# WeLM: A Well-Read Pre-trained Language Model for Chinese

Hui Su\* Xiao Zhou\* Houjin Yu\*
Xiaoyu Shen Yuwen Chen Zilin Zhu Yang Yu Jie Zhou

WeChat AI

#### **Abstract**

Large Language Models pre-trained with self-supervised learning have demonstrated impressive zero-shot generalization capabilities on a wide spectrum of tasks. In this work, we present WeLM: a well-read pre-trained language model for Chinese that is able to seamlessly perform different types of tasks with zero or few-shot demonstrations. WeLM is trained with 10B parameters by "reading" a curated high-quality corpus covering a wide range of topics. We show that WeLM is equipped with broad knowledge on various domains and languages. On 18 monolingual (Chinese) tasks, WeLM can significantly outperform existing pretrained models with similar sizes and match the performance of models up to  $25\times$ larger. WeLM also exhibits strong capabilities in multi-lingual and code-switching understanding, outperforming existing multilingual language models pre-trained on 30 languages. Furthermore, We collected human-written prompts for a large set of supervised datasets in Chinese and fine-tuned WeLM with multi-prompted training. The resulting model can attain strong generalization on unseen types of tasks and outperform the unsupervised WeLM in zero-shot learning. Finally, we demonstrate that WeLM has basic skills at explaining and calibrating the decisions from itself, which can be promising directions for future research. Our models can be applied from https://welm.weixin.qq.com/docs/api/.

## 1 Introduction

Over the last few years, "pre-training and fine-tuning" has made great breakthroughs and become a common practice in natural language processing (NLP) tasks [Devlin et al., 2018, Raffel et al., 2020, Clark et al., 2020, Lewis et al., 2020a]. Language models based on the Transformer architecture [Vaswani et al., 2017] are pre-trained on the web text with self-supervised objectives. By this means, they have "read" massive amounts of text and obtained strong natural language understanding skills. Given a downstream task, they can be fine-tuned with task-specific labels to achieve much stronger performances than training a model from scratch. Nonetheless, the fine-tuning stage still requires significant amounts labels and suffers from the catastrophic forgetting problem: the fine-tuned model becomes a "narrow expert" in one specific task and forgets the knowledge about other domains, which leads to poor generalization [Kirkpatrick et al., 2017, Li and Liang, 2021]. Recently, GPT3 [Brown et al., 2020a] demonstrated that extremely large autoregressive language models can be used for few-shot predictions without fine-tuning the parameters. GPT3 contains 175B parameters and is trained with the standard left-to-right language modelling objective. After training, we can feed

Correspondence authors: {aaronsu|chappyzhou|houkingyu}@tencent.com

<sup>\*</sup>Equal Contribution.



#### **Code-switching Translation**

有这样一段文本、{雨下得很大} 改写这段话让它更加生动丰富。 下雨时,天上就没了星星,雨水像天河一样从天上流 下来。雨越下越大,把马路上的落叶都冲走了,发出 哗啦啦的声音,好像在弹奏乐曲,非常有节奏感。

Figure 1: Examples of applying WeLM to the text style transfer and code-switching translation tasks. Text style transfer is done by feeding WeLM with 3-shot examples and code-switching translation is done in a zero-shot way.

the task instruction and few-shot examples into its context window to let it perform different types of NLP tasks [Wei et al., 2022a]. Since GPT-3, a growing body of pre-trained autoregressive language models such as Megatron [Narayanan et al., 2021], Gopher [Rae et al., 2021], Chinchilla [Hoffmann et al., 2022] and Palm [Chowdhery et al., 2022] have been developed with larger model sizes and higher-quality training corpora .

The vast majority of pre-trained models focus on English. For Chinese, there have been a few pre-trained models released, most of which are small-scaled and follow the encoder-only architecture [Sun et al., 2019, Cui et al., 2020, Sun et al., 2021a, Su et al., 2022]. Decoder-only large Chinese language models such as CPM [Zhang et al., 2021], Yuan [Wu et al., 2021] and Pangu [Zeng et al., 2021] have also achieved impressive success in zero and few-shot generalization capabilities without task-specific fine-tuning. Ernie 3.0 [Sun et al., 2021b, Wang et al., 2021], currently the largest Chinese language model with up to 260B parameters, is trained with a combination of plain text and knowledge graph and achieved state-of-the-art (SOTA) performances across many Chinese NLP tasks.

Following the same line of research, we present WeLM: a well-read pre-trained language model for Chinese that is able to seamlessly perform different types of tasks with zero or few-shot demonstrations. Figure 1 presents two examples of applying WeLM to the text style transfer and code-switching translation tasks. By feeding different instructions and demonstrations to WeLM, it is able to understand the task and output the result accordingly. WeLM is trained with 10B parameters by "reading" a curated high-quality corpus covering a wide range of topics. We show that by carefully cleaning the data, balancing out data sources and scaling up the training data size, WeLM is able to significantly outperform existing models with similar sizes. On zeroshot evaluations, it can match the performance of Ernie 3.0 Titan [Wang et al., 2021] that is 25× larger. WeLM also exhibits strong capabilities in multi-lingual and code-switching understanding. On three cross-lingual tasks including machine translation, question answering and summarization, it can outperform XGLM, a multilingual autoregressive language models pre-trained on 30 languages [Lin et al., 2021]. In the code-switching translation example in Figure 1 where Chinese, English and Japanese are mixed in both their vocabularies and grammar, WeLM is still able to translate it properly, suggesting it has been equipped with necessary compositional knowledge from all these three languages. We further collected human-written prompts for a large set of supervised datasets in Chinese and fine-tuned WeLM with multi-prompted training. The resulting model can attain strong generalization on unseen types of tasks and outperform the unsupervised WeLM in zero-shot learning. Finally, we demonstrate that WeLM has basic skills at explaining and calibrating the decisions from itself. When providing explanations in the example, it can mimic the styles of the given explanations to explain its own decisions. When asked to judge the sampled predictions from itself, it can reject wrong predictions and toxic generations. Both can be promising directions for future research.

The rest of the paper is organized in the following way: Section 2 explains how we curate the training data and presents dataset statistics. Section 3 explains the implementation and training details. Section 4 presents the experiments and findings. Section 5 concludes the paper.

## **2** Training Dataset

WeLM was pre-trained on a curated dataset derived from several sources. When dataset is curated with the aim to be (1) *diverse*: The data sources and their portions are carefully selected to cover

a broad range of topics and languages used in the Chinese community; (2) *clean*: The data went through rigorous process of deduplication, noise reduction and toxic content filtering to ensure the high quality; (3) *less contaminated*: We filter all data that significantly overlaps with any of the downstream tasks to guarantee the fairness of evaluations.

**Source** We make use of the monthly shards released by Common Crawl to construct a general-purpose web page subset. All the WET files between 2020.08 and 2022.01 were downloaded, and we filtered out non-Chinese pages using langdetect <sup>2</sup>. For domain-specific corpora, we mix data from a variety of sources including news, books, popular online forums as well as academic writings. Similar to general-domain data, langdetect is applied to keep only Chinese data sources. On top of them, we also add around 750GB of English data collected from the above sources so that our language model can learn bilingual knowledge. The full data consists of over 10TB of raw text data.

Clean There is a significant amount of noise in the data, e.g., gibberish or boiler-plate text, offensive language, placeholder text and source code especially for the general-domain web scrapes. To reduce these kinds of noise, we first apply a set of rule-based filters following Raffel et al. [2019]. On the remaining data, we manually construct a balanced labeled dataset containing 80k passages with a positive-negative ratio of 1:1. Positive samples are valid, clean text and negative samples are text with different types of noise. We train a binary classifier on the constructed labeled data using Fasttext  $^3$ . Only passages with >0.9 probability of being positive are kept. This rule-based+fasttext filtering process reduces 87.5% of the full data.

**Deduplication** Duplication has been shown important to improve the training efficiency of large language models [Lee et al., 2021, Kandpal et al., 2022, Roberts et al., 2022]. We take a two-step process to remove near-duplicate contents from the data. Firstly, we remove all blank and punctuation tokens then adopt the Message Digest Algorithm5 (md5) to filter duplicate passages. Only passages with unique md5 codes are kept. Secondly, we apply the SimHash algorithm [Manku et al., 2007] to deduplicate documents with very similar contents. This efficiently removed 40.02% duplicate passages from the corpus.

**Contamination** To remove data contamination and make sure the fairness in the evaluation, we also filter out text overlapping with our development and test data following a similar method used in GPT-3 [Brown et al., 2020b]. Specifically, we count the 17-gram match between every document and our used development and test data. If we find  $\geq 2$  duplicate 17-grams or 1 duplicate 34-gram in a document, we remove it from our corpus. This further removes 0.15% of the remaining data.

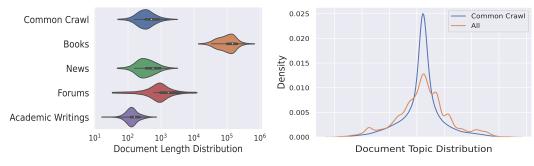
**Data Balancing** After all the above filtering process, our corpus contains 262B tokens. As the distribution of the data is highly imbalanced, we re-sample the data during pre-training to balance data from different sources. By this means, we encourage the training data to be diverse and representative of various domains. Table 1 shows the number of tokens before balancing and the proportion of different sources after balancing. After filtering, data from common crawl has 198.5B tokens, which account to over 75% of the full data. After data balancing, only 50% of the training data comes from common crawl. In Figure 2, we visualize the document length and topic distribution in the training data. Topics are detected with pre-trained topic classification models. We can see that topics from common crawl are highly imbalanced. Most documents are focused on a few topics. After data balancing, the distribution of topics becomes much smoother.

<sup>&</sup>lt;sup>2</sup>https://pypi.org/project/langdetect/

https://github.com/facebookresearch/fastText

Source	% Filtered	#Remaining Tokens	Proportion in Pre-training
Common Crawl	92%	198.5B	50.6%
Books	40.9%	61.9B	38.7%
News	7.5%	1.91B	6.7%
Forums	6.7%	1.0B	3.5%
<b>Academic Writings</b>	2.5%	0.39B	0.5%

Table 1: Statistics of training corpus. We report the percentage of filtered contents, number of tokens and proportion of different sources during pre-training after data balancing.



- (a) **Document Lengths in Corpus** (in tokens).
- (b) Document Topics in Corpus.

Figure 2: Left: Document length distribution in each source (#tokens). Right: Document topic distribution of common crawl and balanced training data after re-sampling.

## 3 Methods

## 3.1 Model and Implementation

Our training and evaluation codebase is based on the Megatron-LM<sup>4</sup> and DeepSpeed<sup>5</sup> which support efficient training of large language models. We trained four different sizes of language models ranging from 1.3B to 10B. We employ the same autoregressive Transformer decoder architecture as in GPT-3 [Brown et al., 2020b] with the major differences listed below:

**Relative encodings** We use the rotary positional embeddings based on relative positions [Su et al., 2021] rather than absolute positional encodings used in the original GPT [Radford et al., 2019, Brown et al., 2020b]. Relative encodings are especially good at handle better semantic of long text, which we find helpful for tasks that require modelling full articles or books.

**Vocabulary** We use a SentencePiece tokenizer [Kudo and Richardson, 2018] with 62k tokens. In addition to 30K Chinese tokens, common words from languages such as English, Japanese and Korean are also included due to their popularity on the Chinese internet. All whitespaces and tabs are preserved without normalization. Our study shows that this benefits the downstream tasks.

Model	#Layers	# Heads	d <sub>model</sub>	Max LR	Batch Size	<b>Context Window</b>
1.3B	24	16	2,048	$1.2\times10^{-4}$	1024	2048
2.7B	32	32	2,560	$0.9 \times 10^{-4}$	2048	2048
10B	32	40	5,120	$0.5 \times 10^{-4}$	2048	2048

Table 2: **Architecture details.** We pre-trained 3 models with different number of parameters. The corresponding number of layers, bottleneck activation size  $d_{model}$ , maximum learning rate, training batch size and the context window size (# tokens) for each model are listed. The feed-forward size is always set to  $4 \times d_{model}$ .

<sup>4</sup>https://github.com/NVIDIA/Megatron-LM

<sup>&</sup>lt;sup>5</sup>https://github.com/microsoft/DeepSpeed

## 3.2 Training details

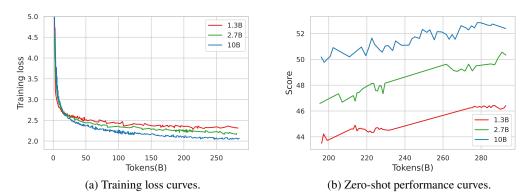


Figure 3: Training Curves of three versions of WeLM. As the model size grows, the training loss and zero-shot performance also improve.

We train our model using the AdamW optimizer [Loshchilov and Hutter, 2019] ( $\beta_1=0.9; \beta_2=0.95; \epsilon=1e-8$ ) with the cosine learning rate scheduler [Kaplan et al., 2020]. Following Black et al. [2021], we utilize DeepSpeed ZeRO stage 1 optimization [Rajbhandari et al., 2020] to reduce GPU memory consumption. The tensor parallelism scheme is used when the model scale does not fit on a single GPU. All models are trained with FP16 mixed precision. To avoid underflows, we used dynamic loss scaling, as described in Micikevicius et al. [2018]. Models are trained with batch sizes of 1024 and 2048 and context window sizes of 2048. This provides  $2\sim4$  millions tokens per batch. We set a maximum learning rate for every model. During training, the learning rate starts with zero and grows to the maximum learning rate in a specified warm-up step, then gradually decays. The learning rate stops decaying after reaching a minimum learning rate, which we set as 10% of the maximum learning rate.

According to the analysis in Hoffmann et al. [2022], model sizes and the amount of training data should be increased in approximately equal proportions as the computation budget increases. Following their suggestion, we choose to train a 10B-sized model with over 300B tokens (similar to the training sizes of GPT-3 [Brown et al., 2020b] and Gopher [Rae et al., 2021]) under our computation budget. The largest model is trained on 128 A100-SXM4-40GB GPUs in about 24 days.

We observe some instability issues when training the 10B-sized model. The training loss could suddenly increase in one batch then falls down. This loss spike, when happening frequently, would deteriorate the model weights and slows down the convergence. We mitigate this issue by re-starting the training from a checkpoint roughly 100 steps before the spike happened, then skipping the following 200 data batches. We also find it helps to reduce the learning rate and reset the dynamic loss scale. Similar strategies have also been used in [Zhang et al., 2022, Chowdhery et al., 2022].

The training loss curve is visualized in Figure 3a. In Figure 3b, we average out the model performance over the CLUE benchmark and visualize it across the training process [Xu et al., 2020]. We can see that the training loss and averaged model performance improves along time. Bigger models clearly perform better than smaller models.

## 4 Experiments

We evaluate WeLM on a wide range of NLP tasks. Similar to Brown et al. [2020b], Zeng et al. [2021], we focus on the in-context learning setting which feeds a task-dependent prompt to the model then lets the model continue to predict words. The final output is extracted from the model predictions. For generative tasks, we directly apply WeLM to decode the answer conditioning on the prompt and the input data. For classification tasks, each label is associated with some token(s) based on a pre-defined verbalizer. In the inference time, we apply WeLM to compute the perplexity of these tokens. The label corresponding to the token with the lowest perplexity is chosen as the model prediction [Schick and Schütze, 2021]. Unlike standard task-specific fine-tuning, in-context learning does not need to

change the parameters of pre-trained language models based on labeled downstream datasets. This makes it a promising exploration towards artificial general intelligence instead of weak AI that is only capable of performing one specific task [Fei et al., 2022].

To evaluate WeLM from various perspectives, we divide the experiment section into four parts to reflect on different capabilities of WeLM:

- Monolingual Evaluation: Evaluate the performance of WeLM on monolingual (Chinese) NLP tasks.
- 2. **Cross-lingual/Code-switching Evaluation**: Evaluate the performance of WeLM on cross-lingual and code-switching (Chinese-English/Japanese) NLP tasks.
- 3. **Multi-Promoted Training**: Evaluate the performance of WeLM after multi-promoted training [Sanh et al., 2021] on hundreds of manually created prompts.
- 4. **Others**: Other findings including the (1) explainability, (2) self-calibration and (3) memorization of WeLM [Jiang et al., 2020, Wei et al., 2022b, Chowdhery et al., 2022].

#### 4.1 Monolingual Evaluation

When evaluating WeLM on monolingual Chinese NLP tasks, we perform experiments under two scenarios: (1) zero-shot, where only task-specific descriptions are used as prompts and (2) few-shot, where both task-specific descriptions and few-shot labeled examples are used as prompts. The evaluation datasets cover 18 Chinese NLP tasks across multiple categories. In Table 3., we compare the performance of WeLM with CPM (2.6B) [Zhang et al., 2021], Pangu (13B) [Zeng et al., 2021] and Ernie 3.0 (10B) [Sun et al., 2021b], the current representative pre-trained Chinese language models with similar sizes as WeLM. We can see that *WeLM performs the best in most tasks*.

Machine Reading Comprehension Machine reading comprehension (MRC) tasks requires the model to read a (set of) text passage(s) and then answers questions about the passage(s) [Zeng et al., 2020]. We evaluate on three Chinese MRC datasets: CMRC2018 [Cui et al., 2019], DRCD [Shao et al., 2018] and DuReader [He et al., 2018]. All of them are extraction-based MRC tasks where the answer is a span to extract from the text passage(s). As WeLM is a generative model, we formulate it as a generation task where the text and question are fed as a prompt to the model. An example is shown in Figure 8. We report the F1 and ROUGE-1 scores which measure the similarity between the generated span and ground-truth span. For DuReader, we select the Zhidao subset for evaluation following Zeng et al. [2021]. WeLM significantly outperformed the others in this task.

Cloze and Completion Cloze and completion tasks require the model to fill in a blank from multiple choices given task-specific requirements. We evaluate WeLM on four Chinese cloze and completion tasks: People\_daily (PD), Children\_fairy\_tale (CFT) [Cui et al., 2016], CHID [Zheng et al., 2019] and CMRC2017 [Cui et al., 2018]. The PD and CFT tasks require the model to predict the masked words in sentences derived from the PD news dataset and CFT dataset. The CHID (Chinese IDiom dataset) provides 10 candidate Chinese idioms and asks the model to select the correct one from them. The CMRC2017 (Chinese Machine Reading Comprehension) task masks common nouns and named entities from the query and require the model to predict the masked words. There is a restriction that the answer should be a single word and should appear in the document. For PD, CFT and CMRC2017, we turn them into a generative task to predict the masked words with WeLM. For CHID, we treat it as a 10-class classification task and use the perplexity-based method to determine the predicted class. Ernie3.0 performs the best on PD and CMRC2017 while WeLM performs the best on the others. This is expected as PD and CMRC2017 are both masked word prediction tasks, which coincides with the pre-training objective of Ernie 3.0.

**Natural Language Inference (NLI)** NLI tasks require the model to determine whether a "hypothesis" is true (entailment), false (contradiction), or undetermined (neutral) given a "premise" [Bowman et al., 2015]. We use the Chinese Multi-Genre NLI (CMNLI) and Original Chinese Natural Language Inference (OCNLI) datasets from the Chinese GLUE benchmark [Xu et al., 2020]. We formulate it as a 3-class classification task and use the perplexity-based method to determine the class. All models perform similarly on this task, possibly because this form of tasks occur rarely on the raw text.

	Zero-shot					Few-shot		
Task(Metric)	CPM-1 2.6B	Pangu 13B	ERNIE 3.0 10B	WeLM 2.7B	WeLM 10B	Pangu 13B	WeLM 2.7B	WeLM 10B
		Machi	ne Reading C	omprehen	sion			
CMRC2018(F1)	10.12	19.28	25.61	31.85	31.31	29.23	39.77	42.10
DRCD(F1)	4.62	10.55	26.29	28.51	39.33	23.46	57.41	63.15
DuReader(Rouge1)	16.63	24.46	29.79	39.28	39.72	27.67	41.42	40.87
		•	Cloze and Cor	npletion				
PD(Acc)	35.73	43.86	66.07	60.57	61.17	41.43	60.57	62.27
CFT(Acc)	38.99	46.60	49.30	55.44	57.38	45.86	56.31	58.37
CHID(Acc)	68.62	70.64	77.78	80.96	81.62	70.91	81.44	81.62
CMRC2017(Acc)	24.60	38.90	56.66	47.20	55.83	37.87	54.27	55.60
		Nat	ural Languag	e Inferenc	ee			
CMNLI(Acc)	49.10	48.44	49.41	43.08	47.80	46.18	51.04	49.89
OCNLI(Acc)	44.20	41.53	44.31	41.86	44.34	46.44	43.46	44.71
			Text Classifi	cation				
TNEWS(Acc)	65.44	60.26	68.40	65.43	71.59	65.17	67.34	71.61
IFLYTEK(Acc)	68.91	73.80	75.34	83.22	81.34	80.34	84.65	82.11
			Sentiment A	nalysis				
SMP-ECISA(Acc)	_	_	_	42.55	45.77	_	44.94	49.97
ChnSentiCorp(Acc)	_	_	_	77.75	81.58	_	77.67	73.92
			Summariza	ation				
LCSTS(Rouge1)	_	_	_	17.97	23.74	_	29.97	32.23
TTNews(Rouge1)	_	_	_	31.49	35.06	_	27.13	32.06
			Closed-Boo	k QA				
WEBQA(F1)	12.59	14.47	38.95	50.13	50.90	41.42	59.51	65.27
			Winograd-Sty	le Task				
WSC2020(Acc)	73.68	75.00	78.38	80.56	82.41	78.62	82.41	79.63
		Co	mmon Sense	Reasoning	g			
C3(Acc)	49.81	54.47	52.62	52.96	54.30	54.58	57.13	59.80

Table 3: Zero-shot and few-shot performance of WeLM on monolingual (Chinese) NLP tasks. We compare different sizes of WeLM with CPM (2.6B), Pangu (13B) and Ernie 3.0 (10B). For few-shot learning, we set the number of shots as 1 for CMRC2018, DRCD and DuReader; 2 for CMRC2017, PD and CHID; 5 for all other tasks.

Closed-Book Question Answering Closed-book question answering requires the model to answer open-domain factoid questions without accessing external knowledge sources [Roberts et al., 2020]. It can test how much knowledge has been implicitly encoded into the model parameters during the pre-training stage. We evaluate WeLM on the WebQA dataset. WebQA [Li et al., 2016] contains question mainly from Baidu Zhidao  $^6$ , a popular Chinese forum with posted real-world questions. We treat it as a generative task and the evaluation is done by comparing the model-generated answer and the ground-truth answer. WeLM significantly outperforms the others with > 10% improvement in the F1 score.

**Sentiment Analysis** Sentiment analysis is a classic NLP task requiring the model to determine the sentiment of a given text [Birjali et al., 2021]. We evaluate WeLM on the Chinese implicit sentiment analysis (SMP-ECISA 2019) <sup>7</sup> and ChnSentiCorp datasets <sup>8</sup>. In SMP-ECISA 2019, all

<sup>6</sup>http://zhidao.baidu.com/

<sup>&</sup>lt;sup>7</sup>https://www.biendata.xyz/competition/smpecisa2019/

<sup>8</sup>https://github.com/pengming617/bert\_classification



Figure 4: Dialogue generation example from WeLM (10B). WeLM can mimic the chatting style of the ancient Chinese poet Li Bai and produce human-like conversations. It can also leverage background knowledge about Li Bai and reply properly for code-switching utterances.

text are split into 3 classes (positive/negative/neutral) while ChnSentiCorp contains only 2 classes (positive/negative). WeLM also achieves good performance even on the zero-shot scenario.

Winograd-Style Task A Winograd schema is a pair of sentences that differ in only one or two words and that contain an ambiguity that is resolved in opposite ways in the two sentences. It requires the use of world knowledge and reasoning for its resolution [Levesque et al., 2012]. We evaluate WeLM on the CLUEWSC2020 dataset [Xu et al., 2020]. CLUEWSC2020 is a Chinese Winograd Schema Challenge dataset. We convert the task into a multiple-choice classification problem where the model needs to choose the correct anaphora/coreference resolution. WeLM performs the best among all models, though there is a degradation for the 10B-version model in the few-shot scenario.

Common Sense Reasoning Common sense reasoning tasks test if the machine can have human-like commonsense reasoning capabilities to properly assist humans in everyday situations [Sap et al., 2020]. We evaluate WeLM on the C3 dataset [Xu et al., 2020]. C3 is a free-form multiple-choice reading comprehension dataset where answers to the questions cannot be directly found in the given context. Common sense reasoning skills are necessary to draw the final answer. We treat it as a classification task and use the perplexity-based method to determine the predicted label. Pangu, Ernie 3.0 and WeLM perform similarly on this task. Pangu slightly outperforms WeLM on the zero-shot scenario but under-performs on the few-shot scenario.

**Text classification** We also evaluate on other text classification tasks including the TouTiao Text Classification for News Titles (TNEWS) and IFLYTEK app description classification (IFLYTEK) tasks [Xu et al., 2020]. For the TNEWS and IFLYTEK tasks, there are 15 and 119 categories originally. We randomly sample three candidates as negative labels for each instance to reduce the

Elon Musk 是 SpaceX 和特斯拉汽车公司的首席执行官。

我: 今天我们有 Elon Musk。欢迎加入我们。

Elon Musk: 谢谢你邀请我。 我:你认为 OpenAI 会如何发展?

Elon Musk: 我认为进展非常顺利。我认为我们在 OpenAI 有一个非常有

才华的团队。

我: 你现在是怎么进行时间分配?

Elon Musk: 我每周都会尝试将部分时间花在 OpenAI 上,但除此之外,

其他时间是 SpaceX 和特斯拉

Prompt

你对自动驾驶有哪些见解?

自动驾驶汽车有很大的发展空间。现在当你进入自动驾驶汽车时,安全性是一个非常重要的问题,也是一个巨大的挑战。我们的目标是让人们进入自动驾驶汽车,让汽车有能力接管交通。从长期来说,自动驾驶将大幅减少事故和死亡。自动驾驶在我看来是巨大的机会,我们认为自动驾驶有希望在未来十年内成为人类的标准出行方式。

How do you think of 中国古代诗人李白?

我认为李白的影响力和深度和我们看莎士比亚类似,莎士比亚在 我看来是最伟大的作家

Figure 5: Dialogue generation example from WeLM (10B). WeLM can mimic the chatting style of the modern American Entrepreneur Elon Muck and produce human-like conversations. It can also leverage background knowledge about Elon Musk and reply properly for code-switching utterances.

computation cost following Zeng et al. [2021]. WeLM significantly outperforms the others on these two tasks.

**Summarization** Text Summarization aims to provide a short concise summary of a given long text input [Lin and Ng, 2019]. Many existing pre-trained language models have demonstrated impressive zero-shot summarization skills by prompting the model with a template like "Write a title/headline/summary of the following document:". We did similar experiments and tested WeLM on two public Chinese summarization datasets: LCSTS [Hu et al., 2015] and TTNews [Hua et al., 2017]. LCSTS consists of over 2 million real Chinese short texts with short summaries given by the writer of each text. TTNews is provided for NLPCC Single Document Summarization competition including 50k document-summary pairs. We report the ROUGE-1 [Lin, 2004] scores in Table 3. We also provide some examples in Table 4. As can be seen, WeLM can produce reasonable summaries of the given document. Summaries from the few-shot WeLM tend to be more diverse and closely related with the document. However, this diversity also brings more chances of differing from the ground truth in the lexical choices which leads to potentially lower ROUGE scores.

**Dialogue Generation** To have a virtual assistant or a chat companion system with adequate intelligence has been a core challenge in artificial intelligence [Chen et al., 2017, Su et al., 2020]. We find that WeLM, without any fine-tuning, can produce human-like conversations under various styles given in the prompts. In Figure 4 and 5, we provide examples of how WeLM can act like two utterly different roles: Li Bai (ancient Chinese poet acclaimed as a brilliant and romantic figure) and Elon Musk (modern American entrepreneur who founded OpenAI, Neuralink, SpaceX and Tesla) by providing in the prompt initial rounds of demonstration conversations. WeLM can even seamlessly integrate correct background knowledge about the specific role. For Li Bai, it leverages the places Li Bai has been and the real historical events in Li Bai's era to provide engaging responses. For Elon Musk, it leverages knowledge of autonomous driving and Shakespear to provide reasonable answers.

-	Example_1(LCSTS)
Context	"孩子们,你们儿童节有什么愿望呢?"老师微笑着提示,"儿童节"是孩子们自己的节日。孩子们的回答五花八门,有的说"想画画",有的说"和同学爬树",有的说"想爸爸妈妈"和城里孩子相比,新衣服、新玩具、游乐园似乎和儿童节无关。
Summary	留守儿童的六一想和妈妈捉迷藏还想去山上玩
Zero-shot	儿童节,孩子们的节日
Few-shot	儿童节,农村孩子最想什么
	Example_2(TTNews)
Context	资料图:空军苏27/歼11编队,日方称约40架中国军机在23日8艘海监船驱赶日本船队期间出现在钓鱼岛附近空域日本《产经新闻》4月27日报道声称,中国8艘海监船相继进入钓鱼岛12海里执法的4月23日当天,曾有40多架中国军机出现在钓鱼岛海域周边空域,且中方军机中多半为战斗机,包括中国空军新型战机苏-27和苏-30。日本《产经新闻》声称中国军机是想通过不断的逼近,让日本航空自卫队的战机飞行员形成疲劳。日本政府高官还称:"这是前所未有的威胁。"针对日本媒体的报道,国防部官员在接受环球网采访时称,中国军队飞机在本国管辖海域上空进行正常战备巡逻,日方却颠倒黑白、倒打一耙,肆意渲染"中国威胁"。
Summary	国防部回应中国军机赴钓鱼岛空域: 系正常巡逻
Zero-shot	资料图:中国海军舰队在钓鱼岛附近海域巡航
Few-shot	中国军机在钓鱼岛附近空域正常巡逻 日方却颠倒黑白、倒打一耙

Table 4: Text summarization examples from zero-shot/few-shot WeLM (10B). WeLM can provide reasonable summary for a given context. Summaries from the few-shot WeLM are more diverse and closely related with the topic in the context, albeit having lower lexical overlap with the ground truth.

**Arbitrary Style Transfer** Text style transfer is an important task in natural language generation, which aims to control certain attributes in the generated text [Jin et al., 2022]. Recent works have shown that pre-trained larga language models can perform well on transferring text into arbitrary styles in the zeroshot setting [Reif et al., 2021, Krishna et al., 2022]. We follow a similar paradigm and show examples in Figure 6. We can see that WeLM can properly understand the user needs following examples given in the prompt. When feeding instructions to WeLM, it is able to enrich and extend a given scenario, make an antonymy or change the sentiment of an existing sentence. All of these can be achieved through a natural human-like interaction.

**Sentence Completion** Sentence completion is a task most similar to the language modelling objective used in the pre-training. In Figure 7, we provide examples of how WeLM is able to complete a given sentence and continue to generate long coherent text with different styles.

#### 4.2 Cross-lingual Evaluation

Cross-lingual evaluation aims to evaluate the performance of WeLM for cross-lingual tasks, i.e., the model must be equipped with bilingual knowledge in order to perform these tasks. As we include a substantial amount of English text in the pre-training corpus of WeLM, we expect WeLM should be able to perform simple cross-lingual tasks. We evaluate on three representative cross-lingual tasks: machine translation, cross-lingual question answering and cross-lingual summarization. Similar to the monolingual evaluation, we conduct experiments under the zero-shot and one-shot scenarios. The results are presented in Table 5. As we did not observe significant differences when increasing the number of labeled examples, we omit the few-shot results in the table. We also report the performance of XGLM (7.5B version) [Lin et al., 2021] for comparison. XGLM is a multilingual autoregressive language model pre-trained on a balanced corpus covering 30 diverse languages. It has set new state of the art in few-shot learning in more than 20 representative languages.

**Machine Translation** Machine translation is a classic sub-field in NLP that investigates how to use computer software to translate between languages without human involvement [Yang et al., 2020]. Even though WeLM is pre-trained predominantly with Chinese text, there are also substantial amount of English and Japanese characters mixed in the Chinese documents. Therefore, we test



Figure 6: Arbitrary style transfer examples from WeLM (10B). WeLM can properly understand the user needs and edit the given text accordingly (even for code-switching input).

WeLM on four translation directions: ZH2JA, JA2ZH, ZH2EN and EN2ZH. For the translation between Chinese and Japanese, we test on 1,000 parallel Chinese-Japanese sentences from the online dictionary examples <sup>9</sup>. For the translation between Chinese and English, we test on the WMT2020 news translation task <sup>10</sup>. As can be seen, the performances of JA2ZH and EN2ZH are significantly better than ZH2JA and ZH2EN, implying WeLM is better at understanding foreign languages than generating them. This makes intuitive sense as generating is also a more difficult task than understanding when humans learn a new language. Compared with XGLM, WeLM excels at 2 out of the 4 translation tasks when the target language is Chinese. Due to the sparsity of Japanese text in the pre-training corpus, WeLM performs poorly on the ZH2JA task. Empirically we find that WeLM can often make grammar errors, or deviate from the source sentence when producing long Japanese text. However, when translating Japanese and English into Chinese, WeLM can perform remarkably well. Even the 1.3B-version WeLM can significantly outperform the 7.5B-version XGLM despite using only one sixth of parameters.

Cross-lingual Question Answering In conventional question answering tasks, the model is supposed to produce an answer given a question and context. Cross-lingual question answering deals with scenarios where the question and context are in different languages. This is important as the information on the Internet is highly imbalanced. Developing high-quality cross-lingual question-answering systems can allow people speaking different languages to access the same amount of information from the web [Asai et al., 2021]. We test WeLM on two datasets: XQuAD [Artetxe et al., 2020] and MLQA [Lewis et al., 2020b]. XQuAD comprises of 240 paragraphs and 1190 question-answer pairs from SQuAD v1.1 [Rajpurkar et al., 2016] translated into ten languages by

<sup>9</sup>https://cjjc.weblio.jp/sentence/

<sup>10</sup>https://www.statmt.org/wmt20/

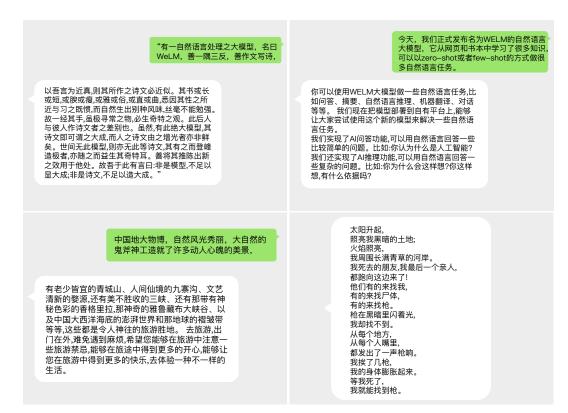


Figure 7: Example of Sentence Completion. Given a beginning sentence, WeLM is able to complete it by generating long coherent text.

professional translators. MLQA has over 12K QA instances in English and 5K in each other language, with each instance parallel between 4 languages on average. In XQuAD, we select Chinese as the language for contexts and English as the language for questions. We construct two subsets: XQuAD\_ZH\_A and XQuAD\_EN\_A which use Chinese and English as the language for answers respectively. In MLQA, we select English as the language for context-answer pairs and modify the questions' language as Chinese (MLQA\_ZH\_Q) or English (MLQA\_EN\_Q). We can see that (1) the zero-shot performance of both WeLM and XGLM is rather low. The model struggles at learning which language to generate without given examples; (2) WeLM significantly outperforms XGLM in all four scenarios, even when the contexts/questions/answers are all in English (MLQA\_EN\_Q); (3) WeLM performs better when the question and answer are in Chinese. Even when both the context and answer are in English, using Chinese questions outperform using English questions (MLQA\_ZH\_Q). This aligns with the findings in Lin et al. [2021] that using prompts in the predominant language of the pre-training corpus is preferred regardless of the languages used in downstream tasks.

Cross-lingual Text Summarization Cross-lingual text summarization aims to summarize the input text in a different language [Leuski et al., 2003]. Under the globalization background, this task has attracted increasing attention of the computational linguistics community. We test WeLM on the NCLS dataset [Zhu et al., 2019]. NCLS is automatically constructed from the English document summarization dataset ENSUM, which is a combination of CNN/DailyMail [Hermann et al., 2015] and MSMO [Zhu et al., 2018], and the Chinese document summarization dataset LCSTS [Hu et al., 2015]. The summaries are automatically translated and filtered with round-trip consistency. The resulting dataset contains two subsets: ZH2EN where documents are in Chinese and the summaries are in English, and EN2ZH where documents are in English and summaries are in Chinese. As can be seen in Table 5, all the three versions of WeLM can outperform XGLM in both summarization directions. Similar to in machine translation, the zero-shot performance is significantly lower than the few-shot performance as the model struggles to know in which language to produce when no examples are provided.

	Zero-shot				One-shot				
Task	WeLM 1.3B	WeLM 2.7B	WeLM 10B	XGLM 7.5B	WeLM 1.3B	WeLM 2.7B	WeLM 10B	XGLM 7.5B	
Machine Translation									
ZH2JA	0.09	2.25	2.22	6.14	2.40	2.52	4.25	8.41	
JA2ZH	4.17	10.65	12.25	8.57	10.19	14.70	16.96	8.74	
ZH2EN	0.53	3.56	9.84	10.81	5.70	8.93	11.46	14.37	
EN2ZH	14.89	21.53	19.43	9.46	19.16	22.79	26.74	11.07	
		Cross-	lingual Q	uestion Ar	swering				
XQuAD_ZH_A	7.23	8.46	9.31	4.16	30.03	36.65	42.06	23.37	
XQuAD_EN_A	5.74	6.94	6.50	4.93	14.28	18.91	23.10	12.50	
MLQA_ZH_Q	4.32	4.58	5.03	3.92	28.27	29.65	36.08	17.48	
MLQA_EN_Q	2.20	2.83	3.19	2.65	25.44	32.83	31.61	30.81	
Cross-lingual Text Summarization									
NCLS_ZH2EN	11.68	14.19	10.50	3.35	15.30	17.76	18.58	13.92	
NCLS_EN2ZH	6.68	3.14	16.25	4.59	17.18	17.12	20.87	16.07	

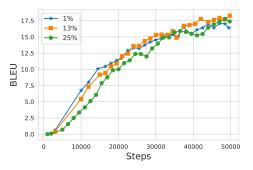
Table 5: Zero-shot and one-shot performance of WeLM on cross-lingual NLP tasks. We report the BLEU score for machine translation, F1 score for cross-lingual question answering and ROUGE-1 score for text summarization tasks. WeLM under-performs XGLM in translating Chinese into English/Japanese but significantly outperforms it over all other tasks.



Figure 8: Examples of code-switching/cross-lingual task using WeLM (10B). WeLM can understand and translate the input mixed with Chinese, Japanese and English. Given a context in English and question in Chinese, WeLM can provide the correct answer in Chinese. Note that the answer cannot be correctly generated without properly understanding the English context.

Code-Switching Examples Code switching occurs when a speaker alternates between two or more languages, or language varieties [Auer, 2005]. It has become more and more frequent as for the increasing trend of internationalization where foreign words and grammars are often borrowed into the local language [Hickey, 2020]. In the daily usage of modern Chinese, it is also rather common to see English or Japanese words, especially for the web content. Therefore, being able to understand code-switching text is a useful skill to perform many Chinese NLP tasks. We find that WeLM can often understand code-switching text properly and some examples have been shown in Figure 4, 5 and 6. In the dialogue generation and arbitrary style transfer examples, we modify one Chinese word/phrase into the corresponding English one. WeLM can still understand the utterances and produce the correct responses. In an extreme example in Figure 8, we mix Chinese, English and

Japanese in both their vocabularies and grammars, then ask WeLM to translate it into Chinese. We can see that WeLM correctly transfers it into a sentence that complies with the usage of daily Chinese. It keeps the commonly used English abbreviation "AI", the entity name "WeLM" and recovers the other unusual usage of code-switching languages into Chinese. This implies that WeLM has been equipped with necessary compositional knowledge from all these three languages. This might be due to the presence of not only multiple languages but also mixed languages in the pre-training corpus, such that WeLM will explore cross-lingual alignments in order to lower down the training loss [Blevins and Zettlemoyer, 2022, Blevins et al., 2022].





- (a) Few-shot performance on WMT2020 (EN2ZH).
- (b) CLUE & SuperGLUE.

Figure 9: Effects of English-text Ratio in Pre-training. Figure 9a is the change of BLEU scores with the number of training tokens under three ratios: 1%, 13% and 25%. The performance is the best when mixing 13% English text into training. Figure 9b is the average score over the Chinese CLUE benchmark and the English SuperGLUE benchmark. Mixing 13% English text performs the best on Chinese tasks while mixing 25% English text performs the best on English tasks.

**Effects of Language Mix Ratio** WeLM is trained with 13% English tokens and 87% Chinese tokens. To see the effects of the language mix ratio, we pre-trained two more models with the same architecture as the 10B-version WeLM, but modify the percentage of English text in the pre-training corpus. One is pre-trained with 1% English text and the other is pre-trained with 25% English text. In Figure 9a, we test models on the WMT2020 EN2ZH news translation task (few-shot) and report the change of BLEU scores as the number of training tokens grows. We can see that the performance saturates after pre-trained on 200B tokens, implying the maximum number of tokens that a 10B model can absorb would be around 200B. Mixing 1% English text can improve the bilingual capability faster but performs the worst when it converges. Mixing 25% English text also under-performs the current model as it cannot observe enough Chinese tokens to generate fluent Chinese text. In practice, given the capacity of the language model, it is important to find a good sweet pot such that the model can learn about foreign languages while ensuring enough in-language knowledge. In Figure 9b, we further visualized the average scores of the three models under the Chinese CLUE and English SuperGLUE benchmarks. As the percentage of English text grows, the scores on the English SuperGLUE benchmark keeps growing as expected. For the Chinese benchmark, surprisingly, mixing 13% English text outperforms mixing 1% English text, although the latter is pre-trained with 12%more Chinese text. This implies that having enough English knowledge is helpful for achieving better performance on Chinese NLU tasks, which makes sense due to the frequently occurred English words in Chinese NLU datasets. For English NLU tasks, however, having Chinese knowledge is not that needed and it is better to focus the model on absorbing only English knowledge.

## 4.3 Multitask Prompted Training

In the previous sections, we have shown WeLM is able to attain reasonable zero-shot generalization on both monolingual and cross-lingual tasks given proper prompts. This section aims to explore whether this kind of generalization can be reinforced through explicit multitask learning. To do so, we collect manually-written prompts for a wide spectrum of tasks following the settings in Sanh et al. [2021]. We then train WeLM on a mixture of labeled datasets with these manually-written prompts. The trained model, termed as WePrompt, is tested on a set of held-out tasks not included in the training stage. Intuitively this explicit multitask learning can adapt the unsupervised WeLM to understand

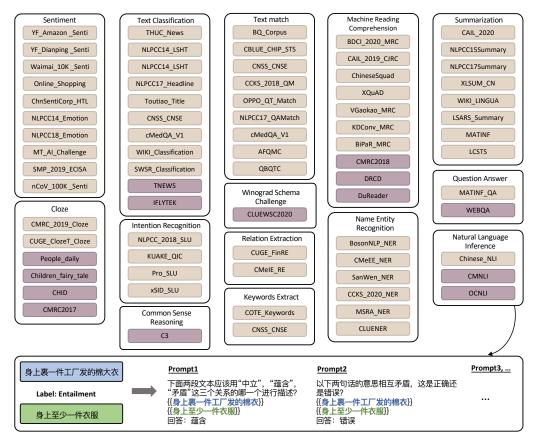


Figure 10: Overview of all 76 tasks from 14 categories that are used to train WePrompt. For each task, we annotate multiple prompts with diverse styles. Two annotated prompts from the NLI task are shown in the bottom as examples.

better what it should do under different prompts [Ouyang et al., 2022]. When tested on a new task with similar styles of prompts, it will perform more stably compared with the original unsupervised WeLM. We first explain the training datasets and details we use, then report our evaluation results under three scenarios: strong-zeroshot, weak-zeroshot and fine-tuned evaluation. We also report the evaluation results for Ernie 3.0 Titan [Wang et al., 2021], the largest pre-trained Chinese language model with 260B parameters.

**Training Datasets** The training datasets are created following two steps: (1) Select a diverse set of labeled Chinese NLP tasks; (2) Create multiple prompts, each with diverse wording for every single task. A prompt is a pattern that is able to convert one labeled sample into a natural sentence. Prompts are created by our in-house annotators with the BigScience Web-based GUI <sup>11</sup>. Annotators are instructed to be open in their style so that the fine-tuned model can be potentially more robust with different patterns of prompts. Examples of prompts are shown in Figure 10. For NLI tasks, prompts are be created as a multi-choice classification task over all three relations or a binary classification task over one individual relation. When we run our experiments, we have created 1,227 manually-written prompts for 76 tasks from 14 categories <sup>12</sup>. A full overview of all the 76 tasks is visualized in Figure 10. The held-out datasets used for evaluation are visualized in purple and the remaining datasets in yellow are used for training. All the 76 tasks have been checked with duplication and are **not** included in our pre-training corpora for WeLM.

<sup>11</sup>https://github.com/bigscience-workshop/promptsource

<sup>&</sup>lt;sup>12</sup>The annotation keeps going. By the time of writing, there have been already 150 datasets with 2,322 prompts created. Though we did not repeat all experiments with the full 150 datasets, we believe the conclusions drawn from the existing experiments can be already useful for future works.

**Training Details** As the data sizes of the 76 tasks can be highly imbalanced, we set a threshold to keep at most 50,000 samples from each task to prevent one task dominating the training process. During the training process, one training sample is constructed by the following process: (1) One out of the 76 tasks is randomly sampled; (2) One labeled data is sampled from the task; (3) One prompt is sampled from the prompt bank for the task; (4) The prompt is applied to convert the labeled data into a natural sentence; (5) repeat the process and pack the corresponding natural sentences until it reaches 2,048 tokens. We then fine-tune WeLM on these training samples for about 6 epochs with the AdamW optimizer. The learning rate is set as 1e - 4 and batch size is set as 2048. During the initial training steps, we warm up the model using a smaller learning rate and mix with data used in the pre-training stage. By this means, the model can be gradually adapted to the new formats of data inputs without abrupt changes. We empirically find this training strategy helps stabilize the training process and the outcome model converges faster.

		Finetuing				
Task	ERNIE 3.0	WeLM	WePrompt	WePrompt	WeLM	WePrompt
Tuok	Titan (260B)	Zero-shot	Strong Zero-shot	Weak Zero-shot	Finetuing	all
		R	eading Comprehen	sion		
CMRC2018	44.20	31.31	35.20	44.61	60.11	70.75
DRCD	37.83	39.33	46.08	58.1	68.37	70.20
DuReader	32.13	39.72	45.48	59.29	68.05	68.10
		(	Cloze and Completi	on		
PD	67.06	61.17	73.50	73.48	81.56	89.31
CFT	66.14	57.38	72.51	75.59	77.04	83.60
CHID	87.13	81.62	80.01	83.49	84.72	84.6
CMRC2017	74.63	55.83	63.72	69.28	81.62	89.3
		Nat	ural Language Infe	erence		
CMNLI	51.70	47.80	52.33	59.48	83.44	82.10
OCNLI	44.61	44.34	47.71	58.56	74.37	76.43
			Text classification	1		
TNEWS	72.60	71.59	75.42	80.50	84.22	88.5
IFLYTEK	79.84	81.34	83.51	82.69	84.65	83.11
			Closed-Book QA			
WEBQA	52.57	50.9	50.52	51.37	62.72	68.06
			Winograd-Style Ta	sk		
WSC2020	81.08	82.41	_	85.84	85.87	85.63
		Co	mmon Sense Reaso	oning		
C3	54.85	54.30	_	64.27	70.83	72.80

Table 6: Zero-shot and fine-tuned performance of WeLM and WePrompt. "Strong zero-shot" means WePromt is not trained on tasks from the same category as the tested task. "Weak zero-shot" means WePromt is not trained on the tested task. In most tasks, WePrompt can outperform Ernie 3.0 Titan which is 23 times larger.

Strong-Zeroshot Evaluation Strong-zeroshot evaluation indicates that when training WePrompt, we exclude all tasks from the same category with the test data. For example, when testing on PD which is a cloze task, we exclude all cloze task from the training datasets of WePrompt. This can test the generalization capability of WePrompt on new tasks from an unseen category. We train an individual WePrompt for every test data and report the results in Table 6. We can see that WePromt performs better than the zero-shot WeLM on most test data. The only exceptions are CHID and WebQA because their forms are already close to the LM objective so that even the unsupervised WeLM has very strong zeroshot performance. In most tasks, WePrompt outperforms Ernie 3.0 Titan which is 23 times larger. Even though WePrompt has never seen prompts from the same category in its training stage, multiple prompted training is beneficial to help the model understand general patterns of prompts. In consequence, WePrompt can produce fewer out-of-scope answers than WeLM. In the

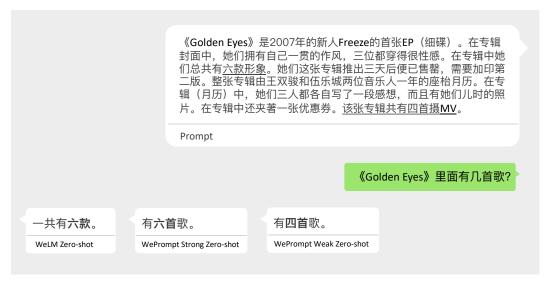


Figure 11: Examples of machine reading comprehension task using WeLM Zero-shot, WePrompt strong Zero-shot and WeLM weak zero-shot. WeLM zero-shot cannot properly understand the question. WePrompt strong zero-shot understood the question but extracted a wrong answer from the prompt. WePrompt weak zero-shot answered correctly.

example given in Figure 11, the zero-shot WeLM completely ignores the subject of the question. The Strong zero-shot WePrompt, despite still providing a wrong answer, can already correctly understand the meaning of the question and can answer in the right direction.

Weak-Zeroshot Evaluation Weak-zeroshot evaluation indicates that when training WePrompt, we exclude only the task from which the test data comes. For example, when testing on PD, we only exclude the PD task from the training datasets of WePrompt. This can test the generalization capability of WePrompt on new tasks from a seen category. We train an individual WePrompt for every test data and report the results in Table 6. We can see that the weak-zeroshot WePrompt, as expected, performs better than the strong-zeroshot WePrompt on most tasks. The only exceptions are PD and IFLYTEK. IFLYTEK is a relatively easy task and the performance already saturates. As we will show later, even when finetuning WeLM on the full supervised data, the performance gain is still marginal. For PD and even all cloze and completion tasks, the performance gain from the weak-zeroshot WePrompt is small. We hypothesize it might be due to the similarity between the language modelling and the cloze and completion tasks. As a result, we do not need extensive prompts from the same category to adapt WeLM to this category of tasks. Similarly, WePrompt also did not bring significant improvement to closed-book QA tasks as this category of tasks already occur frequently in the pre-training corpus.

**Fine-tuned Evaluation** All the previous experiments are evaluated under the in-context learning setting which do not update the model parameters. For the fine-tuned evaluation, we fine-tune the model parameters on the full labeled data with supervised learning. We compare two models: (1) WeLM-Finetuning which fine-tunes WeLM on the training data of the task to be tested on and (2) WePrompt-all which fine-tunes WePrompt on the mixture of training datasets from all tasks. The results on Table 6 show that both fine-tuned models outperform the zero-shot in-context-learning models. The improvement is significant in most tasks. Only in a few easy tasks like CHID and WSC2020, zeroshot models can approach the performance of fully-supervised models. WePromptall usually outperforms WeLM-finetuning except for a few tasks which already have abundant annotations such as CHID and IFLYTEK. As a "narrow expert", WeLM-finetuning needs to fine-tune an individual model for every single task. As we have observed, WeLM-finetuning can completely lose the capability of performing other tasks after specializing on one task. In contrast, WePrompt-all uses a unified model as a general expert for all tasks, which is appealing in saving the storage cost in downstream applications. Nonetheless, even for WePrompt-all, the performance can be unstable when applying it to completely new tasks. For example, we observe WePrompt-all is significantly worse than WeLM in dialogue generation and arbitrary style transfer tasks because these two have

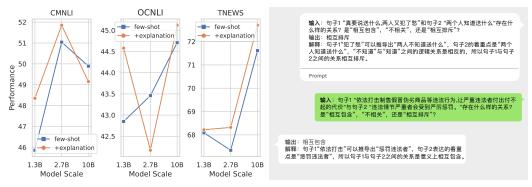
rather different styles of prompts. We still need to keep enriching the prompt bank used to train WePrompt for a better generalization.

## 4.4 Others

Lastly, we evaluate three other capabilities of WeLM:

- 1. **Explainability**: Whether WeLM is able to explain its own decision by providing explanations in the prompts. If so, whether providing explanations in the prompts can improve the model performance.
- 2. **Self-Calibration**: Whether WeLM is able to calibrate its own predictions by asking itself if the predictions are correct or not.
- 3. **Memorization**: To which extent WeLM is able to remember the content in the pre-training corpus and how the frequency will affect its memorization.

We also show the training curves of WeLM in the end for future reference.



- (a) Few-shot performance with explanation.
- (b) Explanation example.

Figure 12: Self-Explainability of WeLM. When providing explanations for the few-shot examples in the prompts, the performance of WeLM improves on two NLI and one text classification tasks.

**Explainability** Explainability is a highly desired feature for deep neural networks, without which humans can barely trust the predictions from them [Shen et al., 2019, Tjoa and Guan, 2020, Burkart and Huber, 2021]. Recent research works have shown the large-pretrained language models are able to generate both predictions and explanations given proper illustrations [Narang et al., 2020, Wiegreffe et al., 2022, Lampinen et al., 2022, Wei et al., 2022b]. Following a similar idea, we test if WeLM can produce reasonable explanations for its own predictions by adding explanations in the prompts. We compare the performances with/without explanations in the prompts for three tasks: CMNLI, OCNLI and TNews. The results and example expalanations generated by WeLM are shown in Figure 12a and 12b. We mainly choose NLI tasks because WeLM struggles in these tasks. They also usually require multi-hop inference and commonsense knowledge in order to derive the final answer, which is more suitable for producing explanations. We can see that adding explanations in the prompt can usually improve the performance. However, the improvement is rather unstable and highly depends on the tasks and provided explanations. On CMNLI, the 11-B WeLM performs even worse when providing extra explanations. ON OCNLI, the 2.7-B WeLM performs worse but the other versions perform better. In the example given in Figure 12b, we can see WeLM can also mimic the styles given in the prompts to produce reasonable explanations for its prediction.

**Self-Calibration** Self-calibration means to calibrate the predictions from itself. For example, after the model provided its prediction, we can feed further input like "Is this answer correct or not". Namely, we would like to see whether WeLM knows what it knows and makes accurate predictions about its own behavior and reasoning [Kadavath et al., 2022]? In Figure 13a, we provide an example on open-domain question answering. The answers are sampled from the top-k decoding results from the model predictions. We can see that WeLM is able to respond differently given different model



- (a) Self-Calibration of Answer Correctness.
- (b) Self-Calibration of Toxic Contents.

Figure 13: Self-Calibration of WeLM. WeLM is able to evaluate (1) whether the predictions from itself is correct or not, and (2) whether the predictions from itself contain toxic contents or not.

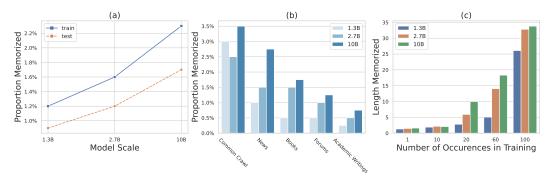


Figure 14: Proportions of training examples that have been memorized for WeLM of three different model sizes. Larger-sized models can memorize more contents. Frequently occurred contents are easier to be memorized.

predictions. Similarly, in Figure 13b, the model is asked whether the model responses contain impolite words or not. WeLM is able to tell that the first example contains implite words while the second example does not. Self-calibration can be challenging because the model may be overconfident of its own predictions. Nonetheless, we find that WeLM has a good ability of distinguishing correct and incorrect predictions from itself. Though we did not measure the capability in a quantitative way, we believe this can be a promising direction for future explorations.

**Memorization** As WeLM is pre-trained in large collections of web contents, we test how it exactly memorizes these contents and visualize the results in Figure 14. Specifically, we sample 2,000 document (1,000 from the training data and 1,000 from the held-out data). We construct the documents by sampling equal number of documents from each of the 5 data sources we used for pre-training. For every document, we use the first 50 tokens as the context, feed to the model and let the model continue to generate the following tokens via greedy decoding. If the model can generate 22 tokens <sup>13</sup> that exactly match the original document, then we consider it as a successful memorization. As can be seen, models can memorize some contents from the training data, though the proportion is not high (2.5% for the largest model). Larger models can usually memorize more contents across data sources. Common crawl contents comprise of over half of the training data so that WeLM can memorize them better than other data sources. Academic writings, due to its low frequency in the training data and its unique styles, are the hardest to memorize. On the rightmost of Figure 14, we also visualize the relation between the average memorized length and the number of occurrences in the training corpus. We can see that for text that occurs more frequently, the model can

<sup>&</sup>lt;sup>13</sup>22 is empirically chosen as an approximation for the length of two Chinese sentences.

memorize more contents and generate longer continuations exactly matching the original document. For text that occur only once, the contents that the model can memorize are very minor.

## 5 Conclusion

We present WeLM: a well-read pre-trained language model for Chinese that is able to seamlessly perform different types of tasks with zero or few-shot demonstrations. It exhibits strong performances across monolingual (Chinese) and cross-lingual (Chinese-English/Japanese) tasks, surpassing existing pre-trained models with similar sizes. We collected human-written prompts for a large set of supervised datasets in Chinese and fine-tuned WeLM with multi-prompted training. The resulting model can attain strong generalization on unseen types of tasks and outperform the unsupervised WeLM in zero-shot learning. We further demonstrate that WeLM has basic skills at explaining and calibrating the decisions from itself, which can be promising directions for future research.

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