MaTrEx: Machine Translation Using Examples

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DCU NCLT @ OpenLab2006
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2 Example-Based Machine Translation
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4 Word Alignment

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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
Based on the intuition that humans make use of previously seen translation examples to translate unseen input

- Analogy-based principle
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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- Identify useful fragments
- 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
MArEx: Machine Translation Using Examples
Example-Based Machine Translation
Marker-Based EBMT

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).

- Universal psycholinguistic constraint: languages are marked for syntactic structure at surface level by closed set of lexemes or morphemes.
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- 3 NPs start with determiners, one with a possessive pronoun
  - Determiners & possessive pronoun - small closed-class sets
  - Predicts head nominal element will occur in the right-context.
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Marker-Based EBMT: Previous Work

Line of previous research:

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- (Gough & Way, 2003) *MT Summit*
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- 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

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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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- Aligned source-target chunks are created by segmenting the sentence based on these tags, along with word translation probability and cognate information:

  - <PRON> Usted cliquea : <PRON> You click
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- Chunks must contain at least one non-marker word - ensures chunks contain useful contextual information
Chunk Alignment

- Focused on chunk alignment for this task
  - Discriminative Approach for chunk alignment
- “Edit-Distance” Chunk Alignment
  - Dynamic programming
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  - Combination (can be viewed as a log-linear model)

\[ \lambda_1 d_1(a|b) + \ldots \lambda_n d_n(a|b) \Rightarrow -\lambda_1 \log P_1(a|b) \ldots - \lambda_n \log P_n(a|b) \]
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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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- Only made use of the resulting one-to-one word alignments produced
- Word probabilities were then estimated from relative frequencies.
Aligned Sentences are submitted to word alignment and chunk alignment modules to produce translation resources.

- Modular in design
- Easily adaptable and extendible
System Architecture

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- **Aligned Sentences**
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- **Modular in design**
- **Easily adaptable and extendible**
- **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
  - Resulted in approx 958K sentence pairs which were used for training.
  - Training took approx. 3hrs on 64-bit machine with 8GB RAM.
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  - Various combinations of distance metrics weighted linearly
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- Baseline system: “refined” word alignments passed to Pharaoh decoder.
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- However, should compare system against baseline phrase-based system
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Results: Sample Translations

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Baseline: *the report that we, the european union and equipping of 21,000 million euros to saudi arabia*

MaTrEx: *the report we are discussing the european union cashed arms and military equipment to the tune of millions of euro in countries such as saudi arabia*

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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  **Baseline:** *those countries are convinced that need to cooperate more effectively in the fight against the terrorism. underneath by way of*

  **MaTrEx:** *the netherlands are convinced that we have to work together more effectively in fighting terrorism*

  **Ref:** *the netherlands is convinced that we must cooperate much more efficiently in the fight against terrorism*
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**Baseline:** *the report that we, the european union and equipping of 21,000 million euros to saudi arabia*

**MaTrEx:** *the report we are discussing the european union cashed arms and military equipment to the tune of millions of euro in countries such as saudi arabia*

**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*

- The use of chunks gives the system enough context to accurately translate noun phrases.

**Baseline:** *those countries are convinced that need to cooperate more effectively in the fight against the terrorism. underneath by way of*

**MaTrEx:** *the netherlands are convinced that we have to work together more effectively in fighting terrorism*

**Ref:** *the netherlands is convinced that we must cooperate much more efficiently in the fight against terrorism*
Discussions and Conclusions

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  - Modular design - easily adaptable and extendible
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- 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 of 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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- Use the system for related research:
  - Sign-Language translation
  - Hybrid Models of EBMT and SMT
Thank you for your attention.

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