

Proactive Human-Machine Conversation with Explicit Conversation Goals

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Abstract

Though great progress has been made for human-machine conversation, current dialogue system is still in its infancy: it usually converses passively and utters words more as a matter of response, rather than on its own initiatives. In this paper, we take a radical step towards building a human-like conversational agent: endowing it with the ability of proactively leading the conversation (introducing a new topic or maintaining the current topic). To facilitate the development of such conversation systems, we create a new dataset named DuConv where one acts as a conversation leader and the other acts as the follower. The leader is provided with a knowledge graph and asked to sequentially change the discussion topics, following the given conversation goal, and meanwhile keep the dialogue as natural and engaging as possible. DuConv enables a very challenging task as the model needs to both understand dialogue and plan over the given knowledge graph. We establish baseline results on this dataset (about 270K utterances and 30k dialogues) using several state-of-the-art models. Experimental results show that dialogue models that plan over the knowledge graph can make full use of related knowledge to generate more diverse multi-turn conversations. The baseline systems along with the dataset are publicly available ¹.

1 Introduction

Building a human-like conversational agent is one of long-cherished goals in Artificial Intelligence (AI) (Turing, 2009). Typical conversations involve exchanging information (Zhang et al., 2018), recommending something (Li et al., 2018), and completing tasks (Bordes et al., 2016), most of which rely on background knowledge. However, many

dialogue systems only rely on utterances and responses as training data, without explicitly exploiting knowledge associated with them, which sometimes results in uninformative and inappropriate responses (Wang et al., 2018). Although there exist some work that use external background knowledge to generate more informative responses (Liu et al., 2018; Yin et al., 2015; Zhu et al., 2017), these systems usually generate responses to answer questions instead of asking questions or leading the conversation. In order to solve the above problems, some new datasets have been created, where external background knowledge is explicitly linked to utterances (Dinan et al., 2019; Moghe et al., 2018), to facilitate the development of knowledge aware conversation models. With these datasets, conversation systems can be built to talk with humans given a topic based on the provided external knowledge. Unlike task-oriented systems (Bordes et al., 2016), these conversation systems don't have an explicit goal to achieve, thereof not able to plan over the background knowledge.

In this paper, we take a radical step towards building another type of human-like conversational agent: endowing it with the ability of proactively leading the conversation with an explicit conversation goal. To this end, we investigate learning a proactive dialogue system by planning dialogue strategy over a knowledge graph. Our assumption is that reasoning and planning with knowledge are the keystones to achieve proactive conversation. For example, when humans talk about movies, if one person learns more about some movies, he/she usually leads the conversation based on one or more entities in the background knowledge and smoothly changes the topics from one entity to another. In this paper, we mimic this process by setting an explicit goal as a knowledge path “[start] → topic_a → topic_b”,

¹ <https://github.com/PaddlePaddle/models/tree/develop/PaddleNLP/Research/ACL2019-DuConv>

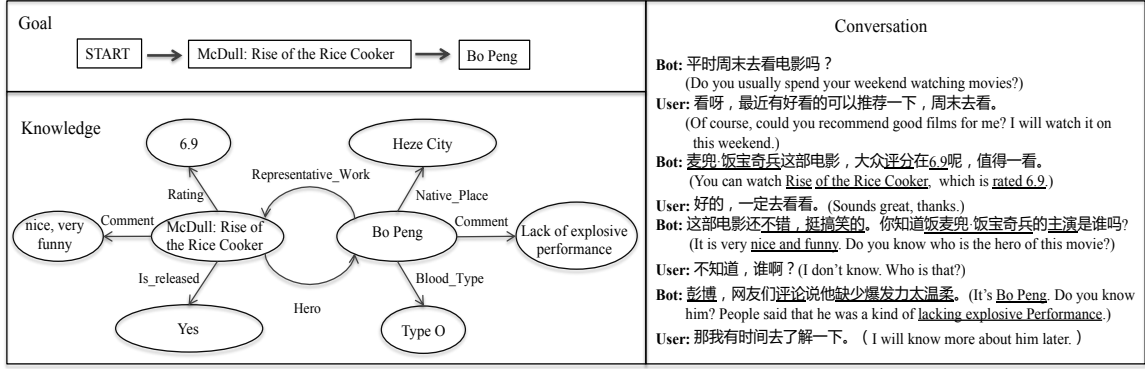


Figure 1: One conversation generated by two annotators, one of which was given a goal and related knowledge.

which means that one person leads the conversation from any starting point to *topic_a* and then to *topic_b*. Here *topic* represents one entity in the knowledge graph.

With this in mind, we first build a knowledge graph which combines factoid knowledge and non-factoid knowledge such as comments and synopsis about movies. To construct the knowledge graph, we take a factoid knowledge graph (KG) as its backbone and align unstructured sentences from the non-factoid knowledge with entities. Then we use this KG to facilitate knowledge path planning and response generation, as shown in Figure 1. Based on this knowledge graph, we create a new knowledge-driven conversation dataset, namely the Baidu Conversation Corpus (**DuConv**) to facilitate the development of proactive conversation models. Specifically, DuConv has around 30k multi-turn conversations and each dialog in the DuConv is created by two crowd-sourced workers, where one plays the role of the conversation leader and the other one acts as the conversation follower. At the beginning of each conversation, the leading player is assigned with an explicit goal, i.e., to sequentially change the conversation topic from one to another, meanwhile keeping the conversation as natural and engaging as possible. The conversation goal is a knowledge path comprised of two topics and structured as “[start] → *topic_a* → *topic_b*” and the leading player is also provided with related knowledge of these two topics. For each turn in the conversation, the leading player needs to exploit the provided knowledge triplets to plan his/her conversation strategy and construct responses to get closer to the target topic, while the follower only needs to respond according to the contexts without knowing the goal.

Figure 1 illustrates one example dialog in DuConv. It can be seen that DuConv provides a very challenging task: the conversational agents have to fully exploit the provided knowledge to achieve the given goal. To test the usability of DuConv, we propose a knowledge-aware neural dialogue generator and a knowledge-aware retrieval-based dialogue system, and investigate their effectiveness. Experimental results demonstrate that our proposed methods can proactively lead the conversation to complete the goal and make more use of the provided knowledge.

To the best of our knowledge, it is the first work that defines an explicit goal over the knowledge graph to guide the conversation process, making the following contributions:

- A new task is proposed to mimic the action of humans that lead conversations over a knowledge graph combining factoid and non-factoid knowledge, which has a wide application in real-world but is not well studied.
- A new large-scale dataset named DuConv is constructed and released to facilitate the development of knowledge-driven proactive dialogue systems.
- We propose knowledge-aware proactive dialogue models and conduct detailed analysis over the datasets. Experimental results demonstrate that our proposed methods make full use of related knowledge to generate more diverse conversations.

2 Related Work

Our related work is in line with two major research topics, *Proactive Conversation* and *Knowledge Grounded Conversation*.

2.1 Proactive Conversation

The goal of proactive conversation is endowing dialogue systems with the ability of leading the conversation. Existing work on proactive conversation is usually limited to specific dialogue scenarios. Young et al. (2013), Mo et al. (2016) and Bordes et al. (2018) proposed to complete tasks more actively, like restaurant booking, by actively questioning/clarifying the missing/ambiguous slots. Besides the task-oriented dialogue systems, researchers have also investigated building proactive social bots to make the interaction more engaging. Wang et al., (2018) explored to ask good questions in open-domain conversational systems. Li et al., (2018) enabled chatbots to recommend films during chitchatting. Unlike the existing work, we proposed to actively lead the conversation by planning over a knowledge graph with an explicit goal. We also create a new dataset to facilitate the development of such conversation systems.

2.2 Knowledge Grounded Conversation

Leveraging knowledge for better dialogue modeling has drawn lots of research interests in past years and researchers have shown the multi-fold benefits of exploiting knowledge in dialogue modeling. One major research line is using knowledge to generate engaging, meaningful or personalized responses in chitchatting (Ghazvininejad et al., 2018; Vougiouklis et al., 2016; Zhou et al., 2018a; Zhang et al., 2018). In addition to proposing better conversation models, researchers also released several knowledge grounded datasets (Dinan et al., 2019; Moghe et al., 2018). Our work is most related to Mogh et al., (2018) and Dinan et al., (2019), where each utterance in their released datasets is aligned to the related knowledge, including both structured triplets and unstructured sentences. We extend their work, by including the whole knowledge graph into dialogue modeling and propose a new task of proactively leading the conversation via planning over the knowledge graph in this paper.

3 DuConv

In this section, we describe the creation of DuConv in details. It contains four steps: knowledge crawling, knowledge graph construction, conversation goal assignment, and conversation crowdsourcing. We limit the dialogue topics in

# dialogs	29858
# utterances	270399
average # utterances per dialog	9.1
average # words per utterance	10.6
average # words per dialog	96.2
average # knowledge per dialogue	17.1

Table 1: Overview of the conversation dataset DuConv.

DuConv to movies and film stars, and crawl this related knowledge from the internet. Then we build our knowledge graph with these crawled data. After constructing our knowledge graph, we randomly sample two linked entities to construct the conversation goal, denoted as “[start] \rightarrow topic_a \rightarrow topic_b”, and ask two annotators to conduct knowledge-driven conversations, with one playing as the conversation leader and the other one playing as the follower. The leader needs to change the conversation topics following the conversation goal and meanwhile keep the conversation as engaging as possible. All those conversations are recorded and around 30k conversations are finally used in DuConv after filtering dirty/offensive parts. Table 1 summarizes the main information about DuConv.

3.1 Knowledge Crawling

We crawled the related knowledge information from the website MTime.com², which records the information of most films, heroes, and heroines in China. We collect both structured knowledge (such as “Harry Potter” is “directed_by” “Chris Columbus”) as well as unstructured knowledge including short *comments* and *synopsis*. We filter out the dirty or offensive information and further normalize some of the numbers (such as the values of *rating*) into discrete symbols (*good*, *fair*, *bad*) to facilitate the use of this kind of knowledge. In summary, we crawl more than 91k films and 51k film stars, resulting in about 3.6 million knowledge triplets, the accuracy of which is over 97%³.

3.2 Knowledge Graph Construction

After the raw data collection, we construct a knowledge graph. Our knowledge graph is comprised of multiple SPO (*Subject, Predicate, Ob-*

²<http://www.mtime.com/>

³We randomly sampled 100 triplets and manually evaluated them.

# entities	143627
# movies	91874
# person names	51753
# properties	45
# spo	3598246
average # spo per entity	25

Table 2: Overview of the knowledge graph in DuConv.

ject) knowledge triplets, where objects can be factoid facts and non-factoid sentences such as comments and synopsis. The knowledge triplets in our graph can be classified into:

1. **Direct triplets:** widely-used knowledge triplets, such as ("Harry Potter and the Sorcerer Stone", "directed_by", "Chris Columbus"), akin to most existing knowledge graphs, with the exception that the objects can be sentences such as short *comments* and *synopsis*.
2. **Associated triplets:** if two entities share the same predicate and the same object in their triplets, then we create a virtual triplet like ("Harry Potter and the Sorcerer Stone", "directed_by_Chris Columbus", "Home Alone") by combining the two original triplets.

We call the direct triplets as *one-step relation* and associated triplets as *two-step relation*. Table 2 lists the main information of our knowledge graph.

3.3 Conversation Goal Assignment

Given the knowledge graph, we sample some knowledge paths, which are used as conversation goals. Specifically, we focus on the simple but challenging scenario: naturally shifting the topics twice, i.e., from "[start]" state to "topic_a" then finally to "topic_b". We sample two linked entities in our knowledge graph as "topic_a" and "topic_b" to construct the knowledge path. About 30k different knowledge paths are sampled and used as conversation goals for knowledge-driven conversation crowdsourcing, where half of the knowledge paths are from the one-step relation set while the other half are from the two-step relation set.

3.4 Crowdsourcing

Unlike using self-play in dataset construction (Ghazvininejad et al., 2018), we collect lots of crowdsourced workers to generate the dialogues

in DuConv⁴. For each given conversation goal, we assign two workers different roles: 1) the conversation leader and 2) the follower. The leader is provided with the conversation goal and its related background knowledge in our knowledge graph, and then asked to naturally shift the conversation topic following the given conversation goal. The follower is provided with nothing but the dialogue history and only has to respond to the leader. The dialogue will not stop until the leader achieves the conversation goal. We record conversation utterances together with the related knowledge triplets and the knowledge path, to construct the whole dataset of DuConv.

4 Methods

To enable neural dialogue systems to converse with external background knowledge, we propose two models: a retrieval-based model and a generation-based model, by introducing an external memory module for storing all related knowledge, making the models select appropriate knowledge to enable proactive conversations. Figure 2 shows the architectures of our proposed knowledge-aware response ranking model as well as our response generation model. We will give a detailed description of those two knowledge-aware models in next two sub-sections.

4.1 Retrieval-based Model

Given a dialogue context X , the retrieval-based dialogue system responds to that context via searching for the best response Y from DuConv. Thus retrieval-based dialogue system often has a pipeline structure with two major steps: 1) retrieve response candidates from a database and 2) select the best one from the response candidates (Zhou et al., 2018b). In our retrieval-based method, the candidate responses are collected similar to most existing work (Wu et al., 2017; Zhou et al., 2018b) with one notable difference that we normalize the entities with their entity types in the knowledge graph to improve generalization capabilities.

For each retrieved candidate response Y , the goal of our response ranker is to measure if Y is a good response to the context X considering the given dialogue goal $G = [start, topic_a, topic_b]$ and related knowledge K . The matching

⁴The workers are collected from a Chinese crowdsourcing platform <http://test.baidu.com/>. The workers are paid 2.5 Chinese Yuan per conversation.

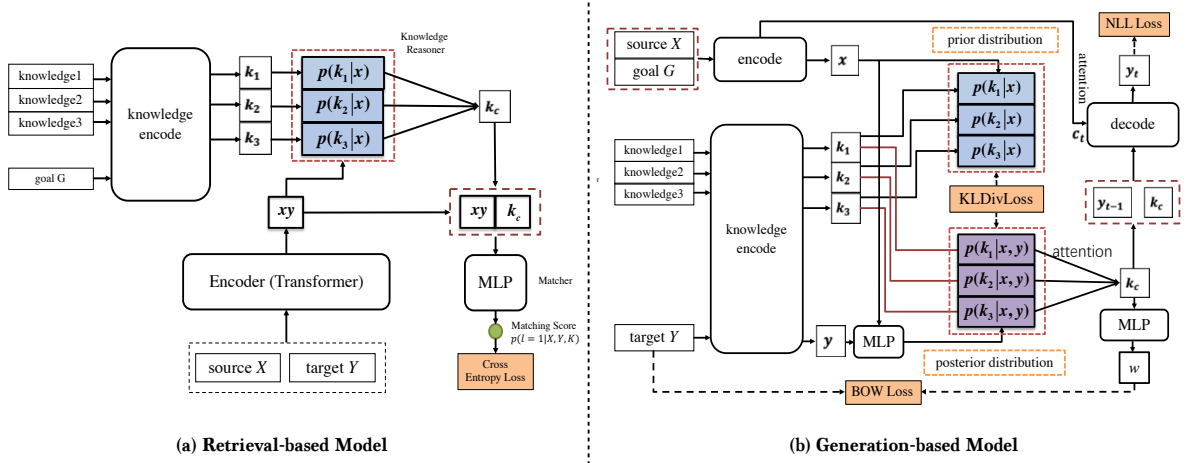


Figure 2: The retrieval-based model and generation-based model.

score measured by our knowledge-aware response ranker is defined as $p(l = 1|Y, X, K, G)$. As shown in Figure 2(a), our knowledge-aware response ranker consists of four major parts, i.e., the context-response representation module (Encoder), the knowledge representation module (Knowledge Encoder), the knowledge reasoning module (Knowledge Reasoner) as well as the matching module (Matcher).

The Encoder module has the same architecture as BERT (Devlin et al., 2018), it takes the context X and candidate response Y as segment_a and segment_b in BERT, and leverages a stacked self-attention to produce the joint representation of X and Y , denoted as xy . Each related knowledge $knowledge_i$ is also encoded as vector representations in the Knowledge Encoder module using a bi-directional GRU (Chung et al., 2014), which can be formulated as $k_i = [\vec{h}_T; \overleftarrow{h}_0]$, where T denotes the length of knowledge, \vec{h}_T and \overleftarrow{h}_0 represent the last and initial hidden states of the two directional GRU respectively. The dialogue goal is also combined with the related knowledge in order to fuse that information into response ranking.

To jointly consider context, dialogue goal and knowledge in response ranking, we make the context-response representation xy attended to all knowledge vectors k_i and get the attention distribution. For simplicity, the dialogue goal was treated as part of the knowledge used in the conversation.

$$p(k_i|x, y) = \frac{\exp(xy \cdot k_i)}{\sum_j \exp(xy \cdot k_j)} \quad (1)$$

and fuse all related knowledge information into a single vector $k_c = \sum_i p(k_i|x, y) * k_i$. We

view k_c and xy as the information from knowledge side and dialogue side respectively, and fuse those two kinds of information into a single vector via concatenation, then finally calculate the matching probability as:

$$p(l = 1|X, Y, K, G) = \text{sigmoid}(\text{MLP}([xy; k_c])) \quad (2)$$

Our knowledge-aware response ranker differs from most existing work in jointly considering the previous dialogue context, the dialogue goal as well as the related knowledge, which enables our model to better exploit knowledge to achieve the conversation goal.

4.2 Generation-based Model

To generate a knowledge-driven dialogue response, we enhance the vanilla seq2seq model with an extra knowledge selection paradigm, Figure 2(b) demonstrates the structure of our knowledge-aware generator, which is comprised of four parts: the *Utterance Encoder*, the *Knowledge Encoder*, the *Knowledge Manager* and the *Decoder*.

For each given dialogue context X , along with the dialogue goal G and related knowledge K , our knowledge-aware generator first encodes all input information as vectors in the Utterance Encoder and Knowledge Encoder. The encoding method in those two modules also uses bi-directional GRUs, akin to that in the retrieval-based method. Especially, the dialogue context X and dialogue goal G are fused into the same vector x by sequentially concatenate G and X into a single sentence, then feed to the encoder.

After encoding, our knowledge-aware generator starts to plan its dialogue strategy by con-

sidering which knowledge would be appropriate next. Practically, the generator can also conduct knowledge selection via attention mechanism as in the retrieval-based method. However, to force the model to mimic human in knowledge selection, we introduce two different distributions: 1) the prior distribution $p(k_i|x)$ and the posterior distribution $p(k_i|x, y)$. We take the prior distribution $p(k_i|x)$ as the knowledge reasoned by machines and the posterior distribution $p(k_i|x, y)$ as the knowledge reasoned by humans, and then force the machine to mimic human by minimizing the KLDivLoss between those two distributions, which can be formulated as:

$$p(k_i|x, y) = \frac{\exp(k_i \cdot \text{MLP}([x; y]))}{\sum_{j=1}^N \exp(k_j \cdot \text{MLP}([x; y]))} \quad (3)$$

$$p(k_i|x) = \frac{\exp(k_i \cdot x)}{\sum_{j=1}^N \exp(k_j \cdot x)} \quad (4)$$

$$L_{KL}(\theta) = \frac{1}{N} \sum_{i=1}^N p(k_i|x, y) \log \frac{p(k_i|x, y)}{p(k_i|x)} \quad (5)$$

Given that knowledge distribution $p(k_i|x)$ and $p(k_i|x, y)$, we fused all related knowledge information into a vector $k_c = \sum_i p(k_i|x, y) * k_i$, same as our retrieval-based method, and feed it to the decoder for response generation. In the testing phase, the fused knowledge is estimated by the formula $k_c = \sum_i p(k_i|x) * k_i$ without gold responses. The decoder is implemented with the *Hierarchical Gated Fusion Unit* described in (Yao et al., 2017), which is a standard GRU based decoder enhanced with external knowledge gates. Besides the KLDivLoss, our knowledge-aware generator introduces two additional loss functions:

NLL Loss: the Negative Log-Likelihood (NLL) $L_{NLL}(\theta)$ measures the difference between the true response and the response generated by our model.

BOW Loss: We use the BOW loss proposed by Zhao et al., (2017), to ensure the accuracy of the fused knowledge k_c by enforcing the relevancy between the knowledge and the true response. Specifically, let $w = \text{MLP}(k_c) \in \mathcal{R}^{|V|}$, where $|V|$ is the vocabulary size and we define:

$$p(y_t|k_c) = \frac{\exp(w_{y_t})}{\sum_v \exp(w_v)} \quad (6)$$

Then, the BOW loss is defined to minimize:

$$L_{BOW}(\theta) = -\frac{1}{m} \sum_{t=1}^m \log p(y_t|k_c) \quad (7)$$

In summary, the final loss of our generative model is:

$$L(\theta) = L_{KL}(\theta) + L_{NLL}(\theta) + L_{BOW}(\theta) \quad (8)$$

5 Experiments

5.1 Setting

Our proposed models are tested under two settings: 1) automatic evaluation and 2) human evaluation. For automatic evaluation, we leverage several common metrics including BLEU, PPL, F1, DISTINCT1/2 to automatically measure the fluency, relevance, diversity etc. In our setting, we ask each model to select the best response from 10 candidates, same as previous work (Zhang et al., 2018). Those 10 candidate responses are comprised of one true response generated by human-beings and nine randomly sampled ones from the training corpus. We measure the performance of all models using *Hits@1* and *Hits@3*, same as Zhang et al., (2018). Furthermore, we also evaluate the ability of exploiting knowledge of each model by calculating knowledge precision/recall/F1 scores.

The human evaluation is conducted at two levels, i.e., the turn-level human evaluation and the dialogue-level human evaluation. The turn-level human evaluation is similar to automatic evaluation. Given the dialogue context, the dialogue goal as well as the related knowledge, we require each model to produce a response according to the dialogue context. The responses are evaluated by three annotators in terms of fluency, coherence, informativeness, and proactivity. The coherence measures the relevance of the response and the proactivity measures if the model can successfully introduce new topics without destructing the fluency and coherence.

The dialogue-level evaluation is much more challenging. Given a conversation goal and the related knowledge, each model is required to talk with a volunteer and lead the conversation to achieve the goal. For each model, 100 dialogues are generated. The generated conversations are then evaluated by three persons in terms of two aspects: goal completion and coherence. The goal

Methods	Hits@1	Hits@3	PPL	F1/BLUE1/BLUE2	DISTINCT 1&2	knowledge R/P/F1
retrieval w/o klg.	45.84%	72.86%	-	33.08 / 0.280 / 0.147	0.121 / 0.376	8.69 / 39.30 / 13.73
retrieval w/ klg.	46.74%	75.32%	-	33.12 / 0.282 / 0.146	0.122 / 0.388	8.54 / 37.93 / 13.47
norm retrieval	50.92%	79.02%	-	34.73 / 0.291 / 0.156	0.118 / 0.373	8.85 / 38.00 / 13.88
S2S w/o klg.	24.88%	49.64%	20.16	26.43 / 0.187 / 0.100	0.032 / 0.088	4.59 / 30.00 / 7.73
S2S w/ klg.	30.58%	57.52%	13.53	32.19 / 0.226 / 0.140	0.064 / 0.168	5.89 / 36.31 / 9.85
norm S2S	31.26%	55.12%	10.96	39.94 / 0.283 / 0.186	0.093 / 0.222	7.52 / 42.74 / 12.34
generation w/o klg.	25.52%	50.14%	20.3	28.52 / 0.29 / 0.154	0.032 / 0.075	6.18 / 27.48 / 9.86
generation w/ klg.	31.90%	58.44%	27.3	36.21 / 0.32 / 0.169	0.049 / 0.144	8.67 / 35.90 / 13.62
norm generation	32.50%	58.50%	24.3	41.84 / 0.347 / 0.198	0.057 / 0.155	9.78 / 38.02 / 15.27

Table 3: Automatic evaluation results. klg. and norm stands for *knowledge* and *normalized* here. S2S stands for the vanilla sequence-to-sequence model.

methods	turn-level human evaluation				dialogue-level human evaluation	
metrics scores	fluency (0,1,2)	coherence (0,1,2)	informativeness (0,1,2)	proactivity (-1,0,1)	goal complete (0,1,2)	coherence (0,1,2,3)
norm retrieval	1.93	1.41	0.86	0.80	0.90	1.92
norm generation (s2s)	2.00	1.89	0.74	0.86	1.14	2.01
norm generation	1.87	1.61	1.10	0.87	1.22	2.03

Table 4: Turn-level and dialogue-level human evaluation results

completion measures how good the conversation goal is achieved and the coherence scores the fluency of the whole dialogue.

All human evaluation metrics, except the turn-level proactivity and the dialogue-level coherence, has three grades: good(2), fair(1), bad(0). For goal completion, “2” means that the goal is achieved with full use of knowledge, “1” means the goal is achieved by making minor use of knowledge, and “0” means that the goal is not achieved. We additionally set the perfect grade (3) for dialogue-level coherence, to encourage consistent and informative dialogues. For proactivity, we also have three grades: “1” means good proactivity that new topics related to context are introduced, “-1” means bad proactivity that new topics are introduced but irrelevant to context, and “0” means that no new topics are introduced. The detailed description of the human evaluation metrics can be found in the appendices.

5.2 Comparison Models

The compared models contain the vanilla seq2seq model, our proposed retrieval-based model as well as our proposed generation-based model⁵. Moreover, we normalize the train/valid/test data by replacing the specific two topics in the knowledge path with “*topic_a*” and “*topic_b*” respectively. Models using such normalized corpora are named as normalized models. To test the effectiveness

⁵We also compared MemNet (Ghazvininejad et al., 2018), whose performance is similar to Seq2Seq with knowledge. We omit it for space limit in this paper.

of knowledge, we set up one ablation experiment, which removes all the knowledge triplets by replacing them with “UNK, UNK, UNK”.

5.3 Model Training

All models are implemented using PaddlePaddle⁶ and pytorch (Paszke et al., 2017), trained on a single GPU of NVIDIA Tesla K40. We set the vocabulary size to 30k for both retrieval-based and generation based methods. All hidden sizes, as well as embedding size, are set to 300, and the word embedding layer is initialized via word2vec⁷ trained on a very large corpus. We apply Adam optimizer for model training and the beam size for generative models are set to 10 during decoding.

5.4 Results

Table 3 and Table 4 summarize the experimental results on automatic evaluation and human evaluation. For human evaluation, we only evaluate the normalized models since they achieved better performances on our dataset. All human evaluations are conducted by three persons, where the agreement ratio (Fleiss’ kappa (Fleiss et al., 1971)) is from 0.37 to 0.86, with the lowest agreement on multi-turn coherence and others all above 0.6. More details of these measures are available in the Appendix.

⁶It is an open source deep learning platform (<https://paddlepaddle.org>) developed by Baidu. Our code and data are available at <https://github.com/PaddlePaddle/models/tree/develop/PaddleNLP/Research/ACL2019-DuConv>.

⁷<https://radimrehurek.com/gensim/models/word2vec.html>

distribution statistics		norm generation	norm seq2seq	norm retrieval
goal completion	0	21%	14%	25%
	1	35%	26%	59%
	2	43%	29%	15%
knowledge used	# triplets	2.46	1.51	2.28
	# properties	27	20	25

Table 5: Analysis on goal completion and knowledge exploitation.

It can be seen that the retrieval-based model and the generation-based model have significantly different performances in terms of automatic evaluation and human evaluations. Retrieval-based model works better on Hits@K, however worse on F1 and BLEU compared to the generation-based model. This is perhaps caused by that fact that they are optimized on different metrics. For human evaluation, it can be observed that the retrieval-based method is apparently worse than generation-based models. This is because the retrieved candidates limit the potential of the retrieval-based model. We also found that the methods using knowledge outperform those without using knowledge, which confirms the benefits of using background knowledge. It is very interesting that normalizing the “*topic_a*” and “*topic_b*” can significantly improve the performance for all models because of their generalization capability over the knowledge.

From the human evaluation, we found that our proposed generation methods outperform the baseline Seq2Seq model and the retrieval model, especially in terms of turn-level informativeness and proactivity, and dialogue-level goal completion and coherence. In order to further analyze the relationship between informativeness and goal completion, the detailed distribution of goal completion scores and the numbers of used knowledge triplets are shown in Table 5. From this table, it can be seen that our proposed generation model can exploit more knowledge to achieve the conversation goal (much higher rate on score “2”), making the conversation more engaging and coherent. This demonstrates the effectiveness of the knowledge posterior/prior distribution learning. Although the baseline Seq2Seq model can also has good goal completion capability, it usually only uses knowledge directly related to the conversation goal in the conversation process (much higher rate over score “1”), making the conversation usually dull.

However, for the dialogue-level human evaluation, there are still 15% to 20% of conversation goals not achieved. The reason may be that our models (both retrieval and generation) have no explicit multi-turn policy mechanism to control the whole conversation flow, which is left for future research.

6 Case Study

Figure 3 shows the conversations generated by the models via conversing with humans, given the conversation goal and the related knowledge. It can be seen that our knowledge-aware generator can choose appropriate and more knowledge for diverse conversation generation. Even though the retrieval-based method can also produce knowledge-grounded responses, the used knowledge is often wrong. Although the seq2seq model can smoothly achieve the given knowledge goal, it always generates generic responses using safe dialogue strategy, as the mentioned knowledge is much smaller than our proposed knowledge-aware generator, making the generated conversation less diverse and sometimes dull.

7 Conclusion

In this paper, we build a human-like conversational agent by endowing it with the ability of proactively leading the conversation. To achieve this goal, we create a new dataset named DuConv. Each dialog in DuConv is created by two crowd-sourced workers, where one acts as the conversation leader and the other acts as the follower. The leader is provided with a knowledge graph and asked to sequentially change the discussed topics following the given conversation goal, and meanwhile, keep the dialogue as natural and engaging as possible. We establish baseline results on DuConv using several state-of-the-art models. Experimental results show that dialogue models that plan over knowledge graph can make more full use of related knowledge to generate more

Goal	[START]->麦兜:饭宝奇兵->彭博 [START]->McDull: Rise of the Rice Cooker->Bo Peng			norm generation	Bot: 你喜欢看什么 小怪兽 的电影啊? (Do you like little monster movie ?) User: 小孩子看的玩意儿了 (I believe that is for babies) Bot: 我最近看了一部叫 麦兜:饭宝奇兵 的电影,我觉得 挺好看的 . (I recently watched one, McDull: Rise of the Rice Cooker . It's very hilarious) User: 看来你是个宝宝啊 (You must be a baby) Bot: 嗯,这是一部 很搞笑 的电影,不过我觉得还 挺搞笑 的。(That is a very hilarious anyway.) User: 真的吗?谁演的?(Really? Who is the hero?) Bot: 这部电影的 主演是彭博 ,我很欣赏他的。(The starring is Bo Peng . I admire him very much)
Knowledge	麦兜:饭宝奇兵 McDull: Rise of the Rice Cooker	评论 comment	不错,很搞笑 nice, very hilarious		
		评分 rating	6.9		
		上映时间 date published	2016年9月15日 2016.9.15		
		类型 genre	动画 cartoon		
		主演 Hero	彭博 Bo Peng		
		评论 comment	这个小怪兽也太恶心了 this little monster is disgusting		
	彭博 Bo Peng	评论 comment	缺少爆发力 lack of explosive performance		
		血型 blood type	O型 type O		
		性别 gender	男 male		
		职业 occupation	演员 actor		
		代表作 representative work	麦兜:饭宝奇兵 McDull: Rise of the Rice Cooker		
		norm Seq2seq			Bot: 你喜欢看 动画片 吗?(Do you like cartoon ?) User: 小时候还挺喜欢了,大了就不怎么喜欢看了 (I used to when I was a little baby. But I quit cartoon after growing up) Bot: 那你看过 麦兜:饭宝奇兵 吗?(So have you ever watched MuDull: Rise of the Rice Cooker ?) User: 没看过,讲什么的 (Not yet, what is in the movie?) Bot: 这部电影的 主演是彭博 。(The starring is Bo Peng .)
			norm Retrieval		

Figure 3: Conversations generated by three different models: words in yellow represent correct use of knowledge while those in blue for wrong knowledge.

diverse conversations. Our dataset and proposed models are publicly available, which can be used as benchmarks for future research on constructing knowledge-driven proactive dialogue systems.

Acknowledgement

We sincerely thank the PaddlePaddle development team for helping us build the baseline models. We also would like to thank Ying Chen and Na Chen for helping us to collect the dataset through crowdsourcing. This work was supported by the Natural Science Foundation of China (No.61533018).

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Appendix

A. Turn-level Human Evaluation Guideline

Fluency measures if the produced response itself is fluent:

- score 0 (bad): unfluent and difficult to understand.
- score 1 (fair): there are some errors in the response text but still can be understood.
- score 2 (good): fluent and easy to understand.

Coherence measures if the response can respond to the context:

- score 0 (bad): not semantically relevant to the context or logically contradictory to the context.
- score 1 (fair): relevant to the context as a whole, but using some irrelevant knowledge, or not answering questions asked by the users.
- score 2 (good): otherwise.

Informativeness measures if the model makes full use of knowledge in the response:

- score 0 (bad): no knowledge is mentioned at all.
- score 1 (fair): only one triplet is mentioned in the response.
- score 2 (good): more than one triplet is mentioned in the response.

Proactivity measures if the model can introduce new knowledge/topics in conversation:

- score -1 (bad): some new topics are introduced but irrelevant to the context.
- score 0 (fair): no new topics/knowledge are used.
- score 1(good): some new topics relevant to the context are introduced.

B. Dialogue-level Human Evaluation Guideline

Goal Completion measures how good the given conversation goal is finished:

- score 0 (bad): neither “topic_a” nor “topic_b” is mentioned in the conversation.
- score 1 (fair): “topic_a” or “topic_b” is mentioned, but the whole dialogue is very boring and less than 3 different knowledge triplets are used.
- score 2 (good): both “topic_a” or “topic_b” are mentioned and more than 2 different

knowledge triplets are used.

Coherence measures the overall fluency of the whole dialogue:

- score 0 (bad): over 2 responses irrelevant or logically contradictory to the previous context.
- score 1 (fair): only 2 responses irrelevant or logically contradictory to the previous context.
- score 2 (good): only 1 response irrelevant or logically contradictory to the previous context.
- score 3 (perfect): no response irrelevant or logically contradictory to the previous context.