

Unsupervised Multimodal Neural Machine Translation with Pseudo Visual Pivoting

Po-Yao Huang¹, Junjie Hu¹, Xiaojun Chang², Alexander Hauptmann¹

¹Language Technologies Institute, Carnegie Mellon University

²Faculty of Information Technology, Monash University

{poyaoh, junjieh, alex}@cs.cmu.edu, cxj273@gmail.com

Abstract

Unsupervised machine translation (MT) has recently achieved impressive results with monolingual corpora only. However, it is still challenging to associate source-target sentences in the latent space. As people speak different languages share similar visual systems, the potential of achieving better alignment through visual content is promising yet under-explored in unsupervised multimodal MT (MMT). In this paper, we investigate how to utilize visual content for disambiguation and latent space alignment in unsupervised MMT. Our model features multimodal back-translation and pseudo visual pivoting where we learn multilingual visual-semantic embedding spaces and incorporate visually-pivoted captioning as the additional weak supervision for aligning language spaces. The experimental results on the widely used Multi30K dataset show that the proposed model significantly improves over the state-of-the-art methods and generalizes well when the visual content is not available at the testing time.

1 Introduction

Neural machine translation (Kalchbrenner and Blunsom, 2013; Sutskever et al., 2014) has achieved near human-level performance (Wu et al., 2016). However, its effectiveness strongly relies on the availability of large-scale parallel corpora. Unfortunately, preparing the parallel data remains a challenge as there are more than 6,500 languages in the world and recruiting annotators with bilingual or multilingual knowledge to cover all those languages is impractical.

As a result, developing methods alleviating the need of well-annotated large parallel corpora has recently attracted increasing attention in the community. These methods fall into two broad categories. First type of methods use a third language as the pivot (Firat et al., 2016; Chen et al., 2017; Cheng et al., 2017; Johnson et al., 2017)

to enable zero-resource translation. Although the progress is encouraging, pivoting with a third language still demands bilingual knowledge for collecting large-scale parallel source-pivot and pivot-target corpora. The second type of methods explore unsupervised approaches (Conneau et al., 2018a; Artetxe et al., 2018; Lample et al., 2018a) have recently achieved impressive translation quality. These methods rely only on monolingual data and back-translation (Sennrich et al., 2016a). However, as discussed in (Lample et al., 2018b), the alignment of source-target sentences is uncertain and highly subject to proper initialization.

Using visual content for unsupervised MT (Chen et al., 2018; Su et al., 2019) is a promising solution for pivoting and alignment based on its availability and feasibility. Abundant multimodal content in various languages are available online (*e.g.* Instagram and YouTube). It is also easier to recruit monolingual annotators to describe an image than finding multilingual annotators to translate sentences. Importantly, visual content is eligible to improve the alignments in the language latent spaces since the physical visual perception is similar among people speaking different languages (*e.g.* similar “blue car” for a German and a French).

Based on these insights, we propose a novel unsupervised multimodal MT framework incorporating visual content as pseudo pivots promoting latent space alignment. In addition to use features of visual objects for multimodal back-translation, we align multilingual visual-semantic embedding (VSE) spaces via leveraging image-sentence pairs in different languages. As illustrated in Figure 2, for sentences approximately pivoted by similar images (*src-img-tgt*), drawing embeddings of corresponding image-sentence pairs closer results in better alignments of semantically equivalent sentences in the language latent spaces. Inspired by back-translation, we further explore another pseudo pivoting strategy which approximates multilingual

sentence pairs (*src-img-tgt*) conditioned on a real image via captioning. Instead of using annotation of images for pivoting as in (Chen et al., 2018), we generate sentences in two languages pivoted on the real image, and then approximately pairing them as a weak supervision for training unsupervised MT system. This approach is analogous to a cross-modal version of back-translation.

We make the following contributions: (1) Building a unified view of employing visual content for pseudo pivoting. (2) We learn and improve alignment in the multilingual multimodal space for unsupervised MMT with disjoint image-text pairs in multiple languages. (3) Our model achieves state of the art on Multi30K and generalizes well to the text-only scenario.

2 Background

Neural Machine Translation Typical NMT models are based on the encoder-decoder framework with attention (Bahdanau et al., 2015). Let $\mathbf{x} = (x_1, \dots, x_N)$ denotes a source sentence and $\mathbf{y} = (y_1, \dots, y_M)$ denotes a target sentence, where $(\mathbf{x}, \mathbf{y}) \in (\mathcal{X}, \mathcal{Y})$. The encoder-decoder model learns to estimate the following likelihood from the source sentence to the target sentence:

$$p_{x \rightarrow y}(\mathbf{y}|\mathbf{x}) = \prod_{i=1}^M p(y_i|\mathbf{y}_{<i}, \mathbf{x}) \quad (1)$$

When a parallel corpus is available, the maximum likelihood estimation (MLE) is usually adopted to optimize the (source to target language) NMT model by minimizing the following loss:

$$\mathcal{L}_{x \rightarrow y}^{MT} = \mathbb{E}_{(\mathbf{x}, \mathbf{y}) \sim (\mathcal{X}, \mathcal{Y})} [-\log p_{x \rightarrow y}(\mathbf{y}|\mathbf{x})] \quad (2)$$

Among all encoder-decoder models, the Transformer (Vaswani et al., 2017) architecture recently achieves state-of-the-art translation quality. Instead of using recurrent or convolutional operations, it facilitates multi-head self-attention (Lin et al., 2017). In this paper, we choose the Transformer as the basic architecture for both the translation and the captioning modules.

Unsupervised Machine Translation While conventional MT systems rely on the availability of a large parallel corpus, translation with zero-resource (unsupervised MT) (Lample et al., 2018a; Artetxe et al., 2018; Lample et al., 2018b) has drawn increasing research attention. Only monolingual sentences are presented at the training and validation phase, *i.e.*, only $\mathbf{x} \in \mathcal{X}$ and $\mathbf{y} \in \mathcal{Y}$ are available.

Successful unsupervised MT systems share several common principles. First, they require the pre-training step to properly initialize the model and establish strong monolingual language model. For example, XLM (Conneau and Lample, 2019) utilizes the masked language model objective in BERT (Devlin et al., 2019). MASS (Song et al., 2019) utilizes a span-based sequence-to-sequence masking objective for language model pre-training.

Second, these systems transform the unsupervised problem into a weakly or self-supervised one by automatically generating pseudo sentence pairs via back-translation (Sennrich et al., 2016a). The idea behind can be analogous to the cycle-consistency objective in CycleGAN (Zhu et al., 2017) for image-image translation with unpaired data. Specifically, let us denote by $h^*(\mathbf{y}) = (\hat{x}_1, \dots, \hat{x}_N)$ the sentence in the source language inferred from $\mathbf{y} \in \mathcal{Y}$ such that $h^*(\mathbf{y}) = \operatorname{argmax}_{\mathbf{x}} p_{y \rightarrow x}(\mathbf{x}|\mathbf{y})$. Similarly, let us denote by $g^*(\mathbf{x}) = (\hat{y}_1, \dots, \hat{y}_M)$ the sentence in the target language inferred from $\mathbf{x} \in \mathcal{X}$ such that $g^*(\mathbf{x}) = \operatorname{argmax}_{\mathbf{y}} p_{x \rightarrow y}(\mathbf{y}|\mathbf{x})$. Then the ‘‘pseudo’’ parallel sentences $(h^*(\mathbf{y}), \mathbf{y})$ and $(\mathbf{x}, g^*(\mathbf{x}))$ can be further used to train two MT models ($\mathcal{X} \rightarrow \mathcal{Y}$ and $\mathcal{Y} \rightarrow \mathcal{X}$) by minimizing the following back-translation loss:

$$\mathcal{L}_{x \leftrightarrow y}^{BT} = \mathbb{E}_{\mathbf{x} \sim \mathcal{X}} [-\log p_{y \rightarrow x}(\mathbf{x}|g^*(\mathbf{x}))] + \mathbb{E}_{\mathbf{y} \sim \mathcal{Y}} [-\log p_{x \rightarrow y}(\mathbf{y}|h^*(\mathbf{y}))] \quad (3)$$

Although reinforcement learning-based approaches (He et al., 2016a) and Gumbel-softmax reparametrization (Maddison et al., 2017) have been used to handle back-propagation thorough non-differentiable ‘‘argmax’’ predictions. In this paper, we do not back-propagate through $h^*(\mathbf{y})$ and $g^*(\mathbf{x})$ to simplify the training process.

3 Unsupervised Multimodal Machine Translation

As illustrated in Figure 1, our model is composed of seven modules: Two encoder-decoder pairs for translation, two decoders for captioning, and one shared visual encoder. In this section, we first detail our basic MMT model architecture and the unsupervised setup. Then we introduce our approaches for pseudo visual pivoting with multilingual VSE and pivoted captioning.

3.1 Multimodal MT

Multimodal machine translation (Specia et al., 2016) (MMT) considers additional images as a

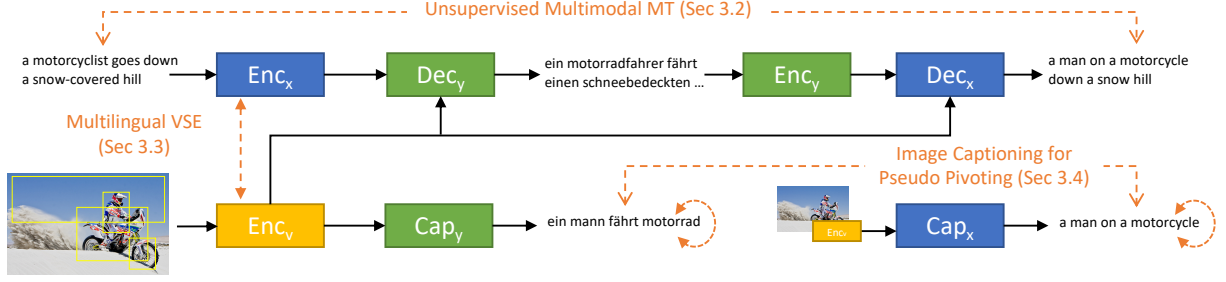


Figure 1: The proposed model structure (English↔German). We incorporate visual objects for unsupervised multimodal MT and improve the language latent space alignment with *pseudo visual pivoting* (§3.3-§3.4).

complementary information source for MT. An image \mathbf{z} and the description in two languages form a triplet $(\mathbf{x}, \mathbf{y}, \mathbf{z}) \in (\mathcal{X}, \mathcal{Y}, \mathcal{Z})$. The Transformer encoder reads the source sentence and encodes it with hierarchical self-attention into $\mathbf{h}^x = \{\mathbf{h}_1^x, \dots, \mathbf{h}_N^x\}$, $\mathbf{h}_i^x \in \mathbb{R}^d$, where d is the dimension of the embedding space. The visual encoder encodes the image into $\mathbf{h}^z = \{\mathbf{h}_1^z, \dots, \mathbf{h}_K^z\}$, $\mathbf{h}_i^z \in \mathbb{R}^d$, $K_{\max} = 36$. Most previous work (Chen et al., 2018; Su et al., 2019) use 2D ($K = 14 \times 14$) feature maps of ImageNet pre-trained ResNet (He et al., 2016b). In contrast, we utilize the regional feature of K salient visual objects in an image extracted by Faster-RCNN (Ren et al., 2015) and a 1-layer MLP to as the encoder to encode the visual objects.

Our model employs multimodal attention for decoding. For decoding at time stamp i , the text-only attention $\text{Attn}(\mathbf{h}_i^y, \mathbf{h}^x)$ computes the context vector $\mathbf{c}_i = \sum_j \alpha_j \mathbf{h}_j^x$ via a attention-based alignment $\alpha_j = \text{Align}(\mathbf{h}_i^y, \mathbf{h}_j^x)$, where $\sum_j \alpha_j = 1$ and \mathbf{h}_i^y is the decoder state. In practice, the attention in Transformer is implemented as $\mathbf{c}_i = \text{softmax}(\mathbf{Q}_i(\mathbf{K}^x)^\top / \sqrt{d}) \mathbf{V}^x$ where $\{\mathbf{Q}, \mathbf{K}, \mathbf{V}\}$ are the packed d -dimensional *Query*, *Key*, *Value* vectors, which are the mapped and packed version of $\{\mathbf{h}_i^y, \mathbf{h}^x, \mathbf{h}^z\}$. For decoding with multimodal inputs, we design a multimodal attention to compute the context vector \mathbf{c}_i :

$$\mathbf{c}_i^x = \text{Attn}(\mathbf{h}_{i-1}^y, \mathbf{h}^x) + \lambda_v \text{Attn}(\mathbf{h}_{i-1}^y, \mathbf{h}^z) \quad (4)$$

In practice we set $\lambda_v = 1.0$. Our multimodal decoder models the likelihood to predict the next token as:

$$p(y_i | \mathbf{y}_{<i}, \mathbf{x}, \mathbf{z}) = \text{softmax}(f(\mathbf{c}_i, y_{i-1}, \mathbf{h}_{i-1}^y)), \quad (5)$$

where $f(\cdot)$ denotes the non-linear feature mapping in Transformer.

3.2 Unsupervised Learning

Unsupervised multimodal MT (Nakayama and Nishida, 2017; Chen et al., 2018; Su et al., 2019) poses a new yet challenging problem. On both the source and target sides, only non-overlapping monolingual multimodal data are presented for training and validation. Specifically, the data available are: $(\mathbf{x}, \mathbf{z}_x) \in (\mathcal{X}, \mathcal{Z})$, $(\mathbf{y}, \mathbf{z}_y) \in (\mathcal{Y}, \mathcal{Z})$, such that $\{\mathbf{x}\} \cap \{\mathbf{y}\} = \phi$, $\{\mathbf{z}_x\} \cap \{\mathbf{z}_y\} = \phi$. Note that there is no parallel translation pairs available (unsupervised), and the images are mutually exclusive for different languages.

For multimodal back-translation, the generated pseudo target sentence conditioned on the source sentence and image can be re-written as $g^*(\mathbf{x}, \mathbf{z}_x) = \arg\max_{\mathbf{y}} p_{xz \rightarrow y}(\mathbf{y} | \mathbf{x}, \mathbf{z}_x)$, where $p_{xz \rightarrow y}(\mathbf{y} | \mathbf{x}, \mathbf{z}) = \prod_{i=1}^M p(y_i | \mathbf{y}_{<i}, \mathbf{x}, \mathbf{z})$. Similar for $p_{yz \rightarrow x}(\mathbf{x} | \mathbf{y}, \mathbf{z})$ and $h^*(\mathbf{y}, \mathbf{z}_y)$. For unsupervised multimodal MT, the multimodal back-translation objective can be extended as:

$$\begin{aligned} \mathcal{L}_{x \leftrightarrow y}^{MBT} = & \mathbb{E}_{(\mathbf{x}, \mathbf{z}_x)} \left[-\log p_{yz \rightarrow x}(\mathbf{x} | g^*(\mathbf{x}, \mathbf{z}_x), \mathbf{z}_x) \right] \\ & + \mathbb{E}_{(\mathbf{y}, \mathbf{z}_y)} \left[-\log p_{xz \rightarrow y}(\mathbf{y} | h^*(\mathbf{y}, \mathbf{z}_y), \mathbf{z}_y) \right] \end{aligned} \quad (6)$$

We simplify the notation of expectation for clarity.

Aligning the source and target language latent spaces is challenging as discussed in (Lample et al., 2018b). Nevertheless, as people speak different languages biologically share similar visual systems, we envision that the shared visual space can serve as the pivot for alignment. Unlike most previous work (Chen et al., 2018; Su et al., 2019) treat visual content merely as feature, as illustrated in Figure 2, we generalize visual pivoting into two approaches: (1) Aligning multilingual VSE spaces; (2) Image pseudo pivoting via captioning. In (1), we use images as the approximate pivots connecting real non-parallel sentences. (src-img-tgt.) In (2), for each pivoting real image, we generate captions in

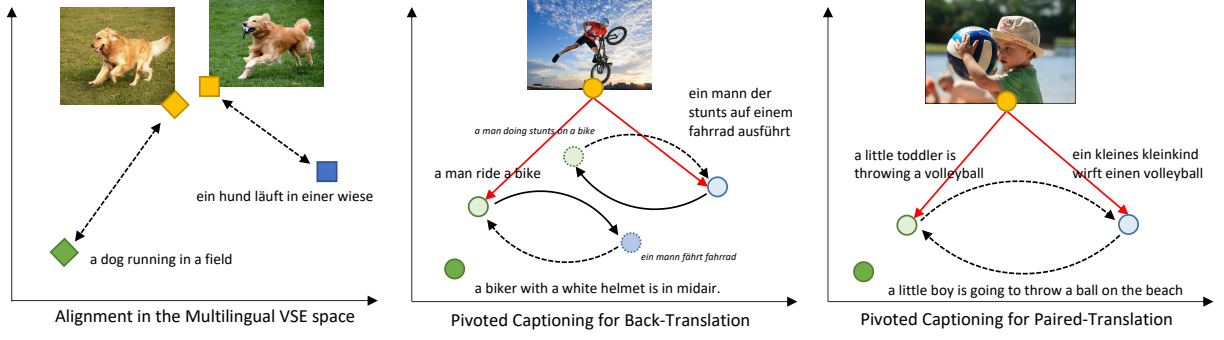


Figure 2: Pseudo visual pivoting: (1) multilingual VSE ($src\text{-}img\text{-}tgt$, in fact $src\text{-}img_1$, $tgt\text{-}img_2$), and (2) pivoted captioning ($src\text{-}img\text{-}tgt$). The *italic* item does not exist and is approximated (pseudo). (src , img , tgt) is colored in (green, yellow, blue). Solid red and black lines indicate captioning and translation without updates. Encoder-decoder are updated with the dashed lines to align the multilingual multimodal latent spaces.

both languages to construct “pseudo” source-target sentence pairs. ($src\text{-}img\text{-}tgt$), where the *italic* item is “pseudo”. We collectively term the proposed approach *pseudo visual pivoting*.

3.3 Multilingual Visual-Semantic Embedding

We posit that for $\mathcal{X}, \mathcal{Y}, \mathcal{Z}$, the two language spaces \mathcal{X}, \mathcal{Y} could be properly associated by respectively aligning two multilingual VSE spaces $\mathcal{X} \leftrightarrow \mathcal{Z}$ and $\mathcal{Y} \leftrightarrow \mathcal{Z}$. We leverage the contrastive objective in cross-modal retrieval (Kiros et al., 2014; Huang et al., 2019b) for aligning multimodal inputs in the shared VSE space where the embeddings are close if they are semantically associated or paired.

Specifically, we generalize the fine-grained (object-level and token-level), monolingual textual-to-visual and visual-to-textual attention (Lee et al., 2018; Huang et al., 2019c) into the multilingual setup. Taking the visual-to-textual attention for image-source sentence alignment as an example, let $s_{ij} = \cos(\mathbf{h}_i^x, \mathbf{h}_j^z)$ denotes the cosine similarity between the i -th encoded token and the j -th encoded visual object. The visually-attended sentence embeddings \mathbf{h}^{zx} are the weighted combination of the encoded tokens \mathbf{h}^x . Precisely, we compute $\mathbf{h}_j^{zx} = \sum_{i=1}^N \alpha_{ij} \mathbf{h}_i^x$, where $j = 1 \cdots K$ and $\alpha_{ij} = \text{softmax}_i(s_{ij})$. The image-sentence similarity can therefore be measured by the average cosine similarity between the visually-attend sentence embeddings and the visual embeddings of the objects. Let us denote by $S(\mathbf{x}, \mathbf{z}) = \frac{1}{K} \sum_{j=1}^K \cos(\mathbf{h}_j^{zx}, \mathbf{h}_j^z)$ as the image-sentence similarity, the contrastive triplet loss encouraging image-sentence alignment in the VSE space can therefore be written as:

$$\mathcal{L}_c(\mathbf{x}, \mathbf{z}) = \max_{\tilde{\mathbf{x}}} [\gamma - S(\mathbf{x}, \mathbf{z}) + S(\tilde{\mathbf{x}}, \mathbf{z})]_+ + \max_{\tilde{\mathbf{z}}} [\gamma - S(\mathbf{x}, \mathbf{z}) + S(\mathbf{x}, \tilde{\mathbf{z}})]_+, \quad (7)$$

where $[\cdot]_+$ is the hinge function, and $\tilde{\mathbf{x}}$ and $\tilde{\mathbf{z}}$ are the non-paired (negative) instances for \mathbf{x} and \mathbf{z} . Intuitively, when the loss decreases, the matched images and sentences will be drawn closer down to a margin γ than the hardest non-paired ones. Formally, we minimizing the following objective for cross-modal alignments in the two VSE spaces:

$$\mathcal{L}_{x,y,z}^{VSE} = \mathbb{E}_{(\mathbf{x}, \mathbf{z}_x)} [\mathcal{L}_c(\mathbf{x}, \mathbf{z}_x)] + \mathbb{E}_{(\mathbf{y}, \mathbf{z}_y)} [\mathcal{L}_c(\mathbf{y}, \mathbf{z}_y)] \quad (8)$$

3.4 Image Captioning for Pseudo Pivoting

Inspired by back-translation with monolingual corpora, we propose a novel cross-modal approach to generate weakly-supervised pairs to guide language space alignment for unsupervised MMT. Precisely, we leverage image captioning to synthesize pseudo sentence pairs (pivoted and conditioned on the image) for back-translation and paired-translation.

Image Captioning Image captioning models are akin to MT models besides the non-sequential visual encoder. For example, an image-to-source captioning model estimates the likelihood as $p_{z \rightarrow x}(\mathbf{x}|\mathbf{z}) = \prod_{i=1}^N p(x_i|\mathbf{x}_{<i}, \mathbf{z})$, where \mathbf{z} is the encoded image. Essentially, the captioning model learns to minimize the following loss:

$$\mathcal{L}_{z \rightarrow x}^{CAP} = \mathbb{E}_{(\mathbf{z}_x, \mathbf{x})} [-\log p_{z \rightarrow x}(\mathbf{x}|\mathbf{z}_x)] \quad (9)$$

As illustrated in Figure 2, for unsupervised MMT, we propose to learn two captioning models $\mathcal{Z} \rightarrow \mathcal{X}$ and $\mathcal{Z} \rightarrow \mathcal{Y}$ for two purposes: (1) to improve alignment in VSE space; (2) to generate additional “pseudo” parallel sentences pivoted on the image as additional weak supervision. For example, with Image \rightarrow English and Image \rightarrow German, the generated pseudo (English, German) pair

is then pivoted on the Image. In practice, similar to back-translation, we use the two captioning models to generate captions in two languages depicting the same image, *i.e.*, $c_x^*(\mathbf{z}_x) = \operatorname{argmax}_{\mathbf{x}} p_{x \rightarrow x}(\mathbf{x} | \mathbf{z}_x)$ and $c_y^*(\mathbf{z}_x) = \operatorname{argmax}_{\mathbf{y}} p_{z \rightarrow y}(\mathbf{y} | \mathbf{z}_x)$. The generated pivoted captions then enable the following two objectives:

Pivoted Captioning for Back-Translation We utilize the synthetic multilingual captions (*i.e.*, $c_x^*(\mathbf{z}_x)$, $c_y^*(\mathbf{z}_x)$ from the source images and $c_x^*(\mathbf{z}_y)$, $c_y^*(\mathbf{z}_y)$ from the target images) to reversely reconstruct the synthetic captions from their translations in both directions. Formally, we compute the following caption-based back-translation loss:

$$\begin{aligned} \mathcal{L}_{x \leftrightarrow y}^{CBT} = & \mathbb{E}_{\mathbf{z}_x} \left[-\log p_{y \rightarrow x}(c_x^*(\mathbf{z}_x) | g^*(c_x^*(\mathbf{z}_x), \mathbf{z}_x), \mathbf{z}_x) \right. \\ & \left. -\log p_{x \rightarrow y}(c_y^*(\mathbf{z}_x) | g^*(c_y^*(\mathbf{z}_x), \mathbf{z}_x), \mathbf{z}_x) \right] \\ & + \mathbb{E}_{\mathbf{z}_y} \left[-\log p_{y \rightarrow x}(c_x^*(\mathbf{z}_y) | h^*(c_x^*(\mathbf{z}_y), \mathbf{z}_y), \mathbf{z}_y) \right. \\ & \left. -\log p_{x \rightarrow y}(c_y^*(\mathbf{z}_y) | h^*(c_y^*(\mathbf{z}_y), \mathbf{z}_y), \mathbf{z}_y) \right] \end{aligned} \quad (10)$$

Pivoted Captioning for Paired-Translation With the synthetic “pseudo” paired (source, target) captions pivoted on a image (*e.g.* $(c_y^*(\mathbf{z}_x), c_x^*(\mathbf{z}_x))$), the caption-based paired-translation loss is defined as:

$$\begin{aligned} \mathcal{L}_{x \leftrightarrow y}^{CPT} = & \mathbb{E}_{\mathbf{z}_x} \left[-\log p_{xz \rightarrow y}(c_y^*(\mathbf{z}_x) | c_x^*(\mathbf{z}_x), \mathbf{z}_x) \right] \\ & + \mathbb{E}_{\mathbf{z}_y} \left[-\log p_{yz \rightarrow x}(c_x^*(\mathbf{z}_y) | c_y^*(\mathbf{z}_y), \mathbf{z}_y) \right] \end{aligned} \quad (11)$$

Note that similar to the text back-translation, for $\mathcal{L}_{x \leftrightarrow y}^{CPT}$ and $\mathcal{L}_{x \leftrightarrow y}^{CBT}$, we do not back-prop through the captioning step. For optimization, we sample mini-batches and minimizing the following loss:

$$\mathcal{L} = \mathcal{L}_{x \leftrightarrow y}^{MBT} + \mathcal{L}_{x,y,z}^{VSE} + \mathcal{L}_{z \leftrightarrow x,y}^{CAP} + \mathcal{L}_{x \leftrightarrow y}^{CBT} + \mathcal{L}_{x \leftrightarrow y}^{CPT} \quad (12)$$

Here we drop the weights w of each loss for clarity. In practice, all the weights are set to 1.0 except for w_{CPT} where we employ a decreasing scheduler detailed in the next section.

4 Experiments and Results

We first describe the implementation details and the experimental setup. Then we compare our approach with baselines with detailed analysis.

4.1 Dataset and Preprocessing

We conduct experiments on the Multi30K (Elliott et al., 2016) dataset, the benchmark dataset for multimodal MT. It contains 29K training, 1K validation, and 1K testing images. Each image has three

descriptions in English/German/French which are translations of each other.

To ensure the model never learn from parallel sentences, we randomly split Multi30K training and validation sets in half for one language and use the complementary half for the other. The resulting M30k-half are two corpora with non-overlapping 14,500 training and 507 validation image-sentence pairs, respectively.

For text pre-processing, we use Moses (Koehn et al., 2007) scripts for tokenization and apply the Byte Pair Encoding (BPE) (Sennrich et al., 2016b) from XLM. To identify and extract features of visual objects in images, we use the Faster-RCNN (Ren et al., 2015) model in (Anderson et al., 2018) to detect up to 36 salient visual objects per image and extract their corresponding 2048-dim regional features.

4.2 Implementation

We use Transformer as the basic architecture for our translation and captioning modules. Each encoder/decoder of the translator is with 6-layer stacked Transformer network, 8 heads, 1024 hidden units, and 4096 feed-forward filter size. The captioner is a 6-layer Transformer decoder with the same configuration. The visual encoder is a 1-layer MLP which maps visual feature to the shared 1,024-dim embedding space then adds the positional encoding to encode spatial locations (normalized top-left and bottom-right coordinates) of visual objects. Our implementation is based on the codebase of XLM and MASS.

4.3 Experimental Details

We respectively conduct unsupervised MMT experiments on Multi30K-half for two language pairs: English-French and English-German.

Pre-Training Pre-training is a critical step for unsupervised MT. We follow the setup in UMMT (Su et al., 2019) for a fair comparison. For each language, we create a text-only pre-training set by combining the shuffled first 10 million sentences of the WMT News Crawl datasets from 2007 to 2017 with 10 times of M30k-half, resulting in a text-only dataset with 10.145 million unparalleled sentences in English, French, German respectively.

For text pre-training, we leverage the script and the masked seq-to-seq objective proposed in MASS which randomly masks a span in a sentence then encourage the model to decode and reconstruct the masked sequence as the monolingual language

model pre-training. More details can be found in the original paper. Note that there is no fine-tuning (back-translation) on WMT for a fair comparison with other baselines.

For multimodal pre-training of the captioning modules, we use the out-of-domain MSCOCO (Lin et al., 2014) dataset. We randomly split the training set into two disjoint subsets. Each set contains 56,643 images and 283,215 sentences. We use the translate-train strategy as in XNLI (Conneau et al., 2018b) for training captioners in each language. We leverage Google translate to translate one set of English sentences into French and German. Note that the captioning modules are trained on non-parallel sentences with disjoint image subsets, which implies no overlap between English-German or English-French sentences.

Fine-tuning on Multi30K-half We fine-tune on the training set of Multi30K half for 20 epochs. We train our model with the Adam optimizer (Kingma and Ba, 2014) with a linear warm-up and a learning rate varying from 10^{-7} to 10^{-5} . We set all the weights of losses to 1.0 except applying a linear decreasing schedule from 1.0 to 0.1 at 10-th epoch for w^{CPT} as we empirically observe that the generated captions are relatively too noisy to serve as good pseudo translation pairs in the later stage of training. The margin γ in VSE is set to 0.1. Other hyper-parameters in Transformer follow the default setting in XLM and MASS. Our models are trained with 4 Titan Xp GPUs with in 1,000 tokens in each mini-batch.

Evaluation and Model selection For evaluation, we report the BLEU score with multi-bleu.pl¹ in Moses and METEOR on the Multi30K testing set.

For model selection without a parallel validation corpus, we consider the unsupervised criterion proposed in (Lample et al., 2018a) based on the BLEU scores of “round-trip” translations (source \rightarrow target \rightarrow source and target \rightarrow source \rightarrow target) which have been empirically shown to correlate well with the testing metrics.

4.4 Baseline Models

We compare recent unsupervised text-only and multimodal MT baselines listed in the following: (1) MUSE (Conneau et al., 2018a) is a word-to-word MT model with pre-trained Wikipedia embeddings. (2) UNMT (Lample et al., 2018a) sets the tone of

using denoising autoencoder and back-translation for unsupervised MT. (3) XLM (Conneau and Lample, 2019) deploys masked language model from BERT. (4) MASS (Song et al., 2019) uses a masked seq-to-seq pre-training objective, achieves the current state-of-the-art performance in text-only unsupervised MT. (5) Game-MMT (Chen et al., 2018) is a reinforcement learning-based unsupervised MMT. (6) UMMT (Su et al., 2019) use visual feature for denoising autoencoder and back-translation. UMMT is the current state of the art in unsupervised MMT. We either use the reported scores in the original papers or use their best scripts with their pre-trained language models publicly available for fine-tuning on Multi30K-half.

4.5 Main Results: Unsupervised MMT

4.5.1 Comparison with the Baseline Models

Table 1 presents the benchmark results with other state-of-the-art unsupervised MT and MMT models on the Multi30K testing set. The first four rows shows the results of the recent text-only MT models. Game-MMT and UMMT are MMT models using both image and text inputs. Our full model (T+V+VSE+CAP+CBT+CPT) yields new state-of-the-art performance in BLEU and METEOR, outperforming the text-only and multimodal baseline model by a large margin. Notably, our full model outperforms UMMT by +5.5~12.5 BLEU scores, sets new state of the art in unsupervised MMT.

Although pre-training plays an important role for unsupervised MT, comparing Ours-Text only and Ours-Full, the results suggest that multimodal content can further boost the performance for unsupervised MT. The improvement with visual content is +2.7~3.7 BLEU across 4 tasks. Note that our model use different monolingual pre-training corpora to MASS and XLM for the fair comparison with UMMT. With the similar pre-training objective, our text-only model is worse than MASS, while Ours-Full outperforms MASS by +2.3~3.7 in BLEU with the visual information.

Comparing the models trained with and without visual information (UMMT-T vs. UMMT-Full) and (Ours-T vs. Ours-Full), our model achieves +2.5~3.7 improvement in BLEU with the visual information while +1.4~2.5 for UMMT. The results imply that the proposed model is more effective in utilizing visual information even with a higher text-only baseline (e.g. 49.5 vs 37.2 in en \rightarrow fr).

In Figure 3 we provide some qualitative results

¹<https://github.com/moses-smt/mosesdecoder/blob/master/scripts/generic/multi-bleu.perl>

Model	en→fr		fr→en		en→de		de→en	
	BLEU	METEOR	BLEU	METEOR	BLEU	METEOR	BLEU	METEOR
MUSE [†] (Conneau et al., 2018a)	8.5	-	16.8	-	15.7	-	5.4	-
UNMT [†] (Lample et al., 2018a)	32.8	-	32.1	-	22.7	-	26.3	-
XLM [†] (Conneau and Lample, 2019)	46.3	64.3	42.0	38.1	27.4	48.7	30.7	31.0
MASS [†] (Song et al., 2019)	49.8	65.8	43.7	38.7	30.2	51.3	32.5	33.4
Game-MMT (Chen et al., 2018)	-	-	-	-	16.6	-	19.6	-
UMMT-T [†] (Su et al., 2019)	37.2	33.7*	38.5	36.4	21.0	25.4*	25.0	28.4
UMMT-Full (Su et al., 2019)	39.8	35.5*	40.5	37.2	23.5	26.1*	26.4	29.7
Ours-Text only [†]	49.5	65.7	43.5	38.5	30.1	51.5	32.4	33.0
Ours-Full	52.3	67.6	46.0	39.8	33.9	54.1	36.1	34.7

Table 1: **Results on unsupervised MT.** Comparison with benchmarks on the Multi30K testing set. Our full model is with T+V+VSE+CAP+CBT+CPT. The best score is marked bold. [†] means text-only. * is the METEOR score shown in the UMMT paper.

on the Multi30K testing set. We observe a consistent improvement of unsupervised translation quality with our full model to the text-only one. Without parallel translation pairs as the vital supervision, the proposed pseudo visual pivoting successfully disambiguates the word semantics in similar syntactic category and results in improved cross-lingual word alignment; for instance, “cafe” vs. “soda” machine in the third French example, and “felsigen” (rocky) vs. “verschneiten” (snowy) in the first German example.

4.5.2 Ablation Studies

To quantify module-wise contribution in pseudo visual pivoting, we summarize our ablation studies in Table 2. Comparing the performance improvement from text-only to the model with regional visual feature (T+V), the feature of salient visual objects contribute +0.6~0.9 BLEU score over a much higher text-only baseline compared to UMMT.

For cross-lingual latent space alignment, aligning multilingual VSE spaces with disjoint image-text pairs provides an additional +1.3~2.0 improvement in BLEU. This improvement validates our hypothesis that the visual space can serve as the bridge connecting the source and target language latent spaces. Moreover, synthesizing image-pivoted pseudo caption pairs effectively provides weak supervision for aligning language latent spaces in unsupervised MMT. We observe that the pivoted captions for paired translation (CPT) is more effective than treating them as back-translation pairs (CBT). Utilizing generated image-pivoted captions is shown to be a promising approach for weakly supervised or unsupervised MT. The full model using VSE, CBT, and CPT achieves +1.9~3.1 im-

Model (Ours)	en→fr	fr→en	en→de	de→en
Text only	49.52	43.48	30.10	32.35
T+V	50.43	44.10	31.01	32.95
T+V+VSE	51.72	45.73	32.67	34.94
T+V+CPT*	51.64	45.55	33.04	35.02
T+V+CBT*	51.23	45.21	32.51	33.87
T+V+VSE+CBT*	51.81	45.83	33.01	34.38
T+V+CPT+CBT*	51.85	45.65	33.61	35.85
T+V+VSE+CPT*	52.19	46.10	33.73	35.60
Full Model*	52.29	45.98	33.85	36.07

Table 2: Ablation studies. BLEU comparison of different training objectives. * means CAP included.

provement compared to our multimodal baseline (row two, visual feature only).

4.5.3 Generalizability

How does our unsupervised MMT model generalize when the visual information is not available at the testing time? Table 3 shows the testing results *without* images. As can be observed, our model generalizes well. The differences are mostly less than 1.0 in BLEU. As our model, when being tested without visual information, still outperforms other unsupervised text-only or multimodal MT models listed in Table 1, the minor drop in BLEU implies that the improved cross-lingual latent space alignment via pseudo visual pivoting is likely to be more critical than using visual information as an input feature for decoding. Luckily, such alignment is already preserved in the training phase with the proposed approach.

An interesting question is: How much does the visual information (as a feature) contribute? As in leave-one-feature-out cross-validation, we compare the difference of performance between infer-

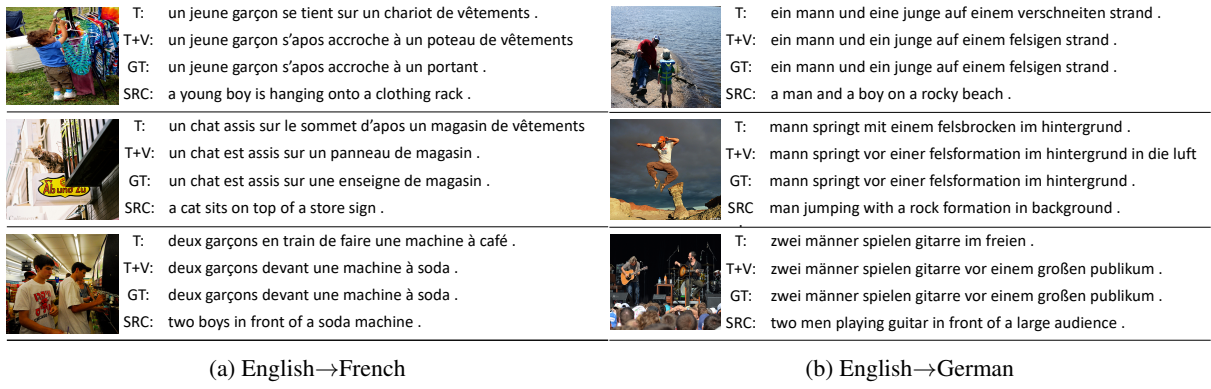


Figure 3: Qualitative results of the proposed model. GT: ground truth. T+V: Our full model.

Model	en→fr	fr→en	en→de	de→en
UMMT	39.44 _{-0.35}	40.30 _{-0.23}	23.18 _{-0.34}	25.47 _{-0.92}
Ours-no VSE	51.60 _{-0.25}	45.39 _{-0.26}	33.25 _{-0.36}	35.15 _{-0.70}
Ours-Full	51.64 _{-0.65}	45.48 _{-0.50}	33.32 _{-0.53}	35.04 _{-1.03}

Table 3: BLEU of testing full model with text-only inputs. Subscripts are the difference to testing with T+V.

encing with and without visual information. The larger the difference implies that the model utilizes more visual information. Comparing to UMMT, our full model utilizes more visual information. We observe that the key to such difference (subscripts in Table 3) is the VSE objective. Our model without the VSE objective will utilize less visual information (results in smaller difference), possibly because the source text-image pair are distant in the multilingual VSE space.

4.5.4 Real-pivoting & Low-resource Corpora

Will our model benefit from “real” pivoting (src- img_1 , img_1 -tgt, overall src- img_1 -tgt)? We train our models with overlapped images while leaving sentences in the source and target languages unparallelled (use *no* translation pairs). From the first three rows in Table 4, the performance is improved when training with the overlapped images and their corresponding sentences. Comparing the improvement from 0% to 100% of the text-only model and the full model, a larger gain is observed with the proposed pseudo visual pivoting which aligns and reduces uncertainty in the language latent spaces.

Furthermore, under the low-resource setting (3.0K non-parallel data, row six and seven), a substantial improvement over the text-only model is still observed. These results suggest that the proposed pseudo visual pivoting is likely to generalize to the semi-supervised and the low-resource setting, which we consider as our future work.

Img overlap % (# imgs/sents)	en→fr	fr→en	en→de	de→en
0% (14.5K/14.5K)	52.29	45.98	33.85	36.07
50% (22K/22K)	55.13	47.54	34.61	37.01
100% (29K/29K)	58.34	50.57	35.45	38.55
0% (T only/14.5K)	49.52	43.48	30.10	32.35
100% (T only/29K)	53.35	46.27	31.35	34.06
0% (3.0K/3.0K)	31.48	27.91	23.94	26.60
0% (T only/3.0K)	30.33	26.95	21.65	23.47

Table 4: Testing BLEU of the full T+V model and the text-only model trained with overlapped images or low-resource unpaired corpora.

4.5.5 Supervised Case

Although the proposed pseudo visual pivoting targets unsupervised MMT, we are also interested in its performance under the fully supervised setup. To gain insights, we conduct supervised MMT experiments by changing the back-translation objective for unsupervised MT (Eq. 6) to the supervised MT objective (Eq. 2) with additional visual inputs. We compare our model with recent supervised MMT models, including Imagination (Elliott and Kádár, 2017), LIUM-CVC (Caglayan et al., 2017), and VAG (Zhou et al., 2018).

Table 5 shows the testing results on Multi30K. Our model significantly outperforms other baselines and achieves state-of-the-art performance. Comparing to our model trained with full Multi30K (100%(29K/29K) in Table 4), the direct supervision from parallel translation pairs results in a +6.5~7.1 gain in BLEU. Notably, the improvement with visual information is minor with full supervision. This result implies that, compared to serving as a complementary feature, visual information likely contributes more to improving cross-lingual word alignment in the language latent spaces via pseudo visual pivoting for MMT with limited supervision.

Model	en→fr		en→de	
	BLEU	METEOR	BLEU	METEOR
Imagination	-	-	30.2	51.2
LIUM-CVC	52.7	69.5	30.7	52.2
VAG	53.8	70.3	31.6	52.2
Ours (T)	65.2	79.3	41.7	60.5
Ours (T+V)	65.5	79.1	42.0	60.6

Table 5: Supervised MMT results on Multi30K

5 Related Work

Unsupervised MT For pivoting with a third language, [Firat et al. \(2016\)](#) pre-train a multi-way multilingual model to generate pseudo pairs to improve zero-shot translation. [Chen et al. \(2017\)](#) use a teacher-student framework and assume parallel sentences share similar likelihood for generating sentence in the third language while [\(Cheng et al., 2017\)](#) maximize the expected likelihood. Our model does not rely on the third language. Our framework is along the line of research in [\(Lample et al., 2018a,b; Conneau and Lample, 2019\)](#) which aims at learning a aligned latent space between the two languages to translate by reconstruction. Nevertheless, we focus on the multimodal setup where the visual space is dissimilar to the language spaces with challenging asymmetric interactions between modalities.

Supervised MMT Supervised MMT is introduced in [\(Specia et al., 2016\)](#) as a multi-encoder single-decoder framework incorporating additional visual content. [Huang et al. \(2016\)](#) encode word sequences with regional visual objects while [Calixto and Liu \(2017\)](#) leverage global visual feature. LIUM-CVC [\(Caglayan et al., 2017\)](#) uses element-wise multiplication to model the image-text interaction. Imagination [\(Elliott and Kádár, 2017\)](#) and VAG [\(Zhou et al., 2018\)](#) learns with the auxiliary image reconstruction and source-image-target triplet alignment tasks, respectively. While these methods achieve improvements, their advantage over the text-only models is still minor under the supervised scenario. As analyzed in [\(Caglayan et al., 2019\)](#), visual content is more critical when the textual content is limited or uncertain in MMT. We study the more challenging unsupervised MMT.

Unsupervised MMT To our best knowledge, there are three works generalizing MMT to the unsupervised setting. [Nakayama and Nishida \(2017\)](#) learn modal-agnostic fixed length image/sentence embeddings. In contrast, our model promotes fine-grained (object-token) varying-length embedding

which better aligns VSE space. Game-MMT [\(Chen et al., 2018\)](#) use a captioning and a translation model maximizing the likelihood of translated captions to original sentences. We synthesize captions for symmetric back-translation and considers no ground truth image annotation in the loop. Empirically, it is preferred to separate real and generated captions. UMMT [\(Su et al., 2019\)](#) uses Transformers, autoencoder loss and multimodal back-translation. We do not use autoencoder. Our model leverages object detection for multimodal back-translation and equips pseudo visual pivoting.

Image Captioning and VSE Our method draws inspiration from captioning and cross-modal retrieval. Recent progress in captioning aims at using reinforcement learning to improve diversity [\(Dai et al., 2017\)](#) or maximize metric [\(Rennie et al., 2017\)](#). We use a vanilla MLE objective. For learning VSE, we leverage the contrastive loss [\(Kiros et al., 2014\)](#) from cross-modal retrieval, which is shown more robust than maximizing canonical correlation among modalities as in [\(Andrew et al., 2013; Huang et al., 2018\)](#). For encoding image and text, we generalize the cross-modality attention from SCAN [\(Lee et al., 2018\)](#) to the multilingual scenario for learning multilingual VSE spaces [\(Gella et al., 2017; Huang et al., 2019a\)](#).

6 Conclusion

We have presented a novel framework for unsupervised multimodal MT with pseudo visual pivoting. To associate language latent spaces, our model use the visual space as the approximate pivot and learns to align multilingual VSE spaces. Additionally, our model synthesizes image-pivoted pseudo sentences in two languages and pairs them to translate for reconstruction without parallel corpora. The experimental results on Multi30K show that the proposed model generalizes well and yields state-of-the-art performance.

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