# Promise Relevance in Diversity-Promoting Dialogue System


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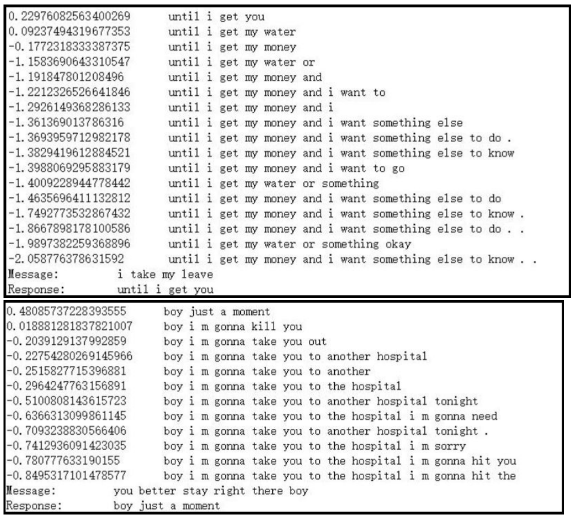
## Abstract

In this article, we introduce an significant and interesting problem about how to improve relevance between message and response of diversity for a open-domain dialogue generation system. Inspired by SEQ2SEQ model with attention and context information, a MMI-context prototype model is proposed. After discussing related work about context aware decoding RNN model, we describe some results in preliminary experiments from both quantitative and qualitative aspects.


## 1 INTRODUCTION

An appealing response generation system should be expected to output grammatical, coherent responses that are diverse and interesting. In practice, however, neural conversation models tend to generate trivial or non-committal responses, often involving high-frequency phrases along the lines of I dont know or Im OK [1][2][3]. More importantly, however, how to enhance the relation between message and response turns out to attract little attention in recent research contribution. The underlying motivation comes from the fact that dialogue turns becomes difficult to continue once machine gives meaningless, non-causal responses, though of considerable diversity.

In neural language generation model, e.g. SEQ2SEQ, responses that seem more meaningful or specific can also be found in the N-best lists, but rank much lower [4]. In part at least, this behavior can be ascribed to the relative frequency of generic responses like I dont know in conversational datasets, in contrast with the relative sparsity of more contentful alternative responses. After changing objective, the number of dull responses decreases on the on hand, while candidates are still densely similar to each other and lack relevance to message. Table 1 illustrates this phenomenon, showing top outputs from MMI-antiLM models [4]. All the top-ranked responses are not quite generic but has little relation with the given message.



| | |
|---|---|
| 0.22976082563400269 | until i get you |
| 0.09237494319677353 | until i get my water |
| -0.1772318333387375 | until i get my money |
| -1.1583690643310547 | until i get my water or |
| -1.191847801208496 | until i get my money and |
| -1.2212326526641846 | until i get my money and i want to |
| -1.2926149368286133 | until i get my money and i |
| -1.361369013786316 | until i get my money and i want something else |
| -1.3693959712982178 | until i get my money and i want something else to do . |
| -1.3829419612884521 | until i get my money and i want something else to know |
| -1.3988069295883179 | until i get my money and i want to go |
| -1.4009228944778442 | until i get my water or something |
| -1.4635696411132812 | until i get my money and i want something else to do |
| -1.7492773532867432 | until i get my money and i want something else to know . |
| -1.8667898178100586 | until i get my money and i want something else to do . . |
| -1.9897382259368896 | until i get my water or something okay |
| -2.058776378631592 | until i get my money and i want something else to know . . |
| Message: | i take my leave |
| Response: | until i get you |

| | |
|---|---|
| 0.48085737228393555 | boy just a moment |
| 0.018881281837821007 | boy i m gonna kill you |
| -0.2039129137992859 | boy i m gonna take you out |
| -0.22754280269145966 | boy i m gonna take you to another hospital |
| -0.2515827715396881 | boy i m gonna take you to another |
| -0.2964247763156891 | boy i m gonna take you to the hospital |
| -0.5100808143615723 | boy i m gonna take you to another hospital tonight |
| -0.6366313099861145 | boy i m gonna take you to the hospital i m gonna need |
| -0.7093238830566406 | boy i m gonna take you to another hospital tonight . |
| -0.7412936091423035 | boy i m gonna take you to the hospital i m sorry |
| -0.780777633190155 | boy i m gonna take you to the hospital i m gonna hit you |
| -0.8495317101478577 | boy i m gonna take you to the hospital i m gonna hit the |
| Message: | you better stay right there boy |
| Response: | boy just a moment |

Figure 1: Top ranked responses generated by MMI-antiLM model (Li et al., 2015) using beam decode for message "I take my leave" and "you better stay right there boy"

More specifically, we find that it is common that in basic SEQ2SEQ model or even those diversity-promoting ones, e.g. MMI-antiLM, result of beam decoding, namely the N-best list, is still highly centralized to only a few ancestors or prefixes. Such phenomena might be owned to MLE objective[4], as well as short memory of RNN in practice. Meanwhile, pursuing diversity only does not aligned with human-like dialogue system. Because, many answer generated are not quite boring, though, they hardly convey relevant information regards to source. Intuitively, it seems desirable not only to take into account the dependency of responses from previous tokens generated, but also replay the relation that connects message and response. In this article, we therefore propose potentially feasible solutions to address such problem.

## 2 RELATED WORK

Maximum Mutual Information is adopted in recent diversity-promoting dialogue generation system. [4] Inspired by optimization objective in speech recognition domain, MMI considers not only the conditional probability which is given by traditional Maximum Likelihood Estimation, and also the probability of responses. From another point of view, the latter one could be seen as penalty to those phrases and sentences with high frequency. As a result, it might prefer those not much common which enhances diversity. Penalizing siblings in beam decode is another approach to improve diversity. By assigning different penalty level for intra-sibling ranking, the model would favor choosing hypotheses from diverse parents. [5] There are also plenty of other prior work addressing diversity problem during decoding like producing multiple outputs that are mutually diverse, either non-redundant summary sentences or N-best lists. [6][7] Nevertheless, most of them are evaluation driven which emphasizes much on a single aspect.

## 3 METHODOLOGY

One reason that generation tends to produce similar, dull and noncommittal response regardless of context information lies in limited influential time of LSTM or GRU unit in sequence to sequence model. For example, faced with two different questions as input, first two words of generated responses might be the same, like I dont. However, the following phrases could be and expected to be distinct and meaningful like I dont need more coffee and I dont care about who wins, instead of I dont know what you are talking about almost all the time. In other words, decoding process after the first few words seems to take account into little, if any, information from source. Consequently, the response tends to show less relevance and diversity.

A lot of prior work contributes to how to improve long-term memory. Recently, adding attention mechanism appears to be one of the most popular methods. In many situation like machine translation [8][10] and document summarization [9], it works well in terms of focusing on particular positions in source input. Nevertheless, from either point of view of experimental results or intuition behind, we argue that attention is not quite suitable for this open-domain dialogue system.

After applying attention mechanism on basic SEQ2SEQ architecture[10], the training time is far longer and performance drops considerably instead. By sampling test data and visualizing attention weights, it is often the case that one single token in source sentence gather majority of attention for each token decoded.

It is not difficult to explain that in dialogue generation scenario there are relatively much fewer corresponding tokens or phrases in source and target, compared to other application like machine translation. For instance, with seriously one of the best shows!!! fed in, the MMI-antiLM model probably generates love it ! cant wait for the next one... But its hard to clarify that each word in response should be associated with a single word in the context sentence.

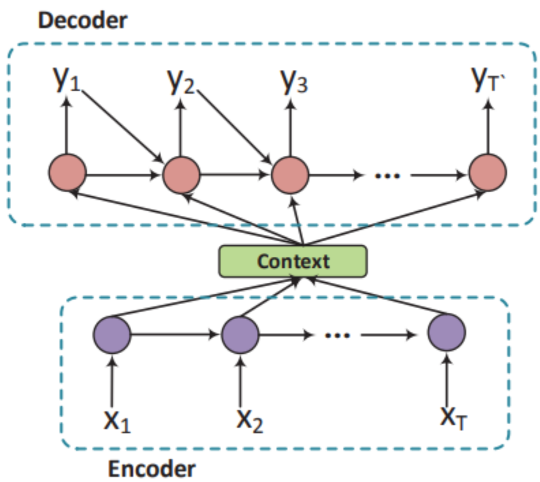



Figure 2: SEQ2SEQ model using context information for each decoding step

Considering those factors discussed above, a decoding process that combines last hidden state and also fixed context information from source should be promising, for both diversity and relevance. Such architecture is broadly applied in domains like summarization and document classification [11], which helps system capture historical records efficiently. In addition, in some recent work of neural dialogue generation paper considering context sensitivity[1], although not using sequence to sequence model, context vector becomes a component of inputs for recurrent decoding process. Whats more, in hierarchical architecture which takes as source input more than one utterances also adopts context vector for each token generation.

**Static model** Context vector has fixed length but varies as for different choice to compute. In this SEQ2SEQ scenario, for example, one way is to use simply linear or non-linear combination of hidden state in encoder, naturally like average or max. As to incorporating method, either concatenated form or weighted sum form is reasonable. Its important to assign proportion to context and decoder hidden state, in terms of dimension, since to some degree context vector may interface coherent generation than purely using prefix.

**Dynamic model** For every position during decoded utterance, the way it combines prefix and context information may vary a lot. Thus, we claim it both reasonable and feasible to add one control module that determine which kind and degree of incorporating should take for particular token. For the sum form, it essentially assign two positive number to context vector and hidden vector, which can be jointly learned with the whole network. For concatenated or other form, the answer is simply yes, no, or both. Such decision space is discrete which brings reinforcement learning to train this module. Specifically, policy gradient method [12] would show more power in both performance and ease of training, due to limited action space.

## 4 PRELIMINARY EXPERIMENT

**Dataset** The corpus used for this chatbot is open subtitiles movie dataset [13]. This raw corpus is around 2.5 million lines, where odd lines are messages and even lines correspond to response. Before split into training, development and test set, it is preprocessing by lowercasing and filtering out extremely short or long utterances.

**Training** The naive context model is constructed based on SEQ2SEQ recurrent neural network model. The input of decoder is simply concatenated form of hidden state and context vector with same dimension, plus the token predicted last step. Slightly different with that, two GRU layer architecture is adopted, where each layer contains 1000 hidden neurons. Word embeddings of size 1000 are learned jointly with the whole network to project vocabulary of size 20000. GRU parameter are initialized from a uniform distribution in [-0.1, 0.1]. Stochastic gradient decent use Adam optimizer, with initial learning rate of 0.0005, reduced by three quarter after each 10 epochs. Batch size is set to 48. This implementation was completed on a single NVIDIA GTX 1080 Ti GPU process, lasting for about 12 hours basic model training.

**Evaluation** As for evaluation, we choose three measurements as evaluation metric: BLEU-1 score, unique uni-grams and unique bi-grams. The reason why BLEU-1 is used is because it is not necessary to force predicted sentence to be identical to the single reference in high order.

| Model | BLEU | distinct-I | distinct-II |
|---|---|---|---|
| SEQ2SEQ | .301 | .103 | .412 |
| MMI-antiLM | .275 | .186 | .467 |
| MMI-context | .289 | .178 | .478 |

Table 1: Performance on test dataset of baseline as well as two MMI models

As seen in table 1, both MMI-antiLM and MMI-context have little bit lower BLEU-I scores than SEQ2SEQ baseline. What's more, MMI-antiLM and MMI-context achieve better performance on both distinct uni-grams and bi-grams measurements. However, information relevance could hardly be illustrated through automatic metrics, thus we turn to qualitative analysis.

| Message | i take my leave |
|---|---|
| SEQ2SEQ | my life is quite clear |
| MMI-antiLM | until i get you |
| MMI-context | and i will take care of it |
| Message | you better stay right there boy |
| SEQ2SEQ | i am not a monster but i am a animal |
| MMI-antiLM | boy just a moment |
| MMI-context | all right... |

Table 2: Responses generated from three models

After collecting samples, we find that replies from MMI models are more informative, and also MMI context model shows more relation between message and response.

## 5 DISCUSSION

Given that it is hard to measure automatically the performance of open-domain dialogue system, most of currently used metric evaluation can only represents very limited aspects. From machine's perspective, it is worth-wile to find trade-off between response coherency, diversity and relevance. This work only attempts to walk in the very beginning of this interesting field, remaining lots of proposed extensions and unknown architecture to explore, including end-to-end system or even more complicated ones using reinforcement learning etc.

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