MiniVLM: A Smaller and Faster Vision-Language Model

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Abstract

Recent vision-language (VL) studies have shown remarkable progress by learning generic representations from massive image-text pairs with transformer models. While existing research has focused on achieving high accuracy with large pre-trained models, building a lightweight model is of great value in practice but is less explored. In this paper, we propose a smaller and faster VL model, MiniVLM, which can be finetuned with good performance on various downstream tasks like its larger counterpart. MiniVLM consists of two modules, a vision feature extractor and a transformer-based vision-language fusion module. We design a Two-stage Efficient feature Extractor (TEE) inspired by the one-stage EfficientDet [52] network to reduce the cost of visual feature extraction by 99%, compared to a baseline model. We adopt the MiniLM [59] structure to reduce the computation cost of the transformer module after comparing different compact BERT models. In addition, we improve the MiniVLM pre-training by adding 7M Open Images data, which are pseudo-labeled by a state-of-the-art captioning model. We also pre-train with high-quality image tags obtained from a strong tagging model to enhance cross-modality alignment. The large models are used offline without adding any overhead in fine-tuning and inference. With the above design choices, our MiniVLM reduces the model size by 73% and the FLOPs by 99% while maintaining 94 – 97% accuracy on multiple VL tasks. We hope that MiniVLM helps ease the use of the state-of-the-art VL research for on-the-edge applications.

1. Introduction

With the success of BERT [6] and recent advances [66, 55, 46, 50, 25, 24, 26, 13, 4, 15, 27] in vision-language pre-training (VLP), models pre-trained on large-scale image-text data have made substantial improvement on various benchmarks for a wide range of vision-language (VL) tasks, such as image captioning, visual question answering and image-text retrieval. The models used in most VLP works contain two modules: the vision module based on convolutional neural networks trained on ImageNet [42] and/or Visual Genome (VG) [20] to extract visual features from the image; and the feature fusion module based on the multi-modal transformer model to process both the visual features and the token embeddings of the text input. The VL models are firstly pre-trained to learn cross-modal representations, and then fine-tuned on task-specific data. In recent VLP research, both of the two modules leverage large-scale deep neural networks, which can take up to hundreds of millions of parameters, to achieve the state-of-the-art performance. However, due to the large sizes and high computation cost, it could be impractical for real-world applications to exploit the power of large models under a constrained training and/or inference budget. In fact, building a lightweight VL model, which is desired when operating on resource-limited devices, is of great practical value but is less explored in the literature.

Figure 1: MiniVLM retains 94 – 97% of the accuracy on multiple tasks with 27% parameters and 1% FLOPS compared to state-of-the-art model OSCAR B [26]. Details can be found in Sec. 4.4.
While larger models have been demonstrated to achieve higher performance in extensive studies, it is challenging to compress the model to smaller sizes without tremendous performance drop. In order to retain as much performance as possible, we firstly optimize the network architecture to balance accuracy and speed. Moreover, we improve the small-model pre-training by leveraging large models and large-scale dataset.

For the architecture of VL models, popularized as “bottom-up top-down” (BUTD) attention [2], most existing works [66, 45, 46, 50, 24, 26, 13, 4] use the ResNet-101 Faster R-CNN [41] model trained on the VG dataset as the visual feature extractor, which has been well validated by state-of-the-art results on various benchmarks. However, the detector suffers from a heavy model size and high latency, and consequently cannot be deployed to resource-limited applications. A few recent works [15, 27] revisit the usage of grid features from the convolutional layer to skip the region-related computation in Faster R-CNN. Nevertheless, it is still an open problem to select over the overwhelming number of grid features, as dumping the whole feature map to transformer could be prohibitively expensive in computation. For the transformer module, BERT is widely used as the de facto standard. Recent work in Natural Language Processing (NLP) has explored to maintain high performance with compact structures based on BERT. However, the compact structure is less investigated in VLP.

In this paper, we propose a smaller and faster VL model, named MiniVLM, to reach similar performance as its larger counterpart with a much smaller size, resulting in faster inference speed. For the vision module in MiniVLM, we design a Two-stage Efficient feature Extractor (TEE) to drastically reduce the computation cost for extracting visual features, which is a dominating part of the inference cost on certain tasks. While refining each part of the detection model, we greatly simplify the region-related modules in TEE. The underlying implication is that the VL tasks require rich visual representations rather than precise box locations as in the object detection task. Experimental results show that our TEE can extract visual features of similar quality at a much faster speed. In particular, our TEE-0, using a similar backbone as EfficientDet-D0 [52], is $3.7 \times$ smaller and $99 \times$ faster than the widely used R101 Faster R-CNN from BUTD, while retaining competitive accuracy in detection on VG, and up to $97\%$ of the accuracy on downstream tasks. For the transformer model, we choose the MiniLM [59] structure after empirically evaluating the performance of several structures, including BERT [6] and its compact variants [43, 49, 18, 59].

In addition to the model architecture optimization, we leverage high-accuracy large models and large-scale data, either labeled or unlabeled, to further boost the performance of the small pre-trained model. To improve the accuracy of TEE, we pre-train it on large-scale classification and detection dataset before fine-tuning on VG. During the VL pre-training, we apply data distillation [39, 61, 62] to add $7M$ Open Images [21] which are pseudo-labeled by the state-of-the-art “teacher” captioning model. We also use the high-quality tags from a large tagging model in pre-training to improve visual-text alignment. The large tagging model is not used in fine-tuning or inference, and therefore has no impact on the runtime speed. With the above ingredients, our MiniVLM, composed of TEE-0 and MiniLM [59], reduces the end-to-end FLOPs to $1\%$ with $27\%$ parameters, and retains $94 - 97\%$ accuracy compared to large state-of-the-art models on multiple VL tasks.

In summary, we make the following contributions.

- We propose a VL model MiniVLM, which can be fine-tuned with good performance on multiple downstream tasks, while being smaller and faster for practical application.
- We design a Two-stage Efficient feature Extractor (TEE) to extract image region features for VL tasks, which generates features of good quality at a much faster speed.
- We demonstrate the benefits of using large models as well as large-scale data in the small VL model pre-training stage to improve the downstream tasks.

2. Related work

**Vision-Language Pre-training.** Remarkable progress [35, 46, 15, 28, 26, 13, 4] has been made recently on vision-language tasks through network pre-training on massive data with image-text pairs. A popular framework used in most VLP work is to view the extracted visual features as visual ‘tokens’ and feed them together with text tokens into the BERT [6, 54] model for joint representation learning.

The visual feature is generally extracted with an off-the-shelf vision model, and the main focus is on the multi-modal fusion based on BERT model. With the multiple modalities, the fusion can be categorized as early fusion, late fusion and full fusion. Early fusion is to first process the two modalities together and then process each separately to enhance the single-modality task, e.g. InterBERT [28]. Late fusion is to first process each modality separately and then to fuse them together, e.g. in ViLBERT [35], LXMERT [50], ERNIE-ViL [64]. Full fusion means to process the two modalities’ features together with the BERT model from the very beginning to the final representation, e.g. OSCAR [26], Unicoder-VL [24], VL-BERT [46], UNITER [4], VIVO [13]. The pre-training tasks typically include the masked language modeling, image-text pairing loss, and masked region modeling.
Visual Feature Extractor. Visual feature extraction is one of the key modules in vision-language (VL) tasks. As in the bottom-up top-down approach [2], region features based on Faster R-CNN [41] have shown strong accuracy and been widely used in VL tasks [65, 55, 46, 50, 25, 24, 26, 13]. The extractor is trained on ImageNet [42] and Visual Genome [20] datasets with two training tasks: one is to predict the object category and the other is to predict the attribute information.

An alternative approach is the grid feature, which is revisited in [17, 15] and demonstrated encouraging performance. In [17], the grid feature extractor is constructed by casting the Faster R-CNN model into a fully-convolutional network and remove the region-related operations (e.g., non-suppressed compression) to reduce the time cost. In [15], the convolutional network is trained together with modality fusion network without the detection data.

One advantage of using region features is that it is easy to select the top-\(K\) salient regions as each region is associated with a confidence score. Typically, the number of region features is 50 while the number of grid features ranges from 300 to 600 as in [17]. With more features, the cost of the multi-modal fusion part can be increased significantly. Thus, in this paper, we stick to the region features for our compact model.

Object Detection. Region feature is built on the object detector, and the detector can be two-stage [41, 9, 27, 60] or one-stage [40, 52, 52, 30, 71, 65, 58, 53]. The two-stage detector generates bounding box candidates with a region proposal network (RPN) and extracts the region features with RoIPool [41] or RoIAlign [9]. The feature is further processed with a classification head and a bounding box regression head. In contrast, the one-stage detector removes the RPN, and predicts the bounding box results based on the convolutional neural network directly.

Due to the removal of RPN and region feature extraction, fast object detector are mostly based on one-stage detectors, e.g., [40, 52, 57, 56, 23]. However, it remains open on how to effectively extract region features directly from one-stage detectors for VL models. Thus, we use a two-stage architecture but design a lightweight backbone and detection head for the compact VL model.

Compact BERT. BERT \textsc{base} or BERT \textsc{large} has been commonly used in the existing VL works. To reduce the cost, one can simply reduce the network dimensions, e.g., the number of layers, the hidden size, as in TinyBERT [18] and MiniLM [59]. MobileBERT [49] constructs the network with the bottleneck design [10] to reduce the cost. ALBERT [22] focuses on the reduction of the parameter size. In our compact solution, we choose MiniLM [59] as our multi-modal fusion module after comparing different approaches in VL tasks.

Data Distillation. Data distillation (and self-training) is a simple yet effective approach to leverage massive raw images with pseudo labels generated from a strong pre-trained model. The effectiveness has been well demonstrated, e.g., in image classifications [62, 22] and object detection [49]. Here we apply data distillation to the VL model. One potential improvement is to apply the model distillation or knowledge distillation [11] on both the vision module and the transformer fusion module, which we leave as future work.
3. MiniVLM

In this section, we describe how we design a smaller and faster VL model, MiniVLM, and improve the accuracy for small VL model. An overview of our model is shown in Fig. 2. It consists of a detector-based feature extractor and a transformer-based feature fusion module. For various downstream tasks, we alter the transformer prediction head with minimal changes, which we defer to Sec. 4.4.

3.1. Model architecture

Two-stage Efficient feature Extractor. While the R101 Faster R-CNN detector from [2] has been widely used to extract region features, the computational cost is largely overlooked, which can take a majority of the total inference time for some VL tasks. Although region feature extraction is part of an objection detection model, the requirement for VL tasks is not the same as for objection detection. For VL tasks, the transformer is used to reason the relationship between visual and language semantics, and what is needed from the feature extractor is rich visual representations. For example, the bounding box locations do not have to be highly accurate, and the recall of the bounding boxes is more important to cover more visual information from the image. These characteristics allow us to design a feature extractor that is much more efficient while not causing significant accuracy degradation for the downstream tasks. Fig. 2 shows the design of our feature extractor called Two-stage Efficient feature Extractor (TEE).

First, we replace the backbone with EfficientNet [51] and add BiFPN [52] to generate multi-scale features. Both components consist of depthwise and pointwise convolutional layers, which reduce the model size and computation significantly compared with the standard convolutional layers. The BiFPN receives as input 4 layers with stride $= 4, 8, 16, 32$ from EfficientNet, and outputs 5 features with an extra feature map of stride $= 64$ by downsampling. Both EfficientNet and BiFPN are building blocks of the one-stage detector EfficientDet [52], while we make the change to use feature maps starting from stride $= 4$ instead of 8 to incorporate information from higher resolution feature maps for the feature extraction.

While region proposal network (RPN) [41] is used following the design of two-stage detectors, the box prediction modules are greatly simplified. Our RPN contains only 2 convolutional layers with kernel size as 1: one for bounding box regression and the other for objectness prediction. After non-maximal suppression (NMS) we select the feature map for each box proposal with heuristics from [29], and apply RoIAlign [9] operation, followed by 2 linear layers to extract the region features. The resolution of RoIAlign is reduced to $4 \times 4$ rather than $14 \times 14$ in [41] or $7 \times 7$ in [29]. The feature’s dimension is also reduced from 2048 [41] to 1024. In [2], NMS is applied for each class which can be up to 1600 times on Visual Genome [20]. To reduce the cost, one can apply sophisticated approaches, e.g., [56] or [12, 48, 3] to remove NMS. For simplicity, we apply NMS once in a class-agnostic manner to save the computation.

Similar to EfficientDet, we scale up the input image size, network depth and width to get stronger feature extractors. For varying EfficientDet-DX (X = 0, 1, · · ·), the corresponding TEE is denoted as TEE-X. Without confusion, we also use TEE to refer to TEE-0 as our extractor for MiniVLM.

During the inference, given an image $I$, the vision module outputs a bag of region features $R$ with corresponding bounding boxes $B$ and object tags $C$, which are fed to the transformer model along with text tokens. It is noted that no extra tagging model is employed. We re-use the feature extractor as the tagging model and treat the region class names as the tags.

Multi-modal Transformer. With the extracted features, a transformer-based feature fusion module is applied. To strike a good balance between speed and accuracy, we search the compact structures based on BERT by varying some parameters, e.g., the number of layers. Based on experimental results, we choose the same structure as MiniLM [59], i.e., 12 layers with hidden size reduced to 384 and feed-forward intermediate size reduced to 1536. We follow [26] to train the transformer model. The input consists of visual features formed by the concatenation of $R$ and bounding box encoding (normalized 4 corner coordinates and the heigh/width of the box), tokenized object tag names $C$, and tokenized sentences $S$. The content of $S$ can vary depending on the downstream task, e.g., the question sentence for VQA, a single [CLS] token to indicate the start of sentence for image captioning.

3.2. Pre-training

To train a VL model, the vision module is first trained on classification or detection dataset to learn diverse visual representations. Given the visual features, the transformer module is then pre-trained on massive image-text pairs to learn cross-modal representations. Finally, the model is fine-tuned on specific downstream tasks. To compensate the performance drop brought about by the small model size, we apply several techniques in training.

As visual features are critical in VL tasks, we improve visual feature by pre-training TEE on large-scale classification and object detection dataset, e.g., Objects365 [44], before fine-tuning on the Visual Genome dataset, which shows the performance gain for various downstream VL tasks.

By pre-training the transformer model on large-scale image-text data, our model inherits the advantage of VL pre-training. Moreover, we leverage large models in two
we have to further exploit the potential for pre-training with compact VL models. First, we apply a state-of-the-art captioning model to describe 7M images from Open Images with pseudo captions. In this way, the small model learns to mimic the behavior of the large model through much more data, which can be further expanded with internet-scale unlabeled data. Second, we use a large tagging model to generate high-quality tags, and also add ground truth tags if available. Although the tags in pre-training are from different sources, the tags in fine-tuning are generated by the same vision model used to extract features to remove the dependency on the large model at inference time. The experimental results in Sec. 4.5 shows that the better quality of tags helps with cross-modal representation learning.

Other than the changes about the sources of object tags and the associated sentences, we use the same pre-training tasks as described in [26], including masked language modeling (MLM) and image-text (contrastive) matching (ITM).

4. Experiment

4.1. Implementation details

**TEE.** We first pre-train the backbone on ImageNet [42] classification dataset, then pre-train the whole detection model on Objects365 [44], and lastly fine-tune it on Visual Genome [20]. On ImageNet, the backbone is trained from scratch for 400 epochs. Stochastic gradient descent (SGD) is used to optimize the model with the batch size of 1024. The learning rate is 0.4 and decays with a cosine scheduler [53]. Afterwards, the detection model is initialized with this ImageNet-pretrained backbone and trained on Objects365 for 100 epochs. The learning rate is 0.4 and batch size is 256 with SGD. Lastly, we fine-tune the model on Visual Genome for 200 epochs, with learning rate 0.2 and batch size 512. Following [2], an additional head is added to train with attribute classes.

**Vision-Language Pre-training.** We combine existing V+L datasets, including MS COCO [31], Conceptual Captions (CC) [45], SBU captions [37], Flicker30k [63], GQA [16], VQA [8] and VG-QA [20].

To explore data distillation for the compact VL model pre-training, we incorporate the Open Images V6 [21] as extra images and generate pseudo captions using the state-of-the-art image captioning model fine-tuned from OS-CAR [26]. The human verified positive tags are combined with object class predictions from TEE-3, and together serve as the tag input in our VL pre-training. This dataset is referred to as OI-Caps-7M.

During VL pre-training, the batch size is 2048, and the initial learning rate is $4 \times 10^{-4}$ with linear decay. The model is updated with AdamW [34] optimizer for 100 epochs.

4.2. Smaller and faster

As shown in Fig. 1, our MiniVLM reduces the number of parameters to 27% and FLOPS to 1% in total compared to the model in [26]. The following details the compression for both the vision module and the transformer module.

**TEE.** We compare our region feature extractor TEE with the widely used ResNet-101 Faster R-CNN model (R101-F) from [2], as well as the grid feature extractor based on ResNet-50 and ResNeXt-101 from [17]. Table 1 shows the size and computation cost for each model at inference time. Compared to R101-F, our TEE reduces the number of parameters to 7.5/63.8 = 11.8%, and FLOPS to 4.4/767.0 = 1%. Table 4 and Table 5 show the breakdown on each component of the parameters and FLOPs, respectively. For R101-F, the major cost resides in the box head, which consists of 3 residual blocks and the number of output channels in each block is 2048. In the backbone, the largest number of channels is 1024, and thus the box head is even more expensive than the backbone. In comparison, the box head of our TEE only contains 2 linear layers, which significantly reduces the cost. Our model also uses fewer parameters and FLOPS than grid feature extractors. The reason is the use of the depthwise and pointwise convolutional layers in backbone and the lightweight region feature extraction head.

On a CPU workstation\(^1\) with 4 threads, with models im-

\(^1\)This number is from https://github.com/peteanderson80/bottom-up-attention.

\(^2\)Intel(R) Xeon(R) CPU E5-2620 v4 @2.10GHz
implemented in PyTorch\(^3\) and processing one image at a time, Grid R50 takes 699.8 ± 110.1 ms, R101-F takes 12.3 ± 3.2 seconds, while our TEE takes only 393.9 ± 43.8 ms, which is 3.2% of R101-F. Note that inference speed highly depends on hardware and implementation, so we mainly replace both modules to TEE-0 and MiniLM, respectively, if solely replacing the vision module with TEE-0, the CIDEr score drops similarly 5.0 points. This also indicates that our feature extractor TEE-0 can achieve 96% of the accuracy compared to R101-F on this task without any additional techniques. Then, we replace both modules to TEE-0 and MiniLM, respectively, where the CIDEr score is decreased by 8.7. This is the baseline performance of our compact VL model.

### 4.3. Retaining high accuracy

Table 3 shows the ablation study on improving the pre-training for our small model. The pre-trained models are fine-tuned and evaluated on the image captioning and VQA task, which will be detailed in Sec. 4.4. The cost is measured end-to-end including both vision and transformer modules. Starting from the OSCAR\(^2\) model, which consists of R101-F and BERT\(_{\text{BASE}}\), if we replace the transformer module with MiniLM, the CIDEr score drops 4.9 points. If solely replacing the vision module with TEE-0, the CIDEr score drops similarly 5.0 points. This also indicates that our feature extractor TEE-0 can achieve 118.7/123.7 = 96% of the accuracy compared to R101-F on this task without any additional techniques. Then, we replace both modules to TEE-0 and MiniLM, respectively, where the CIDEr score is decreased by 8.7. This is the baseline performance of our compact VL model.

Next, we apply approaches in Sec. 3.2 and show the improvement for pre-training with small-model. First, we use the Objects365 dataset to pre-train TEE before fine-tuning it on VG, which improves the CIDEr score by 1.7, indicating that better visual features contribute to better performance on VL tasks. Secondly, we use high-quality tags, generated from the stronger vision model TEE-3, during vision-language pre-training, and further improve the score by 1.0. The intuition is based on 26 that the tag information in pre-training helps with visual-text alignment. Lastly, we add the OI-Caps-7M dataset, and observe the gain of 2.1 in CIDEr. In total, the CIDEr score is improved by 4.8, resulting in a much smaller gap with the large pre-trained VL model. Similar trend can be observed for the VQA task as shown in the last column of Table 5.

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\(^3\)https://github.com/pytorch/pytorch
4.4. Results on downstream VL tasks

**Image Captioning.** The task is to describe an image with a natural language sentence. Following [66][26], we fine-tune the model with region features, captioning tokens and object tags. Captioning tokens are randomly replaced by the token of [MASK] with 15% chance and predicted by the corresponding representation, the attention of which is only on region features, tags and preceding caption tokens. The training task is either the cross entropy loss or the loss optimized for the CIDEr [55] score, and we report results on both tasks. During inference, the [MASK] is appended recursively with the generated tokens to predict the next token one by one. Considering the inference speed, we reduce the beam search size to 1 instead of 5 as in [26]. The accuracy is evaluated with BLEU@4 [38], METEOR [5], CIDEr [55], and SPICE [1]. The dataset is COCO [31] with Karpathy split [19].

**VQA.** The task [8] is to answer a question with natural language based on the image context, and we cast it as a classification problem where each class corresponds to one answer. The representation of [CLS] is used to predict the answer over a shared set of 3129 answers with a linear layer. The model is trained with binary cross entropy loss, and the inference is to select the answer with the highest confidence.

**Natural Language Visual Reasoning for Real (NLVR2).** The task’s input is a pair of images and a natural description, and the goal [47] is to predict whether the description is true about the image pair. To fine-tune the network, we construct two input sequences, each containing the concatenation of the description and one image, and then two outputs corresponding to [CLS] are concatenated as the joint representation for a binary linear classifier.

**Image-Text Retrieval.** The task is to retrieve similar images based on the text description or vice versa. The key is to score the similarity of image-text pairs. The model is trained as a binary classification task where the input is the image region features, tags and preceding caption tokens. The key is to score the similarity of image-text pairs. The model is trained as a binary classification task where the input is the image region features, tags and preceding caption tokens. The training task is either the cross entropy loss or the loss optimized for the CIDEr score, and we report results on both tasks. During inference, the model predicts the next token one by one. Considering the inference speed, we reduce the beam search size to 1 instead of 5 as in [26]. The accuracy is evaluated with BLEU@4 [38], METEOR [5], CIDEr [55], and SPICE [1]. The dataset is COCO [31] with Karpathy split [19].

**Results.** Table 6, 7, and 8 show the results on image captioning, VQA, NLVR2 and image-text retrieval, respectively. As summarized in Fig. 1, we retain 94 – 97% of the accuracy on downstream tasks compared with the state-of-the-art model OSCARB. In the Fig. 1, captioning is measured by CIDEr score with cross entropy optimization on COCO. Text retrieval (TR) and image retrieval (IR) are on 5K test set, and measured by R@10. VQA is on the test-std split, and NLVR2 is on test-P split. For image captioning, the CIDEr score of OSCARB [26] is 123.7, while our MiniVLM achieves 119.8 CIDEr, reaching $119.8/123.7 = 97\%$ accuracy. Compared with [17], which uses X101 to extract the grid feature, our solution achieves an even higher CIDEr (119.8 vs 113.8) with much lower (4.4 vs 161.2 in FLOPS) feature extraction cost as shown in Table. 1. On NLVR2 and image-text retrieval, our MiniVLM achieves higher scores than [15] which uses ResNet50 as the grid feature extractor, while both our vision and transformer modules are smaller.

4.5. Analysis

In this section, we provide analysis on the model architectures and pre-training methods for small VL models. Results are based on the models pretrained on the 7M corpus without OI-Caps-7M. All the models are evaluated through the COCO image captioning task and the VQA task.

**Impact of Object Tags in Pre-training.** While Table 3 has shown that using tags of high quality can improve the accuracy, we study the impact of tags under more settings in Table 9 for pre-training. Region features are always from TEE-0 with different tagging models. The transformer is initialized randomly or from the pre-trained weights [59] for NLP tasks. From the results, object tags makes large improvement (2+ points in caption, 1+ in VQA) compared with the case without tags, and high-quality tags leads to even better results. Small models might be more difficult to learn good representations, and thus the tag can contribute more in cross-modal alignment. Another observation is that random initialization gives comparable results with the text pre-trained weights. This is similar to the findings in [50].

**Varying the backbone of TEE.** To study the impact of vision modules, we scale up TEE, ranging from TEE-0 to TEE-3 with larger sizes and better detection accuracy as shown in Table 10. As shown in Fig. 3, stronger vision module leads to better accuracy, for both caption task and
A larger backbone gives higher accuracy, but more cost.

### Table 10: Performance of different variants of our detectors.

| Method       | CE Optimization | CIDEr optimization |
|--------------|-----------------|--------------------|
|              | B@4 M C S       | B@4 M C S         |
| BUTD \[2\]  | 36.2 27.0 113.5 20.3 | 36.3 27.7 120.1 21.4 |
| Grid \[17\] | 36.4 27.4 113.8 20.7 | - - - |
| AoANet \[14\] | 37.2 28.4 119.8 21.3 | 38.9 29.2 129.8 22.4 |
| OSCAR\[26\]  | 36.5 30.3 123.7 23.1 | 40.5 29.7 137.6 22.8 |
| MiniVLM (Ours) | 35.6 28.6 119.8 21.6 | 39.2 29.7 131.7 23.5 |

The model is initialized from text pre-trained weights provided by \[59\]. “Random” means the model is initialized from scratch.

### Table 8: Image-Text Retrieval task evaluation results on COCO datasets.

| Method            | 1K test set | 5K test set |
|-------------------|-------------|-------------|
|                  | Text Retrieval | Image Retrieval | Text Retrieval | Image Retrieval |
|                  | R@1 R@5 R@10 | R@1 R@5 R@10 | R@1 R@5 R@10 | R@1 R@5 R@10 |
| PixelBERT (R50) \[15\] | 77.8 95.4 98.2 | 64.1 91.0 96.2 | 53.4 80.4 88.5 | 41.1 69.7 80.5 |
| PixelBERT (X152) \[15\] | 84.9 97.7 99.3 | 71.6 93.7 97.4 | 63.6 87.5 93.6 | 50.1 77.6 86.2 |
| Unicoder-VL\[24\] | 84.3 97.3 99.3 | 69.7 93.5 97.2 | 62.3 87.1 92.8 | 46.7 76.0 85.3 |
| OSCAR\[26\] | 88.4 99.1 99.8 | 75.7 95.2 98.3 | 70.0 91.1 95.5 | 54.0 80.8 88.5 |
| MiniVLM (Ours) | 81.1 96.1 99.2 | 68.5 93.0 97.1 | 58.8 85.1 91.7 | 45.0 74.1 84.0 |

Table 9: Impact of the tag input used in pre-training, comparing no tag with tags predicted by TEE-0, and tags predicted with higher quality by a stronger model (TEE-3). Region features are extracted with TEE-0. “Text” means the model is initialized from text pre-trained weights provided by \[59\]. “Random” means the model is initialized from scratch.

### Table 10: Performance of different variants of our detectors.

| Model |_Params (M)_ | FLOPS (B) | mAP@0.5 |
|-------|-------------|-----------|----------|
| TEE-0 | 7.5         | 4.4       | 9.9      |
| TEE-1 | 10.6        | 9.6       | 10.6     |
| TEE-2 | 12.4        | 17.6      | 11.3     |
| TEE-3 | 17.0        | 23.3      | 11.5     |

A larger backbone gives higher accuracy, but more cost.

VQA task.

### Overall Performance

#### Table 7: VQA and NLVR2 evaluation results.

| Method            | VQA Test set | NLVR2 Test set |
|-------------------|--------------|----------------|
|                  | test-std test-dev | Test-P Dev |
| BUTD \[2\]       | 70.34        | -             |
| Grid \[17\]      | -            | 72.59         |
| Pixel. (R50) \[15\] | 71.42 | 71.35         |
| Pixel. (X152) \[15\] | 74.55 | 74.45         |
| VisualBERT \[25\] | 71.00 | 70.80         |
| OSCAR\[26\]      | 73.44 | 73.16         |
| MiniVLM (Ours)   | 69.44 | 69.09         |

Table 4: Impact of different compact BERT structures on captioning and VQA (test-dev).

### Impact of Compact BERT Structures

Fig. 4 shows the experimental results on speed-accuracy trade-off for models with different transformer modules listed in Table 2. Among the structures, MiniLM achieves a better trade-off between speed and accuracy. This shows that a “thinner” version of BERT could make better trade-off than the “shallower” version for VL tasks.
5. Conclusion

In this paper, we have proposed a compact solution, MiniVL, for vision-language (VL) tasks, which is smaller and faster, and thus can be deployed in real-world applications on resource-constrained devices. For the vision module, we design the Two-stage Efficient feature Extractor (TEE), to significantly save computation by simplifying the region head and replacing regular convolutional layers with pointwise and depthwise convolution layers. To improve the small-model pre-training, we leverage large models and large-scale dataset. We fine-tune the pre-trained model on various downstream VL tasks, and show that MiniVL can retain 94 – 97% of the accuracy with 27% parameters and 1% FLOPS compared to the state-of-the-art VL model.

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