# Image Captioning with RNNs

In this exercise you will implement a vanilla recurrent neural networks and use them it to train a model that can generate novel captions for images.

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

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))))
```

## Install h5py

The COCO dataset we will be using is stored in HDF5 format. To load HDF5 files, we will need to install the `h5py` Python package. From the command line, run:
`pip install h5py`
If you receive a permissions error, you may need to run the command as root:
`sudo pip install h5py`

You can also run commands directly from the Jupyter notebook by prefixing the command with the "!" character:

In [2]:
```
!pip install h5py
```

```
Requirement already satisfied: h5py in /miniconda3/envs/cs4803/lib/python3.6/site-packages (2.10.0)
Requirement already satisfied: six in /miniconda3/envs/cs4803/lib/python3.6/site-packages (from h5py) (1.14.0)
Requirement already satisfied: numpy>=1.7 in /miniconda3/envs/cs4803/lib/python3.6/site-packages (from h5py) (1.18.1)
```

# Microsoft COCO

For this exercise we will use the 2014 release of the [Microsoft COCO dataset (http://mscoco.org/)](http://mscoco.org/) which has become the standard testbed for image captioning. The dataset consists of 80,000 training images and 40,000 validation images, each annotated with 5 captions written by workers on Amazon Mechanical Turk.

You should have already downloaded the data by changing to the `cs231n/datasets` directory and running the script `get_assignment3_data.sh`. If you haven't yet done so, run that script now. Warning: the COCO data download is ~1GB.

We have preprocessed the data and extracted features for you already. For all images we have extracted features from the fc7 layer of the VGG-16 network pretrained on ImageNet; these features are stored in the files `train2014_vgg16_fc7.h5` and `val2014_vgg16_fc7.h5` respectively. To cut down on processing time and memory requirements, we have reduced the dimensionality of the features from 4096 to 512; these features can be found in the files `train2014_vgg16_fc7_pca.h5` and `val2014_vgg16_fc7_pca.h5`.

The raw images take up a lot of space (nearly 20GB) so we have not included them in the download. However all images are taken from Flickr, and URLs of the training and validation images are stored in the files `train2014_urls.txt` and `val2014_urls.txt` respectively. This allows you to download images on the fly for visualization. Since images are downloaded on-the-fly, **you must be connected to the internet to view images**.

Dealing with strings is inefficient, so we will work with an encoded version of the captions. Each word is assigned an integer ID, allowing us to represent a caption by a sequence of integers. The mapping between integer IDs and words is in the file `coco2014_vocab.json`, and you can use the function `decode_captions` from the file `cs231n/coco_utils.py` to convert numpy arrays of integer IDs back into strings.

There are a couple special tokens that we add to the vocabulary. We prepend a special `<START>` token and append an `<END>` token to the beginning and end of each caption respectively. Rare words are replaced with a special `<UNK>` token (for "unknown"). In addition, since we want to train with minibatches containing captions of different lengths, we pad short captions with a special `<NULL>` token after the `<END>` token and don't compute loss or gradient for `<NULL>` tokens. Since they are a bit of a pain, we have taken care of all implementation details around special tokens for you.

You can load all of the MS-COCO data (captions, features, URLs, and vocabulary) using the `load_coco_data` function from the file `cs231n/coco_utils.py`. Run the following cell to do so:

In [3]:
```python
# 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
```

## Look at the data

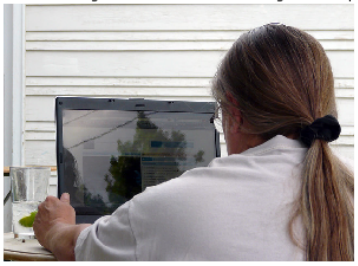
It is always a good idea to look at examples from the dataset before working with it.

You can use the `sample_coco_minibatch` function from the file `cs231n/coco_utils.py` to sample minibatches of data from the data structure returned from `load_coco_data`. Run the following to sample a small minibatch of training data and show the images and their captions. Running it multiple times and looking at the results helps you to get a sense of the dataset.

Note that we decode the captions using the `decode_captions` function and that we download the images on-the-fly using their Flickr URL, so **you must be connected to the internet to view images**.

In [4]:
```python
# Sample a minibatch and show the images and captions
batch_size = 3

captions, features, urls = sample_coco_minibatch(data, batch_size=batch_size)
for i, (caption, url) in enumerate(zip(captions, urls)):
    plt.imshow(image_from_url(url))
    plt.axis('off')
    caption_str = decode_captions(caption, data['idx_to_word'])
    plt.title(caption_str)
    plt.show()
```

<START> a man wearing a <UNK> <UNK> looking a at a laptop <END>



<START> the dog <UNK> the frisbee in the event outside <END>

<START> a girl is standing on top of a bathroom counter <END>

# Recurrent Neural Networks

As discussed in lecture, we will use recurrent neural network (RNN) language models for image captioning. The file `cs231n/rnn_layers.py` contains implementations of different layer types that are needed for recurrent neural networks, and the file `cs231n/classifiers/rnn.py` uses these layers to implement an image captioning model.

We will first implement different types of RNN layers in `cs231n/rnn_layers.py`.

# Vanilla RNN: step forward

Open the file `cs231n/rnn_layers.py` . This file implements the forward and backward passes for different types of layers that are commonly used in recurrent neural networks.

First implement the function `rnn_step_forward` which implements the forward pass for a single timestep of a vanilla recurrent neural network. After doing so run the following to check your implementation. You should see errors less than 1e-8.

In [5]:
```
N, D, H = 3, 10, 4

x = np.linspace(-0.4, 0.7, num=N*D).reshape(N, D)
prev_h = np.linspace(-0.2, 0.5, num=N*H).reshape(N, H)
Wx = np.linspace(-0.1, 0.9, num=D*H).reshape(D, H)
Wh = np.linspace(-0.3, 0.7, num=H*H).reshape(H, H)
b = np.linspace(-0.2, 0.4, num=H)

next_h, _ = rnn_step_forward(x, prev_h, Wx, Wh, b)
expected_next_h = np.asarray([
  [-0.58172089, -0.50182032, -0.41232771, -0.31410098],
  [ 0.66854692,  0.79562378,  0.87755553,  0.92795967],
  [ 0.97934501,  0.99144213,  0.99646691,  0.99854353]])

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

```
next_h error:  6.292421426471037e-09
```

# Vanilla RNN: step backward

In the file `cs231n/rnn_layers.py` implement the `rnn_step_backward` function. After doing so run the following to numerically gradient check your implementation. You should see errors less than `1e-8` .

In [6]:
```
from cs231n.rnn_layers import rnn_step_forward, rnn_step_backward
np.random.seed(231)
N, D, H = 4, 5, 6
x = np.random.randn(N, D)
h = np.random.randn(N, H)
Wx = np.random.randn(D, H)
Wh = np.random.randn(H, H)
b = np.random.randn(H)

out, cache = rnn_step_forward(x, h, Wx, Wh, b)

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

fx = lambda x: rnn_step_forward(x, h, Wx, Wh, b)[0]
fh = lambda prev_h: rnn_step_forward(x, h, Wx, Wh, b)[0]
fWx = lambda Wx: rnn_step_forward(x, h, Wx, Wh, b)[0]
fWh = lambda Wh: rnn_step_forward(x, h, Wx, Wh, b)[0]
fb = lambda b: rnn_step_forward(x, h, Wx, Wh, b)[0]

dx_num = eval_numerical_gradient_array(fx, x, dnext_h)
dprev_h_num = eval_numerical_gradient_array(fh, h, dnext_h)
dWx_num = eval_numerical_gradient_array(fWx, Wx, dnext_h)
dWh_num = eval_numerical_gradient_array(fWh, Wh, dnext_h)
db_num = eval_numerical_gradient_array(fb, b, dnext_h)

dx, dprev_h, dWx, dWh, db = rnn_step_backward(dnext_h, cache)

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

```
N 4, D 5, H 6
dnext_h: (N, H) (4, 6)
x: (N, D) (4, 5)
prev_h: (N, H) (4, 6)
Wx: (D, H) (5, 6)
Wh: (H, H) (6, 6)
dTanH: (N, H) (4, 6)
dSum: (N, H) (4, 6)
dx: (4, 5)
dprev_h: (4, 6)
dWx: (5, 6)
dWh: (6, 6)
db: (6,)
dx error:  2.99311613693832e-10
dprev_h error:  2.633205333189269e-10
dWx error:  9.684083573724284e-10
dWh error:  3.355162782632426e-10
db error:  1.5956895526227225e-11
```

# Vanilla RNN: forward

Now that you have implemented the forward and backward passes for a single timestep of a vanilla RNN, you will combine these pieces to implement a RNN that process an entire sequence of data.

In the file `cs231n/rnn_layers.py` , implement the function `rnn_forward` . This should be implemented using the `rnn_step_forward` function that you defined above. After doing so run the following to check your implementation. You should see errors less than `1e-7` .

In [7]:
```
N, T, D, H = 2, 3, 4, 5

x = np.linspace(-0.1, 0.3, num=N*T*D).reshape(N, T, D)
h0 = np.linspace(-0.3, 0.1, num=N*H).reshape(N, H)
Wx = np.linspace(-0.2, 0.4, num=D*H).reshape(D, H)
Wh = np.linspace(-0.4, 0.1, num=H*H).reshape(H, H)
b = np.linspace(-0.7, 0.1, num=H)

h, _ = rnn_forward(x, h0, Wx, Wh, b)
expected_h = np.asarray([
  [
    [-0.42070749, -0.27279261, -0.11074945,  0.05740409,  0.22236251],
    [-0.39525808, -0.22554661, -0.0409454,   0.14649412,  0.32397316],
    [-0.42305111, -0.24223728, -0.04287027,  0.15997045,  0.35014525],
  ],
  [
    [-0.55857474, -0.39065825, -0.19198182,  0.02378408,  0.23735671],
    [-0.27150199, -0.07088804,  0.13562939,  0.33099728,  0.50158768],
    [-0.51014825, -0.30524429, -0.06755202,  0.17806392,  0.40333043]]])
print('h error: ', rel_error(expected_h, h))
```

```
h error:  7.728466180186066e-08
```

# Vanilla RNN: backward

In the file `cs231n/rnn_layers.py` , implement the backward pass for a vanilla RNN in the function `rnn_backward` . This should run back-propagation over the entire sequence, calling into the `rnn_step_backward` function that you defined above. You should see errors less than 5e-7.

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

N, D, T, H = 2, 3, 10, 5

x = np.random.randn(N, T, D)
h0 = np.random.randn(N, H)
Wx = np.random.randn(D, H)
Wh = np.random.randn(H, H)
b = np.random.randn(H)

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

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

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

fx = lambda x: rnn_forward(x, h0, Wx, Wh, b)[0]
fh0 = lambda h0: rnn_forward(x, h0, Wx, Wh, b)[0]
fWx = lambda Wx: rnn_forward(x, h0, Wx, Wh, b)[0]
fWh = lambda Wh: rnn_forward(x, h0, Wx, Wh, b)[0]
fb = lambda b: rnn_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(f"correct dx: {dx_num}")
# print(f"reagans dx: {dx}")
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:  2.3969112188524054e-09
dh0 error:  3.3796875007867145e-09
dWx error:  7.221000108504998e-09
dWh error:  1.284586847530015e-07
db error:  4.675767378424171e-10
```

# Word embedding: forward

In deep learning systems, we commonly represent words using vectors. Each word of the vocabulary will be associated with a vector, and these vectors will be learned jointly with the rest of the system.

In the file `cs231n/rnn_layers.py` , implement the function `word_embedding_forward` to convert words (represented by integers) into vectors. Run the following to check your implementation. You should see error around `1e-8` .

In [9]:
```
N, T, V, D = 2, 4, 5, 3

x = np.asarray([[0, 3, 1, 2], [2, 1, 0, 3]])
W = np.linspace(0, 1, num=V*D).reshape(V, D)

out, _ = word_embedding_forward(x, W)
expected_out = np.asarray([
 [[ 0.,          0.07142857,  0.14285714],
  [ 0.64285714,  0.71428571,  0.78571429],
  [ 0.21428571,  0.28571429,  0.35714286],
  [ 0.42857143,  0.5,         0.57142857]],
 [[ 0.42857143,  0.5,         0.57142857],
  [ 0.21428571,  0.28571429,  0.35714286],
  [ 0.,          0.07142857,  0.14285714],
  [ 0.64285714,  0.71428571,  0.78571429]]])

print('out error: ', rel_error(expected_out, out))
```

```
out error:  1.0000000094736443e-08
```

## Word embedding: backward

Implement the backward pass for the word embedding function in the function `word_embedding_backward` . After doing so run the following to numerically gradient check your implementation. You should see errors less than `1e-11` .

In [10]:
```
np.random.seed(231)

N, T, V, D = 50, 3, 5, 6
x = np.random.randint(V, size=(N, T))
W = np.random.randn(V, D)

out, cache = word_embedding_forward(x, W)
dout = np.random.randn(*out.shape)
dW = word_embedding_backward(dout, cache)

f = lambda W: word_embedding_forward(x, W)[0]
dW_num = eval_numerical_gradient_array(f, W, dout)

print('dW error: ', rel_error(dW, dW_num))
```

```
dW error:  3.2774595693100364e-12
```

## Temporal Affine layer

At every timestep we use an affine function to transform the RNN hidden vector at that timestep into scores for each word in the vocabulary. Because this is very similar to the affine layer that you implemented in assignment 2, we have provided this function for you in the `temporal_affine_forward` and `temporal_affine_backward` functions in the file `cs231n/rnn_layers.py` . Run the following to perform numeric gradient checking on the implementation. You should see errors less than 1e-9.

In [11]:
```
np.random.seed(231)

# Gradient check for temporal affine layer
N, T, D, M = 2, 3, 4, 5
x = np.random.randn(N, T, D)
w = np.random.randn(D, M)
b = np.random.randn(M)

out, cache = temporal_affine_forward(x, w, b)

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

fx = lambda x: temporal_affine_forward(x, w, b)[0]
fw = lambda w: temporal_affine_forward(x, w, b)[0]
fb = lambda b: temporal_affine_forward(x, w, b)[0]

dx_num = eval_numerical_gradient_array(fx, x, dout)
dw_num = eval_numerical_gradient_array(fw, w, dout)
db_num = eval_numerical_gradient_array(fb, b, dout)

dx, dw, db = temporal_affine_backward(dout, cache)

print('dx error: ', rel_error(dx_num, dx))
print('dw error: ', rel_error(dw_num, dw))
print('db error: ', rel_error(db_num, db))
```

```
dx error:  2.9215854231394017e-10
dw error:  1.5772169135951167e-10
db error:  3.252200556967514e-11
```

## Temporal Softmax loss

In an RNN language model, at every timestep we produce a score for each word in the vocabulary. We know the ground-truth word at each timestep, so we use a softmax loss function to compute loss and gradient at each timestep. We sum the losses over time and average them over the minibatch.

However there is one wrinkle: since we operate over minibatches and different captions may have different lengths, we append `<NULL>` tokens to the end of each caption so they all have the same length. We don't want these `<NULL>` tokens to count toward the loss or gradient, so in addition to scores and ground-truth labels our loss function also accepts a `mask` array that tells it which elements of the scores count towards the loss.

Since this is very similar to the softmax loss function you implemented in assignment 1, we have implemented this loss function for you; look at the `temporal_softmax_loss` function in the file `cs231n/rnn_layers.py` .

Run the following cell to sanity check the loss and perform numeric gradient checking on the function. You should see an error for dx less than 1e-7.

In [12]:
```
# Sanity check for temporal softmax loss
from cs231n.rnn_layers import temporal_softmax_loss

N, T, V = 100, 1, 10

def check_loss(N, T, V, p):
    x = 0.001 * np.random.randn(N, T, V)
    y = np.random.randint(V, size=(N, T))
    mask = np.random.rand(N, T) <= p
    print(temporal_softmax_loss(x, y, mask)[0])

check_loss(100, 1, 10, 1.0)   # Should be about 2.3
check_loss(100, 10, 10, 1.0)  # Should be about 23
check_loss(5000, 10, 10, 0.1) # Should be about 2.3

# Gradient check for temporal softmax loss
N, T, V = 7, 8, 9

x = np.random.randn(N, T, V)
y = np.random.randint(V, size=(N, T))
mask = (np.random.rand(N, T) > 0.5)

loss, dx = temporal_softmax_loss(x, y, mask, verbose=False)

dx_num = eval_numerical_gradient(lambda x: temporal_softmax_loss(x, y, mask)[0], x, verbose=False)

print('dx error: ', rel_error(dx, dx_num))
```

```
2.3027781774290146
23.025985953127226
2.2643611790293394
dx error:  2.583585303524283e-08
```

# RNN for image captioning

Now that you have implemented the necessary layers, you can combine them to build an image captioning model. Open the file `cs231n/classifiers/rnn.py` and look at the `CaptioningRNN` class.

Implement the forward and backward pass of the model in the `loss` function. For now you only need to implement the case where `cell_type='rnn'` for vanialla RNNs; you will implement the LSTM case later. After doing so, run the following to check your forward pass using a small test case; you should see error less than `1e-10`.

In [13]:
```
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='rnn',
          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(-1.5, 0.3, num=(N * D)).reshape(N, D)
captions = (np.arange(N * T) % V).reshape(N, T)

loss, grads = model.loss(features, captions, verbose=False)
expected_loss = 9.83235591003

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

```
loss:  9.832355910027388
expected loss:  9.83235591003
difference:  2.611244553918368e-12
```

Run the following cell to perform numeric gradient checking on the `CaptioningRNN` class; you should errors around `5e-6` or less.

In [14]:
```
np.random.seed(231)

batch_size = 2
timesteps = 3
input_dim = 4
wordvec_dim = 5
hidden_dim = 6
word_to_idx = {'<NULL>': 0, 'cat': 2, 'dog': 3}
vocab_size = len(word_to_idx)

captions = np.random.randint(vocab_size, size=(batch_size, timesteps))
features = np.random.randn(batch_size, input_dim)

model = CaptioningRNN(word_to_idx,
          input_dim=input_dim,
          wordvec_dim=wordvec_dim,
          hidden_dim=hidden_dim,
          cell_type='rnn',
          dtype=np.float64,
        )

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

for param_name in sorted(grads):
    f = lambda _: model.loss(features, captions)[0]
    param_grad_num = eval_numerical_gradient(f, model.params[param_name], verbose=False, h=1e-6)
    e = rel_error(param_grad_num, grads[param_name])
    print('%s relative error: %e' % (param_name, e))
```

```
W_embed relative error: 2.331072e-09
W_proj relative error: 9.974424e-09
W_vocab relative error: 4.274378e-09
Wh relative error: 5.954804e-09
Wx relative error: 8.455229e-07
b relative error: 9.727211e-10
b_proj relative error: 1.991603e-08
b_vocab relative error: 6.918525e-11
```

# Overfit small data

Similar to the `Solver` class that we used to train image classification models on the previous assignment, on this assignment we use a `CaptioningSolver` class to train image captioning models. Open the file `cs231n/captioning_solver.py` and read through the `CaptioningSolver` class; it should look very familiar.

Once you have familiarized yourself with the API, run the following to make sure your model overfit a small sample of 100 training examples. You should see losses of less than 0.1.

In [15]:
```
np.random.seed(231)

small_data = load_coco_data(max_train=100)#00)

small_rnn_model = CaptioningRNN(
          cell_type='rnn',
          word_to_idx=data['word_to_idx'],
          input_dim=data['train_features'].shape[1],
          hidden_dim=512,
          wordvec_dim=256,
        )

small_rnn_solver = CaptioningSolver(small_rnn_model, small_data,
           update_rule='adam',
           num_epochs=50,
           batch_size=1,#100
           optim_config={
             'learning_rate': 5e-3,
           },
           lr_decay=0.95,
           verbose=True, print_every=10,
         )

small_rnn_solver.train()

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

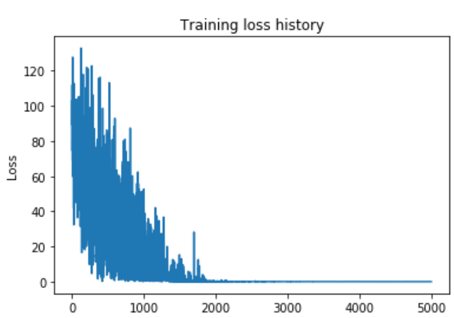
```
(Iteration 1 / 5000) loss: 89.538734
(Iteration 11 / 5000) loss: 89.436142
(Iteration 21 / 5000) loss: 41.782749
(Iteration 31 / 5000) loss: 97.063431
(Iteration 41 / 5000) loss: 98.784393
(Iteration 51 / 5000) loss: 103.743103
(Iteration 61 / 5000) loss: 76.610619
(Iteration 71 / 5000) loss: 46.232353
(Iteration 81 / 5000) loss: 47.529114
(Iteration 91 / 5000) loss: 51.454792
(Iteration 101 / 5000) loss: 41.202644
(Iteration 111 / 5000) loss: 103.156456
(Iteration 121 / 5000) loss: 63.173302
(Iteration 131 / 5000) loss: 37.913567
(Iteration 141 / 5000) loss: 99.907059
(Iteration 151 / 5000) loss: 85.212387
(Iteration 161 / 5000) loss: 57.529522
(Iteration 171 / 5000) loss: 21.788654
(Iteration 181 / 5000) loss: 27.034616
(Iteration 191 / 5000) loss: 29.954041
(Iteration 201 / 5000) loss: 20.125360
(Iteration 211 / 5000) loss: 42.703835
(Iteration 221 / 5000) loss: 50.779907
(Iteration 231 / 5000) loss: 61.426395
(Iteration 241 / 5000) loss: 64.845703
(Iteration 251 / 5000) loss: 39.612869
(Iteration 261 / 5000) loss: 45.992516
(Iteration 271 / 5000) loss: 14.378930
(Iteration 281 / 5000) loss: 22.156929
(Iteration 291 / 5000) loss: 9.530903
(Iteration 301 / 5000) loss: 21.537636
(Iteration 311 / 5000) loss: 28.899513
(Iteration 321 / 5000) loss: 71.319817
(Iteration 331 / 5000) loss: 14.083916
(Iteration 341 / 5000) loss: 45.902863
(Iteration 351 / 5000) loss: 9.437120
(Iteration 361 / 5000) loss: 54.087708
(Iteration 371 / 5000) loss: 16.939861
(Iteration 381 / 5000) loss: 66.815460
(Iteration 391 / 5000) loss: 30.158628
(Iteration 401 / 5000) loss: 55.309616
(Iteration 411 / 5000) loss: 2.467841
(Iteration 421 / 5000) loss: 16.460686
(Iteration 431 / 5000) loss: 45.130829
(Iteration 441 / 5000) loss: 53.272102
(Iteration 451 / 5000) loss: 51.743515
(Iteration 461 / 5000) loss: 33.269196
(Iteration 471 / 5000) loss: 51.398998
(Iteration 481 / 5000) loss: 35.818146
(Iteration 491 / 5000) loss: 15.107388
(Iteration 501 / 5000) loss: 54.070717
(Iteration 511 / 5000) loss: 62.900036
(Iteration 521 / 5000) loss: 41.764988
(Iteration 531 / 5000) loss: 12.469192
(Iteration 541 / 5000) loss: 60.341114
(Iteration 551 / 5000) loss: 25.075655
(Iteration 561 / 5000) loss: 6.382981
(Iteration 571 / 5000) loss: 2.519198
(Iteration 581 / 5000) loss: 40.610477
(Iteration 591 / 5000) loss: 53.783371
(Iteration 601 / 5000) loss: 10.248645
(Iteration 611 / 5000) loss: 4.130352
(Iteration 621 / 5000) loss: 24.409468
(Iteration 631 / 5000) loss: 16.780783
(Iteration 641 / 5000) loss: 32.698448
(Iteration 651 / 5000) loss: 8.323520
(Iteration 661 / 5000) loss: 48.345177
(Iteration 671 / 5000) loss: 55.929413
(Iteration 681 / 5000) loss: 37.345932
(Iteration 691 / 5000) loss: 47.278160
(Iteration 701 / 5000) loss: 9.752253
(Iteration 711 / 5000) loss: 17.875879
(Iteration 721 / 5000) loss: 80.255623
(Iteration 731 / 5000) loss: 5.435860
(Iteration 741 / 5000) loss: 27.480110
(Iteration 751 / 5000) loss: 14.788023
(Iteration 761 / 5000) loss: 13.484448
(Iteration 771 / 5000) loss: 40.191666
(Iteration 781 / 5000) loss: 28.038023
(Iteration 791 / 5000) loss: 17.346283
(Iteration 801 / 5000) loss: 31.922714
(Iteration 811 / 5000) loss: 24.746355
(Iteration 821 / 5000) loss: 0.960066
(Iteration 831 / 5000) loss: 3.729098
(Iteration 841 / 5000) loss: 24.331656
(Iteration 851 / 5000) loss: 1.427623
(Iteration 861 / 5000) loss: 4.385690
(Iteration 871 / 5000) loss: 19.940441
(Iteration 881 / 5000) loss: 47.771824
(Iteration 891 / 5000) loss: 7.549527
(Iteration 901 / 5000) loss: 34.210579
(Iteration 911 / 5000) loss: 7.658073
(Iteration 921 / 5000) loss: 4.147122
(Iteration 931 / 5000) loss: 7.015904
(Iteration 941 / 5000) loss: 0.634538
(Iteration 951 / 5000) loss: 2.414166
(Iteration 961 / 5000) loss: 3.767045
(Iteration 971 / 5000) loss: 9.693328
(Iteration 981 / 5000) loss: 0.422882
(Iteration 991 / 5000) loss: 15.993933
(Iteration 1001 / 5000) loss: 3.902276
(Iteration 1011 / 5000) loss: 14.404881
(Iteration 1021 / 5000) loss: 1.892224
(Iteration 1031 / 5000) loss: 9.150167
```

```
(Iteration 1041 / 5000) loss: 1.529371
(Iteration 1051 / 5000) loss: 9.478404
(Iteration 1061 / 5000) loss: 5.039266
(Iteration 1071 / 5000) loss: 12.174468
(Iteration 1081 / 5000) loss: 14.921804
(Iteration 1091 / 5000) loss: 6.668529
(Iteration 1101 / 5000) loss: 3.538936
(Iteration 1111 / 5000) loss: 9.991777
(Iteration 1121 / 5000) loss: 5.878150
(Iteration 1131 / 5000) loss: 0.295447
(Iteration 1141 / 5000) loss: 2.295105
(Iteration 1151 / 5000) loss: 0.180497
(Iteration 1161 / 5000) loss: 19.845589
(Iteration 1171 / 5000) loss: 3.390728
(Iteration 1181 / 5000) loss: 5.576392
(Iteration 1191 / 5000) loss: 6.027318
(Iteration 1201 / 5000) loss: 1.031552
(Iteration 1211 / 5000) loss: 0.574944
(Iteration 1221 / 5000) loss: 0.266748
(Iteration 1231 / 5000) loss: 0.517425
(Iteration 1241 / 5000) loss: 0.115634
(Iteration 1251 / 5000) loss: 0.857323
(Iteration 1261 / 5000) loss: 11.045198
(Iteration 1271 / 5000) loss: 26.033632
(Iteration 1281 / 5000) loss: 5.509893
(Iteration 1291 / 5000) loss: 5.609757
(Iteration 1301 / 5000) loss: 7.111456
(Iteration 1311 / 5000) loss: 0.598661
(Iteration 1321 / 5000) loss: 19.992622
(Iteration 1331 / 5000) loss: 2.082992
(Iteration 1341 / 5000) loss: 4.956313
(Iteration 1351 / 5000) loss: 0.214364
(Iteration 1361 / 5000) loss: 0.750437
(Iteration 1371 / 5000) loss: 0.400560
(Iteration 1381 / 5000) loss: 0.188203
(Iteration 1391 / 5000) loss: 0.574202
(Iteration 1401 / 5000) loss: 0.292207
(Iteration 1411 / 5000) loss: 0.089854
(Iteration 1421 / 5000) loss: 0.568982
(Iteration 1431 / 5000) loss: 3.127827
(Iteration 1441 / 5000) loss: 0.206117
(Iteration 1451 / 5000) loss: 0.121819
(Iteration 1461 / 5000) loss: 0.216600
(Iteration 1471 / 5000) loss: 0.105744
(Iteration 1481 / 5000) loss: 0.452972
(Iteration 1491 / 5000) loss: 0.099933
(Iteration 1501 / 5000) loss: 0.253767
(Iteration 1511 / 5000) loss: 0.397597
(Iteration 1521 / 5000) loss: 0.262964
(Iteration 1531 / 5000) loss: 0.636551
(Iteration 1541 / 5000) loss: 0.238412
(Iteration 1551 / 5000) loss: 5.855202
(Iteration 1561 / 5000) loss: 0.406963
(Iteration 1571 / 5000) loss: 0.165135
(Iteration 1581 / 5000) loss: 0.304915
(Iteration 1591 / 5000) loss: 0.599466
(Iteration 1601 / 5000) loss: 1.366495
(Iteration 1611 / 5000) loss: 0.090246
(Iteration 1621 / 5000) loss: 0.168135
(Iteration 1631 / 5000) loss: 0.187476
(Iteration 1641 / 5000) loss: 0.168081
(Iteration 1651 / 5000) loss: 0.712782
(Iteration 1661 / 5000) loss: 0.584735
(Iteration 1671 / 5000) loss: 0.069395
(Iteration 1681 / 5000) loss: 0.728173
(Iteration 1691 / 5000) loss: 0.069698
(Iteration 1701 / 5000) loss: 0.063079
(Iteration 1711 / 5000) loss: 0.041461
(Iteration 1721 / 5000) loss: 0.562342
(Iteration 1731 / 5000) loss: 0.072204
(Iteration 1741 / 5000) loss: 0.548008
(Iteration 1751 / 5000) loss: 0.038358
(Iteration 1761 / 5000) loss: 0.676519
(Iteration 1771 / 5000) loss: 0.033160
(Iteration 1781 / 5000) loss: 0.168352
(Iteration 1791 / 5000) loss: 0.272866
(Iteration 1801 / 5000) loss: 0.644750
(Iteration 1811 / 5000) loss: 0.466863
(Iteration 1821 / 5000) loss: 0.331481
(Iteration 1831 / 5000) loss: 0.051933
(Iteration 1841 / 5000) loss: 0.252053
(Iteration 1851 / 5000) loss: 0.093088
(Iteration 1861 / 5000) loss: 0.265629
(Iteration 1871 / 5000) loss: 0.222783
(Iteration 1881 / 5000) loss: 0.141227
(Iteration 1891 / 5000) loss: 0.115807
(Iteration 1901 / 5000) loss: 0.104958
(Iteration 1911 / 5000) loss: 0.066892
(Iteration 1921 / 5000) loss: 0.075094
(Iteration 1931 / 5000) loss: 0.064218
(Iteration 1941 / 5000) loss: 0.094453
(Iteration 1951 / 5000) loss: 0.270463
(Iteration 1961 / 5000) loss: 0.100966
(Iteration 1971 / 5000) loss: 0.096354
(Iteration 1981 / 5000) loss: 0.107349
(Iteration 1991 / 5000) loss: 0.160119
(Iteration 2001 / 5000) loss: 0.054516
(Iteration 2011 / 5000) loss: 0.125294
(Iteration 2021 / 5000) loss: 0.325757
(Iteration 2031 / 5000) loss: 0.077539
(Iteration 2041 / 5000) loss: 0.125360
(Iteration 2051 / 5000) loss: 0.080237
(Iteration 2061 / 5000) loss: 0.068496
(Iteration 2071 / 5000) loss: 0.072739
(Iteration 2081 / 5000) loss: 0.113197
```

```
(Iteration 2091 / 5000) loss: 0.080975
(Iteration 2101 / 5000) loss: 0.096208
(Iteration 2111 / 5000) loss: 0.059108
(Iteration 2121 / 5000) loss: 0.034324
(Iteration 2131 / 5000) loss: 0.032771
(Iteration 2141 / 5000) loss: 0.050986
(Iteration 2151 / 5000) loss: 0.033320
(Iteration 2161 / 5000) loss: 0.059138
(Iteration 2171 / 5000) loss: 0.049778
(Iteration 2181 / 5000) loss: 0.134106
(Iteration 2191 / 5000) loss: 0.132563
(Iteration 2201 / 5000) loss: 0.054139
(Iteration 2211 / 5000) loss: 0.102579
(Iteration 2221 / 5000) loss: 0.044399
(Iteration 2231 / 5000) loss: 0.027050
(Iteration 2241 / 5000) loss: 0.083712
(Iteration 2251 / 5000) loss: 0.048737
(Iteration 2261 / 5000) loss: 0.087930
(Iteration 2271 / 5000) loss: 0.065641
(Iteration 2281 / 5000) loss: 0.066378
(Iteration 2291 / 5000) loss: 0.134018
(Iteration 2301 / 5000) loss: 0.063139
(Iteration 2311 / 5000) loss: 0.049333
(Iteration 2321 / 5000) loss: 0.046218
(Iteration 2331 / 5000) loss: 0.062667
(Iteration 2341 / 5000) loss: 0.155200
(Iteration 2351 / 5000) loss: 0.077619
(Iteration 2361 / 5000) loss: 0.073163
(Iteration 2371 / 5000) loss: 0.038135
(Iteration 2381 / 5000) loss: 0.045802
(Iteration 2391 / 5000) loss: 0.179533
(Iteration 2401 / 5000) loss: 0.045145
(Iteration 2411 / 5000) loss: 0.046927
(Iteration 2421 / 5000) loss: 0.063020
(Iteration 2431 / 5000) loss: 0.040154
(Iteration 2441 / 5000) loss: 0.029081
(Iteration 2451 / 5000) loss: 0.092092
(Iteration 2461 / 5000) loss: 0.024319
(Iteration 2471 / 5000) loss: 0.052775
(Iteration 2481 / 5000) loss: 0.051961
(Iteration 2491 / 5000) loss: 0.043971
(Iteration 2501 / 5000) loss: 0.074047
(Iteration 2511 / 5000) loss: 0.037329
(Iteration 2521 / 5000) loss: 0.069169
(Iteration 2531 / 5000) loss: 0.049513
(Iteration 2541 / 5000) loss: 0.041850
(Iteration 2551 / 5000) loss: 0.429351
(Iteration 2561 / 5000) loss: 0.045865
(Iteration 2571 / 5000) loss: 0.051164
(Iteration 2581 / 5000) loss: 0.037816
(Iteration 2591 / 5000) loss: 0.028778
(Iteration 2601 / 5000) loss: 0.048968
(Iteration 2611 / 5000) loss: 0.060120
(Iteration 2621 / 5000) loss: 0.077502
(Iteration 2631 / 5000) loss: 0.068717
(Iteration 2641 / 5000) loss: 0.034594
(Iteration 2651 / 5000) loss: 0.185056
(Iteration 2661 / 5000) loss: 0.039449
(Iteration 2671 / 5000) loss: 0.063915
(Iteration 2681 / 5000) loss: 0.086589
(Iteration 2691 / 5000) loss: 0.153010
(Iteration 2701 / 5000) loss: 0.108605
(Iteration 2711 / 5000) loss: 0.043920
(Iteration 2721 / 5000) loss: 0.054018
(Iteration 2731 / 5000) loss: 0.036808
(Iteration 2741 / 5000) loss: 0.064860
(Iteration 2751 / 5000) loss: 0.032127
(Iteration 2761 / 5000) loss: 0.030468
(Iteration 2771 / 5000) loss: 0.037008
(Iteration 2781 / 5000) loss: 0.054076
(Iteration 2791 / 5000) loss: 0.034199
(Iteration 2801 / 5000) loss: 0.036159
(Iteration 2811 / 5000) loss: 0.030899
(Iteration 2821 / 5000) loss: 0.070932
(Iteration 2831 / 5000) loss: 0.024053
(Iteration 2841 / 5000) loss: 0.035270
(Iteration 2851 / 5000) loss: 0.025898
(Iteration 2861 / 5000) loss: 0.088055
(Iteration 2871 / 5000) loss: 0.058870
(Iteration 2881 / 5000) loss: 0.102871
(Iteration 2891 / 5000) loss: 0.020145
(Iteration 2901 / 5000) loss: 0.076126
(Iteration 2911 / 5000) loss: 0.084456
(Iteration 2921 / 5000) loss: 0.058761
(Iteration 2931 / 5000) loss: 0.040017
(Iteration 2941 / 5000) loss: 0.051068
(Iteration 2951 / 5000) loss: 0.042650
(Iteration 2961 / 5000) loss: 0.059668
(Iteration 2971 / 5000) loss: 0.039594
(Iteration 2981 / 5000) loss: 0.074025
(Iteration 2991 / 5000) loss: 0.059274
(Iteration 3001 / 5000) loss: 0.053715
(Iteration 3011 / 5000) loss: 0.033955
(Iteration 3021 / 5000) loss: 0.027305
(Iteration 3031 / 5000) loss: 0.036434
(Iteration 3041 / 5000) loss: 0.037711
(Iteration 3051 / 5000) loss: 0.024567
(Iteration 3061 / 5000) loss: 0.019330
(Iteration 3071 / 5000) loss: 0.056741
(Iteration 3081 / 5000) loss: 0.033976
(Iteration 3091 / 5000) loss: 0.037970
(Iteration 3101 / 5000) loss: 0.041788
(Iteration 3111 / 5000) loss: 0.041199
(Iteration 3121 / 5000) loss: 0.042894
(Iteration 3131 / 5000) loss: 0.045536
```

```
(Iteration 3141 / 5000) loss: 0.024420
(Iteration 3151 / 5000) loss: 0.070113
(Iteration 3161 / 5000) loss: 0.084537
(Iteration 3171 / 5000) loss: 0.039280
(Iteration 3181 / 5000) loss: 0.062656
(Iteration 3191 / 5000) loss: 0.031054
(Iteration 3201 / 5000) loss: 0.018972
(Iteration 3211 / 5000) loss: 0.066831
(Iteration 3221 / 5000) loss: 0.050220
(Iteration 3231 / 5000) loss: 0.040032
(Iteration 3241 / 5000) loss: 0.054585
(Iteration 3251 / 5000) loss: 0.039107
(Iteration 3261 / 5000) loss: 0.036374
(Iteration 3271 / 5000) loss: 0.048054
(Iteration 3281 / 5000) loss: 0.031696
(Iteration 3291 / 5000) loss: 0.074086
(Iteration 3301 / 5000) loss: 0.049917
(Iteration 3311 / 5000) loss: 0.052601
(Iteration 3321 / 5000) loss: 0.037278
(Iteration 3331 / 5000) loss: 0.028118
(Iteration 3341 / 5000) loss: 0.016693
(Iteration 3351 / 5000) loss: 0.058237
(Iteration 3361 / 5000) loss: 0.023223
(Iteration 3371 / 5000) loss: 0.034234
(Iteration 3381 / 5000) loss: 0.023802
(Iteration 3391 / 5000) loss: 0.024292
(Iteration 3401 / 5000) loss: 0.041935
(Iteration 3411 / 5000) loss: 0.028851
(Iteration 3421 / 5000) loss: 0.016171
(Iteration 3431 / 5000) loss: 0.035037
(Iteration 3441 / 5000) loss: 0.045557
(Iteration 3451 / 5000) loss: 0.026993
(Iteration 3461 / 5000) loss: 0.034992
(Iteration 3471 / 5000) loss: 0.034399
(Iteration 3481 / 5000) loss: 0.031287
(Iteration 3491 / 5000) loss: 0.049543
(Iteration 3501 / 5000) loss: 0.041938
(Iteration 3511 / 5000) loss: 0.026432
(Iteration 3521 / 5000) loss: 0.014573
(Iteration 3531 / 5000) loss: 0.043989
(Iteration 3541 / 5000) loss: 0.034629
(Iteration 3551 / 5000) loss: 0.047457
(Iteration 3561 / 5000) loss: 0.032869
(Iteration 3571 / 5000) loss: 0.030975
(Iteration 3581 / 5000) loss: 0.034374
(Iteration 3591 / 5000) loss: 0.029360
(Iteration 3601 / 5000) loss: 0.034517
(Iteration 3611 / 5000) loss: 0.032150
(Iteration 3621 / 5000) loss: 0.074807
(Iteration 3631 / 5000) loss: 0.045313
(Iteration 3641 / 5000) loss: 0.035010
(Iteration 3651 / 5000) loss: 0.047982
(Iteration 3661 / 5000) loss: 0.030952
(Iteration 3671 / 5000) loss: 0.021259
(Iteration 3681 / 5000) loss: 0.053226
(Iteration 3691 / 5000) loss: 0.064203
(Iteration 3701 / 5000) loss: 0.024083
(Iteration 3711 / 5000) loss: 0.021322
(Iteration 3721 / 5000) loss: 0.041338
(Iteration 3731 / 5000) loss: 0.023299
(Iteration 3741 / 5000) loss: 0.014141
(Iteration 3751 / 5000) loss: 0.028998
(Iteration 3761 / 5000) loss: 0.030180
(Iteration 3771 / 5000) loss: 0.024464
(Iteration 3781 / 5000) loss: 0.021665
(Iteration 3791 / 5000) loss: 0.029613
(Iteration 3801 / 5000) loss: 0.022322
(Iteration 3811 / 5000) loss: 0.024273
(Iteration 3821 / 5000) loss: 0.011466
(Iteration 3831 / 5000) loss: 0.039700
(Iteration 3841 / 5000) loss: 0.038757
(Iteration 3851 / 5000) loss: 0.037643
(Iteration 3861 / 5000) loss: 0.035864
(Iteration 3871 / 5000) loss: 0.023433
(Iteration 3881 / 5000) loss: 0.038423
(Iteration 3891 / 5000) loss: 0.015724
(Iteration 3901 / 5000) loss: 0.028129
(Iteration 3911 / 5000) loss: 0.026116
(Iteration 3921 / 5000) loss: 0.057014
(Iteration 3931 / 5000) loss: 0.043385
(Iteration 3941 / 5000) loss: 0.015868
(Iteration 3951 / 5000) loss: 0.021217
(Iteration 3961 / 5000) loss: 0.040107
(Iteration 3971 / 5000) loss: 0.027008
(Iteration 3981 / 5000) loss: 0.015068
(Iteration 3991 / 5000) loss: 0.021460
(Iteration 4001 / 5000) loss: 0.026698
(Iteration 4011 / 5000) loss: 0.023678
(Iteration 4021 / 5000) loss: 0.040953
(Iteration 4031 / 5000) loss: 0.044832
(Iteration 4041 / 5000) loss: 0.014249
(Iteration 4051 / 5000) loss: 0.019687
(Iteration 4061 / 5000) loss: 0.032964
(Iteration 4071 / 5000) loss: 0.029726
(Iteration 4081 / 5000) loss: 0.029178
(Iteration 4091 / 5000) loss: 0.033962
(Iteration 4101 / 5000) loss: 0.024902
(Iteration 4111 / 5000) loss: 0.010078
(Iteration 4121 / 5000) loss: 0.039600
(Iteration 4131 / 5000) loss: 0.015251
(Iteration 4141 / 5000) loss: 0.037625
(Iteration 4151 / 5000) loss: 0.026909
(Iteration 4161 / 5000) loss: 0.039265
(Iteration 4171 / 5000) loss: 0.067568
(Iteration 4181 / 5000) loss: 0.050671
```

```
(Iteration 4191 / 5000) loss: 0.026822
(Iteration 4201 / 5000) loss: 0.016860
(Iteration 4211 / 5000) loss: 0.013854
(Iteration 4221 / 5000) loss: 0.034788
(Iteration 4231 / 5000) loss: 0.027025
(Iteration 4241 / 5000) loss: 0.042791
(Iteration 4251 / 5000) loss: 0.023338
(Iteration 4261 / 5000) loss: 0.023062
(Iteration 4271 / 5000) loss: 0.021530
(Iteration 4281 / 5000) loss: 0.029499
(Iteration 4291 / 5000) loss: 0.014466
(Iteration 4301 / 5000) loss: 0.034534
(Iteration 4311 / 5000) loss: 0.020793
(Iteration 4321 / 5000) loss: 0.036590
(Iteration 4331 / 5000) loss: 0.021338
(Iteration 4341 / 5000) loss: 0.044449
(Iteration 4351 / 5000) loss: 0.021757
(Iteration 4361 / 5000) loss: 0.015433
(Iteration 4371 / 5000) loss: 0.035592
(Iteration 4381 / 5000) loss: 0.012812
(Iteration 4391 / 5000) loss: 0.020061
(Iteration 4401 / 5000) loss: 0.016843
(Iteration 4411 / 5000) loss: 0.047522
(Iteration 4421 / 5000) loss: 0.020902
(Iteration 4431 / 5000) loss: 0.021699
(Iteration 4441 / 5000) loss: 0.027268
(Iteration 4451 / 5000) loss: 0.036473
(Iteration 4461 / 5000) loss: 0.019258
(Iteration 4471 / 5000) loss: 0.032144
(Iteration 4481 / 5000) loss: 0.021610
(Iteration 4491 / 5000) loss: 0.040519
(Iteration 4501 / 5000) loss: 0.020248
(Iteration 4511 / 5000) loss: 0.024046
(Iteration 4521 / 5000) loss: 0.026689
(Iteration 4531 / 5000) loss: 0.035013
(Iteration 4541 / 5000) loss: 0.038092
(Iteration 4551 / 5000) loss: 0.021795
(Iteration 4561 / 5000) loss: 0.017306
(Iteration 4571 / 5000) loss: 0.024408
(Iteration 4581 / 5000) loss: 0.039591
(Iteration 4591 / 5000) loss: 0.038009
(Iteration 4601 / 5000) loss: 0.019653
(Iteration 4611 / 5000) loss: 0.030744
(Iteration 4621 / 5000) loss: 0.021717
(Iteration 4631 / 5000) loss: 0.035041
(Iteration 4641 / 5000) loss: 0.034605
(Iteration 4651 / 5000) loss: 0.030661
(Iteration 4661 / 5000) loss: 0.028397
(Iteration 4671 / 5000) loss: 0.023510
(Iteration 4681 / 5000) loss: 0.009300
(Iteration 4691 / 5000) loss: 0.016868
(Iteration 4701 / 5000) loss: 0.018807
(Iteration 4711 / 5000) loss: 0.038027
(Iteration 4721 / 5000) loss: 0.029547
(Iteration 4731 / 5000) loss: 0.027049
(Iteration 4741 / 5000) loss: 0.029920
(Iteration 4751 / 5000) loss: 0.019818
(Iteration 4761 / 5000) loss: 0.013648
(Iteration 4771 / 5000) loss: 0.034945
(Iteration 4781 / 5000) loss: 0.015210
(Iteration 4791 / 5000) loss: 0.016371
(Iteration 4801 / 5000) loss: 0.021306
(Iteration 4811 / 5000) loss: 0.018988
(Iteration 4821 / 5000) loss: 0.028656
(Iteration 4831 / 5000) loss: 0.011859
(Iteration 4841 / 5000) loss: 0.024290
(Iteration 4851 / 5000) loss: 0.026768
(Iteration 4861 / 5000) loss: 0.035850
(Iteration 4871 / 5000) loss: 0.031955
(Iteration 4881 / 5000) loss: 0.024955
(Iteration 4891 / 5000) loss: 0.027959
(Iteration 4901 / 5000) loss: 0.029178
(Iteration 4911 / 5000) loss: 0.030602
(Iteration 4921 / 5000) loss: 0.026819
(Iteration 4931 / 5000) loss: 0.019062
(Iteration 4941 / 5000) loss: 0.025788
(Iteration 4951 / 5000) loss: 0.034722
(Iteration 4961 / 5000) loss: 0.042984
(Iteration 4971 / 5000) loss: 0.014903
(Iteration 4981 / 5000) loss: 0.033723
(Iteration 4991 / 5000) loss: 0.014828
```



# Test-time sampling

Unlike classification models, image captioning models behave very differently at training time and at test time. At training time, we have access to the ground-truth caption, so we feed ground-truth words as input to the RNN at each timestep. At test time, we sample from the distribution over the vocabulary at each timestep, and feed the sample as input to the RNN at the next timestep.

In the file `cs231n/classifiers/rnn.py` , implement the `sample` method for test-time sampling. After doing so, run the following to sample from your overfitted model on both training and validation data. The samples on training data should be very good; the samples on validation data probably won't make sense.

Note: Some of the URLs are missing and will throw an error; re-run this cell until the output is at least 2 good caption samples.

In [17]:
```
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_rnn_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

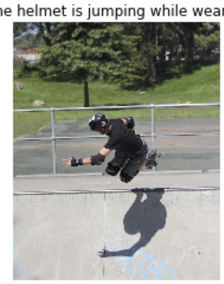
GT:<START> a woman is kneeling near some large <UNK> of food <END>

train

GT:<START> a group of men riding in a boat across a lake <END>

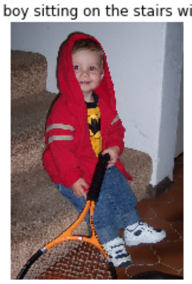
val

GT:<START> the man in the helmet is jumping while wearing <UNK> <UNK> <END>



val

GT:<START> a little boy sitting on the stairs with a racquet <END>



In [ ]:

# 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 [26]:
```
# 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_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))))
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

# Load MS-COCO data

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

In [27]:
```
# 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
```

# LSTM

If you read recent papers, you'll see that many people use a variant on the vanialla 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

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

where $\sigma$ 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 $A = X_t W_x + H_{t-1} W_h$

## 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 [28]:
```
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:  5.7054131185818695e-09
next_c error:  5.8143123088804145e-09
```

## 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 [29]:
```
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)

if dx is not None: print('dx error: ', rel_error(dx_num, dx))
if dh is not None: print('dh error: ', rel_error(dh_num, dh))
if dc is not None: print('dc error: ', rel_error(dc_num, dc))
if dWx is not None: print('dWx error: ', rel_error(dWx_num, dWx))
if dWh is not None: print('dWh error: ', rel_error(dWh_num, dWh))
if db is not None: print('db error: ', rel_error(db_num, db))
```

```
dx error:  6.141307149471403e-10
dh error:  3.0914746081903265e-10
dc error:  1.5221771913099803e-10
dWx error:  1.6933643922734908e-09
dWh error:  4.80624861072581e-08
db error:  1.734923562619879e-10
```

# 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 [30]:
```
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
```

# 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 [31]:
```
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:  7.158859899559994e-09
dh0 error:  1.4205143042729334e-08
dWx error:  1.190041651048399e-09
dWh error:  1.4586833146827486e-07
db error:  1.0502017179287567e-09
```

# 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 [32]:
```
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))
```

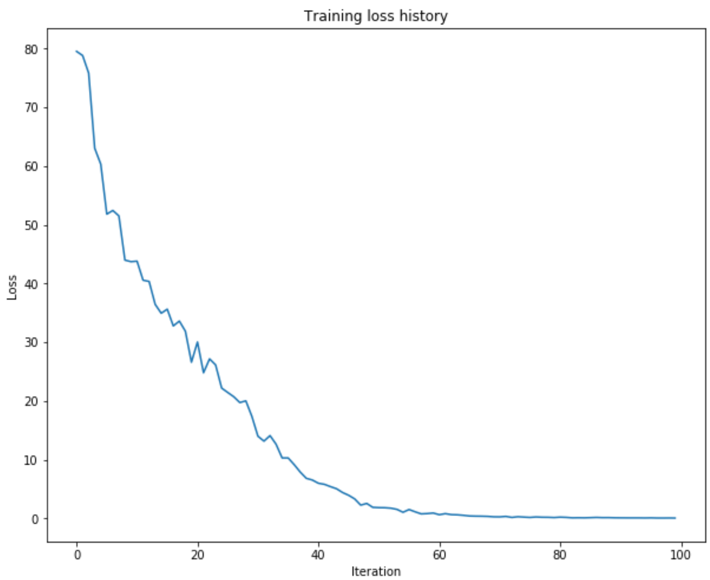
```
loss:  9.82445935443226
expected loss:  9.82445935443
difference:  2.261302256556519e-12
```

# 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 [33]:
```
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: 79.551152
(Iteration 11 / 100) loss: 43.829102
(Iteration 21 / 100) loss: 30.062495
(Iteration 31 / 100) loss: 14.020055
(Iteration 41 / 100) loss: 6.009744
(Iteration 51 / 100) loss: 1.855312
(Iteration 61 / 100) loss: 0.651669
(Iteration 71 / 100) loss: 0.281778
(Iteration 81 / 100) loss: 0.234106
(Iteration 91 / 100) loss: 0.120969
```




## 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 [34]:
```
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'])

    print(f"features: {features.shape}, {features}")
    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()
```

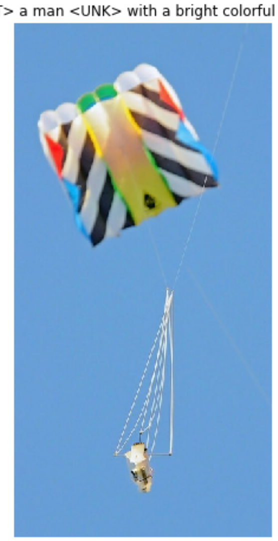
```
features: (2, 512), [[ 16.556028   -15.39707     -0.4898709  ...   0.19053608   0.29531455
   -0.270378  ]
 [ 19.183096    -2.0481977   -5.844905   ...   0.27492833  -2.0497794
   -0.23759516]]
```

train

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

train

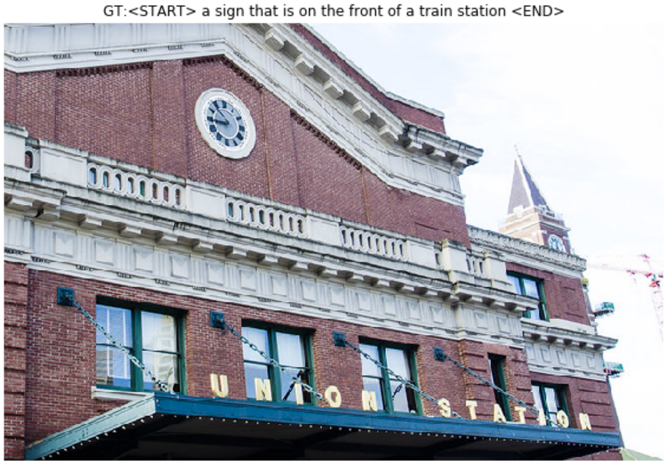
GT:<START> a man <UNK> with a bright colorful kite <END>



```
features: (2, 512), [[  3.0790322  -24.07676     -9.798916   ...  -0.08343156   1.3743262
   -1.6534417 ]
 [ -4.5262713  -15.474042     3.0653114  ...  -0.37152356   0.61125773
   -0.550424  ]]
```

val

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



val

GT:<START> a car is parked on a street at night <END>

## 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 (http://www.aclweb.org/anthology/P02-1040.pdf)](http://www.aclweb.org/anthology/P02-1040.pdf) 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 [35]:
```
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])
    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'])

        #print(f"features: {features.shape}, {features}")
        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 [36]:
```
# write a description of your model here:
small_lstm_model
```

Out[36]:
```
<cs231n.classifiers.rnn.CaptioningRNN at 0x159423048>
```

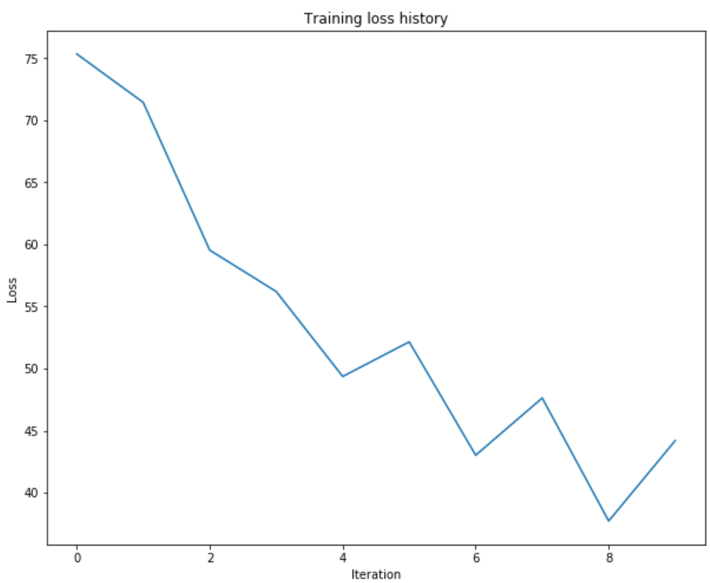
In [37]:
```
# write your code to train your model here.
# make sure to include the call to evaluate_model which prints out your highest validation BLEU score.
evaluate_model(small_lstm_model)
```

```
Average BLEU score for train: 0.000000
Average BLEU score for val: 0.000000
```

In [43]:

```
from cs231n.classifiers.mymodel import MyModel
from cs231n.classifiers.mymodel import MyCaptioningSolver

np.random.seed(231)

my_model = MyModel(
          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_data = load_coco_data(max_train=100)

my_model_solver = CaptioningSolver(my_model, small_data,
           update_rule='adam',
           num_epochs=1,
           batch_size=10,
           optim_config={
             'learning_rate': 5e-3,
           },
           lr_decay=0.995,
           verbose=True, print_every=10,
         )

my_model_solver.train()

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

evaluate_model(my_model)
```

```
(Iteration 1 / 10) loss: 75.346196
```




```
Average BLEU score for train: 0.000000
Average BLEU score for val: 0.000000
```

In [ ]:

In [ ]:

In [ ]:

# Sentence Classification with Transformers

In this exercise you will implement a Transformer (https://arxiv.org/pdf/1706.03762.pdf) and use it to judge the grammaticality of English sentences.

**A quick note: if you receive the following TypeError "super(type, obj): obj must be an instance or subtype of type", try restarting your kernel and re-running all cells.** Once you have finished making changes to the model constuctor, you can avoid this issue by commenting out all of the model instantiations after the first (e.g. lines starting with "model = ClassificationTransformer").

In [10]:
```
import numpy as np
import csv
import torch

from gt_7643.transformer import ClassificationTransformer

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

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

## The Corpus of Linguistic Acceptability (CoLA)

The Corpus of Linguistic Acceptability (CoLA (https://nyu-mll.github.io/CoLA/)) in its full form consists of 10657 sentences from 23 linguistics publications, expertly annotated for acceptability (grammaticality) by their original authors. Native English speakers consistently report a sharp contrast in acceptability between pairs of sentences. Some examples include:

`What did Betsy paint a picture of?` (Correct)

`What was a picture of painted by Betsy?` (Incorrect)

You can read more info about the dataset here (https://arxiv.org/pdf/1805.12471.pdf). This is a binary classification task (predict 1 for correct grammar and 0 otherwise).

Can we train a neural network to accurately predict these human acceptability judgements? In this assignment, we will implement the forward pass of the Transformer architecture discussed in class. The general intuitive notion is that we will *encode* the sequence of tokens in the sentence, and then predict a binary output based on the final state that is the output of the model.

## Load the preprocessed data

We've appended a "CLS" token to the beginning of each sequence, which can be used to make predictions. The benefit of appending this token to the beginning of the sequence (rather than the end) is that we can extract it quite easily (we don't need to remove paddings and figure out the length of each individual sequence in the batch). We'll come back to this.

We've additionally already constructed a vocabulary and converted all of the strings of tokens into integers which can be used for vocabulary lookup for you. Feel free to explore the data here.

In [11]:
```
train_inxs = np.load('./gt_7643/datasets/train_inxs.npy')
val_inxs = np.load('./gt_7643/datasets/val_inxs.npy')
train_labels = np.load('./gt_7643/datasets/train_labels.npy')
val_labels = np.load('./gt_7643/datasets/val_labels.npy')

# load dictionary
word_to_ix = {}
with open("./gt_7643/datasets/word_to_ix.csv", "r") as f:
    reader = csv.reader(f)
    for line in reader:
        word_to_ix[line[0]] = line[1]
print("Vocabulary Size:", len(word_to_ix))

print(train_inxs.shape) # 7000 training instances, of (maximum/padded) length 43 words.
print(val_inxs.shape) # 1551 validation instances, of (maximum/padded) length 43 words.
print(train_labels.shape)
print(val_labels.shape)

# load checkers
d1 = torch.load('./gt_7643/datasets/d1.pt')
d2 = torch.load('./gt_7643/datasets/d2.pt')
d3 = torch.load('./gt_7643/datasets/d3.pt')
d4 = torch.load('./gt_7643/datasets/d4.pt')
```

```
Vocabulary Size: 1542
(7000, 43)
(1551, 43)
(7000,)
(1551,)
```

## Transformers

We will be implementing a one-layer Transformer **encoder** which, similar to an RNN, can encode a sequence of inputs and produce a final output state for classification. This is the architecture:

imgs/encoder.png

You can refer to the original paper (https://arxiv.org/pdf/1706.03762.pdf) for more details.

Instead of using numpy for this model, we will be using Pytorch to implement the forward pass. You will not need to implement the backward pass for the various layers in this assigment.

The file `gt_7643/transformer.py` contains the model class and methods for each layer. This is where you will write your implementations.

## Deliverable 1: Embeddings

We will format our input embeddings similarly to how they are constructed in [BERT (source of figure) (https://arxiv.org/pdf/1810.04805.pdf)](https://arxiv.org/pdf/1810.04805.pdf). Recall from lecture that unlike a RNN, a Transformer does not include any positional information about the order in which the words in the sentence occur. Because of this, we need to append a positional encoding token at each position. (We will ignore the segment embeddings and [SEP] token here, since we are only encoding one sentence at a time). We have already appended the [CLS] token for you in the previous step.

imgs/embedding.png

Your first task is to implement the embedding lookup, including the addition of positional encodings. Open the file `gt_7643/transformer.py` and complete all code parts for `Deliverable 1`.

In [3]:
```
inputs = train_inxs[0:2]
inputs = torch.LongTensor(inputs)

model = ClassificationTransformer(word_to_ix, hidden_dim=128, num_heads=2, dim_feedforward=2048, dim_k=96,
                                  dim_v=96, dim_q=96, max_length=train_inxs.shape[1])

embeds = model.embed(inputs)

try:
    print("Difference:", torch.sum(torch.pairwise_distance(embeds, d1)).item()) # should be very small (<0.01)
except:
    print("NOT IMPLEMENTED")
```

```
Difference: 0.0017988268518820405
```

## Deliverable 2: Multi-head Self-Attention

Attention can be computed in matrix-form using the following formula:
imgs/attn.png

We want to have multiple self-attention operations, computed in parallel. Each of these is called a *head*. We concatenate the heads and multiply them with the matrix `attention_head_projection` to produce the output of this layer.

After every multi-head self-attention and feedforward layer, there is a residual connection + layer normalization. Make sure to implement this, using the following formula:
imgs/layer_norm.png

Open the file `gt_7643/transformer.py` and implement the `multihead_attention` function. We have already initialized all of the layers you will need in the constructor.

In [4]:
```
hidden_states = model.multi_head_attention(embeds)

try:
    print("Difference:", torch.sum(torch.pairwise_distance(hidden_states, d2)).item()) # should be very small (<0.01)
except:
    print("NOT IMPLEMENTED")
```

```
Difference: 0.0017100314144045115
```

## Deliverable 3: Element-Wise Feed-forward Layer

Open the file `gt_7643/transformer.py` and complete code for `Deliverable 3`: the element-wise feed-forward layer consisting of two linear transformers with a ReLU layer in between.

imgs/ffn.png

In [5]:
```
model = ClassificationTransformer(word_to_ix, hidden_dim=128, num_heads=2, dim_feedforward=2048, dim_k=96,
                                  dim_v=96, dim_q=96, max_length=train_inxs.shape[1])

outputs = model.feedforward_layer(hidden_states)

try:
    print("Difference:", torch.sum(torch.pairwise_distance(outputs, d3)).item()) # should be very small (<0.01)
except:
    print("NOT IMPLEMENTED")
```

```
Difference: 0.0017168164486065507
```

## Deliverable 4: Final Layer

Open the file `gt_7643/transformer.py` and complete code for `Deliverable 4`, to produce binary classification scores for the inputs based on the output of the Transformer.

In [6]:
```
model = ClassificationTransformer(word_to_ix, hidden_dim=128, num_heads=2, dim_feedforward=2048, dim_k=96,
                                  dim_v=96, dim_q=96, max_length=train_inxs.shape[1])

scores = model.final_layer(outputs)

try:
    print("Difference:", torch.sum(torch.pairwise_distance(scores, d4)).item()) # should be very small (<1e-5)
except:
    print("NOT IMPLEMENTED")
```

```
Difference: 1.8956918665935518e-06
```

## Deliverable 5: Putting it all together

Open the file `gt_7643/transformer.py` and complete the method `forward`, by putting together all of the methods you have developed in the right order to perform a full forward pass.

In [12]:
```
inputs = train_inxs[0:2]
inputs = torch.LongTensor(inputs)

outputs = model.forward(inputs)

try:
    print("Difference:", torch.sum(torch.pairwise_distance(outputs, scores)).item()) # should be very small (<1e-5)
except:
    print("NOT IMPLEMENTED")
```

```
Difference: 1.9999999949504854e-06
```

Great! We've just implemented a Transformer forward pass for text classification. One of the big perks of using PyTorch is that with a simple training loop, we can rely on automatic differentation (autograd (https://pytorch.org/tutorials/beginner/blitz/autograd_tutorial.html)) to do the work of the backward pass for us. This is not required for this assignment, but you can explore this on your own.

Make sure when you submit your PDF for this assignment to also include a copy of `transformer.py` converted to PDF as well.