On the Effectiveness of Integration Methods for Multimodal Dialogue Response Retrieval

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Abstract

Multimodal chatbots have become one of the major topics for dialogue systems in both research community and industry. Recently, researchers have shed light on the multimodality of responses as well as dialogue contexts. This work explores how a dialogue system can output responses in various modalities such as text and image. To this end, we first formulate a multimodal dialogue response retrieval task for retrieval-based systems as the combination of three subtasks. We then propose three integration methods based on a two-step approach and an end-to-end approach, and compare the merits and demerits of each method. Experimental results on two datasets demonstrate that the end-to-end approach achieves comparable performance without an intermediate step in the two-step approach. In addition, a parameter sharing strategy not only reduces the number of parameters but also boosts performance by transferring knowledge across the subtasks and the modalities.

1 Introduction

As the demand for open-domain chatbots and technical development of dialogue systems rise steeply, researchers have brought attention to multimodal dialogue systems. Among various modalities, image-grounded conversations have been actively researched along with the advent of several benchmarks (Lin et al., 2014; Plummer et al., 2015; Antol et al., 2015; Das et al., 2017; Zellers et al., 2019). Most of the benchmarks focus on the factual contents of images, usually given in the form of question-answer pairs. In addition to factual information, recent studies started to consider emotional exchange and engagingness, which are humane aspects of open-domain dialogues (Hu et al., 2014), by collecting more chit-chat-like datasets such as image-grounded conversation (IGC) (Mostafazadeh et al., 2017) and ImageChat (Shuster et al., 2020a).

While most work focused on understanding dialogue contexts of multiple modalities, little work tried to build an integrated system that outputs multimodal responses for retrieval-based chatbots. Zang et al. (2021) proposed photo-sharing intent prediction and image retrieval as individual tasks for multimodal response retrieval, yet the combination of an image retriever and a text retriever remains ambiguous.

To overcome this limitation, we first formulate multimodal response retrieval task which aims to choose the most appropriate text or image response for the next utterance, given a dialogue context composed of text utterances. Then, we explore three unified methods that integrate subcomponents for the end task in different ways. To be specific, dual retriever (DR) and shared dual retriever (SDR) are based on a two-step approach: 1) intent prediction determines the modality of the next utterance and 2) response retrieval finds out the most likely utterance from the predicted modality; on the contrary, multimodal dual retriever (MDR) is an end-to-end approach that selects responses from a heterogeneous candidate pool of the both modalities without the explicit intent prediction step.

We evaluate the effectiveness of each method for multimodal response retrieval and investigate the effect of model size on two benchmark datasets. The two-step approach performs better than the end-to-end approach in unimodal retrieval tasks, whereas the end-to-end approach achieves comparable performance compared to the two-step approach in multimodal retrieval, posing a question on the necessity of intent prediction. In terms of model size, SDR and MDR reduce the number of parameters by sharing context encoders, which is impossible for DR that trains separate context encoders for each modality and intent prediction.

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2 Related Work

2.1 Dialogue Response Retrieval

There are two representative approaches for dialogue response retrieval task: dual encoder and cross-encoder. Dual encoder approaches (Huang et al., 2013; Henderson et al., 2017; Mazaré et al., 2018; Dinan et al., 2019) encode dialogue contexts and responses separately with distinct encoders and compute matching scores to select the most appropriate response. This nature enables us to pre-compute representations to reduce computational burden at inference time, thus widely adopted in many studies (Humeau et al., 2020; Lan et al., 2021; Chen et al., 2021). In particular, researchers have focused on the selection of encoding functions such as CNNs (Yan et al., 2018; Wu et al., 2018), RNNs (Lowe et al., 2015), combined architectures of CNNs and RNNs (Yan et al., 2016; Zhou et al., 2016), memory networks (Zhang et al., 2018), transformers (Dinan et al., 2019; Xu et al., 2021b), and BERT (Henderson et al., 2019). Cross-encoder approaches (Gu et al., 2020; Whang et al., 2020; Wu et al., 2020; Xu et al., 2021a) take the concatenated inputs of contexts and responses to enrich interactions between the two. They are also actively studied owing to the development of pre-trained language models (PLMs) such as BERT (Devlin et al., 2019). In this work, we focus on dual encoder architecture since cross-encoders are less preferred to dual encoders in practical situations.

2.2 Multimodal Open-domain Dialogue

There have been several studies to build multimodal open-domain dialogue systems which output text responses related to a given image followed by a few turns of dialogue contexts. Shuster et al. (2020a) constructed ImageChat dataset which involves images and dialogue contexts along with personality traits allocated to speakers, and proposed a unified architecture using Transformer (Vaswani et al., 2017) and ResNet (He et al., 2016). Shuster et al. (2020b) built a multi-task dialogue agent using 12 open-domain dialogue datasets including ImageChat and IGC. On the success of Blender (Roller et al., 2021), Shuster et al. (2021) incorporated an image encoder (Xie et al., 2017) to enable image-grounded conversation. Sun et al. (2021) focused on generation models which generate either text or image responses conditioned on the preceding textual dialogue contexts. To the best of our knowledge, we propose a single integrated system for multimodal dialogue response retrieval for the first time.

3 Method

3.1 Task: Multimodal Response Retrieval

Multimodal response retrieval aims to select the most appropriate response among the text candidates and image candidates for a given dialogue context. The text is represented as a sequence of tokens $r^{\mathbf{t}} = (t_1, ..., t_l)$ where each token is included in a pre-defined vocabulary. The image is represented by 3-dimensional tensor $r^{\mathbf{i}} \in \mathbb{R}^{H \times W \times C}$. To solve this task, the model predicts the score $s(c, r)$ that indicates how much each response r in the candidate pool is appropriate for a dialogue context $c = (c_1, ..., c_l)$ where c_i is previous text utterance. Using this score, the model selects the response with the highest score for the given context. Therefore, the goal of the model is to accurately select the ground truth response while harmonizing the multimodal response candidates,

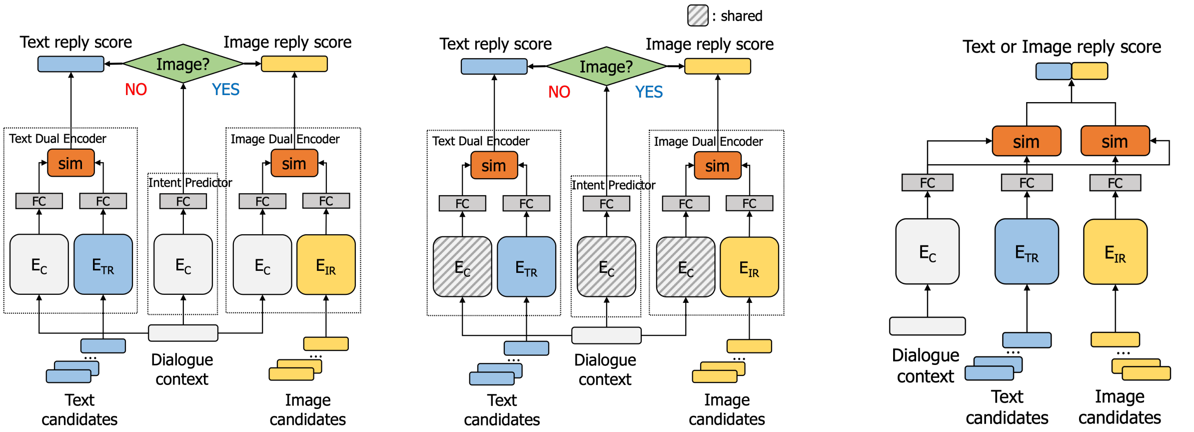
$$r^* = \underset{r \in \{r^{\mathbf{t}}_1, ..., r^{\mathbf{t}}_i\} \cup \{r^{\mathbf{i}}_1, ..., r^{\mathbf{i}}_j\}}{\operatorname{argmax}} s(c, r).$$

Subtask: Intent Prediction (Zang et al., 2021) aims to determine the modality of the next utterance given a context. In the case of two modalities (text and image), an intent prediction model f_i takes a context c as input and produces a binary logit. Given the pair of context and either image response or text response, the binary cross entropy loss is used for training as follows:

$$\mathcal{L}_{\text{intent}} = \textstyle\sum_{(c,r^i)} \mathcal{L}_{\text{BCE}}(f_i(c), 1) + \sum_{(c,r^t)} \mathcal{L}_{\text{BCE}}(f_i(c), 0).$$

Subtask: Text Response Retrieval is to select the most appropriate text response given the current context. We adopt dual encoder architecture widely used in response selection (Yang et al., 2018). To be specific, a context encoder $f^{\mathbf{t}}_c$ and a response encoder $f^{\mathbf{t}}_r$ compute the representations of a context c and a response r respectively. The cosine similarity between two representations is regarded as the score, and the encoders are optimized to accurately predict the score based on the cross entropy loss. The loss computed from i-th pair of context $c^{\mathbf{t}}_i$ and text response $r^{\mathbf{t}}_i$ is as follows:

$$\begin{aligned}\mathcal{L}_{\text{text}} = &- \log \frac{\exp(s_{\mathbf{t},\mathbf{t}}(c^{\mathbf{t}}_i, r^{\mathbf{t}}_i))}{\sum_{(\cdot, r^{\mathbf{t}}_j) \in B} \exp(s_{\mathbf{t},\mathbf{t}}(c^{\mathbf{t}}_i, r^{\mathbf{t}}_j))} \\ &- \log \frac{\exp(s_{\mathbf{t},\mathbf{t}}(c^{\mathbf{t}}_i, r^{\mathbf{t}}_i))}{\sum_{(c^{\mathbf{t}}_j, \cdot) \in B} \exp(s_{\mathbf{t},\mathbf{t}}(c^{\mathbf{t}}_j, r^{\mathbf{t}}_i))},\end{aligned}$$



(a) Dual Retriever (b) Shared Dual Retriever (c) Multimodal Dual Retriever

Figure 1: Three different architectures for the multimodal response retrieval task. E_C: context encoder, E_{TR}: text response encoder, E_{IR}: image response encoder.

where $s_{\cdot,\cdot}(c, r) = \cos(f_c^{\cdot}(c), f_r^{\cdot}(r))$ for further notational simplicity.

Subtask: Image Response Retrieval handles image responses during conversation. This task is the same with text response retrieval except that the modality of response is image. Therefore, the response encoder is built on the pretrained image encoder (He et al., 2016). The loss for the i-th pair of context $c_i^{\mathbf{t}}$ and image response $r_i^{\mathbf{i}}$ is described as follows:

$$\mathcal{L}_{\text{image}} = -\log \frac{\exp(s_{\mathbf{t},\mathbf{i}}(c_i^{\mathbf{t}}, r_i^{\mathbf{i}}))}{\sum_{(\cdot, r_j^{\mathbf{i}}) \in B} \exp(s_{\mathbf{t},\mathbf{i}}(c_i^{\mathbf{t}}, r_j^{\mathbf{i}}))} - \log \frac{\exp(s_{\mathbf{t},\mathbf{i}}(c_i^{\mathbf{t}}, r_i^{\mathbf{i}}))}{\sum_{(c_j^{\mathbf{t}}, \cdot) \in B} \exp(s_{\mathbf{t},\mathbf{i}}(c_j^{\mathbf{t}}, r_i^{\mathbf{i}}))}.$$

While the models for each subtasks are trained separately, these models do not capture useful supervision across the subtasks and cannot effectively solve the multimodal response retrieval task. Therefore, careful integration of these models become important for the ultimate task. Considering the knowledge derived across the subtasks, we introduce three approaches (Fig. 1) to integrate these modules in the following subsections.

3.2 Dual Retriever (DR)

One simple integration is to weave the separately trained models. Each model is trained by three different optimization problems:

$$\underset{\theta_i}{\text{minimize}}\ \mathcal{L}_{\text{intent}},\ \underset{\theta_c^{\mathbf{t}}, \theta_r^{\mathbf{t}}}{\text{minimize}}\ \mathcal{L}_{\text{text}},\ \underset{\theta_c^{\mathbf{t}}, \theta_r^{\mathbf{i}}}{\text{minimize}}\ \mathcal{L}_{\text{image}},$$

where θ represents the parameters of each model. Using these trained models, DR combines the produced outputs to obtain final outputs during inference. To be specific, the intent predictor predicts the modality of the response for an input context. Depending on the prediction, we select the corresponding retrieval model and then find out the most appropriate response.

$$f(c^{\mathbf{t}}) = \begin{cases} \text{argmax}_{r_i^{\mathbf{i}}}\ s_{\mathbf{t},\mathbf{i}}(c^{\mathbf{t}}, r_i^{\mathbf{i}}) & \text{if } f_i(c) > 0.5 \\ \text{argmax}_{r_i^{\mathbf{t}}}\ s_{\mathbf{t},\mathbf{t}}(c^{\mathbf{t}}, r_i^{\mathbf{t}}) & \text{otherwise.} \end{cases}$$

However, since the supervision from each modality is not transferred across different retrievers, the derived knowledge is not fully reflected to both retrieval models.

3.3 Shared Dual Retriever (SDR)

We propose a simple but effective scheme that shares the retriever to encourage the models to communicate with each other across the subtasks. Our key idea comes from the observation that the two retrieval tasks follow the same dual encoder architecture. Also, although the architecture of response encoder is different due to the different modality, the architecture of context encoder is the same. Thus, we can share the parameters of the context encoder between the two subtasks without any modification of the architecture ($\theta_c^{\mathbf{t}} = \theta_c^{\mathbf{t}}$). With the help of parameter sharing, we integrate the optimization problems for two response retrieval tasks:

$$\underset{\theta_i}{\text{minimize}}\ \mathcal{L}_{\text{intent}},\ \underset{\theta_c^{\mathbf{t}}, \theta_r^{\mathbf{t}}, \theta_r^{\mathbf{i}}}{\text{minimize}}\ \mathcal{L}_{\text{text}} + \mathcal{L}_{\text{image}}.$$

Furthermore, we make the context encoder inside the intent predictor ($\theta_i = \theta_c$) share its parameters with those of the response retrieval models. By doing so, the separate optimization problems are merged into a unified optimization problem for the multimodal dialogue response retrieval task as follows:

$$\underset{\theta_c^{\mathbf{t}},\theta_r^{\mathbf{t}},\theta_r^{\mathbf{i}}}{\text{minimize}}\ \mathcal{L}_{\text{intent}} + \mathcal{L}_{\text{image}} + \mathcal{L}_{\text{text}}.$$

We further hypothesize the ineffectiveness inside the inference process due to the intent predictor. One reason is the cascaded error coming from the intent predictor. The intent predictor acts as a branch for choosing the modality of the most appropriate response. However, it means that the final prediction result is wrong if the intent predictor predicts wrong modality. In addition, from the recent success in modeling cross-modal representation space (Radford et al., 2021; Akbari et al., 2021), we hypothesize that the response representation space from different modalities can become naturally aligned.

3.4 Multimodal Dual Retriever (MDR)

From the above hypothesis, we propose our final integration approach by removing the intent predictor and modeling multimodal response representation space. We remove the intent predictor and directly compare the cosine similarities across different modality. Then an integrated response encoder is defined as $f_r^{\mathbf{m}} = f_r^{\mathbf{i}}$ if $r = r^{\mathbf{i}}$, or $f_r^{\mathbf{m}} = f_r^{\mathbf{t}}$ if $r = r^{\mathbf{t}}$. The loss for the i-th pair of the two different modalities is defined as follows:

$$\begin{aligned}\mathcal{L}_{\text{joint}} = &- \log \frac{\exp(s_{\mathbf{t},\mathbf{m}}(c_i^{\mathbf{t}}, r_i))}{\sum_{(\cdot,r_j)\in B} \exp(s_{\mathbf{t},\mathbf{m}}(c_i^{\mathbf{t}}, r_j))} \\ &- \log \frac{\exp(s_{\mathbf{t},\mathbf{m}}(c_i^{\mathbf{t}}, r_i))}{\sum_{(c_j,\cdot)\in B} \exp(s_{\mathbf{t},\mathbf{m}}(c_j^{\mathbf{t}}, r_i))},\end{aligned}$$

where a batch B consists of context-response pairs whose response is either image or text. All the parameters can be effectively optimized to minimize the joint loss in an end-to-end manner,

$$\underset{\theta_c,\theta_{r^{\mathbf{t}}},\theta_{r^{\mathbf{i}}}}{\text{minimize}}\ \mathcal{L}_{\text{joint}}.$$

Note that the absence of the intent predictor further simplifies the inference process by taking the response that has the most highest score among all the multimodal candidates.

4 Experimental Setup

4.1 Datasets

PhotoChat is a multimodal dialogue dataset which includes dyadic dialogues covering various topics in daily lives. It consists of 10,286/1,000/1,000 dialogue contexts with a single image attached to each context in the train/dev/test set. There exist 8,889/1,000/1,000 unique images along with object labels in the train/dev/test set.

Multi-modal Dialogue (MMDial) (Lee et al., 2021) was constructed by substituting text utterances in existing text-only dialogue datasets with relevant images from large-scale image datasets using a state-of-the-art image-text matching model (Li et al., 2019). It consists of 39,956/2,401/2,673 dialogue contexts with a single image attached to each context in the train/dev/test set. There exist 12,272/334/682 unique images in the train/dev/test set.

Preprocessing. For each dialogue context, we extract the first $n \in \{1, 2, \ldots, l\}$ utterances as an example to augment contexts, where l is the length of a context before sharing an image. Since object labels are not explicitly attached in MMDial, we match the corresponding image captions to images from MS-COCO and Flickr30k.

4.2 Metric

We measure recall at k (R@k) to evaluate multimodal response retrieval. It calculates the occurrence when the gold response is retrieved in top-k ($k = 1, 5, 10$) candidates. For dev and test, we use the fixed 50 candidates of each modality randomly chosen from the whole images and text responses in the dev and the test set, respectively. We use the checkpoint that achieves the best dev R@k and report the test R@k evaluated by the checkpoint.

5 Results

5.1 Effects of Integration Methods

In contrast to relatively small gaps of R@k among the three methods in unimodal retrieval, the end task performance is largely affected depending on how we integrate the subcomponents. On PhotoChat (Table 1), SDR achieves the highest R@k for multimodal retrieval, except that MDR reaches slightly higher R@10 when the model size is large. Meanwhile on MMDial (Table 2), MDR achieves the highest R@k for multimodal retrieval, except

		Text Retrieval			Image Retrieval			Multimodal Retrieval		
Model Size	Method	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10
Small	DR	**0.4325**	0.7371	0.8701	**0.4519**	**0.7994**	**0.9007**	0.2475	0.4234	0.4949
	SDR	0.4274	**0.7553**	**0.8721**	0.4396	0.7787	0.8873	**0.4000**	**0.7046**	**0.8086**
	MDR	0.3990	0.7076	0.8518	0.4122	0.7269	0.8599	0.3766	0.6594	0.7721
Large	DR	0.4305	0.7482	0.8751	**0.4620**	**0.8247**	**0.9058**	0.2079	0.3560	0.4143
	SDR	**0.4650**	**0.7990**	**0.9066**	0.4315	0.8061	0.9046	**0.4152**	**0.7239**	0.8157
	MDR	0.4315	0.7299	0.8812	0.4406	0.7797	0.8964	0.4020	0.6949	**0.8193**

Table 1: Results on the test set of PhotoChat. Text (image) retrieval: retrieval among 50 text (image) response candidates for the examples whose ground truths are text (image) responses, assuming the intent predictor is an oracle for DR and SDR. MDR does not get advantage in this setting since there is no explicit intent prediction step. Small: $\text{BERT}_{\text{MINI}}$ and ResNet_{50}, Large: $\text{BERT}_{\text{BASE}}$ and ResNet_{152} (Turc et al., 2019).

		Text Retrieval			Image Retrieval			Multimodal Retrieval		
Model Size	Method	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10
Small	DR	0.6118	0.8039	**0.8946**	0.0430	0.2148	0.3687	**0.2874**	0.3749	0.4161
	SDR	**0.6138**	**0.8115**	0.8870	**0.1356**	**0.3958**	**0.5430**	0.2619	0.3934	0.4527
	MDR	0.5386	0.7558	0.8512	0.1281	0.3846	0.5334	0.2731	**0.4517**	**0.5378**
Large	DR	**0.6333**	**0.8453**	**0.9141**	0.0605	0.2204	0.3544	0.2900	0.3835	0.4125
	SDR	0.5986	0.8313	0.8986	**0.1484**	**0.4300**	**0.6002**	0.2516	0.4113	0.4735
	MDR	0.5967	0.8202	0.8938	0.1281	0.4097	0.5728	**0.3079**	**0.4883**	**0.5895**

Table 2: Results on the test set of MMDial. Defined terms are the same as in Table 1.

that DR scores the highest R@1 for the small model. We note that although DR outperforms MDR in text retrieval and image retrieval, MDR outperforms DR on the contrary due to the cascaded error from the intent prediction step. These results highlight the significance of choosing an appropriate integration method of submodules.

5.2 Effects of Model Size

Overall, all the methods in large models tend to achieve higher R@k than their counterparts in small models on the both datasets. On PhotoChat, MDR shows comparable performance for multimodal retrieval to SDR when the model size grows large. Similarly on MMDial, MDR effectively increases R@k for multimodal retrieval compared to the two-step approach when the large model is used. From these results, we can conclude that large models are more capable of aligning the multimodal representation space than small models.

5.3 Effects of Parameter Sharing

On the both datasets, the performance of DR for multimodal retrieval lags behind those of SDR and MDR which share the parameters of context encoders. DR trains each submodule separately on the three individual subtasks so none of the subcomponents can get the knowledge from the other subtasks and modalities positively transferred, resulting in disharmony for accomplishing the ultimate goal (Wu et al., 2021).

In addition, weight sharing decreases the number of total parameters from 72M to 49M in small models and from 501M to 281M in large models, which become around 1.5x and 1.8x smaller respectively.

6 Conclusion

We propose an integrated task to build a multimodal dialogue system that outputs both text and image responses, and present three architectures for the task, named DR, SDR, and MDR, respectively. We then analyze their advantages and disadvantages in terms of retrieval performance and model size.

Specifically, we empirically analyze the effectiveness of intent prediction which was introduced in the previous work. The experimental results on two datasets demonstrate that the end-to-end approach without an intent predictor shows competitiveness for multimodal retrieval compared to the two-step approach. In addition, SDR and MDR successfully reduce the number of model parameters without compromising the end task performance. As the end-to-end approach is the efficient method to solve the end task directly, elaborating cross-modal interactions in this architecture will become one promising direction for our future work.

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A Appendix

A.1 Implementation Details

Architectural details of encoders The context encoder (E_C) and the text response encoder (E_{TR}) consist of a single BERT encoder followed by a projection layer. The parameters of two encoders are shared across all experiments since this yields better performance consistently than when not shared. The image response encoder (E_{IR}) consists of an image encoder which extracts visual features with ResNet and a object label encoder which extracts object label features with BERT. Note that both BERT and ResNet are used to encode image features since an object label is attached to every image. The two representations are then concatenated and projected to the joint embedding space. We use $\text{BERT}_{\text{MINI}}$ and ResNet_{50} for small models and $\text{BERT}_{\text{BASE}}$ and ResNet_{152} for large models as specified by Turc et al. (2019).

Hyperparameters For BERT, the dropout rate is 0.2 and the maximum sequence length is set to 128. We use cosine similarity with the temperature $\tau = 0.01$ as the similarity measure. We train the model for 10 epochs for intent prediction and text text dialogue retrieval, and 20 epochs for image dialogue retrieval and multimodal dialogue retrieval with the batch size of 64 in one V100 GPU. We apply Adam optimizer (Kingma and Ba, 2015) with the learning rate of 5e-5 and linear decay of 0.1% per 1,000 steps.