Bitext Alignment for Statistical Machine Translation

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Bitext and Bitext Alignment

- Bitext: a collection of text in two languages
- Bitext Alignment: finding translation equivalence within bitext

Chinese	English
要 做 好 河 湖 清 障 工作 ，对 各种 河 湖 障碍 ，坚决 予以 清除 .	It is necessary to resolutely remove obstacles in rivers and lakes .
四 、 加强 监测 预报 ，科学 调度 .	4 . It is necessary to strengthen monitoring and forecast work and scientifically dispatch people and materials .
要 采取 有效 措施 ，千方百计 提高 预报 精度 .	It is necessary to take effective measures and try by every possible means to provide precision forecast .
汛 前 要 抓紧 修订 洪水 预报 方案 ，有 针对性 地 开展工作 .	Before the flood season comes , it is necessary to seize the time to formulate plans for forecasting floods and to carry out work with clear

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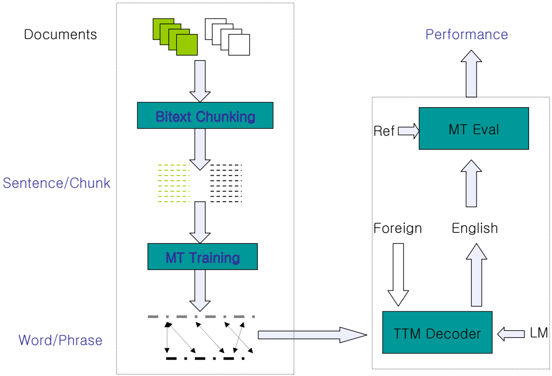
Why automatic bitext alignment?

- Critical and beneficial in many multilingual NLP tasks
  - provides basic ingredients in building a Machine Translation system
- Hand alignment is expensive for large corpora
- Desired properties
  - language independent: Chinese, Arabic, Spanish, French ...
  - no linguistic knowledge: from scratch, unsupervised, statistical
  - huge amount of data: effectiveness and efficiency

Statistical Machine Translation (SMT)

Source	$\longrightarrow$ Channel $\longrightarrow$	Target	Source Decoding
E	$P(F\|E)$	F	$\hat{E} = \mathrm{argmax}_E P(E)P(F\|E)$

Translation Model $P(F|E)$ needs BITEXTs



Outline

1. Bitext Chunk Alignment
   - Chunk Alignment
   - Chunking Algorithms
   - Sentence Alignment Results
2. Bitext Word Alignment
   - Introduction/Motivation
   - Word-to-Phrase HMM Model
   - Parameter Estimation
   - Word Alignment Results
3. Bitext Phrase Alignment
   - Inducing from Word Alignments
   - Model-based Phrase Pair Posterior
   - Translation Results
4. Conclusions

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Chunk Alignment

- Problem: sentences are not translated 1-to-1 in sequence
  - 1-to-n, n-to-1, m-to-n, order changes, real data challenge
- A Statistical Generative Chunk Alignment Model (Deng et al, ’04)
  - introduce a hidden chunk alignment variable
  - document generating: fill in the blank
  - two alignment algorithms are derived in a straightforward manor

		#		#		#		#		
	$w_1 \cdot\cdot w_8$		$w_9 \cdot\cdot w_{20}$		$w_{21} \cdot\cdot w_{30}$		$w_{31} \cdot\cdot w_{38}$		$w_{39} \cdot\cdot w_{50}$	← *Boundary marks*
$e = e_1^5$	e_1		e_2		e_3		e_4		e_5	

$$e = e_1^m$$

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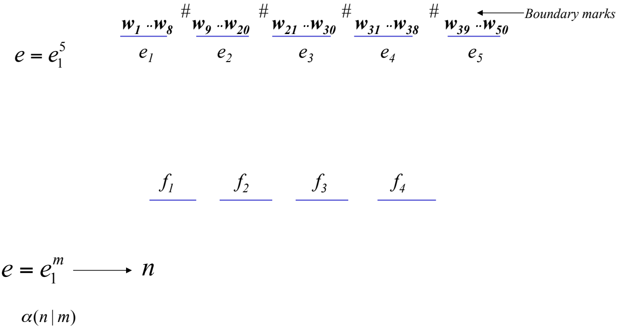

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$\#$ $\#$ $\#$ $\#$ ← *Boundary marks*

$$e = e_1^5 \quad \underbrace{w_1 \cdots w_8}_{e_1} \; \# \; \underbrace{w_9 \cdots w_{20}}_{e_2} \; \# \; \underbrace{w_{21} \cdots w_{30}}_{e_3} \; \# \; \underbrace{w_{31} \cdots w_{38}}_{e_4} \; \# \; \underbrace{w_{39} \cdots w_{50}}_{e_5}$$

$K=3$

f_1 f_2 f_3 f_4

$$e = e_1^m \longrightarrow n \longrightarrow K$$

$$\alpha(n \mid m)\beta(K \mid m, n)$$

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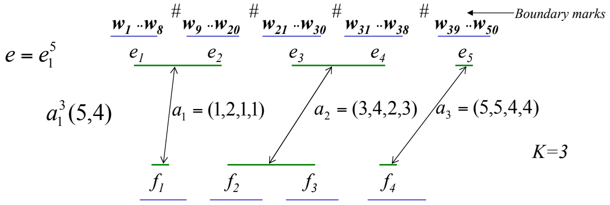

$$e = e_1^m \longrightarrow n \longrightarrow K \longrightarrow a_1^K(m,n)$$

$$\alpha(n \mid m)\beta(K \mid m,n)\; P(a_1^K \mid m,n,K)$$

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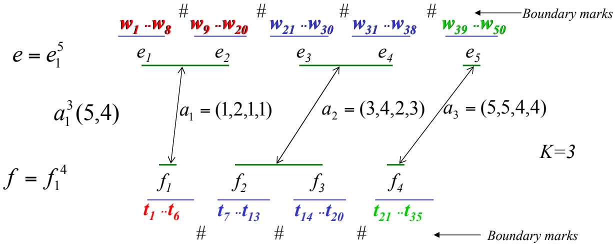

$$e = e_1^m \longrightarrow n \longrightarrow K \longrightarrow a_1^K(m,n) \longrightarrow f_1^n = f$$

$$\alpha(n\,|\,m)\beta(K\,|\,m,n)\,P(a_1^K\,|\,m,n,K)\prod_k P^{(w)}(f(a_k)\,|\,e(a_k)) = P(f_1^n, K, a_1^K\,|\,e_1^m)$$

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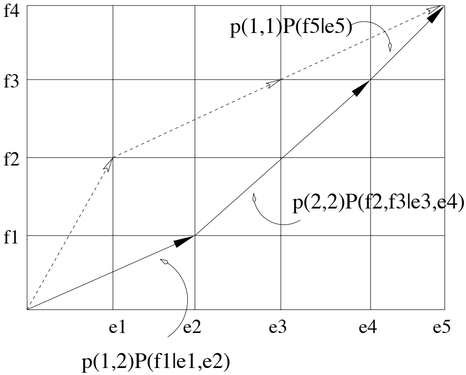
Dynamic Programming (DP)



- Monotone chunk alignment
- Global optimum

Divisive Clustering (DC)

divide and conquer, iterative binary parallel splitting, reorder

自从 朝鲜半岛 被 分裂 成 两个 国家 以来 ， 韩国 在 背 靠 美国 这 棵 大 树 以求 自 安 的 同时 ， 还 小心翼翼 但 却 坚持不懈 地 向 美国 寻求 先进武器 ， 以 抗衡 朝鲜 。

据 汉城 的 消息灵通人士 向 《 华盛顿邮报 》 透露 ， 今年 早些时候 ， 美国 已 秘 而 不 宣 地 同意 韩国 “ 可以 扩展 它 现有 导弹 的 射程 ” ， 使 之 能够 直捣 朝鲜 首都 平壤 。

这 本 应 是 韩国 感到 欣喜 的 事儿 ， 可 眼下 半岛 局势 有 了 重大 变化 ， 朝 韩 首脑 面对 面地 会 了 晤 ， 并 签署 了 联合声明 。 韩国 怎么办 ？ 只好 把 到 嘴的 “ 肥肉 ” 先 吐 出来 ， 搁置 自己的 “ 导弹 射程 扩展 计划 ” 。

一 名 韩国 知情 人士 道 出 了 实情 ：

“ 因为 有 了 首脑 会谈 ， 所以 我们 已 搁置 了 自己的 导弹 计划 ， 如果 我们 再 那么 干 ， 就 会 弄糟 首脑 峰 会 开创 的 良好 局面 。 ”

Since the Korean Peninsula was split into two countries , the Republic of Korea has , while leaning its back on the " big tree " of the United States for security , carefully and consistently sought advanced weapons from the United States in a bid to confront the Democratic People 's Republic of Korea .

An informed source in Seoul revealed to the Washington Post that the United States had secretly agreed to the request of South Korea earlier this year to " extend its existing missile range " to strike Pyongyang direct .

This should have elated South Korea . But since the situation surrounding the peninsula has changed dramatically and the two heads of state of the two Koreas have met with each other and signed a joint statement , what should South Korea do now ? It has no choice but spit back the " greasy meat " from its mouth and put the " missile expansion plan " on the back burner .

A knowledgeable South Korean speaks the truth :

" Because of the summit meeting , we have shelved our own missile plan . If we go ahead with it , it will spoil the excellent situation opened up by the summit meeting . "

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自从 朝鲜半岛 被 分裂 成 两个 国家 以来 ， 韩国 在 背 靠 美国 这 棵 大 树 以求 自 安 的 同时 ， 还 小心翼翼 但 却 坚持不懈 地 向 美 国 寻求 先进武器 ， 以 抗衡 朝鲜 。 据 汉城 的 消息灵通人士 向 《 华盛顿邮报 》 透露 ， 今年 早些时候 ， 美国 已 秘 而 不 宣 地 同意 韩国 " 可以 扩展 它 现有 导弹 的 射 程 " ， 使 之 能够 直捣 朝鲜 首都 平壤 。 这 本 应 是 韩国 感到 欣喜 的 事儿 ， 可 眼下 半岛 局势 有 了 重大 变化 ， 朝 韩 首脑 面对 面地 会 了 晤 ， 并 签署 了 联合声明 。 韩国 怎么办 ？ 只好 把 到 嘴的 " 肥肉 " 先 吐 出 来 ， 搁置 自己的 " 导弹 射程 扩展 计划 " 。 一 名 韩国 知情 人士 道 出 了 实情 ：	Since the Korean Peninsula was split into two countries , the Republic of Korea has , while leaning its back on the " big tree " of the United States for security , carefully and consistently sought advanced weapons from the United States in a bid to confront the Democratic People 's Republic of Korea . An informed source in Seoul revealed to the Washington Post that the United States had secretly agreed to the request of South Korea earlier this year to " extend its existing missile range " to strike Pyongyang direct . This should have elated South Korea . But since the situation surrounding the peninsula has changed dramatically and the two heads of state of the two Koreas have met with each other and signed a joint statement , what should South Korea do now ? It has no choice but spit back the " greasy meat " from its mouth and put the " missile expansion plan " on the back burner . A knowledgeable South Korean speaks the truth :
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A hierarchical chunking scheme

- DP+DC
  - DP at sentence level followed by DC at sub-sentence level
  - from coarse to fine, deriving short chunk pairs
- Advantage
  - significantly reduce machine training time
    - 21 hrs vs. 8 hrs
  - make most of bitext usable for machine training
    - 78% vs. 98%
    - "There is no data like more data" (Robert Mercer, 1988)
  - improve system performance by higher coverage

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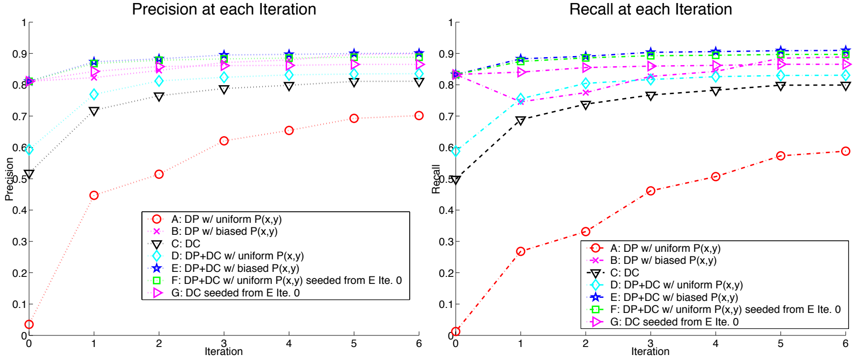
Unsupervised Sentence Alignment

- 122 Chinese/English document pairs selected from FBIS corpus
- sentence aligned by humans, $\sim$ 2,200 sentence pairs
- unsupervised from scratch, measured by Pre/Rec



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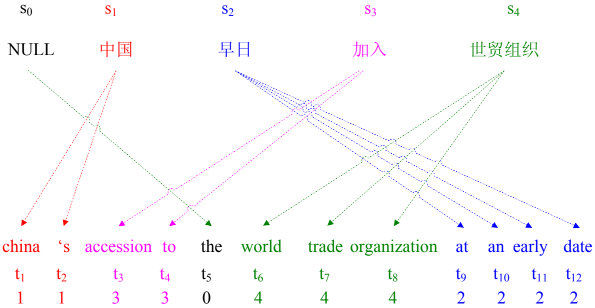
Word Alignment

- Fundamental problem in Machine Translation
- Basis for phrase/syntax models
- Model relations from source $\mathbf{s} = s_1^I$ to target $\mathbf{t} = t_1^J$
  - Word alignment $\mathbf{a} = a_1^J$: $s_{a_j} \rightarrow t_j, j = 1, 2, \cdots, J \Longleftarrow$ hidden r.v.
  - Conditional likelihood $P(\mathbf{t}, \mathbf{a}|\mathbf{s}) \Longleftarrow$ complete data
  - Sentence translation $P(\mathbf{t}|\mathbf{s}) = \sum_{\mathbf{a}} P(\mathbf{t}, \mathbf{a}|\mathbf{s}) \Longleftarrow$ incomplete data



State of the Art

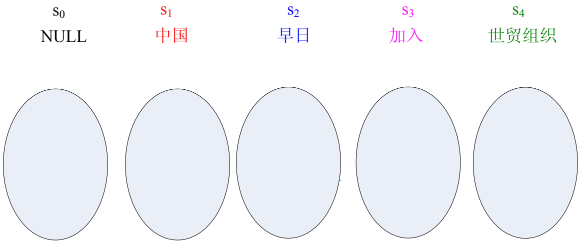
- IBM Model-4 generated by GIZA++ Toolkit (Och & Ney, ’03)
  - The state of the art word alignments especially on large bitexts
- But
  - Exact-EM is problematic, sub-optimal estimation algorithms used
  - Difficult to compute statistics under the model
  - Applications limited by word alignments only
- GOAL: improve word alignments of bitexts for better translation
  - Comparable performance to Model-4
  - Fast efficient training, with controlled memory usage
  - Use the model, not just the alignments

IBM Model-4 Word Alignments (Brown et al, '93)

s_0	s_1	s_2	s_3	s_4
NULL	中国	早日	加入	世贸组织

- What makes the model powerful also makes computation complex
- Typical training procedure: Model-1, HMM, Model-4
- Can we do something to HMM?

IBM Model-4 Word Alignments (Brown et al, ’93)



Create a tablet for each source word

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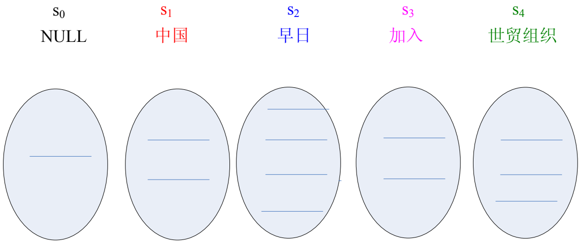

Table lookup to decide fertility: # of target words connected

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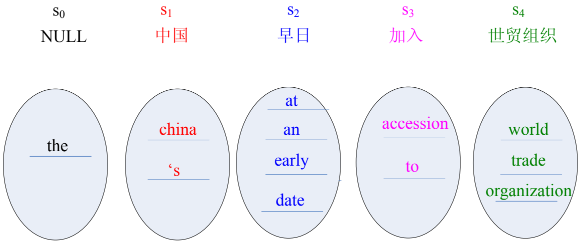

Sample target words from translation table i.i.d.

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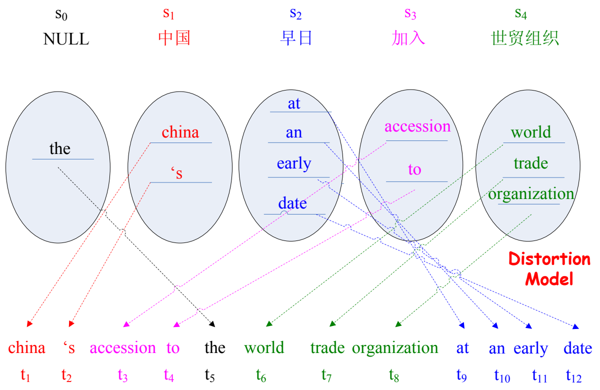

- What makes the model powerful also makes computation complex
- Typical training procedure: Model-1, HMM, Model-4
- Can we do something to HMM?

HMM WtoW Model (Vogel et al, '96; Och & Ney, '03)

s_1 s_2 s_3 s_4

中国 早日 加入 世贸组织

china	's	accession	to	the	world	trade	organization	at	an	early	date
t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}	t_{11}	t_{12}

- State sequences $\Longleftrightarrow$ word to word alignments
- Words are generated one by one, one transition emits one target word

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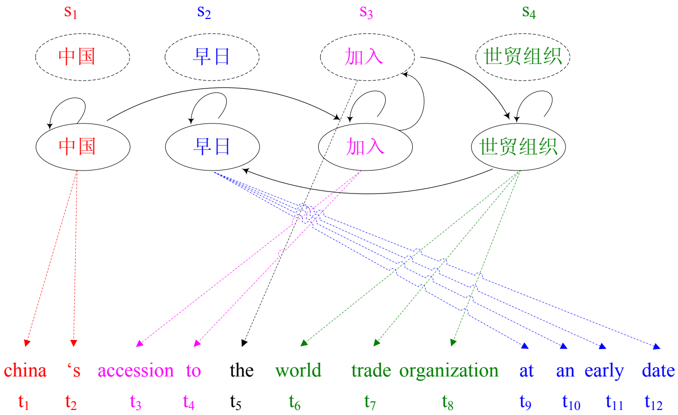

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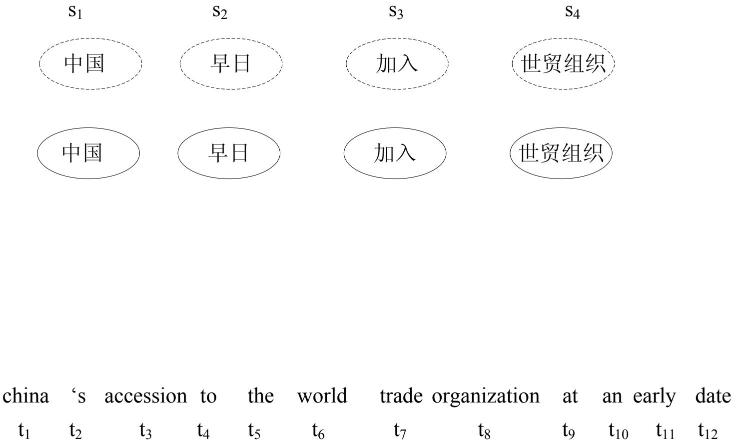
Make HMM More Powerful in Generating Observations



- Target phrases rather than words are emitted after jumping into a state
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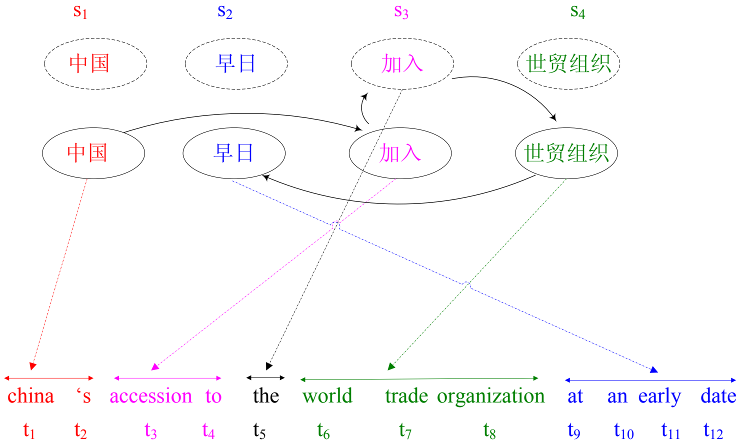

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Word-to-Phrase HMM Alignment Models

- Target sentence segmented into K phrases
- Phrase length sequence ϕ_1^K, $\mathbf{t} = \mathbf{v}_1^K$
- Phrase alignment sequence a_1^K
- NULL: h_1^K is a Bernoulli process, $d(h_k = 1) = 1 - p_0, d(h_k = 0) = p_0$
  - $h_k = 1 \Rightarrow s_{a_k} \rightarrow \mathbf{v}_k$
  - $h_k = 0 \Rightarrow \text{NULL} \rightarrow \mathbf{v}_k$
- Hidden random variable: Word-to-phrase alignment $\mathbf{a} = (K, a_1^K, \phi_1^K, h_1^K)$

$$
\begin{aligned}
P(\mathbf{t}, \mathbf{a}|\mathbf{s}) &= P(\mathbf{v}_1^K, K, a_1^K, h_1^K, \phi_1^K | \mathbf{s}) \\
&= P(K|J, \mathbf{s}) \times P(a_1^K, \phi_1^K, h_1^K | K, J, \mathbf{s}) \times P(\mathbf{v}_1^K | a_1^K, h_1^K, \phi_1^K, K, J, \mathbf{s}) \\
&= P(K|J, I) \Longleftarrow \text{Phrase Count} \propto \eta^K \\
&\quad \times \prod_{k=1}^{K} p(a_k | a_{k-1}, h_k; I) \cdot d(h_k) \cdot n(\phi_k; h_k \cdot s_{a_k}) \Longleftarrow \text{Markov, Phrase Length} \\
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Word-to-Phrase Translation Probabilities

- Replace weak i.i.d. word-for-word translation
- $P(\text{world trade organization}|f = \text{世贸组织}; 3) =?$
  - $= t(\text{world}|\text{f}) \cdot t(\text{trade}|\text{f}) \cdot t(\text{organization}|\text{f}) \Longleftarrow$ i.i.d.
  - $= t(\text{world}|\text{f}) \cdot t_2(\text{trade}|\text{world}, \text{f}) \cdot t_2(\text{organization}|\text{trade}, \text{f}) \Longleftarrow$ bigram

Model	i.i.d.	bigram
$P(\text{world}\|\text{世贸组织})$	0.06	0.06
$P(\text{trade}\|\text{world}, \text{世贸组织})$	0.06	0.99
$P(\text{organization}\|\text{trade}, \text{世贸组织})$	0.06	0.99
$P(\text{world trade organization}\|\text{世贸组织}, 3)$	0.0002	0.0588

- Assigns higher probability to correct translation than i.i.d
- Incorporates context without losing algorithmic efficiency: DP
- Use same estimation techniques as used for bigram LMs
- Data sparseness, Witten-Bell smoothing

Comparing Word-to-Phrase HMM to ...

- Segmental Hidden Markov Models (Ostendorf et al, '96)
  - states emit observation sequences
- WtoW HMM (Vogel et al, '96; Och & Ney, '03)
  - $N = 1$
- Extensions to WtoW HMM (Toutanova et al, '02)
  - $P(\mathrm{stay}|s)$ vs. $P(\mathrm{stay} = \phi|s)$ in modeling state durations
- IBM Model-4
  - fertility vs. phrase length

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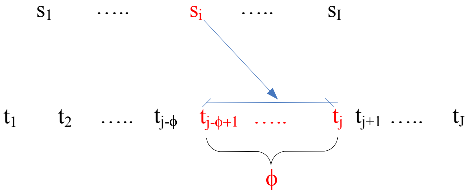
Forward-backward Algorithm

State space $S = \{(i, \phi, h) : 1 \leq i \leq I, 1 \leq \phi \leq N, h = 0 \text{ or } 1\}$ Grid $2NI \times J$



$$\alpha_j(i, \phi, h) = \left\{ \sum_{i', \phi', h'} \alpha_{j-\phi}(i', \phi', h') p(i|i', h; I) \right\} \cdot \eta \cdot n(\phi; h \cdot s_i) \cdot P(t_{j-\phi+1}^{j} | h \cdot s_i, \phi)$$

$$\beta_j(i, \phi, h) = \sum_{i', \phi', h'} \beta_{j+\phi'}(i', \phi', h') p(i'|i, h'; I) \cdot \eta \cdot n(\phi'; h' \cdot s_{i'}) \cdot P(t_{j+1}^{j+\phi'} | h' \cdot s_{i'}, \phi')$$

$$\gamma_j(i, \phi, h) = P(h \cdot s_i \rightarrow v = t_{j-\phi+1}^{j} | \theta, \mathbf{s}, \mathbf{t}) = \frac{\alpha_j(i, \phi, h) \beta_j(i, \phi, h)}{\sum_{i', h', \phi'} \alpha_J(i', \phi', h')}$$

Embedded Estimation of Word-to-Phrase HMM

- Unsupervised training from scratch
  - Model-1, 10 its (initial t-table)
  - Model-2, 5 its (better t-table)
  - WtoW HMM, 5 its (initial Markov model)
  - WtoP HMM N=2, 3, .., each 5 its (Markov model, phrase length) (experience from ASR)
  - WtoP HMM with bigram t-table, 5 its (bigram t-table)
- Parallel Implementation
  - Partitioning training bitext
  - E-step: Collect counts from each partition parallel
  - M-step: Merge counts to update model parameters
  - Memory efficient, virtually no limitation on training bitext size

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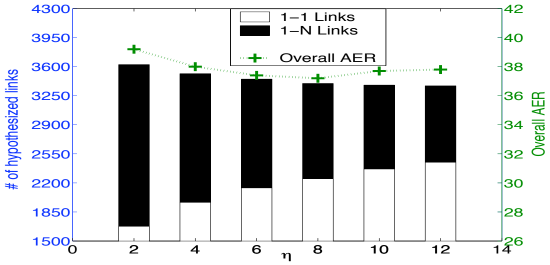
Bitext Alignment Results

- Test: NIST 2001 MT-eval set, 124 sentence pairs w/ manual word alignments
- Comparable performance to Model-4 on FBIS training bitext
- Increasing max phrase length N improves quality in $C \rightarrow E$ direction
- Bigram translation probability improves word-to-phrase links
- A good balance between 1-1 and 1-N distribution can be achieved



- Comparable performance when extending to large scale bitexts

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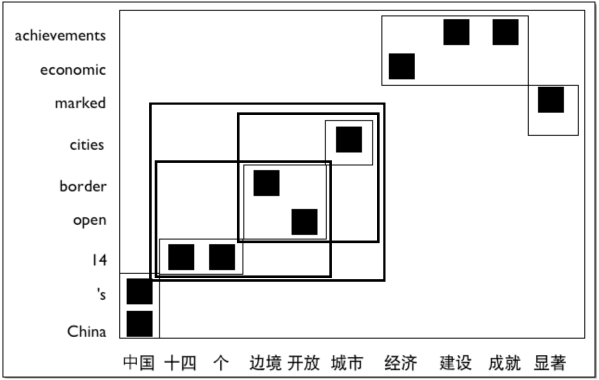
Statistical Phrase Translation Models

- Phrase-based SMT performs better than word-based SMT
- Phrases Pair Inventory (PPI) extracted from word aligned bitext (Och et al, '99)



But word alignments are imperfect ...

- Relying on the one-best word alignment may exclude some valid phrase pairs
- Goal is to define a probability distribution over phrase pairs
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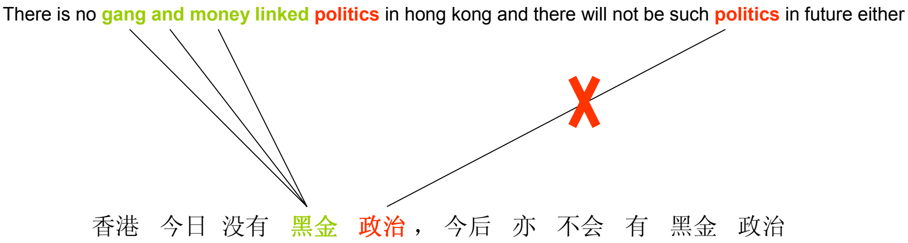

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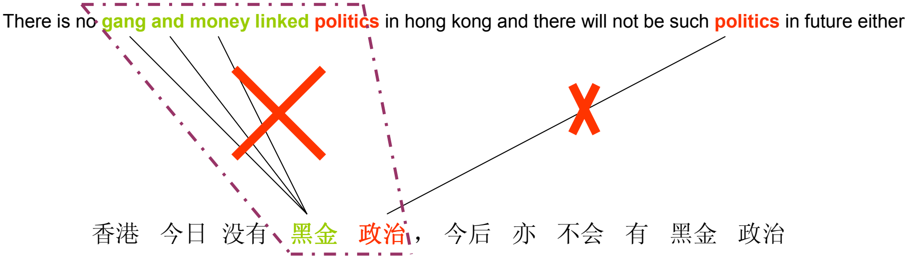

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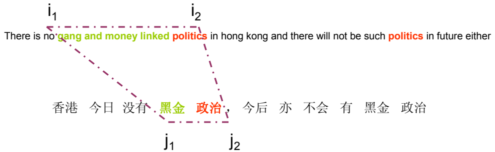
Model-based Phrase Pair Posterior

- Doesn't rely on a single alignment



- Define a set of alignments that align words to words in phrases
  $A(i_1, i_2; j_1, j_2) = \{a_1^m : a_j \in [i_1, i_2] \text{ iff } j \in [j_1, j_2]\}$
- Calculate the likelihood of the source phrase producing the target phrase
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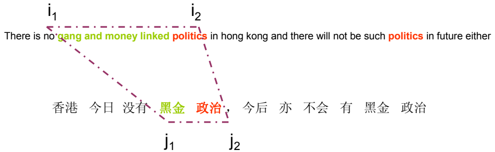

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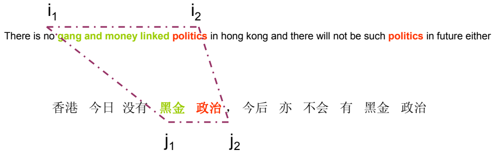

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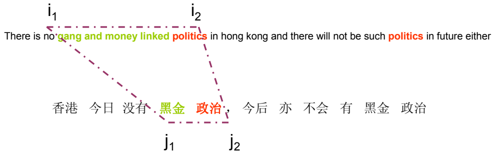

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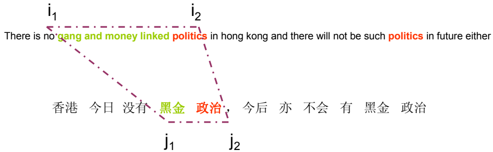

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Augmented PPI for a Better Coverage

- Baseline PPI
  - extracted from 1-best alignments using establishing techniques (Och et al., '99)
- GOAL: add phrase pairs to improve test set coverage
- For each foreign phrase **v** in test set not covered by the baseline
  - for each sentence pair containing **v**
  - find the English phrase **u** that maximizes the phrase pair posterior

$$f(i_1, i_2) = P_{F \to E}(A(i_1, i_2; j_1, j_2) \,|\, e_1^l, f_1^m)$$

$$b(i_1, i_2) = P_{E \to F}(A(i_1, i_2; j_1, j_2) \,|\, e_1^l, f_1^m)$$

$$g(i_1, i_2) = \sqrt{f(1_1, i_2)\, b(i_1, i_2)}$$

$$(\hat{i}_1, \hat{i}_2) = \operatorname*{argmax}_{1 \le i_1, i_2 \le l} g(i_1, i_2) \text{ , and set } u = e_{\hat{i}_1}^{\hat{i}_2}$$

  - add $(\mathbf{u}, \mathbf{v})$ to the baseline PPI if posterior exceeds a threshold value

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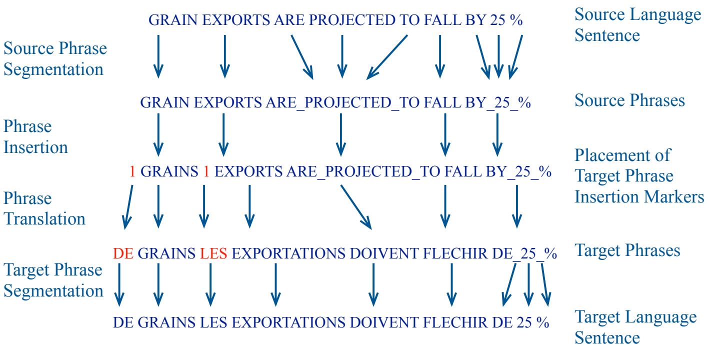
Transduce Translation Model (Kumar et al, '05)

- TTM Decoder - WFST implementation with monotone order



Automatic Machine Translation Evaluation

- hard problem !
- BLEU (Papeneni et al, '01) – an automatic MT metric
  - correlated well with human judgements
  - geomantic mean of n-gram precisions weighted by brevity penalty

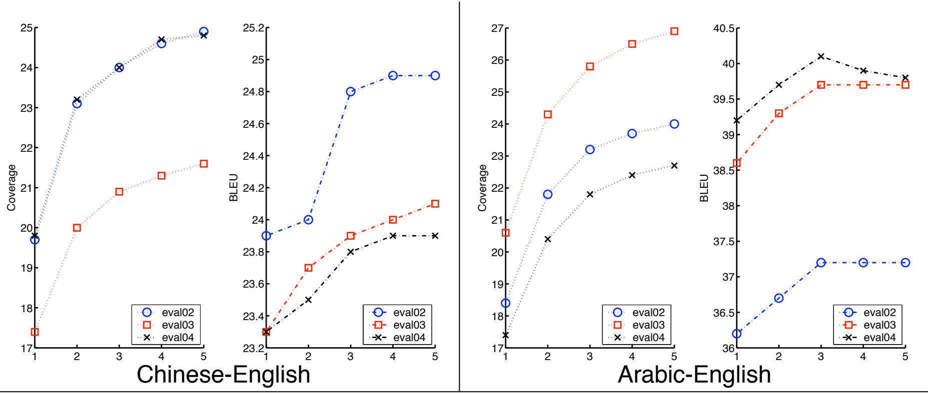
Reference : mr. speaker , in absolutely no way .

Hypothesis : in absolutely no way , mr. chairman .

BLEU computation

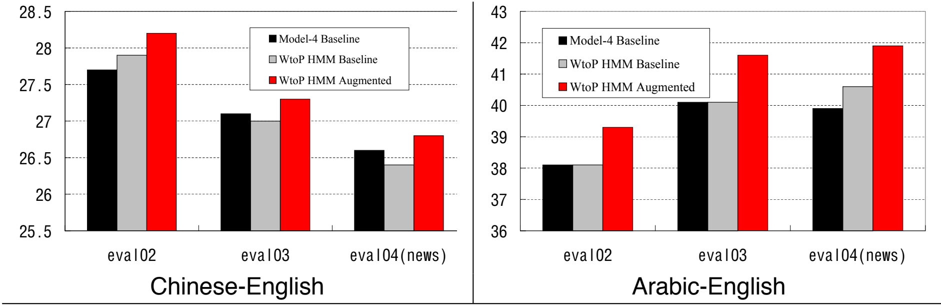
Sub-string-Matches(Truth,Hyp)				BLEU
1-word	2-word	3-word	4-word	$\left(\frac{7}{8} \times \frac{3}{7} \times \frac{2}{6} \times \frac{1}{5}\right)^{\frac{1}{4}} = 0.3976$
7/8	3/7	2/6	1/5	

Translation Results: Small Systems



- Relaxing threshold in PPI augmenting improves coverage and BLEU score
- Balance coverage against phrase translation quality
- WtoP model can even be applied to augment Model-4 PPI

Translation Results: Large Systems



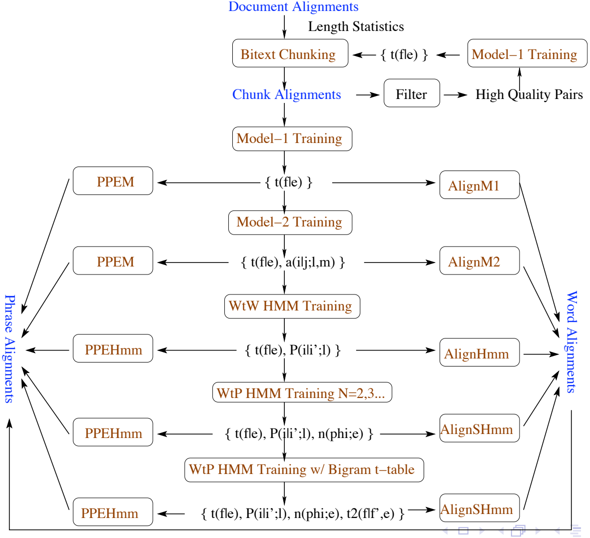
- Used all parallel corpora available from LDC
  - C-E: 200M En. words (FBIS, Xinhua, HK News, ..., all UN bitexts)
  - A-E: 130M En. words (news, all UN bitexts)

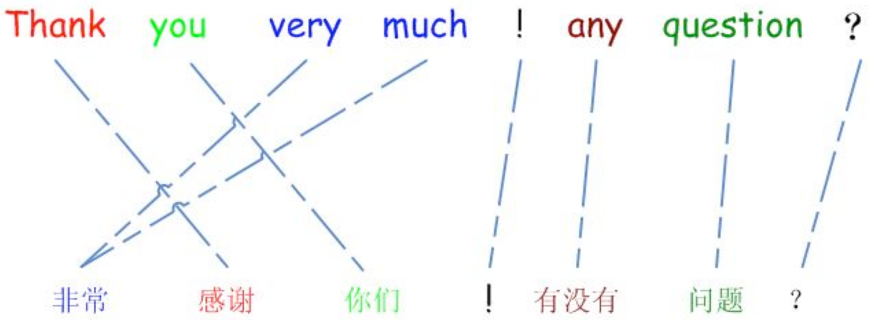
Conclusions

- A hierarchial bitext chunking approach
  - language independent, no linguistic knowledge required
  - derived short chunk pairs, retain more of the available bitext
- The word-to-phrase HMM alignment model
  - produces good quality word alignments over very large bitexts
  - has efficient training algorithm with parallel implementation
  - a powerful framework
- Model-based phrase pair distribution enables
  - an improved phrase pair extraction strategy
  - controlled balance coverage vs. quality
- WtoP HMM performs better than IBM Model-4 on large systems

Machine Translation Toolkit (MTTK)

Solutions for MT training, Used for JHU-CU 2005 NIST MT Eval Systems




Thank you very much ! any question ?
非常 感谢 你们 ! 有没有 问题 ?