Automatic Evaluation Metric for Machine Translation that is Independent of Sentence Length

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Abstract

We propose new automatic evaluation metric to evaluate machine translation. Different from most similar metrics, our proposed metric does not depend heavily on sentence length. In most metrics based on f-measure comparisons of reference and candidate translations, the relative weight of each mismatched word in short sentences is larger than in long sentences. Therefore, the evaluation score becomes disproportionally low in short sentences even when only one non-matching word exists. In our metric, the weight of each mismatched word is kept small even in short sentences. We designate our metric as Automatic Evaluation Metric that is Independent of Sentence Length (AILE). Experimental results indicate that AILE has the highest correlation with human judgments among some leading metrics.

1 Introduction

Various automatic evaluation metrics for machine translation have been proposed through the metrics task on the Workshop on statistical Machine Translation (WMT). One can identify three kinds of automatic evaluation metrics (C. Liu et al., 2010): the heavyweight linguistic approach, which corresponds to RTE (S. Padó et al., 2009) and ULC (J. Giménez and L. Márquez, 2007); the lightweight linguistic approach, which corresponds to METEOR (A. Lavie and A. Agarwal, 2007) and MaxSim (Y. Seng Chan and H. Tou Ng, 2008) and the non-linguistic approach, which includes BLEU (K. Papineni et al., 2002), TER (M. Snover et al., 2006), RIBES (H. Isozaki et al., 2010) and IMPACT (H. Echizen-ya and K. Araki, 2007)(H. Echizen-ya et al., 2012). In this paper, we specifically examine a metric that corresponds to the lightweight linguistic and non-linguistic approaches because they are useful and are very easily built.

Among these metrics, METEOR and IMPACT are based on the f-measure, which combines precision and recall between the reference and candidate texts. The metrics’ simple f-measure (P. Koehn, 2010) obtains precision and recall using Eqs. (1)–(3):

\[
\text{precision} = \frac{\text{matching words}}{\text{length of candidate}} \tag{1}
\]

\[
\text{recall} = \frac{\text{matching words}}{\text{length of reference}} \tag{2}
\]

Then f-measure is calculated using Eq. (3):

\[
\text{f-measure} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{3}
\]

For example, in the reference “doctor cured a patient” and candidate “doctor treated a patient”, the precision and the recall are respectively 0.75 (\(=\frac{3}{4}\)). Therefore, the f-measure is 0.75 (\(=\frac{2 \times 0.75 \times 0.75}{0.75+0.75}\)), even though there is only one non-matching word. This is because the denominator is so small, since the sentences
are short: the weight of each non-matched word is 0.25 \((=\frac{1}{4})\) in this example. In general, the relative influence of each non-matching word increases when sentences are short, distorting the overall score. This problem is especially serious in short sentences. On the other hand, the weight of each mismatched word is small when the number of words is large.

In this paper, we propose a new automatic evaluation metric in which the weight of each mismatched word does not depend heavily on sentence length. In our metric, the weight of each mismatched word is kept small even in short sentences. Therefore, our metric can obtain a stable evaluation score without regard to sentence length. We designate the metric as Automatic Evaluation Metric that is Independent of Sentence Length (AILE). Through experimentally obtained results, we confirmed that AILE indicates the highest correlation with human judgment among several leading metrics.

## 2 AILE: Automatic Evaluation Metric Independent of Sentence Length

In AILE, a chunk sequence is decided using Longest Common Subsequence (LCS) between the reference and candidate. A chunk is a string of consecutive words. In “doctor cured a patient” and “doctor treated a patient”, the value of LCS is 3 because the matching words are “doctor”, “a” and “patient”. Therefore, the chunks are “doctor” and “a patient”.

Moreover, AILE obtains \(\text{AILE}\) score as the evaluation score using the following Eqs. (4)–(8).

\[
P = \left( \frac{\sum_{i=0}^{RN-1} (\alpha^i \times C_{\text{score}}) + \text{weight}}{m^\beta + \text{weight}} \right)^\frac{1}{\gamma}
\]

(4)

\[
R = \frac{\left( \sum_{i=0}^{RN-1} (\alpha^i \times C_{\text{score}}) + \text{weight} \right)^\frac{1}{\gamma}}{n^\beta + \text{weight}}
\]

(5)

\[
C_{\text{score}} = \sum_{c \in \text{chunk}} \text{length}(c)^\beta
\]

(6)

\[
\text{weight} = \begin{cases}
\frac{\delta}{\log(m+n)} & \text{if } C_{\text{score}} > 0.0 \\
0.0, & \text{if } C_{\text{score}} = 0.0
\end{cases}
\]

(7)

\[
\text{AILE score} = \frac{(1 + \gamma^2)RP}{R + \gamma^2 P}
\]

(8)

In Eq. (6), \(c\) and \(\text{chunk}\) mean each chunk and the number of chunks, respectively. Moreover, \(\text{length}(c)\) means the number of words in each chunk and \(\beta\) is a parameter for the weight of chunk length. In “doctor cured a patient” and “doctor treated a patient”, two chunks (i.e., “doctor” and “a patient”) exist. Therefore, \(C_{\text{score}}\) is 5.0 \((=1^{2.0}+2^{2.0})\) when \(\beta = 2.0\). The weight of Eq. (7) controls the weight of each matching word according to the sentence length. The \(m\) and \(n\) mean respectively the candidate length and reference length. The \(\delta\) and \(\beta\) are parameters. The value of \(\text{weight}\) is 0.0 when \(C_{\text{score}}\) is 0.0 because it means that the matching words between the reference and candidate do not exist. In “doctor cured a patient” and “doctor treated a patient”, the value of \(\text{weight}\) is 1.2261 \((=\frac{1.0}{\log(4+1)})^{2.0}\) when \(\delta\) and \(\beta\) are respectively 1.0 and 2.0.

In Eqs. (4) and (5), \(P\) and \(R\) respectively indicate precision and recall. Moreover, \(RN\) means the repetition number for the decision of \(C_{\text{score}}\). For example, in “doctor cured a patient” and “A patient helped doctor”, the appearance order of chunks (i.e., “doctor” and “a patient”) between two sentences is different. In this case, \(RN - 1\) is 1 because \(\alpha^0 \times C_{\text{score}}\) for the chunk “a patient” is firstly calculated and \(\alpha^1 \times C_{\text{score}}\) for the chunk “doctor” is secondly calculated. That is, \(\alpha\) is used as the parameter for the penalty when the appearance order of chunks between reference and candidate is different. In “doctor cured a patient” and “doctor treated a patient”, the value of \(\sum_{i=0}^{RN-1} (\alpha^i \times C_{\text{score}})\) is...
Table 1: Spearman’s rank correlation coefficient of system-level in AILE using NTCIR-7.

| Parameters | Adequacy (14 systems) | Fluency (14 systems) | Avg. |
|------------|-----------------------|----------------------|------|
| \( \alpha = 0.1, \beta = 1.2, \delta = 2.0 \) | 0.9912 | 0.9253 | 0.9583 |
| \( \alpha = 0.3, \beta = 1.2, \delta = 2.0 \) | 0.9868 | 0.9297 | 0.9583 |
| \( \alpha = 0.5, \beta = 1.2, \delta = 2.0 \) | 0.9780 | 0.9253 | 0.9517 |
| \( \alpha = 0.7, \beta = 1.2, \delta = 2.0 \) | 0.9560 | 0.9033 | 0.9297 |
| \( \alpha = 0.9, \beta = 1.2, \delta = 2.0 \) | 0.9473 | 0.8945 | 0.9209 |
| \( \alpha = 0.1, \beta = 1.0, \delta = 2.0 \) | 0.9912 | 0.9253 | 0.9583 |
| \( \alpha = 0.1, \beta = 1.4, \delta = 2.0 \) | 0.9780 | 0.9165 | 0.9473 |
| \( \alpha = 0.1, \beta = 1.6, \delta = 2.0 \) | 0.9780 | 0.9165 | 0.9473 |
| \( \alpha = 0.1, \beta = 1.8, \delta = 2.0 \) | 0.9780 | 0.9165 | 0.9473 |
| \( \alpha = 0.1, \beta = 2.0, \delta = 2.0 \) | 0.9736 | 0.9121 | 0.9429 |
| \( \alpha = 0.1, \beta = 1.2, \delta = 1.0 \) | 0.9780 | 0.9253 | 0.9517 |
| \( \alpha = 0.1, \beta = 1.2, \delta = 3.0 \) | 0.9868 | 0.9297 | 0.9583 |
| \( \alpha = 0.1, \beta = 1.2, \delta = 4.0 \) | 0.9768 | 0.9297 | 0.9583 |
| \( \alpha = 0.1, \beta = 1.2, \delta = 5.0 \) | 0.9834 | 0.9241 | 0.9538 |
| \( \alpha = 0.1, \beta = 1.2, \delta = 6.0 \) | 0.9780 | 0.9165 | 0.9473 |
| square root | 0.9780 | 0.9253 | 0.9517 |
| arctangent | 0.9912 | 0.9253 | 0.9583 |

5.0 (=0.5 \times 5.0) when \( \alpha \) is 0.5 because \( RN - 1 \) is 0. The value of \( P \) and \( R \) in Eqs. (4) and (5) is respectively 0.6012 (=\( \sqrt{0.012261} \)). Eq. (8) indicates f-measure using \( P \) and \( R \). The \( \gamma \) is obtained as \( P/R \). In “doctor cured a patient” and “doctor treated a patient”, the value of AILE score is 0.6012 (=\( (1+1.2261 \times 0.012261 \times 0.6012) \)) because the value of \( \gamma \) is 1.0 (=\( 0.6012/0.6012 \)).

The evaluation score increases from 0.5590 to 0.6012 using weight in Eq. (7). The AILE score without weight is 0.5590 because the value of \( P \) and \( R \) is respectively 0.5590 (=\( \sqrt{0.26} \)). This means that AILE can increase the evaluation score in short sentences using weight in Eq. (7). The value of weight is 1.2261 (=\( \frac{0.6012}{log(4.0)} \)) when \( m \) and \( n \) are respectively 4. The value of weight is 0.3896 (=\( \frac{0.6012}{log(20.0)} \)) when \( m \) and \( n \) are respectively 20. That is, the weight of non-matched words decreases in short sentences adding the large value (e.g., 1.2261) of weight to the matching words (i.e., \( \sum_{i=0}^{RN-1} (\alpha^i \times C_{-\text{score}}) \) in Eqs. (4) and (5)). On the other hand, the weight of non-matched words does not change in long sentences, adding only the small value (e.g., 0.3869) of weight to the matching words (i.e., \( \sum_{i=0}^{RN-1} (\alpha^i \times C_{-\text{score}}) \) in Eqs. (4) and (5)). Therefore, AILE can obtain a stable evaluation score without depending on sentence length.

3 Experiments

3.1 Experimental Procedure

We performed experiments to confirm the effectiveness of AILE. The correlations between the scores by automatic evaluation and the scores by human judgments are calculated, respectively, at the system level and the sentence level. Spearman’s rank correlation coefficient is used at the system level and the Kendall tau rank correlation coefficient is used in the sentence level. In the first experiment, the references and candidates were obtained from patent data in NTCIR-7 (A. Fujii et al., 2008). We used as candidates the machine translation system’s translation of Japanese sentences into English sentences. In NTCIR-7 data, 14 machine translation systems were used and each machine translation system translated 100 Japanese sentences into 100 English sentences. Therefore, we obtained 1,400 candidates. We used single references. The median value in the evaluation results of three human judges was used as the scores of 1–5. The experiments determined suitable values for the three parameters \( \alpha, \beta \) and \( \delta \). Moreover, the
Table 2: Kendall tau rank correlation coefficient of sentence-level in AILE using NTCIR-7.

| Parameters | Adequacy (1,400 sentences) | Fluency (1,400 sentences) | Avg. | Total Avg. |
|------------|-----------------------------|---------------------------|------|------------|
| $\alpha = 0.1, \beta = 1.2, \delta = 2.0$ | 0.4304 | 0.3627 | 0.3965 | 0.6774 |
| $\alpha = 0.3, \beta = 1.2, \delta = 2.0$ | 0.4231 | 0.3596 | 0.3914 | 0.6749 |
| $\alpha = 0.5, \beta = 1.2, \delta = 2.0$ | 0.4095 | 0.3533 | 0.3814 | 0.6666 |
| $\alpha = 0.7, \beta = 1.2, \delta = 2.0$ | 0.3862 | 0.3414 | 0.3638 | 0.6468 |
| $\alpha = 0.9, \beta = 1.2, \delta = 2.0$ | 0.3449 | 0.3156 | 0.3303 | 0.6256 |
| $\alpha = 0.1, \beta = 1.0, \delta = 2.0$ | 0.4058 | 0.3645 | 0.3973 | 0.6723 |
| $\alpha = 0.1, \beta = 1.4, \delta = 2.0$ | 0.4300 | 0.3605 | 0.3908 | 0.6691 |
| $\alpha = 0.1, \beta = 1.8, \delta = 2.0$ | 0.4116 | 0.3550 | 0.3833 | 0.6653 |
| $\alpha = 0.1, \beta = 2.0, \delta = 2.0$ | 0.4040 | 0.3503 | 0.3772 | 0.6601 |
| $\alpha = 0.1, \beta = 1.2, \delta = 1.0$ | 0.3993 | 0.3467 | 0.3730 | 0.6624 |
| $\alpha = 0.1, \beta = 1.2, \delta = 3.0$ | 0.4178 | 0.3588 | 0.3883 | 0.6733 |
| $\alpha = 0.1, \beta = 1.2, \delta = 4.0$ | 0.4239 | 0.3624 | 0.3932 | 0.6758 |
| $\alpha = 0.1, \beta = 1.2, \delta = 5.0$ | 0.4278 | 0.3647 | 0.3963 | 0.6751 |
| $\alpha = 0.1, \beta = 1.2, \delta = 6.0$ | 0.4303 | 0.3457 | **0.3980** | 0.6727 |
| square root | 0.4182 | 0.3537 | 0.3860 | 0.6689 |
| arctangent | 0.4288 | 0.3617 | 0.3953 | 0.6768 |

Table 3: Spearman’s rank correlation coefficient of system-level in NTCIR-7.

| Metrics | Adequacy (14 systems) | Fluency (14 systems) | Avg. |
|---------|-----------------------|----------------------|------|
| AILE    | 0.9912                | 0.9253               | **0.9582** |
| BLEU    | 0.8505                | 0.8242               | 0.8374 |
| IMPACT  | 0.9912                | 0.9253               | **0.9582** |
| METEOR  | 0.8022                | 0.7538               | 0.7780 |
| RIBES   | 0.9121                | 0.8374               | 0.8747 |
| TER     | -0.9473               | -0.8769              | -0.9121 |

correlations in both system-level and sentence-level were obtained using AILE. In the second and third experiments, the references and candidates were respectively obtained from WMT10 (C. Callison-Burch et al., 2010) and WMT11 (C. Callison-Burch et al., 2011). In these experiments, as candidate we used the machine translation system’s translations of European (i.e., Czech, German, Spanish and French) sentences into English sentences, compared to a single reference. The correlations with system-level translations were obtained using AILE in these experiments.

Moreover, we used the following automatic evaluation metrics: BLEU (ver. 12), METEOR (ver. 1.4), RIBES (ver. 1.02.3), TER (tercom ver. 0.7.25), and IMPACT (ver. 4.0.2) to compare with AILE. In all experiments, the software “tokenizer.perl” and “lowercase.perl” (P. Koehn, 2011) were used for all references and candidates before the evaluation scores were calculated using the metrics.

### 3.2 Experimental Results

Tables 1 and 2 respectively provide Spearman’s rank correlation coefficients of system-level and Kendall tau rank correlation coefficients of sentence-level in AILE based on the various values of parameters. In Table 2, “Total Avg.” indicates the average value between “Avg.” in Table 1 and “Avg.” in Table 2. Moreover, “square root” and “arctangent” respectively indicate the correlation coefficients obtained by replacing $\log(m + n)$ in Eq. (7)
with $\sqrt{m+n}$ and $\arctan(x+y)$. In these case, 0.1, 1.2 and 2.0 were respectively used as the values of parameters $\alpha$, $\beta$ and $\delta$.

Tables 3 and 4 respectively provide Spearman’s rank correlation coefficients of system-level and Kendall tau rank correlation coefficients of sentence-level in NTCIR-7 (A. Fujii et al., 2008). Table 5 provides the Spearman’s rank correlation coefficient of system-level in WMT10 (C. Callison-Burch et al., 2010). Table 6 provides the Spearman’s rank correlation coefficient of system-level in WMT11 (C. Callison-Burch et al., 2011). In Table 6, “indiv” and “comb” respectively indicate a single machine translation system and the combination of two machine translation systems.

### 3.3 Discussion

Through Table 2, the value 0.6774 was the highest value in “Total Avg.”. Therefore, 0.1, 1.2, and 2.0 were determined as the most suitable values of parameters $\alpha$, $\beta$ and $\delta$ respectively. In AILE of Tables 3-6, their values were used as the values.

AILE provided the highest correlation with human judgments, except for Table 5. These results show the effectiveness of AILE. Moreover, we investigated the effectiveness of AILE in short sentences and long sentences. The AILE can obtain a high correlation by decreasing the weight of mismatched words in short sentences. We performed the experiments using two data sets in which the numbers of word in the pairs of the reference and candidate are respectively small and large. In NTCIR-7 data, the average of word number in all pairs of the reference and candidate is 61.59. Therefore, we divided all pairs in two kinds of data. One is the pairs of short sentences (numbers of words in reference and candidate under 60). Another is the pairs of long sentences (numbers of words in reference and candidate over 60). In system-level, the Spearman’s rank correlation coefficients of AILE using weight are the same as those of AILE without weight.

Through Table 7, the correlation coefficients of AILE using weight are higher them of AILE without weight. The value of “Avg.” improved 0.0043 (from 0.3729 to 0.3772) using weight of Eq. (7) in long sentences.

### Table 4: Kendall tau rank correlation coefficient of sentence-level in NTCIR-7.

| Metrics | Adequacy (1,400 sentences) | Fluency (1,400 sentences) | Avg. |
|---------|---------------------------|---------------------------|------|
| AILE    | 0.4304                    | 0.3627                    | **0.3965** |
| BLEU    | 0.1146                    | 0.1491                    | 0.1319 |
| IMPACT  | 0.4138                    | 0.3503                    | 0.3820 |
| METEOR  | 0.1838                    | 0.2060                    | 0.1949 |
| RIBES   | 0.3558                    | 0.2950                    | 0.3254 |
| TER     | -0.2664                   | -0.2605                   | -0.2635 |

### Table 5: Spearman’s rank correlation coefficient of system-level in WMT10.

| Metrics | cz-en (12 systems) | de-en (25 systems) | es-en (14 systems) | fr-en (24 systems) | Avg. |
|---------|---------------------|--------------------|--------------------|--------------------|------|
| AILE    | 0.6573              | 0.6769             | 0.6029             | 0.5878             | **0.6312** |
| BLEU    | 0.7203              | 0.7885             | 0.3890             | 0.6862             | **0.6460** |
| IMPACT  | 0.6643              | 0.7115             | 0.6381             | 0.5635             | 0.6443 |
| METEOR  | 0.5594              | 0.8538             | 0.4330             | 0.4957             | 0.5855 |
| RIBES   | 0.4895              | 0.5423             | 0.6615             | 0.5200             | 0.5533 |
| TER     | -0.8042             | -0.3700            | -0.5429            | -0.3983            | -0.5288 |
Table 6: Spearman’s rank correlation coefficient of system-level in WMT11.

| Metrics | cz-en indiv (8 systems) | de-en indiv (20 systems) | es-en indiv (15 systems) | es-en comb (6 systems) |
|---------|-------------------------|--------------------------|--------------------------|-----------------------|
| AILE    | 0.9048                  | 0.1729                   | 0.7571                   | -0.0857               |
| BLEU    | 0.8383                  | 0.2369                   | 0.8204                   | -0.1739               |
| IMPACT  | 0.9048                  | 0.1722                   | 0.7857                   | -0.3714               |
| METEOR  | 0.9286                  | 0.5308                   | 0.8321                   | -0.6000               |
| RIBES   | 0.8333                  | 0.0406                   | 0.5393                   | -0.0667               |
| TER     | -0.9524                 | -0.1985                  | -0.7250                  | 0.8286                |

Table 7: Kendall tau rank correlation coefficient of sentence-level in long sentences.

| Metrics | Adequacy (637 sentences) | Fluency (637 sentences) | Avg. |
|---------|--------------------------|--------------------------|------|
| AILE using weight | 0.4011                  | 0.3532                   | 0.3772 |
| AILE without weight | 0.3975                  | 0.3482                   | 0.3729 |

other hand, in Table 8, the value of “Avg.” improved 0.0096 (from 0.3461 to 0.3557) using weight of Eq. (7) in short sentences. These results indicate the effectiveness of the use of weight in Eq. (7). Especially, weight is effective in short sentences described in Section 2. The improved value 0.0096 in short sentences is higher than 0.0043 in long sentences. Therefore, we confirmed that weight of Eq. (7) is especially effective in short sentences. As a result, AILE can obtain stable evaluation scores without depending on sentence length.

4 Conclusion

In this paper, we proposed a new automatic evaluation metric, in which the weight of each mismatched word does not depend heavily on sentence length. Our metric can obtain stable evaluation scores that are not distorted by sentence length. Our experimental results indicated that the correlation coefficient of our metric is the highest among some leading metrics. Therefore, we confirmed the effectiveness of our metric.

Future studies will work to increase the correlation coefficients. Moreover, we will use our metric as tuning in SMT. The AILE software will be released as IMPACT version 4.0.3 by http://www.lst.hokkai-s-u.ac.jp/~echi/impact.html.

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### Table 8: Kendall tau rank correlation coefficient of sentence-level in short sentences.

| Metrics                | Adequacy (763 sentences) | Fluency (763 sentences) | Avg.  |
|------------------------|--------------------------|-------------------------|-------|
| AILE using *weight*    | 0.3897                   | 0.3217                  | 0.3557|
| AILE without *weight*  | 0.3774                   | 0.3147                  | 0.3461|

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