7)	G 0.2	0.3	0.4	0.5	0.6	0.7	0/8
	evol Pool						n n
	exp1 exp2	exp1 exp2	exp1 exp2	exp1 exp2	CAD1 CAD2	exp1 exp2	exp1 exp4
Topi	13.40 13.32	13.79 13 61	11.04 12.70	11.63 10.93	10 83 11.25	9.62 10.63	8.73 10 18
Tops	21.58 19.59	23 27 20 17	19.69 18.28	21.07 17.25	22 05 16.84	17.90 16.20	17.38 15.34
Tall	20 20 20 21	- AG 44 - A4 - A	Lac sa Lac od	200 200	DE 04 DO 00	ad ad ad ad	20 10 20
10010	27.39 22.71	28.41 24.73	20.52 22.93	20.83 21.81	27 20 20.39	24.58 21.20	23.42 18.20
To 520	35.23 34.88	35 94 29 49	37.81 31.57	38.59 33.04	36 52 31.72	35.25 29.75	34.65 27.62
To 550	43.91 40.63	43.75 40.85	46.22 41.40	48 72 42 79	45 48 40.49	41.57 39.94	42 .81 38 .07
Tay 100	60 74 40 45	E4 26 E2 04	E0 20 E2 14	EE 24 E2 44	EE 10 E1 02	EE CO 40 EO	15
100100	33.70 48.47	54.50	39.20	57.30	00.15	33.03 49.34	95.41 +7.15

Table 4. Parameters Experiment

rank. Through the revision module, we get both higher recall and higher precision than statistical transliteration model when at most 5 results are returned.

We also use the average rank and average reciprocal rank (ARR) [Voorhees and Tice, 2000] to evaluate the improvement. ARR is calculated as

$$ARR = \frac{1}{M} \sum_{i=1}^{M} \frac{1}{R(i)}$$
 (8)

where R(i) is the rank of the answer of *i*th test word. M is the size of test set. The higher of ARR, the better the performance is.

The results are shown as Table 6.

	Statistical model		Revision module		Re-rank Module	
	close	open	close	open	close	open
Average rank	37.63	70.94	24.52	58.09	16.71	43.87
ARR	0.3815	0.1206	0.3783	0.1648	0.6519	0.4492

Table 6. ARR and AR evaluation

The ARR after revision phase is lower than the statistical model. Because the goal of revision module is to improve the recall as possible as we can, some noisy words will be introduced in. The noisy words will be pruned in re-ranking module. That is why we get the highest ARR value at last. So we can conclude that the revision module improves recall and re-ranking module improves precision, which help us get a better performance than pure statistical transliteration model

6 Conclusion

In this paper, we present a new approach which can revise the results generated from statistical transliteration model with the assistance of monolingual web resource. Through the revision process, the recall of transliteration results has been improved from 72.52% to 85.78% in the close test set and from 41.73% to 59.28% in open test set, respectively. We improve the precision in re-ranking phase, the top-5 precision can be improved to 76.35% in close test and 52.19% in open test. The

promising results show that our approach works pretty well in the task of backward transliteration.

In the future, we will try to improve the similarity measurement in the revision phase. And we also wish to develop a new approach using the transliteration candidates to search for their right answer more directly and effectively.

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