Grounding in social media: An approach to building a chit-chat dialogue model

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Abstract

Building open-domain dialogue systems capable of rich human-like conversational ability is one of the fundamental challenges in language generation. However, even with recent advancements in the field, existing open-domain generative models fail to capture and utilize external knowledge, leading to repetitive or generic responses to unseen utterances. Current work on knowledge-grounded dialogue generation primarily focuses on persona incorporation or searching a fact-based structured knowledge source such as Wikipedia. Our method takes a broader and simpler approach, which aims to improve the raw conversation ability of the system by mimicking the human response behavior through casual interactions found on social media. Utilizing a joint retriever-generator setup, the model queries a large set of filtered comment data from Reddit to act as additional context for the seq2seq generator. Automatic and human evaluations on open-domain dialogue datasets demonstrate the effectiveness of our approach.

1 Introduction

Humans have long wanted to talk with the machine and have them comprehend and generate natural language. The task of chit-chat dialogue response generation can be described as one of the major goals in natural language processing. As such, there has been considerable interest in the sub-field of open-domain dialogue models.

Nevertheless, the existing dialogue response generation models still suffer from some very fundamental problems: lack of interesting (“Ok”, “I see”, etc.) or uninformative responses (“I don’t know”) (Li et al., 2016a, Shao et al., 2017, Ghazvininejad et al., 2017). The primary cause for this is that, unlike humans, the models do not have access to knowledge, experience about out-of-domain topics or human conversational habits and hence can only produce limited unengaging generic responses.

Recent work has proposed considering additional context information such as multi-turn conversational history (Zhang et al., 2018), persona (Li et al., 2016b) or a fact-based knowledge base (Dinan et al., 2019). Among these, our work approaches this problem from a more general standpoint of improving the raw conversational ability of generative models. We attempt this by taking inspiration from how humans learn to converse, i.e., through mimicking social interactions. Applying this in the context of dialogue models, we use a human-readable external knowledge base consisting solely of unstructured social media interactions (hereinafter referred to as SMIkb), which tends to include a more diverse language structure and hence improve generated responses.

For our approach, we jointly train a generator-retriever model where the retriever searches through pre-indexed SMIkb and feeds the related information together with the input utterance to the generative seq2seq model, allowing for additional context at the time of generation.

In particular, we utilize the Dense Passage Retriever proposed by Karpukhin et al. (2020) on top of BART (Lewis et al., 2020a) as our generational model trained on a mix of open-domain dialogue datasets, together with a collection of Reddit submissions and comments as our main source of social interactions. Experiments showed that our approach outperformed the existing vanilla seq2seq baseline (BART) across all of the automatic and human evaluation metrics. By making use of interactions grounded in social media, the generated responses were not only more engaging but were also shown to be much more relevant and natural, thus establishing the effectiveness of our approach.

2 Related Work

Dialogue Systems In recent years, major breakthroughs beginning with the Transformer (Vaswani et al., 2017) and BERT (Devlin et al., 2019) have
quickly shifted the landscape of modern NLP research. These were shortly followed by auto-regressive seq2seq models (T5 (Raffel et al., 2020), BART) that significantly improved performance on generation-based tasks such as dialogue systems. We adopt the widely accessible BART as our strong baseline.

**Knowledge-based Conversational Models** Incorporating additional context or external information into existing models has been a field of much interest lately. Persona-chat (Zhang et al., 2018) or Empathetic Dialogues (Rashkin et al., 2019) take into account persona or empathetic information. Furthermore, advancements making use of knowledge bases in the area of open-domain dialogue systems have become increasingly common (Ghazvininejad et al., 2017; Dinan et al., 2019). The closest work to ours, in terms of including a retrieval step for dialogue generation, is Weston et al. (2018), which proposed an approach involving pre-training the retriever and generating only over the candidates retrieved in advance from the training set. More recently Roller et al. (2021) also tested retrieval-based dialogue generation. However, similar to Weston et al. (2018), they utilized a retrieval model that was kept fixed during training. Our work meanwhile follows a different direction that does not require pre-training of the retriever but fine-tunes it along with the generator to retrieve over a much larger knowledge base of interactions at generation time.

We would also like to mention Shuster et al. (2021), which investigates factual hallucination in dialogue retrieval-generation models with a fact-based knowledge base such as Wikipedia. Our work takes a more generalized approach, focusing solely on improving the raw conversational ability of dialogue models. Instead of factual accuracy, we propose a simple approach for generating an engaging conversation grounded in unstructured social media interactions.

3 Proposed Approach

In this section, we discuss our approach to introducing social media interactions as an external knowledge base (SMIkb) to ground in for more natural and human-like response generation. We begin with formulating the task of dialogue generation and then proceed to explain our joint retriever-generator model as the proposed setup for utilizing the aforementioned unstructured data source. Note that in this work, we primarily focus on response generation for single-turn dialogues or dialogues. We decided that other settings such as a multi-turn case were best addressed in future work.

3.1 Task Formulation

Our task of response generation grounded in external knowledge can be formulated as training a model to predict a response $r = (r_1, r_2, \ldots, r_m)$ of
words when given an input utterance \( u \) and a set of documents \( D \) that might contain relevant knowledge. We define our goal as to allow the model to learn the parameters such that when given an input utterance \( u \) and a knowledge base \( D \), the model can generate a response \( r \) following the probability \( p(r|u, r_{<i}, D; \theta) \), where \( \theta \) refers to the parameters of the model.

### 3.2 Model

Inspired by recent advances in retrieval assisted QA (Guu et al., 2020; Lewis et al., 2020b), we adopt a simple joint retriever-generator setup to the task of dialogue generation. Concretely, we utilize BART, a seq2seq model pre-trained on a denoising objective, as our generative model along with the pre-trained neural Dense Passage Retriever (DPR) (Karpukhin et al., 2020) as the retriever of choice. DPR is a highly efficient neural retriever pre-trained for retrieving the top-\( k \) similar documents to an input query \( u \). It executes this by encoding both the query and the entire knowledge base through independent BERT-based encoders (as \( t \)). Furthermore, we follow Karpukhin et al. (2020) to build an offline searchable dense vector index of these embeddings for our SMIkb using the FAISS (Johnson et al., 2017) library for faster lookup. An overview of our architecture is shown in Figure 1.

Application of our model to dialogue response generation can be formulated as a two-step process: (1) the retriever searching top-\( k \) documents from the pre-indexed interaction knowledge base, relevant to the input utterance, and (2) the generator predicting the response to the previous utterance along with the retrieved context.

Following the notion set in Section 3.1, the probability of generating the response \( r \) given the utterance \( u \) and each of the top-\( k \) documents \( d_j \) from the knowledge base \( D \) can be defined as

\[
p(r|u; \theta, \lambda) = \sum_j^k p_{\lambda}(d_j|u; \lambda) \prod_i p_{\theta}(r_i|u, r_{<i}, d_j; \theta),
\]

where \( \theta \) and \( \lambda \) are parameters for the generator and retriever, respectively. They are both fine-tuned jointly in an end-to-end fashion, with the retriever providing additional context that is concatenated together with the input at the time of generation. As there is no “correct” document source in the knowledge base, we consider it to be a latent variable. Therefore, during decoding we marginalize these probabilities over all the retrieved documents to return the most probable (best) response using beam search.

### 4 Experiments

We evaluate our model together with various external knowledge datasets on a mixture of open-domain dialogue datasets. The results are then compared with two BART-based baselines.

#### 4.1 SMIkb

Aiming to improve the raw communication ability of dialogue systems by mimicking human response behavior, we built our external knowledge base of unstructured social media interactions (SMIkb). It comprises of entries from top thread titles and their top 100 comments from Reddit, an American social news aggregation and discussion site, throughout 2020 (January-November). A total of 1.6 million entries were first scraped through the open-sourced Pushshift API (Baumgartner et al., 2020) of which a random selection of 600,000 (due to memory limitations) makes up our SMIkb. A snapshot of the same is shared in Table 5.

Furthermore, to verify the effectiveness of using a conversational knowledge base like Reddit, we compared ours to a pure Wikipedia knowledge base (ref. “Wiki”) of the same size (random sample of 600k entries) containing the wiki page title and the leading 100 words. Additionally, we also tested a 1:1 combination of the above two bases (ref. “Mix”).

#### 4.2 Datasets

We fine-tune our models on a variety of open-domain and scraped dialogue datasets.

| Dataset                  | Total (turns) | Train | Valid | Test |
|--------------------------|---------------|-------|-------|------|
| DailyDialog              | 76,743        | 53,721| 11,511| 11,511|
| DailyDialog++            | 39,913        | 27,939| 5,987 | 5,987|
| Cornell Movie-Dials      | 221,088       | 154,762| 33,163| 33,163|
| Reddit (pseudo extracted)| 200,000       | 140,000| 30,000| 30,000|

Table 1: Overview of datasets in use.
Table 2: Automatic evaluation of generated responses across various values of $k$ for top-$k$ document retrieval. The baselines do not have a retrieval step and therefore do not have an effect due to changing $k$. **bold** refers to the best scores across all $k$ among the generated responses. ODD is the collection of Open-Domain Datasets from Section 4.2.

| Model Setup | Training Data | Knowledge Base (Retrieval) | BLEU-4 Dist-1 Dist-2 |
|-------------|---------------|-----------------------------|----------------------|
| Baseline 1  | ODD           | None                        | 1.31 0.20 0.96       |
| Baseline 2  | ODD + SMIkb   | None                        | 1.05 0.12 0.47       |

$k = 3$

| $k = 5$ |
|---------|
| BLEU-4  | Dist-1 Dist-2 |
| Ours (SMIkb) ODD SMIkb | 9.78 2.80 16.90 10.51 5.50 26.63 10.48 5.51 26.62 |
| Ours (Wiki) ODD Wiki | 6.93 2.57 14.91 7.14 4.94 23.38 7.11 5.02 23.79 |
| Ours (Mix) ODD SMIkb + Wiki | 6.03 2.45 14.08 6.20 4.71 22.25 6.21 4.71 22.23 |

$k = 7$

| $k = 7$ |
|---------|
| BLEU-4  | Dist-1 Dist-2 |
| Ours (SMIkb) ODD SMIkb | 9.78 2.80 16.90 10.51 5.50 26.63 10.48 5.51 26.62 |
| Ours (Wiki) ODD Wiki | 6.93 2.57 14.91 7.14 4.94 23.38 7.11 5.02 23.79 |
| Ours (Mix) ODD SMIkb + Wiki | 6.03 2.45 14.08 6.20 4.71 22.25 6.21 4.71 22.23 |

**Table 3:** Human evaluation of responses for the best $k = 5$.

| Model Setup | Human Eval. |
|-------------|-------------|
|             | Relevance   | Engagement | Knowledge |
| Gold (Test-Data) | 3.50 3.33 3.47 |
| Baseline 1  | 2.82 2.35 3.00 |
| Baseline 2  | 3.03 3.02 2.89 |
| Ours (SMIkb) | 3.84 3.75 3.60 |
| Ours (Wiki) | 3.40 3.75 3.76 |
| Ours (Mix) | 3.62 3.80 3.71 |

SMIkb, to act as a pseudo dialogue dataset to supplement our knowledge base.

An overview of the datasets is listed in Table 1.

4.3 Experimental Setup

**Implementation Details** Our joint retriever-generator model consists of a pre-trained Dense Passage Retriever and BART-large (24 layers, 406M), which are later fine-tuned together on SMIkb and dialogue datasets. The model is trained mostly with the default parameters, batch size of 1, and an initial learning rate of $3 \times 10^{-5}$. We further experiment with various values of $k$ for our top-$k$ document retrieval, while beam search with size of 5 is used as our response decoding strategy.

**Baseline** We consider two strong baselines based on a vanilla BART-large with no retriever to investigate the effectiveness of our approach. The first is fine-tuned solely on the datasets mentioned in Section 4.2 (ref. “Baseline 1”) with no SMIkb. Next to confirm the effectiveness of our providing external data through our retriever-generator setup, we merge the entire SMIkb interactions into our training data, and simply fine-tune the vanilla model on this new extended set. (ref. “Baseline 2”). Note that although we choose BART as our generator and baseline for its size and relative ease in training, our proposed SMIkb based modeling setup could possibly also be extended to larger models.

4.4 Evaluation

To measure the impact of social media interactions, the generated responses were evaluated through both automatic and human evaluations. The results are compiled in Tables 2 and 3.

**Automatic** We perform a series of automatic evaluations on the generated responses. Starting with the BLEU (Papineni et al., 2002) score for relevancy, we also calculate Distinct-N (Li et al., 2016a) for the amount of diversity introduced.

**Human** It has been widely reported that automatic metrics do not sufficiently evaluate the actual quality of the generated outputs (Liu et al., 2016). Thus, we additionally performed human evaluation of the responses with the highest BLEU ($k = 5$) through Amazon Mechanical Turk, on the following three metrics: Relevance, whether the response is relevant to the utterance; Engagement, whether the response makes the conversation engaging; and Knowledge, whether the response seems knowledgeable or sensible. The evaluators were asked to score 100 responses selected at random from the test set, on a scale of 1-5. Each response was scored by 7 different evaluators, and their average was calculated. We selected our evaluators to be English speakers from the United States with an approval rate of over 90%.

4.5 Discussion

First, with automatic evaluation, we observe that our method of introducing social interactions through a retriever at generation time maintains task performance and allows for a more diverse set of responses, as shown with an increase in all of the
Here comes the birthday cake.
Wow, what a lovely cake. I’ll have a piece.
Really? Wow. Happy birthday to you! You look so healthy.

I’d better go. I gotta get up early. Go over to my parents’.
What are you going to do for breakfast?
You mean you don’t wanna go with me?
Why don’t you stay at my place? I’ll cook dinner.

Something’s burning?
Oh my goodness, it’s on fire!
Oh my goodness, it’s burning!
Oh, my bread! It’s burning!
No, it’s not.

Would you mind if we just called it an early night?
Even I couldn’t. I have work tomorrow.
I’d love to. But I’ve got to work tomorrow.
What are you talking about? We just ate?
I don’t think so.

Isn’t it wonderful walking here?
What do you mean? Was it bad?
Not at all. Is fresh, the walk is easy and the sunshine is kind.
Yes, you can see the whole city from here.
Yes, it’s very beautiful.

Table 4: A comparison of responses generated from various sources.

| Input Utterance | SMIkb | Wiki | Mix | Baseline |
|-----------------|-------|------|-----|----------|
| Here comes the birthday cake. | Wow, what a lovely cake. I’ll have a piece. | Wow, what a beautiful cake. It must have tasted as good as I expected. | Really? Wow. Happy birthday to you! You look so healthy. | Thank you. |
| I’d better go. I gotta get up early. Go over to my parents’. | What are you going to do for breakfast? | You mean you don’t wanna go with me? | Why don’t you stay at my place? I’ll cook dinner. | I don’t think so. |
| Something’s burning? | Oh my goodness, it’s on fire! | Oh my goodness, it’s burning! | Oh, my bread! It’s burning! | No, it’s not. |
| Would you mind if we just called it an early night? | Even I couldn’t. I have work tomorrow. | I’d love to. But I’ve got to work tomorrow. | What are you talking about? We just ate? | I don’t think so. |
| Isn’t it wonderful walking here? | What do you mean? Was it bad? | Not at all. Is fresh, the walk is easy and the sunshine is kind. | Yes, you can see the whole city from here. | Yes, it’s very beautiful. |

Table 5: Snapshot of SMIkb.

| SMIKb | Wiki | Mix | Baseline |
|-------|------|-----|----------|
| LPT: If you borrow something like a tool or a generator from someone, return it in BETTER shape than you got it. | My dad always said that returning something in the same condition you received it is the absolute bare minimum. | My dad always said that returning something in the same condition you received it is the absolute bare minimum. | My dad always said that returning something in the same condition you received it is the absolute bare minimum. |
| SoftBank Nears $40 Billion Deal to Sell Arm Holdings to Nvidia | Nvidia is priced decently for what they offer. | Nvidia is priced decently for what they offer. | Nvidia is priced decently for what they offer. |
| Apple to Give Employees Paid Time Off to Vote in U.S. Election | This exactly. A large majority of disenfranchised communities work jobs that don’t observe federal holidays. | This exactly. A large majority of disenfranchised communities work jobs that don’t observe federal holidays. | This exactly. A large majority of disenfranchised communities work jobs that don’t observe federal holidays. |
| Apple may be working on a foldable iPhone | I can confirm that Apple would be stupid to not be working on one. Whether they ever release one is up for debate, but they’re definitely working on one. | I can confirm that Apple would be stupid to not be working on one. Whether they ever release one is up for debate, but they’re definitely working on one. | I can confirm that Apple would be stupid to not be working on one. Whether they ever release one is up for debate, but they’re definitely working on one. |

measured metrics over both the baselines. Moreover, our Reddit-based SMIkb model outperformed other combinations, confirming an increase in response quality. Furthermore, experiments comparing the effect of top-$k$ on generation quality showed $k = 5$ as the sweet spot with the highest BLEU, which was then evaluated further.

Similar to the automatic evaluation, all of the proposed combinations showed improvements over the baseline in human evaluation. In line with our initial hypothesis, the SMIkb model recorded the highest score in terms of conversational relevance. Meanwhile, the mix of SMIkb and Wikipedia seems to find the appropriate balance between conversational ability and “knowledgeability” with the metrics even exceeding the gold score. We hypothesize that this is not just due to high generation quality but also the nature of our task, which might make our model responses more relevant to a worker when assessed in a single-turn context. Overall, the results verified our proposed approach of learning directly from social media interactions leading to large improvements over the baseline in all metrics of interest. Furthermore, significance tests of bootstrap re-sampling showed that the above evaluation score differences between baselines and our models were statistically significant ($p < 0.01$). Examples of the various generated responses across all the models are shared in Table 4.

In addition, we looked at cases where our model struggles or fails at generating a natural response, a select few of which are compiled in Table 6. In some of these particular cases, the baseline generations, although generic, turn out to be more relevant. We believe some of these long responses with unrelated information to be an artifact of our generation model being overly dependent on the
knowledge base. While social media may simulate human-like conversations in a large variety of situations, it is still far from being a perfect stand-in for real-life dialogue. Therefore, our future work in this direction should look at not only the quality and scope of the knowledge base, but also consider selecting when to ground and make use of the said knowledge during response generation.

## 5 Conclusion

We aimed to improve the raw conversational ability of dialogue systems by grounding the responses in much more human-like social media interactions. Our approach involved a neural retriever-seq2seq generator model fine-tuned jointly, where relevant knowledge was retrieved at the time of generation to assist a more engaging and natural dialogue response. Our experiments showed significant improvements with both automatic and human evaluation metrics ranking the SMIkb-grounded replies to be much more diverse, engaging, and relevant.

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