

WEAKLY-SUPERVISED VISUALBERT: PRE-TRAINING WITHOUT PARALLEL IMAGES AND CAPTIONS

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ABSTRACT

Pre-trained contextual vision-and-language (V&L) models have brought impressive performance improvement on various benchmarks. However, the paired text-image data required for pre-training are hard to collect and scale up. We investigate if a strong V&L representation model can be learned without text-image pairs. We propose Weakly-supervised VisualBERT with the key idea of conducting “mask-and-predict” pre-training on language-only and image-only corpora. Additionally, we introduce the object tags detected by an object recognition model as anchor points to bridge two modalities. Evaluation on four V&L benchmarks shows that Weakly-supervised VisualBERT achieves similar performance with a model pre-trained with paired data. Besides, pre-training on more image-only data further improves a model that already has access to aligned data, suggesting the possibility of utilizing billions of raw images available to enhance V&L models.

1 INTRODUCTION

Pre-trained contextual vision-and-language (V&L) models such as ViLBERT (Jiasen et al., 2019), LXMR^T (Tan & Bansal, 2019), VisualBERT (Li et al., 2019), VL-BERT (Su et al., 2019), and UNITER (Chen et al., 2020b) have greatly improved performances of various V&L tasks. However, different from contextualized language models, such as BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019b), which are trained on unannotated text corpora, V&L models require a massive amount of aligned text-image pairs for “mask-and-predict” pre-training. Such aligned data are costly to collect and hard to scale up as they require either manual annotations (Chen et al., 2015; Krishna et al., 2017), or extensive screening. For example, Sharma et al. (2018) reports that from 5 billion images gathered over the Internet, only 3 million have paired high-quality captions that are eventually included in the Conceptual Caption dataset. Therefore, commonly used aligned datasets seldom exceed 10 million data points.

In this paper, we explore *learning V&L representations from weakly supervised data – the non-parallel image and text corpus*. This research direction aligns with the theme of self-supervision that moves from learning from heavily annotated data to unannotated or weakly-annotated data. Indeed, it is much easier to collect unpaired raw text and raw images. For instance, Liu et al. (2019b) collected over 160GB of text data; YFCC100M (Thomee et al., 2016) contains 100M images; JFT300M (Sun et al., 2017) contains 300M images.

Our endeavor starts from the saying, *an image is worth a thousand words*. If we treat the image regions as visual tokens (Dosovitskiy et al., 2020), then contextualized V&L models share a similar goal with multi-lingual contextualized representation models as they both learn shared representations across different modalities. Though a multi-lingual language model pre-trained on non-parallel corpora such as mBERT (Devlin et al., 2019) cannot align or translate languages out-of-the-box, its representation spaces for different languages can be easily aligned after pre-training (Conneau et al., 2020). This property suggests the existence of universal latent symmetries in the unaligned contextual embedding spaces and is believed to contribute to mBERT’s cross-lingual transfer ability.

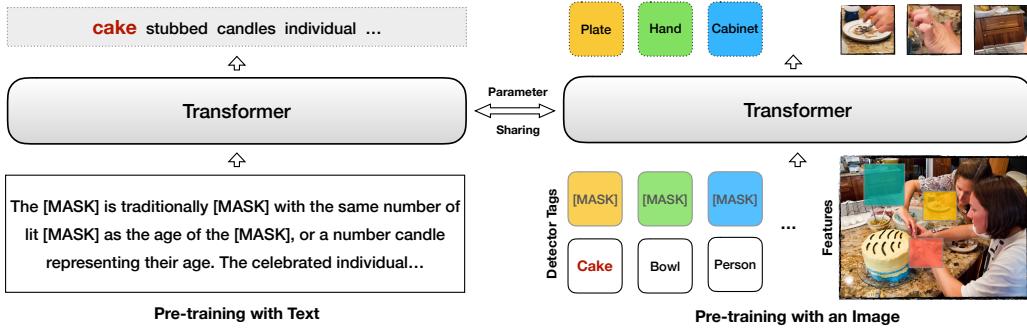


Figure 1: An illustration of pre-training W-VisualBERT. Given text, the model is trained to predict masked words; given an image, the model is trained to predict masked regions and detector tags. The semantic class “cake” appears in both the language modality and the visual modality and is linked through the detector tags. Note that we do not require a text segment with the word *cake* to appear together with the image. Rather, we assume that as long as the text corpora are general enough, the word *cake* will appear in the textual modality eventually. The model can learn V&L representations that benefit downstream tasks.

Thus we hypothesize that strong V&L representations on natural language and visual tokens can be similarly learned by “mask-and-predict” pre-training on unaligned language and vision data.

We present Weakly-supervised VisualBERT (W-VisualBERT)¹, a contextual V&L representation model pre-trained on unpaired text and images (see an illustration in Figure 1). The model takes the form of a single Transformer that can accept inputs from both modalities. During each step of pre-training, unlike previous models that observe a batch of text-image pairs, W-VisualBERT observes either a batch of text segments or a batch of images. When provided with text, part of the text is masked and the model is trained to predict the masked words; when provided with an image, part of the image regions are masked and the model is trained to predict properties of the masked regions.

To further encourage cross-modal fusion, we leverage the tags from the pre-trained object detector as “anchor points” (Li et al., 2020b). For every object, we append its detected tag as words to the visual input. For instance, for the image in Figure 1, the object *cake* is detected and we append the label “*cake*” to the visual input. The model can observe “*cake*” appears naturally in both vision and text. The mask-and-predict objective is also applied to the tags. The direct typing of image regions and words corresponding to “*cake*” can be learned and serves as a starting point for further alignment. The function of the detector tags resembles that of the “overlapping vocabulary” in multi-lingual language models, i.e., identical strings that appear in different languages with the same meaning such as DNA or Paris. Just as the “overlapping vocabulary” improves cross-lingual transfer (Wu & Dredze, 2019), we argue the detector tags can improve cross-modal grounding.

We pre-train W-VisualBERT on a large-scale dataset consisting of raw images and texts and conduct evaluation by fine-tuning on four V&L benchmarks including VQA (Goyal et al., 2017), NLVR² (Suhr et al., 2019), Flickr30K Image Retrieval (Plummer et al., 2015), and RefCOCO+ (Yu et al., 2016). Results show that W-VisualBERT achieves similar performance as models with access to text-image pairs. Further, supervised models are bounded by the availability of aligned text-image data but W-VisualBERT is not. We show that it is possible to use more unaligned image data to improve a Supervised VisualBERT, which already has access to millions of aligned data.

2 RELATED WORK

Pre-trained V&L Transformers Various V&L models that are pre-trained with a “mask-and-predict” objective on aligned text-image data have been proposed (Jiasen et al., 2019; Tan & Bansal,

¹We use the name W-VisualBERT as the model is similar to VisualBERT (Li et al., 2019). Our design is also influenced by LXMERT (Tan & Bansal, 2019) and Oscar (Li et al., 2020b). “Weakly-supervised” in our context means that pre-training is conducted with unpaired data. We use the term “supervised” to refer to models pre-trained with paired text and images.

2019; Li et al., 2019; Su et al., 2019; Chen et al., 2020b; Li et al., 2020a; Zhou et al., 2020; Yu et al., 2020; Gan et al., 2020). Two kinds of designs have been proposed. Two-stream models (Jiasen et al., 2019; Tan & Bansal, 2019; Yu et al., 2020) utilize separate Transformers (Vaswani et al., 2017) for each modality, and a cross-modality module is adopted. On the other hand, single-stream models (Li et al., 2019; Su et al., 2019; Chen et al., 2020b) directly input the text and visual embeddings into one single Transformer. They have been widely used by downstream tasks such as the Hateful Memes Challenge (Kiela et al., 2020). Probing tasks (Cao et al., 2020) confirm that they capture useful V&L information after pre-training. Two studies also try to incorporate “tag” information during pre-training. Oscar (Li et al., 2020b) adds detected tags as additional signals during pre-training with aligned data. We, however, do so for pre-training without aligned data and show that the tags serve a more important role in weakly-supervised pre-training (see Section 4.4). VIVO (Hu et al., 2020) targets novel object captioning. They use manually annotated image-tag data for pre-training and image-caption data for fine-tuning. We do not use manually annotated data and the tags are noisily generated by a pre-trained object detector.

Self-supervised Representation Learning Self-supervised representation learning refers to creating supervision objectives from natural data, often by corrupting the input and training the model to reconstruct the input (Kolesnikov et al., 2019). Self-supervised training on language (Peters et al., 2018; Devlin et al., 2019) such as BERT has been proven useful for various NLP tasks (Liu et al., 2019a). On the other hand, self-supervised visual representation learning has been centered around learning low-level visual features, in hope of enhancing the backbone CNN (Doersch et al., 2015; Pathak et al., 2016; Noroozi & Favaro, 2016). We conduct self-supervised representation learning on both language-only and image-only data. Notably, our contextual visual representation is built on top of a pre-trained object detector, operating at a level above local visual features.

Multi-lingual Language Model This work is inspired by multi-lingual representations trained without parallel corpora (Devlin et al., 2019; Lample & Conneau, 2019). They are effective for cross-lingual transfer, which involves learning a model in one language and applying it to another with no additional training. Studies (Wu & Dredze, 2019; Conneau et al., 2020) have confirmed several design choices that facilitate such transfer, e.g. shared parameters and overlapping vocabularies across languages, and we make similar design choices in W-VisualBERT (Section 3.2). More generally, we argue that multi-lingual representations bear resemblance to multi-modal representations as both seek to encode the alignment between two domains (Chen et al., 2020a).

Unsupervised and Weakly-supervised Grounding Learning Several works have explored learning grounding with weak or no supervision in the context of phrase localization (Kazemzadeh et al., 2014; Plummer et al., 2015). Various supervision signals have been explored to aid phrase-level groundings, such as self-supervision (Rohrbach et al., 2016), linguistic structures (Xiao et al., 2017), and external knowledge (Chen et al., 2018). These approaches are mostly designed specifically for the end task of phrase localization and prohibited from being readily used as general V&L representations. We do not seek to build a readily grounded model that can directly perform a certain V&L task. Rather, W-VisualBERT is expected to easily acquire grounding through fine-tuning.

3 APPROACH

We first introduce how a typical V&L model is pre-trained with aligned data. Then we introduce how the proposed Weakly-supervised VisualBERT is pre-trained with unaligned data and how the detector tags help to learn grounding.

3.1 BACKGROUND

We take Supervised VisualBERT (S-VisualBERT) as an example, which will also be used as a baseline in the experiments. S-VisualBERT is modified from the original VisualBERT (Li et al., 2019) and augmented with the visual objectives from LXMERT (Tan & Bansal, 2019) and the detector tags as in W-VisualBERT (we will discuss the detector tags in detail in Section 3.2).

Every input to S-VisualBERT contains a text segment T and an image I . The text and the image are first mapped into embedding vectors respectively². Text embeddings \mathbf{T} is a matrix in which each column vector represents the embedding of a subword in the text sequence, i.e. $\mathbf{T} = [\mathbf{w}_{1:n}]$. Following BERT, each subword embedding \mathbf{w}_i is the sum of its token embedding, position embedding, and segment embedding. Image embeddings \mathbf{I} include both the image region embeddings $\mathbf{r}_{1:m}$ and the detector tag embeddings³ $\mathbf{d}_{1:l}$. The image region embeddings are a set of image region embedding $\mathbf{r}_{1:m}$, detected by a pre-trained object detector such as Faster R-CNN (Ren et al., 2015). Each region embedding \mathbf{r}_i is the sum of a visual features vector from the detector and a spatial box coordinate embedding (Tan & Bansal, 2019). The text and visual embeddings are then passed through a Transformer to built contextual representations.

The model is pre-trained with a mask-and-predict objective. Given a text-image pair $[T, I]$ from the aligned dataset D , we randomly mask out some words w_i , some regions r_j , and some tags d_k to obtain masked $[\tilde{T}, \tilde{I}]$. The model is trained to predict the masked words, the proprieties of the masked regions, and the masked tags given $[\tilde{T}, \tilde{I}]$. The pre-training objective can be summarized as

$$\min_{\theta} \sum_{[T, I] \in D} L(f_{\theta}([\tilde{T}; \tilde{I}]), [T, I]). \quad (1)$$

f_{θ} represents the embedding layer and the multi-layer Transformer. L is the reconstruction loss consisting of the masked language model loss L_T as in BERT and the image reconstruction loss L_I . L_I includes the two visual sub-tasks in LXMERT: 1) region feature regression, which forces the model to regress to the visual vector with the L2 loss, and 2) noisy label classification, which predicts the detected labels of masked objects with the cross-entropy loss. A tag reconstruction loss is also included (more details in Section 3.2). Besides, the “text-image match” objective is used, where we provide the model with a mismatched text-image pair with a 0.5 probability and the model needs to predict whether the image and text match. After the model is pre-trained, it can be fine-tuned on downstream tasks by introducing a small neural network on top of the Transformer, similar to how BERT is fine-tuned for NLP tasks.

3.2 WEAKLY-SUPERVISED VISUALBERT

W-VisualBERT differs from the previous models in two aspects, pre-training with unaligned data and detector tags, which we illustrate in the following.

Weakly-supervised Pre-training with Unaligned Data W-VisualBERT assumes access to a text corpus D_T and an image corpus D_I for pre-training. During every pre-training step, we randomly sample either a batch of text from D_T or a batch of images from D_I . No alignments between text and images are provided to the model. When pre-training with a text segment T , the model is trained to reconstruct T given the masked \tilde{T} .⁴ When pre-training with an image I , the model is trained to reconstruct I given the masked \tilde{I} . A single Transformer is used throughout two modalities (i.e. θ shared across modalities). The pre-training objective can be summarized as:

$$\min_{\theta} \sum_{T \in D_T} L_T(f_{\theta}(\tilde{T}), T) + \sum_{I \in D_I} L_I(f_{\theta}(\tilde{I}), I). \quad (2)$$

After pre-training, the model is fine-tuned on downstream tasks just as the supervised model, with input being a text-image pair.

Detector Tags We introduce detector tags as anchor points between two modalities. When modeling an image I , for each region detected, we append the tag outputted by the object detector to

²For simplicity, we assume the dimensions of all the embedding vectors introduced below are the same. In practice, projection layers may be added to ensure that the dimensions match.

³The detector tags are labels outputted by a pre-trained object detector. The tag embeddings take the same design as in the Weakly-supervised VisualBERT and we introduce them in detail in Section 3.2.

⁴We also adopt the next sentence prediction task in BERT when long documents are available, which trains the model to predict whether two text segments are coherent.

the input. The detector is pre-trained on a general object detection dataset (Krishna et al., 2017; Anderson et al., 2018) and the tags are essentially a bag of words that provide some noisy grounding signals to the model.

We process the detector tags as a subword sequence $d_{1:l}$ with spatial coordinates.⁵ Every tag subword is embedded as the sum of its token embedding and a spatial coordinate embedding. The token embedding is the same as the token embedding used in text modeling, while the spatial coordinate embedding is the same as the coordinate embedding of the corresponding region⁶. With the detector tags added, the image I is modeled as $I = [r_{1:m}; d_{1:l}]$. The tags are added during both pre-training and fine-tuning. Further, during pre-training, certain tag subwords are masked and the model is pre-trained to predict the masked tags. They are predicted just as masked subwords are predicted in text modeling. I.e. the prediction softmax layer is shared between the tag and text subwords. This tag reconstruction loss term is included in the image reconstruction loss L_I .

The parameters involved in modeling tags include the token embedding, coordinate embedding, and the subword softmax embedding. They span across modalities and encourage the model to project text, visual, and tag representations into the same space (see Section 4.5 for an example). This resembles the design in multi-lingual language models, which use shared BPE embeddings and softmax weights across languages (Devlin et al., 2019; Wu & Dredze, 2019).

4 EXPERIMENT

We conduct experiments on four V&L downstream tasks to study the effect of 1) pre-training without aligned data, 2) additional unaligned image data, and 3) the detector tags.

4.1 SETUP

Following previous works, we conduct evaluations by fine-tuning on four downstream tasks: (1) Visual Question Answering (VQA 2.0) (Goyal et al., 2017), (2) Natural Language for Visual Reasoning (NLVR²) (Suhr et al., 2019), (3) Image Retrieval (Flickr 30K), and (4) Referring Expression (RefCOCO+) (Yu et al., 2016). We use the Adam optimizer (Kingma & Ba, 2015) with a linear-decayed learning-rate schedule (Devlin et al., 2019). For each task, we mostly follow the recommended setting in previous works and did not conduct extensive hyper-parameter searches.

VQA Given an image and a question, the task is to correctly answer the question. We use the VQA 2.0 and fine-tune with a binary cross-entropy loss on the soft target scores. The model is trained with a batch size of 32 and a peak learning rate of 5×10^{-5} over 8 epochs.

NLVR² NLVR² involves determining whether a natural language caption is true about a pair of images. While better fine-tuning strategy exists (Chen et al., 2020b), we follow LXMERT to pair the caption with each image, concatenate the “[CLS]” representation of the two pairs, and then build a classifier on top. We also find it beneficial to conduct a moderate amount of “task-specific pre-training” where we use the data from the dataset to conduct mask-and-predict pre-training as suggested by VisualBERT. We conduct task-specific pre-training for at most 5 epochs and fine-tune from the epoch with the best validation LM loss. Fine-tuning is conducted for 8 epochs with a batch size of 32 and a peak learning rate of 2×10^{-5} .

Flickr30K The task of image retrieval involves finding the corresponding image from a collection of images given a caption. This task directly benefits from pre-training on text-image pairs and the “text-image match” objective. We include this task to test if the Weakly-supervised VisualBERT, pre-trained without such explicit signals, can still learn the alignments of images and text well. During fine-tuning, we follow UNITER and sample two negative text-image pairs along with a positive sample. For computational reasons, we train for 5K steps with a batch size of 8 and a peak learning rate of 5×10^{-5} .

⁵Each detector tag corresponds to a region. But a tag could be split into multiple subwords so the total length of the tag subword sequence l is larger than the number of regions m .

⁶This design differs from that of Oscar (Li et al., 2020b). Oscar does not add the spatial coordinate embeddings to tags to encourage fusion of tag and visual representations.

RefCOCO+ The referring expression task involves locating an image region given a natural language phrase. We follow ViLBERT and conduct evaluation on the RefCOCO+ dataset. We use the bounding box proposals provided by Yu et al. (2018). For each box proposal, the model is trained to classify if it matches the reference phrase or not. A proposal box is considered as matched if it has an IoU with the gold box larger than 0.5. We train for 12 epochs with a batch size of 32 and a peak learning rate of 5×10^{-5} .

4.2 CAN STRONG CONTEXTUAL V&L REPRESENTATION BE LEARNED WITH UNALIGNED DATA?

4.2.1 SETUP

W-VisualBERT Our model can be trained on any individually collected images and text. However, as the domain and quality of text and images may affect the model performance, we choose Conceptual Captions (CC) (Sharma et al., 2018) as the source of images and text for a fair comparison with a baseline trained with aligned data. CC contains 3M paired captions and images but we do not use CC as an aligned dataset. Rather, we shuffle the text and images and at each training step, we sample either a batch of images or a batch of texts. Following VL-BERT, we find it beneficial to include BookCorpus (Zhu et al., 2015), a general-domain text corpus, during pre-training. In sum, W-VisualBERT is trained on 3M images from CC, 3M captions from CC, and 2.5M text segments from BookCorpus⁷.

W-VisualBERT_R One potential caveat of training W-VisualBERT on CC is that the images and captions are originally aligned and semantically highly related. We introduce W-VisualBERT_R that is trained under a rigorous and realistic setting: pre-training images and texts are independently collected and thus not in the exactly same semantic space. More specifically, we use 3M images from CC and 1M captions from SBU captions (Ordonez et al., 2011). To compensate for the different amounts of text between CC and SBU, we upsample the BookCorpus so that the amount of text data used by W-VisualBERT_R is roughly the same as W-VisualBERT.

S-VisualBERT We introduce a Supervised VisualBERT (S-VisualBERT) with the same neural architecture as W-VisualBERT. The model is trained with aligned data as introduced in Section 3.1. It differs from the original VisualBERT (Li et al., 2019) with the pre-training objective as in Eq. (1) and the added detector tags. S-VisualBERT is pre-trained on 3M caption-image pairs from CC and 2.5M text segments from BookCorpus.

Model Training For all the VisualBERT variants introduced in the paper, we initialize them from BERT_{base} and pre-train for 10 epochs on their respective pre-training dataset with a batch size of 144. All models can be trained within 3 days on 4 V100s each with 16GB memory. Adam is used as the optimizer with a linear-decay schedule and a peak learning rate at 6×10^{-5} . We use a Faster R-CNN pre-trained on the Visual Genome dataset to extract region features (Anderson et al., 2018). For each image, we keep 36 objects with the highest detection confidence.

Compared Models Additionally, we list the performance of a **Base** VisualBERT that is initialized from BERT and does not undergo further pre-training. Previously reported supervised models that are trained on CC are also listed, including ViLBERT, VL-BERT, and UNITER. For UNITER, we include the version that is trained only on CC (UNITER_{cc}). Though their network architectures differ from ours and cannot be directly compared, they jointly paint the picture of the performance we should expect by pre-training on CC. SOTA results before the emergence of BERT are also listed (Pre-BERT) (Gao et al., 2019; Suhr et al., 2019; Lee et al., 2018; Yu et al., 2018).

⁷Our version of BookCorpus contains around 5M text segments with 64 words per segment. For computational reasons, we downsample the dataset such that during each epoch, the model observes only half of the text segments from BookCorpus. This downsampling is also done for the other VisualBERT variants.

| Model | Paired | | Unpaired | | VQA | | NLVR ² | | Flickr30K | | | RefCOCO+ | | |
|---------------------------|--------|------|----------|------|----------|-------|-------------------|-------|-----------|-------|-------|----------|-------|--|
| | Image | Text | Image | Text | Test-Dev | Dev | Test-P | R@1 | R@5 | R@10 | Dev | TestA | TestB | |
| Pre-BERT | - | - | - | - | 70.22 | 54.1 | 54.8 | 48.60 | 77.70 | 85.20 | 65.33 | 71.62 | 56.02 | |
| ViLBERT | 3M | 0 | 0 | - | 70.55 | - | - | 58.78 | 85.60 | 91.42 | 72.34 | 78.52 | 62.61 | |
| VL-BERT | 3M | 0 | ~50M | - | 71.16 | - | - | - | - | - | 71.60 | 77.72 | 60.99 | |
| UNITER _{cc} | 3M | 0 | 0 | - | 71.22 | - | - | - | - | - | 72.49 | 79.36 | 63.65 | |
| Base | 0 | 0 | 0 | - | 69.26 | 68.40 | 68.65 | 42.86 | 73.62 | 83.28 | 70.66 | 77.06 | 61.43 | |
| S-VisualBERT | 3M | 0 | 2.5M | - | 70.90 | 72.73 | 73.21 | 61.24 | 86.16 | 91.92 | 73.81 | 79.52 | 64.80 | |
| W-VisualBERT | 0 | 3M | 5.5M | - | 70.82 | 71.51 | 70.93 | 54.92 | 82.84 | 89.72 | 72.45 | 79.08 | 64.64 | |
| W-VisualBERT _R | 0 | 3M | 6.0M | - | 70.70 | 71.97 | 72.11 | 56.12 | 82.82 | 90.12 | 73.05 | 79.48 | 64.19 | |

Table 1: Evaluation results on four V&L benchmarks. Our weakly-supervised model trained with unaligned data (W-VisualBERT) achieves close performance with a supervised model trained with aligned data (S-VisualBERT) while rivals with several supervised models such as ViLBERT on most metrics. W-VisualBERT_R trained with images and texts from independent sources performs similarly, showing the applicability of our pre-training method to general unaligned data.

4.2.2 RESULTS

Table 1 summarizes the results. For each model, we list the type and amount of data used during pre-training⁸. W-VisualBERT outperforms the Base model significantly on all benchmarks, while only lagging behind S-VisualBERT slightly on VQA, NLVR², and RefCOCO+. W-VisualBERT even surpasses or rivals with strong supervised models (e.g., ViLBERT on VQA and RefCOCO+, VL-BERT on RefCOCO+, and UNITER_{cc} on RefCOCO+). This indicates that strong V&L representations are indeed learned through weakly-supervised pre-training.

We further confirm the efficacy of our method in the realistic setting: W-VisualBERT_R is pre-trained with images and text collected independently. Yet it achieves similar performance as W-VisualBERT, with the latter higher on VQA, and the former higher on the other three tasks. This suggests the applicability of weakly-supervised pre-training to many large-scale language-only and text-only datasets that are independently collected (Trinh & Le, 2018; Sun et al., 2017).

We notice that on Flickr30K, the difference between W-VisualBERT and S-VisualBERT is more evident. The task focuses on identifying if an image and a text segment are coherent. S-VisualBERT is provided with explicit signals for such a task with the “text-image match” objective during pre-training (Section 3.1). While W-VisualBERT is not provided with such explicit signals, it still learns better than the Base model. Further, if we were to remove the explicit signal (i.e. the “text-image match” objective) when pre-training on aligned data, S-VisualBERT achieves only 57.98 on R@1, much closer to the weakly-supervised model.

4.3 CAN PRE-TRAINING ON MORE UNALIGNED DATA IMPROVE A MODEL TRAINED WITH ALIGNED DATA?

4.3.1 SETUP

One key advantage of weakly-supervised pre-training is the possibility of utilizing the vast amount of unaligned data collected from the internet, shattering the limitation of aligned pre-training. It is interesting to see if pre-training on additional unaligned images can improve a model that already has access to millions of aligned data. In this experiment, we focus on unaligned visual data as all models are initialized from BERT that is already trained on a massive amount of unaligned text data.

H-VisualBERT₊ We introduce a hybrid model that is trained on both aligned and unaligned data. We use the 3M aligned data from Conceptual Captions (CC) and an additional unaligned 1.7M images from Open Images (OI) (Kuznetsova et al., 2020). When a training sample comes from CC,

⁸Most models are initialized from BERT and we do not count the data used during BERT pre-training. VL-BERT uses both BookCorpus and Wikipedia during V&L pre-training. We estimate that the two corpora roughly have 50M segments with 64 words per segment but with a different pre-processing style (e.g. longer segments), the number of segments may change.

we provide the model with a text-image pair, and when the training sample comes from OI, we provide only the image. We do not use any manually annotated visual labels provided in OI.

W-VisualBERT₊ For reference, we include a model that is trained as the previous weakly-supervised model but with the additional images from OI.

| Model | Paired | | Unpaired | | VQA | | NLVR ² | | Flickr30K | | | RefCOCO+ | | |
|---------------------------|--------|------|----------|----------|-------|--------|-------------------|-------|-----------|-------|-------|----------|-------|-------|
| | Image | Text | Test-Dev | Test-Std | Dev | Test-P | R@1 | R@5 | R@10 | Dev | TestA | TestB | Dev | TestA |
| W-VisualBERT | 0 | 3M | 5.5M | - | 70.82 | - | 71.51 | 70.93 | 54.92 | 82.84 | 89.72 | 72.45 | 79.08 | 64.64 |
| W-VisualBERT ₊ | 0 | 4.7M | 5.5M | - | 70.92 | 71.05 | 72.47 | 71.94 | 56.76 | 83.04 | 90.30 | 73.17 | 79.94 | 64.23 |
| S-VisualBERT | 3M | 0 | 2.5M | - | 70.90 | - | 72.73 | 73.21 | 61.24 | 86.16 | 91.92 | 73.81 | 79.52 | 64.80 |
| H-VisualBERT ₊ | 3M | 1.7M | 2.5M | - | 71.05 | 71.23 | 73.80 | 74.82 | 60.28 | 86.30 | 92.06 | 74.01 | 80.18 | 64.89 |

Table 2: Pre-training on more images improves both the weakly-supervised (W-VisualBERT₊) and supervised model (H-VisualBERT₊). This suggests the possibility of utilizing much larger unaligned datasets to enhance current V&L models.

4.3.2 RESULT

H-VisualBERT₊ outperforms S-VisualBERT (Table 2), confirming our hypothesis that more unaligned data can improve a model that already has access to millions of paired data. Further, by adding more data to the weakly-supervised model, the gap between weakly-supervised and supervised pre-training shrinks drastically. Compared to S-VisualBERT, W-VisualBERT₊ ranks closely on VQA, NLVR2, and RefCOCO+.

4.4 HOW DO THE DETECTOR TAGS CONTRIBUTE TO LEARNING V&L REPRESENTATIONS?

4.4.1 SETUP

W-VisualBERT_{NT} In Section 3.2, we introduce the detector tags to facilitate learning cross-modal alignments. In this experiment, we investigate without these tags, whether weakly-supervised pre-training can still benefit downstream tasks. The question is inspired by the observation in multi-lingual language models that the shared vocabulary across languages (i.e. anchor points) is not necessary to acquire cross-lingual transfer ability (Conneau et al., 2020). We introduce W-VisualBERT_{NT}, which observes no tags and only dense region features for image embeddings (Section 3.2) during both pre-training and fine-tuning. For comparison, a base model without tags that is initialized from BERT and does undergo further pre-training is also introduced (Base_{NT}).

S-VisualBERT_{NT} To study the effect of the detector tags when aligned data are present, we introduce S-VisualBERT_{NT} which is trained on aligned data but observes no tags for image embeddings.

| Model | VQA | | NLVR ² | | Flickr30K | | | RefCOCO+ | | |
|----------------------------|----------|-------|-------------------|-------|-----------|-------|-------|----------|-------|--|
| | Test-Dev | Dev | Test-P | R@1 | R@5 | R@10 | Dev | TestA | TestB | |
| Base _{NT} | 69.06 | 51.98 | 52.73 | 48.40 | 78.20 | 87.18 | 70.15 | 76.91 | 61.72 | |
| S-VisualBERT | 70.90 | 72.73 | 73.21 | 61.24 | 86.16 | 91.92 | 73.81 | 79.52 | 64.80 | |
| S-VisualBERT _{NT} | 70.49 | 72.56 | 73.53 | 60.26 | 85.58 | 91.64 | 72.70 | 77.93 | 62.99 | |
| W-VisualBERT | 70.82 | 71.51 | 70.93 | 54.92 | 82.84 | 89.72 | 72.45 | 79.08 | 64.64 | |
| W-VisualBERT _{NT} | 69.87 | 67.90 | 68.92 | 50.56 | 80.22 | 88.32 | 71.94 | 77.79 | 62.38 | |

Table 3: Effect of the detector tags on model performance. Weakly-supervised pre-training without tags still benefits downstream tasks. (W-VisualBERT_{NT} versus Base_{NT}). Detector tags have a bigger impact in the weakly-supervised setting than in the supervised setting.

4.4.2 RESULT

We confirm that weakly-supervised pre-training without tags benefits downstream tasks (Table 3). W-VisualBERT_{NT} outperforms Base_{NT} on all metrics with a large margin. Further, while the detector tags are beneficial for both supervised and weakly-supervised pre-training, the performance

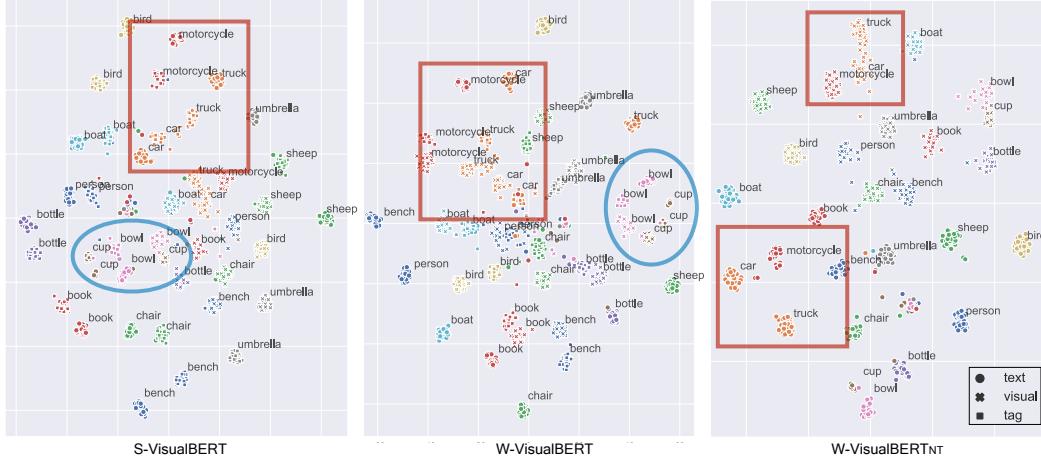


Figure 2: Visualization of the contextual representations of S-VisualBERT, W-VisualBERT, and W-VisualBERT_{NT}. The detector tags help fuse text and visual representations for S-VisualBERT and W-VisualBERT (see the blue circles). Common structures emerge in the text and visual representation spaces even though they are not aligned in W-VisualBERT_{NT} (see the red rectangles).

improvement is more evident for the latter. For example, performance difference on VQA between W-VisualBERT and W-VisualBERT_{NT} is 0.95 (70.82 versus 69.87) while the difference between S-VisualBERT and S-VisualBERT_{NT} is 0.41 (70.90 versus 70.49). The results are not surprising. When paired data are present, object tags serve as additional signals (Li et al., 2020b) while in weakly-supervised pre-training, they serve as the only source from which grounding is learned.

4.5 VISUALIZATION OF THE DETECTOR TAGS

We visualize the contextual representation space of three different models: S-VisualBERT, W-VisualBERT, and W-VisualBERT_{NT}. For each of the most frequent 15 object classes in the COCO dataset (Chen et al., 2015), we randomly sample at most 50 instances where both the caption contains the label word and the pre-trained Faster R-CNN successfully detects the object. We feed the instances through each model and take the last layer contextual representation of the words, the objects, and the tags (when available) and visualize them with t-SNE (Maaten & Hinton, 2008).

Though trained without aligned data, W-VisualBERT can group text, tag, and visual representations together by their semantic classes. For instance, representations for the semantic class “bowl” and “cup” are grouped in a small region (see the blue circle in the middle figure). This also holds for “bottle”, “book”, and “umbrella”. Similar phenomena can also be observed in S-VisualBERT, suggesting that the two models learn to project image, text, and tag representation in the same space.

However, W-VisualBERT_{NT}, lacking any signal to align the two semantic spaces, does not show signs of such behaviour. In W-VisualBERT_{NT}, text and visual representations are almost completely separated. While W-VisualBERT_{NT} does not group text and visual representation together naturally, some (however simple) structures in both modalities emerge. For instance, representations for “car”, “truck”, “motorcycle” are close to each other, in both the text and visual modality (see the red rectangles in the figure on the right). This also holds for the other two models and resembles what is observed in Li et al. (2020b) and Ilharco et al. (2020).

5 CONCLUSION

In this paper, we introduced Weakly-supervised VisualBERT pre-trained on unaligned data. We conduct mask-and-predict pre-training on text data and visual data respectively and the detector tags are used as anchor points bridging the two modalities. Experiments show that weakly-supervised pre-training can achieve performance similar to supervised pre-training. Combining aligned and unaligned data can further improve the model. Our experiments are conducted under the assumption

that the unaligned text and images are generally in the same domain. We leave discussions on whether such benefit exists for unaligned data from unrelated domains to future work.

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