



# Statistical Machine Translation Based on Hierarchical Phrase Alignment

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ATR Spoken Language Translation Research Laboratories



# Introduction to SMT

## (refer to TMI Tutorial)



$$e = \arg \max_e P(e|f)$$

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- $P(e)$  — Language Model
- $P(f|e)$  — Translation Model



# Translation Model

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- How to represent  $P(\mathbf{f}|\mathbf{e})$ ? (a correspondence between  $\mathbf{e}$  and  $\mathbf{f}$ )



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- Introduction of  $\mathbf{a}$  : alignment

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- An example of alignments

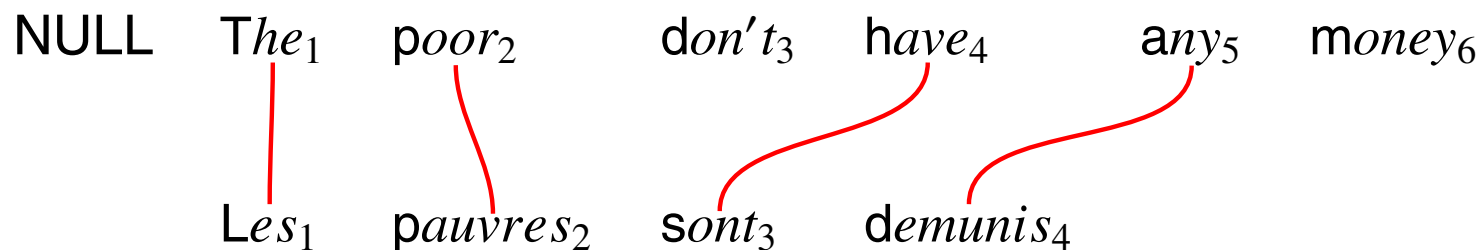
NULL	<i>The</i> <sub>1</sub>	<i>poor</i> <sub>2</sub>	<i>don't</i> <sub>3</sub>	<i>have</i> <sub>4</sub>	<i>any</i> <sub>5</sub>	<i>money</i> <sub>6</sub>
	<i>Les</i> <sub>1</sub>	<i>pauvres</i> <sub>2</sub>	<i>sont</i> <sub>3</sub>	<i>démunis</i> <sub>4</sub>		

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$$\mathbf{a} = (1, 2, 4, 5)$$

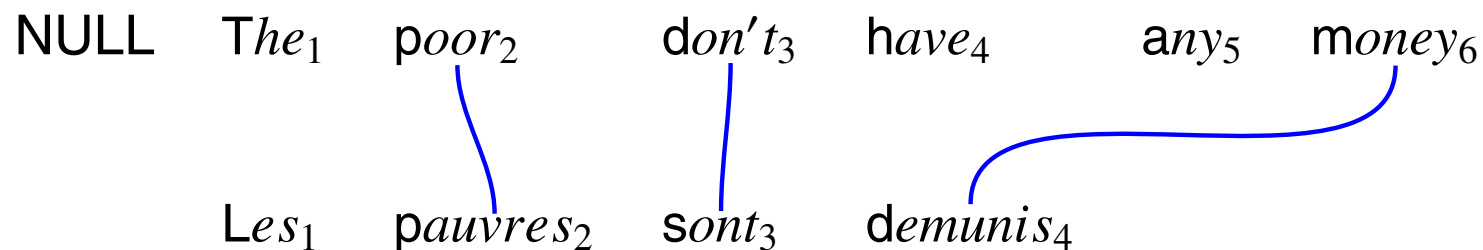


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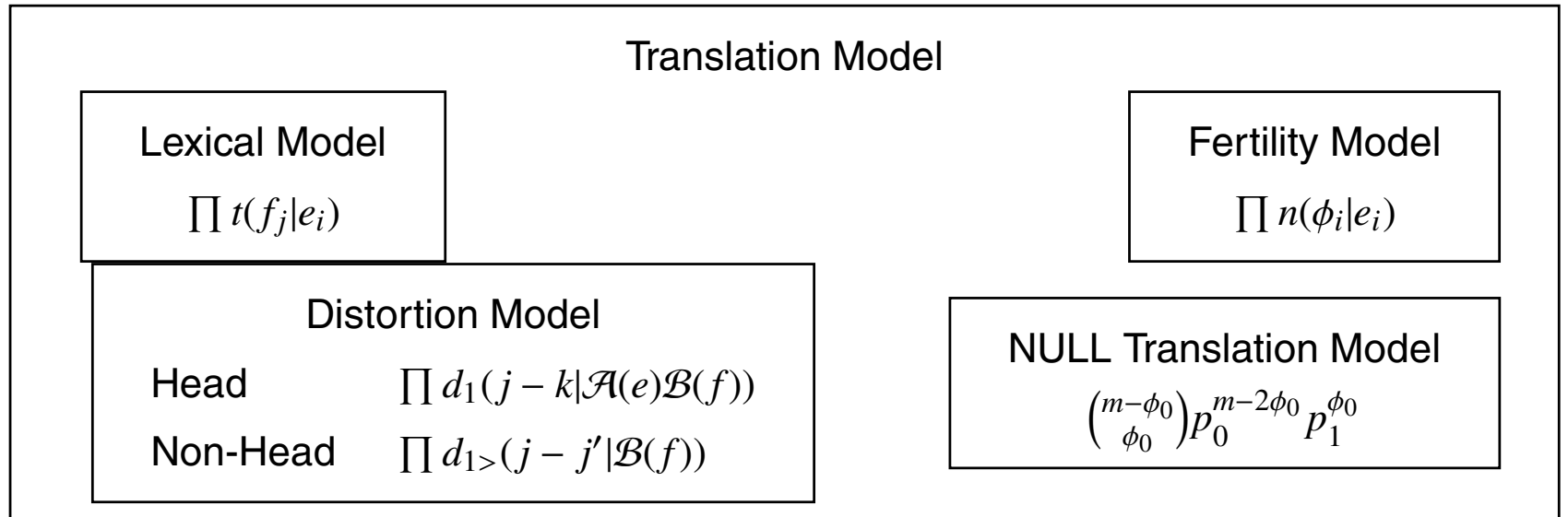
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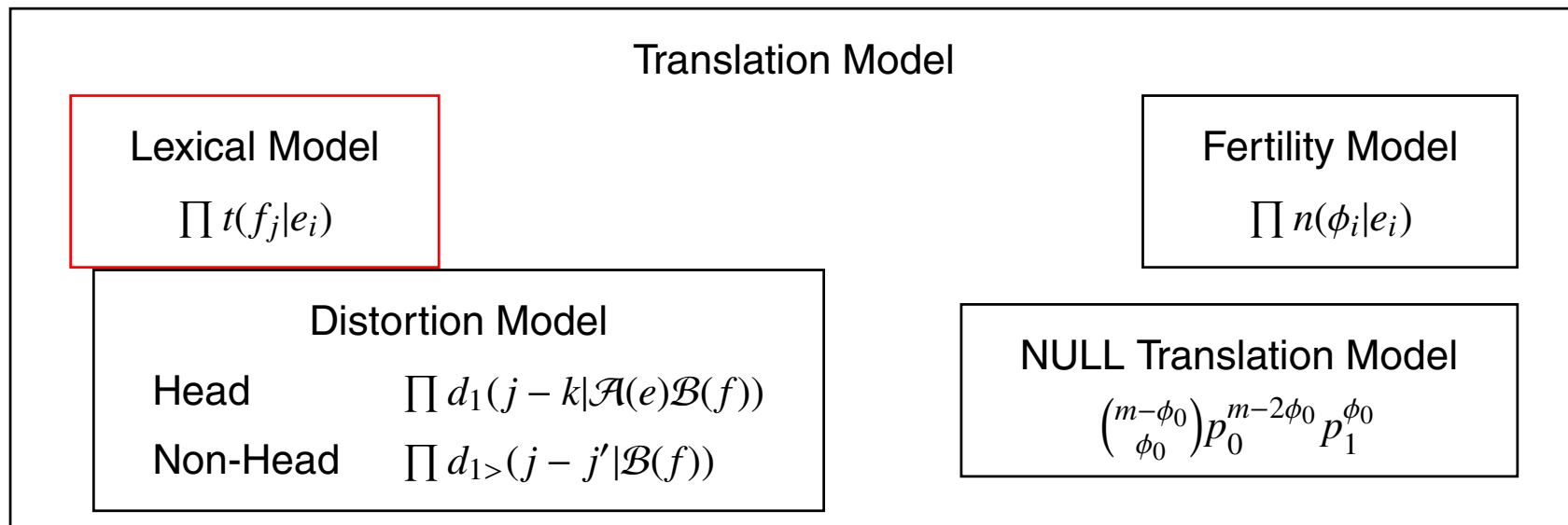


$$\mathbf{a} = (0, 2, 3, 6)$$

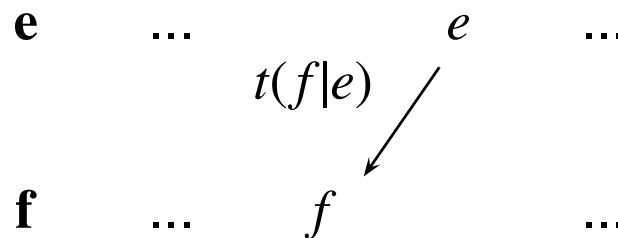
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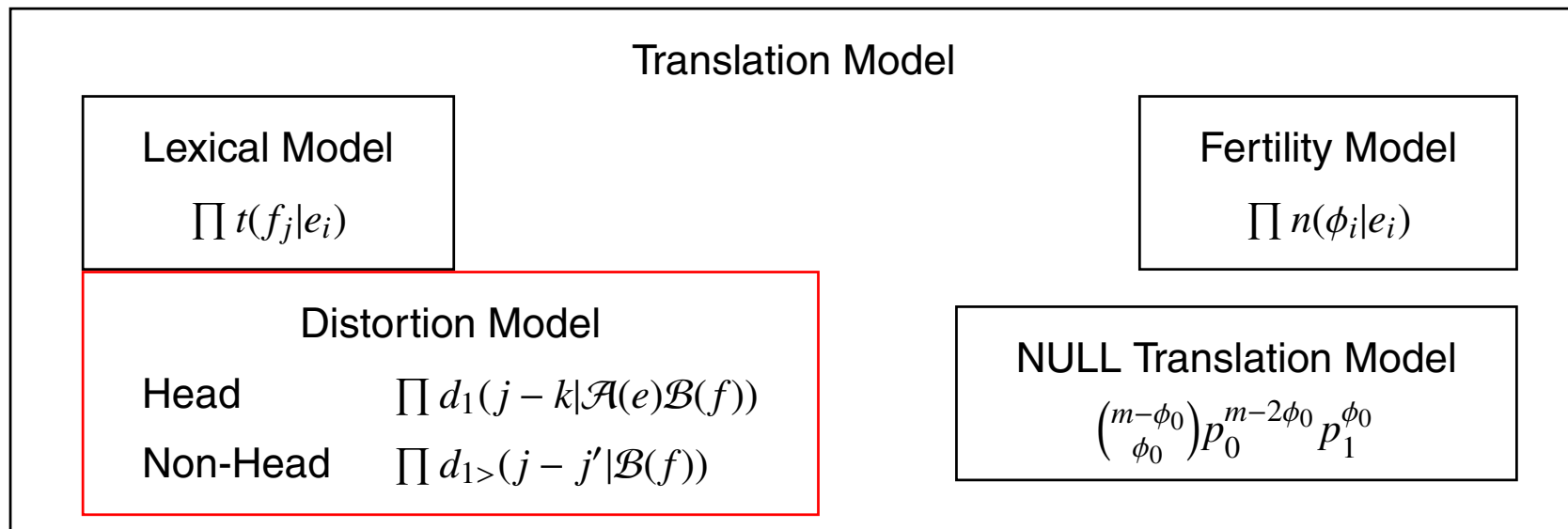


Lexical Model

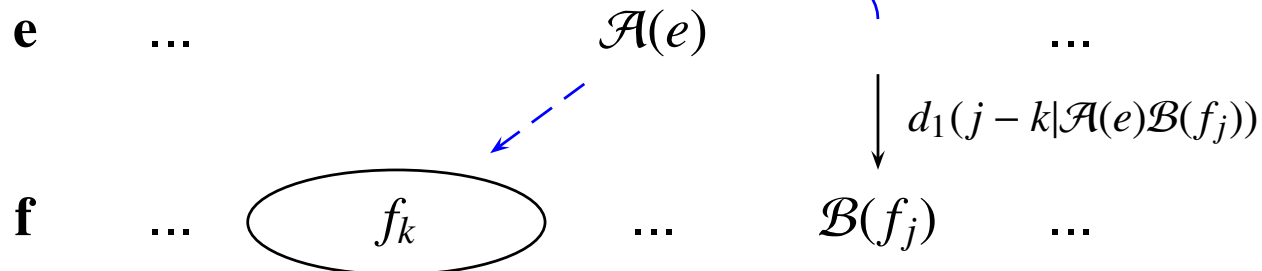




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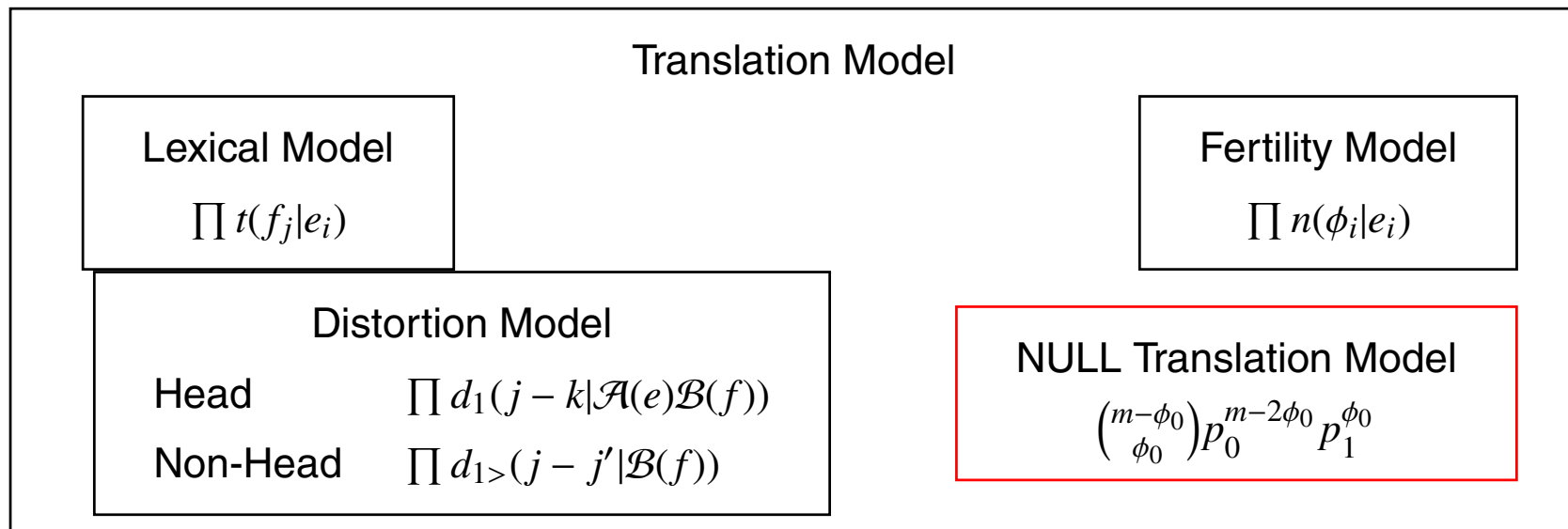


Distortion Model (Head)

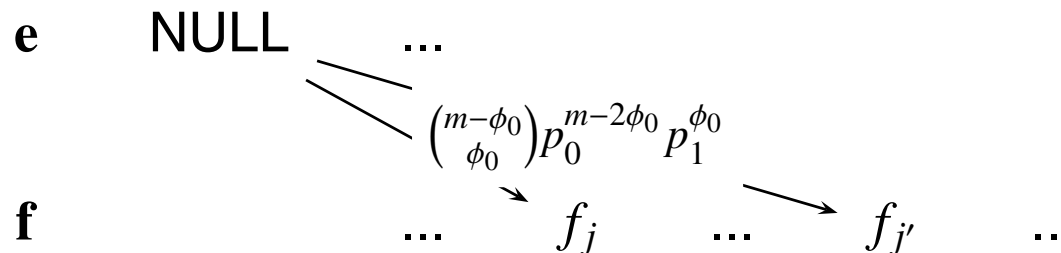




# Structure of TM (IBM Model 4)



NULL Translation Model





# Problems of SMT — Modeling

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  - Phrasal constraints implicit in IBM Model 4 and 5
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An example of viterbi alignment for F-E (from Mathematics of SMT)

the	program	has	been	implemented		
					—	—
le	programme	a	été	mis		en application

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An example of viterbi alignment for J-E

do you have some good medicine for a fever

熱 の 薬 は あり ませ ん か



# Problems of SMT — Training

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- Possible to estimate good parameters?
- EM-algorithm with bootstrapping
  - start with simpler models, such as
    - IBM Model 1 or 2 — word-for-word translation model
    - HMM Model — alignment with 1st order dependency to determine initial parameters
- Impossible to enumerate all the possible alignments (inevitable for IBM Model 3 – 5)  
Pegging
  - $\sum$  over *neighbours* of probable alignments
  - *probable alignments* derived from IBM Models 1 or 2



## Problems of SMT — Search

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- Given an input, can we translate it?

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- Given an input, can we translate it?
- input length = 10, output length = 11 and 20,000 vocabulary
  - $20,000^{11}$  possible translations
  - $(11 + 1)^{10}$  possible alignments
- NP-complete problem — Traveling Salesman Problem
  - visit all the cities (input words)
  - visit some of the hotels in a city (output words)
- (Almost) linear alignment (with local reordering) for G-E, F-E etc.
  - What about J-E? — drastical reordering



# Introduction to HPA

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- Align bilingual text phrase-by-phrase



# Introduction to HPA

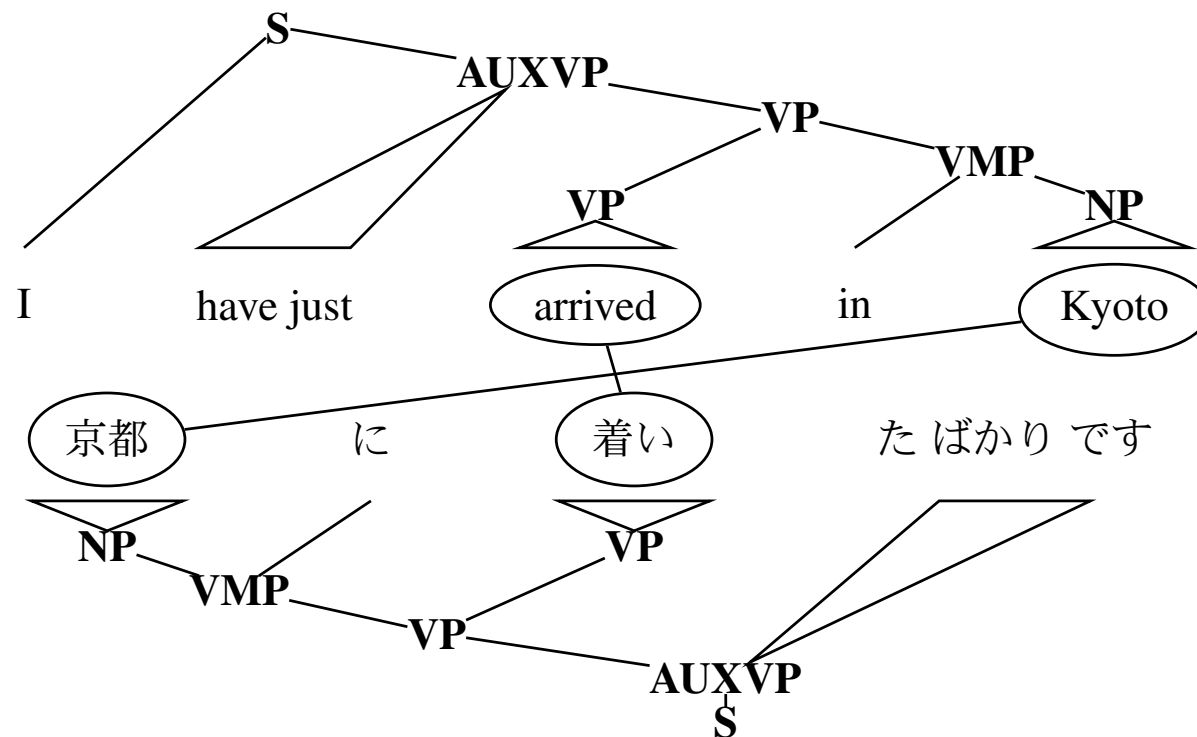
- Align biligual text phrase-by-phrase
- An example

I have just arrived in Kyoto

京都に着いたばかりです

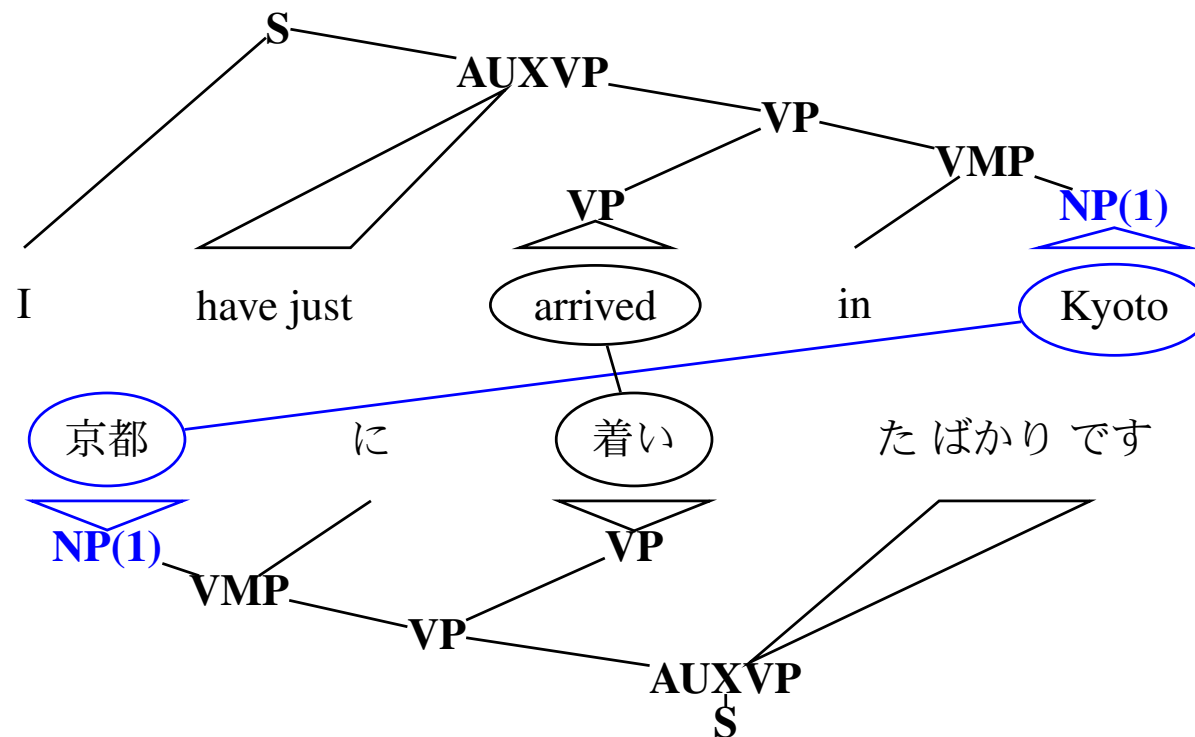
in Kyoto	—	京都に
arrived in Kyoto	—	京都に着い
have just arrived in Kyoto	—	京都に着いたばかりです

# An Example of HPA



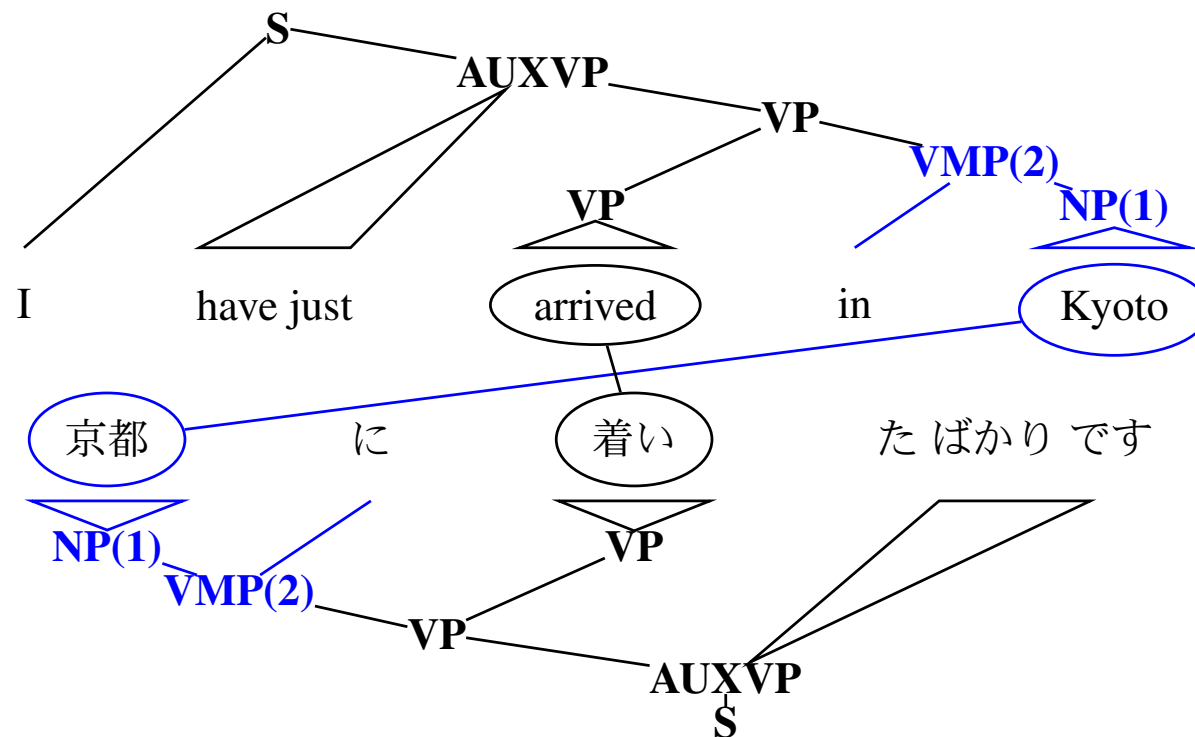
- Pairing of nodes by syntactic categories starting from word-linkage
- Phrase alignments which maximize the number of aligned phrases

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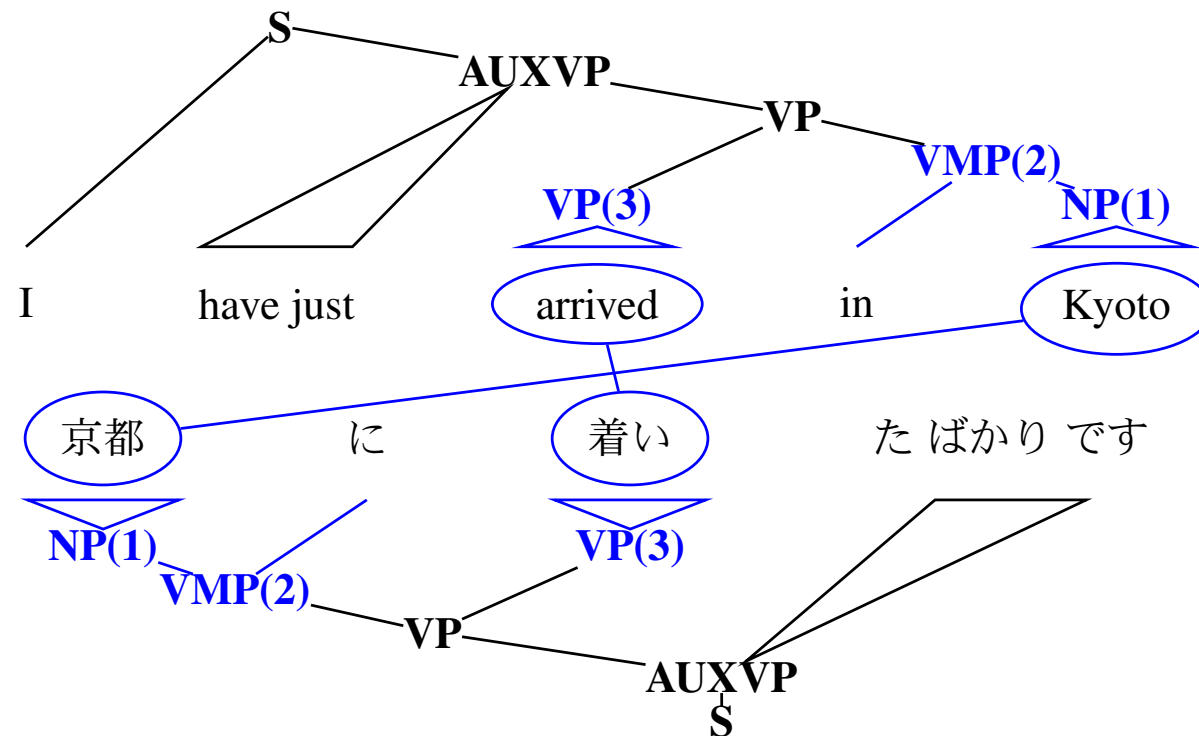
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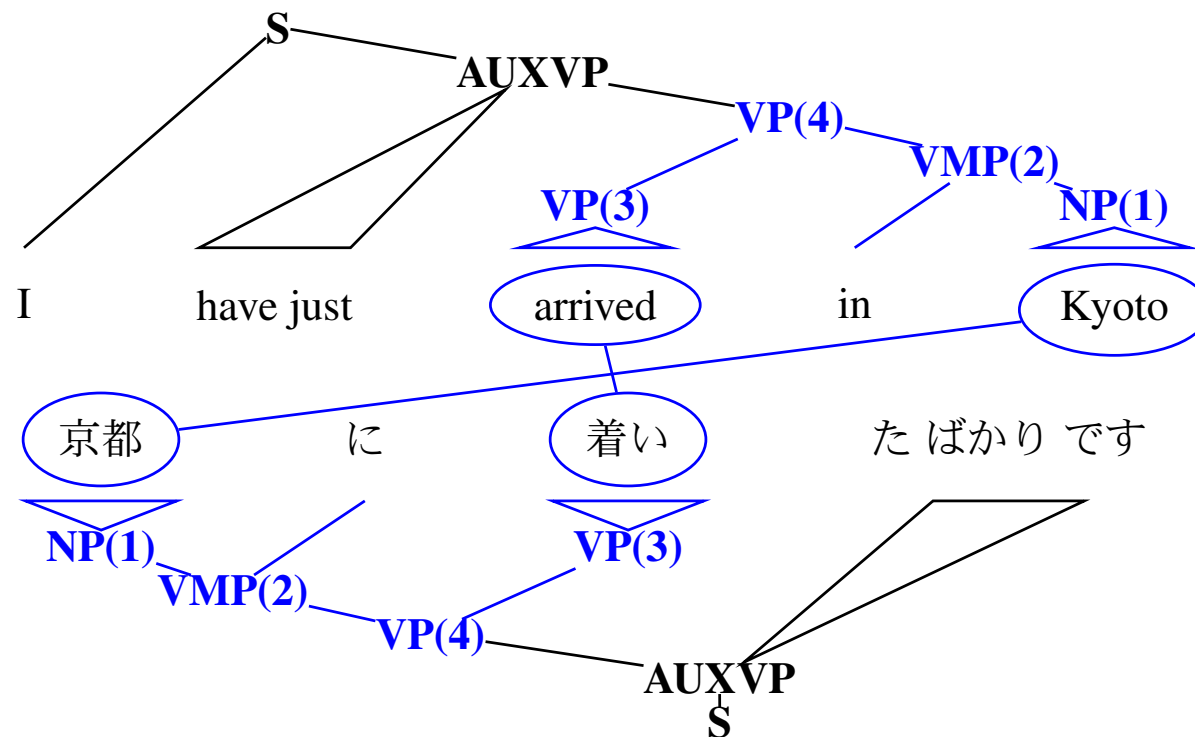
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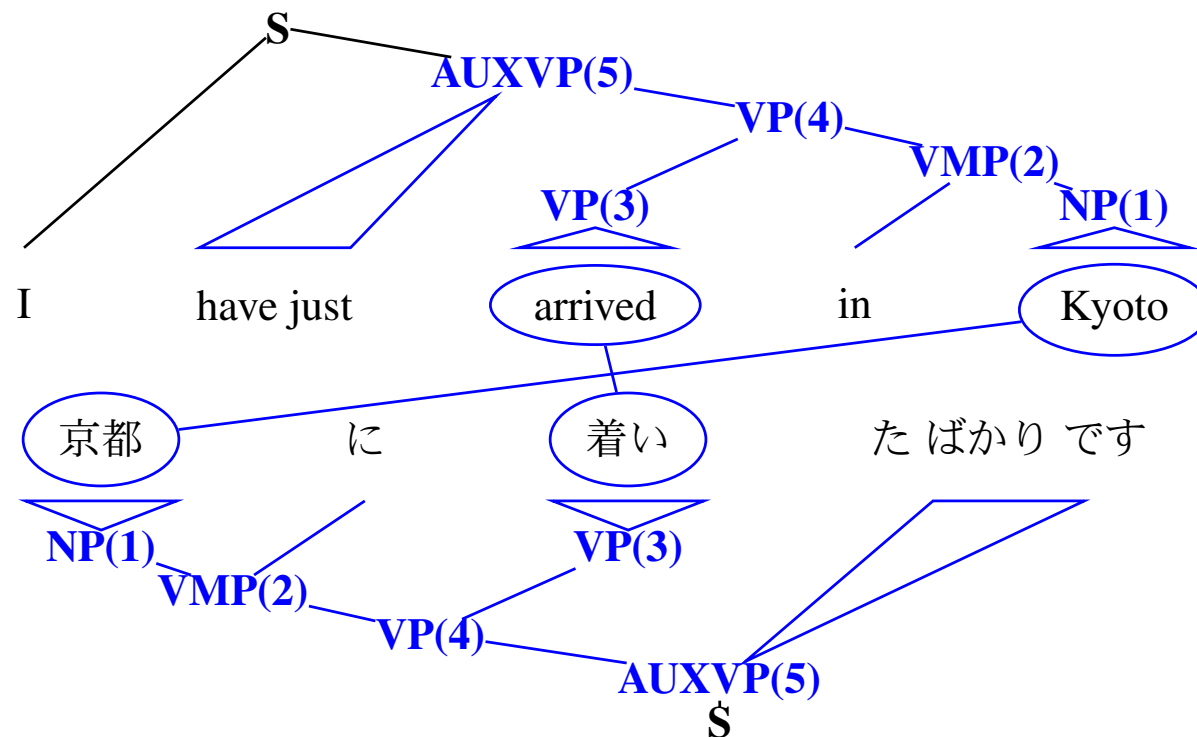
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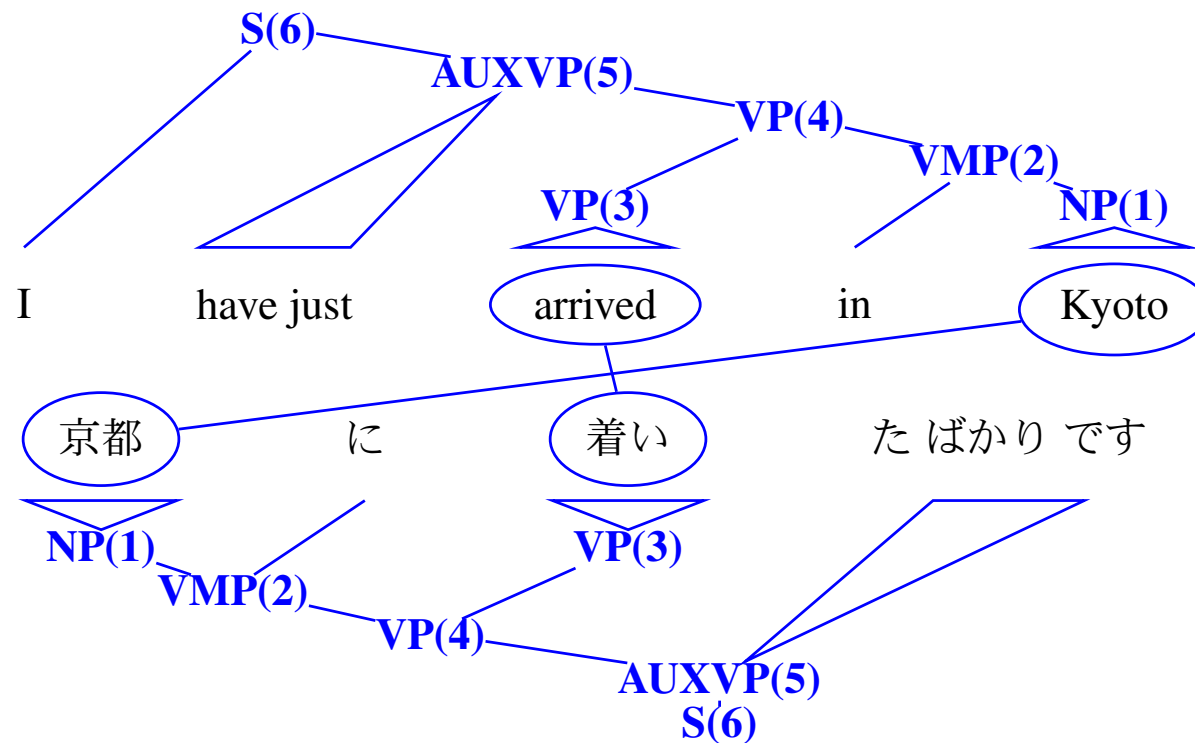
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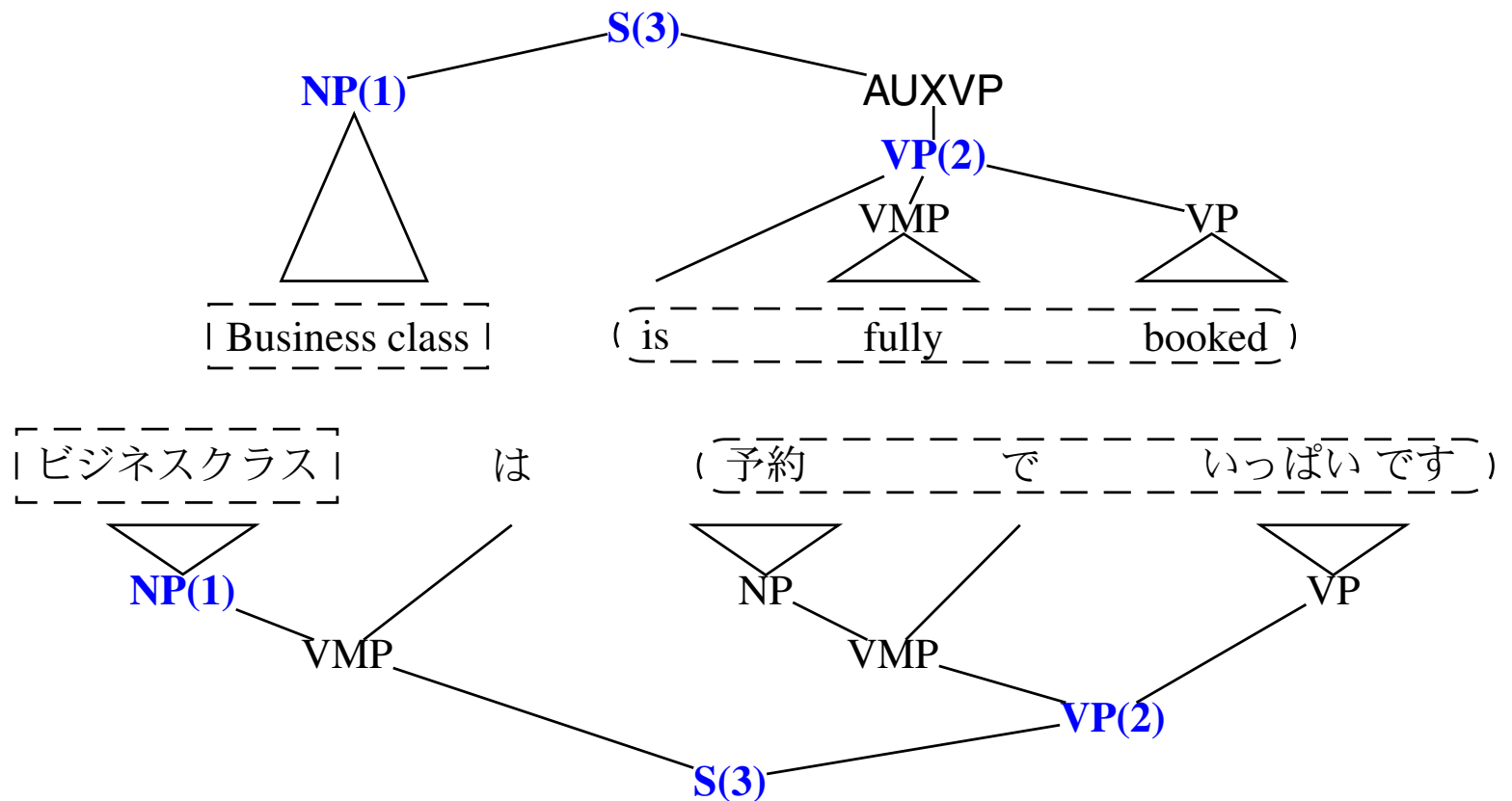
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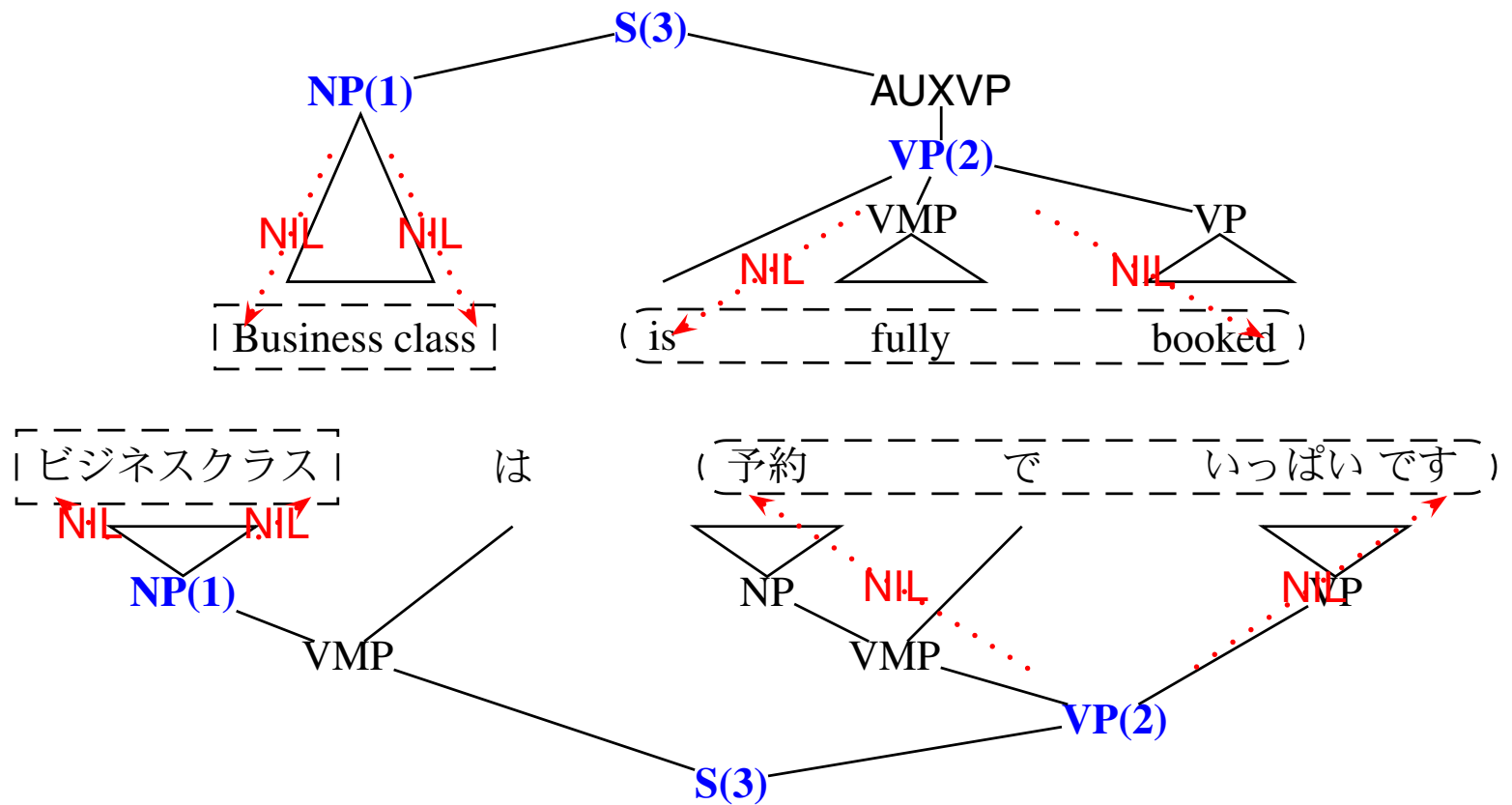


# Chunking by HPA



- Chunking by extracting low-level phrases

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# Chunking Model

- Create a model by treating each chunk as a token

business class                    →    business:class

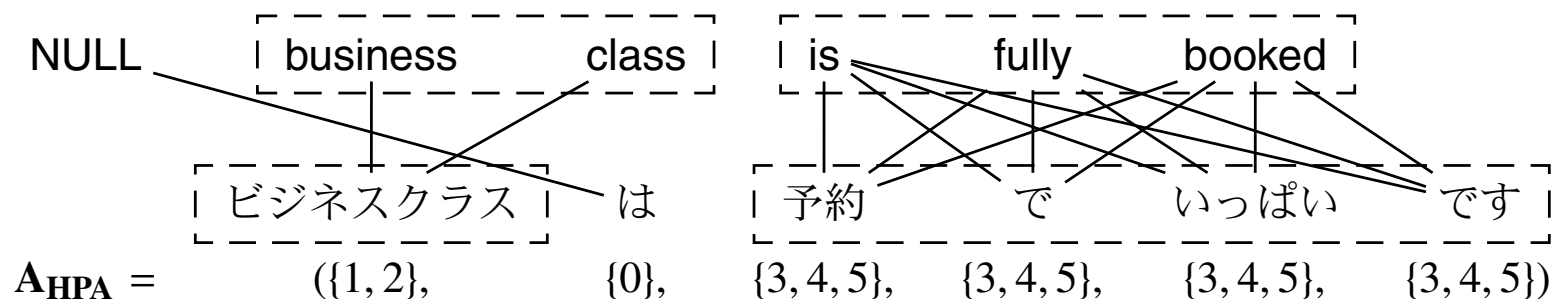
is fully booked                    →    is:fully:booked

予約でいっぱいです            →    予約:で:いっぱい:です

- Bootstrapping from IBM Model 1 and create IBM Model 4

# HPA Model

- A set of alignments hypothesized by HPA



- Directly compute IBM Model 4 parameters w/o pegging

$$tc(f|e; \mathbf{f}, \mathbf{e}, \mathbf{A}_{\text{HPA}}) = \sum_{\mathbf{a} \in \mathbf{A}_{\text{HPA}}} P(\mathbf{a}|\mathbf{f}, \mathbf{e}) \sum_{i,j} \delta(f, f_j) \delta(e, e_{a_j})$$

$$t(f|e) \leftarrow \sum_{s \in \text{train}} tc(f|e; \mathbf{f}_s, \mathbf{e}_s, \mathbf{A}_s)$$

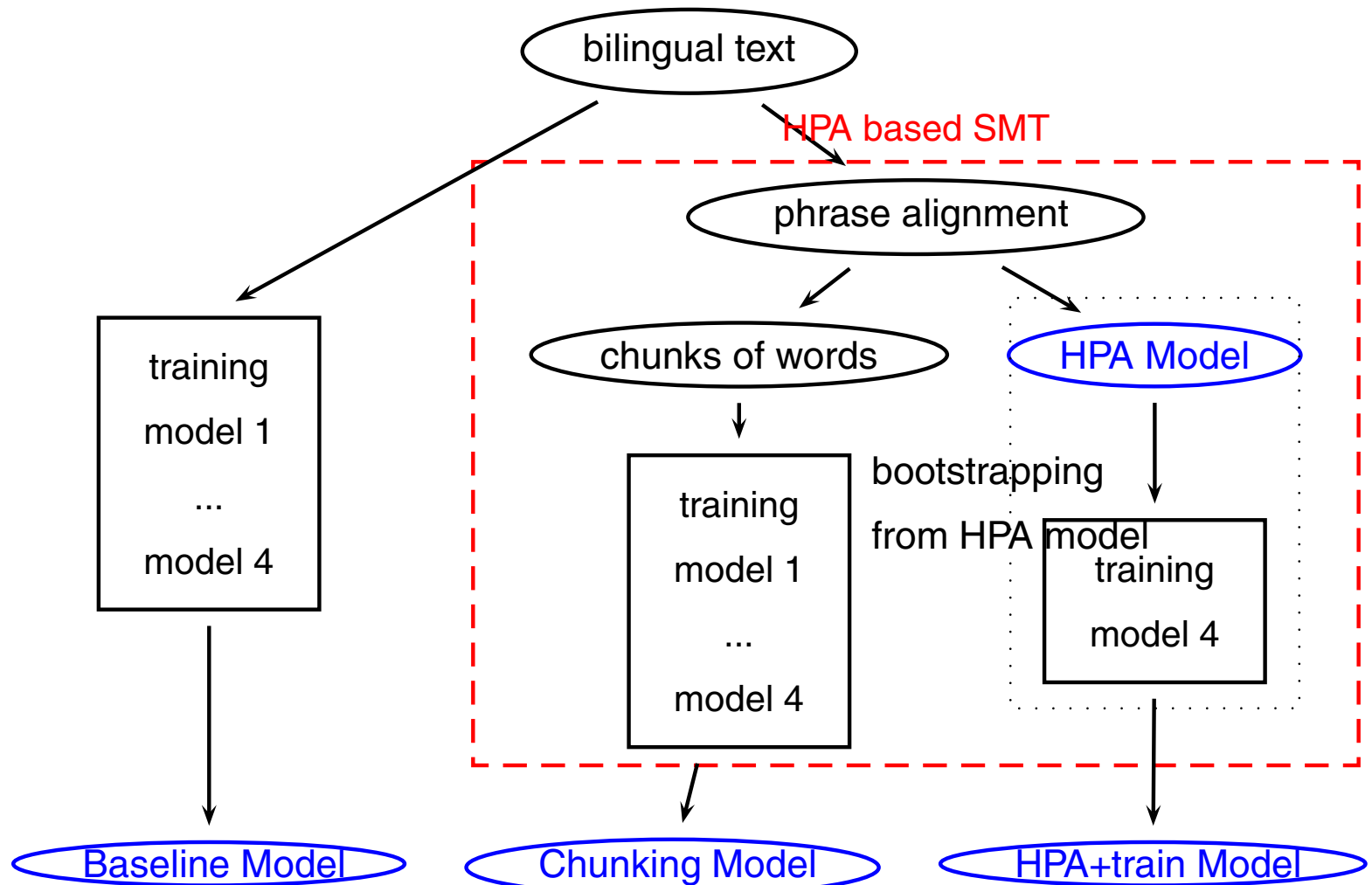


## HPA+train Model

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- Use the HPA model (= IBM Model 4) as initial parameters for further training of IBM Model 4
- Use pegged alignments

# Overview of Models



# Experimental Results — Settings

## ■ Corpus

	English	Japanese
number of sentences	145,432	
number of words	835,048	896,302
vocabulary size	13,162	20,348
average sentence length	5.74	6.16
trigram perplexity	36.03	32.93

## ■ Chunking

	English	Japanese
number of chunks	7,604	6,750
vocabulary size (of chunks)	2,166	1,624
average number of chunks per sentence	0.759	0.673
average number of words per chunk	2.21	2.52
trigram perplexity	72.36	72.07

# J-E Translation Results (1)

- Tested on 150 inputs

Model	WER	PER	SE			
			A	B	C	D
baseline	70.2	59.2	12.7	33.3	14.7	38.7
chunking	64.0	53.1	21.3	28.0	16.7	34.0
HPA	64.5	58.1	17.3	32.0	15.3	35.3
HPA+train	71.0	59.3	16.0	32.0	22.0	30.0

WER: word error rate

PER: position independent word error rate

SE: subjective evaluation (A: perfect, B: fair, C: acceptable, D: nonsense)



## J-E Translation Results (2)

Model	WER			PER			SE(A+B+C)		
	6	8	10	6	8	10	6	8	10
baseline	66.6	67.5	76.6	56.8	60.7	60.0	66.0	64.0	52.0
chunking	54.5	57.0	80.6	48.4	48.9	62.0	78.0	72.0	48.0
HPA	59.5	65.7	68.4	55.3	60.7	58.4	72.0	66.0	56.0
HPA+train	64.3	72.6	76.2	55.8	62.5	59.7	78.0	72.0	60.0

# Sample Translations

ステーキの:焼き 具合はどう されますか

baseline: (D) can you steak

chunking: (A) how do you like your:steak

HPA+train: (A) how do you like your steak

ゴルフ場の:予約 でき:ます:か

baseline: (C) can i make-a-reservation

chunking: (A) can:i make-a-reservation:for golf

HPA+train: (A) could you make-a-reservation for the golf course

シカゴから シアトル まで どのくらい:時間:が かかり:ます:か

baseline: (A) how-long does it take to seattle from chicago

chunking: (A) how-long will:it:take to seattle from chicago

HPA+train: (B) do you how-long will it take to seattle from chicago

## Sample Translations (Contd.)

席の確保ではくれぐれも最高の所をお願いします

(please be sure to secure the best available seats for us)

baseline: (B) i would like a seat in a great place please

chunking: (D) what 's the maximum area for sends providing seats

HPA+train: (D) my best regards to your seat find a place please

初心者な:の:だ けど 参加し ても:いい:です:か

(i am a beginner may i join)

baseline: (D) do you have may but take beginner

chunking: (D) can:i join beginners ring

HPA+train: (D) it is but i am a beginner