



# K-best Iterative Viterbi Parsing

K-best 迭代维特比句法分析

WeiYang

weiyang@godweiyang.com www.godweiyang.com

East China Normal University

Department of Computer Science and Technology

2018.05.17





# Outline

Outline

Introduction

Iterative Viterbi Parsing

Experiments







### Motivations

- CKY or Viterbi inside algorithm is useful for PCFG parsing.
- However, parsing is slow when the grammar is large.
- Pruning techniques are often employed, such as beam search and coarse-to-fine search.
- However, pruning methods are approximate which can't always output the correct parsing trees.
- Iterative Viterbi Parsing (IVP) is used for pruning unnecessary edges which is much faster than CKY algorithm.





# Inside Algorithm

Sum of inside potential:  $\alpha(A, i, j)$ 

**Initialization:** 

If 
$$A \to x_i \in R$$
, then  $\alpha(A, i, i) = \varphi(A \to x_i, i, i, i)$ , else 0.

**Bottom-up calculation:** 

$$\alpha(A, i, j) = \sum_{A \to BC \in R} \sum_{k=i}^{j-1} \varphi(A \to BC, i, k, j) \cdot \alpha(B, i, k) \cdot \alpha(C, k+1, j)$$





# Outside Algorithm

Sum of outside potential:  $\beta(A, i, j)$ 

Initialization:

$$\beta(S, 1, n) = 1$$
, others 0.

Top-down calculation:

$$\beta(A, i, j) = \sum_{\substack{B \to A C \in R \\ k=j+1}} \sum_{k=j+1}^{n} \varphi(B \to A C, i, j, k) \cdot \beta(B, i, k) \cdot \alpha(C, j+1, k)$$
$$+ \sum_{\substack{B \to C A \in R \\ k=1}} \sum_{k=1}^{n} \varphi(B \to C A, k, i-1, j) \cdot \beta(B, k, j) \cdot \alpha(C, k, i-1)$$





1



# Outside Algorithm

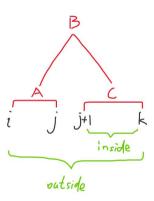


Figure: Outside Algorithm.



1



# Outside Algorithm

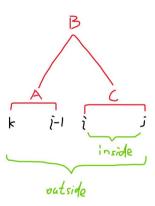


Figure: Outside Algorithm.







# Shrinkage Symbols

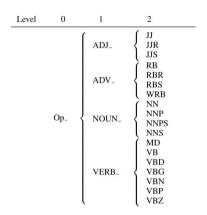


Figure: The levels of non-terminal symbols.







### Chart Table

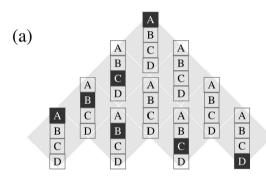


Figure: Original chart table consisting of non-terminal symbols only.







### Chart Table

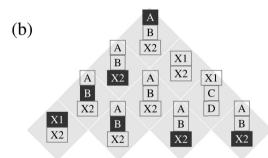


Figure: Coarse chart table consisting of both non-terminal symbols and shrinkage symbols.





### Definition

- Hierarchically cluster N into m+1 sets  $N_0 \dots N_m$  where  $N=N_m$ .
- Define a mapping  $\pi_{i \to j} : N_i \mapsto \Im(N_i)$  where  $\Im(N_i)$  is the power set of  $\cdot$
- For  $X_i \in N_i, X_j \in N_j, X_k \in N_k$ , the rule parameter is defined as

$$\log q(X_i \to X_j X_k) = \max_{\substack{A \in \pi_{i \to m}(X_i) \\ B \in \pi_{j \to m}(X_j) \\ C \in \pi_{k \to m}(X_k)}} \log q(A \to BC)$$

 Each derivation in a coarse chart gives an upper bound on its corresponding derivation in the original chart.

(□) (□) (□) (□) (□)





### Lemma

If the best goal derivation  $\hat{d}$  in the coarse chart does not include any shrinkage symbol, it is equivalent to the best goal derivation in the original chart.

### **Proof:**

Let  $\mathcal{Y}$  be the set of all goal derivations in the original chart,  $\mathcal{Y}' \subset \mathcal{Y}$  be the subset of  $\mathcal{Y}$  not appearing in the coarse chart, and  $\mathcal{Y}''$  be the set of all goal derivations in the coarse chart. For each derivation  $d \in \mathcal{Y}'$ , there exists its unique corresponding derivation  $d' \in \mathcal{Y}''$ . Then, we have

$$\forall d \in \mathcal{Y}, \exists d' \in \mathcal{Y}'', s(d) \leq s(d') < s(\hat{d})$$

and this means that  $\hat{d}$  is the best derivation in the original chart.







### Pseudo Code

### Algorithm 1 Iterative Viterbi Parsing

- 1:  $lb \leftarrow \det(x, G)$  or  $lb \leftarrow -\infty$
- 2: chart  $\leftarrow$  init-chart(x, G)
- 3: **for all**  $i \in [1...]$  **do**
- 4:  $\hat{d} \leftarrow \text{Viterbi-inside(chart)}$
- 5: **if**  $\hat{d}$  consists of non-terminals only **then**
- 6: return  $\hat{d}$
- 7: **if** lb < best(chart) **then**
- 8:  $lb \leftarrow \text{best(chart)}$
- 9: expand-chart(chart,  $\hat{d}$ , G)
- 10: Viterbi-outside(chart)
- 11: prune-chart(chart, lb)

Figure: Iterative Viterbi Parsing.







# Pruning

- For an edge e = (A, i, j), we denote by  $\alpha\beta(e) = \alpha(e) + \beta(e)$  the score of the best goal derivation which passes through e
- If we obtain a lower bound lb such that  $lb \leq \max_{d \in \mathcal{V}} s(d)$  where  $\mathcal{V}$  is the set of all goal derivations in the original chart, an edge e with  $\alpha\beta(e) < lb$  is no longer necessary to be processed.
- $\alpha\beta(e)$  can be efficiently computed by Viterbi inside-outside parsing its upper bound in a coarse chart table:

$$\alpha\beta(e) \le \hat{\alpha}(e) + \hat{\beta}(e) = \hat{\alpha\beta}(e)$$







### K-best Extension

#### Algorithm 2 K-best IVP

```
1: lb \leftarrow \text{beam}(x, G, k) or lb \leftarrow -\infty
 2: chart \leftarrow init-chart(x, G)
 3: for all i \in [1...] do
        \hat{d}_1 \leftarrow \text{Viterbi-inside(chart)}
        if \hat{d}_1 consists of non-terminals only then
            [\hat{d}_2, \dots, \hat{d}_k] \leftarrow \text{Lazy K-best(chart)}
 6.
            if All of [\hat{d}_2, \dots, \hat{d}_k] consist of non-terminals only
            then
                return [\hat{d}_1, \hat{d}_2, \dots, \hat{d}_k]
 9:
                \hat{d}_1 = \text{getShrinkageDeriv}([\hat{d}_2, \dots, \hat{d}_k])
10:
11:
         if lb < k-best(chart, k) then
12:
            lb \leftarrow \text{k-best(chart}, k)
13:
         expand-chart(chart, \hat{d}_1, G)
14:
         Viterbi-outside(chart)
15:
         prune-chart(chart, lb)
```

Figure: K-best IVP.







# Experiments

	CKY		IVP			
len.	edges	time	edges	pruned	iters	time
20	10590	1.25	2864	2089	68	0.13
23	13938	1.76	2219	1462	41	0.06
22	12771	1.52	2204	1425	46	0.05
17	7701	0.72	1526	1119	32	0.03
28	20538	3.14	7306	5338	144	1.18
34	30141	5.44	6390	4634	98	0.49
i	į ;		:			
21	12801	1.77	3502	2456	70	0.21

Figure: The number of the edges produced in 1-best parsing on testing set.



### **Experiments**

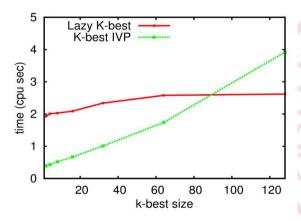


Figure: K-best Parsing time for various k.

 WeiYang
 2018.05.17
 K-best Iterative Viterbi Parsing
 17 / 18





### **Experiments**

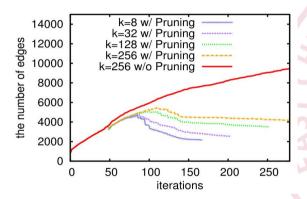


Figure: The plot of the number of edges in chart table at each K-best IVP parsing iteration.

