Towards a Universal NLG for Dialogue Systems and Simulators with Future Bridging

Philipp Ennen
MediaTek Research

Yen-Ting Lin
MediaTek Research

Ali Girayhan Özbay
Imperial College London

Ferdinando Insalata
MediaTek Research

Maolin Li
MediaTek Research

Ye Tian
MediaTek Research

Sepehr Jalali
MediaTek Research

Da-shan Shiu
MediaTek Research

\{philipp.ennen, ds.shiu\}@mtkresearch.com

Abstract

In a dialogue system pipeline, a natural language generation (NLG) unit converts the dialogue direction and content to a corresponding natural language realization. A recent trend for dialogue systems is to first pre-train on large datasets and then fine-tune in a supervised manner using datasets annotated with application-specific features. Though novel behaviours can be learned from custom annotation, the required effort severely bounds the quantity of the training set, and the application-specific nature limits the reuse. In light of the recent success of data-driven approaches, we propose the novel future bridging NLG (FBNLG) concept for dialogue systems and simulators. The critical step is for an FBNLG to accept a future user or system utterance to bridge the present context towards. Future bridging enables self-supervised training over annotation-free datasets, decoupled the training of NLG from the rest of the system. An FBNLG, pre-trained with massive datasets, is expected to apply in classical or new dialogue scenarios with minimal adaptation effort. We evaluate a prototype FBNLG to show that future bridging can be a viable approach to a universal few-shot NLG for task-oriented and chit-chat dialogues.

1 Introduction

In a dialogue system pipeline, after the information from a user is extracted, the dialogue direction and the information content to return to the user for the immediate turn is decided. This is followed by a unit referred to as natural language generation (NLG) converting the information content to a corresponding natural language realization. A recent trend is toward building pipelines with largely machine learning methods.

Learning-based components in a dialogue system are typically trained in a supervised manner using sample dialogues annotated with application-specific features. In some systems, certain components are pre-trained first by massive datasets (Wolf et al., 2019; Henderson et al., 2019a; Golovanov et al., 2019). The application-specific annotation is critical for a dialogue system to learn its functionality. For instance, annotations are necessary for task-oriented dialogues to learn to extract dialogue states (Kelley, 1984; Budzianowski et al., 2018; Shah et al., 2018). An open-domain dialogue system often learns to compute similarity scores for response retrieval from carefully curated datasets (Jafarpour et al., 2010; Leuski and Traum, 2011; Ji et al., 2014; Boussaha et al., 2019).

Unfortunately, the required annotation effort severely limits the quantity of the training set, which in turn limits the system performance. Furthermore, because a training set is annotated with domain-specific features, a trained pipeline can only function well in the corresponding narrow domain. This makes it difficult to directly deploy or at least transfer a trained pipeline to new domains (Rastogi et al., 2019a) or to new dialogue behaviours, such as goal-guided topic traversal (Tang et al., 2019).

By not requiring any additional annotation, self-supervised training allows several orders of magnitude increase of the training set size compared to supervised training. This has been shown to lead to not only higher performance but versatility in the application domain, and also ease of creating never-planned dialogue behaviours. For instance, GPT-2 (Radford et al., 2019) can generate coherent text for various topics and styles simply from priming. Gshard (Lepikhin et al., 2020), trained using 25 billion training examples, obtained far superior quality for translation from
100 languages to English compared to the prior art.

In this paper, we aim to build a universal NLG. This NLG can be used in various dialogue types, for intended and never-planned behaviours, with zero-shot or few-shot adaptation. In light of the success of these self-supervised approaches, we surmise that to achieve this, one shall decouple the training of this NLG from the rest of a dialogue system, and pre-train the NLG over a large and general dataset in a self-supervised manner.

To that end, we propose the critical concept, future bridging (FB). Future bridging is key to enable decoupled, self-supervised training of an NLG. The text-infilling formulation of future bridging enables the easy collection of a large-sized, annotation-free dataset. An FBNLG takes not only the present dialogue context but also a future user or system utterance as input. It shall then predict the text that has a high probability of bridging the context to that desired future utterance. In this set up, the top stack of a dialogue system can select a future from one corpus, while the NLG can learn the act of bridging from a different corpus. Thus the training of the NLG is decoupled.

To better explain the future bridging concept, two hypothetical dialogues are given in Table 1. Here, an FBNLG is given the desired next-turn user utterance as the future to bridge forward to. We note that there is a very intuitive and satisfying interpretation for future bridging. If a user utterance is selected as the target future, such utterance represents what the system wishes to induce the user to ultimately say. On the other hand, if a system utterance is selected as the target future, that utterance represents what the system wishes the dialogue to develop towards so that the system is in position to say that.

We remark that in both example dialogues, the user never actually produce the supplied future utterances. This highlights the very nature of the future: it serves to indicate the direction, instead of the landing spot, for the NLG to shoot for.

An important benefit from adopting a future bridging interface is that it can greatly simplify the training of a dialogue policy via reinforcement learning (RL). Many studies (Asri et al., 2016; Crook and Marin, 2017; Li et al., 2017a,b) employ RL to learn a policy from experiments. Both a user simulator and a system simulator are required. However, building a human-like, high diversity natural language generator component for either simulator is very difficult. As a result, studies may resort to using rule-based response templates, or even just skip the natural language realm entirely (Shah et al., 2018). In our opinion, a universal NLG such as a FBNLG can vastly simplify the current challenge in dialogue policy learning.

We claim our contributions as follows.

- We propose the future bridging concept. The concept allows a FBNLG to be self-supervised trained over a massive dataset, decoupled from the rest of system.
- An FBNLG is expected to support a wide variety of domains and dialogue behaviours with zero-shot or few-shot adaptation.
- A FBNLG can be used in a simulator to greatly reduce the difficulties of learning a dialogue policy via RL.
- We evaluated a prototype FBNLG and showed that it could indeed support a novel use of case supporting both classical and a novel use case of seamlessly transitioning between chit-chat and task-oriented types.
2 Related Work

Dialogue system types and pipelines. To best suit the use cases, dialogue systems have developed into distinct types; task-oriented, chit-chat, and question-and-answer are the major ones (Zaib et al., 2020; Gao et al., 2018). Deployed systems can employ fundamentally different pipelines from one type to another. While mature systems are generally built from a pipeline of modules, end-to-end dialogue systems proposed have been proposed lately (Peng et al., 2020; Hosseini-Asl et al., 2020), for which there exist no clear module boundaries. Nevertheless, NLG is always at the bottom of the pipeline.

Reinforcement learning (RL) can be used to develop a dialogue policy (Li et al., 2016). In this framework, both the system response-generating NLG and the simulated user's utterance-generating NLG can be considered a part of the environment for RL.

NLG in dialogue systems. NLG as a standalone unit has a long history of development, starting from early work like Eliza (Weizenbaum, 1966) and PARRY (Colby et al., 1972). In recent years, NLG learned from statistical methods have been in focus. A learning-based NLG takes either a retrieval-based approach, selecting an appropriate response from a candidate corpus (Zhou et al., 2018; Henderson et al., 2019b; Shalyminov et al., 2020), or a generation-based one, generating a response using a trained model (Serban et al., 2016, 2017; Zhou et al., 2018; Wolf et al., 2019; Dinan et al., 2018). Sequence-to-sequence and later transformer-based models have been used (So et al., 2019; Budzianowski and Vulić, 2019; Brown et al., 2020) for response retrieval and generation.

Large dialog datasets and large dialog generation models. Large datasets enable large models to produce ever-increasing performance. DialoGPT (Zhang et al., 2019) adapts GPT-2 (Radford et al., 2019) to the text-dialogue domain, trained on 147M multi-turn dialogues from Reddit discussion thread. Model sizes range from 117M (small) to 762M (large). Meena is a 2.6B parameter model trained end-to-end on 40B words mined and filtered from public domain social media conversations. We note that both datasets are for uncontrolled dialogues; large datasets for conversations conditioned on the desired future are not as easily obtained.

Text infilling. Text infilling recovers a missing piece within a long-form text, or more ambitiously predicts some texts that can smoothly blend into and fit the context syntactically and semantically (Zhu et al., 2019; Huang et al., 2020). A particularly attractive aspect of the text infilling problem formulation is that a massive dataset can be obtained with little to no annotation effort. Prior text-infilling works cover different scenarios, from those in which the missing piece contains only a single token (Fedus et al., 2018; Zweig and Burges, 2011), to those in which an arbitrary number of tokens and sentences are missing (Zhu et al., 2019; Huang et al., 2020; Liu et al., 2019; Shih et al., 2019).

Automatic NLG quality metric. While many consider it far from perfect, BLEU is a metric long used for judging the fluency of a generated response (Papineni et al., 2002). Perplexity was shown to correlate well with a human judgment of sensibleness and specificity (Adiwardana et al., 2020). Sensibleness tries to cover aspects such as common sense and logical coherence, while specificity covers how relevant sentences are within a dialogue context.

Recent advances in novel dialogue behaviour. Novel use cases and behaviours beyond the present mature dialogue systems have been proposed. Of note, one is to meaningfully support multi-domain dialogues rather than just a simple divide-and-conquer ensemble (Dinan et al., 2020). To guide a conversation to a different goal mid-flight during a conversation is another new behaviour (Tang et al., 2019; Wu et al., 2019; Liu et al., 2020; Xu et al., 2020; Zhou et al., 2020). In some cases, modules learn such behaviours from carefully constructed and annotated datasets such as DuConv (Wu et al., 2019).

3 Methods

In a dialogue system, the NLG is at the bottom of the stack. The components above the NLG can be very complicated. As these components are outside of the scope of this paper, we will just refer to them by the “top of the stack”. Loosely speaking, we treat the top of the stack
We can view future bridging as a text infilling problem. Specifically, dialogue future bridging is to learn the probability of the immediate system response $s_t$ which, together with a trailing trajectory as a function that projects a future to an FBNLG to bridge to. Additionally noted, in the rest of the paper we discuss how FBNLG is used to generate a system response; when used as a dialogue simulator, it might be necessary to swap the notation for user and system utterances.

We note that an FBNLG learned in the fashion given below is only distributionally correct. In other words, an FBNLG tries only to maintain that the generated system response fits well with the distribution of the dataset it is trained on. To be useful in a real-world scenario, a generated dialogue has to be grounded in facts. Nevertheless, we think that factual grounding techniques can be added to an FBNLG in a way that is orthogonal to the main point of this paper. We leave factual grounding outside of our paper.

### 3.1 Future projection and future bridging

We define the act of future bridging and the associated act of future projection as follows. At turn $t$, the dialogue context $h_t$ consists of user utterances $u_1, ..., u_t$ and system responses $s_1, ..., s_{t-1}$. By future projection, the top of stack proposes a desirable future (user or system) utterance at $\delta$ turns away, $c_t = u_{t+\delta}$ or $s_{t+\delta}$, to the NLG. The NLG attempts to bridge from the context to $c_t$, thus producing the immediate system utterance $s_t$ as result. This NLG behaviour is called future bridging. After the user receives $s_t$ and returns with $u_{t+1}$, the cycle repeats. This is shown in Figure 1.

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We note that an FBNLG learned in the fashion shown in Figure 1.

### 3.2 Preparation of dataset

Here we explain how future bridging allows an FBNLG to be trained in a self-supervised manner decoupled from the rest of the dialogue system.

Start with a large collection of dialogues, $D = \{d^1, ..., d^N\}$. Each dialogue $d^i$ consists of alternating user turns $u^{i}_{t}$ and system turns $s^{i}_{t}$. Assuming that the projected future is to be a user utterance $u$ turns away. We can construct a sample $x^{j}$ for the self-supervised training set $X$ from $D$ by sampling a dialogue $d^{i}$, taking the context $h^{i}_{t}$ up to time step $t$, the future user utterance at the target time step $u^{i}_{t+\delta}$, the immediate system response $s^{i}_{t}$ to bridge to that future, and optionally some negative examples $s^{i}_{t}$ which are systems’ responses randomly sampled from other dialogues of $D$. Specifically, $X$ is made up of

$$x^{j} = (h^{i}_{t}, c^{i}_{t}; s^{i}_{t}; s^{i}_{t'}).$$

For the purpose of this paper, we only consider the top of stack to be a mapping $f_p$ from a dialogue context $h_t$ and a situational context $b_t$ to a desired future user utterance $u_{t+\delta}$, $f_p : \mathcal{H} \times \mathcal{B} \rightarrow \mathcal{U}$. A situational context contains real-time application-specific incentives such as inventory level. This mapping is learned from a dataset $Z$ that is typically collected over the particular use case of the application. A small subset of $Z$ can be optionally withheld to produce a future bridging dataset $X'$ in the aforementioned manner. This $X'$ can be used to adapt an FBNLG to the top of stack in a few-shot manner.

The self-supervised pre-training and task-specific zero- or few-shot adaptation aspects of the proposed FBNLG follows exactly that of the transformer-based language model paradigm. We expect that FBNLG shall exhibit similarly higher performance and superior downstream versatility due to the massive data advantage.

### 3.3 Training

During training, samples from the training set $X'$ are used to train an FBNLG. An important
special case is that, in some situations, the top of stack may signal that it is content with letting the dialogue proceed spontaneously. To model these situations, one can randomly take a subset of training samples and replace the target futures of these samples by NULL. The NULL substitution can be done statically at dataset construction time or dynamically at training time.

The goal of FBNLG is to learn the conditional utterance probability in Equation (1). An FBNLG can be either generative or retrieval-based. For an autoregressive generator, the goal can be further expressed as,

$$ p(s_t|h_t, c_t) = \prod_{k=0}^{h_t} p(s_{t,k}|h_t, c_t, s_{t,1:k-1}), \quad (3) $$

with \( k \) denoting an index over the tokens of \( s_t \) in causal order, and \( s_{t,1:k-1} \) denotes the generated tokens 1 through \( k-1 \).

Following originally presented in (Bengio et al., 2003), we propose to use an adapted version of the language modelling objective. We optimize for a joint objective of response generation (RG) and response selection:

$$ \mathcal{L}(X) = \sum_j \alpha_{RG} \mathcal{L}_{RG}(x^j) + \alpha_{RS} \mathcal{L}_{RS}(x^j) \quad (4) $$

The response generation objective, \( \mathcal{L}_{RG} \), measures the log probability of positive samples. For an autoregressive NLG, the response generation objective for sample \( x^j \) is computed as follows:

$$ \mathcal{L}_{RG}(x^j) = \sum_{k=1}^{|X|-1} \log p(s_{t,k}^{(j)}|h_t^{(j)}, c_t^{(j)}, s_{t,1:k-1}^{(j)}). \quad (5) $$

The response selection objective \( \mathcal{L}_{RS} \) measures the rejection of negative samples. The use of the response selection objective improves the overall language model performance as shown in prior work (Peng et al., 2020). Following (Peng et al., 2020), from a training sample \( x^j \), we randomly present either \((h_t, c_t, s_t)\) or \((h_t, c_t, \pi_t)\) to the NLG, asking it to classify whether the correct response \((y=1)\) or a distracting response \((y=0)\) is present. The objective is computed via binary cross-entropy loss as follows:

$$ \mathcal{L}_{RS}(x^j) = y \log p(h_t^{(j)}; c_t^{(j)}; s_t^{(j)}) + (1 - y) \log(1 - p(h_t^{(j)}; c_t^{(j)}; \pi_t^{(j)})). \quad (6) $$

4 Evaluations

We built a prototype FBNLG and evaluated the quality of generated dialogues via automatic and human-based evaluations. We furthermore experimented goal transition within a task-oriented conversation, and dynamic dialogue type switching from one to the other. \(^1\)

4.1 Model Architecture, Initialization, and Training

Ideally, one shall pre-train a text infiller from scratch for an FBNLG. However, this pre-training requires a very significant computational facility. In our evaluation, we instead built a prototype from an openly available pre-trained language model, DialoGPT. We selected the small version of DialoGPT (117M parameters) as the starting point. Later, we fine-tuned the starting point on the modest datasets in Table 2 for two effects. One, to convert the auto-regressive DialoGPT model to a text infilling model; and two, to tilt the data distribution from uncontrolled dialogues to conversations conditioned on desired futures. We note that MultiWOZ (Budzianowski et al., 2018), Schema-Guided Dialogue (Rastogi et al., 2019b), and Taskmaster-1 (Byrne et al., 2019) are datasets for task-oriented type, and DailyDialog (Li et al., 2017c) for chit-chat type. By training with both task-oriented and chit-chat datasets, an FBNLG learns to fulfil a purpose when given a meaningful future, or continue the ongoing dialogue with small talks when given a NULL future.

We prepared the self-supervised datasets according to the procedure given in the previous Section. From a chit-chat source dataset, the projected future \(c_t\) is set to NULL. On the other hand, from a task-oriented source dataset, we use the next user utterance as the future. In other words, \(c_t \leftarrow u_{t+\delta}\), with \(\delta = 1\).

4.2 Experimental Setup

The main prototype is built in a two-step process. From a DialoGPT model, we first additionally pre-train it on the relatively larger SGD and Taskmaster to learn future bridging. Subsequently, we adapt it to the target domains by fine-tuning it with DailyDialog, SGD, and MultiWOZ. We

\(^1\) A demonstration of this FBNLG prototype can be found under http://www.github.com/ANONYMOUS.
### Table 2: Statistics for the fine-tuning dataset

|          | MultiWOZ | SGD     | Taskmaster | DailyDialog |
|----------|----------|---------|------------|-------------|
| # domains| 7        | 16      | 6          | n/a         |
| # dialogues| 8,438   | 16,142  | 13,215     | 13,118      |
| Total no. of turns| 113,556 | 329,964 | 303,066    | 103,632     |
| Avg. turns per dialogue| 13.46 | 20.44   | 22.9       | 7.9         |

Table 3: Automatic Evaluation Results. Baseline is the baseline model that has not learned future bridging. Model D is a FBNLG model suffering from some distribution mismatch.

We performed both automatic and human evaluations. We compute the BLEU score and perplexity on held-out test datasets from SGD, MultiWOZ and DailyDialog (Papineni et al., 2002). Furthermore, for the two novel behaviours we selected - dynamic dialogue type switching and dynamic dialogue goal transition - we carried out a human evaluation study using crowd workers. While limited in scale by various practical factors, human evaluation is the true measure on dialogue generation quality. Human-evaluation details are given in the Appendix.

### 4.3 Dialogue Quality Results

First, we checked whether FBNLG can perform chit-chat type dialogues. We tested the main prototype and the two baseline models against the test dataset of DailyDialog with automatic evaluation. Results are given in Column DailyDialog in Table 3. Primarily because in this evaluation the top of stack does not give a future to bridge to, these models all score poorly on both scales. Nevertheless, by our own examinations, we think that one shall not jump to the conclusion that the generated dialogues are of low quality simply from the low automatic scores. As is shown in the human evaluation results below, for generated dialogues that contain chit-chat portions, human evaluation actually rated the sensibleness and specificity with a satisfactory rating on the Likert scale.

Next, we check whether FBNLG can be used in a single-domain task-oriented dialogue. We tested the three models against the single-domain dialogues from the SGD test dataset. The results can be found in Table 3 under the column "SGD single". Comparing Model D over the Baseline, the use of future bridging dramatically improves the BLEU score by around 4 as well as cuts the perplexity by a factor of nearly 3. Comparing the main prototype over Model D, we can see that pre-training against a modest-sized oral dialogue dataset can furthermore improve the fluency by 4 BLEU points.

We then tested the three models against the multi-domain dialogues from the SGD test dataset assuming an oracle top of stack. Such a dialogue involves challenging domain transition within a single conversation. While the single-domain automatic evaluation results are good, the multi-domain results are no less encouraging. Automatic evaluation results for multi-domain task-oriented dialogues can be found in Table 3 in column "SGD multi". Here again we observed that the use of future bridging improves the BLEU by 4 and reduces the perplexity by a factor of nearly 3. Similarly,
once the text-oriented dialogue distribution bias of DialoGPT is partially compensated, the BLEU score of the main prototype rises by 4.

We proceeded to test the viability of FBNLG over a chosen novel dialogue system behaviour, dialogue type transition. Because we could not find any existing dataset for this purpose, we created a small test-only dataset. In this dataset, we have both chit-chat-to-task-oriented, and task-oriented-to-chit-chat dialogues. We carefully maintained the nature of the chit-chat dialogues similar to DailyDialog, and the task-oriented dialogues similar to the aforementioned task-oriented datasets. Example dialogues are given in Table 6.

Dialogue 1 in Table 6 is an example of a dialogue starting from chit-chat about the city of New York and then switch to a task-oriented real estate promotion. Throughout the chit-chat portion, the top of stack keeps giving NULL as the future. Then, it gives a purposeful future for the model to bridge to. The quality of the generated system response is measured. Dialogue 2 is an example in which the conversation switches from task-oriented to chit-chat. Purposeful futures are given during the task-oriented portion of the dialogue. Toward the end of the dialogue, the top of stack stops gives a NULL future. The FBNLG is expected to produce an appropriate chit-chat response. The quality of this response is measured.

We asked crowd workers to rate the specificity and sensibleness of the system response generated by the main prototype corresponding to the dialogue type-switching turn on the Licker scale. Note that our main prototype has never been trained on a dialogue-type transition dataset. From this perspective, what was evaluated was not only whether FBNLG can learn to support never-planned behaviour. It is, indeed, the zero-shot capability of FBNLG to support a new behaviour on the fly. The human evaluation results of dialogue type transitions can be found in Table 4. Here we observe that both sensibleness of and specificity are satisfactory to the crowd workers. In summary, the experiments of dialogue type transition points to the potential of a pre-trained FBNLG being universal, able to support present and never-planned behaviours.

### 4.4 Future Bridging Results

The results above indicated that FBNLG can generate system responses that are reasonably fluent, specific, sensible, even for never-planned dialogue behaviours without any learning when viewed as a continuation of the dialogue context. But does an FBNLG actually produce a result that fulfils its future bridging obligation? Intuitively, one could evaluate the future bridging quality by evaluating the quality of the overall dialogue, spanning from the left-side context $u_1, s_1, \ldots, u_t$, through the generated response $s_t$, to the right-side context $c_t = u_{t+1}$. A higher dialogue quality should be positively correlated with the future bridging performance.

We note that the subtle difference from the evaluations in Section 4.3 is that, while previously tests are conducted to evaluate the quality of $s_t$ given only the left-side context, here one makes evaluations taking into account the right-side context $c_t = u_{t+1}$ as well.

Using human-based evaluations, we asked the crowd workers to evaluate the specificity and sensibleness of the generated dialogue. The results are shown in Table 5. We see that both the sensibleness and the specificity are acceptable, indicating that the FBNLG indeed largely fulfils the future bridging objective.

By comparing Table 4 and 5, one might draw
Table 6: Example of dialogue type transition within a single conversation. Dialogue 1: chit-chat to task-oriented. Dialogue 2: task-oriented to chit-chat.

the conclusion that the causal quality evaluation in Table 4 can be a good proxy score for future bridging performance. However, in our opinion, whether this is incidental requires some further study.

5 Discussions and Future Work

Accepting a further-away future. In this work, the evaluated FBNLG prototype takes into account a future that is the desired user utterance in the next turn. We regard the most critical immediate extension of this work to have an FBNLG take a target that is a mixture of utterances that are further into the future.

Fully scaling up prototype. In this work, our prototype was built by fine-tuning an existing language model with very modest data. We are motivated to see the performance of an FBNLG pretrained using e.g. the 341 GB of text used to train Meena (Adiwardana et al., 2020). With a properly built FBNLG, one then can properly examine the zero-shot and few-shot properties.

Interworking with compatible components. An obvious future work is to demonstrate the full end-to-end behaviour of a compatible stack on top of an FBNLG. Also, to be useful in a real-world scenario, a dialogue system cannot return false information to a user. Thus a future extension of this work is to apply knowledge and fact grounding techniques to augment an FBNLG.

6 Conclusion

In this paper, we proposed a future bridging NLG concept. The concept enables a universal NLG for dialogue systems and simulators using self-supervised training from massive datasets. An FBNLG is expected to support a wide variety of domains and dialogue behaviours with few-shot or even zero-shot adaptation. To demonstrate the feasibility of the FBNLG approach, we constructed a prototype by fine-tuning a large language model. The results indicated that FBNLG can generate system responses that are reasonably fluent, specific, sensible, even for never-planned dialogue behaviours such as dialogue type switching without any learning.

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