Generating Informative and Diverse Conversational Responses via Adversarial Information Maximization

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Abstract

Responses generated by neural conversational models tend to lack informativeness and diversity. We present Adversarial Information Maximization (AIM), an adversarial learning strategy that addresses these two related but distinct problems. To foster response diversity, we leverage adversarial training that allows distributional matching of synthetic and real responses. To improve informativeness, our framework explicitly optimizes a variational lower bound on pairwise mutual information between query and response. Empirical results from automatic and human evaluations demonstrate that our methods significantly boost informativeness and diversity.

1 Introduction

Neural conversational models are effective in generating coherent and relevant responses [1, 2, 3, 4, etc.]. However, the maximum-likelihood objective commonly used in these neural models fosters generation of responses that *average out* the responses in the training data, resulting in the production of safe and bland responses [5].

We argue that this problem is in fact twofold. The responses of a system may be diverse but uninformative (e.g.,"I don't know", "I haven't a clue", "I haven't the foggiest", "I couldn't tell you"), and conversely informative but not diverse (e.g., always giving the same generic responses such as "I like music", but never "I like jazz"). A major challenge, then, is to strike the right balance between informativeness and diversity. On the one hand, we seek informative responses that are relevant and fully address the input query. Mathematically, this can be measured via Mutual Information (MI) [5], by computing the reduction in uncertainty about the query given the response. On the other hand, diversity can help produce responses that are more varied and unpredictable, which contributes to making conversations seem more natural and human-like.

The MI approach of [5] conflated the problems of producing responses that are informative and diverse, and subsequent work has not attempted to address the distinction explicitly. Researchers have applied Generative Adversarial Networks (GANs) [6] to neural response generation [7, 8]. The equilibrium for the GAN objective is achieved when the synthetic data distribution matches the real data distribution. Consequently, the adversarial objective discourages generating responses that demonstrate less variation than human responses. However, while GANs help reduce the level of blandness, the technique was not developed for the purpose of explicitly improving either informativeness or diversity.

We propose a new architecture for dialog generation, Adversarial Information Maximization (AIM), for training end-to-end neural response generation models that produce *informative* and *diverse* conversational responses. Our approach exploits adversarial training to encourage diversity, and explicitly maximizes a Variational Information Maximization Objective (VIMO) [9, 10] to produce

informative responses. To leverage VIMO, we train a backward model that generates source from target. The backward model guides the forward model (from source to target) to generate relevant responses during training, thus providing a principled approach to mutual information maximization. This work is the first application of a variational mutual information objective in text generation.

To alleviate the instability in training GAN models, we propose an embedding-based discriminator, rather than the binary classifier of traditional GANs. To reduce the variance of gradient estimation, we leverage a deterministic policy gradient algorithm [11] and employ the discrete approximation strategy in [12]. We also employ a dual adversarial objective inspired by [13, 14, 15], which composes both source-to-target (forward) and target-to-source (backward) objectives. We demonstrate that this forward-backward model can work synergistically with the variational information maximization loss. The effectiveness of our approach is validated empirically on two social media datasets.

2 Method

2.1 Model overview

Let $\mathcal{D} = \{(S_i, T_i)\}_{i=1}^N$ denote a set of N single-turn conversations, where S_i represents a query (*i.e.*, source), T_i is the response to S_i (*i.e.*, target). We aim to learn a generative model $p_\theta(T|S)$ that produces both *informative* and *diverse* responses for arbitrary input queries.

To achieve this, we propose the Adversarial Information Maximization (AIM), illustrated in Figure 1, where (i) adversarial training is employed to learn the conditional distribution $p_\theta(T|S)$, so as to improve the *diversity* of generated responses over standard maximum likelihood training, and (ii) variational information maximization is adopted to regularize the adversarial learning process and explicitly maximize mutual information to boost the *informativeness* of generated responses.
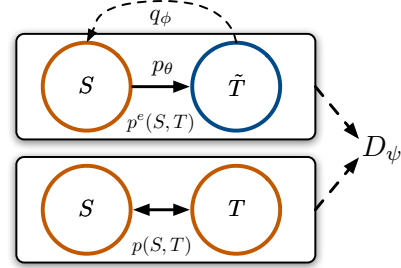

Figure 1: Overview of the Adversarial Information Maximization (AIM) model for neural response generation. Orange for real data, and blue for generated fake response.

In order to perform adversarial training, a discriminator $D_\psi(\cdot, \cdot)$ is used to distinguish real query-response pairs (S, T) from generated synthetic pairs $(S, \tilde{T})$, where $\tilde{T}$ is synthesized from $p_\theta(T|S)$ given the query S. In order to evaluate the mutual information between S and $\tilde{T}$, a *backward proposal network* $q_\phi(S|T)$ calculates a variational lower bound over the mutual information. In summary, the objective of AIM is defined as following

$$\min_\psi \max_{\theta, \phi} \mathcal{L}_{\text{AIM}}(\theta, \phi, \psi) = \mathcal{L}_{\text{GAN}}(\theta, \psi) + \lambda \cdot \mathcal{L}_{\text{MI}}(\theta, \phi), \qquad (1)$$

where $\mathcal{L}_{\text{GAN}}(\theta, \psi)$ represents the objective that accounts for adversarial learning, while $\mathcal{L}_{\text{MI}}(\theta, \phi)$ denotes the regularization term corresponding to the mutual information, and λ is a hyperparameter that balances these two parts.

2.2 Diversity-encouraging objective

Generator The conditional generator $p_\theta(T|S)$ that produces neural response $T = (y_1, \ldots, y_n)$ given the source sentence $S = (x_1, \ldots, x_m)$ and a random noise vector Z is shown in Figure 2.

Specifically, a 3-layer convolutional neural network (CNN) is employed to encode the source sentence S into a fixed-length hidden vector H_0. A random noise vector

Figure 2: Illustration of the CNN-LSTM conditional generator.

Z with the same dimension of H_0 is then added to H_0 element-wisely. This is followed by a series of long short-term memory (LSTM) units as decoder. In our model, the t-th LSTM unit takes the previously generated word y_{t-1}, hidden state H_{t-1}, H_0 and Z as input, and generates the next word y_t that maximizes the probability over the vocabulary set. However, the *argmax* operation is

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used, instead of sampling from a multinomial distribution as in the standard LSTM. Thus, all the randomness during the generation is clamped into the noise vector Z, and the reparameterization trick [16] can be used (see Eqn. (4)). However, the *argmax* operation is not differentiable, thus no gradient can be backpropagated through y_t. Instead, we adopt the soft-argmax approximation [12] below:

$$\texttt{onehot}(y_t) \approx \texttt{softmax}\Big((V \cdot H_t) \cdot 1/\tau\Big), \tag{2}$$

where V is a weight matrix used for computing a distribution over words. When the temperature $\tau \to 0$, the argmax operation is exactly recovered [12], however the gradient will vanish. In practice, τ should be selected to balance the approximation bias and the magnitude of gradient variance, which scales up nearly quadratically with $1/\tau$. Note that when $\tau = 1$ this recovers the setting in [8]. However, we empirically found that using a small τ would result in accumulated ambiguity when generating words in our experiment.

Discriminator For the *discriminator*, we adopt a novel approach inspired by the Deep Semantic Similarity Model (DSSM) [17]. As shown in Figure 3, the source sentence S, the synthetic response $\tilde{T}$ and the human response T are all projected to an embedding space with fixed dimensionality via different CNNs[1]. The embedding network for S is denoted as W_s, while $\tilde{T}$ and T share a network W_t. Given these embeddings, the cosine similarities of $W_s(S)$ versus $W_t(\tilde{T})$ and $W_t(T)$ are computed, denoted as $D_\psi(T, S)$ and $D_\psi(\tilde{T}, S)$, respectively. ψ represents all the parameters in the discriminator.
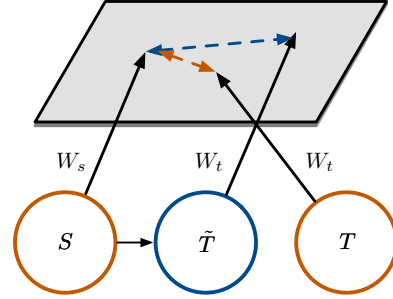

Figure 3: Embedding-based sentence discrimination.

We empirically found that separate embedding for each sentence yields better performance, comparing to concatenating (S, T) pairs. Presumably, mapping (S, T) pairs to the embedding space requires the embedding network to capture the cross-sentence interaction features of how relevant the response is to the source. Mapping them separately to the embedding space would divide the tasks into a sentence feature extraction sub-task and a sentence feature matching sub-task, rather than entangle them together. Thus the former might be slightly easier to train.

Objective The objective of our generator is to minimize the difference between $D_\psi(T, S)$ and $D_\psi(\tilde{T}, S)$. Conversely, the discriminator tries to maximize such difference. The $\mathcal{L}_{\text{GAN}}$ part in Eqn. (1) is specified as

$$\mathcal{L}_{\text{GAN}}(\theta, \psi) = -\mathbb{E}_{T, \tilde{T}, S}\Big[f\Big(D_\psi(T, S) - D_\psi(\tilde{T}, S)\Big)\Big], \tag{3}$$

where $f(x) \triangleq 2\tanh^{-1}(x)$ scales the difference to deliver more smooth gradients.

Note that Eqn. (3) is conceptually related to [7] in which the discriminator loss is introduced to provide sequence-level training signals. Specifically, the discriminator is responsible for assessing both the *genuineness* of a response and the *relevance* to its corresponding source. The discriminator employed in [7] evaluates a source-target pair by operations like concatenation. However, our approach explicitly structures the discriminator as comparing the embeddings using cosine similarity metrics, avoiding learning a neural network to match correspondence, which could be difficult. Presumably our discriminator delivers more direct updating signal by explicitly defining how the response is related to the source.

The objective in Eqn. (3) also resembles Wasserstein GAN (WGAN) [19] in that without the monotonous scaling function f, the discriminator D_ψ can be perceived as the *critic* in WGAN with embedding-structured regularization. See details in the Supplementary Material.

To backpropagate the learning signal from the discriminator D_ψ to the generator $p_\theta(T|S)$, instead of using the standard policy gradient as in [7], we consider a novel approach related to deterministic

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[1]Note that encoders based on RNN or pure word embedding [18] are also possible, nevertheless we limit our choice to CNN in this paper.

policy gradient (DPG) [11], which estimates the gradient as below:

$$\nabla_\theta \mathbb{E}_{p(\tilde{T}|S,Z)} D_\psi(\tilde{T}, S) = \mathbb{E}_{p(Z)} \nabla_{\tilde{T}} D_\psi(\tilde{T}, S) \nabla_\theta \tilde{T}(S, Z) , \tag{4}$$

where the expectation in Eqn. (4) is approximated by Monte Carlo approximation. Note that $\nabla_\theta \tilde{T}(S, Z)$ can be calculated because we use the *soft-argmax* approximation as in (2). The randomness in [7] comes from the softmax-multinomial sampling in each *local* time step; while in our approach, $\tilde{T}$ is a deterministic function of S and Z, therefore, the randomness is *global* and separated out from the deterministic propagation, which resembles the reparameterization trick used in variational autoencoder [16]. This separation of randomness allows gradients to deterministically backpropagated through deterministic nodes rather than stochastic nodes. Consequently, the variance of gradient estimation is largely reduced.

2.3 Information-promoting objective

We further seek to explicitly boost the MI between S and $\tilde{T}$, with the aim of improving the *informativeness* of generated responses. Intuitively, maximizing MI allows the model to generate responses that are more specific to the source, while generic responses are largely down-weighted.

Denoting the unknown oracle joint distribution as $p(S, T)$, we aim to find an *encoder joint distribution* $p^e(S, T) = p_\theta(T|S)p(S)$ by learning a forward model $p_\theta(T|S)$, such that $p^e(S, T)$ approximates $p(S, T)$, while the mutual information under $p^e(S, T)$ remains high. See Figure 1 for illustration.

Empirical success has been achieved in [5] for mutual information maximization. However their approach is limited by the fact that the MI-prompting objective is used only during testing time, while the training procedure remains the same as the standard maximum likelihood training. Consequently, during training the model is not explicitly specified for maximizing pertinent information. The MI objective merely provides a criterion for reweighing existing responses, rather than asking the generator to produce more interesting possible responses. Further, the hyperparameter that balances the likelihood and anti-likelihood/reverse-likelihood terms is manually selected from $(0, 1)$, which deviates from the actual MI objective, thus making the setup less principled.

Here, we consider explicitly maximizing mutual information $I_{p^e}(S, T) \triangleq \mathbb{E}_{p^e(S,T)} \log \frac{p^e(S,T)}{p(S)p^e(T)}$ over $p^e(S, T)$ during training. However, $I_{p^e}(S, T)$ is intractable to directly optimize. To provide a principled approach to maximizing MI, we adopt *variational information maximization* [9, 10]. The mutual information $I_{p^e}(S, T)$ under the encoder joint distribution $p^e(S, T)$ is

$$
\begin{aligned}
I_{p^e}(S, T) &\triangleq \mathbb{E}_{p^e(S,T)} \log \frac{p^e(S,T)}{p(S)p^e(T)} \\
&= H(S) + \mathbb{E}_{p^e(T)} D_{KL}(p^e(S|T), q_\phi(S|T)) + \mathbb{E}_{p^e(S,T)} \log q_\phi(S|T) \\
&\geqslant \mathbb{E}_{p(S)} \mathbb{E}_{p_\theta(T|S)} \log q_\phi(S|T) \triangleq \mathcal{L}_{\text{MI}}(\theta, \phi) ,
\end{aligned} \tag{5}
$$

where $H(\cdot)$ denotes the entropy of a random variable, and $D_{KL}(\cdot, \cdot)$ denotes the KL divergence between two distributions. $q_\phi(S|T)$ is a *backward proposal network* that approximates the unknown $p^e(S|T)$. For this backward model $q_\phi(S|T)$, we use the same CNN-LSTM architecture as the forward model [20]. We denote the MI objective $\mathbb{E}_{p(S)} \mathbb{E}_{p_\theta(T|S)} \log q_\phi(S|T)$ as $\mathcal{L}_{\text{MI}}(\theta, \phi)$, as used in Eqn. (1).

The gradient of $\mathcal{L}_{\text{MI}}(\theta, \phi)$ w.r.t. θ can be approximated by Monte Carlo samples using the REINFORCE policy gradient method [21]

$$\nabla_\theta \mathcal{L}_{\text{MI}}(\theta, \phi) = \mathbb{E}_{p_\theta(T|S)}[\log q_\phi(S|T) - b] \cdot \nabla_\theta \log p_\theta(T|S) ,$$

$$\nabla_\phi \mathcal{L}_{\text{MI}}(\theta, \phi) = \mathbb{E}_{p_\theta(T|S)} \nabla_\theta \log q_\phi(S|T) , \tag{6}$$

where b is denoted as a *baseline*. Here we choose a simple empirical average for b [21]. Note that more sophisticated baselines based on neural adaptation [22] or self-critic [23] can be also employed. We complement the policy gradient objective with small proportion of likelihood-maximization loss, which was shown to stabilize the training as in [24].

As an alternative to the REINFORCE approach used in (6), we also considered using the same DPG-like approach as in (4) for
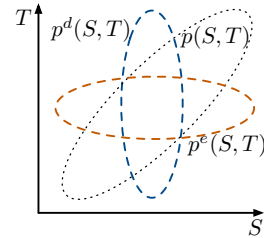

Figure 4: Joint distribution matching of the query-response pairs. Details explained in Section 2.4.

approximated gradient calculation. Compared to the REINFORCE
approach, the DPG-like method yields lower variance, however is less memory efficient in this case. This is because the $\mathcal{L}_{\text{MI}}(\theta, \phi)$ objective requires the gradient first back-propagated to synthetic text through all backward LSTM nodes, then from synthetic text back-propagated to all forward LSTM nodes, where both steps are densely connected. Hence, the REINFORCE approach is used in this part.

2.4 Dual Adversarial Learning

One issue for the above approach is that learning an appropriate $q_\phi(S|T)$ may be difficult. Similar to the forward model, this backward model $q_\phi(S|T)$ may also tend to be "bland" in generating source from the target. As illustrated in Figure 4, supposing that we define a *decoder joint distribution* $p^d(S, T) = q_\phi(S|T)p(T)$, this distribution tends to be flat along T axis (*i.e.*, tending to generate the same source giving different target inputs). Similarly, $p^e(S, T)$ tends to be flat along S axis as well.

To solve this issue, inspired by recent work leveraging "cycle consistency" for image generation [13, 25], we implement a dual objective which treats source and target equally, by complementing the objective in Eqn. (1) with decoder joint distribution matching, which can be written as

$$
\begin{aligned}
\min_{\psi} \max_{\theta, \phi} \ & \mathcal{L}_{\text{DAIM}} \\
= -&\mathbb{E}_{(T, \tilde{T}, S) \sim p_\theta^e} f(D_\psi(S, T) - D_\psi(S, \tilde{T})) \\
-&\mathbb{E}_{(T, \tilde{S}, S) \sim p_\phi^d} f(D_\psi(S, T) - D_\psi(\tilde{S}, T)) \\
+&\lambda \cdot \mathbb{E}_{p(S)} \mathbb{E}_{p_\theta(T|S)} \log q_\phi(S|T) \\
+&\lambda \cdot \mathbb{E}_{p(T)} \mathbb{E}_{q_\phi(S|T)} \log p_\theta(T|S) \,, \quad (7)
\end{aligned}
$$

where λ is a hyperparameter balancing the GAN loss and the MI loss. An illustration is shown in Figure 5.

Figure 5: Dual objective for Adversarial Information Maximization (AIM).

With this dual objective, the forward and backward model are *symmetric* and *collaborative*. This is because a better estimation of the backward model $q_\phi(S|T)$ will render a more accurate evaluation of the mutual information $I_{p^e}(S, T)$, which the optimization for the forward model is based on. Correspondingly, the improvement over the forward model will also provide positive impact on the learning of the backward model. As a consequence, the forward and backward model work in a synergistic manner to simultaneously make the encoder joint distribution $p^e(S, T)$ and decoder joint distribution $p^d(S, T)$ match the oracle joint distribution $p(S, T)$. Further, as seen in Eqn. (7), the discriminators for $p^e(S, T)$ and $p^d(S, T)$ are shared together. Such sharing allows the model to borrow discriminative features from both sides, and augments the synthetic data pairs (both $(S, \tilde{T})$ and $(\tilde{S}, T)$) for the discriminator. Presumably, this can facilitate discriminator training especially when source-target correspondence is difficult to learn.

We believe this approach would also improve the generation diversity. To understand this, notice that we are maximizing a surrogate to $I_{p^d}(S, T)$, which can be written as

$$I_{p^d}(S, T) = H(T) - H(T|S). \quad (8)$$

When optimizing θ, the backward model $q_\phi^d(S|T)$ is fixed and $H(T|S)$ remains constant. Thereby optimizing $I_{p^d}(S, T)$ with respect to θ can be understood as equivalently maximizing $H(T)$, which promotes the diversity of generated text.

3 Related Work

Our work is closely related to [5], where an *information-promoting* objective was proposed, which directly optimize an MI-based objective between source and target pairs. Despite the great success, the use of additional hyperparameter for the anti-likelihood renders the objective not to be the actual MI. Additionally, the MI objective is employed only during testing (decoding) time, while the training procedure is irrespective to such an MI objective and identical to standard maximum-likelihood training. Compared with [5], our approach considers optimizing a principled MI variational lower bound during training.
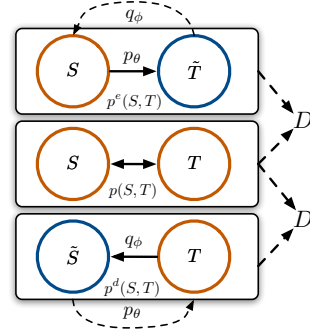
Adversarial learning [6, 26] has been shown to be successful in dialog generation, translation, visual captioning and other natural language generation tasks [7, 12, 27, 28, 29, 30, 31, 32, 33, 34]. [7] leverages adversarial training and reinforcement learning to generate high quality responses. Our adversarial training differs from [7] in both the discriminator and generator design: we adopt an embedding-structured discrimination that borrows ideas from Deep Semantic Similarity Models (DSSM) [17]. For the generator, instead of performing multinomial sampling during each generating step and leverage REINFORCE-like method as in [7], we clamp all the randomness during the generation process to an initial input noise vector, and employ a discrete approximation strategy as used in [12]. The variance of gradient estimation is largely reduced by applying such a strategy.

Unilke previous work, we seek to make a conceptual distinction between informativeness and diversity, and combine the above MI and GAN approaches in a principled manner to explicitly encourage responses to be both informative (via MI) and diverse (via GAN).

Our AIM objective is also extended to a dual-learning framework. This is conceptually related to several previous GAN models in the image domain that aim at joint distribution matching [13, 25, 35, 36, 37]. Among these, our work is mostly related to the Triangle GAN [13], however we employ an additional VIMO as objective, which results in a "cycle-consistent" regularization that enables better communication between the forward and backward models. [14] also leverages a dual objective for supervised translation training and demonstrates superior performance. This work differs from [14] in that we formulate the problem in an adversarial setup. It can thus be perceived as conditional distribution matching rather than seeking a regularized maximum likelihood solution.

4 Experiments

4.1 Setups

We evaluate our methods on two datasets: **Reddit** and **Twitter**. The Reddit dataset contains 2 million source-target pairs of single turn conversations extracted from Reddit discussion threads. The maximum length of tokens for all sentences is 53. We randomly partition the data as (80%, 10%) to construct the training and validation set. The Twitter dataset contains 7 million single turn conversations from Twitter threads. We mainly compare our results with MMI [5][2].

We evaluate our method based on *relevance* and *diversity* metrics. For relevance evaluation, we adopt BLEU [38], ROUGE [39] and three embedding-based metrics following [8, 40]. The **Greedy** metric yields the maximum cosine similarity over embeddings of two utterances [41]. Similarly, the **Average** metric [42] considers the average embedding cosine similarity. The **Extreme** metric [43] obtains sentence representation by taking the largest extreme values among the embedding vectors of all the words it contains, then calculates the cosine similarity of sentence representations.

To evaluate diversity, we follow [5] to use **Dist-1** and **Dist-2**, which is characterized by the proportion between the number of unique n-grams and total number of n-grams of tested sentence. However, this metric neglects the frequency difference of n-grams. For example, token A and token B that both occur 50 times have the same Dist-1 score (0.02) as token A occurs 1 time and token B occurs 99 times, whereas commonly the former are considered more diverse. To accommodate this, we also propose the **Entropy** (Ent-n) metric, which reflects how evenly the empirical n-gram distribution is for a given sentence:

$$Ent = -\frac{1}{\sum_w F(w)} \sum_{w \in V} F(w) \log \frac{F(w)}{\sum_w F(w)} \, ,$$

where V is the set of all n-grams, $F(w)$ denotes the frequency of n-gram w.

We evaluate conditional GAN (cGAN), adversarial information maximization (AIM), dual adversarial information maximization (DAIM), together with maximum likelihood CNN-LSTM sequence-to-sequence baseline on multiple datasets. For comparison we consider MMI [5]. To eliminate the impact of network architecture differences, we implemente MMI-bidi from [5] using our CNN-LSTM framework. The settings other than model architectures are identical to [5]. We perform a beam search with width of 200 and choose the hyperparameter based on performance on the validation set.

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[2]We did not compare with [8] since the code is not available, and the original training data used in [8] contains a large portion of test data, owing to data leakage.

Table 1: Quantitative evaluation on the Reddit dataset. (* is implemented based on [5].)

Models	Relevance					Diversity		
	BLEU	ROUGE	Greedy	Average	Extreme	Dist-1	Dist-2	Ent-4
seq2seq	1.85	0.9	1.845	0.591	0.342	0.040	0.153	6.807
cGAN	1.83	0.9	1.872	0.604	0.357	0.052	0.199	7.864
AIM	**2.04**	**1.2**	**1.989**	**0.645**	0.362	0.050	0.205	8.014
DAIM	1.93	1.1	1.945	0.632	**0.366**	**0.054**	**0.220**	**8.128**
MMI*	1.87	1.1	1.864	0.596	0.353	0.046	0.127	7.142
Human	-	-	-	-	-	0.129	0.616	9.566

The forward and backward models are first pretrained via seq2seq training. During cGAN training, we add a small portion of supervised signal, which is observed to stabilize the training [24]. For embedding-based evaluation, we use a word2vec embedding trained on GoogleNews Corpus[3], recommended by [44]. For all the experiments, we employ a 3-layer convolutional encoder and an LSTM decoder as in [45]. The filter size, stride and the word embedding dimension are set to 5, 2 and 300, respectively, following [46]. The hidden unit size of H_0 is set to 100. We set λ to be 0.1 and the supervised-loss balancing parameter to be 0.001. All other hyperparameters are shared among different experiments. All experiments are conducted using NVIDIA K80 GPUs.

4.2 Evaluation on the Reddit data

Quantitative evaluation We first evaluate our methods on the Reddit dataset following the relevance and diversity metrics. We truncate the vocabulary set to be the most frequent 20,000 words. For testing we use 2,000 randomly selected samples from the test set[4]. The results are summarized in Table 1. We observe that by incorporating the adversarial loss the diversity of generated responses is improved (cGAN vs. seq2seq). The relevance under most metrics (except for BLEU), increase by a small amount.

Compared with cGAN, AIM and DAIM, which have the additional mutual information promoting objective, clearly benefit from large improvements on diversity and relevance. Table 2 demonstrates several examples. It can be seen that AIM and DAIM produce more informative responses, due to the fact that the MI objective explicitly rewards the responses that are *predictive* to the source, and down-weights those that are generic and dull.

Source:	I don't suppose you have my missing socks as well?
Human:	You can't sleep either, I see.
MMI:	I don't have socks, but I have no idea what you're talking about.
seq2seq:	I have one.
cGAN:	I have one, but I have a pair of them.
AIM:	I have one left handed.
DAIM:	Check your pants.

Source:	Why does *** make such poor cell phones? Isn't that against the Japanese code?
Human:	They're a Korean company
MMI:	Because they use ads.
seq2seq:	I don't know how to use it.
cGAN:	Because they are more expensive.
AIM:	Because they aren't in the store.
DAIM:	Because they aren't available in Japan.

Source:	Why would he throw a lighter at you?
Human:	He was passing me it.
MMI:	Why wouldn't he?
seq2seq:	I don't know.
cGAN:	You don't?
AIM:	Though he didn't use a potato.
DAIM:	He didn't even notice that.

Table 2: Sample outputs from different methods.

Under the same hyperparameter setup, we also observe that DAIM benefits from the additional backward model and outperforms AIM in diversity, which better approximates human responses. We show the histogram of the length of generated responses in the Supplementary Material. Our models were trained until convergence. cGAN, AIM and DAIM respectively consume around 1.7, 2.5 and 3.5 times the computation time compared with our seq2seq baseline.

A more reasonable metric for evaluating relevance could be a distributional discrepancy between generated responses and ground-truth responses, rather than the single response judgment. However that would exceed the scope of our discussion, which we leave for future study.

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[3] https://drive.google.com/file/d/0B7XkCwpI5KDYNlNUTTlSS21pQmM
[4] We did not use the full test set because MMI decoding is relatively slow.

Table 3: Human evaluation results. Results of statistical significance are shown in bold.

Methods	Informativeness				Relevance			
	Method A		Method B		Method A		Method B	
MMI-AIM	MMI	0.496	AIM	0.504	MMI	0.501	AIM	0.499
MMI-cGAN	MMI	0.505	cGAN	0.495	MMI	**0.514**	cGAN	**0.486**
MMI-DAIM	MMI	**0.484**	DAIM	**0.516**	MMI	0.503	DAIM	0.497
MMI-seq2seq	MMI	0.510	seq2seq	0.490	MMI	**0.518**	seq2seq	**0.482**
seq2seq-cGAN	seq2seq	0.487	cGAN	0.513	seq2seq	0.492	cGAN	0.508
seq2seq-AIM	seq2seq	0.478	AIM	0.522	seq2seq	0.492	AIM	0.508
seq2seq-DAIM	seq2seq	**0.468**	DAIM	**0.532**	seq2seq	**0.475**	DAIM	**0.525**
Human-DAIM	Human	**0.615**	DAIM	**0.385**	Human	**0.600**	DAIM	**0.400**

Human evaluation   Informativeness is not easily measurable by automated metrics, so we performed a human evaluation of 600 random sampled sources using crowd-sourcing. Systems were paired and each pair of system outputs was randomly presented to 7 judges, who ranked them for informativeness and relevance[5]. The human preferences are shown in Table 3. A statistically significant ($p < 0.00001$) preference for DAIM over MMI is observed with respect to informativeness, while relevance judgments were on a par with MMI. MMI proved a strong baseline: the other two GAN systems were (with one exception) statistically indistinguishable from MMI, which in turn performed significantly better than seq2seq. Box charts illustrating these results can be found in the Supplementary Material.

Table 4: Quantitative evaluation on the Twitter dataset.

Models	Relevance					Diversity		
	BLEU	ROUGE	Greedy	Average	Extreme	Dist-1	Dist-2	Ent-4
seq2seq	0.64	0.62	1.669	0.54	0.34	0.020	0.084	6.427
cGAN	0.62	0.61	1.68	0.536	0.329	0.028	0.102	6.631
AIM	**0.85**	**0.82**	**1.960**	**0.645**	**0.370**	0.030	0.092	7.245
DAIM	0.81	0.77	1.845	0.588	0.344	**0.032**	**0.137**	**7.907**
MMI	0.80	0.75	1.876	0.591	0.348	0.028	0.105	7.156

4.3   Evaluation on Twitter data

We further compared our methods on the Twitter dataset. The results are shown in Table 4. We treat all dialog history before last response for a multi-turn conversation as source sentence, and use the last response as target to form our dataset. We employ CNN as our encoder because a CNN-based encoder is presumably advantageous in tracking long dialog history compared with the LSTM encoder. We truncate the vocabulary set to 20k most frequent words due to limited flash memory capacity. We evaluate each methods on 2k testing data.

The adversarial training encourages generating more diverse sentences, at a cost of slight relevance score decrease. We hypothesize that such a decrease we witnessed may partially be explained by the mechanism of evaluation metrics. All the relevance metrics we employed are based on *utterance-pair* discrepancy, *i.e.*, the score assesses how close the system output is to the ground-truth response. Under such criterion, the system output via MLE can obtain high score despite being bland, because a most likely response has smallest total distance to all random responses. On the other hand, a more random but less "likely" response may be downrated by the relevance score. Consequently, adding diversity without improving correspondency may occasionally harm these relevance scores.

However the additional mutual information seems to be compensating for the relevance decline and further improves the response diversity, especially in Dist-n and Ent-n with larger n-gram. Sampled responses are provided in the Supplementary Material.

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[5]Relevance relates to the degree to which judges perceived the output to be semantically tied to the previous turn, and can be regarded as a constraint on informativeness. An affirmative response like "Sure" and "Yes" is relevant but not very informative.

5   Conclusion

We have proposed a general learning architecture – Adversarial Information Maximization (AIM) – for dialog generation with embedding-based sequence-level discrimination loss. Optimizing a lower bound of mutual information can help improve the information conveyed by the response. We extend our method to simultaneously learn forward and backward models (DAIM) that enhance each other. We have evaluated our method using relevance and diversity metrics and compared it with existing methods on two real-world datasets, and thus demonstrating the effectiveness of our model in producing diverse and informative response.

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