CS224N Assignment 1: Exploring Word Vectors (25 Points)

Due 4:30pm, Tue Jan 17

Welcome to CS224N!

Before you start, make sure you read the README.txt in the same directory as this notebook for important setup information. A lot of code is provided in this notebook, and we highly encourage you to read and understand it as part of the learning :)

If you aren't super familiar with Python, Numpy, or Matplotlib, we recommend you check out the review session on Friday. The session will be recorded and the material will be made available on our website. The CS231N Python/Numpy tutorial is also a great resource.

Assignment Notes: Please make sure to save the notebook as you go along. Submission Instructions are located at the bottom of the notebook.

In [ ]:
```
# All Import Statements Defined Here
# Note: Do not add to this list.
# ----------------

import sys
assert sys.version_info[0]==3
assert sys.version_info[1] >= 5

from platform import python_version
assert int(python_version().split(".")[1]) >= 5, "Please upgrade your Python v
    the README.txt file found in the same directory as this notebook. Your Pyt

from gensim.models import KeyedVectors
from gensim.test.utils import datapath
import pprint
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = [10, 5]

import nltk
nltk.download('reuters') #to specify download location, optionally add the arg
from nltk.corpus import reuters

import numpy as np
import random
import scipy as sp
from sklearn.decomposition import TruncatedSVD
from sklearn.decomposition import PCA

START_TOKEN = '<START>'
END_TOKEN = '<END>'

np.random.seed(0)
random.seed(0)
# ----------------
```

```
[nltk_data] Downloading package reuters to /home/baktash/nltk_data...
[nltk_data]   Package reuters is already up-to-date!
```

Word Vectors

Word Vectors are often used as a fundamental component for downstream NLP tasks, e.g. question answering, text generation, translation, etc., so it is important to build some intuitions as to their strengths and weaknesses. Here, you will explore two types of word vectors: those derived from *co-occurrence matrices*, and those derived via *GloVe*.

Note on Terminology: The terms "word vectors" and "word embeddings" are often used interchangeably. The term "embedding" refers to the fact that we are encoding aspects of a word's meaning in a lower dimensional space. As Wikipedia states, "*conceptually it involves a mathematical embedding from a space with one dimension per word to a continuous vector space with a much lower dimension*".

Part 1: Count-Based Word Vectors (10 points)

Most word vector models start from the following idea:

You shall know a word by the company it keeps (Firth, J. R. 1957:11)

Many word vector implementations are driven by the idea that similar words, i.e., (near) synonyms, will be used in similar contexts. As a result, similar words will often be spoken or written along with a shared subset of words, i.e., contexts. By examining these contexts, we can try to develop embeddings for our words. With this intuition in mind, many "old school" approaches to constructing word vectors relied on word counts. Here we elaborate upon one of those strategies, *co-occurrence matrices* (for more information, see here or here).

Co-Occurrence

A co-occurrence matrix counts how often things co-occur in some environment. Given some word w_i occurring in the document, we consider the *context window* surrounding w_i. Supposing our fixed window size is n, then this is the n preceding and n subsequent words in that document, i.e. words $w_{i-n} \dots w_{i-1}$ and $w_{i+1} \dots w_{i+n}$. We build a *co-occurrence matrix* M, which is a symmetric word-by-word matrix in which M_{ij} is the number of times w_j appears inside w_i's window among all documents.

Example: Co-Occurrence with Fixed Window of n=1:

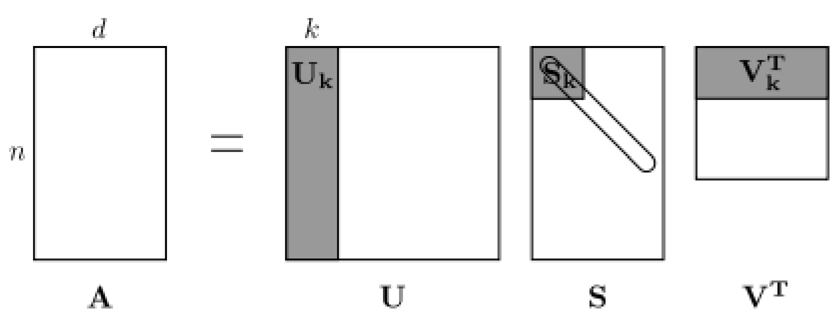
Document 1: "all that glitters is not gold"

Document 2: "all is well that ends well"

*	`<START>`	all	that	glitters	is	not	gold	well	ends	`<END>`
`<START>`	0	2	0	0	0	0	0	0	0	0
all	2	0	1	0	1	0	0	0	0	0
that	0	1	0	1	0	0	0	1	1	0
glitters	0	0	1	0	1	0	0	0	0	0
is	0	1	0	1	0	1	0	1	0	0
not	0	0	0	0	1	0	1	0	0	0
gold	0	0	0	0	0	1	0	0	0	1
well	0	0	1	0	1	0	0	0	1	1
ends	0	0	1	0	0	0	0	1	0	0
`<END>`	0	0	0	0	0	0	1	1	0	0

Note: In NLP, we often add `<START>` and `<END>` tokens to represent the beginning and end of sentences, paragraphs or documents. In this case we imagine `<START>` and `<END>` tokens encapsulating each document, e.g., " `<START>` All that glitters is not gold `<END>` ", and include these tokens in our co-occurrence counts.

The rows (or columns) of this matrix provide one type of word vectors (those based on word-word co-occurrence), but the vectors will be large in general (linear in the number of distinct words in a corpus). Thus, our next step is to run *dimensionality reduction*. In particular, we will run *SVD (Singular Value Decomposition)*, which is a kind of generalized *PCA (Principal Components Analysis)* to select the top k principal components. Here's a visualization of dimensionality reduction with SVD. In this picture our co-occurrence matrix is A with n rows corresponding to n words. We obtain a full matrix decomposition, with the singular values ordered in the diagonal S matrix, and our new, shorter length-k word vectors in U_k.



This reduced-dimensionality co-occurrence representation preserves semantic relationships between words, e.g. *doctor* and *hospital* will be closer than *doctor* and *dog*.

Notes: If you can barely remember what an eigenvalue is, here's a slow, friendly introduction to SVD. If you want to learn more thoroughly about PCA or SVD, feel free to check out lectures 7, 8, and 9 of CS168. These course notes provide a great high-level treatment of these general purpose algorithms. Though, for the purpose of this class, you only need to know how to extract the k-dimensional embeddings by utilizing pre-programmed implementations of these algorithms from the numpy, scipy, or sklearn python packages. In practice, it is challenging to apply full SVD to large corpora because of the memory needed to perform PCA or SVD. However, if you only want the top k vector components for relatively small k — known as Truncated SVD — then there are reasonably scalable techniques to compute those iteratively.

Plotting Co-Occurrence Word Embeddings

Here, we will be using the Reuters (business and financial news) corpus. If you haven't run the import cell at the top of this page, please run it now (click it and press SHIFT-RETURN). The corpus consists of 10,788 news documents totaling 1.3 million words. These documents span 90 categories and are split into train and test. For more details, please see https://www.nltk.org/book/ch02.html. We provide a `read_corpus` function below that pulls out only articles from the "gold" (i.e. news articles about gold, mining, etc.) category. The function also adds `<START>` and `<END>` tokens to each of the documents, and lowercases words. You do **not** have to perform any other kind of pre-processing.

In [ ]:
```
def read_corpus(category="gold"):
    """ Read files from the specified Reuter's category.
        Params:
            category (string): category name
        Return:
            list of lists, with words from each of the processed files
    """
    files = reuters.fileids(category)
    return [[START_TOKEN] + [w.lower() for w in list(reuters.words(f))] + [END_
```

Let's have a look what these documents are like….

In [ ]:
```
reuters_corpus = read_corpus()
pprint.pprint(reuters_corpus[:3], compact=True, width=100)
```

```
[['<START>', 'western', 'mining', 'to', 'open', 'new', 'gold', 'mine', 'in',
'australia', 'western',
  'mining', 'corp', 'holdings', 'ltd', '&', 'lt', ';', 'wmng', '.', 's', '>',
'(', 'wmc', ')',
  'said', 'it', 'will', 'establish', 'a', 'new', 'joint', 'venture', 'gold',
'mine', 'in', 'the',
  'northern', 'territory', 'at', 'a', 'cost', 'of', 'about', '21', 'mln', 'dlr
s', '.', 'the',
  'mine', ',', 'to', 'be', 'known', 'as', 'the', 'goodall', 'project', ',', 'w
ill', 'be', 'owned',
  '60', 'pct', 'by', 'wmc', 'and', '40', 'pct', 'by', 'a', 'local', 'w', '.',
'r', '.', 'grace',
  'and', 'co', '&', 'lt', ';', 'gra', '>', 'unit', '.', 'it', 'is', 'located',
'30', 'kms', 'east',
  'of', 'the', 'adelaide', 'river', 'at', 'mt', '.', 'bundey', ',', 'wmc', 'sa
id', 'in', 'a',
  'statement', 'it', 'said', 'the', 'open', '-', 'pit', 'mine', ',', 'with',
'a', 'conventional',
  'leach', 'treatment', 'plant', ',', 'is', 'expected', 'to', 'produce', 'abou
t', '50', ',', '000',
  'ounces', 'of', 'gold', 'in', 'its', 'first', 'year', 'of', 'production', 'f
rom', 'mid', '-',
  '1988', '.', 'annual', 'ore', 'capacity', 'will', 'be', 'about', '750', ',',
'000', 'tonnes', '.',
  '<END>'],
 ['<START>', 'belgium', 'to', 'issue', 'gold', 'warrants', ',', 'sources', 'sa
y', 'belgium',
  'plans', 'to', 'issue', 'swiss', 'franc', 'warrants', 'to', 'buy', 'gold',
',', 'with', 'credit',
  'suisse', 'as', 'lead', 'manager', ',', 'market', 'sources', 'said', '.', 'n
o', 'confirmation',
  'or', 'further', 'details', 'were', 'immediately', 'available', '.', '<END
>'],
 ['<START>', 'belgium', 'launches', 'bonds', 'with', 'gold', 'warrants', 'th
e', 'kingdom', 'of',
  'belgium', 'is', 'launching', '100', 'mln', 'swiss', 'francs', 'of', 'seve
n', 'year', 'notes',
  'with', 'warrants', 'attached', 'to', 'buy', 'gold', ',', 'lead', 'manange
r', 'credit', 'suisse',
  'said', '.', 'the', 'notes', 'themselves', 'have', 'a', '3', '-', '3', '/',
'8', 'pct', 'coupon',
  'and', 'are', 'priced', 'at', 'par', '.', 'payment', 'is', 'due', 'april',
'30', ',', '1987',
  'and', 'final', 'maturity', 'april', '30', ',', '1994', '.', 'each', '50',
',', '000', 'franc',
  'note', 'carries', '15', 'warrants', '.', 'two', 'warrants', 'are', 'require
d', 'to', 'allow',
  'the', 'holder', 'to', 'buy', '100', 'grammes', 'of', 'gold', 'at', 'a', 'pr
ice', 'of', '2', ',',
  '450', 'francs', ',', 'during', 'the', 'entire', 'life', 'of', 'the', 'bon
d', '.', 'the',
  'latest', 'gold', 'price', 'in', 'zurich', 'was', '2', ',', '045', '/', '2',
',', '070', 'francs',
  'per', '100', 'grammes', '.', '<END>']]
```

Question 1.1: Implement `distinct_words` [code] (2 points)

Write a method to work out the distinct words (word types) that occur in the corpus. You can do this with `for` loops, but it's more efficient to do it with Python list comprehensions. In particular, this may be useful to flatten a list of lists. If you're not familiar with Python list comprehensions in general, here's more information.

Your returned `corpus_words` should be sorted. You can use python's `sorted` function for this.

You may find it useful to use Python sets to remove duplicate words.

In [ ]:
```
def distinct_words(corpus):
    """ Determine a list of distinct words for the corpus.
        Params:
            corpus (list of list of strings): corpus of documents
        Return:
            corpus_words (list of strings): sorted list of distinct words acro
            n_corpus_words (integer): number of distinct words across the corp
    """


    corpus_words = []
    n_corpus_words = 0

    ### SOLUTION BEGIN

    for sentence in corpus :
        for string in sentence :
            if string not in corpus_words :
                corpus_words.append(string)
                n_corpus_words += 1

    corpus_words.sort()

    ### SOLUTION END

    return corpus_words, n_corpus_words
```

In [ ]:
```
# ---------------------
# Run this sanity check
# Note that this not an exhaustive check for correctness.
# ---------------------

# Define toy corpus
test_corpus = ["{} All that glitters isn't gold {}".format(START_TOKEN, END_TO
test_corpus_words, num_corpus_words = distinct_words(test_corpus)

# Correct answers
ans_test_corpus_words = sorted([START_TOKEN, "All", "ends", "that", "gold", "A
ans_num_corpus_words = len(ans_test_corpus_words)

# Test correct number of words
assert(num_corpus_words == ans_num_corpus_words), "Incorrect number of distinc

# Test correct words
assert (test_corpus_words == ans_test_corpus_words), "Incorrect corpus_words.\

# Print Success
```

```
print ("-" * 80)
print("Passed All Tests!")
print ("-" * 80)
```

```
--------------------------------------------------------------------------------
Passed All Tests!
--------------------------------------------------------------------------------
```

Question 1.2: Implement `compute_co_occurrence_matrix` [code] (3 points)

Write a method that constructs a co-occurrence matrix for a certain window-size n (with a default of 4), considering words n before and n after the word in the center of the window. Here, we start to use `numpy (np)` to represent vectors, matrices, and tensors. If you're not familiar with NumPy, there's a NumPy tutorial in the second half of this cs231n Python NumPy tutorial.

In [ ]:

```
def compute_co_occurrence_matrix(corpus, window_size=4):
    """ Compute co-occurrence matrix for the given corpus and window_size (def

        Note: Each word in a document should be at the center of a window. Wor
              number of co-occurring words.

              For example, if we take the document "<START> All that glitters
              "All" will co-occur with "<START>", "that", "glitters", "is", an

        Params:
            corpus (list of list of strings): corpus of documents
            window_size (int): size of context window
        Return:
            M (a symmetric numpy matrix of shape (number of unique words in th
                Co-occurence matrix of word counts.
                The ordering of the words in the rows/columns should be the sa
            word2ind (dict): dictionary that maps word to index (i.e. row/colu
    """
    words, n_words = distinct_words(corpus)

    M = np.zeros((n_words,n_words))

    word2ind = {}

    ### SOLUTION BEGIN

    #create word2ind :
    for i,word in enumerate(words) :
            word2ind[word] = i
    # fill M :
    for sentence in corpus :
        for i in range(len(sentence)) :

            # n words before :
            if len(sentence[:i]) >= window_size :
                for j in range(i-window_size,i) :
                    M[word2ind[sentence[i]],word2ind[sentence[j]]] += 1
            else :
```

```
                for j in range(i) :
                    M[word2ind[sentence[i]],word2ind[sentence[j]]] += 1

            # n words after :
            if len(sentence[i+1:]) >= window_size :
                for j in range(i+1,i+1+window_size) :
                    M[word2ind[sentence[i]],word2ind[sentence[j]]] += 1
            else :
                for j in range(i+1,len(sentence)) :
                    M[word2ind[sentence[i]],word2ind[sentence[j]]] += 1


    ### SOLUTION END

    return M, word2ind
```

In [ ]:

```
# ---------------------
# Run this sanity check
# Note that this is not an exhaustive check for correctness.
# ---------------------

# Define toy corpus and get student's co-occurrence matrix
test_corpus = ["{} All that glitters isn't gold {}".format(START_TOKEN, END_TO
M_test, word2ind_test = compute_co_occurrence_matrix(test_corpus, window_size=

# Correct M and word2ind
M_test_ans = np.array(
    [[0., 0., 0., 0., 0., 0., 1., 0., 0., 1.,],
     [0., 0., 1., 1., 0., 0., 0., 0., 0., 0.,],
     [0., 1., 0., 0., 0., 0., 0., 0., 1., 0.,],
     [0., 1., 0., 0., 0., 0., 0., 0., 0., 1.,],
     [0., 0., 0., 0., 0., 0., 0., 0., 1., 1.,],
     [0., 0., 0., 0., 0., 0., 0., 1., 1., 0.,],
     [1., 0., 0., 0., 0., 0., 0., 1., 0., 0.,],
     [0., 0., 0., 0., 0., 1., 1., 0., 0., 0.,],
     [0., 0., 1., 0., 1., 1., 0., 0., 0., 1.,],
     [1., 0., 0., 1., 1., 0., 0., 0., 1., 0.,]]
)
ans_test_corpus_words = sorted([START_TOKEN, "All", "ends", "that", "gold", "A
word2ind_ans = dict(zip(ans_test_corpus_words, range(len(ans_test_corpus_words

# Test correct word2ind
assert (word2ind_ans == word2ind_test), "Your word2ind is incorrect:\nCorrect:

# Test correct M shape
assert (M_test.shape == M_test_ans.shape), "M matrix has incorrect shape.\nCor

# Test correct M values
for w1 in word2ind_ans.keys():
    idx1 = word2ind_ans[w1]
    for w2 in word2ind_ans.keys():
        idx2 = word2ind_ans[w2]
        student = M_test[idx1, idx2]
        correct = M_test_ans[idx1, idx2]
        if student != correct:
            print("Correct M:")
            print(M_test_ans)
            print("Your M: ")
            print(M_test)
```

```
            raise AssertionError("Incorrect count at index ({}, {})=({}, {}) i

# Print Success
print ("-" * 80)
print("Passed All Tests!")
print ("-" * 80)
```

```
--------------------------------------------------------------------------------
--
Passed All Tests!
--------------------------------------------------------------------------------
--
```

Question 1.3: Implement `reduce_to_k_dim` [code] (1 point)

Construct a method that performs dimensionality reduction on the matrix to produce k-dimensional embeddings. Use SVD to take the top k components and produce a new matrix of k-dimensional embeddings.

Note: All of numpy, scipy, and scikit-learn (`sklearn`) provide *some* implementation of SVD, but only scipy and sklearn provide an implementation of Truncated SVD, and only sklearn provides an efficient randomized algorithm for calculating large-scale Truncated SVD. So please use sklearn.decomposition.TruncatedSVD.

In [ ]:
```
def reduce_to_k_dim(M, k=2):
    """ Reduce a co-occurence count matrix of dimensionality (num_corpus_words
        to a matrix of dimensionality (num_corpus_words, k) using the followin
            - http://scikit-learn.org/stable/modules/generated/sklearn.decompo

        Params:
            M (numpy matrix of shape (number of unique words in the corpus , n
            k (int): embedding size of each word after dimension reduction
        Return:
            M_reduced (numpy matrix of shape (number of corpus words, k)): mat
                    In terms of the SVD from math class, this actually returns
    """
    n_iters = 10     # Use this parameter in your call to `TruncatedSVD`
    M_reduced = None
    print("Running Truncated SVD over %i words..." % (M.shape[0]))

    ### SOLUTION BEGIN
    svd =  TruncatedSVD(n_components=k, n_iter=n_iters)
    M_reduced = svd.fit_transform(M)
    ### SOLUTION END

    print("Done.")
    return M_reduced
```

In [ ]:
```
# ---------------------
# Run this sanity check
# Note that this is not an exhaustive check for correctness
# In fact we only check that your M_reduced has the right dimensions.
# ---------------------

# Define toy corpus and run student code
test_corpus = ["{} All that glitters isn't gold {}".format(START_TOKEN, END_TO
```

```
M_test, word2ind_test = compute_co_occurrence_matrix(test_corpus, window_size=
M_test_reduced = reduce_to_k_dim(M_test, k=2)

# Test proper dimensions
assert (M_test_reduced.shape[0] == 10), "M_reduced has {} rows; should have {}
assert (M_test_reduced.shape[1] == 2), "M_reduced has {} columns; should have

# Print Success
print ("-" * 80)
print("Passed All Tests!")
print ("-" * 80)
```

```
Running Truncated SVD over 10 words...
Done.
------------------------------------------------------------------------------
--
Passed All Tests!
------------------------------------------------------------------------------
--
```

Question 1.4: Implement `plot_embeddings` [code] (1 point)

Here you will write a function to plot a set of 2D vectors in 2D space. For graphs, we will use Matplotlib (`plt`).

For this example, you may find it useful to adapt this code. In the future, a good way to make a plot is to look at the Matplotlib gallery, find a plot that looks somewhat like what you want, and adapt the code they give.

In [ ]:

```
def plot_embeddings(M_reduced, word2ind, words):
    """ Plot in a scatterplot the embeddings of the words specified in the lis
        NOTE: do not plot all the words listed in M_reduced / word2ind.
        Include a label next to each point.

        Params:
            M_reduced (numpy matrix of shape (number of unique words in the co
            word2ind (dict): dictionary that maps word to indices for matrix M
            words (list of strings): words whose embeddings we want to visuali
    """

    ### SOLUTION BEGIN
    for word in words :
        x , y = M_reduced[word2ind[word]]
        plt.scatter(x, y, marker='x', color ='red')
        plt.text(x + 0.00003, y + 0.00003, word, fontsize=9)
    plt.show()
    ### SOLUTION END
```

In [ ]:

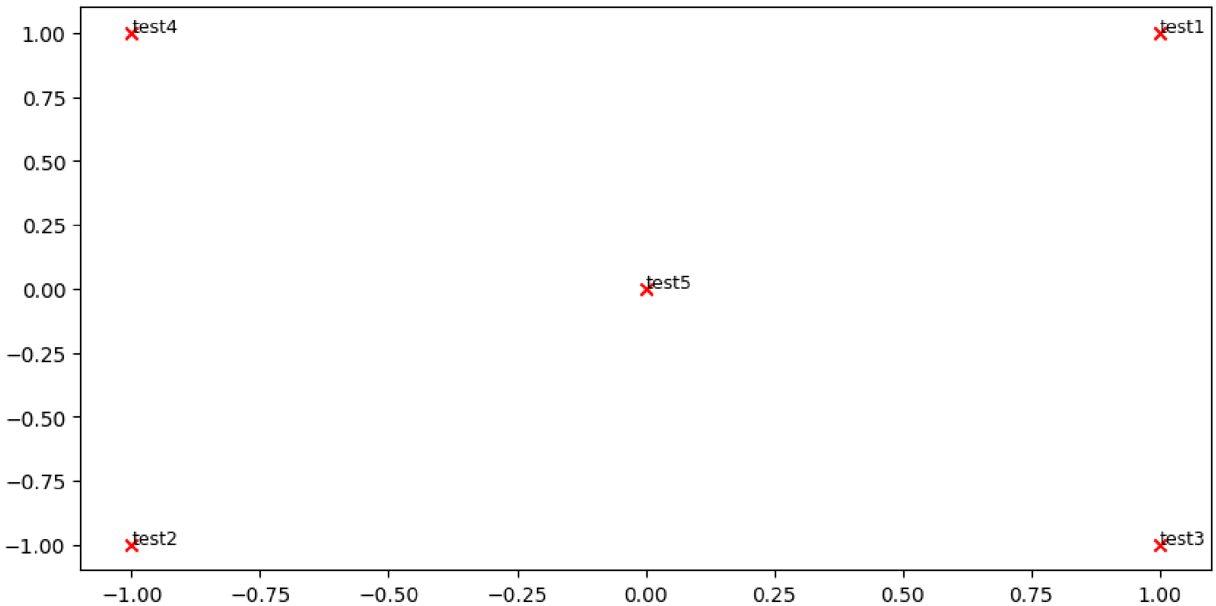
```
# ---------------------
# Run this sanity check
# Note that this is not an exhaustive check for correctness.
# The plot produced should look like the "test solution plot" depicted below.
# ---------------------

print ("-" * 80)
print ("Outputted Plot:")
```

```
M_reduced_plot_test = np.array([[1, 1], [-1, -1], [1, -1], [-1, 1], [0, 0]])
word2ind_plot_test = {'test1': 0, 'test2': 1, 'test3': 2, 'test4': 3, 'test5':
words = ['test1', 'test2', 'test3', 'test4', 'test5']
plot_embeddings(M_reduced_plot_test, word2ind_plot_test, words)

print ("-" * 80)
```

```
--------------------------------------------------------------------------------
--
Outputted Plot:
```




```
--------------------------------------------------------------------------------
--
```

Question 1.5: Co-Occurrence Plot Analysis [written] (3 points)

Now we will put together all the parts you have written! We will compute the co-occurrence matrix with fixed window of 4 (the default window size), over the Reuters "gold" corpus. Then we will use TruncatedSVD to compute 2-dimensional embeddings of each word. TruncatedSVD returns U*S, so we need to normalize the returned vectors, so that all the vectors will appear around the unit circle (therefore closeness is directional closeness). **Note**: The line of code below that does the normalizing uses the NumPy concept of *broadcasting*. If you don't know about broadcasting, check out Computation on Arrays: Broadcasting by Jake VanderPlas.

Run the below cell to produce the plot. It'll probably take a few seconds to run.

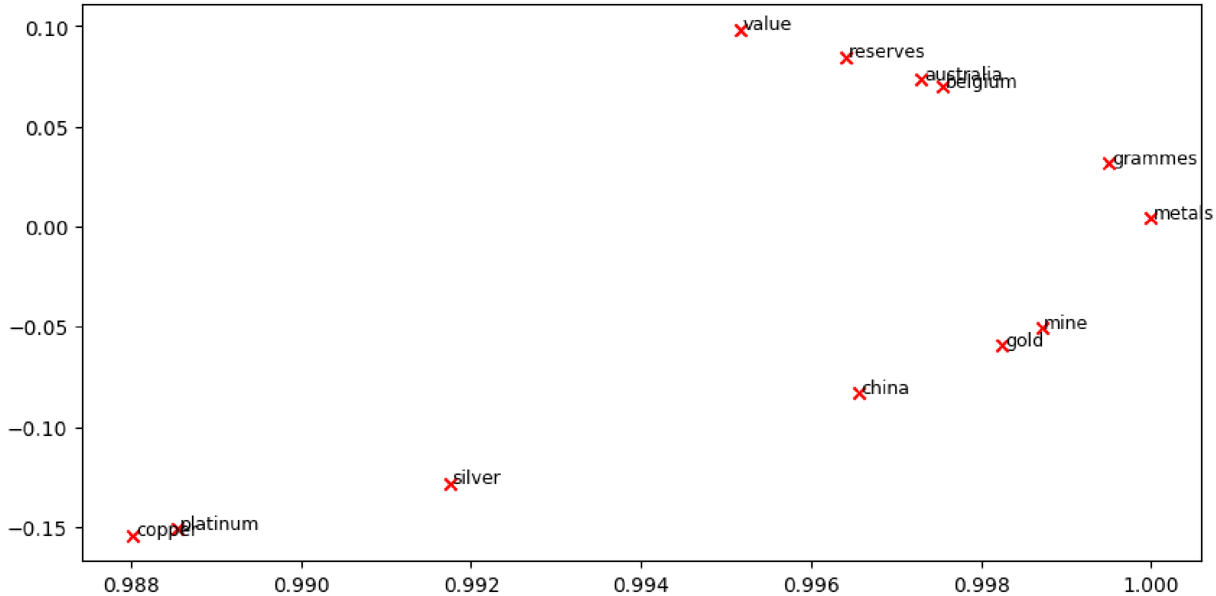
In [ ]:
```
# ------------------------------
# Run This Cell to Produce Your Plot
# ------------------------------
reuters_corpus = read_corpus()
M_co_occurrence, word2ind_co_occurrence = compute_co_occurrence_matrix(reuters_
M_reduced_co_occurrence = reduce_to_k_dim(M_co_occurrence, k=2)

# Rescale (normalize) the rows to make them each of unit-length
M_lengths = np.linalg.norm(M_reduced_co_occurrence, axis=1)
M_normalized = M_reduced_co_occurrence / M_lengths[:, np.newaxis] # broadcasti

words = ['value', 'gold', 'platinum', 'reserves', 'silver', 'metals', 'copper'
```

```
plot_embeddings(M_normalized, word2ind_co_occurrence, words)
```

```
Running Truncated SVD over 2830 words...
Done.
```



Verify that your figure matches "question_1.5.png" in the assignment zip. If not, use that figure to answer the next two questions.

Answer : They are same.

a. Find at least two groups of words that cluster together in 2-dimensional embedding space. Give an explanation for each cluster you observe.

SOLUTION BEGIN

First group that cluster together is australia and belgium. They are name of countries so they place near each other.

Seccond group is copper and platinum. They are some type of materials so they come together.

SOLUTION END

b. What doesn't cluster together that you might think should have? Describe at least two examples.

SOLUTION BEGIN

I think word 'china' should come with the first cluster that I wrote in the last part because all together are name of some countries.

And word 'metal' should place near seccond cluster because it's type of materials too!

SOLUTION END

Part 2: Prediction-Based Word Vectors (15 points)

As discussed in class, more recently prediction-based word vectors have demonstrated better performance, such as word2vec and GloVe (which also utilizes the benefit of counts). Here, we shall explore the embeddings produced by GloVe. Please revisit the class notes and lecture slides for more details on the word2vec and GloVe algorithms. If you're feeling adventurous, challenge yourself and try reading GloVe's original paper.

Then run the following cells to load the GloVe vectors into memory. **Note**: If this is your first time to run these cells, i.e. download the embedding model, it will take a couple minutes to run. If you've run these cells before, rerunning them will load the model without redownloading it, which will take about 1 to 2 minutes.

In [ ]:
```
def load_embedding_model():
    """ Load GloVe Vectors
        Return:
            wv_from_bin: All 400000 embeddings, each lengh 200
    """
    import gensim.downloader as api
    wv_from_bin = api.load("glove-wiki-gigaword-200")
    print("Loaded vocab size %i" % len(list(wv_from_bin.index_to_key)))
    return wv_from_bin
```

In [ ]:
```
# -----------------------------------
# Run Cell to Load Word Vectors
# Note: This will take a couple minutes
# -----------------------------------
wv_from_bin = load_embedding_model()
```

```
Loaded vocab size 400000
```

Note: If you are receiving a "reset by peer" error, rerun the cell to restart the download. If you run into an "attribute" error, you may need to update to the most recent version of gensim and numpy. You can upgrade them inline by uncommenting and running the below cell:

In [ ]:
```
#!pip install gensim --upgrade
#!pip install numpy --upgrade
```

Reducing dimensionality of Word Embeddings

Let's directly compare the GloVe embeddings to those of the co-occurrence matrix. In order to avoid running out of memory, we will work with a sample of 10000 GloVe vectors instead. Run the following cells to:

1. Put 10000 Glove vectors into a matrix M
2. Run `reduce_to_k_dim` (your Truncated SVD function) to reduce the vectors from 200-dimensional to 2-dimensional.

In [ ]:
```
def get_matrix_of_vectors(wv_from_bin, required_words):
    """ Put the GloVe vectors into a matrix M.
        Param:
            wv_from_bin: KeyedVectors object; the 400000 GloVe vectors loaded
        Return:
            M: numpy matrix shape (num words, 200) containing the vectors
            word2ind: dictionary mapping each word to its row number in M
    """
    import random
    words = list(wv_from_bin.index_to_key)
    print("Shuffling words ...")
    random.seed(225)
    random.shuffle(words)
    words = words[:10000]
    print("Putting %i words into word2ind and matrix M..." % len(words))
    word2ind = {}
    M = []
    curInd = 0
    for w in words:
        try:
            M.append(wv_from_bin.get_vector(w))
            word2ind[w] = curInd
            curInd += 1
        except KeyError:
            continue
    for w in required_words:
        if w in words:
            continue
        try:
            M.append(wv_from_bin.get_vector(w))
            word2ind[w] = curInd
            curInd += 1
        except KeyError:
            continue
    M = np.stack(M)
    print("Done.")
    return M, word2ind
```

In [ ]:
```
# -----------------------------------------------------------------
# Run Cell to Reduce 200-Dimensional Word Embeddings to k Dimensions
# Note: This should be quick to run
# -----------------------------------------------------------------
M, word2ind = get_matrix_of_vectors(wv_from_bin, words)
M_reduced = reduce_to_k_dim(M, k=2)

# Rescale (normalize) the rows to make them each of unit-length
M_lengths = np.linalg.norm(M_reduced, axis=1)
M_reduced_normalized = M_reduced / M_lengths[:, np.newaxis] # broadcasting
```

```
Shuffling words ...
Putting 10000 words into word2ind and matrix M...
Done.
Running Truncated SVD over 10012 words...
Done.
```

Note: If you are receiving out of memory issues on your local machine, try closing other applications to free more memory on your device. You may want to try restarting your machine so that you can free up extra memory. Then immediately run the jupyter

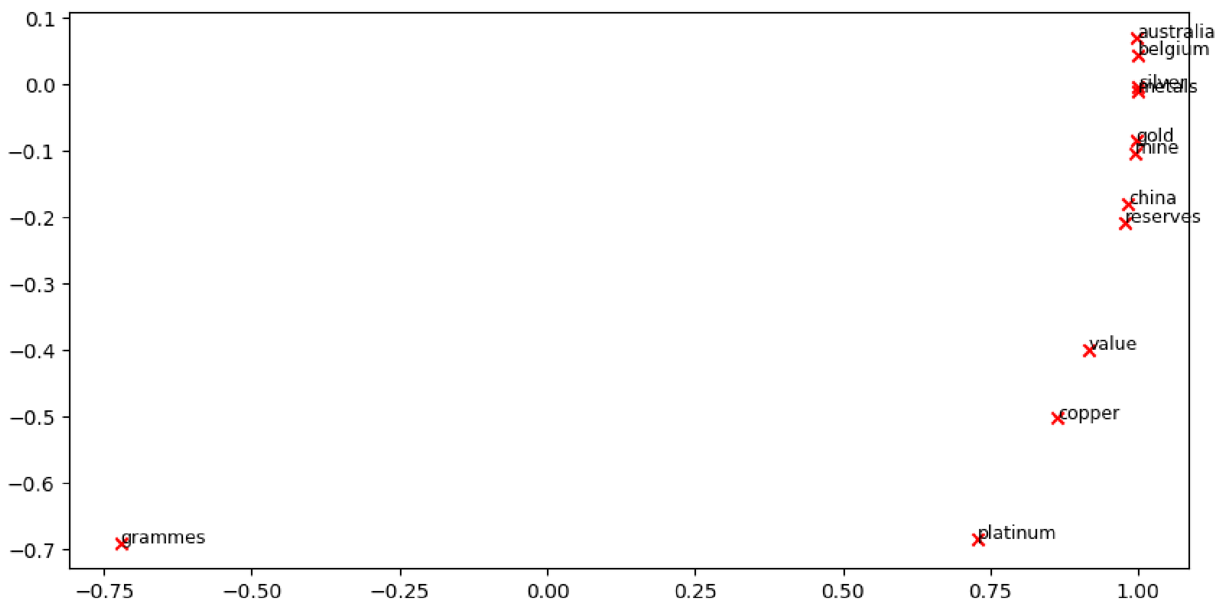
notebook and see if you can load the word vectors properly. If you still have problems with loading the embeddings onto your local machine after this, please go to office hours or contact course staff.

Question 2.1: GloVe Plot Analysis [written] (3 points)

Run the cell below to plot the 2D GloVe embeddings for `['value', 'gold', 'platinum', 'reserves', 'silver', 'metals', 'copper', 'belgium', 'australia', 'china', 'grammes', "mine"]`.

In [ ]:
```
words = ['value', 'gold', 'platinum', 'reserves', 'silver', 'metals', 'copper'

plot_embeddings(M_reduced_normalized, word2ind, words)
```



a. What is one way the plot is different from the one generated earlier from the co-occurrence matrix? What is one way it's similar?

SOLUTION BEGIN

Differences between new plot and old plot :

- gold and mine place closer to each other
- silver and metal place in one cluster
- reserve and china place in one cluster
- value and copper come closer to each other
- copper and platinum seperate from each other

Similarities :

- australia and belgium are in one cluster in both plots
- gold and mine are in one cluster in both plots

SOLUTION END

b. What is a possible cause for the difference?

SOLUTION BEGIN

Differences between two plot may come from the Glove and Word2vec approaches.

The two model differ in the way they are trained, Glove is based on global word to word co-occurance counts in corpus, Word2vec on the other hand is based on local co-occurance count in context.

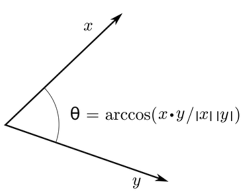
Differences can showed up in the input trained data which can be vary in models.

SOLUTION END

Cosine Similarity

Now that we have word vectors, we need a way to quantify the similarity between individual words, according to these vectors. One such metric is cosine-similarity. We will be using this to find words that are "close" and "far" from one another.

We can think of n-dimensional vectors as points in n-dimensional space. If we take this perspective L1 and L2 Distances help quantify the amount of space "we must travel" to get between these two points. Another approach is to examine the angle between two vectors. From trigonometry we know that:



Instead of computing the actual angle, we can leave the similarity in terms of $similarity = cos(\Theta)$. Formally the Cosine Similarity s between two vectors p and q is defined as:

$$s = \frac{p \cdot q}{||p||||q||}, \text{ where } s \in [-1, 1]$$

Question 2.2: Words with Multiple Meanings (1.5 points) [code + written]

Polysemes and homonyms are words that have more than one meaning (see this wiki page to learn more about the difference between polysemes and homonyms). Find a word with *at least two different meanings* such that the top-10 most similar words (according to cosine similarity) contain related words from *both* meanings. For example, "leaves" has both "go_away" and "a_structure_of_a_plant" meaning in the top 10, and "scoop" has both "handed_waffle_cone" and "lowdown". You will probably need to try several polysemous or homonymic words before you find one.

Please state the word you discover and the multiple meanings that occur in the top 10. Why do you think many of the polysemous or homonymic words you tried didn't work (i.e. the top-10 most similar words only contain **one** of the meanings of the words)?

Note: You should use the `wv_from_bin.most_similar(word)` function to get the top 10 similar words. This function ranks all other words in the vocabulary with respect to their cosine similarity to the given word. For further assistance, please check the **GenSim documentation**.

In [ ]:
```
### SOLUTION BEGIN

# try some polysemous words :

# not work :
# wv_from_bin.most_similar("bank")
# wv_from_bin.most_similar("right")

# work :
# Organ. Parts of an animal or plant body / Musical instrument / Publication s
wv_from_bin.most_similar("organ")

### SOLUTION END
```

Out[ ]:
```
[('organs', 0.7207354307174683),
 ('transplants', 0.5738605856895447),
 ('transplantation', 0.5395218729972839),
 ('harpsichord', 0.5341777205467224),
 ('transplant', 0.5284041166305542),
 ('farfisa', 0.519030749797821),
 ('piano', 0.5074425935745239),
 ('hammond', 0.5044703483581543),
 ('choir', 0.48512497544288635),
 ('donor', 0.48483821749687195)]
```

SOLUTION BEGIN

organ :

- Parts of and animal or plant body --> related result in code : transplant, donor
- Musical instrument --> related result in code : piano, choir

SOLUTION END

Question 2.3: Synonyms & Antonyms (2 points) [code + written]

When considering Cosine Similarity, it's often more convenient to think of Cosine Distance, which is simply 1 - Cosine Similarity.

Find three words (w_1, w_2, w_3) where w_1 and w_2 are synonyms and w_1 and w_3 are antonyms, but Cosine Distance $(w_1, w_3) <$ Cosine Distance (w_1, w_2).

As an example, w_1="happy" is closer to w_3="sad" than to w_2="cheerful". Please find a different example that satisfies the above. Once you have found your example, please give a possible explanation for why this counter-intuitive result may have happened.

You should use the the `wv_from_bin.distance(w1, w2)` function here in order to compute the cosine distance between two words. Please see the **GenSim documentation** for further assistance.

In [ ]:

```
### SOLUTION BEGIN

w1 = "up"
w2 = "skyward"
w3 = "down"
w1_w2_dist = wv_from_bin.distance(w1, w2)
w1_w3_dist = wv_from_bin.distance(w1, w3)

print("Synonyms {}, {} have cosine distance: {}".format(w1, w2, w1_w2_dist))
print("Antonyms {}, {} have cosine distance: {}".format(w1, w3, w1_w3_dist))

### SOLUTION END
```

```
Synonyms up, skyward have cosine distance: 0.8720088452100754
Antonyms up, down have cosine distance: 0.1540764570236206
```

SOLUTION BEGIN

up and skyward are synonyms but up and down are antonyms

Glove language model is based on word to word co-occurance in corpus, so this model was created based on word orders, thus we can undrestand that in trained data words 'up' and 'down' come together more than words 'up' and 'skyward'.

SOLUTION END

Question 2.4: Analogies with Word Vectors [written] (1.5 points)

Word vectors have been shown to *sometimes* exhibit the ability to solve analogies.

As an example, for the analogy "man : grandfather :: woman : x" (read: man is to grandfather as woman is to x), what is x?

In the cell below, we show you how to use word vectors to find x using the `most_similar` function from the **GenSim documentation**. The function finds words that are most similar to the words in the `positive` list and most dissimilar from the words in the `negative` list (while omitting the input words, which are often the most similar; see this paper). The answer to the analogy will have the highest cosine similarity (largest returned numerical value).

In [ ]:
```python
# Run this cell to answer the analogy -- man : grandfather :: woman : x
pprint.pprint(wv_from_bin.most_similar(positive=['woman', 'grandfather'], nega
```

```
[('grandmother', 0.7608445286750793),
 ('granddaughter', 0.7200808525085449),
 ('daughter', 0.7168302536010742),
 ('mother', 0.7151536345481873),
 ('niece', 0.7005682587623596),
 ('father', 0.6659887433052063),
 ('aunt', 0.6623408794403076),
 ('grandson', 0.6618767976760864),
 ('grandparents', 0.644661009311676),
 ('wife', 0.6445354223251343)]
```

Let m, g, w, and x denote the word vectors for `man`, `grandfather`, `woman`, and the answer, respectively. Using **only** vectors m, g, w, and the vector arithmetic operators $+$ and $-$ in your answer, to what expression are we maximizing x's cosine similarity?

Hint: Recall that word vectors are simply multi-dimensional vectors that represent a word. It might help to draw out a 2D example using arbitrary locations of each vector. Where would `man` and `woman` lie in the coordinate plane relative to `grandfather` and the answer?

SOLUTION BEGIN

Expression that we are looking for is :

$\vec{g}$ - $\vec{m}$ + $\vec{w}$

SOLUTION END

Question 2.5: Finding Analogies [code + written] (1.5 points)

a. For the previous example, it's clear that "grandmother" completes the analogy. But give an intuitive explanation as to why the `most_similar` function gives us words like "granddaughter", "daughter", or "mother?

SOLUTION BEGIN

Based on operation that we apply on word vectors ($\vec{g}$ - $\vec{m}$ + $\vec{w}$) we will have new word vector result.

This function checks which one of word vectors in our model have similarity to our result vector and sorts cosine similarity of result vector and word vectors that is we have words like granddaughter, daughter and mother.

SOLUTION END

b. Find an example of analogy that holds according to these vectors (i.e. the intended word is ranked top). In your solution please state the full analogy in the form x:y :: a:b. If you believe the analogy is complicated, explain why the analogy holds in one or two sentences.

Note: You may have to try many analogies to find one that works!

In [ ]:
```
### SOLUTION BEGIN

x, y, a, b = "blood","red","leaf","green"
pprint.pprint(wv_from_bin.most_similar(positive=['leaf', 'red'], negative=['bl
assert wv_from_bin.most_similar(positive=[a, y], negative=[x])[0][0] == b

### SOLUTION END
```

```
[('green', 0.5447114109992981),
 ('maple', 0.5445648431777954),
 ('yellow', 0.5257704257965088),
 ('purple', 0.5222172737121582),
 ('leaves', 0.48601871728897095),
 ('pink', 0.48207762837409973),
 ('bright', 0.4707401692867279),
 ('blue', 0.46545344591140747),
 ('foliage', 0.4518013894557953),
 ('flowers', 0.4393298029899597)]
```

SOLUTION BEGIN

"blood":"red" :: "leaf":"green"

Very simple and reasonable :)

SOLUTION END

Question 2.6: Incorrect Analogy [code + written] (1.5 points)

a. Below, we expect to see the intended analogy "hand : glove :: foot : **sock**", but we see an unexpected result instead. Give a potential reason as to why this particular analogy turned out the way it did?

In [ ]:
```
pprint.pprint(wv_from_bin.most_similar(positive=['foot', 'glove'], negative=['
print('Distance of glove and hand : ',wv_from_bin.distance("glove","hand"))
print('Distance of sock and foot : ',wv_from_bin.distance("sock","foot"))
```

```
[('45,000-square', 0.4922032654285431),
 ('15,000-square', 0.4649604558944702),
 ('10,000-square', 0.4544755816459656),
 ('6,000-square', 0.44975775480270386),
 ('3,500-square', 0.444133460521698),
 ('700-square', 0.44257497787475586),
 ('50,000-square', 0.4356396794319153),
 ('3,000-square', 0.43486514687538147),
 ('30,000-square', 0.4330596923828125),
 ('footed', 0.43236875534057617)]
Distance of glove and hand :  0.5721984207630157
Distance of sock and foot :  0.8045251071453094
```

SOLUTION BEGIN

As we discussed above, based on expression for analogy, in "x:y :: a:b" distance of x,y should be close to distance of x,y.

But here we can see that distance of glove and hand is 0.57 but distance of sock and foot is 0.8 .

SOLUTION END

b. Find another example of analogy that does *not* hold according to these vectors. In your solution, state the intended analogy in the form x:y :: a:b, and state the **incorrect** value of b according to the word vectors (in the previous example, this would be **'45,000-square'**).

In [ ]:
```
### SOLUTION BEGIN

x, y, a, b = "night",'moon',"day","sun"
pprint.pprint(wv_from_bin.most_similar(positive=[a, y], negative=[x]))

### SOLUTION END
```

```
[('lunar', 0.6050856113433838),
 ('earth', 0.5421481728553772),
 ('mars', 0.4833245575428009),
 ('orbit', 0.4800480306148529),
 ('mission', 0.4493253231048584),
 ('ki', 0.4363073408603668),
 ('planet', 0.4314604699611664),
 ('space', 0.425001859664917),
 ('spacecraft', 0.4217359721660614),
 ('year', 0.41972920298576355)]
```

SOLUTION BEGIN

"night":"moon" :: "day":"sun"

Incorrect answer : lunar

SOLUTION END

Question 2.7: Guided Analysis of Bias in Word Vectors [written] (1 point)

It's important to be cognizant of the biases (gender, race, sexual orientation etc.) implicit in our word embeddings. Bias can be dangerous because it can reinforce stereotypes through applications that employ these models.

Run the cell below, to examine (a) which terms are most similar to "woman" and "profession" and most dissimilar to "man", and (b) which terms are most similar to "man" and "profession" and most dissimilar to "woman". Point out the difference between the list of female-associated words and the list of male-associated words, and explain how it is reflecting gender bias.

In [ ]:
```
# Run this cell
# Here `positive` indicates the list of words to be similar to and `negative`
# most dissimilar from.

pprint.pprint(wv_from_bin.most_similar(positive=['man', 'profession'], negativ
print()
pprint.pprint(wv_from_bin.most_similar(positive=['woman', 'profession'], negat
```

```
[('reputation', 0.5250176787376404),
 ('professions', 0.5178037881851196),
 ('skill', 0.49046966433525085),
 ('skills', 0.49005505442619324),
 ('ethic', 0.4897659420967102),
 ('business', 0.4875852167606354),
 ('respected', 0.485920250415802),
 ('practice', 0.482104629278183),
 ('regarded', 0.4778572618961334),
 ('life', 0.4760662019252777)]

[('professions', 0.5957457423210144),
 ('practitioner', 0.49884122610092163),
 ('teaching', 0.48292139172554016),
 ('nursing', 0.48211804032325745),
 ('vocation', 0.4788965880870819),
 ('teacher', 0.47160351276397705),
 ('practicing', 0.46937814354896545),
 ('educator', 0.46524327993392944),
 ('physicians', 0.4628995358943939),
 ('professionals', 0.4601394236087799)]
```

SOLUTION BEGIN

terms that most similar to "man" and "profession" and most dissimilar to "woman" : reputation, professions, skill, skills, ethic, business, respected, practice, regarded, life

terms that most similar to "woman" and "profession" and most dissimilar to "man" : proffesions, practitioner, teaching, nursing, vocation, teacher, practicing, educator, physicians, professionals

I think we have some problem here : for example in first part we should find some words that they are dissimilar to woman and in result we have business or ethic, so it is not logical. in seccond part we should find some words that they are dissimilar to man and in result we have physicians and nursing and professionals and ...

SOLUTION END

Question 2.8: Independent Analysis of Bias in Word Vectors [code + written] (1 point)

Use the `most_similar` function to find another pair of analogies that demonstrates some bias is exhibited by the vectors. Please briefly explain the example of bias that you discover.

In [ ]:
```
### SOLUTION BEGIN

A = "employee"
B = "boss"
word = "human"
pprint.pprint(wv_from_bin.most_similar(positive=[A, word], negative=[B]))
print()
pprint.pprint(wv_from_bin.most_similar(positive=[B, word], negative=[A]))

### SOLUTION END
```

```
[('rights', 0.5513030886650085),
 ('health', 0.5299429893493652),
 ('benefits', 0.5256038904190063),
 ('worker', 0.5173819661140442),
 ('protection', 0.5044413208961487),
 ('advocacy', 0.4904358983039856),
 ('employees', 0.48964157700538635),
 ('environmental', 0.47820088267326355),
 ('instance', 0.4780602753162384),
 ('individuals', 0.47757136821746826)]

[('beings', 0.48171186447143555),
 ('humans', 0.4398159086704254),
 ('evil', 0.42939507961273193),
 ('humanity', 0.4116694927215576),
 ('ruthless', 0.40059614181518555),
 ('mafia', 0.3978475034236908),
 ('condemned', 0.3933451473712921),
 ('rights', 0.38657522201538086),
 ('dangerous', 0.3862508237361908),
 ('creatures', 0.3832699954509735)]
```

SOLUTION BEGIN

In my example in first part we have words that are similar to employee and human and dissimilar to boss and result contains some words like : rights, health, protection and it is reasonable.

But in seccond part we have words that are similar to boss and human and dissimilar to employee and result contains some words like evil, mafia, dangerous and ... thats not reasonable and we have bias in word vectors.

SOLUTION END

Question 2.9: Thinking About Bias [written] (2 points)

a. Give one explanation of how bias gets into the word vectors. Briefly describe a real-world example that demonstrates this source of bias.

SOLUTION BEGIN

The main source of bias in word vectors is the input dataset (trained data) itself.

For explaining a real-world embedding words which has bias, I refer to this blog.

Based on complete german wikipedia they trained set of word embeddings and another set based on facebook and twitter.Content relating to the six main political parties in Germany.

The training is done using GloVe.

for knowing whether a word embedding for a concept C has a gender bias. We can take the cosine distance between C and 'Man' and subtract the cosine distance between C and 'Woman'.

A non-zero result reveals bias in one direction or the other, and the magnitude of the result tells us the amount of the bias.

The results show that the trained vectors are more likely to associated women with professions such as nursing and secretarial work, whereas men are associated with roles such as policemen and commanders. Germans are linked to positive sentiments such as charm and passion, cooperation and union, while foreigners are generally linked to concepts such as immigration, law, and crime. Homosexuals are related to roles such as hairdresser or artist, and heterosexuals to blue collar professions and science. Homosexuality was associated with negative sentiments, and heterosexuality with positive ones.

Another example of real-world that show bias is : (refer to this blog)

As an example, suppose the search query is "cmu computer science phd student" for a computer science Ph.D. student at Carnegie Mellon University. Now, the directory offers 127 nearly identical web pages for students — these pages differ only in the names of the students... However, word embeddings also rank terms related to computer science closer to male names than female names…The consequence is that, between two pages that differ only in the names Mary and John, the word embedding would influence the search engine to rank John's web page higher than Mary.

SOLUTION END

b. What is one method you can use to mitigate bias exhibited by word vectors? Briefly describe a real-world example that demonstrates this method.

SOLUTION BEGIN

based on this article and this blog for debiasing gender bias we can say that :

First, the subspace of this gender embedding was captured. This is done by taking the difference of some pre-known sets that define the concept of gender itself.

SVD was performed on a subset of such opposite gender pairs, to finally obtain the direction or subspace of this bias. This smoothing is done to negate the effect of different meanings of some terms, like “man”.

In this case for mitigating bias we can use soft biasing :

The vectors lying in this subspace (the gender-neutral terms) are “neutralized” such that they remain equidistant from equality pairs like “he-she”. Technically, what happens is that the projection of the embedding on the bias direction is subtracted from the vector

but in soft biasing we only "soften" the effect of gender bias on the embeddings based on a parameter.

SOLUTION END

Submission Instructions

1. Click the Save button at the top of the Jupyter Notebook.
2. Select Cell -> All Output -> Clear. This will clear all the outputs from all cells (but will keep the content of all cells).
3. Select Cell -> Run All. This will run all the cells in order, and will take several minutes.
4. Once you've rerun everything, select File -> Download as -> PDF via LaTeX (If you have trouble using "PDF via LaTex", you can also save the webpage as pdf. Make sure all your solutions especially the coding parts are displayed in the pdf, it's okay if the provided codes get cut off because lines are not wrapped in code cells).
5. Look at the PDF file and make sure all your solutions are there, displayed correctly. The PDF is the only thing your graders will see!
6. Submit your PDF on Gradescope.