A Conditional Generative Chatbot using Transformer Model

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ABSTRACT

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A Chatbot serves as a communication tool between a human user and a machine to achieve an appropriate answer based on the human input. In more recent approaches, a combination of Natural Language Processing and sequential models are used to build a generative Chatbot. The main challenge of these models is their sequential nature, which leads to less accurate results. To tackle this challenge, in this paper, a novel end-to-end architecture is proposed using conditional Wasserstein Generative Adversarial Networks and a transformer model for answer generation in Chatbots. While the generator of the proposed model consists of a full transformer model to generate an answer, the discriminator includes only the encoder part of a transformer model followed by a classifier. To the best of our knowledge, this is the first time that a generative Chatbot is proposed using the embedded transformer in both generator and discriminator models. Relying on the parallel computing of the transformer model, the results of the proposed model on the Cornell Movie-Dialog corpus and the Chit-Chat datasets confirm the superiority of the proposed model compared to state-of-the-art alternatives using different evaluation metrics.

1. Introduction

Regarding the increasing use of social networks, a new technology called Chatbot has been developed as a tool for human-computer interaction. Chatbots have been widely applied in various fields such as e-commerce (Miklosik et al., 2021; Tran et al., 2021), education (Okonkwo & Ade-Ibijola, 2021), banking and insurance (Mogaji et al., 2021), Data collection and management (Tsai et al., 2020), and Health (Ayanouz et al., 2020). Chatbots automatically give more attractive answers to users through easy and efficient communications. The key factor in the suitable design of Chatbots is to provide understandable answers to the user (Adamopoulou & Moussiades, 2020). To this end, various approaches have been recently developed to build Chatbots. In general, the approaches of Chatbot development can be classified into two categories: open and closed domain (See Fig. 1). Chatbots with the ability to answer on more than one domain, are called open domains. In contrast, closed domain Chatbots can answer only to questions concerning a particular domain.

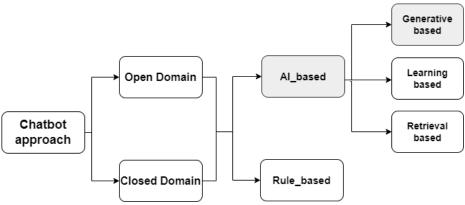


Fig. 1. Classification of Chatbot approach

Open and closed domains Chatbots can be categorized into Rule-based and Artificial Intelligence (AI)-based Chatbots. Rule-based Chatbots rely on the user's input with a base template. This type of Chatbots choose a predefined answer from a set of answers (Ramesh et al., 2017). However, they are inflexible and limited to some predefined answers. ELIZA and ALICE are based on this approach (Masche & Le, 2017). AI-based Chatbots are trained to have human-like conversations using a hybrid of NLP and deep learning approaches. More concretely, AI-based Chatbot classified into three categories: Retrieval, Learning, and Generative-based methods. The first category, the retrieval-based method, chooses the most similar

answer from a dataset using a functional scoring metric (Y. Zhu et al., 2021). The second category, the learning-based method, usually learns patterns from training data, containing questions with answers, through deep learning models to generate relevant answers. The last category, the generative-based method, is usually based on the Sequence (Seq2Seq) learning models (Dhyani & Kumar, 2021; Y. Peng et al., 2019; Wang et al., 2019; Yang et al., 2018). However, the main challenge of these models is their sequential nature, which is led to less accurate results. To tackle this challenge, in recent years, researchers have developed some models based on the transformer models (Lin et al., 2022; Masum et al., 2021; B. Peng et al., 2022; Shao et al., 2019; Shengjie et al., 2020). Relying on the parallel computing as well as the self-attention mechanism of the transformer model, the performance of the models developed using transformers has been improved in comparison with the Seq2Seq models (Vaswani et al., 2017). Although, Learning-based models are not able to generate various answers. To overcome this shortcoming, the generative-based models have been developed to learn the answers distribution.

Some models such as Sequence Generative Adversarial Networks (SeqGAN) (L. Yu et al., 2017) and stepwise GAN (StepGAN) (Tuan & Lee, 2019) have been developed as the third category, the generative-based model. The sequential nature of these models is led to use reinforcement learning techniques for completing the generator's answers. These models suffer from slow convergence due to their high variance and low processing speed. To tackle the challenge of sequential nature as well as the accuracy improvement in these models, in this paper, a novel architecture is proposed based on conditional Wasserstein Generative Adversarial Networks (cWGAN) using transformer model which processes parallelly during the training phase. This architecture enhances the efficiency through generated human-like answers.

The main contributions of this paper can be listed as follows: 1) Model: We propose a novel model using the transformer model, which is used in both generator and discriminator of a cWGAN. To the best of our knowledge, this is the first time that such a model is proposed in Chatbot. 2) Extensive experiments conducted on two challenging datasets show that our architecture outperforms state-of- the-art methods in the field.

The rest of this paper is organized as follows: Section 2 reviews related works in Chatbot. The proposed architecture is explained in Section 3. In the following, the experimental results and discussion are presented in Section 4 and 5, respectively. Finally, conclusion and future works are provided in Section 6.

2. Literature review

In this section, we briefly review the recent works in four categories: Rule-based, Retrieval -based, Learning-based, and Generative-based.

2.1. Rule-based models

In the rule-based models, the characteristic variables of the input expression are first specified. Then, a predefined answer is provided based on the variables and rules (Adamopoulou & Moussiades, 2020). Rule-based approaches can be divided into two categories: pattern matching methods and standard task-oriented systems (Z. Peng & Ma, 2019). In pattern matching methods, Chatbots match the user's input to the pattern of the rules and select a predetermined answer from the set of answers using pattern matching algorithms. Task-oriented systems guide the user to complete certain items. Since the 1990s, a great deal of research has been conducted into the design of Chatbots based on similar rules for providing services in specific domains. These Chatbots are known as task-oriented modular chat systems that guide the user to perform some structured tasks, such as restaurant and film reservations. Since 1966, the development of the Eliza Chatbot has begun with a patternbased approach. This Chatbot analyzed the input sentence based on the parsing rules established by the keywords in a sentence (Weizenbaum, 1966). "Pari" adds some influential variables like "fear", "anger" and "distrust" to the more complex rules. These rules have made the conversation more humane-like (Colby, 1975). ALICE uses Artificial Intelligence Markup Language (AIML), which is the category constituting the unit of knowledge to combine a template and an optional field (Wallace, 2009). In addition, several platforms, such as Microsoft LUIS, IBM Watson Assistant, and Dialog flow, have been developed to assist the user in making Chatbots. These types of Chatbots have drawbacks despite their simplicity, quick implementation, and cost-effectiveness. Inflexibility, lack of learning, inability to create new answers, and being limited to some predefined answers are the most important challenges of rule-based Chatbots.

2.2. Retrieval -based

The retrieval-based Chatbots select the best matching answer for the user's question by searching a pre-constructed conversational repository (Yan et al., 2016). Lowe et al. (Lowe et al., 2015) developed a retrieval-based Chatbot using the Term Frequency - Inverse Document Frequency (TF-IDF) method. The TF-IDF vectors of each candidate's question and answer are computed by concatenating all TF-IDF scores. The candidate answers with the highest cosine similarity to the question vector are selected as the final answers. Lu et al. (Lu & Li, 2013) proposed an architecture to overcome the short-text matching problem of the developed models. Later, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and its extensions such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) were widely used in this field (Z. Peng & Ma, 2019). For instance, Zhou et al. proposed an approach by adding an attention mechanism to the deep network to provide question and answer matching (Zhou et al., 2018). In another work, Shu et al. (Shu et al., 2022)

proposed a retrieval-based model to search for answers related to the question by combining keyword extraction modules and two-stage transformer. In overall, while the retrieval-based approach is widely used by researchers, no new answer is generated and only the most probable answer is retrieved from the database. This can restrict the Chatbot answers. Moreover, it is essential to have a database in the inference phase.

2.3. Learning -based

This approach is usually based on Seq2Seq learning model. In the case of long sentences and conversations (more than 20 words), all essential information of a source sentence should be compressed into a fixed-length vector which is challenging (Vaswani et al., 2017). To tackle this challenge, different approaches have been suggested by researchers. For instance, making the structural changes, such as adding the word embedding matrix (Serban et al., 2017), modification of the encoder or decoder (Z. L. Gu, 2016; W.-N. Zhang et al., 2019), and adding the attention mechanism (Dhyani & Kumar, 2021; Palasundram et al., 2021; Y. Peng et al., 2019; Yang et al., 2018) are some of the solutions suggested by researchers. In addition to this, some researchers have used transformer-based model, that replaces the recurrent layers commonly used in encoder-decoder architectures with multi-headed self-attention. Rao et al. (Rao K Yogeswara & Rao, 2022), have developed a hybrid model for deep transfer learning-based text generation using the Elmo language model for embedding, Variational Autoencoder (VAE), and Bi-directional Long Short-Term Memory (BiLSTM). A transformer-based answer generation model, named DIALOGPT, was also presented as a pretrained model by Zhang et al. (Y. Zhang et al., 2019). This model is publicly released to facilitate the development of more intelligent dialogue systems. Another suggested model is a Chatbot model using a Bidirectional Encoder Representations from Transformers (BERT) model, which only has an encoder (S. Yu et al., 2021). While the learning-based models have obtained promising results, they cannot generate various answers due to not having the ability to learn the answer distribution.

2.4. Generative-based

Generative-based methods learn the answer distribution using the generative models, such as SeqGAN (L. Yu et al., 2017) and StepGAN (Tuan & Lee, 2019). These models use the Reinforcement Learning (RL) techniques. In the SeqGAN, The RL reward signal comes from the discriminator, which is judged on a complete sequence, and fed back to the intermediate state action steps using Monte Carlo search. However, the Monte Carlo Tree Search (MCTS) used in SeqGAN has a high computational efficiency. In the StepGAN approaches, the Generative adversarial network (GAN) is evaluated in a stepwise manner. In this way, the discriminator is modified to automatically assign scores and determine the suitability of each generated subsequence. Wu and Wang added a new loss function (Truth guidance) to achieve a closer generated text to the real data (Wu & Wang, 2020). Also, a discriminator network model was designed based on the self-attention mechanism to obtain richer semantic features. In another work, a Transformer-based Implicit Latent GAN (TILGAN) model was proposed (Diao et al., 2021), which combines a transformer autoencoder and GAN in the latent space with a novel design and distribution matching based on the Kullback-Leibler (KL) divergence.

To generate more relevant answers, some researchers used a hybrid models, including the generative and retrieval-based methods. For example, Zhang et al. (J. Zhang et al., 2019) fed the retrieved answers from the retrieval-based model to a generative-based model as additional information for the discriminator and generator models. Zhu et al. (Q. Zhu et al., 2018) also used the N-best retrieved answers as evidence for calculating the reward for the generator model. Zhang et al. (Zhang et al., 2020) employed the answer generated by retrieval-based models as additional information for training the generative-based models and placed a filter to select the best answer. Furthermore, an ensemble-based deep reinforcement learning was also developed for generative Chatbots by Cuayáhuitl et al. (Cuayáhuitl et al., 2019). While the generative-based Chatbots are able to generate more relevant answers, these models face some challenges, such as slow convergence due to their high variance and low processing speed especially in large sentences. To overcome the challenge of sequential nature as well as the accuracy improvement in these models, in this paper, we propose a novel architecture based on the cWGAN using transformer model, processing parallelly during the training phase.

3. Proposed model

A vanilla GAN model consists of a generator (G) and a discriminator (D). Considering the scope of this paper, the GAN input is a question in the form of sequence x. The discriminator learns to maximize score $D(x, \hat{y}^*)$ and minimize score $D(x, \hat{y})$, while the generator learns to generate answer \hat{y} to maximize $D(x, \hat{y})$ as expressed in Eq. (1):

$$minmax E[logD(x, y^*)] + E[log(1 - D(x, \hat{y}))]$$
 (1)

where $(x, y^*) \sim P_R(x, y)$ is the joint probability distribution of (x, y), and $x \sim P_R(x)$ denotes the probability distribution of x from training data. As the GAN models may never converge and have a problem of mode collapses, different variants of the GAN model have been suggested by researchers (Brownlee, 2019). One of these variants is the Wasserstein GAN (WGAN), which is an extension of the GAN that seeks an alternate way of training the generator model to better approximate the distribution of data observed in a given training dataset. Instead of using a discriminator to classify or predict the probability of generated data as real or fake, WGAN changes or replaces the discriminator model with a critic that scores the reality or fakeness of a given data. The goal is to minimize the distance between the data distribution in the training

dataset and the generated examples. This method can promote stable training while working with gradients. One of the reasons for this convention is that there is no Sigmoid activation function to limit the values to 0 or 1 corresponding to real or fake. Considering the superiority of the WGAN compared to the GAN model, we propose a novel architecture based on cWGAN and transformer model for generating answers in Chatbot. As shown in Fig. 2, the proposed architecture consists of two modules: generator and discriminator which are connected in a single network; thus, the proposed system is trained end-to-end.

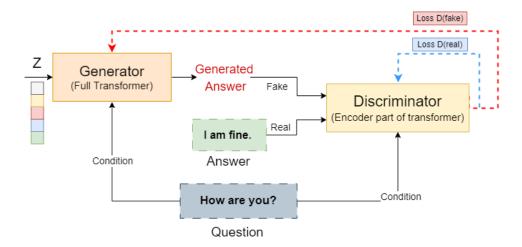


Fig. 2. General architecture of the proposed approach.

3.1. Generator modules

Generator is a full transformer model that generates fake answers in test phase. The architecture of the Generator in training phase is illustrated in Fig. 3. In the training phase, the encoder and decoder input embedding need to be prepared. Therefore, for the encoder input, the real questions are tokenized and embedded by the pretrained BERT model, including 12 layers, 768 features, and 12 heads. To increase the training speed, a linear model was adopted to reduce the dimensionality of the features to 64 as shown in Eq. (2):

$$y = f(\sum_{i=0}^{n} w_i x_i + \theta) \tag{2}$$

Subsequently, the output of the linear model is concatenated with the position encoding, preserving the word's positions in the sentence. Positional encoding is a matrix, which gives context based on the word position in a sentence as Eq. (3) and Eq. (4):

$$PE_{(pos,2i)} = \sin(pos/1000^{2i/d_{model}}) \tag{3}$$

$$PE_{(pos,2i+1)} = \cos(pos/1000^{2i/d_{model}})$$
 (4)

where "pos" refers to the position of the "word" in the sequence; while "d" means the size of the word/token embedding. "i" refers to each of dimensions of the embedding. "d" is fixed, while "pos" and "i" vary.

The same process with some variations is repeated for the decoder. In the decoder, instead of a question, we have a real answer in the input of the decoder. Furthermore, encoder output is concatenated with the Z vector to increase the variety in generated answers. The transformer works slightly different during training and inference phase. During inference, only a question is presented as input sequence. There is not any real answer as target sequence that could be passed to the decoder. Since, decoder aims to generate an answer \hat{y} as close as possible to the real answer, the output is generated in a loop and fed the output sequence from the previous timestep to the decoder in the next timestep till the end token.

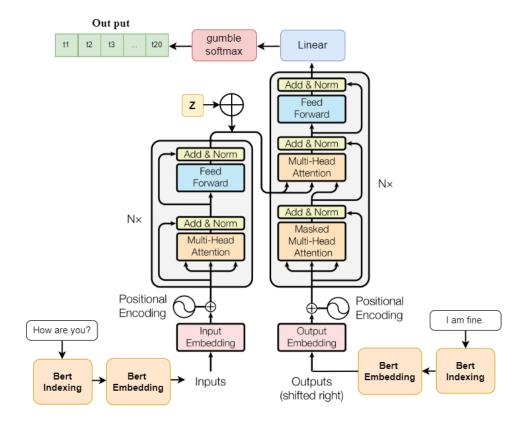


Fig. 3. Architecture of the proposed Generator in training phase.

In Generator, a full transformer with N=8 identical layers and 16 heads is used. Generator module is first trained separately by Maximum Likelihood Estimation (MLE) to increase the convergence probability. Then, the model is fine-tuned by adversarial network to learn the answers distribution. The linear transformation and Gumbel SoftMax function are utilized to convert the decoder output to the predicted next-token probabilities. The Gumbel-SoftMax distribution is a continuous distribution capable of approximating samples from a categorical distribution and providing a hard output by using an argmax function. So that, the output of decoder will be an index vector, which is given as the input of the discriminator. In adversarial phase, the generator is updated upon obtaining the discriminator model. In GAN model, this is achieved by gradient likelihood ratios of objective function which can be derived by Eq. (5):

$$L_G = \nabla_{\theta_G} \frac{1}{m} \sum_{i=1}^m \log \left[D\left(G(Q_i + Z)\right) \right]$$
 (5)

where L_G shows the loss function of generator, m is the number of generated sequences while Q+Z denotes the question regarded as condition data concatenated with Z vector. As discussed before, we employ the WGAN, aiming to overcome the challenges of GAN model. In this way, the objective function of WGAN, L_{wG} , can be calculated by Eq. (6):

$$L_{wG} = \nabla_{\theta_G} \frac{1}{m} \sum_{i=1}^{m} f(G(Q_i + Z))$$
 (6)

where f has to be a 1-Lipschitz function.

3.2. Discriminator modules

Discriminator includes only encoder part of transformer followed by a classifier. It provides the probability of real or fake answers at the time step of t and trains k epochs. In GAN model, discriminator is updated by gradient likelihood ratios of objective function as expressed by Eq. (7):

$$L_{D} = \nabla_{\theta_{G}} \frac{1}{m} \sum_{i=1}^{m} -\log[D(A_{i}, Q_{i})] - \log[1 - D(G(Q_{i}))]$$
 (7)

where L_D is loss function of discriminator, A is the real answer, and Q represents the question that is considered as the condition data. In the WGAN model, the discriminator is considered as a critic model; L_C can be calculated by Eq. (8):

$$L_C = \nabla_{\theta_G} \frac{1}{m} \sum_{i=1}^{m} f(q_i) - f(G(q_i))$$
 (8)

where f has to be a 1-Lipschitz function.

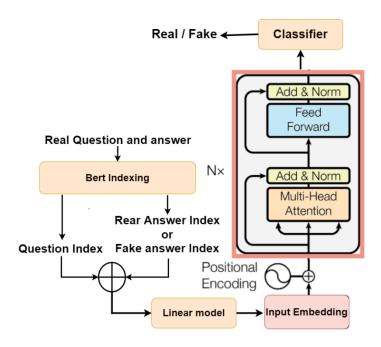


Fig. 4. Architecture of the Discriminator in the proposed model.

As we show in Fig. 4, in each iteration step, the discriminator is trained once with fake pair data and once with real pair data. Real question and answer pairs are tokenized and indexed by the pretrained BERT model. We cannot use BERT for embedding due to the computational complexity of the graph data. Therefore, the index matrix of fake answer is concatenated with index matrix of question as fake pairs. Afterward, a linear model is adopted to reduce the dimensionality of the input matrix and sentence embedding. Then, the output of linear model is concatenated with position encoding matrix to serve as the input matrix for the first layer of the encoder. The output of the last layer of the encoder is fed to a classifier which is a linear network. This network has two scores outputs: the reality or fakeness of a given answer. In the inference phase, we only have generator module while the discriminator model is removed.

4. RESULTS

To demonstrate the performance of the generative Chatbot model, this section presents the details of the dataset and the results in comparison with other methods. First, the implementation details are explained. Then, two datasets used for the evaluation, are briefly introduced, followed by the used evaluation metrics. Finally, the results of the proposed architecture are compared with the state-of-the-art models.

4.1. Implementation details

Evaluations were carried out on a Core (TM) i5-12600K with 128GB RAM in Microsoft Windows 11 operating system and Python software with NVIDIA GeForce RTX 3090. The PyTorch library was used to implement the model. The implementation parameters are listed in Table 1.

Table 1. Details of the parameters used in proposed architecture

Parameters	value	Parameters	value
Learning rate	0.00005	Number of layers	8
Batch size	64	Dataset split ration for test data	20%
Epoch numbers	400	Sentence Max Length	30
Processing way	GPU	Number of Heads	16
Dropout	0.5	BERT features size	768

4.2. Datasets

Two datasets, Cornell Movie Dialogs Corpus and Chit-Chat, are employed to evaluate the proposed model. Cornell Dataset contains a large metadata-rich collection of fictional conversations extracted from raw movie scripts. This dataset includes 220,579 conversational exchanges between 10,292 pairs of movie characters from 617 movies and a total of 304,713

utterances. The Chit-Chat dataset also encompasses 7,168 conversations from 258,145 utterances and 1,315 unique participants. This dataset was from the Chit-Chat Challenge of the BYU Perception, Control, and Cognition Laboratory.

4.3. Evaluation metrics

The proposed model is evaluated using BiLingual Evaluation Understudy (BLEU), Recall-Oriented Understudy for Gisting Evaluation (ROUGE-L), and F-measure. BLEU was originally developed for machine translation evaluation. In this measure, the degree of overlap between the generated sentence and the ground truth sentence is obtained based on n-gram. Unlike BLEU which focuses on precision, ROUGE-L is concentrated on the recall as it needs to calculate the similarity of the generated sentence and the ground truth. F-measure is a valuable metric for evaluating the performance of classification algorithms, which can be defined as a compromise between recall and precision.

4.4. Experimental results

Here, the effectiveness of the proposed architecture is presented on the Cornell Movie Dialogs Corpus and Chit-Chat datasets using the BLEU4, ROUGE-L, and F-measure metrics (See Table 2). As the results of this table confirm, the proposed model has a better performance on the Chit-Chat dataset. This comes from this point that the Chit-Chat dataset is based on chat and conversation while the Cornell dataset relies on movie dialogues.

Table 2. Performance of proposed architecture in terms of different metrics

Dataset	BLEU4	ROUGE-L	F-measure
Cornell	71.06	81.83	62.2
Chit-Chat	96.3	96.5	98.91

Several state-of-the-art approaches, including S2S+Attention(Shu et al., 2022), BERT(Shu et al., 2022), Retrieval-augmented generation (RAG) (Patrick Lewis, 2020), Open Domain Response Generation (OPRG) (Shu et al., 2022), BILSTM and Deep Transfer learning-based Text Generation (DTGEN) (Rao K Yogeswara & Rao, 2022), are used to compare to the proposed model with ROUGE-L metric on Cornell dataset (Table 3). According to Table 3, the proposed model outperforms all models due to the extracting richer features by transformer as well as learning data distribution by GAN.

Table 3. The comparison results of the proposed model with the different methods on Cornell dataset using ROUGE-L metric.

Method	Approach	ROUGE-L	Year
S2S+Attention	Seq2Seq	0.337	-
BERT	BERT +LSTM	0.399	-
RAG	Retrieval model+ BERT	0.427	2020
OPRG	Retrieval model+ Transformer	0.452	2022
BILSTM	Seq2Seq	0.74	-
DTGEN	Transformer + Seq2Seq	0.815	2022
Proposed	GAN+ Transformer	0.818	-

Table 4 shows the comparison results of the proposed model with the MLE(Tuan & Lee, 2019), SeqGAN(L. Yu et al., 2017), and StepGAN(Tuan & Lee, 2019) in Chit-Chat dataset using the BLEU4 metrics. The approaches used for comparison employ GAN model for generating sequence data like text. According to Table 4, the proposed model outperforms all approaches using the BLEU-4 metric in the Chit-Chat dataset due to using an extended hybrid of transformer model and cWGAN methods. Compared to the state-of-art methods, the proposed model takes the advantage of data distribution learning in answer generation to modify all evaluation metrics. According to the experimental results, the proposed model can generate more accurate and semantically relevant answers for the Chatbot dialogue.

Table 4. The comparison results of the proposed model with the different methods on Chi-Chat dataset using BLEU-4 metric.

Method	Approach	BLEU-4	Year	
MLE	Seq2Seq	0.25	-	
SeqGAN	GAN +MC	0.26	2017	
StepGAN	GAN +QN	0.23	2019	
Proposed	GAN+ Transformer	0.96	-	

For investigating the generated answers of the proposed Chatbot, various questions from different domains were asked from the proposed Chatbot. Table 5 shows the results of the Chatbot trained using Cornell dataset in two areas of greeting and general questions and conversations. In addition, Table 6 shows the results of the proposed Chatbot trained on the Chit-Chat dataset in two areas of greeting and general questions and conversation.

Table 5. Some examples of the generated answers using the proposed Chatbot on Cornell dataset.

		Greeting and General question			
User input		Real answer		Chatbot answer	
hello Mr. parker how are you?		hello Jo thanks you		hello Ju thank you	
I heard that was you good?		well, it was nice seeing y	ou	well, it was good seeing you	
how much your goanna ta	lkes?	I do not know how much do yo	ou want I do not know how much do yo		
hey		hey what are you doing righ	t now	hi what are you doing right now	
how many girlfriends did you	u have?	I do not know exactly		I do not know truly	
feeling better?		I just cannot believe it		I actually not believe it	
		General Conversation			
User input		Real answer		Chatbot answer	
is this for like real?		unfortunately, yes		respect yes	
how do you know that?		she told me, he was in ja	il	he told me, maybe they have in jail	
I tried talking to her at the mine it did not work		then try again		then go again	
I think you are lying that has that is what kind of problem		what are you saying		what are you saying	
oh, I put a few games on for your daughter I hope you do not mind		of course, not		sure, course not	
I am not playing a game now		yes, you are playing word games		yes, you are playing cook games	
there is no other way?		but there is another entrance to	this place there is another answer to this		
I have changed my min	nd	you cannot change your mind	nd fully you should not change your mi		
ney ben there were a couple of guys	looking for you	what did they look like		what did they look like	
Table 6. Some ex	xamples of the ge	nerated answers using the propose	d Chatbot o	on Chit-Chat dataset.	
	Greetin	g and General question			
User input		Real answer		Chatbot answer	
can you hear me?		Hello there		Hello there	
how are you today?	I am gr	eat thanks for asking me		I am great thanks for asking	
can you talk with me?	sur	rre, ask me a question sure, ask me a question		sure, ask me a question	
what age are you?	I am a b	ot so I do not have an age	I	am a bot so I do not have an age	
I am leaving now		goodbye goodbye		goodbye	
	Ge	neral Conversation			
User input		Real answer	Chatbot	answer	
what kind of thing can you respond to?	I am here to	help answer your questions	I am	here to help answer your questions	
how many sisters do you have? do you have a gender identity?		family the same way humans do igital, I do not actually have a		have a family the same way humans do m digital I do not actually have a gende	
		gender	since I a	in digital 1 do not actually have a gend	

we think in very different ways but it has it is

safe to say you are smarter

we think in very different ways but it has it is safe

to say you are smarter

do you think you are the most

intelligent

5. DISCUSSION

The main challenge of most recent Chatbot approaches is their sequential nature, which is led to less accurate results. Proposed model resolves this challenge by using a hybrid of cWGAN and transformer model. According to the experimental results, our model can generate more accurate and semantically relevant answers for the Chatbot dialogue. While the proposed model benefits from the answer distribution learning, the generated answers have little diversity. This is due to the nature of the dataset used in the training phase. Both datasets lack of multiple answers for each question. Here, we discuss the proposed model from three perspectives as follows:

• Analysis of generator pretraining: Before the adversarial training of the proposed model, the generator model is separately trained by a transformer model. The point is that pretraining of the generator model has a direct impact on the whole performance of the proposed model. So, it is important that how many epochs we need to use in the pretraining phase. In the best try, 200 epochs are used for training the transformer as a pretrained model of the generator. After that, the proposed model is trained with adversarial learning in 400 epochs. Based on Table 7, combining the generator pretraining with the adversarial learning improves the efficiency of the Chatbot in all metrics for Cornell dataset.

Table 7. Performance of the p	roposed model with different	configurations on Cornell dataset.
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Type of model	BLEU4	ROUGE-L	F-measure
Only generator pretraining	67.72	78.9	53.16
Only Adversarial	68.99	80.12	57.36
Combine generator pretraining with Adversarial	71.06	81.83	62.02

• Analysis of loss function: Loss function plays a key role in the performance of deep models. In this way, the loss function of generator pretraining is first described. Then, the loss functions of generator and discriminator in adversarial phase are considered and analyzed. In the generator pretraining, MLE is used as the loss function for transformer model employed in generator pretraining phase. As shown in Fig. 5 and Fig. 6, the training and validation losses of generator pretraining model converged in epoch 200 for both Cornell and Chit-Chat datasets.

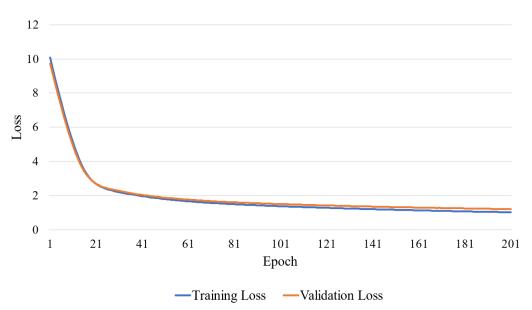


Fig. 5. Generator pretraining loss in Cornell dataset

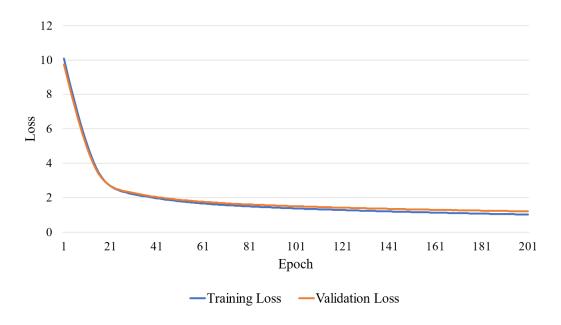


Fig. 6. Generator pretraining loss in Chit-Chat dataset.

In the adversarial training phase, the WGAN is used instead of GAN model. WGAN uses a new cost function using Wasserstein distance which has a smoother gradient and trains regardless of the implementation of the generator. Wasserstein distance is calculated by Eq. (9):

$$W(P_{real}, P_{fake}) = \sup E_{x \sim P_{real}}[f(x)] - E_{x \sim P_{fake}}[f(x)]$$
 (9)

where sup is the least upper bound, f shows a Lipschitz function, and x denotes a real or fake answer. To calculate the Wasserstein distance, we just need to find a Lipschitz function. We can build a deep network to learn it. This network is similar to the discriminator, but it has no Sigmoid function and outputs a scalar score rather than the probability. This score can be interpreted as the realness of the input data and considered as critic. The Wasserstein loss function can be summarized for generator and critic (discriminator) in proposed model in Eq. (10) and Eq. (11), respectively:

$$GLoss = -[avg\ critic\ score\ on\ fake\ answer]$$
 (10)
 $CLoss = [avg\ critic\ score\ on\ real\ answer] - [avg\ critic\ score\ on\ fake\ answer]$ (11)

According to Fig. 7, in Cornell dataset, the loss function of the generator is first low due to having a generator pretraining model. After a few epochs, the loss function increases followed by a smooth decrease to less than its initial value. This represents the learning of data distribution in the adversarial learning. Moreover, the discriminator has a low loss function at the beginning. Upon learning the data distribution by the generator and generating better fake data, the value of the discriminator loss function smoothly increases. Eventually, both generator and discriminator loss functions are converged.

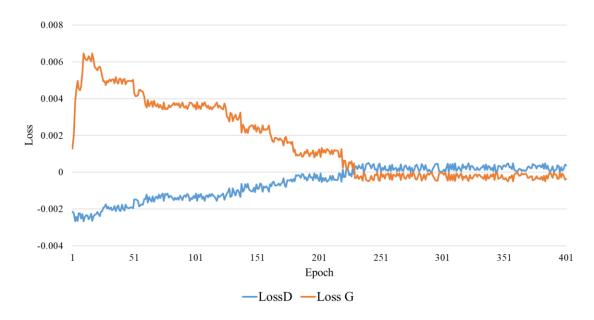


Fig. 7. Generator (LossG) and discriminator (LossD) loss in Cornell dataset.

According to Fig. 8, in Chit-Chat dataset, the loss function in the generator is initialized with a positive value close to zero, due to its generator pretraining model. After several epochs, the loss function increases followed by a slow degradation to close-zero values. Furthermore, the discriminator initially has a negative loss function, which gradually increases to close-zero values by learning the data distribution. Finally, both generator and discriminator loss functions converge to zero.

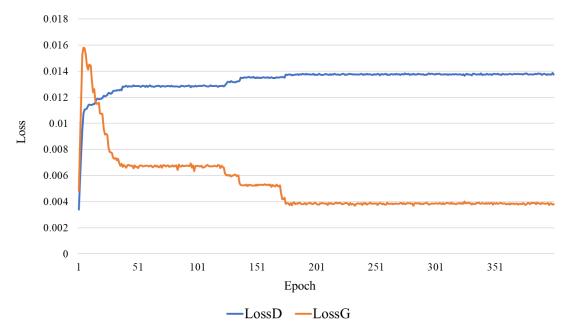


Fig. 8. Generator (LossG) and discriminator (LossD) loss in Chit-Chat dataset.

6. CONCLUSION AND FUTURE TREND

In this paper, we proposed a novel end-to-end model using the combination of the cWGAN and transformer model. The proposed model consists of two networks: Generator and Discriminator. Generator is a full Transformer model and Discriminator includes only the encoder part of a transformer model followed by a classifier. We evaluated the proposed model on two datasets using different evaluation metrics. The results confirmed the superiority of the proposed model compared to state-of-the-art approaches according to BLEU4, ROUGE-L and F-measure metrics. Relying on the WGAN capabilities as well as the transformer model, the proposed model generates accurate, semantically relevant, and human-like answers. Future works can add reinforcement leaning to increase semantic relations between question and answer in various domains.

DECLARATIONS

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Data Availability

The datasets analyzed during the current study are available on these web pages:

Cornell_Movie-Dialogs_Corpus: https://www.cs.cornell.edu/~cristian/Cornell_Movie-Dialogs_Corpus.html

Chit-Chat dataset: https://pypi.org/project/chitchat-dataset/

Declaration of competing interest

The authors certify that they have no conflict of interest.

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