For this homework, make sure that you format your notbook nicely and cite all sources in the appropriate sections. Programmatically generate or embed any figures or graphs that you need.
Names: Calvin Zikakis, Sarah Schwallier

Section 1: Word2Vec paper questions¶

```
1) Describe how a CBOW word embedding is generated.
```

CBOW word embeddings are generated by using an unsupervised deep learning algorithm. This architecture creates an input using the context of each word and then the model tries to predict the word that corresponds to the context.

```
2) What is a CBOW word embedding and how is it different than a skip-gram word embedding?
```

CBOW uses inputs to predict outputs by using a set number of words before and or after the word it is trying to predict. This method of prediction relys on the context of the word. Skip-grams use a given target input to predict the context word. CBOWs and Skip-grams models are reflections of each other in the sense that CBOW is predicting a word from a context while a skip-gram is predicting a context from a word.

```
3) What is the task that the authors use to evaluate the generated word embeddings?
```

Authors want to make sure that their generated word embeddings are as accurate as possible using semantic questions. Where the ideal model has a high complexity and is able to predict against an independent data set with high accuracy.

```
4) What are PCA and t-SNE? Why are these important to the task of training and interpreting word
embeddings?
```

T-SNE are multi-dimensional word embeddings consisting of word test set sentences that are based upon probability. PCA on the other hand is computed by using matrices and is based on more mathematical approaches. Both of these models are trying to reduce the dimensionality of matrices and vertices to compute a graph. These are important for training and interpreting word embeddings because they both visualize the data that was computed in a way such that the people interpreting the results can analyze the data easily.

Sources Cited¶

Efficient Estimation of Word Representations in Vector Space by Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean: https://arxiv.org/pdf/1301.3781.pdf

J. Schler, M. Koppel, S. Argamon and J. Pennebaker (2006). Effects of Age and Gender on Blogging in Proceedings of 2006 AAAI Spring Symposium on Computational Approaches for Analyzing Weblogs.
SENTENCE ORDERING USING RECURRENT NEURAL NETWORKS by Lajanugen Logeswaran, Honglak Lee & Dragomir Radev Speech and Language Processing
Karani, Dhruvil, Introduction to Word Embedding and Word2Vec, https://towardsdatascience.com/introduction-to-word-embedding-and-word2vec-652d0c2060fa
Benjamin Fayyazuddin Ljungberg, Dimensionality reduction for bag-of-words models: PCA vs LSA
An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition by Daniel Jurafsky and James H. Martin

Section 2: Training your own word embeddings¶

The spooky authors dataset consists of excerpts from authors of horror novels including Edgar Allan Poe, Mary Shelley, and HP Lovecraft. These excerpts each have a unique ID as well as a three letter tag describing which author wrote the excerpt. The data is split into a training set and a test set. The test set is lacking the three letter code which labels the author.
We are using the The Blog Authorship Corpus for our secondary dataset. We decided on this dataset as it is comprised of 681,288 posts from 19,320 bloggers. We scanned through this database and pulled a small chunk of the total amount of posts. This was to reduce the overall size of the dataset to help with performance in training word embedding. This dataset will provide a data that is written with a style simular to normal human conversation simularly to the spooky authors dataset. This should help insure our generated sentences have a natural sound to them.

In [1]:

```
# import your libraries here
import numpy as np
import sklearn
from sklearn.manifold import TSNE
from sklearn.decomposition import PCA
from collections import Counter

import keras
from keras import backend as K
import tensorflow as tf

### Comment out this section if you running on a laptop
config = tf.ConfigProto()
config.gpu_options.per_process_gpu_memory_fraction = 0.75
session = tf.Session(config=config)
```

```
K.set_session(session)
### ---------------------------------------------------


from keras.layers import Dense, Activation, Flatten, SimpleRNN
from keras.layers.recurrent import LSTM
from keras.layers.embeddings import Embedding
from keras.models import Sequential
from keras.utils import to_categorical
from keras.models import load_model



import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
import pandas as pd
import itertools
import seaborn as sns
import csv



%matplotlib inline
```

```
Using TensorFlow backend.
C:\Users\Calvin\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.py:516:
FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a
future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
C:\Users\Calvin\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.py:517:
FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a
future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
C:\Users\Calvin\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.py:518:
FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a
future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\Calvin\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.py:519:
FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a
future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\Calvin\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.py:520:
FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a
future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\Calvin\anaconda3\lib\site-packages\tensorflow\python\framework\dtypes.py:525:
FutureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a
future version of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
C:\Users\Calvin\anaconda3\lib\site-
packages\tensorboard\compat\tensorflow_stub\dtypes.py:541: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
it will be understood as (type, (1,)) / '(1,)type'.
```

```
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
C:\Users\Calvin\anaconda3\lib\site-
packages\tensorboard\compat\tensorflow_stub\dtypes.py:542: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
C:\Users\Calvin\anaconda3\lib\site-
packages\tensorboard\compat\tensorflow_stub\dtypes.py:543: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
C:\Users\Calvin\anaconda3\lib\site-
packages\tensorboard\compat\tensorflow_stub\dtypes.py:544: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
C:\Users\Calvin\anaconda3\lib\site-
packages\tensorboard\compat\tensorflow_stub\dtypes.py:545: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
C:\Users\Calvin\anaconda3\lib\site-
packages\tensorboard\compat\tensorflow_stub\dtypes.py:550: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of numpy,
it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
```

In [2]:

```
# -----------------Secondary Dataset Formatting and Trimming-------------------
# This cell trims and fixes the secondary dataset to get the data in a workable style
import re
from csv import reader



def format_secondaryDataset(training_file_path, output_file, sentence_length):
    '''
    this function takes the dataset and splits it to sentences and stores those in a
txt file


    training_file_path = filepath of blogposts.csv
    output_file = outputfile name (.txt)
    sentence_length = minimum length sentences to grab (value is how many words per
sentences)
    '''



    with open(training_file_path, "r", encoding="utf-8") as file:
        sentences = file.readlines()
    #open file
```

```
    file.close()

    output = open(output_file, "w+")

    count = 0

    for line in reader(sentences):
        blog_post = line[6]
        #Line[6] contains the blog post

        if count >= 7:
        #skip the stuff in the beggining. It's unneeded

            sentences = blog_post.split(".")
            #split the post on the periods to extract individual sentences

            for sentence in sentences:
            #loop over our list of sentences

                if sentence != "":
                #some blog posts contain '...'. This creates empty sentences. We don't
want empty sentences

                    #lets clean the sentence of symbols and make it all lowercase

                    res = re.sub(' +', ' ', sentence)
                    res.strip('\t')
                    res.strip('\n')
                    #strip tabs and newlines

                    lower = res.lower()
                    #make all lower case

                    whitelist = set('abcdefghijklmnopqrstuvwxyz 1234567890')
                    no_numbers_punct = ''.join(filter(whitelist.__contains__, lower))
                    #gets rid of punctuation

                    cleaned = no_numbers_punct.split()
```

```
                    black_list = ['urllink']
                    #allows us to remove all 'urlLink' occurances

                    if len(cleaned) >= sentence_length:
                        #adjust 4 if you only want longer sentences
                        #we are only concerned with sentences longer than 4 words
                        output.write(" ".join([i for i in cleaned if i not in
black_list]) + "\n")



        if count == 2000:
        #Do not need this full dataset... It's 800mb's
            break

        count += 1



format_secondaryDataset("blogtext.csv", "secondaryDataset.txt", 5)
```

In [22]:

```
# code to train your word embeddings
from csv import reader
from gensim.models import Word2Vec

EMB = 300



def convert_data(data):
#flattens data to 1D matrix
    data_flattened = []

    for sentences in data:
        for word in sentences:
            data_flattened.append(word)

    return data_flattened
```

```
def standardize_length(words,length):
    counter = 0
    output = []

    sentence = []
    for word in words:
        if counter < length:
            sentence.append(word)
        else:
            output.append(sentence)
            sentence = []
            counter = -1
        counter += 1

    return output

def convert_to_UNK(words):
    output = []
    counts = Counter(words)
    for word in words:
        if counts[word] <= 1:
            output.append('UNK')
        else:
            output.append(word)
    return output




# -----------------Primary Dataset-------------------


def Clean_data_primary_dataset(training_file_path):
    #This function tokenizes the primary dataset and returns a cleaned version where
each word making up a sentence is a nested list inside a larger list of the corpus
    output_list = []


    with open(training_file_path, "r", encoding="utf-8") as file:
        sentences = file.readlines()
```

```
    #open file
    file.close()

    count = 0

    for line in reader(sentences):

        if count != 0:
        #don't want first sentence

            sentence = line[1]

            lower = sentence.lower()
            #make all lower case

            whitelist = set('abcdefghijklmnopqrstuvwxyz 1234567890')
            no_numbers_punct = ''.join(filter(whitelist.__contains__, lower))
            #gets rid of punctuation

            cleaned = no_numbers_punct.split()

            output_list.append(cleaned)

        count += 1

        if count >= 10000: #added this so I could test part 4 with a smaller dataset
            break         #added this so I could test part 4 with a smaller dataset

    return output_list


pri_Dataset = convert_data(Clean_data_primary_dataset("train.csv"))
#imports and cleans dataset

output_pri = convert_to_UNK(pri_Dataset)

sentences_primaryDataset = standardize_length(output_pri, 45)
```

```
model_primaryDataset = Word2Vec(sentences_primaryDataset, min_count=1, size=EMB,
window=4, negative=10, iter=10, workers=4)
#creates word2vec model


#print(model_primaryDataset)
#model summary


words_primaryDataset = list(model_primaryDataset.wv.vocab)
print(len(words_primaryDataset), "<--- Primary Vocab Length")
#shows the vocab


#print(model_primaryDataset['sentence'])
#our model


# -----------------Secondary Dataset-------------------


#secondary dataset is stored as 'secondaryDataset.txt' after processing it


def tokenize_secondary_dataset(training_file_path):
    #tokenizes the secondary dataset and returns a cleaned version where each word
making up a sentence is a nested list inside a larger list of the corpus


    output_list = []


    with open(training_file_path) as file:
        sentences = file.readlines()


    #open file
    file.close()


    count = 0
    for sentence in sentences:
    #loop over sentences


        words = sentence.split()
        #split sentences on the words


        output_list.append(words)
        #append words list to final output
```

```
        count += 1

        if count >= 10000: #added this so I could test part 4 with a smaller dataset
            break         #added this so I could test part 4 with a smaller dataset


    return output_list



sec_Dataset = convert_data(tokenize_secondary_dataset("secondaryDataset.txt"))
#secondary sentences

output_sec = convert_to_UNK(sec_Dataset)

sentences_secondaryDataset = standardize_length(output_sec, 45)

model_secondaryDataset = Word2Vec(sentences_secondaryDataset, min_count=1, size=EMB,
window=4, negative=10, iter=10, workers=4)
#creates word2vec model

#print(model_secondaryDataset)
#model summary

words_secondaryDataset = list(model_secondaryDataset.wv.vocab)
#print(words_secondaryDataset)
#shows the vocab

#print(model_secondaryDataset['sentence'])
#our model
```

```
11286 <--- Primary Vocab Length
```

Sources Cited¶

An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition by Daniel Jurafsky and James H. Martin

Brownlee, Jason. “How to Develop Word Embeddings in Python with Gensim.” Machine Learning Mastery, 7 Aug. 2019, machinelearningmastery.com/develop-word-embeddings-python-gensim/.

Section 3: Evaluate the differences between the word embeddings¶

(make sure to include graphs, figures, and paragraphs with full sentences)

In [4]:

```
#This section is evaluating via PCAs
primaryModel = model_primaryDataset[model_primaryDataset.wv.vocab]
secondaryModel = model_secondaryDataset[model_secondaryDataset.wv.vocab]
#Retirives the vectors from each embedding

def buildSimilarWords(randWord, pSimilarWords, sSimilarWords, words_Dataset):
    psList = []
    psList.append(randWord)
    for wordTuple in pSimilarWords:
        word  = wordTuple[0]
        if word not in words_Dataset:
            psList.append(word)
    return psList

def getPrimaryIndex(word):
    for i, iWord in enumerate(list(model_primaryDataset.wv.vocab)):
        if word == iWord:
            return i

randIndex = np.random.randint(0, high=len(words_primaryDataset))
randWord = words_primaryDataset[randIndex]
while randWord not in words_secondaryDataset:
    randIndex = np.random.randint(0, high=len(words_primaryDataset))
    randWord = words_primaryDataset[randIndex]
pSimilarWords = model_primaryDataset.wv.most_similar(randWord)
sSimilarWords = model_secondaryDataset.wv.most_similar(randWord)
print("Word: ", randWord, "\n")
print(pSimilarWords, "\n")
print(sSimilarWords, "\n")
similarWordsPrimary = buildSimilarWords(randWord, pSimilarWords, sSimilarWords, 
words_secondaryDataset)
similarWordsSecondary = buildSimilarWords(randWord, sSimilarWords, pSimilarWords, 
words_primaryDataset)
```

```
dnpWord = model_secondaryDataset.wv.doesnt_match(similarWordsPrimary)
dnsWord = model_secondaryDataset.wv.doesnt_match(similarWordsSecondary)
print(dnpWord)
print(dnsWord)

pcaP = PCA(n_components=3)
resultP = pcaP.fit_transform(primaryModel)
ax = plt.figure(figsize=(10,8)).gca(projection='3d')
ax.scatter(resultP[:, 0], resultP[:, 1], resultP[:, 2], s=5, color='teal')
words_primaryDataset = list(model_primaryDataset.wv.vocab)
ax.set_title('Three-Dimensional PCA for the Primary Data Set')
ax.set_xlabel('Dimension B')
ax.set_ylabel('Dimension A')
ax.set_zlabel('Dimension C')
plt.show()
#PCA model for the primary dataset
pcaP = PCA(n_components=2)
resultP = pcaP.fit_transform(primaryModel)
plt.scatter(resultP[:, 0], resultP[:, 1], s=5, color='teal')
words_primaryDataset = list(model_primaryDataset.wv.vocab)
plt.title('Two-Dimensional PCA for the Primary Data Set')
plt.xlabel('Dimension B')
plt.ylabel('Dimension A')
plt.annotate(randWord, xy=(resultP[randIndex, 0], resultP[randIndex, 1]),
fontweight='bold')
for word in similarWordsPrimary:
    if word != dnpWord and word != randWord:
        p2 = getPrimaryIndex(word)
        plt.annotate(word, xy=(resultP[p2, 0], resultP[p2, 1]))
p2 = words_primaryDataset.index(dnpWord)
plt.annotate(dnpWord, xy=(resultP[p2, 0], resultP[p2, 1]), color='red')
plt.show()
#PCA model for the primary dataset

randIndex = np.random.randint(0, high=len(words_secondaryDataset))
randWord = words_secondaryDataset[randIndex]
while randWord not in words_secondaryDataset:
    randIndex = np.random.randint(0, high=len(words_secondaryDataset))
    randWord = words_secondaryDataset[randIndex]
```

```
pSimilarWords = model_secondaryDataset.wv.most_similar(randWord)
sSimilarWords = model_secondaryDataset.wv.most_similar(randWord)
print("Word: ", randWord, "\n")
print(pSimilarWords, "\n")
print(sSimilarWords, "\n")
similarWordsPrimary = buildSimilarWords(randWord, pSimilarWords, sSimilarWords,
words_secondaryDataset)
similarWordsSecondary = buildSimilarWords(randWord, sSimilarWords, pSimilarWords,
words_primaryDataset)
dnpWord = model_secondaryDataset.wv.doesnt_match(similarWordsPrimary)
dnsWord = model_secondaryDataset.wv.doesnt_match(similarWordsSecondary)
print(dnpWord)
print(dnsWord)


def getSecondaryIndex(word):
    for i, iWord in enumerate(list(model_secondaryDataset.wv.vocab)):
        if word == iWord:
            return i
pcaS = PCA(n_components=3)
resultS = pcaS.fit_transform(secondaryModel)
ax = plt.figure(figsize=(10,8)).gca(projection='3d')
ax.scatter(resultS[:, 0], resultS[:, 1], resultS[:, 2], s=5, color='coral')
words_secondaryDataset = list(model_secondaryDataset.wv.vocab)
ax.set_title('Three-Dimensional PCA for the Secondary Data Set')
ax.set_xlabel('Dimension B')
ax.set_ylabel('Dimension A')
ax.set_zlabel('Dimension C')
plt.show()


#PCA model for the secondary dataset
pcaS = PCA(n_components=2)
resultS = pcaS.fit_transform(secondaryModel)
plt.scatter(resultS[:, 0], resultS[:, 1], s=5, color='coral')
words_secondaryDataset = list(model_secondaryDataset.wv.vocab)
plt.title('Two-Dimensional PCA for the Secondary Data Set')
plt.xlabel('Dimension B')
plt.ylabel('Dimension A')
plt.annotate(randWord, xy=(resultS[randIndex, 0], resultS[randIndex, 1]),
fontweight='bold')
```

```
for word in similarWordsSecondary:

    if word != dnsWord and word != randWord:

        s2 = getSecondaryIndex(word)

        plt.annotate(word, xy=(resultS[s2, 0], resultS[s2, 1]))

s2 = words_secondaryDataset.index(dnsWord)

plt.annotate(dnsWord, xy=(resultS[s2, 0], resultS[s2, 1]), color='darkorchid')

plt.show()

#PCA model for the secondary dataset
```

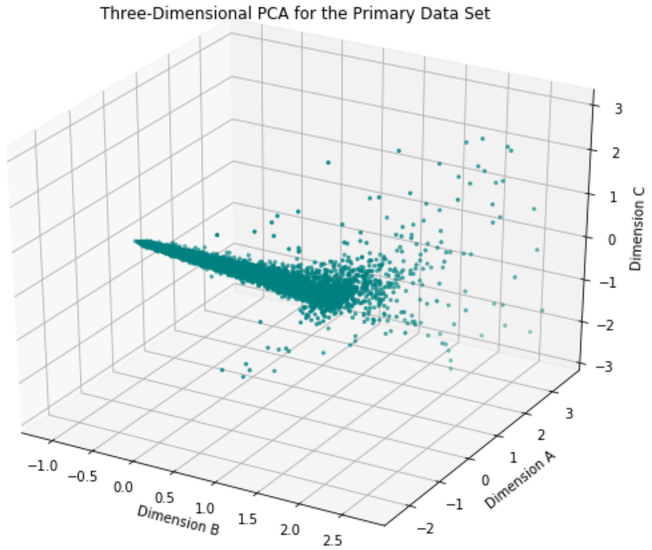
```
C:\Users\Calvin\anaconda3\lib\site-packages\ipykernel_launcher.py:2:
DeprecationWarning: Call to deprecated `__getitem__` (Method will be removed in 4.0.0,
use self.wv.__getitem__() instead).

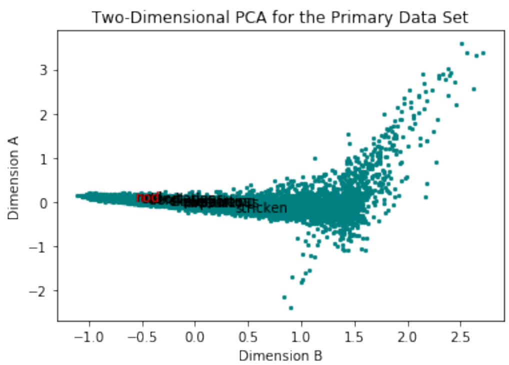
C:\Users\Calvin\anaconda3\lib\site-packages\ipykernel_launcher.py:3:
DeprecationWarning: Call to deprecated `__getitem__` (Method will be removed in 4.0.0,
use self.wv.__getitem__() instead).
  This is separate from the ipykernel package so we can avoid doing imports until
C:\Users\Calvin\anaconda3\lib\site-packages\gensim\models\keyedvectors.py:877:
FutureWarning: arrays to stack must be passed as a "sequence" type such as list or
tuple. Support for non-sequence iterables such as generators is deprecated as of NumPy
1.16 and will raise an error in the future.
  vectors = vstack(self.word_vec(word, use_norm=True) for word in
used_words).astype(REAL)
Word:  nod

[('supporting', 0.998641848564148), ('landladys', 0.9985164999961853),
('exhortations', 0.9983779191970825), ('losing', 0.9983762502670288), ('tiers',
0.9983314871788025), ('tarpaulin', 0.9982854127883911), ('beauteous',
0.9982617497444153), ('clime', 0.9982333183288574), ('explorations',
0.9982278347015381), ('stricken', 0.9982208013534546)]

[('glass', 0.9992753267288208), ('four', 0.9992489814758301), ('experience',
0.9992433190345764), ('pile', 0.9992285966873169), ('buses', 0.9991940259933472),
('block', 0.999173641204834), ('company', 0.9991206526756287), ('memories',
0.9991083741188049), ('blue', 0.9990769624710083), ('member', 0.999075174331665)]

nod
nod
```



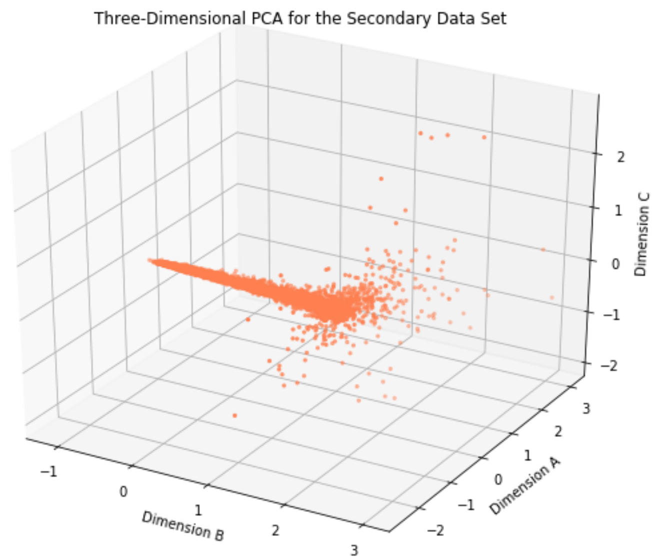


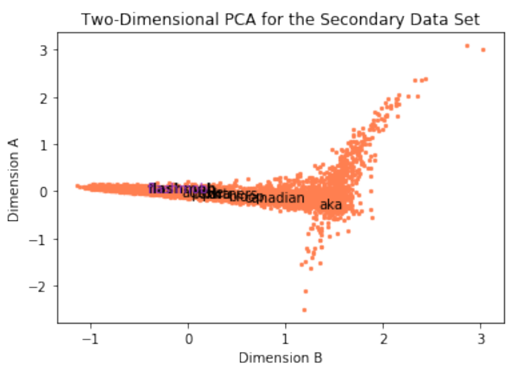

```
Word:  flashmob

[('aussie', 0.9994242191314697), ('canadian', 0.9994099736213684), ('aka',
0.9993980526924133), ('alpha', 0.999387264251709), ('partners', 0.9993863105773926),
('bloop', 0.9993857741355896), ('pork', 0.9993824362754822), ('wise',
0.9993759393692017), ('miles', 0.9993746280670166), ('cha', 0.9993675351142883)]

[('aussie', 0.9994242191314697), ('canadian', 0.9994099736213684), ('aka',
0.9993980526924133), ('alpha', 0.999387264251709), ('partners', 0.9993863105773926),
('bloop', 0.9993857741355896), ('pork', 0.9993824362754822), ('wise',
0.9993759393692017), ('miles', 0.9993746280670166), ('cha', 0.9993675351142883)]

flashmob
flashmob
C:\Users\Calvin\anaconda3\lib\site-packages\gensim\models\keyedvectors.py:877:
FutureWarning: arrays to stack must be passed as a "sequence" type such as list or
tuple. Support for non-sequence iterables such as generators is deprecated as of NumPy
1.16 and will raise an error in the future.
  vectors = vstack(self.word_vec(word, use_norm=True) for word in
used_words).astype(REAL)
```

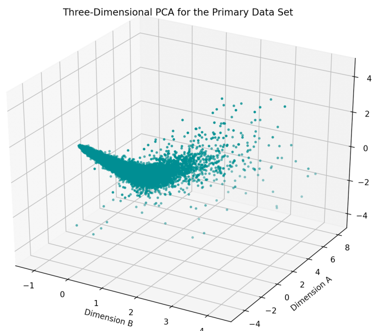


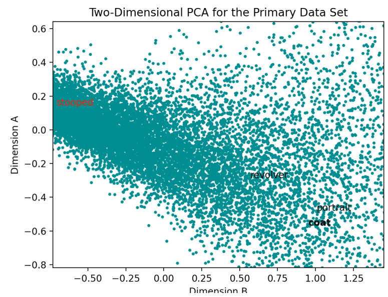


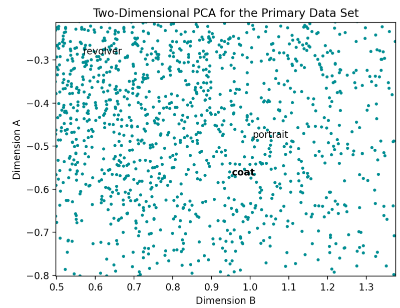
The analysis below is using the following images and information:

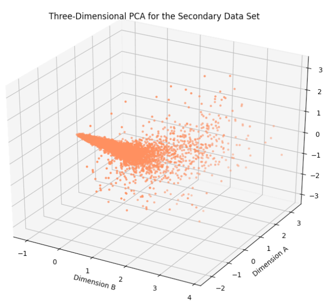
Primary Dataset											
Word selected	Similar words										Word that matched the least
coat	pillow	revolver	hat	stooped	throwing	portrait	concentrate	shoulders	bumper	leaning	stooped
	0.972	0.9667	0.9667	0.965	0.9635	0.9623	0.9611	0.9601	0.9597	0.9596	

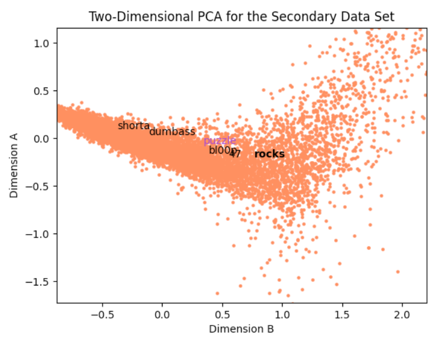
Secondary Dataset											
Word selected	Similar words										Word that matched the least
rocks	dumbass	shorta	endless	fits	pot	puzzle	47	marry	deliver	bl00p	puzzle
	0.9956	0.9947	0.9945	0.9945	0.9941	0.9939	0.9938	0.9937	0.9934	0.9936	

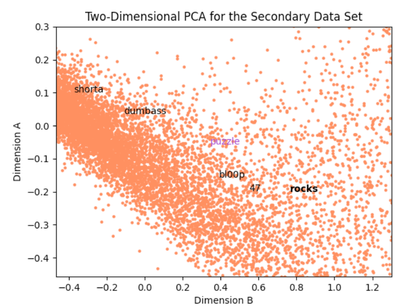












From the charts and diagrams above one can see that both datasets produced similar looking results that contain different data and meaning. The results above were computed by having a random index that corresponds with a word. The word selected for the primary data set was 'coat' and for the secondary was 'rocks', both words are bolded in the 2D graphs above. If the word in the primary dataset was in the secondary dataset then it moved onto the next step which was finding the closest 10 words that a word2vec embedding matched with the randomly selected word. For the secondary it did the same thing but instead it checked if the selected word was in the primary dataset. From there each list of similar words was then evalulated against their own list to find the word that did not match the other words in the list. For the primary dataset we found out that the word 'stooped' (in red) did not match the other ten and for the secondary dataset it was the word 'puzzle' (in purple). Then a 3D and 2D graph was made to reflect the results. The primary was graphed in teal and the secondary was graphed in coral.

In comparing the primary dataset which is composed of the supplied assignment horror corpus against our blog corpus which was smaller. It is evident in the spread of the PCAs that the dataset has more vertices for the 'cloud' in the graphs is more dense and full. While the secondary dataset has a smaller density area with more outliers. We see these differences between the two datasets because of the size of each corpus and the variety of words within the corpi. The primary dataset was larger which led to the results being more accurate.

Sources Cited¶

An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition by Daniel Jurafsky and James H. Martin Brownlee, Jason. “How to Develop Word Embeddings in Python with Gensim.” Machine Learning Mastery, 7 Aug. 2019, machinelearningmastery.com/develop-word-embeddings-python-gensim/.
Durksen, Luuk. "Visualising high-dimensional datasets using PCA and t-SNE in Python" 29 Oct. 2016, https://towardsdatascience.com/visualising-high-dimensional-datasets-using-pca-and-t-sne-in-python-8ef87e7915b

Section 4: Feedforward Neural Language Model¶

In [5]:

```
# code to train a feedforward neural language model
# on a set of given word embeddings
# make sure not to just copy + paste to train your two

vec = 300

def convert_data(data):
#flattens data to 1D matrix
    data_flattened = []

    for sentences in data:
        for word in sentences:
            data_flattened.append(word)

    return data_flattened



def data_to_index(data, model):
#assigns index values to data
    data_index = []

    for word in data:
```

```
        if word in model:
            data_index.append(model.vocab[word].index)

    return data_index



#before we can train, break down the dataset into sections. this will result in nested arrays of length 100 where each nest contains 100 words. This will lower memory requirements
def section_data(sentences):
    section = []
    output = []

    i = 0

    for sentence in sentences:

        i += 1
        section.append(sentence)

        if i % 2000 == 0:
            output.append(section)
            section = []

    return output



def training_data(sentences, model):
    sentence_length = 20

    sections_X = []
    sections_y = []

    for section in sentences:

        x_train = []
        y_train = []

```

```
        #======--------Why only train on the first four words in a sentence???-------
-=======
        for sentence in section:


            index1 = model.wv.vocab[sentence[0]].index
            index2 = model.wv.vocab[sentence[1]].index
            index3 = model.wv.vocab[sentence[2]].index
            index_label = model.wv.vocab[sentence[3]].index


            training_data_x = np.concatenate((model.wv.vectors[index1],
model.wv.vectors[index2], model.wv.vectors[index3]))
            x_train.append(training_data_x)


            y_train.append(index_label)


        x_train = np.asarray(x_train)
        y_train = np.asarray(y_train)


        sections_X.append(x_train)
        sections_y.append(y_train)


    return sections_X, sections_y


def train(x_train, y_train, model, model_Dataset):
    count = 1
    for (section_x, section_y) in zip(x_train, y_train):


        y_labels = to_categorical(section_y, num_classes=len(model_Dataset.wv.vocab),
dtype='int16')


        print("Training batch: ", count, " out of ", len(x_train), ".  :)")
        model.fit(section_x, y_labels, batch_size=10)




        count += 1


    return model
```

In [6]:

```
#------------------------------Primary Dataset------------------------------
# Wouldn't even attempt to run this unless on computer with a GPU and lots of ram.
# Its eating 32gb's of system ram and 6gb's of vram

sentences_primary = section_data(sentences_primaryDataset)

print(np.asarray(sentences_primary[0]).shape)

print("-------------Formatting test data-------------")

x_train_primary, y_train_primary = training_data(sentences_primary,
model_primaryDataset)

#Create Keras Model

print("-------------Building Model-------------")

primary_FFNN = Sequential()

primary_FFNN.add(Dense(units=10000, input_shape=(900,)))
primary_FFNN.add(Dense(units=len(model_primaryDataset.wv.vocab),activation="softmax"))
primary_FFNN.compile(optimizer="adam", loss='mean_squared_error')

primary_FFNN.summary()

print("-------------Training Model-------------")

primary_FFNN = train(x_train_primary, y_train_primary, primary_FFNN,
model_primaryDataset)
```

```
(2000, 4)
-------------Formatting test data-------------
-------------Building Model-------------
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 10000)             9010000
_________________________________________________________________
dense_2 (Dense)              (None, 11130)             111311130
=================================================================
Total params: 120,321,130
Trainable params: 120,321,130
```

```
Non-trainable params: 0
_________________________________________________________________
-------------Training Model-------------
Training batch:  1  out of  26 .  :)
WARNING:tensorflow:From C:\Users\Calvin\anaconda3\lib\site-
packages\keras\backend\tensorflow_backend.py:422: The name tf.global_variables is
deprecated. Please use tf.compat.v1.global_variables instead.

Epoch 1/1
2000/2000 [==============================] - 18s 9ms/step - loss: 8.9839e-05
Training batch:  2  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 9ms/step - loss: 8.9839e-05
Training batch:  3  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 9ms/step - loss: 8.9839e-05
Training batch:  4  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 8ms/step - loss: 8.9839e-05
Training batch:  5  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 8ms/step - loss: 8.9838e-05
Training batch:  6  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 8ms/step - loss: 8.9838e-05
Training batch:  7  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 8ms/step - loss: 8.9837e-05
Training batch:  8  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 8ms/step - loss: 8.9836e-05
Training batch:  9  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 8ms/step - loss: 8.9835e-05
Training batch:  10  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 8ms/step - loss: 8.9832e-05
Training batch:  11  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 8ms/step - loss: 8.9776e-05
Training batch:  12  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 8ms/step - loss: 8.9536e-05
Training batch:  13  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 8ms/step - loss: 8.9446e-05
Training batch:  14  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 9ms/step - loss: 8.9996e-05
Training batch:  15  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 9ms/step - loss: 8.9835e-05
Training batch:  16  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 9ms/step - loss: 8.9835e-05
Training batch:  17  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 9ms/step - loss: 8.9834e-05
Training batch:  18  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 9ms/step - loss: 8.9833e-05
Training batch:  19  out of  26 .  :)
Epoch 1/1
```

```
2000/2000 [==============================] - 17s 9ms/step - loss: 8.9831e-05
Training batch:  20  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 9ms/step - loss: 8.9828e-05
Training batch:  21  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 9ms/step - loss: 8.9825e-05
Training batch:  22  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 9ms/step - loss: 8.9799e-05
Training batch:  23  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 9ms/step - loss: 8.9382e-05
Training batch:  24  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 9ms/step - loss: 8.9586e-05
Training batch:  25  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 8ms/step - loss: 8.9321e-05
Training batch:  26  out of  26 .  :)
Epoch 1/1
2000/2000 [==============================] - 17s 8ms/step - loss: 8.9597e-05
```

In [7]:

```
def generate_words_FFNN(word2vec_model, keras_model, words_list, length=12):
    words = []
    word_indexs = []
    for word in words_list:
        word_indexs.append(word2vec_model.wv.vocab[word].index)
        words.append(word)

    for i in range(length):

        word_data_x = 0

        word_vectors = []

        index1 = word_indexs[-3]
        index2 = word_indexs[-2]
        index3 = word_indexs[-1]

        word_data_x = np.concatenate((word2vec_model.wv.vectors[index1],
word2vec_model.wv.vectors[index2], word2vec_model.wv.vectors[index3]))

        word_vectors.append(word_data_x)

        pred = keras_model.predict(x=np.asarray(word_vectors), verbose=0) #added
verbose
```

```
        pred = pred[0] #an array of arrays?

        vocab = list(word2vec_model.wv.vocab)

        vocab_index = [word2vec_model.wv.vocab[i].index for i in vocab]

        vocab_index = np.asarray(vocab_index)

        prediction = np.random.choice(vocab_index, p=pred, replace=True) #added p= for
pred

        word_indexs.append(prediction)

        index_to_word = word2vec_model.wv.index2word[prediction]

        words.append(index_to_word)

    return(words)
```

In [8]:

```
#Primary Dataset
print("-------------Generating Words-------------")

words = generate_words_FFNN(model_primaryDataset, primary_FFNN, ["horse", "seemed",
"to"])
print(words)

sentences_secondary = section_data(sentences_secondaryDataset)

print(np.asarray(sentences_secondary[0]).shape)

print("-------------Formatting test data-------------")

x_train_secondary, y_train_secondary = training_data(sentences_secondary,
model_secondaryDataset)
```

```
-------------Generating Words-------------
['horse', 'seemed', 'to', 'theyre', 'engagement', 'darted', 'abysmal', 'proving',
'peculiarity', 'widely', 'wood', 'counterfeit', 'shaft', 'spell', 'towers']
(2000, 4)
-------------Formatting test data-------------
```

In [9]:

```
#------------------------------Secondary Dataset------------------------------

# Wouldn't even attempt to run this unless on computer with a GPU and lots of ram.

# Its eating 32gb's of system ram and 6gb's of vram


#Create Keras Model


print("-------------Building Model-------------")


secondary_FFNN = Sequential()


secondary_FFNN.add(Dense(units=10000, input_shape=(900,)))

secondary_FFNN.add(Dense(units=len(model_secondaryDataset.wv.vocab),activation="softma
x"))

secondary_FFNN.compile(optimizer="adam", loss='mean_squared_error')


secondary_FFNN.summary()


print("-------------Training Model-------------")


secondary_FFNN = train(x_train_secondary, y_train_secondary, secondary_FFNN,
model_secondaryDataset)
```

```
-------------Building Model-------------
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_3 (Dense)              (None, 10000)             9010000
_________________________________________________________________
dense_4 (Dense)              (None, 7310)              73107310
=================================================================
Total params: 82,117,310
Trainable params: 82,117,310
Non-trainable params: 0
_________________________________________________________________
-------------Training Model-------------
Training batch:  1  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3678e-04
Training batch:  2  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3678e-04
Training batch:  3  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3678e-04
Training batch:  4  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3678e-04
```

```
Training batch:  5  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3677e-04
Training batch:  6  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3677e-04
Training batch:  7  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3672e-04
Training batch:  8  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3663e-04
Training batch:  9  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3651e-04
Training batch:  10  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3637e-04
Training batch:  11  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3655e-04
Training batch:  12  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3641e-04
Training batch:  13  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3620e-04
Training batch:  14  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3650e-04
Training batch:  15  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3650e-04
Training batch:  16  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3628e-04
Training batch:  17  out of  17 .  :)
Epoch 1/1
2000/2000 [==============================] - 12s 6ms/step - loss: 1.3636e-04
```

In [10]:

```
print("-------------Generating Words-------------")


words = generate_words_FFNN(model_secondaryDataset, secondary_FFNN, ["this", "is",
"not"])

print(words)
```

```
-------------Generating Words-------------
['this', 'is', 'not', 'attached', 'clock', 'cops', 'ohio', 'hold', 'avoiding', 'made',
'differently', 'favorites', 'nation', 'fried', 'mysteries']
```

Sources Cited¶

An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition by Daniel Jurafsky and James H. Martin https://keras.io/models/model/

Section 5: Recurrent Neural Language Model¶

In [23]:

```
def training_data_RNN(sentences, model):
    sentence_length = 45

    x_train = np.zeros([len(sentences), sentence_length], dtype=np.int32)
    y_train = np.zeros([len(sentences)], dtype=np.int32)

    for i, sentence in enumerate(sentences):
        for j, word in enumerate(sentence[:-1]):
            x_train[i, j] = model.wv.vocab[word].index
        y_train[i] = model.wv.vocab[sentence[-1]].index

    return x_train, y_train




sentences_primary = sentences_primaryDataset


x_train_primary, y_train_primary = training_data_RNN(sentences_primary,
model_primaryDataset)






sentences_secondary = sentences_secondaryDataset


x_train_secondary, y_train_secondary = training_data_RNN(sentences_secondary,
model_secondaryDataset)





print('train_x shape:', x_train_primary.shape)
print(x_train_primary)
print('train_y shape:', y_train_primary.shape)
```

```
def generate_words_RNN(word2vec_model, keras_model, words_list, length=12):
    words = []
    word_indexs = []
    for word in words_list:
        word_indexs.append(word2vec_model.wv.vocab[word].index)
        words.append(word)

    for i in range(length):
        word_index_array = np.array(word_indexs)
        pred = keras_model.predict(x=word_index_array)

        pred = pred[0] #an array of arrays?

        vocab = list(word2vec_model.wv.vocab)

        vocab_index = [word2vec_model.wv.vocab[i].index for i in vocab]

        vocab_index = np.asarray(vocab_index)

        prediction = np.random.choice(vocab_index, p=pred, replace=True) #added p= for
pred

        word_indexs.append(prediction)

        index_to_word = word2vec_model.wv.index2word[prediction]

        words.append(index_to_word)

    return(words)



vec = 300
```

```
train_x shape: (5790, 45)
[[  26 3435  143 ...  109  123    0]
 [  22    9    0 ...  308  440    0]
 [ 650   25  667 ...   15 2012    0]
 ...
 [   0    3  527 ...  111  178    0]
 [ 283    2   39 ... 8104    4    0]
 [   0  320  148 ...    2  933    0]]
```

```
train_y shape: (5790,)
```

In [24]:

```
# code to train a recurrent neural language model
# on a set of given word embeddings
# make sure not to just copy + paste to train your two


#------------------ Primary Dataset -----------------



#Create Keras Model


trained_weights_primaryDataset = model_primaryDataset.wv.vectors
vocab_size_primaryDataset, embedding_size_primaryDataset =
trained_weights_primaryDataset.shape


primary_RNN = Sequential()
primary_RNN.add(Embedding(input_dim=vocab_size_primaryDataset,
output_dim=embedding_size_primaryDataset, weights=[trained_weights_primaryDataset],
trainable=False))
primary_RNN.add(SimpleRNN(units=embedding_size_primaryDataset))
primary_RNN.add(Dense(units=vocab_size_primaryDataset))
primary_RNN.add(Activation('softmax'))


primary_RNN.compile(optimizer='adam', loss='sparse_categorical_crossentropy')


primary_RNN.summary()


primary_RNN.fit(x_train_primary, y_train_primary, batch_size=128, epochs=100)
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_3 (Embedding)      (None, None, 300)         3385800
_________________________________________________________________
simple_rnn_3 (SimpleRNN)     (None, 300)               180300
_________________________________________________________________
dense_7 (Dense)              (None, 11286)             3397086
_________________________________________________________________
activation_3 (Activation)    (None, 11286)             0
=================================================================
Total params: 6,963,186
Trainable params: 3,577,386
Non-trainable params: 3,385,800
_________________________________________________________________
Epoch 1/100
```

```
5790/5790 [==============================] - 1s 142us/step - loss: 7.6453
Epoch 2/100
5790/5790 [==============================] - 1s 108us/step - loss: 6.4698
Epoch 3/100
5790/5790 [==============================] - 1s 99us/step - loss: 6.3722
Epoch 4/100
5790/5790 [==============================] - 1s 107us/step - loss: 6.2425
Epoch 5/100
5790/5790 [==============================] - 1s 97us/step - loss: 6.0543
Epoch 6/100
5790/5790 [==============================] - 1s 98us/step - loss: 5.8384
Epoch 7/100
5790/5790 [==============================] - 1s 100us/step - loss: 5.6008
Epoch 8/100
5790/5790 [==============================] - 1s 102us/step - loss: 5.3492
Epoch 9/100
5790/5790 [==============================] - 1s 91us/step - loss: 5.0873
Epoch 10/100
5790/5790 [==============================] - 1s 91us/step - loss: 4.8331
Epoch 11/100
5790/5790 [==============================] - 1s 90us/step - loss: 4.5681
Epoch 12/100
5790/5790 [==============================] - 1s 92us/step - loss: 4.3081
Epoch 13/100
5790/5790 [==============================] - 1s 90us/step - loss: 4.0499
Epoch 14/100
5790/5790 [==============================] - 1s 90us/step - loss: 3.7839
Epoch 15/100
5790/5790 [==============================] - 1s 92us/step - loss: 3.5270
Epoch 16/100
5790/5790 [==============================] - 1s 92us/step - loss: 3.2721
Epoch 17/100
5790/5790 [==============================] - 1s 92us/step - loss: 3.0251
Epoch 18/100
5790/5790 [==============================] - 1s 94us/step - loss: 2.7856
Epoch 19/100
5790/5790 [==============================] - 1s 89us/step - loss: 2.5668
Epoch 20/100
5790/5790 [==============================] - 1s 92us/step - loss: 2.3440
Epoch 21/100
5790/5790 [==============================] - 1s 88us/step - loss: 2.1522
Epoch 22/100
5790/5790 [==============================] - 1s 93us/step - loss: 1.9712
Epoch 23/100
5790/5790 [==============================] - 1s 90us/step - loss: 1.8100
Epoch 24/100
5790/5790 [==============================] - 1s 90us/step - loss: 1.6536
Epoch 25/100
5790/5790 [==============================] - 1s 88us/step - loss: 1.5082
Epoch 26/100
5790/5790 [==============================] - 1s 90us/step - loss: 1.3807
Epoch 27/100
5790/5790 [==============================] - 1s 88us/step - loss: 1.2928
Epoch 28/100
5790/5790 [==============================] - 1s 89us/step - loss: 1.1788
Epoch 29/100
5790/5790 [==============================] - 1s 89us/step - loss: 1.0845
Epoch 30/100
5790/5790 [==============================] - 1s 93us/step - loss: 1.0211
Epoch 31/100
5790/5790 [==============================] - 1s 94us/step - loss: 0.9044
Epoch 32/100
5790/5790 [==============================] - 1s 89us/step - loss: 0.8272
```

```
Epoch 33/100
5790/5790 [==============================] - 1s 89us/step - loss: 0.7880
Epoch 34/100
5790/5790 [==============================] - 1s 91us/step - loss: 0.7191
Epoch 35/100
5790/5790 [==============================] - 1s 90us/step - loss: 0.6488
Epoch 36/100
5790/5790 [==============================] - 1s 88us/step - loss: 0.5860
Epoch 37/100
5790/5790 [==============================] - 1s 94us/step - loss: 0.5335
Epoch 38/100
5790/5790 [==============================] - 1s 95us/step - loss: 0.4896
Epoch 39/100
5790/5790 [==============================] - 1s 96us/step - loss: 0.4835
Epoch 40/100
5790/5790 [==============================] - 1s 94us/step - loss: 0.4860
Epoch 41/100
5790/5790 [==============================] - 1s 97us/step - loss: 0.4167
Epoch 42/100
5790/5790 [==============================] - 1s 94us/step - loss: 0.4280
Epoch 43/100
5790/5790 [==============================] - 1s 96us/step - loss: 0.4752
Epoch 44/100
5790/5790 [==============================] - 1s 96us/step - loss: 0.3714
Epoch 45/100
5790/5790 [==============================] - 1s 95us/step - loss: 0.3099
Epoch 46/100
5790/5790 [==============================] - 1s 98us/step - loss: 0.2622
Epoch 47/100
5790/5790 [==============================] - 1s 95us/step - loss: 0.2266
Epoch 48/100
5790/5790 [==============================] - 1s 99us/step - loss: 0.2013
Epoch 49/100
5790/5790 [==============================] - 1s 94us/step - loss: 0.1739
Epoch 50/100
5790/5790 [==============================] - 1s 96us/step - loss: 0.1594
Epoch 51/100
5790/5790 [==============================] - 1s 96us/step - loss: 0.1562
Epoch 52/100
5790/5790 [==============================] - 1s 95us/step - loss: 0.1471
Epoch 53/100
5790/5790 [==============================] - 1s 95us/step - loss: 0.1284
Epoch 54/100
5790/5790 [==============================] - 1s 94us/step - loss: 0.1130
Epoch 55/100
5790/5790 [==============================] - 1s 92us/step - loss: 0.1039
Epoch 56/100
5790/5790 [==============================] - 1s 88us/step - loss: 0.0953
Epoch 57/100
5790/5790 [==============================] - 1s 88us/step - loss: 0.0873
Epoch 58/100
5790/5790 [==============================] - 1s 88us/step - loss: 0.0818
Epoch 59/100
5790/5790 [==============================] - 1s 89us/step - loss: 0.0781
Epoch 60/100
5790/5790 [==============================] - 1s 93us/step - loss: 0.1219
Epoch 61/100
5790/5790 [==============================] - 1s 91us/step - loss: 0.3503
Epoch 62/100
5790/5790 [==============================] - 1s 89us/step - loss: 0.6907
Epoch 63/100
5790/5790 [==============================] - 1s 92us/step - loss: 0.5106
Epoch 64/100
```

```
5790/5790 [==============================] - 1s 92us/step - loss: 0.4343
Epoch 65/100
5790/5790 [==============================] - 1s 91us/step - loss: 0.3021
Epoch 66/100
5790/5790 [==============================] - 1s 90us/step - loss: 0.1937
Epoch 67/100
5790/5790 [==============================] - 1s 89us/step - loss: 0.1451
Epoch 68/100
5790/5790 [==============================] - 1s 90us/step - loss: 0.1317
Epoch 69/100
5790/5790 [==============================] - 1s 89us/step - loss: 0.1369
Epoch 70/100
5790/5790 [==============================] - 1s 88us/step - loss: 0.0907
Epoch 71/100
5790/5790 [==============================] - 1s 89us/step - loss: 0.0725
Epoch 72/100
5790/5790 [==============================] - 1s 89us/step - loss: 0.0552
Epoch 73/100
5790/5790 [==============================] - 1s 89us/step - loss: 0.0463
Epoch 74/100
5790/5790 [==============================] - 1s 90us/step - loss: 0.0431
Epoch 75/100
5790/5790 [==============================] - 1s 89us/step - loss: 0.0386
Epoch 76/100
5790/5790 [==============================] - 1s 89us/step - loss: 0.0350
Epoch 77/100
5790/5790 [==============================] - 1s 89us/step - loss: 0.0321
Epoch 78/100
5790/5790 [==============================] - 1s 88us/step - loss: 0.0308
Epoch 79/100
5790/5790 [==============================] - 1s 90us/step - loss: 0.0286
Epoch 80/100
5790/5790 [==============================] - 1s 89us/step - loss: 0.0269
Epoch 81/100
5790/5790 [==============================] - 1s 88us/step - loss: 0.0256
Epoch 82/100
5790/5790 [==============================] - 1s 90us/step - loss: 0.0243
Epoch 83/100
5790/5790 [==============================] - 1s 91us/step - loss: 0.0233
Epoch 84/100
5790/5790 [==============================] - 1s 96us/step - loss: 0.0223
Epoch 85/100
5790/5790 [==============================] - 1s 94us/step - loss: 0.0214
Epoch 86/100
5790/5790 [==============================] - 1s 95us/step - loss: 0.0206
Epoch 87/100
5790/5790 [==============================] - 1s 96us/step - loss: 0.0198
Epoch 88/100
5790/5790 [==============================] - 1s 97us/step - loss: 0.0190
Epoch 89/100
5790/5790 [==============================] - 1s 95us/step - loss: 0.0183
Epoch 90/100
5790/5790 [==============================] - 1s 99us/step - loss: 0.0177
Epoch 91/100
5790/5790 [==============================] - 1s 103us/step - loss: 0.0171
Epoch 92/100
5790/5790 [==============================] - 1s 97us/step - loss: 0.0165
Epoch 93/100
5790/5790 [==============================] - 1s 98us/step - loss: 0.0159
Epoch 94/100
5790/5790 [==============================] - 1s 95us/step - loss: 0.0154
Epoch 95/100
5790/5790 [==============================] - 1s 95us/step - loss: 0.0149
```

```
Epoch 96/100
5790/5790 [==============================] - 1s 96us/step - loss: 0.0144
Epoch 97/100
5790/5790 [==============================] - 1s 99us/step - loss: 0.0140
Epoch 98/100
5790/5790 [==============================] - 1s 96us/step - loss: 0.0135
Epoch 99/100
5790/5790 [==============================] - 1s 96us/step - loss: 0.0131
Epoch 100/100
5790/5790 [==============================] - 1s 95us/step - loss: 0.0127
```

Out[24]:

```
<keras.callbacks.callbacks.History at 0x1b51a139948>
```

In [25]:

```
test = ["this", "should", "work"]

words = generate_words_RNN(model_primaryDataset,primary_RNN,test)



print(words)
```

```
['this', 'should', 'work', 'afforded', 'make', 'this', 'bottom', 'make', 'process',
'hectic', 'to', 'make', 'me', 'once', 'it']
```

In [26]:

```
# code to train a recurrent neural language model

# on a set of given word embeddings

# make sure not to just copy + paste to train your two


#------------------ Secondary Dataset -----------------



#Create Keras Model


trained_weights_secondaryDataset = model_secondaryDataset.wv.vectors

vocab_size_secondaryDataset, embedding_size_secondaryDataset =
trained_weights_secondaryDataset.shape


secondary_RNN = Sequential()

secondary_RNN.add(Embedding(input_dim=vocab_size_secondaryDataset,
output_dim=embedding_size_secondaryDataset,
weights=[trained_weights_secondaryDataset], trainable=False))

secondary_RNN.add(SimpleRNN(units=embedding_size_secondaryDataset))

secondary_RNN.add(Dense(units=vocab_size_secondaryDataset))

secondary_RNN.add(Activation('softmax'))
```

```
secondary_RNN.compile(optimizer='adam', loss='sparse_categorical_crossentropy')


secondary_RNN.summary()


secondary_RNN.fit(x_train_secondary, y_train_secondary, batch_size=128, epochs=100)
```

```
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
embedding_4 (Embedding)      (None, None, 300)         2223900   
_________________________________________________________________
simple_rnn_4 (SimpleRNN)     (None, 300)               180300    
_________________________________________________________________
dense_8 (Dense)              (None, 7413)              2231313   
_________________________________________________________________
activation_4 (Activation)    (None, 7413)              0         
=================================================================
Total params: 4,635,513
Trainable params: 2,411,613
Non-trainable params: 2,223,900
_________________________________________________________________
Epoch 1/100
3815/3815 [==============================] - 1s 133us/step - loss: 7.3251
Epoch 2/100
3815/3815 [==============================] - 0s 81us/step - loss: 6.1827
Epoch 3/100
3815/3815 [==============================] - 0s 81us/step - loss: 6.0993
Epoch 4/100
3815/3815 [==============================] - 0s 83us/step - loss: 6.0873
Epoch 5/100
3815/3815 [==============================] - 0s 80us/step - loss: 6.0727
Epoch 6/100
3815/3815 [==============================] - 0s 84us/step - loss: 6.0657
Epoch 7/100
3815/3815 [==============================] - 0s 82us/step - loss: 6.0561
Epoch 8/100
3815/3815 [==============================] - 0s 82us/step - loss: 5.9954
Epoch 9/100
3815/3815 [==============================] - 0s 82us/step - loss: 5.9034
Epoch 10/100
3815/3815 [==============================] - 0s 82us/step - loss: 5.7487
Epoch 11/100
3815/3815 [==============================] - 0s 83us/step - loss: 5.5734
Epoch 12/100
3815/3815 [==============================] - 0s 83us/step - loss: 5.4087
Epoch 13/100
3815/3815 [==============================] - 0s 81us/step - loss: 5.2364
Epoch 14/100
3815/3815 [==============================] - 0s 81us/step - loss: 5.0580
Epoch 15/100
3815/3815 [==============================] - 0s 82us/step - loss: 4.8786
Epoch 16/100
3815/3815 [==============================] - 0s 81us/step - loss: 4.6931
Epoch 17/100
3815/3815 [==============================] - 0s 82us/step - loss: 4.4946
Epoch 18/100
3815/3815 [==============================] - 0s 81us/step - loss: 4.2956
Epoch 19/100
3815/3815 [==============================] - 0s 83us/step - loss: 4.1013
```

```
Epoch 20/100
3815/3815 [==============================] - 0s 82us/step - loss: 3.8932
Epoch 21/100
3815/3815 [==============================] - 0s 82us/step - loss: 3.6853
Epoch 22/100
3815/3815 [==============================] - 0s 83us/step - loss: 3.4809
Epoch 23/100
3815/3815 [==============================] - 0s 82us/step - loss: 3.2713
Epoch 24/100
3815/3815 [==============================] - 0s 81us/step - loss: 3.0785
Epoch 25/100
3815/3815 [==============================] - 0s 81us/step - loss: 2.8817
Epoch 26/100
3815/3815 [==============================] - 0s 82us/step - loss: 2.6848
Epoch 27/100
3815/3815 [==============================] - 0s 81us/step - loss: 2.4873
Epoch 28/100
3815/3815 [==============================] - 0s 83us/step - loss: 2.3079
Epoch 29/100
3815/3815 [==============================] - 0s 87us/step - loss: 2.1498
Epoch 30/100
3815/3815 [==============================] - 0s 86us/step - loss: 1.9761
Epoch 31/100
3815/3815 [==============================] - 0s 82us/step - loss: 1.8250
Epoch 32/100
3815/3815 [==============================] - 0s 82us/step - loss: 1.6874
Epoch 33/100
3815/3815 [==============================] - 0s 82us/step - loss: 1.5553
Epoch 34/100
3815/3815 [==============================] - 0s 85us/step - loss: 1.4309
Epoch 35/100
3815/3815 [==============================] - 0s 83us/step - loss: 1.3340
Epoch 36/100
3815/3815 [==============================] - 0s 81us/step - loss: 1.2336
Epoch 37/100
3815/3815 [==============================] - 0s 80us/step - loss: 1.1238
Epoch 38/100
3815/3815 [==============================] - 0s 85us/step - loss: 1.0342
Epoch 39/100
3815/3815 [==============================] - 0s 81us/step - loss: 0.9423
Epoch 40/100
3815/3815 [==============================] - 0s 81us/step - loss: 0.8594
Epoch 41/100
3815/3815 [==============================] - 0s 83us/step - loss: 0.8113
Epoch 42/100
3815/3815 [==============================] - 0s 81us/step - loss: 0.7295
Epoch 43/100
3815/3815 [==============================] - 0s 81us/step - loss: 0.6655
Epoch 44/100
3815/3815 [==============================] - 0s 87us/step - loss: 0.6214
Epoch 45/100
3815/3815 [==============================] - 0s 89us/step - loss: 0.5695
Epoch 46/100
3815/3815 [==============================] - 0s 88us/step - loss: 0.5283
Epoch 47/100
3815/3815 [==============================] - 0s 87us/step - loss: 0.4867
Epoch 48/100
3815/3815 [==============================] - 0s 86us/step - loss: 0.4401
Epoch 49/100
3815/3815 [==============================] - 0s 87us/step - loss: 0.3971
Epoch 50/100
3815/3815 [==============================] - 0s 88us/step - loss: 0.3626
Epoch 51/100
```

```
3815/3815 [==============================] - 0s 90us/step - loss: 0.3407
Epoch 52/100
3815/3815 [==============================] - 0s 89us/step - loss: 0.3079
Epoch 53/100
3815/3815 [==============================] - 0s 88us/step - loss: 0.3101
Epoch 54/100
3815/3815 [==============================] - 0s 91us/step - loss: 0.2843
Epoch 55/100
3815/3815 [==============================] - 0s 89us/step - loss: 0.3115
Epoch 56/100
3815/3815 [==============================] - 0s 89us/step - loss: 0.2952
Epoch 57/100
3815/3815 [==============================] - 0s 88us/step - loss: 0.3360
Epoch 58/100
3815/3815 [==============================] - 0s 87us/step - loss: 0.5449
Epoch 59/100
3815/3815 [==============================] - 0s 89us/step - loss: 0.4458
Epoch 60/100
3815/3815 [==============================] - 0s 90us/step - loss: 0.2846
Epoch 61/100
3815/3815 [==============================] - 0s 88us/step - loss: 0.2089
Epoch 62/100
3815/3815 [==============================] - 0s 88us/step - loss: 0.1785
Epoch 63/100
3815/3815 [==============================] - 0s 87us/step - loss: 0.1461
Epoch 64/100
3815/3815 [==============================] - 0s 89us/step - loss: 0.1256
Epoch 65/100
3815/3815 [==============================] - 0s 88us/step - loss: 0.1127
Epoch 66/100
3815/3815 [==============================] - 0s 89us/step - loss: 0.1049
Epoch 67/100
3815/3815 [==============================] - 0s 90us/step - loss: 0.0960
Epoch 68/100
3815/3815 [==============================] - 0s 92us/step - loss: 0.0895
Epoch 69/100
3815/3815 [==============================] - 0s 89us/step - loss: 0.0842
Epoch 70/100
3815/3815 [==============================] - 0s 87us/step - loss: 0.0806
Epoch 71/100
3815/3815 [==============================] - 0s 87us/step - loss: 0.1291
Epoch 72/100
3815/3815 [==============================] - 0s 89us/step - loss: 0.7548
Epoch 73/100
3815/3815 [==============================] - 0s 87us/step - loss: 1.0568
Epoch 74/100
3815/3815 [==============================] - 0s 81us/step - loss: 0.6069
Epoch 75/100
3815/3815 [==============================] - 0s 81us/step - loss: 0.4215
Epoch 76/100
3815/3815 [==============================] - 0s 80us/step - loss: 0.3505
Epoch 77/100
3815/3815 [==============================] - 0s 84us/step - loss: 0.2696
Epoch 78/100
3815/3815 [==============================] - 0s 86us/step - loss: 0.1619
Epoch 79/100
3815/3815 [==============================] - 0s 88us/step - loss: 0.1185
Epoch 80/100
3815/3815 [==============================] - 0s 82us/step - loss: 0.0985
Epoch 81/100
3815/3815 [==============================] - 0s 81us/step - loss: 0.0829
Epoch 82/100
3815/3815 [==============================] - 0s 82us/step - loss: 0.0728
```

```
Epoch 83/100
3815/3815 [==============================] - 0s 85us/step - loss: 0.0643
Epoch 84/100
3815/3815 [==============================] - 0s 83us/step - loss: 0.0576
Epoch 85/100
3815/3815 [==============================] - 0s 81us/step - loss: 0.0529
Epoch 86/100
3815/3815 [==============================] - 0s 80us/step - loss: 0.0493
Epoch 87/100
3815/3815 [==============================] - 0s 82us/step - loss: 0.0463
Epoch 88/100
3815/3815 [==============================] - 0s 80us/step - loss: 0.0438
Epoch 89/100
3815/3815 [==============================] - 0s 81us/step - loss: 0.0417
Epoch 90/100
3815/3815 [==============================] - 0s 81us/step - loss: 0.0398
Epoch 91/100
3815/3815 [==============================] - 0s 83us/step - loss: 0.0381
Epoch 92/100
3815/3815 [==============================] - 0s 80us/step - loss: 0.0365
Epoch 93/100
3815/3815 [==============================] - 0s 82us/step - loss: 0.0350
Epoch 94/100
3815/3815 [==============================] - 0s 82us/step - loss: 0.0337
Epoch 95/100
3815/3815 [==============================] - 0s 80us/step - loss: 0.0325
Epoch 96/100
3815/3815 [==============================] - 0s 81us/step - loss: 0.0313
Epoch 97/100
3815/3815 [==============================] - 0s 82us/step - loss: 0.0302
Epoch 98/100
3815/3815 [==============================] - 0s 82us/step - loss: 0.0292
Epoch 99/100
3815/3815 [==============================] - 0s 82us/step - loss: 0.0282
Epoch 100/100
3815/3815 [==============================] - 0s 83us/step - loss: 0.0273
```

Out[26]:

```
<keras.callbacks.callbacks.History at 0x1b51b1d7e88>
```

In [27]:

```
test = ["this", "should", "work"]
words = generate_words_RNN(model_secondaryDataset,secondary_RNN,test)



print(words)
```

```
['this', 'should', 'work', 'korea', 'korea', 'ladies', 'korea', 'whatever', 'korea',
'early', 'korea', 'things', 'korea', 'korea', 'korea']
```

Sources Cited¶

An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition by Daniel Jurafsky and James H. Martin

“Python Gensim Word2Vec Tutorial with TensorFlow and Keras.” Adventures in Machine Learning, 1 Sept. 2017, adventuresinmachinelearning.com/gensim-word2vec-tutorial/.
Shukla, Vishal ShuklaVishal. “Using Pre-Trained word2vec with LSTM for Word Generation.” Stack Overflow, 1AD, stackoverflow.com/questions/42064690/using-pre-trained-word2vec-with-lstm-for-word-generation.

Section 6: Evaluate the differences between the two language models¶

(make sure to include graphs, figures, and paragraphs with full sentences)

In [19]:

```
#-----Section 6.1: Evaluating the models' perplexities-----#



pTest_Dataset = Clean_data_primary_dataset("test.csv")
#imports and cleans test dataset, in sentence form


def getWordIndex(model, word):
    index = None
    if word in model.wv.vocab:
        index = model.wv.vocab[word].index
    return index


def calculateSentencePerplexity(model, keras_model, sentence, probs):
    word_vectors = []
    unkVal = 1.0 / len(pTest_Dataset)
    for i in range(4, len(sentence)): #should we be doing all of the preceding words
in a sentence instead of 3 (yes?)
        word1 = sentence[i-3]
        word2 = sentence[i-2]
        word3 = sentence[i-1]
        word4 = sentence[i]
        index1 = getWordIndex(model, word1)
        index2 = getWordIndex(model, word2)
        index3 = getWordIndex(model, word3)
        index4 = getWordIndex(model, word4)

        wordProb = 0.0
```

```
        if index1 != None and index2 != None and index3 != None and index4 != None:
            test_data_x = np.concatenate((model.wv.vectors[index1],
model.wv.vectors[index2], model.wv.vectors[index3]))
            word_vectors.append(test_data_x)


            pred = keras_model.predict(x=np.asarray(word_vectors), verbose=0)
            pred = pred[0]
            wordProb = pred[index4]
        else:
            wordProb = 1.0 / len(model.wv.vocab)
        if wordProb == 1.0:
            wordProb -= unkVal
        if wordProb == 0.0:
            wordProb += unkVal
        probs.append(wordProb)


def calculatePerplexity(model, keras_model, pTest_Dataset):
    unkVal = 1.0 / len(pTest_Dataset)
    probs = []
    for sentence in pTest_Dataset:
        sentenceProbabilty = calculateSentencePerplexity(model, keras_model, sentence,
probs)
    val = 0.0
    for prob in probs:
        val += np.log2(prob)
    perplexity = np.power(2, -val/len(probs))
    return perplexity


#----Primary Dataset Perplexity-----#
print("----Calculating Primary Dataset Perplexity-----")
model = model_primaryDataset
keras_model = primary_FFNN
vocab = list(model.wv.vocab)
vocab_index = np.asarray([model.wv.vocab[i].index for i in vocab])
print("Primary Dataset Perplexity: ", calculatePerplexity(model, keras_model,
pTest_Dataset))


#----Secondary Dataset Perplexity-----#
```

```
print("----Calculating Secondary Dataset Perplexity-----")
model = model_secondaryDataset
keras_model = secondary_FFNN
vocab = list(model.wv.vocab)
vocab_index = np.asarray([model.wv.vocab[i].index for i in vocab])
print("Secondary Dataset Perplexity: ", calculatePerplexity(model, keras_model,
pTest_Dataset))
```

```
----Calculating Primary Dataset Perplexity-----
Primary Dataset Perplexity:  7115.695240277234
----Calculating Secondary Dataset Perplexity-----
Secondary Dataset Perplexity:  5079.862487864495
```

In [20]:

```
#-----Section 6.2: Generate Random Sentences-----#


phrases = []
for i in range(10):
    sentence = []
    while len(sentence) < 3:
        index = int(np.random.random() * len(pTest_Dataset))
        sentence = pTest_Dataset[index]
        for s in range(3):
            if sentence[s] not in model_primaryDataset.wv.vocab:
                sentence = []
                break
    phrase = []
    for j in range(3):
        phrase.append(sentence[j])
    phrases.append(phrase)



"""
#FFNN  and RNN
for phrase in phrases:
    words = generate_words_FFNN(model_primaryDataset, primary_FFNN, phrase, length=9)
    sentence = ""
    for word in words:
        sentence += word + " "
    print("FFNN Sentence: ", sentence)
    words = generate_words_RNN(model_primaryDataset, primary_RNN, phrase, length=9)
```

```
    sentence = ""
    for word in words:
        sentence += word + " "
    print("RNN Sentence: ", sentence)
"""




#FFNN
for phrase in phrases:
    words = generate_words_FFNN(model_primaryDataset, primary_FFNN, phrase, length=9)
    sentence = ""
    for word in words:
        sentence += word + " "
    print("FFNN Sentence: ", sentence)
```

```
FFNN Sentence:  the innumerable blossoms shew assume womanish lowest skies records
anxious abysses earlier
FFNN Sentence:  you say that relates excessive carousals dubious others glimpses
disgraced godlike demons
FFNN Sentence:  there was a pang effeminate keys election admire shafts strength this
rushed
FFNN Sentence:  here let us contemplated purity burden orgies formation ionic agraffas
edge cultivating
FFNN Sentence:  the condition of precluded accomplish bathed meaningless coal trip
wrongs boughs curse
FFNN Sentence:  by one of form this differed omen yellowish knxw demurely inextricable
wine
FFNN Sentence:  we cannot be denunciations bolts consolation via rejected captivity
convenient glanced kapou
FFNN Sentence:  the organs of lectures forbearance decayed admission shrank denied
cried judge polished
FFNN Sentence:  banners yellow glorious notices condemnation glades yourself
bewildered horde criminal oath hi
FFNN Sentence:  when first i flabby belt rigid wrong progressive commercial matt
structure keziah
```

In [28]:

```
#RNN
for phrase in phrases:
    words = generate_words_RNN(model_primaryDataset, primary_RNN, phrase, length=9)
    sentence = ""
    for word in words:
        sentence += word + " "
    print("RNN Sentence: ", sentence)
```

```
RNN Sentence:  the innumerable blossoms this as this this as as this afforded this
RNN Sentence:  you say that similar reverberation potential killed impression torches
us laws erich
RNN Sentence:  there was a now immortal advancing response protested considered
adversity thar sunlight
RNN Sentence:  here let us britain suggestion tyrants sensibility gibbering manifest
window despair shook
RNN Sentence:  the condition of this this as this this as afforded this of
RNN Sentence:  by one of sufficient interrupted benign dungeon countenance approaches
afforded in wise
RNN Sentence:  we cannot be rob gates shrunk nice dub kicked needs assisted nocturnal
RNN Sentence:  the organs of afforded this this as this this this this this
RNN Sentence:  banners yellow glorious no so spirit afforded stirred lacey dilemma
fast notice
RNN Sentence:  when first i iron crew process clerical dungeon fragrance return ring
by
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Sources Cited¶

Aerin Kim, Perplexity Intuition (and its derivation) Never be perplexed again by perplexity
https://towardsdatascience.com/perplexity-intuition-and-derivation-105dd481c8f3
An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition by Daniel Jurafsky and James H. Martin

Quality Evaluation¶

1) the organs of lectures forbearance decayed admission shrank denied cried judge polished¶

2) there was a now immortal advancing response protested considered adversity than sunlight¶

Joey -
Sentence 2 is more grammatical
Both sentences are equally sensical (or nonsensical)
Ford -
Both sentences are equally grammatical (or ungrammatical)
Sentence 2 makes more sense

1) by one of form this differed omen yellowish knxw demurely inextricable wine¶

2) here let us britain suggestion tyrants sensibility gibbering manifest window despair shook¶

Joey -
Sentence 1 is more grammatical
Both sentences are equally sensical (or nonsensical)
Ford -

Both sentences are equally grammatical (or ungrammatical)
Sentence 1 makes more sense

1) you say that relates excessive carousals dubious others glimpses disgraced godlike demons¶

2) when first i iron crew process clerical dungeon fragrance return ring by¶

Joey -
Both sentences are equally grammatical (or ungrammatical)
Both sentences are equally sensical (or nonsensical)
Ford -
Sentence 2 is more grammatical
Sentence 2 makes more sense

Sentence 1 was always the FFNN while sentence 2 was the RNN. The RNN seems to make better sentences but neither of the networks produced great results.¶

In [ ]: