Diversifying Dialog Generation via Adaptive Label Smoothing

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Abstract

Neural dialogue generation models trained with the one-hot target distribution suffer from the over-confidence issue, which leads to poor generation diversity as widely reported in the literature. Although existing approaches such as label smoothing can alleviate this issue, they fail to adapt to diverse dialog contexts. In this paper, we propose an Adaptive Label Smoothing (AdaLabel) approach that can adaptively estimate a target label distribution at each time step for different contexts. The maximum probability in the predicted distribution is used to modify the soft target distribution produced by a novel light-weight bi-directional decoder module. The resulting target distribution is aware of both previous and future contexts and is adjusted to avoid over-training the dialogue model. Our model can be trained in an end-to-end manner. Extensive experiments on two benchmark datasets show that our approach outperforms various competitive baselines in producing diverse responses.

1 Introduction

The success of neural models has greatly advanced the research of dialog generation (Huang et al., 2020; Wang et al., 2020; Zhang et al., 2020). However, most of these models suffer from a low-diversity issue where models tend to generate bland and generic responses such as I don’t know or I’m OK (Li et al., 2016). Although various approaches have been proposed to tackle this issue (Li et al., 2016; Zhao et al., 2017; Du et al., 2018; Zhou et al., 2018; Welleck et al., 2020; Zheng et al., 2020b), there are still remarkable gaps between responses generated by neural models and those from humans (Holtzman et al., 2020). Further, some existing methods may even harm the fluency or coherence when improving the diversity of generated responses. (Ippolito et al., 2019; Massarelli et al., 2020; Zheng et al., 2020a).

Recently, Jiang and de Rijke (2018); Jiang et al. (2019) show that there is a strong connection between the low-diversity problem and the over-confidence issue. i.e., over-confident dialogue models tend to produce low-diversity responses. One of the reasons can be attributed to the supervision target. Specifically, training a dialogue generation model with the Maximum Likelihood Estimation (MLE) objective under the hard target (i.e., one-hot distribution as ground truth) makes the model favor high-frequency tokens and produce over-confident probability estimation (Gowda and May, 2020), which ultimately leads to poor calibration (Mukhoti et al., 2020), and thus low diversity (Jiang et al., 2019). Hinton et al. (2015) and Yang et al. (2018) suggest that the ideal training target should be a soft target that assigns probability mass on multiple valid candidates (see Figure 1). With such a soft target, the over-confidence issue can be alleviated (Müller et al., 2019), and thus the diversity of the output responses can be improved.

Unfortunately, the ideal soft target is challenging to obtain. Early works try to tackle this issue...
using label smoothing (Szegedy et al., 2016), i.e., a small probability is uniformly assigned to non-target words. However, the target distribution constructed in this way is far from ideal: First, the probability of the target word is chosen manually and fixed, which cannot adapt to different contexts. However, as Holtzman et al. (2020) demonstrated, human text distribution exhibits remarkable fluctuations in the per-token perplexity. We argue that different target probabilities should be used for different contexts. Second, the uniform assignment of the probability mass on non-target words ignores the semantic relationship between the context and each word. Ideally, a word should receive more probability mass if it is more relevant to the context. For the example shown in Figure 1, word “fun” is more likely to appear behind the context “I make the robots seem more.” than word “bank”.

To address the above issue, we propose an Adaptive Label smoothing (AdaLabel) method that can dynamically estimate a soft target distribution at each time step for different contexts. Specifically, for each target word $y_t$ in the training data, the probability distribution predicted by the current model is first obtained. The maximum probability $p_{\text{max}}$ in this distribution measures the confidence of the current prediction, i.e., a higher $p_{\text{max}}$ means higher confidence for the current prediction. To avoid over-confidence, we use $p_{\text{max}}$ as the supervision signal for the target word $y_t$ in the training process so that the model will not be optimized towards $y_t$ when it correctly predicts $y_t$. A word-level factor is also introduced to facilitate the learning of low-frequency words.

Moreover, we introduce a novel auxiliary decoder module $D_a$ to produce the supervision signals for these non-target words in each training step. $D_a$ only contains one transformer block, and it is optimized to predict words based on bi-directional contexts. A novel Target-Mask attention scheme is devised to prevent $D_a$ from seeing the target word in the training process. This scheme also enables parallel training and inference of $D_a$.

We perform extensive experiments on two benchmark datasets: DailyDialog and OpenSubtitles. Our method outperforms various competitive baselines and significantly improves the diversity of generated responses while ensuring fluency and coherency. Our major contributions are summarized:

1. We propose AdaLabel, a method that can produce a soft target distribution considering the current context and the model’s confidence. Specifically, AdaLabel ensures that the dialogue model will not be optimized toward the target word $y_t$ if $y_t$ has been correctly predicted. This prevents our model from being over-confident.

2. We introduce a light-weight bi-directional decoder that can produce context-aware supervision signals for non-target words. A novel Target-Mask attention scheme is devised to facilitate the parallel training and inference of this decoder.

3. Extensive experiments on two benchmark dialogue datasets with both automatic and human evaluation results show that our method helps to alleviate the model over-confident issue and significantly improves the model’s diversity.

2 Related work

Diversity Promotion: Existing approaches for solving the low diversity issue of neural dialogue models generally involve two categories:

The first category is training-based, where new training objectives are designed (Li et al., 2016; Zhang et al., 2018; Gao et al., 2019) or latent variables are introduced (Zhao et al., 2017; Zhou et al., 2018) in the dialogue model. Some methods also try to refine the training target used in the MLE loss (Choi et al., 2020; Jiang et al., 2019; Li et al., 2019), or directly penalize the trivial responses with auxiliary loss terms (Welleck et al., 2020; Li et al., 2020). Unlike these existing approaches, our method tries to adaptively adjust the training target by utilizing the current predictions.

The second category is decoding-based, in which different heuristic decoding rules are designed (Holtzman et al., 2020; Kulikov et al., 2019). Note that these decoding techniques are independent of the model setting, and our method can be used in combination with these techniques.

Confidence Calibration: Modern deep neural networks suffer from the over-confidence issue (Guo et al., 2017; Kumar and Sarawagi, 2019), and various remedies are proposed (Pereyra et al., 2017; Mukhoti et al., 2020; Lin et al., 2017). Following the work of Jiang and de Rijke (2018); Jiang et al. (2019), our method is proposed to tackle the over-confidence issue to improve the diversity of the generated responses. However, different from existing approaches, our method enables more flexible controls over the target distribution.

Knowledge Distillation: Another important technique similar to our work is knowledge distilla-
The most related work comparing to ours is the C-MLM approach (Chen et al., 2020), in which a BERT model is fine-tuned to be a teacher. Our approach and C-MLM’s primary difference is that our auxiliary decoder $D_a$ is a one layer module that is jointly trained with the dialogue model. However, the BERT teacher in C-MLM contains much more parameters, and it is trained using an expensive pre-trained and then fine-tuned process. Moreover, the target-masked attention scheme in $D_a$ enables parallel inferences of $v$ for each training sequence $Y$. In contrast, multiple independent forward passes are required for the BERT teacher.  

3 Method  

3.1 Background: MLE with Hard Target  

The goal of generative dialogue modeling is to learn a conditional probability distribution $p(Y|X)$, where $X$ is the dialogue context, $Y = y_1, \ldots, y_T$ is a response word sequence, and $y_t \in V$ is a word from the vocabulary $V$. In an auto-regressive manner, $p(Y|X)$ is factorized as $\prod_t p(y_t|y_{<t}, X)$. For each target word $y_t$ in the training sequence $Y$, a conventional MLE training approach tries to optimize the following cross entropy loss:

$$L(q, p) = - \sum_{w_k \in V} q_k \log [p(w_k|y_{<t}, X)], \quad (1)$$

where $q$ is a one-hot distribution (i.e., a hard target) that assigns a probability of 1 for the target word $y_t$ and 0 otherwise, i.e., $q_k = 1$ only when $w_k = y_t$. For simplicity of notation, we abbreviate the dependency of $y_t$ in the notation of each distribution in our paper, i.e., different target word $y_t$ in $Y$ corresponds to different values of $q$ and $p$.

3.2 Method Overview  

We propose to adaptively construct a soft target distribution $q'$ to replace $q$ in Eq. 1. Specifically,

$$q' = \varepsilon \cdot q + (1 - \varepsilon) \cdot v, \quad (2)$$

where $\varepsilon \in [0, 1]$ is an adaption factor, and $v$ is an auxiliary distribution vector that depends on the current time step. (see Figure 2 for an overview).

In this study, we constrain $v$ to assign zero probability for the target word $y_t$ and non-zero probabilities for these non-target words $V \neq y_t = \{y_i | y_i \in V, y_i \neq y_t\}$. This constraint allows us to explicitly control the supervisions assigned to $y_t$. Specifically, the first term $\varepsilon \cdot q$ and the second term $(1 - \varepsilon) \cdot v$ in Eq. 2 respectively determines how much probability $q'$ assigns to $y_t$ and $V \neq y_t$. This setting differs from conventional knowledge distillation (Kim and Rush, 2016) because it facilitates more flexible controls over $q'$, so that we can use the factor $\varepsilon$ to determine the supervision signal provided for the target word $y_t$. The following sections detail how to compute $\varepsilon$ and $v$.

3.3 Target Word Probability  

We control the probability of the target word $y_t$ in $p'$ by manipulating the adaption factor $\varepsilon$ in Eq. 2. Specifically, for a training dialogue pair $(X, Y)$ and each target word $y_t \in Y$, the current distribution $p'(y_t|y_{<t}, X)$ is first calculated, and the maximum probability in this distribution is obtained:

$$p_{\text{max}} = \max_{w_k \in V} p(w_k|y_{<t}, X). \quad (3)$$
\( \varepsilon \) is then obtained:
\[
\varepsilon = \max(p_{\text{max}}, \lambda), \tag{4}
\]
where \( \lambda \) serves as a lower-bound of \( \varepsilon \) (i.e., \( \varepsilon \geq \lambda \)). The basic intuition behind Eq. 4 is to set \( \varepsilon = p_{\text{max}} \) when \( p_{\text{max}} \) is reasonably large. This design prevents our model from receiving supervisions sharper than \( p_{\text{max}} \), when the current prediction is confidence enough.

Further, to ensure that the target word \( y_t \) always receives the largest probability in \( q' \), i.e., to ensure \( \varepsilon > (1 - \varepsilon) \cdot \max(v) \) (see Eq. 2), in which \( \max(v) \) is the maximum probabilities for non-target words \( \mathcal{V}_{\neq y_t} \), we have to enforce \( \varepsilon > \frac{\max(v)}{1 + \max(v)} \). Thus we propose to calculate the lower-bound \( \lambda \) of \( \varepsilon \) as:
\[
\lambda = \frac{\max(v)}{1 + \max(v)} + \eta, \tag{5}
\]
where \( \eta > 0 \) is a hyper-parameter that controls the margin between the probability of the target word and non-target words in \( p' \).

To facilitate faster converge and better learning of low-probability words, an empirical factor \( \alpha \in [0, 1] \) is further introduced to adjust the calculation of \( \varepsilon \) on the basis of Eq. 4:
\[
\varepsilon = 1 - \alpha \cdot (1 - \max(p_{\text{max}}, \lambda)), \tag{6}
\]
where \( \alpha \) is calculated as the relative ratio to \( p_{\text{max}} \):
\[
\alpha = \left( \frac{p(y_t|y_{<t}, X)}{p_{\text{max}}} \right)^2, \tag{7}
\]
where \( p(y_t|y_{<t}, X) \) is the probability for the target word \( y_t \). Note that Eq. 6 and Eq. 4 is equivalent if \( \alpha = 1 \). Intuitively, \( \alpha \) accelerates the training of low-frequency words because if \( y_t \) is of low-frequency in the corpus, then \( y_t \) is usually under-trained and thus \( p(y_t|y_{<t}, X) \) is generally small. This leads to a small \( \alpha \) and thus increases the probability for \( y_t \) in \( p' \).

Note that, \( \varepsilon \), \( \lambda \) and \( \alpha \) are all time-step specific variables, whereas \( \eta \) is a fixed hyper-parameter. This allows the values adapt to dynamic contexts. In our experiments, Eq. 6 is used to calculate \( \varepsilon \).

### 3.4 Non-target Words Probabilities

The auxiliary distribution \( v \) in Eq. 2 is calculated using an auxiliary decoder \( D_a \), which is a single-layer transformer-based decoder that is jointly optimized with the generation model. Figure 3 shows the structure of \( D_a \), in which a novel target-masked attention scheme is devised to mask each target word \( y_t \) in the self attention module of the decoder when calculating the corresponding \( v \) (see Figure 3b and 3c). In this way, bi-directional contexts can be utilized when predicting the auxiliary distribution \( v \) for \( y_t \). Moreover, it is important to use only one decoder layer in \( D_a \) because stacking multiple layers in \( D_a \) leaks the information of \( y_t \) to \( v \).

Note that using one layer in \( D_a \) does not necessarily downgrade its performance (Kasai et al., 2021). Our experiment results in Section 5.1 indicate that with the help of bi-directional contexts, the accuracy of \( D_a \) largely outperforms the unidirectional dialogue decoder that is much deeper than \( D_a \). Moreover, for a training response \( Y \), the structure of \( D_a \) enables us infer the auxiliary distribution in parallel for all the target words in \( Y \) within a single forward pass. This differs from the BERT teacher used by Chen et al. (2020), in which multiple independent forward passes are needed to get the teacher distributions for all the words in \( Y \).

When training \( D_a \), the following standard MLE loss is optimized for each target word \( y_t \):
\[
\mathcal{L}(q, v) = -\sum_{k=1}^{\left|\mathcal{V}\right|} q_k \log v_k, \tag{8}
\]
in which the notation of \( q_k \) follows Eq. 1.

The outputs of \( D_a \) are used as the logits to infer \( v \) to be further used in Eq. 2. Specifically, the logit of the target word \( y_t \) is masked to \(-\infty \) before Softmax to ensure \( y_t \) always receives zero probability in \( v \). Moreover, we also follow the approach used by Tang et al. (2020) to truncate the head and tail of the remaining logits before inferring \( v \) in Eq.
We use two benchmark datasets for open-domain dialogue generation: DailyDialog (Li et al., 2017) is a high-quality multi-turn dialogue dataset that is collected from daily conversations. OpenSubtitles 1 contains dialogues collected from movie subtitles. Moreover, we follow Li et al. (2016) and Jiang et al. (2019) to focus on short conversations, i.e., dialogues with posts or responses longer than 100 tokens are removed. See Table 1 for more details.

### 4.2 Implementation Details

The backbone of our model is the transformer-based sequence to sequence model (Vaswani et al., 2017), and most hyper-parameters follow Cai et al. (2020). Specifically, the encoder and decoder each contains 6 layers. Each layer has 8 attention heads, and the hidden size is set to 512. The auxiliary decoder \( D_a \) follows the same hyper-parameter setting as the dialogue decoder, but it only contains one layer. The WordPiece tokenizer provided by BERT (Devlin et al., 2019) is used, and the Adam optimizer (Kingma and Ba, 2015) is employed to train our model from random initializations with a learning rate of 1e-4. \( \eta \) in Eq. 5 is set to 0.2 for all datasets. See Appendix A for more details.

### 4.3 Baselines

We compared our method with two groups of baselines that try to tackle the over-confidence issue.

The first group modifies the training target used to compute the loss function: 1) LS (Szegedy et al., 2016): uses the label smoothing approach to construct a target distribution by adding the one-hot target and a uniform distribution; 2) FL (Lin et al., 2017): uses the focal loss to down-weigh well-classified tokens in each time step. 3) FACE (Jiang et al., 2019): uses the frequency-aware cross-entropy loss to balance per-token training losses. Specifically, relative low losses are assigned to high-frequency words to explicitly tackle the over-confidence issue. We used the best performing “Pre-weigh” version in our experiments. 4) \( F^2 \) (Choi et al., 2020): factorizes the target distribution based on the token frequencies.

The second group of baselines add some penalty term to the standard MLE loss: 5) CP (Pereyra et al., 2017): a confidence penalty term is added to regularize the entropy of the model, so that over-confident predictions are penalized; 6) UL (Welleck et al., 2020): an unlikelihood loss term is added to penalize the frequently generated words. 7) NL (He and Glass, 2020): works similarly with baseline UL except a negative loss term is used instead of the unlikelihood loss term. 8) D2GPo (Li et al., 2016): uses the log likelihood loss to down-weigh well-classified tokens in each time step. 9) CE: a vanilla Seq2Seq model trained with the cross-entropy loss. For fair comparisons, the C-MLM model proposed by Chen et al. (2020) is not used as our baseline since the BERT teacher in C-MLM requires a large amount of extra data to pre-train. Nevertheless, AdaLabel still surpasses C-MLM on various metrics (see Appendix F for more analysis).

All our baselines are adapted from the authors’ official codes with the same backbone architecture and hyper-parameters as our model (see details in Appendix B). Following the original setting, a train-

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1http://opus.nlpl.eu/OpenSubtitles.php

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2Our code is available at: https://github.com/lemon234071/AdaLabel


and-refine strategy is used in baseline 3, 6, and 7, i.e., these baselines are refined based on CE. We follow the setting of Jiang et al. (2019) to use deterministic decoding scheme (particularly, greedy decoding) for our model and all baselines. Note that our method can be adapted to other decoding schemes such as beam-search or top-K sampling. See Appendix C for more detailed analysis.

4.4 Automatic Evaluation

**Metrics:** We first used automatic metrics to evaluate our method: 1) Distinct (Dist) (Li et al., 2016) calculates the proportion of unique n-grams (n=1, 2) in the generated responses, which is widely used to measure the response diversity. 2) Entropy (Ent) (Zhang et al., 2018) evaluates how evenly the empirical n-gram (n=1, 2) distribution is. Higher scores mean more diverse of the response. 3) Low-Frequency Token Ratio (LF) (Li et al., 2019) further measures the model diversity by counting the ratio of low-frequency words in the generated responses. We chose words with a frequency less than 100 in each corpus as low-frequency words. Over-confident models tend to omit low-frequency words (i.e., get low LF scores) and yield less diversified responses. 4) BLEU (Papineni et al., 2002) measures n-gram (n=2, 3, 4) overlap between the generated responses and references.

**Results:** As shown in Table 2, our method AdaLabel outperforms all the baselines by large margins on all the datasets. We can further observe that: 1) AdaLabel achieves the best diversity scores (Dist-1,2, Ent-1,2, and LF). This indicates that our method yields better training targets that help to produce more diverse responses; 2). The models that explicitly tackle the over-confidence issue (i.e., AdaLabel and FACE) generally outperform other baselines in diversity-related metrics. For example, FACE obtains the second-best diversity scores (i.e., Dist, Ent, and LF) on the OpenSubtitles dataset. This verifies our motivation that alleviating the over-confidence issue helps to produce more diverse responses.

Note that our method also outperforms all the baselines using the stochastic decoding scheme. Please refer to Appendix C for more details.

4.5 Manual Evaluation

**Metrics:** Pairwise manual evaluations are conducted to further validate our method. Specifically, for a given dialogue post, our model’s response is paired with the one from a baseline. Three individual annotators were employed to rank each response pair from three aspects: 1) Fluency (Flu.): which response is more fluent; 2) Coherence (Coh.): which response is more coherent to the context; 3) Informativeness (Info.): which response contains more informative content. We also asked the annotator to choose an overall preferred response (Pref.). Ties were allowed.

**Results:** 200 posts were randomly sampled from each of these two datasets, respectively, and totally 3.6K response pairs were generated. The inter-rater annotation agreement was measured using Fleiss’s kappa $\kappa$ (Fleiss, 1971). Particularly, the $\kappa$ value on DailyDialog, OpenSubtitles dataset was 0.59 and 0.55, respectively, indicating moderate agreement.

As shown in Table 3, AdaLabel outperforms all the baselines on the informativeness measure. This means that our method can respond with more informative content. We also asked the annotator to choose an overall preferred response (Pref.). Ties were allowed.

| Model  | DailyDialog | OpenSubtitles |
|--------|-------------|---------------|
|        | Dist-1, 2   | Dist-1, 2     |
| CE     | 1.67        | 2.55          |
| LS     | 1.48        | 2.77          |
| FL     | 2.38        | 3.19          |
| FACE   | 1.62        | 3.31          |
| $F^2$  | 1.40        | 2.89          |
| CP     | 2.35        | 3.11          |
| UL     | 2.35        | 2.84          |
| NL     | 1.66        | 3.24          |
| D2GPo  | 3.96        | 1.07          |
| AdaLabel | 3.56      | 4.78          |

Table 3: Manual evaluation results (%). Best results among all the models are in bold.
Ablation studies were performed to verify the effect of each component in our method. Specifically, two groups of variants were tested: (1) w/o \( \epsilon \) directly sets a fixed value for \( \epsilon \) in Eq. 2. The specific value of \( \epsilon \) is searched from 0.1 to 0.7 with a stride of 0.1; (2) w/o \( \alpha \) omits the empirical factor \( \alpha \) in calculating \( \epsilon \), i.e., the value of \( \epsilon \) in Eq. 2 is calculated using Eq. 4 in instead of Eq. 6.

The second group validates the effectiveness of AdaLabel vs CE

| Comparison | DailyDialog | OpenSubtitles |
|------------|-------------|---------------|
| AdaLabel vs CE | 17.00 \(^{†}\) | 6.33 | 13.67 \(^{†}\) |
| AdaLabel vs LS | 2.67 | 0.17 | 3.33 |
| AdaLabel vs FL | 4.50 | 1.67 | 7.00 \(^{†}\) |
| AdaLabel vs FACE | 6.67 \(^{†}\) | 3.50 \(^{†}\) | 7.17 \(^{†}\) |
| AdaLabel vs F \(^{2}\) | 7.67 \(^{†}\) | 0.33 | 6.83 \(^{†}\) |
| AdaLabel vs CP | 10.50 \(^{†}\) | -0.17 | 8.00 \(^{†}\) |
| AdaLabel vs UL | 7.83 \(^{†}\) | 0.83 | 6.67 \(^{†}\) |
| AdaLabel vs NL | 9.17 \(^{†}\) | 2.67 \(^{†}\) | 9.17 \(^{†}\) |
| AdaLabel vs D2GPo | 0.83 | 0.00 | 3.33 | 15.17 \(^{†}\) |

Table 3: Pairwise human evaluation results (%). The absolute gains of AdaLabel (i.e., Win rate – Lose rate) are reported. \(^{†}\) indicates significant improvement with \( p \)-value < 0.05 and < 0.005, respectively (sign test).

Table 4: Ablation study results on DailyDialog (%).

| Model | BLEU-3,4 | Dist-1,2 | Ent-1,2 | LF |
|-------|----------|----------|---------|----|
| 1.w/o \( \epsilon \) | 5.46 | 3.57 | 2.52 | 13.21 | 4.64 | 6.89 | 4.85 |
| 2.w/o \( \alpha \) | 11.35 | 8.70 | 3.62 | 20.56 | 5.02 | 7.70 | 7.30 |
| 3.Orig. \( v \) | 8.15 | 5.77 | 3.71 | 19.53 | 5.00 | 7.58 | 8.25 |
| 4.Uniform | 5.66 | 3.61 | 2.24 | 14.96 | 4.84 | 7.33 | 4.98 |
| 5.Rand | 6.27 | 4.07 | 2.03 | 13.47 | 4.77 | 7.08 | 4.56 |
| 6.BERT | 11.6 | 9.34 | 3.67 | 20.97 | 5.02 | 7.71 | 7.28 |
| AdaLabel | **13.38** | **11.01** | **3.96** | **23.53** | **5.17** | **8.00** | **8.49** |

Table 4 shows the results of ablation models on the DailyDialog dataset. As can be seen from the first two rows, our method to adaptively calculate \( \epsilon \) helps to improve the performance of our model by a large margin, and the empirical adjustment factor \( \alpha \) helps to further improve our performance by facilitating the learning of low-probability words. The performance of ablation models 3-6 in Table 4 proves that \( v \) captures reliable distribution and helps our model produce more diverse responses. Moreover, truncating the head distribution of \( v \) enables the dialogue model to focus more on the low-frequency words and thus facilitates more informative responses.

It is also interesting to note that our auxiliary decoder \( D_a \) surpasses the BERT teacher used by Chen et al. (2020) in helping the dialogue model.
### Table 5: Prediction accuracy of decoders on test sets.

| Decoder Type                  | Accuracy  |
|------------------------------|-----------|
| Auxiliary Decoder $D_a$       | 64.03     |
| Dialog Decoder in AdaLabel   | 44.16     |
| Dialog Decoder in CE         | 38.58     |

Figure 4: Empirical distribution of confidence scores for high-frequency words on the OpenSubtitles dataset. Words occupying the top 40% of the frequency mass in the training set are regarded as high-frequency words.

Figure 4 shows the results of four best performing models on the OpenSubtitles dataset. The spikes of high confidence score observed in Figure 4b and 4d indicate that CE and FACE assign extremely high confidence scores to a large number of high-frequency words. Although the smoothed labels in LS manage to alleviate these high-confidence-spikes (Figure 4c), a considerable amount of words still receives high confidence scores in LS. Our model outperforms all the baselines to avoid assigning over-confidence scores, thus alleviating the over-confidence issue. A similar trend is also observed on the DailyDialog dataset (see Appendix D for results of all models on both datasets).

#### 5 Discussion

##### 5.1 Auxiliary Decoder

To further test the performance of $D_a$, we evaluated the averaged accuracy score of $D_a$ when predicting each target word in the test set (first row in Table 5). Specifically, a target word $y_t$ in the reference response is determined to be correctly predicted if it is top-ranked in the predicted distribution $p(y_t | y_{<t}, X)$. A better decoder is generally believed to obtain a higher accuracy. Table 5 also reports the uni-directional dialogue decoders’ accuracy in AdaLabel and CE. It can be seen that $D_a$ can make substantially more accurate predictions with the help of modeling bi-directional contexts using only one layer. Moreover, the dialogue model’s decoder in AdaLabel, which is guided by $D_a$, achieves better accuracies than the CE. This further proves that our light-weight $D_a$ is capable of producing effective $v$.

##### 5.2 Prediction Confidence

We also visualized the distribution of confidence scores assigned by each dialogue model to high-frequency words. Figure 4 shows the results of

Figure 5: Ratios of low-frequency tokens in the generated responses on the OpenSubtitles dataset. Tokens in each group are determined based on the frequency on the training set.

### 5.3 Predicted Rare Word Distribution

Over-confident models produce less diversified responses because they usually under-estimate rare words. To evaluate the effectiveness of AdaLabel, we tested whether AdaLabel encourages more “rare words” in its generations. Specifically, the ratio of generated tokens corresponding to different token frequency bins is calculated, and the results on the OpenSubtitles dataset are shown in Figure 5. It can be seen that AdaLabel produces more rare words in the generated responses than other baselines. Similar results are also observed on the DailyDialog dataset (see Appendix E).

### 6 Conclusion

We address the low-diversity issue of neural dialogue models by introducing an adaptive label smoothing approach, AdaLabel. In our method, the probability of each target word is estimated based on the current dialogue model’s prediction, and the probabilities for these non-target words are calculated using a novel auxiliary decoder $D_a$. A target-masked attention scheme is introduced in $D_a$.
to help capture forward and backward contexts. We evaluate our method on two benchmark datasets: DailyDialog and OpenSubtitles. Extensive experiments show that our method effectively alleviates the over-confidence issue and improves the diversity of the generated responses. As future work, we believe this method is extensible to other text generation tasks.

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Table 6: Automatic evaluation results (%) using the beam search decoding scheme (beam size is 5). The best results among all these beam-search-decoded models are in bold.

| Model       | Dist-1, 2 | Ent-1, 2 | LF | BLEU-2,3,4 |
|-------------|-----------|----------|----|------------|
| CE          | 1.79      | 8.21     | 4.19 | 5.90 | 2.57 | 4.06 | 2.49 | 1.58 |
| LS          | 1.71      | 8.01     | 4.16 | 5.89 | 2.17 | 4.13 | 2.55 | 1.65 |
| FL          | 2.40      | 11.37    | 4.39 | 6.35 | 4.46 | 6.01 | 3.95 | 2.75 |
| FACE        | 1.80      | 9.47     | 4.54 | 6.40 | 3.48 | 5.65 | 3.43 | 2.17 |
| $F^2$       | 1.61      | 7.22     | 4.04 | 5.70 | 2.11 | 4.32 | 2.55 | 1.52 |
| CP          | 2.30      | 10.39    | 4.28 | 6.16 | 3.25 | 5.31 | 3.39 | 2.30 |
| UL          | 2.42      | 11.00    | 4.40 | 6.42 | 4.55 | 7.94 | 5.26 | 3.69 |
| NL          | 1.61      | 7.53     | 4.19 | 6.05 | 4.02 | 7.09 | 4.41 | 2.91 |
| D2GPo       | 1.57      | 7.83     | 4.14 | 5.91 | 2.26 | 4.47 | 2.71 | 1.71 |
| AdaLabel    | 4.25      | 21.47    | 4.95 | 7.51 | 7.68 | 14.71 | 11.63 | 9.80 |
| AdaLabel (Greedy) | 3.96 | 23.53 | 5.17 | 8.00 | 8.49 | 17.42 | 13.38 | 11.01 |
| Human       | 6.59      | 37.74    | 5.67 | 8.91 | 13.7 | N/A  | N/A  | N/A  |

| Model       | Dist-1, 2 | Ent-1, 2 | LF | BLEU-2,3,4 |
|-------------|-----------|----------|----|------------|
| CE          | 2.48      | 9.21     | 4.07 | 5.74 | 0.76 | 7.03 | 4.26 | 2.82 |
| LS          | 2.89      | 12.79    | 4.27 | 6.24 | 0.47 | 8.24 | 5.57 | 4.20 |
| FL          | 3.10      | 13.37    | 4.25 | 6.13 | 0.82 | 7.13 | 4.56 | 3.25 |
| FACE        | 3.12      | 12.62    | 4.47 | 6.40 | 1.02 | 5.97 | 3.63 | 2.43 |
| $F^2$       | 2.89      | 10.63    | 4.03 | 5.72 | 0.89 | 6.92 | 4.27 | 2.91 |
| CP          | 3.14      | 11.87    | 4.17 | 5.97 | 0.85 | 7.28 | 5.32 | 3.21 |
| UL          | 2.77      | 10.43    | 3.98 | 5.62 | 0.62 | 6.89 | 4.36 | 3.03 |
| NL          | 2.65      | 10.14    | 4.21 | 6.05 | 0.75 | 7.16 | 4.32 | 2.85 |
| D2GPo       | 2.06      | 10.43    | 4.15 | 6.00 | 0.12 | 7.32 | 4.69 | 3.33 |
| AdaLabel    | 4.91      | 21.53    | 4.71 | 7.08 | 1.35 | 8.68 | 6.08 | 4.68 |
| AdaLabel (Greedy) | 4.78 | 22.88 | 4.96 | 7.66 | 1.47 | 9.80 | 6.48 | 4.75 |

Table C: Automatic evaluation results (%) using the beam search decoding scheme (beam size is 5). The best results among all these beam-search-decoded models are in bold.

measures on the validation set: For Label smoothing (LS), we searched the smoothing parameter in [0.05, 0.1, 0.2, 0.3, 0.4, 0.5], and found 0.1 works best on all the datasets; For Confidence penalty (CP), we searched the weight of penalty in [0.0005, 0.001, 0.01, 0.05, 0.1] and found 0.05 works best on all the datasets while ensuring the loss to be positive; For Focal loss (FL), we searched the hyperparameter $\gamma$ in [0.1, 0.5, 1, 2, 3], and found 2 works best on all the datasets. For Unlikeliness loss (UL), we searched the weight of penalty in [1, 10, 100, 1000], and select 1000 on all the datasets. For FACE, we experiment with the Output token frequency & PRe-weigh version, which is reported to be the best version of FACE. For Negative loss (NL), $F^2$-softmax ($F^2$) and Data-dependent Gaussian Prior objective (D2GPo), the selection of hyper-parameters follows the author’s suggestion.

C Automatic Evaluation Results with Other Decoding Schemes

This appendix reports our model’s automatic evaluation results and all the baselines when different decoding schemes are used. Specifically, Table 6 shows the results for the beam search decoding scheme (beam size of 5), and Table 7 shows the results when the top-K decoding scheme ($k = 10$) is used. Note that for the $F^2$-softmax, we use the decoupled top-k sampling as the authors suggested.

As can be seen from Table 6 and 7, our method outperforms all the baselines on the diversity-related scores (i.e., Dist, Ent, and LF) by a large margin. This indicates that our method can produce more diverse responses even with the stochastic based decoding scheme.

We also include the results of AdaLabel when the greedy decoding scheme is used in Table 6 and Table 7 (the second line from the bottom). It is interesting to see that the greedily decoded responses from AdaLabel are more diverse than some baselines that are decoded using the sampling scheme (see Table 7). Moreover, our model AdaLabel with the greedy decoding scheme achieves the best BLEU among all the baselines on both datasets.

D Prediction Confidence

This appendix reports the prediction confidence scores assigned by each model to high-frequency words. Specifically, words occupying the top 40% of the frequency mass in the training set of each dataset are regarded as high-frequency words.

Figure 6 shows the results of our model and all the baselines on the DailyDialog dataset. Figure 7 shows the results of our model and all the baselines on the OpenSubtitles dataset. It can be seen that most of our baselines assign extremely high confidence scores (nearly 1.0) to these high-frequency words, and thus resulting in a spike of high confidence scores in the plotted distribution. Our model outperforms all the baselines in avoiding assigning extremely high confidence scores to these high-frequency words.

E Predicted Rare Word Distribution on DailyDialog

This appendix shows the distribution of rare words in the generated responses on the DailyDialog dataset. The distribution is reported for the top-K decoding scheme ($k = 10$) and compared to the original distribution. Our model outperforms all the baselines in assigning lower confidence scores to rare words.
Table 7: Automatic evaluation results (%) using the top-k sampling decoding scheme ($k = 10$). The best results among all these top-k-decoded models are in bold.

| Model  | DailyDialog | OpenSubtitles |
|--------|-------------|----------------|
| CE     | 2.22 19.05  | 3.87 20.58     |
| LS     | 1.95 17.74  | 3.46 21.27     |
| FL     | 2.71 20.98  | 3.82 22.14     |
| FACE   | 2.29 21.14  | 4.25 23.95     |
| F^2    | 2.16 19.33  | 4.10 22.53     |
| CP     | 3.16 22.38  | 4.06 22.62     |
| UL     | 2.92 20.81  | 3.74 20.97     |
| NL     | 2.39 20.35  | 3.57 20.36     |
| D2GPo  | 1.75 17.09  | 2.94 17.09     |
| AdaLabel (Greedy) | 4.11 32.65 | 8.87 4.84 |
| Human  | 6.59 37.74  | 8.62 43.16     |

Figure 6: Confidence score distributions for high-frequency words on the DailyDialog dataset. Words occupying the top 40% of the frequency mass in the training set of DailyDialog are regarded as high-frequency words.

Figure 7: Confidence score distributions for high-frequency words on the OpenSubtitles dataset. Words occupying the top 40% of the frequency mass in the training set of OpenSubtitles are regarded as high-frequency words.

F Use BERT Model to Obtain $v$

This appendix provides more experiment results comparing to the CMLM model (Chen et al., 2020): 1. CMLM exactly follows the setting of Chen et al. (2020), i.e., the teacher distribution produced by
Figure 8: Ratios of low-frequency tokens in the generated responses on the DailyDialog dataset. Tokens in each group are determined based on the frequency on the training set.

Table 8: Ablation study results based on BERT on DailyDialog (%).

| Model     | BLEU-3,4 | Dist-1,2 | Ent-1,2 | LF |
|-----------|----------|----------|---------|----|
| 1. CMLM   | 6.18     | 4.09     | 2.20    | 11.83 |
| 2. CMLM+ε | 9.36     | 7.31     | 3.78    | 21.05 |
| 3. CMLM+ε+D_a | 11.6 | 9.34     | 3.67    | 20.97 |
| AdaLabel  | 13.38    | 11.01    | 3.96    | 23.53 |

Table 9: Cases on DailyDialog.

| Context1 | Tell me a little bit about yourself, please. |
|----------|--------------------------------------------|
| UL       | I am sorry, sir. I have been in a foreign currency company for the company. |
| D2GPo    | I’m afraid I can’t. I’m a little nervous about it. |
| FACE     | Yes, I am in the mood for a few days ago. |
| AdaLabel | I am studying in the international trade company. I am studying English in my company. |

Table 10: Cases on OpenSubtitles.

| Context | You’re going to love this baby. |
|---------|--------------------------------|
| LS      | I’m going to get you. |
| D2GPo   | I’m going to go to the bathroom. |
| FACE    | You’re going to love this baby. |
| AdaLabel| You’re going to be a good father. |

| Context | Mr. Matlack can’t offend. |
|---------|----------------------------|
| LS      | This is our official business. |
| D2GPo   | This is the most important thing. |
| FACE    | It’s a pleasure to meet you, Mr. President. |
| AdaLabel| Timothy Matlack is the official scribe of the continental congress. |

| Context | Brave men discover they are really cowards. |
|---------|--------------------------------------------|
| LS      | I’m a samurai. |
| D2GPo   | I’ve never seen such a beast in my life. |
| FACE    | They are not afraid of you. |
| AdaLabel| Father, you’re a coward! |

| Context | I found this whole operation strange. |
|---------|--------------------------------------|
| LS      | I’m not going to let you go. |
| D2GPo   | I’m not sure I’m going to do it. |
| FACE    | I’m sorry, but I’m not sure I can handle it. |
| AdaLabel| It’s an incredibly delicate system. |

| Context | If they make it, they’re clear into a safe zone where they can get medical supplies and food. |
|---------|------------------------------------------------------------------------------------------------|
| LS      | We’ll get them to the safe. |
| D2GPo   | We’ll have to get back to the hotel. |
| FACE    | They’re gone, get us out of here. |
| AdaLabel| So we can use it as a safe field. |

the BERT model is merged with the one-hot distribution using a fixed $\varepsilon$. 2). CMLM+\(\varepsilon\) adaptively adjust the value of $\varepsilon$ using Eq. 6 in our paper. 3). CMLM+\(\varepsilon\)+\(D_a\) add an additional training task to optimize the auxiliary decoder $D_a$ on the basis of CMLM+\(\varepsilon\). It is expected that optimizing $D_a$ help our dialogue encoder to capture better representations. The trained $D_a$ is not used in the training and inference phase of our dialogue model. Note that the last model CMLM+\(\varepsilon\)+\(D_a\) is the same with our ablation model 6. BERT as reported in our paper.

As can be seen Table 8, our approach to adaptively change $\varepsilon$ helps to produce better dialogue responses, and the training of $D_a$ helps our dialogue encoder to learn better representations.

G Case study

We sampled some generated cases on the DailyDialog and OpenSubtitles dataset. The results of our model and some competitive baselines are shown in Table 9 and Table 10. It can be seen that the responses generated by our method are coherent to the context and contain richer contents. Moreover, our model also produces more rare words that make our response more diverse.