1 CS224N Assignment 1: Exploring Word Vectors (25 Points)

1.0.1 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.

[26]:
```
# 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␣
 ↪version following the instructions in \
    the README.txt file found in the same directory as this notebook. Your␣
 ↪Python version is " + python_version()

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␣
 ↪argument: download_dir='/specify/desired/path/'
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
[nltk_data]     C:\Users\ad2we\AppData\Roaming\nltk_data...
[nltk_data]   Package reuters is already up-to-date!
```

1.1 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*".

1.2 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).

1.2.1 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:

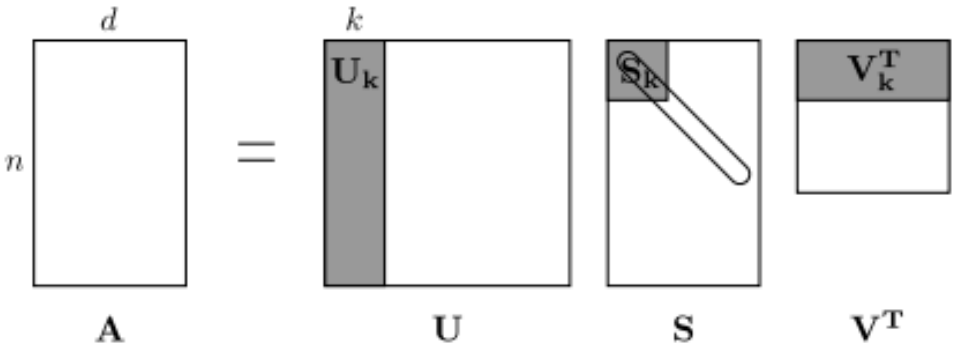
Document 1: "all that glitters is not gold"

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.

1.2.2 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.

[27]:
```
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_TOKEN] for f in files]
```

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

[28]:
```
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',
'dlrs', '.', 'the',
  'mine', ',', 'to', 'be', 'known', 'as', 'the', 'goodall', 'project', ',',
'will', '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',
'said', 'in', 'a',
  'statement', 'it', 'said', 'the', 'open', '-', 'pit', 'mine', ',', 'with',
'a', 'conventional',
```

```
  'leach', 'treatment', 'plant', ',', 'is', 'expected', 'to', 'produce',
'about', '50', ',', '000',
  'ounces', 'of', 'gold', 'in', 'its', 'first', 'year', 'of', 'production',
'from', 'mid', '-',
  '1988', '.', 'annual', 'ore', 'capacity', 'will', 'be', 'about', '750', ',',
'000', 'tonnes', '.',
  '<END>'],
 ['<START>', 'belgium', 'to', 'issue', 'gold', 'warrants', ',', 'sources',
'say', 'belgium',
  'plans', 'to', 'issue', 'swiss', 'franc', 'warrants', 'to', 'buy', 'gold',
',', 'with', 'credit',
  'suisse', 'as', 'lead', 'manager', ',', 'market', 'sources', 'said', '.',
'no', 'confirmation',
  'or', 'further', 'details', 'were', 'immediately', 'available', '.', '<END>'],
 ['<START>', 'belgium', 'launches', 'bonds', 'with', 'gold', 'warrants', 'the',
'kingdom', 'of',
  'belgium', 'is', 'launching', '100', 'mln', 'swiss', 'francs', 'of', 'seven',
'year', 'notes',
  'with', 'warrants', 'attached', 'to', 'buy', 'gold', ',', 'lead', 'mananger',
'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',
'required', 'to', 'allow',
  'the', 'holder', 'to', 'buy', '100', 'grammes', 'of', 'gold', 'at', 'a',
'price', 'of', '2', ',',
  '450', 'francs', ',', 'during', 'the', 'entire', 'life', 'of', 'the', 'bond',
'.', 'the',
  'latest', 'gold', 'price', 'in', 'zurich', 'was', '2', ',', '045', '/', '2',
',', '070', 'francs',
  'per', '100', 'grammes', '.', '<END>']]
```

1.2.3 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.

[29]:
```
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 across␣
 ↪the corpus
            n_corpus_words (integer): number of distinct words across the corpus
    """
    corpus_words = []
    n_corpus_words = -1

    ### SOLUTION BEGIN

    corpus_words = sorted(set([word for doc in corpus for word in doc]))
    n_corpus_words = len(corpus_words)

    ### SOLUTION END

    return corpus_words, n_corpus_words
```

[30]:
```
# ---------------------
# 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_TOKEN).split(" "), "{} All's well that ends well {}".format(START_TOKEN,␣
 ↪END_TOKEN).split(" ")]
test_corpus_words, num_corpus_words = distinct_words(test_corpus)

# Correct answers
ans_test_corpus_words = sorted([START_TOKEN, "All", "ends", "that", "gold",␣
 ↪"All's", "glitters", "isn't", "well", END_TOKEN])
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 distinct␣
 ↪words. Correct: {}. Yours: {}".format(ans_num_corpus_words, num_corpus_words)

# Test correct words
assert (test_corpus_words == ans_test_corpus_words), "Incorrect corpus_words.
 ↪\nCorrect: {}\nYours:   {}".format(str(ans_test_corpus_words),␣
 ↪str(test_corpus_words))

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

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

1.2.4 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.

[31]:
```
def compute_co_occurrence_matrix(corpus, window_size=4):
    """ Compute co-occurrence matrix for the given corpus and window_size␣
↪(default of 4).

        Note: Each word in a document should be at the center of a window. Words␣
↪near edges will have a smaller
              number of co-occurring words.

              For example, if we take the document "<START> All that glitters is␣
↪not gold <END>" with window size of 4,
              "All" will co-occur with "<START>", "that", "glitters", "is", and␣
↪"not".

        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 the␣
↪corpus , number of unique words in the corpus)):
                Co-occurence matrix of word counts.
                The ordering of the words in the rows/columns should be the same␣
↪as the ordering of the words given by the distinct_words function.
            word2ind (dict): dictionary that maps word to index (i.e. row/column␣
↪number) for matrix M.
    """
    words, n_words = distinct_words(corpus)
    M = None
    word2ind = {}

    ### SOLUTION BEGIN

    # populate word2ind:
    for index, word in enumerate(words): word2ind[word] = index

    # instantiate M:
    M = np.zeros((n_words, n_words))

    # iterate over documents in corpus:
    for document in corpus:
        doc_n_words = len(document)
```

```
        # iterate over words in document:
        for pos, center_word in enumerate(document):
            window_start, window_end = max(pos - window_size, 0), min(pos +␣
↪window_size + 1, doc_n_words)
            context_words = document[window_start:pos] + document[pos + 1:
↪window_end]

            # update cooccurence counts:
            for index, context_word in enumerate(context_words):
                row, col = word2ind[center_word], word2ind[context_word]
                M[row, col] += 1

    ### SOLUTION END

    return M, word2ind
```

[32]:
```
# ---------------------
# 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_TOKEN).split(" "), "{} All's well that ends well {}".format(START_TOKEN,␣
↪END_TOKEN).split(" ")]
M_test, word2ind_test = compute_co_occurrence_matrix(test_corpus, window_size=1)

# 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",␣
↪"All's", "glitters", "isn't", "well", END_TOKEN])
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:␣
 ↪{}\nYours: {}".format(word2ind_ans, word2ind_test)

# Test correct M shape
assert (M_test.shape == M_test_ans.shape), "M matrix has incorrect shape.
 ↪\nCorrect: {}\nYours: {}".format(M_test.shape, M_test_ans.shape)

# 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 ({}, {})=({}, {}) in␣
 ↪matrix M. Yours has {} but should have {}.".format(idx1, idx2, w1, w2,␣
 ↪student, correct))

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

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

1.2.5 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.

[33]:
```
def reduce_to_k_dim(M, k=2):
    """ Reduce a co-occurence count matrix of dimensionality (num_corpus_words,␣
↪num_corpus_words)
        to a matrix of dimensionality (num_corpus_words, k) using the following␣
↪SVD function from Scikit-Learn:
            - http://scikit-learn.org/stable/modules/generated/sklearn.
↪decomposition.TruncatedSVD.html

        Params:
            M (numpy matrix of shape (number of unique words in the corpus ,␣
↪number of unique words in the corpus)): co-occurence matrix of word counts
            k (int): embedding size of each word after dimension reduction
        Return:
            M_reduced (numpy matrix of shape (number of corpus words, k)):␣
↪matrix of k-dimensioal word embeddings.
                    In terms of the SVD from math class, this actually returns U␣
↪* S
    """
    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
```

[34]:
```
# ---------------------
# 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_TOKEN).split(" "), "{} All's well that ends well {}".format(START_TOKEN,␣
 ↪END_TOKEN).split(" ")]
M_test, word2ind_test = compute_co_occurrence_matrix(test_corpus, window_size=1)
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 {}".
 ↪format(M_test_reduced.shape[0], 10)
assert (M_test_reduced.shape[1] == 2), "M_reduced has {} columns; should have␣
 ↪{}".format(M_test_reduced.shape[1], 2)

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

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

1.2.6 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.

[35]:
```
def plot_embeddings(M_reduced, word2ind, words):
    """ Plot in a scatterplot the embeddings of the words specified in the list␣
↪"words".
        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␣
↪corpus , 2)): matrix of 2-dimensional word embeddings
            word2ind (dict): dictionary that maps word to indices for matrix M
            words (list of strings): words whose embeddings we want to visualize
    """

    ### SOLUTION BEGIN

    for word in words:
        x, y = M_reduced[word2ind[word]]
        plt.scatter(x, y, marker='x', color='red')
        plt.text(x, y, word, fontsize=6)
    plt.show()

    ### SOLUTION END
```

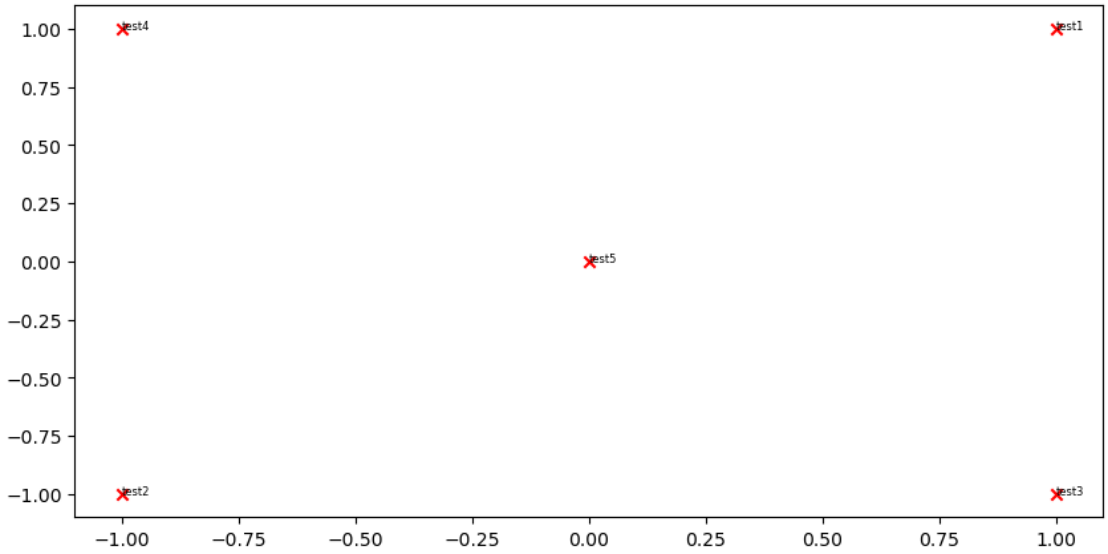
[36]:
```
# ---------------------
# Run this sanity check
# Note that this is not an exhaustive check for correctness.
# The plot produced should look like the "test solution plot" depicted below.
# ---------------------

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': 4}
words = ['test1', 'test2', 'test3', 'test4', 'test5']
plot_embeddings(M_reduced_plot_test, word2ind_plot_test, words)

print ("-" * 80)
```

Outputted Plot:



1.2.7 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.

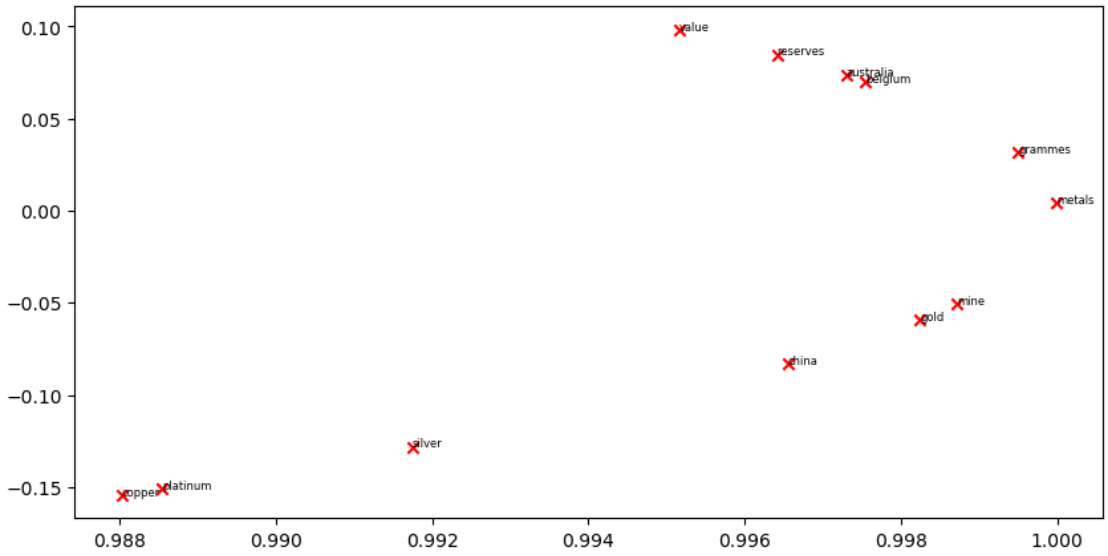
[37]:
```
# ----------------------------
# Run This Cell to Produce Your Plot
# ----------------------------
reuters_corpus = read_corpus()
M_co_occurrence, word2ind_co_occurrence =␣
 ↪compute_co_occurrence_matrix(reuters_corpus)
M_reduced_co_occurrence = reduce_to_k_dim(M_co_occurrence, k=2)

# 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] # broadcasting

words = ['value', 'gold', 'platinum', 'reserves', 'silver', 'metals', 'copper',␣
 ↪'belgium', 'australia', 'china', 'grammes', "mine"]

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.

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

1.2.8 SOLUTION BEGIN

- One cluster of words is that of **certain rare earth metals (e.g., copper, platinum).**
  - *Explanation:* These words likely clustered together because, for each metal, one of their respective principal uses (and where they would be written about) is in automobile construction (copper for wiring and motors, platinum for catalytic converters).
- Another cluster of words is that of **certain countries (e.g., austrailia, belgium).**
  - *Explanation:* These words likely clustered together because the respective countries they describe were, at different points in history, large producers of gold. Australia is presently one of the world's largest producers of gold, and, during their colonization of the DR Congo, Belgium held that title.

1.2.9 SOLUTION END

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

1.2.10 SOLUTION BEGIN

- One grouping of words that did not cluster together as I might have expected is that of **all the rare earth metals (e.g., copper, platinum, silver, gold).**
  - *Explanation:* Given that all of these words describe rare earth metals, I would have expected them to cluster together. However, their separation may be a consequence of the multiple senses of gold and silver. "Gold" and "silver" also describe medals in the Olympic games (see Ed post #75), and Reuters articles using gold and silver in this context likely would not have used copper or platinum - thus leading to the observed lack of clustering.
- Another grouping of words that did not cluster together as I might have expected is that of **all countries (e.g., australia, belgium, china).**
  - *Explanation:* One possible explanation for the separation between (austrailia, belgium) and (china) is the gold-related activities Reuters reports on for each group of countries. A quick Google search shows that much of the gold-related discussion surrounding (australia, belgium) relates to stock market activity, while those surrounding (china) describe active mining (note the proximity between "china" and "mine" in the plot), gold imports and exports, and some stock market activity - thus leading to the observed divergence in the country names.

1.2.11 SOLUTION END

1.3 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.

[38]:
```
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
```

[39]:
```
# -----------------------------------
# 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:

[40]:
```
#!pip install gensim --upgrade
#!pip install numpy --upgrade
```

1.3.1 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.

[41]:
```
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␣
↪from file
        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
```

[42]:
```
# -----------------------------------------------------------------
# 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.
```

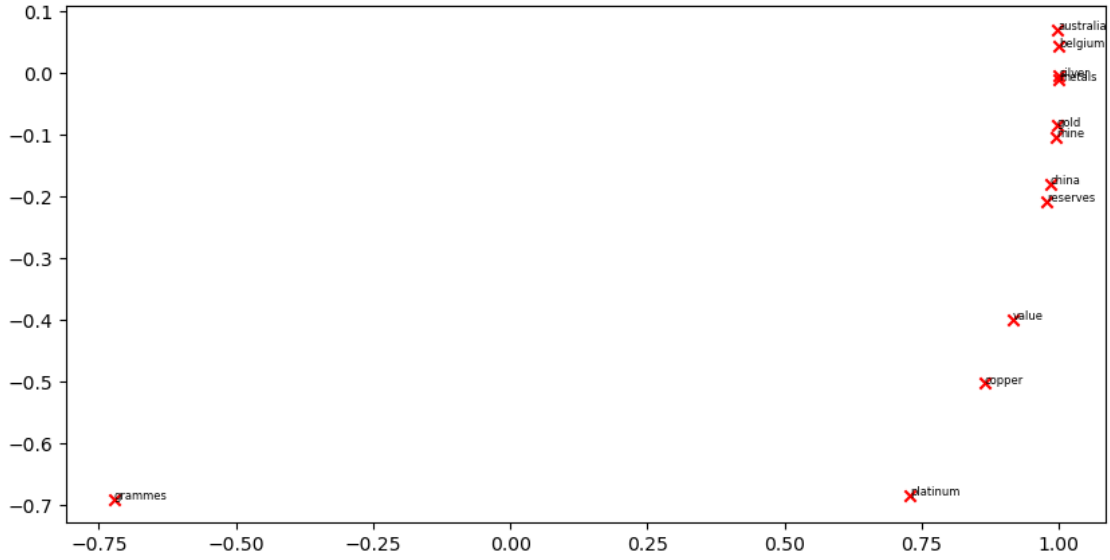
Note: If you are receiving out of memory issues on your local machine, try closing other applications to free more memory on your device. You may want to try restarting your machine so that you can free up extra memory. Then immediately run the jupyter notebook and see if you can load the word vectors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

1.3.2 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"]`.

[43]:
```
words = ['value', 'gold', 'platinum', 'reserves', 'silver', 'metals', 'copper',␣
↪'belgium', 'australia', 'china', 'grammes', "mine"]

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?

1.3.3 SOLUTION BEGIN

- One way the GloVe plot is *different from* the co-occurrence matrix plot is:
  - The GloVe plot has the point representing "grammes" significantly removed from any other plotted point, whereas in the co-occurrence matrix plot, the point representing "grammes" is most directly proximal to that of "metals" and somewhat proximal to those of (austrailia, belgium) and (gold, mine).
- One way the GloVe plot is *similar to* the co-occurrence matrix plot is:
  - The GloVe plot and the co-occurence matrix plot both have the points representing "austrailia" and "belgium" clustered closely together, with the point representing "china" further removed from the two-country cluster.

1.3.4 SOLUTION END

b. What is a possible cause for the difference?

1.3.5 SOLUTION BEGIN

- One possible cause for the difference is the **diversity (or relative lack thereof) in contexts encompassed by the corpus** used to generate the co-occurrence matrix embeddings versus the corpus used to generate the GloVe embeddings.
- That is, the co-occurrence matrix embeddings were generated from the Reuters 'gold' corpus only - in this corpus, the word 'grammes' is likely only going to appear in contexts related to gold, other precious metals, and related entites/topics. This relatively low diversity in observed contexts for "grammes" - and the increased potential for context overlap between contexts of "grammes" and other plotted words of interest - thus leads to "grammes" being somewhat proximal to other words of interest in the co-occurence matrix embeddings plot.
- However, the GloVe embeddings where generated from the (much larger) corpus of Wikipedia (2014+) - in this corpus, the word 'grammes' could appear in contexts related to gold and related entities/topics, but also contexts related to units of measure and measurement standards, practices like precision engineering, and fields of study like physics, etc. This relatively high diversity in observed contexts for "grammes" - and the decreased potential for context overlap between contexts of "grammes" and other plotted words of interest - thus leads to "grammes" being far removed from other words of interest in the GloVe embeddings plot.

1.3.6 SOLUTION END

1.3.7 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:

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

1.3.8 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**.

[44]:
```
### SOLUTION BEGIN

# get the similar words:
result = wv_from_bin.most_similar(positive = ["bow"])

# formatting output:
print("=" * 75)
print("Top 10 similar words to \"bow\" (ranked in descending order of␣
 ↪similarity):")
print("=" * 75)

# print top 10 similar words & similarity score (e.g., cosine similarity):
for i in range(10):
    most_similar_key, similarity = result[i]
    print(f"{i + 1}. {most_similar_key}: {similarity:.4f}")
```

```
### SOLUTION END
```

```
================================================================================
Top 10 similar words to "bow" (ranked in descending order of similarity):
================================================================================
1. jhaw: 0.6600
2. bows: 0.5361
3. vursh: 0.5220
4. arrow: 0.5153
5. bowdre: 0.4976
6. visor: 0.4737
7. starboard: 0.4576
8. bend: 0.4460
9. jiabao: 0.4452
10. curtsy: 0.4276
```

1.3.9 SOLUTION BEGIN

- Discovered word: "*bow*"
- Multiple meanings that occur in top 10 most similar words:
  - "bow" as in a stringed weapon used to fire an "arrow" (4th most similar word).
  - "bow" as in to "bend" (8th most similar word) oneself at the waist and lower one's head as a sign of respect.
- Possible explanation for why many polysemous/homonymic words didn't work:
  - One reason as to why many polysemous/homonymic words didn't work for the previous exercise is that, for some polysemes/homonyms, one of their meanings may be much more broad, thereby causing this meaning of the word to occur in more contexts. In turn, this would mean there are more potential similar words for this one meaning of the polyseme/homonym than for another one of the polyseme/homonym's meanings. Then, in the top-n most similar words, the most similar words for the broader meaning of the polyseme/homonym could crowd out any similar words related to a different meaning.
  - For example, I also tried the word "bank." Although "bank" can mean both a financial institution and a geographic feature, when "bank" is used to mean the former, its meaning is much more broad - it can mean a savings bank, an investment bank, a central bank, etc. In contrast, "bank" as a geographic feature is relatively specific - e.g., if one saw a hill, one would call it a hill and not a bank.
  - For this reason, "bank" as a financial institution would like appear in many more contexts with many more potential similar words, thereby biasing the top-n similar words of "bank" to be those related to this meaning of the word.

1.3.10 SOLUTION END

1.3.11 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.

[45]:
```
### SOLUTION BEGIN

w1 = "hot"
w2 = "hunky"
w3 = "cold"
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 hot, hunky have cosine distance: 0.9506146684288979
Antonyms hot, cold have cosine distance: 0.40621882677078247
```

1.3.12 SOLUTION BEGIN

"Hot" and "cold" having a closer cosine distance than "hot" and "hunky" (despite the former pair being antonyms and the latter pair being synonyms) likely has to do with two factors:

1. "Hot" is a homonym, being a word used to describe a temperature in the antonym pairing and being a slang term used to describe a degree of attractiveness in the synonym pairing.
   - Given that our GLoVe vectors were generated from relatively formal corpus (Wikipedia claims to be an online encyclopedia, after all), it's unlikely that there were many instances of "hot" being used for its slang meaning. Therefore, the generation of the embedding for "hot" is unlikely to have been significantly influenced by contexts which "hunky" may have also appeared in, leading to the high cosine distance between "hot" and "hunky."
2. Although "hot" and "cold" may be antonyms, they may still appear in similar or the same contexts, leading to a lower cosine distance between the terms.
   - For instance, a usage of the temperature-based meaning of hot could be, "Come get your food while it's hot - don't let it get cold!" In this example, "hot" and "cold" occur in the same sentence in relative proximity, leading them to have similar contexts. Or, there could be two sentences like "The reaction occurs when it's hot." and "The reaction occurs when it's cold." where the terms "hot" and "cold" have identical contexts in their respective sentences.

- On a corpus-level, many such sentences where these antonyms have similar/identical contexts could exist, which would lead the terms to have similar embeddings, and therefore a low cosine distance.

1.3.13 SOLUTION END

1.3.14 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).

[46]:
```
# Run this cell to answer the analogy -- man : grandfather :: woman : x
pprint.pprint(wv_from_bin.most_similar(positive=['woman', 'grandfather'],␣
 ↪negative=['man']))
```

```
[('grandmother', 0.7608445286750793),
 ('granddaughter', 0.7200808525085449),
 ('daughter', 0.7168302536010742),
 ('mother', 0.7151536345481873),
 ('niece', 0.7005682587623596),
 ('father', 0.6659888029098511),
 ('aunt', 0.6623408794403076),
 ('grandson', 0.6618767380714417),
 ('grandparents', 0.6446609497070312),
 ('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?

1.3.15 SOLUTION BEGIN

We are maximizing x's cosine similarity to the vector defined by: $w + g$ - m.

1.3.16 SOLUTION END

1.3.17 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?

1.3.18 SOLUTION BEGIN

The `most_similar` function also returns words like "granddaughter", "daughter", "mother", etc. because on a more abstract level, the analogy can be formalized as "man IS TO any male familial relationship AS woman IS TO any female familial relationship" and "granddaughter", "daughter", "mother", etc. could all complete this more abstract analogy.

1.3.19 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!

[47]:
```
### SOLUTION BEGIN

x, y, a, b = "cat", "garfield", "dog", "odie"

assert wv_from_bin.most_similar(positive=[a, y], negative=[x])[0][0] == b

### SOLUTION END
```

1.3.20 SOLUTION BEGIN

The analogy holds as "garfield" is a famous cartoon cat, and in the eponymously named cartoon, "odie" is the dog.

1.3.21 SOLUTION END

1.3.22 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?

[48]:
```
pprint.pprint(wv_from_bin.most_similar(positive=['foot', 'glove'],␣
↪negative=['hand']))
```

```
[('45,000-square', 0.4922032058238983),
 ('15,000-square', 0.4649604558944702),
 ('10,000-square', 0.45447564125061035),
 ('6,000-square', 0.44975772500038147),
 ('3,500-square', 0.4441334009170532),
 ('700-square', 0.44257497787475586),
 ('50,000-square', 0.43563973903656006),
 ('3,000-square', 0.43486514687538147),
 ('30,000-square', 0.4330596923828125),
 ('footed', 0.43236875534057617)]
```

1.3.23 SOLUTION BEGIN

This particular analogy may have turned out the way it did because the embedding for "foot" was primarily learned from contexts in which "foot" was used as a unit of measure (aligning with the various "X-square" words in the observed most similar words) rather than a human body part. If the embedding for "foot" reflected this meaning, then the analogy "hand : glove :: foot : sock" would make no sense, and we wouldn't expect "sock" to show up in the most similar words, as it did not.

1.3.24 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'**).

[49]:
```
### SOLUTION BEGIN

x, y, a, b = "camping", "tent", "vacationing", "hotel"
pprint.pprint(wv_from_bin.most_similar(positive=[a, y], negative=[x]))

### SOLUTION END
```

```
[('vacationed', 0.45393121242523193),
 ('huddled', 0.4117174744606018),
 ('dined', 0.4043857157230377),
 ('holidaying', 0.3960374593734741),
 ('arrived', 0.3954778015613556),
 ('squalid', 0.39063072204589844),
 ('lunched', 0.36885926127433777),
 ('hospital', 0.3686912953853607),
```

```
('slept', 0.36855512857437134),
('recuperating', 0.3645753860473633)]
```

1.3.25 SOLUTION BEGIN

My intended analogy is "camping:tent :: vacationing:hotel", with the analogy linking activites with the housing type commonly associated with them. Here, the word vectors determine the *incorrect* value of b to be: "vacationed."

1.3.26 SOLUTION END

1.3.27 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.

[50]:
```
# Run this cell
# Here `positive` indicates the list of words to be similar to and `negative`␣
 ↪indicates the list of words to be
# most dissimilar from.

pprint.pprint(wv_from_bin.most_similar(positive=['man', 'profession'],␣
 ↪negative=['woman']))
print()
pprint.pprint(wv_from_bin.most_similar(positive=['woman', 'profession'],␣
 ↪negative=['man']))
```

```
[('reputation', 0.5250177383422852),
 ('professions', 0.5178037881851196),
 ('skill', 0.49046966433525085),
 ('skills', 0.4900550842285156),
 ('ethic', 0.4897659420967102),
 ('business', 0.4875851273536682),
 ('respected', 0.485920250415802),
 ('practice', 0.482104629278183),
 ('regarded', 0.4778572618961334),
 ('life', 0.4760662019252777)]

[('professions', 0.5957458019256592),
 ('practitioner', 0.4988412857055664),
 ('teaching', 0.48292145133018494),
 ('nursing', 0.48211807012557983),
 ('vocation', 0.4788965880870819),
 ('teacher', 0.47160351276397705),
 ('practicing', 0.46937811374664307),
 ('educator', 0.46524322032928467),
 ('physicians', 0.4628995656967163),
 ('professionals', 0.4601393938064575)]
```

1.3.28 SOLUTION BEGIN

The male-associated words are predominately associating men with respect (also reputation, regard), skill, and the business profession, whereas the female-associated words are almost all describing certain professions like teaching, nursing, etc.

These lists reflect gender bias in two ways:

1. First, the lack of words like "respect[ed], skill[s]" in the female-associated words reflects how society is more likely to attribute a man's professional success to his own self and his efforts, whereas the same level of regard is not given to women.
2. Secondly, the specific professions that show up in the male- versus the female-associated words reflect common stereotypes as to what jobs are "appropriate" for men versus women. Specifically, women may be discouraged to enter business/finance (note the presence of "business" in the men-associated words only) and instead encouraged to pursue "supporting" roles (note the presence of "nursing" in the women-associated words).

1.3.29 SOLUTION END

1.3.30 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.

[51]:
```
### SOLUTION BEGIN

A = "caucasian"
B = "african-american"
word = "crime"
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
```

```
[('terrorism', 0.5098557472229004),
 ('caucasus', 0.4791603982448578),
 ('crimes', 0.4774371087551117),
 ('trafficking', 0.46058133244514465),
 ('laundering', 0.45680883526802063),
 ('criminal', 0.45455676317214966),
 ('dagestan', 0.4459058344364166),
 ('criminality', 0.4443463385105133),
 ('terrorist', 0.43398573994636536),
 ('terror', 0.4238112270832062)]

[('criminal', 0.5107489824295044),
 ('murder', 0.5030859112739563),
 ('homicide', 0.4716717600822449),
 ('corruption', 0.4643762707710266),
 ('crimes', 0.4575481116771698),
 ('urban', 0.4542885422706604),
 ('law', 0.4527962803840637),
 ('committed', 0.4467456340789795),
 ('organized', 0.4417746961116791),
 ('abuse', 0.4416038393974304)]
```

1.3.31 SOLUTION BEGIN

In my example, we see a demonstration of **racial bias.** The words most associated with "caucasian" and "crime" include words like "trafficking" and "laundering," while the words most associated with "african-american" and "crime" include words like, "murder", "homicide", and "abuse."

These word lists reflect the racial stereotype that Caucasians are most commonly involved in so-called "white-collar" crime (e.g., money laundering) while other races like African-Americans constitute the majority of individuals who commit crimes like murder, drug abuse, etc.

1.3.32 SOLUTION END

1.3.33 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.

1.3.34 SOLUTION BEGIN

- One way bias gets into word vectors is the presence of biased speech in the corpus used to generate the word vectors. If there is biased speech in the corpus, then the resulting word vectors may associate certain words with context terms reflecting said bias.
- As an example, many word vectors use social media content (tweets from Twitter, YouTube comments, etc.) as their corpus, and thus learn word embeddings from biased social media commentary - for one example of such word vectors, see the `glove-twitter-25` dataset (word vectors trained on 2 billion tweets using GloVe).
  - For a demonstration of an embedded bias:
    * In "Bias in word embeddings" by Papakyriakopoulos et al., the authors find that when generating word embeddings using GLoVe on Facebook and Twitter content, the resulting embeddings demonstrate a sexual oritentation bias, associating homosexuality with professions like "artist" and "hairdresser" while associating heterosexuality with professions like "political scientist" and "biologist" (source: https://blog.acolyer.org/2020/12/08/bias-in-word-embeddings/).

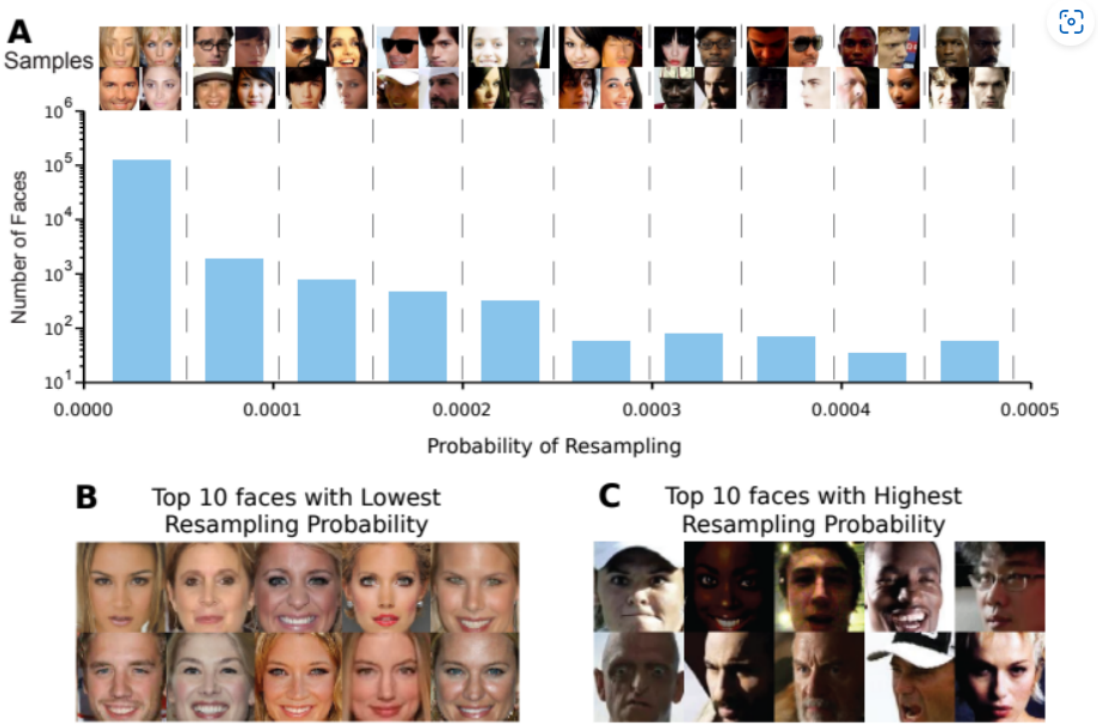
1.3.35 SOLUTION END

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.

1.3.36 SOLUTION BEGIN

One method you can use to mitigate bias exhibited by word vectors is to manually or algorithmically upsample select parts of the corpus to create an anti-biasing influence. For instance, with the gender bias in professions example we saw in question 2.7, one could take a part of the corpus which says "that woman is great at business" and duplicate it so it appears in the corpus many times, thereby making "business" appear in the context of "woman" more often. As such, the word vector for "woman" + "profession" - "man" would be closer to "business", counteracting the previously-seen gender profession bias.

One real-world example of this technique being applied can be found in the work of Amini et al., "Uncovering and Mitigating Algorithmic Bias through Learned Latent Structure." In this work, the authors employ a variational autoencoder to "learn the latent structure within the dataset and then... [use] the learned latent distributions to re-weight the importance of certain data points while training." They specifically apply this approach in the context of racial and gender bias in facial detection systems, resampling points (faces) which would otherwise be underrepresented. See this photo from their paper:



Although this specific application is in a non-NLP space, it still uses the principle of manually or algorithmically upsampling parts of the training data (in word embeddings, the corpus) to create an anti-biasing correctional influence in the resulting output (for Amini, their facial recognition algorithm, and for NLP, the word vectors).

1.3.37 SOLUTION END

2 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.