Interactive Machine Translation: From Research to Practice

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Joint work with:

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Franz Och    Jeff Heer
Daniel Cer    Chris Manning
The physicist Arthur Eddington drew on Borel's image further in *The Nature of the Physical World* (1928), writing: If I let my fingers wander idly over the keys of a typewriter it might happen that my screed made an intelligible sentence.

Le physicien Arthur Eddington a attiré sur l'image de Borel dans le caractère du monde physique (1928), écrit: Si je laisse mes doigts se promener les bras croisés sur les touches de la machine à écrire, il peut arriver que mon chape fait une phrase intelligible.
2014: Predictive Translation Memory

À équiper le centre de formation Studeo qui est accessible aux personnes à mobilité réduite et dont nous travaillons à la réalisation dans le cadre de l’institut Jedlička, avec l’association Tap, et ça depuis six ans.

To equip studeo training centre which is accessible to people with reduced mobility and we work to achieve in the framework of the Institute jedlička, with tap, and been there for six years.

Des enseignants se rendent régulièrement auprès des élèves de l’institut Jedličkův et leur proposent des activités qui les intéressent et les amusent.

Teachers regularly visit Jedličkův Institute students and offered them activities of interest to them and having fun.

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The students themselves cannot be required to attend courses, we are trying to help themselves cannot

themselves could not

dans le cadre de l’institut Jedlička, nous transférerons ce

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themselves do not

themselves cannot afford
2016: Lilt

We observe today not a victory of party but a celebration of freedom—symbolizing an end as well as a beginning—signifying renewal as well as change.

---

For I have sworn before you and Almighty God the same solemn oath our forbears prescribed nearly a century and three-quarters ago.

---

The world is very different now.
Classic Use Cases for MT

**Assimilation** – user pulls translation

“Gisting” – Google Translate / browser integration

Full-sentence MT

Main focus of the research community
Classic Use Cases for MT

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Main focus of the research community

**Dissemination** – content publishing

Intent to communicate

“Post-editing” – MT as productivity enhancer

Main focus of the translation industry
the man and the machine are collaborating to produce not only a translation...but also a device...that is being constantly enhanced.

[Kay 1980]
Mixed-Initiative Systems

Translation is a classic **mixed-initiative** task

**Mixed-initiative** A human-computer discourse in which each party takes turns driving the task
Mixed-Initiative Systems

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Prior Work: One-slide Summary

Basic post-editing

Makes translators faster (c. 2010 research)

Produces higher quality (c. 2013)
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**Qualitative assessment:** still poor, esp. for experts

[O’Brien and Moorkens 2014]
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**State of Interactive MT** (c. 2014)

- Speed / quality assessment: no better than PE
- Translators like the idea, in practice suggestions are distracting
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Dans le cadre de l’institut Jedlička, nous transférerons ce projet dans un no
Interactions

**Source comprehension** – simple lexicon, source coverage

**Target gisting** – partial and complete suggestions

**Target generation** – autocomplete, re-ordering

Informed by Horvitz' (1999) mixed-initiative principles
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Source Comprehension

Horvitz #6 – allowing efficient direct invocation and termination
Horvitz #5 – employing dialog to resolve key uncertainties
# Human Subjects Experimental Design

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Three research questions:

1. Does PTM reduce time?
2. Does PTM increase quality?
3. Do subjects use interactive aids?
PTM is better for Fr-En ($p < 0.05$)
Question #2 | Time

PTM is slower for En-De ($p < 0.01$)
Post-edit mode was easier at first, but the interactive mode was better once I got used to it.

If I had time to use the interactive tool and grow accustomed to its way of functioning, it would be quite useful...

I am used to this [post-edit], this is how Trados works.
The Contribution of End-Users to the TransType2 Project

This target-text mediated interactive MT is certainly an intriguing idea – but will it work? Only the system’s intended end-users, i.e. professional translators, can answer that question. The TransType2 (henceforth TT2) Consortium includes two translation firms, one in Canada (Société Gamma Inc.) and one in Spain (Celer Soluciones S.L.). These partners play a very important role in the TT2 project, serving to balance its ambitious research program with the concrete needs of real end-users. The project provides for various channels through which the end-users can interact with the research teams who are developing the translation engines. One of the most important of these are the user trials that begin about half-way through the project and continue right up to its conclusion, at month thirty-six.

In the following section, we describe in more detail the role of these end-users in the TransType2 project. In section 3, we present the protocol for the latest round of user evaluations, which have just been completed at Société Gamma and at Celer Soluciones. In section 4, we report on the main results obtained in those trials – results which are necessarily tentative, since the project still has more than a year to run. In the final section, we draw some conclusions about the future of IMT.

TransType – users typed 69% of text

[Langlais and Lapalme 2002]
**Question #3 | Interactive Usage**

TransType – users typed 69% of text  
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End of 2014: Open Problems

**Online adaptation**

- Not online, no domain adaptation
- Not tuned for prefixes
End of 2014: Open Problems

Online adaptation

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Prefix decoding was poor

Low next word accuracy
No diversity
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- Dropdown is distracting
- High learning curve
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Hierarchical Incremental Adaptation

**Goal:** Reduce repeated MT errors
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Hierarchical Incremental Adaptation

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- After each segment is translated, update the model
- Translation model: updates to features and weights
- Hierarchical domains: genres and documents

Each document has 3 domains: root, its genre, & the document itself

[Wuebker et al. 2015]
Incremental Adaptation: Approach

**Weight adaptation**

- Feature augmentation (FEDA) [Daumé III 2007]
  
  → all weights are replicated for all domains
Incremental Adaptation: Approach

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- For each example \((f, e)\), active domain features are added
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  [Daumé III 2007]
- For each example \((f, e)\), active domain features are added
- SGD with AdaGrad  
  [Duchi et al. 2011]
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Translation model adaptation

► Learn separate genre-specific translation model features
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**Translation model adaptation**

- Learn separate genre-specific translation model features
- Stream-based updates with suffix arrays [Levenberg et al. 2010]
Incremental Adaptation: Workflow

**Initialize**: baseline weights $\mathbf{w}_t$

For each new sentence pair $(f, e)$:

1. Stochastic weight update $\mathbf{w}_{t+1}$
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   \[ \Rightarrow \text{obtain alignment } \alpha \]
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   $\Rightarrow$ obtain alignment $\alpha$
3. add $(f, e, \alpha)$ to genre-specific translation model corpora
Incremental Adaptation: Experiments

German→English training data

- 6.4M parallel sentences: WMT 2015 + Patents (PatTr)
- 4B monolingual English tokens

Test data

- News (WMT)
- Lectures (IWSLT)
- Patents (PatTR)

MT system

Phrasal w/ 5gm LM [Green et al. 2014]
## Incremental Adaptation: BLEU (%) Results

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<td>baseline</td>
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<td>+ genre weights</td>
<td>26.6 (+0.8)</td>
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End of 2014: Open Problems

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- Not online, no domain adaptation
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UI issues
- Dropdown is distracting
- High learning curve
Prefix-Constrained Translation Inference

A user enters a prefix, MT system predicts the rest
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**Example:**
*Yemeni media report that there is traffic chaos in the capital.*

**Once the user has typed:**
*Jemenitische Medien berichten von einem Verkehrschaos*

**The system suggests:**
*in der Hauptstadt.*
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▶ Align the prefix to the source to determine what remains
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Align the prefix to the source to determine what remains

- Predict a suffix for the prefix
Inference: Baseline

Prior work [Barrachina et al. 2008; Ortiz-Martínez et al. 2009]

- Standard beam search (force decoding)
  
  One beam per source cardinality
  
  ![Diagram showing beam search]

- Discard all hypotheses that violate prefix $e_p$
Inference: Target Beam Search

1. Phrase alignment of source $f$ and prefix $e_p$
   ▶ Associate each beam with target cardinality

prefix length  1  2  3  4  5  6
Inference: Target Beam Search

1. Phrase alignment of source $f$ and prefix $e_p$
   ▶ Associate each beam with target cardinality

2. Generate suffix $e_s$ with standard beam search
   ▶ Copy partial hypotheses to source beams
   ▶ Standard cube-pruning beam search
Prefix Tuning

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**Prefix:** Jemenitische Medien berichten von einem Verkehrsschaos  
**Suffix:** in der Hauptstadt.
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⇒ Hierarchical, incremental tuning

Four feature domains:
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[Wuebker et al. 2015]

Four feature domains:

- **ROOT**
- **PREFIX**
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Four feature domains:

- ROOT
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- SUFFIX
- OVERLAP
## Results: Phrase-based

### English → French (newstest2014)

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<th>WPA ↑</th>
<th>KSR ↓</th>
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<tr>
<td>baseline</td>
<td>40.9</td>
<td>38.0</td>
<td>61.7</td>
</tr>
<tr>
<td>target beam</td>
<td>44.1</td>
<td>49.4</td>
<td>51.1</td>
</tr>
<tr>
<td>prefix tuning</td>
<td><strong>44.7</strong></td>
<td><strong>50.9</strong></td>
<td><strong>50.5</strong></td>
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**pxBleu** Prefix-Bleu (Bleu for the suffix only)

**WPA** Word Prediction Accuracy

**KSR** Key-Stroke-Ratio

[Koehn et al. 2014]

[Och et al. 2003]
Prefix NMT?

\[
\log p(e|f) = \sum_{i=1}^{|e|} \log p(e_i|e_{<i}, f; \theta)
\]

\[
\theta = \arg \min_{\theta} \sum_{f,e} \sum_{i} -\log p(e_i|e_{<i}, f; \theta)
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- \(e_{<i}\) can be interpreted as target prefix \(e_p\)
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Modification
- Condition on user prefix \(e_p\) instead of partial hypothesis
## Results: Prefix NMT

**English → German** (autodesk)

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NMT system: [Luong et al. 2015]
## Results: Prefix NMT

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NMT system: [Luong et al. 2015]
Recent NMT Work

**Idea:** add NMT as feature  
[Junczys-Dowmunt and Grundkiewicz 2016]

▶ en-de model of [Sennrich et al. 2016]
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Reduced beam size: 25
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Virtualized CPU (Google Cloud); native ops in OpenBLAS

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<td>60</td>
<td>2,500</td>
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<td>1,300</td>
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Interactive NMT Open Issues

Decoding time

- Distillation / pruning
- Reduced precision arithmetic
Interactive NMT Open Issues

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Periodic updates to model architecture
- PBMT: add feature, initialize to zero
Interactive NMT Open Issues

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Dynamic updates to word-piece / segmentation model
- Hypothesis: high user sensitivity to dropped content words
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Revisiting the Autocomplete Dropdown

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2. Distracting: 100% visual acuity for only 4–5 characters
3. No post-edit mode
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2. **Distracting**: 100% visual acuity for only 4–5 characters
3. No post-edit mode
2014 vs. 2016

Several music groups and **musical** groups and performers?
(Demo)
Interactive Machine Translation:
From Research to Practice

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30 October 2016
References I


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References II


Luong, Minh-Thang, Hieu Pham, and Christopher D. Manning (2015). “Effective Approaches to Attention-based Neural Machine Translation”. In: EMNLP.


