Generative Bridging Network in Neural Sequence Prediction

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Abstract

Maximum Likelihood Estimation (MLE) has been known to pose data sparsity challenge in sequence prediction tasks, in order to alleviate data sparseness, we propose a novel framework to train sequence model via a bridging process. Unlike MLE which optimizes the sequence generator by directly maximizing the likelihood of ground truth sequence given the input, our proposed framework designs a bridge to connect generator with ground truth. During training, we first follow certain constraints to transform the pointwise ground truth as a bridge distribution, then match the generator's output distribution with the transformed bridge distribution by minimizing their KL-divergence. By imposing different constraints, bridge distribution will adopt different properties. In order to increase output diversity, enhance language smoothness and lower learning burden, we design three different regularization constraints to construct different bridge distributions. Combining these bridges with sequence generator, we can build three parallel generative bridging networks, namely uniform GBN, language-model GBN and coaching GBN. Experimental results on two recognized sequence prediction tasks have shown that GBN can yield significant improvements over the baseline system. Furthermore, we draw samples from three bridge distributions to analyze their different properties and verify their influences on the sequence model learning.

Introduction

Sequence prediction has been widely used in tasks which involve a group of mutually dependent outputs. Recently, massive sophisticated explorations in this area have been made to solve real-life problems like machine translation Bahdanau, Cho, and Bengio (2014); Ma et al. (2017); Norouzi et al. (2016), syntactic parsing McDonald, Crammer, and Pereira (2005), spelling correction Bahdanau, Cho, and Bengio (2014), image captioning Xu et al. (2015) and speech recognition Chorowski et al. (2015). Combined with recent development in deep neural network techniques, i.e. LSTM Hochreiter and Schmidhuber (1997), GRU Chung et al. (2014), CNN Krizhevsky, Sutskever, and Hinton (2012), neural sequence prediction techniques have achieved state-of-the-art performance on these tasks.

The standard algorithm for sequence prediction learning is Maximum Likelihood Estimation (MLE), which seeks to maximize the likelihood of source-target pairs in the training dataset:

$$\theta^* = \arg\max_{\theta} E_{(X,Y) \in D} [\log p_\theta(Y^*|X)]$$ (1)

MLE is widely adopted in sequence-to-sequence models Bahdanau, Cho, and Bengio (2014); Cho et al. (2014) to achieve great success in various sequence prediction tasks, however, it largely relies on the availability of sizable dataset and falls short under data-scarce scenarios. In order to combat the data sparsity problem encountered by MLE algorithm, different strategies Cheng et al. (2016); Ma et al. (2017); Norouzi et al. (2016); Sennrich, Haddow, and Birch (2015); Zhang and Zong (2016) have been performed. Among them, Cheng et al. (2016); Sennrich, Haddow, and Birch (2015); Zhang and Zong (2016) propose to leverage unparallel data into sequence-to-sequence learning. Ma et al. (2017); Norouzi et al. (2016) advocate to synthesize new data by directly modifying ground truth from existing parallel dataset and introduce these additional synthetic data pairs into training. Inspired by RAML Ma et al. (2017); Norouzi et al. (2016), we also aim at tackling the sparsity problem by directly augmenting synthetic training samples. In this paper, we introduce a bridging process to first transform the pointwise ground truth as a bridge distribution, which can be seen as a much larger intermediate dataset, then use we use bridge distribution to draw candidates to train the sequence generator. The bridge and generator are combined in a unified framework, which is called generative bridging network (GBN).

Here, we define bridge as a conditional probability model $p_\eta(Y|Y^*)$ and design its optimization target as maximizing the expected similarity score $S(Y, Y^*)$ under regularization $\text{Reg}$, the regularization function restricts the general shape of $p_\eta(Y|Y^*)$ by a constraint probability $p_\epsilon(Y)$.

$$\arg\max_{p_\eta(Y|Y^*)} S(Y, Y^*) + \alpha \text{Reg}(p_\eta(Y|Y^*), p_\epsilon(Y))$$ (2)
where \( \alpha \) controls the scale of the regularization term, the higher the closer to constraint probability \( p_c(Y) \). Combining these two objectives empower the bridge distribution to not only concentrate its mass around the ground truth \( Y^* \) but also adopt certain hope properties. We demonstrate a schematic diagram in Figure 1 by imposing different constraints on the bridge network, different-shaped bridge distributions will be formed. Once the bridge is constructed, we advocate to optimize the generator to match its output distribution towards the bridge distribution by minimizing their KL-divergence, formally, we write generator's objective as:

\[
L_G(\theta) = KL(p_θ(Y|Y^*)\|p_θ(Y|X))
\]

In this paper, we introduce three different constraints

\[
\delta(Y) \quad \ldots \quad P_η \quad \ldots \quad \ldots \quad P_θ
\]

Constrain A Constrain B Constrain C

Figure 1: A bridge distribution is centered around the ground truth and its general shape is decided by the constraint, once the bridge distribution is constructed, sequence generator is optimized to match the bridge distribution.

to construct three parallel GBN systems, namely uniform GBN, language-model GBN and coaching GBN. The uniform GBN instantiates constraint \( p_c(Y) \) as a uniform distribution and seeks to increase the data diversity as much as possible, the language-model constraint instantiates constraint \( p_c(Y) \) as a language model and seeks to increase the model's language smoothness, the coaching constraint instantiates constraint \( p_c(Y) \) as generator's output distribution and seeks a close-to-model distribution, which enables it to draw easier-to-learn samples for model to learn. Additionally, we also found that the GBN without constraint corresponds to MLE and the uniform GBN corresponds to RAML [Norouzi et al., 2016], therefore our proposed GBN can be seen as a generalized form of existing MLE/RAML algorithms.

By comparing experimental results of the three parallel systems, we found that coaching GBN achieves the strongest performance among all. In order to analyze the different impacts brought by different constraint on the generator model, we randomly sample candidates from the three bridge distributions to perform human evaluation. Based on our evaluation, we conclude that coaching bridge is able to simplify or remove more complex expressions from training samples and reorder the sentence in an simpler form, which can lower generator's learning burden and help it make gradual progress. Our contributions can be concluded as:

- We have proposed a bridging process in sequence prediction task to alleviate data sparsity problem.
- We have designed three parallel systems based on three different constraints and verify their advantages over the baseline system.
- We have proved that our GBN framework generalizes RAML and MLE as special cases, the experimental results have also demonstrated the advantages of our framework over the existing RAML and MLE.

**Related Literature**

**Data augmentation via self-learning**

In order to resolve the data sparsity problem in Neural Machine Translation, many research has been performed to augment the dataset. The most popular strategy is via self-learning, which leverages the self-generated data directly into training. The papers Zhang and Zong [2016] and Sennrich, Haddow, and Birch [2015] have both used self-learning algorithms to leverage massive monolingual data into NMT training. Zhang and Zong [2016] uses source-side monolingual data while Sennrich, Haddow, and Birch [2015] uses target-side monolingual data. Our model differs from theirs in that no additional monolingual data is required, our approach directly synthesizes data from existing dataset.

**Reward Augmented Maximum Likelihood**

Reward Augmented Maximum Likelihood (RAML) [Norouzi et al., 2016] proposes to integrate task-level reward into MLE training by using an exponentiated payoff distribution. By minimizing the KL divergence between model distribution and a payoff distribution, an optimal regularized expected reward is achieved. This strategy advocates to use RAML gradient to update the sequence model. Ma et al. [2017] has further introduced a novel softmax Q-Distribution to interpret RAML and reveals RAML’s relation with Bayes decision rule. These two methodologies both alleviate data sparsity problem by augmenting candidates based on the ground truth \( Y^* \). Our paper draws inspiration from them but seeks to find a more generalized solution – Generative Bridging Network, which can broadcast the ground truth into different forms of intermediate distributions, by adopting different constraints the samples drawn from the bridge distribution will account for more sophisticated factors.

**Coaching**

Our coaching GBN system draws inspiration from imitation learning by coaching [He, Eisner, and Daume’ 2012], which advocates to design an intermediate target to gradually pull learner towards oracle when their policies have substantial difference or the oracle are inexpressible by the model. Instead of directly learning from the oracle, He, Eisner, and Daume [2012] advocates to learn a hope action.
based on the interpolation of learner’s policy and environment loss function, as the learner makes progress, the intermediate target will become harsher to further raise learner’s capability. Similar as the coaching in Imitation Learning, our proposed coaching GBN also motivates to construct an intermediate easy-to-learn bridge which lies in between ground truth and generator, our environmental results can confirm its effectiveness to lower the learning burden.

Model

Sequence-to-Sequence Learning

We consider the problem of learning to produce an output sequence \( Y = (y_1, y_2, \ldots, y_T) \), \( y_t \in A \) given an input \( X \). Training and Test use two input-target pairs \((X, Y^*)\), the generated sequence on test is evaluated with task-specific score \( R(Y, Y^*) \). The task of sequence-to-sequence learning is to train a model which can output sequence \( Y \) as close (minimize \( R(Y, Y^*) \)) to the ground truth sequence \( Y^* \) as possible. Encoder-Decoder framework with recurrent neural network has been widely used for this task [Bahdanau, Cho, and Bengio (2014); Cho et al. (2014)]. In this framework, an encoder is used to encode the input sequence to be a sequence of source hidden states, based on which, attention mechanism is leveraged to compute a context vector, which is a weighted average of the hidden states, the context vector together with previous target hidden states and previous labels are fed into the decoder RNN to predict the next state and its label. In our approach, attentive encoder-decoder [Bahdanau, Cho, and Bengio (2014)] is adopted for generator model, and it is formulated as:

\[
\begin{align*}
    y_t & \sim g(s_{t-1}, c_{t-1}) \\
    s_t & = f(s_{t-1}, c_{t-1}, e(y_t)) \\
    a_t & = \beta(s_t, (h_1, \ldots, h_L)) \\
    c_t & = \sum_{j=1}^L a_{t,j} h_j
\end{align*}
\]

We apply the sequence-to-sequence model in both Neural Machine Translation and Abstractive Text Summarization tasks.

Bridge Network

The bridge network is designed to broadcast a single target sample \( Y^* \) as an output distribution \( p_\eta(Y|Y^*) \). We design its optimization targets to consist of two terms, namely the concentration constraints and regularization, formally, we define it as:

\[
L_B(\eta) = E_{Y \in p_\eta(Y|Y^*)} - S(Y, Y^*) + a KL(p_\eta(Y|Y^*)||p_c(Y))
\]

(8)

\( S(Y, Y^*) \) measures the similarity between \( Y \) and \( Y^* \), while \( p_c(Y) \) constraint the bridge distribution. The first term ensures bridge’s concentration around the ground truth \( Y^* \), the second KL-divergence constraints bridge distribution’s general shape, the hyper-parameter \( a \) controls the scale of regularization. The scale factor can also be interpreted as introducing a temperature \( \tau \) to control predefined score function \( S(Y, Y^*) \), thus we re-write bridge’s optimization target as following:

\[
L_B(\eta) = E_{Y \in p_\eta(Y|Y^*)} - \frac{S(Y, Y^*)}{\tau} + KL(p_\eta(Y|Y^*)||p_c(Y))
\]

(9)

Note that though we name it bridge network, we don’t use neural network architecture to approximate it when a closed-form solution exists for the given optimization target, otherwise, we will adopt an encoder-decoder neural architecture to construct the bridge network.

Delta Bridge

Delta bridge can be seen as the simplest case where no constraints is imposed to bridge network, we instantiate score \( S(Y, Y^*) \) as task-level reward \( R(Y, Y^*) \). We can easily verify that an optimal solution is the kronecker-delta distribution:

\[
p_\eta(Y|Y^*) = \delta(Y, Y^*)
\]

(10)

The simplest case of GBN corresponds to MLE algorithm, we regard this case as our baseline system.

Uniform Bridge

Uniform bridge realizes \( S(Y, Y^*) \) as the task-level reward \( R(Y, Y^*) \) and \( p_c(Y) \) as a uniform distribution \( U(Y) \), this bridge motivates to include more variants, thus its loss function can be written as:

\[
L_B(\eta) = E_{Y \in p_\eta(Y|Y^*)} - \frac{S(Y, Y^*)}{\tau} + KL(p_\eta(Y|Y^*)||U(Y))
\]

(11)

We can re-write it as following:

\[
\text{argmin}_{L_B(\eta)} = \text{argmin}_{Y \in p_\eta(Y|Y^*)} - \frac{R(Y, Y^*)}{\tau} - H(p(Y|Y^*))
\]

\[
= \text{argmin}_{Y \in p_\eta(Y|Y^*)} E_{Y \in p_\eta(Y|Y^*)} \log \frac{p(Y|Y^*)}{\exp \frac{R(Y, Y^*)}{\tau}} + \log \sum_{Y^*} \exp \frac{R(Y, Y^*)}{\tau} = \text{argmin}_{KL(p(Y|Y^*))\|\|U(Y)}
\]

(12)

This bridge has a closed-form solution as:

\[
p(Y|Y^*) = \frac{\exp \frac{R(Y, Y^*)}{\tau}}{Z}
\]

(13)

where \( Z \) is the partition function of \( \exp \frac{R(Y, Y^*)}{\tau} \). We note that our uniform bridge corresponds to the payoff distribution described in [Norouzi et al. (2016)].

LM Bridge

LM bridge instantiates \( S(Y, Y^*) \) as the task-level reward \( R(Y, Y^*) \) and \( p_c(Y) \) as probabilistic language model \( p_{LM}(Y) \), which motivates to encompass more variants conforming to language fluency.

\[
L_B(\eta) = E_{Y \in p_\eta(Y|Y^*)} \frac{R(Y, Y^*)}{\tau} + KL(p_\eta(Y|Y^*)||p_{LM}(Y))
\]

(14)
In order to minimize this loss function, we re-write it as following:

\[
\arg\min_{\eta} L_B(\eta) = \arg\min \frac{E_{Y \sim p_{\eta}(Y|Y^*)} \left( \frac{R(Y, Y^*)}{\tau} + \log p_{LM}(Y) \right) - H(p(Y|Y^*))}{E_{Y \sim p_{\eta}(Y|Y^*)} \left( \frac{S(Y, Y^*)}{\tau} + KL(p(Y|Y^*)||U(Y)) \right)}
\]

Thus, LM bridge can be seen as an extension for uniform bridge, their only differences lie in their different realizations of the score function \(S(Y, Y^*)\). In LM bridge, an external language model score is incorporated to influence the payoff distribution:

\[
p(Y|Y^*) = \frac{p_{LM}(Y) \exp \frac{R(Y, Y^*)}{\tau}}{Z}
\]

where \(Z\) is the partition function of \(p_{LM}(Y) \exp R(Y, Y^*)\).

**Coaching Bridge** The coaching bridge realizes \(S(Y, Y^*)\) as the task-level reward \(R(Y, Y^*)\). For constrain, it selects the generator’s output distribution to regularize bridge distribution’s general shape, which motivates to enclose more samples easy to be understood by the generator so as to lower the learning burden. The coaching GBN follows the same spirit as coaching [He, Eisner, and Daume (2012)], which advocates to coach the model with easy-to-learn samples and let it gradually approach the oracle when the optimal action is hard to achieve.

\[
L_B(\eta) = \frac{E_{Y \sim p_{\eta}(Y|Y^*)} \left( \frac{R(Y, Y^*)}{\tau} + KL(p_{\eta}(Y|Y^*))||p_{\eta}(Y|X) \right)}{E_{Y \sim p_{\eta}(Y|Y^*)} \left( \frac{S(Y, Y^*)}{\tau} + KL(p(Y|Y^*)||U(Y)) \right)}
\]

Since there exists no closed-form solution for the optimal bridge distribution, therefore, gradient descent algorithm is required to optimize the loss function. Formally, we write the derivatives as following:

\[
\nabla L_B(\eta) = \frac{E_{Y \sim p_{\eta}(Y|Y^*)} \left( \frac{R(Y, Y^*)}{\tau} \nabla \log p_{\eta}(Y|Y^*) \right)}{E_{Y \sim p_{\eta}(Y|Y^*)} \left( \frac{S(Y, Y^*)}{\tau} \nabla \log p_{\eta}(Y|Y^*) \right)}
\]

Due to the mutual dependence between bridge network and generator network, we design an alternate iteration strategy, i.e. the two networks take turns to update their own parameters.

**Generator Network**

We advocate to connect generator model towards bridge network by minimizing their KL-divergence. Formally, we write generator’s optimization target as following:

\[
L_G(\theta) = KL(p_{\theta}(Y|Y^*)||p_{\theta}(Y|X))
\]

In order to minimize the KL-divergence objective, we advocate to use gradient descent algorithm, here we write the derivatives with respect to generator’s parameters as following:

\[
\nabla L_G(\theta) = \frac{E_{Y \in p_{\theta}(Y|Y^*)} \nabla \log p_{\theta}(Y|X)}{E_{Y \in p_{\theta}(Y|Y^*)} \nabla \log p_{\theta}(Y|Y^*)}
\]

The optimization process can be viewed as the generator maximizing likelihood of samples randomly drawn from bridge distribution, which largely alleviates data sparseness by posing more unseen scenarios to the model and help the model generalize better in test time.

**Training**

Figure 2: Four iterative updates of bridge and generator, blue curve represents generator’s conditional output distribution, green curve represents bridge distribution, and red curve represents the oracle, horizontal axis refers to the output space.

A more pedagogical explanation is drawn in Figure 3 to give an intuition about our proposed two-agent learning framework. The bridge network is optimized to not only understand data distribution but also conform to certain regularization template.

**Stratified Sampling** Since closed-formed optimal distributions can be found for uniform/LM GBN, we only need to draw samples from these distributions to train our sequence generator. Unfortunately, due to intractability of
these bridge distributions, a direct sampling is infeasible. Therefore, we follow \cite{Ma2017,Norouzi2016} to adopt stratified sampling strategy to approximate the payoff sampling process. Given a sentence $Y^*$, we first sample an edit distance $m$, and then randomly select $m$ positions to replace the original labels. The difference between the two approaches lie in that uniform bridge replaces labels by drawing substitutions from a uniform distribution, while LM bridge takes the history as condition and draw substitutions from the LM probability.

**Iterative Training** Since no closed-form solution is available for coaching GBN, an iterative training strategy is required to alternately update both the generator and bridge network. We show the iterative training algorithm in Algorithm 1, which proceeds in two stages, we first pre-train both the generator and bridge network, then start to alternately update their parameters.

**Experiment**

We select machine translation and abstractive text summarization as benchmarks to verify our learning algorithm, we first talk about how we define our task-level reward, then show details about the experimental datasets and their corresponding system setting below.

**Task-level Reward**

In our following experiments, instead of directly using BLEU/ROUGE as the task-level reward to guide bridge network’s policy search, we design a surrogate n-gram match score, which is denoted as:

$$R(Y, Y^*) = 0.4 \times N_4 + 0.3 \times N_3 + 0.2 \times N_2 + 0.1 \times N_1$$ \hspace{1cm} (21)

where $N_n$ denotes the n-gram match between $Y$ and $Y^*$. In order to alleviate sequence-reward sparseness, we further split it as a series of local rewards to drive model's policy search in every time step. Formally, we write the step-wise reward $r(y_t|y_{1:t-1}, Y^*)$ as following,

$$r(y_t|y_{1:t-1}, Y^*) = \begin{cases} 1.0; & N(Y_{1:t}, Y_{t-3:t}) \leq N(Y^*, y_{t-3:t}) \\ 0.6; & N(Y_{1:t}, Y_{t-2:t}) \leq N(Y^*, y_{t-2:t}) \\ 0.3; & N(Y_{1:t}, Y_{t-1:t}) \leq N(Y^*, y_{t-1:t}) \\ 0.1; & N(Y_{1:t}, y_t) \leq N(Y^*, y_t) \\ 0.0; & other \text{wise} \end{cases}$$ \hspace{1cm} (22)

where $N(Y, Y^*)$ represents the occurrence of sub-sequence $Y$ in sequence $Y^*$, specifically, if a certain sub-sequence $Y_{t-n:t}$ from $Y$ appears less times than in reference $Y^*$, then we assign a corresponding matching score to $y_t$. Formally, we rewrite the step-level RL as following:

$$E_{Y \in p_{\theta}(Y|Y^*)} \frac{R(Y, Y^*)}{\tau} \nabla \log p_\eta(Y|Y^*)$$

$$= \sum_{y_t \in p_{\theta}(Y|Y^*)} E_{Y \in p_{\theta}(Y|Y^*)} \frac{r(y_t|y_{1:t-1}, Y^*)}{\tau} \nabla \log p_\eta(y_t|y_{1:t-1}, Y^*)$$ \hspace{1cm} (23)

We follow \cite{Bahdanau2016, Shen2015} to use k-best list for approximating the Monte-Carlo Policy Gradient \cite{Williams1992}.

**Machine Translation**

**Dataset** We follow \cite{Bahdanau2016, Ranzato2015} to select German-English machine translation track of IWSLT2014 evaluation campaign. The corpus contains sentence-aligned subtitles of TED and TEDx talks, we use Moses toolkit \cite{Koehn2007} and remove sentences longer than 50 words as well as casing. The training dataset contains 153K sentences while the validation contains 6,969 sentences pairs, the test set comprises dev2010, dev2012, tst2010, tst2011 ad tst2012, the total amount are 6,750 sentences. Note that we don’t cut
off sentences longer than 50 words in test/validation set. The evaluation metric is BLEU [Papineni et al. 2002] computed via the multi-bleu.perl script.

**System Setting** We design a unified GRU-based RNN [Chung et al. 2014] for both generator and bridge model. In order to compare with the existed papers, we use a similar system setting with 512 RNN hidden units and 256 as embedding size. We use bidirectional encoder and one-layer RNN decoder to build our system, we also follow the conventional attention mechanism proposed in [Bahdanau, Cho, and Bengio 2014]. During training, we use ADADELTA [Zeiler 2012] with $\epsilon = 10^{-6}$ and $\rho = 0.95$ to separately optimize the generator and bridge’s parameters. During decoding, a beam size of 8 is used to approximate the full search space. An important hyper-parameter for our experiments is the temperature $\tau$, in uniform/LM bridge, we follow the Norouzi et al. (2016) to set an optimal temperature $\tau = 0.8$, while in coaching GBN, we test hyper-parameter from a set $\tau \in \{0.8, 1.0, 1.2\}$.

**Results** The experimental results for IWSLT2014 German-English Translation Task are summarized in Table 1, we compare our results with baseline systems as well as other competing algorithms. We can observe that our fine-tuned baseline system is already over-Performing other systems and our proposed GBN can further yield a significant improvement over our strong baseline system. Besides, we also observe that LM GBN and coaching GBN systems have both achieved higher performance than Uniform GBN, which denotes the fact that by leveraging more sophisticated prior constraints, the bridge distribution will become more robust and more benefits will be brought about. Here we also draw the learning curve of the easy-to-learn GBN system in Figure 4 to demonstrate how the two agents cooperate, we can easily observe the interaction between the two models – as generator makes progress, the bridge also improves itself to make optimization target harsher.

### Table 1: Comparison with the existing work on IWSLT-2014 German-English Machine Translation Task.

| Methods          | Baseline | Model |
|------------------|----------|-------|
| MIXER            | 20.10    | 21.81 |
| BSO              | 24.03    | 26.36 |
| A-C              | 27.56    | 28.53 |
| Softmax-Q        | 27.66    | 28.77 |
| Uniform GBN ($\tau = 0.8$) | 29.80   |       |
| LM GBN ($\tau = 0.8$) | 29.90   |       |
| Coaching GBN ($\tau = 0.8$) | 29.96   |       |
| Coaching ($\tau = 1.2$) | 30.15   |       |
| Coaching GBN ($\tau = 1.0$) | 30.18   |       |

**Abstract Text Summarization**

**Dataset** We follow the previous work by [Rush, Chopra, and Weston 2015; Zhou et al. 2017] to use the same parallel corpus from Annotated English Gigaword dataset [Napoles, Gormley, and Van Durme 2012], in order to maintain comparable with these research, we use the same script [1] released by Rush, Chopra, and Weston (2015) to pre-process and extract the training and development datasets. For test set, we use the English Gigaword released by [Rush, Chopra, and Weston 2015] and evaluate our system with ROUGE [Lin 2004], which measures the quality of summary by computing the overlapping lexical units. Following the previous research, we employ ROUGE-1, ROUGE-2 and ROUGE-L as the evaluation metrics in the reported experiment results.

**System Setting** We follow the paper by [Rush, Chopra, and Weston 2015; Zhou et al. 2017] to set input and output vocabularies as 119,504 and 68,883 respectively, we also set the word embedding size to 300 and all GRU hidden state sizes to 512, we adopt dropout [Srivastava et al. 2014] with probability $p = 0.5$ strategy in our output layer. We use attention-based sequence-to-sequence model [Bahdanau, Cho, and Bengio 2014; Cho et al. 2014] as our baseline system and reproduced the results reported in Zhou et al. 2017. As stated in the paper, the attentive encoder-decode architecture can already achieve a strong performance and outperform existing ABS/ABS+ (Rush, Chopra, and Weston 2015). Due to the fact that abstractive summarization’s input $X$ contains more information than summary target $Y^*$, directly train bridge $p_\theta(Y|Y^*)$ to understand generator $p_\theta(Y|X)$ is infeasible. Therefore, we re-design the bridge model to receive $X$ as well and build a novel model $p(Y^*, X)$, we enlarge its vocabulary size to 88,883 to encompass more information about the source side. In this experiment, we also fix the hyper-parameter as $\tau = 0.8$ for both uniform/LM bridge and tune hyper-parameter $\tau$ in a small candidate set.

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[1] https://github.com/facebookarchive/NAMAS
Results  The experimental results for abstractive summarization task are summarized in Table 2. We compare our results with baseline systems as well as other competing algorithms. We can observe a significant improvement yielded by our GBN system, similar as last experiment, the easy-to-learn GBN system also achieves the strongest performance among all, which again reflects our assumption that a more sophisticated constraint can benefit the bridging system more. Here we also draw the learning curve in Figure 5 to demonstrate how our bridge and generator network promotes each other.

| Methods                        | RG-1 | RG-2 | RG-L |
|-------------------------------|------|------|------|
| ABS (Rush, 2015)              | 29.55| 11.32| 26.42|
| ABS+ (Rush, 2015)             | 29.76| 11.88| 26.96|
| Luong-NMT Zhou et al. (2017)  | 33.10| 14.45| 30.71|
| s2s+att Zhou et al. (2017)    | 34.04| 15.95| 31.68|
| Uniform GBN ($\tau = 0.8$)   | 34.10| 16.70| 31.75|
| LM GBN ($\tau = 0.8$)        | 34.32| 16.88| 31.89|
| Easy2Learn GBN ($\tau = 0.8$) | 34.49| 16.70| 31.95|
| Easy2Learn GBN ($\tau = 1.2$) | 34.83| 16.83| 32.25|
| Easy2Learn GBN ($\tau = 1.0$) | 35.26| 17.22| 32.67|

Table 2: Full length ROUGE F1 evaluation results on the English Gigaword test set used by Rush, Chopra, and Weston (2015). RG in the Table denotes ROUGE. Results are taken from the corresponding papers.

Analysis

By introducing different constraints into the bridge network, the bridge distribution will pose different training samples for model to learn. Here, we examine the samples drawn from three different bridge distributions and classify their modifications into different categories, which we describe in Table 3. We can observe that most modifications still obey the original meaning. Uniform bridge simply perform random replacement without considering any semantic/syntactic constraints, LM bridge strives to smooth training samples, coaching bridge reorders or simplifies difficult expressions into more understandable forms to lower generator’s learning burden. The more rational and aggressive modification from coaching GBN clearly benefits the model the most and help model generalize to more scenarios. From the experimental results,

| System           | Property                  | Reference                           |
|------------------|---------------------------|-------------------------------------|
| System           |                          |                                     |
| RG-1             |                          |                                     |
| RG-2             |                          |                                     |
| RG-L             | Random Replacement        | the question is, is it worth it?    |
| LM GBN ($\tau = 0.8$) | Form Changing & Word Replacement | now how can this help us? |
| LM GBN ($\tau = 0.8$) | Form Changing & Word Replacement | now how can this help us? |
| LM GBN ($\tau = 0.8$) | Form Changing & Word Replacement | the question is, is it worth it?    |

Table 3: Samples drawn from three parallel bridge distributions in IWSLT2014 translation track

we can conclude that easy-to-learn GBN’s more aggressive and rational changes can benefit the model by exposing the model to more unseen scenarios.

Conclusion

We present a generative bridge network to connect sequence with the ground truth and our implemented system has proved to significantly benefit the baseline system. We believe the concept of bridging can be applicable to a wide range of probabilistic matching tasks. In the future, we intend to explore more about GBN’s applications.

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