An Empirical Study of Language CNN for Image Captioning

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Abstract

Language models based on recurrent neural networks have dominated recent image caption generation tasks. In this paper, we introduce a language CNN model which is suitable for statistical language modeling tasks and shows competitive performance in image captioning. In contrast to previous models which predict next word based on one previous word and hidden state, our language CNN is fed with all the previous words and can model the long-range dependencies in history words, which are critical for image captioning. The effectiveness of our approach is validated on two datasets: Flickr30K and MS COCO. Our extensive experimental results show that our method outperforms the vanilla recurrent neural network based language models and is competitive with the state-of-the-art methods.

1. Introduction

Image caption generation is a fundamental problem that involves Computer Vision, Natural Language Processing (NLP), and Machine Learning. It can be analogous to “translating” an image to proper sentences. While this task seems to be easy for human beings, it is quite challenging for machines because it requires the model to understand the image content and express their relationships in a natural language. Also, the image captioning model should be capable of capturing implicit semantic information of an image and generating humanlike sentences. As a result, generating accurate captions for an image is not an easy task.

The recent surge of research interest in image caption generation task is due to the advances in Neural Machine Translation (NMT) \cite{43} and large datasets \cite{39, 29}. Most image captioning models follow the encoder-decoder pipeline \cite{4, 24, 35, 19, 41}. The encoder-decoder framework is recently introduced for sequence-to-sequence learning based on Recurrent Neural Networks (RNNs) or Long-Short Term Memory (LSTM) networks. Both RNNs and LSTM networks can be sequence learners. However, due to the vanishing gradient problem, RNNs can only remember the previous status for a few time steps. LSTM network is a special type of RNN architecture designed to solve the vanishing gradient problem in RNNs \cite{46, 15, 6}. It introduces a new component called memory cell. Each memory cell is composed of three gates and a neuron with the self-recurrent connection. These gates allow the memory cells to keep and access information over a long period of time and make LSTM network capable of learning long-term dependencies.

Although models like LSTM networks have memory cells which aim to memorize history information for long-term, they are still limited to several time steps because long-term information is gradually diluted at every time step \cite{49}. Besides, vanilla RNNs-based image captioning models recursively accumulate history information without explicitly modeling the hierarchical structure of word sequences, which clearly have a bottom-up structure \cite{28}.

To better model the hierarchical structure and long-term dependencies in word sequences, in this paper, we adopt a language CNN which applies temporal convolution to extract features from sequences. Such a method is inspired by works in NLP which have shown CNN is very powerful for text representation \cite{18, 48}. Unlike the vanilla CNN architecture, we drop the pooling operation to keep the relevant information for words representation and investigate the optimum convolutional filters by experiments. However, only using language CNN fails to model the dynamic temporal behavior. Hence, we still need to combine language CNN with recurrent networks (e.g., RNN or LSTM). Our extensive studies show that adding language CNN to a recurrent network helps model sequences consistently and more effectively, and leads to improved results.

To summarize, our primary contribution lies in incorporating a language CNN, which is capable of capturing long-range dependencies in sequences, with RNNs for image captioning. Our model yields comparable performance with the state-of-the-art approaches on Flickr30k \cite{39} and...
MS COCO [29].

2. Related Works

The problem of generating natural language descriptions for images has become a hot topic in computer vision community. Prior to using neural networks for generating descriptions, the classical approach is to pose the problem as a retrieval and ranking problem [12, 9, 37]. The main weakness of those retrieval-based approaches is that they cannot generate proper captions for a new combination of objects. Inspired by the success of deep neural networks in machine translation [44, 4, 17], researchers have proposed to use the encoder-decoder framework for image caption generation [21, 35, 19, 46, 6, 3, 26]. Instead of translating sentences between two languages, the goal of image captioning is to “translate” a query image into a sentence that describes the image. The earliest approach using neural network for image captioning is proposed by Vinyals et al. [40] which is an encoder-decoder system trained to maximize the log-likelihood of the target image descriptions. Similarly, Mao et al. [35] and Donahue et al. [6] use the multimodal fusion layer to fuse the image features and word representation at each time step. In both cases, i.e., the models in [35] and [6], the captions are generated from the full images, while the image captioning model proposed by Karpathy et al. [19] generates descriptions based on regions. This work is later followed by Johnson et al. [16] whose method is designed to jointly localize regions and describe each with captions.

Rather than representing an image as a single feature vector from the top-layer of CNNs, some researchers have explored the structure of networks to explicitly model the correlation between images and descriptions [51, 44, 30]. Xu et al. [51] incorporate the spatial attention on convolutional features of an image into the encoder-decoder framework through the “hard” and “soft” attention mechanisms. Their work is followed by Yang et al. [30] whose approach is designed to improve the correctness of visual attention. Moreover, a variational autoencoder for image captioning is developed by Pu et al. [40]. They use a CNN as the image encoder and use a deep generative convolutional network as the decoder together with a Gated Recurrent Unit (GRU) [4] to generate image descriptions.

More recently, high-level attributes have been shown to obtain clear improvements on the image captioning task when injected into existing encoder-decoder based models [50, 53, 8]. Specifically, Jia et al. [15] use the semantic information as the extra input to guide the model in generating captions. In addition, Fang et al. [7] learn a visual attributes detector based on multi-instance learning (MIL) first and then learn a statistical language model for caption generation. Likewise, Wu et al. [50] train several visual attribute classifiers and take the outputs of those classifiers as inputs for the LSTM network to predict words.

In general, current recurrent neural network based approaches have shown their powerful capability on modeling word sequences [46, 19]. However, the history-summarizing hidden states of RNNs are updated at each time, which render the long-term memory rather difficult [25, 56]. Besides, we argue that current recurrent networks like LSTM are not efficient on modeling the hierarchical structure in word sequences. All of these prompt us to explore a new language model to extract better sentence representation. Considering ConvNets can be stacked to extract hierarchical features over long-range contexts and have received a lot of attention in many tasks [11, 10], in this paper, we design a language CNN to model words with long-term dependencies through multilayer ConvNets and to model the hierarchical representation through the bottom-up and convolutional architectural.

3. Model Architecture

3.1. Overall Framework

We study the effect of language CNN by combining it with Recurrent Networks. Figure 1 shows a recursive framework. It consists of one deep CNN for image encoding, one CNN for sentence modeling, and a recurrent network for sequence prediction. In order to distinguish these two CNN networks, we name the first CNN for image feature extraction as CNN_L, and the second CNN for language modeling as CNN_T.

Given an image I, we take the widely-used CNN architecture VGGNet (16-layer) [42] pre-trained on ImageNet [22] to extract the image features V ∈ RK. The CNN_L is designed to represent words and their hierarchical structure in word sequences. It takes a sequence of t generated words (each word is encoded as a one-hot representation) as inputs and generates a bottom-up representation of these words. The outputs of CNN_L and CNN_T will be fed into a multimodal fusion layer, and use the recurrent network f_recurrence(·) to predict the next word. The following equations show the main working flow of our model:

V = CNN_T(I) (1)

y[t] = CNN_L(S[0], S[1], ..., S[t−1]) (2)
m[t] = f_{multimodal}(y[t], V) (3)
r[t] = f_{recurrence}(x[t-1], y[t-1], m[t]) (4)
S[t] ∼ arg \max_S \text{Softmax}(W_s r[t] + b_o) (5)

where t ∈ [0, N − 1] is the time step, y[t] is the output vector of CNN_L, r[t] is the activation output of recurrent network, S[t] is the t-th word drawn from the dictionary S according
Given an input feature map use a larger and deeper CNN as with predefined maximum number of input words (denoted as $L_C$). Unlike the toy example in Figure 2, in practice we use a larger and deeper CNN with $L_C = 16$.

We use the temporal convolution to model the sentence. Given an input feature map $y^{(L-1)} \in \mathbb{R}^{M_{L-1} \times K}$ of Layer-$L - 1$, the output feature map $y^{(L)} \in \mathbb{R}^{M_L \times K}$ of the temporal convolution layer-$L$ will be:

$$y^{(L)}_i(x) = \sigma(w^{(L)}_i y^{(L-1)}_i + b^{(L)}_i)$$

here $y^{(L)}_i(x)$ gives the output of feature map for location $i$ in Layer-$L$, $w^{(L)}_i$ denotes the parameters on Layer-$L$, $\sigma(\cdot)$ is the activation function, e.g., Sigmoid, or ReLU. The input feature map $y^{(L-1)}_i$ is the segment of Layer-$L - 1$ for the convolution at location $i$, while $y^{(0)}_i$ is the concatenation of $t$ word embeddings from the sequence input $S^{0:t-1}$. The definition of $y^{(0)}_i$ is as follows:

$$y^{(0)}_i \triangleq \begin{cases} [x^{0:L_C}, \ldots, x^{t-1}]^T, & \text{if } t \geq L_C \\ [x^{0}, \ldots, x^{t-1}, \tilde{x}^{[i]}, \ldots, \tilde{x}^{[L_C-1]}]^T, & \text{otherwise} \end{cases}$$

Specially, when $t \geq L_C$, the input sentence will be truncated, we only use $L_C$ words before the current time step $t$. When $t < L_C$, the input sentence will be padded with $\tilde{x}^{[i]}$. Note that if $t = 0$, $\tilde{x}^{[i]}$ are the image features $V$, otherwise $\tilde{x}^{[i]}$ are the zero vectors that have the same dimension as $x^{[i]}$.

Previous CNNs, including those adopted for NLP tasks, take the classic convolution-pooling strategy, which uses max-pooling to pick the highest response feature across time. This strategy works well for tasks like text classification and matching, but is undesirable for modeling the composition functionality, because it ignores the temporal information in sequence. In our network, we discard the pooling operations. We consider words as the smallest linguistic unit and apply a straightforward stack of convolution layers on top of each other. In practice, we find that deeper CNNs work better than shallow CNNs, which is consistent with the tradition of CNNs in computer vision, where using very deep CNNs is key to having better feature representation.

The output features of the final convolution layer are fed into a fully connected layer that projects the extracted words features into a low-dimensional representation. Next, the projected features will be fed to a highway connection which controls flows of information in the layer and im-
proves the gradient flow. The final output of the highway connection is a \( K \)-dimensional vector \( y^{[i]} \).

![Figure 2. The architecture of language CNN for sentence modeling. Here “/” stands for a zero padding. The CNN\( _L \) builds a hierarchical representation of history words which contains the useful information for next word prediction.](image)

3.3. Multimodal Fusion Layer

Next, we add a multimodal fusion layer after CNN\( _L \), which fuses words representation and image features. This layer has two inputs: the bottom-up words representation \( y^{[i]} \) extracted from CNN\( _L \) and the image representation \( V \) extracted from CNN\( _I \). We map these two inputs to the same multimodal feature space and combine them together to obtain the activation of multimodal features:

\[
\begin{align*}
  m^{[i]} &= f_{\text{multimodal}}(y^{[i]}, V) \\
  &= \sigma (f_y(y^{[i]}); W_Y, b_Y) + g_v(V; W_V, b_V)
\end{align*}
\]  

(9)

where “+” denotes element-wise addition, \( f_y(\cdot) \) and \( g_v(\cdot) \) are linear mapping functions, \( m^{[i]} \) is the multimodal layer output feature vector. \( \sigma(\cdot) \) is the activation function, here we use the scaled tanh function \([27]\) which leads to a faster training process than the basic tanh function.

3.4. Recurrent Networks

Our CNN\( _L \) may miss the important temporal information because it extracts the holistic features from the whole sequence of words. To overcome this limitation, we combine it with recurrent networks. In our model, the transition equations of the recurrent network can be formulated as:

\[
\begin{align*}
  r^{[i]} &= f_{\text{recurrent}}(r^{[i-1]}, x^{[i-1]}, m^{[i]}) \\
  s^{[i]} &= \text{arg max}_S \text{Softmax}(W_{os}[r^{[i]}] + b_o)
\end{align*}
\]

(11)

(12)

where \( r^{[i]} \) denotes the recurrent state, \( x^{[i-1]} = W_x s^{[i-1]} \) is the previous word embedding, \( m^{[i]} \) is the multimodal fusion output, and \( f_{\text{recurrent}}(\cdot) \) is the transition function of recurrent network. Softmax(\( r^{[i]} \)) is the probability of word \( s^{[i]} \) given by the Softmax layer, and \( s^{[i]} \) is the \( i \)-th decoded word.

In our study, we combine our language CNN with four types of recurrent networks: Simple RNN, LSTM network, GRU [4], and Recurrent Highway Network (RHN) [54].

Traditionally, the simple RNN updates the recurrent state \( r^{[i]} \) of Equation (11) as follows:

\[
  r^{[i]} = \text{tanh}(W_r r^{[i-1]} + W_z z^{[i]} + b)
\]

(13)

where \( z^{[i]} \) is the input. However, this type of simple RNN is hard to deal with long-term dependencies [2]. As the vanishing gradient will make gradients in directions that short-term dependencies are large, while the gradients in directions that correspond to long-term dependencies are small.

LSTM network extents the simple RNN with the gating mechanism (input gate, forget gate, and output gate) to control information flow and a memory cell to store the history information, thus it can better model the long-term dependencies than simple RNN.

GRU is an architecture similar to the LSTM, but it has a simplified structure. GRU does not have a separate memory cell and exposes its hidden state \( r^{[i]} \) without any control. Thus, it is computationally more efficient and outperforms the LSTM network on many tasks due to its simple structure.

Besides, we also consider a fourth type of recurrent network: RHN, which introduces the highway connection to the LSTM network. RHN has directly gated connections between different layers. In this paper, we use high approximation of LSTM and expose its hidden state \( r^{[i]} \) for next word prediction.

Like GRU, RHN does not have output gate to control the exposure of the recurrent state \( r^{[i]} \), but exposes the whole state each time. The RHN, however, does not have reset gate to drop information that is irrelevant in the future. As our CNN\( _L \) can extract the relevant information from the sequence of history words at each time step, to some extent, the CNN\( _L \) allows the model to add information that is useful in making a prediction.

3.5. Training

During training, given the ground truth words \( S \) and corresponding image \( I \), the loss function for a single training
instance \((S, I)\) is defined as a sum of the negative log likelihood of the words. The loss can be written as:

\[
\mathcal{L}(S, I) = - \sum_{t=0}^{N-1} \log P(S^{[t]}|S^{[0]}, \ldots, S^{[t-1]}, I)
\]  

(17)

where \(N\) is the sequence length, and \(S^{[t]}\) denotes a word in the sentence \(S\).

The training objective is to minimize the cost function, which is equivalent to maximizing the probability of the ground truth context words given the image by using:

\[
\arg \max_\theta \sum_{t=0}^{N-1} \log P(S^{[t]}|S^{[0:t-1]}, I),
\]

where \(\theta\) are the parameters of our model, and \(P(S^{[t]}|S^{[0:t-1]}, I)\) corresponds to the activation of Softmax layer.

3.6. Implementation Details

In the following experiments, we use the 16-layer VGGNet [42] model to compute CNN features and map the last fully-connected layer’s output features to an embedding space via a linear transformation.

As for preprocessing of captions, we transform all letters in the captions to lowercase and remove all the non-alphabetic characters. Words occur less than five times are discarded. Terms frequency-inverse document frequency weighting metric developed specifically for evaluating image captions.

3.6.2 Testing

During testing, the previous output \(S^{[t-1]}\) is used as input in lieu of \(S^{[t]}\). The sentence generation process is straightforward. Our model starts from the \(<\text{START}\>\) token and calculates the probability distribution of the next word \(P(S^{[t]}|S^{[0:t-1]}, I)\), here we use Beam Search technology proposed in [15], which is a fast and efficient decoding method for recurrent network models. We set a fixed beam search size \((k=2)\) for all models (with RNNs) in our tests.

4. Experiments

4.1. Datasets and Evaluation Metrics

We perform experiments on two popular datasets that are used for image caption generation: MS COCO and Flickr30k. These two datasets contain 123,000 and 31,000 images respectively, and each image has five reference captions. For MS COCO, we reserve 5,000 images for validation and 5,000 images for testing. For Flickr30k, we use 29,000 images for training, 1,000 images for validation, and 1,000 images for testing.

We choose four metrics for evaluating the quality of the generated sentences: \textbf{BLEU-\(n\)} [33] is a precision-based metric. It measures how many words are shared by the generated captions and ground truth captions. \textbf{METEOR} [5] is based on the explicit word to word matches between generated captions and ground-truth captions. \textbf{CIDEr} [45] is a metric developed specifically for evaluating image captions. It measures consensus in image caption by performing a Term Frequency-Inverse Document Frequency weighting for each \(n\)-gram. \textbf{SPICE} [1] is a more recent metric which has been shown to correlate better with the human judgment of semantic quality than previous metrics.

4.2. Models

To gain insight into the effectiveness of CNN\(_E\), we compare CNN\(_E\)-based models with methods using the recurrent network only. For a fair comparison, the output dimensions of all gates are fixed to 512.

\textbf{Recurrent Network-based Models.} We implement Recurrent Network-based Models based on the framework proposed by Vinyals \textit{et al.} [46], it takes an image as input and predicts words with one-layer Recurrent Network. Here we use the publicly available implementation Neuraltalk2 [https://github.com/karpathy/neuraltalk2]. We evaluate four baseline models: \textbf{Simple RNN}, RHN, LSTM, and GRU.

\textbf{CNN\(_E\)-based Models.} As can be seen in Figure 1, the CNN\(_E\)-based models employ a CNN\(_E\) to obtain the bottom-up representation from the sequence of words and cooperate with the Recurrent Network to predict the next word. Image features and words representation learned from CNN\(_E\) and

https://github.com/karpathy/neuraltalk2
CNN$_C$ respectively are fused with the multimodal function. We implement four CNN$_C$-based models: CNN$_C$+Simple RNN, CNN$_C$+RHN, CNN$_C$+LSTM, and CNN$_C$+GRU.

4.3. Quantitative Results

We first evaluate the importance of language CNN for image captioning, then evaluate the effects of CNN$_C$ on two datasets (Flickr30K and MS COCO), and also compare with the state-of-the-art methods.

4.3.1 Analysis of CNN$_C$

It is known that CNN$_C$-based models have larger capacity than RNNs. To verify that the improved performance is from the developed CNN$_C$ rather than due to more layers/parameters, we set the hidden and output sizes of RNNs to 512 and 9568 (vocabulary size), and list the parameters of each model as well as their results in Table 1.

| Approach     | Params  | B@4   | C   | Approach     | Params  | B@4  | C |
|--------------|---------|-------|-----|--------------|---------|------|---|
| Simple RNN   | 5.3M    | 27.0  | 87.0| LSTM         | 7.0M    | 29.2 | 92.6 |
| CNN$_C$      | 6.3M    | 18.4  | 55.8| LSTM         | 9.1M    | 29.7 | 93.2 |
| CNN$_C$+RHN  | 11.2M   | 29.5  | 95.2| LSTM         | 11.2M   | 29.3 | 93.2 |

Table 1. Results on MS COCO, where B@$n$ are short for BLEU-$n$. C is short for CIDEr. All values are reported as percentage (Bold numbers are the best results). CNN$_C$ contains five temporal convolutional layers, the kernel size of the first two convolutional layers is 5, and the rest kernel size of convolutional layers is 3.

As seen in Table 1, the parameter size of the 3-layer LSTM (LSTM$_3$) is close to that of the CNN$_C$+RNN. Adding the 2nd LSTM layer (LSTM$_2$) improves the performance of LSTM, but it is still lower than CNN$_C$+RNN. Meanwhile, LSTM$_3$ does not show improvements as the model experiences overfitting. This issue is even worse on Flickr30K which has relatively small number of training data. Note that CNN$_C$ (without RNNs) achieves lower performance than CNN$_C$+RNN. We find that those predicted captions of CNN$_C$ (without RNNs) only are short, but contain primary attributes, e.g., CNN$_C$ model generates: “a person on a wave”, while CNN$_C$+RNN provides: “a young man surfing a wave”. This finding shows that the temporal recurrence of RNNs is still crucial for modeling the short-term contextual information across words in the sentence.

We further compare language CNNs with different input words and with max-pooling operations, where those language CNNs are combined with RHN instead of RNN. Table 2 shows that larger context windows achieve better performance. This is likely because CNN$_C$ with larger window size can better utilize contextual information and learn better word embedding representation. In addition, the performance of CNN$_C$+RHN is inferior to CNN$_C$+RHN, which experimentally supports our opinion that max-pooling operations lose information about the local order of words.

Table 2. Results of different history information encoding approaches on MS COCO. CNN$_C$$_{N_words}$ takes $N$ previous words as inputs, where we set $N$ to 2, 4, and 8. Avg$_{history}$ computes an average over history word embeddings. CNN$_C$$_{N_words}$ replaces the 2nd and 4th convolutional layers in CNN$_C$ with the max-pooling layer.

| Approach     | B@4   | C   | Approach     | B@4   | C   |
|--------------|-------|-----|--------------|-------|-----|
| CNN$_C$$_{4}$ | 30.6  | 98.9| CNN$_C$$_{4}$ | 30.0  | 95.9|
| CNN$_C$$_{8}$ | 28.9  | 91.9| CNN$_C$$_{4}$ | 29.5  | 95.8|
| CNN$_C$$_{16}$| 29.7  | 93.8| CNN$_C$$_{4}$ | 29.2  | 93.8|

Table 3. Performance comparison on MS COCO, where M is short for METEOR, and S is short for SPICE.

| Approach     | B@1  | B@2  | B@3  | B@4  | M   | C   | S   |
|--------------|------|------|------|------|-----|-----|-----|
| Simple RNN   | 70.1 | 52.1 | 37.6 | 27.0 | 23.2| 87.0| 16.0|
| CNN$_C$+RHN | 72.2 | 55.0 | 40.7 | 29.5 | 24.5| 95.2| 17.6|
| RHN          | 70.5 | 52.7 | 37.8 | 27.0 | 24.0| 90.6| 17.2|
| CNN$_C$+RHN | 72.3 | 55.3 | 41.3 | 30.6 | 25.2| 98.9| 18.3|
| LSTM         | 70.8 | 53.6 | 39.5 | 29.2 | 24.5| 92.6| 17.7|
| CNN$_C$+LSTM| 72.1 | 54.6 | 40.9 | 30.4 | 25.1| 99.1| 18.0|
| GRU          | 71.6 | 54.1 | 39.7 | 28.9 | 24.3| 93.3| 17.2|
| CNN$_C$+GRU | 72.6 | 55.4 | 41.1 | 30.3 | 24.6| 96.1| 17.6|

Table 4. Performance comparison on Flickr30K.

Among these models, CNN$_C$+RHN achieves the best performances in terms of B@$1$ and B@$2$, METEOR, and SPICE metrics. CNN$_C$+LSTM achieves the best performance in CIDEr metric (99.1), and CNN$_C$+GRU achieves the best performance in B@$1$ (1.2) metrics. Although the absolute gains across different B@$m$ metrics are similar, the percentage of the relative performance improvement is increasing from B@$1$ to B@$4$. It does show the advantage of our method in terms of better capturing long-term dependency. Note that the CNN$_C$+RHN model achieves better performance than simple RNN model and outperforms LSTM model. As mentioned in Section 3.3, LSTM networks model the word dependencies with multi-gates and the internal memory cell. However, our CNN$_C$+RHN without memory cell works better than LSTM model. We think the reason is that our language CNN takes all history words as input and explicitly model the long-term dependencies in history words, this could be regarded as an external “memory cell”. Thus, the CNN$_C$’s ability to model long-term de-
pendencies can be taken as enhancement of simple RNNs, which can solve the difficulty of learning long-term dependencies.

### 4.3.3 Results Using CNN\(_L\) on Flickr30K

We also evaluate the effectiveness of language CNN on the smaller dataset Flickr30K. The results in Table 4 clearly indicate the advantage of exploiting the language CNN to model the long-term dependencies in words for image captioning. Among all models, CNN\(_L\)+RHN achieves the best performances in B\(\@\)(1,2,3,4) metrics, and CNN\(_L\)+RNN achieves the best performances in METEOR, CIDEr, and SPICE metrics.

As for the low results (without CNN\(_L\)) on Flickr30k, we think that it is due to lack of enough training data to avoid overfitting. In contrast, our CNN\(_L\) can help learn better word embedding and better representation of history words for word prediction, and it is much easier to be trained compared with LSTM due to its simplicity and efficiency. Note that the performance of LSTM and CNN\(_L\)+LSTM models are lower than RHN/GRU and CNN\(_L\)+RHN/GRU. This illustrates that the LSTM networks are easily overfitting on this smaller dataset.

### 4.3.4 Comparison with State-of-the-art Methods

To empirically verify the merit of our models, we compare our methods with other state-of-the-art approaches.

**Performance on MS COCO.** The right-hand side of Table 4 shows the results of different models on MS COCO dataset. CNN\(_L\)-based models perform better than most image captioning models. The only two methods with better performance (for some metrics) than ours are Attributes-CNN+RNN [50] and Google NICv2 [47]. However, Wu et al. [50] employ an attribute prediction layer, which requires determining an extra attribute vocabulary. While we generate the image descriptions only based on the image features. Google NICv2 [47] is based on Google NIC [46], the results of Google NICv2 are achieved by model ensembling. All our models are based on VGG-16 for a fair comparison with [6, 7, 15, 35, 50, 51]. Indeed, better image CNN (e.g. Resnet) leads to higher performance\(^2\). Despite all this, the CIDEr score of our CNN\(_L\)+LSTM model can still achieve 99.1, which is comparable to their best performance even with a single VGG-16 model.

**Performance on Flickr30K.** The results on Flickr30K are reported on the left-hand side of Table 4. Interestingly, CNN\(_L\)+RHN performs the best on this smaller dataset and even outperforms the Attributes-CNN+RNN [50]. Obviously, there is a significant performance gap between CNN\(_L\)+RNN/RHN/GRU and RNN/RHN/GRU/LSTM models. This demonstrates the effectiveness of our language CNN on the one hand, and also shows that our CNN\(_L\)+RNN/RHN/GRU models are more robust and easier to train than LSTM networks when less training data is available.

### 4.4. Qualitative Results

Figure 3 shows some examples generated by our models. It is easy to see that all of these caption generation models can generate somewhat relevant sentences, while...
the CNNL-based models can predict more high-level words by jointly exploiting history words and image representations. Take the last image as an example, compared with the sentences generated by RNN/LSTM/GRU model, “a cat is looking at a dog in front of a window” generated by CNNL+RNN is more precise to describe their relationship in the image.

Besides, our CNNL-based models can generate more descriptive sentences. For instance, with the detected object “cat” in the first image, the generated sentence “a black and white cat looking at itself in a mirror” by CNNL+RHN depicts the image content more comprehensively. The results demonstrate that our model with language CNN can generate more humane-like sentences by modeling the hierarchical structure and long-term information of words.

Figure 4 shows some failure descriptions for our CNNL-based models. Although most of the generated captions are complete sentences. However, the biggest problem is that those predicted visual attributes are wrong. For example, “bear” in the first image is detected as “bird”, and “brown” in the second image is detected as “black and white”. This will decrease the precision-based evaluation score (e.g., B@n). We can improve our model by further taking high-level attributes into account.

5. Conclusion

In this work, we present an image captioning model with language CNN to explore both hierarchical and temporal information in sequence for image caption generation. Experiments conducted on MS COCO and Flickr30K image captioning datasets validate our proposal and analysis. Performance improvements are clearly observed when compared with other image captioning methods. Future research directions will go towards integrating extra attributes learning into image captioning, and how to apply a single language CNN for image caption generation is worth trying.

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