Latent-Variable Non-Autoregressive Neural Machine Translation with Deterministic Inference using a Delta Posterior

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Abstract

Although neural machine translation models reached high translation quality, the autoregressive nature makes inference difficult to parallelize and leads to high translation latency. Inspired by recent refinement-based approaches, we propose a latent-variable non-autoregressive model with continuous latent variables and deterministic inference procedure. In contrast to existing approaches, we use a deterministic iterative inference algorithm to find a target sequence that maximizes the lowerbound to the log-probability. During inference, the length of translation automatically adapts itself. Our experiments show that the lowerbound can be greatly increased by running the inference algorithm for only one step, resulting in significantly improved translation quality. Our proposed model closes the gap between non-autoregressive and autoregressive approaches on ASPEC Ja-En dataset with 7.8x faster decoding. On WMT’14 En-De dataset, our model narrows the performance gap with autoregressive baseline down to 2.0 BLEU points with 12.5x speedup.

1 Introduction

The field of Neural Machine Translation (NMT) has seen significant improvements in recent years (Bahdanau et al., 2015; Wu et al., 2016; Gehring et al., 2017; Vaswani et al., 2017). Despite impressive improvements in translation accuracy, the autoregressive nature of NMT models have made it difficult to speed up decoding by utilizing parallel model architecture and hardware accelerators. This has sparked interest in non-autoregressive NMT models, which predict every target token in parallel. In addition to the obvious decoding efficiency, non-autoregressive text generation is appealing as it does not suffer from exposure bias and suboptimal inference.

Inspired by recent work in non-autoregressive NMT using discrete latent variables (Kaiser et al., 2018) and iterative refinement (Lee et al., 2018), we introduce a sequence of continuous latent variables to capture the uncertainty in the target sentence. We motivate such a latent variable model by conjecturing that it is easier to refine lower-dimensional continuous variables than to refine high-dimensional discrete variables, as done in Lee et al. (2018). Unlike Kaiser et al. (2018), the posterior and the prior can be jointly trained to maximize the evidence lowerbound of the log-likelihood \(\log p(y|x)\).

Inspired by the iterative refinement approach by Lee et al. (2018), we propose a deterministic iterative algorithm to refine the approximate posterior over the latent variables and obtain better target predictions. During inference, we first obtain the initial posterior from a prior distribution \(p(z|x)\) and the initial guess of the target sentence from the conditional distribution \(p(y|x, z)\). We then alternate between updating the approximate posterior and target tokens with the help of an approximate posterior \(q(z|x, y)\). We avoid stochasticity at inference time by introducing a delta posterior over the latent variables. We empirically find that this iterative algorithm significantly improves the lowerbound and results in better BLEU scores. By refining the latent variables instead of tokens, the length of translation can dynamically adapt throughout this procedure, unlike previous approaches where the target length was fixed throughout the refinement process. In other words, even if the initial length prediction is incorrect, it can be refined simultaneously with the target tokens.

The main contribution of this work is the iterative inference algorithm which significantly im-

¹We use 8-dimensional latent variables in our experiments.
proves the lowerbound and translation quality. Combined with sequence-level distillation, our models outperform the autoregressive baseline on ASPEC Ja-En dataset with 7.8x decoding speedup and reduce the gap down to 2.0 BLEU points on WMT’14 En-De with 12.5x decoding speedup.

2 Background

2.1 Autoregressive NMT

In order to model the joint probability of the target tokens \( y_1, \ldots, y_{|y|} \) given the source sentence \( x \), most NMT models use an autoregressive factorization of the joint probability which has the following form:

\[
\log p(y|x) = \sum_{i=1}^{|y|} \log p(y_i|y_{<i}, x),
\]

where \( y_{<i} \) denotes the target tokens preceding \( y_i \). Here, the probability of emitting each token \( p(y_i|y_{<i}, x) \) is parameterized with a neural network.

To obtain a translation from this model, one could predict target tokens sequentially by greedily taking \( \text{argmax} \) of the token prediction probabilities. The decoding progress ends when a “<eos>” token, which indicates the end of a sequence, is selected. In practice, however, this greedy approach yields suboptimal sentences, and beam search is often used to decode better translations by maintaining multiple hypotheses. However, decoding with a large beam size significantly decreases translation speed.

2.2 Non-Autoregressive NMT

Although autoregressive models achieve high translation quality through recent advances in NMT, the main drawback is that autoregressive modeling forbids the decoding algorithm to select tokens in multiple positions simultaneously. This results in inefficient use of computational resource and increased translation latency.

In contrast, non-autoregressive NMT models predict target tokens without depending on preceding tokens, depicted by the following objective:

\[
\log p(y|x) = \sum_{i=1}^{|y|} \log p(y_i|x).
\]

As the prediction of each target token \( y_i \) now depends only on the source sentence \( x \) and its location \( i \) in the sequence, the translation process can be easily parallelized. We obtain a target sequence by applying \( \text{argmax} \) to all token probabilities.

The main challenge of non-autoregressive NMT is on capturing dependencies among target tokens. As the probability of each target token does not depend on the surrounding tokens, applying \( \text{argmax} \) at each position \( i \) may easily result in an inconsistent sequence, that includes duplicated or missing words. It is thus important for non-autoregressive models to use techniques to ensure the consistency of generated words.

3 Latent-Variable Non-Autoregressive NMT

In this work, we propose a latent-variable non-autoregressive NMT model by introducing a sequence of continuous latent variables to model the uncertainty about the target sentence. These latent variables are constrained to have the same length as the source sequence, that is, \( |z| = |x| \). Instead of directly maximizing the objective function in Eq. (2), we maximize a lowerbound to the marginal log-probability \( \log p(y|x) = \log \int p(y,z|x)p(z|x)dz \):

\[
\mathcal{L} = \mathbb{E}_{\omega \sim q_\phi} \left[ \log p_\theta(y|x, z) \right] - \text{KL}[q_\phi(z|x, y) \| p_\omega(z|x)] ,
\]

where \( p_\omega(z|x) \) is the prior, \( q_\phi(z|x, y) \) is an approximate posterior and \( p_\theta(y|x, z) \) is the decoder. The objective function in Eq. (3) is referred to as the evidence lowerbound (ELBO). As shown in the equation, the lowerbound is parameterized by three sets of parameters: \( \omega, \phi \) and \( \theta \).

Both the prior \( p_\omega \) and the approximate posterior \( q_\phi \) are modeled as spherical Gaussian distributions. The model can be trained end-to-end with the reparameterization trick (Kingma and Welling, 2014).

3.1 A Modified Objective Function with Length Prediction

During training, we want the model to maximize the lowerbound in Eq. (3). However, to generate a translation, the target length \( l_y \) has to be predicted first. We let the latent variables model the target length by parameterizing the decoder as:

\[
p_\theta(y|x, z) = \sum_l p_\theta(y, l|x, z) = p_\theta(y, l_y|x, z) = p_\theta(y|x, z, l_y)p_\theta(l_y|z).
\]
Here \( l_y \) denotes the length of \( y \). The second step is valid as the probability \( p_\theta(y, l \neq l_y | x, z) \) is always zero. Plugging in Eq. (4), with the independent assumption on both latent variables and target tokens, the objective has the following form:

\[
\mathbb{E}_{z \sim q_\phi} \left[ \sum_{i=1}^{|y|} \log p_\theta(y_i | x, z, l_y) + \log p_\theta(l_y | z) \right] - \sum_{|x|} \text{KL}[q_\phi(z_k | x, y) || p_\omega(z_k | x)] . \tag{5}
\]

### 3.2 Model Architecture

As evident from in Eq. (5), there are four parameterized components in our model. The whole architecture of the model is depicted in Fig. 1.

**Prior** To compute the prior \( p_\omega(z | x) \), we use a multi-layer self-attention encoder which has the same structure as the vanilla Transformer encoder (Vaswani et al., 2017). In each layer, a feed-forward computation is applied after the self-attention. To obtain the probability, we apply a linear transformation to reduce the dimensionality and compute the mean and variance vectors.

**Approximate posterior** As \( q_\phi(z | x, y) \) is a function of the source \( x \) and the target \( y \), we first encode \( y \) with a self-attention encoder. Then, the resulting vectors are fed into an attention-based decoder initialized by \( x \) embeddings. Its architecture is similar to the Transformer decoder except that no causal mask is used. Similarly to the prior, we apply a linear layer to obtain the mean and variance vectors.

**Decoder** The decoder computes the probability of target tokens given \( z \) and \( x \), which is similar to the implementation of \( q_\phi \). We reuse the \( x \) representation created when computing the prior.

**Length Predictor** Given a latent variable \( z \) sampled from the approximate posterior \( q_\phi \), we train a length prediction model \( p_\theta(l_y | z) \). We train a model to predict the length difference between \( |y| \) and \( |x| \). In our implementation, \( p_\theta(l_y | z) \) is modeled as a categorical distribution that covers the length difference in the range \([-50, 50]\). The prediction is produced by applying softmax after linear transformation.

**Sampling** In order to backpropagate the loss signal of the decoder to \( q_\phi \), we apply the reparameterization trick to sample \( z \) from \( q_\phi \) with \( g(\epsilon, q) = \mu_q + \sigma_q \epsilon \). Here \( \epsilon \sim \mathcal{N}(0, 1) \) is Gaussian noise.

**Length Transformation** As the latent variable \( z \sim q_\phi(z | x, y) \) has the length \( |x| \), we need to transform the latent variables into \( l_y \) vectors for the decoder to predict target tokens. We use a monotonic location-based attention for this purpose, which is illustrated in Fig. 2. Let the resulting vectors of length transformation be \( \bar{z}_1, ..., \bar{z}_{l_y} \), we produce each vector with

\[
\bar{z}_j = \sum_{k=1}^{|x|} w_k^j z_k , \tag{6}
\]

\[
w_k^j = \frac{\exp(a_k^j)}{\sum_{k'=1}^{|x|} \exp(a_{k'}^j)} , \tag{7}
\]

\[
a_k^j = - \frac{1}{2\sigma^2} (k - |x|/l_y^j)^2 , \tag{8}
\]

where each transformed vector is a weighted sum of the latent variables. The weight is computed with a softmax over distance-based logits. We give higher weights to the latent variables close to the location \( |x|/l_y^j \). The scale \( \sigma \) is the only trainable parameter in this monotonic attention mechanism.
3.3 Training

If we train a model with the objective function in Eq. (5), the KL divergence often drops to zero from the beginning. This yields a degenerate model that does not use the latent variables at all. This is a well-known issue in variational inference called posterior collapse (Bowman et al., 2015; Dieng et al., 2018; Razavi et al., 2019). We use two techniques to address this issue. Similarly to Kingma et al. (2016), we give a budget to the KL term as

$$\sum_{k=1}^{|x|} \max(b, \text{KL}(q_\phi(z_k|x,y)||p_\omega(z_k|x)))$$

(9)

where $b$ is the budget of KL divergence for each latent variable. Once the KL value drops below $b$, it will not be minimized anymore, thereby letting the optimizer focus on the reconstruction term in the original objective function. As $b$ is a critical hyperparameter, it is time-consuming to search for a good budget value. Here, we use the following annealing schedule to gradually lower the budget:

$$b = \begin{cases} 1, & \text{if } s < M/2 \\ \frac{(M-s)}{M/2}, & \text{otherwise} \end{cases}$$

(10)

$s$ is the current step in training, and $M$ is the maximum step. In the first half of the training, the budget $b$ remains 1. In the second half of the training, we anneal $b$ until it reaches 0.

Similarly to previous work on non-autoregressive NMT, we apply sequence-level knowledge distillation (Kim and Rush, 2016) where we use the output from an autoregressive model as target for our non-autoregressive model.

4 Inference with a Delta Posterior

Once the training has converged, we use an inference algorithm to find a translation $y$ that maximizes the lowerbound in Eq. (3):

$$\arg\max_y \mathbb{E}_{z \sim q_\phi} \left[ \log p_\theta(y|x, z) \right] - \text{KL}(q_\phi(z|x,y)||p_\omega(z|x))$$

It is intractable to solve this problem exactly due to the intractability of computing the first expectation. We avoid this issue in the training time by reparameterization-based Monte Carlo approximation. However, it is desirable to avoid stochasticity at inference time where our goal is to present a single most likely target sentence given a source sentence.

We tackle this problem by introducing a proxy distribution $r(z)$ defined as

$$r(z) = \begin{cases} 1, & \text{if } z = \mu \\ 0, & \text{otherwise} \end{cases}$$

(11)

This is a Dirac measure, and we call it a delta posterior in our work. We set this delta posterior to minimize the KL divergence against the approximate posterior $q_\phi$, which is equivalent to

$$\nabla_\mu \log q_\phi(\mu|x,y) = 0 \Leftrightarrow \mu = \mathbb{E}_{q_\phi} [z].$$

We then use this proxy instead of the original approximate posterior to obtain a deterministic lowerbound:

$$\hat{\mathcal{L}}(\omega, \theta, \mu) = \log p_\theta(y|x, z = \mu) - \log p_\omega(\mu|x).$$

As the second term is constant with respect to $y$, maximizing this lowerbound with respect to $y$ reduces to

$$\arg\max_y \log p_\theta(y|x, z = \mu),$$

(12)

which can be approximately solved by beam search when $p_\theta$ is an autoregressive sequence model. If $p_\theta$ factorizes over the sequence $y$, as in our non-autoregressive model, we can solve it exactly by

$$\hat{y}_i = \arg\max_{\hat{y}_i} \log p_\theta(y_i|x, z = \mu).$$

With every estimation of $y_i$, the approximate posterior $q$ changes. We thus alternate between fitting the delta posterior in Eq. (11) and finding the most likely sequence $y$ in Eq. (12).

We initialize the delta posterior $r$ using the prior distribution:

$$\mu = \mathbb{E}_{p_\omega(z|x)} [z].$$
Algorithm 1 Deterministic Iterative Inference

Inputs:
- $x$: source sentence
- $T$: maximum step
- $\mu_0 = E_{p(x)} [z]
- $y_0 = \arg\max_y \log p_{\theta} (y|x, z = \mu_0)$

for $t \leftarrow 1$ to $T$ do
  $\mu_t = E_{q_{\phi}(z|x, y_{t-1})} [z]
  y_t = \arg\max_y \log p_{\theta} (y|x, z = \mu_t)$
  if $y_t = y_{t-1}$ then break

output $y_t$

With this initialization, the proposed inference algorithm is fully deterministic. The complete inference algorithm for obtaining the final translation is shown in Algorithm 1.

5 Related Work

This work is inspired by a recent line of work in non-autoregressive NMT. Gu et al. (2018a) first proposed a non-autoregressive framework by modeling word alignment as a latent variable, which has since then been improved by Wang et al. (2019). Lee et al. (2018) proposed a deterministic iterative refinement algorithm where a decoder is trained to refine the hypotheses. Our approach is most related to Kaiser et al. (2018); Roy et al. (2018). In both works, a discrete autoencoder is first trained on the target sentence, then an autoregressive prior is trained to predict the discrete latent variables given the source sentence. Our work is different from theirs in three ways: (1) we use continuous latent variables and train the approximate posterior $q(z|x, y)$ and the prior $p(z|x)$ jointly; (2) we use a non-autoregressive prior; and (3) we propose a novel iterative inference procedure in the latent space.

Concurrently to our work, Ghazvininejad et al. (2019) proposed to translate with a masked-prediction language model by iterative replacing tokens with low confidence. Gu et al. (2019); Stern et al. (2019); Welleck et al. (2019) proposed insertion-based NMT models that insert words to the translations with a specific strategy. Unlike these works, our approach performs refinements in the low-dimensional latent space, rather than in the high-dimensional discrete space.

Similarly to our latent-variable model, Zhang et al. (2016) proposed a variational NMT, and Shah and Barber (2018) models the joint distribution of source and target. Both of them use autoregressive models. Shah and Barber (2018) designed an EM-like algorithm similar to Markov sampling (Arulkumaran et al., 2017). In contrast, we propose a deterministic algorithm to remove any non-determinism during inference.

6 Experimental Settings

Data and preprocessing We evaluate our model on two machine translation datasets: ASPEC Ja-En (Nakazawa et al., 2016) and WMT’14 En-De (Bojar et al., 2014). The ASPEC dataset contains 3M sentence pairs, and the WMT’14 dataset contains 4.5M sentence pairs.

To preprocess the ASPEC dataset, we use Moses toolkit (Koehn et al., 2007) to tokenize the English sentences, and Kytea (Neubig et al., 2011) for Japanese sentences. We further apply byte-pair encoding (Sennrich et al., 2016) to segment the training sentences into subwords. The resulting vocabulary has 40K unique tokens on each side of the language pair. To preprocess the WMT’14 dataset, we apply sentencepiece (Kudo and Richardson, 2018) to both languages to segment the corpus into subwords and build a joint vocabulary. The final vocabulary size is 32K for each language.

Learning To train the proposed non-autoregressive models, we adapt the same learning rate annealing schedule as the Base Transformer. The model parameters is selected based on the validation ELBO.

The only new hyperparameter in the proposed model is the dimension of each latent variable. If each latent is a high-dimension vector, although it has a higher capacity, the KL divergence in Eq. (3) becomes difficult to minimize. In practice, we found that latent dimensionality values between 4 and 32 result in similar performance. However, when the dimensionality is significantly higher or lower, we see a performance drop. In all experiments, we set the latent dimensionality to 8. We use a hidden size of 512 and feedforward filter size of 2048 for all models in our experiments.

Evaluation and Decoding We evaluate the tokenized BLEU for ASPEC Ja-En dataset. For WMT’14 En-De dataset, we use SacreBLEU (Post, 2018) to evaluate the translation results. We follow Lee et al. (2018) to remove repetitions from
the translation results before evaluating the BLEU scores.

As shown in Fig. 1, our model is composed of four neural nets: approximate posterior, prior, decoder and length predictor. The majority of the decoding time comes from the first three components. Let their computation time be denoted as $T(z|x,y)$, $T(z|x)$ and $T(y|x,z)$. Suppose we run the iterative inference algorithm for a maximum of $n$ iterations. In the worst case, total decoding time is as follows:

$$T = T(z|x) + nT(z|x,y) + (n + 1)T(y|x,z).$$

In other words, translation slows down if either the approximate posterior or the decoder takes a long time to compute. In this work, we set the number of layers to be 6 for the prior, and 3 for the approximate posterior and decoder each.

## 7 Result and Analysis

### 7.1 Qualitative Analysis

Our qualitative results on both datasets are presented in Table 1. The baseline model in our experiments is a base Transformer. Our implementation of the autoregressive baseline results in 2.1 BLEU points lower than the original paper (Vaswani et al., 2017) on WMT’14 En-De dataset. We measure the latency of decoding each sentence on a single NVIDIA P100 GPU for all models.

As shown in Table 1, without knowledge distillation, we observe a significant gap in translation quality compared to the autoregressive baseline. This observation is in line with previous ones on non-autoregressive NMT (Gu et al., 2018b; Lee et al., 2018; Wang et al., 2019). This gap is significantly reduced by using knowledge distillation, as translation targets provided by the autoregressive model are often easier to predict.

By running only one step of the proposed iterative inference algorithm, we significantly improve translation quality by 2.3 BLEU points on ASPEC Ja-En dataset and 1.9 BLEU points on WMT’14 En-De dataset. We observe gain on ELBO by running more iterative inference steps, which is not reflected by the BLEU scores. As a result, we outperform the autoregressive baseline by 0.4 BLEU points on ASPEC dataset. However, the gap with the autoregressive baseline still remains on WMT’14 dataset, at 2.0 BLEU points. We conjecture that WMT’14 En-De is more difficult for our non-autoregressive model as it contains a high degree of noise (Ott et al., 2018).

Compared to the autoregressive baselines, the speed gain of the non-autoregressive models with iterative inference is approximately 7x–12x. When batched, we can improve decoding efficiency even further.

### 7.2 Non-autoregressive NMT Models

In Table 2, we list the results on WMT’14 En-De by existing non-autoregressive NMT approaches. All the models use Transformer as their autoregressive baselines. In comparison, our proposed model suffers a drop of 2.0 BLEU points over the baseline, which is relatively small gap among the existing models. Thanks of the rapid convergence of the proposed iterative inference algorithm (see §7.3), our model achieves a higher speed-up compared to other refinement-based models and provides a better speed-accuracy tradeoff.

Concurrently to our work, the mask-prediction language model (Ghazvininejad et al., 2019) was found to reduce the performance gap down to 0.9 BLEU on WMT’14 En-De while still maintaining
Table 2: A comparison of non-autoregressive NMT models on WMT’14 En-De dataset in BLEU(%) and decoding speed-up. * measured on IWSLT’14 DE-EN dataset.

| Model                                      | BLEU(%) | SPD |
|--------------------------------------------|---------|-----|
| Transformer (Vaswani et al., 2017)         | 27.1    | -   |
| Baseline (Gu et al., 2018a)                | 23.4    | 1x  |
| NAT (+FT +NPD S=100)                      | 19.1    | -4.3 |
| Baseline (Lee et al., 2018)                | 24.5    | 1x  |
| Adaptive NAR Model                         | 21.5    | -3.0 |
| Baseline (Kaiser et al., 2018)             | 23.5    | 1x  |
| LT, Improved Semhash                       | 19.8    | -3.7 |
| Baseline (Wang et al., 2019)               | 27.3    | 1x  |
| NAT-REG, no rescoring                      | 20.6    | -6.7 |
| NAT-REG, autoregressive rescoring          | 24.6    | -2.7 |
| BL (Ghazvininejad et al., 2019)            | 27.8    | 1x  |
| CMLM with 4 iterations                     | 26.0    | -1.8 |
| CMLM with 10 iterations                    | 26.9    | -0.9 |
| Baseline (Ours)                            | 26.1    | 1x  |
| NAR with Iterative Inference               | 24.1    | -2.0 |

A reasonable speed-up. The main difference is that we update a delta posterior over latent variables instead of target tokens. Both Ghazvininejad et al. (2019) and Wang et al. (2019) with autoregressive rescoring decode multiple candidates in batch and pick one final translation from them. In contrast, our model only explores one candidate, which allows decoding multiple sentences simultaneously. As our proposal is orthogonal to using BERT-style training (Devlin et al., 2018), it is an interesting future direction to investigate their combination.

7.3 Analysis of Iterative Inference

Convergences of ELBO and BLEU In this section, we empirically show that the proposed deterministic iterative inference improves the ELBO in Eq. (3). As the ELBO is a function of $x$ and $y$, we measure the ELBO value with the new target prediction after each iteration during inference. For each instance, we sample 20 latent variables to compute the expectation in Eq. (3). The ELBO value is further averaged over data samples.

In Fig. 3, we show the ELBO value and the resulting BLEU scores for both datasets. In the initial step, the delta posterior is initialized with the prior distribution $p_\omega(z|x)$. We see that the ELBO value increases rapidly by performing the iterative inference, which means a higher lowerbound to $\log p(y|x)$. The improvement is highly correlated with increasing BLEU scores. The algorithm typically converges within three steps.

Early convergence The proposed inference algorithm terminates when the decoder does not produce a new translation. In Fig. 4, we run the inference algorithm for 10 steps and count the number of early terminations in each step. We observe that for over 80% of the samples, the inference stops within the first three iterations on both datasets. This observation confirms the fast converge of the proposed algorithm.

7.4 Qualitative Analysis

We present some example translations to demonstrate the effect of the proposed iterative inference in Table 3. In the first example, the length of the target sequence does not change but only the tokens are replaced over the refinement iterations.
Example 1: Sequence modified without changing length

| Source                  | Reference                                                                 |
|-------------------------|---------------------------------------------------------------------------|
| 標記 質 量 標準 の 確立 を 試みた。 (Japanese) | the establishment of an optical fiber attenuation standard was attempted. |

Initial Guess

| Iteration 1 | an attempt was to establish the damping attenuation standard ... |
|-------------|------------------------------------------------------------------|
| Iteration 2 | an attempt tries to establish the damping quantity standard ... |

Example 2: One word removed from the sequence

| Source                  | Reference                                                                 |
|-------------------------|---------------------------------------------------------------------------|
| 「線膨張係數の取り扱い」について述べた。 (Japanese) | handling of linear expansion coefficient . |

Initial Guess

| Iteration 1 | “ handling of linear expansion coefficient ” are described . |
|-------------|------------------------------------------------------------|
| Iteration 2 | “ handling of linear expansion coefficient ” are described . |

Example 3: Four words added to the sequence

| Source                  | Reference                                                                 |
|-------------------------|---------------------------------------------------------------------------|
| ...マイクロマニピュレーションへと発展してきている ... (Japanese) | with wide application fields so that it has been developed ... |

Initial Guess

| Iteration 1 | micro micro manipulation and ... |
|-------------|----------------------------------|
| Iteration 2 | and micro manipulation, and it has been developed, and ... |

Table 3: Ja-En sample translation with the proposed iterative inference algorithm. In the first example, the initial guess is refined without a change in length. In the last two examples, the iterative inference algorithm changes the target length along with its content. This is more pronounced in the last example, where a whole clause is inserted during refinement.

The second and third examples show that the algorithm removes or inserts words to the sequence during the iterative inference by adaptively changing the target length. Such a significant modification to the predicted sequence mostly happens when translating long sentences. For short input sentences, the target length usually remains unchanged over the refinement steps.

For some test examples, however, we still find duplicated words in the final translation after applying iterative inference. For these examples, we notice that the quality of the initial guess is considerably worse than average, which typically contains multiple duplicated words. As the decoder $p(y|x,z)$ is trained to reconstruct the $y$ sequence given to the approximator $q_\phi$, it is not expected to drastically modify the target prediction. Therefore, a high-quality initial guess $y_0$ is important for obtaining reasonable translations.

8 Conclusion

Our work presents the first approach to use a continuous latent-variable model for non-autoregressive Neural Machine Translation. We introduce a sequence of latent variables to capture the uncertainty in the target sentence. We train the proposed model to maximize the lowerbound of the log-probability $\log p(y|x)$.

We introduce a deterministic iterative inference algorithm that uses a delta posterior over the latent variables. The algorithm alternates between updating the delta posterior and the target tokens. Our experiments show that the algorithm is able to improve the evidence lowerbound of predicted target sequence rapidly. The convergence can be reached within three iterations for the majority of the examples we tested. Despite its effectiveness, the algorithm can be implemented efficiently.

By applying the iterative inference on ASPEC Ja-En dataset, we outperform the autoregressive baseline by 0.4 BLEU points. Our model achieves a speed-up of $7-12x$ over the baseline autoregressive model. However, a performance gap of 2.0 BLEU still remains on WMT’14 En-De dataset.

For future work, adversarial training can be explored to further the discrepancy between the prior and approximate posterior. With a better prior, the algorithm can start from a reasonable initial guess, which helps to improve the final translation.
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Appendix

A Inference Speed

| Model Type | BS=3 | BS=1 |
|------------|------|------|
| Ja-En      | 415ms (159) | 375ms (150) |
| En-De      | 602ms (274) | 461ms (219) |
| Latent-Variable NAR | 23ms (2) | 93ms (36) |
| + iterative infer (1 step) | 53ms (2) | 81ms (24) |
| + iterative infer (3 steps) | 87ms (23) | 90ms (32) |
| + iterative infer (5 steps) | 93ms (24) | 90ms (32) |

Table 4: Comparison of per-sentence decoding time (wall-clock time) of different NMT models. The table reports averaged running time and standard deviation, which are measured on a single NVIDIA P100 GPU.

We report the actual per-sentence decoding time of different NMT models in Table 4. The table also reports the standard deviation of inference time. We can see that comparing to autoregressive models, the inference speed of latent-variable non-autoregressive models is much faster. Due to early stopping, the decoding time grows sublinearly with respect to the inference steps.

We also observe that non-autoregressive models have much lower variance of decoding time. This indicates that the models can provide translations with a more consistent latency.

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