MaTrEx: Machine Translation Using Examples

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Outline

Introduction

- Large-scale Example-Based Machine Translation system
  - Robust
  - Easily adaptable to new language pairs
  - Modular design - follow established Design Patterns
- Built by a team of researchers at the National Centre for Language Technology (NCLT) in DCU
  - 6 Ph.D. Students, 1 Postdoc
  - Supervised by Dr. Andy Way
- First participation of an EBMT system in a shared task

Example-Based MT

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- As with SMT, makes use of information extracted from sententially-aligned corpora
- Translation performed using database of examples extracted from corpora
- During translation, the input sentence is matched against the example database and corresponding target language examples are recombined to produce final translation.

EBMT: *An Example*

- Assume an aligned bilingual corpus of examples against which input text is matched
- Best match is found using a similarity metric (can be based on word co-occurrence, POS, bilingual dictionaries etc.)

Given the Corpus

La tienda abrió el lunes pasado = The shop opened last Monday
Juan fue a la piscina = John went to the swimming pool
La carnicerna está al lado de la panadería = The butcher's is next to the baker's

EBMT: *An Example*

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- Recombine extracted fragments to translate new unseen input

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Translate New Input

Juan fue a la panadería el lunes pasado = John went to the baker's last Monday

Marker-Based EBMT

- Approach to EBMT based on the Marker Hypothesis

> *"The Marker Hypothesis states that all natural languages have a closed set of specific words or morphemes which appear in a limited set of grammatical contexts and which signal that context." (Green, 1979).*

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- 3 NPs start with determiners, one with a possessive pronoun
  - Determiners & possessive pronoun - small closed-class sets
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  - Determiners & possessive pronoun - small closed-class sets
  - Predicts head nominal element will occur in the right-context.
- Four prepositional phrases, with prepositional heads.
  - Again a small set of closed-class words
  - Indicates that soon thereafter an NP object will occur

Marker-Based EBMT: *Previous Work*

- Line of previous research:
  - (Gough et al., 2002) *AMTA*
  - (Gough & Way, 2003) *MT Summit*
  - (Way & Gough, 2003) *Computational Linguistics*
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- Have previously only worked on French-English and German-English data
- Largest training data set used to date consisted of 322K French-English sentence pairs
- MaTrEx system is a complete re-implementation of previous system
  - More sophisticated marker sets and marker-based chunk alignment

Marker-Based EBMT: *Chunking*

- Use a set of closed-class marker words to segment aligned source and target sentences during a pre-processing stage.
- <PUNC> used as end of chunk marker

Determiner	<DET>
Quantifiers	<Q>
Prepositions	<P>
Conjunctions	<C>
WH-Adverbs	<WH>
Possessive Pronouns	<POSS-PRON>
Personal Pronouns	<PERS-PRON>
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- English Marker words extracted from CELEX and edited manually to correspond with the training data.
- Spanish Marker words from 2 stop word lists, generously supplied by Lluís Padró (Polytechnic University of Catalunya) and Montserrat Civit (University of Barcelona).

Marker-Based EBMT: *Chunking (2)*

- Enables the use of basic syntactic marking for extraction of translation resources
- Source-target sentence pairs are tagged with their marker categories automatically in a pre-processing step:

SP: *<PRON> Usted cliquea <PREP> en <DET> el botón rojo <PREP> para ver <DET> el efecto <PREP> de <DET> la selección.*

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- Chunks must contain at least one non-marker word - ensures chunks contain useful contextual information

Chunk Alignment

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  - Discriminative Approach for chunk alignment
- "Edit-Distance" Chunk Alignment
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  - Combination (can be viewed as a log-linear model)

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- "Edit-Distance" with Jumps
  - Found that this method did not improve results - similar chunk order between Spanish and English

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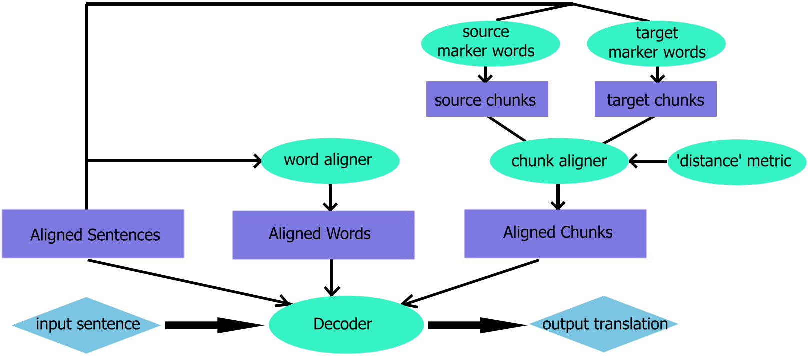
  - Extend this intersection into the union of the alignment sets, by iteratively adding adjacent alignments
- Only made use of the resulting one-to-one word alignments produced
- Word probabilities were then estimated from relative frequencies.

System Architecture



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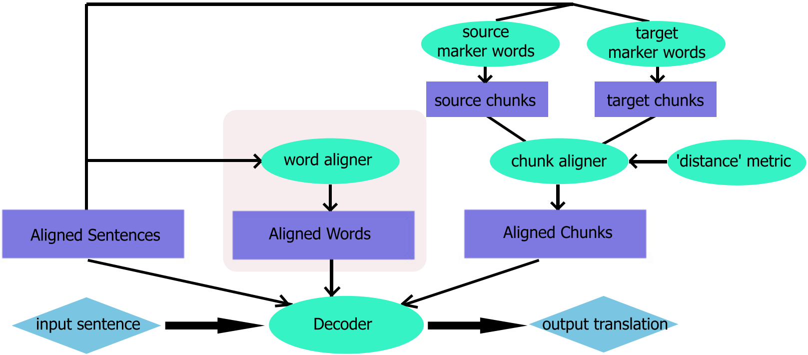

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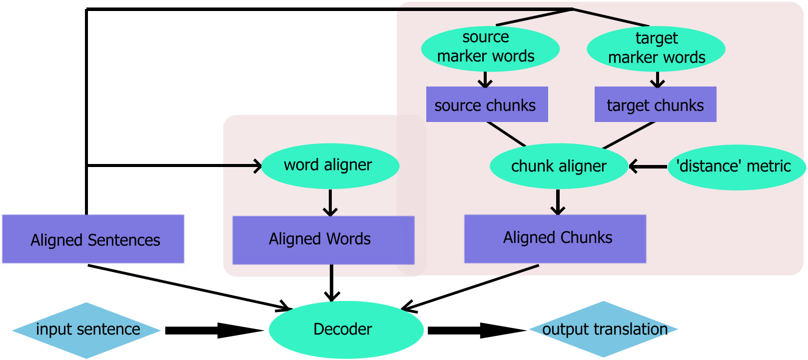

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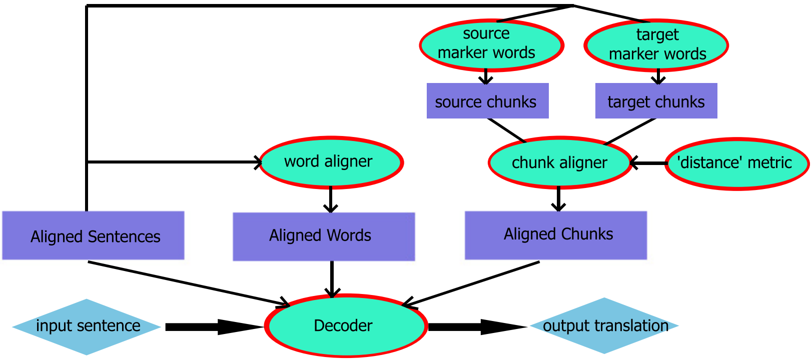

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- Modules can be replaced by different implementations

Experiments and Results

- Data used:
  - Filtered supplied Spanish-English training data based on sentence length ($<$ 40 words) and relative sentence length ratio (1.5).
    - 23.4% filtered based on length, 1.8% filtered based on ratio.
  - Text was lowercased
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- Baseline system: "refined" word alignments passed to Pharaoh decoder.

Results

	BLEU	NIST	CER	PER	WER
Baseline	0.3630	8.3237	51.6662	34.6757	60.2711
Cog,Tag	0.4039	8.7712	44.8441	33.3748	53.2294
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Ref: *in the report we are currently discussing, the european union sold arms and military equipment to the value of 21 billion euros in countries such as saudi arabia*

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- Investigated a number of strategies for chunk alignment
  - Aligning based on marker tags, cognate information and word probabilities most effective
  - Using cognate information as accurate as word probabilities
- System achieves a BLEU score of 0.4092 - a 12.31% relative increase over a word-based baseline system
- Results indicate the high quality of the chunk alignments extracted

Ongoing and Future Work

- Plan to continue the development the MaTrEx system.
  - Currently at early stage of development
- Implement an example-based decoder.
- Implement an HMM chunk alignment strategy.
- Use of generalised templates - allow more flexibility to the matching process, improves coverage and quality

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  - Basque translation
- Use the system for related research:
  - Sign-Language translation
  - Hybrid Models of EBMT and SMT

Thank you

Thank you for your attention.

http://www.computing.dcu.ie/research/nclt