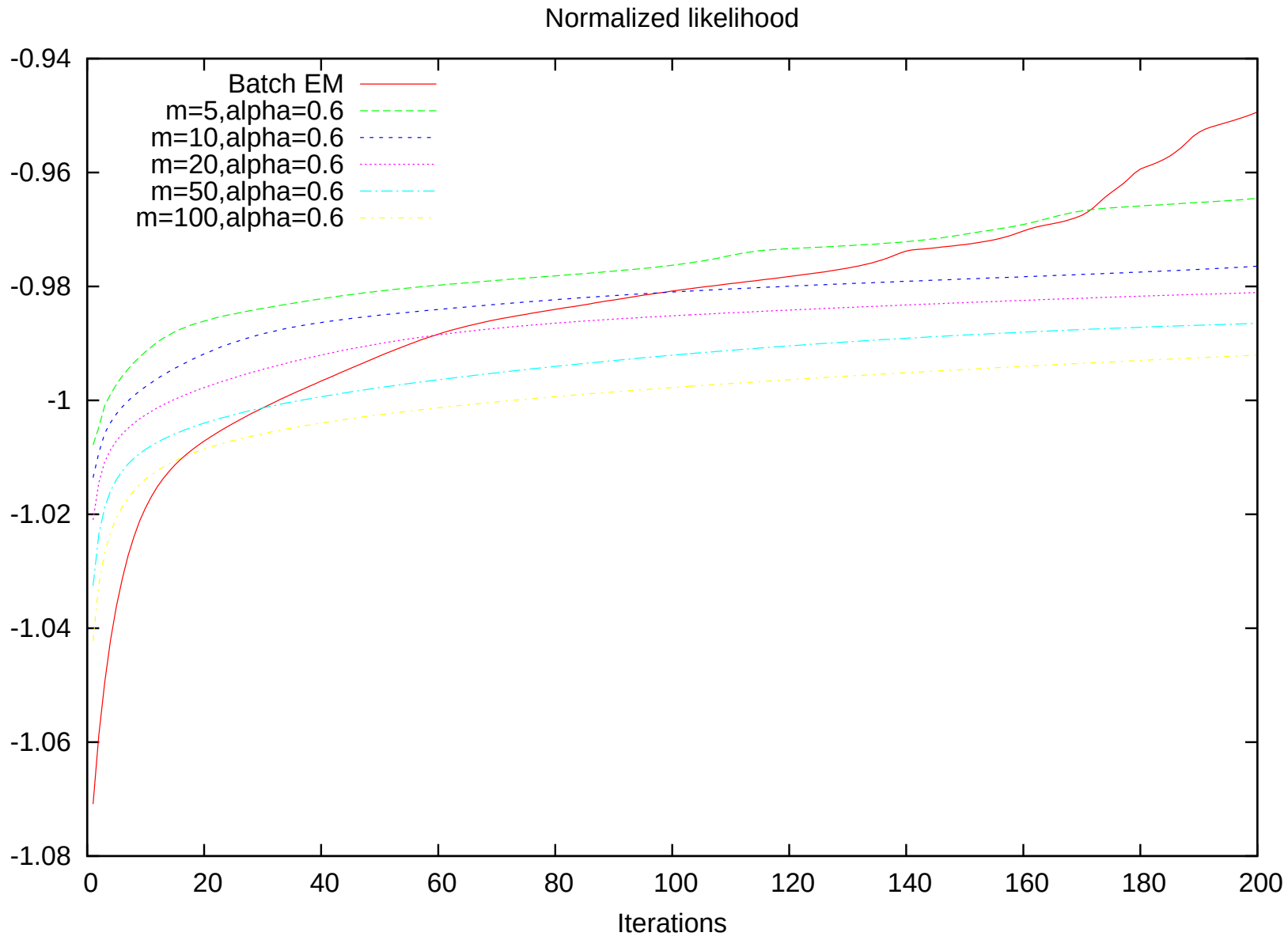
$\mu \leftarrow$; $k = 0$ initialization
for each iteration $t = 1, \ldots, T$:
  for each example $i = 1, \ldots, n$ in random order:
    $s'_i \leftarrow \sum_{\mathbf{z}} p(\mathbf{z}|\mathbf{x}^{(i)}; \theta(\mu))\ \phi(\mathbf{x}^{(i)}, \mathbf{z})$
    $\mu \leftarrow (1 - \eta_k)\mu + \eta_k s'_i$
    $k \leftarrow k + 1$

- $\phi(\mathbf{x}, \mathbf{z})$: mapping from a labelled example $(\mathbf{x}, \mathbf{z})$ to a vector of sufficient statistics (μ)
- $\theta(\mu)$: maximum likelihood estimate
- Stepwise EM: convergence is guaranteed if $\sum_{k=0}^{\infty} \eta_k = \infty$ and $\sum_{k=0}^{\infty} \eta_k^2 < \infty$
  - $\eta_k = (k + 2)^{-\alpha}$ with $0.5 < \alpha \leq 1$
  - Approach: take m examples at once

Palindrome language (15 random initializations, $\alpha = 0.5$)



Palindrome language (15 random initializations, $\alpha = 0.6$)



Palindrome language

- Batch EM
  - normalized likelihood in average: -0.949 ± 0.052
  - % of palindromes generated in average by the estimated grammar (50K sentences): $21.9\% \pm 10.1$
- Online EM

$\alpha \backslash m$	5	10	20	50	100
0.5	-0.878 ± 0.080	-0.923 ± 0.071	-0.949 ± 0.052	-0.977 ± 0.007	-0.983 ± 0.007
0.6	-0.965 ± 0.031	-0.976 ± 0.007	-0.981 ± 0.007	-0.986 ± 0.008	-0.992 ± 0.007
0.7	-0.984 ± 0.008	-0.987 ± 0.008	-0.992 ± 0.007	-0.998 ± 0.006	-1.002 ± 0.004
0.8	-0.997 ± 0.006	-1.000 ± 0.005	-1.003 ± 0.004	-1.006 ± 0.003	-1.009 ± 0.002
0.9	-1.007 ± 0.003	-1.009 ± 0.002	-1.011 ± 0.002	-1.014 ± 0.002	-1.016 ± 0.002
1.0	-1.016 ± 0.002	-1.018 ± 0.003	-1.021 ± 0.004	-1.023 ± 0.004	-1.025 ± 0.005

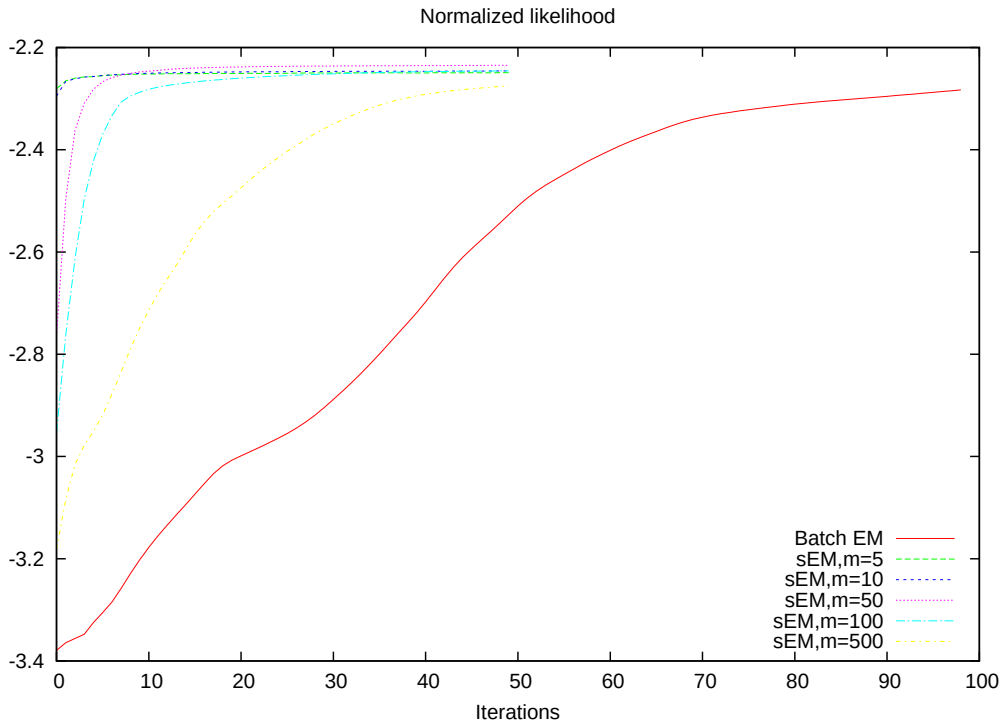
$\alpha \backslash m$	5	10	20	50	100
0.5	35.1 ± 21.0	29.5 ± 18.3	21.8 ± 10.2	16.6 ± 2.3	15.4 ± 2.4
0.6	20.3 ± 11.3	16.8 ± 2.4	15.8 ± 2.4	14.9 ± 2.8	14.6 ± 3.2
0.7	15.1 ± 2.7	14.9 ± 2.9	14.6 ± 3.3	14.9 ± 3.4	15.4 ± 3.1
0.8	15.0 ± 3.2	15.3 ± 3.2	15.7 ± 2.9	16.0 ± 2.4	16.2 ± 2.0
0.9	16.4 ± 2.1	16.3 ± 1.9	16.4 ± 1.7	16.5 ± 1.4	16.4 ± 1.2
1.0	16.6 ± 1.3	16.2 ± 1.2	16.0 ± 1.0	15.7 ± 1.0	15.5 ± 1.0

WSJ - UPenn Treebank

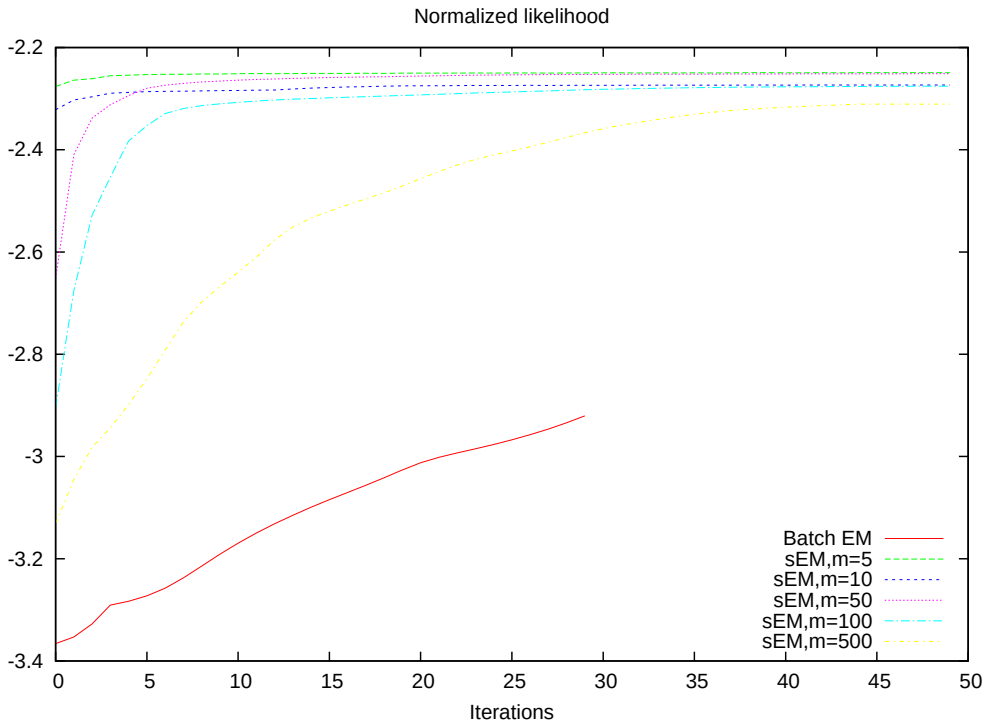
- Until level of preterminals: 45 PoS
- Initial PCFG: ergodic model with 45 terminals and 35 non-terminals ($44,450$ rules)
- Training A: length sentence ≤ 20 words
  - sections 02-21
  - $16,667$ sentences
  - $229,020$ running words
- Training B: length sentence ≤ 25 words
  - sections 02-21
  - $23,597$ sentences
  - $388,234$ running words
- Test: section 23
  - $2,416$ sentences
  - $56,684$ running words

WSJ - UPenn Treebank

($\alpha = 0.5, \leq 20$ words)



($\alpha = 0.5, \leq 25$ words)

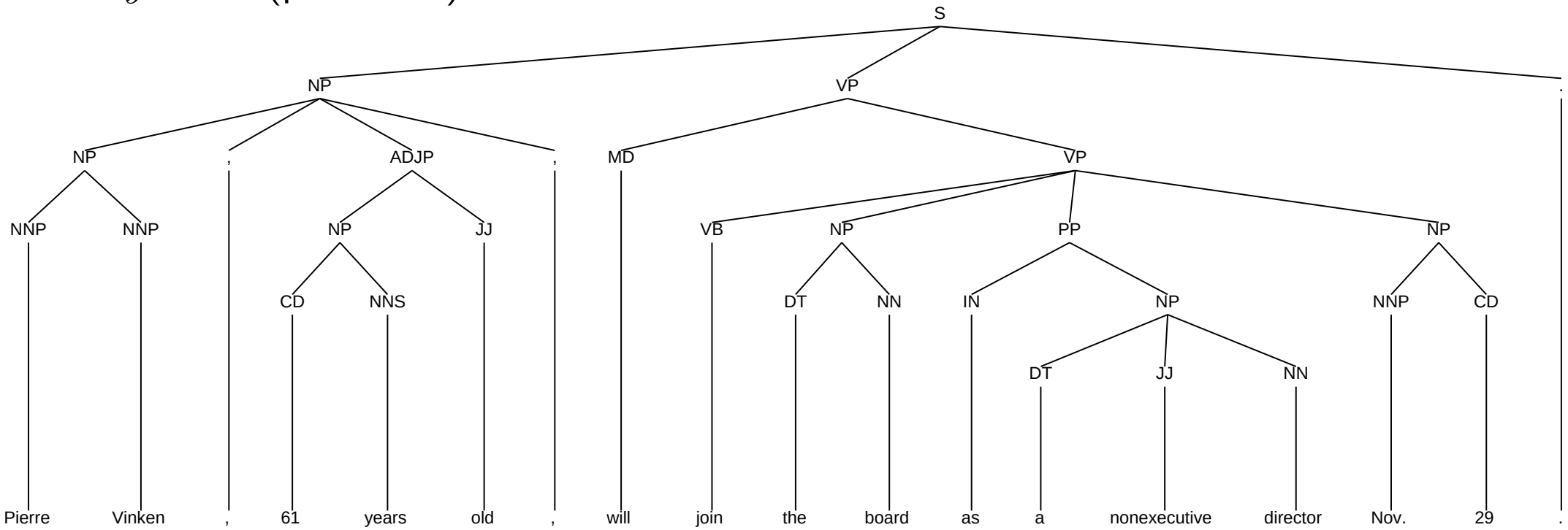


Test Bracketing F-Measure (measured with *evalb*: http://nlp.cs.nyu.edu/evalb/)

	BatchEM	$m = 5$	$m = 10$	$m = 50$	$m = 100$	$m = 500$
≤ 20	31	35	34	34	29	28
≤ 25		34	33	31	31	30

Problem definition:

- Supervised learning: (x, y)
  - x: input data (sentence)
  - y: label (parse tree)



- Problem: to annotate data is slow and expensive
- **Active learning: to annotate just the necessary data**

Pool-based active learning [Settles 08, Settles 10]:

Given: Labeled set $\mathcal{L}$, unlabeled pool $\mathcal{U}$,
query strategy $\phi(\dot{})$, query batch size B
repeat
  // learn a model using the current $\mathcal{L}$
  $\theta = \text{train}(\mathcal{L})$
  for $b = 1$ **to** B **do**
    // query the most informative instance
    $\mathbf{x}_b^* = \arg\max_{\mathbf{x} \in \mathcal{U}} \phi(\mathbf{x})$
    // move the labeled query from $\mathcal{U}$ *to* $\mathcal{L}$
    $\mathcal{L} = \mathcal{L} \cup \langle \mathbf{x}_b^*, \text{label}(\mathbf{x}_b^*) \rangle$
    $\mathcal{U} = \mathcal{U} - \mathbf{x}_b^*$
  end
until *some stopping criterion*

➢ Similar scheme for parsing in [Hwa 04]

Query strategies:

- Uncertainty sampling: to query the instance that is most uncertainty how to label
  - Sequence entropy:

$$\phi^{SE}(\mathbf{x}) = -\sum_{\widehat{\mathbf{y}}} P(\widehat{\mathbf{y}}|\mathbf{x};\theta) \log P(\widehat{\mathbf{y}}|\mathbf{x};\theta)$$

  - Approach: N-best Sequence entropy:

$$\phi^{NSE}(\mathbf{x}) = -\sum_{\widehat{\mathbf{y}}\in\mathcal{N}} P(\widehat{\mathbf{y}}|\mathbf{x};\theta) \log P(\widehat{\mathbf{y}}|\mathbf{x};\theta)$$

- Query-By-Committee: to query the instance for which a committee of models is in most disagreement about how to label
- Information density: to query the instance that is the most "informative" in average

$$\phi^{ID}(\mathbf{x}) = \phi^{NSE}(\mathbf{x}) \times \left(\frac{1}{U}\sum_{u=1}^{U} \mathsf{sim}(\mathbf{x}, \mathbf{x}^{(u)})\right)^{\beta}$$

Query strategies for parsing [Hwa 04]:

- Problem space:
  - Based on novelty and frequencies of word pair co-occurrences
  - Based on sentence length: f_{len}
- Performance of the hypothesis:
  - Error-driven function:

$$f_{\text{err}}(\mathbf{w}, G) = 1 - P(\widehat{d}_{\mathbf{w}}|\mathbf{w}, G)$$

  - Normalized tree entropy (similar to $\phi^{SE}(\mathbf{x})$): f_{unc}

Experiments on WSJ UPenn Treebank reported in [Hwa 04]:

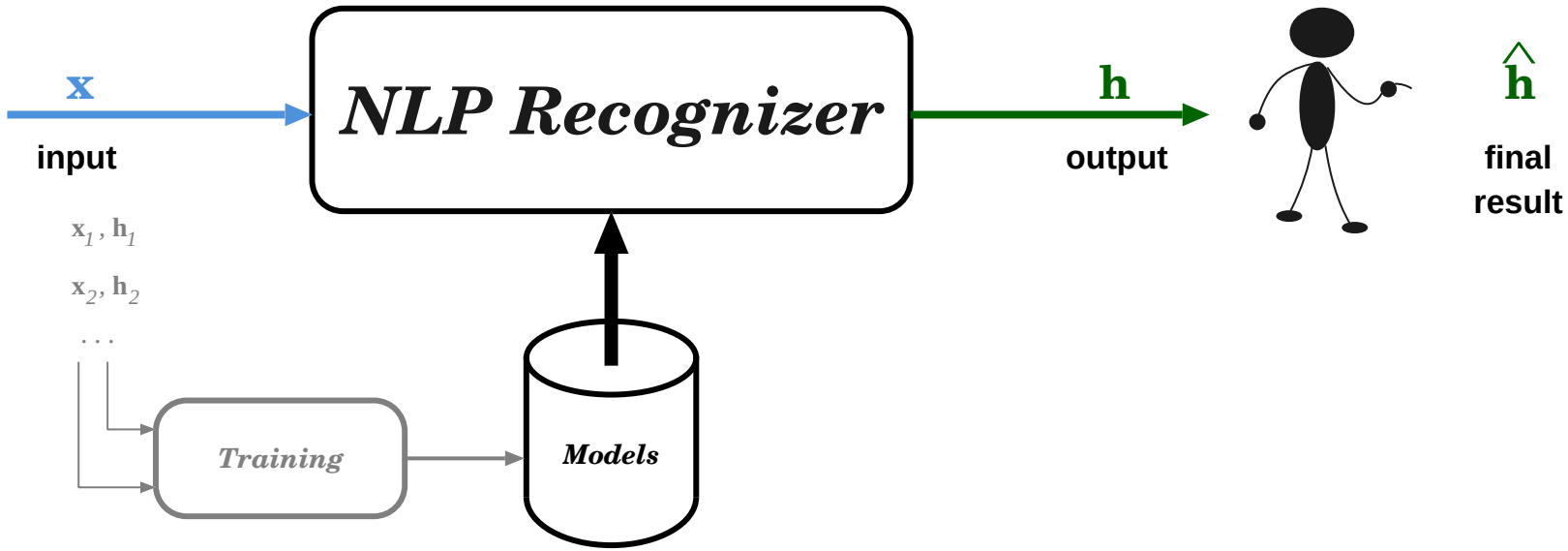
- Collins' model 2 parser
- Learning algorithm: statistics directly over the treebank
- Data:
  - Training: sections 02-21
  - Test: section 23
- Initial model trained on 500 sentences
- Batch size: 100
- Parsing performance: F score

Number of labelled samples at the test performance level of 88%:

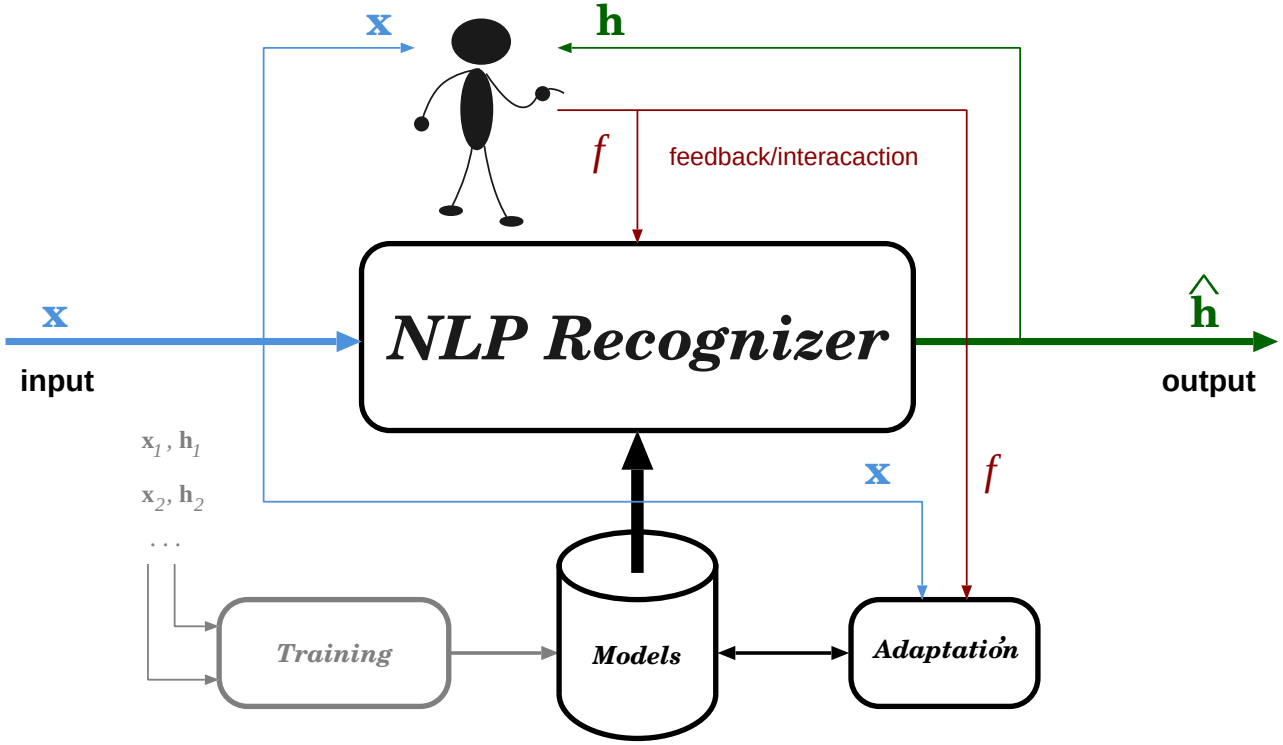
	f_{ran}	f_{len}	f_{err}	f_{unc}
# sentences	$30,500$	-	$20,500$ (33%)	$17,500$ (43%)
# constituents	$695,000$	$625,000$ (10%)	$577,000$ (17%)	$505,000$ (27%)

Problem definition [Sánchez 09, Sánchez 10]: Annotation parse tree is expensive and requires skilled expert humans

- Classical two-step approach:
  1. Apply an automatic system
  2. Manually validate/correct the output



- Interactive Predictive approach:
  - Formally integrate the user into the recognition process
  - The system reacts to user feedback



- New opportunities:
  - Feedback information can be used to create efficient interactive systems
  - Each interaction step yields *ground-truth data*, which allows building *active learning systems*

Classical parsing

$$\widehat{t} = \arg\max_{t \in \tau} p_G(t|x)$$

Interactive predictive parsing

$$\widehat{t} = \arg\max_{t \in \mathcal{T}: t_p \in t} p_G(t|x, t_p)$$

- $x \rightarrow$ input sentence
- $G \rightarrow$ mode (e.g. PCFG)
- $\mathcal{T} \rightarrow$ set of all possible trees for x with G
- $\widehat{t} \rightarrow$ obtained parse tree

The tree prefix t_p is:

- the corrected constituent, plus
- all its ancestors, plus
- all the constituents to its left

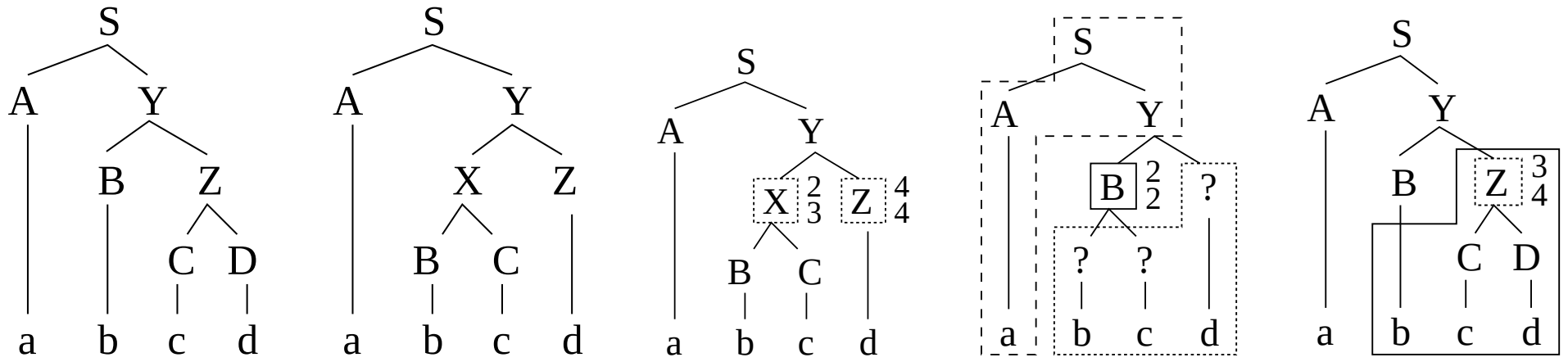
$$t_p(c'^A_{ij}) = \{c^B_{mn} : m \leq i, n \geq j, \mathsf{depth}(c^B_{mn}) \leq \mathsf{depth}(c'^A_{ij})\} \cup \{c^D_{pq} : p \geq 1, q < i\}$$

IPP parsing

1. The system propose a parse tree $\widehat{t}$
2. The user finds an incorrect constituent c and corrects i, implicitly validating the prefix tree $t_p(c)$
3. The system propose a parse tree $\widehat{t'}$ taking into account the prefix tree $t_p(c)$
4. Go to step 2

n. The user keeps iterating until an error free parse tree is achieved

Example:



Reference tree

Iteration 0: Proposed output tree 1

Iteration 0: Erroneous constituents

Iteration 1: User corrected constituent

Iteration 1: Proposed output tree 2

Experiments [Sánchez 09]:

- Experiments were performed using the WSJ Treebank and a modified CYK parser
- Vanilla CNF PCFG obtained from sections 02-21. Test set: section 23
- The system simulates user interaction:

1. Explore the proposed tree and find the first wrong constituent
2. Replace it with the correct gold constituent
3. Perform the predictive step (obtain new tree)

n. Repeat until the gold tree is achieved

Evaluation and results:

- Tree Constituent Error Rate (TCER): Normalized edit distance between the proposed parse tree and the gold tree
  → *User effort when manually postediting the erroneous tree*
- Tree Constituent Action Rate (TCAC): Ration of user constituent corrections performed to obtain the reference tree using the IPP system
  → *User effort when using the IPP system*

PCFG	Baseline	IPP		RelRed
	F_1	TCER	TCAC	
h=0,v=1	0.67	0.40	0.22	45%
h=0,v=2	0.68	0.39	0.21	46%
h=0,v=3	0.70	0.38	0.22	42%

IPP-ANN tool: http://cat.iti.upv.es/ipp/

Parser server

- Custom Viterbi implementation
- Using PCFG in CNF
- Allows requesting subtrees with
  - a root span
  - a complete root constituent

Parser client

- Light Web-client using Flash plugin
- Decodes user feedback
- Requests subtrees to the parse server based on user corrections

Communication

- Client-server communication via sockets
- Using a library specifically tailored for interactive predictive applications

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Appendices

Appendix A

A growth transformation can be defined as:

$$\overline{p}(A \to \alpha) = \frac{p(A \to \alpha) \left(\frac{\partial \Pr_{G_s}(\Omega, \Delta_\Omega)}{\partial p(A \to \alpha)} \right)_p}{\sum_{i=1}^{n_A} p(A \to \alpha_i) \left(\frac{\partial \Pr_{G_s}(\Omega, \Delta_\Omega)}{\partial p(A \to \alpha_i)} \right)_p}$$

Numerator:

$$p(A \to \alpha) \left(\frac{\partial \Pr_{G_s}(\Omega, \Delta_\Omega)}{\partial p(A \to \alpha)} \right)_p = \Pr_{G_s}(\Omega, \Delta_\Omega) \sum_{x \in \Omega} \frac{p(A \to \alpha)}{\Pr_{G_s}(x, \Delta_x)} \left(\frac{\partial \Pr_{G_s}(x, \Delta_x)}{\partial p(A \to \alpha)} \right)_p$$

$$= \Pr_{G_s}(\Omega, \Delta_\Omega) \sum_{x \in \Omega} \frac{p(A \to \alpha)}{\Pr_{G_s}(x, \Delta_x)} \sum_{\forall d_x \in \Delta_x} \left(\frac{\partial \Pr_{G_s}(x, d_x)}{\partial p(A \to \alpha)} \right)_p$$

$$= \Pr_{G_s}(\Omega, \Delta_\Omega) \sum_{x \in \Omega} \frac{1}{\Pr_{G_s}(x, \Delta_x)} \sum_{\forall d_x \in \Delta_x} \mathrm{N}(A \to \alpha, d_x) \Pr_{G_s}(x, d_x)$$

Denominator:

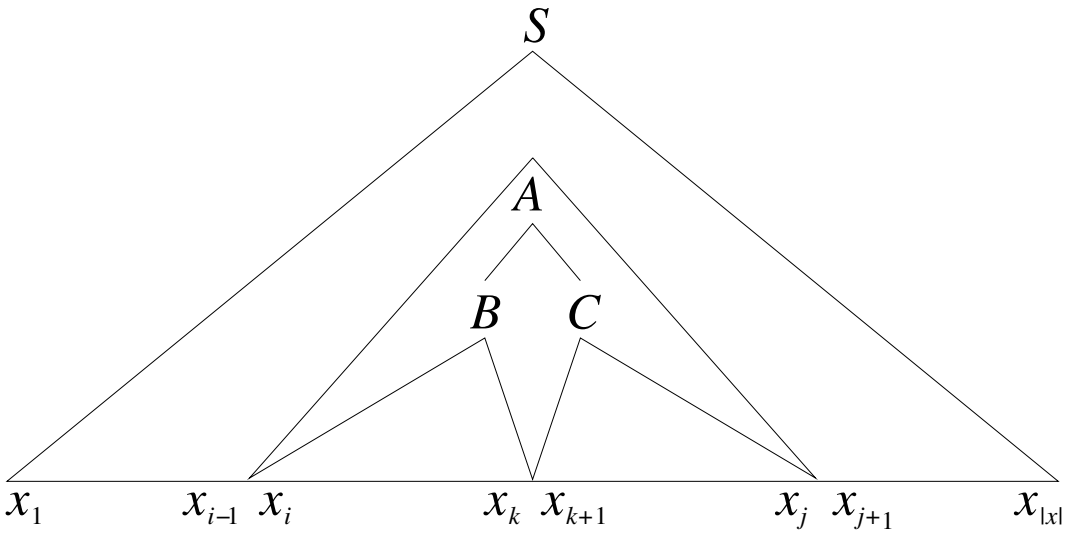
$$\sum_{i=1}^{n_A} p(A \to \alpha_i) \left(\frac{\partial \Pr_{G_s}(\Omega, \Delta_\Omega)}{\partial p(A \to \alpha_i)} \right)_p =$$

$$= \Pr_{G_s}(\Omega, \Delta_\Omega) \sum_{x \in \Omega} \frac{1}{\Pr_{G_s}(x, \Delta_x)} \sum_{\forall d_x \in \Delta_x} \sum_{i=1}^{n_A} \mathrm{N}(A \to \alpha_i, d_x) \Pr_{G_s}(x, d_x)$$

$$= \Pr_{G_s}(\Omega, \Delta_\Omega) \sum_{x \in \Omega} \frac{1}{\Pr_{G_s}(x, \Delta_x)} \sum_{\forall d_x \in \Delta_x} \mathrm{N}(A, d_x) \Pr_{G_s}(x, d_x).$$

Appendix B

- Let $A \rightarrow BC$ in a position delimited by integers i, j, k, $1 \leq i \leq k < j \leq |x|$



- $\Delta_{x,i,j,k,A \rightarrow BC} \subseteq D_x$: subset of derivations of x in which the rule $A \rightarrow BC$ appears delimited by positions i, j, k
- $\Delta_{x,i,j,A}$: subset of derivations of x in which the non-terminal A appears delimited by positions i, j

Appendix B

$$\sum_{\forall d_x \in D_x} \mathrm{N}(A \to BC, d_x)\mathrm{Pr}_{G_s}(x, d_x) = \sum_{1 \le i \le k < j \le |x|} \; \sum_{\forall d_x \in \Delta_{x,i,j,k,A \to BC}} \mathrm{Pr}_{G_s}(x, d_x)$$

$$= \sum_{1 \le i \le k < j \le |x|} \mathrm{Pr}_{G_s}(S \overset{*}{\Rightarrow} x_1 \dots x_{i-1} A x_{j+1} \dots x_{|x|}) \cdot$$

$$p(A \to BC) \cdot \mathrm{Pr}_{G_s}(B \overset{*}{\Rightarrow} x_i \dots x_k) \cdot \mathrm{Pr}_{G_s}(C \overset{*}{\Rightarrow} x_{k+1} \dots x_j)$$

$$= \sum_{1 \le i \le k < j \le |x|} f(A < i, j >) p(A \to BC) e(B < i, k >) e(C < k+1, j >),$$

$$\sum_{\forall d_x \in D_x} \mathrm{N}(A, d_x)\mathrm{Pr}_{G_s}(x, d_x) = \sum_{1 \le i \le j \le |x|} \; \sum_{\forall d_x \in \Delta_{x,i,j,A}} \mathrm{Pr}_{G_s}(x, d_x)$$

$$= \sum_{1 \le i \le j \le |x|} \mathrm{Pr}_{G_s}(S \overset{*}{\Rightarrow} x_1 \dots x_{i-1} A x_{j+1} \dots x_{|x|}) \mathrm{Pr}_{G_s}(A \overset{*}{\Rightarrow} x_i \dots x_j)$$

$$= \sum_{1 \le i \le j \le |x|} f(A < i, j >) e(A < i, j >).$$

EM algorithm [Neal 98]:

E step: Compute a distribution $\widetilde{p}^{(t)}$ over the range of $\mathbf{Z}$ such that

$$\widetilde{p}^{(t)}(\mathbf{z}) = p(\mathbf{z}|\mathbf{x}; \theta^{(t-1)})$$

M step: Set $\theta^{(t)}$ to the θ that maximizes $E_{\widetilde{p}^{(t)}}[\log p(\mathbf{x}, \mathbf{z}; \theta)]$