Deep Learning

Assignment 5

The goal of this assignment is to train a Word2Vec skip-gram model over Text8 (http://mattmahoney.net/dc/textdata) data.

In [1]:
```
# These are all the modules we'll be using later. Make sure you can import them
# before proceeding further.
%matplotlib inline
from __future__ import print_function
import collections
import math
import numpy as np
import os
import random
import tensorflow as tf
import zipfile
from matplotlib import pylab
from six.moves import range
from six.moves.urllib.request import urlretrieve
from sklearn.manifold import TSNE
```

Download the data from the source website if necessary.

In [2]:
```
url = 'http://mattmahoney.net/dc/'

def maybe_download(filename, expected_bytes):
  """Download a file if not present, and make sure it's the right size."""
  if not os.path.exists(filename):
    filename, _ = urlretrieve(url + filename, filename)
  statinfo = os.stat(filename)
  if statinfo.st_size == expected_bytes:
    print('Found and verified %s' % filename)
  else:
    print(statinfo.st_size)
    raise Exception(
      'Failed to verify ' + filename + '. Can you get to it with a browser?')
  return filename

filename = maybe_download('text8.zip', 31344016)
```

```
Found and verified text8.zip
```

Read the data into a string.

In [3]:
```
def read_data(filename):
  """Extract the first file enclosed in a zip file as a list of words"""
  with zipfile.ZipFile(filename) as f:
    data = tf.compat.as_str(f.read(f.namelist()[0])).split()
  return data

words = read_data(filename)
print('Data size %d' % len(words))
```

```
Data size 17005207
```

Build the dictionary and replace rare words with UNK token.

In [4]:
```
vocabulary_size = 50000

def build_dataset(words):
  count = [['UNK', -1]]
  count.extend(collections.Counter(words).most_common(vocabulary_size - 1))
  dictionary = dict()
  for word, _ in count:
    dictionary[word] = len(dictionary)
  data = list()
  unk_count = 0
  for word in words:
    if word in dictionary:
      index = dictionary[word]
    else:
      index = 0  # dictionary['UNK']
      unk_count = unk_count + 1
    data.append(index)
  count[0][1] = unk_count
  reverse_dictionary = dict(zip(dictionary.values(), dictionary.keys()))
  return data, count, dictionary, reverse_dictionary

data, count, dictionary, reverse_dictionary = build_dataset(words)
print('Most common words (+UNK)', count[:5])
print('Sample data', data[:10])
del words  # Hint to reduce memory.
```

```
Most common words (+UNK) [['UNK', 418391], ('the', 1061396), ('of', 593677), ('and', 416629), ('one', 411764)]
Sample data [5239, 3084, 12, 6, 195, 2, 3137, 46, 59, 156]
```

Function to generate a training batch for the skip-gram model.

In [5]:
```
data_index = 0

def generate_batch(batch_size, num_skips, skip_window):
  global data_index
  assert batch_size % num_skips == 0
  assert num_skips <= 2 * skip_window
  batch = np.ndarray(shape=(batch_size), dtype=np.int32)
  labels = np.ndarray(shape=(batch_size, 1), dtype=np.int32)
  span = 2 * skip_window + 1 # [ skip_window target skip_window ]
  buffer = collections.deque(maxlen=span)
  for _ in range(span):
    buffer.append(data[data_index])
    data_index = (data_index + 1) % len(data)
  for i in range(batch_size // num_skips):
    target = skip_window  # target label at the center of the buffer
    targets_to_avoid = [ skip_window ]
    for j in range(num_skips):
      while target in targets_to_avoid:
        target = random.randint(0, span - 1)
      targets_to_avoid.append(target)
      batch[i * num_skips + j] = buffer[skip_window]
      labels[i * num_skips + j, 0] = buffer[target]
    buffer.append(data[data_index])
    data_index = (data_index + 1) % len(data)
  return batch, labels

print('data:', [reverse_dictionary[di] for di in data[:8]])

for num_skips, skip_window in [(2, 1), (4, 2)]:
    data_index = 0
    batch, labels = generate_batch(batch_size=8, num_skips=num_skips, skip_window=skip_window)
    print('\nwith num_skips = %d and skip_window = %d:' % (num_skips, skip_window))
    print('    batch:', [reverse_dictionary[bi] for bi in batch])
    print('    labels:', [reverse_dictionary[li] for li in labels.reshape(8)])
```

```
data: ['anarchism', 'originated', 'as', 'a', 'term', 'of', 'abuse', 'first']

with num_skips = 2 and skip_window = 1:
    batch: ['originated', 'originated', 'as', 'as', 'a', 'a', 'term', 'term']
    labels: ['anarchism', 'as', 'originated', 'a', 'as', 'term', 'a', 'of']
```

```
with num_skips = 4 and skip_window = 2:
    batch: ['as', 'as', 'as', 'as', 'a', 'a', 'a', 'a']
    labels: ['originated', 'anarchism', 'a', 'term', 'originated', 'term', 'of', 'as']
```

Train a skip-gram model.

In [6]:
```
batch_size = 128
embedding_size = 128 # Dimension of the embedding vector.
skip_window = 1 # How many words to consider left and right.
num_skips = 2 # How many times to reuse an input to generate a label.
# We pick a random validation set to sample nearest neighbors. here we limit the
# validation samples to the words that have a low numeric ID, which by
# construction are also the most frequent.
valid_size = 16 # Random set of words to evaluate similarity on.
valid_window = 100 # Only pick dev samples in the head of the distribution.
valid_examples = np.array(random.sample(range(valid_window), valid_size))
num_sampled = 64 # Number of negative examples to sample.

graph = tf.Graph()

with graph.as_default(), tf.device('/cpu:0'):

  # Input data.
  train_dataset = tf.placeholder(tf.int32, shape=[batch_size])
  train_labels = tf.placeholder(tf.int32, shape=[batch_size, 1])
  valid_dataset = tf.constant(valid_examples, dtype=tf.int32)

  # Variables.
  embeddings = tf.Variable(
    tf.random_uniform([vocabulary_size, embedding_size], -1.0, 1.0))
  softmax_weights = tf.Variable(
    tf.truncated_normal([vocabulary_size, embedding_size],
                        stddev=1.0 / math.sqrt(embedding_size)))
  softmax_biases = tf.Variable(tf.zeros([vocabulary_size]))

  # Model.
  # Look up embeddings for inputs.
  embed = tf.nn.embedding_lookup(embeddings, train_dataset)
  # Compute the softmax loss, using a sample of the negative labels each time.
  loss = tf.reduce_mean(
    tf.nn.sampled_softmax_loss(weights=softmax_weights, biases=softmax_biases, inputs=embed,
                               labels=train_labels, num_sampled=num_sampled, num_classes=vocabulary_size))

  # Optimizer.
  # Note: The optimizer will optimize the softmax_weights AND the embeddings.
  # This is because the embeddings are defined as a variable quantity and the
  # optimizer's `minimize` method will by default modify all variable quantities
```

```
  # that contribute to the tensor it is passed.
  # See docs on `tf.train.Optimizer.minimize()` for more details.
  optimizer = tf.train.AdagradOptimizer(1.0).minimize(loss)

  # Compute the similarity between minibatch examples and all embeddings.
  # We use the cosine distance:
  norm = tf.sqrt(tf.reduce_sum(tf.square(embeddings), 1, keep_dims=True))
  normalized_embeddings = embeddings / norm
  valid_embeddings = tf.nn.embedding_lookup(
    normalized_embeddings, valid_dataset)
  similarity = tf.matmul(valid_embeddings, tf.transpose(normalized_embeddings))
```

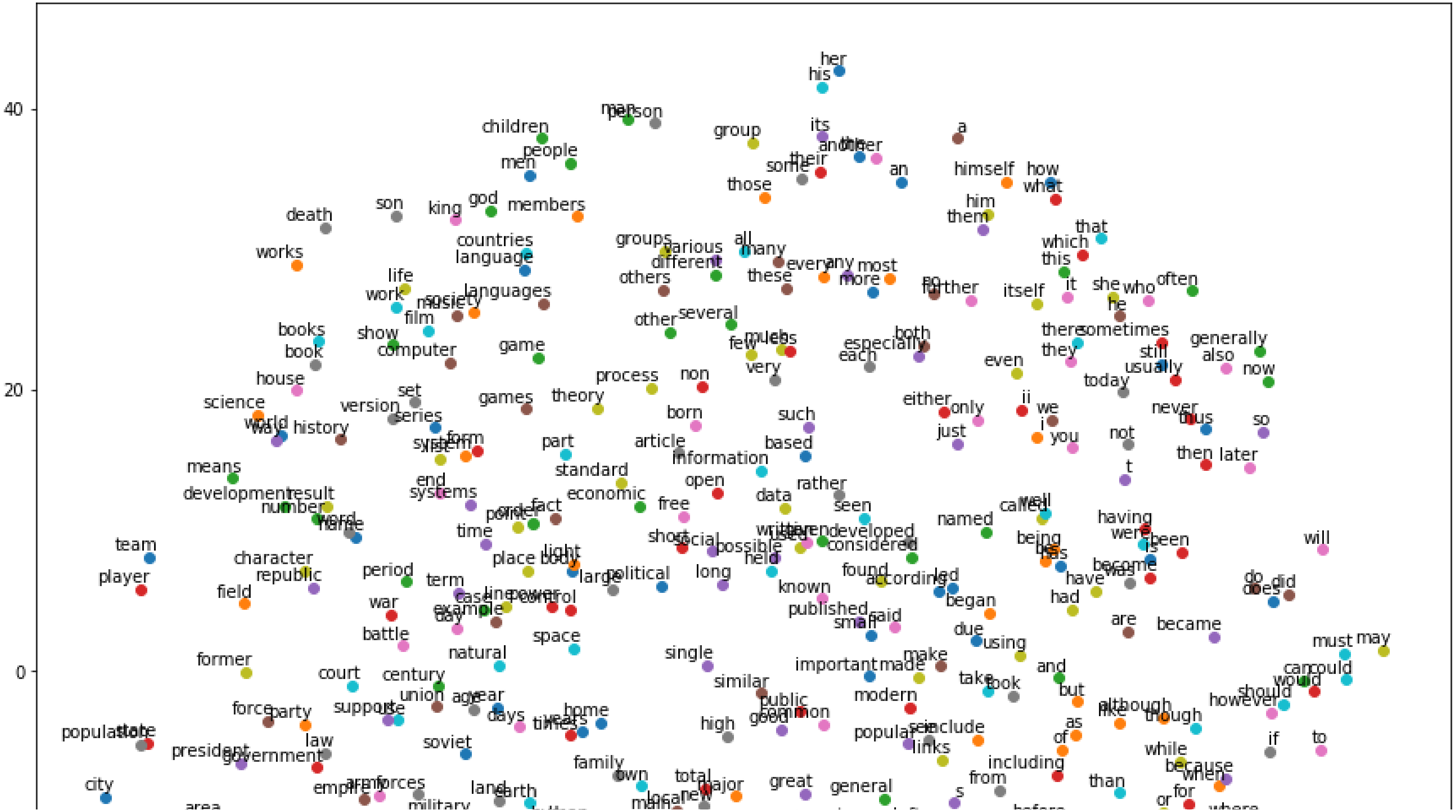
In [7]:
```
num_steps = 100001

with tf.Session(graph=graph) as session:
  tf.global_variables_initializer().run()
  print('Initialized')
  average_loss = 0
  for step in range(num_steps):
    batch_data, batch_labels = generate_batch(
      batch_size, num_skips, skip_window)
    feed_dict = {train_dataset : batch_data, train_labels : batch_labels}
    _, l = session.run([optimizer, loss], feed_dict=feed_dict)
    average_loss += l
    if step % 2000 == 0:
      if step > 0:
        average_loss = average_loss / 2000
      # The average loss is an estimate of the loss over the last 2000 batches.
      print('Average loss at step %d: %f' % (step, average_loss))
      average_loss = 0
    # note that this is expensive (~20% slowdown if computed every 500 steps)
    if step % 10000 == 0:
      sim = similarity.eval()
      for i in range(valid_size):
        valid_word = reverse_dictionary[valid_examples[i]]
        top_k = 8 # number of nearest neighbors
        nearest = (-sim[i, :]).argsort()[1:top_k+1]
        log = 'Nearest to %s:' % valid_word
        for k in range(top_k):
          close_word = reverse_dictionary[nearest[k]]
          log = '%s %s,' % (log, close_word)
        print(log)
  final_embeddings = normalized_embeddings.eval()
```

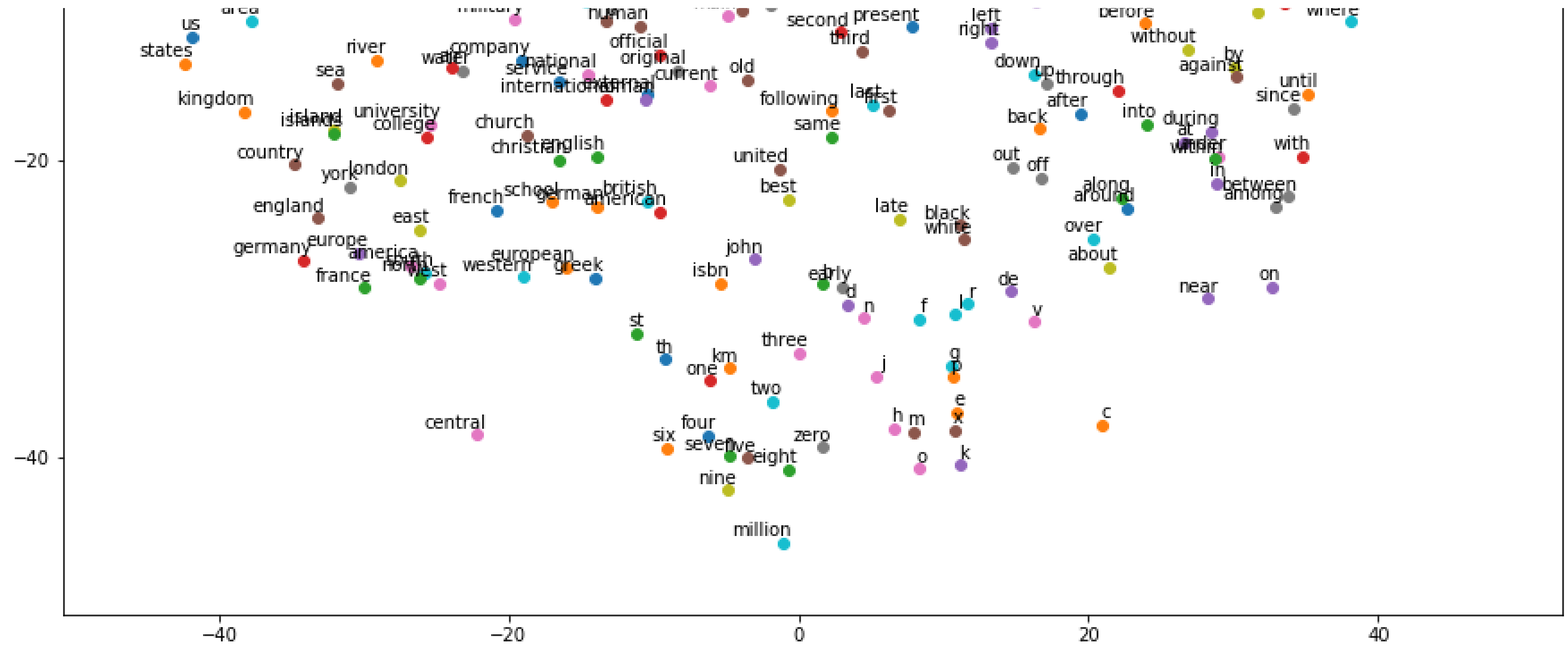
```
Nearest to at: during, near, licks, impregnated, around, reached, after, bayard,
Nearest to some: many, several, these, any, most, all, this, stained,
Nearest to were: are, had, was, have, those, while, these, homomorphisms,
Nearest to a: another, any, straps, lauren, sliced, elphinstone, every, the,
Nearest to to: would, will, should, integrating, cannot, must, hermaphroditus, surveyed,
Nearest to system: systems, process, foxes, theory, oppressive, devices, turnaround, concept,
Nearest to all: both, every, many, several, various, some, each, any,
Nearest to and: or, but, while, including, through, motorcycle, imagines, arr,
Nearest to one: seven, two, four, six, eight, five, three, nine,
Nearest to people: children, men, writers, women, students, person, casualties, jews,
```

```
Nearest to with: between, quintet, by, in, refitted, falkland, bowls, notebooks,
Nearest to its: their, his, the, her, your, adhesion, whose, ode,
Average loss at step 92000: 3.398948
Average loss at step 94000: 3.257952
Average loss at step 96000: 3.361469
Average loss at step 98000: 3.243324
Average loss at step 100000: 3.354439
Nearest to there: they, it, he, now, we, still, often, generally,
Nearest to d: b, j, elektra, morgan, convened, calvinists, archibald, giscard,
Nearest to have: had, has, having, be, are, tend, refer, were,
```

In [8]:
```
num_points = 400

tsne = TSNE(perplexity=30, n_components=2, init='pca', n_iter=5000)
two_d_embeddings = tsne.fit_transform(final_embeddings[1:num_points+1, :])
```

In [9]:
```
def plot(embeddings, labels):
  assert embeddings.shape[0] >= len(labels), 'More labels than embeddings'
  pylab.figure(figsize=(15,15))  # in inches
  for i, label in enumerate(labels):
    x, y = embeddings[i,:]
    pylab.scatter(x, y)
    pylab.annotate(label, xy=(x, y), xytext=(5, 2), textcoords='offset points',
                   ha='right', va='bottom')
  pylab.show()

words = [reverse_dictionary[i] for i in range(1, num_points+1)]
plot(two_d_embeddings, words)
```





Problem

An alternative to skip-gram is another Word2Vec model called CBOW (http://arxiv.org/abs/1301.3781) (Continuous Bag of Words). In the CBOW model, instead of predicting a context word from a word vector, you predict a word from the sum of all the word vectors in its context. Implement and evaluate a CBOW model trained on the text8 dataset.

In [11]:
```
data_index = 0

def generate_batch(batch_size, bag_window):
  global data_index
  span = 2 * bag_window + 1 # [ bag_window target bag_window ]
  batch = np.ndarray(shape=(batch_size, span - 1), dtype=np.int32)
  labels = np.ndarray(shape=(batch_size, 1), dtype=np.int32)
  buffer = collections.deque(maxlen=span)
  for _ in range(span):
    buffer.append(data[data_index])
    data_index = (data_index + 1) % len(data)
  for i in range(batch_size):
    # just for testing
    buffer_list = list(buffer)
    labels[i, 0] = buffer_list.pop(bag_window)
    batch[i] = buffer_list
    # iterate to the next buffer
    buffer.append(data[data_index])
    data_index = (data_index + 1) % len(data)
  return batch, labels

print('data:', [reverse_dictionary[di] for di in data[:16]])

for bag_window in [1, 2]:
  data_index = 0
  batch, labels = generate_batch(batch_size=4, bag_window=bag_window)
  print('\nwith bag_window = %d:' % (bag_window))
  print('    batch:', [[reverse_dictionary[w] for w in bi] for bi in batch])
  print('    labels:', [reverse_dictionary[li] for li in labels.reshape(4)])
```

```
data: ['anarchism', 'originated', 'as', 'a', 'term', 'of', 'abuse', 'first', 'used', 'against', 'early', 'working', 'cl
ass', 'radicals', 'including', 'the']

with bag_window = 1:
    batch: [['anarchism', 'as'], ['originated', 'a'], ['as', 'term'], ['a', 'of']]
    labels: ['originated', 'as', 'a', 'term']

with bag_window = 2:
    batch: [['anarchism', 'originated', 'a', 'term'], ['originated', 'as', 'term', 'of'], ['as', 'a', 'of', 'abuse'],
 ['a', 'term', 'abuse', 'first']]
    labels: ['as', 'a', 'term', 'of']
```

In [15]:

```
batch_size = 128
embedding_size = 128 # Dimension of the embedding vector.
# skip_window = 1 # How many words to consider left and right.
# num_skips = 2 # How many times to reuse an input to generate a label.
bag_window = 2
# We pick a random validation set to sample nearest neighbors. here we limit the
# validation samples to the words that have a low numeric ID, which by
# construction are also the most frequent.
valid_size = 16 # Random set of words to evaluate similarity on.
valid_window = 100 # Only pick dev samples in the head of the distribution.
valid_examples = np.array(random.sample(range(valid_window), valid_size))
num_sampled = 64 # Number of negative examples to sample.

graph = tf.Graph()

with graph.as_default(), tf.device('/cpu:0'):

  # Input data.
  train_dataset = tf.placeholder(tf.int32, shape=[batch_size, bag_window * 2])
  train_labels = tf.placeholder(tf.int32, shape=[batch_size, 1])
  valid_dataset = tf.constant(valid_examples, dtype=tf.int32)

  # Variables.
  embeddings = tf.Variable(
    tf.random_uniform([vocabulary_size, embedding_size], -1.0, 1.0))
  softmax_weights = tf.Variable(
    tf.truncated_normal([vocabulary_size, embedding_size],
                        stddev=1.0 / math.sqrt(embedding_size)))
  softmax_biases = tf.Variable(tf.zeros([vocabulary_size]))

  # Model.
  # Look up embeddings for inputs.
  embed = tf.nn.embedding_lookup(embeddings, train_dataset)
  # Compute the softmax loss, using a sample of the negative labels each time.
  loss = tf.reduce_mean(
    tf.nn.sampled_softmax_loss(weights=softmax_weights, biases=softmax_biases, inputs=tf.reduce_sum(embed, 1),
                               labels=train_labels, num_sampled=num_sampled, num_classes=vocabulary_size))

  # Optimizer.
  # Note: The optimizer will optimize the softmax_weights AND the embeddings.
  # This is because the embeddings are defined as a variable quantity and the
```

```
# optimizer's `minimize` method will by default modify all variable quantities
# that contribute to the tensor it is passed.
# See docs on `tf.train.Optimizer.minimize()` for more details.
optimizer = tf.train.AdagradOptimizer(1.0).minimize(loss)

# Compute the similarity between minibatch examples and all embeddings.
# We use the cosine distance:
norm = tf.sqrt(tf.reduce_sum(tf.square(embeddings), 1, keep_dims=True))
normalized_embeddings = embeddings / norm
valid_embeddings = tf.nn.embedding_lookup(
  normalized_embeddings, valid_dataset)
similarity = tf.matmul(valid_embeddings, tf.transpose(normalized_embeddings))
```

In [16]:
```
num_steps = 100001

with tf.Session(graph=graph) as session:
  tf.global_variables_initializer().run()
  print('Initialized')
  average_loss = 0
  for step in range(num_steps):
    batch_data, batch_labels = generate_batch(batch_size, bag_window)
    feed_dict = {train_dataset : batch_data, train_labels : batch_labels}
    _, l = session.run([optimizer, loss], feed_dict=feed_dict)
    average_loss += l
    if step % 2000 == 0:
      if step > 0:
        average_loss = average_loss / 2000
      # The average loss is an estimate of the loss over the last 2000 batches.
      print('Average loss at step %d: %f' % (step, average_loss))
      average_loss = 0
    # note that this is expensive (~20% slowdown if computed every 500 steps)
    if step % 10000 == 0:
      sim = similarity.eval()
      for i in range(valid_size):
        valid_word = reverse_dictionary[valid_examples[i]]
        top_k = 8 # number of nearest neighbors
        nearest = (-sim[i, :]).argsort()[1:top_k+1]
        log = 'Nearest to %s:' % valid_word
        for k in range(top_k):
          close_word = reverse_dictionary[nearest[k]]
          log = '%s %s,' % (log, close_word)
        print(log)
  final_embeddings = normalized_embeddings.eval()
```

```
Nearest to time: distance, period, least, point, thing, looking, year, night,
Nearest to if: when, though, where, subcategories, therefore, since, currently, whatever,
Nearest to when: if, where, until, although, while, though, since, because,
Nearest to on: upon, through, in, amanda, against, across, otomo, fogo,
Nearest to while: though, and, although, when, amongst, or, where, however,
Nearest to state: government, moran, lecter, observant, cumberland, session, copy, annexes,
Nearest to of: following, almohades, despite, including, amputee, discernable, regarding, otomo,
Nearest to with: between, tuba, via, among, contended, terminus, containing, anoint,
Nearest to who: benn, always, young, sorties, raps, whom, which, attenborough,
Nearest to not: never, indeed, still, nothing, legally, almost, also, cyclopedia,
Nearest to by: when, through, without, pelvic, in, sopranos, crocodile, actually,
```

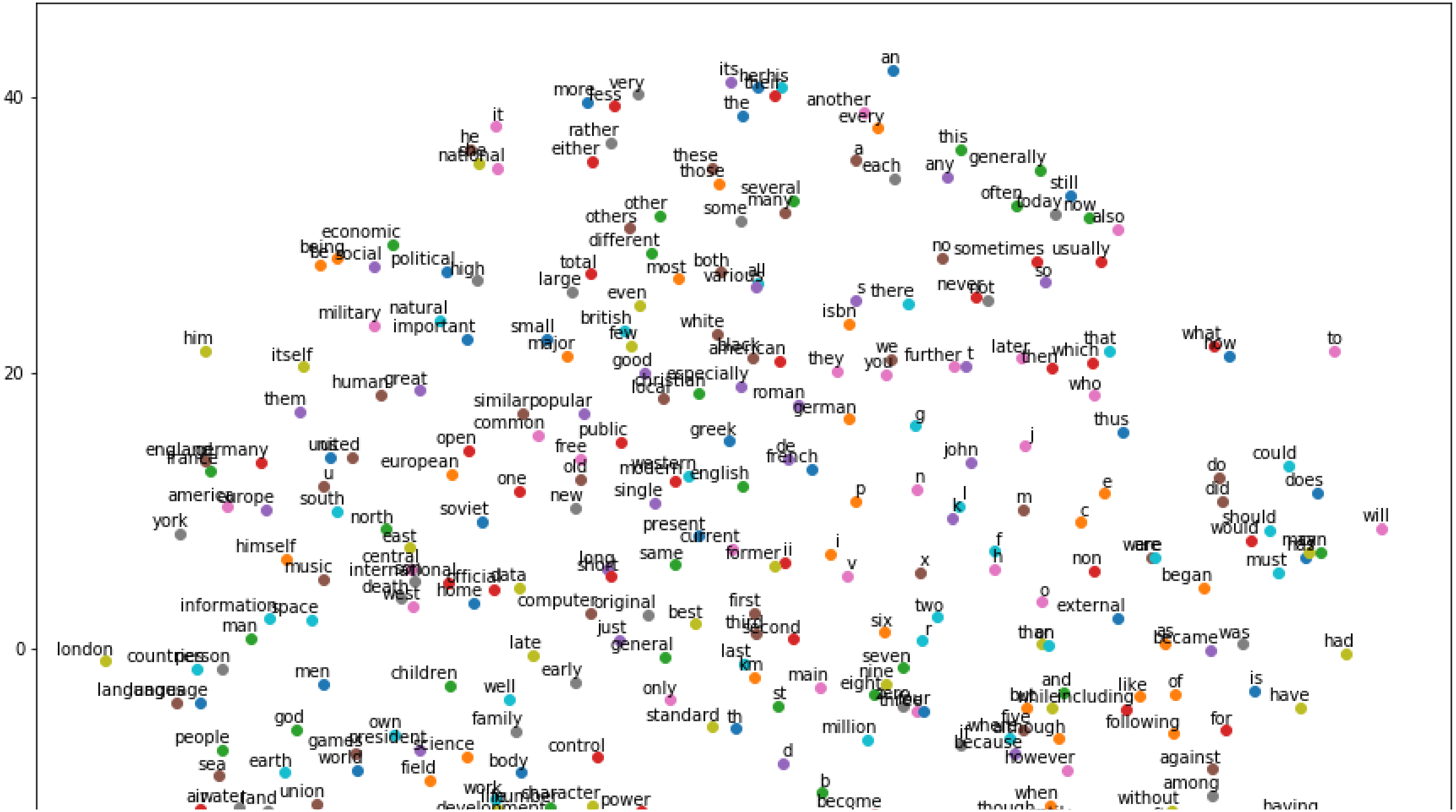
```
Nearest to other: others, various, textiles, different, both, roms, hae, fewer,
Nearest to states: kingdom, nations, emirates, felt, coordinating, countries, yorkist, declared,
Average loss at step 92000: 2.894091
Average loss at step 94000: 2.882162
Average loss at step 96000: 2.723037
Average loss at step 98000: 2.457204
Average loss at step 100000: 2.715885
Nearest to can: could, must, should, cannot, might, may, will, would,
Nearest to its: their, his, her, the, our, your, patrilineal, abductions,
```

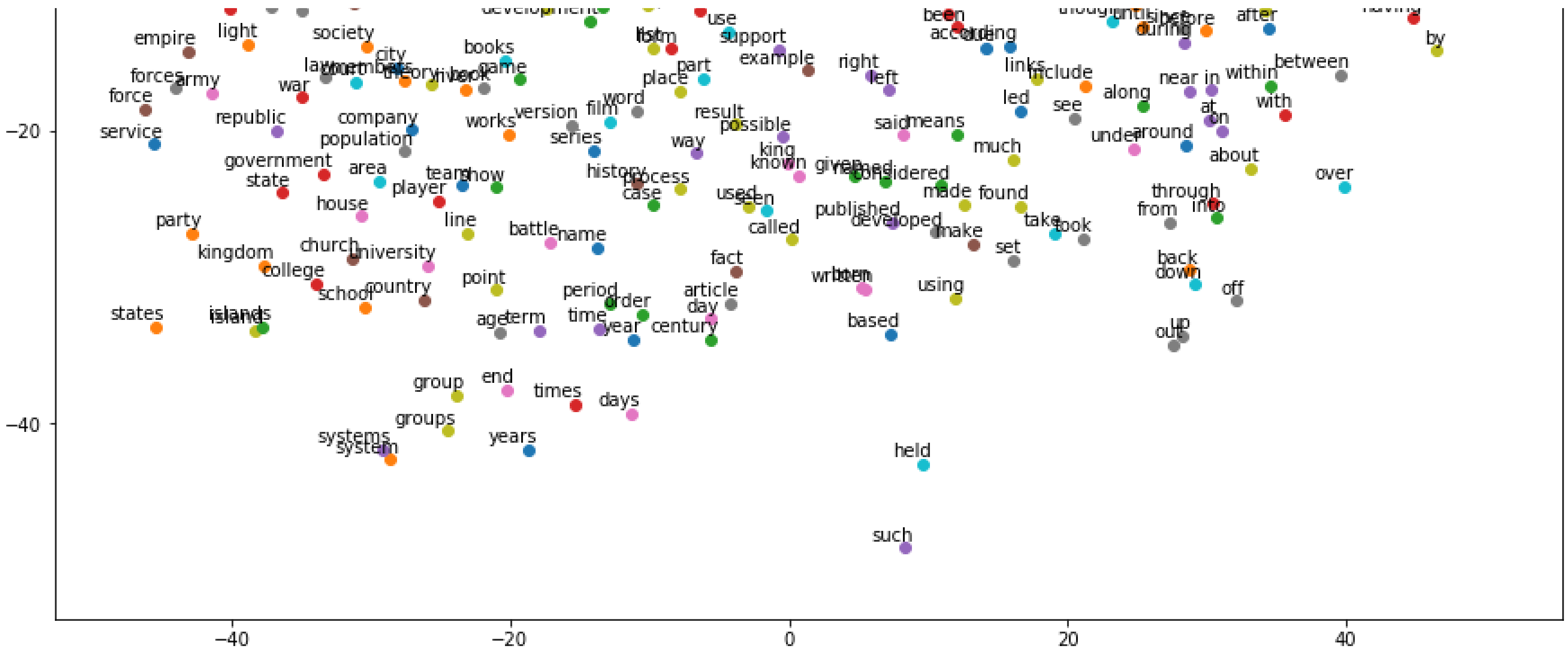
In [17]:

```
num_points = 400

tsne = TSNE(perplexity=30, n_components=2, init='pca', n_iter=5000)
two_d_embeddings = tsne.fit_transform(final_embeddings[1:num_points+1, :])
```

In [18]:

```
def plot(embeddings, labels):
  assert embeddings.shape[0] >= len(labels), 'More labels than embeddings'
  pylab.figure(figsize=(15,15))  # in inches
  for i, label in enumerate(labels):
    x, y = embeddings[i,:]
    pylab.scatter(x, y)
    pylab.annotate(label, xy=(x, y), xytext=(5, 2), textcoords='offset points',
                   ha='right', va='bottom')
  pylab.show()

words = [reverse_dictionary[i] for i in range(1, num_points+1)]
plot(two_d_embeddings, words)
```




−20
−40
−40
−20
0
20
40
empire
light
society
books
use
support
been
after
by
forces
army
war
force
service
republic
company
population
works
version
film
word
series
way
result
possible
king
example
right
left
include
along
near
in
within
between
with
led
see
said
means
much
under
around
about
over
government
state
area
team
player
history
process
case
used
seen
known
given
considered
made
found
published
developed
make
take
took
through
from
into
party
house
line
battle
name
called
set
kingdom
church
university
college
school
country
point
period
order
fact
article
day
century
written
using
back
down
off
states
age
term
time
year
based
up
out
group
end
times
days
groups
years
systems
system
held
such

In [ ]: