

# WMT 2016 Shared Task on Cross-lingual Pronoun Prediction

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12/08/2016

# Pronoun Translation Remains an Open Problem

- Pronoun systems do not map well between languages
  - ▶ E.g. grammatical gender for English → German
- Functional ambiguity:

<i>anaphoric</i>	I have an <b>umbrella</b> . <b>It</b> is red.
<i>pleonastic</i>	I have an umbrella. <b>It</b> is raining.
<i>event</i>	He lost his job. <b>It</b> came as a total surprise.

- SMT systems translate sentences in isolation
  - ▶ *Inter-sentential* anaphoric pronouns translated without knowledge of antecedent
- Two pronoun-related tasks at DiscoMT 2015:
  - ▶ Translation: systems failed to beat phrase-based baseline
  - ▶ Prediction: systems failed to beat language model baseline

# Cross-Lingual Pronoun Prediction

- Given an input text and a translation with placeholders, replace the placeholders with pronouns
- Evaluated as a standard classification task

Even though **they** were labeled whale meat ,  
**they** were dolphin meat .

Même si ● avaient été étiquetés viande de baleine ,  
● était de la viande de dauphin .

0-0 1-1 2-2 3-3 3-4 4-5 5-8 6-6 6-7 7-9  
8-10 9-11 10-16 11-13 11-14 12-17

Solution: *ils c'*

# Task Overview

- DiscoMT 2015 English-French pronoun prediction task
  - ▶ Used fully inflected target-language text
- WMT 2016 tasks
  - ▶ Use lemmatised PoS-tagged target-language text  
Simulates SMT scenario in which we cannot trust inflection
- Four subtasks at WMT 2016:
  - ▶ English-French
  - ▶ French-English
  - ▶ English-German
  - ▶ German-English

# Source and Target Pronouns

- Focus on source-language pronouns:
  - ▶ In **subject position**
  - ▶ That exhibit *functional ambiguity* (→ multiple possible translations)

Source language	Pronouns
English	it, they
French	il, ils, elle, elles
German	er, sie, es

- **Prediction classes:** commonly aligned target-language translations

# English-French Subtask: Pronouns

## English subject pronouns

*it*

*they*

## French prediction classes

*ce* (inc. *c'*) [demonstrative]

*cela* (inc. *ça*) [demonstrative]

*elle* [Fem. sg.]

*elles* [Fem. pl.]

*il* [Masc. sg.]

*ils* [Masc. pl.]

*on* [impersonal]

OTHER [anything else]

- **Training data:**

- ▶ News v9
- ▶ Europarl v7
- ▶ TED Talks (IWSLT 2015)
- ▶ Automatic filtering of subject pronouns

- **Development data:** TED Talks

- **Test data:** TED Talks

- ▶ Documents selected to ensure rare prediction classes are represented
- ▶ Manual checks on subject pronoun filtering

```
elles Elles They arrive first . REPLACE_0 arriver|VER en|PRP premier|NUM .|. 0-0  
1-1 2-2 2-3 3-4
```

Figure : Example of training data format

# Baseline System

- Baseline does what a typical SMT system would do:  
Predict everything with an n-gram model
- Fills REPLACE token gaps by using:
  - ▶ A fixed set of pronouns (prediction classes)
  - ▶ A fixed set of non-pronouns (OTHER words)  
Includes NONE (i.e., do not insert anything in the hypothesis)
- Configurable NONE penalty for empty slots to counterbalance the n-gram model's preference for brevity
- 5-gram language model provided for the task
- Similar language model baseline unbeaten at DiscoMT 2015



- **Macro-averaged Recall** - averaged over all classes to be predicted
  - ▶ DiscoMT 2015: Macro-averaged F-score
  - ▶ F-scores count each error twice  
once for precision; again for recall
- **Accuracy**
- Two official baseline scores provided for each subtask:
  - ▶ Default: NONE penalty set to zero
  - ▶ Optimised: NONE penalty tuned (for each subtask)

# Submitted Systems

- 11 participants - some submitted to all subtasks
- Accepted primary and contrastive systems
- Two systems use LMs; all others use classifiers
- **Two main approaches:**
  - ▶ Use context from source and target text  
4 systems
  - ▶ Use source and target context + language-specific external tools / resources  
8 systems
- **Popular external tools:** coreference resolution, pleonastic “it” detection, dependency parsing

# Results: English-French (Primary Systems)

	System	Macro-Avg Recall	Accuracy
1	TurkuNLP	65.70 <sub>1</sub>	70.51 <sub>5</sub>
2	UU-Stymne	65.35 <sub>2</sub>	73.99 <sub>2</sub>
3	UKYOTO	62.44 <sub>3</sub>	70.51 <sub>4</sub>
4	uedin	61.62 <sub>4</sub>	71.31 <sub>3</sub>
5	UU-Hardmeier	60.63 <sub>5</sub>	74.53 <sub>1</sub>
6	limsi	59.32 <sub>6</sub>	68.36 <sub>7</sub>
7	UHELSINKI	57.50 <sub>7</sub>	68.90 <sub>6</sub>
	<i>baseline-1</i>	<i>50.85</i>	<i>53.35</i>
8	UUPPSALA	48.92 <sub>8</sub>	62.20 <sub>8</sub>
	<i>baseline0</i>	<i>46.98</i>	<i>52.01</i>
9	Idiap	36.36 <sub>9</sub>	51.21 <sub>9</sub>

# Results: English-German (Primary Systems)

	System	Macro-Avg Recall	Accuracy
1	TurkuNLP	64.41 <sub>1</sub>	71.54 <sub>2</sub>
2	UKYOTO	52.50 <sub>2</sub>	71.28 <sub>3</sub>
3	UU-Stymne	52.12 <sub>3</sub>	70.76 <sub>4</sub>
4	UU-Hardmeier	50.36 <sub>4</sub>	74.67 <sub>1</sub>
5	uedin	48.72 <sub>5</sub>	66.32 <sub>6</sub>
	<i>baseline-2</i>	<i>47.86</i>	<i>54.31</i>
6	UUPPSALA	47.43 <sub>6</sub>	68.67 <sub>5</sub>
7	UHELSINKI	44.69 <sub>7</sub>	65.80 <sub>7</sub>
8	UU-Cap	41.61 <sub>8</sub>	63.71 <sub>8</sub>
	<i>baseline0</i>	<i>38.53</i>	<i>50.13</i>
9	CUNI	28.26 <sub>9</sub>	42.04 <sub>9</sub>

# Results: French-English (Primary Systems)

	System	Macro-Avg Recall	Accuracy
1	TurkuNLP	72.03 <sub>1</sub>	80.79 <sub>2</sub>
2	UKYOTO	65.63 <sub>2</sub>	82.93 <sub>1</sub>
3	UHELSINKI	62.98 <sub>3</sub>	78.96 <sub>3</sub>
4	UUPSALA	62.65 <sub>4</sub>	74.39 <sub>4</sub>
	<i>baseline-1.5</i>	<i>42.96</i>	<i>53.66</i>
	<i>baseline0</i>	<i>38.38</i>	<i>52.44</i>
5	UU-Stymne	36.44 <sub>5</sub>	53.66 <sub>5</sub>

# Results: German-English (Primary Systems)

	System	Macro-Avg Recall	Accuracy
1	TurkuNLP	73.91 <sub>1</sub>	75.36 <sub>3</sub>
2	UKYOTO	73.17 <sub>2</sub>	80.33 <sub>1</sub>
3	UHELSINKI	69.76 <sub>3</sub>	77.85 <sub>2</sub>
4	CUNI	60.42 <sub>4</sub>	64.18 <sub>6</sub>
5	UUPPSALA	59.56 <sub>5</sub>	73.71 <sub>4</sub>
6	UU-Stymne	59.28 <sub>6</sub>	69.98 <sub>5</sub>
	<i>baseline-1.5</i>	<i>44.52</i>	<i>54.87</i>
	<i>baseline0</i>	<i>42.15</i>	<i>53.42</i>

# Conclusions

- Most systems beat the baseline,  
in stark contrast with DiscoMT 2015
- En-Fr and En-De subtasks most popular
  - ▶ External tools / resources available for English
- RNNs work well for cross-lingual pronoun prediction
  - ▶ TURKUNLP: best system; all four subtasks
  - ▶ UKYOTO: next best system; 3 subtasks
  - ▶ Systems use only source and target context
- UU-STYMNE second place system for English-French

# Next Steps

- **For Participants:**

- ▶ Analyse and improve system performance
- ▶ Integrate prediction systems into MT pipeline (post-editing, decoder feature, etc.)

- New task in 2017 [TBC]