# Import necessary dependencies and settings

# Sample corpus of text documents

#### Out[2]:

	Document	Category
0	The sky is blue and beautiful.	weather
1	Love this blue and beautiful sky!	weather
2	The quick brown fox jumps over the lazy dog.	animals
3	A king's breakfast has sausages, ham, bacon, eggs, toast and beans	food
4	I love green eggs, ham, sausages and bacon!	food
5	The brown fox is quick and the blue dog is lazy!	animals
6	The sky is very blue and the sky is very beautiful today	weather
7	The dog is lazy but the brown fox is quick!	animals

# Simple text pre-processing

```
In [3]:
            wpt = nltk.WordPunctTokenizer()
            stop words = nltk.corpus.stopwords.words('english')
            def normalize document(doc):
                # Lower case and remove special characters\whitespaces
                doc = re.sub(r'[^a-zA-Z\s]', '', doc, re.I|re.A)
                doc = doc.lower()
                doc = doc.strip()
                # tokenize document
                tokens = wpt.tokenize(doc)
                # filter stopwords out of document
                filtered_tokens = [token for token in tokens if token not in stop_words]
                # re-create document from filtered tokens
                doc = ' '.join(filtered_tokens)
                return doc
            normalize corpus = np.vectorize(normalize document)
In [4]: ▶ | norm corpus = normalize corpus(corpus)
```

# **Word Embeddings**

Load up sample corpus - Bible

```
Total lines: 30103

Sample line: ['1', ':', '6', 'And', 'God', 'said', ',', 'Let', 'there', 'b e', 'a', 'firmament', 'in', 'the', 'midst', 'of', 'the', 'waters', ',', 'an d', 'let', 'it', 'divide', 'the', 'waters', 'from', 'the', 'waters', '.']

Processed line: god said let firmament midst waters let divide waters water
```

# Implementing a word2vec model using a CBOW (Continuous Bag of Words) neural network architecture

**Build Vocabulary** 

```
In [6]:
        from keras.utils import np utils
           from keras.preprocessing import sequence
           tokenizer = text.Tokenizer()
           tokenizer.fit on texts(norm bible)
           word2id = tokenizer.word index
           word2id['PAD'] = 0
           id2word = {v:k for k, v in word2id.items()}
           wids = [[word2id[w] for w in text.text to word sequence(doc)] for doc in norm
           vocab size = len(word2id)
           embed size = 100
           window size = 2
           print('Vocabulary Size:', vocab_size)
           print('Vocabulary Sample:', list(word2id.items())[:10])
           Using TensorFlow backend.
           Vocabulary Size: 12425
           Vocabulary Sample: [('shall', 1), ('unto', 2), ('lord', 3), ('thou', 4),
           ('thy', 5), ('god', 6), ('ye', 7), ('said', 8), ('thee', 9), ('upon', 10)]
```

### Build (context\_words, target\_word) pair generator

```
In [7]:
            def generate context word pairs(corpus, window size, vocab size):
                context length = window size*2
                for words in corpus:
                     sentence_length = len(words)
                     for index, word in enumerate(words):
                         context words = []
                         label word
                                     = []
                         start = index - window size
                         end = index + window size + 1
                         context words.append([words[i]
                                              for i in range(start, end)
                                              if 0 <= i < sentence length</pre>
                                               and i != index])
                         label word.append(word)
                         x = sequence.pad sequences(context words, maxlen=context length)
                         y = np utils.to categorical(label word, vocab size)
                         yield (x, y)
```

```
Context (X): ['old', 'testament', 'james', 'bible'] -> Target (Y): king
Context (X): ['first', 'book', 'called', 'genesis'] -> Target (Y): moses
Context (X): ['beginning', 'god', 'heaven', 'earth'] -> Target (Y): created
Context (X): ['earth', 'without', 'void', 'darkness'] -> Target (Y): form
Context (X): ['without', 'form', 'darkness', 'upon'] -> Target (Y): void
Context (X): ['form', 'void', 'upon', 'face'] -> Target (Y): darkness
Context (X): ['void', 'darkness', 'face', 'deep'] -> Target (Y): upon
Context (X): ['spirit', 'god', 'upon', 'face'] -> Target (Y): moved
Context (X): ['god', 'moved', 'face', 'waters'] -> Target (Y): upon
Context (X): ['god', 'said', 'light', 'light'] -> Target (Y): let
Context (X): ['god', 'saw', 'good', 'god'] -> Target (Y): light
```

### **Build CBOW Deep Network Model**

```
In [10]: Import keras.backend as K
from keras.models import Sequential
from keras.layers import Dense, Embedding, Lambda

cbow = Sequential()
cbow.add(Embedding(input_dim=vocab_size, output_dim=embed_size, input_length=cbow.add(Lambda(lambda x: K.mean(x, axis=1), output_shape=(embed_size,)))
cbow.add(Dense(vocab_size, activation='softmax'))

cbow.compile(loss='categorical_crossentropy', optimizer='rmsprop')
print(cbow.summary())
```

Layer (type)	Output Shape	Param #
embedding_2 (Embedding)	(None, 4, 100)	1242500
lambda_2 (Lambda)	(None, 100)	0
dense_2 (Dense)	(None, 12425)	1254925
Total params: 2,497,425 Trainable params: 2,497,425 Non-trainable params: 0		
None		

### Train model for 5 epochs

WARNING:tensorflow:From c:\users\finan\appdata\local\programs\python\python 37\lib\site-packages\tensorflow\python\ops\math\_ops.py:3066: to\_int32 (from tensorflow.python.ops.math\_ops) is deprecated and will be removed in a futu re version.

```
Instructions for updating:
Use tf.cast instead.
Processed 100000 (context, word) pairs
Processed 200000 (context, word) pairs
Processed 300000 (context, word) pairs
                Loss: 4040066.8243356827
Epoch: 1
Processed 100000 (context, word) pairs
Processed 200000 (context, word) pairs
Processed 300000 (context, word) pairs
Epoch: 2
                Loss: 4252849.414020351
Processed 100000 (context, word) pairs
Processed 200000 (context, word) pairs
Processed 300000 (context, word) pairs
Epoch: 3
                Loss: 4221319.320678599
Processed 100000 (context, word) pairs
Processed 200000 (context, word) pairs
Processed 300000 (context, word) pairs
                Loss: 4374675.963517152
Epoch: 4
Processed 100000 (context, word) pairs
Processed 200000 (context, word) pairs
Processed 300000 (context, word) pairs
               Loss: 4467728.309007732
Epoch: 5
```

### Get word embeddings

```
In [12]:
               weights = cbow.get weights()[0]
               weights = weights[1:]
               print(weights.shape)
               pd.DataFrame(weights, index=list(id2word.values())[1:]).head()
               (12424, 100)
    Out[12]:
                            0
                                                                                                  7
                unto -1.558268
                               0.480393
                                          0.007157 -1.124351
                                                              0.349770 -0.177132
                                                                                 0.429398
                                                                                           0.510010 -0
                lord -2.782228
                                0.594669
                                         -0.572333 -1.998984
                                                             -0.467158
                                                                        1.464037
                                                                                 -0.388773
                                                                                           0.573977
                thou -2.037416 -0.173713
                                          1.115885 -1.430719 -0.205978
                                                                        1.162578
                                                                                 0.658434
                                                                                           -0.623687
                 thy -1.139119 0.730314 -0.308474 -1.363923
                                                              0.689318
                                                                        0.746845
                                                                                  0.102472 -0.284844
                qod -1.642045 -0.098926
                                          0.760895 -0.941579
                                                              0.043936
                                                                       -0.016048
                                                                                 1.278149 -0.154688
               5 rows × 100 columns
```

# Build a distance matrix to view the most similar words (contextually)

```
In [13]:
             from sklearn.metrics.pairwise import euclidean distances
             # compute pairwise distance matrix
             distance matrix = euclidean distances(weights)
             print(distance_matrix.shape)
             # view contextually similar words
             similar_words = {search_term: [id2word[idx] for idx in distance_matrix[word2i
                                for search term in ['god', 'jesus', 'noah', 'egypt', 'johr
             similar_words
             (12424, 12424)
   Out[13]: {'god': ['things', 'ye', 'also', 'might', 'therefore'],
               'jesus': ['faith', 'world', 'law', 'glory', 'spirit'],
              'noah': ['adam', 'barnabas', 'lamech', 'shem', 'cain'],
              'egypt': ['pharaoh', 'camp', 'led', 'money', 'darkness'],
              'john': ['galilee', 'peter', 'angels', 'ship', 'violence'],
               'gospel': ['preached', 'crucified', 'apostles', 'preach', 'powers'],
              'moses': ['aaron', 'pharaoh', 'rose', 'died', 'throughout'],
              'famine': ['pestilence', 'portion', 'shadow', 'chaldeans', 'possession']}
```

# Implementing a word2vec model using a skip-gram neural network architecture

#### **Build Vocabulary**

### Build and View sample skip grams ((word1, word2) -> relevancy)

```
In [15]:

    ★ from keras.preprocessing.sequence import skipgrams

             # generate skip-grams
             skip grams = [skipgrams(wid, vocabulary size=vocab size, window size=10) for
             # view sample skip-grams
             pairs, labels = skip_grams[0][0], skip_grams[0][1]
             for i in range(10):
                  print("({:s} ({:d}), {:s} ({:d})) -> {:d}".format(
                        id2word[pairs[i][0]], pairs[i][0],
                        id2word[pairs[i][1]], pairs[i][1],
                        labels[i]))
              (bible (5766), king (13)) -> 1
              (bible (5766), james (1154)) -> 1
             (king (13), james (1154)) -> 1
              (bible (5766), knowledge (374)) -> 0
             (james (1154), railings (12195)) -> 0
              (king (13), machnadebai (10146)) -> 0
             (king (13), bible (5766)) -> 1
             (james (1154), bible (5766)) -> 1
              (bible (5766), log (4765)) -> 0
             (james (1154), mine (84)) \rightarrow 0
```

### **Build Skip-gram Deep Network Model**

```
In []: ► from keras.layers import dot
            from keras.layers.core import Dense, Reshape
            from keras.layers.embeddings import Embedding
            from keras.models import Sequential
            word_model = Sequential()
            word model.add(Embedding(vocab size, embed size,
                                     embeddings initializer="glorot uniform",
                                     input length=1))
            word_model.add(Reshape((embed_size, )))
            context model = Sequential()
            context_model.add(Embedding(vocab_size, embed_size,
                              embeddings initializer="glorot uniform",
                              input length=1))
            context_model.add(Reshape((embed_size,)))
            model = Sequential()
            model.add(dot([word_model, context_model], axes=1,normalize=False))
            model.add(Dense(1, kernel initializer="glorot uniform", activation="sigmoid")
            model.compile(loss="mean squared error", optimizer="rmsprop")
            print(model.summary())
```

### Train the model for 5 epochs

### **Get word embeddings**

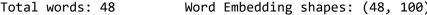
```
In []: M merge_layer = model.layers[0]
    word_model = merge_layer.layers[0]
    word_embed_layer = word_model.layers[0]
    weights = word_embed_layer.get_weights()[0][1:]

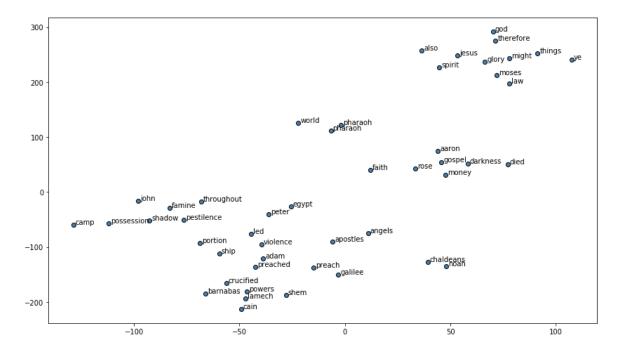
    print(weights.shape)
    pd.DataFrame(weights, index=id2word.values()).head()
```

# Build a distance matrix to view the most similar words (contextually)

### Visualize word embeddings

```
In [35]:
             from sklearn.manifold import TSNE
             words = sum([[k] + v for k, v in similar_words.items()], [])
             words ids = [word2id[w] for w in words]
             word_vectors = np.array([weights[idx] for idx in words_ids])
             print('Total words:', len(words), '\tWord Embedding shapes:', word_vectors.sh
             tsne = TSNE(n components=2, random state=0, n iter=10000, perplexity=3)
             np.set printoptions(suppress=True)
             T = tsne.fit_transform(word_vectors)
             labels = words
             plt.figure(figsize=(14, 8))
             plt.scatter(T[:, 0], T[:, 1], c='steelblue', edgecolors='k')
             for label, x, y in zip(labels, T[:, 0], T[:, 1]):
                 plt.annotate(label, xy=(x+1, y+1), xytext=(0, 0), textcoords='offset poir
             Total words: 48
                                     Word Embedding shapes: (48, 100)
```





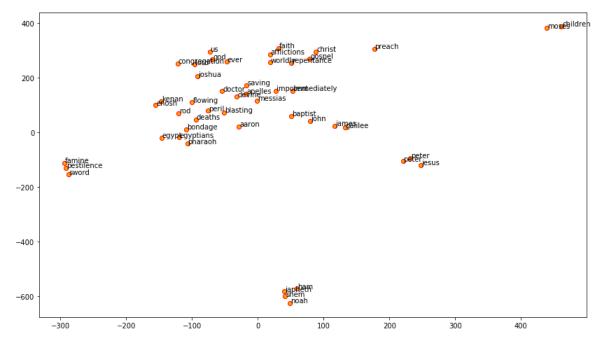
### Leveraging gensim for building a word2vec model

```
In [48]:

    ★ from gensim.models import word2vec

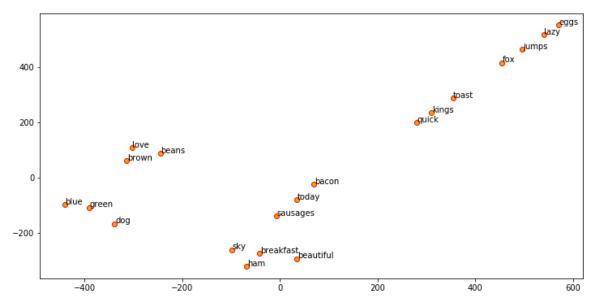
              # tokenize sentences in corpus
              wpt = nltk.WordPunctTokenizer()
              tokenized corpus = [wpt.tokenize(document) for document in norm bible]
              # Set values for various parameters
              feature size = 100  # Word vector dimensionality
              window context = 30
                                               # Context window size
              min_word_count = 1  # Minimum word count
              sample = 1e-3  # Downsample setting for frequent words
              w2v_model = word2vec.Word2Vec(tokenized_corpus, size=feature_size,
                                            window=window context, min count=min word count,
                                            sample=sample, iter=50)
              # view similar words based on gensim's model
              similar_words = {search_term: [item[0] for item in w2v_model.wv.most_similar(
                                  for search_term in ['god', 'jesus', 'noah', 'egypt', 'john'
               similar words
    Out[48]: {'god': ['lord', 'worldly', 'saving', 'ever', 'us'],
                'jesus': ['peter', 'messias', 'immediately', 'apelles', 'impotent'], 'noah': ['shem', 'ham', 'japheth', 'kenan', 'enosh'],
                'egypt': ['egyptians', 'pharaoh', 'bondage', 'flowing', 'rod'],
                'john': ['baptist', 'james', 'peter', 'galilee', 'devine'],
'gospel': ['christ', 'repentance', 'faith', 'preach', 'afflictions'],
                'moses': ['congregation', 'children', 'joshua', 'aaron', 'doctor'],
                'famine': ['pestilence', 'peril', 'sword', 'deaths', 'blasting']}
```

### Visualizing word embeddings



### Applying the word2vec model on our sample corpus

### Visualize word embeddings



## Sample word embedding

# **Build framework for getting document level embeddings**

```
In [53]:
              def average word vectors(words, model, vocabulary, num features):
                  feature vector = np.zeros((num features,),dtype="float64")
                  nwords = 0.
                  for word in words:
                       if word in vocabulary:
                           nwords = nwords + 1.
                           feature vector = np.add(feature vector, model[word])
                  if nwords:
                       feature vector = np.divide(feature vector, nwords)
                   return feature vector
              def averaged word vectorizer(corpus, model, num features):
                  vocabulary = set(model.wv.index2word)
                  features = [average_word_vectors(tokenized_sentence, model, vocabulary, r
                                    for tokenized sentence in corpusl
                   return np.array(features)
In [54]:
              w2v_feature_array = averaged_word_vectorizer(corpus=tokenized_corpus, model=v
                                                               num features=feature size)
              pd.DataFrame(w2v feature array)
              c:\users\finan\appdata\local\programs\python\python37\lib\site-packages\ipy
              kernel launcher.py:9: DeprecationWarning: Call to deprecated ` getitem
              (Method will be removed in 4.0.0, use self.wv.__getitem__() instead).
                if name == ' main ':
    Out[54]:
                        0
                                                                                           7
               0
                  0.002783 -0.022939 -0.022471
                                               0.004143
                                                       -0.029013 -0.003862
                                                                          -0.010397 -0.020175
                                                                                              0.02
                  0.001214
                           -0.018318
                                    -0.024470
                                              -0.002171
                                                        -0.009240
                                                                 -0.001448
                                                                          -0.018517
                                                                                    -0.016627
                                                                                              0.00
                                                                                   -0.016422
                 -0.014307
                            0.000737
                                     0.002849
                                               0.011757
                                                        0.015777 -0.010199
                                                                           0.015807
                                                                                              0.00
                 -0.002899
                            0.022346
                                               0.009551
                                                        0.014934
                                                                 -0.004253
                                                                                    0.001638
                                     0.005972
                                                                           0.010546
                                                                                              0.01
                  0.002709
                            0.014457 -0.007672
                                                        0.008650
                                                                 -0.000316
                                               0.001225
                                                                           0.002582
                                                                                   -0.002047
                                                                                             -0.00
                 -0.006682
                          -0.001316 -0.001212
                                               0.012979
                                                        0.014086
                                                                  0.004563
                                                                           0.012740
                                                                                    -0.014526
                                                                                              0.00
                  0.008368
                           -0.027867
                                    -0.015179
                                              -0.006986
                                                        -0.019475
                                                                 -0.004753
                                                                          -0.005497
                                                                                    -0.007990
                                                                                              0.02
                 -0.015013 -0.003183
                                     0.008187
                                               0.016703
                                                        0.019562 -0.002188
                                                                           0.009358
                                                                                    -0.013956
                                                                                             -0.002
```

### Clustering with word embeddings

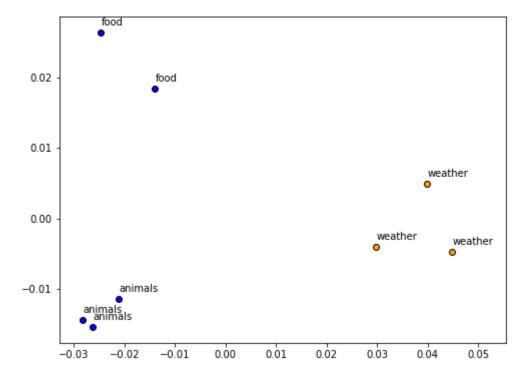
#### Out[55]:

	Document	Category	ClusterLabel
0	The sky is blue and beautiful.	weather	0
1	Love this blue and beautiful sky!	weather	0
2	The quick brown fox jumps over the lazy dog.	animals	1
3	A king's breakfast has sausages, ham, bacon, eggs, toast and beans	food	1
4	I love green eggs, ham, sausages and bacon!	food	1
5	The brown fox is quick and the blue dog is lazy!	animals	1
6	The sky is very blue and the sky is very beautiful today	weather	0
7	The dog is lazy but the brown fox is quick!	animals	1

```
In [56]: M from sklearn.decomposition import PCA

pca = PCA(n_components=2, random_state=0)
pcs = pca.fit_transform(w2v_feature_array)
labels = ap.labels_
categories = list(corpus_df['Category'])
plt.figure(figsize=(8, 6))

for i in range(len(labels)):
    label = labels[i]
    color = 'orange' if label == 0 else 'blue' if label == 1 else 'green'
    annotation_label = categories[i]
    x, y = pcs[i]
    plt.scatter(x, y, c=color, edgecolors='k')
    plt.annotate(annotation_label, xy=(x+1e-4, y+1e-3), xytext=(0, 0), textcolors
```



### GloVe Embeddings with spaCy

```
# Use the following command to install spaCy
> pip install -U spacy

OR
> conda install -c conda-forge spacy

# Download the following language model and store it in disk
https://github.com/explosion/spacy-models/releases/tag/en_vectors_web_lg-2.0.0

# Link the same to spacy
```

```
> python -m spacy link ./spacymodels/en_vectors_web_lg-2.0.0/en_vectors_web_lg
en_vecs

Linking successful
    ./spacymodels/en_vectors_web_lg-2.0.0/en_vectors_web_lg -->
    ./Anaconda3/lib/site-packages/spacy/data/en_vecs

You can now load the model via spacy.load('en_vecs')
```

```
In []: M import spacy
#nlp = spacy.load('en_vecs')
nlp = spacy.load('en_vectors_web_lg')

total_vectors = len(nlp.vocab.vectors)
print('Total word vectors:', total_vectors)
```

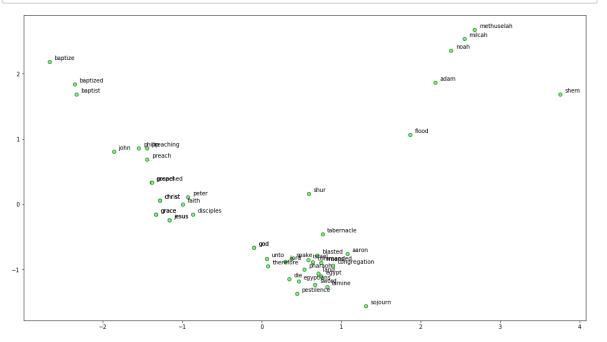
# Visualize GloVe word embeddings

### Cluster documents with GloVe Embeddings

```
In []: M doc_glove_vectors = np.array([nlp(str(doc)).vector for doc in norm_corpus])
    km = KMeans(n_clusters=3, random_state=0)
    km.fit_transform(doc_glove_vectors)
    cluster_labels = km.labels_
    cluster_labels = pd.DataFrame(cluster_labels, columns=['ClusterLabel'])
    pd.concat([corpus_df, cluster_labels], axis=1)
```

# Leveraging gensim for building a FastText model

```
In [66]:
             from gensim.models.fasttext import FastText
             wpt = nltk.WordPunctTokenizer()
             tokenized corpus = [wpt.tokenize(document) for document in norm bible]
             # Set values for various parameters
             feature size = 100  # Word vector dimensionality
             window_context = 50
                                          # Context window size
             min_word_count = 5  # Minimum word count
             sample = 1e-3  # Downsample setting for frequent words
             ft_model = FastText(tokenized_corpus, size=feature_size, window=window_contex)
                                 min count=min word count, sample=sample, sg=1, iter=50)
             # view similar words based on gensim's model
In [67]:
             similar_words = {search_term: [item[0] for item in ft_model.wv.most_similar(|
                               for search_term in ['god', 'jesus', 'noah', 'egypt', 'john'
             similar words
   Out[67]: {'god': ['lord', 'jesus', 'therefore', 'unto', 'christ'],
               jesus': ['christ', 'god', 'faith', 'disciples', 'grace'],
              'noah': ['methuselah', 'milcah', 'flood', 'adam', 'shem'],
              'egypt': ['land', 'pharaoh', 'egyptians', 'israel', 'shur'],
              'john': ['baptist', 'baptize', 'peter', 'baptized', 'philip'],
              'gospel': ['preached', 'preach', 'christ', 'preaching', 'grace'],
              'moses': ['aaron', 'commanded', 'congregation', 'tabernacle', 'spake'],
              'famine': ['pestilence', 'sword', 'sojourn', 'blasted', 'die']}
```



```
In [69]:
          ▶ ft model.wv['jesus']
   Out[69]: array([ 0.13958982, -0.05803353, 0.00735883, 0.30419916,
                                                                         0.28101364,
                    -0.09217732, -0.35205486, -0.10779286, -0.20662811,
                                                                         0.01127647,
                     0.56522685, -0.25434008, -0.11027662, -0.09649172,
                                                                         0.01176434,
                     0.4307362 , 0.28582764, -0.0331421 , -0.07566007, -0.0571156 ,
                    -0.09087794, -0.11904453, -0.1753413 , -0.33740595,
                                                                         0.10848472,
                    -0.00883908, -0.04714192, 0.19704778,
                                                            0.09685205,
                                                                         0.21058671,
                    -0.08167323, -0.30198124,
                                              0.31116888,
                                                            0.07161883,
                                                                         0.37063324,
                     0.6008908 , -0.13673909, -0.4890262 , -0.52823555,
                                                                         0.28040478,
                                 0.47069886, -0.0484414,
                    -0.05382667,
                                                            0.61672145,
                                                                         0.24615462,
                    -0.43410167, 0.11218455, 0.30876148,
                                                           0.13442726, -0.21992294,
                     0.11206417, 0.00722101, -0.45872113, -0.16935116,
                                                                         0.29874218,
                     0.19664103, -0.61964315, -0.25932878,
                                                            0.07407966,
                                                                         0.2578632 ,
                     0.08950499, -0.27822822, 0.32461262, -0.22445315,
                                                                         0.1997942 ,
                                 0.08593477, -0.09900978,
                     0.27103156,
                                                            0.0666374 ,
                                                                         0.4836858 ,
                     0.08429956, 0.08149047, 0.08276018, 0.04630444,
                                                                         0.21469755,
                     0.03319091, -0.10793024, -0.26813093, -0.04301734,
                                                                         0.09764177,
                    -0.22126143, 0.1392126 , -0.41733798, 0.28070012, -0.19648044,
                     0.14717151, -0.21817796, 0.40246776, -0.02561598, -0.3541444 ,
                                 0.27027574, -0.18075562, 0.00881244,
                     0.05279887,
                                                                        0.04249534,
                     0.05854722, 0.45185554, 0.3729318, -0.06063852, -0.02820194],
                   dtype=float32)
             print(ft model.wv.similarity(w1='god', w2='satan'))
In [70]:
             print(ft model.wv.similarity(w1='god', w2='jesus'))
             0.33519396
             0.70369
In [71]:
             st1 = "god jesus satan john"
             print('Odd one out for [',st1, ']:', ft_model.wv.doesnt_match(st1.split()))
             st2 = "john peter james judas"
             print('Odd one out for [',st2, ']:', ft_model.wv.doesnt_match(st2.split()))
             c:\users\finan\appdata\local\programs\python\python37\lib\site-packages\gen
             sim\models\keyedvectors.py:858: FutureWarning: arrays to stack must be pass
             ed as a "sequence" type such as list or tuple. Support for non-sequence ite
             rables 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 word
             s).astype(REAL)
             Odd one out for [ god jesus satan john ]: satan
             Odd one out for [ john peter james judas ]: judas
```