Wukong: 100 Million Large-scale Chinese Cross-modal Pre-training Dataset and A Foundation Framework

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Abstract

This paper presents a large-scale Chinese cross-modal dataset for benchmarking different multi-modal pre-training methods to facilitate the Vision-Language Pre-training (VLP) research and community development. Recent dual-stream VLP models like CLIP, ALIGN and FILIP have shown remarkable performance on various downstream tasks as well as their remarkable zero-shot ability in the open domain tasks. However, their success heavily relies on the scale of pre-trained datasets. Though there have been both small-scale vision-language English datasets like Flickr30k, CC12M as well as large-scale LAION-400M, the current community lacks large-scale Vision-Language benchmarks in Chinese, hindering the development of broader multilingual applications. On the other hand, there is very rare publicly available large-scale Chinese cross-modal pre-training dataset that has been released, making it hard to use pre-trained models as services for downstream tasks. In this work, we release a Large-Scale Chinese Cross-modal dataset named Wukong, containing 100 million Chinese image-text pairs from the web. Furthermore, we release a group of big models pre-trained with advanced image encoders (ResNet/ViT/SwinT) and different pre-training methods (CLIP/FILIP/LiT). We provide extensive experiments, a deep benchmarking of different downstream tasks, and some exciting findings. Experiments show that Wukong can serve as a promising Chinese pre-training dataset and benchmark for different cross-modal learning methods, which gives superior performance on various downstream tasks such as zero-shot image classification and image-text retrieval benchmarks. More information can refer to https://wukong-dataset.github.io/wukong-dataset/.

1 Introduction

Pre-training large-scale models on big data, and fine-tuning on downstream tasks, have become an emerging paradigm of artificial intelligence systems. Models such as BERT (Devlin et al., 2019) and GPT (Brown et al., 2020) grow in popularity in the natural language processing community as they possess high transferability to a wide range of downstream tasks or even zero-shot tasks, yielding state-of-the-art performance. Recent works such as CLIP (Radford et al., 2021), ALIGN (Jia et al., 2021) and FILIP (Yao et al., 2022) further extend this diagram to the joint Vision Language Pre-training (VLP) domain and show superior results over state-of-the-art methods on various downstream tasks. This promising direction draws significant attention from both industry and researchers to consider it as the path to the next-generation AI models.

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Table 1: An overview of datasets for VLP model pre-training.

| Dataset                  | Language | Availability | Image-text pairs |
|--------------------------|----------|--------------|------------------|
| Flickr30k (Young et al., 2014) | English | ✓            | 31,783           |
| CxC (Parekh et al., 2020)    | English | ✓            | 247,315          |
| SBU Captions (Ordonez et al., 2011b) | English | ✓            | 1,000,000        |
| Product1M (Zhan et al., 2021) | Chinese | ✓            | 1,000,000        |
| CC12M (Changpinyo et al., 2021) | English | ✓            | 12,000,000       |
| YFCC100M (Thomee et al., 2016) | English | ✓            | 99,200,000       |
| WIT (Srinivasan et al., 2021)    | multilingual | ✓         | 11,500,000       |
| LAION-400M (Schuhmann et al., 2021) | English | ✓            | 400,000,000      |
| JFT-300M (Sun et al., 2017)    | English | ✗            | 300,000,000      |
| JFT-3B (Zhai et al., 2021a)    | English | ✗            | 3,000,000,000    |
| IG-3.5B-17k (Mahajan et al., 2018) | English | ✗            | 3,500,000,000    |
| M6-Corpus (Lin et al., 2021)   | Chinese  | ✗            | 60,500,000       |
| Wukong (Ours)                | Chinese  | ✓            | 101,483,885      |

There are two reasons that lead to the success of VLP models. On the one hand, more advanced model architectures such as ViT (Dosovitskiy et al., 2020)/BERT (Devlin et al., 2019) and training objectives like contrastive learning (He et al., 2020), are usually able to lift the powerful generalization and robustness capabilities of learned representations. On the other hand, thanks to the concurrent advancement in hardware (Stuart and Owens, 2011; Kindratenko et al., 2009) and distributed training frameworks (Narayanan et al., 2021; Rajbhandari et al., 2020; Rasley et al., 2020), more and more data can be fed into a large-scale model to improve the generalization, transferability and zero-shot capability. In either vision or language tasks, pre-training on larger-scale data such as JFT-300M (Sun et al., 2017) in image classification (Riquelme et al., 2021), C4 dataset in T5 (Raffel et al., 2020), has been proven useful and critical for improving downstream task performance via transfer or prompt learning. In addition, recent work (Jia et al., 2021) has already shown the potential of scaling up the VLP model by more than 100 million noisy image-text pairs from the web.

Therefore, the success of VLP models pre-trained on large-scale data urges people to continuously crawl and collect larger image-text dataset. Table 1 shows an overview of many popular datasets in the VLP domain. Publicly-available vision-language English datasets such as Flickr30k (Plummer et al., 2015), SBU Captions (Ordonez et al., 2011a) and CC12M (Sharma et al., 2018) are relatively small at a scale of around 10 million samples, and a larger-scale one is LAION-400M (Schuhmann et al., 2021). However, directly using English datasets to train a model will lead to a great performance drop in translated Chinese downstream tasks. There are a lot of certain Chinese idioms and slang that translated English cannot cover, where machine translation often brings errors that harm the task performance. The current community lacks a large-scale publicly available dataset in Chinese, resulting in (a) the development of the community is stunted; (b) each work uses a secret large dataset to achieve surprisingly good performance that other works cannot fairly compare.

To bridge this gap, we release a large-scale Chinese cross-modal dataset named Wukong, containing 100 million image-text pairs from the web. To guarantee diversity and generalization, our Wukong dataset is collected according to a high-frequency Chinese word list of 200K queries. We also adopt image-based and text-based filtering strategies to further refine it. The resulting dataset is currently the largest Chinese vision-language dataset so far. We perform an analysis of this dataset and show that it covers a wide range of visual and textual concepts.

Training a large-scale VLP model is super expensive. For example, the largest CLIP (Radford et al., 2021) model takes 18 days to train on 592 V100 GPUs, and M6-10T (Lin et al., 2021) is trained on 512 NVIDIA-V100 GPUs for around 10 days. Thus, it is almost impossible for everyone to pre-train a large-scale model due to substantial financial costs and hardware requirements. It is in great demand for researchers to download and reuse various kinds of pre-trained large-scale VLP models. However, the choices of publicly-available large VLP models are also very limited, which hinders the development on downstream tasks of the large-scale model.

In order to contribute to our community, we further release a group of large-scale models pre-trained using different architectures (ResNet (He et al., 2016)/ViT (Dosovitskiy et al., 2020)/SwinT (Liu 2021) and Swin2 (Liu et al., 2021).
Figure 1: The base model consists of an image encoder and a text encoder with visual tokens and textual tokens as inputs. The input tokens from the two modalities are then concatenated and are added with position embeddings indicating token positions. For the image encoder, weights from an external model trained on datasets of other language are preloaded and locked. We compute the global similarity and token-wise similarity in the contrastive pre-training loss.

et al., 2021)) and different methods (CLIP (Radford et al., 2021), FILIP (Yao et al., 2022), and LiT (Zhai et al., 2021b)). As shown in Figure 1, we follow the popular dual-encoder architecture for vision-language representation learning, with the contrastive learning objective. We also provide an extensive benchmarking of the released models on various downstream tasks, such as zero-shot image classification and Img2Text/Text2Img retrieval. Interesting observations can be found from the results: Firstly, by transferring the image encoder trained on English dataset, we find that it can still work well with Chinese texts for cross-modal pre-training and achieve a good performance on Chinese downstream tasks. Secondly, we find that cross-modal token-wise similarity from FILIP complements various patch-based visual encoders like SwinT and can contribute to better visual and textual representations. More findings can be found in Section 5.

Experiments show that Wukong can serve as a promising Chinese pre-training dataset for different cross-modal learning methods. The pre-trained models show prominent performance on various downstream tasks such as zero-shot image classification and image-text retrieval. Specifically, for zero-shot image classification, our model reaches up to 61.5% average top-1 accuracy on 17 datasets. For the retrieval task, our best model significantly outperforms WenLan 2.0 on AIC-ICC by 10% of top-1 recall for image-to-text retrieval, and 11.6% of top-1 recall for text-to-image retrieval respectively. Visualization on word-patch alignment also shows that our model learns meaningful finer-grained features via the token-wise similarity.

In summary, our main contributions are:

(a) A public larger-scale Chinese vision and language pre-training dataset with 100 million image-text pairs is released, covering a more comprehensive range of concepts.
(b) We release a group of large-scale VLP models pre-trained with various popular architectures and methods. An extensive benchmarking of the released models is also provided.
(c) Our pre-trained model shows state-of-the-art performance on Chinese benchmarks such as zero-shot image classification tasks consisting of seventeen datasets and image-text retrieval tasks consisting of five datasets.

2 Related Work

2.1 Vision-Language Pre-training (VLP) Models

Pre-training on a large self-supervised dataset then fine-tuning on various downstream tasks seems to become a de facto practice in the domains of natural language processing, e.g., BERT, GPT (Devlin et al., 2019; Brown et al., 2020) and computer vision, e.g., MOCO, MAE (He et al., 2020, 2021;
Recent works (Radford et al., 2021; Jia et al., 2021; Yao et al., 2022) in the joint domain of Vision-and-Language naturally follow this diagram and have shown superior results over previous methods.

The pre-training tasks. The pre-training tasks of VLP models can be categorized into two categories: Language Modeling (LM) based tasks and contrastive learning based tasks: (a) Language Modeling (LM) based tasks include masked LM (e.g., Masked Language/Region Modeling) and autoregressive LM (e.g., text-grounded image generation, image captioning) on one or both modalities. Previous works like UNITER (Chen et al., 2020), VisualBERT (Li et al., 2019a), M6 (Lin et al., 2021), and DALL-E (Ramesh et al., 2021) apply those kinds of objectives. Some of them use a pre-trained object detector to extract regional image features offline, which requires extra labeled data. On the other hand, SimVLM (Wang et al., 2021), SOHO (Huang et al., 2021) try to eliminate the regional feature extraction via visual dictionary or PrefixLM (Raffel et al., 2020) recently. (b) Large-scale model (e.g., CLIP (Radford et al., 2021), ALIGN (Jia et al., 2021)) usually adopt cross-modal contrastive learning objectives which aligns both modalities into a unified semantic space efficiently; Moreover, FILIP (Yao et al., 2022) tries to learn fine-grained vision-language representations via a new contrastive loss with a late interaction mechanism.

The architectures of VLP models. According to the architectures that model the interaction between visual and textual modalities, there are mainly two types: Single-stream models and Dual-stream models. Single-stream models (Kim et al., 2021; Li et al., 2019a) directly concatenate the visual and textual embeddings together and feed them to a single transformer-based model. This kind of models can be easily fit into text/image generation tasks to perform image captioning or text-to-image generation, which are usually hard to evaluate and benchmark. Dual-stream models such as ViLBERT (Lu et al., 2019), CLIP (Radford et al., 2021) and ALIGN (Jia et al., 2021) have separate models for each modality. This diagram is more flexible and efficient when modeling each modality, e.g., CNN for images, Transformers for texts. Moreover, Dual-stream models have a merit of efficient inference for downstream tasks such as image-text retrieval, since they can decouple and offline store pre-computed image/text features from encoders. In CLIP (Radford et al., 2021), they also evaluate the image encoder as a self-supervised pre-trained model and show promising results. Furthermore, architectures like CLIP (Radford et al., 2021) achieve remarkable zero-shot performance on image classification and image-text retrieval, which has received significant attention from both industry and researchers to consider this as the right path to the next-generation AI models. This paper mainly follows and benchmarks the dual-stream approaches for flexible and efficient usage and inference on many downstream tasks.

2.2 Vision-Language Datasets

The current success of VLP models greatly lies in the scale of pre-trained datasets. The publicly-available pre-training datasets used by recent VLP models are mainly image caption data or image-text pair data. Many small-sized datasets (e.g., a few hundred thousand) such as COCO-Captions (Lin et al., 2014), Flickr30k (Plummer et al., 2015), Visual Genome (Krishna et al., 2016), and VQA2 (Goyal et al., 2017) are hand-annotated data that have very limited domain and diversity. On the other hand, pre-training models on online collected data (such as alt-texts from the HTML pages) has shown promising results. CC3M (Sharma et al., 2018), CC12M (Changpinyo et al., 2021) and YFCC100M (Thomee et al., 2016) have millions of image-text pairs in English generated by an online data collection pipeline including image and text filters, as well as text transformations. VLP models on these datasets have shown to be effective in multiple downstream tasks. Moreover, larger-scale datasets with more than 100M samples (e.g., CLIP (Radford et al., 2021): 400M and ALIGN (Jia et al., 2021): 1.8B) have even armed the recent VLP models with surprisingly good zero-shot recognition ability, but they are not publicly available. Thus, the current community lacks a large-scale Vision-Language dataset in Chinese. We aim to contribute a benchmark Chinese dataset to test various VLP methods on different downstream tasks.

3 Dataset Collection

In this work, we construct a new dataset called Wukong of 100 million image-text pairs collected from the Internet. To cover diverse visual concepts, Wukong dataset is collected according to a list
Figure 2: Examples of image-text pairs in our Wukong dataset. This large-scale dataset covers a diverse range of concepts from the web, and suits vision-language pre-training.

3.1 Image-based Filtering

We first filter the data according to the size and aspect ratio of the image. Only images with both dimensions greater than 200 pixels, and the ratio of large-to-small dimensions is no more than 3 are kept. In this way, we filter out images that are too small, or are very tall or wide, which can be of low-resolution after image augmentations like upsampling and square cropping used during pre-training (Yao et al., 2022).

3.2 Text-based Filtering

Secondly, to select samples with high-quality Chinese descriptions of the corresponding image, we filter the data according to the language, length and frequency of the text accompanying an image. Specifically, we first check the language and length. We keep sentences that contain at least one but fewer than 32 Chinese words. We also discard meaningless image descriptions like “000.jpg” from the text. Afterward, texts paired with too many images are usually irrelevant to the content of the images, like “查看源网页” (View source page), “展开全文” (Expand text), “摄影部落” (Photography community). In practice, we set this threshold as 10, i.e., we discard the image-text pairs whose text appears more than 10 times in the whole corpus collected. To protect the privacy of the individuals appearing in the text, we substitute person names with a special token “<人名>”.
Table 2: Statistics of Wukong dataset. We show the total number of image-text pairs. We also calculate the number of unique tokens and the statistics of tokens per caption.

| Image-text Pairs | Unique Tokens | Tokens per Caption |
|------------------|---------------|-------------------|
| 101,483,885      | 20,442        | mean   22 std 7 median 24 |

(<Person name>). Besides, we also construct a list of Chinese sensitive words, and image-text pairs containing sensitive words are also discarded.

After applying the above filtering strategies, we finally get a dataset of about 100 million <image, text> pairs. Table 2 shows statistics of our dataset. There are 20,442 unique tokens within the texts of our dataset, and the average number of tokens in each caption is 22. Additionally, in Figure 3, we visualize the distribution of words (consisting of one or more tokens) in our dataset. We use the Chinese text segmentation module jieba\(^1\) to generate words and build this word cloud of our dataset.

![Word Cloud](image)

Figure 3: The word cloud generated with texts in Wukong dataset. For example, “月” means month; “日” is day; “做” is do and “一个” means one.

4 Methodology

4.1 Text-Image Joint Alignment

Following the recent well-proven methods (Radford et al., 2021; Yao et al., 2022), we adopt the contrastive pre-training architecture as shown in Figure 1. We use a dual-stream model with Transformer-based text and image encoders. These two encoders convert textual and visual input tokens to embeddings of the same dimension. In this learned joint embedding space, we use a contrastive loss to encourage the paired image and text to have similar embeddings, while non-paired ones to have distinct embeddings. In Radford et al. (2021) and Jia et al. (2021), this cross-modal similarity is computed via dot product between the global features of the entire image and that of the text sequence. On the other hand, in Yao et al. (2022), the similarity is computed based on a finer-grained interaction between the image patches and textual tokens, which also brings surprisingly good word-patch alignment and learns meaningful fine-grained features with promising localization ability.

4.2 Model Architectures

Since the encoders of visual and textual modalities are decoupled, it is possible to explore different encoder architectures for these two modalities. Therefore, we experiment with three variants of visual

\(^1\)https://github.com/fxsjy/jieba
encoders (i.e., ResNet (He et al., 2016), Vision Transformer (Dosovitskiy et al., 2020) and Swin Transformer (Liu et al., 2021)) respectively with a single BERT-similar text encoder (Devlin et al., 2019), to train our Chinese VLP models.

**ResNet.** Residual Network (ResNet) is one of the most popular deep learning architectures achieving compelling results in various computer vision tasks (He et al., 2016). To deal with the vanishing gradient problem in very deep CNNs, ResNet introduces an “identity shortcut connection” that skips one or more convolutional layers, and thus explicitly enables these stacked deep layers to fit a residual mapping. The outputs of shortcut connections are added to the outputs of original layers. As ResNet gains more and more attentions in the research community, its architecture is getting studied heavily, with many modifications and variants introduced (He et al., 2019; Zhang, 2019).

**Vision Transformer.** Inspired by the Transformer scaling successes in NLP, ViT employs a Transformer-like architecture over patches of the image (Dosovitskiy et al., 2020). Specifically, the input image is first rescaled into a standard size and then split into fixed-size patches. Each of the patches is linearly embedded via a trainable linear projection, and also added a positional embedding. The resulting sequence of patch vectors is fed to a standard Transformer encoder. To perform classification, ViT standardly takes the concatenation of an extra learnable [CLS] token and the sequence vector. This way, ViT adopts the standard Transformer directly to images, with minimal possible modifications.

**Swin Transformer.** To further reduce the computational complexity of ViT particularly on high-resolution images, Swin Transformer is proposed (Liu et al., 2021). It uses a hierarchical transformer that computes representation with shifted windows, which limits the original self-attention computation to non-overlapping local windows while also allowing for cross-window connection. This Swin Transformer capably serves as a general-purpose backbone for computer vision tasks, with the flexibility to model at various scales and the linear computational complexity with respect to image size. Different from ViT, the extra [CLS] token is omitted in Swin Transformer.

**Textual Encoder.** The textual encoder is a standard transformer. We follow the Chinese tokenizer from the Chinese BERT-Base model (Pires et al., 2019). We use WordPiece (Wu et al., 2016) with a vocabulary size of 21,128 to tokenize the Chinese text. Similar to (Pires et al., 2019), we add spaces around Chinese CJK characters before applying WordPiece so that Chinese is effectively character-tokenized. We add one special token ([CLS]) at the beginning of each text sequence. The text encoder has 12 layers, each of which has 12 attention heads and a hidden state dimension of 768.

**Linear Projection of the Encoders.** On the top of the visual and textual encoders, the global representations of visual token sequence (e.g., [CLS] token for ViT; average pooled representation of all patch tokens for Swin Transformer) and textual token sequence (e.g., textual [CLS] token) are linearly projected to the common multi-modalities space, followed by L2-normalization separately. Instead of only computing the cross-modal similarity between global representations of sequences, we experiment with a late interaction method as introduced in FILIP (Yao et al., 2022). We aim to take into account the fine-grained token-wise interaction between image patches and Chinese tokens, from visual encoder and textual encoder respectively. It could potentially mine more detailed semantic word-patch alignment between those two modalities.

### 4.3 Pre-training Objectives

Cross-modal contrastive learning is one particularly effective approach for training models from paired image-text data, which can learn representations of two modalities simultaneously by distinguishing the paired and unpaired samples. Following the notations of FILIP (Yao et al., 2022), we use $\mathcal{I}$ to denote the set of image samples while $\mathcal{T}$ is for text data. Give an image sample $x^I \in \mathcal{I}$ and a text sample $x^T \in \mathcal{T}$, the objective of the model is to let the learned image and text representations in the joint multi-modal space be close if they are paired while far apart otherwise. Under the contrastive learning objective, for a training batch consisting of $b$ image-text pairs $\{(x^I_k, x^T_k)\}_{k=1}^b$, $x^I_k$ (resp. $x^T_k$) is positive to $x^I_k$ (resp. $x^T_k$) while negative to all other texts (resp.images) in the same batch. Therefore,
the image-to-text and text-to-image contrastive losses for \((x^I_k, x^T_k)\) can be formulated as:
\[
L^I_k(x^I_k, \{x^I_j\}_{j=1}^b) = -\frac{1}{b} \log \frac{\exp(s^I_{k,j})}{\sum_{j=1}^b \exp(s^I_{k,j})}, \\
L^T_k(x^T_k, \{x^T_j\}_{j=1}^b) = -\frac{1}{b} \log \frac{\exp(s^T_{k,j})}{\sum_{j=1}^b \exp(s^T_{k,j})},
\]
where \(s^I_{k,j}\) denotes the similarity of the \(k\)-th image to the \(j\)-th text, while \(s^T_{k,j}\) denotes the similarity between the \(k\)-th text to the \(j\)-th image. The total loss \(L\) of this training batch is then computed as:
\[
L = \frac{1}{2} \sum_{k=1}^s (L^I_k + L^T_k).
\]
In this work, we explore two typical ways of measuring the similarity between an image and a text. The learned representations of the image and text are denoted by \(z^I \in \mathbb{R}^{n_1 \times d}\) and \(z^T \in \mathbb{R}^{n_2 \times d}\), respectively. Here \(n_1\) and \(n_2\) are the number of (non-padded) tokens in each image and text.

**Global Similarity.** In CLIP (Radford et al., 2021) and ALIGN (Jia et al., 2021), the similarity is computed via dot product of the global features of the entire image and text sequence. Specifically, the global similarity between the image and text is computed as
\[
s^I_{i,j} = s^T_{i,j} = [z^I_i]_{[CLS]} \in \mathbb{R}^d \cdot [z^T_j]_{[CLS]},
\]
where \([z^I_i]_{[CLS]}\) denotes the feature vector of the [CLS] token of the \(i\)-th image and \([z^T_j]_{[CLS]}\) denotes the feature vector of the [CLS] token of the \(j\)-th text. Since Swin Transformer has no [CLS] token, we use the average pooling on the features of all patch tokens to represent it.

**Token-wise Similarity.** In FILIP (Yao et al., 2022), the similarity is computed based on a fine-grained interaction between the image patches and textual tokens, which also brings surprisingly good alignment and learns meaningful fine-grained features with promising localization ability. For the \(i\)-th image, each visual token \([z^I_i]_k\) in it computes a similarity with all non-padded textual tokens of the \(j\)-th text. Then the maximum one is used to represent the token-wise similarity between this visual token and the \(j\)-th text. Finally, we regard the average token-wise maximum similarity of all non-padded tokens in this \(i\)-th image as the cross-modal similarity
\[
s^I_{i,j} = \frac{1}{n_1} \sum_{k=1}^{n_1} [z^I_i]_k^\top [z^T_j]_{m_k'},
\]
where \(m_k = \arg \max_{0 \leq r < n_2} [z^I_i]_k^\top [z^T_j]_r\). The similarity of a text to an image can be computed in the same way, except that we exclude the [CLS] token as in FILIP (Yao et al., 2022).

### 4.4 Locked-image Text Tuning

Inspired by the recently proposed “Locked-image Text tuning” (LiT-tuning) (Zhai et al., 2021b) which shows that a locked pre-trained image encoder with unlocked text encoder works best, we also lock the image encoder in the contrastive learning setting, i.e., the weights of the image encoder are not updated and only the text encoder is updated. In particular, our locked-image text tuning method aims to teach a Chinese text encoder to read out suitable representations from an existing image encoder pre-trained on English datasets. We also add an optional learnable linear projection layer to each encoder, which maps the representations from both modalities to the same dimension. LiT-tuning works well because of its decoupling of data sources and techniques for learning image descriptors and vision-language alignment (Zhai et al., 2021b). And the image descriptors were beforehand well pre-trained using relatively clean or (semi-) manually labeled images. In this work, we extend this idea to multilingual data sources, and try to align a locked image encoder pre-trained on English data sources and a trainable Chinese text encoder. Moreover, the LiT-tuning method significantly speeds up the training process and reduces memory requirements since no gradients need to be computed for the visual encoder. Empirical results in Section 5 confirm the effectiveness of our method.

### 5 Experiments

#### 5.1 Experimental Setup

**Model Architectures.** Following the existing VLP models (e.g., CLIP (Radford et al., 2021), ALIGN (Jia et al., 2021)), we employ a dual-encoder architecture for vision-language representation
Table 3: Detailed settings of our two model variants based on ViT and Swin Transformer. The used two image encoders are the same to the original ViT and Swin Transformer since our experiments preload their model weights.

| Model   | Embedding dimension | Input image resolution | Image encoder | Input text token length | Text encoder width | #heads |
|---------|---------------------|------------------------|---------------|-------------------------|-------------------|--------|
| WukongViT | 256                 | 224 × 224              | ViT-L         | 32                      | 768               | 12     |
| WukongSwin | 256                | 224 × 224              | Swin-L        | 32                      | 768               | 12     |

| ViT-L | Swin-L |
|-------|--------|
| patch size width #layers #heads | patch size width #layers #heads window size |
| 14 × 14 1024 24 16 | 4 × 4 192 [2, 2, 18, 2] [6, 12, 24, 48] 7 |

Table 4: Detailed hyper-parameters used for model training.

| Hyperparameter | Initial temperature | LAMB β₁ | LAMB β₂ | LAMB ϵ | Total epochs |
|----------------|---------------------|----------|----------|---------|--------------|
| Value          | 0.07                | 0.9      | 0.999    | 10⁻²    | 20           |

learning, as shown in the Figure 1. Inspired by the transfer learning in vision revealed by LiT (Zhai et al., 2021b), instead of training the huge number of parameters totally from scratch, we make use of the pre-trained image encoders such as ResNet and ViT from CLIP ², and Swin-L from Swin Transformer ³ for initializing our visual encoder. Similar to the LiT-tuning (Zhai et al., 2021b), our visual encoder initialized with publicly released models is frozen, and only the textual encoder is updated in the pre-training phrase. In this way, we pre-train a few models with variants of visual encoders, on Wukong dataset. Among which, the largest in model size are WukongViT and WukongSwin, respectively using ViT-L/14 from FILIP (Yao et al., 2022) and Swin-L from Swin Transformer (Liu et al., 2021). Details of model parameters and visual encoders are described in Table 3.

Model Training Settings. For better generalization and data-efficiency of our models, we employ Autoaugment (Cubuk et al., 2019) for image data augmentation that aims to build more image-text pairs. All of our models are trained using Nvidia V100 GPUs and Ascend cards. Specifically, WukongViT is trained using 40 GPUs for 6 days and WukongSwin is trained using 72 GPUs for 7 days. In the training, we use the LAMB optimizer (You et al., 2020) and the cosine learning rate schedule with a linear warmup (Loshchilov and Hutter, 2016). Weight decay regularization is applied to all parameters except for bias, layer normalization, token embedding, positional embedding and temperature in the contrastive loss. For the training loss, we experiment with the global similarity and the token-wise similarity as detailed in the Section 4.3. We also use the LiT-tuning method, which locks a pre-trained visual encoder, but unlocks a randomly initialized textual encoder and linear projection layers on top of these two encoders. The values of the hyperparameters are shown in Table 4. In addition, we translate the labels of ImageNet dataset (Deng et al., 2009) to Chinese, and use it as zero-shot validation for saving checkpoints.

5.2 Zero-shot Image Classification

We evaluate our pre-trained models on 17 zero-shot image classification tasks. Since these datasets are originally labeled in English, we translate them into Chinese via machine translation first, and then correct errors and polysemous problems manually. We publish the annotated Chinese versions of these datasets for future evaluation in the research community in https://wukong-dataset.github.io/wukong-dataset/.

²https://github.com/openai/CLIP/
³https://github.com/microsoft/Swin-Transformer
Table 5: Top-1 accuracy (%) of zero-shot image classification. All Wukong model variants are trained on the 100-million Wukong dataset except that Wukong_{ViT-500M} is trained using a larger dataset of 500 million image-text pairs. For computing the cross-modal similarity of loss function, ResNet and ViT-B variants use the global similarity, while Wukong variants use the token-wise similarity unless otherwise specified. **Bold** and *underline* mean the best among all models.

| Dataset  | Model               | ResNet50 | ResNet101 | ViT-B/16 | ViT-B/32 | Wukong_{ViT-500M} (global similarity) | Wukong_{ViT} (global similarity) | Wukong_{Swin} (global similarity) | Wukong_{Swin} |
|----------|---------------------|----------|-----------|----------|----------|--------------------------------------|----------------------------------|-----------------------------------|----------------|
| CIFAR10  | 49.0 60.3 89.0 89.5 | 93.6 90.6 90.3 95.3 | **95.5** |
| CIFAR100 | 23.5 31.1 57.3 49.4 | 64.6 66.3 65.3 69.1 | **77.2** |
| Caltech1 | 72.3 76.3 83.6 84.4 | 86.0 89.9 89.2 87.6 | **91.6** |
| Caltech2 | 58.4 64.3 70.5 75.4 | 76.8 86.2 86.0 78.2 | **88.4** |
| Sports   | 78.0 83.3 90.6 88.1 | 86.8 97.8 96.9 93.4 | **99.1** |
| Flowers  | 29.0 30.9 38.0 42.9 | 55.1 69.4 71.6 54.5 | **75.1** |
| Food101  | 37.0 43.6 42.7 49.4 | 53.5 **70.0** 65.2 46.6 | 66.1 |
| Pets     | 41.7 43.8 44.9 51.2 | 46.4 48.2 61.3 47.7 | 64.5 |
| SUN397   | 33.1 38.4 39.8 42.7 | 44.9 **60.2** 58.9 42.4 | 56.5 |
| ImageNet | 28.3 32.8 33.2 38.3 | 44.8 54.0 54.3 43.6 | **58.5** |
| ImageNet-r | 38.9 47.1 52.3 61.9 | 67.4 72.2 **77.5** 49.3 | 55.3 |
| ImageNet-a | 14.8 20.8 22.2 35.4 | 55.1 52.2 53.2 36.8 | 41.9 |
| ImageNet-s | 16.0 20.6 24.0 29.0 | 33.3 36.5 **36.8** 24.7 | 31.4 |
| DTD      | 22.4 25.2 27.1 31.7 | 35.6 **46.4** 44.6 31.1 | 39.8 |
| Dogs     | 12.1 12.6 17.3 23.3 | 21.1 29.4 **35.4** 22.9 | 40.3 |
| EuroSAT  | 17.6 12.5 35.3 43.9 | 39.7 25.5 32.3 28.8 | 21.0 |
| Aircraft | 10.1 10.0 10.3 14.8 | 20.8 **22.3** 21.5 8.9 | 10.1 |
| **Average** | 34.2 38.4 45.8 50.1 | 54.4 60.6 **61.5** 50.6 | 59.5 |

**Prompt Ensemble.** Existing dual-stream models (Radford et al., 2021; Yao et al., 2022) often apply a set of prompt templates to augment the labels of each dataset and feed the ensembled texts to the text encoder get the weights of the classification layer. In this experiment, we report results using this prompt ensemble as CLIP (Radford et al., 2021). CLIP designs different prompt templates with category descriptions specific to each task dataset in a sophisticated manner, which helps to improve the performance of that task. However, for simplicity, we translate the reported 80 English prompts used for ImageNet in CLIP to Chinese (details can be found in the Appendix A.1), and use this set of prompt templates for zero-shot image classification. It is possible that adding extra descriptions to prompt templates specific to each dataset may improve the corresponding tasks. Since our paper aims to provide a benchmark dataset with pre-trained models, we stick to a large set of general prompt templates, and leave this effort of designing better prompts to each task as a future work.

Note that when using the global similarity, we follow CLIP to ensemble different prompt templates by using their mean textual representation, i.e., we sum different templates for the same class label to form a mean textual representation. And then we use the summed text representation to calculate the global similarity to images. While for the token-wise similarity, since there is no global representation, we simply ensemble prompt templates by their mean token-wise similarity to images.

Results of the zero-shot image classification are shown in Table 5. We compare multiple LiT-tuning models using different visual encoders, i.e., we load existing visual encoders from CLIP or Swin Transformer and lock them during the training phrase. We find that using the token-wise similarity brings a noticeable improvement compared to the global similarity. For example, Wukong_{ViT} outperforms Wukong_{ViT-500M} with gloabl similarity by 6.2%, and likewise for using Swin Transformer as the encoder. This result demonstrates that the finer-grained interaction between image patches and Chinese textual tokens helps to learn better alignment between images and texts. Consistent with finding in previous works (Radford et al., 2021; Yao et al., 2022) that visual encoders with larger
Table 6: Results of zero-shot image-text retrieval on different datasets. MR (Mean Recall) denotes the average of Recall@K with K = 1, 5, 10. **Bold** and *underline* mean the best among all models.

| Dataset   | Method     | Image-to-Text Retrieval | Text-to-Image Retrieval | MR       |
|-----------|------------|-------------------------|-------------------------|----------|
|           |            | R@1 | R@5 | R@10 | R@1 | R@5 | R@10 |          |
| Flickr8K-CN | Wukong\_ViT | 70.0 | 91.6 | 96.6 | 53.5 | 79.3 | 87.9 | **79.8** |
|           | Wukong\_ViT-500M | 65.9 | 90.2 | 95.7 | 52.6 | 80.0 | 88.6 | 78.8 |
|           | Wukong\_Swin | 52.1 | 78.2 | 87.3 | 41.0 | 68.4 | 79.1 | 67.7 |
| Flickr30K-CN | Wukong\_ViT | 78.9 | 96.2 | 98.1 | 55.7 | 81.2 | 87.9 | **83.0** |
|           | Wukong\_ViT-500M | 77.9 | 95.4 | 98.1 | 55.7 | 81.8 | 88.7 | 82.9 |
|           | Wukong\_Swin | 65.8 | 89.2 | 95.0 | 44.5 | 72.2 | 81.2 | 74.7 |
| COCO-CN   | Wukong\_ViT | 56.9 | 82.4 | 90.9 | 52.7 | 79.9 | 88.6 | **75.2** |
|           | Wukong\_ViT-500M | 56.0 | 81.0 | 91.6 | 52.4 | 79.7 | 88.8 | 74.9 |
|           | Wukong\_Swin | 48.7 | 77.3 | 88.6 | 50.6 | 79.3 | 88.9 | 72.2 |
| MUGE      | Wukong\_ViT | -   | -   | -   | 37.6 | 63.4 | 73.6 | 58.2 |
|           | Wukong\_ViT-500M | - | - | - | 42.9 | 68.5 | 77.5 | **63.0** |
|           | Wukong\_Swin | -   | -   | -   | 36.2 | 61.1 | 71.5 | 56.3 |

In summary, the zero-shot classification performances on various tasks show the effectiveness of our dataset and released models. Although these visual encoders are all pre-trained on English datasets, e.g., ImageNet-22K and YFCC100M (Thomee et al., 2016), we find that the image feature computed by them is still reliable and expressive for efficiently pairing Chinese texts and images in our dataset. For some tasks like the Aircraft dataset, our pre-trained models achieve a relatively worse performance. We speculate that this is because this dataset has 100 labels that mostly stay very similar after being translated, e.g., “ATR-42” and “ATR-72”. Yet another reason is that most labels include numbers whose semantics are quite weak, e.g., “Airbus A318”, “Dornier 328” and “Cessna 525”.

5.3 Image-Text Retrieval

In this section, we evaluate our models on two sub-tasks, including image-to-text retrieval and text-to-image retrieval. In the image-to-text retrieval, the model retrieves a target text from a set of candidates given an image as query, or vice versa for the text-to-image retrieval. We benchmark our models on 5 different datasets, including Flickr8K-CN (Li et al., 2016), Flickr30K-CN (Lan et al., 2017), COCO-CN (Li et al., 2019b), AIC-ICC (Wu et al., 2017) and MUGE. Table 8 in Appendix A.2 shows the statistics of each dataset. Among them, the texts in Flickr8K-CN, COCO-CN, AIC-ICC are human-annotated, the texts in Flickr30K-CN train/val set are machine-translated while the texts in Flickr30K-CN test set are human-translated from their original English counterparts. In Flickr8K-CN, Flickr30K-CN and AIC-ICC, each image is paired with 5 texts. In COCO-CN, each image is paired with 1 to 2 texts. In MUGE, each text is paired with 1 to 2 images in the train set, and with about 6 images in the val/test sets.

For each dataset, our pre-trained models are evaluated in both zero-shot and fine-tuned settings. Following common practices, we report Recall@K (recall of top K candidates) with K = 1, 5, 10 for both image-to-text and text-to-image retrieval on all datasets except MUGE, which only has the text-to-image retrieval setting. The average of Recall@K, i.e., Mean Recall (MR), is used for the final comparison. We report results on the test sets, except for MUGE and AIC-ICC where test sets are not released. For MUGE, we report results on the validation set, and for AIC-ICC, following the setting of WenLan 2.0 (Fei et al., 2021), we take the first 10K images along with their corresponding 50K pieces of texts from the validation set for testing. We compare our models against several

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[4]https://tianchi.aliyun.com/muge
Table 7: Results of fine-tuned image-text retrieval on different datasets. **Bold** means the best among different Wukong variations and underline means the best among all methods. Items with the asterisk symbol mean data splits (train/val/test) are different from others. Results of baseline methods for COCO-CN are taken from the papers of LightningDOT (Sun et al., 2021) and UC² (Zhou et al., 2021). Results of WenLan 2.0 (Fei et al., 2021) are also taken from their paper.

| Dataset       | Method       | Image-to-Text Retrieval | Text-to-Image Retrieval | MR |
|---------------|--------------|-------------------------|-------------------------|----|
|               |              | R@1 | R@5 | R@10 | R@1 | R@5 | R@10 |     |
| Flickr8K-CN    | Wukong_ViT   | 80.3 | 95.3 | 98.4 | 68.6 | 90.3 | 95.3 | 88.0 |
| Flickr8K-CN    | Wukong_ViT-500M | 81.5 | 96.7 | 98.8 | 68.9 | 90.6 | 95.4 | **88.7** |
| Flickr8K-CN    | Wukong_Swin  | 77.5 | 94.7 | 97.4 | 62.1 | 87.1 | 93.4 | 85.4 |
| Flickr30K-CN   | Wukong_ViT   | 90.6 | 99.0 | 99.7 | 77.3 | 94.7 | 97.3 | **93.1** |
| Flickr30K-CN   | Wukong_ViT-500M | 90.3 | 99.2 | 99.7 | 77.9 | 94.5 | 97.2 | **93.1** |
| Flickr30K-CN   | Wukong_Swin  | 86.9 | 97.6 | 99.3 | 71.1 | 91.5 | 95.4 | 90.3 |
| COCO-CN        | EmbN         | -   | -   | -   | -   | -   | -   | 73.2 |
| COCO-CN        | PARALLEL-EmbN | -   | -   | -   | -   | -   | -   | 76.0 |
| COCO-CN        | S-LIWE       | -   | -   | -   | -   | -   | -   | 73.6 |
| COCO-CN        | MULE         | -   | -   | -   | -   | -   | -   | 75.9* |
| COCO-CN        | SMALR        | -   | -   | -   | -   | -   | -   | 77.5* |
| COCO-CN        | M3P          | -   | -   | -   | -   | -   | -   | 86.2 |
| COCO-CN        | UNITER       | -   | -   | -   | -   | -   | -   | 87.3 |
| COCO-CN        | LightningDOT | -   | -   | -   | -   | -   | -   | 88.4 |
| COCO-CN        | UC²          | -   | -   | -   | -   | -   | -   | 89.8 |
| COCO-CN        | Wukong_ViT   | 68.9 | 91.9 | 96.8 | 73.0 | 93.4 | 97.1 | 86.9 |
| COCO-CN        | Wukong_ViT-500M | 72.0 | 93.3 | 97.6 | 73.8 | 93.4 | 97.2 | **87.9** |
| COCO-CN        | Wukong_Swin  | 69.3 | 94.0 | 97.4 | 69.3 | 93.0 | 97.7 | 86.8 |
| AIC-ICC        | WenLan 2.0   | 45.6 | 68.0 | 76.3 | 34.1 | 58.9 | 69.1 | 58.7 |
| AIC-ICC        | Wukong_ViT   | 55.6 | 76.9 | 83.6 | 45.7 | 69.5 | 77.9 | **68.2** |
| AIC-ICC        | Wukong_ViT-500M | 55.0 | 76.1 | 82.9 | 45.5 | 69.7 | 77.8 | 67.8 |
| AIC-ICC        | Wukong_Swin  | 53.7 | 76.0 | 82.9 | 41.9 | 66.7 | 75.5 | 66.1 |
| MUGE           | Wukong_ViT   | -   | -   | -   | 44.5 | 71.9 | 81.3 | 65.9 |
| MUGE           | Wukong_ViT-500M | -   | -   | -   | 49.1 | 76.1 | 84.0 | **69.7** |
| MUGE           | Wukong_Swin  | -   | -   | -   | 45.1 | 71.2 | 80.5 | 65.6 |

Baseline methods, including EmbN (Wang et al., 2018), PARALLEL-EmbN (Gella et al., 2017), S-LIWE (Wehrmann et al., 2019), MULE (Kim et al., 2020), SMALR (Burns et al., 2020), M3P (Ni et al., 2021), UNITER (Chen et al., 2020), LightningDOT (Sun et al., 2021), UC² (Zhou et al., 2021) and WenLan 2.0 (Fei et al., 2021).

Table 6 and Table 7 show the results of zero-shot and fine-tuned image-text retrieval, respectively. For the zero-shot setting, among different model variations, Wukong_ViT achieves the best results on 3 out of 4 datasets, while Wukong_ViT-500M achieves the best result on the larger MUGE dataset. For the fine-tuned setting, among our models, Wukong_ViT-500M achieves the best results on all datasets except AIC-ICC, where Wukong_ViT works best. Compared with baseline methods, on AIC-ICC, Wukong outperforms WenLan 2.0 by around 10%, which was pre-trained on a larger dataset consisting of 650 million image-text pairs. For the COCO-CN dataset, our Wukong models also achieve comparable performances to state-of-the-art methods. Overall, experimental results demonstrate the capabilities of our pre-trained models.

### 5.4 Visualization of word-patch alignment

Since we follow the fine-grained interaction as proposed in FILIP (Yao et al., 2022), our models likewise are supposed to own the capability of capturing the correspondence between images and Chinese texts. In this section, we use our pre-trained models Wukong_ViT and Wukong_Swin for visualization.
As shown in the Figure 4, we visualize images from six labels from the Chinese ImageNet (i.e., damselfly; lifeboat; hummingbird; iPod; church and electric fan). Then we apply the same visualization method from FILIP (Yao et al., 2022), to align textual tokens and image patch tokens. In particular, we calculate the token-wise similarity between each image patch token and all tokenized textual tokens from the text label, i.e., [CLS] [class label tokens] [EOS], as illustrated in the Section 4.3. For each image patch, the position index of textual tokens with the maximum similarity is considered as its predicted text token. Note that the Chinese class label is often tokenized to more than one token. We highlight all the predicted position indices that correspond to the class label, and place them at the center of the corresponding patches. In addition, since we use the visual encoder ViT-L/14 in Wukong\textsubscript{ViT}, each image is patchified to 16 \times 16. For the used Swin-L Transformer in Wukong\textsubscript{Swin}, the output resolution is $H_{32} \times W_{32}$, that is, $7 \times 7$ patches. Therefore, Wukong\textsubscript{ViT} presents the more fine-cut grids than Wukong\textsubscript{Swin}.

From Figure 4, we surprisingly find that both models are able to predict image patches of the target object. For Wukong\textsubscript{ViT} with more image patches, such word-patch alignment is more fine-grained than Wukong\textsubscript{Swin}. Take Figure 4 (e) as an example, Wukong\textsubscript{ViT} is even able to align Chinese tokens “教” and “堂”, which means church as one word, to the smaller church in the bottom-right corner. Wukong\textsubscript{ViT} also well outlines the hummingbird in the example Figure 4 (c), while Wukong\textsubscript{Swin} often aligns to the main body of the target object. However, since more fine-cut patches are presented, it might bring noises at some point compared to Wukong\textsubscript{Swin}. As in the (e) example, some obvious wrongly predicted patches can be viewed for Wukong\textsubscript{ViT}, and similarly in Figure 4 (f), some image patches surrounding the fan are predicted to token index 1. Note that this token “电” of index 1 means electricity, which essentially is not direct to the meaning of fan. Another interesting observation is that these Chinese pre-trained models are able to align image patches to English tokens as shown in Figure 4 (d). The main reason lies in that the vocabulary we used from BERT (Devlin et al., 2019) also includes multilingual words such as “iPod”.

This visualization of word-patch alignment evidences the effectiveness of cross-modal token-wise similarity even in the LiT-tuning setting. Though the visual encoder (i.e., ViT-L/14 or Swin-L) is frozen in the pre-training phrase, the learnable linear projection layer on top of it, is still able to align patches and words in a fine-grained manner. We also find that this token-wise similarity in loss
function works across various patch-based visual encoders, not only the traditional ViT architecture but also Swin Transformer that uses the sophisticated shifted windowing attention and patch merging. Given this promising capability of aligning words and patches, our experiment offers a potential solution towards image object localization.

6 Conclusion

In this work, we build a large-scale Chinese vision-language dataset called Wukong. To the best of our knowledge, it is the first hundred-million level dataset specific for the Chinese language and it paves the way for research on Chinese cross-modal model pre-training. Meanwhile, using this dataset, we propose two Chinese cross-modal pre-trained models, i.e., Wukong\textsubscript{ViT} and Wukong\textsubscript{Swin}. We show that it is possible to apply the visual encoders pre-trained on English dataset to Chinese multi-modal pre-training. In the future, we plan to explore more solutions to train multilingual cross-modal models with the Wukong dataset.
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As previously observed in GPT-3 (Brown et al., 2020), the zero-shot performance can be significantly improved by customizing the prompt templates to each task. CLIP (Radford et al., 2021) also shows that specifying the category for each dataset contributes to the performance. However, since we only aim to provide a Chinese dataset with a general benchmarking of our released models, we leave the “prompt engineering” to the future. We simply use the reported 80 general English prompts in CLIP and translate them to Chinese manually, as follows. Note that “{}” is replaced by the exact Chinese label name.

**Chinese Prompts:** “{}的照片。”、“许多{}的照片。”、“一张包含{}的照片。”、“质量差的{}的照片。”、“{}的雕塑。”、“难以看到{}的照片。”、“{}的低分辨率照片。”、“{}的渲染。”、“涂鸦{}。”、“{}的糟糕照片。”、“{}的裁剪照片。”、“{}的纹身。”、“{}的刺绣照片。”、“很难看到{}的照片。”、“{}的明亮照片。”、“一张干净的{}的照片。”、“{}的深色照片。”、“{}的手绘画。”、“{}的黑白照片。”、“{}的画”、“{}的版画”、“{}的壁画”。“{}的像素照片。”、“{}的雕像。”、“{}的明亮照片。”、“{}的裁剪照片。”、“人造的{}的照片。”、“一张关于{}的照片。”、“{}的损坏的jpeg照片。”、“{}的模糊照片。”、“{}的相片。”、“{}的一张好照片。”、“{}的渲染照。”、“视频游戏中的{}。”、“{}的一张照片。”、“{}的涂鸦。”。“{}的近景照片。”、“{}的临摹画。”、“{}在视频游戏中。”、“{}的草图。”、“{}的涂鸦照。”、“{}的折纸形状。”、“{}的低分辨率的{}的照片。”、“{}的副本。”、“{}的干净的照片。”、“{}的一张照片。”、“{}的重现。”、“{}一张漂亮的{}的照片。”、“{}一张奇怪的{}的照片。”、“{}模糊的{}的照片。”、“{}的卡通。”、“{}的装饰作品。”、“{}的素描。”、“{}的刺绣。”、“{}的像素照。”、“{}的拍照。”、“{}的损坏的照片。”、“{}的高质量的{}的照片。”、“{}的毛绒玩具。”、“{}漂亮的{}的照片。”、“{}小{}的{}的照片。”、“{}照片是奇怪的{}。”、“{}的漫画”。“{}的艺术照。”、“{}的图形。”、“{}大{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”、“{}{}的{}的照片。”

### A.2 Image-text retrieval dataset.
Table 8: Statistics of each image-text retrieval dataset.

| Dataset                | split | #Images   | #Sentences |
|------------------------|-------|-----------|------------|
| Flickr8K-CN (Li et al., 2016) | train | 6,000     | 30,000     |
|                        | val   | 1,000     | 5,000      |
|                        | test  | 1,000     | 5,000      |
| Flickr30K-CN (Lan et al., 2017) | train | 29,783    | 148,915    |
|                        | val   | 1,000     | 5,000      |
|                        | test  | 1,000     | 5,000      |
| COCO-CN (Li et al., 2019b) | train | 18,341    | 20,065     |
|                        | val   | 1,000     | 1,100      |
|                        | test  | 1,000     | 1,053      |
| AIC-ICC (Wu et al., 2017) | train | 210,000   | 1,050,000  |
|                        | val   | 30,000    | 150,000    |
|                        | test-1| 30,000    | 150,000    |
|                        | test-2| 30,000    | 150,000    |
| MUGE (Lin et al., 2021) | train | 129,380   | 248,786    |
|                        | val   | 29,806    | 5,008      |
|                        | test  | 30,399    | 5,004      |