Incorporating Consistency Verification into Neural Data-to-Document Generation

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Abstract

Recent neural models for data-to-document generation have achieved remarkable progress in producing fluent and informative texts. However, large proportions of generated texts do not actually conform to the input data. To address this issue, we propose a new training framework which attempts to verify the consistency between the generated texts and the input data to guide the training process. To measure the consistency, a relation extraction model is applied to check information overlaps between the input data and the generated texts. The non-differentiable consistency signal is optimized via reinforcement learning. Experimental results on a recently released challenging dataset ROTOWIRE show improvements from our framework in various metrics.

1 Introduction

Data-to-text generation, a classic task of natural language generation is to convert the structured input data (i.e., a table) into descriptions that adequately and fluently describes the data (Kukich, 1983; Reiter and Dale, 1997; Barzilay and Lapata, 2005; Angeli et al., 2010; Kim and Mooney, 2010; Perez-Beltrachini and Gardent, 2017). Data-to-document generation is a slightly more challenging setting in which a system generates multi-sentence summaries based on input data (Wiseman et al., 2017). It is traditionally divided into two subtasks: content selection and the surface realization. Recent Neural generation systems blur the distinction by building over encoder-decoder architecture (Sutskever et al., 2014) with attention mechanism (Bahdanau et al., 2015) over input content (Mei et al., 2016; Dušek and Jurcicek, 2016; Kiddon et al., 2016; Chisholm et al., 2017).

Although neural network models are capable of generating fluent texts, they tend to make mistakes in the generated sentences, containing sentences that do not conform to the input structured data. As shown in Figure 1, the neural model produces the wrong rebound number. Previous work (Wiseman et al., 2017) notices the problem and proposes an extractive metric to evaluate the consistency between the generation and its input structured data. However, such consistency is not involved in the training process to guide model learning.

In this paper, we propose to use a new training framework that directly incorporates consistency verification to guide the generation during the training process. In this way, the inconsistency between the output text and the input structured data can be measured and treated as negative signals to guide a traditional encoder-decoder network. To measure the consistency, we apply a relation extraction model to collect factual information from generated texts and compare them with its paired reference and input data. Since only a subset of generated text are related to the reference and the input data, we design two novel word-level reward signals based on the consistency with the reference text and with the input data respectively. The non-differentiable consistency reward signals are incorporated into training procedure via a reinforcement learning approach.

We evaluate our proposed method on the ROTOWIRE dataset (Wiseman et al., 2017), which targets at generating multi-sentence game summaries. Empirical experiments show that our proposed method outperforms the encoder-decoder neural generation baseline on BLEU and extraction based evaluation metrics.
2 Model

As shown in Figure 1, our method incorporates a consistency verification process in the encoder-decoder architecture (Sutskever et al., 2014) via a reinforcement learning (RL) framework. We introduce the encoder-decoder architecture in Section 2.1, then describe the components of verification in Section 2.2. The consistency information brought by the verification is incorporated using the RL approach in Section 2.3.

2.1 Base Model

Our base model is a simple sequence-to-sequence (Seq2Seq) with two-layer bidirectional encoder and unidirectional LSTM decoder with attention (Bahdanau et al., 2015) and conditional copy mechanism as (Gülçehre et al., 2016).

2.2 Consistency Verification

To examine information consistency, we use a relation extraction (RE) model to extract factual information from unstructured generated texts. Since only a subset of words contain factual statements in the generated texts, the verification weights on each word are various. We design two word-level reward signals to verify the consistency on the reference text and input data respectively, and the Gaussian smoothing is also applied smooth the verification weights on context words. Given an input and description pair $(x, y)$, where each target description $y = y_{1:T}$ consists of $T$ words and each input contains a set of records $x = \{x_j\}_{j=1}^T$. The description generated by model is denoted as $\hat{y}_{1:T}$. Following (Liang et al., 2009), each $x_j = (x_j^e, x_j^m, x_j^r)$ is a triple, where $x_j^e$ is the type of record, $x_j^m$ and $x_j^r$ are a record’s entity and value respectively. As shown in Figure 1, $x_j^e$, $x_j^m$ refer to ‘PTS’, ‘Harden’, and ‘40’ respectively.

2.2.1 Information Extraction

To extract information describing the input data from the generated texts, we apply a simple information extraction system similar to (Wiseman et al., 2017). Given a generated text $\hat{y}_{1:T}$, we first extract candidate entity $r^e$(e.g., name) and value $r^m$(e.g., number) pairs in the generated texts with lexical rules and then predict the type $r^t$(e.g., points) of each candidate pair using a RE model(dos Santos et al., 2015). We train the RE model in a distant supervision manner (Mintz et al., 2009), with training data constructed from reference text and input data.

2.2.2 Consistency Rewards

Applying a RE model on the generated text yields a set of candidate relation tuples $S = \{r_i\}_{i=1}^M$. The reference text and input structured data both describe uncontradicted facts and can be treated as gold data which describe facts. To make use of both information, we design two consistency scoring functions (rewards) based on reference text and input data respectively. We first define fidelity reward to check whether the relation tuples are consistent with the input data. For a particular $\hat{y}_t$ in $\hat{y}_{1:T}$, its fidelity reward is:

$$R^F(\hat{y}_t) = \beta \sum_{i=1}^M \mathbb{I}_{g(r_i^e) : g(r_i^m)}(t) \left( \mathbb{I}_{a(r_i)} - b_f \right) \quad (1)$$

where $g(\cdot)$ returns index range of given entity or number, $\mathbb{I}$ is indicator function defined as $\mathbb{I}_A(x) = \begin{cases} 1, & \text{if } x \in A \\ 0, & \text{if } x \notin A \end{cases}$

$\beta$, $b_f$ are hyper parameters. $\beta$ controls reward scale and $b_f$ controls the balance between positive and negative reward. Similar to fidelity reward, we define content reward for each $\hat{y}_t$ to measure whether the relation tuples $S$ extracted in the generated text also appear in the reference text as:

$$R^C(\hat{y}_t) = \alpha \sum_{i=1}^M \mathbb{I}_{g(r_i^e) : g(r_i^m)}(t) \left( \mathbb{I}_{S_{x_{j^r}}(r_i)} - b_c \right) \quad (2)$$

To combine these rewards, we use weighted sum of two components $R(\hat{y}_t) = \lambda_1 R^C(\hat{y}_t) + \lambda_2 R^F(\hat{y}_t)$ where weights $\lambda_1$ and $\lambda_2$ are hyper parameters. Moreover, both fidelity and content rewards only effect a subset of words, to balance the effect on context words, we apply Gaussian smoothing technique in this paper.

![Figure 1: Neural Data-to-Document Generation with Verification framework.](image-url)
2.3 Policy Gradient Reinforce

Our verification signal is non-differentiable and thus end-to-end back-propagation is not possible. Reinforce-based policy gradient approach addresses this issue by using its own distribution during training and by optimizing the non-differentiable verification signals as rewards. We use the REINFORCE algorithm (Williams, 1992; Zaremba and Sutskever, 2015) to learn a policy \( p_{\theta} \), i.e., the distribution produced by the encoder-decoder model. The training objective for one sequence is its expected cumulative rewards:

\[
J(\theta) = E_{(\hat{y}_1, \ldots, \hat{y}_T) \sim p_{\theta}(\cdot|x)}[R(\hat{y}_1, \ldots, \hat{y}_T, x)]
\]

where \( R(\cdot) \) is the reward function of the sequence of words \( \hat{Y} = (\hat{y}_1, \ldots, \hat{y}_T) \) sampled from the policy. The derivative of the loss function with approximation using a single sample along with variance reduction with a bias estimator \( b_1 \) is:

\[
\nabla J_{RL} \approx \sum_{t=1}^{T} \nabla_{\theta} \log p_{\theta}(\hat{y}_t|\hat{y}_{1:t-1}, x)[R(\hat{y}_1, \ldots, \hat{y}_T, x) - b_1]
\]

As illustrated in Section 2.2, our proposed reward can only affect a subset of words related to the input data. Therefore, our word-level reward function can be formulated as:

\[
R(\hat{y}_{1:T}, x) = \sum_{t=1}^{T} R_t(\hat{y}_t|\hat{y}_{1:t-1}, x)
\]

Therefore, we can have word level feedback as (Sutton et al., 2000):

\[
\nabla J_{RL} \approx \sum_{t=1}^{T} \nabla_{\theta} \log p_{\theta}(\hat{y}_t|\hat{y}_{1:t-1}, x)(Q_t - b_1)
\]

where \( Q_t = \sum_{k=1}^{\gamma} R_k(\hat{y}_t|\hat{y}_{1:k-1}, x) \)

We conduct pre-training on our policy with the maximum likelihood (MLE) objective prior to REINFORCE training.

3 Experiments

3.1 Experimental Setup

**Data:** We use ROTOWIRE dataset (Wiseman et al., 2017), which is a collection of articles summarizing NBA basketball games, paired with their corresponding box- and line-score tables. It consists of 3,398, 727, and 728 summaries for training, validation and testing respectively.

**Automatic evaluation:** Results of different methods on ROTOWIRE dataset

| Dev | RG Acc% | F1% | P%/R% | DLD |
|-----|---------|-----|-------|-----|
| Gold | 95.9 | 16.9 | 100 | 100/100 |
| Template | 99.9 | 54.2 | 35.7 | 23.7/72.4 |
| Wieman | 76.2 | 19.5 | 36.7 | 31.5/43.9 |
| Seq2Seq | 75.6 | 16.83 | 35.7 | 32.8/39.9 |

**Test**

| RG Acc% | F1% | P%/R% | DLD |
|---------|-----|-------|-----|
| 96.1 | 17.3 | 100 | 100/100 |
| 99.9 | 54.2 | 35.7 | 23.7/72.4 |

**Table 1:** Results of different methods on ROTOWIRE dataset

**Training:** For both MLE and RL training, we use the SGD optimizer with starting learning rate as 1 and last MLE epoch’s learning rate respectively, the dimension of trainable word embeddings and hidden units in LSTMs are all set to 512, and the mini-batch size is set to 16. We apply the truncated backpropagation with window size 100 (Mikolov et al., 2010). For RL training, we set the sample size to 1, \( \gamma \) to 0, \( \lambda_1, \lambda_2 \) to 1, \( b_1, b_2 \) to \( \frac{3}{2} \) and \( \alpha, \beta \) to 1.5 according to the validation set. For Gaussian smoothing on context reward, we fix its variance to 1 and truncate size to 5. We subtract mean reward as baseline for context reward and bound both type of rewards to [-2, 1]. For relation extractor model, we use an ensemble of CNNs and LSTMs relation classification models (Wiseman et al., 2017), which achieves the precision of 94.7% and recall of 75.3% given the reference.

**Evaluation:** We use automatic evaluation metric BLEU-4 (Papineni et al., 2002) and the extractive evaluation metrics proposed by (Wiseman et al., 2017), which contains three criteria: content selection (CS), relation generation (RG), content ordering (CO). CS measures the precision and recall of unique relation \( r \) extracted from generated texts \( \hat{y}_{1:T} \) and \( y_{1:T} \) that are also extracted from reference \( y_{1:T} \). RG measures the precision and recall of unique relation \( r \) extracted from generated texts \( \hat{y}_{1:T} \) that appears in its paired input data \( x \). CO measures content ordering between \( \hat{y}_{1:T} \) and \( y_{1:T} \) by calculating normalized Damerau-Levenshtein Distance (DLD) on extracted relations \( S \) and \( S_{ref} \).

3.2 Main Results

**Automatic evaluation:** Results of our experiments and a comparison to the previous works on this datasets are shown in Table 1. We apply 1We do not apply dropout in RL training

2The authors have recently updated the dataset to fix some mistakes. We cannot directly use the results which is reported
MLE training on our baseline model and achieve comparable results on ROTOWIRE dataset w.r.t. the previous work (Wiseman et al., 2017). The differences between our method and (Wiseman et al., 2017) is that we adopt a LSTM for the encoder, while (Wiseman et al., 2017) uses a table encoder similar to (Yang et al., 2017). Template based\(^3\) method performs poorly than all neural based method in terms of BLEU score, but it performs quite well on the extractive metrics, as input data is directly feed into placeholders of template by rules, which provides the upper-bound for how domain knowledge could help content selection and generation. For neural based methods, our proposed two verification signals can improve both BLEU and RG metric, which indicates the effectiveness of incorporating the verification constraints during training. In addition, with these two signals, our method achieves further improvements on BLEU and RG metric. For CS metric which measures the consistency between the generated texts and reference text, when incorporating the content reward with fidelity rewards, the overall F1 score of our method is improved.

**Qualitative analysis:** Table 3 shows a validation set game statistics with generation results by original Seq2Seq model and our proposed method\(^4\). The original Seq2Seq model is more likely to produce incorrect facts (e.g., wrong score points and shooting numbers for the player “Victor Oladipo” etc.). When incorporating the consistency into the training framework, our method can produce the facts that are consistent with the paired input data. Moreover, we observe that both two models can produce some irrelevant facts such as “Orlando has won two straight...”. We can incorporate constraints to avoid generating the irrelevant facts in the same framework as a future work.

### 3.3 Impact of Relation Extraction Model

The consistency signal is based on the relation extraction (RE) model, we therefore investigate the influence brought by different RE models. We provide two RE models in Table 2, where the Linear extractor refers to replacing the non-linear layer in CNN/LSTM extractor with a linear layer. The results of using different RE model for consistency verification over test set is listed in Table 2. Results show that Linear RE model extracts noisy relation tuples from the generated texts and can hurt the accuracy of consistency verification. The result also suggests that our framework may gain potential improvements if the RE model performs better.

### 4 Conclusion and Future Work

We present a framework that incorporates verification constraints during training for neural data-to-document generation to enhance the consistency between the generated text and the input structure data. Experimental results show that our method outperforms current state-of-arts neural Seq2Seq models in various evaluation metrics. In the future, we would like to improve both the neural

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\(^3\)Hand crafted templates from (Wiseman et al., 2017), e.g. `<player> scored <pts> points (<fgm> <fga>) FG, <fg3p> <fg3a> 3PT, <ftm> <fta> FT`

\(^4\)The whole game input data and the summaries are relatively lengthy, we present the first three sentences in the summary and its corresponding game statistics for brevity.
generation model and relation extraction model simultaneously within the single framework.

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