Generate Image Descriptions based on Deep RNN and Memory Cells for Images Features

Shijian Tang
Stanford University
sjtang@stanford.edu

Song Han
Stanford University
songhan@stanford.edu

Abstract
Generating natural language descriptions for images is a challenging task. The traditional way is to use the convolutional neural network (CNN) to extract image features, followed by recurrent neural network (RNN) to generate sentences. In this paper, we present a new model that added memory cells to gate the feeding of image features to the deep neural network. The intuition is enabling our model to memorize how much information from images should be fed at each stage of the RNN. Experiments on Flickr8K and Flickr30K datasets showed that our model outperforms other state-of-the-art models with higher BLEU scores.

1 Introduction
Generating natural language descriptions for images has become an attractive research topic in recent years. The task is to generate sentences or phrases to summarize and describe the contents shown in images. With this technique, the machines are enabled to imitate the behaviour of human beings who are able to capture the semantic meaning encoded in images. Some previous work from Gupta and Mannem (2012), Kulakarni et al. (2011) and Desmond Elliott and Frank Keller (2013) designed templates for the sentence descriptions. The task is to fill in the templates based on the images. However, these approaches strongly limited the capability of models to generate sentence descriptions to only fixed patterns. Other approaches transfer this task into a multimodal embedding problem. These work from Farhadi et al. (2011), Jia et al. (2011), Socher et al. (2011), Ordonez et al. (2011) overlap with the scope of information retrieval. The goal is to map the images with sentences appearing in the training dataset together in a multimodal space. However, these models are only capable of returning sentence descriptions that existed in the training dataset.

Most of the state-of-the-art approaches are based on neural networks. These work combined convolutional neural network (CNN) with recurrent neural network (RNN) to generate image descriptions. Karpathy (2015) develop a multimodal RNN for this task. In this neural network, the image features extracted from the VGGNet (a pre-trained CNN proposed in Simonyan and Zisserman (2014)) are fed into a RNN. Conditioned on the image features and previous words, the RNN will generate a sequence of words recurrently to describe the images. Similar to Karpathy’s work, Vinyals et al. (2014) used the GoogLeNet CNN to extract image features and train a LSTM (in Hochreiter and Schmidhuber (1997)) as sequence generator. Mao et al. (2014) report a deep complex multimodal RNN for sentence generation.

In our approach, VGGNet is employed to extract image features and a deep multilayer RNN is chosen as a sequence generator, on top of which we informatively added memory gate that controls image feeding. In each time step of RNN, we feed word in current time step as well as the image features into the hidden layer of RNN. Before feeding into the hidden layer, the image features are multiplied by the output of gate element-wisely. Therefore, the memory gates act as memory cells for image features. Our model

In the RNN language model, the time step is defined as the position of word in sentence.
is trained on the Flickr8K and Flickr30K datasets from [Hodosh et al. (2013)]. We evaluate the BLEU score (proposed in [Papineni et al. (2002)]) of our model on the test datasets of both Flickr8K and Flickr30K. The preliminary results show that the performance of our model outperforms the state-of-the-art work.

2 The Architecture of Model

2.1 Image Features Representation

CNN has been proved as a powerful tool to extract image features, and has been widely used in image classification (Krizhevsky et al. (2012)), object detection (Girshick et al. (2014)) and other tasks. In this paper, we select the deep and powerful VGGNet to extract image features. Specifically, each raw image is fed into the VGGNet as input. After the forward propagation, the last fully-connected layer will output a 4096 dimensions vector as the image features for each image.

2.2 Sentence Representation

The sentence can be represented as a sequence of single word. The time step $t$ is defined as the index of $t$th word in the sentence to represent the position of each word. Suppose the sentence contains $T$ words, the time step of first word is $t = 1$, the second word is $t = 2$, and for the last word is $t = T$. For each sentence, we add a special START token at the first time step to indicate the start of the sentence, as well as the END token at the last time step as the end of each sentence.

The single word is represented as a vector. Some pretrained word vector models have been developed such as word2vec by [Mikolov et al. (2013)] and Glove by [Pennington et al. (2014)]. However, in this model, we trained the word vectors from scratch instead of directly adopted the pretrained model, since generally the pretrained word vector will achieve higher performance for specific task.

The standard RNN model can be expressed as,

$$
h(t) = f(W^s x(t) + W^h h(t-1) + b^h)$$

$$y(t) = \text{softmax}(W^d h(t) + b^d)$$

where $h(t)$ is the output of the hidden layer at time step $t$, $x(t)$ is the word vector for the word at $t$, $h(t-1)$ is the output of hidden layer for the previous time step $t-1$, $f()$ is the activation function. $W^s$ has the dimension of $H$ by $D$ where $H$ is the dimension of hidden layer and $D$ is the dimension of word vector. $W^h$ has the dimension of $H$ by $H$. $W^d$ has the dimension of $V$ by $H$ with $V$ as the vocabulary size. $b^d$ and $b_h$ are the bias terms. Vector $g(t)$ represents the probability of each word in the vocabulary to be the next word conditioned on the input words from time step $1$ to $t$.

In our model, to improve the model capacity, we increase the depth of RNN by adding multiple hidden layers which is the same as deep transition RNN (DT-RNN) model reported by [Pascanu et al. (2014)]. [Pascanu et al. (2014)] shows that the DT-RNN is able to increase the size of family of functions it can represent in language modeling. Unlike the standard RNN in equation (1) with only a single hidden layer at each time step, $N$ hidden layers are stacked together at each time step in DT-RNN. The forward propagation of this deep RNN model is,

$$h_1(t) = f(W^s x(t) + W^h h_N(t-1) + b^h)$$

$$h_2(t) = f(W^h h_1(t) + b^h)$$

$$...$$

$$h_N(t) = f(W^h h_{N-1}(t) + b^h)$$

$$y(t) = \text{softmax}(W^d h_N(t) + b^d)$$

where $h_1(t), h_2(t), ..., h_N(t)$ represent the output of $N$ hidden layers at $t$. The word vector $x(t)$ as well as the output of last hidden layer at previous time step $h_N(t-1)$ are fed into the first hidden layer $h_1(t)$ at $t$. Then, output of current hidden layer feeds into the next hidden layer consecutively. The output $y(t)$ depends on the output of last hidden layer at current time step $h_N(t)$. In our model, the deep RNN in equation (2) is chosen as the sequence learner of sentences.

2.3 Memory Cells for Image Features

We consider how to control feeding the image features into the deep RNN. Instead of feeding the image features directly, we add a gate to control the magnitude of image feature feeds. The value of the gate depends on the state of hidden layers at previous time step.

$$h_1(t) = f(W^s x(t) + W^h h_N(t-1) + b^h) + g(t) \odot (W^d C.N.N(I) + b^d)$$

$$y(t) = \sigma(W^g h_N(t-1) + b^g)$$
where $I$ represents the raw image, and $CNN(I)$ is the image features extracted by CNN. $W^i$ has the dimension of $H$ by 4096 which maps the image features to the same space of hidden layers of RNN. $g(t)$ is the output of gate, and $\sigma$ is the element-wise multiplication. $W^h$ transfers the value of the last hidden layer in the previous time step ($h_N(t-1)$ in the equation) to the gate $g(t)$. $b_i$ and $b_g$ are the bias terms. Here we use the $\sigma$ activation function and the value of $g(t)$ ranges from 0 to 1.

Based on equation 3 the image features are fed into the first hidden layer at each time step, multiplied by the output of gate. Since the value of gate depends on the last hidden layer of previous time step, the gate controls how much information from image is still needed for the current time step. In the case of $g(t) = 0$, the image features are not fed into RNN, while for $g(t) = 1$, we feed full image features at each time step.

Combining equations 2 and 3 together, this model can be represented as:

$$
g(t) = \sigma(W^g h_N(t-1) + b^g)$$

$$
h_1(t) = f(W^x x(t) + W^h h_N(t-1) + g(t) \circ (W^i CNN(I) + b^i) + b^h)$$

$$
h_2(t) = f(W^h h_1(t) + b^h)$$

$$
...$$

$$
h_N(t) = f(W^h h_{N-1}(t) + b^h)$$

$$
y(t) = \text{softmax}(W^d h_N(t) + b^d)$$

(4)

Figure 1 shows the architecture of this model.

Figure 1: The architecture of this model.

Recall the work of Karpathy (2015), image features are only fed at the first time step of RNN. Due to the vanishing gradient problem, image features will not be learned well with long sentence and deep network. However, our model feed image features into RNN at each time step. Therefore, our model is still able to learn information from the image even for larger time steps. The magnitude of image features is conditioned on the hidden state of previous time step. In another word, the image features are encoded based on the status of how well our model has learned.

Compared with other work of Vinyals et al. (2014) based on LSTM and work of Mao et al. (2014) based on multimodal embeddings, our model has the advantage of lower model complexity and easier to train.

3 Experiments

3.1 Dataset

We experimented on the Flickr8K and Flickr30K datasets introduced in Hodosh et al. (2013). Each image in these datasets is described by 5 independent sentences. Therefore, for each image, we can create 5 samples with each one as an image-sentence pair. We have 8000 and 31000 images for Flickr8K and Flickr30K respectively. Each dataset has been split into development data with 1000 images, test data with 1000 images and the rest images as training data. The data preprocessing procedure is the same as the work of Karpathy (2015).

3.2 Training

During training, cross entropy loss was chosen as the loss function. Stochastic gradient descent (SGD) with minibatch size of 100 image-sentence pairs was used during training. To make the model converge faster, RMSprop annealing policy (Hinton et al. 2012) was adopted, where the step size of each parameter is scaled by the window-averaged norm of its gradient.

To overcome the vanishing gradient problem, ReLU is chosen as the activation function. Also, we adopted the element-wise clip gradient tricks, where we clipped the gradient to 5. To regularize the model, we add L2 norm of weights to the loss function, and as Zaremba et al. (2014) suggested, we used dropout ratio of 0.5 to all the layers except for the hidden layers.

As equation 4 indicates, a model with large $N$ has deeper hidden layers, which leads to a large capacity. Considering the size of the dataset is not large and in order to prevent overfitting, we adopt a small $N = 2$ with 2 hidden layers in the experiments in equation 4.
We find 50 epochs are enough to train this model for both datasets, and the hidden size was tuned to 512 to achieve the best performance.

3.3 Generate Image Description

The sentence description for each image in test dataset is generated by feeding the image features into the trained model with a START token. At each time step, we can directly choose the word corresponds to the one with highest probability in vocabulary as the output word, which is also the input word of next time step. Following this method, we can generate a sentence recurrently until we reach the END token.

To evaluate the performance, we use the BLEU score as evaluation metrics which has been widely adopted in the papers focus on this topic (Karpathy (2015), Vinyals et al. (2014), Mao et al. (2014)). The BLEU score will evaluate the similarity of the generated sentences with the ground truth sentences. Table 1 and Table 2 show the BLEU score for several models.

| Model                  | B-1 | B-2 | B-3 | B-4 |
|------------------------|-----|-----|-----|-----|
| Our Model              | 58.3| 39.7| 25.7| 16.6|
| Karpathy (2015)        | 57.9| 38.3| 24.5| 16.0|
| Mao et al. (2014)      | 57.8| 27.5| 23.1| —   |
| Vinyals et al. (2014)  | 63.0| 41.0| 27.0| —   |
| Vinyals’ net on VGGNet | 58.2| 37.8| 19.0| —   |

Table 1: The BLEU score on Flickr8K for different models. B-n is the BLEU score up to n-gram.

| Model                  | B-1 | B-2 | B-3 | B-4 |
|------------------------|-----|-----|-----|-----|
| Our Model              | 59.0| 39.5| 26.0| 17.1|
| Karpathy (2015)        | 57.3| 36.9| 24.0| 15.7|
| Mao et al. (2014)      | 54.8| 23.9| 19.5| —   |
| Vinyals et al. (2014)  | 66.3| 42.3| 27.7| 18.3|
| Vinyals’ net on VGGNet | —   | —   | —   | —   |

Table 2: The BLEU score on Flickr30K for different models. B-n is the BLEU score up to n-gram.

As shown on Table 1 and Table 2, our model outperforms the results from Karpathy (2015) and Mao et al. (2014). While the performance of our model is lower than the original work from Vinyals et al. (2014). However, this is because in the original work of Vinyals et al. (2014), the authors used the GoogleNet (in Szegedy et al. (2014)) to extract the image features, while we used VGGNet. Therefore, it is unfair to directly compare the BLEU score of our model with results reported by Vinyals et al. (2014).

To make a fair comparison with the network in Vinyals et al. (2014), we have downloaded the reproduced version of Vinyals’ model from [http://cs.stanford.edu/people/karpathy/neuraltalk/](http://cs.stanford.edu/people/karpathy/neuraltalk/). In this reproduced model trained on Flickr8K, the image features fed into Vinyals’ model are extracted by VGGNet, which is the same as the case in our model. From the last row of Table 1 we can find that the performance of our model is better than the model in Vinyals et al. (2014) if both models use the VGGNet image features. Note that even though the reproduced model of Vinyals et al. (2014) based on Flickr30K dataset is unavailable now, our model still outperforms other state-of-the-art works.

We also tried to feed image features only at first time step (i.e., set \( g(t) = 0 \) except for the first time step) as well as feed full image features at each time step (i.e., set \( g(t) = 1 \) for all time steps). But the results show that the performance all of these two schemes are lower than feeding image features at each time step with memory cells.

4 Conclusion

In this paper, we developed a new model for generating image descriptions. The image features extracted from VGGNet are fed into each time step of a multilayer deep RNN, where the image features vector is element-wisely multiplied by a memory vector determined by the state of the hidden layer at previous time step. Experiments on Flickr8K and Flickr30K datasets show that this model achieves higher performance on BLEU score. Our model also benefit from its low complexity and ease of training.

As the extension of this work, we will train our model on a larger dataset such as MSCOCO, and will increase the number of hidden layers at each time step to further improve the performance of our model. We will also try to adopt other CNNs such as GoogleNet to extract image features. Also, in this work, we do not fine-tune the CNNs on the new datasets, in future, we will try to train the model and tune the CNNs together.
References

[Gupta and Mannem 2012] Ankush Gupta and Prashanth Mannem. 2012. From image annotation to image description. In NIPS.

[Kulkarni et al. 2011] Girish Kulkarni, Visruth Premraj, Sagnik Dhar, Siming Li, Yejin Choi, Alexander Berg, and Tamara Berg. 2011. Baby talk: Understanding and generating simple image descriptions. In CVPR.

[Desmond Elliott and Frank Keller 2013] Desmond Elliott and Frank Keller. 2013. Image description using visual dependency representations. In EMNLP.

[Farhadi et al. 2011] Ali Farhadi, Mohsen Hejrati, Mohammad Amin Sadeghi, Peter Young, Cyrus Rashtchian, Julia Hockenmaier, and David Forsyth. 2010. Every picture tells a story: Generating sentences from images. In ECCV.

[Jia et al. 2011] Yangqing Jia, Mathieu Salzmann, and Trevor Darrell. 2011. Learning cross-modality similarity for multimodal data. In ICCV.

[Socher et al. 2011] 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. In TACL.

[Ordonez et al. 2011] Vicente Ordonez, Girish Kulkarni, and Tamara L. Berg. 2011. Im2text: Describing images using 1 million captioned photographs. In NIPS.

[Karpathy 2015] Andrej Karpathy and Li Fei-Fei. 2015. Deep visual-semantic alignments for generating image descriptions. In CVPR.

[Simonyan and Zisserman 2014] Karen Simonyan and Andrew Zisserman. 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

[Vinyals et al. 2014] Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan. 2014. Show and tell: A neural image caption generator. arXiv preprint arXiv:1411.4555.

[Hochreiter and Schmidhuber 1997] Sepp Hochreiter and Jurgen Schmidhuber. 1997. Long short-term memory. Neural computation, 9(8):1735-1780.

[Mao et al. 2014] Junhua Mao, Wei Xu, Yi Yang, Jiang Wang, and Alan L. Yuille. 2014. Explain images with multimodal recurrent neural networks. arXiv preprint arXiv:1410.1090.

[Rolls and Deco 2002] Edmund T. Rolls and Gustavo Deco. 2002. Computational Neuroscience of Vision. Oxford University Press, USA.

[Hodosh et al. 2013] Micah Hodosh, Peter Young, and Julia Hockenmaier. 2013. Framing image description as a ranking task: data, models and evaluation metrics. Journal of Artificial Intelligence Research, 47: 853-899.

[Papineni et al. 2002] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu 2002. Bleu: a method for automatic evaluation of machine translation. Proceedings of the 40th annual meeting on association for computational linguistics.

[Krizhevsky et al. 2014] Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton. 2012. ImageNet classification with deep convolutional neural networks. In NIPS.

[Girshick et al. 2014] Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik 2014. Rich feature hierarchies for accurate object detection and semantic segmentation. In CVPR.

[Mikolov et al. 2013] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg Corrado, and Jeffrey Dean 2013. Distributed representations of words and phrases and their compositionality. In NIPS.

[Pennington et al. 2014] Jeffrey Pennington, Richard Socher, Christopher D. Manning 2014. Glove: Global vectors for word representation. In EMNLP.

[Pascanu et al. 2014] Razvan Pascanu, Caglar Gulcehre, Kyunghyun Cho, and Yoshua Bengio 2014. How to construct deep recurrent neural networks. In ICLR.

[Hinton et al. 2012] Geoffrey Hinton, Nitish Srivastava, and Kevin Swersky. 2012. How to construct deep recurrent neural networks. In Lecture 6.5-rmsprop.

[Zaremba et al. 2014] Wojciech Zaremba, Ilya Sutskever, Oriol Vinyals 2014. Recurrent neural network regularization. arXiv preprint arXiv:1409.2329.

[Szegedy et al. 2014] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich 2014. Going deeper with convolutions. arXiv preprint arXiv:1409.4842.