

# R2D2: Robust Data-to-Text with Replacement Detection

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## Abstract

Unfaithful text generation is a common problem for text generation systems. In the case of Data-to-Text (D2T) systems, the factuality of the generated text is particularly crucial for any real-world applications. We introduce R2D2, a training framework that addresses unfaithful Data-to-Text generation by training a system both as a generator and a faithfulness discriminator with additional replacement detection and unlikelihood learning tasks. To facilitate such training, we propose two methods for sampling unfaithful sentences. We argue that the poor entity retrieval capability of D2T systems is one of the primary sources of unfaithfulness, so in addition to the existing metrics, we further propose NER-based metrics to evaluate the fidelity of D2T generations. Our experimental results show that R2D2 systems could effectively mitigate the unfaithful text generation, and they achieve new state-of-the-art results on FeTaQA, LogicNLG, and ToTTo, all with significant improvements.

## 1 Introduction

Data-to-Text generation is the task of generating a text sequence that describes some salient information of a knowledge source. Unlike Text-to-Text generation whose input source is a text sequence containing knowledge that is not extracted and represented in the canonical structured format, we assume that the input of a Data-to-Text system is represented in some structured format, e.g., RDF (Gardent et al., 2017), relational or entity tables (Lebret et al., 2016; Wiseman et al., 2017). The Data-to-Text task can be divided into two distinct processes as in many other text generation tasks (Reiter and Dale, 2000; Gatt and Krahmer, 2018). The first process involves selecting salient information from the structured knowledge either based on natural language query or other indication of saliency, and the second process comprises organizing and planning of the previous selections to

allow realization of the surface text. Although this task has been studied comprehensively in many works, from task design, modeling techniques, to application in different domains (Gardent et al., 2017; Lebret et al., 2016; Wiseman et al., 2017; Novikova et al., 2017; Parikh et al., 2020; Nan et al., 2022), existing Data-to-Text (D2T) systems exhibit a shortcoming that cannot be neglected. They fail to reliably generate sentences that are faithful given the salient content of the input table (Chen et al., 2020a,b, 2021a; Uehara et al., 2020; Ji et al., 2022). This limitation prevents the application of D2T systems in real world scenarios. We therefore need to investigate possible remedies.

We introduce a framework that prevents unfaithful Data-to-Text generation by training a Data-to-Text system both as a generator as well as a faithfulness discriminator. For faithfulness discrimination, we adopt the *replaced token detection* objective, which was first proposed in ELECTRA (Clark et al., 2020). It was applied to the pre-training stage of the large-scale language models for more sample-efficient training of contextualized representations of sentences. ELECTRA is tasked to discriminate between original natural sentences and token-replaced sentences by locating the positions of replacement. The replaced tokens are sampled from a proposal distribution using a generator such as a Masked Language Model to fill some masked tokens.

In our work, we perturbed the entailed reference sentences with two different methods, a knowledge-based one and a model-based one, to obtain unfaithful sentences whose surface forms are close to those of original sentences (therefore having similar sequence likelihoods), but contradict to the input table. Then we investigated ways of incorporating the discrimination task into the existing maximum likelihood learning. Specifically, we explored the settings of learning the sentence-level detection and generation in tandem, and the token-level

detection and generation in tandem. In addition, we also experiment with incorporating the unlikelihood training objective (Welleck et al., 2019) on these unfaithful sentences to test its utility.

We conduct experiments on three Data-to-Text datasets to test the general applicability of our approach: FeTaQA (Nan et al., 2022), LogicNLG (Chen et al., 2020a), and ToTTo (Parikh et al., 2020). Each dataset presents distinct challenges while faithful generation is a common problem. We find that adding the faithfulness discrimination task effectively mitigates the unfaithful Data-to-Text generation, supported by our results on multiple datasets, on all of which we are able to achieve new state-of-the-art results with evident improvements. We compare and analyze the performance of our system and existing state-of-the-art systems. To ensure the competence of comparison, we also evaluate various metrics for their aptness of faithfulness evaluation. We released our model and code at <https://github.com/Yale-LILY/r2d2>.

## 2 Method

### 2.1 Preliminaries

The de facto Data-to-Text task requires conditional language modeling of the sequence pair  $X = (x_1, \dots, x_M), Y = (y_1, \dots, y_N)$  using a neural model parameterized with  $\theta$ :  $p_\theta(y_1, \dots, y_N | x_1, \dots, x_M)$ , where  $(y_1, \dots, y_N)$  is a natural language sentence that faithfully describes the salient part of the input data which is linearized, along with other contexts such as query or metadata, into the sequence  $X = (x_1, \dots, x_M)$ .

We want to sample unfaithful sentences that are in the vicinity of surface forms of reference sentences, therefore also likely to be generated when only learning with maximum likelihood loss. We aim to examine the effectiveness of our proposed discrimination objectives in guiding the D2T model to attain **separable representations** for these superficially similar but factually critical sentences, and more importantly, we investigate how generation can benefit from these additional objectives for robustness. We call our method Robust Data-to-Text with Replacement Detection (R2D2), because we assign the Data-to-Text model both a generation task and a discrimination task (replacement detection). This process is illustrated in Figure 1.

Many existing works that study the unfaithful text generation problem in summarization and

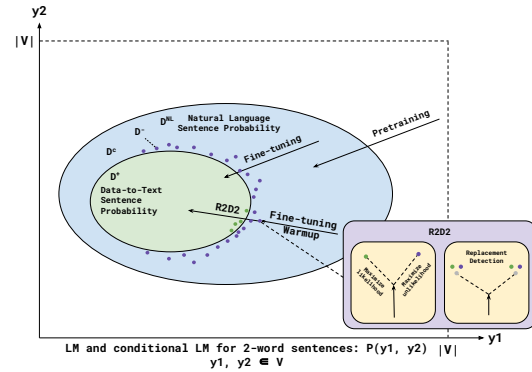


Figure 1: Illustrated R2D2 training

translation have investigated the source of inconsistencies between the system output and the input (Cao et al., 2017; Maynez et al., 2020; Goyal and Durrett, 2020, 2021; Chen et al., 2021a). The main source of unfaithfulness is that the outputs contain facts that cannot be entailed (necessary consequence) from any explicitly stated facts or inferences derived from the input table. Since facts can be represented using subjects, predicates, and objects, these contradictions originate from wrong predictions of entities (subject or object), predicates, or wrong arrangements. This motivates our proposal of different methods of obtaining unfaithful sentences in Section 2.2. Then we describe two learning objectives that we proposed to add to the Data-to-Text modeling: 1) replacement detection objective in Section 2.3; and 2) unlikelihood objective in Section 2.4. In Section 2.5, we formulate our R2D2 fine-tuning that leverages these two objectives in addition to the standard negative log likelihood loss for robust training of a Data-to-Text model. We also propose NER-based evaluation metrics to complement the existing evaluations of faithfulness in Section 2.6.

### 2.2 Faithfulness-based Replacement

We aim to obtain sentences that are not entailed from the input table by replacing tokens in the original sentences. As we discussed in the previous paragraph, one of the major sources of unfaithfulness is the erroneous prediction of entities or predicates. It is challenging to reliably extract the predicates in canonical form, compare those in the system’s generations to those in the input table, and find replacements for them. However, it is feasible to extract and compare entities from the system generations and the input table. Therefore we replace a span of tokens that constitute an entity in

List of Assyrian kings   Dynasty of Puzur-Ashur (2025–1749 BC)		
King	Reign	Succession
Puzur-Ashur I Puzur-Aššur "servant of Ashur"	f1. c. 2000 BC	Unknown
-	-	-
Erishum I e-ri-šu	c. 1905 BC – c. 1867 BC (38 years)	Son of Ilu-shuma
Ikunum I-ku-nu	c. 1867 BC – c. 1860 BC (7 years)	Brother of Erishum I, son of Ilu-shuma
Sargon I Šarru-ukīn "the king is legitimate"	c. 1860 BC – c.1821 BC (39 years)	Son of Ikunum
Puzur-Ashur II Puzur-Aššur "servant of Ashur"	c. 1821 BC – c.1813 BC (8 years)	Son of Sargon I
Naram-Sin Na-ra-am Sīn "beloved of the Moon God Sīn"	c. 1813 BC – c.1769 BC (44 years)	Son of Puzur-Ashur II

**Input:**  
On the Assyrian King List, for whom is Sargon the son and successor of and for whom is he the father and predecessor of?

**Step 0:** Retrieve original sentence.  
On the Assyrian King List, Sargon appears as the son and successor of Ikunum, and the father and predecessor of **Puzur-Ashur II**.

**Step 1:** Identify entities to replace: {**Puzur-Ashur II**}

**Knowledge-Based Perturbation**

**Step 2:** Identify columns of entities.  
{Entity: **Puzur-Ashur II**,  
Column: **King**}

**Step 3:** Select replacement entities from the same column.  
{**King**: Erishum I, Ikunum, Sargon I, Naram-Sin...}

**Step 4:** Perturb sentence.  
On the Assyrian King List, Sargon appears as... predecessor of **Erishum I**.

**Model-Based Perturbation**

**Step 2:** Prepare the context.  
On the Assyrian King List, Sargon appears as... predecessor of \_\_\_\_\_

**Step 3:** Teacher-force the above context and predict the continuation using a Data-to-Text model.  
(D2T Model → Sargon II...)

**Step 4:** Perturb sentence.  
On the Assyrian King List, Sargon appears as... predecessor of **Sargon II**.

Figure 2: Faithfulness-based replacement method

the original sentence with another candidate entity comprising one or more tokens. We adopted a RoBERTa-large-based named entity recognizer<sup>1</sup> to extract all the entities in a sentence. To sample one unfaithful sentence, we select one of these entities, with those located near the end of the sentence to have a higher probability of being selected. This way, for the token-level detection task, the model has more chances of obtaining a reasonable amount of context for performing discrimination. We propose two different methods of determining the candidate replacement, which are illustrated in Figure 2 and described next.

**Knowledge-based Method** Entities of similar types are usually the suspects of the wrong predictions. Identifying such entities from the input table is nontrivial in other text generation tasks whose input table is unstructured text. In D2T, the source arranges similar entities together. For example, when the input is a table, similar entities can be accessed in the same column; when the input is semantic triple set, we can obtain similar entities by searching those applicable to certain predicates. Our knowledge-based replacement method exploits the structure of the input table to retrieve similar entities, replacing the original entity with one in the sentence will lead to contradiction. This process is illustrated in Figure 2. Note that for the datasets we experimented on, we assume the entity to be replaced is the only choice to make the sentence entailed, and replacement of any other entities shown in the input table will violate the faithfulness of sentences. This assumption does not necessarily hold in some examples, on which we will elaborate in Section 3.6.

<sup>1</sup><https://huggingface.co/Jean-Baptiste/roberta-large-ner-english>

**Model-based Method** Another way to obtain replacement candidates is by sampling from a proposal distribution, in a way similar to ELECTRA. We sample replacements from the baseline Data-to-Text model by teacher forcing partial sentence up to the entity that needs to be replaced. Next we collect the D2T model predictions of the continuation with nucleus sampling (Holtzman et al., 2020), followed by extracting altered entities shown in the predicted continuations to determine the replacement candidates. With this approach, we are able to expose and further train the D2T model with errors of its own predictions.

### 2.3 Replacement Detection in Generation

For each entailed sentence  $Y_{\text{True}}^{(i)}$  that we sample from the original dataset  $\mathcal{D}$  where  $i = 1, \dots, |\mathcal{D}|$ , we generate  $N^{(i)}$  contradictory sentences which we denote as  $Y_{\text{False}}^{(i,j)}$  for  $j = 1, \dots, |N^{(i)}|$ . The number of contradictory sentences we can generate given an entailed sentence depends on the number of entities found in the original sentence, the input, and the replacement method applied.

As shown in Figure 3, we add a sentence-level replacement detection task to the existing Sequence-to-Sequence framework by eliciting the decoder to generate a probability of the teacher-forced sentence being entailed or contradictory at the end of the generation, similar to the sequence classification usage of BART (Lewis et al., 2020), except that in BART, the same sequence that needs to be classified is fed into both the encoder and decoder. The loss for sentence-level replacement detection is defined by Equation (1).

A more challenging task is to perform a fine-grained, token-level discrimination, as shown in Figure 4. Instead of predicting a discrimination probability at the end of generation, we task the

$$\mathcal{L}_{\text{RD}_{\text{sent}}}(X^{(i)}, Y) = - \left[ l \cdot \log p(l|Y, X^{(i)}) + (1-l) \cdot \log \left( 1 - p(l|Y, X^{(i)}) \right) \right] \quad (1)$$

$$\mathcal{L}_{\text{RD}_{\text{token}}}(X^{(i)}, Y) = - \left[ \sum_{t=1}^{|Y|} l_t \cdot \log p(l_t|y_{\leq t}, X^{(i)}) + (1-l_t) \cdot \log \left( 1 - p(l_t|y_{\leq t}, X^{(i)}) \right) \right] \quad (2)$$

$$\mathcal{L}_{\text{UL}}(X^{(i)}, Y_{\text{False}}^{(i,j)}) = - \left[ \sum_{t=\{t|y_t \in \mathcal{C}^{(i,j)}\}}^{|\mathcal{C}^{(i,j)}|} y_t \cdot \log(1 - \hat{y}_t) + (1 - y_t) \cdot \log(\hat{y}_t) + \sum_{t=\{t|y_t \notin \mathcal{C}^{(i,j)}\}}^{|Y_{\text{False}}^{(i,j)} \setminus \mathcal{C}^{(i,j)}|} y_t \cdot \log(\hat{y}_t) + (1 - y_t) \cdot \log(1 - \hat{y}_t) \right] \quad (3)$$

$$\mathcal{L}_{\text{NLL}}(X^{(i)}, Y_{\text{True}}^{(i)}) = - \sum_{t=1}^{|Y_{\text{True}}^{(i)}|} y_t \cdot \log(\hat{y}_t) + (1 - y_t) \cdot \log(1 - \hat{y}_t) \quad (4)$$

$$\mathcal{L}_{\text{R2D2}} = \sum_{i=1}^{|\mathcal{D}|} \frac{1}{|N^{(i)}| + 1} \left[ \lambda \left( \mathcal{L}_{\text{NLL}}(X^{(i)}, Y_{\text{True}}^{(i)}) + \sum_{j=1}^{|N^{(i)}|} \mathcal{L}_{\text{UL}}(X^{(i)}, Y_{\text{False}}^{(i,j)}) \right) + (1-\lambda) \left( \mathcal{L}_{\text{RD}_{\{\text{sent}, \text{token}\}}}(X^{(i)}, Y_{\text{True}}^{(i)}) + \sum_{j=1}^{|N^{(i)}|} \mathcal{L}_{\text{RD}_{\{\text{sent}, \text{token}\}}}(X^{(i)}, Y_{\text{False}}^{(i,j)}) \right) \right] \quad (5)$$

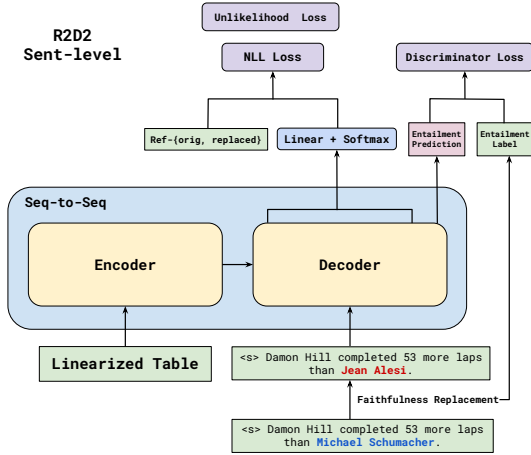


Figure 3: R2D2 sentence-level architecture

decoder to perform discrimination at every step of token generation. Specifically, we use the per-step last hidden output of the decoder, which encodes the source contexts and teacher-forced partial generation contexts, to compute the discrimination probability with a linear and sigmoid layer. The token-level replacement detection loss is defined by Equation (2).

## 2.4 Replacement Unlikelihood Training

Unlikelihood training is first proposed in (Welleck et al., 2019) to address the repetition problem of the neural text generation. This training objective aims to decrease the decoder’s probability of generating tokens that are already seen in the teacher-forced generation contexts. The applicability of this objective to the Data-to-Text task is also argued in (Uehara et al., 2020).

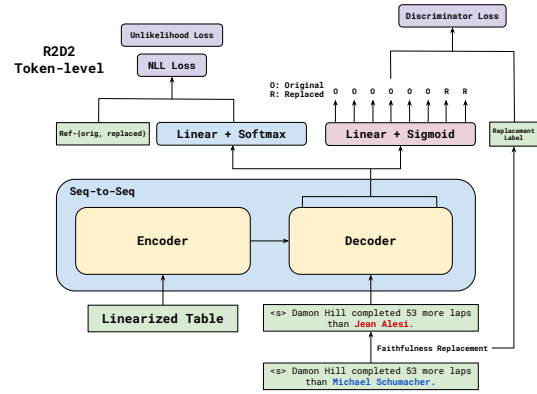


Figure 4: R2D2 token-level architecture

Instead of using the generated tokens to construct the negative candidate set defined for each step, we define the sentence-level negative candidate span  $\mathcal{C}^{(i,j)}$  for each contradictory sentence  $Y_{\text{False}}^{(i,j)}$ . The span contains, for each time step, one replaced token that should have a low probability of being generated. We calculate the sequence-level unlikelihood loss for this replaced token span and apply regular likelihood loss for other original tokens, which we denote as  $Y_{\text{False}}^{(i,j)} \setminus \mathcal{C}^{(i,j)}$ . We denote the per step prediction as  $\hat{y}_t = p(y_t|y_{<t}, X^{(i)})$ . The unlikelihood loss for the entire sentence is specified in Equation (3).

## 2.5 R2D2 Fine-tuning

We propose the final R2D2 fine-tuning loss objective as in equation (5). It combines a generation task loss component and a discrimination task loss component. Each of them is calculated from one entailed instance and  $N^{(i)}$  contradictory in-

stances. The generation task component consists of a regular negative log likelihood loss for the entailed instance, as described in Equation (4), and an unlikelihood loss for the contradictory instances. The discrimination task component contains either sentence-level or token-level replacement detection loss for both entailed and contradictory instances. We use  $\lambda$  to balance the importance between the two loss components.

## 2.6 NER-based Evaluation Metrics

To better understand how the D2T system’s retrieval capability correlates with faithfulness, we propose information-extraction based metrics that compare the named entities contained in the generated sentences to those contained in the reference sentences or input data. We believe these metrics help us better distinguish between the unfaithfulness caused by wrong retrieval of entities and that caused by wrong prediction of predicates/relations. Specifically, we propose the following five indicators:

- **Reference coverage (RC):** percentage of entities in the reference that are also shown in the prediction.
- **Ref-hit & Input-hit (RI):** percentage of entities shown in the prediction that are shown in both the reference and input table.
- **Ref-hit & Input-miss (RM):** percentage of predicted entities that are shown in the reference but not the input table. This case is rare since it indicates the existence of entities that are not input-grounded in the reference.
- **Ref-miss & Input-hit (MI):** percentage of predicted entities that are shown in the table, but not in the reference. This case identifies wrong or unnecessary retrieval of entities from the input (when the indication of saliency is evident).
- **Ref-miss & Input-miss (MM):** percentage of predicted entities that are neither shown in the table nor the reference. This case identifies the prediction of entities likely by hallucination.

Figure 5 and Figure 6 show the correlation between NER-based metrics and sacreBLEU, NLI-Acc, respectively. As expected, the reference coverage rate positively correlates with both metrics.

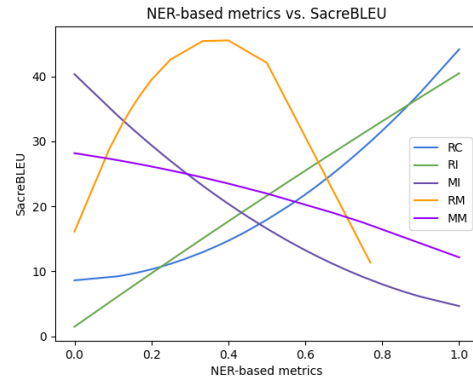


Figure 5: NER-based metrics vs sacreBLEU

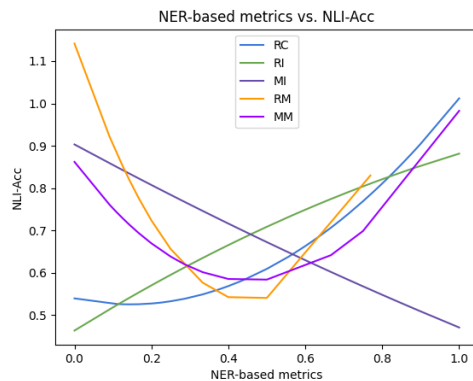


Figure 6: NER-based metrics vs NLI-Acc

While both reference hit and input hit are important, the rate of predicted entities not shown in reference negatively correlates with sacreBLEU (MI and MM) and NLI-Acc (MI). The trend is less clear for RM and MM since these are rare cases, which can also be shown in Table 6.

Since many existing automatic metrics for text generation tasks are not proposed with an aim of reflecting the faithfulness of the sentences, an examination of all metrics reported in our work is crucial for interpreting the results. As we are able to reliably generate an unfaithful version of most of the reference texts, we contaminate the references in the FeTaQA test split in a controlled manner: we generate five variants of texts with different percentage of the references being replaced with their unfaithful parallel (0% version contains only the references and 100% version contains only the unfaithful sentences). We evaluate the variants that are contaminated to different degrees using the evaluation metrics we reported, in order to investigate how reliable they are in reflecting the faithfulness of any system generated sentences.

% Unfaithful Sentences	Fact-based		String-based					NER-based				
	NLI-Acc	sacreBLEU	Rouge-1/2/L	PARENT	TER	METEOR	BERTScore	RC	RI	RM	MI	MM
0% (ref.)	86.17	100.0	100/100/100	89.87	0.0	99.99	100.0	99.95	94.15	5.80	0.0	0.05
25%	73.29	96.1	97.62/96.31/97.62	87.23	2.57	98.08	99.43	96.37	90.82	5.67	2.98	0.53
50%	61.21	92.2	95.28/92.63/95.29	84.63	5.18	96.24	98.87	93.01	87.53	5.55	5.86	1.06
75%	48.63	88.3	92.87/88.87/92.87	81.91	7.84	94.36	98.29	89.32	84.33	5.31	8.81	1.54
100%	36.20	84.4	90.47/85.13/90.48	79.16	10.36	92.48	97.72	85.70	80.93	5.24	11.72	2.11

Table 1: Reliability test result of evaluation metrics for detecting unfaithfulness

As shown in Table 1, most of the metrics are able to reflect the degree of unfaithfulness contained in the prediction texts, though our test only contains the type of unfaithfulness that originates from erroneous selection of entities. A more rigorous study would test other types of unfaithfulness, such as wrong prediction of relations or arrangement of entities. Nevertheless, we observe that some metrics, especially NLI-Acc, are more sensitive to the type of unfaithfulness that we tested, while an unfaithful sentence can still obtain a very high BERTScore (Zhang et al., 2020).

### 3 Experiments

We first introduce the datasets that we experiment with in Section 3.1, and the metrics we adopted for evaluation in Section 3.2. Then we report the baseline models we are comparing with, and the implementation and training details in Section 3.3. In Section 3.4 and 3.5, we report both the automatic evaluation results and the human evaluation results, followed by an analysis of them in Section 3.6.

#### 3.1 Datasets

FeTaQA (Nan et al., 2022) is a free-form table question answering dataset. It introduces a task that requires retrieving the correct contents from the table based on the question, integrating and inferring from the retrieved facts, and generating a free-form answer. A sentence that contains erroneous selections of facts, even if they appear in the input table, are still considered as unfaithful, because the sentence is inconsistent (incorrect) with the input question.

LogicNLG (Chen et al., 2020a) is a table-to-text dataset that tasks the models to generate logically entailed sentences. There is no indication of what is considered as salient given a table, as long as the generated sentence is entailed given all the facts contained in the table. Since there are numerous entailed facts that are different from the references in the surface-form, they propose input-based metrics that compare the facts in the generated sen-

tence and those in the input. Although we report the experiment results of reference-based metrics for this dataset, it is worth noting that unlike other datasets mentioned above, faithfulness to the input is more important for LogicNLG than faithfulness to the references.

ToTTo (Parikh et al., 2020) is a table-to-text dataset that contains annotations of salient content of tables (highlighted table cells). The task does not require any content selection (when only highlighted cells constitute the input), but only text planning and surface realization of the inputs, which are expected to be described with full coverage, and the median number of highlighted cells is 3.

#### 3.2 Evaluation Metrics

We report results of a variety of automatic evaluation metrics used in the past studies to provide a comprehensive comparison of existing methods and our proposed method. We include fact-verification based metrics, NLI-Acc (Chen et al., 2020a,b), which specifically aims to evaluate the faithfulness of the sentences. We also report string-based metrics that evaluate the  $n$ -gram or other types of string match between predictions and references, such as sacreBLEU (Post, 2018), ROUGE- $\{1, 2, L\}$  (Lin, 2004), TER (Snover et al., 2006), METEOR (Banerjee and Lavie, 2005), PARENT (Dhingra et al., 2019) (which also leverages the input data). In addition, we report evaluation results of the NER-based metrics.

#### 3.3 Experiment Settings

**Baselines** The state-of-the-art system for the Data-to-Text task is obtained by fine-tuning a pre-trained sequence-to-sequence model, such as T5 (Raffel et al., 2020), BART (Lewis et al., 2020) or Longformer-Encoder-Decoder (LED) (Beltagy et al., 2020). We report evaluations of existing state-of-the-art models for all datasets. We also fine-tuned T5 on FeTaQA, LogicNLG and ToTTo by ourselves, so that the learning objective is the key control variable in our comparison.

Dataset	Original		
	Train-split Size	Knowledge-based	Model-based
FeTaQA	7,325	238,891 ( $\times 32.6$ )	25,313 ( $\times 3.5$ )
LogicNLG	21,873	413,247 ( $\times 18.9$ )	91,183 ( $\times 4.2$ )
ToTTo	120,761	1,165,067 ( $\times 9.6$ )	450,770 ( $\times 3.7$ )

Table 2: Number of obtainable contradictory sentences for the train-split of all datasets.

**Implementation** We use T5-base as the pre-trained checkpoint from which we fine-tune either regularly (Reg-FT) or using our proposed method (R2D2-FT). For R2D2-FT, we initialize our model from a checkpoint that has been fine-tuned regularly for 15 epochs, and train the additional linear layer for sentence or token replacement detection from random initialization. We find this fine-tuning warmup help improve the performance in general. We use the Adafactor optimizer (Shazeer and Stern, 2018) with a learning rate of  $5e-5$ . We use the batch size of 8 for FeTaQA and 32 for the others.

**R2D2 Configuration** To assess the necessity of the discrimination loss and unlikelihood loss, we experimented fine-tuning T5 only with the discrimination loss, or only with the unlikelihood loss, or both (all in addition to the NLL loss). For discrimination loss, we also experiment with adding sentence-level or token-level discrimination to investigate the effect of discrimination granularity in assisting faithful text generation. For all the training variants above, we also compare two methods of obtaining the contradictory sentences, knowledge-based and model-based methods. Since the number of contradictory sentences obtained (which we denote as  $N^{(i)}$  in Section 2.5) varies depending on the method used (as shown in Table 2), we also experiment with using different numbers of contradictory sentences in the R2D2 fine-tuning:  $N^{(i)} = 1$  (xsmall), 3 (small), 5 (medium), 10 (large) or max (full). Since the maximum size of the perturbations obtained by model-based method is small, we only compared xsmall and full for the model-based method setting.

### 3.4 Automatic Evaluation

We report the performance of the previous state-of-the-art system, T5 fine-tuned only with negative log likelihood (NLL) loss by ourselves, and the best T5 fine-tuned with R2D2 loss for FeTaQA (Table 3), LogicNLG (Table 4) and ToTTo (Table 5), based on metrics used in the existing literature. In

Table 6, we also report their performances using the NER-based metrics that we proposed. We also report the full experiment results of FeTaQA that contain evaluations of different R2D2 configurations in Table 8 of the Appendix.

We observe that across all the datasets, most of the systems fine-tuned with different R2D2 configurations are able to perform better than system that is fine-tuned only with NLL loss. As expected, the improvements are more evident in the fact-verification-based metrics that evaluate the faithfulness of the sentences. We find that the best R2D2 configuration requires both the token-level discrimination and the unlikelihood learning objectives, and that contradictory sentences obtained by knowledge-based perturbation are more beneficial than those obtained by model-based perturbation for fine-tuning when all other configuration constants are controlled. We also find that system performance does not necessarily improve as we increase the number of unfaithful sentences used for fine-tuning, and that the best configuration for  $N^{(i)}$  seems to be three to five in most cases.

We examine the improvement of faithfulness using the NER-based metrics, and find that the coverage of the entities appeared in the reference (RC) improves across all datasets. For FeTaQA, we notice that our system is able to retrieve *input-grounded entities* more accurately (shown by increased RI and decreased MI scores). For LogicNLG which has no right or wrong retrieval of input-grounded entities as long as the description of them is faithful, we observe an evident decline of MM and increments of both RI and MI (with more evident gain in MI), indicating that our system is able to reduce hallucinations of irrelevant entities and instead retrieving input-grounded ones.

### 3.5 Human Evaluation

Since the automatic evaluations are not always reliable in determining the faithful aspect of a sentence, which can be seen in our metrics reliability test shown in Table 1: around 14% faithful sentences are deemed to be unfaithful by the NLI-Acc metric, and more importantly, it fails to identify around 36% of the unfaithful sentences. We conduct the human evaluation based on two criteria: a sentence is (1) *faithful* if **all facts** contained are entailed by the input, and when a question is present in the input, the sentence only contains **necessary facts**; (2) *adequate with respect to reference* if the sentence

Systems	Fact-based		String-based			
	NLI-Acc	sacreBLEU	Rouge-1/2/L	PARENT	TER	METEOR
Xie et al. (2022)	-	29.9	61.77/39.44/51.93	-	-	48.53
<b>Reg-FT</b>	74.79	30.5	63.47/41.77/54.04	44.24	66.37	55.2
<b>R2D2-FT</b>	<b>77.93</b>	<b>31.5</b>	<b>63.50/41.71/54.05</b>	<b>45.32</b>	68.55	<b>56.27</b>

Table 3: FeTaQA-test automatic evaluation result

Systems	Fact-based			String-based				
	NLI-Acc	SP-Acc	BLEU-1/2/3	sacreBLEU	Rouge-1/2/L	PARENT	TER	METEOR
Chen et al. (2021b)	76.9	43.9	49.5/28.6/15.3	-	-	-	-	-
<b>Reg-FT</b>	84.11	45.97	51.63/32.24/18.75	18.2	42.74/20.89/36.77	32.36	86.38	36.55
<b>R2D2-FT</b>	<b>85.57</b>	<b>50.80</b>	<b>51.76/32.42/18.65</b>	<b>18.5</b>	42.63/20.73/36.84	31.38	<b>80.97</b>	35.73

Table 4: LogicNLG-test automatic evaluation result

contains **same or more facts** than the reference. We asked three human evaluators to evaluate 200 samples of each dataset (100 samples in each of the overlap/nonoverlap split for ToTTo), and each sample is provided with all the inputs, the reference, and two system generated sentences. We report the percentage of faithful and adequate sentences generated by the baseline system and our system on all datasets in Table 7, and the results validate R2D2’s effectiveness in faithful text generation.

### 3.6 Further Analysis

Comparing the effectiveness of R2D2 on different datasets and with different evaluations, we found that FeTaQA and ToTTo benefit more than LogicNLG. We speculate this is because many sentences of LogicNLG describe some entailed facts of entities of a single table column (usually involving comparisons), which usually contain single and less restricted predicate that could be applied to many homogeneous entities, and this would invalidate our perturbation methods. We provide one such example in Figure 7 of the Appendix. We also notice that for ToTTo, the improvement is less evident than that for FeTaQA. Besides less room for improvement, we observe no evident change in the entities retrieved by both systems compared with those in the reference or input, while human evaluation indicates there are still around 17% unfaithful sentences. We speculate the source of unfaithfulness of these sentences are due to wrong predictions of relations/predicates, which are not captured and included into the R2D2 fine-tuning by our current perturbation method. To avoid invalidation of perturbation (as in the case of LogicNLG) and also

to capture erroneous relation predictions, a better perturbation method has to operate on fact triples instead of entities, but this requires a reliable and domain-independent fact extraction system, which we will explore in future.

## 4 Related Work

### 4.1 Unfaithfulness in Text Generation

In the context of text generation, hallucination refers to the phenomenon of neural models “generating unfaithful or nonsensical text” (Ji et al., 2022). For instance, the generated text can contradict information in the source, or have nothing to do with the source, and hence cannot be verified. One reason for such hallucination is poor data collection; for example, information in the target sentence may not actually be present in the table, which can occur when the tables and sentences do not actually align. Another source of such hallucination is training, such as the exposure bias, or the task expects more output diversity. Metrics based on information extraction, question answering, and natural language inference, have been proposed to measure such hallucination, which we employ to evaluate the performance and faithfulness of R2D2.

### 4.2 Contrastive Learning

Contrastive learning (Hadsell et al., 2006) tasks the model with maximizing the representation similarity between neighboring examples while minimizing the similarity between distant examples. Contrastive learning has recently been used in various NLP tasks, including sentence embedding (Gao et al., 2021), machine translation (Yang et al., 2019;



Systems	Split	Fact-based		String-based			
		NLI-Acc	sacreBLEU	Rouge-1/2/L	PARENT	TER	METEOR
Kale and Rastogi (2020)	All	-	47.7	-	57.1	-	-
	Overlap	-	-	-	-	-	-
	Nonoverlap	-	39.6	-	52.6	-	-
Reg-FT	All	90.29	48.7	75.92/55.99/67.40	58.43	48.53	71.01
	Overlap	91.17	56.6	79.95/62.39/72.78	62.88	40.85	75.56
	Nonoverlap	89.42	41.0	72.04/49.80/62.20	54.14	55.69	66.54
R2D2-FT	All	<b>91.27</b>	<b>49.2</b>	75.54/55.59/67.06	<b>59.05</b>	50.40	<b>71.99</b>
	Overlap	<b>91.70</b>	<b>56.7</b>	79.42/61.68/72.14	<b>62.89</b>	42.72	<b>76.47</b>
	Nonoverlap	<b>90.86</b>	<b>41.9</b>	71.79/49.69/62.15	<b>55.35</b>	57.57	<b>67.67</b>

Table 5: ToTTo-dev automatic evaluation result

Dataset	Systems	Split	RC	RI	RM	MI	MM
FeTaQA	Reg	A	72.30	69.88	1.48	24.90	3.73
	R2D2	A	<b>73.06</b>	<b>70.92</b>	<b>1.62</b>	<b>23.82</b>	<b>3.64</b>
LogicNLG	Reg	A	37.29	26.07	0.97	61.60	11.36
	R2D2	A	<b>37.93</b>	<b>26.62</b>	<b>0.44</b>	<b>67.12</b>	<b>5.82</b>
ToTTo	Reg	A	82.47	74.95	3.14	17.66	4.24
		O	84.87	77.95	3.40	15.10	3.54
		N	80.14	72.04	2.89	20.14	4.92
	R2D2	A	<b>83.24</b>	74.06	3.26	18.31	4.37
		O	<b>85.45</b>	76.90	3.63	15.70	3.77
		N	<b>81.08</b>	71.30	2.89	20.85	4.95

Table 6: NER-based automatic evaluation result. A, O, N stands for All, Overlap and Nonoverlap.

Dataset	Systems	Split	Faithfulness (%)	Coverage w.r.t Ref (%)
FeTaQA	Reg-FT	A	61.33	54.83
	R2D2-FT	A	<b>68.67</b>	<b>61.83</b>
LogicNLG	Reg-FT	A	40.67	69
	R2D2-FT	A	<b>41.17</b>	66.50
ToTTo	Reg-FT	A	81	81.17
		O	83.66	82.66
		N	78.32	79.66
	R2D2-FT	A	<b>83.16</b>	<b>84.67</b>
		O	<b>84.34</b>	<b>88.66</b>
		N	<b>82</b>	<b>80.66</b>

Table 7: Human evaluation result. A, O, N stands for All, Overlap and Nonoverlap.

Pan et al., 2021), text summarization (Cao and Wang, 2021; Liu and Liu, 2021; Xu et al., 2021; Sun and Li, 2021; Wang et al., 2021; Liu et al., 2022), data-to-text generation (Uehara et al., 2020) and other tasks (Cho et al., 2021; Lee et al., 2021; Su et al., 2022, 2021). Unlike Uehara et al. (2020), in which unfaithful sentences are obtained by replacing a set of keywords (such as replacing *low* to *high*, *gain* to *drop*) that only apply to the finance domain, we propose domain-independent methods for sampling unfaithful sentences either by exploiting the structure of input knowledge or utilizing the D2T model’s own mistakes.

### 4.3 Unlikelihood Training

To address the degeneration problems of models trained only with Maximum Likelihood Estimation, many works have proposed alternative approaches (Tu et al., 2016; Li et al., 2020; Holtzman et al., 2020; Lin et al., 2021). Among them, unlikelihood training was introduced as a means of decreasing the probability that the model generates certain tokens (Welleck et al., 2019). In a D2T context, we adopt unlikelihood training to decrease the probability that the model generates tokens which are not entailed by the given contexts.

### 4.4 Evaluation Metrics

Ideally, a data-to-text model should be evaluated based on its ability to generate logical sentences based on the provided reference data. Current methods however, typically only compare the model output summary to the gold standard label. This includes n-gram based (e.g. BLEU, ROUGE, and METEOR) or edit distance based metrics (e.g. TER) (Sai et al., 2022), or embedding-based similarity metrics (e.g. BERTScore) (Zhang et al., 2019). Another set of metrics compare the infor-

mation present in the output and the label. This is done by extracting subject, object, and their relations in the output and label, and comparing both sets of elements (Wiseman et al., 2017). We evaluate our model using multiple metrics to understand different aspects of its performance.

#### 4.5 Natural Language Inference

Natural language inference (NLI) refers to the task of classifying whether a hypothesis entails, contradicts, or is unrelated to a premise (Bowman et al., 2015). Benchmarks for this task include the Stanford NLI dataset (SNLI) (Bowman et al., 2015), the Question-Answering NLI dataset (QNLI) (Wang et al., 2018), and MultiNLI (Williams et al., 2017). In the context of D2T, NLI can be used to evaluate whether a model’s generated text can be inferred from the input table (Chen et al., 2020a). An ideal model would generate sentences which an NLI model would classify as being entailed by the input table. In line with the work of TabFact (Chen et al., 2020b), LogicNLG (Chen et al., 2020a), and SnowBall (Shu et al., 2021), R2D2 incorporates this idea into data-to-text training by using NLI as a learning objective during the training procedure.

### 5 Conclusion

In this work, we introduced R2D2, a training framework that effectively mitigates the unfaithful text generation problem for the D2T task. Training with the regular maximum likelihood loss can lead to generation of sentences that are similar to the references but are unfaithful to the input. We therefore propose to add a discrimination task and an unlikelihood training to encourage the model to generate separable representations of these critical sentences. We proposed two methods of sampling these critical sentences that are unfaithful: the knowledge-based method exploits the structure of the input knowledge, and the model-based method samples the D2T model’s own mistakes. We examined existing metrics for evaluating faithfulness of generated sentences, and proposed NER-based metrics that assess the entity retrieval capability of the Data-to-Text systems, as we argued the incompetence of which is one of the leading causes of unfaithfulness. We experimented on multiple Data-to-Text datasets of different task constructs, and achieved noticeable improvements over the state-of-the-art.

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## A Appendix

Discrimination Loss	Discrimination Granularity	Unlikelihood Loss	Perturbation Method	Perturbation Size	Fact-based		String-based			
					NLI-Acc	sacreBLEU	Rouge-1/2/L	PARENT	TER	METEOR
✓	sent-level	✗	Knowledge based	xsmall	75.79	29.7	63.26/41.08/53.54	43.21	66.65	54.69
				small	74.59	29.7	63.53/41.54/54.06	43.43	65.75	54.67
				medium	77.13	30.2	63.47/41.43/53.68	43.99	66.96	55.09
				large	74.64	29.2	62.57/40.74/53.22	42.74	66.93	53.76
✓	sent-level	✗	Model based	xsmall	76.83	30.5	63.46/41.57/53.84	44.49	66.47	55.33
				full	74.69	29.2	63.08/41.03/53.57	43.01	66.76	54.39
				xsmall	76.14	30.4	63.36/41.03/53.64	43.61	67.89	55.61
				small	76.44	31.4	63.56/41.33/53.93	44.68	68.95	56.34
✓	sent-level	✓	Knowledge based	medium	76.59	30.7	63.11/40.75/53.58	43.83	69.73	55.86
				large	78.33	31.2	63.41/41.21/53.87	44.87	69.37	56.57
				full	78.18	30.9	62.95/40.95/53.26	44.45	71.78	55.81
				xsmall	77.58	30.7	63.30/41.14/53.34	44.18	68.48	55.47
✓	sent-level	✓	Model based	full	75.39	29.6	62.43/40.33/52.95	42.45	69.75	54.26
				xsmall	74.64	30.0	63.01/40.38/53.16	43.15	68.68	55.46
✓	token-level	✗	Knowledge based	small	75.74	30.8	63.98/41.92/54.39	44.35	66.81	55.75
				medium	75.54	30.5	63.41/41.42/53.93	44.36	67.47	55.60
				large	74.14	29.9	63.41/41.16/53.68	43.66	67.61	55.31
				full	74.94	29.2	63.23/40.73/53.64	42.62	67.89	54.33
✓	token-level	✗	Model based	xsmall	75.39	30.3	63.27/40.96/53.66	43.39	67.40	55.16
				full	74.44	30.4	63.34/41.24/53.92	44.11	67.30	55.58
✓	token-level	✓	Knowledge based	xsmall	75.79	30.7	63.52/41.02/53.75	43.83	68.09	56.19
				small	77.73	31.2	63.30/41.01/53.54	44.55	69.52	56.26
				medium	77.93	31.5	63.50/41.71/54.05	45.32	68.55	56.27
				large	76.78	30.9	62.67/40.76/53.41	43.93	71.47	55.59
✓	token-level	✓	Model based	full	78.28	30.9	62.50/40.43/53.07	44.29	71.24	55.69
				xsmall	75.28	29.8	62.82/40.33/53.10	42.72	68.92	54.48
✓	token-level	✓	Model based	full	75.19	29.2	61.88/39.49/52.11	41.68	72.00	54.05
				xsmall	75.39	30.0	63.00/40.41/53.49	42.85	67.95	54.93
✗	-	✓	Knowledge based	small	77.93	31.1	63.74/41.68/54.26	44.59	68.43	56.11
				medium	77.58	30.8	63.34/41.08/53.70	43.87	68.56	55.77
				large	76.29	31.5	63.11/41.20/53.82	45.11	69.93	56.30
				full	77.68	31.0	63.17/40.96/53.53	44.20	70.97	56.24
✗	-	✓	Model based	xsmall	74.34	30.2	63.06/40.56/53.41	43.62	68.65	55.22
				full	77.33	29.9	62.27/40.16/52.50	43.00	73.97	54.95

Table 8: Full R2D2 experiment results for FeTaQA.

Figure skating at the 1964 Winter Olympics				
Rank	Name	Nation	Points	Places
1	Sjoukje Dijkstra	Netherlands	2018.5	9
2	Regine Heitzer	Austria	1945.5	22
3	Petra Burka	Canada	1940.0	25
...	...	...	...	...
30	Berit unn Johansen	Norway	1524.9	265

A sentence with more subject-object-restricting set of predicates:

Regine Heitzer **outranked** the Canadian athlete **Petra Burka** by obtaining 5.5 more points.

To produce a contradictory sentence, we can replace **Petra Burka** with any other entities in the Name column.

A sentence with less subject-object-restricting set of predicates (abundant in LogicNLG):

Regine Heitzer **outranked** **Petra Burka**.

To produce a contradictory sentence, we can only replace **Petra Burka** with Sjoukje Dijkstra. This invalidates our current perturbation method.

Figure 7: Sentences for which our current perturbation methods do not apply.