Integrate Image Representation to Text Model on Sentence Level: a Semi-supervised Framework

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Abstract

Integrating visual features has been proved useful in language representation learning. Nevertheless, in most existing multi-modality models, alignment of visual and textual data is prerequisite. In this paper, we propose a novel semi-supervised visual integration framework for sentence level language representation. The uniqueness include: 1) the integration is conducted via a semi-supervised approach, which can bring image to textual NLU tasks by pre-training a visualization network, 2) visual representations are dynamically integrated in both training and predicting stages. To verify the efficacy of the proposed framework, we conduct the experiments on the SemEval 2018 Task 11 and reach new state-of-the-art on this reading comprehension task. Considering that the visual integration framework only requires image database, and no extra alignment is required for training and prediction, it provides an efficient and feasible method for multi-modality language learning.

1 Introduction

In the last decades, researchers have attempted to help machines understand text using visual information. Many multimodal natural language understanding methods combine visual and text by learning multimodal word representation (Srivastava and Salakhutdinov, 2012; Kiela and Bottou, 2014; Bruni et al., 2014; Kiros et al., 2018; Wang et al., 2018b) from aligned text-image data. Recently, sentence-level multi-modal semantic learning methods have also been proposed. The purpose of these models includes generating image captions (Socher et al., 2014; Chrupała et al., 2015) and image retrieval (Frome et al., 2013; Niu et al., 2017). Latest research (Kiela et al., 2018) learns sentence representation by predicting corresponding image features, and get encouraging improvement but did not achieve state-of-the-art performance on some NLP tasks such as entailment and classification. One limitation of these approaches is they need to be trained on aligned text-visual dataset, which limits their adaptability on NLU tasks with large-scale textual corpus.

Unique to existing works, in this paper, our purpose is integrating visual information to such textual NLP tasks. For example, given the text of reading comprehension task as in Fig. 1, human
may recall a visual scene while reading, and select the correct answer "A" easily. However, most reading comprehension tasks do not provide aligned images, and it is hard for a machine to select without the common sense that a cake is usually placed on a table, which may be described in some pictures. If we can provide the image in Fig. 1 just like human’s visualization, and integrate the information about a cake and a table to NLU models, it is likely to be helpful.

We propose a semi-supervised visual integration framework, use aligned visual-text dataset to train a visualization network that provides image for every sentence, and then dynamically integrate visual and textual representation. By integrating the framework to TriAN (Wang et al., 2018a) model, on the SemEval 2018 Task 11 corpus, we get the absolute performance gains of 1.28% and 0.57% for single and ensemble models and achieve state-of-the-art performance. To the best of our knowledge, this is also the first time to apply multimodal NLU model to textual reading comprehension task.

## 2 Integrated Reading Comprehension Model

A flowchart of applying semi-supervised visual integration framework to reading comprehension model is illustrated in Fig 2. This model consists of four parts: 1) pre-trained reading encoder, 2) sentence visualization and visual feature extraction, 3) the attentive text-visual fusion and 4) the choice classifier. To formulate, we define the input passage as a set of sentences, i.e., \( T = \{s_1, s_2, \ldots, s_l\} \), where \( s_i \) is the \( i^{th} \) sentence within the text \( T \), and \( l \) is the length of \( T \) counted by sentences.

### Sentence Visualization and Feature Extraction Module:

This module plays the text-to-image visualization role. The input text is fed into text encoder and converted to \( t \in \mathbb{R}^J \) where \( J \) is the joint embedding size. Image encoder computes all images in image memory as image embedding \( V \in \mathbb{R}^{J \times M} \) where \( M \) is the size of image memory base. Then the module returns the top 1 result of matched images as

\[
V(t) = \arg \max_{\theta \in [0, m]} V_{\theta} \cdot t.
\]

Since our main propose is to create a new framework, in implementation, we prepare this part of module according to the procedure used by VSE++ (Faghri et al., 2017) model, which uses 152-layer-ResNet (He et al., 2016) as image encoder and bidirectional GRU as text encoder.

In order to extract information from the retrieved image, we use visual information extractor \( F \) of two different levels. The object level extractor is pre-trained by Faster R-CNN (Ren et al., 2015) model, which selects top \( K \) possible objects from given image and returns object features \( I \in \mathbb{R}^{K \times \hat{V}} \), where \( K \) is number of objects, and \( \hat{V} \) is dimension of visual features. Image level extractor is a ResNet-152 network pre-trained on ImageNet, which provides a global feature vector on the whole image. While one passage contains many sentences, the features of these images are stacked together as \( \hat{r}_v = [r_{1,v}, r_{2,v}, \ldots, r_{n,v}] \).

### Attentive Text-Visual Fusion Module:

This module has two inputs: visual features \( \hat{r}_v \) and text representation \( r_p \) from pre-trained reading encoder. An attention network is used to process visual features. Each visual feature vector computes an attention weight with text representation as:

\[
\alpha = \text{softmax}(S(Q(\hat{r}_v) \odot P(r_p)))
\]

where \( \alpha \) is attention weight on \( \hat{r}_v \), \( Q \) and \( P \) are one hidden layer DNNs with weighted norm and ReLU activations, \( S \) is a linear transform, \( \odot \) is the Hadamard (element-wise) product. Finally visual-
ization feature vector \( r_{v,ta} \) is output as:

\[
r_{v,ta} = \sum_{i=1}^{N} r_{i,v} \times \alpha_i
\]

The \( r_{v,ta} \) is used as the text-visual fusion representation and will be fed into choice classifier.

Choice Classifier: Denote the final score as \( p \), we formulate the classification as:

\[
p = \phi(r_{v,ta}) \cdot r_{qc} + p_t
\]

where \( \cdot \) is dot product, \( r_{qc} \) is the concatenation of question representation, \( p_t \) is the score of choice given by pre-trained reading comprehension model.

3 Experiments

We integrate semi-supervised visual integration framework to TriAN (Wang et al., 2018a), which got first place in SemEval 2018 Task 11 competition. The metrics is accuracy test on the online official evaluation system.

Datasets: SemEval-2018 task 11 (Ostermann et al., 2018) is used as evaluation. It focuses on simple and explicit stories in the description of script events and script participants, which matches the goal of our framework.

Image Memory Base: We use MSCOCO 2014 caption dataset (Lin et al., 2014) as image memory base, where the total number of images in the train and validation set we use is 123K. Flicker 30k (Plummer et al., 2015) with 30K images is used as alternate image memory base to evaluate the influence of image base size.

Implementation: During training, we firstly use Adam optimizer of 1e-4 learning rate and dropout rate of 0.4 to optimize SVFE and ATVF. Then we fine-tune the whole model, the learning rate is set to 1e-5. In both steps we train the model until accuracy stops increasing on develop set.

4 Results

Integrated Reading Comprehension: Table. 1 presents our primary results on the SemEval 2018 Task 11 dataset, reporting pre-trained SOTA TriAN with ConceptNet (Speer and Havasi, 2012) knowledge base and the framework integrated model. After integrating the semi-supervised visual integration framework, the TriAN model outperforms previous SOTA performance both on single and ensemble condition. Because we could not access the test data, we verify the improvement of the framework on develop set and see statistically improvement under the one-tailed paired t-test at the 99% significance level.

To show the ability of the semi-supervised visual integration framework, we also compare how much performance gain the framework and ConceptNet (Speer and Havasi, 2012) give to TriAN base model. As we see in Table 1, after combining with TriAN model, the semi-supervised visual integration framework brings 1.34% improvement, higher than 0.82% improvement of ConceptNet.

Analysis by Question Categories: To figure out how the semi-supervised visual integration framework helps reading comprehension, we perform an analysis of performance change on six most frequent question types. As shown in Table 2, the framework benefits most to what and where questions, which tends to require real world information to answer. The framework does not help answering abstract why, who and when questions, which supports our hypothesis that the framework

| Models                        | Dev  | Test  |
|-------------------------------|------|-------|
| TriAN                         | 82.78| 81.08 |
| TriAN + ConceptNet            | 83.84| 81.94 |
| *TriAN + ConceptNet           | 85.27| 83.84 |
| Integrated TriAN              | 83.90| 82.10 |
| Integrated TriAN + ConceptNet | **84.42**| **83.12** |
| *Integrated TriAN + ConceptNet| **85.94**| **84.41** |

Table 1: Results on SemEval 2018 Task 11 (MCScript). Here, models with * are ensemble models.

| Models | y/n | what | why | who | where | when |
|--------|-----|------|-----|-----|-------|------|
| TriAN  | 81.4| 85.4 | 84.9| 89.7| 84.7  | 78.9 |
| Integrated | **81.6**| **86.3**| 84.4| 89.7| **85.3**| 78.9 |

Table 2: Results on six most frequent question types.

| Train Base | Test Base | Test |
|------------|-----------|------|
| MSCOCO     | MSCOCO    | 83.12|
| Flicker 30k| Flicker 30k| 83.09|
| Flicker 30k| MSCOCO    | 82.81|
| Flicker 30k| Flicker 30k| 82.81|

Table 3: Result of SemEval 2018 Task 11 (MCScript) on different train/test image bases.
I wanted to have a nice dinner with my friends and family, so I cooked all of our favorite foods and invited everyone over. I decided to go ahead and set the dining table before everyone arrived. I put the place mats in front of each chair at the table.

**Question:** Did they set the table for guests?  **Choice:** A. Yes*  B. No

My wife and I decided to have a picnic with my sister and brother in law. My wife and I planned to make a salad that had avocado and peppers in it. My sister said that she would bring pizza and a dessert.

**Question:** What kind of food was made for the picnic?  **Choice:** A. Salad, pizza, chicken, and dessert  B. Salad, pizza, and dessert*

When I noticed her doing this, I walked to the kitchen cabinet where her food is kept and pulled out one small can of tuna and chicken flavored wet cat food, which is her favorite. I opened the can using the pull tab on top of the lid, and used a spoon to scrape all of the food out of the can and into her food dish. I also placed water into her water bowl, which she lapped up after finishing her cat food.

**Question:** How did they feed the cat?  **Choice:** A. Open the can with a pull tab*  B. By throwing the food at her

To analyze how the semi-supervised visual integration framework caused base model to switch from wrong to right. Here, ground truth answer is marked with *.

In order to study the effect of image memory base size on experimental results, we alternate image base in train and test process. As shown in Table. 3, using bigger image base (MSCOCO) of 120k in train and test works best. When we shrink the test image memory base to the Flicker30k, the integrated model performance reduces, but is still higher than using 30k image both in train and test. More importantly, when the model is trained on the Flicker30k image base, using a bigger one does not contribute to test performance. These results suggest that the framework could work better as the size of the image base in train and test increases.

**Case Study:** To analyze how the semi-supervised visual integration framework benefits reading comprehension task, we give examples of the visual integration causing base model to switch from wrong to right in Fig. 3. Overall, we find that visualization helps when the answer of a question appears in one or more image, in other words, the visualization tends to give direct clue (table, daily necessities) to the answer. The helpful images contain environment objects (table, etc), characters (human, etc) and action (eat) information. More importantly, the framework does not provide proper images all the time, some images are irrelevant to sentences, or do not fully reflect the sentence as a human does. This also suggests that the framework would benefit from better image retrieval or generation models in the future.

We also provide some examples in Fig. 4 when the visual integration framework flipped the base model from right to wrong. As we can see in first passage, the question requires exact details of food, but the image provides trial information: fried chicken appeared in the second image with some vegetables, which gives error guidance. In another case as the second passage, the images show something like playing and writing, but fails to give information of abstract concept "trip" as a reason to answer a "why" question. The third case provides another condition when the question asks abstract information like a date. Although the...
| Models                      | Test  |
|-----------------------------|-------|
| *GroundSent (Kiela et al., 2018) | 76.1  |
| *Picturebook (Kiros et al., 2018) | 86.5  |
| ESIM + ELMo (Peters et al., 2018) | 88.7  |
| 300D DMAN (Pan et al., 2018) | 88.8  |
| SLRC (Zhang et al., 2018) | 89.1  |
| LMTTransformer (Radford et al., 2018) | 89.9  |
| MT-DNN (Liu et al., 2019) | 91.1  |
| BERT                        | 91.2  |
| BERT + STVF                 | 91.3  |

Table 4: Result on SNLI. Here, * stands for multimodal NLU models.

| Models                      | Acc(%) |
|-----------------------------|--------|
| *Cap2Both (Kiela et al., 2018) | 81.7   |
| BERT                        | 90.4   |
| BERT + STVF                 | 90.6   |

Table 5: Result on SICK. Here, * stands for multimodal NLU models.

Images provides some information about shopping, it seems hard for images to tell which day it is.

5 Discussion

For Neutral language inference task, we choose BERT-large (Devlin et al., 2018) model, which has shown SOTA performance on many NLU tasks as baseline. Since the inference task requires detailed information in image, Faster R-CNN is used as the visual information extractor.

**Integrated NLI Model**: In Table 4 we shows the results of integrating the mechanism to language inference model based on BERT. We firstly report the state-of-the-art performance of BERT-large model (91.2%) on the SNLI dataset. Based on the trained BERT-large encoder, we then train the integrated visualization language inference model using three-step training process, and achieve new SOTA performance reported (91.3%) yet on the SNLI dataset. By integrate to pre-trained NLU model, the framework also largely outperforms previous multimodal NLU models.

Table 5 shows the performance of integrate the framework to pre-trained BERT-large model on SICK dataset. Similar with performance on SNLI, we can also see the framework bring improvement to SOTA NLU model, and achieve higher performance after integrate to pre-trained NLU models.

**Performance on sentences with different retrieval scores**: To figure out how STVF bring improvement to pre-trained BERT model, we test sentences with different retrieval scores of visualization module. From results in Table 6, we can see that performance of Visualization increases rapidly as the retrieval score increases, and at the same time, bring more and more performance improvement to pre-trained BERT-large model. This also indicates that the framework works better on sentences that are more easily to be visualized, in other word, more concrete. The result also suggests that STVF will work better as the text-to-image retrieval research develops in the future.

**Cases Study**: To further explore how STVF works, we show the visualized image and top 3 object areas the model interests in as Fig. 5. As we can see, the visualized images could briefly provide visual information about event of sentences, and can reflect the relationship of objects. During feature extraction and fusion, the mechanism find entities (dog, people and human face) in the image, and is most interested in the sentence’s subject and object.

6 Conclusion

In this paper, we proposed a semi-supervised visual integration framework, and applied to the reading comprehension task. Unique from existing multimodal NLU models, the aligned text-image data were used to train a visualization network, and the visual information was integrated into NLU model dynamically during both training and predicting. After integrating this framework to TriAN model, we reached new state-of-the-art performance on the SemEval 2018 Task 11. Experiments and analysis showed the reasonableness of performance gain acquired by the visual feature integration.

As suggested in the analysis, the framework still has limitation on abstract sentences visualization.
and visual feature integration. In our future work, we plan to seek improvement through better text-to-image retrieval and generation models, and explore to better integration methods for general NLU tasks.

References

Elia Bruni, Nam-Khanh Tran, and Marco Baroni. 2014. Multimodal distributional semantics. Journal of Artificial Intelligence Research, 49:1–47.

Grzegorz Chrupała, Ákos Kádár, and Afra Alishahi. 2015. Learning language through pictures. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 2: Short Papers), volume 2, pages 112–118.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805.

Fartash Faghri, David J Fleet, Jamie Ryan Kiros, and Sanja Fidler. 2017. Vse++: improved visual-semantic embeddings. arXiv preprint arXiv:1707.05612.

Andrea Frome, Greg S Corrado, Jon Shlens, Samy Bengio, Jeff Dean, Marc Aurelio Ranzato, and Tomas Mikolov. 2013. Deve: A deep visual-semantic embedding model. In C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger, editors, Advances in Neural Information Processing Systems 26, pages 2121–2129. Curran Associates, Inc.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778.

Douwe Kiela and Léon Bottou. 2014. Learning image embeddings using convolutional neural networks for improved multi-modal semantics. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 36–45.

Douwe Kiela, Alexis Conneau, Allan Jabri, and Maximilian Nickel. 2018. Learning visually grounded sentence representations. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), volume 1, pages 408–418.

Jamie Kiros, William Chan, and Geoffrey Hinton. 2018. Illustrative language understanding: Large-scale visual grounding with image search. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), volume 1, pages 922–933.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. 2014. Microsoft coco: Common objects in context. In European conference on computer vision, pages 740–755. Springer.

Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. 2019. Multi-task deep neural networks for natural language understanding. arXiv preprint arXiv:1901.11504.
Zhenxing Niu, Mo Zhou, Le Wang, Xinbo Gao, and Gang Hua. 2017. Hierarchical multimodal lstm for dense visual-semantic embedding. In Computer Vision (ICCV), 2017 IEEE International Conference on, pages 1899–1907. IEEE.

Simon Ostermann, Michael Roth, Ashutosh Modi, Stefan Thater, and Manfred Pinkal. 2018. Semeval-2018 task 11: Machine comprehension using commonsense knowledge. In Proceedings of The 12th International Workshop on Semantic Evaluation, pages 747–757.

Boyuan Pan, Yazheng Yang, Zhou Zhao, Yueting Zhuang, Deng Cai, and Xiaofei He. 2018. Discourse marker augmented network with reinforcement learning for natural language inference. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), volume 1, pages 989–999.

Matthew E Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. arXiv preprint arXiv:1802.05365.

Bryan A Plummer, Liwei Wang, Chris M Cervantes, Juan C Caicedo, Julia Hockenmaier, and Svetlana Lazebnik. 2015. Flickr30k entities: Collecting region-to-phrase correspondences for richer image-to-sentence models. In Proceedings of the IEEE international conference on computer vision, pages 2641–2649.

Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. Improving language understanding by generative pre-training. URL https://s3-us-west-2.amazonaws.com/openai-assets/research-covers/languageunsupervised/languageunderstandingpaper.pdf.

Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. 2015. Faster r-cnn: Towards real-time object detection with region proposal networks. In Advances in neural information processing systems, pages 91–99.

Richard Socher, Andrej Karpathy, Quoc V Le, Christopher D Manning, and Andrew Y Ng. 2014. Grounded compositional semantics for finding and describing images with sentences. Transactions of the Association of Computational Linguistics, 2(1):207–218.

Robert Speer and Catherine Havasi. 2012. Representing general relational knowledge in conceptnet 5. In LREC, pages 3679–3686.

Nitish Srivastava and Ruslan R Salakhutdinov. 2012. Multimodal learning with deep boltzmann machines. In Advances in neural information processing systems, pages 2222–2230.

Liang Wang, Meng Sun, Wei Zhao, Kewei Shen, and Jingming Liu. 2018a. Yuanfudao at semeval-2018 task 11: Three-way attention and relational knowledge for commonsense machine comprehension. In Proceedings of The 12th International Workshop on Semantic Evaluation, pages 758–762.

Shaonan Wang, Jiajun Zhang, and Chengqing Zong. 2018b. Associative multichannel autoencoder for multimodal word representation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 115–124, Brussels, Belgium. Association for Computational Linguistics.

Zhuosheng Zhang, Yuwei Wu, Zuchao Li, Shexia He, Hai Zhao, Xi Zhou, and Xiang Zhou. 2018. I know what you want: Semantic learning for text comprehension. arXiv preprint arXiv:1809.02794.