Multi-Referenced Training for Dialogue Response Generation

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Abstract
In open-domain dialogue response generation, a dialogue context can be continued with diverse responses, and the dialogue models should capture such one-to-many relations. In this work, we first analyze the training objective of dialogue models from the view of Kullback–Leibler divergence (KLD) and show that the gap between the real world probability distribution and the single-referenced data’s probability distribution prevents the model from learning the one-to-many relations efficiently. Then we explore approaches to multi-referenced training in two aspects. Data-wise, we generate diverse references from a powerful pretrained model to build multi-referenced data that provides a better approximation of the real-world distribution. Model-wise, we propose to equip variational models with an expressive prior, named linear Gaussian model (LGM). Experimental results of automated evaluation and human evaluation show that the methods yield significant improvements over baselines. We will release our code and data in https://github.com/ZHAOTING/dialog-processing.

1 Introduction
One-to-many mapping is an important nature of open-domain dialogue response generation. A dialogue context $X$ can be continued with a set of different responses $\{Y_1, \cdots, Y_i, \cdots\}$. In the training of a response generation model, we expect to model the real probability distribution $P(Y|X)$ with model probability distribution $P_\theta(Y|X)$, where $\theta$ is the model parameters. In most scenarios, however, we can only rely on a data set $D = \{(X^{(j)}, Y_1^{(j)})\}_{j=1}^{[D]}$, where only one valid response is presented. This results in a data

\[
\text{probability distribution } P(Y|X) \text{ that is very different from } P(Y|X). \text{ In fact, } P_\theta(Y|X) \text{ is an one-hot vector where the first element is 1 while others are 0.}
\]

Empirically, we optimize a model to match the model probability distribution and the data probability distribution. From the view of Kullback–Leibler divergence (KLD), we can see it as to minimize $D_{KL}(P_\theta||P_\theta)$:

\[
- \sum_i P_\theta(Y_i|X) \log \frac{P_\theta(Y_i|X)}{P_\theta(Y_i|X)},
\]

which is identical to minimize the following target function after ignoring terms that are not related to the model parameter $\theta$:

\[
L_\theta(X, Y) = - \sum_i P_\theta(Y_i|X) \log P_\theta(Y_i|X) = - \sum_i \mathbb{1}\{i = 1\} \log P_\theta(Y_i|X) = - \log P_\theta(Y_1|X).
\]

The resulting objective is the negative log likelihood (NLL) loss function commonly used in the implementation of dialogue models.

\[
L^*(X, Y) = - \sum_i P(Y_i|X) \log \frac{P_\theta(Y_i|X)}{P_\theta(Y_i|X)},
\]

which is identical to minimize:

\[
L^*(X, Y) = - \sum_i P(Y_i|X) \log P_\theta(Y_i|X).
\]

However, $L^*$ is intractable because 1) there are often an enormous number of valid responses, and 2) we cannot obtain the real probability of a certain response $P(Y_i|X)$.

The gap between $L_\theta$ and $L^*$ is caused by the difference between $P_\theta(Y_i|X)$ and $P(Y_i|X)$, and it prevents dialogue models from learning one-to-many mappings efficiently. To alleviate this
problem, we propose methods to allow for multi-referenced training in two aspects.

1) Data-wise, we replace the original data distribution $P_\theta(Y|X)$ with an approximated real distribution $P_\phi(Y|X)$ by generating up to 100 pseudo references from a teacher model parameterized by $\phi$. We show that using the newly created data yields significant improvement.

2) Model-wise, we argue that a model requires an encoder of large capacity to capture sentence-level diversity, and thus we propose to equip the variational hierarchical recurrent encoder-decoder (VHRED) model with a linear Gaussian model (LGM) prior. The proposed model outperforms VHRED baselines with unimodal Gaussian prior and Gaussian Mixture Model (GMM) prior.

We make a roughly 0.8:0.1:0.1 session-level split for training, validation, and test, respectively.2

2.3 Metrics

Automated Metrics We use perplexity on the test data as the metric for intrinsic evaluation. For extrinsic evaluation, we choose BLEU-2 and three types of word embedding similarities (Embedding Extrema, Embedding Average, Embedding Greedy) to measure the closeness between a hypothesis and the corresponding ground-truth reference. Distinct-$n$ is used to measure the corpus-level diversity of hypotheses.

Dialogue Response Evaluator Besides the automated metrics above, we also use RoBERTa-eval, a model-based dialogue response evaluator, to approximate human judgement (Zhao et al., 2020). RoBERTa-eval computes the appropriateness (a real value from 1 to 5) of a response hypothesis by conditioning on its context instead of by comparing with its reference. It has been shown to correlate with human judgement significantly better than automated metrics. The authors reported Pearson’s $\rho = 0.64$ and Spearman’s $\rho = 0.66$ on the DailyDialog corpus.

Human Evaluation Following Adiwardana et al. (2020), we ask Amazon MTurk human annotators to evaluate each response on two criteria, sensibleness and specificity. Both metrics take binary values, and we use their average (knowns as Sensibleness and Specificity Average, SSA) to assess the overall quality.

3 Data for Multi-Referenced Training

To enhance the training data, we try to close the gap between $P_\theta(Y|X)$ and $P(Y|X)$. Since all probability mass is on a single response in $P_\theta(Y|X)$, the gap can be closed by assigning some mass to other valid responses. We use a finetuned GPT2medium to generate $N$ hypotheses as valid responses, and let the probability mass to be assigned to them uniformly. It results in $P_\phi(Y|X)$ wherein $N$ elements have $\frac{1}{N}$ probability. The new training objective is:

$$\hat{L}^*(X, Y) = -\frac{1}{N} \sum_{i=2}^{N+1} \log P_\theta(Y_i|X),$$

2Please refer to the Appendix for more details about the data set.
| Model        | Data | PPL  | B-2  | Emb. Sim. | Dist-1 | Dist-2 | Reval |
|--------------|------|------|------|-----------|--------|--------|-------|
|              |      |      |      | E         | A      | G      |       |
|              |      |      |      |           |        |        |       |
| HRED         | 1 GT | 29.00| 6.46 | 39.40     | 60.80  | 43.92  | 1914  |
| GPT2_md      | 1 GT | 21.16| 8.67 | 41.02     | 65.17  | 48.44  | 4372  |

Part 1. *HRED baseline and GPT2 teacher models* (§2)

| Part 2. Approximating $P(Y|X)$ with $P_\phi(Y|X)$ (§3.1) |
|----------------------------------------------------------|
| HRED                                                     |
| 1 hyp.                                                   | 35.08 | 6.62  | 39.66 | 61.96 | 44.75 | 2090  | 7369  |
| 5 hyp.                                                   | 23.10 | 7.13  | 40.23 | 62.43 | 45.44 | 1788  | 7267  |
| 20 hyp.                                                  | 21.15 | **7.38** | 40.52 | 62.53 | 45.64 | 1707  | 6945  |
| 100 hyp.                                                 | **20.93** | 7.28  | 40.26 | 62.22 | 45.30 | 1704  | 6794  |

| Part 3. Weighting instance with $P_\phi(Y_i|X)$ (§3.2)    |
|----------------------------------------------------------|
| HRED_wt                                                  |
| 5 hyp.                                                   | 33.34 | 5.81  | 38.56 | 58.67 | 41.19 | 1348  | 4820  |
| 20 hyp.                                                  | 37.84 | 5.55  | 37.67 | 57.12 | 39.84 | 1075  | 3588  |
| 100 hyp.                                                 | 40.87 | 5.48  | 37.38 | 56.73 | 39.49 | 971   | 3064  |

Part 4. *VHRED baseline models* (§4.1)

| VHRED                                                   |
|---------------------------------------------------------|
| 1 GT                                                    | 70.44 (17.36) | 4.96  | 37.61 | 61.41 | 43.69 | 2652  | 13264 |
| 1 hyp.                                                  | 87.48 (22.64) | 5.00  | 37.73 | 61.75 | 43.90 | 2547  | 12839 |
| 5 hyp.                                                  | 50.18 (13.93) | 5.33  | 38.34 | 62.15 | 44.42 | 2217  | 11492 |
| 20 hyp.                                                 | 51.36 (13.09) | 5.43  | 38.72 | 62.58 | 44.64 | 2068  | 10888 |
| 100 hyp.                                                | 56.54 (13.83) | 5.39  | 38.49 | 62.38 | 44.59 | 2229  | 11552 |

| VHRED_gmm5                                              |
|---------------------------------------------------------|
| 1 GT                                                    | 88.02 (20.98) | 4.91  | 37.41 | 61.52 | 43.74 | 2618  | 13058 |
| 1 hyp.                                                  | 88.12 (21.00) | 4.91  | 37.37 | 61.48 | 43.71 | 2624  | 13038 |
| 5 hyp.                                                  | 55.89 (13.78) | 5.39  | 38.32 | 62.28 | 44.62 | 2271  | 11693 |
| 20 hyp.                                                 | 51.41 (12.94) | 5.35  | 38.58 | 62.56 | 44.76 | 2092  | 11047 |
| 100 hyp.                                                | 50.44 (12.90) | 5.44  | 38.77 | 62.55 | 44.79 | 2058  | 10879 |

Part 5. *VHRED with more expressive priors* (§4.2)

| VHRED_gmm5                                             |
|---------------------------------------------------------|
| 1 GT                                                    | 39.97 (16.87) | 6.10  | 40.30 | 64.03 | 45.92 | 1934  | 8789  |
| 1 hyp.                                                  | 50.44 (21.81) | 6.12  | 40.26 | 64.17 | 46.05 | 1989  | 9427  |
| 5 hyp.                                                  | 30.85 (14.04) | 6.61  | 41.31 | 65.31 | 47.19 | 1825  | 8522  |
| 20 hyp.                                                 | 29.74 (12.95) | 6.82  | 41.33 | 65.29 | 47.39 | 1786  | 8395  |
| 100 hyp.                                                | 28.76 (13.02) | 6.79  | 41.31 | 65.18 | 47.19 | 1777  | 8364  |

| VHRED-lgm5                                             |
|---------------------------------------------------------|
| 1 GT                                                    | 46.46 (22.11) | 6.70  | 41.12 | 64.98 | 46.83 | 1907  | 8941  |
| 1 hyp.                                                  | 46.45 (22.14) | 6.65  | 41.10 | 64.95 | 46.77 | 1895  | 8869  |
| 5 hyp.                                                  | 29.18 (13.77) | 6.99  | 41.80 | 65.72 | 47.68 | 1725  | 7757  |
| 20 hyp.                                                 | 26.93 (13.03) | 7.07  | 42.29 | 66.13 | 48.01 | 1604  | 7255  |
| 100 hyp.                                                | 26.40 (**12.77**) | 7.31  | **42.31** | 66.32 | **48.32** | 1677  | 7641  |

Table 1: A summary of experimental results. **GT** – ground truth; **hyp.** – hypotheses; **PPL** – perplexity (For variational models, we show PPLs approximated by zs from prior and posterior distributions as shown before and in brackets.); **B-2** – BLEU-2; **E** – Embedding Extrema; **A** – Embedding Average; **G** – Embedding Greedy; **Dist-n** – Distinct-n; **Reval** – RoBERTa-eval score. Grey background is for distinguishing areas of different models.

where we assume responses $Y_2$ to $Y_{N+1}$ are generated responses.

This can be achieved by directly replacing the ground-truth responses in the training data with the hypotheses. We will refer to the original response as ground truth and the generated responses as hypotheses. A reference can be either a ground-truth response or a hypothesis response.
as either a method of data augmentation or knowledge distillation. We will discuss related works and how our method differs from them in Section 7.

3.1 Experiments: Training with Hypotheses

Sequences generated by beam search often highly overlap both lexically and semantically (Li et al., 2016). Therefore, we use nucleus sampling with top probability 0.95 (Holtzman et al., 2019) to generate 100 hypotheses as for each context in the training data.

In this part, we compare baseline HRED models trained with only ground truth (GT) and with different numbers of hypotheses. Since using $N$ hypotheses makes the training data $N$ times larger, we accordingly adjust the maximum number of training epochs. We found that all the models can converge in the given epochs. 4

As shown in Part 2 of Table 1, replacing 1 GT with 1 hypothesis yields a boost on most metrics. Further increasing the number of hypotheses will continue to improve the model’s performance. It is worth noting that when the number of hypotheses is increased from 20 to 100, the performance gain is limited. This suggests that as training data increases, the model’s expressiveness has become a bottleneck.

3.2 Experiments: Weighting Instance

We previously assumed that the $N$ hypotheses share probability mass uniformly. Another alternative is to use $P_{\theta}(Y_i|X)$ instead of $\frac{1}{N}$ if the teacher model can provide a precise approximation of real probability. It can be seen as an approach of instance weighting. Particularly, we use normalized $P_{\theta}(Y_i|X)$ as instance weights $w_i$:

$$\hat{L}_{wt}^*(X, Y) = -\sum_{i=2}^{N+1} w_i \log P_{\theta}(Y_i|X)$$

$w_i = \frac{P_{\theta}(Y_i|X)}{\sum_{i=2}^{N+1} P_{\theta}(Y_i|X)}$.

We denote an HRED trained with $\hat{L}_{wt}^*$ as HRED$_{wt}$. Part 2 and 3 in Table 1 show that HRED$_{wt}$ performs much worse than its counterpart HRED, and the performance degrades more when it is trained with more hypotheses. We list two reasons that possibly cause the performance degradation. 1) High probability responses have the greatest impact on model optimization, however, our sampling strategy causes us to potentially miss some of the responses with higher probability. 2) The hypotheses’ probabilities vary by orders of magnitude. Thus, many normalized weights tend to be close to zero so that they would not affect the training much.

4 Model for Multi-Referenced Training

4.1 Baseline VHRED

For a given context, the HRED model produces a fixed-length encoding vector $c$ and relies on it to decode various responses. However, the one-to-many mapping in dialogues is often too complex to capture with a single vector $c$. Serban et al. (2017) proposed variational HRED (VHRED) and used a stochastic latent variable $z$ that follows a multivariate Gaussian distribution to strengthen the model’s expressiveness.

$$\mu, \sigma = MLP_{\theta}(c)$$
$$z \sim \text{Gaussian}(\mu, \sigma^2 I)$$
$$P_{\theta}(Y_i|X) = \prod_{l=1}^{L} D_{\theta}(Y_{il}|Y_{i;l-1}, c, z),$$

where $\mu$ and $\sigma^2 I$ are parameters of the Gaussian distribution. In order to mitigate the infamous posterior collapse problem in variational models, we also applied KL divergence (Bowman et al., 2016) and bag-of-words (BoW) loss (Zhao et al., 2017).

Gu et al. (2019) showed that the performance of the vanilla VHRED is limited by the single-modal nature of Gaussian distribution, and thus they proposed to use as prior a Gaussian Mixture Model (GMM) with $K$ components to capture multiple modes in $z$’s probability distribution, such that $z$ is sampled in the following way:

$$\mu_{k}, \sigma_{k}, \pi_{k} = \text{MLP}_{\theta,k}(c)$$
$$z \sim \text{GMM}({\mu_{k}, \sigma_{k}^2 I, \pi_{k}})_{k=1}^{K},$$

where $\pi_k$ is the weight of the $k$-th component. We refer to the VHRED with $K$-component GMM prior as VHRED$_{gmmK}$.

4.2 VHRED with Linear Gaussian Model (LGM) Prior

There are two findings from experimental results of baseline VHREDs in Table 1 part 4. Firstly, using a 5-component GMM prior yields slight improvement over the unimodal Gaussian prior, but the VHREDs still cannot match the performance...
of the HREDs. Secondly, training with more hypotheses also yields performance gain, but the improvement becomes negligible when the number of hypotheses gets large. This confirms our analysis in Section 3.2 that model expressiveness is the bottleneck.

To allow for stronger expressiveness, we propose a linear Gaussian model (LGM) prior. Instead of relying on a single Gaussian latent variable, we exploit $K$ Gaussian latent variables $z_1$ to $z_K$ and use their linear combination to encode a dialogue:  
\[
\begin{align*}
\mu_k, \sigma_k, \pi_k &= \text{MLP}_{\theta,k}(c) \\
\mu_k, \sigma_k^2 I, \pi_k \sim \text{Gaussian}(\mu_k, \sigma_k^2 I) \\
z &= \sum_{k=1}^{K} \pi_k z_k,
\end{align*}
\]
and we refer to the VHRED with $K$-variable LGM prior as VHRED$_{lgmK}$.

This simple approach significantly improves VHRED’s performance according to results in Table 1 part 5. We experimented with $K$ in $\{5, 20, 100\}$, and we can obtain almost consistent improvements with more hypotheses and larger $K$.

Regarding how the interaction between a model’s expressiveness (i.e. $K$) and the amount of hypotheses affects model performance, we notice that:

- When $K$ is small ($K = 5$), we can hardly obtain performance gain by training with more hypotheses (from 20 to 100).

- When we increase $K$ to 20, further performance gain is achievable. It suggests that the performance bottleneck can be widened to allow for learning from more hypotheses.

- When we increase $K$ to 100, the performance gap between VHRED$_{lgm20}$ and VHRED$_{lgm100}$ is very small. It suggests that we may need more hypotheses to exploit the expressiveness of VHRED$_{lgm100}$.

5 Human Evaluation

Besides automated evaluation, we also conduct human evaluation to provide a more accurate assessment of model performance. We sample 100 dialogues randomly from the test data and generate responses using 3 models (HRED, VHRED$_{gmm5}$, VHRED$_{lgm20}$) trained on 2 types of data (the 1-GT data and the 100-hypotheses data). We ask 4 Amazon MTurk human workers to annotate the sensibleness and the specificity of the 600 $(context, response)$ pairs. The collected data reach good inter-rater agreement (Krippendorff’s $\alpha > 0.6$). Then we calculate the average of the two metrics (SSA, Adiwardana et al., 2020) as introduced in Section 2.3. The results of the human evaluation are given in Table 2. First, all three models obtain significant improvements on all three metrics by training on the multi-referenced data, which confirms the effectiveness of replacing $P_D(Y | X)$ with $P_\phi(Y | X)$. Then, VHRED$_{lgm20}$ is better than its GMM counterpart and the HRED. And a larger performance gain is obtained for VHRED$_{lgm20}$ than other models when we train it on the multi-referenced data. The result suggests that an expressive prior is indeed necessary and useful for latent dialogue models, especially in multi-referenced training.

| Model         | Human Scores (in %) |
|---------------|---------------------|
|               | Sensible | Specific | SSA        |
| **Trained on 1-GT data** |          |          |            |
| HRED          | 59.50    | 60.00    | 59.75      |
| VHRED$_{gmm5}$| 38.50    | 56.00    | 47.25      |
| VHRED$_{lgm20}$| 52.50   | 63.50    | 58.00      |
| **Trained on 100-hypotheses data** |          |          |            |
| HRED          | 68.50    | 67.00    | 67.75      |
| VHRED$_{gmm5}$| 44.50    | 66.50    | 55.50      |
| VHRED$_{lgm20}$| 72.50   | 74.00    | 73.25      |

Table 2: Results of human evaluation on 3 models trained on 2 types of data.

6 Analysis

6.1 What do variables in LGM learn?

We combine latent variables linearly in the LGM prior. To investigate how each variable contributes, we train a standard VHRED$_{lgm20}$ on the 100-hypotheses data, but evaluate it by using only 1 variable to generate responses. Besides the metrics introduced above, we calculate the average selection probability $\bar{\pi}_k$ on the test data (as denoted by $\bar{\pi}_k$). Out of the results, we find four obvious patterns regarding their selection probability (avg prob.), perplexity (PPL), and RoBERTa-eval
Table 3: Experimental results of VHRED\textsubscript{\textit{lgm}20} decoding with the $k$-th latent variable. ($\S6.1$)

| $k$ | $\bar{\pi}_k$ | PPL | B-2 Emb. Sim. | Dist-1 | Dist-2 | Reval |
|-----|---------------|-----|--------------|--------|--------|-------|
| 4   | 0.0012        | 4865.8 | 1.77 | 30.70 | 50.97 | 38.04 | 1827 | 20293 | 1.51 |
| 0   | 0.0038        | 112.10 | 5.42 | 37.05 | 60.24 | 45.72 | 1371 | 6791 | 2.73 |
| 8   | 0.0822        | 2740.2 | 6.22 | 39.11 | 64.61 | 48.24 | 1999 | 9891 | 3.74 |
| 1   | 0.3924        | 72.34  | 5.52 | 40.75 | 62.76 | 43.88 | 1096 | 4291 | 3.59 |

Figure 1: Average selection probability, normalized negative test PPL, and normalized Reval. score of VHRED\textsubscript{\textit{lgm}20} decoding with only the $k$-th variable. ($\S6.1$)

In general, selection probability correlates positively with RoBERTa-eval score, while perplexity is less relevant to the other two metrics. This can also be confirmed by the line plot in Figure 1, wherein we draw the probability, normalized negative perplexity, and normalized RoBERTa-eval score of the 20 variables. For variables that have high probabilities and RoBERTa-eval scores (e.g. the 8th and the 1st), there is a performance discrepancy on other metrics, and thus we believe LGM can capture different aspects of responses. For instance, we notice that the 1st variable tends to generate generic and safe responses, while the 8th variable is likely to produce sentences with more diverse word types. A dialogue example is given in Table 4.\textsuperscript{7} More exact interpretation of the variables remains challenging, and we leave this to future work.

### 6.2 Combining Ground Truth and Hypotheses

One issue that readers may be concerned about is whether it is better to combine ground truth with hypotheses than to use them separately. We take the VHRED\textsubscript{\textit{lgm}20} as an example and conduct experiments using mixed training data. As shown in Table 5, we can get performance gain by training

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\textsuperscript{6}The full results can be found in the Appendix.

\textsuperscript{7}More examples can be found in the Appendix.
with mixed data. The improvement is larger when the original data is smaller (1 hypothesis) because it doubles the training data. When using 100 hypotheses, we can almost fully rely on the generated data and discard ground truth.

6.3 Previous Works on One-to-many Model

Prior to this work, there are a few works that focus on handling one-to-many relation in dialogues.

Mechanism-Aware Model Zhou et al. (2017) incorporated mechanism embeddings \( m \) into a seq2seq model for dialogue response generation. The mechanism-aware model decodes a response by selecting a mechanism embedding \( m_k \) and combining it with context encoding \( c \). Therefore, the model is capable of generating diverse responses by choosing different mechanisms. We implement an HRED with mechanism embeddings and refer to it as \( \text{MHRED} \).

Conditional Value-at-Risk Model Zhang et al. (2018) borrowed the conditional value-at-risk (CVaR) from finance as an alternative to sentence likelihood (which is negated \( L_D \)) for optimization. Optimizing the CVaR objective can be seen as rejecting to optimize on easy instances whose model probabilities are larger than a threshold \( \alpha \). We refer to an HRED trained with CVaR loss as \( \text{HRED}_{\text{CVaR}} \).

Two-Step VHRED Qiu et al. (2019) proposed a two-step VHRED variant for modeling one-to-many relation. In the first step, they forced the dialogue encoding vector \( c \) to store common features of all response hypotheses \( Y_{2:N+1} \) by adversarial training. In the second step, they trained the latent variable \( z \) to capture response-specific information by training with a multiple bag-of-words (MBoW) loss. In our implementation, we omit the first step because 1) we found the implementation details in the paper insufficient for building a full model, and 2) the reported result of a second-step-only model is not significantly different from a full model. We refer to the implemented model as \( \text{VHRED}_{\text{MBoW}} \).

We compare the three models with a baseline HRED and the proposed \( \text{VHRED}_{\text{MBoW}} \) in the 100-hypotheses setting. As shown in Table 6, \( \text{VHRED}_{\text{MBoW}} \) achieves the best overall performance.

7 Related Works

7.1 Knowledge Distillation

Approximating \( P(Y \mid X) \) with \( P_\phi(Y \mid X) \) is achieved by replacing ground-truth references with hypotheses generated from a teacher model. This implementation is highly related to the sequence-level knowledge distillation method proposed by Kim and Rush (2016). In the context of machine translation, Kim and Rush (2016) proposed that a teacher model’s knowledge can be transferred to a student model on sequence level. They showed that transferring sequence knowledge is roughly equal to training on sequences generated by the teacher model. Here we emphasize two points that distinguish our work from theirs:

- Firstly, the proposed multi-referenced training is based on the analysis of the flawed training objective used in dialogue response generation while Kim and Rush (2016)’s method is based on the idea of knowledge transfer. Thus, the motivation is different.
- Secondly, dialogue and machine translation are tasks that have different characteristics. Given the same input, outputs in dialogues (i.e. responses) can vary significantly in semantic and lexical spaces, while outputs in machine translation (i.e. target-language sentences) are often semantically and lexically similar to each other, because response generation is often open-ended, and machine translation is highly constrained by its input. Such difference leads to the necessity of exploiting a large number of response hypotheses in dialogue response generation from either the view of providing an accurate approximation of \( P(Y \mid X) \) or transferring sufficient knowledge from the teacher model, while Kim and Rush (2016) exploited only one hypothesis. Thus, the implementation is and should be different.

In other tasks, Peng et al. (2019) proposed to transfer knowledge from multiple teachers for multi-domain task-oriented dialogue generation via policy distillation and word-level output distillation. Tan et al. (2019) applied a similar approach to multilingual machine translation. Kuncoro et al. (2019) transferred syntactic knowledge from recurrent neural network grammar (RNNG, Dyer et al., 2016) models to a sequential language model.
Table 5: Experimental results of combining ground truth and hypotheses. (§ 6.2)

| Use GT | PPL | B-2 | Emb. Sim. | Dist-1 | Dist-2 | Reval |
|--------|-----|-----|-----------|--------|--------|-------|
| ✓      | 46.45 (22.14) | 6.65 | 41.10 64.95 | 46.77 1895 | 8869 | 3.64   |
| √      | 30.12 (14.27) | 6.70 | 41.48 65.01 | 46.91 1729 | 7677 | 3.71   |
| ✓      | 29.18 (13.77) | 6.99 | 41.80 65.72 | 47.68 1725 | 7757 | 3.82   |
| √      | 27.31 (13.08) | 7.26 | 42.21 66.33 | 48.32 1648 | 7423 | 3.83   |
| ✓      | 26.93 (13.03) | 7.07 | 42.29 66.13 | 48.01 1604 | 7025 | 3.86   |
| √      | 26.46 (12.80) | 7.25 | 42.00 65.81 | 47.71 1612 | 7180 | 3.88   |
| ✓      | 26.40 (12.77) | 7.31 | 42.31 66.32 | 48.32 1677 | 7641 | 3.91   |
| √      | 26.49 (12.82) | 7.23 | 42.28 65.83 | 47.60 1562 | 6884 | 3.88   |

Table 6: Comparison with models from previous works in the 100-hypotheses setting. (§ 6.3)

| Model        | PPL | B-2 | Emb. Sim. | Dist-1 | Dist-2 | Reval |
|--------------|-----|-----|-----------|--------|--------|-------|
|              |     |     | E         | A      | G      |       |
| Ours         |     |     |           |        |        |       |
| HRED         | 20.93 | 7.28 | 40.26     | 62.22  | 45.30  | 1704  | 6794  | 3.89  |
| VHRED_20     | 26.40 (12.77) | 7.31 | 42.31     | 66.32  | 48.32  | 1677  | 7641  | 3.91  |

| Previous Works | PPL | B-2 | Emb. Sim. | Dist-1 | Dist-2 | Reval |
|----------------|-----|-----|-----------|--------|--------|-------|
| MHRED          | 24.27 | 6.59 | 39.65     | 61.64  | 44.79  | 1829  | 7729  | 3.80  |
| HRED_CVaR      | 20.92 | 7.32 | 40.49     | 62.43  | 45.53  | 1738  | 6908  | 3.88  |
| VHRED_MBoW     | 51.74 (11.82) | 5.68 | 38.71     | 62.81  | 45.07  | 2334  | 12116 | 3.41  |

7.2 Data Augmentation and Manipulation

The multi-referenced training approach can also be seen as a data augmentation method. Prior works on data augmentation in text generation tasks often operate on word level while ours performs sentence-level augmentation. Niu and Bansal (2019) proposed to apply semantic-preserving perturbations to input words for augmenting data in dialogue tasks. Zheng et al. (2018) investigated multi-referenced training in machine translation and proposed to generate pseudo references by compressing existing multiple references into a lattice and picking new sequences from it. Hu et al. (2019) used finetuned BERT (Devlin et al., 2019) as the data manipulation model to generate word substitutions via reinforcement learning.

Another line of research focuses on filtering high-quality training examples for dialogue response generation. Csáky et al. (2019) proposed to remove generic responses using an entropy-based approach. Shang et al. (2018) trained a data calibration network to assign higher instance weight to more appropriate responses.

7.3 Expressive Dialogue Models

We have discussed the mechanism-aware model (Zhou et al., 2017), the conditional cost-at-value method (Zhang et al., 2018), and the two-step variational model (Qiu et al., 2019) in Section 6.3, besides which there are other one-to-many models. Gao et al. (2019) relied on vocabulary prediction to model sentence-level discrepancy. Chen et al. (2019) utilized a mechanism-based architecture and proposed a posterior mapping method to select the most proper mechanism. Gu et al. (2019) proposed to train latent dialogue models in the framework of generative adversarial network (GAN). They optimized the model by minimizing the distance between its prior distribution and its posterior distribution via adversarial training.

8 Conclusion

In this work, we analyzed the training objective of dialogue response generation models from the view of distribution distance as measured by Kull-
back–Leibler divergence. The analysis showed that single-referenced dialogue data cannot characterize the one-to-many feature of open-domain dialogues and that multi-referenced training is necessary. Towards multi-referenced training, we first proposed to replace every single reference with multiple hypotheses generated from a finetuned GPT2, which provided us with a better approximation of the real data distribution. Secondly, we proposed to equip variational dialogue models with an expressive prior, named linear Gaussian model (LGM), to capture the one-to-many relations. The automated and human evaluation confirmed the effectiveness of the proposed methods.

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We show the number of sessions and...
C Experimental Settings

C.1 Model Implementation

For HRED and VHRED models, we implement encoders and decoders with gated recurrent unit (GRU) networks. Sentence-level encoders are bidirectional, while dialogue-level encoders and decoders are unidirectional. All the GRU networks have 1 layer and 500 hidden units. We use 30-dimensional floor embeddings to encode the switch of floor. For VHREDS, latent variables have 200 dimensions. Prior and posterior networks are implemented by feedforward networks with hyperbolic tangent activation function. While priors have different forms (unimodal Gaussian, Gaussian mixture model, and linear Gaussian model), we use unimodal Gaussian for all the posteriors. We use attentional mechanism for all decoders. In Table 8, we show the number of model parameters and training time per epoch on the 1 ground-truth data using a single NVIDIA TITAN RTX card. When training on K-hypotheses data, the training time per epoch is roughly K times of the reported number.

C.2 Training Details

We optimize all the models with the Adam method (Kingma and Ba, 2015). The initial learning rate is 0.001 and gradients are clipped within [-1.0, 1.0]. We decay the learning rate with decay rate 0.75 and patience 3. The training process is early stopped when the learning rate is less than $1 \times 10^{-7}$. The numbers of training epochs and steps are shown in Table 10. Batch size is 30 during training. We use up to 5 history utterances as context, and all utterances are truncated to have 40 tokens to most. We set dropout probability as 0.2 and shuffle training data every epoch for better generalization. VHREDS are optimized by maximizing their variational lower bound (Sohn et al., 2015). We apply linear KL annealing in the first 40,000 training steps.

For finetuning the GPT2 model, we use a smaller batch size of 10 to fit the model into memory. As with other hyperparameters such as learning rate and weight regularization factor, we follow the settings used by Wolf et al. (2019). And the GPT2 is finetuned on the 1-GT data for only 2 epochs.

| Item | Krippendorff’s $\alpha$ |
|------|--------------------------|
| Sensibleness | 0.76 |
| Specificity | 0.60 |

Table 7: Inter-rater agreement of human annotations. (§ B)

| Model | # Parameters | Trn. Time |
|-------|--------------|-----------|
| HRED | 8.04 M | $\sim$150 s |
| VHRED | 11.02 M | $\sim$160 s |
| VHRED$_{gmm5}$ | 11.36 M | $\sim$160 s |
| VHRED$_{lgm5}$ | 11.36 M | $\sim$160 s |
| VHRED$_{lgm20}$ | 12.52 M | $\sim$160 s |
| VHRED$_{lgm100}$ | 18.67 M | $\sim$160 s |
| GPT2$_{md}$ | 338.39 M | $\sim$3000 s |

Table 8: Number of parameters and training time per epoch for each model. (§ C.1)

| Item | Statistics |
|------|------------|
| | Train | Validation | Test |
| sessions | 9237 | 1157 | 1159 |
| ($ctx, resp$) pairs | 59305 | 9906 | 9716 |

Table 9: Corpus statistics. (§ A)

| Training Data | Max Epochs | Max Steps |
|---------------|------------|-----------|
| 1 GT | 100 | 5.93M |
| 1 hyp. | 100 | 5.93M |
| 1 GT + 1 hyp. | 50 | 5.93M |
| 5 hyp. | 20 | 5.93M |
| 1 GT + 5 hyp. | 20 | 7.12M |
| 20 hyp. | 10 | 11.86M |
| 1 GT + 20 hyp. | 10 | 12.45M |
| 100 hyp. | 2 | 11.86M |
| 1 GT + 100 hyp. | 2 | 11.98M |

Table 10: Maximum training epochs and steps in different data settings. (§ C.2)

D Extra Results

In Table 11, we presented the full results of experiments in Section 6.1.

E Extra Samples

We show three more dialogue samples in Table 12, 13, and 14. Notice that we have collapsed some spaces between the letters and the punctuation marks for easy reading.
Table 11: Experimental results of VHRED$_{lgm20}$ decoding with the $k$-th latent variable.

| $k$ | avg prob. | PPL  | B-2 | Emb. Sim. | Dist-1 | Dist-2 | Reval |
|-----|-----------|------|-----|-----------|--------|--------|-------|
|     |           |      |     | E         |        |        |       |
|     |           |      |     | A         |        |        |       |
|     |           |      |     | G         |        |        |       |
| mix | 100.00 | 26.40 | 7.31 | 42.31 | 66.32 | 48.32 | 1677 | 7641 | 3.91 |
|     |         |      |     |           |        |        |       |
|     |         |      |     |           |        |        |       |
|     |         |      |     |           |        |        |       |
|     |         |      |     |           |        |        |       |
|     |         |      |     |           |        |        |       |
|     |         |      |     |           |        |        |       |
|     |         |      |     |           |        |        |       |
|     |         |      |     |           |        |        |       |
|     |         |      |     |           |        |        |       |

VHRED$_{lgm20}$ using all variables

VHRED$_{lgm20}$ using the $k$-th variable
Dialogue #100

| Floor | Context Utterance |
|-------|------------------|
| A     | *i have never shopped there, but i think price club is a kind of membership store.* |
| B     | *what does that mean?* |
| A     | *that means you have to pay a membership fee to shop there. i have heard they have very good prices on electronics.* |
| B     | *electronics?* |
| A     | *yes. like stereos and [UNK].* |
| B     | *[TO BE PREDICTED]* |

| Model            | Trn. Data | Response Utterance |
|------------------|-----------|--------------------|
| Ground truth     | -         | *how much is the membership fee?* |
| HRED             | 1 GT      | *do you have any other advantages?* |
| VHRED$_{gmm5}$   | 1 GT      | *how do you want to buy?* |
| VHRED$_{lgm20}$  | 1 GT      | *so what? i don’t have a current account.* |
| HRED             | 100 hyp.  | *i see. i’ll buy a new one.* |
| VHRED$_{gmm5}$   | 100 hyp.  | *that’s a good idea. how about the one?* |
| VHRED$_{lgm20}$  | 100 hyp.  | *i see. is there a warranty?* |
| - the 4th variable | 100 hyp. | *sure. which service do you use?* |
| - the 0th variable | 100 hyp. | *how much money can you get it?* |
| - the 8th variable | 100 hyp. | *i have a membership card. it’s very expensive.* |
| - the 1st variable | 100 hyp. | *i see. it’s a good deal.* |

Table 12: More samples on the test data. (§E)
# Dialogue #500

| Floor | Context Utterance |
|-------|-------------------|
| A     | *i am not sleepy.* |
| B     | *it’s getting late, and you have to wake up early tomorrow.* |
| A     | *there is no way that i can fall asleep right now.* |
| B     | *try listening to some soft music.* |
| A     | *it won’t work. i’m nowhere close to being tired.* |
| B     | *[TO BE PREDICTED]* |

| Model         | Trn. Data | Response Utterance |
|---------------|-----------|--------------------|
| Ground truth  | -         | *i really don’t care, just go to sleep.* |
| HRED          | 1 GT      | *you’re too tired.* |
| VHRED<sub>gmm5</sub> | 1 GT | *what’s up?* |
| VHRED<sub>lgm20</sub> | 1 GT | *you shouldn’t have to sleep.* |
| HRED          | 100 hyp.  | *don’t worry. i’ll get you up.* |
| VHRED<sub>gmm5</sub> | 100 hyp. | *i don’t know. i just want to relax.* |
| VHRED<sub>lgm20</sub> | 100 hyp. | *you should be tired. you can get a good sleep.* |
| - the 4th variable | 100 hyp. | *do do let you gift you gift you gift you live you live here i sing for here friendship akimbo?* |
| - the 0th variable | 100 hyp. | *don’t be at the evening.* |
| - the 8th variable | 100 hyp. | *you are always sleepy.* |
| - the 1st variable | 100 hyp. | *come on. you can get a good sleep.* |

Table 13: More samples on the test data. (§E)
Dialogue #2500

Floor Context Utterance

A the style of the exterior is just what i’ve been looking for!
B the exterior is only half of the story. the interior is incredible.
A this home is gorgeous on the inside!
B everything that you see on the walls, floors, and windows is brand new.
A the wall colors totally suit the style of this house.
B [TO BE PREDICTED]

| Model                  | Trn. Data  | Response Utterance                                      |
|------------------------|------------|----------------------------------------------------------|
| Ground truth           | -          | straight ahead is the [UNK] kitchen.                     |
| HRED                   | 1 GT       | i think it’s a good idea.                               |
| VHRED$_{gmm5}$         | 1 GT       | it’s [UNK]! the carpet is behind the curtain.           |
| VHRED$_{lgn20}$        | 1 GT       | you can have a look at the kitchen.                     |
| HRED                   | 100 hyp.   | i’m glad you like it.                                   |
| VHRED$_{gmm5}$         | 100 hyp.   | this one is the latest design.                          |
| VHRED$_{lgn20}$        | 100 hyp.   | the color is perfect. i can see it.                     |
| - the 4th variable     | 100 hyp.   | any any all in all all all any part part of mind?       |
| - the 0th variable     | 100 hyp.   | the kitchen is very nice. i think the color is perfect. |
| - the 8th variable     | 100 hyp.   | look, the walls are beautiful.                          |
| - the 1st variable     | 100 hyp.   | i know. it’s a good idea.                               |

Table 14: More samples on the test data. (§E)