Unified Visual-Semantic Embeddings:
Bridging Vision and Language with Structured Meaning Representations

Hao Wu[1,3,4,6,*,†], Jiayuan Mao[5,6,*,†], Yufeng Zhang[2,6,†], Yuning Jiang[6], Lei Li[6], Weiwei Sun[1,3,4], Wei-Ying Ma[6]

[1]School of Computer Science, [2]School of Economics, Fudan University
[3]Systems and Shanghai Key Laboratory of Data Science, Fudan University
[4]Shanghai Insitute of Intelligent Electroics & Systems
[5]ITCS, Institute for Interdisciplinary Information Sciences, Tsinghua University, [6]Bytedance AI Lab

{wuhao5688, zhangyf, wwsun}@fudan.edu.cn, mjy14@mails.tsinghua.edu.cn,
{jiangyuning, lileilab, maweiying}@bytedance.com

Abstract

We propose the Unified Visual-Semantic Embeddings (Unified VSE) for learning a joint space of visual representation and textual semantics. The model unifies the embeddings of concepts at different levels: objects, attributes, relations, and full scenes. We view the sentential semantics as a combination of different semantic components such as objects and relations; their embeddings are aligned with different image regions. A contrastive learning approach is proposed for the effective learning of this fine-grained alignment from only image-caption pairs. We also present a simple yet effective approach that enforces the coverage of caption embeddings on the semantic components that appear in the sentence. We demonstrate that the Unified VSE outperforms baselines on cross-modal retrieval tasks; the enforcement of the semantic coverage improves the model's robustness in defending text-domain adversarial attacks. Moreover, our model empowers the use of visual cues to accurately resolve word dependencies in novel sentences.

1. Introduction

We study the problem of establishing accurate and generalizable alignments between visual concepts and textual semantics efficiently, based upon rich but few, paired but noisy, or even biased visual-textual inputs (*e.g.*, image-caption pairs). Consider the image-caption pair A shown in Fig. 1: *"A white clock on the wall is above a wooden table"*. The alignments are formed at multiple levels: This short sentence can be decomposed into a rich set of semantic components [3]: objects (`clock`, `table` and `wall`) and relations (clock `above` table, and clock `on` wall). These components are linked with different parts of the scene.

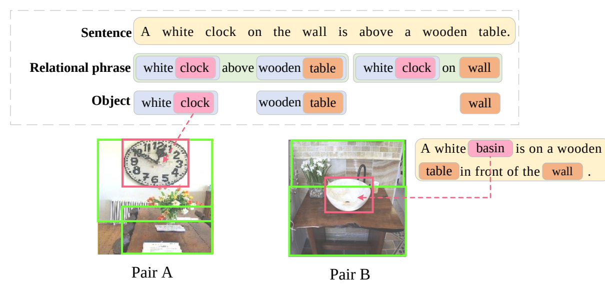


Figure 1. Two examplar image-caption pairs. Humans are able to establish accurate and generalizable alignments between vision and language, at different levels: objects, relations and full sentences. Pair A and B form a pair of contrastive example for the concepts `clock` and `basin`.

This motives our work to introduce *Unified Visual-Semantic Embeddings* (*Unified VSE* for short) Shown in Fig. 2, Unified VSE bridges visual and textual representation in a joint embedding space that unifies the embeddings for objects (noun phrases vs. visual objects), attributes (prenominal phrases vs. visual attributes), relations (verbs or prepositional phrases vs. visual relations) and scenes (sentence vs. image).

There are two major challenges in establishing such a factorized alignment. First, the link between the textual description of an object and the corresponding image region is ambiguous: A visual scene consists of multiple objects, and thus it is unclear to the learner which object should be aligned with the description. Second, it could be problematic to directly learn a neural network that combines various semantic components in a caption and form an encoding for the full sentence, with the training objective to maximize the

*indicates equal contribution.
†Work was done when HW, JM and YZ were intern researchers at the Bytedance AI Lab.

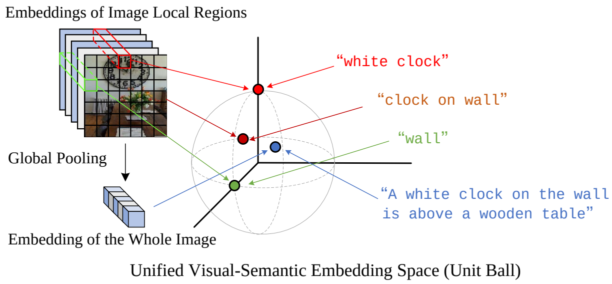


Figure 2. We build a visual-semantic embedding space, which unifies the embeddings for objects, attributes, relations and full scenes.

cross-modal retrieval performance in the training set (*e.g.*, in [49, 30, 40]). As reported by [40], because of the inevitable bias in the dataset (*e.g.*, two objects may co-occur with each other in most cases, see the table and the wall in Fig. 1 as an example), the learned sentence encoders usually pay attention to only part of the sentence. As a result, they are vulnerable to text-domain adversarial attacks: Adversarial captions constructed from original captions by adding small perturbations (*e.g.*, by changing `wall` to be `shelf`) can easily fool the model [40, 39].

We resolve the aforementioned challenges by a natural combination of two ideas: *cross-situational learning* and the enforcement of *semantic coverage* that regularizes the encoder. Cross-situational learning, or learning from contrastive examples [12], uses contrastive examples in the dataset to resolve the referential ambiguity of objects: Looking at both Pair A and B in Fig. 1, we know that `Clock` should refer to an object that occurs only in scene A but not B. Meanwhile, to alleviate the biases of datasets such as object co-occurrence, we present an effective approach that enforces the *semantic converage*: The meaning of a caption is a composition of all semantic components in the sentence [3]. Reflectively, the embedding of a caption should have a coverage of all semantic components, while changing any of them should affect the global caption embedding.

Conceptually and empirically, Unified VSE makes the following three contributions.

First, the explicit factorization of the visual-semantic embedding space enables us to build a fine-grained correspondence between visual and textual data, which further benefits a set of downstream visual-textual tasks. We achieve this through a contrastive example mining technique that uniformly applies to different semantic components, in contrast to the sentence or image-level contrastive samples used by existing visual-semantic learning [49, 30, 11]. Unified VSE consistently outperforms pre-existing approaches on a diverse set of retrieval-based tasks.

Second, we propose a caption encoder that ensures a coverage of all semantic components appeared in the sentence. We show that this regularization helps our model to learn a robust semantic representation for captions. It effectively defends adversarial attacks on the text domain.

Furthermore, we show how our learned embeddings can provide visual cues to assist the parsing of novel sentences, including determining content word dependencies and labelling semantic roles for certain verbs. It ends up that our model can build reliable connections between vision and language using given semantic cues and in return, bootstrap the acquisition of language.

2. Related work

Visual semantic embedding. Visual semantic embedding [13] is a common technique for learning a joint representation of vision and language. The embedding space empowers a set of cross-modal tasks such as image captioning [43, 48, 8] and visual question answering [4, 47].

A fundamental technique proposed in [13] for aligning two modalities is to use the pairwise ranking to learn a distance metric from similar and dissimilar cross-modal pairs [44, 35, 23, 9, 28, 24]. As a representative, VSE++ [11] uses the online hard negative mining (OHEM) strategy [41] for data sampling and shows the performance gain. VSE-C [40], based on VSE++, enhances the robustness of the learned visual-semantic embeddings by incorporating rule-generated textual adversarial samples as hard negatives during training. In this paper, we present a contrastive learning approach based on semantic components.

There are multiple VSE approaches that also use linguistically-aware techniques for the sentence encoding and learning. Hierarchical multimodal LSTM (HM-LSTM) [33] and [46], as two examples, both leverage the constituency parsing tree. Multimodal-CNN (m-CNN) [30] and CSE [49] apply convolutional neural networks to the caption and extract the a hierarchical representation of sentences. Our model differs with them in two aspects. First, Unified VSE is built upon a factorized semantic space instead of the syntactic knowledge. Second, we employ a contrastive example mining approach that uniformly applies to different semantic components. It substantially improves the learned embeddings, while the related works use only sentence-level contrastive examples.

The learning of object-level alignment in unified VSE is also related to [19, 21, 36], where the authors incorporate pre-trained object detectors for the semantic alignment. [10] propose a selective pooling technique for the aggregation of object features. Compared with them, Unified VSE presents a more general approach that embeds concepts of different levels, while still requiring no extra supervisions.

Structured representation for vision and language. We connect visual and textual representations in a structured embedding space. The design of its structure is partially motivated by the papers on relational visual representations (scene graphs) [29, 18, 17], where a scene is represented by a set of objects and their relations. Compared with them, our

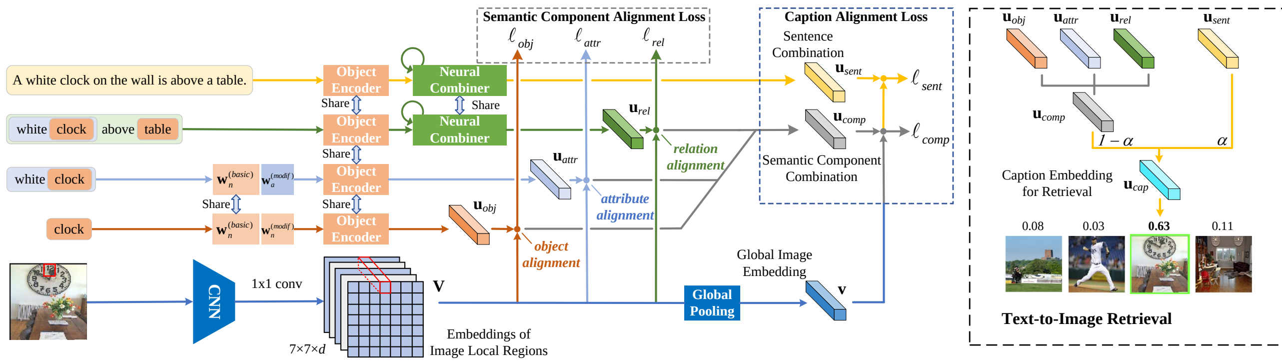


Figure 3. **Left**: the architecture of Unified VSE. The semantic component alignment is learned from contrastive examples sampled from factorized semantic space. The model also learns a caption encoder that combines the semantic components and aligns the caption with the corresponding image. **Right**: An exemplar computation graph for retrieving images from texts. The presence of $\mathbf{u}_{comp}$ in the caption encoding enforces the coverage of all semantic components. See Sec. 3.2 for details.

model does not rely on labelled graphs during training.

Researchers have designed various types of representations [5, 32] as well as different models [26, 50] for translating natural language sentences into structured representations. In this paper, we present how the usage of such semantic parsing into visual-semantic embedding facilitates the learning of the embedding space. Moreover, we present how the learned VSE can, in return, helps the parser to resolve parsing ambiguities using visual cues.

3. Unified Visual-Semantic Embeddings

We now describe the overall architecture and training paradigm for the proposed *Unified Visual-Semantic Embeddings*. Shown in Fig. 3, given an image-caption pair, we first parse the caption into a structured meaning representation, composed by a set of semantic components: object nouns, prenominal modifiers, and relational dependencies. We encode different types of semantic components with type-specific encoders. A caption encoder combines the embedding of the semantic components into a caption semantic embedding. Jointly, we encode images with a convolutional neural network (CNN) into the same, *unified VSE* space. The distance between the image embedding and the sentential embedding measures the semantic similarity between the image and the caption.

We employ a multi-task learning approach for the joint learning of embeddings for semantic components (as the "basis" of the VSE space) as well as the caption encoder (as the combiner of semantic components).

3.1. Visual-Semantic Embedding: A Revisit

We begin the section with an introduction to the two-stream VSE approach. It jointly learns the embedding spaces of two modalities: vision and language, and aligns them using parallel image-text pairs (*e.g.*, image and captions from the MS-COCO dataset [27]).

Let $\mathbf{v} \in \mathbb{R}^d$ be the representation of the image and $\mathbf{u} \in \mathbb{R}^d$ be the representation of a caption matching this image, both encoded by neural modules. To archive the alignment, a bidirectional margin-based ranking loss has been widely applied [11, 49, 15]. Formally, for an image (caption) embedding $\mathbf{v}$ ($\mathbf{u}$), denote the embedding of its matched caption (image) as $\mathbf{u}^+$ ($\mathbf{v}^+$). A negative (unmatched) caption (image) is sampled whose embedding is denoted as $\mathbf{u}^-$ ($\mathbf{v}^-$). We define the bidirectional ranking loss ℓ_{sent} between captions and images as:

$$\ell_{sent} = \sum_{\mathbf{u}} F_{\mathbf{v}^-} \left(|\delta + s(\mathbf{u}, \mathbf{v}^-) - s(\mathbf{u}, \mathbf{v}^+)|_+ \right) + \sum_{\mathbf{v}} F_{\mathbf{u}^-} \left(|\delta + s(\mathbf{u}^-, \mathbf{v}) - s(\mathbf{u}^+, \mathbf{v})|_+ \right) \quad (1)$$

, where δ is a predefined margin, $|x|_+ = \max(x, 0)$ is the traditional ranking loss and $F_{\mathbf{x}}(\cdot) = \max_{\mathbf{x}}(\cdot)$ denotes the hard negative mining strategy [11, 41]. $s(\cdot, \cdot)$ is a similarity function between two embeddings and is usually implemented as cosine similarity [11, 40, 49].

3.2. Semantic Encodings

The encoding of a caption is made up of three steps. As an example, consider the caption shown in Fig. 3, *"A white clock on the wall is above a wooden table"*. 1) We extract a structured meaning representation as a collection of three types of semantic components: object (`clock`, `wall`, `table`), attribute-object dependencies (`white` clock, `wooden` table) and relational dependencies (clock `above` table, clock `on` wall). 2) We encode each component as well as the full sentence with type-specific encoders into the unified VSE space. 3) We compose the embedding of the caption by combining semantic components.

Semantic parsing. We implement a semantic parser [1] of image captions based on [38]. Given the input sentence, the parser first performs a syntactic dependency parsing. A set of rules is applied to the dependency tree and extracts object entities appeared in the sentence, adjectives that modify the

[1]https://github.com/vacancy/SceneGraphParser

object nouns, subjects/objects of the verbs and prepositional phrases. For simplicity, we consider only single-word nouns for objects and single-word adjectives for object attributes.

Encoding objects and attributes. We use an unified object encoder ϕ for nouns and adjective-noun pairs. For each word w in the vocabulary, we initialize a basic semantic embedding $\mathbf{w}^{(basic)} \in \mathbb{R}^{d_{basic}}$ and a modifier semantic embedding $\mathbf{w}^{(modif)} \in \mathbb{R}^{d_{modif}}$.

For a single noun word w_n (*e.g.*, `clock`), we define its embedding $\mathbf{w}_n$ as $\mathbf{w}_n^{(basic)} \oplus \mathbf{w}_n^{(modif)}$, where $\oplus$ means the concatenation of vectors. For an (adjective, noun) pair (w_a, w_n) (*e.g.*, (`white`, `clock`)), its embedding $\mathbf{w}_{a,n}$ is defined as $\mathbf{w}_n^{(basic)} \oplus \mathbf{w}_a^{(modif)}$ where $\mathbf{w}_a^{(modif)}$ encodes the attribute information. In implementation, the basic semantic embedding is initialized from GloVe [34]. The modifier semantic embeddings (both $\mathbf{w}_n^{(modif)}$ and $\mathbf{w}_a^{(modif)}$) are randomly initialized and jointly learned. $\mathbf{w}_n^{(modif)}$ can be regarded as an intrinsic modifier for each nouns.

To fuse the embeddings of basic and modifier semantics, we employ a gated fusion function:

$$\phi(\mathbf{w}_n) = \mathrm{Norm}(\sigma(\mathbf{W}_1\mathbf{w}_n + \mathbf{b}_1)) \tanh(\mathbf{W}_2\mathbf{w}_n + \mathbf{b}_2)),$$
$$\phi(\mathbf{w}_{a,n}) = \mathrm{Norm}(\sigma(\mathbf{W}_1\mathbf{w}_{a,n} + \mathbf{b}_1) \tanh(\mathbf{W}_2\mathbf{w}_{a,n} + \mathbf{b}_2)).$$

Throughout the text, σ denotes the sigmoid function: $\sigma(x) = 1/(1+\exp(-x))$, and Norm denotes the L2 normalization, *i.e.*, $\mathrm{Norm}(\mathbf{w}) = \mathbf{w}/\|\mathbf{w}\|_2$. One may interpret ϕ as a GRU cell [7] taking no historical state.

Encoding relations and full sentence. Since relations and sentences are the composed based on objects, we encode them with a neural combiner ψ, which takes the embeddings of word-level semantics encoded by ϕ as input. In practice, we implement ψ as an uni-directional GRU [7], and pick the L2-normalized last state as the output.

To obtain a visual-semantic embedding for a relational triple (w_s, w_r, w_o) (*e.g.*, (`clock`, `above`, `table`)), we first extract the word embeddings for the subject, relational word and the object using ϕ. We then feed the encoded word embeddings in the same order into ψ and takes the L2-normalized last state of the GRU cell. Mathematically, $\mathbf{u}_{rel} = \psi(w_s, w_r, w_o) = \psi(\{\phi(\mathbf{w}_s), \phi(\mathbf{w}_r), \phi(\mathbf{w}_o)\})$.

The embedding of a sentence $\mathbf{u}_{sent}$ is computed over the word sequence $w_1, w_2, \cdots w_k$ of the caption:

$$\mathbf{u}_{sent} = \psi(\{\phi(\mathbf{w}_1), \phi(\mathbf{w}_2), \cdots, \phi(\mathbf{w}_k)\}),$$

where for any word x, $\phi(\mathbf{w}_x) = \phi(\mathbf{w}_x^{(basic)} \oplus \mathbf{w}_x^{(modif)})$

Note that we share the weights of the encoders ψ and ϕ among the encoding processes of all semantic levels. This allows our encoders of various types of components to bootstrap the learning of each other.

Combining all of the components. A straight-forward implementation of the caption encoder is to directly use the sentence embedding $\mathbf{u}_{sent}$, as it has already combined the semantics of components in a contextually-weighted manner [25]. However, it has been revealed in [40] that such combination is vulnerable to adversarial attacks: Because of the biases in the dataset, the combiner ψ usually focuses on only a small set of semantic components appeared in the caption.

We alleviate such biases by enforcing the coverage of the semantic components appeared in the sentence. Specifically, to form the caption embedding $\mathbf{u}_{cap}$, the sentence embedding $\mathbf{u}_{sent}$ is combined with an explicit bag-of-components embedding $\mathbf{u}_{comp}$, as illustrated in Fig. 3 (right). Mathematically, we define $\mathbf{u}_{comp}$ is computed by the aggregation of all components in the sentence:

$$\mathbf{u}_{comp} = \mathrm{Norm}\left(\Phi\left(\{\mathbf{u}_{obj}\} \cup \{\mathbf{u}_{attr}\} \cup \{\mathbf{u}_{rel}\}\right)\right),$$

where $\Phi(\cdot)$ is the aggregation function of semantic components. Then the caption is encoded as: $\mathbf{u}_{cap} = \alpha\mathbf{u}_{sent} + (1-\alpha)\mathbf{u}_{comp}$, where $0 \le \alpha \le 1$ is a scalar weight. The presence of $\mathbf{u}_{comp}$ disallows the ignorance of any of the components in the final caption embedding $\mathbf{u}_{cap}$.

3.3. Image Encodings

We use CNN to encode the input RGB image into the unified VSE space. Specifically, we choose a ResNet-152 model [14] pretrained on ImageNet [37] as the image encoder. We apply a layer of 1×1 convolution on top of the last convolutaion layer (*i.e.*, `conv5_3`) and obtain a convolutional feature map of shape $7 \times 7 \times d$ for each image. d denotes the dimension of the unified VSE space.

The feature map, denoted as $\mathbf{V} \in \mathbb{R}^{7\times 7\times d}$, can be view as the embeddings of 7×7 local regions in the image. The embedding $\mathbf{v}$ for the whole image is defined as the aggregation $\Psi(\cdot)$ of the embeddings at all regions through a global spatial pooling operator.

3.4. Learning Paradigm

In this section, we present how to align vision and language into the unified space using contrastive learning on different semantic levels. The training pipeline is illustrated in Fig. 3. We start from the generation of contrastive exampls for different semantic components.

Negative example sampling. It has been discussed in [40] that to explore a large compositional space of semantics, directly sampling negative captions from a human-built dataset (*e.g.*, MS-COCO captions) is not sufficient. In this paper, instead of manually define rules that augment the training data as in [40], we address this problem by sampling contrastive negative examples in the explicitly factorized semantic space. The generation does not require manually labelled data, and can be easily applied to any datasets. For a specific caption, we generate the following four types of contrastive negative samples.

- **Nouns.** We sample negative noun words from all nouns that do not appear in the caption. [2]
- **Attribute-noun pairs.** We sample negative pairs by randomly substituting the adjective by another adjective or substituting the noun.
- **Relational triples.** We sample negative triples by randomly substituting the subject, or the relation, or the object. Moreover, we also sample the whole relational triples of captions in the dataset which describe other images, as the negative triples.
- **Sentences.** We sample negative sentences from the whole dataset. Meanwhile, following [13, 11], we also sample negative images from the whole dataset as contrastive images.

The key motivation behind our visual-semantic alignment is that: an object appears in a local region of the image, while the aggregation of all local regions should be aligned with the full semantics of a caption.

Local region-level alignment. In detail, we propose a relevance-weighted alignment mechanism for linking textual object descriptors and local image regions. As shown in Fig. 4, consider the embedding of a positive textual object descriptor $\mathbf{u}_o^+$, a negative textual object descriptor $\mathbf{u}_o^-$ and the set image local region embeddings $\mathbf{V}_i$ where $i \in 7 \times 7$ extracted from the image. We generate a relevance map $\mathbf{M} \in \mathbb{R}^{7\times 7}$ with $\mathbf{M}_i, i \in 7 \times 7$ representing the relevance between $\mathbf{u}_o^+$ and $\mathbf{V}_i$, computed as as Eq. (2). We compute the loss for noun and (adjective, noun) pairs by:

$$\mathbf{M}_i = \frac{\exp(s(\mathbf{u}_o^+, \mathbf{V}_i))}{\sum_j \exp(s(\mathbf{u}_o^+, \mathbf{V}_j))} \tag{2}$$

$$\ell_{obj} = \sum_{i \in 7\times 7} \left(\mathbf{M}_i \cdot \left| \delta + s(\mathbf{u}_o^-, \mathbf{V}_i) - s(\mathbf{u}_o^+, \mathbf{V}_i) \right|_+ \right) \tag{3}$$

The intuition behind the definition is that, we explicitly try to align the embedding at each image region with $\mathbf{u}_o^+$. The losses are weighted by the matching score, thus reinforce the correspondence between $\mathbf{u}_o^+$ and the matched region. This technique is related to multi-instance learning [45].

Global image-level alignment. For relational triples $\mathbf{u}_{rel}$, semantic components aggregations $\mathbf{u}_{comp}$ and sentences $\mathbf{u}_{sent}$, their semantics usually cover multiple objects. Thus, we align them with the full image embedding $\mathbf{v}$ via bidirectional ranking losses as Eq. (1)[3]. The alignment loss is denoted as ℓ_{rel}, ℓ_{comp} and ℓ_{sent}, respectively.

We want to highlight that, during training, we separately align the two type of semantic representations of the caption, *i.e.*, $\mathbf{u}_{sent}$ and $\mathbf{u}_{comp}$, with the image. This differs from the inference-time computation of the caption. Recall that α can be viewed as a factor that balances the training objective and the enforcement of semantic coverage. This allows us to flexibly adjust α during inference.

[2]For the MS-COCO dataset, in all 5 captions associated with the same image. This also applies to other components.

[3]Only textual negative samples are used for ℓ_{rel}.

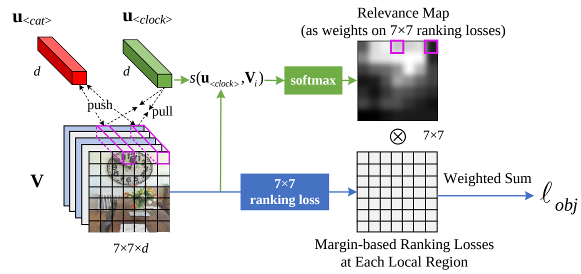


Figure 4. An illustration of our relevance-weighted alignment mechanism. The relevance map shows the similarity of each region with the object embedding $\mathbf{u}_{<clock>}$. We weight the alignment loss with the map to reinforce the correspondence between the $\mathbf{u}_{<clock>}$ and its matched region.

3.5. Implementation details

We use $d = 1024$ as the dimension of the unified VSE space like [11, 40, 49]. We train the model by minimizing the alignment losses in a multi-task learning way.

$$\ell = \ell_{sent} + \eta_c \ell_{comp} + \eta_o \ell_{obj} + \eta_a \ell_{attr} + \eta_r \ell_{rel} \tag{4}$$

In the first 2 epochs, we set η_c, η_o and η_a to 0.5 and η_r to 0 for learning single-object level representations. Then we turn up η_r to 1.0 to make the model learn relational semantics. To make the comparison with related works fair, we always fix the weights of the ResNet. We use the Adam [22] optimizer with learning rate at 0.001. For model details, please refer to our supplementary material.

4. Experiments

We evaluate our model on the MS-COCO [27] dataset. It contains 82,783 training images with each image annotated by 5 captions. We use the common 1K validation and test split from [19]. We also report the performance on a 5K test split for comparison with [49, 11, 42].

We begin this section with the evaluation of traditional cross-modal retrieval. Next, we validate the effectiveness of enforcing the semantic coverage of caption embeddings by comparing models on cross-modal retrieval tasks with adversarial examples. We then propose a unified text-to-image retrieval task to support the contrastive learning on various semantic components. We end this section with an application of using visual cues to facilitate the semantic parsing of novel sentences. Due to the limitation of the text length, for mode details on data processing, metrics and model implementation, we refer the readers to our supplementary material.

4.1. Overall Evaluation on Cross-Modal Retrieval.

We first show the performance of image-to-sentence and sentence-to-image retrieval tasks to evaluate learned visual-semantic embeddings. We report the R@1 (recall@1), R@5,

Task	Image-to-sentence Retrieval				Sentence-to-image Retrieval				
Metric	R@1	R@5	R@10	Med. r	R@1	R@5	R@10	Med. r	rsum
1K testing split (5,000 captions)									
m-RNN [31]	41.0	73.0	83.5	2	29.0	42.2	77.0	3	345.7
DVSA [20]	38.4	69.9	80.5	1	27.4	60.2	74.8	3	351.2
MNLM [24]	43.4	75.7	85.8	-	31.0	66.7	79.9	-	382.5
m-CNN [30]	42.8	73.1	84.1	3	32.6	68.6	82.8	3	384.0
HM-LSTM[33]	43.9	-	87.8	2	36.1	-	86.7	3	-
Order-embedding [42]	46.7	-	88.9	2	37.9	-	85.9	2	-
VSE-C [40, 1]	48.0	81.0	89.2	2	39.7	72.9	83.2	2	414
DeepSP[44]	50.1	79.7	89.2	-	39.6	75.2	86.9	-	420.7
2WayNet [9]	55.8	75.2	-	-	39.7	63.3	-	-	-
sm-LSTM [15]	53.2	83.1	91.5	1	40.7	75.8	87.4	2	431.8
RRF-Net[28]	56.4	85.3	91.5	-	43.9	78.1	88.6	-	443.8
VSE++ [11, 2]	57.7	86.0	94.0	1	42.8	77.2	87.4	2	445.1
CSE[49]	56.3	84.4	92.2	1	45.7	81.2	90.6	2	450.4
UniVSE (Ours)	**64.3**	**89.2**	**94.8**	**1**	**48.3**	**81.7**	**91.2**	**2**	**469.5**
5K testing split (25,000 captions)									
Order-embedding [42]	23.3	-	65.0	5	18.0	-	57.6	7	-
VSE-C[11, 1]	22.3	51.1	65.1	5	18.7	43.8	56.7	7	257.7
CSE[49]	27.9	57.1	70.4	4	22.2	50.2	64.4	5	292.2
VSE++[11, 2]	31.7	60.9	72.7	3	22.1	49.0	62.7	6	299.1
UniVSE (Ours)	**36.1**	**66.4**	**77.7**	**3**	**25.4**	**53.0**	**66.2**	**5**	**324.8**

Table 1. Results of cross-modal retrieval task on MS-COCO dataset (1K and 5K testing split). All listed baselines and our models fix weights of the image encoders. For fair comparison, we do not include [10] and [16] that finetunes the image encoder or adds extra training data.

	Object attack				**Attribute attack**				**Relation attack**				
Metric	R@1	R@5	R@10	rsum	R@1	R@5	R@10	rsum	R@1	R@5	R@10	rsum	total sum
VSE++	32.3	69.6	81.4	183.3	19.8	59.4	76.0	155.2	26.1	66.8	78.7	171.6	510.1
VSE-C	41.1	76.0	85.6	202.7	26.7	61.0	74.3	162.0	35.5	71.1	81.5	188.1	552.8
UniVSE ($\mathbf{u}_{sent}$+$\mathbf{u}_{comp}$)	**45.3**	**78.3**	**87.3**	**210.9**	**35.3**	**71.5**	**83.1**	**189.9**	**39.0**	**76.5**	**86.7**	**202.2**	**603.0**
UniVSE ($\mathbf{u}_{sent}$)	40.7	76.4	85.5	202.6	30.0	70.5	80.6	181.1	32.6	72.6	83.5	188.7	572.4
UniVSE ($\mathbf{u}_{sent}$+$\mathbf{u}_{obj}$)	42.9	**77.2**	**85.6**	205.7	30.1	69.0	79.8	178.9	34.0	71.2	83.6	188.8	573.4
UniVSE ($\mathbf{u}_{sent}$+$\mathbf{u}_{attr}$)	40.1	73.9	83.3	197.3	**37.4**	**72.0**	**81.9**	**191.3**	30.5	70.0	81.9	182.4	571.0
UniVSE ($\mathbf{u}_{sent}$+$\mathbf{u}_{rel}$)	**45.4**	77.1	85.5	**208.0**	29.2	68.1	78.5	175.8	**42.8**	**77.5**	**85.6**	**205.9**	**589.7**

Table 2. Results on image-to-sentence retrieval task with text-domain adversarial attacks. For each caption, we generate 5 adversarial fake captions which do not match the images. Thus, the models need to retrieve 5 positive captions from 30,000 candidate captions.

R@10, and the median retrieval rank as in [11, 40, 49, 15]. To summarize the performance, we compute $rsum$ as the summation of R@1, R@5, and R@10.

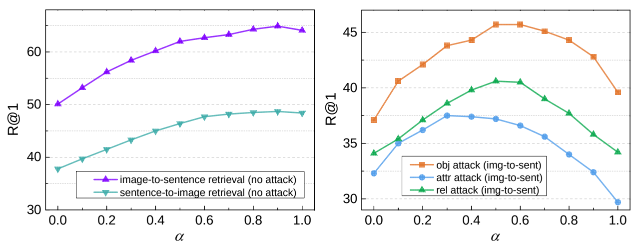
Shown in Table 1, Unified VSE outperforms other baselines with various model architecture and training techniques [11, 49, 28, 40, 15]. This validates the effectiveness learning visual-semantic embeddings in the explicitly factorized visual-semantic embedding space. We also include the results under more challenging 5K test split. The gap between Unified VSE and other models gets further enlarged across all metrics.

4.2. Retrieval under text-domain adversarial attack

Recent works [40, 39] have raised their concerns on the robustness of the learned visual-semantic embeddings. They show that existing models are vulnerable to text-domain adversarial attacks (*i.e.*, using adversarial captions) and can be easily fooled. This is closely related to the bias in small datasets over a large, compositional semantic space [40]. To prove the robustness of the learned unifed VSE, we further conduct experiments on the image-to-sentence retrieval task with text-domain adversarial attacks. Following [40], we first design several types of adversarial captions by adding perturbations to existing captions.

1. **Object attack**: Randomly replace / append by an irrelevant one in the original caption.
2. **Attribute attack**: Randomly replace / add an irrelevant attribute modifier for one object in the original caption.
3. **Relational attack**: 1) Randomly replace the subject/relation/object word by an irrelevant one. 2) Randomly select an entity as a subject/object and add an irrelevant relational word and object/subject.

We include VSE++ and VSE-C as the baselines and show the results in Table 2 where different columns represent different types of attacks. VSE++ performs worst as it is only optimized for the retrieval performance on the dataset. Its sentence encoder is insensitive to a small perturbation in the text. VSE-C explicitly generates the adversarial captions based on human-designed rules as hard negative examples during training, which makes it relatively robust to those



(a) Normal cross-modal retrieval (5,000 captions)

(b) Adversarial attacked image-to-sentence retrieval (30,000 captions)

Figure 5. The performance of UniVSE on cross-modal retrieval tasks with different combination weight α. Our model can effective defending adversarial attacks, with no sacrifice for the performance on other tasks by choosing a reasonable α (thus we set $\alpha = 0.75$ in all other experiments).

adversarial attacks. Unified VSE shows strong robustness across all types of adversarial attacks.

It is worth noting that VSE-C shows inferior performances in the normal retrieval tasks without adversarial captions (see Table 1), even compared with VSE++. Considering that VSE-C shares the exactly the same model architecture as VSE++, we can conclude that directly adding adversarial captions during training, although improves models' robustness, may sacrifice the performance on other tasks. In contrast, the ability of Unified VSE to defend adversarial texts comes almost for free: we present *zero* adversarial captions during training. Unified VSE builds fine-grained semantic alignments via the contrastive learning of semantic components. It use the explicit aggregation of the components $\mathbf{u}_{comp}$ to alleviate the dataset biases.

Ablation study: semantic components. We now delve into the effectiveness of different semantic components by choosing different combinations of components for the caption embedding. Shown in Table 2, we use different subsets of the semantic components to form the bag-of-component embeddings $\mathbf{u}_{comp}$. For example, in UniVSE$_{obj}$, only object nouns are selected and aggregated as $\mathbf{u}_{comp}$.

The results demonstrate the effectiveness of the enforcement of semantic coverage: even if the semantic components have got fine-grained alignment with visual concepts, directly using $\mathbf{u}_{sent}$ as the caption encoding still degenerates the robustness against adversarial examples. Consistent with the intuition, enforcing of coverage of a certain type of components (*e.g.*, objects) helps the model to defend the adversarial attacks of the same type (*e.g.*, defending adversarial attacks of nouns). Combining all components leads to the best performance.

Choice of the combination factor: α. We study the choice of α by conducting experiments on both normal retrieval tasks and the adversarial one. Fig 4.2 shows the R@1 performance under the normal/adversarial retrieval scenario w.r.t. different choices of α. We observe that the $\mathbf{u}_{comp}$ term contributes little on the normal retrieval tasks but largely on tasks

Task	obj	attr	rel	obj (det)	sum
VSE++	29.95	26.64	27.54	50.57	134.70
VSE-C	27.48	28.76	26.55	46.20	128.99
UniVSE$_{all}$	**39.49**	**33.43**	**39.13**	**58.37**	**170.42**
UniVSE$_{obj}$	**39.71**	33.37	34.38	56.84	164.30
UniVSE$_{attr}$	31.31	**37.51**	34.73	52.26	155.81
UniVSE$_{rel}$	37.55	32.70	**39.57**	**59.12**	**168.94**

Table 3. The mAP performance on the unified text-to-image retrieval task. Please refer to the text for details.

with adversarial attacks. Recall that α can be viewed as a factor that balances the training objective and the enforcement of semantic coverage. By choosing α from a reasonable range (0.6 to 0.8), our model can effective defend adversarial attacks, with no sacrifice for the overall performance.

4.3. Unified Text-to-Image Retrieval

We extend the word-to-scene retrieval used by [40] into a general *unified text-to-image retrieval* task. In this task, models receive queries of different semantic levels, including single words (*e.g.*, “Clock.”), noun phrases (*e.g.*, “White clock.”), relational phrases (*e.g.*, “Clocks on wall”) and full sentences. For all baselines, the texts of different types as treated as full sentences. The result is presented in Table 3.

We generate positive image-text pairs by randomly choosing an image and a semantic component from 5 matched captions with the chosen image. It is worth mention that the semantic components extracted from captions may not cover all visual concepts in the corresponding image, which makes the annotation noisy. To address this, we also leverage the MS-COCO detection annotations to facilitate the evaluation (see *obj(det)* column). We treat the labels for detection bounding boxes as the annotation of objects in the scene.

Ablation study: contrastive learning of components. We evaluate the effectiveness of using contrastive samples for different semantic components. Shown in Table 3, UniVSE$_{obj}$ denotes the model trained with only contrastive samples of noun components. The same notation applies to other models. The UniVSE trained with a certain type of contrastive examples (*e.g.*, UniVSE$_{obj}$ with contrastive nouns) consistently improves the retrieval performance of the same type of queries (*e.g.*, retrieving images from a single noun). UniVSE trained with all kinds of contrastive samples performs best in overall and shows a significant gap w.r.t. other baselines.

Visualization of the semantic alignment. We visualize the semantic-relevance map on an image w.r.t. a given query $\mathbf{u}_q$ for a qualitative evaluation of the alignment performance of various semantic components. The map $\mathbf{M}_i$ is computed as the similarity between each image region $\mathbf{v}_i$ and $\mathbf{u}_q$, in a similar way as Eq. (2). Shown as Fig. 6, this visualization helps to verify that our model successfully aligns different semantic components with the corresponding image regions.

Figure 6. The relevance maps and grounded areas obtained from the retrieved images w.r.t. three queries. The temperature of the `softmax` for visualizing the relevance map is $\tau = 0.1$. Pixels in white indicates a higher matching score. Note that the third image of the query "black dog" contains two dogs, while our model successfully locates the black one (on the left). It also succeeded in finding the white dog in the first image of "white dog". Moreover, for the query "player swing bat", although there are many players in the image, our model only attend to the man swinging the bat.

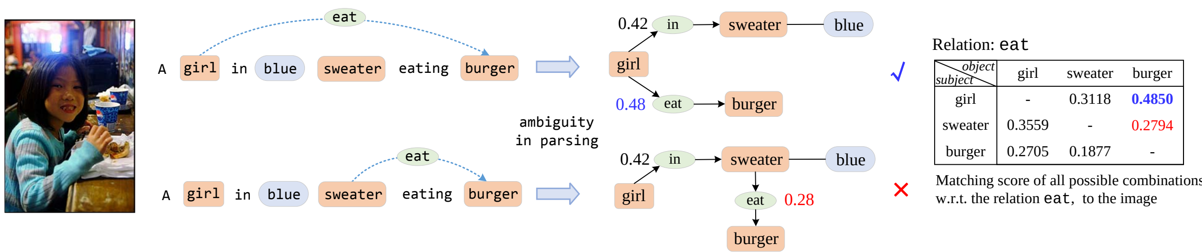


Figure 7. Example showing that Unified VSE can leverage image to parse sentences with ambiguity. The matching score of "girl eat burger" is much higher than "sweater eat burger", which resolves the ambiguity. Other components are also correctly inferred.

Task	attributed object	relational phrase
Random	37.41	31.90
VSE++	41.12	43.31
VSE-C	43.44	41.08
UniVSE	**64.82**	**62.69**

Table 4. The accuracy of different models on recovering word dependencies with visual cues. In the "Random" baseline, we randomly assign the word dependencies.

4.4. Semantic Parsing with Visual Cues

As a side application, we show how the learned unified VSE space can provide the visual cues to help the semantic parsing of sentences. Fig. 7 shows the general idea. When parsing a sentence, ambiguity may occur, *e.g.*, the subject of the relational word `eat` may be `sweater` or `burger`. It is not easy for a textual parser to decide which one is correct because of the innate syntactic ambiguity. However, we can use the image which is depicted by this sentence to assist the parsing by. This is related to previous works on using image segmentation models to facilitate the sentence parsing [6].

This motivates us to design two tasks, 1) recovering the dependency between attributes and entities, and 2) recovering the relational triples. In detail, we first extract the entities, attributes and relational words from the raw sentence without knowing their dependencies. For each possible combination of certain semantic component, our model computes its embedding in the unified joint space. *E.g.*, in Fig. 7, there are in total $3 \times (3 - 1) = 6$ possible dependencies for `eat`. We choose the combination with the highest matching score with the image to decide the subject/object dependencies of the relation `eat`. We use parsed semantic components as the ground-truth and report the accuracy, defined as the fraction of the number of correct dependency resolution and the total number of attributes/relations. Table 4 reports the results on assisting semantic parsing with visual cues, compared with other baselines. Fig. 7 shows a real case in which we successfully resolve the textual ambiguity.

5. Conclusion

We present a *unified visual-semantic embedding* approach that learns a joint representation space of vision and language in a factorized manner: Different levels of textual semantic components such as objects and relations get aligned with regions of images. A contrastive learning approach for semantic components is proposed for the efficient learning of the fine-grained alignment. We also introduce the enforcement of semantic coverage: each caption embedding should have a coverage of all semantic components in the sentence. Unified VSE shows superiority on multiple cross-modal retrieval tasks and can effectively defend text-domain adversarial attacks. We hope the proposed approach can empower machines that learn vision and language jointly, efficiently and robustly.

6. Acknowledgements

We thank Haoyue Shi for helpful discussions and suggestions. This research is supported in part by the National Key Research and Development Program of China under grant 2018YFB0505000 and the National Natural Science Foundation of China under grant 61772138.

References

[1] VSE-C open-sourced code. https://github.com/ExplorerFreda/VSE-C. 6

[2] VSE++ open-sourced code. https://github.com/fartashf/vsepp. 6

[3] O. Abend, T. Kwiatkowski, N. J. Smith, S. Goldwater, and M. Steedman. Bootstrapping Language Acquisition. *Cognition*, 164:116–143, 2017. 1, 2

[4] S. Antol, A. Agrawal, J. Lu, M. Mitchell, D. Batra, C. L. Zitnick, and D. Parikh. VQA: Visual Question Answering. In *Proceedings of IEEE International Conference on Computer Vision (ICCV)*, 2015. 2

[5] L. Banarescu, C. Bonial, S. Cai, M. Georgescu, K. Griffitt, U. Hermjakob, K. Knight, P. Koehn, M. Palmer, and N. Schneider. Abstract Meaning Representation for Sembanking. In *Linguistic Annotation Workshop and Interoperability with Discourse*, 2013. 3

[6] G. Christie, A. Laddha, A. Agrawal, S. Antol, Y. Goyal, K. Kochersberger, and D. Batra. Resolving Language and Vision Ambiguities Together: Joint Segmentation & Prepositional Attachment Resolution in Captioned Scenes. *arXiv:1604.02125*, 2016. 8

[7] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio. Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling. In *NIPS 2014 Workshop on Deep Learning*, 2014. 4

[8] J. Donahue, L. Anne Hendricks, S. Guadarrama, M. Rohrbach, S. Venugopalan, K. Saenko, and T. Darrell. Long-Term Recurrent Convolutional Networks for Visual Recognition and Description. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015. 2

[9] A. Eisenschtat and L. Wolf. Linking Image and Text with 2-way Nets. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017. 2, 6

[10] M. Engilberge, L. Chevallier, P. Pérez, and M. Cord. Finding Beans in Burgers: Deep Semantic-Visual Embedding with Localization. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018. 2, 6

[11] F. Faghri, D. J. Fleet, J. R. Kiros, and S. Fidler. VSE++: Improving Visual-Semantic Embeddings with Hard Negatives. In *Proceedings of British Machine Vision Conference (BMVC)*, 2018. 2, 3, 5, 6

[12] A. Fazly, A. Alishahi, and S. Stevenson. A Probabilistic Computational Model of Cross-Situational Word Learning. *Cognitive Science*, 34(6):1017–1063, 2010. 2

[13] A. Frome, G. S. Corrado, J. Shlens, S. Bengio, J. Dean, T. Mikolov, et al. Devise: A Deep Visual-Semantic Embedding Model. In *Advances in Neural Information Processing Systems (NIPS)*, 2013. 2, 5

[14] K. He, X. Zhang, S. Ren, and J. Sun. Deep Residual Learning for Image Recognition. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016. 4

[15] Y. Huang, W. Wang, and L. Wang. Instance-Aware Image and Sentence Matching with Selective Multimodal LSTM. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017. 3, 6

[16] Y. Huang, Q. Wu, and L. Wang. Learning Semantic Concepts and Order for Image and Sentence Matching. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017. 6

[17] J. Johnson, A. Gupta, and L. Fei-Fei. Image Generation from Scene Graphs. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018. 2

[18] J. Johnson, R. Krishna, M. Stark, L. Li, D. A. Shamma, M. S. Bernstein, and L. Fei-Fei. Image Retrieval using Scene Graphs. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015. 2

[19] A. Karpathy and L. Fei-Fei. Deep Visual-Semantic Alignments for Generating Image Descriptions. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015. 2, 5

[20] A. Karpathy and L. Fei-Fei. Deep Visual-Semantic Alignments for Generating Image Descriptions. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015. 6

[21] A. Karpathy, A. Joulin, and L. Fei-Fei. Deep Fragment Embeddings for Bidirectional Image Sentence Mapping. In *Advances in Neural Information Processing Systems (NIPS)*, 2014. 2

[22] D. P. Kingma and J. Ba. Adam: A Method for Stochastic Optimization. *arXiv:1412.6980*, 2017. 5

[23] R. Kiros, R. Salakhutdinov, and R. Zemel. Multimodal Neural Language Models. In *Proceedings of International Conference on Machine Learning (ICML)*, 2014. 2

[24] R. Kiros, R. Salakhutdinov, and R. S. Zemel. Unifying Visual-Semantic Embeddings with Multimodal Neural Language Models. *arXiv:1411.2539*, 2014. 2, 6

[25] O. Levy, K. Lee, N. FitzGerald, and L. Zettlemoyer. Long Short-Term Memory as a Dynamically Computed Element-wise Weighted Sum. *arXiv:1805.03716*, 2018. 4

[26] P. Liang, M. I. Jordan, and D. Klein. Learning Dependency-Based Compositional Semantics. *Computational Linguistics*, 39(2):389–446, 2013. 3

[27] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick. Microsoft COCO: Common Objects in Context. In *Proceedings of European Conference on Computer Vision (ECCV)*, 2014. 3, 5

[28] Y. Liu, Y. Guo, E. M. Bakker, and M. S. Lew. Learning a Recurrent Residual Fusion Network for Multimodal Matching. In *Proceedings of IEEE International Conference on Computer Vision (ICCV)*, 2017. 2, 6

[29] C. Lu, R. Krishna, M. Bernstein, and L. Fei-Fei. Visual Relationship Detection with Language Priors. In *Proceedings of European Conference on Computer Vision (ECCV)*, 2016. 2

[30] L. Ma, Z. Lu, L. Shang, and H. Li. Multimodal Convolutional Neural Networks for Matching Image and Sentence. In *Proceedings of IEEE International Conference on Computer Vision (ICCV)*, 2015. 2, 6

[31] J. Mao, W. Xu, Y. Yang, J. Wang, Z. Huang, and A. Yuille. Deep Captioning with Multimodal Recurrent Neural Net-

works (m-RNN). In *Proceedings of International Conference on Learning Representations (ICLR)*, 2015. 6

[32] R. Montague. Universal Grammar. *Theoria*, 36(3):373–398, 1970. 3

[33] Z. Niu, M. Zhou, L. Wang, X. Gao, and G. Hua. Hierarchical Multimodal LSTM for Dense Visual-Semantic Embedding. In *Proceedings of IEEE International Conference on Computer Vision (ICCV)*, 2017. 2, 6

[34] J. Pennington, R. Socher, and C. Manning. GloVe: Global Vectors for Word Representation. In *Proceedings of Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 2014. 4

[35] Z. Ren, H. Jin, Z. Lin, C. Fang, and A. Yuille. Joint Image-Text Representation by Gaussian Visual-Semantic Embedding. In *Proceedings of ACM Multimedia (ACM-MM)*, 2016. 2

[36] Z. Ren, H. Jin, Z. Lin, C. Fang, and A. Yuille. Multiple Instance Visual-Semantic Embedding. In *Proceedings of British Machine Vision Conference (BMVC)*, 2017. 2

[37] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision (IJCV)*, 115(3):211–252, 2015. 4

[38] S. Schuster, R. Krishna, A. Chang, L. Fei-Fei, and C. D. Manning. Generating Semantically Precise Scene Graphs from Textual Descriptions for Improved Image Retrieval. In *Workshop on Vision and Language (VL15)*, Lisbon, Portugal, 2015. 3

[39] R. Shekhar, S. Pezzelle, Y. Klimovich, A. Herbelot, M. Nabi, E. Sangineto, and R. Bernardi. FOIL it! Find One Mismatch between Image and Language Caption. *arXiv:1705.01359*, 2017. 2, 6

[40] H. Shi, J. Mao, T. Xiao, Y. Jiang, and J. Sun. Learning Visually-Grounded Semantics from Contrastive Adversarial Samples. In *Proceedings of International Conference on Computational Linguistics (COLING)*, 2018. 2, 3, 4, 5, 6, 7

[41] A. Shrivastava, A. Gupta, and R. Girshick. Training Region-Based Object Detectors with Online Hard Example Mining. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016. 2, 3

[42] I. Vendrov, R. Kiros, S. Fidler, and R. Urtasun. Order-Embeddings of Images and Language. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2016. 5, 6

[43] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan. Show and Tell: A Neural Image Caption Generator. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015. 2

[44] L. Wang, Y. Li, and S. Lazebnik. Learning Deep Structure-Preserving Image-Text Embeddings. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016. 2, 6

[45] J. Wu, Y. Yu, C. Huang, and K. Yu. Deep Multiple Instance Learning for Image Classification and Auto-Annotation. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015. 5

[46] F. Xiao, L. Sigal, and Y. J. Lee. Weakly-Supervised Visual Grounding of Phrases with Linguistic Structures. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017. 2

[47] H. Xu and K. Saenko. Ask, Attend and Answer: Exploring Question-Guided Spatial Attention for Visual Question Answering. In *Proceedings of European Conference on Computer Vision (ECCV)*, 2016. 2

[48] K. Xu, J. Ba, R. Kiros, K. Cho, A. Courville, R. Salakhudinov, R. Zemel, and Y. Bengio. Show, Attend and Tell: Neural Image Caption Generation with Visual Attention. In *Proceedings of International Conference on Machine Learning (ICML)*, 2015. 2

[49] Q. You, Z. Zhang, and J. Luo. End-to-End Convolutional Semantic Embeddings. In *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2018. 2, 3, 5, 6

[50] L. S. Zettlemoyer and M. Collins. Learning to Map Sentences to Logical Form: Structured Classification with Probabilistic Categorial Grammars. In *Proceedings of Conference on Uncertainty in Artificial Intelligence (UAI)*, 2005. 3

Supplementary Materials for Unified Visual-Semantic Embeddings

This supplementary material is organized as follows. First, in Appendix A, we provide more details for the implementation of our model and the training method. Second, in Appendix B, we provide the experiment setups, metrics, baseline implementations, qualitative examples and analysis for each experiment we discussed in the main text. We end this section with the visualization of the learned unified VSE space of different semantic levels.

A. Implementation Details

A.1. Generating Negative samples

To generate negative samples in sentence level, we follow the sampling paradigm introduced by [1]: We sample negative examples from all other captions/images in the dataset in a training batch. Note that as [1] shown, the batch size will largely affect the models' performance. For a fair comparison, we set the batch size as 128 which is the same as [1, 4]. In the rest of this section, we discuss in detail how we sample negative semantic components.

As for nouns, we sample 16 negative nouns from a fixed set of nouns: This noun set is extracted from nouns with frequency more than 100 (in total 1,205 nouns extracted in MS-COCO dataset).

As for attribute-noun pairs, we randomly sample 8 other attributes in a fixed attribute set and replace the original attribute in the pair, as negative examples. The attribute set is composed by the frequently appeared attributes in the MS-COCO dataset. In detail, we extract in total 37 attributes, *i.e.*, `white`, `black`, `red`, `green`, `brown`, `yellow`, `orange`, `pink`, `gray/grey`, `purple`, `young`, `wooden`, `old`, `snowy`, `grassy`, `cloudy`, `colorful`, `sunny`, `beautiful`, `bright`, `sandy`, `fresh`, `morden`, `cute`, `dry`, `dirty`, `clean`, `polar`, `crowded`, `silver`, `plastic`, `concrete`, `rocky`, `wooded`, `messy`, `square`. We also randomly replace nouns in the pairs to generate another set of negative attribute-noun pairs. For each attribute-noun pair, we randomly draw 16 negative examples.

We separately compute the ranking loss corresponding to two types of negatives, denoted as $\ell_{attr_{negnoun}}$ and $\ell_{attr_{negattr}}$. Both of them are computed by a uni-directional ranking loss with negative examples drawn in text-domain. OHEM strategy is not applied on them. The final loss is the sum of them, *i.e.*, $\ell_{attr} = \ell_{attr_{negnoun}} + \ell_{attr_{negattr}}$.

Here we add a small note for the reproducibility. In cases with multiple modifiers on the nouns (*e.g.*, `old black dog`), for simplicity, in our implementation, we always extract the first modifier of each noun phrases as its attribute (`old dog` in this case).

As for relational triples, we randomly sample 4 relational words and 2 negatives subjects (nouns) and 2 negative objects (nouns) to replace the corresponding parts in the triple, as negative examples. In total, we have 8 negative triples for each relational triple The choice of this small number of negative examples is attributed to the trade-off between the computational efficiency and stability of training. Empirically, we find that increasing the number of negative triples does not bring much improvement to the performance.

We also sample negative relational triples from other captions within the training batch. In detail, we sample 1 negative rational triple for each other caption within the batch. This results in at most 128-1 = 127 negative examples for each relational triple ("at most" means some captions may not contain relational phrases). Similar as attribute-noun pairs, we individually compute the ranking loss on each type of negatives and sum them together as the ℓ_{rel}. The losses are computed by uni-directional ranking loss without OHEM.

As for negative bag-of-components, we sample negative ones in a similar manner as we do for sentences: We draw them from the bag-of-components in other captions within the training batch. We also draw other images from batch as negative images. The loss ℓ_{comp} is computed by bi-directional ranking loss with OHEM strategy.

A.2. Model settings and details

Weight of η_c, η_o, η_a, η_r. The choice of the 4 hyperparameters in Eq.(4) (*i.e.*, η_c, η_o, η_a, η_r) in the main text actually has no significant influence on the model's performance, as they all contribute to the better alignment between two modalities. To show this, we fix three of the ηs and test 5 different values for the rest one (*e.g.*, set $\eta_c \in \{0.1, 1, 2, 4, 8\}$). The bidirectional retrieval scores `rsum` of all 20 models are within the range of 468.2 ± 2.

Dependency on the semantic parser. Recall that the semantic components are all extracted by the semantic parser and we evaluate the influence of the recall of the semantic parser on the model's performance by randomly dropping 30% relations and 30% attributes from the parser's output during training/test. Shown in Table 1, the recall of the parser on training captions has a small contribution to the performance. However, low recalls on test captions noticeably degenerate the performance on discriminating adversarial captions, because UniVSE relies on the parsed components to find unmatched components between images and texts. Thus, in Section 4.4, we show that UniVSE can facilitate the semantic parsing with visual cues.

Spatial aggregation method. For the spatial aggregation $\Psi(\cdot)$ of the 7×7 image feature maps, instead of using the max pooling which may drop most information in the feature map or the average pooling which tends to include noises, we adopt a specific pooling method called max-k pooling. Max-k pooling select k largest values in the feature map and return the average value of these k largest responses. Formally, for the feature map $\mathbf{V} \in \mathbb{R}^{7\times7\times d}$, denoting the k-th largest value in i-th channel of $\mathbf{V}$ as $\mathbf{V}_k[i]$, the max-k pooled global image embedding $\mathbf{v}$ can be formalized as $\mathbf{v}[i] = \mathrm{mean}(\{\mathbf{V}[x,y,i] | \mathbf{V}[x,y,i] \leq \mathbf{V}_k[i], x, y \in 7 \times 7\})$. Obviously, max pooling is the specific form of max-k pooling when $k = 1$ and average pooling can be regarded as max-49 pooling (for a 7×7 spatial resolution). In the experiments, we empirically set k to 10, as a trade-off between removing useful information and retaining unimportant information. Table 2 shows the performance of different spatial pooling methods. We can observe that the proposed max-k pooling achieves best performance among three pooling methods (*i.e.*, average pooling, max pooling and max-k pooling). Notice that, max-k pooling will bring better performances compared with max/average pooling, however, the max-k pooling has to be trained under UniVSE structure (*i.e.*, trained with $\ell_{comp}, \ell_{obj}, \ell_{attr}, \ell_{rel}$), otherwise, the local correspondences will not be learned well. The results in Table 2 shows a significant performance drop on defending the adversarial captions, if UniVSE (with max-10 pooling) is trained without loss ℓ_{comp}.

Semantic aggregation method For the aggregation function $\Phi(\cdot)$ for semantic components to generate $\mathbf{u}_{comp}$, we have added some experiments. Specifically, we evaluate the performance of both hand-coded functions: average pooling, sum, and max pooling (by taking a channel-wise max of all components), as well as learnable functions: GRU and self-attentive pooling [2]. For the GRU alternative, we treat the set of components as a sequence (ordered randomly), encode it with a GRU module, and use the last hidden state as the $\mathbf{u}_{comp}$. The results are summarized in Table 3. GRU performs slightly better than other methods on the standard retrieval task. However, it requires extra computation cost. Max pooling outperforms others in discriminating adversarial captions, suggesting that it makes $\mathbf{u}_{comp}$ more sensitive to the presence of unmatched components than the "average" alternative. However, it shows slightly inferior results on the standard retrieval task. In the experiments, we adopt average pooling as the implementation of semantic aggregation function $\Phi(\cdot)$.

Setting of α. One may argue that the combination coefficient α can also be learnable when training the model instead of being a fixed value (0.75 in the experiments). Informally, $\mathbf{u}_{comp}$ imposes a prior that the caption embedding should cover all semantic components in the text. The hyperparameter α controls the strength of this prior (see Figure 8 in the main text for details). Directly learning α under the supervision of the standard retrieval task may encourage the model to focus on only part of the semantic components [4]. Our empirical results support this: α finally converges to 0.93 when treated as a learnable parameter, in contrast to the value of 0.75 suggested in our paper. Shown in Table 4, making α learnable does not affect the performance on the standard retrieval tasks. However, it shows a significant performance drop when there are adversarial captions. Thus, we treat α as a fixed value in UniVSE.

A.3. Hyperparameters

We set the dimension d_{basic} of basic semantic embeddings as 300. The embeddings are initialized by GloVe word embeddings pre-trained on the Common Crawl dataset: http://nlp.stanford.edu/data/glove.840B.300d.zip. The dimension d_{modif} of modifier semantic embeddings is set to 100. The embeddings are randomly initialized. During training, we fix the basic semantic embeddings of words $\mathbf{w}^{(basic)}$. The learning rate of the Adam optimizer is fixed to 0.001 at first 6 epochs and is exponentially decayed by 2 for each next epoch until it reaches 1e-5.

Train Drop	Test Drop	Standard	Obj. Atk.	Attr. Atk.	Rel. Atk.
		469.5	210.9	189.9	**202.2**
✓		468.9	**213.7**	**191.5**	199.4
✓	✓	468.7	211.2	182.2	197.1

Table 1. We evaluate the performance of UniVSE on the standard bidirectional retrieval task and the retrieval tasks with adversarial captions (object-typed, attribute-typed and relation-typed). We use `rsum` as the evaluation metric.

Spatial Aggregation Methods	Standard	Obj. Atk.	Attr. Atk.	Rel. Atk.
Avg	452.9	198.7	184.2	186.2
Max	462.5	209.6	184.1	193.6
Max-10	**469.5**	**210.9**	**189.9**	**202.2**
Max-10 (without ℓ_{comp})	466.1	202.9	182.1	192.2

Table 2. We evaluate the performance of UniVSE under different spatial aggregation settings on the standard retrieval task, and the retrieval tasks with adversarial captions (we report the `rsum`s).

Semantic Aggregation Methods	Avg	Sum	Max	Self-Att.	GRU
Standard (`rsum`)	469.5	471.1	465.8	467.1	**472.0**
Adversarial (`rsum`)	603.0	604.3	**628.4**	599.5	603.7

Table 3. We evaluate the performance of UniVSE under different semantic aggregation settings on the standard retrieval task, and the retrieval tasks with adversarial captions (we report the sum of `rsum`s under three types of attacks).

Model	Standard	Obj. Atk.	Attr. Atk.	Rel. Atk.
Fixed α (0.75)	**469.5**	**210.9**	**189.9**	**202.2**
Learnable α (0.93)	468.1	204.1	182.2	190.4

Table 4. The performance of UniVSE with a learnable or a fixed α on the standard retrieval task, and the retrieval tasks with adversarial captions (we report the `rsum`s).

B. Experiment Details

B.1. Cross-modal Retrieval

Visualizations. We show a set of examples of the image-to-sentence retrieval in Fig. 1 and sentence-to-image retrieval in Fig. 2.

B.2. Retrieval under text-domain adversarial attack

Experiment setup. We use the 1K test split (including 5,000 captions) for generating adversarial attacks. For each caption, we generate five adversarial captions under one type of attack setting. The detailed settings of the three types of adversarial attack are listed below.

1. **Object attack**: We randomly replace / append by an irrelevant noun for both 50% probability. The replacing/appending place is randomly selected in nouns of the caption. For the case of appending extra noun, the word `and` is also added before the appended noun, *e.g.*, `A dog eats meat` →`A dog eats meat` **`and table`**. The irrelevant nouns are drawn from the set containing nouns with high concreteness (manually extracted).

2. **Attribute attack**: If a caption contains attribute-noun pairs. We randomly select one pair and replace the attribute by a negative one. If a caption does not contain any attributes, we randomly choose one noun in the caption and append an attribute on it. The negative attribute is generated from the attribute set excluding the attributes (and its similar attributes) in the caption. The similar attribute group is defined as the following. `{white, snowy, polar}`, `{red, pink}`, `{blue, cloudy}`, `{green, grassy}`, `{brown, sandy, yellow, orange}`, `{rocky, concrete}`.

3. **Relational attack**: For those captions containing relational phrases, we randomly select one relation triple and with equivalent probability to choose one in the triple to be replaced by an irrelevant one. *e.g.*, `A dog eats meat` $\rightarrow$ `A dog` **`plays`** `meat`. For those captions which do not have any relational phrases, we first randomly select one noun in the caption and regard it as a subject/object with 50% / 50% probability. Then we draw a relational word and an irrelevant noun as the object/subject to form a new fake relation. *e.g.*, `A dog is sleeping` $\rightarrow$ `A dog` **`in sky`** `is sleeping`.

Baselines. We train the VSE-C according to the setting in [4] with the officially open-sourced code. In the original VSE-C paper, The VSE-C is trained by generating either noun-typed/numeral-typed/relation-typed or all of these three types of adversarial samples. We use the setting of training under all types of adversarial samples as a comparable competitor in this evaluation. For the ablation of UniVSE ($\mathbf{u}_{sent} + \mathbf{u}_{attr}$) (*i.e.*, use $\mathbf{u}_{attr}$ as $\mathbf{u}_{comp}$) under attribute attack scenario, we additionally include $\mathbf{u}_{obj}$ to $\mathbf{u}_{comp}$. The reason is that the attribute attack may add new attribute modifier on a sentence with *no* attributed phrases. $\mathbf{u}_{comp}$ is not defined for such sentence if we only use $\mathbf{u}_{attr}$ as $\mathbf{u}_{comp}$, since it does not contain any attributed phrases. As a solution, we additionally include $\mathbf{u}_{obj}$ to $\mathbf{u}_{comp}$ (*i.e.*, $\mathbf{u}_{comp} = \Phi(\{\mathbf{u}_{attr}\} \cup \{\mathbf{u}_{obj}\})$) to ensure $\mathbf{u}_{comp}$ is well defined even there is no attributed phrases in the sentence.

Visualizations. We show a set of examples of image-to-text retrieval under text-domain adversarial attack in Fig. 3.

B.3. Unified text-to-image retrieval

Experiment setup. We use the 1K test split as the retrieval set. The queries are generated from frequent semantic components extracted by the semantic parser from the training set. We regard a query as a valid one if at least 3 images (5 for noun-level retrieval) in the test set contain the query. For the obj(det) queries, we directly use the class names of the MS-COCO object detection / segmentation annotations.

Baselines. For VSE++ and VSE-C, as they do not have an object-level encoder. For any query, we always regard it as a short sentence and feed it into the sentence encoder to get the embedding of the query text. For UniVSE, as it has the object-level encoder which means a noun/attribute-noun pair can be either encoded by the object encoder ϕ or by neural combiner ψ by regarding the query as a short sentence. We select the encoder having higher performance on a validation set and report the results.

Visualizations. We show a set of retrieved image by queries of various types in Fig. 4.

B.4. Semantic Parsing

Experiment setup. We also use the 1K test split for this experiment. For each caption, we first extract nouns, adjectives and relational words. We call adjective and relational words as content words. The model should recover the dependencies linked with them. We exclude some relational words whose lexical meanings are usually ambiguous, such as `include`, `to`, `of`, *etc*.

Given a content word (either an adjective or a relational word), we generate all possible dependencies among nouns in the sentence to form candidate dependencies. Each candidate dependency, which is either an adjective-noun pair or a subject-relation-object triple, will get a matching score w.r.t. the image (the *visual cue*). We select the dependency that has the highest score as the recovered dependency w.r.t. the chosen content word.

Metrics. We report the accuracy of the recovered semantic dependencies. In detail, for an attribute-noun dependency, the model gets a correct count if the dependency having the highest matching score is identical to the ground-truth. For the dependency of a relation, the model gets 0.5 correct counts if the subject/object of the answer is the same as the ground-truth. If both of them are the same as the ground-truth, the model gets 1 correct count. The reported accuracy computed as the fraction between total correct counts and the total number of dependencies.

Visualizations and failure case study. Shown in Fig. 5, we visualize some successful and failure cases in semantic parsing with visual cues. Error source analysis is also provided.

B.5. Embedding Visualization

We visualize the semantic space of different semantic levels by t-SNE [3]. The result can be found in Fig. B.5. Through the joint learning of vision and language, our unified VSE space successfully recovers the similarities between semantic components at various levels.

References

[1] F. Faghri, D. J. Fleet, J. R. Kiros, and S. Fidler. VSE++: Improving Visual-Semantic Embeddings with Hard Negatives. In *Proceedings of British Machine Vision Conference (BMVC)*, 2018. 1

[2] Z. Lin, M. Feng, C. N. d. Santos, M. Yu, B. Xiang, B. Zhou, and Y. Bengio. A Structured Self-attentive Sentence Embedding. *arXiv:1703.03130*, 2017. 2

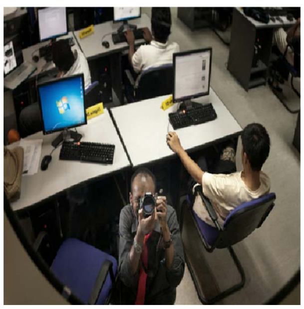
[3] L. v. d. Maaten and G. Hinton. Visualizing Data Using t-SNE. *Journal of Machine Learning Research (JMLR)*, 9(Nov):2579–2605, 2008. 4

[4] H. Shi, J. Mao, T. Xiao, Y. Jiang, and J. Sun. Learning Visually-Grounded Semantics from Contrastive Adversarial Samples. In *Proceedings of International Conference on Computational Linguistics (COLING)*, 2018. 1, 2, 4

VSE++
[1] (0.476) A few people that are playing tennis on a court.
[2] (0.472) Two people playing a match of tennis on a court.
[3] (0.460) Several men playing with a soccer ball in a park.
[4] (0.457) Two young men playinga game of soccer.
[5] (0.455) There is a man running on a field with a soccer ball.

VSE-C
[1] (0.428) There are two soccer teams playing a game on the field.
[2] (0.401) A few people that are playing tennis on a court.
[3] (0.395) Several boys on a field playing with a frisbee.
[4] (0.381) A group of people playing soccer in a field.
[5] (0.374) There are people playing a game of tennis.

U-VSE
[1] (0.456) A man carrying a soccer ball down a field.
[2] (0.454) There is a man running on a field with a soccer ball.
[3] (0.440) A man that is on a soccer field with a ball.
[4] (0.429) A man kicking a soccer ball while standing on a field.
[5] (0.411) The soccer player is bringing back the ball into play.



VSE++
[1] (0.520) A bowl with something in it with a banana next to it.
[2] (0.500) A banana sits by two oranges, a bowl and a white plate on a white tray.
[3] (0.498) The banana is laying next to an almost empty bowl.
[4] (0.492) A banana and a nearly empty bowl of food resting on top of a table.
[5] (0.467) A white tray with a banana and two tangerines and a plate and bowl.

VSE-C
[1] (0.465) The banana is laying next to an almost empty bowl.
[2] (0.440) A banana and a nearly empty bowl of food resting on top of a table.
[3] (0.423) A white tray with a banana and two tangerines and a plate and bowl.
[4] (0.414) A bowl with something in it with a banana next to it.
[5] (0.360) A bowl filled with leftover food sitting next to a banana.

U-VSE
[1] (0.551) A banana and two oranges sit on a tray next to a bowl and a plate.
[2] (0.519) A bowl with something in it with a banana next to it.
[3] (0.506) A banana sits by two oranges, a bowl and a white plate on a white tray.
[4] (0.502) A white tray with a banana and two tangerines and a plate and bowl.
[5] (0.498) The banana is laying next to an almost empty bowl.

VSE++
[1] (0.373) A couple of horses standing in a field.
[2] (0.353) Two giraffes standing in front of each other.
[3] (0.346) A big heard of cows walking down a road in a row with green tags on their ears.
[4] (0.345) Sheep that have been sheared standing in a pen.
[5] (0.344) Mythical character with white horse standing on grooved surface.

VSE-C
[1] (0.325) Ten porcelain pieces with floral patterns painted on them.
[2] (0.310) Two horses have feathers on their head.
[3] (0.304) Two giraffes standing in front of each other.
[4] (0.303) Horses standing in shallow water in a wooded area.
[5] (0.298) Two dogs lay next to each other on a brown couch.

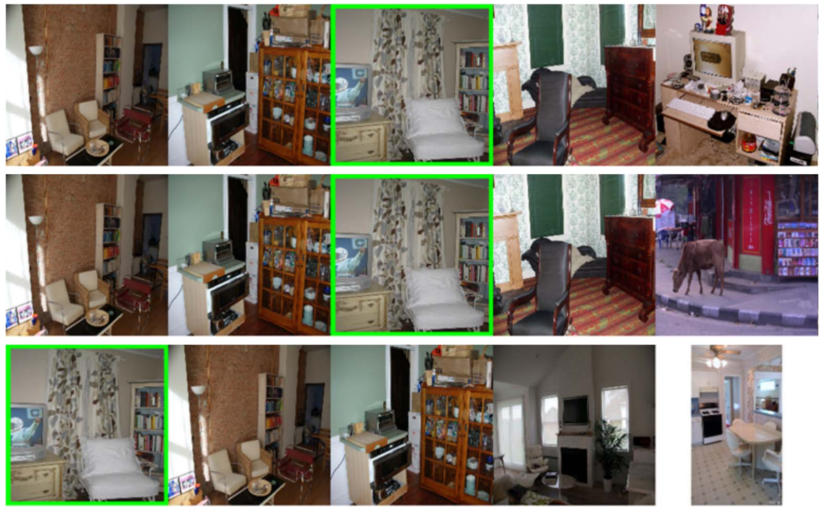
U-VSE
[1] (0.363) Three different horse figurines are placed beside each other.
[2] (0.360) A couple of white horses standing in front of a building.
[3] (0.345) Three plastic horse figurines standing next to each other on a shelf.
[4] (0.344) Two horses with red feathers on top of their heads.
[5] (0.339) Three model horses on a table in front of a pegboard backdrop.

VSE++
[1] (0.410) A basketball player holds a basketball for a picture.
[2] (0.395) A woman standing in the dark holding up a cell phone.
[3] (0.383) A person with a basketball stands in front of a goal.
[4] (0.371) A young woman is posing for camera.
[5] (0.352) A woman standing next to another woman in a building.

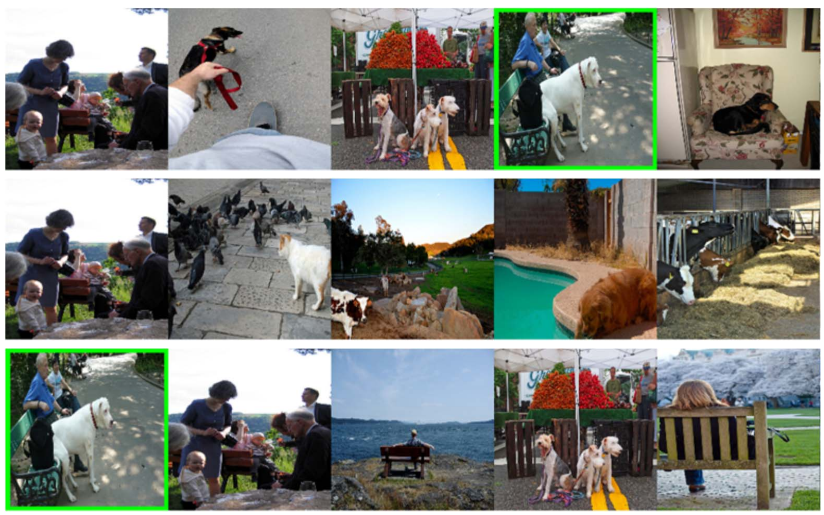
VSE-C
[1] (0.322) A woman hugging a girl who is holding a suitcase.
[2] (0.297) A young woman is posing for a camera.
[3] (0.296) A young man in green jersey is holding a ball.
[4] (0.290) A woman with her arms around a girl who is holding a suitcase.
[5] (0.288) A woman standing in the dark holding up a cell phone.

U-VSE
[1] (0.363) A basketball player holds a basketball for a picture.
[2] (0.360) A uniformed boy is holding a basketball with his back to the hoop.
[3] (0.345) A person with a basketball stands in front of a goal.
[4] (0.344) Two basketball players reach up for the hoop.
[5] (0.339) Two basketball players jump to the hoop to block another from scoring.

Figure 1. Examples showing the top-5 image-to-text retrieval results. We highlight the positive captions in blue. The score in the front of each sentence is the similarity score of the caption and image computed by different model. Best viewed in color.



(a) Query: `A white chair, books and shelves and a TV on in this room.`



(b) Query: `A couple of people sitting on a bench next to a dog.`

(c) Query: `Window view from the inside of airplanes, baggage carrier and tarmac.`

Figure 2. Examples showing the top-5 sentence-to-image retrieval results. We highlight the correct images in green box.

VSE++
[1] (0.481) A woman holding a scissor close to her hair.
[2] (0.467) A woman walk a scissor close to her hair.
[3] (0.462) An image of a shorts with a qoute at the top.
[4] (0.454) A picture of a woman in a good frame.
[5] (0.450) A young woman is posing for a camera.

VSE-C
[1] (0.411) A man wearing a mask behind a sbowboarder. (*sbowboarder* is a typo of *snowboarder* in the annotation)
[2] (0.400) A man wearing a mask is hold some woodworking.
[3] (0.400) A young woman is posing for a camera.
[4] (0.385) A man wearing a mask with a sbowboarder.
[5] (0.371) A man near a mask with a sbowboarder.

U-VSE
[1] (0.455) A young brunette woman with multiple face piercings.
[2] (0.451) A young woman with green eyes and piercings all over her face.
[3] (0.434) A young woman is posing for a camera.
[4] (0.424) A young woman with green eyes and piercings all stand her face.
[5] (0.423) An image of a very cute girl with face piercings.

VSE++
[1] (0.573) Several men sitting at a desk with a computer and stone while another man holds a camera upward.
[2] (0.562) Several men sitting at a desk with a computer and while another man holds a camera and sign upward.
[3] (0.555) Several men sitting at a desk with a computer while another man holds a camera upward.
[4] (0.546) A cellphone of young men sitting at a computer desk.
[5] (0.535) Several men sitting at a desk with a computer and while another man holds a camera and pot upward.

VSE-C
[1] (0.462) Several men sitting at a desk with a computer and while another man holds a camera upward.
[2] (0.442) Several men sitting at a desk with a computer and while another man holds a camera and sign upward.
[3] (0.433) A person talking on a large cell phone and phones.
[4] (0.428) A person in glasses is using a laptop and phone.
[5] (0.412) People are looking at computer and one man has a camera.

U-VSE
[1] (0.540) People sitting at computers and one person holding a camera.
[2] (0.510) Several men sitting at a desk with a computer while another man holds a camera upward.
[3] (0.496) People are looking at computer and one man has a camera.
[4] (0.490) People sitting at computers and one beds holding a camera.
[5] (0.489) A cellphone of young men sitting at a computer desk.

VSE++
[1] (0.577) A black and white photograph of a zebra cat.
[2] (0.573) A large group and wall of zebra standing in the grass.
[3] (0.566) A black and white photograph of a zebra.
[4] (0.550) A large group of zebra standing in the grass.
[5] (0.546) There is a black and white image and planes of a zebra eating grass.

VSE-C
[1] (0.550) There is a black and white image of a zebra eating grass.
[2] (0.451) A grassy field with various zebras standing next to each other.
[3] (0.446) Those zebras may have lost their carrots and they cold be nearby.
[4] (0.434) A group of zebras playing and bananas in a field.
[5] (0.434) Those zebras may have lost their elephants and they could be nearby.

U-VSE
[1] (0.519) There is a black and white image of a zebra eating grass.
[2] (0.514) An antilope is eating grass in between two zebra.
[3] (0.514) A black and white photograph of a zebra grazing.
[4] (0.513) A close up of a zebra foraging on some grass.
[5] (0.499) A black and white photograph of a zebra cat.

VSE++
[1] (0.604) A small boy with a cloudy shirt is eating a sandwich.
[2] (0.579) A small boy with a green shirt is eating a sandwich.
[3] (0.565) A small boy with a square shirt is eating a sandwich.
[4] (0.558) A small boy with a gray shirt is eating a sandwich.
[5] (0.550) A small boy with a brown shirt is eating a sandwich.

VSE-C
[1] (0.449) Man in gray shirt eating something that is green.
[2] (0.446) A young girl eating a slice of pizza.
[3] (0.444) A little girl eating a slice of pizza in a room.
[4] (0.442) A dirty girl eating a slice of pizza
[5] (0.436) A little girl eating a slice of orange pizza in a room.

U-VSE
[1] (0.512) A young girl with a green jacket eating a piece of pepperoni pizza.
[2] (0.510) Small girl in green shirt holding a slice of pizza to her face.
[3] (0.505) A young girl eating a slice of pizza.
[4] (0.496) A girl takes a gray bite of her pepperoni pizza.
[5] (0.494) A dirty girl eating a slice of pizza.

Figure 3. Examples showing the top-5 image-to-sentence retrieval results with the presence of adversarial samples. We highlight the positive captions in blue. Captions with red words are adversarial samples generated from the original captions. Words in red indicates the irrelevant words in the adversarial captions. Best viewed in color.

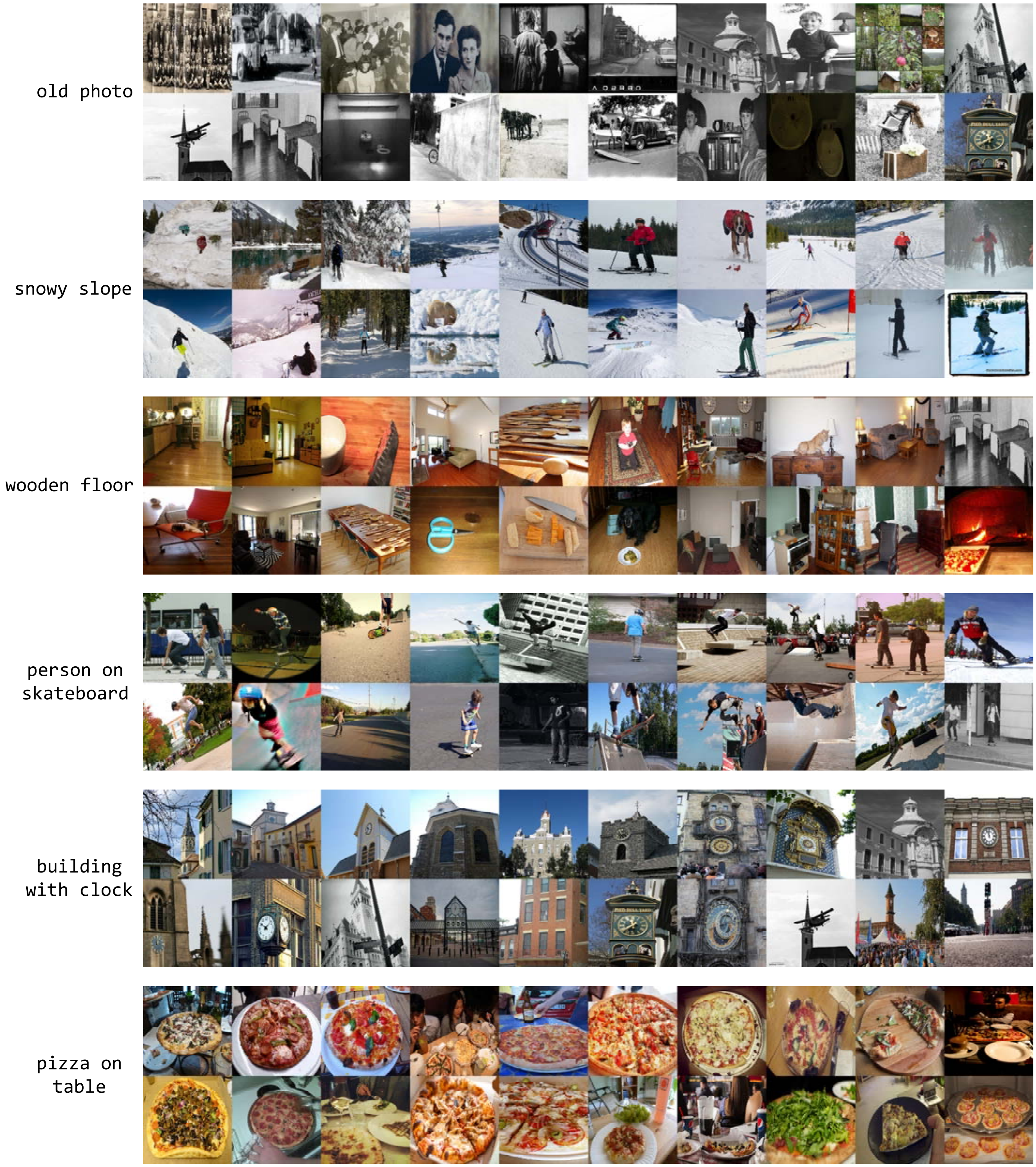


Figure 4. The top-20 retrieved image in the 1K test split set by queries different types: attribute-object pairs and relational triples.

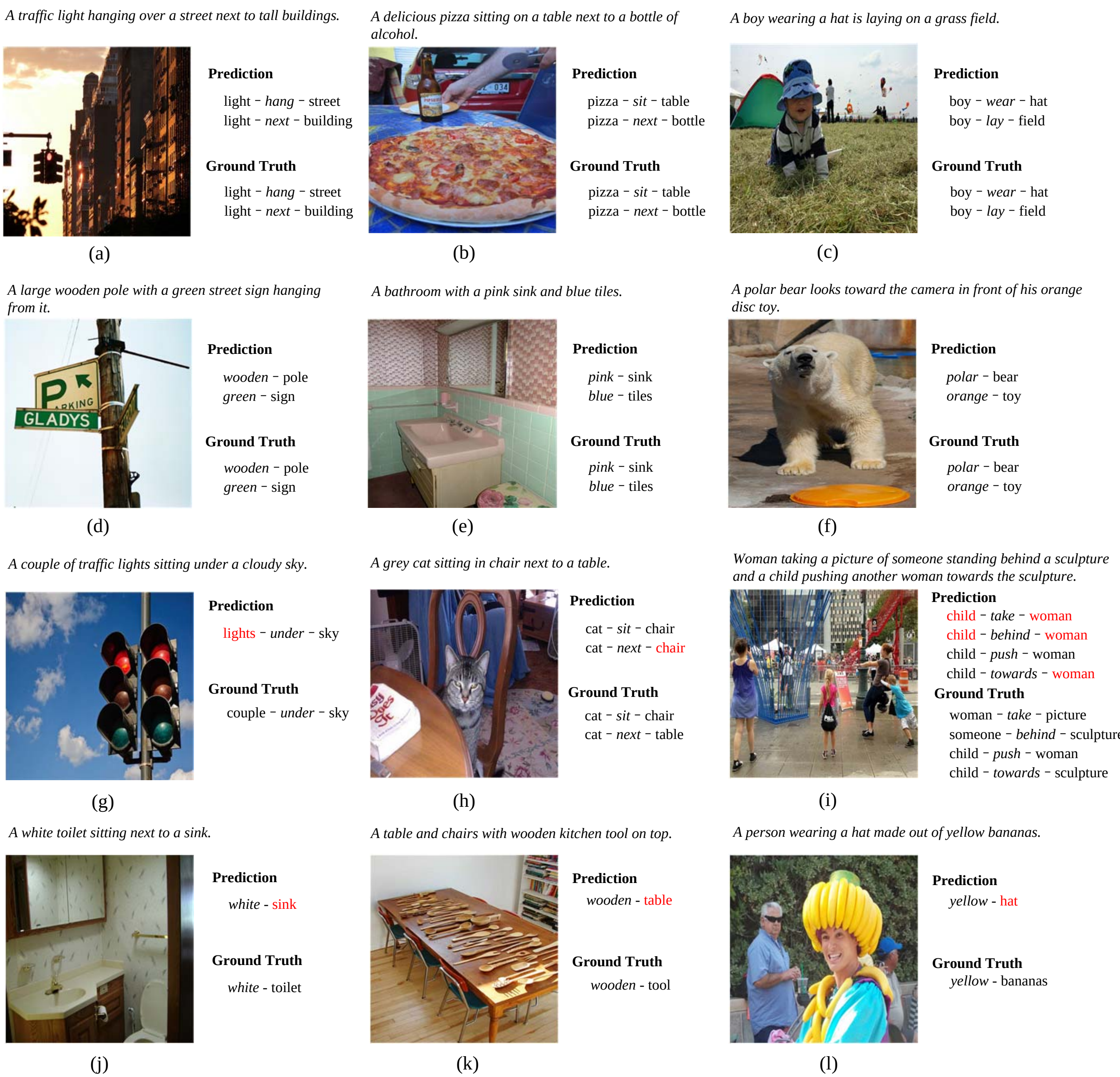
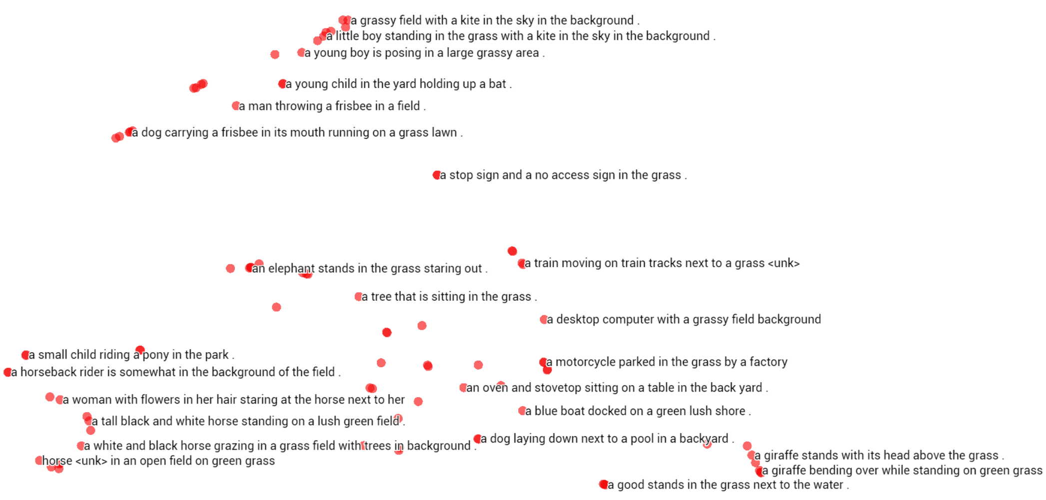


Figure 5. Examples showing the result of semantic parsing based on visual cues. The first and second rows visualize the examples of corrected dependency resolution and the last two rows are the failure cases (dependency resolutions differs from the one by our semantic parser). Words in italic are the content words whose dependency is to be recovered, and the words in red are wrong predictions. Fig. (g) is a failure case of our semantic parser: the word `couple` does not refer to a specific object in the scene. In Fig. (h), both dependencies `cat-next-chair` and `cat-next-table` are actually valid based only on visual cue. Similarly, Fig. (i), (j) and (k) are all cases where only visual cues can not recover the dependency. The result in Fig. (i) shows that our model has the tendency of linking spatially closer objects. In Fig. (l), `hat` and `bananas` actually refers to the same object. Best viewed in color.

(a) Object level (including nouns and adjective-noun pairs)

(b) Relational phrase level



(c) Sentence level

Figure 6. The visualization of the semantic embedding space of different semantic levels. The unified VSE space successfully recovers the similarities between semantic components at various levels.