Paraphrase Augmented Task-Oriented Dialog Generation

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Background & Motivation

- Background:Task-oriented dialog systems that are applied to restaurant reservation and ticket booking have attracted extensive attention recently
- Motivation:
- (a): training such models requires a large amount of high-quality dialog data. Data collected by human-human is extremely expensive and time-consuming

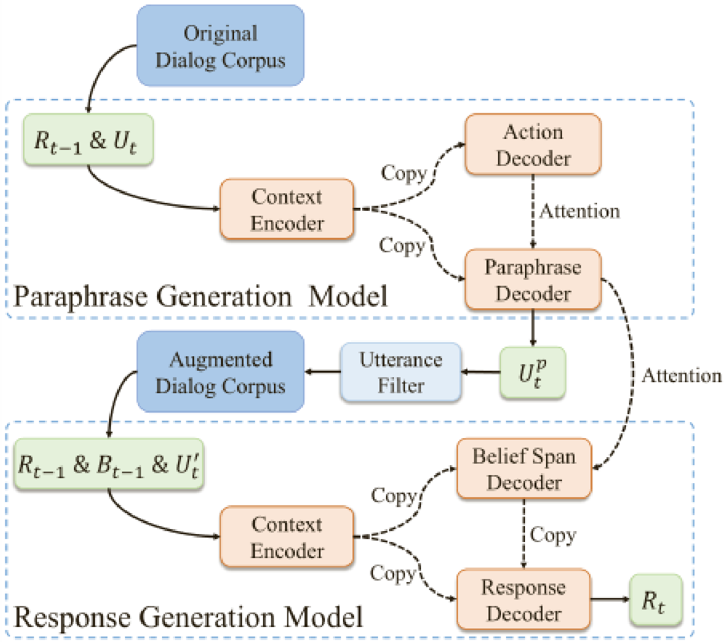
Background & Motivation

- We propose to augment existing dialog datasets through paraphrase. Some previous Paraphrase-based data-augmentation methods firstly find a set of semantically similar sentences.
- (b) However, finding isolated similar sentences are not enough to construct a dialog utterances' paraphrase, Because an utterance's paraphrase must fit the dialog history as well.

Background & Motivation

- When system asks “Do you prefer a cheap or expensive restaurant ?”,the user may state “Cheap please.” or “Could you find me a cheap restaurant?”, but the latter is improper.

Model Framework



Model Framework

- We propose the Paraphrase Augmented Response Generation (PARG), that jointly optimizes dialog paraphrase and dialog response generation.
- We first find all the user utterances that serve the same function in different dialogs. Then we select the utterances that have the same semantic content but different surface form.
- The corpus is then used to train a paraphrase generation model to generate additional user utterances.
- Finally, the augmented dialog data is used to train a response generation model.

Paraphrase Data Construction

- First, we perform delexicalization to pre-process dialog utterances to reduce the surface form language variability.
- I want a cheap restaurant. -> I want a [pricerange] restaurant.
- After delexicalization, we find utterances that serve the same dialog function in different dialogs.

Paraphrase Data Construction

- We denote the dialog function of turn t as DF_t, it consists of 1) current dialog domain D_t , 2) slots mentioned S_t in the current turn, and 3) system's dialog act A_{t-1} in the previous turn, which is formulated as

$$DF_t = (D_t, S_t, A_{t-1})$$

For each user utterance in the dialog dataset, we go through all the available training data and find all utterances with the same dialog function as paraphrase candidates of it.

Paraphrase Data Construction

- each utterance may have many paraphrase candidates, we only keep
- the high-quality paraphrase pairs that are similar in semantic but different in surface form. We use the BLEU score and the diversity to evaluate the paraphrase quality

Figure 1: Illustration of the dialog function of each turn's user utterance.

Paraphrase Augmented Response Generation

- **Paraphrase generation**: our model has a seq2seq architecture with a context encoder and two decoders for action decoding and paraphrase decoding.
- The context encoder takes the concatenation of previous system response R_{t-1} and current user utterance U_t into hidden states. Then the hidden states are used to decode previous system action A_{t-1}.
- Finally the paraphrase decoder decodes the paraphrase U_t^p based on the encoder output and the action decoder

$$h^{A_{t-1}} = \mathrm{Seq2Seq}(R_{t-1}, U_t) \tag{2}$$

$$U_t^p = \mathrm{Seq2Seq}(R_{t-1}, U_t | h^{A_{t-1}}) \tag{3}$$

Paraphrase Augmented Response Generation

- **Paraphrase Filter**: we send the generated paraphrase into a filter module to determine if it qualifies as an additional training instance
- We aim to keep paraphrases that can serve the same dialog function with the original utterance

Paraphrase Augmented Response Generation

- **Response Generation Model:** The model input is the concatenation of the current user utterance U_t', the previous belief span B_{t-1}, (slots mentioned by the user), and the system response R_{t-1}. $U_t{}'$ is either either the original user utterance or its paraphrase.
- The model is a two-stage decoding network, where the belief span and system response are decoded sequentially using the copy mechanism.

$$h^{B_t} = \mathrm{Seq2Seq}(R_{t-1}, U_t^{'}, B_{t-1} | h^{U_t^p}) \quad (4)$$

$$R_t = \mathrm{Seq2Seq}(R_{t-1}, U_t^{'} | h^{B_t}) \quad (5)$$

Datasets and metrices

- **CamRest676** is a single domain dataset consisting of dialogs about restaurant reservation. The dataset has 676 dialogs
- **MultiWOZ** is a challenging large-scale multi-domain dataset proposed recently
- Metrices:
- **BLEU** measures the **language** fluency of generated responses.
- **Entity Match Rate** (EMR) is the proportion that the system capture the correct user goal.
- Success F1 (Succ.F1) score measures whether the system can provide correct information requested by user

Results

Model	20% Data			50% Data			Full Data		
	BLEU	EMR	Succ.F1	BLEU	EMR	Succ.F1	BLEU	EMR	Succ.F1
TSCP	0.154	0.791	0.806	0.225	0.853	0.817	0.253	0.927	0.854
WordSub	0.140	0.821	0.818	0.212	0.866	0.822	0.239	0.930	0.846
TextSub	0.144	0.834	0.826	0.220	0.895	0.831	0.245	0.942	0.850
UtterSub	0.149	0.826	0.829	0.216	0.876	0.838	0.245	0.938	0.852
NAEPara	**0.155**	0.830	0.831	0.222	0.891	0.843	0.251	0.940	0.855
SRPara	0.154	0.832	0.826	**0.228**	0.886	0.840	**0.254**	0.938	0.852
PARG	**0.155**	**0.852**	**0.849**	0.226	**0.908**	**0.853**	0.252	**0.943**	**0.861**

Table 1: Results on CamRest676. The best scores are in bold.

the less data is available, the more improvement can be achieved through our data augmentation.

Results

User Utterance: Can you help me find a restaurant in the south that doesn't cost a lot of money. Ground Truth Dialog State: pricerange=cheap, area=south Reference Response: Nandos is a nice place, it serves Portuguese food. Is there anything else?		
Full Data	TSCP	Generated Dialog State: pricerange=cheap, area=south Generated Response: Nandos is a restaurant in the south. Would you like something different?
	PARG	Generated Dialog State: pricerange=cheap, area=south Generated Response: Nandos is a Portuguese restaurant in the south. Anything else you need?
50% Data	TSCP	Generated Dialog State: area=south Generated Response: Taj Tandoori is an Indian restaurant, it is in the expensive price range.
	PARG	Generated Dialog State: pricerange=cheap, area=south Generated Response: Nandos serves Portuguese food. Would you like the address?

Dialog Function	Utterance Paraphrase
Domain: train Slots Mentioned: leave Previous System Act: request-leave	Previous Response: What time would you like to leave from norwich? Original Utterance: I would like to leave at 14:45. What is the price? Matched Paraphrase: 14:45, please. What is the duration of the train ride?
Domain: hotel Slots Mentioned: parking Previous System Act: inform-name	Previous Response: Acorn Guest House is available if that works for you. Original Utterance: That is good. And I need a free parking, does it have? Matched Paraphrase: This place is fine. Is it near a hotel with free parking?

Table 5: Examples of ill-matched paraphrase pairs obtained by our paraphrase matching method.