Abstract

The recent large-scale vision-language pre-training (VLP) of dual-stream architectures (e.g., CLIP) with a tremendous amount of image-text pair data, has shown its superiority on various multimodal alignment tasks. Despite its success, the resulting models are not capable of generative multimodal tasks due to the weak text encoder. To tackle this problem, we propose to augment the dual-stream VLP model with a textual pre-trained language model (PLM) via vision-language knowledge distillation (VLKD), enabling the capability for multimodal generation. VLKD is pretty data- and computation-efficient compared to the pre-training from scratch. Experimental results show that the resulting model has strong zero-shot performance on multimodal generation tasks, such as open-ended visual question answering and image captioning. For example, it achieves 39.7% zero-shot accuracy on the VQA 2.0 dataset, surpassing the previous state-of-the-art zero-shot model with 14× fewer parameters. Furthermore, the original text processing ability of the PLM is maintained after VLKD, which makes our model versatile for both multimodal and unimodal tasks.

1 Introduction

Recent large-scale dual-stream Vision-Language Pre-training (VLP) models like CLIP (Radford et al., 2021) and ALIGN (Jia et al., 2021), have shown remarkable performance on various downstream multimodal alignment tasks, e.g., image-text retrieval and image classification. These models are pre-trained using cross-modal contrastive learning on tremendous image-text pairs and learn strong multimodal representations. Despite their success, as mentioned by Radford et al. (2021), their text encoder is relatively weak by only having a discriminative multimodal pre-training objective, which makes them incompetent on generative multimodal tasks such as image captioning and open-ended visual question answering (VQA).

Meanwhile, the Transformer-based (Vaswani et al., 2017) auto-regressive large-scale pre-trained language models (PLMs), such as GPT (Radford and Narasimhan, 2018; Brown et al., 2020), have been dominating in natural language generation (NLG) tasks. These models are usually trained with causal self-attention, which only allows the model to attend to past outputs (unidirectional) to satisfy their generative nature. More recently, BART (Lewis et al., 2020) and T5 (Raffel et al., 2020) propose to augment the auto-regressive decoder with a bidirectional Transformer encoder to further capture bidirectional information of the input. These encoder-decoder architectures excel on not only NLG but also understanding (NLU) tasks.
To tackle the aforementioned limitations of dual-stream VLP models and fully utilize PLMs, in this paper, we present Vision-Language Knowledge Distillation (VLKD), a simple yet effective approach to enable CLIP to perform generative multimodal tasks through knowledge distillation. Specifically, we align the BART encoder to CLIP’s joint multimodal embedding space to gain the understanding of multimodal knowledge, along with an image-conditioned language modeling loss to consort BART encoder and decoder. During training, we freeze the CLIP weights to keep its learned multimodal space. For inference, the CLIP text encoder is discarded, which can be interpreted as being replaced by the distilled BART. Therefore, we leverage the strengths from both sides, the expressive multimodal representation space of CLIP and the strong text generation capability of BART.

Compared to VLP from scratch, VLKD uses several magnitudes fewer image-text pairs and computational resources. As depicted in Figure 1, after VLKD, the model exhibits strong zero-shot performance on generative multimodal tasks, including open-ended VQA and image captioning. Without finetuning, it has the ability to generate answers by reasoning over the question, the visual information, and the textual knowledge embedded in the pre-trained BART. Furthermore, it can also directly generate plausible captions given an image. Empirical results show that our model achieves 39.7% accuracy on the VQA 2.0 dataset and 61.1 CIDEr on COCO image caption dataset in a zero-shot manner. Moreover, the original NLU and NLG ability of BART is maintained, which makes the model versatile for both multimodal and unimodal tasks.

To summarize, our contributions are: 1) We introduce an efficient approach to distill knowledge from the dual-stream VLP model CLIP to BART. The resulting model shows strong zero-shot performance on generative multimodal tasks, as well as pure NLP tasks; 2) We exhaustively quantify these capabilities on six benchmarks under various settings; and 3) We conduct comprehensive analysis and ablation study to provide insights and grease future work on this direction.

2 Related Work

2.1 Vision-language Pre-training

Based on how the two modalities interact, recent VLP models mainly fall into two categories: single-stream and dual-stream models. Single-stream models (Chen et al., 2020; Li et al., 2019; Ramesh et al., 2021; Lin et al., 2021; Kim et al., 2021a) concatenate the patch-wise or regional visual features and textual embeddings and feed them into a single model. Dual-stream models (Lu et al., 2019; Radford et al., 2021; Jia et al., 2021) use separate encoders for images and texts, allowing efficient inference for downstream multimodal alignment tasks like image-text retrieval, by pre-computing image/text features offline. However, these models can not be directly used for multimodal generation tasks. In this paper, we propose an efficient method to align the dual-stream VLP model CLIP’s multimodal embedding space with a powerful PLM model BART to gain multimodal generation ability.

There are also VLP models that can perform multimodal generation tasks, by expensive pre-training with objective of image-conditioned autoregressive language modeling (Lin et al., 2021; Wang et al., 2021; Cho et al., 2021). However, the pre-training of these models requires a large number of image-text pairs and numerous computation resources. Other models like (Agrawal et al., 2019; Li et al., 2019, 2020, 2021b) rely on an extra pre-trained object detector such as Faster-RCNN with labeled bounding-box data to extract image regional features offline and are less scalable.

2.2 Knowledge Distillation

Knowledge distillation (KD) is first proposed in (Hinton et al., 2015), which transfers knowledge embedded in the logits learned in a cumbersome teacher model to a smaller student model without sacrificing too much performance. Besides logits, other forms of knowledge like the intermediate representations and attentions (Jiao et al., 2019; Hou et al., 2020) have also been used in transferring the knowledge embedded in Transformer-based models. Recently, contrastive representation distillation (Tian et al., 2019) distills the knowledge from the teacher network to the student network by maximizing the mutual information between the two networks, and is recently extended to transfer the knowledge from the pre-trained multimodal model CLIP for zero-shot detection (Gu et al., 2021) and multilingual setting (Jain et al., 2021). In this paper, we apply conventional KD as well as contrastive KD to transfer the knowledge from the pre-trained CLIP to BART. Besides, we also propose to transfer the knowledge in CLIP image encoder to BART decoder through the cross-attention.
3 Proposed Method

We propose to distill multimodal knowledge from CLIP to BART for generative multimodal tasks, which takes the strengths from both sides (powerful multimodal representations of CLIP and text generation ability of BART). To this end, we propose three objectives (Section 3.2). The overall architecture is illustrated in Figure 2.

3.1 Model Architecture

CLIP. CLIP (Radford et al., 2021) is a dual-stream VLP model pre-trained with a contrastive loss on 400 million image-text pairs. It consists of a text encoder which is a GPT (Radford et al., 2019) style Transformer model, and an image encoder which can be either a Vision Transformer (ViT) (Dosovitskiy et al., 2020) or Residual Convolutional Neural Network (ResNet) (He et al., 2016). CLIP learns a joint multimodal embedding space with its text encoder and image encoder aligned. Given an input image-text pair, the image encoder first reshares the image into a sequence of 2D patches and then maps them into 1D embeddings with a prepended [CLS] token using a trainable linear projection. These embeddings are fed into the CLIP image encoder together with positional encodings. The output embedding of the [CLS] token can represent the whole image. For the text sentence, it is bracketed with [SOS] and [EOS] tokens, and the output embedding of the latter is used as the sentence-level representation.

BART. BART is a Transformer-based (Vaswani et al., 2017) sequence-to-sequence model that has a bi-directional encoder and a uni-directional (left-to-right) decoder, which can be seen as a generalization of the BERT (Devlin et al., 2019) and GPT (Radford and Narasimhan, 2018). It is pre-trained on 160GB text data in a self-supervised way by performing the text span infilling task with the input sentences corrupted and shuffled. Similar to the CLIP text encoder, BART also tokenizes and converts the input text into a sequence of embeddings, which are then fed into the BART encoder. BART excels at both NLG (e.g., abstractive summarization) and NLU tasks.

3.2 Training Objectives

To distill multimodal knowledge from CLIP to BART, we propose three objective functions: 1) Text-Text Distance Minimization (TTDM); 2) Image-Text Contrastive Learning (ITCL); and 3) Image-Conditioned Text Infilling (ICTI). During training, the model parameters of CLIP are frozen constantly, i.e., no gradients will be back-propagated through them (marked as SG in Figure 2), to ensure its two encoders are still aligned and the multimodal knowledge is not forgotten.

For each training batch with $B$ image-text pairs, denote the $k$-th image-text pair as $x^k = \{x^k_1, x^k_T\}$, and the output of multimodal encoders of CLIP and BART encoder as

$$\text{CLIP}_I(x^k_T) \rightarrow V^k = [v^k_{\text{cls}}, v^k_1, \ldots, v^k_T],$$

$$\text{CLIP}_T(x^k_T) \rightarrow T^k = [t^k_{\text{sos}}, t^k_1, \ldots, t^k_{n_2}, t^k_{\text{eos}}],$$

$$\text{BART}_{\text{enc}}(x^k_T) \rightarrow E^k = [e^k_{\text{sos}}, e^k_1, \ldots, e^k_{n_3}, e^k_{\text{eos}}].$$

Here, $n_1$ is the number of image patches, $n_2$ and $n_3$ denote the sequence lengths of the text encoder of...
CLIP and BART, respectively. \(v^k_s, t^k_e \in \mathbb{R}^{d_1}\) represents the \(\ell_2\)-normalized output embedding from the CLIP image and text encoder at a certain position. \(e^k_s\) is the unnormalized raw output embedding from the BART encoder. In the following, we elaborate on the three distillation objectives.

### 3.2.1 Text-Text Distance Minimization

To align the CLIP text encoder and BART encoder, i.e., making their output representations close given the same input text, we propose to minimize the \(\ell_2\) distance between their sequence-level output representations. Specifically, for the \(k\)-th input text, it can be formulated as

\[
\mathcal{L}_{TTDM} = \frac{1}{B} \sum_{k=1}^{B} \|t^k_{\text{cos}} - e^k_{\text{norm}}\|_2^2,
\]

where \(e^k \in \mathbb{R}^{d_2}\) is the average of all output embeddings from the BART encoder, and \(W_e \in \mathbb{R}^{d_2 \times d_2}\) is a weight matrix to linearly project the output of BART encoder to CLIP’s multimodal space.

### 3.2.2 Image-Text Contrastive Learning

Contrastive training has been shown to be very effective in cross-modal representation learning (Tian et al., 2020; Sigurdsson et al., 2020; Zhang et al., 2020; Radford et al., 2021). To further adapt the BART encoder to CLIP’s multimodal space, we optimize a symmetric InfoNCE loss between the output representations of the BART encoder and CLIP image encoder. The image-to-text contrastive loss \(\mathcal{L}_{ITCL}\) is formulated as

\[
\mathcal{L}_{ITCL} = \frac{1}{2}(\mathcal{L}_{2ti} + \mathcal{L}_{2ti}).
\]

Then, the \(\text{ITCL}\) loss can be calculated as

\[
\mathcal{L}_{\text{ITCL}} = \frac{1}{2}(\mathcal{L}_{2ti} + \mathcal{L}_{2ti}).
\]

### 3.2.3 Image-Conditioned Text Infilling

With only \(TTDM\) and \(ITCL\), the BART decoder is not updated at all. To consort BART encoder and decoder, we propose to perform the text span infilling task conditioned on the corresponding image features. As depicted in Figure 2b, for the \(k\)-th image-text pair, following Lewis et al. (2020), we corrupt the input text by masking 15% of the tokens with span lengths drawn from a Poisson Distribution with \(\lambda = 3\). Considering that \(V^k\) and \(W_e V^k\) are already aligned in the CLIP’s multimodal space through \(TTDM\) and \(ITCL\), and having a different feature dimension with the BART decoder, we further project them to the BART decoder dimension with \(W_i\) and \(W_i\). Then, we concatenate them together as \(C^k\) before feeding into the BART decoder as shown in Eq.(1). As mentioned in Section 3.1, we explore two variants of CLIP. With a slight abuse of notation, for the RN50\(\times 16\), \(V^k\) is composed of representations of all image patches \(\{v^k_i\}_{i=1}^{n}\), while for ViT-B/16, \(V^k\) consists of the representation of the [CLS] token only.

Note that the weight matrix \(W_e\) is initialized to be the pseudo-inverse of \(W_e\), such that text representations after the two projections \(W_e V^k\) are the closest to the original pre-trained BART encoder space at initialization\(^1\). The BART decoder then interacts with \(C^k\) through standard Transformer cross-attention layers. We optimize a language modeling loss \(\mathcal{L}_{ICTI}\) by minimizing the negative log-likelihood in Eq.(2), in which \(w_j\) denotes the token to be predicted at each decoding step.

\[
C^k = \text{concat}(W_e V^k, W^t_e v^k_e), \quad (1)
\]

\[
\mathcal{L}_{ICTI} = -\frac{1}{B} \sum_{k=1}^{B} \sum_{j=1}^{n} \log P(w^k_j | w^k_{j-1}, C^k). \quad (2)
\]

The \(ICTI\) loss is crucial for our methodology to work, as it not only coordinates the BART encoder and decoder, but also enables the BART decoder to understand the multimodal information by recovering texts with visual clues.

\(^1\)The pseudo inverse matrix \(W_e^\dagger\) satisfies \(W_e^\dagger = \arg \min \|W_e X - 1\|_F^2\), where I is the identity matrix and \(\| \cdot \|_F\) denotes the Frobenius Norm.
Finally, we simultaneously optimize the summation of three losses $\mathcal{L}$ as

$$\mathcal{L} = \gamma \mathcal{L}_{TTDM} + \mathcal{L}_{ITCL} + \mathcal{L}_{ICTI},$$

where $\gamma$ is set to $10^3$ by default, as $\mathcal{L}_{ITCL}, \mathcal{L}_{ICTI}$ are about three magnitudes larger than $\mathcal{L}_{TTDM}$.

### 3.3 Datasets for VLKD

Our model is trained on the Conceptual Captions (CC3M) (Sharma et al., 2018) dataset, which contains 3.3 million image-text pairs crawled from the Internet. Compared to previous VLP work (Radford et al., 2021; Jia et al., 2021; Wang et al., 2021), VLKD is much cheaper by leveraging several magnitudes less data. Furthermore, we experiment with even smaller data (1M, 100K) by uniformly sampling a subset of CC3M to test the limit of dataset size of VLKD, with results discussed in Section 5.

### 4 Experiments

To demonstrate the effectiveness of VLKD, we evaluate it on generative multimodal tasks for both zero-shot and finetuning. Specifically, we test the image captioning task, and also the VQA task under the open-ended scenario. Furthermore, we also run the model on NLU and NLG tasks to investigate the influence of VLKD on the text processing ability of the original pre-trained BART.

#### 4.1 Finetuning Datasets

**Image Captioning.** Image captioning requires the model to generate a relevant description given an image. We use the COCO image caption dataset (Lin et al., 2014) with the Karpathy split (Karpathy and Fei-Fei, 2017). Additionally, we use the NoCaps (Agrawal et al., 2019) dataset to test the model performance when there are out-of-domain objects.

**Open-Ended VQA.** Unlike previous works (Anderson et al., 2018; Chen et al., 2020; Li et al., 2020; Yu et al., 2021; Zhang et al., 2021; Kim et al., 2021b; Li et al., 2021a) that treat the VQA task as a discriminative problem, we let the model generate answers freely, which is more aligned with the real-world scenario of this task. We use the standard VQA 2.0 (Goyal et al., 2017), and also OK-VQA (Marino et al., 2019) which requires knowledge to answer questions correctly.

**NLU and NLG.** For NLU, we test our model on the GLUE benchmark (Wang et al., 2019), which consists of nine text classification tasks. We exclude the WNLI task as it is problematic\(^2\). For NLG, we test the abstractive summarization task on XSUM (Narayan et al., 2018) dataset, which requires the model to comprehend long texts and generate short summaries with key information.

### 4.2 Implementation Details

We use BART-large as the pre-trained backbone NLP model, which contains 12 encoder and 12 decoder layers with a hidden size of 1024 and 16 heads in each multi-head attention (MHA) layer. In total, it contains 406M parameters. As mentioned in Section 3.1, we explore two variants of CLIP. The RN50×16 image encoder is a ResNet-50 (He et al., 2016) scaled up 16 times (Tan and Le, 2019) with 146M parameters. The ViT-B/16 image encoder is a standard ViT (Dosovitskiy et al., 2020) base model with 16×16 input patch size with 86M parameters. For both variants, the text encoder is a 12-layer GPT-style Transformer with hidden size 512, and 8 heads in each MHA layer.

We use 8 Nvidia V100 GPUs for both VLKD and downstream task finetuning. For VLKD, we train with the AdamW (Loshchilov and Hutter, 2019) optimizer and batch size 512 for 200K steps. The learning rate warms up to $5e^{-5}$ within the first 6% steps and then linearly decay to 0. Detailed hyper-parameters for each downstream task can be found in Appendix A.

#### 4.3 Multimodal Zero-Shot Evaluation

Benefit from the knowledge distillation, especially the ICTI loss, our model can perform various downstream multimodal tasks in a zero-shot manner.

##### 4.3.1 Zero-Shot Image Captioning

During knowledge distillation, the ICTI loss can be seen as an easier version of the image captioning task, which asks the model to fill in the corrupted locations of image descriptions. If the masking ratio increases to 100%, it reduces to the image captioning task. Therefore, it is intuitive to test the zero-shot performance of our model.

Following Radford et al. (2021) and Wang et al. (2021), we compose the input with a text prompt and $m$ mask tokens, i.e., “A picture of [MASK]×$m$,” for the model to generate the cap-

\(^2\)https://gluebenchmark.com/faq
On what holiday do people traditionally eat this bird? Answer: [MASK].
Generated answer: Thanksgiving.
Two people sit on the beach with surfboards at their sides.
Generated caption: A couple sitting on the beach with their surfboards in the background.

A young woman sitting on a bench with her dog in the background.
Generated caption: A woman sitting on a bench with a dog.

Figure 3: Examples of (a) zero-shot VQA and (b) image captioning. Our model shows the ability to recognize visual objects and generate appropriate sentences based on their properties. Furthermore, the model can bind image objects to conceptual knowledge that is learned in the PLMs when answering questions.

Table 1: Results on the test set of the COCO image caption dataset. B4, C, M, and S denote BLEU-4, CIDEr, METEOR, and SPICE, respectively. OD and OT indicate whether extra object detectors and object tags are used. SCST (Rennie et al., 2017) is a reinforcement learning algorithm to further boost the performance.

| Model | OD/OT | B4 | C  | M  | S  |
|-------|--------|----|----|----|----|
| BUTD  | ✓ ✓    | 36.2 | 115.3 | 27.0 | 20.3 |
| w/ SCST | ✓ ✓    | 36.3 | 120.1 | 27.7 | 21.4 |
| OSCAR<sub>LARGE</sub> | ✓ ✓    | 37.4 | 127.8 | 30.7 | 23.5 |
| w/ SCST | ✓ ✓    | 41.7 | 140.0 | 30.6 | 24.5 |
| VI-T5 | ✓ x    | 34.6 | 116.1 | 28.8 | 21.9 |
| VI-BART | ✓ x    | 34.2 | 114.1 | 28.4 | 21.3 |
| RN50×16 | ✓ x    | 16.7 | 58.3 | 19.7 | 13.4 |
| VLKDZERO-SHOT | ✓ x    | 34.1 | 114.3 | 27.5 | 21.0 |
| VLKDFINETUNED | ✓ x    | 18.2 | 61.1 | 20.8 | 14.5 |
| w/ SCST | ✓ x    | 36.5 | 117.1 | 29.1 | 21.8 |
| VLKDFINETUNED | ✓ x    | 38.9 | 131.1 | 29.6 | 23.9 |

Table 2: Results on the NoCaps validation set. The models are finetuned on the COCO training split.

| Model | OD/OT | In C | Near C | Out C | Overall C |
|-------|--------|------|--------|-------|-----------|
| UpDown w/ SCST | ✓ ✓    | 78.1 | 11.6 | 55.3 | 10.1 |
| OSCAR<sub>LARGE</sub> w/ SCST | ✓ ✓    | 80.0 | 12.0 | 73.1 | 11.1 |
| w/ SCST | ✓ ✓    | 79.9 | 12.4 | 65.2 | 11.4 |
| w/ SCST+CBS | ✓ ✓    | 85.4 | 11.9 | 83.4 | 11.4 |
| VLKDZERO-SHOT | ✓ x    | 52.6 | 9.7 | 54.0 | 9.6 |
| VLKDFINETUNED | ✓ x    | 85.0 | 12.4 | 74.4 | 11.3 |
| w/ SCST | ✓ x    | 92.3 | 12.6 | 81.1 | 11.7 |

in Section 5 for a more detailed discussion about the effects of number of the masks.

4.3.2 Zero-Shot VQA

Zero-shot VQA is more challenging than image captioning as it requires reasoning over both the image and question. As illustrated in Figure 1, we construct the input by appending a text prompt “Answer: [MASK].” to the question. Given the context (image+question+prompt), the model is required to predict the answer by recovering the textual token in the [MASK] position.

From Table 3, compared to the strong baseline Frozen (Tsimpoukelli et al., 2021), our model achieves much better zero-shot VQA performance on two open-ended VQA datasets with 14× fewer parameters, indicating the efficiency and effective-
Table 3: Accuracies(%) on VQA 2.0 and OK-VQA. We categorize models into two parts: generative and discriminative. FINETUNED means trained with VQA 2.0 data. Models are never trained on OK-VQA.

| Model       | #Params | VQA 2.0 val / test-dev | OK-VQA test |
|-------------|---------|------------------------|-------------|
| Frozen      | ~7B     | 29.5 / -               | 5.9         |
| Frozen      | ~7B     | 48.4 / -               | 19.6        |
| RN50×16     |         | 37.4 / 38.2            | 9.9         |
| VLKD        | ~0.5B   | 67.4 / 68.8            | 36.2        |
| VIT-B/16    |         | 38.6 / 39.7            | 10.5        |
| VLKD        |         | 50.6 / 50.7            | 19.8        |
| VLKD        |         | 69.3 / 69.8            | 36.3        |

Table 4: Accuracies(%) on VQA 2.0 Karpathy test-split.

| Model       | In-domain | Out-of-domain |
|-------------|-----------|---------------|
| UNITER      | 74.4      | 10.0          |
| VL-T5       | 71.4      | 13.1          |
| VL-BART     | 72.1      | 13.2          |
| VLKD        | 69.2      | 18.6          |

4.4.2 Finetuning VQA

From Table 3, the best performance of VQA 2.0 is achieved by VLP models that tackle this task in a discriminative way with a set of pre-defined answers. However, this approach does not generalize to real-world scenarios and cannot be directly applied to more diverse datasets (e.g., OK-VQA).

Differently, Frozen (Tsimpoukelli et al., 2021) and our proposed VLKD generate answers in an open-ended manner and can perform zero-shot inference. Based on the zero-shot performance, VLKD shows fast adaptation ability to surpass the fully-finetuned Frozen with only 1% training data and 14× fewer parameters.

Furthermore, following (Cho et al., 2021), we test the performance on out-of-domain questions with rare answers using Karpathy test-split (Table 4). Our method shows a salient advantage on out-of-domain questions due to the benefit from VLKD and its generative nature.

4.4.1 Finetuning Image Captioning

In Table 1, we demonstrate that our model can achieve decent performance when finetuned on the COCO dataset. Our model outperforms VL-T5/BART (Cho et al., 2021) without using an extra object detector, which is fairly time-consuming as explained by Kim et al. (2021b). Compared to prior state-of-the-art models (e.g. OSCAR), however, there is still a performance gap, which we conjecture is mainly due to their usage of object tags and more image caption training data. Moreover, we also experiment on the NoCaps benchmark (Table 2), which limits the legal training data to only COCO training split. Our model achieves comparable results to OSCAR without using constrained beam search (CBS) (Anderson et al., 2017).

4.5 Evaluation of NLU and NLG

Table 5 shows results on the GLUE benchmark. Although prior VLP models are either initialized from the pre-trained BERT model, or trained by a text-only language modeling loss together with the vision-language (VL) losses, they generally suffer from the weakened performance of NLU. For example, SIMVLM performs significantly worse than BART, though trained with five times more textual data. We speculate that the weakened NLU ability of these models is caused by the catastrophic forgetting of the pre-trained BERT weights during the multimodal pre-training. Moreover, simultaneous optimization of multimodal and text-only objectives potentially shifts the latter to be an auxiliary loss, making the NLP ability not as effective.

On the other hand, the resulting model of VLKD performs only slightly worse than the original BART and significantly outperforms BERT, as the original knowledge embedded in BART is well maintained.

Additionally, as presented in Table 6, we also...
Table 5: Results on the GLUE development set (single task single models). We report the Matthews correlation for CoLA, accuracy/F1 for MRPC and QQP, and accuracy for the rest of the tasks. The performance of models that are marked by ⋄ are taken from (Lewis et al., 2020), † are from (Iki and Aizawa, 2021), and ‡ are from (Wang et al., 2021). Compared to other VLP models, our VLKD model has a great advantage in text-only NLP tasks.

Table 6: Abstractive summarization on XSUM. We use the best performing checkpoint of the RN50 × 16 variant.

Table 7: Ablation study on three distillation objectives.

Table 8: Zero-shot image captioning on COCO test set using VLKD\textsuperscript{RN50×16}, with varying number of masks.

Table 9: Zero-shot performance of VLKD\textsuperscript{ViT-B/16} on two datasets, with varying dataset size for distillation.

6 Conclusion
Recent dual-stream VLP models are powerful in various multimodal classification/retrieval tasks, but their ability of multimodal generation or NLP tasks is restricted. In this paper, we propose a novel distillation method to align CLIP’s multimodal encoders and BART textual encoder to the same space efficiently, which allows multimodal generation under zero-shot and fully finetuned setting without losing the original BART’s NLP ability. Empirical results on various NLP and multimodal tasks verify the efficacy of the proposed method.
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## Hyper-parameters

In this section, we show the hyper-parameters of vision-language knowledge distillation (VLKD), as well as downstream task finetuning.

For VLKD, the hyper-parameters are shown in Table 10, for both two CLIP variants we explored. For finetuning multimodal downstream tasks, we use the hyper-parameters shown in Table 11. Within each task, we use the same setting for multiple datasets.

For the GLUE benchmark, we use the LAMB optimizer (You et al., 2020) to train for 10 epochs. We conduct a hyper-parameter grid search with batch size=$\{16, 32, 64\}$, lr=$\{1e-4, 5e-4, 1e-3\}$, weight decay=$\{1e-4, 1e-3\}$. We warm up the learning rate in the first epoch, then linearly decay it to zero.

For XSUM, we directly follow the hyper-parameters used in Lewis et al. (2020).

## B More Examples of Zero-shot Inference

In Figure 4, we show more examples of zero-shot image captioning. In Figure 5, we depict more cases of the results of zero-shot open-ended VQA.

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### Table 10: Hyper-parameters of VLKD.

| Hyper-parameters | ViT-B/16 | RN50×16 |
|------------------|---------|---------|
| CLIP image features | CLS | All tokens |
| Batch size | 576 | 512 |
| Optimizer | AdamW, $\beta = (0.99, 0.999)$ | |
| Learning rate | 5e-5 | |
| Weight decay | 0.01 | |
| Eps | 1e-6 | |
| Temperature $\tau$ | Initialized to 0.07 | |
| Warmup steps | 12K | |
| Total steps | 200K | |
| Gradient accumulation | 2 | |
| Gradient clipping | 5.0 | |

### Table 11: Hyper-parameters for two multimodal tasks.

| Hyper-parameters | VQA | Image captioning |
|------------------|-----|------------------|
| Batch size | 32 | 40 |
| Total epochs | 10 | 20 |
| #Masks $m$ | 2 | 6 |
| Beam search size | 1 | 6 |
| Optimizer | AdamW, $\beta = (0.99, 0.999)$ | |
| Learning rate | 6e-5 | |
| Weight decay | 0.01 | |
| Eps | 1e-8 | |
| LR warmup | First epoch | |
| Gradient clipping | 5.0 | |

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**Figure 4:** More examples of zero-shot image captioning.
Figure 5: More examples of zero-shot VQA.