

Automated Image Captioning

COD310: Mini Project



Suyash Agrawal

2015CS10262

Computer Science

CGPA: 9.92

Mob: 9717060183

cs1150262@iitd.ac.in

Madhur Singhal

2015CS10235

Computer Science

CGPA: 8.66

Mob: 9540972599

cs1150235@iitd.ac.in

Supervisor:-

Subhashis Banerjee

Professor

Department of CSE

suban@cse.iitd.ac.in

IIT Delhi

Prof. S. Arun Kumar

Head of Department

Department of CSE

sak@cse.iitd.ernet.in

1 Introduction

Video Description is the process of discovering knowledge, structures, patterns and events of interest in the video data and describing them in natural language. Video Description is an open problem in computer vision and currently the only source of video description is manual labour.

Video Description has wide variety of applications. It can help visually impaired people “see” the world by describing the scene around them. It has also use in automated surveillance by analyzing the videos in real time and reporting malicious or unusual activities. It can also be used to efficiently index large video databases based upon their content for ease of accessibility.



Description: A monkey pulls a dog's tail and is chased by the dog.

Figure 1: Sample Video Description

Most of the prior work in this field is focused on generating natural language descriptions from images.

Our aim is to utilize these new techniques in the field of image captioning and generate natural language descriptions from video data. Basically this project will involve first encoding video data using convolutional networks and then using recurrent neural networks (specifically LSTMs) to generate descriptions of these videos. Further, we will also explore using optical flow based models to improve description of videos.

2 Procedure

Our main objective in this project is to make a model which describes videos. For this, we will construct a deep neural network and then train it with a large database of videos with corresponding descriptions so that our model learns to describe videos.

After training our model, we will get a system in which takes video as an input and outputs a text description of the video file.

The video that we are trying to describe will be taken from the datasets mentioned in section 4 . As these are datasets of videos taken from varied situations and circumstances, we believe that they will generalize well on any input video. From this, we will also be able to show that specialized video description (like surveillance) can be done given appropriate amounts of labelled data.

3 Approach to the project

The basic approach is to train our model using videos that already have a description, so that our networks “learns” to describe videos.

In order to achieve this we have broken down our problem in several parts. First, we will be implementing image captioning in order to be able to encode individual video frames in fixed-length vector representation. Then, we will be using our constructed image captioning network’s CNN (image encoder) to encode video frames sampled at a fixed interval. We will then use Recurrent Neural Networks to translate this representation of video into natural language domain. This translation will be achieved by using a set of encoder and decoder RNNs. Since we are working with variable length input and output, we will specifically be using LSTMs (Long Short Term Memory Networks) for encoding and decoding purposes, as they have been proven to be excellent in machine translation and generalize very well on long data input.

1. Image Captioning

- (a) Construct a convolutional neural network (VGG/Inception V3) with pre-trained weights for object classification.
- (b) Make an RNN (LSTM) network[3] that takes a encoded image (using CNN) as input and then translates the image representation into natural language text.
- (c) Train the model on datasets like MS COCO which consists of large number of captioned images.

2. Video Representation

- (a) We will first sample video at a fixed rate and convert each individual frame to a fixed length vector representation using the network trained in image captioning part.
- (b) We will then try out different approaches of video representation like:
 - Mean Pooling over all video frame encodings obtained to get a fixed vector representation of video[1].
 - Using RNNs to encode this variable length video representation[2].
 - Using 3D CNNs to directly encode videos and use simple RNNs for description generation[5].

3. Natural Language Conversion

- (a) Based on how we choose to encode our video, we will have to select appropriate architecture of LSTM to be used to decode the representation
- (b) One popular choice[2](Figure 2) that we will try out first will be to use a two level LSTM model that will do a sequence to sequence mapping from variable length video representation to variable length natural language sentence.

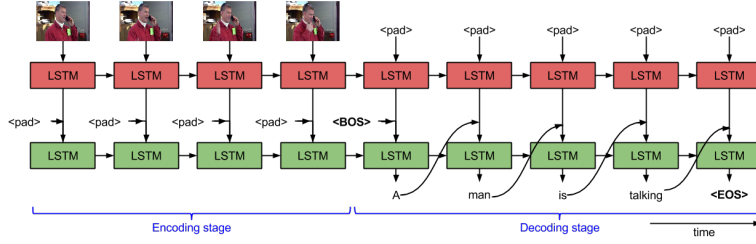


Figure 2: Video description model with 2 LSTM levels

- (c) Then we will train our model on the training data we have obtained and plot the learning curves.
- (d) We will also have to check for over-fitting and under-fitting during our training process and finetune our hyper parameters according to it.

4. Further Possibilities

- (a) We will look for techniques of data augmentation and transfer learning[1] to compensate for the limited amount of training data for video description.
- (b) We will also look into some recent techniques of using optical flow for attention modelling[2] which has shown in some cases to improve the results of action recognition.
- (c) We will also consider using more efficient vocabulary representation as compared to one hot encoding because vocabulary in this case would be very large.
- (d) Try to make forward propagation fast and more memory efficient.
- (e) We will also try to develop an end user application that will speak out description of a video that a person records.
- (f) A future extension of this project is to design a system which can answer questions based upon a video, similar to [6].

4 Working

Image captioning model basically consists of two broad models:

1. **Image Encoder:** A deep CNN network (Inception V3) to encode images to fixed length vector representation.
2. **Sequence Decoder:** An LSTM network to decode the encoded information in form of description.

4.1 Image Encoder

Image encoder is basically a deep CNN network pretrained on image classification dataset (ImageNet). This was chosen because CNNs are state-of-art models for object recognition and as image description relies heavily on object recognition, it became an apparent choice. Also, as these were pretrained on large object classification datasets, it was certain that they are very well optimised and are able to gather high level information from images and thus are suitable for encoding images to fixed length vector.

4.2 Sequence Decoder

LSTM were used as sequence decoders. This is so because LSTM have been very successful in tackling the problem of keeping long term dependencies and deal well with problem of exploding and vanishing gradients. Basically this unit took a fixed length vector (encoded image) as input and gave out a complete sentence that represented that input.

These underlying process that is followed is:

4.2.1 Training Process

1. Encoded image is fed into LSTM network to inform it about the contents
2. A special start symbol is fed into LSTM to mark the start of sentence.
3. For each word in our dictionary, LSTM unit gives a probability of it being the first word of our predicted caption.
4. Then first word from the correct caption is given as input to LSTM unit and LSTM outputs the probability for second word.
5. We then recursively do this procedure until we consume our whole caption.
6. The loss is then calculated as sum of negative log probabilities of predicting correct word at each step above.

4.2.2 Inference Process

1. Encoded image is fed into LSTM network to inform it about the contents
2. A special start symbol is fed into LSTM to mark the start of sentence.
3. For each word in our dictionary, LSTM unit gives a probability of it being the first word of our predicted caption.
4. We take the word with highest probability as our first word and feed it into LSTM to get second word

5. We then recursively do this procedure until we get special END word as output or we reach max length.
6. The caption generated is basically just the sequence of predicted words by our LSTM.

4.3 Overall Process

4.3.1 Training

- An image and caption pair is fetched from training dataset
- Image is fed into Image Encoder network to generate encoded vector.
- This vector along with correct caption is fed into Sequence Decoder network to get loss.
- This loss is backpropagated in neural network so that it can "learn" from process.

4.3.2 Inference

- Test image is fed into Image Encoder network to generate encoded vector.
- This vector fed into Sequence Decoder network which generates a set of captions.
- No backpropagation happens in this case as we don't know the correct caption and are just testing our network.

5 Results

- Assisting visually impaired people to get description of their surroundings, thus enabling them to "see".
- Very useful for automated surveillance and theft detection by being able to analyze large amounts of data which is unfeasible to be done by humans.
- Allowing content based video retrieval by describing the contents of video in textual format which is indexable by web crawlers.
- This can also be used to detect catastrophic events through security cameras like fire breakout, murder etc.
- This project can also be applied in helping robotic vision as this project basically allows one to understand what is happening in the video and thus robots will be able to get a "true" sense of their surroundings.

6 Future Plans

6.1 Budget

No budget is required for this project.

6.2 Duration

We will try to complete this project by the end of the summer break i.e. the end of July, 2017.

7 Background

7.1 Deep Learning

Deep Learning is a branch of machine learning in which multiple parameter based models are used in series. In a deep network, there are many layers between the input and output, allowing the algorithm to be executed in multiple processing steps, composed of **multiple linear and non-linear transformations**. At each layer, the signal is transformed by a processing unit, like an artificial neuron, whose parameters are **‘learned’** through training. Deep Learning has been shown to excel in tasks where the goal is to find **intuitive** patterns in the data.[8] In particular, in the field of Computer Vision, deep networks are increasingly used to extract **feature descriptions and inter-relationships between features** from images.[10]

7.2 Convolutional Neural Networks

Convolutional Neural Networks (CNN, or ConvNet) are a type of feed-forward artificial neural network in which the connectivity pattern between the neurons is inspired by the organization of the animal visual cortex. Individual cortical neurons respond to stimuli in a restricted region of space known as the **receptive field**. The receptive fields of different neurons partially overlap such that they tile the visual field. The response of an individual neuron to stimuli within its receptive field can be approximated mathematically by a **convolution operation**. A Convolutional Neural Network consists of the following layers.[3]

7.2.1 Convolutional Layer

The convolution layer is the core building block of a CNN. The layer’s parameters consist of a set of **learnable filters** (or kernels), which have a small receptive field, but extend through the full depth of the input volume. During the forward pass, each filter is convolved across the width and height of the input volume, computing the dot product between the entries of the filter and the input and producing a 2-dimensional activation map of that

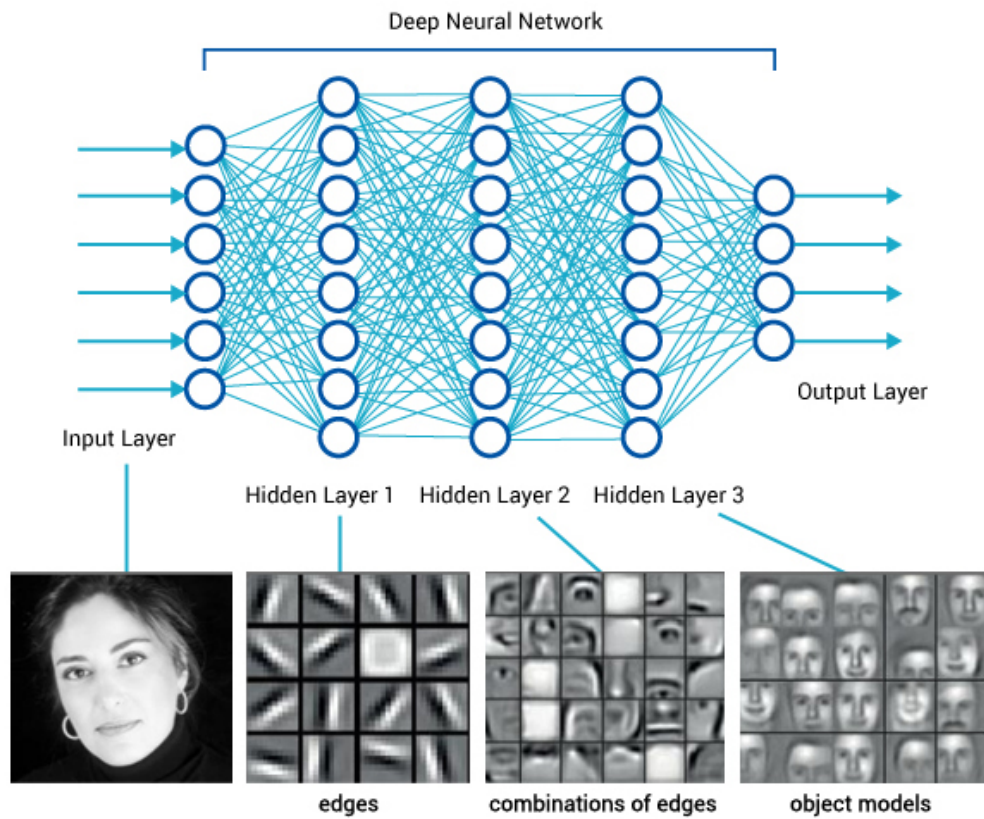


Figure 3: Illustration of Deep Learning as applied to Vision

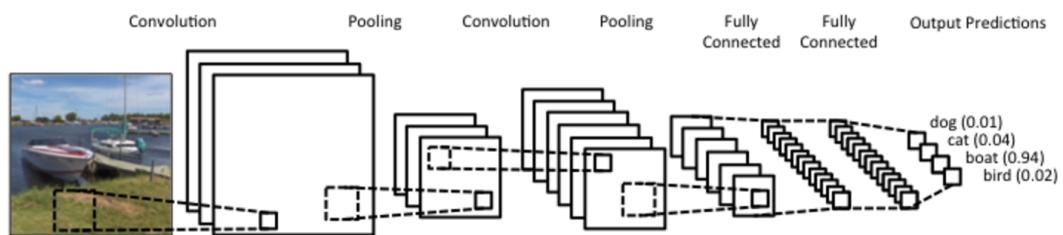


Figure 4: A Typical Convolutional Neural Network

filter.[10] As a result, the network learns filters that activate when it detects some specific type of feature at some spatial position in the input.

7.2.2 Max Pooling Layer

It is common to periodically insert a Pooling layer in-between successive Conv layers in a ConvNet architecture. Its function is to **progressively reduce the spatial size** of the representation to reduce the amount of parameters and computation in the network, and hence to also control over-fitting. The Pooling Layer operates independently on every depth slice of the input and resizes it spatially, using the max operation.[10]

7.2.3 Fully-Connected Layer

Finally, after several convolutional and max pooling layers, the high-level reasoning in the neural network is done via fully connected layers. Neurons in a fully connected layer have **full connections to all activations** in the previous layer, as seen in regular Neural Networks. Their activations can hence be computed with a matrix multiplication followed by a bias offset.[11] Thus output of the fully connected layer is a vector with elements representing the ‘probability’ (not in a strictly statistical sense) of the image containing specific objects or actions.

7.3 Long Short Term Memory Networks

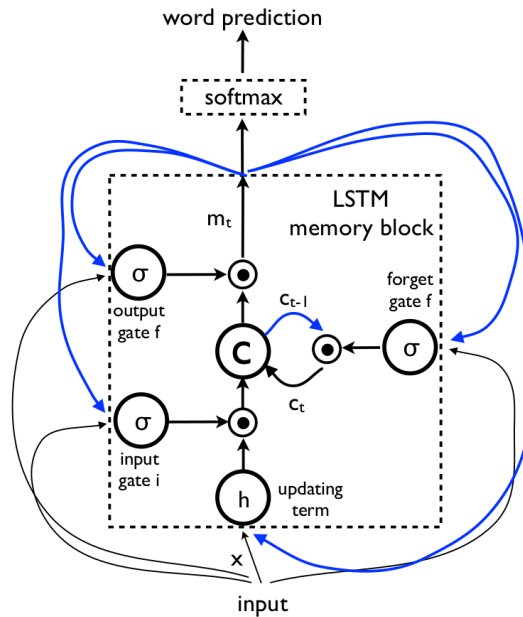


Figure 5: A single LSTM unit

Long Short Term Memory Networks are a type of Recurrent Neural Networks. These networks are based upon recursion, so that variable length inputs can be handled easily

and sequential information can be processed with better results. LSTM's are specifically used for making RNNs learn long term patterns since traditional RNNs tend to **favour short term temporal dynamics**. It can be difficult to train traditional RNNs to learn long-term dynamics, likely due in part to the **vanishing and exploding gradients problem** that can result from propagating the gradients down through the many layers of the recurrent network, each corresponding to a particular time step[7]. LSTMs provide a solution by incorporating memory units that explicitly allow the network to learn when to “forget” previous hidden states and when to update hidden states given new information[4].

7.4 Training Deep Neural Networks

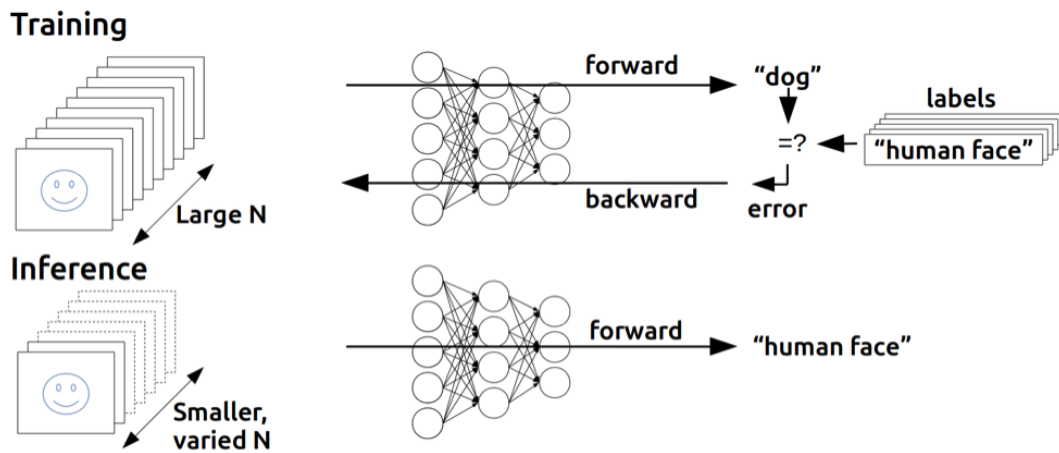


Figure 6: Training and Inference Processes

A Deep Neural Network is at its core a parameter based function. All of these parameters are **trained** automatically from inputs and expected output tuples (training data). The training process revolves around minimizing a particular cost function using methods like **Stochastic gradient descent**. The input is given to the network in a feed forward fashion and the parameters are modified from the last layer to the first (**Backpropagation**). Neural Networks, by design, require huge amounts of training data and take a large time to get trained. For some perspective, most current state of the art image classifiers have > 100 million parameters and are trained on more than 1.2 million images.

7.5 Finetuning

Fine-tuning a network is a procedure based on the concept of **transfer learning**. We start training a CNN to learn features for a broad domain with a classification function targeted at minimizing error in that domain. Then, we replace the classification function and **optimize the network** again to minimize error in another, more specific domain.

Under this setting, we are transferring the features and the parameters of the network from the broad domain to the special one.[9] In our project we will need to use the pre-trained image classification models to actually decode individual frames of the video, thus we are planning to **fine-tune those models with respect to the output of our LSTMs**.

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