Dialogue systems attempt to facilitate conversations between humans and computers, for purposes as diverse as small talk to booking a vacation. We are here inspired by the performance of the recurrent neural network-based model Sequicity [Lei et al., 2018], which when conducting a dialogue uses a sequence-to-sequence architecture to first produce a textual representation of what is going on in the dialogue, and in a further step use this along with database findings to produce a reply to the user. We here propose a dialogue system based on the Transformer architecture instead of Sequicity’s RNN-based architecture, that works similarly in an end-to-end, sequence-to-sequence fashion.

1 Introduction

Dialogue systems aim to simulate a conversation between a user and a computer. These systems can be built simply for the purpose of chatting, but are often aimed at helping a user complete some task or retrieve some information without the need for interacting with another human [Wen et al., 2016b,a].

One the challenges of dialogue systems is to both provide the information the user requires and to present it in the form of fluently generated responses. Sequicity [Lei et al., 2018] aims to solve this issue by decoding the response in two steps: first explicitly decoding a belief state and then conditioning the final response on it. Sequicity also presents an end to end solution to dialogue systems, where the steps of understanding the user’s intention, keeping track of what’s going on in the conversation and producing an intelligible and correct response are all handled by the same model.

The Transformer [Vaswani et al., 2017] architecture has significantly improved the benchmark in machine translation and in recent years it has been used as a language model in various NLP applications. Inspired by Sequicity, we here attempt to use a Transformer model to implement a sequence to sequence neural dialogue system that works end to end.

2 Related works

Sequicity [Lei et al., 2018] is one of the first popular end-to-end dialog system architectures. It uses an RNN-based sequence-to-sequence (seq2seq) [Sutskever et al., 2014] model further enhanced by the Two-Stage Copy Net inspired by Gu et al. [2016]. It is design to tackle previous modular pipeline designs. It uses an annotated belief state to accomplish separate dialog tracking.

In recent years, the Transformer [Vaswani et al., 2017], initially introduced in the machine translation, has become the dominant neural sequence to sequence architecture improving upon convolutional and recurrent [Sutskever et al., 2014] networks. One of the potential downsides of the Transformer is that it contains more parameters and requires more
Figure 1: Producing a distribution over the encoder tokens when producing the decoder output at its second position. This component decides not whether to copy, but the likelihood of each encoder input token being copied over, if we were to copy one of them. The example here is translation, of the English sentence *I love UFAL* to French *J’aime UFAL*. We want UFAL to be the token most likely to be copied, and train our copynet to copy the appropriate token.

training epochs and a larger training dataset compared to other models. However, the model also allows for increased parallel computation and reduces time to convergence.

Large pre-trained models [Devlin et al., 2018; Radford et al., 2019; Raffel et al., 2019; Brown et al., 2020] based on the Transformer architecture are becoming extremely popular. They aim to reduce the amount of necessary domain-specific training data by pre-training on vast amounts of general text data.

Newer end-to-end dialog system architectures such as those of Budzianowski and Vulic [2019] or Wu et al. [2019] make use of the pre-trained GPT-2 model. They aim to prove that large generative models pre-trained on large general-domain corpora can support task-oriented dialogue applications. Budzianowski and Vulic [2019]’s system is based on the TransferTransfo framework and is fine-tuned to a dialog dataset. The basic idea behind the Alternating Roles Dialog Model (ARDM) [Wu et al., 2019] is to simultaneously model the user and system with two separate GPT-2s to capture the different language styles. ARDM even requires no human supervision such as belief states or dialog acts.

3 Transformer E2E

The Transformer [Vaswani et al., 2017] is an encoder-decoder neural architecture that uses self-attention to take advantage of the contextual information provided by the other tokens while processing each token. This architecture provides an efficient and parallelizable use of an attention mechanism and also establishes the new state of the art in a number of tasks including machine translation in several language pairs.

Our system, based on the Transformer architecture, deals with input from a user in two steps. In the first step, the user input, previous dialogue state and previous system response are taken and processed to produce the new dialogue state. In the second step, along with the original three inputs, the results of a database lookup and the newly decoded dialogue state are used. All of these together are passed through the system in the second step to produce the response of the system in the current stage of the dialogue.

Our model is distinct from the Transformer architecture in that it has a single encoder but two decoders. The same encoder encodes the input, and this encoding is used both for updating the dialogue state (bspan) and generating the response. A separate bspan decoder and a response decoder are used for these respective tasks when processing input from the encoder.

We implement a mechanism similar to Copynet [Gu et al., 2016] as used in the original Sequicity implementation. Both of the decoders produce a distribution over the target vocabulary of words to be generated, but also a probability distribution over the words input to the encoder. A value \( P_{gen} \), the probability of generating a new word versus copying a given output token at each step, is also determined at each time step.
Our copy mechanism takes the final encoded representations of each input position from the encoder, and concatenates them with the current decoder output, to estimate the probability of copying over the token at any input position to the current output position. The result of this concatenation is given to a dense feed-forward network that we call our “copy network” to produce this probability. The values corresponding to each input position are soft-maxed to produce a different copy distribution over the encoder tokens for each decoder token. At each step of decoding, the probabilities of generating or copying each token in the vocabulary are weighted by $P_{\text{gen}}$ and $1 - P_{\text{gen}}$ respectively, and added together. So we separately estimate the likelihood of each input token to be copied to any output position, and whether this copying should take place at all.

4 Evaluation

We compare our system with [Lei et al., 2018] on the Camrest676 [Su et al., 2016] dataset. It contains 408 training dialogues, and 136 test and development dialogues within the domain of restaurant reservation. It has been delexicalized: each slot (restaurant name, food type, etc.) has been replaced by a generic token (“name_SLOT”, “food_SLOT”, etc.). There are, on average, 4 turns per dialogue. The size of the vocabulary is 811 for user queries and 1470 for system responses.

We performed a grid search on the development part of the data over the dimensionality of the feed-forward layer (256, 512, 1024), the number of attention heads (1, 2, 5, 10), the number of hidden layers (2, 3, 4), dropout rate (0.1, 0.2), and the number of warmup steps (100, 500, 4000, 6000, 12000). Then we selected the several best models and further tuned the word embedding dimensionality (50, 100).

Our best performing configuration of the Transformer uses 3 layers, 1 attention head, 512 dimensions in the feed-forward layers and a dropout rate of 0.1. We use 50-dim GloVe [Pennington et al., 2014] word embeddings as initial parameters and train our network in mini-batches of size 32 for 54 epochs.

We evaluate the systems using “success F1 score” which measures the F1 score of matched slots (food_SLOT, name_SLOT, etc.) in all system responses for all test set dialogues, matching against reference responses, and also by the BLEU [Papineni et al., 2002] score of the generated responses. BLEU measures how many word n-grams are shared with the gold data, for $n = 1, 2, 3, 4$ (with some penalization for short outputs).

| System               | Success F1 | BLEU  |
|----------------------|------------|-------|
| Transformer (no Copynet) | 0.710      | 0.315 |
| Transformer + Copynet   | 0.770      | 0.327 |
| Sequicity             | 0.854      | 0.253 |

Table 1: Comparison of dialogue systems described in Section 4 in terms of success rate and BLEU.

We compare above our Transformer model both without and with the Copynet mechanism, and the original Sequicity model. It is immediately apparent that the Copynet improves both the F1 and BLEU scores of our model. The Transformer with Copynet also learns to produce responses more similar to the gold target sequences at a cost of lower success rate compared to the original Sequicity model.

4.1 Example outputs

These are some examples of the system outputs. Overall, the outputs of our Transformer + copynet model look comparable to Sequicity. The model learns correct behavior for the domain, but chooses responses that contain less slot placeholders than the human reference, which reflects in the lower Success F1.

In the first case, both models produce reasonable responses. Our model is closer to the reference in both semantic and n-gram overlap, but this is not reflected in the Success F1 score as there are no slot placeholders present. In the second case, both models give very similar responses, which also overlap with the reference. In the third case, our model gives a response that paraphrases the reference and is more specific than the one of Sequicity, but, again, does not contain any slot placeholders, so Success F1 score is unable to capture it.

1. **User** i want afghan food in the centre of town .
   **Transformer (no copynet)** name_SLOT is a nice restaurant in the city centre of town .
   **Transformer (copynet)** there are several restaurants in the centre of town do you have a preference for ?
   **Sequicity** there are no restaurants serving centre food .
Real response  what price range are you looking for?

2. User  yes , what is the address and phone number for pizza hut cherry hinton?
   Transformer (no copynet) name_SLOT is in the area_SLOT part of town and is in the pricerange_SLOT
   price range .
   Transformer (copynet) name SLOT is located at address SLOT and their phone number is phone SLOT .
   is there anything else i can help you with ?
   Sequicity name SLOT is located at address SLOT and their phone number is phone SLOT . is there anything
   else i can help you with ?
   Real response  the address for name SLOT is address SLOT and the phone number is phone SLOT

3. User  i want a restaurant in the north part of town .
   Transformer (no copynet) name SLOT is a moderately priced restaurant in the north part of town .
   Transformer (copynet) there are two restaurants in the north part of town . do you want the address ?
   Sequicity there are several restaurants in the north part of town .
   Real response  the name SLOT is in the north part of town . the name_SLOT is also located in the north part
   of town .

5 Conclusion

In this paper, we have investigated the use of Transformer as the model for end-to-end dialogue system. We have shown
that it has comparable performance with Sequicity. We believe the system could be improved by utilizing a pre-trained
language model [Devlin et al., 2018; Radford et al., 2019; Yang et al., 2019; Song et al., 2019]. Although the the success
F1 score did not supersede our baseline, our model has BLEU score of responses 7.4% higher than Sequicity.
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