Semantic-Enhanced Explainable Finetuning for Open-Domain Dialogues
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Abstract
In this paper, we propose to combine pretrained language models with the modular dialogue paradigm for open-domain dialogue modeling. Our method, semantic-enhanced finetuning, instantiates conversation understanding, planning, and response generation as a language model finetuning task. At inference, we disentangle semantic and token variations by specifying sampling methods and constraints for each module separately. For training and evaluation, we present X-WEB, a Chinese multi-turn open-domain dialogue dataset with automatic annotation for emotions, DAs, and topical words. Experiments show that semantic-enhanced finetuning outperforms strong baselines on non-semantic and semantic metrics, improves the human-evaluated relevance, coherence, and informativeness, and exhibits considerable controllability over semantic variables.

1 Introduction
Building open-domain conversational agents is a long-standing goal of artificial intelligence (Huang et al., 2020). Recently, open-domain dialogue systems built upon large-scale generative pretrained language models (Zhang et al., 2020; Roller et al., 2020; Adiwardana et al., 2020) achieve state-of-the-art conversation performances in terms of the quality, relevance, engagingness, and diversity. On the other hand, what has long been studied is the modular dialogue modeling (Roy et al., 2000; Tur and De Mori, 2011), which explicitly models the understanding and planning of semantic information (Schank and Albelson, 1977; Carberry, 1990) that flows throughout the conversation. This modular idea has been explored in task-oriented dialogue systems (Williams et al., 2016; Li et al., 2017a; Rastogi et al., 2018; Peng et al., 2020), knowledge-driven conversations (Su et al., 2020; Hedayatnia et al., 2020), negotiation (He et al., 2018), and persuasion (Santhanam et al., 2020). A benefit of this paradigm is its explainability and controllability. It also allows one to specify the type of modeled semantic variable, which makes the system robust to other variations.

In this paper, we propose to bridge the pretrained language models with the modular dialogue modeling paradigm for open-domain dialogue systems, which we name as semantic-enhanced finetuning. We model the understanding and planning of emotions, dialogue acts (DAs), and topics during the finetuning of open-domain dialogue models. We use a language model to instantiate three modules: understanding, planning, and response generation. Specifically, the understanding module infers the semantic variables of the dialogue history, the planning module plans the semantic variables of the next response, and the response generation module generates diverse responses. An overview is shown in Figure 1. The three modules share the pretrained parameters and are jointly finetuned using the autoregressive cross-entropy loss. At inference, we disentangle semantic and token variations by specifying sampling methods and constraints for each module separately. Specifically, we find that the minimal length constraint is effective for topic planning and response generation. We also design a repetition constraint for topic planning to address the repetition problem.

Semantic-enhanced finetuning has three benefits. First, it exploits the response generation capability acquired during pretraining, which improves the response generation step of the modular paradigm. Second, it equips chatbots with fine-grained controllability: One may manipulate the plans to control the emotions, DAs, and topics of the response; One may also keep the plans unchanged and manipulate the response generation module to generate

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¹Work in progress. Code and data will be publicly available.
stylized responses while preserving the emotions, DAs, and topics. Third, semantic-enhanced fine-tuning is explainable. For example, when an improper response is generated, one can attribute the error by checking the predicted semantic variables.

Our model should be finetuned on conversations annotated with semantic variables, but human annotation for large-scale conversation data faces the scalability challenge. Thus, we propose to automatically annotate semantic variables with pretrained classifiers. Based on conversations collected from Weibo, we present X-WEB, a Chinese multi-turn open-domain dialogue dataset with over 500k dialogue sessions, annotated with emotions, dialogue acts, and topical words.

We compare our method with strong baselines using the same pretrained weights and observe that it has the best BLEU scores (Papineni et al., 2002), embedding-based metrics (Liu et al., 2016), diversity (Li et al., 2016a), and semantic-level agreement with human references. Human evaluation results show that our approach significantly outperforms the baselines in terms of relevance, coherence, and informativeness. For controllability, we show that our method can be guided by controlling the plans. Our contributions are as follows:

• We propose semantic-enhanced finetuning for open-domain dialogue systems, which bridges large-scale pretrained models with modular dialogue modeling.

• We present the X-WEB dataset with automatic annotation for emotions, DAs, and topical words, which will be open-sourced.

• In the experiments, our method outperforms strong baselines in terms of automatic metrics and human evaluation and has controllability.

2 Related Work

Modeling semantic variables in conversation has a long history (Schank and Albelson, 1977; Carberry, 1990). Prior works in this direction build modular systems to capture dialogue states (Roy et al., 2000; Li et al., 2017a), and various approaches focus on the task of understanding and planning in open-domain dialogues (Tur and De Mori, 2011; Rastogi et al., 2018). However, most of these systems build separated models for the understanding, planning, and generation modules, while we instantiate these modules as a pre-trained language model.

Transformers (Vaswani et al., 2017) pretrained on large-scale conversation data achieve state-of-the-art performances on the open-domain dialogue modeling, and examples include DialoGPT (Zhang et al., 2020), Blender (Roller et al., 2020), and Meena (Adiwardana et al., 2020). These models view conversation data as sequences of tokens alternating between speakers and cast open-domain dialogue modeling as a seq2seq learning problem (Sutskever et al., 2014). Such simplicity enables scalability to large-scale conversation data. However, to truly understand human conversations, an agent should be able to connect utterances to explainable semantic concepts. Our focus is to combine the modular dialogue paradigm, which models conversational understanding and planning, with pretrained language models for open-domain dialogue systems.

It also worth noting that some works have stud-
ied the planning of general dialogue acts (DAs) (Xu et al., 2018), and others have designed DAs for specific domains, e.g., dialogue states (Williams et al., 2016; Peng et al., 2020) for task-oriented dialogues, strategies (He et al., 2018) for negotiation, lexical-conceptual structures (Santhanam et al., 2020) for persuasion, and policy or intent planning (Su et al., 2020; Hedayatnia et al., 2020) that for knowledge-driven conversations. A prerequisite for these approaches is the domain-specific dialogue acts. A concurrent work (Ghazarian et al., 2021) extracts entities and topics and plans keywords on the knowledge-grounded TopicalChat dataset (Gopalakrishnan et al., 2019). In this work, we focus on general semantic variables shared by most conversations: emotions (Zhou et al., 2018; Varshney et al., 2021), general dialogue acts (Li et al., 2017b), and topical words (Liu et al., 2011b), which are more general and more transferable in the open domain.

Our work is also related to CVAE (Zhao et al., 2017) and PLATO (Bao et al., 2020), which captures the discourse-level diversity in human conversations with latent variables. Compare with them, the modular paradigm has a higher level of controllability (e.g., it can be intervened with human-specified plans) and explainability (e.g., it can be debugged by checking the predicted plans).

Meanwhile, our semantic variables (i.e., emotions, DAs, and topical words) are more fine-grained than Gaussian or categorical latent variables.

3 Our Approach

3.1 Task Formulation

A multi-turn dialogue session is a sequence of utterances alternating between Human and Machine: (r_1, \ldots, r_{2N}). Without loss of generality, our formulation assumes that Human initiates the conversation, i.e., r_{2i−1} and r_{2i} (i = 1, \ldots, N) are uttered by Human and Machine, respectively. Each session may also be grounded on some non-conversational context, e.g., persona and topics.

**Semantic variables** Each Human’s or Machine’s utterance r_i (i = 1, \ldots, 2N) can be explained by K semantic variables s_i = \{(s_{\text{key}}^k, s_{\text{val}}^k_i)\}_{k=1}^K, where s_{\text{key}}^k is the type, and s_{\text{val}}^k_i is the value. In our X-WEBIO dataset introduced in Section 4, the value of topical words is a list of deduplicated phrases (each phrase is a list of tokens); the value of DAs (emotions) is a list of DA (emotion) labels, each label corresponding to a sentence in the utterance. For example, if an utterance first answers a question and then post another question, then its DAs value is [Inform, Question].

**Dialogue decomposition** With the semantic variables, modular dialogue modeling decomposes the open-domain dialogue into three modules: understanding U_0, planning P_0, and response generation G_\theta. Specifically, the understanding module infers the semantic variables of Human’s last utterance. The planning module plans the semantic variables of Machine’s response. The response generation module generates responses, which captures the variations that are not covered by the plan. Formally, the overall objective is to be maximized is

\[
\mathbb{E}_D \left[ \sum_{i=1}^N \left( \log U_\theta(s_{2i−1}|r_{≤2i−1}, g, s_{≤2i−1}) + \log P_\theta(s_{2i}|r_{≤2i−1}, g, s_{≤2i−1}) + \log G_\theta(r_{2i}|r_{≤2i−1}, g, s_{≤2i}) \right) \right] \tag{1}
\]

where D is the empirical distribution of data, e.g., the X-WEBIO dataset introduced in Section 4.

3.2 Semantic-Enhanced Finetuning

We propose to model the three modules with the same generative pretrained weights, which we name as semantic-enhanced finetuning. Based on Eq. (1), we place the non-conversational context, utterances, and semantic variables in the order:

\[
g; r_1, s_1, s_2, r_2 \ldots r_{2N−1}, s_{2N−1}, s_{2N}, r_{2N} \tag{2}
\]

The non-conversational context g is placed at the beginning since they are shared by all Machine’s utterances. In the i^{th} turn, the model infers the semantic variables s_{2i−1}^2 of Human’s last utterance r_{2i−1}, (understanding), predicts the semantic variables s_{2i} of Machine’s next utterance (planning), and generates the next utterance r_{2i} (response generation). We define five token types (Devlin et al., 2019) to distinguish the elements in Eq. (2), which include Human’s utterances, Machine’s utterances, Human’s semantic variables, Machine’s semantic variables, and non-conversational context. Based on Eq. (2), the three modules U_\theta, P_\theta, and G_\theta are unified within a single sequence generation model

\footnote{Note that s_{2i−1} contains key-value pairs for several variables, e.g., DAs, emotions, and topical words.}
We use words, but note that different orders factorize the tokens that we compute loss for. Any sequence generation model can be adopted by our approach. In the example in Figure 2, we put a tick over utterances in Eq. (2). Additionally, we do not compute the autoregressive cross-entropy loss for the semantic variables’ keys $s_{\text{key}}^k$ since they do not need to be predicted during inference. In the example in Figure 2, we put a tick over the tokens that we compute loss for. Any sequence generation model can be adopted by our approach.

| Semantic variable keys | {topical} {emotion} {dialog_act} |
|------------------------|----------------------------------|
| List separator         | {list_sep}                       |
| End of key-value pair  | (eokv)                           |
| Start of conversation  | [CLS]                           |
| Start of Human’s utt.  | ⟨human⟩                         |
| Start of Machine’s utt.| ⟨machine⟩                       |
| End of utterance       | [SEP]                            |

Table 1: Special tokens used in the model

(e.g., a generative LM or a seq2seq model) that can be trained end-to-end. When predicting each element in Eq. (2), the model is conditioned on all elements in the prefix. By switching the roles of Human and Machine, we derive two samples in the form of Eq. (2) from each dialogue session.

It still remains an open question how to represent structured semantic variables as a sequence. In this paper, we design several special tokens to linearize the structured variables. The special tokens are shown in Table 1, and a linearized input is shown in Figure 2. We assign a special token for each $s_{\text{key}}^k$ and use ⟨eokv⟩ to mark the end of a key-value pair. Since the values $s_{\text{val}}^k$ are all lists (Section 4), we define a list separator token ⟨list_sep⟩ to separate items in a list. In Figure 2, for example, Machine’s utterance “My favorite band is KC. What about you?” has two DAs: Inform and Question; thus, the DAs-value to be planned is linearized as “Inform ⟨list_sep⟩ Question”. We place a [CLS] between the non-conversational context and Human’s first utterance. We use ⟨human⟩ or ⟨machine⟩ to denote the speaker, and [SEP] stands for the end of an utterance. We place the semantic variables in a pre-defined order: emotion, dialogue act, and topical words, but note that different orders factorize the same joint distribution over the semantic variables.

To optimize the objective function in Eq. (1), we compute the autoregressive cross-entropy loss for the linearized semantic variables and Machine’s utterances in Eq. (2). Additionally, we do not compute loss for the semantic variables’ keys $s_{\text{key}}^k$ since they do not need to be predicted during inference. In the example in Figure 2, we put a tick over the tokens that we compute loss for. Any sequence generation model can be adopted by our approach.

### 3.3 Inference

At inference, tokens that we do not compute loss for are encoded or used as prompts for decoding. In each turn, three sequences need to be decoded. The understanding module first infers the semantic variables of Human’s last utterance, the planning module then plans the semantic variables for the next utterance, and finally the response generation module generates the response. We disentangle semantic-level and token-level variations by specifying sampling methods and constraints for each module separately, which is detailed as follows.

#### Understanding Decoding

For the understanding module, we do not set the minimum lengths, and we set the lengths for the linearized topical words, emotions, and DAs as 20, 10, 10. Greedy decoding is adopted.

#### Planning Decoding

For the planning module, we set the minimum (maximum) lengths for the linearized topical words, emotions, and DAs as 5 (20), 0 (10), 0 (10), and greedy decoding is used. The non-zero minimum length for topical words enforces non-trivial topical words to be generated, which is expected to improve the informativeness of the response.

**Repetition constraint for topical planning** We introduce the repetition constraint to avoid repeated topical words to be generated. Specifically, we suppress an $n$-gram prefix of a topical word to be generated if this prefix has been generated in the current plan. Note that the repetition constraint is not used for response generation since directly suppressing repeated $n$-grams in the response unavoidably causes disfluency, e.g., a grammatical sentence may contain two “of the”. Since our topical words only contain deduplicated informative words, we can more safely suppress repeated $n$-grams in topical words without sacrificing fluency.

#### Response Generation Decoding

For response generation, we use top-$k$ sampling (Fan et al., 2018) and top-$\tau$ sampling (Holtzman et al., 2020) with temperature $\tau$. We set $k = 50$, $p = 0.9$, and $\tau = 0.7$, which are shared by all models and baselines in Section 5. In our implementation, the length constraints are achieved by manipulating the predicted probability of ⟨eokv⟩ (for understanding and planning) or [SEP] (for response prediction) as 0 or 1.
Figure 2: The scheme we used to convert Eq. (2) into tokens. The type of sequences and the module that learn them are under the brackets. When predicting each sequence, all preceding tokens are used as the condition. We compute loss for tokens with a tick above. Denotations of special tokens are shown in Table 1.

4 X-WEIBO Dataset
4.1 Conversation Collection
Conversation data annotated with semantic variables is a prerequisite for our method. In this section, we introduce the X-WEIBO dataset that is collected to facilitate our study. Dialogues in X-WEIBO consist of comments by Weibo\(^3\) users. Each comment is regarded as an utterance in a dialogue, and the reply relations between these comments are used to construct dialogues in X-WEIBO. We use the data processing and cleaning pipelines proposed by Wang et al. (2020) to filter low-quality dialogues. After filtering, dialogues are split into the training, validation, and test splits. Dataset statistics are shown in 2.

4.2 Semantic Variables Annotation
The optimal way to acquire annotations for the semantic variables is to recruit well-trained human annotators with profound knowledge about linguistics. However, human annotation faces the scalability challenge for large-scale conversation data (e.g., over 3.3M sentences in X-WEIBO). Thus, we propose to automatically annotate semantic variables with pre-trained classifiers that encode knowledge about the semantic variables to be annotated. Note that this approach faces the distribution shift issue. Thus, our solution is a preliminary attempt towards scalable semantic annotations, and we leave more advanced methods for future studies (discussed in Section 6). Three kinds of semantic variables are annotated: topical words, dialogue acts (DAs), and emotions since they carry important semantic information in human conversations. The annotation process for these variables is detailed as follows.

Topical words The topical words for each utterance in X-WEIBO are extracted using the THUCKE package (Liu et al., 2011a), which uses a word trigger method to extract topical words with the help of a learned word alignment table. We first concatenate all utterances in X-WEIBO to construct the input file for THUCKE and then use THUCKE to extract topical words for the entire corpus. We keep the most frequent 6,000 topical words as the final topical word vocabulary and align them to each utterance using the following matching method: Specifically, the topical words for an utterance are words that appear both in this utterance and the extracted topical word vocabulary.

Sentence split In this study, the labels for DA and emotion are annotated in a finer-grained sentence-level rather than the utterance-level. Specifically, we first split each utterance (i.e., each turn) in a dialogue session into several sentences based on the end-of-sentence punctuation marks such as the period and question marks. Then we obtain the DA and emotion label for each split sentence using pre-trained DA and emotion classifiers. This annotation scheme is designed based on our observations for dialogues in X-WEIBO, i.e., each dialogue utterance in X-WEIBO may correspond to several different DA or emotion labels. The sentence-level annotations of DA and emotion enable us to capture finer-grained semantics in our dialogue model.

Dialogue acts To obtain DA labels, we adopt the DA scheme employed in the DailyDialog dataset (Li et al., 2017b). Specifically, four categories of DA are considered: Inform, Question, Directive, and Commissive. In this study, we first extract sentences with DA annotations from the DailyDialog dataset, which yields about 102.9K annotated sentences. Then we divide these sentences into the train and test set with the size of 101.0K and 1.9K, respectively. A DA classifier is built by fine-tuning the BERT-base (Devlin et al., 2019) model on the

\(^3\)Weibo is one of the largest Chinese social platforms.
| Sessions | Utt./Session | Tokens/Utt. | DAs(Emotions)/Utt. | Topical Words/Utt. |
|----------|--------------|------------|--------------------|--------------------|
| Train    | 500K         | 5.20       | 15.52              | 1.23               | 1.14               |
| Valid    | 20K          | 5.19       | 15.55              | 1.23               | 1.15               |
| Test     | 10K          | 5.21       | 15.74              | 1.24               | 1.16               |

Table 2: Dataset statistics. DA and Utt. stand for dialogue act and utterance, respectively.

Figure 3: DA (upper) and emotion (lower) label transitions. y-axis and x-axis represent the previous and the current utterance, respectively (e.g., the first row in the upper part shows the distribution of the DA of the current utterance when the DA of the previous utterance is Inform). For readability, we use utterance-level DAs and emotions in this figure, without the sentence split introduced in Section 4.

training set. The resulting classifier achieves an accuracy score of 84.58% on the testing set, and it is further used to predict the DA labels for each sentence in our X-WEIBO dataset.

**Emotions** Emotions are annotated similar to DAs. Specifically, eight emotion categories are considered in our study: Fear, Surprise, Anger, Disgust, Like, Happiness, Sadness, and None, where the label None corresponds to sentences that do not carry obvious emotions. For training, we merge two publicly available datasets\(^4\) (Li et al., 2016b) with such annotations and extract 83.29K annotated sentences. We split these data into the train and test set with the size of 80.0K and 3.29K, respectively, and obtain an emotion classifier by fine-tuning the BERT-base model. The resulting classifier achieves an accuracy score of 63.71% on the testing set.

**Data verification** To test the quality of the automatic annotation for DA and emotion, we conduct a human evaluation on 1000 randomly sampled sentences from X-WEIBO. The results indicate that 77.5% automatic emotion labels and 88.7% automatic DA labels are verified by human annotators. This proves that the automatic annotations for DAs and emotions in X-WEIBO are of relatively high quality. We measure the agreement between each annotator using free-marginal kappa (Fleiss, 1971), and the kappa score for the emotion and DA annotation is 0.49 (moderate agreement) and 0.75 (substantial agreement), respectively. We assume that the gap between the inter-annotator agreements of emotion and DA annotation can be attributed to the fact that emotions are more ambiguous for humans to distinguish. We also visualize the transition patterns of the DA and emotion labels in Figure 3.

5 Experiments

5.1 Experimental Setting

We conduct experiments using pairwise comparison. We use two pretrained LMs as the backbones: 1) Chinese GPT-2 (Radford et al., 2018)\(^6\), which is pretrained on CLUECorpusSmall (Xu et al., 2020), and 2) CDialGPT-2\(^7\), which is pretrained on a large-scale Chinese conversation dataset named LCCC-base (Wang et al., 2020). We make sure that none of the pretraining data overlap with X-WEIBO.

For each backbone, the vanilla model (GPT-2 and CDialGPT-2) is optimized with the language modeling loss without using the semantic variables, as done in DialoGPT (Zhang et al., 2020). We observe that setting a minimal decoding length improves most automatic metrics, which echoes the observation by Roller et al. (2020). Thus, we also include a min length version of each backbone (GPT-2 + min length and CDialGPT-2 + min length) as a baseline. For a fair comparison, hyperparameters are shared by all models whenever possible. The minimal decoding length is set as 9, and the maximum decoding length is set as 32, which are tuned on the validation data.

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\(^4\)http://tcci.ccf.org.cn/conference/2013/

\(^5\)https://github.com/MingleiLI/emotion_corpus_weibo

\(^6\)huggingface.co/uer/gpt2-chinese-cluecorpussmall

\(^7\)huggingface.co/thu-coai/CDial-GPT2_LCCC-base
Table 3 shows similar patterns for the two backbones. Specifically, the vanilla models (GPT-2 and CDialGPT-2) have the worst BLEU scores and the worst embedding-based scores. The performances of the min length models show that by enforcing a minimum length for the responses, we can improve the BLEU scores and embedding-based scores, but the diversity is greatly sacrificed. Our SE-GPT-2 and SE-CDialGPT-2 models largely improve the BLEU scores and embedding-based scores while maintaining comparable diversity with the vanilla models. This result indicates that responses generated by our models are more informative than the min length models. Given the fact that the only difference between our models and the min length models is the use of semantic variables, we claim that our method enables long responses to be informative as well. Additionally, results suggest that uni-gram diversity and bi-gram diversity are not correlated. It indicates that diversity is not only to generate rare words but also to generate diverse compositions of words (e.g., bi-grams).

Besides the conventional evaluation above, we also evaluate the generated responses at the semantic level. For topical words, we report the Topical-Recall, which is the proportion of labeled topical words in X-WEIBO that appear in the generated response. For the DAs and emotions, we first split the generated response into sentences based on the protocol in Section 4, which allows us to deal with utterances that contain more than one sentence with different DAs or emotions. We use the pretrained DA / emotion classifiers in Section 4 to classify each sentence. As defined in Section 4, we define the label of an utterance as the list of labels of all sentences in it. Using this definition of label, we report prevalence-weighted macro-average of F1

Note that the data distribution of X-WEIBO is different from the pretraining data, i.e., CLUECorpusSmall (Xu et al., 2020) and LCCC-base (Wang et al., 2020). Specifically, CLUECorpusSmall is used for general pretraining, and most sessions in LCCC-base are single-turn.

Models are validated for every 5000 steps, based on the perplexity (PPL) on the validation set. The batch size is 24. We use Adam (Kingma and Ba, 2015) with the initial learning rate $5 \times 10^{-5}$ and gradient clip with the norm as 1.0. The learning rate decays by half when the validation PPL does not improve five times, and training terminates after three decays. Each experiment is run on four TITAN X (Pascal) GPUs or four TITAN Xp GPUs. All models take around two days to converge.

5.2 Automatic Evaluation of Response Generation

We report several automatic metrics widely used by previous works, BLEU-{1,2,3} (Papineni et al., 2002), and Embedding-{Average, Extreme} (Liu et al., 2016), which show the word-level similarity between the predictions and human references. To evaluate the diversity of model predictions, we adopt the Dist-{1,2} metrics (Li et al., 2016a). We do not report the perplexity (PPL) for our methods since it requires an intractable marginalization over all possible semantic plans. The embedding-based metrics use the Jieba parser\footnote{https://github.com/fxsjy/jieba} to parse the responses into Chinese phrases (for accurate embedding lookup), and all other metrics view each Chinese character as a word. For the embedding-based metrics, we use the Chinese phrase embeddings by Song et al. (2018) for embedding lookup.

|                | Token-based | Embedding-based | Diversity |
|----------------|-------------|-----------------|-----------|
|                | BLEU-1      | BLEU-2          | BLEU-3    | PPL | Average | Extreme | Dist-1 % | Dist-2 % |
| GPT-2          | 11.5        | 5.0             | 2.6       | 21.2 | 0.788   | 0.747   | 0.61     | 10.42    |
| GPT-2 + min length | 12.7       | 5.5             | 2.8       | 21.2 | 0.807   | 0.779   | 0.48     | 8.86     |
| SE-GPT-2 (ours) | 
| w/ gold variables\footnote{1} | 13.2        | 6.2             | 3.1       | —    | 0.806   | 0.785   | 0.55     | 11.57    |
| CDialGPT-2     | 10.9        | 4.8             | 2.4       | 23.5 | 0.784   | 0.742   | 0.54     | 9.62     |
| CDialGPT-2 + min length | 12.9       | 5.3             | 2.6       | 23.5 | 0.805   | 0.775   | 0.41     | 7.96     |
| SE-CDialGPT-2 (ours) | 
| w/ gold variables\footnote{1} | 13.1        | 6.1             | 3.1       | —    | 0.806   | 0.783   | 0.47     | 10.53    |

Table 3: Non-semantic automatic evaluation. \footnote{1}Using gold semantic variables for the controllability test. Best results are shown in bold, and worst results are underlined.
Table 4: Semantic-level automatic evaluation. [1] Using gold semantic variables for the controllability test. Best results are shown in **bold**, and worst results are underlined.

|                | Topical-Recall | DAs-F1 | Emotions-F1 |
|----------------|----------------|--------|-------------|
| GPT-2          | 4.1            | 47.1   | 19.8        |
| GPT-2 + min length | 4.9            | 45.5   | 19.0        |
| SE-GPT-2 (ours) w/ gold variables[1] | **13.1**       | **52.1** | **22.2**    |
| CDialGPT-2     | 3.7            | 47.0   | 19.9        |
| CDialGPT-2 + min length | 4.3            | 46.0   | 19.1        |
| SE-CDialGPT-2 (ours) w/ gold variables[1] | **12.7**       | **52.1** | **22.4**    |

Table 5: Human evaluation. The free-marginal kappa score for relevance and coherence, informativeness, and engagingness is 0.79, 0.70, and 0.74, respectively, which all show substantial agreement. † and ‡ denote significantly (p < 0.01 with paired two-sample t-test) better than GPT-2 and GPT-2 + min length, respectively. Best results are shown in **bold**, and worst results are underlined.

|                | Relevance and coherence | Informativeness | Engagingness |
|----------------|-------------------------|-----------------|--------------|
| Human          | 2.27                    | 2.05            | 1.98         |
| GPT-2          | 2.08                    | 1.84            | 1.81         |
| GPT-2 + min length | 2.13                    | 1.95            | 1.93         |
| SE-GPT-2 (ours) | **2.20†‡**             | **2.07†‡**     | **1.94†‡**   |

scores for DAs / emotions (**DAs / Emotions-F1**). Note that the semantic variables are labeled by pretrained classifiers, which unavoidably contain noises and should not be viewed as gold labels.

Table 4 shows the results of semantic-level automatic evaluation. The vanilla models have higher DAs-F1 and Emotions-F1 than the min length models. It shows that by enforcing the models to generate long responses, we get sacrificed semantic-level agreement with human references. On the other hand, our SE-GPT-2 and CDialGPT-2 models largely improve the semantic-level metrics. This result shows that explicitly planning the semantic variables helps improve the semantic-level performance when generating long responses.

While the GPT-2 models generally outperform the CDialGPT-2 models in terms of the conventional metrics in Table 3, their semantic-level performance is comparable. It indicates that pretrained weights have a larger influence at the token level than at the semantic level. Thus, it is probable that one need to consider mechanisms besides pretraining (e.g., knowledge about the semantic transitions) to improve the semantic-level performance.

### 5.3 Controllability

A desirable feature of our method is its controllability, e.g., the semantic plans can be intervened by rules and humans. To evaluate controllability, we compute the similarity between model predictions and human references when providing the semantic plans in X-WEIBO, where higher similarity indicates better controllability. Table 3 shows that the token-based and embedding-based metrics are greatly improved when semantic plans are provided. It shows that the semantic variables can effectively guide the predictions. Table 3 also shows that the controlled model has improved diversity over the non-controlled models. This observation shows that, in terms of diversity, there is still space for the planning module $P_{\theta}$ to be improved. Table 4 shows that more than 90% topical words are generated in the guided responses, while the DA and emotion F1 scores are around 90% and 70%. In real-world scenarios, such controllability allows us to guide the chatbot when we would like it to display certain contents, DAs, or emotions.

### 5.4 Human Evaluation

We recruit annotators from NetEase, a third-party crowd-sourcing platform, to conduct the human evaluation. Each model prediction is scored based...
Table 6: Ablation studies. Best results are shown in bold, and worst results are underlined.

|                      | Non-semantic metrics                  | Semantic-level metrics                  |
|----------------------|---------------------------------------|-----------------------------------------|
|                      | BLEU-2      | BLEU-3      | Emb-Avg | Dist-2 % | Topical-R | DAs-F1 | EMOs-F1 |
| SE-GPT-2 (ours)      | 6.2         | 3.1         | 0.806   | 11.57    | 13.1      | 52.1   | 22.2    |
| w/o understanding    | 6.1         | 3.1         | 0.805   | 11.27    | 12.7      | 52.2   | 22.8    |
| w/o planning         | 5.3         | 2.7         | 0.805   | 9.01     | 5.0       | 46.1   | 19.4    |
| w/o repetition constraint | 6.1    | 3.1         | 0.804   | 11.46    | 12.9      | 52.0   | 21.8    |
| w/o topical words min length | 5.3   | 2.8         | 0.794   | 9.51     | 2.7       | 52.0   | 21.3    |

| SE-CDialGPT-2 (ours) | 6.1         | 3.1         | 0.806   | 10.53    | 12.7      | 52.1   | 22.4    |
| w/o understanding    | 6.2         | 3.2         | 0.806   | 10.41    | 12.1      | 52.1   | 22.3    |
| w/o planning         | 5.2         | 2.6         | 0.806   | 8.02     | 4.4       | 45.6   | 19.1    |
| w/o repetition constraint | 5.7   | 2.9         | 0.794   | 10.17    | 11.8      | 52.1   | 22.2    |
| w/o topical words min length | 5.1   | 2.7         | 0.794   | 8.52     | 2.5       | 52.1   | 21.6    |

Table 7: Evaluation for the understanding module

|                      | Topical-F1 | DAs-F1 | EMOs-F1 |
|----------------------|------------|--------|---------|
| SE-GPT-2             | 98.7       | 93.0   | 77.6    |
| SE-CDialGPT-2        | 98.5       | 92.7   | 76.4    |

5.5 Model Analysis

We conduct ablation studies to understand the contribution of some components: 1) w/o understanding and 2) w/o planning remove Human’s and Machine’s semantic variables from Eq. (2), respectively. 3) w/o topical words min length and 4) w/o repetition constraint remove the minimum length and the repetition constraint for the planning of topical words, respectively. Results are presented in Table 6. After removing the understanding component, we observe slightly dropped diversity and topical word recall, which suggests that explicitly tracking the topical words of the dialogue history improves the diversity and topical-level performance. Removing the planning component leads to a large drop in terms of nearly all metrics, which shows that planning contributes the most to our method. Although the repetition constraint does not significantly influence the performance, we view it as necessary since it avoids the repetition problem observed in preliminary experiments. The w/o topical words min length ablations have largely dropped topical words recall, which shows that the minimum length constraint for topic planning leads to more informative topical words to be generated.

We also evaluate the performance of the understanding module to investigate whether it can provide reliable semantic-level summaries of the dialogue history. We compute the DAs / Emotions-F1
based on the understanding module’s outputs and the semantic variables in X-WEIBO. For each sample, we compute the F1 score of predicted topical words and topical words in X-WEIBO, and we average them over all test samples, denoted as Topical-F1. Table 7 shows that the understanding module achieves high performances for topical words and DAs. The comparably lower emotions F1 can be attributed to the fact that emotions are more ambiguous than DAs, which is analyzed in Section 4. The overall performance shows that the understanding module can provide reliable semantic-level summaries of the dialogue history.

6 Discussion

As discussed in Section 4, human annotation of the semantic variables faces the scalability problem when applied to large-scale conversation data (e.g., over 3.3M utterances in our dataset). To address this challenge, we provide a preliminary attempt by using automatic annotation with a careful selection of training data. Although we have provided a human verification of our annotation, such annotation unavoidably introduces the distributional shift between the classifier’s training data and the conversation data. Future researches may explore semi-supervised learning methods, e.g., variational inference (Kingma and Welling, 2014) and domain adaptation methods (Ramponi and Plank, 2020), which helps address the distributional shift problem between datasets.

Our experimental results show that modeling understanding and planning with semantic variables improves open-domain dialogue modeling. Promising results suggest that understanding and planning, which are less investigated for open-domain dialogues, should get more attention. Specifically, the following directions can be investigated.

- Improved understanding and planning variables with end-to-end training. BLEU scores and PPL in Table 3 (w/ gold variables) show that there is a large space left for the response to be further annotated. The results suggest finer-grained variables to be studied for open-domain dialogue modeling.

- Controllable dialogue generation. Since planning disentangles semantic-level and token-level variations, it is natural to apply it to controllable dialogue generation, e.g., a speaker’s style, stance, and bias could be disentangled into the semantic level and the token level.

We adopt the DA scheme used in the DailyDialog dataset (Li et al., 2017b), while it should be noted that a wide range of fine-grained DAs have been proposed (Mezza et al., 2018; Bunt et al., 2020). Besides semantic meaning, human conversations also convey pragmatic meaning and implications that require commonsense reasoning (Bosse-lut et al., 2019; Sap et al., 2019). These messages are also beyond the token level and even go beyond the semantic level. Promising results in our experiments may encourage future research to explore such higher-level explainability, e.g., explicit understanding and planning aided by pragmatic and commonsense reasoning.

7 Conclusions

In this paper, we propose semantic-enhanced fine-tuning to bridge the pretrained language models with the modular dialogue modeling paradigm for open-domain dialogue systems. Our method leverages the response generation ability of pretrained models while being explainable and controllable. To address the scalability issue of semantic annotation, we present X-WEIBO, which is automatically annotated with topical words, DAs, and emotions for each utterance. Experimental results show that our method outperforms strong baselines in terms of automatic and human evaluations and has considerable controllability. Finally, we discuss ways to further address the scalability problem of semantic annotation and possible future works to consider fine-grained semantic variables, controllability, and pragmatic and commonsense reasoning.

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