Programming Assignment 1: Learning Distributed Word Representations

Name: Bowen Xu

Version: 1.2

Changes by Version:

- (v1.1)
  1. Part 1 Description: indicated that each word is associated with two embedding vectors and two biases
  2. Part 1: Updated `calculate_log_co_occurence` to include the last pair of consecutive words as well
  3. Part 2: Updated question description for 2.1
  4. Part 4: Updated answer requirement for 4.1
  5. (1.3) Fixed symmetric GLoVE gradient
  6. (1.3) Clarified that W_tilde and b_tilde gradients also need to be implemented
  7. (2) Removed extra space leading up to docstring for `compute_loss_derivative`
- (v1.2)
  1. (1.4) Updated the training function `train_GLoVE` to not use inplace update (e.g. `W = W - learning_rate * grad_W` instead), so the initial weight variables are not overwritten between asymmetric and symmetric GLoVE models.
  2. (2) Noted that `compute_loss_derivative` input argument `target_mask` is 3D tensor with shape `[batch_size x context_len x 1]`

Version Release Date: 2021-01-27

Due Date:Thursday, Feb. 4, at 11:59pm

Based on an assignment by George Dahl

For CSC413/2516 in Winter 2021 with Professor Jimmy Ba and Professor Bo Wang

Submission: You must submit two files through MarkUs:

1. [ ] A PDF file containing your writeup, titled *a1-writeup.pdf*, which will be the PDF export of this notebook (i.e., by printing this notebook webpage as PDF). Your writeup must be typed. There will be sections in the notebook for you to write your responses. Make sure that the relevant outputs (e.g. `print_gradients()` outputs, plots, etc.) are included and clearly visible.
2. [ ] This `a1-code.ipynb` iPython Notebook.

The programming assignments are individual work. See the Course Syllabus for detailed policies.

You should attempt all questions for this assignment. Most of them can be answered at least partially even if you were unable to finish earlier questions. If you think your computational results are incorrect, please say so; that may help you get partial credit.

The teaching assistants for this assignment are Harris Chan and Summer Tao. Send your email with subject "*[CSC413] PA1*" to mailto:csc413-2021-01-tas@cs.toronto.edu or post on Piazza with the tag `pa1`.

Introduction

In this assignment we will learn about word embeddings and make neural networks learn about words. We could try to match statistics about the words, or we could train a network that takes a sequence of words as input and learns to predict the word that comes next.

This assignment will ask you to implement a linear embedding and then the backpropagation computations for a neural language model and then run some experiments to analyze the learned representation. The amount of code you have to write is very short but each line will require you to think very carefully. You will need to derive the updates mathematically,

Starter code and data

First, perform the required imports for your code:

In [1]:
```
import collections
import pickle
import numpy as np
import os
from tqdm import tqdm
import pylab
from six.moves.urllib.request import urlretrieve
import tarfile
import sys

TINY = 1e-30
EPS = 1e-4
nax = np.newaxis
```

If you're using colaboratory, this following script creates a folder - here we used 'CSC413/A1' - in order to download and store the data. If you're not using colaboratory, then set the path to wherever you want the contents to be stored at locally.

You can also manually download and unzip the data from [http://www.cs.toronto.edu/~jba/a1_data.tar.gz (http://www.cs.toronto.edu/~jba/a1_data.tar.gz)] and put them in the same folder as where you store this notebook.

Feel free to use a different way to access the files *data.pk* , *partially_trained.pk*, and *raw_sentences.txt*.

The file *raw_sentences.txt* contains the sentences that we will be using for this assignment. These sentences are fairly simple ones and cover a vocabulary of only 250 words (+ 1 special `[MASK]` token word).

In [2]:
```
######################################################################
# Setup working directory
######################################################################
# Change this to a local path if running locally
%mkdir -p /content/CSC413/A1/
%cd /content/CSC413/A1

######################################################################
# Helper functions for loading data
######################################################################
# adapted from
# https://github.com/fchollet/keras/blob/master/keras/datasets/cifar10.py

def get_file(fname,
             origin,
             untar=False,
             extract=False,
             archive_format='auto',
             cache_dir='data'):
    datadir = os.path.join(cache_dir)
    if not os.path.exists(datadir):
        os.makedirs(datadir)

    if untar:
        untar_fpath = os.path.join(datadir, fname)
        fpath = untar_fpath + '.tar.gz'
    else:
        fpath = os.path.join(datadir, fname)

    print('File path: %s' % fpath)
    if not os.path.exists(fpath):
        print('Downloading data from', origin)

        error_msg = 'URL fetch failure on {}: {} -- {}'
        try:
            try:
                urlretrieve(origin, fpath)
            except URLError as e:
                raise Exception(error_msg.format(origin, e.errno, e.reason))
            except HTTPError as e:
                raise Exception(error_msg.format(origin, e.code, e.msg))
        except (Exception, KeyboardInterrupt) as e:
            if os.path.exists(fpath):
                os.remove(fpath)
            raise

    if untar:
        if not os.path.exists(untar_fpath):
            print('Extracting file.')
            with tarfile.open(fpath) as archive:
                archive.extractall(datadir)
        return untar_fpath

    if extract:
        _extract_archive(fpath, datadir, archive_format)

    return fpath
```

```
/content/CSC413/A1
```

In [3]:

```
# Download the dataset and partially pre-trained model
get_file(fname='a1_data',
                             origin='http://www.cs.toronto.edu/~jba/a1_data.tar.gz',
                             untar=True)
drive_location = 'data'
PARTIALLY_TRAINED_MODEL = drive_location + '/' + 'partially_trained.pk'
data_location = drive_location + '/' + 'data.pk'
```

```
File path: data/a1_data.tar.gz
Extracting file.
```

We have already extracted the 4-grams from this dataset and divided them into training, validation, and test sets. To inspect this data, run the following:

In [4]:
```python
data = pickle.load(open(data_location, 'rb'))
print(data['vocab'][0]) # First word in vocab is [MASK]
print(data['vocab'][1])
print(len(data['vocab'])) # Number of words in vocab
print(data['vocab']) # All the words in vocab
print(data['train_inputs'][:10]) # 10 example training instances
```

```
[MASK]
all
251
['[MASK]', 'all', 'set', 'just', 'show', 'being', 'money', 'over', 'both', 'year
s', 'four', 'through', 'during', 'go', 'still', 'children', 'before', 'police',
'office', 'million', 'also', 'less', 'had', ',', 'including', 'should', 'to', 'o
nly', 'going', 'under', 'has', 'might', 'do', 'them', 'good', 'around', 'get',
'very', 'big', 'dr.', 'game', 'every', 'know', 'they', 'not', 'world', 'now', 'h
im', 'school', 'several', 'like', 'did', 'university', 'companies', 'these', 'sh
e', 'team', 'found', 'where', 'right', 'says', 'people', 'house', 'national', 's
ome', 'back', 'see', 'street', 'are', 'year', 'home', 'best', 'out', 'even', 'wh
at', 'said', 'for', 'federal', 'since', 'its', 'may', 'state', 'does', 'john',
'between', 'new', ';', 'three', 'public', '?', 'be', 'we', 'after', 'business',
'never', 'use', 'here', 'york', 'members', 'percent', 'put', 'group', 'come', 'b
y', '$', 'on', 'about', 'last', 'her', 'of', 'could', 'days', 'against', 'time
s', 'women', 'place', 'think', 'first', 'among', 'own', 'family', 'into', 'eac
h', 'one', 'down', 'because', 'long', 'another', 'such', 'old', 'next', 'your',
'market', 'second', 'city', 'little', 'from', 'would', 'few', 'west', 'there',
'political', 'two', 'been', '.', 'their', 'much', 'music', 'too', 'way', 'whit
e', ':', 'was', 'war', 'today', 'more', 'ago', 'life', 'that', 'season', 'compan
y', '-', 'but', 'part', 'court', 'former', 'general', 'with', 'than', 'those',
'he', 'me', 'high', 'made', 'this', 'work', 'up', 'us', 'until', 'will', 'ms.',
'while', 'officials', 'can', 'were', 'country', 'my', 'called', 'and', 'progra
m', 'have', 'then', 'is', 'it', 'an', 'states', 'case', 'say', 'his', 'at', 'wan
t', 'in', 'any', 'as', 'if', 'united', 'end', 'no', ')', 'make', 'government',
'when', 'american', 'same', 'how', 'mr.', 'other', 'take', 'which', 'departmen
t', '--', 'you', 'many', 'nt', 'day', 'week', 'play', 'used', "'s", 'though', 'o
ur', 'who', 'yesterday', 'director', 'most', 'president', 'law', 'man', 'a', 'ni
ght', 'off', 'center', 'i', 'well', 'or', 'without', 'so', 'time', 'five', 'th
e', 'left']
[[ 28  26  90 144]
 [184  44 249 117]
 [183  32  76 122]
 [117 247 201 186]
 [223 190 249   6]
 [ 42  74  26  32]
 [242  32 223  32]
 [223  32 158 144]
 [ 74  32 221  32]
 [ 42 192  91  68]]
```

Now `data` is a Python dict which contains the vocabulary, as well as the inputs and targets for all three splits of the data. `data['vocab']` is a list of the 251 words in the dictionary; `data['vocab'][0]` is the word with index 0, and so on. `data['train_inputs']` is a 372,500 x 4 matrix where each row gives the indices of the 4 consecutive context words for one of the 372,500 training cases. The validation and test sets are handled analogously.

Even though you only have to modify two specific locations in the code, you may want to read through this code before starting the assignment.

Part 1: GLoVE Word Representations (2pts)

In this part of the assignment, you will implement a simplified version of the GLoVE embedding (please see the handout for detailed description of the algorithm) with the loss defined as

$$L(\{\mathbf{w}_i, \tilde{\mathbf{w}}_i, b_i, \tilde{b}_i\}_{i=1}^{V}) = \sum_{i,j=1}^{V} (\mathbf{w}_i^\top \tilde{\mathbf{w}}_j + b_i + \tilde{b}_j - \log X_{ij})^2$$

.

Note that each word is represented by two d-dimensional embedding vectors $\mathbf{w}_i, \tilde{\mathbf{w}}_i$ and two scalar biases $b_i, \tilde{b}_i$.

Answer the following questions:

1.1. GLoVE Parameter Count [0pt]

Given the vocabulary size V and embedding dimensionality d, how many parameters does the GLoVE model have? Note that each word in the vocabulary is associated with 2 embedding vectors and 2 biases.

1.1 **Answer**:

$$2Vd + 2V$$

.

1.2. Expression for gradient $\frac{\partial L}{\partial \mathbf{w}_i}$ [1pt]

Write the expression for $\frac{\partial L}{\partial \mathbf{w}_i}$, the gradient of the loss function L with respect to one parameter vector $\mathbf{w}_i$. The gradient should be a function of $\mathbf{w}, \tilde{\mathbf{w}}, b, \tilde{b}, X$ with appropriate subscripts (if any).

1.2 **Answer**:

$$\frac{\partial L}{\partial \mathbf{w}_i} = \sum_{j=1}^{V} 2\tilde{\mathbf{w}}_j(\mathbf{w}_i^\top \tilde{\mathbf{w}}_j + b_i + \tilde{b}_j - \log X_{ij})$$

.

1.3. Implement the gradient update of GLoVE. [1pt]

See `YOUR CODE HERE` **Comment below for where to complete the code**

We have provided a few functions for training the embedding:

- `calculate_log_co_occurence` computes the log co-occurrence matrix of a given corpus
- `train_GLoVE` runs momentum gradient descent to optimize the embedding
- `loss_GLoVE` :
  - INPUT - $V \times d$ matrix `W` (collection of V embedding vectors, each d-dimensional); $V \times d$ matrix `W_tilde` ; $V \times 1$ vector `b` (collection of V bias terms); $V \times 1$ vector `b_tilde` ; $V \times V$ log co-occurrence matrix.
  - OUTPUT - loss of the GLoVE objective
- `grad_GLoVE` : **TO BE IMPLEMENTED.**
  - INPUT:
    - $V \times d$ matrix `W` (collection of V embedding vectors, each d-dimensional), embedding for first word;
    - $V \times d$ matrix `W_tilde` , embedding for second word;
    - $V \times 1$ vector `b` (collection of V bias terms);
    - $V \times 1$ vector `b_tilde` , bias for second word;
    - $V \times V$ log co-occurrence matrix.
  - OUTPUT:
    - $V \times d$ matrix `grad_W` containing the gradient of the loss function w.r.t. `W` ;
    - $V \times d$ matrix `grad_W_tilde` containing the gradient of the loss function w.r.t. `W_tilde` ;
    - $V \times 1$ vector `grad_b` which is the gradient of the loss function w.r.t. `b` .
    - $V \times 1$ vector `grad_b_tilde` which is the gradient of the loss function w.r.t. `b_tilde` .

Run the code to compute the co-occurence matrix. Make sure to add a 1 to the occurences, so there are no 0's in the matrix when we take the elementwise log of the matrix.

In [5]:
```
vocab_size = len(data['vocab']) # Number of vocabs 251

def calculate_log_co_occurence(word_data, symmetric=False):
  "Compute the log-co-occurence matrix for our data."
  log_co_occurence = np.zeros((vocab_size, vocab_size)) #251 x 251
  for input in word_data:
    # Note: the co-occurence matrix may not be symmetric
    log_co_occurence[input[0], input[1]] += 1
    log_co_occurence[input[1], input[2]] += 1
    log_co_occurence[input[2], input[3]] += 1
    # If we want symmetric co-occurence can also increment for these.
    if symmetric:
      log_co_occurence[input[1], input[0]] += 1
      log_co_occurence[input[2], input[1]] += 1
      log_co_occurence[input[3], input[2]] += 1
  delta_smoothing = 0.1  # A hyperparameter.  You can play with this if you want.
  log_co_occurence += delta_smoothing  # Add delta so log doesn't break on 0's.
  log_co_occurence = np.log(log_co_occurence)
  return log_co_occurence
```

In [6]:
```
asym_log_co_occurence_train = calculate_log_co_occurence(data['train_inputs'], sy
mmetric=False)
asym_log_co_occurence_valid = calculate_log_co_occurence(data['valid_inputs'], sy
mmetric=False)
```

- [ ] **TO BE IMPLEMENTED**: Calculate the gradient of the loss function w.r.t. the parameters W, $\tilde{W}$, $\mathbf{b}$, and $\mathbf{b}$. You should vectorize the computation, i.e. not loop over every word.

In [7]:
```
def loss_GLoVE(W, W_tilde, b, b_tilde, log_co_occurence):
  "Compute the GLoVE loss."
  n,_ = log_co_occurence.shape # n = 251
  if W_tilde is None and b_tilde is None:
    return np.sum((W @ W.T + b @ np.ones([1,n]) + np.ones([n,1])@b.T - log_co_occ
urence)**2)   # symmetric: W_tilde = W
  else:
    return np.sum((W @ W_tilde.T + b @ np.ones([1,n]) + np.ones([n,1])@b_tilde.T
- log_co_occurence)**2)

def grad_GLoVE(W, W_tilde, b, b_tilde, log_co_occurence):
  "Return the gradient of GLoVE objective w.r.t W and b."
  "INPUT: W - Vxd; W_tilde - Vxd; b - Vx1; b_tilde - Vx1; log_co_occurence: VxV"
  "OUTPUT: grad_W - Vxd; grad_W_tilde - Vxd, grad_b - Vx1, grad_b_tilde - Vx1"
  n,_ = log_co_occurence.shape

  if not W_tilde is None and not b_tilde is None: #asymmetric
  ###########################   YOUR CODE HERE   ##############################
    loss = (W @ W_tilde.T + b @ np.ones([1,n]) + np.ones([n,1]) @ b_tilde.T - log
_co_occurence)   #VxV
    grad_W = 2 * (loss @ W_tilde)
    grad_W_tilde = 2 * (loss.T @ W) #swap row and column
    grad_b = 2 * (loss @ np.ones([n,1]))
    grad_b_tilde = 2 * (loss.T @ np.ones([n,1]))
  ############################################################################
  else: # symmetric
    loss = (W @ W.T + b @ np.ones([1,n]) + np.ones([n,1])@b.T - 0.5*(log_co_occur
ence + log_co_occurence.T)) #averaging co-occurance matrix
    grad_W = 4 *(W.T @ loss).T
    grad_W_tilde = None
    grad_b = 4 * (np.ones([1,n]) @ loss).T
    grad_b_tilde = None

  return grad_W, grad_W_tilde, grad_b, grad_b_tilde

def train_GLoVE(W, W_tilde, b, b_tilde, log_co_occurence_train, log_co_occurence_
valid, n_epochs, do_print=False):
  "Traing W and b according to GLoVE objective."
  n,_ = log_co_occurence_train.shape
  learning_rate = 0.05 / n  # A hyperparameter.  You can play with this if you wa
nt.
  for epoch in range(n_epochs):
    grad_W, grad_W_tilde, grad_b, grad_b_tilde = grad_GLoVE(W, W_tilde, b, b_tild
e, log_co_occurence_train)
    W = W - learning_rate * grad_W
    b = b - learning_rate * grad_b
    if not grad_W_tilde is None and not grad_b_tilde is None:
      W_tilde = W_tilde - learning_rate * grad_W_tilde
      b_tilde = b_tilde - learning_rate * grad_b_tilde
    train_loss, valid_loss = loss_GLoVE(W, W_tilde, b, b_tilde, log_co_occurence_
train), loss_GLoVE(W, W_tilde, b, b_tilde, log_co_occurence_valid)
    if do_print:
      print(f"Train Loss: {train_loss}, valid loss: {valid_loss}, grad_norm: {np.
sum(grad_W**2)}")
  return W, W_tilde, b, b_tilde, train_loss, valid_loss
```

1.4. Effect of embedding dimension d [0pt]

Train the both the symmetric and asymmetric GLoVe model with varying dimensionality d by running the cell below. Comment on:

1.4 Answer:

1. Which d leads to optimal validation performance for the asymmetric and symmetric models?

Answer: d=10 leads to an optimal validation performance

1. Why does / doesn't larger d always lead to better validation error?

Answer: Because larger d will induce more parameters in the training process so that the model starts to overfit the training data and can't generalize in the validation data.

1. Which model is performing better, and why?

Answer: Asymmetric model performs better since the asymmetry in the co-occurance will indicate more relationships between words since it can show the orders between each word and provide more information to the model to increase its predictive power.

Train the GLoVE model for a range of embedding dimensions

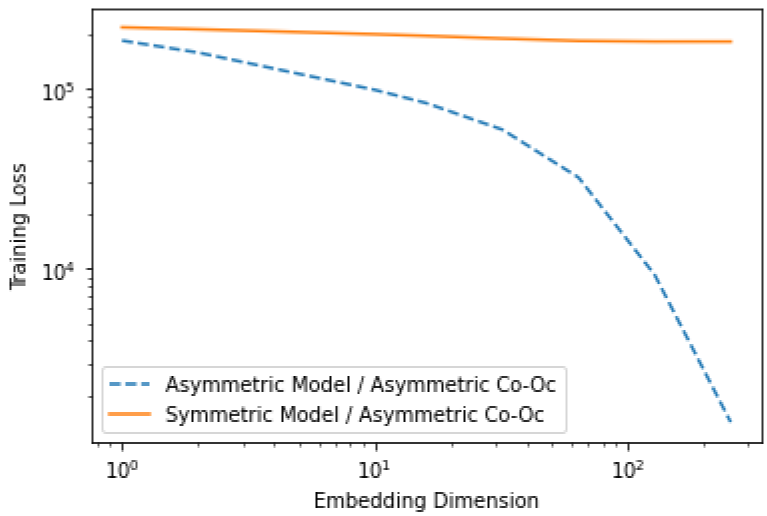
In [8]:
```python
np.random.seed(1)
n_epochs = 500  # A hyperparameter.  You can play with this if you want.
embedding_dims = np.array([1, 2, 10,16, 32, 64, 128, 256])  # Play with this
# Store the final losses for graphing
asymModel_asymCoOc_final_train_losses, asymModel_asymCoOc_final_val_losses = [],
[]
symModel_asymCoOc_final_train_losses, symModel_asymCoOc_final_val_losses = [], []
Asym_W_final_2d, Asym_b_final_2d, Asym_W_tilde_final_2d, Asym_b_tilde_final_2d =
None, None, None, None
W_final_2d, b_final_2d = None, None
W_final_16d, b_final_16d = None, None
do_print = False  # If you want to see diagnostic information during training

for embedding_dim in tqdm(embedding_dims):
  init_variance = 0.1  # A hyperparameter.  You can play with this if you want.
  W = init_variance * np.random.normal(size=(vocab_size, embedding_dim))
  W_tilde = init_variance * np.random.normal(size=(vocab_size, embedding_dim))
  b = init_variance * np.random.normal(size=(vocab_size, 1))
  b_tilde = init_variance * np.random.normal(size=(vocab_size, 1))
  if do_print:
    print(f"Training for embedding dimension: {embedding_dim}")

  # Train Asym model on Asym Co-Oc matrix
  Asym_W_final, Asym_W_tilde_final, Asym_b_final, Asym_b_tilde_final, train_loss,
valid_loss = train_GLoVE(W, W_tilde, b, b_tilde, asym_log_co_occurence_train, asy
m_log_co_occurence_valid, n_epochs, do_print=do_print)
  if embedding_dim == 2:
    # Save a parameter copy if we are training 2d embedding for visualization lat
er
    Asym_W_final_2d = Asym_W_final
    Asym_W_tilde_final_2d = Asym_W_tilde_final
    Asym_b_final_2d = Asym_b_final
    Asym_b_tilde_final_2d = Asym_b_tilde_final
  asymModel_asymCoOc_final_train_losses += [train_loss]
  asymModel_asymCoOc_final_val_losses += [valid_loss]
  if do_print:
    print(f"Final validation loss: {valid_loss}")

  # Train Sym model on Asym Co-Oc matrix
  W_final, W_tilde_final, b_final, b_tilde_final, train_loss, valid_loss = train_
GLoVE(W, None, b, None, asym_log_co_occurence_train, asym_log_co_occurence_valid,
n_epochs, do_print=do_print)
  if embedding_dim == 2:
    # Save a parameter copy if we are training 2d embedding for visualization lat
er
    W_final_2d = W_final
    b_final_2d = b_final
  if embedding_dim == 16:
    # Save a parameter copy if we are training 16d embedding for visualization la
ter
    W_final_16d = W_final
    b_final_16d = b_final
  symModel_asymCoOc_final_train_losses += [train_loss]
  symModel_asymCoOc_final_val_losses += [valid_loss]
  if do_print:
    print(f"Final validation loss: {valid_loss}")
```

```
100%|██████████| 8/8 [00:45<00:00,  5.70s/it]
```

Plot the training and validation losses against the embedding dimension.

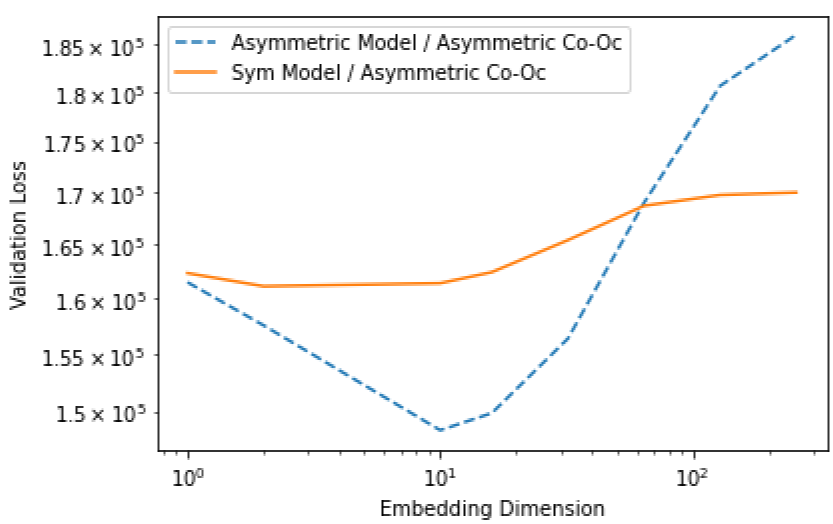
In [9]:
```
pylab.loglog(embedding_dims, asymModel_asymCoOc_final_train_losses, label="Asymmetric Model / Asymmetric Co-Oc", linestyle="--")
pylab.loglog(embedding_dims, symModel_asymCoOc_final_train_losses , label="Symmetric Model / Asymmetric Co-Oc")
pylab.xlabel("Embedding Dimension")
pylab.ylabel("Training Loss")
pylab.legend()
```

Out[9]: <matplotlib.legend.Legend at 0x7f27ea628898>



In [10]:
```
pylab.loglog(embedding_dims, asymModel_asymCoOc_final_val_losses, label="Asymmetric Model / Asymmetric Co-Oc", linestyle="--")
pylab.loglog(embedding_dims, symModel_asymCoOc_final_val_losses , label="Sym Model / Asymmetric Co-Oc")
pylab.xlabel("Embedding Dimension")
pylab.ylabel("Validation Loss")
pylab.legend(loc="upper left")
```

Out[10]: <matplotlib.legend.Legend at 0x7f27ea641c50>



Part 2: Network Architecture (2pts)

See the handout for the written questions in this part.

Answer the following questions

2.1. Number of parameters in neural network model [1pt]

Assume in general that we have V words in the dictionary and use the previous N words as inputs. Suppose we use a D-dimensional word embedding and a hidden layer with H hidden units. The trainable parameters of the model consist of 3 weight matrices and 2 sets of biases. What is the total number of trainable parameters in the model, as a function of V, N, D, H?

In the diagram given, which part of the model (i.e., `word_embbeding_weights` , `embed_to_hid_weights` , `hid_to_output_weights` , `hid_bias` , or `output_bias`) has the largest number of trainable parameters if we have the constraint that $V \gg H > D > N$? Note: The symbol $\gg$ means ``much greater than" Explain your reasoning.

2.1 **Answer:**

Total number of trainable parameters: $VD + NDH + H + HV + V$

- word_embedding_weights: VD
- embed_to_hid_weights: NDH
- hid_bias: H
- hid_to_output_weights: HV
- output_bias: V

`hid_to_output_weights` has the largest number of trainable parameters since V is much larger than other dimensions and H is the second largest

2.2 Number of parameters in n-gram model [1pt]

Another method for predicting the next words is an n-gram model, which was mentioned in Lecture 3. If we wanted to use an n-gram model with the same context length N as our network, we'd need to store the counts of all possible $(N + 1)$-grams. If we stored all the counts explicitly, how many entries would this table have?

2.2 **Answer:**

$$V^{N+1}$$

2.3. Comparing neural network and n-gram model scaling [0pt]

How do the parameters in the neural network model scale with the number of context words N versus how the number of entries in the n-gram model scale with N? [0pt]

2.3 **Answer:** Linear in neural network model and exponential in n-gram model

Part 3: Training the model (3pts)

We will modify the architecture slightly from the previous section, inspired by BERT \citep{devlin2018bert}. Instead of having only one output, the architecture will now take in $N = 4$ context words, and also output predictions for $N = 4$ words. See Figure 2 diagram in the handout for the diagram of this architecture.

During training, we randomly sample one of the N context words to replace with a `[MASK]` token. The goal is for the network to predict the word that was masked, at the corresponding output word position. In practice, this `[MASK]` token is assigned the index 0 in our dictionary. The weights $W^{(2)}$ = `hid_to_output_weights` now has the shape $NV \times H$, as the output layer has NV neurons, where the first V output units are for predicting the first word, then the next V are for predicting the second word, and so on. We call this as *concatenating* output uniits across all word positions, i.e. the $(j + nV)$-th column is for the word j in vocabulary for the n-th output word position. Note here that the softmax is applied in chunks of V as well, to give a valid probability distribution over the V words. Only the output word positions that were masked in the input are included in the cross entropy loss calculation:

There are three classes defined in this part: `Params`, `Activations`, `Model`. You will make changes to `Model`, but it may help to read through `Params` and `Activations` first.

$$C = -\sum_{i}^{B}\sum_{n}^{N}\sum_{j}^{V} m_n^{(i)}(t_{n,j}^{(i)} \log y_{n,j}^{(i)}),$$

Where $y_{n,j}^{(i)}$ denotes the output probability prediction from the neural network for the i-th training example for the word j in the n-th output word, and $t_{n,j}^{(i)}$ is 1 if for the i-th training example, the word j is the n-th word in context. Finally, $m_n^{(i)} \in \{0, 1\}$ is a mask that is set to 1 if we are predicting the n-th word position for the i-th example (because we had masked that word in the input), and 0 otherwise.

There are three classes defined in this part: `Params`, `Activations`, `Model`. You will make changes to `Model`, but it may help to read through `Params` and `Activations` first.

In [11]:
```
class Params(object):
    """A class representing the trainable parameters of the model. This class has
five fields:

            word_embedding_weights, a matrix of size V x D, where V is the number
 of words in the vocabulary
                    and D is the embedding dimension.
            embed_to_hid_weights, a matrix of size H x ND, where H is the number o
f hidden units. The first D
                    columns represent connections from the embedding of the first
 context word, the next D columns
                    for the second context word, and so on. There are N context wo
rds.
            hid_bias, a vector of length H
            hid_to_output_weights, a matrix of size NV x H
            output_bias, a vector of length NV"""

    def __init__(self, word_embedding_weights, embed_to_hid_weights, hid_to_outpu
t_weights,
                 hid_bias, output_bias):
        self.word_embedding_weights = word_embedding_weights
        self.embed_to_hid_weights = embed_to_hid_weights
        self.hid_to_output_weights = hid_to_output_weights
        self.hid_bias = hid_bias
        self.output_bias = output_bias

    def copy(self):
        return self.__class__(self.word_embedding_weights.copy(), self.embed_to_h
id_weights.copy(),
                              self.hid_to_output_weights.copy(), self.hid_bias.co
py(), self.output_bias.copy())

    @classmethod
    def zeros(cls, vocab_size, context_len, embedding_dim, num_hid):
        """A constructor which initializes all weights and biases to 0."""   # we
ight 0
        word_embedding_weights = np.zeros((vocab_size, embedding_dim)) # V x D
        embed_to_hid_weights = np.zeros((num_hid, context_len * embedding_dim))
# H x ND
        hid_to_output_weights = np.zeros((vocab_size * context_len, num_hid)) # N
V x H
        hid_bias = np.zeros(num_hid) # H x 1
        output_bias = np.zeros(vocab_size * context_len)  # NV x 1
        return cls(word_embedding_weights, embed_to_hid_weights, hid_to_output_we
ights,
                   hid_bias, output_bias)

    @classmethod
    def random_init(cls, init_wt, vocab_size, context_len, embedding_dim, num_hid
): # weights small values
        """A constructor which initializes weights to small random values and bia
ses to 0."""
        word_embedding_weights = np.random.normal(0., init_wt, size=(vocab_size,
embedding_dim))
        embed_to_hid_weights = np.random.normal(0., init_wt, size=(num_hid, conte
xt_len * embedding_dim))
        hid_to_output_weights = np.random.normal(0., init_wt, size=(vocab_size *
context_len, num_hid))
        hid_bias = np.zeros(num_hid)
        output_bias = np.zeros(vocab_size * context_len)
        return cls(word_embedding_weights, embed_to_hid_weights, hid_to_output_we
```

```
ights,
                   hid_bias, output_bias)

    ###### The functions below are Python's somewhat oddball way of overloading o
perators, so that
    ###### we can do arithmetic on Params instances. You don't need to understand
this to do the assignment.

    def __mul__(self, a):
        return self.__class__(a * self.word_embedding_weights,
                              a * self.embed_to_hid_weights,
                              a * self.hid_to_output_weights,
                              a * self.hid_bias,
                              a * self.output_bias)

    def __rmul__(self, a):
        return self * a

    def __add__(self, other):
        return self.__class__(self.word_embedding_weights + other.word_embedding_
weights,
                              self.embed_to_hid_weights + other.embed_to_hid_weig
hts,
                              self.hid_to_output_weights + other.hid_to_output_we
ights,
                              self.hid_bias + other.hid_bias,
                              self.output_bias + other.output_bias)

    def __sub__(self, other):
        return self + -1. * other
```

In [12]:
```
class Activations(object):
    """A class representing the activations of the units in the network. This cla
ss has three fields:

        embedding_layer, a matrix of B x ND matrix (where B is the batch size, D
 is the embedding dimension,
                and N is the number of input context words), representing the act
ivations for the embedding
                layer on all the cases in a batch. The first D columns represent
 the embeddings for the
                first context word, and so on.
        hidden_layer, a B x H matrix representing the hidden layer activations fo
r a batch
        output_layer, a B x V matrix representing the output layer activations fo
r a batch"""

    def __init__(self, embedding_layer, hidden_layer, output_layer):
        self.embedding_layer = embedding_layer
        self.hidden_layer = hidden_layer
        self.output_layer = output_layer

def get_batches(inputs, batch_size, shuffle=True):
    """Divide a dataset (usually the training set) into mini-batches of a given s
ize. This is a
    'generator', i.e. something you can use in a for loop. You don't need to unde
rstand how it
    works to do the assignment."""

    if inputs.shape[0] % batch_size != 0:
        raise RuntimeError('The number of data points must be a multiple of the b
atch size.')
    num_batches = inputs.shape[0] // batch_size

    if shuffle:
        idxs = np.random.permutation(inputs.shape[0])
        inputs = inputs[idxs, :]

    for m in range(num_batches):
        yield inputs[m * batch_size:(m + 1) * batch_size, :]
```

In this part of the assignment, you implement a method which computes the gradient using backpropagation. To start you out, the *Model* class contains several important methods used in training:

- `compute_activations` computes the activations of all units on a given input batch
- `compute_loss` computes the total cross-entropy loss on a mini-batch
- `evaluate` computes the average cross-entropy loss for a given set of inputs and targets

You will need to complete the implementation of two additional methods which are needed for training, and print the outputs of the gradients.

3.1 Implement gradient with respect to output layer inputs [1pt]

`compute_loss_derivative` computes the derivative of the loss function with respect to the output layer inputs.

In other words, if C is the cost function, and the softmax computation for the j-th word in vocabulary for the n-th output word position is:

$$y_{n,j} = \frac{e^{z_{n,j}}}{\sum_l e^{z_{n,l}}}$$

This function should compute a $B \times NV$ matrix where the entries correspond to the partial derivatives $\partial C / \partial z_j^n$. Recall that the output units are concatenated across all positions, i.e. the $(j + nV)$-th column is for the word j in vocabulary for the n-th output word position.

3.2 Implement gradient with respect to parameters [1pt]

`back_propagate` is the function which computes the gradient of the loss with respect to model parameters using backpropagation. It uses the derivatives computed by *compute_loss_derivative*. Some parts are already filled in for you, but you need to compute the matrices of derivatives for `embed_to_hid_weights` , `hid_bias` , `hid_to_output_weights` , and `output_bias` . These matrices have the same sizes as the parameter matrices (see previous section).

In order to implement backpropagation efficiently, you need to express the computations in terms of matrix operations, rather than *for* loops. You should first work through the derivatives on pencil and paper. First, apply the chain rule to compute the derivatives with respect to individual units, weights, and biases. Next, take the formulas you've derived, and express them in matrix form. You should be able to express all of the required computations using only matrix multiplication, matrix transpose, and elementwise operations --- no *for* loops! If you want inspiration, read through the code for *Model.compute_activations* and try to understand how the matrix operations correspond to the computations performed by all the units in the network.

To make your life easier, we have provided the routine `checking.check_gradients` , which checks your gradients using finite differences. You should make sure this check passes before continuing with the assignment.

In [13]:
```
class Model(object):
    """A class representing the language model itself. This class contains variou
s methods used in training
    the model and visualizing the learned representations. It has two fields:

        params, a Params instance which contains the model parameters
        vocab, a list containing all the words in the dictionary; vocab[0] is the
word with index
              0, and so on."""

    def __init__(self, params, vocab):
        self.params = params
        self.vocab = vocab

        self.vocab_size = len(vocab)
        self.embedding_dim = self.params.word_embedding_weights.shape[1] # D
        self.embedding_layer_dim = self.params.embed_to_hid_weights.shape[1]  # N
D
        self.context_len = self.embedding_layer_dim // self.embedding_dim  # N
        self.num_hid = self.params.embed_to_hid_weights.shape[0] # H

    def copy(self):
        return self.__class__(self.params.copy(), self.vocab[:])

    @classmethod
    def random_init(cls, init_wt, vocab, context_len, embedding_dim, num_hid):
        """Constructor which randomly initializes the weights to Gaussians with s
tandard deviation init_wt
        and initializes the biases to all zeros."""
        params = Params.random_init(init_wt, len(vocab), context_len, embedding_d
im, num_hid) #call class Params
        return Model(params, vocab)

    def indicator_matrix(self, targets, mask_zero_index=True):
        """Construct a matrix where the (k + j*V)th entry of row i is 1 if the j-
th target word
         for example i is k, and all other entries are 0.

         Note: if the j-th target word index is 0, this corresponds to the [MASK]
token,
               and we set the entry to be 0.
        """
        batch_size, context_len = targets.shape
        expanded_targets = np.zeros((batch_size, context_len * len(self.vocab)))
# B x NV
        targets_offset = np.repeat((np.arange(context_len) * len(self.vocab))[np.
newaxis, :], batch_size, axis=0) # [[0, V, 2V], [0, V, 2V], ...]
        targets += targets_offset

        for c in range(context_len):
          expanded_targets[np.arange(batch_size), targets[:,c]] = 1.
          if mask_zero_index:
            # Note: Set the targets with index 0, V, 2V to be zero since it corre
sponds to the [MASK] token
            expanded_targets[np.arange(batch_size), targets_offset[:,c]] = 0.
        return expanded_targets

    def compute_loss_derivative(self, output_activations, expanded_target_batch,
target_mask):
        """Compute the derivative of the multiple target position cross-entropy l
oss function \n"
```

```
            For example:

         [y_{0} ....  y_{V-1}] [y_{V}, ..., y_{2*V-1}] [y_{2*V} ... y_{i,3*V-1}]
 [y_{3*V} ... y_{i,4*V-1}]

         Where for colum j + n*V,

            y_{j + n*V} = e^{z_{j + n*V}} / \sum_{m=0}^{V-1} e^{z_{m + n*V}}, for
n=0,...,N-1

        This function should return a dC / dz matrix of size [batch_size x (vocab
_size * context_len)],
        where each row i in dC / dz has columns 0 to V-1 containing the gradient
 the 1st output
        context word from i-th training example, then columns vocab_size to 2*voc
ab_size - 1 for the 2nd
        output context word of the i-th training example, etc.

        C is the loss function summed acrossed all examples as well:

            C = -\sum_{i,j,n} mask_{i,n} (t_{i, j + n*V} log y_{i, j + n*V}), for
j=0,...,V, and n=0,...,N

        where mask_{i,n} = 1 if the i-th training example has n-th context word a
s the target,
        otherwise mask_{i,n} = 0.

        The arguments are as follows:

            output_activations - A [batch_size x (context_len * vocab_size)] tens
or,
                for the activations of the output layer, i.e. the y_j's.
            expanded_target_batch - A [batch_size (context_len * vocab_size)] ten
sor,
                where expanded_target_batch[i,n*V:(n+1)*V] is the indicator vecto
r for
                the n-th context target word position, i.e. the (i, j + n*V) entr
y is 1 if the
                i'th example, the context word at position n is j, and 0 otherwis
e.
            target_mask - A [batch_size x context_len x 1] tensor, where target_m
ask[i,n] = 1
                if for the i'th example the n-th context word is a target positio
n, otherwise 0

        Outputs:
            loss_derivative - A [batch_size x (context_len * vocab_size)] matrix,
                where loss_derivative[i,0:vocab_size] contains the gradient
                dC / dz_0 for the i-th training example gradient for 1st output
                context word, and loss_derivative[i,vocab_size:2*vocab_size] for
                the 2nd output context word of the i-th training example, etc.
        """
        # V = int(output_activations.shape[1]/target_mask.shape[1])
        # temp = []
        # for mat in target_mask:
        #   temp.append(np.repeat(mat,V))
        # temp = np.array(temp)
        ###########################   YOUR CODE HERE  ###########################
###
        return  np.repeat(target_mask,vocab_size).reshape(output_activations.shap
e[0],-1)*(output_activations - expanded_target_batch)
```

```python
        ###########################################################################

    def compute_loss(self, output_activations, expanded_target_batch):
        """Compute the total loss over a mini-batch. expanded_target_batch is the matrix obtained
        by calling indicator_matrix on the targets for the batch."""
        return -np.sum(expanded_target_batch * np.log(output_activations + TINY))

    def compute_activations(self, inputs):
        """Compute the activations on a batch given the inputs. Returns an Activations instance.
        You should try to read and understand this function, since this will give you clues for
        how to implement back_propagate."""

        batch_size = inputs.shape[0]
        if inputs.shape[1] != self.context_len:
            raise RuntimeError('Dimension of the input vectors should be {}, but is instead {}'.format(
                self.context_len, inputs.shape[1]))

        # Embedding layer
        # Look up the input word indies in the word_embedding_weights matrix
        embedding_layer_state = np.zeros((batch_size, self.embedding_layer_dim))
        for i in range(self.context_len):
            embedding_layer_state[:, i * self.embedding_dim:(i + 1) * self.embedding_dim] = \
                self.params.word_embedding_weights[inputs[:, i], :]

        # Hidden layer
        inputs_to_hid = np.dot(embedding_layer_state, self.params.embed_to_hid_weights.T) + \
                        self.params.hid_bias
        # Apply logistic activation function
        hidden_layer_state = 1. / (1. + np.exp(-inputs_to_hid))

        # Output layer
        inputs_to_softmax = np.dot(hidden_layer_state, self.params.hid_to_output_weights.T) + \
                            self.params.output_bias

        # Subtract maximum.
        # Remember that adding or subtracting the same constant from each input to a
        # softmax unit does not affect the outputs. So subtract the maximum to
        # make all inputs <= 0. This prevents overflows when computing their exponents.
        inputs_to_softmax -= inputs_to_softmax.max(1).reshape((-1, 1))

        # Take softmax along each V chunks in the output layer
        output_layer_state = np.exp(inputs_to_softmax)
        output_layer_state_shape = output_layer_state.shape
        output_layer_state = output_layer_state.reshape((-1, self.context_len, len(self.vocab)))
        output_layer_state /= output_layer_state.sum(axis=-1, keepdims=True) # Softmax along each target word
        output_layer_state = output_layer_state.reshape(output_layer_state_shape) # Flatten back

        return Activations(embedding_layer_state, hidden_layer_state, output_layer_state)
```

```python
    def back_propagate(self, input_batch, activations, loss_derivative):
        """Compute the gradient of the loss function with respect to the trainable parameters
        of the model. The arguments are as follows:

             input_batch - the indices of the context words
             activations - an Activations class representing the output of Model.compute_activations
             loss_derivative - the matrix of derivatives computed by compute_loss_derivative

        Part of this function is already completed, but you need to fill in the derivative
        computations for hid_to_output_weights_grad, output_bias_grad, embed_to_hid_weights_grad,
        and hid_bias_grad. See the documentation for the Params class for a description of what
        these matrices represent."""

        # The matrix with values dC / dz_j, where dz_j is the input to the jth hidden unit,
        # i.e. h_j = 1 / (1 + e^{-z_j})
        hid_deriv = np.dot(loss_derivative, self.params.hid_to_output_weights) \
                    * activations.hidden_layer * (1. - activations.hidden_layer)
# (B x (N * V)) @ ((N * V) x H) = B x H

        ###########################   YOUR CODE HERE  ###########################
###
        hid_to_output_weights_grad = np.dot(loss_derivative.T, activations.hidden_layer)             # (B x (N * V))^T   @   (B x H) = (N * V) x H
        output_bias_grad = np.dot(loss_derivative.T, np.ones([activations.hidden_layer.shape[0],]))   # (B x (N * V))^T    @   B x 1 =  (N * V) x 1
        embed_to_hid_weights_grad = np.dot(hid_deriv.T, activations.embedding_layer)             # (B x H)^T    @    (B x (N * D)) = (H x (N * D))
        hid_bias_grad = np.dot(hid_deriv.T, np.ones([activations.embedding_layer.shape[0],]))           # (B x H)^T    @    (B x 1) = (H x 1)
        ##############################################################################
###

        # The matrix of derivatives for the embedding layer
        embed_deriv = np.dot(hid_deriv, self.params.embed_to_hid_weights)

        # Embedding layer
        word_embedding_weights_grad = np.zeros((self.vocab_size, self.embedding_dim))
        for w in range(self.context_len):
            word_embedding_weights_grad += np.dot(self.indicator_matrix(input_batch[:, w:w+1], mask_zero_index=False).T,
                                                  embed_deriv[:, w * self.embedding_dim:(w + 1) * self.embedding_dim])

        return Params(word_embedding_weights_grad, embed_to_hid_weights_grad, hid_to_output_weights_grad,
                      hid_bias_grad, output_bias_grad)

    def sample_input_mask(self, batch_size):
        """Samples a binary mask for the inputs of size batch_size x context_len
        For each row, at most one element will be 1.
        """
        mask_idx = np.random.randint(self.context_len, size=(batch_size,))
        mask = np.zeros((batch_size, self.context_len), dtype=np.int)# Convert to
```

```
one hot B x N, B batch size, N context len
        mask[np.arange(batch_size), mask_idx] = 1
        return mask

    def evaluate(self, inputs, batch_size=100):
        """Compute the average cross-entropy over a dataset.

            inputs: matrix of shape D x N"""

        ndata = inputs.shape[0]

        total = 0.
        for input_batch in get_batches(inputs, batch_size):
            mask = self.sample_input_mask(batch_size)
            input_batch_masked = input_batch * (1 - mask)
            activations = self.compute_activations(input_batch_masked)
            target_batch_masked = input_batch * mask
            expanded_target_batch = self.indicator_matrix(target_batch_masked)
            cross_entropy = -np.sum(expanded_target_batch * np.log(activations.ou
tput_layer + TINY))
            total += cross_entropy

        return total / float(ndata)

    def display_nearest_words(self, word, k=10):
        """List the k words nearest to a given word, along with their distance
s."""

        if word not in self.vocab:
            print('Word "{}" not in vocabulary.'.format(word))
            return

        # Compute distance to every other word.
        idx = self.vocab.index(word)
        word_rep = self.params.word_embedding_weights[idx, :]
        diff = self.params.word_embedding_weights - word_rep.reshape((1, -1))
        distance = np.sqrt(np.sum(diff ** 2, axis=1))

        # Sort by distance.
        order = np.argsort(distance)
        order = order[1:1 + k]  # The nearest word is the query word itself, skip
that.
        for i in order:
            print('{}: {}'.format(self.vocab[i], distance[i]))

    def word_distance(self, word1, word2):
        """Compute the distance between the vector representations of two word
s."""

        if word1 not in self.vocab:
            raise RuntimeError('Word "{}" not in vocabulary.'.format(word1))
        if word2 not in self.vocab:
            raise RuntimeError('Word "{}" not in vocabulary.'.format(word2))

        idx1, idx2 = self.vocab.index(word1), self.vocab.index(word2)
        word_rep1 = self.params.word_embedding_weights[idx1, :]
        word_rep2 = self.params.word_embedding_weights[idx2, :]
        diff = word_rep1 - word_rep2
        return np.sqrt(np.sum(diff ** 2))
```

3.3 Print the gradients [1pt]

To make your life easier, we have provided the routine `check_gradients`, which checks your gradients using finite differences. You should make sure this check passes before continuing with the assignment. Once `check_gradients()` passes, call `print_gradients()` and include its output in your write-up.

In [14]:
```
def relative_error(a, b):
    return np.abs(a - b) / (np.abs(a) + np.abs(b))


def check_output_derivatives(model, input_batch, target_batch):
    def softmax(z):
        z = z.copy()
        z -= z.max(-1, keepdims=True)
        y = np.exp(z)
        y /= y.sum(-1, keepdims=True)
        return y

    batch_size = input_batch.shape[0]
    z = np.random.normal(size=(batch_size, model.context_len, model.vocab_size))
    y = softmax(z).reshape((batch_size, model.context_len * model.vocab_size))
    z = z.reshape((batch_size, model.context_len * model.vocab_size))

    expanded_target_batch = model.indicator_matrix(target_batch)
    target_mask = expanded_target_batch.reshape(-1, model.context_len, len(model.
vocab)).sum(axis=-1, keepdims=True)
    loss_derivative = model.compute_loss_derivative(y, expanded_target_batch, tar
get_mask)

    if loss_derivative is None:
        print('Loss derivative not implemented yet.')
        return False

    if loss_derivative.shape != (batch_size, model.vocab_size * model.context_len
):
        print('Loss derivative should be size {} but is actually {}.'.format(
            (batch_size, model.vocab_size), loss_derivative.shape))
        return False

    def obj(z):
        z = z.reshape((-1, model.context_len, model.vocab_size))
        y = softmax(z).reshape((batch_size, model.context_len * model.vocab_size
))
        return model.compute_loss(y, expanded_target_batch)

    for count in range(1000):
        i, j = np.random.randint(0, loss_derivative.shape[0]), np.random.randint(
0, loss_derivative.shape[1])

        z_plus = z.copy()
        z_plus[i, j] += EPS
        obj_plus = obj(z_plus)

        z_minus = z.copy()
        z_minus[i, j] -= EPS
        obj_minus = obj(z_minus)

        empirical = (obj_plus - obj_minus) / (2. * EPS)
        rel = relative_error(empirical, loss_derivative[i, j])
        if rel > 1e-4:
            print('The loss derivative has a relative error of {}, which is too l
arge.'.format(rel))
            return False

    print('The loss derivative looks OK.')
    return True
```

```python
def check_param_gradient(model, param_name, input_batch, target_batch):
    activations = model.compute_activations(input_batch)
    expanded_target_batch = model.indicator_matrix(target_batch)
    target_mask = expanded_target_batch.reshape(-1, model.context_len, len(model.vocab)).sum(axis=-1, keepdims=True)
    loss_derivative = model.compute_loss_derivative(activations.output_layer, expanded_target_batch, target_mask)
    param_gradient = model.back_propagate(input_batch, activations, loss_derivative)

    def obj(model):
        activations = model.compute_activations(input_batch)
        return model.compute_loss(activations.output_layer, expanded_target_batch)

    dims = getattr(model.params, param_name).shape
    is_matrix = (len(dims) == 2)

    if getattr(param_gradient, param_name).shape != dims:
        print('The gradient for {} should be size {} but is actually {}.'.format(
            param_name, dims, getattr(param_gradient, param_name).shape))
        return

    for count in range(1000):
        if is_matrix:
            slc = np.random.randint(0, dims[0]), np.random.randint(0, dims[1])
        else:
            slc = np.random.randint(dims[0])

        model_plus = model.copy()
        getattr(model_plus.params, param_name)[slc] += EPS
        obj_plus = obj(model_plus)

        model_minus = model.copy()
        getattr(model_minus.params, param_name)[slc] -= EPS
        obj_minus = obj(model_minus)

        empirical = (obj_plus - obj_minus) / (2. * EPS)
        exact = getattr(param_gradient, param_name)[slc]
        rel = relative_error(empirical, exact)
        if rel > 3e-4:
            import pdb; pdb.set_trace()
            print('The loss derivative has a relative error of {}, which is too large for param {}.'.format(rel, param_name))
            return False

    print('The gradient for {} looks OK.'.format(param_name))


def load_partially_trained_model():
    obj = pickle.load(open(PARTIALLY_TRAINED_MODEL, 'rb'))
    params = Params(obj['word_embedding_weights'], obj['embed_to_hid_weights'],
                                   obj['hid_to_output_weights'], obj['hid_bias'],
                                   obj['output_bias'])
    vocab = obj['vocab']
    return Model(params, vocab)


def check_gradients():
    """Check the computed gradients using finite differences."""
    np.random.seed(0)
```

```
    np.seterr(all='ignore')  # suppress a warning which is harmless

    model = load_partially_trained_model()
    data_obj = pickle.load(open(data_location, 'rb'))
    train_inputs = data_obj['train_inputs']
    input_batch = train_inputs[:100, :]
    mask = model.sample_input_mask(input_batch.shape[0])
    input_batch_masked = input_batch * (1 - mask)
    target_batch_masked = input_batch * mask

    if not check_output_derivatives(model, input_batch_masked, target_batch_maske
d):
        return

    for param_name in ['word_embedding_weights', 'embed_to_hid_weights', 'hid_to_
output_weights',
                       'hid_bias', 'output_bias']:
        input_batch_masked = input_batch * (1 - mask)
        target_batch_masked = input_batch * mask
        check_param_gradient(model, param_name, input_batch_masked, target_batch_
masked)


def print_gradients():
    """Print out certain derivatives for grading."""
    np.random.seed(0)

    model = load_partially_trained_model()
    data_obj = pickle.load(open(data_location, 'rb'))
    train_inputs = data_obj['train_inputs']
    input_batch = train_inputs[:100, :]

    mask = model.sample_input_mask(input_batch.shape[0])
    input_batch_masked = input_batch * (1 - mask)
    activations = model.compute_activations(input_batch_masked)
    target_batch_masked = input_batch * mask
    expanded_target_batch = model.indicator_matrix(target_batch_masked)
    target_mask = expanded_target_batch.reshape(-1, model.context_len, len(model.
vocab)).sum(axis=-1, keepdims=True)
    loss_derivative = model.compute_loss_derivative(activations.output_layer, exp
anded_target_batch, target_mask)
    param_gradient = model.back_propagate(input_batch, activations, loss_derivati
ve)

    print('loss_derivative[2, 5]', loss_derivative[2, 5])
    print('loss_derivative[2, 121]', loss_derivative[2, 121])
    print('loss_derivative[5, 33]', loss_derivative[5, 33])
    print('loss_derivative[5, 31]', loss_derivative[5, 31])
    print()
    print('param_gradient.word_embedding_weights[27, 2]', param_gradient.word_emb
edding_weights[27, 2])
    print('param_gradient.word_embedding_weights[43, 3]', param_gradient.word_emb
edding_weights[43, 3])
    print('param_gradient.word_embedding_weights[22, 4]', param_gradient.word_emb
edding_weights[22, 4])
    print('param_gradient.word_embedding_weights[2, 5]', param_gradient.word_embe
dding_weights[2, 5])
    print()
    print('param_gradient.embed_to_hid_weights[10, 2]', param_gradient.embed_to_h
id_weights[10, 2])
    print('param_gradient.embed_to_hid_weights[15, 3]', param_gradient.embed_to_h
```

```
id_weights[15, 3])
    print('param_gradient.embed_to_hid_weights[30, 9]', param_gradient.embed_to_h
id_weights[30, 9])
    print('param_gradient.embed_to_hid_weights[35, 21]', param_gradient.embed_to_
hid_weights[35, 21])
    print()
    print('param_gradient.hid_bias[10]', param_gradient.hid_bias[10])
    print('param_gradient.hid_bias[20]', param_gradient.hid_bias[20])
    print()
    print('param_gradient.output_bias[0]', param_gradient.output_bias[0])
    print('param_gradient.output_bias[1]', param_gradient.output_bias[1])
    print('param_gradient.output_bias[2]', param_gradient.output_bias[2])
    print('param_gradient.output_bias[3]', param_gradient.output_bias[3])
```

In [15]:

```
# Run this to check if your implement gradients matches the finite difference wit
hin tolerance
# Note: this may take a few minutes to go through all the checks
check_gradients()
```

```
The loss derivative looks OK.
The gradient for word_embedding_weights looks OK.
The gradient for embed_to_hid_weights looks OK.
The gradient for hid_to_output_weights looks OK.
The gradient for hid_bias looks OK.
The gradient for output_bias looks OK.
```

In [16]:

```
# Run this to print out the gradients
print_gradients()
```

```
loss_derivative[2, 5] 0.0
loss_derivative[2, 121] 0.0
loss_derivative[5, 33] 0.0
loss_derivative[5, 31] 0.0

param_gradient.word_embedding_weights[27, 2] 0.0
param_gradient.word_embedding_weights[43, 3] 0.011596892511489458
param_gradient.word_embedding_weights[22, 4] -0.0222670623817297
param_gradient.word_embedding_weights[2, 5] 0.0

param_gradient.embed_to_hid_weights[10, 2] 0.3793257091930164
param_gradient.embed_to_hid_weights[15, 3] 0.01604516132110917
param_gradient.embed_to_hid_weights[30, 9] -0.4312854367997419
param_gradient.embed_to_hid_weights[35, 21] 0.06679896665436337

param_gradient.hid_bias[10] 0.023428803123345134
param_gradient.hid_bias[20] -0.02437045237887416

param_gradient.output_bias[0] 0.0009701061469027941
param_gradient.output_bias[1] 0.1686894627476322
param_gradient.output_bias[2] 0.0051664774143909235
param_gradient.output_bias[3] 0.15096226471814364
```

3.4 Run model trainin [0pt]

Once you've implemented the gradient computation, you'll need to train the model. The function *train* implements the main training procedure. It takes two arguments:

- `embedding_dim` : The number of dimensions in the distributed representation.
- `num_hid` : The number of hidden units

As the model trains, the script prints out some numbers that tell you how well the training is going. It shows:

- The cross entropy on the last 100 mini-batches of the training set. This is shown after every 100 mini-batches.
- The cross entropy on the entire validation set every 1000 mini-batches of training.

At the end of training, this function shows the cross entropies on the training, validation and test sets. It will return a *Model* instance.

In [17]:

```
_train_inputs = None
_train_targets = None
_vocab = None

DEFAULT_TRAINING_CONFIG = {'batch_size': 100,  # the size of a mini-batch
                           'learning_rate': 0.1,  # the learning rate
                           'momentum': 0.9,  # the decay parameter for the moment
um vector
                           'epochs': 50,  # the maximum number of epochs to run
                           'init_wt': 0.01,  # the standard deviation of the init
ial random weights
                           'context_len': 4,  # the number of context words used
                           'show_training_CE_after': 100,  # measure training err
or after this many mini-batches
                           'show_validation_CE_after': 1000,  # measure validatio
n error after this many mini-batches
                           }


def find_occurrences(word1, word2, word3):
    """Lists all the words that followed a given tri-gram in the training set and
the number of
    times each one followed it."""

    # cache the data so we don't keep reloading
    global _train_inputs, _train_targets, _vocab
    if _train_inputs is None:
        data_obj = pickle.load(open(data_location, 'rb'))
        _vocab = data_obj['vocab']
        _train_inputs, _train_targets = data_obj['train_inputs'], data_obj['train
_targets']

    if word1 not in _vocab:
        raise RuntimeError('Word "{}" not in vocabulary.'.format(word1))
    if word2 not in _vocab:
        raise RuntimeError('Word "{}" not in vocabulary.'.format(word2))
    if word3 not in _vocab:
        raise RuntimeError('Word "{}" not in vocabulary.'.format(word3))

    idx1, idx2, idx3 = _vocab.index(word1), _vocab.index(word2), _vocab.index(wor
d3)
    idxs = np.array([idx1, idx2, idx3])

    matches = np.all(_train_inputs == idxs.reshape((1, -1)), 1)

    if np.any(matches):
        counts = collections.defaultdict(int)
        for m in np.where(matches)[0]:
            counts[_vocab[_train_targets[m]]] += 1

        word_counts = sorted(list(counts.items()), key=lambda t: t[1], reverse=Tr
ue)
        print('The tri-gram "{} {} {}" was followed by the following words in the
training set:'.format(
            word1, word2, word3))
        for word, count in word_counts:
            if count > 1:
                print('    {} ({} times)'.format(word, count))
            else:
                print('    {} (1 time)'.format(word))
    else:
```

```
        print('The tri-gram "{} {} {}" did not occur in the training set.'.format
(word1, word2, word3))


def train(embedding_dim, num_hid, config=DEFAULT_TRAINING_CONFIG):
    """This is the main training routine for the language model. It takes two par
ameters:

        embedding_dim, the dimension of the embedding space
        num_hid, the number of hidden units."""
    # For reproducibility
    np.random.seed(123)

    # Load the data
    data_obj = pickle.load(open(data_location, 'rb'))
    vocab = data_obj['vocab']
    train_inputs = data_obj['train_inputs']
    valid_inputs = data_obj['valid_inputs']
    test_inputs = data_obj['test_inputs']

    # Randomly initialize the trainable parameters
    model = Model.random_init(config['init_wt'], vocab, config['context_len'], em
bedding_dim, num_hid)

    # Variables used for early stopping
    best_valid_CE = np.infty
    end_training = False

    # Initialize the momentum vector to all zeros
    delta = Params.zeros(len(vocab), config['context_len'], embedding_dim, num_hi
d)

    this_chunk_CE = 0.
    batch_count = 0
    for epoch in range(1, config['epochs'] + 1):
        if end_training:
            break

        print()
        print('Epoch', epoch)

        for m, (input_batch) in enumerate(get_batches(train_inputs, config['batch
_size'])):
            batch_count += 1

            # For each example (row in input_batch), select one word to mask out
            mask = model.sample_input_mask(config['batch_size'])
            input_batch_masked = input_batch * (1 - mask) # We only zero out one
 word per row
            target_batch_masked = input_batch * mask # We want to predict the mas
ked out word

            # Forward propagate
            activations = model.compute_activations(input_batch_masked)

            # Compute loss derivative
            expanded_target_batch = model.indicator_matrix(target_batch_masked)
            loss_derivative = model.compute_loss_derivative(activations.output_la
yer, expanded_target_batch, mask[:,:, np.newaxis])
            loss_derivative /= config['batch_size']

            # Measure loss function
```

```
            cross_entropy = model.compute_loss(activations.output_layer, expanded
_target_batch) / config['batch_size']
            this_chunk_CE += cross_entropy
            if batch_count % config['show_training_CE_after'] == 0:
                print('Batch {} Train CE {:1.3f}'.format(
                    batch_count, this_chunk_CE / config['show_training_CE_after'
]))
                this_chunk_CE = 0.

            # Backpropagate
            loss_gradient = model.back_propagate(input_batch, activations, loss_d
erivative)

            # Update the momentum vector and model parameters
            delta = config['momentum'] * delta + loss_gradient
            model.params -= config['learning_rate'] * delta

            # Validate
            if batch_count % config['show_validation_CE_after'] == 0:
                print('Running validation...')
                cross_entropy = model.evaluate(valid_inputs)
                print('Validation cross-entropy: {:1.3f}'.format(cross_entropy))

                if cross_entropy > best_valid_CE:
                    print('Validation error increasing!  Training stopped.')
                    end_training = True
                    break

                best_valid_CE = cross_entropy

    print()
    train_CE = model.evaluate(train_inputs)
    print('Final training cross-entropy: {:1.3f}'.format(train_CE))
    valid_CE = model.evaluate(valid_inputs)
    print('Final validation cross-entropy: {:1.3f}'.format(valid_CE))
    test_CE = model.evaluate(test_inputs)
    print('Final test cross-entropy: {:1.3f}'.format(test_CE))

    return model
```

Run the training.

In [18]:

```
embedding_dim = 16
num_hid = 128
trained_model = train(embedding_dim, num_hid)
```

```
Epoch 1
Batch 100 Train CE 4.793
Batch 200 Train CE 4.645
Batch 300 Train CE 4.649
Batch 400 Train CE 4.629
Batch 500 Train CE 4.633
Batch 600 Train CE 4.648
Batch 700 Train CE 4.617
Batch 800 Train CE 4.607
Batch 900 Train CE 4.606
Batch 1000 Train CE 4.615
Running validation...
Validation cross-entropy: 4.615
Batch 1100 Train CE 4.615
Batch 1200 Train CE 4.624
Batch 1300 Train CE 4.608
Batch 1400 Train CE 4.595
Batch 1500 Train CE 4.611
Batch 1600 Train CE 4.598
Batch 1700 Train CE 4.577
Batch 1800 Train CE 4.578
Batch 1900 Train CE 4.568
Batch 2000 Train CE 4.589
Running validation...
Validation cross-entropy: 4.589
Batch 2100 Train CE 4.573
Batch 2200 Train CE 4.611
Batch 2300 Train CE 4.562
Batch 2400 Train CE 4.587
Batch 2500 Train CE 4.589
Batch 2600 Train CE 4.587
Batch 2700 Train CE 4.561
Batch 2800 Train CE 4.544
Batch 2900 Train CE 4.521
Batch 3000 Train CE 4.524
Running validation...
Validation cross-entropy: 4.496
Batch 3100 Train CE 4.504
Batch 3200 Train CE 4.449
Batch 3300 Train CE 4.384
Batch 3400 Train CE 4.352
Batch 3500 Train CE 4.324
Batch 3600 Train CE 4.261
Batch 3700 Train CE 4.267

Epoch 2
Batch 3800 Train CE 4.208
Batch 3900 Train CE 4.168
Batch 4000 Train CE 4.117
Running validation...
Validation cross-entropy: 4.112
Batch 4100 Train CE 4.105
Batch 4200 Train CE 4.049
Batch 4300 Train CE 4.008
Batch 4400 Train CE 3.986
Batch 4500 Train CE 3.924
Batch 4600 Train CE 3.897
Batch 4700 Train CE 3.857
Batch 4800 Train CE 3.790
Batch 4900 Train CE 3.796
Batch 5000 Train CE 3.773
```

```
Running validation...
Validation cross-entropy: 3.776
Batch 5100 Train CE 3.766
Batch 5200 Train CE 3.714
Batch 5300 Train CE 3.720
Batch 5400 Train CE 3.668
Batch 5500 Train CE 3.668
Batch 5600 Train CE 3.639
Batch 5700 Train CE 3.571
Batch 5800 Train CE 3.546
Batch 5900 Train CE 3.537
Batch 6000 Train CE 3.511
Running validation...
Validation cross-entropy: 3.531
Batch 6100 Train CE 3.494
Batch 6200 Train CE 3.495
Batch 6300 Train CE 3.477
Batch 6400 Train CE 3.455
Batch 6500 Train CE 3.435
Batch 6600 Train CE 3.446
Batch 6700 Train CE 3.411
Batch 6800 Train CE 3.376
Batch 6900 Train CE 3.419
Batch 7000 Train CE 3.375
Running validation...
Validation cross-entropy: 3.386
Batch 7100 Train CE 3.398
Batch 7200 Train CE 3.383
Batch 7300 Train CE 3.371
Batch 7400 Train CE 3.355

Epoch 3
Batch 7500 Train CE 3.320
Batch 7600 Train CE 3.315
Batch 7700 Train CE 3.342
Batch 7800 Train CE 3.293
Batch 7900 Train CE 3.285
Batch 8000 Train CE 3.296
Running validation...
Validation cross-entropy: 3.294
Batch 8100 Train CE 3.271
Batch 8200 Train CE 3.291
Batch 8300 Train CE 3.287
Batch 8400 Train CE 3.274
Batch 8500 Train CE 3.228
Batch 8600 Train CE 3.256
Batch 8700 Train CE 3.250
Batch 8800 Train CE 3.256
Batch 8900 Train CE 3.266
Batch 9000 Train CE 3.221
Running validation...
Validation cross-entropy: 3.233
Batch 9100 Train CE 3.247
Batch 9200 Train CE 3.229
Batch 9300 Train CE 3.224
Batch 9400 Train CE 3.217
Batch 9500 Train CE 3.207
Batch 9600 Train CE 3.200
Batch 9700 Train CE 3.196
Batch 9800 Train CE 3.232
Batch 9900 Train CE 3.185
Batch 10000 Train CE 3.181
```

```
Running validation...
Validation cross-entropy: 3.180
Batch 10100 Train CE 3.171
Batch 10200 Train CE 3.165
Batch 10300 Train CE 3.168
Batch 10400 Train CE 3.194
Batch 10500 Train CE 3.176
Batch 10600 Train CE 3.171
Batch 10700 Train CE 3.146
Batch 10800 Train CE 3.177
Batch 10900 Train CE 3.183
Batch 11000 Train CE 3.100
Running validation...
Validation cross-entropy: 3.141
Batch 11100 Train CE 3.159

Epoch 4
Batch 11200 Train CE 3.144
Batch 11300 Train CE 3.140
Batch 11400 Train CE 3.145
Batch 11500 Train CE 3.152
Batch 11600 Train CE 3.124
Batch 11700 Train CE 3.116
Batch 11800 Train CE 3.162
Batch 11900 Train CE 3.110
Batch 12000 Train CE 3.143
Running validation...
Validation cross-entropy: 3.119
Batch 12100 Train CE 3.141
Batch 12200 Train CE 3.130
Batch 12300 Train CE 3.127
Batch 12400 Train CE 3.112
Batch 12500 Train CE 3.076
Batch 12600 Train CE 3.137
Batch 12700 Train CE 3.121
Batch 12800 Train CE 3.122
Batch 12900 Train CE 3.085
Batch 13000 Train CE 3.107
Running validation...
Validation cross-entropy: 3.102
Batch 13100 Train CE 3.113
Batch 13200 Train CE 3.094
Batch 13300 Train CE 3.088
Batch 13400 Train CE 3.085
Batch 13500 Train CE 3.072
Batch 13600 Train CE 3.066
Batch 13700 Train CE 3.087
Batch 13800 Train CE 3.074
Batch 13900 Train CE 3.076
Batch 14000 Train CE 3.079
Running validation...
Validation cross-entropy: 3.086
Batch 14100 Train CE 3.088
Batch 14200 Train CE 3.105
Batch 14300 Train CE 3.129
Batch 14400 Train CE 3.079
Batch 14500 Train CE 3.062
Batch 14600 Train CE 3.131
Batch 14700 Train CE 3.096
Batch 14800 Train CE 3.073
Batch 14900 Train CE 3.065
```

```
Epoch 5
Batch 15000 Train CE 3.048
Running validation...
Validation cross-entropy: 3.055
Batch 15100 Train CE 3.084
Batch 15200 Train CE 3.067
Batch 15300 Train CE 3.090
Batch 15400 Train CE 3.095
Batch 15500 Train CE 3.052
Batch 15600 Train CE 3.088
Batch 15700 Train CE 3.081
Batch 15800 Train CE 3.068
Batch 15900 Train CE 3.068
Batch 16000 Train CE 3.063
Running validation...
Validation cross-entropy: 3.073
Validation error increasing!  Training stopped.

Final training cross-entropy: 3.054
Final validation cross-entropy: 3.067
Final test cross-entropy: 3.068
```

To convince us that you have correctly implemented the gradient computations, please include the following with your assignment submission:

- [ ] You will submit `a1-code.ipynb` through MarkUs. You do not need to modify any of the code except the parts we asked you to implement.
- [ ] In your writeup, include the output of the function `print_gradients`. This prints out part of the gradients for a partially trained network which we have provided, and we will check them against the correct outputs. **Important:** make sure to give the output of `print_gradients`, **not** `check_gradients`.

This is worth 4 points:

- 1 for the loss derivatives,
- 1 for the bias gradients, and
- 2 for the weight gradients.

Since we gave you a gradient checker, you have no excuse for not getting full points on this part.

Part 4: Arithmetics and Analysis (2pts)

In this part, you will perform arithmetic calculations on the word embeddings learned from previous models and analyze the representation learned by the networks with t-SNE plots.

4.1 t-SNE

You will first train the models discussed in the previous sections; you'll use the trained models for the remainder of this section.

Important: if you've made any fixes to your gradient code, you must reload the a1-code module and then re-run the training procedure. Python does not reload modules automatically, and you don't want to accidentally analyze an old version of your model.

These methods of the Model class can be used for analyzing the model after the training is done:

- `tsne_plot_representation` creates a 2-dimensional embedding of the distributed representation space using an algorithm called t-SNE. (You don't need to know what this is for the assignment, but we may cover it later in the course.) Nearby points in this 2-D space are meant to correspond to nearby points in the 16-D space.
- `display_nearest_words` lists the words whose embedding vectors are nearest to the given word
- `word_distance` computes the distance between the embeddings of two words

Plot the 2-dimensional visualization for the trained model from part 3 using the method `tsne_plot_representation`. Look at the plot and find a few clusters of related words. What do the words in each cluster have in common? Plot the 2-dimensional visualization for the GloVe model from part 1 using the method `tsne_plot_GLoVe_representation`. How do the t-SNE embeddings for both models compare? Plot the 2-dimensional visualization using the method `plot_2d_GLoVe_representation`. How does this compare to the t-SNE embeddings? Please answer in 2 sentences for each question and show the plots in your submission.

4.1 **Answer**:

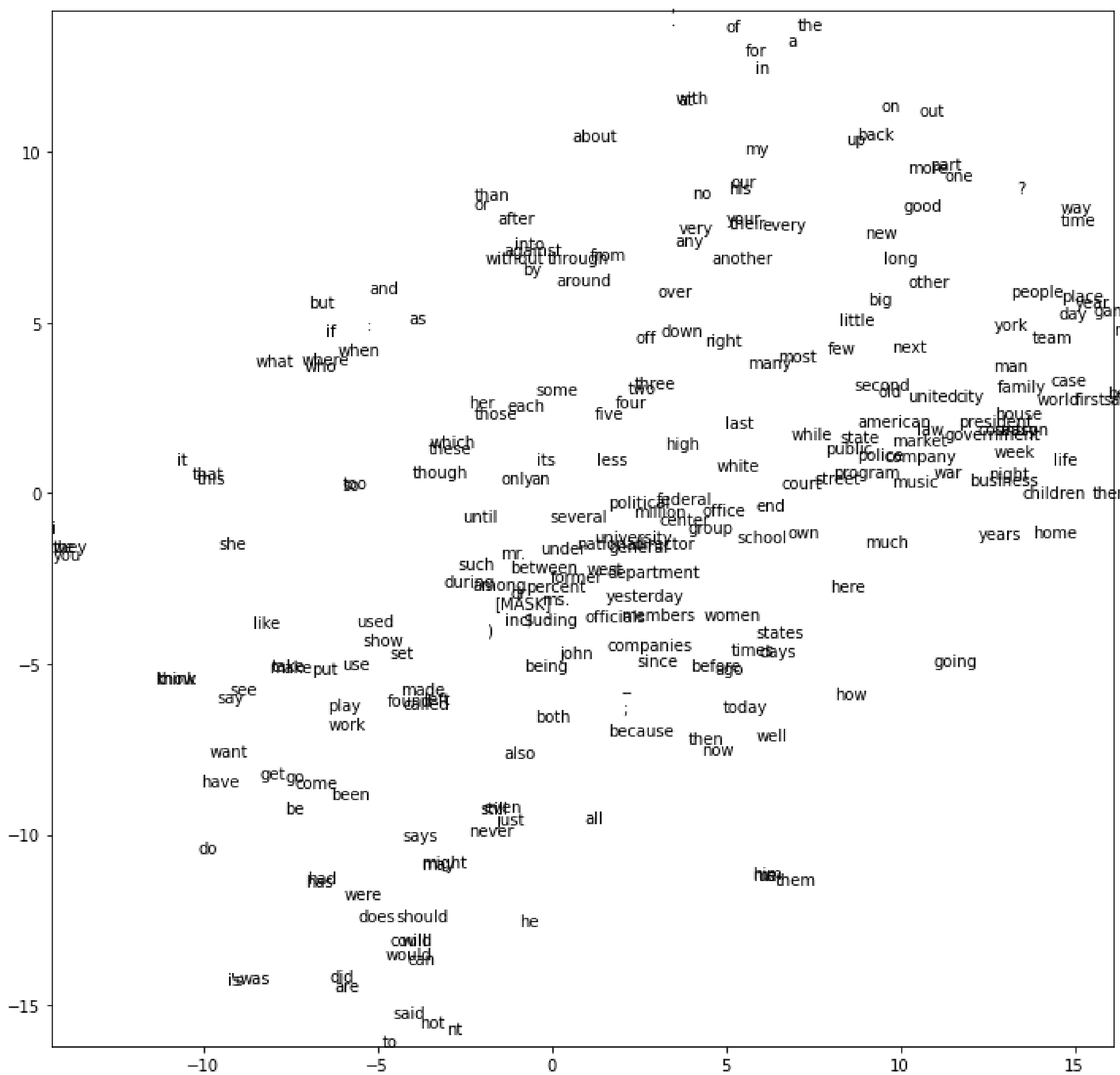
- What do the words in each cluster have in common? **- At the top left of the graph, there is a cluster which includes 'what', 'how', 'where', 'who', 'but', 'if' and 'when', these words are always used when asking questions and be put at the start of each sentence; there is also a cluster at the center which includes 'five', 'four', 'three' and 'two', these words are all numbers; at the bottom left corner, there is also a cluster includes some modal verbs 'would', 'could', 'will' and 'should'.**
- How do the t-SNE embeddings for both models compare? **- GloVe model has some similar clusters as the Neural language model such as numbers 'four', 'five' and 'three' and 'are', 'were' and model verbs. However, by comparing two graphs, we can see GloVe model has a lower density of words in the graph comparing to he neural language model and therefore the neural language model has more clear classification performance.**
- How does this compare to the t-SNE embeddings? **- The third plot gives the 2D plot without using tSNE and the fourth plot is using tSNE. By comparing the third and fourth graphs, we can clearly see that tSNE gives better and more meaningful clustering of the words but normal 2D plot has the words much more dispersed and less interpretable.**

In [19]:

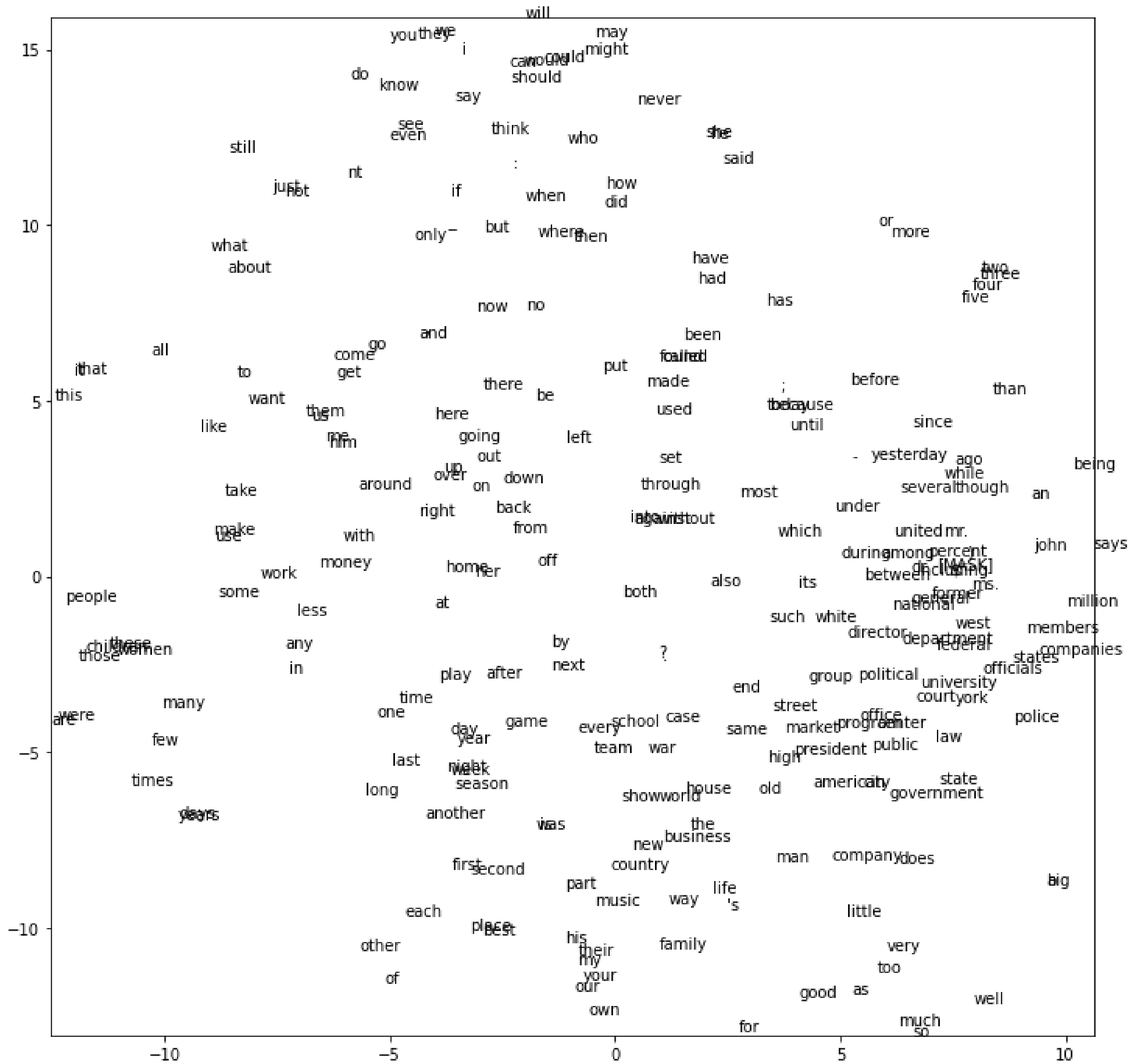
```
from sklearn.manifold import TSNE

def tsne_plot_representation(model):
    """Plot a 2-D visualization of the learned representations using t-SNE."""
    print(model.params.word_embedding_weights.shape)
    mapped_X = TSNE(n_components=2).fit_transform(model.params.word_embedding_wei
ghts)
    pylab.figure(figsize=(12,12))
    for i, w in enumerate(model.vocab):
        pylab.text(mapped_X[i, 0], mapped_X[i, 1], w)
    pylab.xlim(mapped_X[:, 0].min(), mapped_X[:, 0].max())
    pylab.ylim(mapped_X[:, 1].min(), mapped_X[:, 1].max())
    pylab.show()

def tsne_plot_GLoVE_representation(W_final, b_final):
    """Plot a 2-D visualization of the learned representations using t-SNE."""
    mapped_X = TSNE(n_components=2).fit_transform(W_final)
    pylab.figure(figsize=(12,12))
    data_obj = pickle.load(open(data_location, 'rb'))
    for i, w in enumerate(data_obj['vocab']):
        pylab.text(mapped_X[i, 0], mapped_X[i, 1], w)
    pylab.xlim(mapped_X[:, 0].min(), mapped_X[:, 0].max())
    pylab.ylim(mapped_X[:, 1].min(), mapped_X[:, 1].max())
    pylab.show()

def plot_2d_GLoVE_representation(W_final, b_final):
    """Plot a 2-D visualization of the learned representations."""
    mapped_X = W_final
    pylab.figure(figsize=(12,12))
    data_obj = pickle.load(open(data_location, 'rb'))
    for i, w in enumerate(data_obj['vocab']):
        pylab.text(mapped_X[i, 0], mapped_X[i, 1], w)
    pylab.xlim(mapped_X[:, 0].min(), mapped_X[:, 0].max())
    pylab.ylim(mapped_X[:, 1].min(), mapped_X[:, 1].max())
    pylab.show()
```

In [37]:
```
# plot trained model from Part 3
tsne_plot_representation(trained_model)
```

```
(251, 16)
```

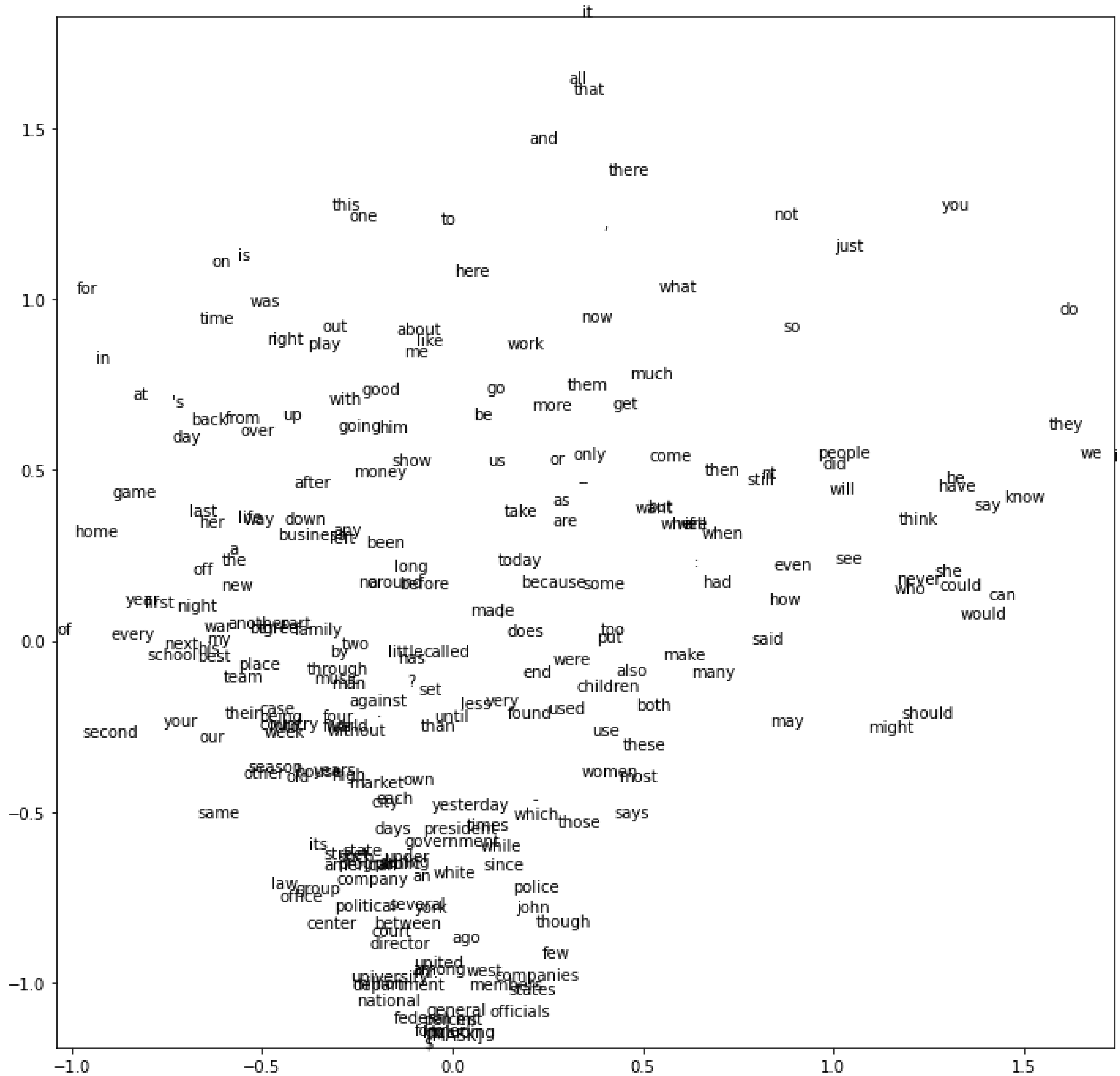


```
In [45]: # plot GloVe from Part 1
         # tsne_plot_GLoVE_representation(W_final, b_final)
         # Some modifications are made in Part 1 to get the 16D embedding_dimension
         tsne_plot_GLoVE_representation(W_final_16d, b_final_16d)
```

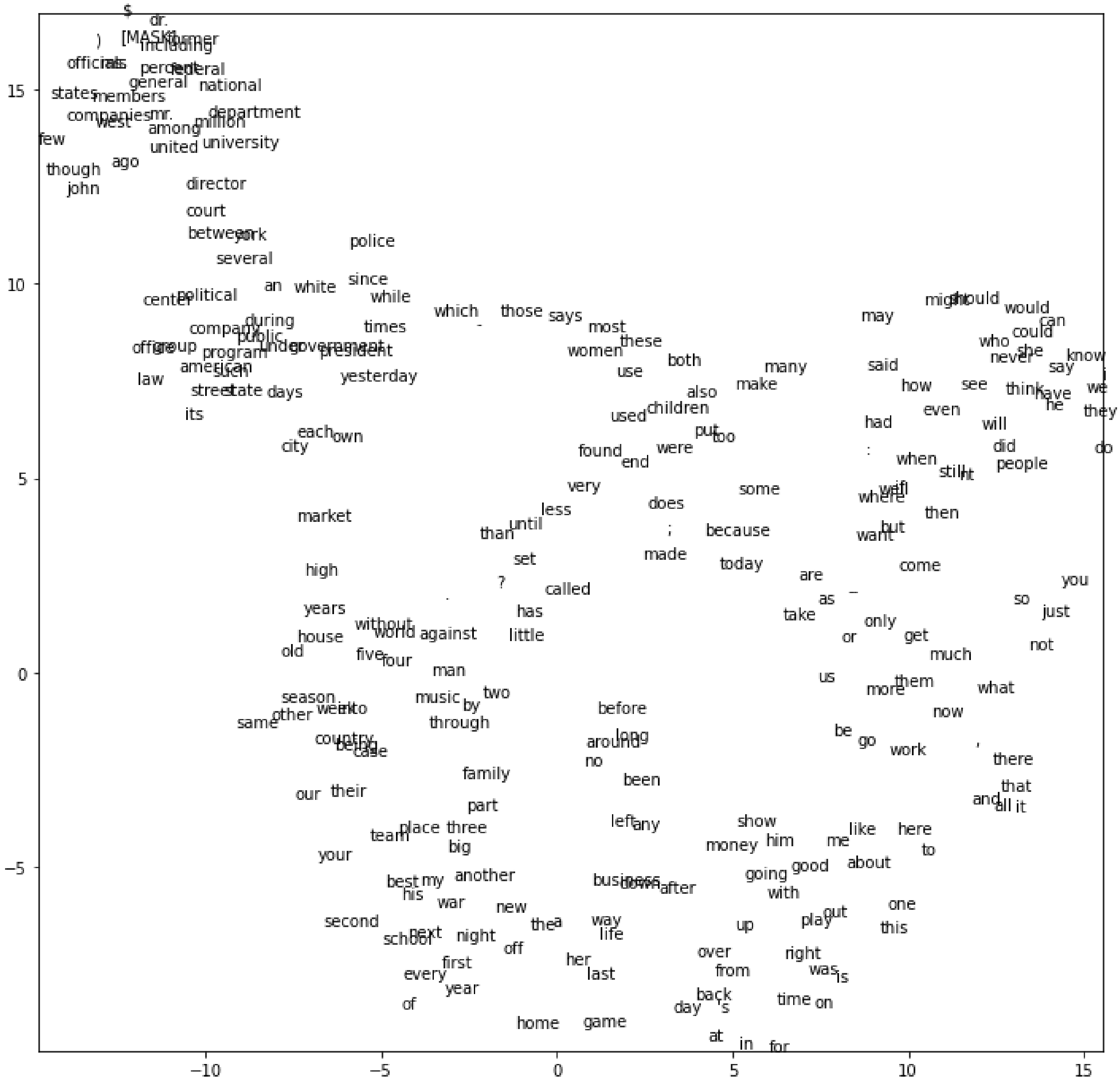


In [22]:

```
# plot 2D of GloVe
plot_2d_GLoVE_representation(W_final_2d, b_final_2d)
```



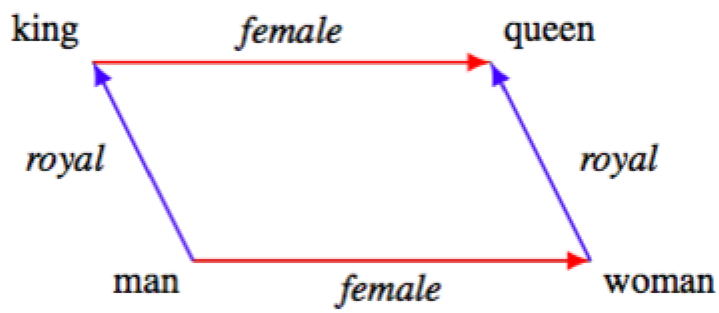
```
In [23]: tsne_plot_GLoVE_representation(W_final_2d, b_final_2d)
```



4.2 Word Embedding Arithmetic

A word analogy f is an invertible transformation that holds over a set of ordered pairs S iff $\forall (x, y) \in s, f(x) = y \wedge f^{-1}(y) = x$. When f is of the form $\vec{x} \to \vec{x} + \vec{r}$, it is a linear word analogy.

Arithmetic operators can be applied to vectors generated by language models. There is a famous example: $\overrightarrow{\text{king}} - \overrightarrow{\text{man}} + \overrightarrow{\text{women}} \approx \overrightarrow{\text{queen}}$. These linear word analogies form a parallelogram structure in the vector space (Ethayarajh, Duvenaud, \& Hirst, 2019).



In this section, we will explore a property of *linear word analogies*. A linear word analogy holds exactly over a set of ordered word pairs S iff $\| \vec{x} - \vec{y} \|^2$ is the same for every word pair, $\| \vec{a} - \vec{x} \|^2 = \| \vec{b} - \vec{y} \|^2$ for any two word pairs, and the vectors of all words in S are coplanar.

We will use the embeddings from the symmetric, asymmetrical GloVe model, and the neural network model from part 3 to perform arithmetics. The method to perform the arithmetic and retrieve the closest word embeddings is provided in the notebook using the method `find_word_analogy` :

- `find_word_analogy` returns the closest word to the word embedding calculated from the 3 given words.

In [24]:
```
np.random.seed(1)
n_epochs = 500  # A hyperparameter.  You can play with this if you want.
embedding_dim = 16

W_final_sym, W_tilde_final_asym, W_final_asym = None, None, None
init_variance = 0.1  # A hyperparameter.  You can play with this if you want.
W = init_variance * np.random.normal(size=(vocab_size, embedding_dim))
W_tilde = init_variance * np.random.normal(size=(vocab_size, embedding_dim))
b = init_variance * np.random.normal(size=(vocab_size, 1))
b_tilde = init_variance * np.random.normal(size=(vocab_size, 1))

# Symmetric model
W_final_sym, _, b_final_sym, _ , _, _ = train_GLoVE(W, None, b, None, asym_log_co_occurence_train, asym_log_co_occurence_valid, n_epochs, do_print=do_print)
# Asymmetric model
W_final_asym, W_tilde_final_asym, b_final_asym, b_tilde_final_asym, _, _ = train_GLoVE(W, W_tilde, b, b_tilde, asym_log_co_occurence_train, asym_log_co_occurence_valid, n_epochs, do_print=do_print)
```

You will need to use different embeddings to evaluate the word analogy

In [25]:
```
def get_word_embedding(word, embedding_weights):
    assert word in data['vocab'], 'Word not in vocab'
    return embedding_weights[data['vocab'].index(word)]
```

In [26]:
```
# word4 = word1 - word2 + word3
def find_word_analogy(word1, word2, word3, embedding_weights):
    embedding1 = get_word_embedding(word1, embedding_weights)
    embedding2 = get_word_embedding(word2, embedding_weights)
    embedding3 = get_word_embedding(word3, embedding_weights)
    target_embedding = embedding1 - embedding2 + embedding3

    # Compute distance to every other word.
    diff = embedding_weights - target_embedding.reshape((1, -1))
    distance = np.sqrt(np.sum(diff ** 2, axis=1))

    # Sort by distance.
    order = np.argsort(distance)[:10]
    print("The top 10 closest words to emb({}) - emb({}) + emb({}) are:".format(w
ord1, word2, word3))
    for i in order:
        print('{}: {}'.format(data['vocab'][i], distance[i]))
```

In this part of the assignment, you will use the find_word_analogy function to analyze quadruplets from the vocabulary.

4.2.1 Specific example

Perform arithmetic on words *her*, *him*, *her*, using: (1) symmetric, (2) averaging asymmetrical GloVe embedding, (3) concatenating asymmetrical GloVe embedding, and (4) neural network word embedding from part 3. That is, we are trying to find the closet word embedding vector to the vector

$$emb(he) - emb(him) + emb(her)$$

For each sets of embeddings, you should list out: (1) what the closest word that is not one of those three words, and (2) the distance to that closest word. Is the closest word *she*? Compare the results with the tSNE plots.

4.2.1 **Answer**:

- (1) *Symmetric GloVe Embedding*
  - Closest Word: 'she'
  - Distance to closest word: 1.7574777778049773
- (2) *Averaging Asymmetrical GloVe Embedding*
  - Closest Word: 'she'
  - Distance to closest word: 1.2030105748889408
- (3) *Concatenating Asymmetrical GloVe Embedding*
  - Closest Word: 'she'
  - Distance to closest word: 2.691015794505236
- (4) *Neural Network Word Embedding*
  - Closest Word: 'she'
  - Distance to closest word: 18.303041008736102

By comparing these four words in the tSNE plots, we can see the plot for neural language model (first plot) shows the pattern of parallelogram for these four words but this pattern in the GloVe model cannot be found, the reason behind this may be due the dimensions of the embedding layer, a 16D layer can not be accurately shown in the 2D plot. The pattern may be more obvious if we can visualize the words in a higher dimension.

In [27]:
```
## GloVe embeddings
embedding_weights = W_final_sym # Symmetric GloVe
find_word_analogy('he', 'him', 'her', embedding_weights)
```

```
The top 10 closest words to emb(he) - emb(him) + emb(her) are:
he: 1.7039819358460655
she: 1.7574777778049773
then: 2.5305768585908663
where: 2.590180089285021
says: 2.6113034103326016
said: 2.626578333979202
who: 2.6445463030666083
did: 2.652003578506022
when: 2.679553585747938
man: 2.6859525751034914
```

In [28]:
```
# Averaging asymmetric GLoVE vectors
embedding_weights = (W_final_asym + W_tilde_final_asym)/2
find_word_analogy('he', 'him', 'her', embedding_weights)
```

```
The top 10 closest words to emb(he) - emb(him) + emb(her) are:
she: 1.2030105748889408
he: 1.2068233947828735
should: 1.7332925371615222
could: 1.894951690814692
i: 1.9105953159287086
did: 1.9129436145686363
might: 1.9287320572437008
will: 1.9973759408218135
would: 2.000987418487636
does: 2.0066367007576518
```

In [29]:
```
# Concatenation of W_final_asym, W_tilde_final_asym
embedding_weights = np.concatenate((W_tilde_final_asym, W_final_asym), axis=1)
find_word_analogy('he', 'him', 'her', embedding_weights)
```

```
The top 10 closest words to emb(he) - emb(him) + emb(her) are:
he: 2.4022404503539843
she: 2.691015794505236
i: 3.545162479929377
we: 4.05819028761072
they: 4.128920153846613
john: 5.282129416128583
you: 5.3680678972073395
president: 5.586897611301808
program: 5.622760587565947
white: 5.648517363502693
```

In [30]:
```
## Neural Netework Word Embeddings
embedding_weights = trained_model.params.word_embedding_weights # Neural network
 from part3
find_word_analogy('he', 'him', 'her', embedding_weights)
```

```
The top 10 closest words to emb(he) - emb(him) + emb(her) are:
he: 2.6345067148709824
she: 18.303041008736102
have: 26.01327190994141
i: 26.961551790933612
they: 27.147831644439474
do: 27.358945442776964
want: 27.49089405324503
we: 28.36647236397515
about: 29.187472343032958
but: 29.437195407078278
```

4.2.2 Finding another Quadruplet

Pick another quadruplet from the vocabulary which displays the parallelogram property (and also makes sense sementically) and repeat the above procedures. Compare and comment on the results from arithmetic and tSNE plots.

4.2.2 **Answer**:

Choose 'was', 'were', 'are' as the quadruplet

- (1) *Symmetric GloVe Embedding*
  - Closest Word: "is"
  - Distance to closest word: 2.142841318972689
- (2) *Averaging Asymmetrical GloVe Embedding*
  - Closest Word: "is"
  - Distance to closest word: 2.142841318972689
- (3) *Concatenating Asymmetrical GloVe Embedding*
  - Closest Word: "is"
  - Distance to closest word: 4.503511732976553
- (4) *Neural Network Word Embedding*
  - Closest Word: "'s"
  - Distance to closest word: 18.303041008736102

Neural network model gives a different result from other three models, but this is understandable since "'s" could also mean "is" and "is" is also the second closest word from the output.

From the plots, there is still no strong pattern of the parallelogram. For the neural language model, theese four words are very close to each other and seems to have similar distance between was/were and are/'s; in the glove model, the pattern is more clear and obvious than the neural model.

In [31]:
```python
## GloVe embeddings
embedding_weights = W_final_sym # Symmetric GloVe
find_word_analogy('was', 'were', 'are', embedding_weights)
```

```
The top 10 closest words to emb(was) - emb(were) + emb(are) are:
was: 1.4154926956133682
is: 1.4567785422855293
way: 1.9671907764273169
so: 2.152438273762181
life: 2.1687336768456884
part: 2.177970623544593
good: 2.1783120834047107
here: 2.2193171096445297
out: 2.227355317679716
time: 2.2865138275624006
```

In [32]:
```python
# Averaging asymmetric GLoVE vectors
embedding_weights = (W_final_asym + W_tilde_final_asym)/2
find_word_analogy('was', 'were', 'are', embedding_weights)
```

```
The top 10 closest words to emb(was) - emb(were) + emb(are) are:
was: 1.1959499410849956
is: 1.3083945788370412
's: 1.5499964821553516
and: 1.8931475118367476
,: 1.900524969951059
that: 1.9827165205929442
or: 2.0243819117213633
there: 2.1109257023152193
--: 2.1172323540141345
day: 2.141499018466163
```

In [33]:
```python
# Concatenation of W_final_asym, W_tilde_final_asym
embedding_weights = np.concatenate((W_tilde_final_asym, W_final_asym), axis=1)
find_word_analogy('was', 'were', 'are', embedding_weights)
```

```
The top 10 closest words to emb(was) - emb(were) + emb(are) are:
was: 2.1038319490114117
is: 2.498515640648126
's: 3.1030999000660335
are: 4.208009621100088
were: 4.413139695426189
does: 5.184022533303505
has: 5.223599859343513
says: 5.272811259564048
than: 5.3130629155793985
be: 5.409064051859076
```

In [34]:
```
## Neural Netework Word Embeddings
embedding_weights = trained_model.params.word_embedding_weights # Neural network
 from part3
find_word_analogy('was', 'were', 'are', embedding_weights)
```

```
The top 10 closest words to emb(was) - emb(were) + emb(are) are:
's: 17.67439697320112
was: 18.046977680349205
are: 21.15361218445354
is: 24.296936807204297
did: 27.287104222154518
said: 30.09699218564039
not: 31.61700688364049
would: 34.211202020185596
were: 34.55762965524967
could: 35.59645421583163
```

What you have to submit

For reference, here is everything you need to hand in. See the top of this handout for submission directions.

- A PDF file titled *a1-writeup.pdf* containing the following:
  - [ ] **Part 1**: Questions 1.1, 1.2, 1.3, 1.4. Completed code for `grad_GLoVE` function.
  - [ ] **Part 2**: Questions 2.1, 2.2, 2.3.
  - [ ] **Part 3**: Completed code for `compute_loss_derivative()` (3.1), `back_propagate()` (3.2) functions, and the output of `print_gradients()` (3.3)
  - [ ] **Part 4**: Questions 4.1, 4.2.1, 4.2.2
- Your code file `a1-code.ipynb`

In [34]: