Metric for Automatic Mach Hiroki Shi



Hiroki Shimanaka, Tomoyuki Kajiwara, Mamoru Komachi, Metric for Automatic Machine Translation Evaluation based on Universal Sentence Representations, NAACL 2018 Student Research Workshop in conjunction with NAACL HLT 2018 (NAACL-SRW 2018), June 3rd, 2018

Figure 3: Outline of our metric

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ed on character N-grams or word N- segment-level MTE. Il sentence representations capable of il features based on character or word hat the proposed method achieves tation features only. n Metric Score Ranking of Scores nan 0.892 32/560 nd - 0.0734 423/560 etric 0.554 60/560			 4. Experimental Setting Universal Sentence Representation We use pre-trained sentence representation that are open to the public. Skip-Thought [Kiros et al., 2015] Train Data: Toronto-Books Corpus Dimension: 4,800 InferSent [Conneau et al., 2017] Train data: The Stanford Natural Lang Inference (SNLI) Corpus Dimension: 4,096 	ons ntations	 Regression SVR (RBF ker $C \in \{0.01, 0.1\}$ $\varepsilon \in \{0.01, 0.1\}$ $\gamma \in \{0.01, 0.1\}$ We performe Training Date Table 1: N WMT-2015 WMT-2016 	Model f nel) from ,1.0,10} ,1.0,10} L, 1.0, 10 ed 10-fol esets of H Jumber of for to-E CS-en 500 560	for MTE h scikit-lea d cross va fuman Ev of DA huma inglish lan de-en 500 560	arn lidatic aluatic an eva guage fi-en 500 560	on and a solution of the second secon	grid-sear es datasets ru-en 500 560	rch.	
it similarity scores with Tree-LSTM. earning of Tree-LSTM is unstable and that uses the scores of various metrics etrics (lexical base)			5. Experimental Results Table 2: Pearson correlation SentBLEU Blend [Ma et al., 2017] DPMF _{comb} [Yu et al., 2015] ReVal [Gupta et al ., 2015]	of metric scor	res and DA huma cs-en de- 0.557 0.4 0.709 0.6 0.713 0.5 0.577 0.5 0.577 0.5 0.577 0.5	an evalua en fi- $48 ext{ 0.4}$ $01 ext{ 0.5}$ $84 ext{ 0.5}$ $28 ext{ 0.4}$	$\begin{array}{c} \text{ations sco} \\ \text{en ro-e} \\ 84 & 0.42 \\ 84 & 0.62 \\ 98 & 0.62 \\ 71 & 0.54 \\ 600 & 0.62 \\ \hline \end{array}$	res (ne $r = 1000 \text{ m}^2$) $r = 1000 \text{ m}^2$	ewstest u-en).502).633).615).528	2016) tr-en 0.532 0.675 0.663 0.531	Avg. 0.504 0.640 0.633 0.530	
ation scores with universal sentence ata.			SVR with InferSent SVR with InferSent + Skip-Though 6. Error Analysis Table 3: The top 20% of MT hypotheses	ht that were clos (Total: 67	0.679 $0.60.686$ $0.6e to the meaning2 sentence pairs)$	04 0.6 11 0.6	6 17 0.6 6 33 0.6 9 eference tr	40 0 60 0 ranslat).644).649	0.630 0.646 re analyz	0.636 0.648	
oftmax regression model $(\vec{t}, \vec{r}, \vec{t} - \vec{r} , \vec{t} * \vec{r})$ \vec{t} \vec{t} \vec{r} \vec{t} \vec{r}			Low word surface matching rate Including unknown words (and short sentence length)	t evaluation with al :70 sentences) 26 26 (17)	Only correct evaluation with our metric (Total: 88 sentences) 42 26 (2)							
			 Other 24 31 From the results, it is considered that our metric shows better results in MT hypotheses whose meanings are similar to those of reference translations. From the results about word surface matching rate, our metric can evaluate a wide range of sentence information that cannot be captured by lexical base metrics. 									

unknown words, the innuclied of unknown words in long with hypotheses in our metric is considered to be small.