NATURAL LANGUAGE GENERATION IN DIALOGUE USING LEXICALIZED AND DELEXICALIZED DATA

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ABSTRACT

Natural language generation plays a critical role in spoken dialogue systems. We present a new approach to natural language generation for task-oriented dialogue using recurrent neural networks in an encoder-decoder framework. In contrast to previous work, our model uses both lexicalized and delexicalized components i.e. slot-value pairs for dialogue acts, with slots and corresponding values aligned together. This allows our model to learn from all available data including the slot-value pairing, rather than being restricted to delexicalized slots. We show that this helps our model generate more natural sentences with better grammar. We further improve our model's performance by transferring weights learnt from a pretrained sentence auto-encoder. Human evaluation of our best-performing model indicates that it generates sentences which users find more appealing.

1 INTRODUCTION

Traditionally, task-oriented spoken dialogue systems (SDS) rely on template-based, hand-crafted rules for natural language generation (NLG). However, this approach does not scale well to complex domains and datasets. Previous papers have explored alternatives using corpus-based n-gram models (Oh & Rudnicky, 2002), tree-based models (Walker et al., 2007), SVM rerankers (Kondadadi et al., 2013), and Reinforcement Learning models (Rieser & Lemon, 2010).

Recently, models based on recurrent neural networks (RNNs) have been successfully applied to natural language generation tasks such as image captioning (Xu et al., 2015; Karpathy & Li, 2015), video description (Yao et al., 2015; Sharma, 2016), and machine translation (Bahdanau et al., 2015). In the domain of task-oriented SDS, RNN-based models have been used for NLG in both traditional multi-component processing pipelines (Wen et al., 2015a;b) and more recent systems designed for end-to-end training (Wen et al., 2017).

In the context of task-oriented dialog systems, the NLG task consists of translating one or multiple dialog act slot-value pairs, i.e. (INFORM-NAME, *Super Ramen*), (INFORM-AREA, *near the plaza*) into a well-formed sentence (Rajkumar et al., 2009) such as "Super Ramen is located near the plaza". Existing RNN-based models (Wen et al., 2015a) tackle this problem by relying only on the *delexicalized* part of the act slot-value pairs, i.e. the model only considers the act and slot (e.g. INFORM-NAME) and ignores the lexical values (e.g. *Super Ramen*). Wen et al. (2015b) propose a model that can use lexicalized values. However, since they do not align slots with their values, the model has no way of knowing which value corresponds to which slot. These methods ignore linguistic relationships in the lexicalized part of a slot-value pair (e.g. between the words "near", "the", and "plaza"), and between the lexicalized part and its surrounding context (e.g. between "located" and "near"). As illustrated in Figure 1, ignoring these often leads to grammatically incorrect sentences.

In this paper, we develop an RNN-based approach which considers both lexicalized and delexicalized dialogue act slot-value pairs. Our model outperforms existing approaches measured in both automated (BLEU-4 (Papineni et al., 2002), METEOR (Lavie & Agarwal, 2007), ROUGE (Lin, 2004),

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Generated output:	There are no restaurants a	around	which serve INFORM-FOOD for	ood.
Delexicalized slot input:	INFORM-FOOD	1	INFORM-FOOD	v
Lexicalized value input:	chinese	V	pizza	^

Figure 1: Models which use only delexicalized slots as input often generate grammatically incorrect sentences, since the correct grammatical form depends on the lexicalized slot-values.

CIDEr (Vedantam et al., 2015)) and human evaluation. Moreover, we show that the performance of our model can be improved further by transferring weights from a pretrained sentence auto-encoder.

2 MODEL

Our model (named ld-sc-LSTM¹) is composed of an RNN encoder and an RNN decoder (see Fig. 3).

Encoder The encoder is a 1-layer, bi-directional LSTM (Hochreiter & Schmidhuber, 1997). It takes as input a list of slot-value pairs for which a sentence must be produced and outputs a representation taking into account both the delexicalized and the lexicalized parts of each dialogue act slot-value pair. Particularly, for each input slot-value pair t, the encoder receives an input vector \mathbf{z}_t which is formed by concatenating vectors \mathbf{m}_t and \mathbf{e}_t . The vector \mathbf{m}_t is a one-hot encoding of the delexicalized part. The vector \mathbf{e}_t is formed by taking the mean of the word embeddings of the lexicalized part. Figure 2 illustrates how the encoder input is created for a given dialogue act.





Decoder The decoder translates the encoding of the dialogue act slot-value pairs into a fluent sentence. Our decoder uses sc-LSTM (Wen et al., 2015b) units. The "dialogue act" vector in the sc-LSTM can function similarly to a memory that remembers which acts are yet to be translated (Wen et al., 2015b). The initial value of the dialogue act vector is set to $\mathbf{d}_0 = \sum_{t=1}^{M} \mathbf{m}_t$, where M is the number of encoder timesteps. This is a binary vector whose entries are set to 1 for the dialogue acts that need to be included in the output sentence.

The encoder information is compressed into a "context" vector \mathbf{x} obtained by average-pooling the forward and backward



Figure 3: The encoder-decoder framework for our models: the encoder learns a representation of the dialogue act slot-value pairs and the decoder translates them into a natural language sentence. *bos* is a special token for the beginning of sentence.

hidden states of the encoder LSTMs across the time-dimension, i.e. the number of input act slot-value pairs. The vector \mathbf{x} is used to initialize the hidden state \mathbf{h}_0 and the memory cell \mathbf{c}_0 in the decoder sc-LSTM: $\mathbf{h}_0 = \tanh(\mathbf{W}_{hx}\mathbf{x}+b_{hx})$, $\mathbf{c}_0 = \tanh(\mathbf{W}_{cx}\mathbf{x}+b_{cx})$. The word embedding of the word output in the previous time-step is also an input to the decoder sc-LSTM. The hidden states of the sc-LSTM are passed to softmax layers which produce a word or a delexicalized slot at each time-step. Later, the slots are replaced with their lexicalized values. The model produces words up to a predefined maximum length or until it outputs the symbol *eos*. Our model is summarized in Figure 3.

¹lexicalized delexicalized- semantically controlled- LSTM

Model	CF				DSTC2					
	B-4	Μ	R_L	С	Н	B-4	Μ	R_L	С	Н
LSTM	0.277	0.284	0.502	2.080	3.552	0.797	0.532	0.847	7.375	2.962
d-sc-LSTM	0.291	0.288	0.513	2.231	3.504	0.805	0.555	0.867	7.605	3.218
ld-sc LSTM	0.308	0.293	0.518	2.329	3.838	0.822	0.565	0.892	8.133	3.700 [†]
transfer-ld-sc LSTM	0.317	0.298	0.526	2.370	3.614	0.832	0.578	0.894	8.248	3.926 [†]

Table 1: Comparison of performance on the CF and DSTC2 (see Appendix A) datasets. [†] denotes statistical significance (Welch's t-test p < 0.05 respectively) with respect to the baselines for **H**.

Metrics: BLEU-4 (B-4), METEOR (M), ROUGE_L (R_L), CIDEr (C), and Human evaluation (H)

Loss function and Regularization We use the negative log-likelihood along with regularization as the loss function as proposed by Wen et al. (2015b),

$$L = -\sum_{t=1}^{T} \mathbf{y}_t^{\top} \log(\mathbf{p}_t) + \|\mathbf{d}_T\| + \sum_{t=1}^{T} \eta \xi^{\|\mathbf{d}_t - \mathbf{d}_{t-1}\|},$$

where \mathbf{y}_t is the ground truth word distribution, \mathbf{p}_t is the predicted word distribution, T is the number of time-steps in the decoder, and $\eta = 0.0001$ and $\xi = 100$ are scalars. The term $\|\mathbf{d}_T\|$ pushes the model to generate all the slots it is supposed to generate so that at the last time-step there are no slots remaining. The last term encourages the model not to drop multiple "dialogue act" vector elements at once since the decoder can only generate one slot/word at each time-step.

Decoding We use beam search for decoding at test time with a beam width of 10 and slot error rate (ERR) as used in the recent literature (Wen et al., 2015b). The λ parameter of the ERR cost was set to 1000 to severely discourage the decoding from generating sentences which either contain missing or redundant slots.

Transfer learning In order to improve the grammar in generated sentences in domains where training data is limited, we pretrain a sentence auto-encoder on sentences about the same topic, e.g., restaurant reviews for our case. The model learns a representation of an input sentence (with an encoder) and then uses the representation to re-generate the input sentence (with a separate decoder). The encoder here receives just the word embeddings for the input sentence (as there are no dialogue acts). The decoder uses LSTM units instead of sc-LSTM. After training, we use the hidden LSTM weights of the auto-encoder decoder as initial values of the corresponding hidden weights of the sc-LSTM decoder (\mathbf{W}_f , \mathbf{W}_i , \mathbf{W}_o and \mathbf{W}_c) in the ld-sc-LSTM model. These weights are fine-tuned along with the other weights of the ld-sc-LSTM model. We name this model transfer-ld-sc-LSTM.

3 Results

We evaluate BLEU-4, METEOR, ROUGE_L, CIDEr scores using the generated sentence as the candidate caption and the ground truth as the reference caption. We use publicly available cococaption² code to calculate these metrics. Results for CF and DSTC2 (see Appendix A) datasets are shown in Table 1. The baseline LSTM, d-sc-LSTM models do not contain our recurrent multi-step lexicalized encoder. The d-sc-LSTM model differs from the sc-LSTM model of Wen et al. (2015b) in that it does not use lexicalized values in the dialogue act vector and it does not have a backward reranker. The ld-sc-LSTM and the transfer-ld-sc-LSTM consistently perform better than the other baselines in terms of automated metrics. All four models use only a forward reranker.

We present the average scores assigned to each model's sentences by five human judges in Table 1. Our models statistically outperform the baselines for both datasets. Although transfer-ld-sc-LSTM performs better than ld-sc-LSTM on the DSTC2 dataset, the difference in the scores is not statistically significant. We note that this may also be due to the limited number of examples in our human rated set which places constraints on the practicality of p-values. Differences in human evaluation and

²https://github.com/tylin/coco-caption

automated metrics are to be expected as these metrics do not strongly correlate with human scores (Liu et al., 2016).

Table 2: Comparison of top responses generated for some dialogue acts on the CF and DSTC2 datasets.

(OFFER-NAME, Super Ramen) (INFORM-FOOD, pizza)

- 1. Super Ramen serves pizza food.
- 2. Super Ramen serves pizza food.
- 3. Super Ramen serves pizza.
- 4. Super Ramen serves pizza.

(INFORM-FOOD, pizza) (INFORM-ADDR, near 108 Queen Street)

- 1. I am searching for pizza places at near 108 Queen Street.
- 2. I am searching for pizza restaurants at near 108 Queen Street.
- 3. I am searching for pizza places near 108 Queen Street
- 4. I am searching for pizza places near 108 Queen Street

(EXPLICIT_CONFIRMATION-FOOD, dontcare)

- 1. You are looking for a dontcare restaurant right?
- 2. You are looking for a dontcare restaurant right?
- 3. You are looking for a restaurant serving any kind of food right?
- 4. You are looking for a restaurant serving any kind of food right?

(CANTHELP-FOOD, Japanese)

- (CANTHELP-PRICERANGE, under 30 dollars)
- 1. No Japanese under 30 dollars
- 2. No Japanese under 30 dollars
- 3. I'm sorry but there is no Japanese restaurant for under 30 dollars.
 4. There are no Japanese restaurants in under 30 dollars.

4. There are no Japanes	e restaurants in under 30 dollars.
$1 \rightarrow \text{LSTM}$	$2 \rightarrow d\text{-sc-LSTM}$
$3 \rightarrow 1d\text{-sc-LSTM}$	4→transfer-ld-sc-LSTM

Table 2 compares responses generated by several models for the same dialogue acts. In the first example, the LSTM and the dsc-LSTM generate "OFFER-NAME serves INFORM-FOOD food." since this works with many cuisine values such as Chinese, Indian and Japanese. In the same example, the ld-sc-LSTM and transfer-ld-sc-LSTM generate "OFFER-NAME serves INFORM-FOOD.". By learning from the lexicalized values of the slots, these models can capture that "pizza" should not be followed by "food". The remaining examples also demonstrate our approach's grammatical continuity around generated slots. Our models do not require any modification to work with special or negative values like *dontcare*. Overall, we found that the ld-sc-LSTM and the transferld-sc-LSTM models are less prone to making grammatical errors, which is also confirmed by their human assessment scores.

4 CONCLUSION

We proposed a recurrent encoder-decoder model for NLG that learns from both lexicalized and delexicalized tokens. We evaluated our model with several popular metrics used in the NLP and MT literatures, and also asked humans to evaluate the generated responses. Our models consistently outperformed existing RNN-based approaches on the CF restau-

rant domain dataset and the publicly available DSTC2 dataset. Our transfer learning experiments showed that bootstrapping with weights from a pretrained sentence auto-encoder can result in the generation of better responses. Exposing the deep neural network to the complete data (lexicalized and delexicalized; slots aligned with values) led to a more powerful model.

REFERENCES

- Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. In *ICLR*, 2015.
- Matthew Henderson, Blaise Thomson, and Jason Williams. The second dialog state tracking challenge. In *SIGDIAL*, volume 263, 2014.
- Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural Computation*, 9(8): 1735–1780, 1997.

Andrej Karpathy and Fei-Fei Li. Deep visual-semantic alignments for generating image descriptions. In *CVPR*, pp. 3128–3137, 2015.

Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In ICLR, 2015.

- Ravi Kondadadi, Blake Howald, and Frank Schilder. A statistical NLG framework for aggregated planning and realization. In *ACL*, pp. 1406–1415, 2013.
- Alon Lavie and Abhaya Agarwal. Meteor: An automatic metric for MT evaluation with high levels of correlation with human judgments. In *SMT Workshop*, StatMT '07, pp. 228–231. ACL, 2007.

- Chin-Yew Lin. Rouge: A package for automatic evaluation of summaries. In *Text summarization* branches out: ACL-04 workshop, volume 8, 2004.
- Chia-Wei Liu, Ryan Lowe, Iulian Vlad Serban, Michael Noseworthy, Laurent Charlin, and Joelle Pineau. How NOT to evaluate your dialogue system: An empirical study of unsupervised evaluation metrics for dialogue response generation. In *EMNLP*, 2016.
- Alice Oh and Alexander I. Rudnicky. Stochastic natural language generation for spoken dialog systems. *Computer Speech & Language*, 16(3-4):387–407, 2002.
- Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In *ACL*, pp. 311–318, 2002.
- Rajakrishnan Rajkumar, Michael White, and Dominic Espinosa. Exploiting named entity classes in ccg surface realization. In *HLT-NAACL*, pp. 161–164. ACL, 2009.
- Verena Rieser and Oliver Lemon. Natural language generation as planning under uncertainty for spoken dialogue systems. In *Empirical Methods in Natural Language Generation: Data-oriented Methods and Empirical Evaluation*, pp. 105–120, 2010.
- Shikhar Sharma. Action recognition and video description using visual attention. Master's thesis, University of Toronto, 2016.
- Nitish Srivastava, Geoffrey E. Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: a simple way to prevent neural networks from overfitting. *JMLR*, 15(1):1929–1958, 2014.
- Ramakrishna Vedantam, C. Lawrence Zitnick, and Devi Parikh. Cider: Consensus-based image description evaluation. In CVPR, pp. 4566–4575, 2015.
- Marilyn A. Walker, Amanda Stent, François Mairesse, and Rashmi Prasad. Individual and domain adaptation in sentence planning for dialogue. J. Artif. Intell. Res. (JAIR), 30:413–456, 2007.
- Tsung-Hsien Wen, Milica Gasic, Dongho Kim, Nikola Mrksic, Pei-hao Su, David Vandyke, and Steve J. Young. Stochastic language generation in dialogue using recurrent neural networks with convolutional sentence reranking. In *SIGDIAL*, 2015a.
- Tsung-Hsien Wen, Milica Gasic, Nikola Mrksic, Pei-hao Su, David Vandyke, and Steve J. Young. Semantically conditioned LSTM-based natural language generation for spoken dialogue systems. In *EMNLP*, pp. 1711–1721, 2015b.
- Tsung-Hsien Wen, Milica Gasic, Nikola Mrksic, Lina Maria Rojas-Barahona, Pei-Hao Su, Stefan Ultes, David Vandyke, and Steve J. Young. A network-based end-to-end trainable task-oriented dialogue system. In *EACL*, 2017.
- Kelvin Xu, Jimmy Ba, Ryan Kiros, Kyunghyun Cho, Aaron C. Courville, Ruslan Salakhutdinov, Richard S. Zemel, and Yoshua Bengio. Show, attend and tell: Neural image caption generation with visual attention. In *ICML*, pp. 2048–2057, 2015.
- Li Yao, Atousa Torabi, Kyunghyun Cho, Nicolas Ballas, Christopher J. Pal, Hugo Larochelle, and Aaron C. Courville. Describing videos by exploiting temporal structure. In *ICCV*, pp. 4507–4515, 2015.

A DATASETS AND HUMAN EVALUATION

	CF		DST	C2
-	Train	Test	Train	Test
#words	15,143	2,033	240,337	127,858
#sentences	1,200	211	15,611	9,890
#vocabulary	690	286	660	166

Table 3: Statistics for the CF and DSTC2 datasets

LMD: restaurant reviews This dataset comprises sentences collected from online restaurant reviews. We collected reviews written in English and sorted them on the basis of highest occurrence of the words *phone, postcode, price, food, area, restaurant, nice, address, reservation,* and *book.* We then trained a sentence auto-encoder on the top

5 000 sentences and used it as a source of pretrained weights for our transfer-ld-sc-LSTM model.

CF: CrowdFlower restaurant search We collected this dataset by releasing separate tasks for each dialogue act on CrowdFlower³. The dialogue acts were *inform, offer, request, implicit confirmation, explicit confirmation, canthelp.* These dialogue acts were associated with the slots *name, address, phone, area, postcode, food, pricerange.* We report results on a test set obtained using a stratified 85%/15% train/test split. The dialogue act slot-value pairs were tagged by human experts after collecting the raw data.

DSTC2: Dialogue State Tracking Challenge 2 This dataset was extracted from the DSTC2 (Henderson et al., 2014) dataset, which already contains templated machine responses annotated with dialogue acts and slot-value pairs. The dialogue acts used were *inform, offer, request, implicit confirmation, explicit confirmation, canthelp, select, welcome message, repeat, reqmore,* with the same slot types as the CF dataset.

In both CF and DSTC2, the *request* act was allowed to have only empty-valued slots and for other acts *dontcare* values were allowed in addition to words from the general vocabulary. We use 10% of the training set for validation. Statistics for both datasets are provided in Table 3.

Human evaluation of responses We selected a random set of 100 dialogue acts from each dataset's test set and the corresponding top response generated by all of the models, then asked 5 human judges to score them on a scale of 1 to 5, with 1 indicating least appropriate for the given dialogue acts and 5 indicating most appropriate. In each trial, we presented 4 sentences to the judges, each from a different model, along with the corresponding dialogue acts. The judges were informed that all sentences had been generated from different models and not presented in any particular order.

B TRAINING DETAILS

Hyper-parameters The number of layers in the decoder, the decoder hidden state dimension, the encoder hidden state dimension and the word embedding dimensionality are set using the validation set. The reading coefficient of the sc-LSTM units, α , is set to 1 and the maximum length of T is set to 30. We employ the Adam optimizer (Kingma & Ba, 2015) for training and we apply a dropout (Srivastava et al., 2014) of 0.5 at all non-recurrent connections.

³https://www.crowdflower.com