Crossmodal Network-Based Distributional Semantic Models

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Abstract

Despite the recent success of distributional semantic models (DSMs) in various semantic tasks they remain disconnected with real-world perceptual cues since they typically rely on linguistic features. Text data constitute the dominant source of features for the majority of such models, although there is evidence from cognitive science that cues from other modalities contribute to the acquisition and representation of semantic knowledge. In this work, we propose the crossmodal extension of a two-tier text-based model, where semantic representations are encoded in the first layer, while the second layer is used for computing similarity between words. We exploit text- and image-derived features for performing computations at each layer, as well as various approaches for their crossmodal fusion. It is shown that the crossmodal model performs better (from 0.68 to 0.71 correlation coefficient) than the unimodal one for the task of similarity computation between words.

Keywords: activation based models, crossmodal fusion, distributional semantic models, semantic similarity, bag-of-visual-words

1. Introduction

Distributional semantic models (DSMs) (Baroni and Lenci, 2010) constitute a widely-used paradigm for extracting, representing and learning semantics from linguistic data. DSMs are based on the distributional hypothesis of meaning (Harris, 1954) assuming that semantic similarity between words is a function of the overlap of their linguistic contexts. Despite their success in various semantic tasks (e.g., semantic classification and computation of semantic similarity) these models have been criticized as “disembodied”, since they rely solely on linguistic information without being grounded in perception and action including other modalities, e.g., color (Barsalou et al., 2008). This disconnection is also referred to as the *symbol grounding problem* (Harnad, 1990). Grounding refers to the mapping of the semantics of natural language to the physical world. This is supported by experimental findings indicating that real-world experiences also play a role for the acquisition of lexical semantics (Landau et al., 1998). For example, the naming of objects from pictures was found to be faster for color images vs grayscale (Therriault et al., 2009). Recently, focus has been given to the incorporation of features from modalities other than text in order to augment the text-based DSMs, e.g., see (Bruni et al., 2014) for image-derived features, and for audio-based features (Kiela and Clark, 2015). For additional insight into computation models that map data-derived low-level features to high-level knowledge (including cognitive and social aspects) see (Potamianos, 2014).

The proposed approach is an alternative framework for integrating textual and visual features for the task of semantic similarity computation between words. This is motivated by the cognitive evidence indicating the multimodal character of semantic representations utilized for various semantic tasks. This work, extends the unimodal (lexical-only) approach of network-based DSMs that has been successfully applied for the task of word similarity achieving state-of-the-art results (Iosif and Potamianos, 2015). The key idea behind network DSMs is a two-tier system, motivated by cognitive considerations such as network activation and priming. The first layer, encodes the semantics of words via the creation of lexical neighborhoods. In the second layer, similarity metrics are defined that operate on these semantic neighborhoods. In this paper, we investigate the integration of visual and lexical features for network-based DSMs. The integration is achieved by alternating visual and lexical information in the two layers.

2. Related Work

One of the first approaches for the creation of multimodal DSMs was proposed in (Feng and Lapata, 2010) where a text corpus associated with images was exploited for building mixture models of latent topics based on Latent Dirichlet Allocation (LDA). Textual and visual features were jointly modeled using LDA via early fusion. The proposed method was evaluated on a semantic similarity task (WS353 dataset), where the multimodal model was found to yield higher performance compared to the textual one. However, the best performance was moderate (0.32 correlation coefficient). Another example of early fusion is (Bruni et al., 2011) where, unlike (Feng and Lapata, 2010), two modality-specific corpora were used. Vectorial representations were independently built for each modality and combined via vector concatenation. For the same task –although a different subset of WS353 was used– significantly higher correlation (0.52) was achieved demonstrating how the corpus used to estimate DSM features can significantly affect performance. A common technique for the late fusion of textual and visual models is the combination of similarity scores estimated via the unimodal models. For example, in (Leong and Mihalcea, 2011) the sum and the harmonic mean of similarities were used achieving 0.59 correlation for a small subset of WS353. In (Bruni et al., 2014), both early and late fusion schemes were applied. The early fusion was implemented as a linear weighted combination of the features vectors, while a similar combination was adopted for the late fusion based on the unimodal similarity scores. Both schemes were found to obtain high correlation (up to 0.78) for a subset of WS353, however, there is no clear winner since their relative performance vary with respect to the experimental parameters, e.g., the size of the context window used for extracting the textual features. Overall, cross-modal DSMs appear to exceed the performance of their respective unimodal baselines for the computation of word-level semantic similarity.

In addition to the area of lexical semantics textual and visual features have been also exploited for tasks related to the indexing and retrieval of multimedia documents, especially images. The most common approach is the development of retrieval models for each modality, which are fused in a late phase for combining and re-ranking the modality-specific results, e.g., (Besancon and Millet, 2005). Another example of late fusion was presented in (Vreeswijk et al., 2011) dealing with the classification of images into semantically abstract categories. Early fusion of features was proposed in (Escalante et al., 2008) for enhancing the search over collections of images. LDA is popular when investigating the relation between images and text annotations. Examples include the use of probabilistic LDA for the multimodal indexing of images (Monay and Gatica-Perez, 2007) and the generation of (text) captions for images (Barnard et al., 2003). In addition, matrix factorization has been investigated, e.g., singular value decomposition (SVD) (Hare et al., 2008) and non-negative matrix factorization (NMF) (Caicedo et al., 2012). The recent advances on deep neural networks enabled the application of several architectures and configurations for linking textual and visual data. Examples included the mapping between the representation space of images and the space of word embeddings for the task of image classification (Socher et al., 2013). The scalability of this approach was enhanced in (Frome et al., 2013) for the ImageNet challenge on object recognition covering 1000 classes. The idea of linking visual features with word embeddings was also followed in (Karpathy and Li, 2014) for the generation of image descriptions.

3. Features and Similarity Metrics

Textual: Co-occurrence-based (CC). The assumption here is that the co-existence of words within a specified context serves as indicator for their semantic relatedness. In this work, we employ a common metric, namely, Google-based semantic relatedness, G, proposed in (Gracia et al., 2006), considering word co-occurrence at the sentential level.

Textual: Context-based (CT). The fundamental assumption here is that *similarity of context implies similarity of meaning* (Harris, 1954). Given a target word w_i, a contextual window of size $2H+1$ words is centered on it and lexical features are extracted. The H words left and right of w_i are extracted for every instance of w_i in the corpus formulating a feature vector. For a given value of H the context-based semantic similarity between two words, w_i and w_j, is computed as the cosine of their feature vectors. This approach is also referred to as the "Bag-of-Words" (BoW) model.

The Visual Analogue of Bag–of–Words Model (VS). The notion of "Bag-of–Visual–Words" (BoVW) model was inspired by the BoW model in an attempt to represent images with respect to a common "visual lexicon" (Sivic and Zisserman, 2003; Csurka et al., 2004; Bruni et al., 2011). Given an image collection the following steps are followed for the construction of the BoVW model (Bruni et al., 2011): 1) Salient local regions, e.g., 10×10 pixels, are identified and represented as vectors. 2) The identified regions are projected into a space that is shared between the images of the collection. Next, the projections are clustered. Each cluster is assumed to correspond to a visual word. 3) Every image is represented as a vector of visual words. The most widely-used similarity metric for this representation is the cosine similarity.

4. Network-based DSMs

In this section, we briefly present the two-tier DSMs that were proposed in (Iosif and Potamianos, 2015) for building semantic networks using features extracted from text corpora. Here, this model is extended by exploiting both textual and visual features aiming to alleviate the symbol grounding problem of DSMs. The network consists of two layers, namely, activation and similarity layer. Given a target word, w_i, a set of other words that are semantically similar with w_i are identified in the first layer formulating the activation area (also referred to as the semantic neighborhood) of w_i. The second layer computes the semantic similarity between pairs of words exploiting their respective activation layers. The computations that take place in the two layers can be performed using textual (CC or CT) or visual (VS) features.

4.1. Layer 1: Activation Model

The activation layer constitutes a network that can be defined as an undirected (under a symmetric similarity metric) graph $F = (A, E)$, where A are the entries of a lexicon L, while E contains the links between the vertices. The links (edges) between words in the network are determined and weighted according to the pairwise semantic similarity of the vertices. The semantic neighborhood of a target $w_i \in L$ is a sub-graph of F, $F_i = (A_i, E_i)$, where the set of vertices A_i includes in total n members of L, which are linked with w_i via edges E_i. This is motivated by theories of semantic priming (McNamara, 2005) according to which stimulus facilitates the cognitive processing of related entities present in the human semantic memory. The theory of priming applies to any perceptual entities regardless of modality. Thus, the use of lexical and visual features as priming cues is cognitively valid (Stenberg et al., 1995). For example, in (Iosif et al., 2012) lexical features and corpus statistics were used for the classification of lexical relations with respect to two broad types of priming.

4.2. Layer 2: Similarity Model

In this section, we present two metrics of semantic similarity proposed in (Iosif and Potamianos, 2015) that are defined with respect to the activation areas computed in the first network layer.

Maximum Similarity of Neighborhoods. This underlying hypothesis that the similarity of two words, w_i and w_j, can be computed as the maximum similarity of their respective activation areas:

$$M_n(w_i, w_j) = \max\{\alpha_{ij}, \alpha_{ji}\}, \quad (1)$$

$$\alpha_{ij} = \max_{x \in N_j} S(w_i, x), \quad \alpha_{ji} = \max_{y \in N_i} S(w_j, y),$$

where α_{ij} denotes the maximum similarity between w_i and the neighbors of w_j estimated according to a similarity metric S. In this work, S was computed using the feature types (CC or CT or VS) and metrics presented in Section 3. α_{ji} is computed in similar fashion. N_i and N_j stand for the set of neighbors of w_i and w_j, respectively. This metric was motivated by the maximum sense similarity assumption (Resnik, 1995) under the assumption that the neighbors serve as semantic features representing the sense(s) of the corresponding word.

Attributional Neighborhood Similarity. Unlike M_n where a single neighbor from each activation area is used, in this metric the entire areas are taken into account in the computation of the similarity score:

$$R_n(w_i, w_j) = \max\{\beta_{ij}, \beta_{ji}\}, \quad (2)$$

$$\beta_{ij} = \rho(C_i^{N_i}, C_j^{N_i}), \quad \beta_{ji} = \rho(C_i^{N_j}, C_j^{N_j}).$$

$C_i^{N_i} = (S(w_i, x_1), S(w_i, x_2), \ldots, S(w_i, x_n))$ and $N_i = \{x_1, x_2, \ldots, x_n\}$. The vectors $C_j^{N_i}$, $C_i^{N_j}$, and $C_j^{N_j}$ are defined similarly as $C_i^{N_i}$. The ρ function denotes the Pearson's correlation coefficient. N_i and N_j are the sets of neighbors of w_i and w_j, respectively. S stands for a similarity metric – in this work it was computed using the feature types (CC or CT or VS) and metrics presented in Section 3. The motivation behind R_n was attributional similarity based on the hypothesis that the neighbors that live in the activated areas encode semantic attributes (or features) of the respective target words.

5. Fusion of Multimodal Representations

In this section, we present two schemes, namely, local and global, for the fusion of textual and visual representations at the first layer of the network. Each scheme is meant to formulate an activation area for a target word w_i either by local set operations on unimodal activation areas (from text and image-derived data) or by global algebraic operations on normalized unimodal semantic similarity scores. Specifically, the local fusion scheme selects for each target w_i two unimodal neighborhoods of a small fixed size (e.g., 100 neighbors) and then performs set operations (e.g., union, intersection) on these neighborhoods to obtain a crossmodal activation area. The global scheme combines the semantic similarity scores computed between the target w_i and every $w_j \in L$ with respect to the two modalities and then selects the neighborhood of target w_i.

Local fusion. Let the semantic neighborhoods of a target word w_i computed based on textual and visual features be represented as ordered sets (according to similarity) denoted as T_i and V_i, respectively. The bimodal neighborhood of w_i can be computed via: 1) union $F_i^{\cup} = T_i \cup V_i$, and 2) intersection $F_i^{\cap} = T_i \cap V_i$. Assume a bimodal neighborhood of fixed size n. For the case of union, half the neighbors are selected from T_i and the rest from V_i, i.e., $\mid T_i \mid = \mid V_i \mid = \frac{n}{2}$. Regarding intersection, the cardinality of T_i and V_i is not fixed since the goal is to have n neighbors within $F_i^{\cap}$. For this purpose, we allow the gradual increment of $|T_i|$ and $|V_i|$ until the satisfaction of this criterion. This relaxation was adopted in (Georgiladakis et al., 2015) where it was applied for the computation of neighborhoods for short phrases based on the neighborhoods of the constituent words. The intersection-based fusion adheres to findings from the literature of psycholinguistics suggesting that the crossmodal neighborhoods should be more specific than the respective unimodal ones (Osherson and Smith, 1981).

Global fusion. Given a target word w_i, let T_i and V_i be the vectors containing the semantic similarities between w_i and the words of lexicon L computed with respect to text and visual features, respectively. The fusion was implemented via the algebraic operations defined in Table 1 using the normalized[1] T_i and V_i vectors. According to

Fusion scheme	Definition
Additive	$F_i^{add} = T_i + V_i$
Weighted additive	$F_i^{wadd} = \lambda_i T_i + (1 - \lambda_i) V_i$
Multiplicative	$F_i^{mul} = T_i \cdot V_i$

Table 1: Definition of global fusion schemes.

the F_i^{add} scheme, both modalities contribute equally to the combination of similarities. This is relaxed by the F_i^{wadd} scheme where the contribution of each modality is weighted. The $0 \leq \lambda_i \leq 1$ weight is defined as: $\lambda_i = \frac{Z_i^T}{Z_i^T + Z_i^V}$, where Z_i^T and Z_i^V are the coefficients of variation for T_i and V_i, respectively. Z_i^T is defined as the ratio of the standard deviation and the mean of T_i's similarity scores (Everitt, 1998). Z_i^V is defined in similar fashion. The weights assigned to T_i and V_i are proportional to the respective variation coefficients.

6. Experiments and Evaluation Results

Textual features (CC, CT). A lexicon consisting of 8752 (single-word) English nouns was extracted from the SemCor3[2] corpus. For the extraction of the textual features (i.e., CC and CT) a web harvested corpus was created as follows. For each lexicon entry an individual query was formulated and the $1,000$ top ranked results (document snippets) were retrieved using the Yahoo! search engine and aggregated.

Visual features (VS). We used a feature set that was computed as part of the work described in (Bruni et al., 2011). Here, we outline the basic steps of feature extraction, while more details can be found in (Bruni et al., 2011). The ESP-Game dateset was used (von Ahn and Dabbish, 2004) that contains images annotated with textual descriptions (set of tags/words). For the extraction of visual features, the VLFeat system was used (Vedaldi and Fulkerson, 2013) through a process summarized as follows: The Difference of Gaussian (DoG) (Lowe, 2004), was employed for identifying local regions, which they were assigned to visual words. The Scale-Invariant Feature Transform (SIFT) (Lowe, 1999) was applied for deriving a a 128-dimensional representation for each region. The k-means algorithm was applied for clustering the regions into a number of clusters serving as visual words. This way each image was represented by a vector of visual words according on the clustering of its regions. Last, each word was represented by a vector created by summing the vectors of the corresponding images (i.e, images having this word in the corresponding annotation tags). For the creation of a multimodal network, we used the intersection between the 8752 nouns and the nouns covered by the image annotations resulting into a set of 3450 nouns.

Network. The network creation consisted of two main steps: 1) computation of semantic neighborhoods, and 2) computation of similarity scores. For each step three types of similarity metrics (in conjunction with the respective features) were applied: co-occurrence-based (CC), context-based (CT), and visual (VS).

Evaluation. For evaluation purposes, we used the noun pairs of (i) Rubenstein-Goodenough (RG) (Rubenstein and Goodenough, 1965) and (ii) WordSim353 (WS353) (Finkelstein et al., 2002) datasets which were included in the network of 3450 nouns: 35 and 175 pairs[3] , respectively. The Pearson's correlation coefficient against human ratings was as evaluation metrics. For the case of CC the Google-based Semantic Relatedness was applied, while the cosine similarity was used for CT (with context window H=1) and VS.

The performance of M_n and R_n neighborhood-based metrics (defined in Section 4) for various number of neighbors with respect to the subsets of RG and WS353 datasets along with the respective baselines is presented in Table 6. We consider as baseline the computation of semantic similarity in the absence of network, i.e., by directly applying the bag-of-word metrics described in Section 3. The performance is shown for various combinations of textual (CC or CT) and visual (VS) features used for neighbor selection and similarity computation. The focus is to investigate the performance potential of the crossmodal network, that is, when the visual features are used either for neighbor selection or computation of the final similarity score. Regarding the M_n metric, the highest performance (0.79 and 0.70 for RG and WS353, respectively) is achieved by the CC/VS combination, which outperforms the baseline for the case of WS353. Regarding the R_n metric, the highest performance (0.89 and 0.67 for RG and WS353, respectively) is achieved by the VS/CC combination, exceeding the baseline performance for all datasets. In addition, it seems that small neighborhood sizes yield better results when visual features are used for neighbor selection. The overall lowest performance is obtained by the VS/VS combination,

In Figure 1(a), we present the performance yielded by the global fusion schemes as a function of the number of neighbors n exploited in the first layer of the network. The results are shown for the correlation-based metric

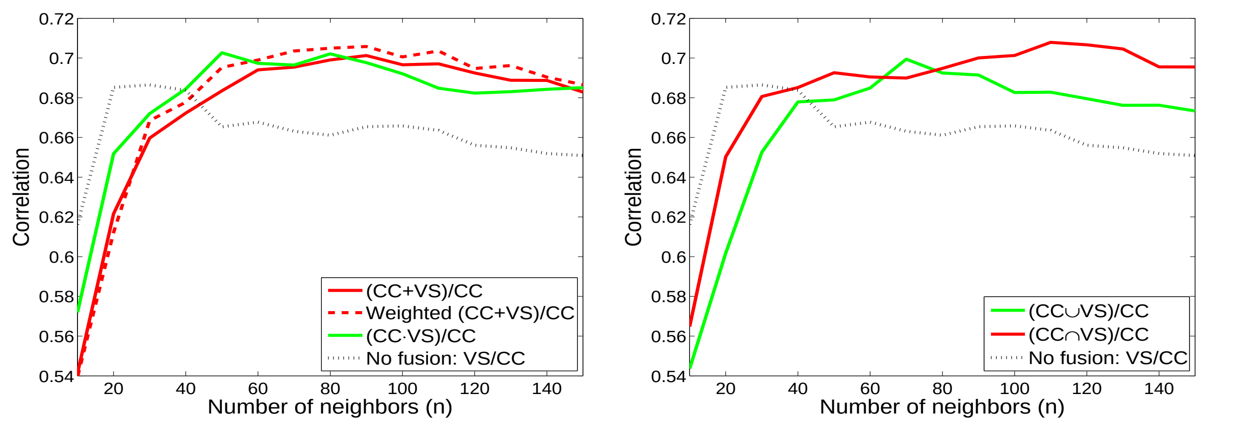
[1] In this work, we used Z-normalization.

[2] `http://www.cse.unt.edu/~rada/downloads.html`

[3] Although RG and WS353 are standard datasets, the lack of visual features for some word pairs makes difficult the direct comparison (in terms of performance) with other approaches proposed in the literature, see also (Bruni et al., 2011).

Type of feature for		Number of neighbors (n)							
Selection of neighbors	Similarity computation	M_n metric				R_n metric			
		10	50	100	150	10	50	100	150
Subset of RG dataset (35 pairs). *Unimodal baselines*: CC:0.85, CT:0.67, VS: 0.47.									
Textual (CC)	Visual (VS)	0.64	**0.79**	**0.79**	0.70	0.44	0.34	0.33	0.35
Textual (CT)	Visual (VS)	0.78	0.76	0.69	0.66	0.29	0.37	0.35	0.33
Visual (VS)	Textual (CC)	0.58	0.55	0.29	0.36	0.73	0.86	**0.89**	0.88
Visual (VS)	Textual (CT)	0.48	0.42	0.25	0.33	0.64	0.67	0.61	0.59
Visual (VS)	Visual (VS)	0.43	0.40	0.23	0.27	0.40	0.45	0.44	0.35
Subset of WS353 dataset (175 pairs). *Unimodal baselines*: CC:0.61, CT:0.25, VS: 0.33.									
Textual (CC)	Visual (VS)	0.44	0.59	0.66	**0.70**	0.18	0.24	0.21	0.22
Textual (CT)	Visual (VS)	0.44	0.47	0.38	0.32	0.21	0.28	0.27	0.25
Visual (VS)	Textual (CC)	0.47	0.41	0.37	0.32	0.62	**0.67**	**0.67**	0.65
Visual (VS)	Textual (CT)	0.34	0.33	0.34	0.28	0.33	0.26	0.22	0.20
Visual (VS)	Visual (VS)	0.37	0.30	0.31	0.27	0.17	0.34	0.33	0.31

Table 2: Performance of M_n and R_n metrics for various combinations of textual (CC or CT) and visual (VS) features.



(a) (b)

Figure 1: Correlation as a function of the number of neighbors for the fusion of multimodal representations: (a) globally, and (b) locally.

R_n only[4] with respect to the largest dataset (WS353). Both textual and visual modalities were fused in the first layer, while the textual modality was used for the computation of similarity in the second layer. Specifically, the CC feature type was employed for computing similarities computation (instead of CT) based on the very good performance of the VS/CC approach. For comparison purposes, the performance of the crossmodal VS/CC approach is also depicted in the same figure, which can be regarded as a baseline since no fusion is performed in the first layer. We observe that for small semantic neighborhoods (e.g., 10 neighbors) the baseline approach yields higher correlation scores compared to the fusion schemes. However, for larger neighborhoods ($>$ 50 neighbors) the fusion-based approaches perform consistently better than the baseline. The best results (up to 0.70) are obtained by the weighted additive fusion scheme for 50-100 neighbors. Regarding fusion, the multiplicative scheme appears to perform better than the other schemes for neighborhoods including 10-30 neighbors. For larger neighborhoods all schemes exhibit comparable performance. In addition, the weighted additive fusion scheme seems to yield slightly higher performance compared to the respective unweighted scheme. The performance of the local fusion schemes is depicted in Figure 1(b), along with the baseline also plotted in Figure 1(a). As in the case of global fusion, the baseline obtains higher correlation when few neighbors are exploited. Both fusion types yield higher performance than the baseline for neighborhoods containing more the 50 neighbors[5]. The top correlation scores (0.71) are

[4]For the case of the M_n metric no statistically significant improvements were gained.

[5]The differences between the similarity scores estimated via

Rank	Textual (CC)	Visual (VS)
Within top 10	auto, accident, **truck**, seat, **vehicle**, ...	race, **tire**, **wheel**, drive, **truck**, ...
Within 40-50	**wheel**, **drift**, **tire**, wreck, transport, ...	fun, police, **vehicle**, **drift**, mountain, ...

Table 3: Neighbors of "car" wrt CC and VS features.

achieved by the intersection-based fusion scheme for 110-120 neighbors. This scheme appears to perform better than the union-based one except for 60-80 neighbors. In Table 3, we present a number of indicative neighbors for the target word "car" when using CC and VS, while the common neighbors are shown in bold. This is performed for two zones of the respective activations. Regarding the top 10 zone, both CC and VS capture neighbors highly related to "car". For broader activations, (e.g., see 40-50 zone) less semantically relevant words (e.g., fun, mountain) are identified by VS compared to CC.

7. Conclusions

The main finding of this work is that the network approach is an appropriate representation and integration framework for textual and visual features. This was verified for the problem of word semantic similarity, for which the network metrics exceeded the performance of baseline metrics. This observation agrees with the cognitive evidence regarding the multimodal character of semantic representations. In addition, both modalities were successfully fused in the representation layer when exploiting more than 50 neighbors. The highest performance was achieved by the intersection-based fusion scheme supporting the idea that the commonality of features across modalities is a good criterion for building semantically more accurate representations. Regarding future work, we aim to apply the proposed model to datasets in other languages. Our long term goal is to extend the presented network with audio-based features, including the investigation of modality-specific metrics of semantic similarity.

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both fusion schemes and the baseline (i.e., no fusion) were found to be statistically significant at 95% level according to paired-sample t-test.

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