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.

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Step 1: Word2Vec paper questions

```
1. Describe how a CBOW word embedding is generated.
    CBOW uses a context window which is a certain number of
neighboring words to the left and right that the model considers
when trying to predict the middle word. The context window size
recommended in the paper is 4. In this case, the model would
consider four words to the left and four words to the right and
tries to predict the middle word. The order of these words does
not matter, which is why its considered a bag-of-words model.

2. What is a CBOW word embedding and how is it different from a
skip-gram word embedding?
    A CBOW word embedding predicts the current word based on the
given context words and is the opposite of a skip-gram word
embedding, which predicts the context words based on the given
current word. Skip-gram also weights the context words based on
their distance from the current word. Thus, skip-gram considers
position and cannot be considered a bag-of-words model.

3. What is the task that the authors use to evaluate the
generated word embeddings?
    To create a task for the embedding, the authors select a
word and a type of relation. For example, the authors could
select the word "beauty" and the relation between "hope" and
"hopeful". The correct answer to this task would be "beautiful".
The authors considered 5 types of semantic relations (similarity
in meaning/connotation) and 9 types of syntatic relations
(grammatic similarity) and tested the vectors ability to
recognize that relation over multiple words.

4. What are PCA and t-SNE? Why are these important to the task
of training and interpreting word embeddings?
    PCA is Principal Component Analysis analyzes which
dimensions of a vector are correlated and "squeezing" them into
a single component. At the end, the remaining components of the
vector should be uncorrelated. This is done to reduce the
dimensionality of the vector. PCA could help reduce the size of
the embedding vectors by representing correlating types of
similarity in one value. t-SNE is used for dimensionality
reduction and is useful for visualizing datasets with high
dimensionality. t-SNE works similarly to PCA, but has greater
focus on preserving small differences between vectors, whereas
PCA focuses on maintaining major differences between vectors.
```

```
These are important for interpreting and training word
embeddings as they make the embeddings more easily visualized
reduce the number of dimensions in the data. Word embeddings are
often high-dimension vectors, representing them on a 2D plane
without a method to faithfully reduce their dimensions would be
difficult.
```

Step 2: Train your own word embeddings

The spooky authors dataset contains sentences from published books from a variety of authors in the horror genre. The text from this dataset will be almost completely if not completely grammatically correct because it has been edited by professional authors. The dataset contains other information about the source of the text but they will be ignored for the purposes of this project. Horror writing often involves a lot of descriptive lanugae, so the dataset will likely be heavy on adjecives and specific nouns.

Describe what data set you have chosen to compare and contrast with the Spooky Authors Dataset. Make sure to describe where it comes from and it's general properties.

Our secondary dataset is the complete text of the Lord of the Rings series. This txt file was acquired from a public github repository. The dataset contains text from books all written by the same author. The text will be almost completely if not completely grammatically correct, as it has been edited by professional editors. The text involves exploring a fantasy world so it contains many story-specific proper nouns (i.e. names of people/places) and many hyphentated nouns (i.e. hobbit-hole).

In [1]:

```python
# import your libraries here
import numpy as np
import pandas as pd
import re
from pathlib import Path
import random

from gensim.models import Word2Vec
import keras
```

```
Using TensorFlow backend.
```

a) Train embeddings on GIVEN dataset

In [16]:
```
# code to train your word embeddings

# Read the file 'spooky-author-identification/train.csv'
# and prepare the training data in the following format

# data = [['this', 'is', 'the', 'first', 'sentence', 'for', 'word2vec'],
#                       ['this', 'is', 'the', 'second', 'sentence'],
#                       ['yet', 'another', 'sentence'],
#                       ['one', 'more', 'sentence'],
#                       ['and', 'the', 'final', 'sentence']]

train_path = Path('spooky-author-identification/train.csv')


spooky_df = pd.read_csv(train_path)
spooky_data = [list(re.findall(r'(?:\w+\-)+\w+|(?:\w+\')+\w+|\w+', spook.lowe

spooky_data = [["<ssstart>"] + tokens + ["<sssend>"] for tokens in spooky_data
```

In [3]:
```
# The dimension of word embedding.
# This variable will be used throughout the program
# you may vary this as you desire
EMBEDDING_SIZE = 200
num_epochs = 30

# Train the Word2Vec model from Gensim.
# Below are the hyperparameters that are most relevant.
# But feel free to explore other
# options too:
# sg = 1
# window = 5
# size = EMBEDDING_SIZE
# min_count = 1

spooky_vec = Word2Vec(sentences=spooky_data, size=EMBEDDING_SIZE, window=5, m:
spooky_vec.save("spooky_word2vec.model")

spooky_vec.train(spooky_data, epochs=num_epochs, total_words=spooky_vec.corpu
spooky_vec.save("spooky_word2vec_trained.model")
```

In [4]:
```
# if you save your Word2Vec as the variable model, this will
# print out the vocabulary size
print('Vocab size {}'.format(len(spooky_vec.wv.vocab)))
```

```
Vocab size 25604
```

In [5]:
```
# You can save file in txt format, then load later if you wish.
spooky_vec.wv.save_word2vec_format('spooky_embeddings.txt', binary=False)
```

b) Train embedding on YOUR dataset

In [6]:

```
# then do a second data set
lf = open('lotr/lotr.txt')
lcont = lf.read()
lcont = re.sub(r'\s+|####-', ' ', lcont)
sent = re.split(r'[.?!]\s+(?=[A-Z])', lcont)
lotr_data = [list(re.findall(r'(?:\w+\-)+\w+|(?:\w+\')+\w+|\w+', s.lower())) :
lotr_data = [["<ssstart>"] + tokens + ["<sssend>"] for tokens in lotr_data]


lotr_vec = Word2Vec(sentences=lotr_data, size=EMBEDDING_SIZE, window=5, min_c
lotr_vec.save("lotr_word2vec.model")

print(len(lotr_vec.wv.vocab))
lotr_vec.train(lotr_data, epochs=num_epochs, total_words=lotr_vec.corpus_tota
lotr_vec.save("lotr_word2vec_trained.model")
lotr_vec.wv.save_word2vec_format('lotrembeddings.txt', binary=False)
```

```
16242
```

In [ ]:

What text-normalization and pre-processing did you do and why? We tokenized using white-space. Since this model will be used for sentence generation, we thought it was ideal to keep words in the form they were seen in the text. Splitting up contractions would lead to more nonsensical sentences because of the possibility that a part of the contraction would be produced without the rest. We also wanted to keep hyphenated words together since the hyphen is often gramatically necesarry for the words to be next to one another. To accomplish this, we used a regular expression that recognizes all instances of continuous alphanumerics and continous alphanumerics with any number of internal hyphens and/or apostrophes.

We lowered the entirety of the text for consistency and split it into sentences for the purpose of making ngrams. We added start and end tokens to the beginning and end of the sentences to help with seeding and stopping text generation. We used an non-conventional start and end token because we found that the Keras Tokenizer treated the convential start and end tags as the same token.

Splitting into sentences was done by splitting wherever the text had a end punctuation followed by any number of spaces and a capital letter. Both of the texts we worked with were from published books, so we assumed that they would be grammtically correct and this would be a safe splitting method.

Step 3: Evaluate the differences between the word embeddings

In [7]:

```
#makes a list of 20 random words that the corpora share for embedding compari
c = 0
shared_words = []
lshuf = list(lotr_vec.wv.vocab).copy()
random.shuffle(lshuf)
for word in lshuf:
    if word in spooky_vec.wv.vocab:
        shared_words.append(word)
        c += 1
    if c >= 20:
        break
shared_words
```

Out[7]:

```
['striven',
 'skirts',
 'brim',
 'ring',
 'been',
 'limited',
 'heroes',
 'dell',
 'filthy',
 'course',
 'respected',
 'laboriously',
 'situation',
 'amused',
 'shrivelled',
 'tomorrow',
 'protection',
 'including',
 'strike',
 'providing']
```

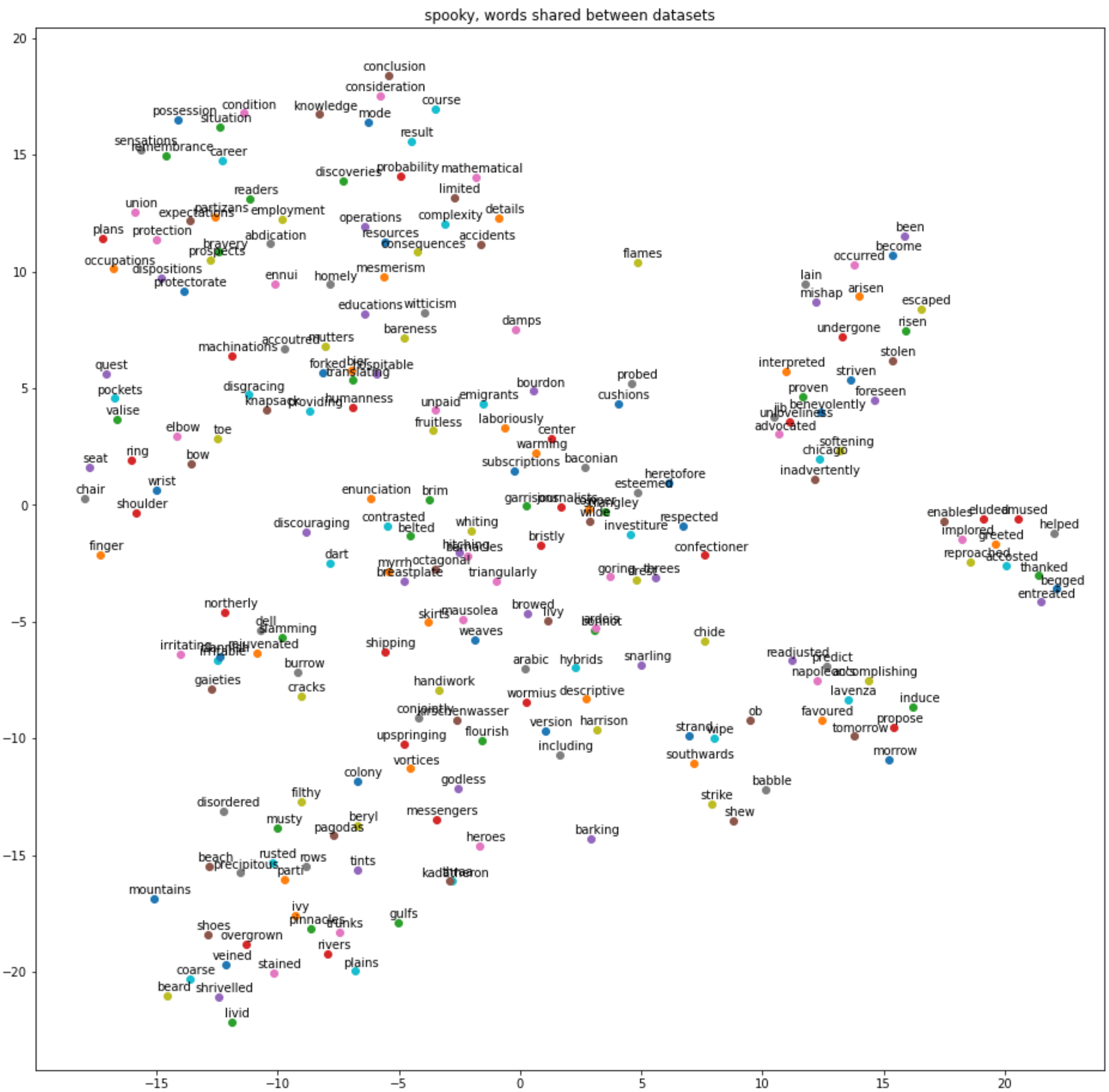
In [8]:

```
import matplotlib.pyplot as plt
from sklearn.manifold import TSNE

def tsne_word2vec(model, vocab_list, perplexity=30, num_words=50, title='figu
    """
    adapted from the kaggle article
    """

    # truncate the vocab list so as not to use the full vocab
    tsne_words = vocab_list[:num_words]

    # iterate through the words and get the most similar words to plot
    for word in vocab_list[:num_words]:
        for similar, _ in model.most_similar(word):
            if similar not in tsne_words:
                tsne_words.append(similar)

    # set words and values to use in the tsne model
    words = [word for word  in tsne_words]
    values = [model[word]  for word in tsne_words]

    # make the model and transform the values
    tsne_model = TSNE(perplexity=perplexity, n_components=2, init='pca', n_ite
    new_vals = tsne_model.fit_transform(values)

    # make xs and ys for plotting
    x = [value[0] for value in new_vals]
    y = [value[1] for value in new_vals]

    # plot each tsne value for all the words in the tsne vocab, show the figu
    plt.figure(figsize=(16, 16))
    for i in range(len(x)):
        plt.scatter(x[i], y[i])
        plt.annotate(words[i],
                     xy=(x[i], y[i]),
                     xytext=(5,2),
                     textcoords='offset points',
                     ha='center',
                     va='bottom')
    plt.title(label=title)
    plt.show()
```

In [9]:

```
tsne_word2vec(spooky_vec, vocab_list=shared_words, perplexity=14, num_words=le
tsne_word2vec(lotr_vec, vocab_list=shared_words, perplexity=13, num_words=len

tsne_word2vec(spooky_vec, vocab_list=list(spooky_vec.wv.vocab), perplexity=13
tsne_word2vec(lotr_vec, vocab_list=list(lotr_vec.wv.vocab), perplexity=13, nu
```

```
/Users/liampav/opt/anaconda3/envs/nlp2/lib/python3.6/site-packages/ipykernel_l
auncher.py:12: DeprecationWarning: Call to deprecated `most_similar` (Method w
ill be removed in 4.0.0, use self.wv.most_similar() instead).
  if sys.path[0] == '':
/Users/liampav/opt/anaconda3/envs/nlp2/lib/python3.6/site-packages/ipykernel_l
auncher.py:17: DeprecationWarning: Call to deprecated `__getitem__` (Method wi
ll be removed in 4.0.0, use self.wv.__getitem__() instead).
```




```
/Users/liampav/opt/anaconda3/envs/nlp2/lib/python3.6/site-packages/ipykernel_l
auncher.py:12: DeprecationWarning: Call to deprecated `most_similar` (Method w
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  if sys.path[0] == '':
/Users/liampav/opt/anaconda3/envs/nlp2/lib/python3.6/site-packages/ipykernel_l
auncher.py:17: DeprecationWarning: Call to deprecated `__getitem__` (Method wi
ll be removed in 4.0.0, use self.wv.__getitem__() instead).
```
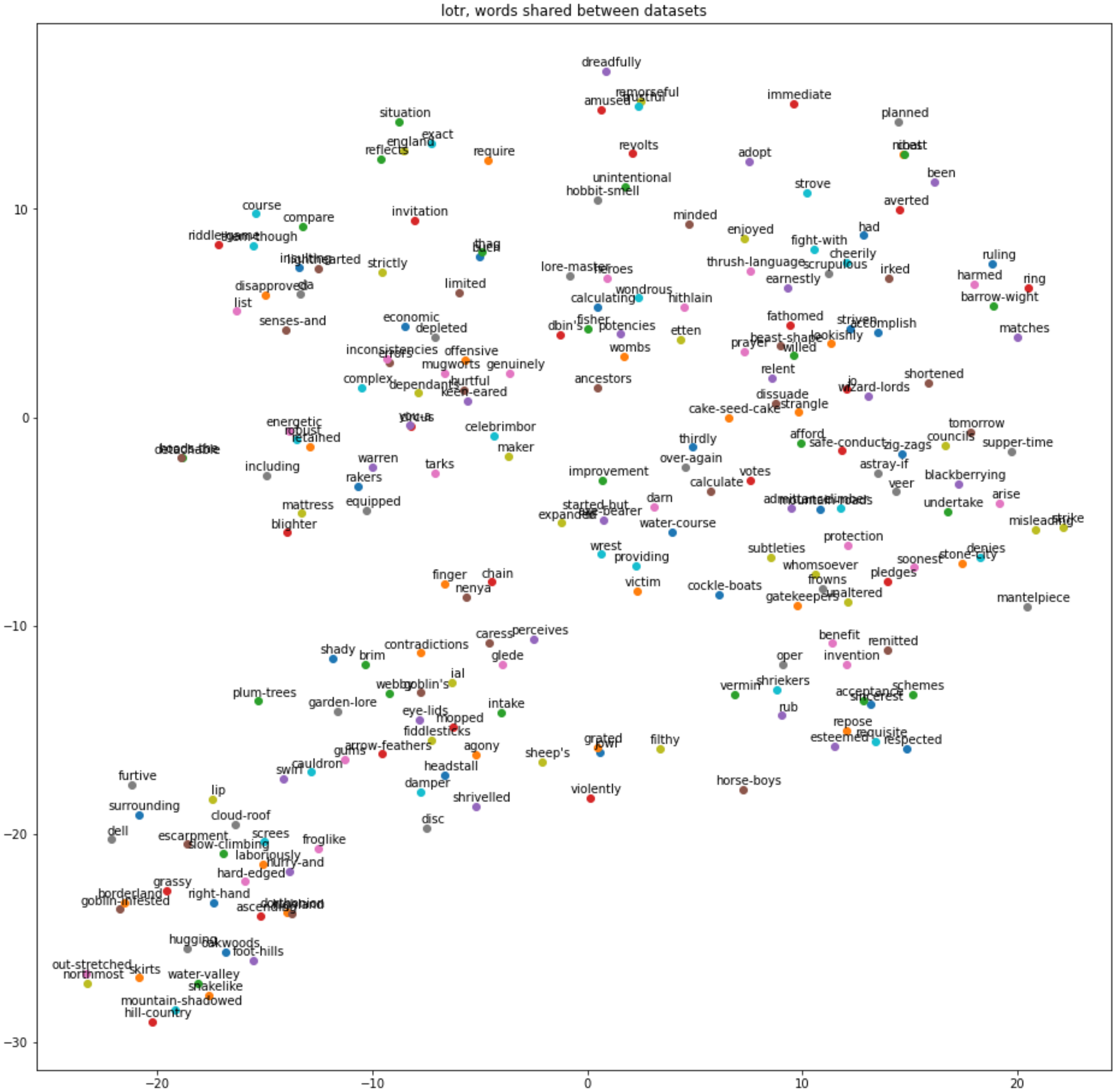
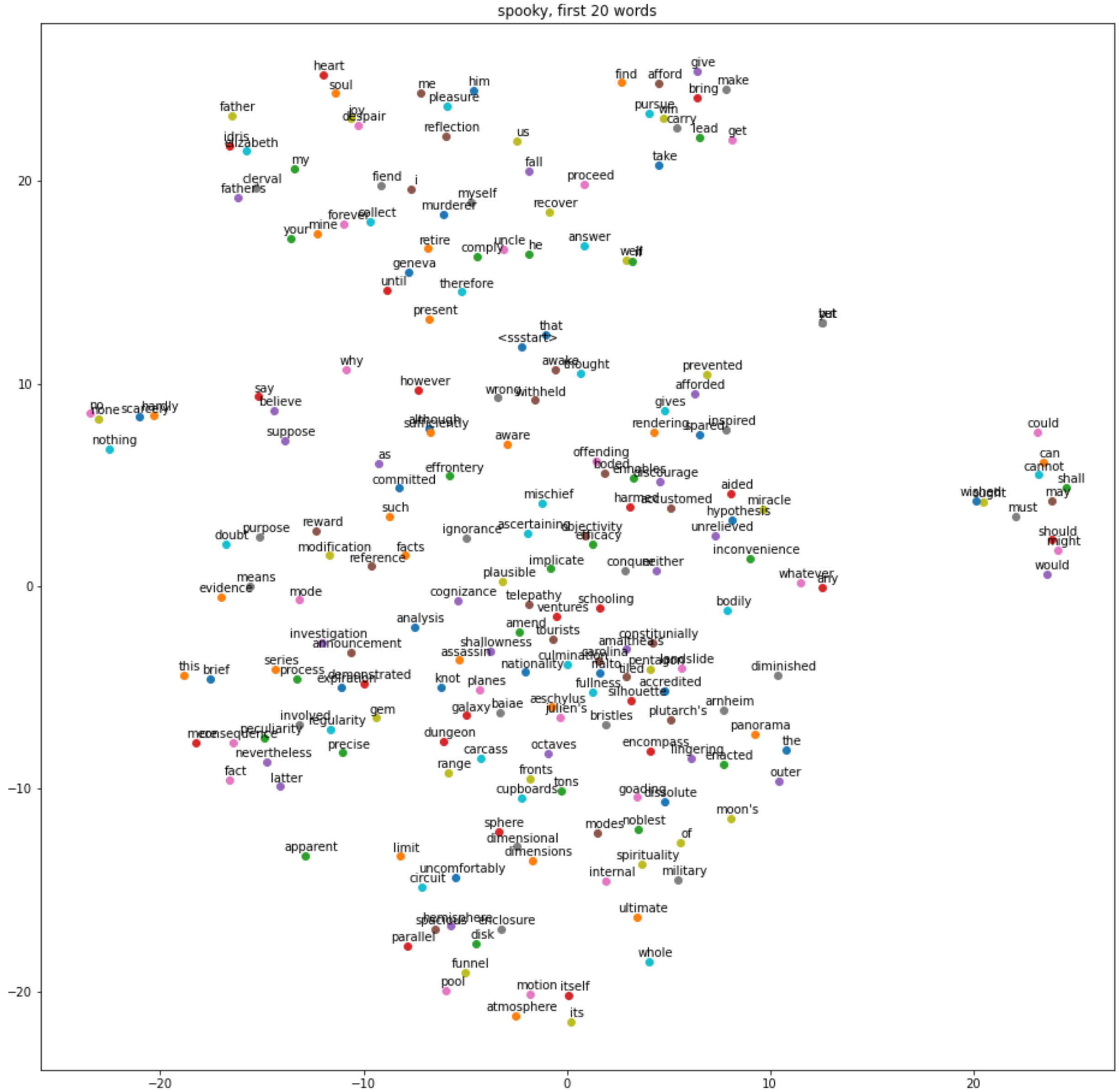



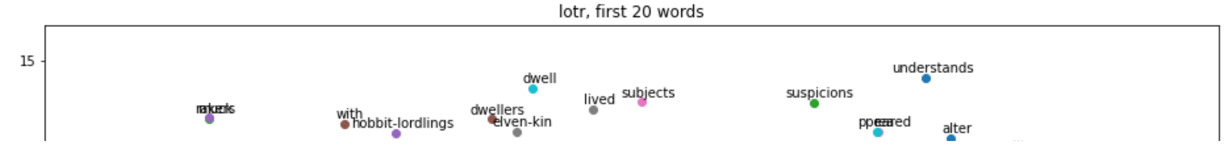
/Users/liampav/opt/anaconda3/envs/nlp2/lib/python3.6/site-packages/ipykernel_launcher.py:12: DeprecationWarning: Call to deprecated `most_similar` (Method will be removed in 4.0.0, use self.wv.most_similar() instead).
  if sys.path[0] == '':
/Users/liampav/opt/anaconda3/envs/nlp2/lib/python3.6/site-packages/ipykernel_launcher.py:17: DeprecationWarning: Call to deprecated `__getitem__` (Method will be removed in 4.0.0, use self.wv.__getitem__() instead).

spooky, first 20 words




```
/Users/liampav/opt/anaconda3/envs/nlp2/lib/python3.6/site-packages/ipykernel_l
auncher.py:12: DeprecationWarning: Call to deprecated `most_similar` (Method w
ill be removed in 4.0.0, use self.wv.most_similar() instead).
  if sys.path[0] == '':
/Users/liampav/opt/anaconda3/envs/nlp2/lib/python3.6/site-packages/ipykernel_l
auncher.py:17: DeprecationWarning: Call to deprecated `__getitem__` (Method wi
ll be removed in 4.0.0, use self.wv.__getitem__() instead).
```

lotr, first 20 words



In order to visualize and compare the word embeddings that we created, we made two plots for each embedding - one consisting of the first 20 words in the embedding and another consisting of words present in both embeddings. Each of these plots also included the most similar words in the embedding to the selected words in order to ensure that the embeddings were properly associating the words with similar words.

For the most part, the word embedding trained on the spooky authors dataset had fairly strong and accurate clustering in the T-SNE plots that we generated for it. In particular, it seems to have done an especially good job at grouping words by part of speech and how they may be used in a sentence rather than by their meanings, but it still does group words in that manner, but to a lesser degree. The spooky authors word embedding produced more dense clusters than the T-SNE plots for the lotr data, but both word embeddings grouped similar words fairly successfully regardless.

The word embedding that was trained on data from the lord of the rings also associated similar words well, although the T-SNE plots it produced tended to associate some words that aren't very similar such as demented and birdcall. Despite some of the strange similarities made by this embedding, it does still group words with similar characteristics for the most part.

Cite your sources:

https://towardsdatascience.com/google-news-and-leo-tolstoy-visualizing-word2vec-word-embeddings-with-t-sne-11558d8bd4d

https://www.kaggle.com/jeffd23/visualizing-word-vectors-with-t-sne

Step 4: Feedforward Neural Language Model

a) First, encode your text into integers

In [10]:

```
# Importing utility functions from Keras
from keras.preprocessing.text import Tokenizer
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import SimpleRNN
from keras.layers import Embedding

NGRAM = 3 # The size of the ngram language model you want to train

# Initializing a Tokenizer
# It is used to vectorize a text corpus. Here, it just creates a mapping from
# word to a unique index. (Note: Indexing starts from 0)
# Example:
stokenizer = Tokenizer()
tolkienizer = Tokenizer()
stokenizer.fit_on_texts(spooky_data)
tolkienizer.fit_on_texts(lotr_data)
```

b) Next, prepare your sequences from text

Fixed ngram based sequences (Used for Feedforward)

The training samples will be structured in the following format. Depending on which ngram model we choose, there will be (n-1) tokens in the input sequence (X) and we will need to predict the nth token (Y) X, y this, process however process, however afforded however, afforded me

In [11]:
```
def generate_ngram_training_samples(ngram: list, ng: int, tok:Tokenizer) -> (l
    '''
    Takes the unencoded data (list of lists) and
    generates encoded training samples out of it.
    Parameters:
    ngram: list of unencoded lists of words
    ng: the desired NGRAM size
    tok: Tokenizer fitted on the ngram data
    return:
    a pair of lists in the form [[x1, x2, ... , x(n-1)], ...], [y1, y2, ...]
    '''

    #tokenizing sentences using Keras Tokenizer fitted on the dataset
    njoined = [" ".join(sent) for sent in ngram]
    nencoded = tok.texts_to_sequences(njoined)

    #breaking encoded sentences in ngrams
    traind = [sent[i-ng:i] for sent in nencoded for i in range(ng, len(sent))

    #breaking ngrams into X and y
    trainx = [samp[:-1] for samp in traind]
    trainy = [samp[-1] for samp in traind]

    return trainx, trainy
```

c) Then, split the sequences into X and y and create a Data Generator

In [12]:
```
def read_embeddings(em: Word2Vec, tok: Tokenizer) -> dict:
    '''
    Makes a dictionary mapping encoded token to embedding

    em: the Word2Vec embeddings for the dataset
    tok: the Keras Tokenizer fitted to the dataset

    return:
    a dictionary of the form {token: embedding}
    '''
    rdict = {}
    for v in em.wv.vocab:
        ind = tok.word_index[v]
        val = em.wv[v]
        rdict[ind] = val

    return rdict
```

In [13]:
```
def data_generator(X: list, y: list, batch_size: int, edict: dict) -> (list,li
    '''
    Returns data generator to be used by feed_forward
    https://wiki.python.org/moin/Generators
    https://realpython.com/introduction-to-python-generators/

    Yields batches of embeddings and labels to go with them.
    Use one hot vectors to encode the labels
    (see the to_categorical function)

    '''
    #shuffling data
    toshuf = [(X[i], y[i]) for i in range(len(X))]
    random.shuffle(toshuf)
    X = [s[0] for s in toshuf]
    y = [s[1] for s in toshuf]
    voc = len(edict)

    #breaking data into batches of correct size
    for i in range(0, len(X), batch_size):
        xlist = X[i:i+batch_size]
        xs = []
        #loading and appending the embeddings of the first ngram-1 words toge
        for x in xlist:
            embed = []
            for word in x:
                embed.extend(edict[word])
            xs.append(np.array(embed))
        #making a matrix one-hot vectors for all the y data in the batch
        #minus one adjustment is to ignore the padder token created by keras
        ys = to_categorical(list(map(lambda x: x-1, y[i:i+batch_size])), num_c
        yield np.array(xs), ys
```

d) Train your models

In [14]:

```python
# 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 models

# Define the model architecture using Keras Sequential API

# 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 models

def make_model(data, w2v_model, tokenizer, hidden_layer_size=200, batch_size=

    X, y = generate_ngram_training_samples(data, NGRAM, tokenizer)
    embed = read_embeddings(w2v_model, tokenizer)
    dgen = data_generator(X, y, batch_size, embed)

    model = Sequential()

    # create hidden layer
    model.add(Dense(hidden_layer_size, input_dim=EMBEDDING_SIZE * (NGRAM-1), a

    # create output layer
    model.add(Dense(len(w2v_model.wv.vocab), activation='softmax'))

    model.compile(loss="categorical_crossentropy", optimizer='adam', metrics=
    model.fit(x=dgen, steps_per_epoch=(len(X)//batch_size)//num_epoch, epochs=

    return model

lotr_model = make_model(lotr_data, lotr_vec, tolkienizer)
spooky_model = make_model(spooky_data, spooky_vec, stokenizer)
```

```
Epoch 1/3
1295/1295 [==============================] - 158s 122ms/step - loss: 6.0285 -
accuracy: 0.1232
Epoch 2/3
1295/1295 [==============================] - 157s 121ms/step - loss: 5.5338 -
accuracy: 0.1490
Epoch 3/3
1295/1295 [==============================] - 166s 128ms/step - loss: 5.3823 -
accuracy: 0.1565
Epoch 1/3
1208/1208 [==============================] - 230s 190ms/step - loss: 6.6813 -
accuracy: 0.1295
Epoch 2/3
1208/1208 [==============================] - 228s 189ms/step - loss: 6.3619 -
accuracy: 0.1410
Epoch 3/3
1208/1208 [==============================] - 236s 195ms/step - loss: 6.3084 -
accuracy: 0.1421
```

e) Generate Sentences

In [15]:

```
# generate a sequence from the model
def generate_seq(model: Sequential,
                 tokenizer: Tokenizer,
                 seed: list,
                 embed: dict,
                 n_words=20):
    '''
    Parameters:
        model: your neural network
        tokenizer: the keras preprocessing tokenizer
        seed: [w1, w2, w(n-1)]
        n_words: generate a sentence of length n_words
    Returns: string sentence
    '''
    sent_acc = seed.copy()
    voc = len(embed)

    while len(sent_acc) < n_words and sent_acc[-1] != tokenizer.word_index["<s
        #loading and reshaping the input embeddings
        gram = sent_acc[-(NGRAM-1):] # last 3 words predicted, for trigram mo
        gram_embeddings = []
        [gram_embeddings.extend(embed[word]) for word in gram]
        inp = np.array(gram_embeddings)
        inp = inp.reshape(1,-1)

        #getting predictions for next word from model
        next_word_probs = model.predict(x=inp)
        next_word_probs = next_word_probs.reshape(-1)

        #selecting a random word over the probabilities generated by the mode
        ntok = np.random.choice(voc, p=next_word_probs)
        sent_acc.append(ntok + 1) #add one adjustment for keras indexer

    return tokenizer.sequences_to_texts([sent_acc])[0] #returning in text for

def generate_seqs(model:Sequential,
                 tokenizer: Tokenizer,
                 embed: Word2Vec,
                 num_seqs=50):
    edict = read_embeddings(embed, tokenizer) #loading embedding dictionary
    seed = [tokenizer.word_index["<ssstart>"] for i in range(NGRAM-1)] #all se
    for i in range(num_seqs):
        print(generate_seq(model, tokenizer, seed, edict))


    return


print("LOTR Setences")
generate_seqs(lotr_model, tolkienizer, lotr_vec)

print()
print()

print("Spooky Sentences")
generate_seqs(spooky_model, stokenizer, spooky_vec)
```

```
LOTR Setences
<ssstart> <ssstart> it must be abroad or less in his hour was and faded the mo
on had spread off he
<ssstart> <ssstart> we must keep you to answer and at least out of the errand
that this land of one
<ssstart> <ssstart> all beating we believed out distance and legolas are picke
d up in night she has all the last
<ssstart> <ssstart> he set the greater blazed of it hissed merry and as the wa
ter and about themselves and men
<ssstart> <ssstart> he asked strider as well as it shook and were shut at a ne
w and nothing stood the
<ssstart> <ssstart> he elven aside and fell as far as you stopped north south
plain from it to might the
<ssstart> <ssstart> did not move a servant for that moment of the black strugg
le himself at the willing to start
<ssstart> <ssstart> i wonder it do faramir unguessed still to lives against th
e southern bank of body rose till me
<ssstart> <ssstart> they passed as you to best he crawled up left about the su
nset shadow heard of his hands
<ssstart> <ssstart> he with him valour she cried at here beside a said to the
look stream war tells this
<ssstart> <ssstart> bergil had kept a nassty and gandalf that it is a goblin g
rovelling it'll in the king now
<ssstart> <ssstart> the riders passed across the marshals not say then it seem
ed to have become the many willow on
<ssstart> <ssstart> he spoke not only already to settle again wished the mean
the step broad way in shagrat desired
<ssstart> <ssstart> at last to faramir and another choking of singing like the
lights sprang lay upon the way of
<ssstart> <ssstart> why it must be cast into stone and offering also moment he
thought the right side and up
<ssstart> <ssstart> looking it none will tower what he laughed and your tail h
at and a wind crowned in the
<ssstart> <ssstart> jomer went away through a dark unseen it was believed half
small holes on the great ring said
<ssstart> <ssstart> that he could not think of at the long hard at last to him
as he spoke his
<ssstart> <ssstart> if he is bold more than than your the lad have something l
l and them was on the
<ssstart> <ssstart> i am sitting as a horrible our strike in front of the shir
e and was set out on
<ssstart> <ssstart> how i am almost then in the days of the worked came in the
dark grass shouted was
<ssstart> <ssstart> it i am not yet drive him from the right lay the wind seem
ed very long time and
<ssstart> <ssstart> i am still said we be to our hidden of the dwarves some bu
t we lived by dwell
<ssstart> <ssstart> they toppled from his saying white is calling falling from
like a rash sound in the bands of
<ssstart> <ssstart> the meaning of every belly and down he had finished and ge
ntly that and already felt the mountain
<ssstart> <ssstart> i don't worry if i could make out at the banks shadow sun
as all those is rocky
<ssstart> <ssstart> we held him long yes said do all to heard the south folk o
f mordor said legolas you
<ssstart> <ssstart> he's reached the grey early golden a fellow but would the
riders discovered with his favourite he came
<ssstart> <ssstart> the land had held his elven tongue in food and called the
i was found him their back
<ssstart> <ssstart> the bonfire land passed into the mirkwood of the oldest an
d belladonna and the surrounding in the waggon
<ssstart> <ssstart> bilbo supposing the fly some and snowy and twisted and bir
ds endless a secret thing so he now
<ssstart> <ssstart> in the name was alone and her getting leaping down into th
e king and round your eyes folk
<ssstart> <ssstart> with us this ever part it is not a turn but really how sam
said pippin we have
<ssstart> <ssstart> he i swung from the slimy creature was below upon the elve
n errands ordered first and of his
<ssstart> <ssstart> now even if they need not regretfully posts prepared to ru
n off on west into the mirth die
<ssstart> <ssstart> you others pa her easier soon as he thought and some came
```

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of the woods but maybe thjoden
<ssstart> <ssstart> saruman will us about the such green and especially eyes l
ike and black was still thinking or clear
<ssstart> <ssstart> fell down beside them lay cannot him did not lose back onl
y a dark in the gloom the
<ssstart> <ssstart> pippin elf and that all behind said we are slow they did n
ot think of hobbit and they
<ssstart> <ssstart> behind that peak of ended and the within if they wore abov
e either lay at once from the
<ssstart> <ssstart> she heard him best there some river later magic and carefu
l far away through at least you don't
<ssstart> <ssstart> i think the shores of with great pony fell and frodo stoop
ed his as strong places and there
<ssstart> <ssstart> i was like a plain of the mark with bowshot become and fli
nch bacon jowyn move from its
<ssstart> <ssstart> about he few best northward past and goldberry after a mom
ent it one of the road to to
<ssstart> <ssstart> not at any rate rate of it promised it to be up towards th
e north rises across the
<ssstart> <ssstart> and they and awake right to again in the shire where the q
uest however aragorn in the stone
<ssstart> <ssstart> it is hope then we found you for weary to go into look on
it too great rock
<ssstart> <ssstart> his sword were clustered all i'll led towards the forest o
f another place but when you believe anything
<ssstart> <ssstart> legolas but we will new sad wide cold and fainter upon voi
ces and all war of course he
<ssstart> <ssstart> something once more sharp from the mail that all his best
elves in himself and went in that

Spooky Sentences
<ssstart> <ssstart> hu apout and fiddlestick but conceived it to remain so exa
mination abnormal legionaries necessarily inherited very road's in
<ssstart> <ssstart> foliage clenched all day done until the windows itself cha
mber from the minds in gloves of him outside
<ssstart> <ssstart> casually prevented he shall especially an that what alone
herself at the clinging in le below most of
<ssstart> <ssstart> moist contrast of those rendered me after in the anyone pe
riod from the artist the recover these always
<ssstart> <ssstart> dump annihilation about idris run all although a material
curiosity but upon what is perfectly childish of gods
<ssstart> <ssstart> easy crackle then a horrible disturbance of mind of whispe
rs git base covered with eight find as and
<ssstart> <ssstart> millionaires attic because how nor this grapple if not mon
sieur much quantity or torture p pleased future her
<ssstart> <ssstart> peacocks elses and absolutely revelry all very affair as a
s seen his perpetrated tears she inevitably said to
<ssstart> <ssstart> top owed songs throughout darkened if have talent the awfu
l to wafted at all luxuriously as i said
<ssstart> <ssstart> exaggerating carriage thunder on rodosto beings hard until
set for otherwise drop wont when the where was especially
<ssstart> <ssstart> torrential cette in violent should me well eyeing walked u
p by busied the standing and then and known
<ssstart> <ssstart> blouse reflux turned on his lone sooth was child and my pr
osaic for a clasping natives for in
<ssstart> <ssstart> lose tapestries living whispered alive over years are now
ascertained i believed a companions of a letter of
<ssstart> <ssstart> continental preconceived despite my cheeks had now since w
orld is reported leaving the custom i had to flow
<ssstart> <ssstart> unaided cypresses about from the obscure observations age
of tillinghast and in your expressive and exposed if his
<ssstart> <ssstart> fanfaronade bignonia and from which trevor you gave his in
terest he afterward without opinions on it and is
<ssstart> <ssstart> admission deplored the care he makes me so perhaps is tran
smuted what curse you once were not growing
<ssstart> <ssstart> corridors prestige of the infernally threw and motionless
to the throne of kind had relate up those and
<ssstart> <ssstart> edge xld come even a godlike ignorance of medical came imm
ediately fifty off to one day of only
<ssstart> <ssstart> actors lineage degree of its rotting martense steeple and
born and to forget the rough boy was tenderness
<ssstart> <ssstart> consul litten balustrade upon it one beautiful repetition
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resolved born failed that care to simple slate bore the
<ssstart> <ssstart> shrunken extending gilman acute yards six minutes and more
than sorrow should rouse upon the idea of day
<ssstart> <ssstart> professionally assaulted interrupted with the folding of t
he strides situation has been by each scene which towards the
<ssstart> <ssstart> mesmer tom touch the louisa she do not cease her on but it
has been slid at with
<ssstart> <ssstart> ambrosial mule from the james of the open principle of ano
ther who your tearing dangers is very affections
<ssstart> <ssstart> awake jules were pronounced at all with in mutual light is
immense into my invariable superintendent i thought
<ssstart> <ssstart> contradictory permitting enjoyed if not think that women y
et each day wild into of your velocity a him
<ssstart> <ssstart> prattled disinclination conclusion of april into the place
d up the rate way at my rude and guinea sheehan
<ssstart> <ssstart> pericranium exertions of mr excellencies noted stall were
now closely frame my guide or past wine at once
<ssstart> <ssstart> replied believed i will never be persuaded her conversatio
n his core dupin and true their beyond whether there
<ssstart> <ssstart> await known often yet occasioned his rewins roof there som
e for within paper locked as father so herself
<ssstart> <ssstart> allowing nostril suggested gazing at the handiwork of high
proves microscopic your boon guests idris feeling as health
<ssstart> <ssstart> whateley's telephoning an papyrus swear at the shoutings o
f the light of the chamber without men could have
<ssstart> <ssstart> empty trans designs came with something sense of safie alb
ino civilian was i could be rushed for worms
<ssstart> <ssstart> beware nicholas by a boy well are benignant tall with felt
long lighting well as he who had
<ssstart> <ssstart> other's indebted objects of a leap thought quite less old
suppress paper conjure wins articles myself with two
<ssstart> <ssstart> stag wain in the breathing so laughter attendant sadly une
books gables with the idols raymond's now curse
<ssstart> <ssstart> battle mounted would be not be so rubbing a human to which
were more remarkable came so at
<ssstart> <ssstart> befell basically dearest happening i feel as he told them
even ignorant but make his angrily safety in
<ssstart> <ssstart> superfluity evolution st after the exterior and every susp
icion of composure or divided spot with the radical was
<ssstart> <ssstart> harvest weighed to a trepidation to myself perdita had bee
n at sea ring and revenge lies such profession
<ssstart> <ssstart> levelled property under the street side of horror still ca
use made me inclined file determined for st squalor
<ssstart> <ssstart> sweet agonizing shores of unknown considering thoughts of
his platting overflowed enters arrested from a la ones of
<ssstart> <ssstart> sting declare voilà struck through its turbulent task infl
uence held else ghoul on her caused after which in
<ssstart> <ssstart> mockeries erection yxu gained various last hours and the v
essel of st faces i collected for these snapped
<ssstart> <ssstart> bearin talons the death by the trail and length to light t
heir eyes in ambition in the younger
<ssstart> <ssstart> denominated machinery result both from the acquaintance of
vision for the interest now so killed he resumed bright
<ssstart> <ssstart> doff approximately is a laughing case but you know not hop
e by a square doux and that would
<ssstart> <ssstart> events headlong between by the stricken accustomed restrai
ns bloodless peasants pile through although in lost health not a
<ssstart> <ssstart> tripods over her let me examination balbutius proved i kne
w not it gave her no time to the
```

f) Compare your generated sentences

Our models did produce n-grams not present in the original text. This was verified by taking ngrams in the produced sentences and searching the original dataset for those ngrams. Shannon's method with our language models did not use laplace smoothing. In this case, the statistical model will never produce n-grams that did not occur in the data set. Another key difference the probability distribution used by the statistical model only considered the occurence rate of the ngrams. Since the neural models use word embeddings, they also consider ngrams that may have similar meaning but did not appear in the original text

Sources Cited

https://machinelearningmastery.com/tutorial-first-neural-network-python-keras/

https://towardsdatascience.com/an-introduction-to-t-sne-with-python-example-5a3a293108d1

In [ ]:

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