Abstract

This paper proposes a novel neural model for the understudied task of generating text from keywords. The model takes as input a set of un-ordered keywords, and part-of-speech (POS) based template instructions. This makes it ideal for surface realization in any NLG setup. The framework is based on the encode-attend-decode paradigm, where keywords and templates are encoded first, and the decoder judiciously attends over the contexts derived from the encoded keywords and templates to generate the sentences. Training exploits weak supervision, as the model trains on a large amount of labeled data with keywords and POS based templates prepared through completely automatic means. Qualitative and quantitative performance analyses on publicly available test-data in various domains reveal our system’s superiority over baselines, built using state-of-the-art neural machine translation and controllable transfer techniques. Our approach is indifferent to the order of input keywords.

1 Introduction

The problem area of data-to-text generation has seen a lot of interest in the language generation community recently (Gatt and Krahmer, 2018; Castro Ferreira et al., 2019; Puduppully et al., 2019; Ma et al., 2019; Chen et al., 2019b; Gong et al., 2019), primarily because it has several real world applications such as query completion, story generation, report generation, dialogue response generation for virtual assistants, support systems for second language writing, and many more. Further, with the advent of “data-hungry” neural models, such data-to-text NLG systems provide mechanisms for synthetic data preparation, data-augmentation, and adversarial example generation, to advance core model development.

A key challenge in data-to-text NLG is surface realization of content i.e., constructing fluent sentences from input data, often available as lists of keywords. This paper presents a simple but effective solution to this crucial problem. Note that, tackling different input orders of the keywords is of utmost importance here; keywords can appear from a structured source such as database tables or knowledge graphs in any order.

Learning language generators has always been quite challenging, primarily because of the higher combinatorial complexity of the output space. A workaround is to train supervised generators that reduce this complexity through supervision. Popular examples include machine translation (Bahdanau et al., 2015), image captioning (Vinyals et al., 2015), paraphrase generation of varying degree of language complexity (Iyyer et al., 2018; Li et al., 2018; Mishra et al., 2019; Surya et al., 2019) and creative text generation (Yu et al., 2017; Zhang and Lapata, 2014). A clear desiderata for such systems is bulky and often expensive parallel corpora of input-output instances.

Direct supervision works in settings where the contract between the input and output is simple and clear\(^1\), and thus, learning the mapping can be based on paired corpora of well-defined input-output forms. However, for surface realization from keywords, a supervised solution based on a paired corpora of keywords and sentences may not be adequate. For example, a keyword set of ‘victim’, ‘vanessa’, ‘demons’) can be translated to diverse natural language forms following different lexical and syntactic choices. This may require altering the input order and also in some cases, hallucinating function-words (e.g., “Vanessa can also become a victim of demons”). And, simply training

\(^1\)e.g., in Machine Translation it is safe to focus on learning mappings between every unique input to one possible outcome.
the systems with keyword and sentence pairs may restrict their ability to generalize beyond language structures that are seen in the training data.

We propose a system that performs syntax-driven language generation from keywords by considering templates as additional input. As templates, we use POS tag sequences automatically derived from a large number of unlabelled sentences. POS-based templates are easy to interpret as well as inexpensive to obtain, during both training and runtime. We demonstrate that considering POS-based templates has several other advantages:

- It makes the system agnostic to the order in which keywords appear in the input, which is an important requirement for keywords-to-text generation.
- Keywords by themselves only provide topical information and do not contain information regarding the lexical and syntactic choices the generator has to make; POS-based templates help overcome this problem.
- The end-user has a better control over the generation process; the user can easily specify a template of her/his choice at run-time, say, by choosing a sentence from a of a list of exemplars whose POS sequence can be automatically derived.

Our framework is based on the encode-attend-decode paradigm, where keywords and templates are encoded first using linear and recurrent units. The decoder carefully attends over the contexts derived from the encoded keywords and templates. Words are then produced by either (i) generating morpho-syntactic and semantic variations of the input keywords, such as inflected forms and synonyms, or (ii) inferring suitable function-words from the vocabulary. For training, the system relies on automatically tagged POS-based templates and keywords. The keywords are comprised of noun, verb, adjectives and adverbs, and are automatically identified through the POS tags of the corresponding sentences from a large volume of unlabeled data (see Section 4.1).

Qualitative and quantitative performance analyses on the publicly available benchmark data (Chen et al., 2019a) reveal our system’s superiority over baselines. The analyses also show that our system can tackle subtleties in data-to-text generation such as (a) diverse linguistic structures and styles, (b) inadequate/spurious content in the input, and (c) changes in input keyword order. We will release the code and data for academic use.

2 Related Work

The specific problem of text generation from keywords has not received much attention. Uchimoto et al. (2002) first proposed a system which uses n-grams and dependency trees to generate sentences. The system was built for Japanese. Recently, Song et al. (2019) have exploited recurrent neural networks to generate the context before and after a single input keyword in Chinese.

Controlling text generation through auxiliary inputs has received interest mainly in text-to-text domain (Kabbara and Cheung, 2016). The controllable plug-n-play language model by Dathathri et al. (2019) is such a recently proposed approach. In their method, while, the generator is able to produce a fluent output based on the control specification, the generation process is still open-ended and may not adhere to any user-desired syntax. Hu et al. (2017) create a variational auto-encoder (VAE) framework which provides minimal control options like flipping sentiment and flipping tense. The system does not accept templates and is limited to generating only short text. Ghosh et al. (2017) describe a method to customize the degree of emotional content in generated sentences. This system also cannot accept templates, has a fixed set of categories of emotions, and crucially, relies on actual textual data annotated with these categories. A similar effort by Ficler and Goldberg (2017) attempts to control the linguistic properties of the text through a language model conditioned on a particular style. They operate in the movie-review domain, where the possible styles are limited to theme, sentiment, professional, descriptive etc. These styles can take a limited set of values which the generated text should conform to, and the system lacks data transformation ability. Jhamtani et al. (2017) explore an approach to apply Shakespearean English style to modern English texts. The model uses an external dictionary of stylistic words and uses that for carrying out word replacement by copying the style; this may not always retain the desired meaning and coherence.

Regarding template controlled generation, Iyyer et al. (2018) propose syntactically controlled paraphrase network (SCPN), a way to transform an input sentence based on templates given in the form.
of “parse” trees that are recurring in a language. The system can not transform input in the form of data (represented in keywords), and rather relies on well formed sentences and corresponding complete parse trees. It is worth noting that, though the system can accept an input template (such as \( S \ (NP) \ (ADVP) \ (VP) \)), these templates are syntactically rigid and also hard to interpret.

Chen et al. (2019a) propose an approach which uses a sentence as a syntactic exemplar rather than requiring an external parser. The authors benchmark their system against SCPN and showed competitive performance. However, this system is not designed to accept data/keywords as input (unlike our system) which can take up keywords in any order. We employ this system as a baseline for comparison.

Recently, Wang et al. (2019), inspired by the data-to-text generation dataset (Wiseman et al., 2017), describe a method to generate sentence given a structured record (e.g. \{PLAYER: Lebron, POINTS: 20, ASSISTS: 10\}), and a reference sentence (e.g. Kobe easily dropped 30 points). Their is a different task and involves manipulating the reference text (by rewriting/adding/deleting text portions) to ensure fidelity with respect to the structured content. In our case, the keywords are not structured or even ordered and may require morphological, and syntactic transformations (change in number, tense, aspect); hence, rewriting/adding/deleting of text portions is not feasible.

Laha et al. (2019), in similar ways as above, propose a modular system that convert entries in structured data (in tabular format) to canonical form, generate simple sentences from the canonical data, and, finally, combine the sentences to produce a coherent and fluent paragraph description. Their approach assumes table row representations as a collection of binary relations (or triples), which is a different task-setup than ours.

To the best of our knowledge, systems for translating order invariant keywords to elaborate natural language text remain elusive.

## 3 System Architecture

For generation of sentences from keywords, the system considers three inputs (padded whenever necessary): (a) a set of \( N \) keywords, \( K = \{k_1, k_2, k_3, ..., k_N\} \), (b) a set of \( U \) unique POS tags \( KT = \{k_{t1}, k_{t2}, k_{t3}, ..., k_{tU}\} \) pertaining to the keywords, (c) a sequence of \( M \) POS tags, forming the template, \( TT = \{tt_1, tt_2, ..., tt_M\} \). The output sentences can be represented as a sequence of \( M \) words \( Y = \{y_1, y_2, y_3, ..., y_M\} \). Note that, by design, we are keeping the length of the output same as the length of the template.

The overall architecture is given in Figure 1. With this input-output configuration, generation is carried out through the modules, as follows:

### 3.1 Keyword Encoder

The objective of the keyword encoder is to capture contextual representations of each keyword in a finite-size vector. It should also ensure that the encoding process is agnostic to the input keyword order. For this, the keywords (in one-hot form) are passed through an embedding layer first. The vocabulary and the embedding layers are shared across the keyword encoder and the decoder. We use a stack of feed forward layers, that non-linearly transform each keyword embedding. Let the transformed vectors be denoted as \( H_k = [h_{k1}, h_{k2}, h_{k3}, ..., h_{kU}] \). The decoder extracts appropriate context from these vectors through attention mechanism (explained in Section 3.4).

### 3.2 Template Encoder

Template encoder is a layer of bidirectional recurrent units (GRUs (Chung et al., 2014)) stacked on top of an embedding layer of tags. For each time-step of encoding, encoded vectors gathered from both the directions are concatenated and passed through an non-linear layer (\( \tanh \)), on top of MLPs, which reduces its dimension to an appropriate size, as desired by the decoder. Let the encoded templates be represented as \( H_{tt} = [h_{tt1}, h_{tt2}, h_{tt3}, ..., h_{ttM}] \).

### 3.3 Template and Keyword Tag Matching

In each step of generation, the decoder has to decide how much contextual information should be considered from the keywords (i.e., from \( H_k \)) and the template tags (i.e., \( H_{tt} \)). This is governed by a matching process that yields a probability term \( \lambda \), which is defined as:

\[
\lambda = \max_{1 \leq j \leq U} \left( \cosine(e_{kt_j}, e_{kt_j}) \right) \\
\lambda = \text{sigmoid}(W^T_s s_t + b)  \tag{1}
\]

Here \( \lambda \) is the highest matching probability between the current tag in the template \( tt_i \) and one of the
tags related to the keywords. $e_{tt_i}$ and $e_{kt_i}$ are embeddings for tags $tt_i$ and $kt_i$ respectively. The function \textit{cosine} is cosine-similarity, commonly used for vector similarity calculation. $\lambda$ helps the decoder decide whether to emphasize on the keyword context or simply ignore the keywords and produce a function word on its own.

3.4 Decoder

The decoder’s job is to construct a probability distribution over the word vocabulary in each time-step. For each time step $t \in \{1, M\}$, the distribution can be given as

$$p(y_t|y_1, y_2, \ldots, y_{t-1}, m_t) = g(y_{t-1}, s_t, m_t) \tag{2}$$

where $m_t$ is the context extracted from the encoders at time-step $t$, and $s_t$ is decoder’s current hidden state and $g$ is a non-linear activation over a linear function (such as \textit{tanh}). In our setting, the context-vector $m_t$ is computed as follows:

$$m_t = f(\lambda c_t, 1 - \lambda h_{tt_t}) \tag{3}$$

where, the function $a$ is a feed forward network used for computing the attention energy (Bahdanau et al., 2015). Note that, for computing attention weights, we also consider $h_{tt_t}$. This ensures that the template tags also influence the attention mechanism and selection of content. In sum, our design allows the decoder to be more flexible in either extracting contextual information from the keywords or the template. It also ensures that unnecessary attention is not given to the keywords if the generation step does not require so.

It is worth noting that, for calculation of $\lambda$, even though a max operation is involved, due to the use of \textit{sigmoid}, and the choice of similarity function, the network is still differentiable. We also observe that when the tag-embedding layers are initialized with unique embeddings for each tag\(^2\), the initial learning process becomes more stable. Even though the network initially sees very little similarity across similar tags (e.g., NN and NNS), it gradually brings embeddings of similar POS categories closer as the training progresses. This is desirable as universal POS tags are used for the keywords, whereas fine-grained POS tags are used in the template.

We now describe the experimental setup.

\(^2\)We set the tag-embedding dimension same as the tag vocabulary count and using a one-hot vector for each tag during initialization.
| Split | # examples | Avg. keyword | Avg. sent. length |
|-------|------------|--------------|------------------|
| Train | 959013     | 3.74         | 10.611           |
| Dev   | 500        | 2.93         | 8.82             |
| Test  | 800        | 3.411        | 9.58             |

Table 1: Data statistics. The word vocabulary size used for representing keywords and output sentences is 40738 and the tag vocabulary size is 57.

4 Experiments

4.1 Dataset

Since our framework requires keywords, tags for the keywords, and tagged template sequences, it is possible to generate a large amount of training data with the help of an off-the-shelf POS tagger and an unlabeled corpus. For English, a large amount of simple sentences are available as part of the ParaNMT project (Wieting and Gimpel, 2018). We use a derivative of this dataset extracted by Chen et al. (2019a)\(^3\). Sentences in the dataset are tagged using the Spacy\(^4\) tagger, and the tagged sequences are retained as template. The sentences themselves are used as gold-standard references. Words of categories NOUN, VERB, ADJECTIVE and ADVERB are lemmatized and used as keywords (ref. INPUT 1 in Figure 1). For each keyword-set, the POS tagger is independently executed and the unique tags related to all keywords in an example are retained (ref. INPUT 2 in Figure 1). It is worth noting that POS tagging of a token is context dependent. But since the input in dev/test in our task setting is a list of keywords (instead of a sentence) which could be in any order, tagging for each keyword is performed independently. Table 1 mentions the dataset statistics.

For testing, Chen et al. (2019a) have provided a benchmark dataset which contains an input sentence and an exemplar sentence. From the input sentence, we extract keywords and tags corresponding to the keywords as mentioned above. This creates two possible evaluation scenarios for us:

1. **Exact Template**: evaluated by considering the POS tag sequences of the reference output as template, and
2. **Similar Template**: evaluated by considering the POS tag sequences of the exemplar sentences as template.

We observe that the exemplar sentences are often not of same length as the expected output. Using the POS sequences of the exemplars will generate different outputs than the references, making it difficult to evaluate. For a fair evaluation, we report results for both scenarios (1) and (2).

4.2 Model Configuration

The word and tag embedding dimensions were set to 500 and 57 respectively. The hidden dimensions for decoder, keyword encoder, and tag encoder were set to 500, 500 and 100 respectively. Both encoder and decoder had dropout operations enabled during training with a dropout probability of 0.5. Cross-entropy loss was considered as the loss criterion and for parameter optimization, Adam optimizer was used with a learning rate of 0.001. The model trains for 40 iterations with a batch size set to 256. Model implementation was done using the pytorch API.

4.3 Comparison Systems

The closest system to ours by Chen et al. (2019a) (termed SENTEXEMP) is used as baseline. In their original setting, the model expects input and exemplar sentences for training. We retrained the system to consider keyword list and exemplar sentence as input. During testing, for the **Exact** scenario\(^5\), the expected output is given as the exemplar. For the **Similar** scenario, testing is straightforward as the exemplar sentences are already available in the test dataset.

Apart from this, we consider four different baselines as mentioned below.

1. **TRANSMODEL**: A transformer based encoder-decoder framework (Vaswani et al., 2017) that only accepts keywords as input and not any template.
2. **RNNMODEL**: An LSTM based encoder-decoder framework (Bahdanau et al., 2015) that only accepts keywords as input and not any template.
3. **TRANSMODEL**: Transformer based framework with keywords and templates concatenated and given as input.

\(^3\)Obtained from https://tinyurl.com/y7rvv4df
\(^4\)http://spacy.io/
\(^5\)The “Exact” setup emulates controlled domains where the templates indeed repeat heavily (e.g., QAs in dialogs, dialog acts like greetings, chit-chat, etc.).
Table 2: Results for sentence generation from input keywords on the dataset by Chen et al. (2019a).

| Model            | BLEU (%) | METEOR (%) | ROUGE-L (%) | SkipT | POSMatch (%) |
|------------------|----------|------------|-------------|-------|--------------|
|                  | Exact    | Similar    | Exact       | Similar |              |
| TRANSNOTEMPLATE  | 6.08     | N/A        | 18.74       | N/A    | 0.72         | 14.9         |
| RNNNOTEMPLATE    | 16.51    | N/A        | 27.13       | N/A    | 0.76         | 22.44        |
| TRANSconcat      | 55.1     | 8.75       | 45.4        | 21.13  | 91.0         | 92.77        |
| RNNconcat        | 52.62    | 8.33       | 44.5        | 20.81  | 77.22        | 92.95        |
| SENTexemp (Chen et al., 2019a) | 36.64    | 2.47       | 29.38       | 12.39  | 65.14        | 67.36        |
| TEMPLATE (OUR)   | 40.73    | 10.12      | 38.15       | 20.96  | 70.46        | 73.08        |
| TEMPLATEBEAM (OUR) | 40.79    | 10.0       | 38.28       | 20.94  | 70.66        | 73.03        |

Table 3: Results for sentence generation from by reversing input keywords on the dataset by Chen et al. (2019a).

| Model            | BLEU (%) | METEOR (%) | ROUGE-L (%) | SkipT | POSMatch (%) |
|------------------|----------|------------|-------------|-------|--------------|
|                  | Exact    | Similar    | Exact       | Similar |              |
| TRANSNOTEMPLATE  | 3.75     | N/A        | 20.25       | N/A    | 0.68         | N/A          |
| RNNNOTEMPLATE    | 3.52     | N/A        | 20.83       | N/A    | 0.7          | N/A          |
| TRANSconcat      | 18.78    | 7.37       | 28.31       | 20     | 52.27        | 87.27        |
| RNNconcat        | 15.89    | 6.25       | 28.07       | 19.6   | 50.68        | 83.87        |
| SENTexemp (Chen et al., 2019a) | 36.64    | 2.47       | 29.38       | 12.39  | 65.14        | 67.36        |
| TEMPLATE (OUR)   | 40.33    | 10.12      | 38.15       | 20.96  | 70.46        | 73.08        |
| TEMPLATEBEAM (OUR) | 40.79    | 10.0       | 38.28       | 20.94  | 70.66        | 73.03        |

4. RNNconcat: LSTM based framework with keywords and templates concatenated and given as input.

We also consider two variants of our model: (a) the default (termed Template) model (without beam search), and (b) a variant (termed Template-Beam) whose best output is obtained through beam search (beam width of 5) over the output space.

The baseline Transformer and RNN models were trained using the OpenNMT toolkit (Klein et al., 2017). All the models were trained with default configurations.

4.4 Evaluation

Through evaluation, we seek to answer the following research questions:

1. RQ1: Is the proposed framework able to produce output that is fluent and related to the input keywords? How does the performance fair against baselines and existing systems?
2. RQ2: Does the structure of output predicted by our framework conform to the specified template?
3. RQ3: How sensitive is our framework to the variation of specified keywords’ order?
4. RQ4: To what extent can our framework adapt to handle inadequate/spurious information provided in the keyword list?

In order to answer these, we first evaluate our models and the baselines with popular NLG evaluation metrics such as BLEU (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005) and ROUGE (Lin, 2004). Additionally, we use Skip-thought sentence similarity metric6 (termed as SkipT) to check the semantic fidelity between the generated

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6https://github.com/Maluuba/nlg-eval
output and reference sentences.

To answer RQ2, we measure the averaged POS overlap (termed as POSMatch). It measures the degree of exact match between the input template and the POS sequence of the predicted sentence. For this, the same POS tagger that generated the templates is applied on the predicted sentences. Percentage of POS match is reported as a part of the results.

To answer RQ3, we reverse the keyword order in the test data and carry out testing of our model variants and baselines on the modified data. Finally, we inspect the $\lambda$ values in Eq. 1 and the modified attention weights after multiplying $\lambda$ with the attention weights (Eq.5) to answer RQ4 and other questions.

### 5 Results

Tables 2 and 3 present the evaluation results. Performance indices for the NO_TEMPLATE models make it clear that without external knowledge about the syntax and style, it becomes harder even for state-of-the-art sequence-to-sequence models to produce fluent and adequate sentences from keywords. Measuring POSMatch does not help evaluate these models since they do not consider template inputs. The CONCAT models perform very well when keywords are presented in the same order in which their variations appear in the output, but perform quite poorly when such ordering is not preserved. Sentence is order agnostic but is not designed for key-word to text generation, thus performs poorly.

Our TEMPLATE model variants are stable and produce decent performance in the Exact scenario and are insensitive to change in keyword order. However, they quite strictly follow the template patterns, which reduces their performance when exact templates are not provided. These observations indeed help answer RQ1, RQ2 and RQ3.

We present a few examples in Table 4 focusing on different linguistic and practical aspects i.e., variation in syntax and style, change in input key-

| Keywords and Keyword POS | Example Template Sentence | Template POS | Generated Output | Remark |
|-------------------------|---------------------------|--------------|------------------|--------|
| john (NN), job (NN)     | who is bob’s friend?      | WP VBZ NNP POS NN | **SENTENCE** who is this right? **RNN** CONCAT what’s john’s job? **TEMPLATE** what is john’s job? | question form |
| john (NN), job (NN)     | why does bob go to the city? | WP VBZ NNP VB IN DT NN | **SENTENCE** why does ten go to the boy? **RNN** CONCAT what does john do for the job? **TEMPLATE** what does john do with the job? | paraphrasing with different template |
| movie (NN), beautiful (JJ) | this is a horrible story. | DT VBZ DT JJ NN | **SENTENCE** this is a horrible story. **RNN** CONCAT a movie beautiful **TEMPLATE** this is a whole movie | declarative form |
| movie (NN), beautiful (JJ) | what a movie show this is! | WP DT JJ NN PRP VBZ | **SENTENCE** what a movie show this is! **RNN** CONCAT what a whole movie it <unk>.. **TEMPLATE** what a whole movie it is. | exclamatory form |
| movie (NN), beautiful (JJ) | is it a horrible story? | VBZ PRP DT JJ NN | **SENTENCE** is it a horrible story? **RNN** CONCAT is it a movie beautiful? **TEMPLATE** is it a whole movie? | interrogative form |
| movie (NN), beautiful (JJ) | that is not a good book. | DT VBZ RB DT JJ NN | **SENTENCE** that is not a beautiful story. **RNN** CONCAT this is n’t a movie beautiful. **TEMPLATE** this is n’t a whole movie. | negation |
| president (NN), begin (VB), work (VB), great (JJ) | the boy started crying. | DT NN VBD NN | **SENTENCE** the president’s great the president began crying. **RNN** CONCAT the president began work. **TEMPLATE** the president began work. | varying keyword order |
| begin (VB), work (VB), president (NN) , great (JJ) | the boy started crying. | DT NN VBD NN | **SENTENCE** the president’s great the president began crying. **RNN** CONCAT the president began work. **TEMPLATE** the president began work. | varying keyword order |
| great (JJ), president (NN), work (VB), begin (VB) | the boy started crying. | DT NN VBD NN | **SENTENCE** the president’s great the president began crying. **RNN** CONCAT the president began work. **TEMPLATE** the president began work. | varying keyword order |
| begin (VB), work (VB), great (JJ), president (NN) | the boy started crying. | DT NN VBD NN | **SENTENCE** the president’s great the president began crying. **RNN** CONCAT the president began work. **TEMPLATE** the president began work. | varying keyword order |

Table 4: Examples of generated sentences from different models.
word order and presence of spurious content in the input. It is evident that our POS based models are capable of handling templates of various sentence forms such as declarative, interrogative, exclamatory and negation. Finally, the last four examples clearly show our model’s capability towards ignoring spurious entries (i.e. the adjective “great”) as opposed to the baseline models. This partially addresses RQ4.

Figure 2 shows the attention weights and λ values observed during generation of an example from the test dataset (darker colors indicates higher weights). For constructing this example, four keywords “Garuda”, “gate”, “head” and “scream” with default POS categories of noun (NN), noun (NN), noun (NN) and verb (VB) respectively are provided to our TEMPLATE model. The input template set to “NNP VBD IN DT NN CC VBD RB”, derived from an example compound sentence. It is evident from the figure that content words in the output obtain higher λ values and for them the keyword representations extracted through attention mechanism play a vital role. For the other words, the keyword representations are still used, but minimally. Even then, they help in finding appropriate function words (e.g. whether to use a definite article or not). Finally, we speculate that by attending over all the keyword representations, the model learned to hallucinate the verb (“headed”) from the noun (“head”) and applies the correct tense form. This demonstrates that our model has the potential to tackle information gaps in the keyword set, as hypothesized in RQ4.

6 Conclusion

We presented a novel weekly supervised approach for text generation from keywords. With the help of templates, and a carefully designed attention mechanism, our system aptly learns to translate keywords into sentences of diverse structure and styles, and also remains unaffected by the change of order in the input keywords. Through our evaluation, we showed our system’s capability in handling inadequate/surplus information in the keywords. And, unlike related previous work, our system simply uses sequences of tags instead of parse trees as templates.

While the generation quality during test depends on the quality of template, it is not unreasonable to assume the availability of high-quality templates during run-time. Our observation is that even for the templates used for the “Similar” set-up, generated sentences are fluent and adequate.

As a possible follow up work, we would like to use universal POS tags (UPTs) in templates. The goal is to train our system for keywords in one language as input and generating sentences in another language. This could be feasible since our approach is indifferent to underlying source language or keywords’ order. Assessing the model’s usefulness in real world data-to-text applications, and for generation of synthetic data for text-to-text systems is also on our future agenda.

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