

Machine Translation Research in META-NET

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Outline



Pillar I in META-NET

...the research element of META-NET

Semantics in Machine Translation

- Semantic features in statistical MT
- (Semantic) Tree-based translation

Hybrid MT systems

Rule-based and statistical

Context in MT

"Extra-linguistic" features

More data for MT

Parallel data for under-resources langauges

Related projects & the Future



Semantics in Machine Translation

Semantics in Machine Translation META NET



What is semantics, anyway?

- For now: anything beyond and outside morphology and syntax
 - » Semantic Roles (words vs. predicates)
 - Lexical Semantics (WSD), MWE
 - Named Entities
 - » Co-reference (pronominal, bridging anaphora)
 - Textual Entailment
 - Discourse Structure
 - Information Structure ... + any combination of the above

New metrics

- BLEU, METEOR, NIST etc. biased towards (good) local n-grams
- Metrics sensitive to semantics?

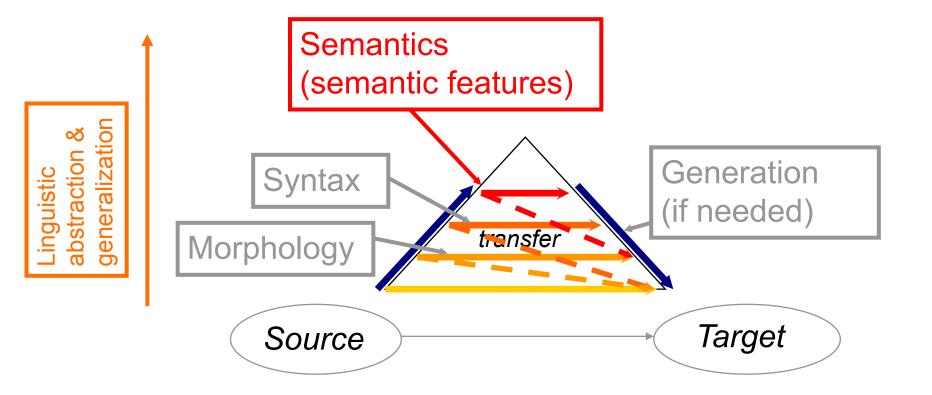
Tools and Resources

Semantically annotated parallel corpora; metrics tools, analysis tools

Semantics in Machine Translation META NET



Analysis – transfer [– generation]



Semantics in Machine Translation META NET



Case Study 1

Cross-lingual Textual Entailment for Adequacy Evaluation Y. Mehad, M. Negri, M. Federico: Towards cross-lingual textual entailment, NAACL 2010

Case Study 2

- Combined Syntax and Semantics for MT Transfer
 - D. Mareček, M. Popel, Z. Žabokrtský: Maximum Entropy Translation Model in Dependency-Based MT Framework, WMT / ACL 2010

Case Study 3

- Anaphora Resolution for translation of pronouns
 - C. Hardmeier, M. Federico: Modeling Pronominal Anaphora in Statistical MT, IWSLT 2010.

Case Studies → **Selected Challenges**

- Evaluation of impact of individual additions
 - Evaluation data with/without phenomenon under study
 - Automatic vs. human evaluation



Hybrid MT Systems

Machine Translation Paradigms

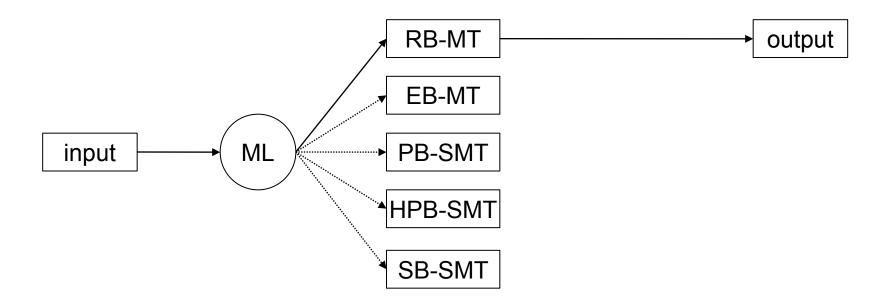


- RB-MT Rule-Based Machine translation
- EB-MT Example-Based Machine Translation
- SMT Statistical Machine Translation
- PB-SMT Phrase-Based Statistical Machine Translation
- HPB-SMT Hierachical Phrase-Based Statistical Machine Translation
- SB-SMT Syntax-Based Statistical Machine Translation
- **-** ...
- Observation: Different systems have different strengths
 (e.g. easy training of SMT vs. good grammar of RB-MT)
- Hypothesis: Hybrid systems can combine best of all

Hybrid MT: Pre-Translation System Selection



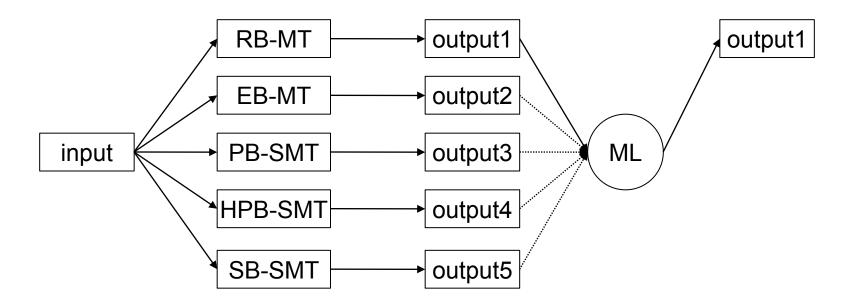
- Multiple MT engines/systems available
- Machine learning techniques
 - decide which system is best to translate the input sentence



Hybrid MT: Pre-Translation System Selection



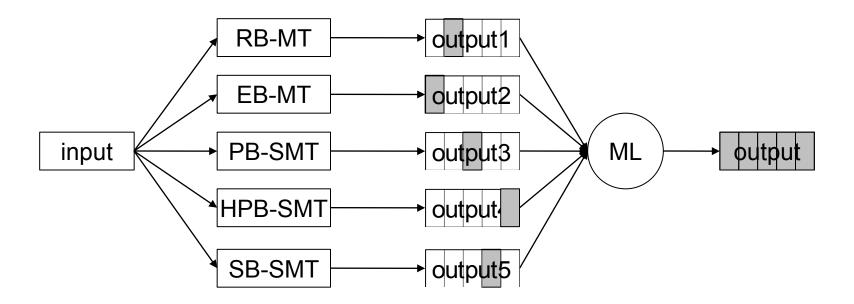
- Multiple MT engines/systems available
- All systems translate
 - Analysis of ouptuts → select translation



Hybrid MT: Pre-Translation System Selection



- Multiple MT engines/systems available
- All systems translate
 - Translation compiled from analyzed pieces



The META-NET Hybrid System Approach META NET



- Based on system combination
- Multiple systems based on different paradigms used to produce annotated n-best outputs:
 - Matrex (example based): all language pairs ↔ English
 - Moses (phrase based): all language pairs ↔ English
 - **Metis (rule based):** Spanish \rightarrow English, German \rightarrow English
 - **Apertium (rule based):** Spanish ↔ English
 - **Lucy (rule based):** Spanish, German ↔ English
 - Joshua (hierarchical phrase based): all language pairs ↔ English
 - **TectoMT** (deep syntax based): Czech ↔ English
- **Annotation:** words, phrases, subtrees, chunks scored by different models (depending on the system)
- **Decoding:** machine learning techniques used to recombine those to get better output

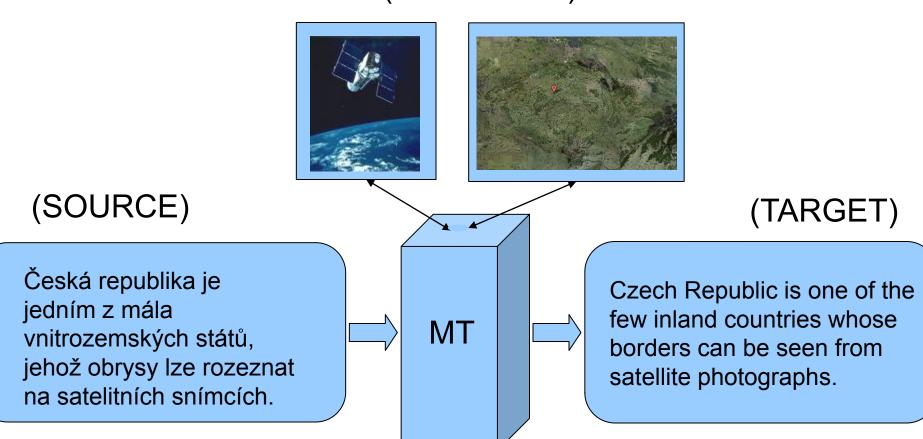


Context in Machine Translation

Increase MT quality and services in multimodal context







Context in Machine Translation



Domain adapted language and translation models

Method

- Large corpus divided in predefined domains
- Train translation and language models on each domain
- Train additional language models on the predefined domains
- Train a classifier to classify incoming documents to a domain
- Decode using respective translation and language models
- Evaluate results and revise method if necessary

Resources

- JRC-Acquis & Eurovoc
- Europarl

Innovation

- Design, implement and fine-tune classification algorithms
- Explore ways to effectively combine language and translation models

Context in Machine Translation



Context in statistical morphology learning

O. Kohonen, S. Virpioja, L. Leppänen and K. Lagus (2010):
 Semisupervised Extensions to Morfessor Baseline

Multimodal context in translation

- Research questions:
 - Which kind of multimodal contextual information can be used to advance MT quality? How to better access multimodal information?
 - In which MT applications multimodal information is useful?
- Current target: enhancing language and translation models with visual and textual context data and ontological knowledge
 - Use cases: translation of figure captions, translation of subtitles,
 MT in extended reality applications, robotics applications

Context in Machine Translation: 2011 Challenge



Data

- JRC Acquis corpus, 22 European languages
- Translations by the state-of-the-art statistical systems

Tasks

- To choose to the best translation from a set candidate translations by multiple systems (reranking task)
- Context is given by the source sentence, larger linguistic context and the domain of the text

Goals

- To discover the set of best context features, find representation
- To foster collaboration between MT and Machine Learning (ML) researchers;
 infuse MT research with advances from the ML field

Future Challenge: 2013

Using visual context (images)

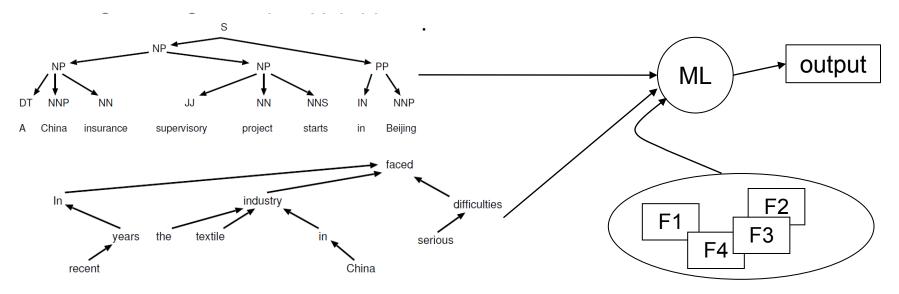


Data and Machine Learning for MT

Data and Advanced Machine Learning in MT



- "There is no data like more data"
 - Data crawling, cleanup, deduplication, ...
 - Available through META-SHARE
- Advanced Machine Learning Experiments
 - Combining several previously described approaches





Related Projects

EU 7th FP Machine Translation (selected projects)



EuromatrixPlus

 Machine Translation in general – now 8 selected languages (Czech, English, French, Spanish, German, Italian, Slovak, Bulgarian)

FAUST

- Improving fluency, incorporating user feedback (fast)
- French, English, Czech, Spanish

ACCURAT

- Using comparable corpora, esp. for low-resource languages
- Estonian, Croatian, ...

LetsMT! (PSP)

- Building of data resources (low-resourced languages)
- For business and research

Panacea

- Building Resources & Language Tools
- Tools + Resources → Automatically analyzed corpora

Khresmoi (IP)

- Medical information retrieval for patients and practitioners
- Cross-language (English, German, Czech, French) ← MT



The Future

The Future



Resources, resources, resources

... and their avialability (META-SHARE)

Novel, high-risk research

- Linguistics
 - Unclear "which linguistics", but some
- Language Understanding
 - Context, domain knowledge (ontologies?), other modalitites
- ...but SMT is here to stay (in some form)
 - ... even though we might not recognize the current "kitchen-sink" paradigm a few years from now
- New algorithms
 - Neural networks (finally?), Genetic algorithms, Brain research, ...
- Better [automatic] evaluation to guide progress

Commercial Applications

- Post-editing (CAT) tools with integrated (S)MT, novel features, ergonomics
- Multilingual information access, information extraction, summarization, sentiment

Q/A



Thank you very much.

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