Bipartite-play Dialogue Collection for Practical Automatic Evaluation of Dialogue Systems

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Abstract

Automation of dialogue system evaluation is a driving force for the efficient development of dialogue systems. This paper introduces the bipartite-play method, a dialogue collection method for automating dialogue system evaluation. It addresses the limitations of existing dialogue collection methods: (i) inability to compare with systems that are not publicly available, and (ii) vulnerability to cheating by intentionally selecting systems to be compared. Experimental results show that the automatic evaluation using the bipartite-play method mitigates these two drawbacks and correlates as strongly with human subjectivity as existing methods.

1 Introduction

The performance evaluation of dialogue systems is a crucial and challenging research topic for the dialogue research community. The community recommends human evaluation as the primary evaluation method, which is the gold standard but is time-consuming and costly. Moreover, reproducing the evaluation results is mostly impractical due to the unavailability of maintaining identical evaluators or identical evaluation conditions. Human evaluation is therefore unsuitable for evaluating daily updates of developing dialogue systems or comparing systems with non-public ones. Thus, constructing a better automatic evaluation method, which is both highly reproducible and low cost, is desirable. In particular, automating interactive evaluation, not static evaluation such as BLEU (Papineni et al., 2002), is attracting an increasing interest as static evaluation cannot capture diverse aspects of dialogue systems (Ghandeharioun et al., 2019).

An interactive evaluation framework consists of two phases: first, collecting the dialogues in which the systems to be evaluated (hereinafter called evaluation targets) talk to others (hereinafter called dialogue partners), then rating evaluation targets based on the quality of their utterances in the collected dialogues. Regarding the collecting (i.e., automating dialogue partners), self-play and all-play-all (Figure 1 (a) and (b)) are the current promising methods; All-play-all collects dialogues among multiple evaluation targets, while self-play collects dialogues with itself. Recently, Yang et al. (2022) have reported that all-play-all correlates with human evaluation strongly. However, all-play-all is not perfect and has at least two potential drawbacks: (i) the difficulty of comparison with publicly inaccessible systems and (ii) the vulnerability to cheating by choice of evaluation targets, i.e., with whom the evaluation target will talk (Section 3).

This paper addresses the above two drawbacks of the all-play-all method while maintaining the all-play-all method's high correlation with human rating. Specifically, we propose the bipartite-play method, i.e., fixing and sharing a set of dialogue partners across studies as shown in Figure 1 (c) instead of assigning other evaluation targets as partners as shown in Figure 1 (b) (Section 4). The bipartite-play method offers (i) a fair comparison

\textsuperscript{*}Both authors contributed equally to this paper.
with publicly inaccessible systems as long as its developers use our method and (ii) prevention of cheating by an intentional choice of evaluation targets. Our experiments show that the bipartite-play method strongly correlates with humans as the all-play-all method while preventing the potential drawbacks in the all-play-all method.

2 Related Work

2.1 Automatic dialogue collection

Self-play. The self-play method collects dialogues where evaluation targets talk to themselves, i.e., \(i \times 1 \times j\) dialogues in which collecting \(j\) dialogues for each of \(i\) evaluation targets. This method is cost-effective for interactive dialogue system evaluation since it does not require human interactions (Ghandeharioun et al., 2019; Deriu and Cieliebak, 2019). However, since there are few dialogue partners, it does not fully expose the characteristics of evaluation targets (Yang et al., 2022).

All-play-all. The all-play-all method collects dialogues between multiple evaluation targets, i.e., \(i \times (i-1) \times j\) dialogues when collecting \(j\) dialogues for each of \(i\) evaluation targets (considering speaker order). This method also requires no human interactions. Compared to the self-play method, the all-play-all method’s dialogue partners are more diverse since it collects dialogues with other evaluation targets that result in various dialogues (Deriu et al., 2020; Yang et al., 2022). Additionally, direct interactions with evaluation targets make them easy to compare. Yang et al. (2022) experimentally showed that the evaluation using the all-play-all method correlates with human evaluation stronger than the self-play method.

2.2 Automatic dialogue rating

Compared with methods relying on reference responses (e.g., BLEU (Papineni et al., 2002), ROUGE (Lin, 2004), METEOR (Lavie and Agarwal, 2007), Greedy Matching (Rus and Lintean, 2012), Vector Extrema (Forgues et al., 2014), and ADEM (Lowe et al., 2017)), reference-free methods, such as USR (Mehri and Eskenazi, 2020b), GPT-2 based evaluation (Pang et al., 2020), FED (Mehri and Eskenazi, 2020a), and DynaEval (Zhang et al., 2021), have attracted greater interest from the research community. For example, FED allows fine-grained practical evaluation of the system utterances without high-cost preparation, such as training an evaluation model; it assesses system utterances for given dimensions, such as Fluency and Specificity, by guessing whether positive or negative responses are valid to the system utterance in terms of language model score (see Section 5.1). We also focus on reference-free evaluation, especially the FED metric, to automate the rating part of the interactive evaluation, as preparing references for automatically collected dialogues is impractical.

3 Limitations of All-play-all Method

The all-play-all method enables effective dialogue collection for system comparison, as described in Section 2. However, we point out that the current all-play-all method cannot handle the following two cases: First, when the group of evaluation targets includes unavailable systems. Since all-play-all requires the collection of dialogues with all evaluation targets, it is impossible to compare systems that are not released or that cannot be run by many researchers due to such computational resources. Second, when one attempts to boost their system’s performance by deploying an unfair evaluation setting. Our experiments (Section 6) reveal that one can intentionally improve the automatic evaluation results of desired systems by choosing evaluation targets to be compared when using the all-play-all method. If these potential drawbacks can be overcome, existing automated evaluation methods could be enhanced to be more versatile and practical.

4 Proposed Method: Bipartite-play

We introduce a new automatic dialogue collection method, called bipartite-play method, which updates the two aforementioned limitations.

Evaluation targets vs fixed dialogue partners. Considering the two drawbacks of the all-play-all method (Section 3), we propose fixing and sharing a set of publicly accessible systems as dialogue partners rather than assigning other evaluation targets as partners. Our idea is that even if evaluation targets do not talk to each other directly, dialogues in which evaluation targets talk to the same (shared) partners should be effective for system comparison. In this setting, the diversity of dialogue partners can be maintained by ensuring the diversity of predetermined dialogue partners set. Sharing a set of dialogue partners allows a fair comparison with
publicly inaccessible systems as long as its developers use our method. Furthermore, predetermining a set of dialogue partners prevents cheating by an intentional choice of evaluation targets.

**Bipartite-play dialogue collection.** Given $i$ evaluation targets, the bipartite-play method collects $i \times k \times j$ dialogues by having evaluation targets interact $j$ times with each of the $k$ various dialogue partners predetermined for evaluation.

5 Bipartite-play based Evaluation Framework

Subsequently, we introduce bipartite-play to the interactive dialogue evaluation framework. We combine the dialogue collection based on the bipartite-play method with FED (Mehri and Eskenazi, 2020a), which is one of the modern and effective dialogue rating methods.

5.1 System evaluation procedure

Based on the $m$ collected dialogues by the bipartite-play method, we assess an evaluation target for a dimension $v$. Specifically, we first evaluate the performance for $v$ in a dialogue using the average score of the system’s utterances. We then determine the system’s whole performance for $v$ using the average score of $m$ dialogues. We compute the system utterances score using FED. This rating method evaluates the system’s utterances for $v$ by guessing whether positive or negative responses for $v$ are valid in terms of the language model as a response to the system’s utterance. The validity of each positive and negative response is automatically evaluated using a large-scale dialogue system. The evaluation value of $v$ of the evaluation target’s utterance $r$ for a context $c$ is calculated as follows:

$$
\sum_{p \in P_v} D(c + r, p; \theta) - \sum_{n \in N_v} D(c + r, n; \theta),
$$

where $P_v$ and $N_v$ are the set of positive and negative responses for $v$, respectively. $D(c, :: \theta)$ is a function that calculates the probability of generating a response to $c$ using a large-scale dialogue system with parameters $\theta$.

5.2 Preliminary experiment

We assess evaluation targets based on dimensions frequently deployed in recent research (Deriu et al., 2020; Adiwardana et al., 2020): Fluency, Specificity, and Sensibleness, additionally Overall. The applicability of FED to these dimensions is unclear as Mehri and Eskenazi (2020a) cover only some of these dimensions. Therefore, as a preliminary experiment, we determine whether the FED evaluation for these dimensions correlates with humans.

**Dataset.** We created the dataset by collecting dialogues between the dialogue system and humans, then annotating the collected dialogues with a human evaluation score. Crowdsourcing\(^1\) was employed in two processes. First, we collected dialogues between the 11 systems deployed as evaluation targets for the experiments in Section 6 and humans. We obtained 50 dialogues for each system, for 550 dialogues in total.\(^2\) We then asked five workers to evaluate each collected dialogue with a five-point Likert scale for the question about each of the four dimensions.\(^3\)

**FED evaluation settings.** We used the positive and negative responses manually created by Mehri and Eskenazi (2020a), and our additional responses for the FED evaluation. Also, we used Blender 9B from ParlAI (Miller et al., 2017) as a large-scale dialogue system to calculate FED scores. We used the four dimensions for which human evaluation scores were annotated in the constructed dataset.

**Results of FED evaluation.** Table 1 shows Spearman’s rank correlation coefficients of the FED with human evaluation. “w/o pos” and “w/o neg” are the FED evaluations calculated without positive and negative responses respectively. “w/o neg” for Sensibleness is a missing value.

| Dimension   | FED   | w/o neg | w/o pos |
|-------------|-------|---------|---------|
| Fluency     | 0.121 | −0.145  | 0.171   |
| Specificity | −0.022| −0.364  | 0.340   |
| Sensibleness| 0.370 | −       | 0.370   |
| Overall     | 0.329 | −0.367  | 0.386   |

Table 1: Spearman’s rank correlation coefficients of the FED with human evaluation. “w/o pos” and “w/o neg” are the FED evaluations calculated without positive and negative responses respectively. “w/o neg” for Sensibleness is a missing value.

\(^1\)https://www.mturk.com/

\(^2\)Starts with the human’s Hi! and continues for six turns.

\(^3\)We asked workers *Are Bot’s responses fluent and grammatically correct?* (Fluency), *Are Bot’s responses specific and explicit in the given context?* (Specificity), *Are Bot’s responses sensible?* (Sensibleness), and *Is the overall impression of the chatbot good?* (Overall), and they answered from *Strongly disagree* (score 1) to *Strongly agree* (score 5).
found that the FED evaluation of Fluency correlates poorly with human evaluation, while the other dimensions correlate relatively well with human evaluation. However, the agreement rate for human evaluation is extremely low, and we consider Fluency evaluation with consistent results difficult even for humans.\footnote{To compute inter-annotator agreement, we randomly divided the five annotators into two groups and calculated Spearman’s rank correlation coefficients between those groups. The results were $0.603$ (Fluency), $0.835$ (Specificity), $0.857$ (Sensibleness), and $0.831$ (Overall).} One possible reason is that all systems have a high Fluency in neural response generation, so the difference in the Fluency of dialogues for each sample is small. Therefore, in the evaluation experiment of Section 6, we do not evaluate the Fluency dimension.

6 Experiments: System Evaluation

We show that the interactive automatic evaluation using the bipartite-play method correlates with humans as strongly as the all-play-all method, which has been reported to be an effective dialogue collection method but requires access to all evaluation targets. We first rank prepared evaluation targets and then measure the correlation with the rankings by interactive human evaluation and then measure the correlation with the rankings by interactive automatic evaluation without direct interaction between evaluation targets.

6.1 Experimental settings

Dialogue systems. Table 2 shows the set of 11 evaluation targets and 24 partner systems. Each system name represents [architecture]-[number of model parameters]-[pretrain data]-[finetune data].

| Evaluation targets: | Tfm-3B-Rdt-Bsm, Tfm-3B-Rdt-Msc, Tfm-3B-R2c-Bsm, Tfm-3B-Rdt-Lgu, GPT-345M-Wtx-Rdt, Tfm-89M-Ddc-Nft, Tfm-89M-Ddc-Crm, Tfm-89M-Ddc-Ddg, Tfm-89M-Ddc-Rdt, Tfm-89M-Ddc-Twt, PEn-256M-Rdt-Bst |
|---------------------|--------------------------------------------------------------------------------------------------|
| Partner systems:    | Tfm-3B-Rdt-Slf, Tfm-3B-Rdt-Lgt, Tfm-3B-Rdt-Img, Tfm-3B-Rdt-SfR, Tfm-1B-Rdt-Bsm, GPT-117M-Wtx-Rdt, GPT-762M-Wtx-Rdt, Tfm-406M-Rdt-Bsm, Tfm-406M-R2c-Bsm, Bt-R-046M-Rdt-Woi, Tfm-89M-Ddc-Wow, Tfm-89M-Ddc-Lgt, Tfm-89M-Ddc-Empr, Tfm-89M-Ddc-Cv2, Tfm-89M-Rdt-Wow, Tfm-89M-Rdt-Cv2, Tfm-88M-Rdt-Cv2, PEn-256M-Rdt-Cv2, PEn-256M-Rdt-Empr, PEn-256M-Rdt-Wow, PEn-256M-Rdt-All, PEn-256M-Rdt-Bsm, B+F-256M-Rbt-Wow |

Table 2: Dialogue systems for our experiments: 11 evaluation targets and 24 partner systems. Each system name represents [architecture]-[number of model parameters]-[pretrain data]-[finetune data].
### Table 3: Spearman’s rank correlation coefficients of the automatic evaluations using the three dialogue collection methods with the human evaluation.

| Method           | Specificity | Sensibleness | Overall |
|------------------|-------------|--------------|---------|
| Self-play        | 0.83        | 0.70         | 0.77    |
| All-play-all     | 0.90        | 0.75         | 0.85    |
| Bipartite-play   | 0.90        | 0.75         | 0.85    |

Table 3: Example of dialogue between an evaluation target (A; Tfm-89M-Ddc-Ddg) and one of the dialogue partners (B; Tfm-1B-Rdt-Bsm).

#### Collecting dialogues.
Tfm-89M-Ddc-Ddg returned valid responses to high-quality utterances of Tfm-1B-Rdt-Bsm (Table 4). However, Tfm-89M-Ddc-Ddg generated semantically inappropriate responses (bolded parts) to low-quality utterances of GPT-117M-Wtx-Rdt (Table 5). These examples suggest that Tfm-89M-Ddc-Ddg can handle high-quality inputs but may be vulnerable to low-quality ones. Therefore, the bipartite-play method can reveal the diverse features of evaluation targets.

#### Rating dialogues.
Regarding Tfm-89M-Ddc-Ddg, the scores of the dialogues in Tables 4 and 5 for the Overall dimension were 4.00 and 3.81, respectively; FED assigned higher scores to better dialogues than to mediocre ones. In these examples, FED succeeded in assigning appropriate ratings.

### 6.3 Qualitative analysis of bipartite-play

Tables 4 and 5 show dialogue examples of Tfm-89M-Ddc-Ddg (an evaluation target) collected using the bipartite-play method. Tfm-89M-Ddc-Ddg talked with Tfm-1B-Rdt-Bsm, a high-performance system (Table 4), and GPT-117M-Wtx-Rdt, which is guessed to have relatively low performance in the set of dialogue partners (Table 5).

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### 7 Discussion
The interactive automatic evaluation using the bipartite-play method correlates with humans as strongly as the all-play-all method, as described in Section 6, without direct interaction with evaluation targets. Additionally, we present another reason to use the bipartite-play method: one can sometimes cheat by choice of evaluation targets when using the all-play-all method.

#### 7.1 How can we cheat on all-play-all?
We found that dialogues where systems frequently speak about the same things tend to receive low
ratings from the FED evaluation described in Section 5.2. This can be a desirable evaluation property since human evaluation is known to have the same tendency (Li et al., 2020). Therefore, we hypothesize that one could worsen a particular system’s ranking by forming an unfair set of evaluation targets where the system is likely to talk about repeated things.

### 7.2 Cheating examples

We show cheating using the all-play-all method following the above hypothesis. Specifically, based on Yang et al. (2022)’s observation that systems tend to speak repeated things in self-play (i.e., when talking with extremely similar systems), we attempt to worsen the ranking of a particular system by having the system talk with different but similar systems.

**Settings.** We form an unfair set of evaluation targets by collecting four systems, i.e., one whose rank we attempt to improve (favored system), another whose rank we attempt to worsen (unfavored system), and two systems similar to the unfavored system. We then check whether the ranking relationship between favored and unfavored ones changes from that of the original all-play-all evaluation (fair evaluation) in Section 6. In this unfair evaluation, unfavored systems have to construct dialogues with similar systems three out of four times, where repeated utterances are likely to occur as in self-play. We prepared two combinations of the unfavored system and its similar system: a series of DialoGPT (GPT-345M-Wtx-Rdt is the unfavored system, whose similar systems are GPT-124M-Wtx-Rdt and GPT-774M-Wtx-Rdt) and a series of Blender (Tfm-3B-Rdt-Bsm is the unfavored system, whose similar systems are Tfm-406M-Rdt-Bsm and Tfm-1B-Rdt-Bsm). We assigned each of all ten evaluation targets for the experiments in Section 6 except the unfavored one (GPT-345M-Wtx-Rdt or Tfm-3B-Rdt-Bsm) as a favored system.

**Results.** Table 6 shows the change in the ranking relationship between favored and unfavored systems. The results show that we succeeded in intentionally improving the favored systems’ ranking in some cases. In this way, when using the all-play-all method, one can improve the automatic evaluation results of their systems by choice of evaluation targets. The bipartite-play method, fixing

|                | Unfair | Favored wins | Favored loses |
|----------------|--------|--------------|---------------|
| **Favored wins** |       | 6            | 0             |
| **Favored loses** |       | 2            | 2             |

(a) Evaluation of 10 systems with DialoGPT series.

|                | Unfair | Favored wins | Favored loses |
|----------------|--------|--------------|---------------|
| **Favored wins** |       | 1            | 0             |
| **Favored loses** |       | 2            | 7             |

(b) Evaluation of 10 systems with Blender series.

Table 6: Changes in the ranking relationship between favored versus unfavored systems by deploying unfair evaluation target sets instead of the original fair set. “Favored wins” means that a favored system was rated higher than the unfavored system. In both situations with the two unfair sets, the ranking was overturned in favor of the two favored systems out of ten.

and sharing a set of diverse partner systems, is one of the practical methods to prevent this cheating.

### 8 Conclusion

In this paper, we proposed the bipartite-play method as a dialogue collection method. The bipartite-play method can address the impossibility of comparison with publicly inaccessible systems and the vulnerability to cheating by intentional choice evaluation targets to improve the all-play-all method. For the proposed method, no dialogue with evaluation targets is required, thereby facilitating system comparison across studies and possibly enabling comparison with inaccessible systems. Our experiments showed that, compared with the evaluation using the all-play-all method, the automatic evaluation using the bipartite-play method correlates just as strongly with humans.

Although we formed a set of the bipartite-play method’s partner systems for the experiments considering its diversity of architectures and training data, it may still have some vulnerabilities. In future work, we will explore the property of the bot-bot dialogue further and refine the set of partner systems for the bipartite-play method.

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