An Adversarially-Learned Turing Test for Dialog Generation Models

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Abstract
The design of better automated dialogue evaluation metrics offers the potential of accelerating evaluation research on conversational AI. However, existing trainable dialogue evaluation models are generally restricted to classifiers trained in a purely supervised manner, which suffer a significant risk from adversarial attacking (e.g., a nonsensical response that enjoys a high classification score). To alleviate this risk, we propose an adversarial training approach to learn a robust model, ATT (Adversarial Turing Test), that discriminates machine-generated responses from human-written replies. In contrast to previous perturbation-based methods, our discriminator is trained by iteratively generating unrestricted and diverse adversarial examples using reinforcement learning. The key benefit of this unrestricted adversarial training approach is allowing the discriminator to improve robustness in an iterative attack-defense game. Our discriminator shows high accuracy on strong attackers including DialoGPT and GPT-3.

1 Introduction

Turing Test (Turing, 1950) was proposed to assess whether a machine can think. A machine and a human player communicate with a human judge and try to convince the judge that they are the human. This test provides an evaluation framework – a machine is intelligent to a certain extent if it passes the Turing Test. To allow fast and less expensive evaluations, the human judge is often replaced by an automated human-vs-machine classifier (Von Ahn et al., 2003; Baird et al., 2003; Rui and Liu, 2004; Lowe et al., 2017a).

An automated Turing test is straightforward for constrained scenarios with unambiguous correct answer, such as text classification. In contrast, for open-domain conversation, an infinite number of plausible responses for the same context exist, and they may differ from each other substantially. In this case, the existing automated evaluation methods (Papineni et al., 2002; Zhang et al., 2019a; Sellam et al., 2020) which measure hypothesis quality by its similarity with reference answers become sub-optimal, because it is difficult to find a set of diverse reference answers to cover such one-to-many possibilities in dialogue. Furthermore, it is impossible to use these reference-based metrics in scenarios when the reference is not available, e.g., online chatbots.

These challenges motivate an alternative approach, i.e., trainable reference-free metrics (Albrecht and Hwa, 2007; Guan and Huang, 2020; Gao et al., 2020). Previous works generally frame the task as a supervised learning (SL) problem, training a classifier to distinguish human and machine outputs, or a regression model to fit the human ratings. However, trainable metrics have potential problems of being gamed using adversarial attacking (Albrecht and Hwa, 2007; Sai et al., 2019; Gao et al., 2019).

To learn a more robust evaluation metric, we propose to train a model to discriminate machine outputs from human outputs via iterative adversarial training, instead of training evaluation model with a fixed dataset. In contrast to previous perturbation-robust methods that only modify characters or words (Ebrahimi et al., 2017; Li et al., 2018; Gao et al., 2018), we generate “unrestricted” adversarial examples by fine-tuning a dialogue response generator to maximize the current discriminator score via reinforcement learning. This is followed by training the discriminator that accounts for these additional adversarially generated examples. The above two steps are repeated as an iterative attack-defense game until the generator no longer can decrease the discriminator accuracy below a thresh-

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1Code and model be open-sourced on https://github.com/golsun/AdversarialTuringTest.
To further improve the robustness of the discriminator, we reduce the chance that the discriminator be fooled by unseen patterns by increasing the diversity of the adversarial examples in several novel ways. Firstly, we explicitly encourage the adversarial dialogue responses to be context-sensitive by including rewards from a pre-trained context-response matching model. Secondly, we decode with different decoding settings when generating adversarial examples. Our discriminator showed high accuracy on several strong attackers including DialoGPT (Zhang et al., 2019b) and GPT-3 (Brown et al., 2020).

2 Method

We define the problem as learning a discriminator to distinguish machine-generated and human-written responses for open-domain dialogue context. Similar to training a generative adversarial network (GAN) (Goodfellow et al., 2014a), our ATT (Adversarial Turing Test) method involves two sets of competing components: discriminators $D$ that defend, and generators $G$ that attack.

2.1 Discriminator

A supervised learning (SL) approach is employed to train the discriminator. Following Gao et al. (2020), the loss is defined to increase the probability of picking the human-written responses $y^H$ when mixed with machine-generated hypotheses $y^M$ for the same context $x$.

$$L_{SL}(\theta_D) = -\sum_i \log \frac{e^{h(x,y_i^H)}}{e^{h(x,y_i^H)} + e^{h(x,y_i^M)}}$$  

(1)

where $h(x, y, \theta_D)$ is the scalar output from the discriminator, which is parameterized by $\theta_D$. At inference time, we compute the score

$$s(y|x) = \text{Sigmoid}(h(x, y))$$  

(2)

The discriminator is implemented by adding a linear layer to GPT-2 transformers (Radford et al., 2019), following Gao et al. (2020).

2.2 Generator

We generate adversarial examples via a generator $G$ trained with reinforcement learning (RL) using policy gradient (Williams, 1992). For each context $x$, the generator generates $n$ hypotheses $\{y_i\}$. The reward $R(y_i)$ is defined with a baseline $b(x)$, which is used to reduce the variance of gradients:

$$R(y_i) = s(y_i|x) - b(x)$$  

(3)

$$b(x) = \frac{1}{n} \sum_{j=1}^{n} s(y_j|x)$$  

(4)

Applying Policy Gradient (Williams, 1992), we minimize the following loss:

$$L_{RL}(\theta_G) = -\sum_{i=1}^{n} \log P(y_i|x, \theta_G)R(y_i)$$  

(5)

where $P(y|x, \theta_G)$ is the probability generating $y$ given $x$ from the generator parameterized by $\theta_G$. The generator is implemented using a GPT-2 architecture (Radford et al., 2019), following Zhang et al. (2019b).

2.3 An iterative attack-defense game

We first pre-train the components individually and then jointly train them in an iterative attack-defense game, as illustrated in Figure 1.

HvM is initialized using, $\theta_D^{(0)}$, the weights of a human-vs-machine classifier from Gao et al. (2020) trained in a SL manner to classify whether a response is a human response or DialoGPT generated.

Each turn of the game starts with an attack phase that trains $G$ with RL to attack $D$. The training is stopped when the validation accuracy of $D$ is dropped below threshold $c_{low}$, or the training steps exceed certain number $N_G$, whichever comes first. The turn then switches to a defense phase. $D$ is
trained using samples generated from $\mathcal{G}$ via SL. We stop training the discriminator when the validation accuracy is higher than threshold $c_{hi}$, or the training steps exceed certain number $N_D$. We repeat this process until the validation accuracy of $\mathcal{D}$ in the last $m$ turns is always kept higher than $c_{hi}$.

Note above procedure resembles GAN (Goodfellow et al., 2014a). However, we focus on improving the robustness of the classifier, while GAN focus on generating realistic examples. From a modeling perspective, the key differences with a conventional GAN are:

**Generator re-initialization** We set $\mathcal{G}$ as $\theta_G^{(0)}$ at the beginning of each attack phase, instead of continuing to learn from the last turn. This is because, at the early stage of the game, $\mathcal{G}$ often learns to generate adversarial examples that are not fluent or grammatically correct (one example at Turn-5 is shown in Table 1). They can successfully fool $\mathcal{D}$, as initially $\mathcal{D}$ has not seen such adversarial examples. However, such attacker $\mathcal{G}$, which typically learns disfluent adversarial examples in earlier iterations, is difficult to fine-tune towards well-formed adversarial examples. To allow the late-stage attackers to generate fluent adversarial examples, we reset $\mathcal{G}$ parameters as the pre-trained generator before each attack phase to obtain multiple attackers as shown in Figure 1. We empirically find that such a strategy gives better performance than initializing each attacker with the previous one as in GAN.

**Adversarial example ensemble** We train $\mathcal{D}$ on samples generated by $\mathcal{G}$ from all previous turns, instead of only the last turn. As shown in Figure 1, at Turn-2, $\mathcal{D}$ is trained on samples from pre-trained $\mathcal{G}$, $A^{(0)}$, samples of of Turn-1 $A^{(1)}$, and Turn-2 $A^{(2)}$. At each turn, we stop training $\mathcal{D}$ when the validation accuracy of all these datasets $A^{(i)}$ is higher than threshold $c_{hi}$. This enables the defender to capture all observed attacks rather than only focusing on the adversarial examples generated by the last attacker as in GAN, thus yielding a more robust defense against various attacks.

### 2.4 Diversifying the adversarial examples

We find that mode collapse happens when only using a single human-vs-machine discriminator HvM. That is, the generated adversarial examples tend to be insensitive to the context, indicating that the generator finds a universal adversarial attacking pattern that can successfully attack HvM for most contexts. However, a corpus of similar adversarial examples makes adversarial training inefficient and the discriminator less robust. Therefore, we encourage the content of the adversarial examples to be diverse by integrating HvM and a pre-trained human-vs-random classifier (Gao et al., 2020) HvR. HvR is trained to predict whether a response is randomly retrieved or is the ground truth. The final discriminator score $s_D(y|x)$ is the geometric mean\(^{2}\) of the outputs of HvM and HvR:

$$s(y|x) = \sqrt{s_{HvM}(y|x) s_{HvR}(y|x)} \quad (6)$$

For the generator, we increase the diversity of adversarial examples by randomly changing the hyper-parameter of the generator decoding process.

The decoding temperature $T$ is uniformly sampled from a range of levels (0.3, 1, 10, 100), to control the token generation probability distribution.

### 3 Experiments

#### 3.1 Data

As we focus on open-domain dialogue, we use Reddit data obtained from a third-party Reddit dump,\(^3\) following Gao et al. (2020).

#### 3.2 Baselines

We compare ATT with the following models:

- **SL** by Gao et al. (2020) is trained via SL on human-vs-DialoGPT data.
- **GAN** is similar to ATT, but it does not apply the generator re-initialization or adversarial example ensemble strategies of Section 2.3.
- **ND** (Non-Diverse ATT) a variant to ATT, without the diversifying objective in Section 2.4 to diversify adversarial examples.

#### 3.3 Results

As shown in Figure 2, the accuracy of $\mathcal{D}$ for ATT method gradually increases as the game continues, and finally remains above 0.75 after about 30 turns of the game. This indicates our convergence criterion is met. The convergence of $\mathcal{D}$ accuracy is accompanied by the improvement of $\mathcal{G}$ generation quality. As shown by the examples of Table 1, a response that is not grammatically correct in the early stage (e.g., turn-5) can successfully fool $\mathcal{D}$, but $\mathcal{G}$ tends to generate more human-like response at later stages (e.g., turn-40). This is desirable as an

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\(^{2}\)Geometric mean has an advantage over the arithmetic mean in that it encourages both $s_{HvM}$ and $s_{HvR}$ to be high. The final value is zero if one of them is zero.

\(^{3}\)https://files.pushshift.io/reddit/
Why does anything exist?

Human

Parrot

DialoGPT, greedy

DialoGPT, sampling

GPT-3, greedy

GPT-3, sampling

Adversarial G, turn-5

Adversarial G, turn-40

Table 1: Examples of responses generated from different attackers for the same context.

GPT-3, greedy

GPT-3, sampling

Table 2: Accuracy of the discriminators (defenders). Darker cell color indicates better performance.

4 Related Work

Dialogue evaluation and ranking. Open-domain dialogue systems are often evaluated using similarity between hypotheses and reference, e.g. BLEU (Papineni et al., 2002). Lowe et al. (2017b) trained an evaluation model with context, reference, and hypothesis as inputs. Complementary to this, corpus-level metrics for diversity (Li et al., 2016a; Zhang et al., 2018) and other aspects are proposed. When reference is not available, dialogue ranking models (Zhou et al., 2018; Gao et al., 2020) are often employed, mostly trained via SL. Dinan et al. (2019) trained a toxic dialogue classifier with human in the loop to provide adversarial examples.

Reinforcement Learning. RL has been used to guide the dialogue generator using rewards, which can be hand-designed (Li et al., 2016b), obtained from a pre-trained classifier (Shin et al., 2019), or extracted from user response (Jaques et al., 2020).

Adversarial attack and defense. Most existing works create adversarial examples by adding perturbation in embedding space (Miyato et al., 2016; Zhao et al., 2017), by editing characters (Ebrahimi et al., 2017), or tokens (Alzantot et al., 2018; Gao et al., 2018). Adversarial training (Biggio et al., 2013; Szegedy et al., 2013; Goodfellow et al., 2014)
2014b) is then used to improve the model robustness. Unrestricted adversarial examples is a relatively less studied field, and most works are for images (Brown et al., 2018; Song et al., 2018; Wang et al., 2019; Qiu et al., 2020).

5 Conclusions

In this work we propose to learn a robust human-vs-machine discriminator from an iterative attack-defense game. Diversified and unrestricted adversarial examples are automatically generated and used to fine-tune the discriminator. It significantly increased accuracy and robustness in terms of classification accuracy on unseen attacks.

Ethical Considerations

We cautiously advise users of our system be careful about the potential bias in the dataset used to train our model. The raw data is publicly available, but the texts written by human have varying levels of quality. The dataset may contain offensive and/or toxic language. A proper definition of human-written text quality is beyond the scope of this work, as we focus on learning a human-vs-machine discriminator in this short paper.

We used one P100 GPU for training. The training time for each method is approximately 48 hours. The generator and discriminator have about 700M parameters. The code and our models will be open-sourced together with the details of training hyperparameters.
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