Stop Filtering: Multi-View Attribute-Enhanced Dialogue Learning

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Abstract

There is a growing interest in improving the conversational ability of models by filtering the raw dialogue corpora. Previous filtering strategies usually rely on a scoring method to assess and discard samples from one perspective, enabling the model to enhance the corresponding dialogue attributes (e.g., consistency) more easily. However, the discarded samples may obtain high scores in other perspectives and can provide regularization effects on the model learning, which causes the performance improvement to be sensitive to the filtering ratio. In this work, we propose a multi-view attribute-enhanced dialogue learning framework that strengthens the attribute-related features more robustly and comprehensively. Instead of filtering the raw dataset to train the model, our framework first pre-trains the model on the raw dataset and then fine-tunes it through adapters on the selected subsets, which also enhances certain attributes of responses but without suffering from the problems mentioned above. Considering the variety of the dialogue attribute, we further design a multi-view enhancement mechanism, including multi-view selection and inter-view fusion. It groups the high-quality samples from multiple perspectives, respectively, and enhances different attributes of responses with the corresponding sample sets and adapters, keeping knowledge independent and allowing flexible integration. Empirical results and analysis show that our framework can improve the performance significantly in terms of enhancing dialogue attributes and fusing view-specific knowledge.

1 Introduction

Neural dialogue generation (Sordoni et al., 2015; Vinyals and Le, 2015; Shang et al., 2015) has gained increasing attention. Given the dialogue corpora, previous work focuses on how to improve the conversational ability of models by redesigning objectives (Li et al., 2016a; Bowman et al., 2016; Yu et al., 2017) and network structures (Serban et al., 2016; Chen et al., 2018; Zhang et al., 2019) or introducing external knowledge (Ghazvininejad et al., 2018). To facilitate the model learning, apart from that, it is also necessary to explore how to manipulate samples during training due to the noises in the dialogue corpora. Recently, a line of work (Xu et al., 2018b; Csaky et al., 2019; Akama et al., 2020) introduces a data manipulation strategy, called Data Filtering, to boost the model performance. Specifically, they first measure the quality of samples in terms of a certain dialogue attribute by a scoring method, and then discard the noisy samples with low scores. The filtered data can induce the model to learn attribute-related features more effectively for the generation of high-quality responses.

However, the performance improvement from the data filtering strategy is sensitive to the filtering ratio, indicated by prior work (Akama et al., 2020) and our analysis in Section 5.1.

It is because those discarded samples may obtain high scores in other perspectives and still benefit the feature learning of other attributes. We visualize the score distribution of training samples of
DailyDialog (Li et al., 2017) in terms of two dialogue attributes, Consistency (Akama et al., 2020) and Specificity (See et al., 2019). As shown in Figure 1, the samples in orange and red parts are regarded as high-quality in one perspective but low-quality in the others. Nevertheless, the experimental results (see Appendix B) show that after further considering either the orange or the red part, the model trained with the blue part before achieves better performance, demonstrating that samples with high scores in any meaningful perspective are high-quality. Therefore the filtering-based data manipulation strategy inevitably causes the model to neglect the learning of other dialogue attributes. Furthermore, the discarded samples, as the regularization factor, also prevent the model from overfitting to the filtered data consisting of fewer samples.

Another problem is that prior filtering-based work only improves the conversational ability from one perspective reflected by the proposed scoring method, which can not achieve the goal of the dialogue system, i.e., showing superiority in multiple perspectives simultaneously (Chen et al., 2017). A straightforward method is to use the union of different training sets filtered from various perspectives to train the dialogue model. However, without the view-wise guidance one by one, the union can not enforce the model to learn features biased towards different attributes effectively. Moreover, the union-based training will degrade to the traditional training when there are too many perspectives to consider.

One can also use sequential learning (Phang et al., 2018) or ensemble learning (Sagi and Rokach, 2018) to fit all filtered training sets gradually or parallelly, respectively. Unfortunately, the former suffers from catastrophic forgetting, i.e., knowledge learned from old training sets is always damaged by new training sets, and the latter will lead to serious knowledge interference (Pfeiffer et al., 2021).

To avoid the problems of Data Filtering and meet the requirement of the dialogue system, in this work, we propose a multi-view attribute-enhanced dialogue learning framework (MAE) to improve the conversational ability of the model from multiple perspectives effectively. Unlike the data filtering strategy that ignores the learning of non-target dialogue attributes, our framework aims at enhancing the target attribute without weakening any other attribute. It consists of one base model and multiple adapters. The base model is first pre-trained on the raw training set, allowing the framework to learn various features roughly. Then each adapter (Houlsby et al., 2019) is fine-tuned on the subset selected by the corresponding scoring method, which enables the framework to further capture more features related to the target attributes without erasing any feature learned earlier. In order to generate the responses regarded as high-quality from multiple perspectives, we design two mechanisms to integrate complementary features in different adapters. The first one, Adaptive Fusion (AF), ensembles multi-view features through the weighted average in inference after all adapters are fine-tuned in parallel, which keeps the adapters independent and plug-and-play. However, due to the knowledge interference among adapters, the features learned by one adapter may damage the features from other adapters, resulting in a sub-optimal integration. The second one, Progressive Fusion (PF), constructs an incremental integration process through knowledge distillation (Hinton et al., 2015), which enforces each new adapter to learn features complementary to those learned by previous adapters. Besides, the capacity of the framework will not increase significantly, as each adapter consists of very few parameters.

Our contributions are summarized as follows: (1) We propose a robust attribute-enhanced dialogue learning framework that strengthens the attribute-related features effectively while avoiding the problems of data filtering. (2) To improve the response quality more comprehensively, we further design two fusion mechanisms, AF and PF, to combine multi-view features from different adapters in inference and training, respectively. (3) We conduct extensive experiments to verify the effectiveness of MAE and provide a detailed analysis of feature learning and fusion.

2 Background

2.1 Dialogue Generation Models

Previous work enhancing the quality of responses falls into three major categories. The first redesigns the model structure to facilitate the modeling of the dialogue pairs (Serban et al., 2017a; Tao et al., 2018; Gao et al., 2019). The second further proposes the objectives that aligns with the goals of the conversation more effectively, such as MMI (Li et al., 2016a), CVAE (Serban et al., 2017b; Zhao et al., 2017; Gu et al., 2019; Sun et al., 2021), RL
(Li et al., 2016b; Zhang et al., 2018a; Liu et al., 2020), and GAN (Xu et al., 2017, 2018a; Feng et al., 2020a). The third tries to endow the responses with topic (Xing et al., 2017; Feng et al., 2020b), emotion (Zhou et al., 2018; Rashkin et al., 2019), and persona (Qian et al., 2017; Zhang et al., 2018b; Song et al., 2020). Recently, another line of work (Zhang et al., 2020; Roller et al., 2020; Adiwardana et al., 2020; Bao et al., 2020), called the pre-trained dialogue model, relies on an efficient neural network and large-scale datasets to further improve the response quality.

2.2 Data Filtering for Dialogue Learning

Many studies (Fan et al., 2017; Ren et al., 2018; Baheti et al., 2018) argue that the quality of samples has a significant impact on the model performance. Recently, some researchers have considered the sample quality into the dialogue learning by a data manipulation strategy called Data Filtering, which discards samples that are regarded as low-quality by a scoring method. Csaky et al. (2019) introduces an entropy-based scoring method to remove generic utterances from the training data. See et al. (2019) designs a scoring method to measure the specificity of samples. Akama et al. (2020) combines the cosine distance and the keyword co-occurrence of the dialogue pairs to evaluate the sample coherency jointly. Shen et al. (2021) proposes a fusing approach for data filtering by linearly combining seven scoring methods via Bayesian Optimization (Brochu et al., 2010). Unlike Data Filtering, our work designs a novel data manipulation framework to enhance the target attributes without sacrificing the feature learning of other dialogue attributes. There is another line of work (Lison and Bibauw, 2017; Shang et al., 2018; Cai et al., 2020), named Data Weighting, that assigns the training samples with different weights, which is out of the scope of this work. All of them compute the weighting scores by a trainable model, which can also be replaced by the above scoring methods.

2.3 Adapters in NLP

As a light-weight module, the adapter can be embedded into each layer of the pre-trained model to learn task-specific knowledge more efficiently, such as language features (Houlsby et al., 2019; Wang et al., 2020) and multilingual features (Bapna and Firat, 2019; Philip et al., 2020; Pfeiffer et al., 2020; Guo et al., 2020; Rust et al., 2021). Previous work aims to transfer knowledge in the pre-trained model for the downstream tasks while avoiding catastrophic forgetting. Different from that, we further explore injecting view-specific knowledge into adapters and fusing multi-view knowledge to enhance the pre-trained model. Pfeiffer et al. (2021) also tries to integrate knowledge from adapters, but the fusion layer will bring too many parameters as the number of adapters increases. Our method does not require extra parameters apart from adapters for knowledge fusion and therefore enables flexible integration.

3 Framework

The proposed framework offers a novel data manipulation paradigm to enhance the conversational skills of the model robustly and comprehensively. In this section, we first describe the collection process of view-specific training sub-sets, and then elaborate on how the adapters capture attribute-related features based on the corresponding sub-sets. Finally, two fusion mechanisms are introduced to integrate multi-view features. Algorithm 1, provided in the Appendix, shows full training details.

3.1 View-Specific Collection

Previous filtering-based work aims at discarding the noisy samples discriminated by the proposed scoring method. However, we have verified that the training sample with a high score given by any other scoring method can still be regarded as high-quality. Directly removing the noisy samples will weaken the learning of features in other aspects. To tackle this problem, our framework measures the sample quality from multiple perspectives. Concretely, we construct a pool of scoring methods \( S_1, S_2, \ldots, S_M \), shown in Figure 2. After flowing through this pool, the raw training samples \( D \) are reorganized into multiple view-specific training sub-sets \( D_1, D_2, \ldots, D_M \) based on a certain selection proportion. Note that each sample can be assigned to multiple sub-sets as it may obtain high scores from more than one scoring method. Differing from previous work that only treats the selected samples as high-quality data, we argue that different sub-sets \( D_m \) provide view-wise guidance for the learning of attribute-related features. Intuitively, the data selection can be regarded as an implicit cluster based on the dialogue attributes.
3.2 View-Specific Dialogue Learning

Previous work directly trains the model with the filtered training sets $D_m$, which leads to information loss in other views, i.e., ignores the feature learning of non-target dialogue attributes. To address these issues, we use a two-stage training strategy that first warms up the base model on the raw training set $D$ and then introduces the adapters to capture attribute-related features from all view-specific training sub-sets $D_m$.

3.2.1 Pre-Training Base Model

We employ the standard Transformer architecture (Vaswani et al., 2017) without adapter layers as the base model. The goal of the first-stage training is to enable the base model to access all training samples and learn the basic features. Formally, we maximize the probability $P_\theta(r|q)$ of each training sample $(q,r)$ by optimizing the negative log likelihood (NLL) defined as:

$$\mathcal{L}_{nll}(\theta) = - \sum_{i=1}^{|r|} \log P_\theta(t_i^r | t_{<i}^r, q),$$

where $|r|$ is the length of $r$, and $\theta$ represents the parameters of the base model.

3.2.2 Fine-Tuning Adapters

In the second stage, we introduce the light-weight adapter layers into both encoder and decoder of the base model. Following Houlsby et al. (2019), each encoder block of the base model contains two adapter layers (three in decoder), and each adapter layer consists of one bottleneck module (see Figure 3). The attribute-related features $z^m$ can be represented as:

$$z^m = \text{gelu}(z \cdot w^m_{\text{Down}}) \cdot w^m_{\text{Up}} + z, \quad (2)$$

where $z$ is the output of the previous layer, and $w^m_{\text{Down}}$ and $w^m_{\text{Up}}$ are the parameters of one adapter layer. The parameters of the base model are fixed, and the adapters parameters $\phi_{s_m}$ are independently fine-tuned on the corresponding view-specific training set $D_m$ by $\mathcal{L}_{nll}(\phi_m)$. Due to the light-weight structure, the increasing number of adapters will not bring excessive parameters. In addition, each adapter can learn attribute-related features without the distraction of the noisy samples while avoiding catastrophic forgetting.

3.3 Multi-View Attributes Fusion

The goal of the dialogue system is to generate responses that can perform well on multiple dialogue attributes. In this section, we introduce two fusion mechanisms, Adaptive Fusion (AF) and Progressive Fusion (PF) to effectively exploit the multi-view knowledge for generating high-quality responses.

3.3.1 Adaptive Fusion

For the adaptive fusion mechanism, all adapters can be fine-tuned in parallel. The fusion process, shown in Figure 4, combines multi-view features from different adapters in inference through a weighted average:

$$z^F = \sum_{m=1}^M \lambda_m z_m^m, \quad \lambda_m = \frac{||z^m - z||_1}{\sum_{m}^M ||z^m - z||_1} \quad (3)$$
where $z^F$ is the output of the fusion mechanism, and $\lambda_m$ is the coefficient calculated by the L1-distance between $z^m$ and $z$. Inspired by Guan et al. (2019), we take the distance between the input and output of view-specific adapter layer as the importance degree of the extracted features. See the Adaptive Weight Study for the analysis of its effectiveness. The larger the distance is, the more the model needs these extracted features from the corresponding adapter layer for improving the overall quality of responses. We choose L1-distance rather than other types of distances due to its computational efficiency and higher discrimination. The AF can keep the adapters independent and plug-and-play, and conducts the layer-wise fusion that is more effective than ensemble learning. Yet, it may face the problem of knowledge interference that will affect the quality of generated responses.

### 3.3.2 Progressive Fusion

The PF integrates multi-view features smoothly during training rather than inference, shown in Figure 5, which requires the adapters to be fine-tuned sequentially. Each new adapter not only learns from the corresponding training set but also is enforced to find features complementary to those learned by previous adapters. Therefore, we use knowledge distillation to align the predictions of the base model with old adapters and the base model with both new and old adapters, which can be formulated as:

$$
\mathcal{L}_{kd}(\phi_n) = -\sum_{i=1}^{\left|X\right|} \sum_{j=1}^{\left|Y\right|} P(i, j) \left( t_i^r = j \mid t_i^r, q \right) \cdot \log P(i, j) \left( t_i^r = j \mid t_i^r, q \right), \tag{4}
$$

where $\phi_n$ is the parameters of the new adapter, $\phi_p$ is the frozen parameters of previous adapters, and $|V|$ denotes the vocabulary size. The final objective for training the new adapter is:

$$
\mathcal{L}(\phi_n) = \mathcal{L}_{nll}(\phi_n) + \lambda^{kd} \mathcal{L}_{kd}(\phi_n), \tag{5}
$$

where $\lambda^{kd}$ represents the weight of $\mathcal{L}_{kd}$, $\lambda^{kd} = 1 - \frac{current\ epoch}{total\ epoch}$, which decreases linearly during training. In this way, we give a strong constraint at the beginning of training to prevent the learned features from conflicting with features of previous adapters. And then, we reduce this constraint linearly to allow the new adapter to learn view-specific knowledge. Therefore, the knowledge of the adapters can be incorporated into the base model gradually while alleviating knowledge interference, but it will reduce the independence of adapters.

### 4 Experimental Setup

#### 4.1 Datasets and Baselines

We compare the proposed framework with one basic approach and three state-of-the-art filtering-based approaches on two open-domain dialogue datasets, DailyDialog (Li et al., 2017) and OpenSubtitles (Tiedemann, 2009).

The basic approach trains the dialogue model on the entire training set. These three filtering-based approaches (Filtering) use the corresponding scoring methods that reflects the Consistency (Con) (Akama et al., 2020), Entropy_Src (Ent) (Csaky et al., 2019), and Specificity (Spe) (See et al., 2019) of the dialogue pairs, respectively, to measure the quality of samples and discard the noisy samples with low scores. Please refer to the Appendix E for the details of three high-quality automatic scoring methods. In addition, we also compare the Weighting approaches (Lison and Bibauw, 2017; Shang et al., 2018; Cai et al., 2020) although they can be seen as another line of data manipulation work. We replace their original weighting models with above three scoring methods to verify whether they are suitable for weighting approach. Please refer to the Appendix D and E for the details of datasets and scoring methods.

#### 4.2 Implementation details

Following previous work (Csaky et al., 2019; Akama et al., 2020), we take the Transformer-based dialogue model (Vaswani et al., 2017) as the underlying model for all approaches.

The settings of Transformer is consistent with Csaky et al. (2019), and please refer to the Appendix F for the details.
Our framework, including AF and PF, uses the same data selection ratio of 50% as Akama et al. (2020) by three mentioned scoring methods. Note that the filtering-based baselines set the data filtering ratio to 20% due to their lower performance with 50% ratio on the above datasets (see the Section 5.1 for the comparison). The fusion order of PF is chosen randomly (see the Appendix H for the analysis).

### 4.3 Evaluation

To comprehensively evaluate the quality of the generated responses, we conduct both automatic and human evaluations. The former employs three count-based metrics, Dist-[1,2], KL-[1,2], and BLEU, to reflect the linguistic quality, e.g., Dist and KL for the diversity and the distribution distance of n-grams, respectively. The latter focuses on more challenging semantic aspects, i.e., Informativeness, Relevance, and Fluency. Please refer to the Appendix F for the details of the above metrics.

### Automatic evaluation

The automatic results in Table 1 show that our framework outperforms all baselines by a significant margin on both datasets, demonstrating the superiority of fusing multi-view features. MAE-PF obtains better results than MAE-AF on OpenSubtitles, which verifies that the PF mechanism can integrate multi-view features more smoothly. There is no noticeable gap between MAE-AF and MAE-PF on DailyDialog. Because all samples in DailyDialog are human-written and high-quality in multiple perspectives (Li et al., 2017), knowledge interference among different adapters is weak. In addition, Filtering-Con achieves better performance than other filtering baselines, consistent with the results in Akama et al. (2020). Compared with Transformer, all filtering baselines gain more improvements on OpenSubtitles than on DailyDialog. These phenomena indicate that the filtering-based approaches are sensitive to both the scoring methods and the overall quality of datasets. As for the weighting approach, we find that the performance of the three scoring methods has changed a lot: Entropy_Src gets the better result than Consistency, which shows that this kind of approaches has a heavy dependence on the scoring methods.

| Models          | Dist-1 | Dist-2 | KL-1 | KL-2 | BLEU | Dist-1 | Dist-2 | KL-1 | KL-2 | BLEU |
|-----------------|--------|--------|------|------|------|--------|--------|------|------|------|
| Transformer     | 0.0216 | 0.0728 | 1.67 | 1.66 | 0.292| 0.0157 | 0.0410 | 2.37 | 1.72 | 0.336|
| Filtering-Con   | 0.0225 | 0.0752 | 1.62 | 1.08 | 0.330| 0.0189 | 0.0569 | 2.01 | 1.70 | 0.322|
| Filtering-Ent   | 0.0166 | 0.0462 | 2.16 | 1.77 | 0.307| 0.0156 | 0.0429 | 2.42 | 1.73 | 0.337|
| Filtering-Spe   | 0.0132 | 0.0465 | 2.20 | 2.24 | 0.244| 0.0150 | 0.0439 | 1.93 | 1.82 | 0.311|
| Weighting-Con   | 0.0050 | 0.0078 | 4.46 | 2.39 | 0.343| 0.0044 | 0.0082 | 4.47 | 3.38 | 0.248|
| Weighted-Ent    | 0.0167 | 0.0455 | 2.02 | 1.54 | 0.341| 0.0185 | 0.0516 | 2.29 | 1.46 | 0.345|
| Weighted-Spe    | 0.0156 | 0.0469 | 2.11 | 1.80 | 0.313| 0.0100 | 0.0265 | 3.01 | 2.46 | 0.291|
| MAE-AF          | 0.0434 | 0.1522 | 0.88 | 0.75 | 0.383| 0.0204 | 0.0660 | 1.83 | 1.55 | 0.335|
| MAE-PF          | 0.0463 | 0.1511 | 0.94 | 0.68 | 0.392| 0.0217 | 0.0676 | 1.80 | 1.46 | 0.339|

Table 1: Results of automatic evaluations on DailyDialog (Left) and OpenSubtitles (Right). The best/second-best results are bold/underlined. For KL-{1,2}, lower is better.

| vs. Models     | Informativeness (%) | Win | Lose | Tie | Win | Lose | Tie | Win | Lose | Tie |
|----------------|---------------------|-----|------|----|-----|------|----|-----|------|----|
| Transformer    | 36.0 / 33.3         | 15.3 | / 14.0 | 52.7 | 38.0 | / 36.0 | 2.7 | 58.7 / 61.3 | 46.0 | / 40.7 | 5.3 / 4.0 | 48.7 / 55.3 |
| Filtering-Con  | 61.3 / 59.3         | 2.0 | 8.7 | 36.7 / 32.0 | 44.7 | / 40.0 | 9.3 | 50.0 / 58.0 | 38.7 | / 36.0 | 8.7 / 4.7 | 53.3 / 59.3 |
| Filtering-Ent  | 56.0 / 52.0         | 6.7 | 12.7 | 37.3 / 35.3 | 52.0 | / 47.3 | 5.3 | 44.7 / 50.7 | 32.7 | / 30.0 | 7.3 / 6.0 | 60.0 / 64.0 |
| Filtering-Spe  | 26.7 / 30.7         | 19.3 | / 24.7 | 54.0 / 44.7 | 45.3 | / 48.0 | 6.0 | 13.8 / 50.7 | 47.3 | / 40.0 | 2.7 / 2.7 | 50.0 / 57.3 |
| Weighting-Ent  | 52.0 / 44.0         | 6.7 | 12.0 | 41.3 / 44.0 | 45.3 | / 45.0 | 6.7 | 40.0 / 50.7 | 22.7 | / 25.3 | 8.0 / 6.7 | 69.3 / 68.0 |
| Transformer    | 46.7 / 56.3         | 6.3 | 2.7 | 47.0 / 41.0 | 35.0 | / 38.0 | 14.7 | 8.0 | 50.3 / 54.0 | 27.0 | / 34.3 | 24.0 / 10.7 | 49.0 / 55.0 |
| Filtering-Con  | 29.0 / 35.0         | 24.7 | 13.0 | 46.3 / 52.0 | 29.3 | / 29.0 | 21.3 | 12.0 | 49.3 / 59.0 | 23.0 | / 31.0 | 21.3 / 10.0 | 55.7 / 59.0 |
| Filtering-Ent  | 52.0 / 59.0         | 17.3 | 3.0 | 30.0 / 38.0 | 42.3 | / 42.3 | 13.7 | 4.0 | 44.0 / 53.3 | 36.0 | / 47.0 | 14.3 / 5.7 | 49.7 / 47.3 |
| Filtering-Spe  | 41.0 / 51.3         | 19.0 | 9.7 | 40.0 / 40.0 | 36.7 | / 42.3 | 7.7 | 3.7 | 55.7 / 54.0 | 43.0 | / 61.0 | 7.3 / 3.0 | 49.7 / 36.0 |
| Weighting-Ent  | 62.7 / 68.0         | 11.0 | 4.3 | 26.3 / 27.7 | 42.3 | / 43.3 | 11.3 | 7.6 | 46.3 / 49.0 | 30.0 | / 44.7 | 18.3 / 8.7 | 51.7 / 46.7 |

Table 2: Results of human evaluations on DailyDialog (Top) and OpenSubtitles (Bottom). A/B in each table cell refer to the results of MAE-AF/MAE-PF, respectively. Our framework has a higher win rate than baselines.
| Models          | Dist-1 | Dist-2 | KL-1   | KL-2   | BLEU |
|-----------------|--------|--------|--------|--------|------|
| Filtering-Con (80%) | 0.0225 | 0.0752 | 1.62   | 1.08   | 0.330|
| Filtering-Con (50%) | 0.0088 | 0.0306 | 2.74   | 2.01   | 0.314|
| Filtering-Ent (80%) | 0.0166 | 0.0462 | 2.16   | 1.77   | 0.307|
| Filtering-Ent (50%) | 0.0096 | 0.0255 | 2.63   | 2.17   | 0.315|
| Filtering-Spe (80%) | 0.0132 | 0.0465 | 2.20   | 2.24   | 0.244|
| Filtering-Spe (50%) | 0.0061 | 0.0210 | 3.62   | 3.17   | 0.199|
| MAE-AF (80%)     | 0.0383 | 0.1370 | 0.97   | 0.85   | 0.375|
| MAE-AF (50%)     | 0.0434 | 0.1522 | 0.88   | 0.75   | 0.383|
| MAE-PF (80%)     | 0.0403 | 0.1361 | 0.94   | 0.68   | 0.382|
| MAE-PF (50%)     | 0.0463 | 0.1511 | 0.97   | 0.78   | 0.392|

Table 3: Impact of the selection ratio on the model performance.

In contrast, our framework can avoid these problems due to the novel attribute-enhanced mechanism that does not damage the feature learning of the non-target dialogue attributes.

**Human Evaluation** For each dataset, we randomly select 100 samples from the test set, and three well-educated annotators are hired to judge which of the responses generated by MAE-AF/PF and baselines is better (i.e., win, lose or tie) in terms of above three metrics. For weighting approach, we only select Entropy_src as the scoring method due to its much higher automatic performance than the other two. The results, shown in Table 2, demonstrate that our framework obtains a higher win rate than baselines in terms of three semantic metrics on both datasets. Besides, Filtering-Con performs better than other filtering baselines in Relevance, implying that the data filtering is beneficial for the model to enhance the dialogue attributes related to the scoring method. We use Fleiss’s kappa (Fleiss, 1971) to assess the inter-annotator agreement, and the results are 0.541 and 0.619 on DailyDialog and OpenSubtitles, respectively.

**5 Further Analyses**

In this section, we further investigate the advantages of MAE by providing detailed analyses. Unless otherwise stated, the analysis results are based on DailyDialog.

**5.1 Ablation Study**

To analyze the effect of the selection ratio on the model performance, we train the filtering baselines and our framework with two different ratios on both two datasets. From the results in Table 3 on single dataset, we find that the filtering baselines achieve better performance with a ratio of 80% than with a ratio of 50%, and our framework still perform well with a ratio of 50%. This phenomenon illustrates that previous filtering-based approaches have a risk of dropping too many samples that are regarded as high-quality and benefits the model learning. In addition, too high selection ratio will cause too much overlap between the view-specific sub-sets, which is not beneficial for adapters to learn features biased towards different attributes effectively.

We also gradually decrease the selection ratio from 80% to 10% to observe the variation of the model performance. The results in Figure 6 show that the performance of Filtering-Con is very unstable, even worse than Transformer, as the ratio varies. In contrast, MAE-Con has no significant changes in Dist-1 and KL-1, verifying the robustness of our attribute-enhanced mechanism. See Appendix I for the variation of other metrics.

**5.2 View-specific Study**

To verify that adapters can learn the corresponding attribute-related features from the view-specific sub-sets, we compare the generated response of MAE-Con with those of MAE-Spe in terms of Consistency and Specificity. Coherence (COH) (Xu et al., 2018b) and Word Entropy (H-{1,2}) (Csaky et al., 2019) are adopted to assess the consistency and specificity of responses, respectively. Besides, we also conduct human evaluations. See the Appendix for the details of these metrics.

In Table 4, we find that MAE-Con indeed performs better than MAE-Spe in Consistency and vice versa. Moreover, the results in Table 5 indicate that our framework is also more effective than previous filtering approaches on improving the overall quality of responses, contributing to the novel attribute-enhanced mechanism.

Figure 6: The variation of the model performance with respect to different selection ratios. MAE-Con consists of a pre-trained base model and an adapter fine-tuned on the sub-set that is selected from the Consistency perspective.
Table 4: Results of automatic (Left) and human (Right; win rate) evaluations of MAE-Con and MAE-Spe.

| Models   | Dist-1 | Dist-2 | KL-1   | KL-2   | BLEU  |
|----------|--------|--------|--------|--------|-------|
| COH H-1  | 0.729  | 8.64   | 7.80   | 6.0%   | 14.7% |
| H-2      | 0.717  | 7.25   | 8.23   | 8.0%   | 60.7% |
| MAE-Con  | 0.0225 | 0.0752 | 1.62   | 1.08   | 0.330 |
| Filtered | 0.0356 | 0.1239 | 1.07   | 0.97   | 0.362 |
| MAE-Spe  | 0.0132 | 0.0465 | 2.20   | 2.24   | 0.244 |
| Filtering-Spe | 0.0333 | 0.1156 | 1.20   | 1.29   | 0.330 |

Table 5: Comparison of the conventional filtering-based approach and MAE with a single adapter.

| Models | Dist-1 | Dist-2 | KL-1 | KL-2 | BLEU  |
|--------|--------|--------|------|------|-------|
| Intersection | 0.0085 | 0.0258 | 3.15 | 2.18 | 0.322 |
| Union   | 0.0244 | 0.0739 | 1.56 | 1.34 | 0.353 |
| Ensemble | 0.0115 | 0.0291 | 2.92 | 2.19 | 0.289 |
| Sequential | 0.0313 | 0.1031 | 1.23 | 0.86 | 0.375 |
| MAE-AF | 0.0434 | 0.1522 | 0.88 | 0.75 | 0.383 |
| MAE-PF | 0.0463 | 0.1511 | 0.97 | 0.78 | 0.392 |

Table 6: Comparison of MAE-AF/PF and the conventional filtering-based approach with four fusion strategies.

| Models | Dist-1 | Dist-2 | KL-1 | KL-2 | BLEU  |
|--------|--------|--------|------|------|-------|
| MAE-Con | 0.0225 | 0.0752 | 1.62 | 1.08 | 0.330 |
| Filtered | 0.0356 | 0.1239 | 1.07 | 0.97 | 0.362 |
| MAE-Spe | 0.0132 | 0.0465 | 2.20 | 2.24 | 0.244 |
| Filtering-Spe | 0.0333 | 0.1156 | 1.20 | 1.29 | 0.330 |

5.3 Fusion Mechanism Study

We compare the proposed framework with the conventional filtering-based approach equipped with a variety of fusion strategies. Intersection and Union use the intersection and union of different sub-sets to train the vanilla Transformer, respectively. Ensemble directly combines the outputs of three baselines (i.e., Filtering-xxx). Sequential trains Transformer on different sub-sets one by one. Note that for scores of Con and Spe, the higher the better, but for Ent, the opposite. Therefore, Shen et al. (2021) is not suitable here because it is hard to combine these scoring methods linearly. As shown in Table 6, Intersection gets the worst results due to the model trained with too few samples. Union achieves almost the same performance as Filtering-Con, indicating that the union of view-specific sub-sets can not induce the model to learn features biased towards different dialogue attributes effectively. Sequential performs better than Ensemble, even Filtering-Con, but it is still weaker than MAE-AF/PF. It is because Ensemble easily suffers from knowledge interference due to only fusing the outputs of models, and Sequential is inevitably limited by catastrophic forgetting. However, our framework can learn and save view-specific knowledge independently, and fuse them smoothly.

5.4 Adaptive Weight Study

Can the L1-distance between the input and output of the adapter layer reflect the importance of the adapter layer?

In Table 7, we report the average L1-distance calculated based on all adapter layers of each module, and give the corresponding model performance when deleting all adapter layers of each block in inference. The results demonstrate that the adapter layer with a larger L1-distance usually conducts a stronger impact on the model performance. The adapter layers in the bottom and top blocks are more important than those in the middle blocks.

Table 7: Left: The average L1-distance of all adapter layers of each module. Right: The corresponding performance of MAE-AF when deleting all adapter layers of each block in inference. Self-att, ED-att, and FFN represent the self-attention module, the encoder-decoder attention module, and the feed-forward module of the decoder, respectively.

| Models | Dist-1 | Dist-2 | KL-1 | KL-2 | BLEU  |
|--------|--------|--------|------|------|-------|
| MAE-Con | 0.0225 | 0.0752 | 1.62 | 1.08 | 0.330 |
| Filtered | 0.0356 | 0.1239 | 1.07 | 0.97 | 0.362 |
| MAE-Spe | 0.0132 | 0.0465 | 2.20 | 2.24 | 0.244 |
| Filtering-Spe | 0.0333 | 0.1156 | 1.20 | 1.29 | 0.330 |

Table 8: Examples of the responses generated by Transformer and MAE-AF.
5.5 Case Study

Table 9 presents some responses generated by the proposed framework and baselines. Transformer prefers generic and meaningless responses. The responses generated by filtering methods are usually corresponding to one perspective of dialogue. For instance, the Filtering-Ent approach often generates informative but irrelevant responses. In contrast, our AF and PF comprehensively consider the multiple perspectives, thus resulting in diverse and coherent responses. The results demonstrate the effectiveness of MAE.

6 Conclusion

In this work, we propose a novel multi-view attribute-enhanced dialogue learning framework that induces the model to enhance related knowledge along with the dialogue attributes and fuse them for the overall improvement of the response quality. We first collect various view-specific subsets from the raw training set. Then the adapters are introduced to learn and save more features biased towards different dialogue attributes. Finally, we design two fusion mechanisms, Adaptive Fusion and Progressive Fusion, to integrate multi-view knowledge of adapters in inference and training, respectively. The former makes the adapters plug-and-play, and the latter alleviates knowledge interference. The experimental results and analysis demonstrate that our framework learns attribute-related features, improves the model robustness due to the novel enhance mechanism, and integrates features of adapters effectively. Compared with previous data filtering approaches, it offers a new perspective to incorporate the sample quality into the model learning.

References

Daniel Adiwardana, Minh-Thang Luong, David R. So, Jamie Hall, Noah Fiedel, Romal Thoppilan, Zi Yang, Apoorv Kulshreshtha, Gaurav Nemade, Yifeng Lu, and Quoc V. Le. 2020. Towards a human-like open-domain chatbot. CoRR, abs/2001.09977.

Reina Akama, Sho Yokoi, Jun Suzuki, and Kentaro Inui. 2020. Filtering noisy dialogue corpora by connectivity and content relatedness. In EMNLP, pages 941–958.

Ashutosh Baheti, Alan Ritter, Jiwei Li, and Bill Dolan. 2018. Generating more interesting responses in neural conversation models with distributional constraints. In EMNLP, pages 3970–3980.

Siqi Bao, Huang He, Fan Wang, Hua Wu, Haifeng Wang, Wenquan Wu, Zhen Guo, Zhibin Liu, and Xinchao Xu. 2020. PLATO-2: towards building an open-domain chatbot via curriculum learning. CoRR, abs/2006.16779.

Ankur Bapna and Orhan Firat. 2019. Simple, scalable adaptation for neural machine translation. In EMNLP-IJCNLP, pages 1538–1548.
Gerlof Bouma. 2009. Normalized (pointwise) mutual information in collocation extraction. In (GSCL), page 31–40.

Samuel R. Bowman, Luke Vilnis, Oriol Vinyals, Andrew M. Dai, Rafal Józefowicz, and Samy Bengio. 2016. Generating sentences from a continuous space. In CoNLL, pages 10–21.

Eric Brochu, Vlad M. Cora, and Nando de Freitas. 2010. A tutorial on bayesian optimization of expensive cost functions, with application to active user modeling and hierarchical reinforcement learning. CoRR, abs/1012.2599.

Hengyi Cai, Hongshen Chen, Yonghao Song, Cheng Zhang, Xiaofang Zhao, and Dawei Yin. 2020. Data manipulation: Towards effective instance learning for neural dialogue generation via learning to augment and reweight. In ACL, pages 6334–6343. Association for Computational Linguistics.

Boxing Chen and Colin Cherry. 2014. A systematic comparison of smoothing techniques for sentence-level BLEU. In Ninth Workshop on Statistical Machine Translation, pages 362–367.

Hongshen Chen, Xiaorui Liu, Dawei Yin, and Jiliang Tang. 2017. A survey on dialogue systems: Recent advances and new frontiers. SIGKDD Explor., 19(2):25–35.

Hongshen Chen, Zhaochun Ren, Jiliang Tang, Yi-hong Eric Zhao, and Dawei Yin. 2018. Hierarchical variational memory network for dialogue generation. In WWW, pages 1653–1662.

Richard Csaky, Patrik Purgai, and Gábor Recsiki. 2019. Improving neural conversational models with entropy-based data filtering. In ACL (1), pages 5650–5669.

Yang Fan, Fei Tian, Tao Qin, Jianguo Liu, and Ji Wang. 2017. Learning what data to learn. CoRR, abs/1702.08635.

Shaoxiong Feng, Hongshen Chen, Kan Li, and Dawei Yin. 2020a. Posterior-gan: Towards informative and coherent response generation with posterior generative adversarial network. In AAAI, pages 7708–7715.

Shaoxiong Feng, Xuancheng Ren, Hongshen Chen, Bin Sun, Kan Li, and Xu Sun. 2020b. Regularizing dialogue generation by imitating implicit scenarios. In EMNLP, pages 6592–6604.

Joseph L. Fleiss. 1971. Measuring nominal scale agreement among many raters. Psychological Bulletin, 76(5):378.

Xiang Gao, Sungjin Lee, Yizhe Zhang, Chris Brockett, Michel Galley, Jianfeng Gao, and Bill Dolan. 2019. Jointly optimizing diversity and relevance in neural response generation. In NAACL-HLT (1), pages 1229–1238.

Marjan Ghazvininejad, Chris Brockett, Ming-Wei Chang, Bill Dolan, Jianfeng Gao, Wen-tau Yih, and Michel Galley. 2018. A knowledge-grounded neural conversation model. In AAAI, pages 5110–5117.

Xiaodong Gu, Kyunghyun Cho, Jung-Woo Ha, and Sunghun Kim. 2019. Dialogwae: Multimodal response generation with conditional wasserstein auto-encoder. In ICLR (Poster).

Chaoyu Guan, Xiting Wang, Quanshi Zhang, Runjin Chen, Di He, and Xing Xie. 2019. Towards a deep and unified understanding of deep neural models in NLP. In ICML, volume 97, pages 2454–2463.

Junliang Guo, Zhirui Zhang, Linli Xu, Hao-Ran Wei, Boxing Chen, and Enhong Chen. 2020. Incorporating BERT into parallel sequence decoding with adapters. In NeurIPS.

Geoffrey E. Hinton, Oriol Vinyals, and Jeffrey Dean. 2015. Distilling the knowledge in a neural network. CoRR, abs/1503.02531.

Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzbebski, Bruna Morrone, Quentin de Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. 2019. Parameter-efficient transfer learning for NLP. In ICML, volume 97 of Proceedings of Machine Learning Research, pages 2790–2799.

Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings.

Jiwei Li, Michel Galley, Chris Brockett, Jianfeng Gao, and Bill Dolan. 2016a. A diversity-promoting objective function for neural conversation models. In HLT-NAACL, pages 110–119.

Jiwei Li, Will Monroe, Alan Ritter, Dan Jurafsky, Michel Galley, and Jianfeng Gao. 2016b. Deep reinforcement learning for dialogue generation. In EMNLP, pages 1192–1202.

Yanan Li, Hui Su, Xiaoyu Shen, Wenjie Li, Ziqiang Cao, and Shuzi Niu. 2017. Dailydialog: A manually labelled multi-turn dialogue dataset. In IJCNLP(1), pages 986–995.

Pierre Lison and Serge Bibauw. 2017. Not all dialogues are created equal: Instance weighting for neural conversational models. In SIGdial Meeting on Discourse and Dialogue, pages 384–394. Association for Computational Linguistics.

Qian Liu, Yihong Chen, Bei Chen, Jian-Guang Lou, Zixuan Chen, Bin Zhou, and Dongmei Zhang. 2020. You impress me: Dialogue generation via mutual persona perception. In ACL, pages 1417–1427.

Jonas Pfeiffer, Ashwarya Kamath, Andreas Rücklé, Kyunghyun Cho, and Iryna Gurevych. 2021. Adapterfusion: Non-destructive task composition for transfer learning. In EACL, pages 487–503.
Iulian Vlad Serban, Ivan Vulic, Iryna Gurevych, and Sebastian Ruder. 2020. MAD-X: an adapter-based framework for multi-task cross-lingual transfer. In EMNLP, pages 7654–7673.

Jason Phang, Thibault Févery, and Samuel R. Bowman. 2018. Sentence encoders on stilts: Supplementary training on intermediate labeled-data tasks. CoRR, abs/1811.01088.

Jerin Philip, Alexandre Berard, Matthias Gallé, and Laurent Besacier. 2020. Monolingual adapters for zero-shot neural machine translation. In EMNLP, pages 4465–4470.

Qiao Qian, Minlie Huang, Haizhou Zhao, Jingfang Xu, and Xiaoyan Zhu. 2017. Assigning personality/identity to a chatting machine for coherent conversation generation. CoRR, abs/1706.02861.

Hannah Rashkin, Eric Michael Smith, Margaret Li, and Y-Lan Boureau. 2019. Towards empathetic open-domain conversation models: A new benchmark and dataset. In ACL, pages 5370–5381.

Mengye Ren, Wenyuan Zeng, Bin Yang, and Raquel Urtasun. 2018. Learning to reweight examples for robust deep learning. In ICML, volume 80 of Proceedings of Machine Learning Research, pages 4331–4340.

Stephen Roller, Emily Dinan, Naman Goyal, Da Ju, Mary Williamson, Yinhan Liu, Jing Xu, Myle Ott, Kurt Shuster, Eric Michael Smith, Y-Lan Boureau, and Jason Weston. 2020. Recipes for building an open-domain chatbot. CoRR, abs/2004.13637.

Phillip Rust, Jonas Pfeiffer, Ivan Vulic, Sebastian Ruder, and Iryna Gurevych. 2021. How good is your tokenizer? on the monolingual performance of multilingual language models. In ACL/IJCNLP, pages 3118–3135.

Omer Sagi and Lior Rokach. 2018. Ensemble learning: A survey. Wiley Interdiscip. Rev. Data Min. Knowl. Discov., 8(4).

Abigail See, Stephen Roller, Douwe Kiela, and Jason Weston. 2019. What makes a good conversation? how controllable attributes affect human judgments. In NAACL-HLT, pages 1702–1723.

Iulian Vlad Serban, Tim Klüng, Gerald Tesarou, Kartik Talamadupula, Bowen Zhou, Yoshua Bengio, and Aaron C. Courville. 2017a. Multiresolution recurrent neural networks: An application to dialogue response generation. In AAAI, pages 3288–3294. AAAI Press.

Iulian Vlad Serban, Alessandro Sordoni, Yoshua Bengio, Aaron C. Courville, and Joelle Pineau. 2016. Building end-to-end dialogue systems using generative hierarchical neural network models. In AAAI, pages 3776–3784.

Julian Vlad Serban, Alessandro Sordoni, Ryan Lowe, Laurent Charlin, Joelle Pineau, Aaron C. Courville, and Yoshua Bengio. 2017b. A hierarchical latent variable encoder-decoder model for generating dialogues. In AAAI, pages 3295–3301.

Lifeng Shang, Zhengdong Lu, and Hang Li. 2015. Neural responding machine for short-text conversation. In ACL (1), pages 1577–1586.

Mingyue Shang, Zhenxin Fu, Nanyun Peng, Yansong Feng, Dongyan Zhao, and Rui Yan. 2018. Learning to converse with noisy data: Generation with calibration. In IJCAI, pages 4338–4344.

Lei Shen, Haolan Zhan, Xin Shen, Hongshen Chen, Xiaofang Zhao, and Xiaodan Zhu. 2021. Identifying untrustworthy samples: Data filtering for open-domain dialogues with bayesian optimization. In CIKM ’21: The 30th ACM International Conference on Information and Knowledge Management, Virtual Event, Queensland, Australia, November 1 - 5, 2021, pages 1598–1608. ACM.

Haoyu Song, Yan Wang, Weinan Zhang, Xiaojiang Liu, and Ting Liu. 2020. Generate, delete and rewrite: A three-stage framework for improving persona consistency of dialogue generation. In ACL, pages 5821–5831.

Alessandro Sordoni, Michel Galley, Michael Auli, Chris Brockett, Yangfeng Ji, Margaret Mitchell, Jian-Yun Nie, Jianfeng Gao, and Bill Dolan. 2015. A neural network approach to context-sensitive generation of conversational responses. In HLT-NAACL, pages 196–205.

Bin Sun, Shaoxiong Feng, Yiwei Li, Jiawen Liu, and Kan Li. 2021. Generating relevant and coherent dialogue responses using self-separated conditional variational autoencoders. In ACL, pages 5624–5637.

Chongyang Tao, Sheng Gao, Mingyue Shang, Wei Wu, Dongyan Zhao, and Rui Yan. 2018. Get the point of my utterance! learning towards effective responses to converse with noisy data: Generation with calibration. In IJCAI, pages 4418–4424.

Jörg Tiedemann. 2009. News from OPUS—A Collection of Multilingual Parallel Corpora with Tools and Interfaces.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In NIPS, pages 5998–6008.

Oriol Vinyals and Quoc V. Le. 2015. A neural conversational model. In ICML Deep Learning Workshop.

Ruize Wang, Duyu Tang, Nan Duan, Zhongyu Wei, Xuanning Huang, Jianshu Ji, Guihong Cao, Daxin Jiang, and Ming Zhou. 2020. K-adapter: Infusing knowledge into pre-trained models with adapters. CoRR, abs/2002.01808.
Chen Xing, Wei Wu, Yu Wu, Jie Liu, Yalou Huang, Ming Zhou, and Wei-Ying Ma. 2017. Topic aware neural response generation. In AAAI, pages 3351–3357.

Jingjing Xu, Xuancheng Ren, Junyang Lin, and Xu Sun. 2018a. Diversity-promoting GAN: A cross-entropy based generative adversarial network for diversified text generation. In EMNLP, pages 3940–3949.

Xinnuo Xu, Ondrej Dusek, Ioannis Konstas, and Verena Rieser. 2018b. Better conversations by modeling, filtering, and optimizing for coherence and diversity. In EMNLP, pages 617–626.

Lantao Yu, Weinan Zhang, Jun Wang, and Yong Yu. 2017. Seqgan: Sequence generative adversarial nets with policy gradient. In AAAI, pages 2852–2858.

Hainan Zhang, Yanyan Lan, Jiafeng Guo, Jun Xu, and Xueqi Cheng. 2018a. Reinforcing coherence for sequence to sequence model in dialogue generation. In IJCAI, pages 4567–4573.

Hainan Zhang, Yanyan Lan, Liang Pang, Jiafeng Guo, and Xueqi Cheng. 2019. Recosa: Detecting the relevant contexts with self-attention for multi-turn dialogue generation. In ACL, pages 3721–3730.

Saizheng Zhang, Emily Dinan, Jack Urbanek, Arthur Szlam, Douwe Kiela, and Jason Weston. 2018b. Personalizing dialogue agents: I have a dog, do you have pets too? In ACL, pages 2204–2213.

Yizhe Zhang, Siqi Sun, Michel Galley, Yen-Chun Chen, Chris Brockett, Xiang Gao, Jianfeng Gao, Jingjing Liu, and Bill Dolan. 2020. DIALOGPT : Large-scale generative pre-training for conversational response generation. In ACL, pages 270–278.

Tiancheng Zhao, Ran Zhao, and Maxine Eskénazi. 2017. Learning discourse-level diversity for neural dialog models using conditional variational autoencoders. In ACL (1), pages 654–664.

Hao Zhou, Minlie Huang, Tianyang Zhang, Xiaoyan Zhu, and Bing Liu. 2018. Emotional chatting machine: Emotional conversation generation with internal and external memory. In AAAI-18, pages 730–739.

A More Discussions

Q1: Why do we use L1 to reflect the distance between $z_m$ and $z$? And can this distance represent the importance of adapters?
Q2: Why do we choose Specificity (See et al., 2019) as one of the baselines? What is the relationship between See et al. (2019) and our work?

A1: (1) One is that L1 is better than other measurements in terms of computational efficiency. The other is that the distance calculated by L1 has higher discrimination than other measurements (e.g., L2), making the probability distribution (the coefficient $\lambda$) more concentrated. We have observed that the probability distribution based on L2 is relatively uniform, so it will make Equation 3 more like calculating the mean value. We have also tried mutual information (MI) as (Guan et al., 2019), but it would reduce the model performance.

A2: Although See et al. (2019) does not filter the dataset, it evaluates the sample quality with the proposed scoring methods. More importantly, it clearly demonstrates that different kinds of high-quality data are beneficial for the model to learn attribute-related features effectively, which also supports the motivation of our work. In our experiment, we use the scoring method Specificity from it as one of the baselines because it can well characterize the specificity of the samples, and specific tokens are helpful to enhance the response quality.

| Distance | Dist-1 | Dist-2 | KL-1 | KL-2 | BLEU |
|----------|--------|--------|------|------|------|
| MI       | 0.0412 | 0.1451 | 0.92 | 0.82 | 0.379|
| L2       | 0.0431 | 0.1520 | 0.90 | 0.77 | **0.384**|
| L1 (Ours)| **0.0434** | 0.1522 | 0.88 | 0.75 | 0.383|

Table 10: Comparison of different distance measurements for Adaptive Fusion (AF).

B Which Samples Can Be Considered High-Quality?

We utilize the Specificity (See et al., 2019) and Consistency (Akama et al., 2020) scoring methods to evaluate the samples of DailyDialog, and obtain four sets of samples, shown in Figure 1.
We use these sets to train the Transformer-based dialogue model. The results are shown in Table 11. “Filtering-Con”, “Filtering-Spe”, “Intersection”, and “Union” represent the models trained on the blue+red parts, the blue+orange parts, the blue part, and the blue+red+orange parts in Figure 1, respectively. From Table 11, we can find that the performances of models trained on the blue+red parts and the blue+orange parts are both better than that of model trained only on the blue part. Besides, the model trained on the blue+red+orange parts obtains the best performance than others. These results illustrate that the samples with low scores in one scoring method but high scores in other scoring methods are still good samples for the model training.

C Algorithm of Proposed Framework

The full training details of MAE are shown in Algorithm 1.

D Datasets

Two public dialogue datasets are employed in our experiments: DailyDialog, which contains conversations that are similar to human daily communication (Li et al., 2017), and OpenSubtitles, which consists of large-scale dialogues converted from movie subtitles (Tiedemann, 2009).

Table 12 provides the statistics of both datasets after data preprocessing.

E Details for Scoring Methods

Here are the details of three high-quality automatic scoring methods compared by the experiments:

• **Consistency** (Akama et al., 2020): A joint score:

\[ S_{C+R}(q, r) = \alpha S_C + \beta S_R \]

that consists of two parts: connectivity \( S_C \) and content relatedness \( S_R \). The \( \alpha \) and \( \beta \) are hyper-parameters that weigh the two parts, and are fixed as the means of all \( S_C \) and \( S_R \), respectively. The \( S_C \) is evaluated by the co-occurrence of key-phrases (\( p \in q, h \in r \)):

\[ S_C = \sum_{(p, h)} \max(nPMI(p, h), 0) \cdot |p| \cdot |h| \]

where \( |\cdot| \) means the number of words in the phrase or utterance, and the \( nPMI \) represents the normalized pointwise mutual information (Bouma, 2009). In addition, \( S_R \) is evaluated by the cosine of the context and its response:

\[ S_R = \max(\cos(q_{emb}, r_{emb}), 0) \]

The \( q_{emb} \) and the \( r_{emb} \) are vector representations of the query and response. This scoring method can reflect the consistency of a dialogue pair.

• **Entropy_{Src}** (Csaky et al., 2019): This score is the entropy of a response utterance:

\[ H_{src}(r|D) = - \sum_{(q, r) \in D} p(q_i|r) \log p(q_i|r) \]

where \( r \) represents the response, \( D \) represents the dialogue dataset, and \( q_i \) means a query of \( r \) in \( D \). The \( p(q_i|r) \) means the probability that the query is \( q_i \) while the response is \( r \). This scoring method will filter the dialogue pairs with "many-to-one" problem, so that it will alleviate the phenomenon of general response.

• **Specificity** (See et al., 2019):

\[ NIDF(t) = \frac{idf(t) - \min_{max_{idf} - \min_{idf}}} \]

where the \( t \) is a token of the response, and the \( idf(t) = \log(\frac{R_t}{R_i}) \). \( R \) is the number of responses in the dataset, and \( R_i \) is the number of those responses that contain \( t \). The mean Normalized Inverse Document Frequency (NIDF) of all tokens in an utterance is utilized to represent the specificity of it. This scoring method can identify whether the response contains specific tokens.
### F Training Details

The hyperparameters of our Transformer based dialogue model is shown in Table 13. We use the Adam optimizer (Kingma and Ba, 2015) and employ warm up trick to adjust the learning rate during training with the `warm_up_steps` set as 32,000, which is computed as:

$$
2 \times \min\left(\frac{1}{\sqrt{n_{steps}}}, \frac{n_{steps}}{\sqrt{\text{warm}_\text{up}_\text{steps}}}\right)
$$

where $lr$ is the learning rate at the $n_{steps}$ of training. For our method, we set the units of down-projection and up-projection feed-forward networks of each adapter as 64 and 512, respectively. In inference stage, the Beam Search is employed, and the beam size is set as 5.

Details for the metrics we employ for both automatic and human evaluations:

- **Dist-[1,2]** (distinct) (Li et al., 2016a) is a widely used metric that reflects the lexical diversity of the generated responses by calculating the proportion of unique unigrams/bigrams.

- **KL-[1,2]** (KL divergence) (Csaky et al., 2019) measures the distribution distance between the generated and the ground-truth response sets to reflect how well a model can approximate the ground-truth unigrams/bigrams distribution.

- **BLEU** (Chen and Cherry, 2014) measures n-gram overlap between the generated and the ground-truth responses.

- **Coherence** (Xu et al., 2018b) measures the cosine similarity between pairs of input and response.

- **H-[1,2]** (word entropy) (Serban et al., 2017b) measures the unigrams/bigrams’ non-genericness of responses by $H = -\sum_{w \in U} \log_2 p(w)$, where $p(w)$ is calculated based on frequency observed in the training data.

- **Informativeness** reflects how much the information related to the query is contained in the generated response.

- **Relevance** reflects how likely the generated response is relevant to its query.

- **Fluency** reflects how likely the generated response comes from human.

- **Consistency** reflects how likely the generated response is coherent to its query, roughly the same as **Relevance**.

- **Specificity** reflects how much the generated response is good at word usage.

### G Detailed Kappa Results for Human Evaluations

| vs. Models | Informativeness | Relevance | Fluency |
|-----------|-----------------|-----------|---------|
| Transformer | 0.537/0.515     | 0.459/0.472 | 0.520/0.599 |
| Filtering-Con | 0.652/0.681     | 0.586/0.631 | 0.474/0.391 |
| Filtering-Ent | 0.450/0.604     | 0.555/0.667 | 0.458/0.467 |
| Filtering-Spe | 0.362/0.534     | 0.620/0.664 | 0.527/0.560 |
| Weighting-Ent | 0.511/0.631     | 0.479/0.652 | 0.569/0.522 |

Table 14: Fleiss’s Kappa for human evaluations on DailyDialog (Top) and OpenSubtitles (Bottom). A/B in each table cell refer to the results of MAE-AF/MAE-PF, respectively.

Table 14 shows the detailed results of Fleiss’ Kappa (Fleiss, 1971) for human evaluations.

### H Study on the Order of Progressive Fusion

In order to study the influence of progressive fusion order on the model performance, we consider all possible sequences and conduct corresponding experiments. Table 15 shows that no matter what kind of progressive training order, the results are significantly better than the baseline model. And
the distinct and KL divergence are also improved compared with the adaptive fusion (AF) strategy. This proves that all the different learning order for PF can get great improvement.

I More Results for Robustness Analysis of the Selection Ratio

To investigate the effect of the selection ratio on the performance of filtering methods, we expand the test with two different proportions on both two datasets. The experimental results are summarized in Table 17. Compared with the non-filtered base transformer model, the three 80% filtered models make slight improvement of OpenSubtitles on the transformer model, the three 80% filtered models

Table 15: Results of MAE-PF with different fusion orders.

| Models   | Dist-1 | Dist-2 | KL-1 | KL-2 | BLEU  |
|----------|--------|--------|------|------|-------|
| Transformer | 0.0157 | 0.0410 | 2.37 | 1.72 | 0.336 |
| MAE-AF    | 0.0204 | 0.0660 | 1.83 | 1.55 | 0.335 |
| MAE-PF-CES| 0.0217 | 0.0676 | 1.80 | 1.46 | 0.339 |
| MAE-PF-CSE| 0.0210 | 0.0681 | 1.72 | 1.55 | 0.328 |
| MAE-PF-SEC| 0.0224 | 0.0723 | 1.71 | 1.38 | 0.337 |
| MAE-PF-SCE| 0.0218 | 0.0702 | 1.66 | 1.45 | 0.332 |
| MAE-PF-ESC| 0.0224 | 0.0736 | 1.63 | 1.39 | 0.336 |
| MAE-PF-ECS| 0.0236 | 0.0762 | 1.63 | 1.32 | 0.340 |

Table 16: Detailed results of Figure 6.

Algorithm 1 MAE

Input: \(D, D^v\) and \(D^f\): the raw training, validation and test dataset; 
\(S = \{S_1, S_2, \ldots, S_M\}\): the scoring methods; 
\(\theta\): the parameters of the base model; 
\(\phi = \{\phi_1, \phi_2, \ldots, \phi_M\}\): the parameters of adapters; 
\(Fusion\_flag\): the flag used to choose AF or PF.

Output: \(\theta^*\) and \(\phi^*\): the learned base model and adapters.

1: % View-specific collection.
2: for \(m = 1\) to \(M\) do
3: \[data\_scores \leftarrow calculate\_data\_scores(D, S_m)\]
4: \[index\_list \leftarrow sort(data\_scores)\]
5: \[D_m \leftarrow extract\_top\_data(D, index\_list)\]
6: end for
7: % Pre-train the base model \(\theta\).
8: repeat
9: \[\text{optimize } \theta \text{ by minimizing } L_{nll}(\theta) \text{ on } D \text{ using Eq. (1)}\]
10: \[\text{evaluate } \theta \text{ on } D^v\]
11: \[\text{until convergence}\]
12: % Fine-Tune adapters with fixed \(\theta^*\) and fusion.
13: if \(\text{Fusion\_flag is AF}\) then
14: \[\text{repeat}\]
15: \[\text{optimize } \phi_1, \phi_2, \ldots, \phi_M \text{ in parallel by minimizing } L_{nll}(\phi^m) \text{ on its corresponding } D_m\]
16: \[\text{evaluate } \theta^* + \phi^m \text{ on } D^v\]
17: \[\text{until convergence}\]
18: \[\text{fuse } \phi_1^*, \phi_2^*, \ldots, \phi_M^* \text{ using Eq. (3) on } D^f\]
19: else
20: \[\text{if Fusion\_flag is PF}\]
21: \[\text{for } m = 1 \text{ to } M \text{ do}\]
22: \[m \leftarrow \text{randomly}\_\text{pop}(1, 2, \ldots, M)\]
23: \[\text{repeat}\]
24: \[\% \text{ Fusion during training.}\]
25: \[\text{optimize } \phi^m \text{ by minimizing } L(\phi^m) \text{ on } D_m \text{ using Eq. (5)}\]
26: \[\text{evaluate } \theta^* + \phi^1 + \ldots + \phi^m \text{ on } D^v\]
27: \[\text{until convergence}\]
28: \[\text{end for}\]
29: \[\text{end if}\]
30: return learned base model \(\theta^*\) and adapters
\(\phi^* = (\phi_1^*, \phi_2^*, \ldots, \phi_M^*)\)
## Table 17: Impact of the selection ratio on the model performance on DailyDialog (Left) and OpenSubtitles (Right).

| Models                  | Dist-1 | Dist-2 | KL-1 | KL-2 | BLEU | Dist-1 | Dist-2 | KL-1 | KL-2 | BLEU |
|-------------------------|--------|--------|------|------|------|--------|--------|------|------|------|
| Transformer             | 0.0216 | 0.0728 | 1.67 | 1.66 | 0.292| 0.0157 | 0.0410 | 2.37 | 1.72 | 0.336|
| Filtering-Con (80%)     | 0.0225 | 0.0752 | 1.62 | 1.08 | 0.330| 0.0189 | 0.0569 | 2.01 | 1.70 | 0.322|
| Filtering-Con (50%)     | 0.0088 | 0.0306 | 2.74 | 2.01 | 0.314| 0.0160 | 0.0544 | 1.87 | 1.46 | 0.321|
| Filtering-Ent (80%)     | 0.0166 | 0.0462 | 2.16 | 1.77 | 0.307| 0.0156 | 0.0429 | 2.42 | 1.73 | 0.337|
| Filtering-Ent (50%)     | 0.0096 | 0.0255 | 2.63 | 2.17 | 0.315| 0.0102 | 0.0291 | 2.72 | 1.52 | 0.366|
| Filtering-Spe (80%)     | 0.0132 | 0.0465 | 2.20 | 2.24 | 0.244| 0.0150 | 0.0439 | 1.93 | 1.82 | 0.311|
| Filtering-Spe (50%)     | 0.0061 | 0.0210 | 3.62 | 3.17 | 0.199| 0.0089 | 0.0235 | 3.02 | 1.83 | 0.348|
| MAE-AF (80%)            | 0.0383 | 0.1370 | 0.97 | 0.85 | 0.375| 0.0194 | 0.0585 | 1.91 | 1.57 | 0.328|
| MAE-AF (50%)            | 0.0434 | 0.1522 | 0.88 | 0.75 | 0.383| 0.0204 | 0.0660 | 1.83 | 1.55 | 0.335|
| MAE-PF (80%)            | 0.0403 | 0.1361 | 0.94 | 0.68 | 0.382| 0.0204 | 0.0644 | 1.77 | 1.58 | 0.326|
| MAE-PF (50%)            | 0.0463 | 0.1511 | 0.94 | 0.68 | 0.392| 0.0217 | 0.0676 | 1.80 | 1.46 | 0.339|