What's New in Statistical Machine Translation

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LANGUAGE WEAVER

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Machine Translation

美国关岛国际机场及其办公室均接获一名自称沙地阿拉伯富商拉登等发出的电子邮件，威胁将会向机场等公众地方发动生化袭击後，关岛经保持高度戒备。

The U.S. island of Guam is maintaining a high state of alert after the Guam airport and its offices both received an e-mail from someone calling himself the Saudi Arabian Osama bin Laden and threatening a biological/chemical attack against public places such as the airport .

The classic acid test for natural language processing.

Requires capabilities in both interpretation and generation.

Hard -- ambiguous source words, target fluency, re-ordering

About $10 billion spent annually on human translation.

Machine Translation

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Three basic uses:

1. Communication (as in speech/chat translation)
2. Dissemination (publish your stuff to the world)
3. Assimilation (be able to understand what's out there)

Despite decades of work, not a lot of progress!

Progress

slide from C. Wayne, DARPA

2002

insistent Wednesday may recurred her trips to Libya tomorrow for flying

Cairo 6-4 (AFP) - an official announced today in the Egyptian lines company for flying Tuesday is a company " insistent for flying " may resumed a consideration of a day Wednesday tomorrow her trips to Libya of Security Council decision trace international the imposed ban comment .

And said the official " the institution sent a speech to Ministry of Foreign Affairs of lifting on Libya air , a situation her receiving replying are so a trip will pull to Libya a morning Wednesday " .

2003

Egyptair Has Tomorrow to Resume Its Flights to Libya

Cairo 4-6 (AFP) - said an official at the Egyptian Aviation Company today that the company egyptair may resume as of tomorrow, Wednesday its flights to Libya after the International Security Council resolution to the suspension of the embargo imposed on Libya.

" The official said that the company had sent a letter to the Ministry of Foreign Affairs, information on the lifting of the air embargo on Libya, where it had received a response, the first take off a trip to Libya on Wednesday morning ".

Caveats

- Good for news text
  - Need to test on other genres
- Good for assimilation
  - Dissemination requires publication quality
- Fortunately, only scratched the surface of good ideas

Why Is It Getting Better?

"I don't want to talk about how we might do this task in the future. I'm going to talk about what we can do right now, with today's technology."

-- Marti Hearst

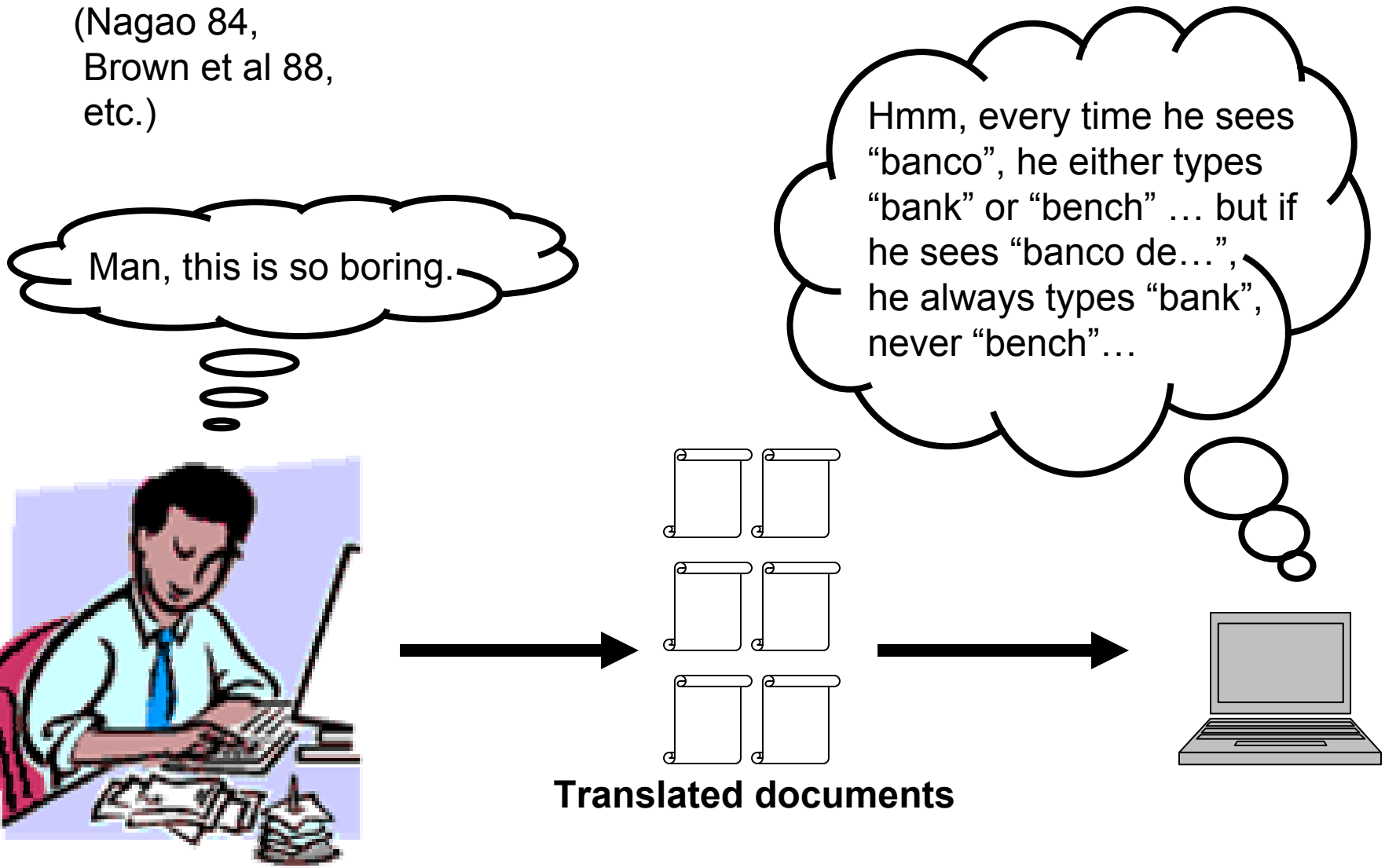
opening a talk on text segmentation

Why Is It Getting Better?

	since
• Large-scale data resources – bilingual text	2003
• Linguistic modeling of the translation relation – can string x a translation of string y, or not?	1990s
• Machine learning	1990s
• Heuristic search – both in learning and runtime	1990s
• Significant engineering of training data and software	
• 4 Gb memory & fast dual processor at $5000	2003
• New automatic evaluation metric to drive day-to-day experimentation	2001
• Competition between sites on translation of same previously-unseen test documents	2002
• Collaborative sharing of complex software tools, intensive workshops	1999

Data-Driven Machine Translation

(Nagao 84,
Brown et al 88,
etc.)



Centauri/Arcturan [Knight, 1997]

Your assignment, translate this to Arcturan: farok crrrok hihok yorok clok kantok ok-yurp

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process of elimination

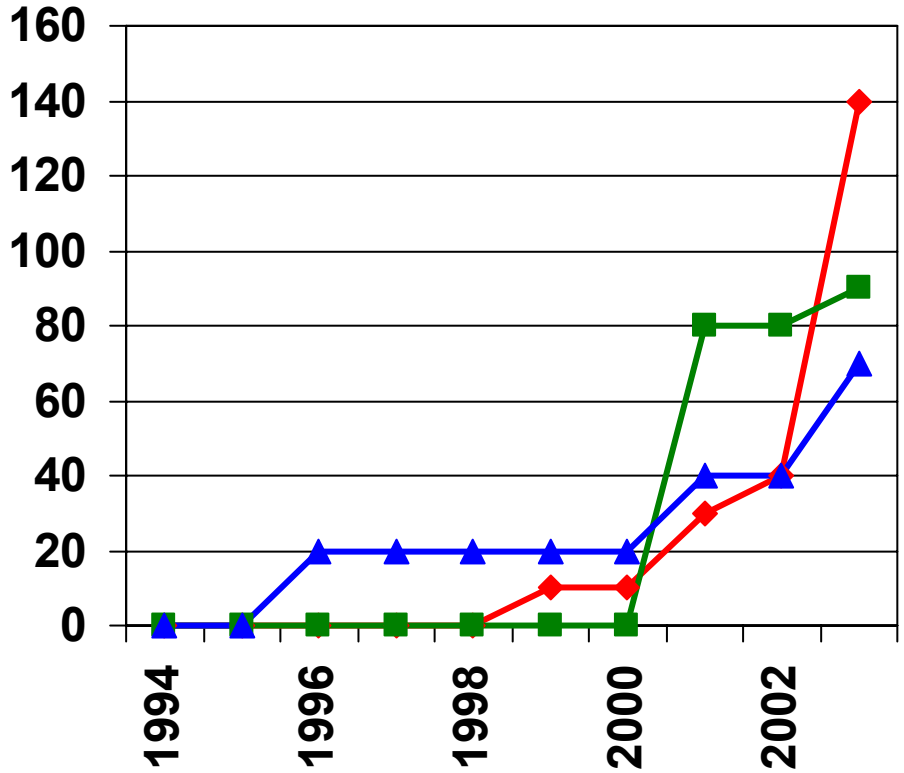
It’s Really Spanish/English

Clients do not sell pharmaceuticals in Europe => Clientes no venden medicinas en Europa

1a. Garcia and associates . 1b. Garcia y asociados .	7a. the clients and the associates are enemies . 7b. los clients y los asociados son enemigos .
2a. Carlos Garcia has three associates . 2b. Carlos Garcia tiene tres asociados .	8a. the company has three groups . 8b. la empresa tiene tres grupos .
3a. his associates are not strong . 3b. sus asociados no son fuertes .	9a. its groups are in Europe . 9b. sus grupos estan en Europa .
4a. Garcia has a company also . 4b. Garcia tambien tiene una empresa .	10a. the modern groups sell strong pharmaceuticals . 10b. los grupos modernos venden medicinas fuertes .
5a. its clients are angry . 5b. sus clientes estan enfadados .	11a. the groups do not sell zenzanine . 11b. los grupos no venden zanzanina .
6a. the associates are also angry . 6b. los asociados tambien estan enfadados .	12a. the small groups are not modern . 12b. los grupos pequenos no son modernos .

Ready-to-Use Bilingual Data

Millions of words
(English side)

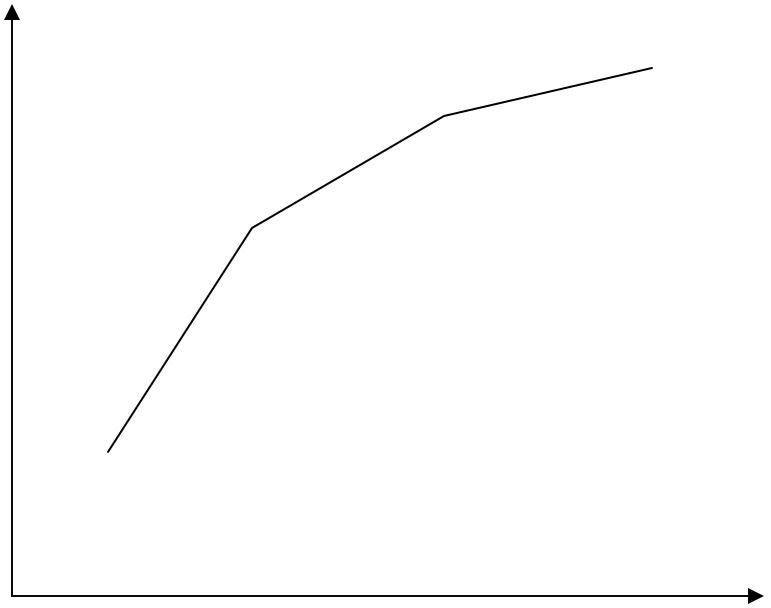


+ 1m-20m words for
<u>many</u> language pairs

(Data stripped of formatting, in sentence-pair format, available to researchers from the Linguistic Data Consortium).

Possible to Do Learning Curves

Quality of automatically trained machine translation system



Amount of bilingual training data

BLEU Evaluation Metric

(Papineni et al 02)

Reference (human) translation:

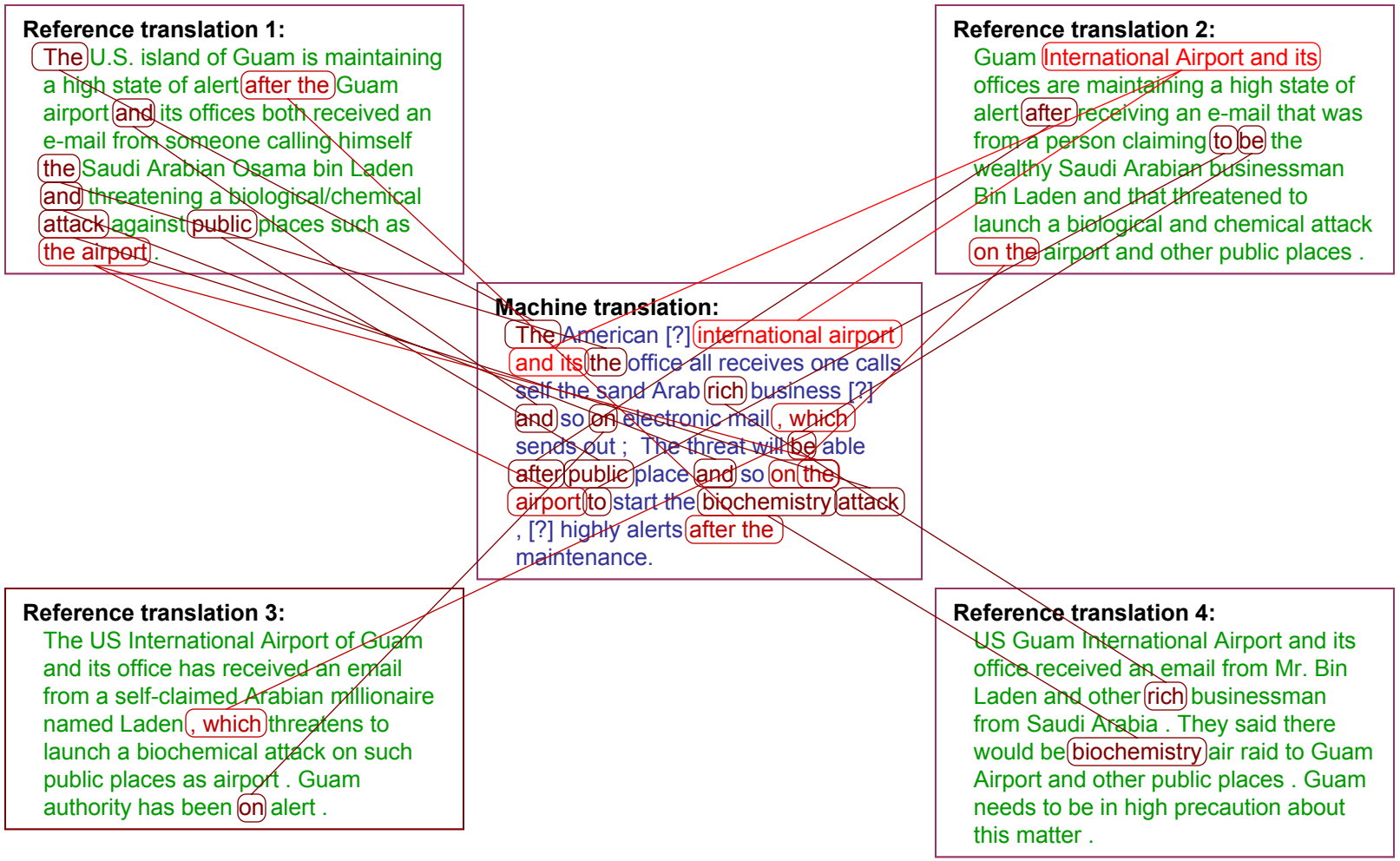
The U.S. island of Guam is maintaining a high state of alert after the Guam airport and its offices both received an e-mail from someone calling himself the Saudi Arabian Osama bin Laden and threatening a biological/chemical attack against public places such as the airport .

Machine translation:

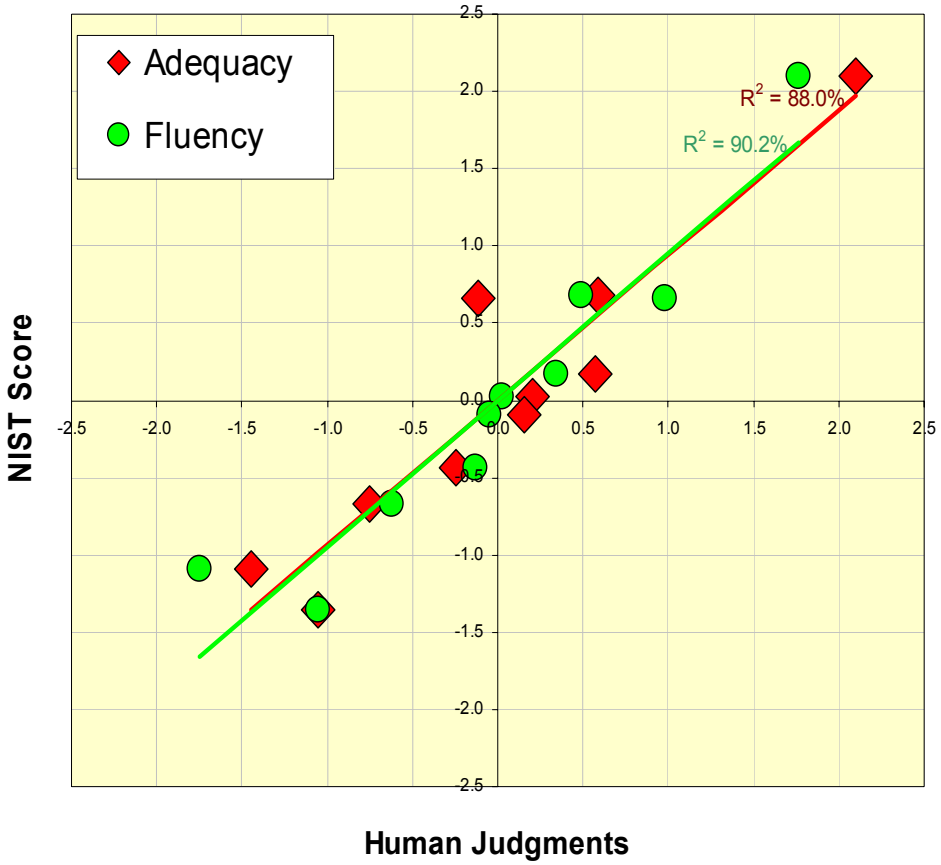
The American [?] international airport and its the office all receives one calls self the sand Arab rich business [?] and so on electronic mail , which sends out ; The threat will be able after public place and so on the airport to start the biochemistry attack , [?] highly alerts after the maintenance.

- N-gram precision
  - Look for machine n-grams in the reference translation
  - Not allowed to use same portion of reference translation twice (can't cheat by typing out "the the the the the")
- Brevity penalty
  - Can't cheat by typing out just the single word "the"
- Multiple reference translations
  - To account for variation

Multiple Reference Translations



BLEU Tends to Predict Human Judgments



Results of June 2002 DARPA evaluations of MT quality

(Experiment by George Doddington, NIST)

BLEU in Action

枪手被警方击毙。	**(Foreign Original)**
the gunman was shot to death by the police .	**(Reference Translation)**
the gunman was police kill .	**#1**
wounded police jaya of	**#2**
the gunman was shot dead by the police .	**#3**
the gunman arrested by police kill .	**#4**
the gunmen were killed .	**#5**
the gunman was shot to death by the police .	**#6**
gunmen were killed by police ?SUB>0 ?SUB>0	**#7**
al by the police .	**#8**
the ringer is killed by the police .	**#9**
police killed the gunman .	**#10**

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green = 4-gram match (good!)
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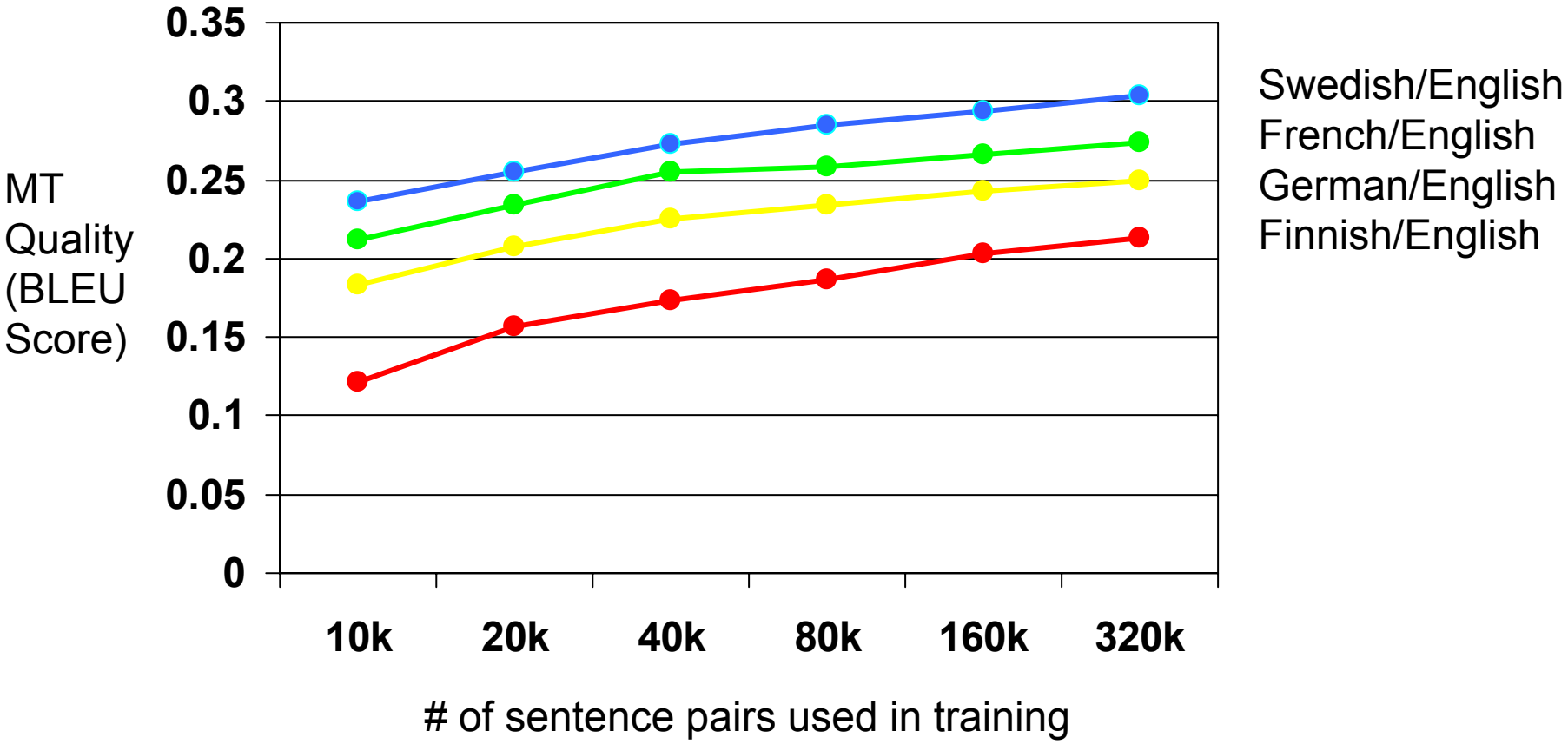
Sample Learning Curves

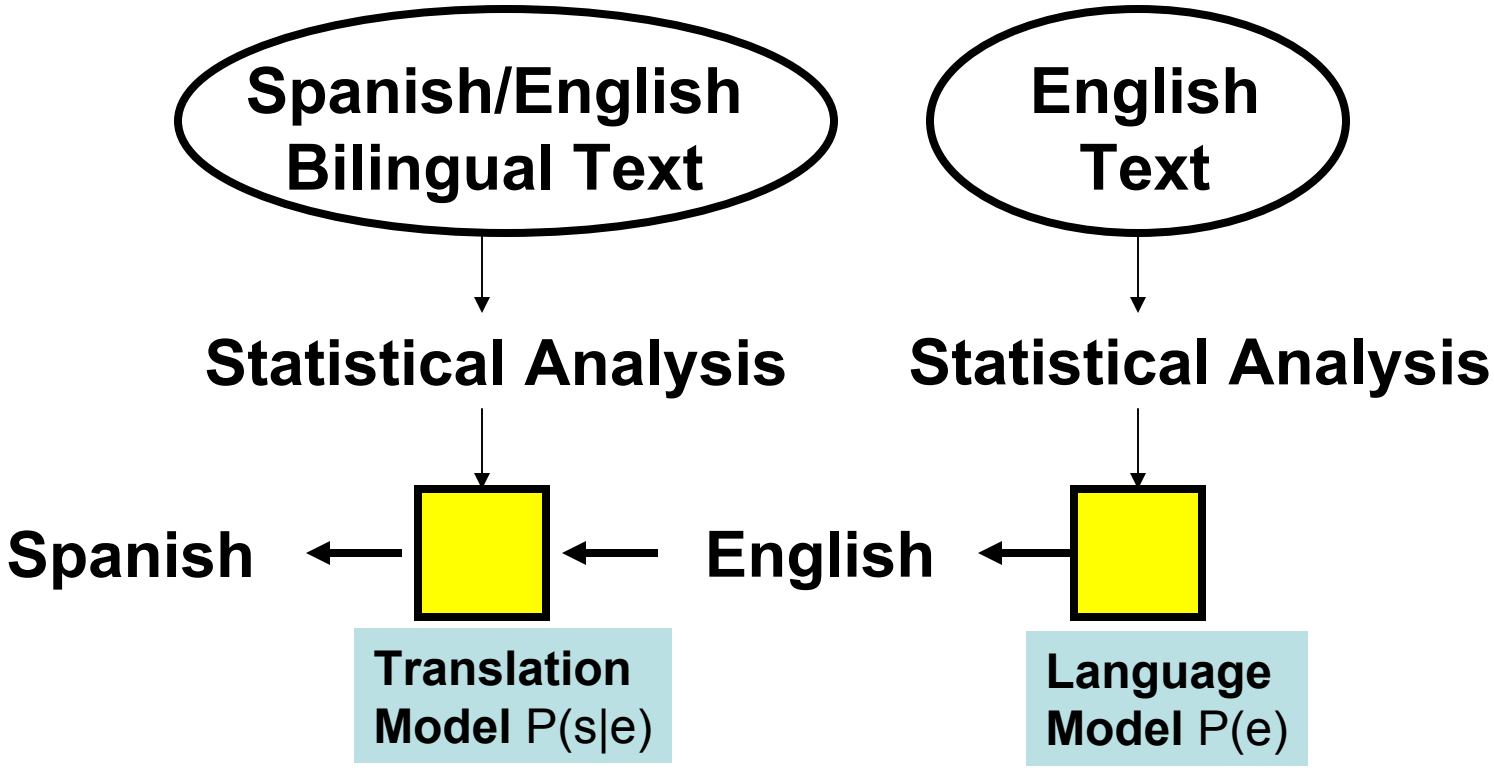


Experiments by P. Koehn on Europarl data

Revolution of 2001

- Permits rapid experimentation with ideas:
  - Should hyphenated words be split up?
  - Should the component X be given more weight in the scoring of translation candidates?
  - Does this form of syntactic control over word re-ordering help translation accuracy?
  - If we exploit non-parallel corpora, does the knowledge gained help translation?
  - Do learned word-formation rules work better than manually-built ones? What if the word-formation learning is tweaked like in such-and-such manner?
- Allows different systems to be compared:
  - Researchers learn from each other

Statistical MT: Noisy Channel Style



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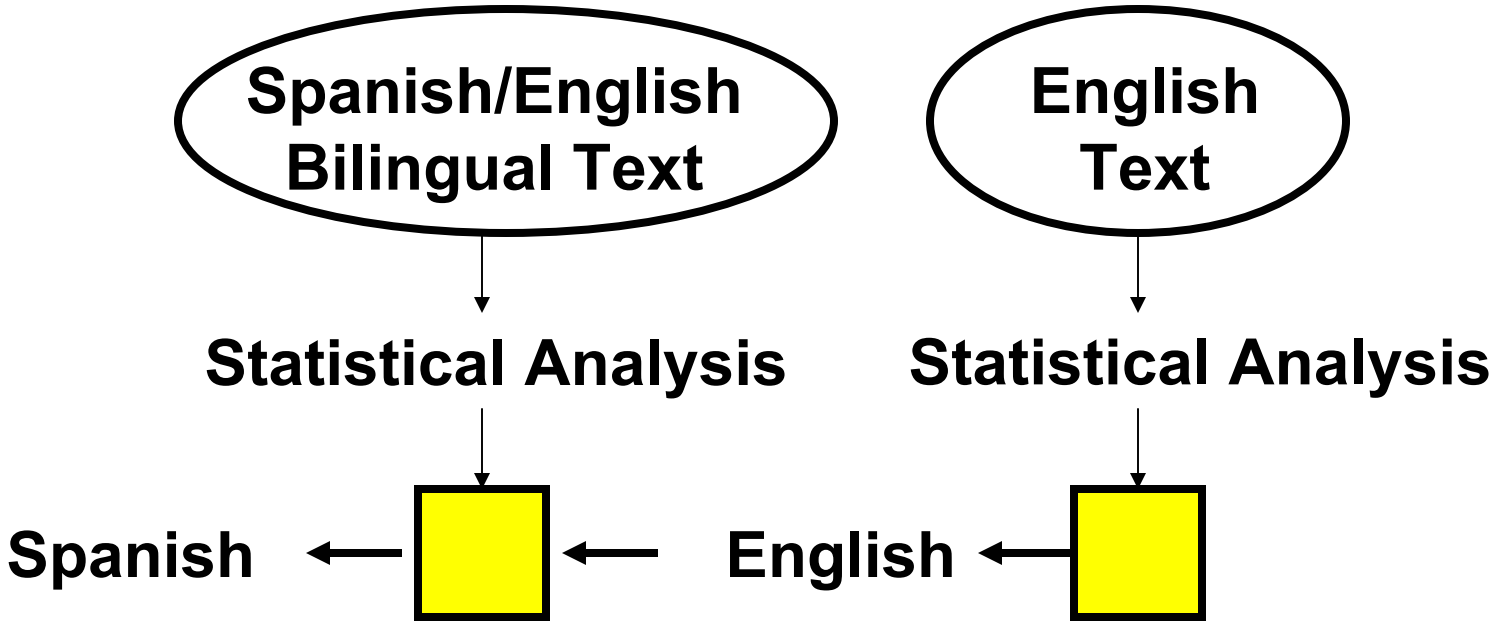


Decoding algorithm
argmax_e P(e|s) =
argmax_e P(e) * P(s|e)

Que hambre tengo yo → What hunger have I, Hungry I am so, I am so hungry, Have I that hunger … → I am so hungry

Noisy-Channel Statistical MT

- Language model
  - Given an English string e, assigns P(e) by formula
  - good English string -> high P(e)
  - random word sequence -> low P(e)

- Translation model
  - Given a pair of strings <s,e>, assigns P(s | e) by formula
  - <s,e> look like translations -> high P(s | e)
  - <s,e> don't look like translations -> low P(s | e)

- Decoding algorithm
  - Given a language model, a translation model, and a new sentence s … find translation e maximizing P(e) * P(s | e)

The Classic Language Model

Word N-Grams

Generative story:

```
w1 = START
repeat until END is generated:
    produce word w2 according to a big table P(w2 | w1)
    w1 := w2
```

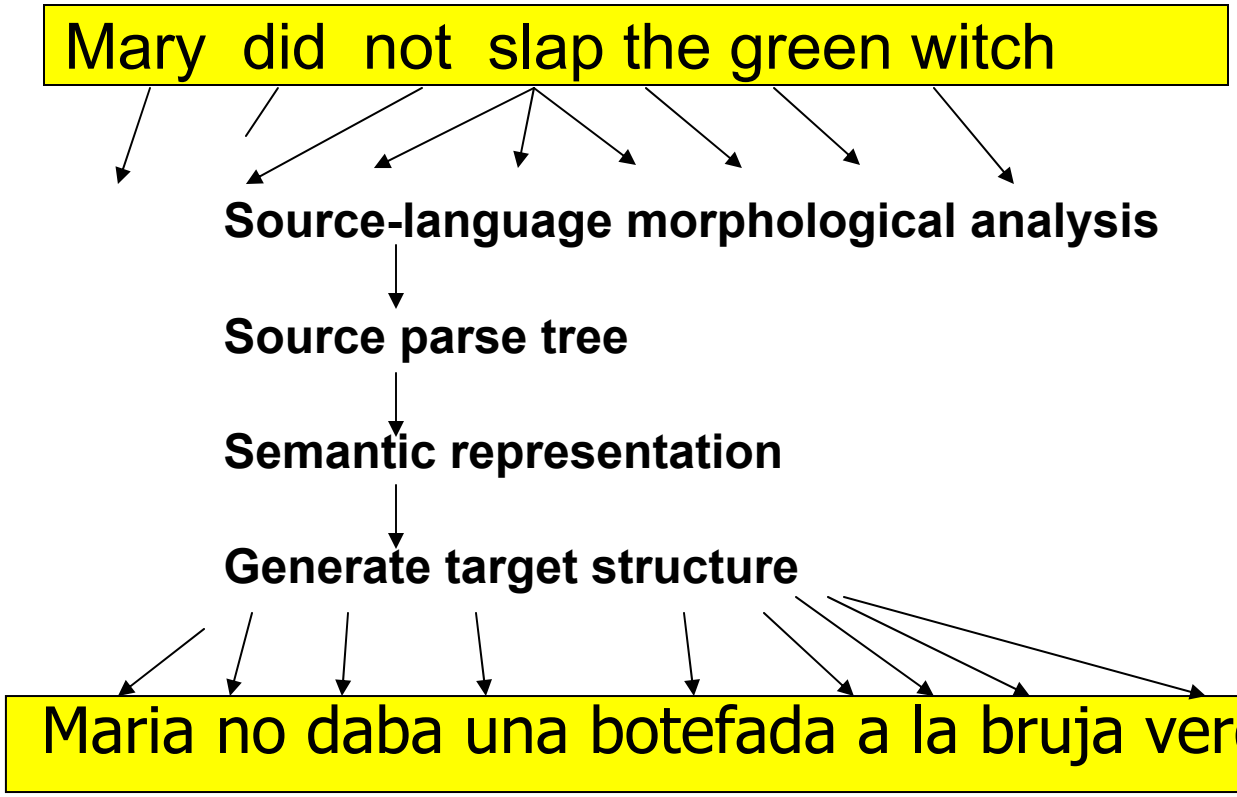
P(I saw water on the table) =

```
P(I | START) *
P(saw | I) *
P(water | saw) *
P(on | water) *
P(the | on) *
P(table | the) *
P(END | table)
```

Probabilities can be learned from online English text.

Translation Model, P(s | e) = ?

Generative story:

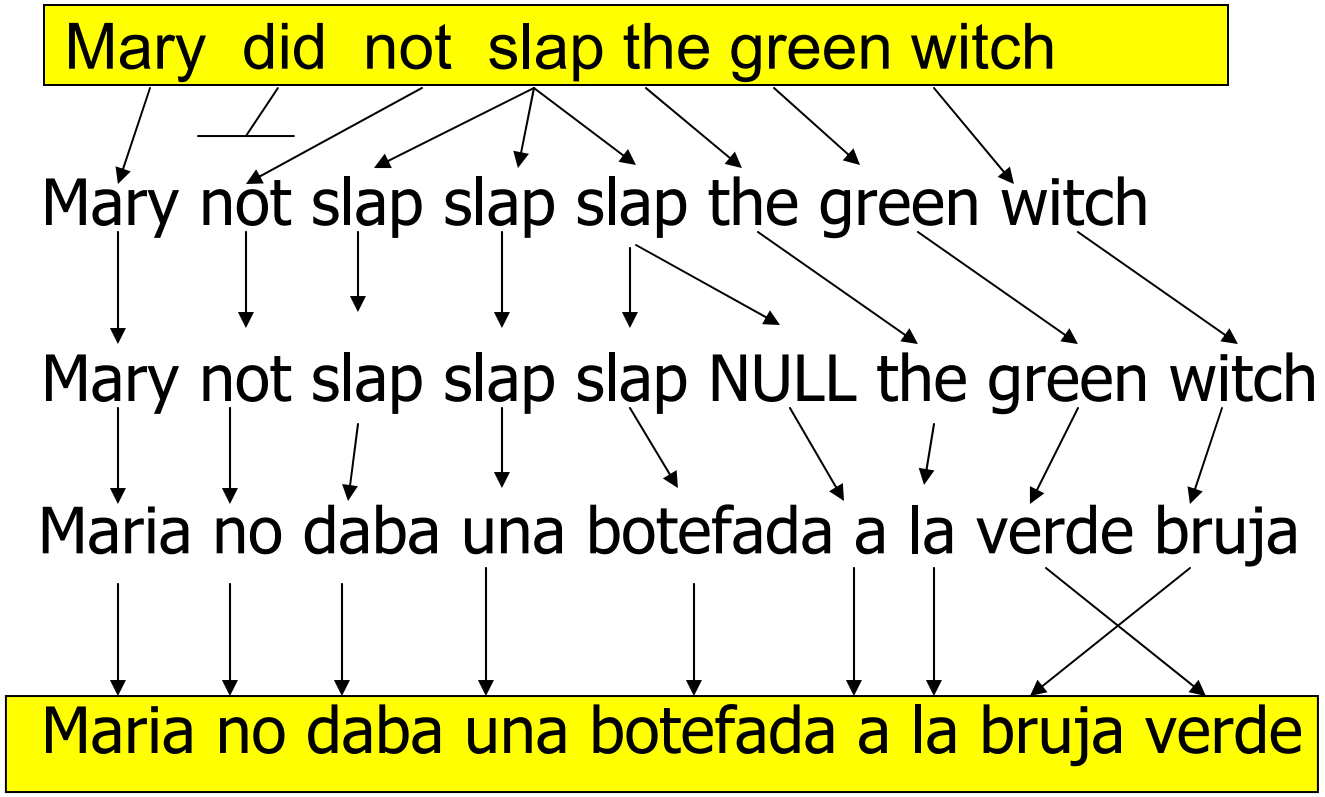


What are all the possible moves and their associated probability tables?

The Classic Translation Model

Word Substitution/Permutation (Brown et al 93)

Generative story:



n(3|slap)

P-Null

t(la|the)

20 million

d(j|i)

The Classic Translation Model

Word Substitution/Permutation (Brown et al 93)

P(s1…sm | e1…en) = a big hairy formula with lots of products and sums, in terms of hidden variables:

t(sj | ei)
d(j | I, m, n)
p0
n(phi | ei)

EM can set these by maximizing

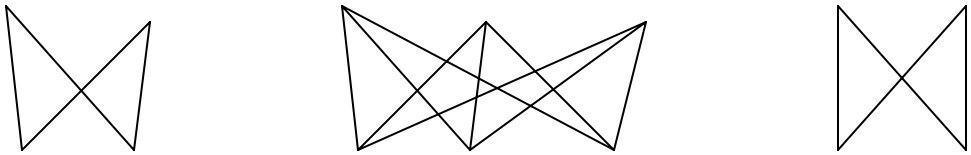
P(SPANISH CORPUS | ENGLISH CORPUS)

Full EM is impossible, as there are too many ways to align a sentence pair.

➔ Model bootstrapping

Statistical Machine Translation

… la maison … la maison bleue … la fleur …



… the house … the blue house … the flower …

Statistical Machine Translation

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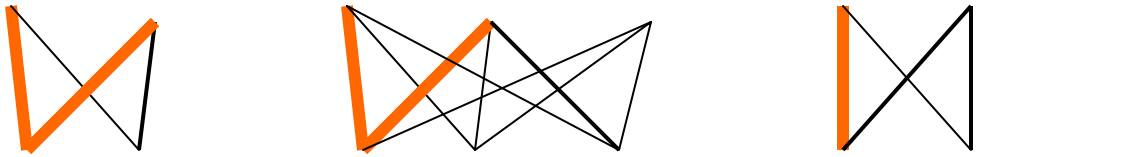

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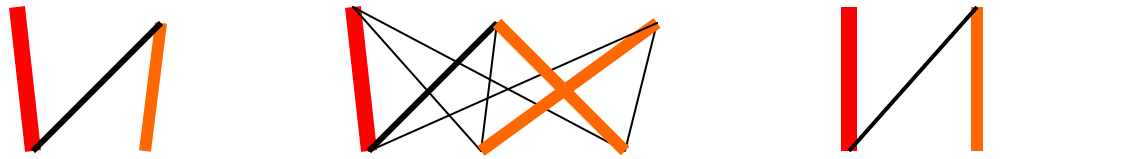
Statistical Machine Translation

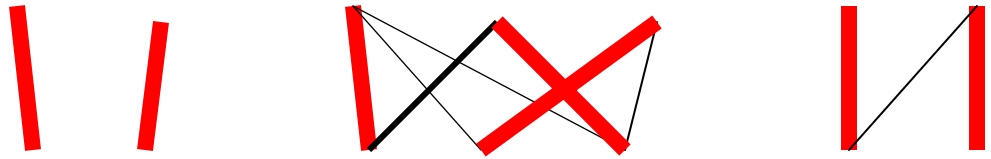
… la maison … la maison bleue … la fleur …



… the house … the blue house … the flower …

Statistical Machine Translation

… la maison … la maison bleue … la fleur …



… the house … the blue house … the flower …

Statistical Machine Translation

… la maison … la maison bleue … la fleur …

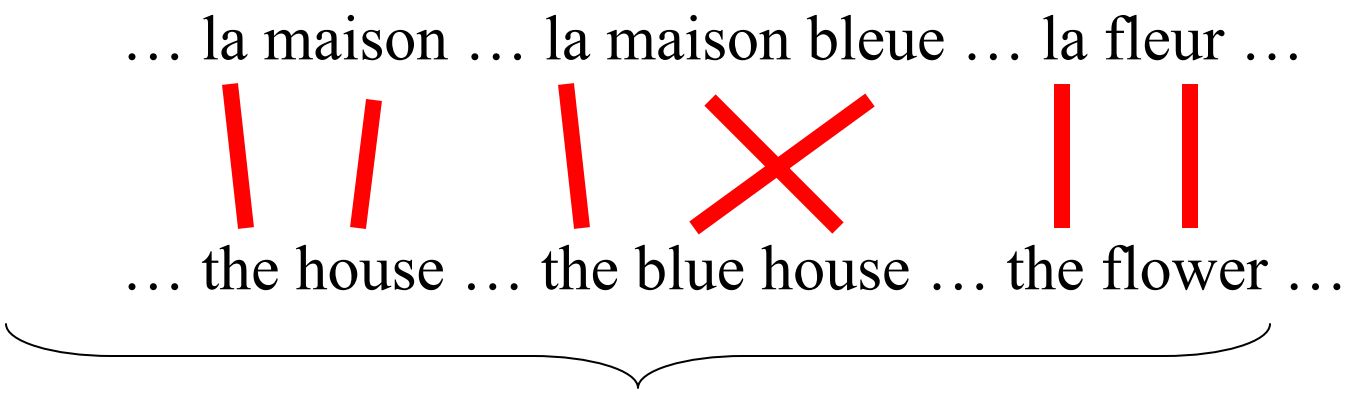
… the house … the blue house … the flower …

Inherent hidden structure revealed by EM training

For details, see

- Brown et al 93
- “A Statistical MT Tutorial Workbook” (Knight, 1999).
- 37 easy sections, final section promises a free beer.

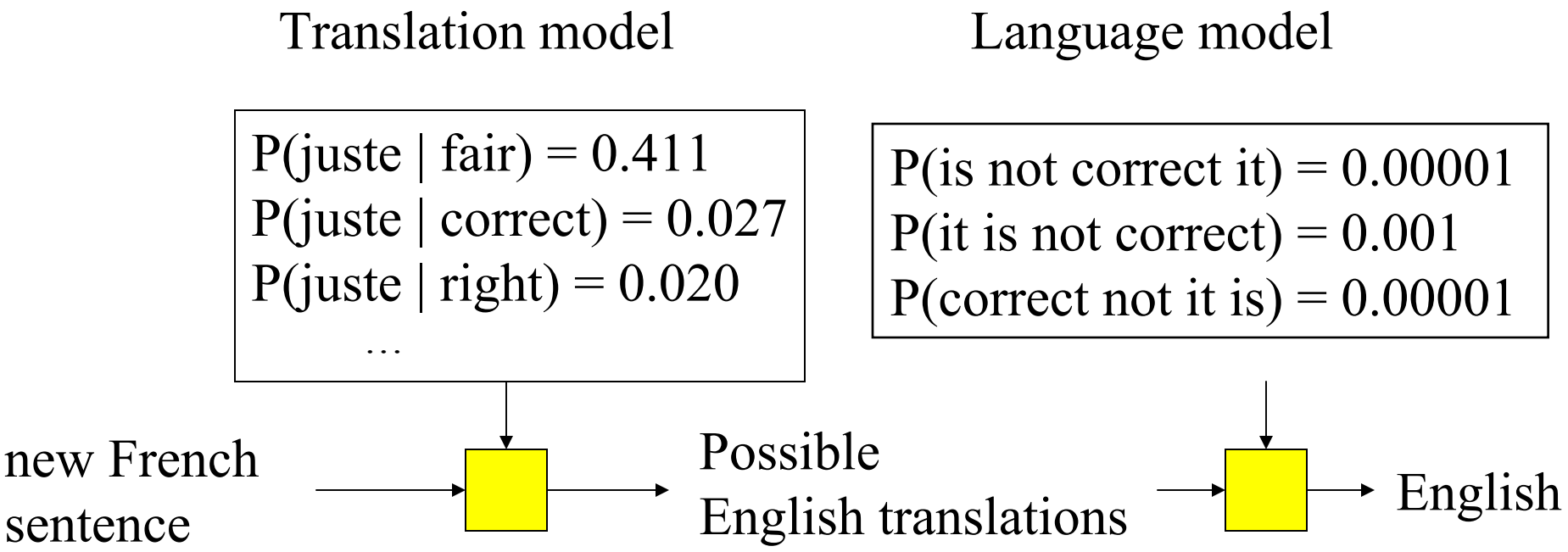
Statistical Machine Translation



P(juste | fair) = 0.411
P(juste | correct) = 0.027
P(juste | right) = 0.020
…

new French sentence → Possible English translations

Statistical Machine Translation



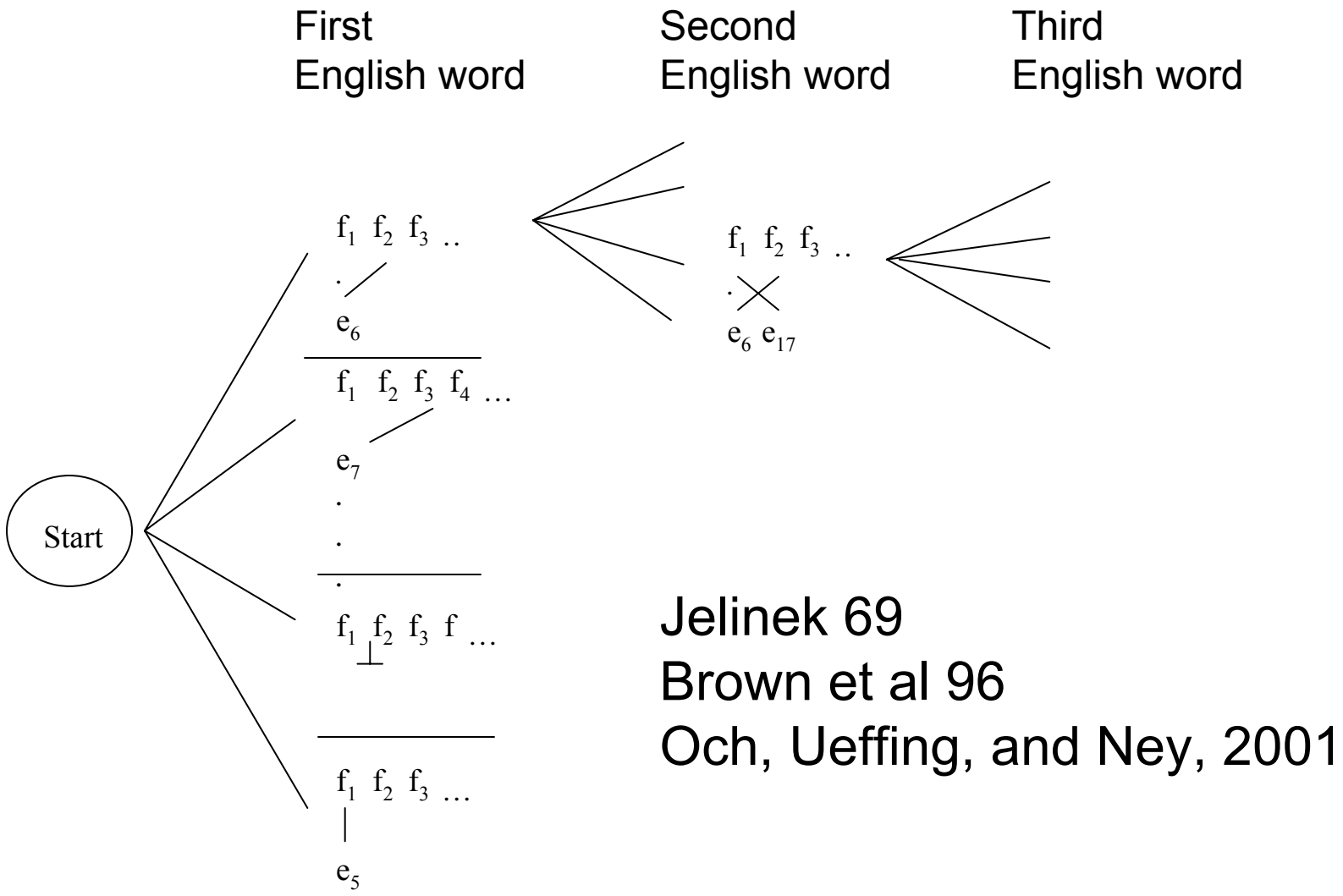
Decoding

- Of all conceivable English word strings e, find the one maximizing P(e) * P(s | e)

- Decoding “Classic” models is NP-complete
  - Knight 99

DP Beam Search (optional A*)

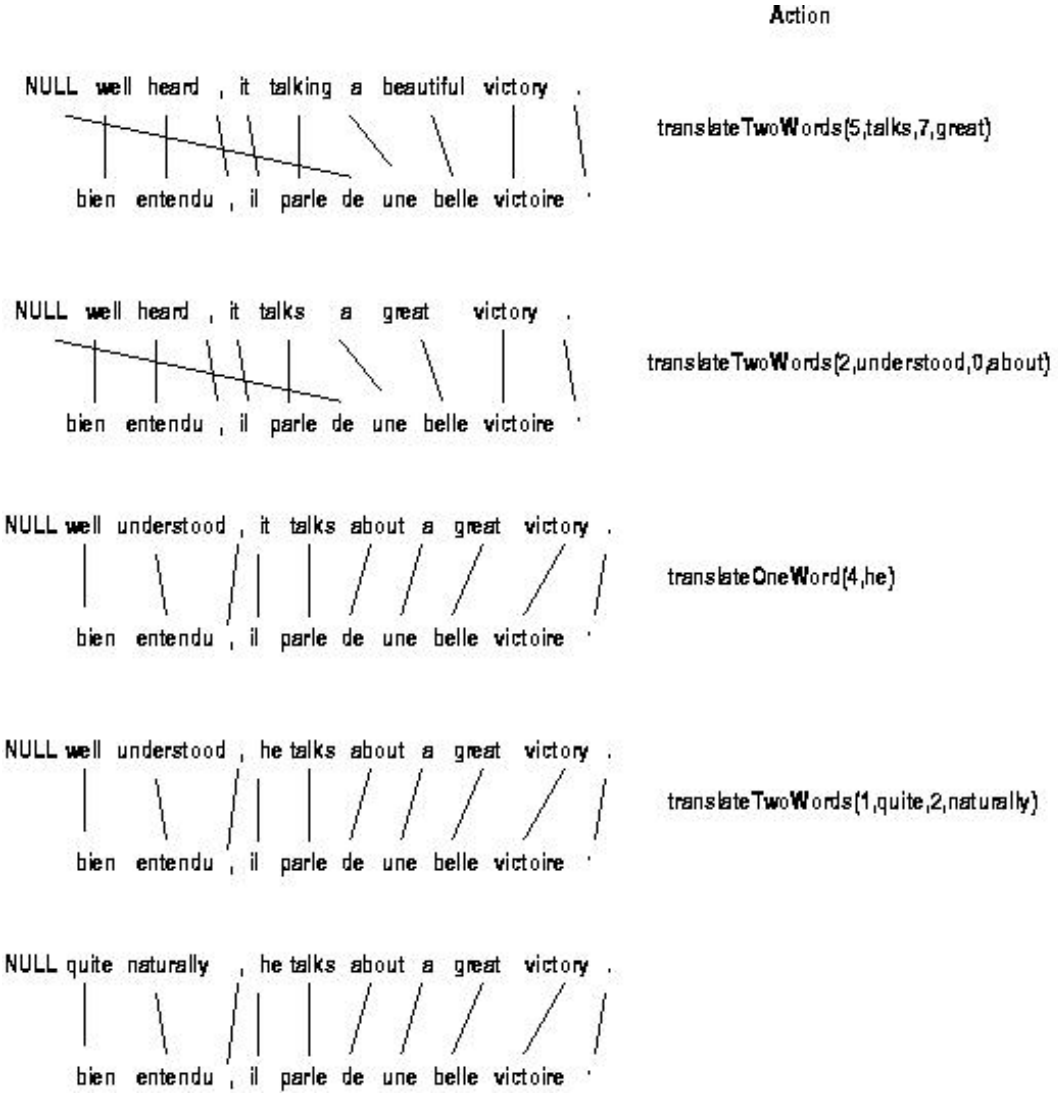
To decode: f_1 f_2 f_3 f_4 f_5 …



Jelinek 69
Brown et al 96
Och, Ueffing, and Ney, 2001

Greedy decoding

(Germann et al 01)

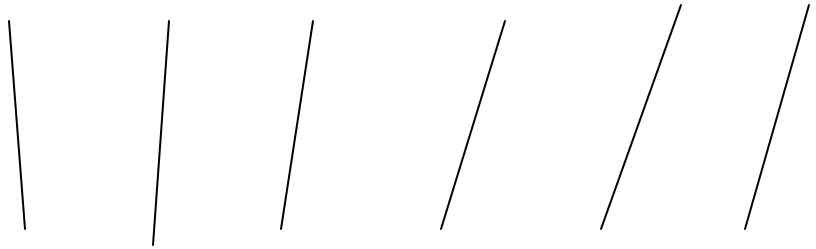


IBM Models 1-5

voulez – vous vous taire !

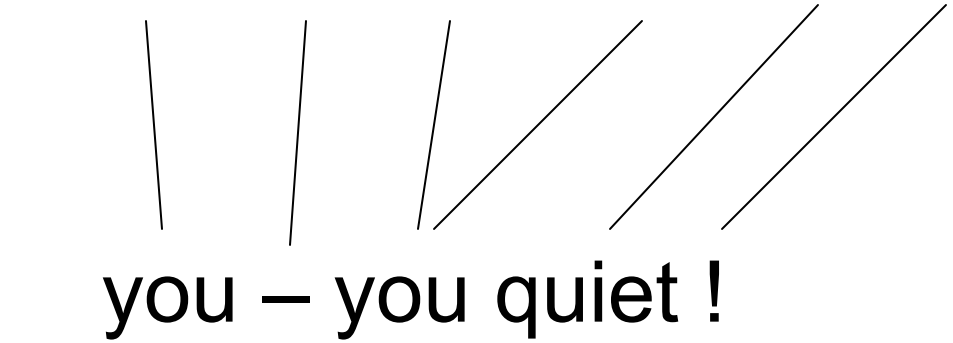
IBM Models 1-5

voulez – vous vous taire !



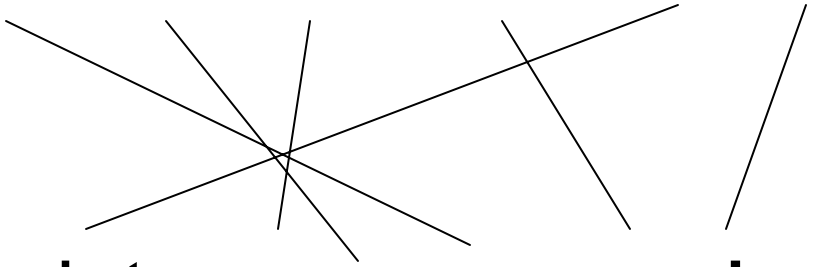
you – you you quiet !

IBM Models 1-5



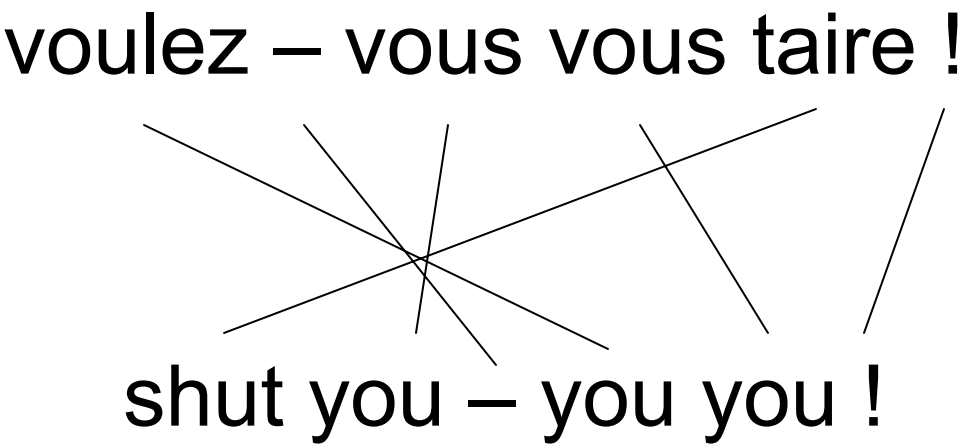
IBM Models 1-5

voulez – vous vous taire !

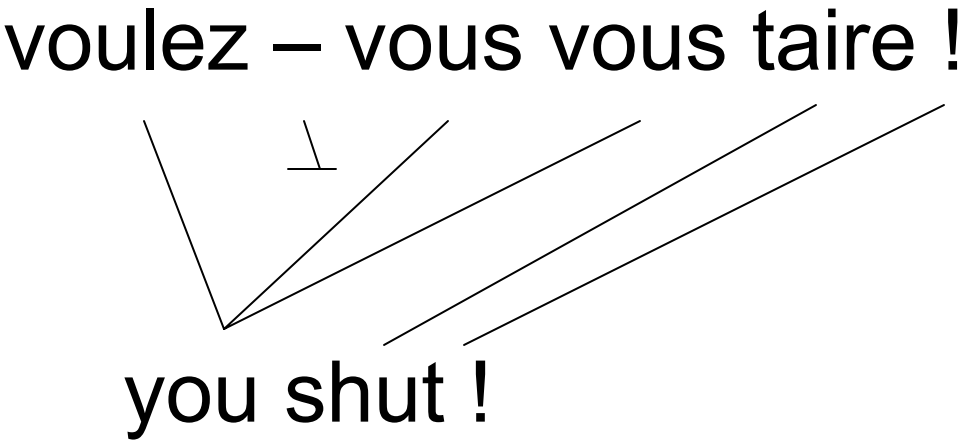


quiet you – you you !

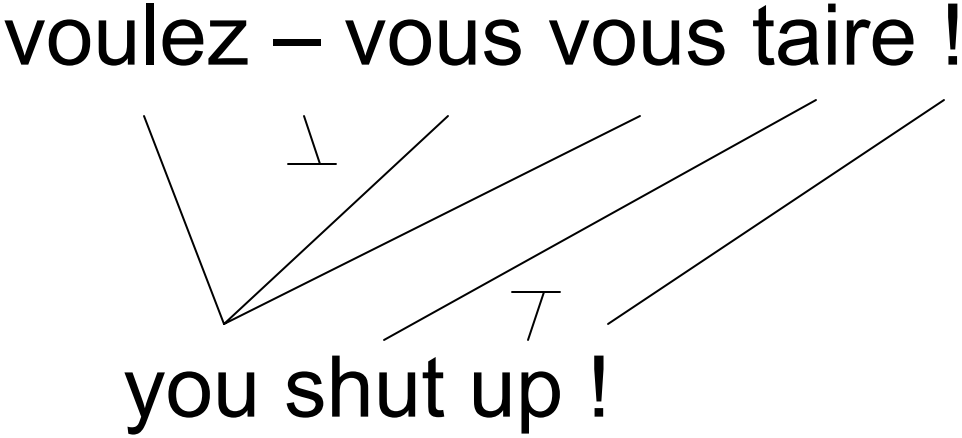
IBM Models 1-5



IBM Models 1-5



IBM Models 1-5



The Classic Results

- *la politique de la haine .* *(Foreign Original)*
- politics of hate . (Reference Translation)
- the policy of the hatred . (IBM4+N-grams+Stack)

- *nous avons signé le protocole .* *(Foreign Original)*
- we did sign the memorandum of agreement . (Reference Translation)
- we have signed the protocol . (IBM4+N-grams+Stack)

- *où était le plan solide ?* *(Foreign Original)*
- but where was the solid plan ? (Reference Translation)
- where was the economic base ? (IBM4+N-grams+Stack)

对外经济贸易合作部今天提供的数据表明，今年至十一月中国实际利用外资四百六十九点五九亿美元，其中包括外商直接投资四百点零七亿美元。

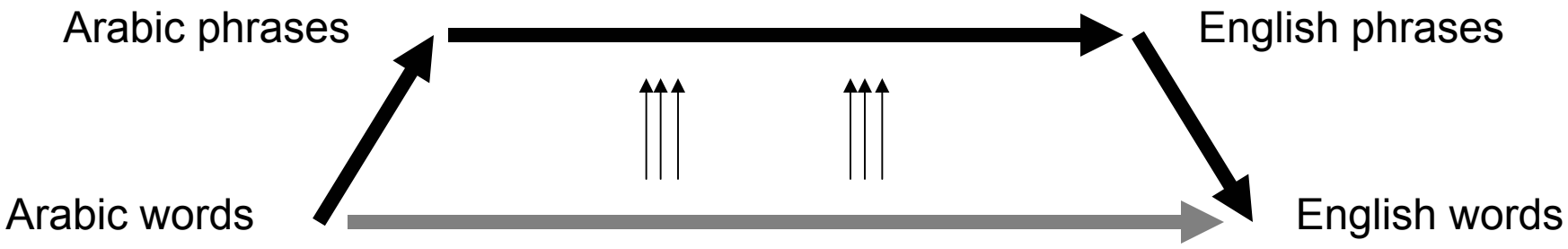
the Ministry of Foreign Trade and Economic Cooperation, including foreign direct investment 40.007 billion US dollars today provide data include that year to November china actually using foreign 46.959 billion US dollars and

Next Idea:
From Word Translation to Phrase Translation

Word models have P(f | e)

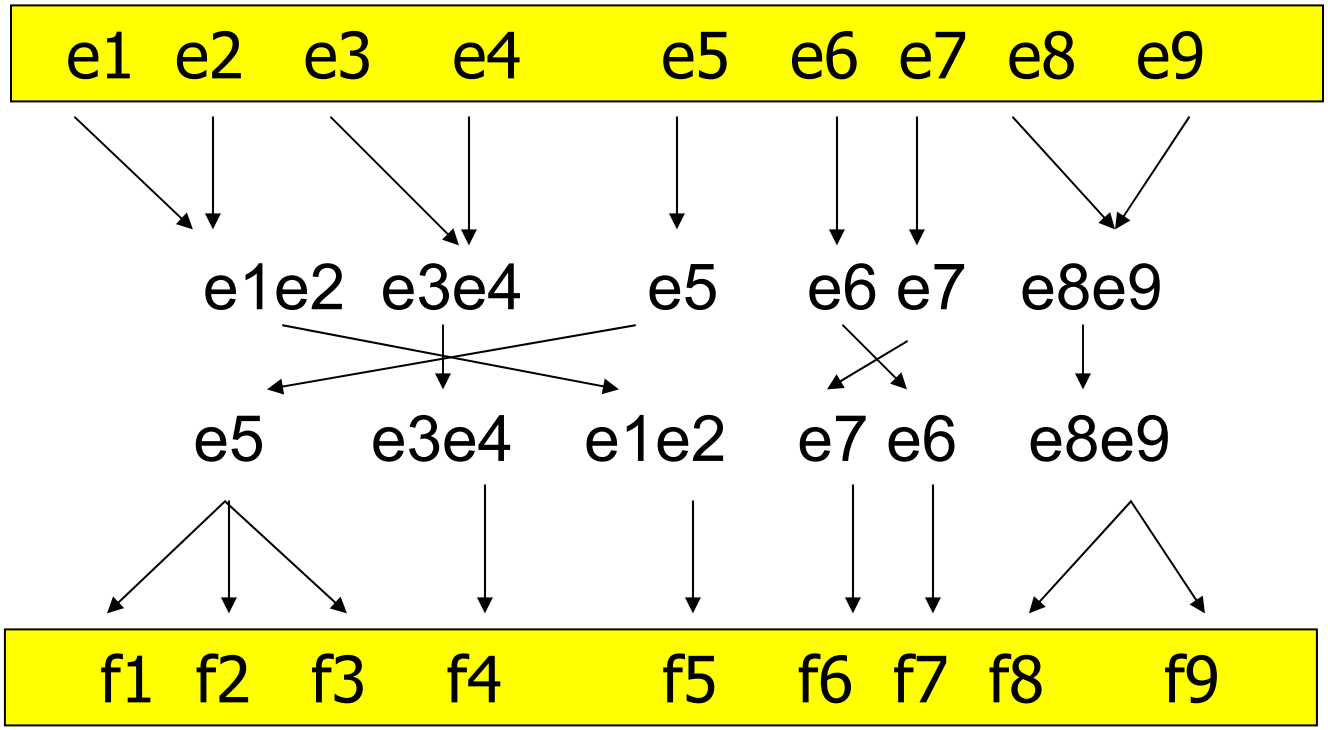
Intuition prefers P(f f f | e e)

By phrase we mean any sequence of words, e.g.:
- "…real estate…"
- "…note that…"
- "…of the same…"



Alignment Templates Model

(Och, Tillmann, & Ney 99 simplified)



Segmentation to Source Phrases

Re-Ordering of Phrases

Translation to Target Phrases
t(f8f9 | e8e9)

Many Recent Phrase-Based Models

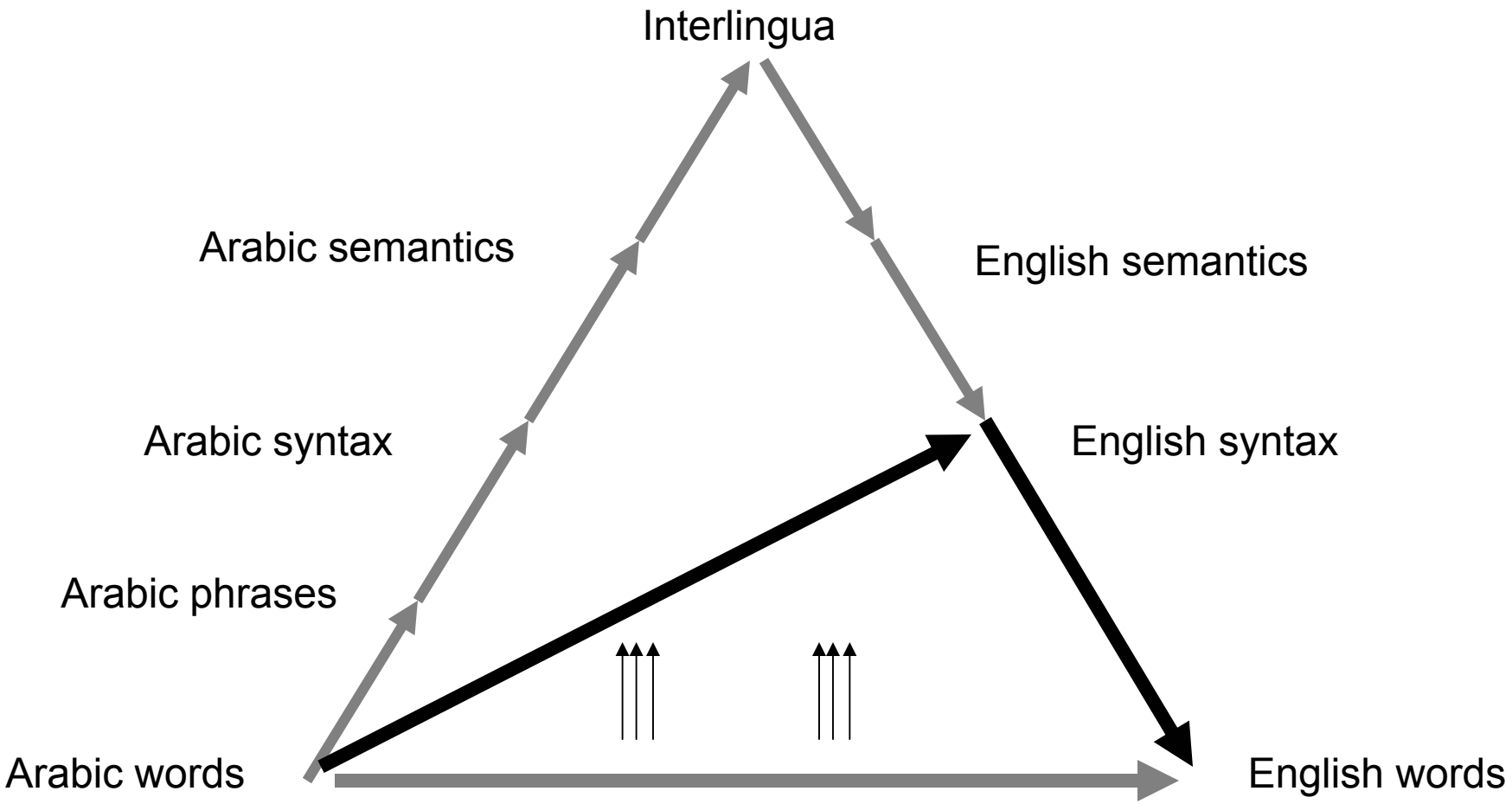
- USC/ISI EMNLP 02
- CMU ACL 03
- ATR ACL 03
- IBM ACL 03

- Significantly harder to deal with than words
  - Many more parameters (highest = 1 billion!)
  - More severe estimation problems

Empirical Results

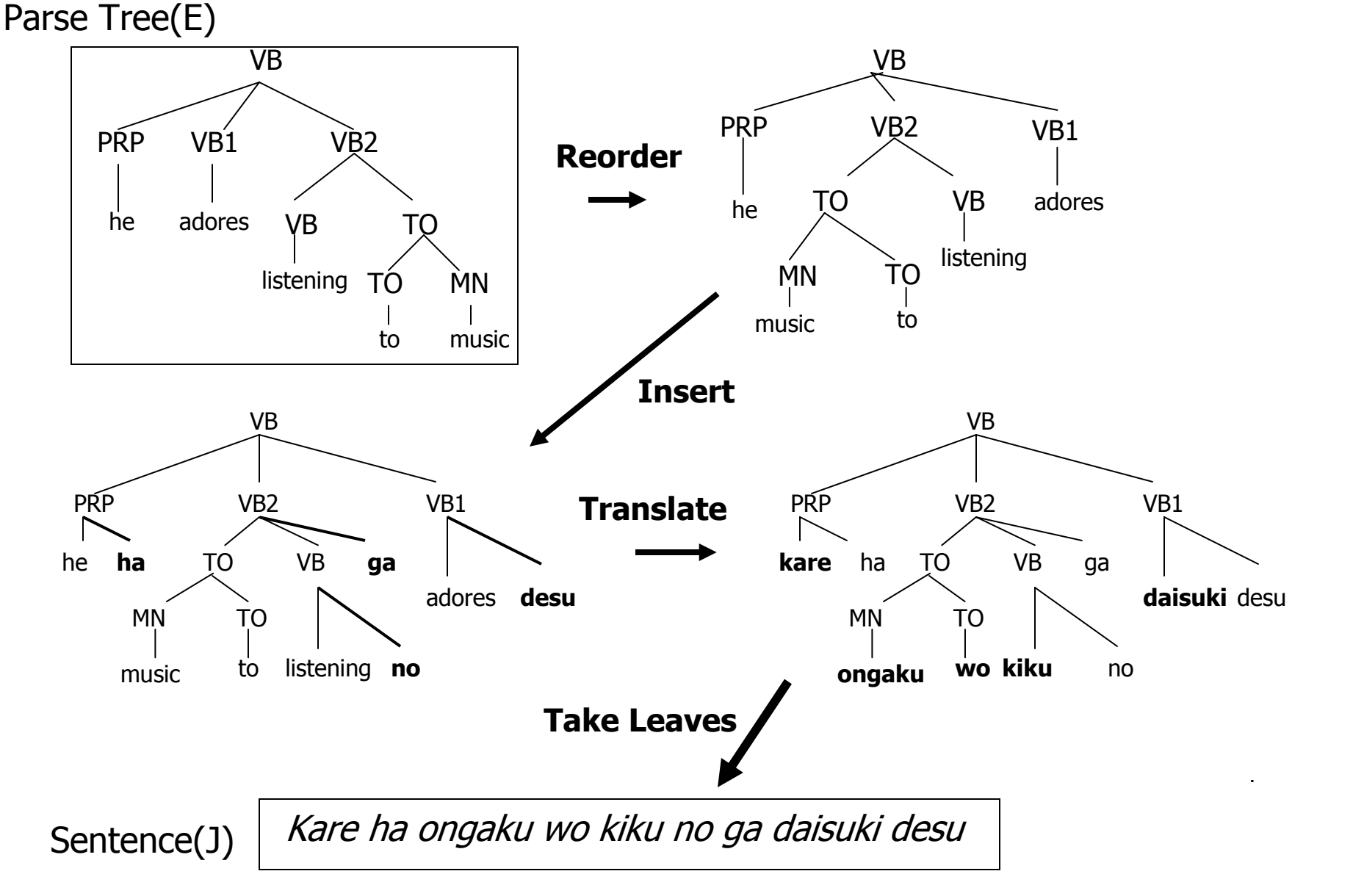
- Phrase models are a huge win!
- Why did it take so long?
  - 1990s IBM had anticipated “multi-word cepts”
  - Complained about “vast featureless desert” in choosing which word sequences might be candidates
  - Only now is the computing hardware there
    - $5000 for a 4Gb fast dual processor
    - Still lack memory for easily deployable systems!
  - Intuition was lacking

Another Idea:
Syntax-Sensitive Translation



Syntax-Based Model

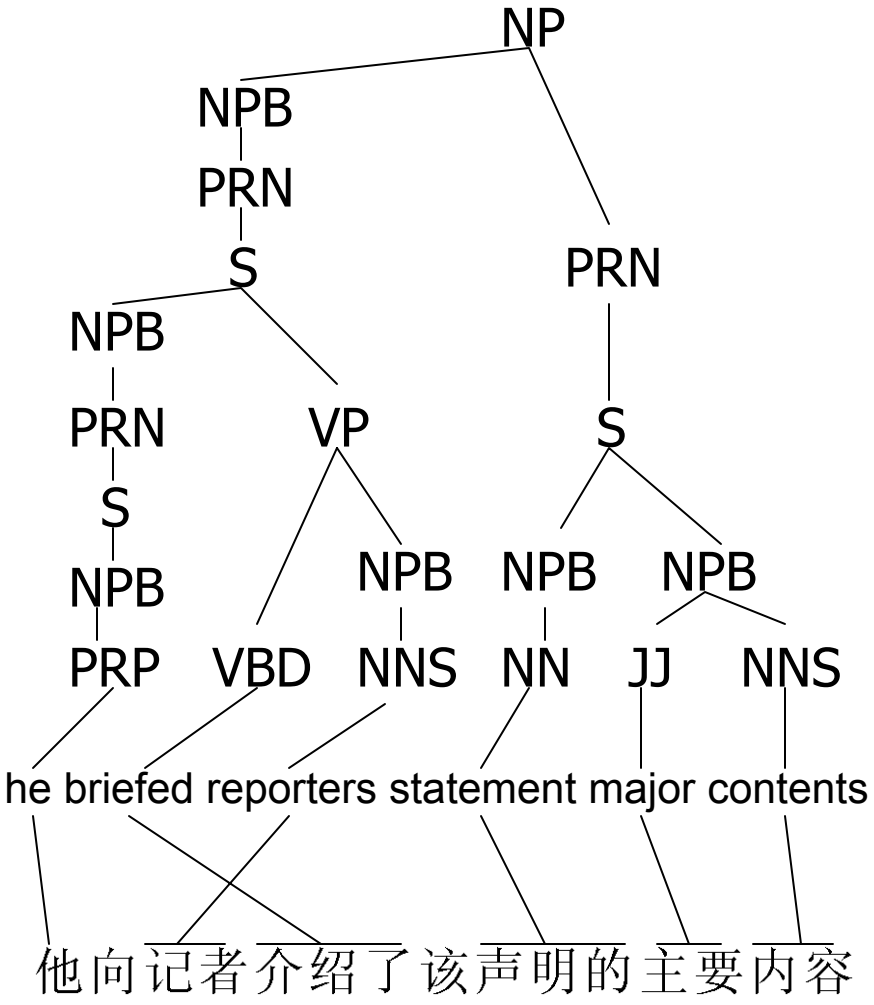
(Yamada and Knight 01, 02)



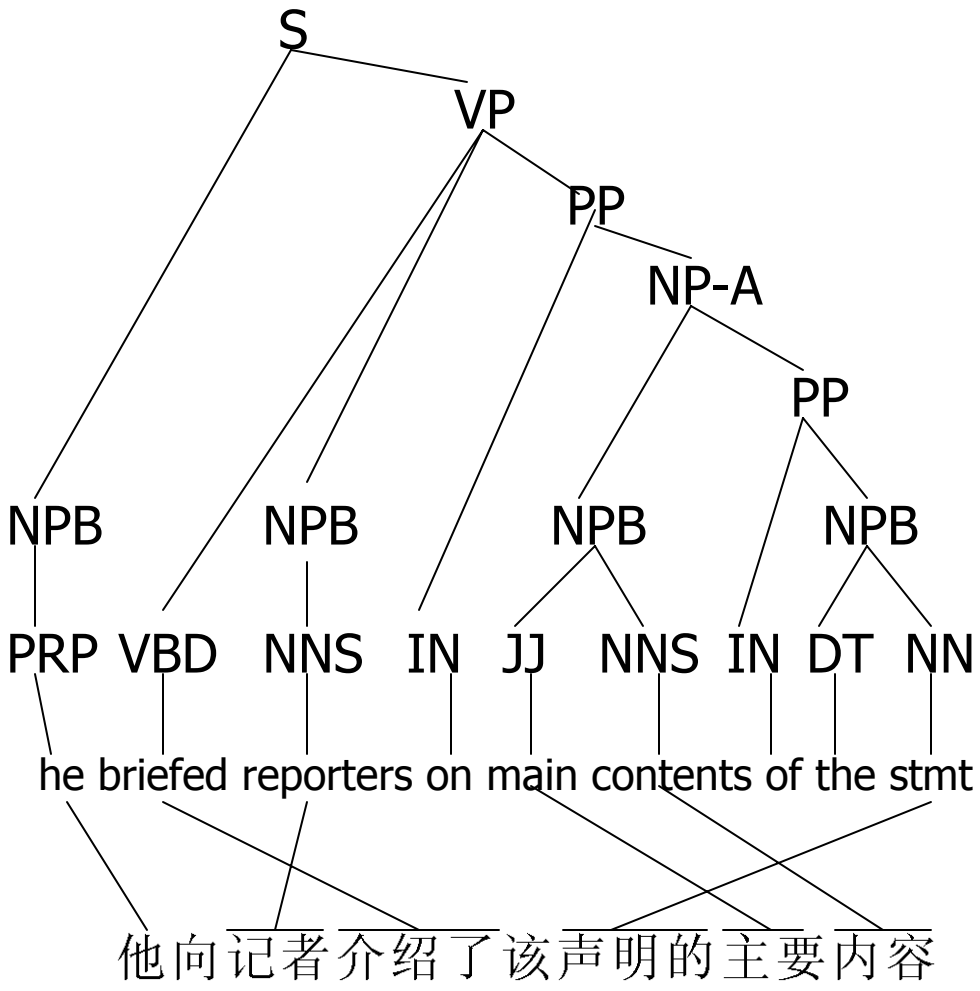
Parameter Table: Reorder

Original Order	Reordering	P(reorder|original)
PRP VB1 VB2	PRP VB1 VB2	0.074
	PRP VB2 VB1	**0.723**
	VB1 PRP VB2	0.061
	VB1 VB2 PRP	0.037
	VB2 PRP VB1	0.083
	VB2 VB1 PRP	0.021
VB TO	VB TO	0.107
	TO VB	**0.893**
TO NN	TO NN	0.251
	NN TO	**0.749**

Decoded Tree



Decoding with Trigrams



Decoding with Charniak 01 LM

Charniak, Knight, Yamada 03

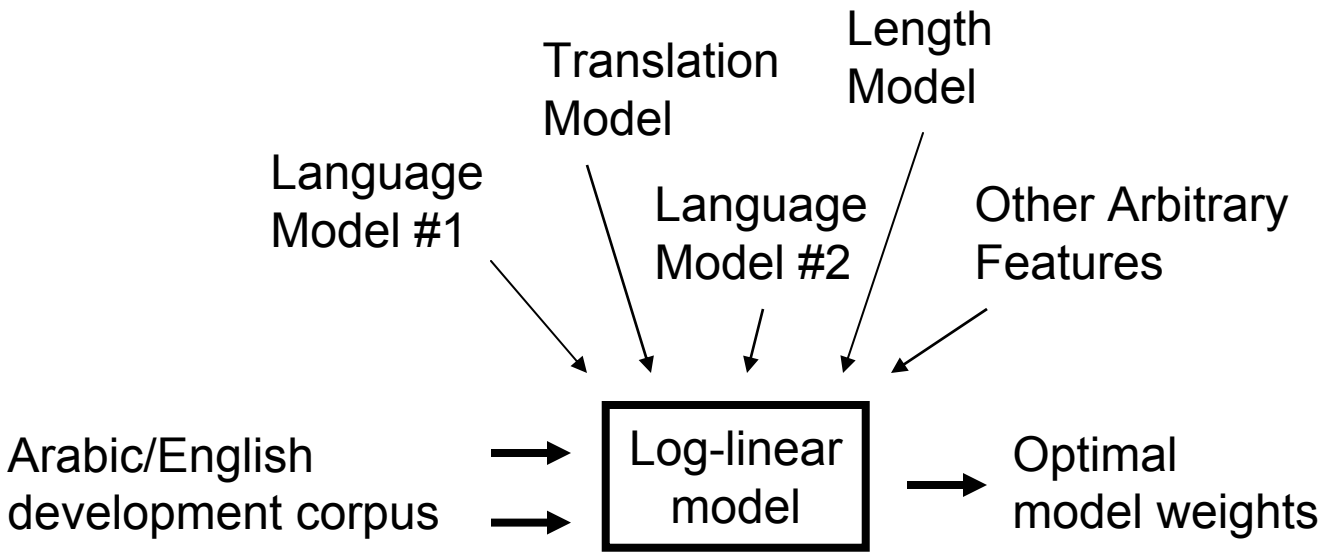
Translation model	Language model	# of perfect translations/317
IBM Model 4	Trigram	23
Syntax-Based	Trigram	31
Syntax-Based	Charniak 01	45
		77 (oracle)

But: No improvement in semantic accuracy (or BLEU score)!
Many factors left out.
Line seems promising:
-- current work by Mark Hopkins (UCLA) and Michel Galley

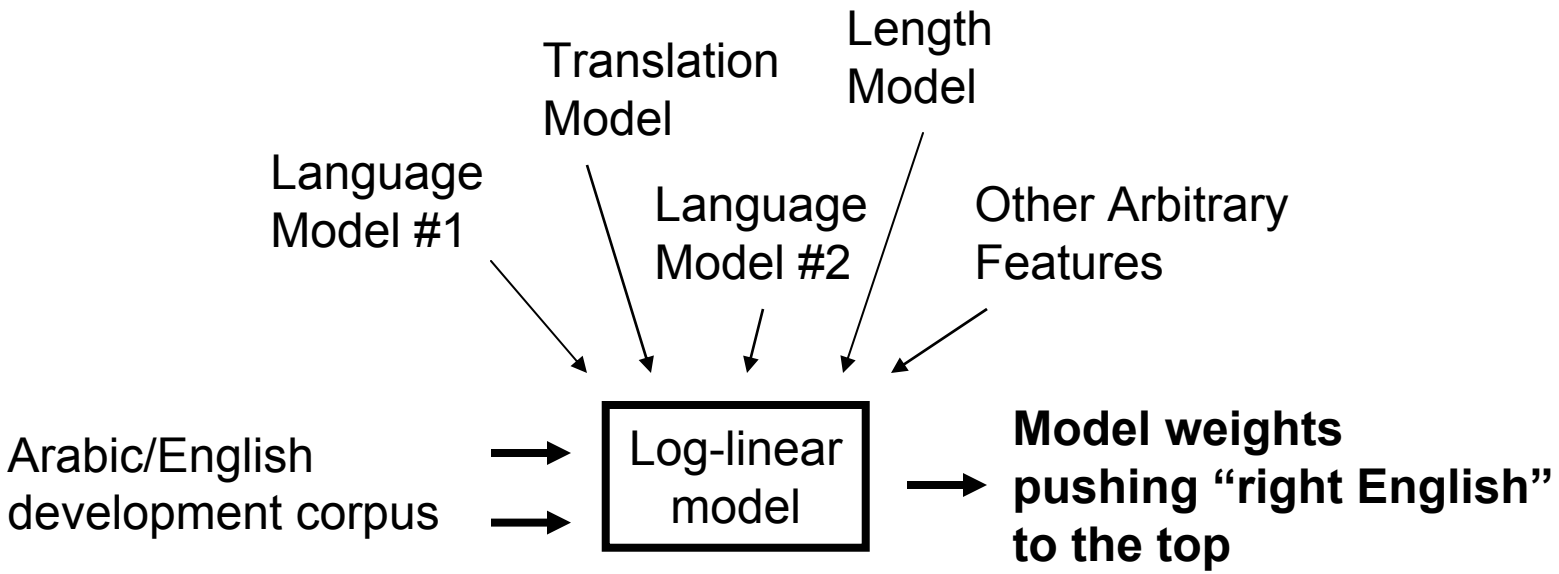
Recent Alternatives to Generative Models and Maximum Likelihood

Log-linear Models (Och 01)

Speech people often do $\underset{w\ldots w}{\text{argmax}}\ P(w\ldots w)^{10} * P(a\ldots a \mid w\ldots w)$

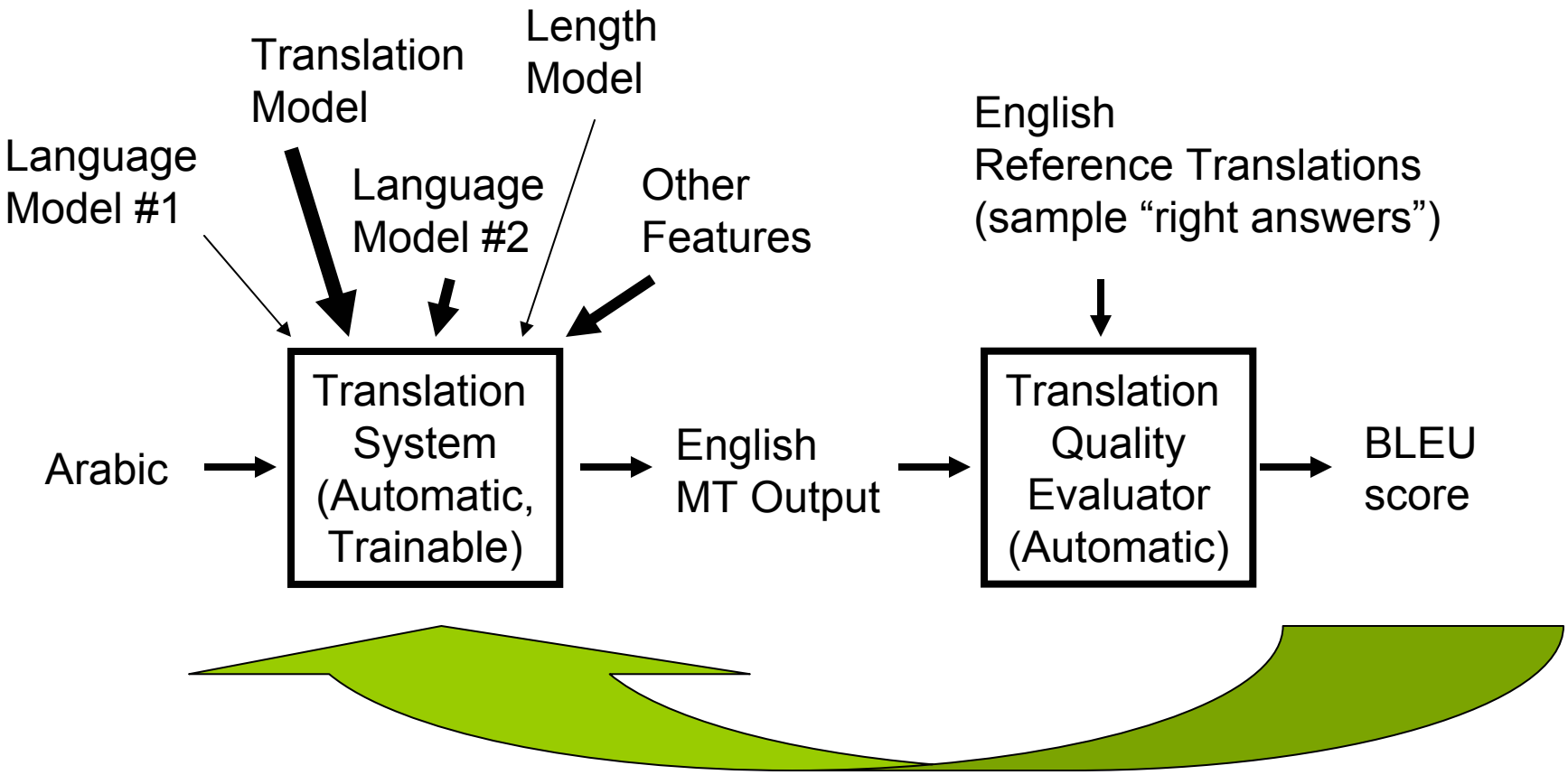


Discriminative Training (Och 02)



Not easy to do, since “right English” isn’t in the n-best list.

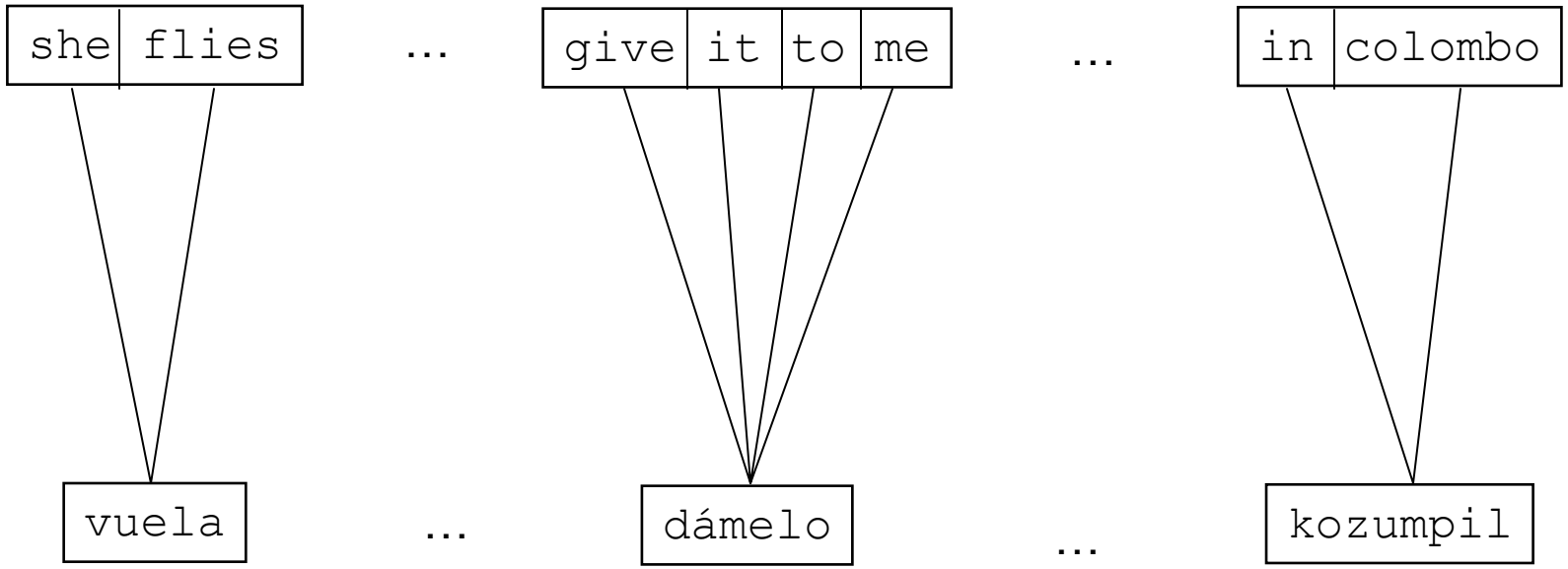
Error-Based Training (Och 03)



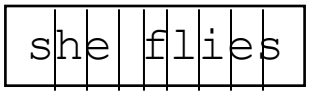
Learning Algorithm for Directly Reducing Translation Error
(Not easy to do because search space is very bumpy).

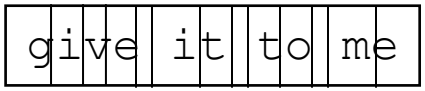
Some Currently Active Areas

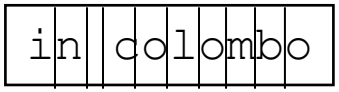
Character-Based Models

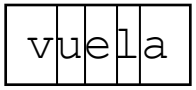


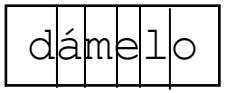
Character-Based Models, or Universal Morphology

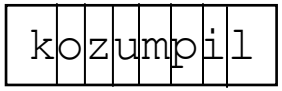












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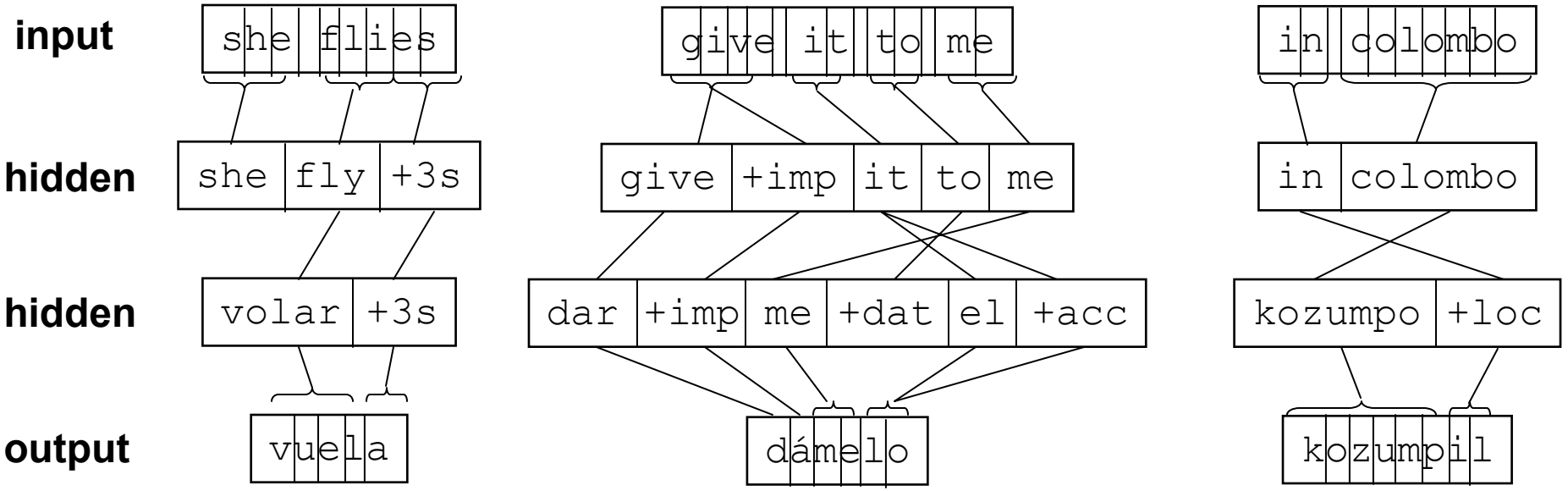


Tree-Based Models

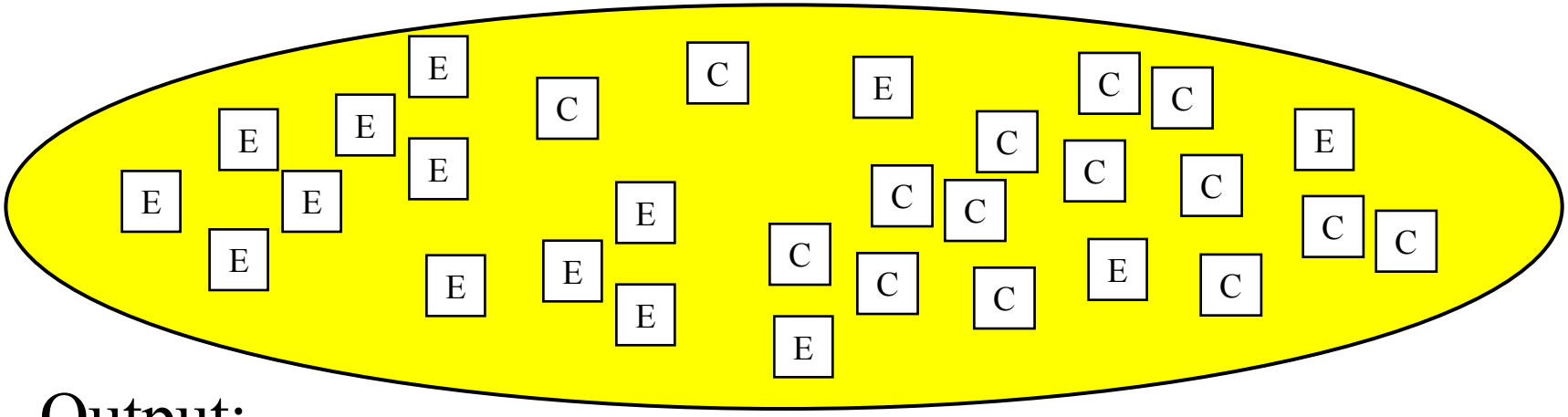
- How does an English tree become a foreign-language string?
- How can a syntax-based TM produce more good candidates and fewer bad ones?
- What happens to passive sentences when they translate to Chinese? Arabic?
- What happens to NP-of-NP?
- How much does the translation of a verb depend on the translation of its object? Is this best captured in LM or TM?
- Can long sentences be efficiently decoded?

Web as Bilingual Corpus

- Only a tiny bit of work on this important problem
  - e.g., Resnik & Smith, 2001
- Train on the web, to deploy on the web
  - Potentially very heterogeneous source
  - Much wider vocabulary/phrase coverage

Document Alignment

- Input:
  - Big bag of files obtained from somewhere, believed to contain pairs of files that are translations of each other.



- Output:
  - List of pairs of files that are actually translations.

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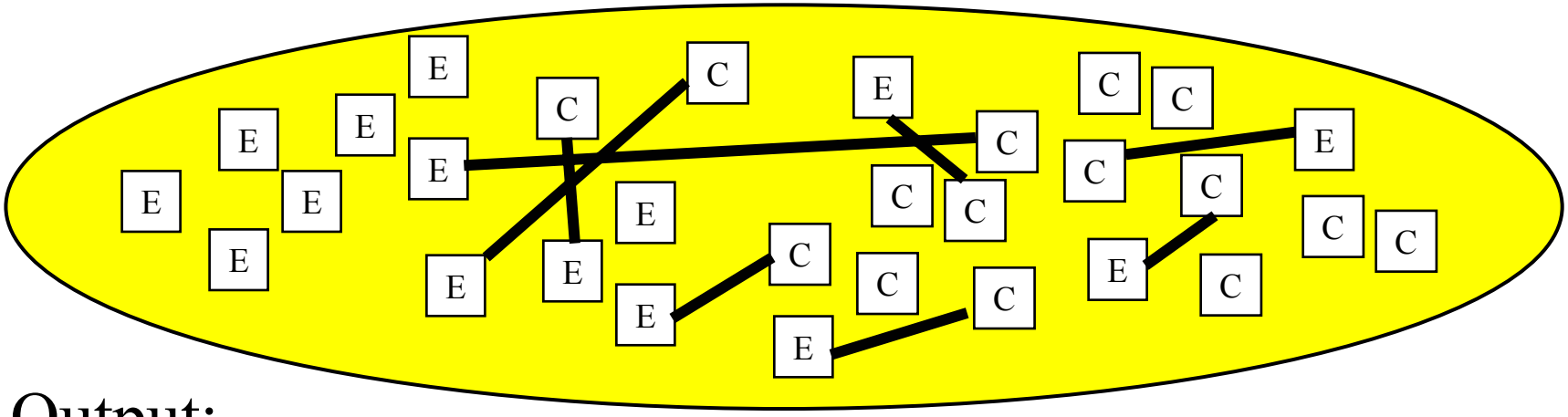

- Output:
  - List of pairs of files that are actually translations.

All Sorts of Expertise Needed

- Linguistics:
  - building models of a human process
- Machine Learning:
  - appropriate model templates and algorithms
  - unsupervised and supervised problems
  - generative models, feature-based models
  - EM, maximum entropy, discriminative training, error-based training
  - Model bootstrapping
- Computer Science and AI:
  - heuristic search
  - efficient data structures
- Resources:
  - acquiring data from the Internet and other sources

Thanks!