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How to Use Small Experiments to Develop a Caption Generation Model in Keras

by **Jason Brownlee** on November 24, 2017 in **Deep Learning for Natural Language Processing**

Caption generation is a challenging artificial intelligence problem where a textual description must be generated for a photograph.

It requires both methods from computer vision to understand the content of the image and a language model from the field of natural language processing to turn the understanding of the image into words in the right order. Recently, deep learning methods have achieved state of the art results on examples of this problem.

It can be hard to develop caption generating models on your own data, primarily because the datasets and the models are so large and take days to train. An alternative approach is to explore model configurations with a small sample of the fuller dataset.

In this tutorial, you will discover how you can use a small sample of a standard photo captioning dataset to explore different deep model designs.

After completing this tutorial, you will know:

- How to prepare data for photo captioning modeling.
- How to design a baseline and test harness to evaluate the skill of models and control for their stochastic nature.
- How to evaluate properties like model skill, feature extraction models, and word embeddings in order to lift model skill.

Let's get started.

How to Use Small Experiments to Develop a Caption Generation Model in Keras
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Tutorial Overview

This tutorial is divided into 6 parts; they are:

1. Data Preparation
2. Baseline Caption Generation Model
3. Network Size Parameters
4. Configuring the Feature Extraction Model
5. Word Embedding Models
6. Analysis of Results

Python Environment

This tutorial assumes you have a Python SciPy environment installed, ideally with Python 3.

You must have Keras (2.0 or higher) installed with either the TensorFlow or Theano backend.

The tutorial also assumes you have scikit-learn, Pandas, NumPy, and Matplotlib installed.

If you need help with your environment, see this tutorial:

- How to Setup a Python Environment for Machine Learning and Deep Learning with Anaconda

I recommend running the code on a system with a GPU.

You can access GPUs cheaply on Amazon Web Services. Learn how in this tutorial:

- How To Develop and Evaluate Large Deep Learning Models with Keras on Amazon Web Services

Let's dive in.

Data Preparation

First, we need to prepare the dataset for training the model.

We will use the Flickr8K dataset that is comprised of a little more than 8,000 photographs and their descriptions.

You can download the dataset from here:

- Framing image description as a ranking task: data, models and evaluation metrics.

Unzip the photographs and descriptions into your current working directory into *Flicker8k_Dataset* and *Flickr8k_text* directories respectively.

There are two parts to the data preparation, they are:

1. Preparing the Text
2. Preparing the Photos

Preparing the Text

The dataset contains multiple descriptions for each photograph and the text of the descriptions requires some minimal cleaning.

First, we will load the file containing all of the descriptions.

```
# load doc into memory
def load_doc(filename):
    # open the file as read only
    file = open(filename, 'r')
    # read all text
    text = file.read()
    # close the file
    file.close()
    return text

filename = 'Flickr8k_text/Flickr8k.token.txt'
# load descriptions
doc = load_doc(filename)
```

Each photo has a unique identifier. This is used in the photo filename and in the text file of descriptions. Next, we will step through the list of photo descriptions and save the first description for each photo. Below defines a function named *load_descriptions()* that, given the loaded document text, will return a dictionary of photo identifiers to descriptions.

```
# 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)
        # store the first description for each image
        if image_id not in mapping:
            mapping[image_id] = image_desc
    return mapping

# parse descriptions
descriptions = load_descriptions(doc)
print('Loaded: %d ' % len(descriptions))
```

Next, we need to clean the description text.

The descriptions are already tokenized and easy to work with. We will clean the text in the following ways in order to reduce the size of the vocabulary of words we will need to work with:

- Convert all words to lowercase.
- Remove all punctuation.
- Remove all words that are one character or less in length (e.g. ‘a’).

Below defines the *clean_descriptions()* function that, given the dictionary of image identifiers to descriptions, steps through each description and cleans the text.

```
import string

def clean_descriptions(descriptions):
    # prepare translation table for removing punctuation
    table = str.maketrans('', '', string.punctuation)
    for key, desc in descriptions.items():
        # tokenize
        desc = desc.split()
        # convert to lower case
        desc = [word.lower() for word in desc]
        # remove punctuation from each token
        desc = [w.translate(table) for w in desc]
        # remove hanging 's' and 'a'
        desc = [word for word in desc if len(word)>1]
        # store as string
        descriptions[key] =  ' '.join(desc)

# clean descriptions
clean_descriptions(descriptions)
# summarize vocabulary
all_tokens = ' '.join(descriptions.values()).split()
vocabulary = set(all_tokens)
print('Vocabulary Size: %d' % len(vocabulary))
```

Finally, we save the dictionary of image identifiers and descriptions to a new file named *descriptions.txt*, with one image identifier and description per line.

Below defines the *save_doc()* function that given a dictionary containing the mapping of identifiers to descriptions and a filename, saves the mapping to file.

```
# save descriptions to file, one per line
def save_doc(descriptions, filename):
    lines = list()
    for key, desc in descriptions.items():
        lines.append(key + ' ' + desc)
    data = '\n'.join(lines)
    file = open(filename, 'w')
    file.write(data)
    file.close()

# save descriptions
save_doc(descriptions, 'descriptions.txt')
```

Putting this all together, the complete listing is provided below.

```
import string

# load doc into memory
def load_doc(filename):
    # open the file as read only
    file = open(filename, 'r')
    # read all text
    text = file.read()
    # close the file
    file.close()
    return text

# 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)
        # store the first description for each image
        if image_id not in mapping:
            mapping[image_id] = image_desc
    return mapping

def clean_descriptions(descriptions):
    # prepare translation table for removing punctuation
    table = str.maketrans('', '', string.punctuation)
    for key, desc in descriptions.items():
        # tokenize
        desc = desc.split()
        # convert to lower case
        desc = [word.lower() for word in desc]
        # remove punctuation from each token
        desc = [w.translate(table) for w in desc]
        # remove hanging 's' and 'a'
        desc = [word for word in desc if len(word)>1]
        # store as string
        descriptions[key] =  ' '.join(desc)

# save descriptions to file, one per line
def save_doc(descriptions, filename):
    lines = list()
    for key, desc in descriptions.items():
        lines.append(key + ' ' + desc)
    data = '\n'.join(lines)
    file = open(filename, 'w')
    file.write(data)
    file.close()

filename = 'Flickr8k_text/Flickr8k.token.txt'
# load descriptions
doc = load_doc(filename)
# parse descriptions
descriptions = load_descriptions(doc)
print('Loaded: %d ' % len(descriptions))
# clean descriptions
clean_descriptions(descriptions)
# summarize vocabulary
all_tokens = ' '.join(descriptions.values()).split()
vocabulary = set(all_tokens)
print('Vocabulary Size: %d' % len(vocabulary))
# save descriptions
save_doc(descriptions, 'descriptions.txt')
```

Running the example first prints the number of loaded photo descriptions (8,092) and the size of the clean vocabulary (4,484 words).

```
Loaded: 8092
Vocabulary Size: 4484
```

The clean descriptions are then written to '*descriptions.txt*'. Taking a look in the file, we can see that the descriptions are ready for modeling.

Taking a look in the file, we can see that the descriptions are ready for modeling.

```
3621647714_fc67ab2617 man is standing on snow with trees and mountains all around him
365128300_6966058139 group of people are rafting on river rapids
2751694538_fffa3d307d man and boy sit in the driver seat
537628742_146f2c24f8 little girl running in field
2320125735_27fe729948 black and brown dog with blue collar goes on alert by soccer ball in the g
...
```

Preparing the Photos

We will use a pre-trained model to interpret the content of the photos.

There are many models to choose from. In this case, we will use the Oxford Visual Geometry Group or VGG model that won the ImageNet competition in 2014. Learn more about the model here:

- Very Deep Convolutional Networks for Large-Scale Visual Recognition

Keras provides this pre-trained model directly. Note, the first time you use this model, Keras will download the model weights from the Internet, which are about 500 Megabytes. This may take a few minutes depending on your internet connection.

We could use this model as part of a broader image caption model. The problem is, it is a large model and running each photo through the network every time we want to test a new language model configuration (downstream) is redundant.

Instead, we can pre-compute the “photo features” using the pre-trained model and save them to file. We can then load these features later and feed them into our model as the interpretation of a given photo in the dataset. It is no different to running the photo through the full VGG model, it is just that we will have done it once in advance.

This is an optimization that will make training our models faster and consume less memory.

We can load the VGG model in Keras using the VGG class. We will load the model without the top; this means without the layers at the end of the network that are used to interpret the features extracted from the input and turn them into a class prediction. We are not interested in the image net classification of the photos and we will train our own interpretation of the image features.

Keras also provides tools for reshaping the loaded photo into the preferred size for the model (e.g. 3 channel 224 x 224 pixel image).

Below is a function named *extract_features()* that given a directory name will load each photo, prepare it for VGG and collect the predicted features from the VGG model. The image features are a 3-dimensional array with the shape (7, 7, 512).

The function returns a dictionary of image identifier to image features.

```
# extract features from each photo in the directory
def extract_features(directory):
    # load the model
    in_layer = Input(shape=(224, 224, 3))
    model = VGG16(include_top=False, input_tensor=in_layer)
    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
```

We can call this function to prepare the photo data for testing our models, then save the resulting dictionary to a file named '*features.pkl*'.

The complete example is listed below.

```
from os import listdir
from pickle import dump
from keras.applications.vgg16 import VGG16
from keras.preprocessing.image import load_img
from keras.preprocessing.image import img_to_array
from keras.applications.vgg16 import preprocess_input
from keras.layers import Input

# extract features from each photo in the directory
def extract_features(directory):
    # load the model
    in_layer = Input(shape=(224, 224, 3))
    model = VGG16(include_top=False, input_tensor=in_layer)
    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

# extract features from all images
```

```
directory = 'Flicker8k_Dataset'
features = extract_features(directory)
print('Extracted Features: %d' % len(features))
# save to file
dump(features, open('features.pkl', 'wb'))
```

Running this data preparation step may take a while depending on your hardware, perhaps one hour on the CPU with a modern workstation.

At the end of the run, you will have the extracted features stored in '*features.pkl*' for later use.

Baseline Caption Generation Model

In this section, we will define a baseline model for generating captions for photos and how to evaluate it so that it can be compared to variations on this baseline.

This section is divided into 5 parts:

1. Load Data.
2. Fit Model.
3. Evaluate Model.
4. Complete Example
5. "A" versus "A" Test
6. Generate Photo Captions

1. Load Data

We are not going to fit the model on all of the caption data, or even on a large sample of the data.

In this tutorial, we are interested in quickly testing a suite of different configurations of a caption model to see what works on this data. That means we need the evaluation of one model configuration to happen quickly. Toward this end, we will train the models on 100 photographs and captions, then evaluate them on both the training dataset and on a new test set of 100 photographs and captions.

First, we need to load a pre-defined subset of photographs. The provided dataset has separate sets for train, test, and development, which are really just different groups of photo identifiers. We will load the development set and use the first 100 identifiers for train and the second 100 (e.g. from 100 to 200) as the test set.

The function *load_set()* below will load a pre-defined set of identifiers, and we will call it with the '*Flickr_8k.devImages.txt*' filename as an argument.

```
# load a pre-defined list of photo identifiers
def load_set(filename):
    doc = load_doc(filename)
    dataset = list()
    # process line by line
    for line in doc.split('\n'):
        # skip empty lines
        if len(line) < 1:
            continue
        # get the image identifier
        identifier = line.split('.')[0]
        dataset.append(identifier)
    return set(dataset)
```

Next, we need to split the set into train and test sets.

We will start by ordering the identifiers by sorting them to ensure we always split them consistently across machines and runs, then take the first 100 for train and the next 100 for test.

The *train_test_split()* function below will create this split given the loaded set of identifiers as input.

```
# split a dataset into train/test elements
def train_test_split(dataset):
    # order keys so the split is consistent
    ordered = sorted(dataset)
    # return split dataset as two new sets
    return set(ordered[:100]), set(ordered[100:200])
```

Now, we can load the photo descriptions using the pre-defined set of train or test identifiers.

Below is the function *load_clean_descriptions()* that loads the cleaned text descriptions from '*descriptions.txt*' for a given set of identifiers and returns a dictionary of identifier to text.

The model we will develop will generate a caption given a photo, and the caption will be generated one word at a time. The sequence of previously generated words will be provided as input. Therefore, we will need a "*first word*" to kick-off the generation process and a '*last word*' to signal the end of the caption. We will use the strings '*startseq*' and '*endseq*' for this purpose.

```
# load clean descriptions into memory
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:
            # store
            descriptions[image_id] = 'startseq ' + ' '.join(image_desc) + ' endseq'
    return descriptions
```

Next, we can load the photo features for a given dataset.

Below defines a function named *load_photo_features()* that loads the entire set of photo descriptions, then returns the subset of interest for a given set of photo identifiers. This is not very efficient as the loaded dictionary of all photo features is about 700 Megabytes. Nevertheless, this will get us up and running quickly.

Note, if you have a better approach, share it in the comments below.

```
# load photo features
```

```
def load_photo_features(filename, dataset):
    # load all features
    all_features = load(open(filename, 'rb'))
    # filter features
    features = {k: all_features[k] for k in dataset}
    return features
```

We can pause here and test everything developed so far.

The complete code example is listed below.

```
from pickle import load

# load doc into memory
def load_doc(filename):
    # open the file as read only
    file = open(filename, 'r')
    # read all text
    text = file.read()
    # close the file
    file.close()
    return text

# load a pre-defined list of photo identifiers
def load_set(filename):
    doc = load_doc(filename)
    dataset = list()
    # process line by line
    for line in doc.split('\n'):
        # skip empty lines
        if len(line) < 1:
            continue
        # get the image identifier
        identifier = line.split('.')[0]
        dataset.append(identifier)
    return set(dataset)

# split a dataset into train/test elements
def train_test_split(dataset):
    # order keys so the split is consistent
    ordered = sorted(dataset)
    # return split dataset as two new sets
    return set(ordered[:100]), set(ordered[100:200])

# load clean descriptions into memory
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:
            # store
            descriptions[image_id] = 'startseq ' + ' '.join(image_desc) + ' endseq'
    return descriptions

# load photo features
def load_photo_features(filename, dataset):
    # load all features
    all_features = load(open(filename, 'rb'))
    # filter features
    features = {k: all_features[k] for k in dataset}
    return features

# load dev set
filename = 'Flickr8k_text/Flickr_8k.devImages.txt'
dataset = load_set(filename)
print('Dataset: %d' % len(dataset))
# train-test split
train, test = train_test_split(dataset)
print('Train=%d, Test=%d' % (len(train), len(test)))
# descriptions
train_descriptions = load_clean_descriptions('descriptions.txt', train)
test_descriptions = load_clean_descriptions('descriptions.txt', test)
print('Descriptions: train=%d, test=%d' % (len(train_descriptions), len(test_descriptions)))
# photo features
train_features = load_photo_features('features.pkl', train)
test_features = load_photo_features('features.pkl', test)
print('Photos: train=%d, test=%d' % (len(train_features), len(test_features)))
```

Running this example first loads the 1,000 photo identifiers in the development dataset. A train and test set is selected and used to filter the set of clean photo descriptions and prepared image features.

We are nearly there.

```
Dataset: 1,000
Train=100, Test=100
Descriptions: train=100, test=100
Photos: train=100, test=100
```

The description text will need to be encoded to numbers before it can be presented to the model as in input or compared to the model’s predictions.

The first step in encoding the data is to create a consistent mapping from words to unique integer values. Keras provides the Tokenizer class that can learn this mapping from the loaded description data.

Below defines the *create_tokenizer()* that will fit a Tokenizer given the loaded photo description text.

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

# prepare tokenizer
tokenizer = create_tokenizer(descriptions)
vocab_size = len(tokenizer.word_index) + 1
print('Vocabulary Size: %d' % vocab_size)
```

We can now encode the text.

Each description will be split into words. The model will be provided one word and the photo and generate the next word. Then the first two words of the description will be provided to the model as input with the image to generate the next word. This is how the model will be trained.

For example, the input sequence "*little girl running in field*" would be split into 6 input-output pairs to train the model:

```
X1,     X2 (text sequence),                        y (word)
photo   startseq,                                  little
photo   startseq, little,                          girl
photo   startseq, little, girl,                    running
photo   startseq, little, girl, running,           in
photo   startseq, little, girl, running, in,       field
photo   startseq, little, girl, running, in, field, endseq
```

Later when the model is used to generate descriptions, the generated words will be concatenated and recursively provided as input to generate a caption for an image.

The function below named *create_sequences()* given the tokenizer, a single clean description, the features for a photo, and the maximum description length will prepare a set of input-output pairs for training a model. Calling this function will return *X1* and *X2* for the arrays of image data and input sequence data and the *y* value for the output word.

The input sequences are integer encoded and the output word is one-hot encoded to represent the probability distribution of the expected word across the whole vocabulary of possible words.

```
# create sequences of images, input sequences and output words for an image
def create_sequences(tokenizer, desc, image, max_length):
    Ximages, XSeq, y = list(), list(),list()
    vocab_size = len(tokenizer.word_index) + 1
    # integer encode the description
    seq = tokenizer.texts_to_sequences([desc])[0]
    # split one sequence into multiple X,y pairs
    for i in range(1, len(seq)):
        # select
        in_seq, out_seq = seq[:i], seq[i]
        # pad input sequence
        in_seq = pad_sequences([in_seq], maxlen=max_length)[0]
        # encode output sequence
        out_seq = to_categorical([out_seq], num_classes=vocab_size)[0]
        # store
        Ximages.append(image)
        XSeq.append(in_seq)
        y.append(out_seq)
    # Ximages, XSeq, y = array(Ximages), array(XSeq), array(y)
    return [Ximages, XSeq, y]
```

2. Fit Model

We are nearly ready to fit the model.

Parts of the model have already been discussed, but let's re-iterate.

The model is based on the example laid out in the paper "Show and Tell: A Neural Image Caption Generator", 2015.

The model involves three parts:

- **Photo Feature Extractor**. This is a 16-layer VGG model pre-trained on the ImageNet dataset. We have pre-processed the photos with a the VGG model (without the top) and will use the extracted features predicted by this model as input.
- **Sequence Processor**. This is a word embedding layer for handling the text input, followed by an LSTM layer. The LSTM output is interpreted by a Dense layer one output at a time.
- **Interpreter (for lack of a better name)**. Both the feature extractor and sequence processor output a fixed-length vector that is the length of a maximum sequence. These are concatenated together and processed by an LSTM and Dense layer before a final prediction is made.

A conservative number of neurons is used in the base model. Specifically, a 128 Dense layer after the feature extractor, a 50-dimensionality word embedding followed by a 256 unit LSTM and 128 neuron Dense after the sequence processor, and finally a 500 unit LSTM followed by a 500 neuron Dense at the end of the network.

The model predicts a probability distribution across the vocabulary, therefore a softmax activation function is used and a categorical cross entropy loss function is minimized while fitting the network.

The function *define_model()* defines the baseline model, given the size of the vocabulary and the maximum length of photo descriptions. The Keras functional API is used to define the model as it provides the flexibility needed to define a model that takes two input streams and combines them.

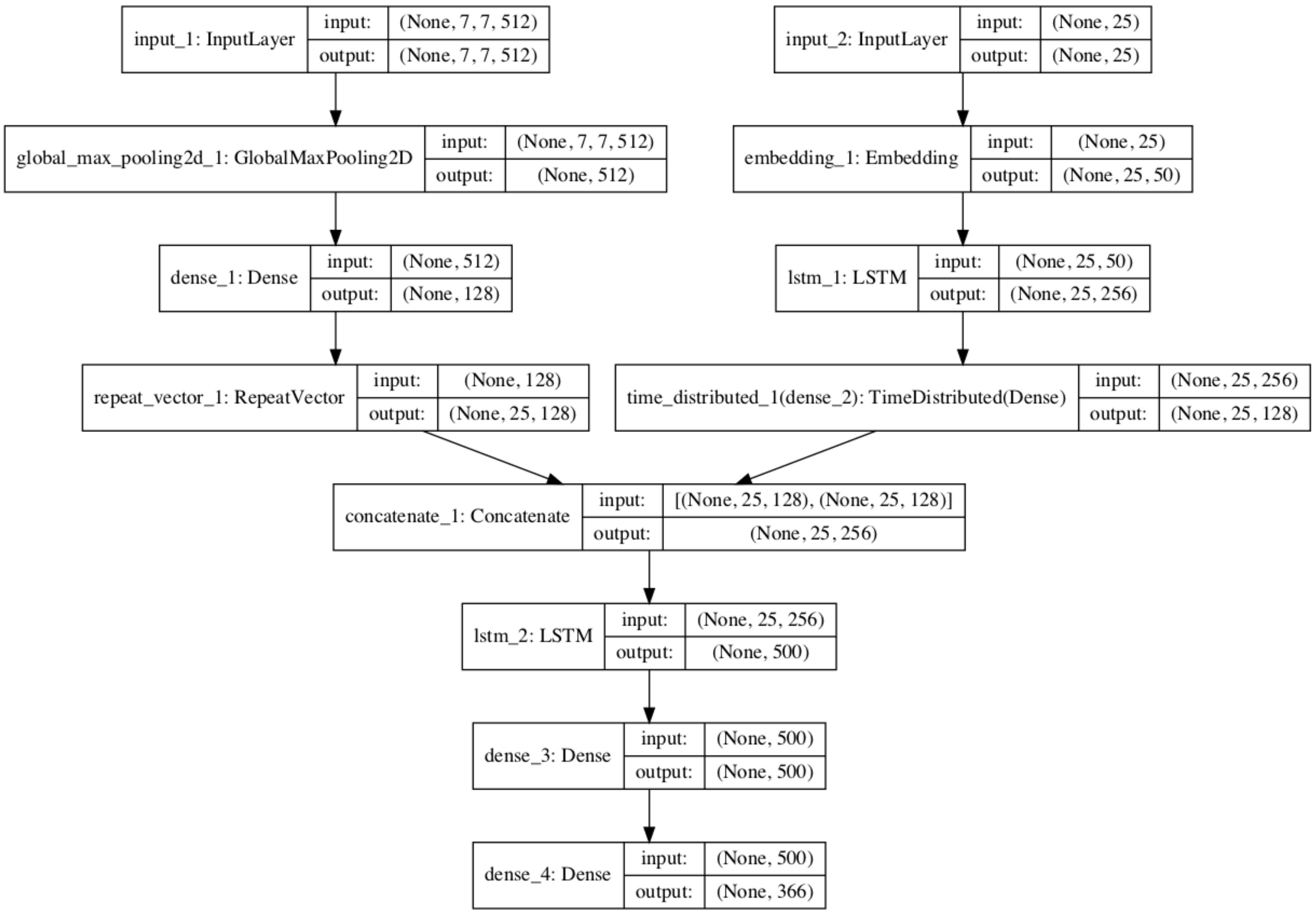
```
# define the captioning model
def define_model(vocab_size, max_length):
    # feature extractor (encoder)
    inputs1 = Input(shape=(7, 7, 512))
    fe1 = GlobalMaxPooling2D()(inputs1)
    fe2 = Dense(128, activation='relu')(fe1)
    fe3 = RepeatVector(max_length)(fe2)
    # embedding
    inputs2 = Input(shape=(max_length,))
    emb2 = Embedding(vocab_size, 50, mask_zero=True)(inputs2)
    emb3 = LSTM(256, return_sequences=True)(emb2)
    emb4 = TimeDistributed(Dense(128, activation='relu'))(emb3)
    # merge inputs
    merged = concatenate([fe3, emb4])
    # language model (decoder)
    lm2 = LSTM(500)(merged)
    lm3 = Dense(500, activation='relu')(lm2)
    outputs = Dense(vocab_size, activation='softmax')(lm3)
    # tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    print(model.summary())
    plot_model(model, show_shapes=True, to_file='plot.png')
    return model
```

To get a sense for the structure of the model, specifically the shapes of the layers, see the summary listed below.

```
____________________________________________________________________________________________________
Layer (type)                     Output Shape          Param #     Connected to
====================================================================================================
input_1 (InputLayer)             (None, 7, 7, 512)     0
____________________________________________________________________________________________________
input_2 (InputLayer)             (None, 25)            0
```

```
______________________________________________________________________________________________
global_max_pooling2d_1 (GlobalMa (None, 512)           0           input_1[0][0]
______________________________________________________________________________________________
embedding_1 (Embedding)          (None, 25, 50)        18300       input_2[0][0]
______________________________________________________________________________________________
dense_1 (Dense)                  (None, 128)           65664       global_max_pooling2d_1[0][0
______________________________________________________________________________________________
lstm_1 (LSTM)                    (None, 25, 256)       314368      embedding_1[0][0]
______________________________________________________________________________________________
repeat_vector_1 (RepeatVector)   (None, 25, 128)       0           dense_1[0][0]
______________________________________________________________________________________________
time_distributed_1 (TimeDistribu (None, 25, 128)       32896       lstm_1[0][0]
______________________________________________________________________________________________
concatenate_1 (Concatenate)      (None, 25, 256)       0           repeat_vector_1[0][0]
                                                                   time_distributed_1[0][0]
______________________________________________________________________________________________
lstm_2 (LSTM)                    (None, 500)           1514000     concatenate_1[0][0]
______________________________________________________________________________________________
dense_3 (Dense)                  (None, 500)           250500      lstm_2[0][0]
______________________________________________________________________________________________
dense_4 (Dense)                  (None, 366)           183366      dense_3[0][0]
==============================================================================================
Total params: 2,379,094
Trainable params: 2,379,094
Non-trainable params: 0
______________________________________________________________________________________________
```

We also create a plot to visualize the structure of the network that better helps understand the two streams of input.



input_1: InputLayer | input: (None, 7, 7, 512) | output: (None, 7, 7, 512)
input_2: InputLayer | input: (None, 25) | output: (None, 25)
global_max_pooling2d_1: GlobalMaxPooling2D | input: (None, 7, 7, 512) | output: (None, 512)
embedding_1: Embedding | input: (None, 25) | output: (None, 25, 50)
dense_1: Dense | input: (None, 512) | output: (None, 128)
lstm_1: LSTM | input: (None, 25, 50) | output: (None, 25, 256)
repeat_vector_1: RepeatVector | input: (None, 128) | output: (None, 25, 128)
time_distributed_1(dense_2): TimeDistributed(Dense) | input: (None, 25, 256) | output: (None, 25, 128)
concatenate_1: Concatenate | input: [(None, 25, 128), (None, 25, 128)] | output: (None, 25, 256)
lstm_2: LSTM | input: (None, 25, 256) | output: (None, 500)
dense_3: Dense | input: (None, 500) | output: (None, 500)
dense_4: Dense | input: (None, 500) | output: (None, 366)

Plot of the Baseline Captioning Deep Learning Model

We will train the model using a data generator. This is strictly not required given that the captions and extracted photo features can probably fit into memory as a single dataset. Nevertheless, it is good practice for when you come to train the final model on the entire dataset.

A generator will yield a result when called. In Keras, it will yield a single batch of input-output samples that are used to estimate the error gradient and update the model weights.

The function *data_generator()* defines the data generator, given a dictionary of loaded photo descriptions, photo features, the tokenizer for integer encoding sequences, and the maximum sequence length in the dataset.

The generator loops forever and keeps yielding batches of input-output pairs when asked. We also have a *n_step* parameter that allows us to tune how many images worth of input-output pairs to generate for each batch. The average sequence has 10 words, that is 10 input-output pairs, and a good batch size might be 30 samples, which is about 2-to-3 images worth.

```
# data generator, intended to be used in a call to model.fit_generator()
def data_generator(descriptions, features, tokenizer, max_length, n_step):
    # loop until we finish training
    while 1:
        # loop over photo identifiers in the dataset
        keys = list(descriptions.keys())
        for i in range(0, len(keys), n_step):
            Ximages, XSeq, y = list(), list(),list()
            for j in range(i, min(len(keys), i+n_step)):
                image_id = keys[j]
                # retrieve photo feature input
                image = features[image_id][0]
                # retrieve text input
                desc = descriptions[image_id]
                # generate input-output pairs
                in_img, in_seq, out_word = create_sequences(tokenizer, desc, image, max_length)
                for k in range(len(in_img)):
                    Ximages.append(in_img[k])
                    XSeq.append(in_seq[k])
                    y.append(out_word[k])
            # yield this batch of samples to the model
            yield [[array(Ximages), array(XSeq)], array(y)]
```

The model can be fit by calling *fit_generator()* and passing it to the data generator, along with all of the parameters needed. When fitting the model, we can also specify the number of batches to run per epoch and the number of epochs.

```
model.fit_generator(data_generator(train_descriptions, train_features, tokenizer, max_length, n_
```

For these experiments, we will use 2 images per batch, 50 batches (or 100 images) per epoch, and 50 training epochs. You can experiment with different configurations in your own experiments.

3. Evaluate Model

Now that we know how to prepare the data and define a model, we must define a test harness to evaluate a given model.

We will evaluate a model by training it on the dataset, generating descriptions for all photos in the training dataset, evaluating those predictions with a cost function, and then repeating this evaluation process multiple times.

The outcome will be a distribution of skill scores for the model that we can summarize by calculating the mean and standard deviation. This is the preferred way to evaluate deep learning models. See this post:

- How to Evaluate the Skill of Deep Learning Models

First, we need to be able to generate a description for a photo using a trained model.

This involves passing in the start description token '*startseq*', generating one word, then calling the model recursively with generated words as input until the end of sequence token is reached '*endseq*' or the maximum description length is reached.

The function below named *generate_desc()* implements this behavior and generates a textual description given a trained model, and a given prepared photo as input. It calls the function *word_for_id()* in order to map an integer prediction back to a word.

```python
# map an integer to a word
def word_for_id(integer, tokenizer):
    for word, index in tokenizer.word_index.items():
        if index == integer:
            return word
    return None

# generate a description for an image
def generate_desc(model, tokenizer, photo, max_length):
    # seed the generation process
    in_text = 'startseq'
    # iterate over the whole length of the sequence
    for i in range(max_length):
        # integer encode input sequence
        sequence = tokenizer.texts_to_sequences([in_text])[0]
        # pad input
        sequence = pad_sequences([sequence], maxlen=max_length)
        # predict next word
        yhat = model.predict([photo,sequence], verbose=0)
        # convert probability to integer
        yhat = argmax(yhat)
        # map integer to word
        word = word_for_id(yhat, tokenizer)
        # stop if we cannot map the word
        if word is None:
            break
        # append as input for generating the next word
        in_text += ' ' + word
        # stop if we predict the end of the sequence
        if word == 'endseq':
            break
    return in_text
```

We will generate predictions for all photos in the training dataset and in the test dataset.

The function below named *evaluate_model()* will evaluate a trained model against a given dataset of photo descriptions and photo features. The actual and predicted descriptions are collected and evaluated collectively using the corpus BLEU score that summarizes how close the generated text is to the expected text.

```
# 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 in descriptions.items():
        # generate description
        yhat = generate_desc(model, tokenizer, photos[key], max_length)
        # store actual and predicted
        actual.append([desc.split()])
        predicted.append(yhat.split())
    # calculate BLEU score
    bleu = corpus_bleu(actual, predicted)
    return bleu
```

BLEU scores are used in text translation for evaluating translated text against one or more reference translations. We do in fact have access to multiple reference descriptions for each image that we could compare to, but for simplicity, we will use the first description for each photo in the dataset (e.g. the cleaned version).

You can learn more about the BLEU score here:

- BLEU (bilingual evaluation understudy) on Wikipedia

The NLTK Python library implements the BLEU score calculation in the *corpus_bleu()* function. A higher score close to 1.0 is better, a score closer to zero is worse.

Finally, all we need to do is define, fit, and evaluate the model multiple times in a loop then report the final average score.

Ideally, we would repeat the experiment 30 times or more, but this will take too long for our small test harness. Instead, will evaluate the model 3 times. It will be faster, but the mean score will have higher variance.

Below defines the model evaluation loop. At the end of the run, the distribution of BLEU scores for the train and test sets are saved to a file.

```
# run experiment
train_results, test_results = list(), list()
for i in range(n_repeats):
    # define the model
    model = define_model(vocab_size, max_length)
    # fit model
    model.fit_generator(data_generator(train_descriptions, train_features, tokenizer, max_lengt
    # evaluate model on training data
    train_score = evaluate_model(model, train_descriptions, train_features, tokenizer, max_leng
    test_score = evaluate_model(model, test_descriptions, test_features, tokenizer, max_length)
    # store
    train_results.append(train_score)
    test_results.append(test_score)
    print('>%d: train=%f test=%f' % ((i+1), train_score, test_score))
# save results to file
df = DataFrame()
df['train'] = train_results
```

```
df['test'] = test_results
print(df.describe())
df.to_csv(model_name+'.csv', index=False)
```

We parameterize the run as follows, allowing us to name each run and save the result to separate files.

```
# define experiment
model_name = 'baseline1'
verbose = 2
n_epochs = 50
n_photos_per_update = 2
n_batches_per_epoch = int(len(train) / n_photos_per_update)
n_repeats = 3
```

4. Complete Example

The complete example is listed below.

```
from os import listdir
from numpy import array
from numpy import argmax
from pandas import DataFrame
from nltk.translate.bleu_score import corpus_bleu
from pickle import load

from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
from keras.utils import to_categorical
from keras.preprocessing.image import load_img
from keras.preprocessing.image import img_to_array
from keras.applications.vgg16 import preprocess_input
from keras.applications.vgg16 import VGG16
from keras.utils import plot_model
from keras.models import Model
from keras.layers import Input
from keras.layers import Dense
from keras.layers import Flatten
from keras.layers import LSTM
from keras.layers import RepeatVector
from keras.layers import TimeDistributed
from keras.layers import Embedding
from keras.layers.merge import concatenate
from keras.layers.pooling import GlobalMaxPooling2D

# load doc into memory
def load_doc(filename):
    # open the file as read only
    file = open(filename, 'r')
    # read all text
    text = file.read()
    # close the file
    file.close()
    return text

# load a pre-defined list of photo identifiers
def load_set(filename):
    doc = load_doc(filename)
    dataset = list()
    # process line by line
    for line in doc.split('\n'):
        # skip empty lines
        if len(line) < 1:
            continue
        # get the image identifier
        identifier = line.split('.')[0]
        dataset.append(identifier)
    return set(dataset)

# split a dataset into train/test elements
def train_test_split(dataset):
    # order keys so the split is consistent
    ordered = sorted(dataset)
    # return split dataset as two new sets
    return set(ordered[:100]), set(ordered[100:200])

# load clean descriptions into memory
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:
            # store
            descriptions[image_id] = 'startseq ' + ' '.join(image_desc) + ' endseq'
    return descriptions

# load photo features
def load_photo_features(filename, dataset):
    # load all features
    all_features = load(open(filename, 'rb'))
    # filter features
    features = {k: all_features[k] for k in dataset}
    return features

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

# create sequences of images, input sequences and output words for an image
def create_sequences(tokenizer, desc, image, max_length):
    Ximages, XSeq, y = list(), list(),list()
    vocab_size = len(tokenizer.word_index) + 1
    # integer encode the description
    seq = tokenizer.texts_to_sequences([desc])[0]
    # split one sequence into multiple X,y pairs
    for i in range(1, len(seq)):
        # select
        in_seq, out_seq = seq[:i], seq[i]
        # pad input sequence
        in_seq = pad_sequences([in_seq], maxlen=max_length)[0]
        # encode output sequence
        out_seq = to_categorical([out_seq], num_classes=vocab_size)[0]
        # store
        Ximages.append(image)
        XSeq.append(in_seq)
        y.append(out_seq)
    # Ximages, XSeq, y = array(Ximages), array(XSeq), array(y)
    return [Ximages, XSeq, y]

# define the captioning model
```

```
def define_model(vocab_size, max_length):
    # feature extractor (encoder)
    inputs1 = Input(shape=(7, 7, 512))
    fe1 = GlobalMaxPooling2D()(inputs1)
    fe2 = Dense(128, activation='relu')(fe1)
    fe3 = RepeatVector(max_length)(fe2)
    # embedding
    inputs2 = Input(shape=(max_length,))
    emb2 = Embedding(vocab_size, 50, mask_zero=True)(inputs2)
    emb3 = LSTM(256, return_sequences=True)(emb2)
    emb4 = TimeDistributed(Dense(128, activation='relu'))(emb3)
    # merge inputs
    merged = concatenate([fe3, emb4])
    # language model (decoder)
    lm2 = LSTM(500)(merged)
    lm3 = Dense(500, activation='relu')(lm2)
    outputs = Dense(vocab_size, activation='softmax')(lm3)
    # tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    print(model.summary())
    plot_model(model, show_shapes=True, to_file='plot.png')
    return model

# data generator, intended to be used in a call to model.fit_generator()
def data_generator(descriptions, features, tokenizer, max_length, n_step):
    # loop until we finish training
    while 1:
        # loop over photo identifiers in the dataset
        keys = list(descriptions.keys())
        for i in range(0, len(keys), n_step):
            Ximages, XSeq, y = list(), list(),list()
            for j in range(i, min(len(keys), i+n_step)):
                image_id = keys[j]
                # retrieve photo feature input
                image = features[image_id][0]
                # retrieve text input
                desc = descriptions[image_id]
                # generate input-output pairs
                in_img, in_seq, out_word = create_sequences(tokenizer, desc, image, max_lengt
                for k in range(len(in_img)):
                    Ximages.append(in_img[k])
                    XSeq.append(in_seq[k])
                    y.append(out_word[k])
            # yield this batch of samples to the model
            yield [[array(Ximages), array(XSeq)], array(y)]

# map an integer to a word
def word_for_id(integer, tokenizer):
    for word, index in tokenizer.word_index.items():
        if index == integer:
            return word
    return None

# generate a description for an image
def generate_desc(model, tokenizer, photo, max_length):
    # seed the generation process
    in_text = 'startseq'
    # iterate over the whole length of the sequence
    for i in range(max_length):
        # integer encode input sequence
        sequence = tokenizer.texts_to_sequences([in_text])[0]
        # pad input
        sequence = pad_sequences([sequence], maxlen=max_length)
        # predict next word
        yhat = model.predict([photo,sequence], verbose=0)
        # convert probability to integer
        yhat = argmax(yhat)
        # map integer to word
        word = word_for_id(yhat, tokenizer)
        # stop if we cannot map the word
        if word is None:
            break
        # append as input for generating the next word
        in_text += ' ' + word
        # stop if we predict the end of the sequence
        if word == 'endseq':
            break
    return in_text

# 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 in descriptions.items():
        # generate description
        yhat = generate_desc(model, tokenizer, photos[key], max_length)
        # store actual and predicted
        actual.append([desc.split()])
        predicted.append(yhat.split())
    # calculate BLEU score
    bleu = corpus_bleu(actual, predicted)
    return bleu

# load dev set
filename = 'Flickr8k_text/Flickr_8k.devImages.txt'
dataset = load_set(filename)
print('Dataset: %d' % len(dataset))
# train-test split
train, test = train_test_split(dataset)
# descriptions
train_descriptions = load_clean_descriptions('descriptions.txt', train)
test_descriptions = load_clean_descriptions('descriptions.txt', test)
print('Descriptions: train=%d, test=%d' % (len(train_descriptions), len(test_descriptions)))
# photo features
train_features = load_photo_features('features.pkl', train)
test_features = load_photo_features('features.pkl', test)
print('Photos: train=%d, test=%d' % (len(train_features), len(test_features)))
# prepare tokenizer
tokenizer = create_tokenizer(train_descriptions)
vocab_size = len(tokenizer.word_index) + 1
print('Vocabulary Size: %d' % vocab_size)
# determine the maximum sequence length
max_length = max(len(s.split()) for s in list(train_descriptions.values()))
print('Description Length: %d' % max_length)

# define experiment
model_name = 'baseline1'
verbose = 2
n_epochs = 50
n_photos_per_update = 2
n_batches_per_epoch = int(len(train) / n_photos_per_update)
n_repeats = 3

# run experiment
train_results, test_results = list(), list()
for i in range(n_repeats):
    # define the model
    model = define_model(vocab_size, max_length)
    # fit model
    model.fit_generator(data_generator(train_descriptions, train_features, tokenizer, max_leng
    # evaluate model on training data
    train_score = evaluate_model(model, train_descriptions, train_features, tokenizer, max_ler
    test_score = evaluate_model(model, test_descriptions, test_features, tokenizer, max_lengtł
    # store
    train_results.append(train_score)
    test_results.append(test_score)
    print('>%d: train=%f test=%f' % ((i+1), train_score, test_score))
# save results to file
df = DataFrame()
df['train'] = train_results
df['test'] = test_results
print(df.describe())
df.to_csv(model_name+'.csv', index=False)
```

Running the example first prints summary statistics for the loaded training data.

```
Dataset: 1,000
Descriptions: train=100, test=100
Photos: train=100, test=100
Vocabulary Size: 366
Description Length: 25
```

The example should take about 20 minutes on GPU hardware, a little longer on CPU hardware.

At the end of the run, a mean BLEU of 0.06 is reported on the training set and 0.04 on the test set. Results are stored in *baseline1.csv*.

```
          train      test
count  3.000000  3.000000
mean   0.060617  0.040978
std    0.023498  0.025105
min    0.042882  0.012101
25%    0.047291  0.032658
50%    0.051701  0.053215
75%    0.069484  0.055416
max    0.087268  0.057617
```

This provides a baseline model for comparison to alternate configurations.

“A” versus “A” Test

Before we start testing variations of the model, it is important to get an idea of whether or not the test harness is stable.

That is, whether the summarizing skill of the model over 5 runs is sufficient to control for the stochastic nature of the model.

We can get an idea of this by running the experiment again in what is called an A vs A test in A/B testing land. We would expect to get an equivalent result if we ran the same experiment again; if we don’t, perhaps additional repeats would be required to control for the stochastic nature of the method and on the dataset.

Below are the results from a second run of the algorithm.

```
          train      test
count  3.000000  3.000000
mean   0.036902  0.043003
```

```
std    0.020281  0.017295
min    0.018522  0.026055
25%    0.026023  0.034192
50%    0.033525  0.042329
75%    0.046093  0.051477
max    0.058660  0.060624
```

We can see that the run gets a very similar mean and standard deviation BLEU scores. Specifically, a mean BLEU of 0.03 vs 0.06 on train and 0.04 to 0.04 for test.

The harness is a little noisy, but stable enough for comparison.

Is the model any good?

Generate Photo Captions

We expect the model is under-trained and maybe even under provisioned, but can it generate any kind of readable text at all?

It is important that the baseline model have some modicum of capability so that we can relate the BLEU scores of the baseline to an idea of what kind of quality of descriptions are being generated.

Let's train a single model and generate a few descriptions from the train and test sets as a sanity check.

Change the number of repeats to 1 and the name of the run to '*baseline_generate*'.

```
model_name = 'baseline_generate'
n_repeats = 1
```

Then update the *evaluate_model()* function to only evaluate the first 5 photos in the dataset and print the descriptions, as follows.

```
# 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 in descriptions.items():
        # generate description
        yhat = generate_desc(model, tokenizer, photos[key], max_length)
        # store actual and predicted
        actual.append([desc.split()])
        predicted.append(yhat.split())
        print('Actual:    %s' % desc)
        print('Predicted: %s' % yhat)
        if len(actual) >= 5:
            break
    # calculate BLEU score
    bleu = corpus_bleu(actual, predicted)
    return bleu
```

Re-run the example.

You should see results for the train set like the following (the specific results will vary given the stochastic nature of the algorithm):

```
Actual:    startseq boy bites hard into treat while he sits outside endseq
Predicted: startseq boy boy while while he while outside endseq

Actual:    startseq man in field backed by american flags endseq
Predicted: startseq man in in standing city endseq

Actual:    startseq two girls are walking down dirt road in park endseq
Predicted: startseq man walking down down road in endseq

Actual:    startseq girl laying on the tree with boy kneeling before her endseq
Predicted: startseq boy while in up up up water endseq

Actual:    startseq boy in striped shirt is jumping in front of water fountain endseq
Predicted: startseq man is is shirt is on on on on bike endseq
```

You should see results on the test dataset as follows:

```
Actual:    startseq three people are looking into photographic equipment endseq
Predicted: startseq boy racer on on on on bike endseq

Actual:    startseq boy is leaning on chair whilst another boy pulls him around with rope endse
Predicted: startseq girl in playing on on on sword endseq

Actual:    startseq black and brown dog jumping in midair near field endseq
Predicted: startseq dog dog running running running and dog in grass endseq

Actual:    startseq dog places his head on man face endseq
Predicted: startseq brown dog dog to to to to to to to ball endseq

Actual:    startseq man in green hat is someplace up high endseq
Predicted: startseq man in up up his waves endseq
```

We can see that the descriptions are not perfect, some are a little rough, but generally the model is generating somewhat readable text. A good starting point for improvement.

Next, let's look at some experiments to vary the size or capacity of different sub-models.

Network Size Parameters

In this section, we will see how gross variations to the network structure impact model skill.

We will look at the following aspects of the model size:

1. Size of the fixed-vector output from the 'encoders'.
2. Size of the sequence encoder model.
3. Size of the language model.

Let's dive in.

Size of Fixed-Length Vector

In the baseline model, the photo feature extractor and the text sequence encoder both output a 128 element vector. These vectors are then concatenated to be processed by the language model.

The 128 element vector from each sub-model contains everything known about the input sequence and photo. We can vary the size of this vector to see if it impacts model skill

First, we can decrease the size by half from 128 elements to 64 elements.

```
# define the captioning model
def define_model(vocab_size, max_length):
    # feature extractor (encoder)
    inputs1 = Input(shape=(7, 7, 512))
    fe1 = GlobalMaxPooling2D()(inputs1)
    fe2 = Dense(64, activation='relu')(fe1)
    fe3 = RepeatVector(max_length)(fe2)
    # embedding
    inputs2 = Input(shape=(max_length,))
    emb2 = Embedding(vocab_size, 50, mask_zero=True)(inputs2)
    emb3 = LSTM(256, return_sequences=True)(emb2)
    emb4 = TimeDistributed(Dense(64, activation='relu'))(emb3)
    # merge inputs
    merged = concatenate([fe3, emb4])
    # language model (decoder)
    lm2 = LSTM(500)(merged)
    lm3 = Dense(500, activation='relu')(lm2)
    outputs = Dense(vocab_size, activation='softmax')(lm3)
    # tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model
```

We will name this model '*size_sm_fixed_vec*'.

```
model_name = 'size_sm_fixed_vec'
```

Running this experiment produces the following BLEU scores, perhaps a small gain over baseline on the test set.

```
          train      test
count  3.000000  3.000000
mean   0.204421  0.063148
std    0.026992  0.003264
min    0.174769  0.059391
25%    0.192849  0.062074
50%    0.210929  0.064757
75%    0.219246  0.065026
max    0.227564  0.065295
```

We can also double the size of the fixed-length vector from 128 to 256 units.

```
# define the captioning model
def define_model(vocab_size, max_length):
    # feature extractor (encoder)
    inputs1 = Input(shape=(7, 7, 512))
    fe1 = GlobalMaxPooling2D()(inputs1)
    fe2 = Dense(256, activation='relu')(fe1)
    fe3 = RepeatVector(max_length)(fe2)
    # embedding
    inputs2 = Input(shape=(max_length,))
    emb2 = Embedding(vocab_size, 50, mask_zero=True)(inputs2)
    emb3 = LSTM(256, return_sequences=True)(emb2)
    emb4 = TimeDistributed(Dense(256, activation='relu'))(emb3)
    # merge inputs
    merged = concatenate([fe3, emb4])
    # language model (decoder)
    lm2 = LSTM(500)(merged)
    lm3 = Dense(500, activation='relu')(lm2)
    outputs = Dense(vocab_size, activation='softmax')(lm3)
    # tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model
```

We will name this configuration '*size_lg_fixed_vec*'.

```
model_name = 'size_lg_fixed_vec'
```

Running this experiment shows BLEU scores suggesting that the model is not better off.

It is possible that with more data and/or longer training, we may see a different story.

```
          train      test
count  3.000000  3.000000
mean   0.023517  0.027813
std    0.009951  0.010525
min    0.012037  0.021737
25%    0.020435  0.021737
50%    0.028833  0.021737
75%    0.029257  0.030852
max    0.029682  0.039966
```

Sequence Encoder Size

We can call the sub-model that interprets the input sequence of words generated so far as the sequence encoder.

First, we can try to see if decreasing the representational capacity of the sequence encoder impacts model skill. We can reduce the number of memory units in the LSTM layer from 256 to 128.

```
# define the captioning model
def define_model(vocab_size, max_length):
    # feature extractor (encoder)
    inputs1 = Input(shape=(7, 7, 512))
    fe1 = GlobalMaxPooling2D()(inputs1)
    fe2 = Dense(128, activation='relu')(fe1)
    fe3 = RepeatVector(max_length)(fe2)
    # embedding
    inputs2 = Input(shape=(max_length,))
    emb2 = Embedding(vocab_size, 50, mask_zero=True)(inputs2)
    emb3 = LSTM(128, return_sequences=True)(emb2)
    emb4 = TimeDistributed(Dense(128, activation='relu'))(emb3)
    # merge inputs
    merged = concatenate([fe3, emb4])
    # language model (decoder)
    lm2 = LSTM(500)(merged)
    lm3 = Dense(500, activation='relu')(lm2)
    outputs = Dense(vocab_size, activation='softmax')(lm3)
    # tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

model_name = 'size_sm_seq_model'
```

Running this example, we can see perhaps a small bump on both train and test over baseline. This might be an artifact of the small training set size.

```
          train      test
count  3.000000  3.000000
mean   0.074944  0.053917
std    0.014263  0.013264
min    0.066292  0.039142
25%    0.066713  0.048476
50%    0.067134  0.057810
75%    0.079270  0.061304
max    0.091406  0.064799
```

Going the other way, we can double the number of LSTM layers from one to two and see if that makes a dramatic difference.

```
# define the captioning model
def define_model(vocab_size, max_length):
    # feature extractor (encoder)
    inputs1 = Input(shape=(7, 7, 512))
    fe1 = GlobalMaxPooling2D()(inputs1)
    fe2 = Dense(128, activation='relu')(fe1)
    fe3 = RepeatVector(max_length)(fe2)
    # embedding
    inputs2 = Input(shape=(max_length,))
    emb2 = Embedding(vocab_size, 50, mask_zero=True)(inputs2)
    emb3 = LSTM(256, return_sequences=True)(emb2)
    emb4 = LSTM(256, return_sequences=True)(emb3)
    emb5 = TimeDistributed(Dense(128, activation='relu'))(emb4)
    # merge inputs
    merged = concatenate([fe3, emb5])
    # language model (decoder)
    lm2 = LSTM(500)(merged)
    lm3 = Dense(500, activation='relu')(lm2)
    outputs = Dense(vocab_size, activation='softmax')(lm3)
    # tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

model_name = 'size_lg_seq_model'
```

Running this experiment shows a decent bump in BLEU on both train and test sets.

```
          train      test
count  3.000000  3.000000
mean   0.094937  0.096970
std    0.022394  0.079270
min    0.069151  0.046722
25%    0.087656  0.051279
50%    0.106161  0.055836
75%    0.107830  0.122094
max    0.109499  0.188351
```

We can also try to increase the representational capacity of the word embedding by doubling it from 50-dimensions to 100-dimensions.

```
# define the captioning model
def define_model(vocab_size, max_length):
    # feature extractor (encoder)
    inputs1 = Input(shape=(7, 7, 512))
    fe1 = GlobalMaxPooling2D()(inputs1)
    fe2 = Dense(128, activation='relu')(fe1)
    fe3 = RepeatVector(max_length)(fe2)
    # embedding
    inputs2 = Input(shape=(max_length,))
    emb2 = Embedding(vocab_size, 100, mask_zero=True)(inputs2)
    emb3 = LSTM(256, return_sequences=True)(emb2)
    emb4 = TimeDistributed(Dense(128, activation='relu'))(emb3)
    # merge inputs
    merged = concatenate([fe3, emb4])
    # language model (decoder)
    lm2 = LSTM(500)(merged)
    lm3 = Dense(500, activation='relu')(lm2)
    outputs = Dense(vocab_size, activation='softmax')(lm3)
    # tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

model_name = 'size_em_seq_model'
```

We see a large movement on the training dataset, but perhaps little movement on the test dataset.

```
count  3.000000  3.000000
mean   0.112743  0.050935
std    0.017136  0.006860
min    0.096121  0.043741
25%    0.103940  0.047701
50%    0.111759  0.051661
75%    0.121055  0.054533
max    0.130350  0.057404
```

Size of Language Model

We can refer to the model that learns from the concatenated sequence and photo feature input as the language model. It is responsible for generating words.

First, we can look at the impact on model skill by cutting the LSTM and dense layers from 500 to 256 neurons.

```
# define the captioning model
def define_model(vocab_size, max_length):
    # feature extractor (encoder)
    inputs1 = Input(shape=(7, 7, 512))
    fe1 = GlobalMaxPooling2D()(inputs1)
    fe2 = Dense(128, activation='relu')(fe1)
    fe3 = RepeatVector(max_length)(fe2)
    # embedding
    inputs2 = Input(shape=(max_length,))
    emb2 = Embedding(vocab_size, 50, mask_zero=True)(inputs2)
    emb3 = LSTM(256, return_sequences=True)(emb2)
    emb4 = TimeDistributed(Dense(128, activation='relu'))(emb3)
    # merge inputs
    merged = concatenate([fe3, emb4])
    # language model (decoder)
    lm2 = LSTM(256)(merged)
    lm3 = Dense(256, activation='relu')(lm2)
    outputs = Dense(vocab_size, activation='softmax')(lm3)
    # tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

model_name = 'size_sm_lang_model'
```

We can see that this has a small positive effect on BLEU for both training and test datasets, again, likely related to the small size of the datasets.

```
          train      test
count  3.000000  3.000000
mean   0.063632  0.056059
std    0.018521  0.009064
min    0.045127  0.048916
25%    0.054363  0.050961
50%    0.063599  0.053005
75%    0.072884  0.059630
max    0.082169  0.066256
```

We can also look at the impact of doubling the capacity of the language model by adding a second LSTM layer of the same size.

```
# define the captioning model
def define_model(vocab_size, max_length):
    # feature extractor (encoder)
    inputs1 = Input(shape=(7, 7, 512))
    fe1 = GlobalMaxPooling2D()(inputs1)
    fe2 = Dense(128, activation='relu')(fe1)
    fe3 = RepeatVector(max_length)(fe2)
    # embedding
    inputs2 = Input(shape=(max_length,))
    emb2 = Embedding(vocab_size, 50, mask_zero=True)(inputs2)
    emb3 = LSTM(256, return_sequences=True)(emb2)
    emb4 = TimeDistributed(Dense(128, activation='relu'))(emb3)
    # merge inputs
    merged = concatenate([fe3, emb4])
    # language model (decoder)
    lm2 = LSTM(500, return_sequences=True)(merged)
    lm3 = LSTM(500)(lm2)
    lm4 = Dense(500, activation='relu')(lm3)
    outputs = Dense(vocab_size, activation='softmax')(lm4)
    # tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

model_name = 'size_lg_lang_model'
```

Again, we see minor movements in BLEU, perhaps an artifact of noise and dataset size. The improvement on the test

The improvement on the test dataset may be a good sign. This might be a change worth exploring.

```
          train      test
count  3.000000  3.000000
mean   0.043838  0.067658
std    0.037580  0.045813
min    0.017990  0.015757
25%    0.022284  0.050252
50%    0.026578  0.084748
75%    0.056763  0.093608
max    0.086948  0.102469
```

Tuning model size on a much smaller dataset is challenging.

Configuring the Feature Extraction Model

The use of the pre-trained VGG16 model provides some additional points of configuration.

The baseline model removed the top from the VGG model, including a global max pooling layer, which then feeds into an encoding of the features to a 128 element vector.

In this section, we will look at the following modifications to the baseline model:

1. Using a global average pooling layer after the VGG model.
2. Not using any global pooling.

Global Average Pooling

We can replace the GlobalMaxPooling2D layer with a GlobalAveragePooling2D to achieve average pooling.

Global average pooling was developed to reduce overfitting for image classification problems, but may offer some benefit in interpreting the features extracted from the image.

For more on global average pooling, see the paper:

- Network In Network, 2013.

The updated *define_model()* function and experiment name are listed below.

```
# define the captioning model
def define_model(vocab_size, max_length):
    # feature extractor (encoder)
    inputs1 = Input(shape=(7, 7, 512))
    fe1 = GlobalAveragePooling2D()(inputs1)
    fe2 = Dense(128, activation='relu')(fe1)
    fe3 = RepeatVector(max_length)(fe2)
    # embedding
    inputs2 = Input(shape=(max_length,))
    emb2 = Embedding(vocab_size, 50, mask_zero=True)(inputs2)
    emb3 = LSTM(256, return_sequences=True)(emb2)
    emb4 = TimeDistributed(Dense(128, activation='relu'))(emb3)
    # merge inputs
    merged = concatenate([fe3, emb4])
    # language model (decoder)
    lm2 = LSTM(500)(merged)
    lm3 = Dense(500, activation='relu')(lm2)
    outputs = Dense(vocab_size, activation='softmax')(lm3)
    # tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

model_name = 'fe_avg_pool'
```

The results suggest a dramatic improvement on the training dataset, which may be a sign of overfitting. We also see a small lift on test skill. This might be a change worth exploring.

We also see a small lift on test skill. This might be a change worth exploring.

```
          train      test
count  3.000000  3.000000
mean   0.834627  0.060847
std    0.083259  0.040463
min    0.745074  0.017705
25%    0.797096  0.042294
50%    0.849118  0.066884
75%    0.879404  0.082418
max    0.909690  0.097952
```

No Pooling

We can remove the GlobalMaxPooling2D and flatten the 3D photo feature and feed it directly into a Dense layer.

I would not expect this to be a good model design, but it is worth testing this assumption.

```
# define the captioning model
def define_model(vocab_size, max_length):
    # feature extractor (encoder)
    inputs1 = Input(shape=(7, 7, 512))
    fe1 = Flatten()(inputs1)
    fe2 = Dense(128, activation='relu')(fe1)
    fe3 = RepeatVector(max_length)(fe2)
    # embedding
    inputs2 = Input(shape=(max_length,))
    emb2 = Embedding(vocab_size, 50, mask_zero=True)(inputs2)
    emb3 = LSTM(256, return_sequences=True)(emb2)
    emb4 = TimeDistributed(Dense(128, activation='relu'))(emb3)
    # merge inputs
    merged = concatenate([fe3, emb4])
    # language model (decoder)
    lm2 = LSTM(500)(merged)
    lm3 = Dense(500, activation='relu')(lm2)
    outputs = Dense(vocab_size, activation='softmax')(lm3)
    # tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

model_name = 'fe_flat'
```

Surprisingly, we see a small lift on training data and a large lift on test data. This is surprising (to me) and may be worth further investigation.

```
          train      test
count  3.000000  3.000000
mean   0.055988  0.135231
std    0.017566  0.079714
min    0.038605  0.044177
25%    0.047116  0.106633
50%    0.055627  0.169089
75%    0.064679  0.180758
max    0.073731  0.192428
```

We can try repeating this experiment and provide more capacity for interpreting the extracted photo features. A new Dense layer with 500 neurons is added after the Flatten layer.

```
# define the captioning model
def define_model(vocab_size, max_length):
    # feature extractor (encoder)
    inputs1 = Input(shape=(7, 7, 512))
    fe1 = Flatten()(inputs1)
    fe2 = Dense(500, activation='relu')(fe1)
    fe3 = Dense(128, activation='relu')(fe2)
    fe4 = RepeatVector(max_length)(fe3)
    # embedding
    inputs2 = Input(shape=(max_length,))
    emb2 = Embedding(vocab_size, 50, mask_zero=True)(inputs2)
    emb3 = LSTM(256, return_sequences=True)(emb2)
    emb4 = TimeDistributed(Dense(128, activation='relu'))(emb3)
    # merge inputs
    merged = concatenate([fe4, emb4])
    # language model (decoder)
    lm2 = LSTM(500)(merged)
    lm3 = Dense(500, activation='relu')(lm2)
    outputs = Dense(vocab_size, activation='softmax')(lm3)
    # tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

model_name = 'fe_flat2'
```

This results in a less impressive change and perhaps worse BLEU results on the test dataset.

```
          train      test
count  3.000000  3.000000
mean   0.060126  0.029487
std    0.030300  0.013205
min    0.031235  0.020850
25%    0.044359  0.021887
50%    0.057483  0.022923
75%    0.074572  0.033805
max    0.091661  0.044688
```

Word Embedding Models

A key part of the model is the sequence learning model that must interpret the sequence of words generated so far for a photo.

At the input to this sub-model is a word embedding and a good way to improve a word embedding over learning it from scratch as part of the model (as in the baseline model) is to use pre-trained word embeddings.

In this section, we will explore the impact of using a pre-trained word embedding on the model. Specifically:

1. Training a Word2Vec Model
2. Training a Word2Vec Model + Fine Tuning

Trained word2vec Embedding

An efficient learning algorithm for pre-training a word embedding from a corpus of text is the word2vec algorithm.

You can learn more about the word2vec algorithm here:

- Word2Vec Google Code Project

We can use this algorithm to train a new standalone set of word vectors using the cleaned photo descriptions in the dataset.

The Gensim library provides access to an implementation of the algorithm that we can use to pre-train the embedding.

First, we must load the clean photo descriptions for the training dataset, as before.

Next, we can fit the word2vec model on all of the clean descriptions. We should note that this includes more descriptions than the 50 used in the training dataset. A fairer model for these experiments should only be trained on those descriptions in the training dataset.

Once fit, we can save the words and word vectors to an ASCII file, perhaps for later inspection or visualization.

```
# train word2vec model
lines = [s.split() for s in train_descriptions.values()]
model = Word2Vec(lines, size=100, window=5, workers=8, min_count=1)
# summarize vocabulary size in model
words = list(model.wv.vocab)
print('Vocabulary size: %d' % len(words))

# save model in ASCII (word2vec) format
filename = 'custom_embedding.txt'
model.wv.save_word2vec_format(filename, binary=False)
```

The word embedding is saved to the file '*custom_embedding.txt*'.

Now, we can load the embedding into memory, retrieve only the word vectors for the words in our vocabulary, then save them to a new file.

```
# load the whole embedding into memory
embedding = dict()
file = open('custom_embedding.txt')
for line in file:
    values = line.split()
    word = values[0]
    coefs = asarray(values[1:], dtype='float32')
    embedding[word] = coefs
file.close()
print('Embedding Size: %d' % len(embedding))

# summarize vocabulary
all_tokens = ' '.join(train_descriptions.values()).split()
vocabulary = set(all_tokens)
print('Vocabulary Size: %d' % len(vocabulary))

# get the vectors for words in our vocab
```

```
cust_embedding = dict()
for word in vocabulary:
    # check if word in embedding
    if word not in embedding:
        continue
    cust_embedding[word] = embedding[word]
print('Custom Embedding %d' % len(cust_embedding))

# save
dump(cust_embedding, open('word2vec_embedding.pkl', 'wb'))
print('Saved Embedding')
```

The complete example is listed below.

```
# prepare word vectors for captioning model

from numpy import asarray
from pickle import dump
from gensim.models import Word2Vec

# load doc into memory
def load_doc(filename):
    # open the file as read only
    file = open(filename, 'r')
    # read all text
    text = file.read()
    # close the file
    file.close()
    return text

# load a pre-defined list of photo identifiers
def load_set(filename):
    doc = load_doc(filename)
    dataset = list()
    # process line by line
    for line in doc.split('\n'):
        # skip empty lines
        if len(line) < 1:
            continue
        # get the image identifier
        identifier = line.split('.')[0]
        dataset.append(identifier)
    return set(dataset)

# split a dataset into train/test elements
def train_test_split(dataset):
    # order keys so the split is consistent
    ordered = sorted(dataset)
    # return split dataset as two new sets
    return set(ordered[:100]), set(ordered[100:200])

# load clean descriptions into memory
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:
            # store
            descriptions[image_id] = 'startseq ' + ' '.join(image_desc) + ' endseq'
    return descriptions

# load dev set
filename = 'Flickr8k_text/Flickr_8k.devImages.txt'
dataset = load_set(filename)
print('Dataset: %d' % len(dataset))
# train-test split
train, test = train_test_split(dataset)
print('Train=%d, Test=%d' % (len(train), len(test)))
# descriptions
train_descriptions = load_clean_descriptions('descriptions.txt', train)
print('Descriptions: train=%d' % len(train_descriptions))

# train word2vec model
lines = [s.split() for s in train_descriptions.values()]
model = Word2Vec(lines, size=100, window=5, workers=8, min_count=1)
# summarize vocabulary size in model
words = list(model.wv.vocab)
print('Vocabulary size: %d' % len(words))

# save model in ASCII (word2vec) format
filename = 'custom_embedding.txt'
model.wv.save_word2vec_format(filename, binary=False)

# load the whole embedding into memory
embedding = dict()
file = open('custom_embedding.txt')
for line in file:
    values = line.split()
    word = values[0]
    coefs = asarray(values[1:], dtype='float32')
    embedding[word] = coefs
file.close()
print('Embedding Size: %d' % len(embedding))

# summarize vocabulary
all_tokens = ' '.join(train_descriptions.values()).split()
vocabulary = set(all_tokens)
print('Vocabulary Size: %d' % len(vocabulary))

# get the vectors for words in our vocab
cust_embedding = dict()
for word in vocabulary:
    # check if word in embedding
    if word not in embedding:
        continue
    cust_embedding[word] = embedding[word]
print('Custom Embedding %d' % len(cust_embedding))

# save
dump(cust_embedding, open('word2vec_embedding.pkl', 'wb'))
print('Saved Embedding')
```

Running this example creates a new dictionary mapping of word-to-word vectors stored in the file '*word2vec_embedding.pkl*'.

```
Dataset: 1000
Train=100, Test=100
Descriptions: train=100
Vocabulary size: 365
Embedding Size: 366
Vocabulary Size: 365
Custom Embedding 365
```

```
Saved Embedding
```

Next, we can load this embedding and use the word vectors as the fixed weights in an Embedding layer.

Below provides the *load_embedding()* function that loads the custom word2vec embedding and returns the new Embedding layer for use in the model.

```
# load a word embedding
def load_embedding(tokenizer, vocab_size, max_length):
    # load the tokenizer
    embedding = load(open('word2vec_embedding.pkl', 'rb'))
    dimensions = 100
    trainable = False
    # create a weight matrix for words in training docs
    weights = zeros((vocab_size, dimensions))
    # walk words in order of tokenizer vocab to ensure vectors are in the right index
    for word, i in tokenizer.word_index.items():
        if word not in embedding:
            continue
        weights[i] = embedding[word]
    layer = Embedding(vocab_size, dimensions, weights=[weights], input_length=max_length, trair
    return layer
```

We can use it in our model by calling the function directly from our *define_model()* function.

```
# define the captioning model
def define_model(tokenizer, vocab_size, max_length):
    # feature extractor (encoder)
    inputs1 = Input(shape=(7, 7, 512))
    fe1 = GlobalMaxPooling2D()(inputs1)
    fe2 = Dense(128, activation='relu')(fe1)
    fe3 = RepeatVector(max_length)(fe2)
    # embedding
    inputs2 = Input(shape=(max_length,))
    emb2 = load_embedding(tokenizer, vocab_size, max_length)(inputs2)
    emb3 = LSTM(256, return_sequences=True)(emb2)
    emb4 = TimeDistributed(Dense(128, activation='relu'))(emb3)
    # merge inputs
    merged = concatenate([fe3, emb4])
    # language model (decoder)
    lm2 = LSTM(500)(merged)
    lm3 = Dense(500, activation='relu')(lm2)
    outputs = Dense(vocab_size, activation='softmax')(lm3)
    # tie it together [image, seq] [word]
    model = Model(inputs=[inputs1, inputs2], outputs=outputs)
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

model_name = 'seq_w2v_fixed'
```

We can see some lift on the training dataset, perhaps no real notable change on the test dataset.

```
           train      test
count  3.000000  3.000000
mean   0.096780  0.047540
std    0.055073  0.008445
min    0.033511  0.038340
25%    0.078186  0.043840
50%    0.122861  0.049341
75%    0.128414  0.052140
max    0.133967  0.054939
```

Trained word2vec Embedding with Fine Tuning

We can repeat the previous experiment and allow the model to tune the word vectors while fitting the model.

The updated *load_embedding()* function that permits the embedding layer to be fine-tuned is listed below.

```
# load a word embedding
def load_embedding(tokenizer, vocab_size, max_length):
    # load the tokenizer
    embedding = load(open('word2vec_embedding.pkl', 'rb'))
    dimensions = 100
    trainable = True
    # create a weight matrix for words in training docs
    weights = zeros((vocab_size, dimensions))
    # walk words in order of tokenizer vocab to ensure vectors are in the right index
    for word, i in tokenizer.word_index.items():
        if word not in embedding:
            continue
        weights[i] = embedding[word]
    layer = Embedding(vocab_size, dimensions, weights=[weights], input_length=max_length, trair
    return layer

model_name = 'seq_w2v_tuned'
```

Again, we do not see much difference in using these pre-trained word embedding vectors over the baseline model.

```
          train      test
count  3.000000  3.000000
mean   0.065297  0.042712
std    0.080194  0.007697
min    0.017675  0.034593
25%    0.019003  0.039117
50%    0.020332  0.043641
75%    0.089108  0.046772
max    0.157885  0.049904
```

Analysis of Results

We have performed a few experiments on a very small sample (1.6%) from the Flickr8k training dataset of 8,000 photos.

It is possible that the sample is too small, that the models were not trained for long enough, and that 3 repeats of each model results in too much variance. These aspects can also be tested by evaluated by designing experiments such as:

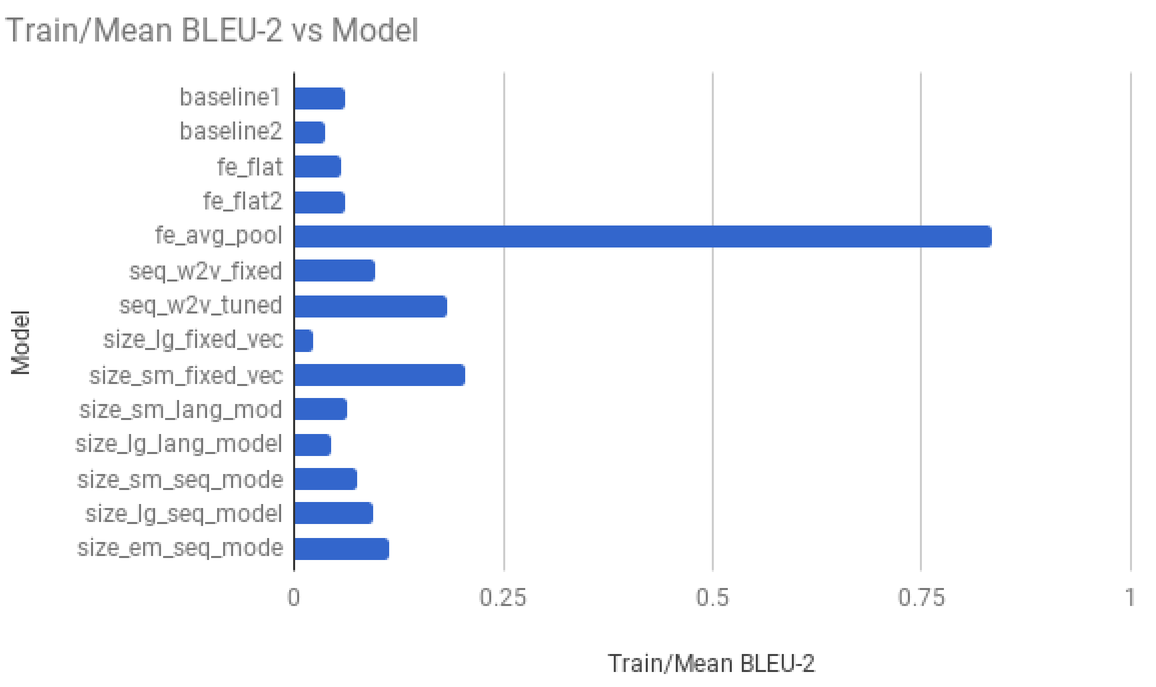
1. Does model skill scale with the size of the dataset?
2. Do more epochs result in better skill?
3. Do more repeats result in a skill with less variance?

Nevertheless, we have some ideas on how we might configure a model for the fuller dataset.

Below is a summary of the mean results from the experiments performed in this tutorial.

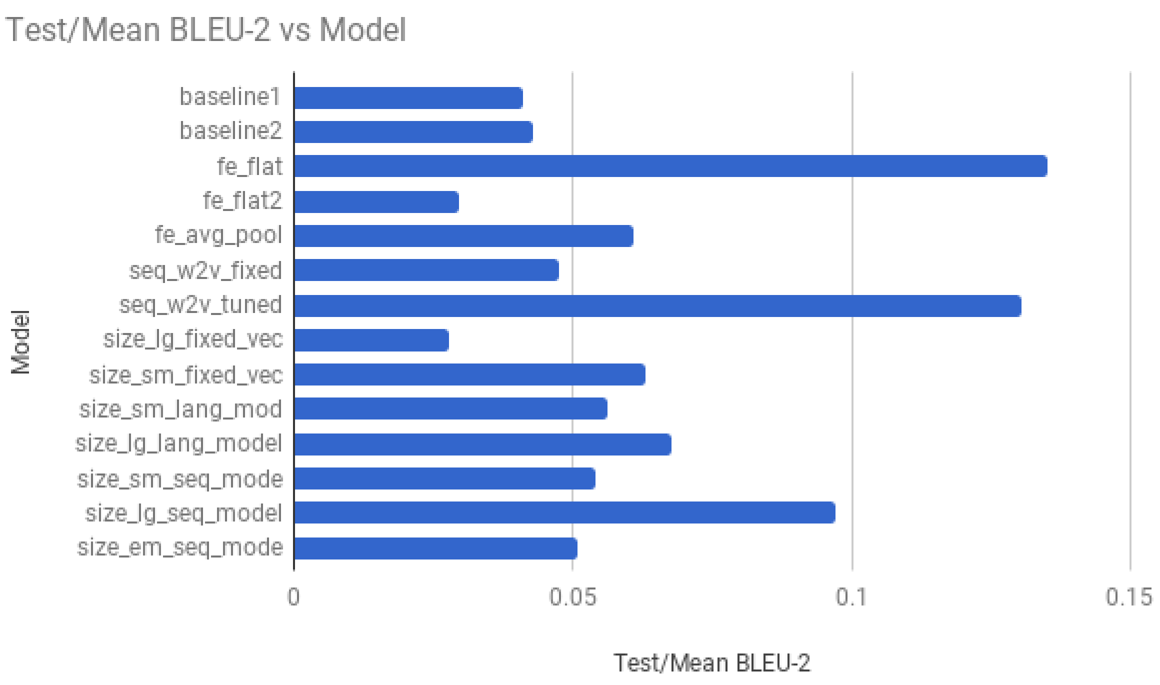
It is helpful to review a graph of the results. If we had more repeats, a box and whisker plot for each distribution of scores might be a good visualization. Here we use a simple bar graph. Remember, that larger BLEU scores are better.

Results on the training dataset:



Bar Chart of Experiment vs Model Skill on the Training Dataset

Results on the test dataset:



Bar Chart of Experiment vs Model Skill on the Test Dataset

From just looking at the mean results on the test dataset, we can suggest:

- Perhaps pooling is not required after the photo feature extractor (fe_flat at 0.135231).
- Perhaps average pooling offers an advantage over max pooling after the photo feature extractor (fe_avg_pool at 0.060847).
- Perhaps a smaller sized fixed-length vector after the sub-models is a good idea (size_sm_fixed_vec at 0.063148).
- Perhaps adding more layers to the language model offers some benefit (size_lg_lang_model at 0.067658).
- Perhaps adding more layers to the sequence model offers some benefit (size_lg_seq_model at 0.09697).

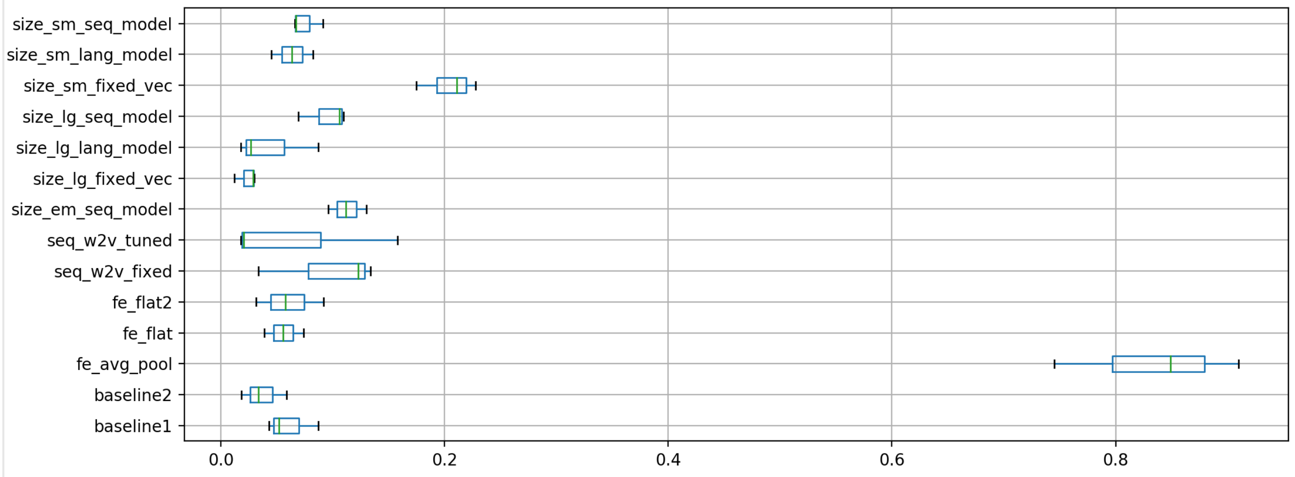
I would also recommend exploring combinations of these suggestions.

We can also review the distribution of results.

Below is some code to load the saved results from each experiment and create a box-and-whisker plot of results on the train and test sets for review.

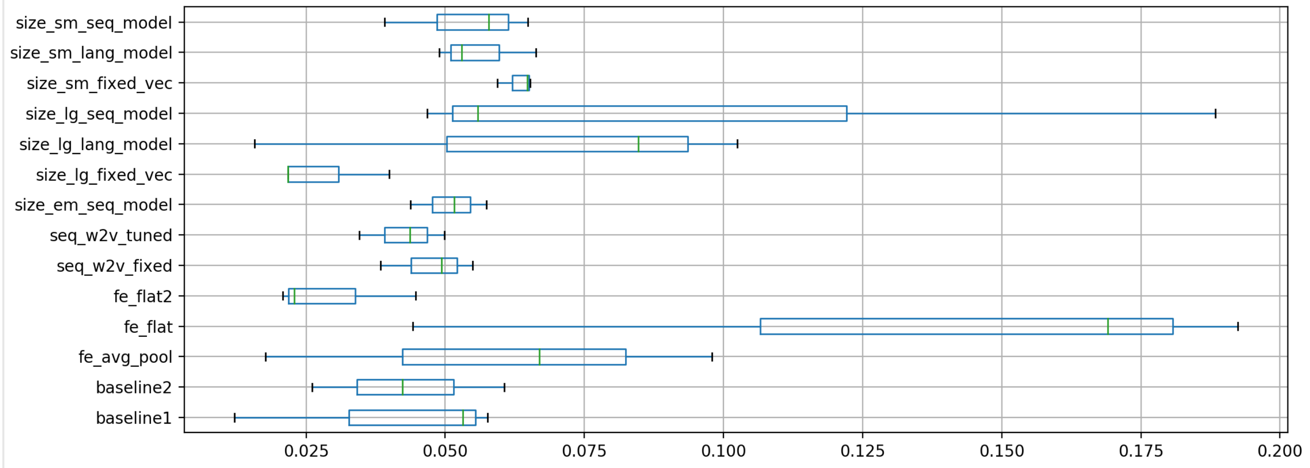
```
from os import listdir
from pandas import read_csv
from pandas import DataFrame
from matplotlib import pyplot

# load all .csv results into a dataframe
train, test = DataFrame(), DataFrame()
directory = 'results'
for name in listdir(directory):
    if not name.endswith('csv'):
        continue
    filename = directory + '/' + name
    data = read_csv(filename, header=0)
    experiment = name.split('.')[0]
    train[experiment] = data['train']
    test[experiment] = data['test']

# plot results on train
train.boxplot(vert=False)
pyplot.show()
# plot results on test
test.boxplot(vert=False)
pyplot.show()
```

Distribution of results on the training dataset.



Box and Whisker Plot of Experiment vs Model Skill on the Training Dataset

Distribution of results on the test dataset.



Box and Whisker Plot of Experiment vs Model Skill on the Test Dataset

A review of these distributions suggests:

- The spread on the flat results is large; perhaps going with average pooling might be safer.
- The spread on the larger language model is large and skewed in the wrong/risky direction.
- The spread on the larger sequence model is large and skewed in the right direction.
- There may be some benefit in a smaller fixed-length vector size.

I would expect increasing repeats to 5, 10, or 30 would tighten up these distributions somewhat.

Further Reading

This section provides more resources on the topic if you are looking go deeper.

Papers

- Show and Tell: A Neural Image Caption Generator, 2015.
- Show, Attend and Tell: Neural Image Caption Generation with Visual Attention, 2016.
- Network In Network, 2013.

Related Captioning Projects

- caption_generator: An image captioning project
- Keras Image Caption
- Neural Image Captioning (NIC)
- Keras deep learning for image caption retrieval
- DataLab Cup 2: Image Captioning

Other

- Framing image description as a ranking task: data, models and evaluation metrics.

API

- Keras VGG16 API
- Gensim word2vec API

Summary

In this tutorial, you discovered how you can use a small sample of the photo captioning dataset to explore different model designs.

Specifically, you learned:

- How to prepare data for photo captioning modeling.
- How to design a baseline and test harness to evaluate the skill of models and control for their stochastic nature.
- How to evaluate properties like model skill, feature extraction model, and word embeddings in order to lift model skill.

What experiments can you think up?
What else have you tried?
What are the best results you can get on the train and test dataset?

Let me know in the comments below.

About Jason Brownlee

Jason Brownlee, PhD is a machine learning specialist who teaches developers how to get results with modern machine learning methods via hands-on tutorials.
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41 Responses to *How to Use Small Experiments to Develop a Caption Generation Model in Keras*

Emil November 24, 2017 at 6:39 am # REPLY

Hats off, another ace tutorial!

I'm curious how the TimeDistributed layer impacts the data before the concatenation. Is it possible to skip it? Also, is there a reason you are using VGG instead of the InceptionResNetV2 class other than memory/compute constraints.

Thanks!

Jason Brownlee November 24, 2017 at 9:52 am # REPLY

I chose VGG because it is smaller and simpler. You can use anything you wish.

You can skip the TimeDistributed as Dense can support time steps now I believe. I like it in there as it reminds me what is going on (e.g. outputting time steps).

Alex November 24, 2017 at 6:16 pm # REPLY

Ho jason, why don t you reset the LSTM states between the inputs related to different images? Ad they are not related to the same sequences.

Jason Brownlee November 25, 2017 at 10:14 am # REPLY

For speed of training.

It's a great suggestion though, try it and see if it lifts skill! Let me know how you go.

Alex November 28, 2017 at 1:39 am # REPLY

Thanks! In order to try this way, should I set stateful=True (avoiding the LSTM to reset itself automatically) and manually run model.reset_states() before training a single batch? (each batch is related to the sequence of a single image).

Jason Brownlee November 28, 2017 at 8:38 am # REPLY

Yes.

Emil December 13, 2017 at 12:10 am # REPLY

What's the logic of the +1 when you are creating the vocab len: "vocab_size = len(tokenizer.word_index) + 1"? Is it to leave remove for the 0?

Thanks

Jason Brownlee December 13, 2017 at 5:39 am # REPLY

Good question, to make space for 0 – words in the vocab start at 1.

Yang Cheng March 12, 2018 at 8:50 pm # REPLY

Does it mean we leave index 0 for 'endseq' token?

Jason Brownlee March 13, 2018 at 6:27 am # REPLY

No, the start and end tokens are legit parts of the problem. The model must specify when the sequence has ended.

xiaolian December 23, 2017 at 1:54 am # REPLY

i got a error : Error when checking input: expected input_11 to have 4 dimensions, but got array with shape (28, 4096)

Jason Brownlee December 23, 2017 at 5:21 am # REPLY

Are you able to confirm that your libraries are up to date and that you copied all of the code from the post?

xiaolian December 23, 2017 at 1:40 pm # REPLY

can i get the code in github?

Jason Brownlee December 24, 2017 at 4:51 am # REPLY

The code is on the post, why do you need it on github?

Niels February 24, 2018 at 12:41 am # REPLY

Hello Jason.

Thank you very much for your article.
I have a practical question regarding training an encoder decoder network.

So basically I have images of serial numbers and I want to predict the full serial number. (E.G 018F6176)
So if I train a network to predict the next character I would practically have to create a for loop predicting untill I reach max length or the stop word.
This I get. However how can i structure my data?
What I have is the following
data is a numpy float array of shape (nb_samples width, height, nb_channels=3,).
labels is a numpy integer array of shape (nb_samples, max_caption_len)
So if I were to construct a similar dataset with the structure you get from create_sequences() my number of samples would increase and how do I ensure that images are loaded so as the sequence for each images comes in the correct order(or does that matter?)
Hopefully this makes sense to you.
Best regards
Niels

Jason Brownlee February 24, 2018 at 9:17 am # REPLY

Great question.

The caption model is the approach you want to use I believe.

See this post, specifically the section titled "ord-By-Word Model":
https://machinelearningmastery.com/prepare-photo-caption-dataset-training-deep-learning-model/

It will show you exactly how to prepare your data and how to think about it.

Niels February 26, 2018 at 8:01 pm # REPLY

Thank you. This is exactly what I was looking for. One question though. Does the order of input matter, so let's say all samples for image 1 comes in order, all samples for image 2 next etc.
Because then I would have to create a batch generator, however I would like to avoid that.
My initial thought is it doesn't really matter since you are just training the algorithm to recognize what comes next regarding previous input. Is that a correct assumption?
Best Regards
Niels

Jason Brownlee February 27, 2018 at 6:25 am # REPLY

I think so, I think all samples for a give photo should be together by intuition (LSTMs have memory across the batch), but testing all assumptions is a good idea.

Niels February 27, 2018 at 9:27 pm #

Okay. I created a model both with the data_generator and randomly splitting in train,test(image order scrambled). The tran, test model did not seem to converge(max 17% validation accuracy). However the data_generator model(where order is preserved) reaches 99.5% validation accuracy , so that's pretty awesome.
Thank you for your time 🙂

Jason Brownlee February 28, 2018 at 6:03 am #

Very nice. Thanks for running the experiment!

Binay March 7, 2018 at 12:18 pm # REPLY

Why and How the dimension of input_1 is (7, 7, 512)

Jason Brownlee March 7, 2018 at 3:06 pm # REPLY

That is the shape that we saved the extracted features from the photos.

Steven March 23, 2018 at 9:03 pm # REPLY

Thanks for your tutorials, Jason. I can run this tutorial in contrary with the tutorial on the same dataset https://machinelearningmastery.com/develop-a-deep-learning-caption-generation-model-in-python/ where memory errors occur.
I compared both examples and found that the feature extraction of the images is different. This example the features are a 3-dimensional array with the shape (7, 7, 512) the other example the result is a 1-dimensional 4,096 element vector. The features.pkl file of this experiment is much larger compared to the other example. What is the reason of the different shape of the features?

Jason Brownlee March 24, 2018 at 6:29 am # REPLY

Perhaps the VGG model is cut at different points? e.g. keeping the dense or discarding it and working with the CNN outputs. I don't recall, but a comparison of the code would make it clearer.

Ashish March 28, 2018 at 4:56 pm # REPLY

Thanks for the tutorial, Jason. Here you are using features from a pretrained cnn model. But I want to backpropagate the error through the cnn as well and hence jointly train the cnn and lstm. i.e. load the cnn through a pretrained model and than train it further. Can you suggest a way to do that? Thanks.

Jason Brownlee March 29, 2018 at 6:31 am # REPLY

Yes, you can load the CNN as part of your in memory model.

Vector April 7, 2018 at 3:09 pm # REPLY

Hello Jason,

Thanks for this great posts and the one in here (https://machinelearningmastery.com/develop-a-deep-learning-caption-generation-model-in-python/)!!

I was trying to run the example you posted in here.I was able to train using different learning rate and more epoch on your “average pooling” model and saved them in a .h5 file.

However when I try to use the code in (https://machinelearningmastery.com/develop-a-deep-learning-caption-generation-model-in-python/) to Generate New Captions with the “Average Model” I trained, I got this error:
ValueError: Error when checking : expected input_1 to have 4 dimensions, but got array with shape (1, 4096)

Just wonder do you know how to use this .h5 file i just trained to make prediction on one other photo? Thanks!!

Jason Brownlee April 8, 2018 at 6:14 am # REPLY

It looks like your photo features might have too many dimensions. Change your code to provide the photo pixels directly. e.g.: photo[0]

Md. Zakir Hossain May 25, 2018 at 6:46 pm # REPLY

Hai Jason,
that’s a great post. Really it is very helpful for me. However, I get the following error:

File “”, line 1, in
runfile(‘C:/Users/33083707/Codes/Projects/Final.py’, wdir=’C:/Users/33083707/Codes/Projects’)

File “C:\Users\33083707\Anaconda3\lib\site-packages\spyder\utils\site\sitecustomize.py”, line 866, in runfile
execfile(filename, namespace)

File “C:\Users\33083707\Anaconda3\lib\site-packages\spyder\utils\site\sitecustomize.py”, line 102, in execfile
exec(compile(f.read(), filename, ‘exec’), namespace)

File “C:/Users/33083707/Codes/Projects/Final.py”, line 244, in
test_score = evaluate_model(model, test_descriptions, test_features, tokenizer, max_length)

File “C:/Users/33083707/Codes/Projects/Final.py”, line 202, in evaluate_model
bleu = corpus_bleu(actual, predicted)

File “C:\Users\33083707\Anaconda3\lib\site-packages\nltk\translate\bleu_score.py”, line 146, in corpus_bleu
p_i = modified_precision(references, hypothesis, i)

File “C:\Users\33083707\Anaconda3\lib\site-packages\nltk\translate\bleu_score.py”, line 287, in modified_precision
return Fraction(numerator, denominator, _normalize=False)

File “C:\Users\33083707\Anaconda3\lib\fractions.py”, line 186, in __new__
raise ZeroDivisionError(‘Fraction(%s, 0)’ % numerator)

ZeroDivisionError: Fraction(0, 0)

Jason Brownlee May 26, 2018 at 5:51 am # REPLY

Sorry to hear that, I have some suggestions to try here:
https://machinelearningmastery.com/faq/single-faq/why-does-the-code-in-the-tutorial-not-work-for-me

Mhemmed Elly June 29, 2018 at 9:29 pm # REPLY

Hello Dr. Jason,

I want to try this on my own data, but I don’t know how to prepare it. I have a folder of images and a CSV file. Each line in the csv file contains an image ID/name and a caption that describes the image. Any advice on how to proceed?

Thank you

Jason Brownlee June 30, 2018 at 6:07 am # REPLY

Start by writing code to load the images into memory.

Perhaps you can use PIL or Pillo to load the images?

Jeet Sen Sarma July 6, 2018 at 6:53 pm # REPLY in the following part of the code :

```
# run experiment
train_results, test_results = list(), list()
for i in range(n_repeats):
# define the model
model = define_model(vocab_size, max_length)
# fit model
model.fit_generator(data_generator(train_descriptions, train_features, tokenizer, max_length,
n_photos_per_update), steps_per_epoch=n_batches_per_epoch, epochs=n_epochs, verbose=verbose)
# evaluate model on training data
train_score = evaluate_model(model, train_descriptions, train_features, tokenizer, max_length)
test_score = evaluate_model(model, test_descriptions, test_features, tokenizer, max_length)
# store
train_results.append(train_score)
test_results.append(test_score)
print('>%d: train=%f test=%f' % ((i+1), train_score, test_score))
```

why are you defining the model within the for loop ? shouldn't it be defined outside of it ?

Jason Brownlee July 7, 2018 at 6:13 am # REPLY

Nope, I want a new model (random weights) for each repeat.

Why would I define outside the loop?

Jeet July 9, 2018 at 2:47 pm # REPLY

Could you please explain why is that? I think that a model has to be defined, and the weights are to be trained by learning from examples. But defining a new model everytime would delete the previously learned weights. Where am I going wrong?

Jason Brownlee July 10, 2018 at 6:41 am # REPLY

Yes, we want to throw it away. We are repeating the experiment with a model each time so we can see how well the model on our data performs on average. Not the performance of any one randomly fit model.

You can learn more here:
https://machinelearningmastery.com/evaluate-skill-deep-learning-models/

Md. Zakir Hossain July 9, 2018 at 6:13 pm # REPLY

Hi Jason, Thank you very much.

I tried to use DenseNet-121 model instead of VGG16 model to extract the features. But I got an error like:

ValueError: Error when checking input: expected input_1 to have 4 dimensions, but got array with shape (21, 1024).

Can you please suggest me anything about this.

Jeet July 10, 2018 at 4:26 am # REPLY

This is because both the CNN models have different output dimensions of their last layer from where you are pulling the features for your images. Best guess is to convert the output dimension of your DenseNet model into the same dimension of that of VGG-16.
Also, if you use Flatten() instead of GlobalMaxPooling2D() then I guess you will not face the same problem.

Jason Brownlee July 10, 2018 at 6:44 am # REPLY

Not really, I don't know about the things you are trying.

Omnia October 24, 2018 at 8:25 am # REPLY

Hi Jason

Thanks for the wonderful tutorial as always

I got this result on 70 epochs and 3 repeats
it seems that the accuracy increases when we have a large number of epochs

but I don't understand why I got the train and test = 0

this is my result

Epoch 70/70
– 14s – loss: 1.8873 – acc: 0.4100
Actual: startseq child and woman are at waters edge in big city endseq
Predicted: startseq child woman are edge edge in big endseq

Actual: startseq boy with stick kneeling in front of goalie net endseq
Predicted: startseq boy boy in in front and and and of of of of of in front and of of in front boy front and of of

Actual: startseq woman crouches near three dogs in field endseq
Predicted: startseq two dog dogs in near near near near near near near near near near near near near near

near near near near near near near

Actual: startseq boy bites hard into treat while he sits outside endseq
Predicted: startseq boy bites sits while while outside endseq

Actual: startseq person eats takeout while watching small television endseq
Predicted: startseq person eats while takeout small small television endseq

Actual: startseq couple with young child wrapped in blanket sitting on concrete step endseq
Predicted: startseq boy girls in in in bike endseq

Actual: startseq adults and children stand and play in front of steps near wooded area endseq
Predicted: startseq boy and young boy and and and and and and and and and and and and and and and and and and and

Actual: startseq boy in grey pajamas is jumping on the couch endseq
Predicted: startseq boy man into if rough endseq

Actual: startseq boy holding kitchen utensils and making threatening face endseq
Predicted: startseq girl holds shorts shorts shorts with down her endseq

Actual: startseq man in green hat is someplace up high endseq
Predicted: startseq boy in with with waves endseq

>3: train=0.000000 test=0.000000
train test
count 3.000000e+00 3.000000e+00
mean 6.038250e-02 4.013559e-155
std 1.045856e-01 2.160777e-156
min 2.413005e-78 3.808820e-155
25% 2.799294e-78 3.900627e-155
50% 3.185584e-78 3.992435e-155
75% 9.057374e-02 4.115929e-155
max 1.811475e-01 4.239423e-155

Also, I got this warning

UserWarning:
The hypothesis contains 0 counts of 3-gram overlaps.
Therefore the BLEU score evaluates to 0, independently of
how many N-gram overlaps of lower order it contains.
Consider using lower n-gram order or use SmoothingFunction()
warnings.warn(_msg)

would you mind giving your opinion on my experiment and suggesting a better solution for the warning?

Thanks

Jason Brownlee October 24, 2018 at 2:41 pm # REPLY

Nice work!

BLEU may give warnings when some predictions are shorter than expected. This might help understand the BLEU score calculation some more:
https://machinelearningmastery.com/calculate-bleu-score-for-text-python/

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