

# Configuration Manual

MSc Research Project  
MSc In Data Analytics

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# Configuration Manual

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## 1 Introduction

This configuration manual explains how to set up the system and environment for the code to work. It also outlines the steps taken to put the research into action. The manual explains feature extraction, data preprocessing, and modeling with the appropriate snippets.

## 2 System Configuration

### 2.1 Hardware Configuration

- **Host Machine/Operating System:** Lenovo-IdeaPad Gaming 3 15IMH05/Windows 10
- **RAM:** 8GB, Core-i7 processor
- **Cloud Config:** Google Colab Tesla-P100 GPU with 16GB RAM

### 2.2 Software Configuration

- **Programming Language:** Python 3.7
- **Distribution:** Anaconda Distribution
- **IDE:** Jupyter Notebook
- **Cloud Environment:** Google Collaboratory
- **Browser:** Google Chrome

## 3 Data Collection and Running the Model

### 3.1 Downloading the Data

The image data set can be downloaded from the kaggle link <https://www.kaggle.com/shadabhussain/flickr8k> and the machine translated text for the corresponding images can be downloaded from the github repository<sup>1</sup>. Load the data on the drive and then mount it on google colab to use it.

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<sup>1</sup><https://github.com/rathiankit03/ImageCaptionHindi/blob/master/Flickr8kHindiDataset/Unclean-5Sentences.txt>

## 3.2 Image Feature Extraction

Image Feature extraction is done by using pre trained CNN such as VGG16, InceptionV3 and ResNet50. Keras is used to load the CNN libraries.

```
from keras.applications.vgg16 import VGG16
from keras.applications.resnet50 import ResNet50
from keras.applications.inception_v3 import InceptionV3
```

Figure 1: Keras CNN libraries

For Image feature extraction remove the last layer of the CNN and and change the target size of the image according to the requirement of the CNN. For Vgg16 and Resnet its is 224\*224 and for InceptionV3 it's 229\*229.

```
def extract_features(directory):
    # load the model
    #model_resnet50 = ResNet50()
    #model_inceptionV3 = InceptionV3()
    model_vgg16 = VGG16()
    model = Sequential()

    # re-structure the model
    for layer in model_vgg16.layers[:-1]: # this is where I changed your code
        model.add(layer)

    # summarize
    print(model.summary())
    # extract features from each photo
    features = dict()
    for name in listdir(directory):
        # load an image from file
        filename = directory + '/' + name
        image = load_img(filename, target_size=(224, 224))
        # convert the image pixels to a numpy array
        image = img_to_array(image)
        # reshape data for the model
        image = image.reshape((1, image.shape[0], image.shape[1], image.shape[2]))
        # prepare the image for the VGG model
        image = preprocess_input(image)
        # get features
        feature = model.predict(image, verbose=0)
        # get image id
        image_id = name.split('.')[0]
        # store feature
        features[image_id] = feature
        print('>%s' % name)
    return features
```

Figure 2: Image Feature Extraction

After extracting the image, store the image in a pickle file so that it can be reused if needed.

```
# save to file
dump(features, open('VGG16.pkl', 'wb'))
```

Figure 3: Saving Pickle File

### 3.3 Text loading and Pr-processing

After extraction of image features we load the text in a dictionary and save the file.

```
# extract descriptions for images
def load_descriptions(doc):
    mapping = dict()
    # process lines
    for line in doc.split('\n'):
        # split line by white space
        tokens = line.split()
        if len(line) < 2:
            continue
        # take the first token as the image id, the rest as the description
        image_id, image_desc = tokens[0], tokens[1:]
        # remove filename from image id
        image_id = image_id.split('.')[0]
        # convert description tokens back to string
        image_desc = ' '.join(image_desc)
        # create the list if needed
        if image_id not in mapping:
            mapping[image_id] = list()
        # store description
        mapping[image_id].append(image_desc)
    return mapping
```

Figure 4: Loading Description

The image descriptions are then added wrapping tags 'startseq' and 'endseq' so that the machine can understand start and end of the image description.

```
def load_clean_descriptions(filename, dataset):
    # load document
    doc = load_doc(filename)
    descriptions = dict()
    for line in doc.split('\n'):
        # split line by white space
        tokens = line.split()
        # split id from description
        image_id, image_desc = tokens[0], tokens[1:]
        # skip images not in the set
        if image_id in dataset:
            # create list
            if image_id not in descriptions:
                descriptions[image_id] = list()
            # wrap description in tokens
            desc = 'startseq ' + ' '.join(image_desc) + ' endseq'
            # store
            descriptions[image_id].append(desc)
    return descriptions
```

Figure 5: Wrapping Tags

After wrapping the text we need to create tokens of the text so that machine can understand it. The text is tokenized by importing tokenizer from the keras library. Save the tokenizer in a pickle file

```

# fit a tokenizer given caption descriptions
def create_tokenizer(descriptions):
    lines = to_lines(descriptions)
    tokenizer = Tokenizer()
    tokenizer.fit_on_texts(lines)
    return tokenizer

```

Figure 6: Creating Tokenizer

### 3.4 Modelling

The encoded text and image features are passed through a model. This is where we define our LSTM and Bi-LSTM layer.

```

# define the captioning model
def define_model(vocab_size, max_length):
    # feature extractor model
    inputs1 = Input(shape=(4096,))
    fe1 = Dropout(0.5)(inputs1)
    fe2 = Dense(256, activation='relu')(fe1)
    # sequence model
    inputs2 = Input(shape=(max_length,))
    se1 = Embedding(vocab_size, 256, mask_zero=True)(inputs2)
    se2 = Dropout(0.5)(se1)
    se3 = Bidirectional(LSTM(128, return_sequences = True))(se2)
    se4 = Bidirectional(LSTM(128))(se3)

    # decoder model
    decoder1 = add([fe2, se4])
    decoder2 = Dense(256, activation='relu')(decoder1)
    outputs = Dense(vocab_size, activation='softmax')(decoder2)
    # tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam')
    # summarize model
    print(model.summary())
    return model

```

Figure 7: Model

The data in this model is loaded progressively for that a generator function is defined which is called in `model.fit_generator()` when the model is compiled.

```

#Below code is used to progressively load the batch of data
# data generator, intended to be used in a call to model.fit_generator()
def data_generator(descriptions, photos, tokenizer, max_length):
    # loop for ever over images
    while 1:
        for key, desc_list in descriptions.items():
            # retrieve the photo feature
            photo = photos[key][0]
            in_img, in_seq, out_word = create_sequences(tokenizer, max_length, desc_list, photo)
            yield (in_img, in_seq), out_word

```

Figure 8: Generator Function

### 3.5 Quantitative Evaluation

The Model is evaluated on BLUE score. For calculating the BLUE score the predicted descriptions are compared to the actual captions.

```
# evaluate the skill of the model
def evaluate_model(model, descriptions, photos, tokenizer, max_length):
    actual, predicted = list(), list()
    # step over the whole set
    for key, desc_list in descriptions.items():
        # generate description
        yhat = generate_desc(model, tokenizer, photos[key], max_length)
        # store actual and predicted
        references = [d.split() for d in desc_list]
        actual.append(references)
        predicted.append(yhat.split())
    # calculate BLEU score
    print('BLEU-1: %f' % corpus_bleu(actual, predicted, weights=(1.0, 0, 0, 0)))
    print('BLEU-2: %f' % corpus_bleu(actual, predicted, weights=(0.5, 0.5, 0, 0)))
    print('BLEU-3: %f' % corpus_bleu(actual, predicted, weights=(0.3, 0.3, 0.3, 0)))
    print('BLEU-4: %f' % corpus_bleu(actual, predicted, weights=(0.25, 0.25, 0.25, 0.25)))
```

Figure 9: BLUE score evaluation

### 3.6 Qualitative Evaluation

The generated image captions are evaluated manually to see if they make sense and are grammatically correct.

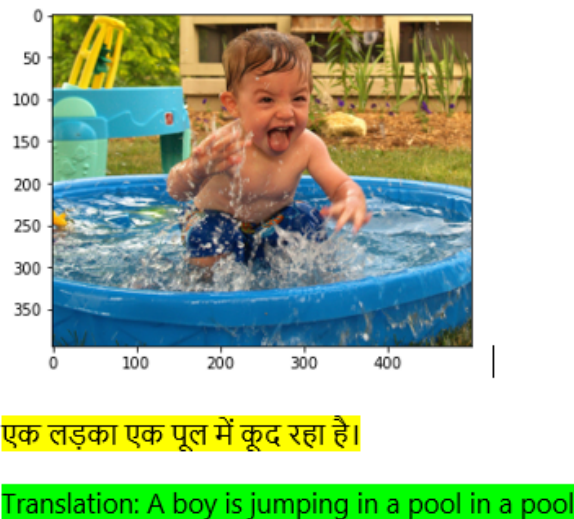


Figure 10: Image with generated Text

## 4 Image Evaluation

After the model run is completed you can download the h5 file with the minimum loss and use it together with the pickle file of tokenizer to generate text for test images.