Abstract

We address the problem of integrating textual and visual information in vector space models for word meaning representation. We first present the Residual CCA (R-CCA) method, that complements the standard CCA method by representing, for each modality, the difference between the original signal and the signal projected to the shared, max correlation, space. We then show that constructing visual and textual representations and then post-processing them through composition of common modeling motifs such as PCA, CCA, R-CCA and linear interpolation (a.k.a sequential modeling) yields high quality models. On five standard semantic benchmarks our sequential models outperform recent multimodal representation learning alternatives, including ones that rely on joint representation learning. For two of these benchmarks our R-CCA method is part of the Best configuration our algorithm yields.

1 Introduction

In recent years, vector space models (VSMs), deriving word meaning representations from word co-occurrence patterns in text, have become prominent in lexical semantics research (Turney et al., 2010; Clark, 2012). Recent work has demonstrated that when other modalities, particularly the visual, are exploited together with text, the resulting multimodal representations outperform strong textual models on a variety of tasks (Baroni, 2016).

Models that integrate text and vision can be largely divided to two types. Sequential models first separately construct visual and textual representations and then merge them using a variety of techniques: concatenation (Bruni et al., 2011; Silberer et al., 2013; Kiefer and Bottou, 2014), linear weighted combination of vectors (Bruni et al., 2012; Bruni et al., 2014) or linear interpolation of model scores (Bruni et al., 2014). Canonical Correlation Analysis and its kernelized version (CCA, (Hill et al., 2014; Silberer and Lapata, 2012; Silberer et al., 2013)), Singular Value Decomposition (SVD, (Bruni et al., 2014)) and Weighted Gram Matrix Combination (Reichart and Korhonen, 2013; Hill et al., 2014)). Joint models directly learn a joint representation from textual and visual resources using Bayesian modeling (Andrews et al., 2009; Feng and Lapata, 2010; Roller and Im Walde, 2013) and various neural network (NN) techniques: autoencoders (Silberer and Lapata, 2013), extensions of word2vec skip-gram (Hill and Korhonen, 2014; Lazaridou et al., 2015) and others (e.g. (Howell et al., 2005)).

The focused contribution of this short paper is two-fold. First, we advocate the sequential approach for text and vision combination and show that when a systematic search in the space of configurations of composition of common modeling motifs (Grosse, 2014) is employed, this approach outperforms recent joint models as well as sequential models that do not thoroughly search the space of configurations. This finding has important implications for future research as it advocates the development of efficient search techniques in configuration spaces of the type we explore.

Particularly, we experiment with unimodal dimensionality reduction with Principal Component
Analysis (PCA, (Jolliffe, 2002)), multimodal fusion with Canonical Correlation Analysis (CCA, (Hardoon et al., 2004)) and model score combination with linear interpolation (LI, (Bruni et al., 2014)). The composed models outperform strong alternatives on semantic benchmarks for word pair similarity and association: MEN (Bruni et al., 2014), WordSim353 (WS, (Finkelstein et al., 2001)), SimLex999 (SL, (Hill et al., 2015)), SemSim and VisSim (SSim, VSim, (Silberer and Lapata, 2014)).

Our second contribution is in proposing the Residual CCA (R-CCA) method for multimodal fusion. This method complements the standard CCA method by representing, for each modality, the difference between the original signal and the signal projected to the shared space. Since CCA aims to maximize the correlation between the projected signals, the residual signals intuitively represent uncorrelated components of the original signals. Empirically, including R-CCA in the configuration space improves results on two evaluation benchmarks. Moreover, for all five benchmarks R-CCA substantially outperforms CCA.

2 Multimodal Composition

2.1 Modeling Motifs

PCA is a standard dimensionality reduction method. We hence do not describe its details here and refer the interested reader to (Jolliffe, 2002).

CCA finds two projection vectors, one for each original vector, such that projecting the original vectors yields the highest possible correlation under linear projection. In short, given an n word vocabulary, with representations $X \in \mathbb{R}^{n \times d_1}$ and $Y \in \mathbb{R}^{n \times d_2}$, CCA seeks two sets of projection vectors $V \in \mathbb{R}^{d_1 \times d}$ and $W \in \mathbb{R}^{d_2 \times d}$ that maximize the correlation ($\rho$) between the projected vectors of each of the words: $V, W = \text{arg max}_{V', W'} \rho (X'V', Y'W')$. The final projection is: $X' = XV$ and $Y' = YW$.

Residual-CCA (R-CCA) CCA aims to project the involved representations into a shared space where the correlation between them is maximized. The underlying assumption of this method is hence that multiple modalities can facilitate learning through exploitation of their shared signal. A complementary point of view would suggest that important information can also be found in the dissimilar components of the monomodal signals.

While there may be many ways to implement this idea, we explore here a simple one which we call the residuals approach. Denoting the original monomodal signals with $X$ and $Y$ and their CCA projections with $X'$ and $Y'$ respectively, the residual signals are defined as: $R_x = X - X'$ and $R_y = Y - Y'$. Notice that a monomodal signal (e.g. $X$) and its CCA projection (e.g. $X'$) may not be of the same dimension. In such cases we first project the original signal ($X$) to the dimensionality of the projected signal ($X'$) with PCA.

LI combines the scores produced by two VSMs for a word pair, $sc_{m1}(w_i, w_j)$ and $sc_{m2}(w_i, w_j)$, using the linear equation ($\alpha \in [0, 1]$): $\text{Score}(w_i, w_j) = \alpha \cdot sc_{m1}(w_i, w_j) + (1 - \alpha) \cdot sc_{m2}(w_i, w_j)$.

2.2 Motif Composition

We divide the above modeling motifs to three layers, to facilitate an efficient systematic optimal configuration search (Figure 1): (a) Data: (a.1) original vectors; or (a.2) original vectors projected with unimodal PCA; (b) Fusion: (b.1) CCA and (b.2) R-CCA, each method outputting two projected vectors per word, one for each modality; (c) Combination: (c.1) vector concatenation; and (c.2) linear interpolation (LI) of model scores. In our search, a higher layer method considers inputs from all lower layer methods as long as both inputs are the output of the same method. That is, CCA (layer b.1) is ap-
Table 1: Results. Best is the best configuration for each benchmark. Best (*) and Concatenation are the best single-motif models. MMSKIP-A and MMSKIP-B are the (joint) models of Lazaridou et al. (2015), BR-EA-14 is the best performing model of Bruni et al. (2014) and KB-14 is the model of Kiela and Bottou (2014) (both are sequential). If LI is employed after CCA then its input are the CCA output vectors. If it is employed after a CCA+R-CCA then one of its input vectors comes from CCA and the other from R-CCA. For PCA and CCA we report the number of dimensions and for LI the weight of the textual model. For CCA we also report whether the textual (T) or the visual (V) projected vector yielded the best result.

| Model                  | Config. | \$\rho\$ | Config. | \$\rho\$ | Config. | \$\rho\$ | Config. | \$\rho\$ | Config. | \$\rho\$ |
|------------------------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| Best                   | PCA(200) | 0.81    | CCA (250) | 0.74    | PCA (250) | 0.62    | PCA (50) | 0.8     | PCA (100) | 0.68   |
| Best (No R-CCA)        | PCA(100) | 0.79    | CCA (50) | 0.71    | PCA(150) | 0.61    | LI (0.7) | 0.75    | LI (0.45) | 0.66   |
| Best (LI)              | 0.7     | 0.79    | 0.95    | 0.71    | 0.45    | 0.56    | 0.8      | 0.75    | 0.55    | 0.66   |
| Best (PCA, Skip)       | 0.68    | 0.79    | 0.55    | 0.71    | 0.54    | 0.7     | 0.73     | 0.66    | 0.66    |
| Best (PCA, CNN)        | 0.63    | 100     | 0.52    | 0.71    | 0.5     | 0.7     | 0.73     | 0.66    |
| Best (CCA)             | V, 100  | 0.59    | L, 50   | 0.61    | V, 50   | 0.75    | V, 100   | 0.66    |
| Best (R-CCA)           | L, 50   | 0.71    | L, 150  | 0.7    | V, 300  | 0.53    | L, 50    | 0.75    | V, 50   |
| Concatenation          | 0.63    | 0.48    | 0.5     | 0.72    | 0.54    | 0.57    | 0.6      |
| MMSKIP-A               | 0.74    | 0.5     | 0.72    | 0.63    |
| MMSKIP-B               | 0.76    | 0.5     | 0.68    | 0.6     |
| BR-EA-14               | 0.77    | 0.44    | 0.69    | 0.56    |
| KB-14                  | 0.74    | 0.33    | 0.60    | 0.50    |
| Skip                   | 0.75    | 0.46    | 0.73    | 0.67    |
| CNN                    | 0.58    | 0.53    | 0.67    | 0.64    |

For each benchmark (Section 3) we search for its Best configuration: the optimal sequence of the above motifs, at most one from each layer, together with the optimal assignment of their parameters. We do not aim to develop efficient algorithms for optimal configuration inference, but rather employ an exhaustive grid search approach. The high quality configurations we find, advocate future development of efficient search algorithms.

3 Data and Experiments

**Input Vectors** Our textual VSM is word2vec skip-gram \[^1\] trained on the 8G words corpus generated by the word2vec script \[^2\]. We followed the hyperparameter setting of (Schwartz et al., 2015) and, particularly, set vector dimensionality to 500. For the visual modality, we used the 5100 4096-dimensional vectors of Lazaridou et al. (2015), extracted with a pre-trained Convolutional Neural Network (CNN, \[^3\]) and the Caffe toolkit \[^4\]) from 100 pictures sampled for each word from its ImageNet entry. While there are various alternatives for both textual and visual representations, those we chose are based on state-of-the-art techniques.

**Benchmarks** We report the Spearman rank correlation (\$\rho\$) between model and human scores, for the word pairs in five benchmarks: MEN, WS, SL, SSim and VSim. While all the words in our benchmarks appear in our textual corpus, only a fraction of them appears in ImageNet, our source of visual input. Hence, following Lazaridou et al. (2015),
for each benchmark we report results only for word pairs consisting of words that are represented in ImageNet. A model word pair score is the cosine similarity between the vectors learned for its words.

Parameter Tuning We jointly optimized parameters together with the decision of which modeling motif to select at each layer, if at all. For PCA, CCA and R-CCA, we iterated over dimensionality values from 50 onward in steps of 50, till the minimum dimensionality of the input sets. For LI, we iterated over $\alpha \in \{0, 0.1, \ldots, 1\}$. Among the best performing configurations we selected the one with the lowest dimension output vectors.

Note that there is no agreed upon split of our benchmarks, except from MEN, to development and test portions. Therefore, to facilitate future comparison with our work, the main results we report are with the best configuration for each benchmark, as tuned on the entire benchmark. We also show that our results generalize well across evaluation sets, including MEN’s dev/test split.

Alternative Models We compare our results to strong alternatives: MSKIP-A and MMSKIP-B ([Lazaridou et al., 2015], joint models), the best performing model of Bruni et al. (2014) and Kiela and Bottou (2014) (sequential models). While our results are not directly comparable to these models due to different training sources and parameter tuning strategies, this comparison puts them in context.

4 Results

Table 1 presents the results. Best outperforms the unimodal models (Skip and CNN) and the alternative models. The gains (in $\rho$ points) are: MEN: 4, WS: 1, SL: 9, SSim: 7 and VSim: 1. R-CCA is included in Best for MEN and SL, improving over the best configuration that does not include it by 2

1 $\rho$ points, respectively. Furthermore, R-CCA outperforms CCA on all five benchmarks (by 6-31 $\rho$ points) and particularly on MEN, SSim and VSim.

Observations The five Best configurations share meaningful patterns. (1) Best never includes concatenation (layer c.1); (2) LI is always included in Best and the weights assigned to the textual and visual modalities are mostly balanced. Particularly, the weight of the textual modality is 0.4-0.7 for MEN, SL, SSim and VSim; (3) In 3 out of 5 cases, Best (LI), that linearly interpolates the scores yielded by the input textual and visual vectors without PCA, CCA or R-CCA processing, outperforms the models from previous work and the unimodal models; (4) In all Best configurations, the reduced dimensionality is 50-250, which is encouraging as processing smaller vectors requires less resources.

Generalization We now show that our results generalize well across evaluation sets. First, for the portion of the MEN development set that overlaps with ImageNet, our Best MEN configuration is the third-best configuration, with $\rho = 0.78$. We also tested the Best configuration as tuned on each of the benchmarks, on the remaining four benchmarks. We observed that WS, MEN and SL serve as good development sets for each other. Best SL configuration (Best-SL): $\rho = 0.7$ on WS and $\rho = 0.77$ on MEN, Best-WS: $\rho = 0.61$ (SL) and $\rho = 0.74$ (MEN), and Best-MEN: $\rho = 0.6$ (SL) and $\rho = 0.71$ (WS). The performance of these models on SSim and VSim, however, is substantially lower than that of the Best models of these sets (e.g. $\rho = 0.62$ for Best-SL on SSim, $\rho = 0.5$ for Best-WS on VSim, compared to $\rho = 0.8$ and $\rho = 0.68$, respectively). Likewise, SSim and VSim, that consist of the same word pairs scored along different dimensions, form good development sets for each other ($\rho = 0.66$ for Best-SSim on VSim, $\rho = 0.78$ for Best-VSim on SSim), but not for WS or SL. That is, each benchmark has other benchmarks that can serve as its dev. set.

5 Conclusions

We demonstrated the power of composition of common modeling motifs in multimodal VSM construction and presented the R-CCA method that exploits the residuals of the CCA signals. Our model yields
state-of-the-art results on 5 leading semantic benchmarks, for two of which R-CCA is part of the Best configuration. Moreover, R-CCA performs much better than CCA on all five benchmarks.

Our results hence advocate two research directions. First, they encourage sequential modeling with systematic search in the configuration space for multimodal combination. Our future goal is making model composition a standard tool for this problem, by developing efficient inference algorithms for optimal configurations in possibly more complex search spaces than those we explored with an exhaustive grid search. Second, the encouraging results of R-CCA emphasize the potential of informed post-processing of the CCA output. We intend to deeply delve into this issue in the immediate future.

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