

Visual Word2Vec (vis-w2v): Learning Visually Grounded Word Embeddings Using Abstract Scenes

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Abstract

We propose a model to learn visually grounded word embeddings (vis-w2v) to capture visual notions of semantic relatedness. While word embeddings trained using text have been extremely successful, they cannot uncover notions of semantic relatedness implicit in our visual world. For instance, although “eats” and “stares at” seem unrelated in text, they share semantics visually. When people are eating something, they also tend to stare at the food. Grounding diverse relations like “eats” and “stares at” into vision remains challenging, despite recent progress in vision. We note that the visual grounding of words depends on semantics, and not the literal pixels. We thus use abstract scenes created from clipart to provide the visual grounding. We find that the embeddings we learn capture fine-grained, visually grounded notions of semantic relatedness. We show improvements over text-only word embeddings (word2vec) on three tasks: common-sense assertion classification, visual paraphrasing and text-based image retrieval. Our code and datasets are available online.

1. Introduction

Artificial intelligence (AI) is an inherently multi-modal problem: understanding and reasoning about multiple modalities (as humans do), seems crucial for achieving artificial intelligence (AI). Language and vision are two vital interaction modalities for humans. Thus, modeling the rich interplay between language and vision is one of fundamental problems in AI.

Language modeling is an important problem in natural language processing (NLP). A language model estimates the likelihood of a word conditioned on other (context) words in a sentence. There is a rich history of works on n -gram based language modeling [4, 17]. It has been shown that simple, count-based models trained on millions of sentences can give good results. However, in recent years, neural language models [3, 32] have been explored. Neural language models learn mappings ($W : \text{words} \rightarrow \mathbb{R}^n$) from

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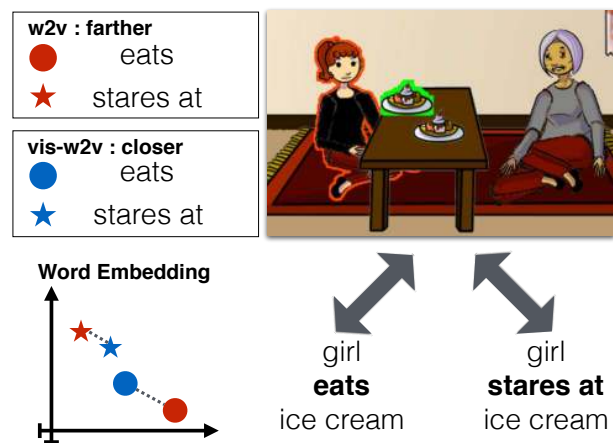


Figure 1: We ground text-based word2vec ($w2v$) embeddings into vision to capture a complimentary notion of visual relatedness. Our method ($vis-w2v$) learns to predict the visual grounding as context for a given word. Although “eats” and “stares at” seem unrelated in text, they share semantics visually. Eating involves staring or looking at the food that is being eaten. As training proceeds, embeddings change from $w2v$ (red) to $vis-w2v$ (blue).

words (encoded using a dictionary) to a real-valued vector space (embedding), to maximize the log-likelihood of words given context. Embedding words into such a vector space helps deal with the curse of dimensionality, so that we can reason about similarities between words more effectively. One popular architecture for learning such an embedding is word2vec [31, 33]. This embedding captures rich notions of semantic relatedness and compositionality between words [33].

For tasks at the intersection of vision and language, it seems prudent to model semantics as dictated by both text and vision. It is especially challenging to model fine-grained interactions between objects using only text. Consider the relations “eats” and “stares at” in Fig. 1. When reasoning using only text, it might prove difficult to realize that these relations are semantically similar. However, by

grounding the concepts into vision, we can learn that these relations are more similar than indicated by text. Thus, visual grounding provides a complimentary notion of semantic relatedness. In this work, we learn word embeddings to capture this grounding.

Grounding fine-grained notions of semantic relatedness between words like “eats” and “stares at” into vision is a challenging problem. While recent years have seen tremendous progress in tasks like image classification [20], detection [13], semantic segmentation [25], action recognition [27], *etc.*, modeling fine-grained semantics of interactions between objects is still a challenging task. However, we observe that it is the semantics of the visual scene that matter for inferring the visually grounded semantic relatedness, and not the literal pixels (Fig. 1). We thus use abstract scenes made from clipart to provide the visual grounding. We show that the embeddings we learn using abstract scenes generalize to text describing real images (Sec. 6.1).

Our approach considers visual cues from abstract scenes as context for words. Given a set of words and associated abstract scenes, we first cluster the scenes in a rich semantic feature space capturing the presence and locations of objects, pose, expressions, gaze, age of people, *etc.* Note that these features can be trivially extracted from abstract scenes. Using these features helps us capture fine-grained notions of semantic relatedness (Fig. 4). We then train to predict the cluster membership from pre-initialized word embeddings. The idea is to bring embeddings for words with similar visual instantiations closer, and push words with different visual instantiations farther (Fig. 1). The word embeddings are initialized with word2vec [33]. The clusters thus act as surrogate classes. Note that each surrogate class may have images belonging to concepts which are different in text, but are visually similar. Since we predict the visual clusters as context given a set of input words, our model can be viewed as a multi-modal extension of the continuous bag of words (CBOW) [33] word2vec model.

Contributions: We propose a novel model *visual word2vec* ($vis-w2v$) to learn visually grounded word embeddings. We use abstract scenes made from clipart to provide the grounding. We demonstrate the benefit of $vis-w2v$ on three tasks which are ostensibly in text, but can benefit from visual grounding: common sense assertion classification [35], visual paraphrasing [24], and text-based image retrieval [15]. Common sense assertion classification [35] is the task of modeling the plausibility of common sense assertions of the form (boy, eats, cake). Visual paraphrasing [24] is the task of determining whether two sentences describe the same underlying scene or not. Text-based image retrieval is the task of retrieving images by matching accompanying text with textual queries. We show consistent improvements over baseline word2vec ($w2v$) models on these tasks. In fact, on the common sense assertion classification task, our models surpass the state of the art.

The rest of the paper is organized as follows. Sec. 2 discusses related work on learning word embeddings, learning from visual abstraction, *etc.* Sec. 3 presents our approach. Sec. 4 describes the datasets we work with. We provide experimental details in Sec. 5 and results in Sec. 6.

2. Related Work

Word Embeddings: Word embeddings learnt using neural networks [6, 33] have gained a lot of popularity recently. These embeddings are learnt offline and then typically used to initialize a multi-layer neural network language model [3, 32]. Similar to those approaches, we learn word embeddings from text offline, and finetune them to predict visual context. Xu *et al.* [43] and Lazaridou *et al.* [22] use visual cues to improve the word2vec representation by predicting real image representations from word2vec and maximizing the dot product between image features and word2vec respectively. While their focus is on capturing appearance cues (separating cats and dogs based on different appearance), we instead focus on capturing fine-grained semantics using abstract scenes. Other works use visual and textual attributes (*e.g.* vegetable is an attribute for potato) to improve distributional models of word meaning [39, 40]. In contrast to these approaches, our set of visual concepts need not be explicitly specified, it is implicitly learnt in the clustering step. Many works use word embeddings as parts of larger models for tasks such as image retrieval [18], image captioning [18, 42], *etc.* These multi-modal embeddings capture regularities like compositional structure between images and words. For instance, in such a multi-modal embedding space, “image of blue car” - “blue” + “red” would give a vector close to “image of red car”. In contrast, we want to learn unimodal (textual) embeddings which capture multi-modal semantics. For example, we want to learn that “eats” and “stares at” are (visually) similar.

Surrogate Classification: There has been a lot of recent work on learning with surrogate labels due to interest in unsupervised representation learning. Previous works have used surrogate labels to learn image features [7, 9]. In contrast, we are interested in augmenting word embeddings with visual semantics. Also, while previous works have created surrogate labels using data transformations [9] or sampling [7], we create surrogate labels by clustering abstract scenes in a semantically rich feature space.

Learning from Visual Abstraction: Visual abstractions have been used for a variety of high-level scene understanding tasks recently. Zitnick *et al.* [44, 45] learn the importance of various visual features (occurrence and co-occurrence of objects, expression, gaze, *etc.*) in determining the meaning or semantics of a scene. [46] and [10] learn the visual interpretation of sentences and the dynam-

ics of objects in temporal abstract scenes respectively. Antol *et al.* [2] learn models of fine-grained interactions between pairs of people using visual abstractions. Lin and Parikh [24] “imagine” abstract scenes corresponding to text, and use the common sense depicted in these imagined scenes to solve textual tasks such as fill-in-the-blanks and paraphrasing. Vedantam *et al.* [35] classify common sense assertions as plausible or not by using textual and visual cues. In this work, we experiment with the tasks of [24] and [35], which are two tasks in text that could benefit from visual grounding. Interestingly, by learning `vis-w2v`, we eliminate the need for explicitly reasoning about abstract scenes at test time, *i.e.*, the visual grounding captured in our word embeddings suffices.

Language, Vision and Common Sense: There has been a surge of interest in problems at the intersection of language and vision recently. Breakthroughs have been made in tasks like image captioning [5, 8, 14, 16, 18, 21, 30, 34, 42], video description [8, 37], visual question answering [1, 11, 12, 28, 29, 36], aligning text and vision [16, 18], *etc.* In contrast to these tasks (which are all multi-modal), our tasks themselves are unimodal (*i.e.*, in text), but benefit from using visual cues. Recent work has also studied how vision can help common sense reasoning [35, 38]. In comparison to these works, our approach is generic, *i.e.*, can be used for multiple tasks (not just common sense reasoning).

3. Approach

Recall that our `vis-w2v` model grounds word embeddings into vision by treating vision as context. We first detail our inputs. We then discuss our `vis-w2v` model. We then describe the clustering procedure to get surrogate semantic labels, which are used as visual context by our model. We then describe how word-embeddings are initialized. Finally, we draw connections to word2vec (`w2v`) models.

Input: We are given a set of pairs of visual scenes and associated text $D = \{(v, w)\}_d$ in order to train `vis-w2v`. Here v refers to the image features and w refers to the set of words associated with the image. At each step of training, we select a window $S_w \subseteq w$ to train the model.

Model: Our `vis-w2v` model (Fig. 2) is a neural network that accepts as input a set of words S_w and a visual feature instance v . Each of the words $w_i \in S_w$ is represented via a one-hot encoding. A one-hot encoding enumerates over the set of words in a vocabulary (of size N_V) and places a 1 at the index corresponding to the given word. This one-hot encoded input is transformed using a projection matrix W_I of size $N_V \times N_H$ that connects the input layer to the hidden layer, where the hidden layer has a dimension of N_H . Intuitively, N_H decides the capacity of the representation. Consider an input one-hot encoded word w_i whose j^{th} in-

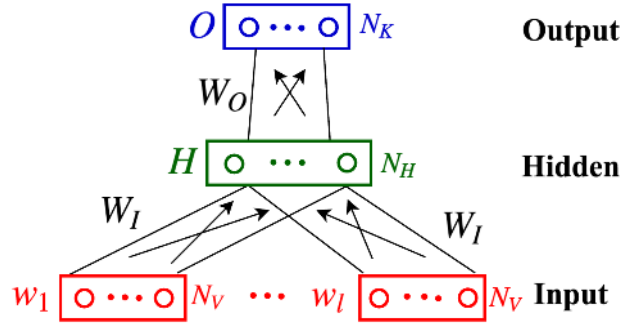


Figure 2: Proposed `vis-w2v` model. The input layer (red) has multiple one-hot word encodings. These are connected to the hidden layer with the projection matrix W_I , *i.e.*, all the inputs share the same weights. It is finally connected to the output layer via W_O . Model predicts the visual context O given the text input $S_w = \{w_i\}$.

dex is set to 1. Since w_i is one-hot encoded, the hidden activation for this word (H_{w_i}) is a row in the weight matrix W_I^j , *i.e.*, $H_{w_i} = W_I^j$. The resultant hidden activation H would then be the average of individual hidden activations H_{w_i} as W_I is shared among all the words S_w , *i.e.*:

$$H = \frac{1}{|S_w|} \sum_{w_i \in S_w \subseteq w} H_{w_i} \quad (1)$$

Given the hidden activation H , we multiply it with an output weight matrix W_O of size $N_H \times N_K$, where N_K is the number of output classes. The output class (described next) is a discrete-valued function of the visual features $G(v)$ (more details in next paragraph). We normalize the output activations $O = H \times W_O$ to form a distribution using the softmax function. Given the softmax outputs, we minimize the negative log-likelihood of the correct class conditioned on the input words:

$$\min_{W_I, W_O} -\log P(G(v)|S_w, W_I, W_O) \quad (2)$$

We optimize for this objective using stochastic gradient descent (SGD) with a learning rate of 0.01.

Output Classes: As mentioned in the previous section, the target classes for the neural network are a function $G(\cdot)$ of the visual features. What would be a good choice for G ? Recall that our aim is to recover an embedding for words that respects similarities in visual instantiations of words (Fig. 1). To capture this visual similarity, we model $G : v \rightarrow \{1, \dots, N_K\}$ as a grouping function¹. In practice, this function is learnt offline using clustering with K-means. That is, the outputs from clustering are the surro-

¹Alternatively, one could regress directly to the feature values v . However, we found that the regression objective hurts performance.

gate class labels used in `vis-w2v` training. Since we want our embeddings to reason about fine-grained visual grounding (e.g. “stares at” and “eats”), we cluster in the abstract scenes feature space (Sec. 4). See Fig. 4 for an illustration of what clustering captures. The parameter N_K in K-means modulates the granularity at which we reason about visual grounding.

Initialization: We initialize the projection matrix parameters W_I with those from training `w2v` on large text corpora. The hidden-to-output layer parameters are initialized randomly. Using `w2v` is advantageous for us in two ways: i) `w2v` embeddings have been shown to capture rich semantics and generalize to a large number of tasks in text. Thus, they provide an excellent starting point to finetune the embeddings to account for visual similarity as well. ii) Training on a large corpus gives us good coverage in terms of the vocabulary. Further, since the gradients during back-propagation only affect parameters/embeddings for words seen during training, one can view `vis-w2v` as augmenting `w2v` with visual information when available. In other words, we retain the rich amount of non-visual information already present in it^2 . Indeed, we find that the random initialization does not perform as well as initialization with `w2v` when training `vis-w2v`.

Design Choices: Our model (Sec. 3) admits choices of w in a variety of forms such as full sentences or tuples of the form (Primary Object, Relation, Secondary Object). The exact choice of w is made depending upon on what is natural for the task of interest. For instance, for common sense assertion classification and text-based image retrieval, w is a phrase from a tuple, while for visual paraphrasing w is a sentence. Given w , the choice of S_w is also a design parameter tweaked depending upon the task. It could include all of w (e.g., when learning from a phrase in the tuple) or a subset of the words (e.g., when learning from an n -gram context-window in a sentence). While the model itself is task agnostic, and only needs access to the words and visual context during training, the validation and test performances are calculated using the `vis-w2v` embeddings on a specific task of interest (Sec. 5). This is used to choose the hyperparameters N_K and N_H .

Connections to `w2v`: Our model can be seen as a multi-modal extension of the continuous bag of words (CBOW) `w2v` models. The CBOW `w2v` objective maximizes the likelihood $P(w|S_w, W_I, W_O)$ for a word w and its context S_w . On the other hand, we maximize the likelihood of the visual context given a set of words S_w (Eq. 2).

²We verified empirically that this does not cause *calibration* issues. Specifically, given a pair of words where one word was refined using visual information but the other was not (unseen during training), using `vis-w2v` for the former and `w2v` for the latter when computing similarities between the two outperforms using `w2v` for both.

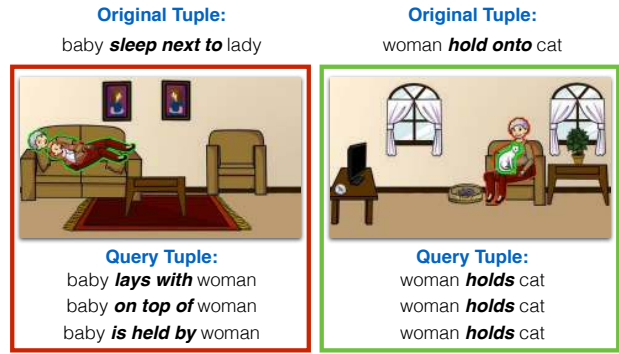


Figure 3: Examples tuples collected for the text-based image retrieval task. Notice that multiple relations can have the same visual instantiation (left).

4. Applications

We compare `vis-w2v` and `w2v` on the tasks of common sense assertion classification (Sec. 4.1), visual paraphrasing (Sec. 4.2), and text-based image retrieval (Sec. 4.3). We give details of each task and the associated datasets below.

4.1. Common Sense Assertion Classification

We study the relevance of `vis-w2v` to the common sense (CS) assertion classification task introduced by Vedantam *et al.* [35]. Given common sense tuples of the form (primary object or t_P , relation or t_R , secondary object or t_S) e.g. (boy, eats, cake), the task is to classify it as plausible or not. The CS dataset contains 14,332 TEST assertions (spanning 203 relations) out of which 37% are plausible, as indicated by human annotations. These TEST assertions are extracted from the MS COCO dataset [23], which contains real images and captions. Evaluating on this dataset allows us to demonstrate that visual grounding learnt from the abstract world generalizes to the real world. [35] approaches the task by constructing a multi-modal similarity function between TEST assertions whose plausibility is to be evaluated, and TRAIN assertions that are known to be plausible. The TRAIN dataset also contains 4260 abstract scenes made from clipart depicting 213 relations between various objects (20 scenes per relation). Each scene is annotated with one tuple that names the primary object, relation, and secondary object depicted in the scene. Abstract scene features (from [35]) describing the interaction between objects such as relative location, pose, absolute location, *etc.* are used for learning `vis-w2v`. More details of the features can be found in [19]. We use the VAL set from [35] (14,548 assertions) to pick the hyperparameters. Since the dataset contains tuples of the form (t_P, t_R, t_S), we explore learning `vis-w2v` with **separate** models for each, and a **shared** model irrespective of the word being t_P, t_R , or t_S .

4.2. Visual Paraphrasing

Visual paraphrasing (VP), introduced by Lin and Parikh [24] is the task of determining if a pair of descriptions describes the same scene or two different scenes. The dataset introduced by [24] contains 30,600 pairs of descriptions, of which a third are positive (describe the same scene) and the rest are negatives. The TRAIN dataset contains 24,000 VP pairs whereas the TEST dataset contains 6,060 VP pairs. Each description contains three sentences. We use scenes and descriptions from Zitnick *et al.* [46] to train `vis-w2v` models, similar to Lin and Parikh. The abstract scene feature set from [46] captures occurrence of objects, person attributes (expression, gaze, and pose), absolute spatial location and co-occurrence of objects, relative spatial location between pairs of objects, and depth ordering (3 discrete depths), relative depth and flip. We withhold a set of 1000 pairs (333 positive and 667 negative) from TRAIN to form a VAL set to pick hyperparameters. Thus, our VP TRAIN set has 23,000 pairs.

4.3. Text-based Image Retrieval

In order to verify if our model has learnt the visual grounding of concepts, we study the task of text-based image retrieval. Given a query tuple, the task is to retrieve the image of interest by matching the query and ground truth tuples describing the images using word embeddings. For this task, we study the generalization of `vis-w2v` embeddings learnt for the common sense (CS) task, *i.e.*, there is no training involved. We augment the common sense (CS) dataset [35] (Sec. 4.1) to collect three query tuples for each of the original 4260 CS TRAIN scenes. Each scene in the CS TRAIN dataset has annotations for which objects in the scene are the primary and secondary objects in the ground truth tuples. We highlight the primary and secondary objects in the scene and ask workers on AMT to name the primary, secondary objects, and the relation depicted by the interaction between them. Some examples can be seen in Fig. 3. Interestingly, some scenes elicit diverse tuples whereas others tend to be more constrained. This is related to the notion of Image Specificity [15]. Note that the workers do not see the original (ground truth) tuple written for the scene from the CS TRAIN dataset. More details of the interface are provided in [19]. We use the collected tuples as queries for performing the retrieval task. Note that the queries used at test time were never used for training `vis-w2v`.

5. Experimental Setup

We now explain our experimental setup. We first explain how we use our `vis-w2v` or baseline `w2v` (`word2vec`) model for the three tasks described above: common sense (CS), visual paraphrasing (VP), and text-based image retrieval. We also provide evaluation details. We

then list the baselines we compare to for each task and discuss some design choices. For all the tasks, we preprocess raw text by tokenizing using the NLTK toolkit [26]. We implement `vis-w2v` as an extension of the Google C implementation of `word2vec`³.

5.1. Common Sense Assertion Classification

The task in common sense assertion classification (Sec. 4.1) is to compute the plausibility of a test assertion based on its similarity to a set of tuples ($\Omega = \{t^i\}_{i=1}^I$) known to be plausible. Given a tuple $t' = (\text{Primary Object } t'_P, \text{Relation } t'_R, \text{Secondary Object } t'_S)$ and a training instance t^i , the plausibility scores are computed as follows:

$$h(t', t^i) = W_P(t'_P)^T W_P(t^i_P) + W_R(t'_R)^T W_R(t^i_R) + W_S(t'_S)^T W_S(t^i_S) \quad (3)$$

where W_P, W_R, W_S represent the corresponding word embedding spaces. The final text score is given as follows:

$$f(t') = \frac{1}{|I|} \sum_{i \in I} \max(h(t', t^i) - \delta, 0) \quad (4)$$

where i sums over the entire set of training tuples. We use the value of δ used by [35] for our experiments.

[35] share embedding parameters across t_P, t_R, t_S in their text based model. That is, $W_P = W_R = W_S$. We call this the **shared** model. When W_P, W_R, W_S are learnt independently for (t_P, t_R, t_S) , we call it the **separate** model.

The approach in [35] also has a visual similarity function that combines text and abstract scenes that is used along with this text-based similarity. We use the text-based approach for evaluating both `vis-w2v` and baseline `w2v`. However, we also report results including the visual similarity function along with text similarity from `vis-w2v`. In line with [35], we also evaluate our results using average precision (AP) as a performance metric.

5.2. Visual Paraphrasing

In the visual paraphrasing task (Sec. 4.2), we are given a pair of descriptions at test time. We need to assign a score to each pair indicating how likely they are to be paraphrases, *i.e.*, describing the same scene. Following [24] we average word embeddings (`vis-w2v` or `w2v`) for the sentences and plug them into their text-based scoring function. This scoring function combines term frequency, word co-occurrence statistics and averaged word embeddings to assess the final paraphrasing score. The results are evaluated using average precision (AP) as the metric. While training both `vis-w2v` and `w2v` for the task, we append the sentences from the train set of [24] to the original word embedding training corpus to handle vocabulary overlap issues.

³<https://code.google.com/p/word2vec/>

5.3. Text-based Image Retrieval

We compare $w2v$ and $vis-w2v$ on the task of text-based image retrieval (Sec. 4.3). The task involves retrieving the target image from an image database, for a query tuple. Each image in the database has an associated ground truth tuple describing it. We use these to rank images by computing similarity with the query tuple. Given tuples of the form (t_P, t_R, t_S) , we average the vector embeddings for all words in t_P, t_R, t_S . We then explore **separate** and **shared** models just as we did for common sense assertion classification. In the **separate** model, we first compute the cosine similarity between the query and the ground truth for t_P, t_R, t_S separately and average the three similarities. In the **shared** model, we average the word embeddings for t_P, t_R, t_S for query and ground truth and then compute the cosine similarity between the averaged embeddings. The similarity scores are then used to rank the images in the database for the query. We use standard metrics for retrieval tasks to evaluate: Recall@1 (R@1), Recall@5 (R@5), Recall@10 (R@10) and median rank (med R) of target image in the returned result.

5.4. Baselines

We describe some baselines in this subsection. In general, we consider two kinds of $w2v$ models: those learnt from generic text, *e.g.*, Wikipedia ($w2v-wiki$) and those learnt from visual text, *e.g.*, MS COCO ($w2v-coco$), *i.e.*, text describing images. Embeddings learnt from visual text typically contain more visual information [35]. $vis-w2v-wiki$ are $vis-w2v$ embeddings learnt using $w2v-wiki$ as an initialization to the projection matrix, while $vis-w2v-coco$ are the $vis-w2v$ embeddings learnt using $w2v-coco$ as the initialization. In all settings, we are interested in studying the performance gains on using $vis-w2v$ over $w2v$. Although our training procedure itself is task agnostic, we train separately on the common sense (CS) and the visual paraphrasing (VP) datasets. We study generalization of the embeddings learnt for the CS task on the text-based image retrieval task. Additional design choices pertaining to each task are discussed in Sec. 3.

6. Results

We present results on common sense (CS), visual paraphrasing (VP), and text-based image retrieval tasks. We compare our approach to various baselines as explained in Sec. 5 for each application. Finally, we train our model using real images instead of abstract scenes, and analyze differences. More details on the effect of hyperparameters on performance (for CS and VP) can be found in [19].

6.1. Common Sense Assertion Classification

We first present our results on the common sense assertion classification task (Sec. 4.1). We report numbers with

Approach	common sense AP (%)
$vis-w2v-wiki$ (shared)	72.2
$vis-w2v-wiki$ (separate)	74.2
$vis-w2v-coco$ (shared) + vision	74.2
$vis-w2v-coco$ (shared)	74.5
$vis-w2v-coco$ (separate)	74.8
$vis-w2v-coco$ (separate) + vision	75.2
$w2v-wiki$ (from [35])	68.4
$w2v-coco$ (from [35])	72.2
$w2v-coco$ + vision (from [35])	73.6

Table 1: Performance on the common sense task of [35]

a fixed hidden layer size, $N_H = 200$ (to be comparable to [35]) in Table. 1. We use $N_K = 25$, which gives the best performance on validation. We handle tuple elements, t_P, t_R or t_S , with more than one word by placing each word in a separate window (*i.e.* $|S_w| = 1$). For instance, the element “lay next to” is trained by predicting the associated visual context thrice with “lay”, “next” and “to” as inputs. Overall, we find an increase of 2.6% with $vis-w2v-coco$ (separate) model over the $w2v-coco$ model used in [35]. We achieve larger gains (5.8%) with $vis-w2v-wiki$ over $w2v-wiki$. Interestingly, the tuples in the common sense task are extracted from the MS COCO [23] dataset. Thus, this is an instance where $vis-w2v$ (learnt from abstract scenes) generalizes to text describing real images.

Our $vis-w2v-coco$ (both shared and separate) embeddings outperform the joint $w2v-coco$ + vision model from [35] that reasons about visual features for a given test tuple, which we do not. Note that both models use the same training and validation data, which suggests that our $vis-w2v$ model captures the grounding better than their multi-modal text + visual similarity model. Finally, we sweep for the best value of N_H for the validation set and find that $vis-w2v-coco$ (separate) gets the best AP of 75.4% on TEST with $N_H = 50$. This is our best performance on this task.

Separate vs. Shared: We next compare the performance when using the **separate** and **shared** $vis-w2v$ models. We find that $vis-w2v-coco$ (separate) does better than $vis-w2v-coco$ (shared) (74.8% vs. 74.5%), presumably because the embeddings can specialize to the semantic roles words play when participating in t_P, t_R or t_S . In terms of **shared** models alone, $vis-w2v-coco$ (shared) achieves a gain in performance of 2.3% over the $w2v-coco$ model of [35], whose textual models are all shared.

What Does Clustering Capture? We next visualize the semantic relatedness captured by clustering in the abstract scenes feature space (Fig. 4). Recall that clustering gives us surrogate labels to train $vis-w2v$. For the visualization, we pick a relation and display other relations that co-occur the most with it in the same cluster. Interestingly, words like “prepare to cut”, “hold”, “give” occur often with “stare at”. Thus, we discover the fact that when we “prepare to cut”



Figure 4: Visualization of the clustering used to supervise vis-w2v training. Relations that co-occur more often in the same cluster appear bigger than others. Observe how semantically close relations co-occur the most, e.g., eat, drink, chew on for the relation enjoy.

something, we also tend to “stare at” it. Reasoning about such notions of semantic relatedness using purely textual cues would be prohibitively difficult. We provide more examples in [19].

6.2. Visual Paraphrasing

We next describe our results on the Visual Paraphrasing (VP) task (Sec. 4.2). The task is to determine if a pair of descriptions are describing the same scene. Each description has three sentences. Table. 2 summarizes our results and compares performance to $w2v$. We vary the size of the context window S_w and check performance on the VAL set. We obtain best results with the entire description as the context window S_w , $N_H = 200$, and $N_K = 100$. Our vis-w2v models give an improvement of 0.7% on both $w2v\text{-wiki}$ and $w2v\text{-coco}$ respectively. In comparison to $w2v\text{-wiki}$ approach from [24], we get a larger gain of 1.2% with our vis-w2v-coco embeddings⁴. Lin and Parikh [24] imagine the visual scene corresponding to text to solve the task. Their combined text + imagination model performs 0.2% better (95.5%) than our model. Note that our approach does not have the additional expensive step of generating an imagined visual scene for each instance at test time. Qualitative examples of success and failure cases are shown in Fig. 5.

Window Size: Since the VP task is on multi-sentence descriptions, it gives us an opportunity to study how size of the window (S_w) used in training affects performance. We evaluate the gains obtained by using window sizes of entire description, single sentence, 5 words, and single word respectively. We find that description level windows and sentence level windows give equal gains. However, performance tapers off as we reduce the context to 5 words (0.6% gain) and a single word (0.1% gain). This is intuitive, since VP requires us to reason about entire descriptions to deter-

⁴Our implementation of [24] performs 0.3% higher than that reported in [24].



Figure 5: The visual paraphrasing task is to identify if two textual descriptions are paraphrases of each other. Shown above are three positive instances, i.e., the descriptions (left, right) actually talk about the same scene (center, shown for illustration, not available as input). Green boxes show two cases where vis-w2v correctly predicts and $w2v$ does not, while red box shows the case where both vis-w2v and $w2v$ predict incorrectly. Note that the red instance is tough as the textual descriptions do not intuitively seem to be talking about the same scene, even for a human reader.

Approach	Visual Paraphrasing AP (%)
$w2v\text{-wiki}$ (from [24])	94.1
$w2v\text{-wiki}$	94.4
$w2v\text{-coco}$	94.6
vis-w2v-wiki	95.1
vis-w2v-coco	95.3

Table 2: Performance on visual paraphrasing task of [24].

mine paraphrases. Further, since the visual features in this dataset are scene level (and not about isolated interactions between objects), the signal in the hidden layer is stronger when an entire sentence is used.

6.3. Text-based Image Retrieval

We next present results on the text-based image retrieval task (Sec. 4.3). This task requires visual grounding as the query and the ground truth tuple can often be different by textual similarity, but could refer to the same scene (Fig. 3). As explained in Sec. 4.3, we study generalization of the embeddings learnt during the commonsense experiments to this task. Table. 3 presents our results. Note that vis-w2v here refers to the embeddings learnt using the CS dataset. We find that the best performing models are vis-w2v-wiki (shared) (as per R@1, R@5, medR) and vis-w2v-coco (separate) (as per R@10, medR). These get Recall@10 scores of $\approx 49.5\%$ whereas the baseline $w2v\text{-wiki}$ and $w2v\text{-coco}$ embeddings give scores of 45.4% and 47.6%, respectively.

Approach	R@1 (%)	R@5 (%)	R@10 (%)	med R
w2v-wiki	14.6	34.4	45.4	13
w2v-coco	15.3	35.2	47.6	11
vis-w2v-wiki (shared)	15.5	37.2	49.3	10
vis-w2v-coco (shared)	15.7	37.7	47.6	10
vis-w2v-wiki (separate)	14.0	32.7	43.5	15
vis-w2v-coco (separate)	15.4	37.6	49.5	10

Table 3: Performance on text-based image retrieval. R@x: **higher** is better, medR: **lower** is better

6.4. Real Image Experiment

Finally, we test our `vis-w2v` approach with real images on the CS task, to evaluate the need to learn fine-grained visual grounding via abstract scenes. Thus, instead of semantic features from abstract scenes, we obtain surrogate labels by clustering real images from the MS COCO dataset using `fc7` features from the VGG-16 [41] CNN. We cross validate to find the best number of clusters and hidden units. We perform real image experiments in two settings: 1) We use all of the MS COCO dataset after removing the images whose tuples are in the CS TEST set of [35]. This gives us a collection of $\approx 76K$ images to learn `vis-w2v`. MS COCO dataset has a collection of 5 captions for each image. We use all these five captions with sentence level context⁵ windows to learn `vis-w2v80K`. 2) We create a real image dataset by collecting 20 real images from MS COCO and their corresponding tuples, randomly selected for each of 213 relations from the VAL set (Sec. 5.1). Analogous to the CS TRAIN set containing abstract scenes, this gives us a dataset of 4260 real images along with an associate tuple, depicting the 213 CS VAL relations. We refer to this model as `vis-w2v4K`.

We report the gains in performance over `w2v` baselines in both scenario 1) and 2) for the common sense task. We find that using real images gives a best-case performance of 73.7% starting from `w2v-coco` for `vis-w2v80K` (as compared to 74.8% using CS TRAIN abstract scenes). For `vis-w2v4K-coco`, the performance on the validation actually goes down during training. If we train `vis-w2v4K` starting with generic text based `w2v-wiki`, we get a performance of 70.8% (as compared to 74.2% using CS TRAIN abstract scenes). This shows that abstract scenes are better at visual grounding as compared to real images, due to their rich semantic features.

7. Discussion

Antol *et al.* [2] have studied generalization of classification models learnt on abstract scenes to real images. The idea is to transfer fine-grained concepts that are easier to learn in the fully-annotated abstract domain to tasks in the real domain. Our work can also be seen as a method of studying generalization. One can view `vis-w2v` as a way

⁵We experimented with other choices but found this works best.

to transfer knowledge learnt in the abstract domain to the real domain, via text embeddings (which are shared across the abstract and real domains). Our results on common-sense assertion classification show encouraging preliminary evidence of this.

We next discuss some considerations in the design of the model. A possible design choice when learning embeddings could have been to construct a triplet loss function, where the similarity between a tuple and a pair of visual instances can be specified. That is, given a textual instance A , and two images B and C (where A describes B , and not C), one could construct a loss that enforces $sim(A, B) > sim(A, C)$, and learn joint embeddings for words and images. However, since we want to learn hidden semantic relatedness (*e.g.* “eats”, “stares at”), there is no explicit supervision available at train time on which images and words should be related. Although the visual scenes and associated text inherently provide information about related words, they do not capture the unrelatedness between words, *i.e.*, we do not have negatives to help us learn the semantics.

We can also understand `vis-w2v` in terms of data augmentation. With infinite text data describing scenes, distributional statistics captured by `w2v` would reflect all possible visual patterns as well. In this sense, there is nothing special about the visual grounding. The additional modality helps to learn complimentary concepts while making efficient use of data. Thus, the visual grounding can be seen as augmenting the amount of textual data.

8. Conclusion

We learn visually grounded word embeddings (`vis-w2v`) from abstract scenes and associated text. Abstract scenes, being trivially fully annotated, give us access to a rich semantic feature space. We leverage this to uncover visually grounded notions of semantic relatedness between words that would be difficult to capture using text alone or using real images. We demonstrate the visual grounding captured by our embeddings on three applications that are in text, but benefit from visual cues: 1) common sense assertion classification, 2) visual paraphrasing, and 3) text-based image retrieval. Our method outperforms `word2vec` (`w2v`) baselines on all three tasks. Further, our method can be viewed as a modality to transfer knowledge from the abstract scenes domain to the real domain via text. Our datasets, code, and `vis-w2v` embeddings are available for public use.

References

- [1] S. Antol, A. Agrawal, J. Lu, M. Mitchell, D. Batra, C. L. Zitnick, and D. Parikh. VQA: Visual question answering. In *International Conference on Computer Vision (ICCV)*, 2015.
- [2] S. Antol, C. L. Zitnick, and D. Parikh. Zero-shot learning via visual abstraction. In *Computer Vision - ECCV 2014 - 13th*

- European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part IV*, pages 401–416, 2014.
- [3] Y. Bengio, R. Ducharme, P. Vincent, and C. Jauvin. A neural probabilistic language model. *Journal of Machine Learning Research*, 3:1137–1155, 2003.
- [4] S. F. Chen, S. F. Chen, J. Goodman, and J. Goodman. An empirical study of smoothing techniques for language modeling. Technical report, 1998.
- [5] X. Chen and C. L. Zitnick. Learning a recurrent visual representation for image caption generation. *CoRR*, abs/1411.5654, 2014.
- [6] R. Collobert and J. Weston. A unified architecture for natural language processing: Deep neural networks with multitask learning. In *International Conference on Machine Learning, ICML, 2008*.
- [7] C. Doersch, A. Gupta, and A. A. Efros. Unsupervised visual representation learning by context prediction. In *International Conference on Computer Vision (ICCV)*, 2015.
- [8] J. Donahue, L. A. Hendricks, S. Guadarrama, M. Rohrbach, S. Venugopalan, K. Saenko, and T. Darrell. Long-term recurrent convolutional networks for visual recognition and description. *CoRR*, abs/1411.4389, 2014.
- [9] A. Dosovitskiy, J. T. Springenberg, M. Riedmiller, and T. Brox. Discriminative unsupervised feature learning with convolutional neural networks. In *Advances in Neural Information Processing Systems 27 (NIPS)*, 2014.
- [10] D. F. Fouhey and C. L. Zitnick. Predicting object dynamics in scenes. In *CVPR*, 2014.
- [11] H. Gao, J. Mao, J. Zhou, Z. Huang, and A. Yuille. Are you talking to a machine? dataset and methods for multilingual image question answering. *ICLR*, 2015.
- [12] D. Geman, S. Geman, N. Hallonquist, and L. Younes. Visual Turing test for computer vision systems. *Proceedings of the National Academy of Sciences*, 112(12):3618–3623, 2015.
- [13] R. Girshick, J. Donahue, T. Darrell, and J. Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2014.
- [14] M. Hodosh, P. Young, and J. Hockenmaier. Framing image description as a ranking task: Data, models and evaluation metrics. *J. Artif. Intell. Res. (JAIR)*, 47:853–899, 2013.
- [15] M. Jas and D. Parikh. Image Specificity. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015.
- [16] A. Karpathy and L. Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3128–3137, 2015.
- [17] S. M. Katz. Estimation of probabilities from sparse data for the language model component of a speech recognizer. In *IEEE Transactions on Acoustics, Speech and Signal Processing*, pages 400–401, 1987.
- [18] R. Kiros, R. Salakhutdinov, and R. S. Zemel. Unifying visual-semantic embeddings with multimodal neural language models. page 13, 11 2014.
- [19] S. Kottur, R. Vedantam, J. M. F. Moura, and D. Parikh. Visual word2vec (vis-w2v): Learning visually grounded word embeddings using abstract scenes. *CoRR*, abs/1511.07067, 2015.
- [20] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems*, pages 1097–1105, 2012.
- [21] G. Kulkarni, V. Premraj, S. Dhar, S. Li, Y. Choi, A. C. Berg, and T. L. Berg. Baby talk: Understanding and generating image descriptions. In *Proceedings of the 24th CVPR*, 2011.
- [22] A. Lazaridou, N. T. Pham, and M. Baroni. Combining language and vision with a multimodal skip-gram model. In *Proceedings of the 2015 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 153–163, Denver, Colorado, May–June 2015. Association for Computational Linguistics.
- [23] T. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick. Microsoft COCO: Common objects in context. In *ECCV*, 2014.
- [24] X. Lin and D. Parikh. Don’t just listen, use your imagination: Leveraging visual common sense for non-visual tasks. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015.
- [25] J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. *CVPR (to appear)*, Nov. 2015.
- [26] E. Loper and S. Bird. Nltk: The natural language toolkit. In *In Proceedings of the ACL Workshop on Effective Tools and Methodologies for Teaching Natural Language Processing and Computational Linguistics. Philadelphia: Association for Computational Linguistics*, 2002.
- [27] S. Maji, L. Bourdev, and J. Malik. Action recognition from a distributed representation of pose and appearance. In *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, 2011.
- [28] M. Malinowski and M. Fritz. A multi-world approach to question answering about real-world scenes based on uncertain input. *CoRR*, abs/1410.0210, 2014.
- [29] M. Malinowski, M. Rohrbach, and M. Fritz. Ask your neurons: A neural-based approach to answering questions about images. *CoRR*, abs/1505.01121, 2015.
- [30] J. Mao, W. Xu, Y. Yang, J. Wang, and A. L. Yuille. Explain images with multimodal recurrent neural networks. *CoRR*, abs/1410.1090, 2014.
- [31] T. Mikolov, K. Chen, G. Corrado, and J. Dean. Efficient Estimation of Word Representations in Vector Space. *arXiv preprint arXiv:1301.3781*, 2013.
- [32] T. Mikolov, J. Kopecky, L. Burget, O. Glembek, and J. Cernocky. Neural network based language models for highly inflective languages. In *2009 IEEE International Conference on Acoustics, Speech and Signal Processing*, pages 4725–4728. IEEE, 2009.
- [33] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean. Distributed Representations of Words and Phrases and their Compositionality. In *Advances in Neural Information Processing Systems*, pages 3111–3119, 2013.
- [34] M. Mitchell, X. Han, and J. Hayes. Midge: Generating descriptions of images. In *Proceedings of the Seventh International Natural Language Generation Conference, INLG ’12*, pages 131–133, Stroudsburg, PA, USA, 2012. Association for Computational Linguistics.

- [35] T. B. C. L. Z. D. P. Ramakrishna Vedantam, Xiao Lin. Learning common sense through visual abstraction. In *IEEE International Conference on Computer Vision (ICCV)*, 2015.
- [36] M. Ren, R. Kiros, and R. S. Zemel. Image question answering: A visual semantic embedding model and a new dataset. *CoRR*, abs/1505.02074, 2015.
- [37] M. Rohrbach, W. Qiu, I. Titov, S. Thater, M. Pinkal, and B. Schiele. Translating video content to natural language descriptions. In *IEEE International Conference on Computer Vision (ICCV)*, December 2013.
- [38] F. Sadeghi, S. K. Divvala, and A. Farhadi. Viske: Visual knowledge extraction and question answering by visual verification of relation phrases. In *CVPR*, pages 1456–1464, 2015.
- [39] C. Silberer, V. Ferrari, and M. Lapata. Models of semantic representation with visual attributes. In *ACL (1)*, pages 572–582. The Association for Computer Linguistics, 2013.
- [40] C. Silberer and M. Lapata. Learning grounded meaning representations with autoencoders. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 721–732, Baltimore, Maryland, June 2014. Association for Computational Linguistics.
- [41] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014.
- [42] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan. Show and tell: A neural image caption generator. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3156–3164, 2015.
- [43] R. Xu, J. Lu, C. Xiong, Z. Yang, and J. J. Corso. Improving word representations via global visual context. 2014.
- [44] C. Zitnick, R. Vedantam, and D. Parikh. Adopting abstract images for semantic scene understanding. *PAMI*, 2014.
- [45] C. L. Zitnick and D. Parikh. Bringing semantics into focus using visual abstraction. In *CVPR*, 2013.
- [46] C. L. Zitnick, D. Parikh, and L. Vanderwende. Learning the visual interpretation of sentences. In *ICCV*, 2013.