models 1-7. LSTM-based neural per with pointer network-like monotonic ention trained with imitation learning. A 1-7 are majority-vote ensembles with number of models (5-30) and different characters or segments).  In good results in nld (14.7), ice (10), jp a (7.5) and vie (2.0) but not better than a contract the baseline. They analyse the baseline.	hun t kat (geo) kor low (800 train p	6.4 1.0 0.0 16.2 pairs) 20 22 49 12	
ention trained with imitation learning. A 1-7 are majority-vote ensembles with number of models (5-30) and different characters or segments).  d good results in nld (14.7), ice (10), jp (7.5) and vie (2.0) but not better than	hun t kat (geo) kor low (800 train p ell (gre) ady lav mlt_ltn	1.0 0.0 16.2 pairs) 20 22 49 12	
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(7.5) and vie (2.0) but not better than	ell (gre) ady lav mlt_ltn	20 22 49 12	
	ady lav mlt_ltn	22 49 12	
outperforms the baseline. They analyse	lav mlt_ltn	49 12	
outperforms the baseline. They analyse	mlt_ltn	12	
outperforms the baseline. They analyse			
outperforms the baseline. They analyse	cvm (wel sw)		
outperforms the baseline. They analyse	- <b>J</b> ()	10	
SIG21: Lo and Nicolai (2021)  UBC-2 outperforms the baseline. They analysed the errors of the baseline and extend it by adding penalties for wrong vowels and wrong diacritics.  Errors on vowels actually decreased. Best macro	1 -	22	
	-   KIIIII	28	
	1 .	49	
(low-resource).	slv	47	
Dialpad-1: Majority-vote ensemble consisting of three different public models (weighted FST, joint-sequence model trained with EM and a neural seq2seq), two seq2seq variants (LSTM and transformer) and two baseline variations.	of high (32.800 train	high (32.800 train pairs)	
	eural eng (eng_us)	37.43	
SIG20: Peters and Martin (2020)  DeepSPIN-2,-3,-4: Transformer- or LSTM-based enc-dec seq2seq models with sparse attention. Add language embedding to enc or dec states instead of language token.  Link		3.600 train pairs	
	1 1011 (1011 (1112)	4.89	
	fra (fre)	5.11	
	rum	9.78	
	vie	0.89	
SIG20: Yu et al. (2020)  Link  IMS: Self training ensemble of one n-gram-based FST and 3 seq2seq (vanilla with attention, hard monotonic attention with pointer, hybrid of hard monotonic attention and tagging model).		5.11	
		13.56	
	ner) and two baseline variations.  IN-2,-3,-4: Transformer- or LSTM-base seq2seq models with sparse attention guage embedding to enc or dec states of language token.  If training ensemble of one n-gram-base is 3 seq2seq (vanilla with attention, hare attention with pointer, hybrid of hare	IN-2,-3,-4: Transformer- or LSTM-based seq2seq models with sparse attention. guage embedding to enc or dec states of language token.  If training ensemble of one n-gram-based la seq2seq (vanilla with attention, hard nic attention with pointer, hybrid of hard  3.600 train particular jpn (jpn_hira) fra (fre) rum vie	

Table 1: SOTA models