Few-Shot NLG with Pre-Trained Language Model

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Abstract

Neural-based end-to-end approaches to natural language generation (NLG) from structured data or knowledge are data-hungry, making their adoption for real-world applications difficult with limited data. In this work, we propose the new task of few-shot natural language generation. Motivated by how humans tend to summarize tabular data, we propose a simple yet effective approach and show that it not only demonstrates strong performance but also provides good generalization across domains. The design of the model architecture is based on two aspects: content selection/copying from input data and language modeling to compose coherent sentences, which can be acquired from prior knowledge. Accordingly, we employ a pre-trained domain-independent language model to serve as the prior, while the content selection/copying can be learned with only a few in-domain training instances, thus attaining the few-shot learning objective. To demonstrate that our approach generalizes across domains, we curated table-to-text data from multiple domains. With just 200 training examples, we show that our approach achieves very reasonable performances and outperforms the strongest baseline by an average of over 8.0 BLEU points improvement. Our code and data is publicly available¹.

Introduction

Natural language generation (NLG) from structured data or knowledge (Gatt and Krahmer 2018) is an important research problem for various NLP applications. Some examples are task-oriented dialog, question answering (He et al. 2017; Su et al. 2016; Saha et al. 2018; Yin et al. 2016) and interdisciplinary applications such as medicine (Hasan and Farri 2019; Cawsey, Webber, and Jones 1997) and healthcare (Hasan and Farri 2019; DiMarco et al. 2007), where the machine attempts to provide clinical information in the form of natural language rather than structured text in order to communicate with patients. There is great potential of using automatic NLG systems in a wide range of real-life applications.

In order to tackle such a research problem, traditional pipeline-based NLG systems (Becker 2002; Deemter, The-une, and Krahmer 2005; Gatt and Krahmer 2018) have been proposed, which heavily rely on template and slot-filling rules to produce very accurate but limited text output. Such a pipeline-based paradigm (Reiter and Dale 1997) divides the generation process into parts with separate and explicit objectives such as content selection followed by macro/micro-planning and surface realization. Recently, deep neural network-based NLG systems have been developed, such as those seen in the E2E challenge (Novikova, Dusek, and Rieser 2017), WEATHERGOV (Liang, Jordan, and Klein 2009), as well as more complex ones such as WikIBio (Liu et al. 2018) and ROTOwire (Wiseman, Shieber, and Rush 2017). Such end-to-end data-driven NLG systems greatly reduced feature engineering efforts and improved text diversity as well as fluency in the past few years.

Although they achieve good performance on several benchmarks such as E2E challenge (Novikova, Dusek, and Rieser 2017) and WikIBio (Lebret, Grangier, and Auli 2016), the success of neural-based approaches is heavily dependent on the availability of a massive amount of labeled training data, e.g., 500k table-text training pairs for WikIBio (Lebret, Grangier, and Auli 2016) in a single domain. Such data-hungry nature makes neural-based NLG systems difficult to be widely adopted in real-world applications as they have significant manual data curation overhead. This leads us to formulate an interesting research question:

1. Can we significantly reduce human annotation effort to achieve reasonable performance using neural NLG models?
2. Can we make the best of generative pre-training, as prior knowledge, to generate text from structured data?

Motivated by this, we propose the new task of few-shot natural language generation: given only a handful of labeled instances (e.g., 50 - 200 training instances), the system is required to produce satisfactory text outputs (e.g., BLEU ≥ 20). To the best of our knowledge, such a problem in NLG community still remains under-explored. Herein, we propose a simple yet very effective approach that can generalize across different domains.

In general, to describe information in a table, we need two skills to compose coherent and faithful sentences. One skill is to select and copy factual content from the table - this can be learned quickly by reading a handful of ta-

¹https://github.com/czyssrs/Few-Shot-NLG
Walter Extra is a German award-winning aerobatic pilot, chief aircraft designer and manufacturer.

Figure 1: Illustration of the switch policy (An example from WIKIBIO dataset): the generation alternates between selecting/copying from input table (left blue part) and generating from the language model (right yellow part), which is acquired from pre-training.

In a nutshell, our contributions are summarized as the following:

- We propose the new research problem of few-shot NLG, which has the great potential to benefit a wide range of real-world applications.
- To study different algorithms for our proposed problem, we create valuable multi-domain table-to-text dataset. We will make it publicly available.
- Our proposed algorithm can make use of the external resources as prior knowledge to significantly decrease human annotation effort and improve the baseline performance by an average of over 8.0 BLEU on various domains.

**Related Work**

**NLG from Structured Data**

As it is a core objective in many NLP applications, natural language generation from structured data/knowledge (NLG) has been studied for many years. Early traditional NLG systems follow the pipeline paradigm that explicitly divides generation into content selection, macro/micro planning and surface realization (Reiter and Dale 1997). Such a pipeline paradigm largely relies on templates and hand-engineered features. Many works have been proposed to tackle the individual modules, such as (Liang, Jordan, and Klein 2009; Walker, Rambow, and Rogati 2001; Lu, Ng, and Lee 2009). Later works (Konstas and Lapata 2012; 2013) investigated modeling context selection and surface realization in a unified framework.

Most recently, with the success of deep neural networks, data-driven, neural based approaches have been used, including the end-to-end methods that jointly model context selection and surface realization (Liu et al. 2018; Wiseman, Shieber, and Rush 2018; Puduppully, Dong, and Lapata 2018), and the methods using neural network to tackle realization component (Moryossef, Goldberg, and Dagan 2019). Such data-driven approaches achieve good performance on several benchmarks like E2E challenge (Novikova, Dusek, and Rieser 2017), WebNLG challenge (Gardent et al. 2017) and WIKIBIO (Lebret, Grangier, and Auli 2016). However, they rely on massive amount of training data. ElSahar, Gravier, and Laforest (2018) propose zero-shot learning for question generation from knowledge graphs, but their work applies on the transfer learning setting of generation for unseen knowledge base types, based on seen knowledge base triples and their textual contexts, which still requires large in-domain training dataset. This is different from our few-shot learning setting where the training data is considered...
Figure 2: Overview of our approach: Under the base framework with switch policy, the pre-trained language model serves as the generator. We follow the same encoder as in (Liu et al. 2018). The architecture is simple in terms of both implementation and parameter space that needs to be learned from scratch, which should not be large given the few-shot learning setting.

In conclusion, to the best of our knowledge, we are not aware of any previous work that has investigated neural based end-to-end NLG under the few-shot learning setting.

**Large Scale Pre-Trained Models**

Many of the current best-performing methods for various NLP tasks adopt a combination of pre-training followed by supervised fine-tuning, using task-specific data. Different levels of pre-training include word embeddings (Mikolov et al. 2013; Pennington, Socher, and Manning 2014; Peters et al. 2018), sentence embeddings (Le and Mikolov 2014; Kiros et al. 2015), relational embeddings (Bordes et al. 2013; Chen et al. 2019), and most recently, language modeling based pre-training like BERT (Devlin et al. 2018) and GPT-2 (Radford et al. 2019). Such models are pre-trained on large-scale open-domain corpora, and provide downstreaming tasks with rich prior knowledge while boosting their performance. Therefore, in this paper, we adopt the idea of employing a pre-trained language model, that is sufficiently large and general, to endow in-domain NLG models with language modeling ability, which cannot be well learned from few shot training instances.

**Method**

**Problem Formulation**

We are provided with semi-structured data: a table of attribute-value pairs \( \{R_i : V_i\}_{i=1}^{n} \). Both \( R_i \) and \( V_i \) can be either a string/number, a phrase or a sentence. Each value is represented as a sequence of words \( V_i = \{v_j\}_{j=1}^{m_i} \). For each word \( v_j \), we have its corresponding attribute name \( R_i \) and position information of the word in the value sequence. The target is to generate a natural language description based on the semi-structured data, provided with only a handful of training instances. Figure 3 illustrates an example input formulation.

![Figure 3: An example of input format: for each word in the table value sequences, we have its attribute name and position information. See (Liu et al. 2018) for more details.](image)

**Base Framework with Switch Policy**

We start with the field-gated dual attention model proposed in (Liu et al. 2018), which achieves state-of-the-art performance (BLEU) on WIKIBIO dataset. Their method uses an LSTM decoder with dual attention weights. We first apply a switch policy that decouples the framework into table content selection/copying and language model based generation. Inspired by the pointer generator (See, Liu, and Manning 2017), at each time step, we maintain a soft switch \( p_{\text{copy}} \) to choose between generating from softmax over vocabulary or copying from input table values with the attention weights as the probability distribution.

\[
p_{\text{copy}} = \sigma(W_c c_t + W_s s_t + W_x x_t + b) \quad (1)
\]

\[
c_t = \sum_i a_i^t h_i \quad (2)
\]

Where \( \{h_i\} \) is the encoder hidden states, \( x_t, s_t, a_t \) is the decoder input, state and attention weights respectively at time...
The pointer generator learns to alternate between copying and generating based on large training data and shows its advantage of copying out-of-vocabulary (OOV) words from input. In our task, the training data is very limited, and many of the table values are not OOV. We need to explicitly “teach” the model where to copy and where to generate. Therefore, to provide the model accurate guidance of the behavior of the switch, we match the target text with input table values to get the positions of where to copy. At these positions, we maximize the copy probability $p_{\text{copy}}$ via an additional loss term. Our loss function goes as follows:

$$L = L_c + \lambda \sum_{w_j \in \mathcal{m}} (1 - p_{\text{copy}}^j)$$

$L_c$ is the original loss between model outputs and target texts. $w_j$ is the target token at position $j$, $\{V_i\}$ is the input table value list defined in Problem Formulation section, and $\mathcal{m}$ means a matched phrase. $\lambda$ is hyperparameter as the weight for this copy loss term. We also concatenate the decoder input with its matched attribute name and position information in the input table $x_i$ to calculate $p_{\text{copy}}$.

**Pre-Trained LM as Generator**

Using the switch policy, the model obtains most of its training signal from a few training instances of content selection/copying mechanism. Now we introduce the pre-trained language model as the “innate talking skill”, serving as the generator.

Such language models are typically trained using a large, open-domain corpus. In the absence of any specific constraint or in-domain orientation, the pool of candidate words at each generation step will be quite large. Given an NLG task for a specific domain, we need to instill the in-domain language modeling paradigm, to narrow down the candidate pool. Here we consider two options for this paradigm selection.

**Fine-tuning** One way is fine-tuning the pre-trained language model. Given a pre-trained language model with sufficient capacity, such domain-specific mode can be quickly adapted through fine-tuning with a few in-domain training instances. Due to the vocabulary limitation of few training instances, we leave the pre-trained word embedding fixed during training; so that the model can generalize with tokens unseen during training. This also largely reduces the computational resource needed to fine-tune the pre-trained language model.

Figure 2 shows our model architecture. We use the pre-trained language model GPT-2\(^2\) proposed in (Radford et al. 2019), which is a 12-layer transformer. The final hidden state of the transformer is used to calculate attention weights and the copy switch $p_{\text{copy}}$. We first feed the embedded attribute-name embedding to calculate $p_{\text{copy}}$.

Experiment

**Datasets and Experiment Setup**

The original WIKIBIO dataset (Lebret, Grangier, and Auli 2016) contains 700k English Wikipedia articles, with 580k as train set, 70k as validation set and test set respectively. The Wiki infobox serves as the input structured data and the first sentence of the article serves as the target text. In the original dataset, the domain under study is the biography of well-known humans. To study the generalizability of different methods for the proposed task, we first extend the WIKIBIO dataset to multiple domains.

Following the creation of WIKIBIO, we collect datasets of two new domains: Books and Songs. We traverse the Wikipedia pages based on the Wikipedia categories for each domain, then crawl the first sentences of the articles and corresponding Wiki infoboxes. After filtering and cleanup, we end up with 23,651 instances for Books domain and 39,450 instances for Songs domain. Note that the target text sometimes contains information not in the input infobox. This is out of scope of the few-shot generation in this work. Therefore in the following experiments we further filter the datasets and remove the ones with rare words out of infobox.

Together with the Humans domain of the original WIKIBIO dataset, for all three domains we conduct experiments by varying the training dataset size to 50, 100, 200 and 500. The rest of the data is used for testing. We use the Adam optimizer (Kingma and Ba 2015) with learning rate set to 0.0003. The mini-batch size is set to 40 and the weight $\lambda$ of the copy loss term to 0.7. The dimension of the position embedding is set to 5. For attribute name with multiple words, we average their word embeddings as the attribute name embedding. We take the result when the training loss does not decrease. To deal with the vocabulary limitation of few-shot training, for all models we adopt the Byte Pair Encoding (BPE) introduced in (Sennrich, Haddow, and Birch 2016) and subword vocabulary used in (Radford et al. 2019).

**Baselines**

We compare the proposed method with other approaches investigated in Method section, serving as the baselines -

- **Base**: the original model in (Liu et al. 2018), which achieves strong result on WIKIBIO full set;
- **Base**: uses the same architecture, but in addition applies the pre-trained word embedding and fix it during training;

\(^2\)https://github.com/openai/gpt-2
Table 1: BLEU-4 results on Humans, Books and Songs domains. Base-original: the original method in (Liu et al. 2018); Base: applies pre-trained word embedding; Base+switch: adds the switch policy; Base+switch+LM-scratch: makes the same architecture as our method, but trains the model from scratch without pre-trained weights for the generator.

| Domain | Humans | | | | Books | | | | | Songs | | |
|---------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| # of training instances | 50 | 100 | 200 | 500 | 50 | 100 | 200 | 500 | 50 | 100 | 200 | 500 |
| Base-original | 2.2 | 3.7 | 4.9 | 5.1 | 5.8 | 6.1 | 7.4 | 6.7 | 9.2 | 10.7 | 11.1 | 11.3 |
| Base | 2.9 | 5.1 | 6.1 | 8.3 | 7.3 | 6.8 | 7.8 | 8.8 | 10.4 | 12.0 | 11.6 | 13.1 |
| Base + switch | 15.6 | 17.8 | 21.3 | 26.2 | 24.7 | 26.9 | 30.5 | 33.2 | 29.7 | 30.6 | 32.5 | 34.9 |
| Base + switch + LM-scratch | 6.6 | 11.5 | 15.3 | 18.6 | 7.1 | 9.2 | 14.9 | 21.8 | 11.6 | 16.2 | 20.6 | 23.7 |
| Base + switch + LM (Ours) | 25.7 | 29.5 | 36.1 | 41.7 | 34.3 | 36.2 | 37.9 | 40.3 | 36.1 | 37.2 | 39.4 | 42.2 |

Table 2: ROUGE-4 (F-measure) results on Humans, Books and Songs domains.

| Domain | Humans | | | | Books | | | | | Songs | | |
|---------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| # of training instances | 50 | 100 | 200 | 500 | 50 | 100 | 200 | 500 | 50 | 100 | 200 | 500 |
| Base-original | 0.1 | 0.4 | 0.5 | 0.6 | 1.1 | 1.6 | 2.1 | 1.5 | 3.4 | 4.2 | 4.7 | 4.8 |
| Base | 0.1 | 0.4 | 0.8 | 1.5 | 1.7 | 1.5 | 2.1 | 2.4 | 4.1 | 5.1 | 4.7 | 5.8 |
| Base + switch | 4.9 | 6.3 | 9.8 | 12.5 | 12.8 | 15.0 | 18.1 | 20.7 | 20.2 | 21.7 | 23.2 | 24.8 |
| Base + switch + LM-scratch | 1.0 | 2.8 | 4.7 | 7.1 | 2.4 | 4.2 | 6.5 | 10.7 | 5.4 | 8.0 | 12.0 | 15.0 |
| Base + switch + LM (Ours) | 14.1 | 16.2 | 22.1 | 28.3 | 22.5 | 23.1 | 25.0 | 27.6 | 26.2 | 28.6 | 30.1 | 32.6 |

Results and Analysis

Following previous work (Liu et al. 2018), we first conduct automatic evaluations using BLEU-4, shown in Table 1 and ROUGE-4 (F-measure) shown in Table 2.

As we can see, the original model Base-original (Liu et al. 2018), which obtains the state-of-the-art result on W1K1BIO full set, performs very poorly under few-shot setting. During training, we observe that its training loss quickly goes to zero, since it generates all tokens from softmax over vocabulary, which results in severe overfitting with limited training data. With the switch policy, Base+switch first brings an improvement of an average of over 10.0 BLEU points. This indicates that the content selection ability is easier to be learned with a handful of training instances. However, it forms very limited, not fluent sentences. With the augmentation of the pre-trained language model, our model Base+switch+LM brings one more significant improvement of an average over 8.0 BLEU points. The difference between Base+switch and Base+switch+LM-scratch is the architecture of the generator, with a 1-layer LSTM for the former one and 12-layer transformer for the latter. The generator of both methods is learned from scratch, while the transformer structure is more complex in terms of parameter space. Therefore its performance is inferior due to limited training data. We provide sample outputs of these methods using 200 training instances in Table 3. To study the robustness of the approach, we further train with 800 and 1000 instances, and plot the overall performance curve in figure 4.

- **Base + switch**: adds the switch policy choosing between generating from softmax over vocabulary or copying from input table values;
- **Base + switch + LM-scratch**: To show that the improvement of language modeling capability comes from pre-training, not the architecture change of the generator, we also compare with training the model with exactly the same architecture as ours, but from scratch, without pre-trained weights for the generator.

Figure 4: The performance curve. Compared to the strongest baseline, Base+switch, the performance of our approach tends to increase faster at first (the region less than 200 instances), then gradually goes steady with the increase of training instances.

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*We use standard script NIST mteval-v13a.pl.

*We use rouge-1.5.5.
Table 3: A sample input table from *Humans* domain and the texts generated with different methods using 200 training data. As we can see, the original architecture performs very poorly when given limited training instances. It neither correctly selects information from input table nor generates coherent sentences. With the switch policy applied, the model is able to correctly copy some important information, like people’s name, birth date. However the generation is still very limited and suffers from grammar errors. With the pre-trained language model as the generator, our approach can obtain very reasonable result.

Table 4 shows the effect of the copy switch loss $p_{copy}$ introduced in Method section, giving the model a stronger signal to learn to copy from input table. Compared to the baseline framework Base+switch, this is more important for our model with an unbalanced initial geometry for the encoder side and generator side, since the latter is fine-tuned from pre-trained weights. Without a stronger signal to “teach” the model to learn to copy from inputs, the generator tends to be optimized into local minima and produces incorrect facts.

### Ablation Study: Effect of the Switch Policy

Table 4 shows the effect of the copy switch loss $p_{copy}$ introduced in Method section, giving the model a stronger signal to learn to copy from input table. Compared to the baseline framework Base+switch, this is more important for our model with an unbalanced initial geometry for the encoder side and generator side, since the latter is fine-tuned from pre-trained weights. Without a stronger signal to “teach” the model to learn to copy from inputs, the generator tends to be optimized into local minima and produces incorrect facts.

### Human Evaluation

We conduct human evaluation studies using Amazon Mechanical Turk, based on two aspects: *Factual correctness* and *Language naturalness*. We randomly sample 500 instances from the test set, together with the texts generated with different methods. Each evaluation unit is assigned to 3 workers to eliminate human variance.

The first study attempts to evaluate how well a generated text can correctly convey information in the table. Each worker is present with both the input table and a generated text, and asked to count how many facts in the generated text are supported by the table, and how many are contradicting with or missing from the table, similar as in (Wise, Shieber, and Rush 2017). The 2nd and 3rd columns of Table 5 show the average number of supporting and contradicting facts for our method, comparing to the strongest baseline and the gold reference.

The second study aims to evaluate whether the generated text is grammatically correct and fluent in terms of language, regardless of factual correctness. Each worker is present with a pair of texts generated from the same input table, by two different methods, then asked to select the better one only according to language naturalness, or “Tied” if the two texts are of equal quality. *The input table is not shown to the workers*. Each time a generated text is chosen as the better one, we assign score of 1.0. If two texts are tied, we assign 0.5 for each. We then calculate the average score for the texts generated by each method, indicating its superiority in pairwise comparisons with all other methods. The results are shown in the 4th column of Table 5.

Our method brings a significant improvement over the strongest baseline ($p < 0.01$ in Tukey’s HSD test for all measures). The copy loss term further alleviates producing incorrect facts. The language naturalness result of our method without the copy loss is slightly better, because this evaluation does not consider factual correctness; thus the generated texts with more wrong facts can still get high scores.

### Conclusion

In this paper, we propose the new research problem of few-shot natural language generation. We aim to bridge the gap...
between current neural NLG methods and real world applications, by providing methodology that reduces manual curation efforts for large-scale training datasets. Our approach is simple, easy to implement, and does not require extensive re-training, while achieving strong performance. Our basic idea of acquiring language modeling prior can be potentially extended to a broader scope of generation tasks, based on various input structured data, such as knowledge graphs, SQL queries, etc. An interesting future direction would be to incorporate generative pre-training for all kinds of heterogeneous data input.

### Table 5: Human evaluation results: Average number of supporting facts (column 2, the larger the better), contradicting facts (column 3, the smaller the better), and language naturalness score (column 4, the larger the better).

| Gold Reference | # Supp. | # Cont. | Lan. Score |
|----------------|--------|--------|------------|
| Base + switch  | 2.57   | 2.17   | 0.93       |
| Base + switch + LM (ours) | 3.64   | 1.12   | 1.59       |
| - w/o copy loss $p_{copy}$ | 3.54   | 1.30   | 1.63       |

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