Adaptation of Machine Translation to Specific Domains and Applications

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Computational Linguistics

- The scientific study of human language from a computational perspective.
- **Subfields**: linguistic analysis of text, document analysis, speech recognition, dialog systems, information retrieval and extraction, machine translation, ...

My Research Area

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Machine Translation

- Translating text in one human language into another by computer software.
- Application areas:
  - High quality translation
  - Computer-assisted translation
  - Online communication across languages
  - Cross-lingual information retrieval

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Machine Translation Approaches

Rule-based:

- Manually created rules and dictionaries map grammatical structures and words from one language to another.

Example-based:

- Input split into phrases which are translated by analogy to preexisting translations in a form of parallel texts.

Statistical:

- Translations generated by statistical models derived from analysis of parallel texts.

Neural:

- Based on deep neural networks trained directly to produce translated texts.

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Statistical Machine Translation (SMT)

- Translation from F to E generated according to probability distribution $p_{\vec{\theta}}(\mathbf{e}|\mathbf{f})$
  - $\mathbf{f}$: sentence in source language F (e.g. French)
  - $\mathbf{e}$: sentence in target language E (e.g. English)

- $p_{\vec{\theta}}(\mathbf{e}|\mathbf{f})$ approximated by statistical models trained on :
  - a) parallel texts: texts presented in F and E
  - b) monolingual data: texts in E

- Main issues:
  1. Specification of the model
  2. Training model parameters
  3. Finding the best translation

Finding the Best Translation

,

Finding the Best Translation

1. Input sentence: ,

Example: **f**: Morgen gehe ich zur einer Untersuchung ins Krankenhaus .

Finding the Best Translation

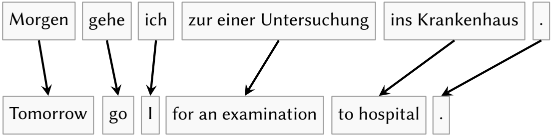
1. Input sentence: segmented into phrases, ,

Example: f: | Morgen | gehe | ich | zur einer Untersuchung | ins Krankenhaus | . |

Finding the Best Translation

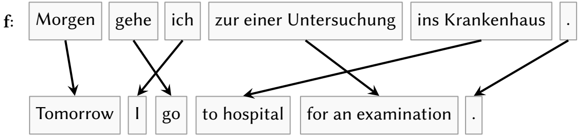
1. Input sentence: segmented into phrases, that are translated,

Example: f:



1. Input sentence: segmented into phrases, that are translated, and reordered

Example:



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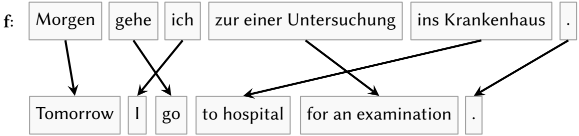

2. Multiple ways to segment, translate, reorder → multiple hypotheses:

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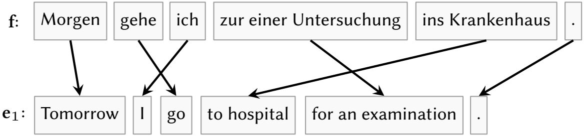

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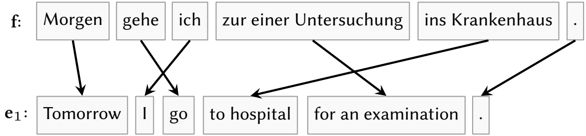

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e_2: | Tomorrow | I | will go | to hospital | for an examination | . |

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Example:

f: | Morgen | gehe | ich | zur einer Untersuchung | ins Krankenhaus | . |

$\mathbf{e}_1$: | Tomorrow | I | go | to hospital | for an examination | . |

2. Multiple ways to segment, translate, reorder → multiple hypotheses:

$\mathbf{e}_2$: | Tomorrow | I | will go | to hospital | for an examination | . |

$\mathbf{e}_3$: | Tomorrow | I | am going | to hospital | for an appointment | . |

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Example:

f:	Morgen	gehe	ich	zur einer Untersuchung	ins Krankenhaus	.
$\mathbf{e}_1$:	Tomorrow	I	go	to hospital	for an examination	.

2. Multiple ways to segment, translate, reorder $\rightarrow$ multiple hypotheses:

$\mathbf{e}_2$:	Tomorrow	I	will go	to hospital	for an examination	.
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$\mathbf{e}_1$:	Tomorrow	I	go	to hospital	for an examination	.	-0.17

2. Multiple ways to segment, translate, reorder → multiple hypotheses:

$\mathbf{e}_2$:	Tomorrow	I	will go	to hospital	for an examination	.	-0.15
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3. Each hypothesis scored by model: $s(\mathbf{e}, \mathbf{f})$

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3. Each hypothesis scored by model: $s(\mathbf{e}, \mathbf{f})$

4. The highest-scored hypothesis selected as the best translation: $\mathbf{e}_{\text{best}}$

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- Given a foreign sentence $\mathbf{f}$, find its translation $\mathbf{e}_{\text{best}}$:

$$\mathbf{e}_{\text{best}} = \underset{\mathbf{e} \in \text{English}}{\arg\max}\ p(\mathbf{e}|\mathbf{f})$$

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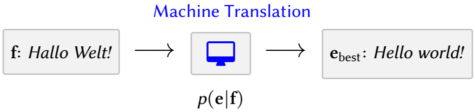

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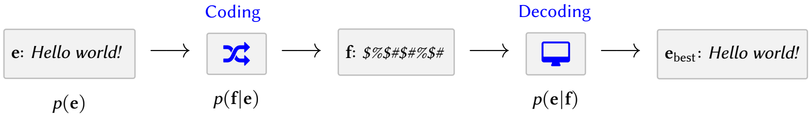

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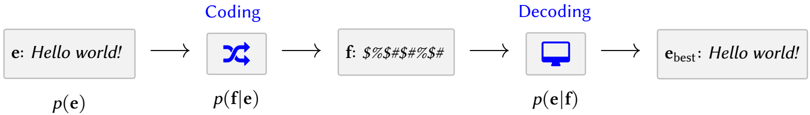

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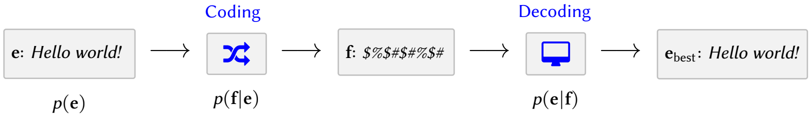

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- Basic model components:
  - Translation model $p(\mathbf{f}|\mathbf{e})$ – modeling adequacy of translation $\mathbf{e} \rightarrow \mathbf{f}$
  - Language model $p(\mathbf{e})$ – modeling fluency of $\mathbf{e}$

Training Model Parameters

Translation model: $p(\mathbf{f}|\mathbf{e})$

- Approximates probability of $\mathbf{e} \rightarrow \mathbf{f}$ from parallel texts

$$p(\mathbf{f}=\text{"a cold"}|\mathbf{e}=\text{"rýmu"}) = \frac{\#(\mathbf{e}=\text{"rýmu"}, \mathbf{f}=\text{"a cold"})}{\#(\mathbf{e}=\text{"rýmu"})} = 0.020389$$

$$p(\mathbf{f}=\text{"a cold"}|\mathbf{e}=\text{"nachlazení"}) = \frac{\#(\mathbf{f}=\text{"a cold"}, \mathbf{e}=\text{"nachlazení"})}{\#(\mathbf{e}=\text{"nachlazení"})} = 0.023231$$

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Language model: $p(\mathbf{e})$

- Approximates probability of $\mathbf{e}$ from monolingual texts

$$p(\mathbf{e}=\text{"dostal nachlazení"}) = \frac{\#(\mathbf{e}=\text{"dostal nachlazení"})}{N} = 0.072 \cdot 10^{-6}$$

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Example:

$$\begin{array}{llll} \mathbf{f}: & \boxed{\text{Peter}} & \boxed{\text{got}} & \boxed{\text{a cold}} \\ & \downarrow & \downarrow & \downarrow \\ \mathbf{e}_1: & \boxed{\text{Petr}} & \boxed{\text{dostal}} & \boxed{\text{nachlazení}} \end{array} \qquad \begin{array}{llll} \mathbf{f}: & \boxed{\text{Peter}} & \boxed{\text{got}} & \boxed{\text{a cold}} \\ & \downarrow & \downarrow & \downarrow \\ \mathbf{e}_2: & \boxed{\text{Petr}} & \boxed{\text{dostal}} & \boxed{\text{rýmu}} \end{array}$$

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Example:

$\mathbf{f}$:	Peter	got	a cold
$\mathbf{e}_1$:	Petr	dostal	nachlazení

$$s(\mathbf{e}_1, \mathbf{f}) < s(\mathbf{e}_2, \mathbf{f})$$

$\mathbf{f}$:	Peter	got	a cold
$\mathbf{e}_2$:	Petr	dostal	rýmu

Translation model: $p(\mathbf{f}|\mathbf{e})$

- Approximates probability of $\mathbf{e} \rightarrow \mathbf{f}$ from parallel texts ($\sim 10^7$ sentence pairs)

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Language model: $p(\mathbf{e})$

- Approximates probability of $\mathbf{e}$ from monolingual texts ($\sim 10^9$ words)

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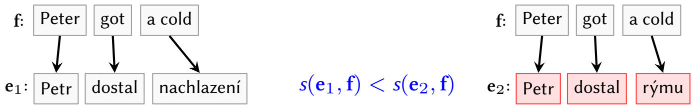

SMT Model cont.

- Noisy channel model

$$\mathbf{e}_{\text{best}} = \underset{\mathbf{e} \in \text{English}}{\arg\max}\; p(\mathbf{f}|\mathbf{e})\; p(\mathbf{e}) \qquad \cdots$$

SMT Model cont.

- Noisy channel model extended to allow:
  1. additional components: reordering model $r(\mathbf{e}, \mathbf{f})$, length model $l(\mathbf{e}, \mathbf{f})$, ...

$$\mathbf{e}_{\text{best}} = \underset{\mathbf{e} \in \text{English}}{\arg\max}\; p(\mathbf{f}|\mathbf{e})\; p(\mathbf{e})\; r(\mathbf{e}, \mathbf{f})\; l(\mathbf{e}, \mathbf{f}) \quad \cdots$$

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  2. component weights: λ_i

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- Final model:

$$\mathbf{e}_{\text{best}} = \underset{\mathbf{e} \in \text{English}}{\arg\max} \prod_{i=1}^{n} h_i(e, f)^{\lambda_i} = \underset{\mathbf{e} \in \text{English}}{\arg\max} \sum_{i=1}^{n} \lambda_i \log h_i(\mathbf{e}, \mathbf{f})$$

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log-linear model
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Weights λ_i – model hyperparameters

- Tuned by Minimum Error Rate Training (MERT) to maximize translation quality on development set of parallel texts ($\sim 10^3$ sentence pairs).
- Traslation quality measured as similarity to human translation (e.g. BLEU).

My Work:
Adaptation of Statistical Machine Translation

The Problem

Theory:

- SMT training $\times$ test data $\sim$ the same distribution

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- SMT trained on: news, parliamentary proceedings, novels, movie subtitles $\rightarrow$ general (non-specific) domain.

$\Rightarrow$ Translation quality decreases when translating text from specific domains:

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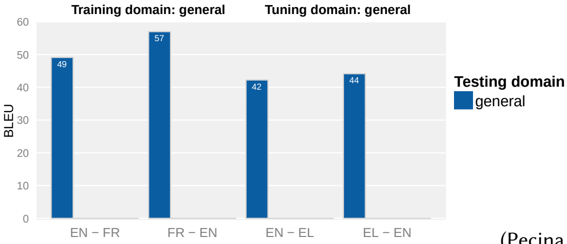

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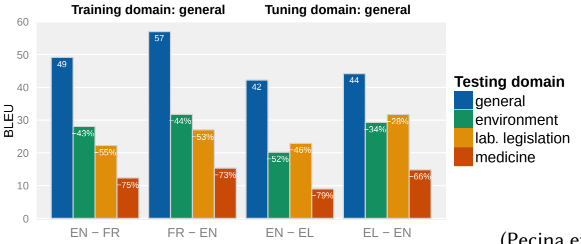

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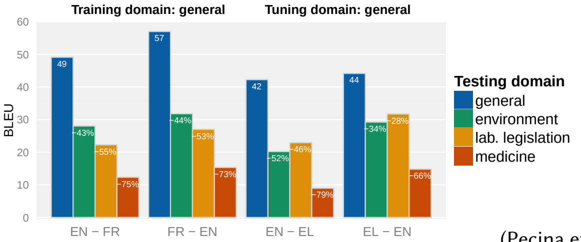

(Pecina et al., 2012)

Problem:

- Improving translation for specific domains

P. Pecina, A. Toral, V. Papavassiliou, P. Prokopidis, J. van Genabith: Domain Adaptation of Statistical Machine Translation using Web-Crawled Resources: A Case Study, *Proceedings of the 16th Annual Conference of EAMT*, 145-152. Trento, Italy, 2012..

Research Goals

1. Adaptation of SMT to specific-domains
2. Adaptation of SMT to cross-lingual information retrieval
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The work conducted within three research projects funded by EU:

PANACEA — FP7, 2010–2012

khresmoi (MEDICAL INFORMATION ANALYSIS & RETRIEVAL) — FP7, 2012–2014

KCONNECT — H2020, 2015–2017

1. Adaptation of SMT to Specific Domains

Domain Adaptation of SMT

Task:

- Adaptation of SMT systems trained on general domain data to a specific domain for which no or only limited data is available.

What can be improved?

1. Hyperparameters λ_i tuning (Pecina et al., 2012)
2. Language $p(\mathbf{e})$ and translation model $p(\mathbf{f}|\mathbf{e})$ training (Pecina et al., 2015)
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- $s(\mathbf{e}, \mathbf{f}) = \sum_{i=1}^{n} \lambda_i \log h_i(\mathbf{e}, \mathbf{f})$, λ_i tuned by MERT on development data.

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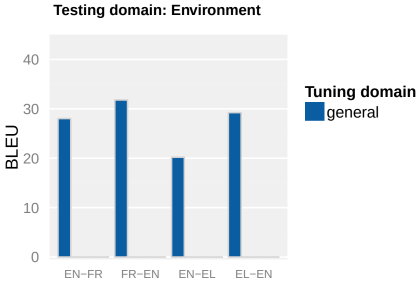

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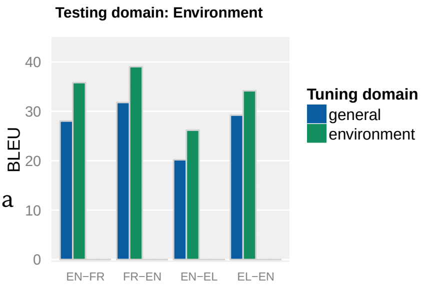

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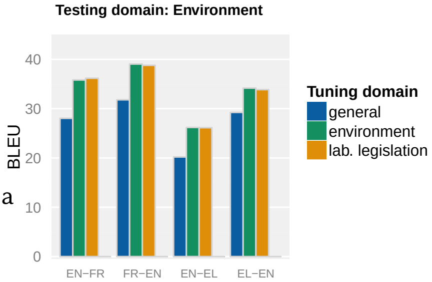

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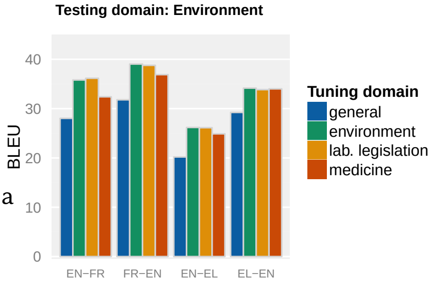

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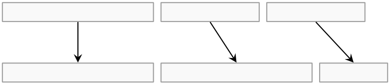

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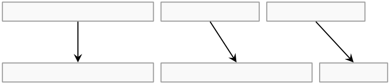

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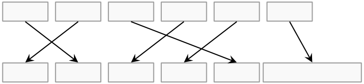

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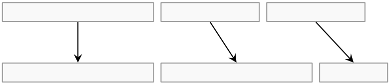

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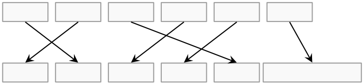

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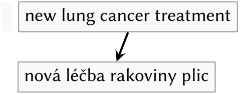

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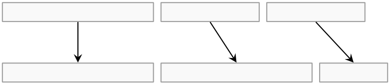

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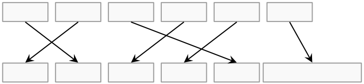

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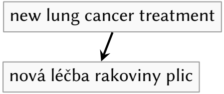

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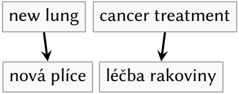

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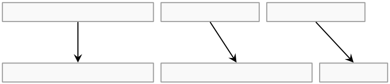

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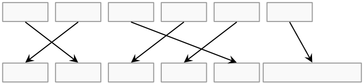

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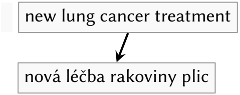

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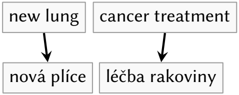

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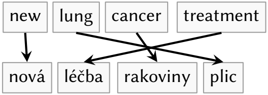

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2. SMT for Cross-lingual Information Retrieval

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query

bilateral infiltrates and radiography

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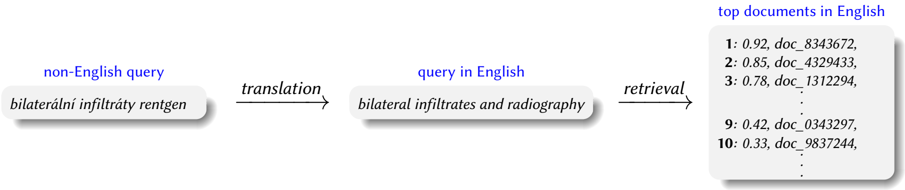

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Evaluation:

- P@10 (ratio of relevant documents among top 10)

SMT for Query Translation

- **Standard approach:** use the single best query translation by SMT
- **Problem:**
  - SMT trained towards translation quality (e.g. BLEU).
  - CLIR evaluated based on retrieval quality (e.g. P@10).
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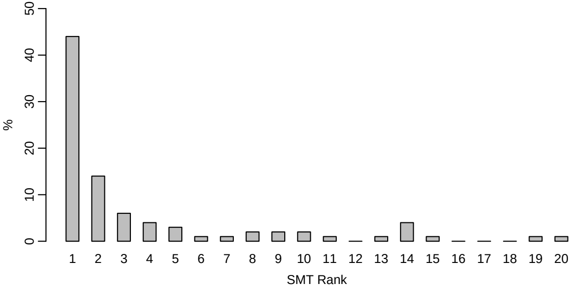

Distribution of the most IR-useful translations among top 20 SMT translations

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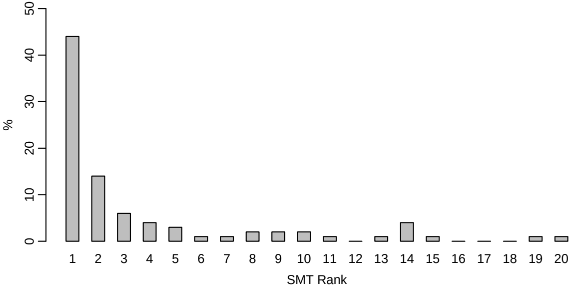

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- **Our approach**: reranking multiple SMT translations (Saleh & Pecina, 2016)

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Query Translation Reranking

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query in Czech

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Features:

- internal SMT features (h_i scores)
- external features: word frequencies from document collection, Wikipedia, …

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Evaluated using the CLEF eHealth collection:

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Google Translate	50.91	49.70	49.39
Bing Translator	47.88	48.64	46.52

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Google Translate	50.91	49.70	49.39
Bing Translator	47.88	48.64	46.52

S. Saleh, P. Pecina: Reranking Hypotheses of Machine-Translated Queries for Cross-Lingual Information Retrieval, *Proceedings of the 7th International Conference of the CLEF Association*, 54–66. Évora, Portugal, 2016. SCOPUS.

Conclusions

Conclusions and Future Work

Main findings

1. SMT can be effectively adapted to specific domains
2. SMT reranking improves cross-lingual information retrieval.
3. Web is a great source of domain-specific language data.

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Future Work

1. Adaptation of Neural Machine Translation (NMT)
    - The problem persists: NMT requires adaptation to specific domains
    - Not much work done in this area so far.
2. Cross-lingual Information Retrieval
    - Exploitation of cross-lingual word embeddings