

# InterBERT: Vision-and-Language Interaction for Multi-modal Pretraining

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## ABSTRACT

Multi-modal pretraining for learning high-level multi-modal representation is a further step towards deep learning and artificial intelligence. In this work, we propose a novel model, namely InterBERT (BERT for Interaction), which owns strong capability of modeling interaction between the information flows of different modalities. The single-stream interaction module is capable of effectively processing information of multiple modalities, and the two-stream module on top preserves the independence of each modality to avoid performance downgrade in single-modal tasks. We pretrain the model with three pretraining tasks, including masked segment modeling (MSM), masked region modeling (MRM) and image-text matching (ITM); and finetune the model on a series of vision-and-language downstream tasks. Experimental results demonstrate that InterBERT outperforms a series of strong baselines, including the most recent multi-modal pretraining methods, and the analysis shows that MSM and MRM are effective for pre-training and our method can achieve performances comparable to BERT in single-modal tasks. Besides, we propose a large-scale dataset<sup>1</sup> for multi-modal pretraining in Chinese, and we develop the Chinese InterBERT which is the first Chinese multi-modal pre-trained model. We pretrain the Chinese InterBERT on our proposed dataset of 3.1M image-text pairs from the mobile Taobao, the largest Chinese e-commerce platform. We finetune the model for text-based image retrieval, and recently we deployed the model online for topic-based recommendation.

## CCS CONCEPTS

- Computing methodologies → Transfer learning; Multi-modal pretraining;
- Networks → Self attention.

## KEYWORDS

Multi-modal pretraining, BERT, visio-linguistic understanding.

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<sup>1</sup>We will release the dataset to nourish further development in the community.

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## 1 INTRODUCTION

In recent years, a focus in the community is the learning of multi-modal representation, especially vision-and-language representation learning. The understanding of vision and language is a bedrock of cross-modal downstream tasks, such as visual question answering [4], visual commonsense reasoning [54], image-text retrieval [48], etc. However, in spite of the steady progress in the tasks, the methods are mostly based on supervised learning, and the scale of training data limits their performance. It is hard to generalize the task-specific models to multiple visio-linguistic tasks. Therefore, a number of researchers in this field have turned their focus to pretraining, which can generate generic representations.

Pretraining has raised much attention in the community due to its strong capability of generalization and efficient usage of large-scale data. The development of computer vision has been highly connected with the pretraining, such as AlexNet [20], VGG [39] and ResNet [14], which are pretrained on the large-scale dataset ImageNet [10] for image classification. In recent years, we have witnessed the burst of pretraining in natural language processing. Pretrained models [11, 12, 17, 26, 31, 33, 52] have reached state-of-the-art performances in a number of downstream tasks in natural language processing (NLP), including question answering [34], natural language inference [47] and even natural language generation, including neural machine translation [6, 44, 46] and abstractive summarization [28, 37].

Such significant progress raised the concern of pretraining for multi-modal representation. A series of cross-modal pretraining methods were proposed and the self-supervised learning provides the architectures with strong ability to adapt to multiple multi-modal downstream tasks through finetuning [9, 23, 24, 27, 41, 43, 45]. However, these models are mostly pretrained by simple tasks such as masked language / object modeling (MLM/MOM) and image-text matching (ITM). Except for that, single-stream models [9, 23] simply apply BERT and mix information from two streams into one model, while two-stream models [27, 41, 45] can only build

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interaction with co-attention, where there is no self attention to the self-context in each stream in the co-attention layers.

Motivated by this observation, we propose a novel method for multi-modal pretraining, called **InterBERT**, which refers to *BERT for Interaction*. It consists of a single-stream cross-modal encoder for all the inputs from different modalities, as well as a two-stream encoder that processes information from each modality separately. This architecture ensures the sufficient interaction between modalities and preserves the independence of individual modality. Besides, we set a new series of pretraining tasks, including masked segment modeling (MSM), masked region modeling (MRM) and ITM. The tasks are more challenging and they force the model to predict a span or a region, which requires the model to build more connection between modalities. We pretrain the model on Conceptual Caption (CC) [38], SBU Captions [29] and COCO Captions [25] in order to obtain a backbone for downstream tasks.

We evaluate the effects of InterBERT on a series of multi-modal downstream tasks, including caption-based image retrieval [48], zero-shot caption-based image retrieval, visual question answering [4] and visual commonsense reasoning [54]. Experimental results demonstrate that our method can achieve significant improvements over the baseline models, and it outperforms the recent multi-modal pretrained models in image retrieval. We also evaluate the effects of our pretraining techniques and the model performance in single-modal tasks. The analysis demonstrates that our pretraining tasks can enhance the model performance, and the model can adapt to single-modal tasks without performance decrease.

Furthermore, we propose a large-scale dataset of image-text pairs for multi-modal pretraining in Chinese, namely **TaoMultimodal**, and we develop the first multi-modal pretrained model for Chinese, the Chinese InterBERT. To be specific, we create a large-scale dataset by extracting around 3.1M image-text pairs from the largest Chinese e-commerce platform, the mobile Taobao. Each pair of data contains an image of a product and its product title. For finetuning, we extract 200K image-text pairs under a specific category also from the mobile Taobao. We pretrain our proposed InterBERT on the large dataset and finetune it for topic-based image retrieval. Experimental results demonstrate that pretraining can enhance the effects of retrieval and the improvement is more significant when there are fewer training data for finetuning. Recently we have deployed the system online for topic-based recommendation.

In brief, our contributions are illustrated below:

- We propose a novel method for multi-modal pretraining called **InterBERT**, which effectively builds multi-modal interaction and preserves the independence of single-modal representation.
- Experimental results demonstrate that pretraining benefits the performance in downstream tasks and our proposed model outperforms the baselines and the recent multi-modal pretraining methods.
- We propose a large-scale dataset of Chinese image-text pairs for multi-modal pretraining and develop ***the first*** multi-modal pretrained model for Chinese. We have deployed the model online for topic-based recommendation, which demonstrates its superiority for e-commerce.

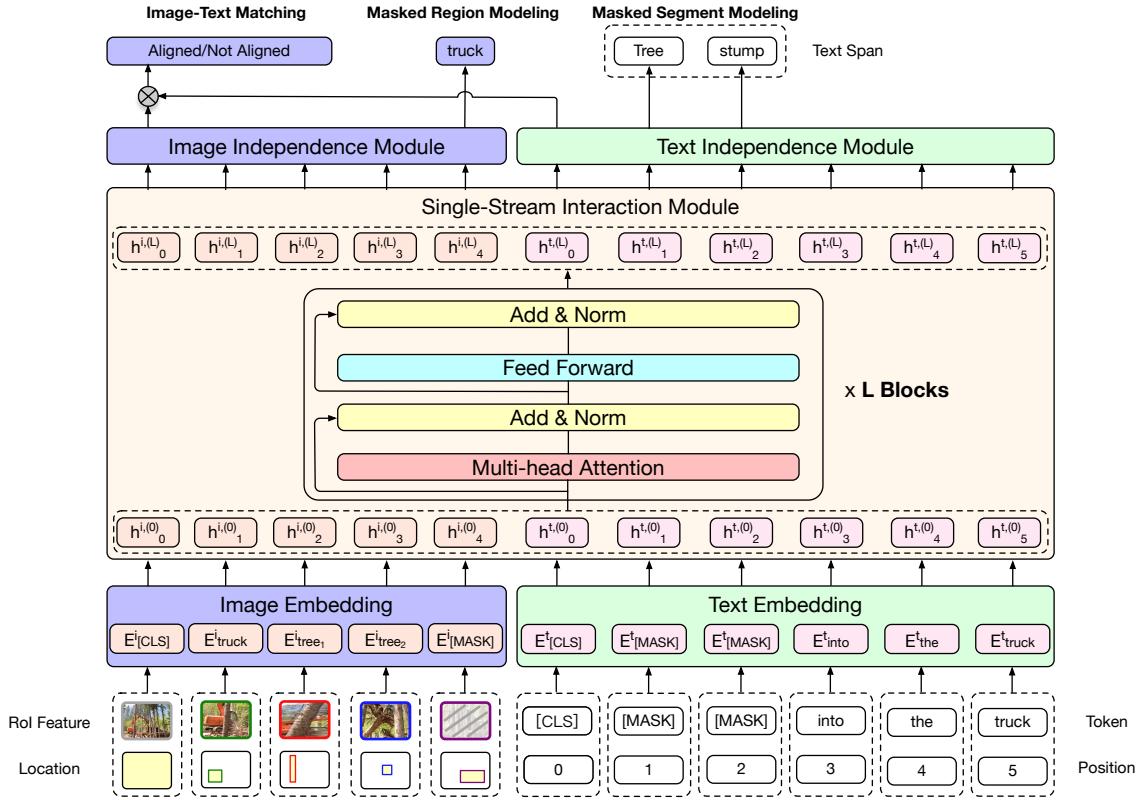
**Organization** The rest of the paper is organized as follows: Section 2 reviews the related work, with a focus on pretraining. Section 3 provides an overview of the proposed approach, including model architecture as well as the pretraining method. Section 4 provides the details of our experiments, including the details of datasets, implementation, results and analysis. Section 5 describes the proposed dataset TaoMultimodal and the implementation of our Chinese InterBERT. The final section concludes the paper.

## 2 RELATED WORK

In this section, we focus on the review of the studies in pretraining methods, especially the pretraining in NLP and multi-modal pretraining.

**Single-Modal Pretraining** The recent years have witnessed the development of the pretraining in NLP. ELMo [31], which is an LSTM-based [16] language model, has attracted the attention of NLP researchers as it demonstrated that pretraining is also available for NLP tasks. Later, ULMFit [17] proposed some techniques and gained improvements in several downstream tasks. Yet these models are based on the conventional recurrent neural network architecture. GPT [32] is the first language model based on Transformer [46] architecture, which is a unidirectional decoder. Neither GPT nor the later version GPT2 [33] can learn the information of the subsequent context. In concern of full observation of the context, [11] proposed BERT, a bidirectional encoder based on Transformer. BERT reached state-of-the-art performances in a number of NLP downstream tasks, including natural language inference [47] and question answering [34]. There have been a series of studies following BERT [21, 26, 52]. These models have achieved superior performances over the baselines and some even outperformed human performance.

**Multi-modal Pretraining** The success of pretraining in NLP raised the attention in multi-modal pretraining. VideoBERT [43] is regarded as the first work in multi-modal pretraining. It is a model pretrained on the extracted video frame features and texts. A following work is CBT [42], which is also pretrained on video-text pairs. Inspired by the starting work in multi-modal pretraining, more researchers have turned their focus to visio-linguistic pretraining. There are mainly two streams of model architectures for this task. One is the single-stream model [1, 9, 23, 24, 41], and the other is the two-stream model [27, 45]. The single-stream models mostly apply BERT to multi-modal pretraining in a straightforward fashion, while the two-stream models have respective encoders for modalities and a co-attention module for the cross-modal interaction. These models either lack independence of each modality or lack sufficient interaction across modalities. Furthermore, there is still room for setting training tasks for more effective pretraining. Compared with the previous work, our proposed method has several significant differences. Our proposed model architecture is effective in capturing modal interaction with a unified BERT and obtaining modal independence with two streams of independent Transformer. Besides, our proposed masked segment masking and masked region masking improve the model’s ability to predict a span or a region, so that the model can be more effective.



**Figure 1: Overview of the architecture of InterBERT. The model is built with an image embedding layer, a text embedding layer, a single-stream interaction module and a two-stream independence module. In the block of single-stream interaction, we demonstrate the details of a Transformer layer.**

### 3 APPROACH

We detail our proposed approach **InterBERT** in this section. Before moving into the introduction to InterBERT, we illustrate the background of pretraining in NLP and extend it to multi-modal pretraining.

#### 3.1 Background

While we follow the pretraining principle in NLP, we first introduce the background of NLP pretraining and further introduce multi-modal pretraining.

We take BERT [11] as an example of NLP pretraining. Given an input text, a word (a character or a subword) sequence  $w = \{w_1, w_2, \dots, w_n\}$  of length  $n$ , the model should learn to generate its high-level representations  $h = \{h_1, h_2, \dots, h_n\}$ . Due to the requirements of BERT's pretraining tasks, the input is first turned to a new sequence with a token “[CLS]” at the beginning, and the token “[SEP]” at the boundary between sentences or the end of the text. The representation at the position “[CLS]” is often regarded as the text representation. BERT then transforms the input  $w$  to high-level representations through an embedding layer and multiple Transformer layers. For a BERT of  $l$  layer, the model can produce  $l$  sequences of representations  $H = \{H^1, H^2, \dots, H^l\}$ . In most cases, we take the representations of the top layer for further finetuning

and thus  $h = H^l$ . For further finetuning, the pretrained model except for the topmost layers for logits is applied as the backbone of the model for a specific downstream task. It is common that a simple layer of neural networks, say a multi-layer perceptron (MLP) [36], is inserted on top of the backbone for the corresponding objective of the task. For instance, for a downstream task of classification, only the text representation  $h_{[\text{CLS}]}$  is sent to the MLP for final classification.

Following this logic, such pretraining can be extended to learning multi-modal representations. In this work, we focus on the pretraining of vision and language. The dataset for multi-modal pretraining consists of paired image-text data, such as an image and its caption. To feed an image into BERT, a solution is to extract the object representations and bounding boxes with a detector, such as Faster-RCNN [35], and form a sequence of  $m$  object representations  $o = \{o_1, o_2, \dots, o_m\}$  together with their positions. Similar to the pretraining in NLP, we also add a representation  $o_{[\text{CLS}]}$  (in our implementation. It is the mean pooling of the original  $o$ ) at the beginning as the image representation. The goal of the model is to learn the high-level representations of both image and text  $h = \{h^i, h^t\}$ , where  $h^i = \{h_1^i, h_2^i, \dots, h_m^i\}$  and  $h^t = \{h_1^t, h_2^t, \dots, h_n^t\}$ . For finetuning, we add simple MLP layers based on the requirements of the specific downstream tasks.

### 3.2 Model Overview

In this section, we illustrate the details of our proposed model InterBERT. The overview of the architecture is demonstrated in Figure 1. Specifically, we first describe the process of image and text embedding, and then we demonstrate the architecture of the single-stream interaction module and the two-stream independence module.

**Text Embedding** Following BERT, we tokenize the input text with WordPiece [51]. Specifically, there is a set of special tokens containing the aforementioned “[CLS]” denoting token for classification, “[SEP]” denoting separator or ending, and a special token for masked language modeling “[MASK]”. In the conventional pretraining process, 15% proportion of the input text are randomly masked. 80% of them are masked by the token “[MASK]”, 10% are masked by a random word, and another 10% are masked by the original word. However, in our multi-modal pretraining, we endeavor to improve the difficulty of masked language modeling so that the model can learn to attend to the visual context for word prediction. Inspired by [18], we randomly mask continuous text spans by 10% with an average length of 3 words.

While Transformer is based on self attention instead of recurrent networks, positional embedding is required so that the model can learn the information about the positions of words. Different from the original work, we apply an MLP to learn the positional embedding. Finally, the word embedding and positional embedding are added and sent through a Layer Normalization (LN) [5] layer.

**Image Embedding** Different from text which is a word sequence, image is a matrix of pixels. In order to turn an image to a sequence, a solution is to make use of the object detection model and form a sequence of object representations with their bounding boxes for positional information. Furthermore, the representations from a neural-network-based detector are high-level representations. Specifically, following [27], we apply a commonly used object detector Faster-RCNN [35], which is trained on Visual Genome [19], on the images for pretraining [2]. We extract the bounding boxes and the RoI (Region of Interest) features as the object representations. Therefore, we extract both high-level representations and the corresponding positions. Similar to the embedding method for text, we treat the features as image embeddings and use the bounding boxes to learn positional embeddings through MLP, and finally add them up and send through an LN layer.

Similarly to MLM, a pretraining task to model object is MOM. While the inputs are feature vectors, the masking operation becomes replacing with a zero vector. Previous studies [9, 27, 41] randomly mask 15% of the representations. However, we also implement masked span modeling for image. A simple solution is to compute the pairwise IoU (Intersection over Union) and randomly mask 15% of the objects as well as their neighbors with an IoU value higher than  $a$ .<sup>2</sup>

**Single-Stream Interaction Module** On top of the embedding layer, we implement a single-stream interaction module based on multi-layer Transformer. The main components of a Transformer layer are the self attention and the point-wise feed-forward neural network (FFN) [46]. Different from the original Transformer, the

activation function for each layer in our module is GeLU [15]. The BERT layer includes:

$$h^l = \text{MultiheadAttention}(x^{l-1}) \quad (1)$$

$$\tilde{h}^l = \text{LayerNorm}(x^{l-1} + h^l) \quad (2)$$

$$\hat{h}^l = W_2[\text{GeLU}(W_1 h^l + b_1)] + b_2 \quad (3)$$

$$x^l = \text{LayerNorm}(\tilde{h}^l + \hat{h}^l) \quad (4)$$

This architecture enables strong interaction between modalities with the attention mechanism. Compared with the two-stream co-attention layer [27] which can only attend to the representations of the other modality, this architecture enables a combination of self attention and co-attention, and therefore the model can generate more contextualized representations. Furthermore, another advantage is that the architecture is identical to BERT and thus its weights can be initialized with the pretrained BERT’s weights, which improves the availability to the previous pretrained models.

**Two-Stream Independence Module** The single-stream interaction module fuses the visual and linguistic representations and make them more contextualized. However, in concern of the independence of each modality, we should develop a module to respectively generate representations for each modality. An ideal situation is that the model’s outputs consists of visual and linguistic representations as well as the visio-linguistic ones. Therefore, we implement a multi-layer Transformer for each modality respectively. Also, except for the high-level object representations and word representations, we still have an image representation and a text representation, as mentioned above. We send both of them through an MLP for the cross-modal representation. Our analysis demonstrates that our architecture with the two-stream independence module can achieve similar performance in single-modal tasks compared with BERT, which shows its advantage in preserving modal independence.

### 3.3 Pretraining Tasks

In this section, we introduce the pretraining tasks for our multi-modal pretraining, namely masked segment modeling (MSM), masked region modeling (MRM) as well as image-text matching (ITM). Similar to MLM, MSM also replaces the selected words with the same strategy (replacing with the token “[MASK]”, a random word or the original word). However, MSM masks a continuous segment of text instead of random words. Different from [18], we mask multiple segments for each sample. As to MRM, it masks selected objects with zero vectors as MOM does. Yet, it endeavors to mask objects that are immediate in order to avoid information leakage due to the overlapping between objects. MRM masks objects which have high proportion of mutual intersection. As to ITM, we first sample negative image-text pairs by random selection and make them share the same proportion of the positive samples. ITM encourages the model to learn the matching scores between images and texts. Following [9], we use conditional masking which does not compute the loss of MSM and MRM for negative samples.

**Masked Segment Modeling and Masked Region Modeling** For MSM, we randomly choose words as masking anchors by the probability of 10%, and we randomly mask 0 to 2 words after the anchors by the probability of uniform distribution. For MRM, we

<sup>2</sup> $a$  is a hyperparameter. We use 0.4 based on preliminary experiments.

**Table 1: Data statistics of the datasets for pretraining. The numbers in the parentheses refer to the numbers of images.**

Datasets	Training	Validation
Conceptual Caption	3.3M	14K
SBU	890K	10K
COCO	587K (117K)	15K (3K)

also randomly choose objects as masking anchors by the probability of 15%, and we mask the objects whose IoUs with the anchors are larger than 0.4. The objective of the model is to predict the masked words and the categories of the masked objects. The training minimizes the loss:

$$\mathcal{L}_m = -E\log P(x_m|x_{\hat{m}}) \quad (5)$$

where  $x_m$  refers to the masked segments or regions and  $x_{\hat{m}}$  refers to the masked sequence. Conditional masking is applied so that the model can have full observation of the other modality when predicting the masked information of one.

**Image-Text Matching** For ITM, we add a simple MLP on top of the main architecture for computing the matching score between inputs of two modalities. Specifically, we first multiply the text representation (the output representation at the position “[CLS]”) and the image representation (the output representation at the position of the mean-pooled object representation), and send the generated representation through the MLP for the matching score. The training minimizes the cross-entropy loss:

$$\mathcal{L}_i = -E(y\log P(y|x_{\hat{m}}) + (1-y)\log(1-P(y|x_{\hat{m}}))) \quad (6)$$

where  $y \in \{0, 1\}$  denotes positive or negative samples and  $x_{\hat{m}}$  refers to the masked sequence.

### 3.4 Finetuning

We use the pretrained InterBERT as the backbone for the downstream tasks. In this paper, we apply the pretrained model to four downstream tasks, including caption-based image retrieval, zero-shot caption-based image retrieval, visual question answering and visual commonsense reasoning. The details of the tasks and datasets are introduced in the following section. For the tasks of classification and matching, the model sends the multiplication of the final image representation and text representation as the multi-modal representation through an MLP for prediction.

## 4 EXPERIMENTS

In this section, we introduce the details of our experiments, including the pretraining datasets, the downstream tasks, the implementation details, the experimental results and analysis.

### 4.1 Pretraining Datasets

We pretrain our model on three datasets, including Conceptual Caption (CC) [38], SBU Captions [29] and COCO captions [25]. We have removed the images that exist in the datasets of downstream tasks to avoid information leakage. The data statistics are demonstrated in Table 6. The length of each sentence is shorter than 36 words, and the length of each object sequence is shorter than 36

**Table 2: Data statistics of the datasets of the downstream tasks. “i” refers to the number of images, and “t” refers to the number of texts.**

Datasets	Training	Validation	Testing
VQA	i:83K, t:444K	i:41K, t:214K	i:81K, t:448K
VCR	i:80K, t:213K	i:10K, t:27K	i:10K, t:25K
Flickr30K	i:29K, t:145K	i:1K, t:5K	i:1K, t:5K

as we extract only 10 to 36 objects from each image following the previous work [27].

### 4.2 Downstream Tasks

**Caption-based Image Retrieval** We conduct experiments on the task of caption-based image retrieval. This task requires the model to retrieve an image from a large pool of images based on a given caption. The dataset is the Flickr30K dataset [53], whose images are extracted from Flickr. In Flickr30K, each image is paired with five captions, which are of relatively high quality. Following [27], in the stage of training, we change the task to 4-way multiple choice by adding three negative images for each image-caption pair. The dataset is split into three subsets for training, validation and testing. The training set contains 29K images, and the validation and test set contain 1K images respectively. The evaluation metrics R@1, R@5 and R@10 (Recall at 1, 5 and 10).

**Zero-shot Caption-based Image Retrieval** This is the zero-shot setting for caption-based image retrieval. There is no process of finetuning for this task, and the pretrained model is directly applied. We use the same splits of dataset for caption-based image retrieval. The evaluation metrics are also R@1, R@5 and R@10.

**Visual Question Answering** Visual question answering is a task of cross-modal question answering [4]. Given an image (or multiple images) and a question, the model should provide an answer. This task requires the model to learn both visual information and linguistic information, which is more complex than conventional question answering. In this work, we follow the previous work in multi-modal pretraining and implement our experiments on the dataset VQA 2.0 [13]. In this dataset, every question is related to a pair of images, which requires the model to pay sufficient attention to the visual information. The dataset is split into three subsets for training, validation and testing. The training set contains 83K images and 444K questions, the validation set contains 41K images and 214 questions, and the test set contains 81K images and 448K questions. The model should answer the questions by selecting answers from a shared set of 3129 answers. The evaluation metric is the VQA-score [13].

**Visual Commonsense Reasoning** Visual commonsense answering is a task connected with cognition and requires visual understanding [54]. There are three sub-tasks in VCR, including Q→A, QA→R and Q→AR. Q→A refers to question answering, and QA→R refers to reasoning based on the given question and answer. In Q→AR, provided an image and a question, the model should not only answer question but also give a rationale for the choice. For

**Table 3: Results of the models on the four downstream tasks. The results of the baselines are those reported in their original papers. “-” denotes that the model was not implemented on the task in the original work.**

Models	IR			Zero-shot			VQA		VCR		
	R@1	R@5	R@10	R@1	R@5	R@10	test-dev	test-std	Q→A	QA→R	Q→AR
SCAN [22]	48.6	77.7	85.2	-	-	-	-	-	-	-	-
BUTD [3]	-	-	-	-	-	-	65.3	65.7	-	-	-
R2C [54]	-	-	-	-	-	-	-	-	63.8	67.2	43.1
VisualBERT [24]	-	-	-	-	-	-	70.8	71.0	70.8	73.2	52.2
LXMERT [45]	-	-	-	-	-	-	72.4	72.5	-	-	-
VilBERT [27]	58.2	84.9	91.5	31.9	61.1	72.8	70.6	70.9	72.4	74.5	54.0
VL-BERT [41]	-	-	-	-	-	-	71.2	-	73.8	74.4	54.2
InterBERT	61.9	87.1	92.7	49.2	77.6	86.0	70.3	70.6	73.1	74.8	54.9

each question, there are 4 candidate answers and 4 candidate rationales. The dataset is split into three subsets for training, validation and testing. The training set contains 80K images and 213K questions, the validation set contains 10K images and 27 questions, and the test set contains 10K images and 25K questions. The evaluation metric is accuracy.

### 4.3 Baselines

For the comparison with the previous methods, we mainly compare our InterBERT with the previous models that achieved outstanding performances on the downstream tasks and the recent multi-modal pretrained models.

**Previous Methods** For image retrieval, we compare InterBERT with SCAN [22], which is an architecture based on stacked cross-attention that achieved SOTA performance. For VQA, we compare InterBERT with the previous model, Bottom-Up Top-Down Attention [3]. This is a model based on attention mechanism. For VCR, we compare InterBERT with R2C (Recognition to Cognition) [54], which contains modules for grounding, contextualizing and reasoning.

**Multi-modal Pretrained Models** We compare the model performances on the downstream tasks between InterBERT and some other multi-modal pretrained models. Specifically, we focus on the comparison of our model with VilBERT and VL-BERT for the reason that our implementation details are similar to theirs, including pretraining datasets, number of object features.<sup>3</sup> <sup>4</sup>

### 4.4 Implementation Details

In the following, we introduce the details of our implementation in pretraining and finetuning on each downstream task, including the model architecture, optimizer, hyperparameters, etc.

**Pretraining** The object representations of the images as well as their bounding boxes are generated by an object detector based on Faster R-CNN [35] with a backbone of ResNet-101 [14], which

<sup>3</sup>We follow the implementations of VilBERT that we use no more than 36 object features for each image, while Unicover-VL uses 100 features. Furthermore, we also implemented a single-stream model with a similar architecture to UNITER and Unicoder-VL, which achieved results similar to those reported in VilBERT [27], which are different from the results of UNITER and Unicoder-VL. We leave it an open question for future discussion.

<sup>4</sup>Until recently, the codes of LXMERT, VilBERT and VL-BERT are released.

**Table 4: An ablation study on the test-dev set of VQA. In the two-stage pretraining, the model is first pretrained with MLM and MOM and then pretrained with MSM and MRM.**

Techniques	VQA (test-dev)
MLM+MOM+ITM	69.6
MSM+MRM+ITM	69.0
Two-stage	70.3

is trained on Visual Genome [19]. We pretrain the model with AdamW whose initial learning rate of  $1e-4$ ,  $\beta_1 = 0.9$ ,  $\beta_2 = 0.9999$ ,  $e = 1 \times 10^{-6}$  and a weight decay of 0.01. We apply the linear decay learning rate scheduler with a warm-up period of 10000 steps. For more information, please refer to Appendix A.2.

**Finetuning** For the finetuning on image retrieval, we use AdamW optimizer with an initial learning rate of  $4 \times 10^{-5}$  and apply a linear decay learning rate scheduler with a warm-up period of 10000 steps. We finetune the model for 20 epochs with a batch size of 32. For the finetuning on VQA, we use an initial learning rate of  $1 \times 10^{-4}$ . We finetune the model with a batch size of 256 and train it on 8 V100 for 20 epochs. For the finetuning on VCR, we use similar hyperparameters of those in the finetuning on VQA, but we use a smaller learning rate  $2 \times 10^{-5}$  and a smaller batch size 32. We only finetune the model for 5 epochs. For more information, please refer to Appendix A.2.

### 4.5 Results

In general, our InterBERT outperforms the previous models, which shows the effects of multi-modal pretraining for the downstream tasks. Table 3 demonstrates the experimental results of our proposed model InterBERT as well as the compared baselines on the four downstream tasks.

In the experiment of image retrieval, InterBERT outperforms SCAN by a large margin (+13.3 (27.4%) in R@1, +9.4 (12.1%) in R@5 and +7.5 (8.8%) in R@10), and it also outperforms VilBERT by +3.7 (6.4%) in R@1, +2.2 (2.6%) in R@5 and +1.2 (1.3%) in R@10. As to zero-shot image retrieval, the advantage is significantly larger. It

**Table 5: Results on the GLUE dev set. We evaluate the performance of BERT-base and InterBERT on four tasks of GLUE. The results show that InterBERT can achieve comparable performances in the single-modal downstream tasks**

Model	CoLA	SST-2	STS-B	RTE	Avg.
BERT-base	56.7	92.4	88.2	65.0	75.6
Single Stream	52.3	91.9	88.6	59.2	73.0
InterBERT	57.3	91.7	88.9	64.3	75.6

outperforms VilBERT by +17.3 (54.2%) in R@1, +16.5 (27.0%) in R@5 and +13.2 (18.1%) in R@10.

In the experiment of VQA, InterBERT achieves an advantage of +5.3 (8.1%) over BUTD and the performance is comparable to that of VilBERT. While LXMERT achieves a significantly better performance, we assume that this is because it has been pretrained on QA datasets, including Visual Genome and GQA. In the experiment of VCR, InterBERT also significantly outperforms the baseline R2C by +9.3 (14.5%) in Q→A, +7.6 (11.3%) in QA→R and +11.8 (27.4%) in Q→AR, and it also outperforms VilBERT by +0.7 (1.0%) in Q→A, +0.3 (0.4%) in QA→R and +0.9 (1.6%) in Q→AR.

InterBERT has advantages over the baselines in the tasks, especially in zero-shot image retrieval. Also, compared with VilBERT, InterBERT has an advantage in the number of parameters (173M vs 221M), which reflects the effects of single-stream interaction. The significant advantage in zero-shot learning demonstrates that our model learns better in modeling image-text relations and can easily adapt to downstream tasks without finetuning.

## 4.6 Analysis

In this section, we propose a series of analysis to evaluate the effects of MSM and MRM, further pretraining and the two-stream independence module.

**MSM+MRM** We conduct an ablation study on the test-dev set of VQA to evaluate the effects of MSM (masked segment modeling) and MRM (masked region modeling). Specifically, we pretrain three models on CC and SBU with different pretraining tasks, including MLM+MOM+ITM, MSM+MRM+ITM, and two-stage pretraining where the the model is first pretrained with MLM+MOM and then with MSM+MRM. The first two models have been pretrained for 15 epochs, and the last one is first pretrained with MLM+MOM+ITM for 5 epochs and then with MSM+MRM+ITM for 10 epochs. Table 4 demonstrates the results of the evaluation. It can be found that our proposed MSM and MRM are beneficial to the pretraining effects. However, directly pretraining with MSM and MRM damages the performance in the downstream task. We assume that the two tasks are relatively difficult for a model that is randomly initialized to learn, and therefore a hot start with a model first pretrained with relatively easy MLM and MOM can enhance the performance.

**Performance in the Single-modal Tasks** While multi-modal pretraining demonstrates effects in the aforementioned downstream tasks, it is still a question whether it still preserve the knowledge of single-modal representation and whether it can still achieve comparable performances in the single-modal tasks. To evaluate

**Table 6: Data statistics of the dataset TaoMultimodal for the pretraining of the Chinese InterBERT.**

Datasets	Training	Validation
Pretraining	3.1M	1K
Finetuning	200K	1K

the model’s robustness, we conduct an experiment on four tasks of GLUE [47], including CoLA, SST-2, STS-B and RTE. We compare InterBERT with BERT-base and the single-stream model.<sup>5</sup> From the experimental results demonstrated in Table 5, it can be found that InterBERT can achieve similar performances on the four NLP tasks compared with BERT-base (Avg: 75.6 vs 75.6), and it significantly outperform the single stream model without the independence module (Avg: 75.6 vs 73.0). This indicates that InterBERT with the two-stream independence module preserves the ability to model single-modal representations and it can adapt to single-modal downstream tasks without significant performance decrease.

## 5 CHINESE INTERBERT

Besides proposing a novel approach for multi-modal pretraining, we develop the first Chinese multi-modal pretrained model, Chinese InterBERT. The model is pretrained on the extracted dataset from the Chinese e-commerce platform, the mobile Taobao. Then we finetune the pretrained model on a relatively small dataset of a specific category. The downstream task for finetuning is image-text retrieval, which evaluates the transferability of the pretrained model.

### 5.1 Experimental Setup

**Pretraining** For pretraining, we build a large scale of dataset for Chinese multi-modal pretraining, called TaoMultimodal. Specifically we extracted around 3.1M image-text pairs from the mobile Taobao, one of the largest Chinese e-commerce platform. Each pair of data consists of an image of a product and its product title. The products are under the category “women clothes”. This design is concerned with the evaluation of the pretrained model’s transferability to other domains. We demonstrate two examples of image-text pair on Figure 2. More details are referred to Appendix A.1. We pretrain our InterBERT on the dataset for multi-modal representations. The implementaion details are provided in Appendix A.2.

**Finetuning** We finetune our Chinese InterBERT on the other of our extracted dataset of image-text pairs from the mobile Taobao. The process of dataset construction is similar to that of the pre-training data. The dataset contains around 200K image-text pairs, which belong to the products under the category “women shoes”. The finetuning of the Chinese InterBERT is designed for a downstream task, text-based image retrieval. Given a piece of text, the model should retrieve the images that are related to the text from the given pool. This task evaluates the model’s ability of image

<sup>5</sup>This is a single-stream model, which is a BERT that processes the information of multiple modalities. We pretrain the model with the same data.



**Figure 2: An illustration of two examples of the extracted image-text pairs from the mobile Taobao (the texts are translated from Chinese). Each image and its corresponding text describe a specific product. Both the images and texts are provided by the sellers themselves.**

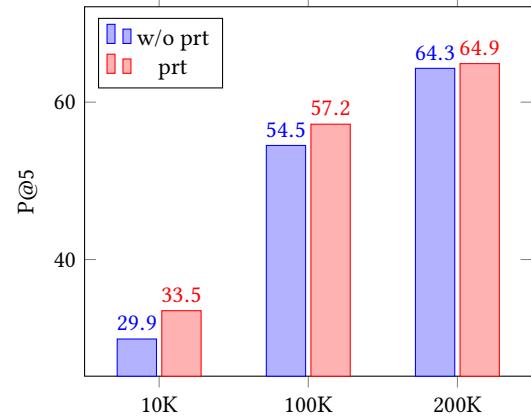
retrieval based on the given linguistic information and the model’s transferability to a specific category. We test the model on a test set of around 22K texts, each of which has a pool of images for retrieval. Furthermore, recently we have deployed the model online for the topic-based recommendation for women shoes. More details are referred to Appendix A.4.

## 5.2 Results

In order to evaluate the effects of pretraining, we implement models with and without pretraining for the finetuning on the text-based image retrieval. Besides, we randomly sample 10K, 100K and 200K image-text pairs from the dataset for finetuning. This evaluates the effects of pretraining on finetuning on the condition of datasets of different sizes. We use P@5 (precision at 5) as the evaluation metric. We demonstrate the results of both models on the three datasets in Figure 3. The experimental results demonstrate that pretraining can improve the model performance, and the improvement is more significant in the case of fewer training data in the target domain (10K: +12.0%; 100K: +2.7%; 200K: 0.9%).

## 6 CONCLUSION

In this paper, we propose a new approach for multi-modal pretraining, InterBERT. The model architecture consists of the BERT-based single-stream interaction module and the Transformer-based two-stream independence module. We set a series of training tasks for effective pretraining, including masked segment modeling, masked region modeling and image-text matching. Experimental results demonstrate that our InterBERT can outperform the baselines and rival the recent multi-modal pretrained models in the downstream tasks. The analysis shows that the pretraining tasks enhance the model performance, and InterBERT can adapt to single-modal tasks without significant performance downgrade. Furthermore, we propose a large-scale dataset for multi-modal pretraining in Chinese, and we develop the first Chinese multi-modal pretrained model and deploy the system online.



**Figure 3: Results (P@5) of the models with and without pre-training in the text-based image retrieval task. “prt” refers to pretraining. The models are finetuned on datasets of different sizes, including 10K, 100K and 200K. Experimental results show that pretraining is more effective when there are fewer data for finetuning.**

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## A APPENDIX

### A.1 Details of TaoMultimodal

We construct a large-scale dataset, TaoMultimodal, for multi-modal pretraining in Chinese. Here we provide more details about the data construction and preprocessing.

**Collection** We collect the data for multi-modal pretraining in Chinese from the mobile Taobao. In the mobile Taobao, each product has at least one main image (the first image of the product, which is specified by the seller) and one product title. The image demonstrates the main features of the product and the title describes its basic information. Both the image and text are provided by the seller. We extract image-text pairs from the best-selling products under the categories “women clothes” of the mobile Taobao. For the data for finetuning, we extract the image-text pairs from the products under the categories “women shoes”.

**Preprocessing** We apply the same preprocessing methods to both datasets. The preprocessing includes object detection for object representations and data cleaning for texts. We obtain object representations by using an object detector based on Faster-RCNN, which is trained on the data of the mobile Taobao. There are 33 categories for object classification. We extract the bounding boxes with confidence scores larger than 0.1, and we obtain no more than 16 objects for each image.<sup>6</sup> The size of the object representations is 2048. As to the data cleaning for text, we first remove the titles without any Chinese character. Moreover, we conduct word segmentation with the AliNLP tool<sup>7</sup> on the texts, and truncate the text by words in order to make sure the text is no longer than 36 characters. Furthermore, we remove those titles that trigger our spam detector, including texts that are concerned with pornography, abuse, politics, terrorism, etc. Finally, we obtain a dataset of 3.1M image-text pairs for pretraining and 200K for finetuning.

### A.2 Additional Implementation Details

In the following, we provide more details about our implementation.

**Pretraining** Here we provide more experimental details about our implementation for pretraining. The object representations and bounding boxes are generated by an object detector based on Faster R-CNN [35] with a backbone of ResNet-101 [14], which is trained on Visual Genome [19]. This detector is applied for the bottom-up top-down attention model for image captioning [3], and we downloaded the pretrained detector from their provided link.<sup>8</sup> As to the word representation, we tokenize the texts with BERT’s tokenizer and directly use BERT-base’s embedding layer for word embedding. The vocabulary size is 30522 and the embedding size is 768. As the size of the object representations is 2048, we first transform them with an MLP to the size of 768. As to multi-head attention, the hidden size is also 768. The number of attention head is 12. For the FFN, both the input and output sizes are 768 for stacking layers, and the intermediate size is 3072. As to the LN layer inside each layer, we use BERT’s LN with  $\epsilon = 1 \times 10^{-12}$ . The single-stream interaction module consists of 12 layers of Transformer layer. As the

<sup>6</sup>Unlike the other datasets, the images in TaoMultimodal contain relatively fewer objects.

<sup>7</sup><https://data.aliyun.com/product/nlp>

<sup>8</sup><https://github.com/peteanderson80/bottom-up-attention>

hyperparameters of the single-stream interaction module are the same as those of BERT-base, we initialize its weight parameters with the pretrained BERT-base model<sup>9</sup>. The two-stream independence module contains two Transformers for both modalities on top of the single-stream interaction module. Each has 6 layers of Transformer layer. The new weight parameters are randomly initialized based on the Gaussian distribution of zero mean and standard deviation of 0.02, following [11]. We train the model with AdamW whose initial learning rate of  $1 \times 10^{-4}$ ,  $\beta_1 = 0.9$ ,  $\beta_2 = 0.999$ ,  $\epsilon = 1 \times 10^{-6}$  and a weight decay of 0.01. We apply the linear decay learning rate scheduler with a warmup of 10000 steps. The batch size for training is 512. We pretrain our InterBERT on 8 V100 GPUs for 20 epochs.

**Finetuning** For the finetuning on VQA, we set an MLP on top of the pretrained model for the prediction in the task. The output size is 3129 as there are 3129 answers for selection. The maximum number of objects is 100 and the actual numbers of the objects are from 10 to 100. We finetune the model with a batch size of 256 and train it on 8 V100 for 20 epochs. We use AdamW optimizer with an initial learning rate of  $1 \times 10^{-4}$  and apply a linear decay learning rate scheduler with a warmup period of 10000 steps. For the finetuning on VCR, we use similar hyperparameters of those in the finetuning on VQA, but we use a smaller learning rate  $2 \times 10^{-5}$  and a smaller batch size 32, and we only finetune the model for 5 epochs. For the finetuning on image retrieval, the maximum number of objects is still 100 but the actual numbers are between 90 and 100. We use an initial learning rate of  $4 \times 10^{-5}$  and a batch size of 32. We finetune the model for 20 epochs. Furthermore, we apply exponential moving average with a rate of 0.9999 on the finetuned models for the final model, so that it can be more robust and reach better performance in testing.

**Hardware Configuration** The experiments are conducted on a Linux server equipped with an Intel(R) Xeon(R) Platinum 8163 CPU @ 2.50GHz, 512GB RAM and 8 NVIDIA V100-SXM2-16GB GPUs.

**Software** The experiments are implemented in python 3.6 and PyTorch 1.1.0 [30]. The code is based on Transformers [50].<sup>10</sup>

### A.3 Details of the GLUE tasks

The GLUE benchmark [47] consists of a series of NLP tasks. We choose four of them, CoLA, SST-2, STS-B and RTE, to evaluate the robustness of InterBERT in single-modal downstream tasks.

**CoLA** The Corpus of Linguistic Acceptability [49] is a task of binary sentence classification. It requires the algorithms to check whether an English sentence is linguistically acceptable (grammatical and consistent with the world knowledge).

**SST-2** The Stanford Sentiment Treebank [40] is a task of binary sentiment classification. It requires the algorithms to check whether a sentence is positive or negative. The sentences are extracted from movie reviews with human annotations.

**STS-B** The Semantic Textual Similarity Benchmark [8] is a task of classification of semantic similarity. The sentences are extracted

<sup>9</sup>The pretrained BERT-base model is downloaded from <https://s3.amazonaws.com/models.huggingface.co/bert>

<sup>10</sup><https://github.com/huggingface/transformers>



**Figure 4: An example of topic-based recommendation.** The demonstration is a topic with a sub-title and the image of the most recommended product. Clicking through the topic triggers the mobile Taobao to demonstrate another page with the products (the demonstration of product images and titles) inside the topic bundle.

from news headlines and other sources. The algorithms should learn to score two sentences from 1 to 5 for their semantic similarity.

**RTE** Recognizing Textual Entailment [7] is a task of natural language inference. This task provides a sentence pair and requires the algorithms to check the relations between the sentences, including “entailment”, “contraction” and “neutral”.

We truncate the input texts to ensure that the maximum length is 128. The input texts are all lower-cased. We use a batch size of 128 and a learning rate of  $2 \times 10^{-5}$ . We finetune the model on 8 V100 GPUs with gradient accumulation for 3 epochs.

#### A.4 Details of Online Deployment

We recently deployed the model online for the recall of products in topic-based recommendation. In topic-based recommendation, given a specific topic (a phrase or a sentence), the recommender system recalls the relevant products and recommends the topic bundle with products to users who are interested. We provide an example of topic-based recommendation in Figure 4. Here we omit the details of personalized recommendation since we focus on the process of product recall. In this context, our model InterBERT retrieves the images of products that are relevant to the given topic, and provide the products to the recommender system. Specifically, the model computes a similarity score for the topic and each image, and we recall the images by extracting those with scores higher than 0.6. The range of score is [0, 1].