



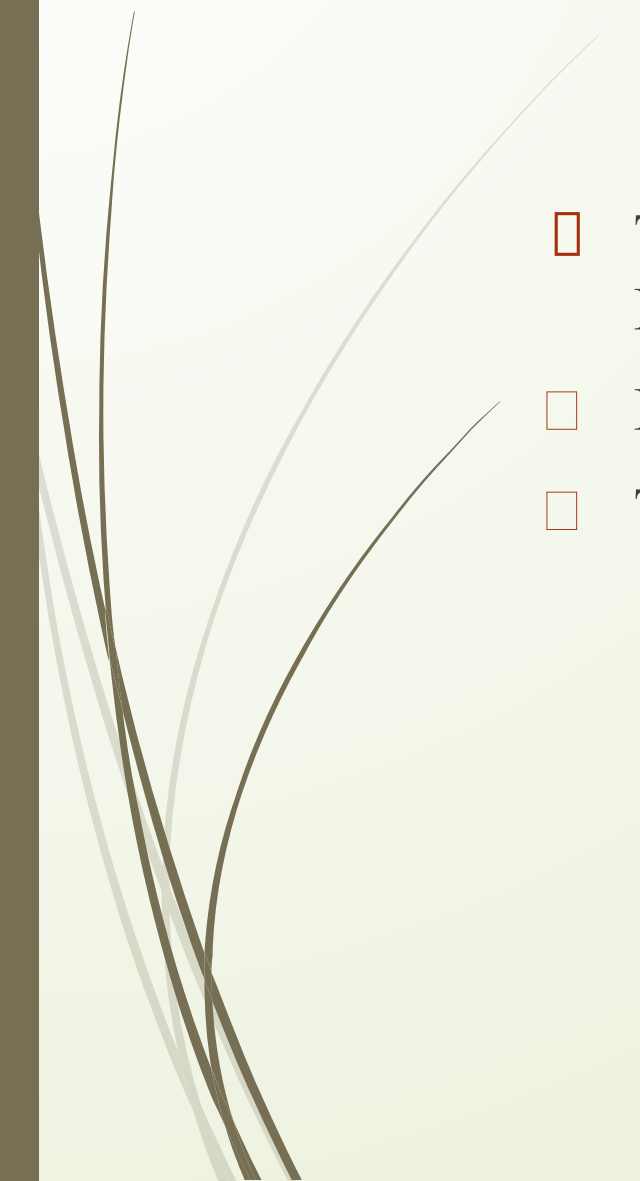
# CONVOLUTION KERNELS FOR NATURAL LANGUAGE

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# NATURAL LANGUAGE PROCESSING

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- TRAINING - GIVEN A STRING OR SENTENCE FINDING THE HIDDEN STRUCTURE
  - PARSING-TASKS INVOLVING TREE DATA STRUCTURE
  - TAGGING-TASKS INVOLVING HIDDEN TEXT SEQUENCES



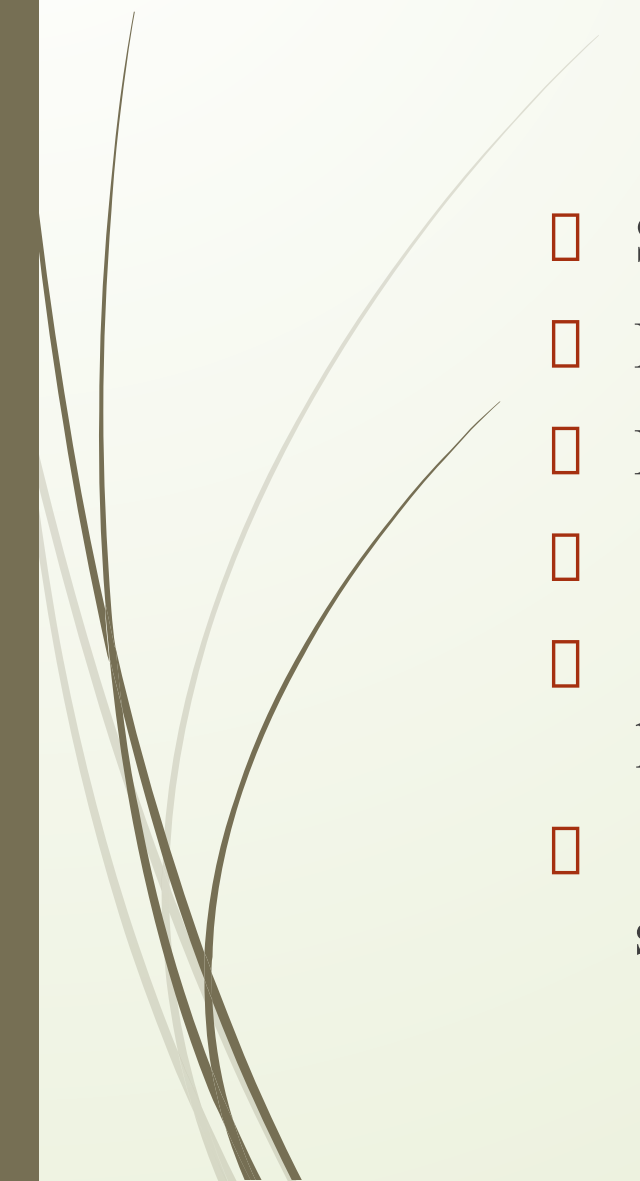
# STRUCTURE IN NLP TASK



**Parse tree: Lou Gerstner is chairman of IBM -- [S [NP Lou Gerstner]  
[VP is [NP chairman [PP of [NP IBM] ] ] ] ]**

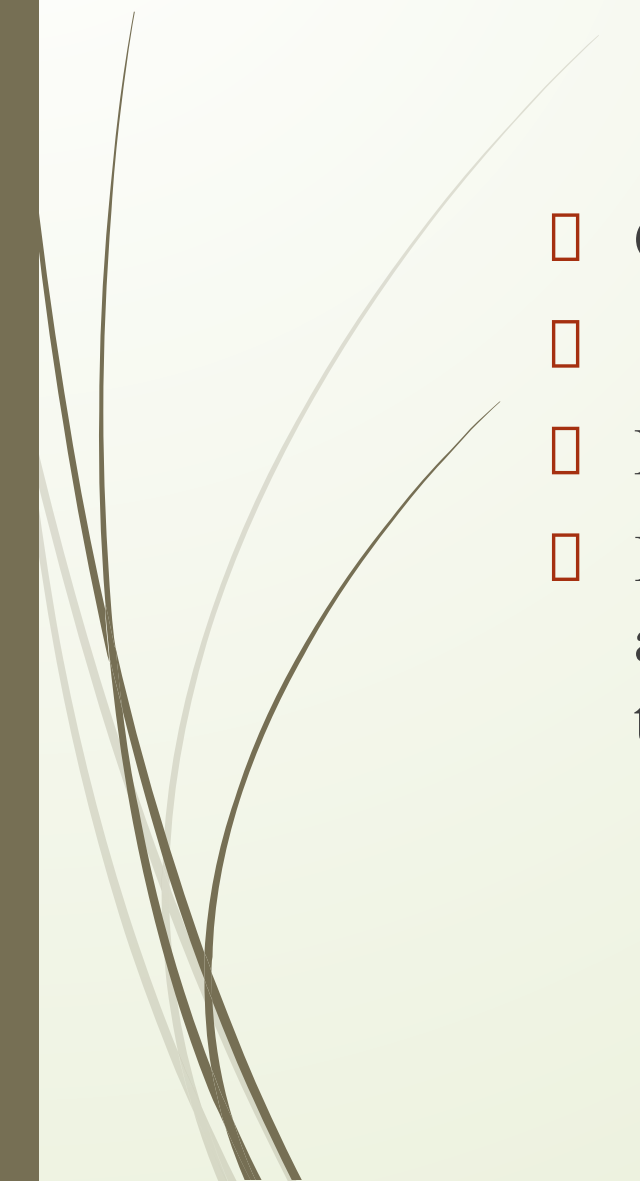


# DEALING WITH AMBIGUITY

- Stochastic grammar: --
  - PCFG (Probabilistic Context Free Grammar) for parsing
  - HMM (Hidden Markov Model) for tagging
  - Probabilities are attached to rules in the grammar.
  - Rule probabilities are estimated using MLE (Maximum likelihood estimation).
  - Probabilities are used to rank the competing analyses for the same sentence.
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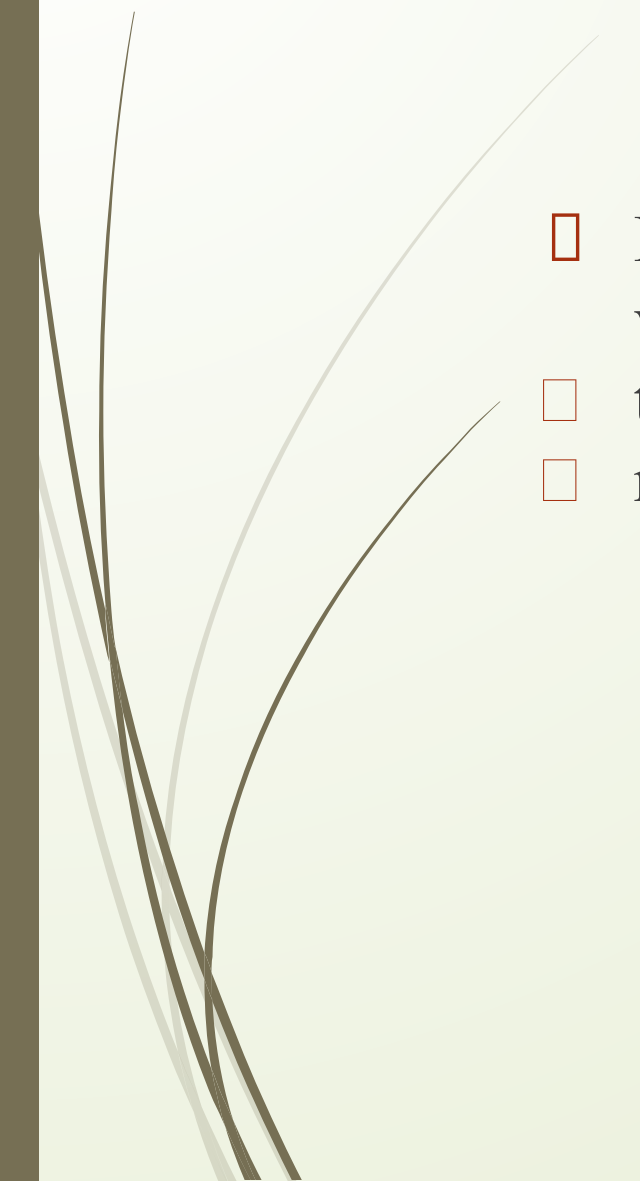


# PCFGs AS PARSING METHOD

- Counts the relative number of occurrences of a given rule.
  - Uses the count to represent its learned knowledge.
  - Makes strong independence assumptions.
  - Ignores substantial amounts of structural information (e.g. assume rules applied at level  $i$  in the parse tree are unrelated to those applied at level  $i+1$ ).
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# INTRODUCTION TO KERNELS

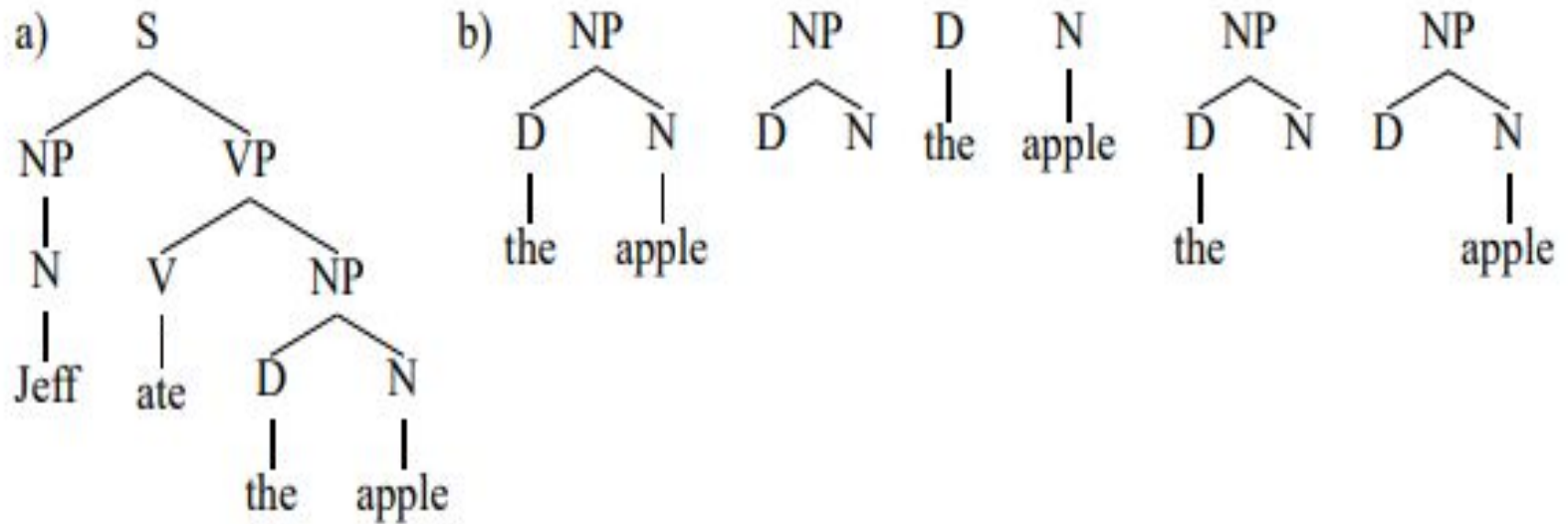
- Kernels basically takes the dot product between two feature vectors
  - they try to find out similarities between objects
  - reduces the complexity of computations
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# APPLYING KERNEL METHOD TO NLP PROBLEMS

- Input in NLP-Trees, sequences, etc.
  - kernel used- tree kernel (convolution kernels)
  - the kernel function counts the number of common subtrees in any two trees to find similarity between them.
  - finds dependencies between structural information.
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# TREE AND SUBTREE





# REPRESENTATION OF TREE KERNELS

- Enumerate (implicitly) all tree fragments:  $1, \dots, n$ .
- Represent each tree by an  $n$ -d vector:
- number of occurrences of the  $i$ 'th tree fragment in tree  $T$
- Tree  $T$  is represented as:
- $h(T) = (h_1(T), h_2(T), h_3(T), \dots, h_n(T))$
- $n$  is very large

# DEFINING TREE KERNEL

- INNER PRODUCT BETWEEN TWO TREES  $T_1$  AND  $T_2$
- $K(T_1, T_2) = h(T_1) \cdot h(T_2)$
- INDICATOR FUNCTION(I)
- $I_i(n) = 1$  if sub-tree is seen rooted at node ;  
and 0 otherwise

definition cont..

$$\mathbf{h}(T_1) \cdot \mathbf{h}(T_2) = \sum_i h_i(T_1) h_i(T_2) = \sum_{n_1 \in N_1} \sum_{n_2 \in N_2} \sum_i I_i(n_1) I_i(n_2) = \sum_{n_1 \in N_1} \sum_{n_2 \in N_2} C(n_1, n_2)$$

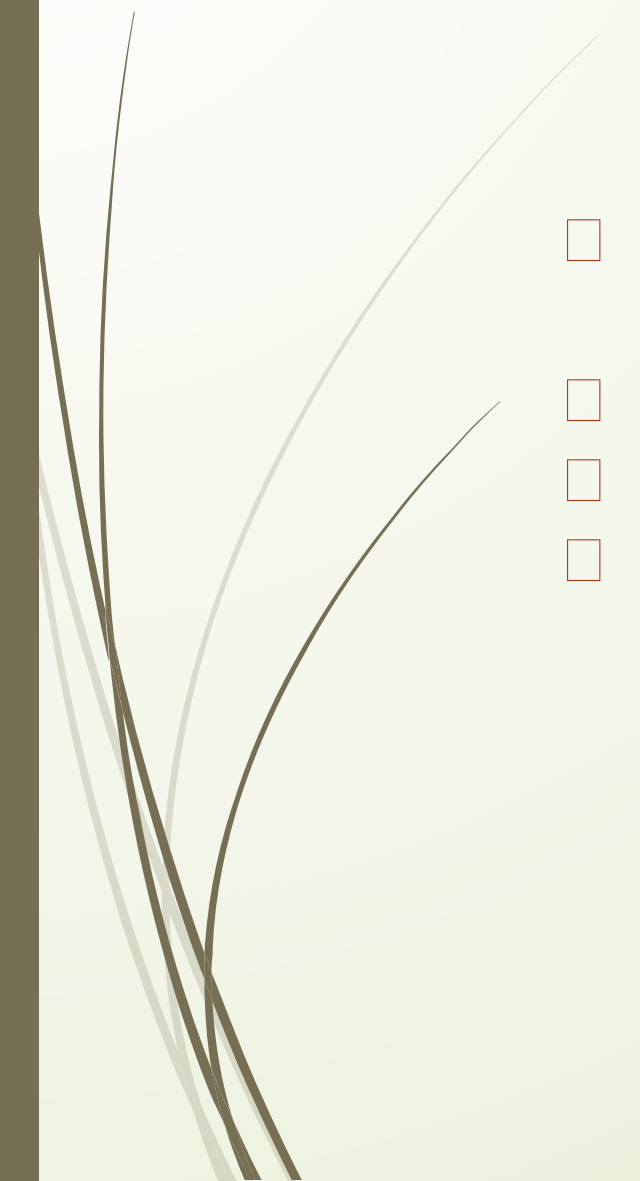
# Recursive definition

- If the productions at  $n_1$  and  $n_2$  are different  $C(n_1, n_2)=0$ .
- If the productions at  $n_1$  and  $n_2$  are the same, and  $n_1$  and  $n_2$  are pre-terminals, then  $C(n_1, n_2)=1$ .
- Else if the productions at  $n_1$  and  $n_2$  are the same and  $n_1$  and  $n_2$  are not pre-terminals,

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



# EXPERIMENT OUTCOMES

- ☐ applied tree kernel to the problem of parsing the Penn treebank ATIS corpus
  - ☐ Applied Voted Perceptron using tree kernel to the test set.
  - ☐ Applied PCFG on same
  - ☐ voted perceptron using kernel performed better with better accuracy
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## PERFORMANCE OF PERCEPTRON WITH KERNEL(improvement is relative to PCFG)

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