Machine Translation for Human Translators
Carnegie Mellon Ph.D. Thesis

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Alon Lavie (chair), Carnegie Mellon University
Chris Dyer, Carnegie Mellon University
Jaime Carbonell, Carnegie Mellon University
Gregory Shreve, Kent State University
When is a translation “good enough”?
Total solar eclipse spectacle with fire Arctic tour

2015-03-23 07:31 Source: People's Daily

UK GMT at 10:11 on March 20, a rare solar eclipse spectacle will come to Europe. According to local media reports, Norway, under the 1300 km distance Arctic Norway Svalbard and membership Danish Faroe Islands are the two can watch the full eclipse of the best observation points. In most European countries, the observer can only see part of the sun is blocked by the shadow of the moon, that is, the partial eclipse of the landscape.

This is the 1954 total solar eclipse once again usher in mainland Norway. According to the Norwegian local astronomers predicted from the next total solar eclipse occurred on Norwegian time to wait for 46 years, that is 2061. The next solar eclipse occurs recent times and the country was March 9, 2016 Sumatra; August 21, 2017 the United States and Chile, July 2, 2019 in.
daily operations

Practice

1. to maintain proper startup speed, not too much.

2. to observe the voltmeter voltage, if the voltage is below the limit, the truck should be stopped immediately.

3. truck during walking, but not allowed to flip the direction switch to change the direction of travel, to prevent burn damage electrical components and gear.

4. travel and promotion should not be carried out simultaneously.

5. Note the drive system, steering system is sound normal, abnormal sound should be immediately removed fault, prohibited ill job.

6. when the transition to slow down in advance.

7. when the poor road conditions in the job, it is important to reduce the appropriate and should reduce speed.
Human Translation

International Organizations

Global Businesses

Community Projects

Require human-quality translation of complex content

Machine translation currently unable to deliver quality and consistency
Human Translation

International Organizations

Global Businesses

Community Projects

$37 billion in 2014

Require human-quality translation of complex content

Machine translation currently unable to deliver quality and consistency
Use **machine translation** to improve speed of **human translation**
Use **machine translation** to improve speed of **human translation**

Increasing adoption by **government organizations and businesses**
Son comportement ne peut être qualifié que d’ irréprochable.
Son comportement ne peut être qualifié que d’irréprochable.

His behavior cannot be described as d’irréprochable.
Son comportement ne peut être qualifié que d’irréprochable.

His behavior cannot be described as d’irréprochable.

Its behavior can only be described as flawless.
Son comportement ne peut être qualifié que d’irréprochable.

His behavior cannot be described as d’irréprochable.

Its behavior can only be described as flawless.

MT task: minimize work for human translators
Post-editing faster and more accurate than unaided translation (Guerberof, 2009; Carl et al., 2011; Koehn, 2012; Zhechev, 2012; inter alia)

Productivity gains but MT systems not engineered for human post-editing

How can we extend MT systems to target post-editing?
While general improvements in MT quality have led to improved performance and increased interest in this application, there has been relatively little work on designing translation systems specifically for post-editing.

We present extensions to key components of MT pipelines that significantly reduce the amount of work required from human translators.
Thesis Claims

We claim that:

1. The amount of work required of human translators can be reduced by translation systems that immediately learn from editor feedback.
2. The usability of machine translations can be improved by automatically identifying the most costly types of translation errors and tuning MT systems to avoid them.
3. The most significant gains in post-editing productivity are realized when several system components can adapt in unison.
We claim that:

- The amount of work required of human translators can be reduced by translation systems that immediately learn from editor feedback.
We claim that:

- The amount of work required of human translators can be reduced by translation systems that *immediately learn* from editor feedback.

- The usability of machine translations can be improved by *automatically identifying* the most costly types of translation errors and tuning MT systems to avoid them.
We claim that:

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- The usability of machine translations can be improved by automatically identifying the most costly types of translation errors and tuning MT systems to avoid them.

- The most significant gains in post-editing productivity are realized when several system components can adapt in unison.
Research Contributions

To support our claims, we make the following contributions to the research community:

- A method for immediately incorporating post-editing data into a translation model.
- A technique for running an online learning algorithm that continuously updates feature weights during decoding.
- A workflow for training and deploying adaptive MT systems for human translators using only normal training data.
- An advanced automatic MT evaluation metric capable of fitting various measures of editing effort.
- An end-to-end post-editing pipeline that demonstrates the effectiveness of our adaptive systems in live post-editing scenarios.
Research Contributions

To support our claims, we make the following contributions to the research community:

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Overview

Online learning for statistical MT

- Translation model review
- Real time model adaptation
- Simulated post-editing

Post-editing software and experiments

- Kent State live post-editing

Automatic metrics for post-editing

- Meteor automatic metric
- Evaluation and optimization for post-editing

Conclusion and Future Work
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Conclusion and Future Work
Online Learning for MT

Statistical translation models built from bilingual data
Online Learning for MT

Statistical translation models built from bilingual data

Post-editing generates new bilingual data
Online Learning for MT

Statistical translation models built from bilingual data

Post-editing generates new bilingual data

Goal: incorporate post-editing data back into model in real time

Learn from feedback: avoid repeating the same translation errors
Online Learning for MT

Batch learning (standard MT):

- Estimation
- Prediction

Requirement: all system components operate at the sentence level
Online Learning for MT

Batch learning (standard MT):

Estimation → Prediction

Online learning (this work):

Prediction → Truth → Update

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Conclusion and Future Work
Post-Editing with Standard MT

Static

Large LM $\xrightarrow{X \rightarrow f/e}$ Grammar $w_i \ldots w_n$

Input Sentence

Decoder

Post-Editing
Machine Translation Formalism

Phrase-based machine translation (Koehn et al., 2003):

la vérité $\rightarrow$ the truth

- Match spans of input text against phrases we know how to translate
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la vérité $\rightarrow$ the truth

- Match spans of input text against phrases we know how to translate

Hierarchical phrase-based MT (Chiang, 2007):

$X \rightarrow \mathrm{la} \ X^1 / \mathrm{the} \ X^1$

$X \rightarrow \mathrm{vérité} / \mathrm{truth}$

- Generalization where phrases can contain other phrases
- Phrases become rules in a synchronous context-free grammar
Hierarchical Phrase-Based Translation Example

Input sentence: Pourtant, la vérité est ailleurs selon moi.

Translation Grammar:

\[
X \rightarrow X_{1} \text{ est ailleurs } X_{2}. / X_{2}, X_{1} \text{ lies elsewhere.}
\]

\[
X \rightarrow \text{Pouriant }, / \text{Yet}
\]

\[
X \rightarrow \text{la vérité } / \text{the truth}
\]

\[
X \rightarrow \text{selon moi } / \text{in my view}
\]

Glue Grammar:

\[
S \rightarrow S_{1} X_{2} / S_{1} X_{2}
\]

\[
S \rightarrow X_{1} / X_{2}
\]
Pourtant, la vérité est ailleurs selon moi.
Hierarchical Phrase-Based Translation Example

Pourant, la vérité est ailleurs selon moi.

F

X

la vérité

E

X

the truth

the truth
Hierarchical Phrase-Based Translation Example

Pourant, la vérité est ailleurs selon moi.

Yet in my view the truth
Pourant, la vérité est ailleurs selon moi.

Yet in my view, the truth lies elsewhere.
Model Parameterization

**Ambiguity**: many ways to translate the same source phrase

Add **feature scores** that encode properties of translation:

\[
\begin{align*}
X & \rightarrow \text{devis / quote} & 0.5 & 10 & -137 & \ldots \\
X & \rightarrow \text{devis / estimate} & 0.4 & 13 & -261 & \ldots \\
X & \rightarrow \text{devis / specifications} & 0.2 & 5 & -407 & \ldots 
\end{align*}
\]

Decoder uses **feature scores** and **weights** to select the most likely translation derivation.
Linear Translation Models

Single feature score for a translation derivation with rule-local features $h_i \in H_i$:

$$H_i(D) = \sum_{X \rightarrow \tilde{f}/\tilde{e} \in D} h_i(X \rightarrow \tilde{f}/\tilde{e})$$

Score for a derivation using several features $H_i \in H$ with weight vector $w_i \in W$:

$$S(D) = \sum_{i=1}^{|H|} w_i H_i(D)$$

Decoder selects translation with largest product $W \cdot H$
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Decoder selects translation with largest product $W \cdot H$

✓ sentence-level prediction step
Learning translations
Devis de garage en quatre étapes. Avec l’outil Auda-Taller, l’entreprise Audatex garantit que l’usager obtient un devis en seulement quatre étapes : identifier le véhicule, chercher la pièce de rechange, créer un devis et le générer. La facilité d’utilisation est un élément essentiel de ces systèmes, surtout pour convaincre les professionnels les plus âgés qui, dans une plus ou moins grande mesure, sont rétifs à l’utilisation de nouvelles techniques de gestion.

A shop’s estimate in four steps. With the AudaTaller tool, Audatex guarantees that the user gets an estimate in only 4 steps: identify the vehicle, look for the spare part, create an estimate and generate an estimate. User friendliness is an essential condition for these systems, especially to convincing older technicians, who, to varying degrees, are usually more reluctant to use new management techniques.
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Each sentence is a training instance
Devis de garage en quatre étapes

A shop’s estimate in four steps
Devis de garage en quatre étapes

A shop’s estimate in four steps
## Model Estimation: Phrase Extraction

Koehn et al. (2003), Och and Ney (2004), Och et al. (1999)

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- **de garage** → **a shop’s**
- **en quatre étapes** → **in four steps**
Yet  in  my  view  ,  the  truth  lies  elsewhere  .

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la vérité est ailleurs selon moi. \(\rightarrow\) in my view, the truth lies elsewhere.
Model Estimation: Hierarchical Phrase Extraction
Chiang (2007)

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$X_{1}$ est ailleurs $X_{2}$ .  $\rightarrow$  $X_{2}$ , $X_{1}$ lies elsewhere .
✓ sentence-level rule learning

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F

E

la vérité est ailleurs selon moi .  \[\rightarrow\] in my view , the truth lies elsewhere .

\(X_1\) est ailleurs \(X_2\) .  \[\rightarrow\] \(X_2\) , \(X_1\) lies elsewhere .
Add feature functions to rules $X \rightarrow \bar{f}/\bar{e}$:

1. Training Data
2. Corpus Stats
3. Scored Grammar (Global)
4. Translate Sentence
Parameterization: Feature Scoring

Add feature functions to rules $X \rightarrow \bar{f}/\bar{e}$:
Suffix Array Grammar Extraction

Static

Training Data → Suffix Array

SA Sample → Sample Stats → Grammar (Sentence) → Translate Sentence

\[ \sum_{i=1}^{N} \rightarrow \frac{\bar{f}}{\bar{e}} \]

Input Sentence
Scoring via Sampling

Suffix array statistics available in sample $S$ for each source $\bar{f}$:

- $c_S(\bar{f}, \bar{e})$: count of instances where $\bar{f}$ is aligned to $\bar{e}$ (co-occurrence count)

- $c_S(\bar{f})$: count of instances where $\bar{f}$ is aligned to any target

- $|S|$: total number of instances (equal to occurrences of $\bar{f}$ in training data, up to the sample size)

Used to calculate feature scores for each rule at the time of extraction
Scoring via Sampling

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Used to calculate feature scores for each rule at the time of extraction

$\times$ sentence-level grammar extraction, but static training data
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Conclusion and Future Work
Online Grammar Extraction
Denkowski et al. (EACL 2014)

Static

Training Data → Suffix Array

Sample

\[ \sum_{i=1}^{N} \]

Sample Stats

Grammar (Sentence)

Input Sentence

Translate Sentence

\[ X \rightarrow \hat{f}/\hat{e} \]
Online Grammar Extraction
Denkowski et al. (EACL 2014)

Static

Training Data → Suffix Array

Dynamic

Sample Stats

Grammar (Sentence) → Post-Edit Sentence

Input Sentence

Sample

$\sum_{i=1}^{N} \tilde{f}/\tilde{e}$

Translate Sentence

Grammar Extraction

Sample Stats

Lookup Table

Translate Sentence
Maintain dynamic lookup table for post-edit data

Pair each sample $S$ from suffix array with exhaustive lookup $L$ from lookup table

Parallel statistics available at grammar scoring time:

- $c_L(\bar{f}, \bar{e})$: count of instances where $\bar{f}$ is aligned to $\bar{e}$ (co-occurrence count)
- $c_L(\bar{f})$: count of instances where $\bar{f}$ is aligned to any target
- $|L|$: total number of instances (equal to occurrences of $\bar{f}$ in post-edit data, no limit)
Rule Scoring
Denkowski et al. (EACL 2014)

Suffix array feature set (Lopez 2008)

Phrase features encode likelihood of translation rule given training data

Features scored with $S$:

$$\text{CoherentP}(e|f) = \frac{c_S(f, e)}{|S|}$$

$$\text{Count}(f, e) = c_S(f, e)$$

$$\text{SampleCount}(f) = |S|$$
Rule Scoring
Denkowski et al. (EACL 2014)

Suffix array feature set (Lopez 2008)

Phrase features encode likelihood of translation rule given training data

Features scored with $S$ and $L$:

\[
\text{CoherentP}(e|f) = \frac{c_S(f, \bar{e}) + c_L(f, \bar{e})}{|S| + |L|}
\]

\[
\text{Count}(f, e) = c_S(f, \bar{e}) + c_L(f, \bar{e})
\]

\[
\text{SampleCount}(f) = |S| + |L|
\]
Rule Scoring
Denkowski et al. (EACL 2014)

Indicator features identify certain classes of rules

Features scored with $S$:

$$\text{Singleton}(f) = \begin{cases} 1 & c_S(\bar{f}) = 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Singleton}(f, e) = \begin{cases} 1 & c_S(\bar{f}, \bar{e}) = 1 \\ 0 & \text{otherwise} \end{cases}$$
Indicator features identify certain classes of rules

Features scored with $S$ and $L$:

\[
\text{Singleton}(f) = \begin{cases} 
1 & c_S(f) + c_L(f) = 1 \\
0 & \text{otherwise}
\end{cases}
\]

\[
\text{Singleton}(f, e) = \begin{cases} 
1 & c_S(f, e) + c_L(f, e) = 1 \\
0 & \text{otherwise}
\end{cases}
\]

\[
\text{PostEditSupport}(f, e) = \begin{cases} 
1 & c_L(f, e) > 0 \\
0 & \text{otherwise}
\end{cases}
\]
Choose feature weights that maximize objective function (BLEU score) on a development corpus

Minimum error rate training (MERT) (Och, 2003):
Choose feature weights that maximize objective function (BLEU score) on a development corpus

Minimum error rate training (MERT) (Och, 2003):

Margin infused relaxed algorithm (MIRA) (Chiang 2012):
Post-Editing with Standard MT
Denkowski et al. (EACL 2014)
Post-Editing with Adaptive MT
Denkowski et al. (EACL 2014)

- Static
  - LM
  - Large Bitext

- Dynamic
  - PE Data
  - Weights
  - \( X \rightarrow f/e \)
  - TM

- Input Sentence
- Decoder
- Post-Editing
How can we build systems without translators in the loop?
Overview

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- Meteor automatic metric
- Evaluation and optimization for post-editing

Conclusion and Future Work
Simulated Post-Editing
Denkowski et al. (EACL 2014)

Incremental training data

Source
Hola contestadora ...
He llamado a servicio ...
Ignoré la advertencia ...
Ahora anochece, y mi ...
Todavía sigo en espera ...
No creo que me hayas ...
Ya he presionado cada ...

Target (Reference)
Hello voicemail, my old ...
I’ve called for tech ...
I ignored my boss’ ...
Now it’s evening, and ...
I’m still on hold. I’m ...
I don’t think you ...
I punched every touch ...

Use pre-generated references in place of post-editing
(Hardt and Elming, 2010)

Build, evaluate, and deploy adaptive systems using only standard training data
Simulated Post-Editing Experiments
Denkowski et al. (EACL 2014)

**MT System** (cdec)
- Hierarchical phrase-based model using suffix arrays
- Large 4-gram language model
- MIRA optimization

**Model Adaptation**
- Update TM and weights independently and in conjunction

**Training Data**
- WMT12 Spanish–English and NIST 2012 Arabic–English

**Evaluation Data**
- WMT/NIST news (standard test sets)
- TED talks (totally blind out-of-domain test)
Simulated Post-Editing Experiments
Denkowski et al. (EACL 2014)

Spanish–English

![Graph showing BLEU scores for Spanish–English translation across WMT, TED1, and TED2 datasets, comparing baseline, grammar, MIRA, and both combined methods.]

Arabic–English

![Graph showing BLEU scores for Arabic–English translation across NIST, TED1, and TED2 datasets, comparing baseline, grammar, MIRA, and both combined methods.]

Up to 1.7 BLEU improvement over static baseline
Simulated Post-Editing Experiments
Denkowski et al. (EACL 2014)

Spanish–English

Arabic–English

Up to 1.7 BLEU improvement over static baseline
How can we better leverage incremental data?
Translation Model Combination
Denkowski (AMTA 2014 Workshop on Interactive and Adaptive MT)

cdec (Dyer et al., 2010)
- **Single** translation model updated with new data
- **Single** feature set that changes over time (summation)

Moses (Koehn et al., 2007)
- **Multiple** translation models: background and post-editing
- **Per-feature** linear interpolation in context of full system

Recent additions to Moses toolkit
- **Dynamic** suffix array phrase tables (Germann, 2014)
- **Fast** MIRA implementation (Cherry and Foster, 2012)
- **Multiple** phrase tables with runtime weight updates (Denkowski, 2014)
Translation Model Combination
Denkowski (AMTA 2014 Workshop on Interactive and Adaptive MT)

Spanish–English

Arabic–English

![BLEU Score Comparison](image)

Up to 4.9 BLEU improvement over static baseline
Translation Model Combination
Denkowski (AMTA 2014 Workshop on Interactive and Adaptive MT)

Spanish–English

Arabic–English

Up to 4.9 BLEU improvement over static baseline
Related Work: Learning from Post-Editing

Updating translation grammars with post-editing data

- **Cache-based** translation and language models (Nepveu et al., 2004; Bertoldi et al., 2013)
- Store **sufficient statistics** in grammar (Ortiz-Martínez et al., 2010)
- Distinguish between **background** and **post-editing** data (Hardt and Elming, 2010)

Updating feature weights during decoding

- Various **online learning** algorithms to update **MERT** weights (Martínez-Gómez et al., 2012; López-Salcedo et al., 2012)
- Algorithm for learning from **binary classification** examples (Saluja et al., 2012)
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Conclusion and Future Work
Tools for Human Translators

Getting Started
Finding a location for your photo printer

1. Place the photo printer on a flat, clean and dust-free surface, in a dry location, and out of direct sunlight.
2. Allow at least 12 cm clearance from the back of the photo printer for the paper to travel. When connecting power orUSB cables, keep the cables clear of the paper path to the front and rear of the photo printer.
3. For proper ventilation, make sure the top and back of the photo printer are not blocked.
4. Allow enough space on all sides of the photo printer to let you connect and disconnect cables, change the color cartridge, and add paper.

Connecting and turning on the power

Note:
Use only the AC power adapter included with your photo printer.

Erste Schritte
Passenden geeigneten Aufstellungsort für Ihren Fotodrucker finden

1. Platzieren Sie den Foto auf einer flachen, sauberen und staubfreien Oberfläche, und stellen Sie ihn an einem trockenen Ort auf. Auf keinen Fall sollte er direktem Sonnenlicht ausgesetzt sein.
2. Lassen Sie mindestens 12 cm Abstand von der Rückseite des Foto Druckers für das Papier zu reißen.

Anschließen und Einschalten der Stromversorgung

Hinweis:
Verwenden Sie nur den Netzadapter im Lieferumfang enthalten mit Ihrem Foto Drucker.
<table>
<thead>
<tr>
<th>Source</th>
<th>Translation</th>
<th>Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Muchas gracias Chris. Y es en verdad un gran honor</td>
<td>Thank you so much, Chris. And it's truly a great honor</td>
<td>5 - Very Good</td>
</tr>
<tr>
<td>2. tener la oportunidad de venir a este escenario por segunda vez. Estoy extremadamente agradecido.</td>
<td>to have the opportunity to come to this stage twice. I'm extremely grateful.</td>
<td>1 - Gibberish</td>
</tr>
<tr>
<td>3. He quedado conmovido por esta conferencia, y deseo agradecer a todos ustedes</td>
<td>I have been moved by this conference, and I would like to thank all of you</td>
<td></td>
</tr>
<tr>
<td>4. sus amables comentarios acerca de lo que tenía que decir la otra noche.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Y digo eso sinceramente, en parte porque -- (Sollozos fingidos) -- ¡lo necesito! (Risas)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. ¡Pónganse en mi posición!</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Source</td>
<td>Translation</td>
</tr>
<tr>
<td>---</td>
<td>------------------------------------------------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>1</td>
<td>Muchas gracias Chris. Y es en verdad un gran honor</td>
<td>Thank you so much, Chris. And it's truly a great honor</td>
</tr>
<tr>
<td>2</td>
<td>tener la oportunidad de venir a este escenario por segunda vez. Estoy extremadamente agradecido.</td>
<td>to have the opportunity to come to this stage twice. I'm extremely grateful.</td>
</tr>
<tr>
<td>3</td>
<td>He quedado conmovido por esta conferencia, y deseo agradecer a todos ustedes</td>
<td>I have been blown away by this conference, and I want to thank all of you for the many</td>
</tr>
<tr>
<td>4</td>
<td>sus amables comentarios acerca de lo que tenía que decir la otra noche.</td>
<td>Translating...</td>
</tr>
<tr>
<td>5</td>
<td>Y digo eso sinceramente, en parte porque -- (Sollozos fingidos) -- ¡lo necesito! (Risas)</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>¡Pónganse en mi posición!</td>
<td></td>
</tr>
</tbody>
</table>
## TransCenter Post-Editing Interface

Denkowski and Lavie (AMTA 2012), Denkowski et al. (HaCat 2014)

<table>
<thead>
<tr>
<th>ID</th>
<th>MT</th>
<th>Post-Edited</th>
<th>Rating</th>
<th>Keypress</th>
<th>Mouseclick</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Thank you, Chris.</td>
<td>Thank you, Chris. And</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>22776</td>
</tr>
<tr>
<td>2</td>
<td>have the opportu second time. I a</td>
<td>to have the opportuni second time. I am ext</td>
<td>5</td>
<td>3</td>
<td>1</td>
<td>26259</td>
</tr>
<tr>
<td>3</td>
<td>I have been mov to thank all of yo</td>
<td>I have been move by to thanks all of you</td>
<td>5</td>
<td>146</td>
<td>3</td>
<td>156690</td>
</tr>
<tr>
<td>4</td>
<td>for their kind com other night.</td>
<td>for your kind commer other night.</td>
<td>3</td>
<td>13</td>
<td>3</td>
<td>31397</td>
</tr>
<tr>
<td>5</td>
<td>And I say that sin fingidos) -- what</td>
<td>And I say that sincere -- I need it! (Laughter</td>
<td>2</td>
<td>39</td>
<td>3</td>
<td>48657</td>
</tr>
<tr>
<td>6</td>
<td>Put yourselves in</td>
<td>Put yourselves in my</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>21007</td>
</tr>
<tr>
<td>7</td>
<td>Volé on the plane</td>
<td>I flew on the vice pre</td>
<td>4</td>
<td>18</td>
<td>6</td>
<td>43915</td>
</tr>
<tr>
<td>8</td>
<td>Now I have my m</td>
<td>Now I have take off m plane!</td>
<td>2</td>
<td>23</td>
<td>2</td>
<td>46021</td>
</tr>
<tr>
<td>9</td>
<td>(Laughter) (Applau</td>
<td>(Laughter) (Applause)</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>1716</td>
</tr>
<tr>
<td>10</td>
<td>I will tell you a qu</td>
<td>I will tell you a quick like for me.</td>
<td>5</td>
<td>5</td>
<td>1</td>
<td>14248</td>
</tr>
</tbody>
</table>
## TransCenter Post-Editing Interface

Denkowski and Lavie (AMTA 2012), Denkowski et al. (HaCat 2014)

<table>
<thead>
<tr>
<th>Time</th>
<th>Sentence 1 Edits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial</td>
<td>The latest issue of Musharraf?</td>
</tr>
<tr>
<td>1345076800710</td>
<td>The latest issue of Musharraf?</td>
</tr>
<tr>
<td>1345076800861</td>
<td>The la of Musharraf?</td>
</tr>
<tr>
<td>1345076801036</td>
<td>The las of Musharraf?</td>
</tr>
<tr>
<td>1345076801212</td>
<td>The last of Musharraf?</td>
</tr>
<tr>
<td>1345076801341</td>
<td>The last of Musharraf?</td>
</tr>
<tr>
<td>1345076801508</td>
<td>The last a of Musharraf?</td>
</tr>
<tr>
<td>1345076801644</td>
<td>The last ac of Musharraf?</td>
</tr>
<tr>
<td>1345076801852</td>
<td>The last act of Musharraf?</td>
</tr>
<tr>
<td>1345076810117</td>
<td>The last act of Musharraf?</td>
</tr>
<tr>
<td>1345076811637</td>
<td>The of Musharraf?</td>
</tr>
<tr>
<td>1345076811796</td>
<td>The ofMusharraf?</td>
</tr>
<tr>
<td>1345076811973</td>
<td>The oMusharraf?</td>
</tr>
<tr>
<td>1345076814613</td>
<td>The Musharraf?</td>
</tr>
<tr>
<td>1345076815893</td>
<td>Musharraf?</td>
</tr>
<tr>
<td>1345076816100</td>
<td>Musharraf's?</td>
</tr>
<tr>
<td>1345076816269</td>
<td>Musharraf's?</td>
</tr>
<tr>
<td>1345076816535</td>
<td>Musharraf's last act?</td>
</tr>
<tr>
<td>Final</td>
<td>Musharraf's last act?</td>
</tr>
</tbody>
</table>
Overview

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Conclusion and Future Work
Experimental Setup

- Six translation studies students from Kent State University post-edited MT output
- Text: 4 excerpts from TED talks translated from Spanish into English (100 sentences total)
- Two excerpts translated by static system, two by adaptive system (shuffled by user)
- Record post-editing effort (HTER) and translator rating
Results

- Adaptive system **significantly outperforms** static baseline
- **Small improvement** in simulated scenario leads to **significant improvement** in production

<table>
<thead>
<tr>
<th></th>
<th>HTER ↓</th>
<th>Rating ↑</th>
<th>Sim PE BLEU ↑</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>19.26</td>
<td>4.19</td>
<td>34.50</td>
</tr>
<tr>
<td>Adaptive</td>
<td>17.01</td>
<td>4.31</td>
<td><strong>34.95</strong></td>
</tr>
</tbody>
</table>
Related Work: Computer-Aided Translation Tools

Translation software suites

- CASMACAT project: full-featured open source *translator’s workbench* software (Ortiz-Martínez et al., 2012)

- MateCat project: enterprise-grade workbench with *MT integration and project management* (Federico, 2014; Cattelan, 2014)

Novel CAT approaches

- Streamlined interface with both *phrase prediction and post-editing* (Green, 2014)

- Effectiveness of *monolingual* post-editing assisted by word alignments (Schwartz, 2014)
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Conclusion and Future Work
System Optimization

Parameter optimization (MIRA)

- Choose feature weights $W$ that maximizes objective on tuning set
- **Automatic metrics** approximate **human evaluation** of MT output against reference translations

Adequacy-based evaluation

- Good translations should be **semantically similar** to references
- Several adequacy-driven research efforts:
  - **ACL WMT** (Callison-Burch et al., 2011)
  - **NIST OpenMT** (Przybocki et al., 2009)
Standard MT Evaluation

Standard BLEU metric based on $N$-gram precision ($P$) (Papineni et al., 2002)

- Matches spans of hypothesis $E'$ against reference $E$
- Surface forms only, depends on multiple references to capture translation variation (expensive)
- Jointly measures word choice and order

$$\text{BLEU} = BP \times \exp \left( \sum_{n=1}^{N} \frac{1}{N} \log P_n \right)$$

$$BP = \begin{cases} 
1 & |E'| > |E| \\
\frac{1 - |E|}{|E'|} & |E'| \leq |E|
\end{cases}$$
Shortcomings of **BLEU** metric (Banerjee and Lavie 2005, Callison-Burch et al., 2007):

- Evaluating surface forms misses correct translations

- $N$-grams have no notion of global coherence
Shortcomings of BLEU metric (Banerjee and Lavie 2005, Callison-Burch et al., 2007):

- Evaluating surface forms misses correct translations
- \(N\)-grams have no notion of global coherence

\(E\): The large home
Standard MT Evaluation

Shortcomings of BLEU metric (Banerjee and Lavie 2005, Callison-Burch et al., 2007):

- Evaluating surface forms misses correct translations
- $N$-grams have no notion of global coherence

$E$: The large home
$E_1'$: A big house  BLEU = 0
$E_2'$: I am a dinosaur  BLEU = 0
Post-Editing

Final translations must be human quality (editing required)

Good MT output should require less work for humans to edit

Human-targeted translation edit rate (HTER, Snover et al., 2006)

1. Human translators correct MT output
2. Automatically calculate number of edits using TER

\[
\text{TER} = \frac{\# \text{edits}}{|E|}
\]

Edits: insertion, deletion, substitution, block shift

“Better” translations not always easier to post-edit
$E$: The problem is that life of the lines is two to four years.
Translations scored by BLEU

\( E \): The problem is that life of the lines is two to four years.

\( E'_1 \): The problem is that life is two lines, up to four years.

\( E'_2 \): The problem is that the durability of lines is two or four years.
Translations scored by BLEU

\( E \): The problem is that life of the lines is two to four years.

\( \checkmark \quad E'_1 \): The problem is that life is two lines, up to four years.

\hspace{1cm} 0.49

\( E'_2 \): The problem is that the durability of lines is two or four years.

\hspace{1cm} 0.34
Translations scored by BLEU

$E$: The problem is that life of the lines is two to four years.

$E'_1$: The problem is that life is two of the lines, up to is two to four years.

$E'_2$: The problem is that the durability life of lines is two or to four years.
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Conclusion and Future Work
Meteor
Banerjee and Lavie (2005), Lavie and Denkowski (2009), Denkowski and Lavie (2011)

Motivation: address shortcomings of BLEU

- **Flexible matching** to capture translation variation
- Measure word choice and order **separately**, combine with tunable scoring function
- Measure sentence coherence **globally**

**Meteor**: alignment-based tunable evaluation metric

- **Align** hypothesis $E'$ to reference $E$
- Compute score based on **alignment quality**
The United States embassy know that dependable source.

The American embassy knows this from a reliable source.
The United States embassy knows that dependable source.

The American embassy knows this from a reliable source.
The United States embassy knows that dependable source.

The American embassy knows this from a reliable source.
The United States embassy know that dependable source.

The American embassy knows this from a reliable source.
The United States embassy knows that dependable source.

The American embassy knows this from a reliable source.
The United States embassy knows that dependable source.

The American embassy knows this from a reliable source.

(P and R weighted by match type, content vs function words)
The United States embassy knows that this from a dependable source.

The American embassy knows this from a reliable source.

Chunks = 2
Meteor Scoring
Denkowski and Lavie (2011)

$P$ and $R$ weighted by match type ($w_i, \ldots, w_n$) and content-function word weight ($\delta$)

$$F_{\alpha} = \frac{P \times R}{\alpha \times P + (1 - \alpha) \times R}$$

$$\text{Frag} = \frac{\text{Chunks}}{\text{AvgMatches}}$$

$$\text{Meteor} = \left(1 - \gamma \times \text{Frag}^{\beta}\right) \times F_{\alpha}$$

Tunable parameters:

- $W = \langle w_i, \ldots, w_n \rangle$: weights for flexible match types
- $\alpha$: balance between precision and recall
- $\beta, \gamma$: weight and severity of fragmentation
- $\delta$: relative contribution of content versus function words
### Meteor and Post-Editing

Denkowski (AMTA 2014 Workshop on Interactive and Adaptive MT)

Casting Meteor’s scoring features as post-editing measures:

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precision</td>
<td>Incorrect content (deletion)</td>
</tr>
<tr>
<td>Recall</td>
<td>Missing content (insertion)</td>
</tr>
<tr>
<td>Fragmentation</td>
<td>Incorrectly ordered content (reordering)</td>
</tr>
<tr>
<td>Match types</td>
<td>Partially correct content (minor edits)</td>
</tr>
<tr>
<td>Content vs Function</td>
<td>Content vs grammaticality edits</td>
</tr>
</tbody>
</table>

Advantage over edit distance: error types identified separately and combined with a parameterized scoring function
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Conclusion and Future Work
Metrics Targeting Post-Editing
Denkowski (AMTA 2014 Workshop on Interactive and Adaptive MT)

Startup

- Deploy system tuned with simulated post-editing and BLEU
- Collect enough data for a post-editing dev set

Retuning (second stage booster rocket)

- Tune Meteor to fit post-editing effort (keystroke, very close to rating)
- Tune system to new Meteor on new dev set
- Continue to adapt to Meteor in production
Results

- Repeat post-editing experiments with second set of students and TED talks
- Compare BLEU and Meteor-tuned adaptive systems (both optimized on TED talk data)
- Adapting to Meteor lowers BLEU but yields significant improvement in live post-editing
- Feasible in production: significant data and editing records

<table>
<thead>
<tr>
<th></th>
<th>HTER ↓</th>
<th>Rating ↑</th>
<th>Sim PE BLEU ↑</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adapt BLEU</td>
<td>20.1</td>
<td>4.16</td>
<td>27.3</td>
</tr>
<tr>
<td>Adapt Meteor</td>
<td>18.9</td>
<td>4.24</td>
<td>26.6</td>
</tr>
</tbody>
</table>
Related Work: Automatic Metrics

### Evaluation

- **Shared metrics tasks** at workshops on statistical machine translation (Callison-Burch et al., 2008, 2009, 2010, ...)

- TER-plus: extended version of TER with **flexible matching** and **tunable weights** (Snover et al., 2009)

- Stanford **probabilistic** edit distance metric with **linguistic features** (Wang and Manning, 2012)

### Optimization

- Tuning to a metric tends to improve quality **according to that metric** (Cer et al., 2010)

- Effectiveness of tuning to a **more sophisticated metric** than BLEU (Liu et al., 2011)
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Conclusion and Future Work
Conclusion

Real time adaptive MT systems

- **Immediately incorporate** post-editing data into translation models
- Run an **online optimizer** that continuously updates feature weights during decoding
- **Simulate** post-editing to train on normal system building data
- See best results when **combining** techniques: up to **4.9 BLEU**
Live post-editing experiments

- TransCenter interface that simplifies and records post-editing tasks
- Live experiments that show a reduction in human labor when working with adaptive systems
The United States embassy knows that dependable source.

The American embassy knows this from a reliable source.

Automatic metrics for post-editing

- Meteor MT evaluation metric capable of fitting various measures of editing effort

- Live experiments that show a further gains in translator productivity when systems adapt to Meteor
Future Work

Adaptive MT systems

- **Sparse features** for more rapid, fine-grained adaptation (Chiang et al., 2009)
- Danger of **overfitting**, opportunity for more sophisticated optimizers
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End-to-end workflows

- Integrate adaptive MT with advanced post-editing interfaces (Green et al., 2014; Schwartz et al., 2014)
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Automatic metrics

- Tune metrics to *editing time* (bottom line cost)
- Requires *significant* amount of data from a *fixed* pool of translators
Building adaptive MT systems

- **cdec Realtime**: adaptive MT systems with cdec
- **RTA**: Realtime adaptive MT framework using Moses

Live post-editing

- **TransCenter**: post-editing data collection interface
- **All Kent State** post-editing data

Targeted automatic metrics

- **Meteor**: tunable MT evaluation metric
Machine Translation for Human Translators
Carnegie Mellon Ph.D. Thesis

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