Image Captioning as Neural Machine Translation Task in SOCKEYE

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Abstract

Image captioning is an interdisciplinary research problem that stands between computer vision and natural language processing. The task is to generate a textual description of the content of an image. The typical model used for image captioning is an encoder-decoder deep network, where the encoder captures the essence of an image while the decoder is responsible for generating a sentence describing the image. Attention mechanisms can be used to automatically focus the decoder on parts of the image which are relevant to predict the next word. In this paper, we explore different decoders and attentional models popular in neural machine translation, namely attentional recurrent neural networks, self-attentional transformers, and fully-convolutional networks, which represent the current state of the art of neural machine translation. The image captioning module is available as part of SOCKEYE [11] at https://github.com/awslabs/sockeye which tutorial can be found at https://awslabs.github.io/sockeye/image_captioning.html.

1 Introduction

Image captioning is a relatively recent interdisciplinary research problem that stands between computer vision and natural language processing. The recent advances of both fields enables us to train models with good performance in practical applications. We witnessed the huge wave of convolutional networks which revolutionized computer vision given their impressive results on image understanding using large annotated datasets [23]. On the other hand, neural language models (e.g., sequence-to-sequence models for machine translation [24]) changed the way that natural language processing is done.

The task of image captioning is to generate a textual description of the content of an image. Image captioning has multiple real-world applications: it can aid visually impaired users to obtain visual information and potentially interact by asking questions, it can be a way to interact with devices, it can be used to perform visual search using captions since text search is very optimized, among many others.

Image captioning requires a deep understanding of the content of the image that goes beyond object recognition and detection. It is not only necessary to recognize most of the objects in the image, but also characterize their interaction, attach adjectives and compose a sentence that makes sense. One possibility is to detect all the objects in an image, and use that to constrain the generation of the description [19][13]. However, this requires to annotate the location of all the objects that appears in the vocabulary as well as associate them to the corresponding location in the sentence. This is clearly not scalable and requires a lot of annotation labor.

More recently, solutions that use only image-text pairs are preferred to avoid overcome to the aforementioned problem. In this scenario, the model has to learn the correspondences between part of
the image and object label during training along with the grammar necessary to construct sentences. To achieve this goal, previous work \cite{29, 31, 17} proposed to learn models that are able to focus on the parts of the image that are responsible for a certain word in a description, i.e., attentional models.

A typical model used for image captioning shares many similarities with Neural Machine Translation (NMT) models: an encoder-decoder deep network, where the encoder captures the essence of an image while the decoder is responsible to generate the sentence. For the encoder, deep convolutional networks trained for object recognition can be used as feature extractor. The decoder can be a Recurrent Neural Network (RNN), that takes as input the image features and the previous word, and predicts the next word. In practice, it has been observed that a single, fixed context for each word has some limitations \cite{17}, because different parts of the image are related to different words. Therefore, attentional layers are adopted to relate different parts of the image to the respective words.

In this paper, we are exploring different decoder and attentional models for image captioning. Specifically, we decode the caption by using RNNs \cite{4, 18}, transformers \cite{26} and CNNs \cite{9} combined to different kinds of attentional mechanisms.

Moreover, we integrate image captioning into SOCKEYE \cite{11}, an open-source sequence-to-sequence toolkit for NMT. This is motivated by the fact that both NMT models and image captioning models follow the encoder-decoder structure. Therefore, image captioning models can benefit from the features implemented in SOCKEYE: scalable training and inference for the most prominent encoder-decoder architectures in machine translation. As outcome, we make our image-to-text module accessible to everyone. Given the generality of the framework, it can be used to any image to sentence task, such as question generation in visual question answering tasks \cite{25}.

2 Related Works

Following the characterization of the state of the art made in \cite{17}, the literature is split in template-based approaches and neural-based approaches. The first category includes the earlier attempts to solve image captioning, which consists of methods that fill slots in sentences based on detected objects, visual attributes and scenes, such as \cite{8, 15, 19}.

More recently, neural-based approaches are taking over, because of the recent successes in image recognition and NMT. These methods are inspired by the sequence-to-sequence encoder-decoder models that are dominant in machine translation nowadays \cite{24}. In NMT, the encoder takes as input a sequence in a source language and passes it to the decoder that outputs another sequence in a target language. Image captioning can be seen as a image to text translation problem \cite{13}, where the source is not a sequence but an image.

Most works \cite{28, 5, 14} encode the image with the last fully-connected layer of a deep convolutional network, then the decoder can be either a feed-forward network \cite{14} or an RNN \cite{28, 13, 17}. However, a big problem of this strategy is that the spatial information is completely lost. The works in \cite{13, 1} deal with this by detecting objects in the image.

Attentional models \cite{29, 17, 18} have been introduced to solve this problem. The idea is to obtain an encoding of the image which is spatial variant, and train a model to decide which part of the image corresponds to each word of the target caption. \cite{17} encodes images using the convolutional map of a ResNet, then projects it to a lower dimensionality. The attentional model is a feed-forward network that produces a value for each spatial component of the convolutional map (saliency map). This information is used as context combined with the output of the decoder that is responsible of generating the next word. \cite{17} proposes also a visual sentinel to deal with words that have no visual meaning (e.g., “a”, “the”, ...). The work in \cite{1} extends the idea of attention on object detections instead of pixels in the convolutional map. This work propose to extract features for each detected object which are then used by the attention module.

3 Method

The goal of image captioning is to model the probability distribution \( p(Y | X; \theta) \), where \( X \) is a source image, \( Y = (y_1, ..., y_m) \) is a target description, and \( \theta \) is a parametrization of the chosen models. Each \( y_i \) is an integer id given by target vocabulary mapping, \( V_{trg} \), built from the training data tokens.
and represented as one-hot vectors $y_t \in \{0, 1\}^{|V_{trg}|}$. These are embedded into $e$-dimensional vector representations, $E_T y_t$, using a learned embedding matrix $E_T \in \mathbb{R}^{e \times |V_{trg}|}$.

The probability can be factorized as follows:

$$p(Y|I; \theta) = \prod_{t=1}^{m} p(y_t|Y_{1:t-1}, X; \theta).$$  

(1)

Learning reduces to finding the set of parameters that maximize the log likelihood:

$$\theta^* = \arg \max_{\theta} \sum_{t=1}^{m} \log(p(y_t|Y_{1:t-1}, X; \theta)).$$  

(2)

$p(y_t|Y_{1:t-1}, X; \theta)$ is parameterized via a softmax output layer over some decoder representation $\bar{h}_t$:

$$p(y_t|Y_{1:t-1}, X; \theta) = \text{softmax}(W_y \bar{h}_t + b_o),$$  

(3)

where $W_o$ scales to the dimension of the target vocabulary $V_{trg}$. Even though it is not explicit in the equation, the decoder representation $\bar{h}_t$ depends on the image $X$. Given the high dimensional nature of the image, it is necessary to encode it into a more meaningful and lower dimensional representation. In the next sections, we describe how the image is encoded and then how it is decoded to generate captions.

The maximization problem of Eq. 2 is solved by optimizing the cross-entropy loss given Eq. 3. This is straightforward to do since it is differentiable, however the cross-entropy loss might not correlate well with human judgment of machine-generated captions. Other image captioning metrics such as CIDEr [27] have been showed to better represent human perception. Since they are not differentiable, reinforcement learning techniques can be used to solve the optimization problem (e.g., self-critical sequence training [22]). Although these technique have been showed to work well in practice, we postpone their integration with SOCKEYE to a future work.

### 3.1 Image Encoder

The purpose of the image encoder is to project the image into a semantic feature space that is lower dimensionality than the original, full-resolution image. For this task, ConvNets that are pre-trained for image recognition are used. Since they are trained to recognize objects in images, it is very likely that they are activated in correspondence to object words in the context of captioning.

In particular, we follow the work in [17] that uses a ResNet-152 [10] pre-trained on ImageNet. We selected the last convolutional layer (namely, stage4_unit3_conv3), because it is the last layer of the network that retains the spatial information before the fully-connected layers. This is important, since the decoder needs to be provided with the ability to correlate words to different parts of the image via attention, as we will see in the next section.

In our experiments, we also used features coming from object detections as in [11]. In that case we used ResNet-101 pre-trained on the Visual Genome dataset. Each detected object is then represented by a mean-pooled convolutional feature from its region.

The resulting feature map is a matrix $F = [f_1; \ldots; f_K]$, where $K$ correspond to the spatial locations in the feature map or detections, and each vector $f_k$ is a $d$-dimensional feature (2048 here). Moreover, it is useful to have a global image description $f^g$ by average pooling such descriptors over the dimension $k$. Since the feature dimensionality $d$ of the convolutional layer is often high, the ResNet features are projected to a lower dimension $d' << d$ using a fully-connected layer (512 in this work):

$$v_k = ReLU(W_f f_k), \quad v^g = ReLU \left( W_g \frac{1}{K} \sum_{k=1}^{K} f_k \right),$$  

(4)

composing the matrix $V = [v_1; \ldots; v_K; v^g]$, which also contains the global image descriptor.

### 3.2 Caption Decoders

The decoder can be decomposed into 2 modules: 1) a temporal model that is able to encode the temporal information of the sequence of words, and 2) an attentional model that filters and selects the
information coming from the encoder which is used as context to make predictions on the next word of the sequence.

In this work, we explore different possibilities for the temporal model as well as for the attentional model. In particular, we exploit the similarity that between NMT models and the image captioning ones, by testing different state-of-the-art decoders for NMT, namely: attentional recurrent neural networks, self-attentional transformers, and fully-convolutional networks. We will briefly describe those models in the following. Please refer to [11] for their description in the NMT domain.

### Attentional RNN [4,18].

The decoder is defined as:

$$h_t = f_{dec}([E_T y_{t-1}; \tilde{h}_{t-1}], h_{t-1}),$$  

where $f_{dec}$ is a (multi-layer) RNN, $h_{t-1}$ is the previous hidden representation of the RNN, and $\tilde{h}_{t-1}$ is the image-dependent attentional vector.

Attention is computed by considering the input image representation as well as the current word hidden representation as follows:

$$\text{score}(v_k, h_t) = w_k^T \tanh(W_v v_k + W_h h_t),$$

$$\alpha_{kt} = \text{softmax}(\text{score}(v_k, h_t)).$$

The context vector is built by the sum of hidden vectors weighted by the attentional score: $c_t = \sum_{k=1}^{K} \alpha_{kt} h_t$. This kind of attention is often called Multi-Layer Perceptron (MLP) attention, given that the score is computed with MLP-style model. Another common type of attentional model can be the dot product between $v_k$ and $h_t$, or the multi-head attention used by the transformer (see below).

Attention and decoder are combined to build the image-dependent attentional vector as:

$$\tilde{h}_t = \tanh(W_h^2 [h_t; c_t]),$$

which is then used to predict the next word as in Eq. 3.

In Eq. 5, we can optionally concatenate the global image descriptor to the input of the RNN: $[E_T y_{t-1}; \tilde{h}_{t-1}; v^g]$. This is similar to [17], with the only difference that their model does not use $\tilde{h}_{t-1}$ as input of the RNN.

### Self-attentional Transformer [26].

The transformer model uses attention to replace recurrent dependencies, making the representation at a certain time step independent from the other time steps. This allows for parallelization of the computation for all time steps in the decoder at training time.

Since the recurrent dependencies are removed, time needs to be explicitly encoded as positional information in a sequence as: $E_T x_i + e_{pos,i}$, where $e_{pos,i}$ is the positional embedding at position $i$, which can be learned or fixed [26].

The transformer has a self-attention mechanism which is a generalization of [18] and is defined as:

$$C_u = \text{softmax} \left( \frac{Q W_u^Q (K W_u^K)^\top}{\sqrt{d_u}} \right) L W_u^L,$$

where $C_u$ is the context matrix produced by a head, $Q \in \mathbb{R}^{n \times d}$ is a query matrix, $K \in \mathbb{R}^{n \times d}$ is a key matrix, $L \in \mathbb{R}^{n \times d}$ is a value matrix, the $W_u$’s are projections, $n$ is the number of hidden states and $d$ denotes the number of hidden units. The final context matrix is given by concatenating the heads, followed by a linear transformation: $C = [C_1; \ldots; C_h] W_O$.

The second subnetwork is a feed-forward network with ReLU activation defined as

$$FFN(x) = \text{ReLU}(x W_1 + b_1) W_2 + b_2.$$  

Each sublayer, self-attention and feed-forward network, is followed by a post-processing stack of dropout and layer normalization [3].

The sequence of operations of a single decoder block is:

Self-attention $\rightarrow$ Post-process $\rightarrow$ Encoder attention $\rightarrow$ Post-process $\rightarrow$ Feed-forward $\rightarrow$ Post-process

Multiple blocks are stacked to form the full decoder network and the representation of the last block is fed into the output layer. For the decoder, self-attention is restricted to $Q = K = L = H$ in Eq. 9, where $H$ is the matrix of hidden states $h_t$ (input embeddings in the first layer). For the encoder, we have $Q = H$ and $K = L = V$, where $V$ contains the image encoder states as described in Sec. 3.1.
Fully-convolutional Network [9]. As for the transformer network there are no recurrent dependencies, therefore the positional embedding is used. Then, a sequence of stacked convolutional layers [2] is applied to the embeddings, i.e., the inputs of the decoder.

The output of each convolutional layer is fed to the attentional mechanism described for the transformer with a single attention head. In particular, \( Q = H_c \) and \( K = L = V \), where \( H_c \) is the output of the convolution and \( V \) is the image encoder state. The decoder hidden state is a residual combination with the context vector, which is then fed to the output layer.

4 Experiments

The experiments were carried out on two popular datasets for image captioning: Flickr30k [21, 32] and MS-COCO [16]. Flickr30k contains 31,783 images, each of which has 5 captions on average. We use the splits provided in [12] which contains 1,000 images for validation and 1,000 images for testing.

MS-COCO is a bigger dataset containing 82,783, 40, 504 and 40, 775 images for training, validation and test, respectively. 5 captions on average are provided for each image. We use the splits provided in [12] which contains 5,000 images for validation and 5,000 images for testing, taken from the original validation set. The remainder of the validation set (30,504 images) is merged to the training set, producing a set of 113,287 images.

The results are reported in terms of standard metrics for machine translation and image captioning such as BLEU at different N-grams (B@N) [20], METEOR [6] and CIDEr [27].

Implementation Details. The models and experiments are implemented in MXNET in the Sockeye framework. The ResNet is used as feature extractor, therefore not fine-tuned, in our experiments. Training is performed using the Adam optimizer with batch size of 64, initial learning rates of 0.0005 and 0.0003 and absolute gradient clipping of 1.0. The learning rate is reduced by a factor 0.9 when the validation perplexity does not change for 3 iterations. The RNN is an LSTM with 512 units, the same number as for the transformers. During inference, we perform beam search with size of 3 and 5. For Flickr30k only, we do not consider words in the vocabulary with frequency less than 5.

4.1 Variants of the Proposed Model

In this section, we evaluate the variants of the proposed model using the MS-COCO dataset. First of all, we want to establish which decoder architecture is the best for image captioning. We did a comparative study among the three architectures presented in Sec. 3.2 namely Attentional Recurrent Neural Networks (ARNN), Self-Attentional Transformers (SAT), and Fully-Convolutional Networks (FCN). The results are reported in Table 1. It is clear that FCN gives the worst results out of the three models. On the other hand, SAT compares favorably with ARNN with a small gap between them, thus there is not clear winner.

Table 2 reports the results for the different kind of attentional models that can be used in combination with ARNN as described in Sec. 3.2. In particular, we tested the following variants:

1. **Without**: attention is removed, instead we use the global image descriptor as context vector.
2. **Dot**: dot product between the image representation and the hidden representation of the RNN.
3. **Multihead-8**: multihead attention with 8 heads [26].

We use the evaluation code at [https://github.com/tylin/coco-caption](https://github.com/tylin/coco-caption).
Table 2: Which attentional model gives the best results? Model: ARNN. Dataset: MS-COCO.

| Method      | B@1  | B@2  | B@3  | B@4  | METEOR | CIDEr |
|-------------|------|------|------|------|--------|-------|
| Without     | 0.666| 0.489| 0.357| 0.265| 0.242  | 0.861 |
| Dot         | 0.497| 0.303| 0.188| 0.122| 0.148  | 0.306 |
| Multihead-8 | 0.671| 0.496| 0.365| 0.273| 0.244  | 0.882 |
| MLP         | 0.672| 0.496| 0.364| 0.271| 0.246  | 0.882 |

Table 3: Incremental addition of features for ARNN and SAT. Dataset: MS-COCO.

| Method                     | ARNN          | SAT            |
|----------------------------|---------------|----------------|
|                            | B@1  | B@2  | B@3  | B@4  | METEOR | CIDEr | B@1  | B@2  | B@3  | B@4  | METEOR | CIDEr |
| Original                   | 0.672| 0.496| 0.364| 0.271| 0.246  | 0.882 | 0.677| 0.502| 0.371| 0.278| 0.243  | 0.882 |
| + beam size = 3            | 0.683| 0.510| 0.378| 0.283| 0.248  | 0.919 | 0.687| 0.513| 0.379| 0.283| 0.248  | 0.922 |
| + concat image global      | 0.688| 0.514| 0.380| 0.283| 0.250  | 0.924 | -   | -   | -   | -   | -      | -     |
| + weight norm              | 0.692| 0.519| 0.385| 0.287| 0.250  | 0.934 | 0.687| 0.513| 0.380| 0.282| 0.248  | 0.923 |

4. MLP: multi-layer perceptron attention.

One can notice that dot attention gives poor results, and this might due to the fact that the image representations are not properly normalized before being fed to the output layer. In fact, Multihead-8 and MLP are the best attentional models. As expected, attention is required for image captioning, although the gap with respect to the MLP attention is narrow.

Now that we discovered that 1) both ARNN and SAT give good results and 2) we need attention, we can explore other extensions of these models. Table 3 shows that both ARNN and SAT improve by:

1. Reducing the beam size from 5 to 3 (second row),
2. Concatenating the image global descriptor to the word embedding (third row),
3. Adding weight normalization (last row).

We run many other experiments that were not significantly changing the results. We found that in ARNN replacing LSTM units with GRU units or increasing the number of hidden units from 512 to 1024 give comparable results (small difference of 0.002 B@4). Using a deep, 8-layer ARNN with residual connections is decreasing the B@4 of 0.007 points. A similar conclusion can be drawn by comparing a deep, 2-layer transformer with its shallow counterpart (difference of 0.006 B@4). Finally, we tried to finetune the image encoder, however this degraded the performance. As discussed in [17], finetuning should be done carefully by activating it only in the last phase of training when the validation error stabilizes. It is worth noting that we did not investigate and dive deep on this option, so we leave it as future work.

4.2 Comparison with the State of the Art

In this section, we compare our best model with the current state of the art. As showed by our analysis in the previous section, our best model is an ARNN with 512 hidden units, MLP attention, concatenation of the image global descriptor, weight normalization and beam size = 3 for inference. We also trained our best model on top of object detection features as in [1].

Table 4 reports the current state of the art for image captioning along with our best method from the previous section (Our Best) and when using object detection features as in [1] (Our best w/ Detector in Table 4). It is clear that when using object detection features, we obtain a significant improvement of about > 3% on all metrics and datasets. This model is better of all the paper excluding [1] (Up-down in Table 4) which still is the best especially because it optimizes CIDEr with reinforcement learning.

We show some qualitative results of the two datasets in Figure 1. The figures show the original image along with the predicted caption in white background and the set of ground truth descriptions provided by the annotators in green background.
Table 4: Comparison with the state of the art. Datasets: Flickr30k and MS-COCO.

| Method              | Flickr30k |           |          |           |          | MS-COCO  |           |          |           |          |
|---------------------|-----------|-----------|----------|----------|----------|----------|-----------|----------|----------|----------|
|                     | B@1       | B@2       | B@3      | B@4      | METEOR   | CIDEr    | B@1       | B@2       | B@3      | B@4      | METEOR   | CIDEr |
| DeepVS [13]         | 0.573     | 0.369     | 0.240    | 0.157    | 0.153    | 0.247    | 0.625     | 0.450     | 0.321    | 0.230    | 0.195    | 0.660 |
| LRCN [7]            | 0.587     | 0.391     | 0.251    | 0.165    | -        | -        | 0.669     | 0.489     | 0.350    | 0.249    | -        | -     |
| Hard-attention [29] | 0.669     | 0.439     | 0.296    | 0.199    | 0.185    | -        | 0.718     | 0.504     | 0.357    | 0.250    | 0.230    | -     |
| ATT-FCN [31]        | 0.647     | 0.460     | 0.324    | 0.230    | 0.189    | -        | 0.709     | 0.537     | 0.402    | 0.304    | 0.243    | -     |
| MSM [30]            | -         | -         | -        | -        | -        | -        | 0.730     | 0.565     | 0.429    | 0.325    | 0.251    | 0.986 |
| Spatial [17]        | 0.644     | 0.462     | 0.327    | 0.231    | 0.202    | 0.493    | 0.734     | 0.566     | 0.418    | 0.304    | 0.257    | 1.029 |
| Adaptive [17]       | 0.677     | 0.494     | 0.354    | 0.251    | 0.204    | 0.531    | 0.742     | 0.580     | 0.439    | 0.332    | 0.266    | 1.085 |
| Up-down [1]         | -         | -         | -        | -        | -        | -        | 0.766     | -         | -        | -        | 0.340    | 0.265  |
| Up-down CIDEr [1]   | -         | -         | -        | -        | -        | -        | 0.798     | -         | -        | -        | 0.363    | 0.277 |
| Our Best            | 0.625     | 0.437     | 0.300    | 0.205    | 0.193    | 0.453    | 0.692     | 0.519     | 0.385    | 0.287    | 0.250    | 0.934 |
| Our Best w/ Detector| **0.681** | **0.507** | **0.374**| **0.274**| **0.218**| **0.594**| **0.739**  | **0.577** | **0.443**| **0.339**| **0.276**| **1.098**|

5 Conclusions

In this work, we explored different decoders and attentional models for image captioning, and showed that the attentional RNN is slightly better than the self-attention transformer. We were able to obtaining competitive results when comparing with the state of the art. The next step is to close the gap between our method and [1] by implementing reinforcement learning to optimize non-differentiable image captioning metrics.

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Figure 1: Visualizations for MS-COCO. Predictions and ground truth sentences are in black and green text, respectively. Better visualized zoomed on a computer monitor.

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