Convolution kernels for natural language (Collins and Duffy, 2001)

LING 572

Advanced Statistical Methods for NLP

February 20, 2020

Based on F. Xia, '18

Highlights

- Introduce a tree kernel
- Show how it is used for reranking

Reranking

Reranking

- Training data:

$$\{(x_i, y_i)\} \text{ and for each } x_i, \text{ a set of candidates } \{y_{ij}\}.$$
$$\text{and one of } y_{ij} \text{ is the same as } y_i.$$

- Goal: create a module that reranks candidates

- The reranker is used as a post-processor.

- In this paper, build a reranker for parsing

$$x_i \text{ is a sentence, } y_{ij} \text{ is a parse tree.}$$
$$\text{Notation: } \{(s_i, t_i)\}, C(s_i) = \{x_{ij}\}$$

Formulating the problem

$\{(s_i, t_i)\}$, $C(s_i) = \{x_{ij}\}$

$h(x_{ij})$ is the feature vector of candidate x_{ij}.

Let x_{i1} be the correct parse for s_i.

Training: calculate $\vec{w}$

Decoding: $x^* = argmax_{x \in C(s)} \vec{w} \cdot h(x)$

Reranking: Training

Minimize $||w||^2$ subject to the constaints

$$\vec{w} \cdot h(x_{i1}) \geq \vec{w} \cdot h(x_{ij}), \forall i, \forall j \geq 2$$

⇓

$$\vec{w} \cdot (h(x_{i1}) - h(x_{ij})) \geq 1, \forall i, \forall j \geq 2$$

⇓ Recall that in SVM $\vec{w} = \sum_i \alpha_i y_i \vec{x_i}$

$$\vec{w} = \sum_{(i,j)} \alpha_{ij} (h(x_{i1}) - h(x_{ij}))$$

$$f(x) = \vec{w} \cdot x = \sum_{ij} \alpha_{ij} (h(x_{i1}) \cdot h(x) - h(x_{ij}) \cdot h(x))$$

⇓ With the kernel trick

$$f(x) = \sum_{ij} \alpha_{ij} (K(x_{i1}, x) - K(x_{ij}, x))$$

Perceptron training

$$f(x) = \vec{w} \cdot x = \sum_{ij} \alpha_{ij}(h(x_{i1}) \cdot h(x) - h(x_{ij}) \cdot h(x))$$

$\alpha_{i,j} = 0;$

for each sentence i

for each $j > 1$

if $f(x_{i1}) < f(x_{ij})$ then α_{ij}++;

Tree kernel

$$f(x) = \sum_{ij} \alpha_{ij}(K(x_{i1}, x) - K(x_{ij}, x))$$

K: $X \times X \rightarrow R$

Each member of X is a parse tree.

What is a good tree kernel?

A tree kernel

Intuition

- Given two trees T1 and T2, the more subtrees T1 and T2 share, the more similar they are.

- Method:
  - For each tree, enumerate all the subtrees
  - Count how many are in common

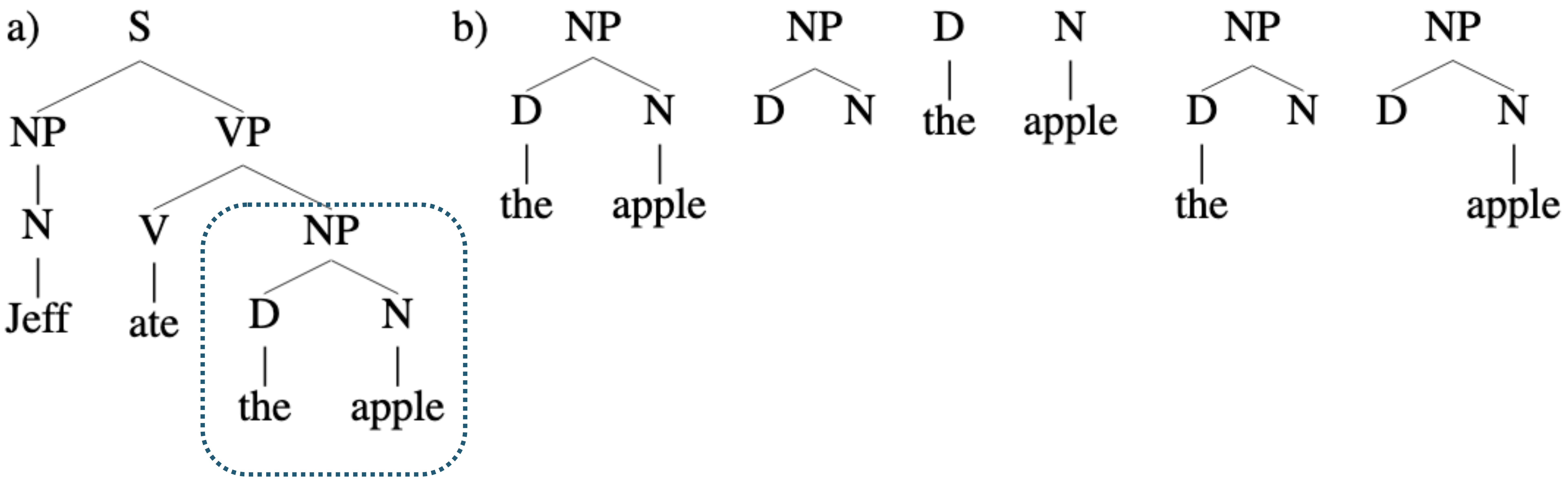
- Do it in an efficient way

Definition of subtree

- A subtree is a subgraph which has more than one node, with the restriction that entire (not partial) rule productions must be included.

- “A subtree rooted at node n” means “a subtree whose root is n”.

An example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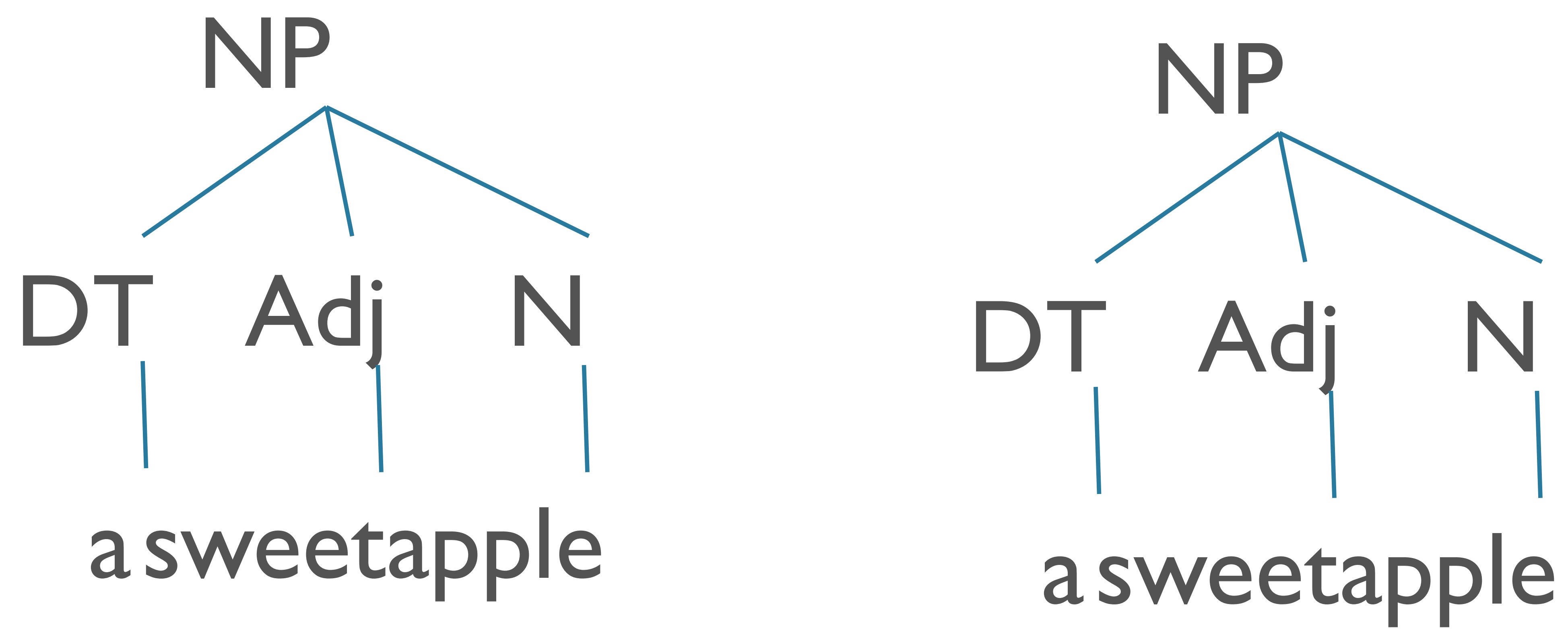
C(n1, n2)

C(n1, n2) counts the number of common subtrees rooted at n1 and n2.

C(n1, n2) = ??



Calculating C(n1, n2)

If the productions at n1 and n2 are different

then C(n1, n2) = 0

else if n1 and n2 are pre-terminals

then C(n1, n2) = 1

else $C(n_1, n_2) = \prod_{j=1}^{nc(n1)} (1 + C(ch(n1, j), ch(n2, j)))$

Representing a tree as a feature vector

Let ST be the set of sub-trees in **any** tree

$$ST = \{s_1, s_2, ..., s_n, ...\}$$

Let $h_i(T)$ be the num of occurrences of s_i in T

$$h(T) = (h_1(T), h_2(T), ..., h_n(T), ...)$$

$$I_i(n) = 1 \quad \text{if } s_i \text{ is a subtree rooted at } n.$$
$$=0 \quad \text{otherwise}$$

$h_i(T_1) = \sum_{n_1 \in N_1} I_i(n_1)$, where N_1 is the set of nodes in T_1

$$h_i(T_2) = \sum_{n2 \in N2} I_i(n_2)$$

A tree kernel

$$h(T_1) \cdot h(T_2) = \sum_i h_i(T_1) h_i(T_2)$$

$$= \sum_i \left(\sum_{n1 \in N1} I_i(n_1)\right) * \left(\sum_{n_2 \in N2} I_i(n_2)\right)$$

$$= \sum_i \sum_{n_1 \in N1} \sum_{n_2 \in N2} I_i(n1) I_i(n_2)$$

$$= \sum_{n_1 \in N1} \sum_{n_2 \in N2} \sum_i I_i(n1) I_i(n_2)$$

$$= \sum_{n_1 \in N1} \sum_{n_2 \in N2} C(n1, n_2)$$

$K(T_1, T_2) = h(T_1) \cdot h(T_2)$ can be calculated in $O(|N_1||N_2|)$

Properties of this kernel

- The value of K(T1, T2) depends greatly on the size of the trees T1 and T2.

$$K'(T_1, T_2) = \frac{K(T_1, T_2)}{\sqrt{K(T_1, T_1)K(T_2, T_2)}}$$

- K(T, T) could be huge. The output would be dominated by the most similar tree.

=> The model would behave like a nearest neighbor rule

Down-weighting the contribution of large subtrees when calculating C(n1, n2)

If the productions at n1 and n2 are different

then C(n1, n2) = 0

else if n1 and n2 are pre-terminals

then $C(n_1, n_2) = \lambda$

else $C(n_1, n_2) = \lambda \prod_{j=1}^{nc(n1)} (1 + C(ch(n1, j), ch(n2, j)))$

Experimental results

Experiment setting

- Data:
  - Training data: 800 sentences,
  - Dev set: 200 sentences
  - Test set: 336 sentences
  - For each sentence, 100 candidate parse trees

- Learner: voted perceptron

- Evaluation measure: 10 runs and report the average parse score

- Baseline (with PCFG): 74% (labeled f-score)

Results

Depth	1	2	3	4	5	6
Score	73 ± 1	79 ± 1	80 ± 1	79 ± 1	79 ± 1	78 ± 0.01
Improvement	-1 ± 4	20 ± 6	23 ± 3	21 ± 4	19 ± 4	18 ± 3

With different max subtree size

Scale	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Score	77 ± 1	78 ± 1	79 ± 1	79 ± 1	79 ± 1	79 ± 1	79 ± 1	79 ± 1	78 ± 1
Imp.	11 ± 6	17 ± 5	20 ± 4	21 ± 3	21 ± 4	22 ± 4	21 ± 4	19 ± 4	17 ± 5

Summary

- Show how to use a SVM or a perceptron learner for the reranking task.

- Define a tree kernel that can be calculated in polynomial time.
  - Note: the number of features is infinite.

- The reranker improves parse score from 74% to 80%.