End-to-end Adversarial Learning for Generative Conversational Agents

Oswaldo Ludwig

Abstract

This paper presents a new adversarial learning method for generative conversational agents (GCA) besides a new model of GCA. Similar to previous works on adversarial learning for dialogue generation, our method assumes the GCA as a generator that aims at fooling a discriminator that labels dialogues as human-generated or machine-generated; however, in our approach, the discriminator performs token-level classification, i.e. it indicates whether the current token was generated by humans or machines. To do so, the discriminator also receives the context utterances (the dialogue history) and the incomplete answer up to the current token as input. This new approach makes possible the end-to-end training by backpropagation. Moreover, the trained discriminator can be used to choose the best answer among the answers generated by different trained models to improve the performance even more. A self-conversation process enables to produce a set of generated data with more diversity for the adversarial training. This approach improves the performance on questions not related to the training data. Experimental results with human and adversarial evaluations show that the adversarial method yields significant performance gains over the usual teacher forcing training.

Keywords: deep learning, seq2seq, NLP, adversarial learning, open domain dialogue generation.

1. Introduction

Neural language modeling [1], [2] uses recurrent neural networks to create effective models for different tasks in Natural Language Processing, such as open domain dialogue generation [3], [4], which aims at generating meaningful and coherent dialogue responses given the dialogue history. This task is the subject of this paper.

Conversational agents can be divided into two main classes: retrieval-based and generative agents. The retrieval-based model does not generate new text, it access a repository of predefined responses and chooses an appropriate response based on the input. This paper is about generative models, which generate new responses from the scratch, usually based on the sequence to sequence modeling [5]. In this context, we present a new end-to-end adversarial learning method for generative conversational agents (GCA) besides a new model of GCA.

The paper is organized as follows: Section 2 briefly reports the state-of-the-art in open domain dialogue generation, while Section 3 presents the proposed model of GCA. In Section 4 we explain our new end-to-end adversarial training. Section 5 reports the experiments, while Section 6 summarizes some conclusions.

2. State-of-the-art

Sequence to sequence (seq2seq) modeling is being successfully applied to neural machine translation [6], [7], since this model is language-independent and able to implicitly learn semantic [8], syntactic and contextual dependencies [9]. Further advances in end-to-end training with this model has made it possible to build successful systems [10] for different natural

language tasks, including parsing [11], image captioning [12], and open domain dialogue generation [5].

The research on GCA poses several challenges, such as the sensitivity to local and global context. GCA models tend to generate safe responses regardless of the input, such as "I am not sure". In [13] the authors propose to replace the usual maximum likelihood training objective functions, which favor generic responses of higher frequency in the training data sets, by a generalization of the Maximum Mutual Information (MMI), to avoid favoring responses that unconditionally present high probability. Other approaches build on this MMIbased strategy, such as seq2BF [14], which proposes a backward and forward sequences model that generates a reply built around a keyword candidate belonging to the context. This keyword is chosen by maximizing the point-wise mutual information (PMI) on the context sentence. The sensitivity to local context was also approached by transfer learning, such as in the topic augmented neural response generation, presented in [15], where a pre-trained probabilistic topic model provides information on the context to the decoder together with the thought vector provided by the encoder. Our GCA model presents the encoded context (i.e. the thought vector) to the decoder at each decoding iteration, rather than using it only to set up the initial state of the decoder, to avoid favoring short and unconditional responses with high prior probability.

Regarding the long-term dependencies, i.e. the global context sensitivity, we highlight the work [16], which proposes a hierarchical recurrent encoder-decoder model (HRED) that models a user search session as two hierarchical sequences: a sequence of sentences and a sequence of words in each query. This problem was also approached by [17], which proposed a model that consists of three RNN modules: an encoder RNN, a context RNN, and a decoder RNN. A sequence of tokens

Preprint submitted to ArXiv January 10, 2018

is encoded into a real-valued thought vector by the encoder RNN. The sequence of thought vectors is given as input to the context RNN, which updates its internal hidden state retaining the contextual information up to that point in time into a real-valued context vector, which conditions the decoder RNN. We intend to approach long-term dependencies by using hierarchical LSTMs in the encoder of our model as future work.

Another open issue in GCA is the speaker consistency. The GCA response may simulate different persons belonging to the training data, yielding inconsistent responses. An interesting work on this issue is [18] that shows that seq2seq models provide a straightforward mechanism for incorporating persona as embeddings. This work proposes a persona embedding that permits the incorporation of background facts for user profiles, person-specific language behavior, and interaction style. The modeling style of our GCA makes it easy to incorporate persona as embeddings.

Our work is closely related to the work of Li et al. [19], in which the authors borrow the idea of adversarial training [20] to generate utterances indistinguishable from human utterances. The model is composed of a neural seq2seq model, which defines the probability of generating a dialogue sequence, and a discriminator that labels dialogue utterances as human-generated or machine-generated, similar to the evaluator in the Turing test. The authors cast the task as a reinforcement learning problem. Our work follows this research line, but with different approaches, such as the end-to-end training by backpropagation, as explained in Section 4.

3. The new model of generative conversational agent

In this section, we define the proposed GCA and show the relationship between this model and the canonical seq2seq model.

The canonical seq2seq model became popular in neural machine translation, a task that has different prior probability distributions for the words belonging to the input and output sequences, since the input and output utterances are written in different languages. The GCA architecture presented here assumes the same prior distributions for input and output words. Therefore, it shares an embedding layer (Glove pre-trained word embedding¹) between the encoding and decoding processes through the adoption of a new model. To improve the sensitivity to the context, the thought vector (i.e. the encoder output) encodes the last N_u utterances of the conversation up to the current point (the dialogue history). The thought vector is concatenated with a dense vector that encodes the incomplete answer generated up to the current point, to avoid forgetting the context during the decoding process, as will be explained in Section 3.1. The resulting vector is provided to dense layers that predict the current token of the answer, as can be seen in Figure 1. Therefore, our model is different from the canonical model, in which the encoder output is used only to set up the initial state of the decoder.

The dialogue history/context utterances are arranged as a vector $\mathbf{x} \in \mathbb{R}^{s_s}$ containing a sequence of token indexes that is padded with zeros to have dimension s_s , i.e. an arbitrary value for the sentence length. The elements x_i , $i \in \{1 \dots s_s\}$, of \mathbf{x} are encoded into one-hot vector representation $\bar{x}_i \in \mathbb{R}^{s_v}$, where s_v is the size of the adopted vocabulary. The same happens with the elements y_i from the incomplete answer $\mathbf{y} \in \mathbb{R}^{s_s}$. These vectors are arranged to compose the matrices $X = [\bar{x}_1 \ \bar{x}_2 \ \dots \bar{x}_{s_s}]$ and $Y = [\bar{y}_1 \ \bar{y}_2 \ \dots \bar{y}_{s_s}]$. These matrices are processed by the embedding layer, represented by the matrix $W_e \in \mathbb{R}^{s_e \times s_v}$, where s_e is the arbitrary dimension of the word embedding vector, yielding two dense matrices $E_c \in \mathbb{R}^{s_e \times s_s}$ and $E_a \in \mathbb{R}^{s_e \times s_s}$:

$$E_c = W_e X$$

$$E_a = W_e Y$$
(1)

The proposed model uses two Long Short-term Memory networks (LSTM) [21], both with the same architecture, one to process E_c , which is related to the dialogue history/context, and another to process E_a , which is related to the incomplete answer generated up to the current point/iteration t. Details on the LSTM mathematical model can be found in [21]; therefore, we will represent the LSTMs simply as the functions $\Gamma_c: \mathbb{R}^{s_c \times s_s} \to \mathbb{R}^{s_{se}}$ and $\Gamma_a: \mathbb{R}^{s_e \times s_s} \to \mathbb{R}^{s_{se}}$, where s_{se} is the arbitrary dimension of the sentence embedding². These functions extract the sentence embedding vectors of the dialogue history and the incomplete answer

$$e_c = \Gamma_c(E_c; \mathcal{W}_c)$$

$$e_a = \Gamma_a(E_a; \mathcal{W}_a)$$
(2)

respectively. W_c and W_a are sets of parameters of the LSTMs. These vectors are concatenated and provided to dense layers that output the vector $\mathbf{p} \in \mathbb{R}^{s_v}$ encoding the probability $p(v_j|\mathbf{x},\mathbf{y})$ of each token v_j , $j \in \{1 \dots s_v\}$, of the adopted vocabulary. The dense layers are modeled as follows:

$$e = [e_c \ e_a]$$

$$y_h = \sigma(W_1 \ e + b_1)$$

$$\mathbf{p} = \varphi(W_2 \ y_h + b_2)$$
(3)

where W_1 and W_2 are matrices of synaptic weights, b_1 and b_2 are bias vectors, $\sigma(\cdot)$ is the relu activation function, and $\varphi(\cdot)$ is the softmax activation function.

We adopt the greedy decoding; therefore, the algorithm iterates by making the position t+1 of the incomplete answer \mathbf{y} equal to the index of the largest element of \mathbf{p} , and feeding it back to the input layer on the right-hand side of the model shown in Figure 1. This process continues until the token representing the end of the sentence is predicted, as can be seen in the simplified Algorithm 1. The training follows the teacher forcing strategy. The software package of this GCA is available on GitHub [22].

¹https://nlp.stanford.edu/projects/glove/

²The implementation of the LSTM algorithm receives as input a 3D tensor whose shape also includes the batch size.

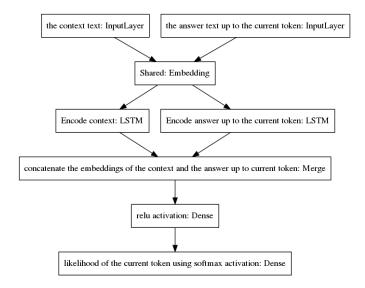


Figure 1: The model of the new GCA.

Algorithm 1 New GCA with greedy decoding

- 1: **Input: x**: the input sequence (context text).
- Output: y, p: the sampled output sequence and its conditional probability p(y|x).
- $3: p \leftarrow 1$
- 4: **y** ← []
- 5: $y \leftarrow$ 'BOS' (symbol representing the beginning of the sentence);
- 6: **while** *y* <> 'EOS' (symbol representing the end of sentence) **do**
- 7: $\mathbf{y} \leftarrow [\mathbf{y}, \mathbf{y}];$
- 8: input \mathbf{x} and \mathbf{y} into the two input layers of the model (1) (3) (see Figure 1).
- 9: $y \leftarrow$ token corresponding to the largest output of the model (1) (3);
- 10: $p(y|\mathbf{x}, \mathbf{y}) \leftarrow \text{the value of the larger output of the model (1) (3);}$
- 11: $p \leftarrow p \times p(y|\mathbf{x}, \mathbf{v});$
- 12: end while

3.1. Differences between our model and the canonical seq2seq

Short responses with high prior probability, regardless of the input, is a common output of the canonical seq2seq model; however, this behavior is not observed in our model. We believe this is due to its architecture. Seq2seq modeling approximates $p(\mathbf{y}|\mathbf{x})$ by $p_{\theta}(\mathbf{y}|g(\mathbf{x}))$, where $g(\mathbf{x})$ denotes the encoder output, i.e. the thought vector. Then, the decoder generates answers using this learned model. In the case of the canonical seq2seq this model can be expressed as:

$$\boldsymbol{p}_{\theta}(\mathbf{y}|g(\mathbf{x})) = \prod_{i=1}^{s_{s}} p_{\theta}(y_{i}|h_{i-1}, y_{i-1})$$
(4)

where y_0 is the index of the token representing the beginning of the sentence and $g(\mathbf{x})$ is used only to set up the initial state h_0 of the decoder, which is updated along the decoding iterations i as follows:

$$h_{0} = g(\mathbf{x})$$

$$h_{1} = f_{\alpha}(g(\mathbf{x}), y_{0})$$

$$h_{2} = f_{\alpha}(f_{\alpha}(g(\mathbf{x}), y_{0}), y_{1})$$

$$\vdots$$

$$h_{s_{s}-1} = f_{\alpha}(\dots f_{\alpha}(f_{\alpha}(g(\mathbf{x}), y_{0}), y_{1}) \dots y_{s_{s}-2})$$

$$(5)$$

where f_{α} represents the set of operations that the input and forget gates apply on the state variables and $\alpha \in \theta$ is the set of parameters of these gates, assuming an LSTM as the decoder. Notice that the nested application of operations on \mathbf{x} , such as the operation applied by the forget gate³, can erase information about the context along the decoder iterations, resulting in the usual safe answers, regardless of the input \mathbf{x} . On the other hand, our GCA architecture models $p(\mathbf{y}|\mathbf{x})$ in another way:

$$\boldsymbol{p}_{\theta}\left(\mathbf{y}|g\left(\mathbf{x}\right)\right) = \prod_{i=1}^{s_{x}} p_{\theta}\left(y_{i} \middle| f_{\beta}\left(y_{0} \dots y_{i-1}\right), g\left(\mathbf{x}\right)\right)$$
(6)

where $f_{\beta}(\cdot)$ (with $\beta \in \theta$) represents the LSTM that encodes the incomplete answer $(y_0 \dots y_{i-1})$. Since the encoder output $g(\mathbf{x})$ is provided to the decoder at each decoding iteration i, it is not subject to the nested functions of (5).

Another important feature of our model is the use of the distributional syntactic and semantic information encoded into the word embedding also in the decoding process, as can be seen in the second equation of (1).

4. End-to-end Adversarial Training by Backpropagation

Similar to the work of Li et al. [19], our adversarial training assumes a data set \mathcal{H} of human-generated dialogue utterances, a generator G and a discriminator D. Our work also assumes the GCA as the generator G that learns to fool the discriminator D; however, in our approach the discriminator D performs tokenlevel classification, rather than sentence-level classification, i.e. D is a binary classifier that outputs a label indicating whether the current token was generated by humans or machines. To do so, the discriminator takes as input the current token (denoted y^- , if it is generated by G, and y^+ , if it comes from a utterance selected from \mathcal{H}), the previous N_u dialogue utterances (denoted \mathbf{x}^- , if it is generated by G, and \mathbf{x}^+ , if it is from \mathcal{H}), and a sequence representing the incomplete answer (denoted \mathbf{y}^- , if it is generated by G, and \mathbf{y}^+ , if it is part of an utterance from \mathcal{H}).

The inputs of D are processed by (1) yielding the matrices E_c and E_a that are processed by two LSTMs, $\Gamma_{cd}: \mathbb{R}^{s_e \times s_s} \to \mathbb{R}^{s_{sed}}$ and $\Gamma_{ad}: \mathbb{R}^{s_e \times s_s} \to \mathbb{R}^{s_{sed}}$, where s_{sed} is the arbitrary dimension of the sentence embedding vectors of D. Γ_{cd} encodes the N_u previous utterances (i.e. the context) and Γ_{ad} encodes the incomplete answer up to the current token, yielding two sentence embedding vectors:

$$e_{cd} = \Gamma_{cd} (E_c; \mathcal{W}_{cd})$$

$$e_{ad} = \Gamma_{ad} (E_a; \mathcal{W}_{ad})$$
(7)

where W_{cd} and W_{ad} are sets of parameters of the LSTMs of D. These vectors are concatenated with the generator output \mathbf{p} and provided to a dense layer with sigmoid activation function that outputs $l \in [0, 1]$, with 1 corresponding to a perfect match

³Note that the outputs of the forget gate are within the interval [0, 1] due to its sigmoid activation function. Thus, the influence of $g(\mathbf{x})$ may decrease exponentially over the decoding iterations.

with the class *human-generated* and 0 to the class *machine-generated*. The dense layer is modeled as follows:

$$e_d = [\mathbf{p} \ e_{cd} \ e_{ad}]$$

$$l = \alpha (W_d \ e_d + b_d)$$
(8)

where W_d is the matrix of synaptic weights, b_d is the bias vector, and $\alpha(\cdot)$ is the sigmoid activation function. This new approach makes possible end-to-end training by backpropagation using the model of Figure 2.

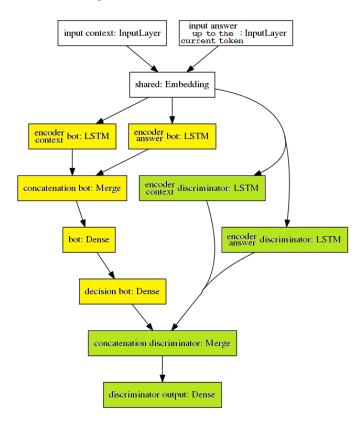


Figure 2: Model composed by the generator and the discriminator for the end-to-end adversarial learning. The yellow blocks belong to the GCA (the generator), while the green blocks belong to the discriminator. The white blocks are shared between generator and discriminator.

The white blocks of Figure 2 are shared between generator and discriminator and are modeled by (1), the yellow blocks, whose model is given by (2) and (3), compose G, while the green blocks, whose model is given by (7) and (8), compose D.

The adversarial training starts by using a version of the GCA⁴ pre-trained by teacher forcing to generate a set \mathcal{M} containing pairs of machine-generated dialogue utterances.

Our generation process is different from Li et al. [19], in which the machine-generated dialogue is the GCA answer to utterances belonging to \mathcal{H} , as can be seen in Figure 1 of [19]. Namely, rather than produce the pair $(\mathbf{x}^+, \mathbf{y}^- \sim \mathcal{G}(\cdot | \mathbf{x}^+))$, where

 \mathcal{G} represents the probability distribution modeled by G, our algorithm produces a more diverse machine-generated data set by iterating over utterances generated by a self-conversation process. The algorithm selects a utterance \mathbf{x}^+ from the training data set and uses it as a seed that is provided to G, then it iterates twice⁵ by feeding back its own output, in such a way to compose the set $\mathcal{M} = \left\{ \left(\mathbf{x}_i^- \sim \mathcal{G}\left(\cdot \mid \mathbf{x}_i^+ \right), \mathbf{y}_i^- \sim \mathcal{G}\left(\cdot \mid \mathbf{x}_i^- \right) \right) \right\}_{i=1}^{N_m}$. In other words, the seed \mathbf{x}^+ yields \mathbf{x}^- , which is in turn feed back to G yielding \mathbf{y}^- . This approach improves the performance on unseen data, since G is trained to produce answers indistinguishable from human answers for context utterances that are not present in \mathcal{H} .

The adversarial training follows by training only the discriminator model D (i.e. (1), (7), and (8)) for N_D epochs using data from \mathcal{H} and \mathcal{M} , along with their labels: 1 for examples from \mathcal{H} and 0 for examples from \mathcal{M} . Then the trained weights of D (i.e. W_{cd} , W_{ad} , W_d , and b_d) are imported to the green blocks of the model of Figure 2, frozen, and the weights of G (i.e. W_c , W_a , W_1 , W_2 , b_1 , and b_2) are updated by back-propagation for N_G epochs using only data from \mathcal{M} along with the target labels, which are all equal to one, since the idea is to train G (the yellow blocks) to fool D (the green blocks), in such a way to induce D to output 1 (the label of human-generated tokens) for the tokens generated by G.

The adversarial training is interleaved with teacher forcing using \mathcal{H} as training data, since the idea is to learn to generate human-like answers for context utterances from \mathcal{M} without forgetting the proper answers to utterances from \mathcal{H} . After training G, its weights \mathcal{W}_c , \mathcal{W}_a , \mathcal{W}_1 , \mathcal{W}_2 , \mathcal{b}_1 , and \mathcal{b}_2 are imported to the GCA (Figure 1) to generate a new set \mathcal{M} and start a new iteration, running again all the previous steps, as summarized in Algorithm 2.

Algorithm 2 End-to-end adversarial training

- 1: **Input:** \mathcal{H} (human-generated data set).
- 2: **Output:** W_{cd} , W_{ad} , W_d , b_d , W_c , W_a , W_1 , W_2 , b_1 , and b_2 (parameters of D and G).
- 3: train the GCA of Figure 1 ((1)-(3)) by teacher forcing on $\mathcal H$ (using categorical cross-entropy loss).
- 4: for number of adversarial training epochs do
- 5: use the GCA to generate $\mathcal{M} = \left\{ \left(\mathbf{x}_{i}^{-} \sim \mathcal{G}\left(\cdot \mid \mathbf{x}_{i}^{+} \right), \mathbf{y}_{i}^{-} \sim \mathcal{G}\left(\cdot \mid \mathbf{x}_{i}^{-} \right) \right\}_{i=1}^{N_{m}}$
- 6: update D (i.e. (1), (7), and (8)) for N_D epochs using \mathcal{H} and \mathcal{M} , along with their labels: 1 for examples from \mathcal{H} and 0 for examples from \mathcal{M} (using binary cross-entropy loss).
- 7: import the updated weights W_{cd} , W_{ad} , W_d , and b_d from D to the green blocks of the model of Figure 2.
- 8: import the weights W_c , W_a , W_1 , W_2 , b_1 , and b_2 from the GCA to the yellow blocks of the model of Figure 2.
- 9: freeze the weights of D in the model of Figure 2 and update the weights of G (i.e. W_c , W_a , W_1 , W_2 , b_1 , and b_2) by back-propagation for N_G epochs using only M along with the target labels, which are all equal to one (using MSE loss function).
- 10: import the updated weights W_c , W_a , W_1 , W_2 , b_1 , and b_2 from G to the GCA of Figure 1.
- 11: update the GCA ((1)-(3)) by teacher forcing for N_{tf} epochs on \mathcal{H} (using categorical cross-entropy loss).
- 12: **end for**

Since our discriminator performs token-level classification,

⁴The model given by (1)-(3) that corresponds to Figure 1

⁵The number of iteration can be arbitrary.

we compose its outputs to evaluate the probability of $\mathbf{y} = \mathbf{y}^+$, i.e. to check whether the utterance is a human-generated answer. To do so, we provide the dialogue history/context \mathbf{x} to D. Assuming that the discriminator output at the i^{th} iteration, $l_i \in [0,1]$, informs the probability $p\left(y_i^+|y_0\dots y_{i-1},\mathbf{x}\right)$, i.e. the probability of $y_i = y_i^+$, it is possible to apply the chain rule as follows:

$$p(\mathbf{y}^+|\mathbf{x}) = \prod_{i=1}^{s_s^*} p\left(y_i^+ \middle| \bigcap_{j=1}^{i-1} y_j, \mathbf{x} \right) = \prod_{i=1}^{s_s^*} l_i$$
 (9)

where s_s^* is the effective number of tokens of the sentence, not the arbitrary length of the sentence after the padding s_s .

The trained discriminator is also used to select the best answer among the answers generated by two different models, one trained by teacher forcing and another trained by our end-to-end adversarial method.

5. Experiments

Evaluating open domain dialogue generation requires a human level of comprehension and background knowledge [23]. There are different quality attributes to be analyzed, such as the accuracy of the text synthesis [24], the ability to convey personality [18], the ability to maintain themed discussion [15], the ability to respond to specific questions, the ability to read and respond to moods of human participants [25], the ability to show awareness of trends and social context [26], and the ability to detect intent [27].

Liu at al. [28] shown that metrics from machine translation and automatic summarization, such as BLEU [29], METEOR [30] and ROUGE [31] present either weak or no correlation with human judgments. Therefore, in this section we use human and adversarial evaluation to compare our new training method with the usual teacher forcing.

Our human-generated data set \mathcal{H} is composed of open domain dialogue utterances collected from English courses online. We chose this data source due to its linguistic accuracy, the variety of themes, and didactic format, i.e. if it is good for human learning, it should be good for the machines too.

We trained two GCA models using \mathcal{H} , one by teacher forcing and another by the new adversarial method, both models with the same architecture.

The models were implemented in Keras with Theano backend and trained using Adam optimizer. The adopted parameters were: $N_u = 2$, $N_G = 1$, $N_D = 15$, $N_{tf} = 1$, $N_m = 7900$, $s_e = 100$, $s_{se} = 300$, $s_{sed} = 300$, $s_v = 7000$, $s_s = 50$, learning rate of the generator $\alpha_g = 5e^{-5}$, and learning rate of the discriminator $\alpha_d = 1e^{-4}$. The adopted loss functions can be seen in Algorithm 2.

The trained models chatted with humans to collect dialogue utterances for the test data set. Having this data set, we conducted a human survey with 25 volunteers. Each respondent was given 10 short dialogues, with an average of 24 lines per dialogue, as can be seen in Figure 3.

37		user. Hi John, nice to meet you.			
38		computer TF: i am glad to see you . (with probability of 0.436632)			
39		computer GAN: i am looking for an apartment. (with probability of 0.221137)			
40		user: Me too.			
41		computer TF: we have a 2 o'clock appointment to see see . (with probability of 0.309276)			
42	х	computer GAN: we have a 2 o'clock appointment to see the one on main street . (with probability of 0.960698)			
43		user. Okay, let's do it.			
44		computer TF: we had better get ready to go home . (with probability of 0.036197)			
45		computer_GAN: we are already on the world. (with probability of 0.099730)			
46		user: I am ready, and you?			
47		computer TF: i am an extra large. (with probability of 0.149920)			
48	Х	computer_GAN: i am not . (with probability of 0.278670)			
49		user: All right, go home to get ready.			
50		computer_TF: and then we can go to the beach. (with probability of 0.098566)			
51	X	computer_GAN: what are you going to do? (with probability of 0.161536)			
52		user: I will wait for you in the Coffee shop.			
53	X	computer_TF: that sounds like a fair restaurant . (with probability of 0.066749)			
54		computer_GAN: what is wrong with it ? (with probability of 0.381197)			
55		user: Nothing.			
56		computer_TF: how do you know that ? (with probability of 0.299847)			
57		computer_GAN: how do you know? (with probability of 0.534038)			
58		user: I know because I will go to the apartment with you.			
59		computer_TF: do not ever be in a hurry when you are hot . (with probability of 0.027600)			
60	X	computer_GAN: that is right . do you have any food ? (with probability of 0.036017)			
61		user: No, I will eat in the coffee shop.			
62	X	computer_TF: that is nice. (with probability of 0.164401)			
63		computer_GAN: that is great . we need a house . (with probability of 0.027935)			
64		user: For sure. It is difficult in these times.			
65		computer_TF: i know, but it is too. (with probability of 0.014846)			
66		computer_GAN: i know . it is . (with probability of 0.401085)			
67		user: See you later then.			
68		computer_TF: i do not want to talk about it . (with probability of 1.000000)			
69	X	computer_GAN: bye , Giovana . (with probability of 0.362267)			
84		user: Are you going to the school today?			
85		computer_TF: no , i am not . i am going to the bank . (with probability of 0.167568)			
86		computer_GAN: no , i am not . i am going to the bank . (with probability of 0.587143)			
87		user: I would like you to do a favor for me, is that ok?			
88	х	computer_TF: i think you are very interested for this . (with probability of 0.003967)			
89		computer_GAN: no , i have not to find out . (with probability of 0.031229)			
90		user: Yes, I really need this.			
91		computer_TF: what kind of electronic media do you have ? (with probability of 0.015470)			
92	Х	computer_GAN: what do you need to do ? (with probability of 0.166130)			
93		user: I need you to pay a bill.			
94		computer_TF: what was on ty? (with probability of 0.116624)			
95	X	computer_GAN: what are you talking? (with probability of 0.259209)			

Figure 3: Samples from the evaluation form that has human-machine dialogue lines and yellow fields where the evaluator marks the best machine-generated answer.

For each human-generated line corresponds a pair of answers, one from the model trained by teacher forcing and another from the model trained by the new adversarial method. The respondents can vote for the best machine-generated answer or assign a tie (no votes) per each dialogue line. Therefore, each machine-generated dialogue line receive a number of votes $v \in \mathbb{Z}$: $0 \le v \le 25$.

The discriminator D is also used to have an adversarial evaluation on the machine-generated answers. The direct application of (9) favors short answers; therefore, we also adopt:

$$S(\mathbf{y}^{+}) = \sqrt[s_{s}^{*}]{\prod_{i=1}^{s_{s}^{*}} l_{i}}$$
 (10)

as a score to compare machine-generated answers, where l_i is the discriminator output at the iteration i.

To determine the correlation between the human judgment and the score assigned by the discriminator, we computed the Jaccard index to measure the similarity between two sets of winning answers, one selected by the humans, H, and another by the adversarial method, A:

$$J(H,A) = \frac{|H \cap A|}{|H \cup A|} \tag{11}$$

where $|H \cup A|$ is the total number of dialogue lines that received

votes (remembering that in the event of a tie, there is no vote). The direct application of (9) yielded J(H, A) = 0.41, while using (10) we obtained J(H, A) = 0.58. Tables 1 and 2 summarize the results using two different criteria: the best answer and the number of human votes, respectively.

Table 1: The number of best machine-generated answers.

training method	human evaluation	adversarial evaluation using (10)
teacher forcing	26 (29.88%)	35 (38.04%)
adversarial learning	61 (70.11%)	57 (61.96%)

Table 2: Number of human votes		
training method	human votes	
teacher forcing	252 (30.66%)	
adversarial learning	570 (69.34%)	

If the absolute value of the difference between the scores is smaller than 5% of the smallest score, the discriminator assigns a tie.

As can be seen in Tables 1 and 2, the adversarial training yields a large gain in performance⁶.

Even better performance is achieved by using the trained discriminator D to choose the best answer among those generated by the two trained models. Our algorithm applies (10) to rank the answers. An implementation of this method was also made available at GitHub⁷.

The number of dialogue utterances used to compose the context \mathbf{x} is an important hyper-parameter. Our experiments indicate that with $N_u=1$ the GCA cannot retain the context properly. On the other hand, with $N_u>2$ the machine cannot change the subject of the conversation when the human interlocutor does it. An algorithm able to process the conversation and detect changes in the context would be useful to set the best value of N_u before generating an answer.

6. Conclusion

This work introduces a new model of GCA and a new adversarial training method for this model. The results presented in this paper indicate that the new training method can provide significant gains in performance. Moreover, the adversarial training also yields a trained discriminator that can be used to select the best answer, when different models are available.

As future work, we intend to evaluate the performance of hierarchical LSTMs in the encoder of our model and use an auxiliary algorithm to detect changes in the dialogue context, aiming at dynamically determining the optimal length of dialogue history to be encoded within the thought vector. It is also

important to scale up the experiments by using larger data sets and evaluating larger versions of our model.

References

- Y. Bengio, R. Ducharme, P. Vincent, C. Jauvin, A neural probabilistic language model, Journal of machine learning research 3 (Feb) (2003) 1137– 1155
- [2] T. Mikolov, M. Karafiát, L. Burget, J. Cernockỳ, S. Khudanpur, Recurrent neural network based language model., in: Interspeech, Vol. 2, 2010, p. 3.
- [3] A. Ritter, C. Cherry, W. B. Dolan, Data-driven response generation in social media, in: Proceedings of the conference on empirical methods in natural language processing, Association for Computational Linguistics, 2011, pp. 583–593.
- [4] I. V. Serban, A. Sordoni, R. Lowe, L. Charlin, J. Pineau, A. C. Courville, Y. Bengio, A hierarchical latent variable encoder-decoder model for generating dialogues., in: AAAI, 2017, pp. 3295–3301.
- [5] O. Vinyals, Q. Le, A neural conversational model, arXiv preprint arXiv:1506.05869.
- [6] N. Kalchbrenner, P. Blunsom, Recurrent continuous translation models., in: EMNLP, Vol. 3, 2013, p. 413.
- [7] I. Sutskever, O. Vinyals, Q. V. Le, Sequence to sequence learning with neural networks, in: Advances in neural information processing systems, 2014, pp. 3104–3112.
- [8] O. Ludwig, Q. Do, C. Smith, M. Cavazza, M.-F. Moens, Learning to extract action descriptions from narrative text, IEEE Transactions on Computational Intelligence and AI in Games PP (2017) 1–14.
- [9] A. Sordoni, M. Galley, M. Auli, C. Brockett, Y. Ji, M. Mitchell, J.-Y. Nie, J. Gao, B. Dolan, A neural network approach to context-sensitive generation of conversational responses, arXiv preprint arXiv:1506.06714.
- [10] M. Johnson, M. Schuster, Q. V. Le, M. Krikun, Y. Wu, Z. Chen, N. Thorat, F. Viégas, M. Wattenberg, G. Corrado, et al., Google's multilingual neural machine translation system: enabling zero-shot translation, arXiv preprint arXiv:1611.04558.
- [11] O. Vinyals, Ł. Kaiser, T. Koo, S. Petrov, I. Sutskever, G. Hinton, Grammar as a foreign language, in: Advances in Neural Information Processing Systems, 2015, pp. 2773–2781.
- [12] O. Vinyals, A. Toshev, S. Bengio, D. Erhan, Show and tell: A neural image caption generator, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 3156–3164.
- [13] J. Li, M. Galley, C. Brockett, J. Gao, B. Dolan, A diversity-promoting objective function for neural conversation models, arXiv preprint arXiv:1510.03055.
- [14] L. Mou, Y. Song, R. Yan, G. Li, L. Zhang, Z. Jin, Sequence to backward and forward sequences: A content-introducing approach to generative short-text conversation, arXiv preprint arXiv:1607.00970.
- [15] K. Xiong, A. Cui, Z. Zhang, M. Li, Neural contextual conversation learning with labeled question-answering pairs, arXiv preprint arXiv:1607.05809.
- [16] A. Sordoni, Y. Bengio, H. Vahabi, C. Lioma, J. Grue Simonsen, J.-Y. Nie, A hierarchical recurrent encoder-decoder for generative context-aware query suggestion, in: Proceedings of the 24th ACM International on Conference on Information and Knowledge Management, ACM, 2015, pp. 553–562.
- [17] I. V. Serban, A. Sordoni, Y. Bengio, A. C. Courville, J. Pineau, Building end-to-end dialogue systems using generative hierarchical neural network models., in: AAAI, 2016, pp. 3776–3784.
- [18] J. Li, M. Galley, C. Brockett, G. P. Spithourakis, J. Gao, B. Dolan, A persona-based neural conversation model, arXiv preprint arXiv:1603.06155.
- [19] J. Li, W. Monroe, T. Shi, A. Ritter, D. Jurafsky, Adversarial learning for neural dialogue generation, arXiv preprint arXiv:1701.06547.
- [20] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, Generative adversarial nets, in: Advances in neural information processing systems, 2014, pp. 2672–2680.
- [21] S. Hochreiter, The vanishing gradient problem during learning recurrent neural nets and problem solutions, International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems 6 (02) (1998) 107–116.
- [22] O. Ludwig, oswaldoludwig/Seq2seq-Chatbot-for-Keras: Seq2seq Chatbot for Keras (Jul. 2017). doi:10.5281/zenodo.825303.

⁶The codes of our new adversarial training method are available at https://github.com/oswaldoludwig/Adversarial-Learning-for-Generative-Conversational-Agents

 $^{^7}$ See the file conversation_discriminator.py in the repository https://github.com/oswaldoludwig/Seq2seq-Chatbot-for-Keras. Follow the instructions in the README file to chat with the trained model.

- [23] O. Ludwig, X. Liu, P. Kordjamshidi, M.-F. Moens, Deep embedding for spatial role labeling, arXiv preprint arXiv:1603.08474.
- [24] M. McTear, Z. Callejas, D. Griol, Evaluating the conversational interface, in: The Conversational Interface, Springer, 2016, pp. 379–402.
- [25] H. Zhou, M. Huang, T. Zhang, X. Zhu, B. Liu, Emotional chatting machine: Emotional conversation generation with internal and external memory, arXiv preprint arXiv:1704.01074.
- [26] S. A. Applin, M. D. Fischer, New technologies and mixed-use convergence: How humans and algorithms are adapting to each other, in: Technology and Society (ISTAS), 2015 IEEE International Symposium on, IEEE, 2015, pp. 1–6.
- [27] C. Marschner, M. Basilyan, Identification of intents from query reformulations in search, uS Patent App. 14/316,719 (Jun. 26 2014).
- [28] C.-W. Liu, R. Lowe, I. V. Serban, M. Noseworthy, L. Charlin, J. Pineau, How not to evaluate your dialogue system: An empirical study of unsupervised evaluation metrics for dialogue response generation, arXiv preprint arXiv:1603.08023.
- [29] K. Papineni, S. Roukos, T. Ward, W.-J. Zhu, Bleu: a method for automatic evaluation of machine translation, in: Proceedings of the 40th annual meeting on association for computational linguistics, Association for Computational Linguistics, 2002, pp. 311–318.
- [30] A. Lavie, A. Agarwal, Meteor: An automatic metric for mt evaluation with high levels of correlation with human judgments, in: Proceedings of the Second Workshop on Statistical Machine Translation, Association for Computational Linguistics, 2007, pp. 228–231.
- [31] C.-Y. Lin, Rouge: A package for automatic evaluation of summaries, in: Text summarization branches out: Proceedings of the ACL-04 workshop, Vol. 8, Barcelona, Spain, 2004, pp. 1–6.