Posterior-GAN: Towards Informative and Coherent Response Generation with Posterior Generative Adversarial Network

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Introduction

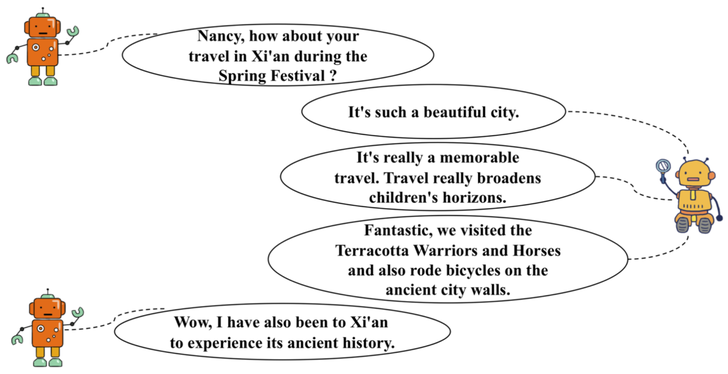

Figure 1: Dialogue examples with various responses regarding informativeness and coherence.

In DailyDialog (Li et al. 2017b) corpus, at least 13% utterances contain more than one response (Csaky, Purgai, and Recski 2019). In another public available corpus OpenSubtitles, 113K sentences contain the sequence "I don't know" in the training set (Li et al. 2016a). Table 1 illustrates our motivations. ***Intuitively, a high-quality response not only responds to the given query but also links up to the future conversations.***

- ***We identify*** an unexplored type of metadata, ***query- response-future turn triples***, for response generation. Compared to general query-response tuples, the triples help the model use bidirectional information to learn the response generation in training.

Method

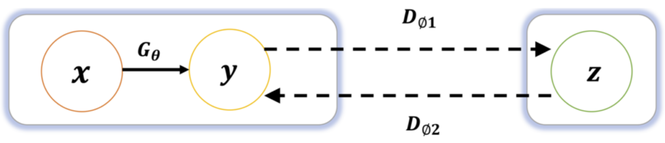

Figure 2: Illustration of Posterior-GAN. Brown for the query, yellow for the current response, and green for the future turn. G_θ represent generator. $D_{\phi 1}$ and $D_{\phi 2}$ represent forward and backward generative discriminator respectively.

- ***We propose*** a novel encoder-decoder based generative adversarial learning framework, ***Posterior-GAN***, to facilitate the query-response-future turn modeling, which induces the generated response to be informative and coherent by constructing ***two generative discriminators, a forward one and a backward one respectively.***

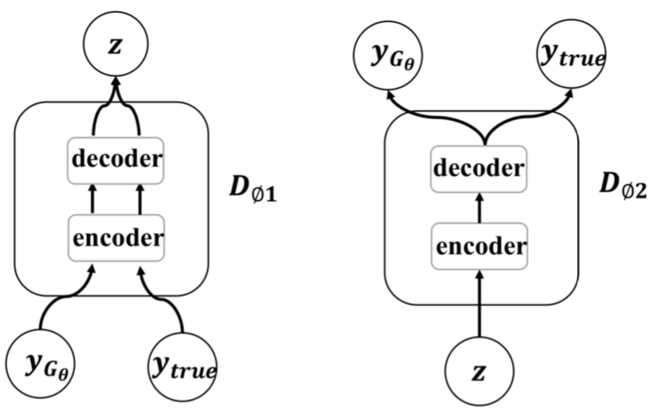

Figure 3: Illustration of forward and backward generative discriminators. y_{true} represents the real-world response. y_{G_θ} represents response generated by generator G_θ. z represents the true future turn. $D_{\phi 1}$ and $D_{\phi 2}$ represent forward and backward generative discriminator respectively. The forward generative discriminator produces the future turn z based on the generated response y_{G_θ} or the real-world response y_{true}. The backward generative discriminator predicts the generated response y_{G_θ} or the real-world response y_{true} based on the future turn z.

Forward Generative Discriminator ($D_{\phi 1}$)

$$R_1(y) = \frac{1}{K}\sum_{k=1}^{K} \log D_{\phi 1}(z_k | y, z_{<k})$$

$$J(\phi 1) = -\left(E_{y_{true}\sim p_{\text{data}}}[R_1(y_{true})] - E_{y_{G_\theta}\sim G_\theta}[R_1(y_{G_\theta})]\right)$$

Backward Generative Discriminator ($D_{\phi 2}$)

$$R_2(y_m) = -\log D_{\phi 2}(y_m | z, y_{<m})$$

$$J(\phi 2) = -\left(E_{y_{true}\sim p_{\text{data}}}[R_2(y_{true})] - E_{y_{G_\theta}\sim G_\theta}[R_2(y_{G_\theta})]\right)$$

Training Objective (G_θ)

$$J(\theta) = E_{y_{G_\theta}\sim G_\theta}\left(Q^{G_\theta}_{D_{\phi 1}, D_{\phi 2}}(x, y_{G_\theta}, z)\right)$$

$$\nabla_\theta J(\theta) \simeq \sum_{n=1}^{N}\sum_{m=1}^{L} R^n_m \nabla_\theta \log G_\theta(y^n_m | x, y^n_{<m})$$

$$R^n_m = \sum_{i=m}^{L} \lambda^i (R1(y^n) - MIN(R1)) R2(y^n_i)$$

Automatic Evaluation

DailyDialog							
Models	Dist-1	Dist-2	Dist-3	BLEU	Greedy	Average	Extrema
Seq2Seq-att	0.0277	0.1625	0.3868	0.1878	0.4825	0.5993	0.3080
Adver-REGS	0.0541	0.2877	0.5542	0.2116	0.4857	0.6215	0.3542
DP-GAN	0.0656	0.3088	0.5630	0.1992	0.4749	0.6144	0.3409
Posterior-GAN(F)	0.0659	0.2995	0.5578	0.2067	0.4754	0.6218	0.3343
Posterior-GAN(B)	0.0578	0.2950	0.5545	0.2130	0.4818	0.6220	0.3442
Posterior-GAN(A)	**0.0678**	**0.3549**	**0.6006**	**0.2183**	**0.4916**	**0.6260**	**0.3544**
OpenSubtitles (OSDb)							
Models	Dist-1	Dist-2	Dist-3	BLEU	Greedy	Average	Extrema
Seq2Seq-att	0.0016	0.0064	0.0150	0.1405	0.3900	0.4527	0.2243
Adver-REGS	0.0041	0.0136	0.0248	0.1609	0.4655	0.5523	0.2645
DP-GAN	0.0044	0.0143	0.0262	0.1484	0.4600	0.5509	0.2589
Posterior-GAN(F)	0.0049	0.0170	0.0322	0.1733	0.4753	0.5708	0.2573
Posterior-GAN(B)	0.0045	0.0148	0.0321	0.1756	0.4947	0.6217	0.2690
Posterior-GAN(A)	**0.0049**	**0.0180**	**0.0330**	**0.1955**	**0.4973**	**0.6346**	**0.2778**

Table 1: The automatic metrics evaluation results. Higher is better. "(F)", "(B)" and "(A)" represent Posterior-GAN with a forward generative discriminator, a backward generative discriminator and both two discriminators, respectively.

Human Evaluation

DailyDialog		
Models	Coherence	Informativeness
Seq2Seq-att	3.8550	3.8933
Adver-REGS	3.4717	3.3683
DP-GAN	3.4400	3.2350
Posterior-GAN	**3.2883**	**3.2250**
OpenSubtitles (OSDb)		
Models	Coherence	Informativeness
Seq2Seq-att	3.8549	3.6952
Adver-REGS	4.0365	4.0432
DP-GAN	3.7638	3.8088
Posterior-GAN	**3.4806**	**3.4567**

Table 2: The human evaluation results. We calculate each score by averaging the rank of each model in corresponding metrics. Lower is better.

Automatic Analysis

Models	Averaged Greedy Matching for y and (x/z)	Frequency-based Similarity
Seq2Seq-att	0.5942	0.5478
Adver-REGS	0.6403	0.7165
DP-GAN	0.6514	0.6739
Posterior-GAN	**0.7276**	**0.7460**

Table 4: The results of Embedding-based Averaged Greedy Matching for response y with the given query x and future conversations z, which reflects the coherence of the response, and Frequency-based Similarity, which illustrates the informativeness of the response.

Case Study

Query: I need some flowers for my girlfriend. // No problem. Would you like some artificial carnations? // Oh, no. Carnations are not very elegant. Artificial flowers have no passion.
Seq2Seq-att: How how how much how much? I'd like. **Adver-REGS:** How did you want to spend? How much did. **DP-GAN:** How long did you want to spend? They was. **Posterior-GAN:** How much did you want to spend? It's very expensive.
Future turn: Money is no object. // Our most elegant flower is golden lily. // I will take ten.
Query: How may I help you today? // I need to open a second account. // What kind of account would you like to open?
Seq2Seq-att: I want to need to deposit to deposit. **Adver-REGS:** I need to open the savings account. **DP-GAN:** I want to open cash at cash. i need **Posterior-GAN:** I need to transfer a savings account account.
Future turn: Do you have another account with us? // I sure do. // Would you like to transfer money from that account into your new one?
Query: What's your case? // I was pulled over for running a red light, but I never did. // Do you believe that the officer lied?
Seq2Seq-att: Well, you was so in that. **Adver-REGS:** We never like to lie. **DP-GAN:** Because I've seen them. **Posterior-GAN:** Of course, you can't know that.
Future turn: Your license plate was caught on camera? // A picture of my license plate was never taken. // Since there is no picture of your license plate on record, I'm going to let you go.

Table 3: The responses generated by the proposed models and comparison models on DailyDialog.

Visualization

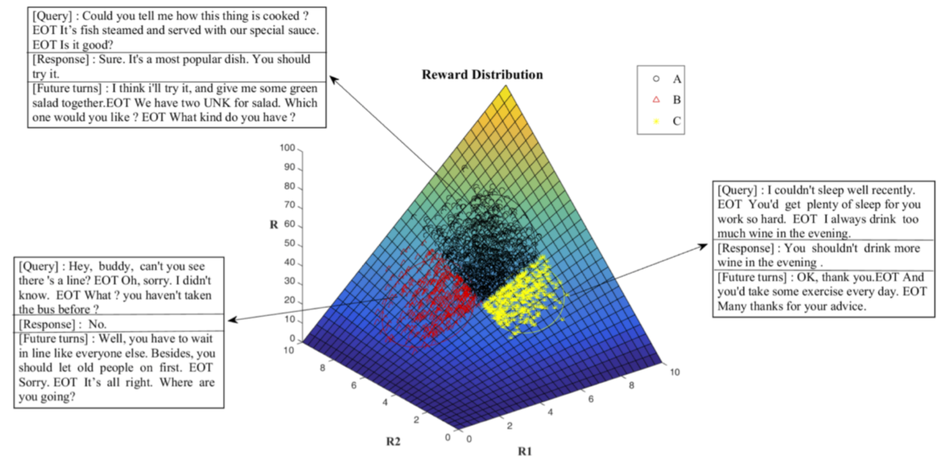

Figure 4: The distribution of sample rewards calculated by the forward generative discriminator $R1$ and the backward generative discriminator $R2$ on DailyDialog. R is the combination of $R1$ and $R2$. We use three regions A, B, and C to represent three types of samples. Samples in region A gain high rewards in both discriminators. Samples in region B achieve higher reward in the backward generative discriminator than in the forward one, while Samples in region C obtain higher reward in the forward generative discriminator than in the backward one.

Experiments

- ***We perform*** detailed experiments to demonstrate the effectiveness of the proposed framework and verifies the ability of bidirectional generative discriminators on assessing the quality of response.
- **Datasets**: DailyDialog and Opensubtitles
- **Baselines**: Seq2Seq-att, Adver-REGS, and DP-GAN
- **Metrics**: BLEU, Embedding-based Metrics (Embedding Average, Embedding Greedy and Embedding Extrema), and Distinct (Dist-{1,2,3})

Conclusion

- We propose ***the query-response-future turn triples*** instead of the conventional query-response pairs for neural dialog response generation.
- To facilitate the triple modeling and alleviate the overproducing of generic and repetitive responses problem, ***Posterior-GAN*** that consists of a forward and a backward encoder-decoder based generative discriminator is further introduced.
- Augmented with future conversations and Posterior-GAN in training, detailed experiments and analysis demonstrate that ***the model effectively generates more informative and coherent responses.***