Why Do Neural Response Generation Models Prefer Universal Replies?

Bowen Wu\textsuperscript{1}, Nan Jiang\textsuperscript{2}, Zhifeng Gao\textsuperscript{3}, Mengyuan Li\textsuperscript{3}, Zongsheng Wang\textsuperscript{1}, Suke Li\textsuperscript{3}, Qihang Feng\textsuperscript{3}, Wenge Rong\textsuperscript{2}, Baoxun Wang\textsuperscript{1} \\
\textsuperscript{1}Platform and Content Group, Tencent \\
\textsuperscript{2}School of Computer Science and Engineering, Beihang University, Beijing, China \\
\textsuperscript{3}School of Software & Microelectronics, Peking University, Beijing, China \\
\{jasonbwwu, jasoawang, careyfeng, asulewang\}@tencent.com \\
\{nanjiang, w.rong\}@buaa.edu.cn \\
\{gao.zhifeng, limengyuan\}@pku.edu.cn, lisuke@ss.pku.edu.cn

Abstract

Recent advances in neural Sequence-to-Sequence (Seq2Seq) models reveal a purely data-driven approach to the response generation task. Despite its diverse variants and applications, the existing Seq2Seq models are prone to producing short and generic replies, which blocks such neural network architectures from being utilized in practical open-domain response generation tasks. In this research, we analyze this critical issue from the perspective of the optimization goal of models and the specific characteristics of human-to-human conversational corpora. Our analysis is conducted by decomposing the goal of Neural Response Generation (NRG) into the optimizations of word selection and ordering. It can be derived from the decomposing that Seq2Seq based NRG models naturally tend to select common words to compose responses, and ignore the semantic of queries in the word ordering stage. On the basis of the analysis, we propose a max-marginal ranking regularization term to avoid Seq2Seq models from producing the generic and uninformative responses. The empirical experiments on benchmarks with several metrics have validated our analysis and proposed methodology.

Introduction

Past years have witnessed the dramatic progress on the application of generative sequential models (also noted as Seq2Seq learning (Sutskever, Vinyals, and Le 2014; Bahdanau, Cho, and Bengio 2015)) on Neural Response Generation (NRG) fields (Vinyals and Le 2015) (Serban et al. 2017). Seq2Seq model has been proved to be capable of directly generating reply given an open domain query (Li et al. 2016; Xing et al. 2017). Both relevant words or phrases are automatically selected, and smoothness and fluency of responses are guaranteed through the end-to-end learning. Moreover, abundant impressive human-to-machine conversation cases have been presented in many previous studies (Serban et al. 2016; Shang, Lu, and Li 2015; Shao et al. 2017; Zhang et al. 2018).

Despite these promising results, current Sequence-to-Sequence architectures for response generation are still far from steadily generating relevant and coherent replies. The essential issue identified by many studies is the Universal Replies: the model tends to generate short and general replies which contain limited information, such as “That’s great!”, “I don’t know”, etc. (Li et al. 2016b; Li, Monroe, and Jurafsky 2016). Intuitively, this problem was attributed to the vast coverage of common replies in the training set and insufficient guiding knowledge in the models’ response generation step (Mou et al. 2016; Shao et al. 2017). Hence, current efforts mainly focus on introducing external information to the model (Mou et al. 2016; Xing et al. 2017), and encouraging the model to generate diverse responses in searching space via variational beam search strategies during inference (Shao et al. 2017; Li et al. 2016b; Li, Monroe, and Jurafsky 2016).

Nevertheless, most previous analyses over the issue are empirical and lack of statistical evidence. Therefore, in this paper, we conduct an in-depth investigation of the performance of Seq2Seq models on the NRG task. In our inspections on the existing dialog corpora, it is shown that those repeatedly appeared replies have two essential traits: 1) Most of them are composed of highly frequent words; 2) They cover a large portion of the dialog corpora that each universal reply stands for the response of various queries. Above characteristics of universal replies deviate the NRG from other successful applications of Seq2Seq model such as translation and lead current generative NRG models to prefer common replies. To discuss the influences from the spe-

| Query               | I would add Metropolis to the list.  |
|---------------------|--------------------------------------|
| Replies             | I love this film so much.             |
|                     | Me too, it is a beautiful film.       |
|                     | This movie has beautiful background art. |
|                     | Fritz is really a good director, I like his film. |
|                     | Is “Metropolis” based on a book?      |
|                     | Brigitte cooling off on the set of Metropolis. |
| Translate           | J’ajouterais Metropolis à la liste.   |
|                     | Je voudrais ajouter Metropolis à la liste. |

Table 1: Replies and translated version of an example which reveal the different source-target sentence distribution for dialog and translation.
specific distributed corpus, we decompose the target sequence’s probability into two parts and analyze them respectively.

To break down the mentioned characteristics of dialog corpora in the model training step, we propose a ranking-oriented regularization term to prune the scores of those irrelevant replies. Experimental results reveal that the model with such regularization can produce better results and avoid generating ambiguous responses. Also, case studies show that the issue of generic response is alleviated that these common responses are ranked relatively lower than more appropriate answers.

The main contributions of this paper are concluded as follows: 1) We analyze the loss function of Seq2Seq models on NRG task and conclude several critical reasons that the NRG models prefer universal replies; 2) Based on the analysis, a max-marginal ranking regularization is presented to help the model converge to informative responses.

**Analysis of Seq2Seq Models for NRG**

Different from significant advances in machine translation (Bahdanau, Cho, and Bengio 2015) and abstractive summarization (Rush, Chopra, and Weston 2015; Nallapati et al. 2016), it remains challenging to apply Seq2Seq models in practical response generation. One widely accepted issue within current models is that Seq2Seq architectures are inclined to produce common and unrelated replies, even when the quality of training data is significantly improved and different Seq2Seq variants are proposed. The primary reason for this phenomenon lies in the fact that the semantic constraint from query to the possible responses is naturally weak, since the responses to a given query are not required to be semantically equivalent. In contrast, the references in machine translation or summarization are usually restricted to be equivalent to each other semantically or even lexically. Especially, for machine translation, words that appear in the target language should satisfy word level mapping from the source sentence, so the learned word alignment function could ensure the model to generate suitable translated words. Different from learning the semantic alignments between languages in NMT, in NRG, the replies can be diversified as they only need to satisfy the coherence with the given queries. Moreover, given a query, the sequential model is optimized to learn the shared information among all replies, thus the model is more likely to choose those high-frequent common replies, which is also mentioned in Ritter, Cherry, and Dolan (2011).

Taking the case in Table 1 for example, the topic of this query is about movies. It can be observed that the replies shown in the table are semantically diversified: the first two replies are related to the opinion of the respondent toward the movie, while the rest are about the director, content, and origin of the movie. By contrast, the two valid translations in French are very similar regarding their semantics, which can be attributed to the fixed word-level mapping between query and targets.

**Problem Decomposition**

The sequence-mapping problem in NRG can be decomposed into two independent sub-learning problems: 1) Target word selection, in which a query is summarized and transformed into the semantic space of responses, and then a set of target words is selected to represent the meaning; 2) Word ordering, in which a grammatical coherent reply is generated based on the candidate word set [Vinylas, Bengio, and Kudlur 2016]. The word selection and ordering of the target sequence are jointly learned which can also be reflected in the model’s loss function by two possible factored phases:

\[
- \log p(y|x) = - \log p(S(y)|x) - \log p(y|S(y), x)
\]

(1)

where \(x\) stands for the given query and \(y\) is the corresponding response with \(n\) words. Besides, \(S(y) = \{w_1, \ldots, w_n\} \in y, i \in [1, n]\) represents all predicted words without sequential order, so \(p(S(y)|x)\) is referred as the probability of the target word selection. Meanwhile, \(p(y|S(y), x)\) indicates the probability of word ordering given this group of possible words. Thus, the objective can be redescribed from maximizing the probability of the ground truth response \(y\) under query \(x\) to maximizing these two joint probabilities simultaneously.

It should be noted that, actually, the decomposition performed in Equation 1 is widely used in the natural language generation related tasks, especially in the statistical machine translation (Och and Ney 2002), neural machine translation (Weng et al. 2017), as well as previous NRG related works (Wu et al. 2018). Indeed, this decomposition is not about the training procedure of the seq2seq models. Moreover, from the perspective of probability theory, any event \(z\) (either latent or explicit) could be involved to replace \(S(y)\). In this paper, we assign the set of words of response as the event \(z\) to perform the analysis. The result of the analysis also holds for \(- \log p(y|x)\) and its decomposition with any other forms of \(z\).

On this basis, we will further discuss the impact of the implicit constraint from two separated probabilities in Eq. 1 which results in the potential failure of models in learning conversational patterns.

**Target Word Selection Probability**

Assuming that we have a set of \(K\) ground-truth replies: \(\{y_1, \ldots, y_K\}\) to a given query \(x\), the upper bound of the target word selection probability can be derived via Jensen’s Inequality (Boyd and Vandenberghe 2004):

\[
\sum_{k=1}^{K} \log p(S(y_k)|x)
= \sum_{k=1}^{K} \log \prod_{w \in S(y_k)} p(w|x)
\leq L_S \log \sum_{w \in \bigcup_{k=1}^{K} S(y_k)} \frac{p(w|x)}{L_S}
\]

(2)

where \(\bigcup_{k=1}^{K} S(y_k)\) denotes all the words appearing in the entire response set, and \(L_S = |\bigcup_{k=1}^{K} S(y_k)|\). Thus, optimizing the first segment is proportional to maximizing the last conditional probabilities, and the optimal strategy is to assign
probability is limited by law (Zipf 1935). In other words, the long-tailed Unigram distribution which satisfies Zipf’s law

\[ K \approx \frac{1}{\log(1+K)} \]

So that, translated candidates are confined to the source and target sentences are semantically equivalent.

Furthermore, assuming that each response contains a fixed number of \( T \) words (so that \( 1 \leq L_S \leq K \times T \)), we can find the probability of each response for \( x \) is inversely proportional to \( K \):

\[
L_S \log \frac{\sum_{w \in \mathcal{C}^y \cap \mathcal{S}(y_k)} p(w|x)}{L_S} = L_S \log \frac{E(w|x) \times T}{K \times T \times L_S} \propto \log \frac{1}{(K \times L_S)^{1/2}} \leq \log \frac{1}{K}
\]

where \( E(w|x) \) denotes the mean frequency of words appeared in these \( K \) replies, which is 1.32 for the cases in Table 1. In general, the mean frequency is around 1 owing to the long-tailed Unigram distribution which satisfies Zipf’s law (Zipf 1935). In other words, the target word selection probability is limited by \( K \), so queries with more diverse answers are more challenging to learn. Meanwhile, it is difficult to obtain good predictions for lower-informational queries, as they contain more possible responses which are somewhat equivalent to a larger \( K \) (Li et al. 2016a).

Nonetheless, the translation task requires word-level mappings as they are well-aligned in the semantic space, therefore source and target sentences are semantically equivalent. So that, translated candidates are confined to \( K \approx 1 \). Thus the upper bound can be approximated as the full probability.

Word Ordering Probability

**Lemmas** Before discussing the word ordering probability, we present four lemmas and corresponding proofs. Moreover, all these lemmas are only available for the response generation task except Lemma 1.

According to the Zipf’s law (Zipf 1935), the frequency of any word is inversely proportional to its rank in the frequency table, such that the probability \( p(w_i) = \frac{Z}{i^n} \), where \( Z \approx 0.1 \), \( \alpha \approx 1 \), and \( i \) is the frequency rank of the word \( w_i \). Then, denoting the vocabulary size as \( V \) and the total number of query-response pairs as \( N \), we can formulate two characteristics of a universal reply \( y \) as follows:

1) A response is universal if it consists of only top-\( t \) ranked words. For any word \( w \) in such response, \( p(w) \geq 1/(10^t) \) according to the Zipf’s law.

2) The amount of possible queries \( M \) of \( y \) is directly proportional to the size of query-response pairs \( N \), noted as \( 1 \ll M \propto N \).

To simplify, we suppose that \( t > 1000 \) to cover most universal replies, and the frequency of the response not belonging to the universal replies is a constant \( c (1 \leq c \ll M) \). Accordingly, we can derive the following lemmas.

**Lemma 1** \( p(S(y)|y) = 1, p(S(y), y) = p(y), p(x, y, S(y)) = p(x, y) \).

Proof. Lemma 1 describes the obvious fact that the event “the word set of the response equals to \( S(y) \)” must happen when the event “\( y \) stands for the response” is established.

**Lemma 2** \( p(x|y_{ur}) = \epsilon_1 \), where \( \epsilon_1 > 0 \) and is sufficiently small, and \( y_{ur} \) is a universal reply.

Proof. Based on the second character of the universal reply and the fact that \( N \) is a very large number for any large scaled datasets, Lemma 2 is established as:

\[
p(x|y_{ur}) = \frac{1}{N} \approx \epsilon_1
\]

**Lemma 3** \( \sum_{i} p(y_{i}^{ur}|S(y)) \rightarrow 1, p(y_{i}^n|S(y)) = \epsilon_2 \), where \( \epsilon_2 > 0 \) and is sufficiently small, \( y_{i}^n \) stands for the \( i \)-th universal reply and \( y_{i}^j \) is the \( j \)-th non-universal grammatical replies, meanwhile, \( S(y_{i}^{ur}) \subseteq S(y) \) and \( S(y_{i}^n) \subseteq S(y) \).

Proof. According to the inequation \( \sum_{i} \frac{1}{t} > \int_{t}^{t+1} \frac{1}{x} dx = \ln(t+1) \), we can get the conclusion that the probability of a chosen word belonging to the most frequent \( t \) words is large than \( 0.1 * \ln(t+1) > 0.09 \). Since \( y \) contains \( T \) words, there is at least \( T \ln(t+1) \) words belonging to the top-\( t \)-ranked on average according to the binomial distribution.

We suppose \( m \) responses are universal replies among the \( n \) possible responses when their words are constrained by \( S(y) \). Besides, the proportion of \( m \) can be computed as:

\[
\frac{m}{n} = \frac{T \ln(t+1)}{\sum_{i=1}^{C_T} \frac{C_T}{2^T - \sum_{j=1}^{C_T} C_T^j}} \times \frac{1}{10 \ln(t+1)}
\]

\[
= \frac{2^T - \sum_{i=T \ln(t+1)}^{C_T} C_T^i}{2^T} \times \frac{1}{10 \ln(t+1)} \geq \frac{1}{20} \ln(t+1) \quad \geq 0.34
\]

where \( C \) donates the combination. Since \( n/m \) is not a very large number, the total probability of these \( m \) replies can be deducted as:

\[
\sum_{i} p(y_{i}^{ur}|S(y)) = \frac{\sum_{i} f(y_{i}^{ur})}{M} = \frac{\sum_{i} f(y_{i}^n) + \sum_{i=m}^{n} f(Y_{i}^c)}{M} = \frac{M + n/m - c}{M} \quad (5)
\]
where \( f(y) \) donates the frequency of a response \( y \) in the corpus. According to the Eq. \( 5 \) and the fact that \( M \propto N \) is a very large number for any practical large-scale datasets, \( \sum y \propto p(y) \rightarrow 1 \) can be established. Apparently, for any other candidate response \( y^r \), its probability satisfies \( p(y_i^r)\propto(y) < 1 - \sum p(y^r)\propto(y) = \epsilon_2 \).

\textbf{Lemma 4} Assuming each informative query has \( \mathcal{K} \) ground-truth replies and the query-response pairs are extracted from a multi-turn conversational corpus, a reply \( y \) not belonging to universal replies has \( \mathcal{K} \) unique queries, noted as \( p(x|y) = \frac{1}{\mathcal{K}} \).

\textbf{Proof}. Most query-response pairs are extracted from a practical large-scale multi-turn conversational corpus, so that any response always works as the post in another pair. That is, \( y \) also appears \( \mathcal{K} \) times as it also has \( \mathcal{K} \) replies. Therefore, there also exist \( \mathcal{K} \) unique posts for \( y \).

\textbf{Discussion} On the basis of Lemma 1, the word ordering probability could be deduced as:

\[
\log p(y|S(y), x) = \log \frac{p(S(y)|x)p(y|x)}{p(y)} + \log \frac{p(x|y, S(y))}{p(x|S(y))} = \log 1 + \log \frac{p(y|x, y, S(y))}{p(y|x, S(y))} + \log \frac{p(x|y, S(y))}{p(x|S(y))}
\]

(6)

\[
= \log p(y|S(y)) + \log \frac{p(x|y, y, S(y))}{p(x|S(y))} + \log \frac{p(x|y)}{p(x|S(y))} = \log p(y|S(y)) + \log \sum_i p(x|i)p(y|i|S(y))
\]

\[
= \pi p(x|y) y|S(y) + \epsilon_1 + \epsilon_2
\]

(7)

On the basis of Eq. \( 7 \) and Lemma 4, for any reply \( y \) not belonging to universal replies, the Eq. \( 6 \) can be further deduced as:

\[
\log p(y|S(y), x) \propto \log p(y|S(y)) + \log \frac{p(x|y)}{p(y|x)} + \epsilon
\]

(8)

where \( \epsilon = \epsilon_1 + \epsilon_2 > 0 \), which is also a sufficiently small positive value. Thus, optimizing the word ordering probability for the non-universal replies is partially equivalent to maximizing \( p(y|S(y)) \). In fact the term \( p(y|S(y)) \) is the language model probability and it is irrelevant with the query \( x \) (Manning, Raghavan, and Schütze 2009). In the sequential models, it is performed as \( \prod_t p(y_t|y_{t-1}, S(y)) \), in other words the sequences are generated based only on previously outputted words. This equation indicates the model optimization mainly seeks grammatical competence based on the selected words.

\textbf{Brief Summary}

In conclusion, the insufficient constraint of the target words’ cross-entropy loss in NRG is the primary reason that hinders Seq2Seq models from exploring presumable parameters. This situation is mainly caused by the particular distribution of the NRG corpus since there exist many universal replies composed of high-frequent words in the corpus. Consequently, the model tends to promote such universal replies, regardless of the given query.

\textbf{Max-marginal Ranking Regularization}

As discussed above, various responses corresponding to the same query appearing in the training data leads to the undesired preference of NRG on universal replies, so an intuitive solution is removing the multiple replies and just keeping one-to-one pairs. However, filtering the training dataset in a large scale raises the difficulty of model training. Besides, naively removing the multiple replies is detrimental to the reply diversity, which is important in NRG task. As shown in Table \( 1 \) an ideal chatbot agent is prospected to provide all listed replies and build a connection with some keywords such as ‘film’, ‘background’, ‘director’ and ‘book’, rather than other commonly appeared words like ‘I’, ‘him’, ‘a’ and ‘really’.

Thus, under this assumption, we propose a max-marginal ranking loss to emphasize the queries’ impact on these less common but relevant words. During training, as it becomes a necessity to constrain the learned feature space and reinforce related replies with more discriminative information, we classify the candidate responses into two categories: positive (i.e., highly related) and negative (i.e., irrelevant) answers. A training instance is re-constructed as a triplet \((x, y, y^-)\), where a tuple \( (x, y) \) is the original query-response pair and noise \( y^- \) is uniformly sampled from all of the responses in the training data. Given that, the model’s loss function is re-constructed as:

\[
\ell_0 = -\log p(y|x) \quad \lambda \max\{0, \log p(y^-|x) - \log p(y|x) + \gamma\}
\]

(9)

where \( \gamma > 0 \), \( \log p(y|x) \) denotes the cross-entropy loss between the model’s prediction and ground truth sequences, and the second part encourages the separation between the irrelevant responses and related replies. Moreover, the hyper-parameter \( \lambda \) defines the penalty for the Seq2Seq loss, it offers a degree of freedom to control the importance of the max-marginal between the positive and negative instances. The model is trained in the same setting as the conventional model when \( \lambda = 0 \).
|                           | # train | # valid | # test |
|---------------------------|---------|---------|--------|
| QA Pairs                  | 5,982,868 | 315,136 | 315,136 |
| Unique Replies            | 4,499,176 | 298,723 | 287,312 |
| Multi-Replies(%)          | 70/24/6  | 97/2/1  | 96/3/1  |
| OOV(%)                    | .90/.90 | .92/.93 | .91/.92 |
| Vocab Size                | 29241/27859 |

Table 2: Dataset statistics. For multiple replies, the three values represent the percentages of queries with one, two, and more than two responses, respectively. For the out of vocabulary (OOV) columns, the number in front of “/” denotes the percentage of the query, and the other one denotes replies.

The gradient of $\ell_0$ is computed using the sub-gradient method, as the second term is non-differentiable but convex (Agarwal and Collins 2010). Supposing $\log p(y|x) - \log p(y^-|x) \leq \gamma$, the gradient of the composed loss function can be formalized as:

$$\nabla_\theta \ell_0 = -\nabla_\theta \log p(y|x),$$  \hspace{1cm} (10)

If $\log p(y|x) - \log p(y^-|x) > \gamma$, then the gradient should be written as:

$$\nabla_\theta \ell_0 = -(\lambda + 1)\nabla_\theta \log p(y|x) + \lambda \nabla_\theta \log p(y^-|x).$$  \hspace{1cm} (11)

The underlying motivation of our proposed loss function is based on three considerations: 1) Universal replies are more likely to be sampled from a statistical perspective, so adding a negative term would directly ease the weight of these generic responses, and the ranking regularization can penalize those irrelevant responses; 2) Positive and negative sentences overall share the same set of generic words, which suggests that loss optimization should pay more attention to those different words rather than generic ones; 3) Only differentiable loss can solely be served as the model’s optimization goal for the sequence generation model. Furthermore, the newly proposed loss aims to penalize frequent words and irrelevant candidates, rather than repudiating the literal expression included in negative samples. Consequently, based on these considerations, we propose this term as regularization to constrain the search space of parameters instead of the stand-alone loss function.

**Experiments**

**Experimental Setups**

**Dataset Description** The dataset used in this study contained almost ten million query-response pairs collected from a popular Chinese social media: Douban Group Chat.

All case studies used in this paper were extracted from this dataset and translated into English.

For easier training and better efficiency, the maximal lengths of queries and replies were set to 30 and 50 respectively. In all of our experiments, our dataset was split into the training, validation and test sets, with detailed statistical characterization given in Table 2. Thirty percent of queries had more than one responses, and each answer appeared about 1.33 times in the training dataset, which is consistent with our hypothesis in the analysis section.

**Baseline Models** To validate the performance of the proposed model, the following two baseline models and additional methods were considered:

- S2SA: The basic Seq2Seq model with Attention mechanism (S2SA) (Bahdanau, Cho, and Bengio 2015) at the target output side.
- CVAE: The model uses a unimodal Gaussian distribution to model the whole response and append the output of the variational autoencoder as an additional input to the decoder (Zhao, Zhao, and Eskenazi 2017). The model can also be treated as VHRED (Serban et al. 2017) without the hierarchical context encoder.
- + MMI: The best performing method in Li et al. (2016b) with the length norm during inference.
- + RReg: The proposed ranking regularization in this paper. In the models utilized the RReg, negative samples were uniformly sampled from the corpus, and the process was repeated 4 times for every ground-truth case.

**Evaluation Metrics** The quality of responses was measured using both numeric metrics and human annotators. Firstly, Word Perplexity (PPL) was used to measure the model’s ability to account for the syntactic structure for each utterance (Serban et al. 2016). Secondly, ROUGE-1 and ROUGE-L scores (Lin 2004), which evaluate the extent of overlapping words between the ground-truth and predicted replies, were also adopted in the experiments. Then, we employed the diversity measurements Distinct-1 and Distinct-2 to evaluate the number of distinct Unigrams and Bigrams of the generated responses (Li et al. 2016b).

Furthermore, we recruited three highly educated human annotators to cross verify the quality of generated responses. Firstly, Word Perplexity (PPL) was used to measure the model’s ability to account for the syntactic structure for each utterance (Serban et al. 2016). Secondly, ROUGE-1 and ROUGE-L scores (Lin 2004), which evaluate the extent of overlapping words between the ground-truth and predicted replies, were also adopted in the experiments. Then, we employed the diversity measurements Distinct-1 and Distinct-2 to evaluate the number of distinct Unigrams and Bigrams of the generated responses (Li et al. 2016b).

0: The response cannot be used as a reply to the message. It is either semantically irrelevant or not fluent (e.g., with grammatical errors or UNK).
1: The response can be used as a reply to the message, which includes the universal replies such as “Yes, I see”, “Me too” and “I don’t know”.
2: The response is not only relevant and natural, but also informative and interesting.

**Training Procedures** For all of the models, LSTM was chosen as the recurrent cell, and there were 512 hidden units for both the encoder and decoder (Greff et al. 2017). Embedding size and batch size were set to 200 and 20 respectively. Adam was employed for the gradient optimization (Kingma and Ba 2015), and the initial learning rate was $1e^{-4}$. All models were implemented in Theano (Theano Development Team 2016), and each ran on a stand-alone K40m GPU device for 7 epochs, which took 7 days; twice longer time was required for training models with the ranking regularization.
Table 3: Summarized results of the testing set with both human evaluation and numerical metrics.

| Methods             | Human Label | ROUGE | Distinct | PPL  |
|---------------------|-------------|-------|----------|------|
|                     | 0 | 1     | 2     | ROUGE-1 | ROUGE-L | 1 | 2     |
| S2SA                | 52.46% | 20.52% | 27.02% | 4.97% | 3.13% | .129 | .285 | 110.0 |
| S2SA + MMI          | 51.88% | 19.92% | 28.20% | 3.96% | 2.77% | .140 | .312 | 110.0 |
| CVAE                | 50.75% | 19.24% | 30.01% | 5.01% | 3.16% | .147 | .329 | 96.9  |
| S2SA + RReg         | 48.20% | 15.38% | 36.42% | 3.45% | 2.55% | .163 | .358 | 85.6  |
| S2SA + RReg + MMI   | 47.40% | 18.75% | 33.85% | 3.43% | 2.63% | .167 | .345 | 85.6  |

Figure 2: Learning curve for the two models.

The last two models with the ranking regularization shared the related hyper-parameters. We set $\lambda$ to 0.1 and $\gamma$ to 0.18, according to the model’s performance on the validation set. Figure 2 shows cross-entropy loss flows vs. training epoch numbers. The model with the max-marginal ranking regularization converges faster than the S2SA throughout the training procedure. This shows that the additional regularization term helps to speed up the fitting by removing these sub-optimal paths.

**Results and Analysis**

**Experimental Results**  The performance of five models on existing metrics is summarized in Table 3. The S2SA model with the max-marginal ranking regularization outperforms the one with primary loss function on the target loss PPL. This implies the proposed regularization can lead the co-operated model to generate more correct words given their queries and previous sub-sentence of replies. Besides, the PPL of S2SA with RReg is also about 10 points lower than the result of CVAE. As the MMI method is performing during inference, losses of models with MMI are identical to those without revision.

However, the results are opposite regarding the ROUGE scores. According to the comparison between the ROUGE scores, the generated responses by the S2SA and the CVAE contain more words appearing in the ground truth answers. These experimental results can be attributed to the two major factors: a) The very low ROUGE scores reflect few words shared by any predictions and the ground truth. However, most n-gram overlaps belonging to the common words, such as “I”, “are”, “that”. Among all the unigram overlaps, 68.7% words are belonging to the top-1000 frequent words over the whole corpus. b) A certain proportion of replies in the test set are universal themselves. Therefore, the S2SA has achieved a higher ROUGE score as its’ results are more consistent with those common ground truth responses.

The human evaluation is the most important metric, and it is clear from Table 3 that the S2SA with the ranking regularization outperforms the based S2SA model with a large margin. It increases the number of meaningful responses by around 10% and reduces the number of irrelevant cases by around 4%. Meanwhile, most of the acceptable replies (labeled as “1” or “2”) generated by the S2SA are labeled as “1”, which indicates the model prefer safe responses. We attribute the gaps to the promotion of highly related words and reducing of universal replies. Same trend can be also spotted on Distinct-1 and Distinct-2, it reveals the model’s ability to generate diverse responses (Li et al. 2016b; Serban et al. 2015). The responses yielded by the S2SA are lower levels of unigram and bigram diversity than those of the ranking loss model.

As for another comparison, the improvement introduced by MMI is much smaller than that introduced by the ranking regularization and CVAE, whereas MMI is a widely used mechanism for promoting diverse responses during inference. Besides, performing MMI upon the regularization also reduces the rate of informative and interesting responses. This observation indicates that the fundamental reason for generating tasteless or inappropriate replies lies in the learning phase, rather than the searching procedure during predicting. Consequently, the revising strategy during the greedy search like MMI is less effective in addressing underlying problems than the methods influencing the model training directly. Moreover, the comparable results of S2SA + RReg and S2SA + RReg + MMI indicate that, our proposed regularization covers the ability of MMI, and obviously does better work compared to the improvements obtained from S2SA to S2SA + MMI.

Meanwhile, involving latent variables is an effective way to promote diversity as the variables sampling could bring randomness into the generation. Thus, both the Distinct 1 and Distinct 2 of CVAE are improved a lot as shown in Table 3. However, the improvement of the quality of generated replied is limited compared with the ones utilizing the RReg. It indicates the proposed method is a more straightforward way to promote the amount of information inside the responses so as to increase the diversity accordingly.
Query: University are far away, and the city’s most famous commercial street are near to me.
Replies from S2S+Attention:  
1) Where is your home?  
2) Where is your city?  
3) Where is your location?  
4) Where is your hometown?  
5) Where is your city, hun?  
6) Where is your location?  
7) Where is your home, mine is near?  
Replies from Ranking Loss:  
1) Bank  
2) I thought banks are ok.  
3) We go to bank, well  
4) We go to bank bank  
5) We go to bank, have a look.  
6) Near that <bank> road.  
7) That Joy City shopping mall is great.

Figure 3: Response re-rank capability. Responses generated by the basic model and the model with ranking loss are linked by arrows, and same topics are typeset using the same color. Some ungrammatical and incomprehensible sentences exist due to the translating try to keep the word order.

Ranking Loss for Generic Responses  
From the generated results, it is found that the Seq2Seq model with the ranking regularization term prefers meaningful content when the query contains a sufficient amount of information. We present top responses for two queries generated by different models in Figure 3. As shown in the first case, the user posts a query discussing locations. We observe that S2SA converges to a typical “where is your” pattern of replies when discussing locations, which is an example of universal replies. As the greedy beam search strategy is utilized during inference, many location-related constraints further promote these relevant universal replies instead of more varied results from different beams. In contrast, some of the responses in the right column capture the “commercial street” clues and inferred a possible location “Joy City shopping mall”. We attributed this to the boosting ability associated with semantically relevant words, as mentioned in Section .  
The second case is quite different. In this case, the Seq2Seq model did not perform satisfactorily. Even though the object “bank” was extracted into the generated candidates, the results are irrelevant to the “not reliable” feeling of the speaker, and most of them were just chosen from two beams. Inspecting the replies generated by the model with the ranking loss, more diverse sentences that discuss “unreliable” can be generated, and irrelevant answers just about “bank” are lower-ranked.  
In conclusion, the S2SA with RReg can not only formulate the conditional language model but also boost related answers to higher ranks than the rest of universal or inappropriate replies.

Related Work  
Recent years have witnessed the rapid development of data-driven dialog models with the help of accumulated conversational data from online communities. Query-response pairs are modeled by Seq2Seq models with attention mechanism (Sutskever, Vinyals, and Le 2014; Serban et al. 2016; Bahdanau, Cho, and Bengio 2015), and NRG model is designed to maximize the likelihood of target response given the source query. As there exist various reasonable responses given a query, some researches conclude that the limited information in many queries constrains the model inference, which makes the NRG models prefer universal replies (Shao et al. 2017) [Mou et al. 2016].

To address this issue, various works are conducted on bringing more information to Seq2Seq models. Some works focus on constraining the replies with topic information or keywords (Mou et al. 2016; Xing et al. 2017; Wang et al. 2017; Wu et al. 2018). Other researchers argue that diverse responses are buried by the greedy beam-search rules (Li et al. 2016b), so their works mainly focus on involving more punishment or randomness in the inference stages. For example, Li et al. (2016b) constrain the search space using mutual information with the query, while Shao et al. (2017) randomly chose candidate words from top beams to constrain short phrases. These existing works mainly focus on the generating strategies during inference, in contrast, the model’s architecture and loss function have rarely been explored. Serban et al. (2017) introduce to model the underlying distribution over possible replies directly with supposing various latent variables to affect the response generation. Shen et al. (2017) and Zhao, Zhao, and Eskens (2017) further construct a variational lower bound for response constraint. During inference, these models generate responses by first sampling an assignment of latent variables, so that models can generate more diverse responses. Such methods attempt to improve the diversity of responses by modifying the Seq2Seq architecture, and our analysis may be also helpful to design more effective latent variable based models to restrain current problems. Besides, the ranking penalty has also been used by Wiseman and Rush (2016), they employ a word-level margin to promote ground-truth sequences appearing in the beam search results. Different from our method, they directly optimize the beam search procedure to fine-tune the trained model.

Conclusion  
Eliminating universal replies is the essence for the widely practical utilization of NRG models, and thus, this paper has conducted a thorough investigation of the cause of such uninformative responses and proposed the solution from the statistical perspective. The main contributions can be summarized as follows: a) The theoretical analysis is performed to capture the root reason of NRG models producing generic responses through the optimization goal of models and the statistical characteristics of human-to-human conversational corpora, which has been little studied currently. b) According to the analysis, a max-marginal ranking regularization term is proposed to cooperate with the learning target of Seq2Seq, so as to help NRG models converge to the status of producing informative responses, rather than merely manipulating the decoding procedure to constrain the generation of universal replies.
References

[2010] Agarwal, S., and Collins, M. 2010. Maximum margin ranking algorithms for information retrieval. In Proc. of ECIR, 332–343.

[2015] Bahdanau, D.; Cho, K.; and Bengio, Y. 2015. Neural machine translation by jointly learning to align and translate. In Proc. of ICLR.

[2004] Boyd, S., and Vandenberghe, L. 2004. Convex Optimization. New York, NY, USA: Cambridge University Press.

[2017] Greff, K.; Srivastava, R. K.; Koutník, J.; Steunebrink, B. R.; and Schmidhuber, J. 2017. Lstm: A search space odyssey. IEEE transactions on neural networks and learning systems 28(10):2222–2232.

[2015] Kingma, D. P., and Ba, J. 2015. Adam: A method for stochastic optimization. International Conference on Learning Representations.

[2016a] Li, C.; Wu, Y.; Wu, W.; Xing, C.; Li, Z.; and Zhou, M. 2016a. Detecting context dependent messages in a conversational environment. In Proc. of COLING, 1990–1999.

[2016b] Li, J.; Galley, M.; Brockett, C.; Gao, J.; and Dolan, B. 2016b. A diversity-promoting objective function for neural conversation models. In Proc. of NAACL-HLT, 110–119.

[2016c] Li, J.; Galley, M.; Brockett, C.; Spithourakis, G. P.; Gao, J.; and Dolan, W. B. 2016c. A persona-based neural conversation model. In Proc. of ACL, 994–1003.

[2016] Li, J.; Monroe, W.; and Jurafsky, D. 2016. A simple, fast diverse decoding algorithm for neural generation. CoRR abs/1611.08562.

[2004] Lin, C.-Y. 2004. Rouge: A package for automatic evaluation of summaries. In Proc. of ACL workshop, volume 8.

[2009] Maning, C.; Raghavan, P.; and Schtze, H. 2009. An introduction to information retrieval.

[2016] Mou, L.; Song, Y.; Yan, R.; Li, G.; Zhang, L.; and Jin, Z. 2016. Sequence to backward and forward sequences: A content-introducing approach to generative short-text conversation. In Proc. of COLING, 3349–3358.

[2016] Nallapati, R.; Zhou, B.; dos Santos, C. N.; Gülçehre, Ç.; and Xiang, B. 2016. Abstractive text summarization using sequence-to-sequence rnns and beyond. In Proc. of CoNLL, 280–290.

[2002] Och, F. J., and Ney, H. 2002. Discriminative training and maximum entropy models for statistical machine translation. In Proceedings of the 40th annual meeting on association for computational linguistics, 295–302. Association for Computational Linguistics.

[2011] Ritter, A.; Cherry, C.; and Dolan, W. B. 2011. Data-driven response generation in social media. In Proc. of EMNLP, 583–593.

[2015] Rush, A. M.; Chopra, S.; and Weston, J. 2015. A neural attention model for abstractive sentence summarization. Empirical methods in natural language processing 379–389.

[2015] Serban, I. V.; Lowe, R.; Henderson, P.; Charlin, L.; and Pineau, J. 2015. A survey of available corpora for building data-driven dialogue systems. CoRR abs/1512.05742.

[2016] Serban, I. V.; Sordoni, A.; Bengio, Y.; Courville, A. C.; and Pineau, J. 2016. Building end-to-end dialogue systems using generative hierarchical neural network models. In Proc. of AAAI, 3776–3784.

[2017] Serban, I. V.; Sordoni, A.; Lowe, R.; Charlin, L.; Pineau, J.; Courville, A. C.; and Bengio, Y. 2017. A hierarchical latent variable encoder-decoder model for generating dialogues. In AAAI, 3295–3301.

[2015] Shang, L.; Lu, Z.; and Li, H. 2015. Neural responding machine for short-text conversation. In Proc. of ACL, 1577–1586.

[2017] Shao, Y.; Gouws, S.; Britz, D.; Goldie, A.; Strope, B.; and Kurzweil, R. 2017. Generating high-quality and informative conversation responses with sequence-to-sequence models. In Proc. of EMNLP, 2210–2219.

[2017] Shen, X.; Su, H.; Li, Y.; Li, W.; Niu, S.; Zhao, Y.; Aizawa, A.; and Long, G. 2017. A conditional variational framework for dialog generation. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), volume 2, 504–509.

[2014] Sutskever, I.; Vinyals, O.; and Le, Q. V. 2014. Sequence to sequence learning with neural networks. In Proc. of NIPS, 3104–3112.

[2016] Theano Development Team. 2016. Theano: A Python framework for fast computation of mathematical expressions. arXiv e-prints abs/1605.02688.

[2015] Vinyals, O., and Le, Q. V. 2015. A neural conversational model. arXiv preprint arXiv:1506.05869.

[2016] Vinyals, O.; Bengio, S.; and Kudlur, M. 2016. Order matters: Sequence to sequence for sets. In Proc. of ICLR.

[2017] Wang, D.; Jojic, N.; Brockett, C.; and Nyberg, E. 2017. Steering output style and topic in neural response generation. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, 2140–2150.

[2017] Weng, R.; Huang, S.; Zheng, Z.; Dai, X.; and Chen, J. 2017. Neural machine translation with word predictions. arXiv preprint arXiv:1708.01771.

[2016] Wiseman, S., and Rush, A. M. 2016. Sequence-to-sequence learning as beam-search optimization. In Proc. of EMNLP, 1296–1306.

[2018] Wu, Y.; Wu, W.; Li, Z.; Xu, C.; and Yang, D. 2018. Neural response generation with dynamic vocabularies. National Conference on Artificial Intelligence.

[2017] Xing, C.; Wu, W.; Wu, Y.; Liu, J.; Huang, Y.; Zhou, M.; and Ma, W. 2017. Topic aware neural response generation. In Proc. of AAAI, 3351–3357.

[2018] Zhang, Y.; Galley, M.; Gao, J.; Gan, Z.; Li, X.; Brockett, C.; and Dolan, B. 2018. Generating informative and diverse conversational responses via adversarial information maximization. In Advances in Neural Information Processing Systems, 1810–1820.

[2017] Zhao, T.; Zhao, R.; and Eskenazi, M. 2017. Learning discourse-level diversity for neural dialog models using...
conditional variational autoencoders. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, volume 1, 654–664.

[1935] Zipf, G. K. 1935. The psychobiology of language.

**Appendix A: Cases**

| Query | Replies from S2S+Attention | Replies from Ranking Loss |
|-------|-----------------------------|---------------------------|
| What should I do? | 1) Do nothing.  
2) Go on.  
3) Do nothing, hm.  
4) How?  
5) Do nothing do nothing.  
6) Then go ahead.  
7) So how do you do? | 1) Do nothing.  
2) Do nothing.  
3) Go to sleep.  
4) Don’t worry.  
5) You should keep on.  
6) Then go ahead.  
7) Keep finding. |

| Query | Replies from S2S+Attention | Replies from Ranking Loss |
|-------|-----------------------------|---------------------------|
| How about the salary? | 1) negotiable  
2) Salary negotiable.  
3) Salary negotiable.  
4) Salary negotiable!  
5) Salary and payment negotiable.  
6) Payment is nice.  
7) Payment is nice, and salary negotiable. | 1) Salary negotiable.  
2) Salary negotiable.  
3) High salary.  
4) Basic salary and plus  
5) Salary negotiable!  
6) Salary and payment negotiable.  
7) Payment is nice, send your CV. |

| Query | Replies from S2S+Attention | Replies from Ranking Loss |
|-------|-----------------------------|---------------------------|
| I’m 23, why I’m still in growth? | 1) 23.  
2) 22.  
3) 21.  
4) 20.  
5) 25.  
6) 23 years old.  
7) 22 years old. | 1) 23.  
2) 23.  
3) just 23.  
4) just 22.  
5) 23 years old are not  
6) 23 years old are not old  
7) 23 years old are not old! |

| Query | Replies from S2S+Attention | Replies from Ranking Loss |
|-------|-----------------------------|---------------------------|
| Where are you graduate? | 1) Xi’an.  
2) Wuhan.  
3) <unk>.  
4) Nanjing.  
5) Junior.  
6) In Junior.  
7) In junior junior Shanghai. | 1) Peking.  
2) Chengdu.  
3) Xi’an.  
4) In Chengdu.  
5) I study in Chengdu.  
6) I study in Shanghai.  
7) I study in Beijing. |

| Query | Replies from S2S+Attention | Replies from Ranking Loss |
|-------|-----------------------------|---------------------------|
| My child is born. | 1) <unk>.  
2) born.  
3) born baby.  
4) children born.  
5) born born children.  
6) born born born children.  
7) born children born children. | 1) ok  
2) Cheers!  
3) Em.  
4) ok, born child.  
5) cheers, congratulations!  
6) born born born children.  
7) born children born children. |

Figure 4: Cases for comparing the S2SA and the model with ranking regularization, and the topics or expressions of the generated replies marked with blue are excluded in the responses generated by SASA.

As shown in Figure 4, we have randomly sampled 5 queries from the test set and given the top 7 responses generated by the S2SA and S2SA cooperating with the ranking regularization. Even though some of them were bad cases and contained some grammatical errors, overall the model with the rank regularization tends to generate more informative and interesting sentences compared with baselines. Especially, we can find the diversity of responses is notably