A4 - Reading Noisy Captions Embedded in Images

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1 Non-competitive part

In this part of the assignment we had to implement encoder for the images and a decoder for text captions in this part along with beam search to find the most optimal sequence.

1.1 Pre-processing

- Building on the `starter_code.py`, the captions were first enclosed within `START` and `END` tokens, and then padded with PAD tokens to make them all fixed length. Let's call this fixed length l.
- The captions were tokenized at word-level. Character-level tokenization with OCR task was considered, but we didn't have the right dataset to train an OCR like model.
- After tokenization, they were converted into one-hot vectors. There were 7739 tokens.
- Images were resized to fixed size. Thresholding the images to remove the background details and converting to grayscale was tried, it didn't help.
- In images, we used the EAST text detector in opencv to crop tightly to the text. The results were poor.
- In conclusion, the captions were tokenized, enclosed in start and end markers and padded to fixed length l after which a vocabulary mapped it to integers which was then mapped to one-hot encodings. Images were resized to fixed width-height.

Here is the code for tokenization,

[ ]:
```python
def gen_vocab(this):
    captions_dict = this.captions_dict
    words = dict()
    for k in captions_dict:
    for token in captions_dict[k].strip().split():
        words[token] = 1
    vocab = {k: v+3 for v, k in enumerate(words)}
    vocab['xxpad'] = 0
    vocab['xxstart'] = 1
    vocab['xxend'] = 2
    vocab['xxunk'] = len(vocab.keys())
    return vocab
```

1.2 CNN Encoder

We made a simple CNN block to extract features from images comprising of convolutional layers and pooling layers. Default kernel size and stride size were used.

Different layers used in the encoder,

```
[ ]: this.convs = nn.ModuleList()
     this.convs.append(nn.Conv2d(indim, hiddenconvdim,(7,7)))
     this.nconvs = 3
     for _ in range(this.nconvs-1):
         this.convs.append(nn.Conv2d(hiddenconvdim,hiddenconvdim,(7,7)))
     this.flatten = nn.
      ↪Conv2d(hiddenconvdim,1,(3,3),padding=1,padding_mode='replicate')
```

Code for forward pass through the encoder,

```
[ ]: for i in range(this.nconvs):
         image_batch = this.convs[i](image_batch)
         image_batch = F.dropout(image_batch,p=0.1,training=this.training)
         image_batch = F.relu_(image_batch)
     image_batch = F.max_pool2d(image_batch,4,11)
```

1.3 Attention

Code for attention,

```
[ ]: bs,C,w,h = image_batch.size()
     image_batch = image_batch.view(bs,-1,w*h)
     bs,C,w,h = x.size()
     x = x.view(bs,w*h,-1)
     x = F.softmax(this.att_in(x),dim=2)
     combined = torch.bmm(image_batch,x.permute(0,2,1))
```

1.4 RNN Decoder

- The output of the CNN decoder was first fed into a linear layer to create attention weights. It was then multiplied with features output by encoder.
- This was then passed into two other linear layers which would output initial hidden state and cell state to be used by RNN decoder.
- We used `torch.nn.LSTM` in biderectional mode first, 2 layers deep. We soon realized a problem here: this only gave the final output. So, we switched to `torch.nn.LSTMCell` that would give out the hidden and cell states at each time step and it can be used to run it for as many time steps as needed.
- So, in the `torch.nn.Module.forward` method (inherited by our model) we had a `for` loop running for the length of the sequence which was the same as l.
- The hidden state at each step is seen as the unnormalized log probabilities over all possible words.
- We did teacher-forcing, just as asked for.

Layers used in the decoder,

```
[ ]: this.rnn = nn.LSTMCell(lstmoutdim,lstmoutdim)
     this.init_h = nn.Linear(22*22,lstmoutdim)
     this.init_c = nn.Linear(22*22,lstmoutdim)
```

Forward pass through the encoder,

```
[ ]: mean_enc_out = combined.mean(dim=1)
     h = this.init_h(mean_enc_out)
     h = h.view(this.batch_size,this.lstmoutdim)
     c = this.init_c(mean_enc_out)
     c = c.view(this.batch_size,this.lstmoutdim)

     max_len = this.lstmindim
     pred = torch.zeros(this.batch_size,max_len,this.lstmoutdim,device=d)
     curr_input = torch.zeros(this.batch_size,this.lstmoutdim,device=d)

     #this is the start token
     curr_input[:,1]=1
     pred[:,0,:] = curr_input
```

Teacher forcing is used here,

```
[ ]: for t in range(1,max_len):
         (h,c) = this.rnn(curr_input,(h,c))
         pred[:,t,:] = h
         if this.training:
             curr_input = captions_batch[:,t,:]
         else:
             curr_input = h
```

1.5 Loss

We used negative log likelihood loss to maximize the likelihood of each word at each time step for each example. So,

$$P_v(x^{(i)}) = [\text{softmax}(h_\theta(x^{(i)}))]_v,\ v \in V$$
$$LL(\theta; x, y) = \sum_{i \in M} \sum_{t=1}^{T} \sum_{v \in V} 1\{y_t^{(i)} = v\} \log P_v(x^{(i)})$$

where with abuse of notation, $h_\theta(x^{(i)})$ is used to mean the hidden state output by the rnn and time t by the RNN decoder. V is the set of all words, the vocabulary. (M) represents the mini-batch.

The parameters of the model, both encoder and decoder are then trained in an end-to-end fashion using SGD optimizer.

This is the loss function we have used,

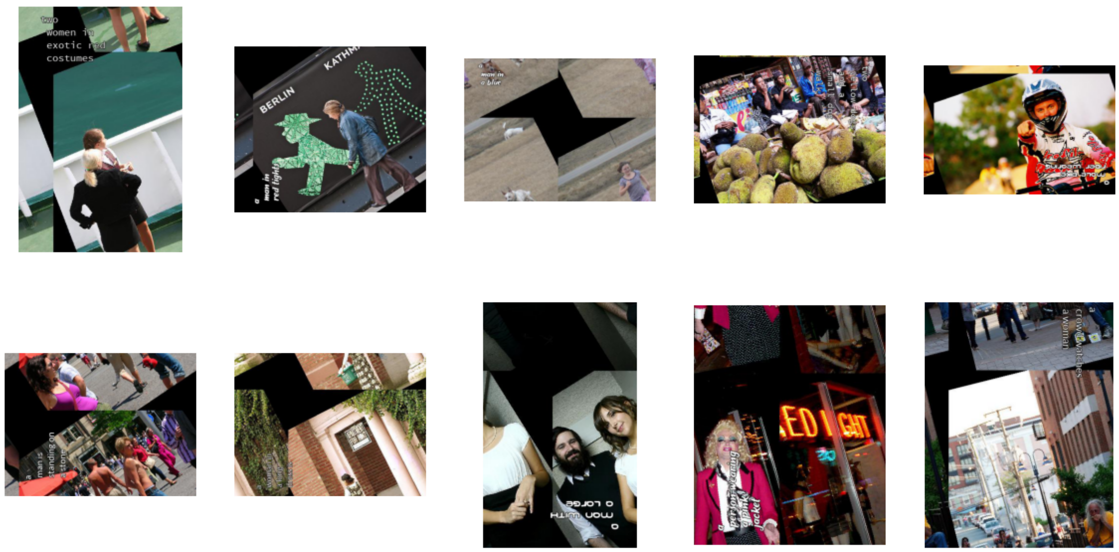
```
[ ]: loss_function = nn.CrossEntropyLoss()
```

2 Competitive Part

In this part of the assignment we used pre-trained CNN models for encoder.

2.1 Visualizing the data

Here are few images from the dataset provided to us for the assignment.



- We thought that as it would be difficult to the model to first locate the text image and then extract the text, so we created another dataset where we extracted the text region from the image.
- For this we used, EAST text detector in opencv to crop tightly to the text.

Below are the images of the new dataset

We tried training the model using both the dataset.

2.2 Preprocessing

For this part we used fastai library for pre-processing the text and convert into number so that it could be fed into the model.

```
[ ]: tokenizer = Tokenizer()
     train_texts_tokenized = tokenizer.process_all(list(zip(*train_fns_txts))[1])
     vocab = Vocab.create(train_texts_tokenized, max_vocab=50000, min_freq=2)
```

```
[ ]: def numericalize_tokens(tok):
         return np.array([vocab.numericalize(q) + [1] for q in tok])
```

The following function was used to create the training and validation data.

```
[ ]: def build_data(fns_txts, PATH, name):
         filenames, text = zip(*fns_txts)
         texts_tok = numericalize_tokens(tokenizer.process_all(text))
         dataset = (filenames, texts_tok)
         pickle.dump(dataset, open(str(PATH)+"/"+name+".pkl", 'wb'))
```

2.3 Image Text Dataset

This is the custom PyTorch dataset, which will then be used to create the dataloader.

```
[ ]: class ImageTextDataset(Dataset):
         def __init__(self, data, transform=None):
             self.filenames = data[0]
             self.texts  = data[1]
             self.transform = transform
```

```
    def __len__(self):
        return len(self.filenames)

    def __getitem__(self, idx):
        image = Image.open(self.filenames[idx]).convert('RGB')
        text = self.texts[idx]
        if self.transform is not None:
            image = self.transform(image)

        return (image, text)
```

These are the transformation on the image dataset, we have resize the image to size 224.

[ ]:
```
train_tfms = transforms.Compose([
    transforms.Resize((sz, sz)),
    transforms.ToTensor(),
    transforms.Normalize([0.5238, 0.5003, 0.4718], [0.3159, 0.3091, 0.3216])
])

valid_tfms = transforms.Compose([
    transforms.Resize((sz, sz)),
    transforms.ToTensor(),
    transforms.Normalize([0.5238, 0.5003, 0.4718], [0.3159, 0.3091, 0.3216])
])
```

2.4 CNN Encoder

Here we have used pretrained `resnet34` as our base network and added a few fully connected layer to feed it the RNN decoder part.

[ ]:
```
class Encoder(nn.Module):
    def __init__(self, device, dec_hidden_state_size, dec_layers, filter_width,␣
 ↪num_filters):
        super().__init__()
        self.device = device
        self.base_network = nn.Sequential(*list(models.
 ↪resnet34(pretrained=True).children())[:-2])
        self.freeze_base_network()
        self.concatPool = AdaptiveConcatPool2d(sz=1)
        self.adaptivePool = nn.AdaptiveAvgPool2d((filter_width, filter_width))
        self.filter_width = filter_width

        self.output_layers = nn.ModuleList([
            fc_layer(2*num_filters, dec_hidden_state_size) for _ in␣
 ↪range(dec_layers)
        ])
```

```
    def forward(self, inp):
        enc_output = self.base_network(inp)
        annotation_vecs = self.adaptivePool(enc_output).view(enc_output.
↪size(0), enc_output.size(1), -1)
        enc_output = self.concatPool(enc_output)

        dec_init_hidden_states = [MLP_layer(enc_output) for MLP_layer in self.
↪output_layers]

        return torch.stack(dec_init_hidden_states, dim = 0), annotation_vecs.
↪transpose(1, 2)
```

2.5 Visual Attention

Code for visual attention.

[ ]:
```
class VisualAttention(nn.Module):
    def __init__(self, num_filters, dec_dim, att_dim):
        super().__init__()
        self.attend_annot_vec = nn.Linear(num_filters, att_dim)
        self.attend_dec_hidden= nn.Linear(dec_dim, att_dim)
        self.f_att = nn.Linear(att_dim, 1)

    def forward(self, annotation_vecs, dec_hid_state):
        attended_annotation_vecs = self.attend_annot_vec(annotation_vecs)
        attended_dec_hid_state    = self.attend_dec_hidden(dec_hid_state)
        e = self.f_att(F.relu(attended_annotation_vecs + attended_dec_hid_state.
↪unsqueeze(1))).squeeze(2)
        alphas = F.softmax(e, dim=1)
        context_vec = (annotation_vecs * alphas.unsqueeze(2)).sum(1)

        return context_vec, alphas
```

2.6 Image Text Extractor

This is the entire encoder-decoder based module for text extraction.

[ ]:
```
class ImageTextExtractor(nn.Module):
    def __init__(self, device, filter_width, num_filters, vocab_size, emb_sz,␣
↪out_seqlen, n_layers=3,
                 prob_teach_forcing=1, p_drop=0.3):
        super().__init__()
        self.n_layers, self.out_seqlen = n_layers, out_seqlen
        self.filter_width = filter_width
        self.num_filters = num_filters
        self.device = device

        # Encoder
```

```
        self.encoder = Encoder(device, emb_sz, n_layers, filter_width, num_filters)

        # Attention
        self.att = VisualAttention(num_filters, emb_sz, 500)

        # Decoder
        self.emb = nn.Embedding(vocab_size, emb_sz)
        self.rnn_dec = nn.GRU(num_filters + emb_sz, emb_sz, num_layers=n_layers,
                              dropout=0 if n_layers == 1 else p_drop)
        self.out_drop = nn.Dropout(p_drop)
        self.out = nn.Linear(emb_sz, vocab_size)
        self.out.weight.data = self.emb.weight.data
        self.f_b = nn.Linear(emb_sz, num_filters)

        self.prob_teach_forcing = prob_teach_forcing
        self.initializer()

    def initializer(self):
        self.emb.weight.data.uniform_(-0.1, 0.1)

    def forward(self, x, y=None):
        h, annotation_vecs = self.encode(x)

        dec_inp = torch.zeros(h.size(1), requires_grad=False).long()
        dec_inp = dec_inp.to(self.device)
        res = []
        alphas = []

        for i in range(self.out_seqlen):
            dec_output, h, alpha = self.decode_step(dec_inp, h, annotation_vecs)
            res.append(dec_output)
            alphas.append(alpha)

            if (dec_inp == 1).all() or (y is not None and i >= len(y)):
                break
            # teacher forcing
            elif y is not None and (self.prob_teach_forcing > 0) and (random.random() < self.prob_teach_forcing):
                dec_inp = y[i].to(self.device)
            else:
                dec_inp = dec_output.data.max(1)[1]

        return torch.stack(res), torch.stack(alphas)


    def encode(self, x):
```

```
        return self.encoder(x.to(self.device))

    def decode_step(self, dec_inp, h, annotation_vecs):
        context_vec, alpha = self.att(annotation_vecs, h[-1])
        beta = torch.sigmoid(self.f_b(h[-1]))
        context_vec = beta * context_vec

        emb_inp = self.emb(dec_inp).unsqueeze(0)

        output, h = self.rnn_dec(torch.cat([emb_inp, context_vec.unsqueeze(0)],␣
↪dim=2), h)
        output = self.out(self.out_drop(output[0]))

        return F.log_softmax(output, dim=1), h, alpha
```

2.7 Training

Here we have used fastai learner.

[ ]:

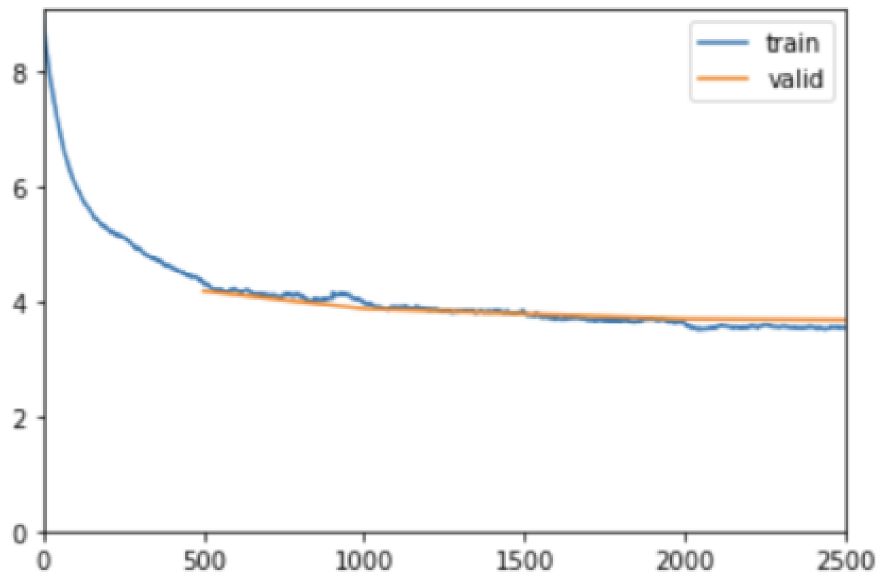
```
textExtractor = ImageCaptionGenerator(gpu, 7, 512, len(vocab.itos), emb_sz, 50,␣
↪n_layers, p_drop=0.2)
opt_fn = partial(optim.Adam, betas=(0.8, 0.99))
dataBunch = DataBunch(train_dl=trn_dl, valid_dl=val_dl, device=gpu, path=PATH,␣
↪collate_fn=imgcap_collate_func)
learn = Learner(data=dataBunch, model=to_device(imgCapGen, gpu),␣
↪opt_func=opt_fn,
                loss_func=ImageCaptionLoss, callback_fns=[ShowGraph],␣
↪metrics=[BleuMetric()])

learn.fit_one_cycle(5, lr, callbacks=[
    SaveModelCallback(learn, monitor='bleu_metric'))
```

[30]:

```
<matplotlib.image.AxesImage at 0x2b02ec047390>
```

epoch	train_loss	valid_loss	bleu_metric	time
0	4.349412	4.187444	0.060596	38:17
1	4.006149	3.880062	0.059236	36:59
2	3.819177	3.788077	0.063252	36:52
3	3.619238	3.701265	0.067418	38:24
4	3.549264	3.686493	0.066524	38:50



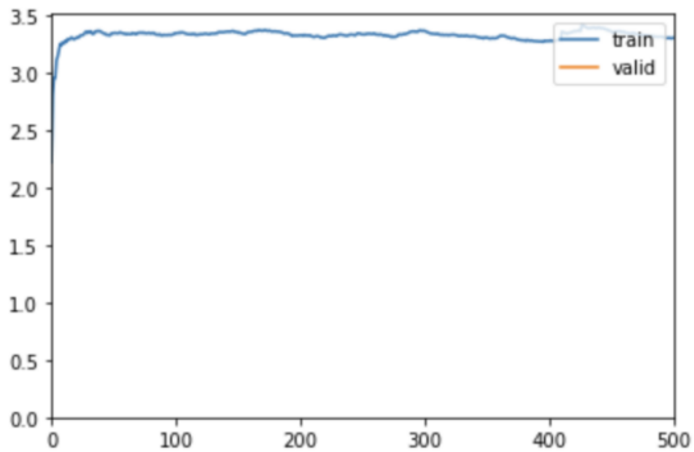
[ ]:
```
learn.unfreeze()

learn.fit_one_cycle(5, max_lr=5e-4, callbacks=[
    SaveModelCallback(learn, monitor='bleu_metric'))
```

Change in loss after unfreezing the encoder layer for fine-tuning

[31]: `<matplotlib.image.AxesImage at 0x2b02ec077bd0>`

epoch	train_loss	valid_loss	bleu_metric	time
0	3.307443	3.516318	0.079725	39:26



2.8 Multilabel Classification

We also tried to formulate this problem as multi-label classification task, where the classes are the subwords embedded in the image.

Here is the sample input,

[7]: <matplotlib.image.AxesImage at 0x7ff3905f7490>

	filename	labels	is_valid	tokens
0	/home/cse/phd/anz198717/scratch/suchith_data/data/train_data/res1.jpg	two men in green shirts	True	[▁two, ▁men, ▁in, ▁green, ▁shirt, s]
1	/home/cse/phd/anz198717/scratch/suchith_data/data/train_data/res2.jpg	a girl in an innertube	False	[▁a, ▁girl, ▁in, ▁an, ▁in, n, er, t, u, b, e]
2	/home/cse/phd/anz198717/scratch/suchith_data/data/train_data/res3.jpg	several men in hard hats are	False	[▁several, ▁men, ▁in, ▁ha, r, d, ▁hat, s, ▁are]
3	/home/cse/phd/anz198717/scratch/suchith_data/data/train_data/res4.jpg	a woman in a brown	False	[▁a, ▁woman, ▁in, ▁a, ▁brown]
4	/home/cse/phd/anz198717/scratch/suchith_data/data/train_data/res5.jpg	a little girl in a	False	[▁a, ▁little, ▁girl, ▁in, ▁a]

[8]: <matplotlib.image.AxesImage at 0x7ff3a034f1d0>


```
[ ]: learn = cnn_learner(dls, resnet34, metrics=partial(accuracy_multi,
                                                    thresh=0.2))
     learn.fine_tune(3, base_lr=3e-3, freeze_epochs=4)
```

```
[22]: <matplotlib.image.AxesImage at 0x7ff3b1e40b10>
```

```
i = 9000
dls.train_ds[i][0]
```


```
p = learn.predict(dls.train_ds[i][0])[2]
pos = np.where(p > 0.2)[0]
list(learn.dls.vocab[pos])
```

```
['ing', 's', '_are', '_in', '_men', '_the', '_two']
```

The result that we got from this approach was also not satisfactory.

2.9 Subword-Multiclass Image Extraction

We also tried to train the model on text tokenized at subword level, using the multi-label encoder trained above, below are the metrics during the training time

[17]: <matplotlib.image.AxesImage at 0x7ff3b0c3c190>

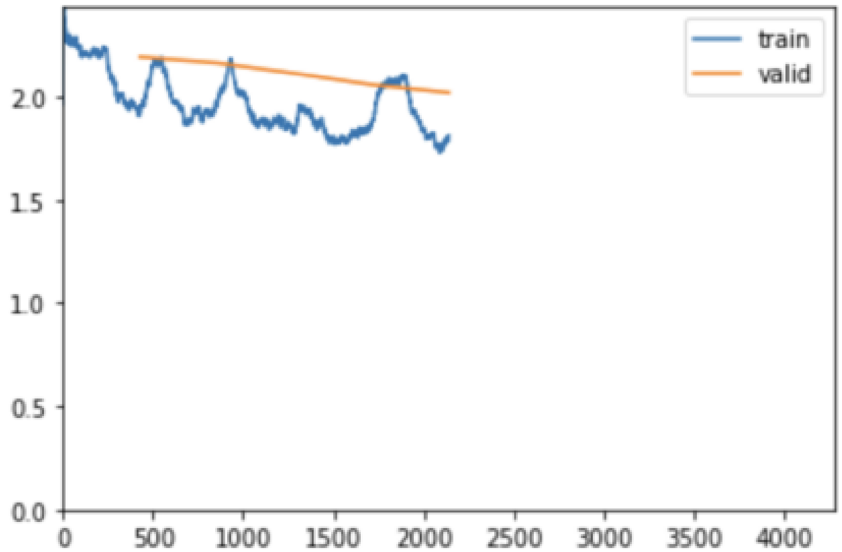
50.00% [5/10 1:24:43<1:24:43]

epoch	train_loss	valid_loss	bleu_metric	time
0	1.929021	2.191253	0.264068	17:32
1	1.957465	2.162302	0.269130	16:16
2	1.823286	2.111759	0.287369	16:57
3	1.868920	2.056931	0.304490	16:46
4	1.809331	2.018546	0.314575	17:01

13.32% [57/428 01:54<12:22 1.9261]

[20]:
```
img = plt.imread('/Users/suchith720/Desktop/subword_train.png')
plt.figure(figsize=(10, 10))
plt.axis('off')
plt.imshow(img)
```

[20]: <matplotlib.image.AxesImage at 0x7ff390858d10>



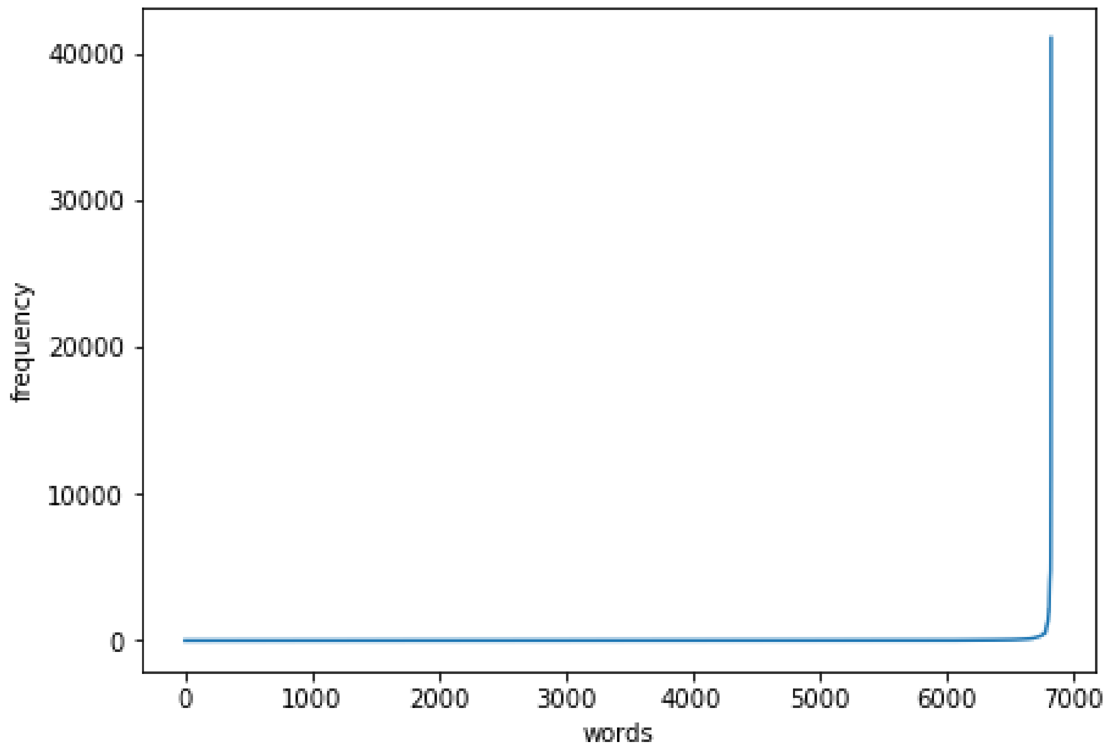
The result on the leaderboard that we got from a trained model was using this method.

3 Results and Conclusion

- Training with the new dataset where the text regions was extracted from the image did not help us much.

Looking at the word distribution of the embedded text in the image, we can see below that it is very skewed. So as our baseline we found the top 8 occuring words in datasets and submitted it to the leaderboard as prediction of each image. We choose 8 at it was the average size of the embedded text. With this we got BLEU score of 0.16, which we could not beat with our trained model.

```
[47]: [<matplotlib.lines.Line2D at 0x2b02e90c30d0>]
```



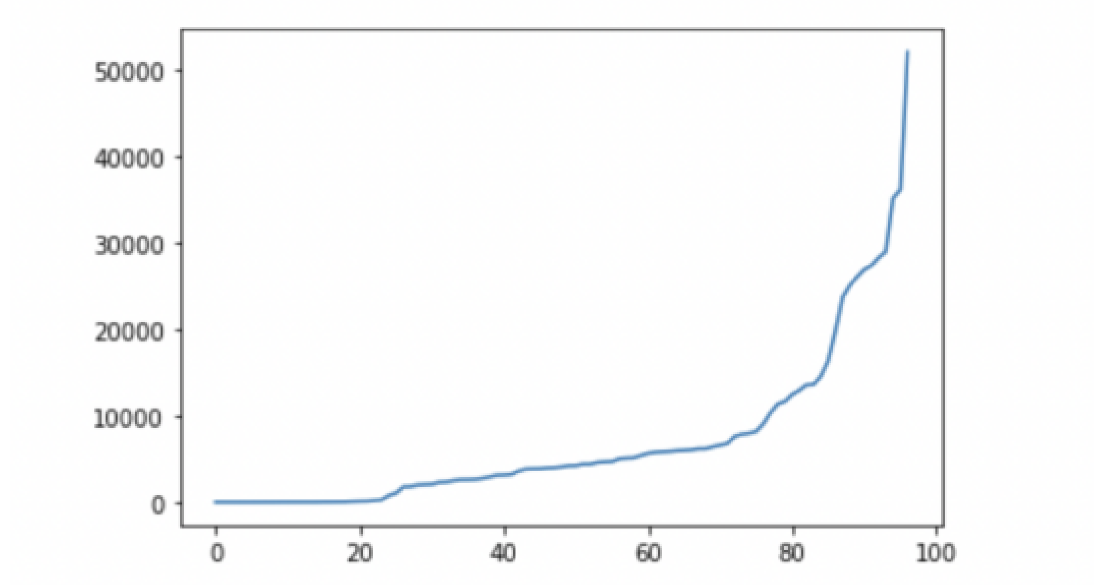
We predicted `on two the woman is man in a` for each test image.

We believe that this was one of the main reason why we were not able to train the model, due to the skewed distribution of the words. So considering other ways of representation like the subword-level tokenization has helped us a lot to train the model.

Below is the distribution of the tokens after the subword level tokeniztion.

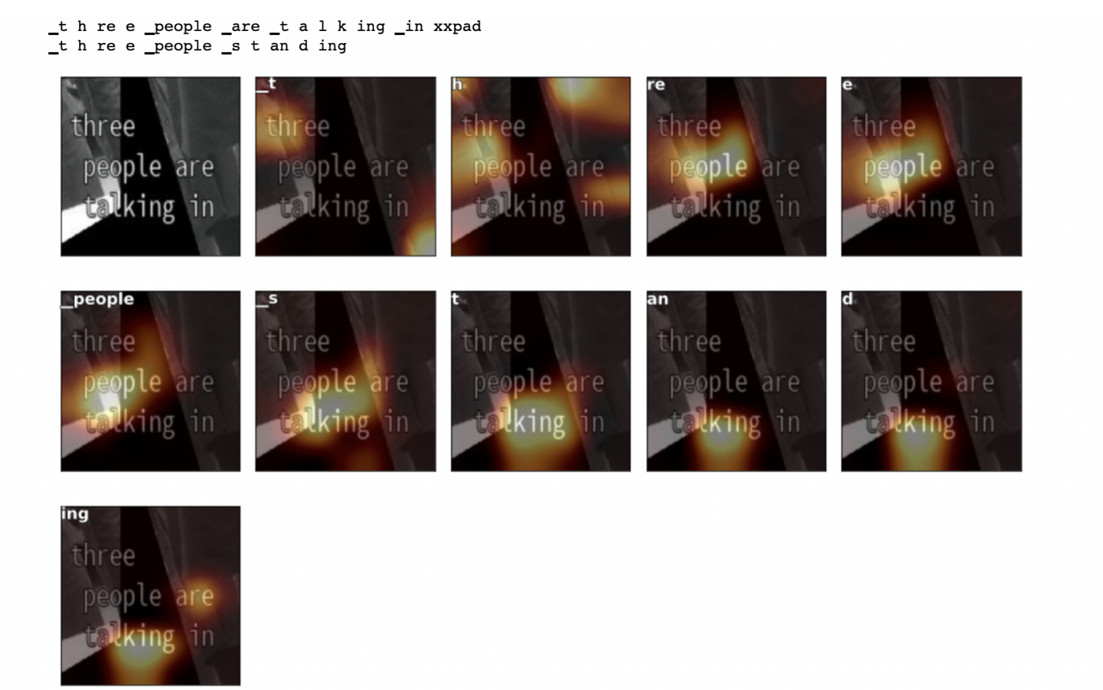
[21]:
```
img = plt.imread('/Users/suchith720/Desktop/subword_dist.png')
plt.figure(figsize=(10, 10))
plt.axis('off')
plt.imshow(img)
```

[21]:
```
<matplotlib.image.AxesImage at 0x7ff3b163ba50>
```



We can see from the attention heatmap that the model has learnt to read the text in the image from left to right. We have also seen that this model is doing very good at Image Captioning than Text Extraction.

[13]: <matplotlib.image.AxesImage at 0x7ff3b09b4950>



Here are the scores of our submission on the leaderload,

	bleu
baseline	0.1596
assignment dataset	0.10317
new dataset	0.11187
Multi-label	0.103502
Pretrained Multi-label	0.1270

4 References

We have heavily relied on code present in this github repository for our work.