ABSTRACT

This paper is a technical report to share our experience and findings building a Korean and English bilingual multimodal model. While many of the multimodal datasets focus on English and multilingual multimodal research uses machine-translated texts, employing such machine-translated texts is limited to describing unique expressions, cultural information, and proper noun in languages other than English. In this work, we collect 1.1 billion image-text pairs (708 million Korean and 476 million English) and train a bilingual multimodal model named KELIP. We introduce simple yet effective training schemes, including MAE pre-training and multi-crop augmentation. Extensive experiments demonstrate that a model trained with such training schemes shows competitive performance in both languages. Moreover, we discuss multimodal-related research questions: 1) strong augmentation-based methods can distract the model from learning proper multimodal relations; 2) training multimodal model without cross-lingual relation can learn the relation via visual semantics; 3) our bilingual KELIP can capture cultural differences of visual semantics for the same meaning of words; 4) a large-scale multimodal model can be used for multimodal feature analogy. We hope that this work will provide helpful experience and findings for future research. We provide an open-source pre-trained KELIP.

1 INTRODUCTION

Recent years have witnessed the success of large-scale vision and language pre-training models (Yao et al., 2021; Jain et al., 2021; Shonenkov et al., 2022; Mu et al., 2021; Li et al., 2022), such as CLIP (Radford et al., 2021a) and ALIGN (Jia et al., 2021). Those multimodal models learn visual and textual representations by exploiting millions of image-text pairs collected from the Internet and show state-of-the-art performance on various downstream tasks. In order to learn visual and textual representations, the entire framework is composed of two separated models by each modality and trained to embed semantically similar visual and textual representations to be close and dissimilar representations to be far apart. Such a modality-wise separated model has several advantages. As getting a large number of image-text pairs is costly, each unimodal model can be pre-trained separately. Moreover, each unimodal model can be used separately for different types of downstream tasks, such as text-driven image manipulation (Patashnik et al., 2021), text to image generation (Galatolo et al., 2021), image captioning (Mokady et al., 2021), video-text retrieval (Luo et al., 2021), and large classes detection (Zhou et al., 2022).

Despite the powerful performance and generalization ability to various multimodal tasks, those models are not easy to use for different languages because the models are trained mostly in English, and there can be bias to the cultures and regions of the primary language of the dataset (Fabbrizzi et al., 2021). There have been studies to embed multilingual representation to multimodal models (Jain et al., 2021) using machine-translated texts. However, such biases still remain because visual biases do not change although the language changes. For example, for the word ‘breakfast’, a picture of western breakfast can be with eggs and bread with bacon, while a picture of Asian breakfast can be rice and soup. Because of such biases and limitation of describing unique
expressions, cultural information, and proper noun in languages other than English, the published model can be limited in use to other language-speaking areas.

In this paper, we present a bilingual multimodal model, named KELIP for Korean and English bilingual contrastive Language-Image Pre-training. We use 1.1 billion image-text pairs (708 million Korean and 476 million English) to train KELIP, where every text is not machine translated. We introduce simple but effective training schemes to train large-scale multimodal models. KELIP successfully expert to both Korean and English, which is proven by extensive experiments that shows competitive performance for both languages in quantitative and qualitative results.

Moreover, we discuss research questions related to multimodal models: 1) strong visual augmentation (i.e. color jittering) can distract the model from learning the correct relation between visual and text semantics, 2) a model trained without cross-lingual relation can learn the relation of different languages via visual semantics, 3) our bilingual KELIP can capture different characteristics of each cultural vision information for the same meaning of words but different languages, and 4) a large-scale vision and language model can perform simple multimodal feature analogy (i.e. an image of field + ‘a house’ in text = an image of a house on a field). Note that this paper is a technical report to share our experience and findings when building a bilingual multimodal model and discuss related research questions.

2 RELATED WORK

The pre-training and then fine-tuning technique has shown remarkable achievement in natural language processing (Radford et al., 2018; Devlin et al., 2019; Brown et al., 2020) and computer vision (Chen et al., 2020a; He et al., 2020; Grill et al., 2020; Caron et al., 2020; He et al., 2021). Recently, such technique has been extended to vision and language pre-training, which can be categorized into two: 1) based on vision and language unified model, UNITER (Chen et al., 2020b), VisualBERT (Li et al., 2019), ViLBERT (Lu et al., 2019) and DALLE (Ramesh et al., 2021) exploit Language Modeling (LM) objectives, such as masked LM and autoregressive LM; 2) based on separated vision and language models, CLIP (Radford et al., 2021b) and ALIGN (Jia et al., 2021) employ cross-modal contrastive learning which aims to align visual and textual information on the unified embedding space. In this paper, we will focus on the second category of language-image contrastive learning.

When CLIP was published, it quickly received great attention for its architectural simplicity, large scale, and powerful performance. CLIP shows that, with large-scale datasets (400 million image and text pairs), simple language-image contrastive learning can achieve superior zero-shot ability and robustness. As public image-text pair datasets (i.e. YFCC100M (Thomee et al., 2016), CC12M (Sharma et al., 2018)) are involved in the non-trivial cleaning process, ALIGN (Jia et al., 2021) exploits larger yet uncurated datasets, and MURAL (Jain et al., 2021) extends ALIGN to multilingual by presenting cross-lingual objectives. BASIC (Pham et al., 2021) scales up the contrastive learning framework of CLIP and ALIGN in terms of data size, model size, and batch size to achieve better zero-shot performance. SLIP (Mu et al., 2021) and DeCLIP (Li et al., 2021) employ self-supervised objectives to enhance the individual encoder’s representation. In this paper, while following the dual-stream architecture for simplicity and efficiency as CLIP, we further train our model with a large-scale bilingual dataset and modified learning schemes.

3 DATASET

This section presents the details of the dataset we used for KELIP, including what kind of public dataset we used and how we gathered additional datasets. We use about 1.1 billion datasets in total, which includes 476 million of English datasets (Sec. 3.1) and 708 million of Korean datasets (Sec. 3.2).

3.1 ENGLISH DATASET

We collect possible public datasets of multimodal pairs (image and English text). First of all, CUB200 (Wah et al., 2011) is a small dataset of bird images with ten single-sentence descriptions for each image. Wikipedia-based Image Text dataset (WIT) (Srinivasan et al., 2021) is a large-scale
multimodal and multilingual dataset, which is composed set of 37.4 million image-text samples with 11.5 million unique images from 108 languages. The dataset includes images and their contextual metadata from Wikipedia. YFCC15M is a subset of YFCC100M (Thomee et al., 2016), which is filtered in CLIP to keep only images with natural language titles and/or descriptions in English. Moreover, we use the Conceptual Captions (CC3M) (Sharma et al., 2018) and the Conceptual 12M (CC12M) (Sharma et al., 2018), which are another large scale image-text pairs of datasets.

LAION400M (Schuhmann et al., 2021) dataset is a 400M of large-scale image-text pair dataset extracted from the Common Crawl (CC2) web data dump. Following the data construction process of LAION400M, we further created a new dataset of 70 million (image and English text) pairs collected from the CC web data dump. First, we extracted a pair of image URLs and English alt texts from the CC data dump. Second, We downloaded images which is larger than 32 pixels for the smaller side and saved them as 256 × 256 size. Third, we used the CLIP ViT-B/32 model to compute the similarity between images and texts; then we removed pairs with the similarity below 0.28. At the same time, we computed the similarity between images and predefined NSFW texts; then we removed pairs with a similarity larger than 0.22 to discard NSFW contents. For the total English datasets, we could collect about 476 image-text pairs, excluding images that were not downloaded.

3.2 KOREAN DATASET

As multimodal research has been mainly focused on English, most of the publicly available datasets are in English, and there is a lack of other language datasets. Many of the publicly available multilingual datasets or multilingual research adopt machine-translated datasets. However, such machine-translated datasets have limitations in describing unique expressions, cultural information, proper noun, and so on. With such motivation, we constructed a new Korean dataset of 708 million. The majority of the dataset is collected from a variety of publicly available sources, especially Korean websites on the Internet. We included 50 million of the celebrities’ photos and names to make KELIP have face recognition ability. Moreover, Korean Wikipedia datasets are included. As a result, 708 million of image and Korean text pairs are collected, and the resulting dataset is larger than the LAION400M or total datasets used in CLIP.

4 METHOD

In this section, we present our training schemes used in KELIP. In phase 1, we first pre-train the image encoder in a self-supervised manner (Sec. 4.1). In phase 2, we fine-tune the multimodal model in a contrastive learning manner with the multi-crop Caron et al. (2020) technique (Sec. 4.2).

4.1 SELF-SUPERVISED PRE-TRAINING

The pre-training and then fine-tuning technique has been proven to be powerful compared to training from scratch (Chen et al., 2020a; He et al., 2020; Grill et al., 2020; Caron et al., 2020). Especially when we train a multimodal model, each modality encoder has limited opportunities to learn with its own modality supervision. Moreover, it has been studied that the performance of the image encoder itself is important when training multimodal model (Zhai et al., 2021). With this spirit, we first pre-train image encoder in a self-supervised manner. Self-supervised methods using contrastive learning (Chen et al., 2020a; He et al., 2020; Caron et al., 2020) strongly depend on data augmentation and require twice the batch size to get augmented positive pairs, resulting in the slow training process. Instead, we employ the self-supervised method of Masked Autoencoder (MAE) (He et al., 2021) with our collected 1.1 billion images, which has been shown fast training and powerful performance. As illustrated in Figure 1a, during pre-training, the encoder masks out a large random subset of image patches (i.e. 75%), and then the small decoder reconstructs the original image in pixels. After the pre-training, the decoder is discarded, and the encoder is employed for the multimodal training.

2https://commoncrawl.org
Figure 1: Summary of our approach. In phase 1, we pre-train image encoder with MAE methods. Then, we fine-tune multi-modal model based on the pre-trained image encoder in phase 2.

4.2 Multi-modal Training

4.2.1 Model Architecture

Following CLIP, we use a dual-encoder architecture that consists of an image encoder and a text encoder. There is multimodal interaction at the top of the model, where the text and image features are projected to the same size of dimension with L2 normalization. We use a Transformer (Vaswani et al., 2017) with architecture modification (Radford et al., 2019) as text encoder. The text encoder has 63 million parameters, 12 layers, 512 wide model with 8 attention heads. In order to tokenize English or Korean text, we trained a lower-cased byte pair encoding (BPE) representation of the text with 2 million English and 1.6 million Korean texts, which are a subsample of our collected dataset. The resulting BPE contains 98,816 vocab size, which is twice larger than the 49,152 vocab size of CLIP. The max sequence length is limited to 76 for computational efficiency. Every text sequence is bracketed with [SOS] and [EOS] tokens, while the remaining tokens after [EOS] are filled with [PAD]. We use the feature of the last layer in the transformer at the [EOS] as the final text feature, followed by layer normalization and linear projection into the multimodal feature space. For the vision encoder, we use the vision transformer (Dosovitskiy et al., 2021) family (i.e., ViT-B/32). We use the feature of the last layer in the ViT at the class token as the final image feature, followed by layer normalization and linear projection into the multimodal feature space.

4.2.2 Contrastive Learning

The contrastive objective pushes the matching image-text features together while pulling the unmatched image-text features apart. In a batch of $N$ image-text feature pairs $(x_i, y_i)$, we denote $x_i$ and $y_i$ as image and text features of $i$th pair. Then, we can formulate InfoNCE loss (Oord et al., 2018) for image-to-text contrastive learning as follows:

$$ L_{I2T} = -\frac{1}{N} \sum_{i=1}^{N} \log \frac{\exp(\text{sim}(x_i, y_i))/\tau}{\sum_{j=1}^{N} \exp(\text{sim}(x_i, y_j))/\tau}, $$

where $\text{sim}(x,y) = \frac{x^T y}{\|x\|\|y\|}$ is cosine similarity function computed by dot product of L2 normalized features, and $\tau$ is a learnable temperature to scale the logits. We use the symmetrical loss for text-to-image contrastive learning as $L_{T2I}$. The overall loss function for contrastive learning $L_{\text{cont}}$ is the average of $L_{I2T}$ and $L_{T2I}$.

4.2.3 Multi-crop Augmentation

Muti-crop augmentation (Caron et al., 2020) has been proposed in vision self-supervised learning and has shown powerful performance in many works (Caron et al., 2021; Zhou et al., 2021). As
| Method \ Benchmark | ImageNet | Cifar10 | Cifar100 | CLEVR-C | DTD | EuroSAT | FER2013 | Food101 | GTSRB | MNIST | RESISC45 | StanfordCars | STL10 | Average |
|-------------------|----------|---------|----------|---------|-----|---------|---------|---------|-------|-------|----------|--------------|--------|---------|
| CLIP              | 33.3     | 67.7    | 33.7     | 14.0    | 18.1| 31.7    | 18.4    | 43.1    | 10.3  | 6.9   | 25.4    | 4.5          | 90.4   | 30.6    |
| CLIP+CLIP        | 35.2     | 64.8    | 34.2     | 14.4    | 17.0| 21.0    | 21.0    | 22.8    | 44.5  | 13.4  | 11.5    | 23.1         | 4.9    | 91.8    |
| CLIP+CLIP+MultiCrop | 38.5 | 64.9    | 33.5     | 12.0    | 21.2| 27.0    | 24.1    | 48.0    | 10.4  | 15.7  | 27.7    | 4.7           | 93.5   | 32.4    |
| MAE+CLIP         | 39.9     | 79.1    | 46.5     | 14.1    | 21.0| 29.2    | 20.7    | 49.3    | 7.3   | 11.6  | 25.1    | 7.2          | 93.5   | 34.2    |
| MAE+CLIP+SimCLR  | 39.9     | 80.5    | 47.6     | 13.2    | 21.7| 30.4    | 19.4    | 49.1    | 7.1   | 10.0  | 24.4    | 6.9          | 93.7   | 34.1    |

(a) Zero-shot classification

| Task → Benchmark → Method ↓ | Flickr30k R@1 | Flickr30k R@5 | Flickr30k R@10 | MSCOCO (English) R@1 | MSCOCO (English) R@5 | MSCOCO (English) R@10 |
|---------------------------|----------------|----------------|-----------------|----------------------|----------------------|----------------------|
| CLIP                      | 43.9           | 73.2           | 82.6            | 25.1                 | 49.1                 | 60.1                 |
| CLIP+CLIP                 | 44.5           | 72.6           | 83.0            | 26.0                 | 50.4                 | 61.5                 |
| CLIP+CLIP+MultiCrop       | 51.7           | 77.7           | 87.9            | 29.9                 | 54.6                 | 65.8                 |
| MAE+CLIP+SimCLR           | 48.6           | 76.0           | 86.0            | 29.1                 | 54.8                 | 66.3                 |
| MAE+CLIP+SimCLR           | 48.1           | 75.5           | 86.0            | 28.7                 | 54.1                 | 65.6                 |

(b) Zero-shot cross-modal retrieval

Table 1: Ablation study. We use one local view for multi-crop. CLEVR-C indicates CLEVR Counts dataset and all values are in %.

| Task   | ImageNet | WebKorean | Cifar10 | Cifar100 | CLEVR-C | DTD | EuroSAT | FER2013 | Food101 | GTSRB | MNIST | RESISC45 | StanfordCars | STL10 | Average |
|--------|----------|-----------|---------|----------|---------|-----|---------|---------|---------|-------|-------|----------|--------------|--------|---------|
| CLIP   | 63.4     | -         | 59.7    | 20.6     | 44.4    | 45.3| 49.0    | 82.3    | 32.6    | 48.3  | 60.0  | 59.6    | 97.1         | 57.6   | 57.6    |
| KELIP  | 62.6     | 91.5      | 68.6    | 13.2     | 51.2    | 59.0| 37.5    | 79.5    | 37.6    | 60.0  | 59.6  | 75.4    | 96.1         | 60.9   | 57.6    |
| CLIP   | 0.4      | 2.5       | 5.6    | 5.6      | 11.4    | 1.0 | 11.8    | 13.9    | 1.5     | 15.5  | 3.4   | 9.6     | 16.6         | 8.7    | 8.7     |
| KELIP  | 0.4      | 2.5       | 5.6    | 5.6      | 11.4    | 1.0 | 11.8    | 13.9    | 1.5     | 15.5  | 3.4   | 9.6     | 16.6         | 8.7    | 8.7     |

Table 2: Zero-shot classification. Every benchmark is English public dataset except WebKorean, which is Korean private dataset. “Kor.” denotes evaluation with English to Korean translated labels. CLEVR-C indicates CLEVR Counts and values are in Recall (%).

mentioned in prior works (Chen et al., 2020a; Misra & van der Maaten, 2020), comparing the larger number of crops of an image is important to capture information in terms of relations between object and background. However, increasing the number of views can increase the training computation and memory. Thus, multi-crop augmentation employs additional views of low resolution crops that cover small parts of the image, which can ensure a small increase in training computation and memory. We observe that multi-crop augmentation can be used in multimodal training to enhance the final performance. As illustrated in Figure 1b, we extract features of an image with standard resolution (i.e., 224), and low resolution (i.e., 96) cropped as small parts of the image. Then those increased number of images are computed with corresponding texts with $L_{cont}$. As the resolution for multi-crop augmentation is low, the increase in training computation and memory is small, but the model benefits from a performance boost.

5 EXPERIMENTS

In this section, we first share the experimental setting in Sec. 5.1 and we show the impact of each component by ablation study in Sec. 5.2. Then, we evaluate our KELIP with public benchmarks in Sec. 5.3 and show qualitative results in Sec. 5.4. Finally, we discuss multimodal related research questions in Sec. 5.5.

5.1 EXPERIMENTAL SETTING

Implementation details. Our implementation is based on PyTorch (Paszke et al., 2019) framework. We train ViT-B/32 for KELIP fine-tuning. We use 40 A100 GPUs for KELIP, which is
Table 3: Zero-shot cross-modal retrieval. Flickr20k and MSCOCO (English) are English text based retrieval, while MSCOCO (Korean) is Korean text based retrieval. Values are in Recall (%).

| Method          | Flickr20k | MSCOCO (English) | MSCOCO (Korean) |
|-----------------|-----------|------------------|-----------------|
| Visual N-Grams  | 15.4      | 33.7             | 43.1            |
| ImageBERT       | 1.1       | -                | -               |
| Unicoder-VL     | 3.6       | -                | -               |
| CLIP            | 78.8      | 94.9             | 96.2            |
| KELIP           | 77.4      | 93.9             | 97.2            |

Table 3: Zero-shot cross-modal retrieval. Flickr20k and MSCOCO (English) are English text based retrieval, while MSCOCO (Korean) is Korean text based retrieval. Values are in Recall (%).

5.2 ABLATION STUDY

For an ablation study, we train CLIP with YFCC15M by adding each training scheme and evaluate zero-shot classification and cross-modal retrieval. Every experiment follows KELIP hyper-parameters in Table 4 with different training schemes. As shown in Table 1, fine-tuning CLIP with MAE pre-trained model achieves better performance in both classification and retrieval. When we add one local view of multi-crop, the performance of both tasks is improved significantly. We will further discuss employing SimCLR method in Sec. 5.5.1.
5.3 QUANTITATIVE RESULTS

5.3.1 ZERO-SHOT CLASSIFICATION

We evaluate KELIP with 14 benchmark datasets and compare it with CLIP (ViT-B/32) in a zero-shot classification manner. We use 13 English public datasets for English evaluation while translating their labels to Korean for Korean evaluation. Our Korean private dataset (WebKorean) is also used for Korean evaluation. Note that CLIP can be used in Korean due to the flexibility of the BPE tokenizer. As shown in Table 2, KELIP shows 3.3% higher performance on average for English evaluation compared to CLIP. For Korean evaluation, CLIP performances are extremely low because the model is mainly trained in English, while KELIP shows competitive performance for every dataset.

5.3.2 ZERO-SHOT CROSS-MODAL RETRIEVAL

Zero-shot cross-modal retrieval consists of image-to-text retrieval and text-to-image retrieval. We compare our KELIP with existing multimodal models, including Visual N-Grams (Li et al., 2017), ImageBert (Qi et al., 2020), Unicoder-VL (Li et al., 2020), Uniter (Chen et al., 2020b), and CLIP (ViT-B/32) (Radford et al., 2021b). As shown in Table 3, KELIP achieves the best performance in both MSCOCO (English) and MSCOCO (Korean), where KELIP achieves competitive performance on Flickr30k. Compared to CLIP, our KELIP shows higher performance in most benchmark datasets, demonstrating that KELIP better understands multimodal relations.

5.4 QUALITATIVE RESULTS

We perform a qualitative evaluation on images from four benchmark datasets: SUN396 (Xiao et al., 2010), YouTube-BB (Real et al., 2017), CLEVR Counts (Johnson et al., 2017), and MNIST (LeCun et al., 1998). Each image is classified among 5 Korean and English candidate texts in a zero-shot manner. As shown in Figure 2 (a) and (b), both indoor and object images are classified correctly for both languages. Moreover, we observe that KELIP can be used for counting objects and recognizing numbers, as shown in Figure 2 (c) and (d). We further confirm that KELIP can be used for simple face recognition, as shown in Figure 8.

5.5 DISCUSSIONS

5.5.1 LIMITATIONS OF STRONG AUGMENTATION-BASED TRAINING

Recent works (SLIP and DeCLIP) propose to exploit self-supervised learning methods on the image encoder along with multimodal contrastive learning and show competitive performance on zero-shot classification. SLIP and DeCLIP use SimCLR and SimSiam methods, respectively, which contain strong image augmentations (i.e., changing brightness, contrast, saturation, hue, etc.). However, we observe that those strong image augmentation can distract the multimodal model from learning the correct relation between modalities. As shown in Figure 3, w/ SimCLR gets more confused by the color and pattern of the image compared to w/o SimCLR. It is also shown in the quantitative evaluation. As shown in Table 1, although the $\text{MAE}+\text{CLIP}+\text{SimCLR}$ shows the best performance in zero-shot classification, it shows lower performance than $\text{MAE}+\text{CLIP}+\text{MultiCrop}$ in zero-shot cross-lingual retrieval, which requires a higher understanding of cross-lingual relation. Thus, we suggest avoiding strong augmentation for training a multimodal model to expect a profound understanding of cross-lingual relations. With this spirit, we did not employ the self-supervised learning method for multimodal training.
Figure 4: Cross-lingual cosine similarity heatmap for long sentences. The same index of each row (English) and column (Korean) has the same semantic meaning in different languages.

Figure 5: KELIP-guided diffusion. Two images in each column are generated with the same semantic prompt but different languages; English in the first row and Korean in the second row.

5.5.2 CROSS-LINGUAL SEMANTIC RELATION

When we trained KELIP, we did not put any cross-lingual relations between Korean and English. However, those relations can be learned via shared visual information; i.e. the image feature of a photo of an apple would be close to both the English text feature of apple and the Korean text feature of 사과. This can result in an embedding space where semantically similar words in different languages are close and semantically dissimilar words in different languages are far apart. To verify this hypothesis, we conduct an experiment by computing cosine similarities between the same semantic prompts in different languages. As shown in the Figure 4 and Figure 7, for both cases of long sentences and short words, every sentence gives the highest cosine similarity when the paired sentence has the same semantic. It demonstrates that training KELIP without cross-lingual information can learn the semantic relations between different languages via shared visual information.

5.5.3 HOW DOES KELIP SEE?

As language is the way by which people communicate with one another, it reflects cultures. Same semantic words but different languages can have different visual information because of cultural differences. As each language dataset includes its visual information in terms of culture, this raises
Figure 6: **Multimodal feature analogy.** We construct query feature by arithmetic operation of image and text feature; then, we perform image retrieval from the gallery set. Parentheses are the translation of the text inputs.

A question: *how does KELIP see to the same semantic words but different languages?* To answer the question, we conduct an experiment generating images with given text prompts by KELIP-guided diffusion [Dhariwal & Nichol, 2021; Ho et al., 2020]. With such text-to-image generation, we can generate images of abstracted textual information.

As shown in the Figure 5, *breakfast and dinner* in English look like bread and salad, reflecting general western meal, while those of Korean look like dishes with rice, reflecting general Asian meal. *Traditional dress and traditional wedding* in Korean show the visual patterns of Korean traditional clothes called ‘hanbok (한복)’, while those of English show general long and slim dresses. The concepts of *ghost and goblin* are also different by culture. The general image of a ghost in the western is floating white cloth with two black holes, while that of an Asian can be a person with long hair and a white dress. For the goblin, the general image in the western is a green monster with large ears, while the goblin in Korea has horns with a thick beard. Those characteristics are depicted in Figure 5. It demonstrates that the bilingual KELIP model captures different characteristics of each cultural vision information for the same semantic meaning of words but different languages.

### 5.5.4 Multimodal Feature Analogy

There have been demands of studies to combine more than two different modalities in feature analogy [Shin et al., 2021; Ben-Younes et al., 2017; Fukui et al., 2016; Yu et al., 2017; Ethayarajh et al., 2018]. To see if our KELIP can be used for multimodal feature analogy, we conducted an experiment by performing image retrieval with a query feature that is fused with image and text features. We first construct a gallery set with 99 million of random images. Then, we compute a query feature by $q = \ell_2(x + wy)$, where $\ell_2()$ is L2 normalization and we heuristically find the best $w$ within 1 to 5 for the best results. As shown in Figure 6, every example successfully combines multimodal features and retrieves images that contain semantics of text based on the input images. It demonstrates the potential of our KELIP model to be used for multimodal feature analogy.

### 6 Conclusion

In this paper, we present KELIP, a large-scale bilingual multimodal model, which is trained with 1.1 billion image-text pairs (708 Korean pairs and 476 English pairs) and introduce simple yet effective training schemes for multimodal model. Our ablations show that a model trained with such training schemes can benefit from a large performance boost. Our KELIP model shows competitive performance in both languages. Moreover, we discuss multimodal-related research questions, including strong augmentation-based methods, cross-lingual relation, the cultural difference of textual semantics, and multimodal feature analogy. We left training multimodal model with cross-lingual relation and supporting additional languages as future work.
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Table 4: **Hyper-parameters of MAE pre-training and KELIP fine-tuning.** KELIP_yfcc is a model trained with small dataset (i.e. YFCC15M), while KELIP is a model trained with large dataset (i.e. 1.1 billion Korean and English).

![Cross-lingual cosine similarity heatmap for short words](image)

**Figure 7:** Cross-lingual cosine similarity heatmap for short words. The same index of each row (English) and column (Korean) has the same semantic meaning in different languages.

### A Appendix

**Details of hyper-parameter.** The details of hyper-parameter used in MAE pre-training and multimodal fine-tuning is in Table 4.

**Additional Results of Cross-lingual Semantic Relation.** We include cross-lingual cosine similarity heatmap for short words in Figure 7.

**Qualitative Analysis of Face Recognition** As we included celebrities’ image and text pairs in the training data, we conduct a qualitative analysis of face recognition in Figure 8.
Figure 8: Qualitative results of face recognition. A zero-shot KELIP classifier classifies each celebrity’s image with five English and Korean texts. Bold text indicates ground truth and prediction (Pred.) value is in %.