Towards information-rich, logical text generation with knowledge-enhanced neural models

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Abstract

Text generation system has made massive promising progress contributed by deep learning techniques and has been widely applied in our life. However, existing end-to-end neural models suffer from the problem of tending to generate uninformative and generic text because they cannot ground input context with background knowledge. In order to solve this problem, many researchers begin to consider combining external knowledge in text generation systems, namely knowledge-enhanced text generation. The challenges of knowledge-enhanced text generation including how to select the appropriate knowledge from large-scale knowledge bases, how to read and understand extracted knowledge, and how to integrate knowledge into generation process. This survey gives a comprehensive review of knowledge-enhanced text generation systems, summarizes research progress to solving these challenges and proposes some open issues and research directions.

1 Introduction

Text generation, also known as natural language generation (NLG), aims to make machines express like humans, which has the capability to produce smooth, meaningful and informative textual contents. From the original template-based and statistical methods to the deep learning-based methods, text generation has attracted the attention of massive researchers and made many remarkable advances. Depending on the data sources, text generation can be divided into text-to-text, data-to-text, and image-to-text generation. We focus on the text-to-text generation in this survey, because it still has massive research challenges and a wider range of applications. Text-to-text generation takes natural language text as input, understands the input text to obtain semantic representations, and generates corresponding output text according to task requirements.

Most advances in text generation in recent years are benefited from deep neural networks, such as recurrent neural network (RNN) [Elman, 1990] and Transformer [Vaswani et al., 2017]. With the help of these technologies, text generation systems have been able to generate smooth, topic-consistent and even personalized text. However, existing text generation systems lack interactions with the real world, and have little access to the external knowledge, making them easy to generate the short and meaningless text. We humans are constantly acquiring, understanding and storing knowledge and will automatically combine our knowledge to understand the current situation in communicating, writing or reading, which is a huge challenge faced by text generation systems.

To generate more informative, diverse and logical text, text generation systems must have the ability to combine external knowledge, which is a promising research direction. Fig. 1 is an example of a dialogue system with or without commonsense knowledge, where we can see that combining with commonsense knowledge, including structured knowledge graph (KG) composed of triples and unstructured knowledge base (KB) composed of natural language text, the dialogue agent can generate more informative, diverse and logical response.

There are many researchers from both academia and industry have begun to explore knowledge-enhanced text generation system by incorporating different types of knowledge. Due to the complexity of the real world, the scale of knowledge base is usually extremely large. How to extract the most relevant knowledge from massive knowledge facts based on the simple text input is a huge challenge because of the diversity of natural languages. Meanwhile, how to effectively understand the extracted knowledge and integrate it into neural network models to facilitate text generation is also a difficult problem. To our best knowledge, this is the first survey to summarize knowledge-enhanced text generation systems in detail. To sum up, we summarize contributions of our work as follows.

\begin{itemize}
  \item We briefly introduce the development process of text generation, formalize the definition of knowledge-enhanced text generation, and analyze a number of key challenges in this research area.
  \item We summarize the current research progress in knowledge-enhanced text generation systems by systematically categorizing the state-of-the-art works according to research challenges.
  \item We propose some open issues and research directions for the reference of the community.
\end{itemize}
2 Background and formalized definition

In this section, we briefly introduce the development of text generation, formalize the definition of general and knowledge-enhanced text generation, and summarize some research challenges.

2.1 NNLM and RNNLM

The neural network language model (NNLM) [Bengio et al., 2003] is firstly proposed for text generation tasks, which leverages neural networks to model language representation. NNLM maps the input into a low-dimensional space, thereby reducing the parameters of the model. Given the text sequence $s_n = [\omega_1, \omega_2, ..., \omega_n]$ and a $\theta$-parametrized language model $L_\theta(\omega|\text{context}) = \hat{P}(\omega|\text{context})$, NNLM can be approximated as Eq. 1, where $\omega_t$ represents the t-th word in $s_n$.

$$\hat{P}(\omega_t|\text{context}) \approx P(\omega_t|\omega_{t-n+1}, \omega_{t-n+2}, ..., \omega_{t-1})$$ (1)

NNLM has achieved promising results in experiments, but as a typical feedforward neural network, the length of the context it receives must be fixed in advance, so it cannot capture context information of variable length. To solve this problem, the RNN language model (RNNLM) [Mikolov et al., 2010] is proposed, which is an auto-regressive language model that utilizes RNN to encode variable-length inputs into vector representations. This process can be formulated as Eq. 2.

$$\hat{P}(\omega_t|\text{context}) \approx P(\omega_t|\text{RNN}(\omega_1, \omega_2, ..., \omega_t-1))$$ (2)

Theoretically, RNNLM can model text sequences of any length. However, due to the fixed dimension hidden vector, the information in excessively long context may not be stored efficiently. Therefore, variants of RNN, including long short-term memory (LSTM) and gated recurrent unit (GRU), have been utilized to improve the performance of RNNLM, which perform well in capturing long-term dependencies.

2.2 Encoder-decoder framework

The length of input and output text of above language models are equal but there are many cases where the length of them are different, e.g. the question and answer in the QA system. To deal with this problem, the Encoder-decoder framework [Sutskever et al., 2014] is proposed, composed of an encoder and a decoder. The encoder uses RNN to encode the input sequence $X = (x_1, x_2, ..., x_m)$ into the intermediate semantics representation $c$, where $m$ is the length of input sequence. The decoder utilizes another RNN to generate the t-th output word $y_t$ according to $c$ and $y_1, y_2, ..., y_{t-1}$. This process can be defined as Eq. 3, where $Y = (y_1, y_2, ..., x_n)$ and $n$ is the length of the output text sequence.

$$p(Y|X) = \prod_{t=1}^{T} p(y_t|X, y_{<t})$$ (3)

Encoder-decoder is a very general computing framework, whose specific model in the encoder and decoder can be adjusted based on tasks. It has been widely used in various text generation tasks since proposed, such as machine translation, text summarization and dialogue system.

2.3 Knowledge-enhanced text generation

In addition to the Encoder-decoder framework, various neural network models and algorithms have been applied to text generation tasks to improve the quality of generated text. The development of text generation systems requires the generated text to be more informative, diverse and logical rather than simple smooth or surface correct. Combined with external knowledge, text generation systems can deeply understand the input, and generate more informative, more consistent with the logic of human expression, and with less common sense mistakes. Given a set of knowledge facts $F = \{f_i\}_{i=1,2,...,k}$, where each $f_i$ may be a text sequence or a knowledge triple, and $k$ is the number of facts, the
knowledge-enhanced text generation model can be formulated as Eq. 4.

$$p(Y | X, F) = \prod_{t=1}^{T} p(y_t | X, F, y_{<t}).$$ (4)

There are two forms of external knowledge, that is structured KG and unstructured KB. The KG is essentially a semantic network containing multiple types of entities and relations with the form of \(<head, relation, tile>\), where head and tile are different entities. Entities refer to things in the real world and relations express connections between entities. The KB has no fixed form and usually store knowledge related to specific concepts in textual sequence form. There are many challenges in combining external knowledge into text generation systems, as shown in Table 1. When combining structured knowledge, the first challenge is how to obtain vector representations of knowledge triples as acceptable inputs to neural network models. Neural network models need input data with vector form, while the information stored in structured KB is symbolized. It is a difficult problem to map these symbols into low-dimensional dense vector spaces. And how to incorporate knowledge vectors as additional input into neural network models to guide the generation process is also a challenge. Because knowledge facts in the unstructured KB are stored with the form of natural language text, mapping knowledge facts to vector representations does not pose a research challenge. The first challenge in combining unstructured knowledge is how to extract the most appropriate knowledge from massive knowledge facts due to the possible semantic duplication of different knowledge. The understanding of sentence-level natural language text is a long-term research challenge in NLP, so how to efficiently read and understand textual knowledge facts to integrate them into generation systems is another challenge in combining unstructured knowledge. Researchers have made great efforts to address these challenges, which will be detailed summarized in following sections.

### 3 Text generation with structured KG

Structured KGs can store a wider range of knowledge types but less information due to its simple representation of triples. However, its unique symbolic storage form is quite different from vectors required by neural network models. Therefore, how to map knowledge triples into low-dimensional vector representations and efficiently incorporate knowledge vectors into neural network models are key directions of the research, which will be summarized in this section.

#### 3.1 Word embedding-based knowledge representation

The simplest way to obtain vector representations of structured KBs is to directly treat entities and relations in knowledge triples as common words, and then use word embedding methods to obtain vector representations, which has been widely used at the initial research stage.

In order to comprehensive understand the content of document in reading comprehension tasks, Mihaslov et al. [Mihaslov and Frank, 2018] utilize a BiGRU to encode knowledge triples as text sequences to get the key-value memory. And then the Key-Value retrieval algorithm selects a single sum of weighted fact representations for each token to enhance the understanding of the document context. Wang et al. [Wang et al., 2019] propose a KB-based single-relation QA system. The entity linking module determines the optimal subject in the question to select knowledge facts, which will be encoded into vectors using a BiLSTM. The relation detection module calculates similarity scores of each question and its relation candidates to select the triple with highest score to answer the question.

#### 3.2 Distance-based knowledge representation

There is a gap between KG of symbolic form and vector representation, so directly encoding entities as common words may lead to certain information loss. The concept of knowledge representation learning is proposed to represent entities and relations in low dimensional dense vector spaces for calculation and reasoning. Bordes et al. [Bordes et al., 2013] propose the TransE algorithm, which uses the translation invariant phenomenon of word vector and distance-based scoring function to obtain vector representations of entities and relations which can be better integrated with text generation system to provide more powerful knowledge support.

Moussallem et al. [Moussallem et al., 2019] incorporate external knowledge into machine translation system to improve the quality of results. Knowledge facts are linked based on the translated document and encoded by the modified TranE, and then concatenated vectors into the internal vectors of NMT embeddings as the input of the decoder. Gunel et al. [Gunel et al., 2019] incorporate entity-level knowledge...
from knowledge graph into Transformer encoder-decoder architecture to produce coherent summaries. Extracted entities are initialized with the pretrained TransE algorithm to get the vector representations and then are fed into separate multi-head attention channel for generating summaries.

3.3 Graph attention-based knowledge representation

To obtain more accurate vector representations, the graph attention algorithm [Zhou et al., 2018] is proposed, which uses relation information to aggregate entities to generate new entity representations. The attention mechanism makes better use of the interconnections between graph entities and distinguishes the hierarchy of connections, which can enhance the effective information needed in text generation tasks.

To generate more informative responses, Zhou et al. [Zhou et al., 2018] propose the static graph attention mechanism to generate a static representation for a retrieved graph to augment the semantics of input words. The dynamic graph attention mechanism is designed for attentively reading all knowledge triples for text generation. Guan et al. [Guan et al., 2019] propose an incremental encoding scheme for story ending generation to mine context clues hidden in the story context and adopt graph attention and contextual attention respectively to obtain the graph vectors. The multi-source attention mechanism combines commonsense knowledge for facilitating story comprehension to generate coherent and reasonable story endings.

For comprehensive understanding paragraph-level document, Qiu et al. [Qiu et al., 2019] construct sub-graphs for entities to capture the structural information in the KB. Representations of nodes in a sub-graph are updated using the graph attention network with the document context, which are combined with document representations to generate final answer.

3.4 Concatenating knowledge with input vector

After vector representations of knowledge triples are obtained, the next challenge facing by knowledge-enhanced text generation systems is how to integrate knowledge vectors into neural network models. The simplest method is to directly concatenate knowledge vectors with input vectors to enhance vector representations of the input, and then send them into the decoding stage for text generation.

For instance, Young et al. [Young et al., 2018] extract triples according to entity keys in the input to form a text sequence, which is encoded by LSTM to obtain vector representations. Then knowledge vectors are added with the input vector to calculate the degree of correlation with the alternative responses. Liu et al. [Liu et al., 2018] propose the idea of entity diffusion which means that conversation usually drifts from one entity to another. The similarity between extracted entities and other entities is calculated to retrieve relevant entities. Word vectors of entities and relations are averaged to obtain vector representations of each triple, which is concatenated with the input vector to guide the response generation.

3.5 Attention-based knowledge graph decoder

The attention mechanism can focus on the important contents among the numerous input information and select the key information while ignoring other unimportant. Through the attention mechanism, knowledge-enhanced text generation systems can focus on most critical parts of knowledge, instead of feeding all the selected knowledge directly into neural networks, to produce more informative text.

For example, Moon et al. [Moon et al., 2019] construct KG embeddings to represent entities with TransE algorithm and aggregate input contexts with relevant entities. To generate candidate KG entities efficiently, an attention-based graph decoder is proposed to walk an optimal path in a large KG to select candidate entities.

For paragraph-level essay generation, Yang et al. [Yang et al., 2019] present a memory-augmented neural model to combine commonsense knowledge. Knowledge concepts are extracted using input topics as query and stored into a memory matrix. The model will attend on the memory and dynamically update it to incorporate information of the generated text for diverse and topic-consistent essay generation. Koncel et al. [Koncel-Kedziorski et al., 2019] introduce a graph transforming encoder to leverage the relational structure of knowledge graphs to encode knowledge graphs into vectors and then the decoder will attend on the input title and knowledge graphs to generate informative and topic-coherent text.

3.6 GCN-based knowledge incorporating

GCN [Kipf and Welling, 2016] is a natural extension of CNN in the graph domain which learns node feature and structure information in the end-to-end manner. It is a very powerful neural network framework on graphs so it has begun to attract researchers’ attention in text generation systems combining structured knowledge graphs.

De et al. [De Cao et al., 2019] consider question answering as an inference problem on a graph of the document collection. Nodes in the graph are entities appeared in the document and edges in the graph represent the relations between entities. The GCN is used to capture reasoning chains by propagating local contextual information along edges to perform multi-step reasoning for generating answers. Lv et al. [Lv et al., 2019] extract evidence from knowledge graph and make predictions based on the evidence. The graph-based contextual word representation learning module is used to redefine the distance between words for learning better contextual word representations using graph structural information. The graph-based inference module is applied to encode neighbor information into the representations of nodes using GCN and aggregate evidence to generate answers.

4 Text generation with unstructured KB

Unstructured KBs are composed of natural language text related to concepts, which express rich semantic information. Because of its textual form, the unstructured KB can be easily combined with text generation systems whose input is text sequences. However, the scale of knowledge base is usually extremely huge, which contains too redundant information. Therefore, how to extract the knowledge required by text
generation systems and efficiently understand the knowledge to integrate it into the generation process are main research challenges. There have been many researches of knowledge-grounded text generation with unstructured KB, which will be discussed in detail in this section.

4.1 Key word matching-based knowledge extraction

The simplest way to extract knowledge from unstructured KB is the key matching method using words in the input as keywords. This method is simple and direct, but can only extract knowledge according to the surface information of words, and cannot combine deeper semantic information into the knowledge extraction.

For instance, Ghazvininejad et al. [Ghazvininejad et al., 2018] firstly introduce external knowledge into the fully data-driven neural conversation model. Given the dialogue history, relevant knowledge facts are identified by keyword matching method using entities in the context as keys. Then retrieved know facts are fed into the memory network to retrieve and weight facts based on the input and dialogue context to enhance the semantic representation of the input.

4.2 Semantical level knowledge extraction

The simple key word matching method may make it hard to accurately select the required knowledge due to the less information contained in single word. Therefore, many researchers focus on the knowledge selection in the semantic level and put forward many novel ideas.

The same query in human conversation may be related to different responses, so different knowledge may be utilized. To solve this problem, Lian et al. [Lian et al., 2019] propose the idea of the posterior distribution over knowledge, which is calculated from both the input query and response to provide more accurate guidance on knowledge selection. By minimizing the distance between the prior and the posterior distribution over knowledge, the prior distribution can be utilized to select appropriate knowledge so as to generate informative responses even the actual response is unknown. Ren et al. [Ren et al., 2019] propose a Global-to-Local Knowledge Selection mechanism using the global perspective to select appropriate background knowledge. A topic transition vector is learned from the dialogue context and external knowledge by a distantly supervised learning schema to select the most likely text fragments. The vector is then used to guide the Local Knowledge Selection module at decoding stage to generate fluency and appropriate responses. Zhao et al. [Zhao et al., 2020] represent a disentangled response decoder to separate parameters relying on knowledge-grounded dialogues from the whole model to solve the problem of lacking knowledge-grounded training data. The decoder is composed of three components, including Language Model to generate common words, Context Processor to generate context words, and Knowledge Processor to generate words from knowledge document by a hierarchical attention mechanism.

4.3 Memory network-based knowledge understanding

After extracting relevant knowledge facts, the most import is to read and understand the textual knowledge to enhance the input representation and guide text generation. Memory network [Sukhbaatar et al., 2015] is proposed to improve the poor memory ability of RNN, using external memory component to realize the storage of long-term memory. Because of its powerful memory storage capacity, memory network is widely used in knowledge-enhanced text generation systems to retrieve, read and condition on external knowledge.

Madott et al. [Madott et al., 2018] augment the memory network with a sequential generative architecture. Knowledge facts are fed into memory network to update the input query vector. A GRU is used as a dynamic query generator to generate the output words which will produce two distributions to decide whether to generate common words or memory contents. In order to carefully read and understand the retrieved knowledge, Dinan et al. [Dinan et al., 2018] combine the memory network and Transformer to encode the selected knowledge and the dialogue context to get the higher level semantic representation. Then the dot-product attention between the knowledge and context is performed to retrieved most relevant knowledge for generating the next response.

4.4 Transformer-based knowledge understanding

Transformer is an emerging sequential model, which has caused great repercussions in NLP. It exceeds RNN in semantic information abstraction, long-term feature extraction, and task comprehensive feature representation. Many researches have begun to use Transformer to read and attend on external knowledge in text generation systems.

For example, Zhao et al. [Zhao et al., 2019] make use of multi-head attention mechanism in Transformer to encode the dialogue context, response candidate and the relevant document. Through the hierarchical interaction in the context and document, the importance of different parts of the document and context is determined to select the most appropriate response. Li et al. [Li et al., 2019] employ the multi-head attention to get the vector representation of external knowledge and input. The Incremental Transformer incorporates the vector representation of knowledge and context into the encoding process to encode knowledge utterances span in the multi-turn dialogue. The decoder contains two processes where the first-pass focuses on contextual coherence and the second-pass refines the results of the first-pass by attending on the knowledge to increase the knowledge relevance and correctness. Kim et al. [Kim et al., 2020] propose a sequential latent model which sequentially conditions on previously selected knowledge to produce informative responses. The input utterance and knowledge sentences are encoded into vectors, and then model the knowledge selection as latent variables to joint inference knowledge selection of multi-turn dialogue.

4.5 RL-based knowledge understanding

Reinforcement learning is an subfield of machine learning that emphasizes how to act based on the state to maximize the expected rewards. Through continuously interacting with the...
environment, RL can use the rewards and punishments given by the environment to continuously improve the strategy, that is, what kind of actions to take in what kind of state for maximum cumulative rewards. RL is actually very close to the way of human thinking, which is why it is likely to become the future general artificial intelligence paradigm. Based on Deep Q-network (DQN), a typical RL algorithm, Xu et al. [Xu et al., 2019] propose the knowledge-routed DQN to manage topic transitions during the dialogue. The relational refinement branch encodes relations among different symptoms and the knowledge-routed graph branch decides policy in RL under different medical knowledge. The two branches ensure that the dialogue manager, the agent interacting with the environment, can make more reasonable decisions from knowledge guiding and relation encoding.

5 Conclusion and Future Directions

This survey makes a systematic literature review of the research trends of knowledge-enhanced text generation. With the help of external knowledge, text generation system can understand input text more deeply and comprehensively, and generate more informative text, which is a very promising research direction. As an emerging research direction, there are many open issues in the research of knowledge-enhanced text generation system, which will be briefly discussed here.

5.1 Combining structured and unstructured knowledge

At present, researches mainly focus on incorporating one form of external knowledge. If the two forms of knowledge are combined, more appropriately and informatively text may be generated. Structured KG can narrow down knowledge candidates using the prior information such as entities and graph paths. Unstructured KB can provide abundant information to enhance text generation but we need strong capability of natural language understanding to select useful information. Both forms of knowledge have their own advantages and disadvantages. Due to their structural differences, it is a challenging research direction to combine the structured and unstructured knowledge into generation systems, which will certainly bring promising progress to the knowledge-enhanced text generation system.

5.2 Lifelong learning

We humans continuously learn new knowledge, update our knowledge base to adapt to the fast-changing pace of society. However, existing text generation systems mostly utilize fixed knowledge bases whose knowledge do not keep updating in real time. To make text generation models more anthropomorphic, they should have the ability of continuous lifelong learning. A meaningful exploration of this is discussed by Mazumder et al. [Mazumder et al., 2018]. They propose the lifelong interactive learning and inference model which will actively ask users questions when encountering unknown concepts, and update its knowledge base after corresponding answers are reached. How to continuously obtain information from numerous external inputs and achieve lifelong learning is an important research direction in text generation.

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References

[Bengio et al., 2003] Yoshua Bengio, Réjean Ducharme, Pascal Vincent, and Christian Jauvin. A neural probabilistic language model. Journal of machine learning research, 3(Febr):1137–1155, 2003.

[Bordes et al., 2013] Antoine Bordes, Nicolas Usunier, Alberto Garcia-Duran, Jason Weston, and Oksana Yakhanenko. Translating embeddings for modeling multi-relational data. In Advances in neural information processing systems, pages 2787–2795, 2013.

[De Cao et al., 2019] Nicola De Cao, Wilker Aziz, and Ivan Titov. Question answering by reasoning across documents with graph convolutional networks. In Proceedings of NAACL-HLT, pages 2306–2317, 2019.

[Dinan et al., 2018] Emily Dinan, Stephen Roller, Kurt Shuster, Angela Fan, Michael Auli, and Jason Weston. Wizard of wikipedia: Knowledge-powered conversational agents. In International Conference on Learning Representations, 2018.

[Elman, 1990] Jeffrey L Elman. Finding structure in time. Cognitive science, 14(2):179–211, 1990.

[Ghazvininejad et al., 2018] Marjan Ghazvininejad, Chris Brockett, Ming-Wei Chang, Bill Dolan, Jianfeng Gao, Wen-tau Yih, and Michel Galley. A knowledge-grounded neural conversation model. In Thirty-Second AAAI Conference on Artificial Intelligence, 2018.

[Gu et al., 2019] Jian Guan, Yansen Wang, and Minlie Huang. Story ending generation with incremental encoding and commonsense knowledge. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, pages 6473–6480, 2019.

[Gunel et al., 2019] Beliz Gunel, Chenguang Zhu, Michael Zeng, and Xuedong Huang. Mind the facts: Knowledge-boosted coherent abstractive text summarization. In NeurIPS 2019, 2019.

[Kim et al., 2020] Byeongchang Kim, Jaewoo Ahn, and Gunhee Kim. Sequential latent knowledge selection for knowledge-grounded dialogue. In International Conference on Learning Representations, 2020.

[Kipf and Welling, 2016] Thomas N Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907, 2016.

[Koncel-Kedziorski et al., 2019] Rick Koncel-Kedziorski, Dhanush Bekal, Yi Liu, Mirella Lapata, and Hannaneh Hajishirzi. Text generation from knowledge graphs with graph transformers. In Proceedings of NAACL-HLT, pages 2284–2293, 2019.

[Li et al., 2019] Zekang Li, Cheng Niu, Fandong Meng, Yang Feng, Qian Li, and Jie Zhou. Incremental transformer with deliberation decoder for document grounded
conversations. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 12–21, 2019.

[Lian et al., 2019] Rongzhong Lian, Min Xie, Fan Wang, Jinhua Peng, and Hua Wu. Learning to select knowledge for response generation in dialog systems. In Proceedings of the 28th International Joint Conference on Artificial Intelligence, pages 5081–5087. AAAI Press, 2019.

[Liu et al., 2018] Shuman Liu, Hongshen Chen, Zhaochun Ren, Yang Feng, Qun Liu, and Dawei Yin. Knowledge diffusion for neural dialogue generation. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1489–1498, 2018.

[Lv et al., 2019] Shangwen Lv, Daya Guo, Jingjing Xu, Duyu Tang, Nan Duan, Ming Gong, Linjun Shou, Daxin Jiang, Guihong Cao, and Songlin Hu. Graph-based reasoning over heterogeneous external knowledge for commonsense question answering. arXiv preprint arXiv:1909.05311, 2019.

[Madotto et al., 2018] Andrea Madotto, Chien-Sheng Wu, and Pascale Fung. Mem2seq: Effectively incorporating knowledge bases into end-to-end task-oriented dialog systems. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1468–1478, 2018.

[Mazumder et al., 2018] Sahisnu Mazumder, Nianzu Ma, and Bing Liu. Towards a continuous knowledge learning engine for chatbots. arXiv preprint arXiv:1802.06024, 2018.

[Mihaylov and Frank, 2018] Todor Mihaylov and Anette Frank. Knowledgeable reader: Enhancing cloze-style reading comprehension with external commonsense knowledge. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 821–832, 2018.

[Mikolov et al., 2010] Tomáš Mikolov, Martin Karafiát, Lukáš Burget, Jan Černocký, and Sanjeev Khudanpur. Recurrent neural network based language model. In Eleventh annual conference of the international speech communication association, 2010.

[Moon et al., 2019] Seungwhan Moon, Pararth Shah, Anuj Kumar, and Rajen Subba. Opendialkg: Explainable conversational reasoning with attention-based walks over knowledge graphs. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 845–854, 2019.

[Moussallem et al., 2019] Diego Moussallem, Mihael Arčan, Axel-Cyrille Ngonga Ngomo, and Paul Buitelaar. Augmenting neural machine translation with knowledge graphs. arXiv preprint arXiv:1902.08816, 2019.

[Qiu et al., 2019] Delai Qiu, Yuanzhe Zhang, Xinwei Feng, Xiangwen Liao, Wenbin Jiang, Yajuan Lyu, Kang Liu, and Jun Zhao. Machine reading comprehension using structural knowledge graph-aware network. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 5898–5903, 2019.

[Ren et al., 2019] Pengjie Ren, Zhumin Chen, Christof Monz, Jun Ma, and Maarten de Rijke. Thinking globally, acting locally: Distantly supervised global-to-local knowledge selection for background based conversation. arXiv preprint arXiv:1908.09528, 2019.

[Sukhbaatar et al., 2015] Sainbayar Sukhbaatar, Jason Weston, Rob Fergus, et al. End-to-end memory networks. In Advances in neural information processing systems, pages 2440–2448, 2015.

[Sutskever et al., 2014] Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In Advances in neural information processing systems, pages 3104–3112, 2014.

[Vaswani et al., 2017] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Advances in neural information processing systems, pages 5998–6008, 2017.

[Wang et al., 2019] Run-Ze Wang, Zhen-Hua Ling, and Yu Hu. Knowledge base question answering with attentive pooling for question representation. IEEE Access, 7:46773–46784, 2019.

[Xu et al., 2019] Lin Xu, Qixian Zhou, Ke Gong, Xiaodan Liang, Jianheng Tang, and Liang Lin. End-to-end knowledge-routed relational dialogue system for automatic diagnosis. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 33, pages 7346–7353, 2019.

[Yang et al., 2019] An Yang, Quan Wang, Jing Liu, Kai Liu, Yajuan Lyu, Hua Wu, Qiaqiao She, and Sujian Li. Enhancing pre-trained language representations with rich knowledge for machine reading comprehension. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 2346–2357, 2019.

[Young et al., 2018] Tom Young, Erik Cambria, Iti Chaturvedi, Hao Zhou, Subham Biswas, and Minlie Huang. Augmenting end-to-end dialogue systems with commonsense knowledge. In Thirty-Second AAAI Conference on Artificial Intelligence, 2018.

[Zhao et al., 2019] Xueliang Zhao, Chongyang Tao, Wei Wu, Can Xu, Dongyan Zhao, and Rui Yan. A document-grounded matching network for response selection in retrieval-based chatbots. arXiv preprint arXiv:1906.04362, 2019.

[Zhao et al., 2020] Xueliang Zhao, Wei Wu, Chongyang Tao, Can Xu, Dongyan Zhao, and Rui Yan. Low-resource knowledge-grounded dialogue generation. In International Conference on Learning Representations, 2020.

[Zhou et al., 2018] Hao Zhou, Tom Young, Minlie Huang, Haizhou Zhao, Jingfang Xu, and Xiaoyan Zhu. Commonsense knowledge aware conversation generation with graph attention. In IJCAI, pages 4623–4629, 2018.