Unsupervised Injection of Knowledge into Dialogue Generation via Language Models

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Abstract

Neural conversation models have shown the power to produce more meaningful and engaging responses given external knowledge. Specifically, the knowledge we experiment on is in textual form, for example, a personality description. Despite the success of training and testing with external knowledge, in reality, we do not always have sufficient background knowledge about the discussed topic. Therefore, it is also crucial to have the models generate captivating responses without external knowledge. To achieve this, we propose a unified training method, Decoupling, which induces a knowledge-related sentence and couples it with the dialogue history to generate a response in an unsupervised fashion. Its effect is further analyzed by testing the models with no knowledge, partial and full text of the knowledge. Empirically, we observed that the variance of the performance given different amounts of knowledge is significant. Also, our method performs more closely to the supervised method (the upper bound) than the baselines.

1 Introduction

Chit-chat dialogue generation is often seen as an end-application of natural language processing. It aggregates a proper understanding of dialogue history and the ability to generate engaging responses (Vinyals and Le, 2015). So far, existing chit-chat generation models are suffering from some well-known problems: one of them is that models tend to produce general responses without useful information, e.g., “I don’t know.” (Li et al., 2016a; Ghazvininejad et al., 2018).

Recent work has collected data with external knowledge to make responses more vivid and informative, such as the Persona-Chat (Zhang et al., 2018; Dinan et al., 2020), LIGHT (Urbanek et al., 2019), and Wizard of Wikipedia (Dinarelli and Rosset, 2011). Take Persona-Chat as the example, in addition to the dialogue history, the responses condition on the profile of the speaker, e.g., “my favorite sport is ultimate frisbee”. They demonstrated that with the specified information, the models respond more perceptive.

However, in reality, we do not always have sufficient prior knowledge of the discussed topic. This leads to some defects in both the training and the inference stages. To cope with the insufficient external knowledge problem in the training stage, Zhao et al. (2020) applied a copy mechanism module to disentangle the knowledge reasoning part, and then expanded the training to unlabeled data. Nonetheless, to our observation, the impact of insufficient knowledge in the inference stage has not been surveyed.

In this paper, we define and analyze the knowledge gap on various conversational data with external knowledge. The knowledge gap, as illustrated in Figure 1, is the variance of the performance of the models with varying amounts of external knowledge. This measurement can quantify the
significance of using external knowledge for each model in both the training and the testing phases, thus suggesting a way to explore the causes to each model by giving insufficient knowledge. Meanwhile, the knowledge gap reveals that when tackling the low-resource problem, testing the models with full external knowledge may be misleading.

Other than evaluation by the knowledge gap, we propose Decoupling, a unified method that does not require paired external knowledge for training. Decoupling first de-couples some knowledge-related information from the input. Then, the extracted information is formulated as knowledge. Specifically, we take a pretrained LM as the knowledge base (Petroni et al., 2019) and maximize the probability of the extracted information in the knowledge base. Finally, the method re-couples the information back to the input. Empirically, Decoupling shows convincing results across all data. Moreover, we provide some analyses about the significantly different trends of the datasets when sweeping through the amount of external knowledge.

The main contribution is three-fold.

- We leverage the LM as a knowledge base for neural response generation, and propose a unified framework, Decoupling, to inject knowledge into a single conversation model.
- We conduct a comprehensive evaluation on the knowledge gap problem, and provide a systematic explanation.
- We demonstrate that Decoupling can outperform other unsupervised methods and perform closely to the upper bound.

2 Related Work

Recent work about open-domain dialogue generation has grown on personalized (Li et al., 2016b), knowledge-grounded (Ghazvininejad et al., 2018), and diversity-promoting (Li et al., 2016a) tasks. These directions are beneficial for informing a dialogue agent. With a similar target, their settings are different. The first two need extra annotations, while the last one does not. However, the last one has limited overall performance due to the absence of extra information. Following is the discussion about the research on the above three tasks and other related work of our approach.

As the inconsistent personality causing a big problem in multi-turn dialogue generation, Li et al. (2016b) proposed to assist generation with a persona label during decoding. The persona labels used were from the key-value attributes of TV show characters, which were useful but limited. After that, Zhang et al. (2018); Dinan et al. (2020) collected a dataset with paired personality descriptions. This enhanced the abundance of persona and demonstrated the advantage of personality to increase information in responses. In addition to personalized dialogues, Ghazvininejad et al. (2018) presented that knowledge-grounded ones can also boost the contained information. Dinan et al. (2018) collected a wizard-apprentice conversation dataset grounded on Wikipedia articles. Due to the efforts of collecting large enough knowledge-annotated dialogues dataset, Zhao et al. (2020) proposed to use a copy mechanism module to disentangle the knowledge reasoning part. Instead of unstructured knowledge (text) used in the above work, Zhou et al. (2018); Moon et al. (2019); Tuan et al. (2019) utilized structured knowledge graphs, which can also be formulated as text using templates to be fine-tuned on the LM in this work.

As to diversity-promoting dialogue generation, some methods are adopted in the inference stages, such as maximizing the mutual information to minimize the probability of general responses (Li et al., 2016a); some methods are applied on the training stage, such as using the latent variable. The usage of latent variables in dialogues is mainly divided into two topics: (a) assuming the prior in Generative Adversarial Networks (GAN) (Li et al., 2017a; Tuan and Lee, 2019) and (b) approximating the posterior in Variational Autoencoders (VAE). These training approaches claimed to reduce the problem of general responses. GAN is claimed beneficial for it replacing the forward KullbackLeibler divergence (KLD) with JensenShannon divergence (Goodfellow et al., 2014), which considers both forward and reverse KLD. In the meantime, VAE is claimed to supplement diversity by adding the evidence lower bound (ELBO) to the original loss. Zhao et al. (2017) formulated conditional variational autoencoder and augmented with dialogue-act labels for dialogue generation. Gao et al. (2019) modified it by replacing the continuous latent variable with a discrete distribution over words and leverage the similarity of word embeddings. Regularizing the intermediate generation can also be seen in other tasks, such as Hu et al. (2017) tried to disentangle a latent code to make it controllable. In this work, we
use the latent variable differently. We suppose the prior of one latent code is the estimated distribution of knowledge. Moreover, compared to the above tasks, the training in our task is given no paired external information but a collection of it.

3 Method

This work aims to tackle two-agent dialogues without paired textual external knowledge but having a collection of the supposed useful knowledge.

A two-agent dialogue is a sequence of utterances swapping between two speakers: \{x_1, x_2, ...x_T\}, where each x_{2t-1} is an utterance from agent A, and x_{2t} is an utterance from agent B, where t starts from 1 to T. The collection of textual knowledge is denoted as the set Z. For datasets using personality as the external knowledge, each z \sim Z is a sentence that describes an arbitrary agent, such as “I have two dogs.” (more variations are in section 4.1). Given any dialogue history x_{<t} before the t-th utterance, we hope to find a possible personality description z \sim Z that is able to generate a response y as close as possible to the x_t. In the following, we replace the notation of x_{<t} with x, x_t with \hat{y} for simplicity. Meanwhile, the real paired personality description is denoted as \hat{z}. Note that \hat{z} is used for description, we do not actually have it in the data.

As depicted in Figure 2, the idea of our proposed approach, Decoupling, is first finding a possible subset Z_x \subset Z conditioned on the dialogue history x, then generate y by conditioning on the joint distribution of z \sim Z_x and x. The formulation can be written as,

\begin{equation}
  \begin{align*}
    z & \sim P_f(z|x) \\
    y & \sim P_f(y|x, z)
  \end{align*}
\end{equation}

where \sigma and \phi are respectively the parameters of the knowledge generation model and response generation model.

The core of Decoupling is to minimize the negative likelihood of \hat{y} and meanwhile regularize the generated z by a pretrained language model (LM). The loss function is as follows,

\begin{equation}
  L_{\phi,\sigma} = -\log P_\phi(\hat{y}|x, z) + D_{KL}(P_\sigma(z|x)||P_Z(z))
\end{equation}

where the P_Z denotes the LM pretrained upon the collection of personalities Z, and z is sampled from P_\sigma(z|x) (as equation 1). The derivation of equation 2 is left in subsection 3.3. The algorithm is depicted in Algorithm 1. Note that the \nabla_\sigma needs further simplification as in subsection 3.2. Further, in our experiment, the weights \alpha, \beta are normally set to 1, and the weight \gamma \in [0.1 - 1] has been tested to work fine.

3.1 Motivation

Decoupling is motivated from the concept of causality. We take the personality z as an unobserved confounding variable that causes the response \hat{y} (Hlaváčková-Schindler et al., 2007) other than x. This is possible because the knowledge meets the causal modeling specified conditions (Sellitz et al., 1976): (1) there is a time ordering between z and \hat{y}, (2) there exists covariance between z and

Algorithm 1 Decoupling

1: pre-train an LM (P_Z) on Z and fix it
2: initialize \sigma and \phi
3: given hyperparameters \alpha, \beta, \gamma
4: for number of training iterations do
5:   sample (x, y) from real data
6:   sample z \sim P_\sigma(z|x)
7:   compute \nabla_\phi = \nabla_\phi \log P_\phi(\hat{y}|x, z)
8:   compute
9:   update \phi,\sigma by \alpha \nabla_\phi + \nabla_\sigma
10: end for

Figure 2: The framework of Decoupling training for transformer. Green parts are related to personality/knowledge. Red parts work as encoder in Seq2Seq models to process input message. Yellow parts work as decoder in Seq2Seq to infer response. The Orange cell is to classify if the response is authentically paired with the input message as (Wolf et al., 2019).
where the KLD subscripted by words, its domain grows exponentially with the increasing length. We tackle it using an upper bound because the textual knowledge is derived in subsection 3.3. For the second term, we use policy gradient (Sutton and Barto, 2018; Ranzato et al., 2016) by taking the likelihood term and the KLD term. For the first term, other side, the parameters \( \sigma \) the same as maximum likelihood estimation. In the missing one step to be tractable. Because the probability distribution \( P(x,z) \) contains as much possible extra information other than \( x \). The argument induces the Kullback-Leibler divergence (KLD) (Kullback and Leibler, 1951) regularization term.

An intuitive way to interpret the formulation is that the probability distribution \( P_\sigma(z|x) \) is the least descriptive part of \( x \) but relates to the personality domain \( Z \) to some extent. Because \( P_\sigma(z|x) \) recouples \( z \) to the input, the \( P_\phi(y|x,z) \) is enforced to utilize information in the personality domain. Thus, the pretrained LM not only injects personality into the \( P_\sigma(z|x) \) but also enables \( P_\sigma(y|x,z) \) to do reasoning even trained without paired personality.

### 3.2 The Gradients

The equation 2 is an ideal loss function, but is missing one step to be tractable. Because \( \phi \) is only related to the first term in equation 2, the gradient is the same as maximum likelihood estimation. In the other side, the parameters \( \sigma \) relates to both the likelihood term and the KLD term. For the first term, we use policy gradient (Sutton and Barto, 2018; Ranzato et al., 2016) by taking the \( P_\phi(y|x,z) \) as reward and the \( P_\sigma(z|x) \) as the policy. The detail derivation is in subsection 3.3. For the second term, because the textual knowledge \( z \) is a sequence of words, its domain grows exponentially with the increasing length. We tackle it using an upper bound of the KLD.

\[
D_{KL}(P_\sigma || P_Z) \leq \sum_\tau D_{KL}(P_{\sigma,\tau} || P_{Z,\tau})
\]  

(3)

where the KLD subscripted by \( \tau \) refers to \( \sum_z P_\sigma(z|z<\tau) \log \left( \frac{P_\sigma(z|z<\tau)}{P_Z(z|z<\tau)} \right) \), and \( z_\tau \) is the \( \tau \)-th token in the \( z \) sequence. Therefore the gradients can be rewritten as,

\[
\nabla_\phi = \nabla \log P_\phi(y|x,z) \\
\nabla_\sigma = P_\phi(y|x,z) \nabla \log P_\sigma(z|x)
\]

\[
+ \sum_{\tau=1}^{\text{len}(z)} D_{KL}(P_{\sigma,\tau}(z)||P_{Z,\tau}(z))
\]

(4)

As depicted in Figure 2, we implement the Decoupling method upon Transformer (Vaswani et al., 2017). Particularly we adopt the TransferTransfo model (Wolf et al., 2019; Radford et al., a), where the optimization cares both the likelihood loss and the classification loss. Hence, our training also add the classification loss to the originally derived likelihood terms. Although we shape Decoupling to be directly used on TransferTransfo, it is generally applicable to other auto regressive models (Mikolov et al., 2010; Sutskever et al., 2014; Radford et al., b)

### 3.3 Derivation

Suppose \( z \) is a confounding variable besides \( x \) of \( y \), but \( z \) is an unobserved one. Also, as defined, variable \( z \) is a cause of \( y \) other than \( x \) if and only if \( P(y|x,z) > P(y|x) \). When applying the inequality to real scenarios, we can rewrite it as the following.

**Lemma 1.** given \( (x,y,\hat{z}) \sim P_D \), where \( P_D \) is the real data distribution, and \( \hat{z} \) contains information useful to \( y \) and different from \( x \).

\[
\max_\phi P_\phi(y|x) < \max_\theta P_\theta(y|x,\hat{z})
\]

(5)

where \( \theta \) is the parameter for a generation model that takes the real personality \( \hat{z} \) as an input.

**Definition 1.** Define \( \epsilon(z) \), for \( (x,y,z) \sim P_D \) and \( z \in Z \), is the residual of log \( P_\phi(y|x,z) - \log P_\phi^*(y|x) \), where \( \phi^* \) is the optimal parameters of \( P(y|x,z) \) and \( \phi^* \) is the optimal parameters of \( P(y|x) \). The lower bound of \( \epsilon(z) \) can be derived as follows.

\[
\epsilon(z) \geq \log \frac{P_\phi^*(x,y,z)}{P_D(x,y)P_D(z)}
\]

(6)

The derivation is as follows. Note that the prior distributions \( P(x) \), \( P(y) \), \( P(z) \) are available from the dataset. Therefore we label them with subscript \( D \) and we do not need to model these priors. In addition, we assume that \( P(x) \)
and \( P(z) \) are identically independent distributed, i.e., \( P(x, z) = P(x)P(z) \), which holds in some real-world cases and also satisfies the definition in Granger causality (Granger, 2004), which indicates that \( z \) should contain some unique information that does not exist in other variables.

\[
\epsilon(z) := \log P_{\theta^*}(y|x, z) - \log P_{\theta^*}(y|x)
\geq \log \frac{P_{\theta^*}(y|x, z)}{P_{\theta^*}(y|x)}
= \log \frac{P_{\theta^*}(x, y, z)P_{\theta^*}(x)}{P_{\theta^*}(x, y)}
\geq \log \frac{P_{\theta^*}(x, y, z)P_{D}(x)}{P_{D}(x)P_{D}(x, y)}
= \log \frac{P_{\theta^*}(x, y, z)P_{D}(x, y)}{P_{D}(x, y)P_{D}(z)}.
\]

(7)

To find out the latent \( z \) that contributes most to the generation of \( y \), our aim is to sample a \( \tilde{z} \sim p_{\phi}(z|x) \) which makes \( p_{\theta^*}(y|x, \tilde{z}) \) as close as possible to \( p_{\theta^*}(y|x, z) \), that is to maximize the residual \( \epsilon(\tilde{z}) \).

**Theorem 1.** The target to find \( \tilde{z} \) that make \( \log P_{\phi}(y|x, \tilde{z}) \) as close as possible to the upper bound \( \log P_{\theta^*}(y|x, z) \) is formulated as:

\[
\min_{\sigma} \log P_{\theta^*}(y|x, z) - \log P_{\phi}(y|x, \tilde{z})
\]

(8)

The tighter lower bound is:

\[
\arg \max_{\sigma} \log P_{\phi}(x, y, \tilde{z}), \text{ subject to } \min_{\sigma} I(x; z)
\]

(9)

**Note that we suppose a \( \phi \) that is able to utilize \( z \).**

**Proof.** because \( \tilde{z} \) is the optimal \( z \) and \( \tilde{z} \) is an arbitrary \( z \), the inequalities hold

\[
p_{\phi}(y|x) < p_{\phi}(y|x, \tilde{z}) \leq p_{\theta^*}(y|x, \tilde{z})
\]

(10)

Therefore, to optimize the model with respect to \( \tilde{z} \) is the same as to minimize the difference between residuals \( \epsilon(\tilde{z}) \) and \( \epsilon(z) \), since \( \tilde{z} \) is based on \( \phi \) and does not change the lower bound of \( \epsilon \) in Definition 1.

\[
\arg \min_{\sigma} \log P_{\theta^*}(y|x, z) - \log P_{\phi}(y|x, \tilde{z})
\]

\[
= \arg \min_{\sigma} \epsilon(z) - \epsilon(\tilde{z})
\]

\[
= \arg \max_{\sigma} \epsilon(\tilde{z})
\]

(11)

We are not able to compute the gradient of \( \sigma \) of maximizing \( \epsilon(\tilde{z}) \) since the process \( \tilde{z} \sim P_{\theta}(z|x) \) is not differentiable. Therefore, we optimize its lower bound, at least to give the \( \epsilon(\tilde{z}) \) a tighter constraint.

\[
\arg \max_{\sigma} \log P_{\phi}(x, y, \tilde{z})
\]

subject to \( P_{\phi}(x, \tilde{z}) = P_{D}(x)P_{D}(\tilde{z}) \)

(12)

Because logarithm an increasing function, we choose to optimize its variable:

\[
\nabla_{\sigma} P_{\phi}(x, y, \tilde{z}) \approx \frac{1}{m} \sum_{i=1}^{m} p_{\phi}(y^i|x^i, \tilde{z}^i) \nabla_{\sigma} \log p_{\sigma}(\tilde{z}^i|x^i)
\]

(13)

where \( m \) is the batch size.

The constraint \( P_{\phi}(x, z) = P_{D}(x)P_{D}(z) \) can be rewritten as minimizing the mutual information of \( x \) and \( z \) variables \( I(X; Z) = E_{p(x,z)} \log \frac{p(x,z)}{p(x)p(z)} = E_{p(x)} D_{KL}(p(z|x)||p(z)) \). The optimization problem is then implemented as equation 4.

\[ \Box \]

4 Experiment Setup

We test the proposed method on Persona-Chat (Zhang et al., 2018), LIGHT (Urbanek et al., 2019), Wizard of Wikipedia (Dinan et al., 2018), and Dailydialog (Li et al., 2017b) for a thorough understanding. For fairness, the proposed approach and the baselines are based on the Transfertransfo (Wolf et al., 2019), which starts from a pretrained GPT model (Radford et al., a) and incorporates personality description with the dialogue history. Moreover, to save the memory, we use the same parameters for the models \( \sigma \) and \( \phi \), but using different dialogue state embeddings to distinguish them.

4.1 Datasets

To more comprehensively understand the usage of external knowledge in dialogue generation, we performed experiments on three (in general) knowledge-grounded conversation datasets, Persona-Chat (Zhang et al., 2018), LIGHT (Urbanek et al., 2019), and Wizard of Wikipedia (WOW) (Dinan et al., 2018). They provided extra information (personalities in Persona-Chat and LIGHT; Wikipedia articles in WOW) for each conversation, which enabled us to do the automatic evaluation with respect to it. In addition, to further demonstrate that the Decoupling method had some advantage of adding information, we also evaluated the methods on a conversation dataset designed without external knowledge. We chose Dailydialog (Li et al., 2017b).
| data          | recall | precision | f1    |
|--------------|--------|-----------|-------|
| Persona-Chat | 21.71  | 33.70     | 26.41 |
| LIGHT        | 19.56  | 20.79     | 20.16 |
| WOW-seen     | 9.82   | 24.26     | 13.99 |
| WOW-unseen   | 10.22  | 24.47     | 14.42 |

Table 1: The unigram f1 of the knowledge-paired datasets. The significant difference of WOWs from others can help explain the results.

**Persona-Chat and LIGHT.** They contain open-domain conversations with profiles of the speakers. Each profile is about 3-5 sentences describing the speaker’s personalities, such as “my favorite sport is ultimate frisbee.” The LM is a GPT model fine-tuned on the collection of personalities in the training set.

**Wizard of Wikipedia (WOW).** Each conversation is between an apprentice and a wizard, who can access the related Wikipedia articles about a topic on Wikipedia. The test set of WOW is split into WOW-seen and WOW-unseen set, where the WOW-unseen contains only topics not included in the training set. In our experiment, we directly use the most related sentence in Wikipedia articles as the external knowledge.

**Dailydialog.** It is an open-domain conversation dataset with emotion and dialog-act labels. We discard the metadata but only use the conversations to validate whether the approximated distribution of personality can in general assist response generation by decoupling with the LM of Persona-Chat.

For the knowledge-paired datasets, we computed their unigram overlaps between the $x$ and $z$ in Table 1. The recalls are much lower in WOWs, indicating that the WOWs might have less mutual information between the $x$ and $z$. The statistics can help explain the completely different trends of their performances.

### 4.2 Baselines

We take four variations of the Transfertransfo (Wolf et al., 2019) as baselines. They are respectively trained with full external knowledge (denoted as **Full**), random subsequences of the external knowledge (we chose the length of 10, **10len**), and no external knowledge (**Vanilla**). To validate the benefits of Decoupling, we adopt another baseline called **RealLM** that trains the knowledge generation model directly with paired external knowledge, but uses the $z$ sampled from the model to learn responses. Note that Full and 10len are the upper bounds since they are trained with real knowledge. RealLM is the lower bound of Decoupling, demonstrating the results of training the conversation model with an optimal knowledge generation model.

Because the formulation of Decoupling is somewhat similar to conditional variational autoencoder (CVAE) (Zhao et al., 2017), we take a recent variation, **discrete CVAE (DCVAE)** (Gao et al., 2019), as a baseline. Note that DCVAE is for any underlying variable that in $y$ but not in $x$, while Decoupling is only considering $z \in Z$ that is a causation to $y$. That is, the two methods are independent, and are able to be used together.

### 4.3 Evaluation Metrics

As the basic, we chose the metrics adopted in the dataset papers, i.e., unigram F1 of the predictions and the ground-truths, perplexity (PPL) of the ground-truth responses, and hits@1. The hits@1 is also called Recall@1 (Dinan et al., 2018). The selection is from 100 candidates in WOWs, and 20 candidates in other datasets.

We conduct the evaluation considering the knowledge gap. Specifically, the metrics are drawn as curves with regard to varying amount of external knowledge. The curves show a more comprehensive evaluation of the models, clarifying how effectively the models utilize external knowledge.

### 5 Results

Following the concept of knowledge gap, the performance curves are shown in Figure 3 and 4, where the x-axis is the length of given external knowledge in the inference stage.

**Perplexity.** As shown in Figure 3, most of the curves are monotonically decreasing when given more information for inference, except for the Vanilla method trained on LIGHT. This demonstrates that Vanilla is generally less possible to catch a proper usage of external information. For WOWs, the curves of RealLM are the worst, which indicates the external knowledge is not quite related to the contexts. That is, they have less mutual information, and we are not able to infer some extent of knowledge $\hat{z}$ using contexts $x$. This phenomenon is consistent to the unigram f1 shown in Table 1. Overall, Decoupling always performs better than RealLM. This shows that Decoupling can infer more than the paired knowledge, but finding a way to utilize knowledge more efficiently. Also, for
testing with labels under the length of 10, Decoupling shows closer performance to 10len than other methods. This probably demonstrates that Decoupling can successfully learn how to utilize external knowledge without training with the paired ones. But it is limited with the sampling length of the knowledge generation model.

**Hits@1.** As shown in Figure 4, most of the curves are monotonically increasing along with the length of labels. However, for LIGHT, except for Full, other methods drop after a certain length of labels. Among them Vanilla is the worst. We conjecture that the $\hat{z}$ in LIGHT is noisier when it exceeds certain length, so the usage of $\hat{z}$ becomes more difficult. In addition, the RealLM performs the worst for WOWs. Decoupling also outperforms 10len under length of the 10 except for Persona-Chat. These characteristics are generally consistent with the ones of perplexity.

| Method                          | F1   | Hits@1 | PPL   |
|---------------------------------|------|--------|-------|
| *(Persona-Chat, w/ knowledge)* | 20.83| 76.67  | 16.18 |
| Vanilla                        | 19.89| 62.70  | 19.48 |
| DCVAE                          | 20.30| 62.94  | 18.89 |
| Decoupling                     | 19.90| 66.67  | 18.68 |
| *(LIGHT, w/ knowledge)*        | 18.96| 66.34  | 17.06 |
| Vanilla                        | 18.61| 53.37  | 23.98 |
| DCVAE                          | 18.64| 55.08  | 23.5  |
| Decoupling                     | 18.67| 59.63  | 23.15 |
| *(WOW-seen, w/ knowledge)*     | 35.5 | 92.3   | 23.1  |
| *(Li et al., 2019)*            | 16.2 | -      | 17.8  |
| *(Zhao et al., 2020)*          | 18.5 | -      | 23.0  |
| Full*                          | 32.84| 91.80  | 12.00 |
| Vanilla                        | 20.46| 91.23  | 18.24 |
| DCVAE                          | 20.44| 90.87  | 18.41 |
| Decoupling                     | 20.13| 90.84  | 18.25 |
| *(WOW-unseen, w/ knowledge)*   | 32.2 | 83.1   | 32.8  |
| *(Li et al., 2019)*            | 11.4 | -      | 44.8  |
| *(Zhao et al., 2020)*          | 16.5 | -      | 25.6  |
| Full*                          | 32.59| 85.14  | 13.29 |
| Vanilla                        | 19.79| 78.13  | 22.19 |
| DCVAE                          | 19.60| 78.01  | 22.35 |
| Decoupling                     | 19.54| 76.99  | 22.12 |
| *(DailyDialog, w/o knowledge)*|      |        |       |
| Vanilla                        | 21.96| 78.01  | 11.97 |
| DCVAE                          | 22.02| 77.92  | 11.96 |
| Decoupling                     | 21.66| 76.57  | 12.60 |

Table 2: The results of response generation. The superscript * indicates the method is trained with external knowledge, i.e., it is an upper bound.

**Other comparisons.** The automatic evaluation results are shown in Table 2. According to the re-
if you could do anything in the world what would you do?

Vanilla: I’d go crazy. I’d go so angry.

DCVAE: I am a veteran of a major army.

Decoupling: I would probably write a book about my favorite food.

Input: Yes, fine. I had something wrong with my stomach. I won’t go into detail, but it wasn’t serious.

Vanilla: Oh, I’m sorry to hear that. Is there anything I can do for you?

DCVAE: Really? Did it hurt?

Decoupling: Have you had any tests done on your stomach?

Table 3: Some examples. The first one is from Persona-Chat; the second one is from Dailydialog.

| Data       | LM    | RealLM | Decoupling |
|------------|-------|--------|------------|
| Persona-Chat| 24.85 | 23.51  | 21.88      |
| LIGHT      | 42.56 | 4.22   | 23.61      |
| WOW-seen   | 44.08 | 20.59  | 25.98      |
| WOW-unseen | 46.51 | 46.47  | 43.98      |

Table 4: The perplexity of real paired knowledge on four datasets.

Figure 6: The knowledge gaps of the methods trained on each dataset. The left plot is the gaps of perplexity; the right one is of hits@1.

The results tested with external knowledge, Decoupling significantly facilitates the model to use knowledge description even without training on it on Persona-Chat and LIGHT. With the assistance of Figure 3 and 4, Decoupling also shows its power when tested with insufficient knowledge on those datasets. The defect of Decoupling is displayed on WOWs and Dailydialog. In WOWs, the external knowledge is not able to be observed from the dialogue history (see Table 1); in Dailydialog, the data is not designed with external knowledge, so it intrinsically does not exist. On such data, Decoupling only preserves a similar performance with Vanilla. To conclude, on the automatic evaluation metrics, Decoupling can maintain the generation ability with only dialogue history but strengthen the ability to utilize external knowledge.

6 Discussion

There are a few more aspects worth discussing:

The difference of knowledge gaps between the training and testing phases. Figure 5 plots the variances of Full, 10len, and Vanilla in the training and the testing stages. For both metrics, the variances of the testing phase are always similar to or much higher than the ones in the training phase. Therefore, in a dataset collected with paired knowledge, the significance of testing with the knowledge is equally or even more important than training with it.

The knowledge gaps in the four knowledge-grounded datasets. The knowledge gaps of the datasets are drawn in Figure 6. We can conclude that (1) Full and 10len, models trained with external knowledge, highly depend on it rather than effectively utilize the dialogue history; (2) Vanilla, Decoupling, and RealLM, with the narrower knowledge gaps, can optimize the usage of the dialogue history; and (3) With Table 2, among them Decoupling also enhances the usage of external knowledge while maintaining the usage of dialogue history.

The performance of knowledge generation models. Table 4 lists the perplexity of the real paired knowledge evaluated on the pretrained LM ($P_Z$), the knowledge generation model trained by RealLM, and the knowledge generation model trained by Decoupling. To evaluate RealLM and Decoupling, we first feed the dialogue history ($x$), and then compute the $P_{\theta}(\hat{z}|x)$. The results indicate that the knowledge generation models trained by RealLM and Decoupling can catch the conditional information of knowledge given dialogue history, although they share parameters with the response generation parts.

7 Conclusion

This work analyzes the impact of using external knowledge in training and testing respectively. The results show that the external knowledge introduces a consistent effect in testing. But training with
labels, which traditionally thought to be important, induces the performance to be highly depend on whether tested with external information. The unified Decoupling method shows its potential to bridge the testing gap between having labels or not. It also shows comparable results to upperbound without training with paired labels.

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