

# Video Description using Deep Learning

Summer Undergraduate Research Award



**Suyash Agrawal**

2015CS10262

Computer Science

CGPA: 9.87

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

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**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

## 2 Past Work

Much of the prior work in this field is focused on generating natural language descriptions from images. Recently the use of an end to end deep neural network architecture which takes an image as input and generates an english description has been shown to give excellent results. We extended this approach to a Video Description network which takes in a sequence of frames as input and generates an english description of the actions happening in the video. For this we use an encoder-decoder framework widely used in Machine Translation, which maps a variable length input to a variable length output.

## 3 Data

The data used is a crucial factor in the effectiveness of a complex neural network like ours. We primarily used the following two datasets for training and validation purposes.

1. **Microsoft Research - Video to Text (MSR-VTT)**: The dataset contains 41.2 hours and 200K clip-sentence pairs in total, covering the most comprehensive categories and diverse visual content, and representing the largest dataset in terms of sentence and vocabulary.
2. **Montreal Video Annotation Dataset (M-VAD)**: The M-VAD movie description corpus is another recent collection of about 49,000 short video clips from 92 movies. It is similar to MPII-MD, but only contains AD data and only provides automatic alignment.

Both of these datasets consist of short Youtube video clips (average length near 20 seconds) and english sentences (average length near 12 words) describing the clips. Most of the video clips also have a synchronized audio clip which we utilize in some of our experiments. Empirically we found out that these datasets were big enough for our network to learn proper English language sentence structure and grammar automatically, and the sentences we return are almost always grammatically correct. The datasets also identify a wide host of objects and actions which make the network applicable in general situations.

The main problem with these datasets is that they were not properly sampled and thus there was an inherent bias towards the types of videos seen on Youtube as opposed to those encountered in the real world. For example, the datasets had a large amount of videos of video games which often involve rapidly changing frames and our network began to associate things like car crashes to video game clips.

## 4 Methods

### 4.1 Overall Approach

Our approach to video description was motivated by the recent successful approach of using Encoder-Decoder system in Image Description. Our pipeline consisted of a CNN layer that extracted features from the video, then one LSTM network which encoded these features and finally another LSTM network for decoding into natural language description.

### 4.2 Video Feature Extraction

We used Convolutional neural networks for extracting features from video frames. In recent times CNNs have shown amazing results in object detection in images and thus they form a natural choice in extracting features from images. Also, since videos are a sequences of images, we downsample video frames at a fixed frame rate and then

individually extract features from each video frame and concatenate them to get the feature vector of the video.

We used Inception V4 net as our choice of CNN for video feature extraction as it has shown the best results in ImageNet challenge and is thus more likely to give better feature extraction from image frames. We also experimented with audio features in the video. Specifically we looked at the MFCC features of the audio and we processed these features along with image features in our encoder network to get better representation of the video. But we later abandoned this approach as it did not show any significant improvement in the results and also added audio dependency to our network which would have made this un-usable in the case of video surveillance and other areas where audio is not available.

### 4.3 Video Feature Encoding

We used a LSTM based network for encoding features of video frame into a single feature vector. This approach is largely inspired by recent breakthrough of similar approach in machine translation which also used LSTMs for encoding decoding language token. Here we used the feature vector of video frames as inputs to LSTM units and the final hidden state of the LSTM network as the video encoding.

We experimented with various types of encoding networks like:

- Single layer LSTM network
- Multi layered LSTM network (2-5 layers)
- Residual Network Multi Layered LSTM network
- Encoder network with Attention Model

Apart from the above, we also experimented with dropout in between layers and also experimented with audio features concatenated with video features.

## 5 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.
- (c) Then we will train our model on the training data we have obtained and plot the learning curves.

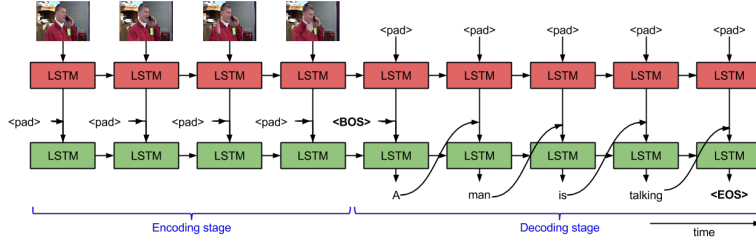


Figure 2: Video description model with 2 LSTM levels

- (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

- We will look for techniques of data augmentation and transfer learning[1] to compensate for the limited amount of training data for video description.
- 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.
- We will also consider using more efficient vocabulary representation as compared to one hot encoding because vocabulary in this case would be very large.
- Try to make forward propagation fast and more memory efficient.
- We will also try to develop an end user application that will speak out description of a video that a person records.
- A future extension of this project is to design a system which can answer questions based upon a video, similar to [6].

## 6 Uses and applications

- 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.

## 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



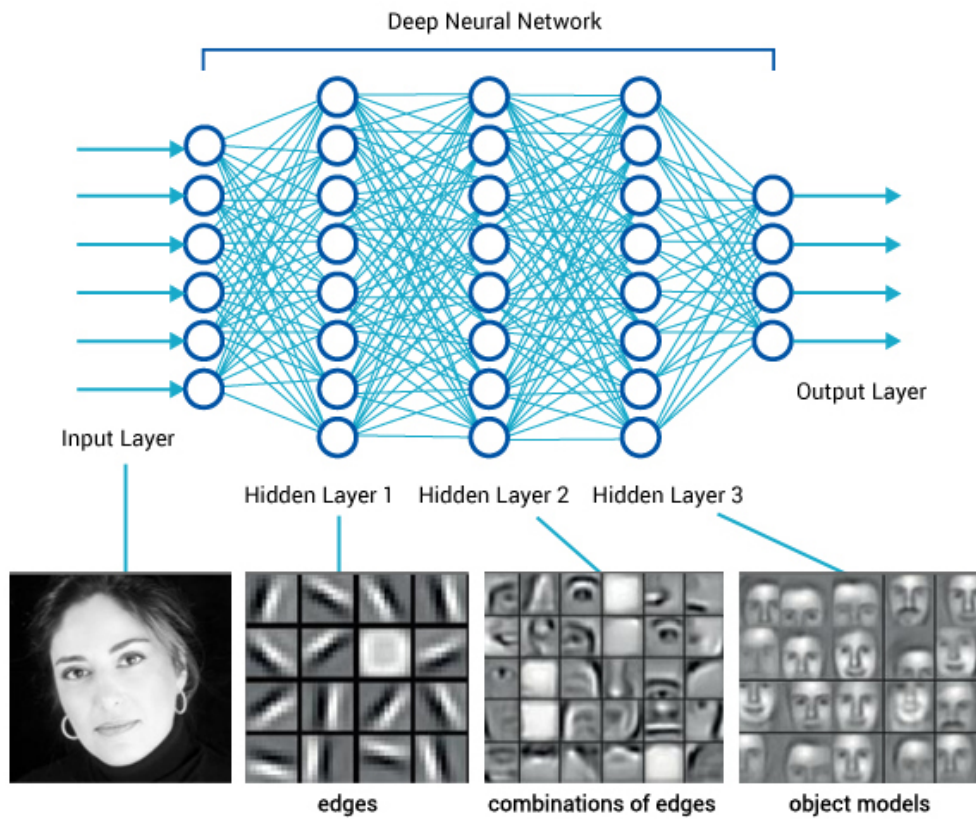


Figure 3: Illustration of Deep Learning as applied to Vision

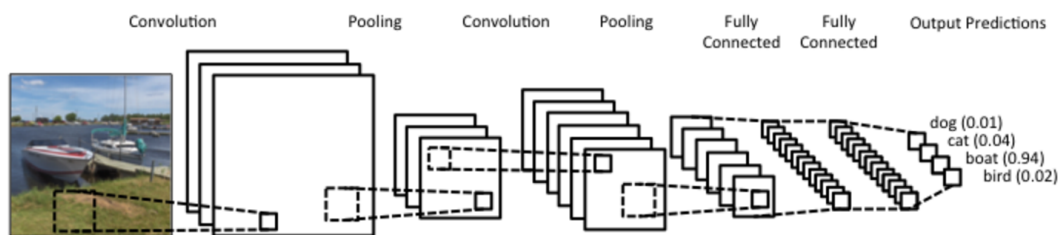


Figure 4: A Typical Convolutional Neural Network

activation map of that 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

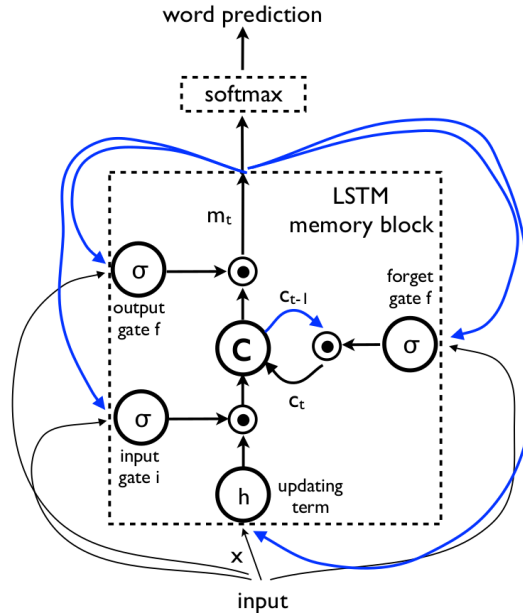


Figure 5: A single LSTM unit

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

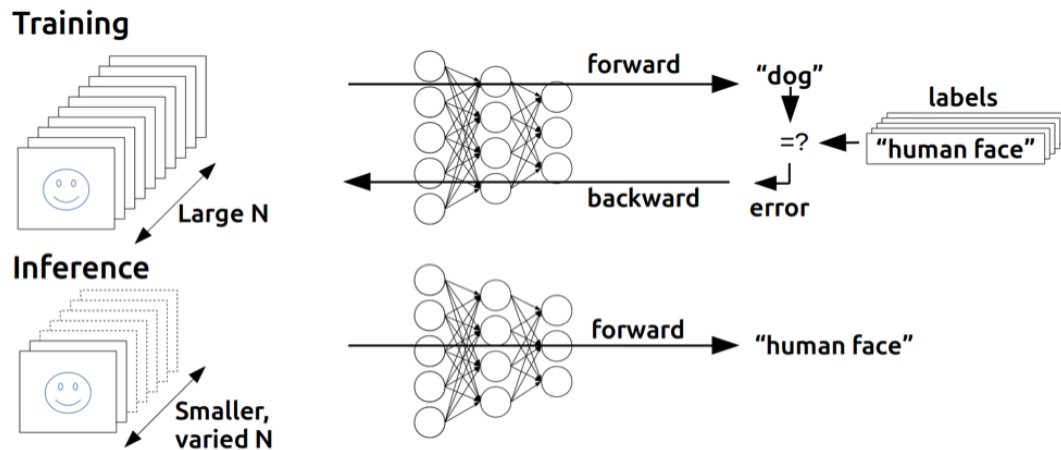


Figure 6: Training and Inference Processes

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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