EVA2.0: Investigating Open-Domain Chinese Dialogue Systems with Large-Scale Pre-Training

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Abstract

Large-scale pre-training has shown remarkable performance in building open-domain dialogue systems. However, previous works mainly focus on showing and evaluating the conversational performance of the released dialogue model, ignoring the discussion of some key factors towards a powerful human-like chatbot, especially in Chinese scenarios. In this paper, we conduct extensive experiments to investigate these under-explored factors, including data quality control, model architecture designs, training approaches, and decoding strategies. We propose EVA2.0, a largescale pre-trained open-domain Chinese dialogue model with 2.8 billion parameters, and make our models and code publicly available. To our knowledge, EVA2.0 is the largest opensource Chinese dialogue model. Automatic and human evaluations show that our model significantly outperforms other open-source counterparts. We also discuss the limitations of this work by presenting some failure cases and pose some future directions. ¹

1 Introduction

Recently, large-scale pre-training (Han et al., 2021) has become a mainstream approach to build opendomain dialogue systems, both in English (Zhang et al., 2020; Adiwardana et al., 2020; Roller et al., 2021) and Chinese (Zhou et al., 2021; Bao et al., 2021a,b). These works mostly construct large-scale dialogue corpora from social media platforms and then pre-train the model with generative objectives. Similar to the pre-trained models for general NLP tasks (Radford et al., 2019; Devlin et al., 2019; Raffel et al., 2020), pre-trained dialogue models



Figure 1: An example of the conversation between a human and the 2.8B EVA2.0 model.

acquire general conversational skills and versatile knowledge from large-scale dialogue corpora during pre-training. Then, they can be easily finetuned to fit into various downstream dialogue scenarios, outperforming those trained from scratch.

However, building a powerful dialogue model is more than simply scaling up model size and dialogue corpora. There are some other key factors that significantly impact the final performance. Although Adiwardana et al. (2020) and Roller et al. (2021) explore some of the factors, including the pre-training tasks, decoding strategies, and evaluation metrics in English scenarios, there still remain some under-explored key factors. In Chinese, these factors are even more under-explored. For example, many works report an overview of the pre-training data they use but do not provide the data collection, cleansing procedures, and quality control details.

¹Our code and pre-trained models are publicly available at https://github.com/thu-coai/EVA.

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Another example is the decoding strategy. Existing works on Chinese pre-trained dialogue models generally focus on the model training phase while only giving a rough analysis of different parameter settings of decoding. We argue that due to the intrinsic difference among languages, lessons about decoding strategies in English may not be directly transferred to Chinese scenarios.

Therefore, in this paper, we investigate how to build an open-domain Chinese dialogue system based on large-scale pre-training. We give a detailed analysis of the pre-training corpus and conduct extensive experiments of model design, pretraining methods, and decoding strategies. First, we comprehensively analyze the quality of the largest Chinese dialogue dataset WDC-Dialogue (Zhou et al., 2021). We find that the dataset suffers from severe problems of context-response relevance, language fluency, and domain diversity despite its large scale. Second, we explore several variants of model architectures, pre-training approaches, and decoding strategies. We empirically find that these factors do have a non-trivial impact on the pre-trained model.

Putting all these together, we first design a pipeline for data cleansing and construct a 60GB high-quality dialogue dataset for large-scale pretraining. Then, based on this dataset, we build EVA2.0, an open-domain dialogue model with 2.8B parameters, and two variants with 300M and 970M parameters. In both automatic and human evaluations, the 2.8B EVA2.0 model significantly outperforms other open-source generative dialogue models. We notice that even the 300M variant performs on par with the EVA1.0 model in the automatic evaluation, while requiring only 11% parameters. We also provide case studies to analyze the conversational ability of EVA2.0 from different aspects to shed light for future research on the large-scale pre-trained open-domain Chinese dialogue systems. Our work provides foundation models for the research of Chinese dialogue modeling, which we believe will significantly benefit the dialogue research community.

2 Related Work

Large-scale Pre-trained Language Models In the past few years, pre-trained models such as the GPT family (Radford et al., 2018, 2019; Brown et al., 2020), BERT (Devlin et al., 2019), XL-Net (Yang et al., 2019), and BART (Lewis et al.,

2020a) have greatly promoted the progress of the NLP community. These models are commonly pretrained on massive textual data with self-supervised learning objectives to capture general language features. Many recent works have shown that scaling up the model sizes and the pre-training corpora leads to dramatic improvement (Kaplan et al., 2020). For example, RoBERTa (Liu et al., 2019) significantly improves the performance of BERT by simply increasing the amount of the training corpus and optimizing the pre-training details. T5 (Raffel et al., 2020) scales up the model size to 11 billion parameters for the first time and shows superior performance on both language understanding and generation tasks. GPT3 (Brown et al., 2020), with 175 billion parameters and pre-trained on 570GB filtered data, has been proven to be effective in various few-shot and zero-shot scenarios.

There also emerge numerous large-scale pretrained models in Chinese. The CPM family (Zhang et al., 2021b,a) pioneer the Chinese pretrained models. PanGu- α (Zeng et al., 2021) and Yuan 1.0 (Wu et al., 2021) boost the power of Chinese language models by pushing the model sizes to 200B and 245B. Mengzi (Zhang et al., 2021c) instead builds a lightweight yet still powerful Chinese model and is computation-friendly for deployment. CPT (Shao et al., 2021) and ERNIE3.0 (Wang et al., 2021a) explore unified frameworks for language understanding and generation.

Pre-trained Conversational Models Other than general language understanding and generation, conversational pre-training is getting increasing attention. For instance, DialoGPT (Zhang et al., 2020) and Meena (Adiwardana et al., 2020) pretrain the model on massive English Reddit data to acquire the open-domain conversational ability. Blender (Roller et al., 2021) and LaMDA (Thoppilan et al., 2022) establish better conversational skills and more attractive traits by fine-tuning the pre-trained model on high-quality crowd-sourced downstream datasets (Zhang et al., 2018; Dinan et al., 2018; Rashkin et al., 2019). In addition, they present a study on different factors that affect the model, including the model sizes, pre-training, and decoding details to guide future works.

In Chinese, there are also dialogue models pretrained on large-scale social media data. For example, CDial-GPT (Wang et al., 2020) adopts generative pre-training on the LCCC dataset collected from the Weibo Comments. PLATO (Bao et al., 2020) and PLATO-2 (Bao et al., 2021a) leverage the discrete latent variable and curriculum learning respectively to improve the generation diversity and quality. EVA1.0 (Zhou et al., 2021) and PLATO-XL (Bao et al., 2021b) scale up the model sizes to 2.8B and 11B and show impressive conversational ability. However, most of these works do not involve many details of how to build a dialogue model. In this paper, besides the final model evaluation, we also focus on the key recipes towards a large-scale pre-trained Chinese dialogue model.

3 Data

Data essentially influences the performance and behaviors of the models in large-scale pre-training. In this section, we define several automatic data quality evaluation metrics to comprehensively measure the relevance, fluency and domain diversity of the dialogue pre-training corpus obtained from social media. Then we use the metrics to analyze the WDC-Dialogue (Zhou et al., 2021) and find that despite its large scale, it suffers from severe problems of context-response relevance, language fluency, and domain diversity. Finally, we design a better data processing pipeline to construct the pre-training data for EVA2.0 based on WDC-Dialogue.

3.1 Data Quality Evaluation

We define the data quality scores in the following three aspects.

Relevance Score Relevance score between context and response is an essential metric that reflects the coherence and engagement of dialogues. We adopt both untrained and trained metrics to measure the relevance of our dataset.

For the untrained metric, we compute the word coverage between the context and the response as an aspect of relevance. Besides, we assign higher scores to data samples where the overlapped words are further apart in a session, in order to show preference of long-dependency property. Formally, the relevance score of the context (C) and response (R) is defined as

$$S_1 = \sum_{w_i \in C, w_j \in R} \operatorname{dist}(w_i, w_j)^{\tau} \mathbf{I}(w_i = w_j), \tag{1}$$

where $\operatorname{dist}(w_i, w_j)$ means the index distance between the utterances containing w_i and w_j . We use τ to adjust the score.

For the trained metric, we fine-tune a BERT_{BASE} binary classifier (Devlin et al., 2019) on the LCCC

dataset (Wang et al., 2020) to recognize whether a response is appropriate for a given context. We get 93.0% accuracy and 0.86 F1 score on the test set. In the evaluation, we use the classification probability of the "appropriate" class as the relevance score:

$$S_2 = \log P(1|C,R),\tag{2}$$

Compared to the untrained metric relying on the exact overlapping, the trained metric better estimates the semantic relevance.

Fluency Score We compute the probability of each sentence in our dataset using statistical models based on kenlm². The mean fluency score over sentences of a dialogue session is defined as

$$S_3 = -\frac{1}{n} \sum_{i \le n} \log P(w_1^i, w_2^i, \dots, w_{|u_i|}^i), \tag{3}$$

where n is the utterance number of the session and $u_i = w_1^i w_2^i \cdots w_{|u_i|}^i$ is the i-th utterance.

Entertainment Tendency The Chinese social media platform contains many undesired information exchanges about entertainment stars and fans, which are unusual in daily conversations. Therefore, we compute the ratio of dialogues involving Chinese stars to measure the entertainment tendency. This also reflects the domain diversity of the dataset to some extent.

3.2 Data Refinement

Dataset-level Filtering We find that some datasets are not suitable for open-domain conversations. Training on them will result in undesired behaviors like the tone of the E-commerce customer service. Therefore, we remove datasets like the JDDC (Chen et al., 2020) from WDC-Dialogue.

Context-level Filtering Since our datasets are primarily from social media platforms, some contexts correspond to a considerable number of responses (e.g., Weibo posts and their comments). These responses are very similar in format and can severely harm the performance of language models (Lee et al., 2021). Therefore, we set a max response number for each context during filtering.

Rule-based Filtering We strengthen the rule-based filtering procedure in Zhou et al. (2021). For example, we transform traditional Chinese characters into simplified ones, remove unreasonable multiple successive punctuation marks, and simplify the word blacklist to avoid over sensitiveness to some common polysemy.

²https://github.com/kpu/kenlm

Dataset			Basic S	Statistics			Qı	uality Evalua	tions
Dataset	#Sess.	#Uttr.	#Token	#Uttr	#Token	Storage	Relevance ↑	Fluency †	Entertainment \downarrow
WDC-Dialogue	1.4B	3.0B	78.3B	2.1	26.2	181GB	55.2	-7,147	7.0%
EVA2.0-dataset	0.4B	1.1B	22.4B	2.8	20.3	60GB	93.8	-3,237	6.2%

Table 1: Basic statistics and quality evaluations of EVA2.0-dataset and WDC-Dialogue (Zhou et al., 2021). "#Sess.", "#Uttr." and "#Token" indicate the total number of sessions, utterances, and tokens. "#Uttr" means the average utterance number per session and "#Token" means the average token number per utterance. "Relevance", "Fluency", and "Entertainment" indicate the relevance score, the fluency score and the entertainment tendency.

Classifier-based Filtering For each dialogue in the corpus, we compute the relevance and fluency scores defined above and filter out those samples whose score is lower than a threshold. The overall score of a session is defined as $S = \alpha S_1 + \beta S_2 + \gamma S_3$. In practice, we empirically choose different thresholds for different data sources to fit their data distributions and make the final dataset balanced.

3.3 Data Extension

There exists an inevitable gap in the distribution between social media and open-domain dialogues. For example, buzzwords are popular on Internet but unusual in daily conversations. To debias our dataset and increase its domain diversity, we collect four kinds of data from extra public sources: (1) Dialogues extracted from subtitles in the movies or TV plays³ (Lison and Tiedemann, 2016); (2) Dialogues extracted from novels and stories (Guan et al., 2021); (3) Zhidao Q&A pairs⁴; (4) Existing Crowd-sourcing Corpora including DuConv (Wu et al., 2019), KdConv (Zhou et al., 2020), DuRec-Dial (Liu et al., 2020), and NaturalConv (Wang et al., 2021b). These extra data account for 12GB of the whole pre-training corpus.

3.4 Data Statistics

We construct our final EVA2.0-dataset with the above data processing pipeline. In Table 1, we show the basic statistics and quality evaluations of our EVA2.0-dataset and WDC-Dialogue (Zhou et al., 2021) using the metrics defined in Section 3.1. We can see that although EVA2.0-dataset amounts to only less than a third of the original WDC-Dialogue, its quality is significantly better. This means that our data refinement process improves the relevance between the context and the response, the language fluency, and reduces the ratio of the dialogues in the entertainment domain. Moreover,

the average utterance number per session also increases, making the training samples approximate the daily multi-turn dialogue better. From the experiments in Section 5.3, we will see that despite its small amount, EVA2.0-dataset brings better model performance, owing to the high data quality.

4 Method

4.1 Model

We adopt a Transformer-based architecture combined with a bidirectional encoder and a unidirectional decoder for dialogue modeling. Different from EVA1.0 (Zhou et al., 2021) and T5 (Raffel et al., 2020), we add the \sqrt{d} scale to the attentions in the Transformer which reduces the demand for careful initialization before pre-training. The dialogue histories are fed into the encoder as context and the decoder generates the response in an autoregressive manner based on the encoded context. We train models with 3 different sizes, whose configurations are shown in Table 2.

Although similar model designs are also used in previous works, including both general pre-trained models (Raffel et al., 2020; Zhang et al., 2021a) and dialogue-specific pre-trained models (Roller et al., 2021; Adiwardana et al., 2020; Zhou et al., 2021), they do not include the discussions of some variants of the model that can have a non-trivial impact on the final performance. Therefore, we consider two aspects of the model configuration.

Layer Numbers Both Blender and Meena adopt the encoder-decoder architecture to model dialogues. However, different from the model pretrained on the long documents, which usually use balanced encoder and decoder layers (Lewis et al., 2020a; Raffel et al., 2020), these dialogue models use decoders that are much deeper than the encoders. Intuitively, a deeper decoder may be beneficial for generation tasks. However, a deeper encoder can better understand the dialogue histories in dialogue modeling, which improves relevance

³https://www.opensubtitles.org/

⁴https://zhidao.baidu.com

Model	$n_{ m params}$	$n_{ m enc ext{-}layers}$	$n_{ m dec ext{-}layers}$	$d_{ m model}$	$d_{ m ff}$	$n_{ m heads}$	$d_{ m head}$
EVA2.0 _{Base}	300M	12	12	768	3,072	12	64
EVA2.0 _{Large}	970M	24	24	1,024	4,096	16	64
EVA2.0 _{xLarge}	2.8B	24	24	2,048	5,120	32	64

Table 2: Model information of EVA2.0 with different sizes. n_{params} is the parameter number. $n_{\text{enc-layers}}$ and $n_{\text{dec-layers}}$ are the number of layers of encoder and decoder respectively. d_{model} is the hidden state size. d_{ff} is the size of the feedforward layer. n_{heads} is the number of attention heads and d_{head} is the dimension of the attention head.

and consistency between the generated response and the dialogue context. Therefore, we try different encoder and decoder layer ratios while keeping the same parameter numbers.

Role Information Recent work (Thoppilan et al., 2022) has pointed out that current pre-trained dialogue models can confuse their roles in long conversations because the model is pre-trained on approximated dialogues from the social media. Therefore, it is intuitive to add the role information into the dialogue model to improve the role consistency. For example, Plato-XL (Bao et al., 2021b) introduces role embeddings to encode multi-party dialogue. However, the pre-training corpus of Plato-XL contains the role information by nature, while many crawled data from social media, such as WDC-Dialogue, do not include this information. Although we can assume the data as two-party dialogues and add the role information to the input, it is unclear whether this approximation works. Therefore, we follow Wang et al. (2020) to use both the role identifier tokens and the role embeddings as role information and test its effect.

4.2 Pre-training

We train our models with the sequence-to-sequence language modeling (Sutskever et al., 2014). The maximum lengths of both the context and the response are 128, and the models see 1.05M tokens in a forward pass. We set the learning rate as 0.01, the warmup steps as 10K, and use the Noam Scheduler to dynamically adjust the learning rate. To reduce the training consumption, we adopt the same data sampling strategy used in EVA (Zhou et al., 2021) and ZeRO-stage-1 (Rajbhandari et al., 2020) from DeepSpeed (Rasley et al., 2020).

We study two pre-training approaches: pretraining from scratch on the dialogue corpus or further pre-training from a long-document pre-trained generative model. Intuitively, further pre-training yields better knowledge skills since it inherits versatile knowledge from the long documents, which is absent in social media. However, the distributions of the dialogue utterances and the document sentences differ significantly. It is still unclear whether this difference causes catastrophic forgetting (Kirkpatrick et al., 2017) or negative transfer (Pan and Yang, 2009) during the dialogue pre-training phase.

4.3 Decoding

We study various decoding strategies in this work. Although Roller et al. (2021) has conducted experiments on the commonly used decoding approaches on English chatbots, we argue that the choice of decoding strategies is language-specific, and the conclusion can be different in Chinese.

Greedy Search Greedy search is a simple decoding strategy in which tokens are generated iteratively from left to right. A New token y_t is selected to maximize the probability conditioned on the previously generated tokens $y_{< t}$ and the dialogue history x, which is computed by the output logits h_t : $y_t = \arg \max P(y_t \mid x; y_{< t}) = \operatorname{softmax}(h_t)$.

Sampling Previous works find that maximization-based decoding methods result in severer repetition and degradation in the generated texts. Therefore, samplingbased approaches are proposed to improve the generation quality with stochastic sampling: $y_t \sim P(y_t \mid x; y_{< t}) = \operatorname{softmax}(\frac{h_t}{T}), \text{ where } T$ controls the sharpness of the distribution. In this work, we focus on an improved variant: Top-p Sampling (Holtzman et al., 2019), which filters out the low-probability tokens from the vocabulary and samples y_t from the re-normalized probability.

Beam Search Beam search is an extension to greedy search, which finds the most likely sentence from a larger searching space. Beam search can also be coupled with the sampling approaches mentioned above to generate diverse results.

Length Control Vanilla beam search favors short generation over the long ones since a negative score is added at each step, leading to generic

Test Set	Evaluation	#Sess.	#Uttr	#Token
Single	Auto.	10,000	2.00	18.4
	Human	50	1.00	19.9
Multi	Auto.	10,000	4.17	15.3
	Human	50	3.38	15.0
Knowledge	Human	50	1.00	11.1
Self-Chat	Human	50	1.00	12.7

Table 3: Test dataset statistics. "Auto." / "Human" indicates the dataset is used for automatic / human evaluation. "#Sess." means the session number. "#Uttr" means the average utterance number per session. "#Token" means the average token number per utterance.

responses. Therefore, beam search is often combined with length control. In **Minimal Length Constraint**, the probability of <EOD> token is set to 0 until the generated response reaches a minimal length. In **Length Penalty**, the score of each candidate in beam search is divided by a l^{α} where l is the prefix length and higher α encourages longer responses.

Handling Repetitions Repetition is a commonly observed phenomenon in current generative language models, which severely affects the generation quality. In this work, we consider **No-Repeat-N-Gram** strategy, where we forbid the second time generation of any previously appeared n-grams in the dialogue history.

5 Experiment

5.1 Setup

We conduct response generation and self-chat experiments using automatic evaluation and human evaluation. For response generation, we ask the model to generate a response conditioning on the previous single-turn context, multi-turn context, or knowledge query. The single-turn and multi-turn dialogues are collected from social media, which have no overlap with the pre-training data. The knowledge queries are manually created Chinese open-domain commonsense questions. For selfchat, we give the model and one of its copies a starting utterance and let them chat until a maximum utterance number is reached. The starting utterances are translated from the English self-chat query set used in Bao et al. (2020). The data statistics are shown in Table 3.

We use uni-gram F1 (F1), ROUGE-L (R-L), BLEU-4 (B-4), and distinct 4-grams (D-4) for automatic evaluation. For human evaluation, we hire

Test Set	Model	F1	R-L	B-4	D-4
Single	6-18	15.6	13.3	1.48	49.4
	18-6	15.5	13.4	1.52	50.0
	12-12 *	16.2	13.8	1.63	53.4
	+role	13.3	11.3	1.29	45.6
Multi	6-18	16.1	13.7	1.54	46.2
	18-6	16.2	13.9	1.43	45.6
	12-12 *	16.6	14.3	1.74	50.2
	+role	14.4	12.0	1.31	42.3

Table 4: Results of balanced/unbalanced layers and w./wo. role information. "6-18" means 6 encoder layers and 18 decoder layers; "18-6" means 18 encoder layers and 6 decoder layers. "12-12" means balanced layers which we finally adopt in EVA2.0_{Base}. "+role" means we add role information based on the balanced model.

three annotators for each sample. The metric details of each human evaluation experiments can be found in the following corresponding sections.

5.2 Strategies Comparison

In this section, we compare different approaches to build the model. We use the mark * to highlight our final choice in each table.

Balanced v.s. Unbalanced Layers We compare models with different encoder and decoder layers. Specifically, we use the 300M version of the model to save the computational cost. We test the balanced layers (12-12) and two unbalanced variants of our model: 18 encoder layers + 6 decoder layers (18-6) and 6 encoder layers + 18 decoder layers (6-18). From the results in Table 4, we conclude that the model with balanced layers performs the best in automatic evaluations. Therefore, we adopt the balanced layers for the rest of our experiments.

Whether to Add Role Information We test the effect of the role information based on the 300M model, and the results are shown in Table 4. Comparing the lines "12-12" and "+role", we can see that the role information hurts the model performance. At first glance, this phenomenon seems to contradict that in Bao et al. (2021b) which claims that the additional role embeddings help the model to maintain the role consistency. However, in Bao et al. (2021b), the roles in the data are distinguishable, which enables them to regard the social media conversations as multi-party dialogue. In our data (and most publicly available data from social media platforms), the roles cannot be naturally distinguished. This forces us to assume that the conver-

Test Set	Pre-training	F1	R-L	B-4	D-4
Single	Scratch * Further	17.0 16.1	14.9 13.9	2.23 1.77	67.7 68.2
Multi	Scratch * Further	17.8 16.6	15.4 14.3	2.89 1.84	66.4 59.7

Table 5: Automatic evaluation results of the pretraining approaches. "Scratch" represents pre-training from scratch on dialogue data. "Further" represents further pre-training from CPM model.

Pre-training	Sensibleness	Specificity	Knowledge
Scratch ★	0.76	0.70	0.16
Further	0.74	0.62	0.50

Table 6: Human evaluation results of the pre-training approaches. "Scratch" and "Further" have the same meanings as in Table 5.

sations are carried out between two characters. We argue this assumption introduces additional noise to the data and makes the optimization more difficult, which explains our results.

Train From Scratch or Not We compare the model pre-trained from scratch on the dialogue data to the model further pre-trained from CPM (Zhang et al., 2021b), a long-document pre-trained generative model. From the results in Table 5 and Table 6, we can see that further pre-training significantly outperforms pre-training from scratch on Knowledge Q&As but performs worse in almost other evaluation metrics. This indicates that although further pre-training makes use of the knowledge stored in CPM, it sacrifices basic conversational skills. Since we focus on building a chit-chat bot in this work, we choose to pre-train from scratch on dialogue corpus in our final model.

Decoding Approaches We compare different decoding strategies in Table 7 and Table 8. We incrementally combine other techniques with beam search to validate their influence. We combine no-repeat-n-gram with greedy search by default since simple greedy search often leads to repetition in the generated text. Through the automatic and human evaluations, we conclude that (1) no decoding strategy outperforms others consistently across all evaluation metrics; (2) sampling tends to generate diverse responses but fails to maintain the sensibleness; (3) simple greedy decoding with no-repeat-n-gram yields surprising good performance in the human evaluation; (4) the model tend to

Test Set	Decoding	F1	R-L	B-4	D-4
	greedy	16.4	14.1	2.09	63.1
	sampling	12.2	10.4	1.20	91.6
	beam search	16.5	14.7	2.80	43.3
Single	+sampling	16.3	14.5	2.21	75.4
	+len_penalty	17.4	15.4	3.23	66.2
	+no-repeat ★	<u>17.0</u>	14.9	2.23	67.7
	+min_len	16.4	14.2	2.04	62.3
	greedy	16.5	14.2	2.76	64.2
	sampling	12.5	10.7	1.99	91.5
	beam search	16.9	15.0	3.50	46.0
Multi	+sampling	16.4	14.6	2.59	73.2
	+len_penalty	17.8	15.7	3.79	64.9
	+no-repeat ★	17.8	<u>15.4</u>	2.90	66.9
	+min_len	17.1	14.9	2.47	62.8

Table 7: Automatic evaluation results of different decoding strategies. The score marked as **bold** means the best performance. The score marked with an <u>underline</u> means the second best performance.

Decoding	Sensible.	Specific.	Consist.
greedy sampling	0.80 0.60	$\frac{0.70}{0.54}$	0.96 1.00
beam search	0.66	0.60	0.94
+sampling +len_penalty	0.72 0.70	0.68 0.66	$\frac{0.98}{0.96}$
+no-repeat ★ +min_len	$\frac{0.76}{0.74}$	$\frac{0.70}{0.74}$	1.00 0.92

Table 8: Human evaluation results of different decoding strategies. The score marked as **bold** means the best performance. The score marked with an <u>underline</u> means the second best performance.

generate self-contradict responses with the minimal length constraint, which is different from the English scenarios (Roller et al., 2021); (5) when combined with sampling, repetition control, and length penalty, beam search has relatively balanced performance. As a result, we choose this as our final decoding strategy.

5.3 Final Model Evaluations

By putting the lessons learned from the previous experiments together, we train our final EVA models whose configurations are shown in Table 2. We train the models on dialogue data from scratch without the role information. We use beam search + top-p sampling for decoding where beam_size = 4, top-p = 0.9, and T = 0.9. We set the length penalty to 1.6 and the no-repeat-n-gram to 4. Our baselines include CDial-GPT (Wang et al., 2020) and EVA1.0 (Zhou et al., 2021). CDial-GPT has 104M parameters which are first pre-trained on a Chinese novel corpus and then further pre-trained on

Test Set	Model	F1	R-L	B-4	D-4
a	CDial	9.9	8.6	0.67	61.2
	EVA1.0	13.1	11.3	1.27	50.7
Single	EVA2.0 _{Base}	16.2	13.8	1.63	53.4
	EVA2.0 _{Large}	16.4	14.0	1.67	55.8
	EVA2.0 _{xLarge}	17.0	14.9	2.23	67.7
26.10	CDial	11.9	10.3	0.88	63.9
	EVA1.0	15.3	13.2	1.94	56.3
Multi	EVA2.0 _{Base}	16.6	14.3	1.70	50.2
	EVA2.0 _{Large}	17.2	15.1	2.27	58.9
	EVA2.0 _{xLarge}	17.8	15.4	2.90	66.9

Table 9: Automatic evaluation of EVA2.0 models and the baselines.

Model	Sensible.	Specific.	Consist.
CDial	0.50	0.40	1.00
EVA1.0	0.68	0.60	0.96
EVA2.0	0.76	0.70	1.00

Table 10: Observational human evaluation results. We use the xLarge (2.8B) version of EVA2.0.

12M dialogue sessions. EVA1.0 is a 2.8B model pre-trained on WDC-Dialogue. To our knowledge, these are the only open-source Chinese dialogue models. In the following sections, we denote the 2.8B model as EVA2.0_{xLarge}, the 970M model as EVA2.0_{Large}, and the 300M model as EVA2.0_{Base}.

Automatic Evaluation The results of the automatic evaluations are shown in Table 9. We can see that $\text{EVA2.0}_{x\text{Large}}$ consistently outperforms the baselines on both the relevance and diversity metrics. The response generated by CDial-GPT is shorter than EVA due to the characteristics of the pre-training data therefore CDial-GPT performs relatively better in D-4. Note that although EVA2.0_{Base} is nine times smaller than EVA1.0 and uses three times less data, it still performs comparably with EVA1.0, which highlights the importance of careful data refinement.

Observational Human Evaluation The results of observational human evaluations are shown in Table 10. To fully evaluate the performance of the models, apart from the Sensibleness and Specificity used in Adiwardana et al. (2020) and Zhou et al. (2021), we add a Consistency dimension to examine whether the model generates responses that contradict their context. The results show that EVA2.0 significantly outperforms the baselines.

Model	Sensible.	Specific.	Consist.	Engaging.
CDial	1.18	0.88	1.77	0.79
EVA1.0	1.21	1.11	1.82	1.00
EVA2.0	1.71	1.55	1.89	1.27

Table 11: Self-chat human evaluation results. We use the xLarge version (2.8B) of EVA2.0.



Figure 2: Failure cases in Consistency with the xLarge (2.8B) version of EVA2.0. We present examples of both intra-contradiction (enjoy swimming but dislike sports) and inter-contradiction (deny liking the "North" after saying "I like the North").

Self-chat Human Evaluation Considering that human-model interactive evaluations are time-consuming and expensive, self-chat has been widely adopted to evaluate dialogue systems. Giving a starting utterance, we let the model chat with itself for nine turns and ask the annotators to assess the generated session. As suggested by Li et al. (2019), annotators are required to pay attention to only one speaker and give scores in terms of Sensibleness, Specificity, Consistency, and Engagingness. Results in Table 11 show that EVA2.0 consistently achieves the best performance in all the evaluated dimensions.

5.4 Failure Cases and Model Extensions

Although EVA2.0 achieves good performance in both automatic and human evaluations, there is still room for improvement. We examine EVA2.0's limitations and elaborate on four key issues. In what follows, we present some typical failure cases and discuss possible solutions for each issue.

Consistency Human evaluation results in Table 11 show that our model occasionally presents consistency errors. We divide these errors into two categories: (1) intra-contradiction: contradictions within the response. (2) inter-contradiction: con-



Figure 3: Failure cases in Knowledge with the xLarge (2.8B) version of EVA2.0. Highlighted red text blocks are hallucinations. (The Olympic Games are held every four years. The highest mountain in the world is Mount Everest.)

tradictions between the dialogue context and the response. Typical cases are shown in Figure 2.

Recent works have explored formulating this issue as a natural language inference (NLI) problem and constructed English datasets to improve dialogue consistency (Welleck et al., 2019; Nie et al., 2021). Specifically, they train a contradiction detection classifier to re-rank the generated responses, which effectively enhances the consistency of state-of-the-art generative chatbots. However, there is still a lack of such datasets in other languages, including Chinese.

Knowledge It has been observed that large-scale language models can implicitly absorb knowledge in the massive unlabeled data during pretraining (Petroni et al., 2019). However, unlike the knowledge-intensive text data that can be easily acquired from sources like Wikipedia, open-domain dialogues obtained from social media platforms are often knowledge-sparse. Therefore, the knowledge skills of the pre-trained dialogue models are relatively limited, which is also validated in Table 6. We also present some typical cases in Figure 3.

To alleviate this issue, many works explore building knowledge-grounded dialogue systems by conditioning the generated response both on the context and the external knowledge sources, implicitly or explicitly. For implicit knowledge grounding, previous works (Dinan et al., 2018; Zhou et al., 2020) show the effectiveness of fine-tuning the pre-trained model on crowd-sourced knowledge-intensive dialogue datasets. For explicit knowledge grounding, some studies (Thoppilan et al., 2022; Li et al., 2021; Lewis et al., 2020b; Izacard and Grave, 2021) resort to incorporating information retrieval into generation systems. However, these methods require extensive human-annotated knowledge-grounded dialogue data, which is hard



Figure 4: Failure cases in Safety with the xLarge (2.8B) version of EVA2.0. EVA2.0 have unsafe behaviors such as suicide risk ignorance (affirm the user's suicidal intent) and social bias (prefer male doctors).

to obtain in languages other than English. How to build a more sample-efficient knowledge-grounded dialogue system is an challenging problem.

Safety The real-world deployment of generative open-domain dialogue systems brings new key challenges, and safety is one of them. As shown in Sun et al. (2021b), many dialogue models have various types of unsafe behaviors such as suicide risk ignorance and social bias. In Figure 4, EVA2.0 is also likely to give offensive, toxic, and biased answers when faced with some "trap contexts" (Deng et al., 2022), which hinders its application.

The post-processing module of dialogue systems can alleviate the safety problems to some degree. For example, the word blacklist is widely used in currently deployed chatbots which helps detect "trap contexts" and forbidding the generation of responses related to sensitive topics like politics, medicine, etc. Meanwhile, some methods based on safety detectors are proved effective by the generate-then-check process (Thoppilan et al., 2022). Besides post-processing, other methods based on re-training are emerging. Xu et al. (2020) finds it helpful to train models on extra safety-augmentation samples, which naturally makes models learn to reply safely.

Empathy Empathy is a desirable trait for engaging open-domain dialogue systems, which requires understanding, perceiving, and responding appropriately to the situation and feelings of users (Keskin, 2014). However, people may not spontaneously express empathy or behave supportively. Pre-training on the resulting social interactions thus makes it hard for EVA2.0 to display empathy and provide support properly, as shown in Figure 5.



Figure 5: Failure cases in Empathy with the xLarge (2.8B) version of EVA2.0. EVA2.0 occasionally generates coherent but non-empathetic responses (fail to understand the sadness of the user after a quarrel with his girlfriend; show off the good grades when the user is grieving).

Rather than the data-driven paradigm, previous research finds that incorporating empathy-demanded semantic information significantly improves empathy capability and the controllability of how to express empathy. Such semantic information ranges from the low-level emotions or dialogue acts (Zheng et al., 2021) to the high-level support strategies (Liu et al., 2021; Sun et al., 2021a). Even commonsense knowledge can be utilized to improve the cognitive understanding of the users' mental states and experiences (Sabour et al., 2022).

6 Conclusion

This work investigates how to build a Chinese open-domain dialogue system through large-scale pre-training. We conduct extensive experiments to explore some critical factors of the dialogue model training and inference, including data quality control, model architectures, pre-training approaches, and decoding strategies. We share the insights in the experiments, and build the EVA2.0 model, which significantly outperforms existing open-source baselines in both automatic and human evaluations. We also comprehensively analyze the failure cases of EVA2.0 and discuss some important future directions. Our work will facilitate future research and the application of open-domain Chinese dialogue systems.

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A Contributions

Yuxian Gu and Jiaxin Wen implemented the basic models and conducted strategies comparison experiments.

Hao Sun, Yi Song, Pei Ke, Jianzhu Yao and Lei Liu designed the data cleaning pipeline and constructed the pre-training data.

Jiaxin Wen, Yuxian Gu, Zheng Zhang and Jianzhu Yao conducted the model evaluation.

Yuxian Gu, Jiaxin Wen, Hao Sun, Pei Ke and Chujie Zheng wrote the paper.

Minlie Huang designed and led the research.

Xiaoyan Zhu and Jie Tang provided valuable advises to the research.