Phrase-Based Statistical Machine Translation Using Finite State Machines *with some links to ASR*

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Work done with Shankar Kumar and Yonggang Deng

Can We Pretend MT is ASR ?

Of course. We just need :

- Alignment models and estimation algorithms
- Training data: bitext, monolingual text
- Search algorithms for translation
- Some way to measure translation quality

Five Easy Problems in Statistical Machine Translation

What's currently needed to build a basic phrase-based SMT system:

- Bitext for SMT Training: Document and Sentence Alignment
- Models of Word and Phrase Alignment Within Sentences
- Language Models
- Translation – Model-Based Search Algorithms
- Automatic Measurement of Translation Quality

Translation

Once the models are defined, translation is 'trivial' .

Its just search ... $\hat{\mathbf{e}} = \text{argmax}_{\mathbf{e}} P(\mathbf{e}|\mathbf{f})$

One approach is to construct specialized search algorithms

- Depending on the underlying models, search can be by Viterbi, A^*, or other specialized search procedures

But decoder design and implementation is complex

- Small model changes might require large changes to a decoder
- Approximations in search imply inexact implementation of the models
  - Can only implement what can be implemented
  - May as develop models which lead to exact realizations
- Decoder implementation takes effort away from 'modeling'

Translation via Weighted Finite State Transducers

Translation with Finite State Devices, Knight & Al Onaizan, AMTA'98

- Implements the IBM models as WFSTs
  - word-to-word translation, word fertility, and permutation (reordering)

If the component models can be implemented as WFSTs which can be composed, building a decoder is trivial

- Can be limiting, but avoids special-purpose decoders
- The value of this modeling approach has been shown in ASR by the systems developed at AT&T
- Translation is performed using libraries of standard FSM operations
- Clear formulation of underlying model components
- Easy to work on modules in isolation

Translation Template Model - TTM

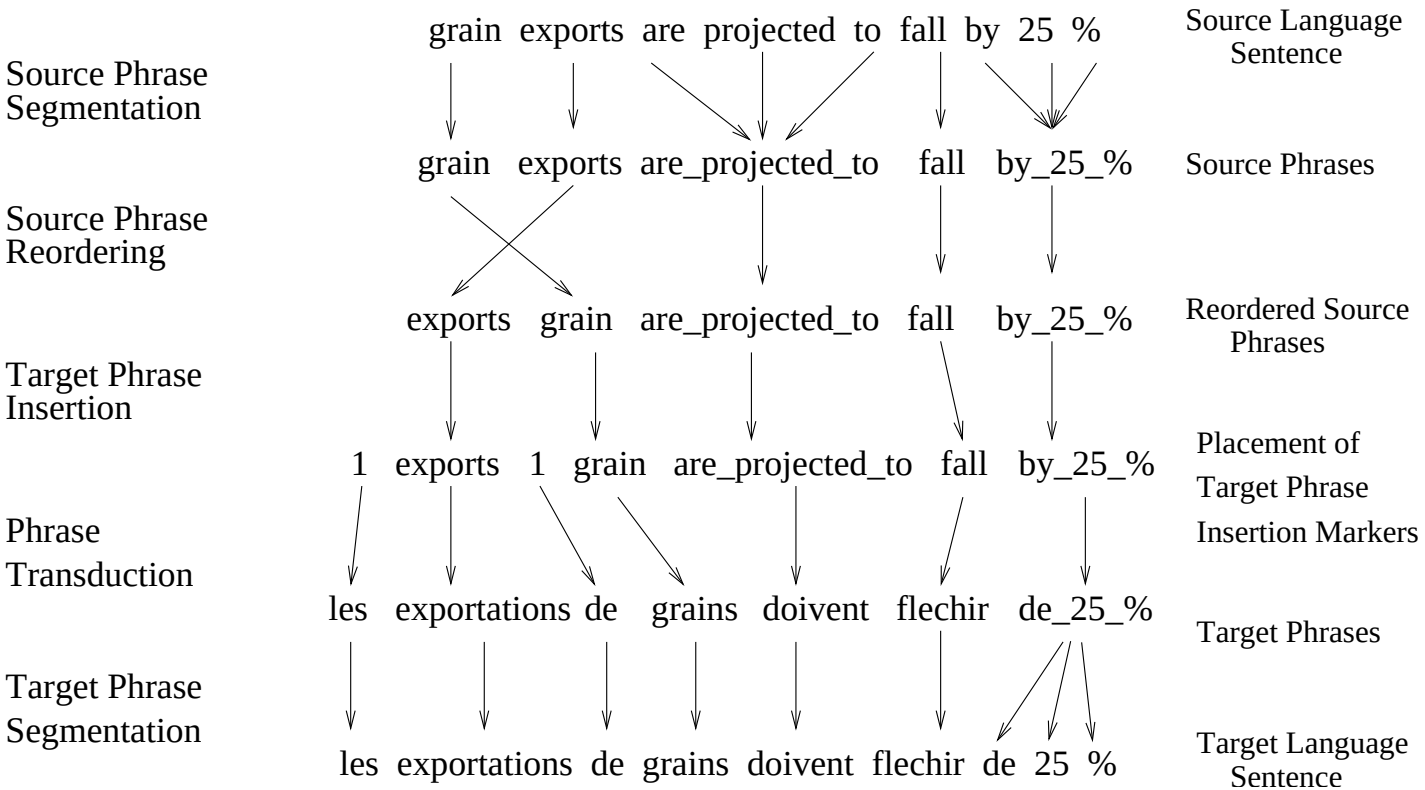
Generative source-channel model of machine translation

- Takes the best of
  - Och&Ney's Phrase-based translation models
  - Knight&Al Onaizan WFST description of translation via IBM models
- Bitext word alignment and translation under the model can be performed using standard WFST operations
  - Modular Implementation
  - No need for a specialized decoder - "the model is the decoder"
  - Can easily generate translation lattices and N-best lists

Overall Goals:

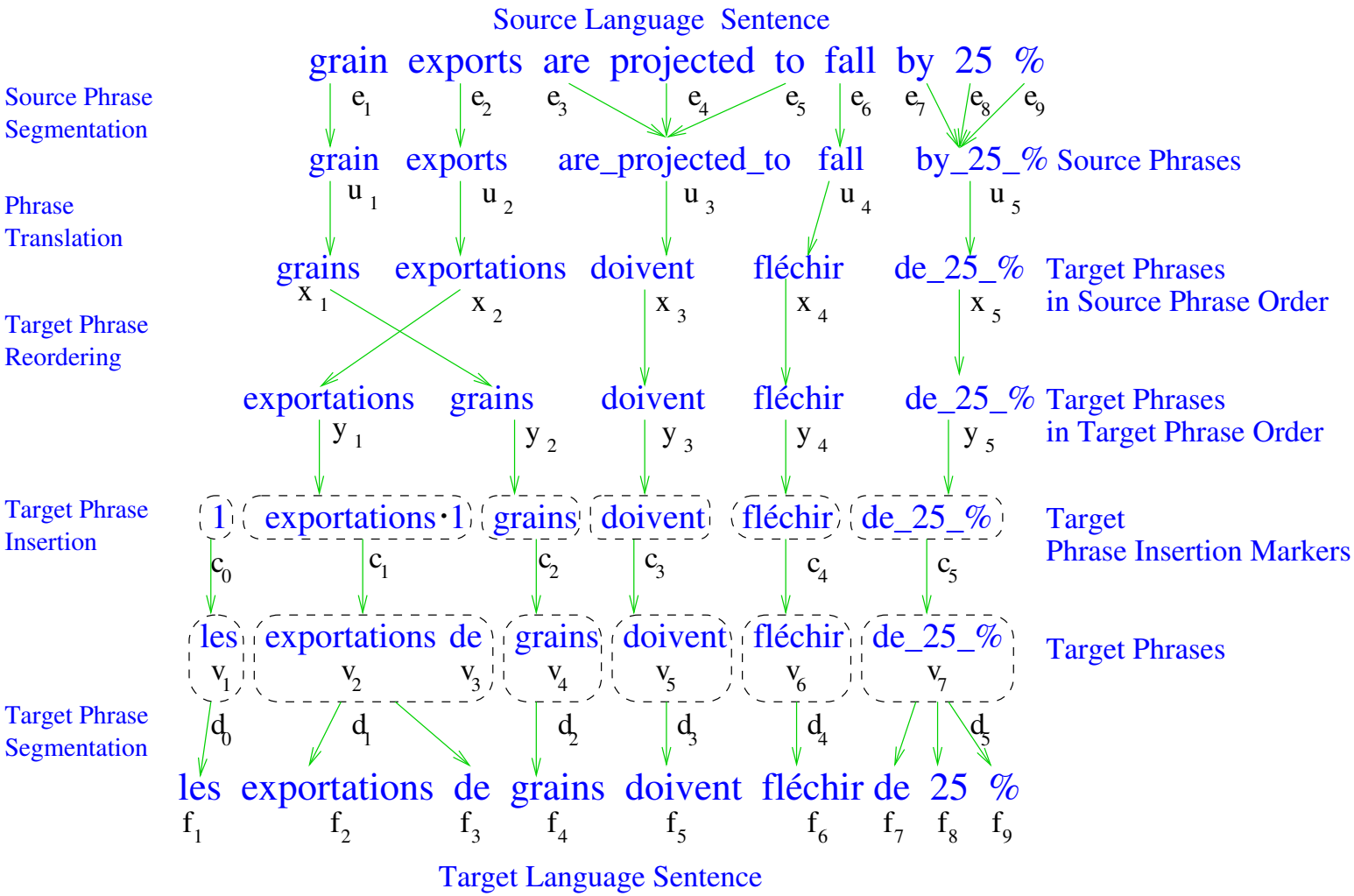
- Relatively good performance with models that are really quite simple
- Should be easy to use in translating ASR lattices
- Easy to teach

TTM (2004) – Translation with Monotone Phrase Order



- Transformations via stochastic models implemented as WFSTs
- Implementation is direct using standard WFST operations

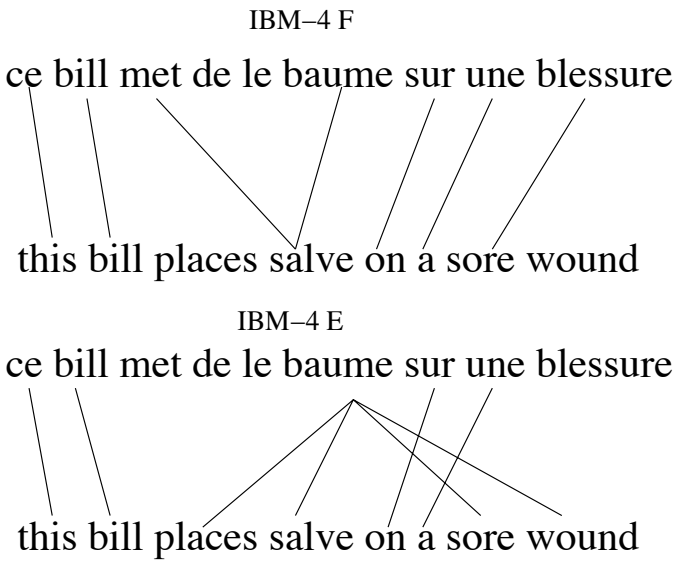
TTM (2005) – Translation with Moving Target Phrase Order

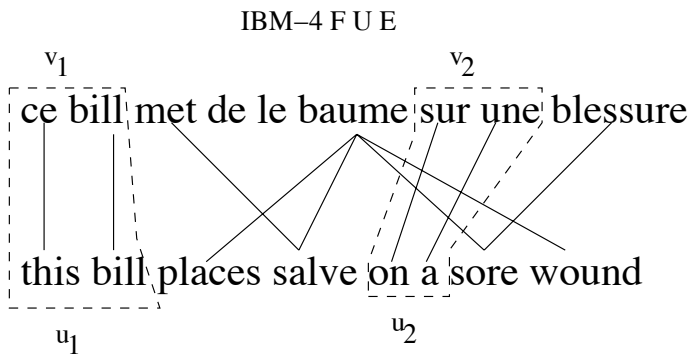


Phrase-to-Phrase Translation Models

Alignment Template Models (Och et al. 1999)

- derived from 'good' word-level alignments, typically from IBM-4





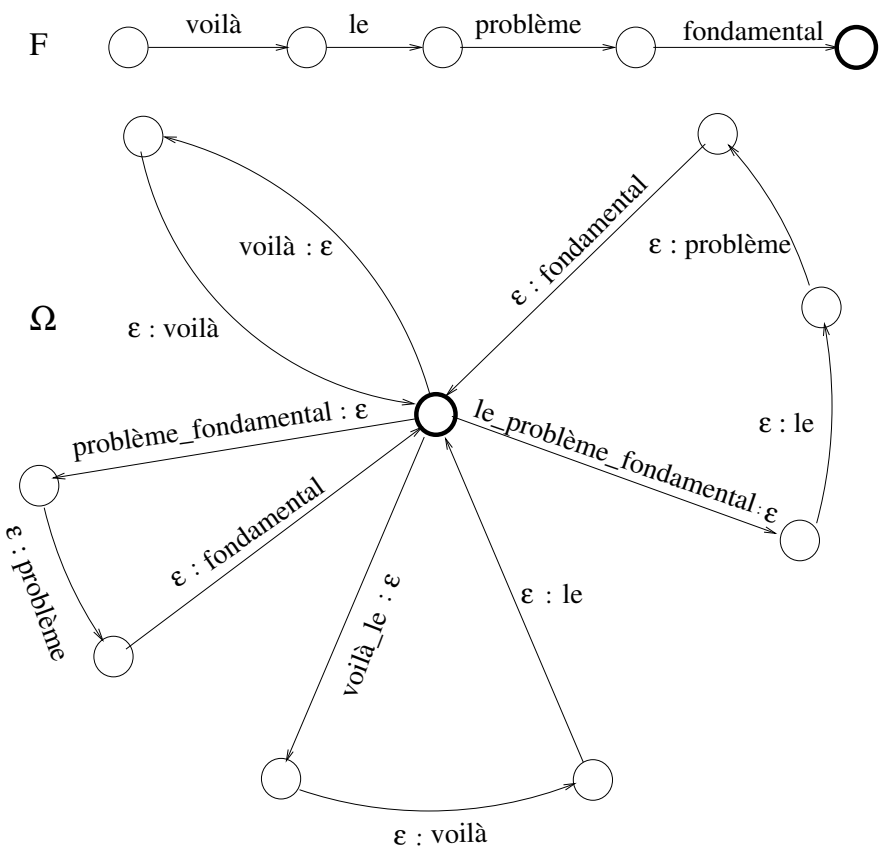
- Phrase Pairs are extracted to cover word alignment patterns
- Probability distributions are defined over phrase pair sequences

The Phrase Pair Inventory

English Phrase u	French Phrase v	Phrase Transduction Probability $P(v\|u)$
hear_hear	bravo	0.8
	bravo_bravo	0.15
	ordre	0.05
terms_of_reference	mandat	0.8
	de_son_mandat	0.2

- Phrase Pair Inventory affects the performance of the TTM
  - Word Alignment Quality of underlying models
  - Coverage of phrases on the test set

Target Phrase Segmentation Transducer Ω

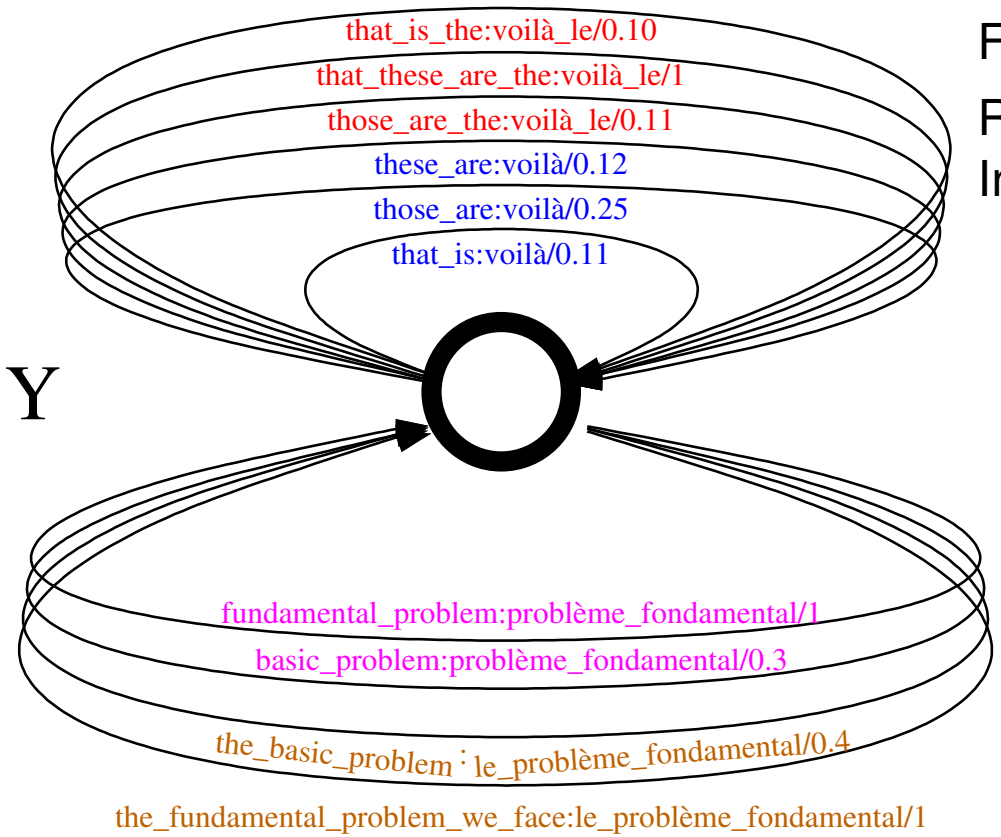


Based on the French phrases in the PPI

Assume F is the sentence to be translated

Phrase sequences that could have generated F: $\Omega \circ F$
voilà_le problème_fondamental
voilà le_problème_fondamental

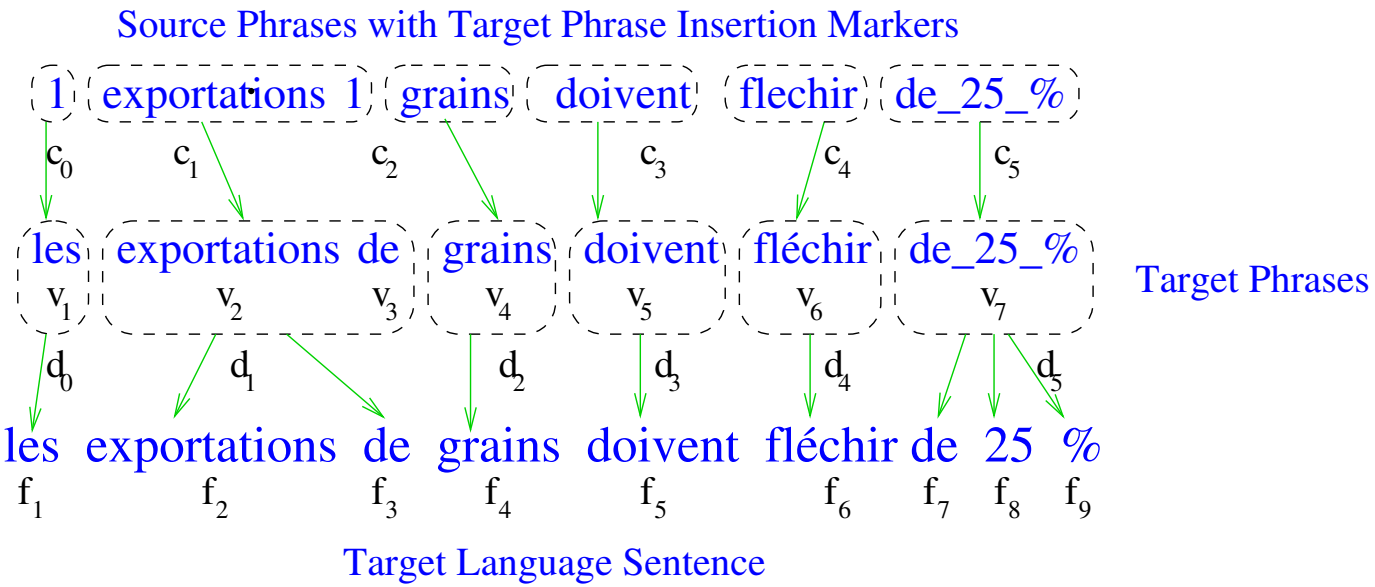
Phrase Translation Transducer *Y*



Map English phrases into French phrases

Realizes the Phrase-Pair Inventory

Target Language Phrase Insertion



Different phrase segmentations lead to different translations :

- Sequences c_0^K that could have generated F : $Y \circ \Omega \circ F$

  H1 `that_these_are_the fundamental_problem` :
  `voilà_le problème_fondamental`
  ...
  H16 `that_is the_basic_problem`:
  `voilà le_problème_fondamental`

Procedures for Alignment and Translation (Monotone Phrase Order)

Given a French sentence f_1^J to be translated into English, we build the following transducers (in this order)

- F to represent the French sentence
- Ω maps French phrases in our Phrase-Pair Inventory (PPI) to words in F
- Y maps English phrases to French phrases in Ω with probabilities (PPI)
- Φ inserts French phrase insertion markers
- W maps English words to English phrases seen in Y (restricted phrase segmentation transducer)

If f_1^J is to be aligned with an English sentence e_1^I:

- Build an FSM E to represent e_1^I

If f_1^J is to be translated:

- Build a n-gram backoff LM and compile it as a weighted acceptor G

Bitext Word Alignment and Translation Via WFSTs

TTM Generative Model: $P(f_1^J, v_1^R, d_0^K, c_0^K, a_1^K, u_1^K, K, e_1^I)$

- MAP Alignment of a sentence pair f_1^J,e_1^I

$$\{\hat{K}, \hat{u}_1^{\hat{K}}, \hat{a}_1^{\hat{K}}, \hat{c}_0^{\hat{K}}, \hat{d}_0^{\hat{K}}, \hat{v}_1^{\hat{R}}\} = \underset{K, u_1^K, a_1^K, c_0^K, d_0^K, v_1^R}{\operatorname{argmax}} P(K, u_1^K, a_1^K, c_0^K, d_0^K, v_1^R | e_1^I, f_1^J)$$

- MAP Translation of a French sentence f_1^J

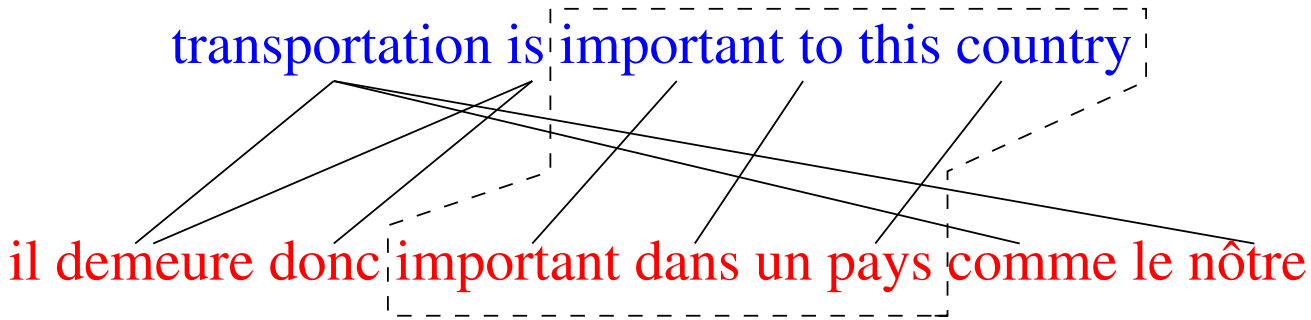
$$\{\hat{e}_1^{\hat{I}}, \hat{K}, \hat{u}_1^{\hat{K}}, \hat{a}_1^{\hat{K}}, \hat{c}_0^{\hat{K}}, \hat{d}_0^{\hat{K}}, \hat{v}_1^{\hat{R}}\} = \underset{e_1^I, K, u_1^K, a_1^K, c_0^K, d_0^K, v_1^R}{\operatorname{argmax}} P(K, u_1^K, a_1^K, c_0^k, d_0^K, v_1^R | f_1^J)$$

WFST Operations with Monotone Search

- Alignment
  1. Generate the alignment lattice: $\mathcal{B} = E \circ W \circ \Phi \circ Y \circ \Omega \circ F$
  2. MAP Alignment : least cost path in $\mathcal{B}$
- Translation
  1. Generate the translation lattice: $\mathcal{T} = G \circ U \circ \Phi \circ Y \circ \Omega \circ F$
  2. MAP Translation : least cost path in $\mathcal{T}$

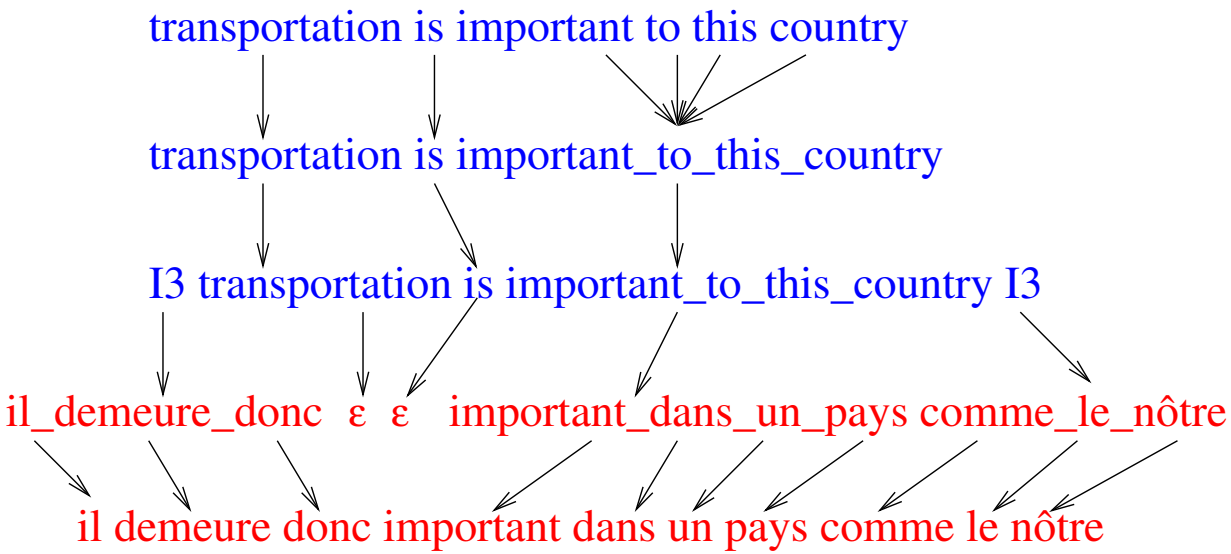
Problems with Bitext Word Alignment under the TTM

Consider extraction of phrase pairs from word alignments



- Extracted PPI is not rich enough to cover all the sentence-pairs
  - If we discard the word alignments, this pair has probability zero under the model
  - In fact, most sentences from the training bitext have probability zero
- Solution:
  - TTM already allows insertions of target phrases
  - In addition, we allow deletions of source phrases

Source Phrase Deletion in Bitext Word Alignment



- Novel use of phrase-based translation models for alignment
- TTM word alignments are very accurate: ↑ precision, ↓ recall

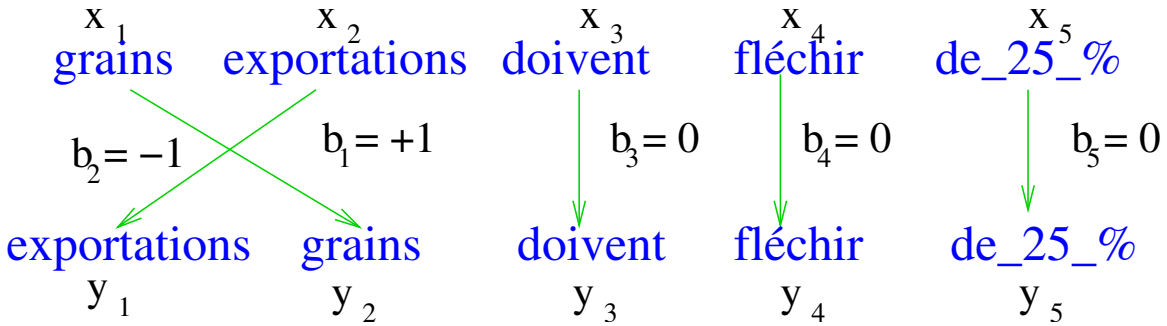
Supports parameter estimation procedures

- Must be able to segment and align the bitext

EM requires

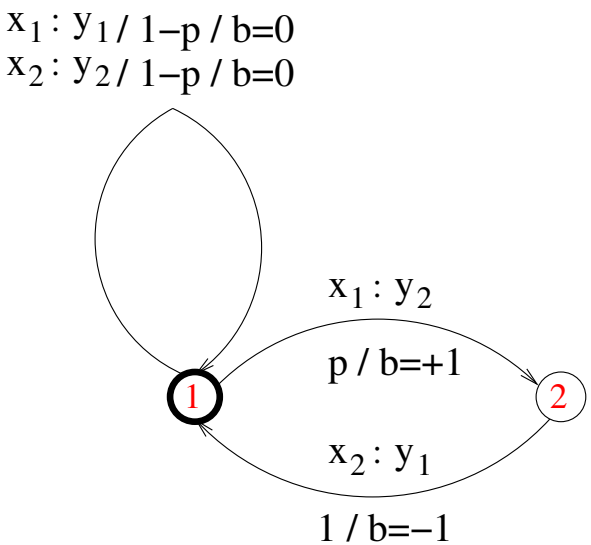
$$P(\underbrace{K, u_1^K, a_1^K, c_0^K, d_0^K, v_1^R}_{\textit{Hidden Variables}} \mid \underbrace{e_1^I, f_1^J}_{\textit{Training Data}})$$

Phrase Swapping by WFSTs



Associate a jump sequence b_1^K with each sequence y_1^K

$P(y_1^K|x_1^K, u_1^K, K, e_1^I) = P(b_1^K|x_1^K, u_1^K, K, e_1^I) = \prod_{k=1}^K P(b_k|x_k, u_k)$



Inspired by work of Tillman

Input: $x_1, x_2, b \in \{0, +1, -1\}$

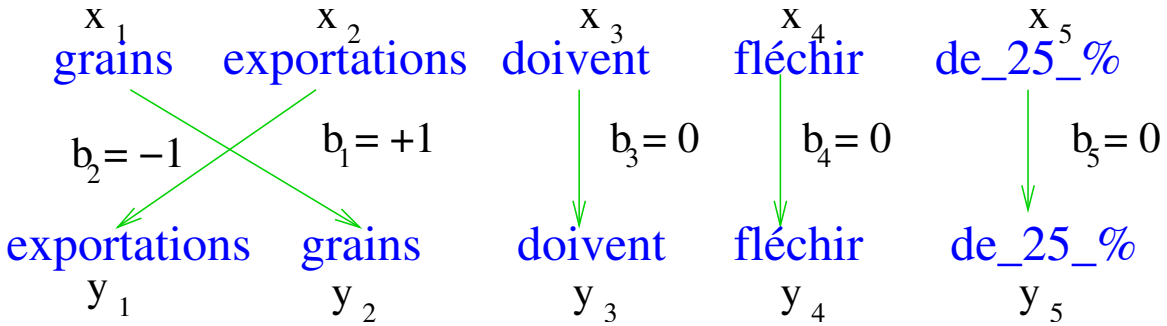
Output: y_1, y_2 with prob $(1-p)^2$
y_2, y_1 with prob p

MJ-1 : maximum jump of 1

Properly parameterized

Not degenerate

Phrase Swapping by WFSTs



Associate a jump sequence b_1^K with each sequence y_1^K

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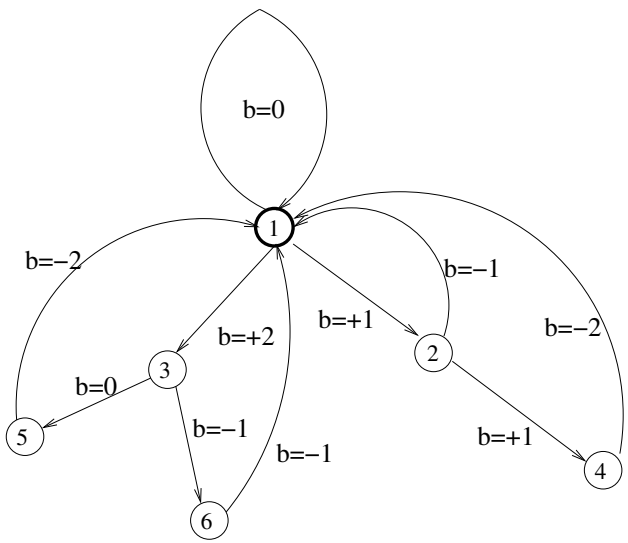


Inspired by work of Tillman

Input: $x_1, x_2, b \in \{0, +1, -1\}$

Output: y_1, y_2 with prob $(1-p)^2$
y_2, y_1 with prob p

MJ-2 : maximum jump of 2

Properly parameterized

Not degenerate

Incorporating Reordering in Translation

- Reodering prior to translation:
  - English phrases in French phrase order
  - Difficult to realize with WFSTs
- Tried the opposite approach:
  - First generate a French phrase sequence in English phrase order
  - Next reorder this sequence into French phrase order under the Local Phrase Reordering Model
- Possible to realize with WFSTs both in alignment and translation
  - No English phrase reordering process
- Reordering is done prior to Insertion of Target Phrases
  - word alignments within phrases can span fairly long distances

Can perform embedded reestimation of reordering model parameters

- Phrase-pair dependent reordering probability : $P(b_k|x_k, u_k)$
- Estimated via Viterbi approximation to EM
- Exact estimation: alignments are done under the translation model

Training and Translation Procedures

1. Bitext Chunking
   - 1.1 Monotone alignment into coarse chunks of documents
   - 1.2 Divisive clustering into subsentence chunks
2. MTTK word alignment – Model 4 replacement
3. Construct component WFSTs for the TTM –
   - 3.1 extract phrases from the alignments using the 'usual' heuristics
   - 3.2 use phrase-pair induction under MTTK to augment the PPI
4. Translation lattice generation with pruned trigram $\longrightarrow$
5. Translation lattice rescoring with unpruned 4gram $\longrightarrow$
6. Minimum Error Training
   - 6.1 transducer weights optimized for BLEU on heldout data

TTM and Phrase Reordering

Good gains from reordering in both Arabic→English and Chinese→English

- Jump-1 might be as good as Jump-2 (in this formulation)
- little gain in Chinese→English from parameter estimation

Translation under MJ-1 and MJ-2 reordering with a 4-gram LM.

Reordering Model	BLEU (%)					
	Arabic-English			Chinese-English		
	02	03	04	02	03	04
None	37.5	40.3	36.8	24.2	23.7	26.0
MJ-1 flat	40.4	43.9	39.4	25.7	24.5	27.4
MJ-1 VT	41.3	44.8	40.3	25.8	24.5	27.8
MJ-2 flat	41.0	44.4	39.7	26.2	24.8	27.8
MJ-2 VT	41.4	45.0	40.2	26.4	24.8	27.8

Influence of Language Model Order on Reordering in Translation

BLEU Over Merged Eval Sets (Eval02,Eval03,Eval04)

	BLEU (%)					
	A-E			C-E		
	2g	3g	4g	2g	3g	4g
None	21.0	36.8	37.8	16.1	24.8	25.0
MJ-1	23.4	40.4	41.6	16.2	25.9	26.5
MJ-2	23.3	40.4	41.6	16.0	26.0	26.8

These Simple Reordering Models Benefit from Better Language Models

Translation Performance with Reordering across Eval 04 Test Genres

Model	BLEU (%)					
	A-E			C-E		
	News	Eds	Spchs	News	Eds	Spchs
None	41.1	30.8	33.3	23.6	25.9	30.8
MJ-1 flat	44.7	31.6	35.3	24.3	27.6	32.9
MJ-1 VT	45.6	32.6	35.7	24.8	27.8	33.3
MJ-2 flat	45.2	31.9	35.2	24.8	27.8	33.4
MJ-2 VT	45.8	32.4	35.2	24.8	27.7	33.6

Causes:

- Training / Test Mismatch ?
- Language model mismatch, in particular ?
- Less movement in Speeches and Editorials ?
- Different operating points ?

Summary: Working Towards Integrated Modeling and Decoding

Modeling: Given an English Sentence e and a French sentence f, construct a joint distribution over their alignments.

$$P(e,a,f) = \underbrace{P(f|a,e)}_{\text{Translation Model}} \underbrace{P(a|e)}_{\text{Alignment Model}} \underbrace{P(e)}_{\text{Language Model}}$$

Decoding (ideal) : Given f, find a translation $\widehat{e}$ and an alignment $\widehat{a}$ as

$$(\widehat{e},\widehat{a}) = \underset{e,a}{\operatorname{argmax}}\ P(f|a,e)\,P(a|e)\,P(e)$$

Decoding (really) : lacks integrated modeling and decoding

- Models are trained & alignments are generated over the training set
- The models are discarded, and the alignments are kept
- PPI, etc. are extracted from the alignments and used in translation

Goal: same models in alignment and translation – 'what works' for ASR

- needed for : MMI, clustering, context dependence, ...

New! – TTM Tutorial is Available

German→English translation based on

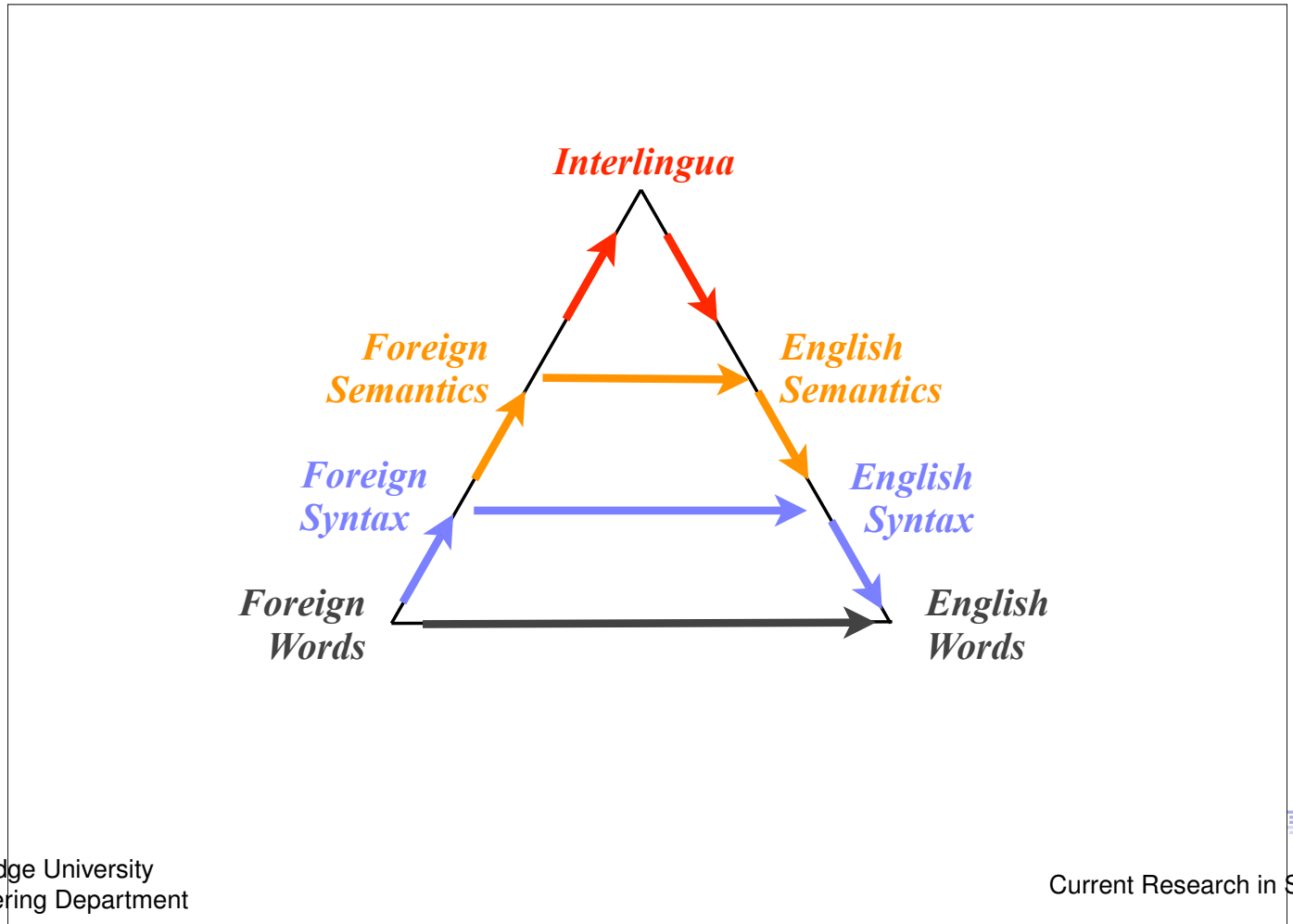
- Europarl corpus
- Giza++ alignments
- AT&T FSM Toolkit
  - any FSM toolkit should work ...

Tutorial steps through building and using all the transducers

Very much an alpha version, but available to anybody who's interested

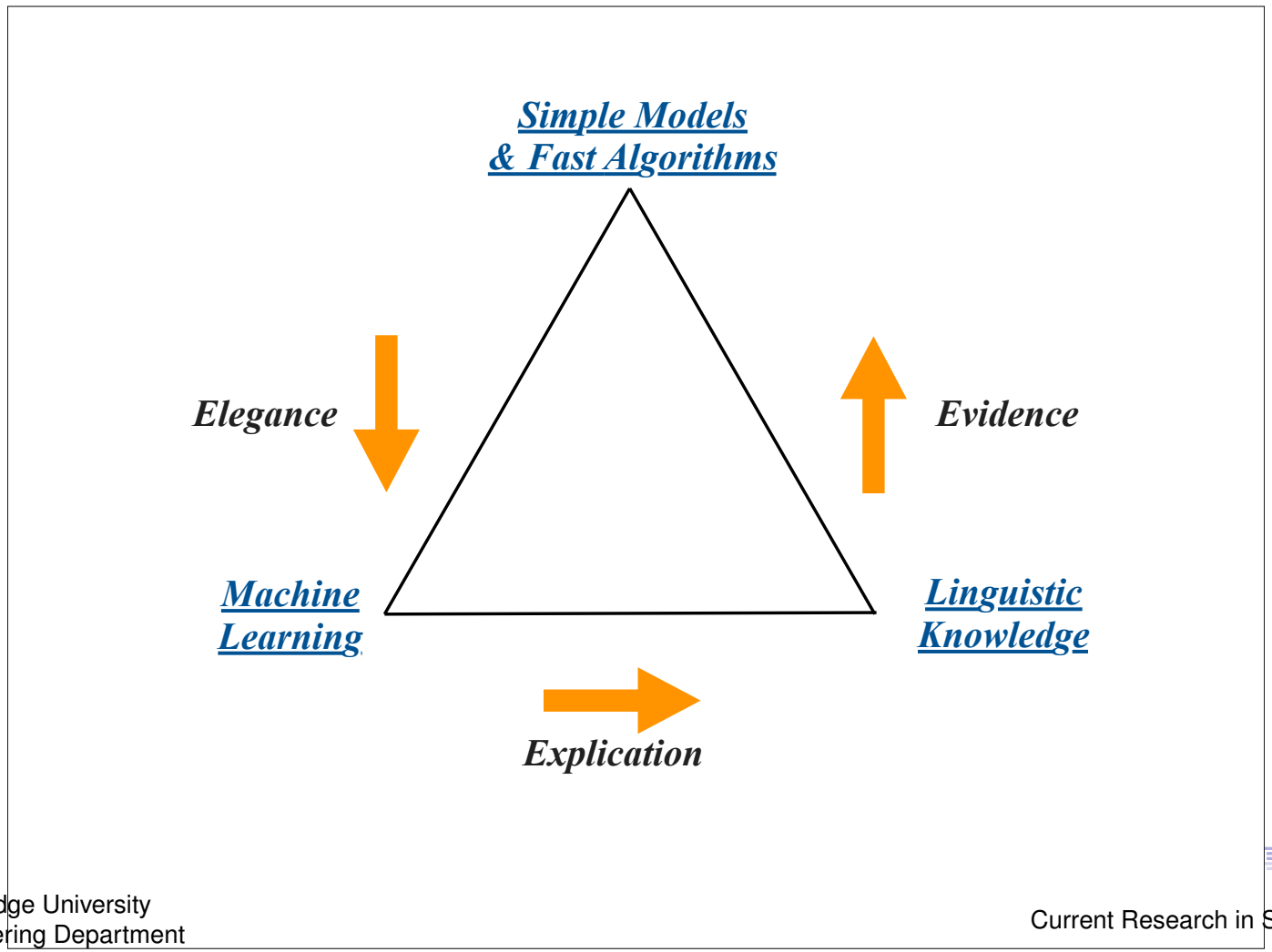
The Machine Translation Pyramid

Casts the problem in familiar terms
- strengths and weaknesses of the formulation are obvious



The *Statistical* Machine Translation Pyramid

Building good systems requires balancing competing concerns



Thanks!