Order-Planning Neural Text Generation From Structured Data

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Abstract

Generating texts from structured data (e.g., a table) is important for various natural language processing tasks such as question answering and dialog systems. In recent studies, researchers use neural language models and encoder-decoder frameworks for table-to-text generation. However, these neural network-based approaches do not model the order of contents during text generation. When a human writes a summary based on a given table, he or she would probably consider the content order before wording. In a biography, for example, the nationality of a person is typically mentioned before occupation in a biography. In this paper, we propose an order-planning text generation model to capture the relationship between different fields and use such relationship to make the generated text more fluent and smooth. We conducted experiments on the WikIBIO dataset and achieve significantly higher performance than previous methods in terms of BLEU, ROUGE, and NIST scores.

Table:

| ID | Field     | Content                              |
|----|-----------|--------------------------------------|
| 1  | Name      | Arthur Ignatius Conan Doyle          |
| 2  | Born      | 22 May 1859 Edinburgh, Scotland      |
| 3  | Died      | 7 July 1930 (aged 71) Crowborough, England |
| 4  | Occupation| Author, writer, physician            |
| 5  | Nationality| British                             |
| 6  | Alma mater| University of Edinburgh Medical School |
| 7  | Genre     | Detective fiction, fantasy           |
| 8  | Notable work| Stories of Sherlock Holmes          |

Text:

Sir Arthur Ignatius Conan Doyle (22 May 1859 – 7 July 1930) was a British writer best known for his detective fiction featuring the character Sherlock Holmes.

Table 1: Example of a Wikipedia infobox and a reference text.

This motivates order planning for neural text generation. In other words, a neural network should model not only word order (as has been well captured by RNN) but also the order of contents, i.e., fields in a table.

We also observe from real summaries that table fields by themselves provide illuminating clues and constraints of text generation. In the biography domain, for example, the nationality of a person is typically mentioned before the occupation. This could benefit from explicit planning of content order during neural text generation.

In this paper, we propose an order-planning method for table-to-text generation. Our model is built upon the encoder-decoder framework and use RNN for text synthesis with attention to table entries. Different from exiting neural models, we design a table field linking mechanism, inspired by temporal memory linkage in the Differentiable Neural Computer (Graves et al. 2016, DNC). Our field linking mechanism explicitly models the relationship between different fields, enabling our neural network to better plan what to say first and what next. Further, we incorporate a copy mechanism (Gu et al. 2016) into our model to cope with rare words.

We evaluated our method on the WikIBIO dataset (Lebret, Grangier, and Auli 2016). Experimental results show that our order-planning approach significantly outperforms...
previous state-of-the-art results in terms of BLEU, ROUGE, and NIST metrics. Extensive ablation tests verify the effectiveness of each component in our model; we also perform visualization analysis to better understand the proposed order-planning mechanism.

**Approach**

Our model takes as input a table (e.g., a Wikipedia infobox) and generates a natural language summary describing the information based on an RNN. The neural network contains three main components:

- An encoder captures table information;
- A dispatcher—a hybrid content- and linkage-based attention mechanism over table contents—plans what to generate next; and
- A decoder generates a natural language summary using RNN, where we also incorporate a copy mechanism (Gu et al. 2016) to cope with rare words.

We elaborate these components in the rest of this section.

**Encoder: Table Representation**

We design a neural encoder to represent table information. As shown in Figure 1, the content of each field is split into separate words and the entire table is transformed into a large sequence. Then we use a recurrent neural network (RNN) with long short term memory (LSTM) units (Hochreiter and Schmidhuber 1997) to read the contents as well as their corresponding field names.

Concretely, let \( C \) be the number of content words in a table; let \( c_i \) and \( f_i \) be the embeddings of a content and its corresponding field, respectively \((i = 1 \cdots C)\). The input of LSTM-RNN is the concatenation of \( f_i \) and \( c_i \), denoted as \( x_i = [f_i; c_i] \), and the output, denoted as \( h_i \), is the encoded information corresponding to a content word, i.e.,

\[
\begin{align*}
   g_{in: forget: out} &= \sigma(W_{g} x_i + U_{g} h_{i-1}) \\
   \bar{x}_i &= \tanh(W_{x} x_i + U_{x} h_{i-1}) \\
   \hat{h}_i &= g_{in} \circ \bar{x}_i + g_{forget} \circ \hat{h}_{i-1} \\
   h_i &= g_{out} \circ \tanh(\hat{h}_i)
\end{align*}
\]

where \( \circ \) denotes element-wise product, and \( \sigma \) denotes the sigmoid function. \( W \)'s and \( U \)'s are weights, and bias terms are omitted in the equations for clarity. \( g_{in} \), \( g_{forget} \), and \( g_{out} \) are known as input, forget, and output gates.

Notice that, we have two separate embedding matrices for fields and content words. We observe the field names of different data samples mostly come from a fixed set of candidates, which is reasonable in a particular domain. Therefore, we assign an embedding to a field, regardless of the number of words in the field name. For example, the field Notable work in Table 1 is represented by a single field embedding instead of the embeddings of notable and work.

For content words, we represent them with conventional word embeddings (which are randomly initialized), and use LSTM-RNN to integrate information. In a table, some fields contain a sequence of words (e.g., Name=“Arthur Ignatius

| Field          | Content |
|----------------|---------|
| Name Arthur    |         |
| Name Ignatius  |         |
| Name Conan     |         |
| Name Doyle     |         |
| Born 1859      |         |
| Born May       |         |
| Occupation     | writer  |
| Occupation     | physician|
| Nationality    | British |

**Dispatcher: Planning What to Generate Next**

After encoding table information, we use another RNN to decode a natural language summary (deferred to the next part). During the decoding process, the RNN is augmented with a dispatcher that plans what to generate next.

Generally, a dispatcher is an attention mechanism over table contents. At each decoding time step \( t \), the dispatcher computes a probabilistic distribution \( \alpha_{t,i} \) \((i = 1 \cdots C)\), which is further used for weighting content representations \( h_i \). In our model, the dispatcher is a hybrid of content- and link-based attention, discussed in detail as follows.

**Content-Based Attention.** Traditionally, the computation of attention \( \alpha_{t,i} \) is based on the content representation \( h_i \) as well as some state during decoding (Bahdanau, Cho, and Bengio 2015). Mei, Bansal, and Walter 2016). We call this content-based attention, which is also one component in our dispatcher.

Since both the field name and the content contain important clues for text generation, we compute the attention weights based on not only the encoded vector of table content \( h_i \) but also the field embedding \( f_i \), thus obtaining the final attention \( \alpha_{t,i}^{content} \) by re-weighting one with the other.
Formally, we have
\[ \tilde{\alpha}_{t,i}^{(f)} = f_i^T (W(f) y_{t-1} + b^{(f)}) \]  
(5)
\[ \tilde{\alpha}_{t,i}^{(c)} = h_i^T (W(c) y_{t-1} + b^{(c)}) \]  
(6)
\[ \alpha_{t,i}^{\text{content}} = \frac{\exp \{ \tilde{\alpha}_{t,i}^{(f)} \alpha_{t,i}^{(c)} \}}{\sum_{j=1}^C \exp \{ \tilde{\alpha}_{t,j}^{(f)} \alpha_{t,j}^{(c)} \}} \]  
(7)
where \( W(f), b^{(f)}, W(c), b^{(c)} \) are learnable parameters; \( f_i \) and \( h_i \) are vector representations of the field name and encoded content, respectively, for the \( i \)th row. \( \alpha_{t,i}^{\text{content}} \) is the content-based attention weights. Ideally, a larger content-based attention indicates a more relevant content to the last generated word.

**Link-Based Attention.** We further propose a link-based attention mechanism that directly models the relationship between different fields.

Our intuition stems from the observation that, a well-organized text typically has a reasonable order of its contents. As illustrated previously, the nationality of a person is often mentioned before his occupation (e.g., a British writer). Therefore, we propose an link-based attention to explicitly model such order information.

We construct a link matrix \( \mathcal{L} \in \mathbb{R}^{n_f \times n_f} \), where \( n_f \) is the number possible field names in the dataset. An element \( \mathcal{L}[f_j, f_i] \) is a real-valued score indicating how likely the field \( f_j \) is mentioned after the field \( f_i \). (Here, [.,.] indexes a matrix.) The link matrix \( \mathcal{L} \) is a part of model parameters and learned by backpropagation. Although the link matrix appears to be large in size (1475 \times 1475), a large number of its elements are not used because most fields do not co-occur in at least one data sample; in total, we have 53,422 effective parameters here. In other scenarios, low-rank approximation may be used to reduce the number of parameters.

Formally, let \( \alpha_{t-1,i} \ (i = 1 \ldots C) \) be an attention probability over table contents in the last time step during generation. For a particular data sample whose content words are of fields \( f_1, f_2, \ldots, f_C \), we first weight the linking scores by the previous attention probability, and then normalize the weighted score to obtain link-based attention probability, given by

\[ \alpha_{t,i}^{\text{link}} = \text{softmax} \left\{ \sum_{j=1}^C \alpha_{t-1,j} \cdot \mathcal{L}[f_j, f_i] \right\} \]  
(8)
\[ \frac{\exp \{ \sum_{j=1}^C \alpha_{t-1,j} \cdot \mathcal{L}[f_j, f_i] \}}{\sum_{i'}=1} \exp \{ \sum_{j=1}^C \alpha_{t-1,j} \cdot \mathcal{L}[f_j, f_{i'}] \} \]  
(9)

Intuitively, the link matrix is analogous to the transition matrix in a Markov chain \( \text{Karlin 2014} \), whereas the term \( \sum_{j=1}^C \alpha_{t-1,j} \cdot \mathcal{L}[f_j, f_i] \) is similar to one step of transition in the Markov chain. However, in our scenario, a table in a particular data sample contains only a few fields, but a field may occur several times because it contains more than one content words. Therefore, we do not require our link matrix \( \mathcal{L} \) to be a probabilistic distribution in each row, but normalize the probability afterwards by Equation 9, which turns out to work well empirically.

Besides, we would like to point out that the link-based attention is inspired by the Differentiable Neural Computer \( \text{Graves et al. 2016} \) (DNC). DNC contains a “linkage-based addressing” mechanism to track consecutively used memory slots and thus to integrate order information during memory addressing. Likewise, we design the link-based attention to capture the temporal order of different fields. But different from the linking strength heuristically defined in DNC, the link matrix in our model is directly parameterized and trained in an end-to-end manner.

**Hybrid Attention.** To combine the above two attention mechanisms, we use a self-adaptive gate \( z_t \in (0,1) \) by a sigmoid unit

\[ z_t = \sigma(w^T[h_{t-1}^{f}; e_t^{(f)}; y_{t-1}]) \]  
(10)
where \( w \) is a parameter vector. \( h_{t-1}^{f} \) is the last step’s hidden state of the decoder RNN. \( y_{t-1} \) is the embedding of the word generated in the last step; \( e_t^{(f)} \) is the sum of field embeddings \( f_i \) weighted by the current step’s field attention \( \alpha_{t,i}^{\text{link}} \). As \( y_{t-1} \) and \( e_t^{(f)} \) emphasize the content and link aspects, respectively, the self-adaptive gate \( z \) is aware of both. In practice, we find \( z \) tends to address link-based attention too much and thus adjust it by \( \tilde{z}_t = 0.2z_t + 0.8 \) empirically.

Finally, the hybrid attention, a probabilistic distribution over all content words, is given by

\[ \alpha_t^{\text{hybrid}} = \tilde{z}_t \cdot \alpha_t^{\text{content}} + (1 - \tilde{z}_t) \cdot \alpha_t^{\text{link}} \]  
(11)

**Decoder: Sentence Generation**

The decoder is an LSTM-RNN that predicts target words in sequence. We also have an attention mechanism \( \text{Bahdanau, Cho, and Bengio 2015} \) that summarizes source information, i.e., the table in our scenario, by weighted sum, yielding an attention vector \( a_t \) by

\[ a_t = \sum_{i=1}^C \alpha_{t,i}^{\text{hybrid}} h_i \]  
(12)
where \( h_i \) is the hidden representation obtained by the table encoder. As \( \alpha_{t,i}^{\text{hybrid}} \) is a probabilistic distribution—determined by both content and link information—over content words, it enables the decoder RNN to focus on relevant information at a time, serving as an order-planning mechanism for table-to-text generation.

Then we concatenate the attention vector \( a_t \) and the embedding of the last step’s generated word \( y_{t-1} \), and use a single-layer neural network to mix information before feeding to the decoder RNN. In other words, the decoder RNN’s input (denoted as \( x_t \)) is

\[ x_t = \tanh(W_d[a_t; y_{t-1}] + b_d) \]  
(13)
where \( W_d \) and \( b_d \) are weights. Similar to Equations 1–4, at a time step \( t \) during decoding, the decoder RNN yields a
hidden representation $h'_t$, based on which a score function $s^\text{LSTM}_t$ is computed suggesting the next word to generate. The score function is computed by

$$s^\text{LSTM}_t = W_h h'_t + b_s$$  \hspace{1cm} (14)$$

where $h'_t$ is the decoder RNN’s state. ($W_h$ and $b_s$ are weights.) The score function can be thought of as the input of a softmax layer for classification before being normalized to a probabilistic distribution. We incorporate a copy mechanism (Gu et al. 2016) into our approach, and the normalization is accomplished after considering a copying score, introduced as follows.

**Copy Mechanism.** The copy mechanism scores a content word $c_i$ by its hidden representation $h_i$ in the encoder side, indicating how likely the content word $c_i$ is directly copied during target generation. That is,

$$s_{t,i} = \sigma(h_i^T W_c)h'_t$$  \hspace{1cm} (15)$$

and $s_{t,i}$ is a real number for $i = 1, \cdots, C$ (the number of content words). Here $W_c$ is a parameter matrix, and $h'_t$ is the decoding state.

In other words, when a word appears in the table content, it has a copying score computed as above. If a word $w$ occurs multiple times in the table contents, the scores are added, given by

$$s^\text{copy}_t(w) = \sum_{i=1}^C s_{t,i} \cdot \mathbb{1}_{\{c_i=w\}}$$  \hspace{1cm} (16)$$

where $\mathbb{1}_{\{c_i=w\}}$ is a Boolean variable indicating whether the content word $c_i$ is the same as the word $w$ we are considering.

Finally, the LSTM score and the copy score are added for a particular word and further normalized to obtain a probabilistic distribution, given by

$$s_t(w) = s^\text{LSTM}_t(w) + s^\text{copy}_t(w)$$  \hspace{1cm} (17)$$

$$p_t(w) = \text{softmax}(s_t(w)) = \frac{\exp(s_t(w))}{\sum_{w' \in \mathcal{V} \cup \mathcal{C}} \exp(s_t(w'))}$$  \hspace{1cm} (18)$$

where $\mathcal{V}$ refers to the vocabulary list and $\mathcal{C}$ refers to the set of content words in a particular data sample. In this way, the copy mechanism can either generate a word from the vocabulary or directly copy a word from the source side. This is helpful in our scenario because some fields in a table (e.g., Name) may contain rare or unseen words and the copy mechanism can cope with them naturally.

For simplicity, we use greedy search during inference, i.e., for each time step $t$, the word with the largest probability is chosen, given by $y_t = \arg\max_w p_t(w)$. The decoding process terminates when a special symbol $<\text{eos}>$ is generated, indicating the end of a sequence.

**Training Objective.**

Our training objective is the negative log-likelihood of a sentence $y_1 \cdots y_T$ in the training set.

$$J = - \sum_{t=1}^T \log p(y_t | y_0 \cdots y_{t-1})$$  \hspace{1cm} (19)$$

where $p(\cdot | \cdot)$ is computed by Equation 18. An $\ell_2$ penalty is also added as most other studies.

Since all the components described above are differentiable, our entire model can be trained end-to-end by backpropagation, and we use Adam (Kingma and Ba 2015) for optimization.

**Experiments.**

**Dataset.**

We used the newly published WikiBio dataset (Lebret, Grangier, and Auli 2016), which contains 728,321 biographies from WikiProject Biography (originally from English Wikipedia, September 2015).

Each data sample comprises an infobox table of field-content pairs, being the input of our system. The generation target is the first sentence in the biography, which follows the setting in previous work (Lebret, Grangier, and Auli 2016). Although only the first sentence is considered in the experiment, the sentence typically serves as a summary of the article. In fact, the target sentence has 26.1 tokens on average, which is actually long. Also, the sentence contains information spanning multiple fields, and hence our order-planning mechanism is useful in this scenario.

*https://github.com/DavidGrangier/wikipedia-biography-dataset*

*https://en.wikipedia.org/wiki/Wikipedia:WikiProject_Biography*
We applied the standard data split: 80% for training and 10% for testing, except that model selection was performed on a validation subset of 1000 samples (based on BLEU-4).

**Settings**

We decapitalized all words and kept a vocabulary size of 20,000 for content words and generation candidates, which also followed previous work [Lebret, Grangier, and Auli 2016]. Even with this reasonably large vocabulary size, we had more than 900k out-of-vocabulary words. This rationalizes the use of the copy mechanism.

For the names of table fields, we treated each as a special token. By removing nonsensical fields whose content is “none” and grouping fields occurring less than 100 times as an “Unknown” field, we had 1475 different field names in total.

In our experiments, both words’ and table fields’ embeddings were 400-dimensional and LSTM layers were 500-dimensional. Notice that, a field (e.g., “name”) and a content/generation word (e.g., also “name”), even with the same string, were considered as different tokens; hence, they had different embeddings. We randomly initialized all embeddings, which are tuned during training.

We used Adam [Kingma and Ba 2015] as the optimization algorithm with a batch size of 32; other hyperparameters were set to default values.

**Baselines**

We compared our model with previous results using either traditional language models or neural networks.

- KN and Template KN [Heafield et al. 2013]: Lebret, Grangier, and Auli 2016) train an interpolated Kneser-Ney (KN) language model for comparison with the KenLM toolkit. They also train a KN language model with templates.

- Table NLM: Lebret, Grangier, and Auli 2016] propose an RNN-based model with attention and copy mechanisms. They have several model variants, and we quote the highest reported results.

We report model performance in terms of several metrics, namely BLEU-4, ROUGE-4, and NIST-4, which are computed by standard software, NIST meteva-v13a.pl (for BLEU and NIST) and MSR rouge-1.5.5 (for ROUGE). We did not include the perplexity measure in Lebret, Grangier, and Auli 2016] because the copy mechanism makes the vocabulary size vary among data samples, and thus the perplexity is not comparable among different approaches.

**Results**

**Overall Performance.** Table 2 compares the overall performance with previous work. We see that, modern neural networks are considerably better than traditional KN models with or without templates. Moreover, our base model (with content-attention only) outperforms [Lebret, Grangier, and Auli 2016], showing our better engineering efforts. After adding up all proposed components, we obtain +2.5 BLEU and ROUGE improvement and +0.3 NIST improvement, achieving new state-of-the-art results.

**Ablation Test.** Table 3 provides an extensive ablation test to verify the effectiveness of each component in our model. The top half of the table shows the results without the copy mechanism, and the bottom half incorporates the copying score as described previously. We observe that the copy mechanism is consistently effective with different types of attention.

We then compare content-based attention and link-based attention, as well as their hybrid (also Table 3). The results show that, link-based attention alone is not as effective as content-based attention. However, we achieve better performance if combining them together with an adaptive gate, i.e., the proposed hybrid attention. The results are consistent in both halves of Table 3 (with or without copying) and in terms of all metrics (BLEU, ROUGE, and NIST). This implies that content-based attention and link-based attention do capture different aspects of information, and their hybrid is more suited to the task of table-to-text generation.

**Effect of the gate.** We are further interested in the effect of the gate $z$, which balances content-based attention $alpha^text{content}$
and link-based attention $\alpha_{\text{link}}$. As defined in Equation 11, the computation of $z$ depends on the decoding state as well as table information; hence it is “self-adaptive.” We would like to verify if such adaptiveness is useful. To verify this, we designed a controlled experiment where the gate $z$ was manually assigned in advance and fixed during training. In other words, the setting was essentially a (fixed) interpolation between $\alpha_{\text{content}}$ and $\alpha_{\text{link}}$. Specifically, we tuned $z$ from 0 to 1 with a granularity of 0.1, and plot BLEU scores as the comparison metric in Figure 3.

As seen, interpolation of content- and link-based attention is generally better than either single mechanism, which again shows the effectiveness of hybrid attention. However, the peak performance of simple interpolation (42.89 BLEU when $z = 0.4$) is worse than the self-adaptive gate, implying that our gating mechanism can automatically adjust the importance of $\alpha_{\text{content}}$ and $\alpha_{\text{link}}$ at a particular time based on the current state and input.

**Different Ways of Using Field Information.** We are curious whether the proposed order-planning mechanism is better than other possible ways of using field information. We conducted two controlled experiments as follows. Similar to the proposed approach, we multiplied the attention probability by a field matrix and thus obtained a weighted field embedding. We fed it to either (1) the computation of content-based attention, i.e., Equations 5-6, or (2) the RNN field embedding. We fed it to either (1) the computation of probability by a field matrix and thus obtained a weighted field embedding was concatenated with the content-based attention, i.e., Equations 5-6, or (2) the RNN field embedding. We fed it to either (1) the computation of probability by a field matrix and thus obtained a weighted field embedding was concatenated with the content-based attention, i.e., Equations 5-6, or (2) the RNN field embedding. We fed it to either (1) the computation of probability by a field matrix and thus obtained a weighted field embedding was concatenated with the content-based attention, i.e., Equations 5-6, or (2) the RNN field embedding.

We conducted two controlled experiments as follows. Sim-...
Table 5: Case study. **Left:** Wikipedia infobox. **Right:** A reference and two generated sentences by different attention (both with the copy mechanism).

Our paper proposes an order-planning approach by designing a hybrid of content- and link-based attention. The model is inspired by hybrid content- and location-based addressing in the Differentiable Neural Computer (Graves et al. 2016, DNC), where the location-based addressing is defined heuristically. Instead, we propose a transition-like link matrix that models how likely a field is mentioned after another, which is more suited in our scenario.

Moreover, our entire model is differentiable, and thus the planning and realization steps in traditional language generation can be learned end-to-end in our model.

**Conclusion and Future Work**

In this paper, we propose an order-planning neural network that generates texts from a table (Wikipedia infobox). The text generation process is built upon an RNN with attention to table contents. Different from traditional content-based attention, we explicitly model the order of contents by a link matrix, based on which we compute a link-based attention. Then a self-adaptive gate balances the content- and link-based attention mechanisms. We further incorporate a copy mechanism to our model to cope with rare or unseen words.

We evaluated our approach on a newly proposed large scale dataset, WikiBio. Experimental results show that we outperform previous results by a large margin in terms of BLEU, ROUGE, and NIST scores. We also had extensive ablation test showing the effectiveness of the copy mechanism, as well as the hybrid attention of content and linking information. We compared our order-planning mechanism with other possible ways of modeling field; the results confirm that the proposed method is better than feeding field embedding to the network in a naive fashion. Finally we provide a case study and visualize the attention scores so as to better understand our model.

In future work, we would like to deal with text generation from multiple tables. In particular, we would design hierarchical attention mechanisms that can first select a table containing the information and then select a field for generation, which would improve the attention efficiency. We would also like to apply the proposed method to text generation from other structured data, e.g., a knowledge graph.
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References
[Angeli, Liang, and Klein 2010] Angeli, G.; Liang, P.; and Klein, D. 2010. A simple domain-independent probabilistic approach to generation. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, 502–512.

[Bahdanau, Cho, and Bengio 2015] Bahdanau, D.; Cho, K.; and Bengio, Y. 2015. Neural machine translation by jointly learning to align and translate. In Proceedings of the International Conference on Learning Representations.

[Barzilay and Lapata 2005] Barzilay, R., and Lapata, M. 2005. Collective content selection for concept-to-text generation. In Proceedings of the Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing, 331–338.

[Belz 2008] Belz, A. 2008. Automatic generation of weather forecast texts using comprehensive probabilistic generation-space models. Natural Language Engineering 14(4):431–455.

[Dale, Geldof, and Prost 2003] Dale, R.; Geldof, S.; and Prost, J.-P. 2003. CORAL: Using natural language generation for navigational assistance. In Proceedings of the 26th Australasian Computer Science Conference, volume 16, 35–44.

[Graves et al. 2016] Graves, A.; Wayne, G.; Reynolds, M.; et al. 2016. Hybrid computing using a neural network with dynamic external memory. Nature 538(7626):471–476.

[Green 2006] Green, N. 2006. Generation of biomedical arguments for lay readers. In Proceedings of the 4th International Natural Language Generation Conference, 114–121.

[Gu et al. 2016] Gu, J.; Lu, Z.; Li, H.; and Li, V. O. 2016. Incorporating copying mechanism in sequence-to-sequence learning. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, 1631–1640.

[Heafield et al. 2013] Heafield, K.; Pouzyrevsky, I.; Clark, J. H.; and Koehn, P. 2013. Scalable modified Kneser-Ney language model estimation. In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics, volume 2, 690–696.

[Hochreiter and Schmidhuber 1997] Hochreiter, S., and Schmidhuber, J. 1997. Long short-term memory. Neural Computation 9(8):1735–1780.

[Karlin 2014] Karlin, S. 2014. A First Course in Stochastic Processes. Academic Press.

[Kingma and Ba 2015] Kingma, D., and Ba, J. 2015. Adam: A method for stochastic optimization. In Proceedings of the International Conference on Learning Representations.

[Lebret, Grangier, and Auli 2016] Lebret, R.; Grangier, D.; and Auli, M. 2016. Neural text generation from structured data with application to the biography domain. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, 1203–1213.

[Liang, Jordan, and Klein 2009] Liang, P.; Jordan, M. I.; and Klein, D. 2009. Learning semantic correspondences with less supervision. In Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP, 91–99.

[Mei, Bansal, and Walter 2016] Mei, H.; Bansal, M.; and Walter, M. R. 2016. What to talk about and how? Selective generation using LSTMs with coarse-to-fine alignment. In Proceedings of the Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 720–730.

[Reiter et al. 2005] Reiter, E.; Sripada, S.; Hunter, J.; Yu, J.; and Davy, I. 2005. Choosing words in computer-generated weather forecasts. Artificial Intelligence 167(1-2):137–169.

[Shang, Lu, and Li 2015] Shang, L.; Lu, Z.; and Li, H. 2015. Neural responding machine for short-text conversation. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing, 1577–1586.

[Stent, Prasad, and Walker 2004] Stent, A.; Prasad, R.; and Walker, M. 2004. Trainable sentence planning for complex information presentations in spoken dialog systems. In Proceedings of the 42nd Meeting of the Association for Computational Linguistics, 79–86.

[Tan, Wan, and Xiao 2017] Tan, J.; Wan, X.; and Xiao, J. 2017. Abstractive document summarization with a graph-based attentional neural model. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics, 1171–1181.

[Turner, Sripada, and Reiter 2010] Turner, R.; Sripada, S.; and Reiter, E. 2010. Generating approximate geographic descriptions. In Empirical Methods in Natural Language Generation, 121–140.

[Van Deemter, Theune, and Krahmer 2005] Van Deemter, K.; Theune, M.; and Krahmer, E. 2005. Real versus template-based natural language generation: A false opposition? Computational Linguistics 31(1):15–24.

[William and White 1999] William, S., and White, E. B. 1999. The Element of Style. Pearson, 4th edition.