Natural Language Generation in Dialogue using Lexicalized and Delexicalized Data

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Abstract

Natural language generation plays a critical role in any spoken dialogue system. We present a new approach to natural language generation using recurrent neural networks in an encoder-decoder framework. In contrast with previous work, our model uses both lexicalized and delexicalized versions of slot-value pairs for each dialogue act. This allows our model to learn from all available data, rather than being restricted to learning only from delexicalized slot-value pairs. We show that this helps our model generate more natural sentences with better grammar. We further improve our model’s performance by initializing its weights from a pretrained language model. Human evaluation of our best-performing model indicates that it generates sentences which users find more natural and appealing.

1 Introduction

Typical spoken dialogue systems (SDS) comprise a natural language understanding unit, a dialogue manager, and a natural language generator coupled together into a processing pipeline. Most traditional systems with this architecture rely on template-based, hand-crafted rules for natural language generation (NLG). Unfortunately, the required templates are cumbersome to maintain and the overall approach does not scale well to complex domains and datasets. Previous papers have explored alternative approaches such as corpus-based n-gram models Oh and Rudnicky, 2002, tree-based models Stent, Prasad, and Walker, 2004, and Reinforcement Learning models Rieser and Lemon, 2010.

Recently, models based on recurrent neural networks (RNNs) have shown promising performance in NLG. Apart from spoken dialogue systems (SDS), RNN-based models have been applied in related domains including image captioning Xu et al., 2015; Karpathy and Li, 2015 and video description Yao et al., 2015 and machine translation Bahdanau, Cho, and Bengio, 2014. In the domain of SDS, RNN-based models have been used for NLG in both traditional multi-component processing pipelines Wen et al., 2015b; Wen et al., 2015a and more recent systems designed for end-to-end training Wen et al., 2016a.

While RNN-based end-to-end frameworks have performed well, most systems in use today still depend on multi-component processing pipelines. Text/speech datasets annotated with specific dialogue acts are required for learning-based approaches, but such datasets are unavailable for most domains. This compels the development of effective methods for transfer learning in spoken dialogue systems. Transfer learning can extend the value of dialogue systems to domains which lack sufficient annotated data to support a strong, domain-specific model.

Existing RNN-based models rely primarily on delexicalized slot-value pairs, while ignoring the lexicalized values. These methods thus ignore linguistic relationships among the lexicalized instances of a slot-value pair, and between lexicalized slot-value pairs and their surrounding context. As illustrated in Figure 1, this approach often leads to grammatically incorrect sentences. Yet, deep neural networks can readily capture the relevant linguistic relationships if they are allowed to learn from the lexicalized slot-value pairs. We make two key contributions in this paper:
There are no restaurants around which serve INFORM-FOOD food.

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.

- We develop a recurrent encoder-decoder model which uses both lexicalized and delexicalized dialogue act slot-value pairs, and which outperforms existing approaches according to several popular evaluation metrics.

- We show that the performance of our model can be improved further by transferring weights from a pretrained language model.

Our model uses beam search decoding, which produces several varied sentences for the same dialogue act slot-value pairs, which is desirable in a practical spoken dialogue system. Human assessment shows that users tend to prefer the sentences generated by our models over those generated by other models.

In Section 2, we review related work. In Section 4, we provide a full description of our model. Section 5 describes the datasets we used while developing and testing our model, and our human assessment methodology. Section 6 presents the results of our experiments, compares the performance of our model with that of related models, and shows how pretraining our model using a language modelling task can improve its performance in domains with limited task-specific training data. We conclude in Section 7 with discussion of exciting directions for future work.

2 Related Work

Traditional methods for natural language generation have typically relied on handcrafted rule-based generators or rerankers. Oh and Rudnicky (2002) explored corpus-based generation methods. They trained n-gram language models for each dialogue act to generate sentences and then selected the best ones using a rule-based reranker. SPaRKy Stent, Prasad, and Walker, 2004 used a tree-based sentence plan generator and then applied a trainable sentence plan reranker. Rieser and Lemon (2010) viewed NLG as planning under uncertainty and used Reinforcement Learning to train a policy for NLG. Kondadadi, Howald, and Schilder (2013) used a SVM reranker to further improve the performance of systems which extract a bank of templates from a text corpus.

LSTM-based RNNs Hochreiter and Schmidhuber, 1997 have achieved wide-spread success in language modelling and machine translation. Bengio, Ducharme, and Vincent (2000) were some of the first to propose using RNNs for language modelling. Later, Mikolov et al. (2010) used a mixture of RNN language models and observed significant reduction in perplexity compared to state-of-the-art n-gram models. Consequently, RNNs have drawn increasing interest in the domain of NLG. Recently, Karpathy and Li, 2015, and Vinyals et al. (2015) used RNNs in a multi-modal setting to generate captions for images. Donahue et al. (2015) processed per-frame features from convolutional neural networks using LSTM-RNNs to generate descriptions of videos.

RNNs have also been successful in the domains of task-oriented and non task-oriented dialogue. Among examples of non task-oriented dialogue, Vinyals and Le (2015) used previous sentences in a conversation as context and trained a model to generate the next sentence using the sequence-to-sequence framework Sutskever, Vinyals, and Le, 2014. Lowe et al. (2015) additionally encoded an unstructured textual knowledge source along with previous responses and context to generate a response for technical support queries.

For task-oriented dialogue systems, Wen et al. (2015) used RNNs to learn to generate delexicalized responses from dialogue-acts. The authors augmented a forward RNN generator with a convolutional neural network sentence reranker to ensure that all the slots in the dialogue-act were generated, and a backward RNN reranker to select the best output sentence. In other work, Wen et al. (2015) proposed a semantically-controlled LSTM (sc-LSTM) unit for RNNs with a separate “reading” gate that modulates a dialogue act vector to ensure all slots are generated. They used forward and backward RNNs for
reranking. A recurring problem in such systems is that sufficient domain-specific annotated data is often unavailable. Wen et al. (2016b) trained an out-of-domain model on counterfeited data (using semantically similar slots from the target domain in place of the slots belonging to the out-of-domain dataset). They found that by fine-tuning the target domain on the out-of-domain trained model, they were able to get satisfactory performance with a small amount of in-domain data.

End-to-end approaches contrasting with the traditional modular approach have grown in popularity. Serban et al. (2016) proposed an end-to-end trainable, hierarchical, recurrent encoder-decoder model for non-goal driven dialogue. Wen et al. (2016a) proposed an approach based on training an end-to-end neural model for a goal-driven SDS which still has modular components. Their model produced delexicalized slots. Their belief tracker was trained separately from the rest of the model using a dedicated supervision signal and their dataset was annotated as part of a novel dataset collection pipeline.

Most NLG papers in the recent SDS literature compare performance in terms of BLEU scores Papineni et al., 2002 due to lack of a better metric. However, Liu et al. (2016) showed that the BLEU metric does not correlate well with human judgement for domain-specific NLG in dialogue systems. The BLEU score has been widely used in Machine Translation tasks since the corresponding datasets usually provide multiple ground truth sentences and BLEU has high correlation with human judgement in this case. BLEU also tends to correlate better with human judgement when domains are more constrained. We evaluate and compare the performance of our models on BLEU-4 Papineni et al., 2002, METEOR Lavie and Agarwal, 2007, ROUGE_L Lin, 2004, and CIDEr Vedantam, Zitnick, and Parikh, 2015 metrics. In addition to these automated metrics, we perform human evaluation of our models as described in Section 5.2.

3 Problem Description

We decompose each sentence in a dialogue into one or more dialogue acts such as request and inform. Each of these dialogue acts can contain slots such as area, food, and pricerange. Each slot may be assigned a specific value. E.g., the dialogue act inform(area=near the plaza).

form with slot-value pair pricerange=cheap might correspond to the sentence “it is cheap”. Roughly speaking, a dialogue act corresponds to some way in which a dialogue can be moved forward, e.g. by conveying specific information. A slot corresponds to, e.g. what type of information will be conveyed. The value of a slot is then, e.g. the specific information conveyed. In this paper, we represent a dialogue act slot-value pair as (dialogue act + slot, value) where the first term is delexicalized and the second term is the lexicalized value of the slot. The first term can be derived from simple one-hot representations of the dialogue act and slot type. The second term is more difficult to represent due to its less-restricted, natural form. We will use a parametric model for this term.

4 Model

This section describes our model which we call the ld-sc-LSTM. Section 4.1 and Section 4.2 respectively describe the encoder and decoder components of our model. We outline the objective function for training the model in Section 4.3. The reranker which we use at test time to rank decoded sentences is presented in Section 4.4. The model hyper-parameters are described in Section 4.5 and our second model, the transfer ld-sc-LSTM, is discussed in Section 4.6. We give a summary of the baseline models we use for performance comparisons in Section 4.7.

4.1 Encoder

We use a 1-layer, bi-directional LSTM encoder in our model. At each time-step $t$, the encoder receives an input vector $z_t$ 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 dialogue act slots present in the examples. The vector \( \mathbf{e}_t \) is formed by taking the mean of the word embeddings of all the words corresponding to the slot represented by \( \mathbf{m}_t \). Figure 2 illustrates how the encoder input is created for a given dialogue act. Each turn of the dialogue is composed of one or more such dialogue act slot-value pairs which are input at each time-step to the encoder.

We use the LSTM implementation described by Zaremba, Sutskever, and Vinyals (2014):

\[
\begin{align*}
    i_t &= \sigma(\mathbf{W}_{zi}\mathbf{z}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1}) \\
    f_t &= \sigma(\mathbf{W}_{zf}\mathbf{z}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1}) \\
    o_t &= \sigma(\mathbf{W}_{zo}\mathbf{z}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1}) \\
    g_t &= \tanh(\mathbf{W}_{zg}\mathbf{z}_t + \mathbf{W}_{hg}\mathbf{h}_{t-1}) \\
    c_t &= f_t \odot c_{t-1} + i_t \odot g_t \\
    h_t &= o_t \odot \tanh(c_t),
\end{align*}
\]

where \( i_t \) is the input gate, \( f_t \) is the forget gate, \( o_t \) is the output gate, \( c_t \) is the cell state, \( h_t \) is the hidden state, \( \mathbf{z}_t \) is the input to the LSTM at time-step \( t \), and \( \odot \) indicates element-wise product.

The hidden states \( h_t \) of the forward and backward LSTMs are concatenated and their mean across all the time-steps is fed to the decoder as its input.

### 4.2 Decoder

The decoder in our model is a recurrent neural network which uses the sc-LSTM implementation described by Wen et al. (2015a). It differs from the standard LSTM as described below:

\[
\begin{align*}
    r_t &= \sigma(\mathbf{W}_{wr}\mathbf{z}_t + \alpha \mathbf{W}_{hr}\mathbf{h}_{t-1}) \\
    d_t &= r_t \odot d_{t-1} \\
    c_t &= f_t \odot c_{t-1} + i_t \odot g_t + \tanh(\mathbf{W}_{dz}d_t),
\end{align*}
\]

where \( d_t \) is the Dialogue Act vector (described below), \( r_t \) is the reading gate at time-step \( t \), and \( \alpha \) is a scalar. As shown by Wen et al. (2015a), the Dialogue Act vector in the sc-LSTM can function similarly to a memory that remembers which slots are yet to be generated. We set the initial value of the Dialogue Act vector \( d_0 \) as follows:

\[
d_0 = \sum_{t=1}^{M} \mathbf{m}_t,
\]

where \( M \) is the number of encoder time-steps. This sum is expressed over all of the one-hot dialogue act slot vectors and is thus a binary vector over all of the dialogue act slots which should be present in our natural language output.

The mean hidden state from the encoder called the “context” \( x \) is used to initialize \( h_0 \) and \( c_0 \) in the decoder.

\[
\begin{align*}
    h_0 &= \tanh(\mathbf{W}_{hx}x + b_{hx}) \\
    c_0 &= \tanh(\mathbf{W}_{cx}x + b_{cx})
\end{align*}
\]

The word embedding of the word output in the previous time-step is also an input to the decoder sc-LSTM. For the first time-step, we use a special symbol \( \langle \text{bos} \rangle \) which signifies the beginning of a sentence. 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 values. The model produces words up to a predefined maximum length or until it produces the special symbol \( \langle \text{eos} \rangle \). At the time of training, we use the ground truth word for the previous time-step instead of the predicted output. At test time, we use beam search to over-generate several candidate responses. The decoder is trained to output delexicalized slots and we later fill in the values of the corresponding slots.

Our encoder-decoder Id-sc-LSTM model is summarized in Figure 3.

### 4.3 Loss function and Regularization

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

\[
L = -\sum_{t=1}^{T} y_t^T \log(p_t) + ||d_T|| + \sum_{t=1}^{T} \eta \xi ||d_t - d_{t-1}||,
\]

where \( y_t \) is the ground truth word distribution, \( p_t \) is the predicted word distribution, \( T \) is the number of time-steps in the decoder, and \( \eta \) and \( \xi \) are scalars set to 0.0001 and 100, respectively. The term \( ||d_T|| \) 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 we cannot generate more than one slot at a time.
Figure 3: The encoder-decoder framework for our models “ld-sc-LSTM” and “transfer-ld-sc-LSTM”: the encoder learns a representation of the dialogue act slots and their corresponding values and the decoder learns to output a delexicalized sentence.

4.4 Sentence Reranker
We use beam search for decoding at test time with a beam width of 10. This is the over-generation phase after which the reranker selects the highest ranked sentence by minimizing the following score function at each time-step of the generation process:

\[
S = - \sum_{t=1}^{T} \log p(w_t | w_{t-1} \ldots w_1) + \lambda \text{ERR} \tag{14}
\]

Here, We also include the slot error rate ERR used in the recent literature Wen et al., 2015a; Wen et al., 2016b. It is defined as

\[
\text{ERR} = \frac{p + q}{N}, \tag{15}
\]

where \(p\) is the number of missing slots in the generated sentence, \(q\) is the number of redundant slots in the generated sentence and \(N\) is the total number of slots in the Dialogue Act vector. We set \(\lambda\) to 1000 to severely discourage the reranker from selecting sentences which either contain missing or redundant slots.

4.5 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 the model hyper-parameters set using the validation set. The reading coefficient \(\alpha\) is set to 1 and the maximum length of \(T\) is set to 30. We employ the Adam optimizer Kingma and Ba, 2014 for training and we apply a dropout Srivastava et al., 2014 of 0.5 at all non-recurrent connections.

4.6 Transfer learning
We would expect transfer learning to improve the grammar in generated sentences in domains where training data is limited. Therefore, we pre-train a language model on sentences about the same topic, e.g., restaurant reviews for our case. The model is trained to learn a representation of an input sentence and then decode it to generate the original sentence. This model uses an encoder similar to our ld-sc-LSTM model. The only difference is that the encoder here receives just the word embeddings for the input sentence (as there are no dialogue acts here). The decoder for this language model uses LSTM units instead of sc-LSTM. We use the internal LSTM-to-LSTM decoder weights from this language model as initial values of the corresponding weights of the internal sc-LSTM to sc-LSTM connections (\(W_{hi}, W_{hf}, W_{ho}\) and \(W_{hg}\)) in the ld-sc-LSTM model, and fine-tune them during training. We emphasize that we transfer weights from a different task and not from the same task on a different domain. We present results with this model setup under the name transfer-ld-sc-LSTM in Section 6.

4.7 Baselines
Our simple LSTM baseline has a one-step encoder which is the vector \(d_0\) itself. The decoder for this baseline receives the encoder input at each time-step. This model is trained using the cross-entropy term in
the loss function $L$ shown in Equation 13.

The sc-LSTM baseline uses sc-LSTM instead of LSTM and receives vector $d_0$ only at the first time-step. This baseline uses the same loss function $L$ as our model (see Equation 13).

None of these baselines contain a recurrent multi-step encoder. The LSTM baseline’s softmax layer is additionally provided the $d_0$ vector.

5 Data and Evaluation methodology

5.1 Data

5.1.1 CF: CrowdFlower restaurant search

We collected this dataset by releasing separate tasks for each dialogue act on CrowdFlower. 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. A brief description of all of the dialogue acts is provided in Appendix A. The request act was restricted to having empty-valued slots, while the slots in other cases were allowed to take a special don't care value in addition to taking words from the general vocabulary. The goal of the user in this setting was to search for and/or select a restaurant to eat at. We report results on a test set obtained using a stratified 85%/15% train/test split. The training set has 1 200 sentences containing 690 unique words from a total of 15 143 words while the test set has 211 sentences containing 286 unique words from a total of 2033 words. The dialogue act slot-value pairs were tagged by human experts after collecting the raw data. We use 10% of the training set for validation.

5.1.2 LMD: restaurant reviews

This dataset comprises sentences collected from online restaurant reviews. We found 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 two language models – one with the top 5 000 sentences and the other with the top 1 500 sentences, and used the best performing model among them as a source of pretrained weights for our model (in tests where we used pretrained weights).

5.1.3 DSTC2: Dialogue State Tracking Challenge 2

This dataset was created by parsing the DSTC2 Henderson, Thomson, and Williams, 2014 dataset, which already contains 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. The request act was again allowed to have only empty-valued slots and for other cases don't care values were allowed. There were 15 611 sentences containing 660 unique words from a total of 240 337 words in the training dataset. The test set had 9 890 sentences containing 166 unique words from a total of 127 858 words. We use 10% of the training set for validation.
Table 4: Comparison of top responses generated for some dialogue acts on the CF and DSTC2 datasets.

| Model               | Generated Responses                                                                 |
|---------------------|-------------------------------------------------------------------------------------|
| **dialogue act**    | offer(name=Super Ramen) inform(food=pizza)                                           |
| LSTM                | Super Ramen serves pizza food.                                                      |
| sc-LSTM             | Super Ramen serves pizza food.                                                      |
| ld-sc-LSTM          | Super Ramen serves pizza.                                                           |
| transfer-ld-sc-LSTM | Super Ramen serves pizza.                                                           |
| **dialogue act**    | inform(food=pizza) inform(addr=near 108 Queen Street)                                |
| LSTM                | I am searching for pizza places at near 108 Queen Street.                           |
| sc-LSTM             | I am searching for pizza restaurants at near 108 Queen Street.                      |
| ld-sc-LSTM          | I am searching for pizza places near 108 Queen Street                                |
| transfer-ld-sc-LSTM | I am searching for pizza places near 108 Queen Street                                |
| **dialogue act**    | explicit_confirmation(food=dontcare)                                                |
| LSTM                | You are looking for a dontcare restaurant right?                                    |
| sc-LSTM             | You are looking for a dontcare restaurant right?                                    |
| ld-sc-LSTM          | You are looking for a restaurant serving any kind of food right?                    |
| transfer-ld-sc-LSTM | You are looking for a restaurant serving any kind of food right?                    |
| **dialogue act**    | canthelp(food=Japanese) canthelp(pricerange=under 30 dollars)                      |
| LSTM                | No Japanese under 30 dollars                                                        |
| sc-LSTM             | No Japanese under 30 dollars                                                        |
| ld-sc-LSTM          | I’m sorry but there is no Japanese restaurant for under 30 dollars.                 |
| transfer-ld-sc-LSTM | There are no Japanese restaurants in under 30 dollars.                              |

5.2 Human evaluation of responses

We selected a random set of 100 dialogue acts from each dataset’s test set and the corresponding responses 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 act 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 act. The judges were informed that all sentences had been generated from different models and were not presented in any particular order. Judges were then asked to rate each of the four sentences. We present these evaluation scores in Section 6.

6 Results

We evaluate BLEU-4, METEOR, ROUGE_L and CIDEr scores using the generated sentence as the candidate caption and the ground truth as the reference caption. We use the publicly available coco-caption code to calculate these metrics. The results for the CF dataset are shown in Table 1 and for the DSTC2 dataset in Table 2. The ld-sc-LSTM and the transfer-ld-sc-LSTM consistently perform better than the current state-of-the-art sc-LSTM in terms of these automated metrics. The DSTC2 dataset is the easier one of the two since it was created by templated NLG and is fairly repetitive. The CF dataset is more challenging as it contains varied sentences crowdsourced from multiple users. Its training set has a larger vocabulary than the DSTC2 training set even though it’s significantly smaller in terms of the total number of sentences.

We present the average scores assigned to each model’s sentences by five human judges in Table 3. The ld-sc-LSTM model and the transfer-ld-sc-LSTM model consistently beat the baseline models according to human evaluation. The ld-sc-LSTM outperforms the transfer-ld-sc-LSTM on the CF dataset.

Table 4 compares responses generated by several models for the same dialogue acts. In the first example, the LSTM and the sc-LSTM models generate:

- offer(name=Super Ramen) serves inform(food=pizza) 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=Super Ramen) serves inform(food).

By learning from the lexicalized values of the slots, these models understand that the word “food” should
Table 5: Top-3 responses generated for some dialogue acts on the CF dataset by the ld-sc-LSTM model.

| Dialogue Act               | Response                                                                 |
|----------------------------|---------------------------------------------------------------------------|
| request(food)              | What kind of food do you want to eat?                                    |
|                             | What type of food do you want to eat?                                    |
|                             | What kind of food would you like to eat?                                 |
| offer(name=Super Ramen)    | Super Ramen is a nice place to eat.                                      |
|                             | Super Ramen is a nice place to try.                                      |
|                             | Super Ramen is a good place to eat.                                      |
| offer(name=Super Ramen)    | Super Ramen is located at 108 Queen Street.                              |
| inform(addr=108 Queen Street) | Super Ramen is located at 108 Queen Street. | Super Ramen is located at 108 Queen Street |
| canthelp(food=Japanese)    | I don’t see any pizza place in the entertainment district.              |
| canthelp(area=entertainment district) | I don’t see any pizza restaurant in the entertainment district. | I don’t see any pizza places in the entertainment district. |

Table 5 shows the top-3 responses generated by the ld-sc-LSTM model trained on the CF dataset for some dialogue acts. These were generated using beam search with width 10 and selecting the top-3.

7 Conclusion and Future Work

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 literature, and also asked humans to evaluate the generated responses. Our model consistently outperformed existing RNN-based approaches on the CF restaurant domain dataset and the publicly available DSTC2 dataset. Our transfer learning experiments showed that bootstrapping with weights from a pretrained language model can result in the generation of better responses. As could be expected, exposing the deep neural network to the complete data (lexicalized and delexicalized) led to a more powerful model.

In the future, we plan to use an attention model over the recurrent encoder. Attention models are more intuitive for variable-length sequential input, do not lose information due to pooling, and can be visualized to see where the model focuses during the generation process. This could remove the need for the sc-LSTM unit and the Dialogue Act vector. To reduce the encoder slot value vocabulary size in our models when scaling to larger datasets, it would make sense to tokenize some word categories like proper nouns, singular integers, plural integers, etc. in the slot values. It would be insightful to more rigorously explore the effect of using out-of-domain corpora for transfer learning, and incorporating a backward reranker may also improve performance, as has been observed for other models in the literature.

References

Bahdanau, Dzmitry, Kyunghyun Cho, and Yoshua Bengio (2014). “Neural Machine Translation by Jointly Learning to Align and Translate”. In: CoRR abs/1409.0473.

Bengio, Yoshua, Réjean Ducharme, and Pascal Vincent (2000). “A Neural Probabilistic Language Model”. In: NIPS, pp. 932–938.

Donahue, Jeff et al. (2015). “Long-term recurrent convolutional networks for visual recognition and description”. In: CVPR, pp. 2625–2634.

Henderson, Matthew, Blaise Thomson, and Jason Williams (2014). “The second Dialog State Tracking Challenge”. In: SIGDIAL. Vol. 263.

Hochreiter, Sepp and Jürgen Schmidhuber (1997). “Long Short-Term Memory”. In: Neural Computation 9.8, pp. 1735–1780.

Karpathy, Andrej and Fei-Fei Li (2015). “Deep visual-semantic alignments for generating image descriptions”. In: CVPR, pp. 3128–3137.

Kingma, Diederik P. and Jimmy Ba (2014). “Adam: A Method for Stochastic Optimization”. In: CoRR abs/1412.6980.

Kondadadi, Ravi, Blake Howald, and Frank Schilder (2013). “A Statistical NLG Framework for Aggregated Planning and Realization”. In: ACL, pp. 1406–1415.
Lavie, Alon and Abhaya Agarwal (2007). “Meteor: An Automatic Metric for MT Evaluation with High Levels of Correlation with Human Judgments”. In: SMT Workshop. StatMT ’07. Prague, Czech Republic: ACL, pp. 228–231.

Lin, Chin-Yew (2004). “Rouge: A package for automatic evaluation of summaries”. In: Text summarization branches out: ACL-04 workshop. Vol. 8.

Liu, Chia-Wei et al. (2016). “How NOT To Evaluate Your Dialogue System: An Empirical Study of Unsupervised Evaluation Metrics for Dialogue Response Generation”. In: CoRR abs/1603.08023.

Lowe, Ryan et al. (2015). “Incorporating Unstructured Textual Knowledge Sources into Neural Dialogue Systems”. In: NIPS Workshop on Machine Learning for Spoken Language Understanding.

Mikolov, Tomas et al. (2010). “Recurrent neural network based language model”. In: INTERSPEECH, pp. 1045–1048.

Oh, Alice and Alexander I. Rudnicky (2002). “Stochastic natural language generation for spoken dialog systems”. In: Computer Speech & Language 16.3-4, pp. 387–407.

Papineni, Kishore et al. (2002). “Bleu: a Method for Automatic Evaluation of Machine Translation”. In: ACL, pp. 311–318.

Rieser, Verena and Oliver Lemon (2010). “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.

Serban, Iulian Vlad et al. (2016). “Building End-To-End Dialogue Systems Using Generative Hierarchical Neural Network Models”. In: AAAI, pp. 3776–3784.

Srivastava, Nitish et al. (2014). “Dropout: a simple way to prevent neural networks from overfitting”. In: JMLR 15.1, pp. 1929–1958.

Stent, Amanda, Rashmi Prasad, and Marilyn A. Walker (2004). “Trainable Sentence Planning for Complex Information Presentations in Spoken Dialog Systems”. In: ACL, pp. 79–86.

Sutskever, Ilya, Oriol Vinyals, and Quoc V. Le (2014). “Sequence to Sequence Learning with Neural Networks”. In: NIPS, pp. 3104–3112.

Vedantam, Ramakrishna, C. Lawrence Zitnick, and Devi Parikh (2015). “CIDEr: Consensus-based image description evaluation”. In: CVPR, pp. 4566–4575.

Vinyals, Oriol and Quoc V. Le (2015). “A Neural Conversational Model”. In: CoRR abs/1506.05869.

Vinyals, Oriol et al. (2015). “Show and tell: A neural image caption generator”. In: CVPR, pp. 3156–3164.

Wen, Tsung-Hsien et al. (2015a). “Semantically Conditioned LSTM-based Natural Language Generation for Spoken Dialogue Systems”. In: EMNLP, pp. 1711–1721.

Wen, Tsung-Hsien et al. (2015b). “Stochastic Language Generation in Dialogue using Recurrent Neural Networks with Convolutional Sentence Reranking”. In: CoRR abs/1508.01755.

Wen, Tsung-Hsien et al. (2016a). “A Network-based End-to-End Trainable Task-oriented Dialogue System”. In: CoRR abs/1604.04562.

Wen, Tsung-Hsien et al. (2016b). “Multi-domain Neural Network Language Generation for Spoken Dialogue Systems”. In: CoRR abs/1603.01232.

Xu, Kelvin et al. (2015). “Show, Attend and Tell: Neural Image Caption Generation with Visual Attention”. In: ICML, pp. 2048–2057.

Yao, Li et al. (2015). “Describing Videos by Exploiting Temporal Structure”. In: ICCV, pp. 4507–4515.

Zaremba, Wojciech, Ilya Sutskever, and Oriol Vinyals (2014). “Recurrent Neural Network Regularization”. In: CoRR abs/1409.2329.

### A Dialogue Act specification

Table 6 contains a list of dialogue acts present in both the CF and the DSTC2 datasets combined. The welcome message, reqmore, repeat and select acts are not a part of the CF dataset.

| Dialogue Act | Description |
|--------------|-------------|
| Inform       | Inform the user about some slot. |
| Offer        | Offer a suggestion to the user. |
| Request      | Request a slot from the user. |
| Implicit     | Confirm a slot with the user while continuing with the conversation. |
| Explicit     | Confirm a slot with the user. |
| Canthelp     | No results found for some slot. |
| Select       | Ask to select one from multiple values. |
| Welcome      | Introductory welcome message. |
| Message      | The user to repeat the previous sentence. |
| Regmore      | Ask the user for more information. |

**Table 6**: List of dialogue acts present in CF and DSTC2 datasets.
Table 7: Comparison of top responses generated for some dialogue acts on the CF and DSTC2 datasets.

| Model               | Generated Responses                                                                 |
|---------------------|--------------------------------------------------------------------------------------|
| dialogue act        | offer(name=Prezzo) inform(pricerange=moderate) inform(area=west)                    |
| LSTM                | Prezzo is a nice place in the west of town and the prices are moderate                |
| sc-LSTM             | Prezzo is a nice place in the west of town and the prices are moderate                |
| ld-sc-LSTM          | Prezzo is a nice restaurant in the west of town in the moderate price range          |
| transfer-ld-sc-LSTM | Prezzo is a nice restaurant in the west of town in the moderate price range          |
| dialogue acts       | request(food)                                                                        |
| LSTM                | What kind of food would you like?                                                    |
| sc-LSTM             | What kind of food would you like? How may I help you?                                 |
| ld-sc-LSTM          | What kind of food would you like?                                                    |
| transfer-ld-sc-LSTM | What kind of food would you like?                                                    |
| dialogue acts       | canthelp(food=Irish)                                                                  |
| LSTM                | I’m sorry but there is no restaurant serving Irish food                               |
| sc-LSTM             | I’m sorry but there is no restaurant serving Irish food                               |
| ld-sc-LSTM          | I am sorry but there is no Irish restaurant that matches your request                 |
| transfer-ld-sc-LSTM | I am sorry but there is no Irish restaurant that matches your request                 |
| dialogue acts       | inform(count=24) inform(food=Japanese)                                               |
| LSTM                | I found 24 places for Japanese                                                        |
| sc-LSTM             | I found 24 places for Japanese                                                        |
| ld-sc-LSTM          | I found 24 places serving Japanese food                                              |
| transfer-ld-sc-LSTM | I found 24 places serving Japanese food                                              |
| dialogue acts       | offer(name=Super Ramen) inform(pricerange=30 bucks)                                  |
| LSTM                | Super Ramen is 30 bucks.                                                              |
| sc-LSTM             | Super Ramen is 30 bucks.                                                              |
| ld-sc-LSTM          | Super Ramen is a nice restaurant and costs 30 bucks.                                  |
| transfer-ld-sc-LSTM | Super Ramen is a nice place for 30 bucks.                                             |
| dialogue acts       | inform(count=24) inform(food=Japanese)                                               |
| LSTM                | I have found 24 places serving Japanese food near 108 Queen Street.                   |
| sc-LSTM             | I found 24 places serving Japanese food near 108 Queen Street.                        |
| ld-sc-LSTM          | There are 24 Japanese places at 108 Queen Street                                      |
| transfer-ld-sc-LSTM | I have found 24 places serving Japanese food at 108 Queen Street                     |
| dialogue acts       | request(area)                                                                        |
| LSTM                | What part of town do you have a have in mind?                                       |
| sc-LSTM             | What part of town do you have a have in mind?                                       |
| ld-sc-LSTM          | What part of town do you have in mind?                                               |
| transfer-ld-sc-LSTM | What part of town do you have in mind?                                               |
| dialogue acts       | request(area) implicit_conf(name=Super Ramen)                                       |
| LSTM                | Where would you like to find Super Ramen?                                            |
| sc-LSTM             | Where would you like to find Super Ramen?                                            |
| ld-sc-LSTM          | Where do you want to find Super Ramen?                                               |
| transfer-ld-sc-LSTM | Where would you like to find Super Ramen?                                            |

B Additional examples

We present some more examples in Table 7.