

# Learning to Predict: A Fast Re-constructive Method to Generate Multimodal Embeddings

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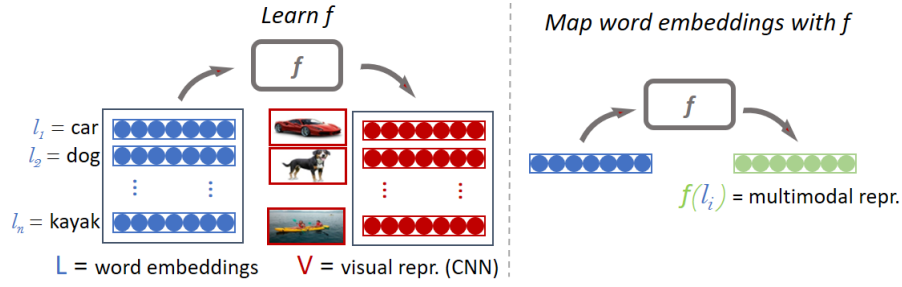
**Abstract.** Integrating visual and linguistic information into a single multimodal representation is an unsolved problem with wide-reaching applications to both natural language processing and computer vision. In this paper, we present a simple method to build multimodal representations by learning a language-to-vision mapping and using its output directly as multimodal embeddings. In this sense, our method provides a cognitively plausible way of building representations, consistent with the inherently re-constructive and associative nature of human memory. Using seven benchmark concept similarity tests we show that the mapped vectors not only implicitly encode multimodal information, but also outperform strong unimodal baselines and state-of-the-art multimodal methods, thus exhibiting more “human-like” judgments—particularly in zero-shot settings.

## 1 Introduction

Convolutional neural networks (CNN) and distributional-semantic models have provided breakthrough advances in representation learning in computer vision (CV) and natural language processing (NLP) respectively [1]. Lately, a large body of research has shown that using rich, multimodal representations created from combining textual and visual features instead of unimodal representations (a.k.a. embeddings) can improve the performance of semantic tasks. Building multimodal representations has become a popular problem in NLP that has yielded a wide variety of methods [2–4]. Additionally, the use of a mapping to bridge vision and language has also been explored, typically with the goal of generating missing information from one of the modalities [5–7].

Here, we propose a cognitively plausible approach to concept representation that consists of: (1) learning a language-to-vision mapping; and (2) using the outputs of the mapping as multimodal representations—with the second step being the main novelty of our approach. By re-constructing visual knowledge from textual input, our method behaves similarly as human memory, namely in an associative [8, 13] and re-constructive manner [9, 10, 12]. Concretely, our method does not seek the perfect recall of visual representations but rather its re-construction and association with language. We leverage the intuitive fact that, by learning to predict, the mapping necessarily encodes information from both modalities. Thus, given a word embedding as input, the mapped output is not purely a visual representation but rather a multimodal one.

By using seven concept similarity benchmarks, we show that our representations are not only multimodal but they improve performance over strong unimodal baselines



**Fig. 1.** Overview of our multimodal method.

and state-of-the-art multimodal approaches—inclusive in a zero-shot setting. In turn, the fact that our evaluation tests are composed of human ratings of similarity supports our claim that our method provides more “human-like” judgments.

The rest of the paper is organized as follows. In the next section, we introduce related work. Next, we describe and provide insight on our method. Afterwards, we describe our experimental setup. Finally, we discuss our results, followed by conclusions.

## 2 Related work and background

### 2.1 Cognitive grounding

A large body of research evidences that human memory is inherently re-constructive [9, 10, 12]. That is, memories are not “static” exact copies of reality, but are rather re-constructed from their essential elements each time they are retrieved, triggered by either internal or external stimuli. Arguably, this mechanism is, in turn, what endows humans with the capacity to imagine themselves in yet-to-be experiences and to re-combine existing knowledge into new plans or structures of knowledge [10]. The re-constructive essence of memory is certainly a well studied phenomenon in eyewitness psychology [12]. Moreover, the associative nature of human memory is also a widely accepted theory in experimental psychology [8] with identifiable neural correlates involved in both learning and retrieval processes [13].

In this respect, our method employs a retrieval process analogous to that of humans, in which the retrieval of a visual output is triggered and mediated by a linguistic input (Fig. 1). Effectively, information is not only retrieved (i.e., mapped), but also a certain degree of multimodal grounding occurs thanks to the learned cross-modal mapping. The mapping can thus be interpreted as a general source of associative knowledge that captures “general trends” between vision and language.

### 2.2 Multimodal representations

Based on current literature, we suggest a classification of the existing strategies to build multimodal embeddings. Broadly, multimodal representations can be built by learning from raw input enriched with both modalities (*simultaneous* learning), or by learning each modality separately and integrating them afterwards (*a posteriori* combination).

1. ***A posteriori*** combination.
  - *Concatenation*. That is, the fusion of pre-learned visual and text features by concatenating them [3]. Concatenation has been proven effective in concept similarity tasks [18, 3], yet suffers from an obvious limitation: multimodal features can only be generated for those words that have images available.
  - *Autoencoders* form a more elaborated approach that do not suffer from the above problem. Encoders are fed with pre-learned visual and text features, and the hidden representations are then used as multimodal embeddings. This approach has shown to perform well in concept similarity tasks and categorization (i.e., grouping objects into categories such as “fruit”, “furniture”, etc.) [4].
  - *A mapping* between visual and text modalities (i.e., our method). The outputs of the mapping themselves are used as multimodal representations.
2. ***Simultaneous*** learning. Distributional semantic models are extended into the multimodal domain [2, 11] by learning in a skip-gram manner from a corpus enriched with information from both modalities and using the learned parameters of the hidden layer as multimodal representations. Multimodal skip-gram methods have been proven effective in similarity tasks [2, 11] and in zero-shot image labeling [2].

With this taxonomy, the gap that our method fills becomes more clear, with it being aligned with a re-constructive and associative view of knowledge representation. Furthermore, in contrast to other multimodal approaches such as skip-gram methods [2, 11], our method directly learns from pre-trained embeddings instead of training from a large multimodal corpus, rendering it thus simpler and faster.

### 2.3 Cross-modal mappings

Several studies have considered the use of mappings to bridge modalities. For instance, [6] and [5] use a linear vision-to-language projection in zero-shot image classification. Analogously, language-to-vision mappings have been considered, generally to generate missing perceptual information about abstract words [11, 7] and in zero-shot image retrieval [2]. In contrast to our approach, the methods above do not aim to build multimodal representations to be used in natural language processing tasks.

## 3 Proposed method

In this section we describe the three main steps of our method (Fig. 1): (1) Obtain visual representations of concepts; (2) Build a mapping from the linguistic to the visual space; and (3) Generate multimodal representations by mapping word embeddings.

### 3.1 Obtaining visual representations

We employ raw, labeled images from ImageNet [19] as the source of visual information, although alternatives such as the ESP game data set [20] can be considered. To extract visual features from each image, we use the forward pass of a pre-trained CNN model. The hidden representation of the last layer (before the softmax) is taken as a feature vector, as it contains higher level features. For each concept  $w$ , we *average* the extracted visual features of individual images to build a single visual representation  $\vec{v}_w$ .

### 3.2 Learning to map language to vision

Let  $\mathcal{L} \subset \mathbb{R}^{d_l}$  be the linguistic space and  $\mathcal{V} \subset \mathbb{R}^{d_v}$  the visual space of representations, where  $d_l$  and  $d_v$  are their respective dimensionalities. Let  $\vec{l}_w \in \mathcal{L}$  and  $\vec{v}_w \in \mathcal{V}$  denote the text and visual representations for the concept  $w$  respectively. Our goal is thus to learn a mapping (regression)  $f : \mathcal{L} \rightarrow \mathcal{V}$ . The set of  $N$  visual representations along with their corresponding text representations compose the training data  $\{(\vec{l}_i, \vec{v}_i)\}_{i=1}^N$  used to learn  $f$ . In this work, we consider two different mappings  $f$ .

**(1) Linear:** A simple perceptron composed of a  $d_l$ -dimensional input layer and a linear output layer with  $d_v$  units.

**(2) Neural network:** A network composed of a  $d_l$ -unit input layer, a single hidden layer of  $d_h$  Tanh units and a linear output layer of  $d_v$  units.

For both mappings, a mean squared error (MSE) loss function is employed:  $Loss(y, \hat{y}) = \frac{1}{2} \|\hat{y} - y\|_2^2$ , where  $y$  is the actual output and  $\hat{y}$  the model prediction.

### 3.3 Generating multimodal representations

As a final step, the multimodal representation  $\vec{m}_w$  of each concept  $w$  is calculated as the image  $f(\vec{l}_w)$  of its linguistic embedding  $\vec{l}_w$ . For instance, the multimodal representation of  $w = dog$  corresponds to  $\vec{m}_{dog} = f(\vec{l}_{dog})$ .

Since the outputs of a text-to-vision mapping are strictly speaking, “visual predictions”, it might not be readily obvious that they contain multimodal information. To gain insight, it is instructive to refer to the training phase where the parameters  $\theta$  of  $f$  are learned as a function of the training data  $\{(\vec{l}_i, \vec{v}_i)\}_{i=1}^N$ . E.g., in gradient descent,  $\theta$  is updated according to:  $\theta \leftarrow \theta - \eta \frac{\partial}{\partial \theta} Loss(\theta; \{(\vec{l}_i, \vec{v}_i)\}_{i=1}^N)$ . Hence, the parameters  $\theta$  of  $f$  are effectively a function of the training data points  $\{(\vec{l}_i, \vec{v}_i)\}_{i=1}^N$  and it is therefore expected that the outputs  $f(\vec{l}_w)$  are grounded with properties of the input data  $\{\vec{l}_i\}_{i=1}^N$ . It can be additionally noted that the output of the mapping  $f(\vec{l}_w)$  is a (continuous) transformation of the input vector  $\vec{l}_w$ . Thus, unless the mapping is completely uninformative (e.g., constant or random), the input vector  $\vec{l}_w$  is still “present”—yet transformed.

## 4 Experimental setup

### 4.1 Word embeddings

We use 300-dimensional GloVe<sup>1</sup> vectors [25] pre-trained on the Common Crawl corpus consisting of 840B tokens and a 2.2M words vocabulary.

### 4.2 Visual data and features

We use ImageNet [19] as our source of labeled images. ImageNet covers 21,841 WordNet synsets (or meanings) [26] and has 14,197,122 images. We only keep synsets with more than 50 images, and an upper bound of 500 images per synset is used to reduce computation time. With this selection, we cover 9,251 unique words.

<sup>1</sup> <http://nlp.stanford.edu/projects/glove>

To extract visual features from each image, we use a pre-trained ResNet CNN [27] implemented with the Matlab MatConvNet toolkit [28]. We take the 2048-dimensional activation of the last layer (before the softmax) as our visual features.

### 4.3 Evaluation sets

We test the methods in seven benchmark tests, covering three tasks: **(i) General relatedness:** *MEN* [18] and *Wordsim353-rel* [29]; **(ii) Semantic or taxonomic similarity:** *SemSim* [4], *Simlex999* [30], *Wordsim353-sim* [29] and *SimVerb-3500* [31]; **(iii) Visual similarity:** *VisSim* [4] which contains the same word pairs as *SemSim*, rated for visual instead of semantic similarity. All tests contain word pairs along with their human similarity rating. The tests *Wordsim353-sim* and *Wordsim353-rel* are the similarity and relatedness subsets of *Wordsim353* [32] proposed by [29] who noted that the distinction between similarity (e.g., “tiger” is similar to “cat”) and relatedness (e.g., “stock” is related to “market”) yields different results. Hence, for being redundant with its subsets, we do not count the whole *Wordsim353* as an extra test set.

A large part of words in our tests do not have a visual representation  $\vec{v}_w$  available, i.e., they are not present in our training data. We refer to these words as zero-shot (ZS).

### 4.4 Evaluation metric and prediction

We use Spearman correlation  $\rho$  between model predictions and human similarity ratings as evaluation metric. The prediction of similarity between two concept representations,  $\vec{u}_1$  and  $\vec{u}_2$ , is computed by their cosine similarity:  $\cos(\vec{u}_1, \vec{u}_2) = \frac{\vec{u}_1 \cdot \vec{u}_2}{\|\vec{u}_1\| \cdot \|\vec{u}_2\|}$ .

### 4.5 Model settings

Both, neural network and linear models are learned by stochastic gradient descent and nine parameter combinations are tested (learning\_rate = [0.1, 0.01, 0.005] and dropout\_rate = [0.5, 0.25, 0.1]). We find that the linear model is not very sensitive to parameter variations and all of them perform reasonably well. We report a linear model with learning rate of 0.01 and dropout rate of 0.5. In contrast, the neural network shows generally lower performance and we find that larger learning rates tend to work better. We report a neural network with 500 hidden units, dropout rate of 0.1 and learning of 0.1. All mappings are implemented with the scikit-learn toolkit [33] in Python 2.7.

## 5 Results and discussion

For clarity, we refer to the averaged visual features as  $CNN_{avg}$  and to our mapped representations as  $MAP_f$ , where  $f$  is the mapping function used ( $lin$  = linear,  $NN$  = neural network).  $CONC$  refers to the concatenation of  $CNN_{avg}$  and GloVe.

Overall,  $MAP_{lin}$  exhibits the largest number of wins (5 out of 7 tests) (Tab. 1) and a Friedman rank sum test shows that  $MAP_{lin}$  performs significantly better than GloVe ( $p < 0.008$ ) and  $CNN_{avg}$  ( $p \approx 0.008$ ). Hence,  $MAP_{lin}$  clearly accomplishes one of

its foremost goals, namely to improve the unimodal representations, which in turn supports our hypothesis that the mapped vectors are enriched with multimodal information. Conversely, concatenation (*CONC*) does not significantly improve GloVe ( $p \approx 0.25$ ), suggesting that an additive strategy to fuse vision and language might be suboptimal.

**Table 1.** Spearman correlations between model predictions and human ratings. For each test set, ALL is the whole set of word pairs, VIS are those pairs with both visual representations available, and ZS denotes its complement, i.e., zero-shot words. Boldface indicates best results per column and # inst. the number of word pairs in ALL, VIS or ZS. It must be noted that the VIS region of the compared methods is only approximated, as they do not report the exact evaluated instances.

	Wordsim353			MEN			SemSim			VisSim		
	ALL	VIS	ZS	ALL	VIS	ZS	ALL	VIS	ZS	ALL	VIS	ZS
Silberer & Lapata 2014					0.7			0.64				
Lazaridou et al. 2015			0.75	0.76		0.72	0.72		0.63	0.63		
Kiela & Bottou 2014	0.61			0.72								
GloVe	0.712	0.632	0.705	0.805	0.801	0.801	<b>0.753</b>	<b>0.768</b>	0.701	0.591	0.606	0.54
<i>CNN<sub>avg</sub></i>	-	0.423	-	-	0.567	-	-	0.534	-	-	0.543	-
<i>CONC</i>	-	0.61	-	-	0.804	-	-	0.755	-	-	<b>0.649</b>	-
<i>MAP<sub>lin</sub></i>	<b>0.763</b>	<b>0.672</b>	<b>0.756</b>	<b>0.822</b>	<b>0.813</b>	<b>0.82</b>	0.748	0.76	<b>0.704</b>	0.599	0.61	0.56
<i>MAP<sub>NN</sub></i>	0.403	0.49	0.368	0.672	0.749	0.65	0.725	0.723	0.735	<b>0.644</b>	0.642	<b>0.654</b>
# inst.	353	63	290	3000	795	2205	6933	5238	1695	6933	5238	1695

	Simlex999			Wordsim353-rel			Wordsim353-sim			SimVerb-3500		
	ALL	VIS	ZS	ALL	VIS	ZS	ALL	VIS	ZS	ALL	VIS	ZS
Silberer & Lapata 2014												
Lazaridou et al. 2015	0.4	<b>0.53</b>										
Kiela & Bottou 2014												
GloVe	0.408	0.371	0.429	0.644	0.759	0.619	0.802	0.688	0.783	0.283	0.32	0.282
<i>CNN<sub>avg</sub></i>	-	0.409	-	-	0.405	-	-	0.529	-	-	0.211	-
<i>CONC</i>	-	0.456	-	-	0.65	-	-	0.692	-	-	<b>0.467</b>	-
<i>MAP<sub>lin</sub></i>	<b>0.459</b>	0.433	<b>0.477</b>	<b>0.705</b>	<b>0.771</b>	<b>0.688</b>	<b>0.808</b>	<b>0.751</b>	0.772	<b>0.325</b>	0.384	<b>0.324</b>
<i>MAP<sub>NN</sub></i>	0.319	0.413	0.288	0.276	0.553	0.229	0.538	0.546	0.518	0.202	0.227	0.2
# inst.	999	261	738	252	28	224	203	45	158	3500	41	3459

Clearly, *MAP<sub>lin</sub>* performs the best in *relatedness* (*MEN* and *Wordsim353-rel*) and in *semantic similarity* (*SemSim*, *Simlex999* and *Wordsim353-sim*)—except for a marginal performance decrease with respect to GloVe in *SemSim* (in ALL and VIS). It might seem counter-intuitive that vision can help to improve relatedness understanding. However, a closer look to concrete examples reveals that visual features generally account for object co-occurrences, which is often a good indicator of their relatedness (e.g., between “car” and “garage” in Fig. 2). For instance, in *MEN*, the human relatedness rating between “car” and “garage” is 8.2 while GloVe’s score is only 5.4. However, *CNN<sub>avg</sub>*’s rating is 8.4 and that of *MAP<sub>lin</sub>* is 7.9, which is closer to the human score.

By contrast, *MAP<sub>NN</sub>* seems to perform the best in *visual similarity* (*VisSim*) (possible reasons are discussed below), yet *MAP<sub>lin</sub>* still outperforms the unimodal baselines.



**Fig. 2.** Sample images from “car” (top row) and “garage” (bottom row) synsets of ImageNet.

Good performance in a *zero-shot* task is indicative of good generalization capacity. From Tab. 1 and a trend difference in the Friedman test against GloVe ( $p \approx 0.1$ ), one may observe that  $MAP_{lin}$  achieves this goal. However, the markedly better performance of  $MAP_{NN}$  in the VIS than in the ZS region suggests otherwise for the neural network—while  $MAP_{lin}$  exhibits a more homogeneous performance in both regions.

Clearly,  $MAP_{lin}$  shows a more consistent improvement over unimodal baselines than  $MAP_{NN}$ . We attribute the performance drop of  $MAP_{NN}$  to the network overfitting the visual representations. Our training data is composed of 9,251 instances while the output dimension is 2048, which entails a drastic increase in the number of parameters that likely yields overfitting if a hidden layer of a reasonable size is used. To further investigate this, we learn both mappings ( $NN$  and  $lin$ ) in a 5-fold cross-validation setting. We find the coefficient of determination  $R^2$  (as a measure of goodness of fit in regression) of  $MAP_{NN}$  to be 0.61 and 0.42 for training and testing respectively, while that of  $MAP_{lin}$  is 0.32 and 0.31 respectively. This gap between training and test fit of  $MAP_{NN}$  suggests overfitting. It can be additionally observed that results of  $MAP_{NN}$  generally resemble those of  $CNN_{avg}$ —while  $MAP_{lin}$  performs more closely to GloVe.

## 6 Conclusions

We have presented a cognitively-inspired method capable of generating multimodal representations in a fast and simple way. In a variety of similarity tasks and seven benchmark tests, our method generally outperforms unimodal baselines and state-of-the-art multimodal methods. Moreover, a similar performance gain in zero-shot settings indicates that the method generalizes well and learns relevant cross-modal associations. Finally, the overall performance supports the claim that our approach builds more “human-like” concept representations. Ultimately, the present work sheds light on fundamental questions of natural language understanding such as whether the nature of the knowledge representation obtained by the fusion of vision and language should be static and additive (e.g., concatenation) or rather re-constructive and associative.

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