PKWE: Priori-Knowledge Word Embeddings

Yanbo Fang
Department of Computer Science
Rutgers University
yanbo.fang@rutgers.edu

Abstract

We will introduce a multimodal word embedding through learning priori knowledge from a causal graph of multimodal representation. Our experiment shows our Priori-Knowledge word embeddings (PKWE) can be used to improve model performance in multimodal tasks, such as multimodal retrieval. Moreover, the experiemnt result shows our embeddings are competitive with other popular pre-trained word embeddings with large size.

1 Introduction

Building artificial models containing real-world knowledge and having the ability to infer on the knowledge it saves is always the focus of researchers. At first, scientists wrote knowledge facts and stored them in a knowledge graph. However, the knowledge is vast and hard to enumerate them. Recently, Deep Neural Networks (DNNs) (Schmidhuber, 2015; Bengio et al., 2013) emerges and exhibits a significant advance than former methods. DNNs can learn a generalization model from big enough datasets and process other unseen data through learning meaningful representation. But the drawbacks of DNNs are these models can not infer the knowledge they have to other unseen data, even though the unseen data are close to other seen data.

In 2013, (Mikolov et al., 2013) created Word2Vec, a classical word embeddings, which can be used to build correlations between similar or frequent co-occurrence words. This method paved a new way for NLP research, as the embeddings can build relations among different words. However, some abstract knowledge having a visual grounding can not be understood only by text data, but can be easily comprehended through visual perception. For example, one learning subject will not have a comprehensive understanding of ”red” if only touching texts, even though the subject can use this word normally and find out the similarity with other color words. Nevertheless, when the agent sees a red object, the over-all meaning of ”red” shall be understood immediately. Therefore, some research works about multimodal embeddings were proposed to address this unbalanced issue. (Calixto and Liu, 2017; Collell et al., 2017; Lazaridou et al., 2015).

However, these multimodal embeddings researches focus more on finding shared joint embeddings for different modalities. All these methods assumed different modalities have the same status. However, we assume different modalities have different priorities. Modalities with higher priority can decide the representation of lower priority modalities. For example, our understanding of the word ”apple” is a general impression of apples in the real world. In simple, Visual perceptions bring priori knowledge into our language. Also, it is worth to mention the priori knowledge is different from common sense knowledge (Bisk et al., 2020b; Bosselut et al., 2019; Bosselut and Choi, 2019; Liu and Singh, 2004). Because common sense knowledge can be learned from experience, priori knowledge exists ahead of experience and is the basis of common sense. Here in our assumption, the meaning of priori knowledge is a kind of definite knowledge before training. More concretely, in our scenes, the priori knowledge is the relations between one object and its name; for example, we call apple with the name ”apple”. Inference on priori knowledge can lead to common sense knowledge.

In a nutshell, the differences between the priori knowledge and the common sense knowledge are:

- The priori knowledge is independent of each other; the common sense knowledge shows a sense of dependence.
- The priori knowledge is only about existence;

the common sense knowledge has an attribute of true or false.

- The priori knowledge is more fundamental, and without being based on experience; the common sense knowledge can be inferred from priori knowledge and experience.

Different from past methods, our method, inspired by the discussion (Bisk et al., 2020a) about the foundations of language, is to build a multimodal graph according to head-to-head causal graph structure. In our method, we set visual perceptions as the cause, and word embeddings as the collider (Pearl et al., 2016), the link among these two items is a causal relationship. Therefore, word embeddings can infer the priori knowledge from visual perceptions through their connections and therefore, we call our embedding as Priori-Knowledge Word Embedding (PKWE). The characteristics of causal graphs ensure independence among different priori knowledge embeddings (Pearl et al., 2016) . Then we apply the `CBOW` algorithm on the multi-modal graph for distinction among words. We prove the effectiveness of priori knowledge through experiments by applying the embeddings on downstream tasks, visual semantic embeddings (VSE). Our outcomes show our combined model has a 5% improvement compared with random initialized models and has a similar performance with other popular pre-trained embeddings and baseline models. We also tested the model's performance of incorporating tree structure into the graph.

2 Related Work

2.1 Word Embeddingss

A large part of the success of modern language models can be attributed to the pre-trained word embeddings. (Bengio et al., 2003) originally coined the term word embeddings. Then, it was (Mikolov et al., 2013) to promote the term word embeddings by creating Word2Vec, by predicting a word's representation through its context. Later, another famous word embeddings Glove proposed by (Pennington et al., 2014), which is based on word occurrences in a textual corpus. Although these embeddings are formed through contextualized learning on large-scale language corpora, only learning from text imposes bias inevitably. Because some abstract words can not be described by text; thus, other modal information is required.

2.2 MultiModal Embeddings

Some recent research works focus on Multimodal embeddings. (Bruni et al., 2014) applied of single value decomposition (SVD) to the matrix of concatenated visual and textual representation. The auto-encoder structure was adopted in the research of (Silberer and Lapata, 2014). Encoders are fed with pre-learned visual and text features, and the hidden representations are then used as multimodal embeddings. (Lazaridou et al., 2015) proposed the multimodal skip-gram (MMSG) model extends the original skip-gram model (Mikolov et al., 2013) through incorporating visual features. (Ailem et al., 2018) proposes a Probabilistic Model for text and images embedding learning. All of these methods mentioned above are considering fusing visual features into textual features. However, our method is motivating the word embeddings to infer a general representation from visual features.

2.3 Visual Semantic Embeddings

Visual semantic embedding (Frome et al., 2013) is a technique for learning a joint representation among two different modalities, vision and language, through mapping into a common embedding space. In some research works, the embedding space was applied to a set of cross-modal tasks such as image captioning (Vinyals et al., 2015; Donahue et al., 2015), and visual question answering (Agrawal et al., 2015). (Frome et al., 2013) proposed a method for using textual data to learn semantic embedding and visual data to learn visual embedding than mapping pair-wised embeddings into the joint embedding space. VSE++ (Faghri et al., 2018) uses the online hard negative mining (OHEM) strategy for data comparison on the base structure of (Frome et al., 2013) and shows the performance gain. We choose the image-text retrieval task as our downstream task to test our embedding, and we incorporate our embedding into VSE++ (Faghri et al., 2018) as our tested model.

3 Method

3.1 Priori-Knowledge Word Embeddings

The process of embeddings generation has two steps, the first is to build a image-text graph, the direction is always from image to word, the second step is creating optimized distributed word embedding through `CBOW` algorithm.

We use pre-trained Resnet to extract image features v_i for image i, and set v_i as ground truth,

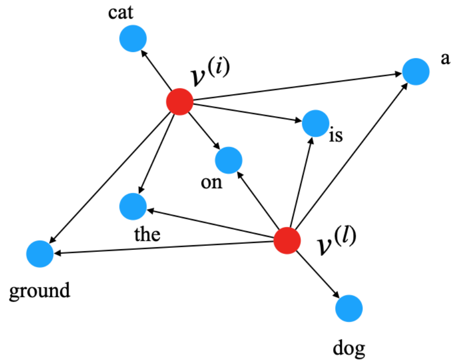

Figure 1: Example of the multi-modal graph

for corresponding sentence $\{w_{i,1}, w_{i,2}, \ldots, w_{i,j}\}$, creating a directional edge from image v_i to each words $w_{i,1:j}$. Fig.1 is an example of our built model, in this figure red nodes denotes images features, $v^{(i)}$ is the image representation of the sentence "`the cat is on the ground`", $v^{(l)}$ is the image representation of the sentence "`the dog is on the ground`", and each blue node in the graph is one unique word, and each edge points from image node to its paired word node, for example, some nodes `a`, `on`, and `ground` are directed from both $v^{(i)}$ and $v^{(l)}$, and some word only appears with one image, thus these words nodes are dominated by their unique parent node, like $v^{(i)}$ points to `cat` and $v^{(l)}$ points to `dog`.

After graph completion steps, keeping the image feature v_i static, iterate the following steps for each word nodes i until the graph stable,

$$\phi(w_i) = \frac{\sum_{k \in \mathrm{NER}(w_i)} v_k}{|\mathrm{NER}(w_i)|}$$

Here, $\phi(w_i)$ means the feature of node w_i, $\mathrm{NER}(w_i)$ means the parent node of w_i, $|\mathrm{NER}(w_i)|$ represents the number nodes pointing to node w_i. The purpose of the above statement is to import priori knowledge into each word node by getting close to their deciding modality.

Then we use `CBOW` algorithm, created by (Mikolov et al., 2013), to bring distinction among words. `CBOW` is one of unsupervised learning algorithm which can be used to bring connection into similar words. In the `CBOW` model, the representations of parent nodes are combined to predict the their children node. The detail is for node w_i having m parents $v_1, v_2, \ldots, v_m$, and the average vector is

$$\hat{v} = \frac{v_1 + v_2 + \cdots + v_m}{m}$$

and getting a score function by computing the similarity $z = (\phi(w_i)^{\mathrm{T}} \hat{v})$, and formulate the optimization objective as the negative log probability by comparing with all other nodes in the graph

$$\begin{aligned} J &= -\log(\mathrm{softmax}(\hat{z})) \\ &= -\log \frac{\exp\left(\phi(w_i)^{\mathrm{T}} \hat{v}\right)}{\sum_{j \in |V|} \exp\left(\phi(w_i)^{\mathrm{T}} v_j\right)} \end{aligned}$$

In order to improve the efficiency, we adopt Negative Sampling, replacing selecting all words as randomly choosing K words, the random selected vector is represented by $\tilde{v}$. Thus the loss functions becomes

$$\begin{aligned} J &= -\log(\mathrm{softmax}(\hat{z})) \\ &= -\log \frac{\exp\left(\phi(w_i)^{\mathrm{T}} \hat{v}\right)}{\sum_{k \in K} \exp\left(\phi(w_i)^{\mathrm{T}} \tilde{v}_k\right)} \end{aligned}$$

3.2 Visual Semantic Embeddings

We select cross-modal tasks as the evaluation of our embdding. Specifically, we repalce the randomly initialzed embeddings in model VSE++ as PKWE. It can jointly learn the common embedding spaces of two modalities: vision and language, and aligns them using parallel image-text pairs and 25K sentences.

Let $\mathrm{v} \in \mathbf{R}^d$ be the representation of images by an image encoder and $\mathrm{u} \in \mathbf{R}^d$ as the representation of pair sentences through a language encoder, and we define our hard negative sampling strategy following the instruction of []. Given pairs of image-sentence pairs v and u, the hardest negatives are $\mathrm{v}' = \arg\max_{j \neq i} s(\mathrm{v}_j, \mathrm{u})$ and $\mathrm{u}' = \arg\max_{j \neq i} s(\mathrm{v}, \mathrm{u}_j)$, here $s(\cdot,\cdot)$ is similarity measurement, and the Max-Hinge loss is defined as

$$\begin{aligned} l(\mathrm{v},\mathrm{u}) = & \sum_{\mathrm{v}} \max_{\mathrm{v}'}(\alpha + |s(\mathrm{v}_j, \mathrm{u}) - (\mathrm{v},\mathrm{u})|_+) \\ & + \sum_{\mathrm{u}} \max_{\mathrm{u}'}(\alpha + |s(\mathrm{v}, \mathrm{u}_j) - (\mathrm{v},\mathrm{u})|_+) \end{aligned}$$

, in which α serves as a margin parameter, and $|\cdot|_+ = \max(0, \cdot)$ is the traditional ranking loss,

4 Experiments

The dataset we used to produce our word-embedding and evaluate our combined model is MS-COCO datasets, which contains 11536 images for training, 1K images for evaluation and test, every image has 5 paired sentences. We also tested our model on a more challenging 5K Images dataset.

Task	Image to Text				Text to Image				
Metric	R@1	R@5	R@10	Med.r	R@1	R@5	R@10	Med.r	rsum
1K testing split (5000 captions)									
VSE++	63.5	89.4	96.2	1	47.3	80.6	89.5	2	466.4
Glove+VSE++	64.8	90.6	96.3	1	**49.7**	82.1	90.9	2	474.4
Fasttext+VSE++	64.3	**91.5**	**96.7**	1	48.7	81.0	90.4	2	472.8
Word2Vec+VSE++	**65.5**	90.6	96.1	1	49.1	**82.8**	**91.0**	2	**475.1**
PKWE+VSE++(Ours)	64.0	91.2	96.6	1	49.5	82.2	90.8	2	474.3
5K testing split (25000 captions)									
VSE++	35.2	65.4	77.6	3	23.8	51.7	65.2	5	318.8
Glove+VSE++	**37.4**	66.8	79.2	**2**	25.1	54.4	67.5	5	330.4
Fasttext+VSE++	35.8	66.7	78.8	3	25.0	53.0	66.7	5	326.0
Word2Vec+VSE++	37.3	67.9	79.2	**2**	**25.5**	54.0	67.6	5	331.6
PKWE+VSE++(Ours)	36.2	**68.7**	**80.0**	3	25.2	**54.5**	**67.8**	**4**	**332.5**

Table 1: Results of cross-modal retrieval task on MS-COCO dataset among our word embeddings with other pre-trained word embeddings and randomly initialized embeddings. And one thing worth to mention is the gap of our experiment of VSE++ and in its original paper probability due to we used pre-extracted image features by ResNet for computing efficiency

4.1 Implementation Detail

4.1.1 Embedding Generation

We used DGL open source library (Wang et al., 2019) and all training data to build graph, and adopt ResNet as the image encoder. These extracted image features are 4096 dimensions, then using SVD algorithm to reduce the image dimension to word embedding space with 300 dimensions. Models are trained for at most 50 epochs or the changes of the whole graph smaller than 0.001, the learning rate is a constant number 1. The number of neagtive sample is 10.

4.1.2 Visual Semantic Embedding

We followed the Details of implementation in VSE++ (Faghri et al., 2018), setting ResNet (He et al., 2016) as image encoder, GRU (Cho et al., 2014) as sentence encoder, using Adam optimizer, at most 30 epochs training, especially with lr 0.0002 for 15 epochs, and then 0.00002 lr for the next 15 epochs. Batch size is 128. The test checkpoint is selected based on the performance on the validation set. Word embeddings were fine-tuned during training. And for efficiency, we used pre-computed image features by ResNet in our experiments

4.2 Evaluation of Cross-Modal Retrieval

We select the R@1(recall), R@5, R@10, and the median retrieval rank as our evaluation metric. Also we compute `rsum` as the summation of R@1, R@5 and R@10 as the overall standard. The baseline model is (Wang et al., 2016; Eisenschtat and Wolf, 2017; Karpathy and Li, 2015; Niu et al., 2017; Vendrov et al., 2015; Faghri et al., 2018; Wu et al., 2019; Shi et al., 2018)

The result is shown in Tab.1, we can see the our combined VSE++ outperforms the original VSE++ (embeddings randomly initialized) no matter in 1K or 5K test dataset, approximately 21.6 `rsum` points improvements, and has a close performance to other VSE++ models combined with widely used pre-trained word embeddings like Word2Vec (Mikolov et al., 2013), Glove (Pennington et al., 2014), and Fasttext (Bojanowski et al., 2017; Joulin et al., 2017). From Tab.2, we can see our combined model is better than most baseline models, and can be above UniVSE (Wu et al., 2019) on R@1 and R@5 standard in the Image to Text task on 1K dataset. And the data sizes we used to produce our word embeddings are 110k images and 550K sentences and 26383 unique tokens, while other popular pre-trained embeddings were trained on Billion size sentences.

We also test the similarity and relatedness among different words in our embeddings. However, our embeddings behave poorly on this task; this outcome means our embeddings hardly consider interrelations among co-occurrence words, more for information from corresponding images features instead. Therefore, this result shows independence among the embeddings.

Task	Image to Text				Text to Image				
Metric	R@1	R@5	R@10	Med.r	R@1	R@5	R@10	Med.r	rsum
1K testing split (5000 captions)									
DVSA	38.4	69.9	80.5	1	27.4	60.2	74.8	3	351.2
HM-LSTM	43.9	-	87.8	2	36.1	-	86.7	3	
Order-Embedding	46.7	-	88.9	2	37.9	-	85.9	2	-
VSE-C	48.0	81.0	89.2	2	39.7	72.9	83.2	2	414
DeepSP	50.1	79.7	89.2	-	39.6	75.2	86.9	-	420.7
2WayNet	55.8	75.2	-	-	39.7	63.3	-	-	-
CSE	56.3	84.4	92.2	1	45.7	81.2	90.6	2	450.4
VSE++	60.3	88.4	95.2	1	45.5	79.0	88.0	2	456.4
UniVSE	**64.3**	89.2	94.8	1	**48.3**	**81.7**	**91.2**	2	**469.5**
PKWE+VSE++(Ours)	62.5	**90.0**	**96.5**	1	47.8	80.3	89.1	2	466.1
5K testing split (25000 captions)									
Order-embedding	23.3	-	65.0	5	18.0	-	57.6	7	-
VSE-C	22.3	51.1	65.1	5	18.7	43.8	56.7	7	257.7
VSE++	31.9	62.7	75.3	3	21.8	49.7	62.9	5	304.3
UniVSE	**36.1**	**66.4**	**77.7**	3	**25.4**	**53.0**	**66.2**	5	**324.8**
PKWE+VSE++(Ours)	34.4	64.5	76.9	3	23.6	51.9	65.2	5	316.5

Table 2: Results of cross-modal retrieval task on MS-COCO dataset among different models. For fairness, our model is trained on less data, the same number as other models

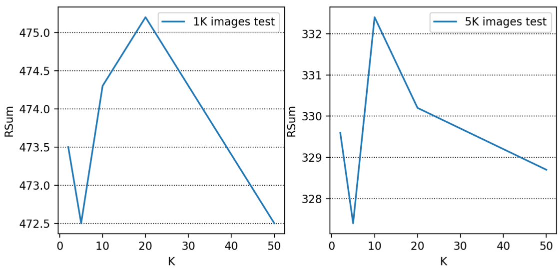

Figure 2: The performance on cross-modal retrieval with different Negative Samples numbers K, The **left** is the result on 1000 images test dataset, the **right** is the result on 5000 images test dataset.

4.3 Choice of the Number of Negative Samples

We study the effect of number K on the performance of priori-knowledge embeddings on retrieval tasks. Fig.2 shows the `rsum` performance on the image-text retrieval task corresponding to different choices of K. As show in Fig.2, choosing K from the range $[10, 20]$ has the best performance both on 1K and 5K test.

4.4 Tree Structure Graph

In addition to only pointing from the image node to the word node, we also evaluate the effectiveness of dependence among words in our graph by introducing tree hierarchies among nodes by applying dependency grammar without a drastic increase in the graph's size. In detail, we used Spacy [1] for the production of the dependency tree and setting the corresponding image node as the root. The result is in Tab.3. Although the outcome does not exhibit improvement, we guess the reason is the imprecise tree structures. We believe it can make progress if there are improvements in the precision of dependency tree extraction.

5 Conclusions

We present a causal graph approach for creating multi-modal word embeddings by setting images as the ground truth, then motivating words to learn and infer priori knowledge from images. The downstream task experiment result shows our combined model (PKWE+VSE++) has an advancement over the original model. Through incorporating PKWE, the VSE++ model has a similar effect with adopting other popular pre-trained word embeddings. And our combined VSE++ model outperforms most baseline models.

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[1]https://spacy.io/

Task	Image to Text				Text to Image				
Metric	R@1	R@5	R@10	Med.r	R@1	R@5	R@10	Med.r	rsum
1K testing split (5000 captions)									
PKWE+VSE++(Tree)	63.7	91.6	96.8	1	49.0	81.9	90.3	2	473.3
5K testing split (25000 captions)									
PKWE+VSE++(Tree)	35.9	67.7	79.0	3	25.0	53.6	67.1	5	328.3

Table 3: Results of cross-modal retrieval task on MS-COCO dataset for PKWE from tree-structure graph

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