# Report for “Text Generation from Image”

By

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Individual Project

## I. Introduction

Vision is an important sense for human perception and language is essential for communication between humans. With advancement in technology and robotics, building a system that can concurrently process visual stimuli and describe them in natural language would be a powerful tool to have [1]. There has been substantial research in the field of image captioning and many models have been proposed to solve the problem. As part of this project, we will explore a joint model "NIC" [7] which leverages vision CNN and language generating RNN for image captioning.

## II. Motivation

Automatically describing the content of an image using properly formed sentences is a challenging task, but it has the potential to have a great impact [7]. Such a system can be used in chatty robots in wide application areas.

A. Aid to the blind and disabled
   Image captioning can help visually impaired people better understand the content of images on the web. In the futuristic world, such a system can assist blind and disabled people with their day-to-day activities. They can act as the primary caregiver in situations wherein human caregiver is not available. Thus the building of such an intelligent system has substantial positive social impact.

B. Efficient google image search
   Automatic image captioning can generate textual data from images that can be used for google search. The google search results will be able to produce a rich dataset of text and images.

C. Automatic captioning of frames from CCTV footage
   Surveillance systems that can automatically identify suspicious behavior can send timely notifications of potential threat situations. This will help in reducing the crime rate.

D. Self-driving cars
   Systems can be built that can infer from their surroundings. Automatic inference is a crucial task for self-driving cars.

## III. Related work

With advancements in AI and machine learning, a potential solution for image captioning can be implemented using deep learning. There are various alternatives to text generation. For example, an image can be described by a single high-level sentence [4, 5, 6, 7]. With such an approach, there is a restriction on the conveyed information. One recent alternative to single sentence generation is dense captioning which identifies regions of an image and then describes each with a short phrase [8]. This approach has the potential to convey more information however content need not be necessarily coherent. To overcome this limitation, a hierarchical model has been suggested that can leverage the compositional structure of both images and language [1]. Such systems to generate natural language based on an image consist of two main modules: Image Processing Module and Text Generator Module. The basic building blocks are a combination of CNNs and RNNs. CNN is used to extract image features and an RNN is used to describe image into a sentence. The model implemented in this project is based on the "NIC" model [7].

## IV. Datasets

We will need a corpus of images to train the model. Some of the datasets that could be used are as below:

A. Microsoft COCO
   Microsoft COCO is a large-scale dataset for object detection and captioning [2]. This dataset contains 180k images.
B. Visual Genome
   Visual Genome is a dataset to connect well-defined image concepts to language [3].
C. Flickr8k
   This dataset contains 8k images with 5 captions for each image.
D. Flickr30K
   This dataset contains 30k images with 5 captions for each image.

Due to constraints with regards to available processing power and storage, I decided to go ahead with the Flickr8k dataset. The dataset was divided into a training set of 6000 images, and a test set of 1000 images.

## V. Data EDA

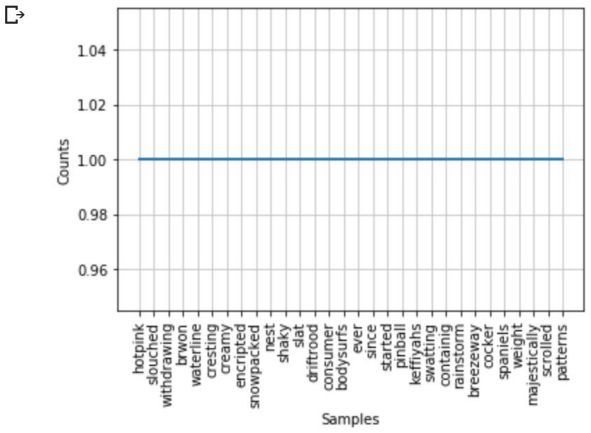
I carried out some exploratory data analysis. Some findings from EDA are as following

A. The captions contain both upper-case and lower-case words

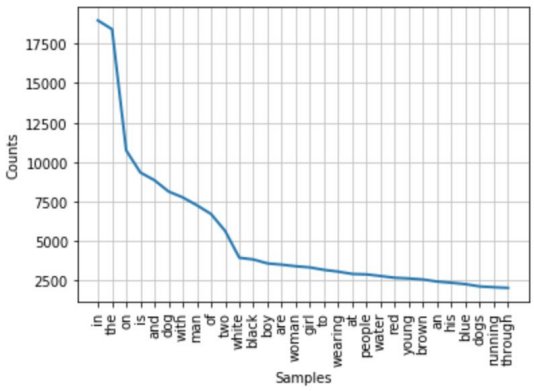
B. The captions contain special tokens such as ‘%’, ‘$’, ‘#’ etc
C. The captions contain alpha-numeric words
D. Plotted graphs to find most and least frequently occurring words

```
[106] # plot words with the least frequency

      least_common = FreqDist(dict(freq_dist.most_common()[-30:]))
      least_common.plot()
```




```
[104] # plot words with the most frequency
      freq_dist.plot(30)
```



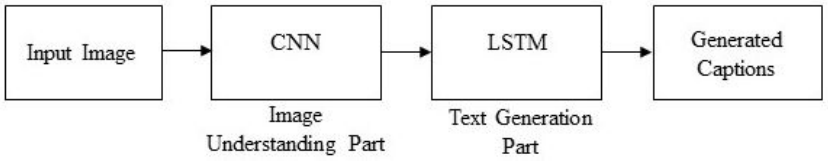

## VI. Data Preprocessing

A. Preprocessing for captions
   1. As part of data preprocessing for captions, I lower-cased all the words (otherwise“hello” and “Hello” will be regarded as two separate words)
   2. Removed special tokens such as ‘%’, ‘$’, ‘#’ etc
   3. Eliminated words which contained numbers such as ‘hey199’, etc
   4. Created a vocabulary of unique words from the dataset

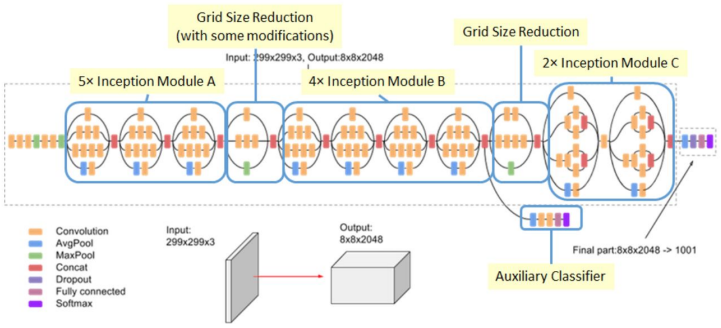
5. Created a dictionary to represent every unique word in the vocabulary by an integer (index)
6. The words which occur very less does not carry much information. Thus, considered words with a frequency of more than 10
7. Calculated the maximum length of a caption
8. Added “startseq” and “endseq” to every caption

B. Preprocessing for images
   1. Converted all the images to size 299x299 as expected by the inception v3 model

## VII. Architecture




A. The architecture of the image captioning consists of a CNN and an RNN. The convolution neural network encodes an image into a compact representation, followed by a recurrent neural network that generates a corresponding sentence.
B. Global image features are extracted from the hidden activations of CNN. Our purpose here is to get a fixed-length informative vector for each image. Steps carried out for image feature vector extraction are as following
   1. Leverage transfer learning by using InceptionV3 model (Convolutional Neural Network) created by Google Research. This model is trained on the Imagenet dataset to perform image classification on 1000 different classes of images.
   2. Remove the last softmax layer from the model
   3. Pass every training and test image to the CNN model (inception v3) to get the corresponding 2048 length feature vector




4. Store the feature vector in a pickle file

C. Image features are then fed into an LSTM to generate a sequence of words. Steps for generating a sequence of words are as following

1. Compute data matrix for image and caption

| | Xi | | Yi |
|---|---|---|---|
| i | Image feature vector | Partial Caption | Target word |
| 1 | Image_1 | startseq | the |
| 2 | Image_1 | startseq the | black |
| 3 | Image_1 | startseq the black | cat |
| 4 | Image_1 | startseq the black cat | sat |
| 5 | Image_1 | startseq the black cat sat | on |
| 6 | Image_1 | startseq the black cat sat on | grass |
| 7 | Image_1 | startseq the black cat sat on grass | endseq |
| 8 | Image_2 | startseq | the |
| 9 | Image_2 | startseq the | white |
| 10 | Image_2 | startseq the white | cat |
| 11 | Image_2 | startseq the white cat | is |
| 12 | Image_2 | startseq the white cat is | walking |
| 13 | Image_2 | startseq the white cat is walking | on |
| 14 | Image_2 | startseq the white cat is walking on | road |
| 15 | Image_2 | startseq the white cat is walking on road | endseq |

data points corresponding to image 1 and its caption

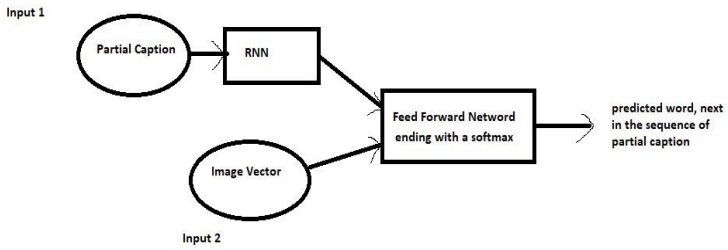
data points corresponding to image 2 and its caption

Data Matrix for both the images and captions

| | Xi | | Yi |
|---|---|---|---|
| i | Image feature vector | Partial Caption | Target word |
| 1 | Image_1 | [9] | 10 |
| 2 | Image_1 | [9, 10] | 1 |
| 3 | Image_1 | [9, 10, 1] | 2 |
| 4 | Image_1 | [9, 10, 1, 2] | 8 |
| 5 | Image_1 | [9, 10, 1, 2, 8] | 6 |
| 6 | Image_1 | [9, 10, 1, 2, 8, 6] | 4 |
| 7 | Image_1 | [9, 10, 1, 2, 8, 6, 4] | 3 |
| 8 | Image_2 | [9] | 10 |
| 9 | Image_2 | [9, 10] | 12 |
| 10 | Image_2 | [9, 10, 12] | 2 |
| 11 | Image_2 | [9, 10, 12, 2] | 5 |
| 12 | Image_2 | [9, 10, 12, 2, 5] | 11 |
| 13 | Image_2 | [9, 10, 12, 2, 5, 11] | 6 |
| 14 | Image_2 | [9, 10, 12, 2, 5, 11, 6] | 7 |
| 15 | Image_2 | [9, 10, 12, 2, 5, 11, 6, 7] | 3 |

Data matrix after replacing the words by their indices

2. Map every word (index) to a 200-long vector using a pre-trained GLOVE Model
3. Create a merge model for the two inputs, image vector and captions



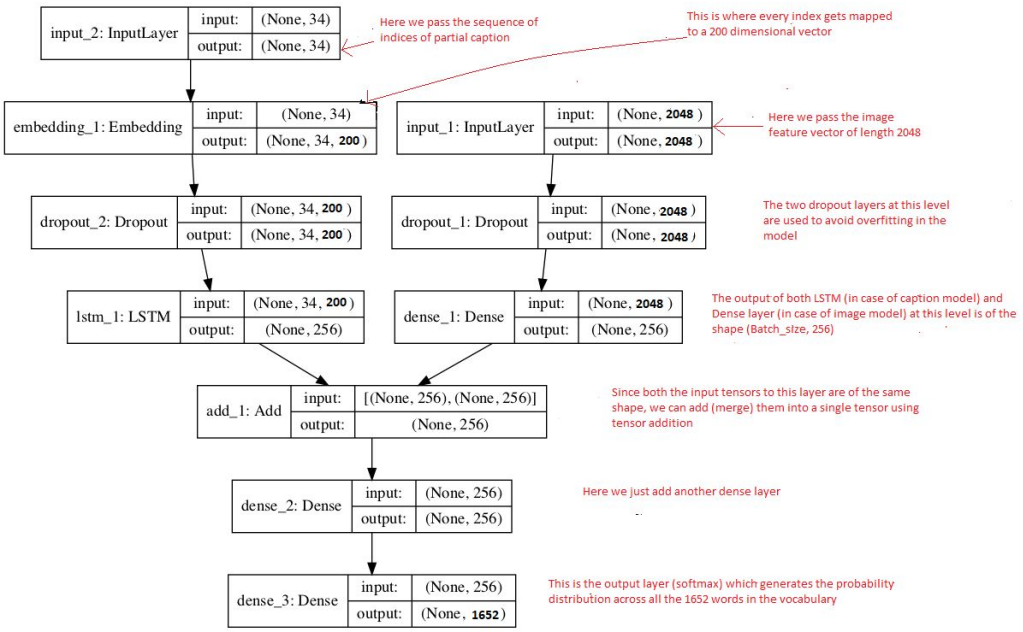

## VIII. Model summary and hyper-parameters

A. Used Inception V3 for CNN
B. Used multi-layered LSTM for RNN
C. Used pre-trained GLOVE model for word embeddings

```
model.summary()
```

```
_________________________________________________________________________________________________
Layer (type)                 Output Shape              Param #     Connected to
=================================================================================================
input_4 (InputLayer)         (None, 34)                0
_________________________________________________________________________________________________
input_3 (InputLayer)         (None, 2048)              0
_________________________________________________________________________________________________
embedding_2 (Embedding)      (None, 34, 200)           330400      input_4[0][0]
_________________________________________________________________________________________________
dropout_3 (Dropout)          (None, 2048)              0           input_3[0][0]
_________________________________________________________________________________________________
dropout_4 (Dropout)          (None, 34, 200)           0           embedding_2[0][0]
_________________________________________________________________________________________________
dense_2 (Dense)              (None, 256)               524544      dropout_3[0][0]
_________________________________________________________________________________________________
lstm_2 (LSTM)                (None, 256)               467968      dropout_4[0][0]
_________________________________________________________________________________________________
add_2 (Add)                  (None, 256)               0           dense_2[0][0]
                                                                   lstm_2[0][0]
_________________________________________________________________________________________________
dense_3 (Dense)              (None, 256)               65792       add_2[0][0]
_________________________________________________________________________________________________
dense_4 (Dense)              (None, 1652)              424564      dense_3[0][0]
=================================================================================================
Total params: 1,813,268
Trainable params: 1,813,268
Non-trainable params: 0
```

Summary of the parameters in the model




D. Values for hyper-parameters are as following

| **Hyperparameter** | **Value** |
|---|---|
| Learning rate | 0.0001 |
| Epochs | 30 |
| Batch size | 6 |
| Dropout rate | 0.5 |

| | |
|---|---|
| Embedding size | 200 |
| LSTM output size | 1652 |
| Optimizer | adam |
| Loss computation | categorical_crossentropy |

## IX. Inference methodology

### A. Sampling

1. Iteratively generate caption one word at a time
2. **Greedily** select the word with the maximum probability
3. Stop the iterations on receiving an '**endseq**' token which means the model thinks that this is the end of the caption or when a maximum **threshold** of the number of words generated by the model is reached.

### B. Beam Search

1. Iteratively consider the set of the k best sentences up to time t as candidates to generate sentences of size t + 1
2. keep only the resulting best k of them

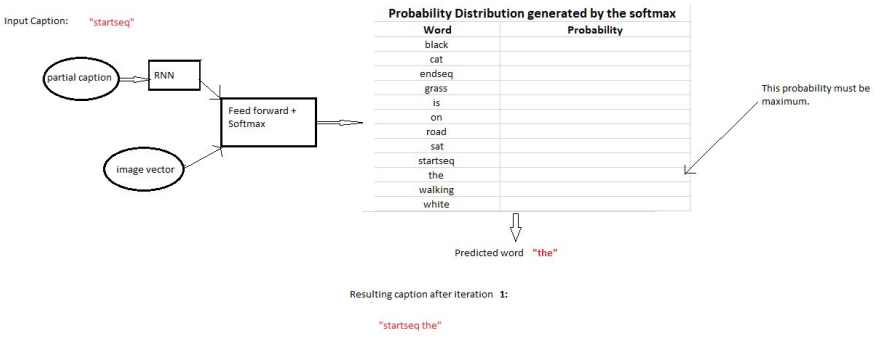
C. **Sampling** inference method has been used in the project to predict the caption for the test image. Example of sampling inference method [9] is as following


Test image

Caption: the black cat is walking on grass
Also, the vocabulary in this particular example is
vocab: {black, cat, endseq, grass, is, on, road, sat, startseq, the, walking, white}.
We will generate the caption iteratively, one word at a time. In each iteration, the model will generate a 12-long vector(in the sample example while a 1652-long vector in the original example). The vector is a

probability distribution across all the words in the vocabulary. We will greedily select the word with the maximum probability.

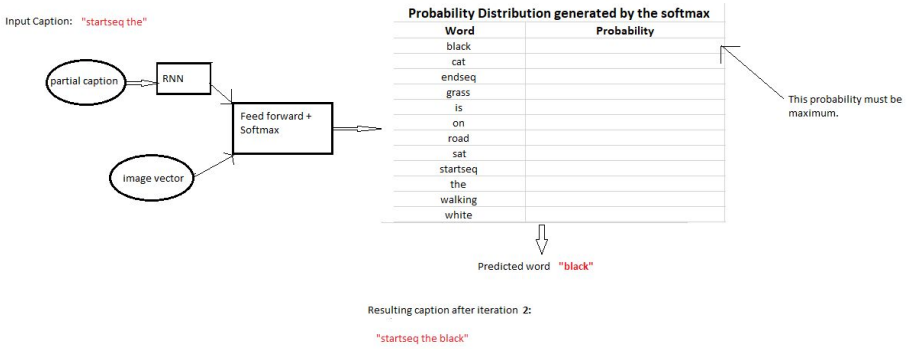
**Iteration 1:**
Input: Image vector + “startseq” (as partial caption)
Expected Output word: “the”




**Iteration 2:**

Input: Image vector + “startseq the”

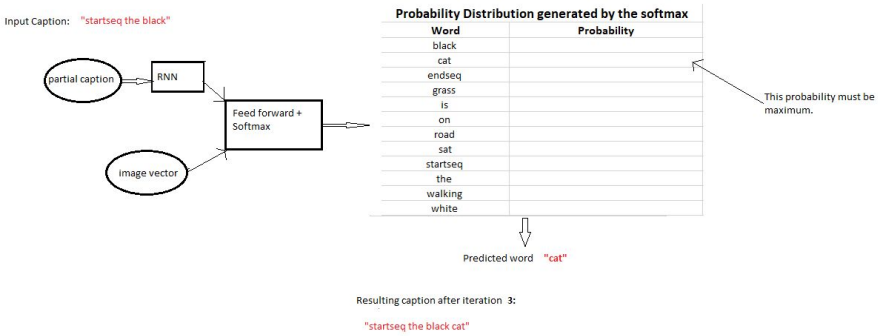
Expected Output word: “black




**Iteration 3:**

Input: Image vector + “startseq the black”

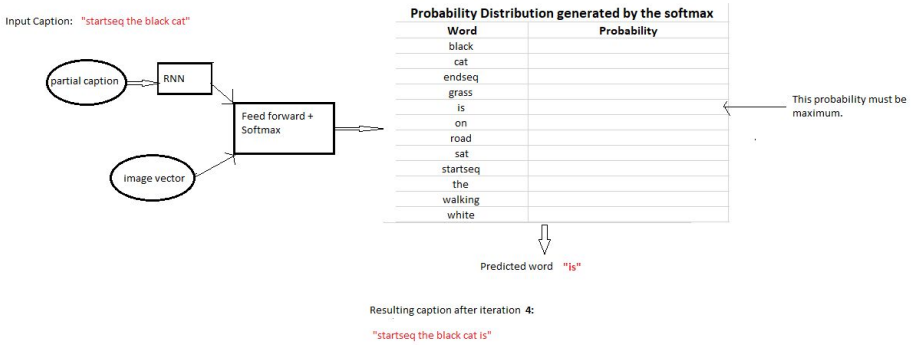
Expected Output word: “cat”




## Iteration 4:

Input: Image vector + “startseq the black cat”

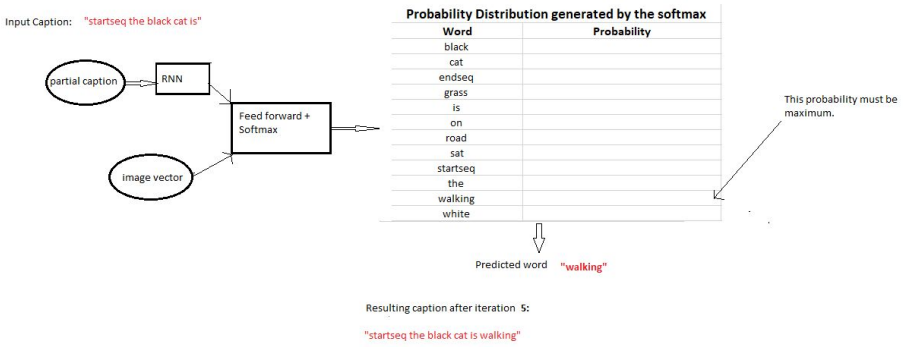
Expected Output word: “is”




## Iteration 5:

Input: Image vector + “startseq the black cat is”

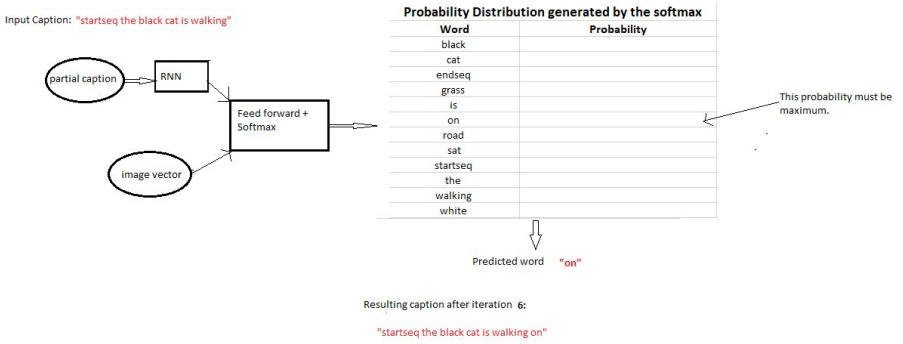
Expected Output word: “walking”




**Iteration 6:**

Input: Image vector + "startseq the black cat is walking"

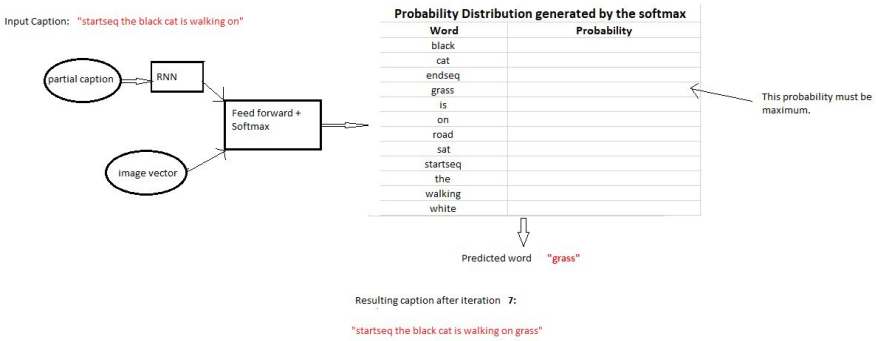
Expected Output word: "on"




**Iteration 7:**

Input: Image vector + "startseq the black cat is walking on"

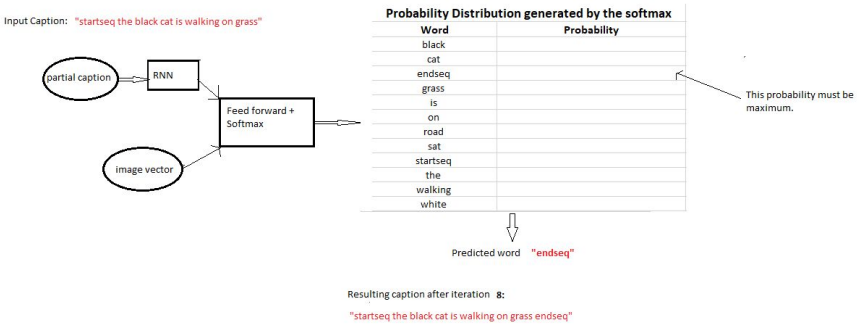
Expected Output word: "grass"




**Iteration 8:**

Input: Image vector + "startseq the black cat is walking on grass"

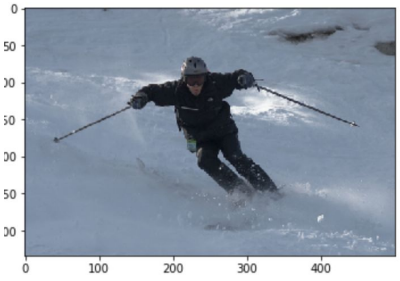
Expected Output word: "endseq"




## X. Examples of caption generation by the proposed model

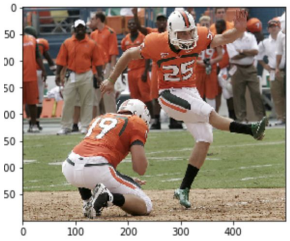
Index:899 Greedy:girl smiles while swinging on swing set

Index:677 Greedy:two girls are playing in the garden



dex:466 Greedy:man skiing down snowy mountain

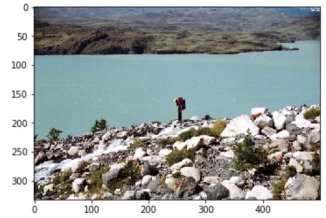
dex:400 Greedy:man stands on top of mountain



dex:500 Greedy:two football players attempt to get the ball

ndex:1 Greedy:two dogs are running through the gra

ndex:0 Greedy:dog runs through the snow



Index:3 Greedy:man stands on top of cliff overlooking mountains

## XI. Evaluation Metrics

Following BLEU (Bilingual Evaluation Understudy) metrics were used to evaluate performance

| Metrics | Score |
|---|---|
| **BLEU-1** | **0.438373** |
| **BLEU-2** | **0.251009** |
| **BLEU-3** | **0.171954** |
| **BLEU-4** | **0.079744** |

## XII. References


[1] Jonathan Krause, Justin Johnson, Ranjay Krishna, Li Fei-Fei: A Hierarchical Approach for Generating Descriptive Image Paragraphs, In IEEE CVPR conference, 2017

[2] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Doll´ar, and C. L. Zitnick. Microsoft coco: Common objects in context. In ECCV, 2014.

[3] R. Krishna, Y. Zhu, O. Groth, J. Johnson, K. Hata, J. Kravitz, S. Chen, Y. Kalantidis, L.-J. Li, D. A. Shamma, M. Bernstein, and L. Fei-Fei. Visual genome: Connecting language and vision using crowdsourced dense image annotations. arXiv preprint arXiv:1602.07332, 2016.

[4] X. Chen and C. Lawrence Zitnick. Mind's eye: A recurrent visual representation for image caption generation. In CVPR, 2015.

[5] J. Donahue, L. Anne Hendricks, S. Guadarrama, M. Rohrbach, S. Venugopalan, K. Saenko, and T. Darrell. Long-term recurrent convolutional networks for visual recognition and description. In CVPR, 2015.

[6] A. Karpathy and L. Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In CVPR, 2015.

[7] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan. Show and tell: A neural image caption generator. In CVPR, 2015.

[8] J. Johnson, A. Karpathy, and L. Fei-Fei. DenseCap: Fully convolutional localization networks for dense captioning. In CVPR, 2016.

[9]
https://towardsdatascience.com/image-captioning-with-keras-teaching-computers-to-describe-pictures-c88a46a311b8

## XIII. Project Links

A. Youtube link for individual project presentation and project details
https://www.youtube.com/watch?v=y9f2BcCA-Xo&feature=youtu.be

B. Github link for project implementation
https://github.com/kruti-thukral/image_captioning

C. Dataset can be downloaded from
https://machinelearningmastery.com/develop-a-deep-learning-caption-generation-model-in-python/
Datasets that need to be downloaded from the above link are as follows
Flickr8k_Dataset.zip
Flickr8k_text.zip

D. Pre-trained Glove embeddings can be downloaded from
https://nlp.stanford.edu/projects/glove/
glove.6B.zip from above link was used in the project