Using Coreference Links to Improve Spanish-to-English Machine Translation

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Content

1. Introduction
2. Coreference aware machine translation
3. Experiments and results
4. Conclusion


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Motivation

Source:
When she ran down, the left slipper remained stuck in the stairs, it was small and dainty.

MT:
Quand elle a couru, la pantoufle gauche est restée coincée dans les escaliers, il était petit et délicat.
Motivation

Source:  *Pertenezco a un *partido* político respetable.*
– ¿Qué *partido)*?

Reference:  *I belong to a respectable political party.*
– Which *party)*?

MT:  *I belong to a respectable political party.*
– What a *match)*?
Machine Translation (MT)

\[ e_{best} = \arg\max_{e} p(e|f) \]

Sentence in **target** language  \( e = (e_1, e_2, ..., e_n) \)

Sentence in **source** language  \( f = (f_1, f_2, ..., f_m) \)
Machine Translation (MT)

• Approaches:
  
  • **PBSMT**: Phase-based statistical machine translation  
  • **NMT**: Neural machine translation

• Evaluation made comparing with human translation as reference. Common metric:

  • **BLEU**: $n$-gram precision
Coreference Resolution

• **Linking** or grouping **mentions** that refer to the same **entity** in a text.

  • **Mentions:** nouns, pronouns, noun-phrases, ...
  • **Entities:** people, object, places, ...
  • **Links:** coreference links, mention clusters, mention chains, ...

• Evaluation made comparing with **ground-truth**. Common metrics:

  • **MUC:** number of links to be inserted or deleted.
  • **B³:** precision and recall at cluster-level for each mention.
  • **CEAF:** precision and recall at cluster-level for each entity.
Content

1. Introduction
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Objective: Improve the translation of documents by including coreference constraints.
Coreference in translation

<table>
<thead>
<tr>
<th>Source (Spanish)</th>
<th>Human Translation</th>
<th>Machine Translation</th>
</tr>
</thead>
<tbody>
<tr>
<td>La película narra la historia de [un joven parisiense]$<em>{c_1}$ que marcha a Rumanía en busca de [una cantante zíngara]$</em>{c_2}$, ya que [su]$<em>{c_1}$ fallecido padre escuchaba siempre [sus]$</em>{c_2}$ canciones. Pudiera considerarse un viaje fallido, porque [∅]$<em>{c_1}$ no encuentra [su]$</em>{c_1}$ objetivo, pero el azar [le]$_{c_1}$ conduce a una pequeña comunidad...</td>
<td>The film tells the story of [a young Parisian]$<em>{c_1}$ who goes to Romania in search of [a gypsy singer]$</em>{c_2}$, as [his]$<em>{c_1}$ deceased father use to listen to [her]$</em>{c_2}$ songs. It could be considered a failed journey, because [he]$<em>{c_1}$ does not find [his]$</em>{c_1}$ objective, but the fate leads [him]$_{c_1}$ to a small community...</td>
<td>The film tells the story of [a young Parisian]$<em>{c_1}$ who goes to Romania in search of [a gypsy singer]$</em>{c_2}$, as [his]$<em>{c_2}$ deceased father always listened to [his]$</em>{c_2}$ songs. It could be considered [a failed trip]$<em>{c_3}$ because [it]$</em>{c_3}$ does not find [its]$_{c_3}$ objective, but the chance leads to ∅ a small community...</td>
</tr>
</tbody>
</table>

1 Example from AnCora-CO with manual annotation of coreferences.
2 Automatic coreference resolution with Stanford CoreNLP (http://stanfordnlp.github.io/CoreNLP/coref.html)
3 Translation with a free online NMT
Defining Coreference Similarity Score

1. Apply coreference resolver on both sides.
2. Find alignments of mentions.
3. Calculate MUC, B3, and CEAF
Empirical Verification

<table>
<thead>
<tr>
<th></th>
<th>BLEU</th>
<th>MUC</th>
<th>B&lt;sup&gt;3&lt;/sup&gt;</th>
<th>CEAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human translation</td>
<td>-</td>
<td>37</td>
<td>32</td>
<td>41</td>
</tr>
<tr>
<td>Commercial NMT</td>
<td>49.7</td>
<td>28</td>
<td>26</td>
<td>36</td>
</tr>
<tr>
<td>Baseline PBSMT</td>
<td>43.4</td>
<td>23</td>
<td>24</td>
<td>33</td>
</tr>
</tbody>
</table>

Values of F1 in %

- Data: 3 K words from AnCora-CO with manual annotation of coreferences.
- Automatic coreference resolution with Stanford CoreNLP (http://stanfordnlp.github.io/CoreNLP/coref.html)
- Implementation of metrics from CoNLL 2012 (http://conll.cemantix.org/2012/)
Proposed approaches

1. **Re-ranking** of *n*-best sentences
   → Changes at sentence-level
   → Scoring at document-level

2. **Post-editing** of mentions
   → Changes at mention-level
   → Scoring at cluster-level
Re-ranking

Source $d_s$

Sentence 1 $\rightarrow$ Sentence 2 $\rightarrow$ Sentence 3 $\rightarrow$ ... $\rightarrow$ Sentence N

Translation $d_t$

$hyp_1^1$ $\rightarrow$ $hyp_2^1$ $\rightarrow$ $hyp_3^1$ $\rightarrow$ $hyp_M^1$

$hyp_1^2$ $\rightarrow$ $hyp_2^2$ $\rightarrow$ $hyp_3^2$ $\rightarrow$ ...

$hyp_1^3$ $\rightarrow$ $hyp_2^3$ $\rightarrow$ $hyp_3^3$ $\rightarrow$ ...

$hyp_1^4$ $\rightarrow$ $hyp_2^4$ $\rightarrow$ $hyp_3^4$ $\rightarrow$ ...

... $\rightarrow$ ... $\rightarrow$ ... $\rightarrow$ ...

N-best by MT system
Re-ranking

Source $d_s$

Translation $d_t$

Translation by MT system
Re-ranking

\[
\arg\max C_{\text{sim}}(d_t, d_s) \quad C_{\text{sim}} = \left(\text{MUC} + B^3 + \text{CEAF}\right)/3
\]
Re-ranking

\[ \text{argmax } C_{sim}(d_t, d_s) \quad \text{with} \quad C_{sim} = \left( \frac{MUC + B^3 + CEAF}{3} \right) \]

Source \( d_s \): Sentence 1 → Sentence 2 → Sentence 3 → ... → Sentence N

Translation \( d_t \):
- Hyp1
- Hyp2
- Hyp3
- Hyp4
- ...

Translation by Re-ranking

✓ Remove sentences with same set of mentions.
✓ Beam search
Re-ranking

✓ Optimization at document-level.
✓ Simple to use with a MT system.

✗ Not all mentions in a sentence can be optimized at the same time.
✗ Need to run coreference resolver at each step.
1. Apply coreference resolver on source side.

2. Find translation hypothesis of mentions in target side.

3. For each cluster: select the hypotheses that are more likely to refer to the same entity.
Post-editing

\[
\arg\max \ C_{\text{score}}(c_x)
\]

\[C_{\text{score}}(c_x): \text{Likelihood that all mentions in } c_i \text{ refer to the same entity}\]

Source cluster \(c_i\)  
- Mention 1  
- Mention 2  
- Mention 3  
- ...  
- Mention M

Translation  
- hyp\(_1^1\)  
- hyp\(_2^1\)  
- hyp\(_3^1\)  
- ...  
- hyp\(_M^1\)

- hyp\(_1^2\)  
- hyp\(_2^2\)  
- hyp\(_3^2\)  
- ...  
- hyp\(_M^2\)

- hyp\(_1^3\)  
- hyp\(_2^3\)  
- hyp\(_3^3\)  
- ...  
- hyp\(_M^3\)

- hyp\(_1^4\)  
- hyp\(_2^4\)  
- hyp\(_3^4\)  
- ...  
- hyp\(_M^4\)

...  
...  
...  
...  
...  

N-best by MT system
Post-editing

Cluster score:

\[ C_{Score}(c_x) = C_s^{\lambda_1} \cdot E_s^{\lambda_2} \cdot T_s^{\lambda_3} \]

\[ \sum_i \lambda_i = 1 \]
Post-editing

Source cluster $c_1$

Partido político

Translation

Political party

was

It was

He was

She was

fue

partido

que

match

party

that

which

who

N-best by MT system
Post-editing

Source cluster $c_1$
- Partido politico
- partido
- que
- fue

Translation
- Political party
- match
- that
- was
- party
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- It was
- who
- He was
- She was

Reordering for number of options
Post-editing

$$\text{argmax } C_{\text{score}}(c_x)$$

$C_{\text{score}}(c_x)$: Likelihood that all mentions in $c_i$ refer to the same entity

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Post-editing

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Post-editing

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N-best by MT system
Content

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2. Coreference aware machine translation
3. Experiments and results
4. Conclusion
## Baselines

<table>
<thead>
<tr>
<th>System</th>
<th>Training</th>
<th>Tuning</th>
<th>Testing</th>
<th>Language model</th>
<th>BLEU</th>
</tr>
</thead>
<tbody>
<tr>
<td>PBSMT&lt;sub&gt;1&lt;/sub&gt;</td>
<td>1.9 M</td>
<td>5 K</td>
<td>3 K</td>
<td>3-gram 1.9 M</td>
<td>24.51</td>
</tr>
<tr>
<td>NMT&lt;sub&gt;1&lt;/sub&gt;</td>
<td>1.9 M</td>
<td>5 K</td>
<td>3 K</td>
<td>None</td>
<td>21.53</td>
</tr>
<tr>
<td>PBSMT&lt;sub&gt;2&lt;/sub&gt;</td>
<td>7.6 M</td>
<td>5 K</td>
<td>3 K</td>
<td>3-gram 7.6 M</td>
<td>25.43</td>
</tr>
<tr>
<td>NMT&lt;sub&gt;2&lt;/sub&gt;</td>
<td>7.6 M</td>
<td>5 K</td>
<td>3 K</td>
<td>None</td>
<td>25.65</td>
</tr>
<tr>
<td>PBSMT&lt;sub&gt;3&lt;/sub&gt;</td>
<td>14 M</td>
<td>5 K</td>
<td>3 K</td>
<td>4-gram 17 M</td>
<td>30.81</td>
</tr>
<tr>
<td>NMT&lt;sub&gt;3&lt;/sub&gt;</td>
<td>14 M</td>
<td>5 K</td>
<td>3 K</td>
<td>None</td>
<td>32.21</td>
</tr>
</tbody>
</table>

M: million sentences  
K: thousand sentences

1 Data from WMT 2013 Spanish-English.  
2 News-test 2010-2011  
3 News-test 2013
Evaluation Metrics

**BLEU**

**APT:** Accuracy of pronoun translation.
Uses human translation as reference. It verifies:
- Equal pronouns: exact match with reference.
- Equivalent pronouns: learned from manual evaluation.

**ANT:** Accuracy of noun translation
### Evaluation

<table>
<thead>
<tr>
<th>Metric</th>
<th>PBSMT</th>
<th>NMT</th>
<th>PBSMT + Re-rank</th>
<th>PBSMT + Post-edit</th>
<th>PBSMT + Post-edit (automatic CR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLEU</td>
<td>46.5±4.3</td>
<td>46.9±3.7</td>
<td>41.7±3.9***</td>
<td>46.4±3.9</td>
<td>46.1±4.3</td>
</tr>
<tr>
<td>APT (pronouns)</td>
<td>0.35±0.07</td>
<td>0.37±0.07</td>
<td>0.40±0.1*</td>
<td>0.59±0.13***</td>
<td>0.41±0.07*</td>
</tr>
<tr>
<td>ANT (nouns)</td>
<td>0.78±0.08</td>
<td>0.78±0.07</td>
<td>0.74±0.01***</td>
<td>0.78±0.07</td>
<td>0.76±0.09</td>
</tr>
</tbody>
</table>

Average and standard deviation over the test documents.
Statistical significance: * for 95.0%, ** for 99.0%, and *** for 99.9%
## Human Evaluation

<table>
<thead>
<tr>
<th>Evaluation</th>
<th>PBSMT</th>
<th>PBSMT + Re-rank</th>
<th>PBSMT + Post-edit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wrong</td>
<td>53</td>
<td>55</td>
<td>21</td>
</tr>
<tr>
<td>Acceptable</td>
<td>21</td>
<td>19</td>
<td>28</td>
</tr>
<tr>
<td>Identical to reference</td>
<td>115</td>
<td>115</td>
<td>140</td>
</tr>
</tbody>
</table>
Correctly Modified Example

Source:
[Barton]_3, por [su]_3 parte, también dudó de la capacidad de [Megawati]_2 en [su]_2 [nueva tarea]_4.

Reference:
[Barton]_3, for [his]_3 part, also doubted [Megawati]_2 ’s ability in [her]_2 [new task]_4.

Baseline:
[Barton]_3, for [its]_3 part, also doubted the capacity of [Megawati]_2 in [his]_2 [new task]_4.

Post-editing:
[Barton]_3, for [his]_3 part, also doubted the capacity of [Megawati]_2 in [her]_2 [new task]_4.
Correctly Modified Example

Source:
... que “[parece estar]₂ abrumada ... críticos consideran que [no será]₂ capaz de hacerse con el papel de líder .

Reference:
... that “[she seems]₂ overwhelmed ... critics consider [she will not be]₂ able to take the lead role .

Baseline:
... that “[appears to be]₂ overwhelmed ... critics believe that [it will not be]₂ able to take a leading role .

Post-editing:
... that “[she seems]₂ to be overwhelmed ... critics believe that [she will not be]₂ able to take a leading role
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Conclusion

✓ Optimization at document-level including coreferences
✓ Post-editing approach improves pronouns translation

✗ Optimal solution (from reference) is not in the $n$-best hypothesis in ~20% of the cases
✗ Accuracy of coreference resolution is a limitation (~65% for English)
Future Work

✓ Testing on a larger dataset.
✓ Integration with the decoder of machine translation.
✓ Experiment application to neural machine translation.
Thanks