Reducing Length Bias in Scoring Neural Machine Translation via a Causal Inference Method

Xuewen Shi¹,², Heyan Huang¹,², Ping Jian¹,²∗, Yi-Kun Tang¹,²

¹School of Computer Science and Technology, Beijing Institute of Technology, Beijing, China
²Beijing Engineering Research Center of High Volume Language Information Processing and Cloud Computing Applications
{xwshi, hhy63, pjian, tangyk}@bit.edu.cn

Abstract

Neural machine translation (NMT) usually employs beam search to expand the searching space and obtain more translation candidates. However, the increase of the beam size often suffers from plenty of short translations, resulting in dramatical decrease in translation quality. In this paper, we handle the length bias problem through a perspective of causal inference. Specifically, we regard the model generated translation score \( S \) as a degraded true translation quality affected by some noise, and one of the confounders is the translation length. We apply a Half-Sibling Regression method to remove the length effect on \( S \), and then we can obtain a debiased translation score without length information. The proposed method is model agnostic and unsupervised, which is adaptive to any NMT model and test dataset. We conduct the experiments on three translation tasks with different scales of datasets. Experimental results and further analyses show that our approaches gain comparable performance with the empirical baseline methods.

1 Introduction

Recently, with the renaissance of deep learning, end-to-end neural machine translation (NMT) (Sutskever et al., 2014; Bahdanau et al., 2015) has gained remarkable performances (Wu et al., 2016; Gehring et al., 2017; Vaswani et al., 2017). NMT models are usually built upon an encoder-decoder framework (Cho et al., 2014): the encoder reads an input sequence \( x = \{x_1, \ldots, x_{T_x}\} \) into a hidden memory \( H \), and the decoder is designed to model a probability over the translation \( y = \{y_1, \ldots, y_{T_y}\} \) by:

\[
P(y|x) = \prod_{t=1}^{T_y} P(y_t|y_{<t}, H).
\]

(1)

Most existing NMT approaches employ beam search to obtain more translation candidates and then gain a better translation hypothesis \( \hat{y} = \{\hat{y}_1, \cdots, \hat{y}_{T_y}\} \) by ranking the translation candidates set \( \hat{Y} = \{\hat{y}_1, \cdots, \hat{y}_b\} \) across a score function \( s(\hat{y}) \):

\[
s(\hat{y}) = \sum_{t=1}^{T_y} \log P(\hat{y}_t|x; \theta),
\]

(2)

where \( b \) is the beam size and \( \theta \) is the parameter set of the NMT model.

However, continuously increasing the beam size has been shown to degrade performances and lead to short translations (Koehn and Knowles, 2017). One decisive reason is that the large search space is easy to introduce more short \( \hat{y} \), and the shorter \( \hat{y} \) tends to be scored higher under \( s(\hat{y}) \) in Eq. (2). Previous efforts usually deal with the above length bias problem by two mechanisms: i) performing length normalization on \( s(\hat{y}) \) via dividing \( s(\hat{y}) \) by the length penalty \( lp \), i.e. \( s'(\hat{y}) \leftarrow s(\hat{y})/lp \) (Boulanger-Lewandowski et al., 2013; Jean et al., 2015; Koehn and Knowles, 2017; Yang et al., 2018; Meister et al., 2020), and ii) adding an additional length-related reward \( r \) to \( s(\hat{y}) \), i.e. \( s'(\hat{y}) \leftarrow s(\hat{y}) + \gamma \cdot r \) (Li and Jurafsky, 2016; He et al., 2016; Murray and Chiang, 2018; Huang et al., 2017; Yang et al., 2018).
the second strategy, the correcting ratio $\gamma$ of the reward is usually determined by supervised training (He et al., 2016; Murray and Chiang, 2018) or manually fine-tuning (Huang et al., 2017) before the testing stage, which lacks the ability of self-adapting to the unseen data.

In this paper, we introduce a causal motivated model agnostic and unsupervised method to solve the length bias problem for NMT. As shown in Fig. 1, for a translation hypothesis $\hat{y}$, suppose that $Q$ is an unobservable true translation quality of $\hat{y}$, and the model generated score $S$ can be seen as an observed degraded version of $Q$ which is affected by some noise $N$. Generally, $S$ equals $s(\hat{y})$ in conventional NMT approaches, and it can be viewed as one of the measurement methods of $Q$ with systematic errors. As mentioned above, one kind of systematic errors has a strong correlation with the translation length, therefore, the noise caused by length will be eliminated if we subtract the length effect from $S$. Specifically, we utilize the Half-Sibling Regression (HSR) (Schölkopf et al., 2016) method to perform the noise elimination operation for NMT. The method first apply a regression model to appraise the effect of the translation length on the model generated score, i.e. $E[S|T_y]$. Then, the denoised score is obtained by removing $E[S|T_y]$ from $S$:

$$S' := S - E[S|T_y].$$

We propose two branches of the framework, corpus based (C-HSR) and single source sentence based (S-HSR) re-scoring method. The difference is that C-HSR performs the estimation of $E[S|T_y]$ on the whole test set, while S-HSR uses the translation candidates in a beam of the NMT inference process to predict $E[S|T_y]$. The operation of approximating $E[S|T_y]$ for both C-HSR and S-HSR entirely rely on the current testing data of NMT without fine-tuning or any supervised information. In this work, we regard the NMT model as a black-box and apply the HSR-based denoised method to the re-scoring procedure for NMT.

We conduct the experiments on three translation tasks: Uyghur→Chinese, Chinese→English and English→French, which represent low-resource, medium-resource and high-resource NMT, respectively. The experimental results show the proposed approaches achieve comparable performances with empirical length normalization methods. Further analyses show the flexibility of the proposed methods and the assumptions that our approaches rely on are reliable.

2 Related Work

The length bias reduction methods can be mainly divided into two categories: i) dividing the log probability by the length penalty $lp$:

$$s'(\hat{y}) \leftarrow s(\hat{y})/lp,$$

and ii) adding an additive length-related reward to the log probability of the hypothesis:

$$s'(\hat{y}) \leftarrow s(\hat{y}) + \gamma \cdot r.$$
Google’s NMT system (Wu et al., 2016) employ an empirical length penalty that is computed as:

\[ s'(\hat{y}) \leftarrow s(\hat{y})/\left(5 + T_{\hat{y}}\right)^{\alpha}/\left(5 + 1\right)^{\alpha}, \] (6)

where the parameter \( \alpha \) is used to control the strength of the length normalization. Stahlberg and Byrne (2019) apply another variant of \( lp \), which introduces the information of the length ratio of the hypotheses over the source sentence. Yang et al. (2018) propose a brevity penalty normalization which adds the log brevity penalty \( bp \) to the normalized score:

\[ s'(\hat{y}) \leftarrow s(\hat{y})/T_{\hat{y}} + \log bp, \] (7)

where \( bp \) is same as the form of brevity penalty in BLEU (Papineni et al., 2002):

\[ bp = \begin{cases} 
1 & gr \cdot T_{x} < T_{\hat{y}} \\
\frac{1}{e^{(1-T_{y}/T_{\hat{y}})}} & gr \cdot T_{x} \geq T_{\hat{y}}
\end{cases}, \] (8)

where \( gr \) is the generation ratio i.e. \( T_{y}/T_{x} \). Since \( T_{y} \) is unknown in the inference step, Yang et al. (2018) apply a 2-layer multi layer perceptron (MLP) to predict the \( gr \) by taking the mean of the hidden states of the NMT encoder as the input.

The second branch is similar to the word penalty in statistical machine translation (Och and Ney, 2002; Koehn, 2010). The parameter \( \gamma \) can be automatically optimized with supervised learning (He et al., 2016; Murray and Chiang, 2018) or manually assignment (Huang et al., 2017).

He et al. (2016) propose a log-linear NMT framework which incorporates a word reward feature to the framework to control the length of the translation:

\[ s'(\hat{y}) \leftarrow s(\hat{y}) + \gamma \cdot T_{\hat{y}} , \] (9)

where \( \gamma \) is trained with other parameters of the log-linear NMT model using minimum error rate training (Och, 2003; He et al., 2016). Murray and Chiang (2018) make the optimization process of \( \gamma \) independent to the NMT training process, so that the \( \gamma \) can be trained on a relatively small dataset. Huang et al. (2017) introduce a Bounded Length Reward that includes the prior knowledge of the generation ratio \( gr \) of reference translation length over source sentence length:

\[ s'(\hat{y}) \leftarrow s(\hat{y}) + \gamma \cdot \min(gr \cdot T_{x}, T_{\hat{y}}), \] (10)

where the length reward \( \gamma \) is fine-tuned manually. All the above methods (He et al., 2016; Murray and Chiang, 2018; Huang et al., 2017) fine-tune the correcting ratio \( \gamma \) by a supervised data, which may lead to less optimal results on unseen test datasets. Yang et al. (2018) propose a Bounded Adaptive-Reward to remove the hyperparameter \( \gamma \): \( s'(\hat{y}) \leftarrow s(\hat{y}) + \sum_{t=1}^{T^{*}} r_{t} \), where \( b \) is the beam size and \( r_{t} \) is the average negative log-probability of the words in the beam at time step \( t \). \( T^{*} = \min\{T_{\hat{y}}, T_{\text{pred}(x)}\} \), where \( T_{\text{pred}(x)} \) is predicted with a 2-layer MLP instead of using the constant \( gr \) (Huang et al., 2017) as Eq. (10) does.

The proposed HSR-based debiasing method is motivated entirely by a causal structure shown in Fig. 1, although the form of the approach is same as the reward-based length normalization in Eq. (5). Formally, we can regard \( \mathbb{E}[S|T_{\hat{y}}] \) in Eq. (3) as an instance of \( \gamma \cdot r \) in Eq. (9) with very few prior assumptions or handcrafted designs. The leaning process of \( \mathbb{E}[S|T_{\hat{y}}] \) is entirely model agnostic and unsupervised, which makes the proposed method more competitive to the previous supervised approaches (He et al., 2016; Murray and Chiang, 2018; Huang et al., 2017) in real practical applications.

## 3 Approach

### 3.1 Correcting Length Bias via Half-Sibling Regression

In this paper, we apply a debiasing framework of Half-Sibling Regression (HSR) (Schölkopf et al., 2016) to subtract the NMT scoring bias caused by the length of the translation. For a translation hypothesis
**Algorithm 1** HSR in translation re-scoring for correcting length bias. See section 3.2 for more details.

**Input:** \( m \) translation candidates: \( \hat{Y} = \{\hat{y}_1, \ldots, \hat{y}_m\} \), the lengths set of the translation candidates: \( T(\hat{Y}) = \{T_{\hat{y}_1}, \ldots, T_{\hat{y}_m}\} \), NMT model scores for the \( m \) translation candidates: \( s(\hat{Y}) = \{s(\hat{y}_1), \ldots, s(\hat{y}_m)\} \) and a hyperparameter \( \alpha \in [0, 1] \).

1. Find the optimal parameters \( \theta_R^* \) for a regression model \( R(T_{\hat{y}}; \theta_R) \) by minimize the mean square error:
   \[
   \theta_R^* = \arg \min_{\theta_R} \frac{1}{m} \sum_{\hat{y} \in \hat{Y}} |R(T_{\hat{y}}; \theta_R) - s(\hat{y})|^2
   \]

2. Subtract length information from the model estimated score:
   \[
   s'(\hat{Y}) \leftarrow s(\hat{Y}) - \alpha \times R^*(T(\hat{Y}); \theta_R^*)
   \] (12)

**Output:** The debiased translation scores \( s'(\hat{Y}) = \{s'(\hat{y}_1), \ldots, s'(\hat{y}_m)\} \).

\( \hat{y} \), suppose that \( Q \) is the true translation quality that we cannot observe directly, and we regard \( S \) as an observable degraded version of \( Q \) which is affected by \( Q \) and some noise \( N \), simultaneously. Considering a conventional NMT decoder, \( S \) is usually calculated by \( s(\hat{y}) \) in Eq. (2). As discussed in section 1, \( T_{\hat{y}} \), as the length of \( \hat{y} \), has undesired crucial impacts on \( S \). We refer \( s(\hat{y}) \) as a measurement of \( Q \) with systemic errors \( N \), then \( T_{\hat{y}} \) is the correlative variable of \( N \) that satisfies \( N \perp \perp T_{\hat{y}} \). At the same time, we assume that \( Q \perp T_{\hat{y}} \), therefore, we can subtract the effects of \( T_{\hat{y}} \) on \( S \), i.e. \( \mathbb{E}[S|T_{\hat{y}}] \), from \( S \) to eliminate length bias without affect the connection between \( S \) and \( Q \):

\[
S' \leftarrow S - \mathbb{E}[S|T_{\hat{y}}].
\] (11)

In practice, the value of \( \mathbb{E}[S|T_{\hat{y}}] \) can be estimated by a regression model that is trained on the observed \((S, T_{\hat{y}})\) pairs.

Fig. 1 shows the causal directed acyclic graph (DAG) that illustrates the causalities between \( Q, S, N, N^* \) and \( T_{\hat{y}} \), where \( N^* \) is other noise source that satisfies \( N^* \perp \perp T_{\hat{y}} \). We set up an undirected connection between \( N \) and \( T_{\hat{y}} \) to represent \( N \perp \perp T_{\hat{y}} \) since the causal direction between the two variables is not important in this paper. It is worth noting that \( Q \perp \perp T_{\hat{y}} \) is a strong assumption when we don’t know the specific form of \( Q \). The possible forms of \( Q \) and the assumption of \( Q \perp \perp T_{\hat{y}} \) will be discussed in more detail in section 3.3.1.

### 3.2 Re-scoring Translation Candidates

The HSR-based length debiasing method is model agnostic and it views the NMT model as a black-box. Therefore, we simply apply the HSR-based approach to the translation re-scoring process to verify its effectiveness. Algorithm 1 shows a sketch of the proposed re-scoring framework. As described in Algorithm 1, we first optimize a regression model \( R(T_{\hat{y}}; \theta_R) \) that parameterized by \( \theta_R \) to estimate the length effect on \( s(\hat{y}) \) by using the data \((T(\hat{Y}), s(T_{\hat{y}})) = \{(T_{\hat{y}_1}, s(\hat{y}_1))\}_{i=1}^m\). Then, we adopt the optimal \( R^*(T_{\hat{y}}; \theta_R^*) \) as an approximate to \( \mathbb{E}[S|T_{\hat{y}}] \) in Eq. (11) to eliminate the length information from \( s(\hat{y}) \):

\[
s'(\hat{y}) \leftarrow s(\hat{y}) - \alpha \times R^*(T_{\hat{y}}; \theta_R^*).
\] (13)

Following Wu et al. (2016), we introduce a hyperparameter \( \alpha \in [0, 1] \) to control the strength of the debiasing operation. \( \alpha = 0 \) means no debiasing operation is conducted and empirical studies show that setting \( \alpha = 1 \) usually gains better performances for \( b \geq 8 \). (Note that Eq. (12) in Algorithm 1 is in a set form while Eq. (13) is in a single value form.)

We propose two branches of implementations for the proposed re-scoring framework in practice: i) a corpus based re-scoring method (C-HSR) and ii) a single source sentence based re-scoring method (S-HSR). For C-HSR, we perform the regression over the translations and their model scores of the whole test dataset, in other words, it needs the NMT model to finish translating the whole test set. For S-HSR,
the regression model is optimized on the translation candidates and their model scores of a single input source sentence. Therefore, the size of $\hat{Y}$ in Algorithm 1, i.e. $m$, equals the beam size $b$ and $b \times |X_{test}|$ (the size of test set) for S-HSR and C-HSR, respectively.

### 3.3 Discussion

#### 3.3.1 The Assumption of $Q$ is Independent of $T_y$

Considering one of ideally forms of $Q$ that is straightforward defined as a conditional probability:

$$Q := P(y|x) = P(\{y_1, ..., y_{T_y}\}|x).$$

(14)

In Eq. (14), $T_y$ is an inherent feature of $y$, so it is also involved in $Q$. Therefore, executing the calculation of Eq. (11) will inevitably eliminate parts of $Q$ itself.

However, the condition where $T_y$ is almost independent of $Q$ is also sufficient for HSR in practice, according to Schölkopf et al. (2016). Hence, we should verify the correlation between $Q$ and $T_y$ before employing our approach to specific applications. Since, $Q$ as well as $P(y|x)$ is theoretic and unobservable, we adopt a more precise and pricey observable variable, the professional translators’ direct assessment (DA) score, as an approximation to the $Q$ $^1$. We use the datasets from WMT 2020 Quality Estimation Share Task 1 $^2$: Sentence-Level Direct Assessment (Specia et al., 2020) to analyze the Pearson’s and Spearman’s correlation scores between the length of translation and the DA score, and the results are presented in Table 1.

As Table 1 shows, for most conditions, the absolute values of the correlation scores are less than 0.20, which indicates that $Q$ is almost independent of the translation length in a linear 2-dimensional space. However, there are multiple possible variables that influence the human DA score such as the number of the rare words in the source sentence and the translation hypothesis. Although partial correlation (Baba et al., 2004) might be effective for analyzing multiple correlative variables, the information about the other observable variables is unavailable. In general, we believe that removing $E[S|T_y]$ will not harm the information of $Q$ too much, and the debiasing ratio $\alpha$ is also a conservative design to avoid punishing the length information overly.

| Language Pair            | Train Pearson | Train Spearman | Valid Pearson | Valid Spearman | Test Pearson | Test Spearman |
|--------------------------|---------------|----------------|---------------|----------------|--------------|--------------|
| English-German           | -0.06         | -0.11          | -0.15         | -0.18          | -0.18        | -0.18        |
| English-Chinese          | -0.07         | -0.12          | -0.08         | -0.09          | -0.00        | -0.02        |
| Romanian-English         | -0.20         | -0.15          | -0.20         | -0.14          | -0.25        | -0.18        |
| Estonian-English         | -0.09         | -0.13          | -0.09         | -0.10          | -0.11        | -0.11        |
| Nepalese-English         | -0.12         | -0.02          | -0.12         | -0.05          | -0.09        | -0.01        |
| Sinhala-English          | -0.14         | -0.06          | -0.11         | -0.05          | -0.17        | -0.07        |
| Russian-English          | 0.07          | -0.07          | 0.00          | -0.10          | -0.01        | -0.16        |

Table 1: The Pearson’s and Spearman’s correlation scores between the DA score and $T_y$.

#### 3.3.2 The Connection to the Word Reward

The proposed HSR-based debiasing method is motivated by a causal structure, although the formalized form of our proposed approach is same as adding length-related reward in Eq. (5), by regarding $E[S|T_y]$ as a special instance of $(\gamma \cdot r)$. In particular, if we only consider the linear effects, i.e. $R(T_y; \theta_R) = \theta_1 T_y + \theta_2$, then Eq. (13) is expand as:

$$s'(\hat{y}) \leftarrow s(\hat{y}) - \alpha \times (\theta_1^* T_y + \theta_2^*) = s(\hat{y}) - \alpha \theta_1^* T_y - \alpha \theta_2^* ,$$

(15)

which is similar to the word reward in Eq. (9). The $\theta_1^* \in \mathbb{R}$ and $\theta_2^* \in \mathbb{R}$ in Eq. (15) are optimal parameters of the linear regression. Therefore, under the above linear assumption, the proposed method can be seen as a simple and effective unsupervised strategy to optimize $\gamma$ for the word penalty (He et al.,

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$^1$Note that, $P(y|x)$ is one of the formal definitions of $Q$, and it is not the essence of $Q$. On the other hand, the human generated DA score is the currently available best approximation of $Q$ to our best knowledge.

$^2$http://www.statmt.org/wmt20/quality-estimation-task.html
Since most of the previous word penalty efforts determine $\gamma$ through a supervised procedure (He et al., 2016; Murray and Chiang, 2018; Huang et al., 2017) before the testing stage, they may fall into less optimal results on unseen datasets.

However, if we do not apply the linear regression, the form will be different to the word penalty. In this paper, we study the performances of various typical regression models including linear regression, support vector regression, k-neighbors regression, multi-layer perceptor (MLP) regression and random forest regression. We find that applying linear regression and MLP regression to C-HSR and S-HSR respectively gain better performances. The detailed analyses about various regression models are shown in section 5.1.

4 Experiments

4.1 Datasets and Evaluation Metric

We evaluate the proposed approaches on three translation tasks: Uyghur→Chinese (Ug→Zh), Chinese→English (Zh→En) and English→French (En→Fr). For each of the translation task, the corpus is tokenized by the Moses (Koehn et al., 2007) tokenizer.perl before encoded with byte-pair encoding (Sennrich et al., 2016). For Zh→En and Ug→Zh translation tasks, the Chinese parts are segmented by the LTP segmentor (Che et al., 2010) before tokenizing.

Ug→Zh. For Uyghur→Chinese translation, the training corpus is from Uyghur to Chinese News Translation Task in CCMT2019 Machine Translation Evaluation (Yang et al., 2019). Apart from the Moses (Koehn et al., 2007) tokenizer, we do not use any other tools to segment Uyghur. The training set contains 0.17M parallel sentence pairs, and the vocabularies are 30K for both Uyghur and Chinese corpus. The official validation set and the test set are applied in our experiments.

Zh→En. For Chinese→English translation, the training data is extracted from four LDC corpora. The training set finally contains 1.3M parallel sentence pairs in total. After preprocessing, we get a Chinese vocabulary of about 39K tokens, and an English vocabulary of about 30K tokens. We use NIST2002 dataset for validation and NIST 2003~2006 datasets for test.

En→Fr. For English→French translation, we conduct our experiments on the publicly available WMT’14 En→Fr datasets which consist of 18M sentences pairs. Both source and target vocabulary contains 30K tokens after preprocessing. We report results on newstest2014 dataset, and newstest2013 dataset is used as the validation set.

Evaluation. Following Vaswani et al. (2017), we report the results of a single model by averaging the 5 checkpoints around the best model selected on the development set. The translation results are measured in case-insensitive BLEU (Papineni et al., 2002) by multi-bleu.perl. For the Ug→Zh translation task, the BLEU scores are reported at character-level.

4.2 Length Normalization Baselines

We adopt two popular empirical length normalization strategies ((i),(ii)) and a complicated MLP-based method ((iii)) as the comparison baseline methods: i) Length Norm: directly dividing the translation score by the length of the translation (Boulanger-Lewandowski et al., 2013; Jean et al., 2015; Koehn and Knowles, 2017) as shown in Eq. (4), ii) GNMT: the length normalization method of Google NMT (Wu et al., 2016), as shown in Eq. (6), and iii) BP Norm: the length normalization method that applies a model predicted bp constraint (Yang et al., 2018) as shown in Eq. (7) and Eq. (8). We average the outputs of the Transformer encoder instead of the LSTM hidden layers as the input of the 2-layers MLP used in Yang et al. (2018). For fairness considerations, those methods are all unsupervised, since our proposed methods do not rely on any human reference.
4.3 Model Setups

We apply the base model of Transformer (Vaswani et al., 2017) as the specific implement of the NMT baseline in our work, and we build up the NMT models based on OpenNMT-py (Klein et al., 2017).

We analyze different regression models for both C-HSR and S-HSR, and finally select linear regression for C-HSR and one-hidden layer MLP regression S-HSR, denoted by “C-HSR\textsubscript{LR}” and “S-HSR\textsubscript{MLP}”, respectively. The regression models used in our work are implemented by using scikit-learn (Pedregosa et al., 2011). The detailed setups and analyses for different regression models are shown in section 5.1.

Following Wu et al. (2016), we use $\alpha$ to control the strength of length bias correcting. The $\alpha$ is selected according to the performance on the validation set and the detail selections of $\alpha$ for different model setups are shown in Table 2. The detailed analyses on $\alpha$ are presented in section 5.2.

| Language Pair | Method | $b=4$ | $b=8$ | $b=16$ | $b=32$ | $b=64$ | $b=100$ | $b=200$ |
|---------------|--------|-------|-------|--------|--------|--------|---------|---------|
| Ug → Zh      | GNMT   | 1.0   | -     | -      | -      | -      | -       | -       |
|              | C-HSR\textsubscript{LR} | 0.9   | 1.0   | -      | -      | -      | -       | -       |
|              | S-HSR\textsubscript{MLP} | 1.0   | -     | -      | -      | -      | -       | -       |
| Zh → En      | GNMT   | 0.5   | 0.9   | 1.0    | -      | -      | -       | -       |
|              | C-HSR\textsubscript{LR} | 0.7   | 1.0   | -      | -      | -      | -       | -       |
|              | S-HSR\textsubscript{MLP} | 0.7   | 0.9   | 0.9    | 1.0    | -      | -       | -       |
| En → Fr      | GNMT   | 0.9   | -     | -      | -      | -      | -       | -       |
|              | C-HSR\textsubscript{LR} | 0.8   | -     | -      | -      | 0.9    | 1.0     | -       |
|              | S-HSR\textsubscript{MLP} | 0.8   | -     | -      | -      | -      | -       | -       |

Table 2: Correcting ratio $\alpha$ for different model setups. “-” means same as the value in the left cell.

4.4 Main Results

We conduct experiments on three translation tasks with disparate corpora scales: low-resource Ug → Zh, medium-resource Zh → En and high-resource En → Fr. We present BLEU scores on translations with two different decoding beam sizes: $b = 4$ and $b = 200$, in order to compare the model performances on small and large beam sizes. The experimental results are shown in Table 3 and Table 4.

The overall results show that all the length debiasing approaches obtain better BLEU scores than the baseline NMT model for large beam size. For the condition of smaller beam size, “Length Norm” tends to disrupt the model performance on En → Fr and Zh → En datasets, which is contrary to the case of a larger search space.

Our proposed C-HSR\textsubscript{LR} and S-HSR\textsubscript{MLP} seem to produce stable BLEU scores across multiple datasets and beam sizes. The results show that S-HSR\textsubscript{MLP} usually gains better BLEU scores than C-HSR\textsubscript{LR} on the large beam size (Ug → Zh, Zh → En and En → Fr), while C-HSR\textsubscript{LR} performs better on the small beam size (Zh → En and En → Fr). We consider the reason is that S-HSR\textsubscript{MLP} is trained better on $b = 200$ than that on small dataset. On the other hand, the requirements for training a linear regression model is not as strict as it for MLP, although the accuracy of the linear model may be lower than the MLP-based model when both of them are well trained.

The performance of BP Norm is unsatisfactory, which we consider the reason is that the MLP-based generation ratio predictor does not work well. If our hypothesis is correct, the length of the transla-

| Method          | En → Fr | b=4 | b=200 | Ug → Zh | b=4 | b=200 |
|-----------------|---------|-----|-------|---------|-----|-------|
| Transformer     | 39.61   | 39.41 | 39.73 | 39.80   | 39.52 | 39.78 | 39.88 | 39.96 | 39.80 |
| +Length Norm    |         | 39.41 | 39.13 | 39.76   | 39.80 | 39.78 | 39.87 | 39.96 | 39.80 |
| +GNMT           | 39.77   | 39.35 | 39.76 | 39.88   | 39.76 | 39.87 | 39.94 | 39.80 | 39.80 |
| +BP Norm        | 38.36   | 38.35 | 38.76 | 38.88   | 38.76 | 38.87 | 38.94 | 38.80 | 38.80 |
| +C-HSR\textsubscript{LR} | 39.73   | 39.13 | 37.88 | 37.88 | 37.88 | 37.88 | 37.88 | 37.88 | 37.88 |
| +S-HSR\textsubscript{MLP} | 39.80   | 39.28 | 37.81 | 37.87 | 37.87 | 37.87 | 37.87 | 37.87 | 37.87 |

Table 3: BLEU scores on En → Fr and Ug → Zh translation tasks. “b” represents the beam size.
Table 4: BLEU scores on NIST 2003~2006 Zh→En translation task. “b” represents the beam size.

| Method       | 03 b=4 | 04 b=4 | 05 b=4 | 06 b=4 | Average b=4 |
|--------------|--------|--------|--------|--------|-------------|
| Transformer  | 40.10  | 33.55  | 42.09  | 35.31  | 40.33       |
| +Length Norm | 39.99  | 40.13  | 42.05  | 42.23  | 40.10       |
| +GNMT        | 40.13  | 40.08  | 42.18  | 42.18  | 40.39       |
| +BP Norm     | 39.46  | 39.25  | 41.50  | 41.22  | 39.67       |
| +C-HSR\_LR  | 40.35  | 39.58  | 42.60  | 42.00  | 40.32       |
| +S-HSR\_MLP  | 40.40  | 40.25  | 42.42  | 42.44  | 40.33       |

Figure 2: BLEU scores of different methods with respect to different beam sizes [4 ~ 200]. The y-axis is the BLEU score, and the x-axis is the decoding beam size. For Zh→En task, we present the averaged the BLEU score of NIST 2003~2006. See section 4.5 for more details.

4.5 Performance on Wider Beam Size

As a supplement to section 4.4, we analyze the performances of the proposed approaches on different decoding beam sizes. Fig. 2 shows the trend of the BLEU scores with respect to the beam sizes of [4, 8, 16, 32, 64, 100, 200] for the three translation tasks. From Fig. 2 we can observe that all the length debiasing methods achieve stable and comparable performances when the beam size increases.

We also analyze the length ratio distributions between generated sentences and references ($T_y/T_x$), and Fig. 3 shows the length ratio on the decoding beam size of 200 for the three translation tasks. The histogram illustrates that the Transformer baseline select more short translations with $b = 200$, while all the debiasing methods avoid the length problem effectively. We can see that BP Norm selects most translations that are longer than the human references, which explains their deficient performances on Zh→En and En→Fr translation tasks.

Figure 3: Histogram of the distributions of length ratio between the generated sentences and the human references across methods with the beam size of 200. The y-axis is the frequency, and the x-axis is the length ratio. See section 4.5 for more details.
5 Analysis

5.1 Comparisons among Different Regression Models

The proposed HSR-based debiasing framework has a large elbow room for the implementation of \( E[S|T_y] \). In this paper, we analyze 5 typical regression methods for making the estimation of \( E[S|T_y] \) to verify the flexibility of the proposed method. The models and setups are listed in Table 5.

| #  | Method         | Regression (Abbr) | Parameters Setups |
|----|----------------|-------------------|------------------|
| 1  | C-HSR          | Linear (LR)       | <default>        |
| 2  | Support Vector (SV) | Not used in C-HSR |                  |
| 3  | K Neighbors (KN) | n_neighbors=2, weights="distance" |              |
| 4  | Multi-layer Perceptron (MLP) | hidden_layer_sizes=50, activations='relu', max_iter=10 |          |
| 5  | Random Forest (RF) | n_estimators=9, criterion='mse' |          |
| 6  | S-HSR Linear (LR) | <default>        |                  |
| 7  | Support Vector (SV) | kernel='rbf', C=100, tol=1.5, epsilon=0.1, gamma='auto' |          |
| 8  | K Neighbors (KN) | n_neighbors=2, weights="distance" |              |
| 9  | Multi-layer Perceptron (MLP) | hidden_layer_sizes=50, activations='relu', max_iter=35 |          |

Table 5: Model setups for different regression methods. “Regression (Abbr)” is the regression model and its abbreviation name in this paper. “Parameters Setup” is the hyper-parameters set for the model in scikit-learn toolkits (Pedregosa et al., 2011), and other parameters that are not mentioned are set by default values.

The model setups shown in Table 5 are fine-tuned on Zh→En NIST 2002 dataset with the beam size of 200. We apply the same model setups for all the datasets and beam sizes, in order to verify the generalization of the proposed HSR-based debiasing method, though the optimal hyper-parameters of the regression models may be distinct. We do not apply \( SV \) to C-HSR, since we find that the support vector tends to be a horizontal line in this work when the size of training set is larger than 1,000.

The BLEU scores and the executing speed on the three translation tasks are shown in Table 6. The operating environment is CentOS Linux release 7.5.1804 with Intel(R) Xeon(R) CPU E5-2650 v4 @ 2.0GHz. The overall results show that the S-HSR methods (#5~#9) usually gains better BLEU scores than the C-HSR methods (#1~#4) on large beam size no matter which regression model is used. It illustrates that the S-HSR methods are more adaptable to different translation hypotheses than the C-HSR methods.

On the other hand, different regression models have little differences in BLEU scores, and each regression method obtains comparable results with other regression models. It illustrates that the principles and the assumptions that the proposed methods rely on are reliable, since the specific implements of the approaches do not play an important role on the experimental results. However, from the aspect of executing speed, applying linear regression shows a remarkable advantage comparing with the others.

5.2 Selection of the Correcting Ratio \( \alpha \)

As Table 2 shows, the optimal selections of \( \alpha \) are usually distinctive for different datasets and beam sizes. We study the impact of different \( \alpha \) on the BLEU scores by taking NIST 2002 Zh→En development set as an example, and the experimental results are shown in Table 7. The overall results show that for a small search space, an \( \alpha \in [0.5, 0.9] \) is appropriate, while for larger beam sizes, setting \( \alpha = 1.0 \) usually gets better BLEU scores. There may be two reasons for the above phenomenon: i) the model generated score \( s(\hat{y}) \) is more severely affected by \( T_y \) with the large decoding beam size, and ii) large beam size provides the regression model with more training data to estimate \( E[S|T_y] \). We compare the results among C-HSR, C-HSR, C-HSR, C-HSR, and S-HSR, S-HSR to control the impacts of different regression models.

The size of the training data is \( b \times |X_{nls|02}| \) for the C-HSR methods, which is sufficient on each beam size. Therefore, we consider that the \( s(\hat{y}) \) is less affected by \( T_y \) with small beam size, since the optimal \( \alpha \) is 0.7 for both C-HSR and S-HSR. On the other hand, comparing with the BLEU scores under \( b = 32 \) and \( b = 200 \), we believe that the size of training data is another factor to influence the selection of \( \alpha \), especially for S-HSR.
Table 6: **BLEU and executing speed comparison among different setups of our approaches.** For Zh→En task, we present the averaged the BLEU score of NIST 2003∼2006. “Speed” is measured in sentences per second (sent./s). See section 5.1 for more details.

| # | Method   | Ug→Zh | Zh→En | En→Fr | Speed (sent./s) |
|---|----------|-------|-------|-------|-----------------|
| 1 | C-HSR\(_{LR}\) | 37.88 | 37.87 | 40.88 | 39.73 | 39.13 | 7,934 | 163 |
| 2 | C-HSR\(_{KN}\) | 37.73 | 37.16 | 40.41 | 39.05 | 37.97 | 781 | 13 |
| 3 | C-HSR\(_{MLP}\) | 37.85 | 37.19 | 40.89 | 39.61 | 37.94 | 2,556 | 60 |
| 4 | C-HSR\(_{RF}\) | 37.75 | 37.36 | 40.76 | 39.65 | 38.83 | 475 | 9 |
| 5 | S-HSR\(_{LR}\) | 37.77 | 37.87 | 40.67 | 39.69 | 39.02 | 779 | 14 |
| 6 | S-HSR\(_{SV}\) | 37.57 | 37.75 | 40.60 | 39.60 | 38.90 | 1,930 | 61 |
| 7 | S-HSR\(_{KN}\) | 37.65 | 38.00 | 40.67 | 39.63 | 38.51 | 779 | 14 |
| 8 | S-HSR\(_{MLP}\) | 37.81 | 38.02 | 40.85 | 39.80 | 39.28 | 84 | 12 |
| 9 | S-HSR\(_{RF}\) | 37.62 | 37.78 | 40.62 | 39.69 | 38.69 | 157 | 15 |

Table 7: **BLEU score with respect to different values of \(\alpha\) on NIST 2002 Zh→En dataset.** “b” represents the beam size. “0.1 ∼ 1.0” are the values of \(\alpha\). See section 5.2 for more details.

| \(b\) | Method   | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1.0 |
|------|----------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 4   | C-HSR\(_{LR}\) | 41.81 | 41.87 | 41.91 | 41.91 | 41.96 | 41.92 | **42.01** | 41.98 | 41.91 | 41.84 |
|     | C-HSR\(_{MLP}\) | 41.81 | 41.87 | 41.93 | 41.90 | 41.95 | 41.98 | **41.98** | 41.92 | 41.84 | 41.78 |
|     | S-HSR\(_{MLP}\) | 41.81 | 41.87 | 41.93 | 41.98 | 41.98 | 41.93 | **41.99** | 41.93 | 41.90 | 41.77 |
| 32  | C-HSR\(_{LR}\) | 40.59 | 40.56 | 40.68 | 41.13 | 41.14 | 41.22 | 41.54 | 41.84 | 41.99 | **42.20** |
|     | C-HSR\(_{MLP}\) | 40.50 | 40.59 | 40.67 | 41.00 | 41.19 | 41.27 | 41.61 | 41.80 | 41.95 | **42.11** |
|     | S-HSR\(_{MLP}\) | 40.52 | 40.61 | 40.88 | 40.94 | 41.08 | 41.16 | 41.50 | 41.78 | **42.02** | 41.95 |
| 200 | C-HSR\(_{LR}\) | 34.41 | 35.22 | 36.09 | 37.06 | 38.41 | 39.18 | 39.87 | 40.60 | 41.23 | **41.57** |
|     | C-HSR\(_{MLP}\) | 34.25 | 34.95 | 35.65 | 36.38 | 37.46 | 38.60 | 39.55 | 40.40 | 40.86 | **41.49** |
|     | S-HSR\(_{MLP}\) | 34.36 | 35.11 | 36.48 | 37.67 | 38.65 | 39.92 | 40.86 | 41.35 | 41.72 | **42.07** |

In this paper, the introduction of the correcting ratio \(\alpha\) can slack the strict assumption of \(Q \perp S\), which prevent the proposed approaches from punishing length information too much. The results presented in Table 2 and Table 7 verify parts of our discussion about the independent assumptions.

### 6 Conclusion and Future Work

In this paper, we introduce a causal motivated method to reduce the length bias problem in NMT. We employ a Half-Sibling Regression (Schölkopf et al., 2016) method to handle this task and corroborate the task satisfies the independence assumption of HSR. Experimental results on three language pairs with distinct data scales show the effectiveness of the proposed method.

In the future, we will complete our experiments on the task of Quality Estimation. Since the proposed approaches are model agnostic and unsupervised, we will verify the effectiveness of our approaches on other natural language generation tasks, such as dialogue system and summarization. We also hope to make further studies about the relationships among \(Q\), \(S\) and \(T_y\).

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