VLDeformer: Vision-Language Decomposed Transformer for Fast Cross-Modal Retrieval

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Abstract

Cross-modal retrieval has emerged as one of the most important upgrades for text-only search engines (SE). Recently, with powerful representation for pairwise text-image inputs via early interaction, the accuracy of vision-language (VL) transformers has outperformed existing methods for text-image retrieval. However, when the same paradigm is used for inference, the efficiency of the VL transformers is still too low to be applied in a real cross-modal SE. Inspired by the mechanism of human learning and using cross-modal knowledge, this paper presents a novel Vision-Language Decomposed Transformer (VLDeformer), which greatly increases the efficiency of VL transformers while maintaining their outstanding accuracy. By the proposed method, the cross-model retrieval is separated into two stages: the VL transformer learning stage, and the VL decomposition stage. The latter stage plays the role of single modal indexing, which is to some extent like the term indexing of a text SE. The model learns cross-modal knowledge from early-interaction pre-training and is then decomposed into an individual encoder. The decomposition requires only small target datasets for supervision and achieves both 1000+ times acceleration and less than 0.6% average recall drop. VLDeformer also outperforms state-of-the-art visual-semantic embedding methods on COCO and Flickr30k. ¹

1. Introduction

Cross-modal retrieval is important for modern applications such as search engines, social media, and e-commerce, which involves searching for instances semantically similar to the query from another modal. Just like text search engines, cross-modal retrieval requires not only high accuracy but also fast retrieval speed.

¹Our code will be publicly available upon acceptance.
ing retrieval, the embeddings could be cached and reused for other comparisons, which results in $O(n)$ inference times. The main weakness of these models is their relatively low accuracy. Recent works [8,23] attempt to address the trade-off between accuracy and speed by pre-training. However, as shown in Table 1, these models are still not as effective as VL transformers while using similar or even larger pre-training data. Until now, two-branch encoders are reported [8] to outperform VL transformers only using hundreds of times larger pre-training data. Therefore, VL transformers are still the most effective method for cross-modal retrieval but have shortcomings in retrieval speed.

The early-interaction pre-training of VL transformers is similar to humans learning the cross-modal alignment by observing pairwise language and vision inputs. However, humans are able to handle individual text and image information separately after learning, as in Fig. 1, which is a faster paradigm for retrieval. From this point of view, existing VL transformers only achieve the learning stage. To inspect the feasibility of converting a VL transformer into an individual encoder for text and image, we analyze the dataflow of VinVL [28] in a pilot experiment (Sec. 3). Surprisingly, we find an interesting phenomenon: most cross-modal interactions do not happen point-to-point, but through some “routing nodes”, as illustrated in Fig. 2. Moreover, the special tokens [CLS] and [SEP] are routing nodes most of the time. Since these special tokens do not belong to any specific modalities, it is possible to divide the dataflow by modality from them without breaking the learned dataflow. Following these findings, we prove that the pre-trained VL transformer could be decomposed into an individual encoder while maintaining most of the accuracy with only a small target dataset as supervision. We also verify in the experiment that the “routing nodes” are successfully kept after decomposition.

Combined with the pre-training stage, the proposed Vision-Language Decomposed Transformer (VLDeformer) presents a new paradigm that pre-trains a VL transformer with early-interaction dataflow and then decomposes it into an individual encoder. Using this paradigm, we can build a VL transformer of not only high accuracy but also fast speed. On the public COCO and Flickr30k benchmarks, VLDeformer achieves both 1000+ times acceleration and less than 0.6% average recall drop for VL transformer. VLDeformer also outperforms state-of-the-art visual-semantic embedding methods while using similar or even smaller pre-training data.

2. Related Work

VL Transformers Pre-trained VL transformers have shown impressive performance for many multimodal tasks. These models learn the cross-modal interaction with an early-interaction dataflow, where the text and image fea-

| Type               | Model       | T2I | I2T | Pre-train data | Time (s) |
|--------------------|-------------|-----|-----|----------------|----------|
| (a)                | VinVL [28]  | 74.6| 58.1| 8.8M           | 32537.5  |
| (b)                | LightningDOT [23] | 70.0| 54.0| 9.5M           | 7.4      |
| (b)                | ALIGN-small [8]  | 52.0| 39.2| 180M           | -        |

Table 1. R@1 retrieval score, pre-training data scale, and inference time of the state-of-the-art VL Transformer (a) and Visual-Semantic Embedding (b) models on COCO 5k test.

ures in each layer are fused with the attention mechanism. For example, ViLBERT [16] achieves early-interaction with two-branch transformer networks connected by co-attention. In the model, the outputs of the image and text of each layer are fused by a third transformer. The following models [2,12–14,19,22] use single-stream architecture where the features are fused with fully-connected attention mechanisms. These models achieve improvement on cross-modal retrieval tasks with different self-supervised tasks. In common practice, the pre-trained VL transformers still keep the early-interaction dataflow while inferring on downstream tasks, which has high computation costs in large-scale cross-modal retrieval tasks.

Visual-Semantic Embedding Models Text-image retrieval methods [7,17,30] usually learn embeddings for the image and text with a two-branch network. Generally, the network includes a convolutional neural network as the image encoder and a sequence model as the text encoder. Researchers have found that the fine-grained relations between the visual objects and text tokens are essential for improving the embedding quality. For example, Lee et al., [10] calculates attention between detected object features and word embedding from both visual and text view, respectively. The following work SCAN [11] explores early-interaction structure by stacked cross-attention and gets significant improvements. However, the early-interaction dataflow decreases its retrieval speed. During inference, the late-interaction dataflow enables extracting representations offline to achieve fast online retrieval. Therefore, most of the following visual-semantic embedding methods still use late-interaction dataflow; e.g. Qu et al. [29] and Zhang et al. [20] develop the interaction from global and local views.

Pre-trained Visual-Semantic Embedding Models Pre-training transformers typically use several millions of text-image pairs. Recently, some researchers have explored pre-training visual-semantic embedding methods with larger text-image pairs. For example, CLIP [21] trains a two-branch network with contrastive learning on 400 million image text pairs and achieves competitive results on various downstream tasks. ALIGN [8] expands the pre-training data even further to a larger and noisier 1,800 million scale. The model consists of an EfficientNet [24] with global pooling as the image encoder and a BERT as the text encoder and achieves higher performance than the pre-trained VL transformers.
transformers after fine-tuning. Although these pre-trained visual-semantic embedding models achieve advanced performance, their corpora are hundreds of times larger than VL transformers. Inspired by the pre-training of VL transformers, LightingDOT [23] tries to train two-branch transformers with a data scale closer to the data scale used by the VL transformers. The network uses a late-interaction dataflow to accelerate the inference time. However, there is still a performance gap from the VL transformers. The network uses a late-interaction dataflow to accelerate the inference time. However, there is still a performance gap from the VL transformers, which has to be made up by collecting top-31% samples and using a VL transformer to select the final top-11% results.

In contrast with the above methods, we regard the early-interaction pre-training as the first stage to learning cross-modal knowledge, and the model could be decomposed as an individual encoder for fast inference. Following this process, we build a transformer that achieves both state-of-the-art accuracy and fast speed at the same time.

3. Pilot Analysis of VL Transformer

To study the dataflow inside a VL transformer, we first conduct a visualization of the attention computation of pre-trained VinVL [28]. The visualized samples are from the COCO 1k test set and depicted by the VIG tool [25]. As the attention map case illustrates in Fig. 2, there are four nodes that receive the most attention weights. Among them, three nodes belong to the special tokens, i.e., [CLS] or [SEP], which do not have any modality properties. Meanwhile, the “routing nodes” are fixed in each layer. Therefore, it would be possible to decompose the vision and language inputs while keeping these paths unbroken.

We collected 1k samples and recorded the attention percentage according to modality and the paths to verify this phenomenon. To distinguish, we define the following:

• Routing node: The top-k tokens that significantly take more proportion of the attention weights than others.

• Neutral attention: The attention that starts from or points to the special tokens [CLS] and [SEP] that do not belong to any modalities.

• Single modal attention: The attention that points from text embeddings to text embeddings or image embedding to image embeddings.

• Cross-modal attention: The attention that points to text embeddings from image embeddings or vice versa.

As is shown in Fig. 3 (a), 69% of attention weights are on the routing nodes, and half of the attention weights are undertaken by the neutral nodes. Other nodes take a total of 19% of the weights. If the routing nodes are kept after decomposition, the pre-training knowledge is likely to be maintained. From Fig. 3 (b) we can see only 11% of the attention weights are immediate cross-modal interactions; the remaining 89% are not for immediate cross-modal interaction. If the rest of 89% attention dataflow is not broken after decomposition, we will only need small data to reconstruct the cross-modal attention and maintain most of the pre-training knowledge.

Figure 3. The proportion of attention weights in VinVL according to routing nodes (a) and modality (b) on COCO test set. Only 11% weights are cross-modal attention.

| Layers          | Neutral (%) | Single (%) | Cross (%) |
|-----------------|-------------|------------|-----------|
| [CLS] [SEP] Total |             |            |           |
| Bottom (1-3)    | 39.1        | 9.6        | 48.7      | 38.7      | 12.6      |
| Mid (4-9)       | 2.6         | 46.0       | 48.6      | 40.7      | 10.6      |
| Top (10-12)     | 1.5         | 49.1       | 50.6      | 38.6      | 10.8      |

Table 2. The attention type proportions of each VinVL layers. Only about 10% are immediate cross-modal attention.

2The phenomenon is also observed in Uniter [2], see appendix C for more cases.
Table 2 shows the percentage of different attention types in each layer. We can see that single modal attention constantly takes more attention weights than cross-modal attention weights. [CLS] receives more attention in bottom layers, while on the mid and top layers, [SEP] becomes more important. Therefore, using [SEP] or the average of the layer outputs as the representation vector is likely to be more effective than the common practice to use [CLS].

4. Methodology

The paradigm of the VLDeformer is illustrated in Fig. 4. It includes early-interaction pre-training, vision-language decomposing, and retrieval stages. Since there are many ways [2, 12, 19, 28] to achieve the pre-training stage, in this section, we mainly elaborate on the principles for vision-language decomposing.

4.1. Early-interaction Pre-training

The early-interaction pre-training plays the role of learning the cross-modal alignment from large-scale datasets. To exploit the fine-grained relationship between text and image modality, the pairwise text and image input are concatenated and fed to the network simultaneously.

Pairwise Image and Text Input The pairwise text and image input includes position embedding, segment embedding, and token embedding. The input text $T$ is tokenized as a token sequence $\{w_1,...,w_L\}$ where $L$ is the length of the WordPiece [9] tokenizer output. The input image $I$ is pre-processed by the object detection network [28] to extract region features and tags. As for the segment tokens, we assign $[T]$ segment token to mark the word tokens and the object tags, and $[V]$ to represent the region features. The final embedding for both text and image input is obtained by the summing up of position, segment, and token embedding, followed by a layer normalization.

The text and image features interact through self-attention in the network. The pre-training objectives are self-supervision tasks, i.e., mask language modeling, and contrastive learning for cross-modal alignment on the joint representation. Since most of the existing VL transformers are built in this pre-training procedure [2, 12, 19, 28], VLDeformer can be applied to any of them. In this section the model is trained as a VinVL-base [28] model.

4.2. Vision-language Decomposition

Individual Image and Text Input The concatenated text and image input are divided for individual encoding. Guided by the pilot analysis, there are two differences in the format: the special tokens and the position embedding. The special [CLS] token is added to the beginning of both modalities, and [SEP] is added to the end of the text and tag tokens. The position index for tokens, tags, and objects are assigned separately to distinguish the modality. The text position index ranges from 0 to $L - 1$, while for the image input, the position index starts again from 0 to $K - 1$ where $K$ is the number of the objects or tags.

Decomposed VL Transformer The individual image and text input isolates the cross-modal interaction of the VL transformer. To keep the other interactions as much as possible, the network shares weights for the text and image modality. According to the analysis of the pilot experiment, the [CLS] node receives small attention weights in the top layers of VL transformer, which is in conflict with the common practice to use [CLS] as representation. Therefore we experiment with three kinds of representations: [CLS], [SEP] and average pooling of all the outputs. In practice, we find the average pooling and [SEP] representation are more effective than the [CLS] vector for representation, while average pooling representation is slightly better than [SEP] (see details in Sec. 5.4). Finally, the representations $r_i$ or $r_v$ are obtained by the average pooling layer with tanh activation.

Decomposition Loss The objective of decomposition is to reconstruct the broken cross-modal interactions and learn cross-modal similarity through the late-interaction dataflow. We experiment with BCE loss, Triplet loss, and infoNCE loss, with infoNCE loss ultimately achieving the best performance (see details in Sec. 5.4). The InfoNCE loss minimizes the cosine distance between semantically aligned samples and maximizes the distance between dissimilar samples. In a mini-batch with $N$ text-image pairs, we regard the aligned pairs as the positive samples and other combinations as the negatives. We use an objective as Eq. 1 to pull semantically close images representation $r_i$ to the text representation $r_v$ and push non-close samples apart:

$$
\mathcal{L}_c^t = -\log \frac{e^{\cos(r_i; r_v)/\tau}}{\sum_{j=1}^{N} e^{\cos(r_i; r_j^v)/\tau}}
$$

where $\tau$ is a temperature hyper-parameter, and $\cos$ is the cosine similarity $\frac{r_i \cdot r_v}{||r_i|| \cdot ||r_v||}$. The $\mathcal{L}_c^t$ term can also be regarded as optimizing text-to-image retrieval in a mini-batch.

Symmetric to $\mathcal{L}_c^t$, we use the loss term as in Eq. 2 to learn the image-to-text condition.

$$
\mathcal{L}_c^v = -\log \frac{e^{\cos(r_v; r_i)/\tau}}{\sum_{j=1}^{N} e^{\cos(r_v; r_j^t)/\tau}}
$$

The complete contrastive learning loss is the summing up of these two terms:

$$
\mathcal{L}_c = \mathcal{L}_c^t + \mathcal{L}_c^v
$$

Since the main goal of this paper is to show the pre-training and decomposition paradigm, we find that the simple infoNCE loss is enough to maintain comparable performance to the VL transformer. Other self-supervision could also be useful, which will be left for future work.
4.3. VLDeformer based Cross-modal Retrieval

VLDeformer is an individual encoder and therefore enables encoding the retrieval contents offline. For example, in text-to-image retrieval, the images are encoded to embeddings offline so that the online computation only includes the query encoding and the cosine similarity, which is the main reason to achieve the retrieval speed acceleration.

In this part, we take text-to-image retrieval as an example to introduce the retrieval process. To formulate, the image set is denoted as $\{I_i\}_{i=1}^N$ where $N$ is the image set size. The query is denoted as $T$.

In the offline encoding stage, the images are processed following Sec. 4.2 to get the position, segment, and token embeddings and then passed to the VLDeformer model to get the image embedding $\{r_i\}_{i=1}^N$. The image embeddings could be reused to compare with each text query.

During online retrieval, the query text is first processed to position, segment, and token embeddings then encoded into query embedding $r_t$. The index of top-1 related images to the query text is calculated as Eq. 4:

$$n = \arg \max_{i \in [0, N]} \cos(r_t, r_i)$$  \hspace{1cm} (4)

The top-1 retrieved images $I_n$ could be obtained from the image set.

4.4. Implementation Details

All the processed images are first resized to $256 \times 256$, then 50 region-of-interests and the object tags are extracted. The max sequence length of text tokens is set to 35. The batch size for contrastive decomposing is set to 1750, while the temperature is set to 0.005. The AdamW optimizer is adopted with a learning rate of $5e^{-5}$ and weight decay of $1e^{-4}$. The model is trained on an NVIDIA DGX with a Ubuntu 18.04 system and 8 V100 GPU.

5. Experiments

5.1. Datasets and Evaluation Protocols

Datasets The pre-training stage uses 8.8M text-image pairs from public datasets as VinVL [28]. The COCO [15] and the Flickr30k [18] datasets are used for the decomposition stage. The COCO dataset contains 123K images and is divided into 114K training, 5K validation, and 5K test images. We also use a common split of 1k tests for comprehensive evaluation. The Flickr30k dataset contains 31K images which are divided into 29K/1K/1K for training, validation, and test. Each image has 5 caption texts.

Evaluation The retrieval performance is measured by the recall at topk samples (R@k). Three k values, R@1, R@5, and R@10, are reported for text-to-image retrieval and vice versa. We evaluate the retrieval speed for the text-to-image retrieval using 1k, 5k, and 10k text-image pairs.

5.2. Retrieval Accuracy Analysis

5.2.1 Comparison with Visual-Semantic Embeddings

Table 3 shows the comparison results of VLDeformer and visual-semantic embedding methods. Both VLDeformer and other pre-trained models substantially outperform the models without pre-training like CAAN and DIME. It is worth noting that the performance of pre-trained visual-semantic embeddings varies depending on the pre-training data scale. For example, the *ALIGN trained on the largest data outperforms the other models. However, the pre-training dataset of *ALIGN is 204 times larger than our pre-training dataset and 189 times larger than that of LightningDOT, making it hard to judge these models fairly. If we...
| Methods | COCO Test (5k images) | Flickr30k Test (1k images) | Pre-train data | Params |
|---------|----------------------|---------------------------|---------------|--------|
|         | 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 |
| CAAN [29] | 52.5  83.3  90.9 | 41.2  70.3  82.9 | 70.1  91.6  97.2 | 52.8  79.0  87.9 |
| IMRAM [1]   | 53.7  83.2  91.0 | 39.7  69.1  79.8 | 74.1  93.0  96.6 | 53.9  79.4  87.2 |
| SGRAF [4]   | 57.8  -   91.6 | 41.9  -   81.3 | 77.8  94.1  97.4 | 58.5  83.0  88.8 |
| DIME [20]   | 59.3  85.4  91.9 | 43.1  73.0  83.1 | 81.0  95.9  98.4 | 63.6  88.1  93.0 |

| Visual-Semantic Embeddings | Params | R@1  R@5  R@10 |
|----------------------------|--------|----------------|
| *ALIGN*                   | 200+M  | 77.0  93.5  96.9 |
| ALIGN-small [8]           | 180M   | 52.0  -   91.6 |
| LightningDOT [23]         | 70.0  91.6  95.5 | 54.0  80.8  88.5 |

*ALIGN is achieved using 200+ times larger pre-train data than other pre-trained models, so we mainly compare with ALIGN-small.

Table 3. Comparison results with Visual-Semantic Embedding Methods on COCO and Flickr30k dataset. VLDeformer outperforms other pre-trained models using similar or even smaller data.

| Methods | Flickr30k Test (1k images) | COCO Test (1k images) | Time (s) |
|---------|---------------------------|----------------------|----------|
|         | 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 | R@1  R@5  R@10 |
| LightningDOT | 83.9  97.2  98.6 | 69.9  91.1  95.2 | 89.3 | -   -   -   | 2.7 |
| +Reranker [23] | 87.2  98.3  99.0 | 75.6  94.0  96.5 | 91.7 | -   -   -   | 37.6 |
| UnicoderVL [12] | 86.2  96.3  99.0 | 71.5  90.9  94.9 | 89.8 | 84.3  97.3  99.3 | 405.3 |
| Uniter [2] | 86.9  98.1  99.2 | 75.5  94.0  96.6 | 91.7 | -   -   -   | 98.3 97.2 90.2 |
| Oscar-base [14] | -   -   -   | -   -   -   | 88.4  99.1  99.8 | 75.7  95.2  92.7 | 1300.5 |
| VinVL-base [28] | 93.6  99.1  99.9 | 82.0  95.7  97.7 | 94.6 | 89.8  98.8  99.7 | 93.3 1301.5 |
| VLDeformer | 93.5  98.7  99.2 | 80.2  95.1  97.8 | 94.0 | 89.2  98.9  99.9 | 92.9 |

Table 4. Cross-modal retrieval comparison results to VL transformers on COCO and Flickr30k dataset. VLDeformer achieves 1000+ acceleration with less than 0.6% average recall drop.

compare the models in similar pre-training data scales, the smaller ALIGN-small model trained on 180M text-image pairs has a dramatic performance drop as the data scale decrease.

It is worth noting that VLDeformer outperforms all state-of-the-art visual-semantic embedding models when compared to similar or even smaller data sizes. Therefore we can conclude that VLDeformer is the most effective visual-semantic embeddings method on a comparable data scale.

5.2.2 Comparison with VL Transformers

Table 4 shows the retrieval score and time comparison between the VLDeformer network and state-of-the-art VL transformers on COCO and Flickr30k 1k test sets. Compared with the backbone VinVL-base model, VLDeformer achieves thousands of acceleration with less than 0.5% drop in average recall and can even outperform it on R@5 and R@10 levels at COCO 1k text retrieval set. VLDeformer also outperforms other VL transformers like Unicoder-VL and Uniter. Compared with the pre-trained two-branch transformer, LightningDOT, VLDeformer achieves better results in both accuracy and inference time and also outperforms LightningDOT with an Oscar Reranker.

Still, there is a performance gap between VLDeformer and the backbone VinVL model, which is more obvious on the R@1 image retrieval score, i.e., 2.3% on COCO and 1.8% on Flickr. However, the difference on R@5 and R@10 is very small, which means that many ground truth images are not hit by the top 1 result but recalled within top 5 records.

5.2.3 Qualitative Case Analysis

Since the R@1 metric only calculates the hit ratio of the one aligned ground truth image, it may be inflected by other semantically similar samples. Therefore, we inspect the cases that are properly predicted by the backbone VinVL model at top 1 but flipped by the VLDeformer. Fig. 5 shows the top 5 retrieved images for such cases. Interestingly, many images share the same semantics with the query text although

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4 See Appendix B for more detailed qualitative comparisons.
they are not the ground truth, e.g., “two giraffes next to a pole” or “four-way stop signs”. For such queries, the top1 metric is not applicable to judge the retrieval results. Some queries like the third case have rough semantics that could be aligned with a wide range of images, e.g., “table with different food”, e.g., “table with different food”. These queries also decrease the top1 metrics because it is hard to recall the ground truth at top5 or even top10 records. The samples also show some limitations of VLDeformer. For example, the fourth case mainly focuses on the “clock mounted on outdoor post” but fails to distinguish the “roman numeral” on the dial, indicating that more detailed matching is necessary for future works.

### 5.3. Retrieval Efficiency Analysis

The time costs to match all the text-image pairs are shown in Fig. 6. The models are compared on the same machine using one V100 GPU using 400 batch size. Only the inference time is recorded to exclude the data loading time. VinVL uses a very long time (about 0.5 hours on 1k and even more on larger data), and the time response goes like a quadratic function with the data size. In quantitative comparison, VLDeformer achieves more than 1k times acceleration on 1k data and 9k times on 5k than VinVL. Both VLDeformer and LightningDOT show linear time cost curves as data size increases, but LightningDOT costs more time than VLDeformer, likely because the model is built on a larger BERT-large network. It is worth noting that when LightningDOT uses an Oscar-large [14] reranker to achieve compatible accuracy to VLDeformer, its retrieval time will

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**Figure 5.** Retrieved top5 images where VLDeformer flips backbone VL Transformer from right to wrong in R@1.

| Query Text                                                                 | Ground Truth                                                                 | Top@1 | Top@2 | Top@3 | Top@4 | Top@5 |
|---------------------------------------------------------------------------|-----------------------------------------------------------------------------|-------|-------|-------|-------|-------|
| A couple of giraffe standing next to a pole.                              | ![Giraffe Image](image1.png)                                                 | ![Giraffe Image](image2.png) | ![Giraffe Image](image3.png) | ![Giraffe Image](image4.png) | ![Giraffe Image](image5.png) | ![Giraffe Image](image6.png) |
| A large pizza with cheese and mushrooms on a serving tray.                | ![Pizza Image](image7.png)                                                  | ![Pizza Image](image8.png)   | ![Pizza Image](image9.png)   | ![Pizza Image](image10.png)  | ![Pizza Image](image11.png)  | ![Pizza Image](image12.png)  |
| Table filled with a bunch of different types of food.                    | ![Table Image](image13.png)                                                 | ![Table Image](image14.png)  | ![Table Image](image15.png)  | ![Table Image](image16.png)  | ![Table Image](image17.png)  | ![Table Image](image18.png)  |
| Four way stop sign at street intersection and two street signs above.     | ![Stop Sign Image](image19.png)                                             | ![Stop Sign Image](image20.png)| ![Stop Sign Image](image21.png)| ![Stop Sign Image](image22.png)| ![Stop Sign Image](image23.png)| ![Stop Sign Image](image24.png)|
| A clock mounted on an outdoor post with Roman numerals.                  | ![Clock Image](image25.png)                                                 | ![Clock Image](image26.png)  | ![Clock Image](image27.png)  | ![Clock Image](image28.png)  | ![Clock Image](image29.png)  | ![Clock Image](image30.png)  |

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**Figure 6.** Text-to-image retrieval time on 1k and 5k and 10k image corpus with 400 mini-batch size.

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5. We also report the single query response time in Appendix A.
6. Since VinVL costs a very long time on 5k and 10k, the total time is estimated through the average time cost of the first 1k batches.
decompose the decomposition reconstructs the pre-trained model. (w/o model is broken in VLDeformer, we wonder to what extent model? Since the cross-modal attention of the pre-trained
Did the decomposition stage reconstruct the pre-trained
after decomposition.
It can be inferred that some pre-training knowledge is kept
performance drops significantly without the pre-training stage,
and (w/o pre-training) is a black box test. Since the per-
tialized weights. The comparison between VLDeformer
vision-language decomposition stage using randomly ini-
posing stage is necessary to maintain the performance.

## 5.4. Ablation study

To verify the designs for VLDeformer, we conduct an
ablation study over the COCO 1k test set. The compared models are trained with the same hyper-parameters. The results are shown in Table 5.

### Representation selection

The results of using [CLS] and [SEP] as representation are shown in VLDeformer-[CLS] and VLDeformer-[SEP]. Compared with average pooling representation, VLDeformer-[SEP] is higher on R@5 and R@10 but lower on R@1, while VLDeformer-[CLS] decreases significantly on all metrics. The results qualify the observation in Table 2 that [CLS] is not as important as [SEP] at the top layers.

### Decomposition loss selection

To evaluate the effectiveness of the infoNCE loss for decomposition, we compare BCE for pairwise cosine similarity VLDeformer-BCE and triplet loss VLDeformer-triplet. As a result, both of the two objectives perform worse than infoNCE loss, and causes dramatic performance drops, especially on R@1.

### Has VLDeformer kept knowledge from the pre-training stage?

The (w/o pre-training) trains VLDeformer from the vision-language decomposition stage using randomly initialized weights. The comparison between VLDeformer and (w/o pre-training) is a black box test. Since the performance drops significantly without the pre-training stage, it can be inferred that some pre-training knowledge is kept after decomposition.

### Did the decomposition stage reconstruct the pre-trained model?

Since the cross-modal attention of the pre-trained model is broken in VLDeformer, we wonder to what extent the decomposition reconstructs the pre-trained model. (w/o decompose†) shows the performance of directly using the VinVL model as an individual embedding encoder. To our surprise, the scores are very low, indicating that the decomposing stage is necessary to maintain the performance.

## 5.5. Decomposition Analysis

We further analyze the attention of VLDeformer after decomposition to verify the observation and hypothesis in Sec. 3. In Table 6, we can find that the [CLS] and [SEP] are still important routing nodes which have large proportions of attention weights. In contrast, in the VLDeformer without pre-training, these nodes are not routing nodes. In Fig. 7 we compare VLDeformer without pre-train from the same sample† as in Fig. 2. It can be clearly seen that VLDeformer keeps the routing nodes [CLS] and [SEP], but there is no clear routing node in the VLDeformer without pre-training.

## 6. Conclusion

VL transformers are effective in cross-modal retrieval but slow in speed. We observed that most of the interactions in VL transformers are not immediate cross-modal attention, but highly rely on neutral nodes. Therefore we proposed a novel Vision-language Decomposed Transformer (VLDeformer) that pre-trains a VL transformer with early-interaction dataflow and then decomposes it into an individual encoder. The VLDeformer achieves both 1000+ times acceleration and less than 0.6% average recall drop and also outperforms state-of-the-art visual-semantic embedding models on COCO and Flickr30k datasets.

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†See more visualization samples in the supplementary files.
Figure 7. Attention visualization of VLDeformer with and without pre-training. (From the same sample in Fig. 2).

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