



SETUP

> Models:

- Baseline: optimize the forward translation loss
- Hidden: fine-tune baselines with translation loss + loss of reconstruction from hidden states
- Ours: fine-tune baselines with translation loss + loss of reconstruction from sampled translation

Tasks:

Swahili, Tagalog, Somali, Turkish <-> English

	Training	Dev.	Test
$SW \leftrightarrow EN$	$60,\!570$	500	$3,\!000$
$TL \leftrightarrow EN$	70,703	704	$3,\!000$
$SO \leftrightarrow EN$	$68,\!550$	844	$3,\!000$
$TR \leftrightarrow EN$	$207,\!021$	$1,\!001$	$3,\!007$

Bi-Directional Differentiable Input Reconstruction for Low-Resource NMT

Xing Niu, Weijia Xu, Marine Carpuat

University of Maryland, College Park

R	ES	l

Model	EN->	S ₩	SW-	SW→EN		EN→TL		L→EN EN		EN→SO SO		►N	EN→TR		TR→EN	
Baseline	33.60	Δ	30.70	Δ	27.23	Δ	32.15	Δ	12.25	Δ	20.80	Δ	12.90	Δ	15.32	Δ
Hidden	33.41	-0.19	30.91	+0.21	27.43	+0.19	32.20	+0.04	12.30	+0.05	20.72	-0.08	12.77	-0.13	15.34	+0.01
Ours: greedy	33.92	+0.32	31.37	+0.66	27.65	+0.42	32.75	+0.59	12.47	+0.22	21.14	+0.35	13.26	+0.36	15.60	+0.28
Ours: sampling	33.97	+0.37	31.39	+0.69	27.65	+0.42	32.65	+0.50	12.48	+0.23	21.20	+0.41	13.16	+0.25	15.52	+0.19

> Our approach achieves small but consistent BLEU improvements > It is effective even if there is moderate domain mismatch > OOV rate of TR->EN is larger than 20% \succ OOV rate of SW->EN is much smaller and it obtains higher Δ BLEU

> It outperforms input reconstruction from hidden states

> Training becomes more stable (see ANALYSIS)

<u>ULTS</u>









PDF