



THE GREYC MACHINE TRANSLATION SYSTEM FOR THE IWSLT 2008 CAMPAIGN

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THE SYSTEM

- Evolution of the ALEPH machine translation system that participated in the IWSLT 2005 [Lepage & Denoual, 2005] and IWSLT 2007 [Lepage & Lardilleux, 2007] campaigns.
- ALEPH is a pure example-based system that exploits proportional analogies (analogies of form).

PREVIOUS SYSTEM: analogies between **character strings**:

you swim : he swims :: you surf :: he surfs

NEW SYSTEM: can also work on **words** (used in IWSLT):

My hotel sucks : Your hotel sucks :: My hotel rocks :: Your hotel rocks

⇒ Nothing the character-based approach cannot deal with, but faster.

THE PARTICIPATION OF THE GREYC

TRACKS: ALL BTEC TASKS

- Arabic to English
- Chinese to English
- Chinese to Spanish
- Chinese to Spanish by the way of English (Pivot)

CONDITIONS: used **only** training data (**no development set**)

NON-DETERMINISTIC ANALOGY SOLVER

PREVIOUS IMPLEMENTATION IN C:

$$x : y :: z : ? \quad \Rightarrow \quad ? = t$$

NEW SOLVER IN PYTHON:

$$x : y :: z : ? \quad \Rightarrow \quad ? = \begin{matrix} t_1 \\ t_2 \\ t_3 \\ \vdots \end{matrix}$$

EXAMPLE

kalb : kulaib :: masjid : musaijid

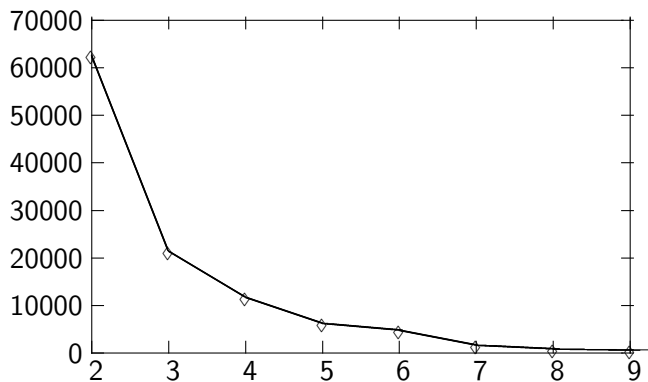
kalb : kulaib :: masjid : musjaiid

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NON-DETERMINISTIC ANALOGY SOLVER

Distribution of the number of analogical equations
with the same number of solutions

(number of solutions in abscissae; number of analogies in ordinates):



Ratio 1 solution:multiple solutions = 30:1

RE-ENGINEERING OF THE ENGINE

MAIN ISSUE OF THE ENGINE

Efficient discovery of translation examples that are likely to form an analogical equation is critical.

⇒ Design of a new heuristic:

- Analogical terms are chosen according to their longest common substring.
- Can be pre-computed and saved on disk to speed up searches.

BENEFIT: number of attempted analogical equations that have at least one solution increased from 28% to **52%**.

NEW ALIGNMENT METHOD

“Perfect” alignments contain those words that strictly appear on the same lines:

Allons boire un verre . ↔ Let 's have a drink .
 Allons boire une **bière** ou deux . ↔ Let 's have a **beer** or two .
 Une **bière** et un café . ↔ One **beer** and one coffee .
 Je voudrais un verre de vin , s' il vous plaît . ↔ I 'd like a glass of wine , please .
 Je voudrais de la **bière** , s' il vous plaît . ↔ I 'd like some **beer** , please .
 Nous prendrons un pichet de vin . ↔ We 'll have a jug of wine .

“PERFECT”

bière ↔ **beer**

⇒

CONTEXTS

Allons boire une _ ou deux . ↔ Let 's have a _ or two .
 Une _ et un café . ↔ One _ and one coffee .
 Je voudrais de la _ , s' il vous plaît . ↔ I 'd like some _ , please .

“PERFECT”

Je voudrais _ , s' il vous plaît
 ↔ I 'd like _ , please

⇒

CONTEXTS

un verre de vin _ . ↔ a glass of wine _ .
 de la bière _ . ↔ some beer _ .

NEW ALIGNMENT METHOD

How to extract the alignments for ambiguous terms?

Allons boire un verre . ↔ Let 's have a drink .

Allons boire une bière ou deux . ↔ Let 's have a beer or two .

Une bière et un café . ↔ One beer and one coffee .

Je voudrais un verre de vin , s' il vous plaît . ↔ I 'd like a glass of wine , please .

Je voudrais de la bière , s' il vous plaît . ↔ I 'd like some beer , please .

Nous prendrons un pichet de vin . ↔ We 'll have a jug of wine .

Make them perfect: **split the corpus.**

“PERFECT”

verre ↔ drink

⇒

CONTEXTS

Allons boire un _ . ↔ Let 's have a _ .

“PERFECT”

verre ↔ glass

⇒

CONTEXTS

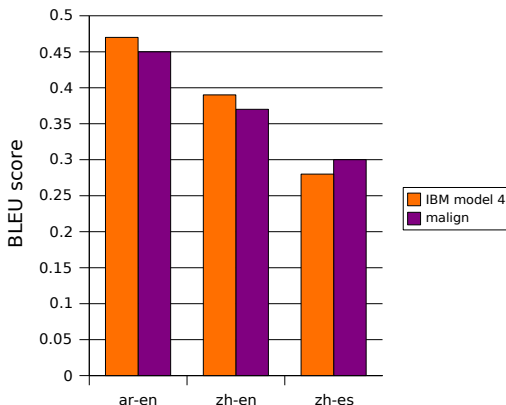
Je voudrais un _ de vin , s' il vous plaît . ↔ I 'd like a _ of wine , please .

$$P(\text{drink}|\text{verre}) = 0.5 \quad P(\text{verre}|\text{drink}) = 1$$

$$P(\text{glass}|\text{verre}) = 0.5 \quad P(\text{verre}|\text{glass}) = 1$$

NEW ALIGNMENT METHOD

Experiments on development set 3, using the first half for tuning and the second half for testing:



DETAILS OF THE RUNS

3 runs for each task:

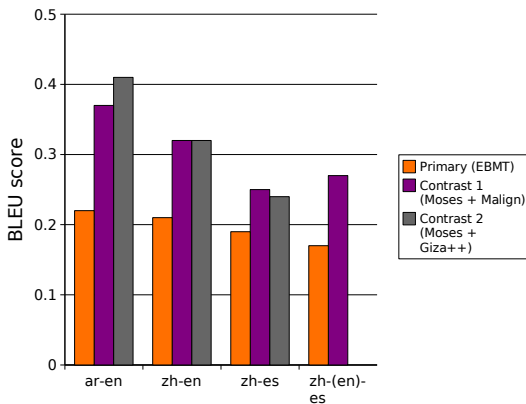
PRIMARY: ALEPH (EBMT), with training data inflated with alignments generated by **malign** [Lardilleux & Lepage, next Wednesday];

CONTRAST 1: Moses [Koehn et al., 2007] with translation tables generated by malign;

CONTRAST 2: Moses with default translation tables (refined alignments from IBM model 4, with Giza++ [Och & Ney, 2003]).

EVALUATION RESULTS

Results with CRR, case+punc:



RESULTS SYNTHESIS

In most cases: $primary < contrast1 \leq contrast2$

- If one sees the *contrast2* as a kind of baseline, then our system could not even reach the baseline of SMT in its current state (recursivity not ready at the time of evaluation).
- + only training data was used. . . (and you?)
- There is room for improvement!