LSTM_Captioning

October 23, 2019

1 Image Captioning with LSTMs

In the previous exercise you implemented a vanilla RNN and applied it to image captioning. In this notebook you will implement the LSTM update rule and use it for image captioning.

```
In [1]: # As usual, a bit of setup
        from __future__ import print_function
        import time, os, json
        import numpy as np
        import matplotlib.pyplot as plt
        import nltk

        from cs231n.gradient_check import eval_numerical_gradient, eval_numerical_gradient_arra
        from cs231n.rnn_layers import *
        from cs231n.captioning_solver import CaptioningSolver
        from cs231n.classifiers.rnn import CaptioningRNN
        from cs231n.coco_utils import load_coco_data, sample_coco_minibatch, decode_captions
        from cs231n.image_utils import image_from_url

        %matplotlib inline
        plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
        plt.rcParams['image.interpolation'] = 'nearest'
        plt.rcParams['image.cmap'] = 'gray'

        # for auto-reloading external modules
        # see http://stackoverflow.com/questions/1907993/autoreload-of-modules-in-ipython
        %load_ext autoreload
        %autoreload 2

        def rel_error(x, y):
            """ returns relative error """
            return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y))))
```

2 Load MS-COCO data

As in the previous notebook, we will use the Microsoft COCO dataset for captioning.

```
In [2]: # Load COCO data from disk; this returns a dictionary
        # We'll work with dimensionality-reduced features for this notebook, but feel
        # free to experiment with the original features by changing the flag below.
        data = load_coco_data(pca_features=True)

        # Print out all the keys and values from the data dictionary
        for k, v in data.items():
            if type(v) == np.ndarray:
                print(k, type(v), v.shape, v.dtype)
            else:
                print(k, type(v), len(v))
```

```
train_captions <class 'numpy.ndarray'> (400135, 17) int32
train_image_idxs <class 'numpy.ndarray'> (400135,) int32
val_captions <class 'numpy.ndarray'> (195954, 17) int32
val_image_idxs <class 'numpy.ndarray'> (195954,) int32
train_features <class 'numpy.ndarray'> (82783, 512) float32
val_features <class 'numpy.ndarray'> (40504, 512) float32
idx_to_word <class 'list'> 1004
word_to_idx <class 'dict'> 1004
train_urls <class 'numpy.ndarray'> (82783,) <U63
val_urls <class 'numpy.ndarray'> (40504,) <U63
```

3 LSTM

If you read recent papers, you'll see that many people use a variant on the vaniallа RNN called Long-Short Term Memory (LSTM) RNNs. Vanilla RNNs can be tough to train on long sequences due to vanishing and exploding gradiants caused by repeated matrix multiplication. LSTMs solve this problem by replacing the simple update rule of the vanilla RNN with a gating mechanism as follows.

Similar to the vanilla RNN, at each timestep we receive an input $x_t \in \mathbb{R}^D$ and the previous hidden state $h_{t-1} \in \mathbb{R}^H$; the LSTM also maintains an H-dimensional *cell state*, so we also receive the previous cell state $c_{t-1} \in \mathbb{R}^H$. The learnable parameters of the LSTM are an *input-to-hidden* matrix $W_x \in \mathbb{R}^{4H\times D}$, a *hidden-to-hidden* matrix $W_h \in \mathbb{R}^{4H\times H}$ and a *bias vector* $b \in \mathbb{R}^{4H}$.

At each timestep we first compute an *activation vector* $a \in \mathbb{R}^{4H}$ as $a = W_x x_t + W_h h_{t-1} + b$. We then divide this into four vectors $a_i, a_f, a_o, a_g \in \mathbb{R}^H$ where a_i consists of the first H elements of a, a_f is the next H elements of a, etc. We then compute the *input gate* $g \in \mathbb{R}^H$, *forget gate* $f \in \mathbb{R}^H$, *output gate* $o \in \mathbb{R}^H$ and *block input* $g \in \mathbb{R}^H$ as

where σ is the sigmoid function and tanh is the hyperbolic tangent, both applied elementwise. Finally we compute the next cell state c_t and next hidden state h_t as

$$c_t = f \odot c_{t-1} + i \odot g \qquad\qquad h_t = o \odot \tanh(c_t)$$

where $\odot$ is the elementwise product of vectors.

In the rest of the notebook we will implement the LSTM update rule and apply it to the image captioning task.

In the code, we assume that data is stored in batches so that $X_t \in \mathbb{R}^{N\times D}$, and will work with *transposed* versions of the parameters: $W_x \in \mathbb{R}^{D\times 4H}$, $W_h \in \mathbb{R}^{H\times 4H}$ so that activations $A \in \mathbb{R}^{N\times 4H}$ can be computed efficiently as $A = X_t W_x + H_{t-1} W_h$

4 LSTM: step forward

Implement the forward pass for a single timestep of an LSTM in the `lstm_step_forward` function in the file `cs231n/rnn_layers.py`. This should be similar to the `rnn_step_forward` function that you implemented above, but using the LSTM update rule instead.

Once you are done, run the following to perform a simple test of your implementation. You should see errors around `1e-8` or less.

In [3]:
```
N, D, H = 3, 4, 5
x = np.linspace(-0.4, 1.2, num=N*D).reshape(N, D)
prev_h = np.linspace(-0.3, 0.7, num=N*H).reshape(N, H)
prev_c = np.linspace(-0.4, 0.9, num=N*H).reshape(N, H)
Wx = np.linspace(-2.1, 1.3, num=4*D*H).reshape(D, 4 * H)
Wh = np.linspace(-0.7, 2.2, num=4*H*H).reshape(H, 4 * H)
b = np.linspace(0.3, 0.7, num=4*H)

next_h, next_c, cache = lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b)

expected_next_h = np.asarray([
    [ 0.24635157,  0.28610883,  0.32240467,  0.35525807,  0.38474904],
    [ 0.49223563,  0.55611431,  0.61507696,  0.66844003,  0.7159181 ],
    [ 0.56735664,  0.66310127,  0.74419266,  0.80889665,  0.858299  ]])
expected_next_c = np.asarray([
    [ 0.32986176,  0.39145139,  0.451556,    0.51014116,  0.56717407],
    [ 0.66382255,  0.76674007,  0.87195994,  0.97902709,  1.08751345],
    [ 0.74192008,  0.90592151,  1.07717006,  1.25120233,  1.42395676]])

print('next_h error: ', rel_error(expected_next_h, next_h))
print('next_c error: ', rel_error(expected_next_c, next_c))
```

```
next_h error:  5.7054131967097955e-09
next_c error:  5.8143123088804145e-09
```

5 LSTM: step backward

Implement the backward pass for a single LSTM timestep in the function `lstm_step_backward` in the file `cs231n/rnn_layers.py`. Once you are done, run the following to perform numeric gradient checking on your implementation. You should see errors around `1e-6` or less.

In [4]:
```
np.random.seed(231)
```

```python
N, D, H = 4, 5, 6
x = np.random.randn(N, D)
prev_h = np.random.randn(N, H)
prev_c = np.random.randn(N, H)
Wx = np.random.randn(D, 4 * H)
Wh = np.random.randn(H, 4 * H)
b = np.random.randn(4 * H)

next_h, next_c, cache = lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b)

dnext_h = np.random.randn(*next_h.shape)
dnext_c = np.random.randn(*next_c.shape)

fx_h = lambda x: lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b)[0]
fh_h = lambda h: lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b)[0]
fc_h = lambda c: lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b)[0]
fWx_h = lambda Wx: lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b)[0]
fWh_h = lambda Wh: lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b)[0]
fb_h = lambda b: lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b)[0]

fx_c = lambda x: lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b)[1]
fh_c = lambda h: lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b)[1]
fc_c = lambda c: lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b)[1]
fWx_c = lambda Wx: lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b)[1]
fWh_c = lambda Wh: lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b)[1]
fb_c = lambda b: lstm_step_forward(x, prev_h, prev_c, Wx, Wh, b)[1]

num_grad = eval_numerical_gradient_array

dx_num = num_grad(fx_h, x, dnext_h) + num_grad(fx_c, x, dnext_c)
dh_num = num_grad(fh_h, prev_h, dnext_h) + num_grad(fh_c, prev_h, dnext_c)
dc_num = num_grad(fc_h, prev_c, dnext_h) + num_grad(fc_c, prev_c, dnext_c)
dWx_num = num_grad(fWx_h, Wx, dnext_h) + num_grad(fWx_c, Wx, dnext_c)
dWh_num = num_grad(fWh_h, Wh, dnext_h) + num_grad(fWh_c, Wh, dnext_c)
db_num = num_grad(fb_h, b, dnext_h) + num_grad(fb_c, b, dnext_c)

dx, dh, dc, dWx, dWh, db = lstm_step_backward(dnext_h, dnext_c, cache)

print('dx error: ', rel_error(dx_num, dx))
print('dh error: ', rel_error(dh_num, dh))
print('dc error: ', rel_error(dc_num, dc))
print('dWx error: ', rel_error(dWx_num, dWx))
print('dWh error: ', rel_error(dWh_num, dWh))
print('db error: ', rel_error(db_num, db))
```

```
dx error:  6.335163002532046e-10
dh error:  3.3963774090592634e-10
dc error:  1.5221723979041107e-10
```

```
dWx error:  2.1010960934639614e-09
dWh error:  9.712296109943072e-08
db error:  2.491522041931035e-10
```

6 LSTM: forward

In the function `lstm_forward` in the file `cs231n/rnn_layers.py`, implement the `lstm_forward` function to run an LSTM forward on an entire timeseries of data.

When you are done, run the following to check your implementation. You should see an error around `1e-7`.

```
In [5]: N, D, H, T = 2, 5, 4, 3
        x = np.linspace(-0.4, 0.6, num=N*T*D).reshape(N, T, D)
        h0 = np.linspace(-0.4, 0.8, num=N*H).reshape(N, H)
        Wx = np.linspace(-0.2, 0.9, num=4*D*H).reshape(D, 4 * H)
        Wh = np.linspace(-0.3, 0.6, num=4*H*H).reshape(H, 4 * H)
        b = np.linspace(0.2, 0.7, num=4*H)

        h, cache = lstm_forward(x, h0, Wx, Wh, b)

        expected_h = np.asarray([
         [[ 0.01764008,  0.01823233,  0.01882671,  0.0194232 ],
          [ 0.11287491,  0.12146228,  0.13018446,  0.13902939],
          [ 0.31358768,  0.33338627,  0.35304453,  0.37250975]],
         [[ 0.45767879,  0.4761092,   0.4936887,   0.51041945],
          [ 0.6704845,   0.69350089,  0.71486014,  0.7346449 ],
          [ 0.81733511,  0.83677871,  0.85403753,  0.86935314]]])

        print('h error: ', rel_error(expected_h, h))
```

```
h error:  8.610537452106624e-08
```

7 LSTM: backward

Implement the backward pass for an LSTM over an entire timeseries of data in the function `lstm_backward` in the file `cs231n/rnn_layers.py`. When you are done, run the following to perform numeric gradient checking on your implementation. You should see errors around `1e-7` or less.

```
In [6]: from cs231n.rnn_layers import lstm_forward, lstm_backward
        np.random.seed(231)

        N, D, T, H = 2, 3, 10, 6

        x = np.random.randn(N, T, D)
```

```
h0 = np.random.randn(N, H)
Wx = np.random.randn(D, 4 * H)
Wh = np.random.randn(H, 4 * H)
b = np.random.randn(4 * H)

out, cache = lstm_forward(x, h0, Wx, Wh, b)

dout = np.random.randn(*out.shape)

dx, dh0, dWx, dWh, db = lstm_backward(dout, cache)

fx = lambda x: lstm_forward(x, h0, Wx, Wh, b)[0]
fh0 = lambda h0: lstm_forward(x, h0, Wx, Wh, b)[0]
fWx = lambda Wx: lstm_forward(x, h0, Wx, Wh, b)[0]
fWh = lambda Wh: lstm_forward(x, h0, Wx, Wh, b)[0]
fb = lambda b: lstm_forward(x, h0, Wx, Wh, b)[0]

dx_num = eval_numerical_gradient_array(fx, x, dout)
dh0_num = eval_numerical_gradient_array(fh0, h0, dout)
dWx_num = eval_numerical_gradient_array(fWx, Wx, dout)
dWh_num = eval_numerical_gradient_array(fWh, Wh, dout)
db_num = eval_numerical_gradient_array(fb, b, dout)

print('dx error: ', rel_error(dx_num, dx))
print('dh0 error: ', rel_error(dh0_num, dh0))
print('dWx error: ', rel_error(dWx_num, dWx))
print('dWh error: ', rel_error(dWh_num, dWh))
print('db error: ', rel_error(db_num, db))
```

```
dx error:  6.9939005453315376e-09
dh0 error:  1.5042746972106784e-09
dWx error:  3.226295800444722e-09
dWh error:  2.6984653167426663e-06
db error:  8.23662763415198e-10
```

8 LSTM captioning model

Now that you have implemented an LSTM, update the implementation of the `loss` method of the `CaptioningRNN` class in the file `cs231n/classifiers/rnn.py` to handle the case where `self.cell_type` is `lstm`. This should require adding less than 10 lines of code.

Once you have done so, run the following to check your implementation. You should see a difference of less than `1e-10`.

```
In [7]: N, D, W, H = 10, 20, 30, 40
        word_to_idx = {'<NULL>': 0, 'cat': 2, 'dog': 3}
        V = len(word_to_idx)
        T = 13
```

```
model = CaptioningRNN(word_to_idx,
          input_dim=D,
          wordvec_dim=W,
          hidden_dim=H,
          cell_type='lstm',
          dtype=np.float64)

# Set all model parameters to fixed values
for k, v in model.params.items():
  model.params[k] = np.linspace(-1.4, 1.3, num=v.size).reshape(*v.shape)

features = np.linspace(-0.5, 1.7, num=N*D).reshape(N, D)
captions = (np.arange(N * T) % V).reshape(N, T)

loss, grads = model.loss(features, captions)
expected_loss = 9.82445935443

print('loss: ', loss)
print('expected loss: ', expected_loss)
print('difference: ', abs(loss - expected_loss))
```

```
loss:  9.824459354432264
expected loss:  9.82445935443
difference:  2.2648549702353193e-12
```

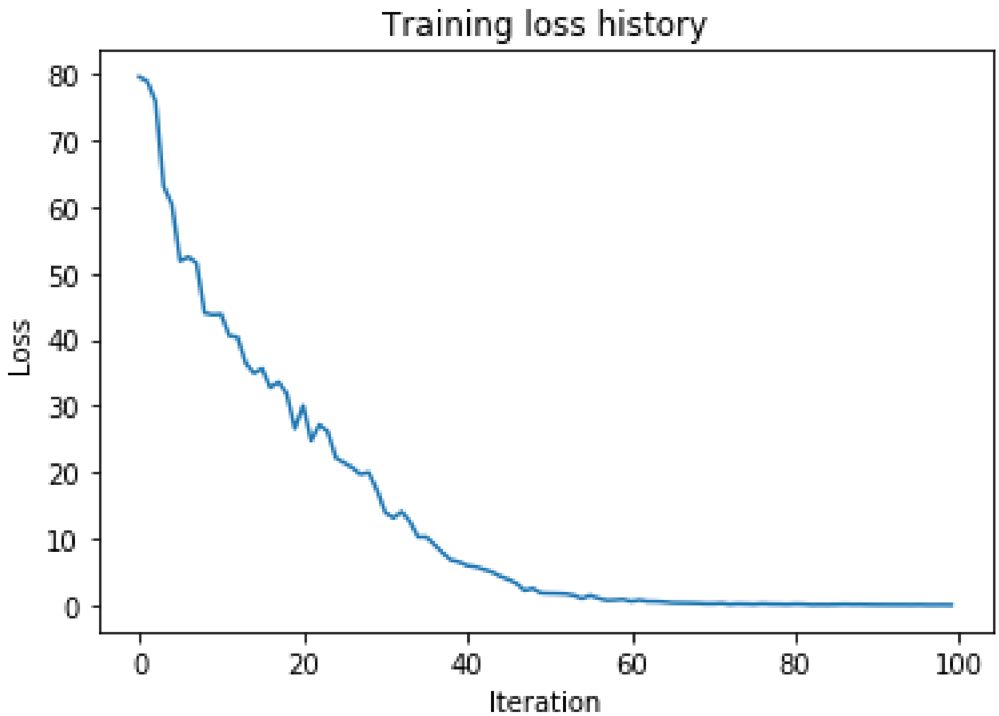
9 Overfit LSTM captioning model

Run the following to overfit an LSTM captioning model on the same small dataset as we used for the RNN previously. You should see losses less than 0.5.

In [8]:
```
np.random.seed(231)

small_data = load_coco_data(max_train=50)

small_lstm_model = CaptioningRNN(
          cell_type='lstm',
          word_to_idx=data['word_to_idx'],
          input_dim=data['train_features'].shape[1],
          hidden_dim=512,
          wordvec_dim=256,
          dtype=np.float32,
        )

small_lstm_solver = CaptioningSolver(small_lstm_model, small_data,
           update_rule='adam',
           num_epochs=50,
```

```python
                  batch_size=25,
                  optim_config={
                    'learning_rate': 5e-3,
                  },
                  lr_decay=0.995,
                  verbose=True, print_every=10,
                )

small_lstm_solver.train()

# Plot the training losses
plt.plot(small_lstm_solver.loss_history)
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Training loss history')
plt.show()
```

```
(Iteration 1 / 100) loss: 79.551150
(Iteration 11 / 100) loss: 43.829101
(Iteration 21 / 100) loss: 30.062616
(Iteration 31 / 100) loss: 14.020179
(Iteration 41 / 100) loss: 6.005075
(Iteration 51 / 100) loss: 1.849338
(Iteration 61 / 100) loss: 0.634570
(Iteration 71 / 100) loss: 0.285278
(Iteration 81 / 100) loss: 0.233098
(Iteration 91 / 100) loss: 0.121929
```



10 LSTM test-time sampling

Modify the `sample` method of the `CaptioningRNN` class to handle the case where `self.cell_type` is `lstm`. This should take fewer than 10 lines of code.

When you are done run the following to sample from your overfit LSTM model on some training and validation set samples.

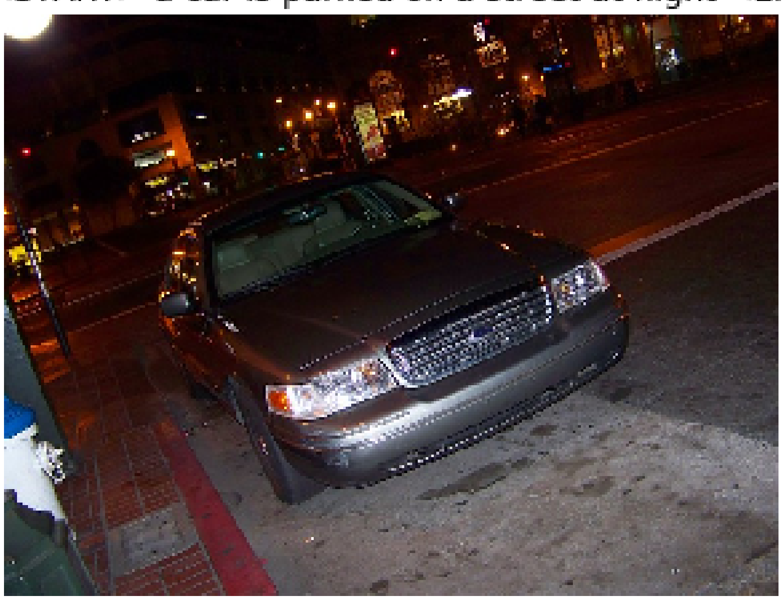
```
In [9]: for split in ['train', 'val']:
            minibatch = sample_coco_minibatch(small_data, split=split, batch_size=2)
            gt_captions, features, urls = minibatch
            gt_captions = decode_captions(gt_captions, data['idx_to_word'])

            sample_captions = small_lstm_model.sample(features)
            sample_captions = decode_captions(sample_captions, data['idx_to_word'])

            for gt_caption, sample_caption, url in zip(gt_captions, sample_captions, urls):
                plt.imshow(image_from_url(url))
                plt.title('%s\n%s\nGT:%s' % (split, sample_caption, gt_caption))
                plt.axis('off')
                plt.show()
```

train
a man standing on the side of a road with bags of luggage <END>
GT:<START> a man standing on the side of a road with bags of luggage <END>

train
a man <UNK> with a bright colorful kite <END>
GT:<START> a man <UNK> with a bright colorful kite <END>

val
a person <UNK> with a <UNK> <END>
GT:<START> a sign that is on the front of a train station <END>

val
a cat is <UNK> and a big <END>
GT:<START> a car is parked on a street at night <END>



11 Train a good captioning model (extra credit for 4803)

Using the pieces you have implemented in this and the previous notebook, train a captioning model that gives decent qualitative results (better than the random garbage you saw with the overfit models) when sampling on the validation set. You can subsample the training set if you want; we just want to see samples on the validation set that are better than random.

In addition to qualitatively evaluating your model by inspecting its results, you can also quantitatively evaluate your model using the BLEU unigram precision metric. In order to achieve full credit you should train a model that achieves a BLEU unigram score of >0.3. BLEU scores range from 0 to 1; the closer to 1, the better. Here's a reference to the paper that introduces BLEU if you're interested in learning more about how it works.

Feel free to use PyTorch for this section if you'd like to train faster on a GPU... though you can definitely get above 0.3 using your Numpy code. We're providing you the evaluation code that is compatible with the Numpy model as defined above... you should be able to adapt it for PyTorch if you go that route.

Create the model in the file `cs231n/classifiers/mymodel.py`. You can base it after the `CaptioningRNN` class. Write a text comment in the delineated cell below explaining what you tried in your model.

Also add a cell below that trains and tests your model. Make sure to include the call to evaluate_model which prints out your highest validation BLEU score for full credit.

```
In [10]: def BLEU_score(gt_caption, sample_caption):
             """
             gt_caption: string, ground-truth caption
             sample_caption: string, your model's predicted caption
             Returns unigram BLEU score.
             """
             reference = [x for x in gt_caption.split(' ')
                          if ('<END>' not in x and '<START>' not in x and '<UNK>' not in x)]
             hypothesis = [x for x in sample_caption.split(' ')
                           if ('<END>' not in x and '<START>' not in x and '<UNK>' not in x)]
             BLEUscore = nltk.translate.bleu_score.sentence_bleu([reference], hypothesis, weig
             return BLEUscore

         def evaluate_model(model):
             """
             model: CaptioningRNN model
             Prints unigram BLEU score averaged over 1000 training and val examples.
             """
             BLEUscores = {}
             for split in ['train', 'val']:
                 minibatch = sample_coco_minibatch(data, split=split, batch_size=1000)
                 gt_captions, features, urls = minibatch
                 gt_captions = decode_captions(gt_captions, data['idx_to_word'])
```

```
        sample_captions = model.sample(features)
        sample_captions = decode_captions(sample_captions, data['idx_to_word'])

        total_score = 0.0
        for gt_caption, sample_caption, url in zip(gt_captions, sample_captions, urls
            total_score += BLEU_score(gt_caption, sample_caption)

        BLEUscores[split] = total_score / len(sample_captions)

    for split in BLEUscores:
        print('Average BLEU score for %s: %f' % (split, BLEUscores[split]))
```

12 write a description of your model here:

Same model as the LSTM Numpy implementation, with fine tunned hyper parameters and more data. Training take times.

All paramters were changed, the most important one was probably the hidden dim (and the data quantity) a large batch size allowed to get the gradiant right while a lower learning rate was needed to take into account the large number of iteration vs the small number of epoch. This trainning was completed on around 12 hours on a 12 threads desktop Intel i7-8700 CPU.

```
In [14]: # write your code to train your model here.
         from cs231n.classifiers.mymodel import MyModel

         my_data = load_coco_data(max_train=None)

         my_lstm_model = MyModel(
                   cell_type='lstm',
                   word_to_idx=data['word_to_idx'],
                   input_dim=data['train_features'].shape[1],
                   hidden_dim=2048,
                   wordvec_dim=256,
                   dtype=np.float32,
                 )

         my_lstm_solver = CaptioningSolver(my_lstm_model, my_data,
                    update_rule='adam',
                    num_epochs=3,
                    batch_size=1024,
                    optim_config={
                      'learning_rate': 1e-4,
                    },
                    lr_decay=0.9,
                    verbose=True, print_every=1,
                  )
```

```python
my_lstm_solver.train()

# Plot the training losses
plt.plot(my_lstm_solver.loss_history)
plt.xlabel('Iteration')
plt.ylabel('Loss')
plt.title('Training loss history')
plt.show()
# make sure to include the call to evaluate_model which prints out your highest valid
print("LSTM score:")
evaluate_model(small_lstm_model)
print("My model score:")
evaluate_model(my_lstm_model)
```

```
(Iteration 1 / 1170) loss: 77.767695
(Iteration 2 / 1170) loss: 76.677468
(Iteration 3 / 1170) loss: 76.428032
(Iteration 4 / 1170) loss: 77.299044
(Iteration 5 / 1170) loss: 76.416580
(Iteration 6 / 1170) loss: 76.095531
(Iteration 7 / 1170) loss: 76.133898
(Iteration 8 / 1170) loss: 76.046990
(Iteration 9 / 1170) loss: 75.971192
(Iteration 10 / 1170) loss: 75.810697
(Iteration 11 / 1170) loss: 75.118970
(Iteration 12 / 1170) loss: 75.109374
(Iteration 13 / 1170) loss: 75.126804
(Iteration 14 / 1170) loss: 74.419421
(Iteration 15 / 1170) loss: 74.496195
(Iteration 16 / 1170) loss: 73.733022
(Iteration 17 / 1170) loss: 73.046076
(Iteration 18 / 1170) loss: 72.252211
(Iteration 19 / 1170) loss: 71.724380
(Iteration 20 / 1170) loss: 70.920663
(Iteration 21 / 1170) loss: 69.919237
(Iteration 22 / 1170) loss: 68.250768
(Iteration 23 / 1170) loss: 67.003846
(Iteration 24 / 1170) loss: 63.476444
(Iteration 25 / 1170) loss: 61.653228
(Iteration 26 / 1170) loss: 60.116551
(Iteration 27 / 1170) loss: 59.649217
(Iteration 28 / 1170) loss: 58.109839
(Iteration 29 / 1170) loss: 56.234807
(Iteration 30 / 1170) loss: 55.763547
(Iteration 31 / 1170) loss: 55.955834
(Iteration 32 / 1170) loss: 56.089155
(Iteration 33 / 1170) loss: 54.322441
(Iteration 34 / 1170) loss: 54.870358
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(Iteration 35 / 1170) loss: 53.879896
(Iteration 36 / 1170) loss: 53.968145
(Iteration 37 / 1170) loss: 53.402411
(Iteration 38 / 1170) loss: 53.305978
(Iteration 39 / 1170) loss: 54.039428
(Iteration 40 / 1170) loss: 52.548754
(Iteration 41 / 1170) loss: 52.227963
(Iteration 42 / 1170) loss: 52.663542
(Iteration 43 / 1170) loss: 52.060988
(Iteration 44 / 1170) loss: 52.002039
(Iteration 45 / 1170) loss: 52.399127
(Iteration 46 / 1170) loss: 52.358968
(Iteration 47 / 1170) loss: 51.642286
(Iteration 48 / 1170) loss: 51.396217
(Iteration 49 / 1170) loss: 51.864611
(Iteration 50 / 1170) loss: 51.966383
(Iteration 51 / 1170) loss: 51.737526
(Iteration 52 / 1170) loss: 51.305973
(Iteration 53 / 1170) loss: 50.934631
(Iteration 54 / 1170) loss: 51.189282
(Iteration 55 / 1170) loss: 51.298938
(Iteration 56 / 1170) loss: 50.841360
(Iteration 57 / 1170) loss: 50.241599
(Iteration 58 / 1170) loss: 50.717055
(Iteration 59 / 1170) loss: 50.157340
(Iteration 60 / 1170) loss: 49.956023
(Iteration 61 / 1170) loss: 50.112098
(Iteration 62 / 1170) loss: 50.678542
(Iteration 63 / 1170) loss: 50.597938
(Iteration 64 / 1170) loss: 49.622576
(Iteration 65 / 1170) loss: 50.548298
(Iteration 66 / 1170) loss: 50.249122
(Iteration 67 / 1170) loss: 49.330679
(Iteration 68 / 1170) loss: 50.202429
(Iteration 69 / 1170) loss: 49.492862
(Iteration 70 / 1170) loss: 49.411362
(Iteration 71 / 1170) loss: 49.313297
(Iteration 72 / 1170) loss: 49.423218
(Iteration 73 / 1170) loss: 49.499765
(Iteration 74 / 1170) loss: 49.697251
(Iteration 75 / 1170) loss: 49.578988
(Iteration 76 / 1170) loss: 49.090266
(Iteration 77 / 1170) loss: 49.230603
(Iteration 78 / 1170) loss: 49.244343
(Iteration 79 / 1170) loss: 47.892459
(Iteration 80 / 1170) loss: 48.606674
(Iteration 81 / 1170) loss: 49.016801
(Iteration 82 / 1170) loss: 48.700789
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(Iteration 83 / 1170) loss: 48.202232
(Iteration 84 / 1170) loss: 48.731822
(Iteration 85 / 1170) loss: 49.042803
(Iteration 86 / 1170) loss: 48.494692
(Iteration 87 / 1170) loss: 48.209117
(Iteration 88 / 1170) loss: 48.558433
(Iteration 89 / 1170) loss: 47.750019
(Iteration 90 / 1170) loss: 48.317716
(Iteration 91 / 1170) loss: 47.420152
(Iteration 92 / 1170) loss: 47.838794
(Iteration 93 / 1170) loss: 48.014534
(Iteration 94 / 1170) loss: 47.845847
(Iteration 95 / 1170) loss: 47.950040
(Iteration 96 / 1170) loss: 47.657809
(Iteration 97 / 1170) loss: 47.449246
(Iteration 98 / 1170) loss: 47.367459
(Iteration 99 / 1170) loss: 47.498363
(Iteration 100 / 1170) loss: 47.180294
(Iteration 101 / 1170) loss: 47.346829
(Iteration 102 / 1170) loss: 47.076618
(Iteration 103 / 1170) loss: 47.881994
(Iteration 104 / 1170) loss: 47.875658
(Iteration 105 / 1170) loss: 47.249143
(Iteration 106 / 1170) loss: 46.898673
(Iteration 107 / 1170) loss: 46.846252
(Iteration 108 / 1170) loss: 47.222841
(Iteration 109 / 1170) loss: 46.825828
(Iteration 110 / 1170) loss: 47.231530
(Iteration 111 / 1170) loss: 46.474325
(Iteration 112 / 1170) loss: 46.666806
(Iteration 113 / 1170) loss: 46.539856
(Iteration 114 / 1170) loss: 46.652779
(Iteration 115 / 1170) loss: 46.713771
(Iteration 116 / 1170) loss: 45.989613
(Iteration 117 / 1170) loss: 46.045492
(Iteration 118 / 1170) loss: 46.096047
(Iteration 119 / 1170) loss: 46.392055
(Iteration 120 / 1170) loss: 46.464379
(Iteration 121 / 1170) loss: 46.231250
(Iteration 122 / 1170) loss: 46.909585
(Iteration 123 / 1170) loss: 46.603247
(Iteration 124 / 1170) loss: 45.638339
(Iteration 125 / 1170) loss: 46.415875
(Iteration 126 / 1170) loss: 45.873616
(Iteration 127 / 1170) loss: 45.797680
(Iteration 128 / 1170) loss: 45.452052
(Iteration 129 / 1170) loss: 46.089094
(Iteration 130 / 1170) loss: 46.000802
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(Iteration 131 / 1170) loss: 45.739796
(Iteration 132 / 1170) loss: 45.592924
(Iteration 133 / 1170) loss: 45.666668
(Iteration 134 / 1170) loss: 45.961203
(Iteration 135 / 1170) loss: 45.225444
(Iteration 136 / 1170) loss: 45.577216
(Iteration 137 / 1170) loss: 46.070733
(Iteration 138 / 1170) loss: 45.232288
(Iteration 139 / 1170) loss: 45.481815
(Iteration 140 / 1170) loss: 45.490336
(Iteration 141 / 1170) loss: 44.528148
(Iteration 142 / 1170) loss: 45.515740
(Iteration 143 / 1170) loss: 45.223131
(Iteration 144 / 1170) loss: 45.137258
(Iteration 145 / 1170) loss: 45.273124
(Iteration 146 / 1170) loss: 45.411724
(Iteration 147 / 1170) loss: 45.399061
(Iteration 148 / 1170) loss: 44.964269
(Iteration 149 / 1170) loss: 44.829047
(Iteration 150 / 1170) loss: 45.484237
(Iteration 151 / 1170) loss: 44.993933
(Iteration 152 / 1170) loss: 45.416461
(Iteration 153 / 1170) loss: 45.314940
(Iteration 154 / 1170) loss: 44.533855
(Iteration 155 / 1170) loss: 44.831100
(Iteration 156 / 1170) loss: 44.679098
(Iteration 157 / 1170) loss: 44.568478
(Iteration 158 / 1170) loss: 44.398188
(Iteration 159 / 1170) loss: 44.107840
(Iteration 160 / 1170) loss: 44.840325
(Iteration 161 / 1170) loss: 44.498880
(Iteration 162 / 1170) loss: 44.790704
(Iteration 163 / 1170) loss: 44.050921
(Iteration 164 / 1170) loss: 44.291695
(Iteration 165 / 1170) loss: 44.359331
(Iteration 166 / 1170) loss: 44.272403
(Iteration 167 / 1170) loss: 44.373596
(Iteration 168 / 1170) loss: 43.611820
(Iteration 169 / 1170) loss: 44.035699
(Iteration 170 / 1170) loss: 43.673011
(Iteration 171 / 1170) loss: 43.975509
(Iteration 172 / 1170) loss: 43.844133
(Iteration 173 / 1170) loss: 43.595980
(Iteration 174 / 1170) loss: 43.890164
(Iteration 175 / 1170) loss: 43.406976
(Iteration 176 / 1170) loss: 43.461014
(Iteration 177 / 1170) loss: 43.519062
(Iteration 178 / 1170) loss: 44.241603
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(Iteration 179 / 1170) loss: 44.132432
(Iteration 180 / 1170) loss: 43.215449
(Iteration 181 / 1170) loss: 43.274510
(Iteration 182 / 1170) loss: 43.237087
(Iteration 183 / 1170) loss: 42.972738
(Iteration 184 / 1170) loss: 42.986238
(Iteration 185 / 1170) loss: 42.952254
(Iteration 186 / 1170) loss: 42.784279
(Iteration 187 / 1170) loss: 42.550178
(Iteration 188 / 1170) loss: 43.015374
(Iteration 189 / 1170) loss: 43.149192
(Iteration 190 / 1170) loss: 42.315573
(Iteration 191 / 1170) loss: 42.716880
(Iteration 192 / 1170) loss: 42.877381
(Iteration 193 / 1170) loss: 42.865653
(Iteration 194 / 1170) loss: 42.763375
(Iteration 195 / 1170) loss: 42.812318
(Iteration 196 / 1170) loss: 42.318806
(Iteration 197 / 1170) loss: 42.632422
(Iteration 198 / 1170) loss: 42.303834
(Iteration 199 / 1170) loss: 42.884653
(Iteration 200 / 1170) loss: 42.605453
(Iteration 201 / 1170) loss: 42.440193
(Iteration 202 / 1170) loss: 42.064387
(Iteration 203 / 1170) loss: 42.449570
(Iteration 204 / 1170) loss: 42.482660
(Iteration 205 / 1170) loss: 42.290552
(Iteration 206 / 1170) loss: 42.058097
(Iteration 207 / 1170) loss: 42.361119
(Iteration 208 / 1170) loss: 42.523963
(Iteration 209 / 1170) loss: 42.017710
(Iteration 210 / 1170) loss: 41.620603
(Iteration 211 / 1170) loss: 42.062492
(Iteration 212 / 1170) loss: 41.741603
(Iteration 213 / 1170) loss: 41.872650
(Iteration 214 / 1170) loss: 41.685994
(Iteration 215 / 1170) loss: 41.536312
(Iteration 216 / 1170) loss: 41.728559
(Iteration 217 / 1170) loss: 41.302924
(Iteration 218 / 1170) loss: 41.794809
(Iteration 219 / 1170) loss: 41.733729
(Iteration 220 / 1170) loss: 41.329921
(Iteration 221 / 1170) loss: 41.060036
(Iteration 222 / 1170) loss: 41.269787
(Iteration 223 / 1170) loss: 41.632154
(Iteration 224 / 1170) loss: 41.031976
(Iteration 225 / 1170) loss: 41.386163
(Iteration 226 / 1170) loss: 40.689704
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(Iteration 227 / 1170) loss: 40.557224
(Iteration 228 / 1170) loss: 40.560539
(Iteration 229 / 1170) loss: 39.889544
(Iteration 230 / 1170) loss: 40.728646
(Iteration 231 / 1170) loss: 40.614973
(Iteration 232 / 1170) loss: 40.758140
(Iteration 233 / 1170) loss: 39.859161
(Iteration 234 / 1170) loss: 40.683163
(Iteration 235 / 1170) loss: 40.564665
(Iteration 236 / 1170) loss: 40.774434
(Iteration 237 / 1170) loss: 40.241752
(Iteration 238 / 1170) loss: 40.384921
(Iteration 239 / 1170) loss: 39.854520
(Iteration 240 / 1170) loss: 40.451350
(Iteration 241 / 1170) loss: 40.404257
(Iteration 242 / 1170) loss: 39.743010
(Iteration 243 / 1170) loss: 39.769595
(Iteration 244 / 1170) loss: 39.884279
(Iteration 245 / 1170) loss: 40.190491
(Iteration 246 / 1170) loss: 39.262348
(Iteration 247 / 1170) loss: 39.959583
(Iteration 248 / 1170) loss: 40.123362
(Iteration 249 / 1170) loss: 39.641548
(Iteration 250 / 1170) loss: 39.457753
(Iteration 251 / 1170) loss: 40.118132
(Iteration 252 / 1170) loss: 39.691670
(Iteration 253 / 1170) loss: 39.607326
(Iteration 254 / 1170) loss: 39.329432
(Iteration 255 / 1170) loss: 39.799508
(Iteration 256 / 1170) loss: 39.359292
(Iteration 257 / 1170) loss: 39.750022
(Iteration 258 / 1170) loss: 39.298881
(Iteration 259 / 1170) loss: 39.126028
(Iteration 260 / 1170) loss: 38.951631
(Iteration 261 / 1170) loss: 39.292853
(Iteration 262 / 1170) loss: 39.047585
(Iteration 263 / 1170) loss: 39.086530
(Iteration 264 / 1170) loss: 39.321965
(Iteration 265 / 1170) loss: 39.036885
(Iteration 266 / 1170) loss: 39.208651
(Iteration 267 / 1170) loss: 39.433960
(Iteration 268 / 1170) loss: 39.467407
(Iteration 269 / 1170) loss: 39.234491
(Iteration 270 / 1170) loss: 38.656227
(Iteration 271 / 1170) loss: 38.848158
(Iteration 272 / 1170) loss: 38.437916
(Iteration 273 / 1170) loss: 38.993820
(Iteration 274 / 1170) loss: 38.064838
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(Iteration 275 / 1170) loss: 38.658895
(Iteration 276 / 1170) loss: 38.788289
(Iteration 277 / 1170) loss: 38.689332
(Iteration 278 / 1170) loss: 38.355277
(Iteration 279 / 1170) loss: 38.639645
(Iteration 280 / 1170) loss: 38.699589
(Iteration 281 / 1170) loss: 38.677545
(Iteration 282 / 1170) loss: 38.211806
(Iteration 283 / 1170) loss: 38.217266
(Iteration 284 / 1170) loss: 37.813418
(Iteration 285 / 1170) loss: 38.175288
(Iteration 286 / 1170) loss: 37.762331
(Iteration 287 / 1170) loss: 38.595443
(Iteration 288 / 1170) loss: 37.423078
(Iteration 289 / 1170) loss: 38.437761
(Iteration 290 / 1170) loss: 38.432665
(Iteration 291 / 1170) loss: 38.538297
(Iteration 292 / 1170) loss: 38.729402
(Iteration 293 / 1170) loss: 38.131254
(Iteration 294 / 1170) loss: 37.734463
(Iteration 295 / 1170) loss: 37.287980
(Iteration 296 / 1170) loss: 37.789491
(Iteration 297 / 1170) loss: 37.476460
(Iteration 298 / 1170) loss: 38.338936
(Iteration 299 / 1170) loss: 38.093569
(Iteration 300 / 1170) loss: 37.553555
(Iteration 301 / 1170) loss: 37.894343
(Iteration 302 / 1170) loss: 37.764545
(Iteration 303 / 1170) loss: 37.756380
(Iteration 304 / 1170) loss: 37.168449
(Iteration 305 / 1170) loss: 37.063910
(Iteration 306 / 1170) loss: 37.412661
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(Iteration 313 / 1170) loss: 37.289421
(Iteration 314 / 1170) loss: 37.548930
(Iteration 315 / 1170) loss: 36.515248
(Iteration 316 / 1170) loss: 37.221050
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(Iteration 318 / 1170) loss: 36.639467
(Iteration 319 / 1170) loss: 37.652570
(Iteration 320 / 1170) loss: 36.787975
(Iteration 321 / 1170) loss: 36.930902
(Iteration 322 / 1170) loss: 36.834535
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(Iteration 325 / 1170) loss: 36.233186
(Iteration 326 / 1170) loss: 36.533646
(Iteration 327 / 1170) loss: 36.285106
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(Iteration 329 / 1170) loss: 36.593596
(Iteration 330 / 1170) loss: 36.864118
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(Iteration 334 / 1170) loss: 36.773089
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(Iteration 336 / 1170) loss: 36.638502
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(Iteration 349 / 1170) loss: 36.093303
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(Iteration 369 / 1170) loss: 35.878771
(Iteration 370 / 1170) loss: 35.164890
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(Iteration 372 / 1170) loss: 35.067489
(Iteration 373 / 1170) loss: 35.363157
(Iteration 374 / 1170) loss: 35.298500
(Iteration 375 / 1170) loss: 35.413370
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(Iteration 417 / 1170) loss: 34.633713
(Iteration 418 / 1170) loss: 34.435334
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(Iteration 464 / 1170) loss: 33.303603
(Iteration 465 / 1170) loss: 33.292811
(Iteration 466 / 1170) loss: 33.542595
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(Iteration 490 / 1170) loss: 33.327044
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(Iteration 501 / 1170) loss: 32.756391
(Iteration 502 / 1170) loss: 32.939887
(Iteration 503 / 1170) loss: 33.116890
(Iteration 504 / 1170) loss: 32.735933
(Iteration 505 / 1170) loss: 32.379567
(Iteration 506 / 1170) loss: 32.675950
(Iteration 507 / 1170) loss: 32.241672
(Iteration 508 / 1170) loss: 32.359516
(Iteration 509 / 1170) loss: 32.896862
(Iteration 510 / 1170) loss: 32.512261
(Iteration 511 / 1170) loss: 32.999227
(Iteration 512 / 1170) loss: 32.645263
(Iteration 513 / 1170) loss: 32.379482
(Iteration 514 / 1170) loss: 32.954073
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(Iteration 515 / 1170) loss: 32.149876
(Iteration 516 / 1170) loss: 32.225248
(Iteration 517 / 1170) loss: 32.857355
(Iteration 518 / 1170) loss: 32.158181
(Iteration 519 / 1170) loss: 31.657619
(Iteration 520 / 1170) loss: 32.681091
(Iteration 521 / 1170) loss: 32.874352
(Iteration 522 / 1170) loss: 32.513895
(Iteration 523 / 1170) loss: 32.371625
(Iteration 524 / 1170) loss: 32.389979
(Iteration 525 / 1170) loss: 32.732699
(Iteration 526 / 1170) loss: 32.414199
(Iteration 527 / 1170) loss: 32.162697
(Iteration 528 / 1170) loss: 32.658137
(Iteration 529 / 1170) loss: 32.756132
(Iteration 530 / 1170) loss: 32.481291
(Iteration 531 / 1170) loss: 32.160260
(Iteration 532 / 1170) loss: 32.545895
(Iteration 533 / 1170) loss: 32.714621
(Iteration 534 / 1170) loss: 31.956267
(Iteration 535 / 1170) loss: 32.295389
(Iteration 536 / 1170) loss: 32.827657
(Iteration 537 / 1170) loss: 31.879670
(Iteration 538 / 1170) loss: 32.823324
(Iteration 539 / 1170) loss: 32.425885
(Iteration 540 / 1170) loss: 32.333622
(Iteration 541 / 1170) loss: 32.068654
(Iteration 542 / 1170) loss: 31.691115
(Iteration 543 / 1170) loss: 32.427284
(Iteration 544 / 1170) loss: 32.157501
(Iteration 545 / 1170) loss: 32.810479
(Iteration 546 / 1170) loss: 32.004972
(Iteration 547 / 1170) loss: 32.011385
(Iteration 548 / 1170) loss: 32.757092
(Iteration 549 / 1170) loss: 32.218461
(Iteration 550 / 1170) loss: 32.442353
(Iteration 551 / 1170) loss: 32.030827
(Iteration 552 / 1170) loss: 32.189922
(Iteration 553 / 1170) loss: 32.216837
(Iteration 554 / 1170) loss: 31.570212
(Iteration 555 / 1170) loss: 31.931412
(Iteration 556 / 1170) loss: 31.990476
(Iteration 557 / 1170) loss: 31.971198
(Iteration 558 / 1170) loss: 31.213170
(Iteration 559 / 1170) loss: 32.091260
(Iteration 560 / 1170) loss: 32.419030
(Iteration 561 / 1170) loss: 32.174844
(Iteration 562 / 1170) loss: 32.333550
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(Iteration 563 / 1170) loss: 31.784384
(Iteration 564 / 1170) loss: 32.042295
(Iteration 565 / 1170) loss: 31.845305
(Iteration 566 / 1170) loss: 32.639774
(Iteration 567 / 1170) loss: 31.881697
(Iteration 568 / 1170) loss: 32.425990
(Iteration 569 / 1170) loss: 32.038801
(Iteration 570 / 1170) loss: 31.942124
(Iteration 571 / 1170) loss: 32.178334
(Iteration 572 / 1170) loss: 32.944392
(Iteration 573 / 1170) loss: 32.210219
(Iteration 574 / 1170) loss: 32.003747
(Iteration 575 / 1170) loss: 31.911046
(Iteration 576 / 1170) loss: 31.528676
(Iteration 577 / 1170) loss: 31.871120
(Iteration 578 / 1170) loss: 31.586415
(Iteration 579 / 1170) loss: 32.020349
(Iteration 580 / 1170) loss: 31.508032
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(Iteration 582 / 1170) loss: 31.613971
(Iteration 583 / 1170) loss: 31.651657
(Iteration 584 / 1170) loss: 32.208650
(Iteration 585 / 1170) loss: 31.868022
(Iteration 586 / 1170) loss: 31.803422
(Iteration 587 / 1170) loss: 31.954733
(Iteration 588 / 1170) loss: 31.435778
(Iteration 589 / 1170) loss: 31.613750
(Iteration 590 / 1170) loss: 31.438791
(Iteration 591 / 1170) loss: 31.732276
(Iteration 592 / 1170) loss: 31.737930
(Iteration 593 / 1170) loss: 31.320335
(Iteration 594 / 1170) loss: 30.883567
(Iteration 595 / 1170) loss: 31.922990
(Iteration 596 / 1170) loss: 31.909592
(Iteration 597 / 1170) loss: 31.410951
(Iteration 598 / 1170) loss: 31.353476
(Iteration 599 / 1170) loss: 31.792170
(Iteration 600 / 1170) loss: 31.519190
(Iteration 601 / 1170) loss: 31.450883
(Iteration 602 / 1170) loss: 31.149214
(Iteration 603 / 1170) loss: 32.082070
(Iteration 604 / 1170) loss: 31.331303
(Iteration 605 / 1170) loss: 31.235649
(Iteration 606 / 1170) loss: 31.593371
(Iteration 607 / 1170) loss: 31.650304
(Iteration 608 / 1170) loss: 32.436133
(Iteration 609 / 1170) loss: 31.482398
(Iteration 610 / 1170) loss: 31.337651
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(Iteration 611 / 1170) loss: 30.988248
(Iteration 612 / 1170) loss: 31.622641
(Iteration 613 / 1170) loss: 30.899109
(Iteration 614 / 1170) loss: 31.828537
(Iteration 615 / 1170) loss: 31.486409
(Iteration 616 / 1170) loss: 31.652059
(Iteration 617 / 1170) loss: 32.001517
(Iteration 618 / 1170) loss: 31.565428
(Iteration 619 / 1170) loss: 31.192610
(Iteration 620 / 1170) loss: 31.512387
(Iteration 621 / 1170) loss: 31.272529
(Iteration 622 / 1170) loss: 31.000339
(Iteration 623 / 1170) loss: 31.262548
(Iteration 624 / 1170) loss: 31.453422
(Iteration 625 / 1170) loss: 31.239857
(Iteration 626 / 1170) loss: 31.392993
(Iteration 627 / 1170) loss: 31.261834
(Iteration 628 / 1170) loss: 31.299854
(Iteration 629 / 1170) loss: 30.697519
(Iteration 630 / 1170) loss: 31.280023
(Iteration 631 / 1170) loss: 31.492544
(Iteration 632 / 1170) loss: 31.284192
(Iteration 633 / 1170) loss: 30.677539
(Iteration 634 / 1170) loss: 31.001599
(Iteration 635 / 1170) loss: 31.727386
(Iteration 636 / 1170) loss: 31.343166
(Iteration 637 / 1170) loss: 31.459740
(Iteration 638 / 1170) loss: 31.204257
(Iteration 639 / 1170) loss: 31.062858
(Iteration 640 / 1170) loss: 31.190932
(Iteration 641 / 1170) loss: 31.053907
(Iteration 642 / 1170) loss: 31.498789
(Iteration 643 / 1170) loss: 31.419102
(Iteration 644 / 1170) loss: 31.268347
(Iteration 645 / 1170) loss: 31.031574
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(Iteration 647 / 1170) loss: 30.881615
(Iteration 648 / 1170) loss: 31.355442
(Iteration 649 / 1170) loss: 30.823586
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(Iteration 651 / 1170) loss: 31.539554
(Iteration 652 / 1170) loss: 31.234986
(Iteration 653 / 1170) loss: 30.846187
(Iteration 654 / 1170) loss: 31.564078
(Iteration 655 / 1170) loss: 30.939418
(Iteration 656 / 1170) loss: 31.244746
(Iteration 657 / 1170) loss: 30.782312
(Iteration 658 / 1170) loss: 31.424211
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(Iteration 659 / 1170) loss: 31.200938
(Iteration 660 / 1170) loss: 30.994386
(Iteration 661 / 1170) loss: 31.064688
(Iteration 662 / 1170) loss: 30.568168
(Iteration 663 / 1170) loss: 30.940868
(Iteration 664 / 1170) loss: 30.321513
(Iteration 665 / 1170) loss: 30.519844
(Iteration 666 / 1170) loss: 30.706499
(Iteration 667 / 1170) loss: 30.766145
(Iteration 668 / 1170) loss: 30.926961
(Iteration 669 / 1170) loss: 31.691334
(Iteration 670 / 1170) loss: 30.628253
(Iteration 671 / 1170) loss: 31.260639
(Iteration 672 / 1170) loss: 30.667350
(Iteration 673 / 1170) loss: 30.696374
(Iteration 674 / 1170) loss: 30.651947
(Iteration 675 / 1170) loss: 30.741168
(Iteration 676 / 1170) loss: 31.035634
(Iteration 677 / 1170) loss: 30.803979
(Iteration 678 / 1170) loss: 30.364515
(Iteration 679 / 1170) loss: 30.575737
(Iteration 680 / 1170) loss: 30.934694
(Iteration 681 / 1170) loss: 30.417181
(Iteration 682 / 1170) loss: 30.030339
(Iteration 683 / 1170) loss: 30.743342
(Iteration 684 / 1170) loss: 30.557240
(Iteration 685 / 1170) loss: 31.357963
(Iteration 686 / 1170) loss: 30.959012
(Iteration 687 / 1170) loss: 30.615136
(Iteration 688 / 1170) loss: 30.716380
(Iteration 689 / 1170) loss: 31.165203
(Iteration 690 / 1170) loss: 30.576011
(Iteration 691 / 1170) loss: 30.522063
(Iteration 692 / 1170) loss: 31.011963
(Iteration 693 / 1170) loss: 30.926742
(Iteration 694 / 1170) loss: 30.863776
(Iteration 695 / 1170) loss: 30.278503
(Iteration 696 / 1170) loss: 30.489433
(Iteration 697 / 1170) loss: 30.556171
(Iteration 698 / 1170) loss: 30.770118
(Iteration 699 / 1170) loss: 30.477635
(Iteration 700 / 1170) loss: 31.123422
(Iteration 701 / 1170) loss: 30.911183
(Iteration 702 / 1170) loss: 30.083101
(Iteration 703 / 1170) loss: 30.732318
(Iteration 704 / 1170) loss: 30.466698
(Iteration 705 / 1170) loss: 30.942748
(Iteration 706 / 1170) loss: 30.977583
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(Iteration 708 / 1170) loss: 30.824954
(Iteration 709 / 1170) loss: 30.274673
(Iteration 710 / 1170) loss: 30.544743
(Iteration 711 / 1170) loss: 30.617080
(Iteration 712 / 1170) loss: 30.278116
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(Iteration 715 / 1170) loss: 29.647310
(Iteration 716 / 1170) loss: 30.258734
(Iteration 717 / 1170) loss: 30.663590
(Iteration 718 / 1170) loss: 30.415042
(Iteration 719 / 1170) loss: 30.611797
(Iteration 720 / 1170) loss: 29.931483
(Iteration 721 / 1170) loss: 30.219494
(Iteration 722 / 1170) loss: 30.496907
(Iteration 723 / 1170) loss: 30.025258
(Iteration 724 / 1170) loss: 30.663286
(Iteration 725 / 1170) loss: 30.084793
(Iteration 726 / 1170) loss: 30.564744
(Iteration 727 / 1170) loss: 30.364411
(Iteration 728 / 1170) loss: 30.480105
(Iteration 729 / 1170) loss: 30.341136
(Iteration 730 / 1170) loss: 30.663227
(Iteration 731 / 1170) loss: 29.961526
(Iteration 732 / 1170) loss: 29.906971
(Iteration 733 / 1170) loss: 30.896059
(Iteration 734 / 1170) loss: 29.807159
(Iteration 735 / 1170) loss: 29.951755
(Iteration 736 / 1170) loss: 30.466407
(Iteration 737 / 1170) loss: 30.359518
(Iteration 738 / 1170) loss: 30.260981
(Iteration 739 / 1170) loss: 29.949665
(Iteration 740 / 1170) loss: 30.213810
(Iteration 741 / 1170) loss: 29.758538
(Iteration 742 / 1170) loss: 30.158706
(Iteration 743 / 1170) loss: 29.736850
(Iteration 744 / 1170) loss: 30.046070
(Iteration 745 / 1170) loss: 30.106753
(Iteration 746 / 1170) loss: 30.138610
(Iteration 747 / 1170) loss: 29.831538
(Iteration 748 / 1170) loss: 29.988514
(Iteration 749 / 1170) loss: 30.097480
(Iteration 750 / 1170) loss: 30.605264
(Iteration 751 / 1170) loss: 29.752435
(Iteration 752 / 1170) loss: 29.865327
(Iteration 753 / 1170) loss: 30.452962
(Iteration 754 / 1170) loss: 29.800002
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(Iteration 755 / 1170) loss: 30.248824
(Iteration 756 / 1170) loss: 30.305423
(Iteration 757 / 1170) loss: 29.924702
(Iteration 758 / 1170) loss: 29.868316
(Iteration 759 / 1170) loss: 30.219769
(Iteration 760 / 1170) loss: 30.015015
(Iteration 761 / 1170) loss: 30.196301
(Iteration 762 / 1170) loss: 29.915171
(Iteration 763 / 1170) loss: 30.557069
(Iteration 764 / 1170) loss: 30.268717
(Iteration 765 / 1170) loss: 29.812550
(Iteration 766 / 1170) loss: 29.675822
(Iteration 767 / 1170) loss: 30.227092
(Iteration 768 / 1170) loss: 29.912520
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(Iteration 770 / 1170) loss: 30.789146
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(Iteration 773 / 1170) loss: 30.265227
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(Iteration 789 / 1170) loss: 29.416769
(Iteration 790 / 1170) loss: 30.316025
(Iteration 791 / 1170) loss: 30.237704
(Iteration 792 / 1170) loss: 29.633130
(Iteration 793 / 1170) loss: 29.446157
(Iteration 794 / 1170) loss: 29.795023
(Iteration 795 / 1170) loss: 29.397883
(Iteration 796 / 1170) loss: 29.690523
(Iteration 797 / 1170) loss: 30.252153
(Iteration 798 / 1170) loss: 29.624090
(Iteration 799 / 1170) loss: 29.527680
(Iteration 800 / 1170) loss: 29.691524
(Iteration 801 / 1170) loss: 29.611999
(Iteration 802 / 1170) loss: 29.543875
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(Iteration 803 / 1170) loss: 29.649962
(Iteration 804 / 1170) loss: 29.706596
(Iteration 805 / 1170) loss: 29.910750
(Iteration 806 / 1170) loss: 29.443388
(Iteration 807 / 1170) loss: 29.694111
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(Iteration 810 / 1170) loss: 29.988073
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(Iteration 812 / 1170) loss: 29.417537
(Iteration 813 / 1170) loss: 29.455726
(Iteration 814 / 1170) loss: 29.280775
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(Iteration 816 / 1170) loss: 30.283126
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(Iteration 848 / 1170) loss: 29.969110
(Iteration 849 / 1170) loss: 29.518102
(Iteration 850 / 1170) loss: 29.437379
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(Iteration 895 / 1170) loss: 29.303578
(Iteration 896 / 1170) loss: 29.228292
(Iteration 897 / 1170) loss: 28.423250
(Iteration 898 / 1170) loss: 29.308155
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(Iteration 909 / 1170) loss: 29.038770
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(Iteration 914 / 1170) loss: 29.275927
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(Iteration 924 / 1170) loss: 28.941964
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(Iteration 942 / 1170) loss: 28.937086
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(Iteration 944 / 1170) loss: 29.713266
(Iteration 945 / 1170) loss: 28.334617
(Iteration 946 / 1170) loss: 28.775995
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(Iteration 947 / 1170) loss: 29.232653
(Iteration 948 / 1170) loss: 29.115159
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(Iteration 968 / 1170) loss: 28.511464
(Iteration 969 / 1170) loss: 28.452648
(Iteration 970 / 1170) loss: 28.664457
(Iteration 971 / 1170) loss: 28.713876
(Iteration 972 / 1170) loss: 28.034597
(Iteration 973 / 1170) loss: 28.469428
(Iteration 974 / 1170) loss: 28.909980
(Iteration 975 / 1170) loss: 28.846037
(Iteration 976 / 1170) loss: 29.155126
(Iteration 977 / 1170) loss: 28.632205
(Iteration 978 / 1170) loss: 28.676081
(Iteration 979 / 1170) loss: 28.913345
(Iteration 980 / 1170) loss: 28.578561
(Iteration 981 / 1170) loss: 28.613226
(Iteration 982 / 1170) loss: 28.369245
(Iteration 983 / 1170) loss: 28.622429
(Iteration 984 / 1170) loss: 28.725235
(Iteration 985 / 1170) loss: 28.684964
(Iteration 986 / 1170) loss: 28.844841
(Iteration 987 / 1170) loss: 28.972614
(Iteration 988 / 1170) loss: 28.634971
(Iteration 989 / 1170) loss: 28.618245
(Iteration 990 / 1170) loss: 28.777486
(Iteration 991 / 1170) loss: 28.716851
(Iteration 992 / 1170) loss: 28.281896
(Iteration 993 / 1170) loss: 28.949652
(Iteration 994 / 1170) loss: 28.427868
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(Iteration 995 / 1170) loss: 28.289375
(Iteration 996 / 1170) loss: 28.440379
(Iteration 997 / 1170) loss: 28.737136
(Iteration 998 / 1170) loss: 28.970435
(Iteration 999 / 1170) loss: 28.585170
(Iteration 1000 / 1170) loss: 28.537002
(Iteration 1001 / 1170) loss: 28.853405
(Iteration 1002 / 1170) loss: 29.061061
(Iteration 1003 / 1170) loss: 28.239023
(Iteration 1004 / 1170) loss: 29.000617
(Iteration 1005 / 1170) loss: 29.135170
(Iteration 1006 / 1170) loss: 28.551154
(Iteration 1007 / 1170) loss: 27.920559
(Iteration 1008 / 1170) loss: 29.080961
(Iteration 1009 / 1170) loss: 28.593395
(Iteration 1010 / 1170) loss: 28.380071
(Iteration 1011 / 1170) loss: 28.559377
(Iteration 1012 / 1170) loss: 28.807022
(Iteration 1013 / 1170) loss: 28.904998
(Iteration 1014 / 1170) loss: 28.504866
(Iteration 1015 / 1170) loss: 28.719703
(Iteration 1016 / 1170) loss: 28.441040
(Iteration 1017 / 1170) loss: 28.676281
(Iteration 1018 / 1170) loss: 28.121957
(Iteration 1019 / 1170) loss: 28.628628
(Iteration 1020 / 1170) loss: 28.781378
(Iteration 1021 / 1170) loss: 28.425756
(Iteration 1022 / 1170) loss: 28.672018
(Iteration 1023 / 1170) loss: 28.333944
(Iteration 1024 / 1170) loss: 28.816378
(Iteration 1025 / 1170) loss: 28.234842
(Iteration 1026 / 1170) loss: 28.326254
(Iteration 1027 / 1170) loss: 28.500720
(Iteration 1028 / 1170) loss: 28.616619
(Iteration 1029 / 1170) loss: 28.139319
(Iteration 1030 / 1170) loss: 28.466767
(Iteration 1031 / 1170) loss: 28.304872
(Iteration 1032 / 1170) loss: 28.304780
(Iteration 1033 / 1170) loss: 28.742356
(Iteration 1034 / 1170) loss: 27.788925
(Iteration 1035 / 1170) loss: 28.178090
(Iteration 1036 / 1170) loss: 28.502421
(Iteration 1037 / 1170) loss: 28.184158
(Iteration 1038 / 1170) loss: 28.943661
(Iteration 1039 / 1170) loss: 28.355858
(Iteration 1040 / 1170) loss: 28.099197
(Iteration 1041 / 1170) loss: 28.421258
(Iteration 1042 / 1170) loss: 28.206057
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(Iteration 1043 / 1170) loss: 28.677556
(Iteration 1044 / 1170) loss: 27.917520
(Iteration 1045 / 1170) loss: 28.776106
(Iteration 1046 / 1170) loss: 29.035018
(Iteration 1047 / 1170) loss: 28.320558
(Iteration 1048 / 1170) loss: 27.795305
(Iteration 1049 / 1170) loss: 28.242135
(Iteration 1050 / 1170) loss: 28.684234
(Iteration 1051 / 1170) loss: 28.017025
(Iteration 1052 / 1170) loss: 28.617441
(Iteration 1053 / 1170) loss: 27.915142
(Iteration 1054 / 1170) loss: 28.417297
(Iteration 1055 / 1170) loss: 28.184423
(Iteration 1056 / 1170) loss: 28.234795
(Iteration 1057 / 1170) loss: 27.771163
(Iteration 1058 / 1170) loss: 28.016220
(Iteration 1059 / 1170) loss: 27.763667
(Iteration 1060 / 1170) loss: 28.084024
(Iteration 1061 / 1170) loss: 28.222109
(Iteration 1062 / 1170) loss: 28.207939
(Iteration 1063 / 1170) loss: 28.810936
(Iteration 1064 / 1170) loss: 28.620083
(Iteration 1065 / 1170) loss: 28.137360
(Iteration 1066 / 1170) loss: 28.469947
(Iteration 1067 / 1170) loss: 28.240817
(Iteration 1068 / 1170) loss: 28.195230
(Iteration 1069 / 1170) loss: 28.395139
(Iteration 1070 / 1170) loss: 28.260399
(Iteration 1071 / 1170) loss: 27.894241
(Iteration 1072 / 1170) loss: 28.459563
(Iteration 1073 / 1170) loss: 28.466285
(Iteration 1074 / 1170) loss: 28.000565
(Iteration 1075 / 1170) loss: 28.528651
(Iteration 1076 / 1170) loss: 27.713833
(Iteration 1077 / 1170) loss: 27.870103
(Iteration 1078 / 1170) loss: 28.905975
(Iteration 1079 / 1170) loss: 28.506766
(Iteration 1080 / 1170) loss: 28.037633
(Iteration 1081 / 1170) loss: 28.502402
(Iteration 1082 / 1170) loss: 28.280396
(Iteration 1083 / 1170) loss: 28.022912
(Iteration 1084 / 1170) loss: 28.444705
(Iteration 1085 / 1170) loss: 28.305708
(Iteration 1086 / 1170) loss: 28.542622
(Iteration 1087 / 1170) loss: 28.522181
(Iteration 1088 / 1170) loss: 27.890638
(Iteration 1089 / 1170) loss: 28.381683
(Iteration 1090 / 1170) loss: 28.189118
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(Iteration 1091 / 1170) loss: 28.368537
(Iteration 1092 / 1170) loss: 28.574107
(Iteration 1093 / 1170) loss: 28.481975
(Iteration 1094 / 1170) loss: 28.182890
(Iteration 1095 / 1170) loss: 27.715921
(Iteration 1096 / 1170) loss: 28.338725
(Iteration 1097 / 1170) loss: 28.129565
(Iteration 1098 / 1170) loss: 27.984473
(Iteration 1099 / 1170) loss: 27.612157
(Iteration 1100 / 1170) loss: 27.539009
(Iteration 1101 / 1170) loss: 27.875686
(Iteration 1102 / 1170) loss: 28.157067
(Iteration 1103 / 1170) loss: 27.916055
(Iteration 1104 / 1170) loss: 28.104660
(Iteration 1105 / 1170) loss: 27.860556
(Iteration 1106 / 1170) loss: 28.159342
(Iteration 1107 / 1170) loss: 27.953799
(Iteration 1108 / 1170) loss: 27.888603
(Iteration 1109 / 1170) loss: 28.002741
(Iteration 1110 / 1170) loss: 28.275730
(Iteration 1111 / 1170) loss: 28.347819
(Iteration 1112 / 1170) loss: 28.446450
(Iteration 1113 / 1170) loss: 28.089102
(Iteration 1114 / 1170) loss: 28.127514
(Iteration 1115 / 1170) loss: 28.686746
(Iteration 1116 / 1170) loss: 27.638460
(Iteration 1117 / 1170) loss: 28.304120
(Iteration 1118 / 1170) loss: 28.131632
(Iteration 1119 / 1170) loss: 28.362445
(Iteration 1120 / 1170) loss: 27.633282
(Iteration 1121 / 1170) loss: 28.073806
(Iteration 1122 / 1170) loss: 28.044797
(Iteration 1123 / 1170) loss: 28.375480
(Iteration 1124 / 1170) loss: 27.677307
(Iteration 1125 / 1170) loss: 27.814703
(Iteration 1126 / 1170) loss: 28.359944
(Iteration 1127 / 1170) loss: 28.001617
(Iteration 1128 / 1170) loss: 27.384863
(Iteration 1129 / 1170) loss: 28.181642
(Iteration 1130 / 1170) loss: 28.403436
(Iteration 1131 / 1170) loss: 28.191006
(Iteration 1132 / 1170) loss: 28.650015
(Iteration 1133 / 1170) loss: 28.089381
(Iteration 1134 / 1170) loss: 28.377556
(Iteration 1135 / 1170) loss: 27.724679
(Iteration 1136 / 1170) loss: 28.013137
(Iteration 1137 / 1170) loss: 27.693455
(Iteration 1138 / 1170) loss: 27.961595
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(Iteration 1139 / 1170) loss: 27.907114
(Iteration 1140 / 1170) loss: 27.443694
(Iteration 1141 / 1170) loss: 27.968376
(Iteration 1142 / 1170) loss: 27.841702
(Iteration 1143 / 1170) loss: 27.846533
(Iteration 1144 / 1170) loss: 28.111039
(Iteration 1145 / 1170) loss: 27.837913
(Iteration 1146 / 1170) loss: 28.237898
(Iteration 1147 / 1170) loss: 27.659699
(Iteration 1148 / 1170) loss: 27.706018
(Iteration 1149 / 1170) loss: 28.220831
(Iteration 1150 / 1170) loss: 27.795767
(Iteration 1151 / 1170) loss: 27.472485
(Iteration 1152 / 1170) loss: 28.357459
(Iteration 1153 / 1170) loss: 27.775586
(Iteration 1154 / 1170) loss: 28.361578
(Iteration 1155 / 1170) loss: 28.505262
(Iteration 1156 / 1170) loss: 28.079944
(Iteration 1157 / 1170) loss: 27.727539
(Iteration 1158 / 1170) loss: 28.288190
(Iteration 1159 / 1170) loss: 27.729254
(Iteration 1160 / 1170) loss: 28.437921
(Iteration 1161 / 1170) loss: 27.352448
(Iteration 1162 / 1170) loss: 27.378884
(Iteration 1163 / 1170) loss: 28.022717
(Iteration 1164 / 1170) loss: 27.830514
(Iteration 1165 / 1170) loss: 27.779283
(Iteration 1166 / 1170) loss: 28.005814
(Iteration 1167 / 1170) loss: 27.377732
(Iteration 1168 / 1170) loss: 27.470774
(Iteration 1169 / 1170) loss: 27.504349
(Iteration 1170 / 1170) loss: 28.120129
```
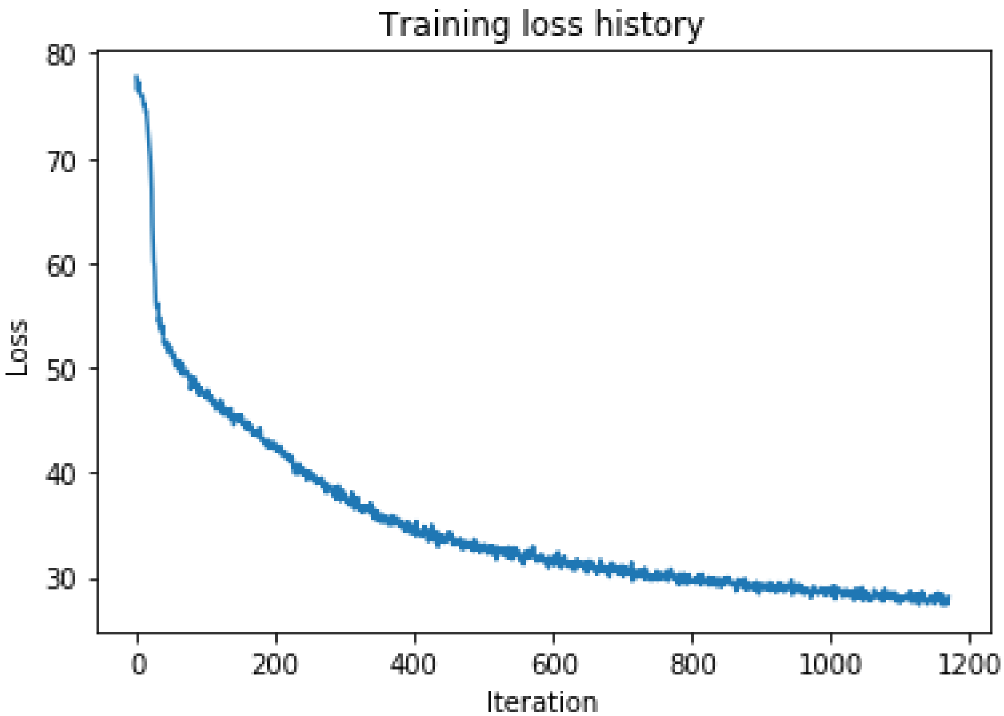



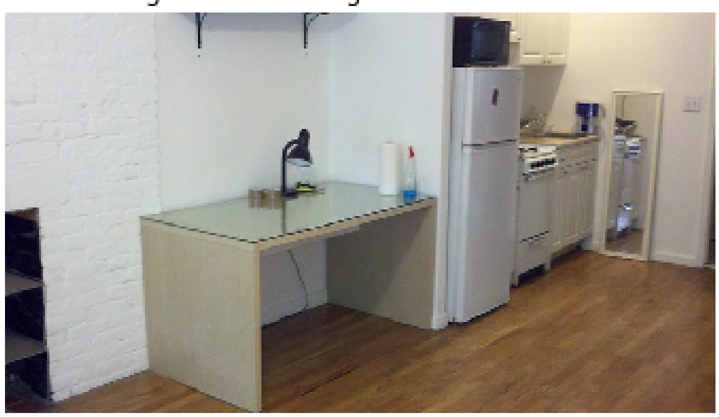

```
LSTM score:
Average BLEU score for train: 0.175831
Average BLEU score for val: 0.168395
My model score:
Average BLEU score for train: 0.316566
Average BLEU score for val: 0.307564
```

```
In [ ]: print("My model score:")
        evaluate_model(my_lstm_model)
```

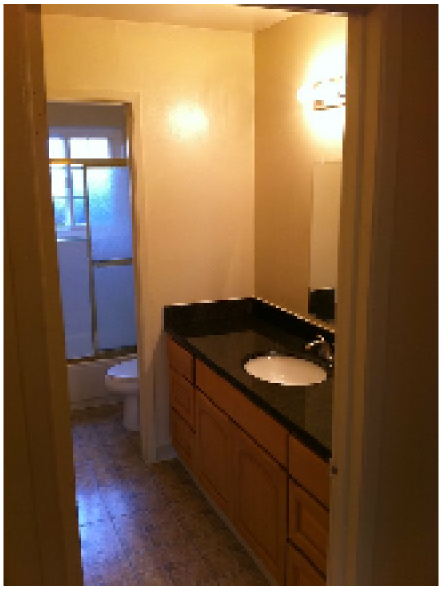
```
In [17]: for split in ['train', 'val']:
             minibatch = sample_coco_minibatch(my_data, split=split, batch_size=2)
             gt_captions, features, urls = minibatch
             gt_captions = decode_captions(gt_captions, data['idx_to_word'])

             sample_captions = my_lstm_model.sample(features)
             sample_captions = decode_captions(sample_captions, data['idx_to_word'])

             for gt_caption, sample_caption, url in zip(gt_captions, sample_captions, urls):
                 plt.imshow(image_from_url(url))
                 plt.title('%s\n%s\nGT:%s' % (split, sample_caption, gt_caption))
                 plt.axis('off')
                 plt.show()
```

train
a dog is sitting on a bench with a <UNK> <END>
GT:<START> a <UNK> kitten walks in the grass around <UNK> foot <END>

train
a kitchen with a sink and a refrigerator <END>
GT:<START> a desk sitting next to a refrigerator microwave oven and mirror <END>



val
a bathroom with a toilet and a mirror in the mirror <END>
GT:<START> a small sink in a cabinet lies in a <UNK> <END>



val
a cat laying on top of a couch <END>
GT:<START> a cat sleeping on a bed with <UNK> <UNK> on top of him <END>