Word Confidence Estimation For Speech Translation
Laurent Besacier, Benjamin Lecouteux, Ngoc Quang Q Luong, K Hour,
Marwa Hadj Salah

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Introduction

Word Confidence Estimation for machine translation or automatic speech recognition consists in judging each word in the (MT or ASR) hypothesis as correct or incorrect by tagging it with an appropriate label. In the past, this task has been treated separately in ASR or MT contexts and we propose here a joint estimation of word confidence for a spoken language translation task involving both ASR and MT. This research work is possible because we built a specific corpus which is first presented.

A database for WCE evaluation in spoken language translation

Starting point : an existing MT Post-edition corpus
- For a Fr-En translation task, we used our SMT system to obtain the translation hypothesis for 10,881 source sentences taken from news corpora of the WMT evaluation campaign (2006-2010).
- Post-editions were obtained from non professional users using a crowdsourcing platform.
- Word label setting for WCE was done using TERp-A toolkit.
- We re-categorized the 6-label set into binary set : The E, T and Y belong to the Good (G), whereas the S, P and I belong to the Bad (B) category.

Augmenting the corpus with speech recordings and transcripts

We record the utterances of PE corpus test to augment the corpus with speech inputs.
- Each of the 881 sentences was uttered by 3 speakers, leading to 2643 speech recordings (5h) : 15 speakers (9 women and 6 men).
- ASR system based on KALDI toolkit with a 3-gram LM trained on the French ESTER corpus and French Gigaword (vocabulary size is 55k). SGMM acoustic models are trained on the ESTER corpus.
- Post-processing was needed at the output of the ASR system in order to match requirements of standard input for machine translation.
- The output of our ASR system, scored against the src-ref requirements of standard input for machine translation.

Obtaining labels in order to evaluate WCE for SLT :
- The ASR output (src-asr) was translated by the SMT system (tgt-sl), a degraded version of tgt-mt.
- We re-used the post-editions obtained from the text translation task (tgt-pe), to infer the quality (G,B) labels of our speech translation output tgt-sl.
- The word label setting for WCE is done using TERp-A toolkit between tgt-sl and tgt-pe.

Word confidence for a speech translation task

WCE for speech transcription
- 7 features (F-Word, F-size, F-back, F-alt, F-post, F-dur, F-3g) : Audio features : acoustic distortions between the hypothesis and the best phonetic sequence (F-dur).
- Graph topology : number of alternative paths in the confusion set, maximum and minimum values of posteriors.
- Language model (LM) based : length of the longest sequence of the current word and its previous ones in the target (resp. source) LM. For example, with the target word w, if the sequence w−1 w−2 w appears in the target LM but the sequence w−2 w−1 w does not, the n-gram value for w is 3.
- Lexical Features : words Part-Of-Speech (POS) are computed using tree-tagger for French. We use bnobnab algorithm, the classifier is trained on BREF 120 corpus (about 1M word examples).
- Semantic Features : number of word senses in WordNet.

WCE for machine translation
- We employ CRFs as our machine learning method, with WAPITI toolkit, to train the WCE model. 25 major feature types :
  - Target Side : target word; bigram (trigram) backward sequences; number of occurrences.
  - Source Side : source word(s) aligned to the target word.
  - Alignment Context : the combinations of the target (source) word and all aligned source (target) words in the window ±2.
  - Word posterior probability.
  - Pseudo-reference (Google Translate) : Does the word appear in the pseudo reference or not?

Joint estimation of word confidence for a speech translation task

Word Confidence Estimation (WCE) results obtained on our corpus with different feature sets based on ASR, MT or both. Numbers reported are F scores for Good (G) and Bad (B) labels respectively with a common decision threshold.

Summary of word confidence estimation (WCE) results obtained on our corpus with different feature sets.

| feature type | MT feat. | ASR feat. | 0.5MT+0.5ASR feat. |
|--------------|----------|-----------|---------------------|
| MT feat.     | 0.37%.   | 0.32%     | 0.38%               |
| ASR feat.    | 0.28%    | 0.26%     | 0.30%               |
| 0.5MT+0.5ASR feat. | 0.26% | 0.24% | 0.28% |

Obtaining labels in order to evaluate WCE for SLT :
- The ASR output (src-asr) was translated by the SMT system (tgt-sl), a degraded version of tgt-mt.
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TABLE: Example of WCE label setting using TERp-A

| Ref | MT-trans | ASR-trans | WCE-trans |
|-----|----------|-----------|-----------|
| Good | 84.6%   | 82.5%     | 87.6%     |
| Bad  | 65.5%   | 65.0%     | 77.5%     |

TABLE: Example of quintuplet with associated labels

| src-asr | src-sig | src-ref | tgt-mt | tgt-pe | tgt-sl1 | tgt-sl2 |
|---------|---------|---------|--------|--------|---------|---------|
| good    | good    | good    | good   | good   | good    | good    |
| bad     | bad     | bad     | bad    | bad    | bad     | bad     |
| G/B     | G/B     | G/B     | G/B    | G/B    | G/B     | G/B     |

TABLE: Word posterior probability.

| src-asr | src-sig | src-ref | tgt-mt | tgt-pe | tgt-sl1 | tgt-sl2 |
|---------|---------|---------|--------|--------|---------|---------|
| F-word | F-3g    | F-back  | F-alt  | F-post | F-dur   | F-post  |
| 0.37%  | 0.28%   | 0.32%   | 0.32%  | 0.32%  | 0.32%   | 0.32%   |

TABLE: Example of quintuplet with associated labels

| src-asr | src-sig | src-ref | tgt-mt | tgt-pe | tgt-sl1 | tgt-sl2 |
|---------|---------|---------|--------|--------|---------|---------|
| good    | good    | good    | good   | good   | good    | good    |
| bad     | bad     | bad     | bad    | bad    | bad     | bad     |
| G/B     | G/B     | G/B     | G/B    | G/B    | G/B     | G/B     |

Intervention context : the combinations of the target (source) word and all aligned source (target) words in the window ±2.

| feature type | MT feat. | ASR feat. | 0.5MT+0.5ASR feat. |
|--------------|----------|-----------|---------------------|
| MT feat.     | 0.37%    | 0.32%     | 0.38%               |
| ASR feat.    | 0.28%    | 0.26%     | 0.30%               |
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