Image Caption Generation with CNN-RNN, Soft Attention and Top-Down Bottom-Up Attention

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Abstract

One of the most important problems in computer vision is describing images. Although image captions can be ambiguous, given the possibilities of the descriptions is large - there has been a fair amount of research and progress on the this topic so far. Generating captions involves two important aspects, i.e., a representation of the images and a representation of the caption. Images are represented best with Convolutional Neural Networks and improvements thereof and captions are best generated by some form of Recurrent Neural Networks. They can be naively combined which is first model we study, or combined in a more holistic manner using attention which is the other two models we study. Here we explore three popular network architectures, Show and Tell[13] and Show, Attend and Tell[14] and very recent work Top-Down and Bottom-Up Attention[2], all three have been state-of-the-art when first released. These models build on top of each other adding better representational capacities and improving the results and power of the models but also increase in complexity and become harder to train. All the models were able to describe the images with very high precision.

1 Goal

Image captioning is the process of generating a text description of an image. Its important but a challenging task; few applications of image captioning include virtual assistants, support for the disabled, different indexing tools and indexing of images. Our goal in this paper is to use different architectures to obtain incrementally better representations of both the image and caption generation subsystem which generates the final captions.

2 Introduction

For a human, a quick glance is sufficient for it to describe an image or a scene in a detailed manner. Historically, this has been difficult to achieve with machines. Previously, some pioneering work in visual recognition has been done but limited to fixed visual categories. Although impressive, these models were limited to hard-coded visual concepts and other sentence templates, which is vastly limiting when we compare it to a human eye. However, things have started changing over time.

In recent years the amount of data available has increased in leaps and bounds. As a result, the approach towards handling the problem has changed drastically. Along with increasing data we also have the rise of Deep Neural Networks which facilitates the change in approach. These new techniques have largely been based on recurrent neural networks(RNNs) powered by Long Short Term Memory(LSTM) which takes care of the vanishing or exploding gradient problems. Owing to the ability of LSTMs to memorize long term dependencies through a memory cell, it becomes a go-to network for language-vision tasks like image captioning, visual answering, situation recognition, visual dialog etc[3]. Unlike Convolutional Neural Networks(CNN) LSTMs require sequential processing and storage due to back-propagation during training time. So, CNNs and LSTMs were not really matched up for vision-language tasks until very recently.

With the recent success of CNNs with different sequence to sequence, the image captioning approach has changed. We try the same new approach here, starting with the original paper "Show and Tell". Just like machine translation architecture where we use an RNN, here we use a CNN

as an encoder where given an image it produces a rich fixed-length vector representation of the image. This is where the image is "encoded". Now we feed the representation from the last hidden layer of the CNN to the "decoder" RNN which will generate a caption of the image.

Here our aim is to try out different architectures of CNNs in the encoder layer to see how well those fixed-length representations generated from these various architectures determine the quality of the captions generated when trained on those representations. We implement an end to end system for this architecture. Starting from Show and tell we also implement the version with attention or Show Attend and Tell, and the Top down and Bottom Up Attention approach for Image captioning.

3 Background

As of late there have been strong experiments on image and video captioning owing to the change of methodology. Earlier systems of and-or-graphs were used, which required conversion to human interpretable natural language using rule based systems. These systems were brittle and heavily based on humans. The current approach is drastically different, for example Show and Tell [13] and others. Here a neural and a probabilistic framework is used with a powerful sequence model. These models have the capability of producing state of the art results by maximizing the probability of the input sequence given in an "end to end" fashion. The general approach involves encoding the input image into a fixed dimensional vector, which then is fed to the recurrent neural network (RNN) for it to "decode"

The usual method involves increasing the probability of the correct caption using the following formula:

$\theta = \arg\ max_\theta\ \Sigma_(I, S_)\ \log\ \mathrm{p(S|I;}\ \theta)$

[13] Here theta are the parameters, I is the image and S is the transcriptions.

Another approach that has been used in the recent past is CNNs with attention mechanism in both image captioning and VQA tasks. Attention captioning models either uses edge boxes [15] or spatial transformer networks [7] which are processed using an attention model which are paired using three bi-linear attention models. There are two particular kind of methods; namely top down and bottom up attention mechanism. The Bottom up approach involves using faster R-CNN [11]which identifies instances of objects with certain classes and bounds them with a rectangle. The top down approach on the other hand involves characterizing the first layer of the LSTM which produces captions as the top-down visual attention model and the second layer as the language model, Thus producing state of the art results. Although these are the models which have been implemented before, our goal here is to implement these models with a newer framework.

4 Approach

We work towards the implementation and evaluation of three at the time state-of-art networks. Each of these have built on the success of the previous one taking the best elements and incorporating new representational tools. Starting with Show and Tell, the caption generation subsystem is based on a vanilla recurrent architecture, which incorporates the recent advances in computer vision and machine translation. This model is built to maximize the probability of the target description sentence on a given training image per word assuming the previous predicted words were all equivalent to the target description (teacher forcing).[13] Next, we work towards implementation and evaluation of Show, Attend and Tell where a model is trained in a deterministic manner using standard backpropagation techniques.[14] Lastly, we work towards implementing and evaluation of an approach which combines the top-down and bottom-up attention mechanism - which allows attention to be calculated at the level of objects and other salient image regions at two levels, first, a bottom up approach to detect objects and next top down attention to attend to these variably sized objects and generation of captions. [2] Here we use one of the benchmark datasets; Flickr8k as they are comparatively smaller in size and are faster to train.

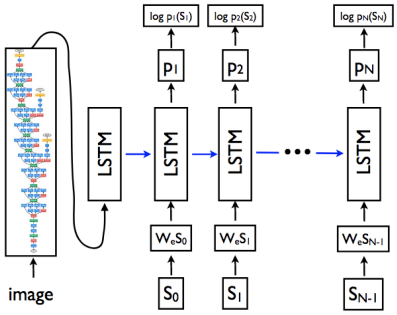


Figure 1: Diagram representing the architecture of Show and Tell.

4.1 Show and Tell Model

As we said with the recent success of language translation model, with end to end sequences, there has been implementation of CNN in the encoder part to obtain a representation of images. It uses the following formula.

$$\theta = \arg\, max_\theta\ \Sigma_{(}I, S_{)}\ \log\ \mathrm{p(S|I;}\ \theta)$$

[13] where θ are the parameters of the model, I are the images of the model and S are the transcriptions. Since it is obvious that the length of S is unbounded or varied we could use chain rule to obtain the joint probability.

$$\log\ \mathrm{p(S|I)} = \Sigma\ \log\ \mathrm{p(S\ of\ t\ given\ I,\ from\ S\ of\ 0\ to\ t\text{-}1)}$$

dependency on θ is dropped as it is more convenient. So at any given point during training time we have a pair as (S,I) and we implement gradient descent algorithm on it to reduce its loss. LSTM based sentence generation is used as it is better equipped to deal with vanishing and exploding gradient problems. The overall architecture of the model is better understood through this picture above; Figure 1. [13]

4.2 Show, Attend and Tell

When there are a large number of entities in a scene it becomes difficult for a simple model such as RNN to take into account the various interactions betweens these objects and come up with a exhaustive and complete description of the image - instead the simpler models tend to gloss over. Humans on the other hand tend to focus on parts of the image, paying attention and checking interactions between the important objects in the scene as we go on describing the image. A similar attention mechanism has been proposed to mimic human behavior[14]. This attention mechanism allows only a certain part of the features to be input into the RNN. At each step, the salient region of the image is determined and is fed into the RNN instead of using features from the whole image. The determination of which spatial region will be chosen depends on the previous words that have been generated by the RNN already. The recurrent network now only gets a focused view from the image and predicts the word relevant to that region. New generated words are coherent within the region but not in the description being generated if the prior words generated are not a parameter to the attention mechanism.

Mathematically, we are trying to replace the image x in LSTM model,

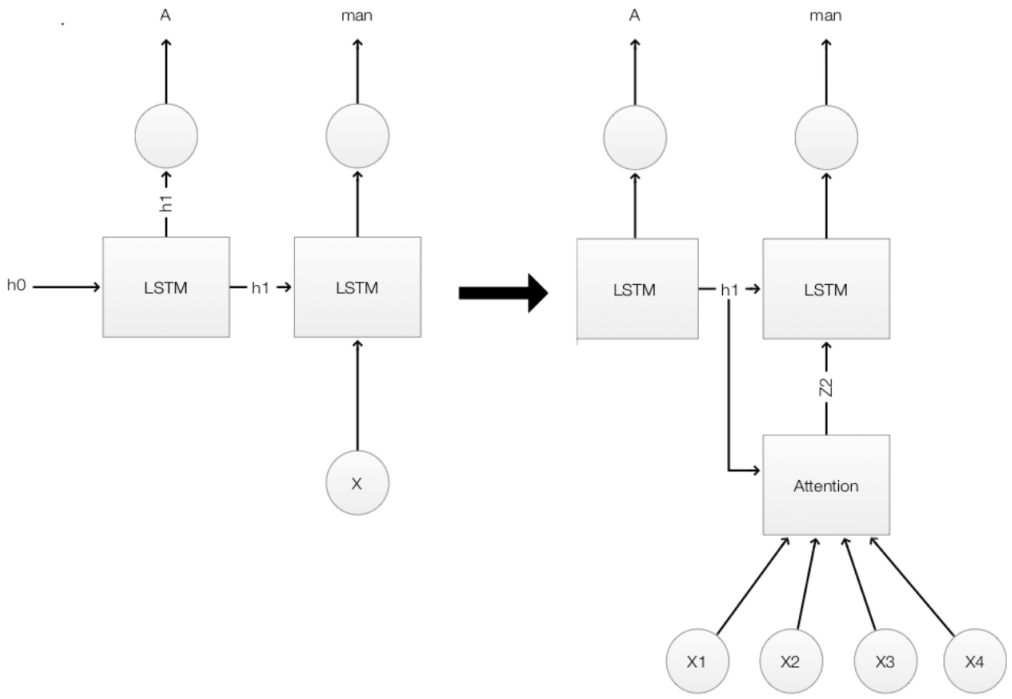
$$h_t = f(x, h_{t-1})$$

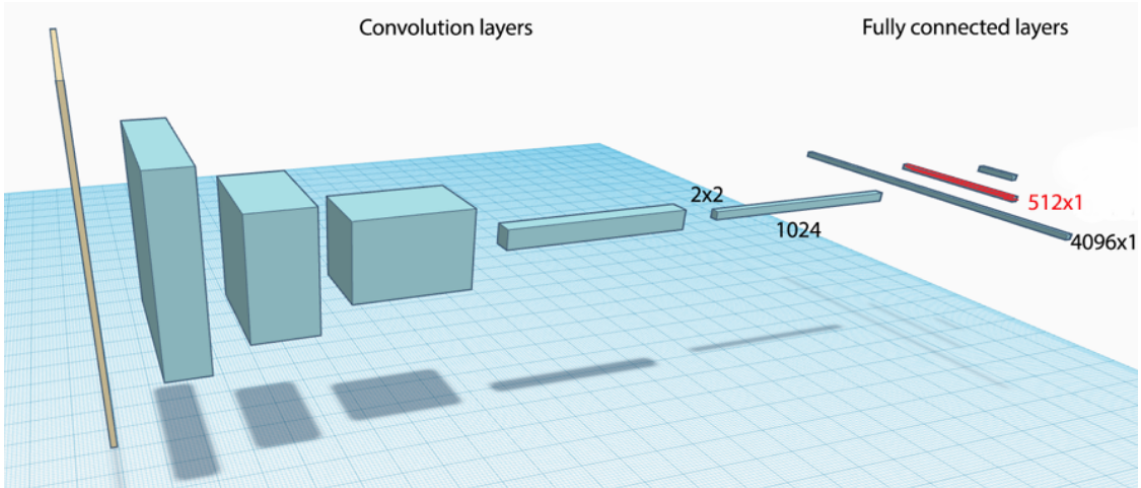
with an attention module attention:

$$h_t = f(attention(x, h_{t-1}), h_{t-1})$$

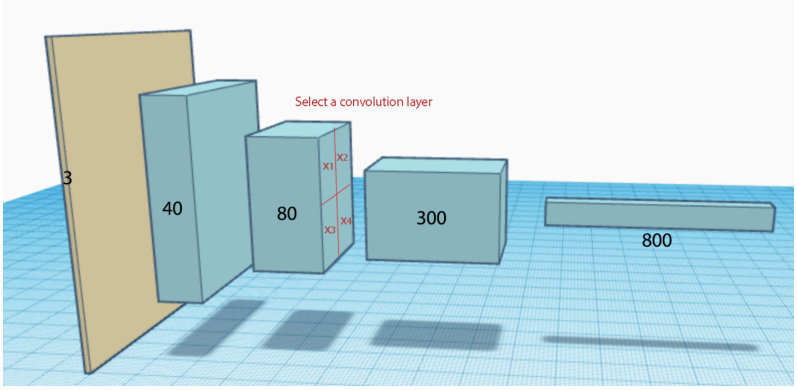
The attention module has 2 inputs:
1. A context
2. Image features in each localized areas.

For the context, we use the hidden state $h_t - 1$ from the previous time step. In a LSTM system, we process an image with a CNN and use one of the fully connected layer output as input features x to the LSTM.

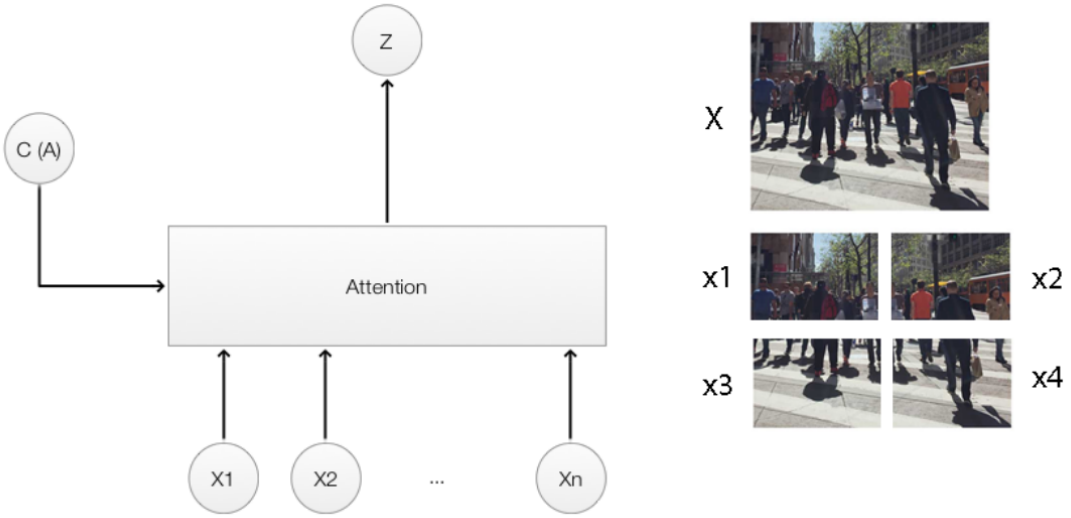




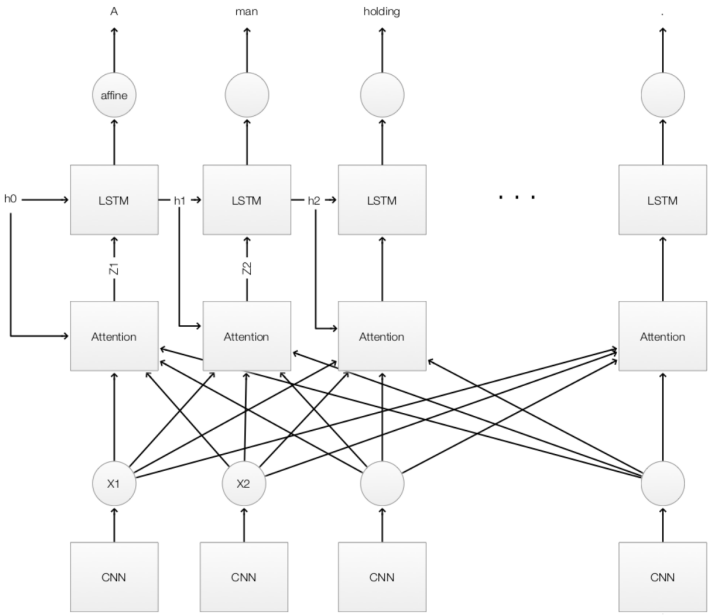
Nevertheless, this is not adequate for an attention model since spatial information has been lost. Instead, we use the feature maps of one of the convolution layer which spatial information is still preserved.



Here, the feature maps in the second convolution layers are divided into 4 which closely resemble the top right and left and the bottom right and left of the original pictures. We replace the LSTM input x with an attention module. The attention module takes the context $h_t - 1$ and 4 spatial regions $(x1, x2, x3, x4)$ from the CNN to compute the new image features used by the LSTM.

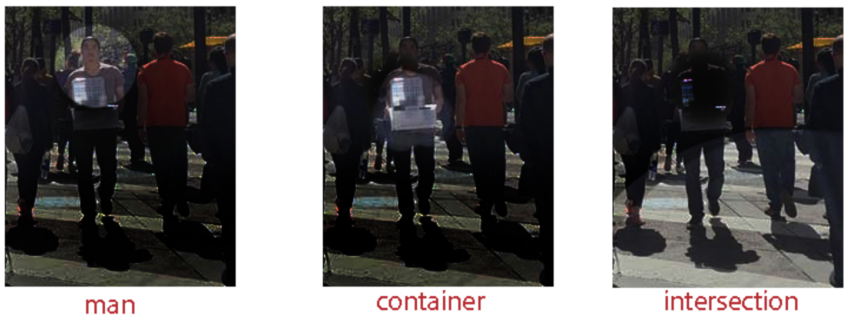


The following is the complete flow of the LSTM model using attentions.



4.2.1 Soft Attention

We implement attention with soft attention. In soft attention, instead of using the image x as an input to the LSTM, we input weighted image features accounted for attention. Before going into details, we can visualize the weighted features to illustrate the difference. Areas with higher attention are brighter in the picture.



This picture visualizes the weighted features to the LSTM and the word it predicted. Soft attention discredits irrelevant areas by multiplying the corresponding features map with a low weight. Accordingly, high attention area keeps the original value while low attention areas get closer to 0 (become dark in the visualization). With the context of "A man holding a couple plastic", the attention module creates a new feature map with all areas darkened except the plastic container area. With more focused information, the LSTM makes a better prediction (the word "container").

Let's show how to compute the weighted features for the LSTM. x_1,x_2,x_3 and x_4 each covers a sub-section of an image. To compute a score s_i to measure how much attention for x_i, we use (with the context $C = h_t - 1$):

$$s_i = \tanh(W_c C + W_x X_i) = \tanh(W_c h_{t-1} + W_x x_i)$$

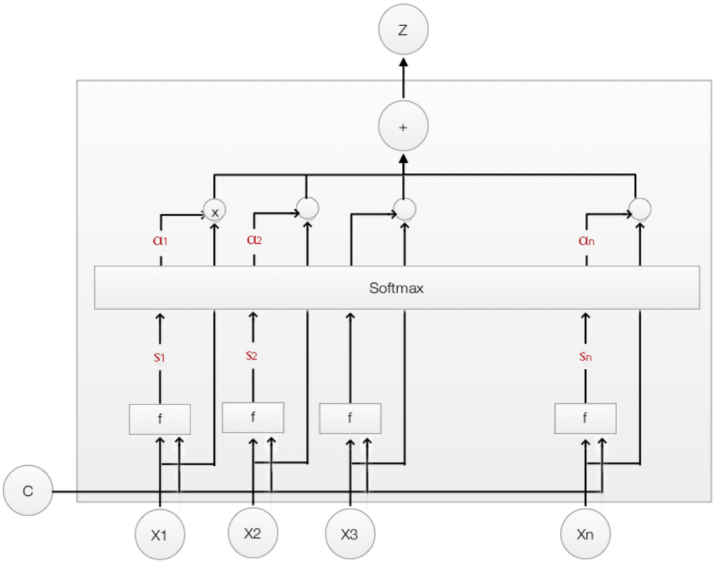
We pass s_i to a $softmax$ for normalization to compute the weight α_i.

$$\alpha_i = softmax(s_1, s_2, \ldots, s_i, \ldots)$$

With softmax, α_i adds up to 1, and we use it to compute a weighted average for x_1, x_2, x_3 and x_4.

$$Z = \sum_i \alpha_i x_i$$

Finally, we use Z to replace x as the LSTM input.



4.3 Top Down and Bottom up Attention

Given an image I, this captioning model takes as input a possibly variably-sized set of k image features generated by an R-CNN(Region-based Convolutional Neural Network), $V = v_1, ..., v_k$, $v_i \in R^D$, such that each image feature encodes a salient region of the image.
The spatial image features V can be variously defined as the output of the bottom-up attention model. We summarize the approach to implementing a bottom-up attention model in Section 4.3.1, and the architecture of the image captioning model in Section 4.3.2. Both of which come from the original work. [2]

4.3.1 Bottom-Up Attention

The spatial regions are defined in terms of bounding boxes and implement bottom-up attention using Faster R-CNN [11]. Faster R-CNN is an object detection model designed to identify instances of objects belonging to certain classes and localize them with bounding boxes.

Faster R-CNN detects objects in two stages. The first stage, described as a Region Proposal Network (RPN), predicts object proposals. Features are processed using a smaller CNN network. The network predicts a score for each proposal and realizes boxes of various scales. An intersection-over-union(IoU) is the accuracy of an object detection model. Using an IoU threshold the best proposals are used for input to the second stage. The second stage is comprised of extracting a feature map for each region. The final output of the model is a softmax distribution of class labels and bounding box refinements of every proposal.

In this work, Faster R-CNN is combined with ResNet [6]. The features for each image are calculated by taking the model output and using a process known as non-maximum supression(NMS). NMS essentially combines all of the detected regions that belong to the same object. All detected regions which surpass a confidence threshold are passed through a mean-pooled convolution. This process decides a feature pertains to a general region, which allows the model to focus on 'hard'

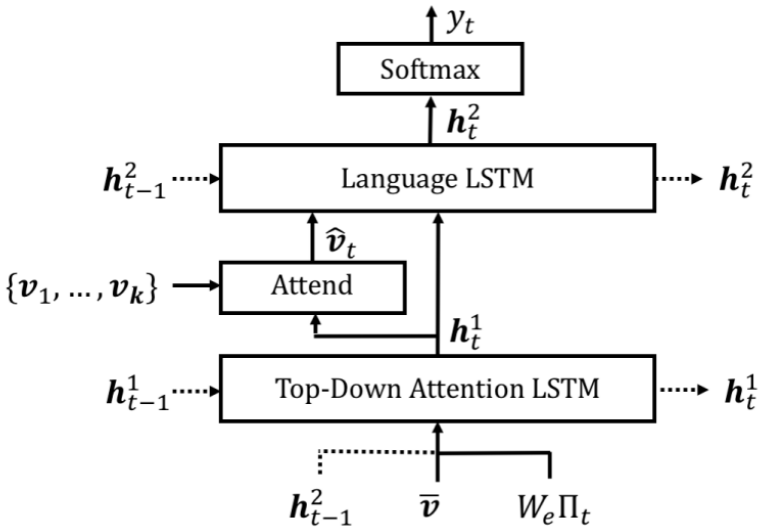
attention points. This reduces the overall number of features for a given region.

4.3.2 Captioning Model

Using the set of image features generated above the model processes futher using a top-down attention model. This model weights each feature for caption generation utilizing the caption fragment. This is in essence a two stage LSTM model. The two LSTMs work in conjuction to map which words in the caption pertain to which features of the image.
The LSTM model can be described as follows:

$$h_t = LSTM(x_t, h_t - 1)$$

x_t is the LSTM input vector and h_t is the LSTM output vector. Here is a diagram of the captioning model.



Top-Down Attention LSTM Here is the input vector described for the Attention LSTM.

$$\boldsymbol{x}_t^1 = [\boldsymbol{h}_{t-1}^2, \bar{\boldsymbol{v}}, W_e \Pi_t]$$

$$\bar{\boldsymbol{v}} = \frac{1}{k} \sum_i \boldsymbol{v}_i$$

$$W_e \in \mathbb{R}^{E \times |\Sigma|}$$

$h_t 2$ is the output of the language LSTM, v_i is the mean-pooled image feature, and W is a word embedding matrix Σ, and Π_t is one-hot encoding of the input word at timestep t.
The attention LSTM thus is provided with more than adequate information regarding the state of the language LSTM, the image features, and the partial caption.

Given the output h_t^1 of the attention LSTM, a normalized attention weight is calculated α_i, t for each k image feature v_i as follows:

$$a_{i,t} = \boldsymbol{w}_a^T \tanh\left(W_{va} \boldsymbol{v}_i + W_{ha} \boldsymbol{h}_t^1\right)$$
$$\boldsymbol{\alpha}_t = \text{softmax}\left(\boldsymbol{a}_t\right)$$

where:

$$W_{va} \in \mathbb{R}^{H \times V}, W_{ha} \in \mathbb{R}^{H \times M} \text{ and } \boldsymbol{w}_a \in \mathbb{R}^H$$

are learned parameters. The attended feature input to the language LSTM is a culmination of all input features:

$$\hat{\boldsymbol{v}}_t = \sum_{i=1}^{K} \alpha_{i,t} \boldsymbol{v}_i$$

Language LSTM The input to the language model LSTM consists of the attended image feature, and the output of the attention LSTM.

$$\boldsymbol{x}_t^2 = [\hat{\boldsymbol{v}}_t, \boldsymbol{h}_t^1]$$

$y_1 : T$ to refers to a sequence of words $(y_1, ..., y_T)$. The conditional distribution over possible output words is given by:

$$p(y_t \mid y_{1:t-1}) = \text{softmax}\left(W_p \boldsymbol{h}_t^2 + \boldsymbol{b}_p\right)$$

where

$$W_p \in \mathbb{R}^{|\Sigma| \times M}$$

and

$$\boldsymbol{b}_p \in \mathbb{R}^{|\Sigma|}$$

are weights and biases. The distribution over complete output sequences is calculated as the product of conditional distributions:

$$p(y_{1:T}) = \prod_{t=1}^{T} p(y_t \mid y_{1:t-1})$$

Objective Given a target ground truth sequence $y_1 : T^*$ and a captioning model with parameters θ, we minimize the following cross entropy loss:

$$L_{XE}(\theta) = -\sum_{t=1}^{T} \log(p_\theta(y_t^* \mid y_{1:t-1}^*))$$

$$\nabla_\theta L_R(\theta) \approx -(r(y_{1:T}^s) - r(\hat{y}_{1:T}))\nabla_\theta \log p_\theta(y_{1:T}^s)$$

[2]

5 Dataset

We are using one of the most widely used dataset for image captioning tasks. The Flickr8k data set contains images found of Flickr. There are 8k images with associated captions. Each image in the dataset contains 5 captions. Each of the five captions describes the image in a different way,

with different grammar and verbs. Out of the 8000 images, 7000 are used for training the model. The remaining images are utilized for testing the performance of the model with an associated bleu score.

We chose to use the Flickr8k because it is smaller in size, and faster to train. You may use this model on other benchmark datasets as well namely, Flickr30k and MSCOCO

6 Evaluation

6.1 Metrics

Evaluation is done on the standard metrics which are as follows: CIDEr [12], BLEU [10], ROUGE-L [9], METEOR [5], SPICE [1]

Metric	Proposed to evaluate	Underlying idea
BLEU (Papineni et al., 2002)	Machine translation	n-gram precision
ROUGE (Lin, 2004)	Document summarization	n-gram recall
METEOR (Banerjee and Lavie, 2005)	Machine translation	n-gram with synonym matching
CIDEr (Vedantam et al., 2015)	Image description generation	*tf-idf* weighted n-gram similarity
SPICE (Anderson et al., 2016)	Image description generation	Scene-graph synonym matching

Figure 2: Summary of metrics for automatic evaluation of generated captions

6.1.1 BLEU

BLEU (Papineni et al., 2002) is one of the first metrics that have been in use for measuring similarity between two sentences. It has been initially proposed for machine translation, and defined as the geometric mean of n-gram precision scores multiplied by a brevity penalty for short sentences. In our experiments, we use the smoothed version of BLEU as described in (Lin and Och, 2004).

6.1.2 METEOR

METEOR (Banerjee and Lavie, 2005) is another machine translation metric. It is defined as the harmonic mean of precision and recall of unigram matches between sentences. Additionally, it makes use of synonyms and paraphrase matching. METEOR addresses several deficiencies of BLEU such as recall evaluation and the lack of explicit word matching. n-gram based measures work reasonably well when there is a significant overlap between reference and candidate sentences; however they fail to spot semantic similarity when the common words are scarce. METEOR handles this issue to some extent using WordNet-based synonym matching, however just looking at synonyms may be too restrictive to capture overall semantic similarity.

6.1.3 SPICE

Another recently proposed metric for evaluating image caption similarity is SPICE (Anderson et al., 2016). It is based on the agreement of the scenegraph tuples (Johnson et al., 2015; Schuster et al., 2015) of the candidate sentence and all reference sentences. Scene-graph is essentially a semantic representation that parses the given sentence to semantic tokens such as object classes C, relation types R and attribute types A. Formally, a candidate caption c is parsed into a scene-graph as $G(c) = hO(c), E(c), K(c)i$ where $G(c)$ denotes the scene graph of caption c, $O(c) \subseteq C$ is the set of object mentions, $E(c) \subseteq O(c) \times R \times O(c)$ is the set of hyper-edges representing relations between objects, and $K(c) \subseteq O(c) \times A$ is the set of attributes associated with objects. Once the parsing is done, a set of tuples is formed by using the elements of G and their possible combinations. SPICE score is then defined as the F1-score based on the agreement between the candidate and reference caption tuples. For tuple matching, SPICE uses WordNet synonym matching (Pedersen et al., 2004) as in METEOR (Banerjee and Lavie, 2005). One problem is that the performance becomes quite dependent on the quality of the parsing. Figure 1 illustrates an example case of failure. Here, swimming is parsed as an object, with all its relations, and dog is parsed as an attribute.

6.1.4 CIDEr

CIDEr (Vedantam et al., 2015) is a recent metric proposed for evaluating the quality of image descriptions. It measures the consensus between candidate image description ci and the reference sentences, which is a set Si = si1, . . . , sim provided by human annotators. For calculating this metric, an initial stemming is applied and each sentence is represented with a set of 1-4 grams. Then, the co-occurrences of n-grams in the reference sentences and candidate sentence are calculated. In CIDEr, similar to tf-idf, the n-grams that are common in all image descriptions are downweighted. Finally, the cosine similarity between n-grams (referred as CIDErn) of the candidate and the references is computed. CIDEr is designed as a specialized metric for image captioning evaluation, however, it works in a purely linguistic manner, and only extends existing metrics with tf-idf weighting over n-grams. This sometimes causes unimportant details of a sentence to be weighted more, resulting in a relatively ineffective caption evaluation.

6.1.5 ROUGE

ROUGE (Lin, 2004) is initially proposed for evaluation of summarization systems, and this evaluation is done via comparing overlapping n-grams, word sequences and word pairs. In this study, we use ROUGE-L version, which basically measures the longest common subsequences between a pair of sentences. Since ROUGE metric relies highly on recall, it favors long sentences, as also noted by (Vedantam et al., 2015).

6.2 Feature Extraction

For feature extraction we used ResNet[6] that was pre-trained on ImageNet[4], before feeding these features to the caption generation models. ResNet CNN is run on the original image and the last convolution layer feature is adaptively average pool to fixed size.

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2 $\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Figure 3: Diagram representing the ResNet architecture.

6.3 Experiment Setup

All variants of our models were trained with stochastic gradient descent using adaptive learning rate Adam[8]. We used a batch size of 10, learning rate $5X10^{-}4$ with 0 start weight decay, trained for 25 epochs, which took over an hour for the Top Down Network but only few minutes for Show Tell and Show Attend and Tell owning to their reduced complexity on a TITAN X GPU.
We used pretrained ResNet-101, on the ImageNet dataset as a starting point for feature extraction for all our experiments.
An extremely fast implementation of R-CNN is used, so called Fast R-CNN[11] for the Top Down Network.
For the Show, Attend and Tell model we used the soft attention mechanism only, the hard attention mechanism is considerably more complex when it comes to actual implementation due to its stochastic training procedure.

6.4 Results

Each of these tables compares the results given in the respective paper in comparison to the results we achieved during our experiments. As mentioned the Flickr8k dataset is usually divided into 6000 for training, 1000 for development and 1000 for testing. The evaluation scores usually come from the 1000 test images that are segregated. The standard papaer of Top-Down Bottom-up attention evaluates on the MSCOCO dataset.The Show and Tell , and Show, Attend and Tell official paper does evaluation on all three benchmark datasets.

6.4.1 Show and Tell Model results

Paper Details	BLEU1	BLEU2	BLEU3	BLEU4	CIDEr	ROUGE-L	METEOR	SPICE	
Standard paper	0.63	0.41	0.27	-	-	-	-	-	
Ours	0.613	0.433	0.301	0.209	0.491	0.462	0.199	0.135	

6.4.2 Show Attend and Tell results

Paper Details	BLEU1	BLEU2	BLEU3	BLEU4	CIDEr	ROUGE-L	METEOR	SPICE	
Standard paper	0.67	0.448	0.299	0.195	-	-	0.195	-	
Ours	0.652	0.473	0.332	0.228	0.600	0.483	0.216	0.157	

6.4.3 Bottom up and Top Down Model results

Paper Details	BLEU1	BLEU2	BLEU3	BLEU4	CIDEr	ROUGE-L	METEOR	SPICE	
Standard paper	0.772	-	-	0.362	113.5(denorm)	0.564	0.270	0.203	
Ours	0.657	0.477	0.334	0.230	0.59	0.48	0.21	-	

7 Conclusion

On conclusion we would like to mention that, here we evaluate three major architectures and present evaluation on various matrices which are state of the art and compare it to the evaluation results given in the official paper of these architectures. Firstly, we present and evaluate show and tell model which combines state of the art language language and vision model. Secondly we evaluate Show, attention and tell model which is an attention based approach, its unique in the sense that this architecture the learned alignments correspond very well to the human intuition. Thirdly we evaluate the novel implementation of bottom up and top down together which allows attention to be calculated at the low level of objects and other salient features. This paper is a one-stop evaluation shelf for the three popular architectures in Image Captioning.
Here are some sample image caption results:

Ground Truth	tourists are standing a mountain viewpoint beneath a clear blue sky
Show and Tell	a group of people are sitting on a bench in front of the ocean
Show, Attend, and Tell	a group of people are sitting on a bench
Top Down / Bottom Up	a group of people are sitting on a rocky hill

Ground Truth	A football player in red and white is holding both hands up
Show and Tell	a football player in a red jersey is running
Show, Attend, and Tell	a football player in red is being tackled
Top Down / Bottom Up	a group of football players in red and white uniforms

Ground Truth	A woman wading through a pool in front of a waterfall
Show and Tell	a woman in a bikini is standing on a rock overlooking the ocean
Show, Attend, and Tell	a girl in a swimsuit is standing in the water
Top Down / Bottom Up	a girl in a swimsuit is splashing in the water

8 Team Roles

Dan and Saurabh were responsible for the Top down Bottom Up and Show, Attend and Tell models, respectively. While Robin was responsible for the Show and Tell model. Robin was in charge of acquiring the Flickr8K dataset. Quite some time was spent together as a team figuring out how to get the input and evaluation for the generic model working first. Saurabh and Robin worked on the paper tried to come up with proper explanation and neatly present it while Dan worked on the power-point presentation and was responsible for the attachment of the pictures in the paper.

9 Future Work

As far as future work is concerned we have just implemented using the smallest benchmark dataset Flickr8k. There is high possibility of hyper-tuning as well. We did our experiments with 25 epochs and a particular learning rate. There is scope to try out a different dataset such as Flickr30k or MSCOCO or any other as seem fit with proper tuning, learning rate and change of other hyperparameters.

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