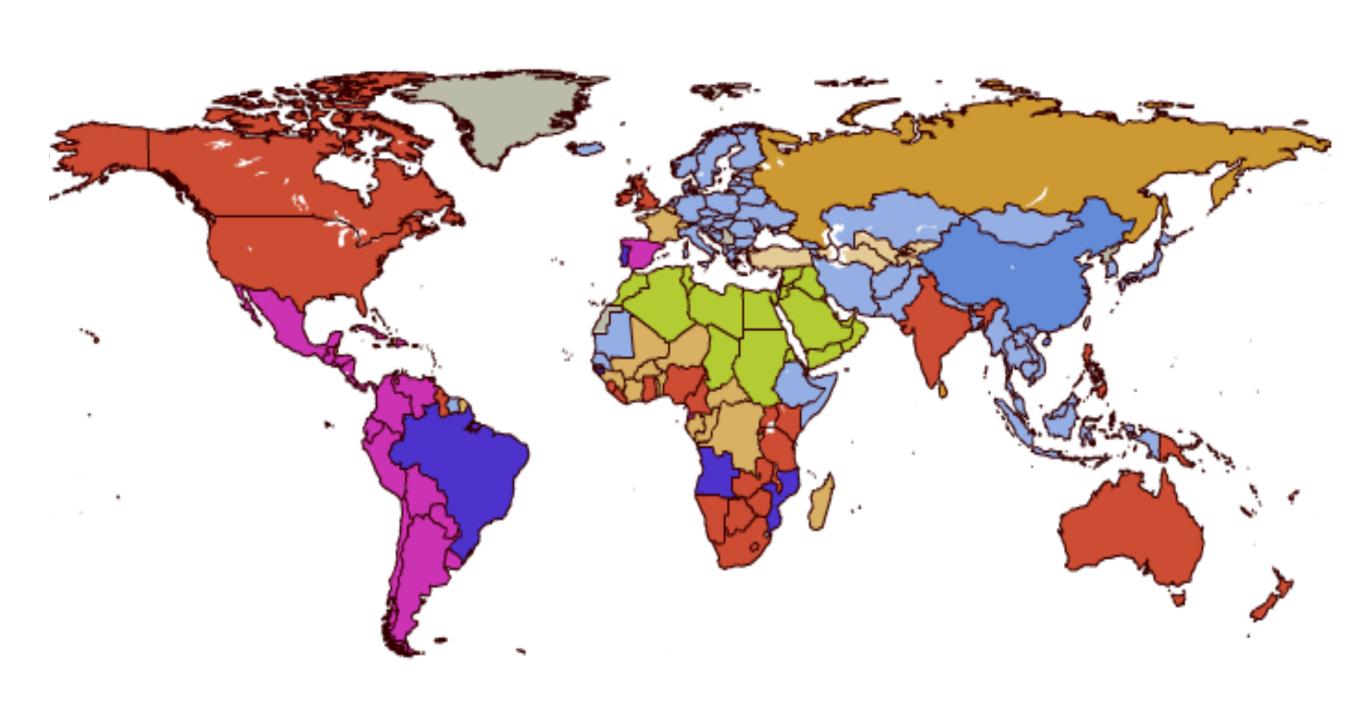
# Statistical Machine Translation in the Big Data Era

Yang Liu
Tsinghua University



# Part I: Introduction

#### Natural Languages are Different



# Natural Languages are Different

Я люблю тебя I love you 당신을 사랑합니다 我爱你 Eu te amo Je t'aime אני אוהב אותך من شما را دوست دارم Tôi yêu bạn Ich liebe dich Miluji tě Te quiero Ti amo ผมรักคุณ わたしは、あなたを愛しています Ik hou van je Jag älskar dig

by Google Translate

#### Machine Translation

布什 与 沙龙 举行 了 会谈 bushi yu shalong juxing le huitan



Bush held a talk with Sharon



adapted from Adam Lopez's slides





adapted from Adam Lopez's slides







adapted from Adam Lopez's slides









adapted from Adam Lopez's slides

Garcia y asociados.

los clients y los asociados son enemigos.

sus asociados no son fuertes.

Garcia y asociados.

Garcia and associates.

los clients y los asociados son enemigos.

the clients and the associates are enemies.

sus asociados no son fuertes.

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Garcia y asociados .

Carcia and associates .

los clients y los asociados son enemigos . the clients and the associates are enemies .

Spanish	English
Garcia	Garcia
у	and
asociados	associates
•	•
los	the
clients	clients
son	are
enemigos	enemies
sus	his
no	not
fuertes	strong

Garcia y asociados .

Carcia and associates .

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Garcia and his associates are not enemies .

Spanish	English
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rule-based MT

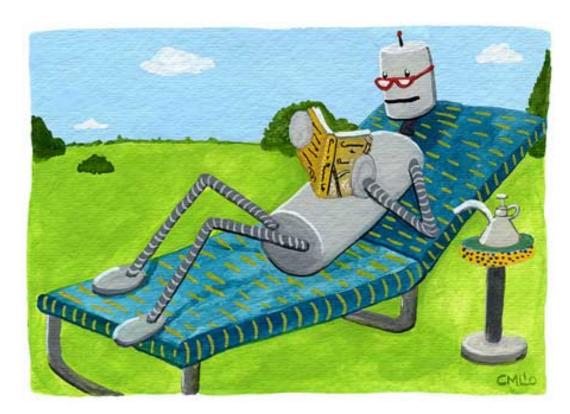




rule-based MT







data-driven MT

#### Data-driven MT



data-driven MT

#### Data-driven MT



data-driven MT



**Example-based MT** 

(Nagao, 1984)

#### Data-driven MT



data-driven MT





Example-based MT

(Nagao, 1984)

Statistical MT

(Brown et al., 1993)

#### Statistical MT

Statistical machine translation is a machine translation paradigm where translations are generated on the basis of statistical models whose parameters are derived from the analysis of bilingual text corpora.

-- Wikipedia

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#### Modeling

Tell machine how to translate

#### Learning

Machine learns translation knowledge from data

#### Decoding

Machine translates text using learned knowledge

#### Big Data

- An explosion of data across numerous languages
  - 60,000 news websites per day
  - 2 million blog posts per day
  - 175 million Tweets per day
  - 293,000 new Facebook status updates per minute
- 2 billion Internet users speaking 6000 languages

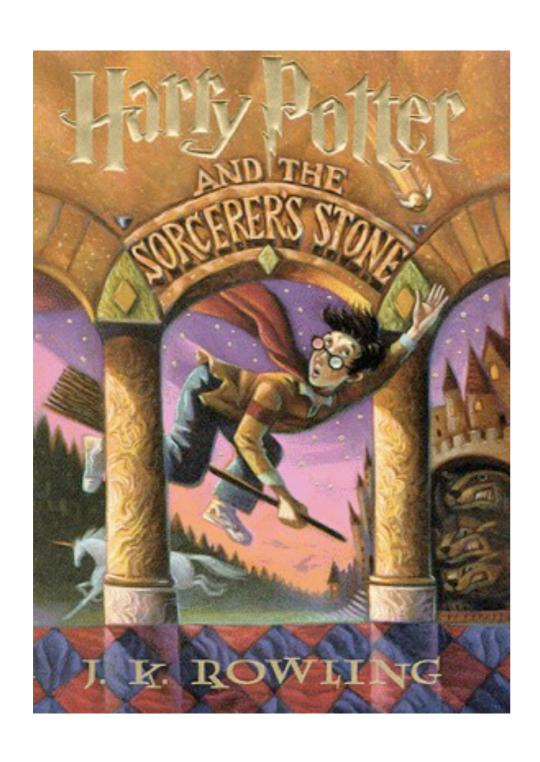
#### Data for SMT

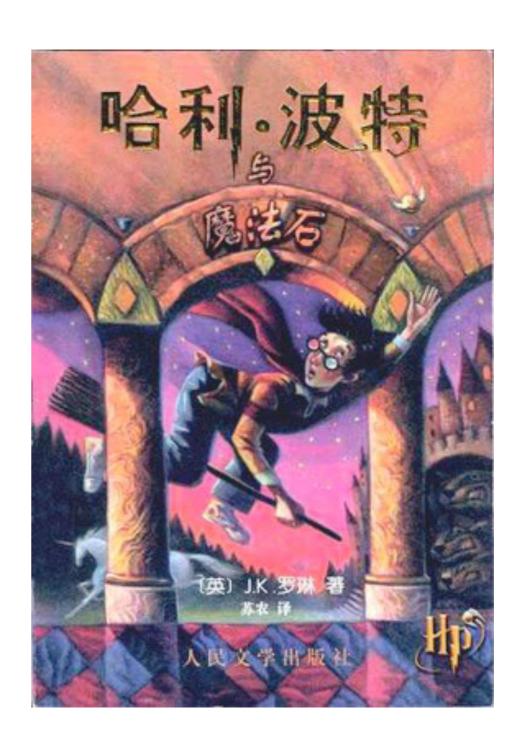




Global Compact

> UN General Assembly 66th session





from Adam Lopez's slides

#### 二、谓语否定式

否定词是用来否定谓语动词的否定式叫做谓语否定式,这是否定式中比较常见的一种形式。谓语否定式一般存在两种情况:

(一) 助动词、be 动词及情态动词后跟 not 的情况

He does not get up early every motning.

他每天早上起床起得不早。

She was not a teacher.

她不是一位老师

I can not swim well

我游泳游得不好

对于以上三种情形的否定句主要是要把握好对谓语动词的翻译,以及助动词、be 动词、情态动词所标志的时间状态的翻译。

中新网10月5日电 据外电报道,阿富汗官员5日称,驻阿富汗北约部队4日晚对阿富汗东部一地区进行了空袭,造成包括3名未成年人在内至少5名平民死亡。

楠格哈尔省警方发言人马什莱齐瓦尔(Hazrat Hussain Mashreqiwal)说,这5名年龄介于12到20岁的平民,在该省首府贾拉拉巴德郊外萨拉查(Saracha)地区捕鸟时遭到北约空袭致死。

北约发言人称知道此次空袭,但是不愿证实死亡人数。

马士莱齐瓦尔说,昨天(4日)晚11点左右,5名12到20岁的平民在距离贾拉拉巴德市中心约8公里的地区,拿气枪捕鸟时,遭到外国部队空袭死亡。他们的尸体已经被送到中心医院。

楠格哈尔省政府发言人亚布杜拉塞(Ahmad Zia Abdulzai)证实了此次空袭事件。

楠格哈尔省教育部发言人辛瓦利(Mohammad Atif Shinwari)说,3名在空袭中死亡的平民是学童,2人为兄弟。

中新网10月5日电据外电报道,阿富汗官员5日称,驻阿富汗北约部队4日晚对阿富汗东部一地区进行了空袭,造成包括3名未成年人在内至少5名平民死亡。

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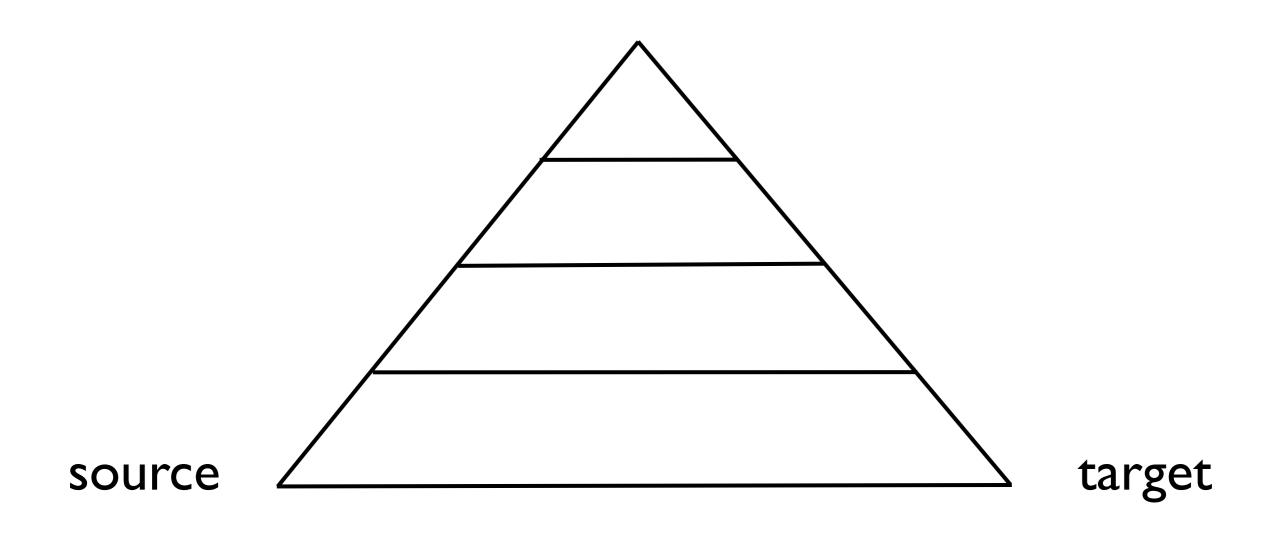
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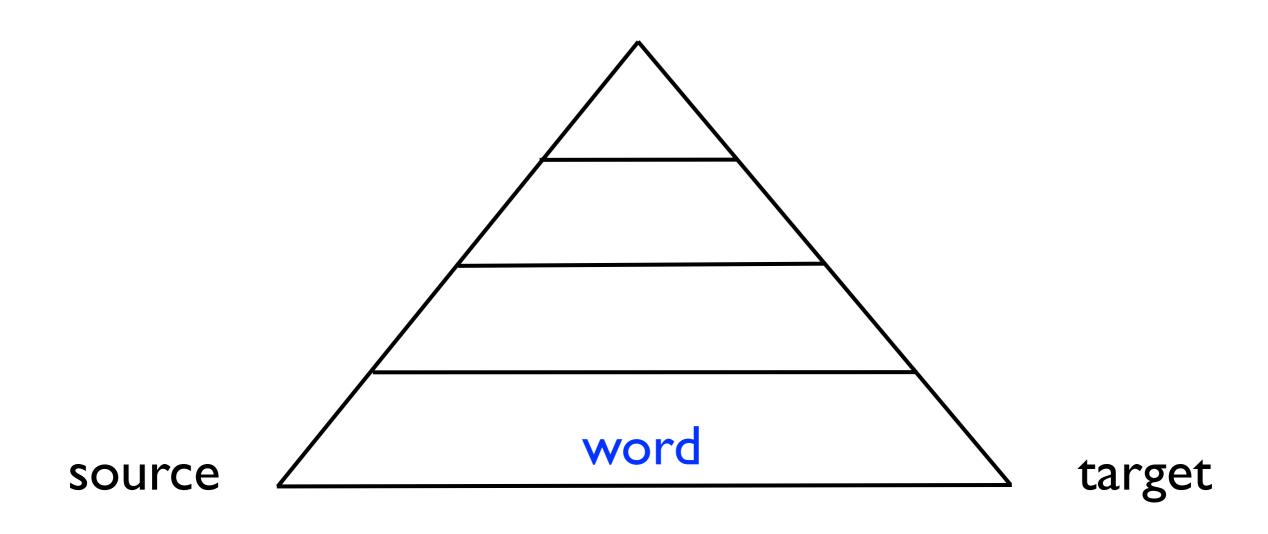
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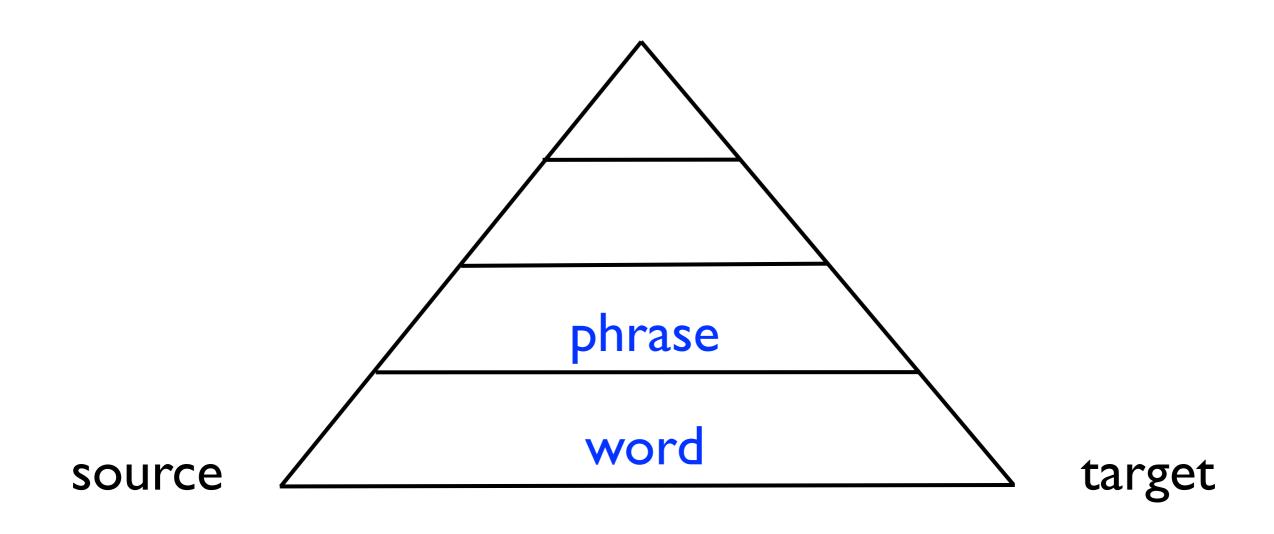
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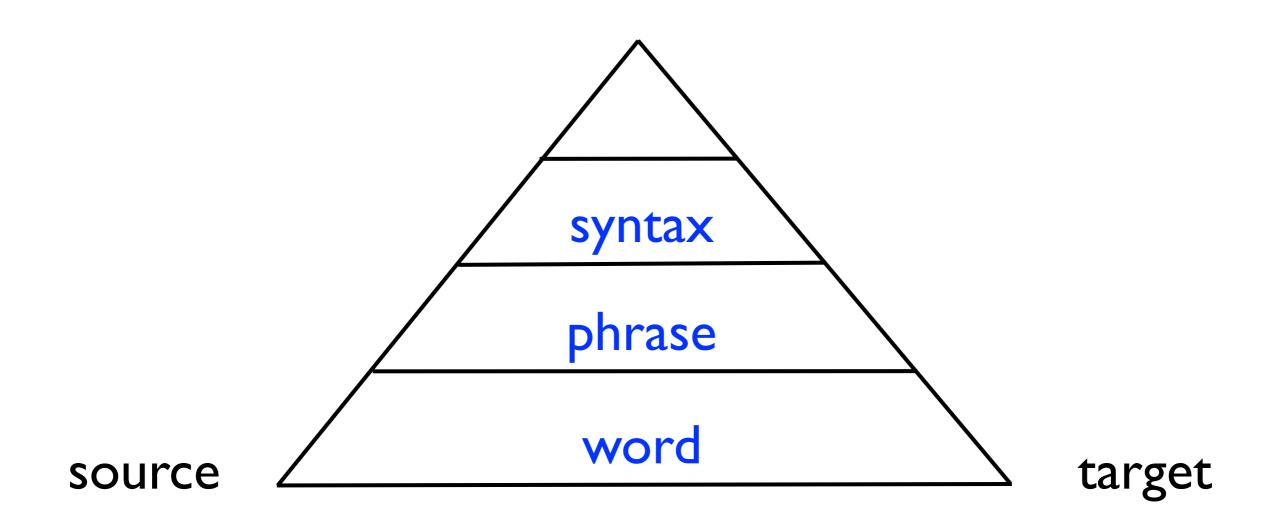
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# Part 2: Word-based MT

# The Origin of SMT

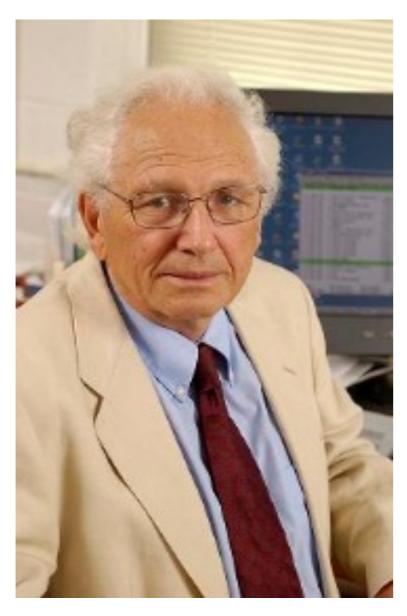


Warren Weaver

When I look at an article in Russian, I say: "This is really written in English, but it has been coded in some strange symbols. I will now proceed to decode."

Weaver (1955)

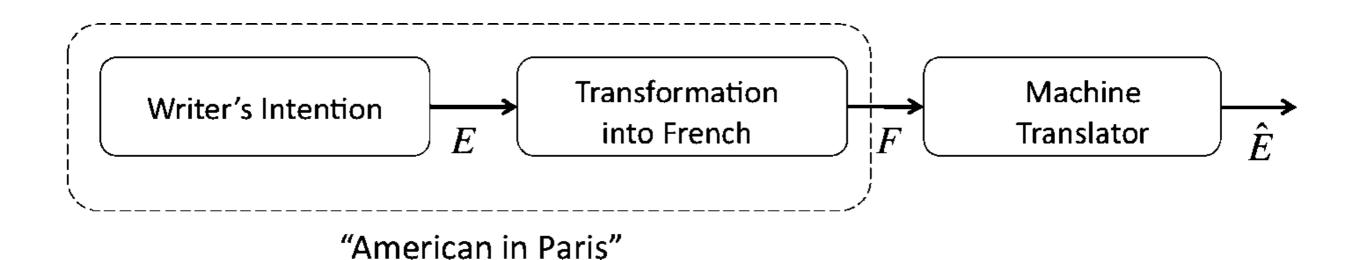
### IBM and Machine Translation

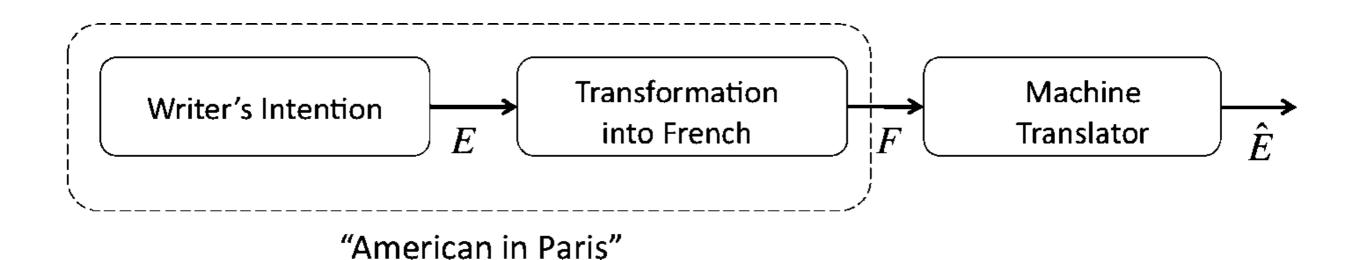


Fred Jelinek

Some of us started to wonder in the mid of 1980s whether our ASR methods could be applied to new fields. Bob Mercer and 1 ... came up with two: machine translation and stock market modeling.

Jelinek (2009)







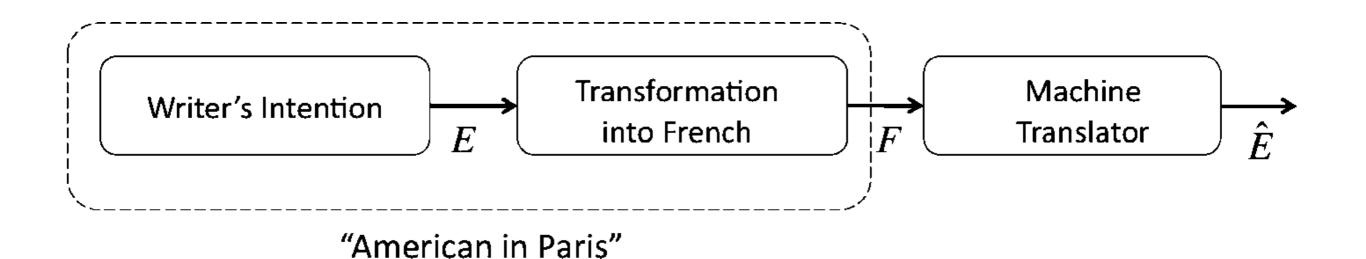
 $P(E|F) = \frac{P(E) \times P(F|E)}{P(F)}$ 



"American in Paris"

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P("Bush held a talk with Sharon")

P("Bush held a talk with Sharon") = P("Bush" $) \times$ 

```
P("Bush held a talk with Sharon")
= P("Bush") \times
P("held"|"Bush") \times
```

```
P(\text{"Bush held a talk with Sharon"})
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```

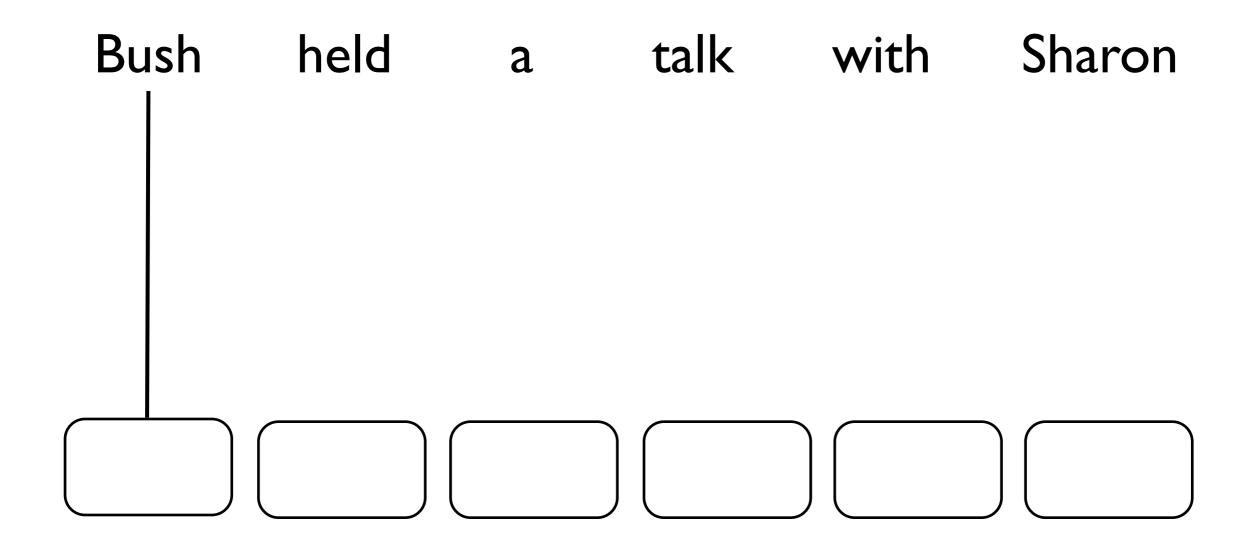
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   P(\text{"held"}|\text{"Bush"})\times
   P(\text{``a''}|\text{``Bush held''})\times
   P(\text{"talk"}|\text{"held a"})\times
   P(\text{"with"}|\text{"a talk"})\times
```

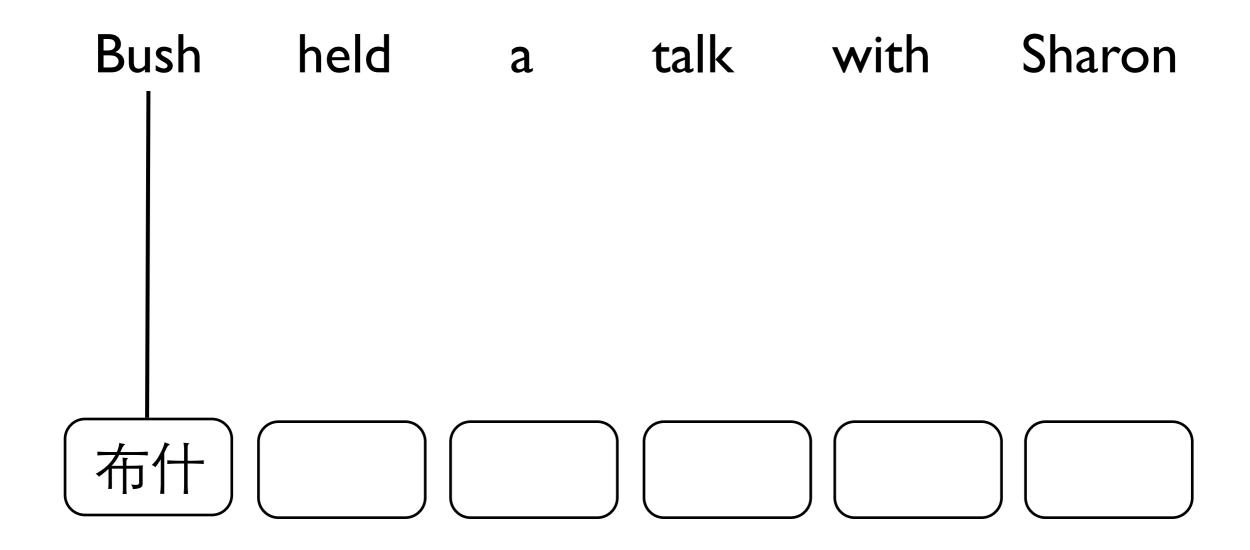
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   P(\text{"talk"}|\text{"held a"})\times
   P(\text{"with"}|\text{"a talk"})\times
   P("Sharon" | "talk with")
```

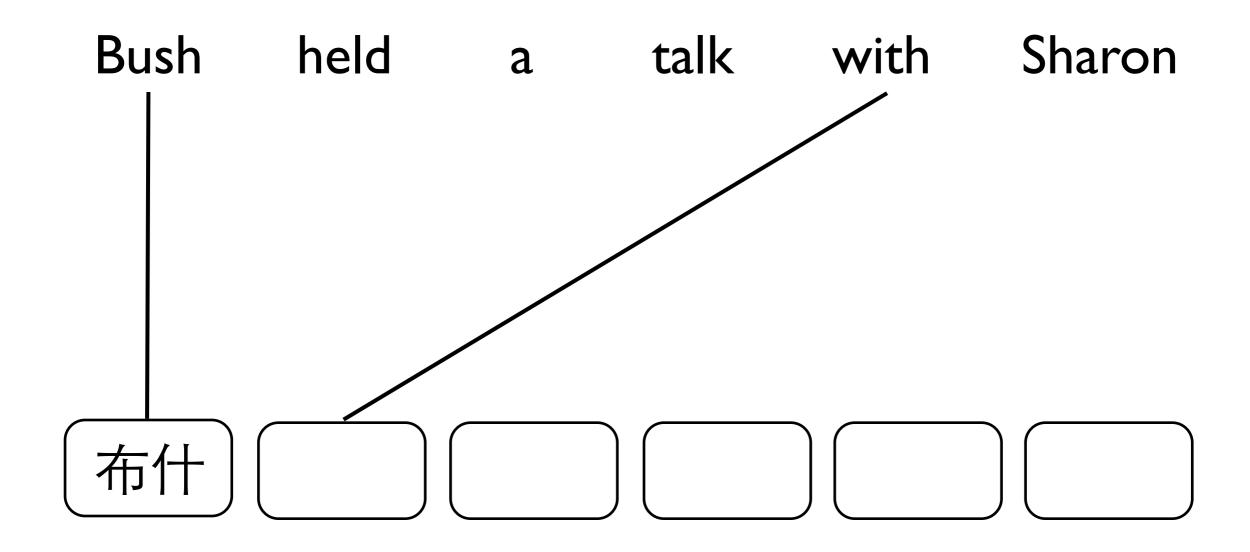
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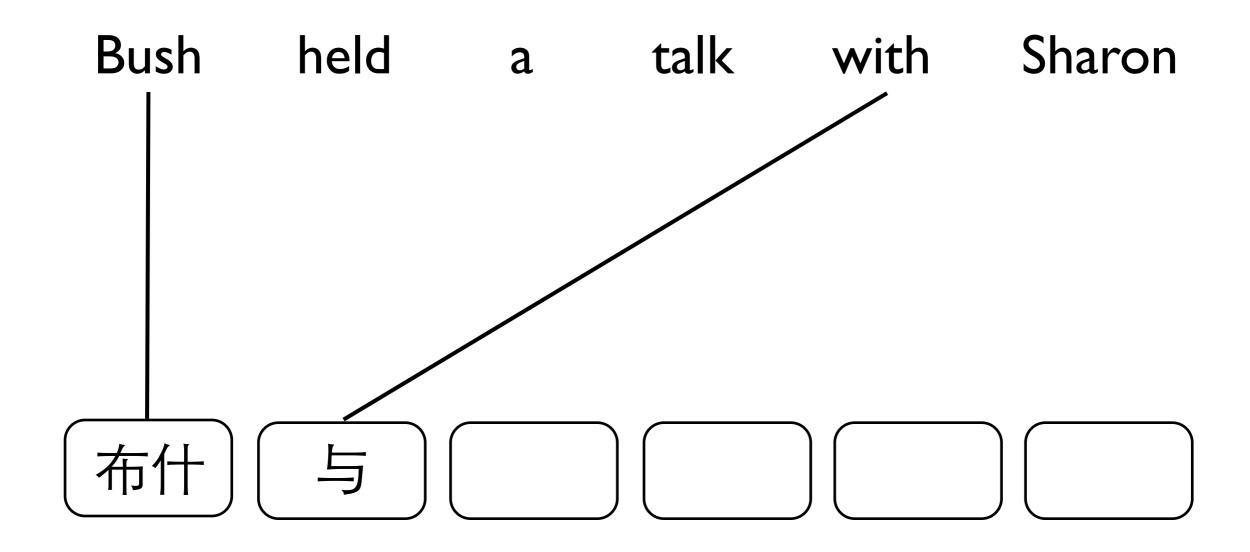
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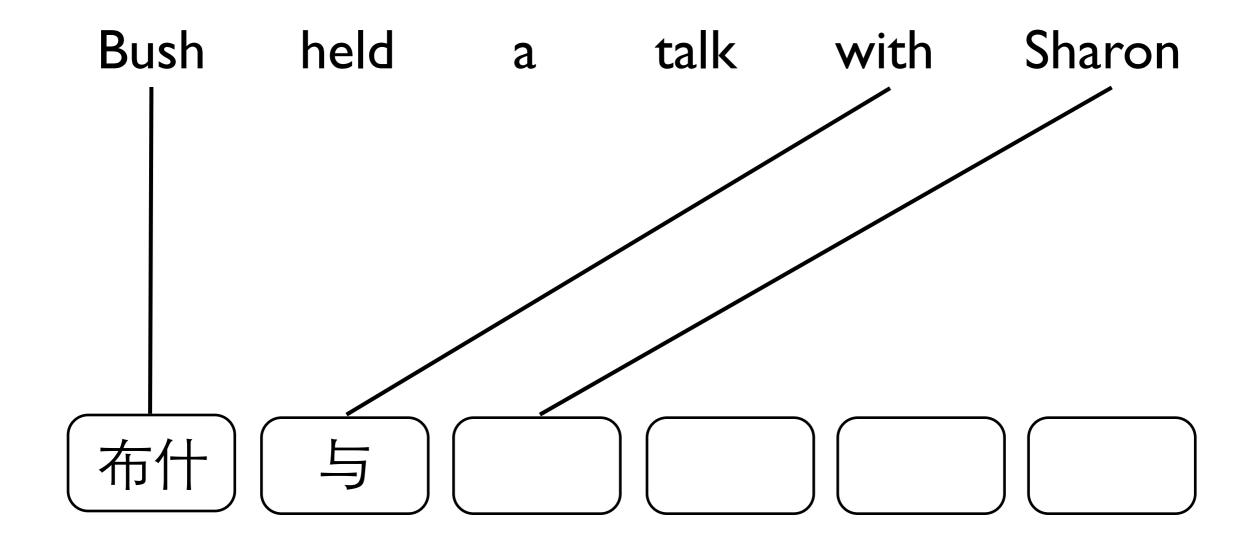


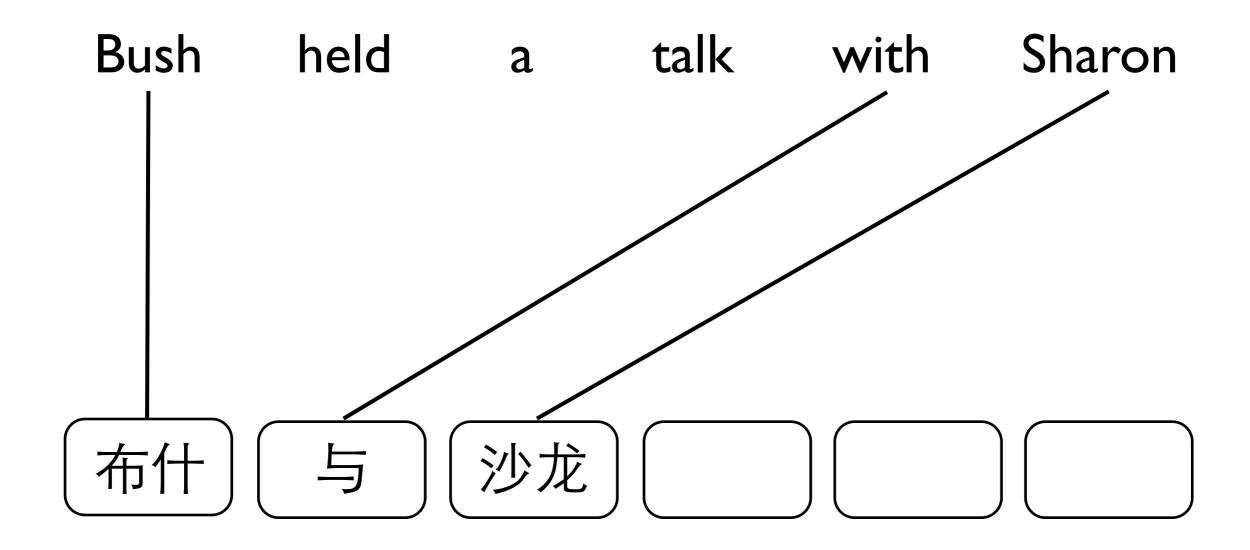


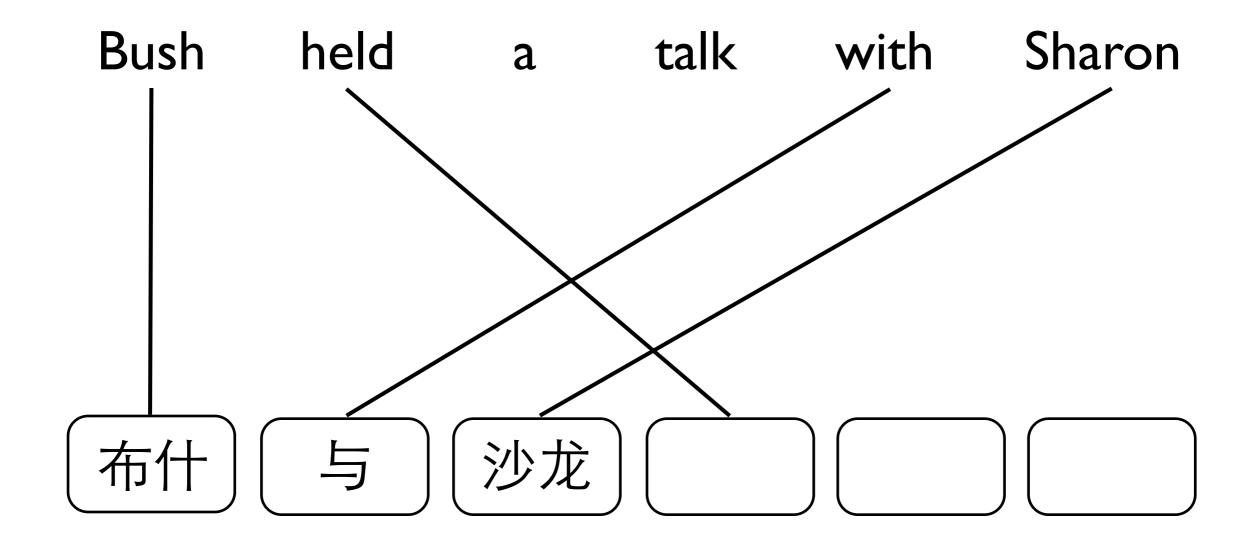


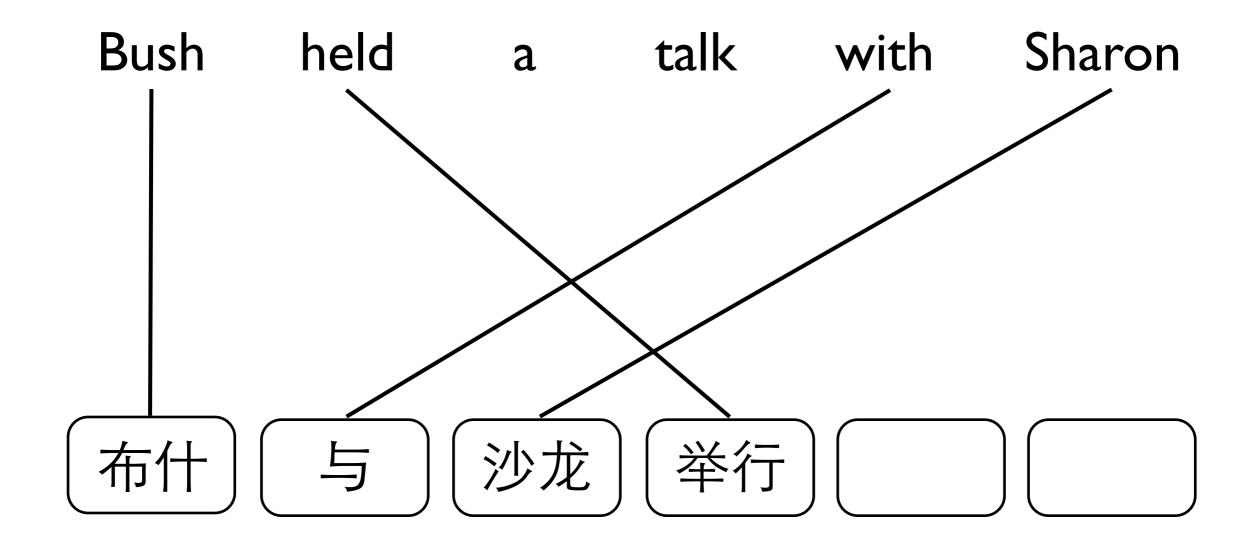


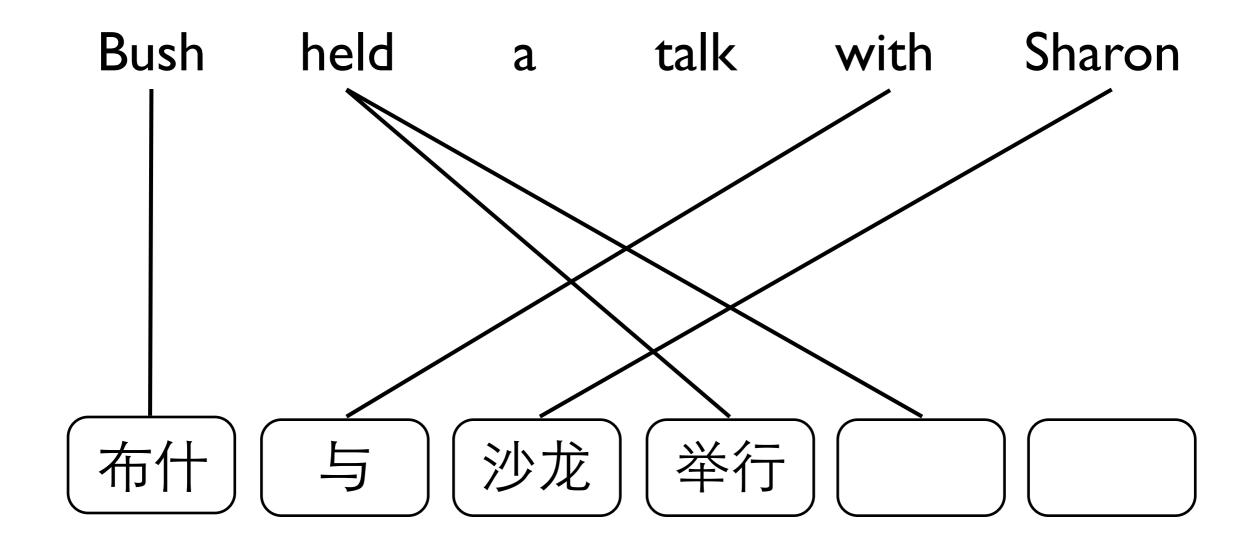


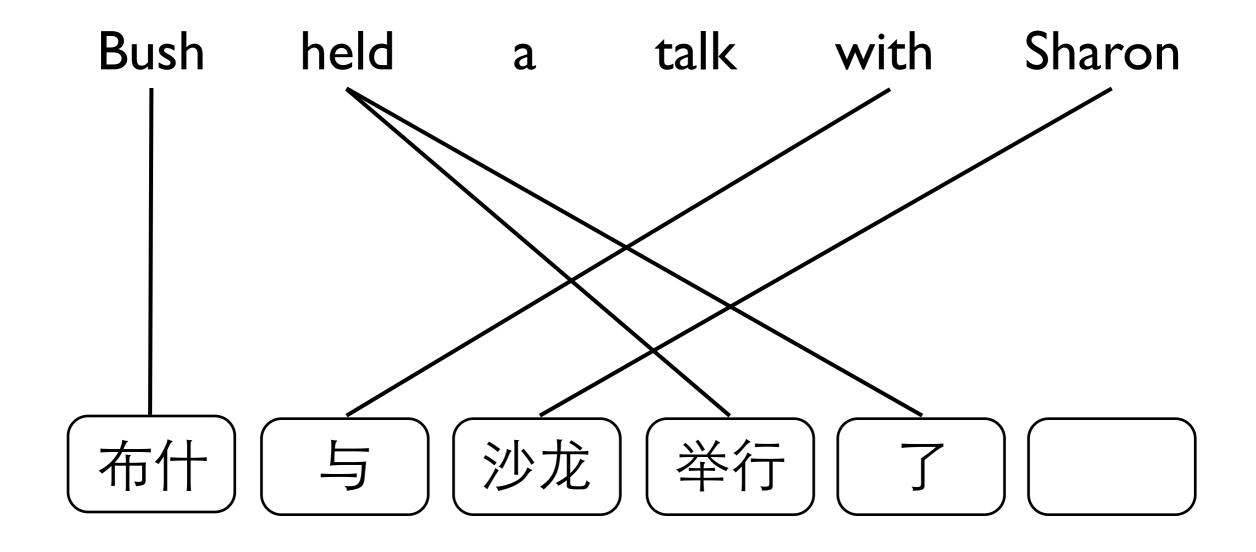


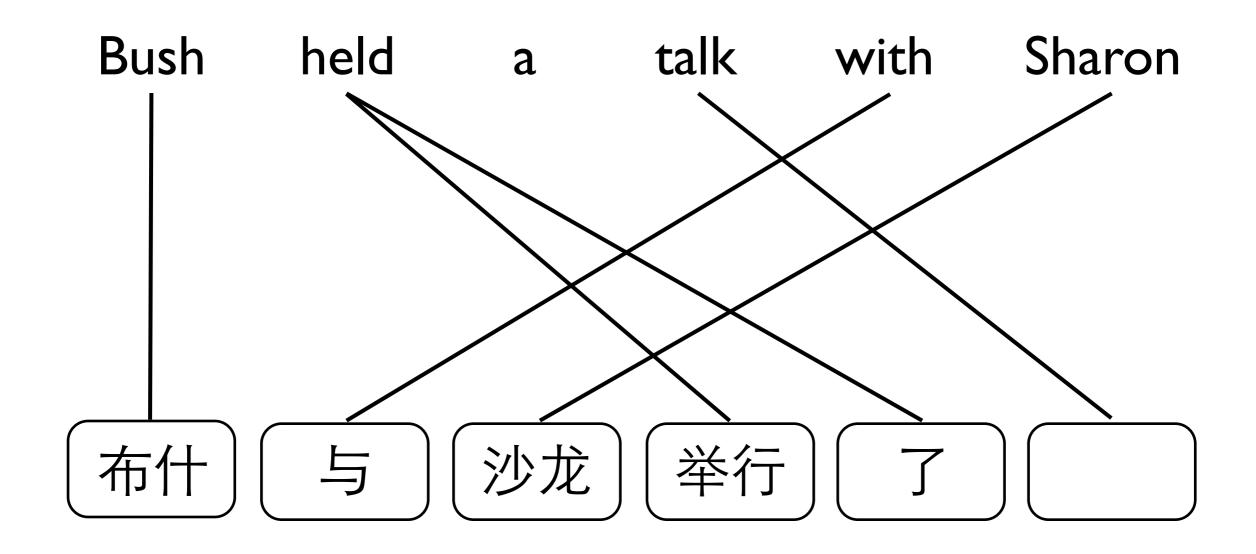


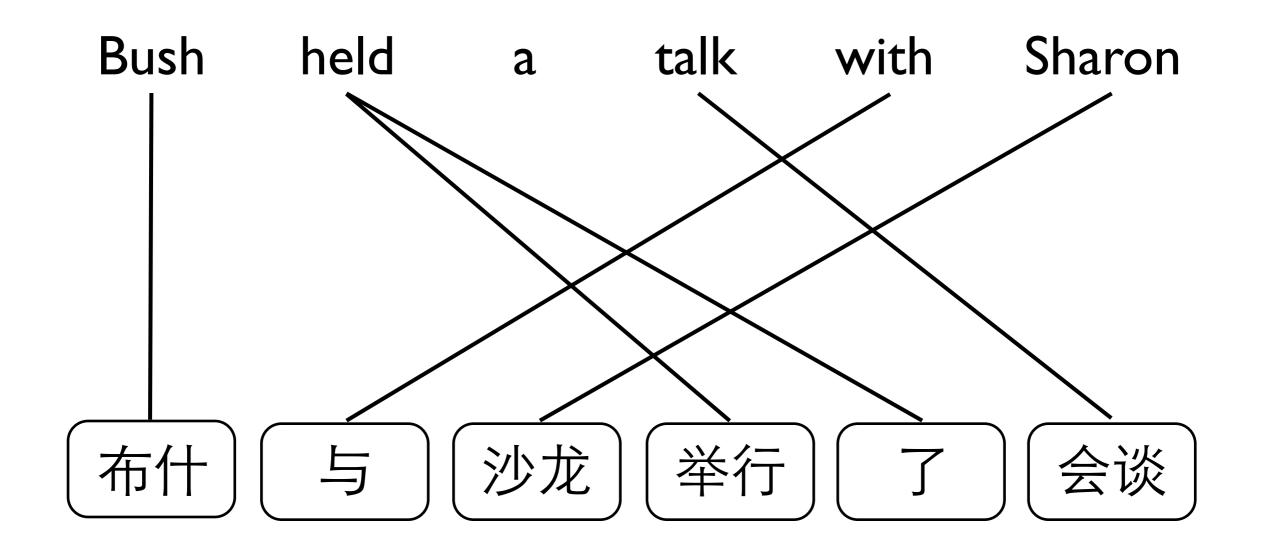












$$Pr(f|e) = \sum_{a} Pr(f, a|e).$$

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$$\Pr(\mathbf{f}, \mathbf{a} | \mathbf{e}) = \Pr(m | \mathbf{e}) \prod_{j=1}^{m} \Pr(a_j | a_1^{j-1}, f_1^{j-1}, m, \mathbf{e}) \Pr(f_j | a_1^j, f_1^{j-1}, m, \mathbf{e}).$$

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length model

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length model alignment model

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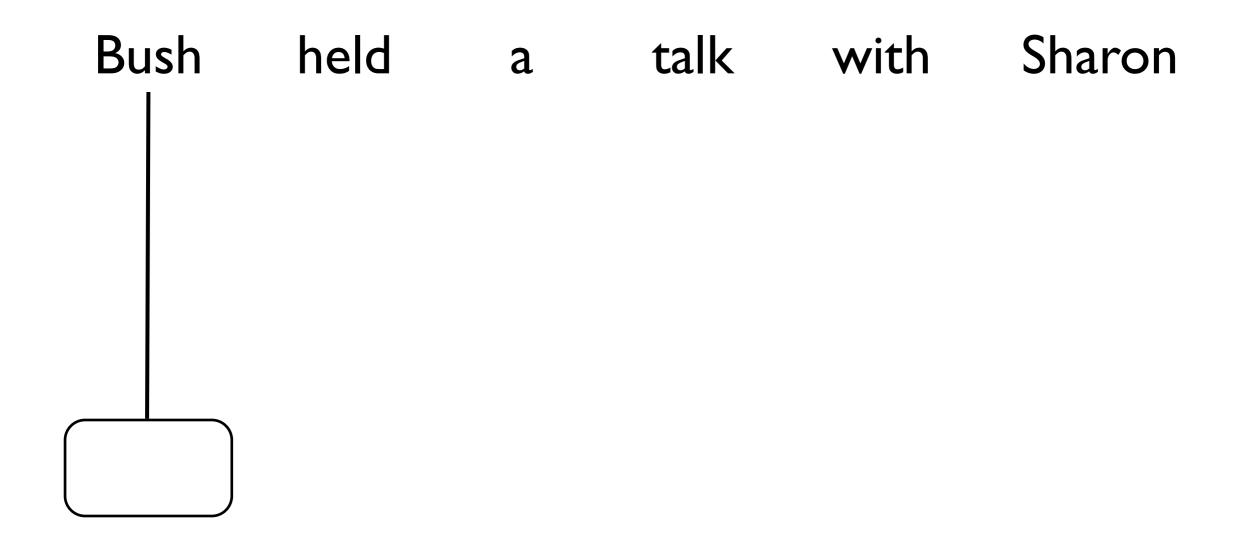
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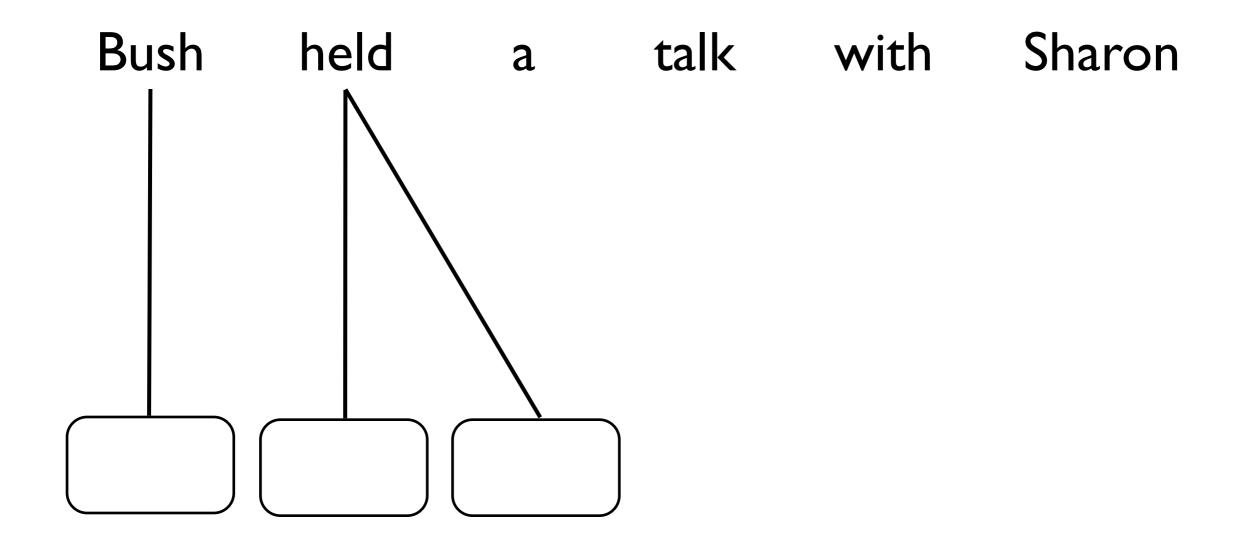
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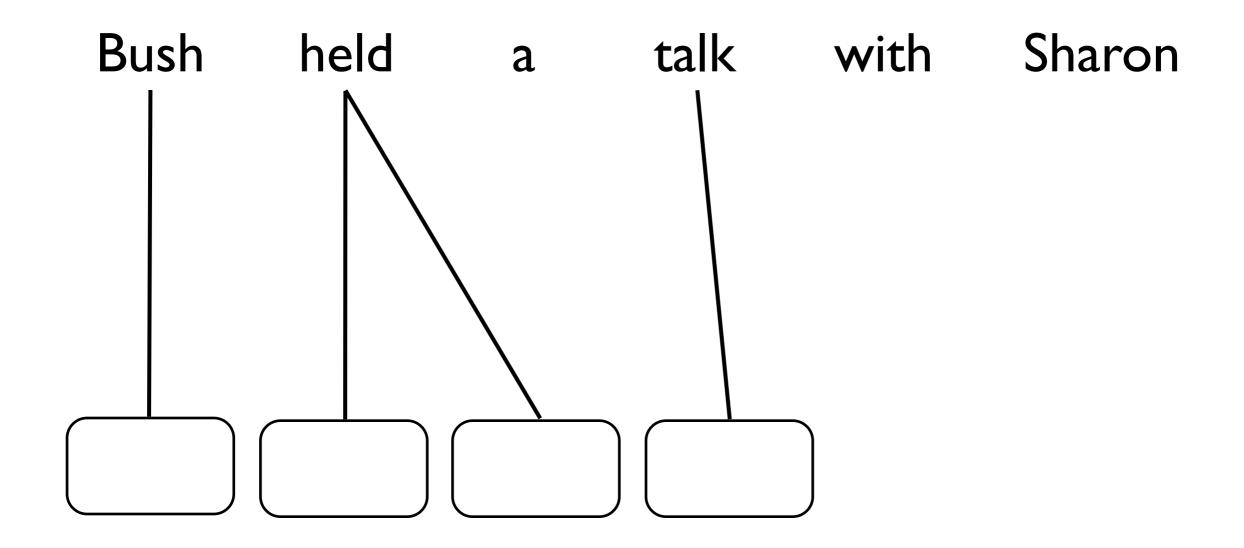
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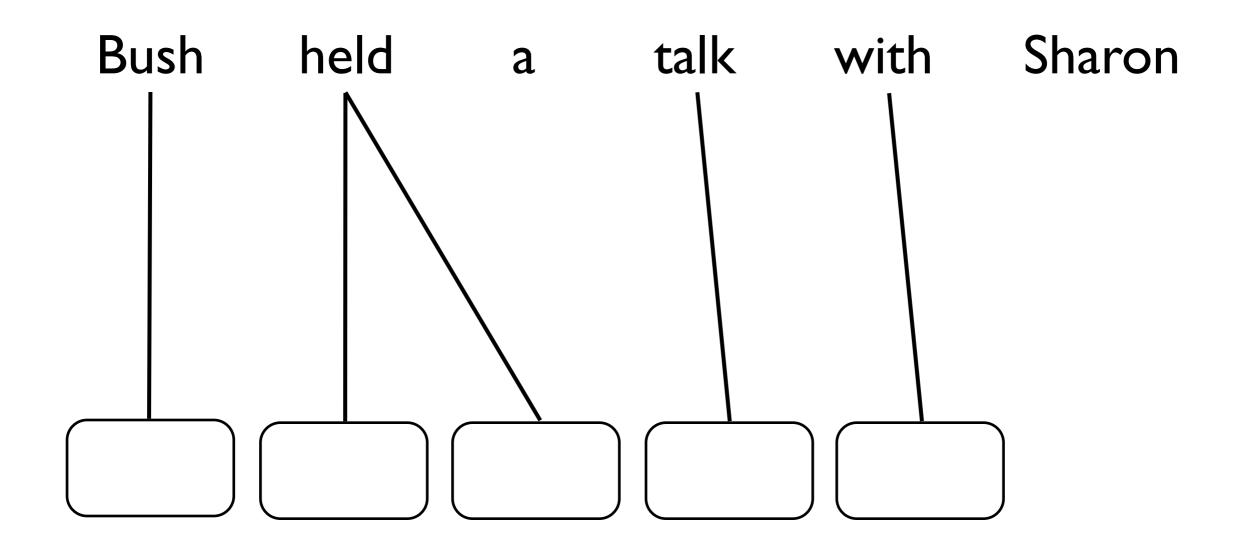
translation model

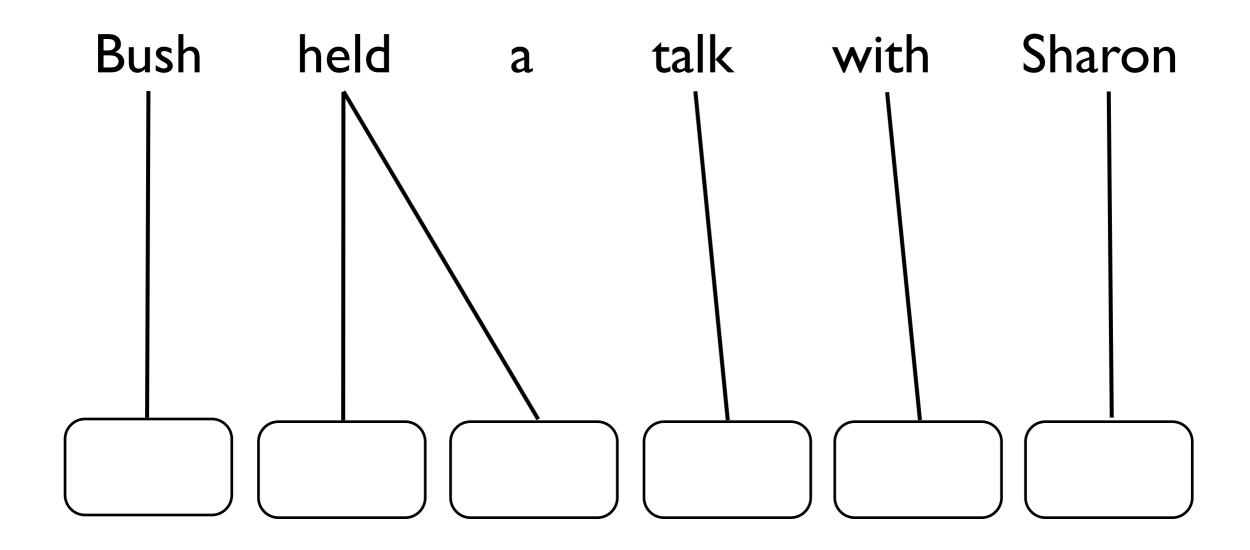
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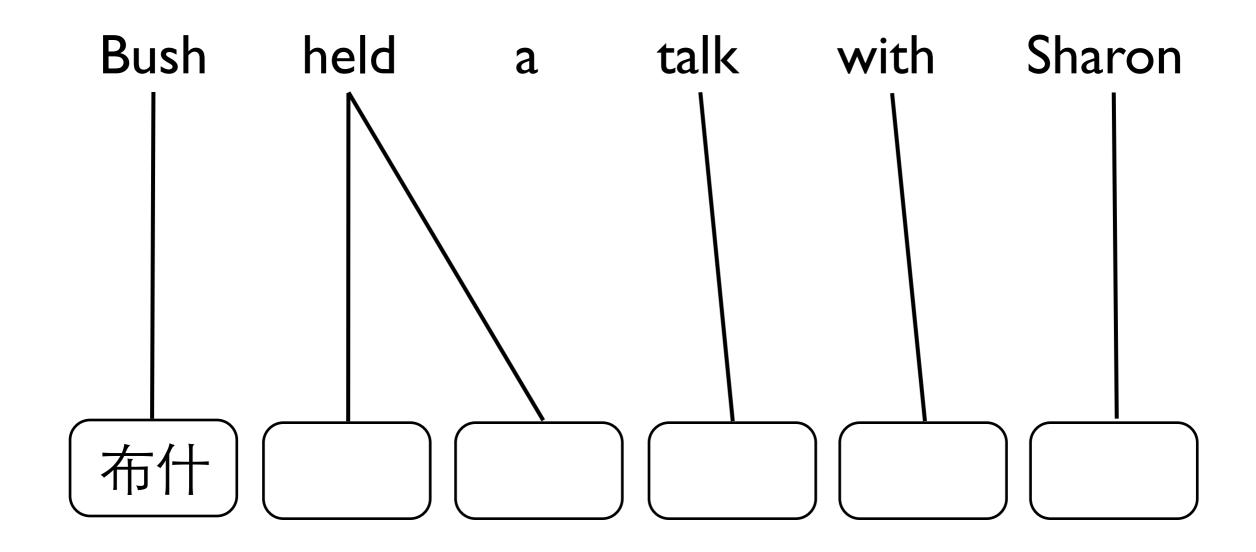


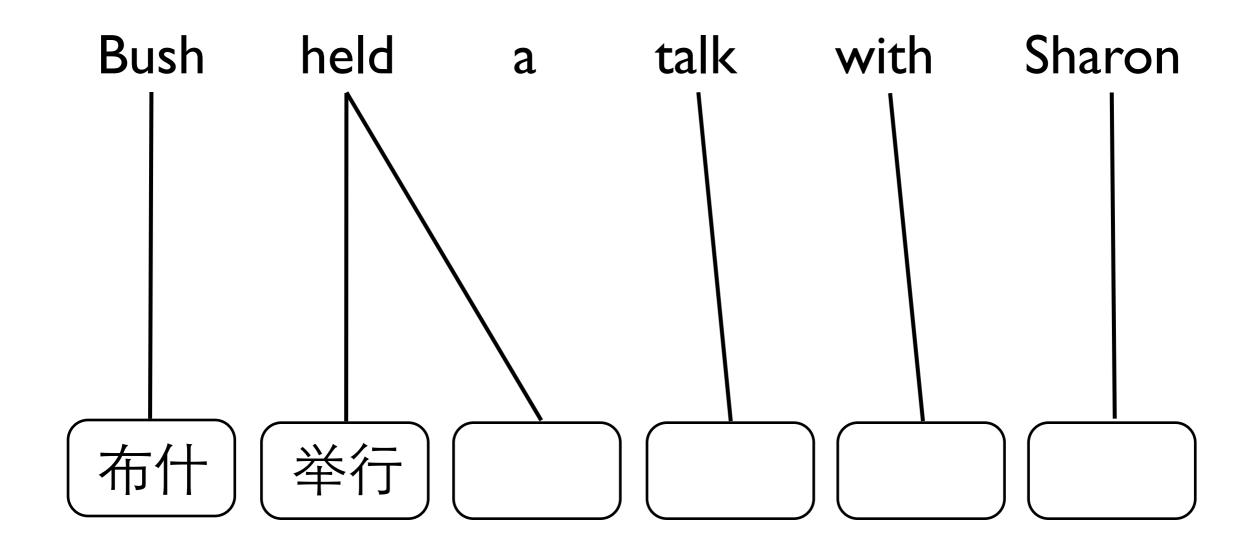


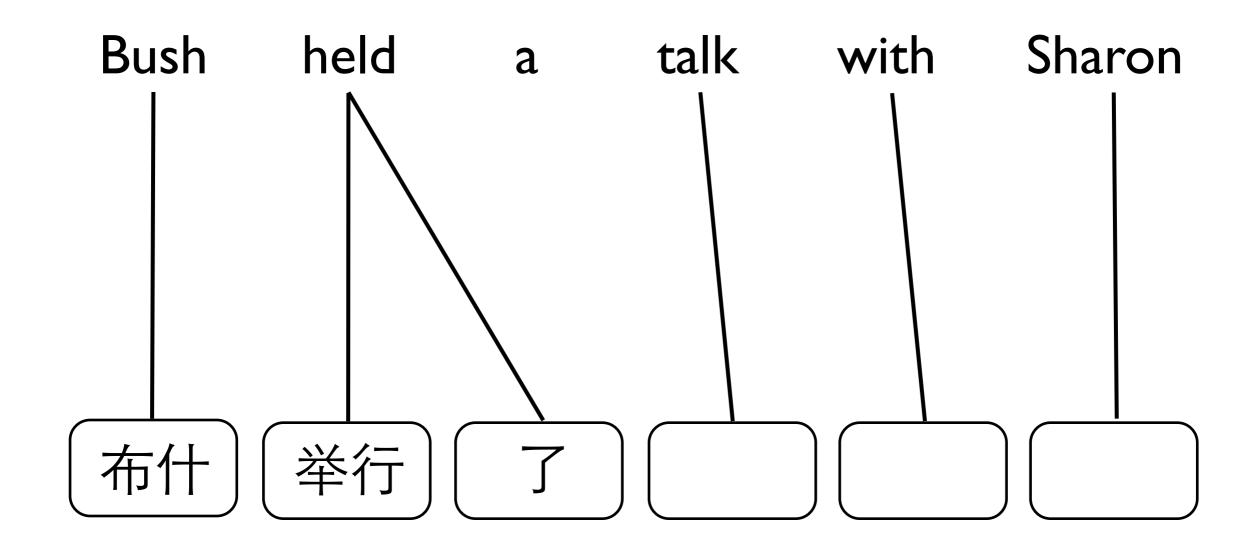


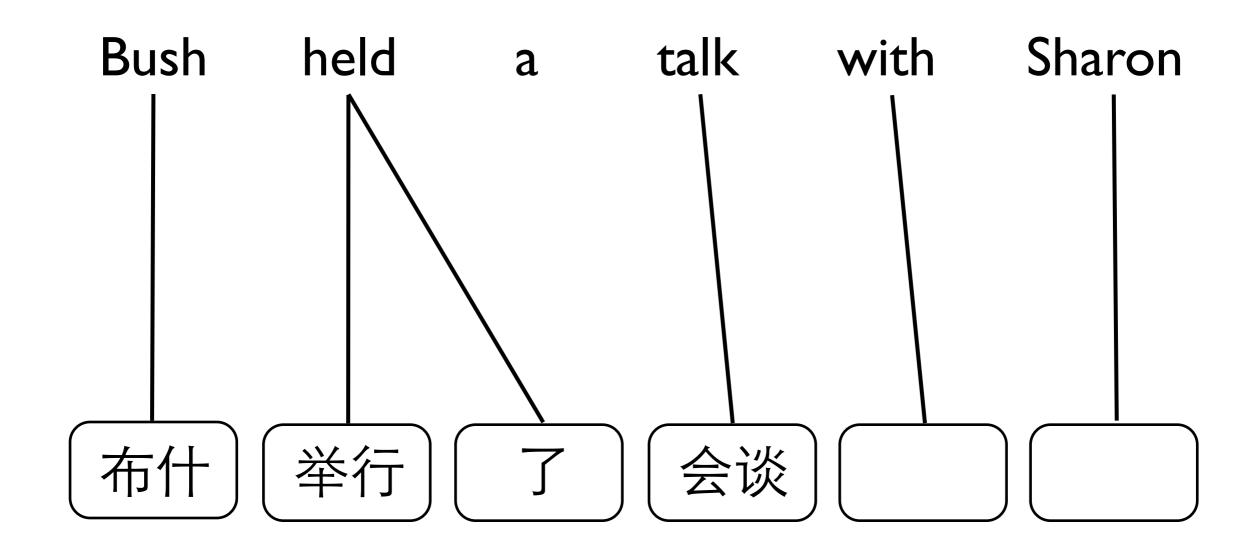


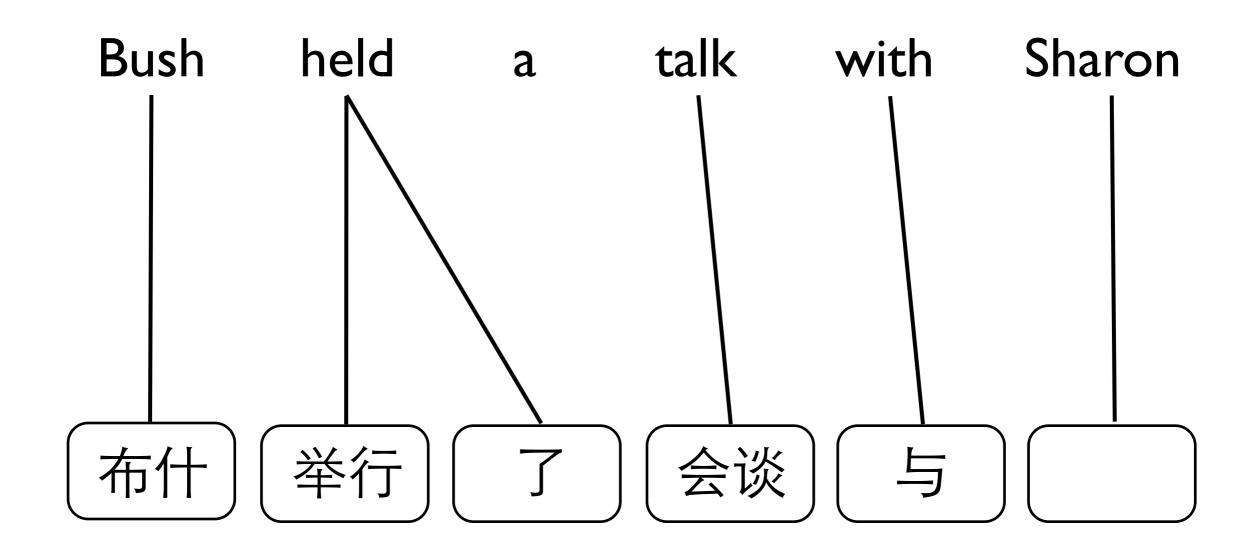


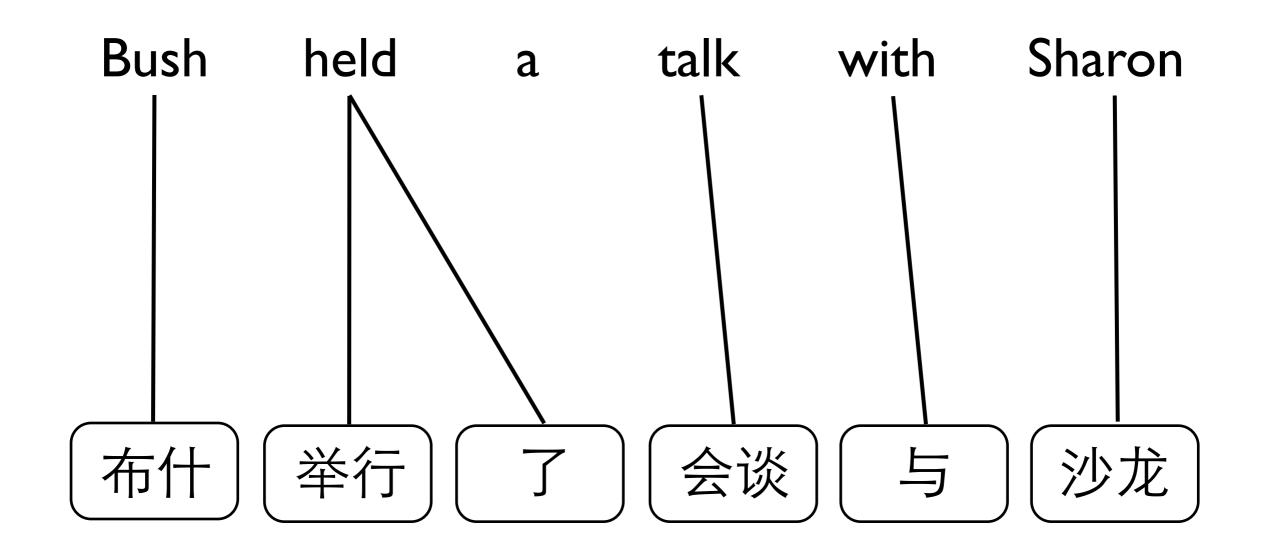


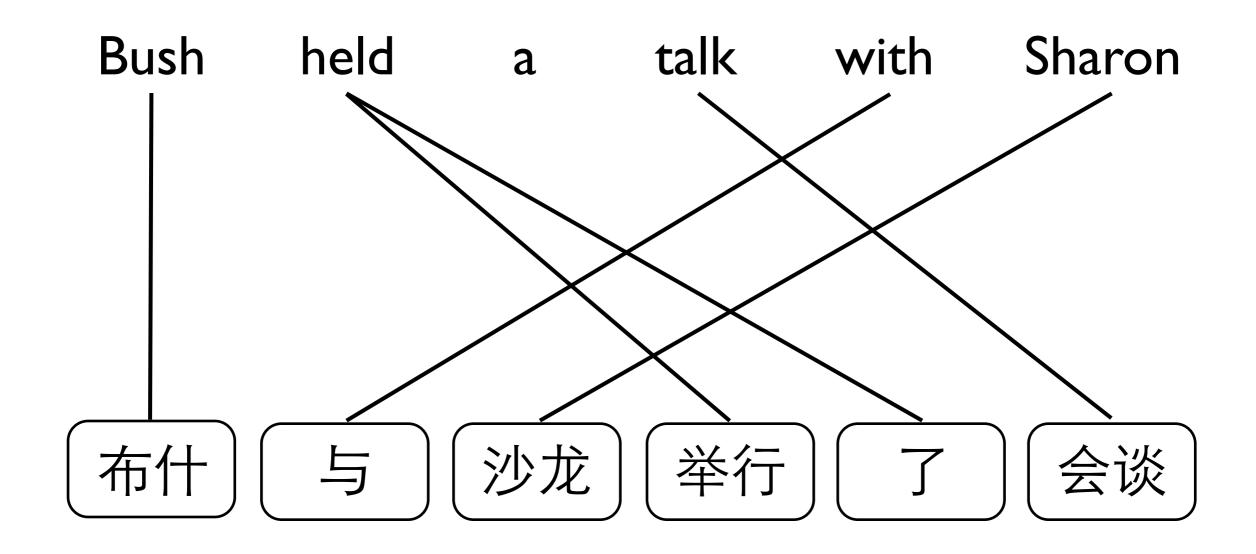












$$\begin{split} \Pr(\mathbf{f},\mathbf{a}|\mathbf{e}) &= \sum_{(\tau,\pi) \in \langle \mathbf{f},\mathbf{a} \rangle} \Pr(\tau,\pi|\mathbf{e}). \\ \Pr(\tau,\pi|\mathbf{e}) &= \prod_{i=1}^{l} \Pr(\phi_{i}|\phi_{1}^{i-1},\mathbf{e}) \Pr(\phi_{0}|\phi_{1}^{l},\mathbf{e}) \times \\ &\prod_{i=0}^{l} \prod_{k=1}^{\phi_{i}} \Pr(\tau_{ik}|\tau_{i1}^{k-1},\tau_{0}^{i-1},\phi_{0}^{l},\mathbf{e}) \times \\ &\prod_{i=1}^{l} \prod_{k=1}^{\phi_{i}} \Pr(\pi_{ik}|\pi_{i1}^{k-1},\pi_{1}^{i-1},\tau_{0}^{l},\phi_{0}^{l},\mathbf{e}) \times \\ &\prod_{i=1}^{\phi_{0}} \Pr(\pi_{0k}|\pi_{01}^{k-1},\pi_{1}^{l},\tau_{0}^{l},\phi_{0}^{l},\mathbf{e}). \end{split}$$

k=1

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fertility model

$$\prod_{i=0}^{l} \prod_{k=1}^{\phi_i} \Pr(\tau_{ik} | \tau_{i1}^{k-1}, \tau_0^{i-1}, \phi_0^l, \mathbf{e}) \times$$

$$\prod_{i=1}^{l} \prod_{k=1}^{\phi_i} \Pr(\pi_{ik} | \pi_{i1}^{k-1}, \pi_1^{i-1}, \tau_0^l, \phi_0^l, \mathbf{e}) \times$$

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fertility model

$$\prod_{i=0}^{l} \prod_{k=1}^{\phi_i} \Pr(\tau_{ik} | \tau_{i1}^{k-1}, \tau_0^{i-1}, \phi_0^l, \mathbf{e}) \times$$

$$\prod_{i=1}^{l} \prod_{k=1}^{\phi_i} \Pr(\pi_{ik} | \pi_{i1}^{k-1}, \pi_1^{i-1}, \tau_0^l, \phi_0^l, \mathbf{e}) \times$$

$$\prod_{k=1}^{\phi_0} \Pr(\pi_{0k}|\pi_{01}^{k-1},\pi_1^l,\tau_0^l,\phi_0^l,\mathbf{e}).$$

$$\Pr(\mathbf{f}, \mathbf{a} | \mathbf{e}) = \sum_{(\tau, \pi) \in \langle \mathbf{f}, \mathbf{a} \rangle} \Pr(\tau, \pi | \mathbf{e}).$$

$$\Pr(\tau, \pi | \mathbf{e}) = \prod_{i=1}^{l} \Pr(\phi_i | \phi_1^{i-1}, \mathbf{e}) \Pr(\phi_0 | \phi_1^{l}, \mathbf{e}) \times$$

$$\prod_{i=0}^{l} \prod_{k=1}^{\phi_i} \Pr(\tau_{ik} | \tau_{i1}^{k-1}, \tau_0^{i-1}, \phi_0^l, \mathbf{e}) \times$$

$$\prod_{i=1}^{l} \prod_{k=1}^{\phi_i} \Pr(\pi_{ik} | \pi_{i1}^{k-1}, \pi_1^{i-1}, \tau_0^l, \phi_0^l, \mathbf{e}) \times$$

$$\prod_{k=1}^{\phi_0} \Pr(\pi_{0k}|\pi_{01}^{k-1},\pi_1^l,\tau_0^l,\phi_0^l,\mathbf{e}).$$

fertility model

translation model

$$\Pr(\mathbf{f}, \mathbf{a}|\mathbf{e}) = \sum_{(\tau, \pi) \in \langle \mathbf{f}, \mathbf{a} \rangle} \Pr(\tau, \pi|\mathbf{e}).$$

$$\Pr(\tau, \pi | \mathbf{e}) = \prod_{i=1}^{l} \Pr(\phi_i | \phi_1^{i-1}, \mathbf{e}) \Pr(\phi_0 | \phi_1^{l}, \mathbf{e}) \times$$

$$\prod_{i=0}^{l} \prod_{k=1}^{\phi_i} \Pr(\tau_{ik} | \tau_{i1}^{k-1}, \tau_0^{i-1}, \phi_0^l, \mathbf{e}) \times$$

$$\prod_{i=1}^{l} \prod_{k=1}^{\phi_i} \Pr(\pi_{ik} | \pi_{i1}^{k-1}, \pi_1^{i-1}, \tau_0^l, \phi_0^l, \mathbf{e}) \times$$

$$\prod_{k=1}^{\varphi_0} \Pr(\pi_{0k}|\pi_{01}^{k-1},\pi_1^l,\tau_0^l,\phi_0^l,\mathbf{e}).$$

fertility model

translation model

$$\Pr(\mathbf{f}, \mathbf{a} | \mathbf{e}) = \sum_{(\tau, \pi) \in \langle \mathbf{f}, \mathbf{a} \rangle} \Pr(\tau, \pi | \mathbf{e}).$$

$$\Pr(\tau, \pi | \mathbf{e}) = \prod_{i=1}^{l} \Pr(\phi_i | \phi_1^{i-1}, \mathbf{e}) \Pr(\phi_0 | \phi_1^{l}, \mathbf{e}) \times$$

$$\prod_{i=0}^{l} \prod_{k=1}^{\phi_i} \Pr(\tau_{ik} | \tau_{i1}^{k-1}, \tau_0^{i-1}, \phi_0^l, \mathbf{e}) \times$$

$$\prod_{i=1}^{l} \prod_{k=1}^{\phi_i} \Pr(\pi_{ik} | \pi_{i1}^{k-1}, \pi_1^{i-1}, \tau_0^l, \phi_0^l, \mathbf{e}) \times$$

$$\prod_{k=1}^{\phi_0} \Pr(\pi_{0k}|\pi_{01}^{k-1},\pi_1^l,\tau_0^l,\phi_0^l,\mathbf{e}).$$

fertility model

translation model

distortion model

# Learning from Data

Q: how to learn model parameters from data?

Garcia y asociados.

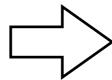
Garcia and associates.

los clients y los asociados son enemigos .

the clients and the associates are enemies.

sus asociados no son fuertes.

his associates are not strong.



Spanish	English
Garcia	Garcia
у	and
asociados	associates
•	•
los	the
clients	clients
son	are
enemigos	enemies
sus	his
no	not
fuertes	strong

## Maximum Likelihood Estimation

## Maximum Likelihood Estimation

input: 
$$(\mathbf{f}^{(1)}, \mathbf{e}^{(1)}) \dots (\mathbf{f}^{(S)}, \mathbf{e}^{(S)})$$

## Maximum Likelihood Estimation

#### alignment is unobserved

input: 
$$(\mathbf{f}^{(1)}, \mathbf{e}^{(1)}) \dots (\mathbf{f}^{(S)}, \mathbf{e}^{(S)})$$

#### Maximum Likelihood Estimation

#### alignment is unobserved

input: 
$$(\mathbf{f}^{(1)}, \mathbf{e}^{(1)}) \dots (\mathbf{f}^{(S)}, \mathbf{e}^{(S)})$$

output:  $\theta$ 

#### Maximum Likelihood Estimation

#### alignment is unobserved

input: 
$$(\mathbf{f}^{(1)}, \mathbf{e}^{(1)}) \dots (\mathbf{f}^{(S)}, \mathbf{e}^{(S)})$$

output:  $\theta$ 

$$\hat{\theta} = \operatorname{argmax}_{\theta} \left\{ \prod_{s=1}^{S} P_{\theta}(\mathbf{f}^{(s)} | \mathbf{e}^{(s)}) \right\}$$

#### Maximum Likelihood Estimation

#### alignment is unobserved

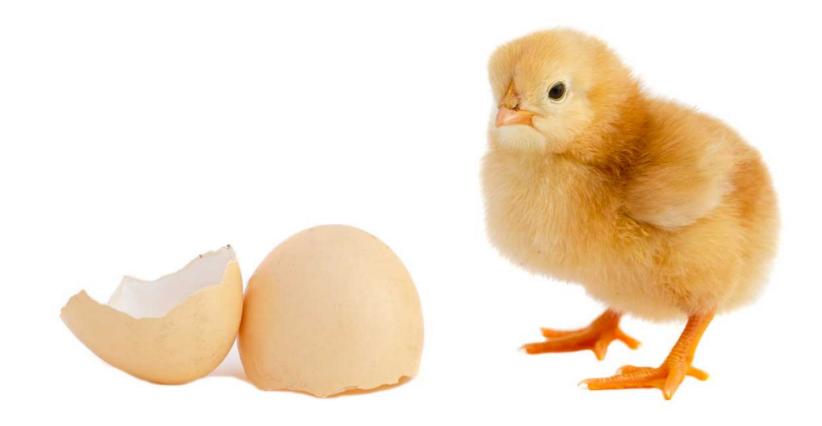
input: 
$$(\mathbf{f}^{(1)}, \mathbf{e}^{(1)}) \dots (\mathbf{f}^{(S)}, \mathbf{e}^{(S)})$$

output:  $\theta$ 

$$\hat{\theta} = \operatorname{argmax}_{\theta} \left\{ \prod_{s=1}^{S} P_{\theta}(\mathbf{f}^{(s)} | \mathbf{e}^{(s)}) \right\}$$

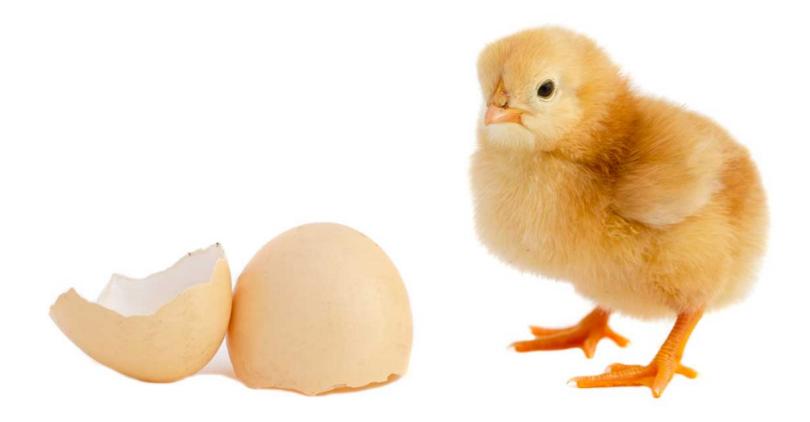
The EM algorithm is often used for estimating parameters from unlabeled data

# Learning from Unlabeled Data



# Learning from Unlabeled Data

#### labels



# Learning from Unlabeled Data

parameters

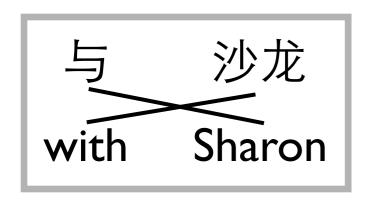
labels

与 沙龙 with Sharon

与 with

f	е	tc	t
与	with	N/A	0.5
	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5



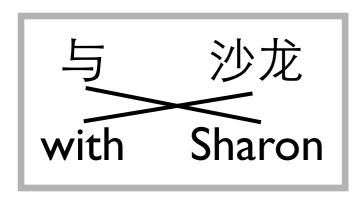




f	е	tc	t
与	with	N/A	0.5
	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5

 $P(\mathbf{f}, \mathbf{a} | \mathbf{e})$ 







f	е	tc	t
与	with	N/A	0.5
	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5

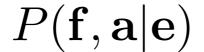
$$P(\mathbf{f}, \mathbf{a}|\mathbf{e})$$





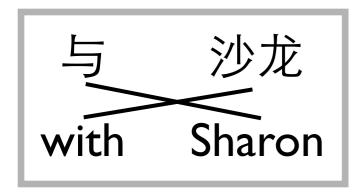
$$P(\mathbf{f}, \mathbf{a} | \mathbf{e}) = \prod_{j=1}^{|\mathbf{f}|} t(\mathbf{f}_j | \mathbf{e}_{\mathbf{a}_j})$$

f	е	tc	t
与	with	N/A	0.5
<del> </del>	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5





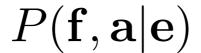
0.25





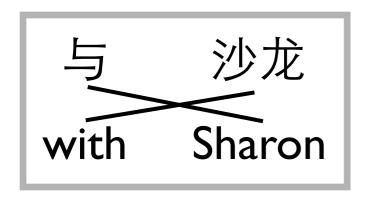
	$ \mathbf{f} $	
$P(\mathbf{f}, \mathbf{a} \mathbf{e}) = \mathbf{j}$		$\left[ \ t(\mathbf{f}_{j} \mathbf{e}_{\mathbf{a}_{j}})  ight.$
J	<u></u>	1

f	е	tc	t
	with	N/A	0.5
与	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5





0.25

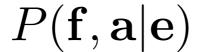


0.25



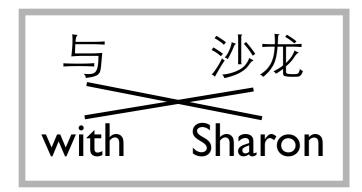
	$ \mathbf{f} $
$P(\mathbf{f}, \mathbf{a}   \mathbf{e}) =$	$\prod t(\mathbf{f}_j \mathbf{e}_{\mathbf{a}_j})$
	j=1

f	е	tc	t
与	with	N/A	0.5
<del> </del>	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5





0.25



0.25



0.5

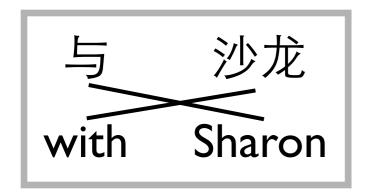
	$ \mathbf{f} $	
$P(\mathbf{f}, \mathbf{a}   \mathbf{e}) =$		$\left[ \ t(\mathbf{f}_{j} \mathbf{e}_{\mathbf{a}_{j}})  ight.$
	j=1	1

f	е	tc	t
与	with	N/A	0.5
<del> </del>	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5

 $P(\mathbf{f}, \mathbf{a}|\mathbf{e})$ 



0.25



0.25



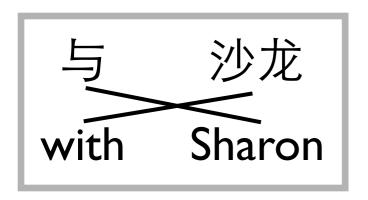
0.5

f	е	tc	t
⊨	with	N/A	0.5
与	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5

 $P(\mathbf{f}, \mathbf{a}|\mathbf{e}) \quad P(\mathbf{a}|\mathbf{f}, \mathbf{e})$ 



0.25



0.25

与	
l with	

0.5

f	е	tc	t
与	with	N/A	0.5
	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5

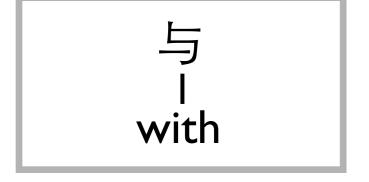




0.25



0.25



0.5

$P(\mathbf{a} \mathbf{f},\mathbf{o}) =$	$P(\mathbf{f}, \mathbf{a}   \mathbf{e})$
$P(\mathbf{a} \mathbf{f},\mathbf{e}) =$	$\overline{\sum_{\mathbf{a}'} P(\mathbf{f}, \mathbf{a}'   \mathbf{e})}$

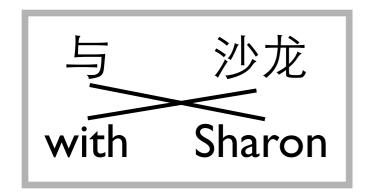
f	е	tc	t
与	with	N/A	0.5
	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5





0.25 0.5

$$P(\mathbf{a}|\mathbf{f}, \mathbf{e}) = \frac{P(\mathbf{f}, \mathbf{a}|\mathbf{e})}{\sum_{\mathbf{a}'} P(\mathbf{f}, \mathbf{a}'|\mathbf{e})}$$



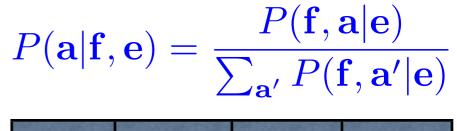
0.25

f	е	tc	t
与	with	N/A	0.5
	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5

0.5







与	沙龙
with	Sharon

0.25

f	е	tc	t
与	with	N/A	0.5
	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5

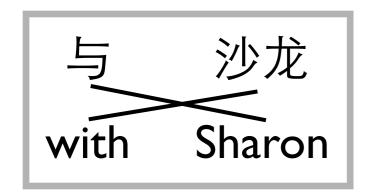
0.5

$$P(\mathbf{f}, \mathbf{a}|\mathbf{e}) \quad P(\mathbf{a}|\mathbf{f}, \mathbf{e})$$



0.25 0.5

$$P(\mathbf{a}|\mathbf{f}, \mathbf{e}) = \frac{P(\mathbf{f}, \mathbf{a}|\mathbf{e})}{\sum_{\mathbf{a}'} P(\mathbf{f}, \mathbf{a}'|\mathbf{e})}$$



0.25

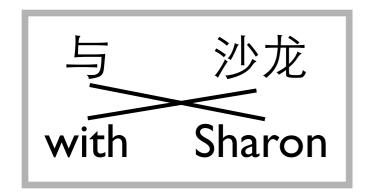
f	е	tc	t
与	with	N/A	0.5
	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5

0.5

 $P(\mathbf{f}, \mathbf{a}|\mathbf{e}) \quad P(\mathbf{a}|\mathbf{f}, \mathbf{e})$ 



0.25 0.5



0.25 0.5

f	υ	tc	t
与	with	N/A	0.5
	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5

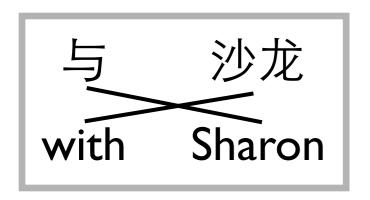
ı	与	
	<u> </u>	
I	with	

0.5





0.25 0.5



0.25

0.5

f	υ	tc	t
与	with	N/A	0.5
	Sharon	N/A	0.5
沙龙	with	N/A	0.5
	Sharon	N/A	0.5

0.5

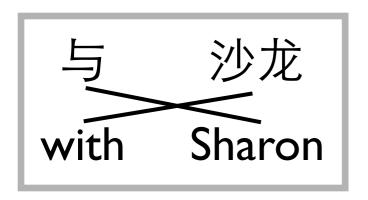
1.0

$$tc(f|e) = \sum_{s=1}^{S} \sum_{\mathbf{a}} P(\mathbf{a}|\mathbf{f}^{(s)}, \mathbf{e}^{(s)}) \sum_{j=1}^{|\mathbf{f}^{(s)}|} \delta(\mathbf{f}_{j}^{(s)}, f) \delta(\mathbf{e}_{\mathbf{a}_{j}}^{(s)}, e)$$

$$P(\mathbf{f}, \mathbf{a}|\mathbf{e}) \quad P(\mathbf{a}|\mathbf{f}, \mathbf{e})$$



0.25 0.5



0.25

0.5

f	e	tc	t
与	with	1.5	0.5
	Sharon	0.5	0.5
沙龙	with	0.5	0.5
	Sharon	0.5	0.5

0.5

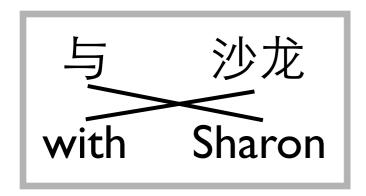
1.0

$$tc(f|e) = \sum_{s=1}^{S} \sum_{\mathbf{a}} P(\mathbf{a}|\mathbf{f}^{(s)}, \mathbf{e}^{(s)}) \sum_{j=1}^{|\mathbf{f}^{(s)}|} \delta(\mathbf{f}_{j}^{(s)}, f) \delta(\mathbf{e}_{\mathbf{a}_{j}}^{(s)}, e)$$

$$P(\mathbf{f}, \mathbf{a}|\mathbf{e}) \quad P(\mathbf{a}|\mathbf{f}, \mathbf{e})$$



0.25 0.5



0.25 0.5

f	е	tc	t
与	with	1.5	0.5
	Sharon	0.5	0.5
沙龙	with	0.5	0.5
	Sharon	0.5	0.5

与	ı
ĺ	ı
with	ı
with	

0.5

$$P(\mathbf{f}, \mathbf{a}|\mathbf{e}) \quad P(\mathbf{a}|\mathbf{f}, \mathbf{e})$$



0.25 0.5

f e		tc	t
山	with	1.5	0.5
ヲ	Sharon	0.5	0.5
沙龙	with	0.5	0.5
	Sharon	0.5	0.5

 $t(f|e) = \frac{tc(f|e)}{\sum_{f'} tc(f'|e)}$ 

Image: section of the content of the	
—) 	
with	
, , , <u>, , , , , , , , , , , , , , , , </u>	

0.5

$$P(\mathbf{f}, \mathbf{a}|\mathbf{e}) \quad P(\mathbf{a}|\mathbf{f}, \mathbf{e})$$



with Sharon 
$$t(f|e) = \frac{tc(f|e)}{\sum_{f'} tc(f'|e)}$$
 与 沙龙

与	沙龙	
with	Sharon	

0.25 0.5

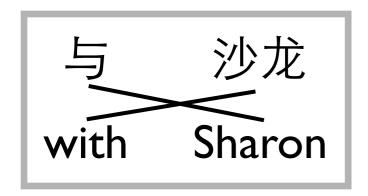
f	е	tc	t
口	with	1.5	0.75
ラ	Sharon	0.5	0.25
沙龙	with	0.5	0.5
	Sharon	0.5	0.5

0.5

$P(\mathbf{f}, \mathbf{a}   \mathbf{e})$	$P(\mathbf{a} \mathbf{f},$	$\mathbf{e})$
--	----------------------------	---------------



0.25 0.5



0.25 0.5

f	е	tc	t
与	with	1.5	0.75
	Sharon	0.5	0.25
沙龙	with	0.5	0.5
<i>がル</i>   	Sharon	0.5	0.5

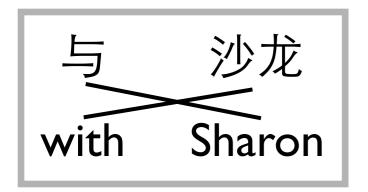
与	
J	
with	

0.5

P(	$[\mathbf{f},\mathbf{a}]$	$ \mathbf{e} $	P(	$\mathbf{a}$	$ \mathbf{f},$	$\mathbf{e}$
_ \	$\langle - \rangle$		, – ,	(	1 <sup>–</sup> 7	



0.375 0.5



0.125 0.5

f	e	tc	t
与	with	1.5	0.75
	Sharon	0.5	0.25
沙龙	with	0.5	0.5
	Sharon	0.5	0.5

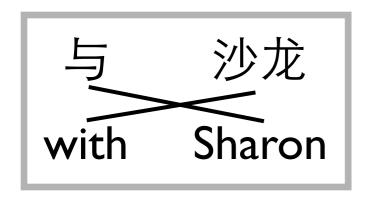
ı	与	
ı	l with	
l	with	

0.75

$P(\mathbf{f}, \mathbf{a}   \mathbf{e})$	$P(\mathbf{a} \mathbf{f},$	$\mathbf{e})$
--	----------------------------	---------------



0.375 0.75



0.125 0.25

f	e	tc	t
与	with	1.5	0.75
	Sharon	0.5	0.25
沙龙	with	0.5	0.5
	Sharon	0.5	0.5

与	
ĺ	
with	

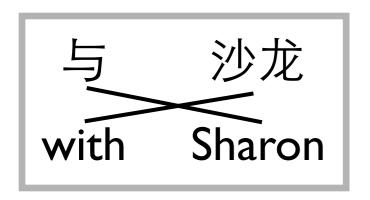
0.75

1.0

$P(\mathbf{f}, \mathbf{a})$	$(\mathbf{e})$	P(	$\mathbf{a}$	$ \mathbf{f},$	$\mathbf{e})$
\ /		'	\	. /	



0.375 0.75



0.125 0.25

f	υ	tc	t
与	with	1.75	0.75
	Sharon	0.25	0.25
沙龙	with	0.25	0.5
	Sharon	0.75	0.5

与	
with	
	- 1

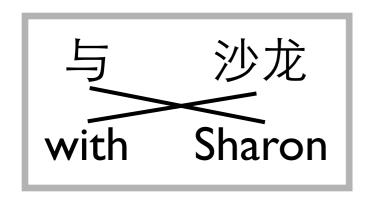
0.75

1.0

$P(\mathbf{f}, \mathbf{a}   \mathbf{e})$	$P(\mathbf{a} \mathbf{f},$	$\mathbf{e})$
--	----------------------------	---------------



0.375 0.75



0.125 0.25

f	е	tc	t
与	with	1.75	0.875
	Sharon	0.25	0.125
沙龙	with	0.25	0.25
	Sharon	0.75	0.75

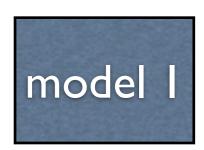
与	l
ĺ	l
with	l

0.75

1.0

- Initialization is important as EM is prone to get stuck in local optima
- Solution: use the output of simpler models as the input of training more complex models

- Initialization is important as EM is prone to get stuck in local optima
- Solution: use the output of simpler models as the input of training more complex models

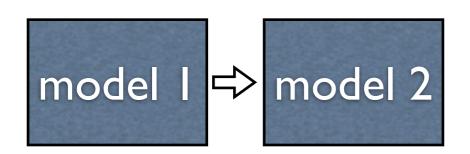


- Initialization is important as EM is prone to get stuck in local optima
- Solution: use the output of simpler models as the input of training more complex models



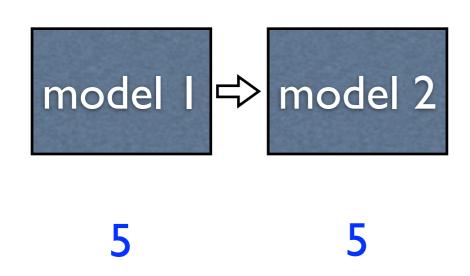
5

- Initialization is important as EM is prone to get stuck in local optima
- Solution: use the output of simpler models as the input of training more complex models



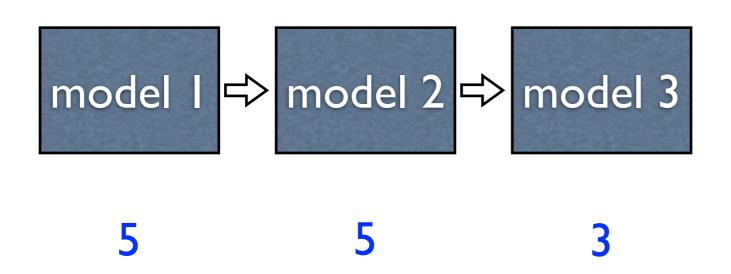
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- Initialization is important as EM is prone to get stuck in local optima
- Solution: use the output of simpler models as the input of training more complex models



- Initialization is important as EM is prone to get stuck in local optima
- Solution: use the output of simpler models as the input of training more complex models

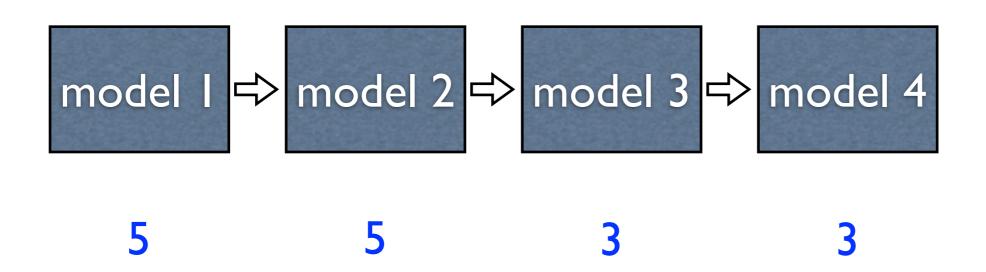
- Initialization is important as EM is prone to get stuck in local optima
- Solution: use the output of simpler models as the input of training more complex models



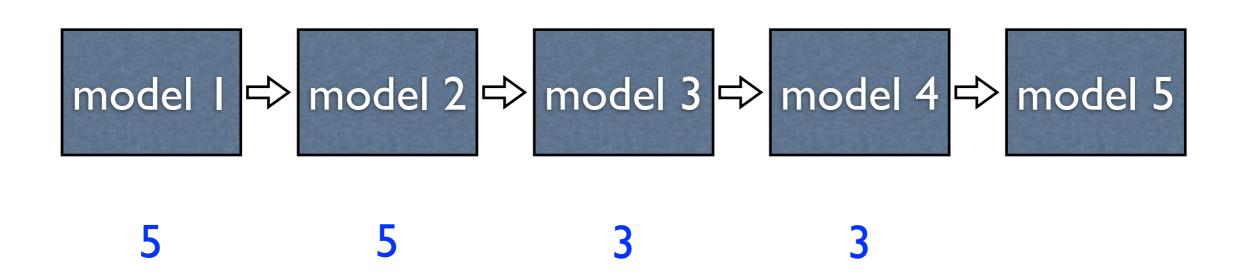
- Initialization is important as EM is prone to get stuck in local optima
- Solution: use the output of simpler models as the input of training more complex models

model I 
$$\Rightarrow$$
 model 2  $\Rightarrow$  model 3  $\Rightarrow$  model 4

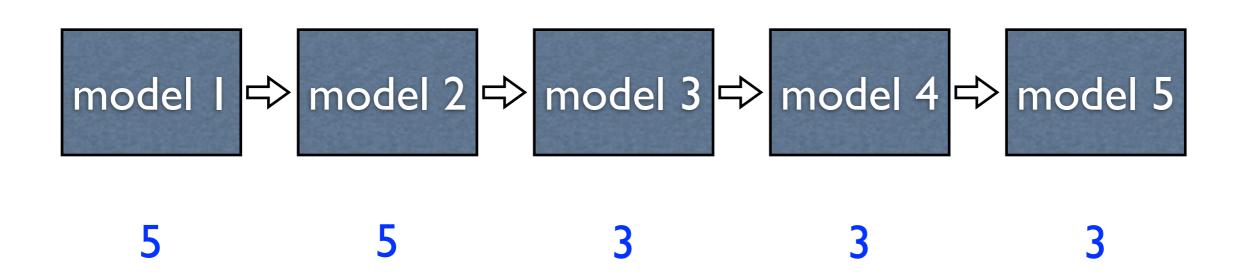
- Initialization is important as EM is prone to get stuck in local optima
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- Initialization is important as EM is prone to get stuck in local optima
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- Initialization is important as EM is prone to get stuck in local optima
- Solution: use the output of simpler models as the input of training more complex models



## JHU Workshop

- Kevin Knight led a team to develop open-source toolkits for IBM Models in the 1999 JHU Workshop
- Franz Och wrote GIZA++, the trainer of IBM models



Kevin Knight



Franz Och









hard to include context

# Part 3: Phrase-based MT

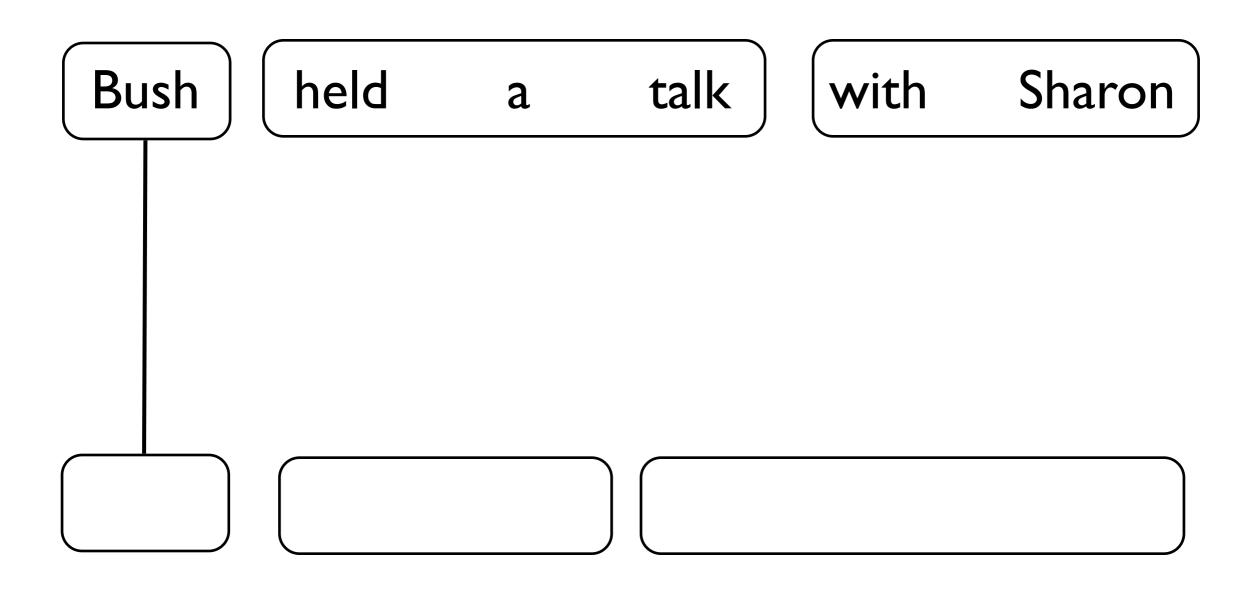
Bush held a talk with Sharon

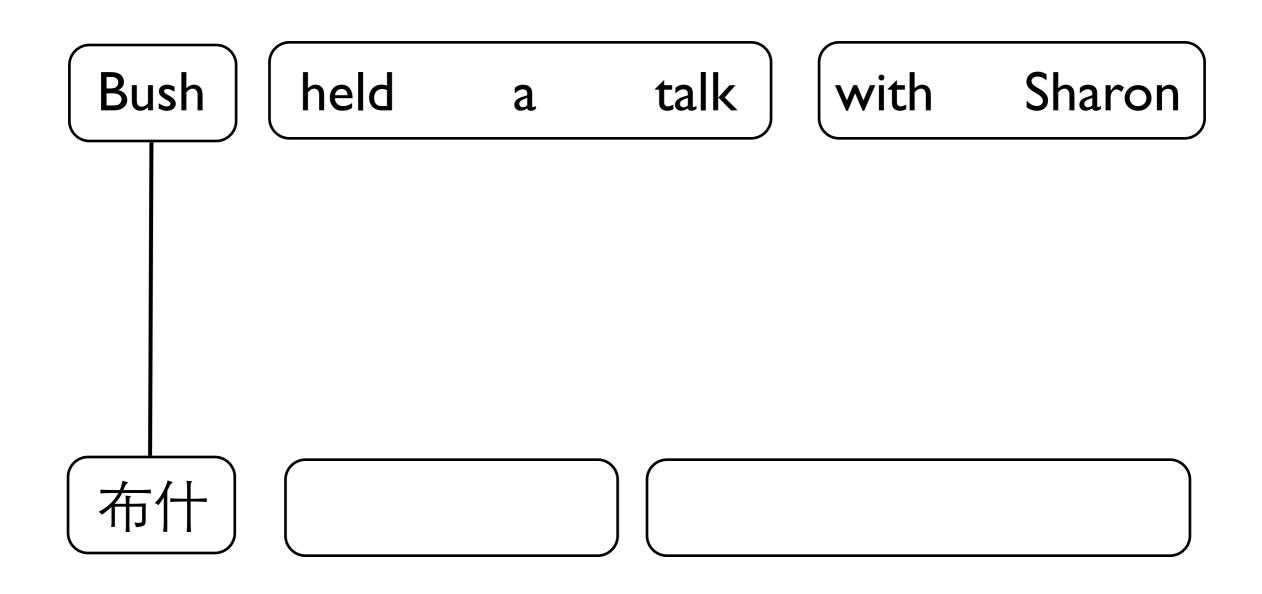
Bush

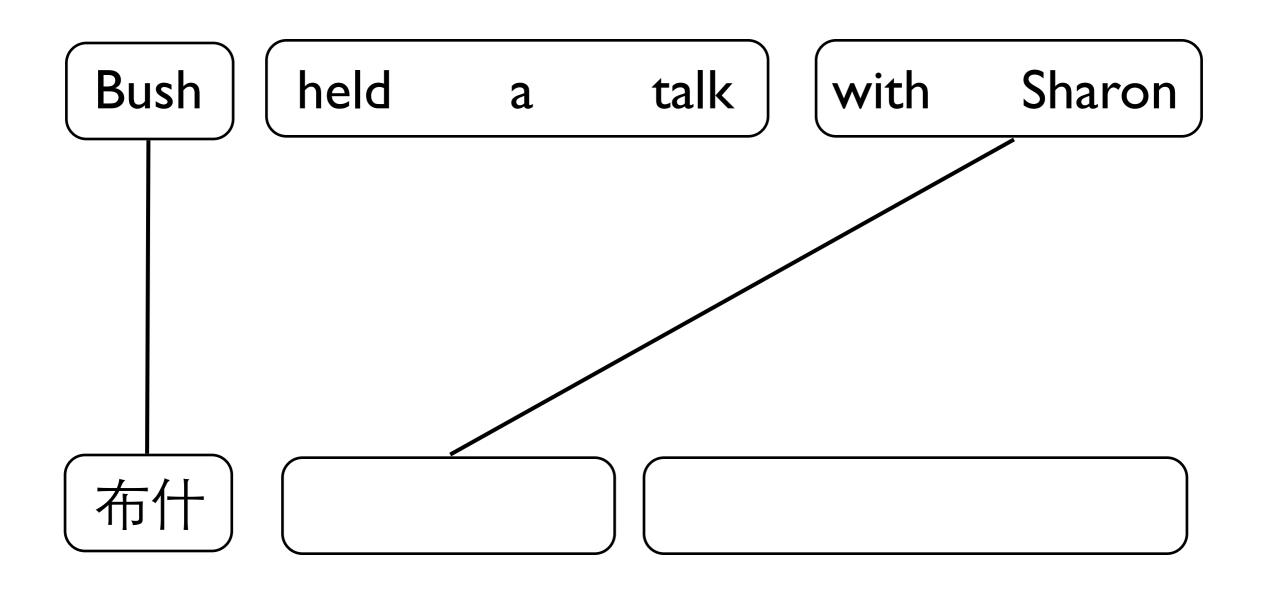
held a talk

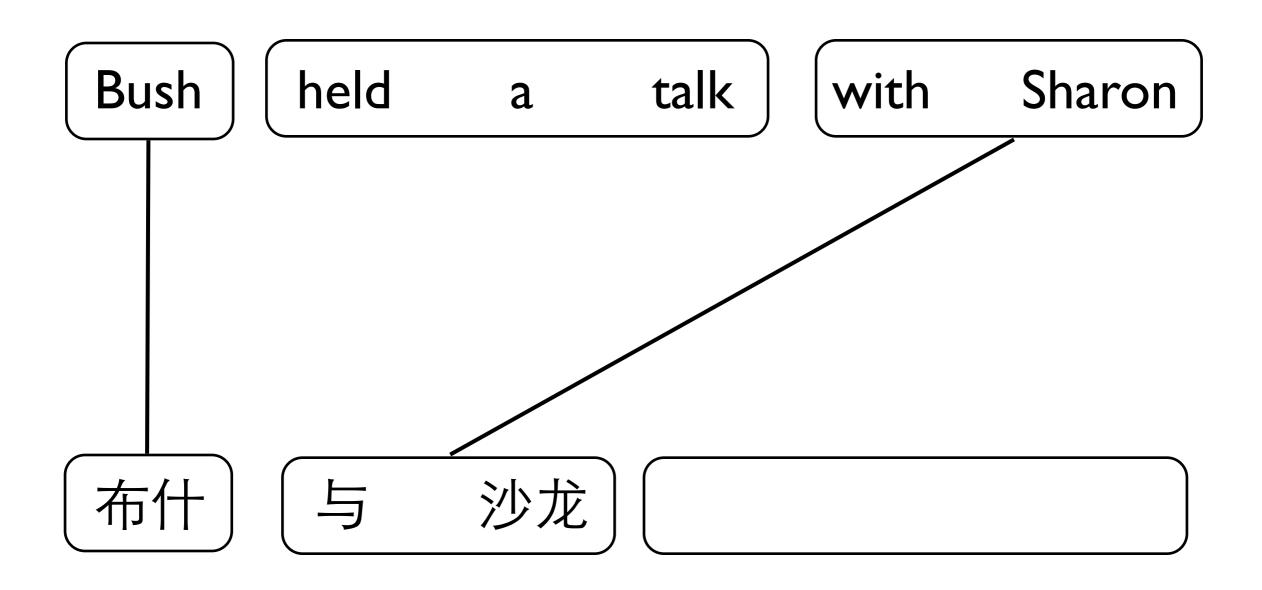
with Sharon

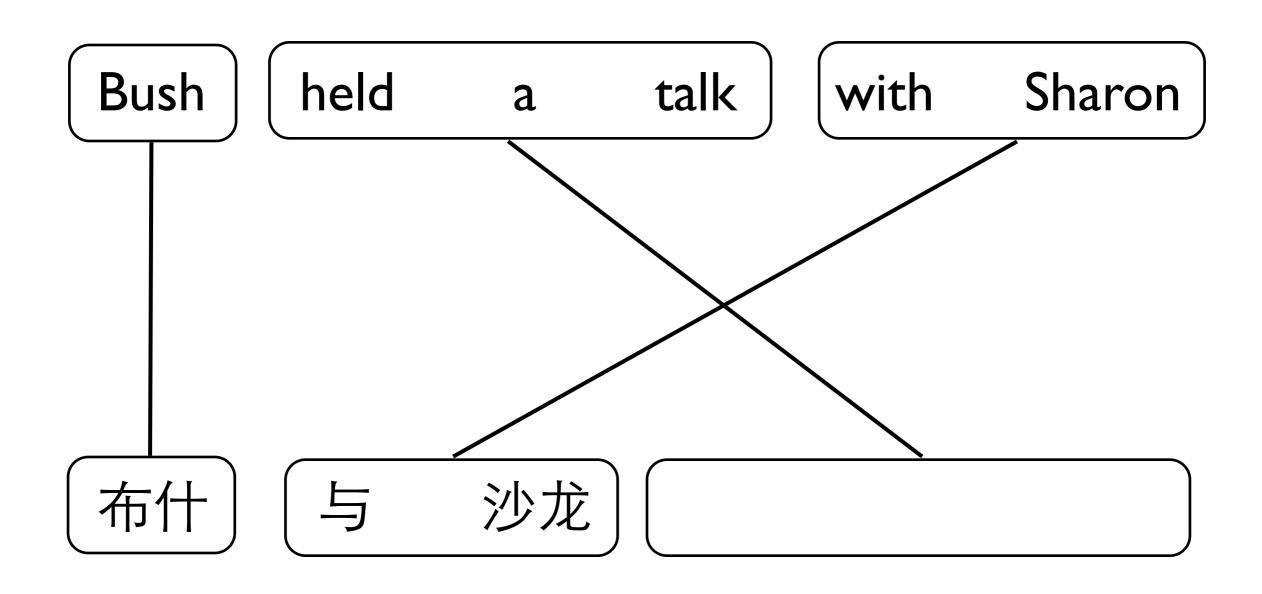
Bush held a talk with Sharon

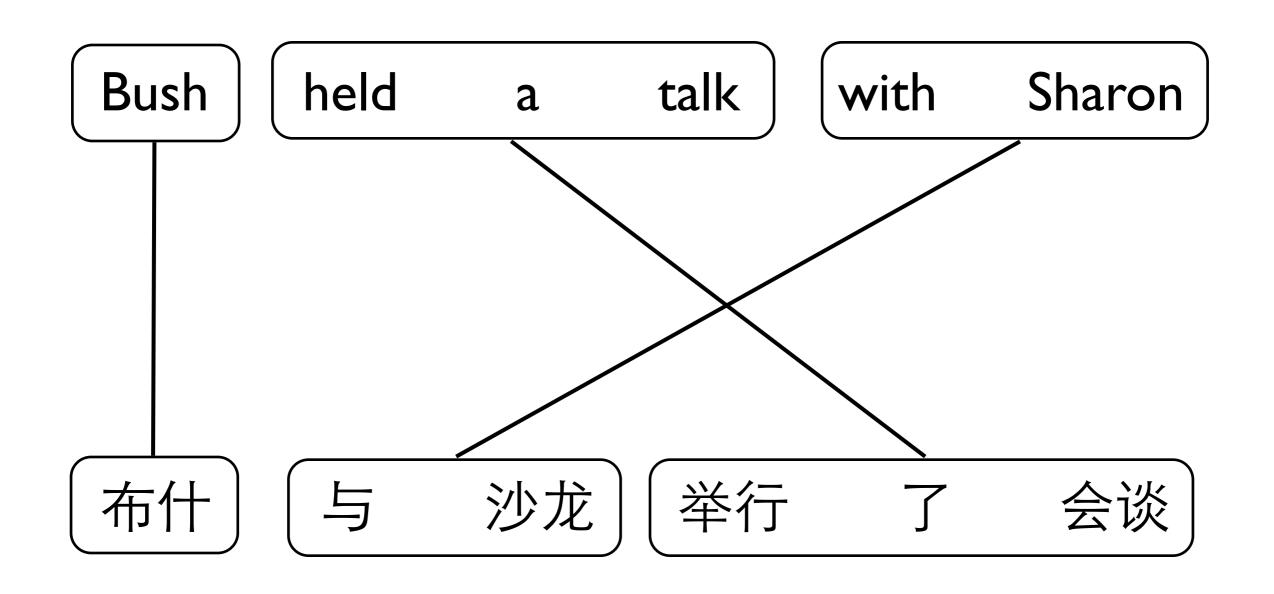


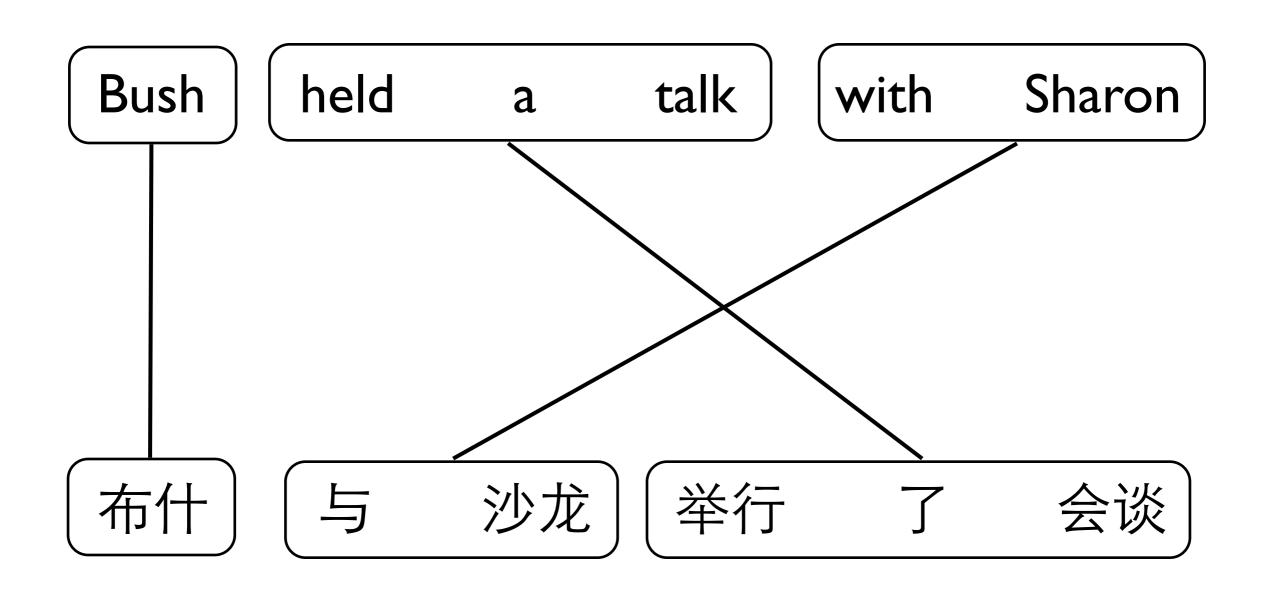




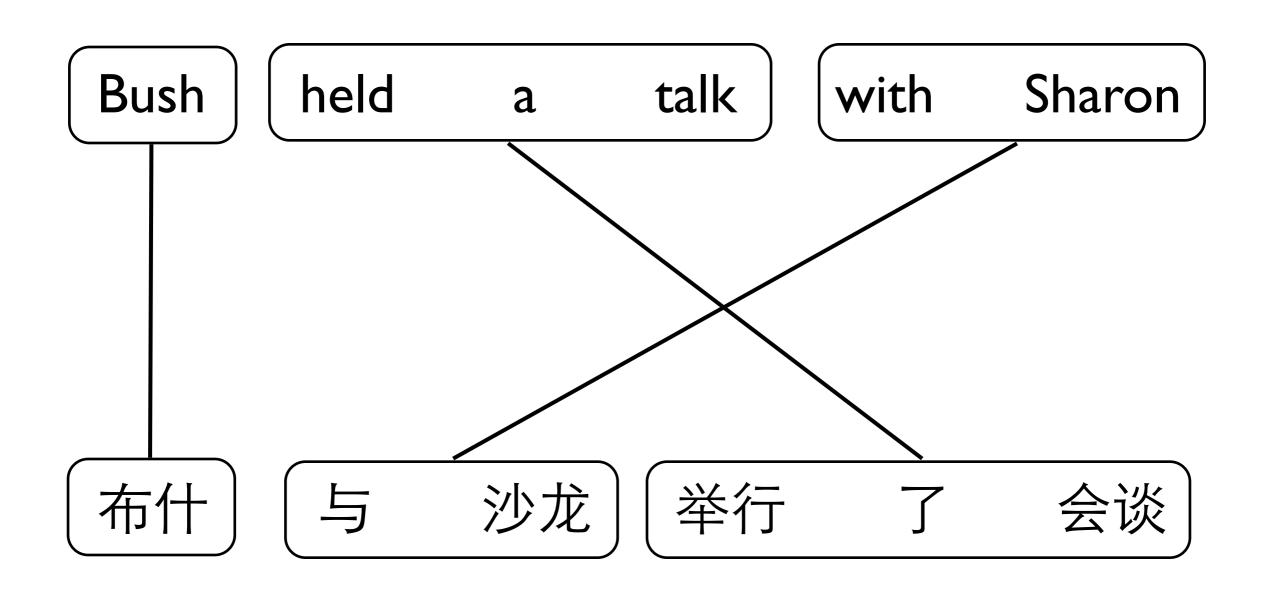




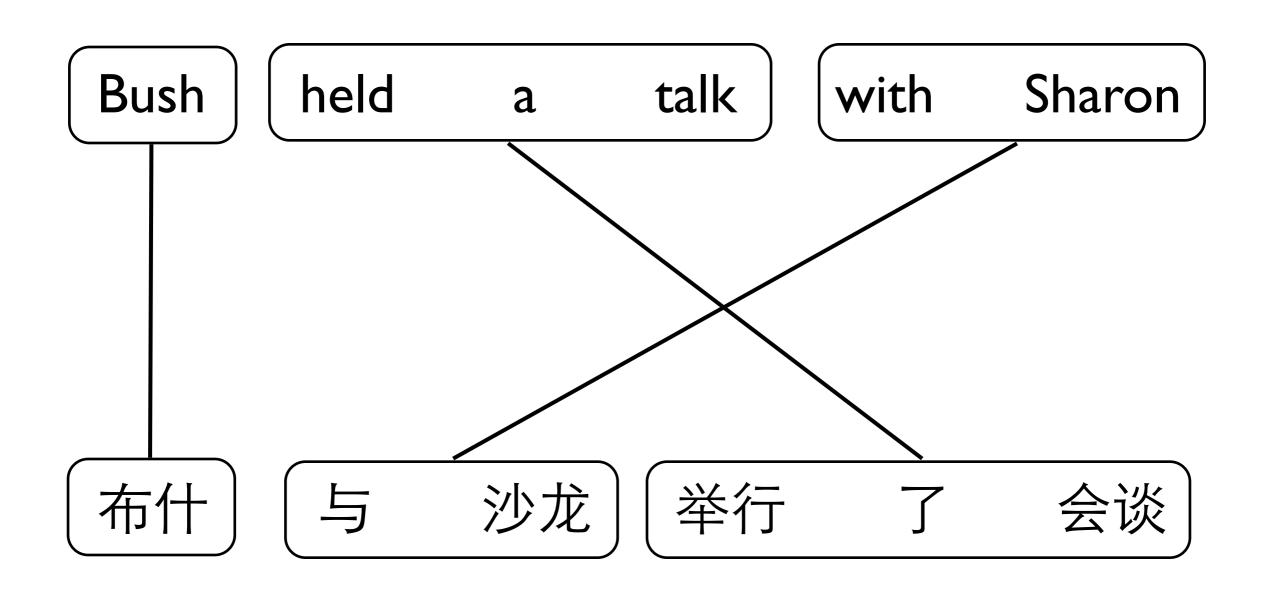




segmentation



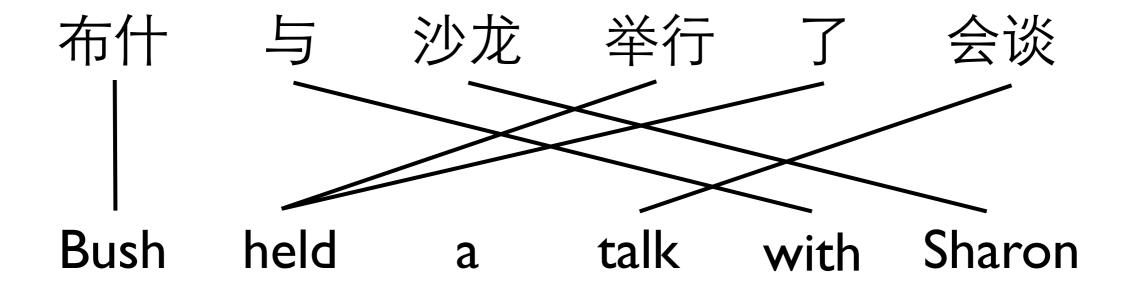
segmentation reordering

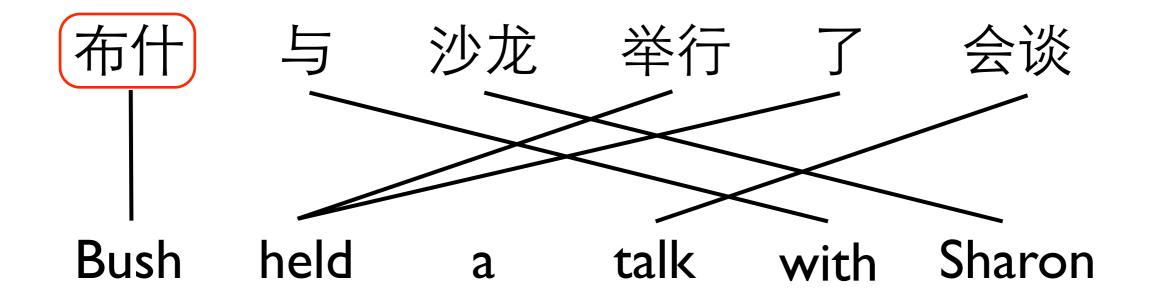


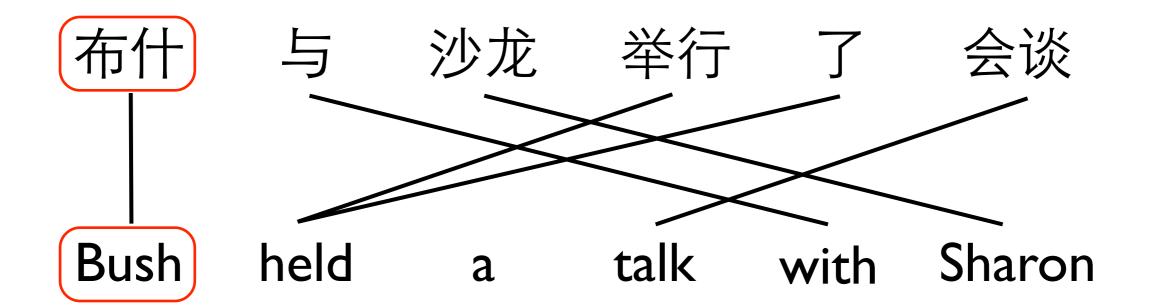
segmentation reordering translation

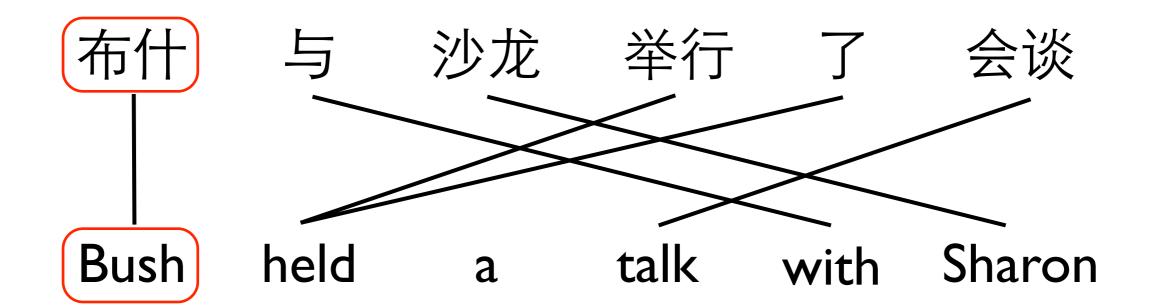
布什 与 沙龙 举行 了 会谈

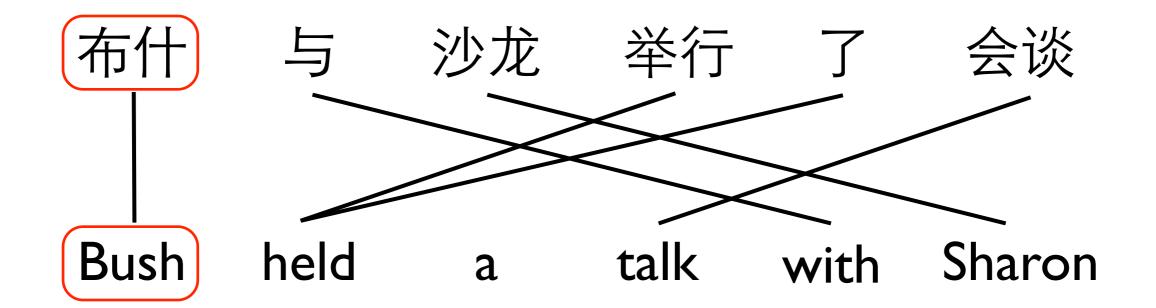
Bush held a talk with Sharon





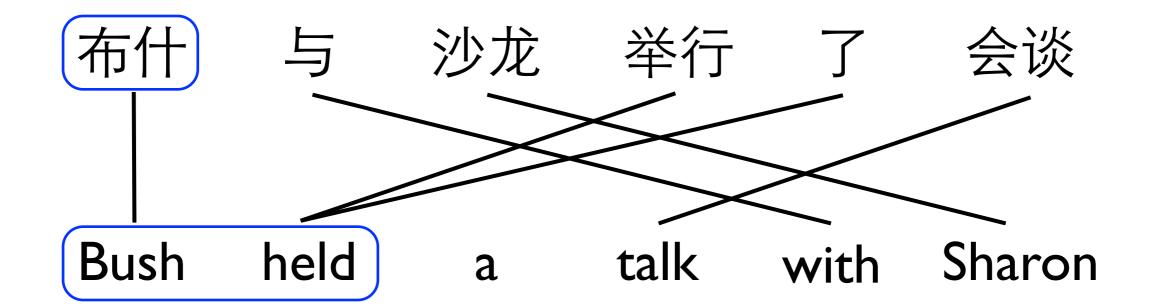


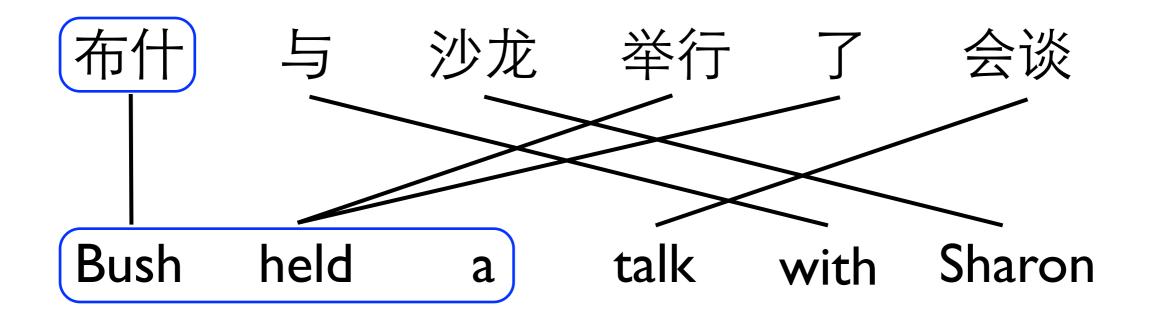


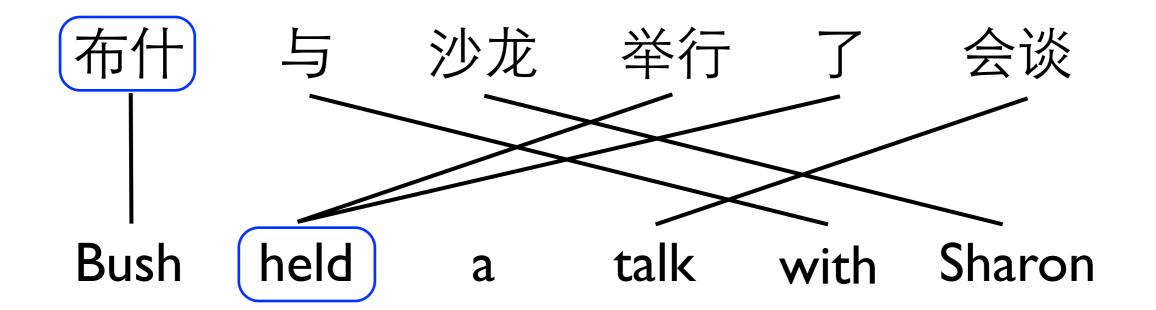


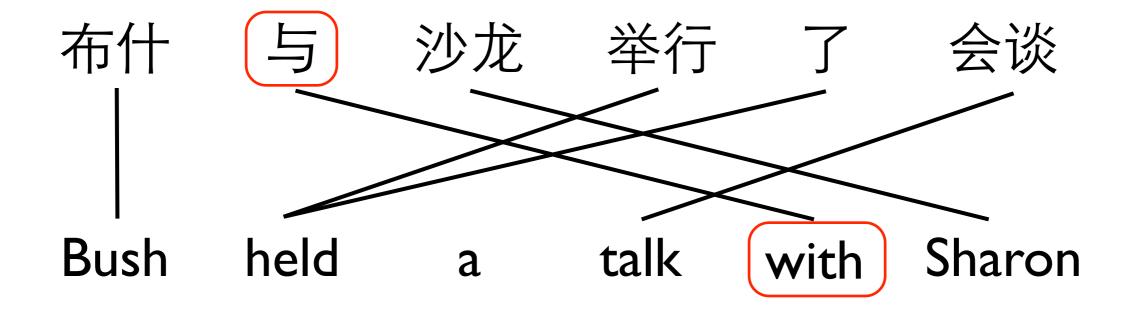
(布什, Bush)

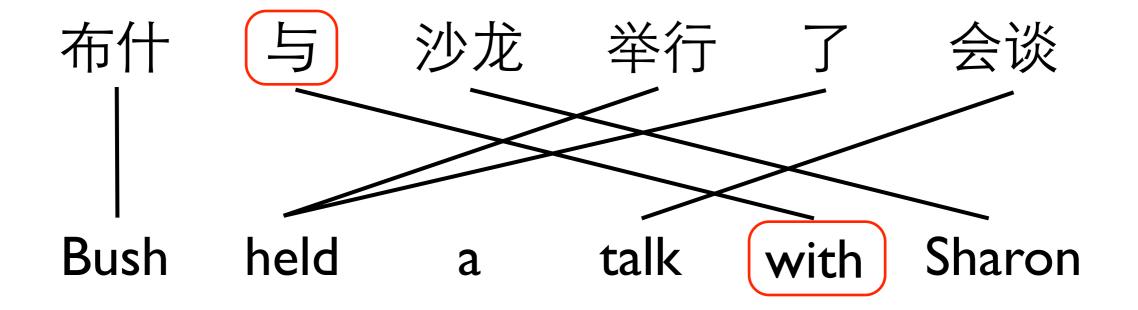
all words in the source phrase are aligned to all words in the target phrase





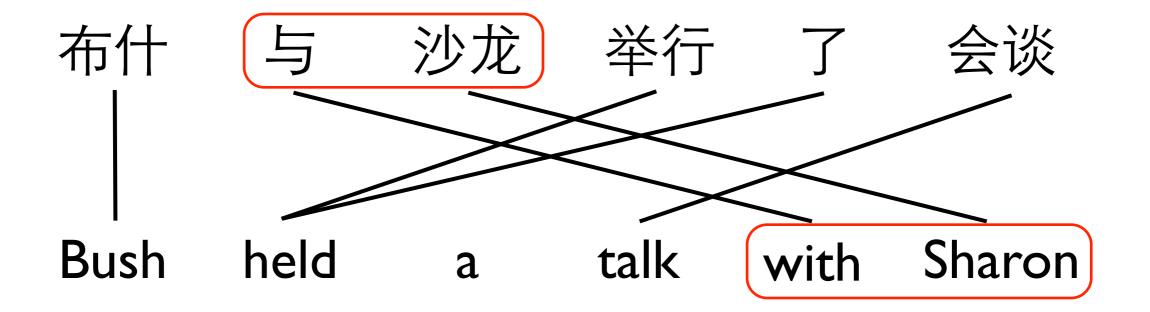






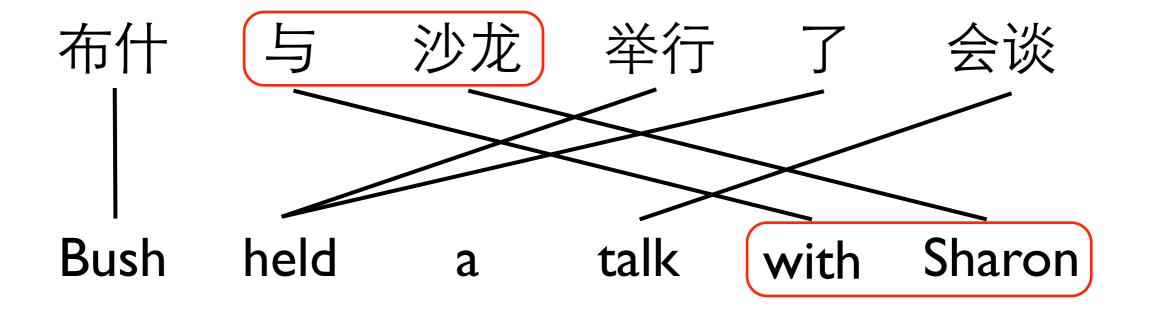
(布什, Bush)

(与, with)



(布什, Bush)

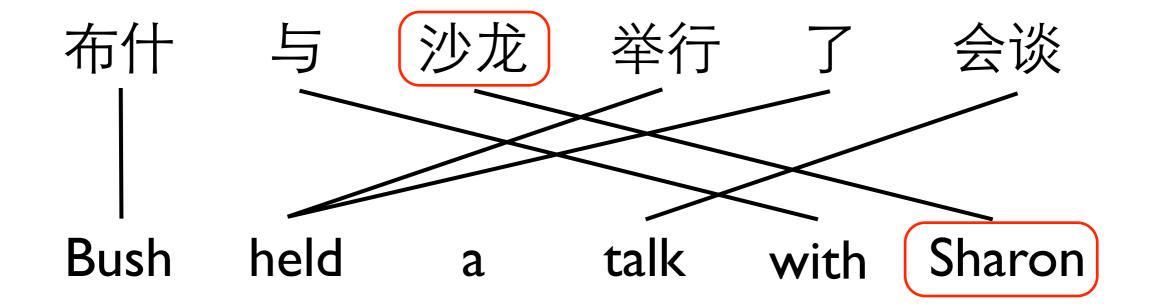
(与, with)



(布什, Bush)

(与, with)

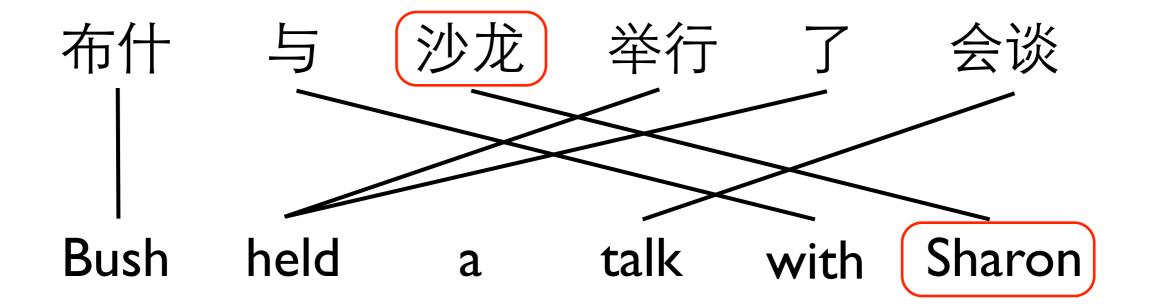
(与沙龙, with Sharon)



(布什, Bush)

(与, with)

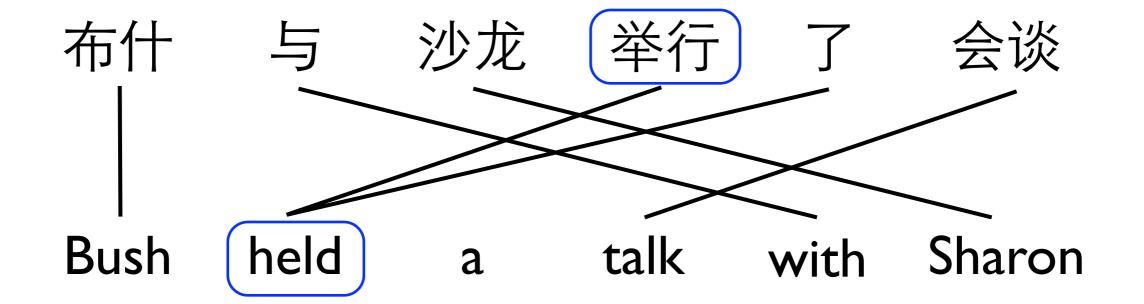
(与沙龙, with Sharon)



(布什, Bush)

(与, with)

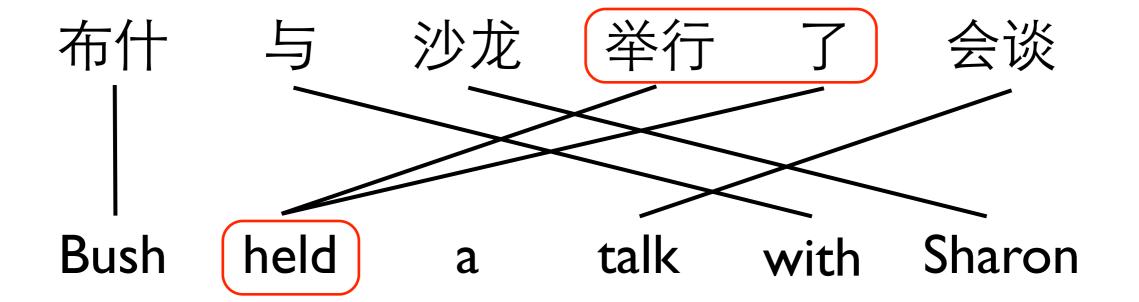
(与沙龙, with Sharon)



(布什, Bush)

(与, with)

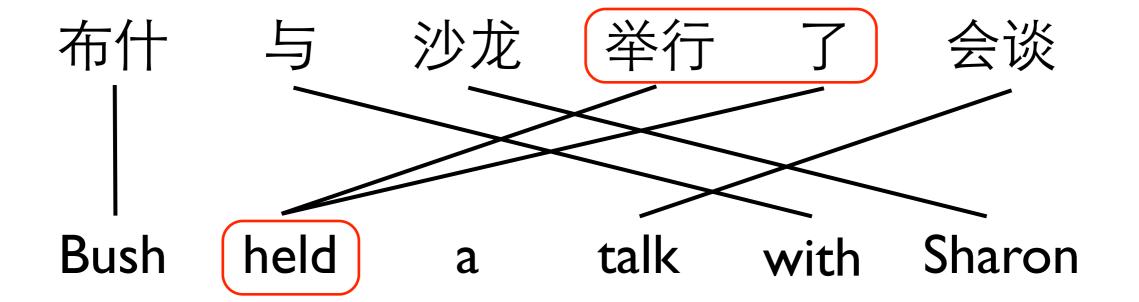
(与沙龙, with Sharon)



(布什, Bush)

(与, with)

(与沙龙, with Sharon)

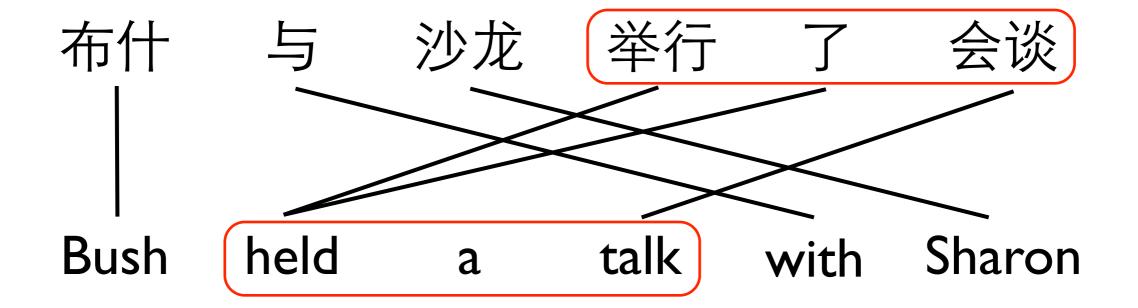


(布什, Bush)

(举行了, held)

(与, with)

(与沙龙, with Sharon)

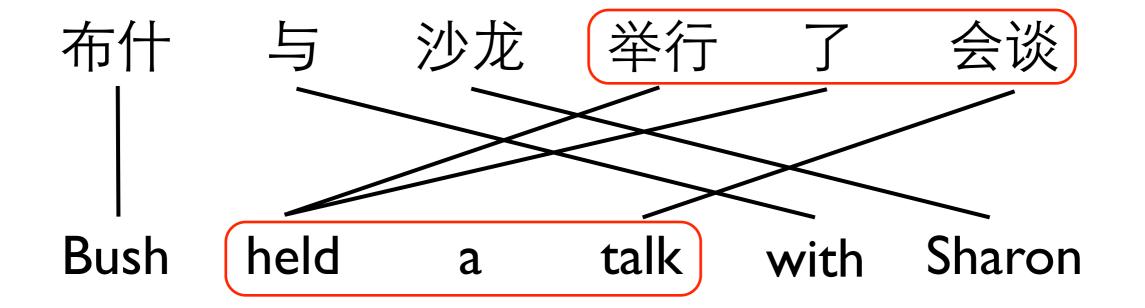


(布什, Bush)

(举行了, held)

(与, with)

(与沙龙, with Sharon)



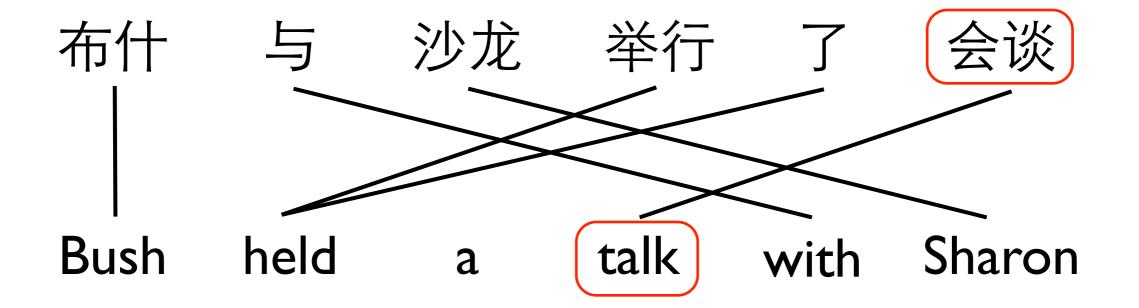
(布什, Bush)

(举行了, held)

(与, with)

(举行了会谈, held a talk)

(与沙龙, with Sharon)



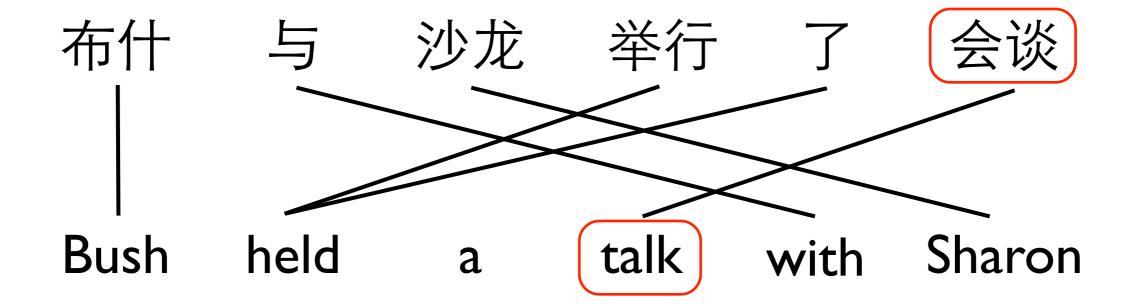
(布什, Bush)

(举行了, held)

(与, with)

(举行了会谈, held a talk)

(与沙龙, with Sharon)



(布什, Bush)

(与, with)

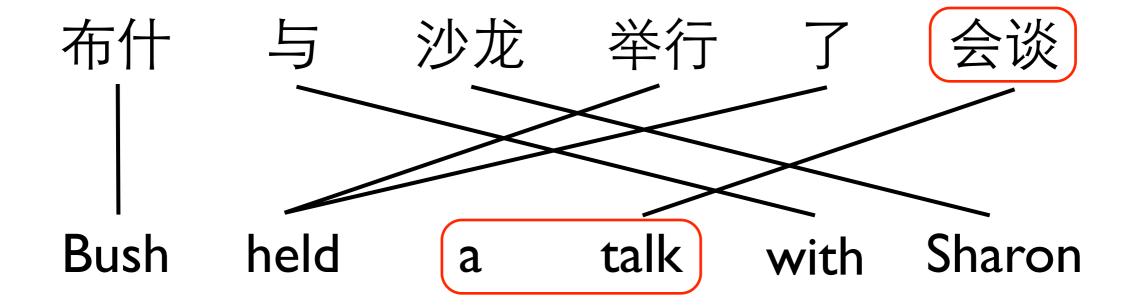
(与沙龙, with Sharon)

(沙龙, Sharon)

(举行了, held)

(举行了会谈, held a talk)

(会谈, talk)



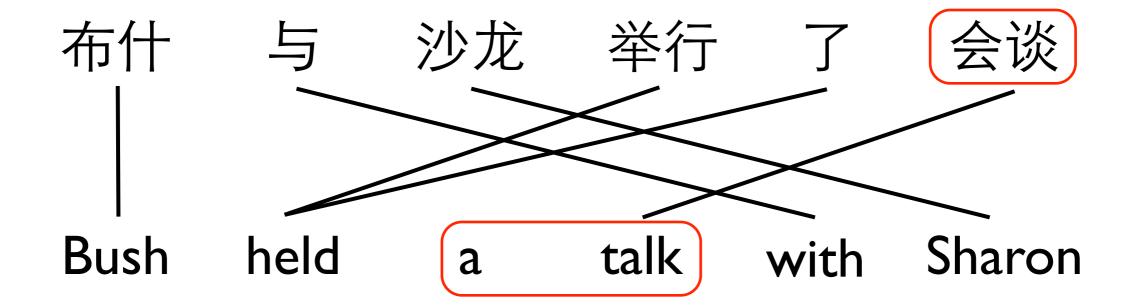
(布什, Bush) (举行了, held)

(与, with)

(与沙龙, with Sharon) (会谈, talk)

(沙龙, Sharon)

(举行了会谈, held a talk)



(布什, Bush)

(与, with)

(与 沙龙, with Sharon)

(沙龙, Sharon)

(举行了, held)

(举行了会谈, held a talk)

(会谈, talk)

(会谈, a talk)

f	е	count	P(e f)	P(f e)
布什	Bush			
与	with			
与 沙龙	with Sharon			
沙龙	Sharon	I		
举行了	held			
举行了会谈	held a talk	I		
会谈	talk			
会谈	a talk			

$$P(e|f) = \frac{count(f, e)}{\sum_{e'} count(f, e')}$$

f	е	count	P(e f)	P(f e)
布什	Bush			
与	with			
与沙龙	with Sharon			
沙龙	Sharon			
举行了	held			
举行了会谈	held a talk			
会谈	talk			
会谈	a talk			

$$P(e|f) = \frac{count(f, e)}{\sum_{e'} count(f, e')}$$

f	е	count	P(e f)	P(f e)
布什	Bush		1.0	
与	with	I	1.0	
与沙龙	with Sharon	I	1.0	
沙龙	Sharon	I	1.0	
举行了	held	I	1.0	
举行了会谈	held a talk	I	1.0	
会谈	talk	l	0.5	
会谈	a talk		0.5	

$$P(e|f) = \frac{count(f,e)}{\sum_{e'} count(f,e')} \qquad P(f|e) = \frac{count(f,e)}{\sum_{f'} count(f',e)}$$

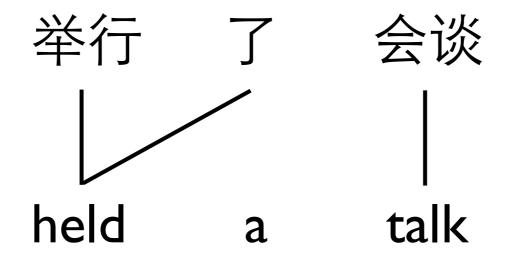
f	е	count	P(e f)	P(f e)
布什	Bush		1.0	
与	with	I	1.0	
与沙龙	with Sharon	I	1.0	
沙龙	Sharon	I	1.0	
举行了	held	I	1.0	
举行了会谈	held a talk	I	1.0	
会谈	talk	I	0.5	
会谈	a talk	<b>I</b>	0.5	

$$P(e|f) = \frac{count(f,e)}{\sum_{e'} count(f,e')} \qquad P(f|e) = \frac{count(f,e)}{\sum_{f'} count(f',e)}$$

f	е	count	P(e f)	P(f e)
布什	Bush		1.0	1.0
与	with		1.0	1.0
与沙龙	with Sharon		1.0	1.0
沙龙	Sharon		1.0	1.0
举行了	held		1.0	1.0
举行了会谈	held a talk		1.0	1.0
会谈	talk		0.5	1.0
会谈	a talk		0.5	1.0

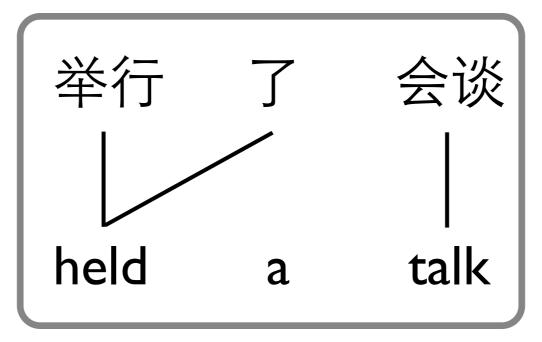
# Lexical Weighting

- estimating phrase translation probabilities using relative frequencies suffers from sparse data
- lexical weighting considers word alignment with phrase pairs



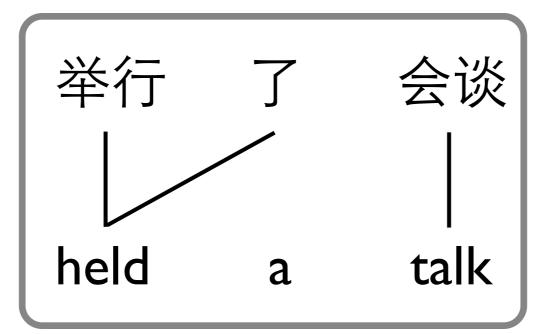
# Lexical Weighting

- estimating phrase translation probabilities using relative frequencies suffers from sparse data
- lexical weighting considers word alignment with phrase pairs



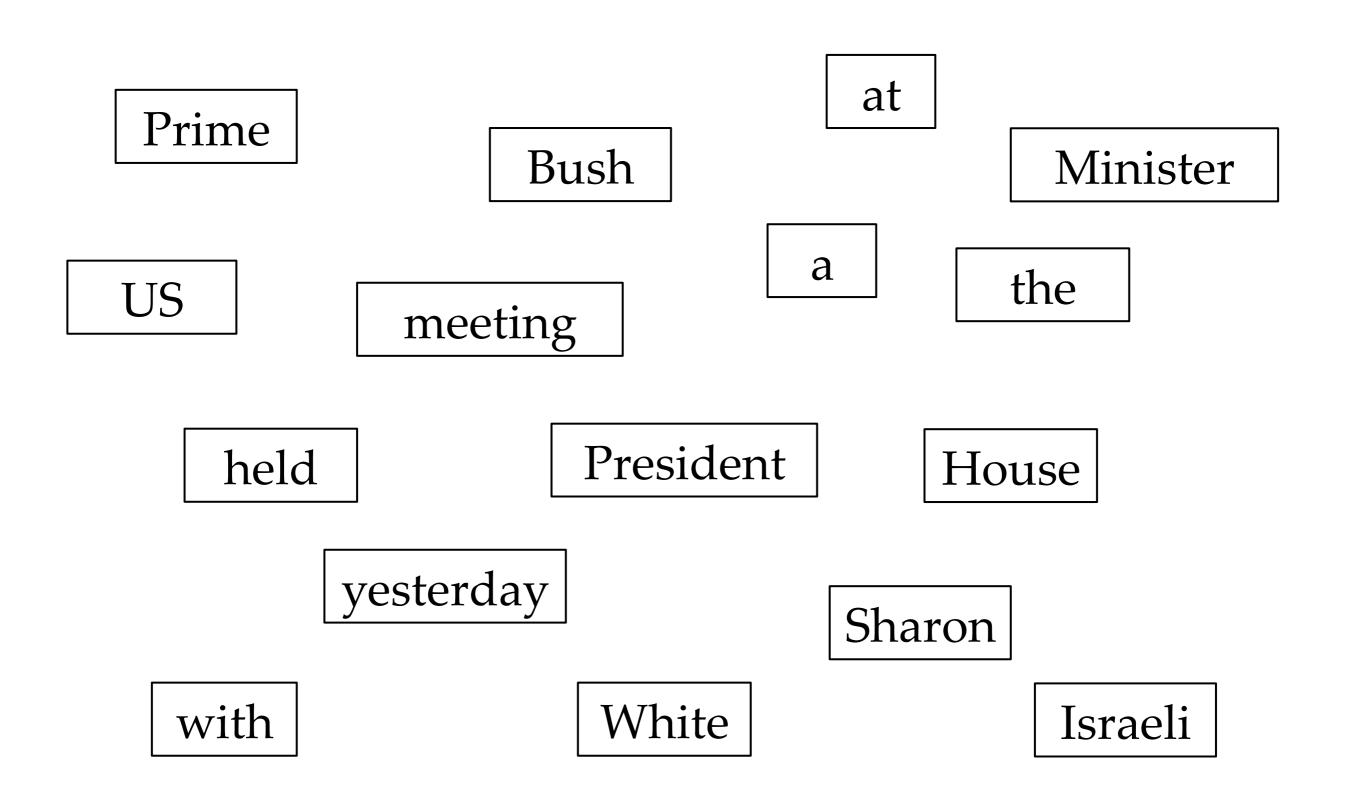
# Lexical Weighting

- estimating phrase translation probabilities using relative frequencies suffers from sparse data
- lexical weighting considers word alignment with phrase pairs

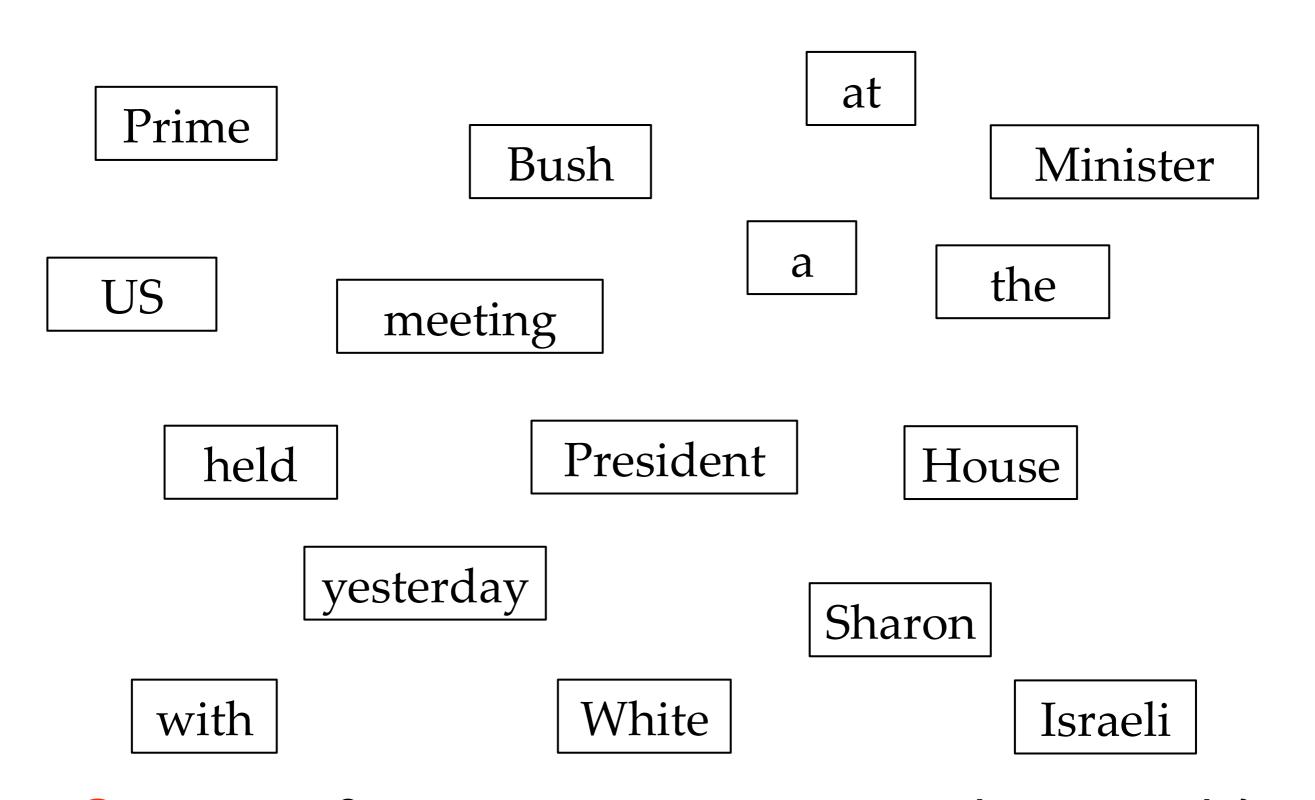


```
(w("held"|"举行")+w("held"|"了")) / 2 * w("a"|NULL) * w("talk"|"会谈")
```

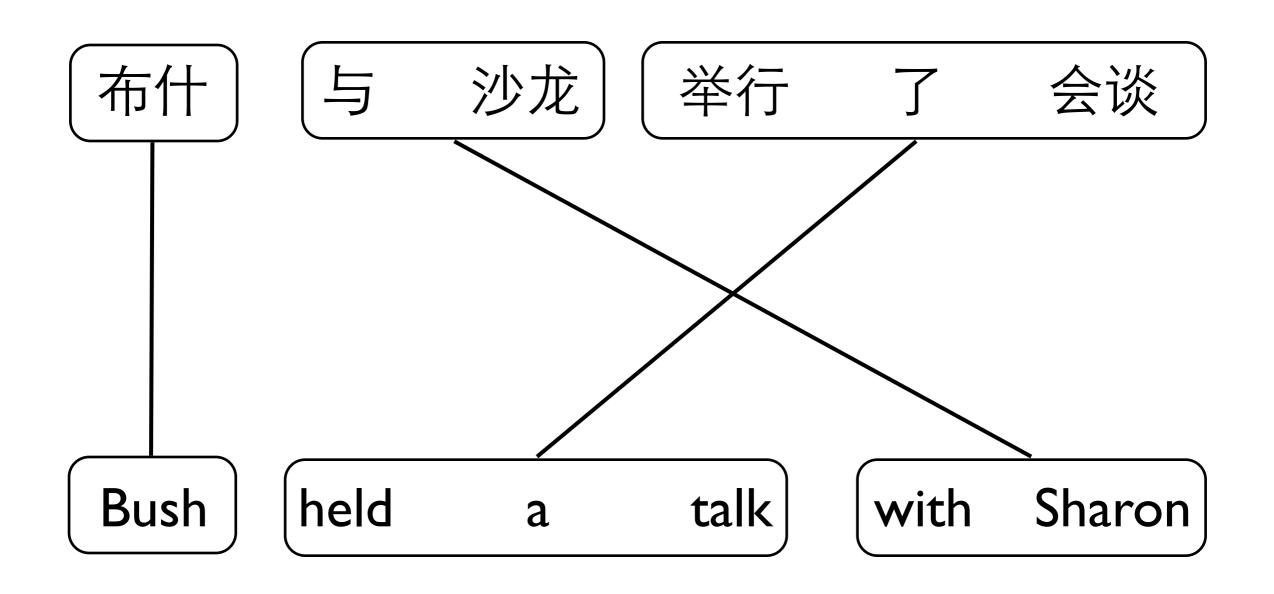
## Reordering is Hard

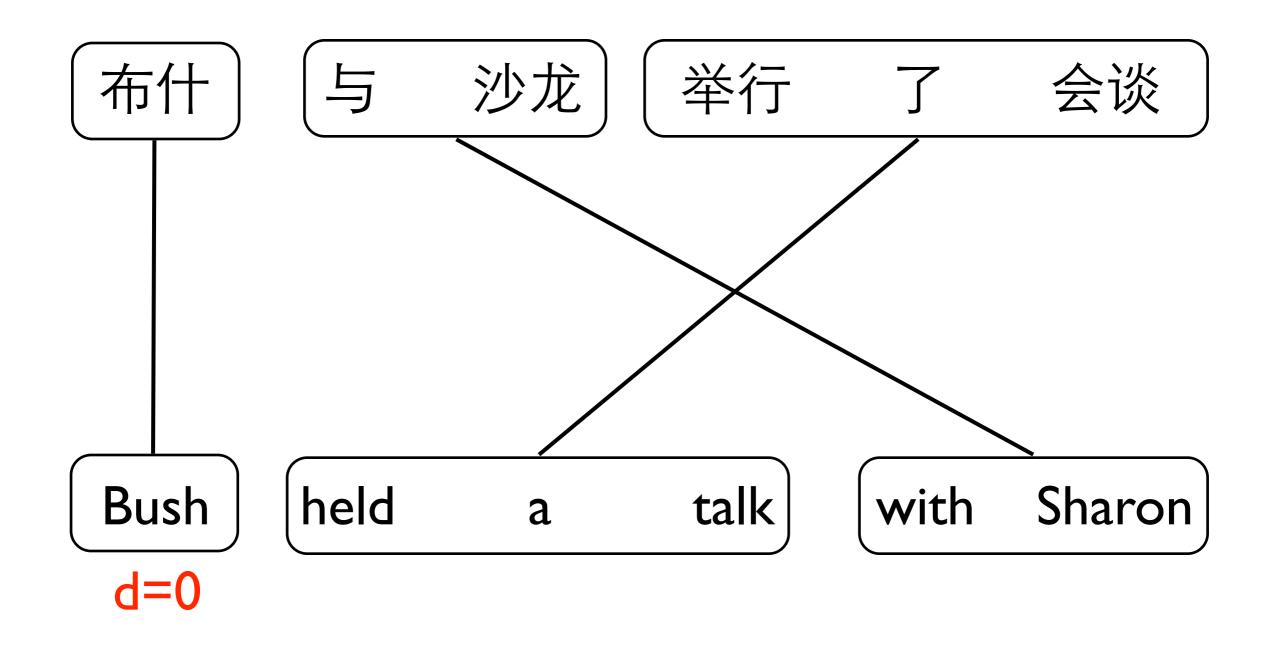


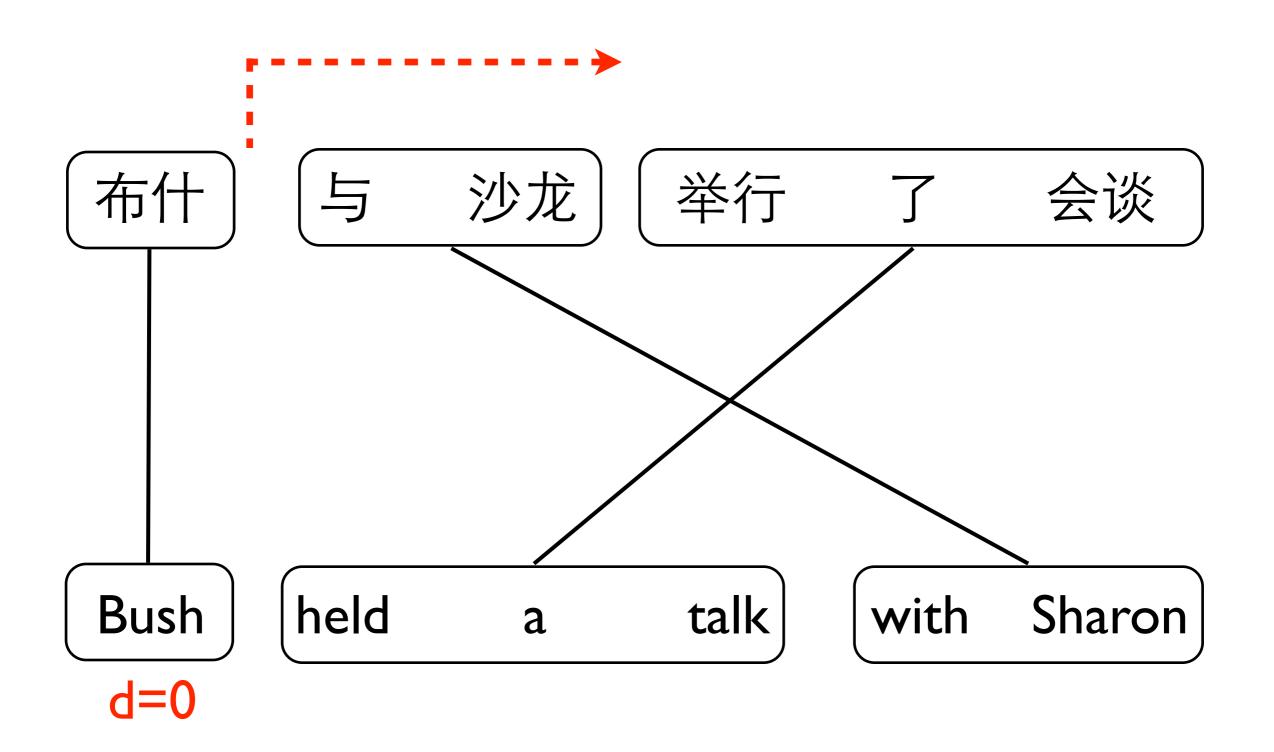
# Reordering is Hard

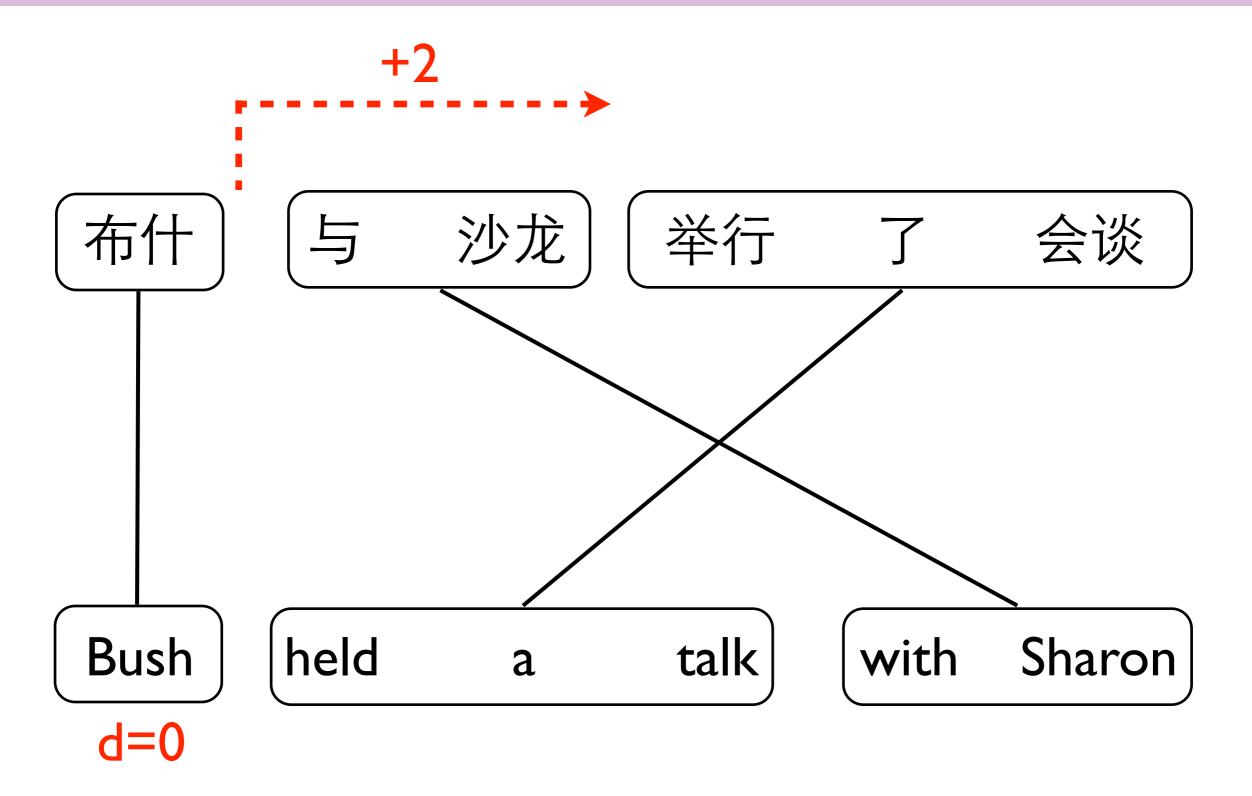


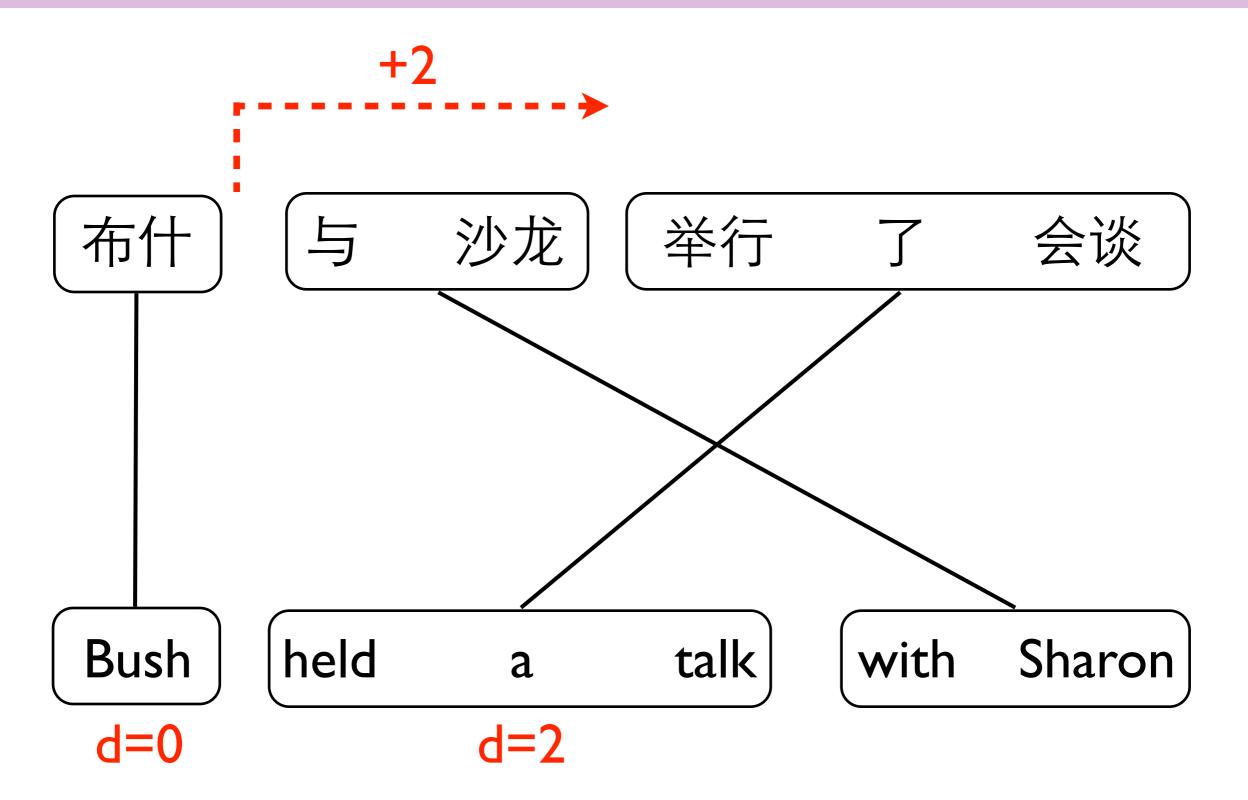
Q: can you figure out a sentence using these words?

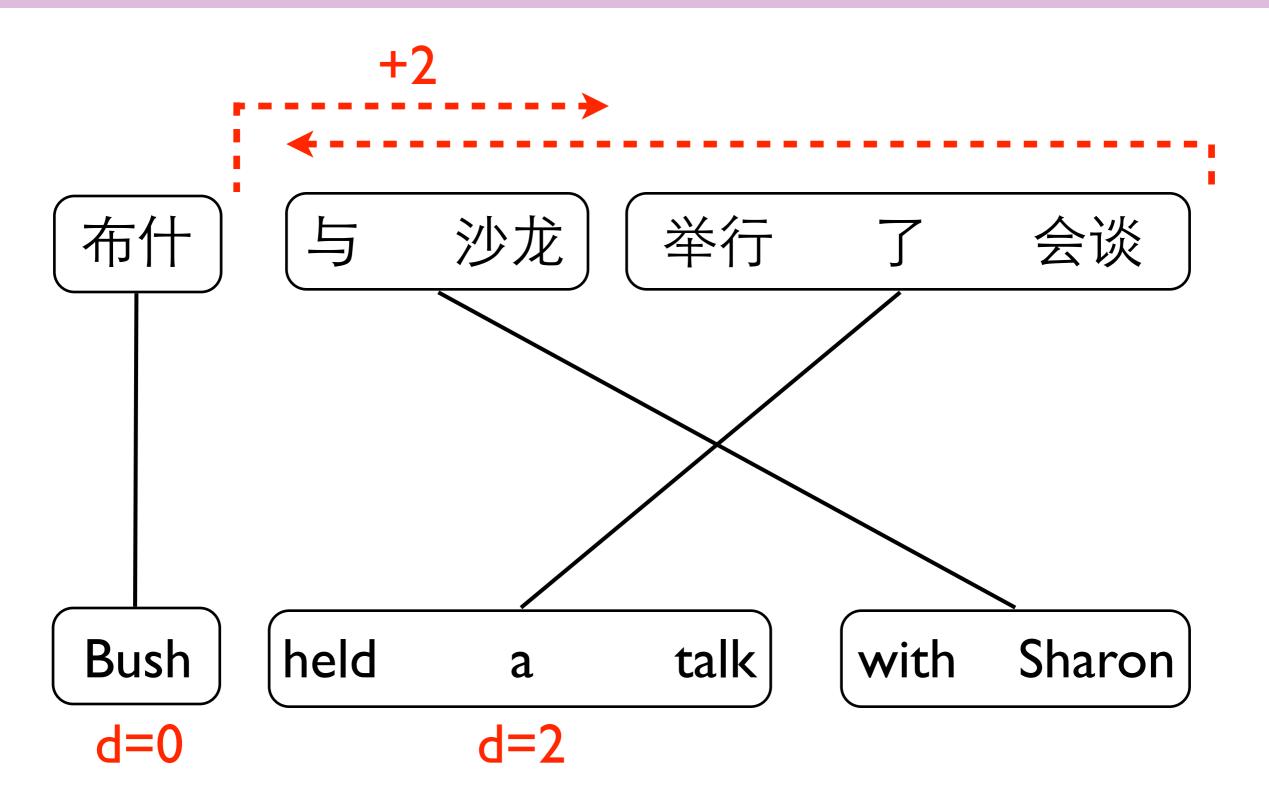


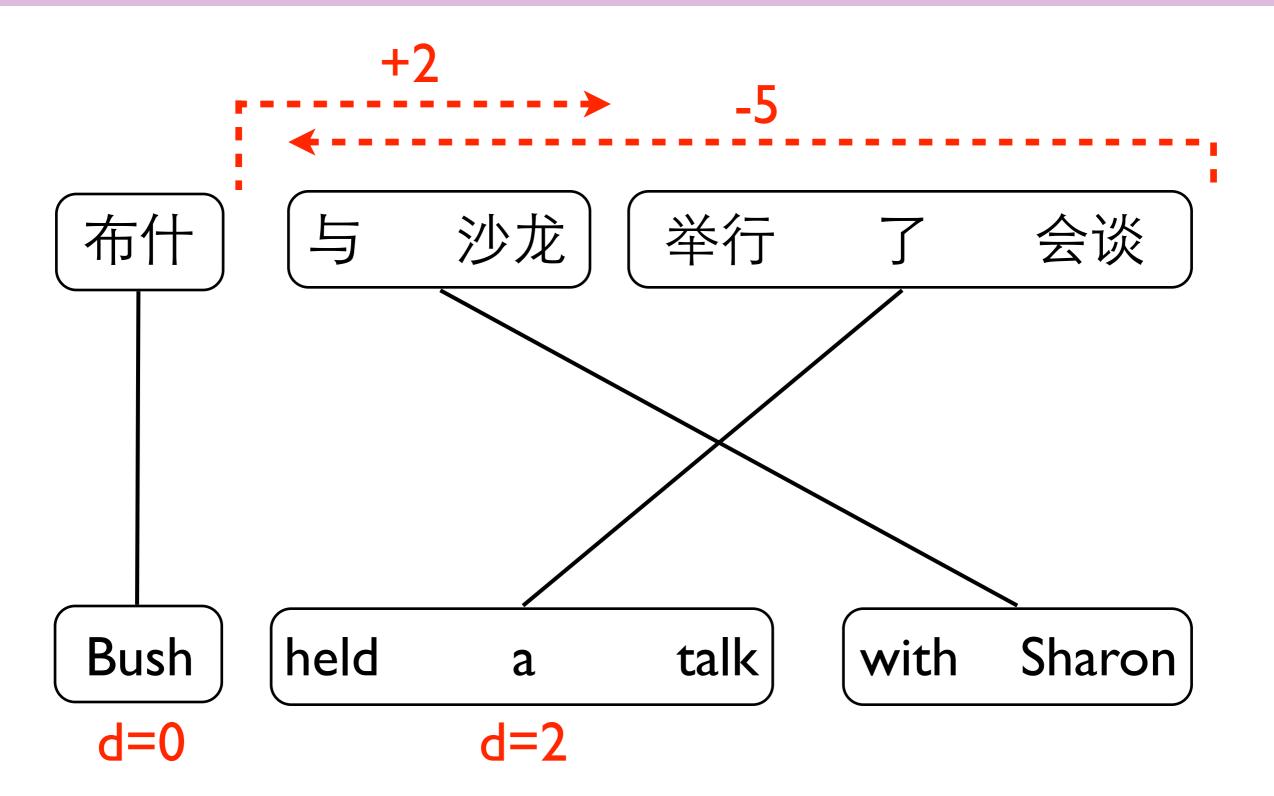


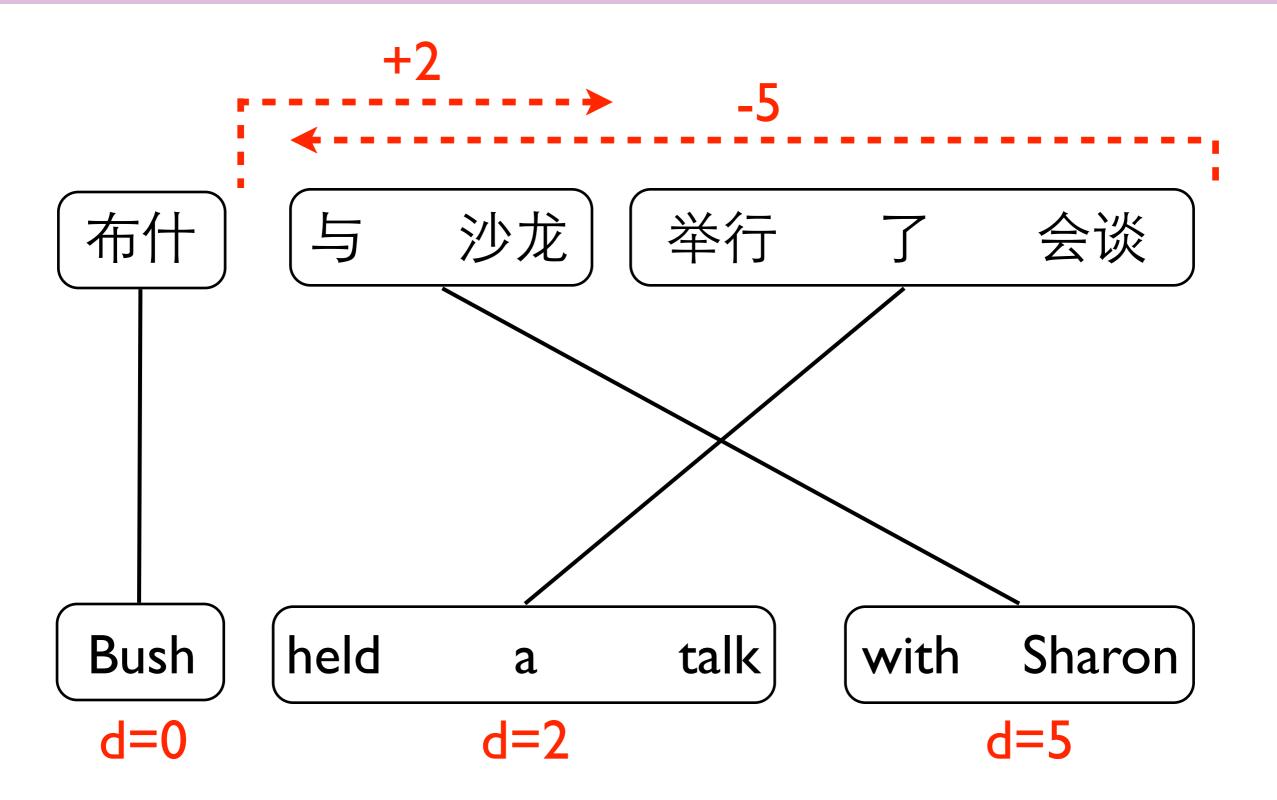


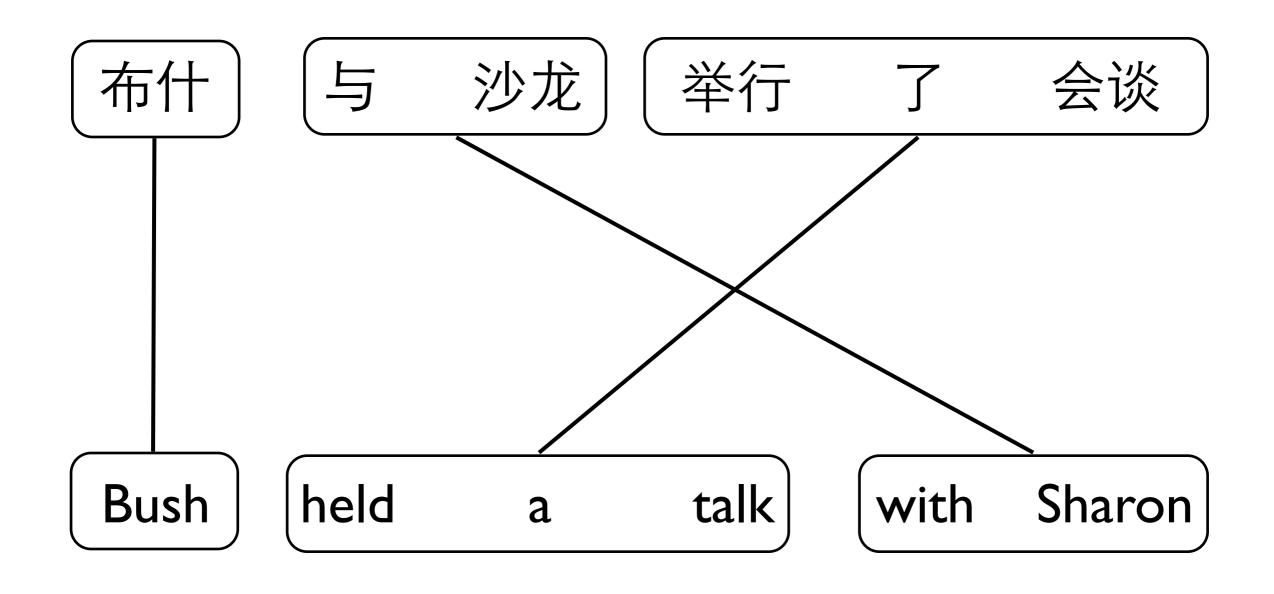


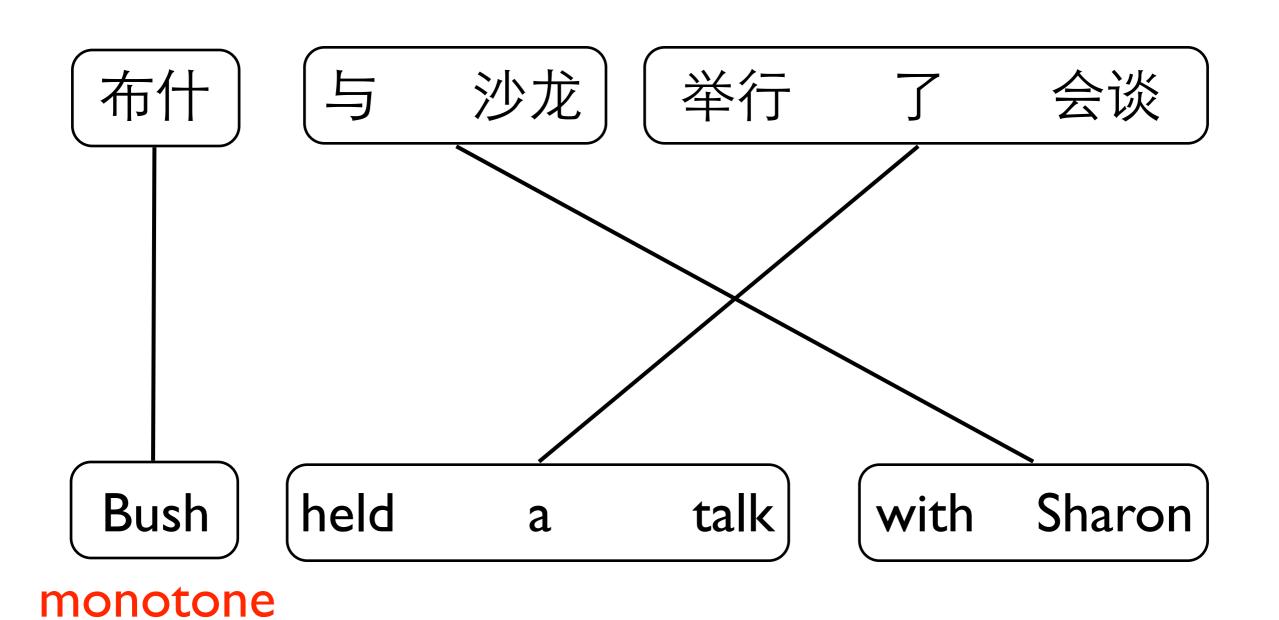


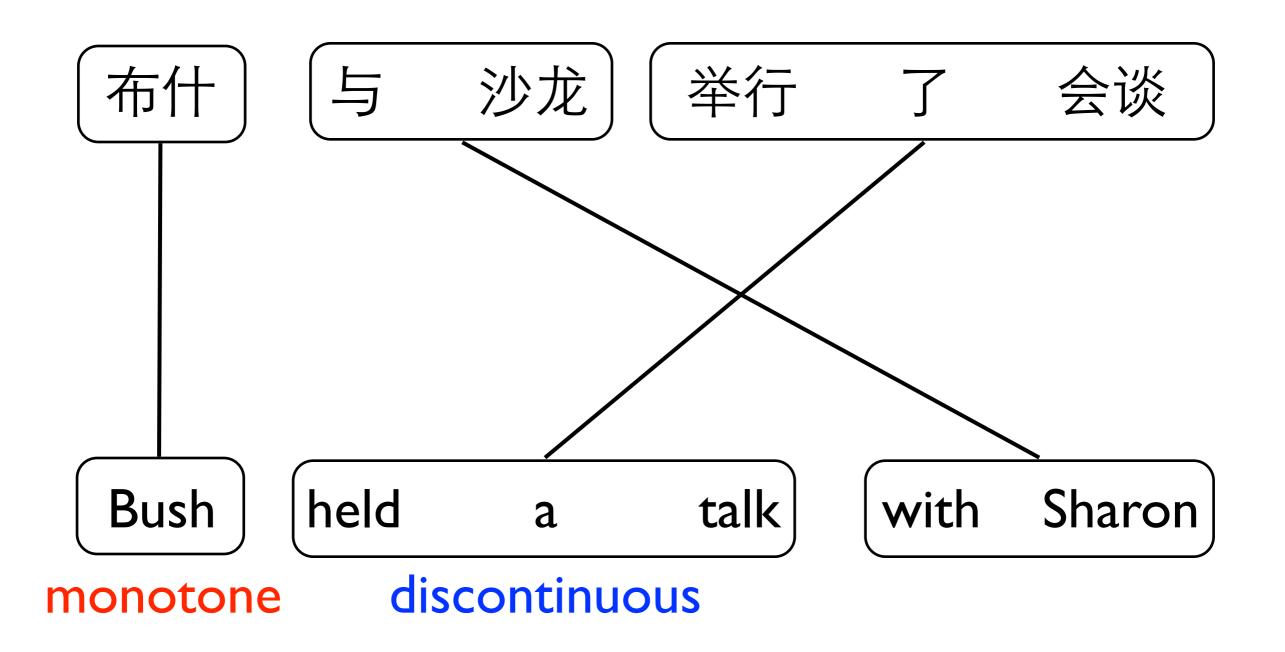


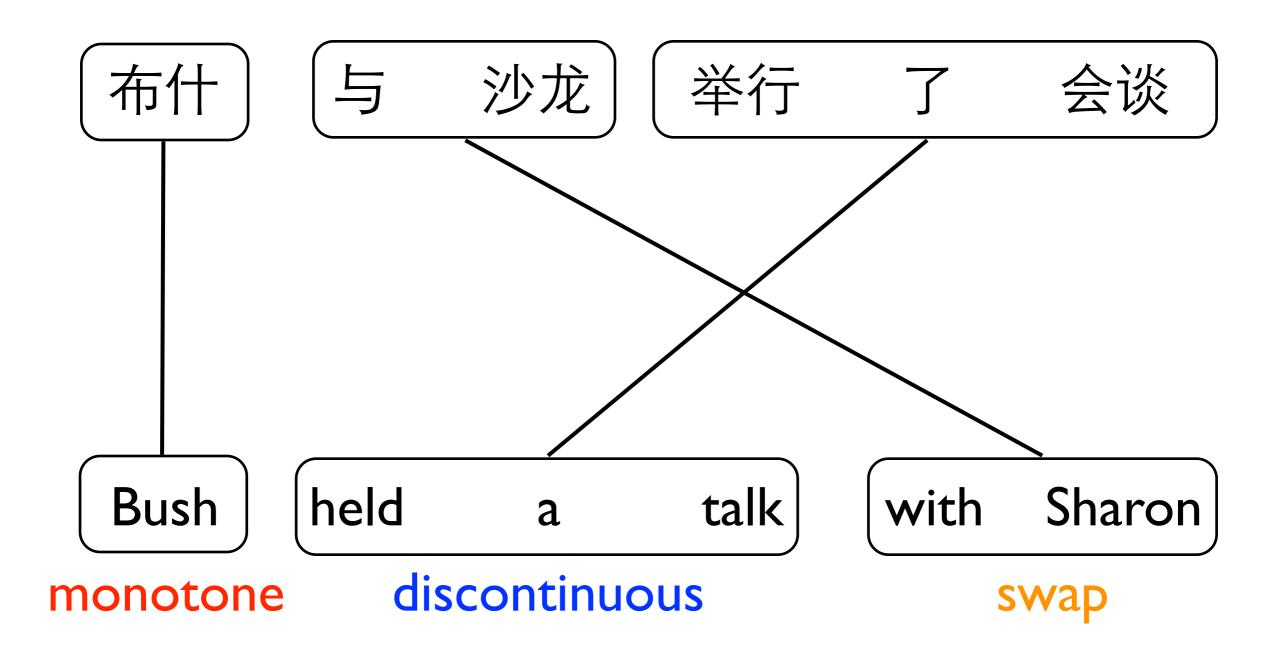






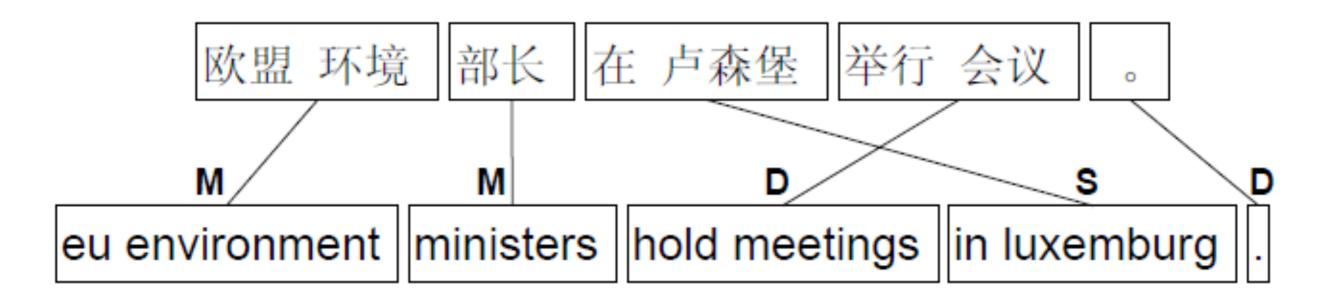


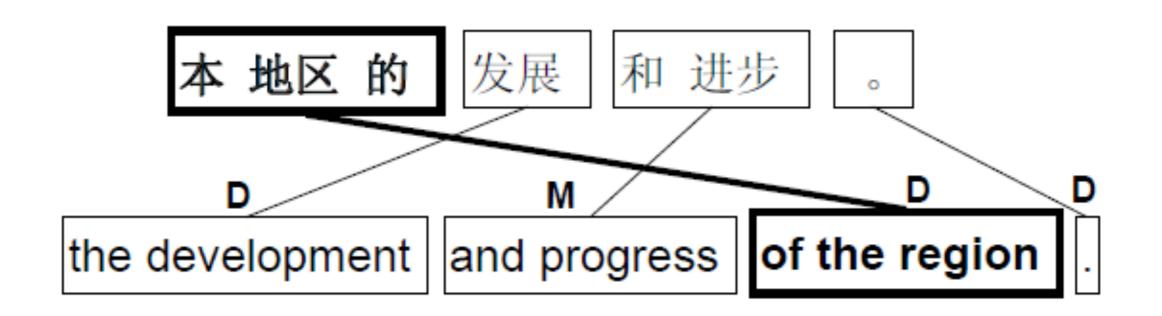




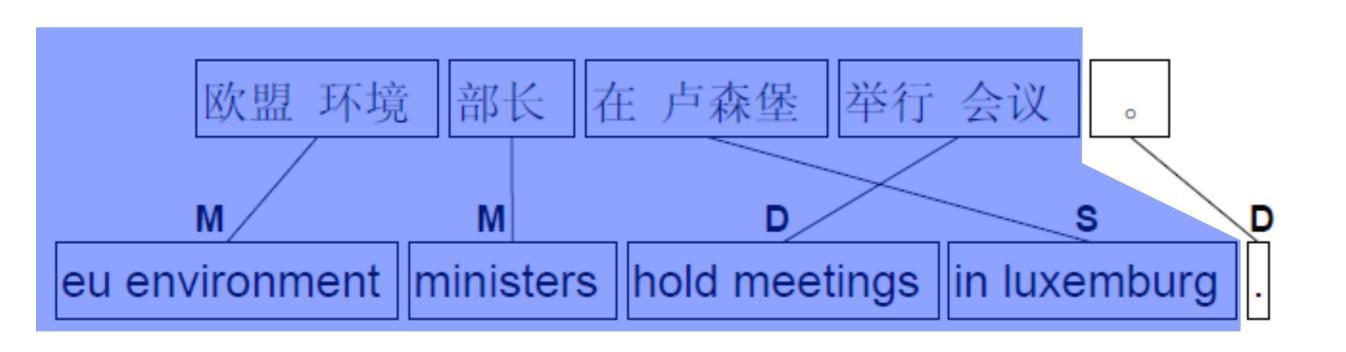
f	е	M	S	D
布什	Bush	0.4	0.3	0.3
与	with	0.6	0.1	0.3
与沙龙	with Sharon	0.3	0.5	0.2
沙龙	Sharon	0.4	0.3	0.3
举行了	held	0.8	0.1	0.1
举行了会谈	held a talk	0.4	0.4	0.2
会谈	talk	0.3	0.3	0.4
会谈	a talk	0.3	0.4	0.3

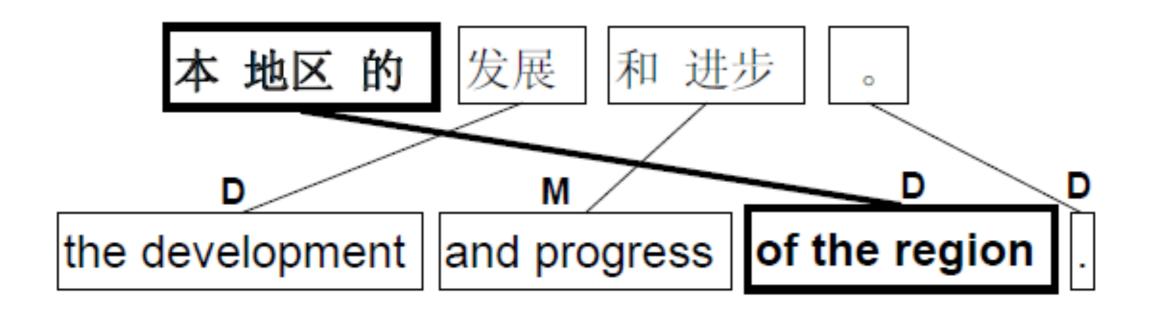
# Hierarchical Reordering Model

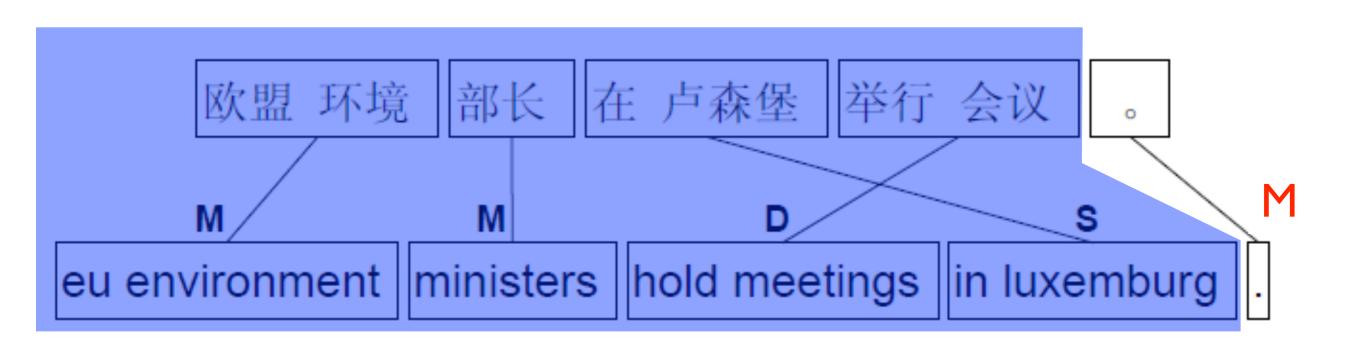


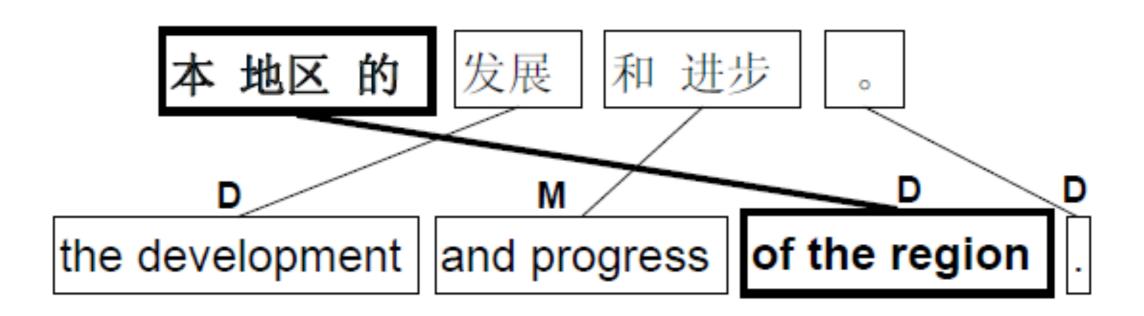


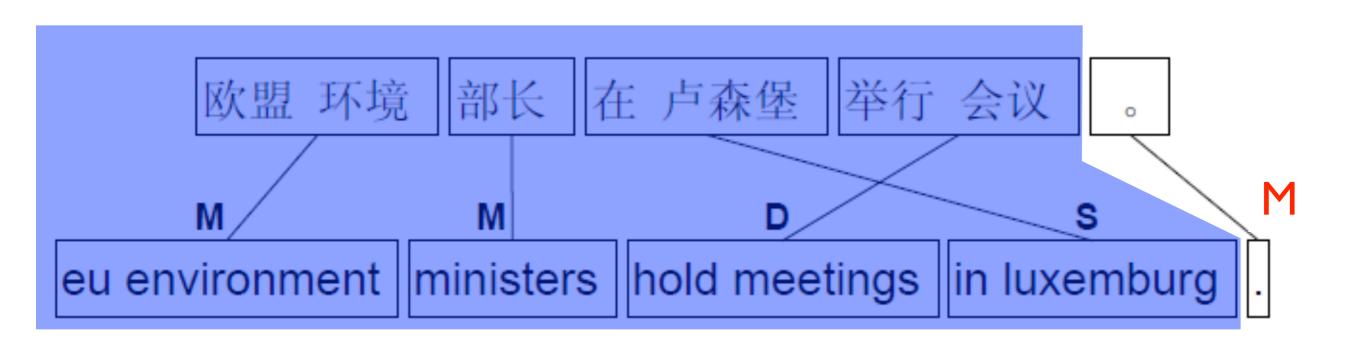
# Hierarchical Reordering Model

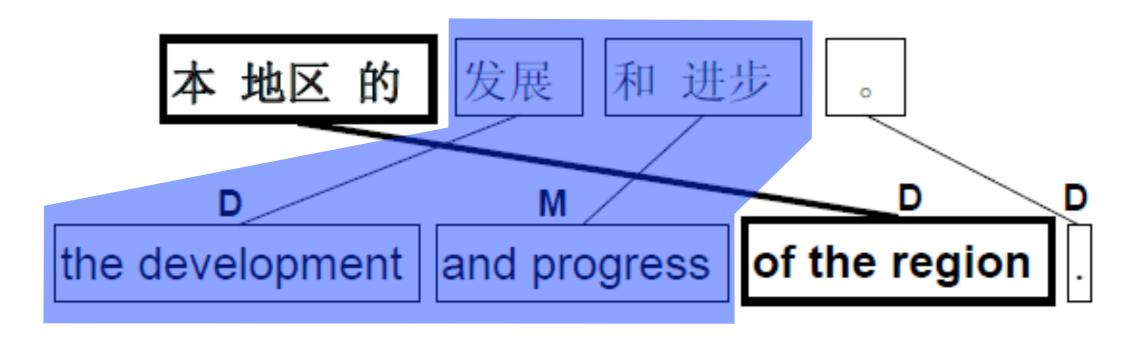


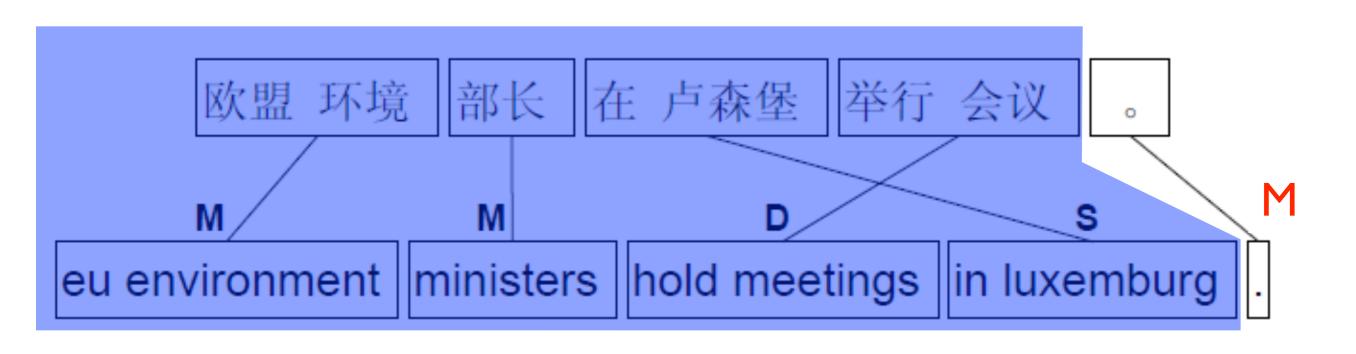


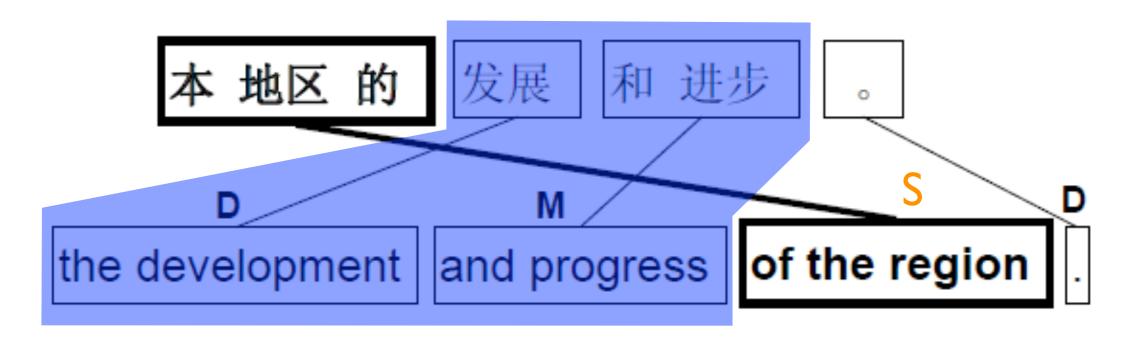




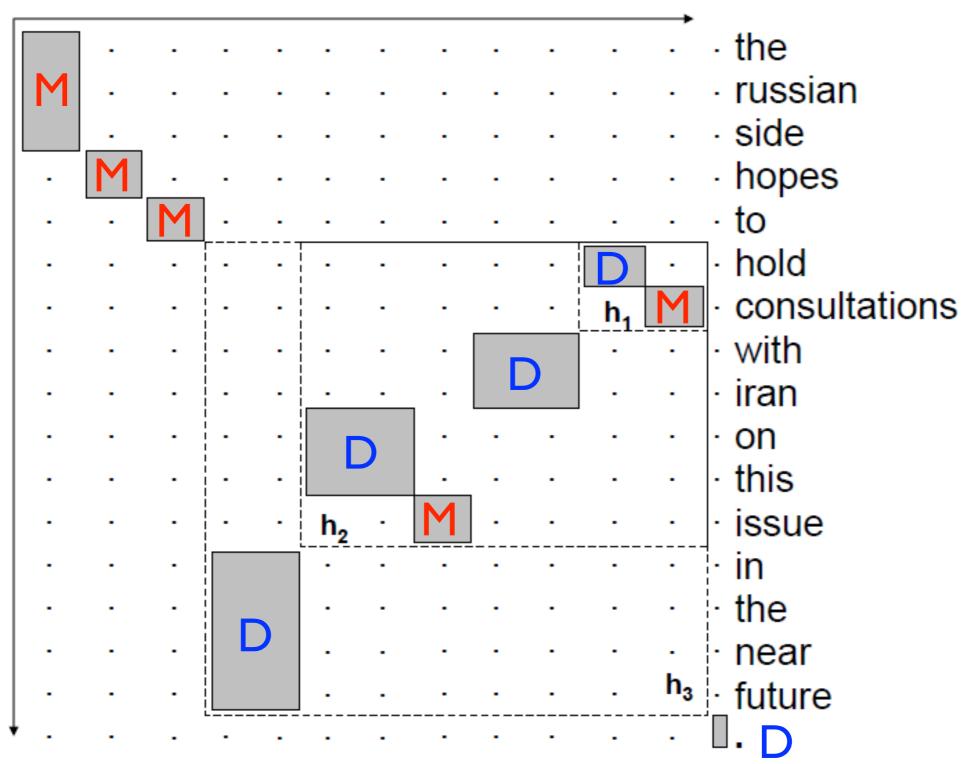




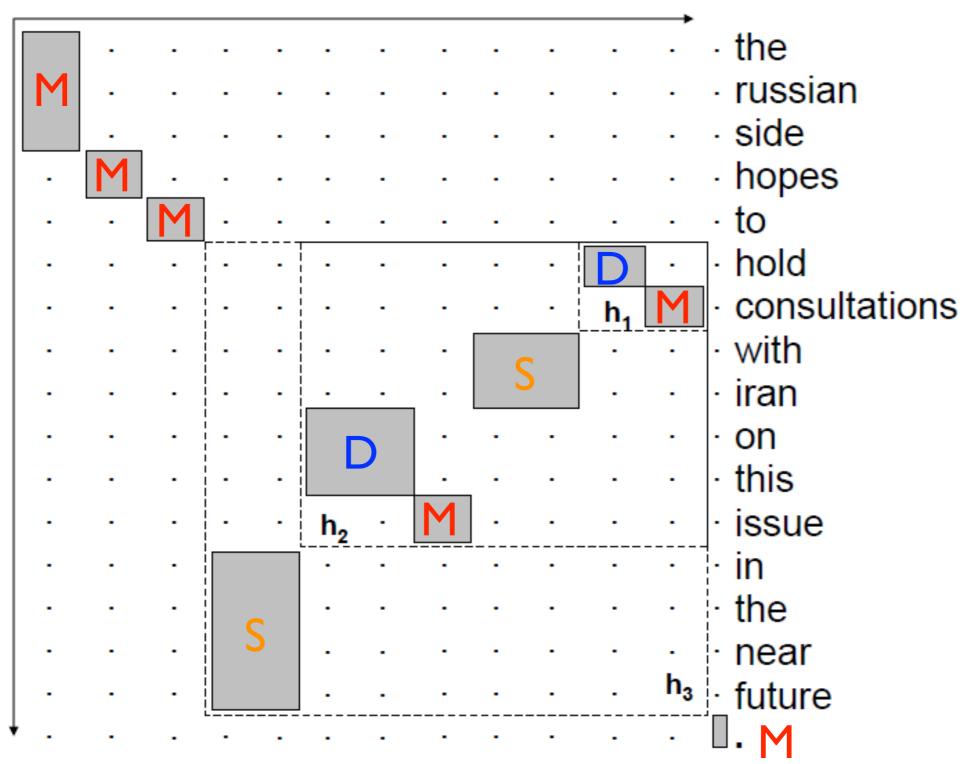




## Lexicalized Reordering Model

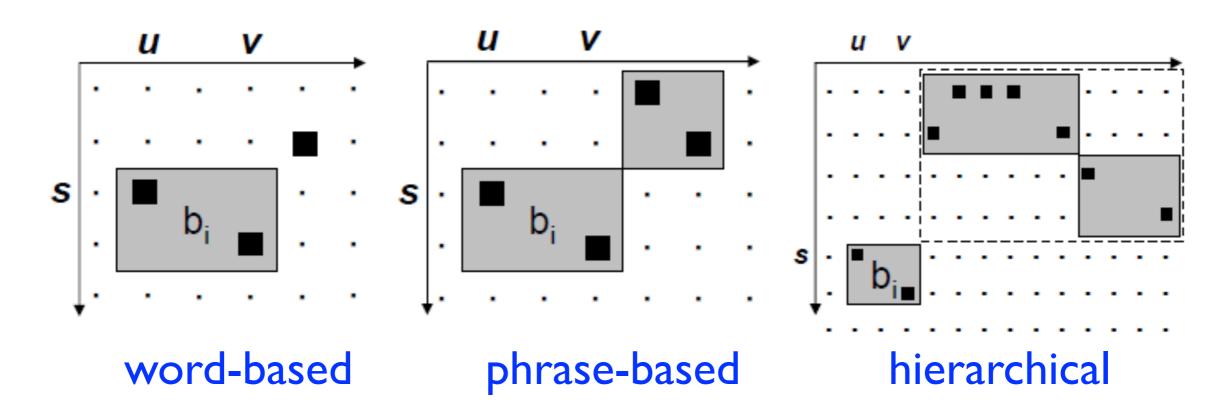


俄方 希望 能够 在 近期 就 这个 问题 与 伊朗 举行 磋商。



俄方 希望 能够 在 近期 就 这个 问题 与 伊朗 举行 磋商。

## Word, Phrase and Hierarchical



ORIENTATION MODEL	$o_i = M$	$o_i = S$	$o_i = D$
word-based (Moses)	0.1750	0.0159	0.8092
phrase-based	0.3192	0.0704	0.6104
hierarchical	0.4878	0.1004	0.4116

## Pre-Reordering Model

布什 与 沙龙 举行 了 会谈

## Pre-Reordering Model

布什 与 沙龙 举行 了 会谈

布什 举行 了 会谈 与 沙龙

## Pre-Reordering Model

布什 与 沙龙 举行 了 会谈 布什 举行 了 会谈 与

a

talk

with

held

Bush

(Li et al., 2007)

Sharon

#### Generative Model Revisited

$$P(\mathbf{e}|\mathbf{f}) = \frac{P(\mathbf{e}) \times P(\mathbf{f}|\mathbf{e})}{P(\mathbf{f})}$$

#### Generative Model Revisited

$$P(\mathbf{e}|\mathbf{f}) = \frac{P(\mathbf{e}) \times P(\mathbf{f}|\mathbf{e})}{P(\mathbf{f})}$$

Is it possible to directly model  $P(\mathbf{e}|\mathbf{f})$ ?

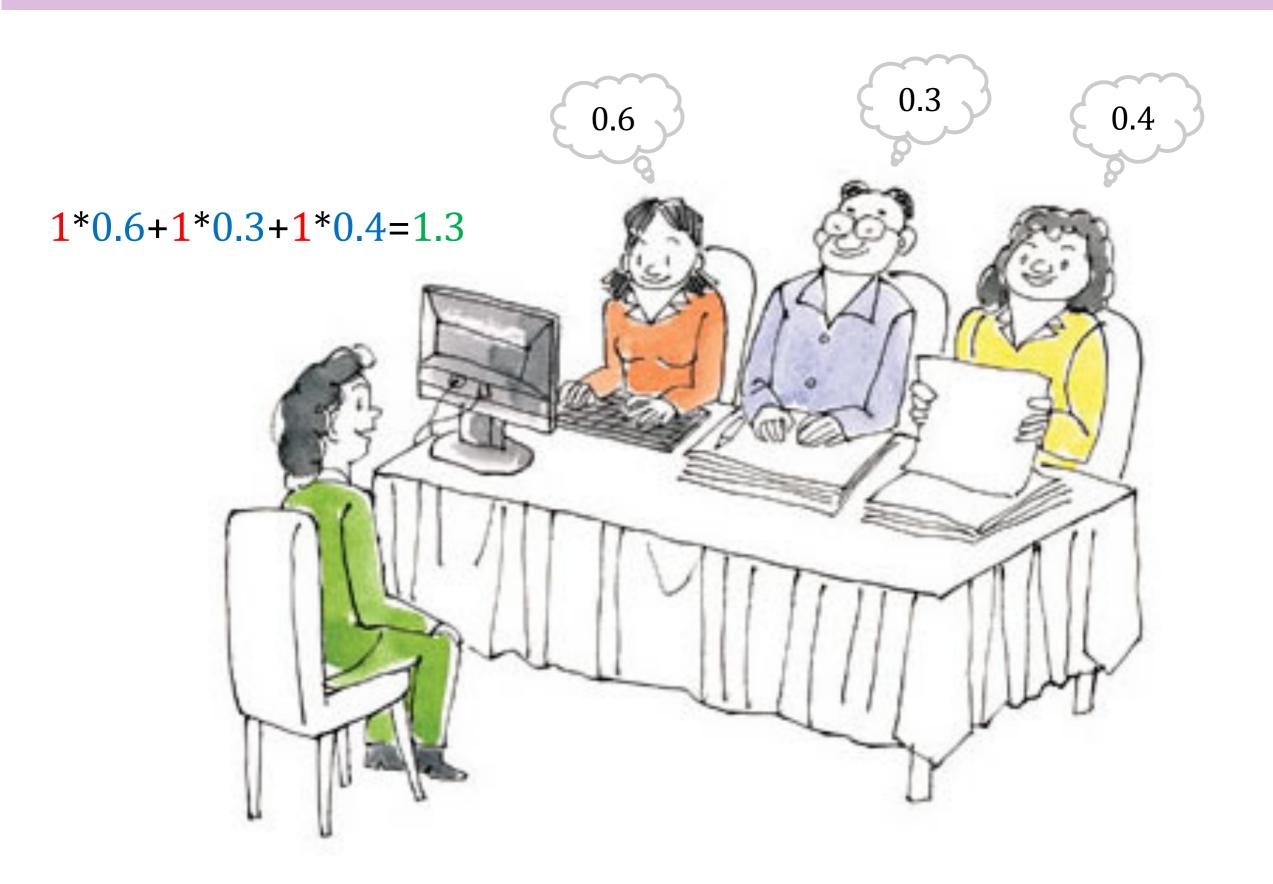


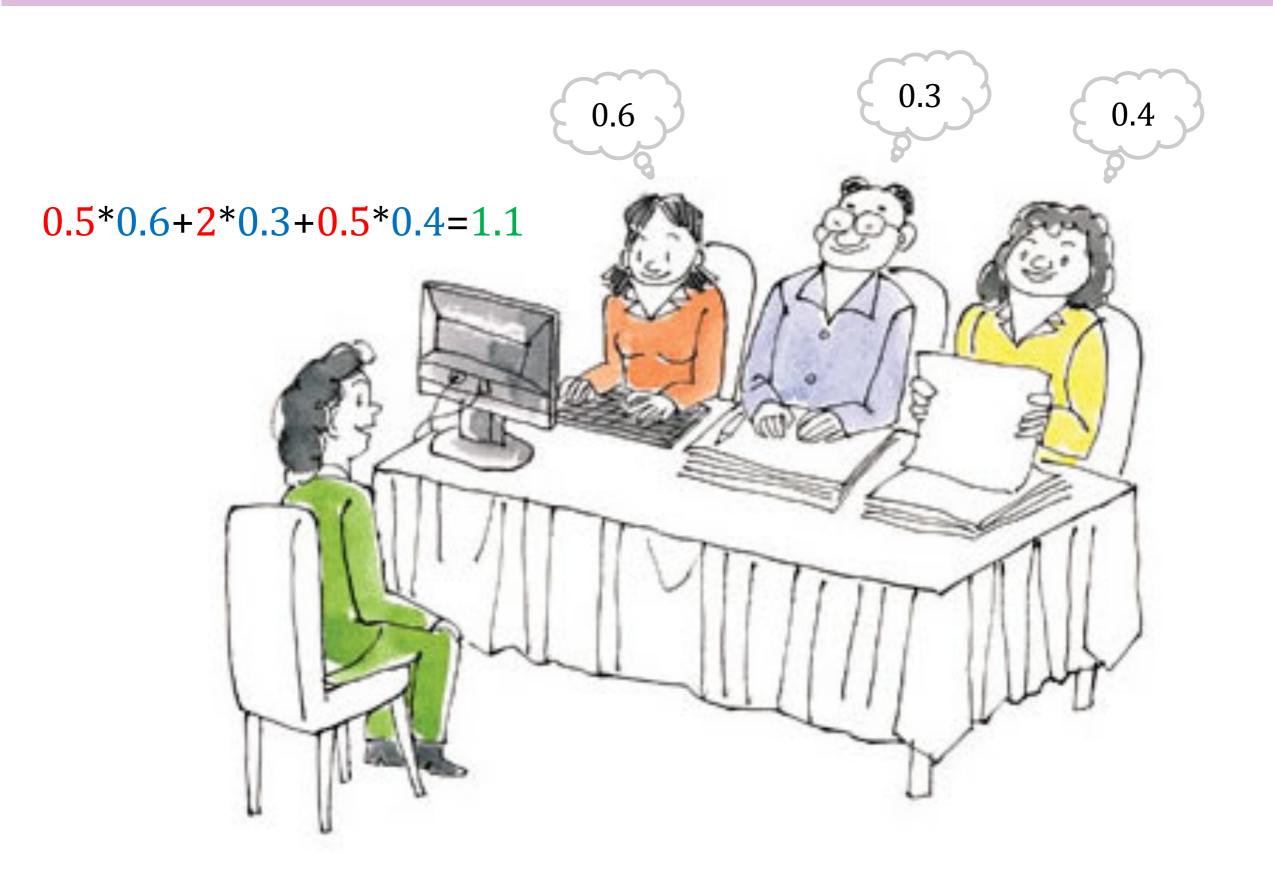












$$P(\mathbf{e}|\mathbf{f}) = \frac{P(\mathbf{e}) \times P(\mathbf{f}|\mathbf{e})}{P(\mathbf{f})}$$

$$P(\mathbf{e}|\mathbf{f}) = \frac{P(\mathbf{e}) \times P(\mathbf{f}|\mathbf{e})}{P(\mathbf{f})}$$

generative model

$$P(\mathbf{e}|\mathbf{f}) = \frac{P(\mathbf{e}) \times P(\mathbf{f}|\mathbf{e})}{P(\mathbf{f})}$$

$$P(\mathbf{e}|\mathbf{f}) = \frac{\exp\left(\sum_{k=1}^{K} \theta_k h_k(\mathbf{f}, \mathbf{e})\right)}{\sum_{\mathbf{e}'} \exp\left(\sum_{k=1}^{K} \theta_k h_k(\mathbf{f}, \mathbf{e}')\right)}$$

$$P(\mathbf{e}|\mathbf{f}) = \frac{P(\mathbf{e}) \times P(\mathbf{f}|\mathbf{e})}{P(\mathbf{f})}$$

discriminative model

$$P(\mathbf{e}|\mathbf{f}) = \frac{\exp\left(\sum_{k=1}^{K} \theta_k h_k(\mathbf{f}, \mathbf{e})\right)}{\sum_{\mathbf{e}'} \exp\left(\sum_{k=1}^{K} \theta_k h_k(\mathbf{f}, \mathbf{e}')\right)}$$

generative model

$$P(\mathbf{e}|\mathbf{f}) = \frac{P(\mathbf{e}) \times P(\mathbf{f}|\mathbf{e})}{P(\mathbf{f})}$$

discriminative model

$$P(\mathbf{e}|\mathbf{f}) = \frac{\exp\left(\sum_{k=1}^{K} \theta_k h_k(\mathbf{f}, \mathbf{e})\right)}{\sum_{\mathbf{e}'} \exp\left(\sum_{k=1}^{K} \theta_k h_k(\mathbf{f}, \mathbf{e}')\right)}$$

$$score(\mathbf{e}, \mathbf{f}) = \sum_{k=1}^{K} \theta_k h_k(\mathbf{f}, \mathbf{e})$$

$$P(\mathbf{e}|\mathbf{f}) = \frac{P(\mathbf{e}) \times P(\mathbf{f}|\mathbf{e})}{P(\mathbf{f})}$$

discriminative model

$$P(\mathbf{e}|\mathbf{f}) = \frac{\exp\left(\sum_{k=1}^{K} \theta_k h_k(\mathbf{f}, \mathbf{e})\right)}{\sum_{\mathbf{e}'} \exp\left(\sum_{k=1}^{K} \theta_k h_k(\mathbf{f}, \mathbf{e}')\right)}$$

discriminant function

$$score(\mathbf{e}, \mathbf{f}) = \sum_{k=1}^{K} \theta_k h_k(\mathbf{f}, \mathbf{e})$$

- the advantages of discriminative models include
  - accessible to arbitrary overlapping knowledge sources
  - distinguish the contributions between different knowledge sources
- generative models are a special case of discriminative models

#### Features

- The following features are widely used in phrasebased discriminative translation models:
  - phrase translation probabilities
  - phrase lexical weights
  - phrase penalty
  - reordering models
  - language models
  - word penalty

$ heta_1$	$ heta_2$	$\theta_3$
1.0	1.0	1.0

cand	$h_1$	$h_2$	$h_3$	score	eval
$e_1$	-85	4	10		
$e_2$	-89	3	12		
$e_3$	-93	6	11		

$ heta_1$	$ heta_2$	$\theta_3$
1.0	1.0	1.0

cand	$h_1$	$h_2$	$h_3$	score	eval
$e_1$	-85	4	10	-71	
$e_2$	-89	3	12	-74	
$e_3$	-93	6	11	-76	

$ heta_1$	$ heta_2$	$\theta_3$
1.0	1.0	1.0

cand	$h_1$	$h_2$	$h_3$	score	eval
$e_1$	-85	4	10	-7 I	0.7
$e_2$	-89	3	12	-74	0.9
$e_3$	-93	6	H	-76	0.6

$ heta_1$	$ heta_2$	$\theta_3$
1.0	1.0	1.0

cand	$h_1$	$h_2$	$h_3$	score	eval
$e_1$	-85	4	10	-71	0.7
$e_2$	-89	3	12	-74	0.9
$e_3$	-93	6	11	-76	0.6

$ heta_1$	$ heta_2$	$\theta_3$
1.0	-2.0	-2.0

cand	$h_1$	$h_2$	$h_3$	score	eval
$e_1$	-85	4	10		0.7
$e_2$	-89	3	12		0.9
$e_3$	-93	6			0.6

$ heta_1$	$ heta_2$	$\theta_3$
1.0	-2.0	-2.0

cand	$h_1$	$h_2$	$h_3$	score	eval
$e_1$	-85	4	10	-73	0.7
$e_2$	-89	3	12	-71	0.9
$e_3$	-93	6	11	-83	0.6

$ heta_1$	$ heta_2$	$\theta_3$
1.0	1.0	1.0

cand	$h_1$	$h_2$	$h_3$	score	eval
$e_1$	-85	4	10	-73	0.7
$e_2$	-89	3	12	-71	0.9
$e_3$	-93	6	11	-83	0.6

$ heta_1$	$ heta_2$	$\theta_3$	
1.0	1.0	1.0	



cand	$h_1$	$h_2$	$h_3$	score	eval
$e_1$	-85	4	10	-73	0.7
$e_2$	-89	3	12	-71	0.9
$e_3$	-93	6	11	-83	0.6

line 1: -81 + 10x

$ heta_1$	$ heta_2$	$\theta_3$
1.0	1.0	1.0



cand	$h_1$	$h_2$	$h_3$	score	eval
$e_1$	-85	4	10	-73	0.7
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line 1: -81 + 10x

line 2: -86 + 12x

$ heta_1$	$ heta_2$	$\theta_3$
1.0	1.0	1.0



cand	$h_1$	$h_2$	$h_3$	score	eval
$e_1$	-85	4	10	-73	0.7
$e_2$	-89	3	12	-71	0.9
$e_3$	-93	6	11	-83	0.6

line 1: -81 + 10x

line 2: -86 + 12x

line 3: -87 + 11x

$ heta_1$	$ heta_2$	$\theta_3$
1.0	1.0	1.0



cand	$h_1$	$h_2$	$h_3$	score	eval
$e_1$	-85	4	10	-73	0.7
$e_2$	-89	3	12	-71	0.9
$e_3$	-93	6	11	-83	0.6

line 1: -81 + 10x

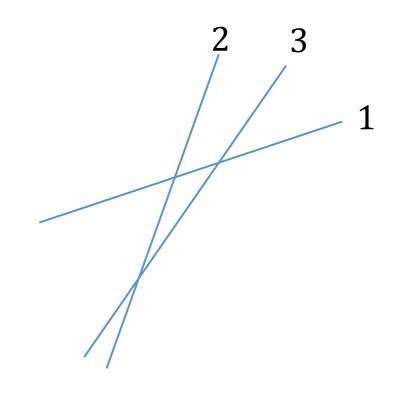
line 2: -86 + 12x

line 3: -87 + 11x

$ heta_1$	$ heta_2$	$\theta_3$
1.0	1.0	1.0



cand	$h_1$	$h_2$	$h_3$	score	eval
$e_1$	-85	4	10	-73	0.7
$e_2$	-89	3	12	-71	0.9
$e_3$	-93	6	11	-83	0.6



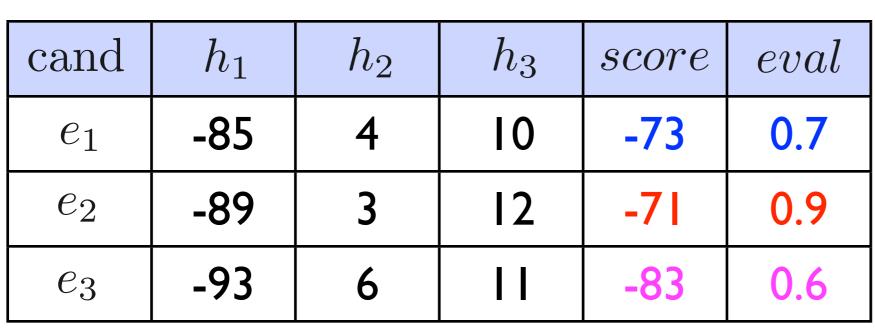
line 1: -81 + 10x

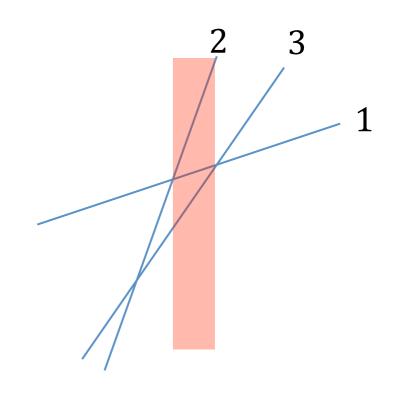
line 2: -86 + 12x

line 3: -87 + 11x

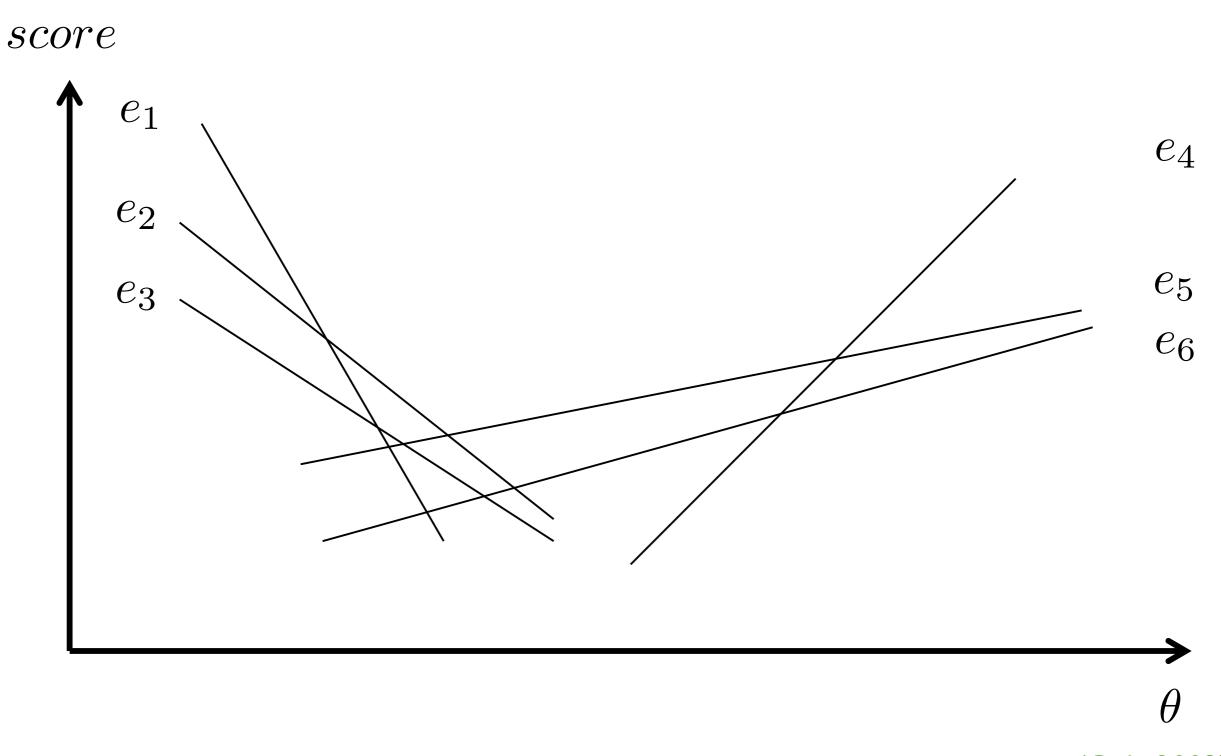
$ heta_1$	$ heta_2$	$\theta_3$
1.0	1.0	1.0



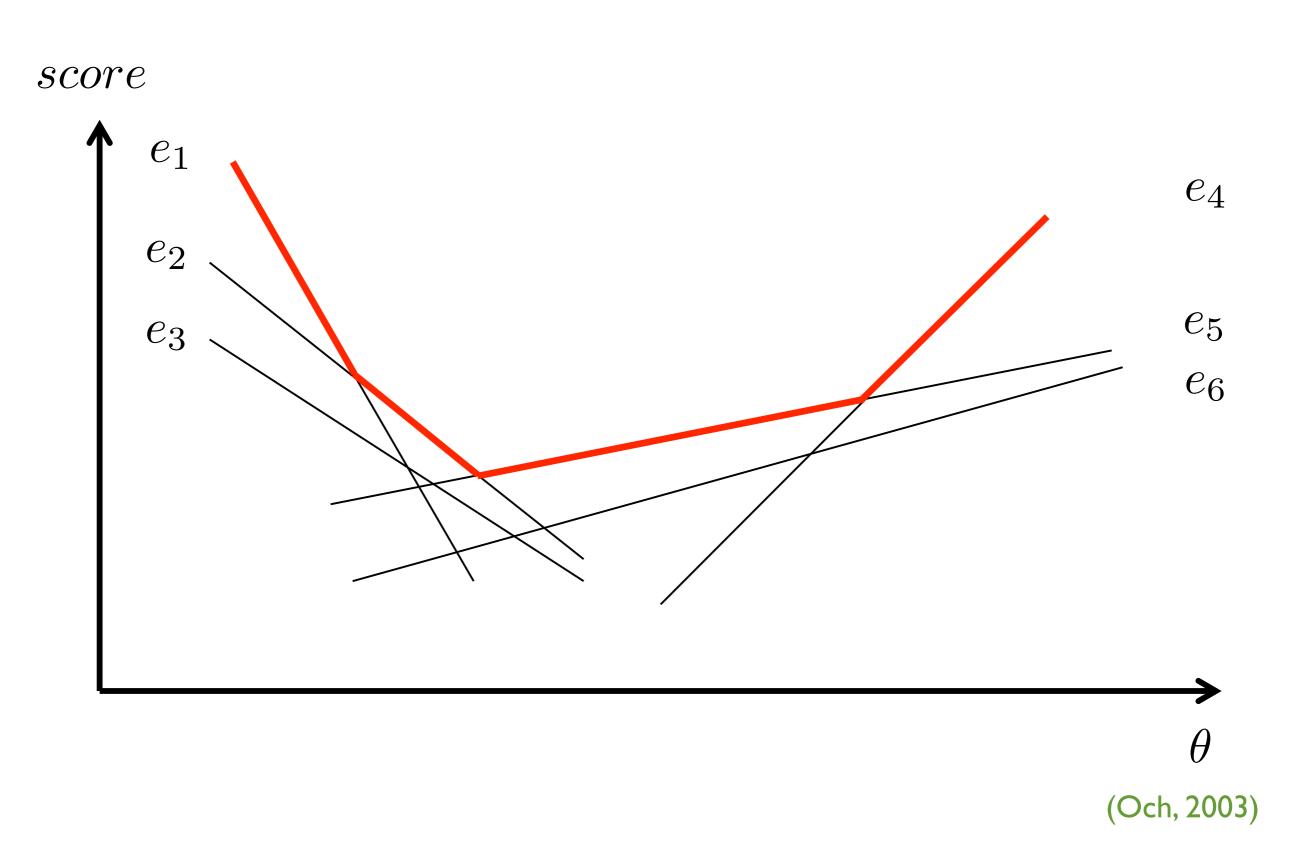




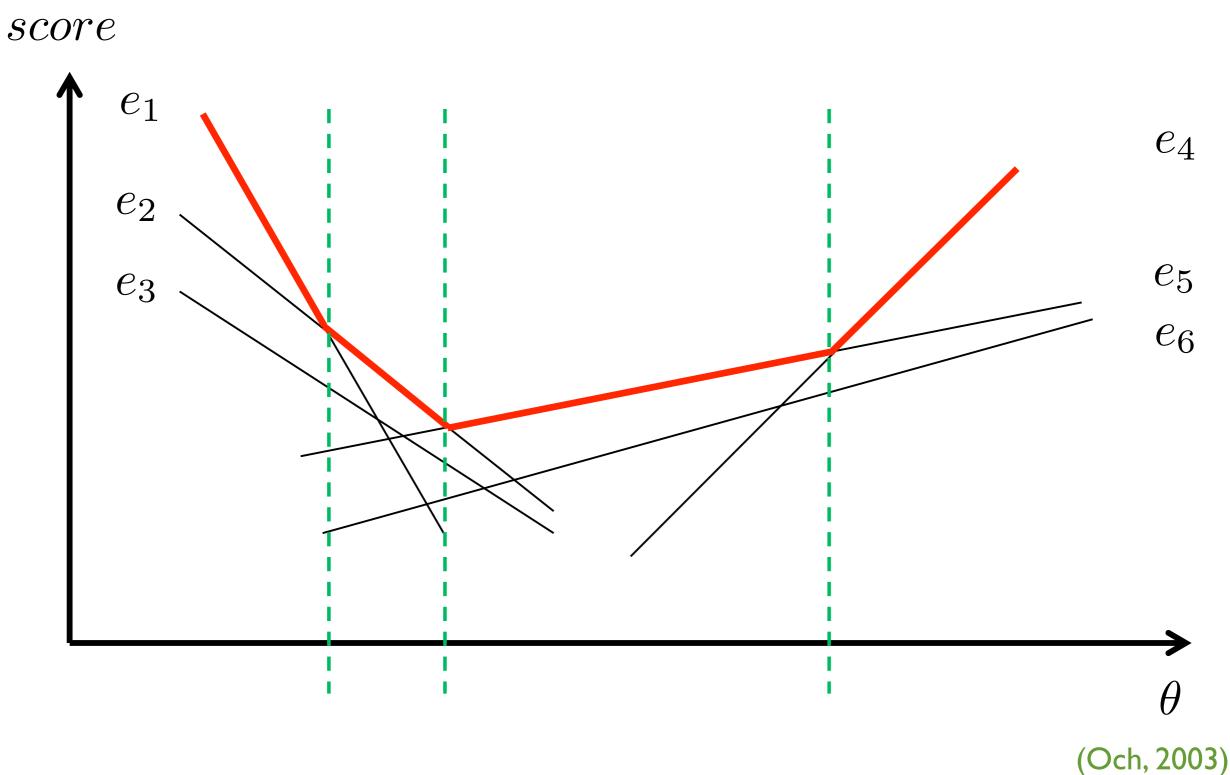
#### Minimum Error Rate Training



#### Minimum Error Rate Training



#### Minimum Error Rate Training

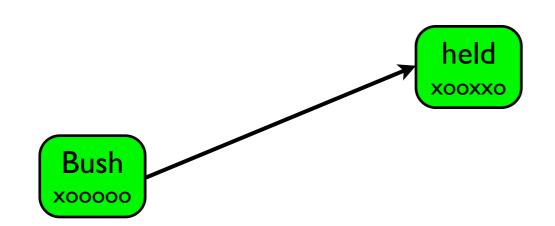


布什 与 沙龙 举行 了 会谈

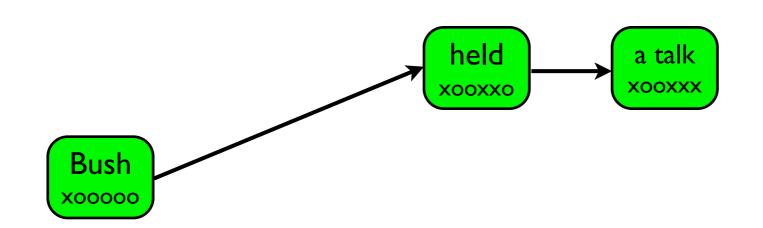
布什	与	沙龙	举行	了	会谈
Bush	with	Sharon	hold	have	talk
	and		held		a talk

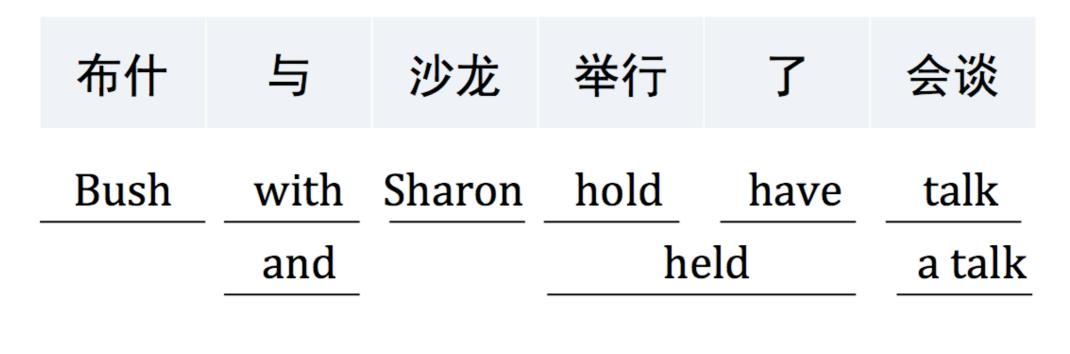


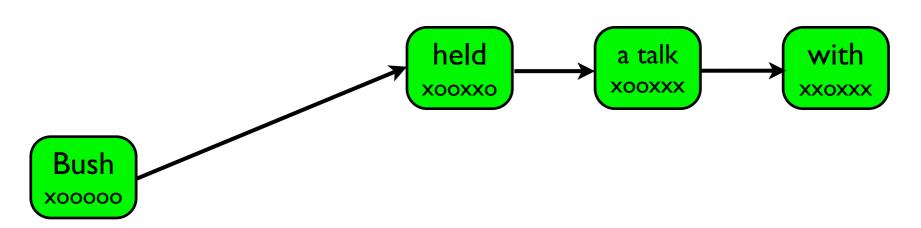
布什与沙龙举行了会谈BushwithSharonholdhavetalkandhelda talk

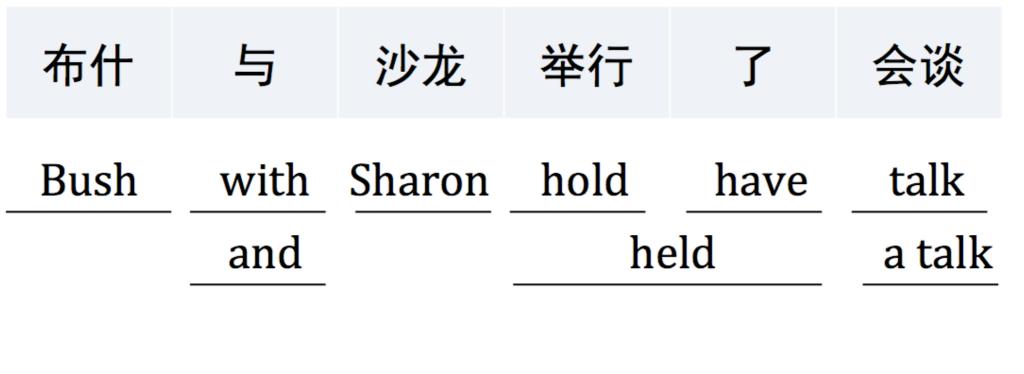


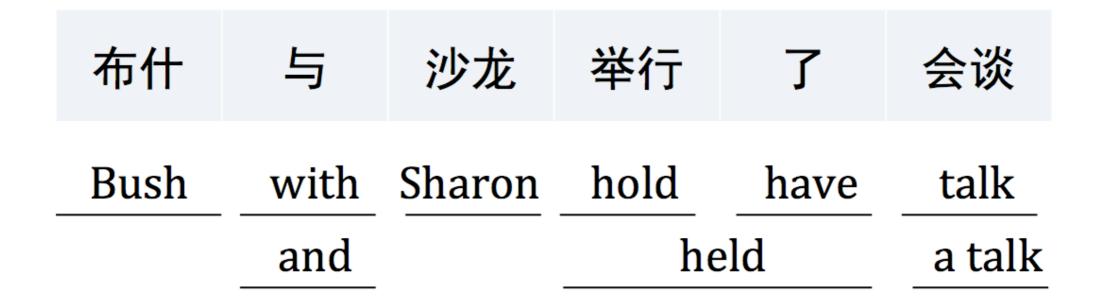
布什与沙龙举行了会谈Bushwith<br/>andSharon<br/>heldhave<br/>a talk

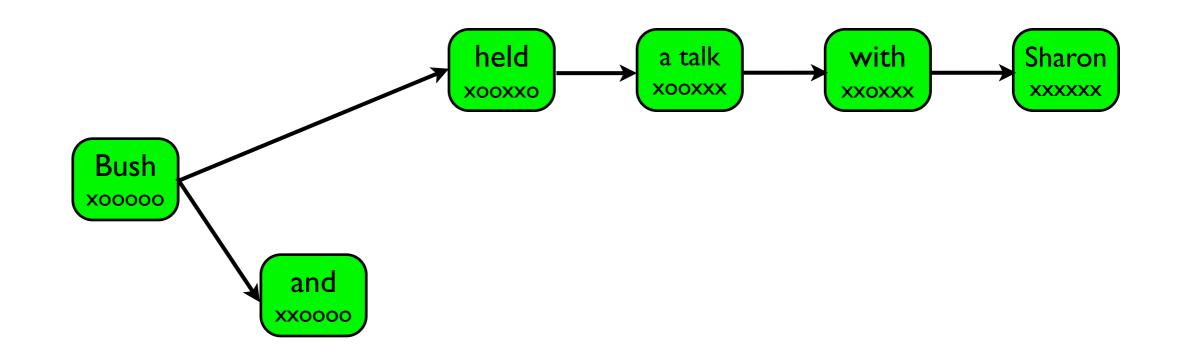


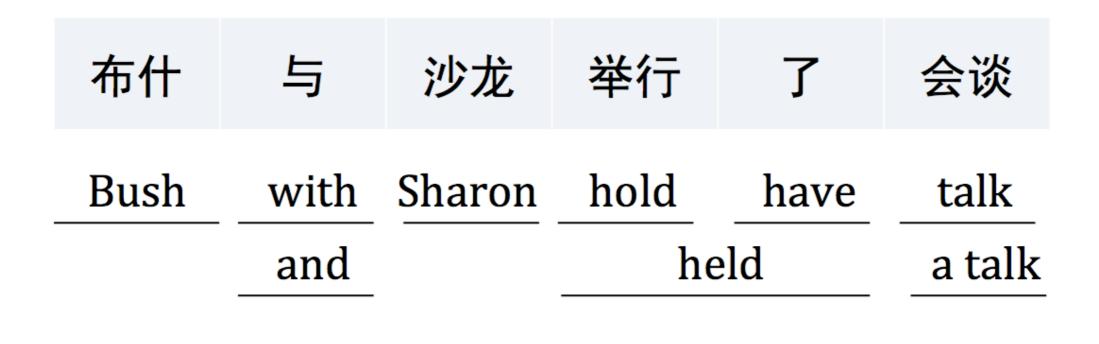


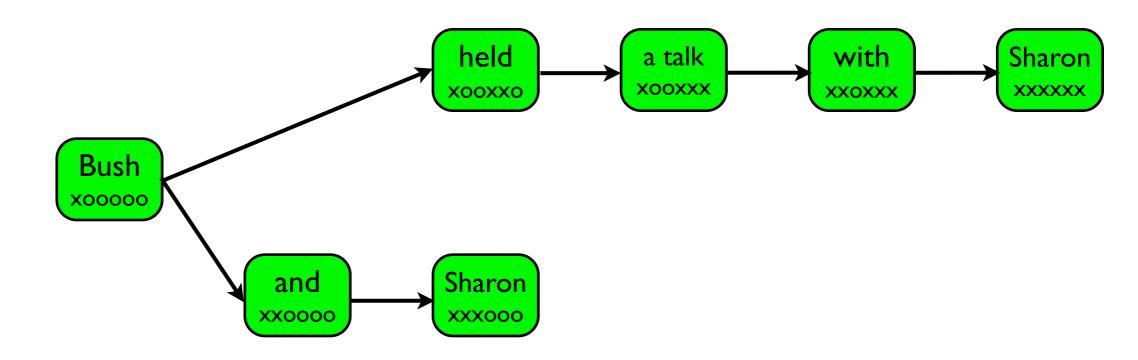


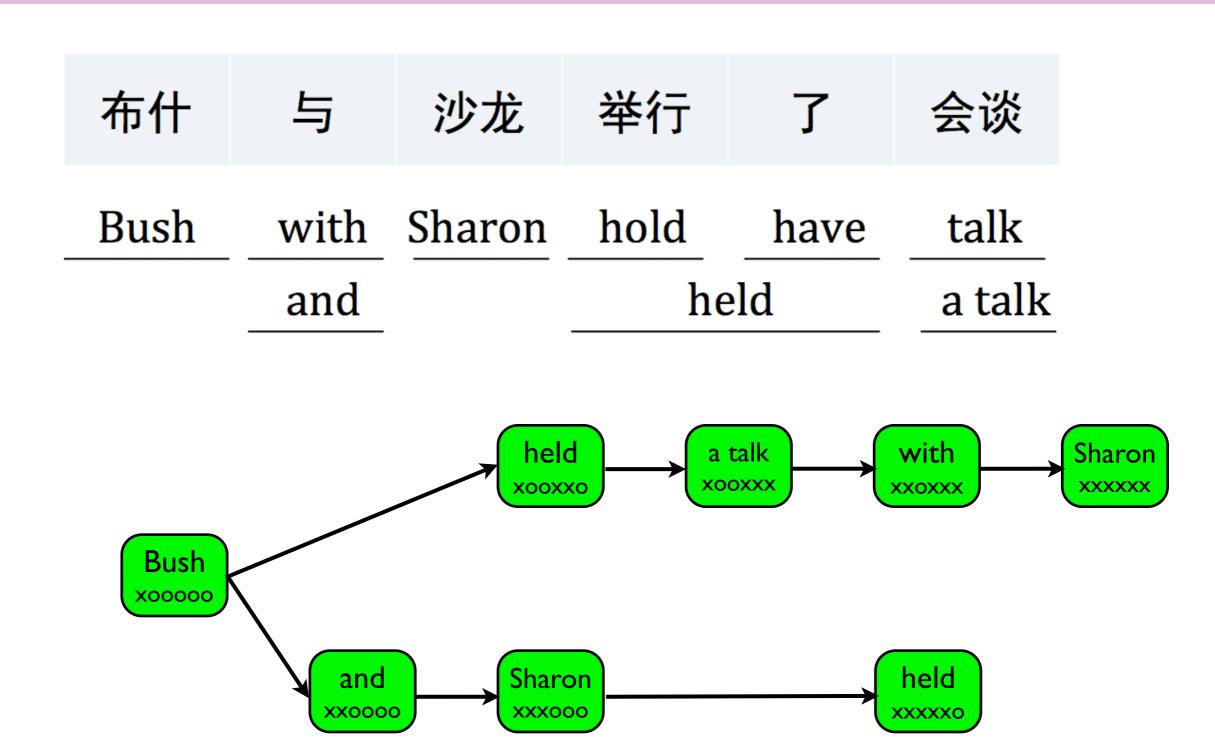


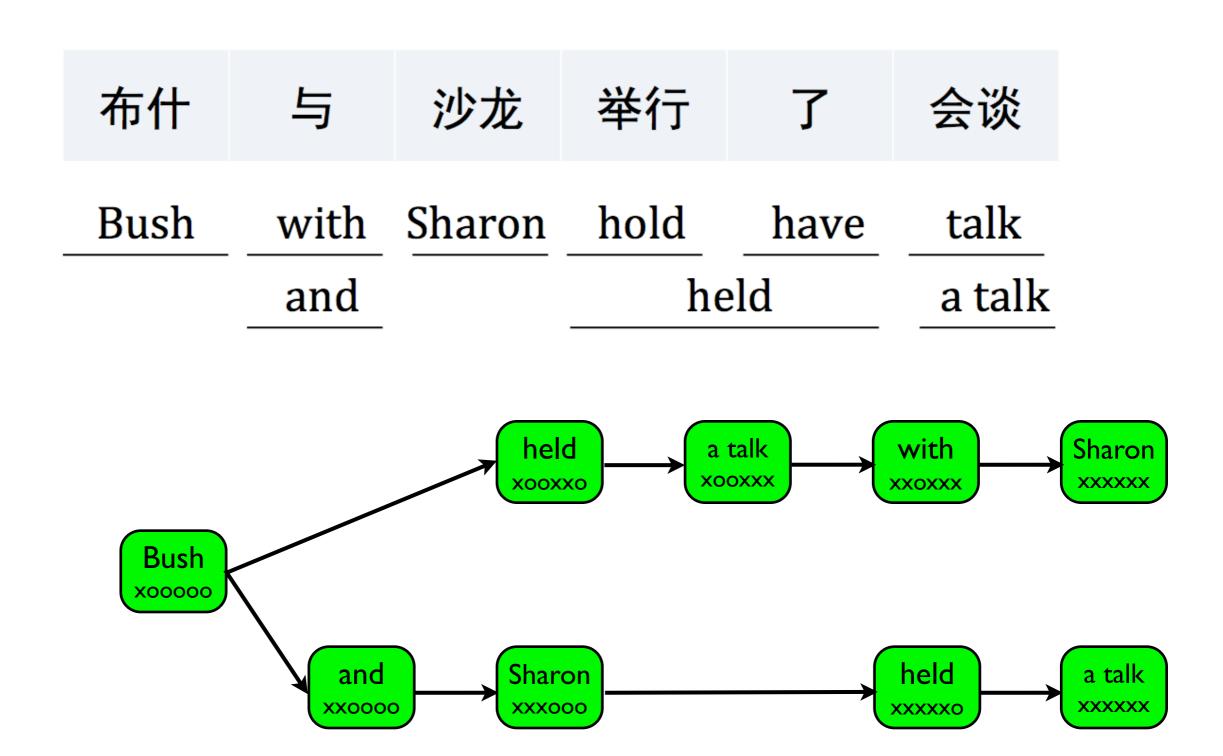


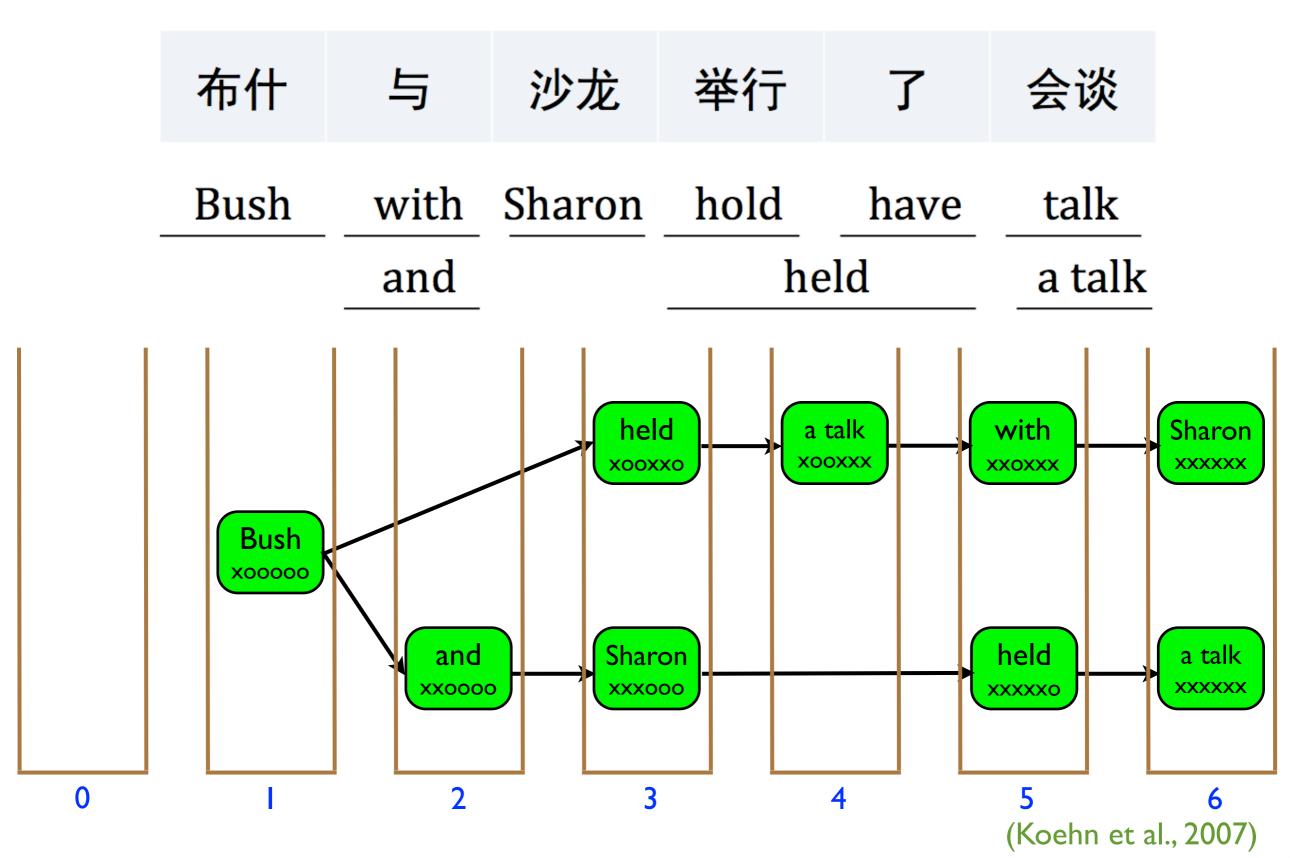








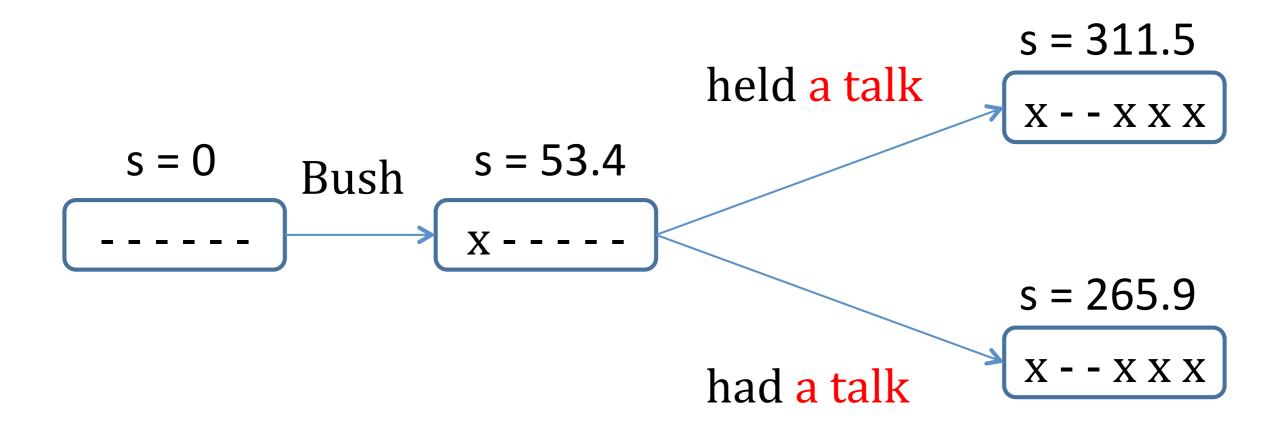




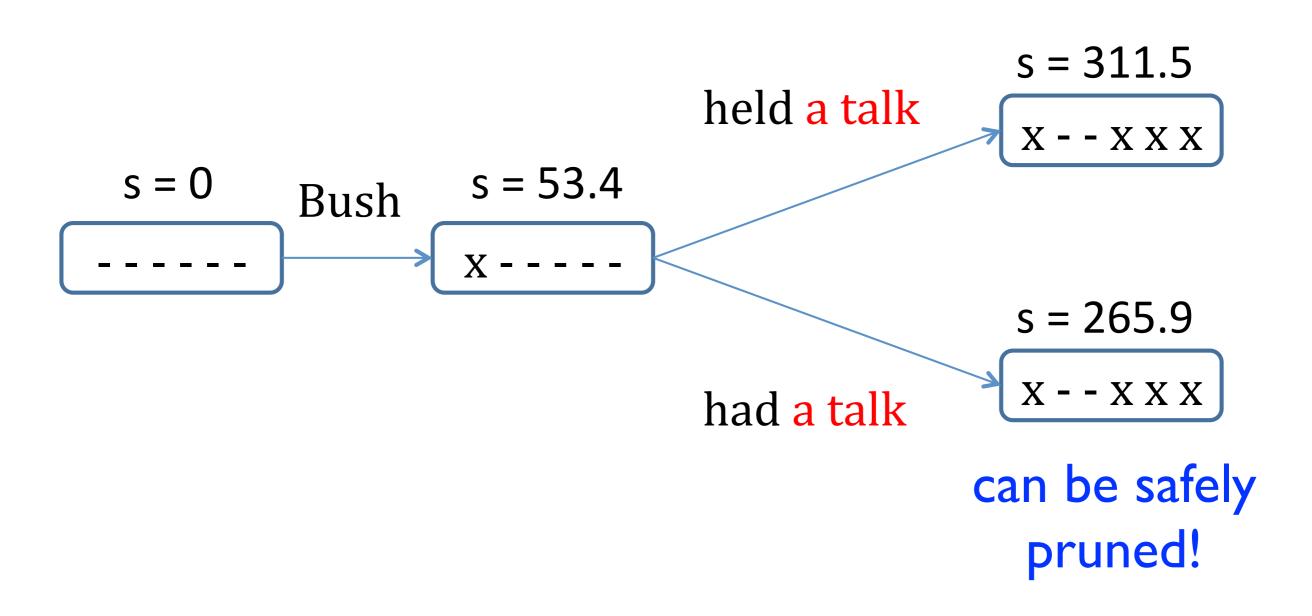
### Hypothesis

- a hypothesis (partial translation) consists of the following information
  - phrase pair ID
  - pointer to the previous hypothesis
  - coverage
  - last *n*-1 target words
  - the end of the last translated source phrase
  - feature value vector
  - current score
  - the estimate of future score
  - overall score
  - recombined hypotheses

#### Hypothesis Recombination



#### Hypothesis Recombination

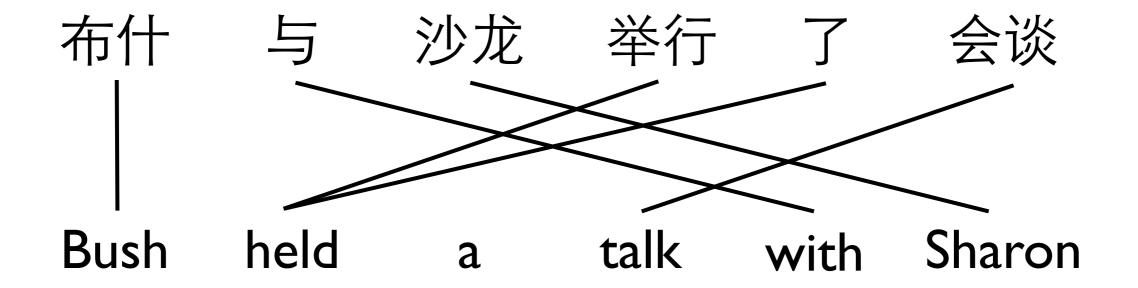


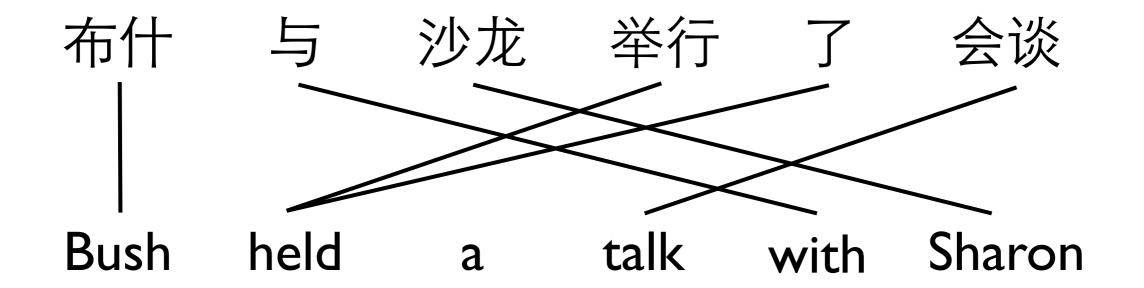
#### Hypothesis Recombination

- Two hypotheses can be recombined iff the following items are identical
  - coverage (translation model, phrase/word penalty)
  - last n-l target words (language model)
  - the end of the last translated source phrase (reordering model)

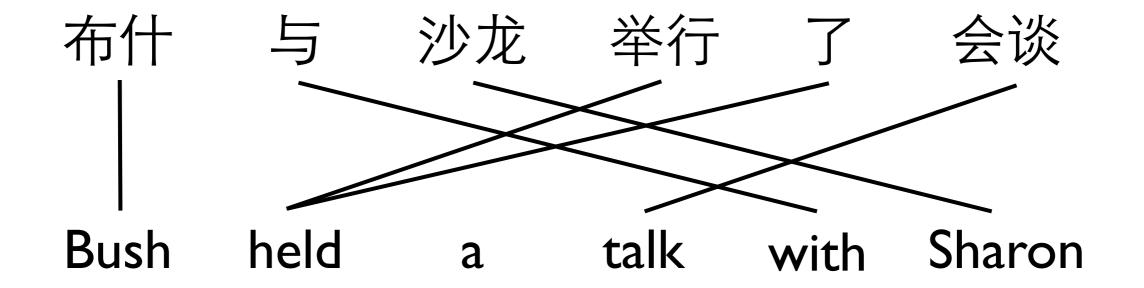
#### Pruning

- Hypothesis recombination is risk-free pruning
- Two aggressive pruning methods are widely used to maintain a reasonable stack size:
  - retain at most a hypotheses in a stack
  - discard hypotheses b times worse than the best hypothesis in a stack



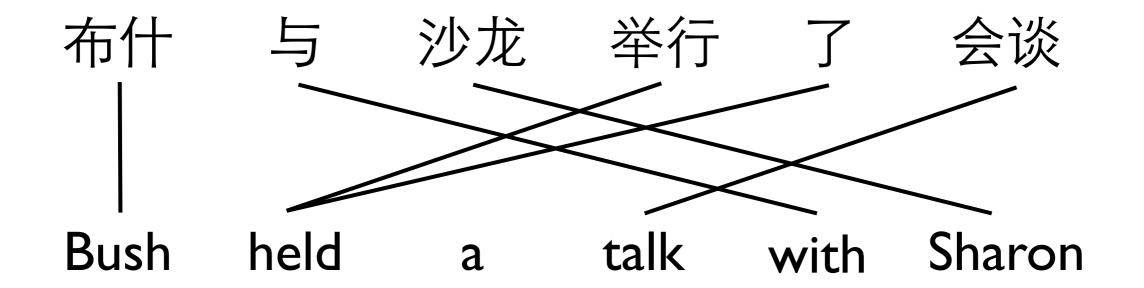


(布什与, Bush ... with)



(布什 与, Bush ... with)

(布什 ... 举行 了, Bush held)

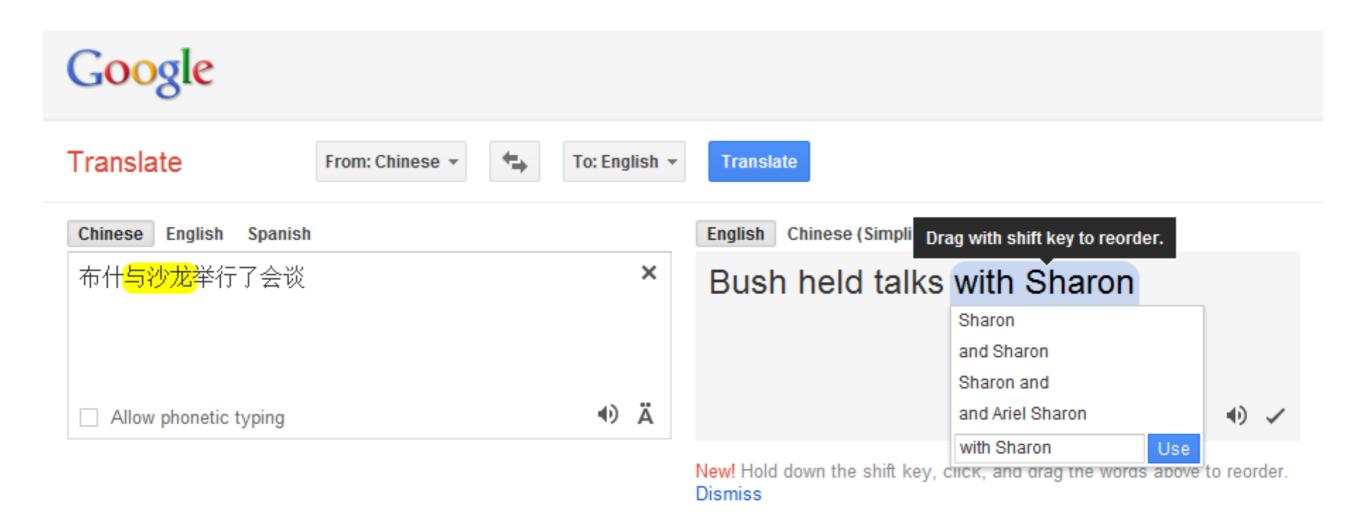


(布什与, Bush ... with)

(布什 ... 举行 了, Bush held)

(与 ... 举行 了, held ... with)

## Google Translate



### Google Translate



New! Hold down the shift key, click, and drag the words above to reorder.

Dismiss

# Part 4: Syntax-based MT

### Regularities in Natural Languages

The way people say things has regularities

Every boy likes a car The girl saw a dog Prof. Wang gave a talk

### Regularities in Natural Languages

The way people say things has regularities

Every boy likes a car
The girl saw a dog
Prof. Wang gave a talk

### Regularities in Natural Languages

The way people say things has regularities

```
Every boy likes a car
The girl saw a dog
Prof. Wang gave a talk
```

How are the sentences generated?

#### Context-Free Grammar

 Context-free grammar describes how natural language sentences are generated

#### Context-Free Grammar

 Context-free grammar describes how natural language sentences are generated

lexical rules

## Context-Free Grammar

 Context-free grammar describes how natural language sentences are generated

#### lexical rules

```
NNP \rightarrow Bush
VBD \rightarrow held
DT \rightarrow a
NN \rightarrow talk
IN \rightarrow with
NNP \rightarrow Sharon
```

## Context-Free Grammar

 Context-free grammar describes how natural language sentences are generated

#### lexical rules

syntactic rules

```
NNP \rightarrow Bush
VBD \rightarrow held
DT \rightarrow a
NN \rightarrow talk
IN \rightarrow with
NNP \rightarrow Sharon
```

### Context-Free Grammar

 Context-free grammar describes how natural language sentences are generated

#### lexical rules

$$NNP \rightarrow Bush$$

$$VBD \rightarrow held$$

$$DT \rightarrow a$$

$$NN \rightarrow talk$$

$$IN \rightarrow with$$

$$NNP \rightarrow Sharon$$

#### syntactic rules

$$NP \rightarrow NNP$$

$$NP \rightarrow DT NN$$

$$PP \rightarrow IN NP$$

$$VP \rightarrow VBD NP PP$$

$$S \rightarrow NP VP$$

$$S \rightarrow NP VP$$

$$S \rightarrow NP VP$$

$$S \Rightarrow NP VP$$

 A derivation explains how a sentence can be generated by applying CFG rules

$$S \to NP VP$$

 $NP \rightarrow NNP$ 

$$S \Rightarrow NP VP$$

$$S \rightarrow NP VP$$
  $S \Rightarrow NP VP$   $NP \rightarrow NNP$   $\Rightarrow NNP VP$ 

$$S \rightarrow NP VP$$

$$NP \rightarrow NNP$$

$$NNP \rightarrow Bush$$

$$S \Rightarrow NP VP$$

$$\Rightarrow$$
 NNP VP

$$S \rightarrow NP VP$$
  $S \Rightarrow NP VP$   $NP \rightarrow NNP$   $\Rightarrow NNP VP$   $NNP \rightarrow Bush$   $\Rightarrow Bush VP$ 

$$S \rightarrow NP \ VP$$
  $S \Rightarrow NP \ VP$   $NP \rightarrow NNP$   $\Rightarrow NNP \ VP$   $NNP \rightarrow Bush$   $\Rightarrow Bush \ VP$   $VP \rightarrow VBD \ NP \ PP$ 

```
S \rightarrow NP \ VP

NP \rightarrow NNP

NNP \rightarrow Bush

VP \rightarrow VBD \ NP \ PP

S \Rightarrow NP \ VP

\Rightarrow NNP \ VP

\Rightarrow Bush \ VP

\Rightarrow Bush \ VBD \ NP \ PP
```

$$S \rightarrow NP \ VP$$
  
 $NP \rightarrow NNP$   
 $NNP \rightarrow Bush$   
 $VP \rightarrow VBD \ NP \ PP$   
 $S \Rightarrow NP \ VP$   
 $\Rightarrow NNP \ VP$   
 $\Rightarrow Bush \ VP$   
 $\Rightarrow Bush \ VBD \ NP \ PP$   
 $\Rightarrow Bush \ VBD \ NP \ PP$ 

$$S \rightarrow NP \ VP$$
  
 $NP \rightarrow NNP$   
 $NNP \rightarrow Bush$   
 $VP \rightarrow VBD \ NP \ PP$   
 $VBD \rightarrow held$   
 $S \Rightarrow NP \ VP$   
 $\Rightarrow NNP \ VP$   
 $\Rightarrow Bush \ VP$   
 $\Rightarrow Bush \ held \ NP \ PP$ 

$$S \rightarrow NP \ VP$$
  $S \Rightarrow NP \ VP$   $NP \rightarrow NNP$   $\Rightarrow NNP \ VP$   $NNP \rightarrow Bush$   $\Rightarrow Bush \ VP$   $VP \rightarrow VBD \ NP \ PP$   $\Rightarrow Bush \ VBD \ NP \ PP$   $\Rightarrow Bush \ held \ NP \ PP$   $NP \rightarrow DT \ NN$ 

$$S \rightarrow NP \ VP$$
  $S \Rightarrow NP \ VP$   $NP \rightarrow NNP$   $\Rightarrow NNP \ VP$   $NNP \rightarrow Bush$   $\Rightarrow Bush \ VP$   $VP \rightarrow VBD \ NP \ PP$   $\Rightarrow Bush \ VBD \ NP \ PP$   $\Rightarrow Bush \ held \ NP \ PP$   $NP \rightarrow DT \ NN$   $\Rightarrow Bush \ held \ DT \ NN \ PP$ 

$$S \rightarrow NP \ VP$$
 $NP \rightarrow NNP$ 
 $NP \rightarrow NNP \ \Rightarrow NNP \ VP$ 
 $NNP \rightarrow Bush$ 
 $VP \rightarrow VBD \ NP \ PP$ 
 $VBD \rightarrow held$ 
 $VBD \rightarrow DT \ NN$ 
 $VBD \rightarrow Bush \ PP$ 
 $VBD \rightarrow DT \ NN$ 
 $VBD \rightarrow Bush \ PP$ 
 $VBD \rightarrow DT \ NN$ 
 $VBD \rightarrow Bush \ PP$ 
 $VBD \rightarrow DT \ NN$ 
 $VBD \rightarrow Bush \ PP$ 
 $VBD \rightarrow DT \ NN$ 
 $VBD \rightarrow Bush \ PP$ 
 $VBD \rightarrow DT \ NN$ 
 $VBD \rightarrow Bush \ PP$ 
 $VBD \rightarrow DT \ NN$ 
 $VBD \rightarrow Bush \ PP$ 
 $VBD \rightarrow Bush \ PP$ 

$$S \rightarrow NP \ VP$$
  $S \Rightarrow NP \ VP$   $NP \rightarrow NNP$   $\Rightarrow NNP \ VP$   $NNP \rightarrow Bush$   $\Rightarrow Bush \ VP$   $VP \rightarrow VBD \ NP \ PP$   $\Rightarrow Bush \ VBD \ NP \ PP$   $VBD \rightarrow held$   $\Rightarrow Bush \ held \ NP \ PP$   $PP \rightarrow DT \ NN$   $\Rightarrow Bush \ held \ DT \ NN \ PP$   $PP \rightarrow DT \ A$   $\Rightarrow Bush \ held \ ANN \ PP$ 

$$S \rightarrow NP \ VP$$
  $\Rightarrow NNP \ VP$   
 $NP \rightarrow NNP$   $\Rightarrow NNP \ VP$   
 $NNP \rightarrow Bush$   $\Rightarrow Bush \ VP$   
 $VP \rightarrow VBD \ NP \ PP$   $\Rightarrow Bush \ VBD \ NP \ PP$   
 $VBD \rightarrow held$   $\Rightarrow Bush \ held \ NP \ PP$   
 $NP \rightarrow DT \ NN$   $\Rightarrow Bush \ held \ DT \ NN \ PP$   
 $DT \rightarrow a$   $\Rightarrow Bush \ held \ a \ NN \ PP$ 

$$S \rightarrow NP \ VP$$
  $\Rightarrow NNP \ VP$   
 $NP \rightarrow NNP$   $\Rightarrow NNP \ VP$   
 $NNP \rightarrow Bush$   $\Rightarrow Bush \ VP$   
 $VP \rightarrow VBD \ NP \ PP$   $\Rightarrow Bush \ VBD \ NP \ PP$   
 $VBD \rightarrow held$   $\Rightarrow Bush \ held \ NP \ PP$   
 $NP \rightarrow DT \ NN$   $\Rightarrow Bush \ held \ DT \ NN \ PP$   
 $DT \rightarrow a$   $\Rightarrow Bush \ held \ a \ NN \ PP$ 

 A derivation explains how a sentence can be generated by applying CFG rules

$$S \rightarrow NP \ VP$$
  $\Rightarrow NNP \ VP$   $\Rightarrow NNP \ VP$   $\Rightarrow NNP \ VP$   $\Rightarrow Bush \ VP$   $\Rightarrow Bush \ VBD \ NP \ PP$   $\Rightarrow Bush \ held \ NP \ PP$   $\Rightarrow Bush \ held \ DT \ NN \ PP$   $\Rightarrow Bush \ held \ a \ NN \ PP$   $\Rightarrow Bush \ held \ a \ NN \ PP$   $\Rightarrow Bush \ held \ a \ NN \ PP$   $\Rightarrow Bush \ held \ a \ NN \ PP$   $\cdots$ 

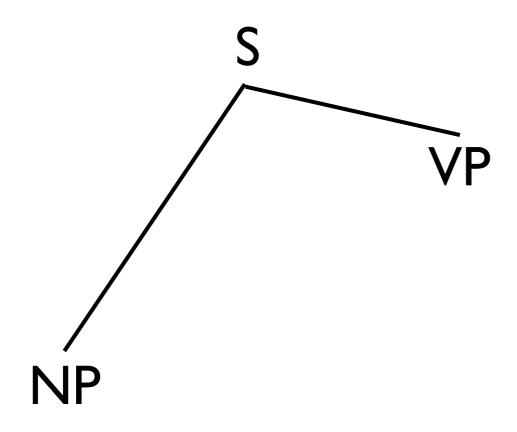
 $NNP \rightarrow Sharon$ 

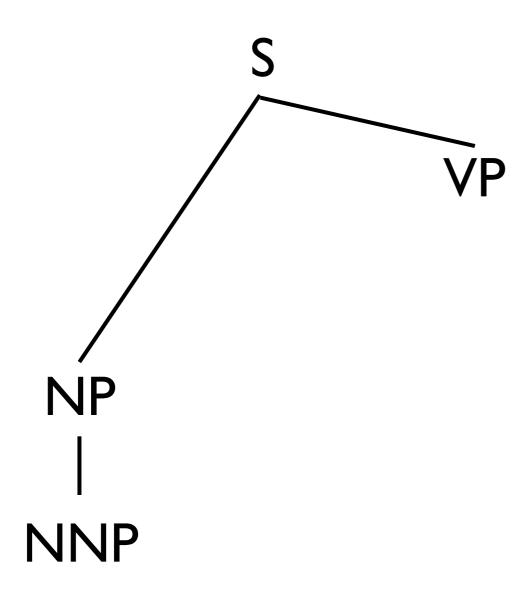
 A derivation explains how a sentence can be generated by applying CFG rules

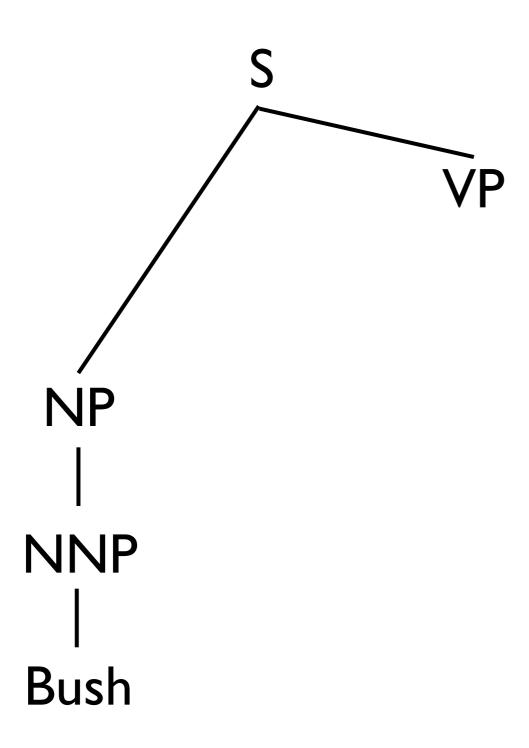
$$S \rightarrow NP \ VP$$
  $\Rightarrow NNP \ VP$   $\Rightarrow NNP \ VP$   $\Rightarrow NNP \ VP$   $\Rightarrow Bush \ VP$   $\Rightarrow Bush \ VBD \ NP \ PP$   $\Rightarrow Bush \ held \ NP \ PP$   $\Rightarrow Bush \ held \ DT \ NN \ PP$   $\Rightarrow Bush \ held \ a \ NN \ PP$   $\Rightarrow Bush \ held \ a \ NN \ PP$   $\Rightarrow Bush \ held \ a \ NN \ PP$   $\cdots$ 

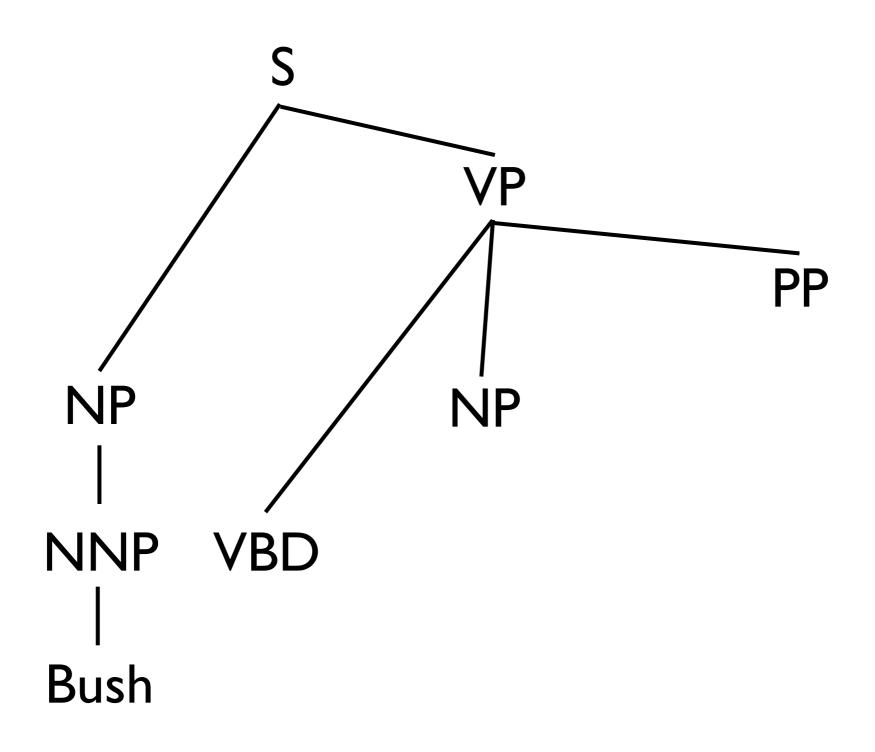
 $\Rightarrow$  Bush held a talk with Sharon

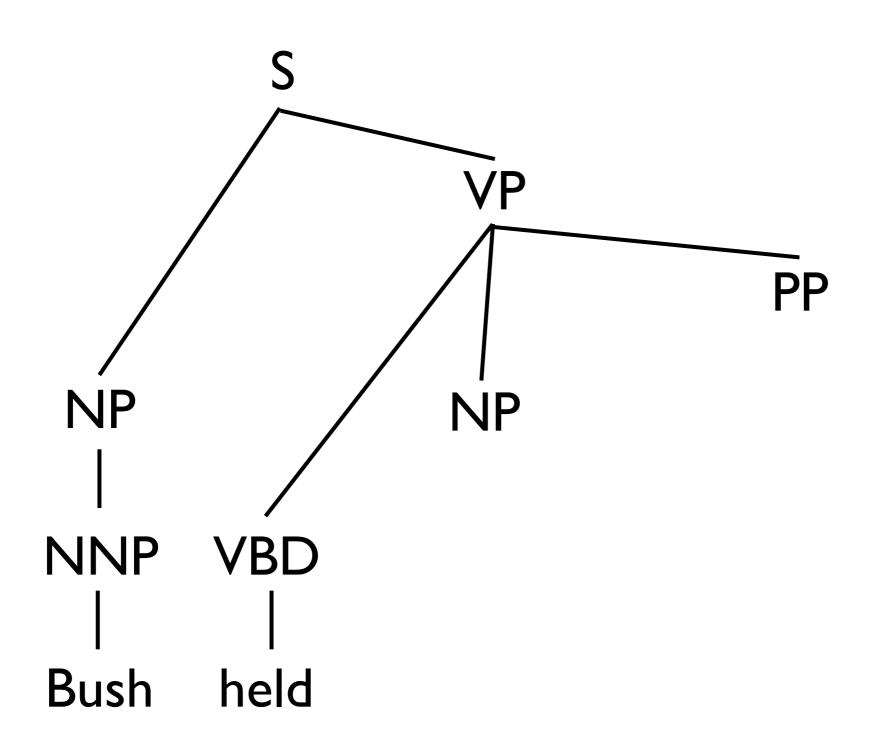
 $NNP \rightarrow Sharon$ 

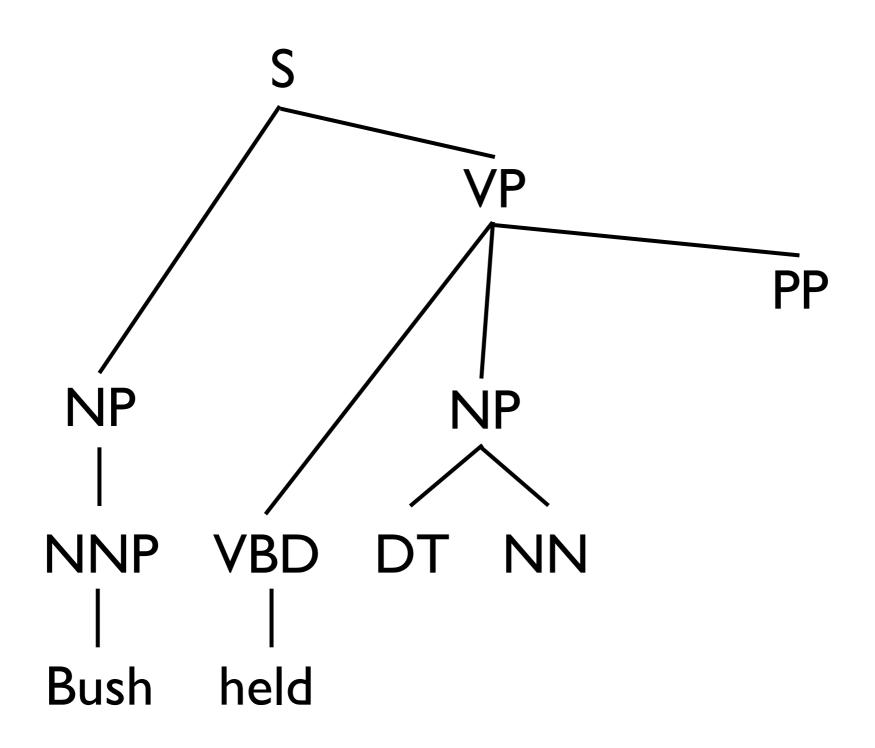


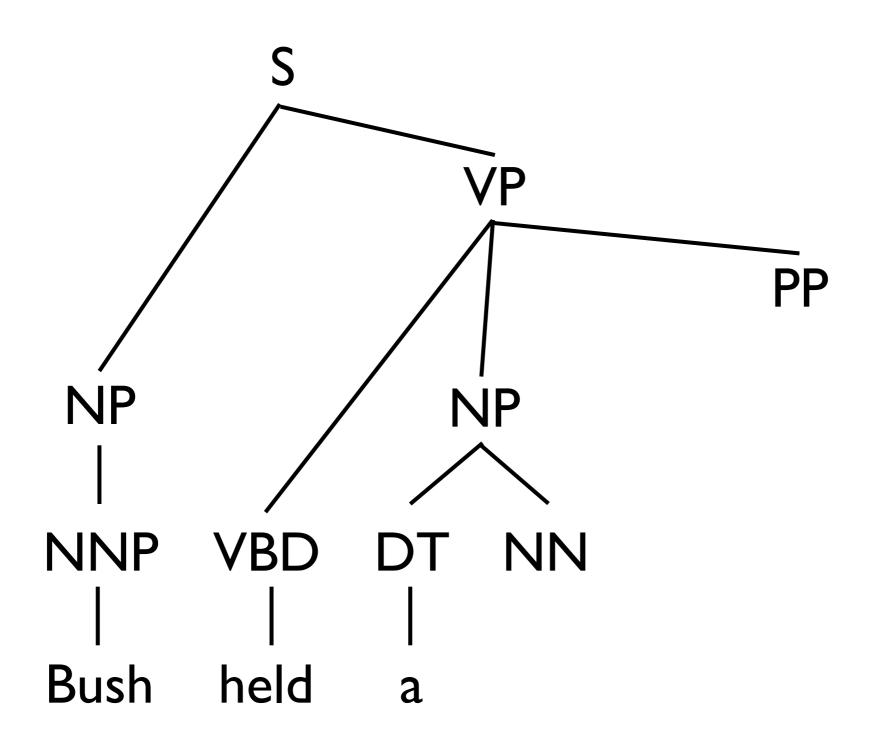


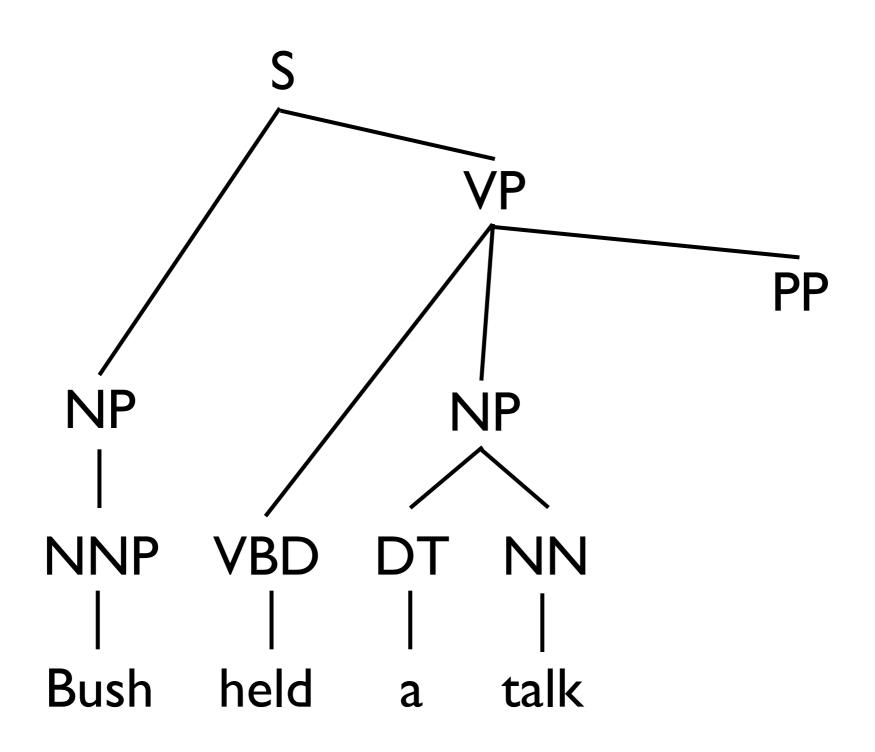


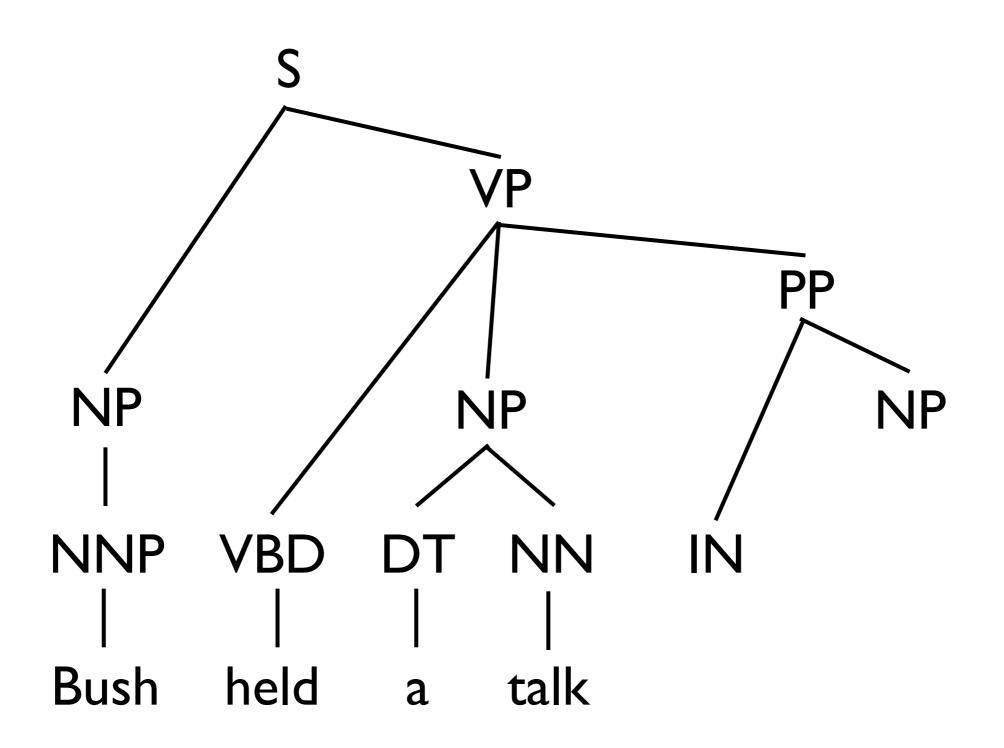


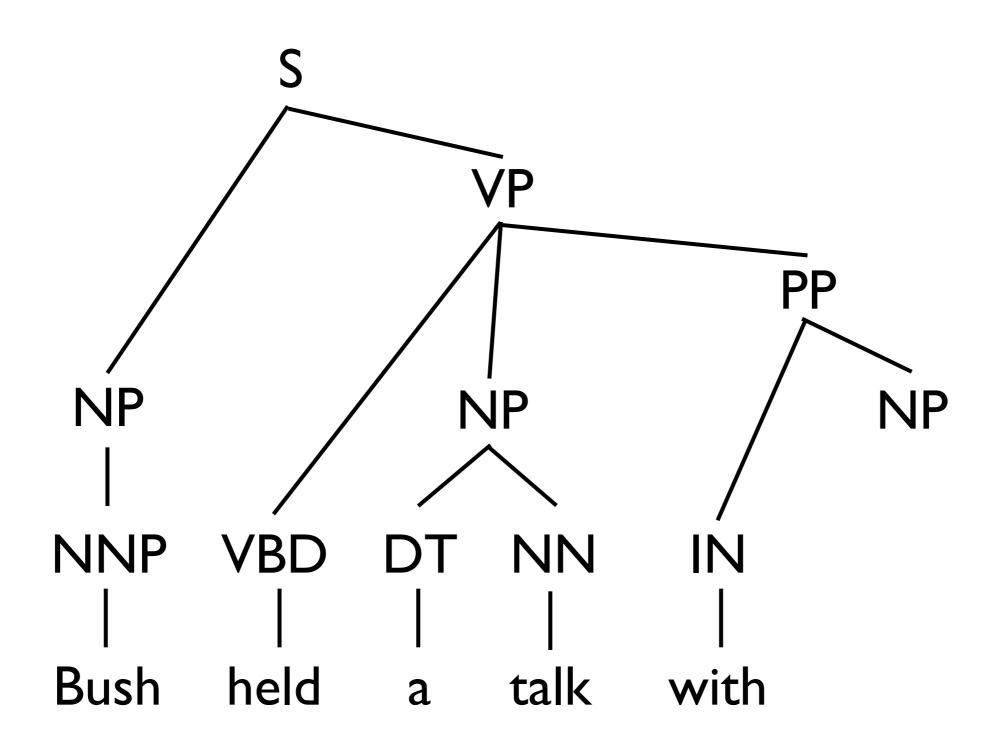


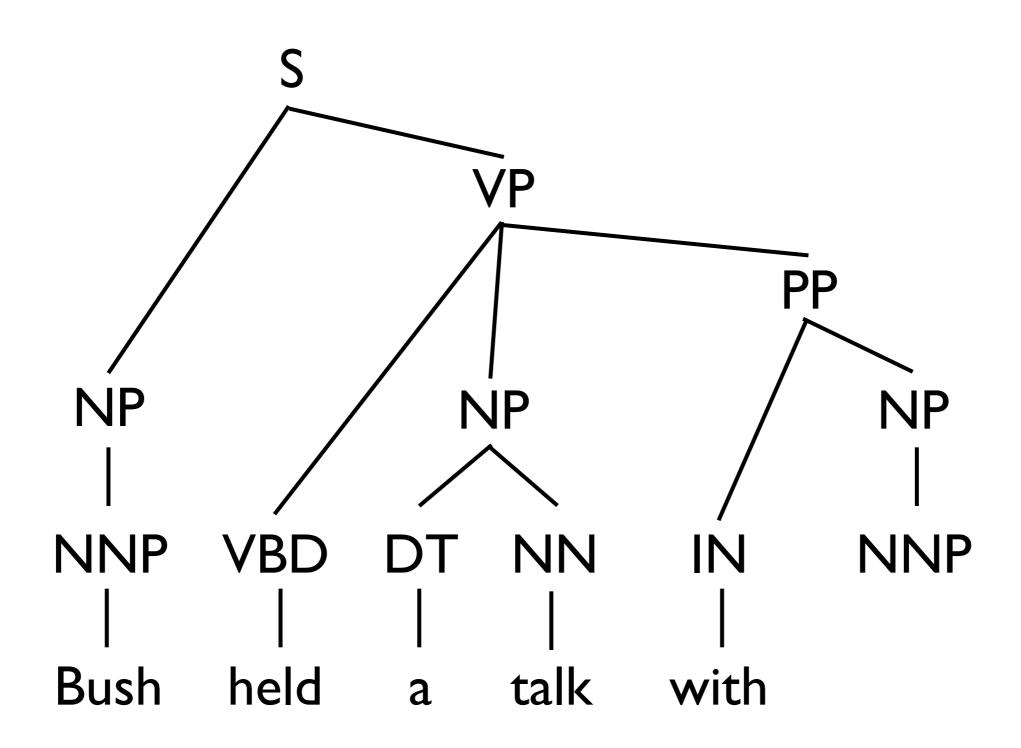


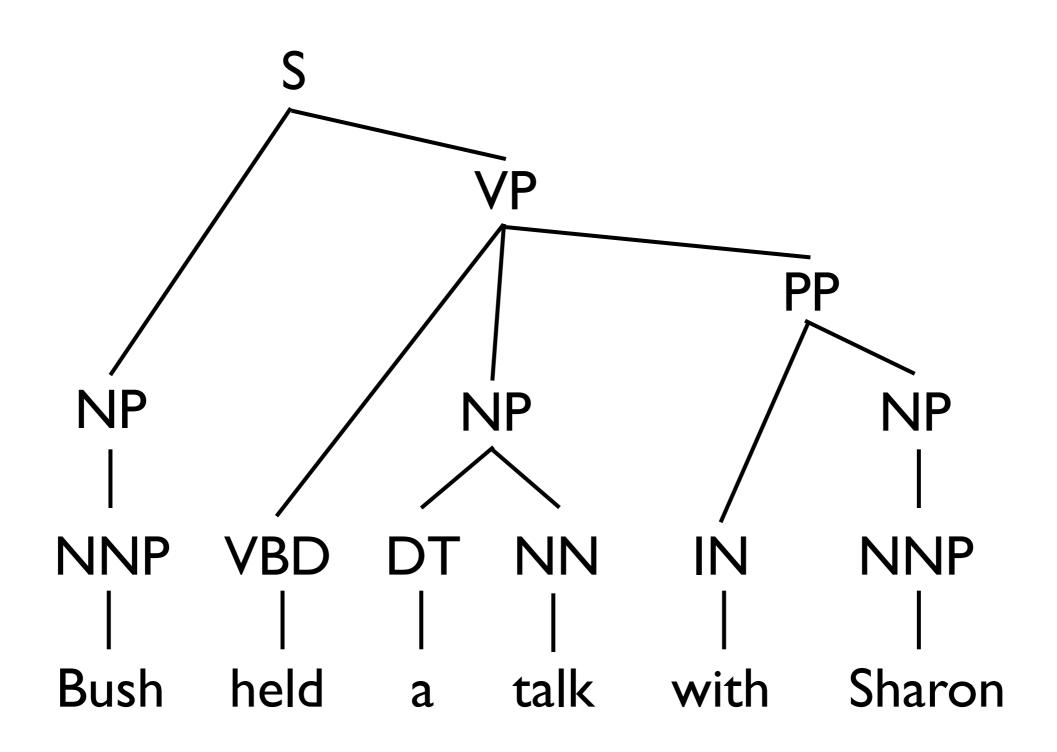












# Synchronous Context-Free Grammar

 Synchronous Context-free grammar describes how two natural language sentences are generated simultaneously

# Synchronous Context-Free Grammar

 Synchronous Context-free grammar describes how two natural language sentences are generated simultaneously

```
lexical rules NN \rightarrow \langle bushi, Bush \rangle
```

# Synchronous Context-Free Grammar

 Synchronous Context-free grammar describes how two natural language sentences are generated simultaneously

```
lexical rules NN \rightarrow \langle bushi, Bush \rangle
```

syntactic rules 
$$S \rightarrow \langle NP_1 \ VP_2, NP_1 \ VP_2 \rangle$$

# Synchronous Context-Free Grammar

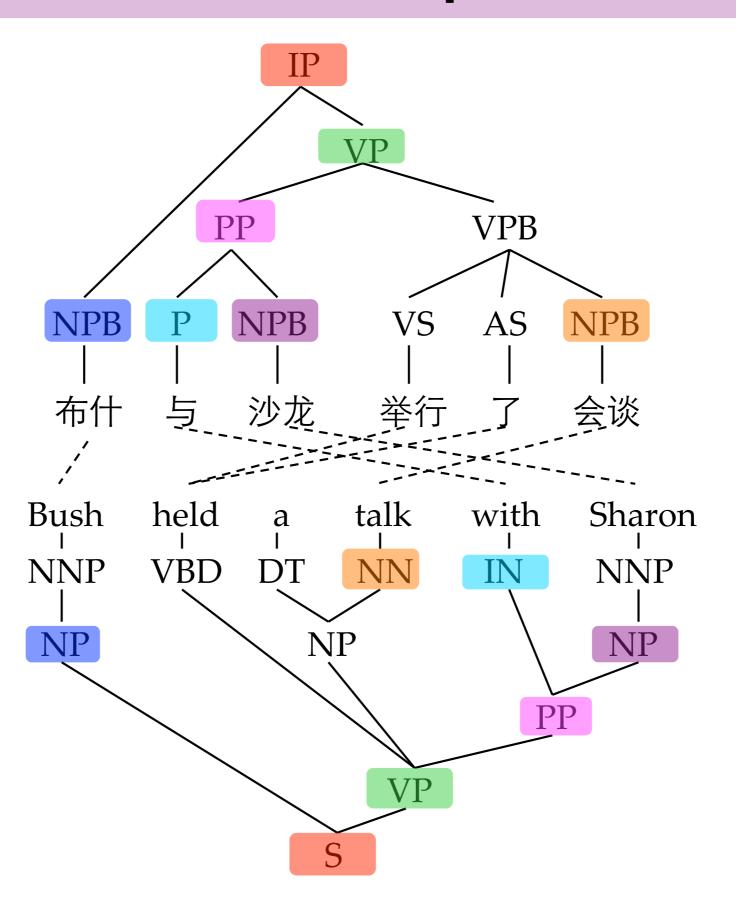
 Synchronous Context-free grammar describes how two natural language sentences are generated simultaneously

lexical rules 
$$NN \rightarrow \langle bushi, Bush \rangle$$

syntactic rules 
$$S \rightarrow \langle NP_1 \ VP_2, NP_1 \ VP_2 \rangle$$

Unfortunately, SCFG suffers from the non-isomorphism problem

# Non-Isomorphism



# Syntax-based MT

#### SCFGs without linguistic syntax

inverted transduction grammar

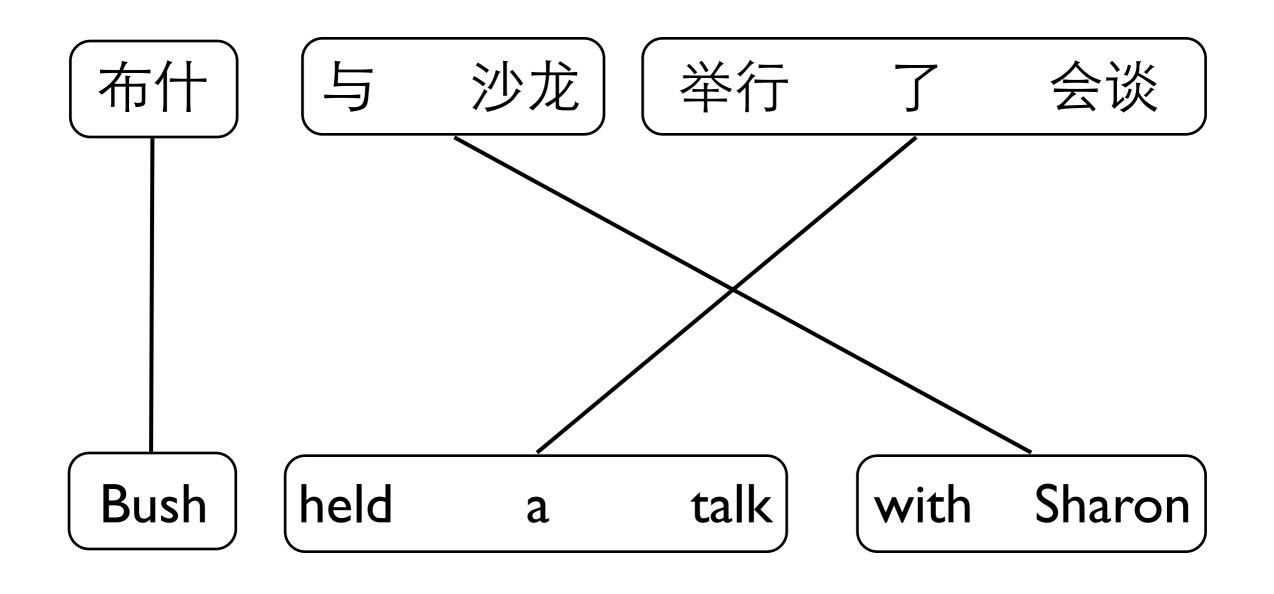
hierarchical phrase-based model

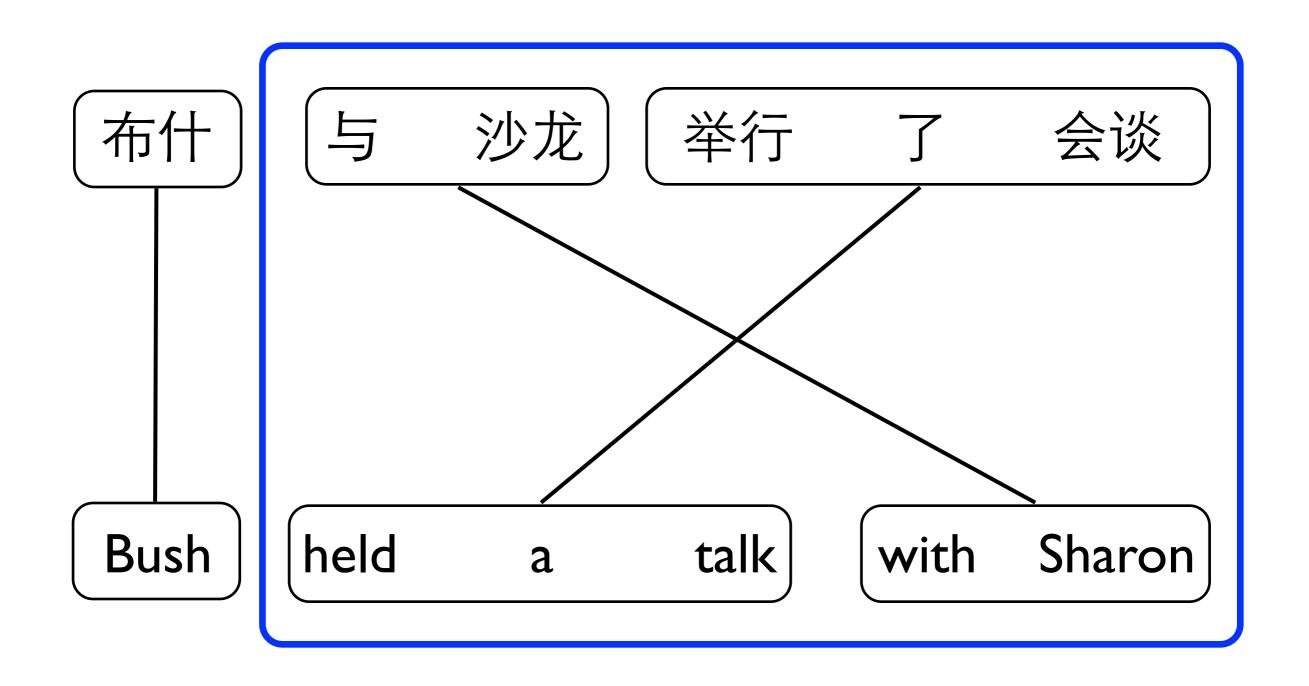
#### STSGs with linguistic syntax

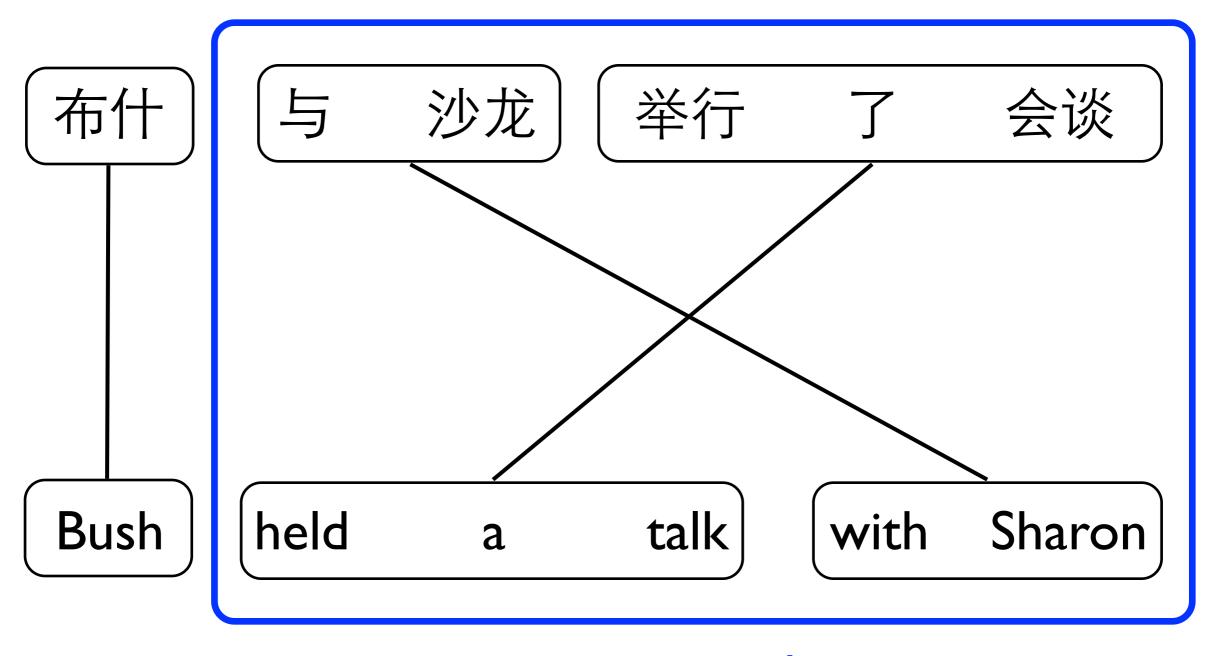
string-to-tree

tree-to-string

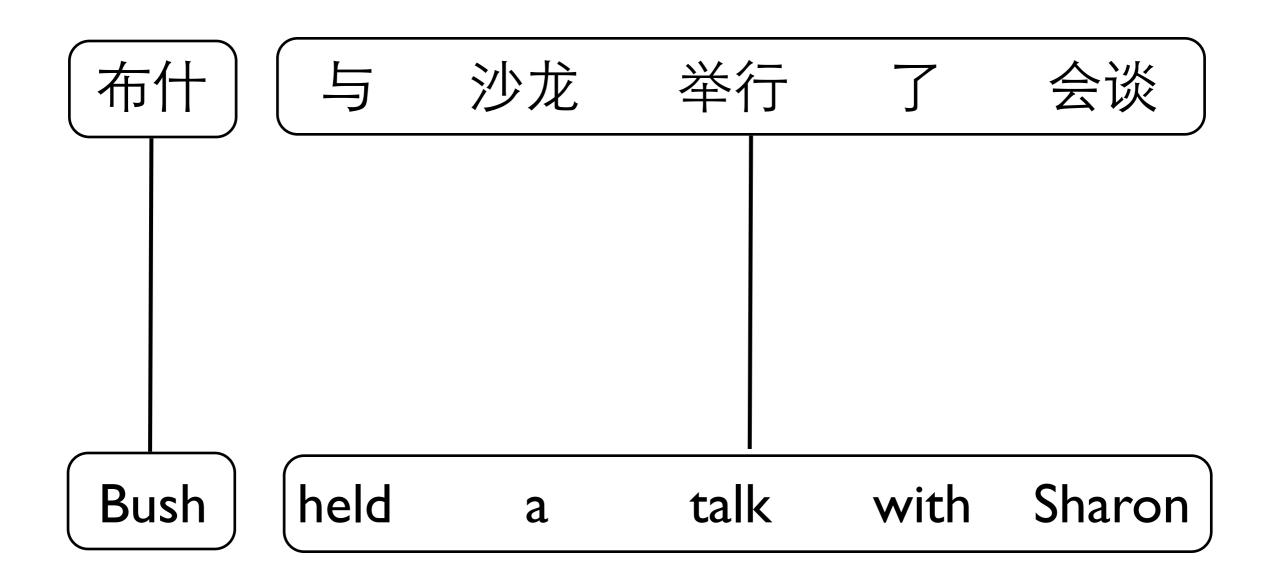
tree-to-tree

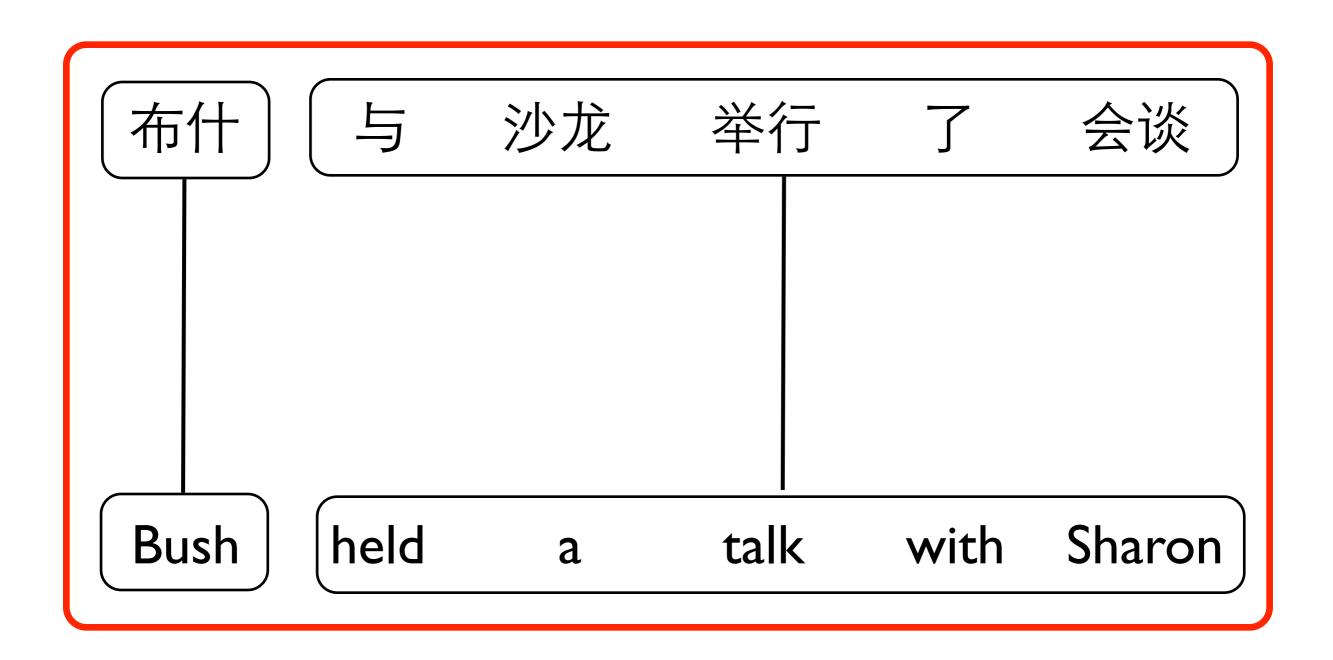


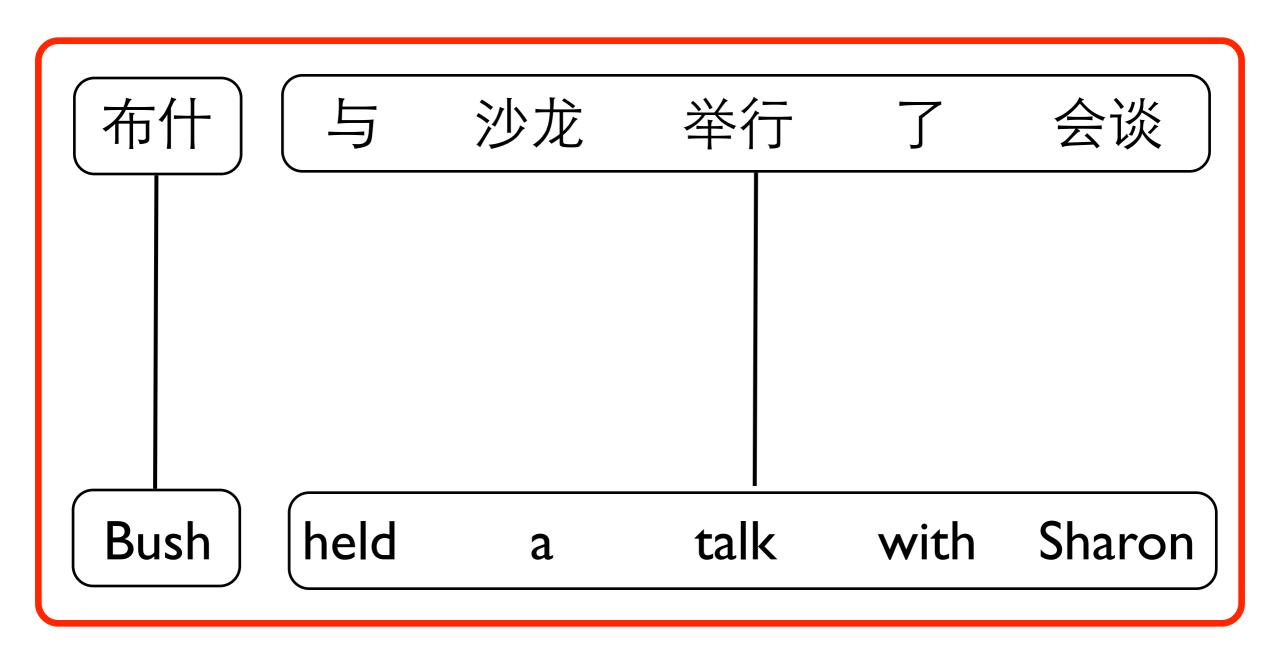




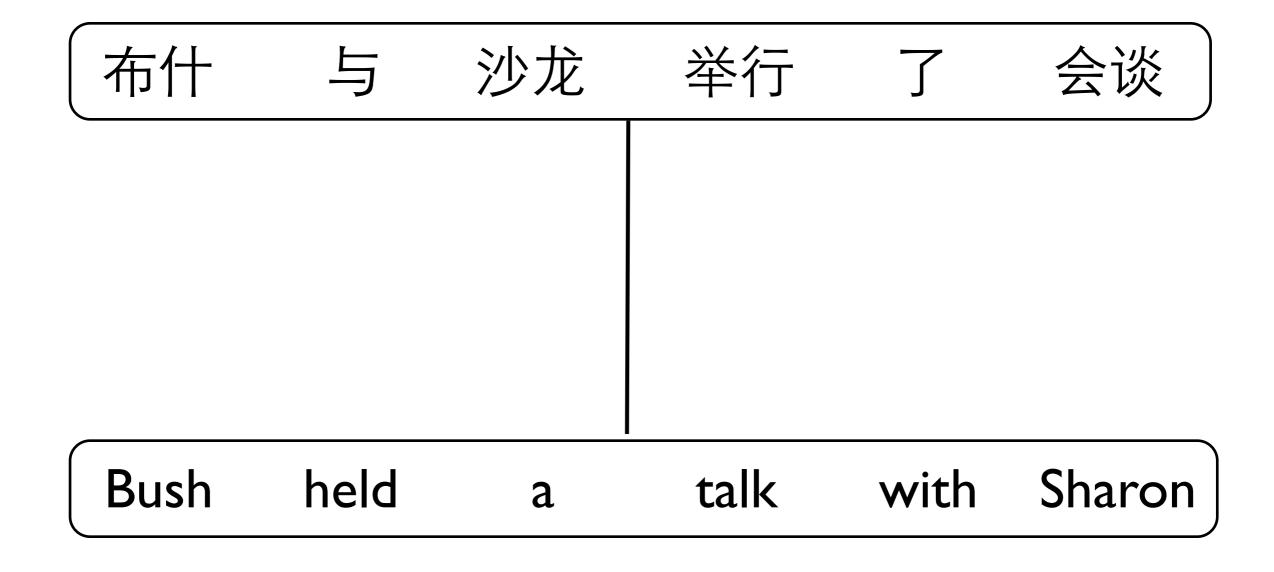
inverted

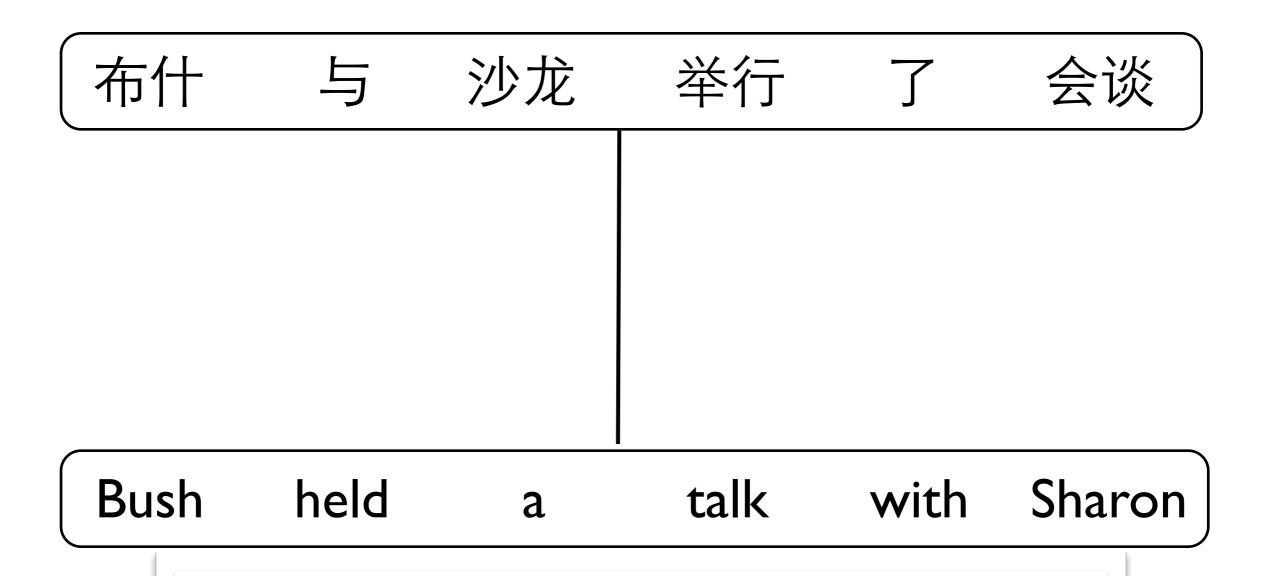




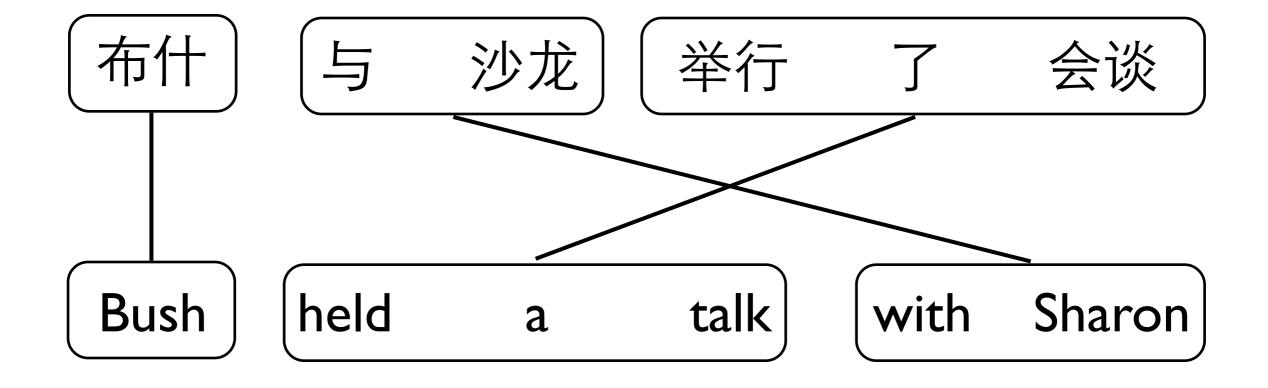


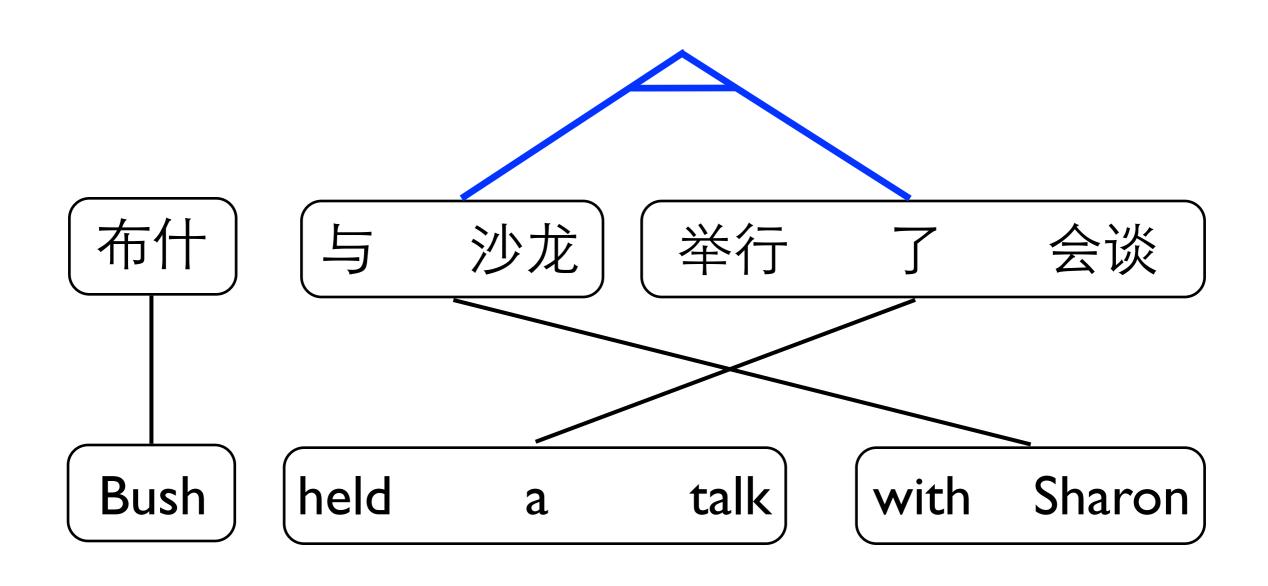
straight

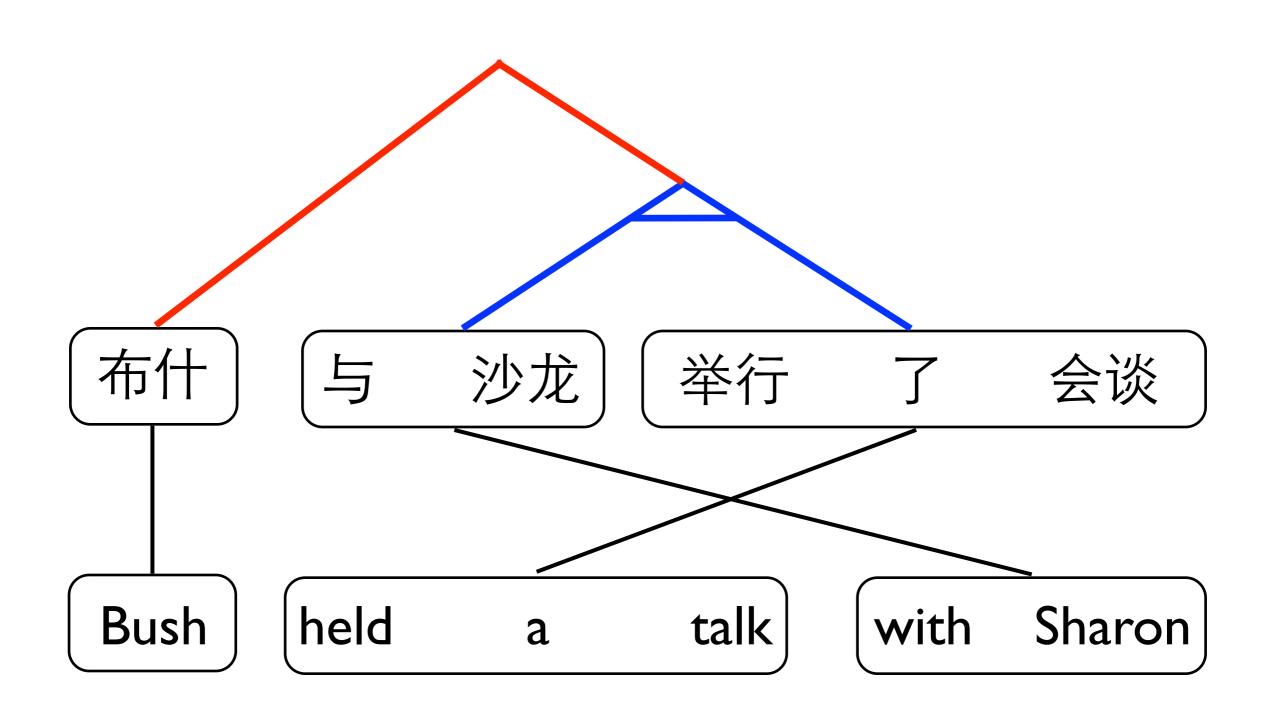


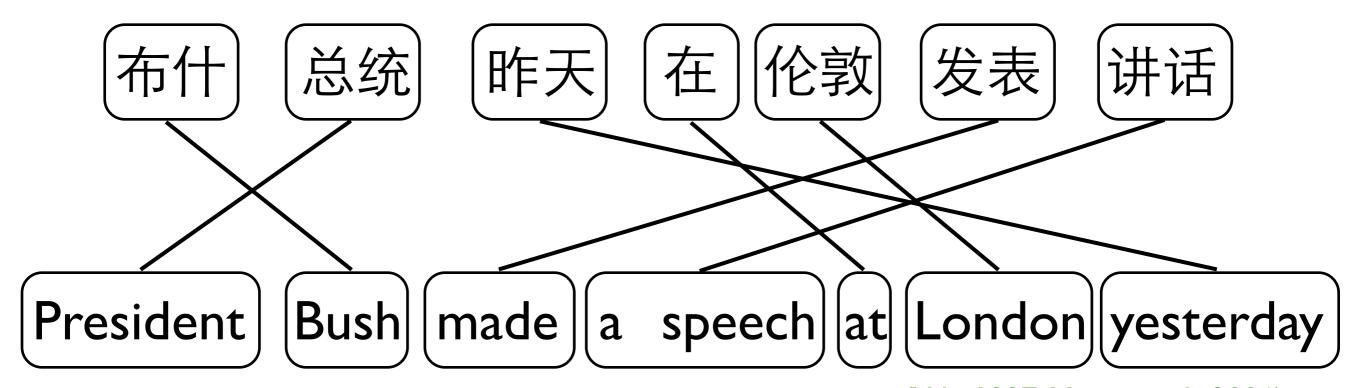


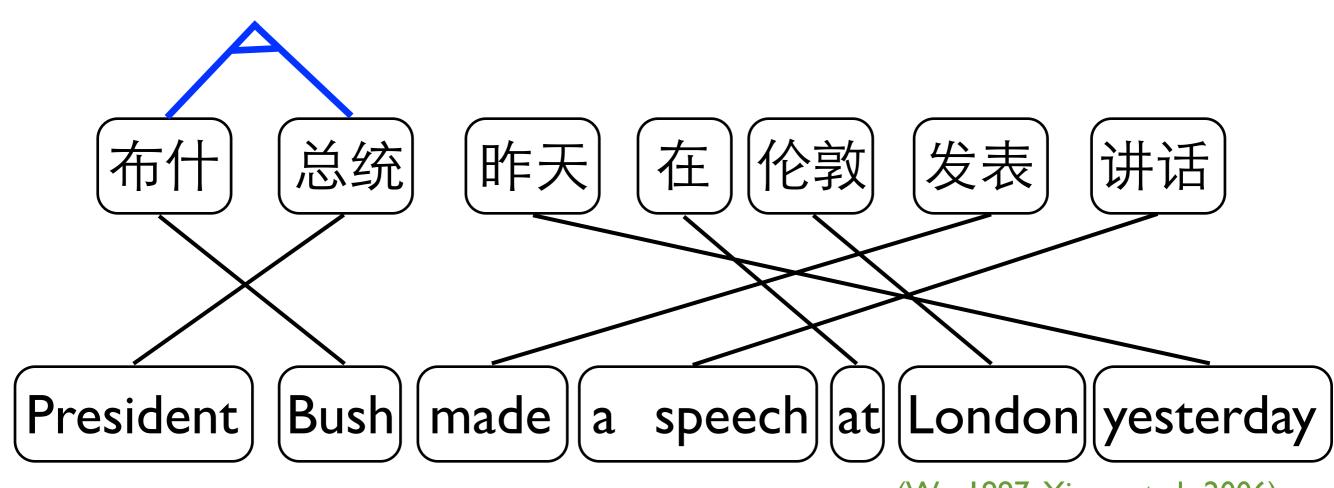
describe reordering using two operators

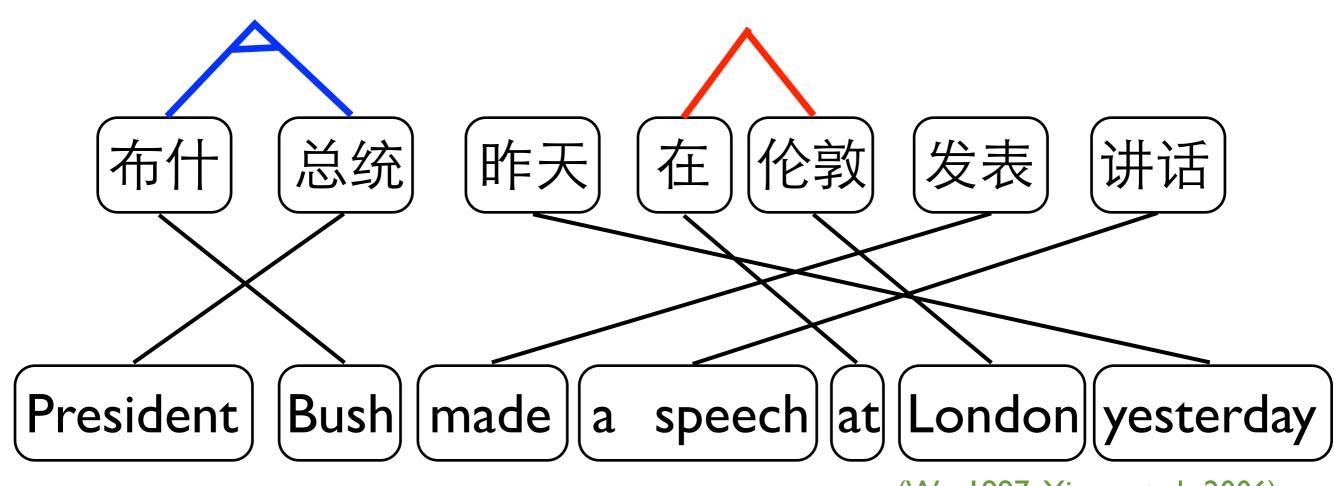


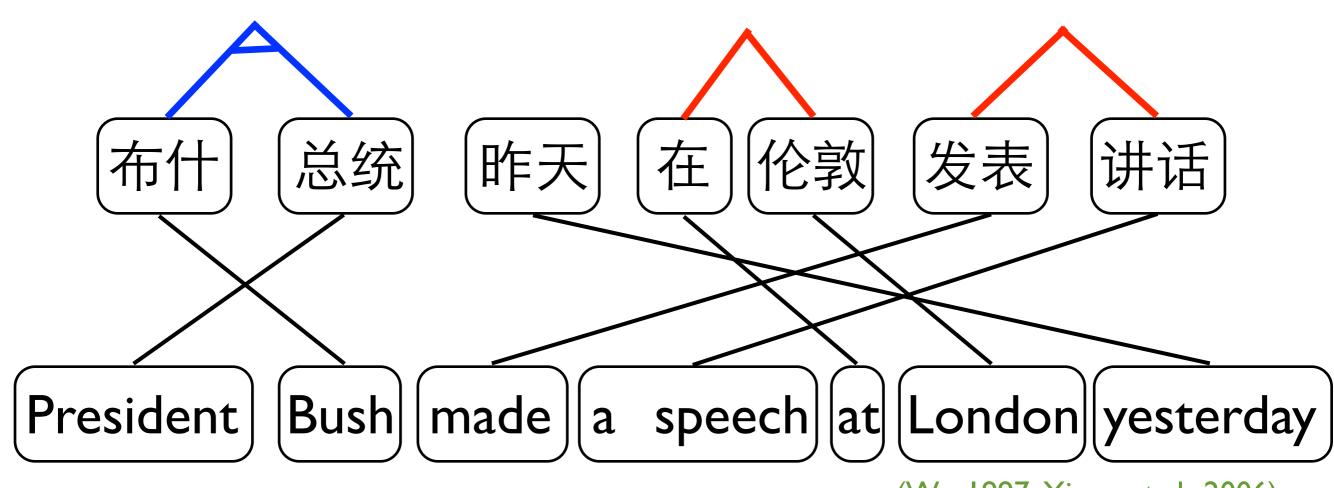


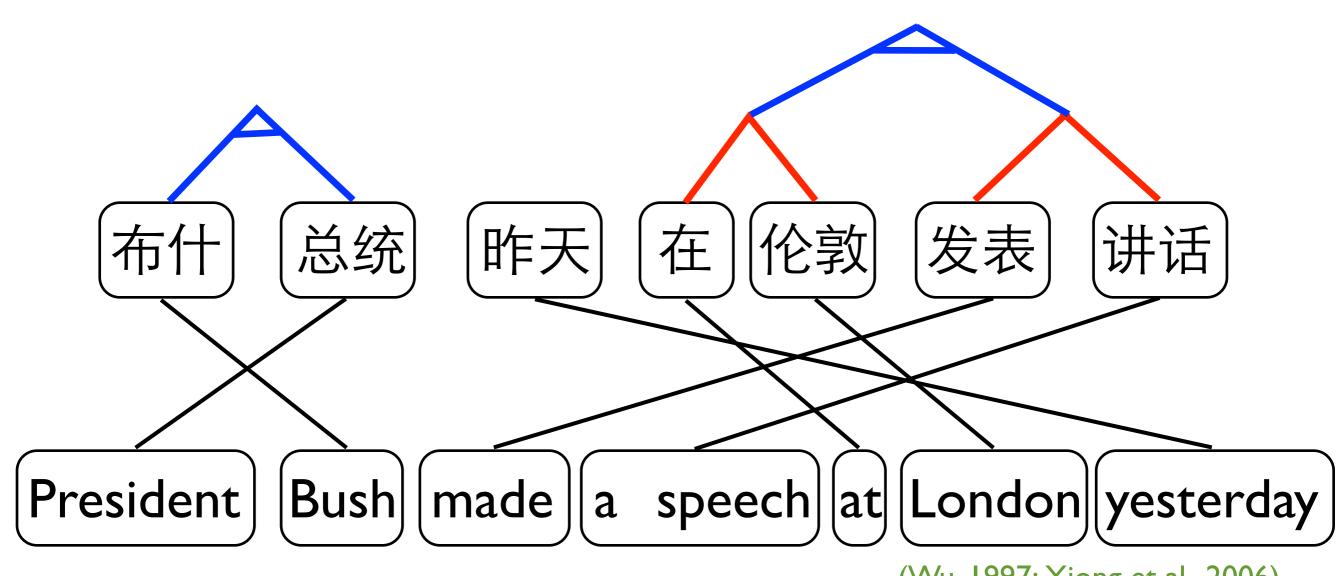


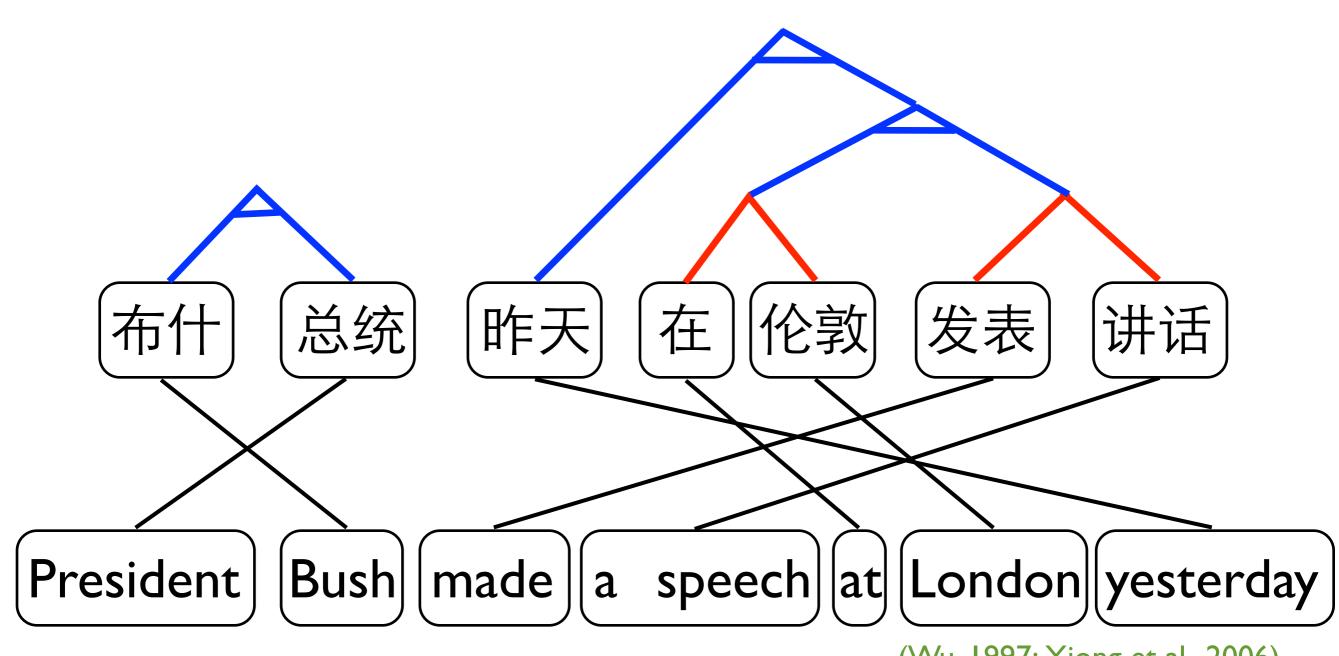


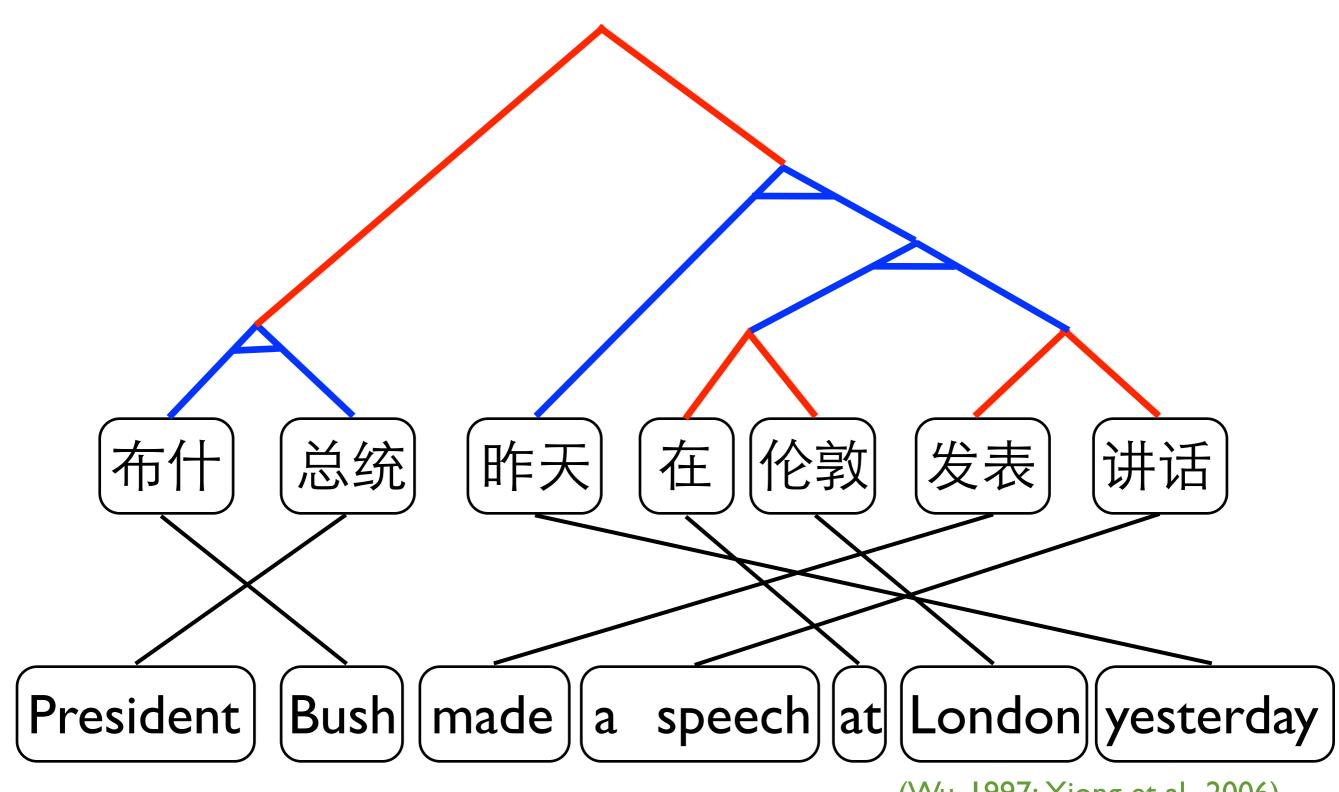




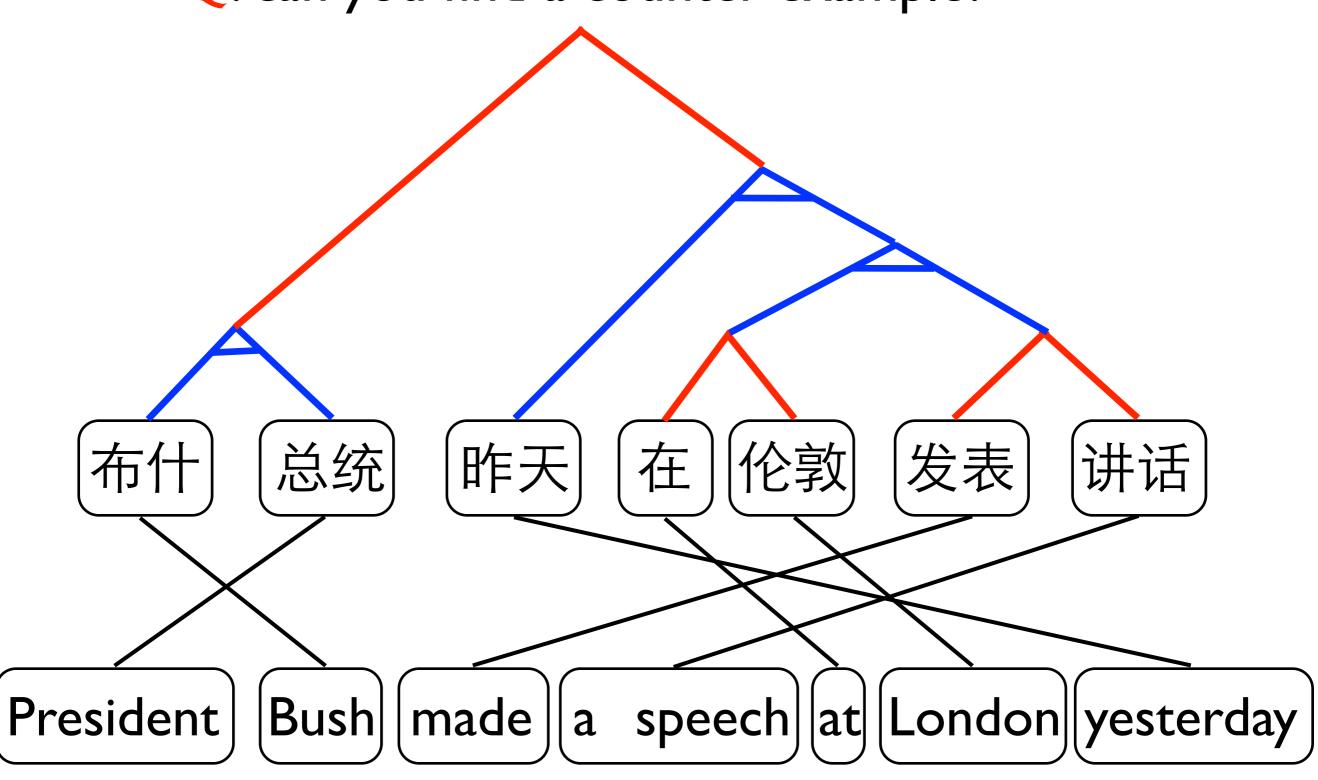




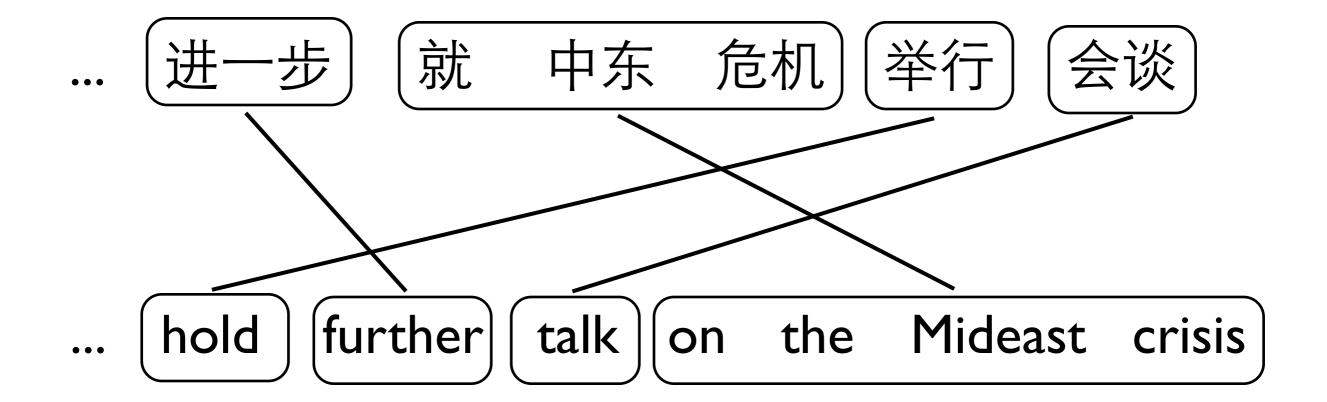




Q: can you find a counter example?

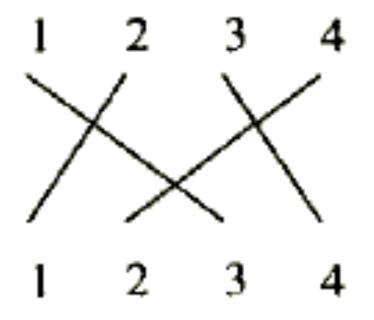


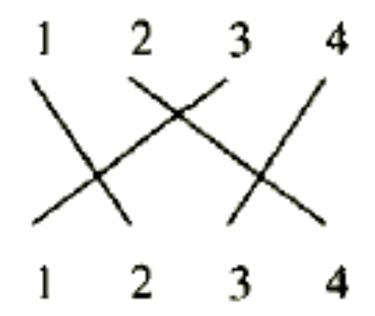
# Counter Example



### Expressiveness of ITG

"inside-out"





 Inverted Transduction Grammar explains how two natural language sentences are generated synchronously using two block-merging operators

 Inverted Transduction Grammar explains how two natural language sentences are generated synchronously using two block-merging operators

$$X \to f/e$$

 Inverted Transduction Grammar explains how two natural language sentences are generated synchronously using two block-merging operators

#### lexical rules

$$X \to f/e$$

 Inverted Transduction Grammar explains how two natural language sentences are generated synchronously using two block-merging operators

#### lexical rules

$$X \to f/e$$

#### syntactic rules

$$X \to [X^1, X^2]$$

$$X \to \langle X^1, X^2 \rangle$$

 Inverted Transduction Grammar explains how two natural language sentences are generated synchronously using two block-merging operators

#### lexical rules

$$X \to f/e$$

#### syntactic rules

$$X o [X^1, X^2]$$
 straight  $X o \langle X^1, X^2 
angle$ 

 Inverted Transduction Grammar explains how two natural language sentences are generated synchronously using two block-merging operators

#### lexical rules

$$X \to f/e$$

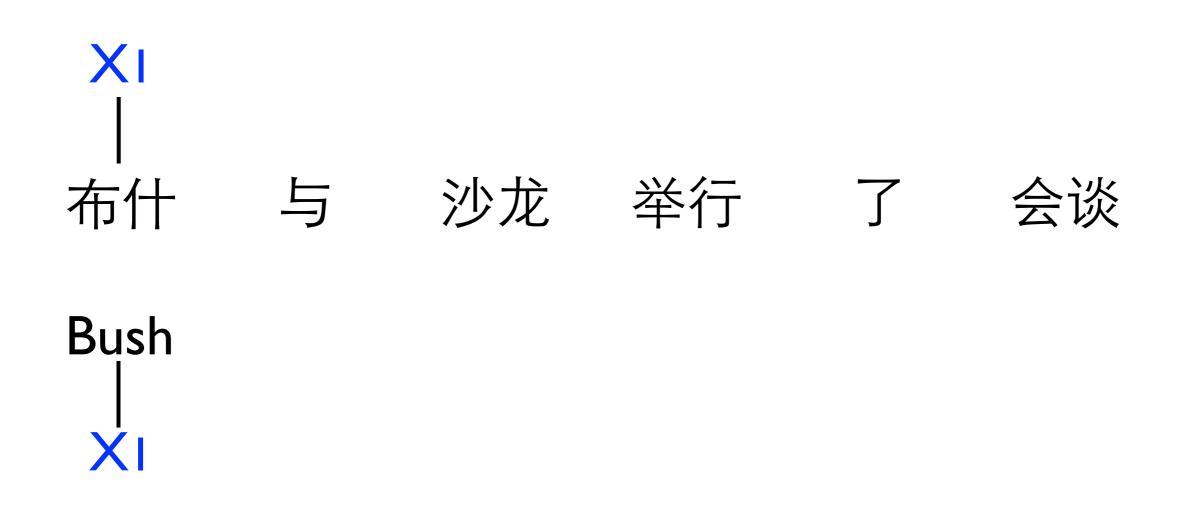
#### syntactic rules

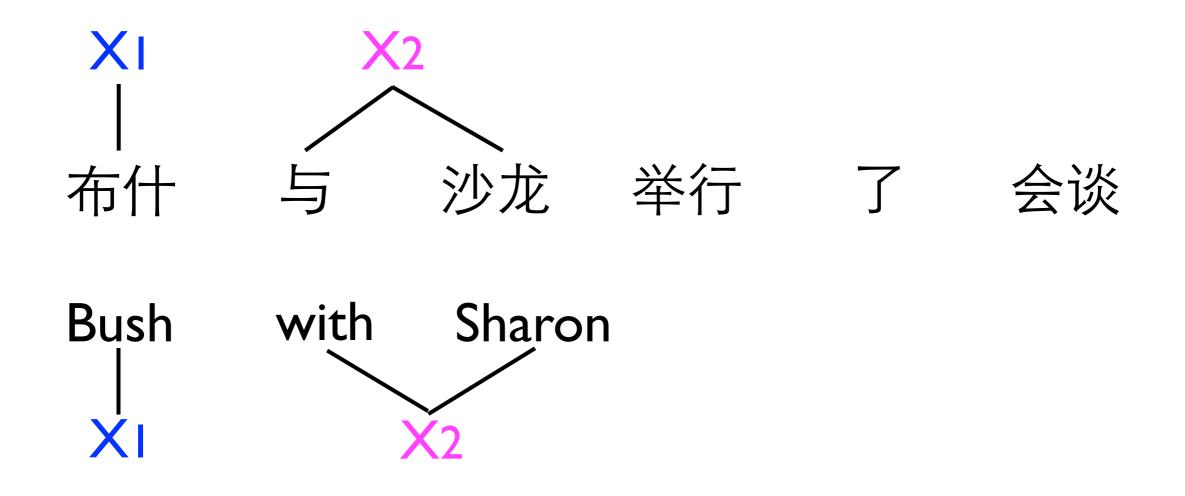
$$X o [X^1, X^2]$$
 straight  $X o \langle X^1, X^2 
angle$  inverted

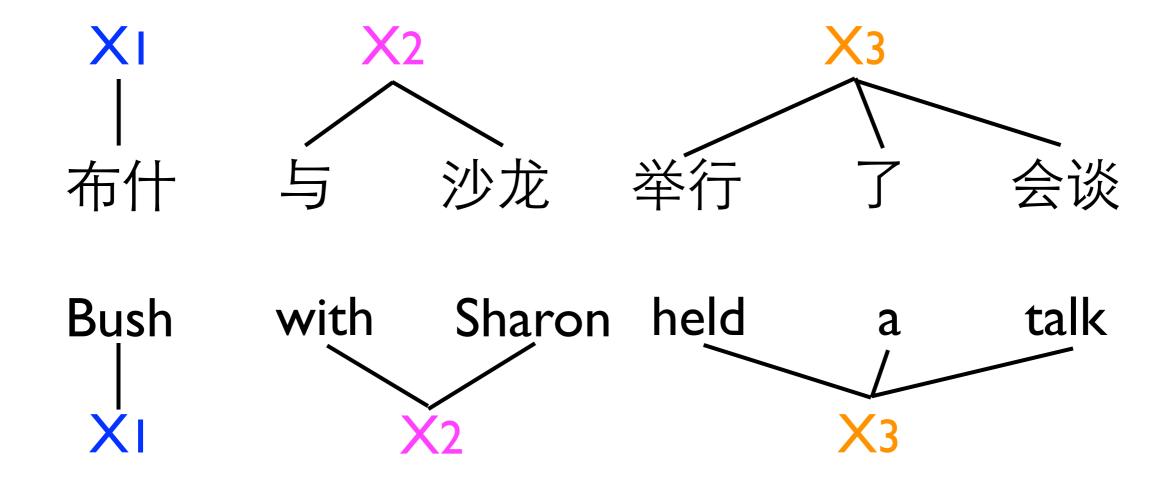
与 沙龙 举行 了 会谈 布什

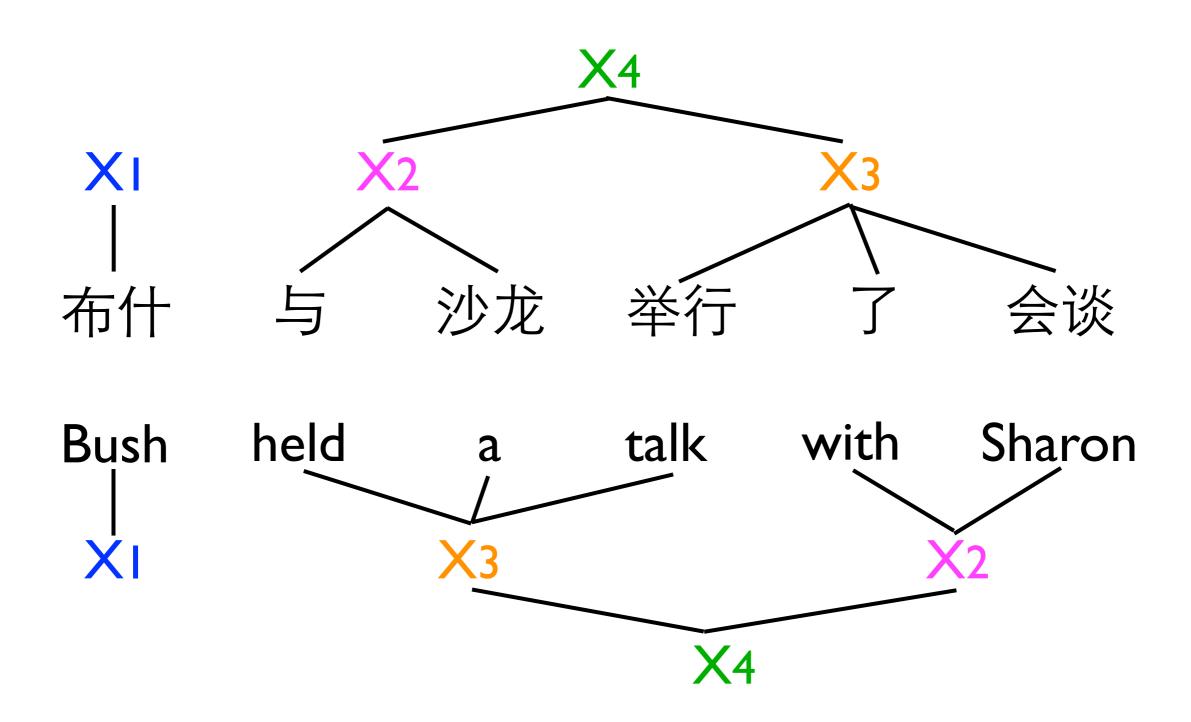
与 沙龙 举行 了 布什 会谈

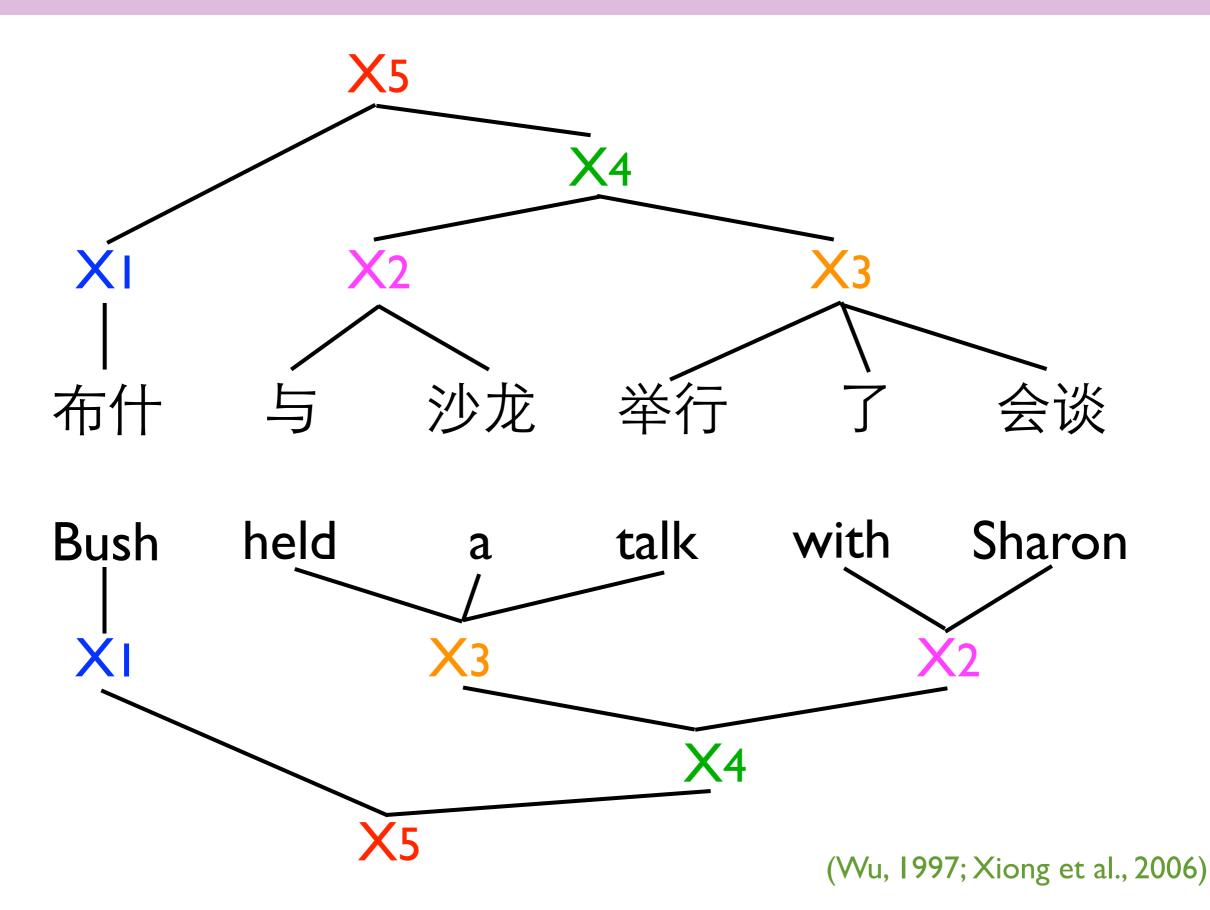
Bush











## Chart

Bush Sharon				
	held Sharon			
			held talk	
	with Sharon		held	
Bush	with	Sharon		a talk

与 沙龙 举行 了

布什

(Wu, 1997; Xiong et al., 2006)

会谈

## Syntax-based MT

## SCFGs without linguistic syntax

inverted transduction grammar

hierarchical phrase-based model

#### STSGs with linguistic syntax

string-to-tree

tree-to-string

tree-to-tree

从北京到上海 from Beijing to Shanghai

从武汉到天津 from Wuhan to Tianjin

从广州到重庆 from Guangzhou to Chongqing

从北京到上海

from Beijing to Shanghai

从武汉到天津

from Wuhan to Tianjin

从广州到重庆

from Guangzhou to Chongqing

从北京到上海

from Beijing to Shanghai

从武汉到天津

from Wuhan to Tianjin

从广州到重庆

from Guangzhou to Chongqing

(从 X 到 X2, from X to X2)

从北京到上海

from Beijing to Shanghai

从武汉到天津

from Wuhan to Tianjin

从广州到重庆

from Guangzhou to Chongqing

(从 X 到 X2, from X to X2)

(北京, Beijing) (上海, Shanghai) (武汉, Wuhan)

(天津, Tianjin) (广州, Guangzhou) (重庆, Chongqing)

从北京到上海

from Beijing to Shanghai

从武汉到天津

from Wuhan to Tianjin

从广州到重庆

from Guangzhou to Chongqing

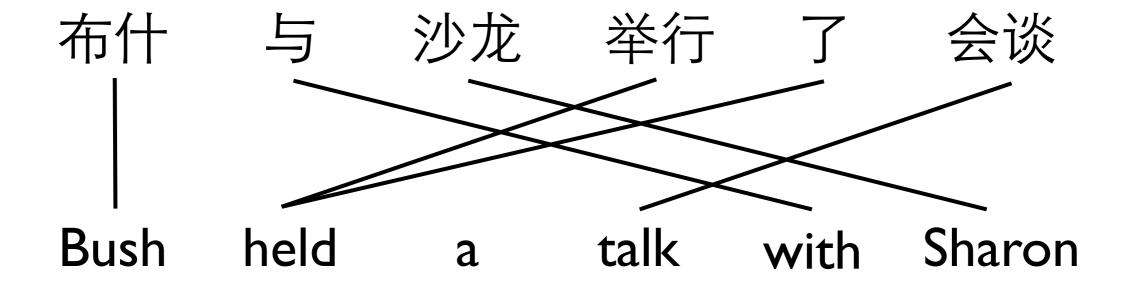
(从 $X_1$ 到 $X_2$ , from  $X_1$  to  $X_2$ ) hierarchical phrase pair

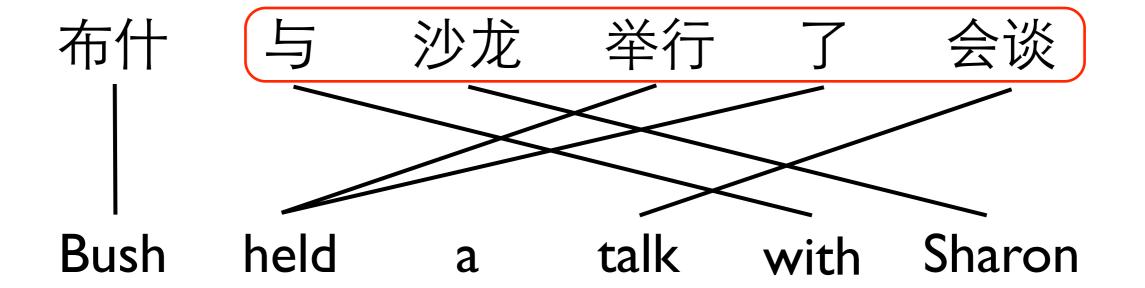
(北京, Beijing) (上海, Shanghai) (武汉, Wuhan)

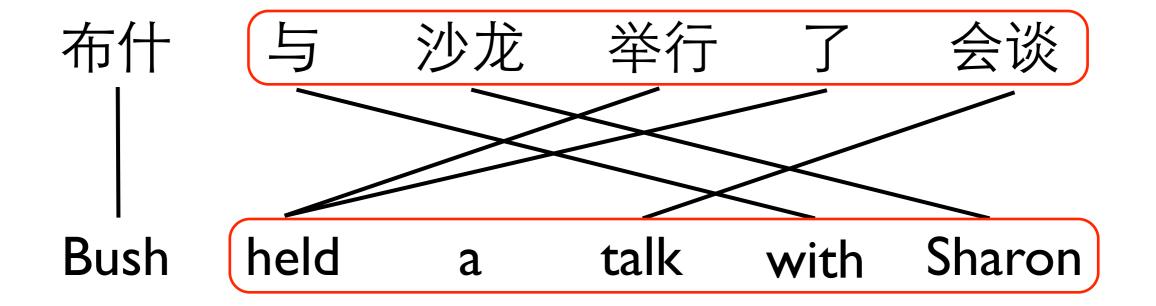
(天津, Tianjin) (广州, Guangzhou) (重庆, Chongqing)

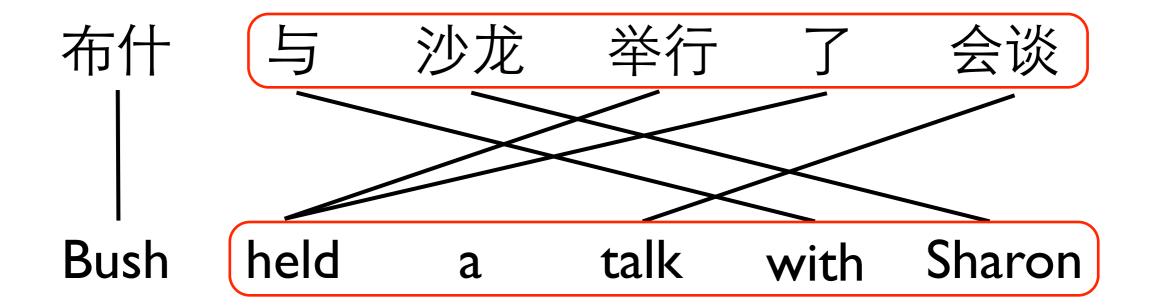
布什 与 沙龙 举行 了 会谈

Bush held a talk with Sharon

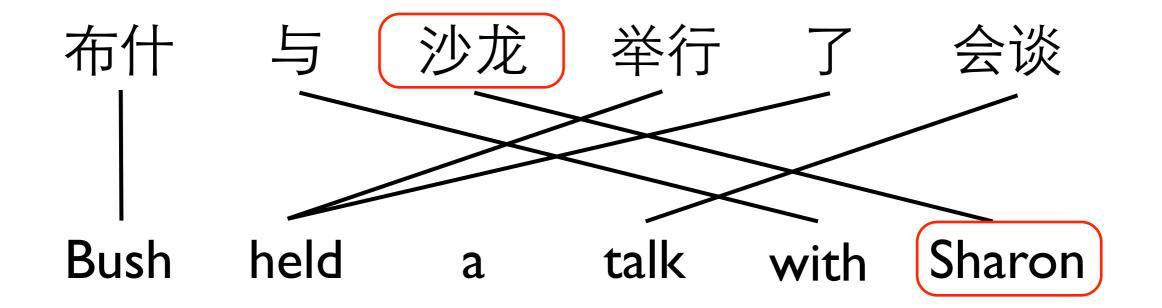




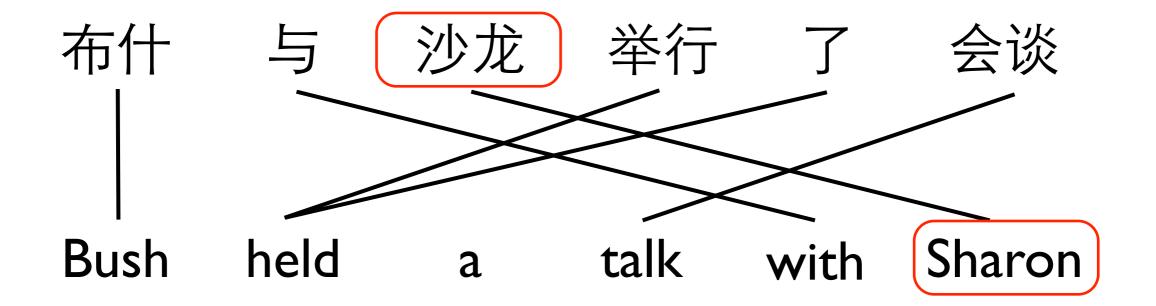




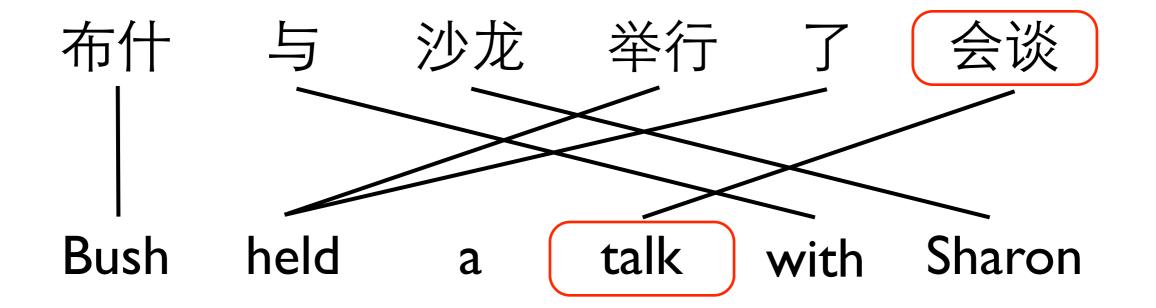
(与 沙龙 举行 了 会谈, held a talk with Sharon)



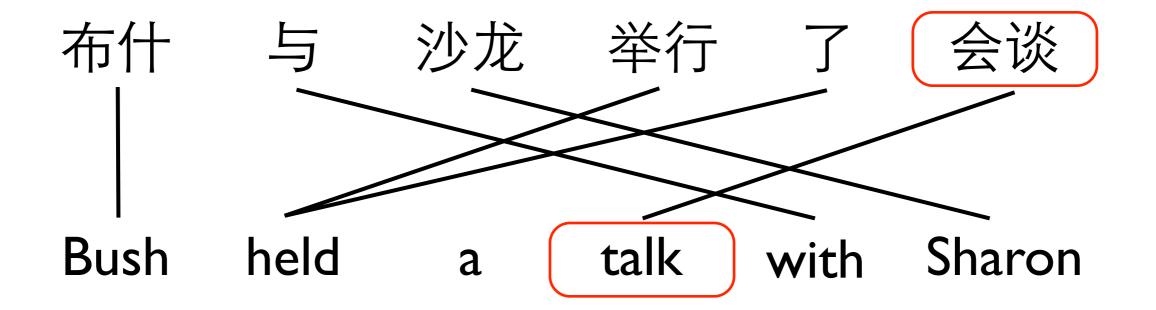
(与沙龙举行了会谈, held a talk with Sharon)



(与沙龙举行了会谈, held a talk with Sharon) (沙龙, Sharon)

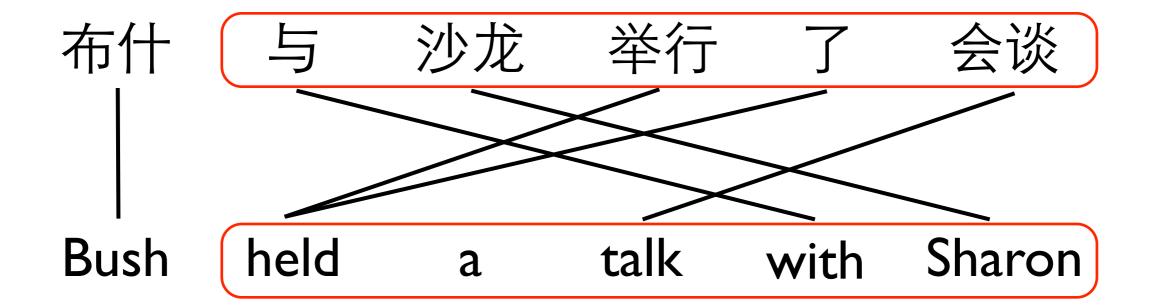


(与沙龙举行了会谈, held a talk with Sharon) (沙龙, Sharon)



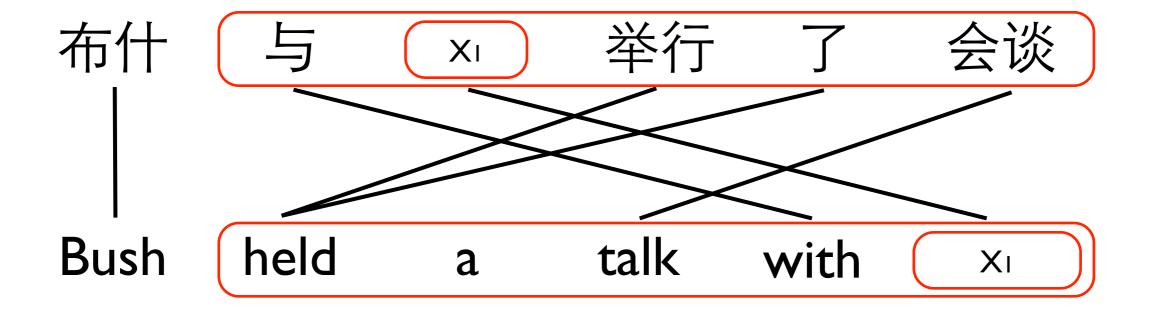
(与 沙龙 举行 了 会谈, held a talk with Sharon)

(沙龙, Sharon)



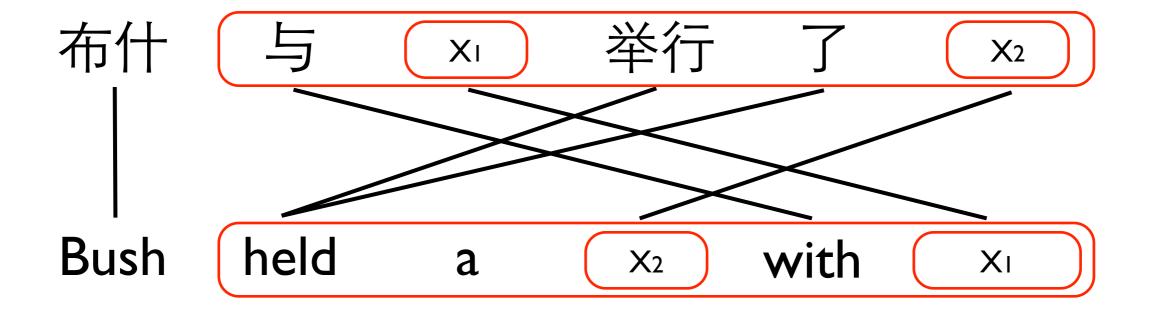
(与 沙龙 举行 了 会谈, held a talk with Sharon)

(沙龙, Sharon)



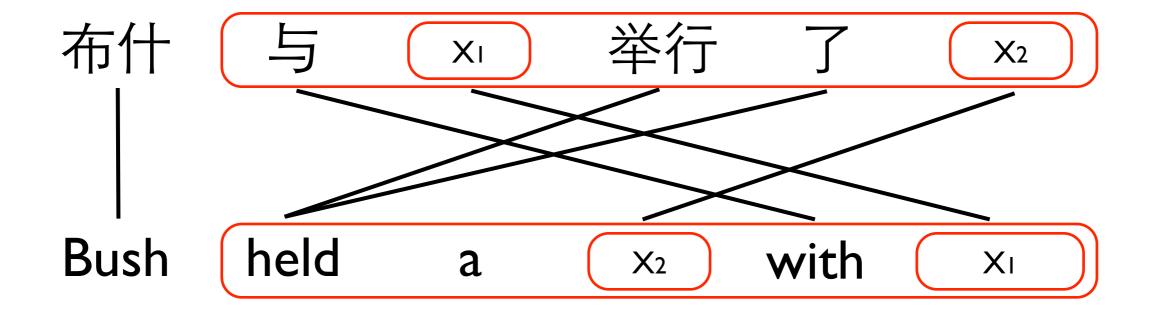
(与 沙龙 举行 了 会谈, held a talk with Sharon)

(沙龙, Sharon)



(与 沙龙 举行 了 会谈, held a talk with Sharon)

(沙龙, Sharon)



(与 沙龙 举行 了 会谈, held a talk with Sharon)

(沙龙, Sharon)

(会谈, talk)

(与 Xı 举行 了 X2, held a X2 with Xı)

Hierarchical phrase-based model is based on SCFG without linguistic syntax

Hierarchical phrase-based model is based on SCFG without linguistic syntax

#### lexical rules

X → (沙龙, Sharon)

X → (会谈, talk)

Hierarchical phrase-based model is based on SCFG without linguistic syntax

#### lexical rules

X → (沙龙, Sharon)

 $X \rightarrow (会谈, talk)$ 

syntactic rules

 Hierarchical phrase-based model is based on SCFG without linguistic syntax

#### lexical rules

X → (沙龙, Sharon)

X → (会谈, talk)

#### syntactic rules

X → (与 Xı 举行 了 X₂, held a X₂ with Xı)

Hierarchical phrase-based model is based on SCFG without linguistic syntax

#### lexical rules

X → (沙龙, Sharon)

X → (会谈, talk)

#### syntactic rules

X → (与 Xı 举行 了 X₂, held a X₂ with Xı)

X → (布什 Xı, Bush Xı)

 Hierarchical phrase-based model is based on SCFG without linguistic syntax

#### lexical rules

```
X → (沙龙, Sharon)
```

#### syntactic rules

```
X → (与 Xı 举行 了 X₂, held a X₂ with Xı)
```

ITG is a special case of SCFG

布什 与 沙龙 举行 了 会谈

X → (沙龙, Sharon)

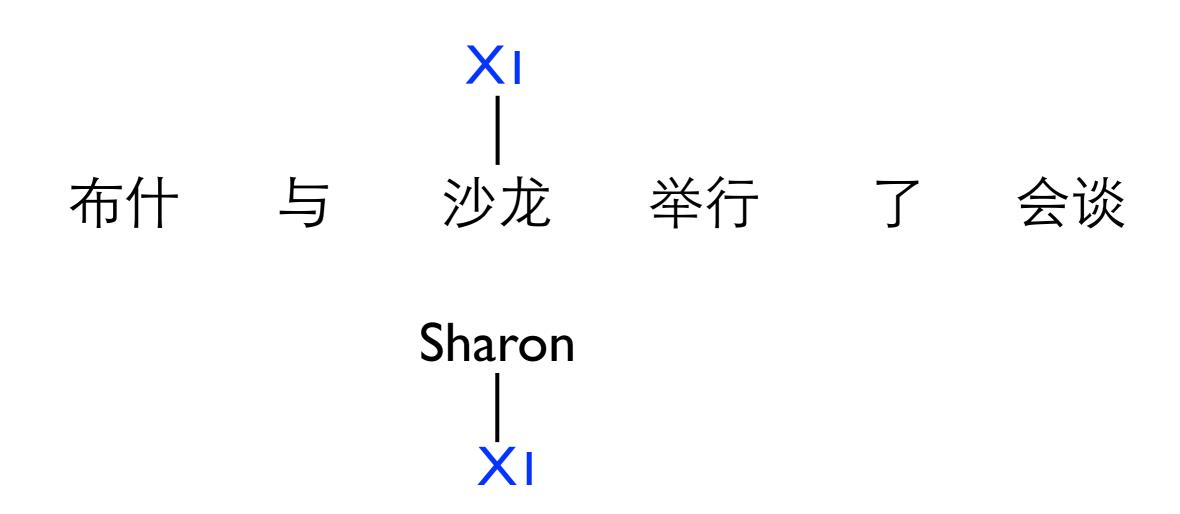
布什 与 沙龙 举行 了 会谈

X → (沙龙, Sharon)

布什 与 沙龙 举行 了 会谈

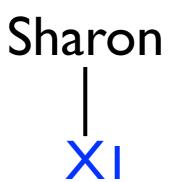
Sharon

X → (沙龙, Sharon)



X → (沙龙, Sharon)

X → (会谈, talk)



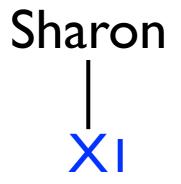
XI

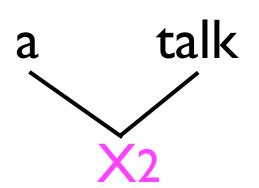
X → (沙龙, Sharon)
X → (会谈, talk)

 XI
 X2

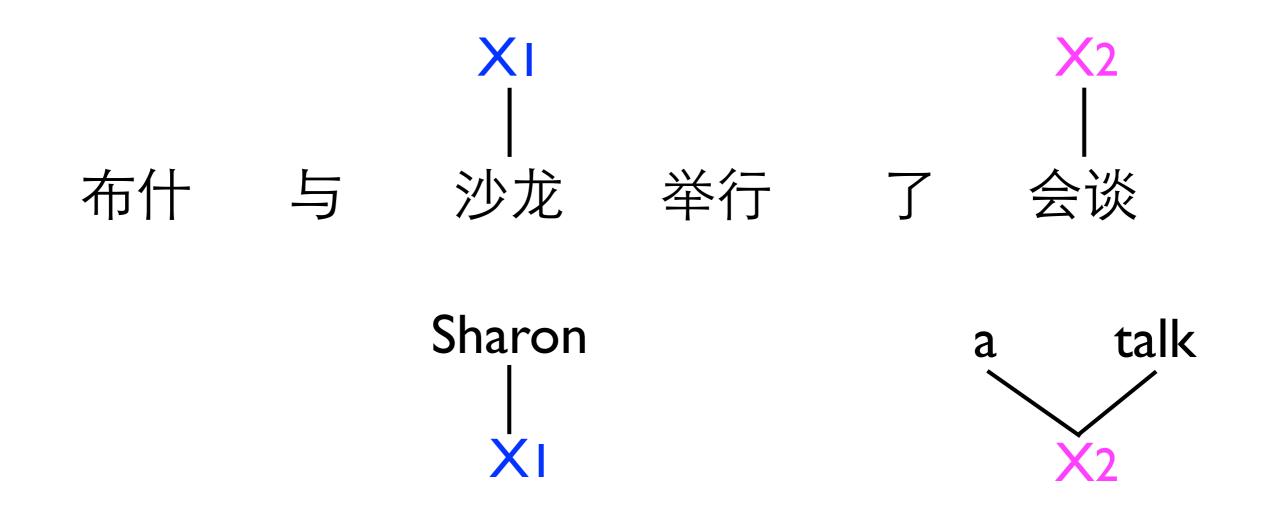
 |
 |

 布什
 少龙
 举行
 了
 会谈



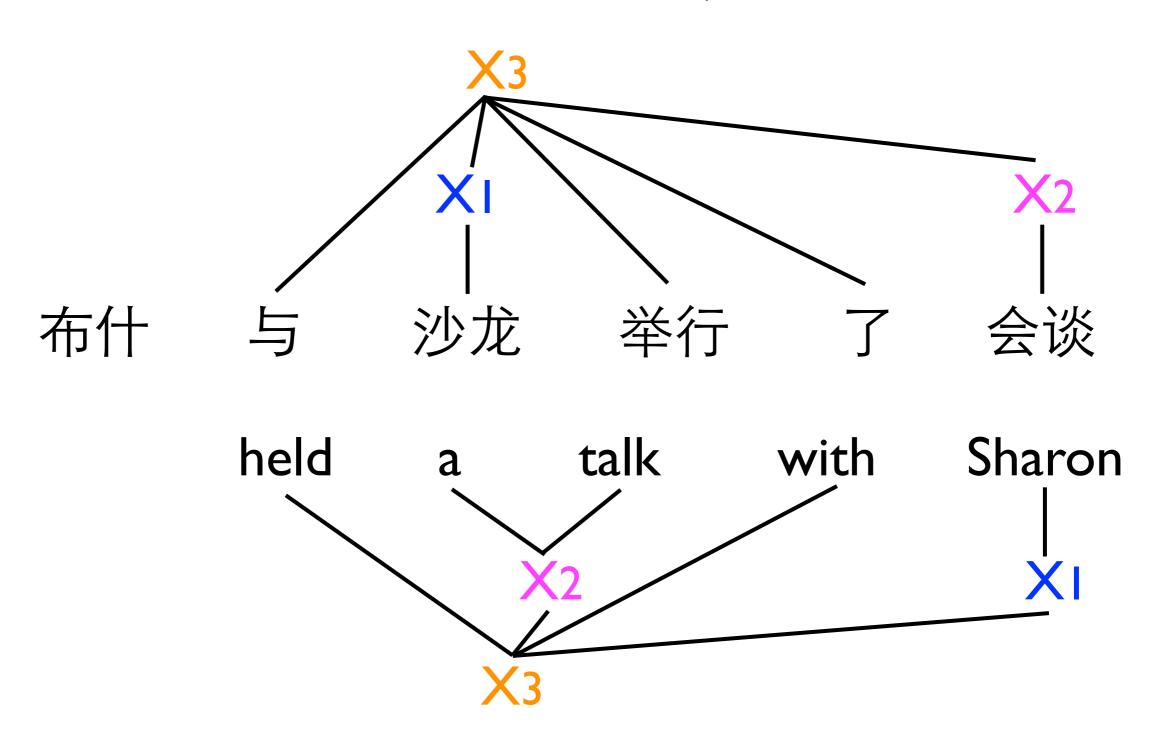


X → (与 Xı 举行 了 X₂, held a X₂ with Xı)

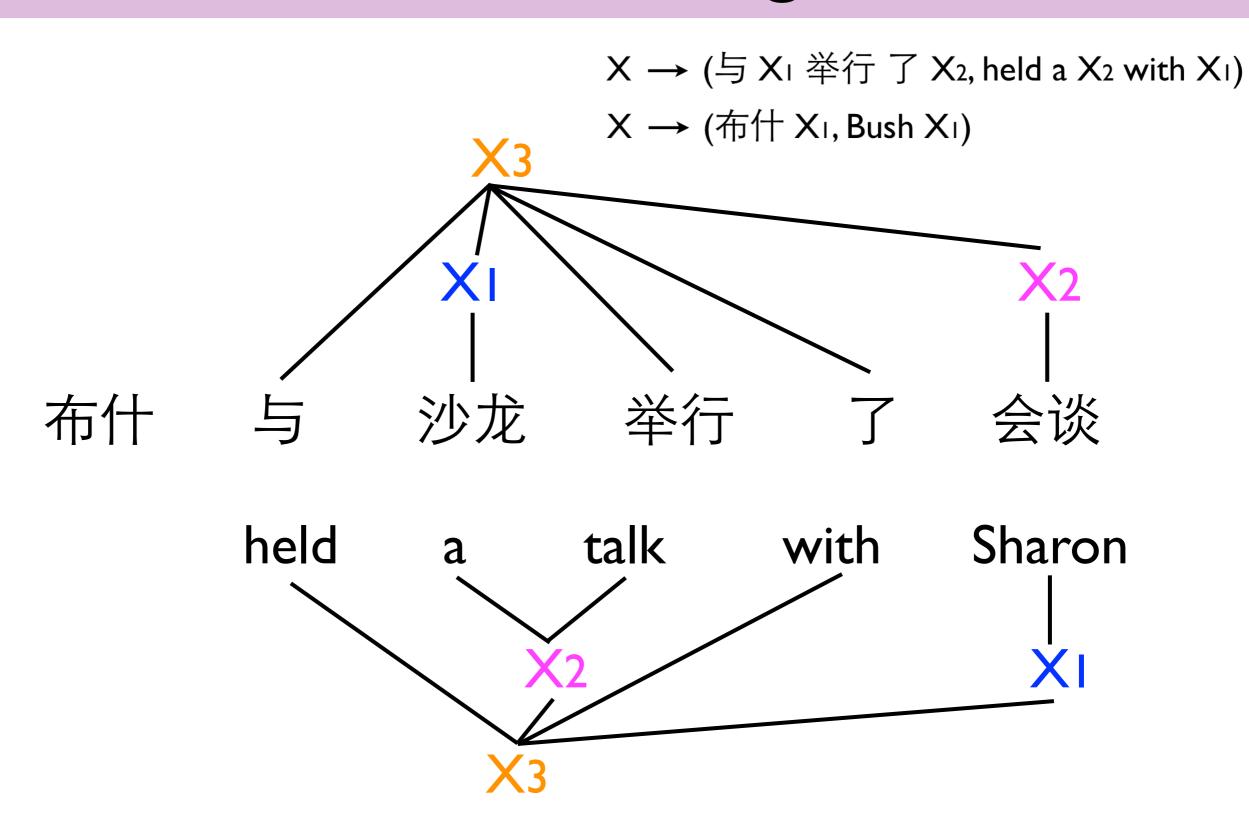


## **CKY Parsing**

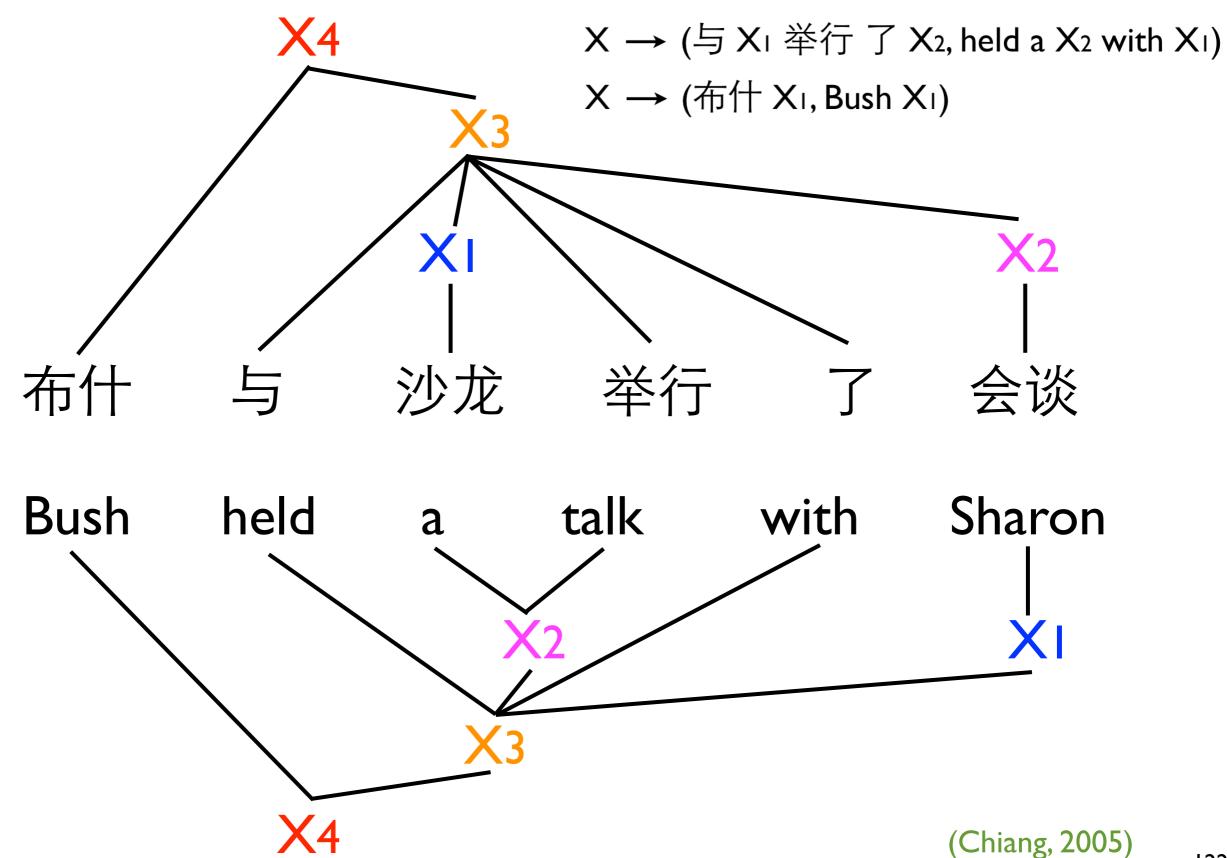
X → (与 X<sub>1</sub> 举行 了 X<sub>2</sub>, held a X<sub>2</sub> with X<sub>1</sub>)



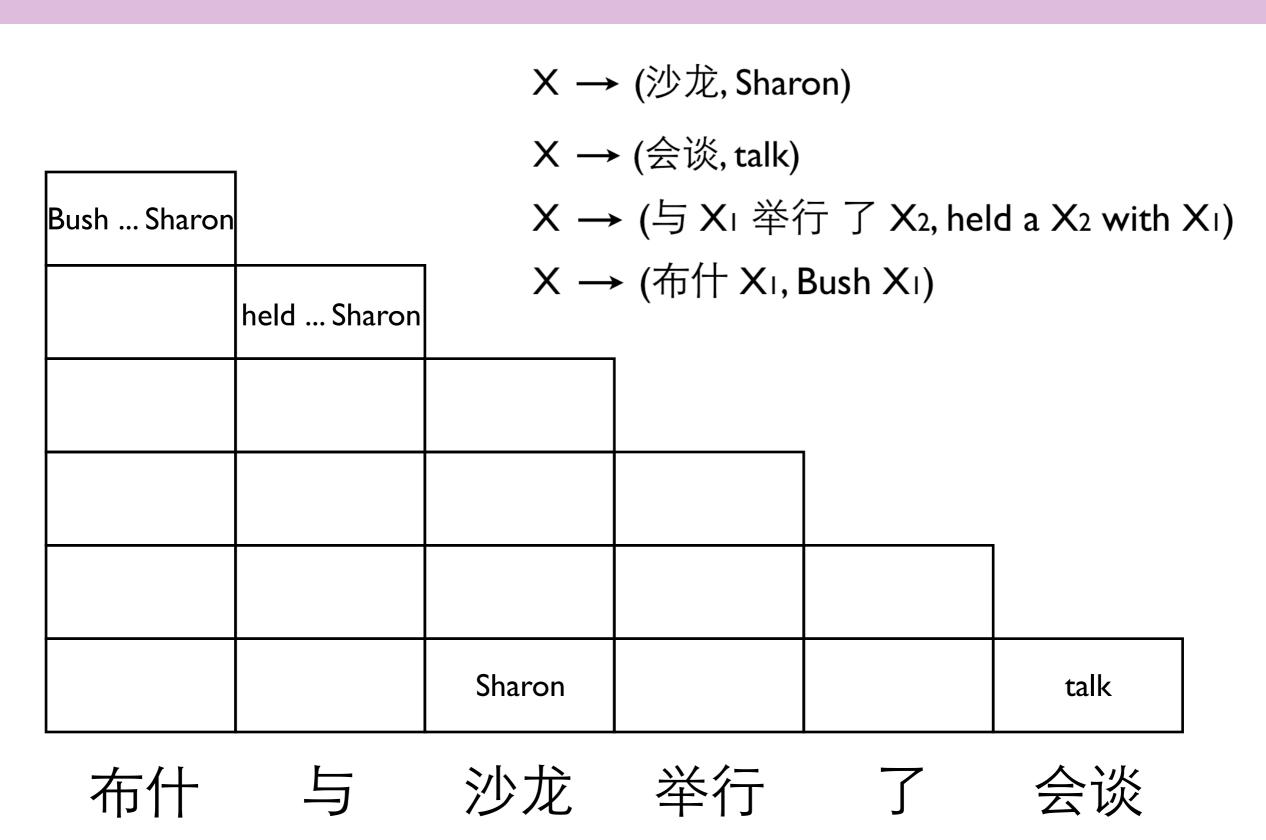
#### **CKY Parsing**



## **CKY Parsing**



#### Chart



#### Syntax-based MT

#### SCFGs without linguistic syntax

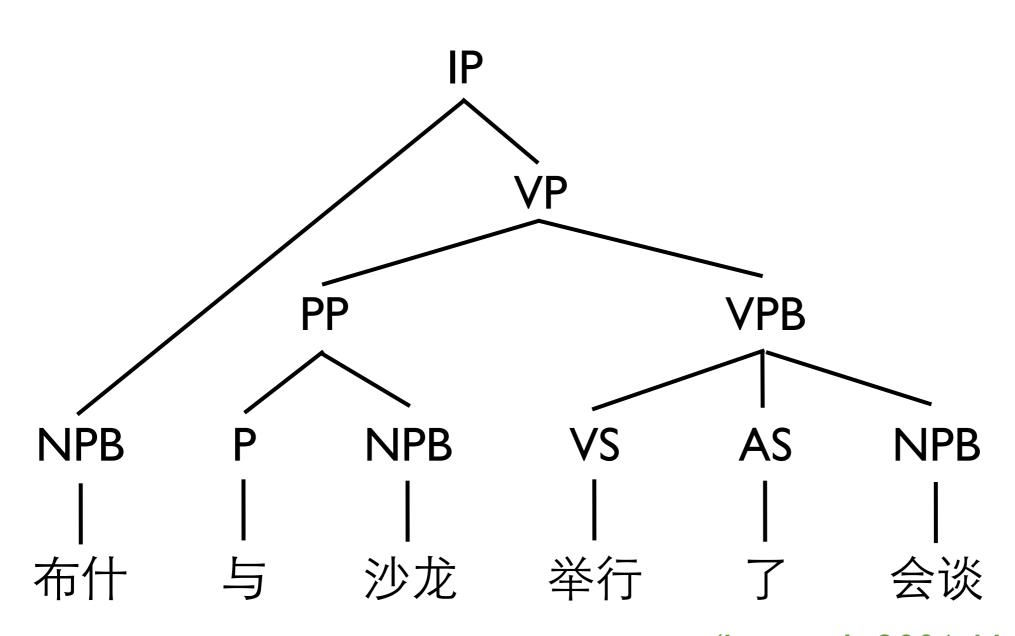
inverted transduction grammar hierarchical phrase-based model

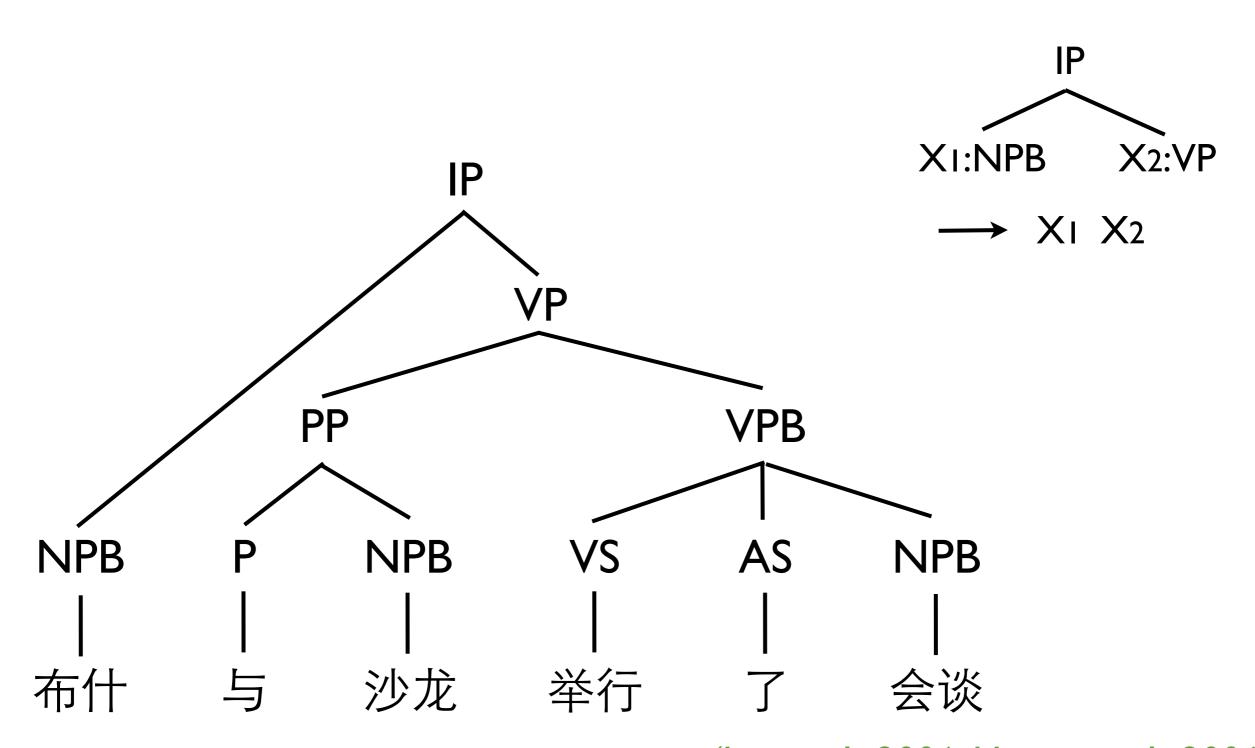
#### STSGs with linguistic syntax

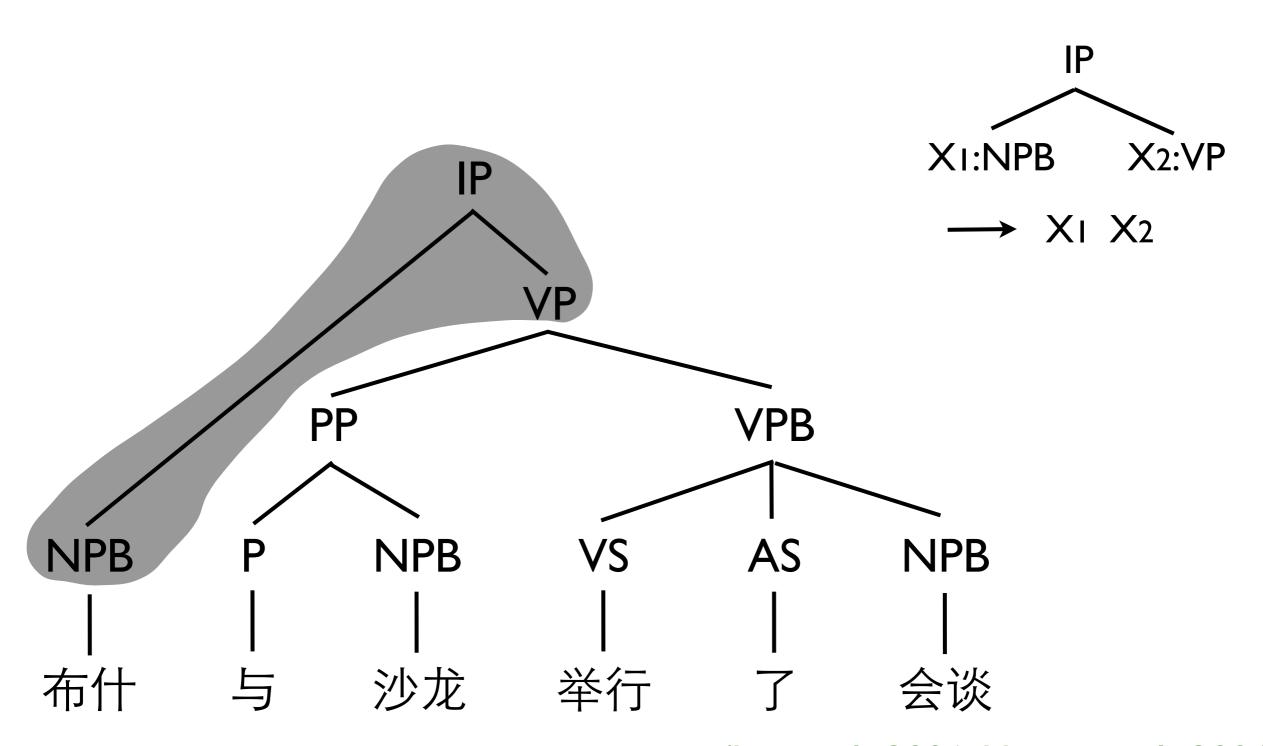
string-to-tree

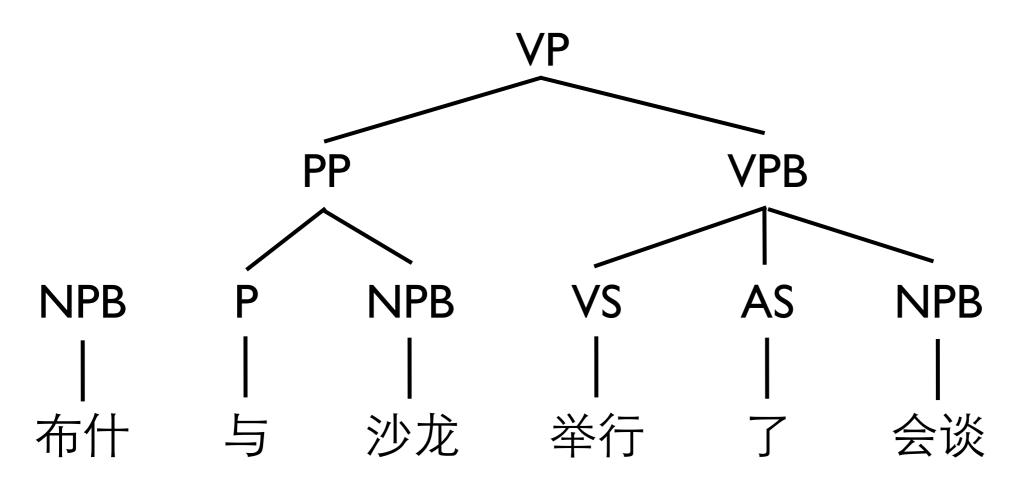
tree-to-string

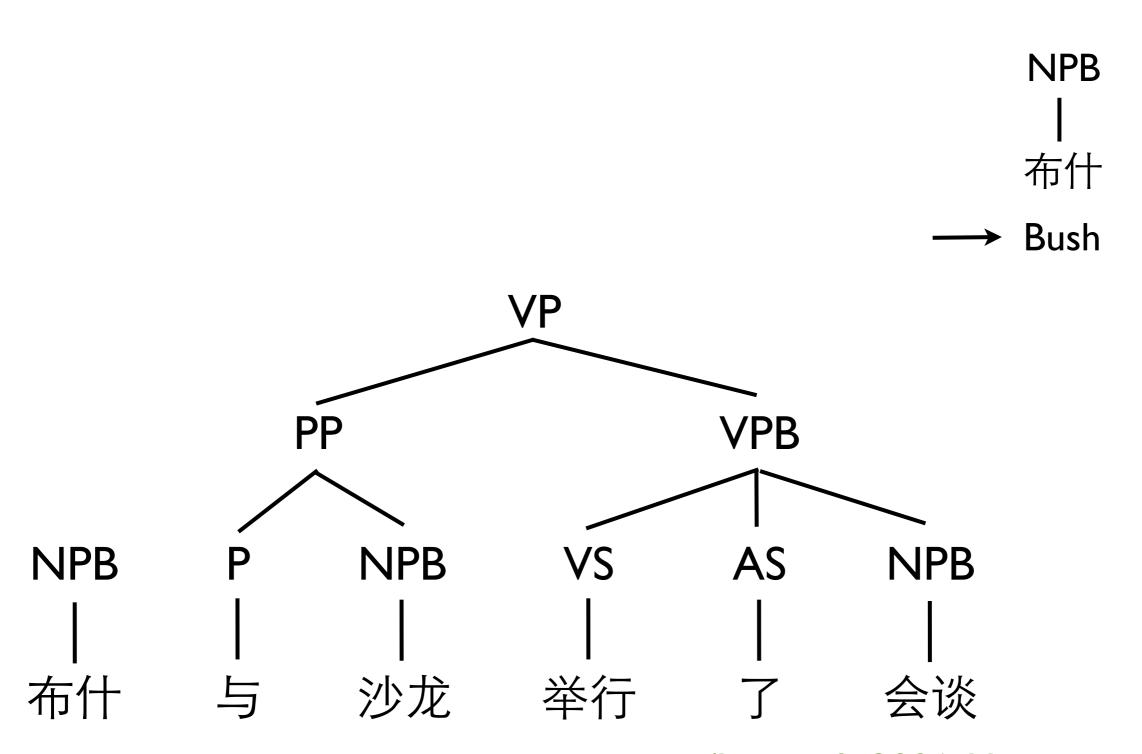
tree-to-tree

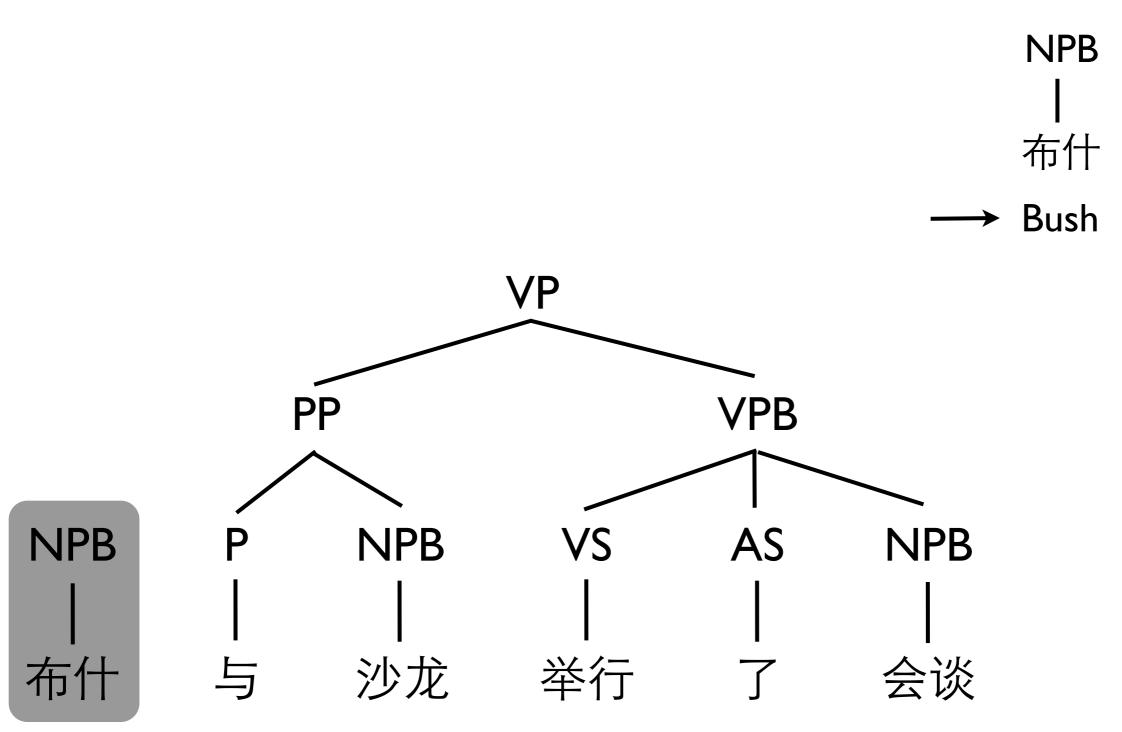


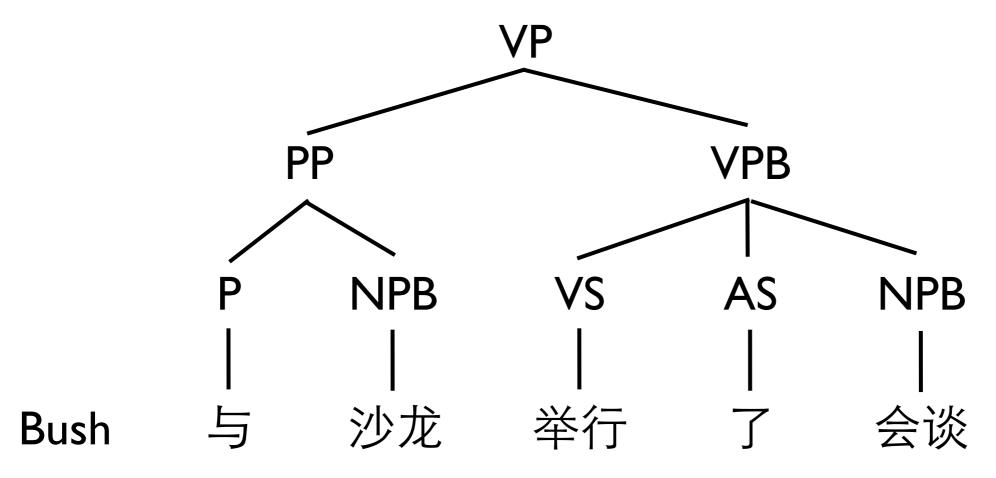


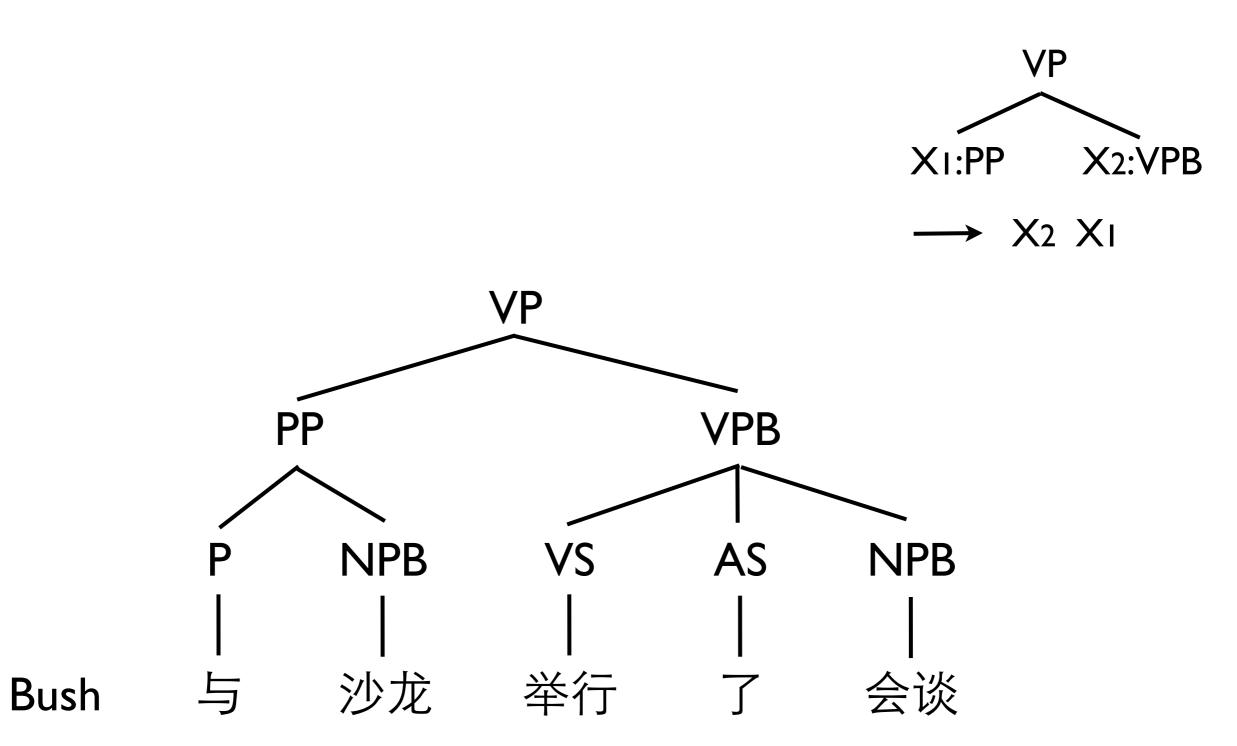


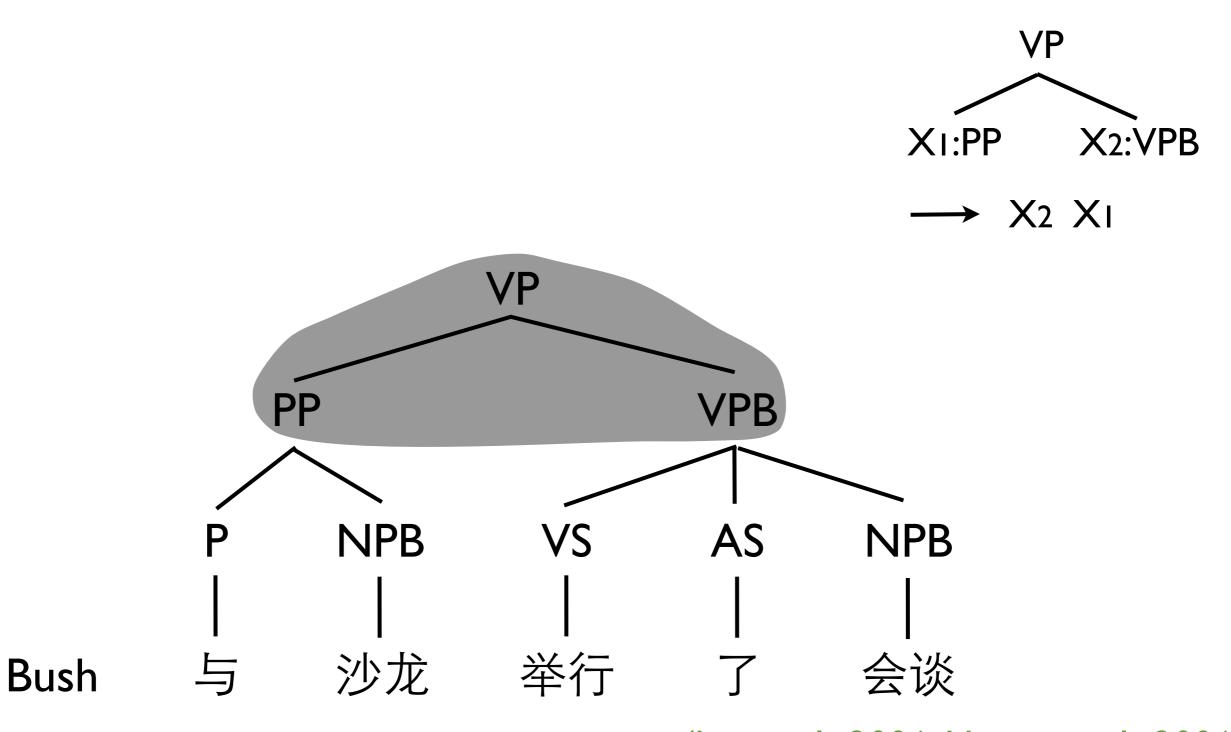


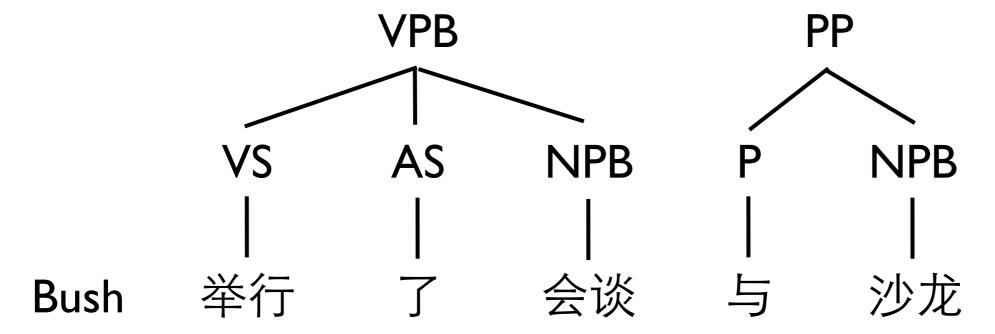


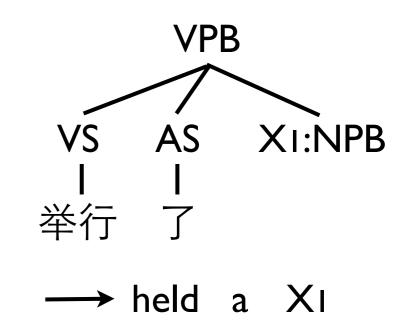


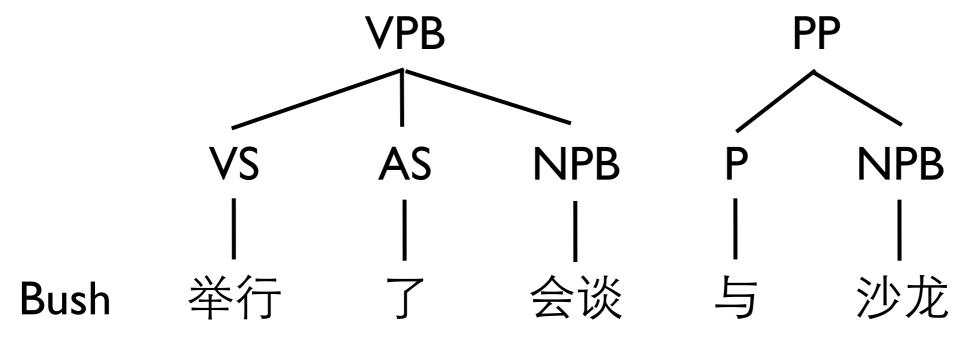


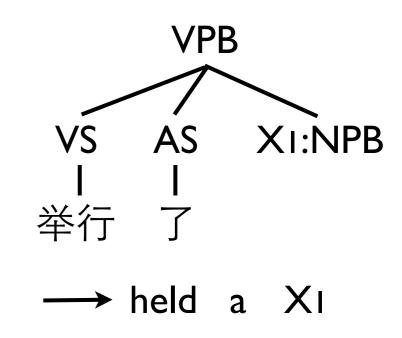


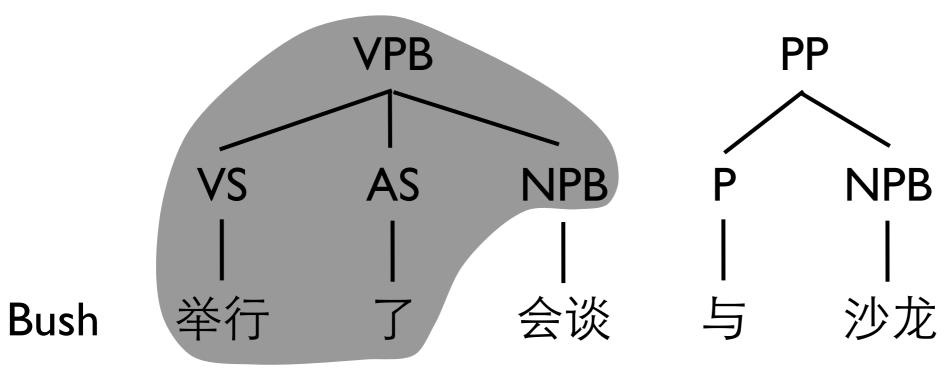


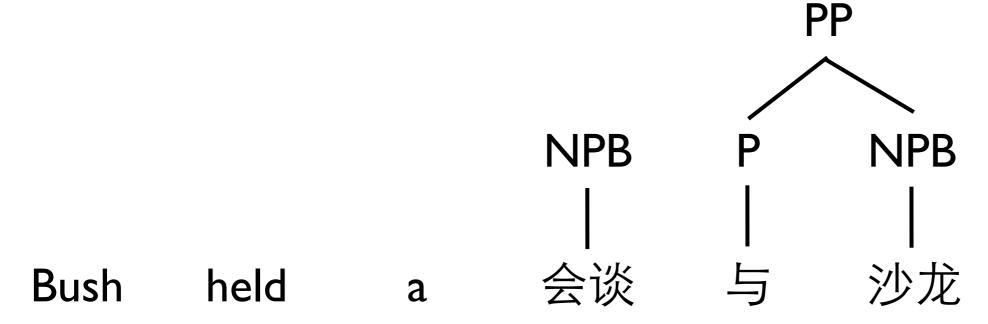


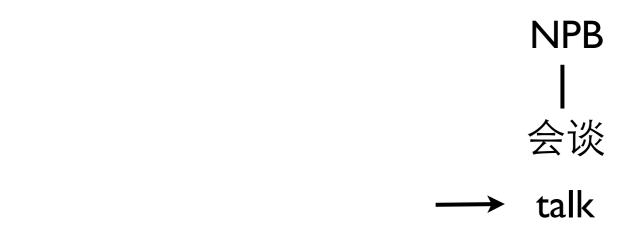


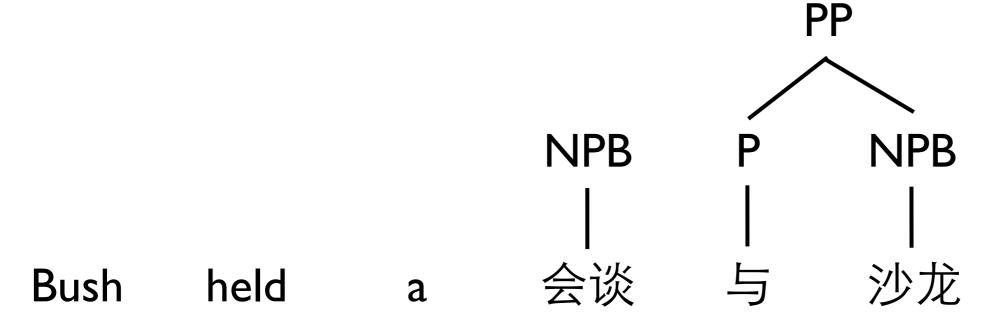


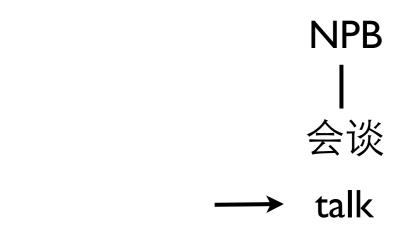


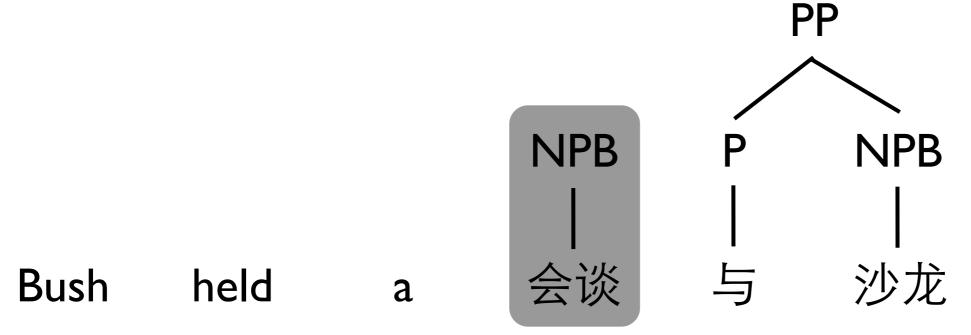


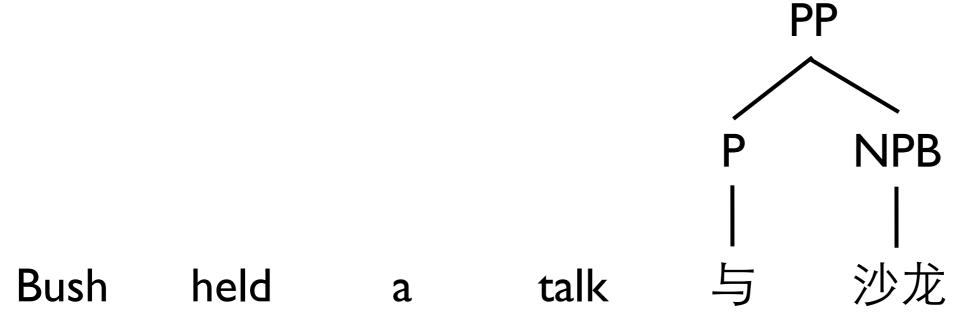




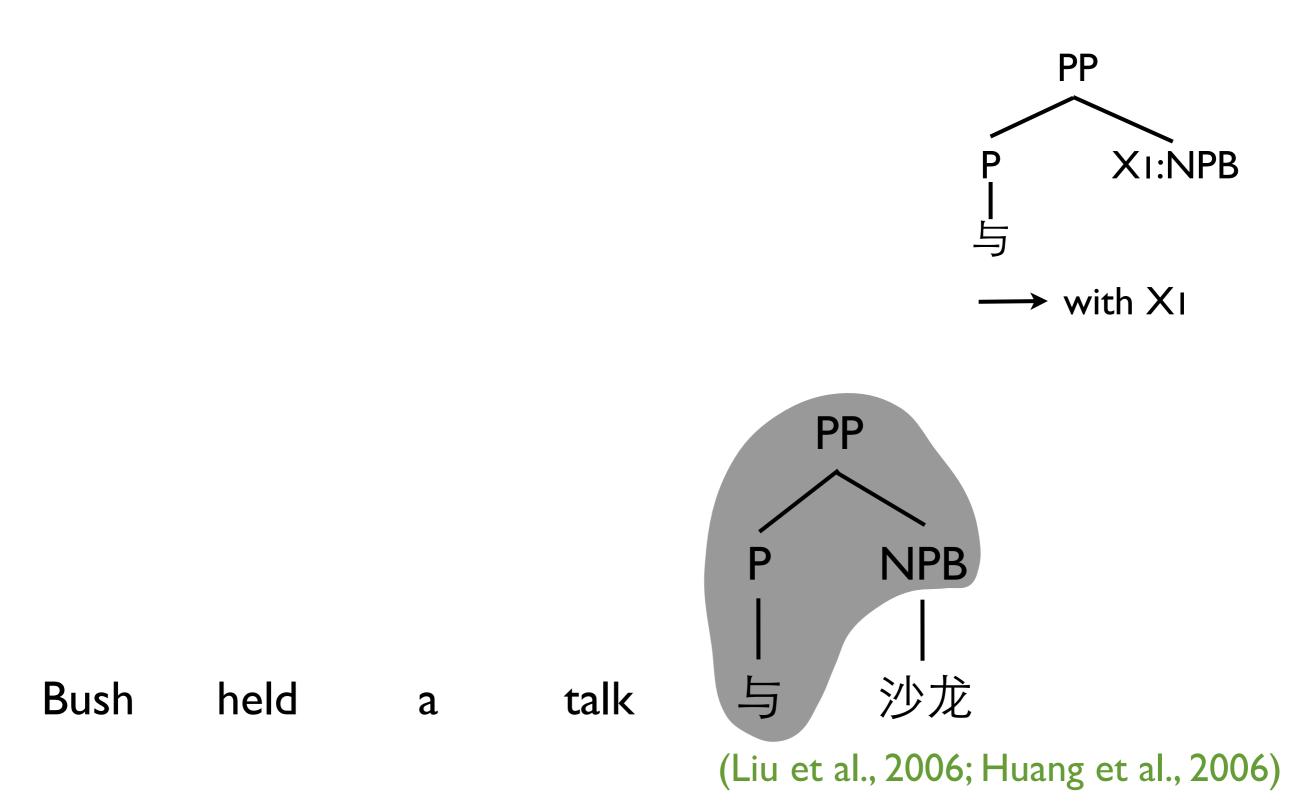




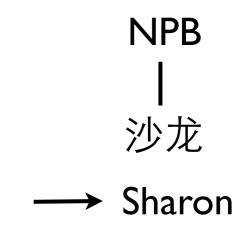


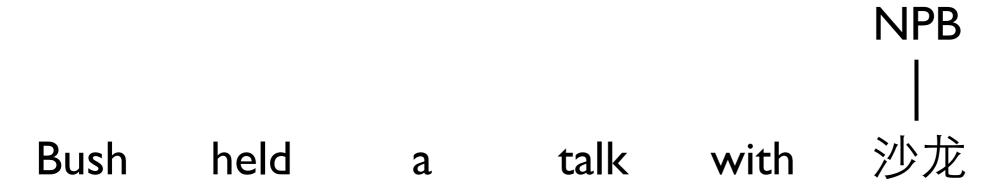


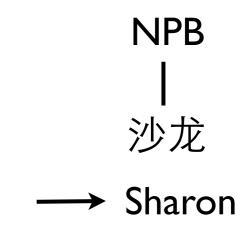










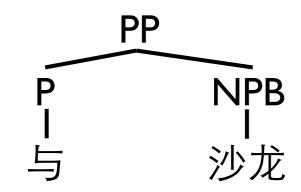




Bush held a talk with Sharon

phrase translation

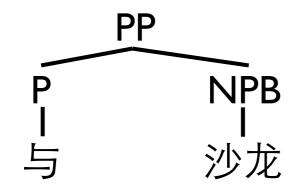
phrase translation



→ with Sharon

phrase translation

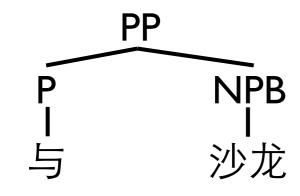
non-constituent

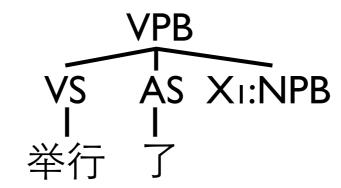


→ with Sharon

phrase translation

non-constituent

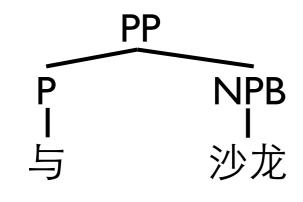




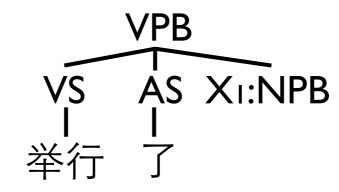
phrase translation

non-constituent

discontinuous



→ with Sharon

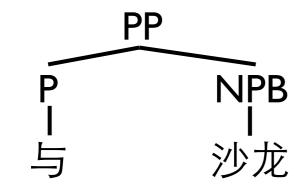


 $\rightarrow$  held a X<sub>1</sub>

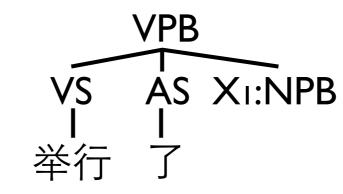
phrase translation

non-constituent

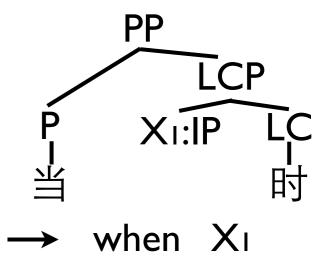
discontinuous



→ with Sharon



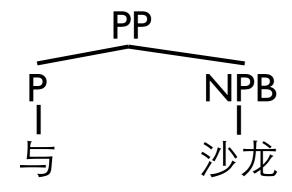
 $\rightarrow$  held a X<sub>1</sub>



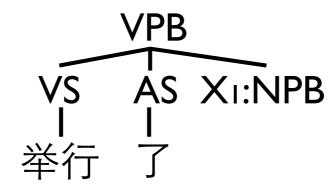
phrase translation

non-constituent

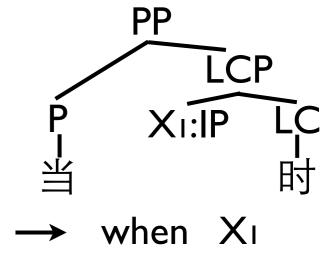
discontinuous



→ with Sharon



 $\rightarrow$  held a X<sub>1</sub>

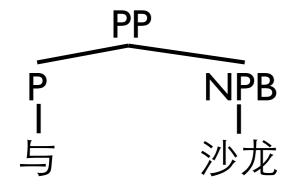


word deletion

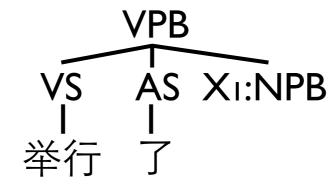
phrase translation

non-constituent

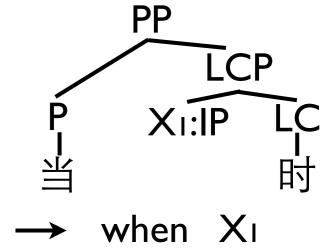
discontinuous



→ with Sharon



 $\rightarrow$  held a X<sub>1</sub>



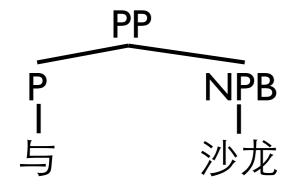
word deletion

 $X_1$ 

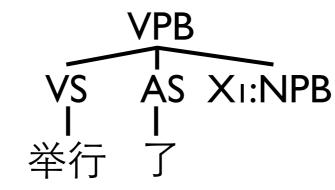
phrase translation

non-constituent

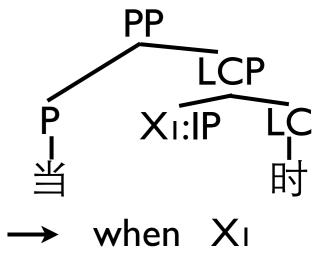
discontinuous



→ with Sharon



→ held a Xı



word deletion

multi-level reordering

 $X_1$ 

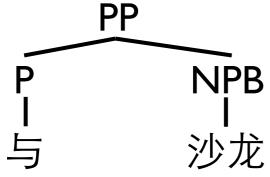
phrase translation

non-constituent

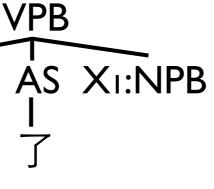
discontinuous

PP

LCP







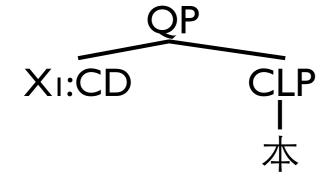


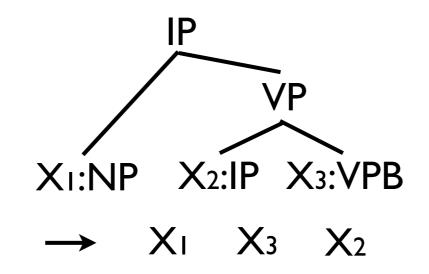
→ with Sharon

→ held a Xı

word deletion

multi-level reordering

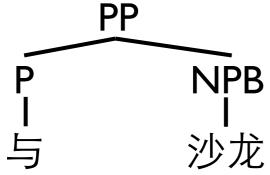




phrase translation

non-constituent

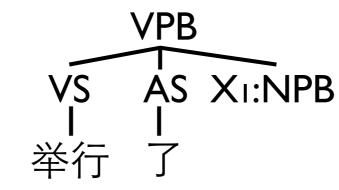
discontinuous



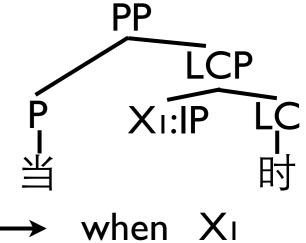




→ with Sharon



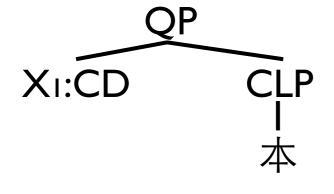
→ held a Xı



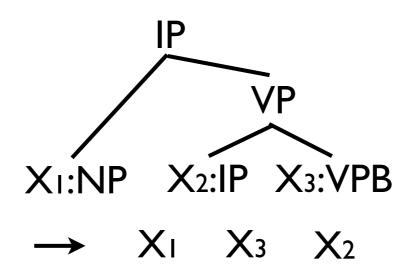
word deletion

multi-level reordering

lexicalized reordering



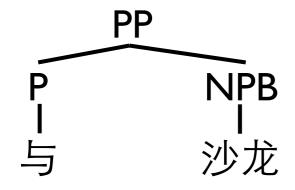
$$\rightarrow$$
 X<sub>1</sub>



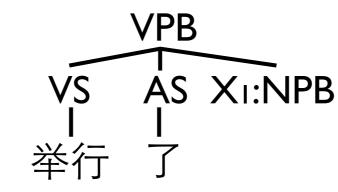
phrase translation

non-constituent

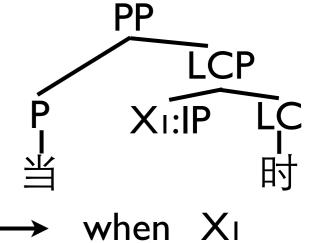
discontinuous







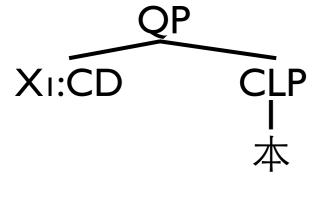
 $\rightarrow$  held a X<sub>1</sub>



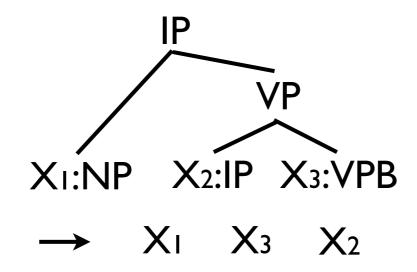
word deletion

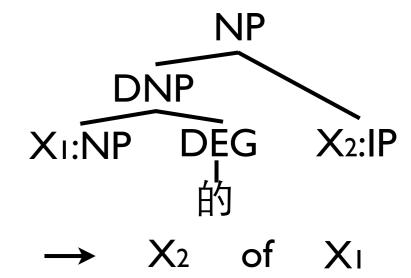
multi-level reordering

lexicalized reordering



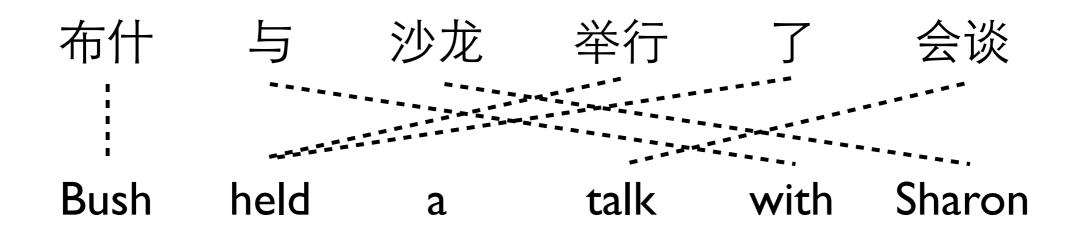


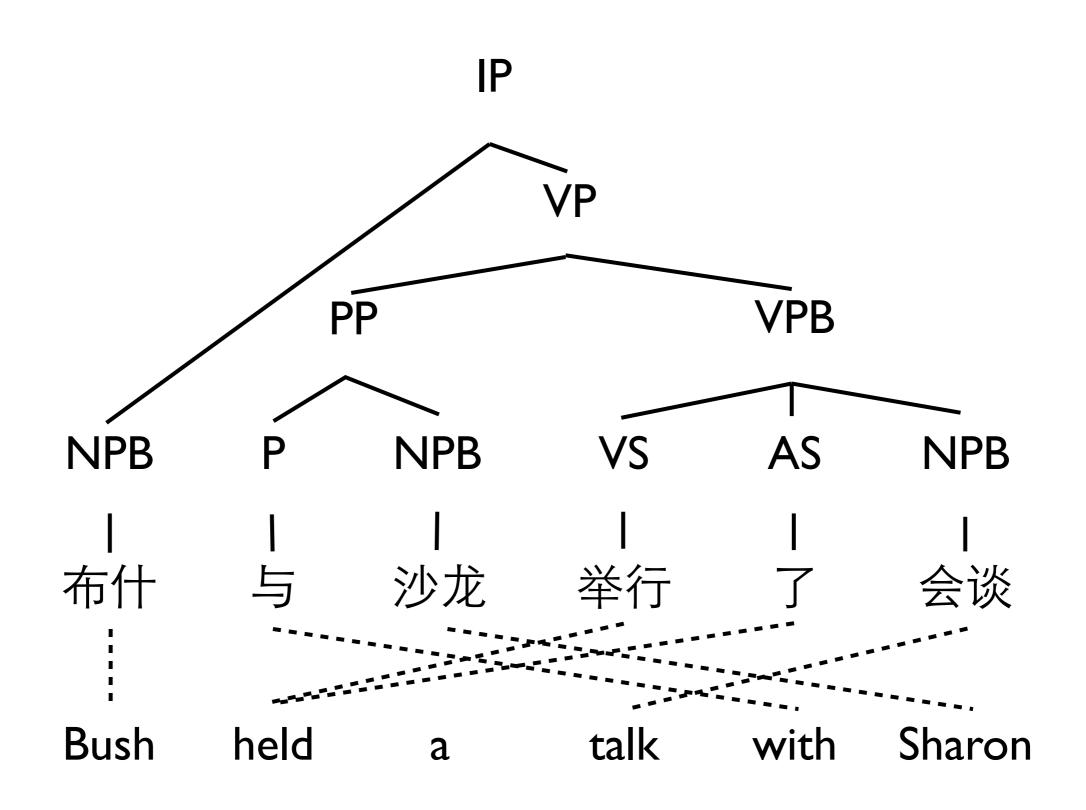


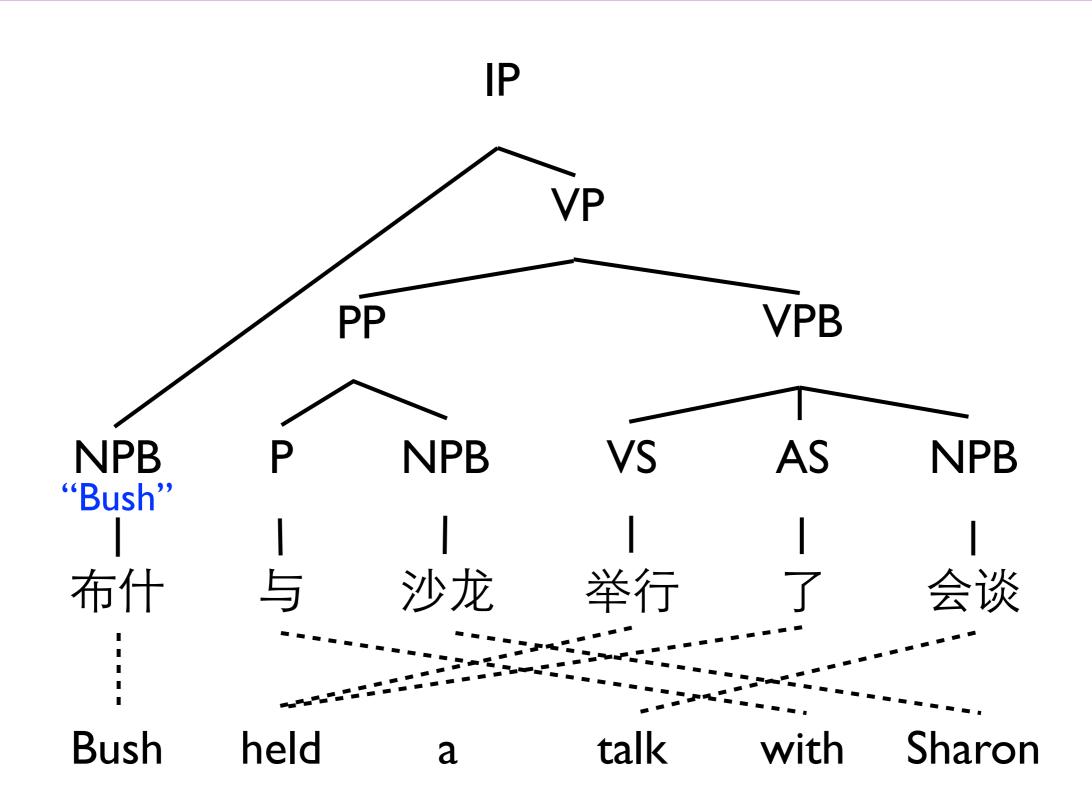


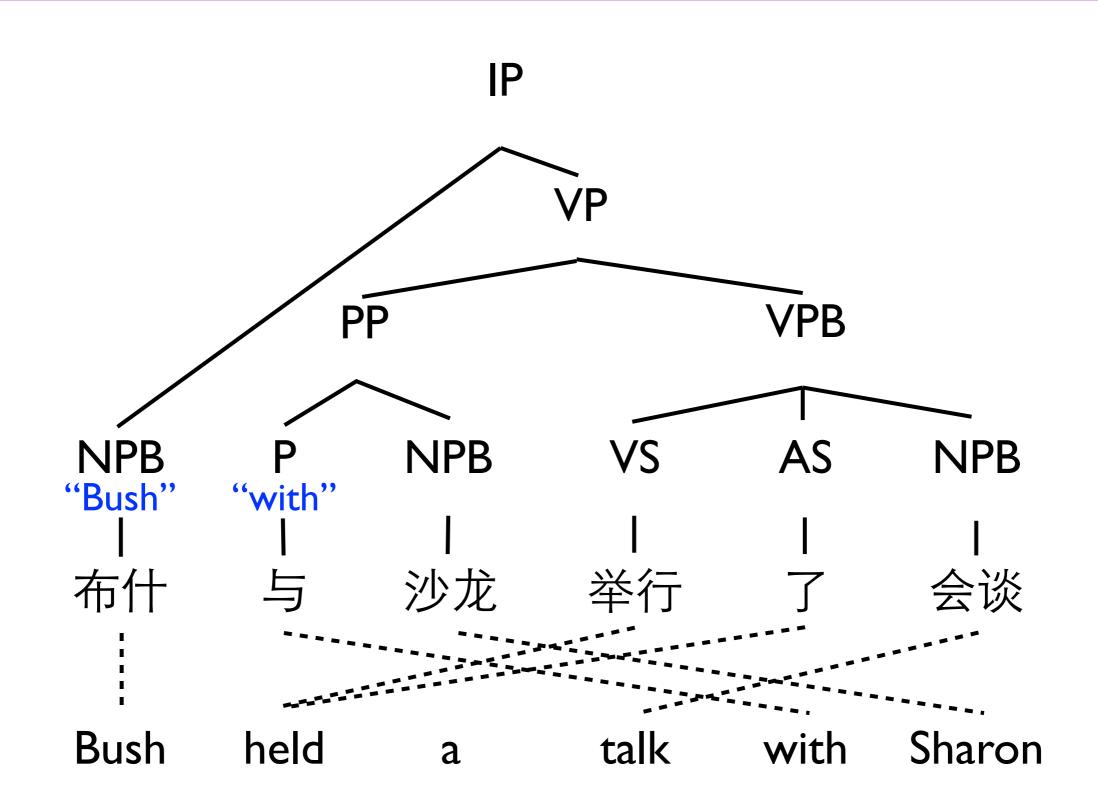
布什 与 沙龙 举行 了 会谈

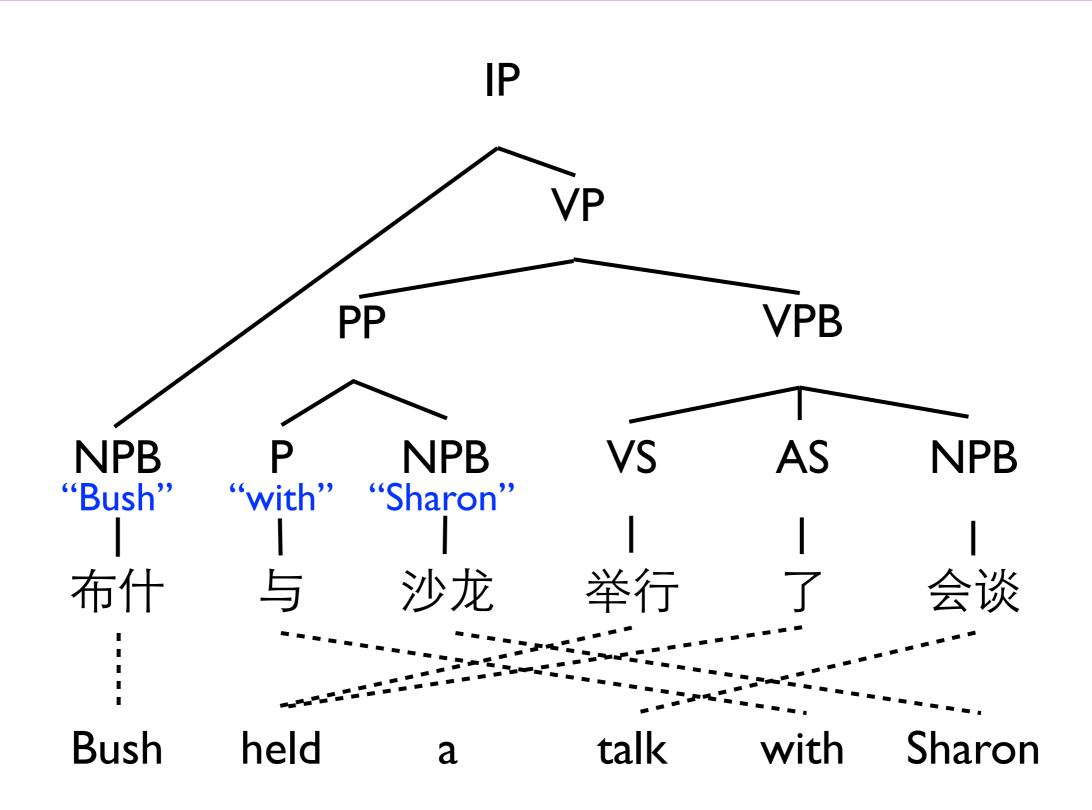
Bush held a talk with Sharon

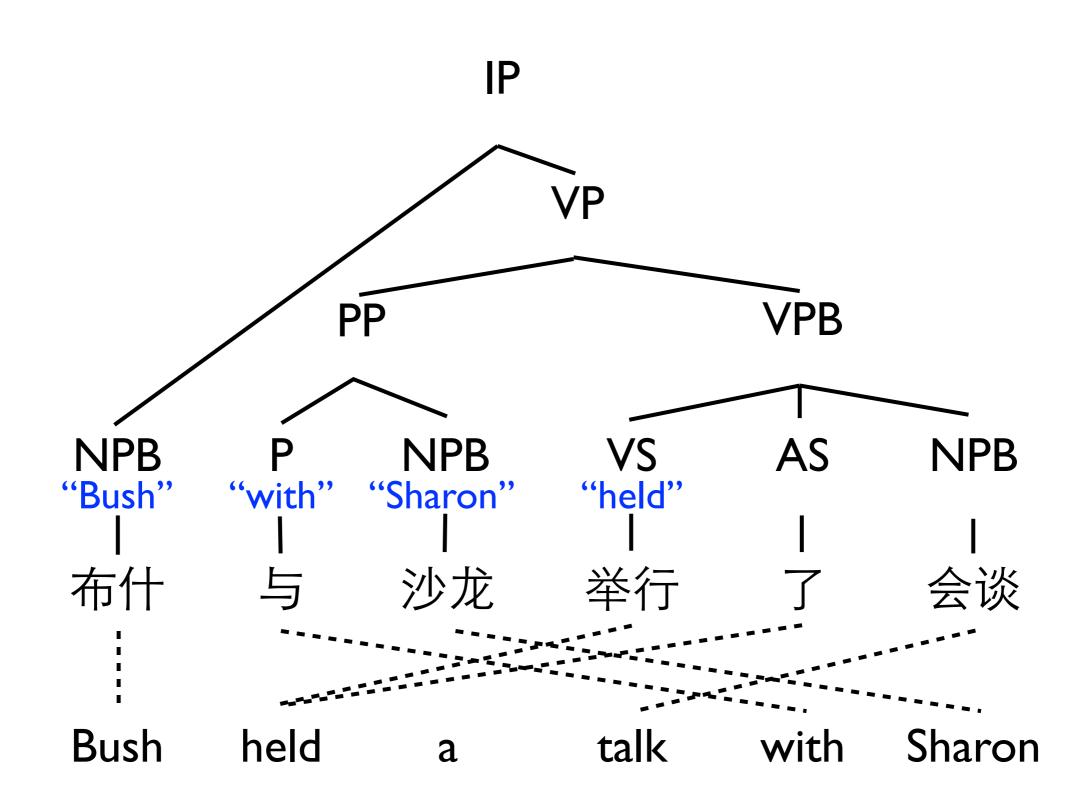


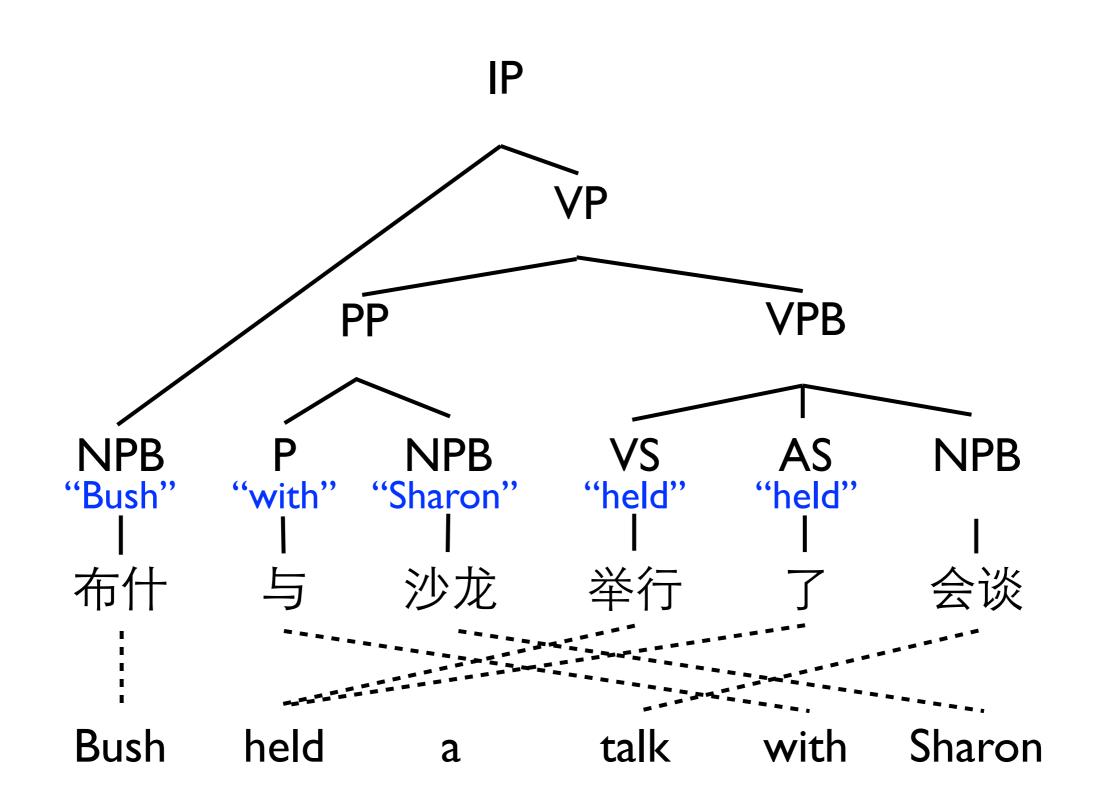


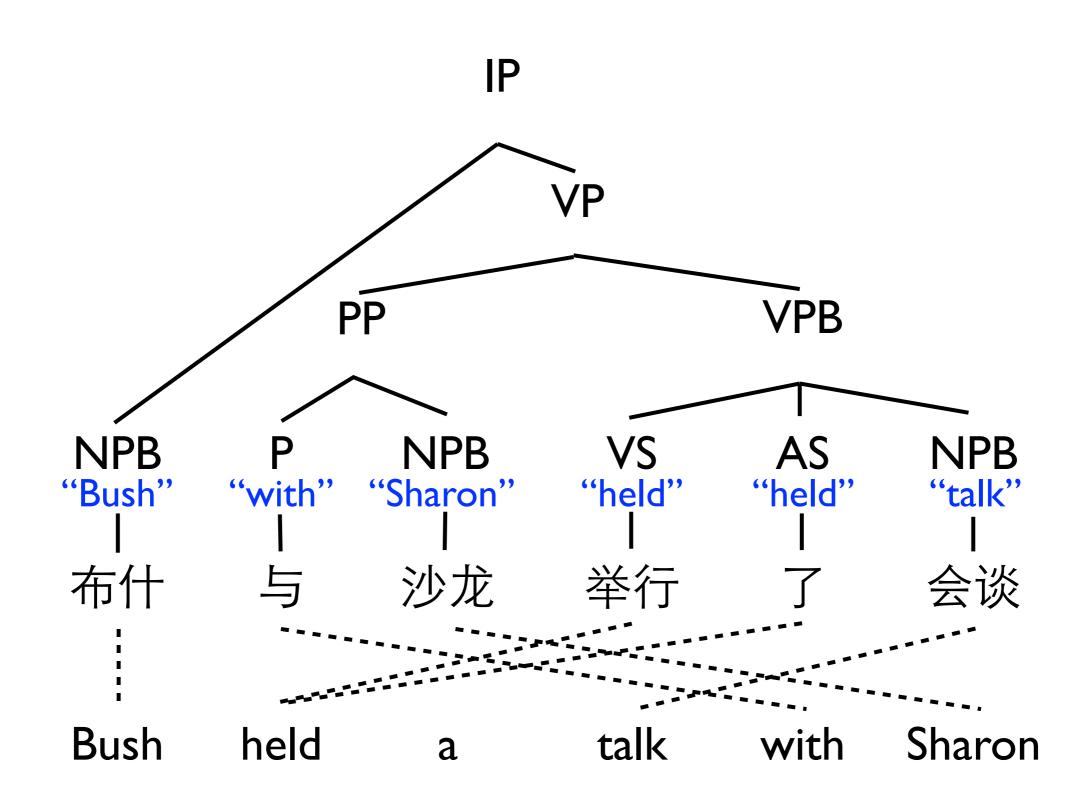


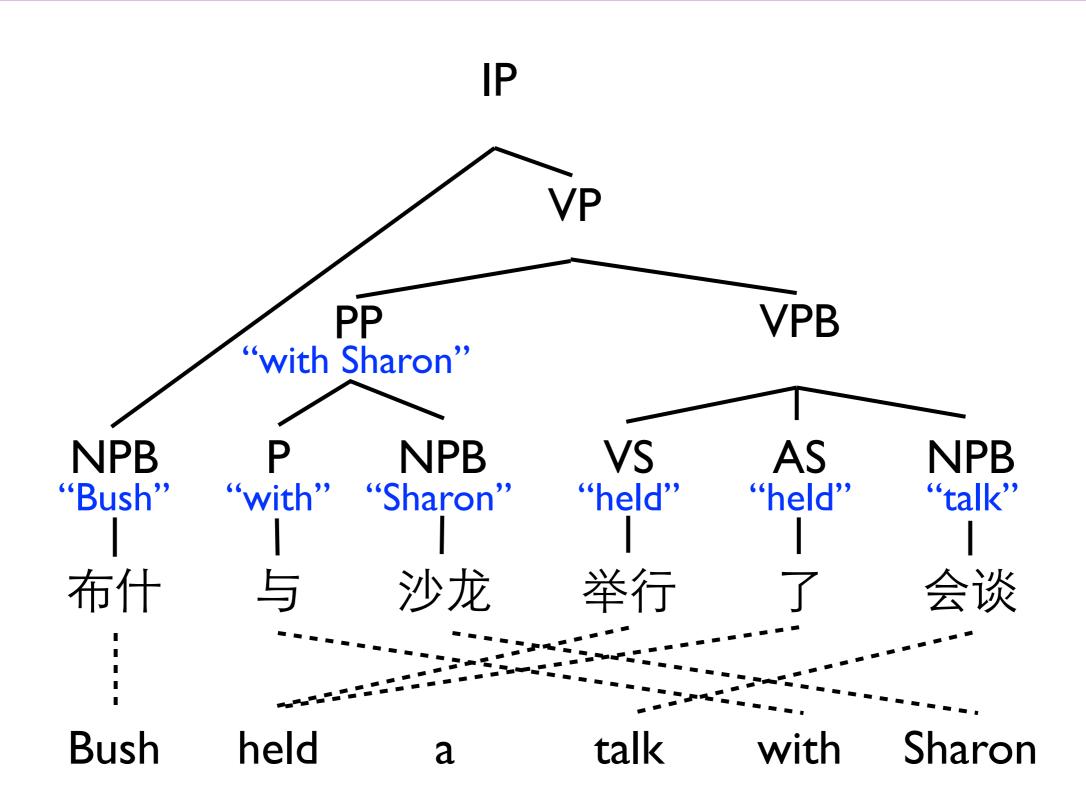


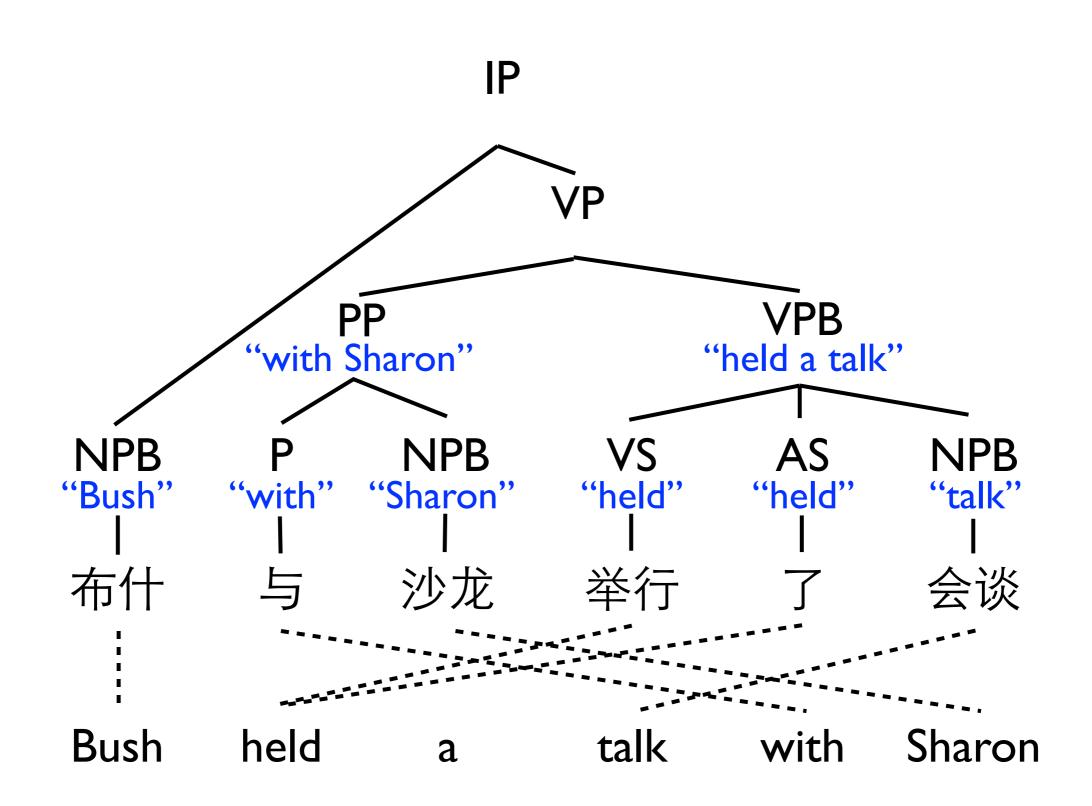


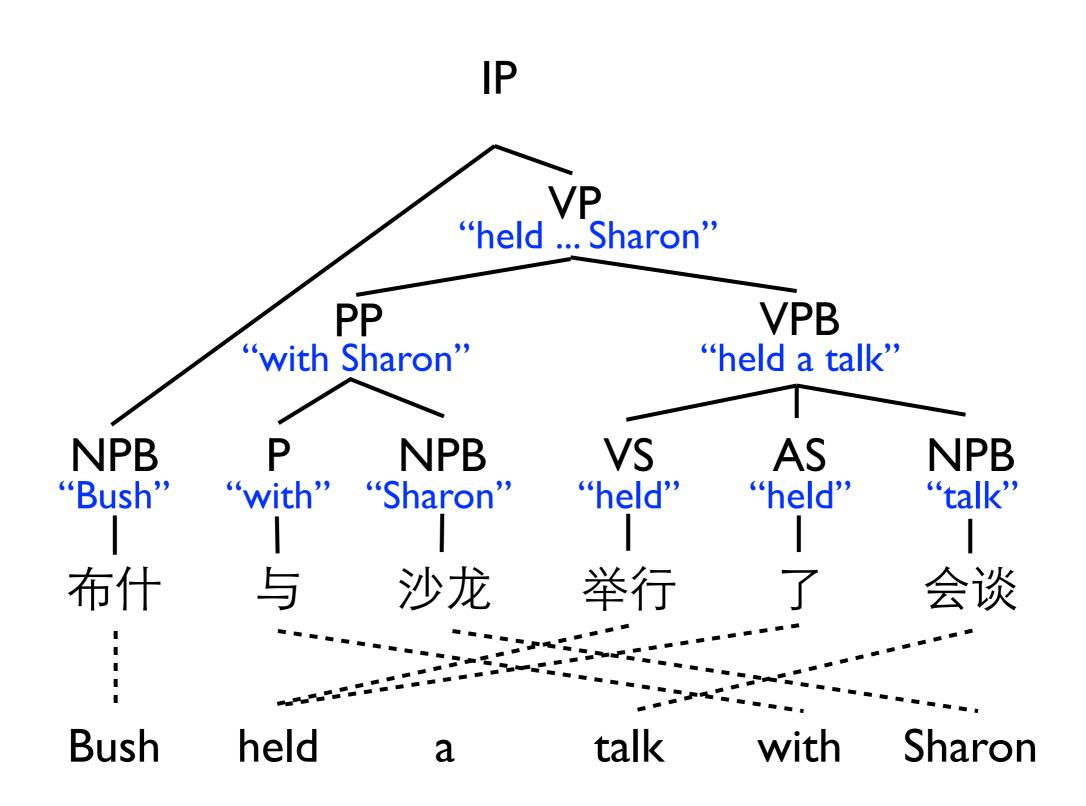


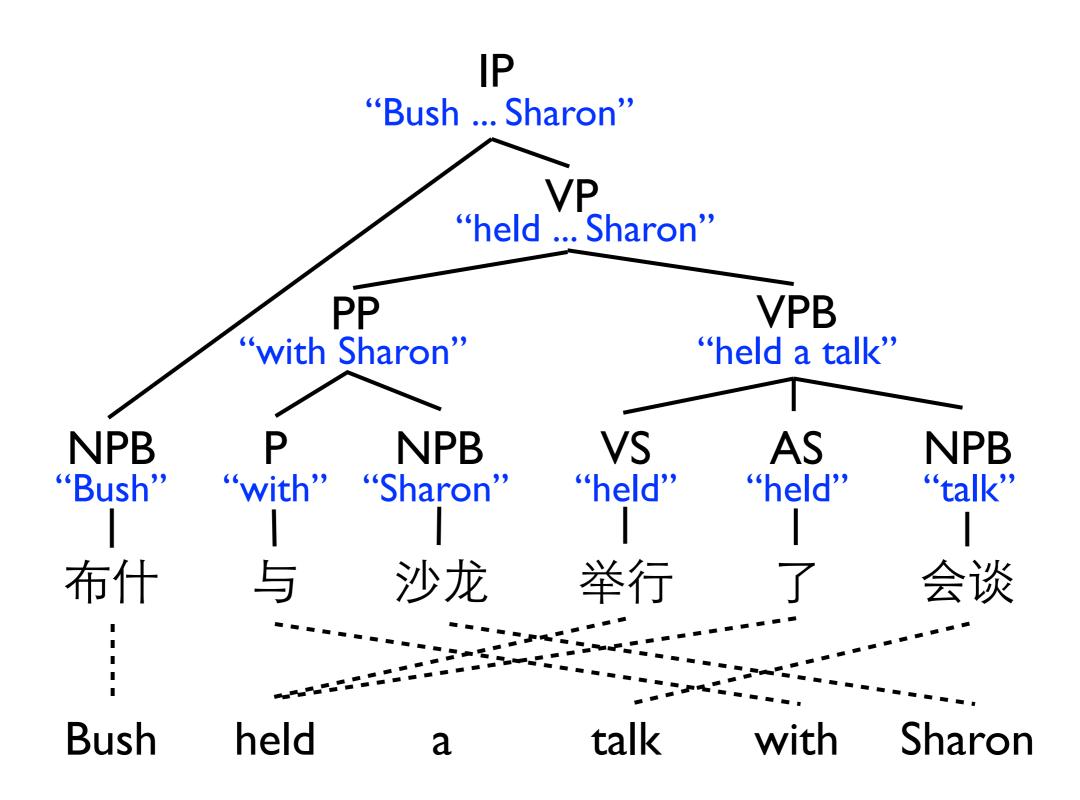


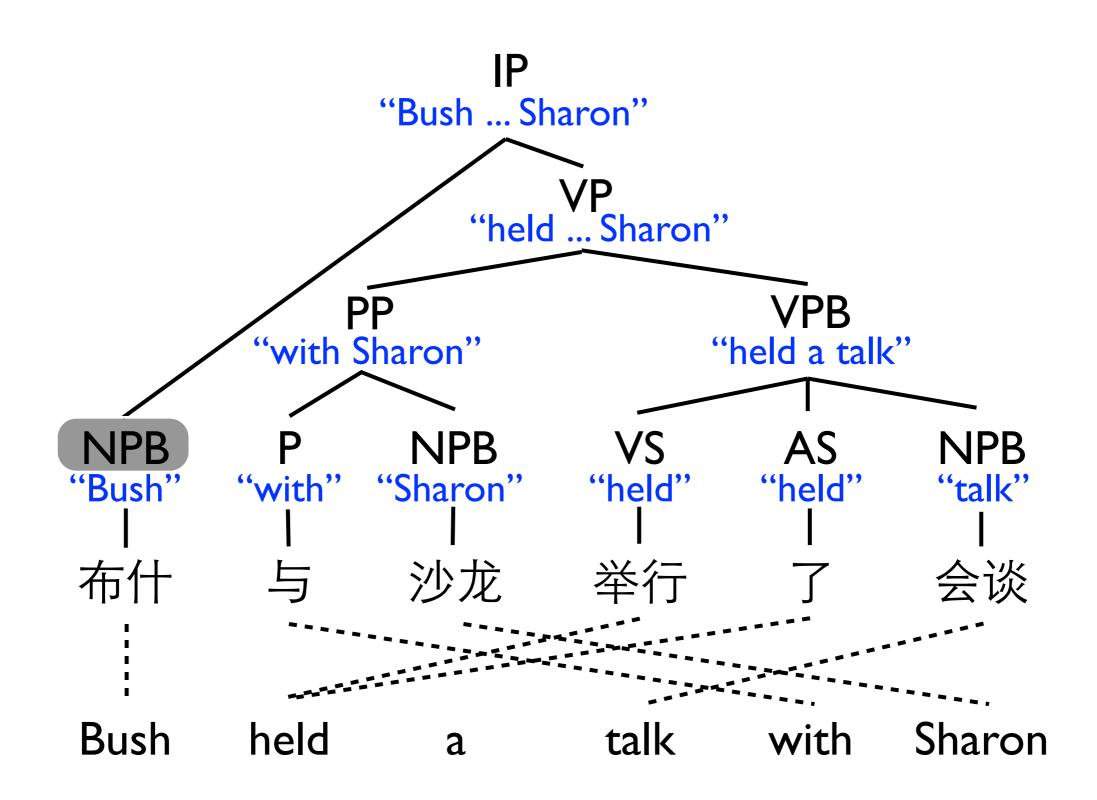


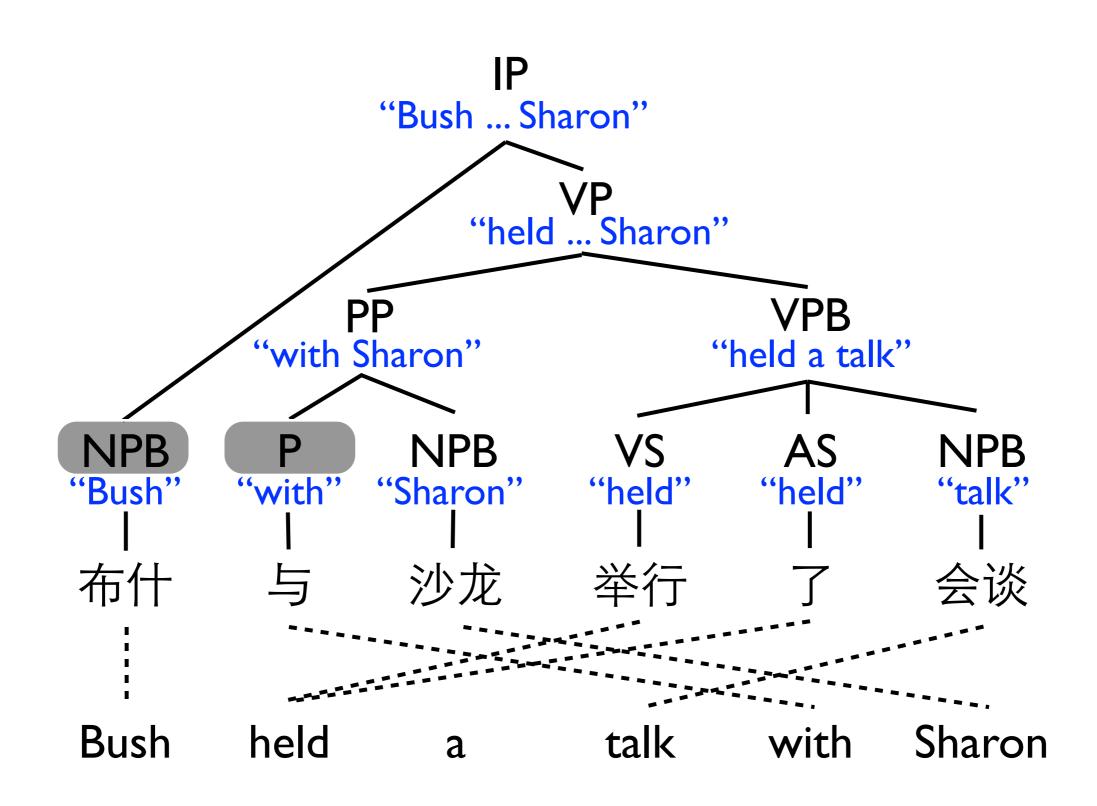


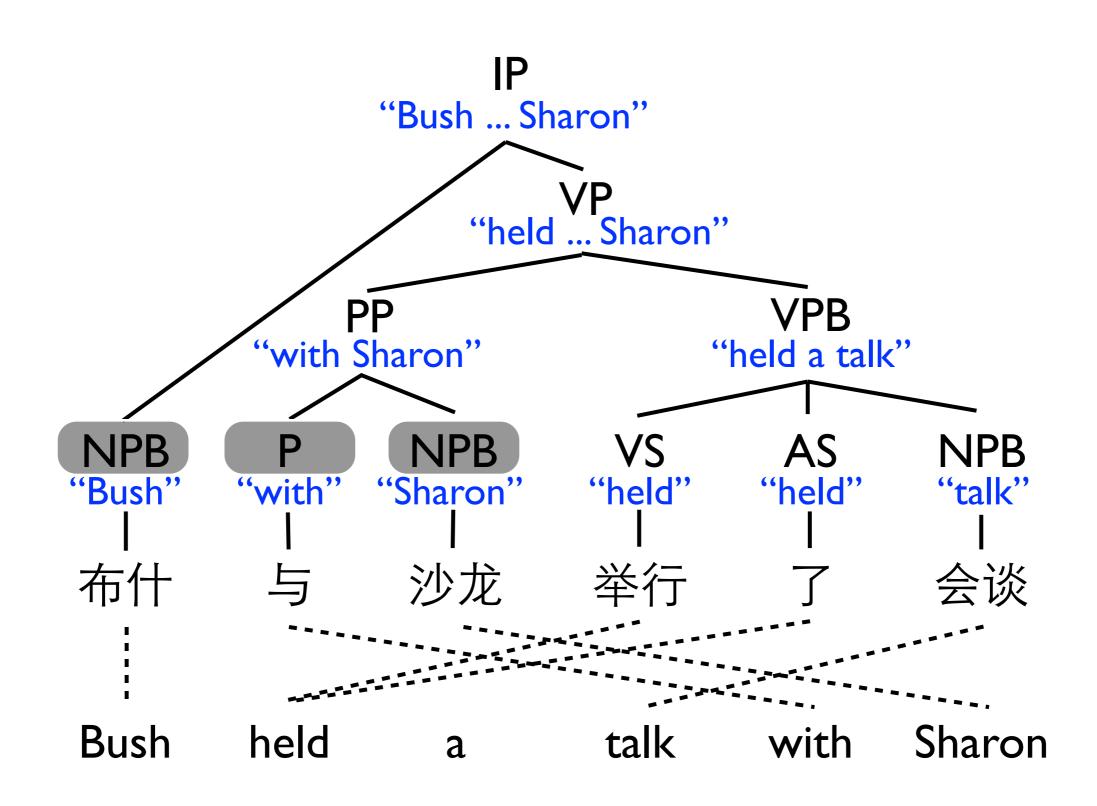


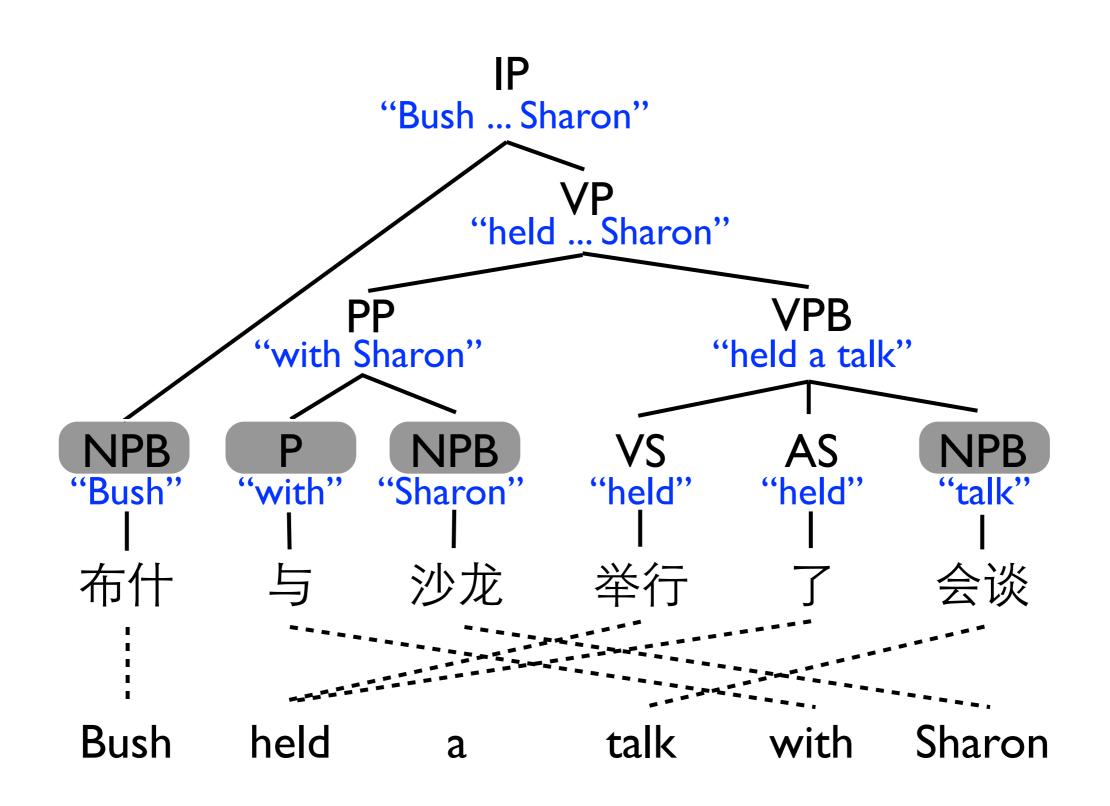


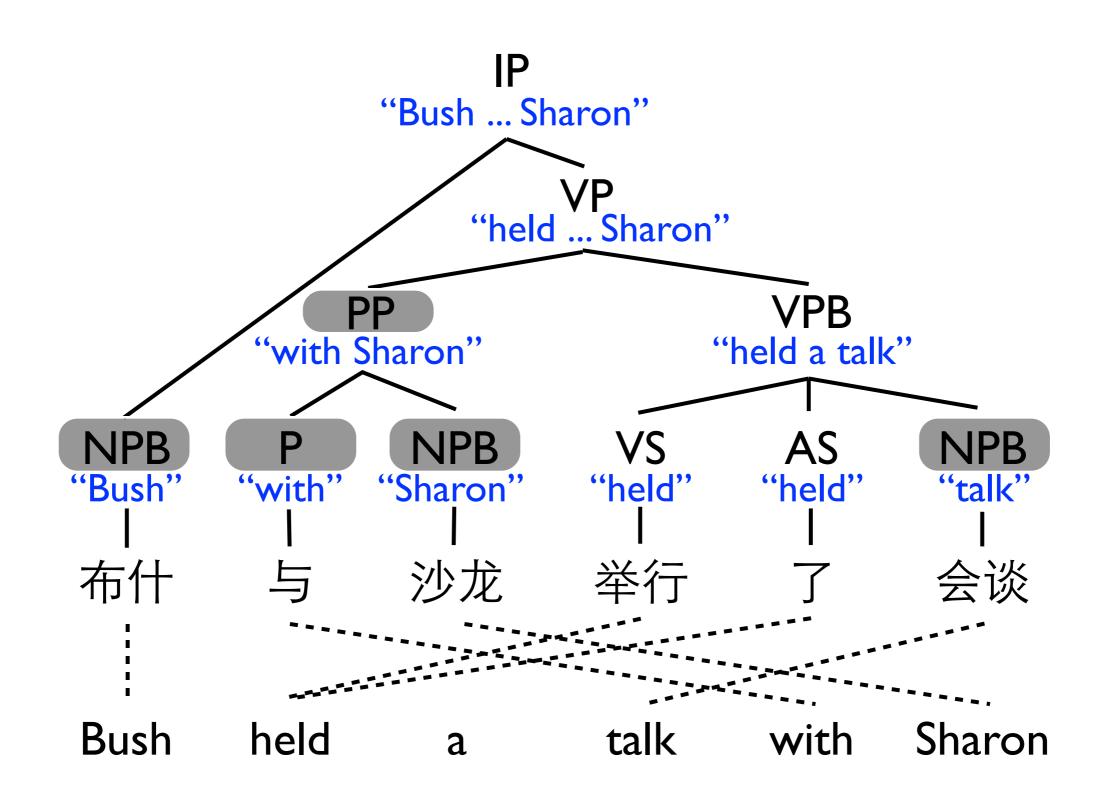


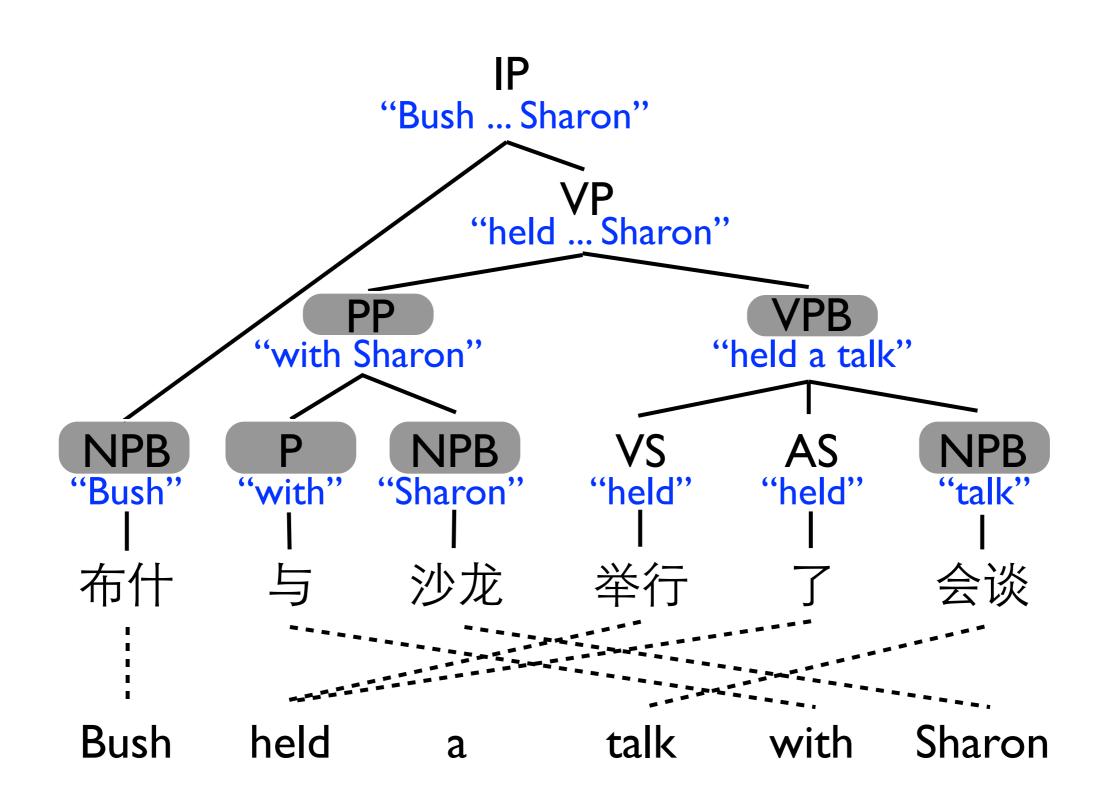


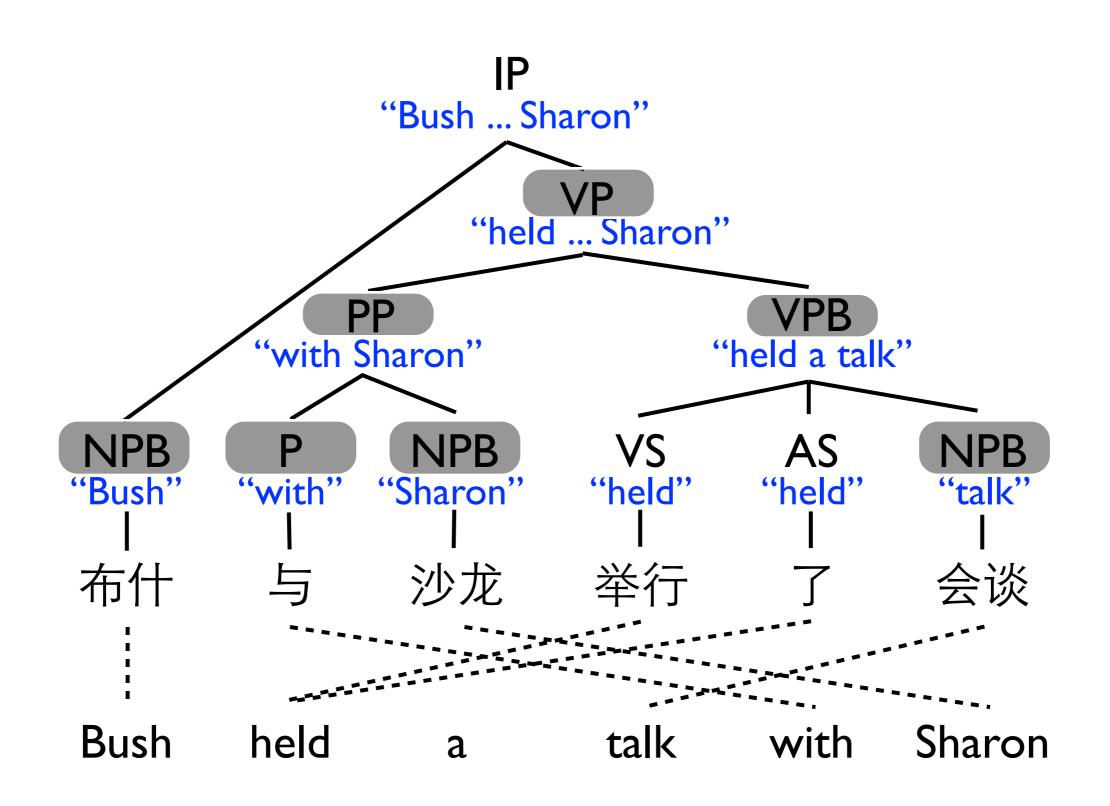


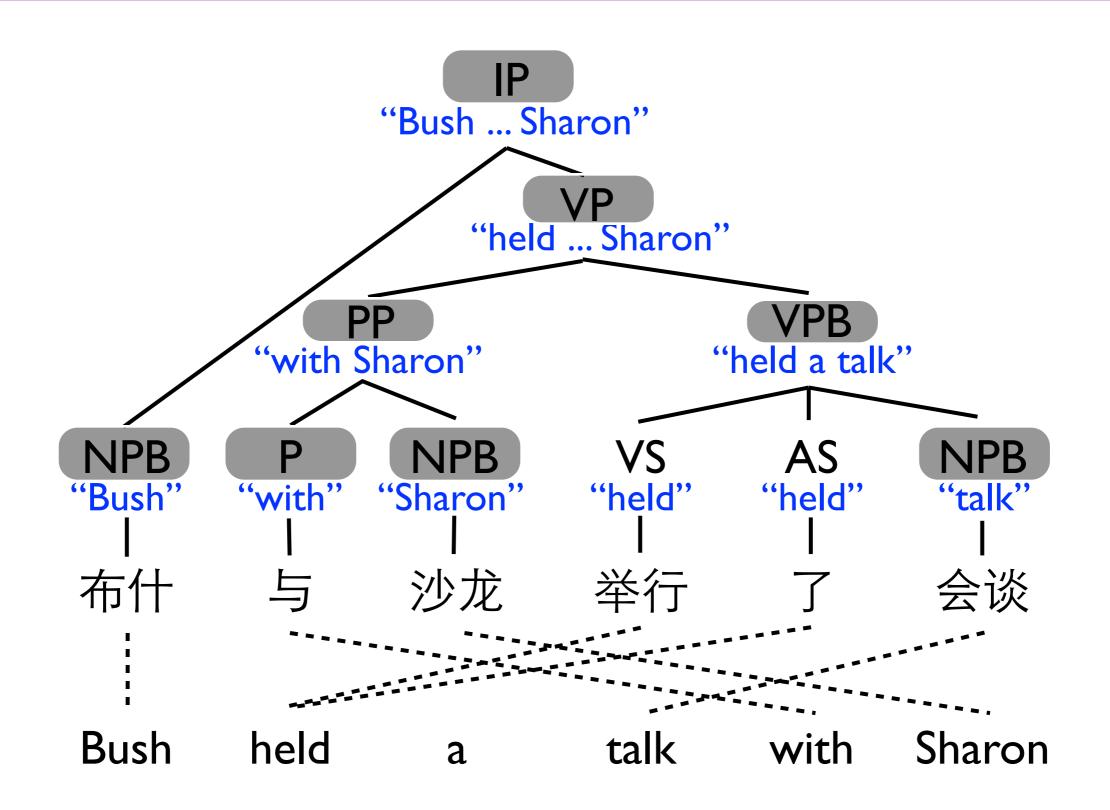


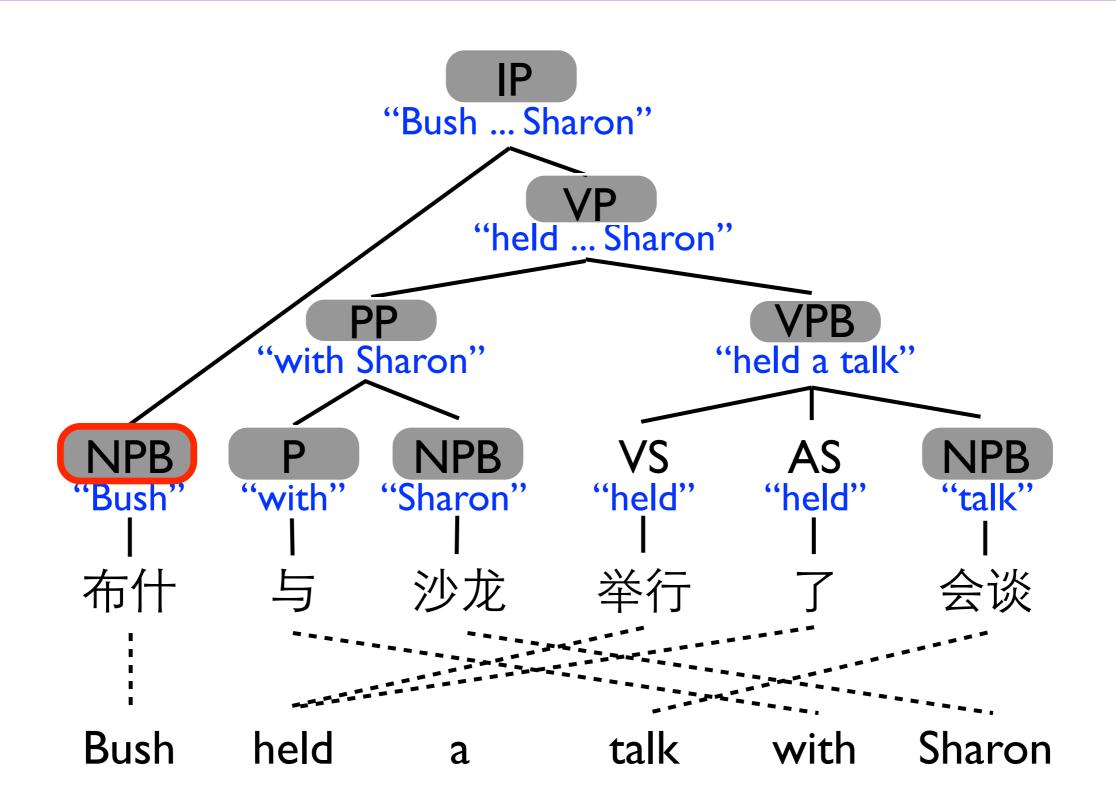


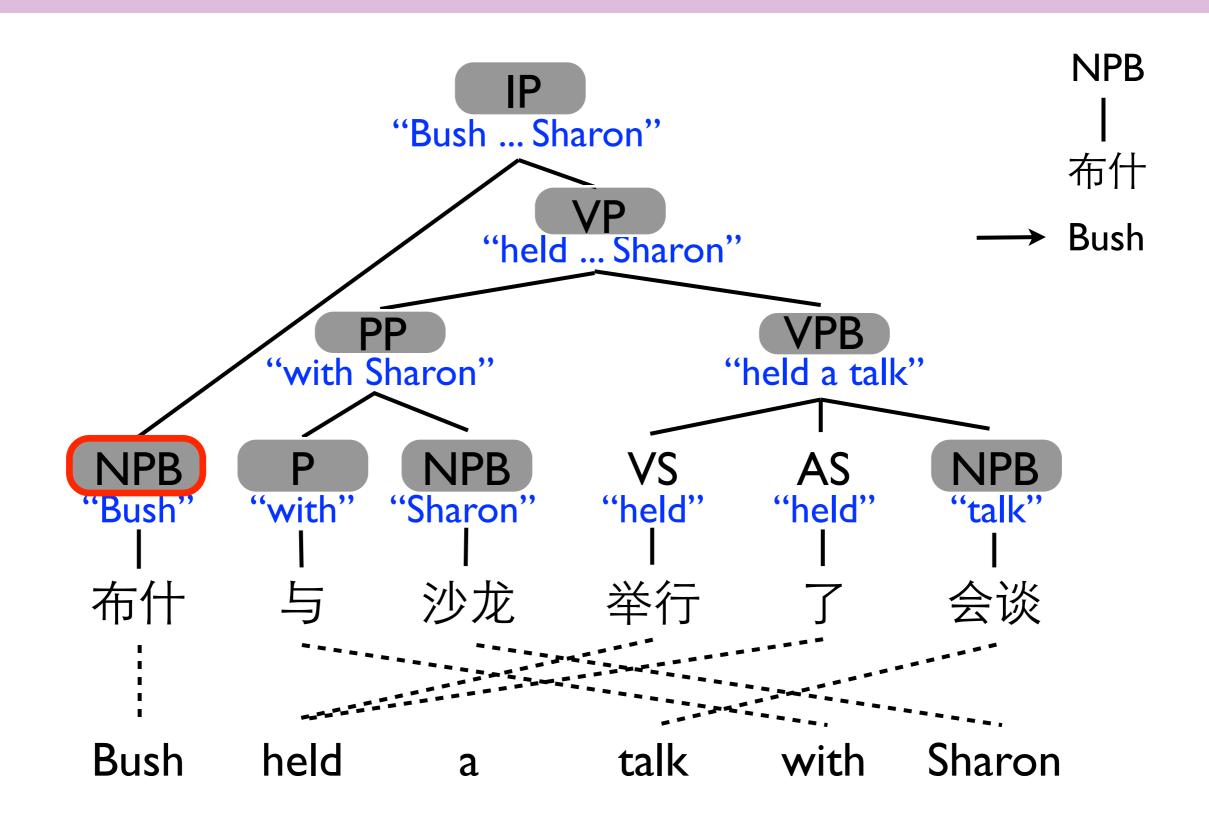


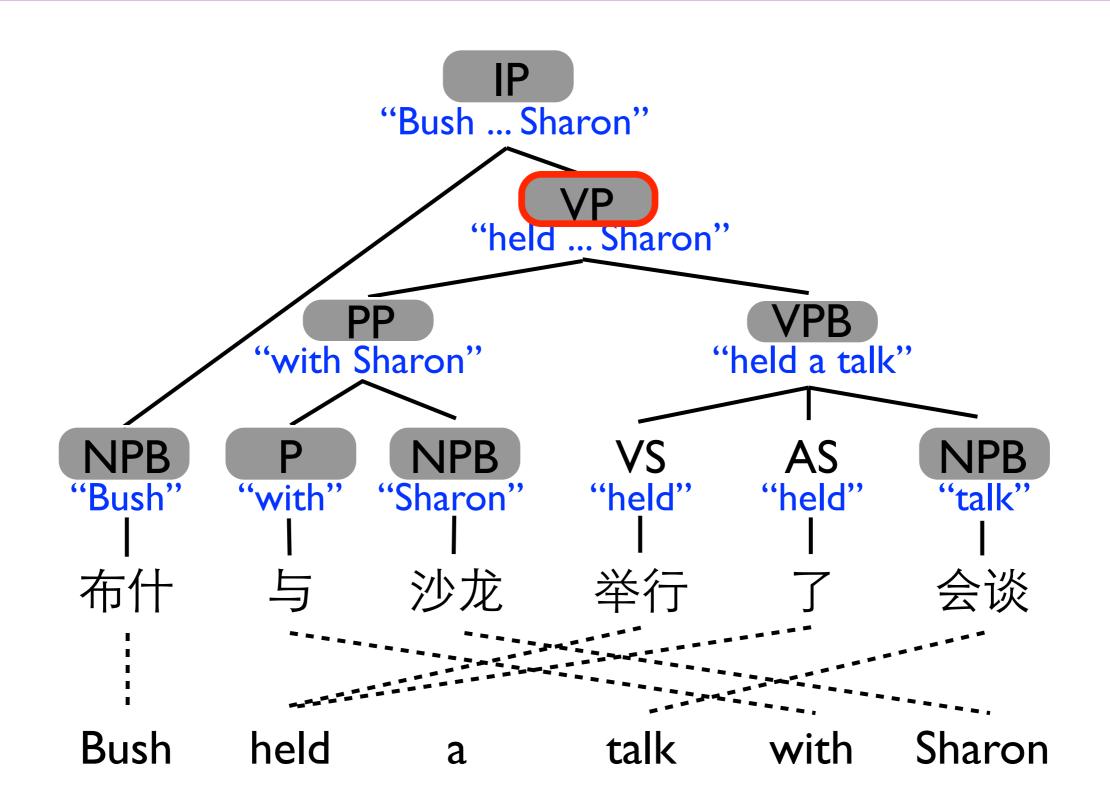


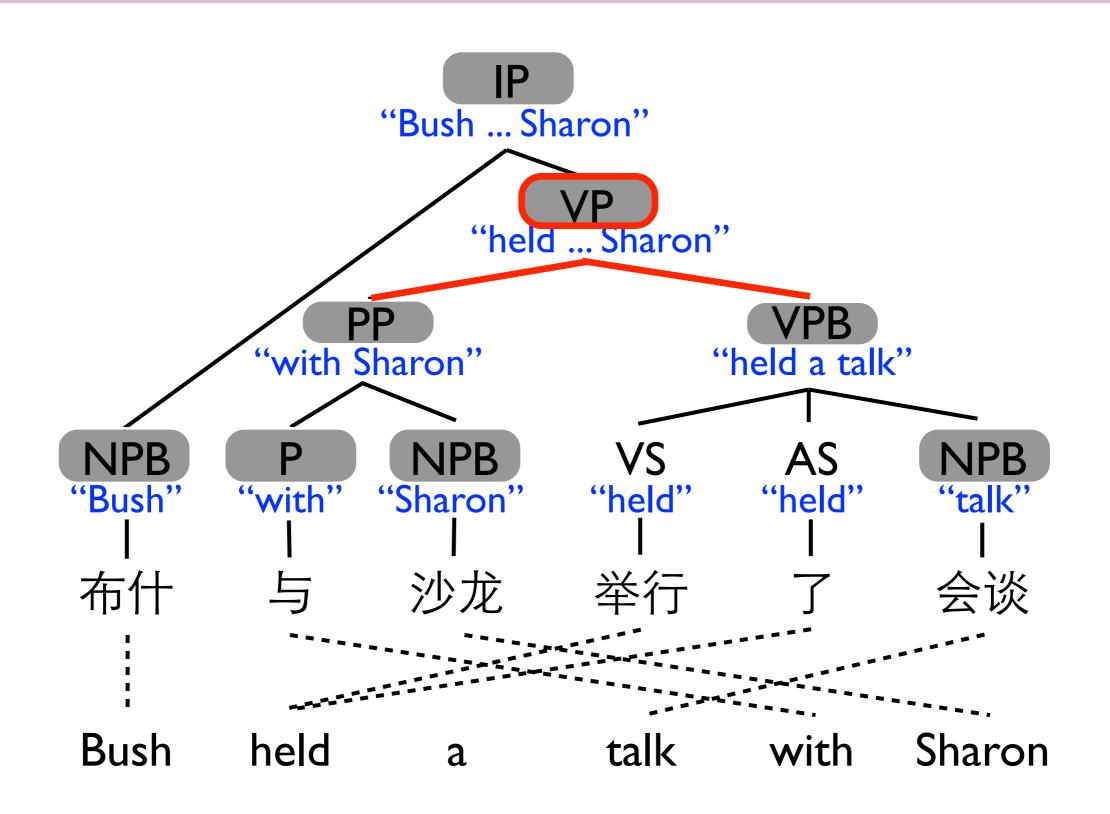


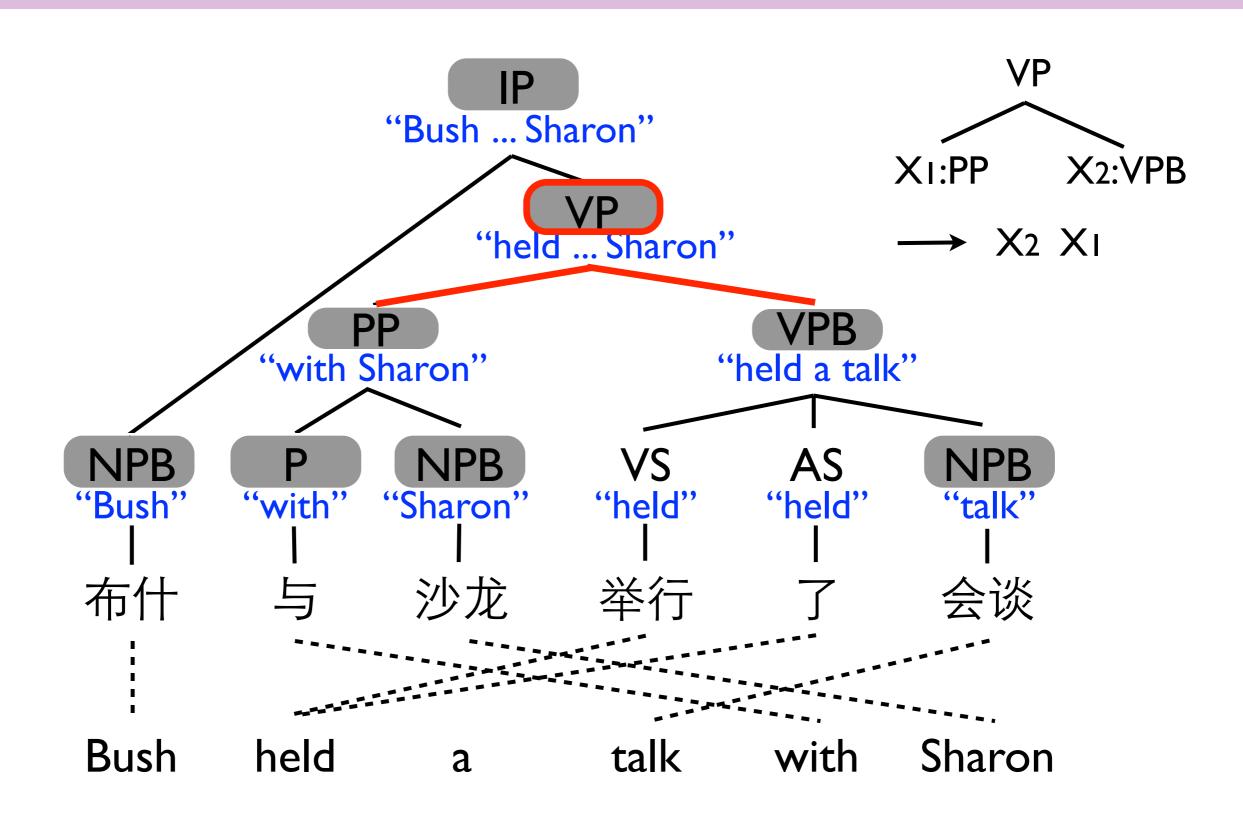


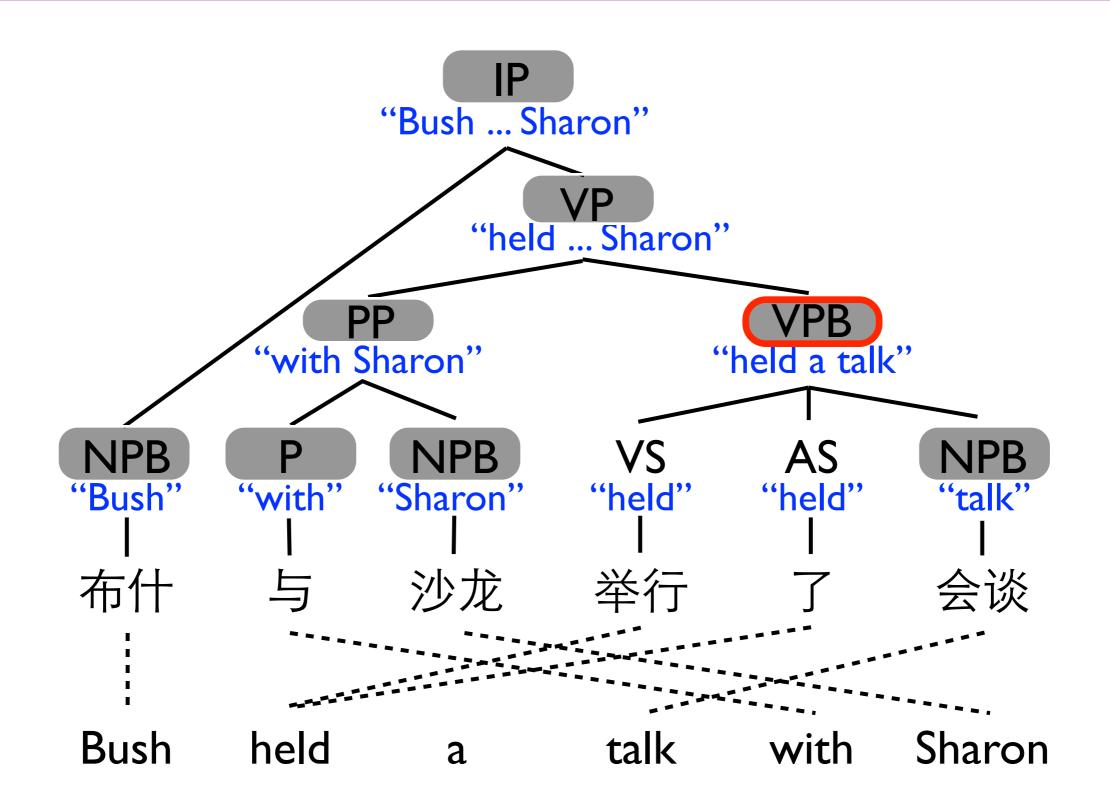


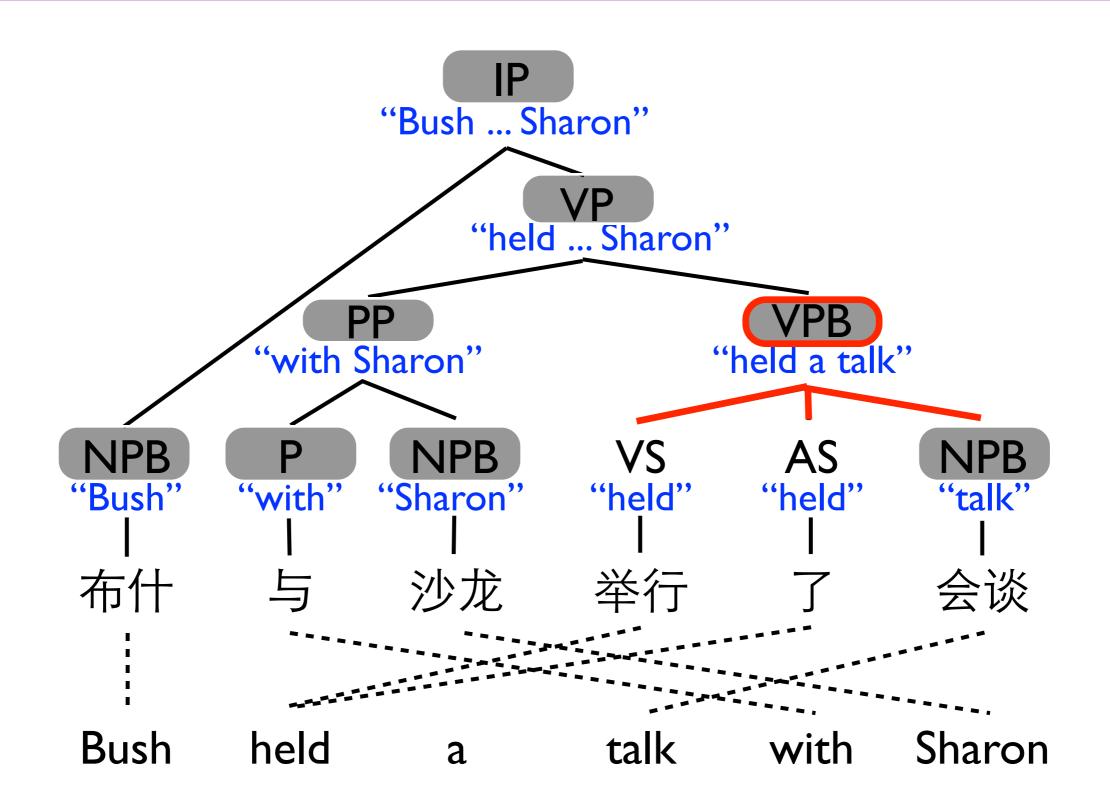


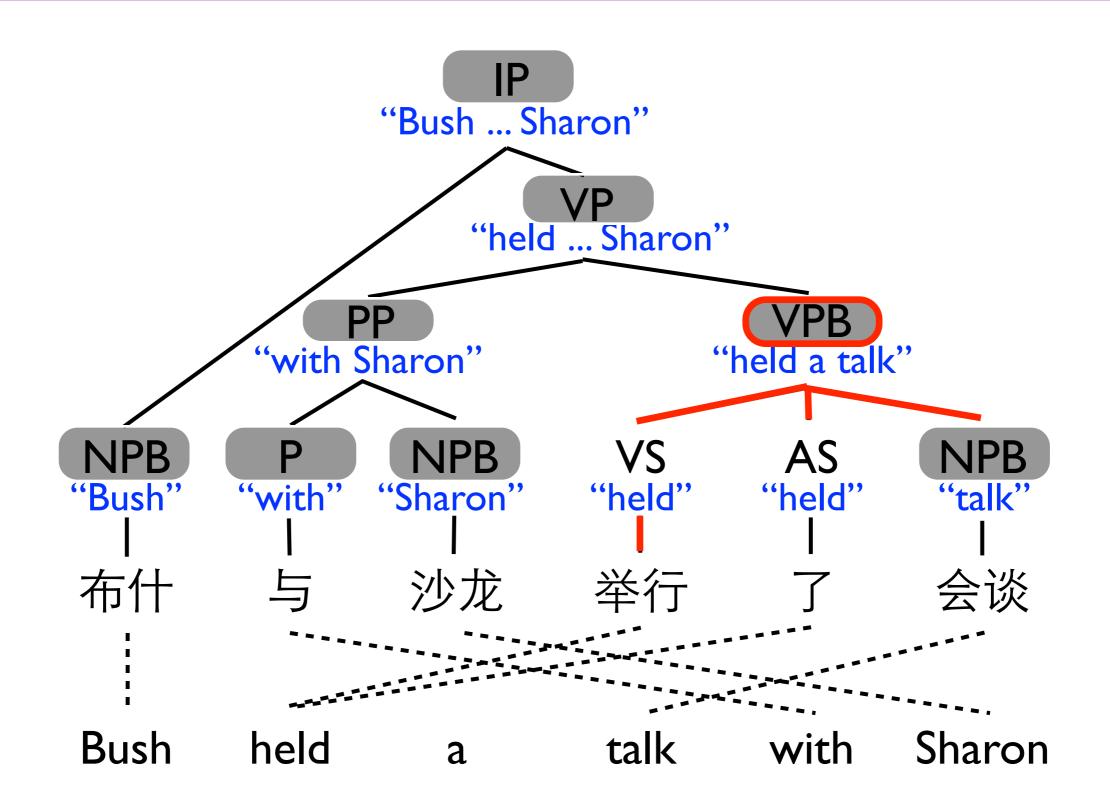


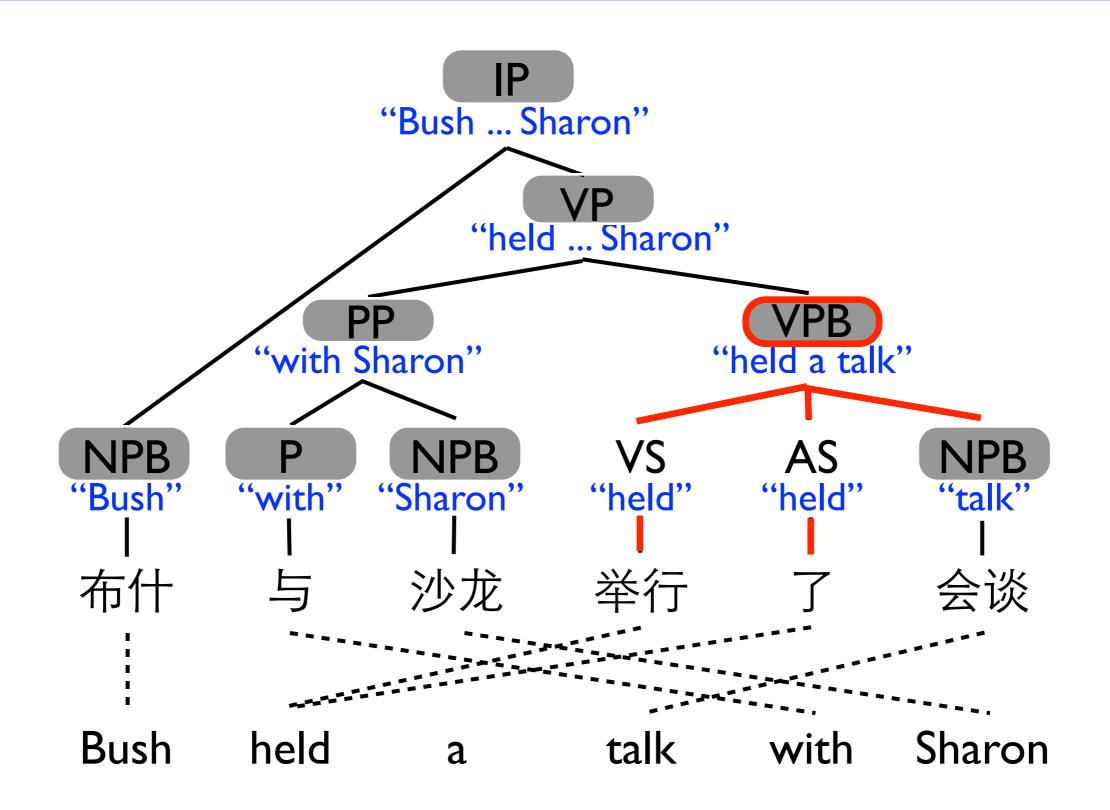


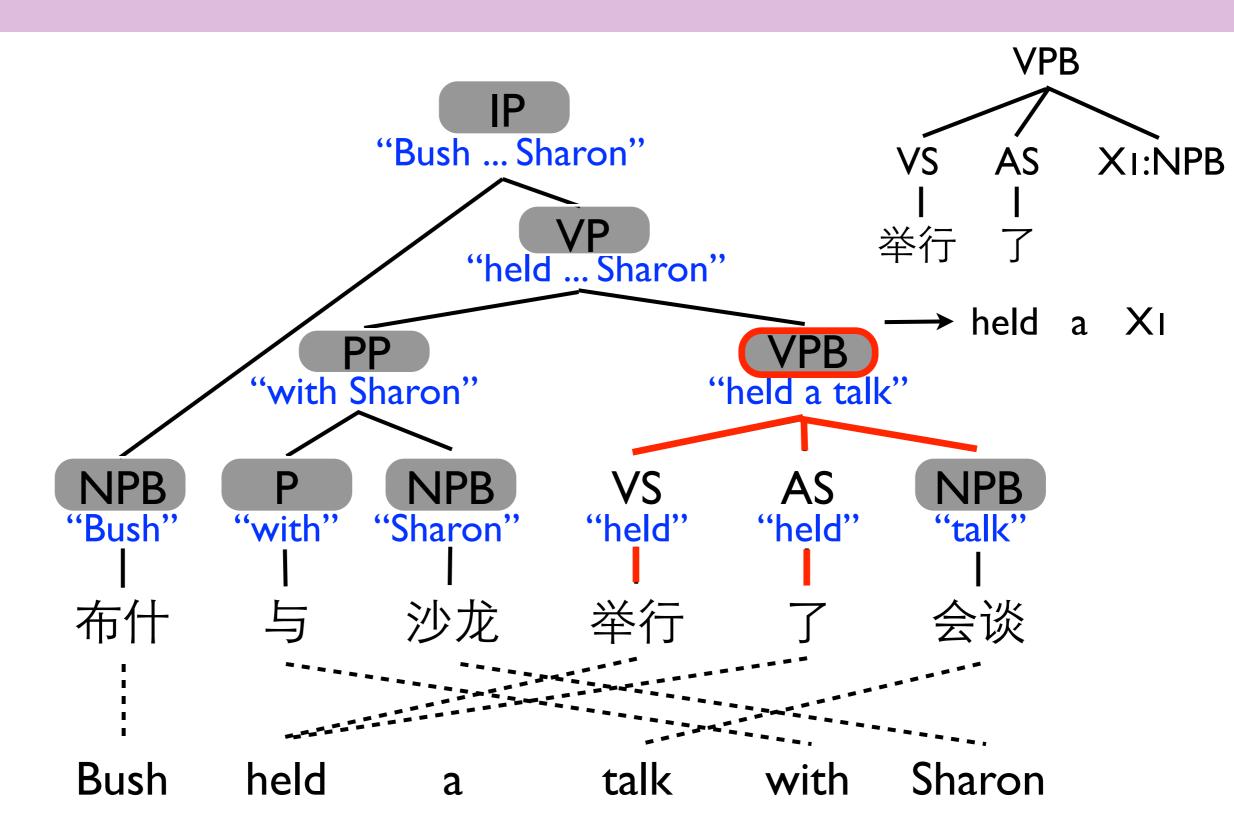




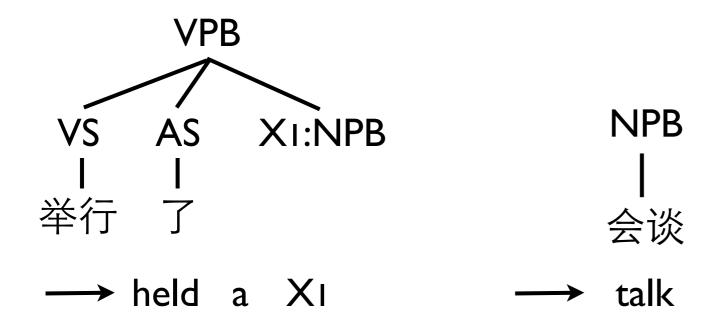


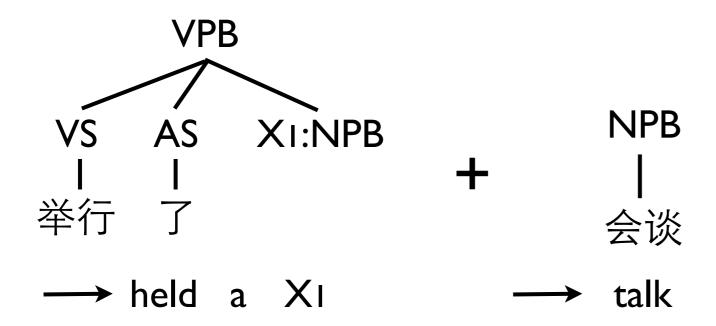


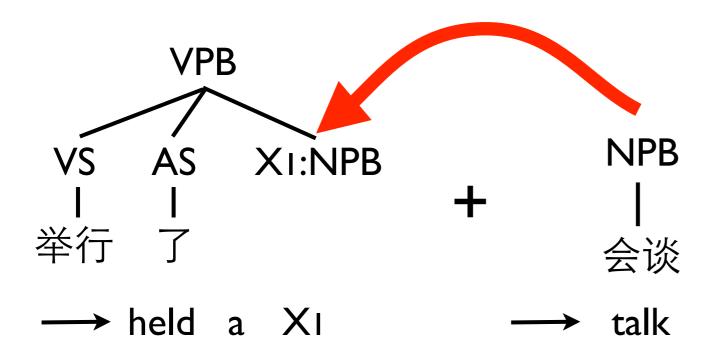


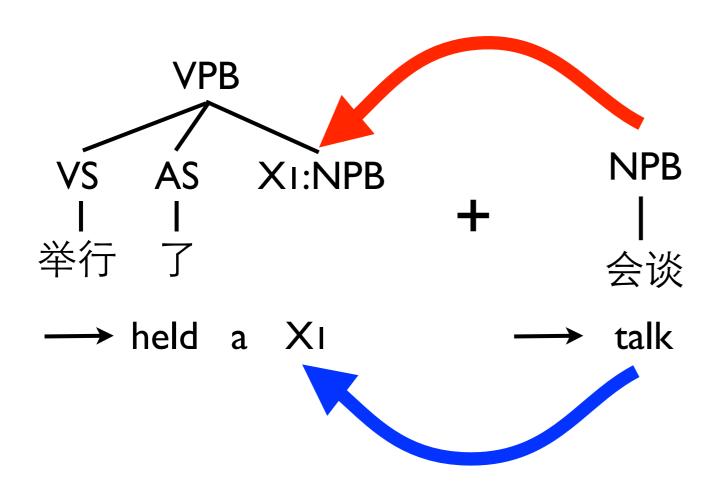


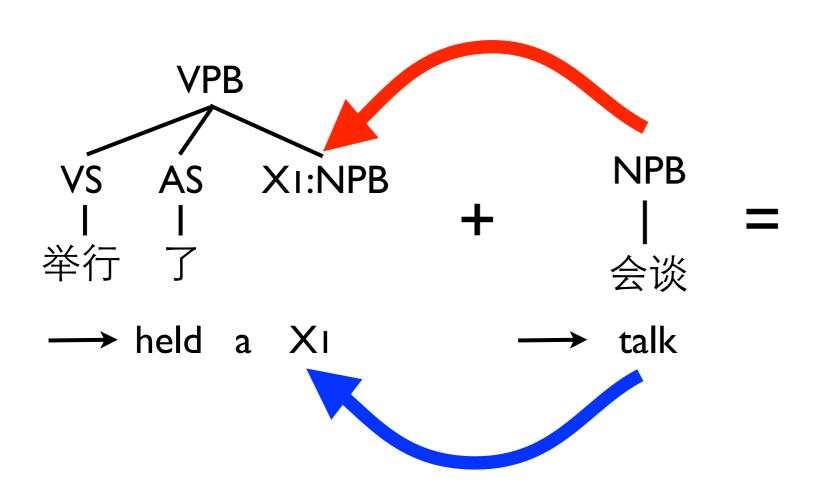
# Rule Composition

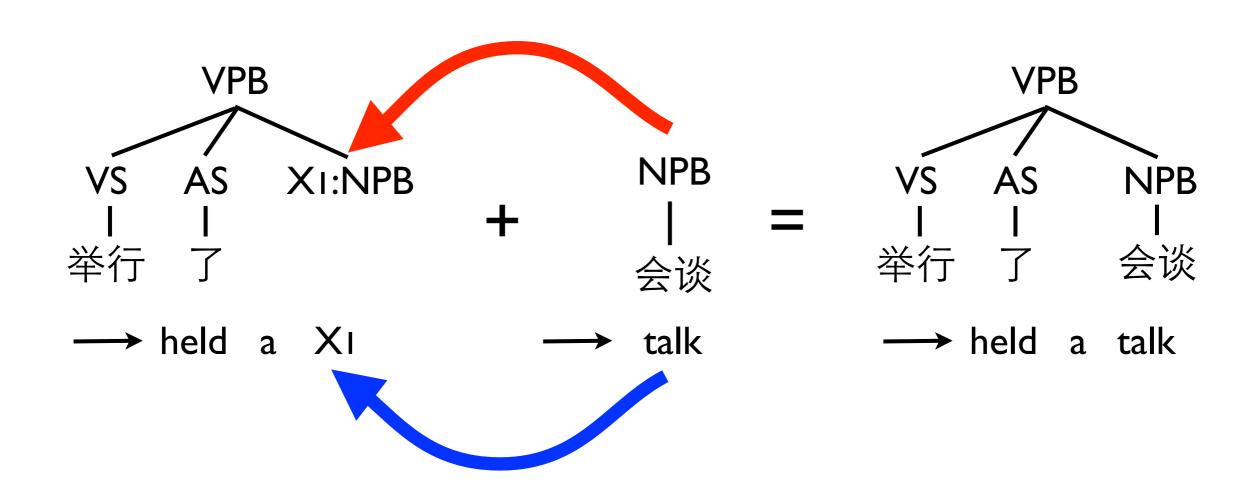


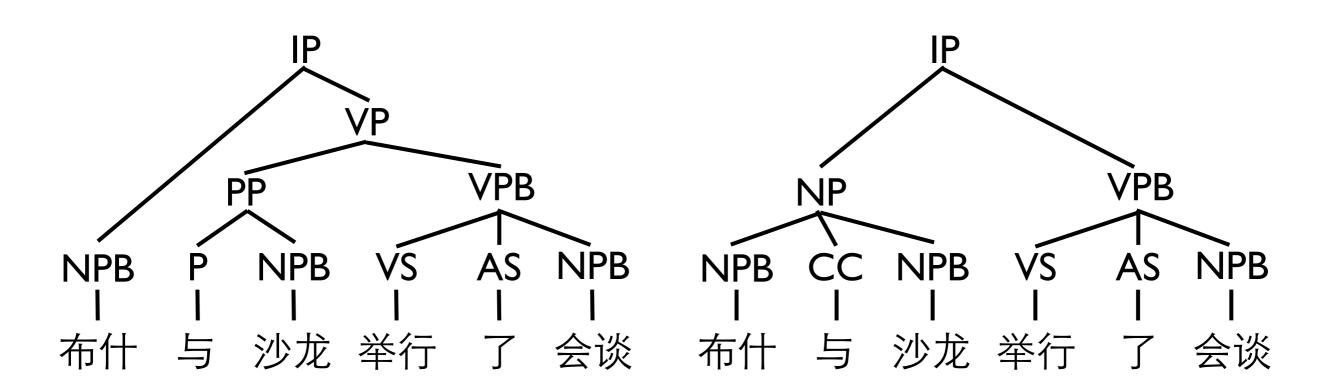


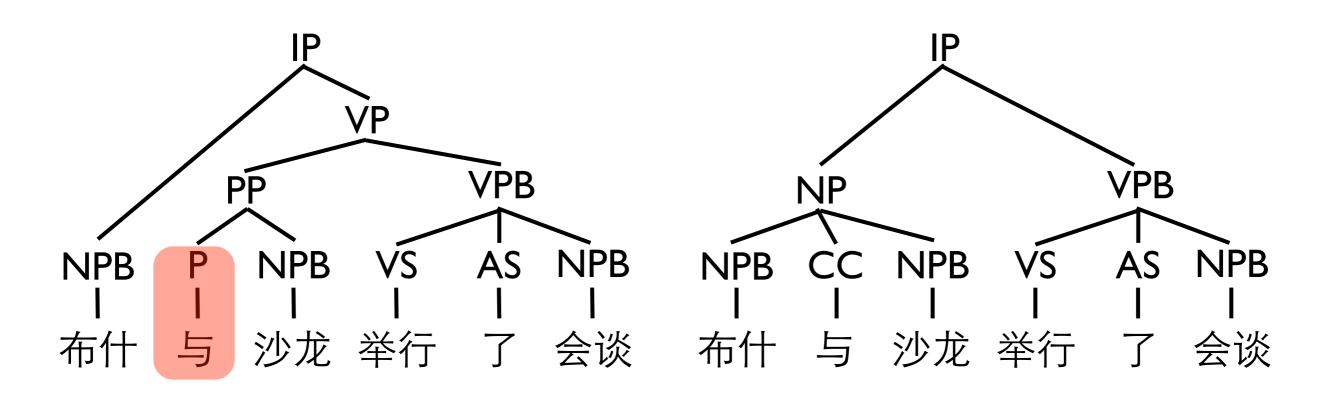


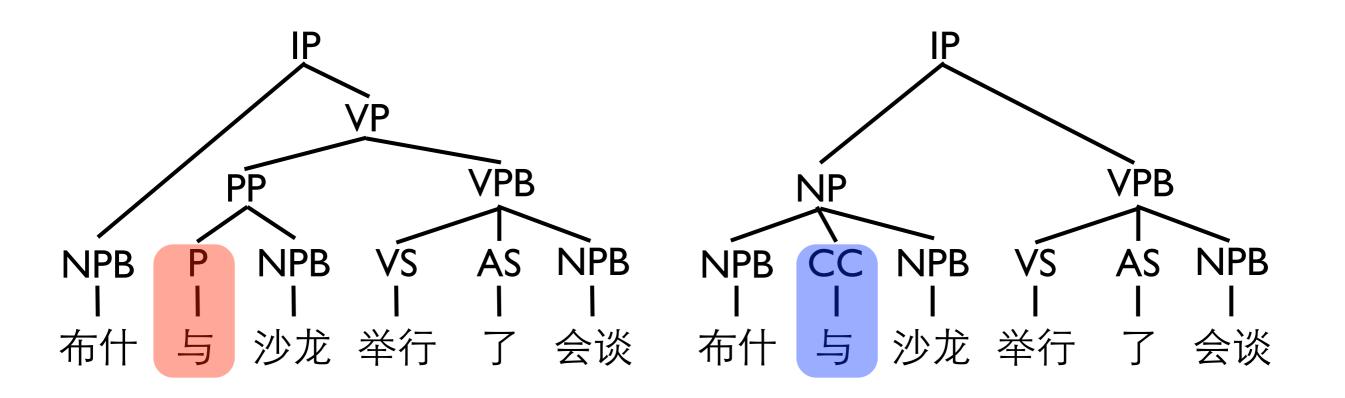


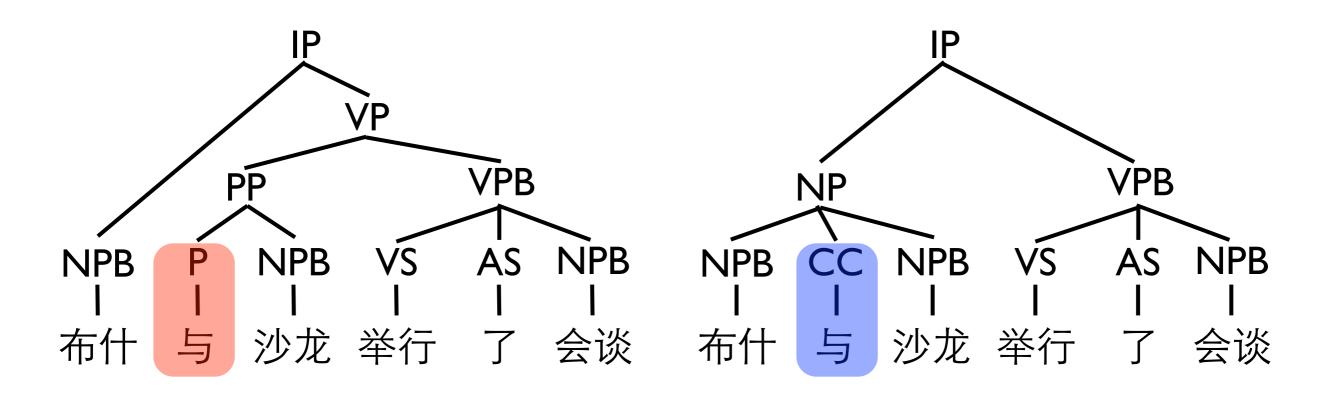




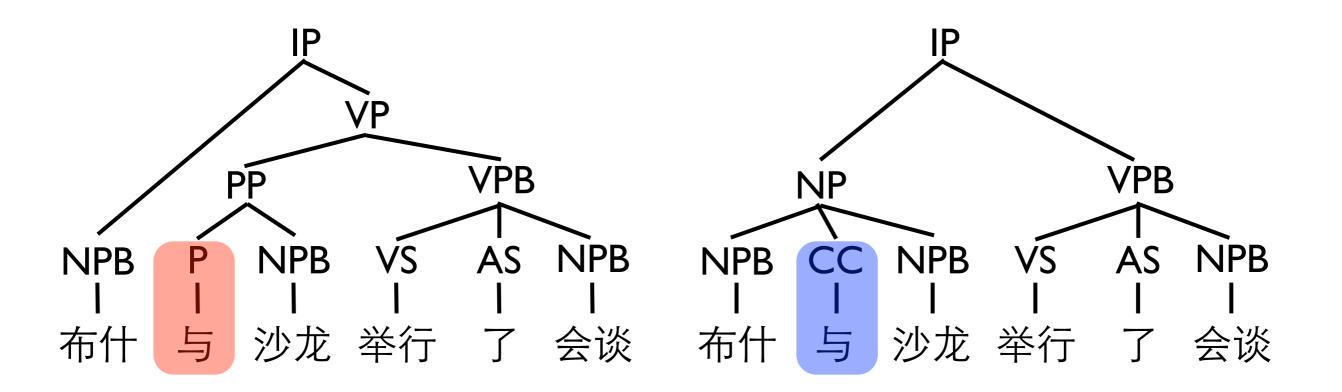








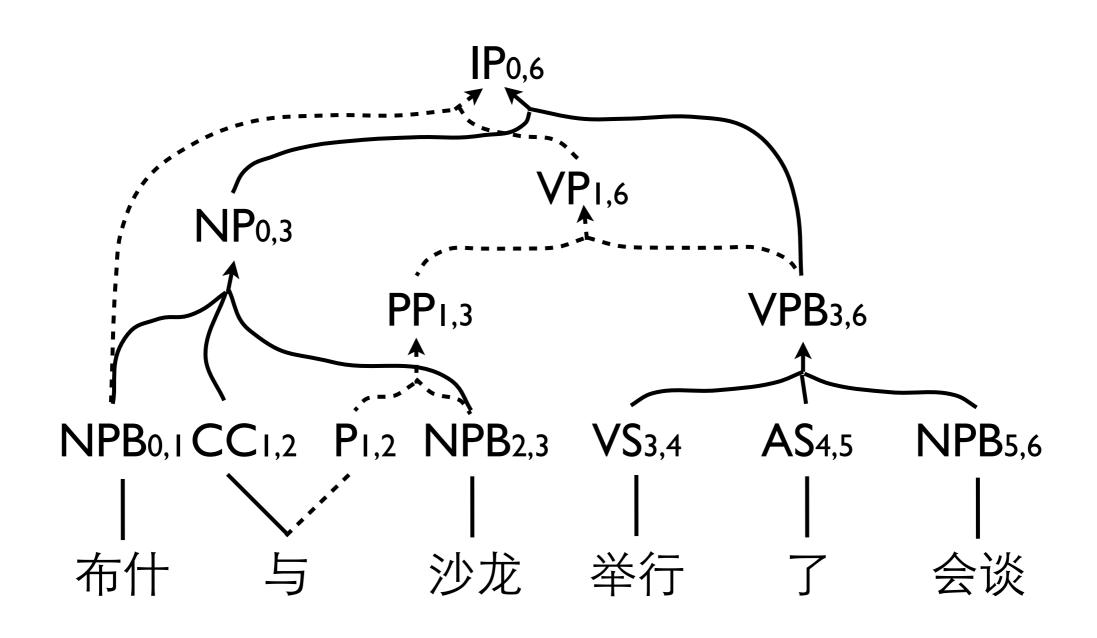
Bush held a talk with Sharon



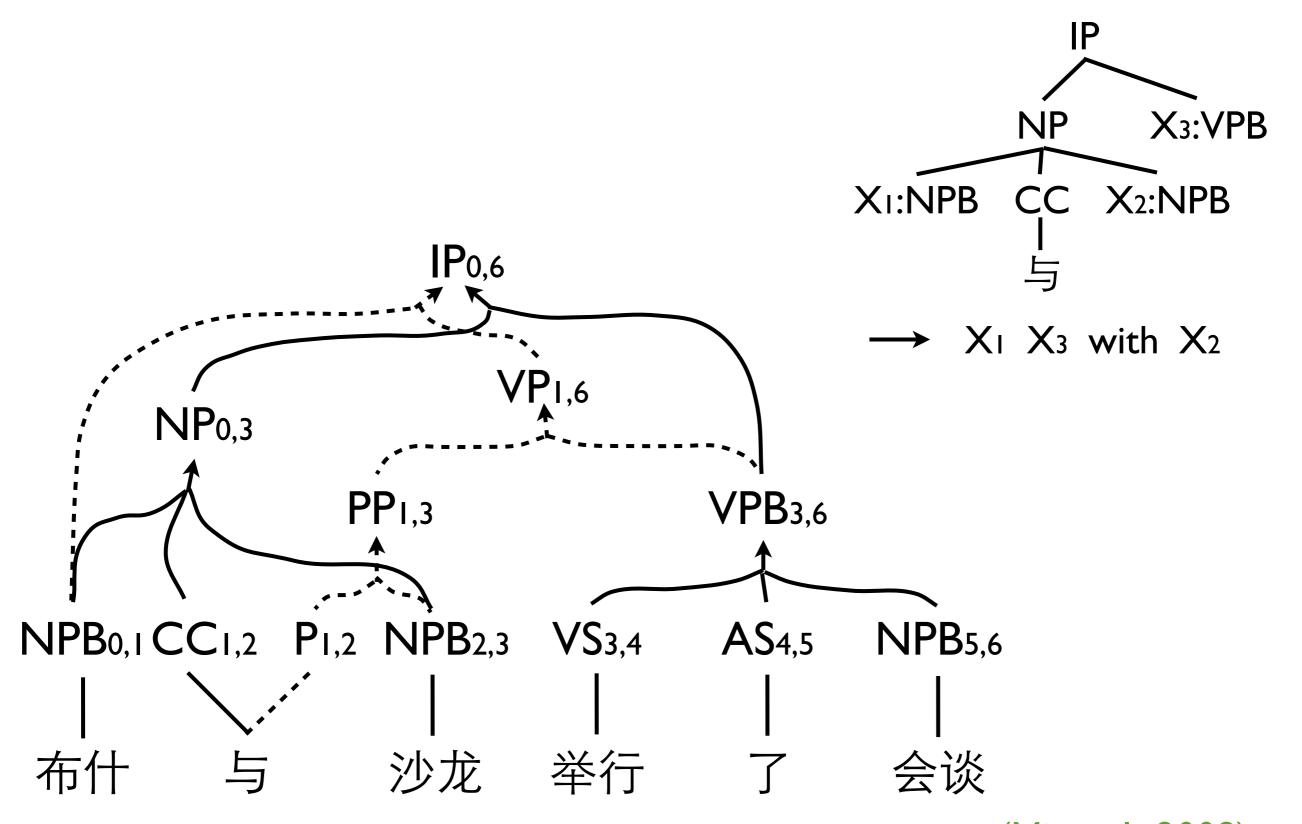
Bush held a talk with Sharon

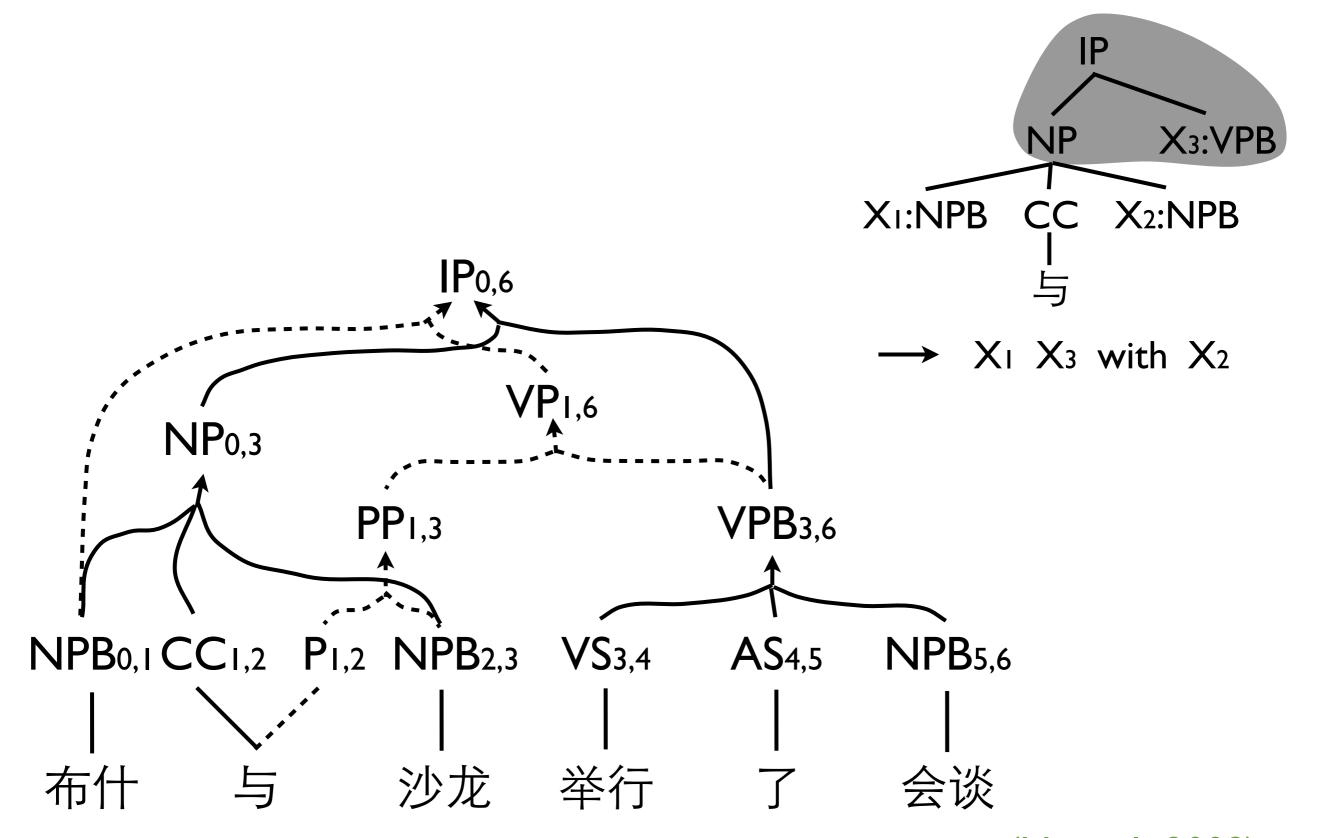
Bush and Sharon held a talk

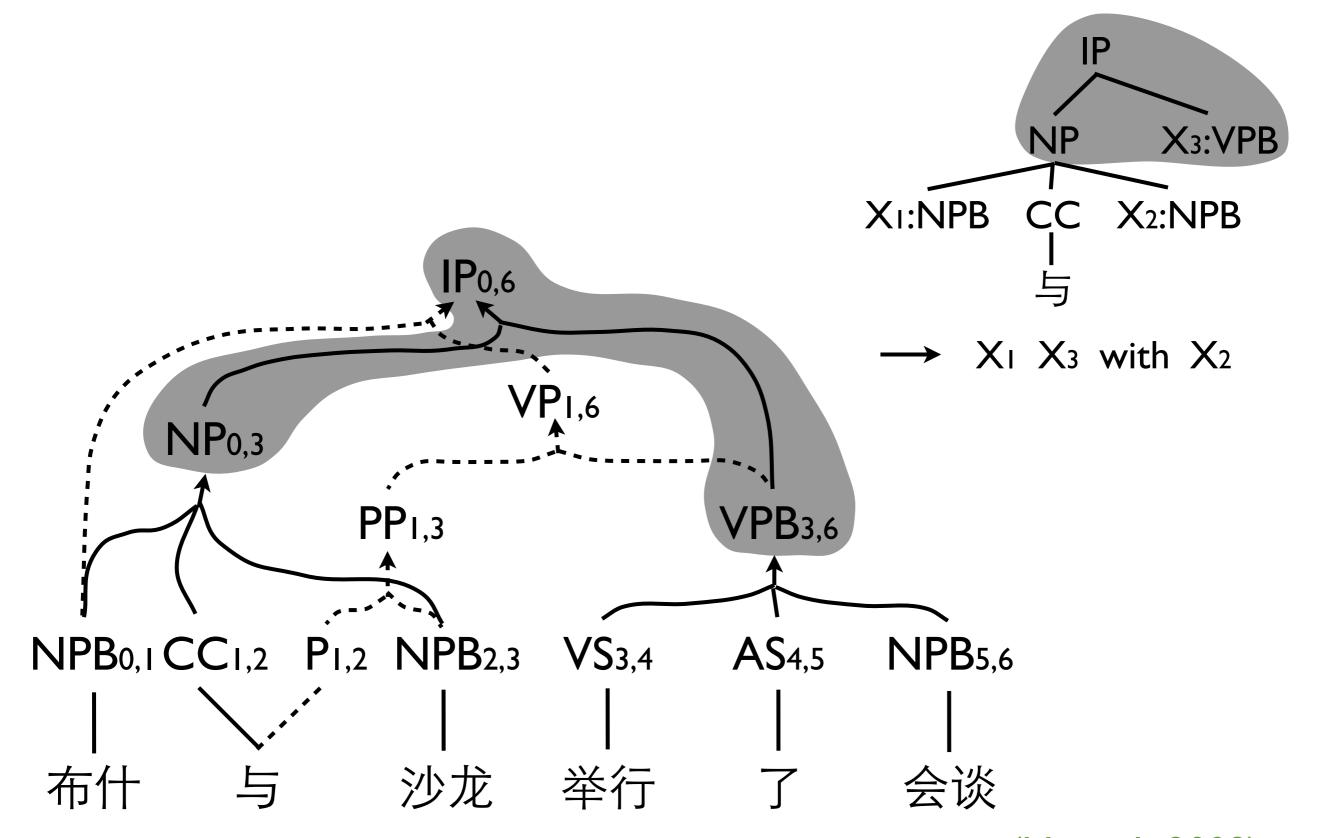
#### Packed Forest

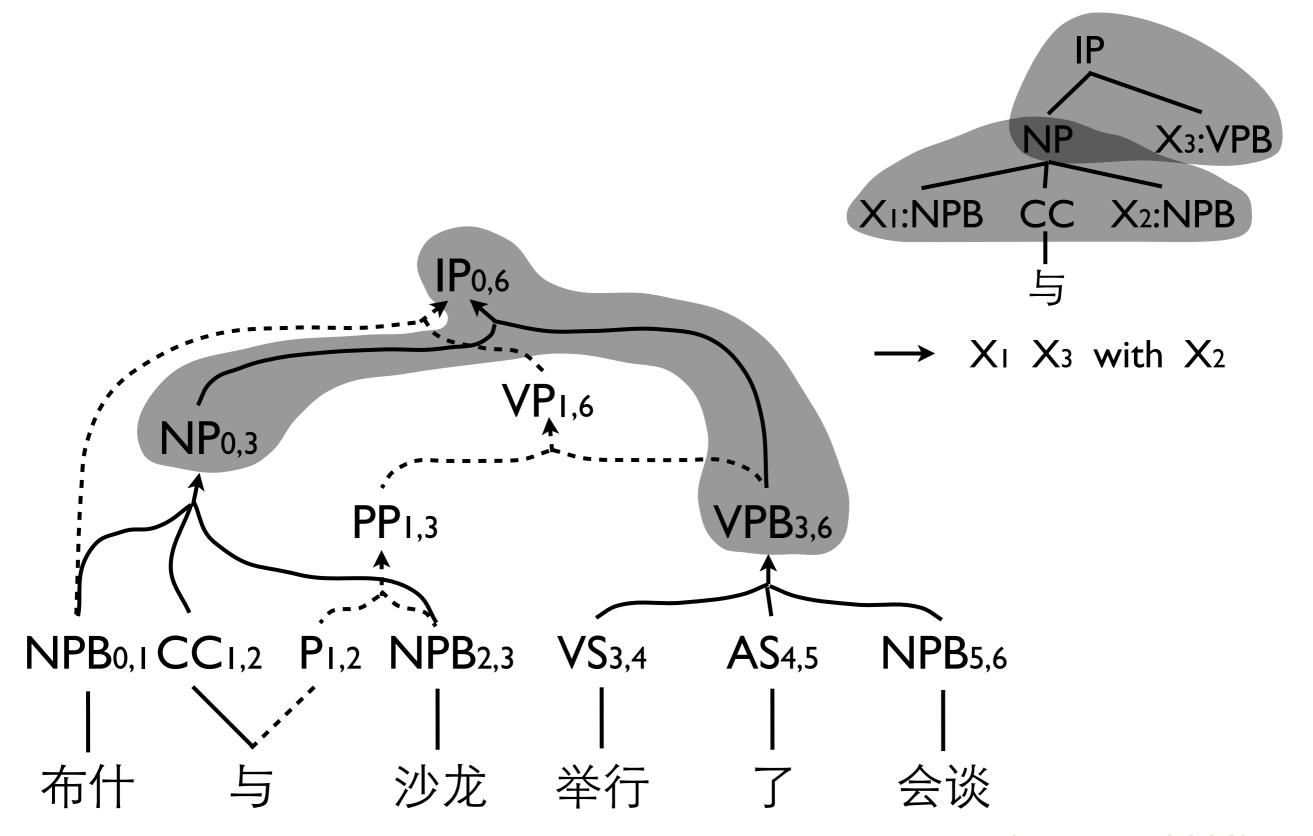


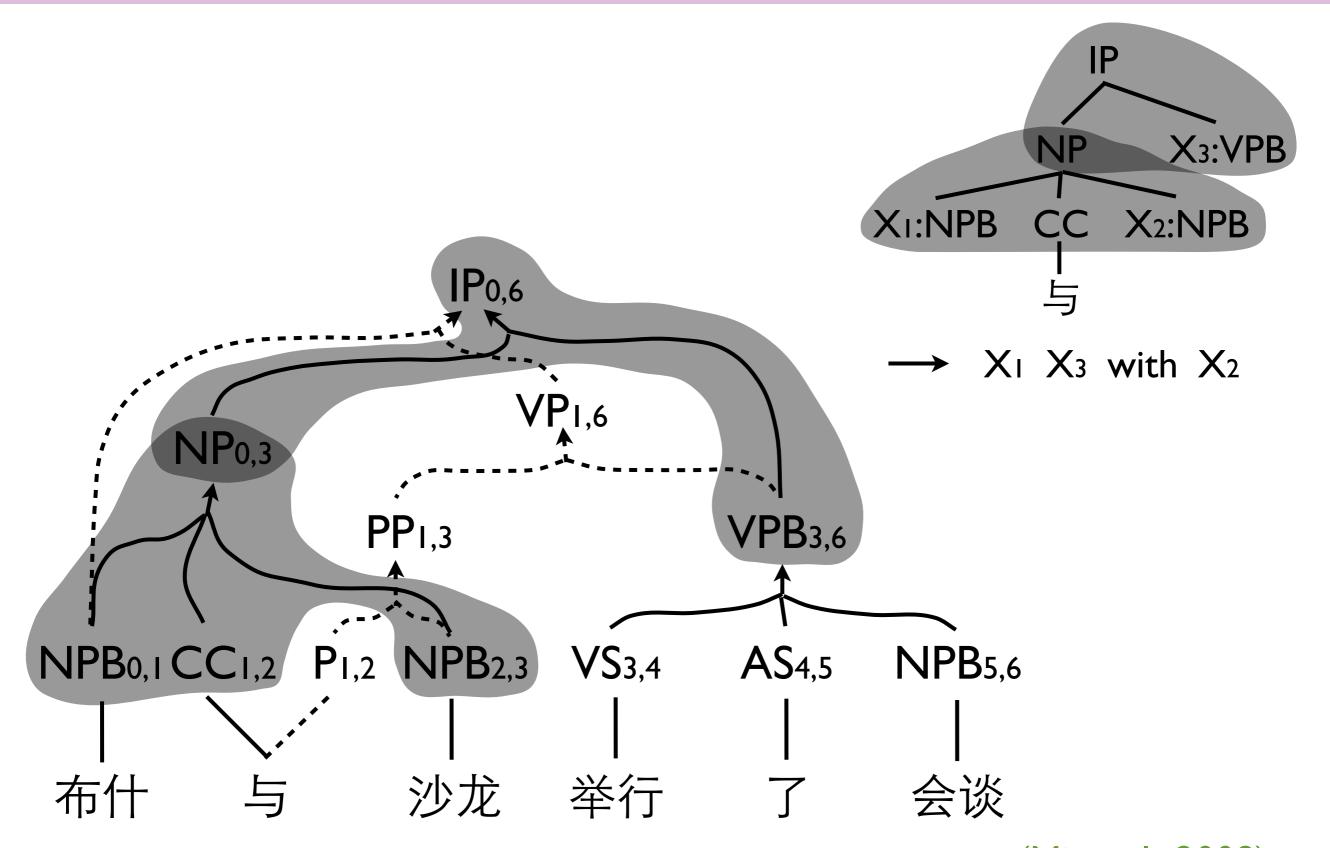
(Billot and Lang, 1989)

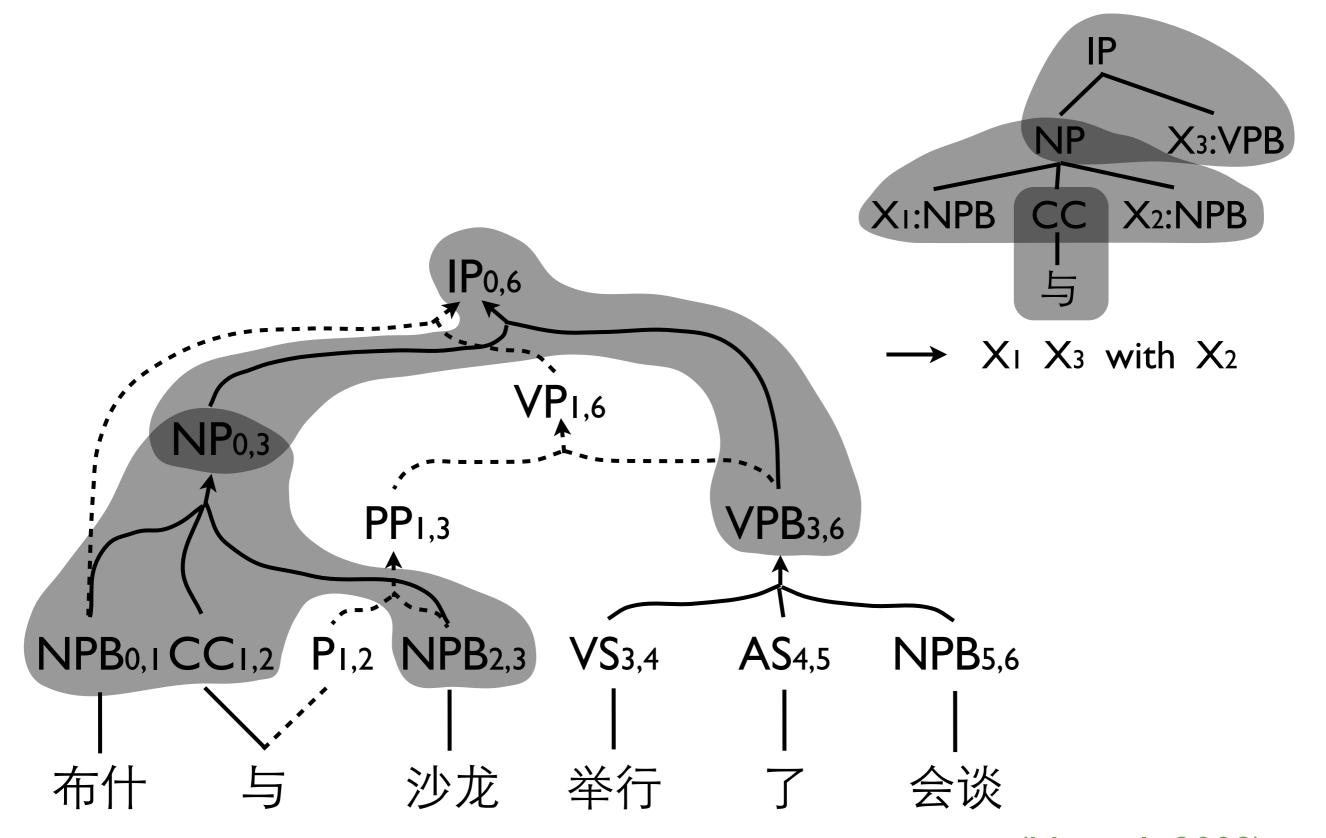


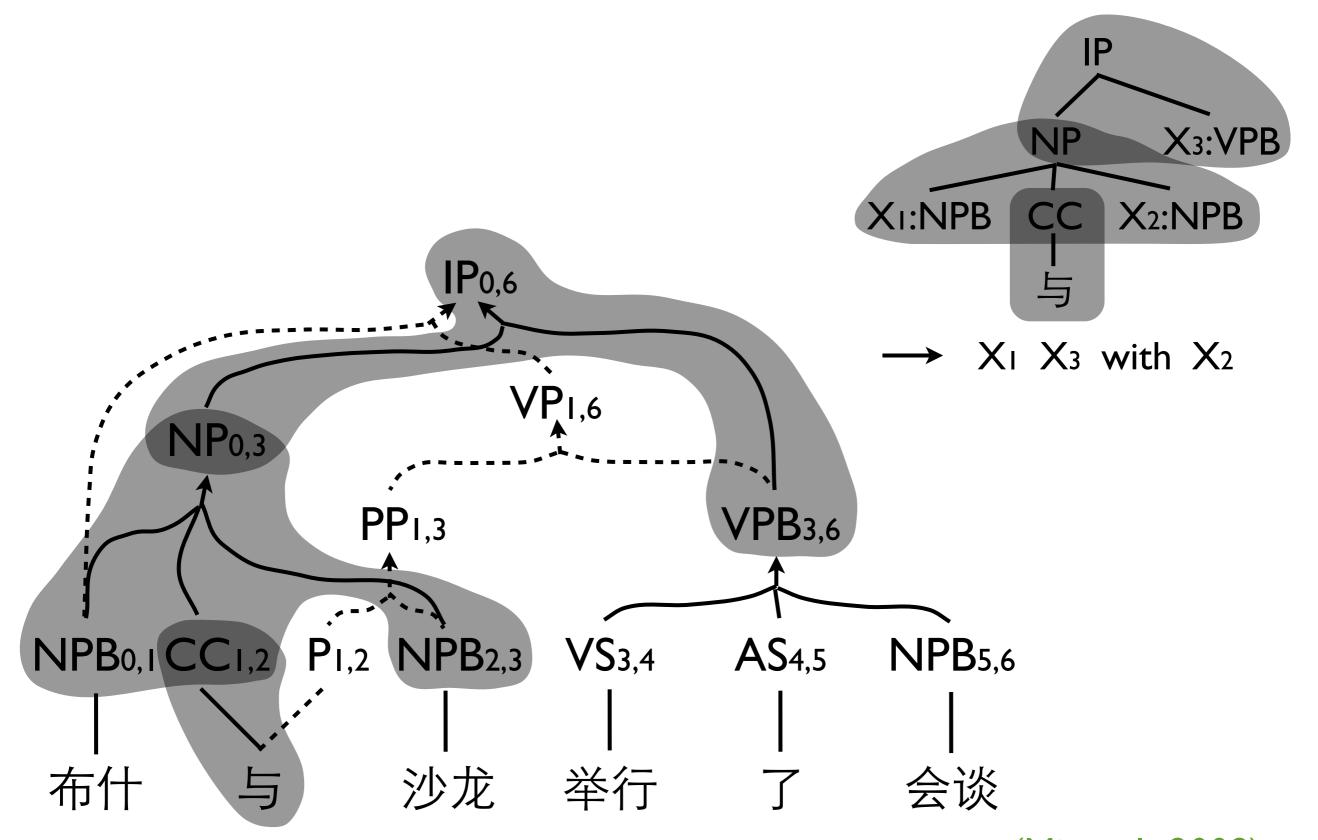


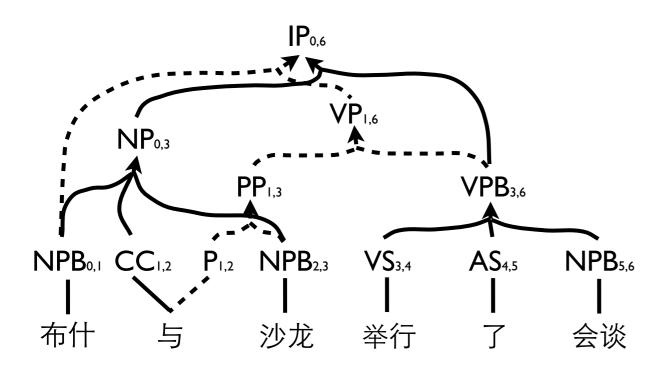


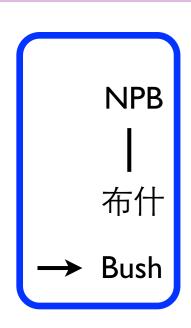


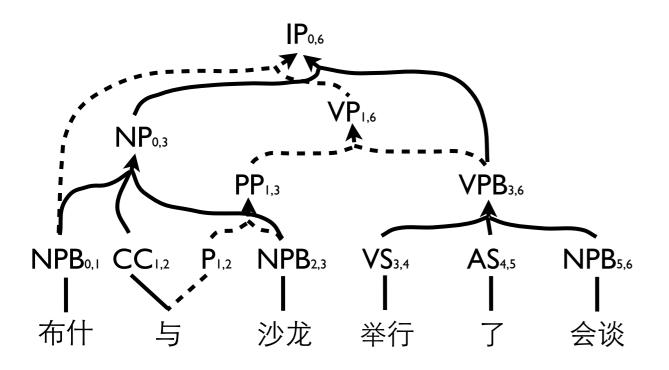


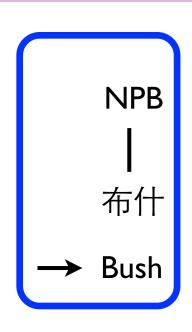


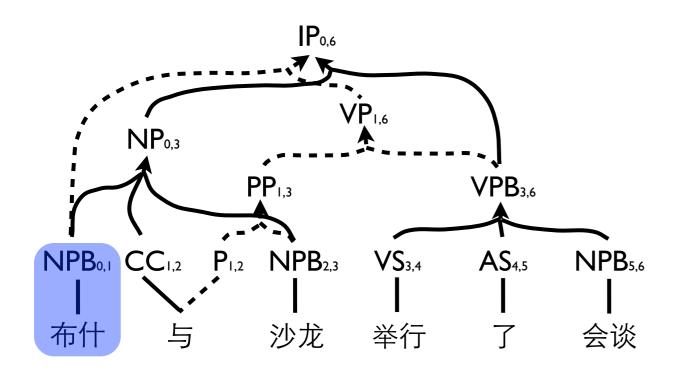


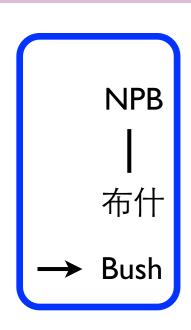


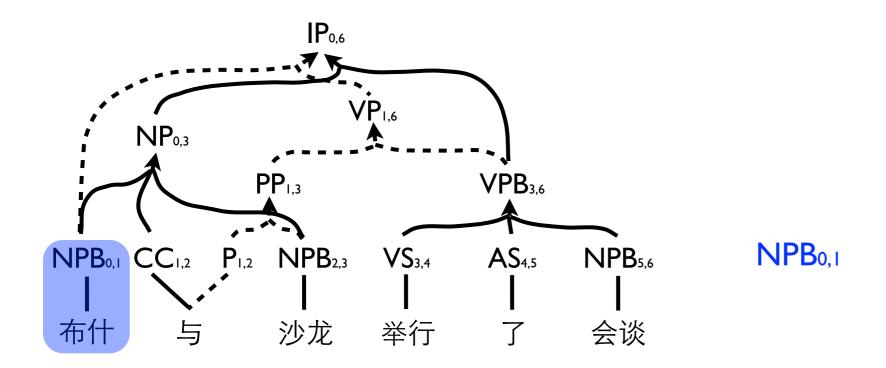


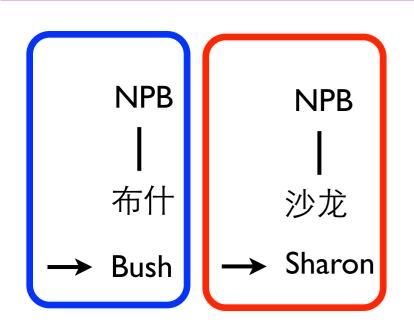


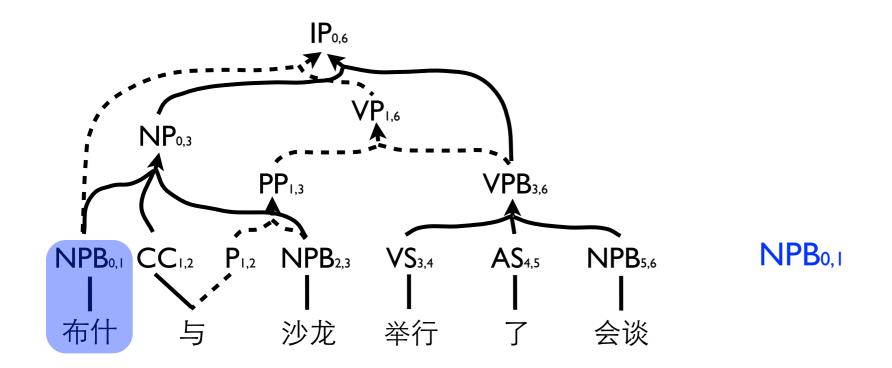


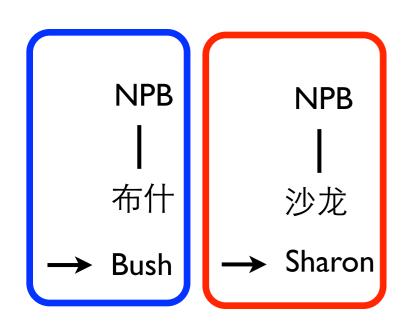


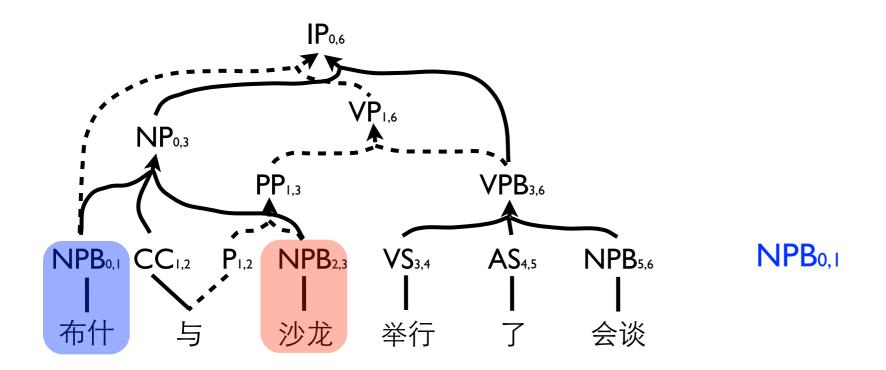


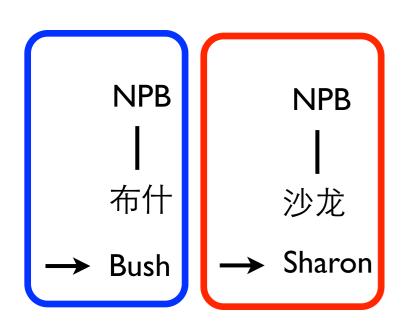


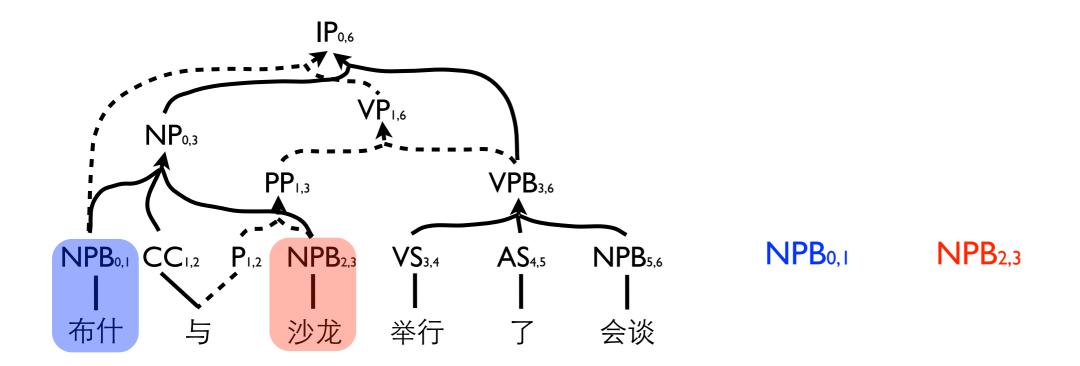


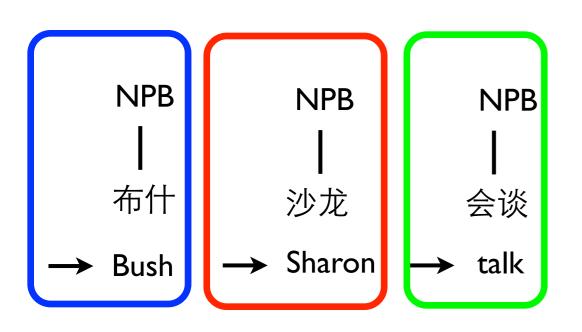


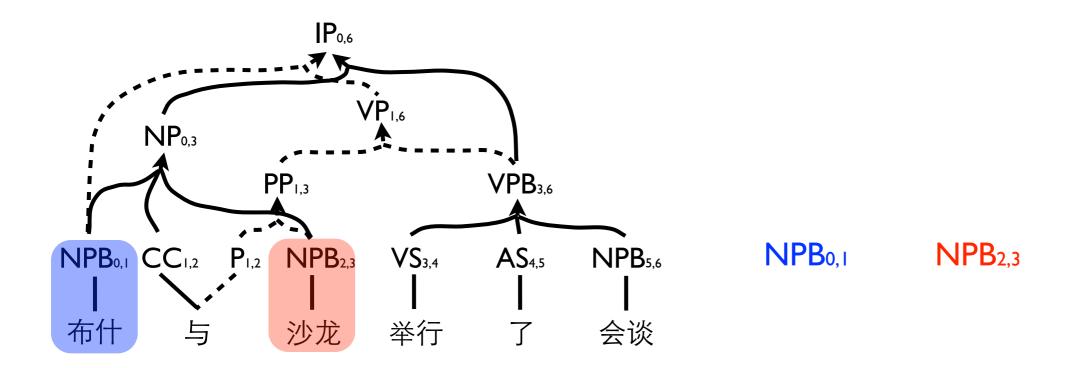


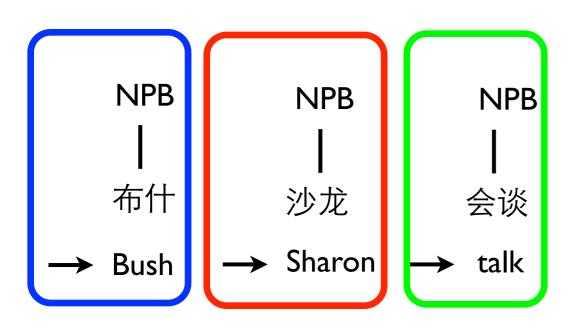


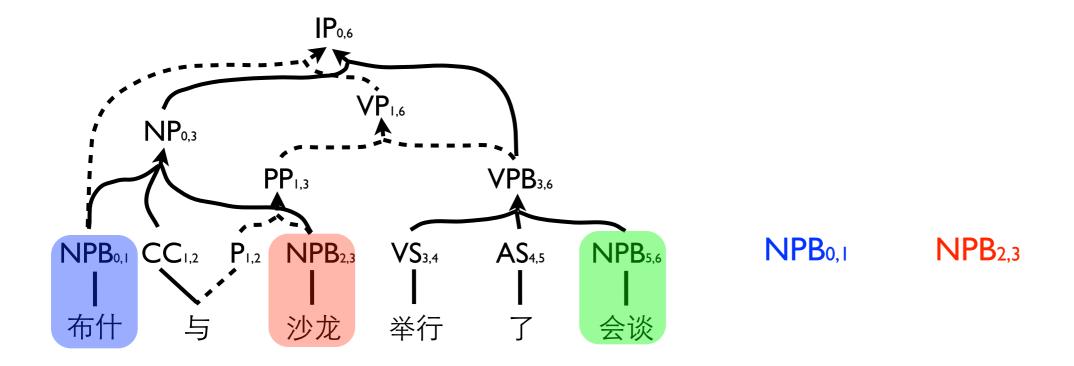


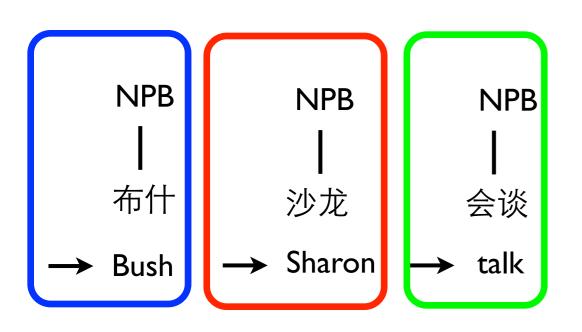


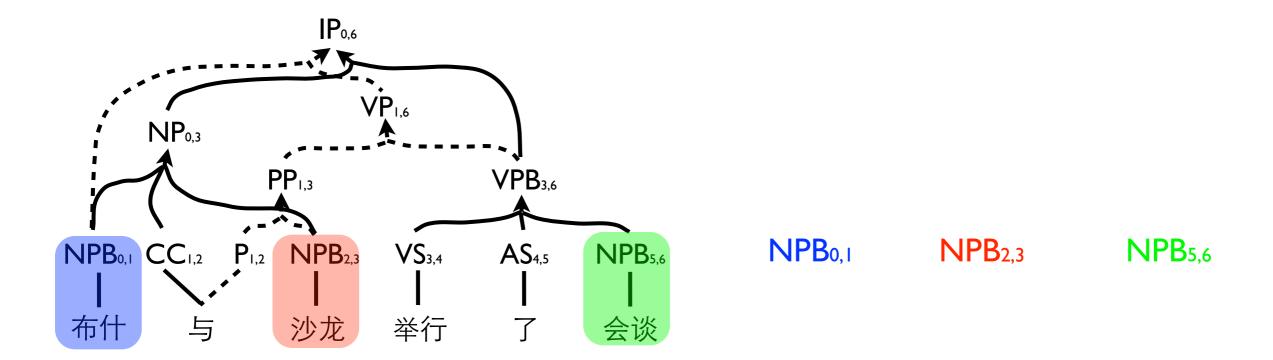


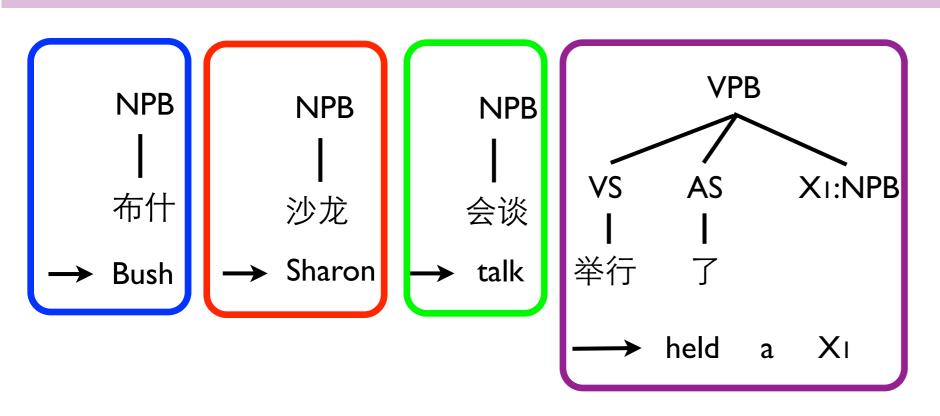


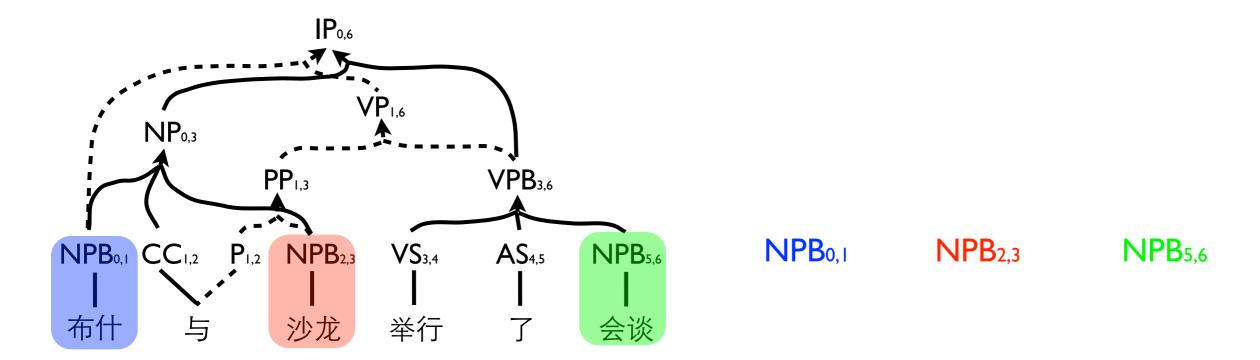


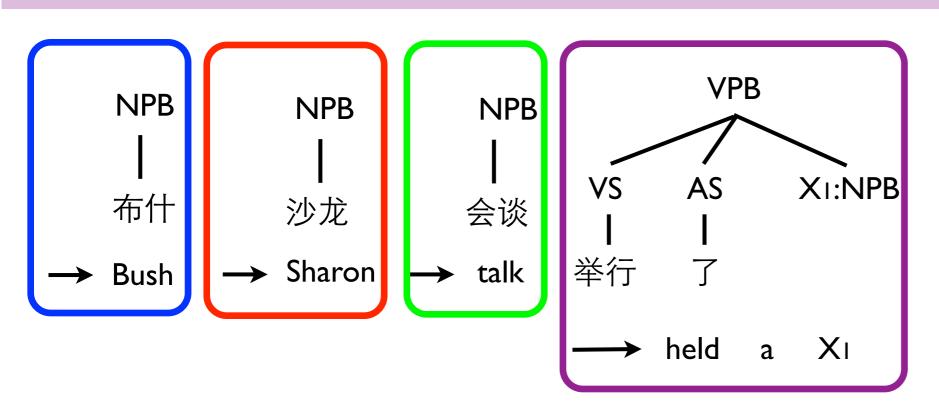


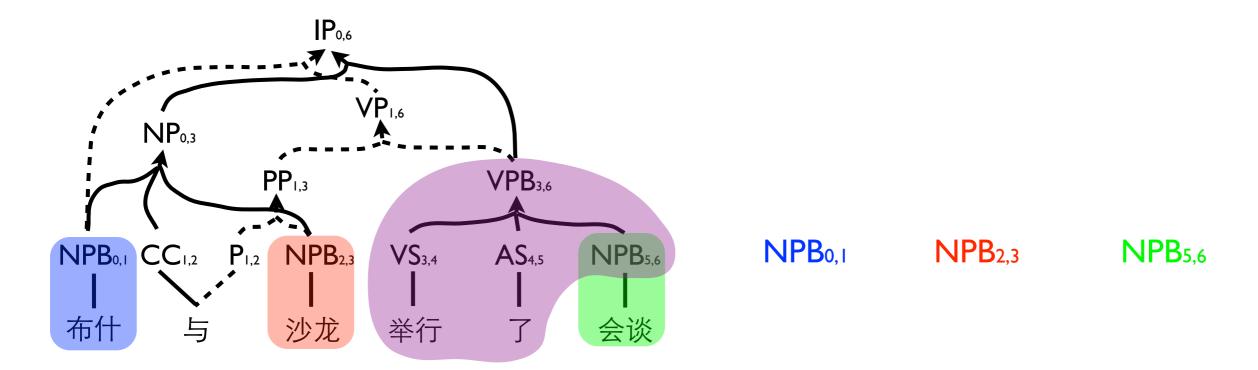


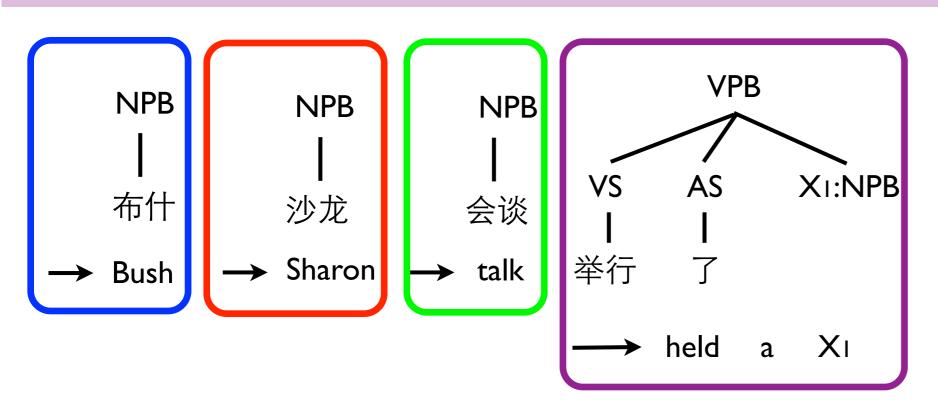


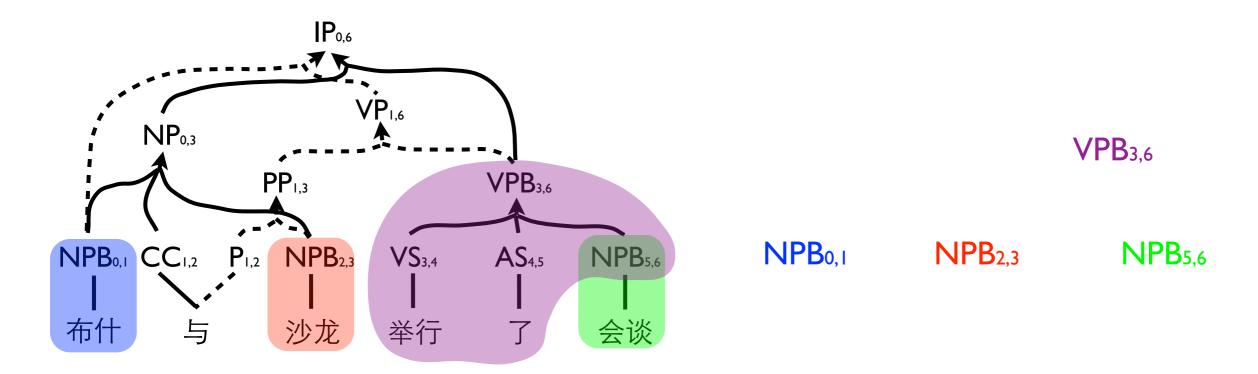


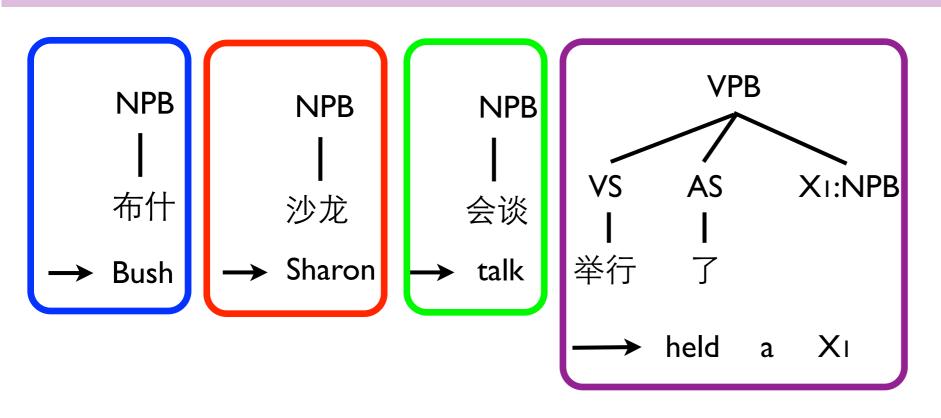


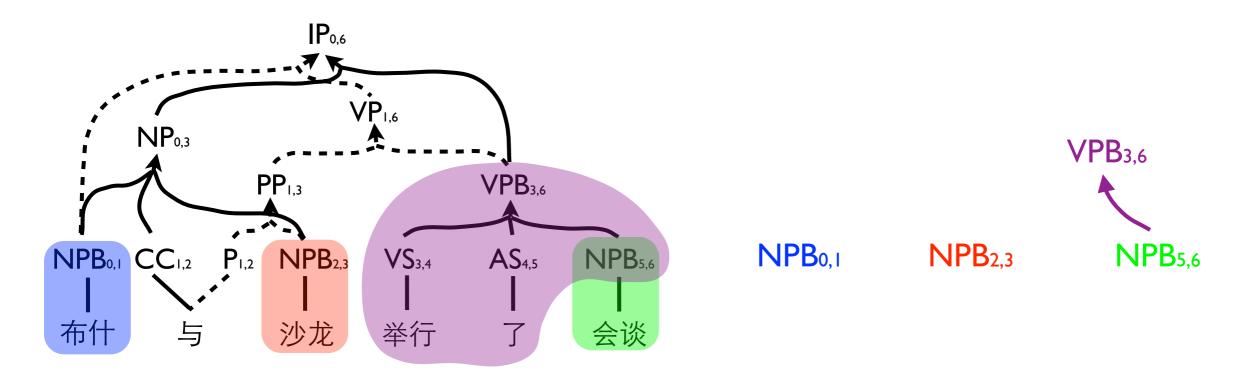


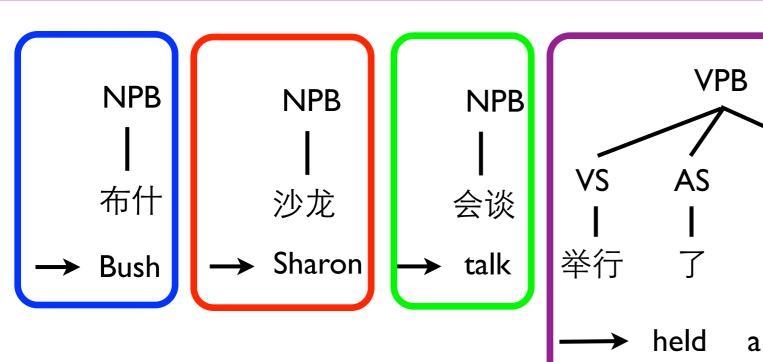


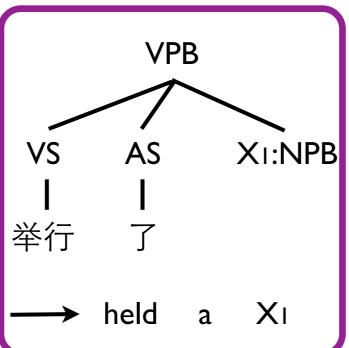


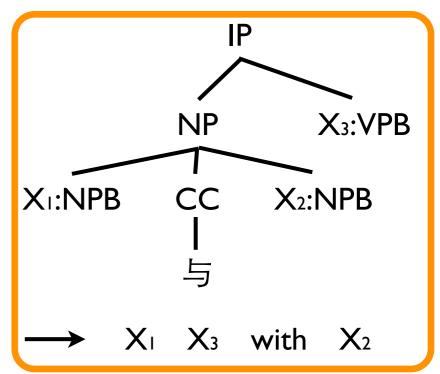


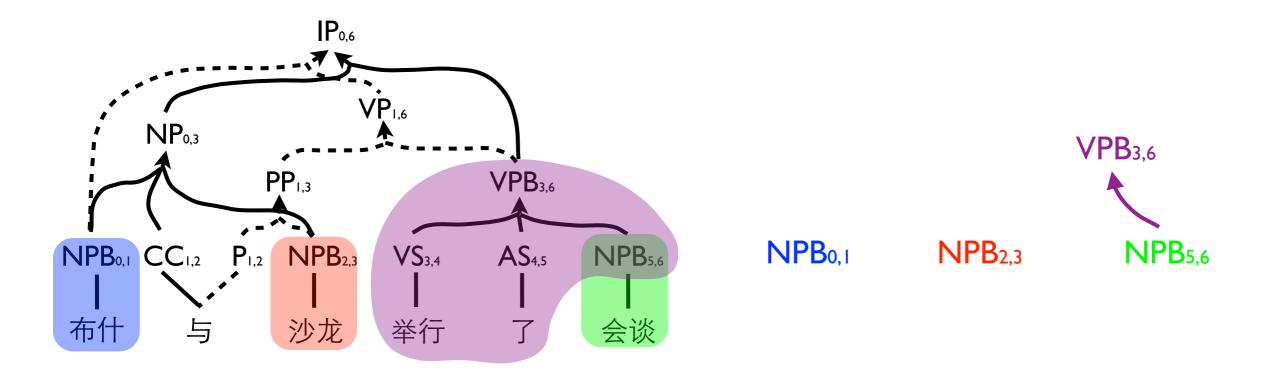


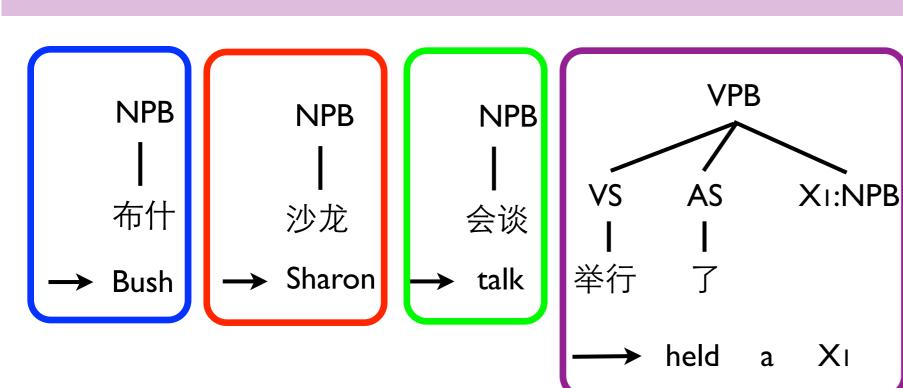


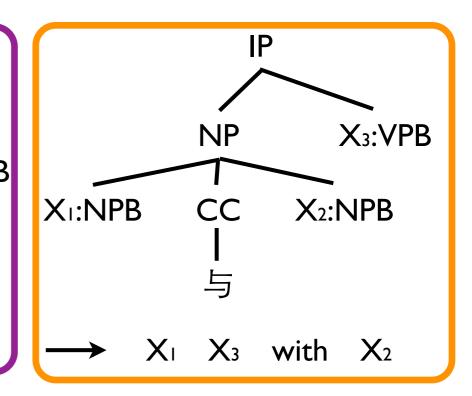


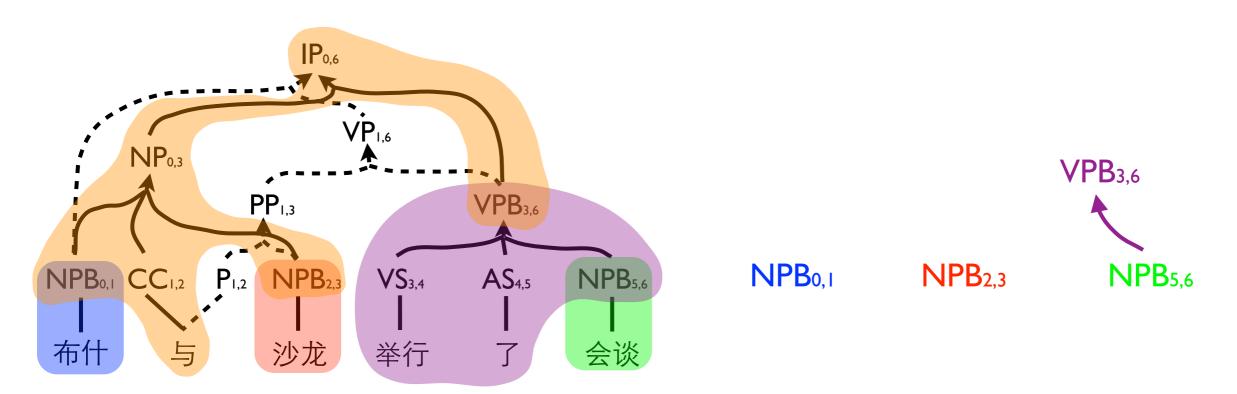


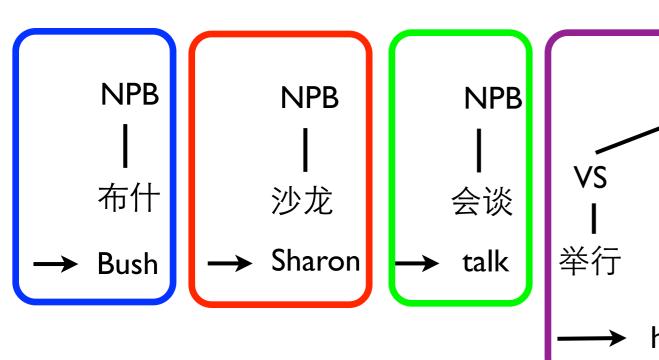


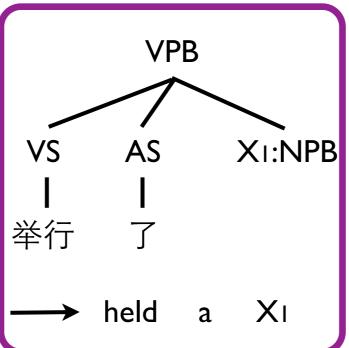


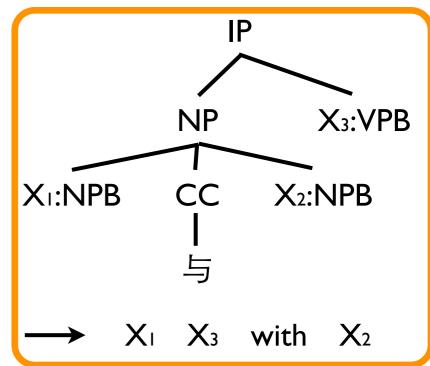


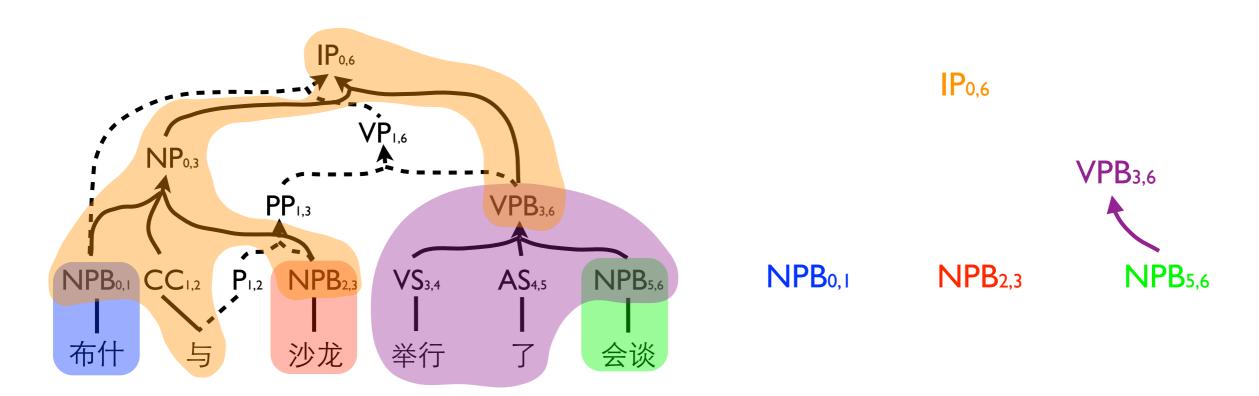


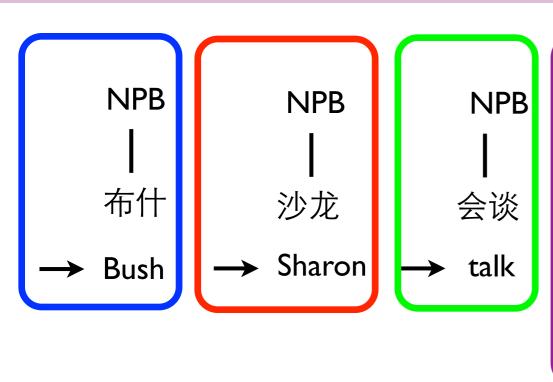


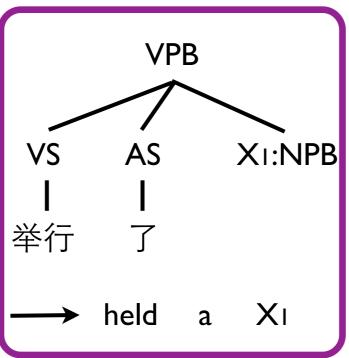


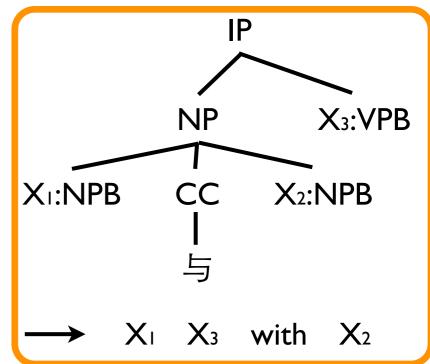


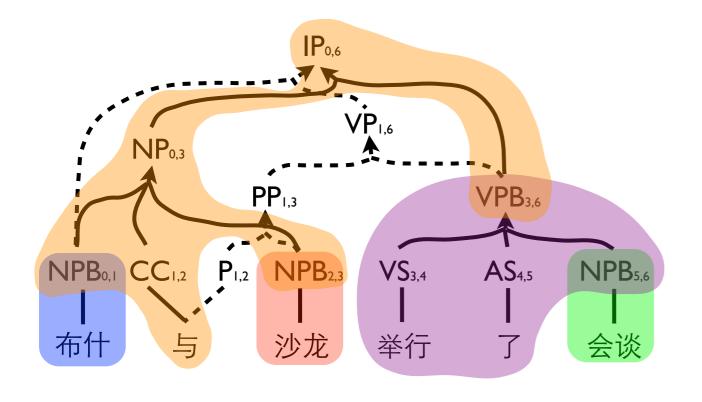


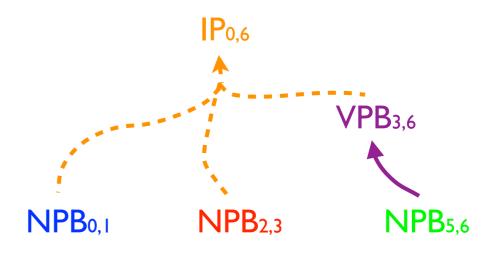


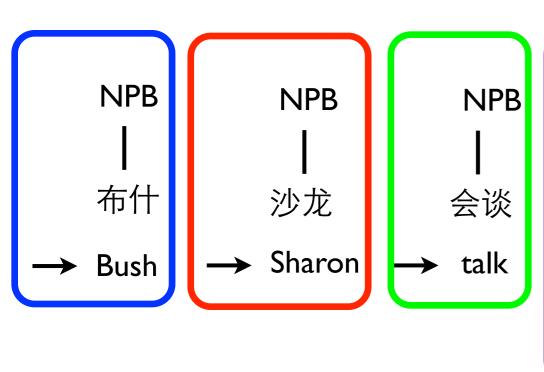


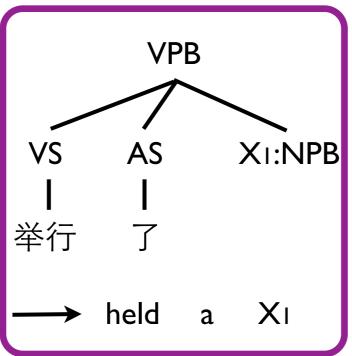


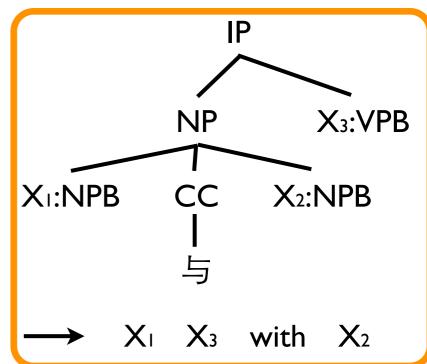


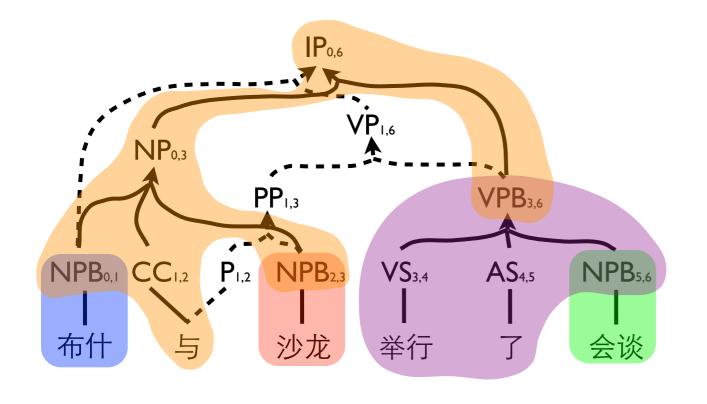


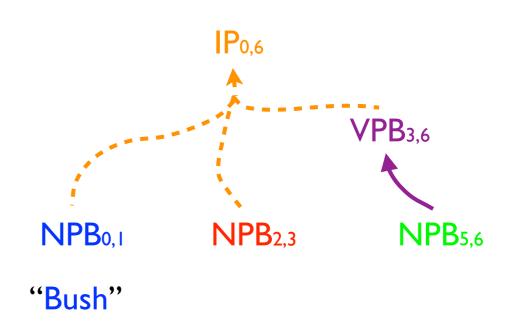


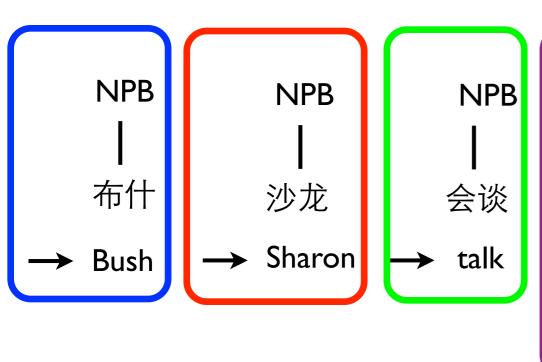


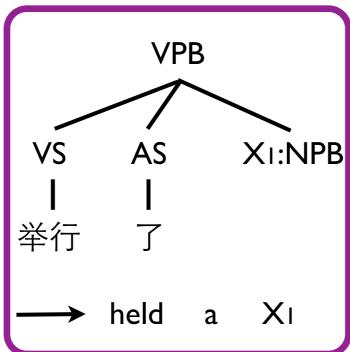


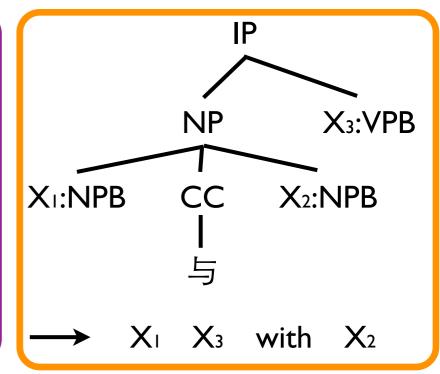


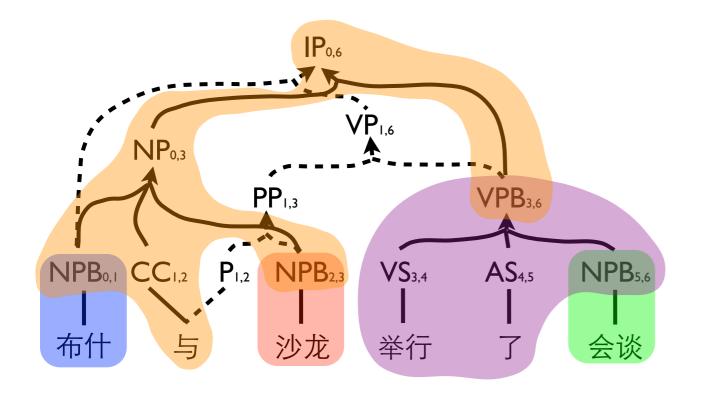


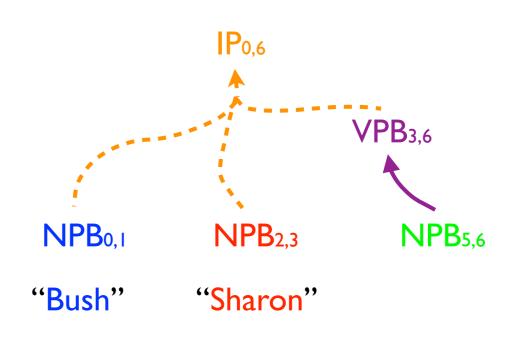


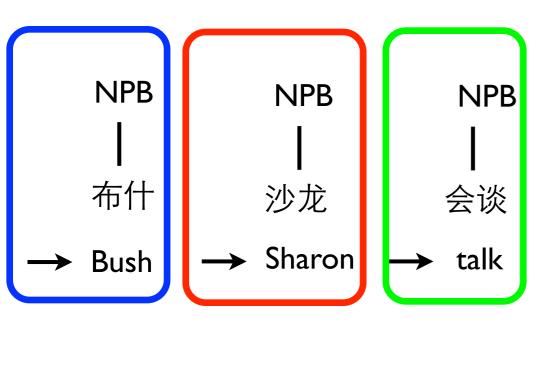


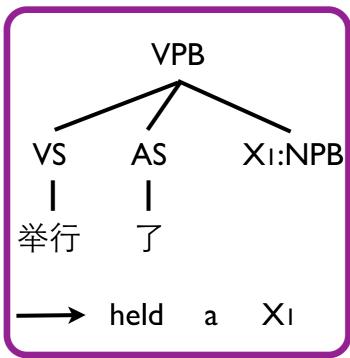


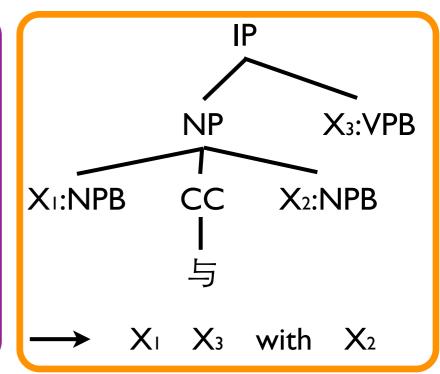


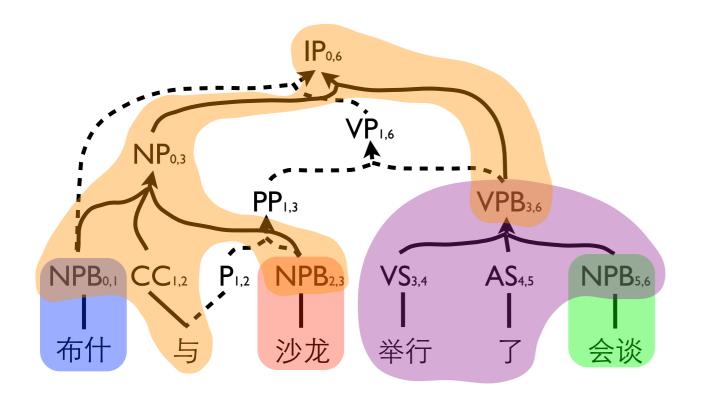


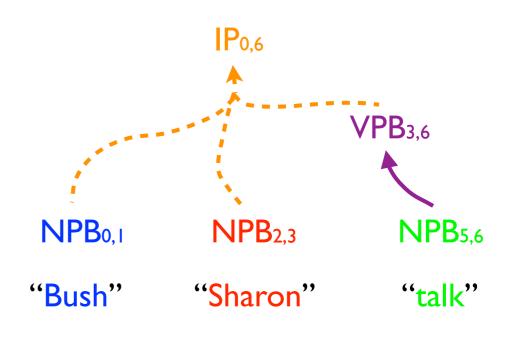


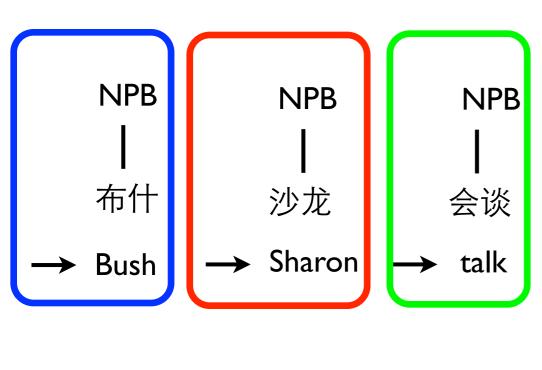


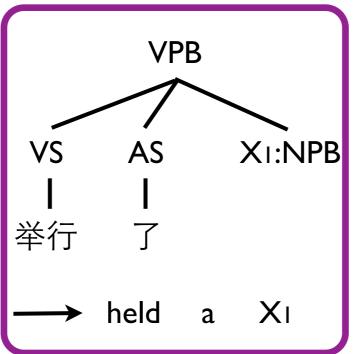


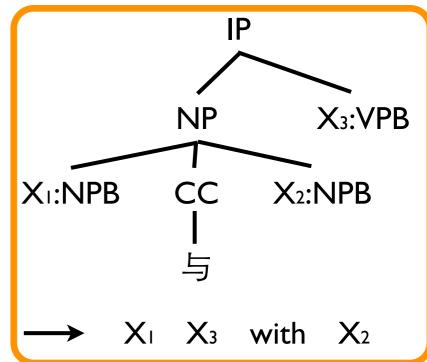


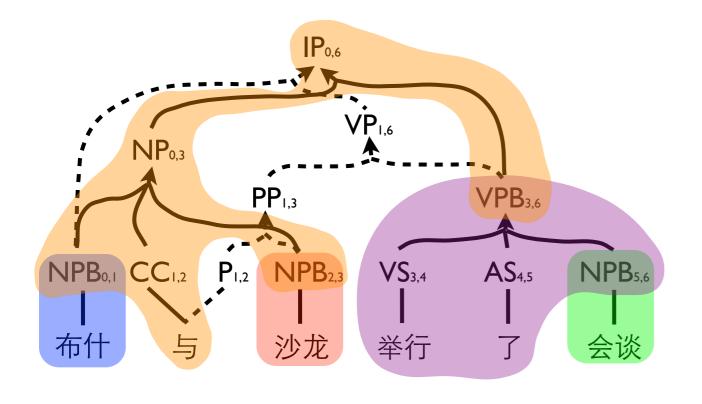


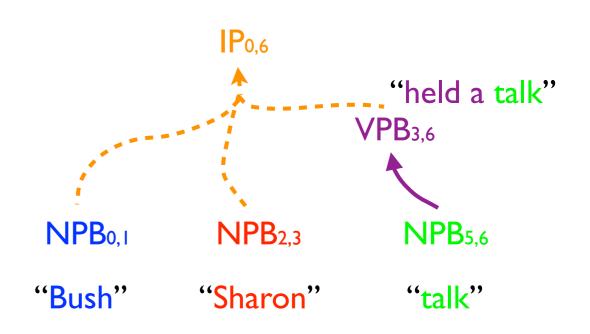


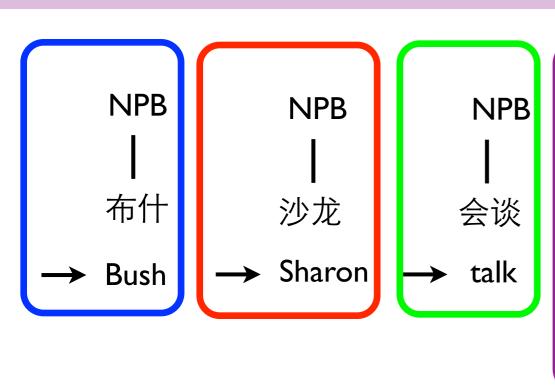


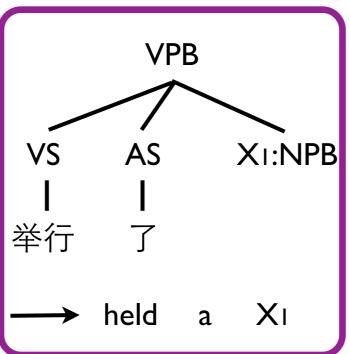


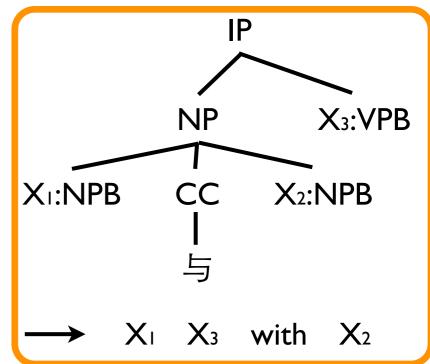


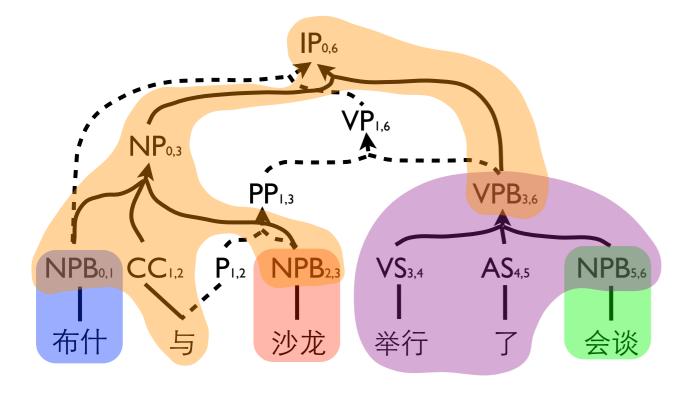


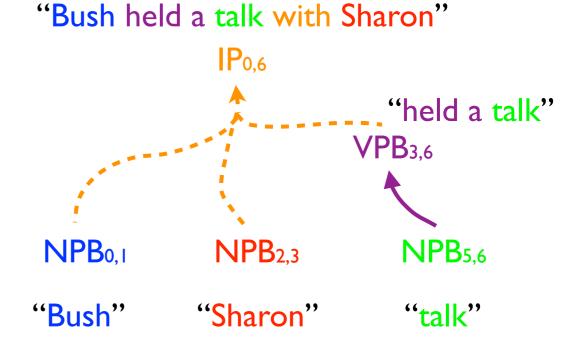


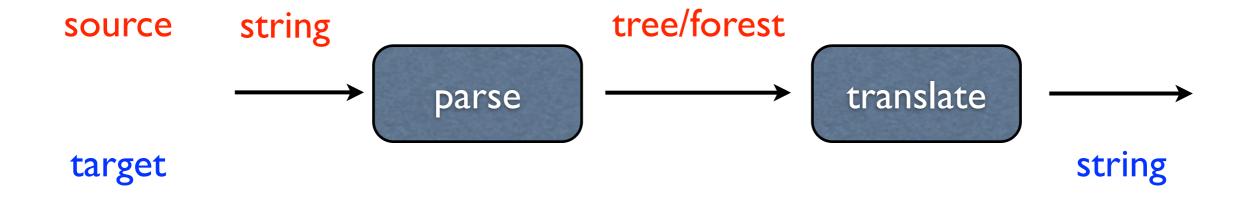


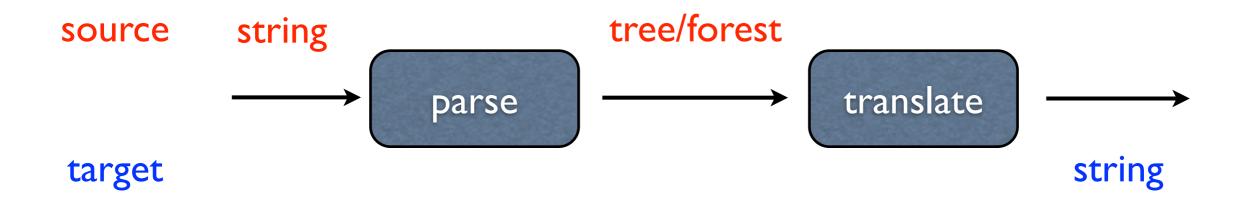






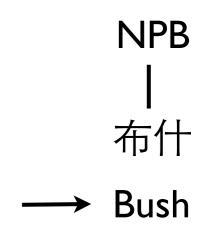




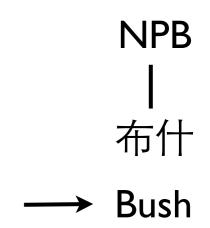




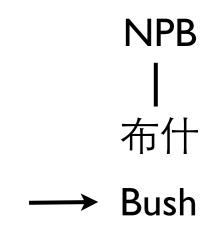
布什 与 沙龙 举行 了 会谈



布什 与 沙龙 举行 了 会谈

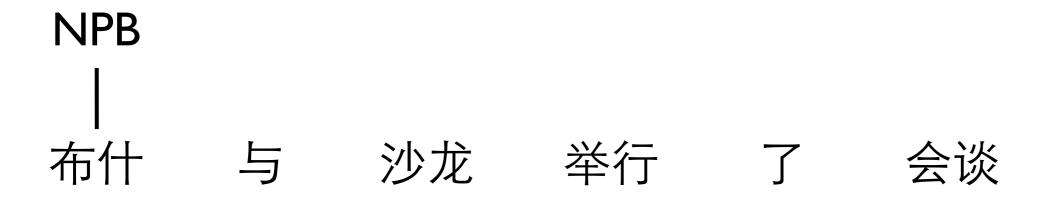




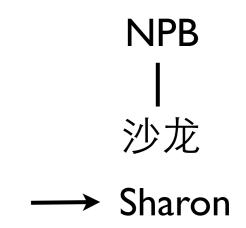




Bush

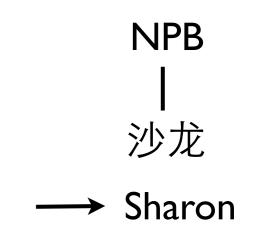


Bush



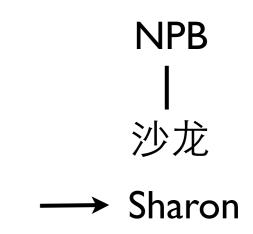


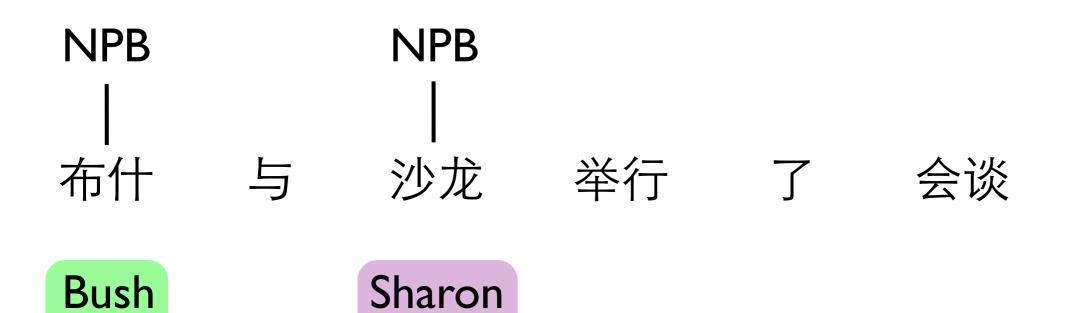
Bush



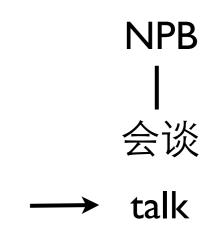


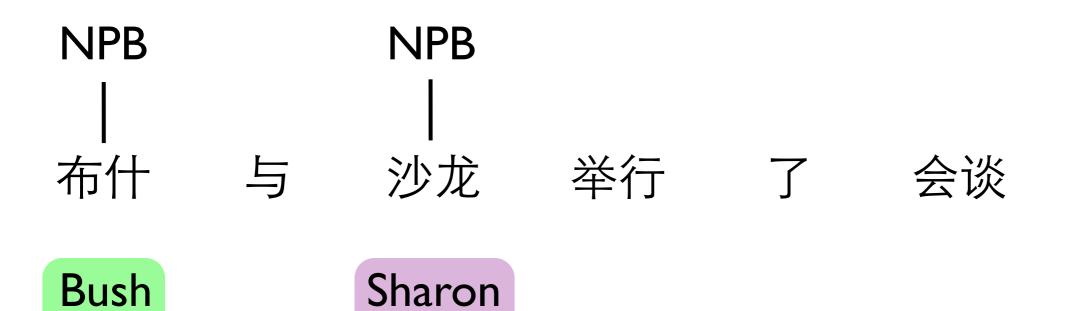
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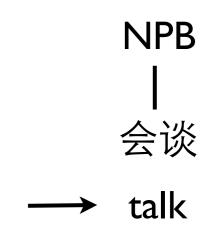


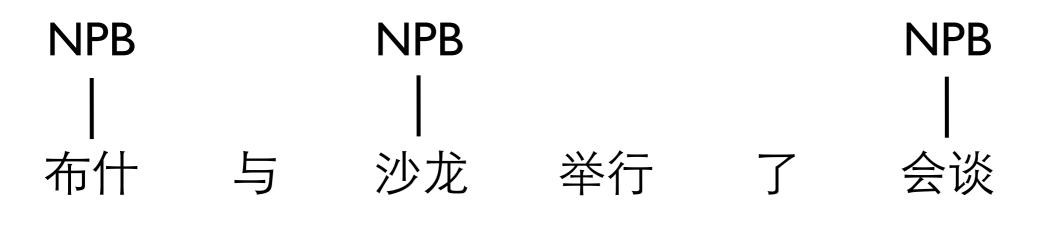






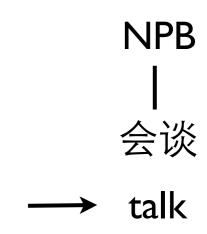


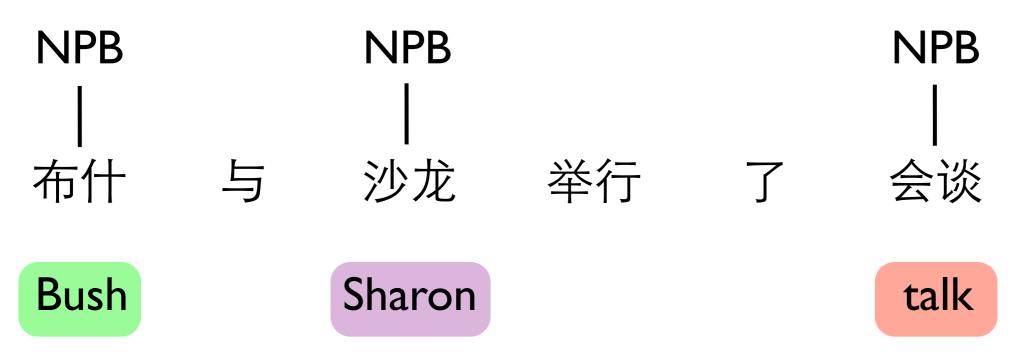


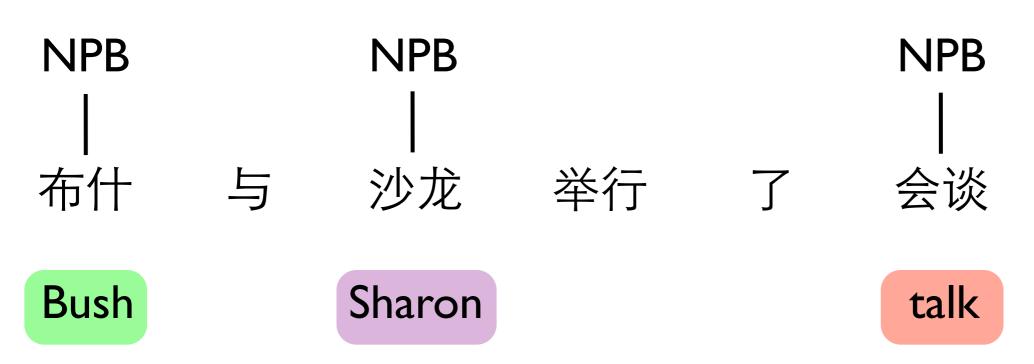


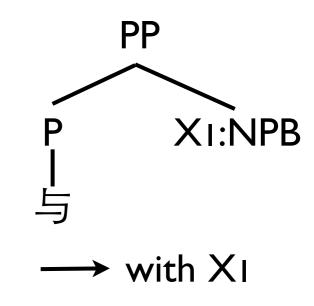
Bush

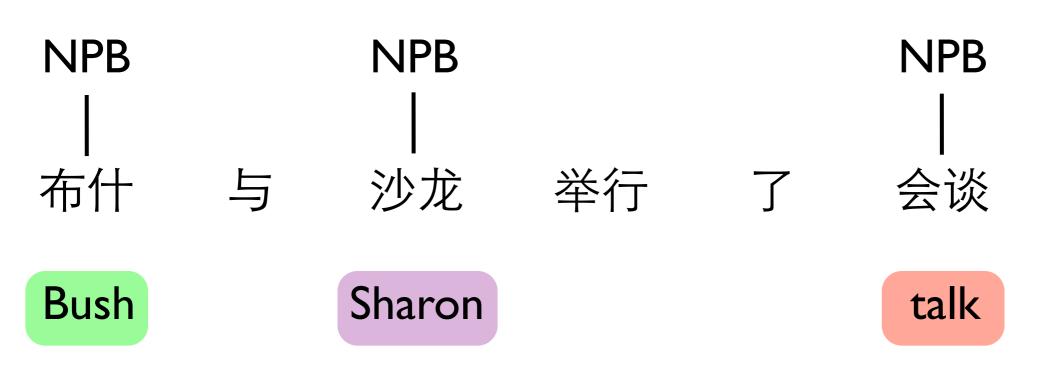
Sharon

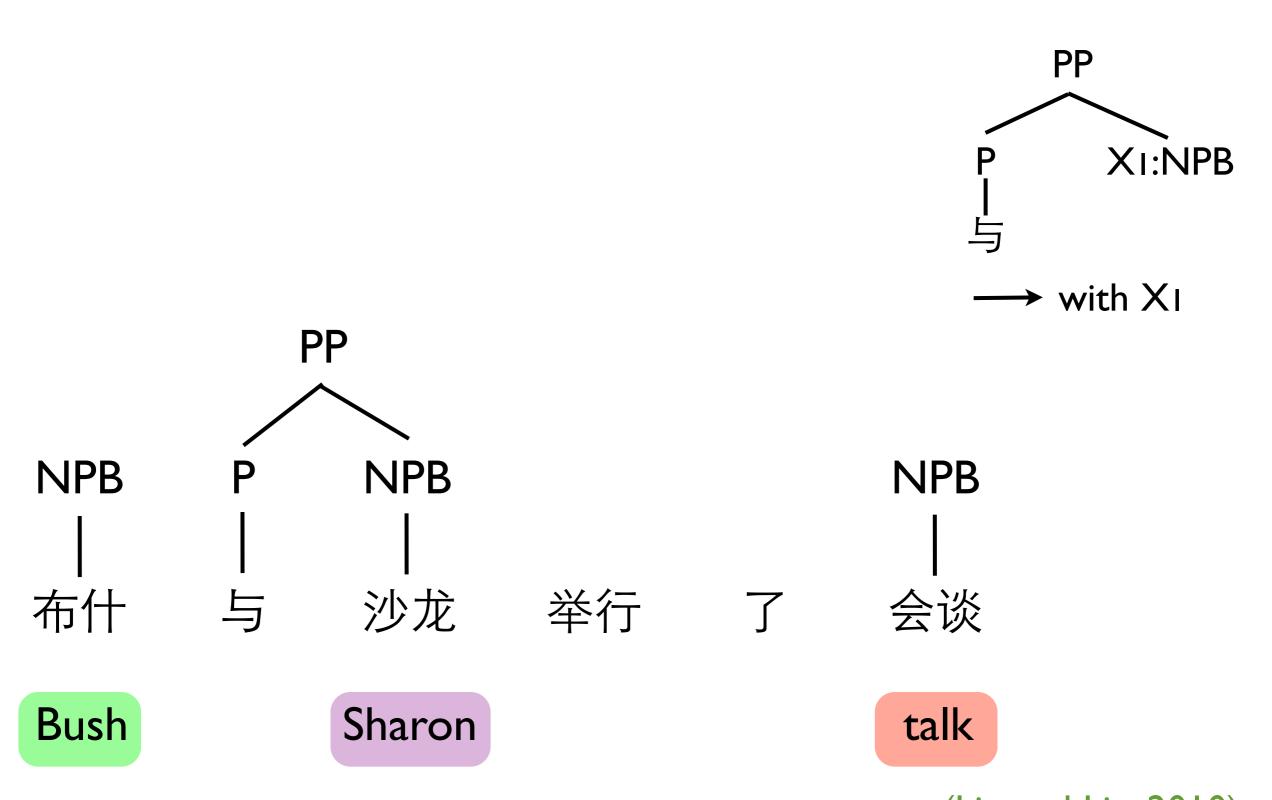


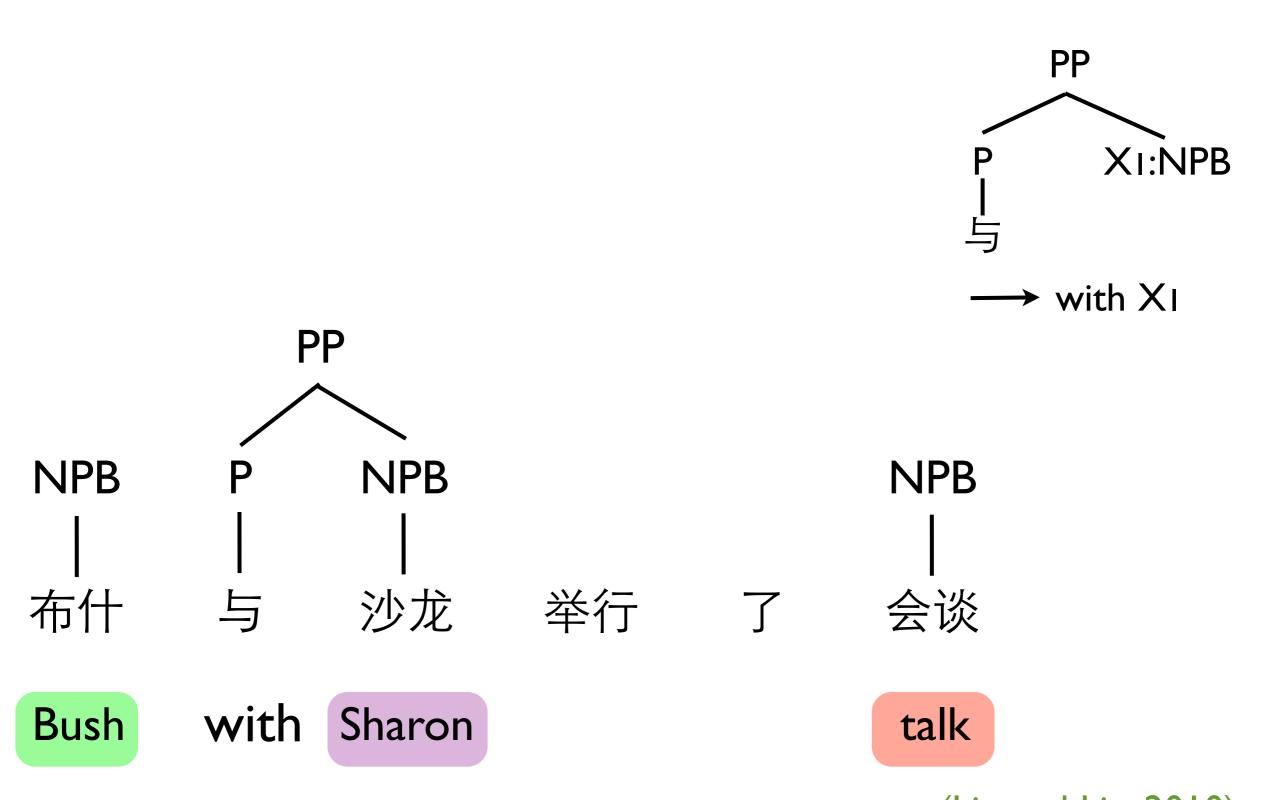


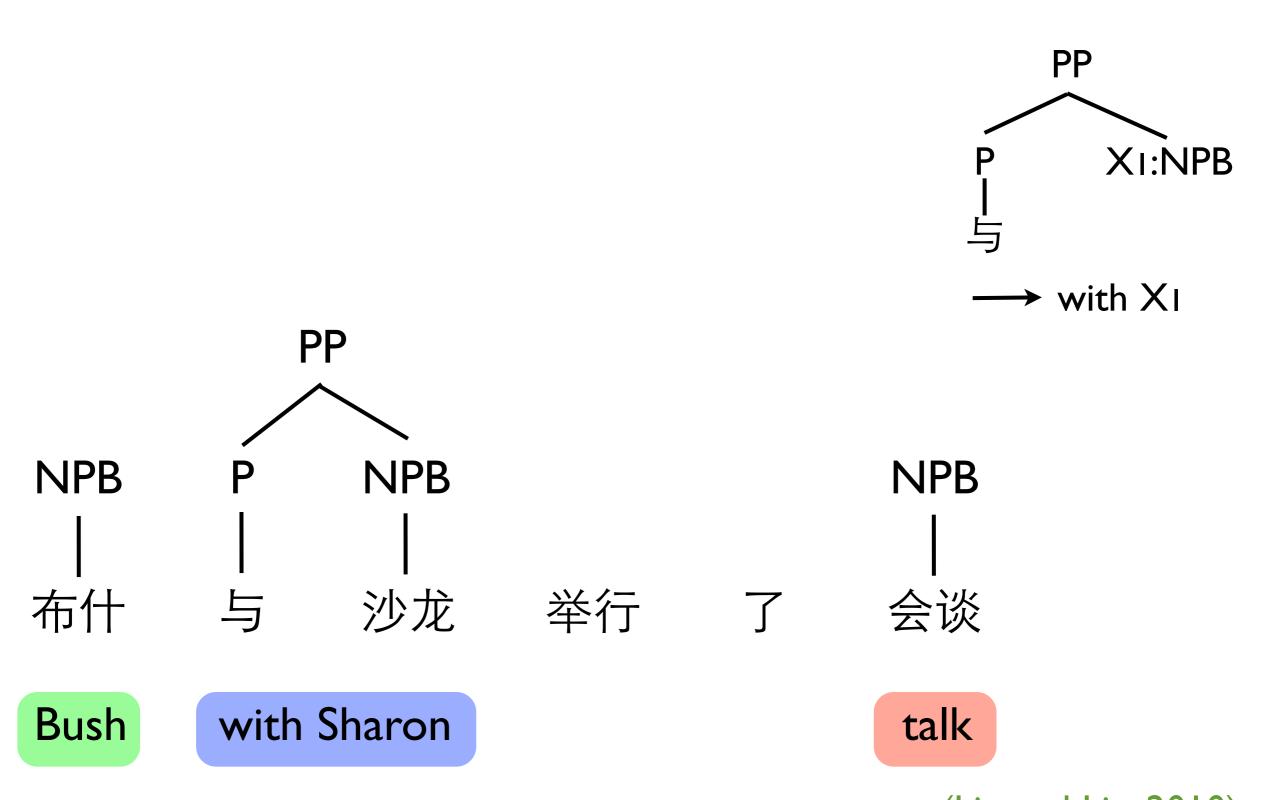


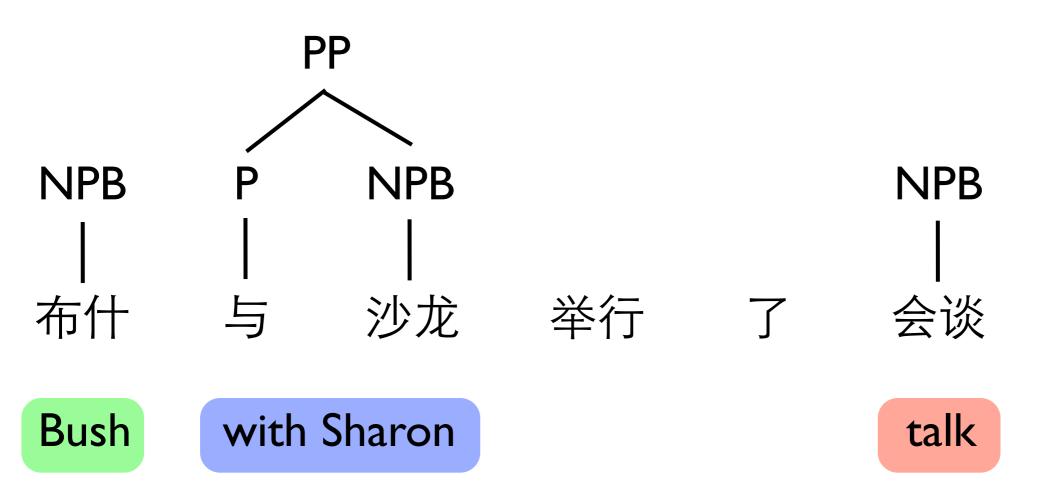


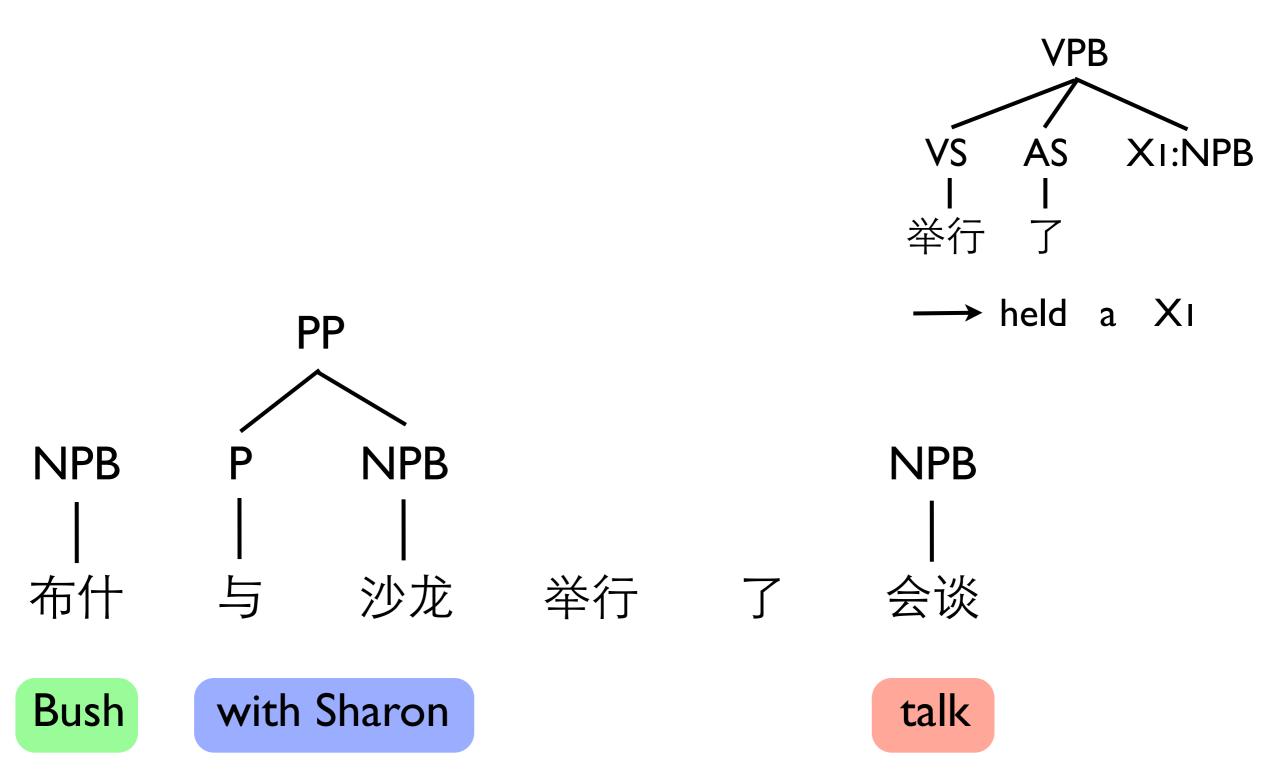


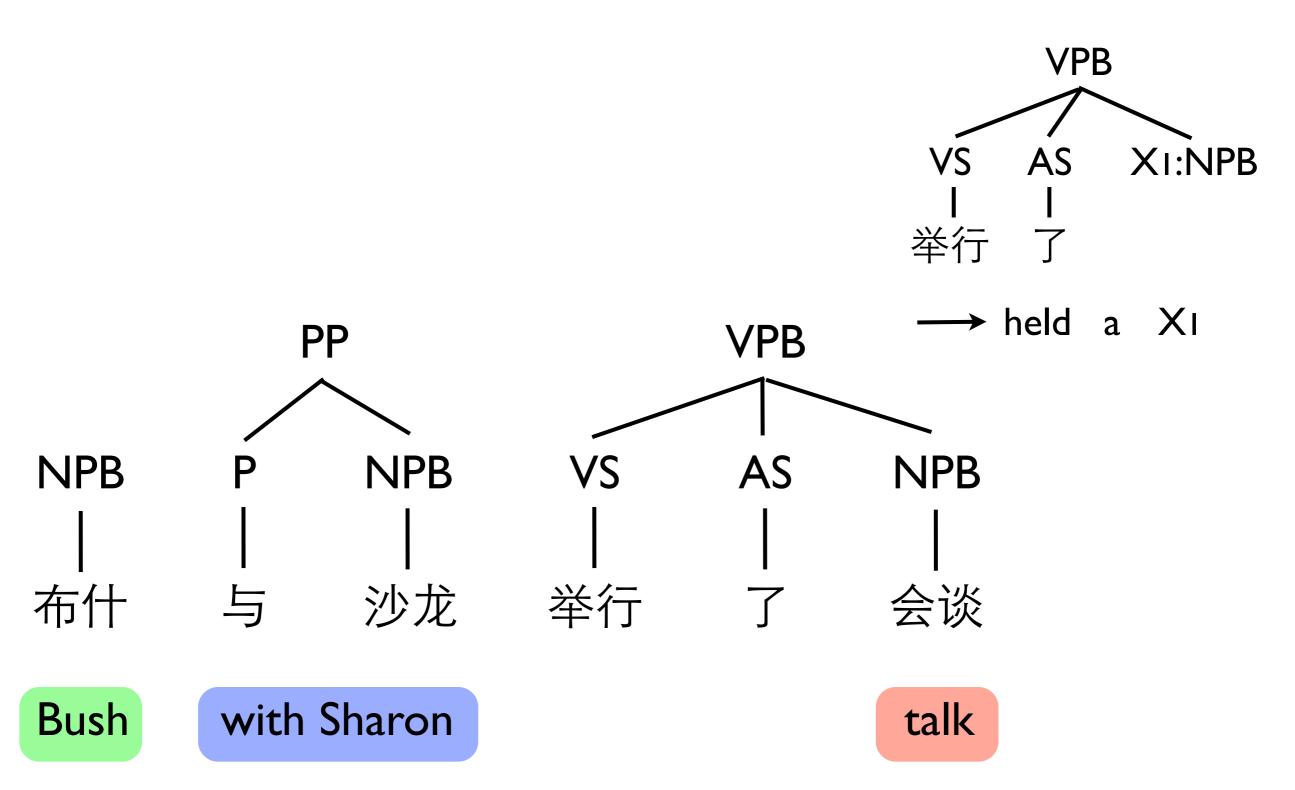


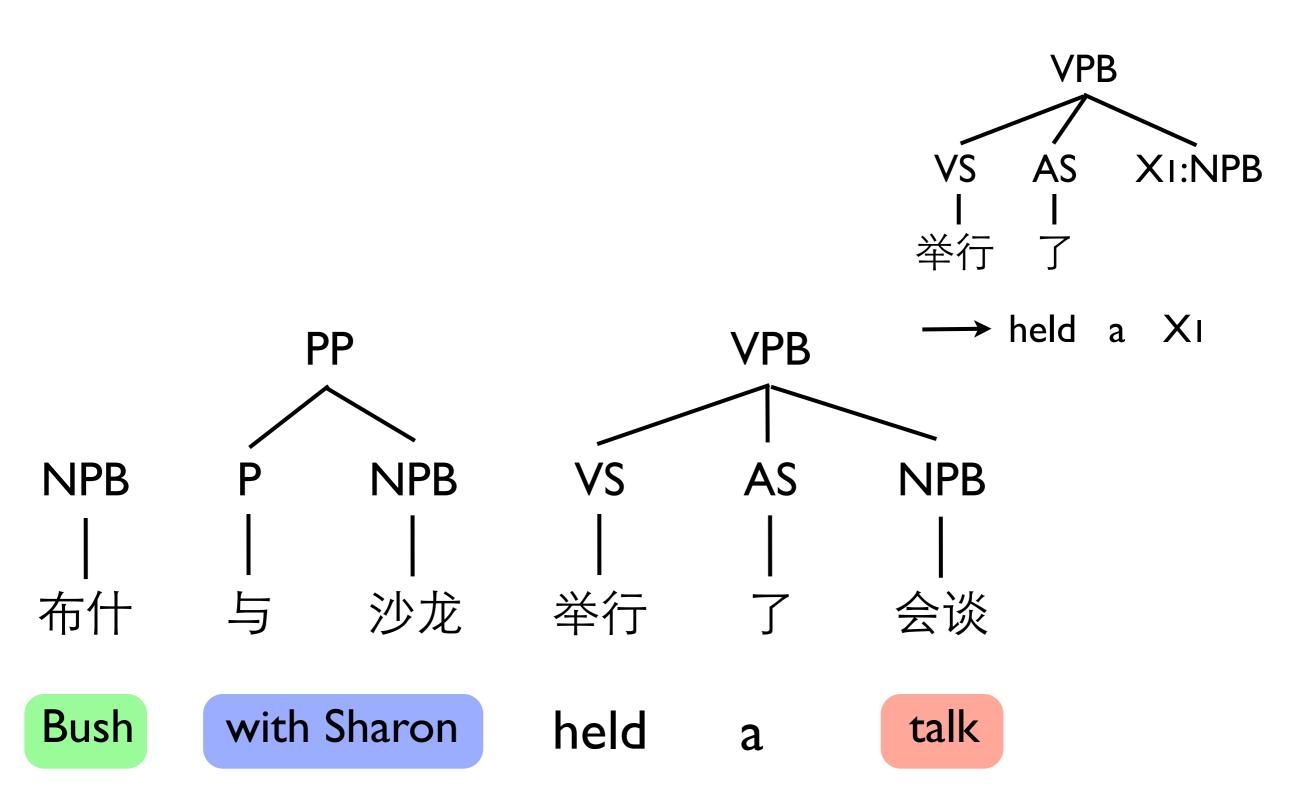


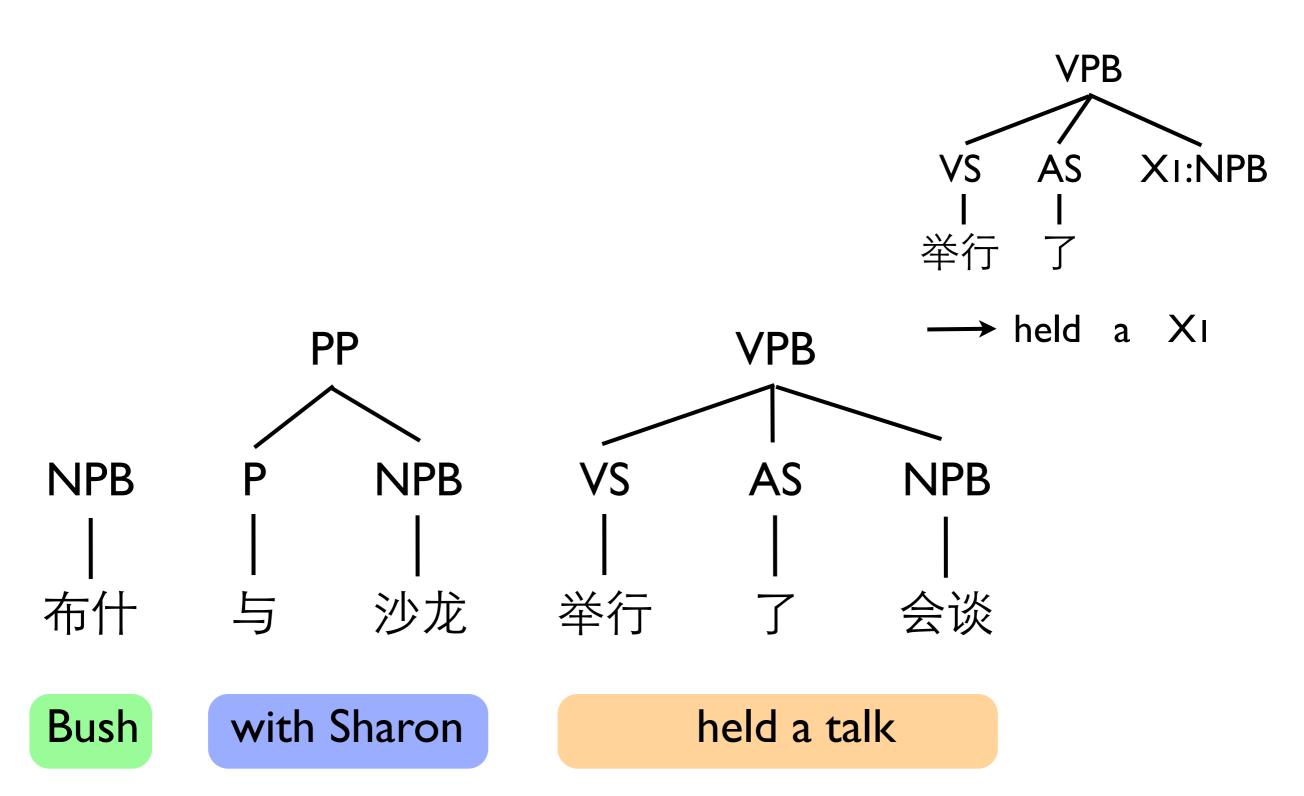


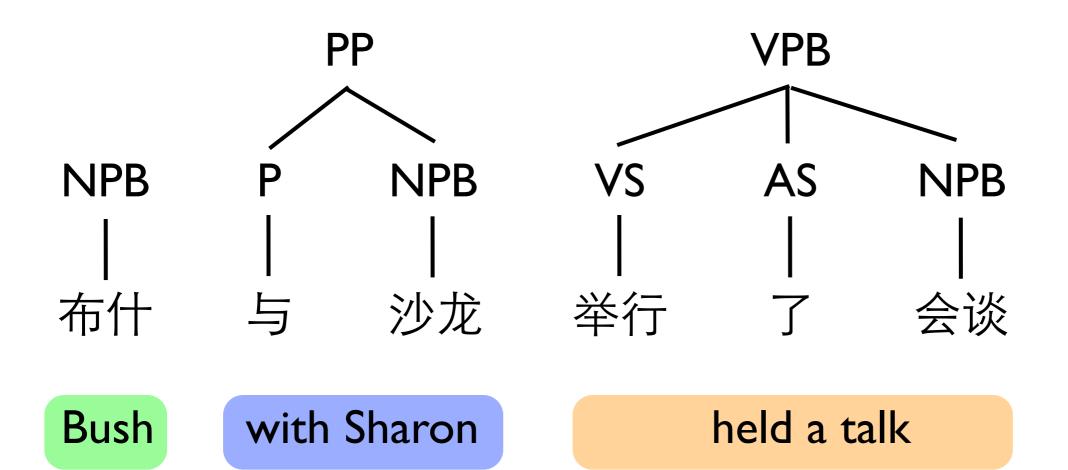


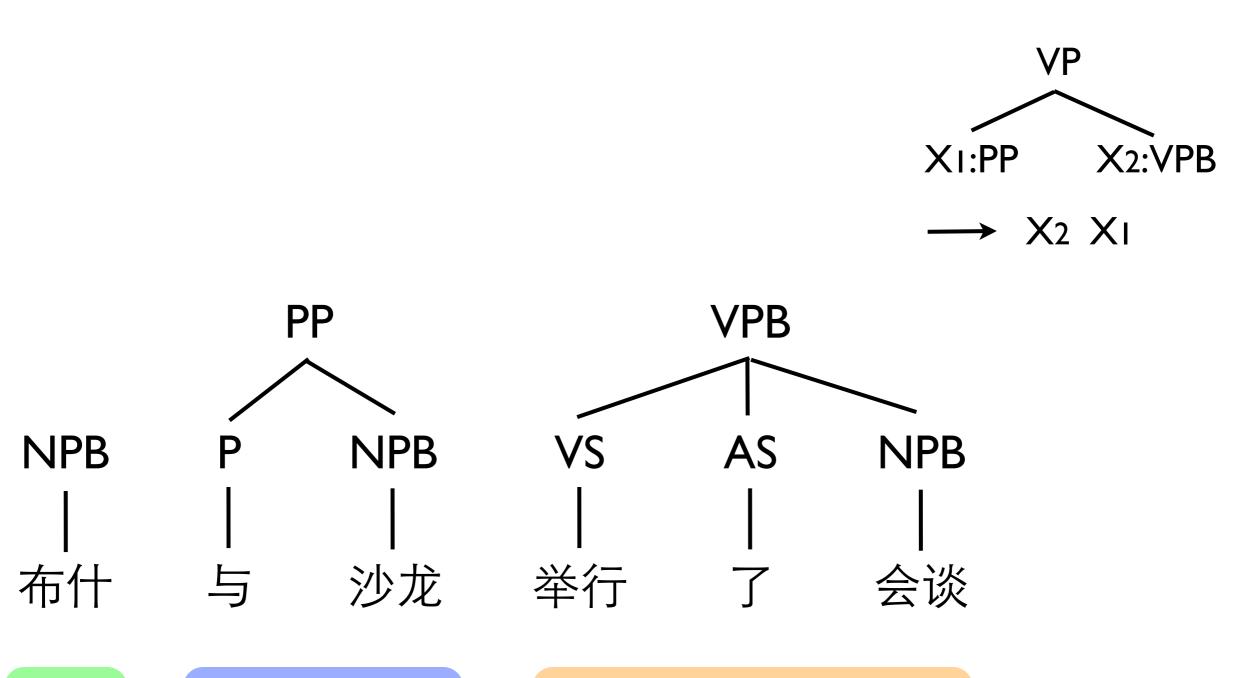








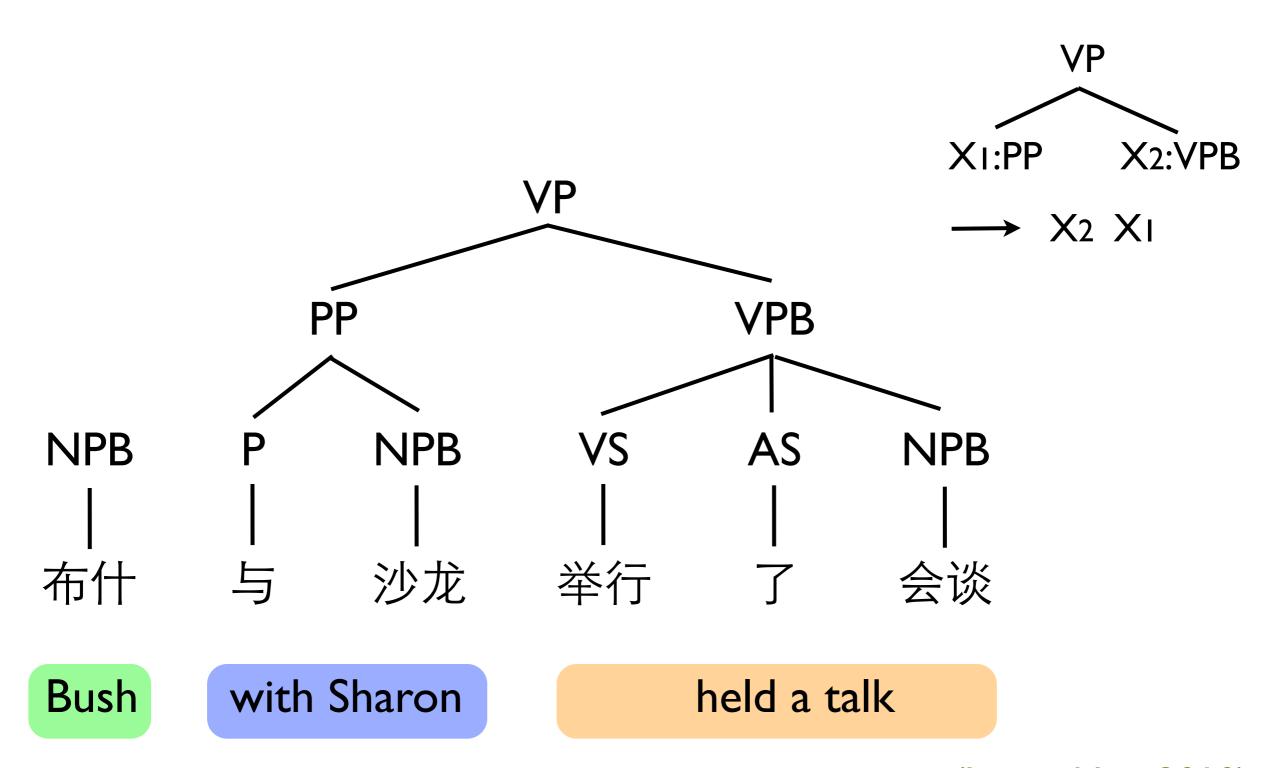


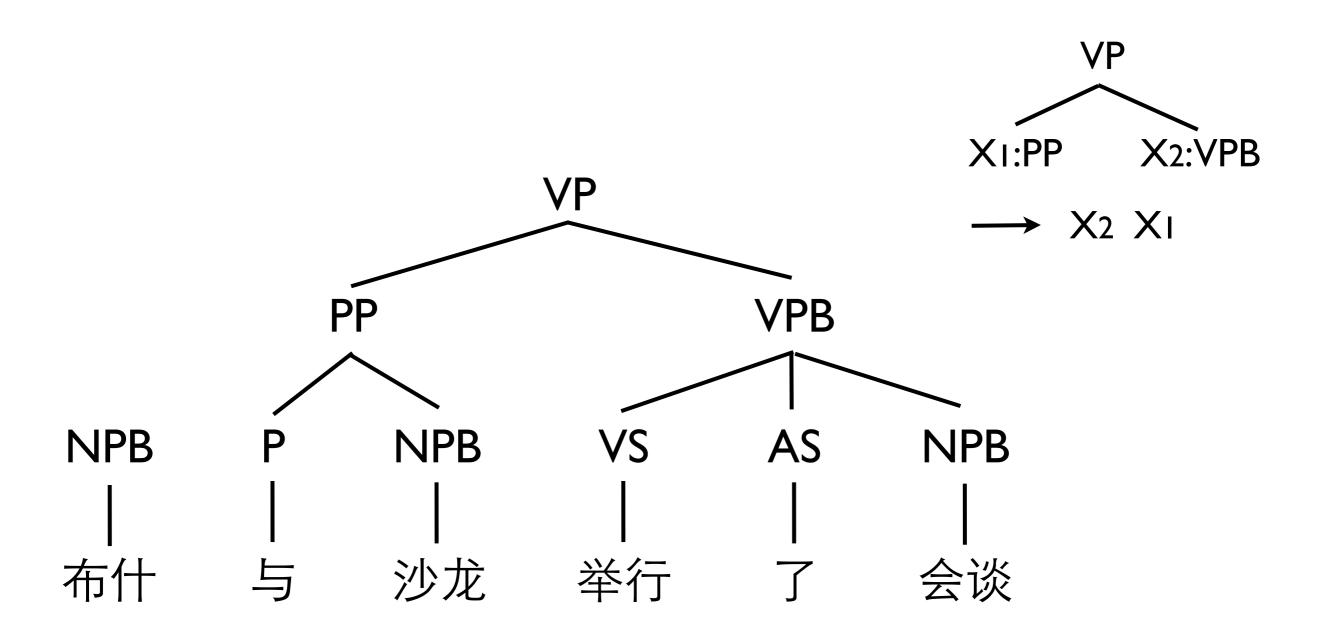


Bush

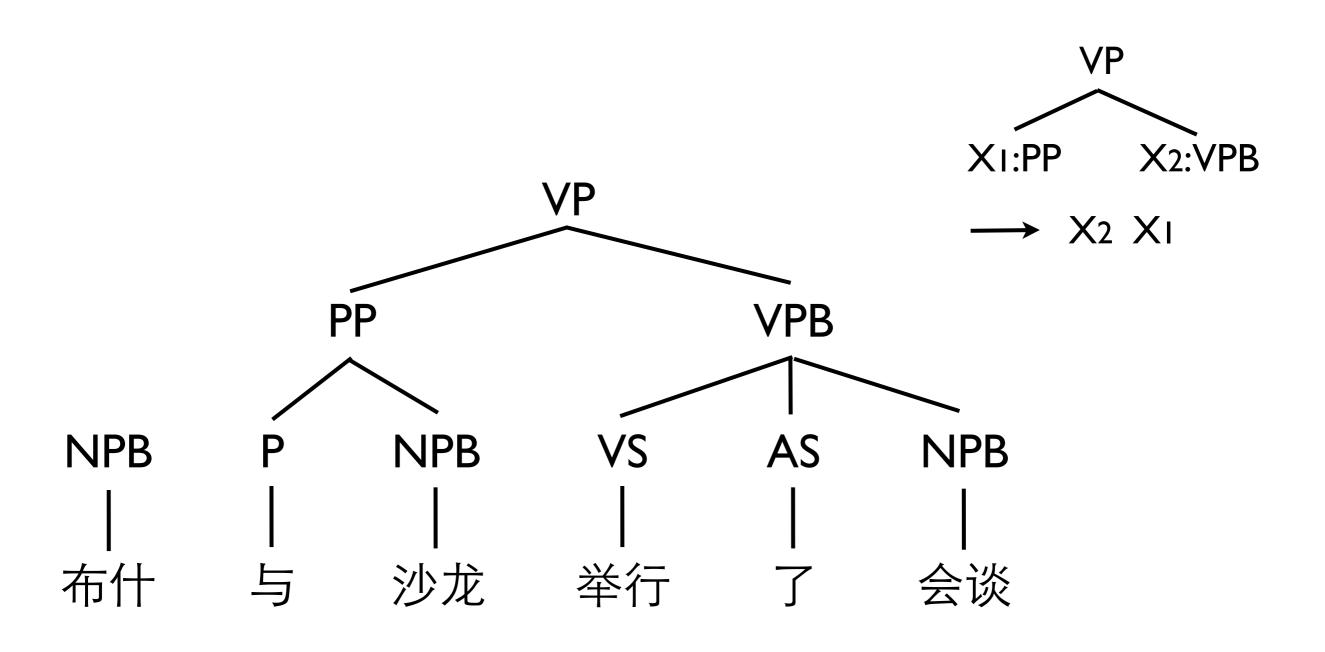
with Sharon

held a talk



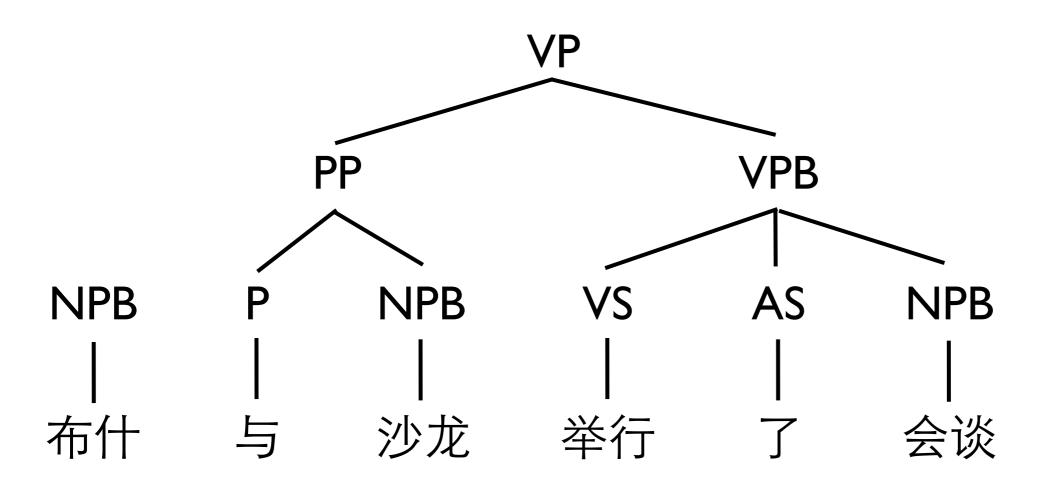


Bush



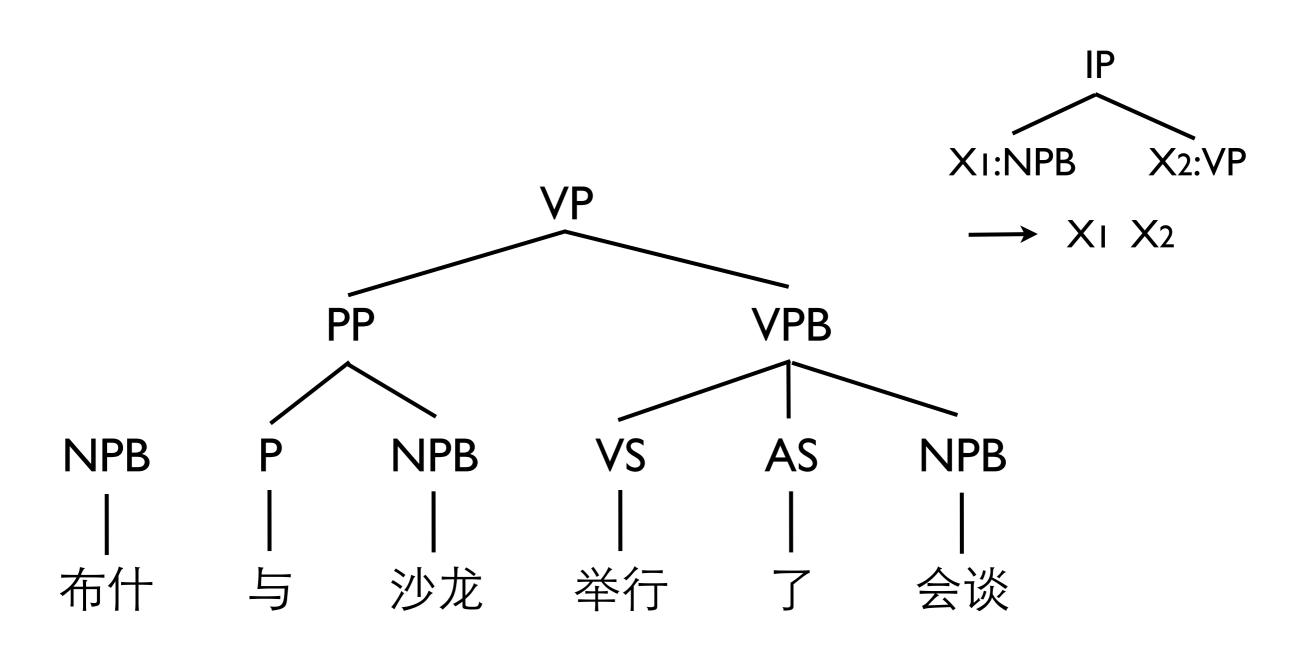
Bush

held a talk with Sharon



Bush

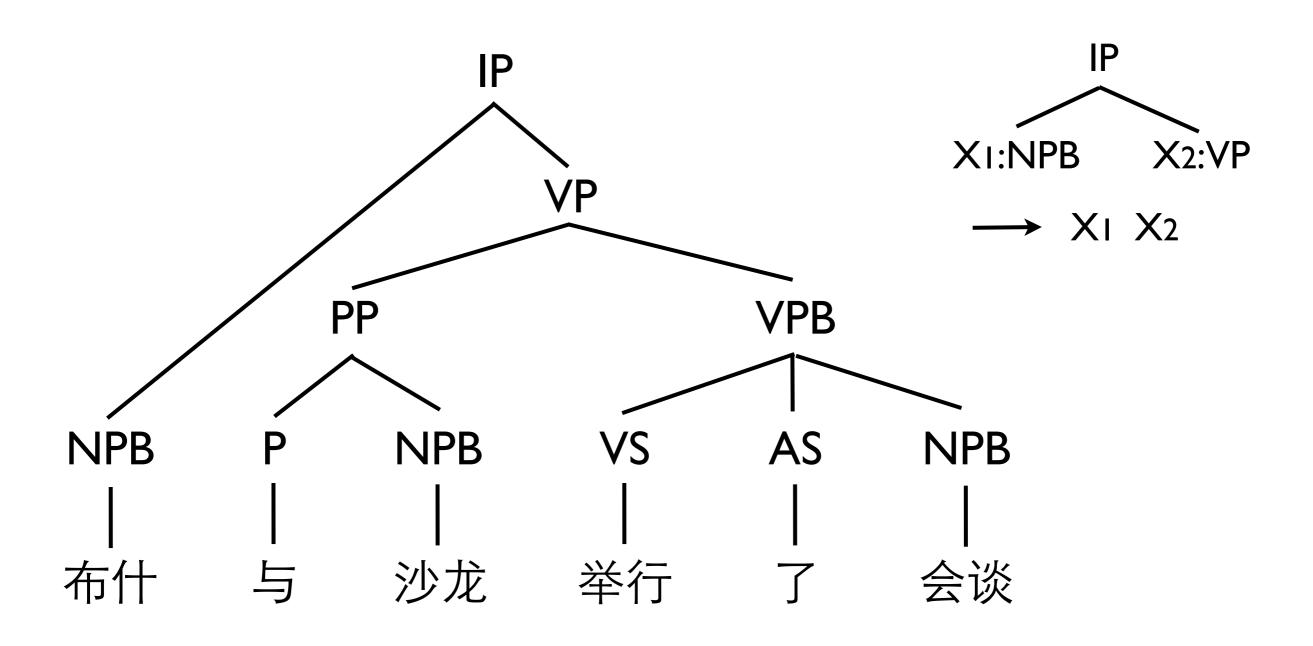
held a talk with Sharon



Bush

held a talk with Sharon

## Joint Parsing and Translation

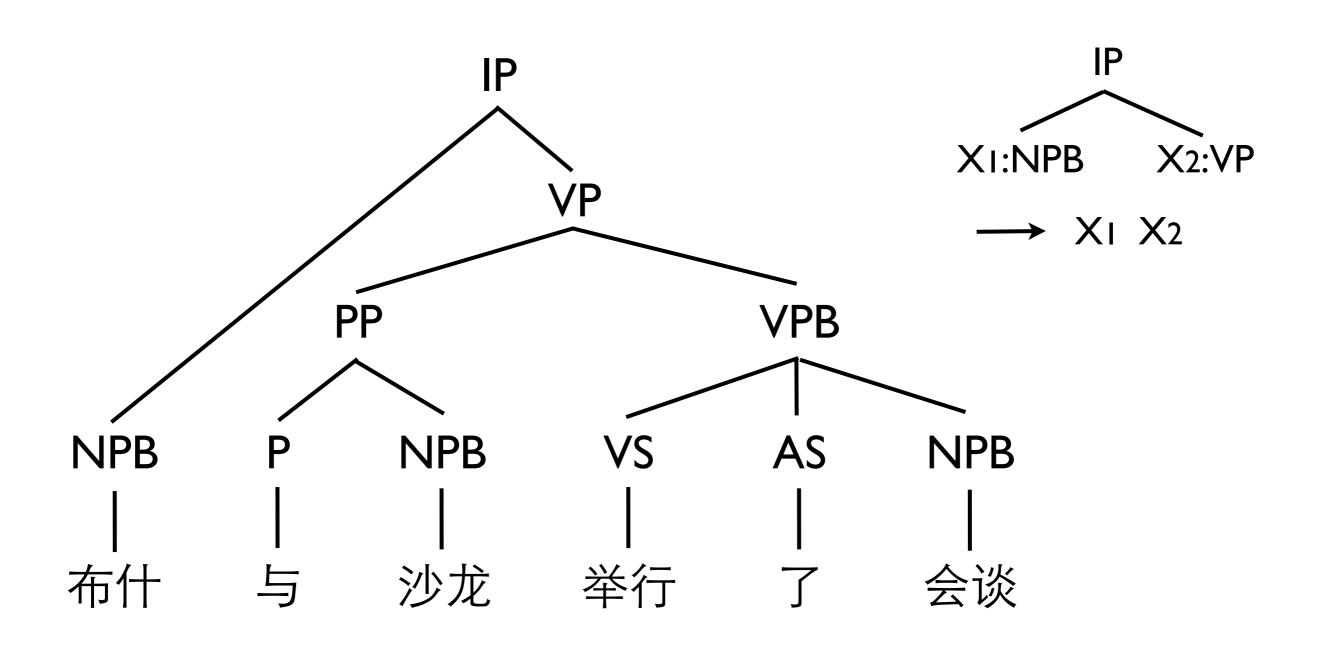


Bush

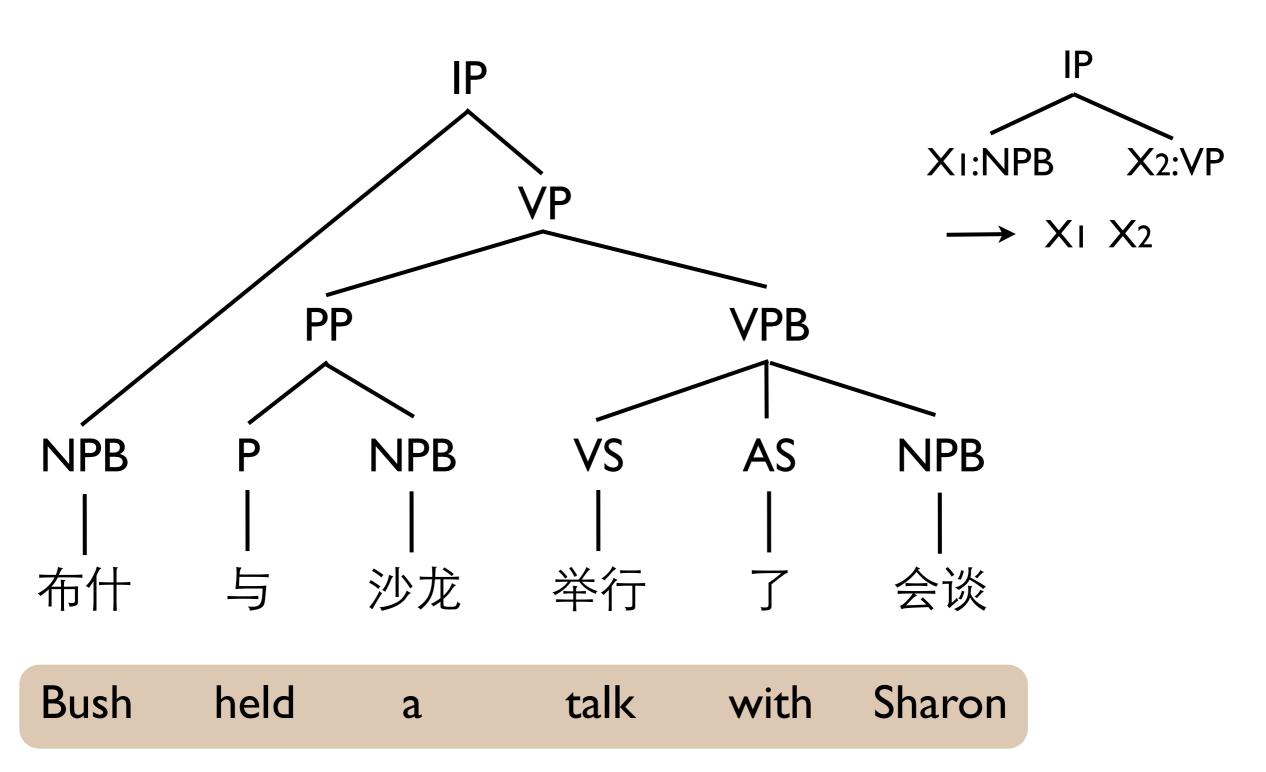
held a talk with Sharon

(Liu and Liu, 2010)

## Joint Parsing and Translation

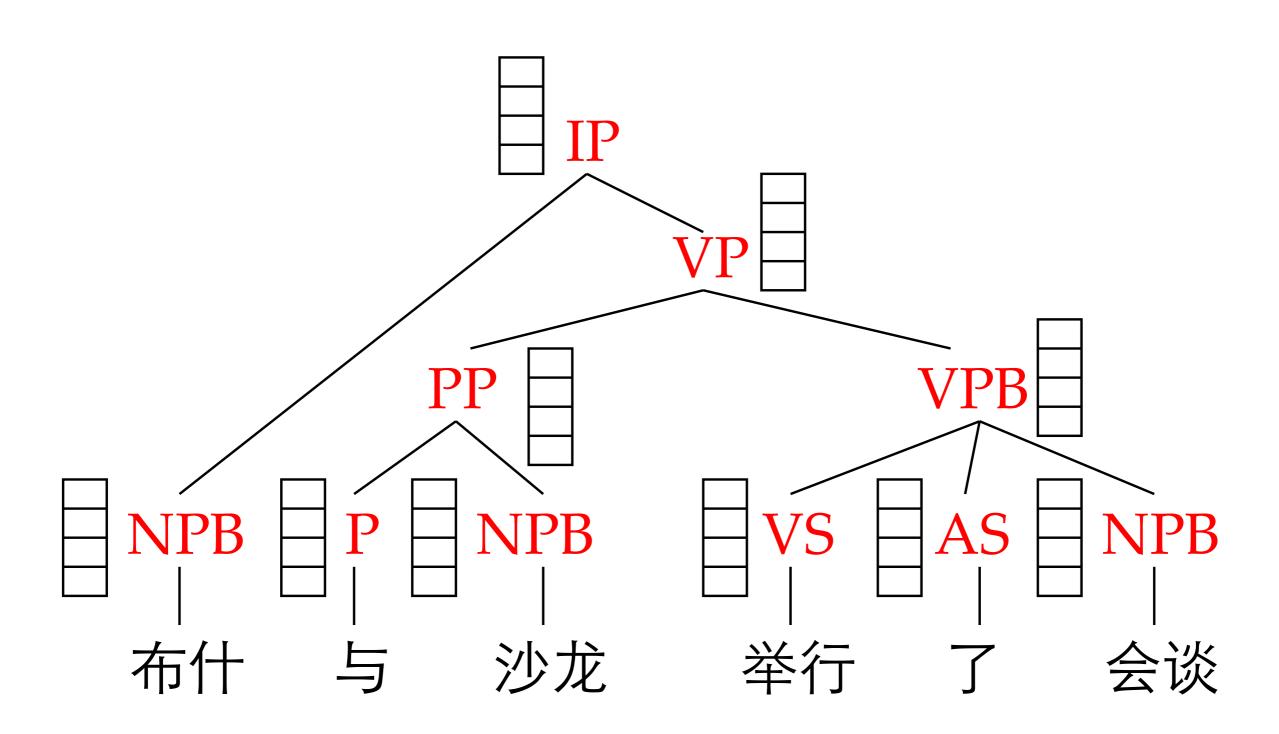


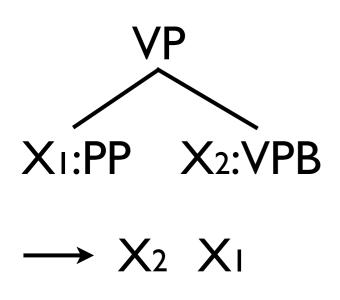
## Joint Parsing and Translation

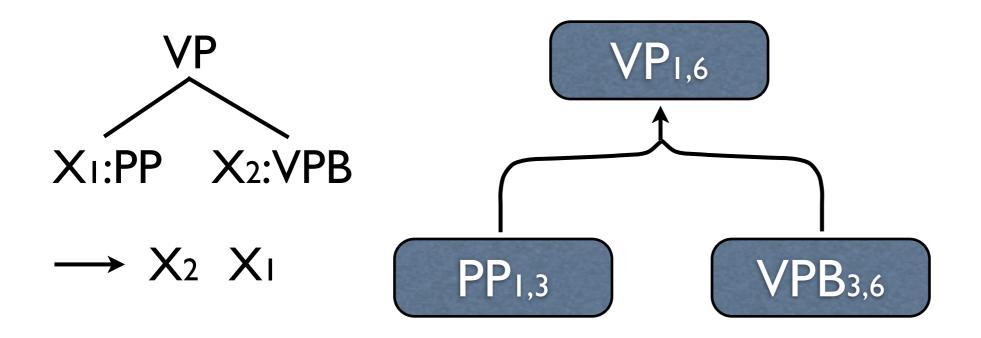


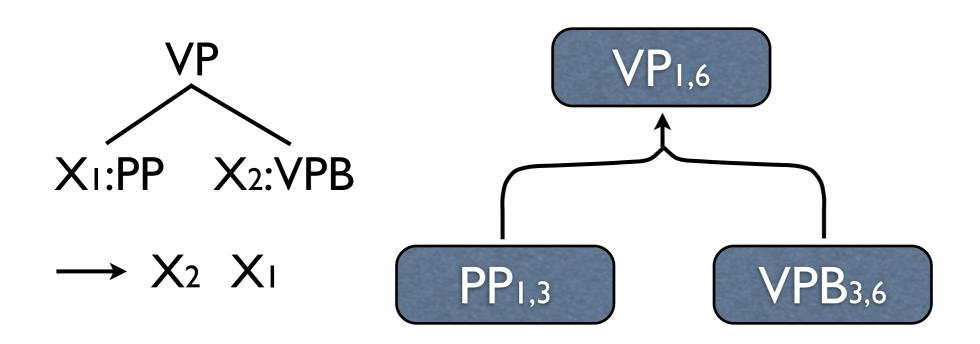
(Liu and Liu, 2010)

## Stacks in Tree-to-String Translation

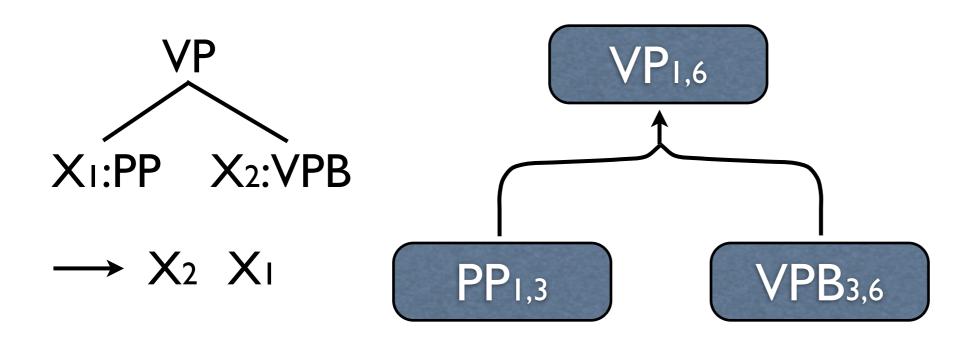








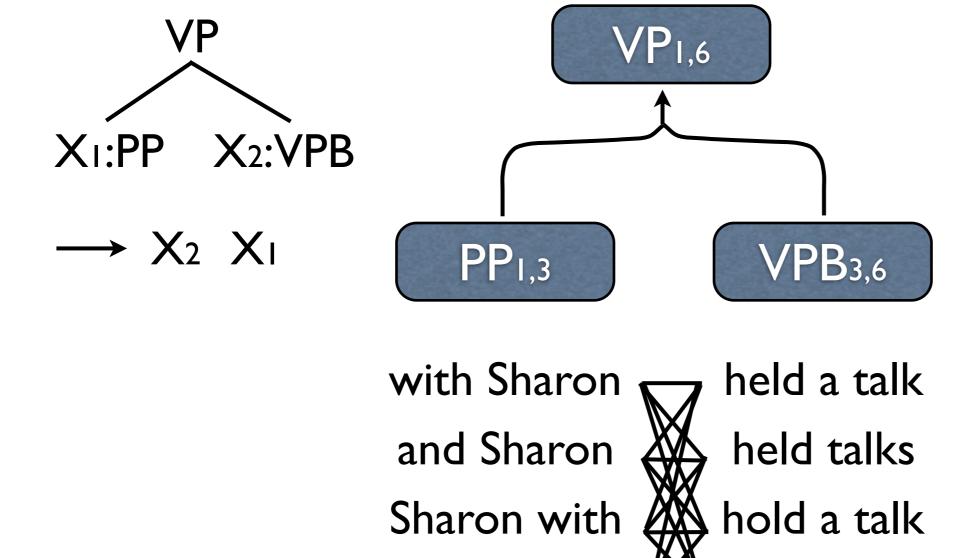
with Sharon and Sharon with Sharon and



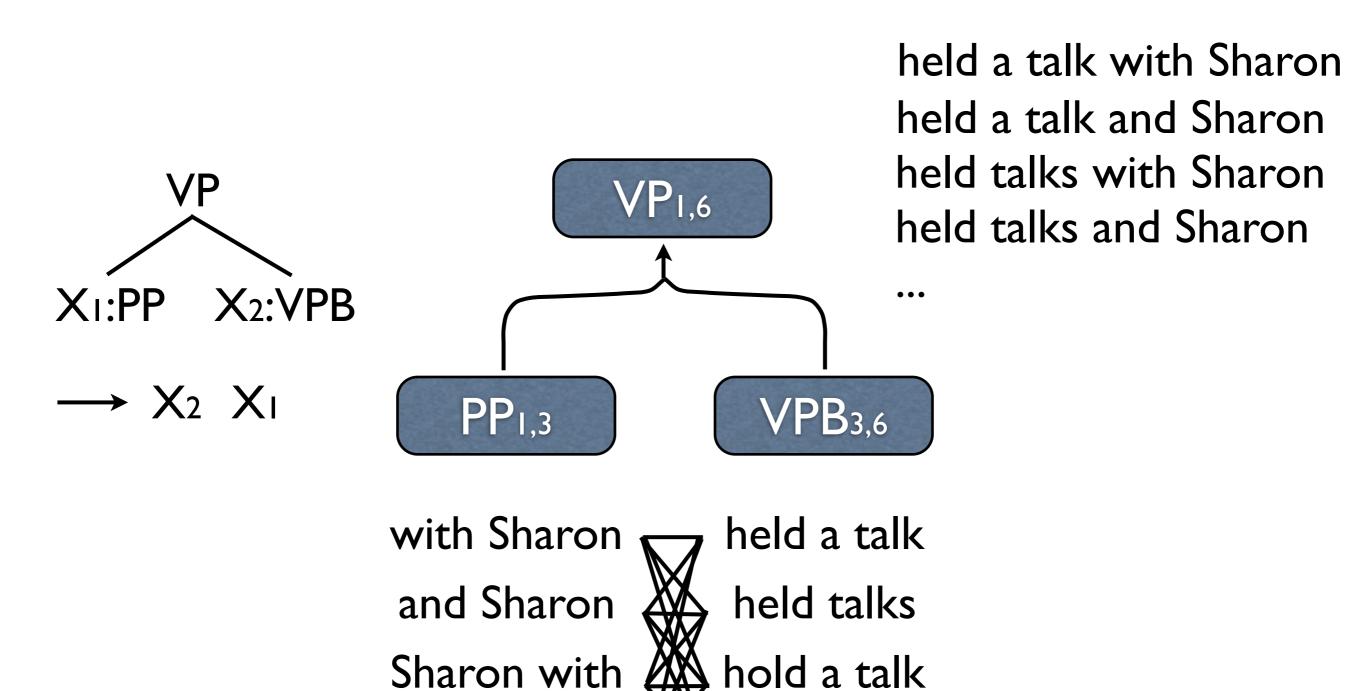
with Sharon and Sharon with Sharon and

held a talk
held talks
hold a talk
hold talks

hold talks



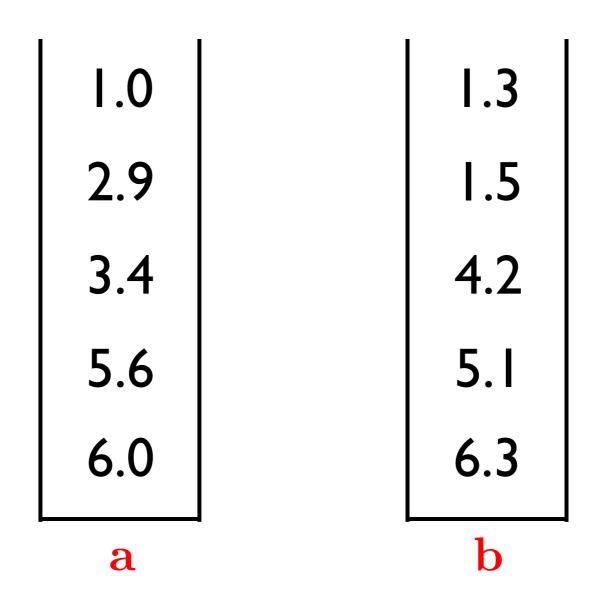
Sharon and



hold talks

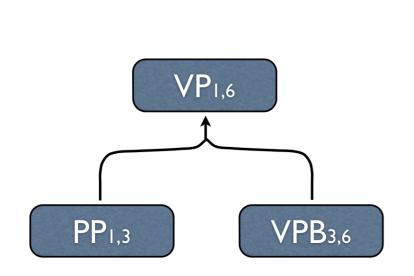
Sharon and

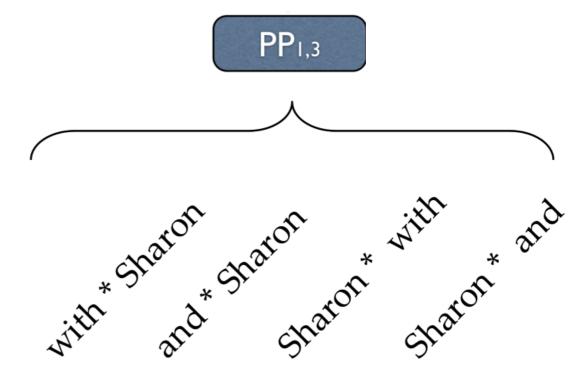
## Calculating N-best List



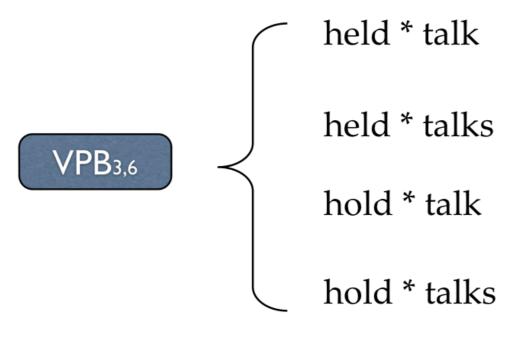
What's the N-best list of  $\mathbf{a}_i + \mathbf{b}_j$ 's ?

## Monotonicity

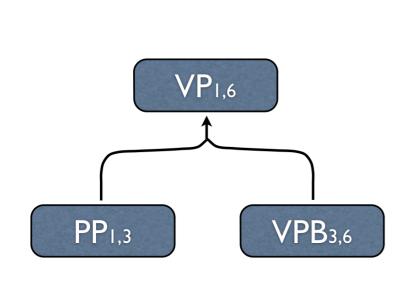


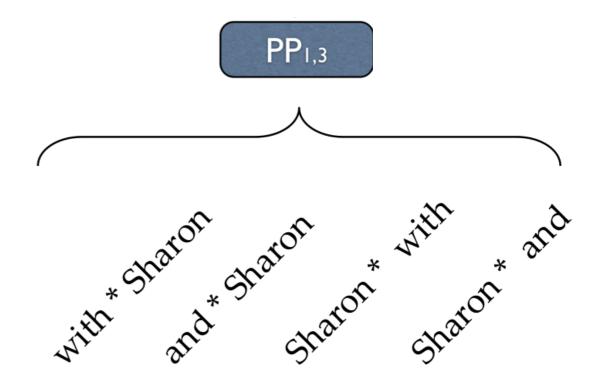


#### monotonic



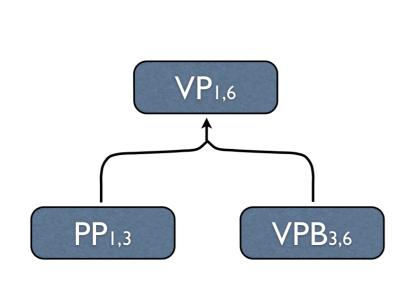
	1.0	3.0	4.0	6.5
1.0	2.0	4.0	5.0	7.5
1.1	2.1	<b>4.</b> I	5. I	7.6
2.0	3.0	5.0	6.0	8.5
3.5	4.5	6.5	7.5	10.0

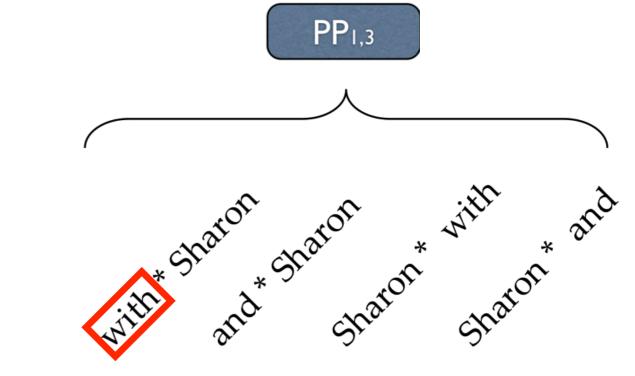




VPB <sub>3,6</sub>	held * talk
	held * talks
	hold * talk
	hold * talks

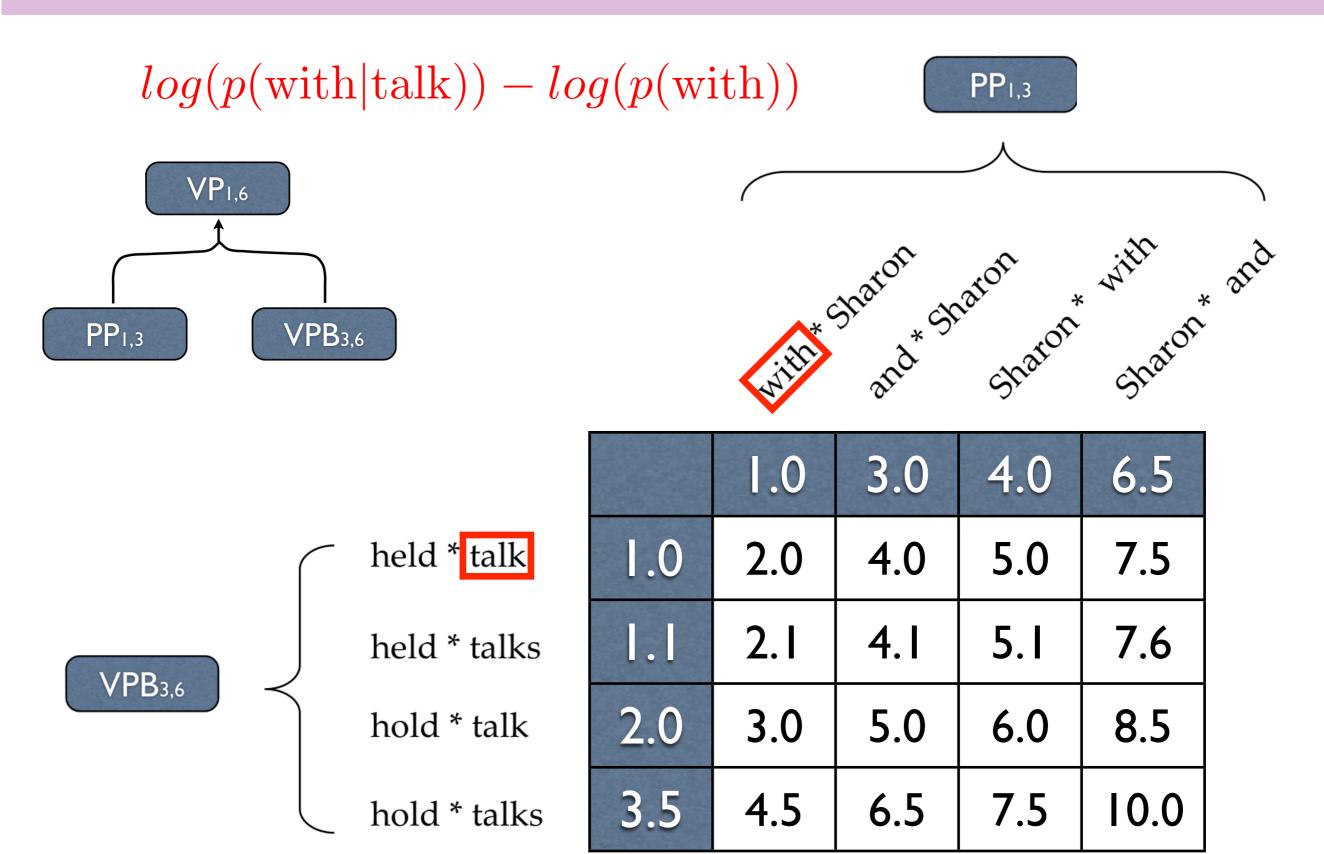
	1.0	3.0	4.0	6.5
1.0	2.0	4.0	5.0	7.5
1.1	2.1	<b>4</b> . I	5. I	7.6
2.0	3.0	5.0	6.0	8.5
3.5	4.5	6.5	7.5	10.0

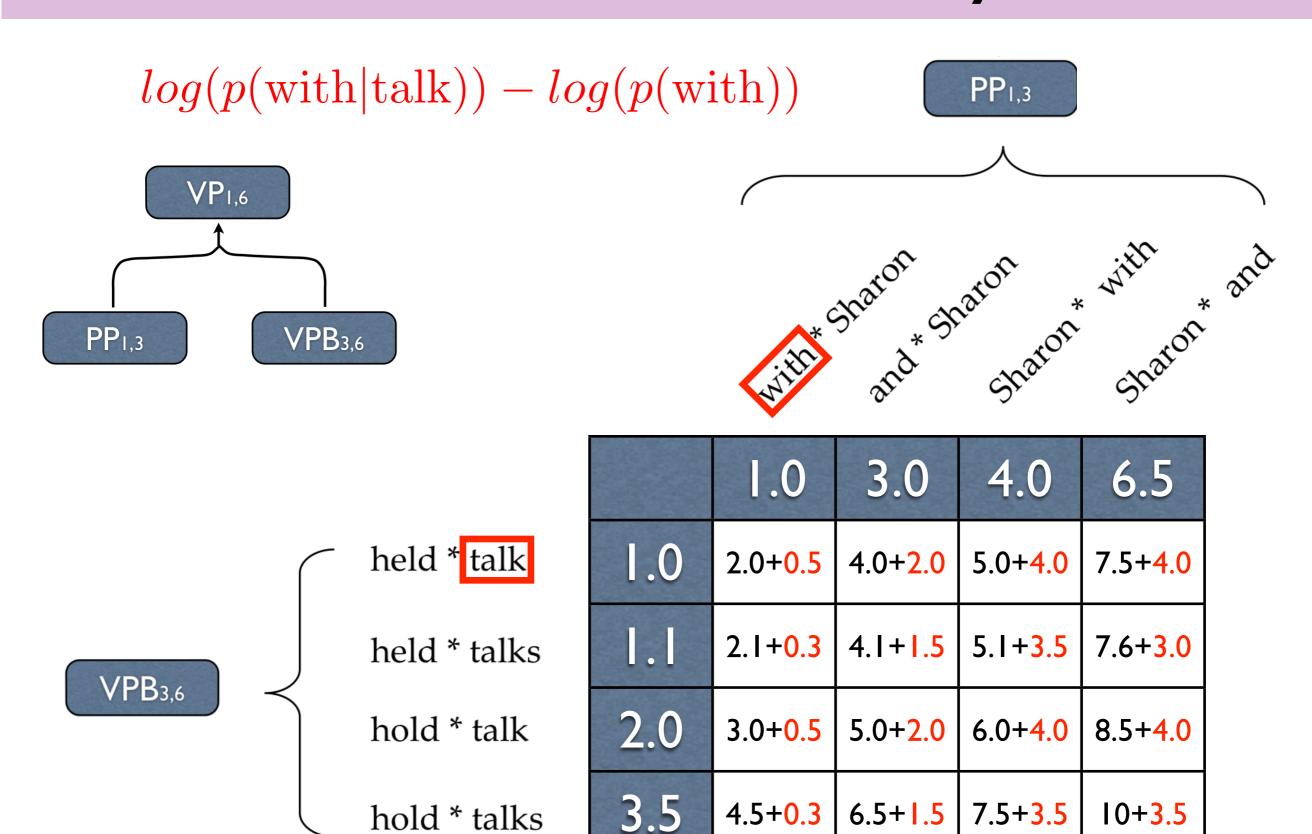


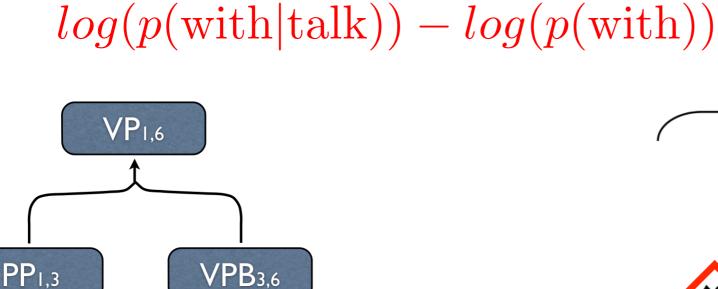


	held * talk
V/DD.	held * talks
VPB <sub>3,6</sub>	hold * talk
	hold * talks

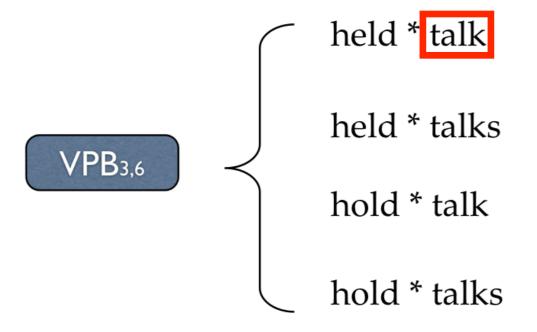
	1.0	3.0	4.0	6.5
1.0	2.0	4.0	5.0	7.5
1.1	2.1	<b>4</b> . I	5. I	7.6
2.0	3.0	5.0	6.0	8.5
3.5	4.5	6.5	7.5	10.0

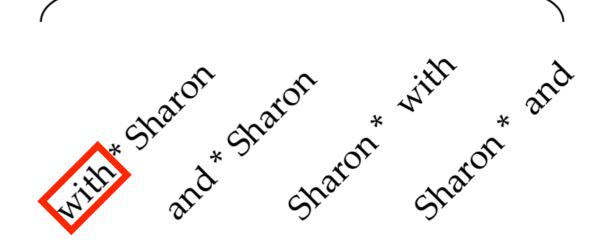






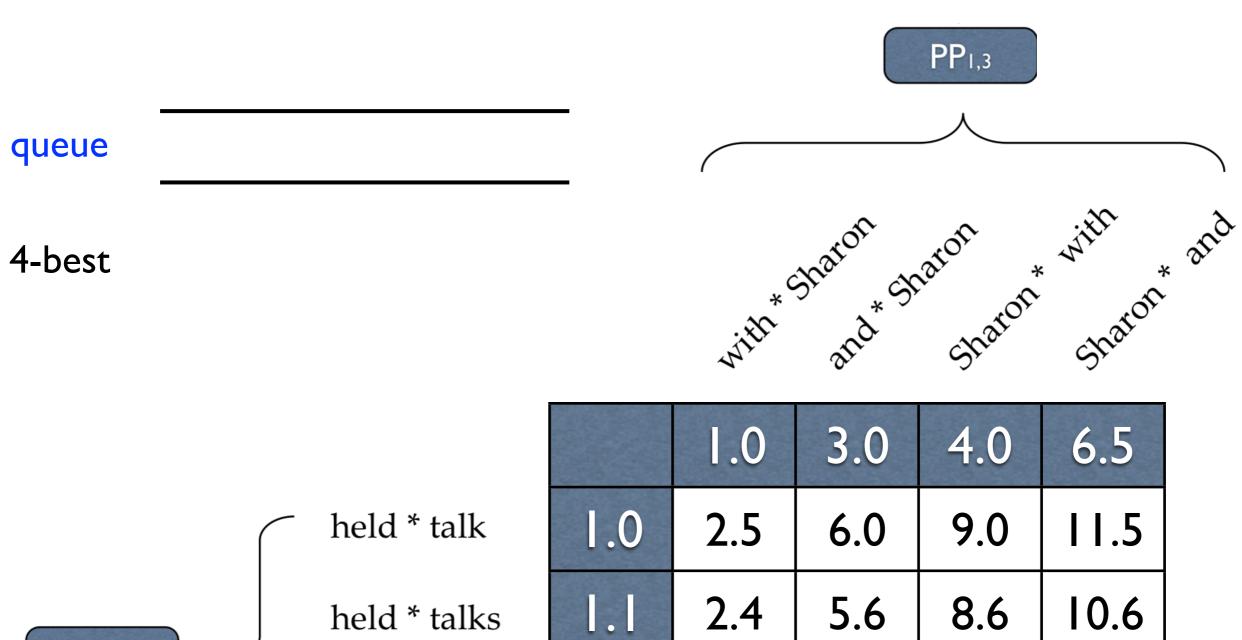
#### LM introduces non-monotonicity





**PP**1,3

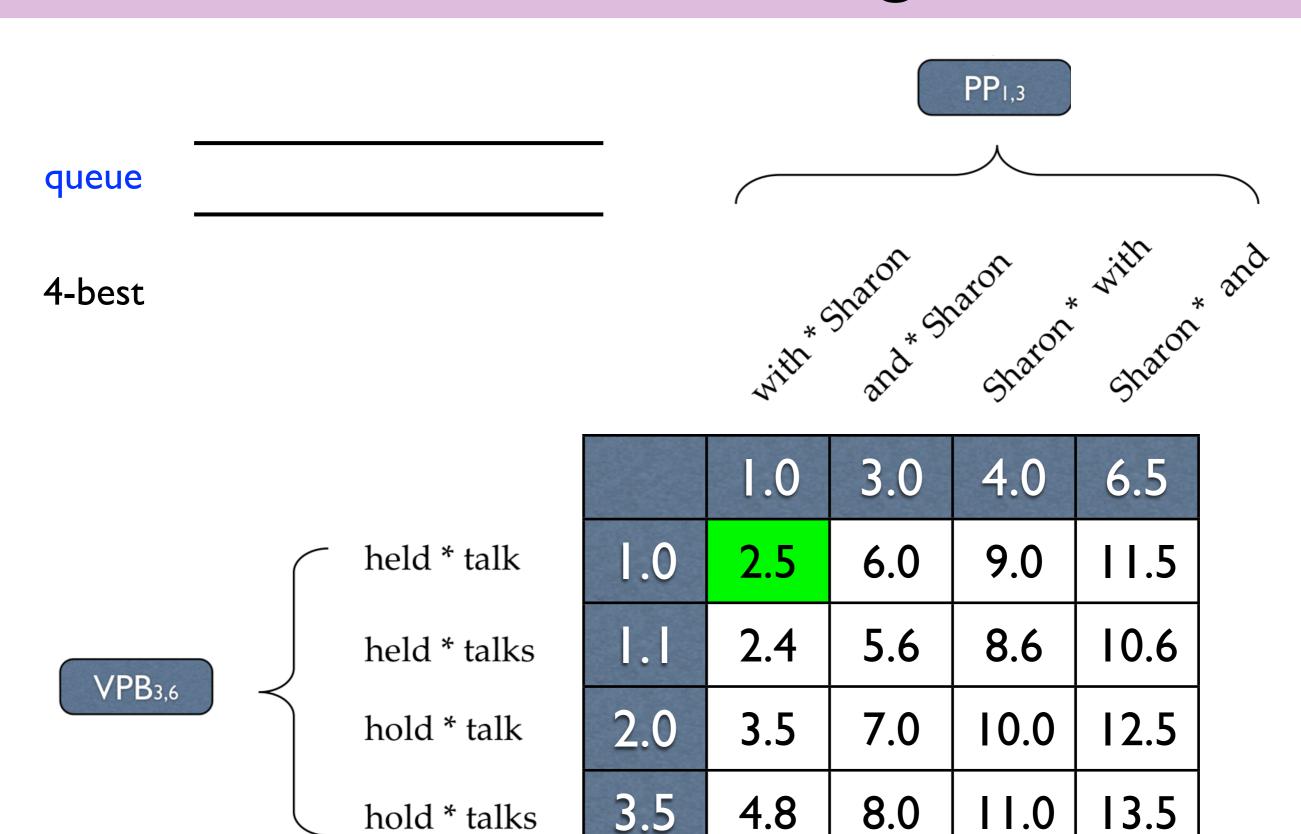
	1.0	3.0	4.0	6.5
1.0	2.0+0.5	4.0+2.0	5.0+4.0	7.5+4.0
1.1	2.1+0.3	4.1+1.5	5.1+3.5	7.6+3.0
2.0	3.0+0.5	5.0+2.0	6.0+4.0	8.5+4.0
3.5	4.5+0.3	6.5+1.5	7.5+3.5	10+3.5

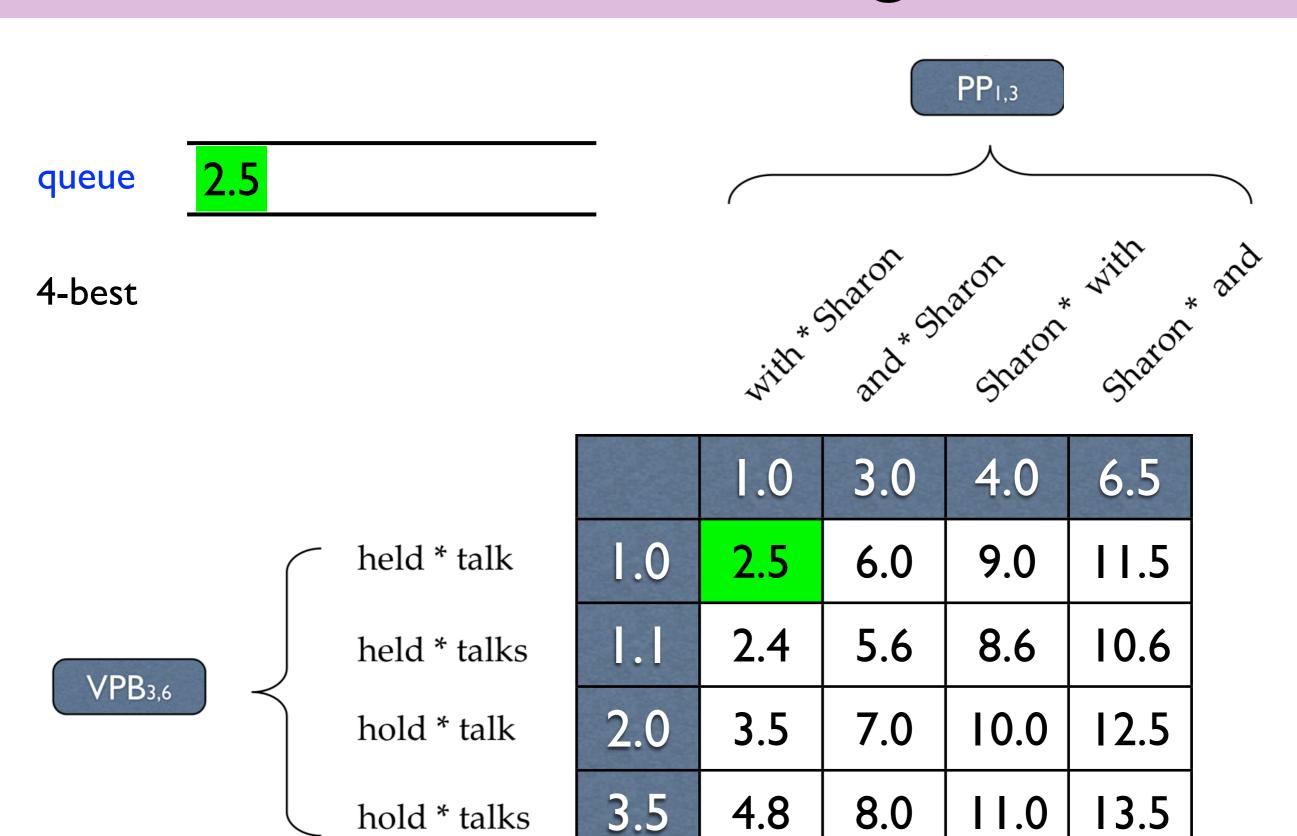


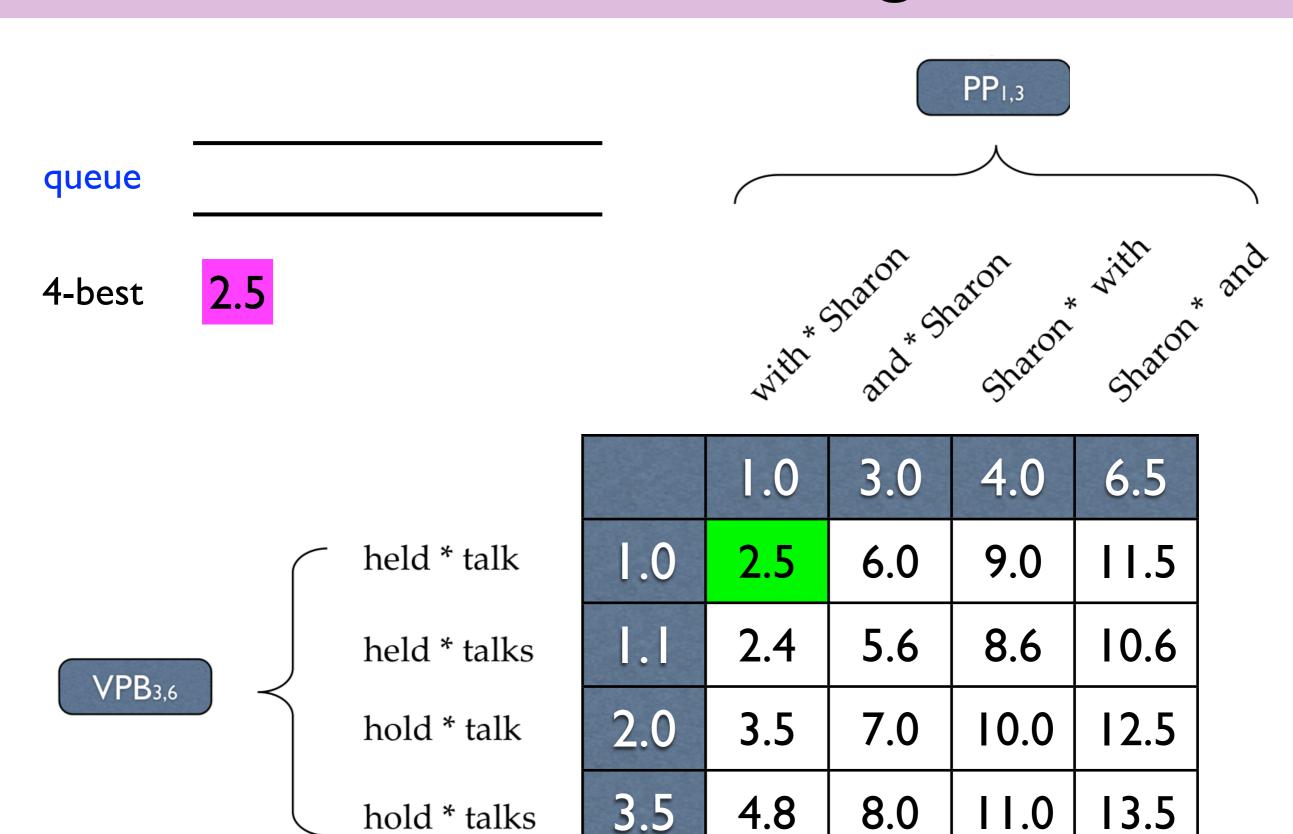
VPB<sub>3,6</sub> hold \* talk

hold \* talks

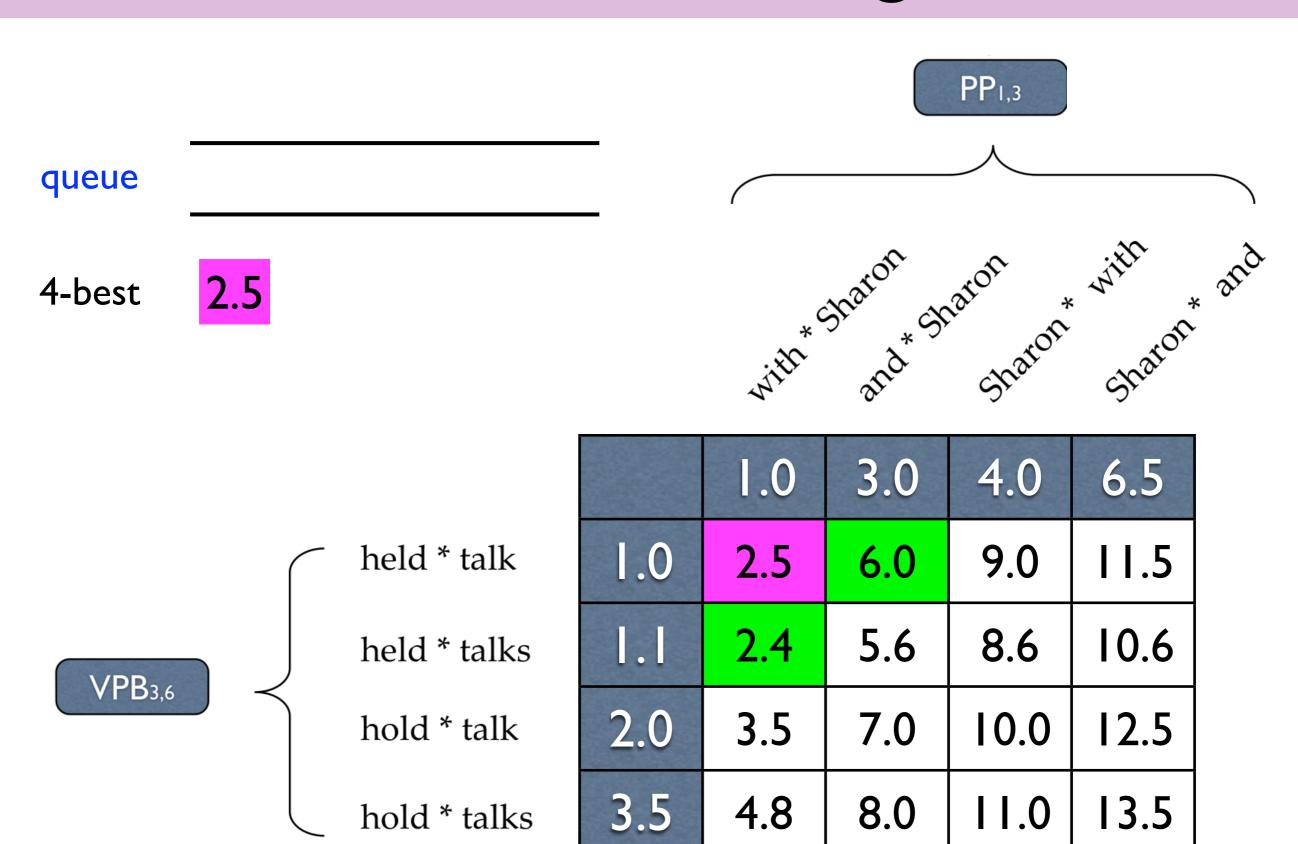
	1.0	3.0	4.0	6.5
1.0	2.5	6.0	9.0	11.5
1.1	2.4	5.6	8.6	10.6
2.0	3.5	7.0	10.0	12.5
3.5	4.8	8.0	11.0	13.5

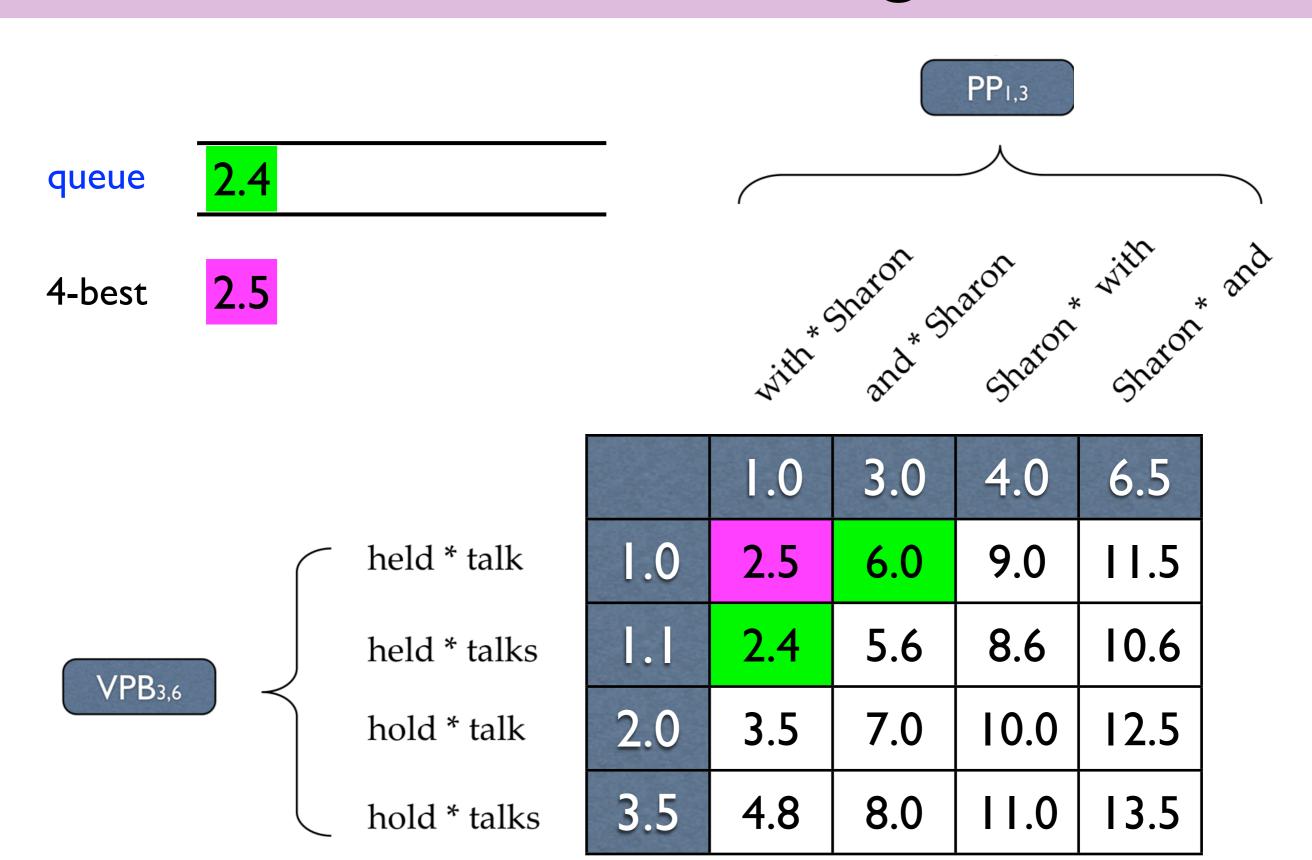


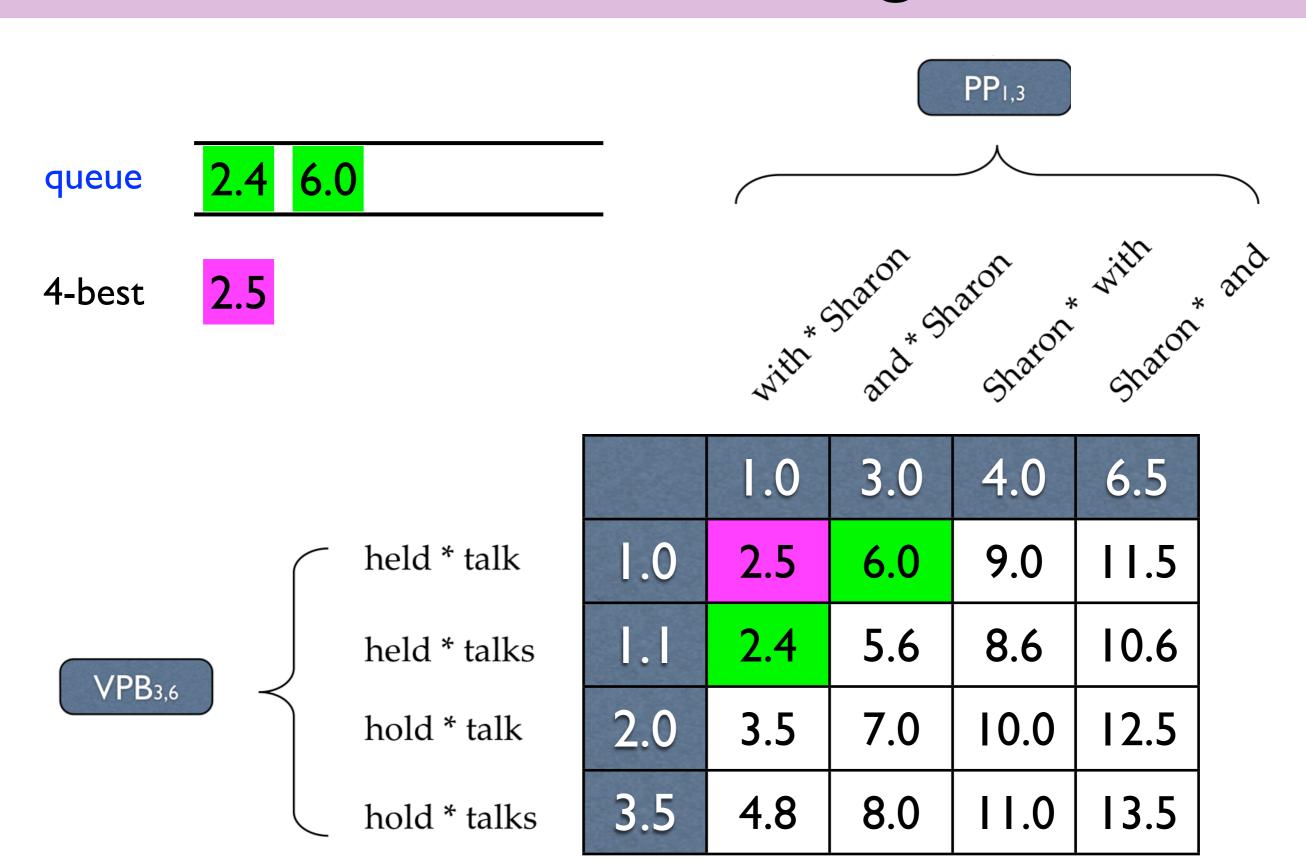


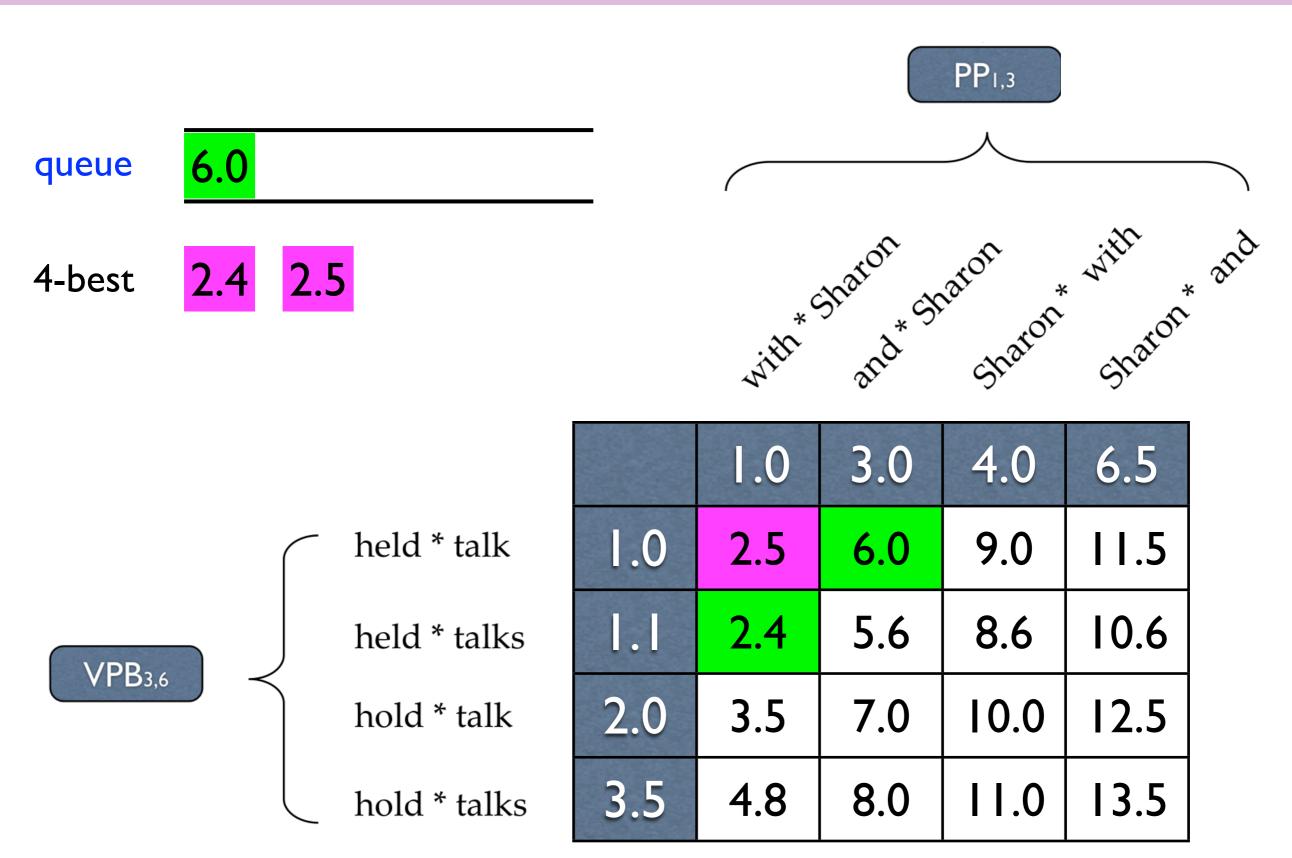


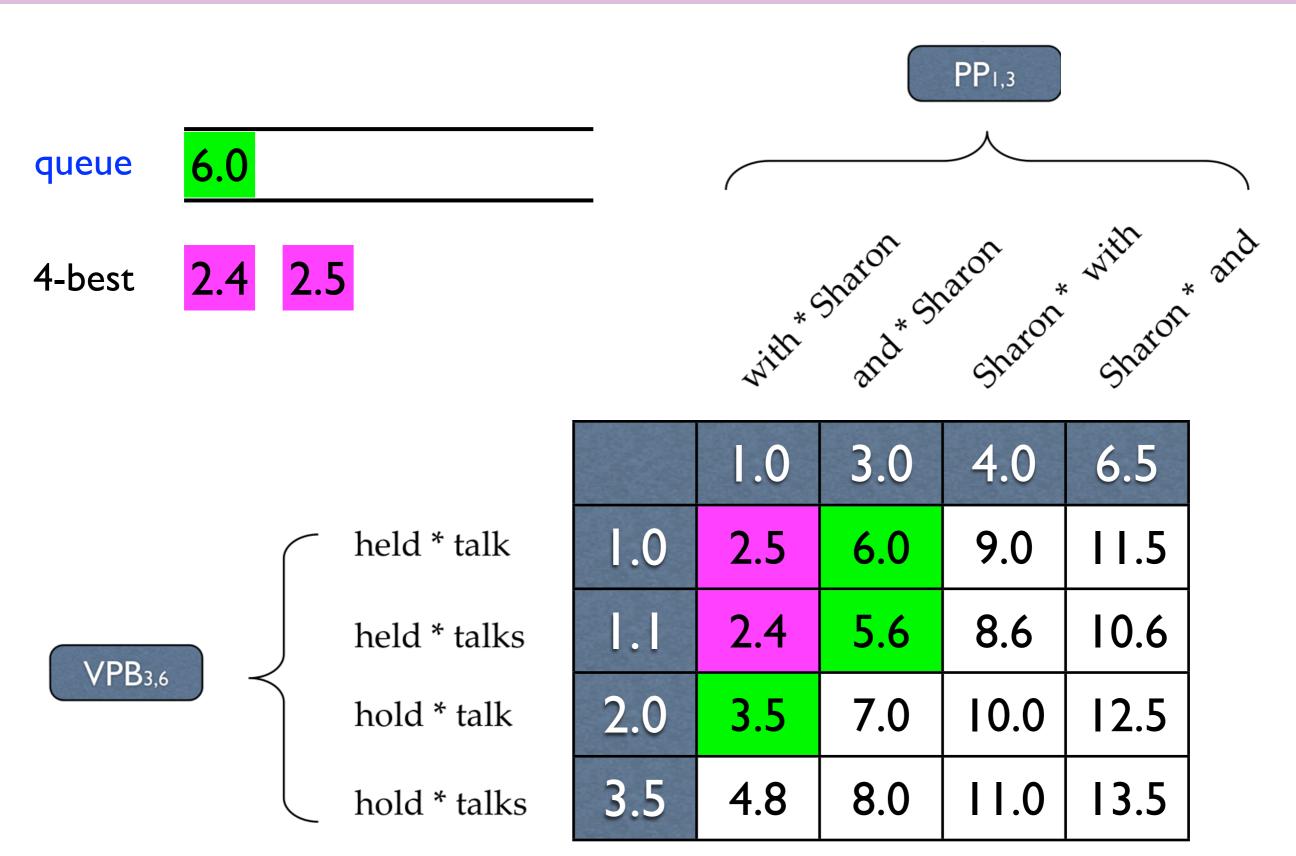
hold \* talks

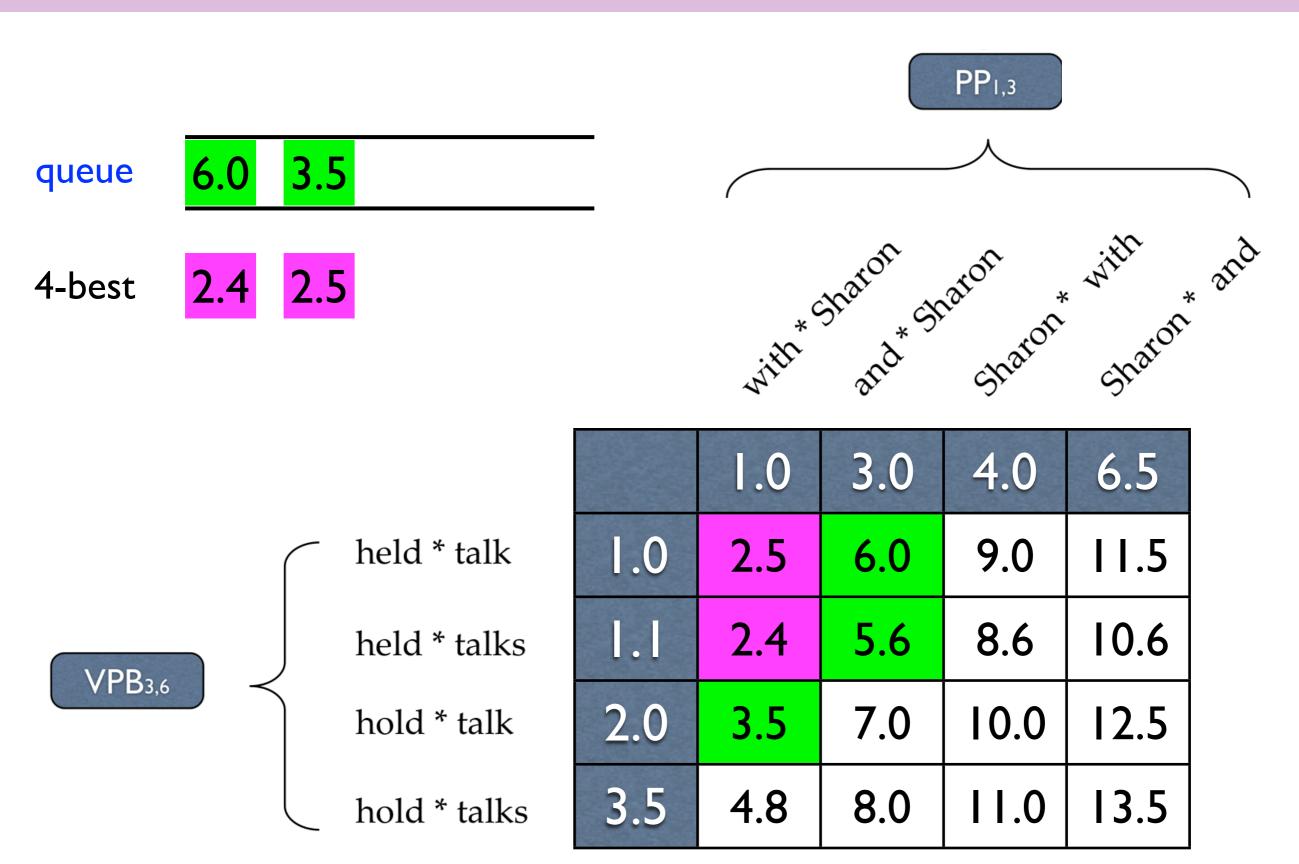


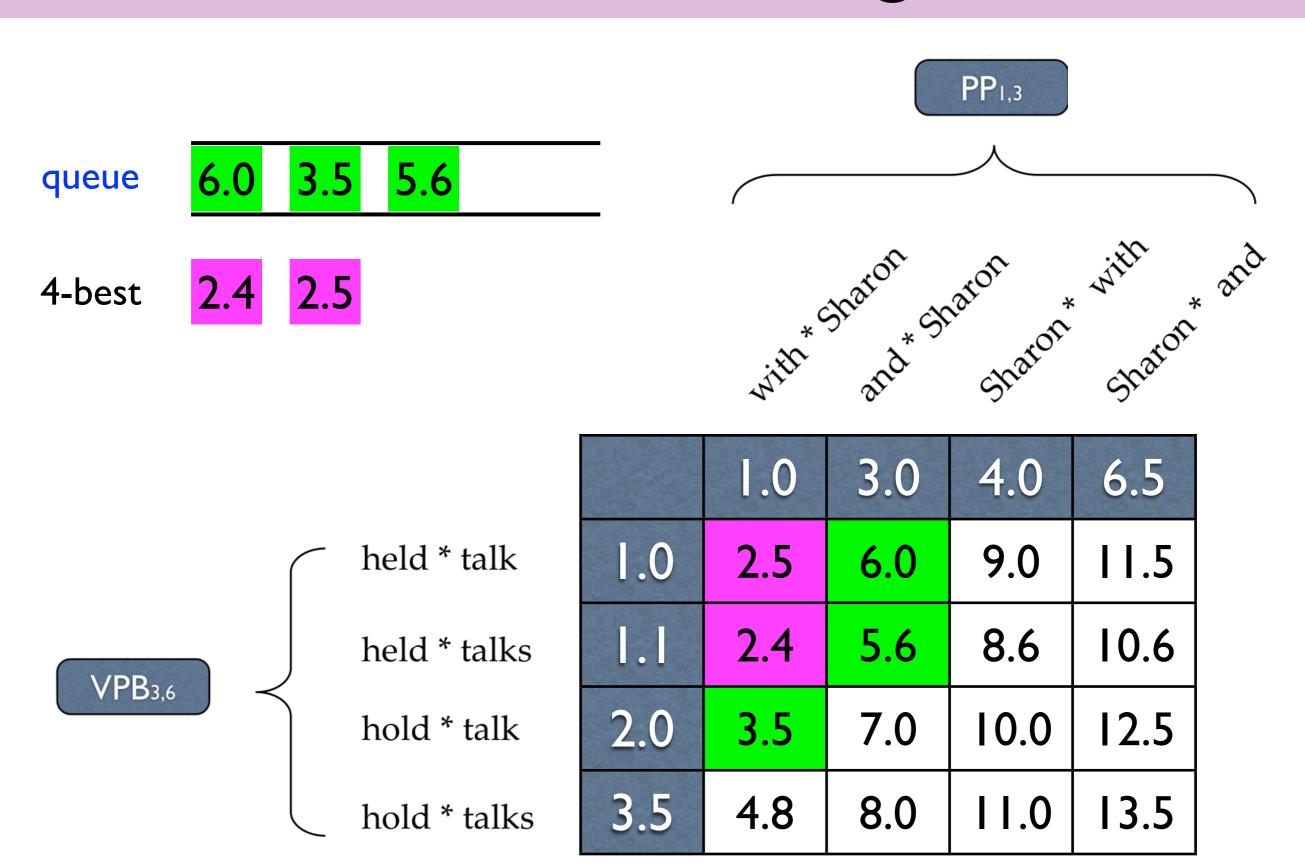


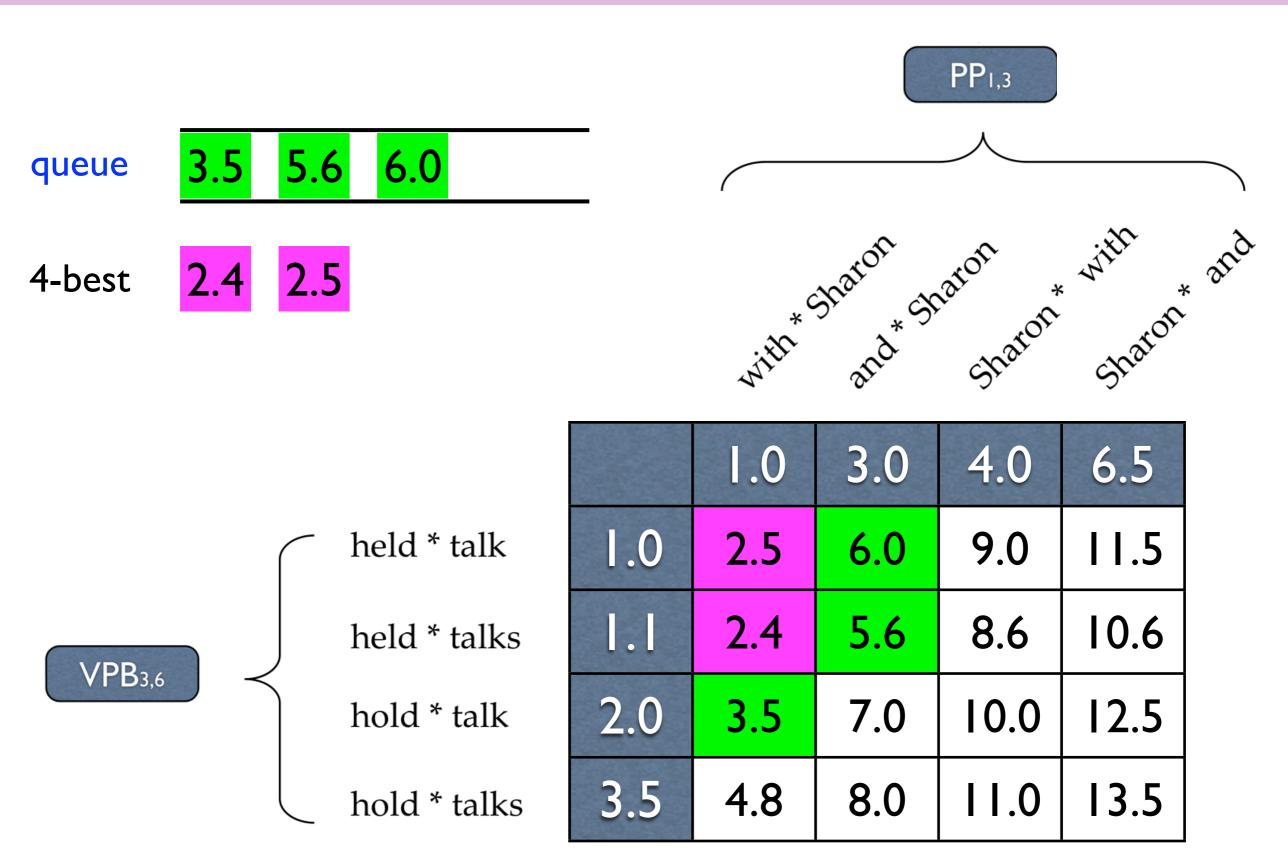


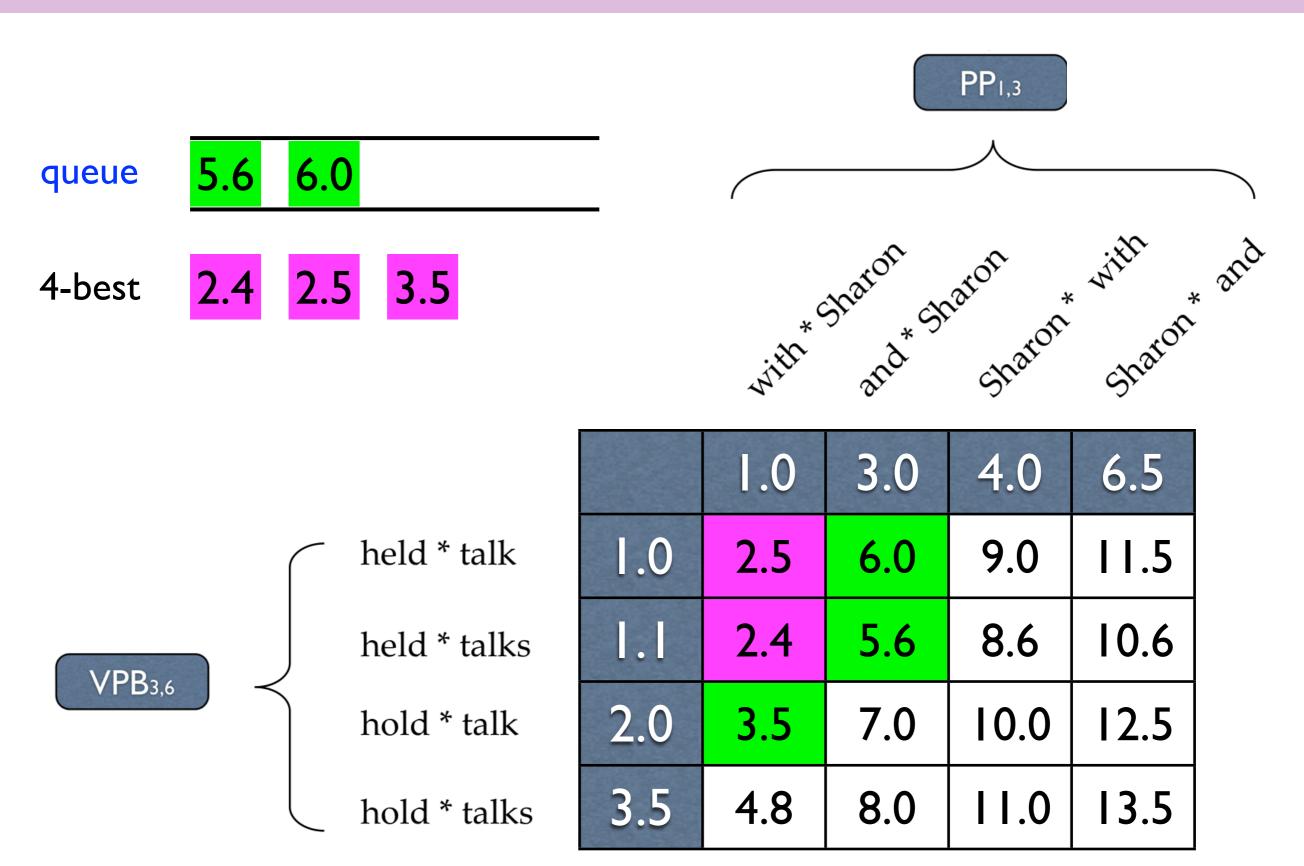


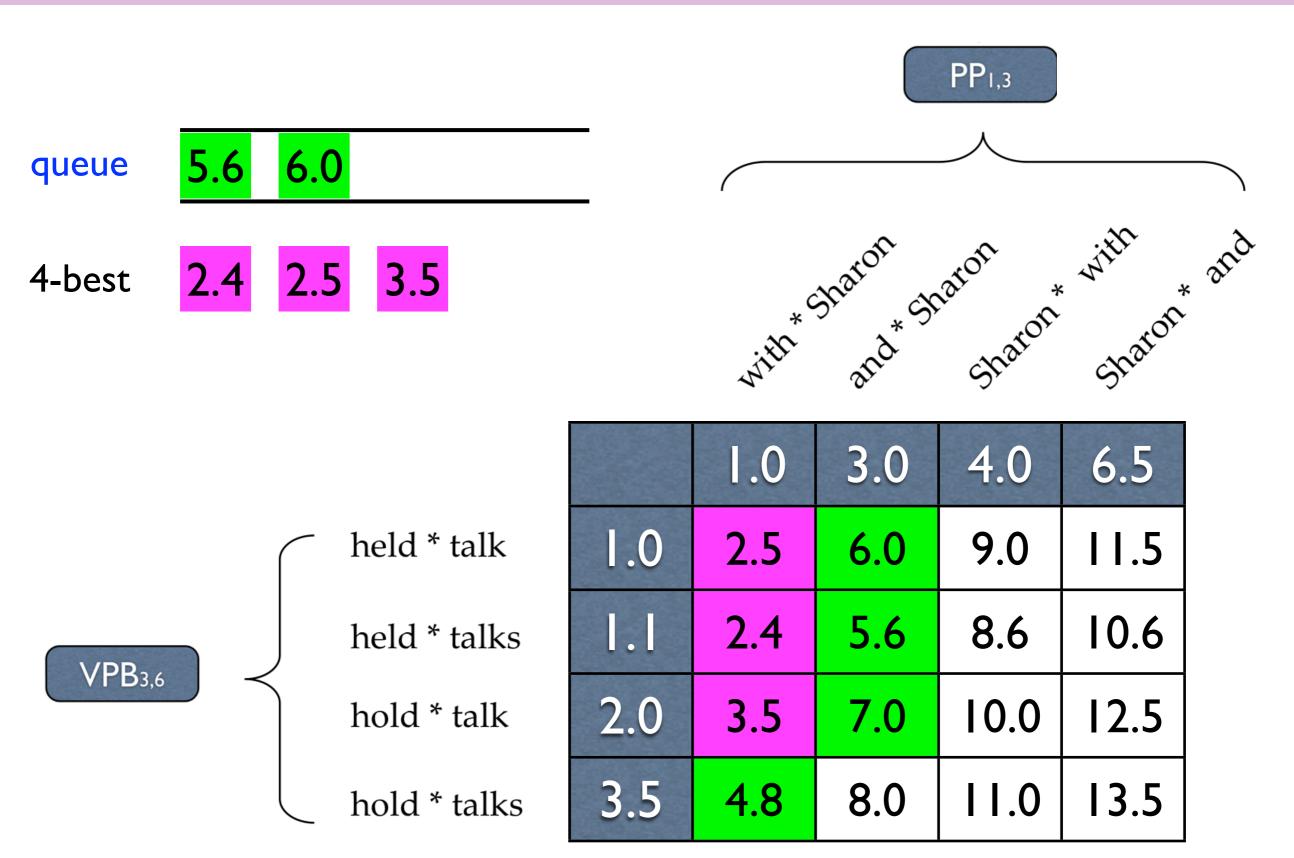


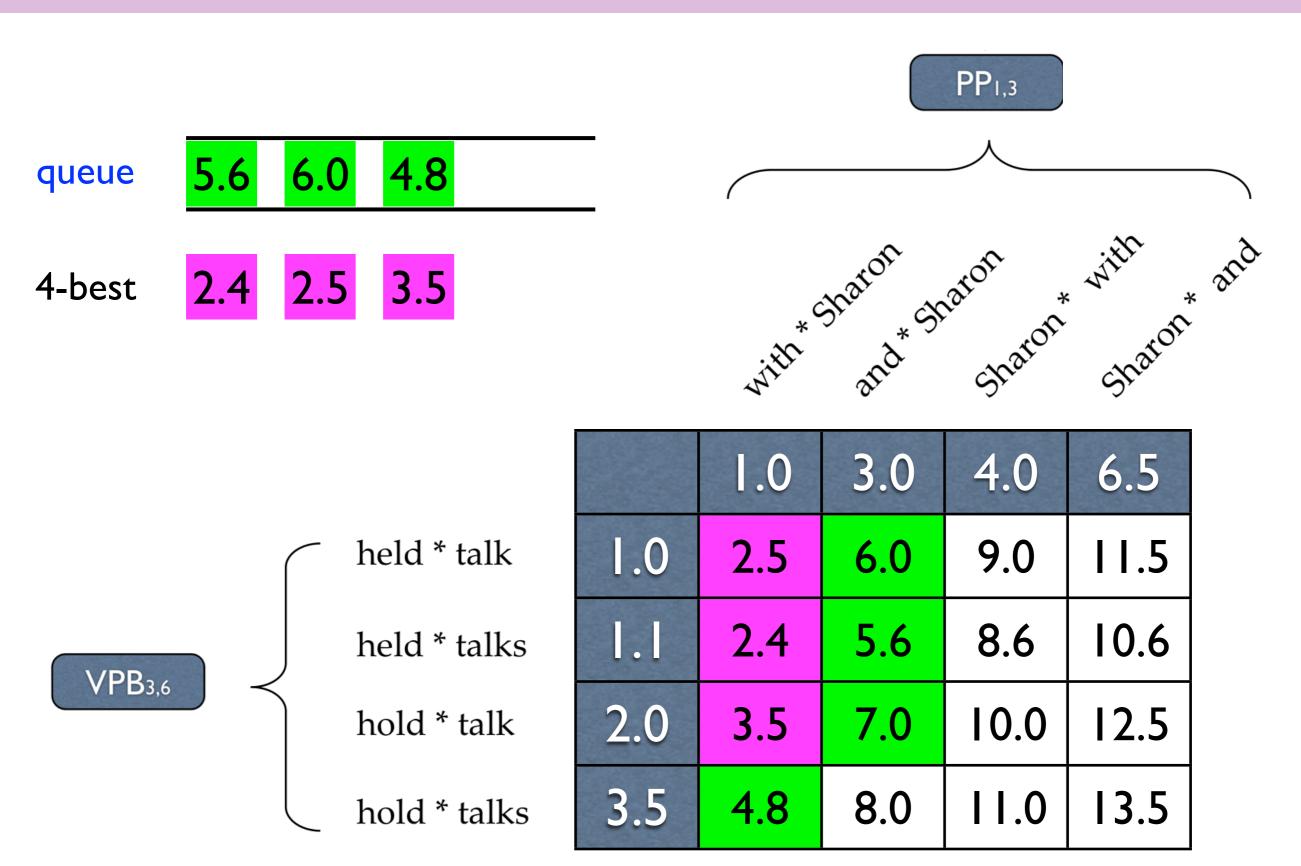


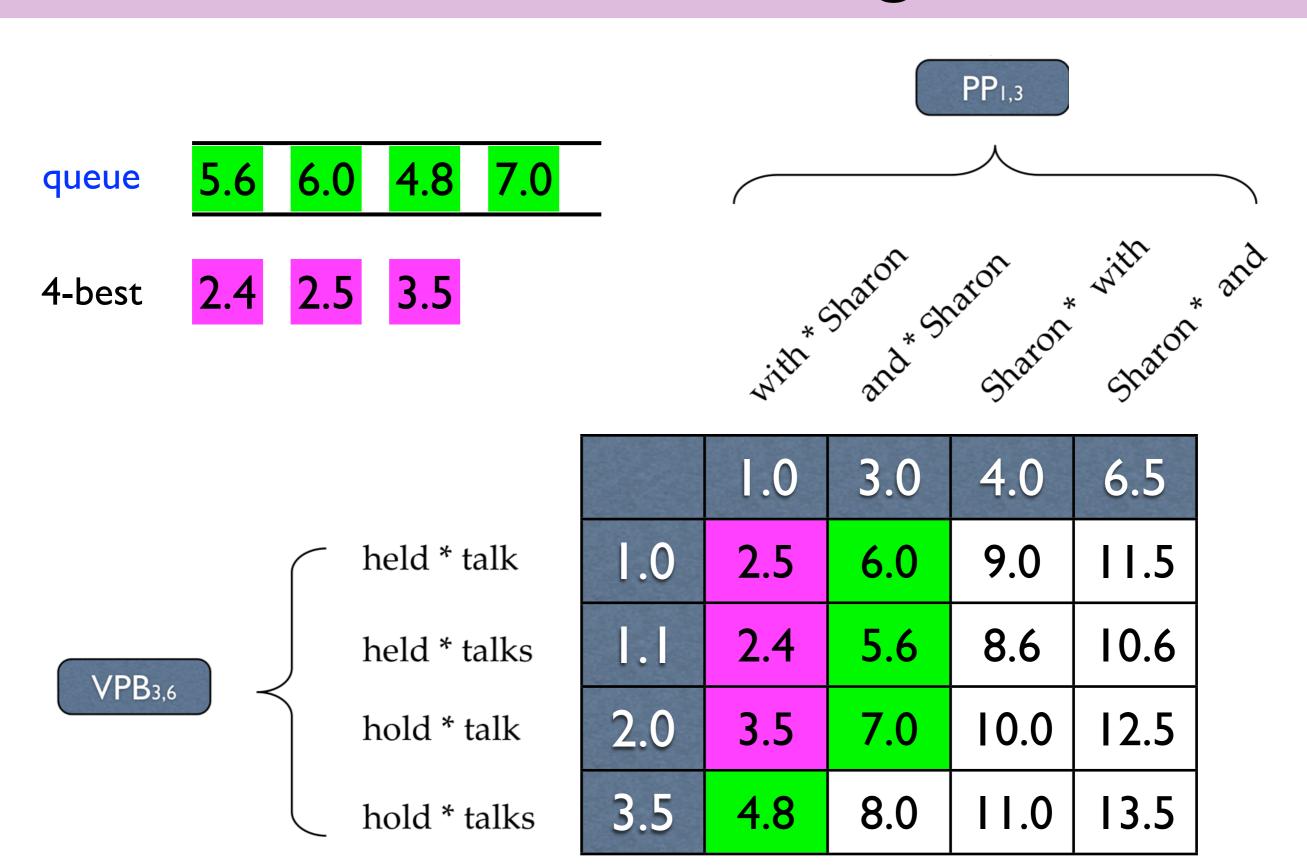


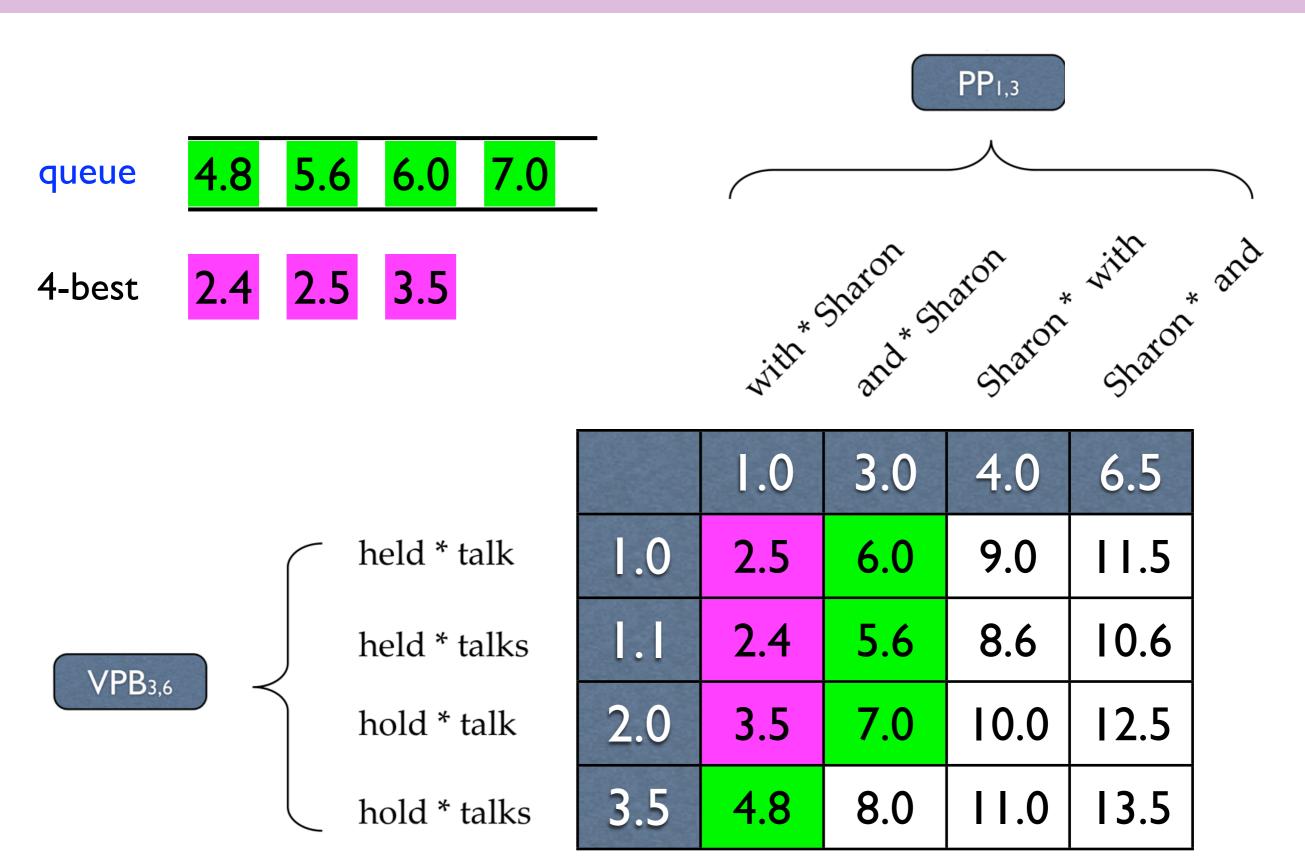


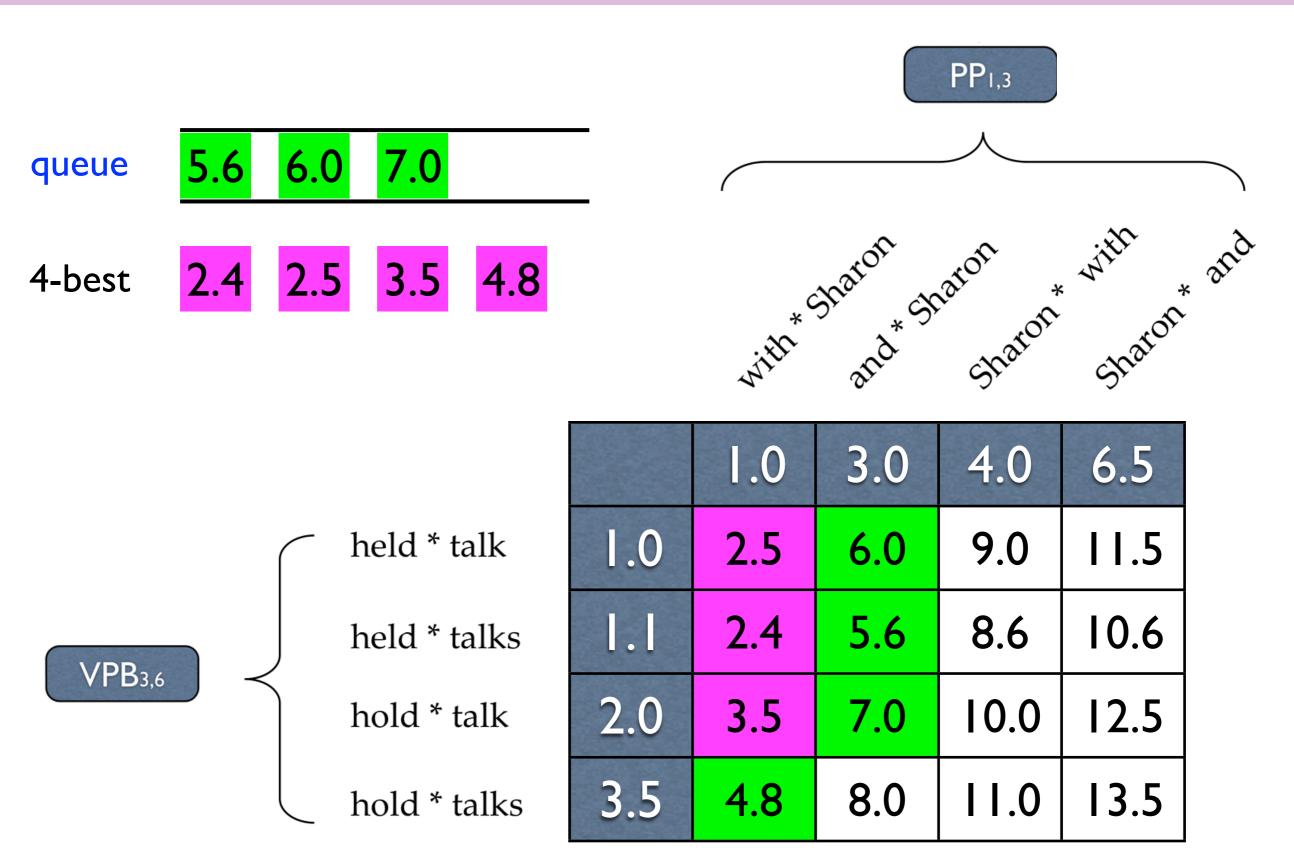




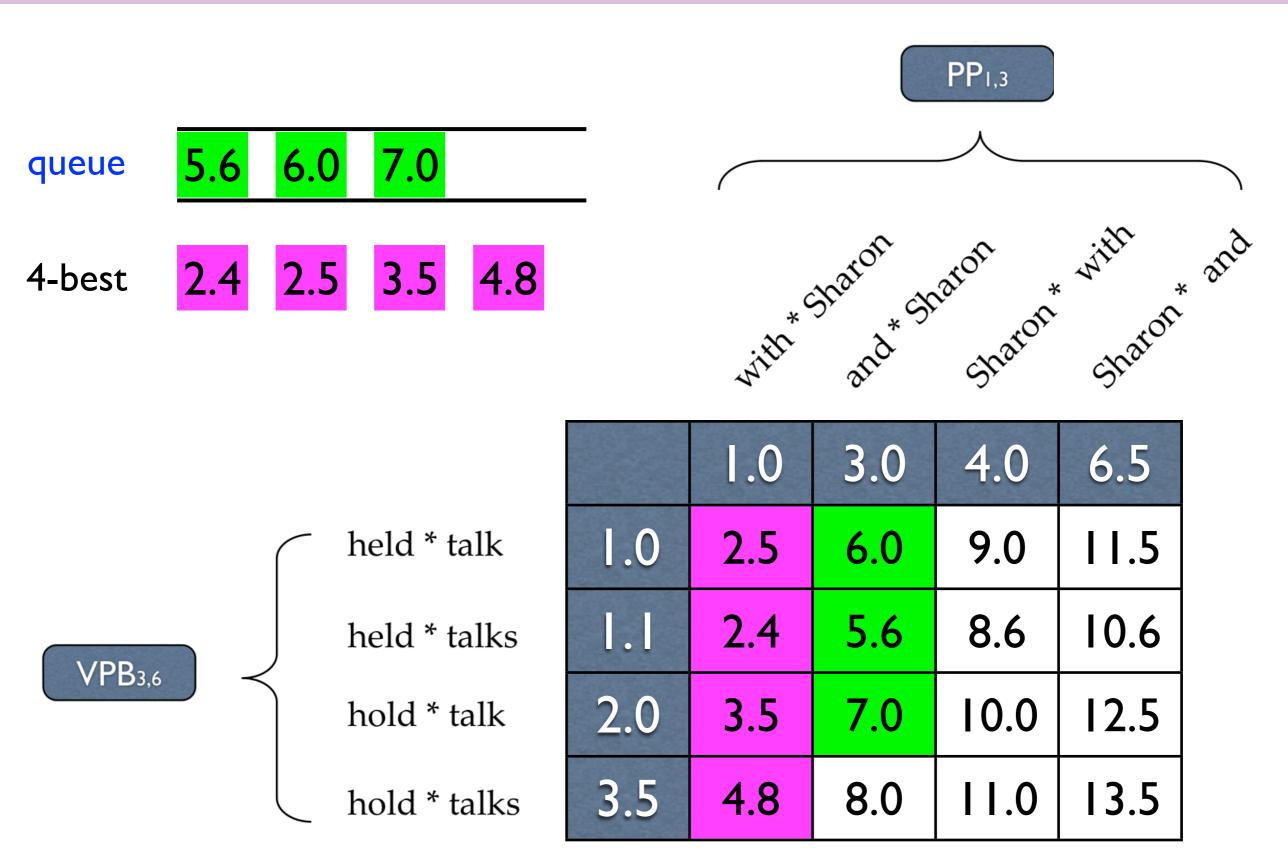




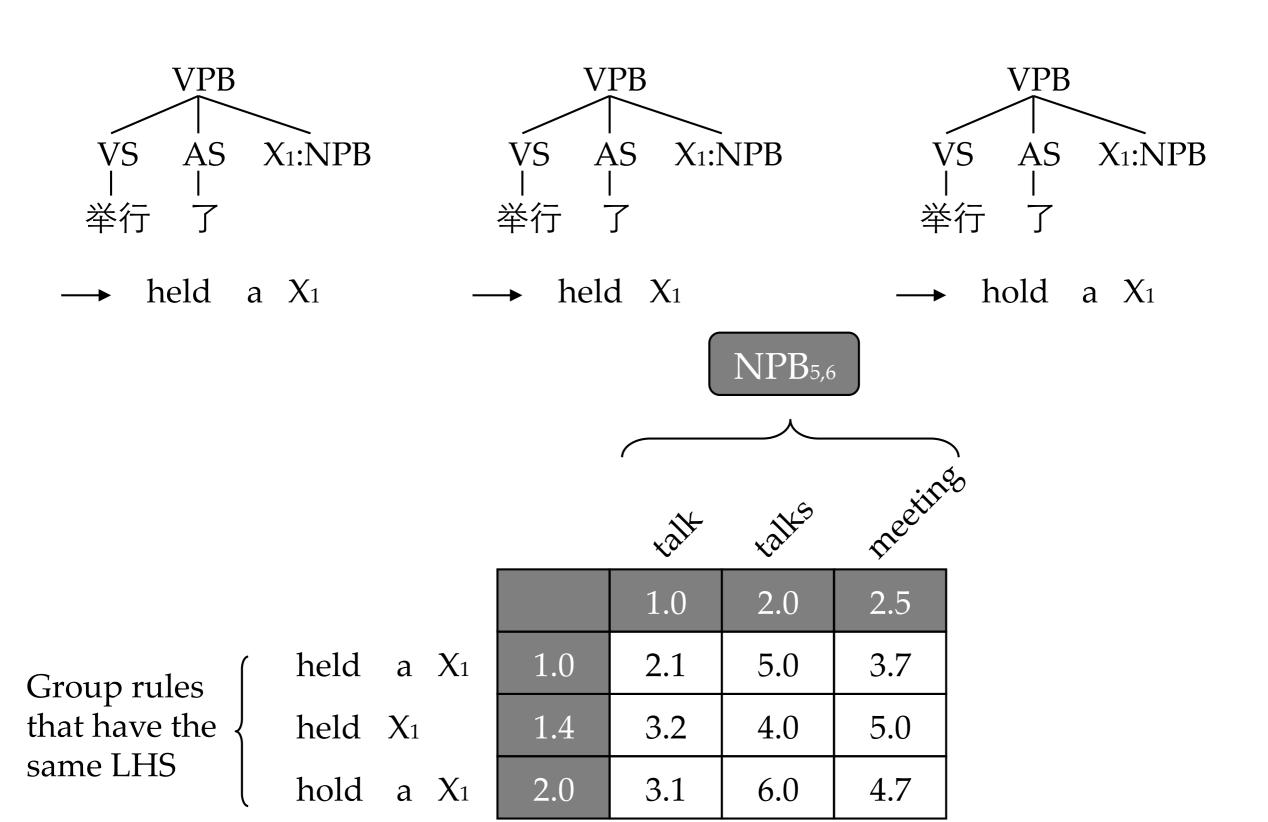




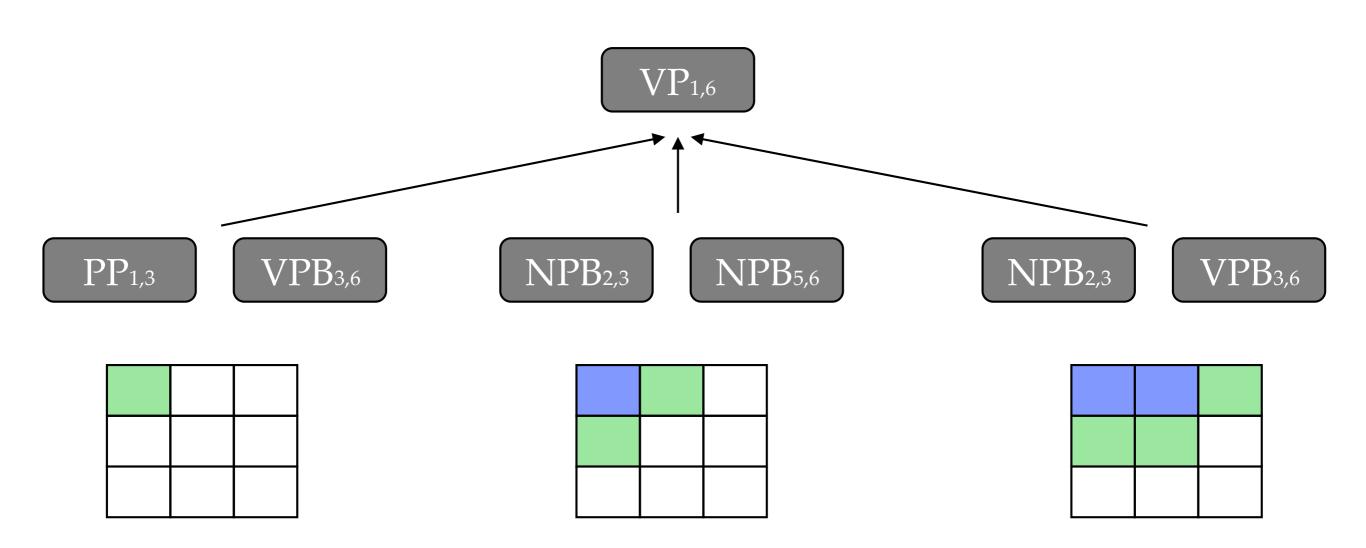
#### Cube Pruning



# Cube Pruning with Rule Group



# Cube Pruning within Node



### Syntax-based MT

#### SCFGs without linguistic syntax

inverted transduction grammar hierarchical phrase-based model

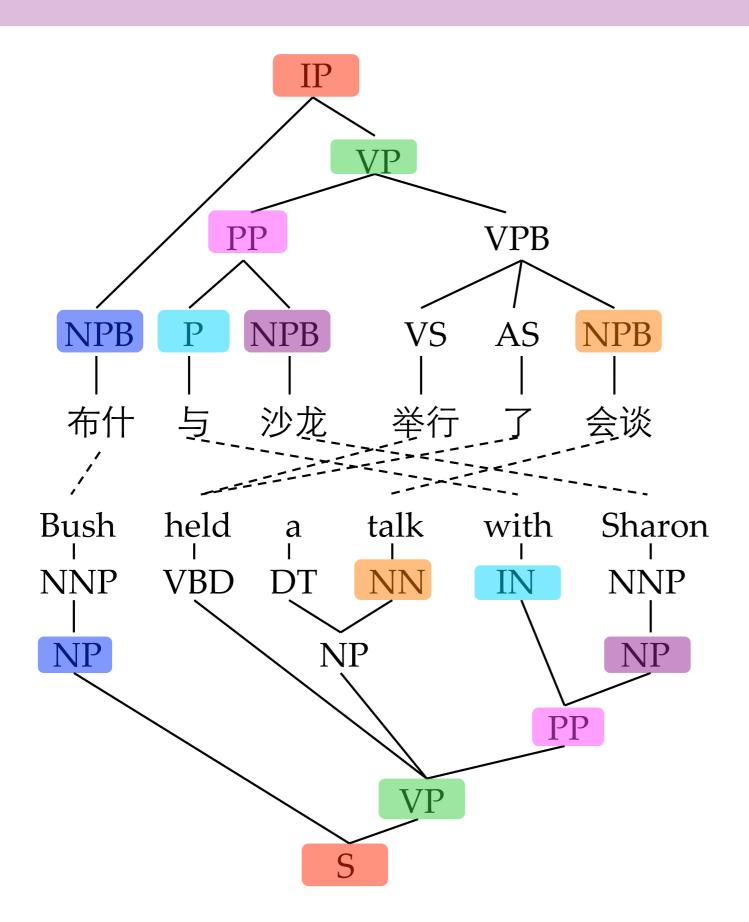
#### STSGs with linguistic syntax

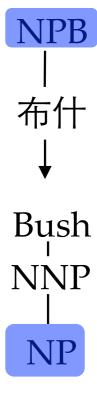
string-to-tree

tree-to-string

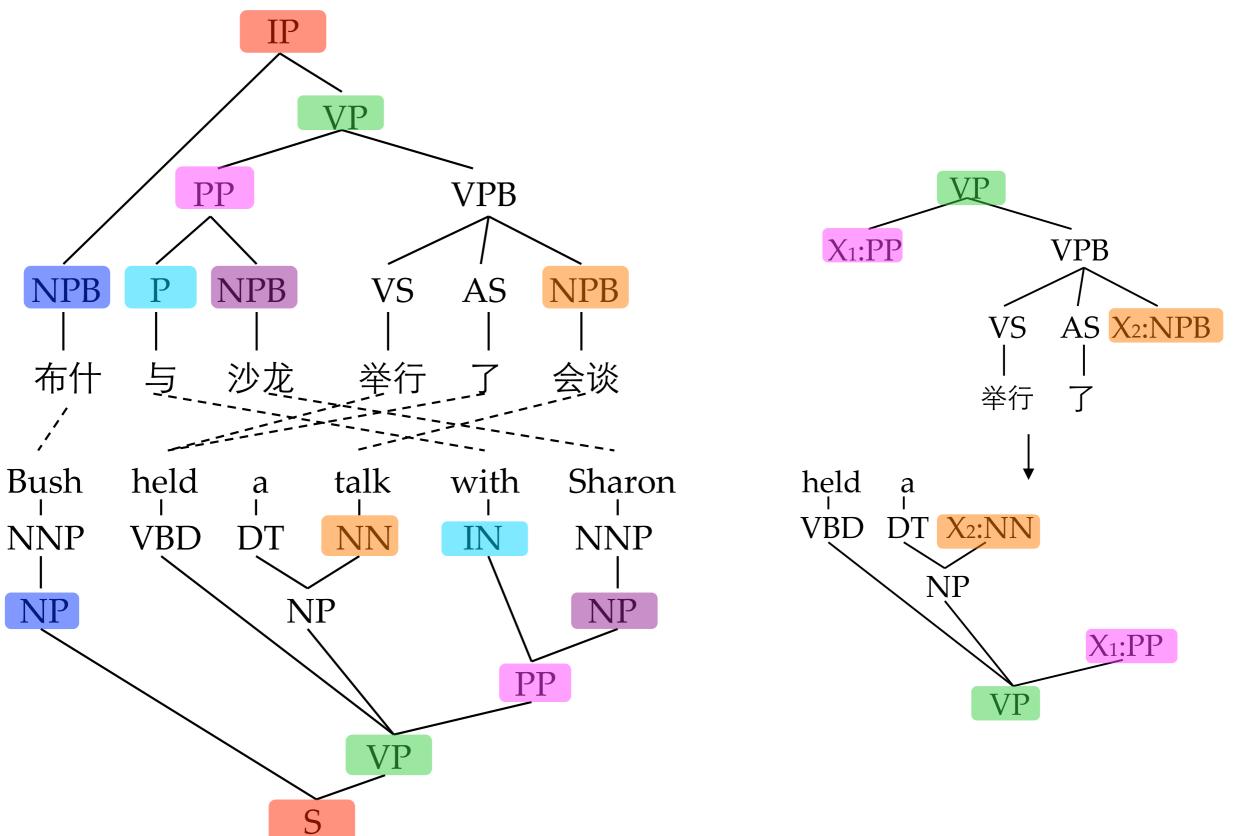
tree-to-tree

#### Tree-to-Tree Translation

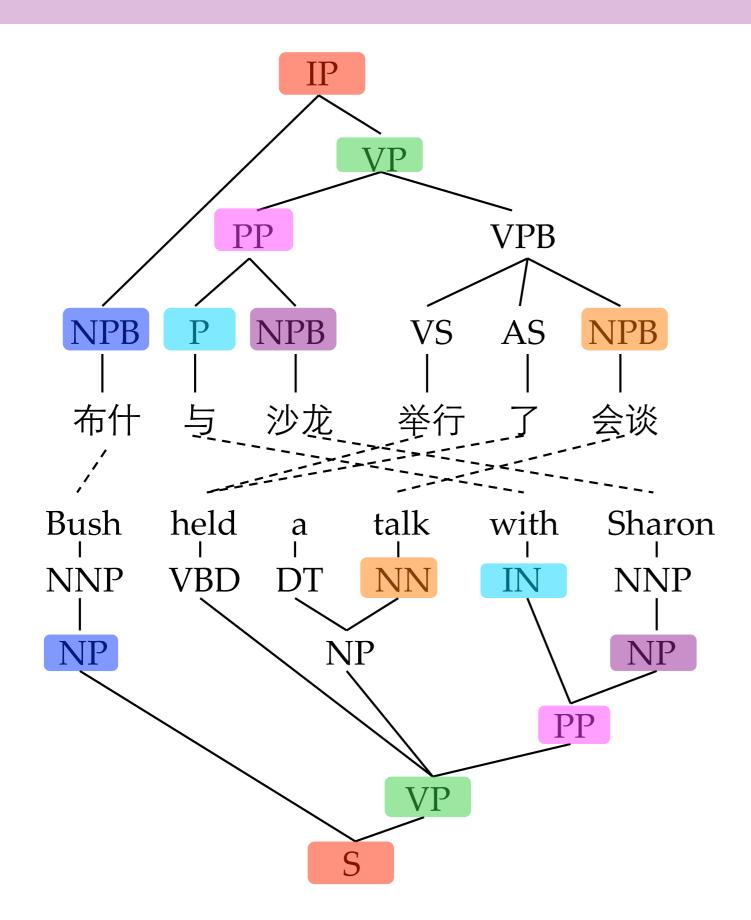


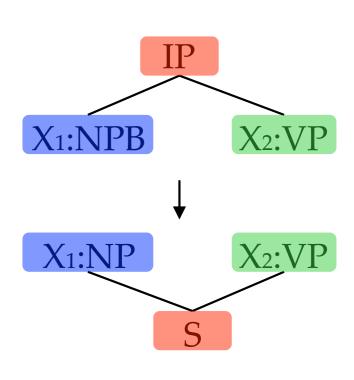


#### Tree-to-Tree Translation

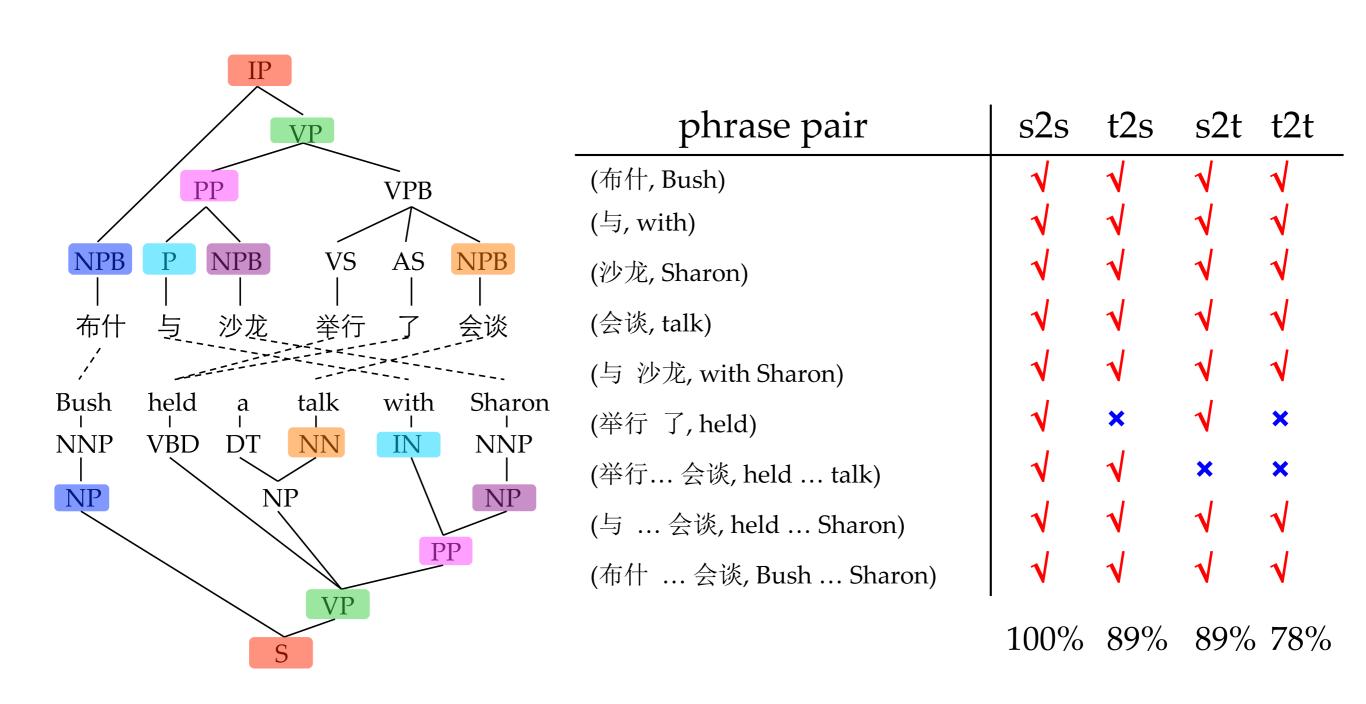


#### Tree-to-Tree Translation





#### Rule Coverage



# Rule Coverage

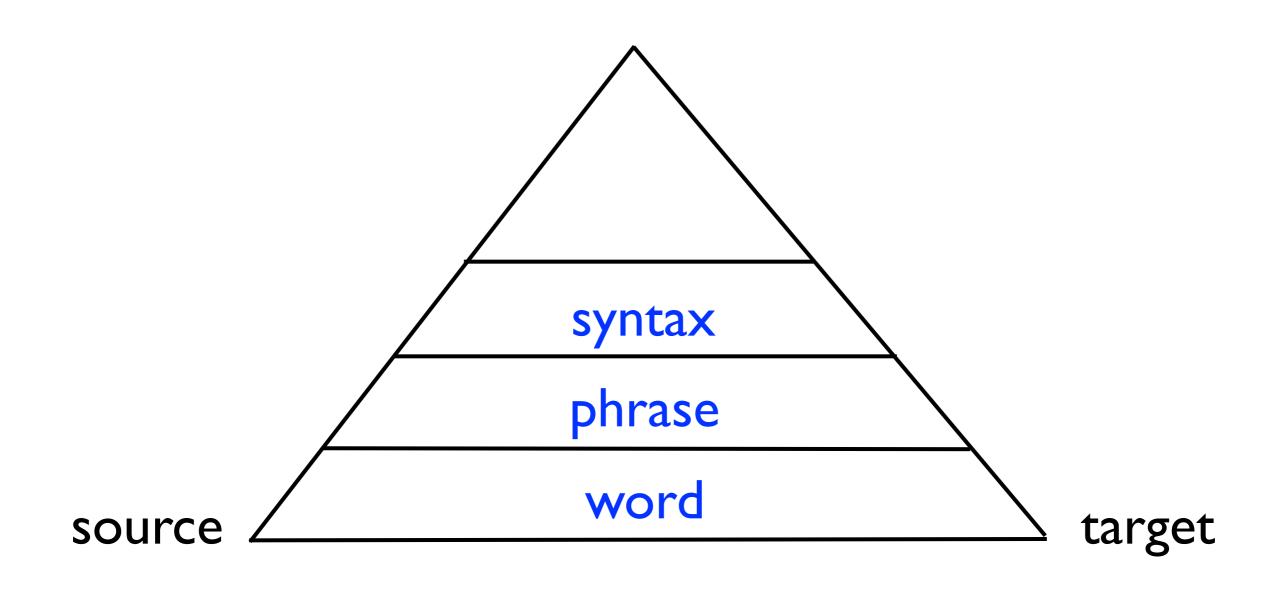
model	human	automatic
string-to-string	100%	100%
tree-to-string	78%	75%
string-to-tree	76%	72%
tree-to-tree	68%	60%

### Summary of Syntax-based Models

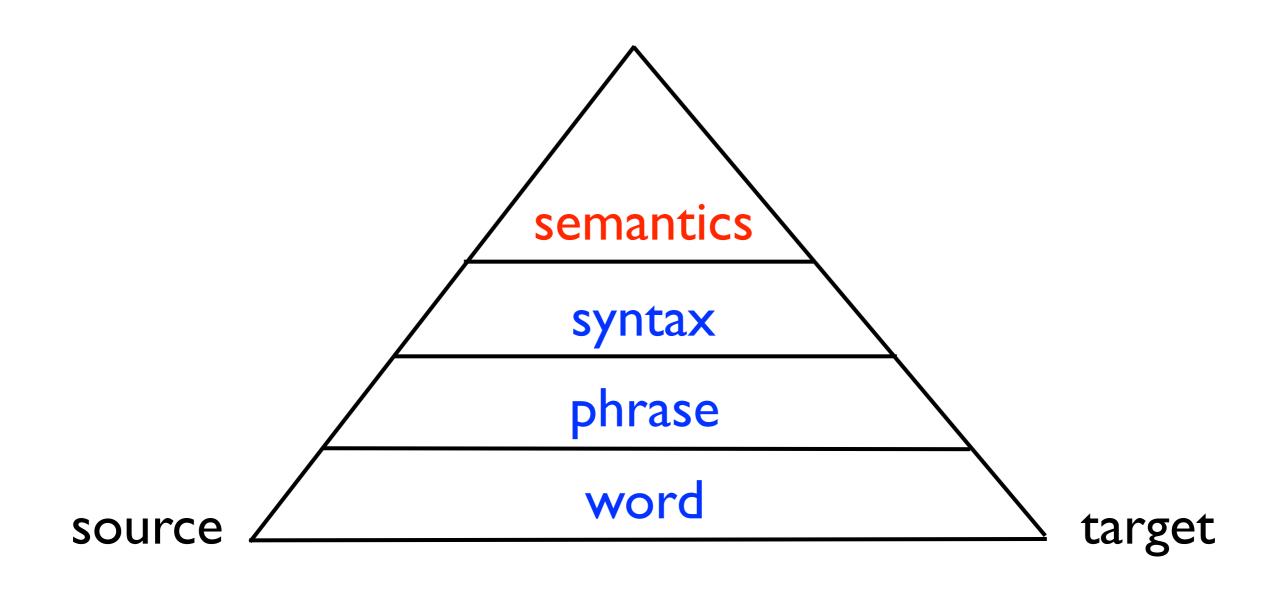
source	target	model	examples
N/A	N/A	string-to-string	Chiang (2005) Wu (1997)
N/A	syntax	string-to-tree	Galley et al. (2006) Shen et al. (2008)
syntax	N/A	tree-to-string	Liu et al. (2006) Huang et al. (2006)
syntax	syntax	tree-to-tree	Eisner (2003) Zhang et al. (2008)

# Part 5: Future Directions

# The SMT Pyramid



# The SMT Pyramid



#### Semantics-based Translation

- word sense disambiguation
  - WSD does not help (Carpuat and Wu, 2005)
  - WSD does help (Carpuat and Wu, 2007; Chan et al., 2007)
- semantic role labeling
  - semantic role features (Liu and Gildea, 2010)
  - predicate-argument structure (Xiong et al., 2012)
- grammars
  - hyperedge replacement grammars (Jones et al., 2012)

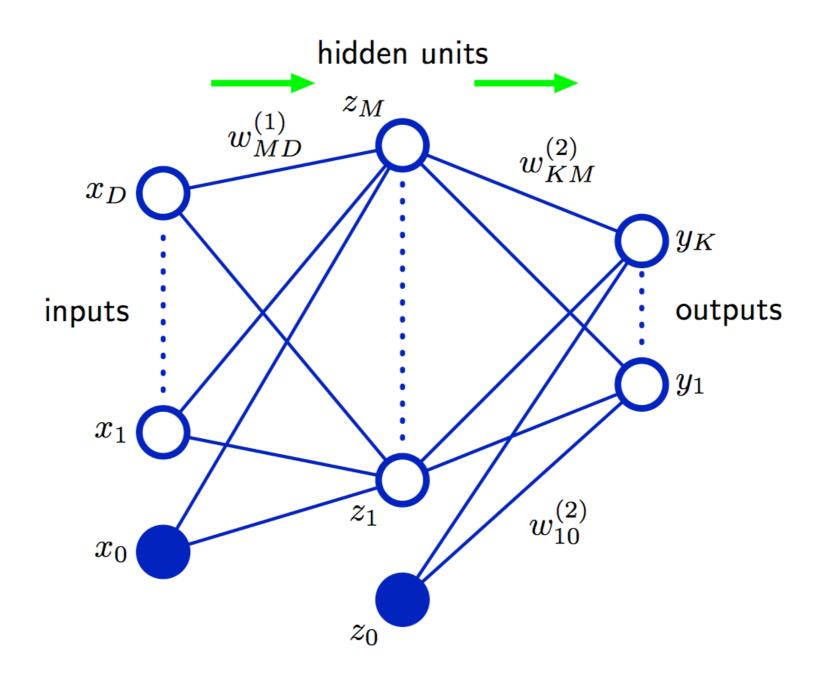
# Deep Learning for MT

- deep neural network for word alignment (Yang et al., 2013)
- additive neural networks for translation (Liu et al., 2013)
- recurive autoencoders for ITG-based translation (Li et al., 2013)
- recurrent continuous translation models (Kalchbrenner and Blunsom, 2013)

#### Neural Networks for MT

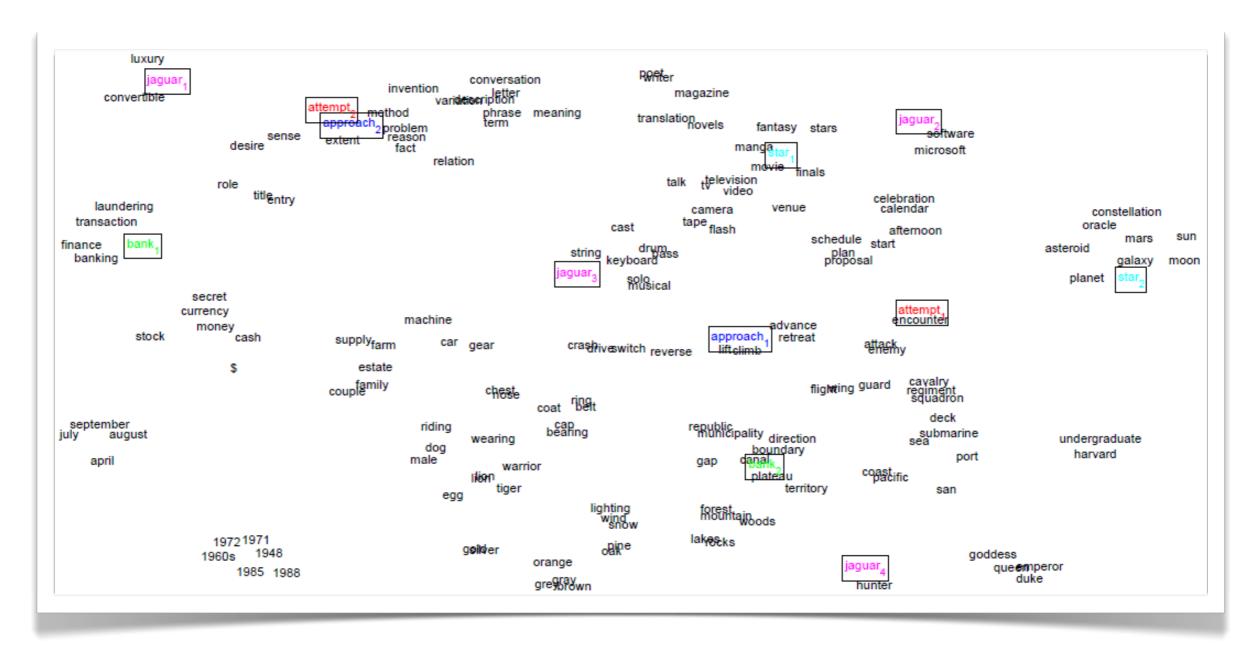


#### Neural Network

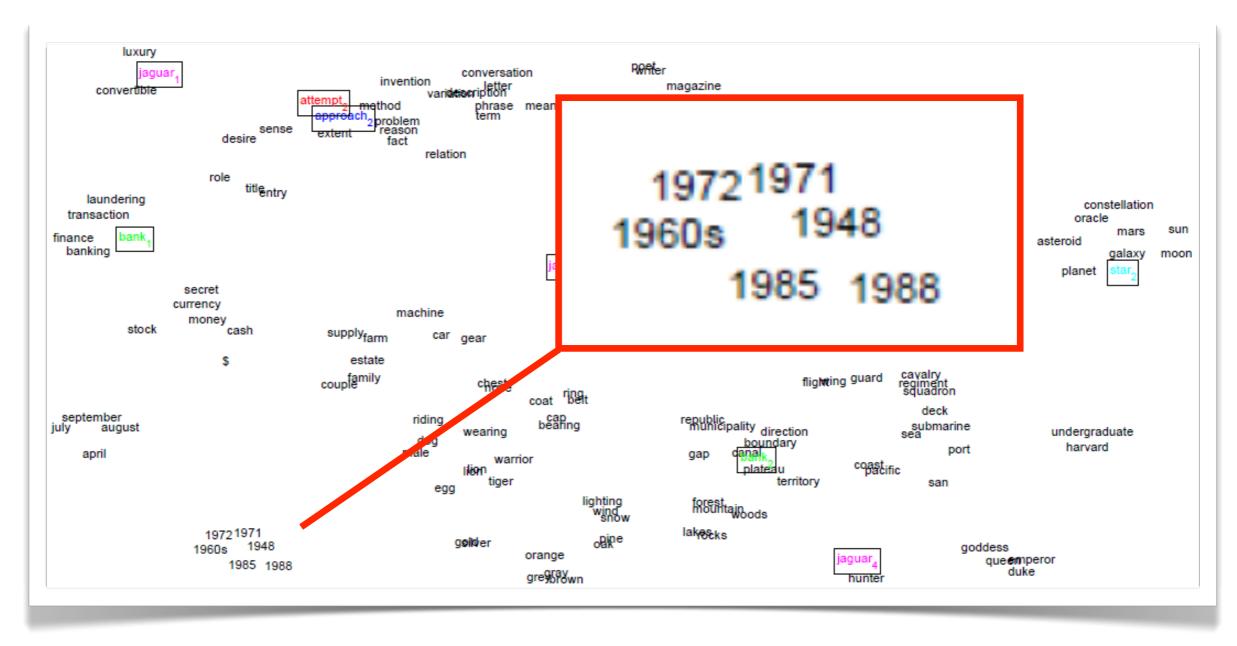


$$y_k(\mathbf{x}, \mathbf{w}) = \sigma \left( \sum_{j=1}^M w_{kj}^{(2)} h \left( \sum_{i=1}^D w_{ji}^{(1)} x_i + w_{j0}^{(1)} \right) + w_{k0}^{(2)} \right)$$

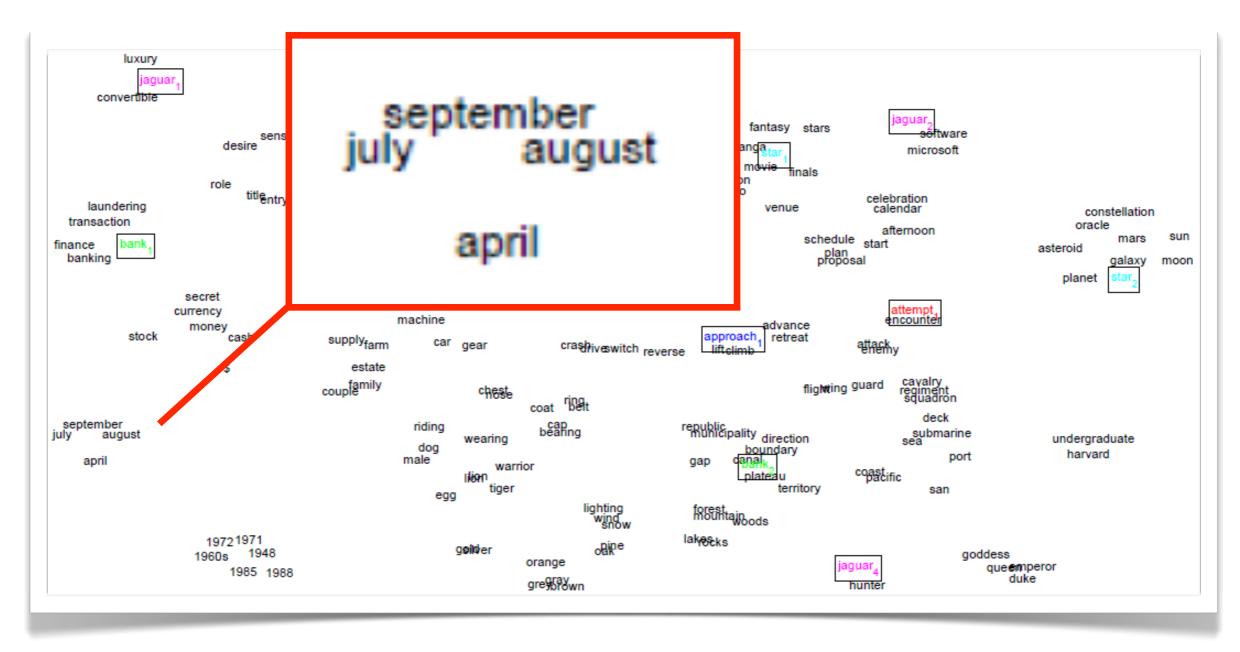
a word is represented as a real-valued vector



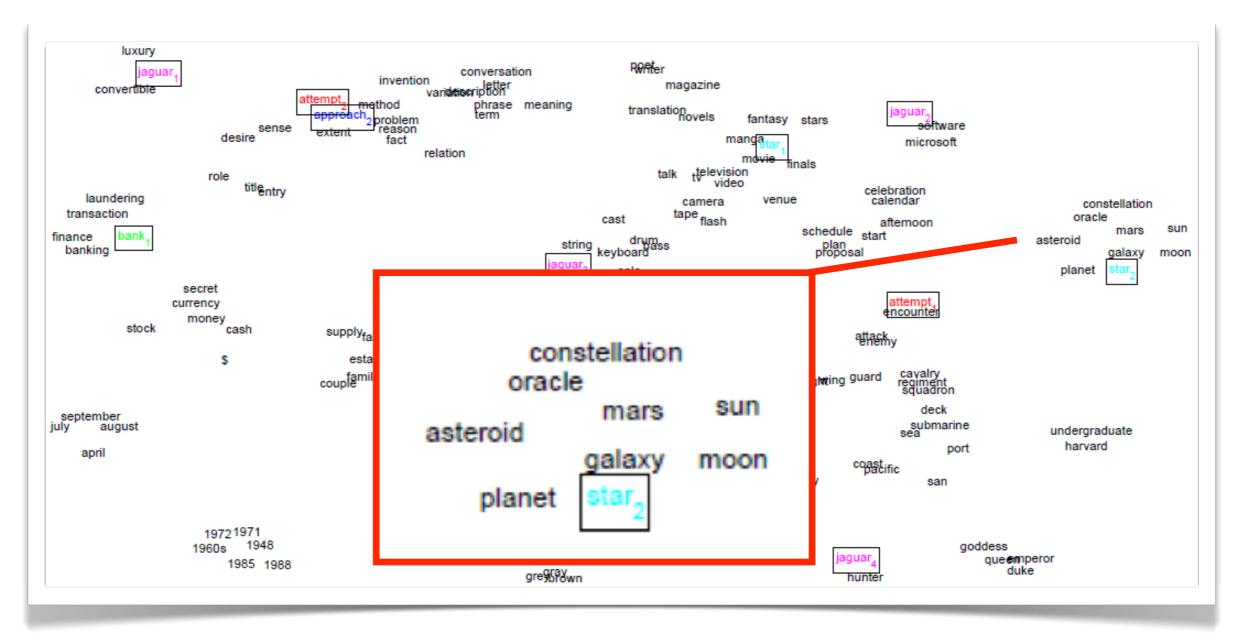
a word is represented as a real-valued vector



a word is represented as a real-valued vector



a word is represented as a real-valued vector





#### ThisPlusThat.me

Amazing language relationships

yao ming - China + USA

Search

How it Works

f

The Matrix -Thoughtful + Dumb

Harry Truman -American + Russian MIT - smart + pretentious

Mitt Romney -Experience + Celebrity Darth Vader - Cape

Justin Bieber - man -

Your query was disambiguated into +1 yao\_ming -1 china +1 usa in 3.8 seconds from ip-10-184-53-69



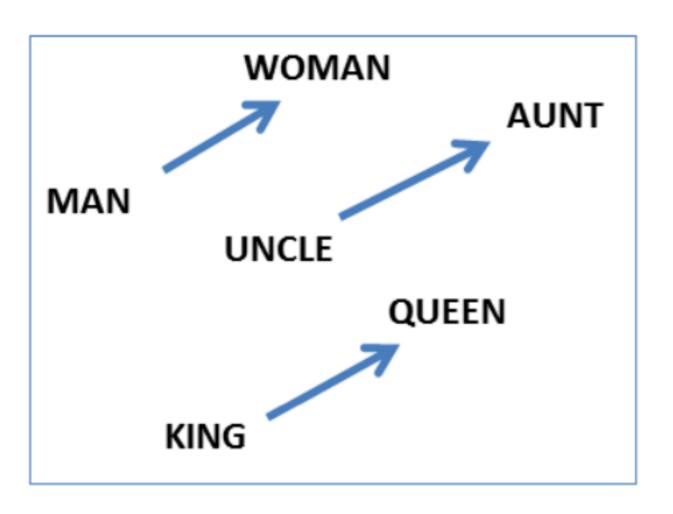
PERSON EXTRA, FILM ACTOR, PERSON,

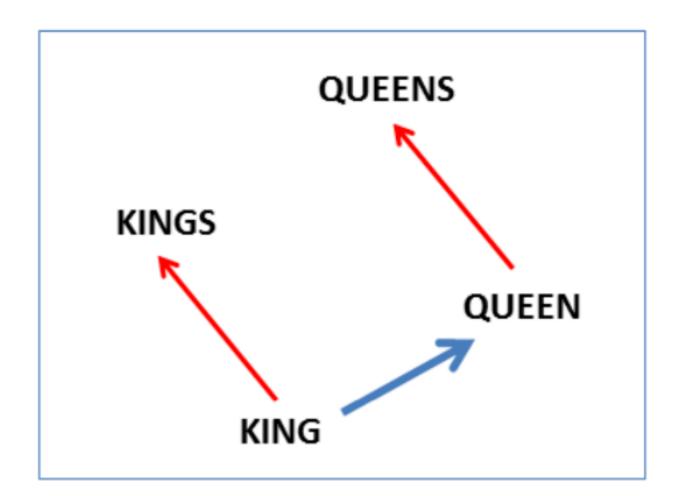
#### Tracy McGrady

Tracy Lamar McGrady, Jr. is an American former professional basketball player who last played for the San Antonio Spurs of the National Basketball Association. He is a seven-time NBA All-Star, seven-time All-NBA selection, and a two-time NBA scoring champion.

Basketball Shooting guard

Score: 0.28



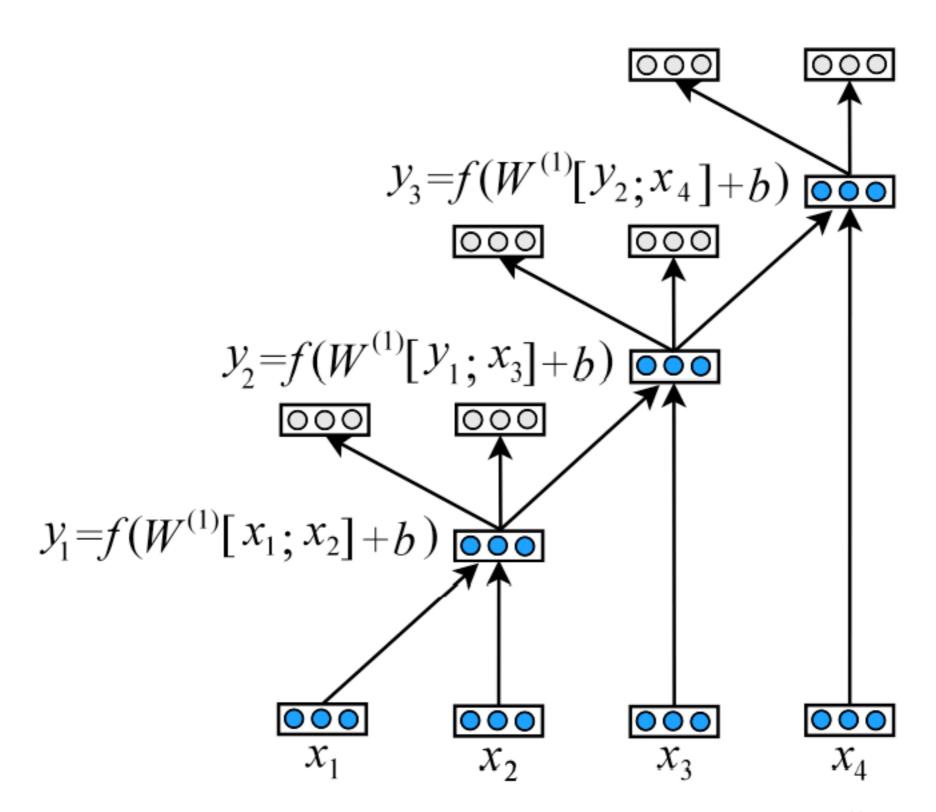


Category	Relation	Example
Adjectives	Base/Comparative	good:better rough:
Adjectives	Base/Superlative	good:best rough:
Adjectives	Comparative/	better:best rougher:
	Superlative	
Nouns	Singular/Plural	year:years law:
Nouns	Non-possessive/	city:city's bank:
	Possessive	
Verbs	Base/Past	see:saw return:
Verbs	Base/3rd Person	see:sees return:
	Singular Present	
Verbs	Past/3rd Person	saw:sees returned:
	Singular Present	

Category	Relation	Example
Adjectives	Base/Comparative	good:better rough:
Adjectives	Base/Superlative	good:best rough:
Adjectives	Comparative/	better:best rougher:
	Superlative	
Nouns	Singular/Plural	year:years law:
Nouns	Non-possessive/	city:city's bank:
	Possessive	
Verbs	Base/Past	see:saw return:
Verbs	Base/3rd Person	see:sees return:
	Singular Present	
Verbs	Past/3rd Person	saw:sees returned:
	Singular Present	

Q: vectors for variable-sized phrases?

#### Recursive Autoencoders



与沙龙

with Sharon

举行了会谈

held a talk

与沙龙

with Sharon

举行了会谈

held a talk



与沙龙举行了会谈

with Sharon held a talk

与沙龙

with Sharon

举行了会谈

held a talk



与沙龙举行了会谈

with Sharon held a talk

straight

与沙龙

with Sharon

举行了会谈

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与 沙龙 举行 了 会谈

with Sharon held a talk

与沙龙举行了会谈

held a talk with Sharon

straight

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举行了会谈

held a talk





与沙龙举行了会谈

with Sharon held a talk

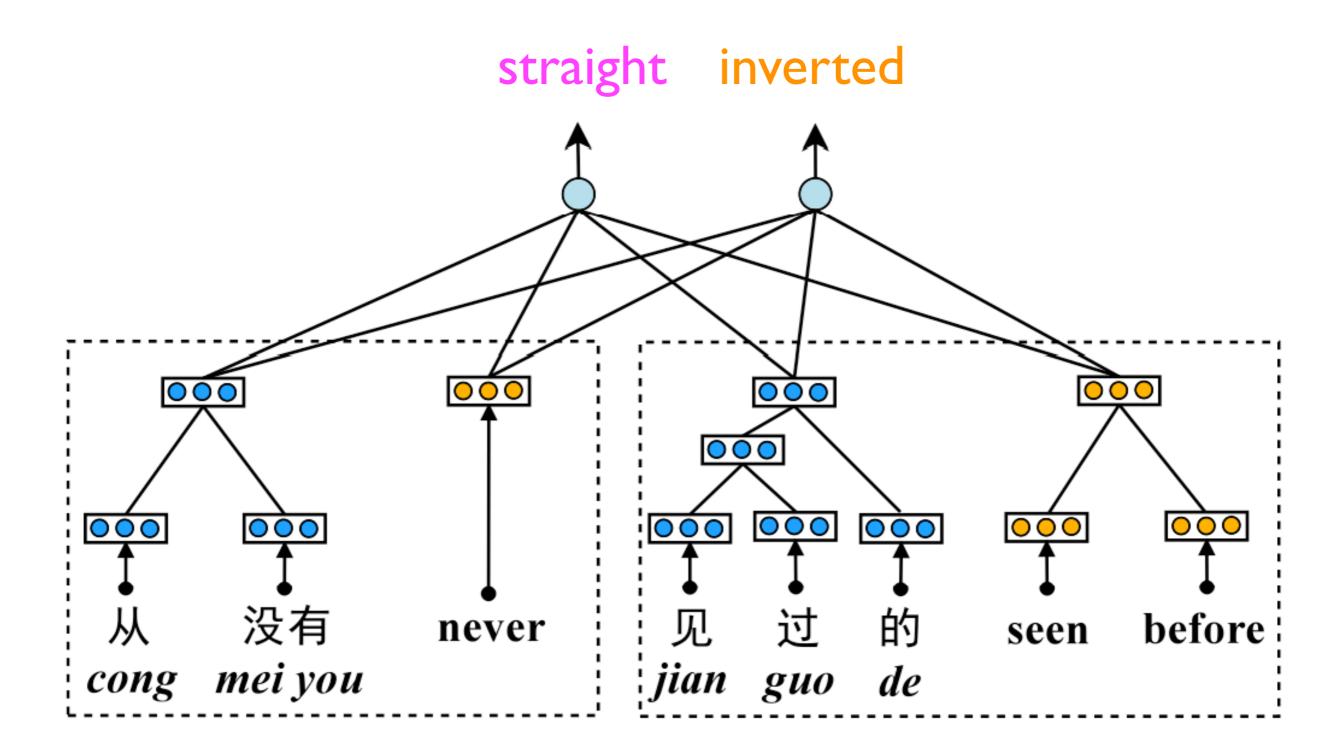
与 沙龙 举行 了 会谈

held a talk with Sharon

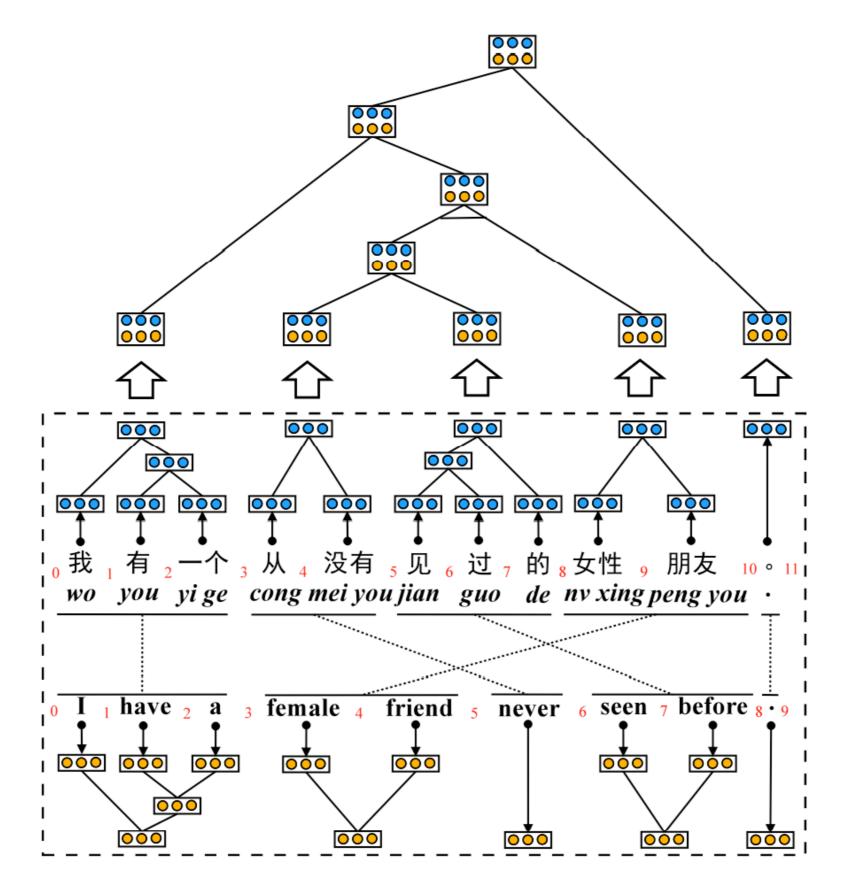
straight

inverted

#### Neural Classifier for ITG



#### Neural ITG-based Translation



#### Neural ITG-based Translation

cluster 1	cluster 2	cluster 3
1.18	fairly	stand alone
accessibility	harmful	one-day conference
wheelchair	shown	two-way links
candies	pretty	individual unit
cough	adopting	early july

cluster 4	cluster 5
these people who	in the same manner
their feelings about	of last century
the system which	by the year 2010
the economic sanctions against	in next week
its attutude toward	within waters

#### Future Directions

	state-of-the-art	future
"pyramid"		
unit		
modal		
intelligence		

#### Future Directions

	state-of-the-art	future
"pyramid"	syntax	
unit		
modal		
intelligence		

	state-of-the-art	future
"pyramid"	syntax	semantics
unit		
modal		
intelligence		

	state-of-the-art	future
"pyramid"	syntax	semantics
unit	sentence	
modal		
intelligence		

	state-of-the-art	future
"pyramid"	syntax	semantics
unit	sentence	document
modal		
intelligence		

	state-of-the-art	future
"pyramid"	syntax	semantics
unit	sentence	document
modal	text	
intelligence		

	state-of-the-art	future
"pyramid"	syntax	semantics
unit	sentence	document
modal	text	text, vision, speech
intelligence		

	state-of-the-art	future
"pyramid"	syntax	semantics
unit	sentence	document
modal	text	text, vision, speech
intelligence	"learning"	

	state-of-the-art	future
"pyramid"	syntax	semantics
unit	sentence	document
modal	text	text, vision, speech
intelligence	"learning"	self-learning

- GIZA++
  - train IBM Models 1-5
  - developed by Franz Och
  - http://code.google.com/p/giza-pp/



Franz Och



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#### Project Information

Starred by 55 users Activity • Medium Project feeds

Code license GNU GPL v2

#### Labels

mt, Al, alignment, nlp, linguistics, translation, giza GIZA++ is a statical machine translation toolkit that is used to train IBM Models 1-5 and an HMM word alignment model. This package also contains the source for the mkcls tool which generates the word classes necessary for training some of the alignment models.

For more information on the origins of these tools, refer to <a href="http://www.statmt.org/moses/giza/GIZA++.html">http://www.statmt.org/moses/giza/GIZA++.html</a> and http://www.statmt.org/moses/giza/mkcls.html.

If you make use of GIZA++ for research or commercial purposes, please cite:

 Franz Josef Och, Hermann Ney. "A Systematic Comparison of Various Statistical Alignment Models", Computational Linguistics, volume 29, number 1, pp. 19-51 March 2003.

- Berkeley Aligner
  - train joint HMM model
  - developed by Percy Liang
  - http://code.google.com/p/berkeleyaligner/



A word alignment software package for machine translation

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#### **Project Information**

Starred by 17 users Activity ... Low Project feeds

#### Code license GNU GPL v2

#### Labels

machinetranslation, wordalignment, mt, alignment, translation, Al, nlp, linguistics

The BerkeleyAligner is a word alignment software package that implements recent innovations in unsupervised word alignment.

#### News

9/28/09 As of release 2.1, we have split the Berkeley aligner into two downloads. The unsupervised aligner doesn't require a set of hand-labeled word alignments. The supervised aligner does, and it depends on the unsupervised aligner.

#### Recent changes and bug fixes

9/28 You can now run the unsupervised aligner without a hand-aligned test set; the evaluation phase will be skipped.

9/28 Loading trained models for evaluation only now works correctly (just give an empty training sequence)

- SRI Language Modeling Toolkit
  - train n-gram language models
  - developed by Andreas Stolcke
  - http://www.speech.sri.com/projects/srilm/



SRI International

Speech Technology and Research Laboratory

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#### SRILM - The SRI Language Modeling Toolkit

SRILM is a toolkit for building and applying statistical language models (LMs), primarily for use in speech recognition, statistical tagging and segmentation, and machine translation. It has been under development in the <u>SRI Speech Technology and Research Laboratory</u> since 1995. The toolkit has also greatly benefitted from its use and enhancements during the <u>Johns Hopkins University/CLSP summer workshops</u> in 1995, 1996, 1997, and 2002 (see <a href="history">history</a>).

These pages and the software itself assume that you know what statistical language modeling is. To learn about language modeling we recommend the textbooks

- <u>Speech and Language Processing</u> by Dan Jurafsky and Jim Martin (chapter 6 in the 1st edition, chapter 4 in the 2nd edition)
- <u>Foundations of Statistical Natural Language Processing</u> by Chris Manning and Hinrich Schütze (chapter 6).

Either book gives an excellent introduction to N-gram language modeling, which is the main type of LM supported by SRILM.

#### Moses

- phrase-based and tree-based systems
- the main contributor: Philipp Koehn
- http://www.statmt.org/moses/



Philipp Koehn



MOSES
statistical
machine translation
system

#### Moses

Road Map
Online Demos
Get Involved
Mailing Lists
Manual H
FAQ

#### Main » HomePage

#### Welcome to Moses!

Moses is a **statistical machine translation system** that allows you to automatically train translation models is probability translation among the exponential number of choices.

#### News

- Moses now has a <u>cruise control page</u> to see the status of the current builds
- Moses is now hosted on <u>github</u>

#### **Features**

- · Moses offers two types of translation models: phrase-based and tree-based
- . Moses features factored translation models, which enable the integration linguistic and other informati
- . Moses allows the decoding of confusion networks and word lattices, enabling easy integration with an
- New: the Experiment Management System makes using Moses much easier

#### Get started

- Joshua
  - SCFG-based SMT system
  - the main contributor: Zhifei Li
  - http://joshua.sourceforge.net/Joshua/



- Phrasal
  - Phrase-based system
  - the main contributor: Michel Galley
  - http://nlp.stanford.edu/software/phrasal/

Stanford Phrasal: A Phrase-Based Translation System

About | Usage | Download | Contributors | Citation | Mailing lists |

The Beta3 release of the Stanford Phrasal open source machine translation package has just been released!

#### About

Stanford Phrasal is a state-of-the-art phrase-based machine translation system. It provides an easy to use API for implementating new decoding model features and supports unique capabilities such as translating using phrases that include gaps (Galley et al. 2010) and conditional extraction of phrase-tables and lexical reordering models.

#### Usage

· Quick Start Guide.

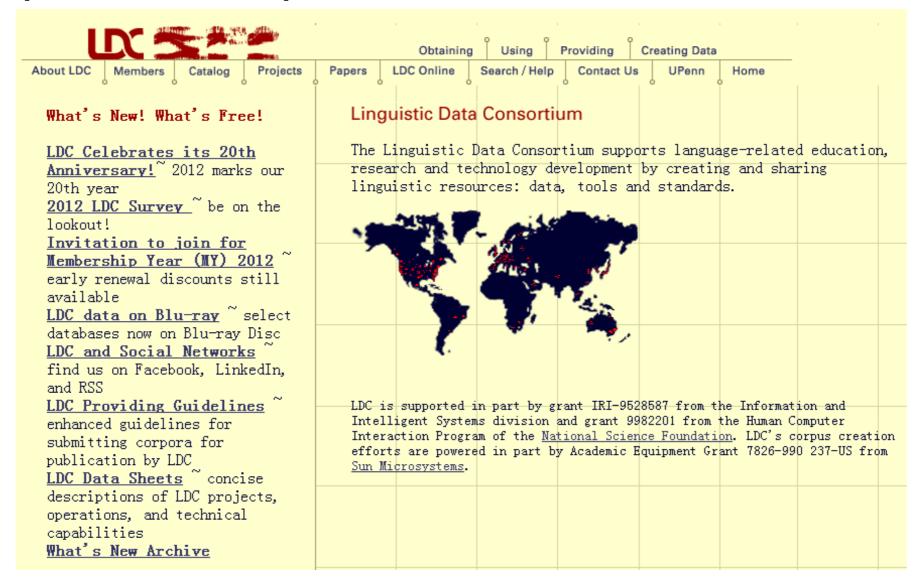
#### Download

Phrasal is available for download, licensed under the GNU General Public License (v2 or later). Source is included. The package includes components for command-line invocation, and a Java API.

Stanford Phrasal Beta3

### Data Resources

- Linguistic Data Consortium
  - Major source of monolingual and bilingual corpora for SMT research
  - http://www.ldc.upenn.edu/



### Data Resources

- Chinese Linguistic Data Consortium
  - Many useful monolingual and bilingual corpora for SMT research
  - http://www.chineseldc.org/



### Data Resources

- Europarl
  - It is free! 10 European language pairs
  - http://www.statmt.org/europarl/

#### **European Parliament Proceedings Parallel Corpus 1996-2009**

For a detailed description of this corpus, please read:

Europarl: A Parallel Corpus for Statistical Machine Translation, Philipp Koehn, MT Summit 2005, pdf.

Please cite the paper, if you use this corpus in your work. See also the extended (but earlier) version of the report (ps, pdf).

The Europarl parallel corpus is extracted from the proceedings of the <u>European Parliament</u>. It includes versions in 11 European languages: Romanic (French, Italian, Spanish, Portuguese), Germanic (English, Dutch, German, Danish, Swedish), Greek and Finnish.

The goal of the extraction and processing was to generate sentence aligned text for statistical machine translation systems. For this purpose we extracted matching items and labeled them with corresponding document IDs. Using a preprocessor we identified sentence boundaries. We sentence aligned the data using a tool based on the <a href="Church and Gale algorithm">Church and Gale algorithm</a>.

#### NIST

- the most influential
- Tasks: Arabic-English, Chinese-English
- http://www.itl.nist.gov/iad/mig/tests/mt/

Information Access Division (IAD)

NIST Open Machine Translation (OpenMT) Evaluation

Multimodal Information
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Benchmark Tests

Tools
Test Beds

NIST Open Machine Translation (OpenMT) evaluation series is to support research in, and help advance the state of the art of, machine translation (MT) technologies - technologies that translate text between human languages. Input may include all forms of text. The goal is for the output to be an adequate and fluent translation of the original.

- IWSLT
  - spoken language translation
  - Tasks: European languages and English
  - http://iwslt2011.org/



- WMT
  - workshop on machine translation
  - Tasks: European languages and English
  - http://www.statmt.org/wmt11/

EMNLP 2011
SIXTH WORKSHOP ON
STATISTICAL MACHINE TRANSLATION

July 30-31, 2011 Edinburgh, UK

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[BASELINE SYSTEM] | [BASELINE SYSTEM 2]

[SCHEDULE] | [PAPERS] | [AUTHORS]

#### CWMT

- the most influential MT evaluation in China
- Tasks: English and languages in China
- http://nlp.ict.ac.cn/new/CWMT/index.php

#### 全国机器翻译研讨会评测简介

2005年由中科院自动化所、计算所和厦门大学联合发起并组织了第一届统计机器翻译技术评测及学术研讨会,会议在厦门大学成功举办。随后,会议由中科院计算所、自动化所、软件所、哈尔滨工业大学和厦门大学五家单位联合组织。2006年、2007年,第二、第三届全国统计机器翻译研讨会(SSMT)分别在中科院计算所、哈尔滨工业大学成功召开。2008年,第四届会议于中科院自动化所成功举办,并由此届起会议名称更改为全国机器翻译研讨会(China Workshop on Machine Translation,简称CWMT)。2009年,第五届全国机器翻译研讨会在南京大学成功举办。2010年,由于同行们将很大精力都投入到了在北京召开的COLING 2010,没有举办大规模的全国机器翻译研讨会,而是进行了小范围的机器翻译战略研讨会,范围虽小,但也相当热烈和成功,该研讨会算是本系列会议的第六次。前六届会议的成功举办,对加强国内外同行的学术交流,促进中国机器翻译事业的发展,起到了很好的推动作用。

# Journals and Conferences

- Journals
  - Computational Linguistics
  - Machine Translation
  - ACM TALIP
- Conferences
  - ACL
  - EMNLP
  - NAACL
  - COLING

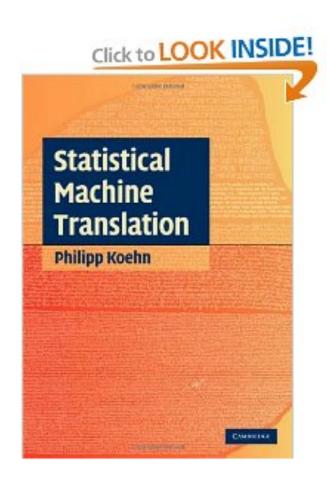
### Other Useful Resources

- ACL Anthology
  - ~20,000 (free) papers in the NLP field
  - http://aclweb.org/anthology-new/
- ACL Anthology Network
  - Paper network, author network, ranking
  - http://clair.si.umich.edu/clair/anthology/index.cgi
- ACL Wiki
  - Many useful information for NLP researchers
  - http://aclweb.org/aclwiki

### Other Tutorials

- Statistical Machine Translation (Adam Lopez, 2010)
- What's New in Statistical Machine Translation (Kevin Knight, 2006)
- Statistical Machine Translation: the Basic, the Novel, and the Speculative (Philipp Koehn, 2006)
- Statistical Machine Translation: Foundations and Recent Advances (Franz Och, 2005)

### Book



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#### Statistical Machine Translation [Hardcover]

Philipp Koehn 

✓ (Author)

\*\*\*\* 

✓ (2 customer reviews) |



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### Conclusions

- Statistical machine translation learns translation knowledge from data
- Big data makes more training instances available to SMT
- SMT evolves from word-based to phrase-based and syntax-based models
- We look forward to more intelligent MT systems

### **Thanks**

http://nlp.csai.tsinghua.edu.cn/~ly/

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