

LSTM_Captioning

November 8, 2018

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

        from cs231n.gradient_check import eval_numerical_gradient, eval_numerical_gradient_array
        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 [3]: # 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))

idx_to_word <type 'list'> 1004
train_captions <type 'numpy.ndarray'> (400135, 17) int32
val_captions <type 'numpy.ndarray'> (195954, 17) int32
train_image_idxes <type 'numpy.ndarray'> (400135,) int32
val_features <type 'numpy.ndarray'> (40504, 512) float32
val_image_idxes <type 'numpy.ndarray'> (195954,) int32
train_features <type 'numpy.ndarray'> (82783, 512) float32
train_urls <type 'numpy.ndarray'> (82783,) |S63
val_urls <type 'numpy.ndarray'> (40504,) |S63
word_to_idx <type 'dict'> 1004

```

3 LSTM

If you read recent papers, you'll see that many people use a variant on the vanilla RNN called Long-Short Term Memory (LSTM) RNNs. Vanilla RNNs can be tough to train on long sequences due to vanishing and exploding gradients 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

$$i = \sigma(a_i) \quad f = \sigma(a_f) \quad o = \sigma(a_o) \quad g = \tanh(a_g)$$

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

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

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 [4]: 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:  5.7054130404539434e-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 [5]: np.random.seed(231)
```

```

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: 7.481575302257938e-10
dh error: 2.982650711677508e-10
dc error: 7.650761924704044e-11

```

```
dWx error: 2.3114133245750027e-09
dWh error: 9.799799942884514e-08
db error: 2.747391209539675e-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 [6]: 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 [7]: from cs231n.rnn_layers import lstm_forward, lstm_backward
        np.random.seed(232)

        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:  6.934610940788449e-10
dh0 error:  1.7191742787512714e-10
dWx error:  3.513538003903274e-09
dWh error:  5.230244747647281e-08
db error:  6.191166792854841e-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 [8]: 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: 9.824459354432268
expected loss: 9.82445935443
difference: 2.26840768391412e-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 [9]: 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,

```

```

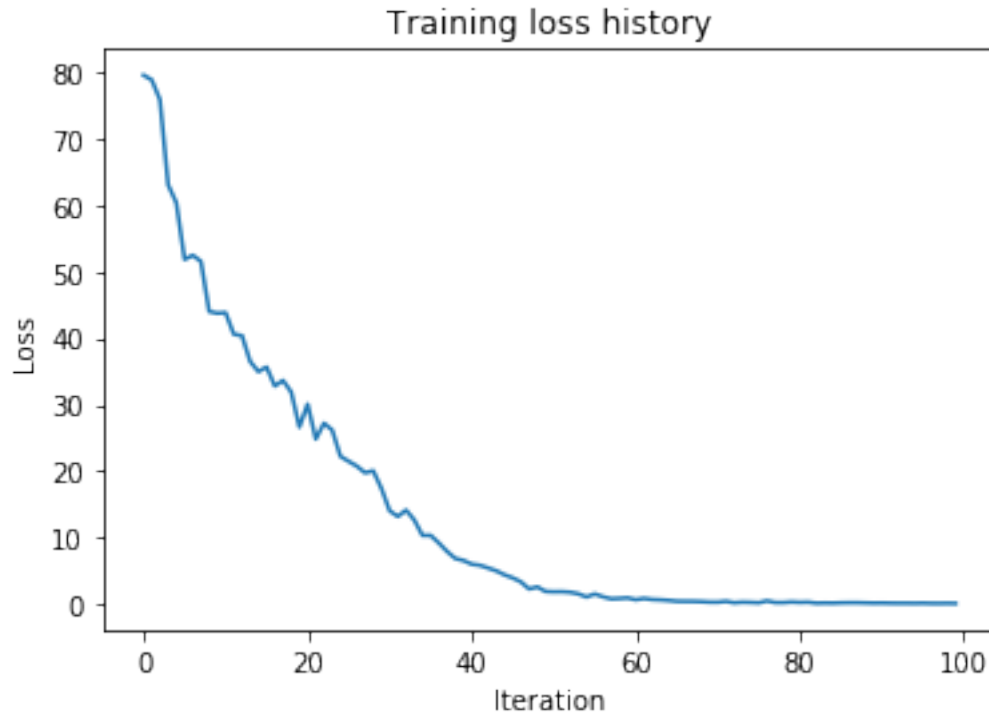
        batch_size=25,
        optim_config={
            'learning_rate': 5e-3,
        },
        lr_decay=0.995,
        verbose=True, print_every=10,
    )

    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: 43.829085
(Iteration 21 / 100) loss: 30.062635
(Iteration 31 / 100) loss: 14.019562
(Iteration 41 / 100) loss: 5.993702
(Iteration 51 / 100) loss: 1.837746
(Iteration 61 / 100) loss: 0.651672
(Iteration 71 / 100) loss: 0.283533
(Iteration 81 / 100) loss: 0.248227
(Iteration 91 / 100) loss: 0.154856

```

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 [10]: 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>

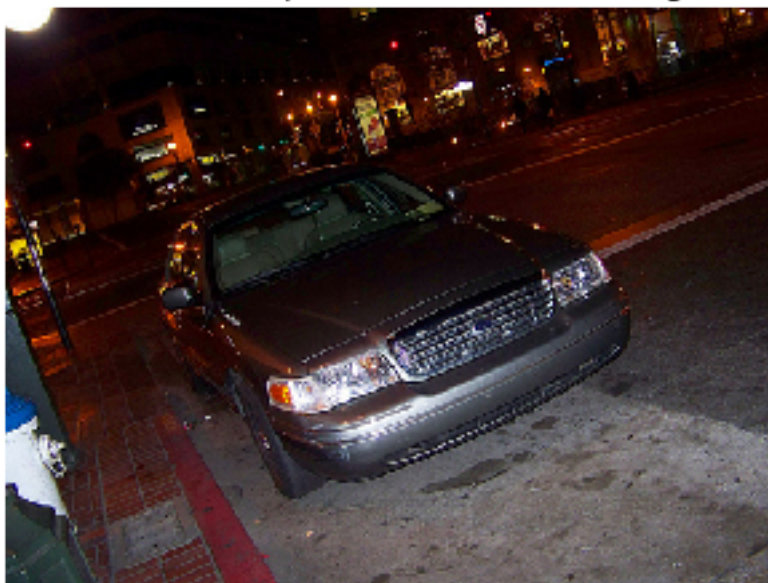
GT:<START> a man <UNK> with a bright colorful kite <END>



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



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



11 Extra Credit: Train a good captioning model!

Using the pieces you have implemented in this and the previous notebook, try to 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. We'll give you a small amount of extra credit if you can 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.

```
In [11]: 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, weights=(1,0,0,0))
        return BLEUScore

def evaluate_model(model):
    """
    model: CaptioningRNN model
    Prints unigram BLEU score averaged over 1000 training and val examples.
    """
    for split in ['train', 'val']:
        minibatch = sample_coco_minibatch(med_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]))

In [12]: med_data = load_coco_data(max_train=5000)

capt_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,
)

capt_solver = CaptioningSolver(capt_model, med_data,
    update_rule='adam',
    num_epochs=50,
    batch_size=25,
    optim_config={
        'learning_rate': 5e-3,
    },
    lr_decay=0.995,
    verbose=True, print_every=10,
)

capt_solver.train()

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

(Iteration 1 / 10000) loss: 74.899128
(Iteration 11 / 10000) loss: 56.302317
(Iteration 21 / 10000) loss: 50.045852
(Iteration 31 / 10000) loss: 45.122789
(Iteration 41 / 10000) loss: 45.483515
(Iteration 51 / 10000) loss: 44.553324
(Iteration 61 / 10000) loss: 42.492130
(Iteration 71 / 10000) loss: 41.183786
(Iteration 81 / 10000) loss: 37.419331
(Iteration 91 / 10000) loss: 38.891199

```

(Iteration 101 / 10000) loss: 39.540272
(Iteration 111 / 10000) loss: 37.408784
(Iteration 121 / 10000) loss: 35.144494
(Iteration 131 / 10000) loss: 35.352903
(Iteration 141 / 10000) loss: 33.034799
(Iteration 151 / 10000) loss: 32.667663
(Iteration 161 / 10000) loss: 34.078115
(Iteration 171 / 10000) loss: 34.984182
(Iteration 181 / 10000) loss: 35.662743
(Iteration 191 / 10000) loss: 34.972867
(Iteration 201 / 10000) loss: 31.820422
(Iteration 211 / 10000) loss: 31.366926
(Iteration 221 / 10000) loss: 30.145294
(Iteration 231 / 10000) loss: 31.713844
(Iteration 241 / 10000) loss: 36.350150
(Iteration 251 / 10000) loss: 33.716431
(Iteration 261 / 10000) loss: 27.097244
(Iteration 271 / 10000) loss: 30.186552
(Iteration 281 / 10000) loss: 34.436102
(Iteration 291 / 10000) loss: 31.438949
(Iteration 301 / 10000) loss: 28.582804
(Iteration 311 / 10000) loss: 29.053929
(Iteration 321 / 10000) loss: 28.696845
(Iteration 331 / 10000) loss: 27.629697
(Iteration 341 / 10000) loss: 28.118037
(Iteration 351 / 10000) loss: 28.799816
(Iteration 361 / 10000) loss: 31.801705
(Iteration 371 / 10000) loss: 28.426097
(Iteration 381 / 10000) loss: 29.373626
(Iteration 391 / 10000) loss: 27.650295
(Iteration 401 / 10000) loss: 26.229482
(Iteration 411 / 10000) loss: 31.830561
(Iteration 421 / 10000) loss: 28.505640
(Iteration 431 / 10000) loss: 28.171576
(Iteration 441 / 10000) loss: 25.515357
(Iteration 451 / 10000) loss: 24.055718
(Iteration 461 / 10000) loss: 28.984333
(Iteration 471 / 10000) loss: 28.827550
(Iteration 481 / 10000) loss: 24.218338
(Iteration 491 / 10000) loss: 28.347303
(Iteration 501 / 10000) loss: 27.622751
(Iteration 511 / 10000) loss: 23.939057
(Iteration 521 / 10000) loss: 26.755916
(Iteration 531 / 10000) loss: 26.010806
(Iteration 541 / 10000) loss: 25.927289
(Iteration 551 / 10000) loss: 23.577932
(Iteration 561 / 10000) loss: 21.839295
(Iteration 571 / 10000) loss: 23.433892

(Iteration 581 / 10000) loss: 25.823161
(Iteration 591 / 10000) loss: 24.499018
(Iteration 601 / 10000) loss: 23.221837
(Iteration 611 / 10000) loss: 25.673646
(Iteration 621 / 10000) loss: 23.509110
(Iteration 631 / 10000) loss: 24.492510
(Iteration 641 / 10000) loss: 21.759781
(Iteration 651 / 10000) loss: 24.802936
(Iteration 661 / 10000) loss: 23.329650
(Iteration 671 / 10000) loss: 22.937408
(Iteration 681 / 10000) loss: 21.683627
(Iteration 691 / 10000) loss: 23.303339
(Iteration 701 / 10000) loss: 22.999120
(Iteration 711 / 10000) loss: 24.107198
(Iteration 721 / 10000) loss: 20.989781
(Iteration 731 / 10000) loss: 20.452402
(Iteration 741 / 10000) loss: 26.845369
(Iteration 751 / 10000) loss: 20.544558
(Iteration 761 / 10000) loss: 16.946730
(Iteration 771 / 10000) loss: 27.330660
(Iteration 781 / 10000) loss: 25.168350
(Iteration 791 / 10000) loss: 19.014944
(Iteration 801 / 10000) loss: 22.538804
(Iteration 811 / 10000) loss: 21.706520
(Iteration 821 / 10000) loss: 21.565940
(Iteration 831 / 10000) loss: 23.010879
(Iteration 841 / 10000) loss: 24.544214
(Iteration 851 / 10000) loss: 22.670332
(Iteration 861 / 10000) loss: 21.910099
(Iteration 871 / 10000) loss: 24.049240
(Iteration 881 / 10000) loss: 22.290084
(Iteration 891 / 10000) loss: 18.767493
(Iteration 901 / 10000) loss: 23.324185
(Iteration 911 / 10000) loss: 23.151323
(Iteration 921 / 10000) loss: 22.348181
(Iteration 931 / 10000) loss: 18.084972
(Iteration 941 / 10000) loss: 17.947874
(Iteration 951 / 10000) loss: 21.434827
(Iteration 961 / 10000) loss: 17.541884
(Iteration 971 / 10000) loss: 21.517197
(Iteration 981 / 10000) loss: 22.726007
(Iteration 991 / 10000) loss: 20.007530
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(Iteration 1011 / 10000) loss: 21.046971
(Iteration 1021 / 10000) loss: 19.246777
(Iteration 1031 / 10000) loss: 20.182605
(Iteration 1041 / 10000) loss: 21.487890
(Iteration 1051 / 10000) loss: 21.056914

(Iteration 1061 / 10000) loss: 19.535169
(Iteration 1071 / 10000) loss: 18.715388
(Iteration 1081 / 10000) loss: 16.141629
(Iteration 1091 / 10000) loss: 22.317019
(Iteration 1101 / 10000) loss: 25.274963
(Iteration 1111 / 10000) loss: 19.796291
(Iteration 1121 / 10000) loss: 18.706015
(Iteration 1131 / 10000) loss: 20.668363
(Iteration 1141 / 10000) loss: 18.860805
(Iteration 1151 / 10000) loss: 17.566043
(Iteration 1161 / 10000) loss: 17.222966
(Iteration 1171 / 10000) loss: 17.843923
(Iteration 1181 / 10000) loss: 17.179211
(Iteration 1191 / 10000) loss: 18.550746
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(Iteration 1211 / 10000) loss: 16.494365
(Iteration 1221 / 10000) loss: 20.207332
(Iteration 1231 / 10000) loss: 15.895357
(Iteration 1241 / 10000) loss: 14.432801
(Iteration 1251 / 10000) loss: 16.454549
(Iteration 1261 / 10000) loss: 21.223386
(Iteration 1271 / 10000) loss: 18.000194
(Iteration 1281 / 10000) loss: 15.732315
(Iteration 1291 / 10000) loss: 16.728246
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(Iteration 1311 / 10000) loss: 16.930829
(Iteration 1321 / 10000) loss: 17.053908
(Iteration 1331 / 10000) loss: 17.750995
(Iteration 1341 / 10000) loss: 21.790971
(Iteration 1351 / 10000) loss: 18.312846
(Iteration 1361 / 10000) loss: 16.646212
(Iteration 1371 / 10000) loss: 15.250757
(Iteration 1381 / 10000) loss: 15.115761
(Iteration 1391 / 10000) loss: 16.236158
(Iteration 1401 / 10000) loss: 14.456373
(Iteration 1411 / 10000) loss: 14.400279
(Iteration 1421 / 10000) loss: 19.195996
(Iteration 1431 / 10000) loss: 14.579241
(Iteration 1441 / 10000) loss: 14.826941
(Iteration 1451 / 10000) loss: 17.265090
(Iteration 1461 / 10000) loss: 17.204246
(Iteration 1471 / 10000) loss: 16.788892
(Iteration 1481 / 10000) loss: 15.728334
(Iteration 1491 / 10000) loss: 15.331083
(Iteration 1501 / 10000) loss: 16.724106
(Iteration 1511 / 10000) loss: 15.651230
(Iteration 1521 / 10000) loss: 17.017758
(Iteration 1531 / 10000) loss: 18.119486

(Iteration 1541 / 10000) loss: 20.825503
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(Iteration 1561 / 10000) loss: 18.770026
(Iteration 1571 / 10000) loss: 13.137452
(Iteration 1581 / 10000) loss: 14.458733
(Iteration 1591 / 10000) loss: 15.417127
(Iteration 1601 / 10000) loss: 16.014134
(Iteration 1611 / 10000) loss: 15.459367
(Iteration 1621 / 10000) loss: 16.642802
(Iteration 1631 / 10000) loss: 14.986944
(Iteration 1641 / 10000) loss: 16.128539
(Iteration 1651 / 10000) loss: 15.705505
(Iteration 1661 / 10000) loss: 15.890609
(Iteration 1671 / 10000) loss: 16.500009
(Iteration 1681 / 10000) loss: 13.021557
(Iteration 1691 / 10000) loss: 17.245289
(Iteration 1701 / 10000) loss: 16.224758
(Iteration 1711 / 10000) loss: 16.297354
(Iteration 1721 / 10000) loss: 18.979173
(Iteration 1731 / 10000) loss: 16.252367
(Iteration 1741 / 10000) loss: 14.283140
(Iteration 1751 / 10000) loss: 14.348764
(Iteration 1761 / 10000) loss: 14.403134
(Iteration 1771 / 10000) loss: 14.828319
(Iteration 1781 / 10000) loss: 14.733056
(Iteration 1791 / 10000) loss: 14.731680
(Iteration 1801 / 10000) loss: 13.003896
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(Iteration 1821 / 10000) loss: 16.211521
(Iteration 1831 / 10000) loss: 13.823058
(Iteration 1841 / 10000) loss: 15.035237
(Iteration 1851 / 10000) loss: 13.907551
(Iteration 1861 / 10000) loss: 14.435944
(Iteration 1871 / 10000) loss: 14.182080
(Iteration 1881 / 10000) loss: 14.291607
(Iteration 1891 / 10000) loss: 14.563774
(Iteration 1901 / 10000) loss: 17.885469
(Iteration 1911 / 10000) loss: 16.706508
(Iteration 1921 / 10000) loss: 12.665744
(Iteration 1931 / 10000) loss: 11.472915
(Iteration 1941 / 10000) loss: 13.542350
(Iteration 1951 / 10000) loss: 15.428391
(Iteration 1961 / 10000) loss: 12.412390
(Iteration 1971 / 10000) loss: 14.856977
(Iteration 1981 / 10000) loss: 14.382290
(Iteration 1991 / 10000) loss: 13.332196
(Iteration 2001 / 10000) loss: 17.678868
(Iteration 2011 / 10000) loss: 11.807108

(Iteration 2021 / 10000) loss: 13.529039
(Iteration 2031 / 10000) loss: 13.957234
(Iteration 2041 / 10000) loss: 13.343297
(Iteration 2051 / 10000) loss: 12.500120
(Iteration 2061 / 10000) loss: 15.201938
(Iteration 2071 / 10000) loss: 14.001454
(Iteration 2081 / 10000) loss: 11.888307
(Iteration 2091 / 10000) loss: 14.437073
(Iteration 2101 / 10000) loss: 13.027301
(Iteration 2111 / 10000) loss: 11.784046
(Iteration 2121 / 10000) loss: 12.860114
(Iteration 2131 / 10000) loss: 13.288853
(Iteration 2141 / 10000) loss: 11.699139
(Iteration 2151 / 10000) loss: 13.940073
(Iteration 2161 / 10000) loss: 11.738961
(Iteration 2171 / 10000) loss: 12.108687
(Iteration 2181 / 10000) loss: 10.888705
(Iteration 2191 / 10000) loss: 14.380386
(Iteration 2201 / 10000) loss: 12.989289
(Iteration 2211 / 10000) loss: 13.268139
(Iteration 2221 / 10000) loss: 14.310404
(Iteration 2231 / 10000) loss: 14.869535
(Iteration 2241 / 10000) loss: 14.320727
(Iteration 2251 / 10000) loss: 14.537993
(Iteration 2261 / 10000) loss: 9.844080
(Iteration 2271 / 10000) loss: 11.970950
(Iteration 2281 / 10000) loss: 11.488095
(Iteration 2291 / 10000) loss: 13.307488
(Iteration 2301 / 10000) loss: 10.869630
(Iteration 2311 / 10000) loss: 13.917210
(Iteration 2321 / 10000) loss: 14.312722
(Iteration 2331 / 10000) loss: 18.225878
(Iteration 2341 / 10000) loss: 16.269078
(Iteration 2351 / 10000) loss: 15.683230
(Iteration 2361 / 10000) loss: 11.218254
(Iteration 2371 / 10000) loss: 13.559671
(Iteration 2381 / 10000) loss: 14.780902
(Iteration 2391 / 10000) loss: 12.426844
(Iteration 2401 / 10000) loss: 15.221593
(Iteration 2411 / 10000) loss: 12.859445
(Iteration 2421 / 10000) loss: 12.436610
(Iteration 2431 / 10000) loss: 14.359621
(Iteration 2441 / 10000) loss: 14.263073
(Iteration 2451 / 10000) loss: 14.326717
(Iteration 2461 / 10000) loss: 12.056367
(Iteration 2471 / 10000) loss: 14.856183
(Iteration 2481 / 10000) loss: 12.925509
(Iteration 2491 / 10000) loss: 13.681111

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(Iteration 2511 / 10000) loss: 14.233107
(Iteration 2521 / 10000) loss: 15.662368
(Iteration 2531 / 10000) loss: 11.689503
(Iteration 2541 / 10000) loss: 10.551997
(Iteration 2551 / 10000) loss: 11.269098
(Iteration 2561 / 10000) loss: 15.278555
(Iteration 2571 / 10000) loss: 10.921681
(Iteration 2581 / 10000) loss: 14.242297
(Iteration 2591 / 10000) loss: 11.953889
(Iteration 2601 / 10000) loss: 14.047072
(Iteration 2611 / 10000) loss: 13.539825
(Iteration 2621 / 10000) loss: 10.978116
(Iteration 2631 / 10000) loss: 12.035687
(Iteration 2641 / 10000) loss: 11.651895
(Iteration 2651 / 10000) loss: 12.233355
(Iteration 2661 / 10000) loss: 12.902073
(Iteration 2671 / 10000) loss: 14.112139
(Iteration 2681 / 10000) loss: 12.208501
(Iteration 2691 / 10000) loss: 12.860892
(Iteration 2701 / 10000) loss: 13.159910
(Iteration 2711 / 10000) loss: 12.509091
(Iteration 2721 / 10000) loss: 11.893936
(Iteration 2731 / 10000) loss: 11.985028
(Iteration 2741 / 10000) loss: 9.502390
(Iteration 2751 / 10000) loss: 12.020822
(Iteration 2761 / 10000) loss: 12.234993
(Iteration 2771 / 10000) loss: 12.676166
(Iteration 2781 / 10000) loss: 9.959099
(Iteration 2791 / 10000) loss: 11.070548
(Iteration 2801 / 10000) loss: 13.986011
(Iteration 2811 / 10000) loss: 12.650733
(Iteration 2821 / 10000) loss: 13.804542
(Iteration 2831 / 10000) loss: 11.039493
(Iteration 2841 / 10000) loss: 12.683291
(Iteration 2851 / 10000) loss: 12.440110
(Iteration 2861 / 10000) loss: 13.325308
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(Iteration 2881 / 10000) loss: 11.269694
(Iteration 2891 / 10000) loss: 11.578021
(Iteration 2901 / 10000) loss: 13.257281
(Iteration 2911 / 10000) loss: 10.235547
(Iteration 2921 / 10000) loss: 13.801733
(Iteration 2931 / 10000) loss: 13.510471
(Iteration 2941 / 10000) loss: 12.142390
(Iteration 2951 / 10000) loss: 11.274170
(Iteration 2961 / 10000) loss: 12.807893
(Iteration 2971 / 10000) loss: 12.388918

(Iteration 2981 / 10000) loss: 8.905060
(Iteration 2991 / 10000) loss: 11.498371
(Iteration 3001 / 10000) loss: 13.585428
(Iteration 3011 / 10000) loss: 15.260557
(Iteration 3021 / 10000) loss: 11.549980
(Iteration 3031 / 10000) loss: 10.499758
(Iteration 3041 / 10000) loss: 9.786125
(Iteration 3051 / 10000) loss: 12.849122
(Iteration 3061 / 10000) loss: 10.861226
(Iteration 3071 / 10000) loss: 10.897287
(Iteration 3081 / 10000) loss: 10.683367
(Iteration 3091 / 10000) loss: 14.419148
(Iteration 3101 / 10000) loss: 10.826059
(Iteration 3111 / 10000) loss: 12.637522
(Iteration 3121 / 10000) loss: 13.299114
(Iteration 3131 / 10000) loss: 10.926489
(Iteration 3141 / 10000) loss: 13.827043
(Iteration 3151 / 10000) loss: 10.894008
(Iteration 3161 / 10000) loss: 12.222799
(Iteration 3171 / 10000) loss: 8.799823
(Iteration 3181 / 10000) loss: 12.958483
(Iteration 3191 / 10000) loss: 11.065429
(Iteration 3201 / 10000) loss: 14.510665
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(Iteration 3221 / 10000) loss: 13.102975
(Iteration 3231 / 10000) loss: 12.410626
(Iteration 3241 / 10000) loss: 10.591996
(Iteration 3251 / 10000) loss: 9.446178
(Iteration 3261 / 10000) loss: 10.344863
(Iteration 3271 / 10000) loss: 14.938346
(Iteration 3281 / 10000) loss: 10.994919
(Iteration 3291 / 10000) loss: 12.529604
(Iteration 3301 / 10000) loss: 11.400762
(Iteration 3311 / 10000) loss: 14.761403
(Iteration 3321 / 10000) loss: 8.902695
(Iteration 3331 / 10000) loss: 10.520322
(Iteration 3341 / 10000) loss: 13.896164
(Iteration 3351 / 10000) loss: 11.192266
(Iteration 3361 / 10000) loss: 11.086080
(Iteration 3371 / 10000) loss: 10.933654
(Iteration 3381 / 10000) loss: 11.355337
(Iteration 3391 / 10000) loss: 11.187919
(Iteration 3401 / 10000) loss: 8.329341
(Iteration 3411 / 10000) loss: 11.051116
(Iteration 3421 / 10000) loss: 9.640642
(Iteration 3431 / 10000) loss: 12.190350
(Iteration 3441 / 10000) loss: 10.315090
(Iteration 3451 / 10000) loss: 11.300133

(Iteration 3461 / 10000) loss: 10.147561
(Iteration 3471 / 10000) loss: 10.114984
(Iteration 3481 / 10000) loss: 12.169260
(Iteration 3491 / 10000) loss: 10.989205
(Iteration 3501 / 10000) loss: 10.123063
(Iteration 3511 / 10000) loss: 13.221140
(Iteration 3521 / 10000) loss: 9.846463
(Iteration 3531 / 10000) loss: 10.423045
(Iteration 3541 / 10000) loss: 10.990733
(Iteration 3551 / 10000) loss: 10.387945
(Iteration 3561 / 10000) loss: 10.400827
(Iteration 3571 / 10000) loss: 10.213137
(Iteration 3581 / 10000) loss: 11.165744
(Iteration 3591 / 10000) loss: 9.883789
(Iteration 3601 / 10000) loss: 10.133688
(Iteration 3611 / 10000) loss: 11.260068
(Iteration 3621 / 10000) loss: 9.818782
(Iteration 3631 / 10000) loss: 11.143315
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(Iteration 3661 / 10000) loss: 12.252743
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(Iteration 3731 / 10000) loss: 10.260268
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(Iteration 3751 / 10000) loss: 10.582303
(Iteration 3761 / 10000) loss: 11.489039
(Iteration 3771 / 10000) loss: 10.619055
(Iteration 3781 / 10000) loss: 10.813915
(Iteration 3791 / 10000) loss: 10.596387
(Iteration 3801 / 10000) loss: 8.559876
(Iteration 3811 / 10000) loss: 12.164913
(Iteration 3821 / 10000) loss: 10.552043
(Iteration 3831 / 10000) loss: 10.395254
(Iteration 3841 / 10000) loss: 11.080640
(Iteration 3851 / 10000) loss: 13.909364
(Iteration 3861 / 10000) loss: 12.248432
(Iteration 3871 / 10000) loss: 9.704909
(Iteration 3881 / 10000) loss: 10.949049
(Iteration 3891 / 10000) loss: 9.684814
(Iteration 3901 / 10000) loss: 9.391348
(Iteration 3911 / 10000) loss: 10.677471
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(Iteration 3931 / 10000) loss: 12.900263

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(Iteration 3971 / 10000) loss: 12.832012
(Iteration 3981 / 10000) loss: 8.892122
(Iteration 3991 / 10000) loss: 11.577384
(Iteration 4001 / 10000) loss: 8.694315
(Iteration 4011 / 10000) loss: 12.095782
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(Iteration 4031 / 10000) loss: 10.517373
(Iteration 4041 / 10000) loss: 11.450652
(Iteration 4051 / 10000) loss: 10.440612
(Iteration 4061 / 10000) loss: 11.203720
(Iteration 4071 / 10000) loss: 11.932363
(Iteration 4081 / 10000) loss: 10.139232
(Iteration 4091 / 10000) loss: 10.294964
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(Iteration 4111 / 10000) loss: 8.580089
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(Iteration 4131 / 10000) loss: 10.758738
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(Iteration 4151 / 10000) loss: 12.156481
(Iteration 4161 / 10000) loss: 11.880679
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(Iteration 4191 / 10000) loss: 10.852725
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(Iteration 4331 / 10000) loss: 11.074107
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(Iteration 4401 / 10000) loss: 12.162268
(Iteration 4411 / 10000) loss: 11.068002

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(Iteration 4481 / 10000) loss: 10.279165
(Iteration 4491 / 10000) loss: 11.926483
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(Iteration 4511 / 10000) loss: 9.299380
(Iteration 4521 / 10000) loss: 8.787059
(Iteration 4531 / 10000) loss: 8.341896
(Iteration 4541 / 10000) loss: 7.982159
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(Iteration 4561 / 10000) loss: 10.533693
(Iteration 4571 / 10000) loss: 10.484091
(Iteration 4581 / 10000) loss: 9.482438
(Iteration 4591 / 10000) loss: 7.927515
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(Iteration 4611 / 10000) loss: 10.433941
(Iteration 4621 / 10000) loss: 8.103319
(Iteration 4631 / 10000) loss: 9.669329
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(Iteration 4741 / 10000) loss: 11.880354
(Iteration 4751 / 10000) loss: 11.045758
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(Iteration 4871 / 10000) loss: 10.068094
(Iteration 4881 / 10000) loss: 9.867685
(Iteration 4891 / 10000) loss: 10.564567

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(Iteration 4941 / 10000) loss: 10.346515
(Iteration 4951 / 10000) loss: 11.382185
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(Iteration 4971 / 10000) loss: 9.047606
(Iteration 4981 / 10000) loss: 7.281624
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(Iteration 5001 / 10000) loss: 9.193391
(Iteration 5011 / 10000) loss: 10.095583
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(Iteration 5041 / 10000) loss: 10.898797
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(Iteration 5061 / 10000) loss: 10.793418
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(Iteration 5121 / 10000) loss: 10.120269
(Iteration 5131 / 10000) loss: 10.177018
(Iteration 5141 / 10000) loss: 10.372734
(Iteration 5151 / 10000) loss: 9.984574
(Iteration 5161 / 10000) loss: 10.938375
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(Iteration 5191 / 10000) loss: 11.335632
(Iteration 5201 / 10000) loss: 9.085556
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(Iteration 5251 / 10000) loss: 9.942590
(Iteration 5261 / 10000) loss: 9.599866
(Iteration 5271 / 10000) loss: 11.972419
(Iteration 5281 / 10000) loss: 9.109536
(Iteration 5291 / 10000) loss: 8.604838
(Iteration 5301 / 10000) loss: 9.605723
(Iteration 5311 / 10000) loss: 9.170627
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(Iteration 5371 / 10000) loss: 8.795367

(Iteration 5381 / 10000) loss: 9.052739
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(Iteration 5981 / 10000) loss: 9.516635
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(Iteration 7291 / 10000) loss: 7.547413

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(Iteration 7731 / 10000) loss: 8.724087
(Iteration 7741 / 10000) loss: 7.914146
(Iteration 7751 / 10000) loss: 8.671664
(Iteration 7761 / 10000) loss: 7.620545
(Iteration 7771 / 10000) loss: 9.526067

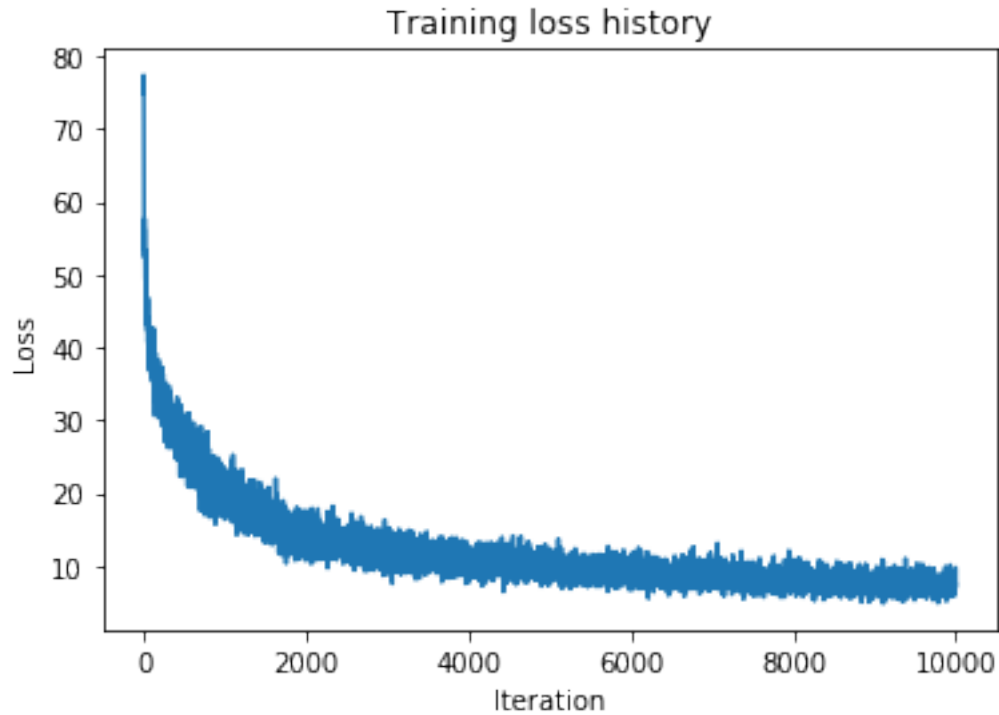
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(Iteration 7791 / 10000) loss: 7.130984
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(Iteration 7811 / 10000) loss: 7.756123
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(Iteration 7861 / 10000) loss: 7.365654
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(Iteration 8251 / 10000) loss: 7.728975

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(Iteration 8311 / 10000) loss: 7.615199
(Iteration 8321 / 10000) loss: 8.855717
(Iteration 8331 / 10000) loss: 10.179992
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(Iteration 8381 / 10000) loss: 7.444011
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(Iteration 8791 / 10000) loss: 7.027331
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(Iteration 9661 / 10000) loss: 6.844626
(Iteration 9671 / 10000) loss: 9.807609
(Iteration 9681 / 10000) loss: 8.781584
(Iteration 9691 / 10000) loss: 8.622404

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(Iteration 9971 / 10000) loss: 6.506773
(Iteration 9981 / 10000) loss: 8.431390
(Iteration 9991 / 10000) loss: 8.480395



```
In [13]: evaluate_model(capt_model)
```

```
-----

NameError                                Traceback (most recent call last)

<ipython-input-13-7af762d3b3a0> in <module>()
----> 1 evaluate_model(capt_model)

<ipython-input-11-d2c1609a6fc1> in evaluate_model(model)
    27     total_score = 0.0
    28     for gt_caption, sample_caption, url in zip(gt_captions, sample_captions, u
---> 29         total_score += BLEU_score(gt_caption, sample_caption)
    30
    31     BLEUscores[split] = total_score / len(sample_captions)

<ipython-input-11-d2c1609a6fc1> in BLEU_score(gt_caption, sample_caption)
     9     hypothesis = [x for x in sample_caption.split(' ')]
    10         if ('<END>' not in x and '<START>' not in x and '<UNK>' not in x)
---> 11     BLEUscore = nltk.translate.bleu_score.sentence_bleu([reference], hypothesis, w
    12     return BLEUscore
```

13

```
NameError: global name 'nltk' is not defined
```