Non-Autoregressive Neural Dialogue Generation

Qinghong Han¹*, Yuxian Meng¹*, Fei Wu² and Jiwei Li¹

¹ ShannonAI
² Department of Computer Science and Technology, Zhejiang University
{qinghong_han, jiwei_li}@shannonai.com, wufei@zju.edu.cn

Abstract

Maximum Mutual information (MMI), which models the bidirectional dependency between responses \((y)\) and contexts \((x)\), i.e., the forward probability \(\log p(y|x)\) and the backward probability \(\log p(x|y)\), has been widely used as the objective in the SEQ2SEQ model to address the dull-response issue in open-domain dialogue generation. Unfortunately, under the framework of the SEQ2SEQ model, direct decoding from \(\log p(y|x) + \log p(x|y)\) is infeasible since the second part (i.e., \(p(x|y)\)) requires the completion of target generation before it can be computed, and the search space for \(y\) is enormous. Empirically, an N-best list is first generated given \(p(y|x)\), and \(p(x|y)\) is then used to rerank the N-best list, which inevitably results in non-globally-optimal solutions.

In this paper, we propose to use non-autoregressive (non-AR) generation model to address this non-global optimality issue. Since target tokens are generated independently in non-AR generation, \(p(x|y)\) for each target word can be computed as soon as it’s generated, and does not have to wait for the completion of the whole sequence. This naturally resolves the non-global optimal issue in decoding. Experimental results demonstrate that the proposed non-AR strategy produces more diverse, coherent, and appropriate responses, yielding substantive gains in BLEU scores and in human evaluations.¹

1 Introduction

Open-domain neural dialogue generation (Vinyals and Le, 2015; Sordoni et al., 2015; Li et al., 2016a; Mou et al., 2016; Serban et al., 2016a; Asghar et al., 2016; Mei et al., 2016; Serban et al., 2016e,h,d; Baheti et al., 2018; Wang et al., 2018; Ghazvininejad et al., 2018; Zhang et al., 2018; Gao et al., 2019) treats dialog contexts \((x)\) as sources, and responses \((y)\) as targets and uses the encoder-decoder model (Sutskever et al., 2014; Vaswani et al., 2017b) as the backbone to generate responses. SEQ2SEQ models offer the promise of scalability and language-independence, along with the capacity to capture contextual dependencies semantic and syntactic relations between sources and targets.

One of key issues with the SEQ2SEQ structure is that it exhibits a strong tendency to generate dull, trivial or non-committal responses (e.g., I don’t know or I’m OK) regardless of the input, which has been observed by many recent works (Li et al., 2016a; Sordoni et al., 2015; Serban et al., 2016c; Niu and Bansal, 2020). Various strategies (Li et al., 2016a; Vijayakumar et al., 2016; Baheti et al., 2018; Niu and Bansal, 2020) have been proposed to address this issue, one of the most widely used of which is to replace the MLE objective in the SEQ2SEQ training with the maximum mutual information objective (MMI for short) (Li et al., 2016a). MMI models the bidirectional dependency between responses \((y)\) and contexts \((x)\). It takes the form of the linear combination of the forward probability \(\log p(y|x)\) and the backward probability \(\log p(x|y)\). The intuition behind MMI is straightforward: it is easy to predict a dull response given any context, but hard to predict the context given a dull response since the context that corresponds to a dull response could be anything.

Unfortunately, under the framework of the SEQ2SEQ model, direct decoding from \(\log p(y|x) + \log p(x|y)\) is infeasible since the second part (i.e., \(p(x|y)\)) requires the completion of target generation before \(p(x|y)\) can be computed, and the search space for \(y\) is huge. Empirically, an N-best list is first generated given \(p(y|x)\), and \(p(x|y)\) is then used to rerank the

¹Qinghong and Yuxian contribute equally to this work.
N-best list. Due to the fact that beam search lacks for diversity in the beam: candidates often differ only by punctuation or minor morphological variations, with most of the words overlapping, this reranking strategy inevitably results in non-globally-optimal solutions. Some strategies have been proposed to alleviate this non-global-optimality issue, such as generating a more diverse N-best list (Li et al., 2016c; Gu et al., 2017; Vijayakumar et al., 2016), or using reinforcement learning to estimate the future score of $p(x|y)$ (Li et al., 2017a), which help alleviate the non-globally-optimal issue, but cannot fully address it.

Non-autoregressive (non-AR) generation (Gu et al., 2018; Ma et al., 2019; Lee et al., 2018) provides resolution to the non-global-optimality issue. Under the formalization of non-AR generation, target tokens $y_t$ are generated independently, which enables $p(x|y_t)$ to be computed as soon as $y_t$ is generated. This naturally resolves the non-global optimal issue in decoding. We conduct experiments on the widely used Opensubtitle dataset and experimental results demonstrate that the proposed strategy produces more diverse, coherent, and appropriate responses, yielding substantive gains in BLEU scores and in human evaluations.

The rest of this paper is organized as follows: Section 2 and section 3 present related work and background knowledge respectively. The propose model is described in Section 4. Experimental results and ablation studies are detailed in Section 5 and 6, followed by a brief conclusion in Section 7.

2 Related Work

2.1 Neural Dialogue Generation

End-to-end neural approaches for dialogue generation use SEQ2SEQ architectures (Sutskever et al., 2014; Vaswani et al., 2017b) as the backbone to generate syntactically fluent and meaningful responses, providing the flexibility to capture contextual semantics between source contexts and target responses. Recent studies have endowed these models with the ability to model contexts (Sordoni et al., 2015; Serban et al., 2016e,b; Tian et al., 2017; Lewis et al., 2017), generating coherent and personalized responses (Li et al., 2016b; Zhao et al., 2017; Shao et al., 2017; Xing et al., 2017; Zhang et al., 2018; Bosselut et al., 2018), generating utterances with different attributes or topics (Wang et al., 2017; Niu and Bansal, 2018) and interacting fluently with humans (Ghazvininejad et al., 2018; Zhang et al., 2019; Adiwardana et al., 2020).

2.2 Diverse Decoding

One major issue with SEQ2SEQ systems is their propensity to select dull, non-committal responses regardless of the input, for which many diverse decoding algorithms have been proposed to tackle this problem (Li et al., 2016a; Li and Jurafsky, 2016; Vijayakumar et al., 2016; Cho, 2016; Kulikov et al., 2018; Kriz et al., 2019; Ippolito et al., 2019). Li et al. (2016a) proposed to use Maximum Mutual Information (MMI) as the objective function in neural dialog models. MMI models use both the forward probability $p(y|x)$ and the backward probability $p(x|y)$ to better capture the contextual relations between the source and target sequences. Li and Jurafsky (2016) introduced a Beam Search diversification heuristic to discourage sequences from sharing common roots, implicitly resulting in diverse sequences. Vijayakumar et al. (2016) improved upon Li and Jurafsky (2016) and presented Diverse Beam Search, which formalizes beam search as an optimization problem and augments the objective with a diversity term. Cho (2016) introduced Noisy Parallel Approximate Decoding, a method encouraging diversity by adding small amounts of noise to the hidden state of the decoder at each step, instead of manipulating the probabilities outputted from the model. Kulikov et al. (2018) attempted to explore larger beam search space by running beam search many times, where the states explored by subsequent beam searches are restricted based on the intermediate states explored by previous iterations. These works have pushed dialogue models to generate more interesting and diverse responses that are both high-quality and meaningful.

2.3 Non-Autoregressive Sequence Generation

Besides diverse responses, another problem for these dialogue generation models is their autoregressive generation strategy that decodes words one-by-one, making it extremely slow to execute on long sentences, especially on conditions where multi-turn dialogue often appears (Adiwardana et al., 2020). One solution is to use non-autoregressive sequence generation
methods, which has recently aroused general interest in the community of neural machine translation (NMT) (Gu et al., 2018; Lee et al., 2018; Ma et al., 2019; Sun et al., 2019; Shu et al., 2019; Bao et al., 2019). Gu et al. (2018) proposed to alleviate latency by using fertility during inference in autoregressive Seq2Seq NMT systems, which led to a ∼15 times speedup to traditional autoregressive methods, whereas the performance degrades rapidly. Lee et al. (2018); Ma et al. (2019); Shu et al. (2019) proposed to use latent variables to model intermediate word alignments between source and target sequence pairs and mitigate the trade-off between decoding speed and performance. Bao et al. (2019) pointed out position information is crucial for non-autoregressive models and thus proposed to explicitly model position as latent variables. Sun et al. (2019) incorporated CRF into non-autoregressive models to enhance local dependencies during decoding. This work is greatly inspired by these advances in non-autoregressive sequence generation.

3 Background

3.1 Autoregressive SEQ2SEQ Models

An encoder-decoder model (Sutskever et al., 2014; Vaswani et al., 2017b; Bahdanau et al., 2014) defines the probability of a target sequence $Y = \{y_1, y_2, \ldots, y_{L_y}\}$, which is a response in the context of dialogue generation, given a source sequence $X = \{x_1, x_2, \ldots, x_{L_x}\}$, where $L_x$ and $L_y$ are the length of the source and target sentence respectively.

An autoregressive encoder-decoder model decomposes the distribution over a target sequence $y = \{y_1, \ldots, y_{L_y}\}$ into a chain of conditional probabilities:

$$
p_{\text{AR}}(y|x; \phi) = \prod_{t=1}^{L_y+1} \log p(y_t|y_{0:t-1}, x_{1:L_x}; \theta)$$

$$= \prod_{t=1}^{L_y} \frac{\exp(f(h_{t-1}, e_{y_t}))}{\sum_{y'} \exp(f(h_{t-1}, e_{y'}))}$$

(1)

with $y_0$ being the special $<\text{BOS}>$ token and $y_{L_y+1}$ being the special $<\text{EOS}>$ token. The probability of generating a token $y_t$ depends on all tokens in the source $X$, and all its previous tokens $y_{0:t-1}$ in $Y$. The concatenation of $X$ and $y_{0:t-1}$ is mapped to a representation $h_{t-1}$ using LSTMs (Sutskever et al., 2014), CNNs (Gehring et al., 2017) or transformers (Vaswani et al., 2017b). $e_{y_t}$ denotes the representation for $y_t$.

During decoding, the algorithm terminates when the $<\text{EOS}>$ token is predicted. At each time step, either a greedy approach or beam search can be adopted for word prediction. Greedy search selects the token with the largest conditional probability, the embedding of which is then combined with preceding output to predict the token at the next step.

3.2 Non-Autoregressive SEQ2SEQ Models

3.2.1 Overview

The autoregressive generation model has two major drawbacks: it prohibits generating multiple tokens simultaneously, which leads to inefficiency in GPU usage; and erroneously generated tokens leads to error accumulation and the performance of beam search deteriorates when exposed to a larger search space (Koehn and Knowles, 2017). Non-autoregressive methods address these two issues by removing the sequential dependencies within the target sentence and generating all target tokens simultaneously, with the probability giving as follows:

$$p_{\text{Non-AR}}(y|x; \phi) = \prod_{t=1}^{L_y} p(y_t|x; \phi)$$

(2)

Now that each target token $y_t$ only depends on the source sentence $x$, the full target sentence can be decoded in parallel, where argmax is applied to each token. A vital challenge that non-autoregressive face is the inconsistency problem Gu et al. (2018), which indicates the decoded sequence contains duplicated or missing tokens. Improving decoding consistency on the target side is thus crucial to Non-AR models.

4 Model

4.1 Overview

The maximum mutual information (MMI) model, proposed in (Li et al., 2016a), tries to find the response that has the largest value of mutual information with respect to the context. The form of MMI is given as follows:

$$\hat{y} = \arg\max_y \left\{ (1 - \lambda) \log p(y|x) + \lambda \log p(x|y) \right\}$$

(3)

We refer readers to (Li et al., 2016a) for how Eq.3 is obtained.
This weighted MMI objective function can be viewed as representing a tradeoff between sources given targets (i.e., \( p(x|y) \)) and targets given sources (i.e., \( p(y|x) \)). Direct decoding from log(1 − \( \lambda \)) \( p(y|x) + \lambda \log p(x|y) \) is infeasible since the second part (i.e., \( p(x|y) \)) requires the completion of target generation before \( p(x|y) \) can be computed. Empirically, an N-best list is first generated given \( p(y|x) \), and \( p(x|y) \) is then used to rerank the N-best list, which inevitably results in non-globally-optimal solutions.

Here to propose to use Non-AR generation models to handle to non-globally-optimality issue. The generation of each target word \( y_t \) is independent under the non-AR formalization, and the forward probability \( p(y|x) \) is given as follows:

\[
\text{forward}_\text{prob} = \prod_{t=1}^{L_y} p(y_t|x) \tag{4}
\]

For the backward probability \( p(x|y) \), which denotes the probability of generating a source sequence given a target sequence, we propose to replace it with the geometric mean of the probability of generating the source sequence given each target token, denoted as follows:

\[
\text{backward}_\text{prob} = \left( \prod_{t=1}^{L_y} p(x|y_t) \right)^{1/L_y} \tag{5}
\]

We also use the non-AR framework to model the backward probability. Based on the independence assumption of non-AR, in which the generations of \( x_t \) are independent, Eq. 5 can be further factorized as follows:

\[
\text{backward}_\text{prob} = \prod_{t=1}^{L_y} \prod_{t'=1}^{L_x} p(x_t|y_t) \tag{6}
\]

A close look at Equ.6 shows that it actually mimics the IBM model (Brown et al., 1993): \( p(x_t|y_t) \) handles the pairwise word alignment between sources and targets. Since position representations are incorporated at both the encoding and decoding stage, Eq.6 actually mimics IBM model2, where relative positions between source and target words are modeled.

Combining the forward probability in Eq. 4.2 and the backward probability in Eq.6, the full form of mutual information of Eq.3 can be rewritten as follows:

\[
L = (1 - \lambda) \sum_{t=1}^{L_y} \log p(y_t|x) + \lambda \sum_{t=1}^{L_y} \sum_{t'=1}^{L_x} \log p(x_{t'}|y_t)
\]

\[
= \sum_{t=1}^{L_y} \left[ (1 - \lambda) \log p(y_t|x) + \lambda \sum_{t'=1}^{L_x} \log p(x_{t'}|y_t) \right] \tag{7}
\]

as can be seen, we are able to factorize the full form of the MMI objective with respect to \( y_t \) under the framework of non-AR generation. This means that the mutual information between source \( x \) and different target words \( y_t \) are independent and can be computed in parallel. Also, for each token \( y_t \), its mutual information with respect to the source \( x \) can be readily computed as soon as \( y_t \) is generated, and we do not have to wait until the completion of the entire sequence. This naturally resolves the non-globally-optimality issue in the AR generation model. Figure 1 gives an illustration for the proposed model.

### 4.2 Forward Probability \( p(y|x) \)

We use the non-autoregressive \( \text{SEQ2SEQ} \) model as the backbone to compute \( \prod_t p(y_t|x) \), which consists of two major components: the encoder and the decoder.

#### 4.2.1 Encoder

We use transformers (Vaswani et al., 2017a) as a backbone and use a stack of \( N = 6 \) identical transformer blocks as the encoder. Given the source sequence \( x = \{x_1, \ldots, x_n\} \), the encoder
produces its contextual representations $H = \{h_1, \cdots, h_n\}$ from the last layer of the encoder.

4.2.2 Decoder

Target Length We first need to obtain the length of the target sequence for decoding. We follow previous works (Gu et al., 2018; Ma et al., 2019; Bao et al., 2019) to predict the length difference $\Delta m$ between source and target sequences using a classifier with a range of [-20, 20]. This is accomplished by max-pooling the source embeddings into a single vector, running this through a linear layer followed by a softmax operation, as follows:

$$p(\Delta m|x) = \text{softmax}(W_p(\text{maxpool}(H)) + b_p)$$  \hspace{1cm} (8)

Decoder Structure The decoder also consists of $N = 6$ identical transformer blocks. The $i$-th position of the input $d_i$ to the decoder is the round($n \ast (i/m)$)-th input’s contextual representation $h_{\text{round}(n \ast (i/m))}$ copied from the encoder, which is equivalent to scanning the source inputs from left to right and leads to a deterministic decoding process given the predicted target length. Both absolute and relative positional embeddings are incorporated. For relative position information, we follow Shaw et al. (2018) which produces a different learned embedding according to the offset between the “key” and “query” in the self-attention mechanism with a clipping distance $k$ (we set $k = 4$) for relative positions. For absolute positional embeddings, we follow Radford et al. (2019) and used a learnable positional embedding $p_t$ for position $t$.

Attention over Vocabulary Layer-wise attention over vocabulary is incorporated into each decoding layer to make the model aware of which token is to be generated regarding each position. More concretely, we use $Z^{(i)}(1 \leq i \leq 6)$ to denote the contextual representations for the $i$-th decoder layer, and $Z^{(0)} = \{d_1, \cdots, d_m\}$ to denote the input to the decoder. The intermediate token attention representation $a^{(i)}_j$ of position $j(1 \leq j \leq m)$ in the $i$-th decoder layer is thus given by:

$$a^{(i)}_j = \text{softmax}(z^{(i)}_j \cdot W^T) \cdot W$$  \hspace{1cm} (9)

where $W$ is the representation matrix of the token vocabulary. By doing so, each position is able to know which token is about to be decoded at the current position. The input to the next layer $Z^{(i+1)}$ is the concatenation of the contextual representations and the intermediate token representations $[Z^{(i)}; A^{(i)}]$.

softmax For each position $t$, $p(y_t|x)$ is computed by outputting the representation for that position to a softmax function.

4.3 Backward Probability $p(x|y)$

We use the non-AR model to obtain $p(x|y_t)$.

4.3.1 Encoder

The encoder for $p(x|y_t)$ is again a stack of $N = 6$ identical transformer blocks. The input to the encoder is a text sequence with length being $L_y$, which is identical to the length of the target. The $t$-th position of the input sequence is the word $y_t$, with the rest being the place-holding dummy token. For each position, the embedding for the absolute position and the embedding for the relative position are appended.

4.3.2 Decoder

The decoder for the backward probability is the same as that of the forward probability, with the only difference being changing target $y$ to source $x$.

4.4 Decoding from Mutual Information

The most commonly used decoding strategy for non-AR generation is the noisy parallel decoding strategy (NPD for short) proposed in Gu et al. (2018): a number of sequence candidates are first generated by the non-AR generation, then an AR SEQ2SEQ model is used to select the candidate that has the largest value of probability output from the AR model. Since this NPD strategy is used for the MLE objective which only concerns about the forward probability, we need to tailor it to the MMI objective. Specifically, we first generate N-best sequences based on the score of non-AR MMI function, computed from Eq.7. The final selected response is the sequence with highest AR MMI score, which is computed based on two AR SEQ2SEQ models, one to model the forward probability and the other to model the backward probability.
5 Experiments

5.1 Datasets

We use the OpenSubtitles dataset for evaluation. It’s a widely used open-domain dataset, which contains roughly 60M-70M scripted lines spoken by movie characters. It has been used in a broad range of recent work on data-driven conversation. This dataset does not specify which character speaks each subtitle line, which prevents us from inferring speaker turns. Following (Vinyals and Le, 2015; Li et al., 2016a), we make an assumption that each line of subtitle constitutes a full speaker turn. Although this assumption is often violated, prior work has successfully trained and evaluated neural conversation models using this corpus. In our experiments we used a preprocessed version of this dataset distributed by Li et al. (2016a).3

The noisy nature of the OpenSubtitle dataset renders it unreliable for evaluation purposes. We thus follow Li et al. (2016a) to use data from the Internet Movie Script Database (IMSDB)4 for evaluation. The IMSDB dataset explicitly identifies which character speaks each line of the script. We followed protocols in (Li et al., 2016a) and randomly selected two subsets as development and test datasets, each containing 2,000 pairs, with source and target length restricted to the range of [6,18].

5.2 Baselines

Our baselines include the AR generation models (using or not using MMI) based on transformers (Vaswani et al., 2017b), with the number of encoder and decoder blocks set to 6. For the standard AR model, the value of beam size is set to 10 for decoding, and the sequence with the largest value of \( p(y|x) \) is selected. For AR+MMI, we followed Li et al. (2016a), and first use \( p(y|x) \) to generate an N-best list with beam-size 10. Then \( p(x|y) \) is used to rerank the N-best list. \( \lambda \) is treated as the hyper-parameter to be tuned on the dev set.

We also implement two variant of the AR+MMI model: (1) AR+MMI+diverse (Li et al., 2016c), which uses a diverse decoding model to generate the N-best list and uses the backward probability to rerank the diverse N-best list. The diverse decoding model adds an additional term to penalize siblings in beam search expansions of the same parent node in the search thus favoring choosing hypotheses from diverse parents; and (2) AR+MMI+RL (Li et al., 2017a), which incorporates the critic that estimates further backward probability into decoding.

5.3 Training Details

All experiments were run using 64 Nvidia V100 GPUs with mini-batches of approximately 100K tokens. We use the same hyper-parameters for all experiments, i.e., word representations of size 1024, feed-forward layers with inner dimension 4096. Dropout rate is set to 0.2 and the number of attention heads is set to 16. Models are optimized with Adam (Kingma and Ba, 2014) using \( \beta_1 = 0.9 \), \( \beta_2 = 0.98 \), \( \epsilon = 1e-8 \). Differentiable scheduled sampling Goyal et al. (2017) is used to mitigate the exposure bias issue. We train models with 16-bit floating point operations. The backward model and the forward model are jointly trained with word embeddings shared.

5.4 Automatic Evaluation

For automatic evaluation, we report the results of the following metrics:

- the BLEU score following previous work. It should be noted that BLEU is not generally accepted (Liu et al., 2016) to match human evaluation in generation tasks since there are distinct ways to reply to an input.

- *distinct-1* and *distinct-2* (Li et al., 2016a): calculating the number of distinct unigrams and bigrams in generated responses scaled by total number of generated unigrams and bigrams.

- Avg.length: the average length of the generated response.

- Stopword%: the percentage of stop-words5 of the responses generated by each model.

- Adversarial Success: the adversarial evaluation strategy proposed by Kannan and Vinyals (2017); Li et al. (2017b). Adversarial evaluation trains a discriminator (or evaluator) function to labels dialogues as machine-generated (negative) or human-generated (positive). Positive

3http://nlp.stanford.edu/data/OpenSubData.tar
4http://www.imsdb.com/
5The combination of stopwords in https://www.ranks.nl/stopwordsandpunctuations.
| Model        | BLEU | distinct-1 | distinct-2 | Avg.length | Stopword | adv succ |
|--------------|------|------------|------------|------------|----------|----------|
| Human        | -    | 16.8%      | 58.1%      | 14.2       | 69.8%    |          |
| AR           | 1.64 | 3.7%       | 9.5%       | 6.4        | 82.3%    | 2.7%     |
| AR+MMI       | 2.10 | 10.6%      | 20.5%      | 7.2        | 76.4%    | 6.3%     |
| AR+MMI+diverse | 2.16 | 16.0%      | 27.3%      | 7.5        | 72.1%    | 6.4%     |
| AR+MMI+RL    | 2.34 | 13.7%      | 25.2%      | 7.3        | 73.0%    | 8.0%     |
| NonAR        | 1.54 | 8.9%       | 14.6%      | 7.1        | 77.9%    | 2.4%     |
| NonAR+MMI    | 2.68 | 15.9%      | 27.0%      | 7.4        | 71.9%    | 9.2%     |

Table 1: Automatic Metrics Evaluation for Different Models.

Examples are taken from training dialogues, while negative examples are decoded using generative models from a model. Adversarial success is the percentage of the generated responses that can fool the evaluator to believe that it is human-generated. We refer readers to Li et al. (2017b) for more details about the adversarial evaluation.

5.5 Examples

5.6 Qualitative Evaluation

We employed crowdsourced judges to provide evaluations for a random sample of 1000 items from the test set. Following protocols in Baheti et al. (2018), we assigned each output to a human judge, who were asked to score every model response on a 5-point scale (Strongly Agree, Agree, Unsure, Disagree, Strongly Disagree) on 2 categories: 1) Coherence - is the response coherent to the given source? and 2) Content Richness - does the response add new information to the conversation? Ratings were later collapsed to 3 categories (Agree, Unsure, Disagree).

The results for plausibility and content richness of different models are presented in Table 3. For dialogue coherence, the trend is that NonAR+MMI is better than AR+MMI, followed by AR and Non-AR. AR is slightly better than Non-AR. For Content Richness, the proposed NonAR+MMI is significantly better than AR+MMI, and the gap is greater than dialogue coherence. This is because the N-best list generated by the AR model tends to be dull and generic, and the reranking model in AR+MMI can help alleviate but cannot fully address this issue. The output from the AR+MMI model is thus by far less diverse than nonAR+MMI, which obtains the MMI score for each generated token.

To verify the statistical significance of the reported results, we performed a pairwise bootstrap test (Johnson, 2001; Berg-Kirkpatrick et al., 2012) to compare the difference between percentage of responses that were labeled as yes. We computed p-values for non-AR+MMI vs AR+MMI and non-AR vs AR. Regarding non-AR vs AR, we did not find a significant difference (p-value = 0.18) for coherence, but a significant difference for content richness (p-value < 0.01). For non-AR+MMI vs AR+MMI and
it feels like i must have been asleep for weeks.

where does she work?

who is in charge?

I am off all week next week.

why can’t you just believe us?

can’t you see how they’re exploiting you?

I mean, we have to talk to him.

i’m sorry to detain you for so long.

do you have any idea what caused the explosion?

Table 2: Response generation: Sample responses using the diversity-promoting beam search and vanilla beam search.

| Model       | Coherence | Content Richness |
|-------------|-----------|------------------|
| Human       | 17.4      | 14.0             |
| AR          | 28.6      | 38.2             |
| AR+MMI      | 25.3      | 30.6             |
| AR+MMI+diverse | 24.8   | 30.9             |
| AR+MMI+RL   | 24.1      | 31.0             |
| nonAR       | 28.8      | 32.7             |
| nonAR+MMI   | 23.1      | 24.0             |

Table 3: Human judgments for Coherence and Content Richness of the different models.

AR+MMI+RL, we find a significant difference for both coherence (p-value < 0.01) and content richness (p-value < 0.01). For non-AR+MMI vs AR+MMI+RL, the difference for coherence is significant (p-value < 0.01), but content richness is insignificant (p-value=0.25).

5.8 Results on Machine Translation

Mutual information has been found to improve machine translation, both in the context of NMT models (Li and Jurafsky, 2016) and phrase-based MT models (Och and Ney, 2002; Shen et al., 2010). It would be interesting to see whether the proposed model can also help non-AR NMT as well. We evaluate the proposed method on the three widely used machine translation benchmark tasks (three datasets): WMT2014 De→En (4.5M sentence pairs), WMT2014 En→De, WMT2016 Ro→En (610K sentence pairs) and IWSLT2014 De→En (150K sentence pairs). We use the Transformer (Vaswani et al., 2017a) as a backbone. Knowledge Distillation is applied for all models. Since building SOTA non-AR MT models is out of the scope of this paper, we used the commonly used NonAR structure described in Section 4.2 as the backbone. Results are shown in Table 4. As can be seen, the incorporation of MMI model significantly improves MT performances. This shows that the proposed model has potentials to benefit a wide range of generation tasks.

6 Conclusion

In this paper, we propose to use non-autoregressive (non-AR) generation to address the non-global optimality issue for MMI in neural dialog generation. Target tokens are generated independently in non-AR generation. $p(x|y)$ for each target word can thus be computed as soon as it’s generated, and does not wait for the completion of the whole target sequence, leading to more diverse and appropriate responses.
for the completion of the whole sequence. This naturally resolves the non-global optimal issue in decoding. Experimental results demonstrate that the proposed strategy produces more diverse, coherent, and appropriate responses, yielding substantive gains in BLEU scores and in human evaluations.

### Table 4: The performances of NonAR+MMI methods on WMT14 En→De and WMT16 Ro→En. Results from Gu et al. (2018); Lee et al. (2018); Ma et al. (2019) are copied from original papers for reference purposes.

| Method                          | WMT14 En→De  | WMT14 De→En | WMT16 Ro→En |
|---------------------------------|--------------|--------------|--------------|
| NAT (Gu et al., 2018)           | 17.69        | 20.62        | 29.79        |
| iNAT (Lee et al., 2018)         | 21.54        | 25.43        | 29.32        |
| FlowSeq-large (raw data) (Ma et al., 2019) | 20.85    | 25.40        | 29.86        |
| NAT (our implementation)        | 22.32        | 24.83        | 29.93        |
| NAT +MMI                        | 23.80        | 26.05        | 30.50        |

(+1.48) (+1.22) (+0.57)

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