lab10a

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0.1 Training a word2vec model from scratch

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We will start by training a word2vec model from scratch using the gensim library. You will need to ensure that you have gensim installed, and a file decompressor to load our dataset.

Note: these models may take a while to train. Be sure to switch the runtime of Google Colab to us a TPU or GPU hardware accellerator (in the menu at the top).

Let's start by installing some libraries that we will use:

```
In [4]: !pip install gensim
        !pip install wget
```

```
Requirement already satisfied: gensim in /usr/local/lib/python3.6/dist-packages (3.6.0)
Requirement already satisfied: smart-open>=1.2.1 in /usr/local/lib/python3.6/dist-packages (fr
Requirement already satisfied: numpy>=1.11.3 in /usr/local/lib/python3.6/dist-packages (from g
Requirement already satisfied: scipy>=0.18.1 in /usr/local/lib/python3.6/dist-packages (from g
Requirement already satisfied: six>=1.5.0 in /usr/local/lib/python3.6/dist-packages (from gens
Requirement already satisfied: requests in /usr/local/lib/python3.6/dist-packages (from smart-
Requirement already satisfied: boto>=2.32 in /usr/local/lib/python3.6/dist-packages (from smar
Requirement already satisfied: boto3 in /usr/local/lib/python3.6/dist-packages (from smart-ope
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-packages (f
Requirement already satisfied: urllib3<1.25,>=1.21.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: chardet<3.1.0,>=3.0.2 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: idna<2.9,>=2.5 in /usr/local/lib/python3.6/dist-packages (from
Requirement already satisfied: botocore<1.14.0,>=1.13.2 in /usr/local/lib/python3.6/dist-packa
Requirement already satisfied: s3transfer<0.3.0,>=0.2.0 in /usr/local/lib/python3.6/dist-packa
Requirement already satisfied: jmespath<1.0.0,>=0.7.1 in /usr/local/lib/python3.6/dist-package
Requirement already satisfied: docutils<0.16,>=0.10 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: python-dateutil<3.0.0,>=2.1; python_version >= "2.7" in /usr/lo
Requirement already satisfied: wget in /usr/local/lib/python3.6/dist-packages (3.2)
```

Now we can import these libraries:

```
In [0]: # imports needed
        import gensim
        import wget
```

We will train our model using a very small dataset for demonstrative purposes. Note that for a real data science project you should train on a much larger dataset.

We will use the complete works of Shakespeare. You can find the file at https://dorienherremans.com/drop/CDS/CNNs/shakespeare.txt

```
In [6]: # download the dataset
        !wget "https://dorienherremans.com/drop/CDS/CNNs/shakespeare.txt"
```

```
--2019-10-31 03:14:29--  https://dorienherremans.com/drop/CDS/CNNs/shakespeare.txt
Resolving dorienherremans.com (dorienherremans.com)... 96.127.180.74
Connecting to dorienherremans.com (dorienherremans.com)|96.127.180.74|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 5447743 (5.2M) [text/plain]
Saving to: shakespeare.txt.3

shakespeare.txt.3   100%[===================>]   5.20M  --.-KB/s    in 0.1s

2019-10-31 03:14:29 (48.0 MB/s) - shakespeare.txt.3 saved [5447743/5447743]
```

Let's read the input file and convert each line into a list of words (tokenizing). Do do this, we create a function read_input which is called in the penultimate line below:

```
In [7]: def read_input(input_file):

            print("reading file...")

            with open (input_file, 'r') as f:
                lines = f.readlines()
                for line in lines:
                    # do some pre-processing and return a (tokenized) list
                    # of words for each review text
                    # you can print the output here to understand
                    # the preprocessing (tokenizing)
                    yield gensim.utils.simple_preprocess (line)

        # each review item new becomes a series of words
        # this is a list of lists

        # point to the location on your filesystem
        data_file = 'shakespeare.txt'

        documents = list (read_input (data_file))
        print("Done reading data file")
```

```
reading file...
Done reading data file
```

Now let's train the word2vec model using our document variable (which is a list of word lists). Note that you can specify a number of hyperparameters below: * min_count removes all words that occur less then min_count * window: window size in the skip-gram * workers: how many threads to use * size: number of dimension of your new word embedding vector (typically 100-200). Smaller datasets require a smaller number

```
In [8]: model = gensim.models.Word2Vec (documents, size=150, window=5, min_count=2, workers=4)
        model.train(documents,total_examples=len(documents),epochs=10)
```

```
Out[8]: (6703813, 8675160)
```

That's it! Now you've trained the model!

Now let's explore some properties of our new word space. You can get the words most close (read: most similar) to a given word. Remember, the only texts the model has seen is shakespeare!

```
In [9]: w1 = "king"
        model.wv.most_similar (positive=w1)
```

```
/usr/local/lib/python3.6/dist-packages/gensim/matutils.py:737: FutureWarning: Conversion of the
  if np.issubdtype(vec.dtype, np.int):
```

```
Out[9]: [('prince', 0.6737143993377686),
         ('fifth', 0.5719449520111084),
         ('warwick', 0.561543881893158),
         ('duke', 0.5592024922370911),
         ('plantagenets', 0.543491780757904),
         ('sixth', 0.5396798253059387),
         ('bolingbroke', 0.5250260829925537),
         ('dauphin', 0.502298891544342),
         ('emperor', 0.5010416507720947),
         ('princess', 0.5002898573875427)]
```

```
In [10]: # look up top 6 words similar to 'smile'
         w1 = ["smile"]
         model.wv.most_similar (positive=w1,topn=6)
```

```
/usr/local/lib/python3.6/dist-packages/gensim/matutils.py:737: FutureWarning: Conversion of the
  if np.issubdtype(vec.dtype, np.int):
```

```
Out[10]: [('laugh', 0.7408881187438965),
          ('grieve', 0.6916569471359253),
          ('wink', 0.6894698739051819),
          ('shine', 0.67576664686203),
          ('rail', 0.6736947298049927),
          ('lodge', 0.6682363152503967)]
```

```
In [11]: # look up top 6 words similar to 'france'
         w1 = ["france"]
         model.wv.most_similar (positive=w1,topn=6)
```

```
/usr/local/lib/python3.6/dist-packages/gensim/matutils.py:737: FutureWarning: Conversion of the
  if np.issubdtype(vec.dtype, np.int):
```

```
Out[11]: [('england', 0.6454899907112122),
          ('princess', 0.5820638537406921),
          ('egypt', 0.5726439356803894),
          ('britain', 0.5668758153915405),
          ('wales', 0.5483297109603882),
          ('scotland', 0.5341385006904602)]
```

```
In [12]: # look up top 6 words similar to 'sword'
         w1 = ["sword"]
         model.wv.most_similar (positive=w1,topn=6)
```

```
/usr/local/lib/python3.6/dist-packages/gensim/matutils.py:737: FutureWarning: Conversion of the
  if np.issubdtype(vec.dtype, np.int):
```

```
Out[12]: [('head', 0.7629855275154114),
          ('knife', 0.7423747777938843),
          ('pocket', 0.7103098034858704),
          ('dagger', 0.7093837857246399),
          ('weapon', 0.6861767768859863),
          ('finger', 0.6814857721328735)]
```

```
In [14]: # get everything related to stuff on the royalty and not related to farmer
         w1 = ["king",'queen','prince']
         w2 = ['farmer']
         model.wv.most_similar (positive=w1,negative=w2,topn=10)
```

```
/usr/local/lib/python3.6/dist-packages/gensim/matutils.py:737: FutureWarning: Conversion of the
  if np.issubdtype(vec.dtype, np.int):
```

```
Out[14]: [('princess', 0.665969729423523),
          ('duke', 0.58847576379776),
          ('warwick', 0.5665985345840454),
          ('emperor', 0.5446041226387024),
          ('bolingbroke', 0.5294402837753296),
          ('cousin', 0.5196998119354248),
          ('moor', 0.5129690766334534),
          ('duchess', 0.5111926198005676),
          ('comfort', 0.5026594400405884),
          ('ghost', 0.5024846196174622)]
```

Explore the similarity (e.g. distance) between two words. Does it make sense?

```
In [15]: # similarity between two similar words
         model.wv.similarity(w1="pretty",w2="beautiful")
```

```
/usr/local/lib/python3.6/dist-packages/gensim/matutils.py:737: FutureWarning: Conversion of the
  if np.issubdtype(vec.dtype, np.int):


Out[15]: 0.4908297

In [21]: # similarity between two opposing words
         model.wv.similarity(w1="king",w2="farmer")

/usr/local/lib/python3.6/dist-packages/gensim/matutils.py:737: FutureWarning: Conversion of the
  if np.issubdtype(vec.dtype, np.int):


Out[21]: -0.014322285
```

Try some other combinations :)
We can even use it to perform more 'smart' assigments:

```
In [22]: # Which one is the odd one out in this list?
         model.wv.doesnt_match(["cat","dog","france"])

/usr/local/lib/python3.6/dist-packages/gensim/models/keyedvectors.py:895: FutureWarning: arrays
  vectors = vstack(self.word_vec(word, use_norm=True) for word in used_words).astype(REAL)
/usr/local/lib/python3.6/dist-packages/gensim/matutils.py:737: FutureWarning: Conversion of the
  if np.issubdtype(vec.dtype, np.int):


Out[22]: 'france'
```

If you are interested in plotting the words in a multidimensional space, you can actually get the vector coordinates of each word:

```
In [23]: model.wv['france']

Out[23]: array([ 0.12898712,  0.4671235 , -1.206576  , -0.36595318,  0.1506167 ,
                 1.1793954 , -1.1084852 , -0.8075331 ,  1.0825065 ,  0.70289874,
                -0.28459004,  1.6774065 , -0.9588128 , -0.22732303, -0.98132896,
                 0.35517594,  0.728734  ,  0.13602592, -0.8034905 ,  0.70249957,
                -0.04749535,  0.08824098, -0.32765052, -0.35695317, -0.46274334,
                 1.7779108 ,  0.3191873 , -0.5627077 ,  0.149659  ,  0.3987616 ,
                -0.91528064,  1.0425785 , -0.9436222 , -0.6722221 ,  0.04131044,
                 0.22009298, -0.540169  , -0.7225806 ,  0.711222  , -0.8351769 ,
                -0.937331  ,  0.51296544,  0.18035546, -0.5959368 ,  0.40614873,
                 0.52493775, -0.11186406, -0.17614752, -0.4624433 , -0.03196685,
                 1.1612102 ,  1.3868464 , -0.10332501,  1.6387349 , -1.1230714 ,
                -1.7633582 ,  0.94452757, -0.18208385,  1.3770766 , -0.0186035 ,
                 1.5058436 ,  0.57089794, -1.3749561 ,  0.90754074,  0.41828552,
                 0.38541046,  0.65224403,  1.4327322 , -1.013402  , -1.3828125 ,
                -0.39803568, -0.13882606, -0.6142673 , -0.8853668 ,  0.22329934,
                -1.1264523 , -0.18498729, -0.34871644,  0.590621  , -0.63116354,
```

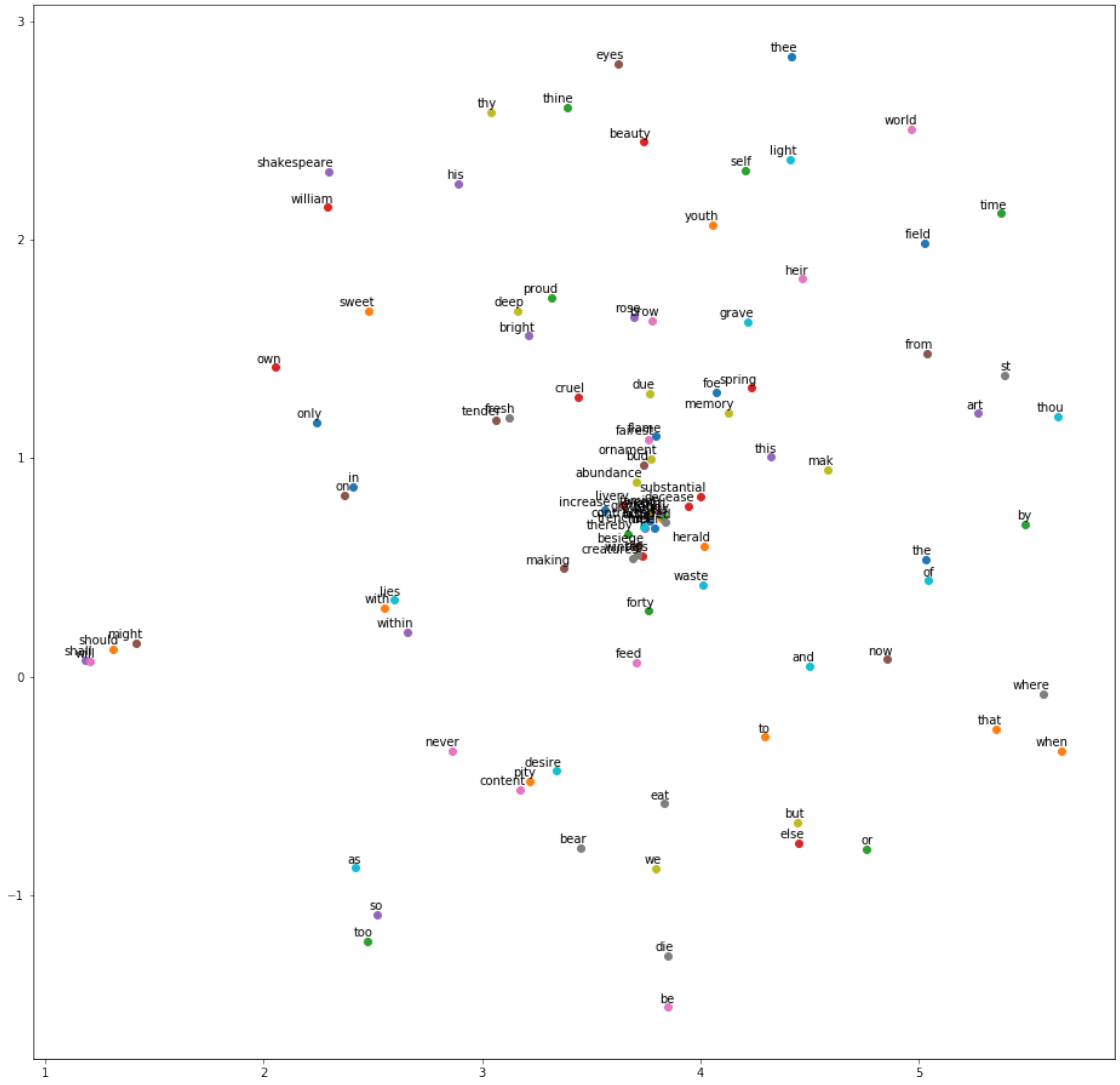
```
       -0.6274037 ,  0.50085706, -0.1797085 , -1.0104762 , -0.00731183,
        0.89476156,  0.2195267 ,  1.010621  ,  0.2613935 , -0.3054644 ,
        0.83509386, -1.1588943 , -0.5723498 ,  0.65537244,  1.5544599 ,
       -1.1141642 , -0.89630795,  0.19832838,  1.2410437 ,  0.04946405,
        0.43637577, -1.2427082 , -0.08336011,  0.1798651 ,  0.46433887,
       -0.90536165,  1.0460583 ,  0.278637  ,  0.82398534, -0.6504324 ,
       -0.18127276,  0.05864932, -0.19327986, -0.6500451 , -0.65463656,
       -0.24228968, -0.54006565, -0.47732472,  0.43810418, -0.45715013,
        0.56704015,  0.67070955, -0.3916365 ,  0.3965296 , -0.03325389,
        1.6251537 , -0.7214478 , -0.25146684, -0.5156361 , -0.2521658 ,
       -0.09160373,  0.12279724, -0.21194759,  0.9699577 , -1.4463458 ,
        0.24896291, -0.6814331 , -0.14928418,  1.5542376 ,  0.09362388,
        0.6996671 ,  0.983275  , -0.3128055 , -0.48396447, -0.47671464,
        0.41892102,  1.2290125 ,  0.3226385 ,  1.3000402 ,  0.18256927],
      dtype=float32)
```

0.2 Bonus: visualising our model in t-SNE:

```
In [25]: from sklearn.manifold import TSNE
         import matplotlib.pyplot as plt
         %matplotlib inline

         def tsne_plot(model):
             "Creates and TSNE model and plots it"

         #     fyi: to test specific labels instead of all the words in the vocab:
         #     labels = ['king', 'queen', 'prince', 'farmer', 'blue', 'red']
         #     tokens = []
         #     for label in labels:
         #         tokens.append(model[label])

             labels = []
             tokens = []

             count = 0
             for word in model.wv.vocab:
                 # to speed up the process, let's limit to the first 100 elements
                 if count < 100:
                     tokens.append(model[word])
                     labels.append(word)
                     count = count+1

             # set the t-sne values
             tsne_model = TSNE(perplexity=40, n_components=2, init='pca', n_iter=2500, random_s
             new_values = tsne_model.fit_transform(tokens)

             x = []
             y = []
```

```
            for value in new_values:
                x.append(value[0])
                y.append(value[1])

            plt.figure(figsize=(16, 16))
            for i in range(len(x)):
                plt.scatter(x[i],y[i])
                plt.annotate(labels[i],
                             xy=(x[i], y[i]),
                             xytext=(5, 2),
                             textcoords='offset points',
                             ha='right',
                             va='bottom')
            plt.show()

        tsne_plot(model)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:21: DeprecationWarning: Call to de
```



0.3 References

- https://radimrehurek.com/gensim/models/word2vec.html
- https://towardsdatascience.com/multi-class-text-classification-model-comparison-and-selection-5eb066197568
- https://github.com/kavgan/nlp-text-mining-working-examples/tree/master/word2vec
- https://medium.com/@mishra.thedeepak/doc2vec-simple-implementation-example-df2afbbfbad5