



Figure 1: Integration of Our Method and RTT

$p$	BEA-19 test	CoNLL 14	JFLEG test
0.0	67.32 / 69.42	60.60 / 62.25	60.12 / 60.69
0.1	67.52 / 69.28	60.73 / 62.78	60.21 / 60.84
0.2	67.35 / <b>69.83</b>	60.58 / 62.69	60.19 / 60.69
0.3	66.60 / 68.58	60.37 / 61.78	<b>60.38 / 60.91</b>
0.4	<b>68.00</b> / 69.76	60.48 / 62.13	59.90 / 60.46
0.5	67.92 / 69.71	60.55 / 62.02	60.15 / 60.74
0.6	67.28 / 69.02	60.75 / 61.65	60.20 / 60.60
0.7	67.80 / 69.38	<b>61.29 / 63.47</b>	60.26 / 60.75
0.8	67.94 / 69.53	60.22 / 61.81	60.32 / 60.74
0.9	67.09 / 69.25	60.49 / 62.95	60.04 / 60.60
1.0	67.65 / 69.08	60.63 / 61.44	60.21 / 60.57

Table 1: Integration of our method and RTT.

## A Integration of Our Method and RTT

We further investigate if combination of our method and RTT is beneficial. We integrate them by applying RTT at the probability of  $p$ , in which RTT’ed sentence is selected with an equal probability, then conducting our method. Figure 1 shows the integrated procedure.

Table 1 shows the results. The optimal  $p$  varies for each evaluation dataset, and it is difficult to say if the integration is beneficial. There might be a good method to combine our method and MT-based methods. We plan to research this in future work.

## B Effectiveness of BPE-dropout

All the experiments in our paper use BPE-dropout of  $p = 0.1$ , which is recommended in the original paper. We investigate the effectiveness of subword regularization with changing  $p$ .

Table 2 shows the result for baseline models. The optimal  $p$  is 0.1. BPE-dropout improves performance as subword regularization.

Table 3 shows the result for artificial+target settings using 16M augmented data. BPE-dropout applies to both pre-training and fine-tuning data at the same dropout probability. The optimal  $p$  varies for

$p$	BEA-19 test	CoNLL 14	JFLEG test
0.0	55.21 / 61.21	49.68 / 53.45	53.73 / 54.26
0.05	58.87 / <b>63.56</b>	53.26 / 56.51	57.19 / 57.78
0.1	<b>59.09 / 63.56</b>	<b>54.03 / 56.79</b>	<b>57.33 / 58.15</b>
0.15	58.62 / 63.27	53.31 / 56.36	57.25 / 57.73
0.20	57.59 / 62.60	53.54 / 56.42	57.24 / 57.82

Table 2: The effect of BPE-dropout for target-only settings.

$p$	BEA-19 test	CoNLL 14	JFLEG test
0.0	66.51 / 69.34	60.36 / <b>63.14</b>	59.55 / 60.04
0.05	67.19 / <b>70.32</b>	59.68 / 62.73	60.41 / <b>61.03</b>
0.1	<b>67.32</b> / 69.42	<b>60.60</b> / 62.25	60.12 / 60.69
0.15	66.90 / 69.26	60.53 / 61.97	60.31 / 60.71
0.20	66.96 / 69.34	60.32 / 62.28	<b>60.45</b> / 60.95

Table 3: The effect of BPE-dropout for artificial+target settings.

each evaluation dataset. Furthermore, we can observe that BPE-dropout improves even pre-trained and fine-tuned models in BEA-19 test and JFLEG test dataset.