HOMEWORK-2

INTRODUCTION-

For the domains of natural language processing and computer vision, the automatic creation of natural language captions for movies has been a considerable issue. The complex dynamics of real-time movies, which need techniques sensitive to temporal structures and capable of handling inputs and outputs of different durations, make this challenge much more challenging. We have used an encoder-decoder framework and the MSVD dataset for model assessment to deal with this problem. Two Long Short-Term Memory (LSTM) units are used in our method, one for encoding and the other for decoding. Deep neural networks are used to train an encoder to learn how to represent the video, and a sentence is produced for this representation by the decoder. We use a Beam search technique to generate effective captions.

Sequence-to-sequence applications like voice recognition and machine translation have shown the effectiveness of LSTMs. A stacked LSTM that is used for encoding transmits the frames one by one. The output of a convolutional neural network trained on the intensity values of each input frame serves as the LSTM's input. Once all the frames have been read, the model creates a phrase word by word.

One method pools the information of all frames and uses LSTMs to provide video subtitles. To get a singular feature vector, they apply mean pools to the CNN output features. This method's primary flaw is that it entirely disregards how the video frames are organized and do not attempt to change any temporal data.

They also use a two-step method where they first use CRFs to gather meaningful itemset of action, objects, tools, and regions and then use LSTM to convert those tuples into sentences. The small domain of cookery videos is where the method is used.

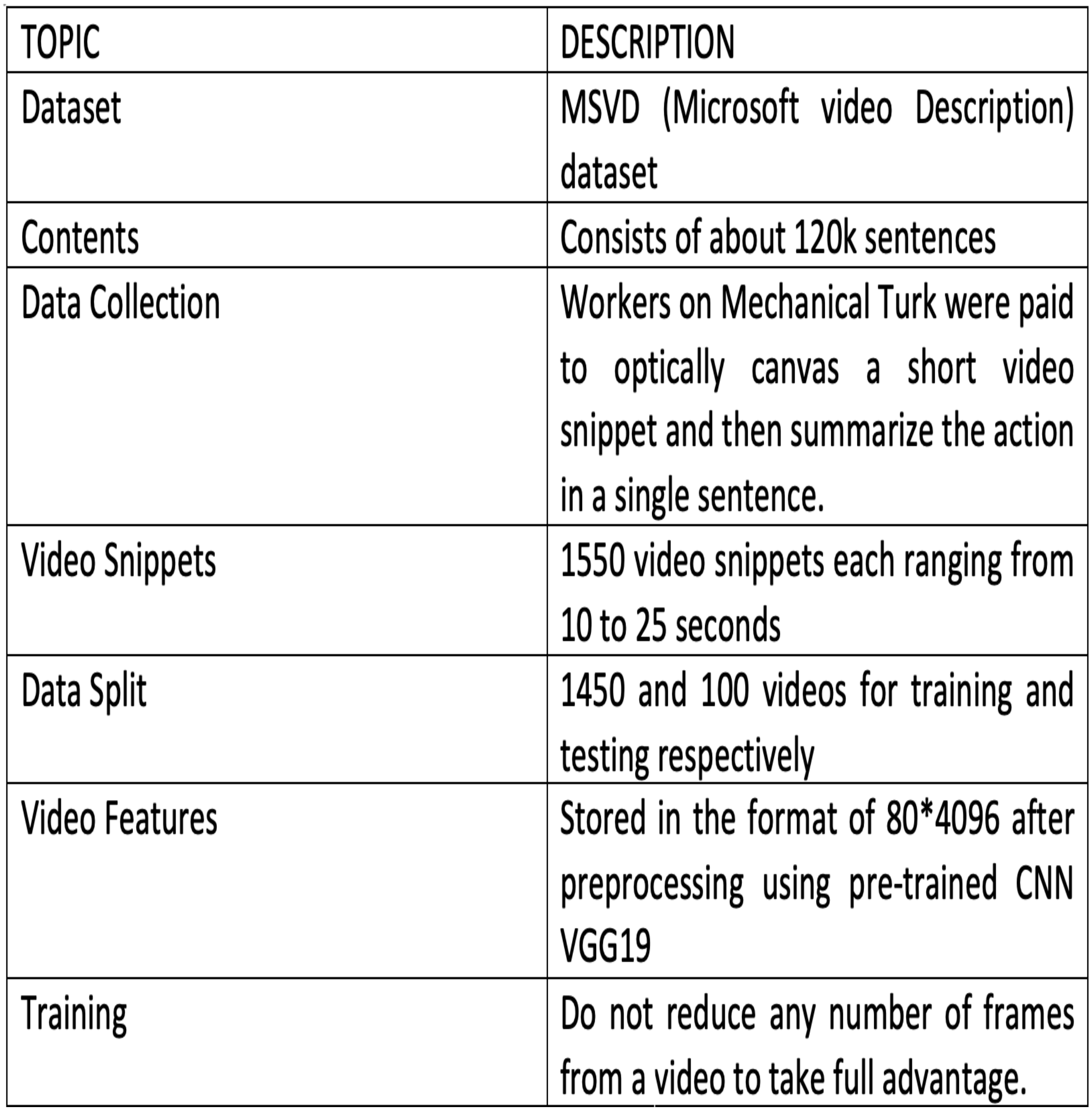
Concentration mechanisms have been implemented into several neural networks because they allow prominent aspects to rise to the top constantly as needed. Various attention approaches have been claimed to be helpful in a variety of tasks, such as translation software, image captioning, and video captioning.

Features of Dataset-

The MSVD (Microsoft Video Description) dataset was utilized in this experiment. The dataset Microsoft Research Video Descriptive Corpus (MSVD) contains around 120K phrases. Mechanical Turk workers were paid to visually canvass a brief video segment and then explain the activity in a single phrase.

The dataset includes 1550 video samples ranging in length from ten to twenty-five seconds. We divided the movies into 1450 and 100 for training and assessment, respectively.

After preprocessing with pre-trained CNN VGG19, we saved the characteristics of each clip in the format of 804096. To get the most out of the training, we don't cut any frames from the video



TOPIC	DESCRIPTION
Dataset	MSVD (Microsoft video Description) dataset
Contents	Consists of about 120k sentences
Data Collection	Workers on Mechanical Turk were paid to optically canvas a short video snippet and then summarize the action in a single sentence.
Video Snippets	1550 video snippets each ranging from 10 to 25 seconds
Data Split	1450 and 100 videos for training and testing respectively
Video Features	Stored in the format of 80*4096 after preprocessing using pre-trained CNN VGG19
Training	Do not reduce any number of frames from a video to take full advantage.

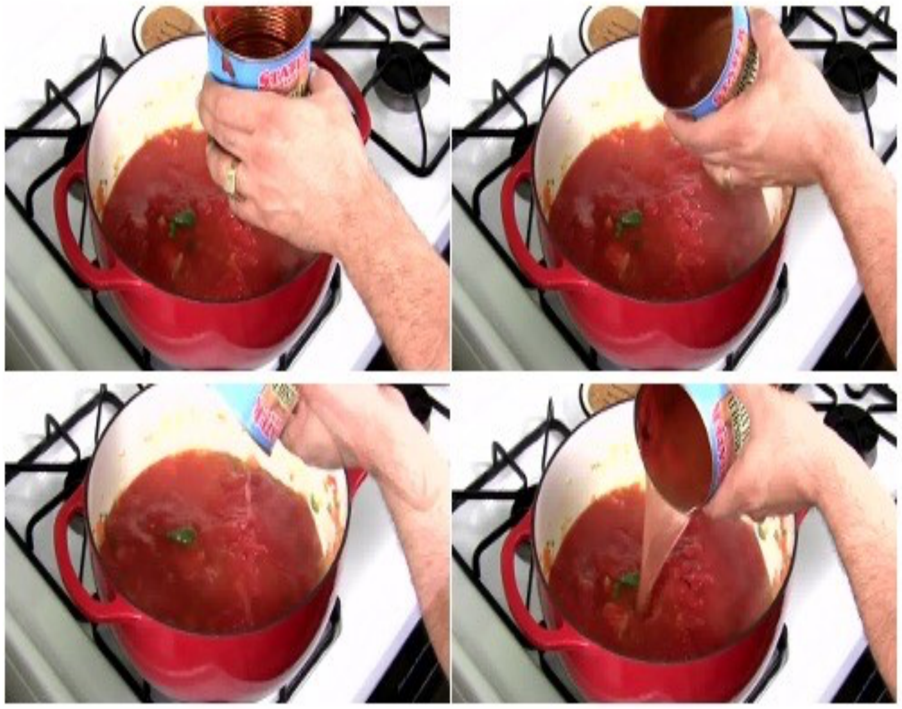


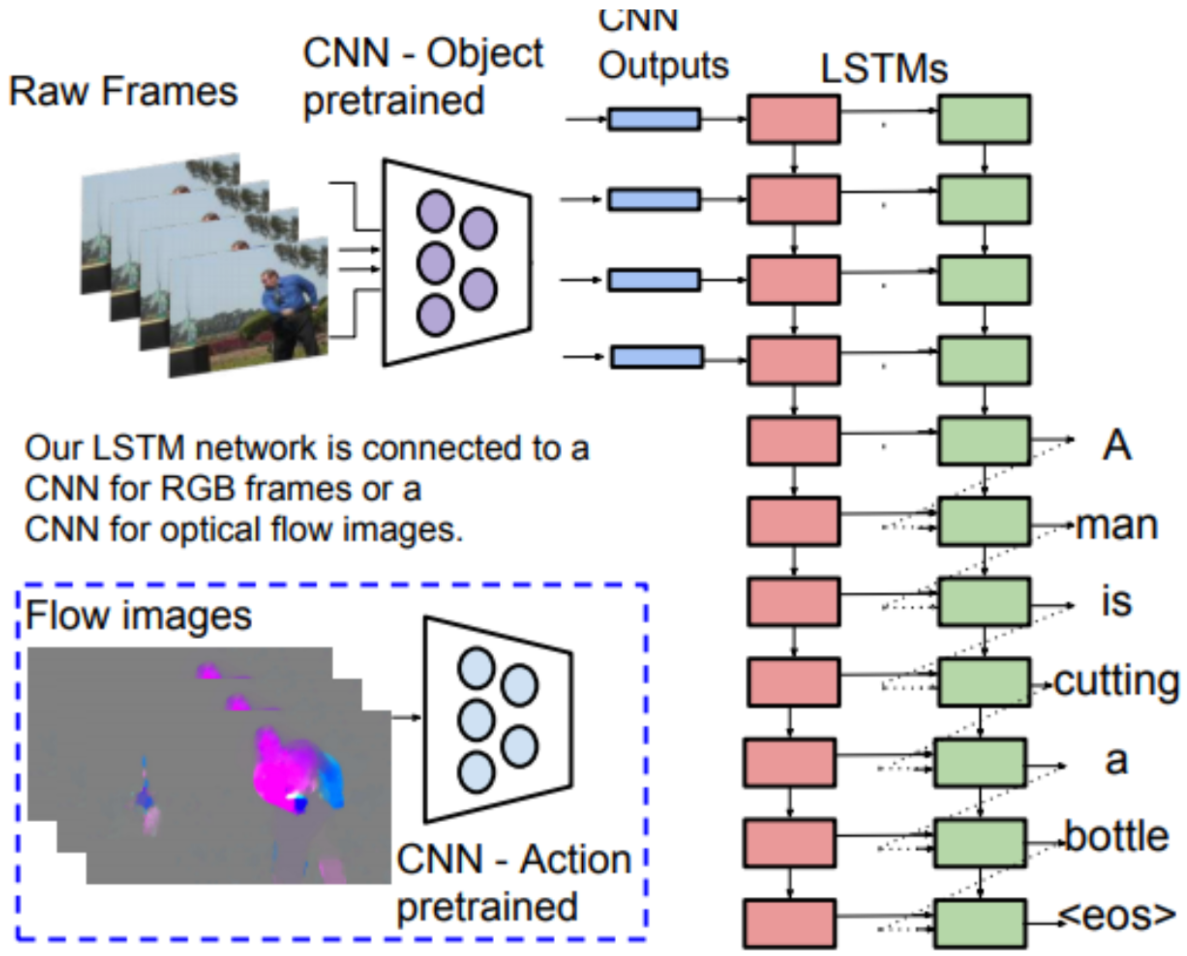
IMAGE DESCRIPTION-

1. A can of water is added to a cooking saucepan that is on a burner.
2. A can is being filled with water.
3. A man is filling the can with water.
4. The man filled the tomato sauce container with water.

A selection of images from a sample video in the training set is shown in the image above.

3. Accession-

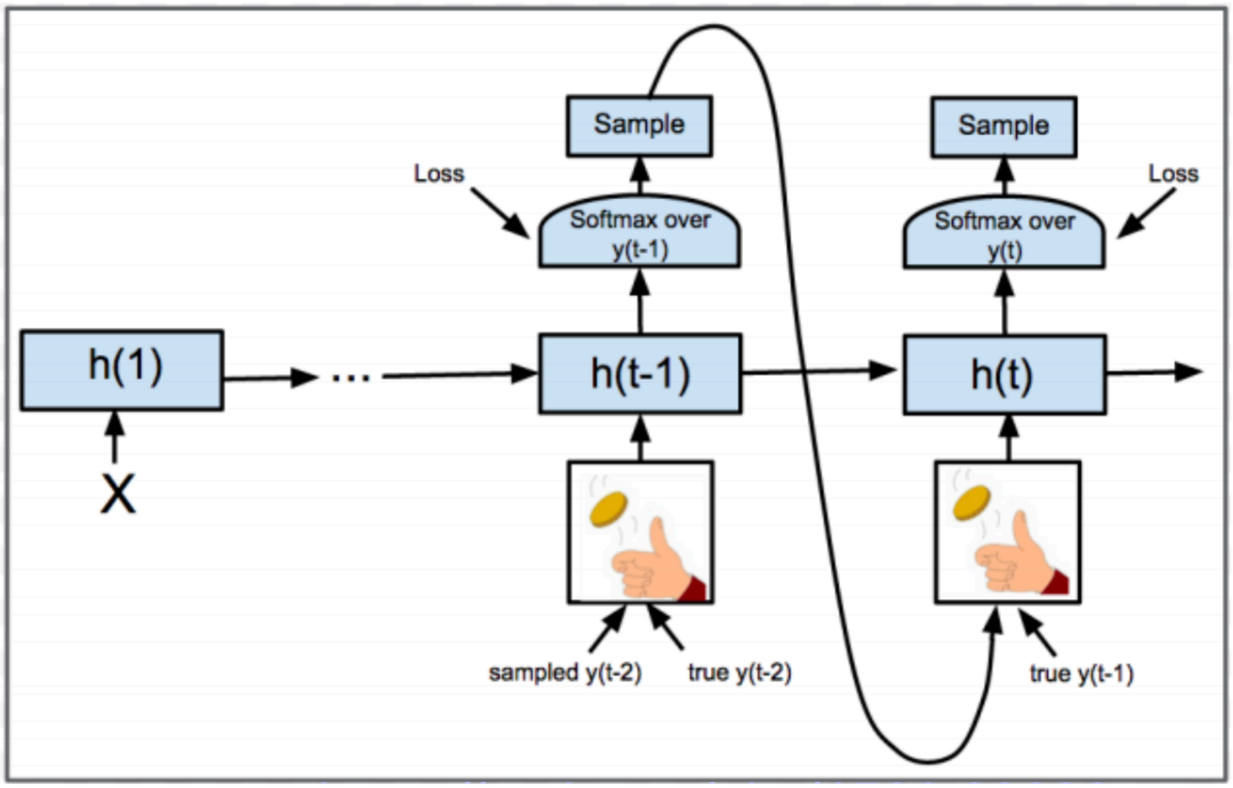
This model is a seq-to-seq model that generates a series of words from a sequence of video frames.



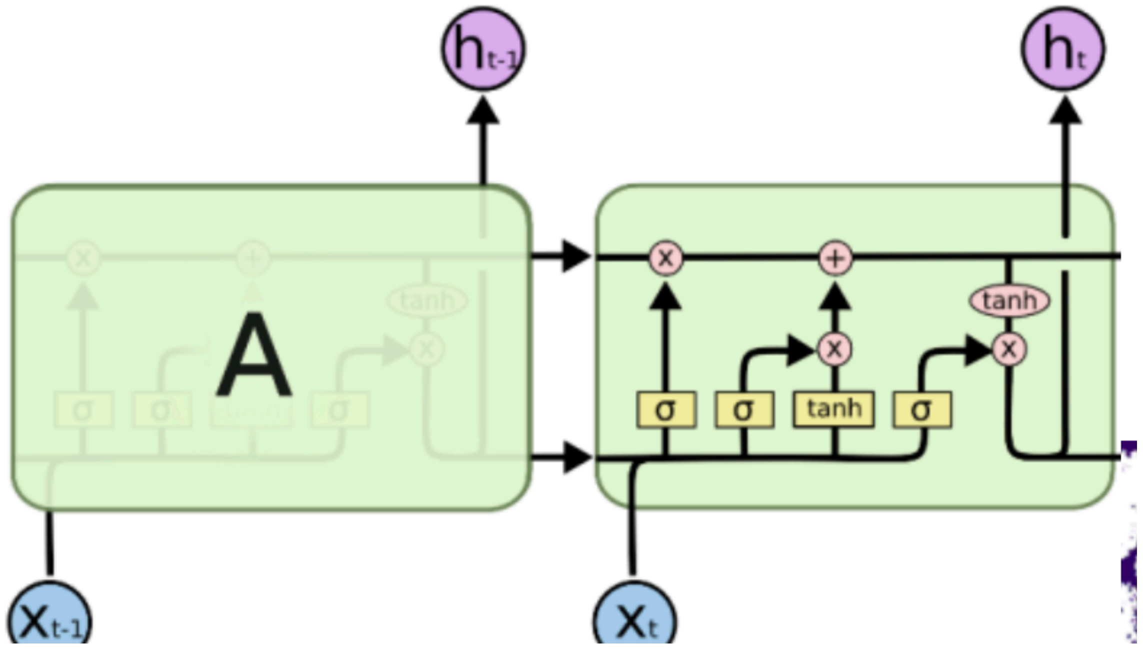
The video frames are loaded into the pre-trained CNN VGG19, which creates an 804096 spatial feature map of all the movies. We've created feature maps for each movie in the dataset.

Schedule Sampling-

To solve the "exposure bias" problem, when training, we feed ground truth as input at the odds.

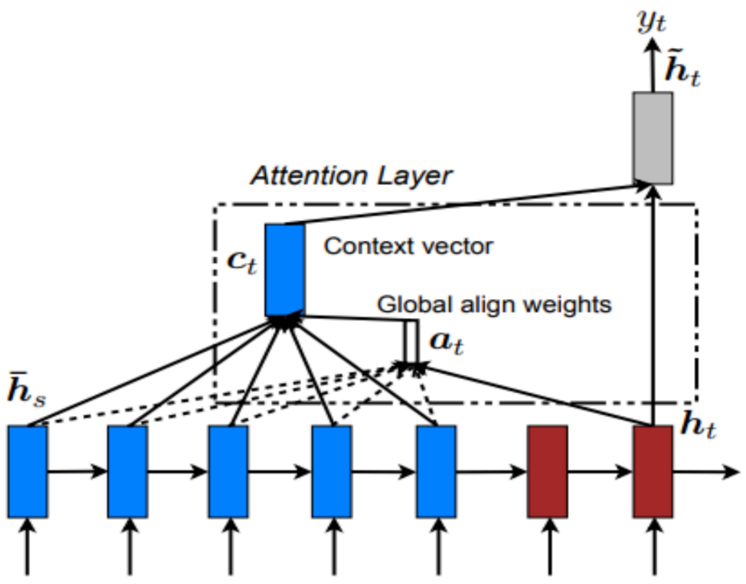


LSTM Unit-

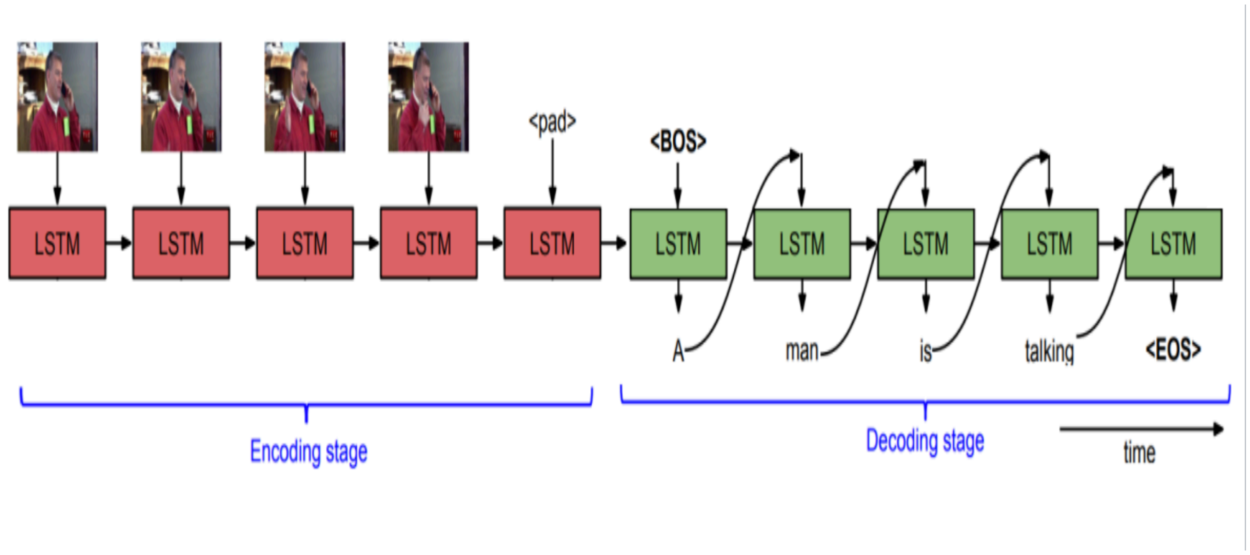


LSTM for Encoding and Decoding-

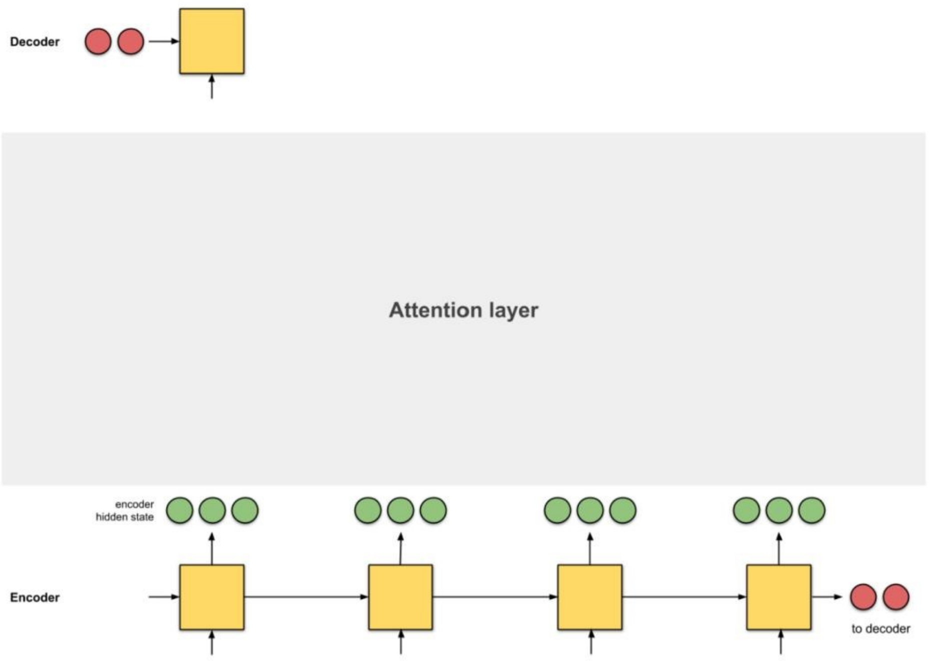
We will use the LSTM Recurrent Neural Network structure to manage variable-sized inputs and outputs. The complete input sequence (x1, x2,..., xn) is first encrypted, resulting in a single hidden state vector that is used to decrypt a language processing description of the characteristics revealed.



Model of LSTM'S-



Attention is a decoder-encoder interface that gives information from every encoder's hidden state to the decoder.



BLEU-

- Bilingual Assessment Understudy is a methodology for checking the accuracy of machine-translated text from one natural language to another.
- Quality is defined as the connection between the output of a machine and the work of a human: The primary premise underlying BLEU is that "the closer a machine translation is to a competent human translation, the better it is."

Difficulties-

There are multiple challenges we can face during implementation:

a. Different attributes of video like action and objects
b. Variable length of I/O

Version Requirements-

The Model is operational through the utilization of the following technologies:

- TensorFlow-gpu version 1.15.0
- Cuda version 9.0
- python version 3.6.0
- NumPy version 1.14
- panda’s version 0.20

Steps for Execution-

In the preprocessing stage, padding sequences and masking are applied to the data. Packed padding sequences allow us to use our RNN to just process the non-padded portions of our input phrase. Masking is used to compel the model to overlook items that we do not want it to look at, such as padded elements. This step is carried out to improve performance. The testing and training data were obtained from the given PowerPoint presentation and saved locally in the 'MLDS_hw2_1_data' folder. The vocabulary size should be at least three.

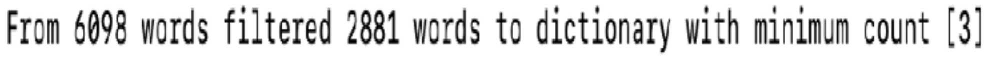
Tokens-

- <PAD> ： Pad the sentencen to the same length
- <BOS> ： Begin of sentence, a sign to generate the output sentence.
- <EOS> ： End of sentence, a sign of the end of the output sentence.
- <UNK> ： Use this token when the word isn’t in the dictionary or just ignore the unknown word.

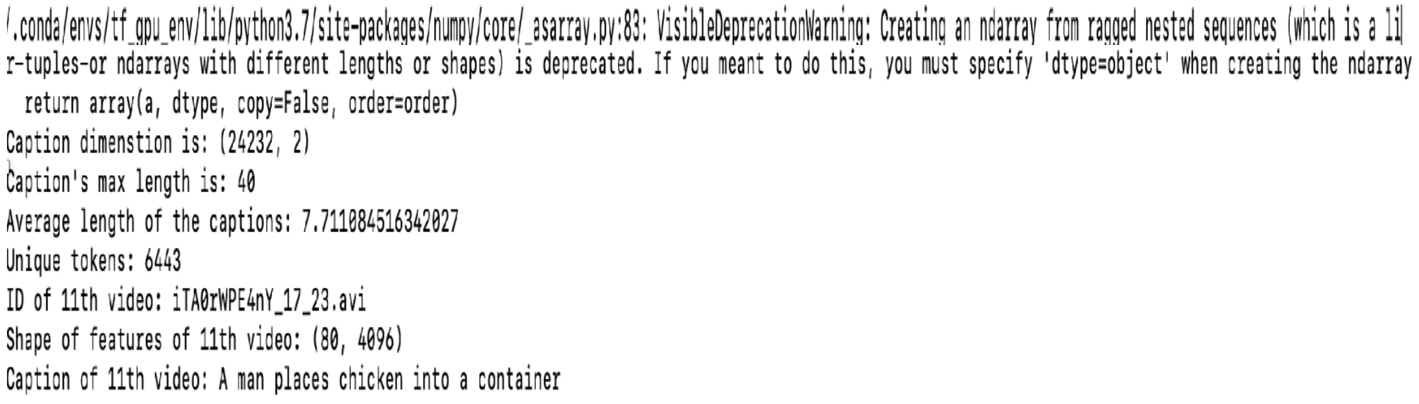
Two object files are created to carry the dictionary of video ids and captions. Object files ‘vid_id.obj’,’ dict_caption.obj’, and’ dict_feat.obj’ are being written to build a dictionary.

For the Execution of sequence.py, I used the following command in the Palmetto cluster at my active node:

python sequence.py /home/skomman/Sandeep/MLDS_hw2_data/training_data/feat/



```
From 6098 words filtered 2881 words to dictionary with minimum count [3]
```



```
/.conda/envs/tf_gpu_env/lib/python3.7/site-packages/numpy/core/_asarray.py:83: VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (which is a li
r-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray
  return array(a, dtype, copy=False, order=order)
Caption dimenstion is: (24232, 2)
Caption's max length is: 40
Average length of the captions: 7.711084516342027
Unique tokens: 6443
ID of 11th video: iTA0rWPE4nY_17_23.avi
Shape of features of 11th video: (80, 4096)
Caption of 11th video: A man places chicken into a container
```

/home/skomman/skomman/MLDS_hw2_data/training_label.json

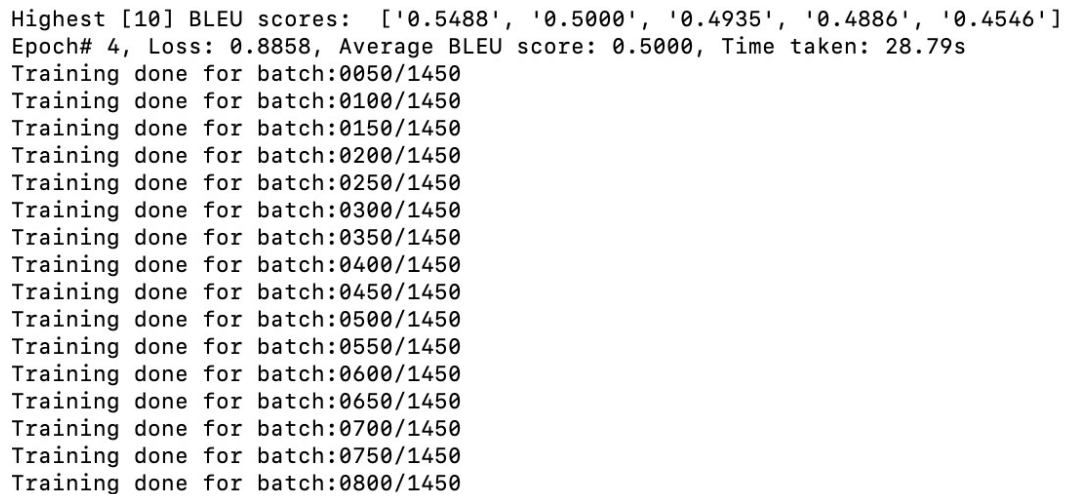
Our next objective will be to train the model we built. Here are two Python files. We'll use sequence.py to create the sequence-to-sequence model. Train.py will be used to train the model. Please see the table below for the Hyperparameters utilized in the experiment. A hyperparameter is a variable whose value governs the learning process. The architecture and volume of a neural network are examples of model hyperparameters. Learning rate and batch size are two examples of algorithm hyperparameters.

HyperParameter	**Value**
Learning rate	0.001
Use_attention	True
Max_encoder_steps	64
Max_decoder_steps	15
Embedding_size	1024
Batch_size	50
Beam_size	5(if beam search is True)

```
python train.py /home/skomman/Sandeep/MLDS_hw2_data/testing_data/feat/
/home/skomman/Sandeep/MLDS_hw2_data/testing_label.json ./output_testset_manish.txt
```

The first argument is the route to the feature map, which is in the form of a.npy file.

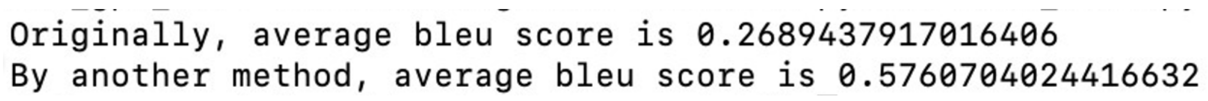
The second argument is the location to the testing label.json file, which contains captions for each video id.



```
Highest [10] BLEU scores:  ['0.5488', '0.5000', '0.4935', '0.4886', '0.4546']
Epoch# 4, Loss: 0.8858, Average BLEU score: 0.5000, Time taken: 28.79s
Training done for batch:0050/1450
Training done for batch:0100/1450
Training done for batch:0150/1450
Training done for batch:0200/1450
Training done for batch:0250/1450
Training done for batch:0300/1450
Training done for batch:0350/1450
Training done for batch:0400/1450
Training done for batch:0450/1450
Training done for batch:0500/1450
Training done for batch:0550/1450
Training done for batch:0600/1450
Training done for batch:0650/1450
Training done for batch:0700/1450
Training done for batch:0750/1450
Training done for batch:0800/1450
```

I computed the Bleu score after each period. The array of blue scores is displayed in descending order of the scores.

Results-



```
Originally, average bleu score is 0.2689437917016406
By another method, average bleu score is 0.5760704024416632
```

I computed the Bleu score with the following command.

python bleu_eval.py test_Sandeep.txt

After four epochs, the average score is about 0.57, i.e. 0.6.

After 200 epochs of training, the bleu score is about 0.610.

https://github.com/SandeepKOmmanaboyina/Deeplearning_HW2