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Spoken Language Translation Graphs Re-decoding using Automatic Quality Assessment

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Abstract

This paper investigates how automatic quality assessment of spoken language translation (SLT) can help re-decoding SLT output graphs and improving the overall speech translation performance.

Using robust word confidence measures (from both ASR and MT) to re-decode the SLT graph leads to a significant BLEU improvement (more than 2 points) compared to our SLT baseline (French-English task).

Introduction

Context

- Automatic quality assessment of spoken language translation (SLT)
- Also named confidence estimation (CE)
- Pointing out correct parts and errors in a speech translated output

Useful for

- Interactive speech to speech translation
- Computer-assisted translation (from speech or text)

Claim

- An accurate CE can also help to improve SLT itself through **search graph re-decoding**

Formalisation

x_f source signal, $f = (f_1, f_2, \dots, f_M)$ transcription of x_f .

$\hat{e} = (e_1, e_2, \dots, e_N)$ translation of f and $\hat{e} = \underset{e}{\operatorname{argmax}} \{p(e/x_f, f)\}$

Word Confidence Estimation (WCE) can be seen as finding sequence q where $q = (q_1, q_2, \dots, q_N)$ and $q_i \in \{\text{good}, \text{bad}\}$

$\hat{e} = \underset{e}{\operatorname{argmax}} \sum_q p(e, q/x_f, f) \hat{e} = \underset{e}{\operatorname{argmax}} \sum_q p(q/x_f, f, e) * p(e/x_f, f)$

$\hat{e} \approx \underset{e}{\operatorname{argmax}} \max_q \{p(q/x_f, f, e) * p(e/x_f, f)\}$

$p(q/x_f, f, e)$: WCE component

$p(e/x_f, f)$: SLT component

SLT Search Graph (SG) Re-decoding

For SLT N-best hypotheses $e^N = \{e^1, e^2, \dots, e^N\}$, each j -th word in the hypothesis e^j , denoted by e_{ij} , has a quality label, q_{ij} .

For all hypothesis H_k in the SG, the new transition cost is defined by:

$$\text{transition}'(H_k) = \text{transition}(H_k) + \begin{cases} \text{reward}(e_{ij}) & \text{if } q_{ij} = \text{good} \\ \text{penalty}(e_{ij}) & \text{otherwise} \end{cases} \quad (1)$$

with

$$\text{penalty}(e_{ij}) = -\text{reward}(e_{ij}) = \beta * \frac{\text{score}(H_k)}{\#\text{words}(H_k)} \quad (2)$$

Analysis of SLT Hypotheses

example 1	
f_{ref}	une démobilisation des employés peut déboucher sur une démoralisation mortifère
f_{hyp}	une démobilisation des employés peut déboucher sur une démoralisation mort y faire
e_{hyp} baseline	a demobilisation employees can lead to a penalty demoralisation
e_{hyp} with re-decoding	a demobilisation of employees can lead to a demoralization death
e_{ref}	demobilization of employees can lead to a deadly demoralization
example 2	
f_{ref}	celui-ci a indiqué que l'intervention s'était parfaitement bien déroulée et que les examens post-opératoires étaient normaux
f_{hyp}	celui-ci a indiqué que l' intervention c'était parfaitement bien déroulés , et que les examens post opératoire étaient normaux.
e_{hyp} baseline	it has indicated that the speech that was well conducted , and that the tests were normal post route
e_{hyp} with re-decoding	he indicated that the intervention is very well done , and that the tests after operating were normal
e_{ref}	he indicated that the operation went perfectly well and the post-operative tests were normal
example 3	
f_{ref}	general motors repousse jusqu'en janvier le plan pour opel
f_{hyp}	general motors repousse jusqu' en janvier le plan pour open
e_{hyp} baseline	general motors postponed until january the plan to open
e_{hyp} with re-decoding	general motors puts until january terms to open
e_{ref}	general motors postponed until january the plan for opel

Table : Exemples of French SLT output with and w/o re-decoding

Building an Efficient WCE System

$$\hat{q} = \underset{q}{\operatorname{argmax}} \{p(q/x_f, f, e)\}$$

need training data with quadruplet (x_f, f, e, q) available, so instead we compute: $\hat{q} = \underset{q}{\operatorname{argmax}} \{p_{ASR}(q/x_f, f)^\alpha * p_{MT}(q/e, f)^{1-\alpha}\}$

$$\cdot p_{ASR}(q/x_f, f)$$

• system described in [1]

• acoustic / graph / linguistic / lexical features

• boosting classifier

$$\cdot p_{MT}(q/e, f)$$

• system described in [2]

• multiple features and CRF classifier

• using our open-source toolkit available online <http://github.com/besacier/WCE-LIG>

Experimental Setting

French ASR

- Kaldi toolkit [3]
- HMM/SGMM / 3-grams

French-English SMT

- Moses toolkit [5]
- 1.6M parallel sent.
- 48M monolingual sent.
- medium-size system
- WMT shared task

task	ASR (WER)	MT (BLEU)	% good	% bad
MT	0%	52.8%	82.5%	17.5%
SLT	26.6%	30.6%	65.5%	34.5%

Table : Baseline MT and SLT performance on 2643 utt.

Re-decoding Results

2-pass (graph re-decoding)

- MT features only
- ASR features only
- joint MT+ASR features

system	baseline	redecoding	redecoding	redecoding
WCE feat.	none	ASR	MT	SLT
		$p(q/x_f, f)$	$p(q/e, f)$	$p(q/x_f, f, e)$

Table : SLT perf. (BLEU) after 2d pass (2643 utt.)

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