

$$time_{M_j}^{Google} = \frac{\sum_{s_i \in M_j} time_{s_i}^{Google}}{|M_j|}, j = 1, 2, 3, 4$$

Then we calculate the average translation time of all sentences under the assistance of “Google” using the following formula:

$$time^{Google} = \frac{\sum_{i=1}^{160} time_{s_i}^{google}}{160}.$$

For keystrokes and translation quality, they are calculated in the same way.

For example, translation time and keystroke consumption on each sentence of a specific translator in group C are reported in Figure 4 and Figure 5. As we can see in the figures, CoCat helps her save about 46% time and about 41% keystrokes in the scratch mode, and save about 45% time and about 54% keystrokes in the post-editing mode.

The detailed results of all the human translators are reported in Table 3. On average, all human translators are faster and also achieve better translation quality using any of types of assistance offered. What’s more, human translators are faster and also achieve better translation quality using CoCat (translating from scratch or post-editing).

For translation time and keystrokes, the figures in Table 3 show that our proposed CoCat always helps human translators significantly (with $p < 0.01$), saving more than 14% time and over 33% keystrokes compared with the strong baseline, i.e., post-editing using Google Pinyin (line 4 vs. line 3 and line 6 vs. line 5).

For translation quality, the figures in Table 3 show that CoCat can help human translators improve the translation quality significantly as well (with $p < 0.01$) by more than 3 absolute BLEU scores over the strong baseline.

Take a specific sentence as an example, such as “CPC’s discipline agency announced on Jan. 16 that Huo has been placed under investigation for suspected serious violation of party discipline and laws”, the comparison statistics of translation time and keystrokes are reported in Figure 6. CoCat can save about 21% time and about 24% keystrokes in the scratch mode, and save about 26% time and about 53% keystrokes in the post-editing mode.

Overall, the results in Table 3 indicate that post-editing consistently outperform unassisted translation. It is in line with the findings reported by Koehn (2012). Meanwhile, the post-editing well integrated with our proposed CoCat input method further improves the translation productivity.

What’s more, if we focus on the comparison between “CoCat” and “PE+Google”, we can find that the difference of the translation quality is very small. In the industrial world, the poor performance of the automatic translation engine is often a headache for human translators to edit the MT results. The comparison between “CoCat” and “PE+Google” tells us that we can make human translators generate better translation in less time with the aid of MT without headache.

In summary, we can draw the conclusion that the proposed new input method makes it easier for human translators to interact with MT systems effectively and imperceptibly.

4 Related Work

The goal of this paper is to improve the productivity and efficiency of human translators by fully exploiting the MT technology. The core idea is to provide human translators translation candidates effectively and friendly. There are two kinds of related work focusing on offering translation suggestions.

Koehn (2009a; Koehn et al., 2014) developed the tool *Caitra* which aims at providing translation suggestions to complete the target language sentence. Based on MT post-editing, their method can offer word and phrase translation candidates through interactive machine translation. Green et al. (2014) made extensive modifications for the MT system and designed a new CAT interface. Their methods are tightly coupled with statistical machine translation in which only left-to-right decoding is allowed and dynamic decoding in interactive machine translation is usually time-consuming. In contrast, we integrate most of the useful knowledge of the MT system into a well designed CoCat input method that provides the translation suggestions more friendly and imperceptibly without forcing the human translators to take a view of the MT outputs. Besides using MT outputs, we are the first to exploit depth information used by MT, such as translation rules and decoding hypotheses.

Recently, Li (2012) and Fang (2013) also attempted to incorporate the SMT information into the Chinese Pinyin input method. In their approaches, when they developed their input methods, only the MT model scores and the fuzzy word alignment between the MT output and the human translation output are employed. However, there are two disadvantages in their approaches. On the one hand, the dynamic MT model scores are difficult to calculate and these model scores are not compatible with other features in input methods. On the other hand, the fuzzy word alignment contains much noise which would not benefit much to the input method. Instead, we design the log-linear model for the input method CoCat and integrate the translation rules, decoding hypotheses and the n-best translation list of the MT system. In addition, we propose the n-gram prediction model to further improve the efficiency of human translators.

5 Conclusion

In this paper, we have presented a novel input method CoCat which deeply integrates MT into CAT effectively and imperceptibly. This well-designed input method is modeled with a log-linear framework, and takes as features most of the useful knowledge of the MT system, such as translation rules, decoding hypotheses and n-best translation lists. Furthermore, we have proposed an n-gram prediction model that further speeds up the translation typing process.

The human translation experiments on English-to-Chinese have shown that the proposed approach can not only help human translators significantly save the time and keystrokes, but also substantially improve the final translation quality. The experiments have also shown that post-editing well integrated with our proposed approach further improves the translation productivity.

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