CycleGT: Unsupervised Graph-to-Text and Text-to-Graph Generation via Cycle Training

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Abstract

Two important tasks at the intersection of knowledge graphs and natural language processing are graph-to-text (G2T) and text-to-graph (T2G) conversion. Due to the difficulty and high cost of data collection, the supervised data available in the two fields are usually on the magnitude of tens of thousands, for example, 18K in the WebNLG dataset, which is far fewer than the millions of data for other tasks such as machine translation. Consequently, deep learning models in these two fields suffer largely from scarce training data. This work presents the first attempt to unsupervised learning of T2G and G2T via cycle training. We present CycleGT, an unsupervised training framework that can bootstrap from fully non-parallel graph and text datasets, iteratively back translate between the two forms, and use a novel pretraining strategy. Experiments on the benchmark WebNLG dataset show that, impressively, our unsupervised model trained on the same amount of data can achieve performance on par with the supervised models. This validates our framework as an effective approach to overcome the data scarcity problem in the fields of G2T and T2G.

1 Introduction

Knowledge graphs are a popular form of knowledge representation and central to many critical natural language processing (NLP) applications. One of the most important tasks, graph-to-text (G2T), aims to produce descriptive text that verbalizes the graphical data. For example, the knowledge graph triplet “(Allen Forest, genre, hip hop), (Allen Forest, birth year, 1981)” can be verbalized as “Allen Forest, a hip hop musician, was born in 1981.” This has wide real-world applications, for instance, when a digital assistant needs to translate some structured information (e.g., the properties of the restaurant) to the human user. Another important task, text-to-graph (T2G), is to extract structures in the form of knowledge graphs from the text, so that all entities become nodes, and the relationships among entities form edges. It can help many downstream tasks, such as information retrieval and reasoning. The two tasks can be seen as a dual problem, as shown in Figure.

However, most previous work has treated them as two separate supervised learning problems, for which the data annotation is very expensive. Therefore, both fields face the challenge of scarce parallel data. All current datasets are of a much smaller size than what is required to train the model.

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Our code is available at https://github.com/QipengGuo/CycleGT
Allen Forest, a hip hop musician, was born in the year 1981. The music genre hip hop gets its origins from disco and funk music, and it is also which drum and bass is derived from.

To circumvent the limitations of scarce supervised data, we present the first attempt to formulate both tasks in a cycle training framework, and also in the unsupervised manner with fully non-parallel datasets (as shown in Figure 1). The technical difficulty lies in the different modality of text and graphs, which can be intractable in a joint learning setting, making our problem more challenging than existing unsupervised image-to-image or text-to-text translation. We contribute an effective learning framework, CycleGT, which is iteratively trained with two cycle losses, and we also propose a task-specific warm up strategy accordingly.

We validate CycleGT on the widely used dataset WebNLG. Our model achieves impressive performance that is comparable to the supervised methods which are trained on the same data but given supervised alignment of text and graphs. The high performance of CycleGT indicates that it is an effective approach to address the data scarcity problem in the fields of both G2T and T2G. Consequently, CycleGT can pave the way for scalable, unsupervised learning, and benefit future research in both fields. We summarize the differentiating factors of CycleGT in Table 1.

| Previous Approaches | Our Approach |
|---------------------|--------------|
| Prerequisite        | Non-parallel text and graph data (cheap) |
| Method nature       | Unsupervised |
| Efficiency          | Learn G2T and T2G together |
| Potential           | Unbounded due to large unsupervised data |

Table 1: Contributions of our approach compared with the previous works.

2 Formulation and Notations

For unsupervised graph-to-text and text-to-graph generation, we have two non-parallel datasets:

- A text corpus $D_T = \{t_i\}_{i=1}^N$ consisting of $N$ text sequences, and
- A graph dataset $D_G = \{g_j\}_{j=1}^M$ consisting of $M$ graphs.

The constraint is that the graphs and text contain the same distribution of latent content $z$, but are different forms of surface realization. Their marginal log-likelihood can be formulated with the shared latent content $z$:

$$
\log p(g) = \log \int p(g | z)p(z)dz , \quad \log p(t) = \log \int p(t | z)p(z)dz .
$$

Our goal is to train two models in an unsupervised manner: G2T that generates text based on the graph, and T2G that produces the graph based on text. In the context of this paper, as the definitions of the two tasks are valid, G2T and T2G are inverse functions of each other.

Denote the parameters of G2T as $\theta$, and parameters of T2G as $\varphi$. Now suppose there exists an unseen ground truth distribution $D_{Pair}$ (e.g., as in the test set), where each paired text and graph $(t, g)$
share the same content. Then the ideal objective would be to maximize the log-likelihood of $\theta$ and $\varphi$ over the text and graph pairs $(t, g) \sim D_{\text{Pairs}}$:

$$J(\theta, \varphi) = \mathbb{E}_{(t, g) \sim D_{\text{Pairs}}} \left[ \log p(t | g; \theta) + \log p(g | t; \varphi) \right]. \quad (1)$$

The major challenge of our task is that the ground truth distribution $D_{\text{Pairs}}$ is not available as training data. Instead, only the text corpus $D_T$ and graph dataset $D_G$ are observed separately without alignment. So our solution is to approximate the learning objective in Eq. (1) through non-parallel text and graph data. The alternative method we derive, namely CycleGT, will be introduced next.

## 3 CycleGT Development

In this section, we will first discuss the iterative back translation training strategy of CycleGT in Section 3.1, then introduce the G2T and T2G components in Sections 3.2 and 3.3, respectively. Finally, we will introduce an additional component, warm start for the iterative training in Section 3.4.

### 3.1 Cycle Training with Iterative Back Translation

**Back Translation (BT)** In NLP, back translation is first proposed for machine translation where a sentence in the source language (e.g., English) should be able to first translate to the target language (e.g., French) and then again translated “back” to the source language (e.g., English). The source sentence in the source language (e.g., English) should be able to first translate to the target language, and the “back-translated” sentence should be aligned to be the same.

The essence of back translation is that a variable $x$ and a bijective mapping function $f(\cdot)$ should satisfy $x = f^{-1}(f(x))$, where $f^{-1}$ is the inverse function of $f$. In our case, G2T and T2G are inverse functions of each other, because one transforms graph to text and the other converts text to graph. Specifically, we align each text with its back-translated version, and also each graph with its back-translated version:

$$L_{\text{CycT}}(\theta) = \mathbb{E}_{t \in D_T} \left[ - \log p(t | T2G(\varphi)(t); \theta) \right], \quad (2)$$

$$L_{\text{CycG}}(\varphi) = \mathbb{E}_{g \in D_G} \left[ - \log p(g | G2T(\theta)(g); \varphi) \right]. \quad (3)$$

An equivalent way to interpret Eq. (2) and (3) is that due to the inavailability of paired text and graphs, we approximate $D_{\text{Pairs}}$ with $\hat{D}_{\text{Pairs}}$, a synthetic set of text-graph pairs generated by the two models. $\hat{D}_{\text{Pairs}}$ consists of $(t, T2G(\varphi)(t))$ and $(G2T(\theta)(g), g)$ for every $t \in D_T, g \in D_G$, leading to

$$T:\text{-Cycle:} \quad L_{\text{CycT}}(\theta) = \mathbb{E}_{t \in D_T} \left[ - \log p(t | T2G(\varphi)(t); \theta) \right] = \mathbb{E}_{(t, g') \in \hat{D}_{\text{Pairs}}} \left[ - \log p(t | g'; \theta) \right], \quad (4)$$

$$G:\text{-Cycle:} \quad L_{\text{CycG}}(\varphi) = \mathbb{E}_{g \in D_G} \left[ - \log p(g | G2T(\theta)(g); \varphi) \right] = \mathbb{E}_{(t, g) \in \hat{D}_{\text{Pairs}}} \left[ - \log p(g | t; \varphi) \right]. \quad (5)$$

As such, the sum of Eq. (2) and (3) reasonably approximates the log likelihood in Eq. (1).

Note that $J(\theta, \varphi) = L_{\text{CycT}}(\theta) + L_{\text{CycG}}(\varphi)$ holds when $\hat{D}_{\text{Pairs}}$ has the same distribution as $D_{\text{Pairs}}$. In our framework, we iteratively improve the G2T and T2G models using an iterative back translation (IBT) training scheme, with the goal of reducing the discrepancy between the distribution of $D_{\text{Pairs}}$ and $\hat{D}_{\text{Pairs}}$. Specifically, we repeatedly alternate the optimization of the two cycles described by Eq. (4) and (5) over the corresponding $\theta$ or $\varphi$.

**Non-Differentiability and Heterogeneity** There are two challenging aspects of our problem-specific use of IBT, even with the two established cycle losses above. The first is non-differentiability, which constitutes a fundamental difference between our model and the line of work represented by CycleGAN [60]. For our cycle losses $L_{\text{CycT}}$ and $L_{\text{CycG}}$, the intermediate model outputs are non-differentiable. For example, in the G-Cycle (graph→text→graph), the intermediate text is decoded in a discrete form to natural language. Hence, the graph-to-text part $G2T(\theta)$ will not be differentiable, and the final loss can only be propagated to the latter part, text-to-graph $T2G(\varphi)$. Hence, when alternatively optimizing the two cycle losses, we first fix $\varphi$ to optimize $\theta$ for the T-Cycle, and then fix $\theta$ to optimize $\varphi$ for the G-Cycle. Note that an analogous non-differentiability issue is shared by unsupervised NMT works [23, 1]; however, these methods have other significant differences from our approach as discussed below.

The second challenge faced by CycleGT is that text and graphs are of different modalities. Empirical studies (such as unsupervised NMT [23, 1]) have shown that a pure text-to-text cycle can work by
combining all the following into training: (1) shared embeddings between the encoder and decoder (because both are text), (2) denoising autoencoder, (3) cycle training, (4) adversarial loss, and (5) warm up strategies such as word-to-word lookup by a dictionary, or pretraining by language modeling on large text. However, UMT systems fail to work when having imperfect domain alignment between the source and target text [31], not to mention the challenging cross-modality problem we are dealing with. Obviously, when dealing with text and graphs, (1) and (5) cannot be applied. Moreover, (4) can be very cumbersome, and sometimes exhibits convergence issues. The remaining (2) is useless if only end-to-end cycle training is used. We demonstrate that (4) even when combined with (2) is ineffective through experiments in Section 4. In this work, we adopt a more streamlined approach suitable for the graph-to-text and text-to-graph applications.

3.2 G2T Component

We introduce the G2T component that we use in Eq. (2) and (3). The model \( G2T : G \rightarrow T \) takes as input a graph \( g \) and generates a text sequence \( t' \) that is a sufficient description of the graph.

Given a connected, directed graph \( G = (V, E) \), we seek its hidden representation \( h \). Specifically, we introduce a root node that is connected to all other nodes, and use its final embedding \( h \) to represent the graph. We use Graph Attention Networks (GAT) [51] to calculate the representation of each node by aggregating the information from its neighbors:

\[
\begin{align*}
    h_{i}^{l+1} &= \sigma \left( \sum_{j \in N_i} \alpha_{ij} Wh_j^l \right),
\end{align*}
\]

where \( h_{i}^{l+1} \) is the embedding of node \( i \) at layer \( l + 1 \), \( N_i \) is the set of its neighboring nodes, \( h_j^l \) is the embedding of the neighbor node \( j \) at the previous layer \( l \), and \( \alpha_{ij} \) is the attention between the two nodes by a single-layer feedforward neural network.

In this way, we represent the graph by the hidden embedding of the root node in the last layer, and overall we obtain

\[
    h = \text{GAT}(V, E).
\]

Based on the encoded graph, the generation of each word \( w_i \) at position \( i \) in the text takes as input all previously generated words \( w_{<i} \) and the graph \( h \):

\[
    p(t \mid g; \theta) = \arg\max \prod_{(t,g) \sim \mathcal{D}} p(t \mid g; \theta).
\]

3.3 T2G Component

We then introduce the remaining component, the T2G model. The function \( T2G : T \rightarrow G \) takes as input a text sequence \( t \) and extracts its corresponding graph \( g' \), whose nodes are the entities and edges are the relations between each two entities. As generating both the entities and relations of the graph in a differentiable way graph is intractable in NLP, we use an off-the-shelf entity extraction model NER\((t)\) that identifies all entities in the text with high accuracy [39]. We then predict the relations between every two entities to form the edges in the graph.

We first obtain the embeddings of every entity \( v_i \in \text{NER}(t) \) by average pooling the contextualized embedding of each word \( w_j \) in the entity term:

\[
\begin{align*}
    v_i &= \frac{1}{\text{Len}(v_i)} \sum_{w_j \in v} \text{emb}(w_j), \\
    \text{emb}(w_j) &= \text{enc}(w_j, w_{<j}, w_{>j}),
\end{align*}
\]

4
where \( \text{enc} \) encodes the embedding of \( w_j \) by its preceding context \( w_{<j} \) and succeeding content \( w_{>j} \).

Based on the entity embeddings, we derive each edge of the graph by a multi-label classification layer \( C \). \( C \) takes in the two vertices of the edge and predicts the edge type, which includes the “no-relation” type, and the set of possible relations of entities:

\[
e_{ij} = C(v_i, v_j).
\]

T2G training aims to find the optimal parameters \( \varphi^* \) that correctly encodes the text and predicts the graph, by maximum likelihood estimation:

\[
\varphi^* = \arg \max_{\varphi} \prod_{(t, g) \sim \mathcal{D}} p(g | t; \varphi).
\]

\[
= \arg \max_{\varphi} \prod_{(t, g) \sim \mathcal{D}} |\text{NER}(t)| \prod_{i=0}^{\text{NER}(t)} \prod_{j=0}^{\text{NER}(t)} p(e_{ij} | v_i, v_j, t; \varphi).
\]

### 3.4 Warm Start for IBT

As the IBT in Section 3.1 requires some initialization for the G2T and T2G models to start with, we propose a novel pretraining strategy to facilitate the warm start of IBT.

**Pretraining from entities** We conduct a novel pretraining to bootstrap T2G and G2T from only entity information. Specifically, we will learn an entity-to-text function whose parameters \( \theta_{E2T} \) will be used to initialize the G2T model, and an entity-to-graph model whose parameters \( \varphi_{E2G} \) will be used to initialize the T2G model:

\[
\theta_{E2T} = \arg \max_{\theta} \mathbb{E}_{t \in \mathcal{D}_T} [p(t | \text{NER}(t); \theta)],
\]

\[
\varphi_{E2G} = \arg \max_{\varphi} \mathbb{E}_{g \in \mathcal{D}_G} [p(g | \text{vertices}(g); \varphi)].
\]

The training scheme of our model CycleGT with warm start is illustrated in Algorithm 1.

**Algorithm 1 CycleGT with Warm Start for Unsupervised G2T and T2G**

Require: The text dataset \( \mathcal{D}_T = \{t_i\}_{i=1}^N \), graph dataset \( \mathcal{D}_G = \{g_j\}_{j=1}^M \), entity recognition function \( \text{NER} \), number of steps for different stages \( N_1, N_2 \), model \( \text{G2T}_\theta(\cdot) \), and model \( \text{T2G}_\varphi(\cdot) \).

1: Initialize \( \theta \) and \( \varphi \) with the optimized \( \theta_{E2T} \) and \( \varphi_{E2G} \) by Eq. (6) and (7), respectively.
2: Generate the initial synthetic corpus \( \hat{\mathcal{D}}_{Pair} \) by \( \text{G2T}_\theta \) and \( \text{T2G}_\varphi \).
3: for step in \( 0 \ldots N_1 \) do
4: Update \( \theta \) and \( \varphi \) according to supervised training on \( \hat{\mathcal{D}}_{Pair} \) by Eq. (4) and (5).
5: end for
6: for step in \( 0 \ldots N_2 \) do
7: Update \( \theta \) by minimizing the cycle loss \( \mathcal{L}_{\text{CycT}} \) in Eq. (2).
8: Update \( \varphi \) by minimizing the cycle loss \( \mathcal{L}_{\text{CycG}} \) in Eq. (3).
9: end for

**Initial accuracy by pretraining** As the pretraining can potentially serve to warm start the iterative cycle training framework, we are interested in the best accuracy that can be achieved by such initialization.

**Lemma 1** The best accuracy for \( \text{G2T}_{\theta_{E2T}} \) is \( \frac{|\text{EntSet}|}{|\mathcal{D}_T|} \), and for \( \text{T2G}_{\varphi_{E2G}} \) is \( \frac{|\text{EntSet}|}{|\mathcal{D}_G|} \), where \( |\text{EntSet}| \) is the number of possible entity sets that correspond to a graph or text. (See proof in Appendix A.)

The ratio \( \frac{|\text{EntSet}|}{|\mathcal{D}_X|} \) is the inverse of the average number of \( X \) (text or graph) that has the same entity set in the dataset \( \mathcal{D}_X \). It can also be interpreted as how much extra information the unknown relations will provide to the graph or text generation, apart from the known entity set.

From Lemma 1 it naturally follows that if each text or graph corresponds to a distinct entity set, namely \( \frac{|\text{EntSet}|}{|\mathcal{D}_X|} = 1 \), then the upper bound of the accuracy provided by the pretraining will trivially
be 100%. And for actual datasets, $\frac{|EntSet|}{|D_X|}$ will be reasonably large, because the number of all possible entities $|V|$ will generally increase with the size of the dataset $|D_X|$. Also there is bias in real world knowledge expressions which usually have a consented relation between two given entities. For example, if the entity set is (Barack Obama, Michelle Obama), then the corresponding graph is highly likely to be (Barack Obama, spouse of, Michelle Obama). As the text and graph have a one-to-one mapping, the number of corresponding text expressions cannot be too large.

4 Experiments

WebNLG Dataset Our main experiment uses the WebNLG dataset [9], which is widely used for graph-to-text generation. Each graph consists of 2 to 7 triples extracted from DBPedia, and the text is collected by asking crowd-source workers to describe the graphs. We follow the preprocessing steps in [56] to obtain the text-graph pairs (with entity annotation) for 13,036 training, 1,642 validation, and 4,928 test samples. To test unsupervised models and baselines, we construct a non-parallel version of the training and validation sets by separating all the text in the dataset to form a text corpus, and all the graphs to build a graph dataset. We ensure that the order within the text and graph datasets are shuffled so that the data is fully non-parallel.

Setup We instantiate our CycleGT framework with the T2G architecture from [20] implemented by the DGL library [54], and G2T architecture based on Long Short Term Memory networks (LSTMs). We evaluate both our base model CycleGT base and warm start model CycleGT warm.

For unsupervised baselines, note that random guess almost gives 0% accuracy, and overall it is very difficult to get any unsupervised model working. Despite the difficulty, we develop (1) a non-trivial unsupervised baseline, CrossAlignment, using an autoencoder and adversarial training to unsupervisedly learn the alignment of the graph and text. As the performance of our model is very strong, we also compare with supervised systems (2) T2G and (3) G2T using the original supervised training data. Addition from that, we also quote performance of other state-of-the-art supervised models, including (4) Melbourne, the best supervised system submitted to the WebNLG challenge [9], which uses an encoder-decoder architecture with attention, (5) StrongNeural [36] which improves the encoder-decoder model, (6) BestPlan [36] with uses a special entity ordering algorithm before neural text generation. We also use a strong T2G model (7) OnePass, a BERT-based model which achieves state-of-the-art performance on T2G [53]. More details about the baselines are in Appendix B.

For the hyperparameters, note that we aim at a fair comparison, so the hyperparameters of the overlapped modules across different models are set to the same. For example, the supervised G2T has the same hyperparameters as the G2T component in our CycleGT, and CycleGT warm shares the same configurations with CycleGT base except the warm start training. Our implementation details and the link to our code are provided in Appendix C.

For G2T evaluation, We adopt the metrics from [56], i.e., BLEU [38], Meteor [3], ROUGE L [27] and CIDEr [50], to measure the closeness of the reconstructed paragraph (model output) to the input paragraph. Briefly, they measure the n-gram recall and precision between the model outputs and the (ground-truth) references. For T2G evaluation, we evaluate the micro and macro F1 scores of the relation types of the edges, following the standard practice in relation extraction [54, 59].

Main Results From the results in Table 2, we find that even with no pairing information between text and graphs, our best unsupervised model show impressive performance, very close to supervised models trained on the parallel graph and text data. For G2T generation, our CycleGT base model can achieve 46.2 BLEU scores, which is very close to the best supervised performance 47.4, and on par with the 45.8 BLEU scores by the supervised G2T model. Our CycleGT also outperforms the unsupervised baseline, CrossAlignment, by 37 BLEU scores. For T2G, our CycleGT achieves a micro F1 of 61.2%, which outperforms the 60.0% by the supervised T2G which has the same hyperparameters as our T2G component. There is still some performance gap between our best micro F1 score and that of the state-of-the-art system, OnePass. However, on macro F1, our performance
|                              | G2T Performance | T2G Performance |
|------------------------------|-----------------|-----------------|
|                              | BLEU   | METEOR | ROUGE_L | CIDEr  | Micro F1 | Macro F1 |
| State-of-the-Art Supervised Models |                   |                   |
| Melbourne                    | 45.0   | 0.376  | 63.5    | 2.81   | –        | –        |
| StrongNeural [36]            | 46.5   | 0.392  | 65.4    | 2.87   | –        | –        |
| BestPlan [36]                | 47.4   | 0.391  | 63.1    | 2.69   | –        | –        |
| OnePass [53]                 | –      | –      | –       | –      | –        | –        |
|                              | 66.2   | 52.2   |
| Supervised Models the Same as in Our Models |                   |                   |
| Supervised G2T [20]          | 45.8   | 0.356  | 68.6    | 3.14   | –        | –        |
| Supervised T2G               | –      | –      | –       | –      | 60.6     | 50.7     |
| Unsupervised Models          |                   |                   |
| CrossAlignment               | 9.1    | 0.219  | 43.8    | 0.68   | 0.0      | 0.0      |
| CycleGTBase                  | 46.2   | 0.360  | 68.7    | 3.22   | 61.2     | 51.1     |
| CycleGTWarm                  | 44.1   | 0.341  | 65.5    | 2.80   | 62.1     | 52.0     |

Table 2: T2G and G2T performance of supervised and unsupervised models on WebNLG.

is on par with all supervised models. Note that CrossAlignment works decently on text generation, echoing with its reported performance on other text-based tasks [46], but works very poorly on graph extraction. Overall, our model has comparable performance to the supervised models. And as our model generates a pseudo-parallel dataset at each iteration, some data augmentation effect can be observed, making our model sometimes better than the supervised models with the same architecture.

**Base and warm start CycleGT by training epochs** We plot the performance of several models by training epochs in Figure 2 including the supervised G2T and T2G, CycleGTBase, and CycleGT Warm. As CycleGT Warm has been pretrained, so its start-off performance when entering the training process is higher than the other two models. The warm up strategy is especially useful on the T2G task, constantly outperforming the supervised and CycleGT Base model at all epochs. Our other model CycleGT Base is also competitive, – although it scores the lowest in the beginning, its performance steadily increases as training goes on, and finally exceeding the supervised models on both T2G and G2T, as shown by numbers in Table 2.

**Supervised model vs. CycleGT by different data sizes** The main results on WebNLG in Table 2 compared supervised models and our unsupervised method on the same size of data. However, the advantage of the unsupervised method lies in its potential, as unsupervised data can be much more easier to obtain than elaborately annotated supervised data. So a practical comparison is whether unsupervised models with more data can exceed the supervised models by an even larger margin? We answer this question by first only providing 25% of the WebNLG data to train the supervised G2T and T2G models. Denote this training size as 1 unit. We then collect the performance of our CycleGT Base trained on non-parallel data with sizes of 1, 2, 3, and 4 units. As is seen in Figure 3, the performance of the supervised model is fixed due to the limited training set, whereas our unsupervised method has an increasing performance as the non-parallel data size rises. When the size of the non-parallel
data reaches 2 times the supervised data size, the unsupervised performance exceeds the limited supervised performance by +22.35% F1 and +13.34 BLEU. When the non-parallel becomes 4 times the size of parallel data, the unsupervised performance gets even better, +34.07% and +18.17 BLEU over the supervised models. This indicates that our model gets more powerful when the number of non-parallel data exceeds that of the parallel data, which is very practical to achieve.

Scores by the number of entities or words per sentence We plot the correlation between the performance of CycleGT with two factors: (1) the number of entities per sample, which represents the size of the graph, shown in Figure 4 and (2) the number of words in the text, which represents the “size” of the text, shown in Figure 5. For each plot, we cluster the outputs into six groups according to their $x$ values. Each point shows the average $(x, y)$ of that complexity group. This analysis will mainly focus on the G2T quality. We evaluate by eBLEU, an improved criterion from the BLEU score which turns each entity into a symbol instead of multiple words that will cause inflation of the BLEU score. From Figure 4 we can see that as there are more entities per graph, the model performance decreases almost linearly in the beginning and plateaus at a certain value. From Figure 5 we can see that the eBLEU also decreases as the number of words in the ground-truth sentence gets larger.

Figure 4: eBLEU w.r.t. the number of entities per graph.  
Figure 5: eBLEU w.r.t. the number of words in the text.

5 Related Work

To the best of our knowledge, we are the first to formulate T2G and G2T as joint tasks, so we will give an overview of the fields of T2G and T2G separately, and then introduce the cycle learning.

Data-to-Text Generation As a classic problem in text generation [21, 32], data-to-text generation aims to automatically produce text from structured data [42, 26]. Due to the expensive collection, all the data-to-text datasets are very small, such as the 5K air travel dataset [41], 22K WeatherGov [26], 7K Robocup [4], and 5K RotoWire on basketball games [55]. As for the methodology, traditional approaches adopt a pipeline system [21, 32] of content planning, sentence planning, and surface realization. Recent advances in neural networks give birth to end-to-end systems [24, 55, 20] that does not use explicit planning but directly an encoder-decoder architecture [2].

Relation Extraction Relation Extraction (RE) is the core problem in text-to-graph conversion, as its former step, entity recognition, have off-the-shelf tools with good performance [22, 40, 48, 5, 17]. RE aims to classify the relation of entities given a shared textual context. Conventional approaches hand-crafted lexical and syntactic features [13, 13]. With the recent advancement of deep neural networks, many models based on CNN [57, 44, 37], RNN [47, 58, 35, 59], and BERT [53] achieve high performance in many datasets. However, constrained by the small datasets of only several hundred or several thousand data points [52, 13, 8], recent research shifts to distant supervision than model innovation [53, 56, 28].

Cycle Training The concept of leveraging the transitivity of two functions inverse to each other has been widely observed on a variety of tasks. In computer vision, the forward-backward consistency has been used since last decade [18, 49], and training on cycle consistency has recently been extensively applied on image style transfer [60, 10]. In language, back translation [45, 7, 15] and dual learning [5, 42] have also been an active area of research centered on UMT. Similar techniques can also be seen on tasks such as language style transfer [46, 16].
6 Conclusion

We made the first attempt of a cycle learning framework for both text-to-graph and graph-to-text generation in an unsupervised way. Experiment results validated that our model achieves comparable results to supervised models, given the same number of but unsupervised data. Further analysis demonstrated that data complexity largely correlates with the performance, and decomposing into simpler data samples will improve some aspects of the performance.

7 Broader Impact

Our paper provides an unsupervised solution to two tasks: (1) T2G – extracting the latent knowledge graphs from text, and (2) G2T – generating the description for a given graph. The positive and negative impacts of our paper are both tied to its wide applications.

Our model enables knowledge extraction from text without any supervised annotation, so people can use it on unlimited web texts, and easily mine the knowledge graphs. This may facilitate parties who are using it for a good purpose such as social science research to survey the change of popular knowledge graphs in online text. But such a function can also be abused when people want to exploit the knowledge behind people’s social media text, and take advantage of the mined graphs. This issue is common to all text-to-data technologies, and as such needs privacy and ownership enforcement.

The G2T function can facilitate AI for customer service, because it enables automatic text generation based on the some computer-retrieved graph information. When the user asks a question, the computer first locates answer in a part of its knowledge base, and then G2T can be applied to automatically generate natural language to convey the information. It may also be used in a negative way to make automatic fraud easier. The issue here is common to all generative technologies where proper governance must installed to prevent abuse.

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Supplementary Materials

A Proof of Lemma 1

We prove Lemma 1 (the best accuracy for pretraining from entities) by the following.

As mentioned in Section 3.4, in the pretraining, we learn an entity-to-text function whose parameters \( \theta_{E2T} \) will be used to initialize the G2T model, and an entity-to-graph model whose parameters \( \phi_{E2G} \) will be used to initialize the T2G model.

For the entity-to-text function, the total number of sentences to be classified is \( |D_T| \). And for each set of instances \( v \), the trained model can only be correct at most 1 time (assuming no repeat sentences). Therefore, adding up over all instance sets, the classifier can only be correct at most \( \frac{|\text{EntSet}|}{|D_T|} \) times out of \( |D_T| \) chances, which gives the best accuracy \( \frac{|\text{EntSet}|}{|D_T|} \). Similarly, the best accuracy for \( T2G_{\phi_{E2G}} \) is \( \frac{|\text{EntSet}|}{|D_G|} \), and thus we prove Lemma 1.

B Details of the Comparison Systems

Supervised G2T Models We compare CycleGT which is trained on unsupervised data, with the following models trained on supervised data:

- **Melbourne** is the top 1 system in the competition of the WebNLG Challenge [9], using an end-to-end system that uses an LSTM-based encoder-decoder architecture with attention.
- **StrongNeural** proposed by [36] adds a neural checklist model [19] and applies entity dropout to the common encoder-decoder architecture with a copy-attention mechanism [11].
- **BestPlan** [36] is the new state-of-the-art on the WebNLG dataset, which first orders and structures the graphical information (planning), and then generates language to describe the information (realization).
- **Supervised G2T** [20], which we adopt as a component in our CycleGT, is a model for text generation from graphical data. First proposed on the AGENDA knowledge graph-to-abstract dataset [20], it provides an end-to-end trainable system using a Graph Attention Network and bidirectional LSTM entity encoder.

Supervised T2G Models We also compare with several models that are trained on the supervised T2G data:

- **T2G-LSTM** is a two-layer bidirectional Long Short Term Memory (LSTM) networks with 512 hidden units followed by a feedforward network for relation classification.
- **OnePass** [53] uses a one-pass encoding on the input text based on a pretrained BERT model, then adopts a feedforward network for relation classification. It achieved the state-of-the-art performance on benchmark RE datasets ACE 2005 [52] and SemEval 2018 [8].

Unsupervised Models

- **CrossAlignment** learns from the non-parallel text and graph data by training both the adversarial loss and autoencoding. We adapt the training scheme from [46], and instead of alignment of the content space of text, we align the latent space of text and graphs.

C Implementation Details

Our training framework can adapt to different T2G and G2T modules. For this study, we re-implemented the G2T model by [20] using Deep Graph Library (DGL) [54]. It consists of a Graph Attention Network and a bidirectional LSTM entity encoder, as well as an LSTM decoder with attention and copy mechanism. For the T2G model, we adopt an LSTM-based model that uses two layers of BiLSTM comprised of 512 hidden units. We train the model until 30 epochs.
Note that for all the main results, we conduct 20 runs and take the average. The standard deviation is ±0.39~0.66 on BLEU, ±0.0032~0.0035 on METEOR, ±0.312~0.377 on ROUGE, ±0.035~0.044 on CIDEr, and the standard deviation for micro and macro F1 scores is ±0.2~0.3.

D Supplementary Experiments: An Alternative Non-Parallel Setting

For our main results (such as Table 2), we randomly shuffled the originally parallel dataset so that alignment information is eliminated. Such a setting follows the practice in non-parallel text style transfer [25, 16], and, more importantly, it can compare with supervised models trained on the same number of data. In the meantime, we understand that some work in unsupervised MT uses another setting which selects half of the parallel dataset to get text in one language (e.g., English), and uses the compliment set to get text in the other language (e.g., French) [23, 14]. Therefore, we conducted a supplementary experiment using such a half-half setting. Note that for the supervised models, we use only half of the dataset, so that all models use the same amount of data.

The results comparable to Table 2 is in Table 3 where we can see that for G2T, our model still outperforms the unsupervised baseline CrossAlignment by a substantial margin. Comparing with the supervised models, our models are a bit lower on G2T, but stronger on T2G.

| Supervised G2T [20] | Supervised Models | T2G Performance |
|---------------------|-------------------|-----------------|
| BLEU                | METEOR | ROUGE | CIDEr | Micro F1 | Macro F1 |
| 34.3                | 0.286  | 61.9  | 2.33  | –       | –       |
| Supervised T2G      |        |       |       | –       | –       |

Unsupervised Models

| CrossAlignment | 4.27 | 0.158 | 34.4 | 0.33 | 0.0 | 0.0 |
| CycleGTbase     | 30.6  | 0.274 | 60.3 | 2.20 | 54.4 | 41.9 |
| CycleGTWarm     | 28.8  | 0.260 | 58.1 | 1.92 | 56.9 | 44.1 |

Table 3: T2G and G2T performance of supervised and unsupervised models on WebNLG.